Understanding rule-breaking behaviour in conservation

Aidan Keane

Centre for Environmental Policy & Department of Life Sciences
Imperial College London

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Declaration

This dissertation is the result of my own work and includes nothing which is the outcome of work done by or in collaboration with others, except where specifically indicated in the text.

Aidan Keane, May 2010

Abstract

Conservation interventions often aim to change people's behaviour by discouraging actions which damage species or ecosystems. An important tool for achieving this goal is the creation and enforcement of rules. To date, however, the role of enforcement has been neglected as a subject of study in conservation. This thesis outlines a theoretical framework for understanding rule-breaking behaviour and highlights practical issues which must be addressed to improve the effectiveness of conservation strategies.

Understanding illegal behaviour requires understanding the factors which motivate potential rule-breakers' decisions. I begin by reviewing economic models of crime and their application to natural resource management. In general, these models assume that rules are perfectly understood. I demonstrate that this need not be true using a case study of knowledge of wildlife laws in Madagascar. Knowledge was generally poor and varied between individuals. Encouragingly, improvements in understanding were associated with involvement with local conservation initiatives.

Previous analyses have often focused on top-down approaches and on the effects of certainty and severity of punishment. I extend these models, using an individual-based simulation of community-based wildlife management to explore the effects of strategic decision-making and individual heterogeneity. Their importance varies according to the manager's choice of policy levers, with changes to the fine level producing more robust outcomes than changes to the fees paid to monitors.

For effective deterrence it is also necessary to understand spatio-temporal patterns of rule-breaking. Patrol data are commonly used for this, but are difficult to interpret. Using a 'Virtual Ranger' model, I demonstrate that both rule-breakers' and enforcement agents' behaviour can introduce bias into analyses of patrol data based on catch-per-unit-effort measures. Finally, I review the use of encounter data, a class of data which includes patrol data, and highlight how sharing lessons learned with other fields could bring mutual benefits.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Rules and regulations are essential components of many conservation interventions, including contracts promising payment in return for the provision of ecosystem services (e.g., Pagiola, 2008), quotas regulating the exploitation of natural resources (e.g., Hatcher and Gordon, 2005), and laws protecting habitats and species (e.g., Rowcliffe et al., 2004). These rules might be agreed at any scale from the international (e.g., EU fishing quotas) or national (e.g., National Parks) right down to the local (e.g., community reserves), can involve a range of institutions, from governments to rural communities, and may be externally imposed or have evolved in situ. The purpose of rules is to change people's behaviour, discouraging actions that are harmful to species or ecosystems and encouraging those which are beneficial, and they are just as necessary in participatory, community-based projects as they are in the top-down management of protected areas. However, the mere existence of rules does not guarantee that they will be followed (Rowcliffe et al., 2004), so the success of conservation interventions often depends upon their ability to secure the compliance of key stakeholders. Understanding why rule-breaking occurs and how it can be prevented should therefore be a central concern in conservation, but to date the topic has been under-researched.

Gavin et al. (2010) identified four broad questions that research into rule-breaking should seek to answer. These asked (1) which rules are broken, (2) where rule-breaking occurs, (3) who breaks rules, and (4) why rules are broken. Two further questions that could fruitfully be added to this list are (5) what impact rule-breaking has on conservation, and (6) how rule-breaking can be reduced efficiently and fairly. In many cases such questions have proved difficult to answer because the threat of punishment creates incentives for rule-breakers to conceal evidence of illicit behaviours (Blank and Gavin, 2009; St. John et al., 2010). Furthermore, few factors which are thought to influence rule-breaking decisions, such as the level of resources devoted to enforcing rules and the availability of alternative livelihood opportunities (Skonhoft and Solstad, 1996; Damania et al., 2005), are amenable to experimental manipulation, due to ethical concerns and practical limitations.

Empirical studies of rule-breaking in conservation have relied largely on data derived from the patrol reports of protected area guards (e.g., Holmern et al., 2007), survey techniques specially adapted to preserve the anonymity of respondents (e.g., the randomised response and nominative techniques; St. John et al., 2010) and inferences from indirect measures of illegal activity (e.g., analyses of illegal goods reaching markets; Lee et al., 2005; Clarke et al., 2006). However, the potential of these methods for generating data suitable for monitoring rule-breaking and for assessing strategies to improve compliance has yet to be fully explored (Gavin et al., 2010).

Modelling approaches have also been important, allowing researchers to predict the likely outcomes of different conservation strategies on levels of compliance (e.g., Milner-Gulland and Leader-Williams, 1992), but the theory underpinning models of rule enforcement in conservation is underdeveloped. For example, the effects of enforcement on compliance in fisheries have been explored using simple bioeconomic models (e.g., Sutinen and Andersen, 1985) and household utility models have been used to explore the effects of different enforcement strategies on decisions about whether or not to poach at the local scale (e.g., Damania et al., 2005). However, decisions about whether or not to break rules are likely to be complex and vary between individuals and situations. For example, in many conservation settings an individual's decision about whether or not to break the rules will depend on the behaviour of others around them, but only a few studies have incorporated the effects of strategic decision-making on compliance with rules (e.g., Mesterton-Gibbons and Milner-Gulland, 1998; Byers and Noonburg, 2007). Similarly, models of enforcement have tended to ignore the heterogeneity that occurs between different individuals in terms of their skills, personalities and opportunities, and assume that this does not affect their decision-making. The lack of a well-developed theoretical framework to guide the development of models of enforcement and compliance means it is often difficult to translate the findings from existing models into practical advice for managers and policy makers that are applicable to the situations faced in conservation projects. Consequently, there is considerable scope for further work to strengthen the theoretical underpinnings and enhance the practical relevance of modelling approaches to understanding rule-breaking and compliance in conservation.

Perhaps the most difficult questions to address are why rule-breaking occurs, and how rule-breaking can be reduced, but these issues are crucial to planning and implementing effective conservation action. A prerequisite for rules to bring about changes in behaviour is that they are well known and understood (Page and Radomski, 2006; Nkonya et al., 2008) but there has been no attempt to identify factors which predict knowledge of important rules in conservation. Even well known and understood rules may not change behaviour if there are no incentives for individuals to follow them. Managers have many different tools at their disposal which are intended to create incentives for conservation. Although enforcement has remained widely used and a crucial component of many conservation interventions, research in the last two decades has focused more on other methods (Oates, 1999). For example, Integrated Conservation and Development Projects and Community Based Conservation approaches have been promoted as a means of improving compliance while encouraging local development (Brandon and Wells, 1992; Barrett and Arcese, 1995; Wells, 1999). Others have argued that by making positive incentives conditional on conservation performance, direct payment schemes are an efficient way of achieving conservation (Ferraro, 2001; 2002). The way in which these approaches work has been well explored, both in theory (e.g., Agrawal and Gibson, 1999; Berkes, 2004; Wunder, 2007; Sommerville et al., 2009) and in practice (e.g., Flintan and Hughes, 2001; Engel et al., 2008; Wunder et al., 2008), but compliance with rules has received little attention.

1.2 Aims & Objectives

The aim of this thesis is to improve the study of rule-breaking in conservation, drawing upon the lessons that have been learned in other fields to develop a theoretical basis for understanding the incentives that rule-breakers face, and to develop methods for collecting and using field data in a way that informs decision-making for more effective law enforcement.

I address a number of gaps in the literature concerning local people's understanding of conservation rules, the role of individual incentives in promoting or undermining compliance, understanding how law enforcement activities can change rule-breaking incentives, and assessing the usefulness of patrol data as a source of information about rule-breaking.

Specific objectives contributing to the thesis's aim included

- to review work from other fields which has dealt with the causes of rule-breaking in order to draw lessons for conservation
- to test which factors are associated with higher awareness of conservation rules
- to examine how the decision making of potential rule-breakers and enforcement agents influences the effectiveness of enforcement strategies
- to test the suitability of patrol data as a source of information for learning about the effectiveness of enforcement as a deterrent to rule-breaking
- to compare patrol data with other forms of encounter data in order to improve their analysis

1.3 Thesis outline

The thesis is structured as follows:

Chapter 2 reviews work from other fields which has asked why people choose to break rules and how enforcement measures can best be used to increase levels of compliance. Economic models of decision-making have played a key role in understanding rule-breaking, but there have been relatively few attempts to apply these approaches to conservation. Models will continue to be useful tools for studying compliance, but improvements are needed in the realism with which they reflect key aspects of human behaviour.

Chapter 3 examines levels of understanding of an important set of wildlife conservation laws among rural villagers living close to Madagascar's eastern rainforests. I show that, although awareness of these laws is generally low, there is considerable variation between individuals, with higher levels of education and involvement with community resource management and tourism associated with greater understanding.

Chapter 4 uses an individual-based simulation model to explore the effects of differences in the incentives faced by individuals, be they rule-breakers or enforcement agents, in determining the effectiveness of enforcement measures. Novel factors considered within this model are the effects of individual heterogeneity, avoidance measures taken by rule-breakers and the incentives for enforcement agents to monitor effectively.

Chapter 5 uses a "Virtual Ranger" simulation model to explore the properties of encounters-per-unit-effort indices as a measure of rule-breaking, and asks whether analyses of patrol data based upon these indices can provide useful information about the effectiveness of enforcement for policy-makers and managers in the face of biases caused by the behaviour of rule-breakers and patrols.

Chapter 6 takes a broader look at patrol data as a sub-class of encounter data, sharing many properties with fisheries catch data and bushmeat offtake data, as well as with encounter data generated during ecological surveys. I argue that a recognition of the similarities between these types of data, and of the biases that are common to all, as well as exchange of ideas concerning methods to counter these biases, could help to improve the analysis of encounter-based data in all of these areas.

Chapter 7 offers a discussion of the thesis's key findings and conclusions and suggests useful avenues along which future research might proceed.

Chapter 2

The Sleeping Policeman: Understanding issues of enforcement and compliance in conservation

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2.1 Introduction: Rules in Conservation

Managing biological resources requires that rules of behaviour are followed. These rules might be agreed at any scale, from the international (e.g., EU fishing quotas) or national (e.g., National Parks) right down to the local (e.g., community reserves). They can involve a range of institutions, from governments to rural communities, and may be externally imposed or have evolved in situ. Whatever their provenance, rules, and the management systems which depend on them, are worthless without compliance. However compliance with the rules of resource management systems cannot be taken for granted. Resistance to conservation measures can arise because of differences in the spatial and temporal distributions of the resulting costs and benefits (Wells, 1992). For example, significant costs are often borne by local individuals who depend heavily on the resource, while the benefits arising from conservation may be less immediate and accrue to society as a whole (Balmford and Whitten, 2003; Chan et al., 2007). Successful management of natural resources therefore requires consideration of how rule-breaking behaviour can be discouraged in resource users. Despite its importance, this issue has not received sufficient attention in the conservation literature.

Enforcement—monitoring adherence to rules and agreements and punishing infractions when they are detected—is an essential part of successful conservation and natural resource management (NRM) (Ostrom, 1990; Gezelius, 2002; Walsh et al., 2003; Rowcliffe et al., 2004; Gibson et al., 2005). Punishments may take various forms, from fines and prison terms to social sanctioning, depending on the enforcement system. Several studies of illegal hunting have shown that reducing the effort devoted to enforcement (e.g., lowering investment in equipment and training, or patrolling less frequently) increases the number of poaching incidents and can harm wildlife populations (Arcese et al., 1995; Jachmann and Billiouw, 1997; de Merode et al., 2007). For example, investment in enforcement has been an important determinant of changes in the buffalo, elephant and black rhino populations in the Serengeti National Park, Tanzania (Hilborn et al., 2006). Similar effects have been seen in marine systems where effective enforcement of marine protected areas has been shown to reduce poaching-driven changes to reef fish communities (Walmsley and White, 2003; Floeter et al., 2006; Samoilys et al., 2007).

Enforcement is costly, however, requiring investment in training, equipment and salaries. It may also have other costs. For example enforcement activities can erode trust between local people and conservation authorities (Infield and Namara, 2001) and undermine traditional systems of resource management (Wilshusen et al., 2002; Horning, 2006; Gelcich et al., 2006). With limited resources available to conservation, particularly in the developing world (Balmford et al., 2002), enforcement at a level which produces no infractions can be prohibitively expensive. Techniques for optimizing enforcement strategies—maximising benefit while minimising cost—should therefore be of great interest to practical conservation.

Directly studying compliance and its determinants is problematic since rule-breakers are usually unwilling to reveal themselves or to discuss their motivations freely for fear of punishment. Data on illegal activity are therefore potentially prone to unquantifiable biases. Consequently, much of our understanding of this topic stems from modelling studies which provide powerful methods for explicitly addressing these uncertainties and help managers and policy makers to predict the impacts of future changes to enforcement regimes. We review models of compliance with rules, focusing on those that have been applied to conservation and NRM. We structure our review according to the scale at which decisions are analysed, moving from the individual to the group and institutional levels. African elephants are used as a case study to illustrate how such approaches have been applied in practice. Finally, we highlight several areas where we feel modelling can contribute more to our understanding of rule-breaking behaviour by resource users.

2.2 Individual level models

Many theories attempt to explain why non-compliant behaviour occurs and how it can be discouraged. Psychological theories of compliance with rules and social norms often assume that the decision-making processes of rule-breakers differ from those of other people. Cognitive theories of compliance argue that these behaviours stem from differences in personal moral development (e.g., Goslin, 1973; Tapp et al., 1977; Kohlberg, 1981). Another important group, the social learning theories (e.g., Burgess and Akers, 1966; Akers, 1985; Sutherland et al., 1992), suggest that individuals decision-making processes are conditioned by interactions with their environment.

By contrast, sociological and economic theories of compliance assume that the decision-making process in rule-breakers is not fundamentally different from that in other people. Normative theories argue that an individuals perceptions of the legitimacy and fairness of rules are crucial to decision-making (Tyler, 2006). Instrumental theories, on the other hand, hold that acts of non-compliance occur because the benefits anticipated by the decision-maker outweigh the costs (Becker, 1968).

2.2.1 Economic incentives

The study of optimal enforcement has largely focussed on instrumental approaches, using economic models to answer the question of how best to modify individual incentives in favour of compliance. An individuals supply of offences may be modelled as a decreasing function of two factors of enforcement: the probability of an act of non-compliance being detected and punished and the severity of punishment that results (Becker, 1968). The process of detection is inherently costly, requiring law enforcers to be paid and equipped, whereas punishments may take the form of fines (assumed to be a costless transaction). This suggests that the optimal enforcement strategy is to reduce the amount of costly monitoring while increasing the size of penalty, thereby maintaining offences at an acceptable level with lower enforcement costs.

There are, however, several reasons why severe penalties may be undesirable. Extensions to Beckers model suggest that if sanctions are socially costly (Kaplow, 1990) or if corruption is present (Becker and Stigler, 1974), the optimal fine level may not be the highest possible. Similarly, if individuals are risk averse (Polinsky and Shavell, 1979), are imperfectly informed about their probability of being caught (Bebchuk and Kaplow, 1992), respond to penalties by trying to avoid detection (Malik, 1990), or vary in their wealth (Polinsky and Shavell, 1991) the optimal level of fines may be reduced. Severe penalties are also morally questionable and can lead to an increase in serious crimes relative to less damaging offences due to the loss of marginal deterrence (Stigler, 1970).

A large number of studies have attempted to empirically test the deterrence effect of enforcement measures upon crime rates in developed countries, with mixed results (see Cameron 1988 for a review). Ehrlich (1996) argues that there is such an effect and that the probability of detection may be more influential than severity of punishment. However, issues such as the use of data at different levels of aggregation, uncertainty about the level of private protection and the difficulty in separating the influence of deterrence and incapacitation leave many studies open to criticism (Cameron, 1988; Ehrlich, 1996).

Early bioeconomic models of NRM assumed enforcement was costless and produced perfect compliance (e.g., Clark, 1990). The implications of imperfect enforcement in NRM were first explored in commercial fisheries. In quota-restricted single-species fisheries, for example, enforcement costs may be modelled as an increasing function of the stock size and the legal quota. Consequently, the larger the desired stock size (above the open-access equilibrium) the greater the necessary expenditure on enforcement (Sutinen and Andersen, 1985). More generally, the optimal level of enforcement is attained when the marginal cost of enforcement is equal to its marginal benefit (Becker, 1968; Sutinen and Andersen, 1985; Hallwood, 2004). Other models of fisheries enforcement have considered differences between input controls (e.g., time at sea, equipment) and output controls (e.g., landing quotas; Mazany et al. 1989), and shown that avoidance behaviour affects the socially optimal level of enforcement (Anderson and Lee, 1986; Anderson, 1987).

Several studies have attempted to empirically test the predictions of fisheries enforcement models. Survey data from the Massachusetts lobster fishery show an increasing rate of compliance as the perceived probability of being caught increases (Sutinen and Gauvin, 1989). Similarly, data from Quebec fisheries show a greater influence of the probability of detection than severity of punishment on offences (Furlong, 1991). Data from federally managed US groundfish fisheries, on the other hand, suggest that a decline in compliance from 1982 to 1988 was best explained by poor stock conditions and high market prices, with enforcement having a negligible effect (Sutinen et al., 1990).

The effects of the design of enforcement on poaching decisions have also been explored. Using a model of multi-species bushmeat hunting as a component of the household economy, measures targeting bushmeat sales were shown to be more effective than those targeting hunting directly (Damania et al., 2005). The benefits for different hunted species are complicated by technology switching (e.g., between snaring and gun-hunting), however, and are therefore ambiguous. Clayton et al. (1997) investigated economic deterrents to hunting two wild pig species in Indonesia, only one of which can be legally hunted. A fine on market dealers for selling the illegal species was shown to be most effective, and more equitable than other approaches considered since it does not affect the welfare of individuals who hunt the legal species.

2.2.2 Morality, equity and justice

Alternative models of compliance with regulations emphasise the role of normative factors, such as moral obligation and perceptions of fairness and justice. Normative factors have been incorporated into economic frameworks by assuming that an individuals utility is increased by performing actions that are socially acceptable or beneficial (Sutinen and Kuperan, 1999; Nielsen, 2003b). The perceived legitimacy of rules, related to both the fairness and efficiency of the regulatory process and the justice and effectiveness of its outcomes, also affects their acceptance by resource users (Hønneland, 1999; Sutinen and Kuperan, 1999).

In Norway and Newfoundland, some small fisheries achieve high levels of compliance despite low levels of formal enforcement. Gezelius (2002; 2004) suggests that this results from informal sanctions based upon collective moral judgements. Non-compliant individuals are subjected to social opprobrium if their actions are perceived to confer unfair advantages or to be carried out for monetary gain, but not if they are necessary to secure an adequate basic income.

Quantitative empirical evidence on the influence of normative influences on compliance is, however, weak. Nielsen (2003a) identify factors which have a major influence on compliance in small Danish fisheries. The most important factors were instrumental: economic gains and deterrence measures, but normative considerations such as the fairness of rules were also represented. Hatcher et al. (2000) similarly reported a significant positive relationship between perceptions of fairness and participation and levels of compliance in the UK fishery, but Hatcher and Gordon (2005) failed to reproduce this result, finding instead that economic incentives dominate.

2.3 Group level models

In many situations an individuals costs and benefits are affected by the behaviour of others. Understanding decision-making then requires a strategic perspective which has been modelled using game theory. For example, game theoretic approaches have been applied to study the interaction between an enforcement officer and a resource user. In inspection games one player chooses whether or not to monitor the behaviour of another, who chooses whether or not to commit an offence (Tsebelis, 1989). Enforcers are treated as rational, utility-maximising entities. If players interact only once, increasing the severity of penalty does not reduce the number of offences, but instead lowers the (costly) effort devoted to detection by enforcers (Andreozzi, 2004; Tsebelis, 1989). With repeated interactions, increasing the reward enforcers receive for catching criminals does not reduce the number of offences, and might increase it since enforcers can maximise their profit by monitoring less, reducing their costs and encouraging a greater number of offences and bonuses (Andreozzi, 2004). That these results are sensitive to the precise formulation of the game (see Weissing and Ostrom, 1991) highlights the complexity of modelling strategic behaviour in enforcement problems.

Game theoretic approaches have also been used to study common-pool resources (CPR) where monitoring and enforcement are not the preserve of specific individuals or designated agencies but are instead carried out by the resource-users themselves as part of a cooperative effort to manage a natural resource (see Heckathorn 1996 for a review of games which display the properties of cooperative systems). Early paradigms in the analysis of CPR (e.g., Hardin, 1968; Olson, 1971) were formalised as a prisoners dilemma game (Dawes, 1973) and dealt with open access situations where there is little incentive for rational, self-interested individuals to moderate their exploitation in anticipation of future benefits since others may not follow suit. Cooperation can be achieved in the prisoners dilemma under certain conditions (e.g., relatively small group sizes) by allowing repeated interactions (Axelrod and Hamilton, 1981). As described above in small fisheries (Gezelius, 2002; 2004), cooperation can also emerge and persist under less restrictive circumstances if, despite incurring a cost, individuals enforce rules by voluntarily punishing non-cooperators: the strategy of altruistic punishment (Fehr and Gachter, 2002; Fowler, 2005).

Game theoretic models also allow the long-term stability of cooperative agreements to be assessed. Mesterton-Gibbons and Milner-Gulland (1998) model a cooperative NRM system to identify conditions under which a community who do not poach and monitor each others compliance can be stable against invasion by individuals who poach and do not monitor. They find that people must be paid to monitor, even in the absence of poaching. Shared benefits are not sufficient to motivate protection of a communal resource without incentives for enforcement. Furthermore, cooperation breaks down at small community sizes because the likelihood of an infraction being detected becomes too low.

2.4 Institution level models

Some aspects of enforcement are better explored from the point of view of an institution, rather than individuals. For example, the ability of a private authority with legal harvesting rights to prevent poaching has been modelled under different property structures and economic environments (Skonhoft and Solstad, 1996). With well defined but imperfectly enforced rights, the effective property structure and long term stock levels are affected by economic variables such as the profitability of alternatives, cost of enforcement, owners discount rate and the resources market price and non-consumptive value. Some effects are surprising. For example, Skonhoft and Solstad's model predicts that a government intervention to lower enforcement costs would not raise the optimal wildlife stock but allows the owner increase legal harvest since the illegal harvest can be further reduced for the same expenditure.

In many cases, management agencies may be required to cover a proportion of their operating costs. Where non-consumptive uses of wildlife such as tourism are not viable, revenue might be generated by selling permits to hunt common species and fining unlicensed exploitation. A model of a Western African wildlife department suggests that this approach could indeed benefit endangered species (Robinson, 2008). However, hunters using non-selective technologies (e.g., snares) may not be able to restrict their catch to legal species

(Bowen Jones et al., 2003). Punishing the capture of rare species therefore risks causing significant waste by encouraging hunters to discard animals that were killed illegally rather than risk sanctions (cf. bycatch in quota-limited fisheries).

2.5 A case study: Elephants

In the 1970s and 1980s high levels of poaching, stimulated by high ivory prices, threatened the survival of the African elephant (*Loxodonta africana*) and prompted much debate about how illegal hunting should be controlled given the resource-constraints of governments in the elephants range states. The species therefore provides an illustration of how models of enforcement and compliance have been used to inform conservation policy.

The elephant population of the Luangwa Valley, Zambia, has been particularly well studied. From 1972 to the mid-1980s the area lost approximately 75% of its 100,000-strong population (Leader-Williams and Albon, 1988). Although anti-poaching patrols received significant investment from 1979 they largely failed to prevent further decline (Leader-Williams and Albon, 1988). Data from 1979–1985 suggest that although these patrols were well motivated and effective, they were not sufficiently numerous to control illegal hunting over the entire area (Leader-Williams et al., 1990).

Bioeconomic modelling of individual behaviour provides a means of predicting how effective different approaches to tackling poaching in the Luangwa Valley would have been. One such model shows that a fine which increases according to the number of trophies in a poachers possession is a more effective deterrent than a fixed fine, but that increasing the severity of punishment is less effective than increasing the effort devoted to detecting and prosecuting poachers (Milner-Gulland and Leader-Williams, 1992; Leader-Williams and Milner-Gulland, 1993). However, sensitivity analyses suggest that the returns to hunting were so high during this period that unrealistic increases in enforcement effort would have been necessary to reduce poaching to an acceptable level (Milner-Gulland and Leader-Williams, 1992).

By 1989 continuing elephant declines across the continent (Stiles, 2004) led to the species being listed on Appendix 1 of the Convention on the International Trade in Endangered Species of Wild Flora and Fauna (CITES). Banning the international trade in ivory was intended to depress demand at a global scale, reducing the incentives to hunt illegally and thereby facilitating the enforcement of national anti-poaching laws. However the success of the ban is unclear. A series of models intended to assess the ban's effects on incentives to poach have produced ambiguous results, varying according to their particular assumptions and parameterisations (Stiles, 2004).

For example, Jachmann and Billiouw (1997) compare a set of institution-level models of investment in enforcement, arguing that the variation in elephant mortality observed in the Luangwa Valley between 1988–1995 can be explained by changes in enforcement, without any need to invoke the effect of the ban. Bulte and van Kooten (1999), on the other hand, argue that within the range of parameter values estimated for the period 1979–1985, and assuming a discount rate greater than 5%, the ivory ban should have increased elephant numbers. Their analysis also suggests that the response of elephant populations to changing enforcement levels is greater if trade is allowed than if it is not.

Expectation of future management policies can affect current prices and therefore influence incentives to poach. Kremer and Morcom (2000) warned that anti-poaching policies that are expected to reduce the future supply of ivory could raise incentives to poach by creating the expectation of price rises. Using a dynamic institution-level model Kremer and Morcom (2000) argued that if managers can credibly commit to tough enforcement should elephant populations fall, the incentives to poach caused by anticipated higher ivory prices may be reduced. Where tough enforcement is not credible, creating stockpiles of ivory and threatening to sell this should populations fall, may also be effective at reducing poaching. Bulte (2003) counter that the CITES ban might create incentives for governments to harvest their elephant populations to extinction if the prices for stored ivory are sufficiently high and if extinction is expected to precipitate the lifting of the trade-ban. Although limited by the availability of suitable data, an attempt to assess the effects of a one-off sale of stockpiled ivory in 1999 using mortality data from Kenya and Zimbabwe suggests that it had little effect on overall elephant poaching levels (Bulte et al., 2007).

2.6 Challenges for future studies of enforcement and compliance

The preceding sections have highlighted the strengths of modelling approaches as tools to inform debate about the design and implementation of enforcement measures. However, we feel there are several ways in which models of enforcement and compliance can be further improved. Our review demonstrates that models of enforcement have tended to focus on economic factors influencing decision making, with less emphasis on research from the fields of psychology and sociology. Below we discuss the scope for creating richer models of human behaviour, relaxing common assumptions about rationality, uncertainty and intertemporal trade-offs by rule breakers. Both our review and the case study of elephant conservation highlight the sensitivity of model outputs to their precise specification. Models must therefore be developed with a good understanding of the realities of the system being studied and parameterised with appropriate data. We briefly discuss the challenges of collecting such data below.

2.6.1 Rationality and uncertainty

Decisions under uncertainty, such as whether to break an imperfectly enforced rule, have traditionally been modelled using the expected utility framework. Utility is a measure of relative satisfaction and expected utility is defined as the mean utility received under risk. However, the use of the expected utility framework to explain decision-making under risk is undermined by experimental evidence that its core assumptions are frequently violated in practice (Schoemaker, 1982). For example, people have been shown to evaluate losses and gains differently, to make decisions based on reference points rather than absolute values and to be influenced by the framing of choices as well as their anticipated values (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992).

Indeed, although economic models of human decision-making generally assume that individuals are rational and act to maximise their utility, much of the psychological research into decision-making suggests that these assumptions are not realistic (McFadden, 1999). Instead individuals may have bounded rationality, limited by cognitive resources, and employ a variety of heuristic procedures to achieve outcomes that are good enough rather than truly optimal (Conlisk, 1996). Differences in the decision-making processes employed by different individuals might arise from their previous experiences, as suggested by psychological theories of compliance, and render some more likely to break rules than others.

The significance of deviations from rationality assumptions for models of enforcement and compliance is currently unknown. Future research in this area could focus on identifying and testing the "rules of thumb" used for decision-making in specific situations. Work is also needed to assess how adopting alternatives to expected utility, such as prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), could affect model predictions.

2.6.2 Intertemporal choice

Many choices made by individuals depend on how they trade-off costs and benefits at different points in time (Frederick et al., 2002). Models of NRM have generally dealt with intertemporal issues in a simplistic manner, with individuals having a single, fixed discount rate for all situations. Such models have suggested that slowly reproducing populations are more likely to be harvested to extinction if hunters have high discount rates (Clark, 1973). High discount rates may also affect the perceived severity of punishments, with future consequences (e.g., the later portions of long prison terms) devalued relative to more immediate sanctions (Leader-Williams and Milner-Gulland, 1993).

In reality discount rates, as well as other factors influencing an individuals decision-making, may change through their life and with their circumstances (Edwards-Jones, 2006) and are likely to vary between individuals. Currently, however, factors affecting intertemporal choices are poorly understood. For example, it has been claimed that poverty forces individuals to make decisions on a short term basis, neglecting resource conservation, but there is evidence of desperately poor people choosing long term gains (or long term stability) despite a short-term cost (Moseley, 2001). Further work is needed in this area to study the determinants of discount rates in order to better predict how intertemporal trade-offs will affect rule-breaking behaviour.

2.6.3 Information requirements

Ultimately, models can only take us so far. Our case-study of elephant conservation illustrates that while models can be powerful aids to decision-making, the details of their implementation and parameterisation are crucial to their interpretation. The development of a theoretical framework for enforcement must therefore be underpinned by good data if it is to provide a solid basis for action. Many attempts to validate theories of enforcement with empirical evidence have been unconvincing, often because suitable data are simply not available (Cameron, 1988; Ehrlich, 1996). In conservation settings, data on non-compliance are frequently a by-product of attempts to deter rule-breaking, limiting their quality. However collecting more detailed data, such as spatial patterns of non-compliance and enforcement effort, poses serious logistical challenges and may not be justified under local conservation budgets.

In order to ensure research into rule-breaking can be used in practical conservation, a close reciprocal relationship between models and data is needed. Models can guide data collection and help to determine the minimal data requirements for robust decision-making. Salafsky et al. (2001) have promoted an adaptive management approach to ecological monitoring and project appraisal. Such an approach could be taken with enforcement to allow data to be collected in a more targeted and systematic manner. Future research should also explore other potential avenues for the collection of data about rule-breaking including novel interview methods for the collection of sensitive information, such as the randomized response technique (Solomon et al., 2007).

Ultimately, as models become more complex, their data requirements might render them impractical as tools for management decision-making. Although this trade-off between complexity and reality is common to all modelling approaches, the paucity of data for many exploited species amplifies the problem in NRM (e.g., Smith, 1993) and good data are rarely available for threatened species. In some cases, therefore, it may be desirable to identify situations where rules of thumb can adequately inform day-to-day decision-making.

2.7 Conclusions

Rules, whether implicit or explicit, are at the heart of every conservation and NRM system but compliance cannot be taken for granted. Success depends on the ability of managers to influence the behaviour of resource users, and enforcement therefore has a vital role to play in the conservation of natural resources. To date the literature on this issue has been scattered among a number of disciplines, and theoretical insights from other fields have not been fully and consistently applied to NRM. We believe there is a need to develop a new field of robust theory and practice for enforcement and compliance in conservation, building on the experience of others. Models of enforcement have been important in predicting how individual incentives can be modified to improve compliance with rules but further work is urgently required to broaden our understanding, to validate models with empirical data and ultimately to produce practical guidelines for the optimal use of enforcement measures in conservation. If conservationists are caught napping on issues of enforcement, both the natural resources that we set out to manage and those who depend on them may suffer.

Chapter 3

Evidence for the effects of environmental engagement and education on knowledge of wildlife laws in Madagascar

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3.1 Introduction

Rules and regulations are of central importance to conservation, underpinning a whole spectrum of approaches from community-based wildlife management and payments for ecosystem services to fishing quotas and protected areas (Chapter 2). However, the existence of a rule does not guarantee that it will be respected (Rowcliffe et al., 2004). Various factors influence compliance with rules (Chapter 2), but if they are not widely known, rules cannot change behaviour. For example, studies of anglers in the USA (Page and Radomski, 2006) and community-based natural resource management in Uganda (Nkonya et al., 2008) have shown that compliance is higher in groups with better awareness of the rules. It is therefore important for conservationists to understand which factors most strongly influence awareness of rules, but the topic has been neglected. Nkonya et al. (2008) found that, at the community level, awareness of locally-enacted regulations protecting privately owned natural resources was lower among isolated groups, but was improved by the presence of environmental organisations. However, there has been no attempt to identify factors which improve awareness of rules at the individual level, where decisions about hunting and persecution are made.

Madagascar is recognised as one of the hottest biodiversity hotspots (Mittermeier et al., 2004). Much of the islands diverse and highly endemic flora and fauna is threatened by habitat destruction (Green and Sussman, 1990), overhunting (O'Brien et al., 2003; Golden, 2009), persecution (Hawkins, 2006) and collection for the pet trade (Andreone et al., 2005). Recent political difficulties have further exacerbated the situation (Barrett and Ratsimbazafy, 2009). This year it is 50 years since the first Malagasy wildlife law was passed (which made lemur hunting illegal). Malagasy wildlife law (principally Law 60–126 and Decree 2006–400) now divides species into three categories: protected (may not be hunted or killed); game (may be hunted only during specific periods and with a permit); and nuisance (not subject to any controls). There is considerable evidence that these laws are not well respected (García and Goodman, 2003; Goodman, 2006; Jenkins and Racey, 2008; Golden, 2009) but there has been no investigation of how well they are known and understood.

This study quantifies the effects of various factors on individuals awareness of species conservation laws among rural people in the eastern rainforest area of Madagascar. The involvement of local communities in tourism (Durbin and Ratrimoarisaona, 1996) and, more recently, in the management of forests and their resources (Antona et al., 2004; Raik and Decker, 2007) are key components of Madagascars environmental policy, intended to improve conservation and resource management through a variety of mechanisms. We therefore ask whether involvement with these activities increases awareness of Madagascars species protection laws. Formal education is often cited as a key determinant of environmental awareness (Howe, 2009). We therefore also test whether having a higher level of education improves knowledge of the law. Finally we examine the effect of these factors on knowledge of the law among a key target group for rule enforcement, those most likely to have the inclination and opportunity to hunt; young adult males (Kümpel et al., 2010) who have previously encountered the species in question.

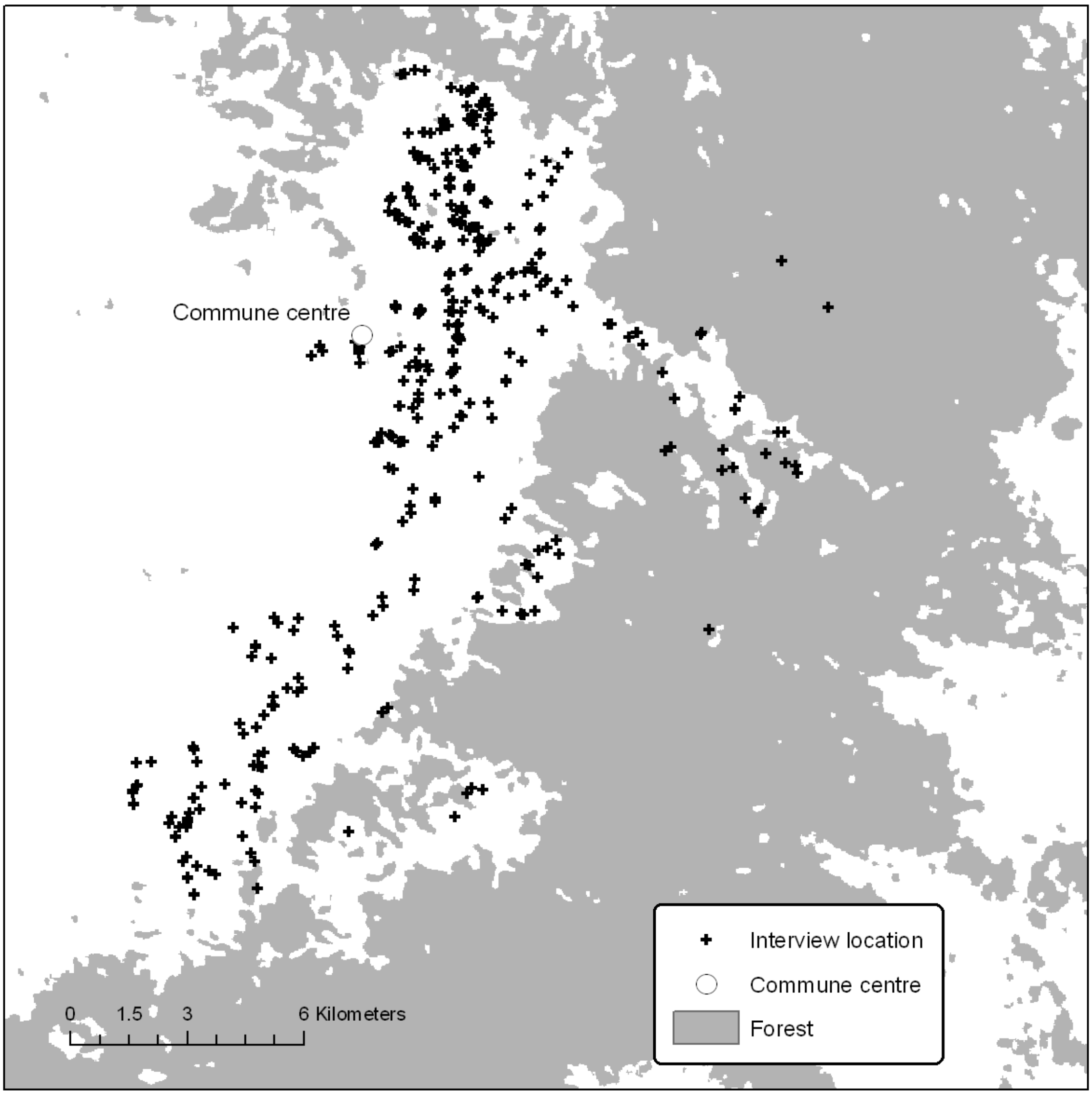

Figure 3.1: Map showing the location of each interview relative to the forest corridor and the commune centre. In order to preserve the anonymity of respondents, the names of *fokontany* and settlements are not given. Isolation is not clearly related to distance from the main town or the forest edge due to the shape of the forest and the proximity of other towns.

3.2 Methods

3.2.1 Study area

Our study was carried out in a rural area of Madagascar, adjacent to the forest corridor which runs along the country's eastern escarpment (Figure 3.1). Livelihoods in the region are based on small scale farming with collection of forest products and hunting to supplement income and protein (Ferraro and Kiss, 2002; Jones et al., 2006). Between December 2007 and April 2008 interviews were conducted with 602 individuals from 7 small administrative units known as *fokontany* within one commune.

In four *fokontany*, management of natural resources within defined areas of forest has been devolved to community-based forest management organisations (Antona et al., 2004; Raik and Decker, 2007). Individuals may choose whether or not to participate in the activities of the forest management organisations, although membership is subject to a fee. Some respondents were also members of the forest management committees.

The area receives a small but increasing number of tourists, with local environmental and development NGOs helping the commune to develop the eco- and ethno-tourism potential of the area, specifically its primary rainforest and picturesque sacred mountain. The main livelihood activity of all respondents was farming, but some also engaged with the tourism industry, acting as tourist guides or hosting tourists. The commune has no protected areas or major conservation interventions.

3.2.2 Data collection and analysis

Interviews were conducted in Malagasy, primarily by AAR with the help of a research assistant and a local guide. JPGJ (fluent in spoken Malagasy) and AK attended some interviews. Participants were selected at random and questioned about 23 animal species found in the area (Table 3.1). First, participants were shown a photograph and asked to name it. If they were unable to identify the species correctly, they were given a hint and allowed to try again. The interviewees were then asked if they had ever seen the species and, finally, to indicate whether it was a protected, nuisance or game species by placing the photograph into one of three piles. This procedure was repeated for each species. After the interview, the respondents demographic characteristics were recorded (Table 3.2).

Before analysis, we discarded responses where a species was not correctly identified from the photograph and the hint (30.2% of the total) and those with missing data, leaving a sample of 8,059 responses from 542 individuals. The percentage of discarded responses was similar for each category (protected = 8.4%, game = 8.8%, nuisance = 6.8%). A series of multilevel logistic models were fitted to the data. The response was binary, indicating whether the respondent was able to place the species in the correct legal category.

Table 3.1: Names, legal categories and IUCN Red List status of species included in study. Red List status is denoted using abbreviations, LC = least concern, NT = near threatened, VU = vulnerable, EN = endangered.

Scientific name	English name	Malagasy name at study site	Legal category	Red List status
Centropus toulou	Madagascar coucal	*Toloho*	Game	LC
Cuculus rochii	Madagascar cuckoo	*Kakafotra*	Game	LC
Foudia madagascariensis	Madagascar red fody	*Fody*	Game	LC
Mantidactylus pulcher		*Sahona maintso*	Game	LC
Pteropus rufus	Madagascar flying fox	*Fanihy*	Game	LC
Tenrec ecaudatus	Tenrec	*Trandraka*	Game	VU
Acridotheres tristis	Common myna	*Martin*	Nuisance	LC
Potamochoerus larvatus	Bush pig	*Lambo*	Nuisance	LC
Rattus rattus	Black rat	*Voalavo*	Nuisance	LC
Alectroenas madagascariensis	Madagascar blue-pigeon	*Finengo manga*	Protected	LC
Cryptoprocta ferox	Fossa	*Fosa*	Protected	VU
Daubentonia madagascariensis	Aye-Aye	*Hay-Hay*	Protected	VU
Fossa fossana	Malagasy civet	*Fanaloka*	Protected	NT
Furcifer lateralis	Jewelled chameleon	*Tanalahy*	Protected	—
Hapalemur griseus	Eastern lesser bamboo lemur	*Bokombolo*	Protected	VU
Leptopterus chabert	Chaberts Vanga	*Tsramaso*	Protected	LC
Limnogale mergulus	Aquatic tenrec	*Voalvorano*	Protected	VU
Lophotibis cristata	Madagascar Crested Ibis	*Akoholahinala*	Protected	NT
Mantella madagascariensis	Painted mantella	*Sahona mivolomiaramila menafe*	Protected	VU
Microcebus rufus	Gray mouse lemur	*Tsidy*	Protected	LC
Propithecus edwardsii	Diademed sifaka	*Simpona*	Protected	EN
Sanzinia madagascariensis	Madagascar ground boa	*Mandotra*	Protected	VU
Setifer setosus	Spiny tenrec	*Sora*	Protected	LC

3.2.3 Statistical modelling

Eleven explanatory variables were grouped into six functional groups. The first was the species' legal category. The remaining five described differences in the respondents' individual characteristics; their education (highest level of education attained), involvement with natural resource management or tourism activities (whether they pursue other livelihood activities in addition to farming, such as guiding tourists; whether they belong to a household which hosts tourists; whether they belong to a forest management organisation), demographic characteristics (age; sex), familiarity with the species (whether they have ever seen the species), and their location (the *fokontany* to which they belong; distance from the forest edge; distance from the commune centre). Due to the geographic characteristics of the study site (Figure 3.1), it was not possible to test specific hypotheses regarding location (such as the potential effects of isolation), so this group of variables was included to account for spatial dependency in the data.

Differences between species were modelled through the inclusion of a random effect because we were primarily interested in social rather than species-specific factors influencing awareness of conservation rules. This allowed us to quantify the variation between species without the need to estimate large numbers of parameters. Differences between species were examined informally by disaggregating the random effect. A second random effect, for individual, was included to account for the grouping structure of the data since every respondent answered questions about each species.

A candidate set of models was chosen a priori. Each model included species category with varying combinations of the remaining groups of explanatory variables and their interactions with species category. The full set of 61 models was fitted in R 2.10.0 (R Development Core Team, 2009) using the glmer function from the lme4 package, version 0.999375-32 (Bates and Maechler, 2009). AIC was used to rank the fitted models and construct a 99% confidence set. Model weightings were calculated based on this confidence set (Burnham et al., 2002).

Parameter estimates derived from these models are difficult to interpret directly because of the presence of interactions and non-linearity. We therefore present average predictive comparisons, calculating the means and confidence intervals of responses simulated from the fitted models to evaluate their predictions at different values of one or more focal variables, holding all others constant (Gelman and Hill, 2007). Both parameter uncertainty and model selection uncertainty were incorporated in these comparisons. Uncertainty in

Table 3.2: Summary of the predictor variables considered for inclusion in the models.

Continuous variables Variable	Unit	Median
Age	Years	37.5
Distance from forest edge	Kilometers	1.90
Distance from commune centre	Kilometers	4.83
Categorical variables **Variable**	**Level**	**Count**
Sex	Male	310
	Female	232
Level of education	Primary school (EPP)	431
	Secondary school (CEG)	92
	Lycée	19
Main occupation	Farmer	327
	Crafts	85
	Tourist guide	4
	Official	12
	Other	114
Forest management involvement	None	123
	Organisation member	380
	Committee member	50
Tourist host	Yes	21
	No	521
Has seen the species?	Yes	510
	No	32
Fokontany	A	23
	B	160
	C	20
	D	119
	E	112
	F	86
	G	22

parameter estimates was incorporated by simulating every scenario 1000 times, each time drawing parameter values at random from Normal distributions whose means and standard deviations equalled the means and standard errors of the fitted models' parameter estimates (Gelman and Hill, 2007). Model selection uncertainty was incorporated by repeating this process for each of the models in the 99% confidence set, averaging their predictions weighted by their Aikaike weights (Burnham et al., 2002).

3.3 Results

The respondents' ability to classify species into their legal categories was poor, with only 42.9% (n = 8059) correct responses in the raw data (cf. the expectation of 33.3% for unin-

Table 3.3: Summary of the 99% confidence set of models selected based on AIC. The inclusion of different functional groups of predictor variables in each model is indicated by M (the main effects for these variables were included) and I (the interactions of these variables with species legal category were included). RE:species and RE:individual indicate the standard deviation of the random effects terms for species and individuals respectively. ΔAIC is the difference in AIC between the model in question and the AIC-best model (Model 1). w is the Aikaike weight of the model.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Demographic	M + I	M + I	M + I	M + I	M + I	M + I	M + I
Education	M + I	M + I	M + I	M	M		
NRM/Tourism	M + I	M + I	M + I	M + I	M + I	M + I	M + I
Familiarity	M + I	M		M + I	M	M + I	
Location	M + I	M + I	M + I	M + I	M + I	M + I	M + I
RE:species	1.06	1.06	1.05	1.06	1.06	1.06	1.05
RE:individual	0.54	0.55	0.55	0.54	0.55	0.55	0.56
AIC	7603.34	7603.67	7604.27	7606.18	7606.79	7606.83	7607.91
ΔAIC	0	0.32	0.93	2.84	3.44	3.49	4.57
w	0.31	0.27	0.20	0.08	0.06	0.06	0.03

formed guesses). However, there were substantial differences between the three categories. Nuisance species were correctly identified most often (63.8% of 1428 responses), followed by protected species (56.5% of 3137 responses), with game species rarely placed in the correct category (9.2% of 2494 responses).

Model selection resulted in a 99% confidence set of 7 models (Table 3.3). The AIC-best model included all explanatory variables and their interactions with legal category, but this model only received a weighting of 0.31 reflecting a high degree of model selection uncertainty (Burnham et al., 2002). Other selected models dropped groups of variables representing the respondents education and familiarity with the species. Model-averaged predictions generated from the confidence set correspond well with the observed data (Figure 3.2).

Average predictive comparisons for combinations of species legal category and other predictor variables are presented in Figure 3.3. As in the raw data, the most important effect is that of species legal category, with nuisance species correctly categorised more often than protected species, while game species are almost always miscategorised. The effects of other predictors also interacted with legal category.

The involvement of respondents with resource-management activities was associated with substantial improvements in categorising protected species (Figure 3.3). Members of forest management associations were 21.1% more likely to categorise protected species

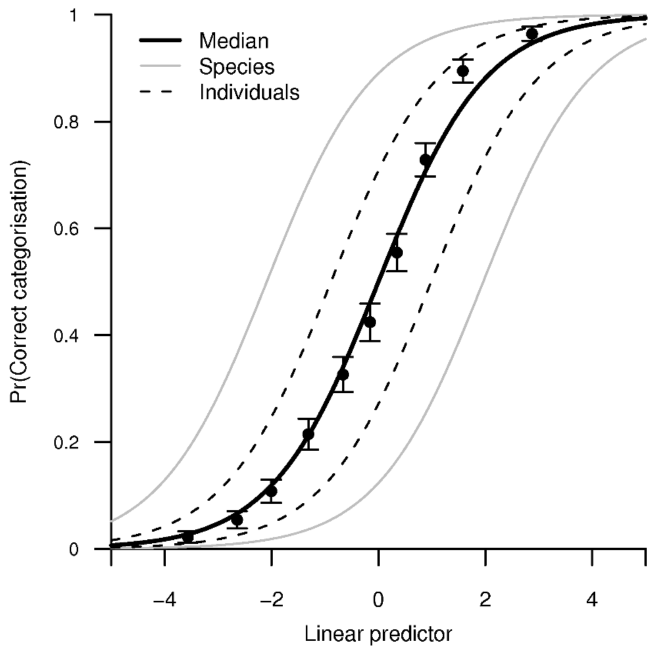

Figure 3.2: Model fit and variability attributable to random effects for species and individual respondents. The heavy black line indicates the predicted fit, averaged over the 99% confidence set of models. Black circles show the mean of the response variable binned into 1 unit intervals, with error bars of +/- 2 standard errors. The broken black lines and solid grey lines indicate the minimum and maximum values of the conditional modes of the random effects for individuals and species respectively taken from the best fitting model, illustrating the range of variability.

correctly than non-members, but there was little difference between ordinary members and committee members. Predictions regarding the categorisation of nuisance species were more variable, but there were indications that the members of forest management associations categorised nuisance species correctly less often than non-members. Hosting tourists had a lesser effect, but there was some indication that respondents from households which hosted tourists were slightly better at categorising protected and game species, but worse at categorising nuisance species.

Large differences were associated with occupation, with respondents holding an official position or who acted as tourist guides being respectively 25.0% and 36.4% more likely to correctly categorise protected species that those who were just farmers. Guides were also more likely to classify game species correctly, but officials very rarely categorised game species correctly. Occupation produced no convincing effect on the categorisation of nuisance species.

Respondents' level of education was also important for the categorisation of protected species but had little effect for nuisance or game species. There was little difference between those with only primary (EPP) education and those who had attended secondary (CEG)

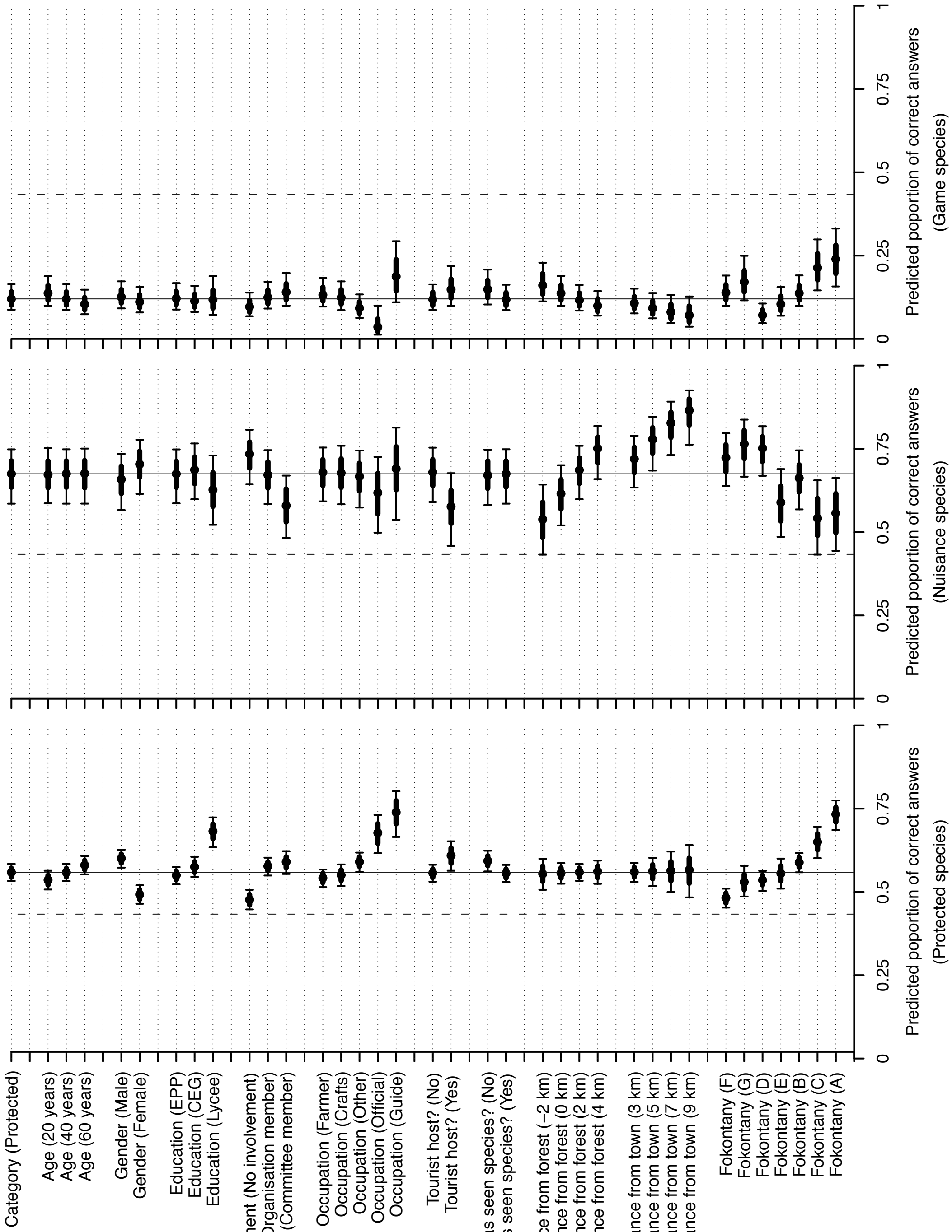

Figure 3.3: Model-averaged average predictive comparisons illustrating the effect of each predictor variable on the probability of correctly categorising a species, and their interactions with the species' legal category. The dashed vertical line indicates the predicted overall mean response for the original dataset. The solid vertical line in each panel indicates the predicted mean response for the sample population if all of the species were protected, nuisance or game respectively. Heavy lines indicate approximate 67% confidence intervals, obtained by simulation. Light lines indicate approximate 95% confidence intervals. See Table 3.2 for descriptions of the variables.

education. However, respondents who were educated at a lycée were 24.1% more likely to categorise protected species correctly than those with only primary education.

We observed few clear differences associated with respondents' demographic characteristics, but males were 22.0% more likely to categorise protected species correctly than females. There was also a slight improvement in the categorisation of protected species with age, so that respondents aged 60 were 8.4% more likely to categorise protected species correctly than respondents aged 20. There was no clear effect of whether or not the respondent had ever encountered the species in question on their ability to categorise it correctly. There were substantial changes in levels of knowledge attributable to location. For example, respondents from *fokontany* A were 52.1% more likely than those from *fokontany* F to categorise protected species correctly.

From the perspective of a policy maker or conservation NGO, a key question is the extent to which education, or involvement with environmentally-based activities such as tourism and local resource governance, affects awareness of laws among the individuals who most often hunt wildlife. We therefore used the model to predict how these factors change awareness in the group most likely to hunt; young (aged 25 years) male farmers with only primary education (Figure 3.4). Baseline levels of knowledge for this group are predicted to be much lower for protected species (47.2% categorised correctly) than for nuisance species (72.5% correct). However, guiding, membership of forest management organisations and belonging to a household which hosts tourists all improved categorisation, as does a lycée education. Individuals with all these characteristics were almost twice as likely to correctly classify protected species as those who did none of them (89.1% correct).

The fitted models suggest that approximately 21% of the remaining variation is attributable to variation between individuals, while 41% is between species. Of the protected species, lemurs were most often categorised correctly, followed by the birds and reptiles (Figure 3.5). The two carnivore species (*Fossa fossana* and *Cryptoprocta ferox*) and two protected insectivores (*Setifer setosus* and *Limnogale mergulus*) were least well categorised. In particular, the rare and cryptic aquatic tenrec (*Limnogale mergulus*) was very rarely categorised correctly.

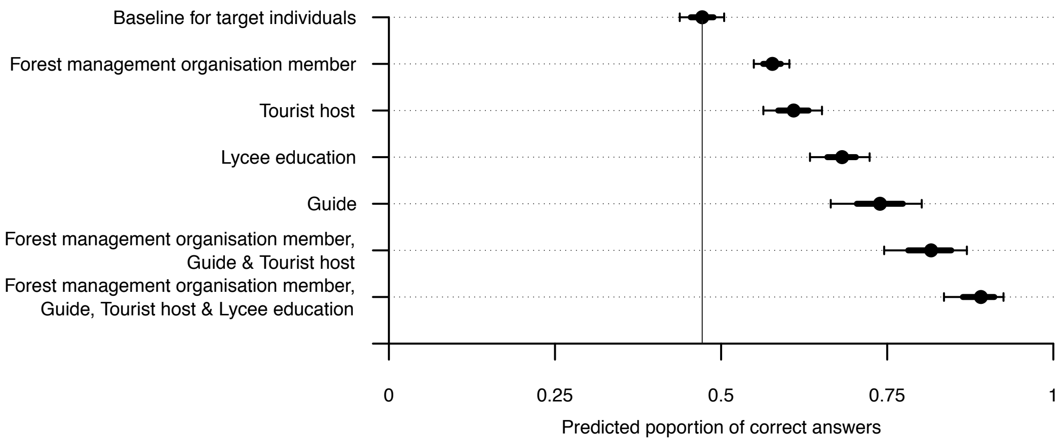

Figure 3.4: Average predictive comparisons illustrating the effect of conservation related activities and education on ability correctly to classify protected species amongst a target group of individuals likely to hunt wildlife. For the purposes of the scenario, this group was defined as young (aged 25 years) male farmers who have received only primary education. The solid vertical line indicates the baseline predicted mean response of the target population. Heavy lines indicate 67% confidence intervals. Light lines indicate 95% confidence intervals.

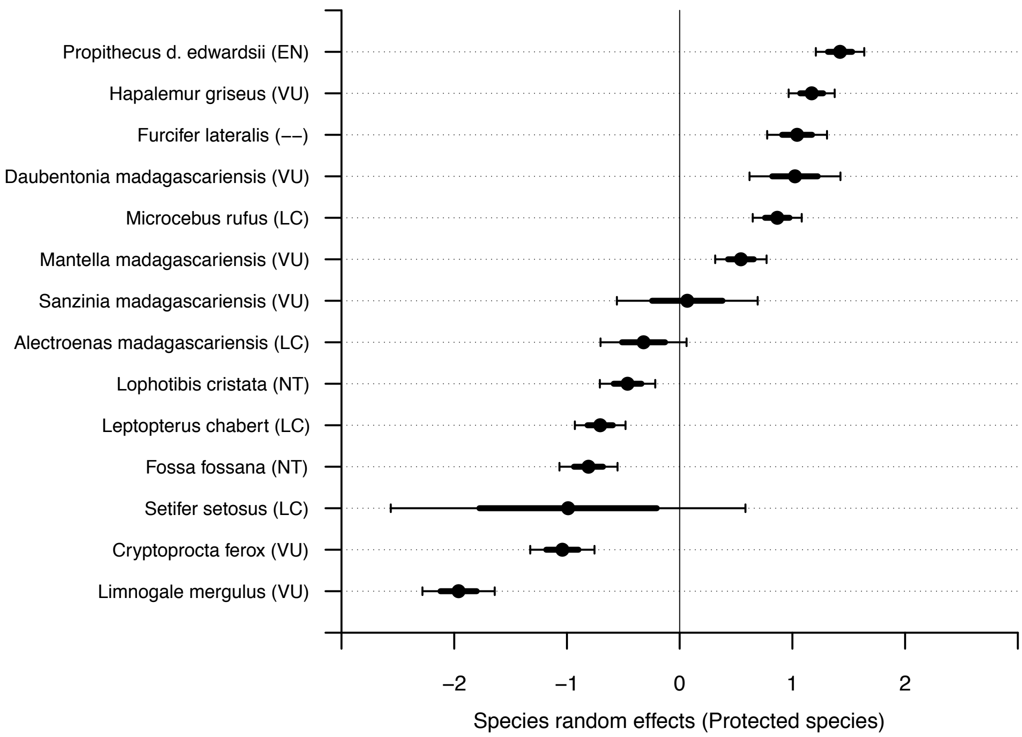

Figure 3.5: The conditional modes of the species random effect for protected species included in our questions, indicating the differences in probabilities that the species were categorised correctly. Positive values indicate that a species was more likely to be correctly categorised. Heavy lines indicate an interval of +/- 1 SE and the lighter lines +/- 2 SE. Species are referred to by their Latin names. For common names, please refer to the Table 3.1. The letters in brackets after each species correspond to their status on the IUCN Red List: LC = least concern, NT = near threatened, VU = vulnerable, EN = endangered (IUCN, 2009). *Furcifer lateralis* is not currently IUCN listed.

3.4 Discussion

We found the level of knowledge about Madagascar's wildlife laws to be generally poor in our study area. One way to improve awareness of conservation rules is through dedicated education campaigns (e.g., Padua, 1994), but these are expensive and can trade off with other conservation activities (Alder, 1996). Consequently, it is important to know which factors predispose individuals to be better informed about conservation rules so that awareness-raising interventions can be effectively targeted.

For protected species, levels of awareness are substantially higher in better educated individuals and those involved with tourism and community-based resource management. These findings are largely in agreement with those of previous studies which have examined the effects of ecotourism (e.g., Gadd, 2005; Waylen et al., 2009), level of schooling (e.g., Howe, 2009) and participation in community-based projects (e.g., Kideghesho et al., 2007) on awareness of and attitudes towards other aspects of conservation. From a post hoc assessment, it is difficult to be certain of the direction of causality and we cannot rule out the possibility that these relationships could be partly endogenous. We feel, however, that an individual's awareness of the law is very unlikely to affect their probability of receiving employment as a guide or joining a forest management organisation.

Providing better education and creating tourism-based livelihood opportunities are common goals for development and conservation interventions, and improving awareness and understanding of wildlife laws is a useful byproduct of these activities. Currently, however, only a small subset of the population are guides or have been educated to lycée level (4 and 19 individuals respectively). By contrast, the majority of the respondents in our study (430 individuals) participated in forest management organisations. Previous studies have questioned whether community-based approaches to conservation can be effective (e.g., Agrawal and Gibson, 1999). In Madagascar, the partial devolution of natural resource management to communities has shifted many responsibilities to the local level (Antona et al., 2004; Raik and Decker, 2007) but forest management organisations have often received little support since their creation, and concerns have been raised that this could undermine their success (Hockley and Andriamarovololona, 2007). However our results suggest that, irrespective of whether other benefits are realised, involvement with local forest management organisations helps to sensitise people to conservation laws.

Another striking finding is the very poor recognition of game species' legal status. Although bushmeat has recently gained prominence as a conservation issue in Madagascar (e.g., García and Goodman, 2003; Goodman, 2006; Golden, 2009), the focus has been on protected species such as lemurs. The exploitation of game species has received very little attention, although it is likely to be wider in extent (Jenkins and Racey, 2008). Our findings suggest that the laws regarding game species are currently too poorly known to stand any chance of influencing people's behaviour.

In general, the factors which improved respondents' ability to categorise protected species also tended to improve categorisation of game species, but due to smaller sample sizes the effects are less well estimated. By contrast, these same factors had little effect or even reduced the ability of respondents to categorise nuisance species. One interpretation is that increased exposure to conservation messages (through resource-management, tourism and the like) biases individuals towards assuming, or reporting, that species are subject to legal protection.

Although our primary focus here was relating differences in awareness to respondents' individual characteristics, we also observed species-related differences. The causes of these differences are beyond the scope of this study but might reflect differing levels of agreement between national laws and local attitudes and beliefs. Although often viewed in isolation, national laws are part of a larger system of formal and informal rules recognised by local Malagasy, which incorporates traditional taboos or fady (Jones et al., 2008b). In some cases, pre-existing attitudes towards a species might correspond with its legal status. For example, the lemur *Propithecus edwardsii*, is legally protected and is also considered taboo by many people in the area (Jones et al., 2008a) so it might be expected to be categorised correctly more often than protected species which are not locally revered (such as the aquatic tenrec, known as 'water rat' [*voalavorano*] in Magalasy). Awareness might also have been affected by taxon-specific conservation measures, such as the extensive efforts devoted to lemur conservation in many parts of Madagascar.

Ultimately, rules in conservation can only be effective if they are known and understood by the people whose behaviour they are intended to regulate. Changing peoples behaviour requires a concerted body of research to assess how knowledge, attitudes and behavioural intentions are formed and influence one another (Holmes, 2003). Understanding the determinants of awareness of rules and regulations is therefore a vital, but often overlooked, first step towards building an evidence base for the creation of robust, successful and scientifically informed policies to promote behavioural change.

Chapter 4

Modelling the effect of individual incentives for monitoring and rule-breaking on conservation outcomes

4.1 Introduction

Effective enforcement is essential to conservation success (Chapter 2) but enforcement measures may be very costly (Jachmann, 2008b; Robinson, 2008; Wilkie et al., 2001) so questions about how enforcement measures can be efficiently designed and implemented are of considerable importance to conservation practice (Robinson et al., 2010). The economics literature contains an extensive body of theory on optimal deterrence (Becker, 1968; Garoupa, 1997; Winter, 2008) which aims to understand how many resources should be devoted to preventing rule-breaking, but there have been relatively few applications to conservation and natural resource management (Chapter 2). Since Becker (1968) models of deterrence and compliance have routinely focused on two components of enforcement; the probability that a rule-breaker is detected and punished and the severity of sanction that they incur (e.g., size of fine, length of prison term). Together these factors determine the expected costs of enforcement that a potential rule-breaker will face, with increases in either expected to reduce the amount of rule-breaking that occurs (e.g., Milner-Gulland and Leader-Williams, 1992).

Although this theory provides a useful framework for understanding the role of enforcement in compliance, its usefulness implicitly depends on the assumption that policy makers and managers are able easily and precisely to control the severity and probability of sanctions faced by rule-breakers. However, this will rarely be true and certain aspects of enforcement are more easily manipulated than others. For example, statutory punishments and sentencing guidelines may help to ensure that particular categories of rule-breaking always receive the same level of sanction (although the actual level of punishment may still show considerable variation, e.g., Leader-Williams et al. 1990). Similarly, it may be reasonably assumed that improvements in training and equipment will improve the ability of monitors to detect rule-breaking. However, the *actual probability* of detection is likely to be much more difficult to control since it depends strongly on the behavioural decisions of both the individuals charged with monitoring and reporting non-compliance and the rule-breakers themselves (Akella and Canon, 2004; Robinson et al., 2010).

The people responsible for monitoring non-compliance, be they police, customs officials or protected area staff, face their own set of incentives, and there are several reasons why these may differ from those of the manger or policy maker who nominally decides the level of enforcement (Tsebelis, 1989; Andreozzi, 2004). Monitoring has opportunity costs, may be dangerous (Hart et al., 1997) and risks inviting recriminations from peers (Robinson et al., 2010) so monitors may face incentives to 'cheat' at their job (e.g., not patrolling as they are meant to, or failing to report infractions when they are encountered). The position of authority occupied by monitors may also create opportunities for corruption (Mookherjee and Png, 1995). For managers, the main tools available to incentivise monitors to perform their duties effectively are the payment of fees and salaries and the provision of performance related bonuses (e.g., Jachmann and Billiouw, 1997; Jachmann, 2008b; Mesterton-Gibbons and Milner-Gulland, 1998), but the effectiveness of such payments has received little attention and remains poorly understood (e.g., Tsebelis, 1989; Andreozzi, 2004; Mookherjee and Png, 1995).

There are also many factors which can influence the choices and motivation of potential rule-breakers. Models of rule-breaking assume that individuals are rational and act to maximise their utility (Becker, 1968). Their decisions are therefore influenced by their perception of the risk of punishment (which depends on both the probability that they are detected and punished, and the severity of the sanctions that they would incur), but also depend upon a range of individual characteristics that are rarely considered in such models.

For example, the returns a hunter can expect from a day's poaching depends upon their skills at catching animals, their choice of hunting strategy and the resources that are available to them (e.g., guns and cartridges or wire for snares; Hill and Kintigh 2009). These things vary from one hunter to the next, and can result in large differences in hunting success between individuals (Coad, 2007), with the result that poaching may be intrinsically more attractive to some individuals than others. Other forms of individual heterogeneity may produce similar effects. For example, the decision about whether or not to poach might also vary according to an individuals opportunity costs (e.g., Damania et al., 2005), with individuals who are able to find regular paid employment potentially facing lower incentives to hunt (Muchaal and Ngandjui, 1999), or according to differences in their ability to avoid detection and capture by enforcement agents (Malik, 1990).

Understanding how the motivations of enforcement agents and rule-breakers interact to produce conservation outcomes is particularly important—and particularly challenging—in community-based projects where the responsibility for ensuring compliance with conservation rules has been devolved to the local level (e.g., Gibson, 1995). In these settings, there is a greater symmetry between the choices facing individuals, since each person could in theory have the option to poach or not to poach, and to monitor or not to monitor (in contrast to top-down approaches to enforcement where the roles of monitor and rule-breaker may be more strictly delineated; cf. Mesterton-Gibbons and Milner-Gulland 1998). A common criticism of the community-based approach has been that it often fails to take account of the heterogeneous nature of communities, and the differing motivations of individuals within them (e.g., Agrawal and Gibson, 1999; Berkes, 2004). However, there continues to be considerable interest in local communities as targets for conservation action, and this looks set to grow further with the spread of community-based approaches to implementing payments for environmental services (e.g., Sommerville et al., 2009). Consequently, there is a pressing need to develop a better understanding of the incentives faced by individuals, and how they play out to produce community-level outcomes.

Individual-based models (IBMs) are simulation models that treat individuals as discrete entities with at least one property in addition to age that changes over time (Grimm and Railsback, 2005). They have been widely applied in ecology and are conceptually similar to agent-based models or multi-agent simulation models (Bousquet and Le Page, 2004). IBMs have previously been used in the study of human decision-making and social organisation in natural resource management and conservation (Berger, 2001; Bousquet, 2001; Castella et al., 2005; Milner-Gulland et al., 2006). In contrast to other models of enforcement and compliance, the adoption of an IBM framework allows the functional form of a community's response to policy levers to emerge from the aggregation of individual decisions, rather than being assumed a priori, and provides a natural avenue for incorporating heterogeneity between individuals. Here, I use an IBM of a community-based conservation project to explore the effects on compliance of changing (1) the fine incurred by poachers if they are caught, (2) the fees paid to individuals for carrying out monitoring duties, and (3) the size of bonus payments made to monitors for catching a rule-breaker. These parameters were chosen since they represent realistic policy levers which managers could be expected to have at their disposal, allowing us to explore the effect of individual heterogeneity within a community on the effectiveness of conservation rules.

4.2 Methods

4.2.1 Model structure

I model a small community-based project intended to reduce poaching of a protected species (cf. Child, 1996; Hackel, 1999; Holmern et al., 2007). To achieve this, the project tries to create incentives for the local people (a) to refrain from poaching, and (b) to monitor whether others poach, using a combination of rewards and sanctions. Rewards for desirable behaviour include the payment of a community-level benefit, monitoring fees and bonus payments for reporting poaching. Sanctions include fines if individuals are caught poaching, or if monitors are found to be neglecting their duties. The model follows and extends that of Mesterton-Gibbons and Milner-Gulland (1998).

The modelled community consists of n individuals who differ from one another in three respects: (1) their opportunity costs of participating in monitoring and of hunting, (2) their average hunting success (which incorporates hunting effort in the traditional sense of the word, the 'catchability' of their prey and other factors such as their equipment, innate skill and experience), and (3) the degree to which they are willing to invest in avoidance behaviour to improve their chances of escaping punishment when breaking rules. These characteristics are sampled randomly from Normal distributions and are independent of one another. Once assigned to an individual they are fixed and do not vary from round to round.

Each individual adopts one of six strategies in a given round, related to both their monitoring and their poaching behaviour. Individuals can choose either to poach or not,

Table 4.1: Payoffs to each strategy component. An 'x' in one of the final six columns indicates that the strategy receives that row's payoff component. The strategies are denoted by the abbreviations: PM = poach and monitor; PC = poach and cheat; PO = poach and neither monitor nor cheat; NM = do not poach but monitor; NC = do not poach but cheat; NO = do not poach and neither cheat nor monitor.

		Strategy					
Component	Payoff equation	PM	PC	PO	NM	NC	NO
Community benefit, W	$W = B_t$	x	x	x	x	x	x
Monitor's payoff, M	$M = Y_{i,t}$	x			x		
Poacher's payoff, P	$P = \Pi_{i,t} - U_{i,t} - A_{i,t}$	x	x	x			
Cheat's payoff, C	$C = F_{i,t}$		x			x	
Alternative payoff, o_i	o_i						x

and either to monitor, cheat (pretend to monitor without performing their duties) or do neither. This leads to the following combinations of behaviour: "poach but also monitor for others poaching" (PM); "poach and cheat at monitoring" (PC); "poach and neither cheat nor monitor" (PO); "don't poach and monitor for others poaching" (NM); and "don't poach and cheat at monitoring" (NC); "neither poach, monitor nor cheat" (NO). NO individuals are assumed to be pursuing an alternative livelihood strategy. The utility derived by an individual from their actions in a given round depends upon their strategy choice (Table 4.1), the choices of the rest of the population, their individual characteristics and, for poachers, the size of the animal population. I assume that these strategies do not require special skills or investment in particular technologies, so there are no barriers to individuals switching between them.

4.2.2 Community benefit

Every individual, regardless of their strategy choice, receives a share of a communal benefit. In each round a shared payment is made to the community by an external organisation. For the first 5 rounds it is fixed at its maximum, B_{max}, so every individual receives a share, B_t, where n is the number of individuals in the population

$$B_t = \frac{B_{max}}{n}. \tag{4.1}$$

After this initial grace period the amount paid is reduced in proportion to the number of poachers caught in the previous round, $n_{C,t-1}$.

The payment per individual is therefore

$$B_t = \frac{B_{max}}{n}\left(1 - \frac{n_{C,t-1}}{n}\right). \tag{4.2}$$

4.2.3 Payoff from poaching

Individual i's revenue from poaching in round t, $\Pi_{i,t}$, is a function of the number of animals caught, $h_{i,t}$, and the revenue from catching a single animal, v

$$\Pi_{i,t} = vh_{i,t}. \tag{4.3}$$

The number of animals caught by individual i in round t, $h_{i,t}$, is drawn from a Poisson distribution with mean equal to the size of the prey population in that round, X_t, multiplied by the focal individual's average hunting success, e_i. Only the variable costs of hunting are considered in this analysis and are incorporated into the revenue per animal. The effect of hunting on the market for bushmeat is assumed to be negligible, and individual effort does not vary, so v is constant.

The population dynamics of the hunted species are described by the discrete logistic equation. The number of animals in round t, X_t, is given by

$$X_t = X_{t-1} + \rho X_{t-1}\left(1 - \frac{X_{t-1}}{K}\right) - \sum_{i=1}^{n} h_{i,t-1} \tag{4.4}$$

where ρ is the intrinsic growth rate and K is the environmental carrying capacity in the previous round.

Any individual who poaches faces the risk of being caught and punished but poachers expend resources on avoidance in order to reduce the chance that they are detected breaking rules (Malik, 1990). Avoidance behaviour has costs (e.g., time spent evading detection that is not spent hunting or using less noticeable but less efficient equipment). I assume a fixed cost, a, per unit of avoidance behaviour. The total cost of investment in avoidance behaviour by individual i in round t, $A_{i,t}$, is a function of the proportion of poachers who were detected by monitors in the previous round (representing the perceived current risk of poaching) and the focal individual's 'propensity to avoid', α_i, a measure of his willingness and ability to engage in avoidance behaviour

$$A_{i,t} = a\alpha_i \frac{n_{C,t-1}}{n_{P,t-1}}. \tag{4.5}$$

The probability that an individual is detected poaching by any monitor is reduced by his level of avoidance, with increasing levels of avoidance behaviour suffering diminishing returns. The probability that individual i is caught poaching in round t, $d_{i,t}$, is given by

$$d_{i,t} = 1 - \left(1 - \frac{p}{\alpha_i \left(\frac{n_{C,t-1}}{n_{P,t-1}}\right) + 1}\right) \tag{4.6}$$

p is the baseline probability that a poacher is detected by any monitor before avoidance behaviour is taken into account and n_M is the number of monitors.

If a poacher is detected, their punishment takes the form of a fine, u, per animal caught. The fine paid by poacher i in round t, $U_{i,t}$, is therefore

$$U_{i,t} = \begin{cases} h_{i,t}u & \text{if caught} \\ 0 & \text{if not caught} \end{cases} \tag{4.7}$$

4.2.4 Payoff from monitoring

Monitors receive a fee, f, per round but face resentment from poachers which imposes an additional cost proportional to the proportion of poachers that are caught during round t and the unit cost of social opprobrium, s. The net gain from monitoring, $Y_{i,t}$, is therefore

$$Y_{i,t} = f - s\left(\frac{n_{C,t}}{n_{P,t}}\right) \tag{4.8}$$

The first individual to report a poaching incident is also paid a bonus, j, as an incentive to monitor effectively. The bonuses paid to monitor i in round t, $J_{i,t}$, are therefore

$$J_{i,t} = jn_{C,t} \tag{4.9}$$

4.2.5 Payoff from cheating

The costs of monitoring mean that an individual may also face incentives to cheat, claiming their fee, but failing to perform their duties. Cheating does not incur the social opprobrium of monitoring, but cannot earn bonuses and risks punishment if detected. The probability that individual i is caught cheating in round t, $g_{i,t}$, is

$$g_{i,t} = 1 - (1 - q)^{n_{M,t}} \tag{4.10}$$

where q is the probability that a cheat is detected by any individual monitor.

If caught, cheats have their monitoring fee for the round taken away and are fined a fixed amount, k. The payoff to cheating in round t for individual {i} is therefore

$$F_{i,t} = \begin{cases} -k & \text{if caught} \\ f & \text{if not caught} \end{cases} \tag{4.11}$$

4.2.6 Payoff from alternative livelihoods

Poaching, monitoring or cheating are assumed to occupy all of an individual's time. They are therefore unable to pursue other activities. Individuals who do not pursue these activities may instead adopt other livelihood activities. The payoff to individual i from alternative livelihood activities is o_i, and represents the opportunity costs of participating in the wildlife management scheme.

4.2.7 Parameterisation and implementation

The model was implemented in R-2.10.1 (R Development Core Team, 2009). There are few data in the literature to guide the model's parameterisation so baseline parameter values were chosen based on exploratory runs to ensure that the system did not lie at the extremes of parameter space (see Table 4.2). Similar 'paradigmatic' IBMs (Grimm and Railsback, 2005) have a long history of use in theoretical ecology to explore the consequences of individual-level processes on patterns at more aggregated levels (e.g., Łomnicki, 1978; Uchmański, 1985; 1999; Grimm and Uchmański, 2002).

During a typical run of the model, the system slowly approached an equilibrium. For a given set of parameter values, this equilibrium displayed relatively little variation. Each simulation was therefore allowed to run for 2000 rounds, to ensure that the system reached equilibrium. To reduce the effects of stochastic differences between simulation runs, each simulation was repeated 5 times and an average taken.

Table 4.2: Description of model parameters and their default values.

Parameter	Description (Units)	Baseline value
ρ	Intrinsic growth rate	0.3
X_1	The initial size of the animals population (animals)	7,000
K	Environmental carrying capacity (animals)	15,000
B_{max}	Maximum community benefit	10,000
n	Community size	498
p	Baseline probability that any individual monitoring detects an incidence of poaching, before avoidance behaviour	0.015
q	Baseline probability that any individual monitoring detects an incidence of pretending to monitor, before avoidance behaviour	0.010
v	Returns to poaching per animal caught	40
u	Fine incurred per animal caught if detected poaching	40
k	Fine incurred if detected pretending to monitor	20
f	Fee paid to monitors per round	25
j	Bonus paid to monitors as a reward for being the first to report an incidence of poaching	40
s	Unit cost of social opprobrium incurred in response to monitoring	0.5
a	Cost of one unit of avoidance behaviour for poaching	3
o_i	Payoff to alternative livelihoods for individual i	N(20,6)
e_i	Average hunting success of individual i	N(0.0150,0.0045)
α_i	Propensity to invest in avoidance behaviour of individual i	N(10,3)

The human population was not subject to immigration or emigration so the number of individuals remained constant. Community size is set at 498 individuals, a realistic size for a small community, and at the beginning of a run individuals are assigned evenly to each of the six available strategy options. At the end of every round individual payoffs are calculated, and the 30 people receiving the lowest payoff are allowed to change their strategy. 24 are randomly assigned one of the strategies adopted by the 24 most successful individuals while the remaining 6 choose a new strategy at random. This process is designed to reflect imperfect knowledge about the success of different strategies and prevents the population from settling at local optima.

4.2.8 Analyses

My analyses sought to test how changes to each of the three potential policy levers under consideration—(1) the fine for individuals caught poaching, (2) the fee paid to monitors, and (3) the bonus paid to monitors if they are the first to report a poaching incident—affected levels of poaching and monitoring. First, the behaviour of the system was determined for a

Table 4.3: Parameter values for the fine for poaching (k), and the size of fees (f) and bonuses (j) paid to monitors in the 'zero-enforcement' baseline (S1) and subsequent scenarios (S2–8).

Scenario	k	f	j
S1, zero enforcement	0	0	0
S2, fines alone	40	0	0
S3, fees alone	0	25	0
S4, bonuses alone	0	0	40
S5, fines and fees	40	25	0
S6, fines and bonuses	40	0	40
S7, fees and bonuses	0	25	40
S8, fines, fees and bonuses	40	25	40

baseline scenario in which the level of enforcement was as low as possible (i.e., a fine level of zero, and no expenditure on paying either fees or bonuses to monitors). Next, I modelled a series of scenarios corresponding to the use of one or more of the policy levers to encourage monitoring and discourage poaching (Table 4.3).

4.3 Results

4.3.1 "Zero-enforcement" baseline

With no fines for poaching and no resources devoted to encouraging monitoring (scenario S1), the poaching strategies are dominant. The model reaches equilibrium with the animal population at approximately 38% of carrying capacity (Figure 4.1). Few individuals monitor or cheat so the probability that poachers are detected is small. The majority of individuals therefore spend their time poaching (strategy PO) while a smaller group pursue alternative livelihoods (strategy NO). Individuals choose to pursue alternative livelihoods because their opportunity costs outweigh the revenues they receive from poaching, which are a function of both the animal population size X_t and their hunting success, e_i.

4.3.2 Enforcement scenarios

In a scenario where fines are implemented alone (S2), approximately half of the community poaches while the others pursue alternative livelihoods (NO) because the risk of fines reduces the relative profitability of poaching. Very few individuals adopt a monitoring strategy, so there is little increase in the probability that poachers are detected, but the equilibrium

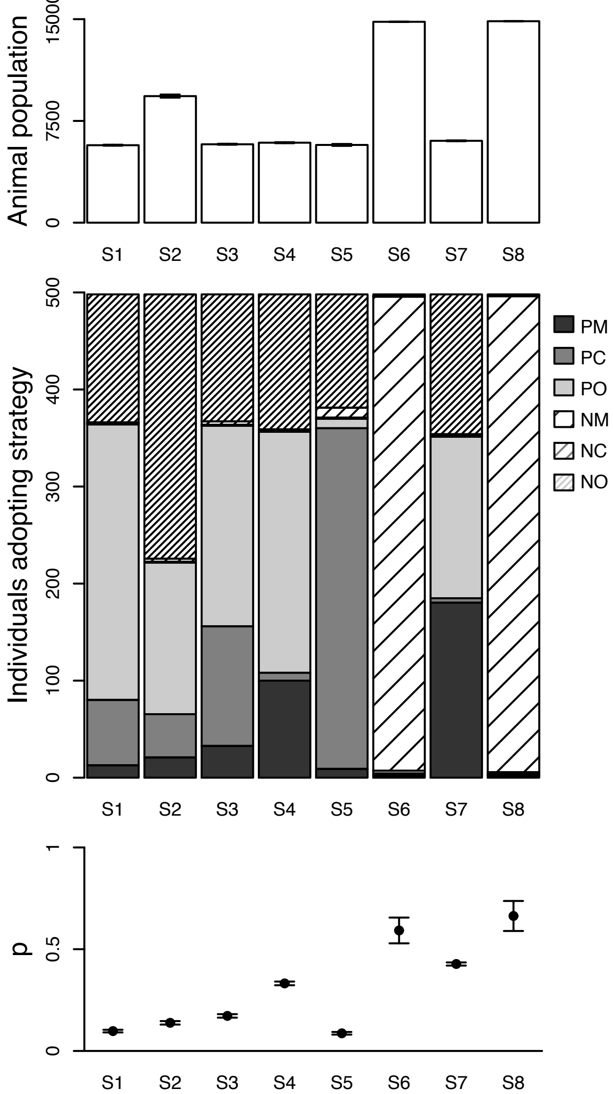

Figure 4.1: Comparison of a 'zero enforcement' baseline (S1) with scenarios where different combinations of fines for poaching and fees and bonuses for monitoring are used to try to encourage compliance. The top panel shows the equilibrium animal population under each scenario, the middle panel shows the proportion of the community that adopts each strategy and the bottom panel shows the resultant probability that poachers are detected, p.

animal population increases to 62% of carrying capacity because there are fewer individuals poaching than in the baseline.

By contrast, the payment of fees or bonuses for monitoring, on their own or together, does not affect the equilibrium animal population in the absence of fines. Paying fees alone (S3) causes a increase in the proportion of poachers who also cheat (strategy PC) but only a small increase in the number of individuals monitoring. The small number of monitors means that cheats are unlikely to be detected, and so the cost of social opprobrium for monitors outweigh the potential rewards from bonus payments. Consequently, the probability of detecting poachers rises only slightly and the overall number of poachers is unaffected. The payment of bonuses (S4) cause an increase in the proportion of the community who both poach and monitor, but is not sufficient for the strategy of monitoring without poaching to become profitable for any individuals. This results in a higher probability that poachers are detected. The pattern is similar when fees and bonuses are paid together (S7), with further increases in the number of individuals who poach and monitor and in the probability that poachers are detected. None of the scenarios where fees and bonuses are paid without the implementation of fines cause a change in the in the equilibrium animal population (Figure 4.1) because although the probability of being caught poaching increases, there are no consequences so the poaching remains profitable for individuals with lower opportunity costs.

Counterintuitively, the implementation of fines and fees together (S5) results in a lower probability of detecting poaching and smaller equilibrium resource population than using fines on their own (S2). This occurs because the majority of the community chooses to poach and cheat (strategy PC). The payment of fees increases the returns to both monitoring and cheating strategies, but only monitoring strategies incur the costs of social opprobrium and only cheats bear the costs of being punished if they are caught. In S3, where fees are implemented alone, a large number of poachers choose to neither monitor nor cheat to avoid these costs. However, the addition of fines for poaching reduces the returns to poaching. Monitoring is still not profitable because of the costs of social opprobrium, so in S5 the balance of incentives is tipped in favour of cheating.

By contrast, the scenarios with fines and bonuses together (S6) or fines, bonuses and fees (S8) are dramatically different, with virtually the entire community choosing to refrain from poaching themselves and to monitor the behaviour of others (NM) because the payment of bonuses to monitors, in combination with the imposition of fines for poaching, makes this strategy the most profitable for all individuals. Under both scenarios the probability of detecting poaching is high and the resource population is close to carrying capacity.

4.3.3 Responses of human and animal populations to varying policy levers

Changes to each of the policy levers may affect the probability that poachers are detected, the proportion of the community that monitors, and the size of the resource population. The specific responses to these changes vary between the policy levers and according to the economic context in which they are used.

The probability of detecting poachers shows two distinct regions, depending on the level of fine. Above a threshold fine level, the probability of detection is quite variable, but does not respond to changes in either the fees or bonuses paid to monitors. Below the threshold fine level, however, the probability of detection rises steadily with both fees and bonuses (Figure 4.2a–c). These changes in the probability of detection are only partially reflected in the size of the resource population (Figure 4.2d–f). Again, two regions of distinct behaviour can be distinguished above and below a threshold fine level. Unlike the probability of detection, however, the sizes of the monitoring fees and bonuses paid only have a significant influence on the resource population at intermediate fine levels. Here, the effects of small changes to bonuses and fees are ambiguous and can produce either increases or decreases in the resource population.

Two examples illustrating the potential for perverse effects caused by raising the fees and bonuses paid to monitors are given in Figure 4.3. The left hand panel shows changes in the strategy set and outcome variables in response to increasing bonuses, for an intermediate level of fine, relatively low fees and profitable alternative livelihoods. When no bonuses are paid, the community has a high proportion of individuals poaching and cheating (PC). Initially, increases in the size of bonuses see the number of cheats decline and disappear, with some individuals poaching and monitoring (PM) but the majority pursuing alternative livelihoods (NO). Further increases are counterproductive, however, as the strategy of poaching and monitoring becomes more profitable and is adopted by an increasing proportion of the community. Consequently, the number of poachers begins to rise again, and the resource population begins to fall. Finally, at very high bonus levels, monitoring without poaching (NM) begins to be profitable, and starts to replace both the poaching and monitoring and alternative livelihoods strategies.

The right hand panel shows a similar effect, this time for increases in the size of monitoring fees with an intermediate fine for poaching but no bonuses paid to monitors. When no fees are paid, the community is split fairly evenly between the three poaching strategies and alternative livelihoods. In this case, raising the fee initially leads to more poaching, with the largest group poaching and cheating. Since the probability of being caught cheating or poaching is small, at low levels the payment of a monitoring fee actually helps to subsidise poaching and, as a result, the resource population falls. Further increases in the fee eventually tip the balance in favour of monitoring, with the majority of the community also stopping poaching.

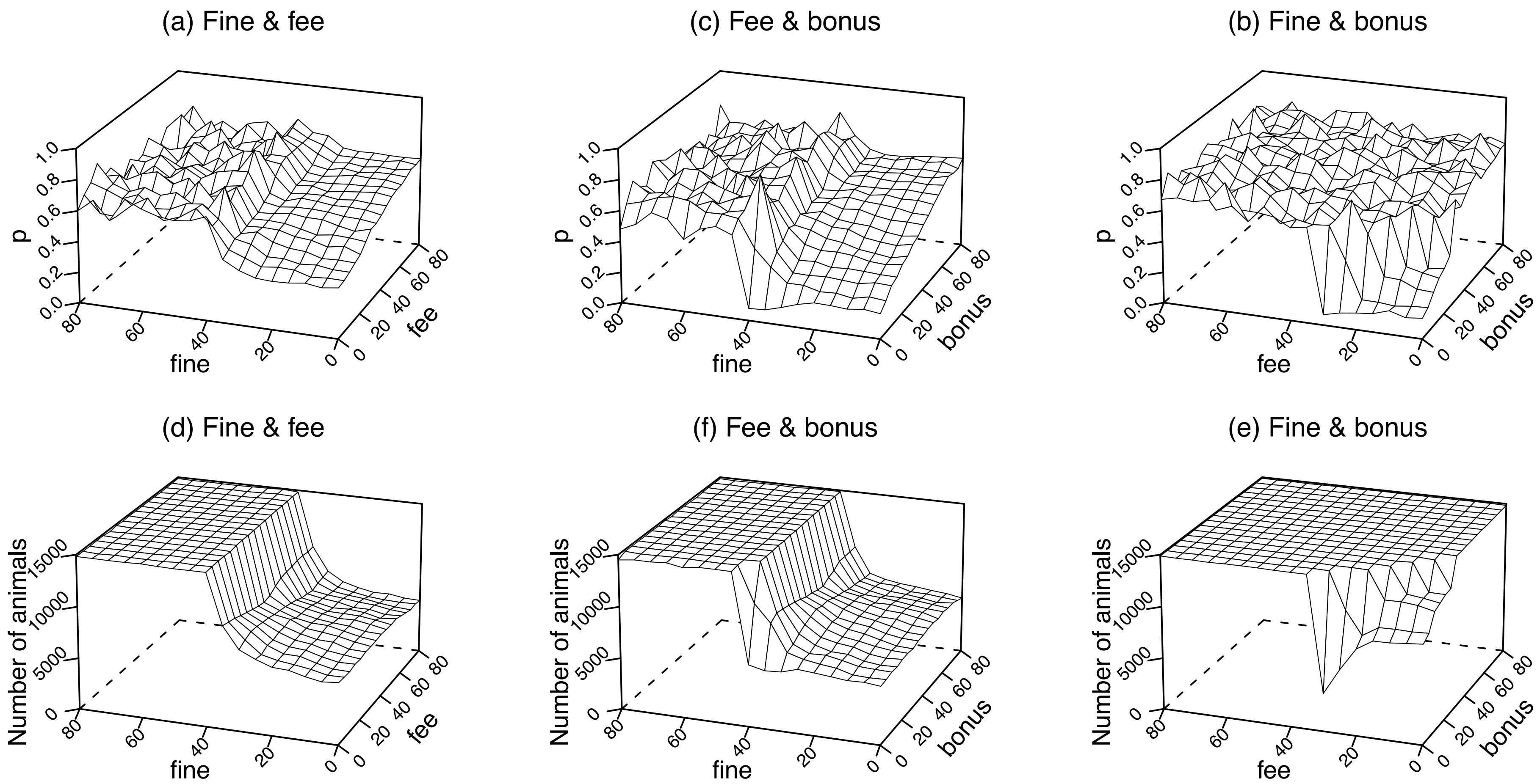

Figure 4.2: Changes in the probability that poachers are detected (upper panel) and the size of the equilibrium resource population (lower panel) in response to to changes in pairs of the three policy levers. All other parameters values are held at their baseline levels, including the third policy lever (Table 4.2).

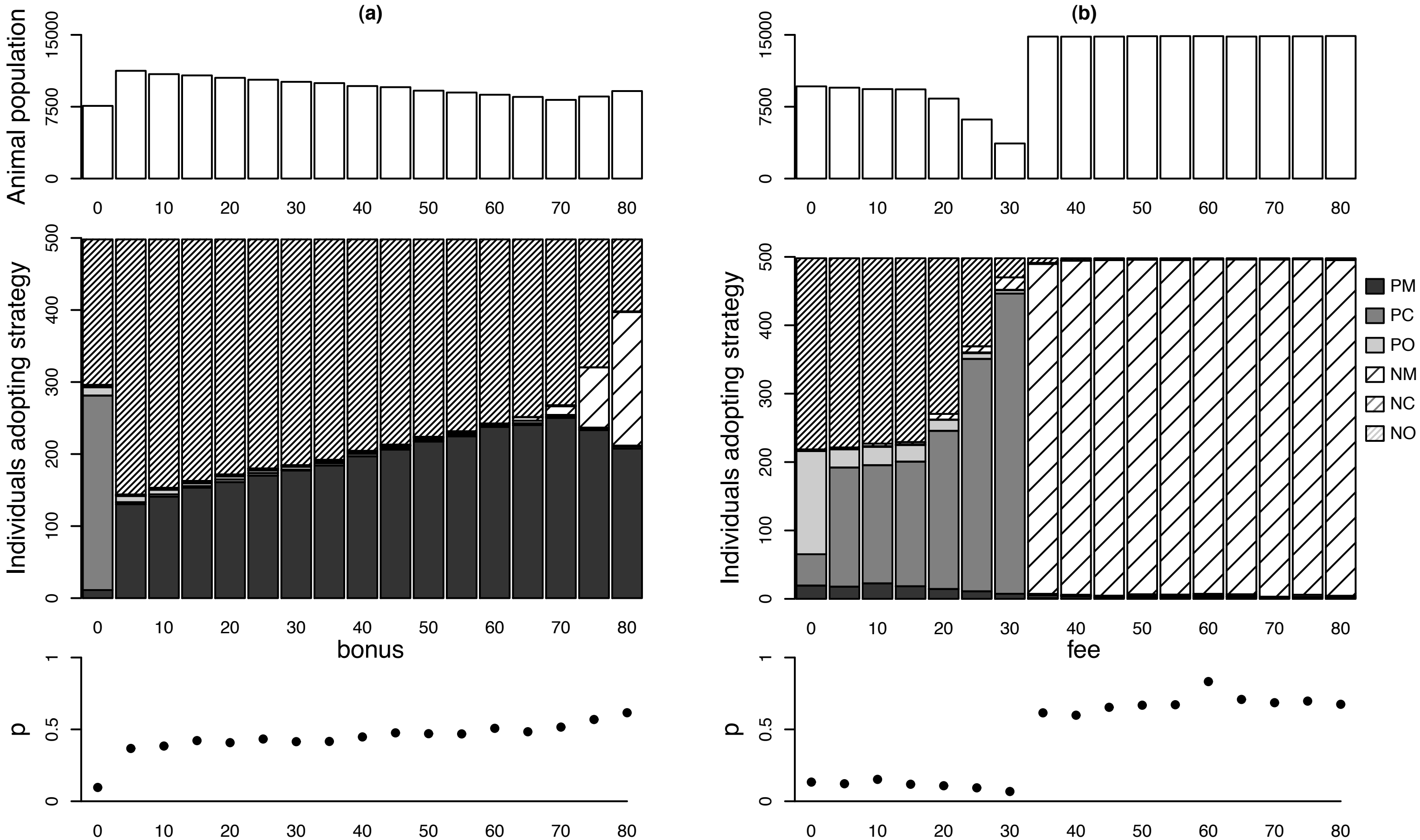

Figure 4.3: Examples illustrating the potential for perverse effects of payments intended to increase compliance by encouraging monitoring. The left hand column, (a), shows the effects of increasing the size of bonus paid to monitors given an intermediate fine for poaching, relatively low fees paid to monitors ($k = 35$, $f = 25$) and higher mean payoffs to alternative livelihoods (mean $o_i = 40$) . The right hand column, (b), shows the effects of increasing the size of fee paid to monitors given intermediate fines for poaching but no bonuses paid to monitors ($k = 40$, $j = 0$).

4.3.4 Influence of external factors on policy levers' effects

The results of changes to the three policy levers are also affected by the context in which they are applied. One important influence is the value of the resource to poachers (Figure 4.4). Increases or decreases in the returns to poaching shift the threshold fine level higher and lower respectively, with the threshold occurring approximately at the point where the returns per animal killed are equal to the fine for poaching.

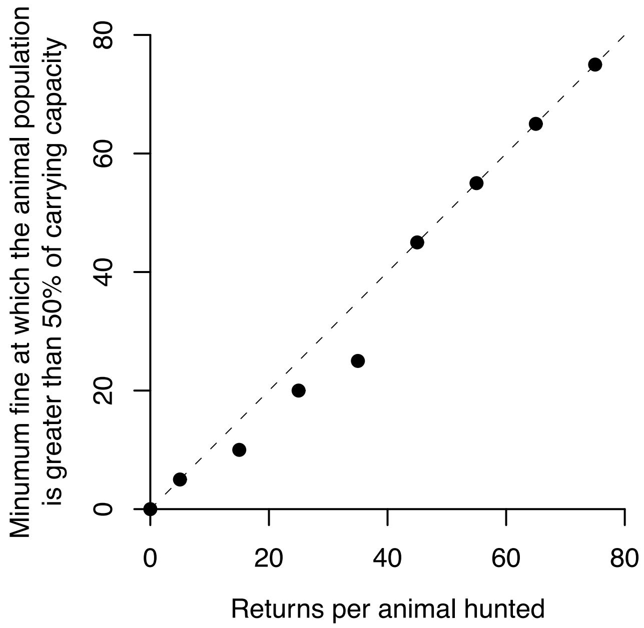

Figure 4.4: The relationship between the returns to poaching per animal hunted and the minimum level of fine per animal hunted which results in an equilibrium animal population at greater than 50% of carrying capacity. All other parameters are held at their baseline value (Table 4.2).

Differences in the ease of detecting cheats primarily affect the response to changes in the size of fees. For example, when it is very difficult to detect cheats, the range over which increases in fees perversely reduce the resource population becomes much larger (Figure 4.5a). By contrast, there are no perverse effects of paying fees when cheats are easily detected (Figure 4.5c).

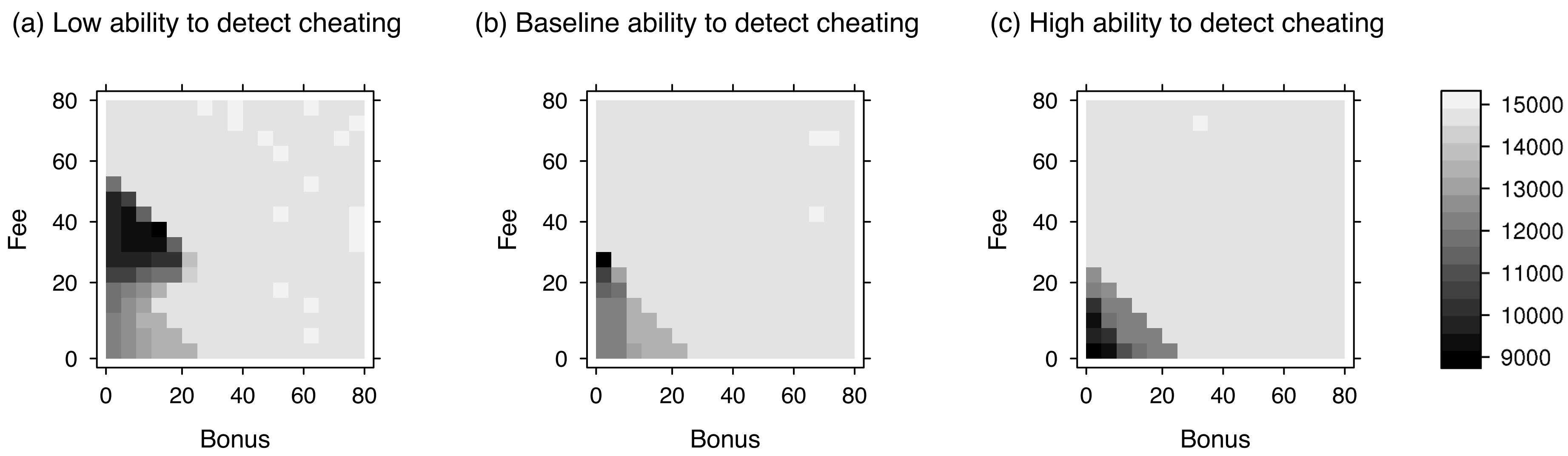

Figure 4.5: The effect on the equilibrium animal population of changing the size of fees and bonuses paid to monitors for three scenarios, differing according to the ease of detecting cheats, q. The scenarios are (a) $q = 0.002$, (b) $q = 0.01$, and (c) $q = 0.05$. All other parameters values are held at their baseline levels (Table 4.2). Larger equilibrium animal populations are indicated by lighter grey cells, while smaller populations are indicated by darker cells (see the colour key to the right hand side of the figure).

Changes in the average payoff to alternative livelihoods modify the effects of all three policy levers (Figure 4.6). For example, when the profitability of alternative livelihoods is low, increases in the size of bonus payments rapidly increase the resource population. Increases to the size of the fee paid to monitors initially have a perverse effect, producing a large fall in the resource population because cheating, rather than monitoring, is favoured, reducing the threat of punishment for poachers. When the profitability of alternative livelihoods increases, increases to the size of bonus payments produce a slower increase in the size of the resource population so bonuses must be much higher for the population to reach carrying capacity. Also, the region over which increasing the payment of fees causes a reduction in the resource population becomes smaller and then disappears.

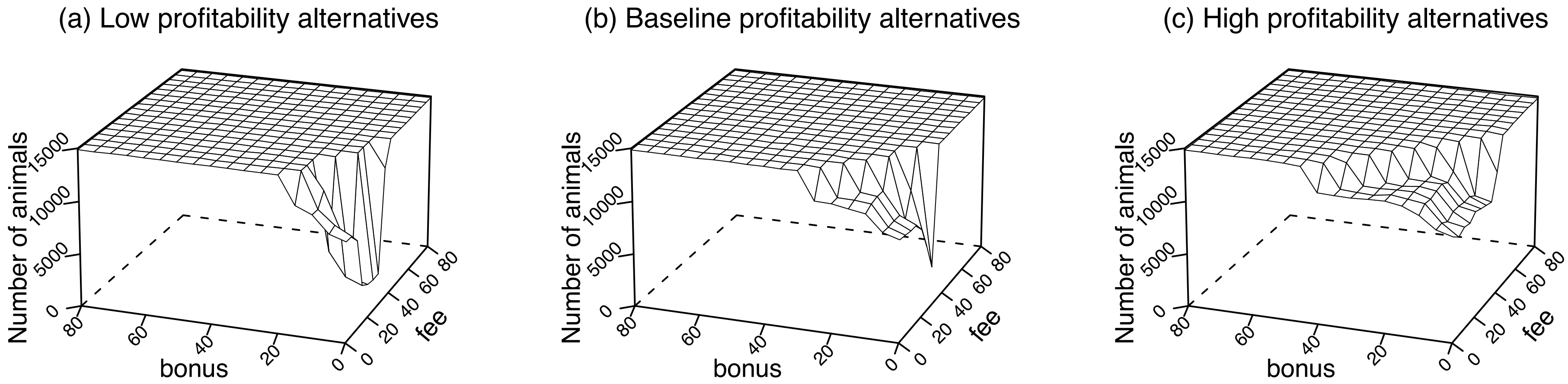

Figure 4.6: The effect of changing the size of fees and bonuses paid to monitors for three scenarios, differing according to the mean returns to alternative livelihoods, mean o_i. The scenarios are (a) mean $o_i = 10$, (a) mean $o_i = 20$, and (c) mean $o_i = 40$. All other parameters values are held at their baseline levels (Table 4.2).

4.4 Discussion

Changing peoples behaviour is an important goal of many conservation interventions. Over time, the emphasis of discussions about how to achieve this has shifted from the enforcement of rules and protected areas (Oates, 1999), to community-based, participatory conservation (e.g., Lewis et al., 1990) and, more recently, the potential of payments for environmental services (Ferraro, 2002; Engel et al., 2008). However, these approaches share considerable common ground since they all represent strategies for changing individual incentives to abide by rules or agreements. Understanding these incentives, and how they can be modified in beneficial ways, has increasingly been recognised as crucial for effective conservation, particularly in the growing literature on market-based instruments (Ferraro, 2002; Engel et al., 2008; Sommerville et al., 2009).

Previous studies examining the enforcement of conservation or resource management rules in the context of incentives have tended to concentrate on the resource users (e.g., fishermen or poachers; Leader-Williams and Milner-Gulland 1993; Skonhoft and Solstad 1996; Damania et al. 2005). However, the success of enforcement also depends crucially on the incentives monitors have to carry out their duties (Mesterton-Gibbons and Milner-Gulland, 1998; Mookherjee and Png, 1995; Robinson et al., 2010). The model I have presented here explores the effects on conservation outcomes of changes to three potential policy levers intended to promote monitoring and discourage poaching. Within the region of parameter space explored, I found that increasing the fine for poaching was generally the most robust tool for improving outcomes. However, this finding must be weighed against the disadvantages of high fines. Early economic models of crime and enforcement saw changes to the probability that rule-breakers were detected and punished and the severity of subsequent penalties as having equivalent effects on deterrence. From this, it was concluded that the optimal strategy for managers should be to raise fines as high as possible—since this was seen as costless—so that the deterrent effect upon rule-breaking could be maintained with lower levels of costly monitoring (Becker, 1968). Subsequently, however, many extensions to Beckers model demonstrated why fines cannot, in practice, be set at very high levels (Chapter 2; Garoupa 1997; Robinson et al. 2010). In conservation, 'fences and fines' approaches have gradually fallen out of favour (Oates, 1999) and there is evidence that harsh enforcement regimes can undermine relationships between conservation and local people (e.g., Infield and Namara, 2001; Wilshusen et al., 2002).

Increases in the size of fees and bonuses paid to monitors generally produced smaller changes than increases in fines, and in some cases led to perverse effects. Mesterton-Gibbons and Milner-Gulland (1998) found that the payment of fees was essential for the stability of monitoring as a strategy. The discrepancy between this finding and my results is caused by differences in the range of behaviours which modelled individuals are allowed to adopt. In particular, I consider an additional component of individuals strategies (monitor cheating) and allow both poachers and cheats to invest in avoidance behaviours in order to reduce their risk of being detected and punished. Both of these behaviours are commonly observed in studies of enforcement and compliance with rules (e.g., Malik, 1990; Polinsky and Shavell, 2001; Randall, 2004).

In my model, the robustness of fines in comparison to fees and bonuses is because their effect is more direct; raising the level of fines in the model always lowers the profitability of poaching, on average. By contrast, I observed two ways in which the payment of fees or bonuses could lead to more poaching. These payments both increase the profitability of monitoring for individuals who poach as well as those that do not, so do not necessarily favour monitoring without poaching over monitoring and poaching. Similarly, the payment of fees can encourage monitoring, but it can also lead to more cheating. The additional income that an individual gains from the fee for monitoring can therefore increase the profitability of poaching strategies PM and PC, and this can result in individuals switching from non-poaching to poaching strategies. Previous studies have suggested that the introduction of payments for actions which were previously voluntary, such as monitoring illegal behaviour, could 'crowd out' intrinsic motivations and produce the opposite of their intended effect (Frey and Jegen, 2001). However, the psychological mechanisms proposed to explain the phenomenon cannot operate in this model (e.g. changes from 'other-regarding' behaviours to more self-interested decision-making; Cardenas 2000; Vollan 2008). Instead, the apparent crowding out arises purely from rational utility-maximising behaviour.

My model highlights an important limitation of models of optimal enforcement, in which the severity of sanctions and the probability of detection have generally been discussed as separate inputs (see e.g., Becker, 1968; Milner-Gulland and Leader-Williams, 1992; Garoupa, 1997). By contrast, I show that the probability of detection experienced by rule-breakers can be partially determined by the level of the fine, rather than the two being independent of one another. This can occur because increasing the level of fine for poachers reduces the profitability of poaching so that, when the returns to alternative livelihoods are low, the most profitable strategy is not to poach, but to monitor. The effect is therefore likely to be particularly pronounced where monitors are recruited from small communities and have relatively few other livelihood options. A formal optimisation of enforcement strategies based on my model is beyond the scope of this investigation, but this result suggests that care should be taken to account for such interactions. If the probability of detecting rule-breaking and the severity of sanctions are jointly determined, models of enforcement which assume that they are independent would tend to overestimate the amount of investment in enforcement needed to produce a desired level of compliance.

Finally, this study serves to re-emphasise the importance of context and individual heterogeneity in determining the effectiveness of management interventions. In particular, it highlights how different strategies for creating incentives can interact with one another in communities where individuals differ in their underlying skills and motivations. The outcome of changes to the three policy levers in the model depends strongly on their interactions with one another, and on the broader socio-economic and ecological context in which they are embedded. With the prospect of many more payment for environmental services schemes being implemented (Engel et al., 2008; Wunder et al., 2008), there is an urgent need to understand how they will interact with existing institutions and incentives. Analyses on simulated systems, such as the one presented in this chapter, have their advantages, allowing manipulations which would be unethical and challenging to perform in the real world, and enabling thorough exploration of system behaviour. However they should be seen only as a starting point for empirical investigations. More research is needed to determine which characteristics of individuals and populations must be included in models of human behaviour if they are to inform robust decision making (Chapter 2; Travers 2009). Ultimately, improving our ability to chose effective strategies in situations where management of human behaviour and biological populations must go hand in hand requires discussions of our interventions—including enforcement, education, alternative livelihood strategies and direct payment schemes—to be grounded in a unified theoretical framework of incentives at the individual level.

Chapter 5

Testing the value of patrol data for conservation decision-making using a “Virtual Ranger” model

5.1 Introduction

A large proportion of conservation expenditure goes towards enforcement measures (e.g., Wilkie et al., 2001; Jachmann, 2008a; Robinson et al., 2010). Higher levels of investment in enforcement are known to be associated with higher levels of compliance with conservation rules (e.g., Bruner et al., 2001; Hilborn et al., 2006), but conservation practitioners invariably work with limited resources so enforcement measures must also be cost-effective (James et al., 1999). To rigorously assess the effectiveness of enforcement strategies, however, there is an urgent need for reliable data relating levels of rule-breaking to enforcement effort (Gavin et al., 2010). Gathering these data is challenging because of the illicit nature of rule-breaking (Fox and Tracy, 1986). One way of learning about the effects of enforcement would be to implement dedicated surveys of rule-breaking, using interview techniques designed to reduce response bias (e.g., Blank and Gavin, 2009; St. John et al., 2010) but this requires additional resources and expertise to implement. Consequently, a common approach to studying the effectiveness of enforcement has been to analyse the records collected by ranger patrols or other enforcement agents as they go about their duties (e.g., Leader-Williams et al., 1990; Jachmann, 2008b). This is attractive because collecting data in the course of patrolling is viewed as a relatively cheap way to enhance the value of patrols (Gray and Kalpers, 2005), and in many cases patrol records may be the only source of information available to managers. However the interpretation of these data is not straightforward (for a full discussion, see Chapter 6).

A measure of the effectiveness of enforcement strategies is the extent to which increases in the resources devoted to enforcement cause a reduction in the amount of rule-breaking. However, observed patterns in the number of infractions detected by patrols only partially reflect the amount of rule-breaking, as they also depend upon changes in the detectability of infractions and on the effects of external factors on poacher decisions (e.g., the availability of legal sources of income; Skonhoft and Solstad 1996; Damania et al. 2005), as well as on patterns of patrol effort in time and space. It is therefore difficult to use patterns observed in patrol data (e.g., changes in the number of snares detected over time) to draw inferences about the underlying processes of interest (e.g., the amount of poaching). Previous analyses of patrol data have generally applied simple catch per unit effort (CPUE) methodologies to account for increased detection due to increased patrol effort (e.g., Leader-Williams et al., 1990; Jachmann, 2008b) but the use of such methods implicitly assumes that infractions are distributed randomly with respect to patrol effort (cf. Hilborn and Walters, 1992). This assumption rarely holds (Chapter 6). Furthermore, most previous studies have tended to examine trends in CPUE aggregated at the scale of entire protected areas and over relatively long periods of time, making it more difficult to detect whether patterns of patrolling approximate a random sample or whether they suffer from biased spatial patterns of patrol coverage (Chapter 6). Consequently, analyses of patrol data face a problem of separating the deterrent effect of patrolling from the effects of other processes and biases. With perfect information about the behaviour of both patrols and rule-breakers this task would be trivial, but this is never the case.

Similar problems of inferring processes from observed patterns are common in ecology (e.g., Halle, 1999; Wyszomirski, 1999). The validity of such inferences has been studied through the construction of "virtual ecologist" models. By simulating both the underlying phenomenon that is being studied and the observation process which is used to gather data, virtual ecology allows investigators to relate observed patterns to the processes within the model which generate them (Berger, 1999; Tyre et al., 2001). Conceptually similar modelling approaches known as Management Strategy Evaluations have also found practical applications in fisheries management, where simulations are increasingly being advocated as a means to predict the robustness of potential management scenarios (e.g., Kell et al., 2007).

In this study, I construct a simulation model in which 'virtual rangers' collect data about simulated rule-breaking events. I use this model to ask under what conditions simple CPUE analyses of patrol data are useful for evaluating the effectiveness of patrolling as a deterrent to poaching. Specifically, I examine (1) whether observable patterns that are attributable to deterrence can be distinguished from those that arise if rule-breakers display other behavioural responses to patrolling, and whether or not these patterns are robust to (2) non-random spatial distribution of patrol effort, and (3) temporal lags in the responses of rule-breakers and patrols caused by infractions persisting in the landscape after they are committed, and rule-breakers basing their decisions on their memory of previous patrol activity. I finish by considering the potential of the virtual ranger approach for testing approaches to improving the effectiveness of law enforcement more generally.

5.2 Methods

5.2.1 Model structure

The model structure and parameterisation were broadly based upon the situation in Masoala National Park in Madagascar (see Chapter 6). In this protected area, as is commonly the case, poachers live around the park and come into it from the edge in order to lay snares. The simulations were carried out in a 10km^2 square area which was assumed to be part of a larger protected area, positioned so that one side lies on the park boundary. A population of potential rule-breakers lives in the vicinity of the area and commits infractions within the protected area. Evidence of these infractions remains present within the cell for a period of time, such as might be typical of snaring. Ranger patrols are carried out in the area to improve compliance with laws prohibiting poaching. The landscape was divided into smaller cells, 100m^2 in size, and time within the model was divided into units of one day. The principal outputs of the model were the number of new infractions committed by rule-breakers and the number of infractions detected by patrols. These quantities could be expressed at various spatial and temporal scales (e.g., the number of infractions detected in the entire park or in smaller subdivisions, over days or weeks). An overview of the model structure is given in Figure 5.1. The model was implemented in R version 2.10.1 (R Development Core Team, 2009).

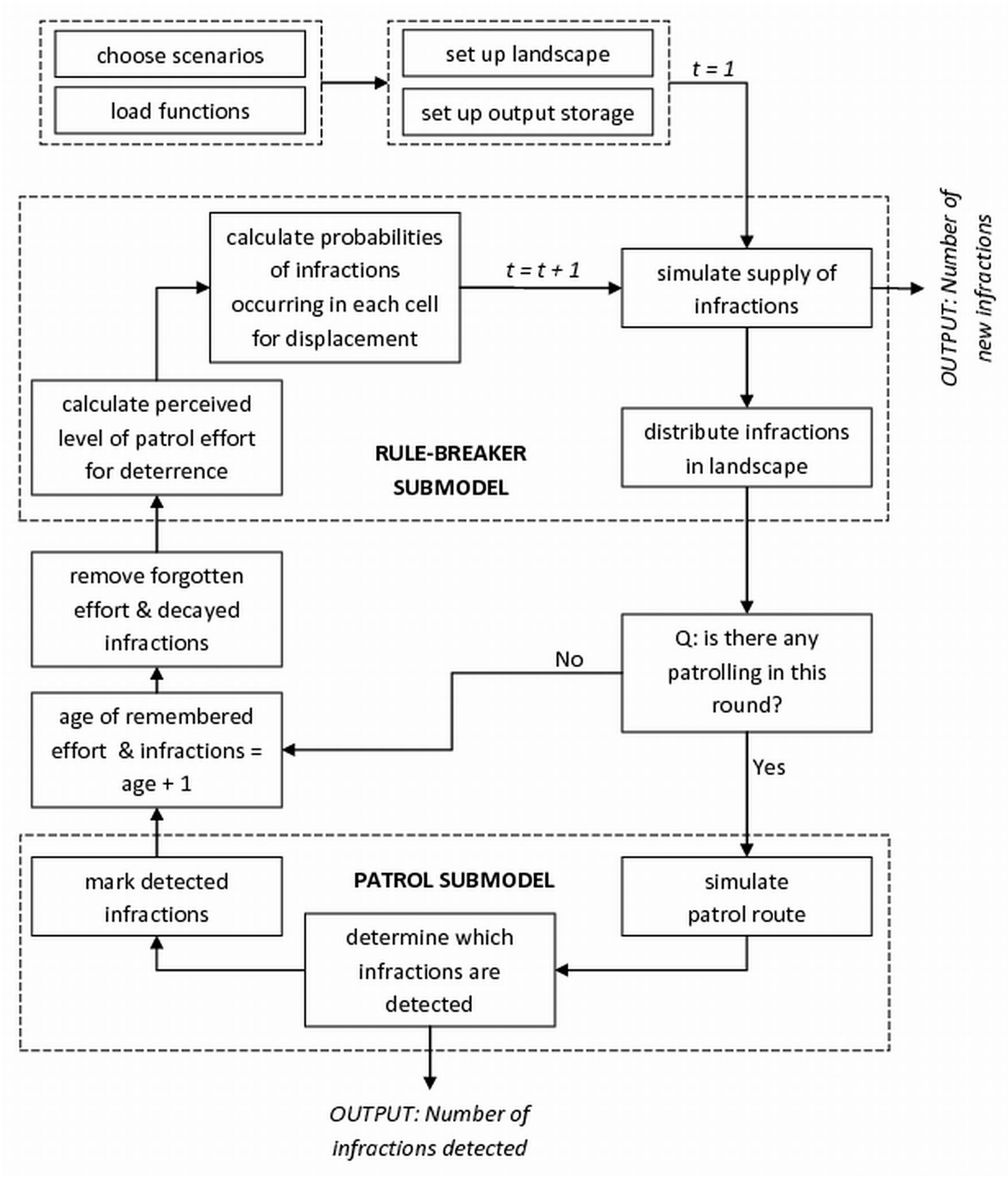

Figure 5.1: Outline structure of the Virtual Ranger simulation model. The figure shows the process at the whole area scale.

5.2.2 Rule-breaker sub-model

In the model, rule-breakers were allowed to react to patrol effort in one of four ways: (1) they could be insensitive to patrolling, meaning that their behaviour did not change in response to changes in patrol effort, (2) they could be deterred by patrols, meaning that the total number of infractions committed within the entire area in a round declined as the perceived threat of patrols increased, (3) they could be displaced, moving away from locations where the perceived threat of patrolling was higher, or (4) they could be both deterred and displaced.

The supply of infractions in round t, N_t, was given by

$$N_t = a - \frac{b + a}{1 + e^{c(d - D_t)}} \tag{5.1}$$

a determined the right-hand asymptote, b the left-hand asymptote, c was a scale parameter controlling the rate of change, d set the midpoint and D_t was a measure of the rule-breakers' perception of the threat they faced from patrolling at time t (see Equation 5.2, below). For the simulations these parameters were set at a = 50, b = -1, c = 0.5 and d = 8. The resulting relationship between the perceived threat of patrolling and the supply of infractions was a sigmoid curve falling from 49 infractions committed per round when D_t = 0 to 2 infractions committed per round when D_t = 1 (Figure 5.2a).

When the scenario required that patrolling should produce no deterrent effect, D_t = 0. However, when patrolling did result in deterrence the perceived threat in round i was calculated as a weighted sum of the patrol efforts, E_t, expended in previous rounds. The weighting given to patrol effort in previous rounds grew exponentially smaller the further back in time that patrol had taken place. The perceived threat from patrolling at time t, D_t, was

$$D_t = \sum E_t \lambda^0 + E_{t-1}\lambda^1 + \ldots + E_t - m\lambda^m - 1 \tag{5.2}$$

where λ was the rate of forgetting and m was the length of the rule-breakers' memories. For all simulations $m = 10$, but λ was varied between scenarios. In the baseline scenario the rate of forgetting was set to be very fast ($\lambda = 0.01$) so that the effects of patrolling did not last once the patrol was over. This parameter value reflects a situation where rule-breakers have good information about when and where patrols are operating, and are able to respond

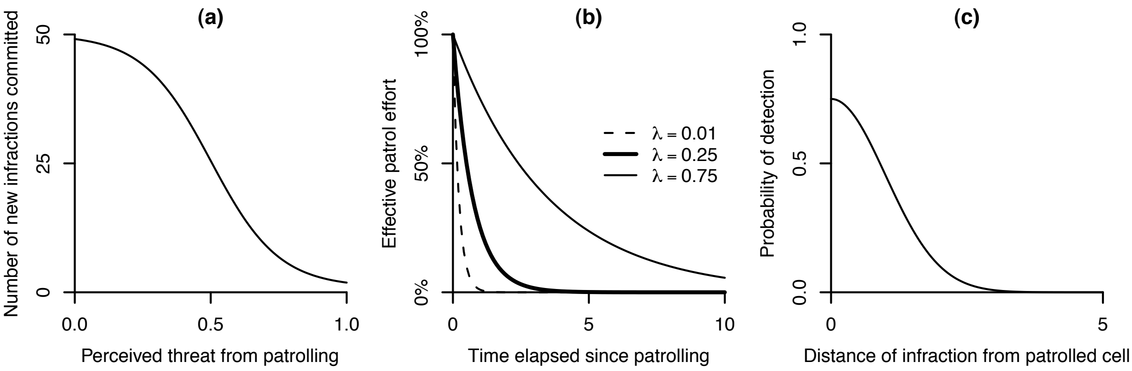

Figure 5.2: Shapes of processes within the model: (a) supply of infractions against patrol effort, (b) decrease in the weighting given to patrol effort over time when calculating rule-breakers' perception of the threat of patrolling for three levels of discounting of older information (fastest discounting when $\lambda = 0.01$, slowest when $\lambda = 0.75$), and (c) decrease in the probability that an infraction is detected with its distance from a patrolled cell.

quickly when a patrol enters or leave an area. Other scenarios, reflecting situations where rule-breakers' assessments of the current level of threat include older information, used slower rates of forgetting ($\lambda = 0.25$ or $\lambda = 0.75$) so that the deterrent and displacement effects of patrolling persisted for some time after the patrol departed the area (Figure 5.2b). In order to make results easily comparable between scenarios with different rates of forgetting, D_t was normalised to lie between 0 and 1 by dividing it by its maximum possible value given the value of λ in that scenario.

The new infractions committed in each round were then distributed in the landscape. When patrolling produced no displacement effect, the locations of new infractions were chosen at random. However, in scenarios where rule-breakers responded to patrolling by displacing their activity to new locations, the probability that an infraction was placed within cell i at time t, $\pi_{i,t}$, depended on the previous history of patrolling in that cell

$$\pi_{i,t} \; = \sum e_{i,t}\lambda^0 + e_{i,t-1}\lambda^1 + \ldots + e_{i,t-m}\lambda^{m-1} \tag{5.3}$$

$e_{i,t}$ was the level of patrol effort in cell i at time t and took the value 1 if the cell was patrolled in round t, and 0 if not.

In the baseline scenario the lifetime of infractions, ζ, was set to 1, meaning that each infraction was removed from the landscape after a single round (i.e., it was only present during the round in which it was committed). In some situations this assumption is likely to be reasonable (e.g., poachers using guns may leave little sign of their presence once they leave an area), but in many cases the local effects of rule-breaking may persist after the event (e.g., setting traps or snares). Scenarios in which evidence of infractions persisted in the landscape for longer were achieved by setting $\zeta = 4$ or $\zeta = 7$, meaning that infractions were removed at the end of the fourth or seventh round after they were committed, respectively.

5.2.3 Patrol sub-model

Unlike rule-breakers, whose behaviour was modelled at the group level, the movements of ranger patrols were modelled individually. In each round where a patrol occurred, a set amount of patrol effort was available for use. The cells patrolled were either (a) chosen at random, or (b) placed along simulated patrol routes. Although it is unrealistic for cells to be patrolled entirely at random, this option was included to represent a "perfect" sampling scenario, and provided a baseline against which the performance of more realistic patterns of patrolling could be measured.

The simulated patrol routes were constructed from a series of discrete decisions modelled as a Markov process. The starting position for each patrol was a cell on the boundary of the protected area, chosen at random. At each step, the patrol was able to move to a directly or diagonally adjacent cell. The probability of each transition was determined by the relative distance from a specified target point. This target point was a randomly chosen cell on the border of the landscape furthest from the protected area boundary (i.e., patrols begin at the boundary of the protected area and tend to move inwards meaning that, on average, cells closer to the boundary of the protected area were more likely to be patrolled). The probability of transitioning from the currently occupied cell, i, to adjacent cell, j, $u_{i \to j}$, was

$$u_{i \to j} = \frac{r_j^{-s}}{\sum r_j^{-s}} \tag{5.4}$$

r_j was the rank of the distance between cell j and the target point, with the mean taken of tied ranks. The sinuosity parameter, s ($s > 0$), affected the directness of the route with larger values producing more direct routes on average. For the simulations, $s = 1.5$. The patrol route continued to grow in this fashion until the number of cells visited reached the set amount of patrol effort invested in that round (Figure 5.3). In rounds where the available patrol effort was greater than 100, the route was split into smaller sections, each involving 100 units of effort or fewer, to ensure that the patrol did not leave the edges of the landscape. To achieve this, a new start point and target point were chosen every time the length of a patrol segment reached 100.

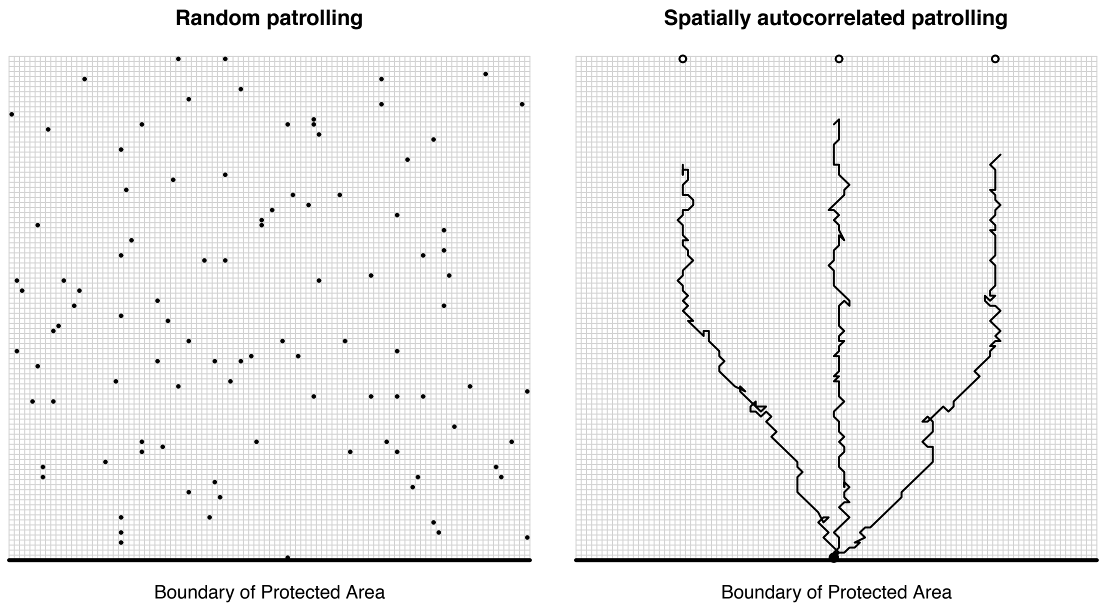

Figure 5.3: Examples of the two patterns of patrolling: random, and spatially autocorrelated. The three target points for spatially autocorrelated patrolling are indicated by hollow circles. 100 units of patrol effort are expended in the random patrolling example, and for each of the three spatially autocorrelated patrolling examples. Note that the target points are never reached with spatially autocorrelated patrolling.

When an infraction occurred in a cell on or close to a patrol route, there was a probability that it would be detected by the rangers but detection was never perfect. The probability that an infraction was detected when the patrol was in cell i, p_i, depended on the distance of the infraction from the cell, with $p_i = 0.75$ for infractions occurring in cells directly on the patrol route (Figure 5.2c). For a unit of patrol effort in cell i the probability of detecting an infraction in another cell was given by a standardised half-normal function

$$p_i = 0.75\frac{h_z}{h_0} \tag{5.5}$$

where h_z represents the z^{th} quantile ($z \geq 0$) of the probability density of a normally distributed variable with mean zero and standard deviation of 1, N(0,1). h_0 equals the value of h_z when $z = 0$, and was included as a standardising constant. z is a function of the distance of an infraction from the patrolled cell, δ,

$$z = \frac{\delta}{\rho} \tag{5.6}$$

where ρ was a constant which described how rapidly p_i declined with distance. For all simulations, $\rho = 1$. Once discovered, an infraction was marked as having been detected within the model, and subsequently was not counted again if it was re-encountered.

Table 5.1: List of symbols used for parameters and quantities within the model.

Symbol	Description
t	Round number
i	Cell number
T	ID for aggregated group of rounds
I	ID for aggregated group of cells
N_t	The total number of infractions committed at time t
a	Right hand asymptote for supply of infractions
b	Left hand asymptote for supply of infractions
c	Scale parameter for supply of infractions
d	Midpoint parameter for supply of infractions
D_t	Threat from patrolling perceived by rule-breakers at time t
E_t	Patrol effort in entire landscape at time t
λ	Rule-breakers' rate of forgetting for previous patrolling
m	Maximum length of rule-breakers' memories
$\pi_{i,t}$	Probability that an infraction is placed within cell i at time t
$e_{i,t}$	Level of patrol effort in cell i at time t
ζ	Lifespan of infractions
$u_{i \to j}$	Probability that a patrol moves from cell i to an adjacent cell j
R_j	Rank of the distance between cell j and the patrol's target point
s	Sinuosity parameter of patrols
p_i	Probability that an infraction is detected when a patrol in in cell i
h_z	z^{th} quantile ($z \geq 0$) of probability density of a normally distributed variable N(0,1)
δ	Distance of an infraction from the patrolled cell
ρ	Rate of decline of p_i with distance

The symbols used to denote parameters and quantities within the model are summarised in Table 5.1.

5.2.4 Analyses

To study the importance of the behaviour of rule-breakers and ranger patrols in determining the number of infractions detected by patrols I used the model to compare a series of scenarios, incorporating different behaviours. For each scenario I examined how changes in the number of infractions committed and the proportion of infractions detected interacted to produce observable patterns in the number of infractions detected with patrol effort and whether the scenario's assumptions led to bias in CPUE. Although all processes were modelled at a spatial resolution of 100m^2 and a temporal resolution of 1 day, I analysed the data at several different levels of aggregation by grouping sets of adjacent cells or days into larger units.

CPUE was therefore defined as

$$\frac{C_{I,T}}{E_{I,T}} = q_{I,T}N_{I,T} \tag{5.7}$$

In an aggregated group of cells, I, during time period T, $C_{I,T}$ was the number of infractions detected, $E_{I,T}$ was the amount of patrol effort expended (measured as the number of cells visited), $N_{I,T}$ was the total number of infractions present and $q_{I,T}$ was the detectability coefficient. Detectability is the proportion of the infractions in the area that are detected by one unit of patrol effort (cf. the harvesting literature where the analogous constant, catchability, may be defined as the proportional mortality caused by one unit of harvesting effort; Chapter 6). Since $N_{I,T}$ was known in the model, I used the detectability coefficient as a basis for comparisons between scenarios where there were differing total numbers of infractions present.

The data were initially aggregated at the scale of the entire park and a single day, but for each scenario comparisons were made with the data grouped spatially into blocks of 50 x 50 cells or 25 x 25 cells and temporally into blocks of 5 or 10 days. Due to the definition of effort as number of cells visited per round, detectability depends partly on the spatial and temporal scale of analysis. The value of the detectability coefficient in the baseline scenario is a simple function of the effective area being analysed. For example, if the unit of aggregation was blocks of 25 x 25 cells (i.e., the landscape was split into 16), the detectability constant was approximately 16 times larger than if the data were aggregated over the entire 100 x 100 cell area. Similarly, if the data were aggregated into blocks of 10 days (thus increasing the 'effective' area tenfold), the detectability constant was 10 times smaller than when the data were analysed one day at a time. To facilitate comparisons between the different scales I therefore routinely standardised the detectability coefficient in a given scenario by dividing it by its value calculated in the baseline scenario at the same spatial and temporal scale.

Initially, the model was set up so that patrols were carried out in every round and the level of patrol effort per round was held constant within each model run. Consequently, the number of infractions committed and detected on average per round reached equilibrium. Each run began with a 20 round initialisation period to allow the model to equilibrate, during which no results were collected, and then ran for 500 rounds. For each scenario, the model was run for 13 different levels of available patrol effort, from 10 to 250 in steps of 20 units.

In the baseline scenario, patrols visited cells in the landscape entirely at random. Infractions did not persist in the landscape after the round in which they were committed, and rule-breakers did not remember patrol effort once the patrol had left the area. Subsequent scenarios were compared to this baseline in order to quantify the effects of different behavioural processes (Table 5.2). My first comparison was between scenarios where rule breakers did not respond to patrolling, were deterred (i.e., responded by reducing the number of new infractions that were committed), or were displaced (i.e., responded by changing the location of new infractions, moving away from patrolled areas). Next I examined how differences in spatial patterns of patrolling could affect CPUE measures, comparing scenarios where patrol effort was assigned at random with scenarios where effort was spatially autocorrelated with those where effort was joined together into simulated patrol routes (Figure 5.3a vs. b). Finally I varied parameters in the model to allow evidence of infractions to persist in the landscape beyond the round in which the infractions were committed and to allow the behavioural responses of rule-breakers to continue after patrols had left the area.

Table 5.2: Scenarios analysed using the model.

Scenario	Pattern of patrolling	Rule-breaker responses considered	Lifetime of infractions, ζ	Rule-breakers' rate of forgetting, λ
Baseline	Random	None, deterrence, displacement, deter. & displace.	1 (shortest)	0.01 (fastest)
Spatially autocorrelated patrolling	Spatially autocorrelated	None, deterrence, displacement, deter. & displace.	1	0.01
Persistence of infractions	Random	None, deterrence, displacement.	1, 4 or 7	0.01, 0.25 or 0.75
Rule-breakers' memory of patrolling	Random	None, deterrence, displacement.	1, 4 or 7	0.01, 0.25 or 0.75

5.3 Results

5.3.1 Effects of behavioural responses to patrolling

Analysed at the level of changes over the entire landscape per day, the number of new infractions committed per round in the baseline scenario, and in the absence of any behavioural responses to patrolling, was fixed so did not vary according to the amount of patrol effort (Figure 5.4a). As patrol effort increased, an increasing proportion of the total landscape was sampled and the proportion of infractions detected increased linearly (Figure 5.4b). Together, these two processes produced changes in the number of infractions that were detected by patrols, which is the only one of the three quantities that would be observable in reality (Figure 5.4c). The mean number of infractions detected increased linearly with patrol effort, before flattening very slightly due to patrol saturation. The variance in the number of infractions detected was approximately equal to the mean, and also increased linearly with patrol effort.

When rule-breakers responded to patrolling by displacement (i.e., moving away from patrolled areas), the observed patterns in the mean and variance of the number of infractions encountered with increasing patrol effort were similar, but the proportion of infractions detected was consistently lower than when there was no displacement (approximately 53% of the proportion detected when there is no displacement; Figure 5.4f). Consequently, CPUE was a biased measure of the number of infractions being committed when there was a displacement response to patrolling, even though patrol effort was randomly distributed (Figure 5.5a). This occurred because the model allowed rule-breakers to react instantaneously to the presence of patrols, becoming less likely to commit infractions in the vicinity of patrolled cells than would be expected by chance.

If, instead of displacement, the effect of patrolling was to deter rule-breakers from committing infractions, the number of new infractions committed decreased with increasing patrol effort (Figure 5.4g). However, the proportion (but not necessarily number) of those infractions which were detected still increased linearly with patrol effort (Figure 5.4h). Consequently, the observed relationship between the number of infractions encountered and patrol effort was humped (Figure 5.4i). The mean number of infractions detected rose at first while detection dominated, before declining again at higher effort levels as deterrence came to dominate. The variance in the number of infraction detected was again approximately equal to the mean so was greatest at intermediate levels of patrol effort (although the vari-

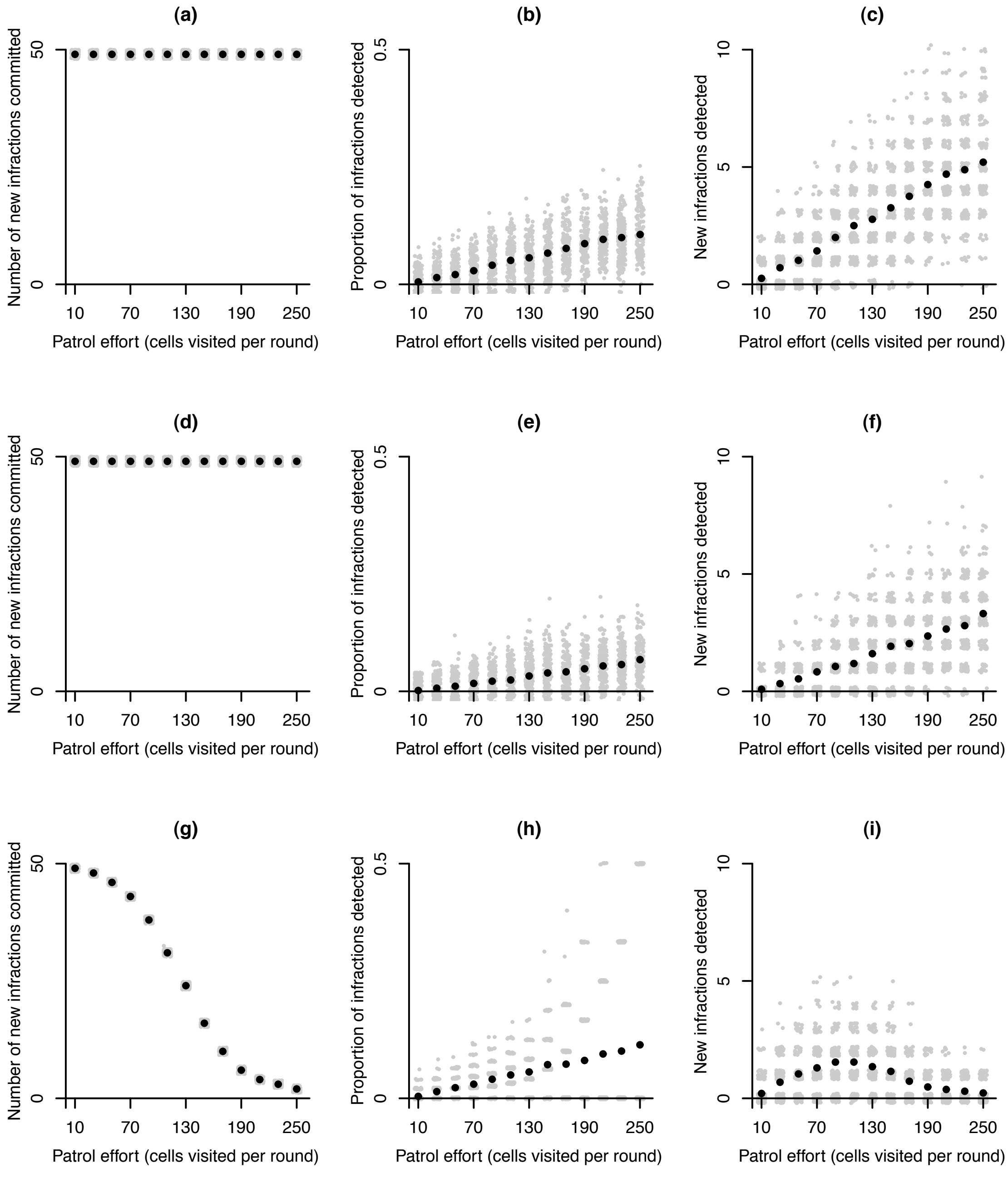

Figure 5.4: The effects of differing behavioural responses to patrolling on the number of infractions committed, the proportion of infractions that are detected and the observed number of infractions detected as patrol effort changes. Rule-breakers show no behavioural responses to enforcement in the top row (a–c), respond with displacement in the middle row (d–f) and with deterrence in the bottom row (g–h). Light grey dots show the distribution of the data (jittered by a small amount to allow the density of points to be judged more easily), black points are the mean values binned over 20 units of effort.

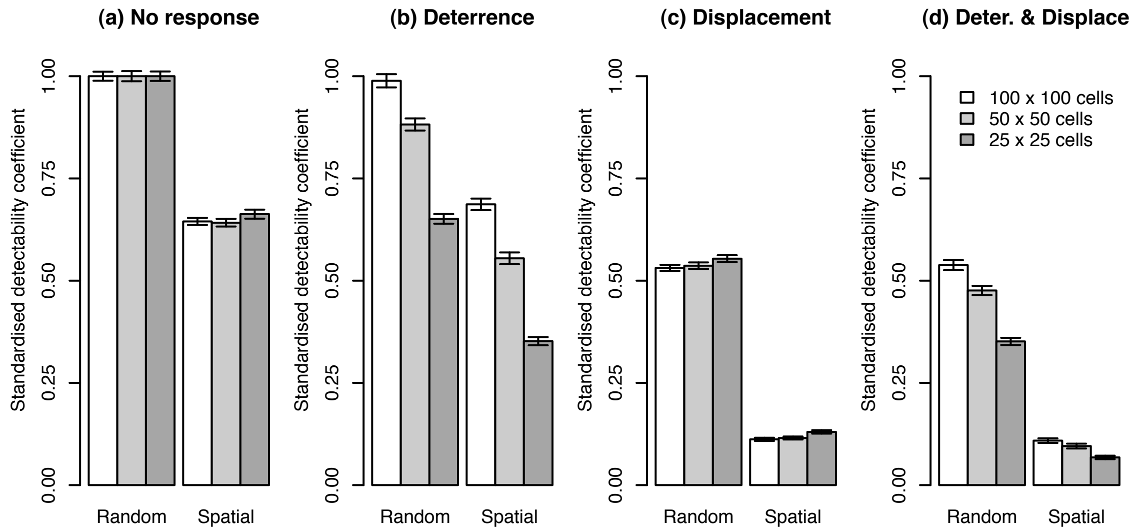

Figure 5.5: Comparison of detectability coefficients for different rule-breaker responses to enforcement and spatial patterns of patrolling at three different spatial scales. Detectability coefficients were standardised by dividing by the detectability coefficient in the baseline case with no behavioural responses to enforcement and randomly distributed patrol effort at each scale. Lower detectability coefficients represent situations in which CPUE underestimates the true number of infractions present in the landscape.

ance in the proportion of infractions detected increased more rapidly with effort because the total number of infractions is smaller at higher effort levels).

5.3.2 Effects of spatial sampling

When patrol effort was linked together along patrol routes, the shapes of the relationships between the level of patrol effort and the means and variances of the number of infractions committed, proportion of infractions detected or number of infractions detected were similar to those that arose when cells were patrolled at random. However, the proportion of infractions detected was lower, meaning that CPUE is a biased measure of the number of infractions committed when sampling effort is not randomly distributed throughout space (Figure 5.5a). With randomly distributed infractions, this effect was attributable to the greater probability of overlap between the areas sampled by each unit of patrol effort when patrol effort was closely grouped in space. Hence with no behavioural responses to enforcement, mean CPUE for the spatially autocorrelated pattern of patrolling modelled was approximately 64% of the mean CPUE for random patrolling .

Spatially autocorrelated patterns of patrolling interacted with displacement responses to patrolling, producing even more pronounced reductions in CPUE. When rule-breakers responded to patrolling by moving away from patrolled areas the mean CPUE for spatially autocorrelated patrolling with displacement was approximately 17% of the mean CPUE observed for spatially autocorrelated patrolling without displacement, and only 11% of the mean CPUE for random patrolling with no displacement. The greater bias in this case (compared with the bias due to displacement with randomly distributed patrol effort) occurred because areas of the landscape furthest from the protected area boundary acted as a refuge in which infractions were more likely to be committed (because of displacement) but less likely to be detected (because these cells were patrolled less often).

5.3.3 Interactions between rule-breaker and patrol behaviour and the scale of analysis

The biases in CPUE caused by rule-breakers' behavioural responses to enforcement and non-random patterns of patrolling are summarised at three different spatial scales in Figure 5.5, standardised to show changes relative to the baseline scenario at the relevant scale. The spatial scale of analysis had a large effect on estimates of the detectability coefficients when patrolling produced a deterrent effect. Analysed at the whole-landscape scale with random distribution of patrol effort, the presence of a deterrent effect did not change the detectability coefficient relative to the baseline. However, analysed in blocks of 50 x 50 cells or 25 x 25 cells the presence of deterrence caused a reduction in detectability (to 88% and 65% of the baseline detectability coefficient, respectively). With spatial patrolling, the presence of a deterrent effect resulted in a small increase in detectability when analysed at the whole-landscape scale, but decreases in detectability at smaller spatial scales.

The overall decreases in detectability when data featuring deterrence were analysed at smaller spatial scales arose because a larger proportion of areas contained no infractions and were therefore treated as having a detectability coefficient of zero (a form of zero inflation, Chapter 6). The lower number of infractions present in the landscape due to deterrence also caused the counterintuitive increase in detectability with spatially autocorrelated patrolling. This increase occurred because of a reduction in the negative bias caused by overlap in the areas sampled by patrol effort.

There were also much smaller interactions between the effects of both displacement and spatially autocorrelated patterns of patrolling and the spatial scale at which the data were analysed. For both sets of behaviour, analysing the data at finer spatial scales leads to small increases in the estimated detectability coefficients. These increases relative to the same data analysed at the whole-landscape scale occurred because the process of calculating a simple mean detectability gives equal weighting to groups of cells which have received a lot of patrol effort and those that have received very little. Thus, the effects of spatial differences in the distribution of either infractions or patrol effort are reduced.

The effects of aggregating the data into groups of 5 or 10 days were also examined, but I found no interactions between the behavioural effects and temporal scale.

5.3.4 Persistence of infractions

The effects of infractions persisting in the landscape were similar whether patterns of patrolling were spatially autocorrelated or random, and depended strongly on the behavioural responses of rule-breakers to patrolling (Figure 5.6). For clarity, only the results from randomly distributed patrol effort are presented. When rule-breakers did not change their behaviour in response to patrolling, increases in the persistence of infractions produced decreases in the detectability coefficient. The reduction in detectability occurred because, when infractions had longer lifespans, the probability that a patrol would re-encounter an infraction which had previously been detected was increased. These re-encountered infractions were not included in the calculation of CPUE, so the recorded number of infractions encountered was a smaller proportion of the total number of infractions present in the landscape.

When rule-breakers displayed behavioural responses to patrolling, the detectability coefficient depended upon both the type of behavioural response (deterrence or displacement) and the spatial scale of analysis, but not on the temporal scale of analysis. Analysed at the whole-landscape scale, the effects of infractions persisting for longer when rule-breakers were deterred were very similar to those when rule-breakers did not respond to patrolling. However, the persistence of infractions served to counteract the negative bias caused by deterrence when the data were analysed at finer spatial scales. Longer-lived infractions meant that the total number of infractions present in the landscape at any point of time was larger and therefore fewer areas contained zero infractions, reducing the bias due to zero inflation.

Changes to the lifespan of infractions also had a pronounced effect when infractions were displaced away from patrolled areas. When evidence of infractions remained in the landscape after they are committed, the effects of displacement are reduced and detectability is close to the value observed when there are no rule-breaker responses to enforcement. In this case, the increase occurs because infractions that are already present in the landscape cannot respond to the presence of patrols and are therefore not displaced.

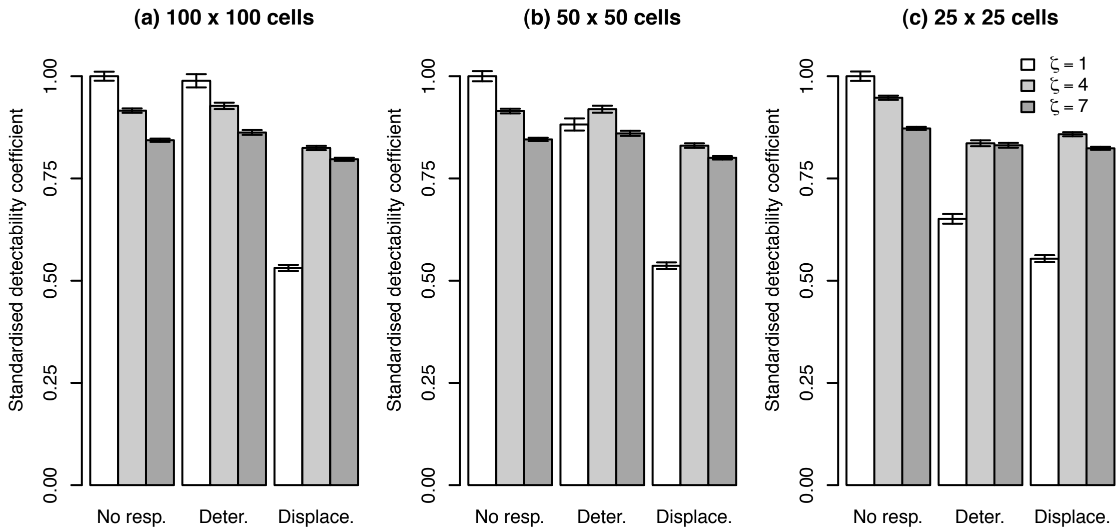

Figure 5.6: Comparison of detectability coefficients for different rule-breaker responses to enforcement between scenarios where infractions persisted in the landscape for differing periods of time, carried out at three different spatial scales. In each case patrol effort was randomly distributed. At the baseline (white bars) infractions disappeared from the landscape at the end of the round in which they were committed ($\zeta = 1$), with larger values of ζ meaning that infractions were longer-lived. Detectability coefficients were standardised by dividing by the detectability coefficient in the baseline case with no behavioural responses to enforcement and randomly distributed patrol effort at each scale. Lower detectability coefficients represent situations in which CPUE underestimates the true number of infractions present in the landscape.

Together, a consequence of these effects is that differences in the behavioural responses of rule-breakers to patrolling produce much smaller biases in detectability when infractions have longer lifespans.

5.3.5 Lasting effects of patrolling

If rule-breakers have a memory of previous enforcement effort, their behavioural responses to patrolling continue to have an effect on the number and location of new infractions after the patrol has left the area. The rate at which rule-breakers discount information about locations that have previously been patrolled had no consistent effect on detectability when rule-breakers showed no responses to patrolling, or were deterred without changing their spatial patterns of infractions (Figure 5.7). However, when rule-breakers gave greater weight to information from older patrols (i.e., higher values of λ), detectability was higher. This was because older information gave no indication of where new patrols would take place within the model, so its use reduced the effectiveness of displacement in avoiding patrols. These results were robust to both the spatial and temporal scales at which the data were analysed, although the increase in detectability when greater weight was given to older

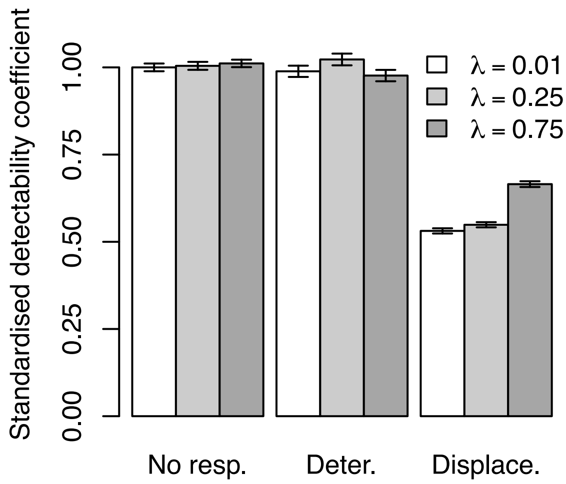

Figure 5.7: Comparison of detectability coefficients for different rule-breaker responses to enforcement when these responses continue after the patrol has finished, analysed at the whole-area scale. In each case patrol effort was randomly distributed. At the baseline (white bars) information about previous patrols was discounted very rapidly ($\lambda = 0.01$), with larger values of λ meaning that information from old patrols was discounted more slowly. Detectability coefficients were standardised by dividing by the detectability coefficient in the baseline case with no behavioural responses to enforcement and randomly distributed patrol effort. Lower detectability coefficients represent situations in which CPUE underestimates the true number of infractions present in the landscape.

information was slightly more pronounced at smaller spatial scales.

5.4 Discussion

CPUE-based methodologies have often been used to analyse patrol data in order to learn about the effect of patrolling on rule-breaking behaviour in conservation (e.g., Leader-Williams et al., 1990; Jachmann, 2008b). However, the properties of CPUE as a measure of rule-breaking activity have not previously been examined. In the study of fisheries and bushmeat, where CPUE measures have been widely used, many discussions of the adequacy of CPUE measures have focussed on whether CPUE is proportional to the abundance of harvested species (Harley et al., 2001; Rist et al., 2008). Many phenomena which can lead to non-linear relationships between CPUE and abundance are likely to have parallels in the study of enforcement (see Chapter 6, Table 6.2). However, the use of CPUE measures derived from patrol data for studying the effectiveness of enforcement may face additional problems.

In this context, CPUE-based analyses require rather contradictory assumptions. On the one hand, simple CPUE measures assume that the distribution of infractions is random with respect to the placement of patrol effort (Hilborn and Walters, 1992), which requires rule-breakers not to alter their behaviour in response to the presence of patrols. However, in order for patrolling to be effective in protecting resources it is essential that rule-breakers are deterred from committing infractions—that is, that they do respond to the threat of being caught. Here I examined the effects of two different types of behavioural response to patrolling: deterrence and displacement. With deterrence, the response of rule-breakers to patrolling is to reduce the number of infractions being committed per round. With displacement, however, the same number of infractions may be committed, but their spatial distribution is altered.

I have demonstrated that both types of behavioural response can result in CPUE being a biased measure of the total number of infractions committed, but that their effects also depend upon the spatial scale at which patrol data are analysed, the spatial patterns of patrolling, the length of time that evidence of infractions persists in the landscape after they have been committed and the length of time after patrolling that rule-breakers respond to patrolling. It has often been assumed that even a biased measure of abundance can be useful as an 'index' as long as the bias remains constant (Pollock et al., 2002). However, indices are difficult to interpret if underlying behavioural processes change (McConville et al., 2009) and several assessments of the reliability of indices for wildlife monitoring have demonstrated that this is a common problem (e.g., Norvell et al., 2003; Hochachka and Fiedler, 2008). It seems highly likely that similar issues will arise in the use of index measures such as CPUE to monitor rule-breaking.

Temporal lags, such as those caused by long-lived infractions and rule-breakers' use of information about previous patrolling, are inherent in many types of rule-breaking. Although my results show that these lags can reduce the biases caused by spatially autocorrelated patterns of patrolling and rule-breakers' behavioural responses to enforcement, they may not improve the usefulness of CPUE as a measure of deterrence because they also serve to decouple the total number of infractions in the landscape from the number of new infractions being committed. Consequently, even if CPUE is a reasonable index of the total number of infractions that exist in the landscape, it may not be suitable for measuring the effect of patrols on the number of new infractions being committed. Ecological surveys which sample signs of a species presence, rather than encounters with the species itself, have to deal with similar temporal lags. For example, in order to use dung counts to estimate the abundance of forest elephants, researchers must also be able to estimate the rate at which elephants produce dung, and the rate at which dung decays (Barnes, 1996). For enforcement data, it might be possible to estimate the rate at which evidence of different forms of rule-breaking decays (e.g., Coad 2007 measured snare decay rates in a Gabonese bushmeat hunting system) but there is rarely independent information available about the rate at which individual rule-breakers respond to changes in law enforcement efforts (cf. Milner-Gulland and Clayton 2002 showed how responses to inspections in a bushmeat market became less pronounced and more short-lived over time).

The choice of spatial scale at which patrol data are analysed is important for their interpretation. Previous applications of CPUE methodologies to patrol data have tended to make comparisons at the spatial scale of entire protected areas over a timescale of years (e.g., Leader-Williams et al., 1990; Hilborn et al., 2006) or months (Jachmann, 2008b). However, data analysed at larger spatial scales may be more prone to biases due to autocorrelated patterns of patrolling and rule-breakers' responses to enforcement, while at smaller spatial scales the effects of zero inflation become problematic. (Walters, 2003) has previously highlighted the 'fantasy' of assuming that measures derived from spatially autocorrelated samples are representative of the wider, unsampled area over long time periods. As a result, it is unlikely that simple changes to the level of aggregation at which patrol data are analysed will be sufficient to overcome the problems of bias.

This study serves to highlight the potential of 'virtual ecology' approaches to answer questions that fall outside of the traditional sphere of ecological research. I have considered the possible effects of a small number of key processes upon the patterns that are observed in patrol data, but the methods could easily be extended. My focus has been on quantifying levels of bias, but the same framework could also be used to ask questions about precision, which have an important bearing on the practicality of patrol data as a monitoring tool. For example, ranger patrols have been proposed as a cost-effective way of gathering information about trends in animal populations and the processes that threaten them (Gray and Kalpers, 2005). If sufficient data were available to parameterise my model for a real-world case study, it could provide an ideal framework for assessing the statistical power of typical patterns of patrolling to detect trends in threats or abundances, and to assess potential trade-offs that might arise.

Learning about rule-breaking and how it can be deterred is vitally important, but presents serious challenges (Gavin et al., 2010). Despite the need for enforcement to be efficient there has been little research done to understand how the design of enforcement measures relates to their effectiveness as a deterrent to rule-breaking and, as a result, there is often little practical information available to guide managers in their design and implementation. Although patrol data are often seen as a cheap way to achieve this aim, they are prone to many different unobservable biases. Modelling approaches such as that presented here are one way of assessing the situations under which biases are likely to arise, and what their effects are, but considerable research is still needed to determine whether, in practice, patrol data can be used as a basis for robust decision-making at useful temporal and spatial scales. Ultimately, the information that can be recovered from patrol data will always depend on the extent to which patrols approximate a true random sample of rule-breaking activity, and its potential may only be fulfilled if cheap and practical means of regularly validating it against independent measures of rule-breaking can be found.

Chapter 6

Using encounter data in ecology and resource management: pitfalls and possibilities

6.1 Introduction

Data on the numbers of "encounters" with a subject of interest are widely used in ecological studies to monitor spatial and temporal patterns of abundance or occupancy (Williams et al., 2002). Similar data are also collected opportunistically, for example through off-take records from harvested populations (e.g., commercial fisheries, Maunder et al. 2006; bushmeat, Rist et al. 2010), or through volunteer-based "citizen-science" initiatives such as the North American Breeding Bird Survey (Sauer et al., 1994). In conservation, encounter data derived from the reports of rangers patrolling protected areas (e.g., Leader-Williams et al., 1990; Brashares and Sam, 2005) or community based projects (e.g., Stuart-Hill et al., 2005; Poulsen and Luanglath, 2005) are seen as potential sources of information for learning about rule-breaking behaviour. Rules and agreements are ubiquitous in conservation, so it is important to be able to study patterns of rule-breaking and to understand the factors which motivate illegal behaviour (Gavin et al., 2010). Ranger-based monitoring has been advocated as an effective means of gathering a variety of data for natural resource management, including both poaching signs and encounters with species of interest (Arcese et al., 1995; Gray and Kalpers, 2005). In some cases analysis of encounter data has also been formally incorporated into decision-making processes (e.g., the Convention on the International Trade in Endangered Species of Wild Fauna and Flora makes use of ranger data collected through the MIKE project: Monitoring the Illegal Killing of Elephants).

All forms of encounter data are prone to violations of the assumptions that are used to model them. A large body of theoretical and empirical research has therefore examined the processes which might lead to violations of these assumptions, the extent to which models are robust to violations and strategies for overcoming these issues (e.g. imperfect detectability, MacKenzie et al. 2005; non-linear relationships, Maunder and Punt 2004; inter-observer differences and learning effects, Sauer et al. 1994). In the case of ecological surveys, the collection of encounter data proceeds via carefully designed sampling regimes allowing various simplifying assumptions to be made in the modelling of abundance or occupancy (Williams et al., 2002). Analysing data on encounters of target species or poaching signs collected opportunistically by enforcement agents in the course of their duties is attractive because these data are relatively cheap and readily available, given that the patrols are already operating. However, few studies have attempted to determine whether the approaches taken to the analysis of other forms of encounter data are also appropriate for patrol data.

Since the primary purpose of patrols is to uncover and deter rule-breaking, with data-collection often a secondary concern, violations of the assumptions normally made when modelling encounter data are very likely, and may be severe. Consequently, there are many questions to be answered about how such data can best be analysed, and whether they can be a useful source of information about rule-breaking. These questions are important for conservation practitioners who want to know whether patrol data can be used to inform management decisions and whether improvements could be made to the collection and analysis of the data. However, I believe that many of the biases present in patrol data are also likely to exist to a greater or lesser degree in the other forms of encounter data used in ecology and resource management. Consequently, a better understanding of how patrol data can be analysed is also likely to have broader relevance to all those who use encounter data.

In this chapter, I explore the use of patrol data—and similar datasets—as a source of information about rule-breaking. I begin by illustrating the typical features of a patrol dataset and outlining parallels with other forms of encounter data. By analogy with the catch-per-unit effort approach used in the fisheries and bushmeat literatures, an obvious strategy is to treat the number of infractions detected per unit effort as an index of offences committed. However, despite its intuitive appeal, I show that the interpretation of this index may not be straightforward. Observed patterns in any type of encounter data are the result of the behaviours of two sets of actors—for example, ranger patrols and rule-breakers, or scientists and the target species—whose actions are unlikely to conform perfectly to analytical assumptions. Furthermore, the usefulness of these data depends on incentives for accurate reporting and the scale at which they are analysed. Analyses which do not consider these effects risk misinterpreting observed patterns. I next propose improvements to the collection and analysis of patrol data that might help to overcome these difficulties. Finally I suggest ways in which these insights could also improve the understanding and treatment of similar issues in other forms of encounter data commonly used in ecological and resource management settings.

6.2 A typical patrol dataset

A typical patrol data set might record the activities carried out by the patrol and the indicators of illegal behaviour that have been encountered. For example, the Cullman-Hurt Community Wildlife Project (CHCWP) runs successful anti-poaching patrols in five areas of Tanzania, in addition to various community-based initiatives with local villages. CHCWP maintains detailed records of the date, location name, duration (in number of days) and personnel involved with each patrol, along with any signs of rule-breaking behaviour encountered, including poaching, snaring and illegal timber extraction. In recent years, the patrols have been equipped with GPS units and note a pair of co-ordinates for each area patrolled. The patrols also record when confiscations (e.g., of skins, timber, snares or firearms) or arrests are made. As a result, it is possible to ask how the number of infractions detected change over time and in relation to changes in patrol effort (Figure 6.1). Project managers might seek to use this information to learn about the effectiveness of their enforcement measures, and to make decisions about how to allocate their resources. However, in order to be useful, it is necessary to understand what can be inferred with confidence from changes in the number of infractions detected by patrols.

6.3 Encounters per unit effort

The data collected by patrols share many similarities with those commonly used to study patterns of abundance in harvested populations (Table 6.1), and consequently it is appealing to try to adapt methods from ecology and resource management to the study of rule-breaking. In many cases, measuring abundance directly is difficult, so managers must base

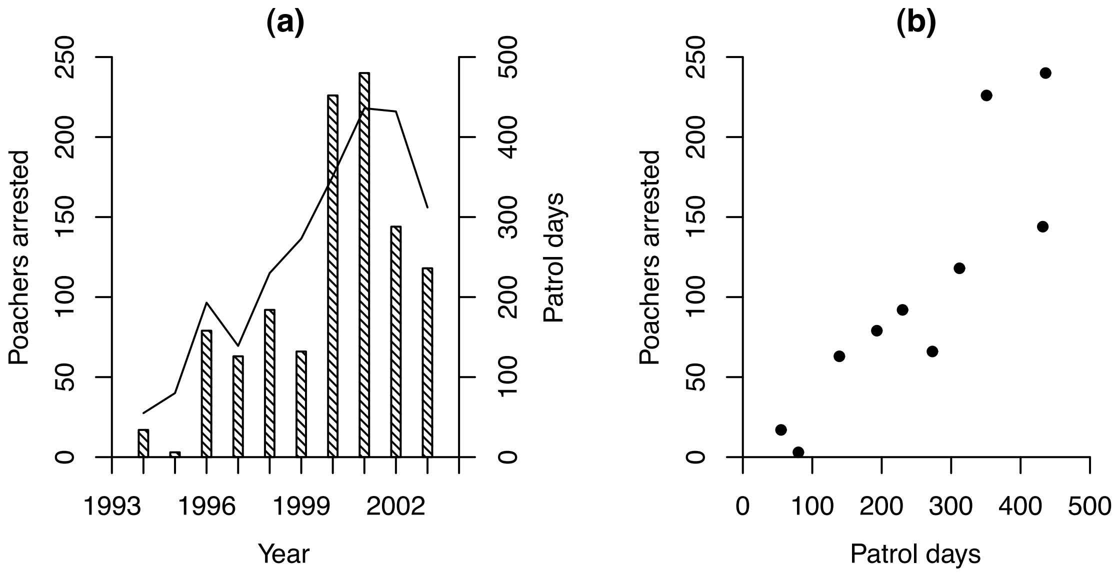

Figure 6.1: An example of patrol data collected by the Cullman-Hurt Community Wildlife Project in Tanzania, showing (a) changes in the number of poachers arrested (shaded vertical bars) and patrol effort (solid line) between 1994 and 2003, and (b) the relationship between patrol effort (measured in patrol days) and the number of poachers arrested over the same period. The crude analysis in (b) would suggest that more patrolling leads to more arrests. On their own, however, these data are insufficient to distinguish this hypothesis from plausible alternatives (e.g., the possibility that the increases in both quantities are caused by a third, unmeasured factor).

their decisions upon surrogate measures derived from changes in the observed levels of offtake over time (Milner-Gulland and Rowcliffe, 2007). A common choice is catch per unit effort (CPUE). The use of CPUE as an index of abundance relies on the assumption that offtake, or catch, is proportional to both the abundance of the harvested population and the amount of effort invested in hunting (Hilborn and Walters, 1992)

$$C = qNE \tag{6.1}$$

where C is the observed catch, E is the effort required to realise the catch, N is the size of the harvested population and q is a constant known as catchability. More generally, catch could to refer to encounters of any type, in which case C is the observed number of encounters and q is detectability (since encounters do not necessarily result in capture or mortality). For example, in analyses of patrol data the number of infractions encountered per unit of patrol effort has been used as an index of the number of infractions committed (Jachmann and Jeffery, 1998).

Table 6.1: A comparison between three common forms of encounter data and the extent to which assumptions are likely to be violated (0 = unlikely to be violated; + = quite likely to be violated; ++ = very likely to be violated, ? = currently unknown).

	Encounter-based ecological surveys	Fisheries and harvesting records	Enforcement patrols
Collector	Scientists; research assistants	Fishermen; hunters; harvesters	Enforcement agents (e.g., rangers)
Generator	Study species	Exploited species	Rule-breakers (e.g., poachers)
Main aim of collector	Abundance estimation; occupancy modelling	Fishing; hunting; harvesting	Detecting and punishing rule-breakers
Choice of route	Randomly located straight line transects	Expert-led; chosen to maximise profitability	Expert-led; chosen to maximise encounters with rule-breakers
Encounters are removed from population?	No	Yes	Yes
Extent of violation of assumptions			
Accurate reporting by collector	0	+	++
Generator does not respond to collector	+	+	++
Perfect detection on the line	+	0	0
Effort measures are appropriate	?	+	+
Linear CPUE-abundance relationship	?	++	++
Catchability does not vary	++	++	++

Due to the ready availability of catch data, CPUE has been amongst the most widely used indices of abundance in resource management, particularly in fisheries stock assessments (Hoggarth et al., 2006), but also in the bushmeat literature (e.g., Vickers, 1991; Hill et al., 2003). However, choosing an appropriate measure for each of the variables and for the catchability coefficient is not trivial and requires considerable care.

6.3.1 What is the appropriate unit for encounters?

In general, the definition of an encounter should be determined by a study's objectives. For example, the number of elephants spotted along an aerial transect is an obvious unit for encounters if the aim is to estimate the size of that species population in an area (e.g., Jachmann, 2002). In other cases, the unit of encounter might be a specific sign of a species presence (e.g., mink scats and footprints, Bonesi and Macdonald 2004; chimpanzees' nests, Plumptre 2000) or an event (e.g., a burst of birdsong, Buckland 2006). In patrol data many different types of rule-breaking behaviour are commonly reported, including direct encounters with poachers, finding traps or snares, and other signs of illegal extraction such as tree stumps or camp remains, and even these categories may be subdivided further. For example, snares are generally considered to be unselective (Noss, 1998; Lee, 1999; Rao et al., 2005), but some snaring methods can be very specific (e.g., *laly*, a technique used for catching lemurs Golden, 2009).

Sometimes, however, the appropriate unit for encounters may be less clear. Tropical trawl fisheries targeting shrimp are unselective and catch large quantities of non-target species (Andrew and Pepperell, 1992), including hundreds of different types of fish (Stobutzki, 2001). In interpreting catch data from these fisheries one must therefore consider whether the catches of different species should be analysed separately, or aggregated according to taxonomic group or some other factor. Similar questions arise in the analysis of patrol data. For example, in studying the effect of an ivory trade ban on elephant poaching an obvious response variable is the number or proportion of elephants killed illegally (e.g., Burton, 1999; Kahindi et al., 2010). By contrast, using patrol data to assess the effectiveness of enforcement measures as a conservation strategy (e.g., Hilborn et al., 2006) requires a decision about whether different types of infractions should be considered separately, or analysed together. In general, analysing different types of infractions separately may be preferable if they are subject to different influences. However, various studies of crime have shown that different types of infractions can act as substitutes for one another (Cameron, 1988; Ehrlich, 1996) meaning that a reduction in one type of infraction need not result in an overall reduction in rule-breaking.

6.3.2 How should effort be measured?

Data on numbers of encounters cannot be interpreted without a measure of the effort that produced them. In ecological surveys estimating abundance, effort is often measured in terms of the area searched, calculated from the length of transects walked or the number of point counts conducted (Buckland, 2001). In fisheries, where CPUE approaches are widely used, several different measures of effort have been suggested. Effort may be simply defined as the fishing power of a vessel multiplied by an appropriate measure of the time invested in fishing (Beverton and Holt, 1957; Gulland, 1964; Marchal et al., 2006), but the reality is usually more complicated. Fishing effort is a compound measure of several factors, which can include the number of fishermen, the type of gear and other technologies used (Hovgård, 1996; Rose, 1998; Sangster, 1998), time spent fishing or area searched and the strategies employed to find fish (Hilborn, 1985; Abrahams and Healey, 1990; Rijnsdorp et al., 1998; Marchal et al., 2006). Similarly, many different measures of hunter effort have been used in studies of bushmeat hunting, including time spent hunting, distance travelled and number of hunters occupying an area (Rist et al., 2008). In both fisheries and bushmeat systems, the most commonly used measures of effort are likely to reflect the inputs to harvesting more accurately than harvesting-induced mortality (Bordalo-Machado, 2006; Rist et al., 2008).

Patrol effort has also been measured in many different ways. Based on experiences in Malawi's National Parks, McShane and McShane-Caluzi (1984) discusses the merits of four different measures: (a) the number of times a grid cell is entered by patrol per unit time, (b) number of effective patrol days per unit area per unit time, (c) distance patrolled per unit area per unit time, (d) area surveyed per unit area per unit time. The number of patrol days appears to have been the most widely used measure in the published literature (e.g., Leader-Williams and Albon, 1988; Leader-Williams et al., 1990; Jachmann and Billiouw, 1997; de Merode et al., 2007). Other studies have incorporated the number of patrol personnel into their measures of effort, calculating "effective patrol man-days" (Jachmann, 2008b) or including time spent patrolling and number of scouts employed as separate predictors of the number of infractions detected (Jachmann and Billiouw, 1997; Holmern et al., 2007). Hilborn et al. (2006) used a cruder measure, ranger patrols per day, while Gaveau et al. (2009) simply classify their study area into inferred "high" and "low" enforcement effort sectors based on vegetation re-growth, interviews and models of accessibility.

In all encounter data, there is an important distinction between periods spent actively searching—the effective effort—and time spent on other activities which result in a lower probability of recording an encounter. However, this can be problematic. When conducting line transect surveys for a rare species, field biologists might be faced with a question about whether or not to include chance 'off-transect' sightings. If they are included, how should effort then be measured? The measurement of effective effort may also be complicated if some of the apparent effort is directed towards areas (or times) which are unsuitable for the species or event being studied. The ability of longline fishing gear to catch bigeye tuna (*Thunnus obesus*) is strongly dependent on the depth the gear reaches and the position of tuna in the water column. Consequently, the effective effort in these fisheries must be adjusted to take into account both the gear specification and the behaviour of tuna in the fishing areas (Bigelow et al., 2002). To properly estimate the effective patrol effort, McShane and McShane-Caluzi (1984) and Jachmann and Jeffery (1998) argue that a good measure of patrol effort should recognise the difference between time spent actively patrolling and time spent travelling to and from camps and the like. For example, Jachmann and Jeffery (1998) classifies scout activity in Luangwa Integrated Resource Development Project in Zambia into 12 categories, only 5 of which are considered to be directly related to patrol activity.

6.3.3 What does the 'catchability' coefficient represent?

In fisheries and bushmeat analyses, the catchability coefficient is generally described as the effectiveness with which a specific type of fishing gear or hunting equipment catches a particular species (e.g., Hilborn and Walters, 1992). This is analogous to the probability of detecting a species or event within the area sampled by a strip transect. In distance sampling approaches the probability of detection is generalised to be a function of the distance from the transect line at which the encounter occurs (Buckland, 2001). For patrol data, the detectability coefficient relates the number of infractions detected to both the total number of infractions committed and the amount of patrol effort invested in discovering them, and is therefore related to the efficiency of patrolling.

In each of these cases, an assumption of the simplest models is that catchability, or detectability, does not change over time or between areas. In reality, however, these coefficients incorporate the effects of many different influences on the probability of an encounter, including characteristics of the target species or event and temporal and spatial heterogeneity in environmental conditions (Arreguín-Sánchez, 1996) which may not remain constant. Patrol efficiency is likely to be affected by the type of patrol (e.g., on foot, by vehicle, aerial surveys), expenditure on equipment, training and incentive payments (Leader-Williams and Albon, 1988; Jachmann and Billiouw, 1997; Jachmann, 2008b), the morale and individual abilities of different patrol officers, differences in terrain, weather conditions and the like. If not explicitly modelled, changes in these factors may result in violations of the assumption of constant detectability.

Where multiple gear types or species are involved in fisheries, or catchability varies, CPUE measures are often 'standardized' using by including relevant covariates in Generalised Linear Models (GLMs; McCullagh and Nelder, 1989) to explicitly model the differences (Maunder and Punt, 2004; Bordalo-Machado, 2006). The effects of spatially and temporally heterogeneous probabilities of detection are similarly incorporated into distance sampling approaches and models of occupancy (Buckland, 2001; MacKenzie et al., 2005). These approaches have not been used to date in analyses of patrol data.

6.4 Interpreting patterns seen in encounter data

A key feature shared by all types of encounter data is that they are the product of two sets of actors: a generator and a collector (Table 6.1). This is clearly true in the case of patrol data where the number of infractions detected depends upon the behaviour of both patrols and rule-breakers. In other forms of encounter data, this feature of the data has received less attention, perhaps because one of the sets of actors is usually non-human, but it can still have important consequences. To successfully interpret encounter data it is therefore necessary to understand how these two sets of behaviours interact.

6.4.1 How does CPUE relate to the size of the sampled population?

Referring to the use of CPUE measures in analyses of commercial fisheries, Hilborn and Walters (1992) note

> "The simplest assumption regarding the relationship between commercial catch and abundance is that the catch rate (CPUE) is directly proportional to abundance. ... [This assumption] has been demonstrated to be wrong in almost every case where it has been possible to test - simply stated it is almost impossible for this relationship to be true."

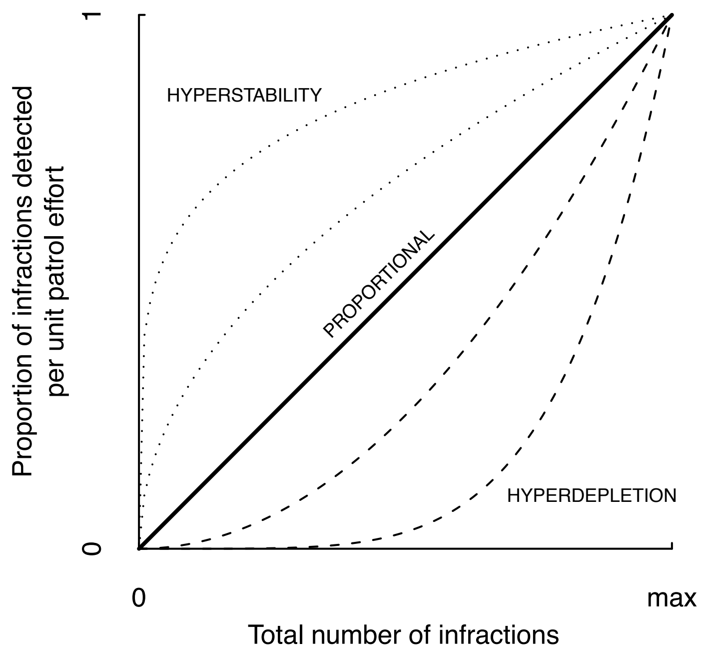

Figure 6.2: Two general classes of non-linear relationships between the infractions detected per unit effort and the total number of infractions committed. Hyperstability describes relationships where the number of infractions detected per unit effort declines more slowly than the number of infractions, while hyperdepletion describes relationships where the number of infractions detected per unit effort declines more rapidly than the number of infractions. Aspects of patrol and rule-breaker behaviour which can result in these non-linear relationships are described in Table 6.2.

In the fisheries literature, the two general classes of non-linear relationship between CPUE and the true stock abundance are termed *hyperstability* and *hyperdepletion* (Figure 6.2, Hilborn and Walters 1992), with hyperstability the more common (Hilborn and Walters, 1992; Harley et al., 2001; Lorenzen et al., 2006). Hyperstability describes situations where the number of encounters per unit effort remains high while the size of the sampled population declines. Hyperdepletion is the converse situation, where the encounters per unit effort drops off more rapidly than the size of the sampled population. In some cases these relationships may be linked directly to the changes in the size of the sampled population (e.g., when individuals differ in their probability of detection, those that are more easily caught will tend to be detected first and proportionally more effort will be needed to detect those that remain, resulting in hyperstability). However, non-linear relationships can also be produced by changes which are independent of changes in the status of the underlying population of interest but occur simultaneously (e.g., improvements in equipment or training while the number of infractions declines can appear as hyperstability; spatial shifts in fishing effort or learnt avoidance can appear as hyperdepletion; Walters 2003).

Although the sources of these non-linear relationships have primarily been studied in the context of fisheries, many can also apply to other types of encounter data (e.g., bushmeat Rist, 2007). In patrol data, changes in the behaviour or efficiency of patrols or rule-breakers over time could produce either hyperstability or hyperdepletion (Table 6.2). If not recognised, both non-proportional relationships can have important consequences. In patrol data, hyperdepletion might encourage complacency, with managers believing that enforcement efforts are more effective than they really are, while hyperstability could result in overspending in the mistaken belief that the problem is worse than it really is. To date I are aware of no studies of enforcement activities within conservation or resource management which have explicitly assessed the functional form of the relationship between the number of infractions detected per unit effort and the underlying number of infractions.

6.4.2 How does the number of encounters detected change with effort?

An obvious complication in the interpretation of patrol data arises because patrols are both a source of information about and a deterrent to rule-breaking. In general, therefore, an increase in patrol effort is expected to produce two opposing effects: a decrease in the total number of infractions due to deterrence (and possibly removal of rule-breakers from the population through incarceration) and an increase in the proportion of those infractions which are detected (Burton, 1999).

In discussions of rule-breaking, deterrence is often treated as a single process, but in reality changes in the recorded number of infractions reflect the aggregate effects of multiple behavioural responses. Consider poachers hunting with guns. Increases in enforcement effort may lead some individuals to make fewer hunting trips, and others to cease to poach altogether. Alternatively, however, rule-breakers might substitute one type of infraction for another (Becker, 1968). For example, in the ADMADE project in Zambia poachers responded to increasing costs of enforcement by reducing the offtake of certain species, substituting smaller mammals for their standard prey and switching to less conspicuous technologies such as wire snares (Gibson, 1995). Rule-breakers may also adopt other forms of avoidance behaviours, trading off increased costs or lower efficiency for a reduction in the probability of being caught (Robinson et al., 2010). In the Serengeti, for example, hunters primarily travel at night and spatially heterogeneous patterns of enforcement effort result in the displacement of hunting effort from higher-risk to lower-risk areas (Hofer et al., 2000; Nyahongo et al., 2005).

Table 6.2: Hypothesised causes of hyperdepletion and hyperstability in the relationship between the number of infractions detected per unit effort (CPUE) and the actual supply of infractions, based on findings from fisheries. Adapted from Hilborn and Walters (1992).

	Patrol behaviour (Data collector)	
	Hyperstability	Hyperdepletion
Non-random search	Patrols preferentially target areas of high infractions.	Patrols deliberately avoid areas with more infractions (e.g., due to social pressure, or threats to safety).
Significant handling time	Proportion of time spent processing infractions or apprehending rule-breakers is not negligible—areas with high infractions are effectively undersampled due to a higher proportion of total effort being handling time.	
Extent of search area	Changes to patrol patterns which increase the density of infractions in the search area (i.e. patrolling new areas with high levels of infractions).	Changes to patrol patterns which reduce the density of infractions in the search area.
Patrol efficiency	Increases in patrol efficiency (e.g., due to improved technology, better training).	Reductions in patrol efficiency (e.g., due to poor equipment maintenance, drop in morale, loss of trained personnel).
	Rule-breaker behaviour (Data generator)	
	Hyperstability	Hyperdepletion
Predictable behaviour	Patterns of rule-breaking are predictable (e.g., clustered).	
Heterogeneous ability to avoid detection		Ability to avoid detection (or strength of deterrence) varies between individuals—the more easily detected/deterred individuals are removed from the system first.
Changing ability to avoid detection	Rule-breakers become less able to avoid detection over time(e.g., due to loss of shared information from others).	Rule-breakers become better able to avoid detection (e.g., learning to predict patrol behaviour; improving ability to disguise actions).

Similar behaviours are also seen in animals in response to the presence of hunters or observers, but their effects are rarely considered in analyses of encounter data. For example, cod and other fish are known to move in response to fishing gear (e.g., Hemmings, 1973; Suuronen, 1997; Handegard et al., 2003). Diana monkeys have been shown to fall silent and retreat in response to the presence of humans (Zuberbühler, 1997) and both Adélie penguins and red and eastern grey kangaroos move in response to aerial surveys (Fewster et al., 2008). These types of behavioural responses could be an important source of bias in many types of encounter data.

Detecting and quantifying these biases, and separating the contributions of different processes to observed patterns in CPUE data, cannot easily be achieved using encounter data alone (Figure 6.3). In fisheries this problem is frequently tackled by conducting fishery-independent surveys so that CPUE measures can be independently validated (Hilborn and Walters, 1992). However, alternative data sources must be carefully chosen if they are not to suffer from similar biases. For example, orange roughy have been shown to move away from camera systems as well as fishing gear (Koslow et al., 1995) and herring display avoidance behaviours towards acoustic survey vessels (Vabø, 2002). In the study of rule-breaking, there have been few attempts to date to compare patrol records with data derived from other sources (Gavin et al., 2010).

6.4.3 Data collectors' incentives

Another important consideration which is often neglected in analyses of encounter datasets is the effect of the incentives faced by the data collectors (Chapter 4). In fisheries, every vessel has an incentive to fish as efficiently as possible since the profits from fishing relate directly to catch. However, the implementation of restrictions on the total allowable catch can lead to catches being misreported (e.g., Patterson, 1998). In conservation, the link between rangers rewards and the effort they invest, or number of infractions they detect, is not always clear. Indeed, rangers may face strong pressures to turn a blind eye to offences committed by friends, family or neighbours (Abbot and Mace, 1999) or may face threats to their safety (Hart et al., 1997). Patrol reports (Jachmann, 2008a) and fisheries records may therefore be subject to technical error, accidental or deliberate omissions, and falsification. Ecological surveys are likely to be less prone to deliberate manipulation, but in many situations there may be few incentives for local assistants to invest more than the minimum required effort.

Well designed management programmes can provide incentives for effective patrolling

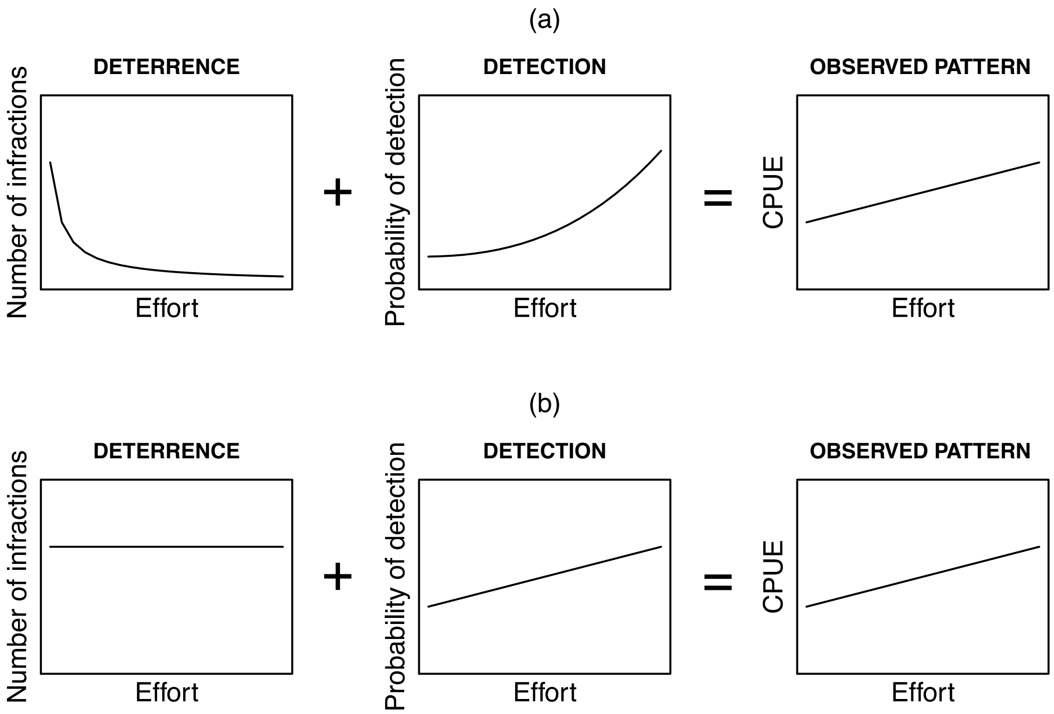

Figure 6.3: A hypothetical example illustrating how a single relationship between CPUE (the number of infractions detected per unit effort) and effort could arise in different ways. In the first example, (a), increasing patrol effort increases detection and also produces a deterrent effect, leading to fewer infractions being committed. In the second example, (b), there is no deterrent effect of enforcement. However, both scenarios produce the same relationship between CPUE and effort.

and accurate reporting. For example, the number of senior staff visits to ranger camps in Ghana's National Parks was found to be positively correlated with the amount of effort rangers expended on patrolling duties (Jachmann, 2008b). Similarly, increases in the payment of cash bonuses to scouts in the Luangwa Valley, Zambia, correlated with reductions in the numbers of elephants that were illegally killed (Jachmann and Billiouw, 1997). However, using a model of decision-making in a community-based conservation setting, Mesterton-Gibbons and Milner-Gulland (1998) showed that paying bonuses is not sufficient to ensure that mutual monitoring persists in the long term: individuals must also be paid a basic salary which at least compensates their opportunity costs. Incentives for effective enforcement can also be created by instituting competition between different patrol groups and by encouraging them to monitor each other's performance (Jachmann, 2008a).

6.4.4 Non-random patterns of sampling

Sampling regimes in ecological monitoring are carefully designed to allow robust inferences to be drawn about the studied population. This generally requires samples to have been drawn at random, or at random from within defined strata (i.e., groupings based on similarity; Cochran 1977; Burnham et al. 1980). For the sake of efficiency, however, ranger patrols, hunters and fishing vessels all tend to concentrate their effort in areas where there is a high probability of encounters. When effort is "intelligence-led" (i.e., acting based on prior information about where encounters are likely), the relationship between effort and the number of encounters may be difficult to predict. Comparing the efficiency of different approaches to enforcement, Jachmann and Billiouw (1997) incorporated the effective number of investigation days as an additional predictor of the number of infractions detected, alongside the amount of traditional patrol effort. However, if investigative approaches and information derived from traditional patrols feed back to one another this approach may produce biased results.

In addition to the difficulties it creates for defining an appropriate measure of effort, directing patrols towards areas identified by informants may complicate attempts to understand spatial patterns of rule-breaking by introducing unquantifiable biases (Chapter 4). Holmern et al. (2007) recognise the potential problems the use of informants raise for analyses of patrol effort. They note that the Village Game Scouts policing community based conservation agreements around the Serengeti National Park "did not record if they acted on information from fellow villagers or if they conducted a patrol without any prior knowledge of illegal activities". Similar problems are encountered in some forms of ecological monitoring. For example, the traditional distance sampling approaches to monitoring populations of forest elephants are expensive, and non-random 'recce' sampling has been proposed as a cheaper alternative (Walsh and White, 1999). However, it has been argued that without extensive calibration these approaches are likely to be prone to biases (Burn and Underwood, 2000).

Other factors can also lead to non-random sampling patterns, such as ease of access (e.g., Gaveau et al., 2009). Several studies of enforcement measures in conservation have compared rule-breaking at the level of entire national parks over a number of years (e.g., Jachmann and Billiouw, 1997; Hilborn et al., 2006; Jachmann, 2008b). This approach is reasonable so long as the patrol effort is near-randomly distributed within the parks in question but, if patrol coverage is patchy or inconsistent, apparent changes in the level of illegal activity might be real or might be caused by biases due to changing sampling or poaching patterns (cf. Walters, 2003). When the resources available to carry out patrols are small relative to the area to be managed, difficult-to-reach areas may go unpatrolled for long

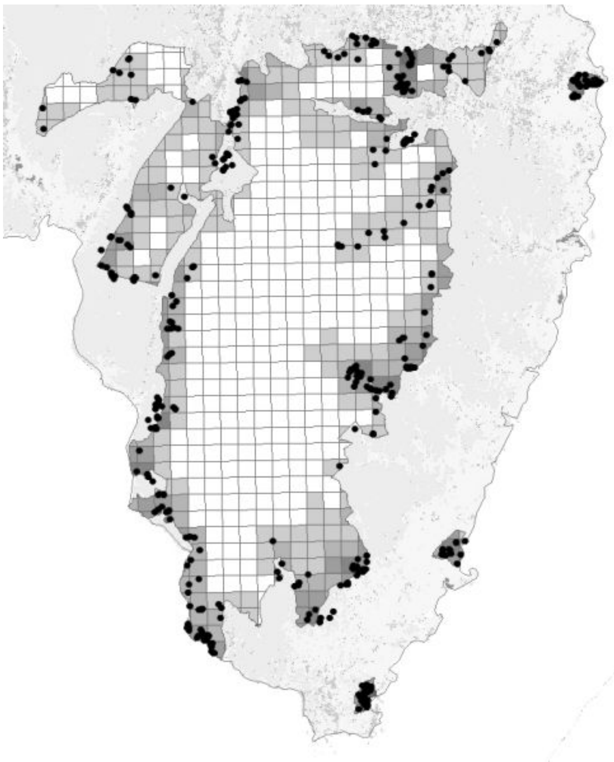

Figure 6.4: A map showing the distribution of patrol effort in Masoala National Park, Madagascar, between 2005 and 2007. The shaded areas show an index of patrol effort, indicating that the patrol resources are concentrated around the periphery of the park, with darker grey shading representing more heavily patrolled cells. Large areas have not been patrolled at all during this period (white cells). Individual grid cells are 9km^2 in size.

periods of time meaning that there is essentially no information about the level of illegal activity occurring in these areas (Figure 6.4). If data are analysed at an appropriately fine scale to distinguish between patrolled and unpatrolled areas this need not be a problem, but inferences cannot be made about the areas which are not adequately represented within the sample (Walters, 2003).

6.5 Spatial and temporal scale in analyses of encounter data

Clearly, the complex and interacting processes that produce encounter data take place over a range of spatial and temporal scales. In analyses of patrol data, for example, forest clearance can affect whole parcels of land, and its effects remain detectable for long periods of time. By contrast, individual poaching incidents are localised and once the hunter has left an area little evidence may remain. Similarly, the spatio-temporal scales of rule-breakers' behavioural responses to enforcement may vary considerably. For example, lags can occur between increases in enforcement effort and any subsequent deterrent effect, since potential rule-breakers must first learn about the change. Subsequently, if the higher level of effort is not maintained, the level of deterrence may decay over time (Clayton et al., 1997). Small scale avoidance behaviours, on the other hand, may change rapidly (e.g., hiding to evade detection by an active patrol). Some forms of punishment, such as imprisonment, also have longer lasting effects and should reduce the number of offences whether or not they produce a deterrent effect (i.e., simply by removing potential rule-breakers altogether). The scale at which patrol and other forms of encounter data are collected therefore has important consequences for how it can be used, and how it must be analysed. Analyses of highly aggregated data risk drawing misleading conclusions (Walters, 2003) and data which are unable to describe fine-scale patterns are likely to be informative for decision-making at relevant temporal and spatial scales for management. However, achieving high resolution requires greater patrol effort and interpreting data at finer scales may require sophisticated analytical techniques.

Standard statistical techniques applied to encounter data, such as generalised linear models (McCullagh and Nelder, 1989), assume that every data point is independent. However, at finer scales this assumption breaks down. For example, if a hunter takes a route through a forest, setting snare traps as his goes, observations made close to one another in space will tend to be more similar to one another than expected if they were independent. Similarly, if groups of animals or of hunters tend to avoid overlapping (e.g., if they have clearly defined territories), then closely adjacent samples might be expected to show negative autocorrelation (i.e., sampled points close to one another are likely to be less similar than would be expected by chance). If not corrected for, autocorrelation can inflate the risk of "false positive" errors (e.g., Legendre, 1993; Lichstein et al., 2002; Diniz-Filho et al., 2003). In ecological surveys, careful design can ensure that the potential effects of autocorrelation are minimised. When surveying clustered species or events, a common approach is to treat each cluster as a single encounter and then scale subsequent estimates according to the average (e.g., Rosenstock et al., 2002). Where data are collected opportunistically, as is the case in fisheries and patrolling, autocorrelation cannot be reduced "by design" but may be tackled by the incorporation of spatial covariates or explicit modelling of the autocorrelation (e.g., Nishida and Chen, 2004).

Encounter data collected at relatively fine spatial and temporal scales also often include large numbers of zero observations with no encounters. This may complicate statistical inference, and is referred to as zero-inflation if the number of zeroes is greater than can be adequately modelled by standard probability distributions (Zuur, 2009). Zero observations may be classified as 'true' zeroes (i.e., areas in which the species or event was not present) and 'false' zeroes (i.e., areas where the species or event was present, but remained undetected for some reason; Martin et al. 2005). In patrol data, large numbers of true zeroes can occur when patrols sample areas which are unsuitable for the illegal behaviour of interest or if patterns of illegal activity are spatially autocorrelated (cf., Flores et al., 2009). Patterns of suitability in particular may be complex and difficult to incorporate in analyses. For example, clearing an area of forest of animals or removing its valuable timber can render it unsuitable for further extraction for a period following the initial offence. The suitability of an area at any point in time would therefore depend on the history of extraction up to that point, and the time taken for the area to regenerate.

False zeroes can arise from imperfect detection (Martin et al., 2005; MacKenzie et al., 2005). In patrol data, the probability of detecting infractions may sometimes be close to 1 (e.g., Jachmann and Billiouw 1997 argue that they were able to detect all new elephant carcasses within their study area), but it will often be the case that some illegal activities go undetected despite patrol efforts. False zeroes can also occur if rangers fail to report infractions, either because they face incentives to cover them up, or because of inadequate training or equipment failure. Similar problems occur in the reporting of bycatch data from commercial fisheries, complicating assessments of the effect of bycatch on the mortality of threatened taxa, such as albatrosses and sea turtles (Lewison et al., 2004). Methods for modelling imperfect detection are well established in the field of occupancy modelling (e.g., MacKenzie et al., 2005; Royle et al., 2005). Modifications of distance sampling methodologies incorporating mark-recapture protocols can also allow for imperfect detection on a transect line (Buckland, 2004).

6.6 How can the usefulness of patrol data be improved?

Although they can appear to be simple and intuitive, encounter data and CPUE measures must be treated very carefully if they are to be useful sources of information. In the preceding sections I have drawn parallels between different forms of encounter data, and highlighted their similarities. In this final section, I apply lessons learned in other fields to provide practical suggestions for modifying the collection and analysis of patrol data to improve its suitability for answering questions about the amount and distribution of rule-breaking in conservation. Of course, there are important differences. Commercial fisheries, in particular, are often highly profitable businesses so there are sizeable incentives for ensuring that they are well monitored and managed. As a result, it may be feasible to conduct fishery-independent surveys and employ highly trained specialists to ensure that the appropriate analytical techniques are adopted for monitoring stocks. By contrast, conservation managers must often operate with restrictive budgets and limited technical support (James et al., 1999). Bearing in mind these limitations, however, I believe that there are a variety of ways in which efforts to collect and analyse data on illegal behaviours could be improved.

6.6.1 Improving the recording of patrol data

The cheapest way to improve the usefulness of patrol data is simply to improve recording practices. The keeping of detailed, standardised records of ranger patrols has long been advocated (e.g., McShane and McShane-Caluzi, 1984). However, recording a greater variety of information about patrols would enhance our ability to distinguish between the many possible sources of variation in that exist within these data. For example, rangers differ in their ability and motivation to uncover and report rule-breaking which can cause inter-observer variation, while changes in the effectiveness of personnel over time could introduce bias into records of infractions detected. Data collected by fishermen, fisheries observers and 'citizen scientists' suffer from similar problems (Thomas, 1996). For example, inter-observer variability has been demonstrated in data from the North American Breeding Bird Survey, along with a tendency for observers to count a greater number of species as they gain experience (Sauer et al., 1994). If properly recorded, the variability between patrols could be incorporated into analyses in a variety of ways depending on factors such as the number and turnover of personnel (cf. Punt, 2000; Brandão et al., 2002; Candy, 2004).

More accurate recording of the routes taken by patrols would help to determine whether there are spatial biases in sampling, and is essential for answering questions about fine-scale patterns of behaviour. Technological innovations such as GPS recorders and the Cyber-Tracker system can help (Steventon, 2002), but simple paper and pen recording systems can also be very effective if well designed and supported (e.g., the Event Book System Stuart-Hill et al., 2005). In fisheries, the International Council for the Exploration of the Sea coordinates a large standardised database containing information on commercial fisheries catches as well as trawl surveys and oceanographic information (http://www.ices.dk/). This and similar projects help to facilitate the use of fisheries data for stock management and research. Greater standardisation of the data collected by patrols, perhaps via the use of tailored databases such as the MIST system pioneered by WCS (BPAMP, 2006) and WWF's IRVES system, could enable large scale comparisons of enforcement and illegal behaviour between different regions.

Understanding the patterns and drivers of rule-breaking in conservation requires an understanding of how conservation measures affect individual decision-making by resource users (Chapter 2). Deterrence is generally understood to be a function of both the probability of detection and the severity of punishment (Becker, 1968) but many patrol records fail to track what happens to offenders once they are caught, particularly in systems where punishments are decided by other authorities (e.g., the courts system Akella and Canon, 2004). In practice the actual punishment that a rule-breaker incurs may differ from the theoretical sanction and can vary considerably from case to case (Leader-Williams and Milner-Gulland, 1993). As a result, it is difficult for analysts to infer the true risk involved in rule-breaking after the fact. To address this there is a need for more systematic collection of data about the individuals who break conservation rules: from the point of detection, through capture and processing, to prosecution, sentencing and the true level of sanction imposed and, ultimately, to recidivism rates. Furthermore, to properly understand how this risk is perceived by potential rule-breakers, there is also a need for research into levels of knowledge and attitudes towards rules and enforcement measures (see Chapter 3).

6.6.2 Improving the patrolling that is done

Irrespective of the types of data that are collected by patrols, their potential uses are constrained by their resolution and the sampling patterns used to collect them. Choosing an appropriate scale for the collection and subsequent analysis of patrol data involves a trade-off between the loss of relevant information at coarse spatial and temporal scales, and increased cost and analytical complexity at finer scales. With greater resources, considerable improvements in the usefulness of patrol data could be achieved by choosing sampling regimes in order to maximise the potential information that might be gained (e.g., stratifying patrol effort between different areas based on an understanding of human behaviour) or by adaptively managing patrolling patterns (cf. Thompson and Seber, 1996). Clearly, however, the benefits of this approach must be weighed against its costs and possible trade-offs (e.g., reductions in the deterrent effect of patrols). I are not aware of any studies that have attempted to address whether ranger patrols can efficiently achieve multiple aims.

6.6.3 Improving the analysis of patrol data

The collection of better data must also go hand in hand with the adoption of appropriate analytical techniques, and each process should be designed with the other in mind. As described in previous sections, useful approaches to many of the problems encountered in the analysis of patrol data have already been explored for other types of encounter data. However, other questions deserve further exploration. For example, traditional ecological analyses have sometimes been criticised for paying too little attention to whether they are able correctly to identify causal processes (Ferraro, 2005; Armsworth et al., 2009). The standard, regression-based approach to patrol data implies that causality is strictly unidirectional, with the number of infractions committed being partially determined by the deterrent effects of patrolling, but not the other way around. In practice, however, this is rarely true. The principal aim of patrolling is efficiently to prevent rule-breaking, so managers may commonly direct more patrol effort towards areas where a greater number of infractions are thought to be committed. Consequently, at least at some scales of analysis, patrol effort may be partially endogenous (i.e., the level of patrol effort may be partly determined by the number of infractions committed in an area rather than being independently arrived at).

A related problem is that of selection bias (Ferraro, 2005). Patrols and rule breakers occupy heterogeneous landscapes, and factors such as ease of access may influence the decisions of both sets of actors about where they concentrate their effort. Consequently, areas that are easily accessed (e.g., near to paths or rivers) may be used more often by rule-breakers and also patrolled more often, potentially creating spurious correlations. Similarly, fishermen are known to use cues such as the presence of dolphins or seabirds to target areas that are suspected to contain more fish (Polacheck, 1988). These problems of endogeneity and selection bias are common in the social sciences (e.g., Maddala, 1992; Kennedy, 2001), so the analysis of patrol data (and other forms of encounter data) is an area where closer collaboration with economists and other social scientists may be particularly fruitful.

6.6.4 Validating patrol data with alternative sources of information

Some of the problems of interpreting patrol data may only be overcome through comparisons with alternative sources of information on illegal behaviour. For example, Hilborn et al. (2006) model the effects of changes in expenditure on enforcement on buffalo, elephant and rhino populations in the Serengeti National Park system, finding close correspondence between their predictions and abundance estimates from ecological surveys. In fisheries, studies attempting to quantify non-linearities in CPUE-abundance relationships have relied heavily on the existence of alternative measures of abundance (e.g., Harley et al., 2001). A number of alternative approaches to gathering data on illegal behaviour are available to researchers (see Gavin et al., 2010). These include self-reporting (e.g., Gavin and Anderson, 2005), direct questioning (e.g., Jones et al., 2008a), information from other observers and informants, the randomized response technique - an indirect, anonymous method for estimating rate of rule-breaking at the population level (e.g., Blank and Gavin, 2009; St. John et al., 2010) and wildlife forensics (e.g., Wasser et al., 2008). Each of these approaches has its own strengths and weaknesses, but comparisons between different sources of data on illegal behaviour are rare (Gavin et al., 2010).

There is also considerable scope for borrowing approaches from the field of experimental economics to answer questions about individual responses to threats of punishment or conditional rewards, the role of different institutional structures in legitimising rules and sanctions, the psychological effects of different enforcement regimes and the effectiveness of strategic dissemination of information about enforcement outcomes. So far, conservation has been slow to adopt these methodologies (but see Travers, 2009).

6.6.5 Considering rule-breaking behaviour in the context of wider incentives

Ultimately, successfully interpreting data on how individuals respond to conservation measures such as ranger patrols requires approaches which consider enforcement as a part of a wider system, taking into account the myriad other factors which affect individual choices (Chapter 2). In Sumatra, for example, high international coffee prices increased rates of deforestation inside Bukit Barisan Selatan National Park, confounding the effects of law enforcement (O'Brien et al., 2003; Gaveau et al., 2009). Illegal behaviour can also be affected by changes in prices of legal goods, as demonstrated by models of bushmeat hunter behaviour (Damania et al., 2005). Here effects were found to be ambiguous: higher prices for agricultural commodities can lead to a greater proportion of effort being devoted to farming, but could also stimulate greater consumption of bushmeat. In the absence of obvious price-driven effects, it has also been shown that changes to the socio-political context of enforcement due to war or civil unrest can undermine its effectiveness (e.g., de Merode et al., 2007). I will only be able to assess the true role of enforcement and other conservation measures when they are understood within the broader context in which they operate (Ferraro, 2005; Ferraro and Pattanayak, 2006).

6.7 Conclusions

There is a strong desire within the conservation community to learn about and improve the effectiveness of our actions (Pullin and Knight, 2001; Sutherland, 2004). The enforcement of rules and agreements is widely recognised as being crucial to the success of conservation (Chapter 2), and expenditure on enforcement consumes a large part of conservation budgets in many areas of the world (e.g., Jachmann, 2008b; Robinson, 2008; Robinson et al., 2010). Patrol datasets represent a commonly used and widely available source of information about rule-breaking, but are complex and difficult to interpret successfully. Here, I have shown how patrol datasets share many similarities with other forms of encounter data, and highlighted how such datasets can be made more informative, through improvements to data collection and analysis. However, the technical skills required to perform appropriate analyses of such challenging datasets presents a serious capacity-building issue. A program of research is needed which establishes the power of different methods to detect change and to provide policy-relevant information, and which examines the effects of enforcement within a broader framework of individual incentives, as one of many factors contributing to successful conservation outcomes. As is so often the case, conservation can learn a great deal from the experiences of other disciplines. However, by highlighting the importance of crucial sources of bias that might otherwise be neglected, a better understanding of patrol data stands to benefit every field that relies on encounter data.

Chapter 7

Discussion

7.1 Background

Conservation interventions often seek to change people's behaviour, discouraging actions which cause damage to species or ecosystems, or promoting those which are beneficial. There are many different approaches to achieving these goals, and over time the dominant paradigm has undergone several shifts. Early conservation interventions, for example, were often based entirely on the creation and enforcement of rules, usually focused around the designation of protected areas from which local people were excluded to reduce the damaging effects of habitat destruction and overexploitation (Pullin and Knight, 2001). Subsequently, approaches emphasising the importance of inclusion and community participation have received greater attention (e.g., Lewis et al., 1990). Most recently, payments for environmental services (Ferraro, 2002; Engel et al., 2008) have been promoted as an efficient way to achieve conservation goals.

All of these different approaches remain central to the practice of conservation today, and it is therefore important the details of their design and implementation are based upon robust foundations of theory and evidence (Pullin and Knight, 2001; Sutherland, 2004; Ferraro and Pattanayak, 2006). In recent years, a considerable amount of empirical and theoretical research has been carried out in order to understand approaches that focus on provision of benefits (e.g., improving livelihood opportunities through the development of ecotourism, Kiss 2004; paying private landowners to maintain flows of environmental services, Engel et al. 2008). However, similar work has generally been lacking for enforcement measures in conservation. Consequently there is a clear need for research which answers both theoretical and practical questions regarding the enforcement of conservation rules. This thesis sets out to address some of these questions. By focussing on behaviour at the level of individual actors, my research has advanced discussions of enforcement and compliance in conservation in a number of important areas.

7.2 Contributions

7.2.1 Individual decision-making and incentives

An important contribution made by this thesis has been to draw together the various strands of research on enforcement and compliance that exist in other fields, establishing the basis of a theoretical framework for understanding these issues in conservation (Chapter 2). The effectiveness of rules in conservation, and the measures taken to enforce them, depend upon the decision-making of several distinct sets of actors. For example, the choice of strategy for improving compliance with conservation rules is generally taken by managers or policy makers (i.e., at the institutional level). However, the ultimate effects of these choices depend upon how these decisions are implemented by the individuals who are directly responsible for carrying out enforcement (e.g., rangers), and the responses of potential rule-breakers (e.g., poachers). To be able to understand the factors which influence the effectiveness of rules in conservation, it is therefore necessary to understand the differing incentives faced by individuals at different levels of the enforcement chain (Akella and Canon, 2004) and how they interact. My research shows that these incentives depend on both the role played by an individual, and their particular abilities and characteristics.

7.2.2 Individual heterogeneity and the behaviour of rule-breakers

At the level of rule-breakers, understanding compliance requires a consideration of many determinants of behaviour, right the way through from an individual's awareness and understanding of rules, to the incentives that they face to break them, and the way in which enforcement changes these incentives in favour of compliance. Logically, the creation of rules can only change behaviour if people are aware of their existence. However, previous studies of rule-breaking have tended to assume that rules are perfectly known by the people whose behaviour they are intended to change and this assumption had gone largely untested. The research presented in Chapter 3 begins to address this gap, reporting the first study to examine factors which affect awareness of conservation rules at the individual level. Although knowledge of rules was found to be generally poor—a potentially serious barrier to their effectiveness—the research also found evidence of large differences in understanding between individuals which could be explained to some extent by personal characteristics. In particular, levels of education and involvement with tourism, and community resource management were all found to improve awareness.

Even if awareness is high, rules are only effective if they are able to change the motivations of potential rule-breakers, whether this occurs directly (e.g., through the presence of enforcement creating a threat of punishment) or indirectly (e.g., mediated through effects on norms of acceptable behaviour; Ostrom 2000). Here too, individual differences are important. In the individual-based model presented in Chapter 4, the availability of several potential courses of action ('strategies') that an individual can pursue, and the heterogeneity of outcomes for different individuals pursuing the same strategy, means that equilibria where multiple strategies (e.g., poaching, monitoring and alternative livelihoods) can coexist are common (cf. Tsebelis, 1989; Mesterton-Gibbons and Milner-Gulland, 1998; Walker, 2009). In this situation, the level of compliance that results from changes to policy levers (e.g., the size of fine for poaching, or of fees paid to enforcement agents) is shown to be highly sensitive to the context in which they are embedded (e.g., the profitability of poaching and of livelihood alternatives; the ease with which monitors are detected if they cheat).

The tendency of conservationists to think of communities as homogenous entities has previously been criticised for ignoring important details of human behaviour in the design of community-based projects (e.g., Agrawal and Gibson, 1999) and there is evidence that individual differences (e.g., in opportunity or transaction costs, or social status) within groups can also affect the outcomes of approaches based on payments for environmental services (Sommerville et al., 2010). Understanding of the effects of individual heterogeneity upon responses to incentives is an issue that requires further attention, not only in the study of enforcement but throughout conservation.

7.2.3 The behaviour of enforcement agents

Traditionally, discussions of enforcement have often assumed that managers have two main options at their disposal for manipulating the incentives created by enforcement: change the probability that an individual is caught and punished if they break a rule, or change the severity of punishment that is subsequently incurred. Since Becker (1968), models of rule-breaking and compliance have regarded the deterrent effect of enforcement as a function of these two key variables. However, translating the results of such models into practical recommendations for conservation has proved difficult (Robinson et al., 2010). One important reason for this may be that the probability of detection and punishment cannot be precisely controlled by managers (Chapters 4 and 5). Instead, the probability that a rule-breaker is detected emerges from the interaction between rule-breakers' behaviour, and the behaviour of enforcement agents (Mookherjee and Png, 1995; Mesterton-Gibbons and Milner-Gulland, 1998). Consequently, to analyse properly the effectiveness of different policy options for improving enforcement it is necessary to understand how they affect the incentives of enforcement agents to perform their duties (Walker, 2009; Robinson et al., 2010).

Chapter 4 addresses this issue in the context of a community-based conservation project where local people are able to both poach and monitor. I show that the question of how to design effective measures for incentivising locally-based monitoring and enforcement is complex, and care must be taken to avoid perverse effects when individuals differ in their skills and motivation. Very few previous studies have addressed the issue of monitors' incentives in conservation. Mesterton-Gibbons and Milner-Gulland (1998) argued that locally-based monitoring cannot be sustainable unless monitors are paid a fee which compensates their opportunity costs. While this finding is likely to hold true, I show that the effects of paying larger fees—and, similarly, larger bonuses—to monitors are not always beneficial. In some contexts, such as those where it is difficult to determine whether enforcement agents are carrying out the duties properly (i.e., it is easy to 'cheat'), the payment of higher fees could undermine conservation success. Within the limits of the scenarios I explored, Chapter 4 suggests that changes in policy levers which produce their effects more directly (e.g., fines) may be more robust than those which are mediated through changes in enforcer behaviour (e.g., performance bonuses for rangers) because they are less susceptible to these perverse effects. However, there is evidence that in some cases the imposition of harsher penalties can erode co-operation between local people and conservation authorities (e.g., Infield and Namara, 2001). Further research will be needed to ascertain how changing the severity of punishment compares to the use of alternative policy levers in practical settings.

7.2.4 The usefulness of patrol data as a source of information

Understanding both rule-breaker and enforcer behaviour is also vital to interpreting sources of data on enforcement and compliance. Establishing a theoretical basis for understanding rule-breaking in conservation provides a framework around which empirical studies can be structured. However, empirical testing of the effectiveness of strategies to improve compliance in conservation requires accurate sources of data about rule-breaking (Gavin et al., 2010). An obvious source of information about the effectiveness of enforcement is the data collected by enforcement agents themselves, and many empirical studies of enforcement measures in conservation have made use of ranger patrol data (e.g., Leader-Williams et al., 1990; Jachmann and Billiouw, 1997; Hilborn et al., 2006). Previously however, little consideration has been given to the suitability of patrol data for this purpose. This thesis presents the first thorough examination of the properties of patrol data as a source of information about rule-breaking, and shows that understanding the behaviour of both rule-breakers and enforcement agents is crucial to interpreting observable patterns (Chapters 6 and 5).

Many behavioural processes which are known to occur frequently in systems of rule-breaking and enforcement (e.g., spatially autocorrelated patterns of patrolling; avoidance of patrols by rule-breakers) introduce biases in patrol data and, as a consequence, interpreting patterns observed in patrol data can be challenging (Chapter 5). The use of catch per unit effort (CPUE) methods for the analysis of patrol data has been recommended in order to try to remove the biases caused by variations in the level of total patrol effort over time and space (McShane and McShane-Caluzi, 1984; Jachmann and Jeffery, 1998), but this simple approach fails to remove biases if the data are highly aggregated. Chapters 5 and 6 also suggest that is unlikely that analyses of patrol data alone can readily distinguish between different behavioural responses by rule-breakers, so despite the attractions of patrol data as a ready source of information, its promise for measuring the deterrent effect of patrolling is questionable.

A comparison of patrol data with other forms of encounter data (for example those used in fisheries stock assessments, analyses of bushmeat hunting and wildlife population surveys), reveals many similarities and perhaps offers opportunities to improve the usefulness of patrol data (Chapter 6). In these contexts, the main approaches to dealing with bias have been the implementation of rigorous sampling schemes (e.g., random allocation of survey effort with distance sampling; Buckland 2001), the calibration of CPUE measures with independent data (e.g., data from survey vessels in commercial fisheres; Hilborn and Walters, 1992) and the standardisation of CPUE measures through modelling approaches which correct for measurable sources of variability (e.g., changes in the capacity of fishing vessels; Maunder and Punt, 2004; Bordalo-Machado, 2006). Even so, analyses of CPUE data in other fields have tended to neglect the possibility that their subjects of study might respond to the presence of observers, and an improved understanding of the importance of such behavioural responses may have benefits beyond the study of rule-breaking. Ultimately, my research suggests that the practicality of patrol data as a source of useful information for management decision-making depends on the extent to which it is feasible for patrol routes to mimic a statistically robust sampling design, and whether suitable patrol-independent data can be collected cheaply and easily enough for regular calibration to be carried out (Chapters 5 and 6).

7.3 Limitations and further research

The study of enforcement in conservation is at an early stage, and many questions relating to the theory and practical implementation of enforcement measures remain to be answered. The following section outlines directions for future work which would help to verify and build upon the research presented in this thesis.

There is a large body of existing theory in other fields which tries to understand rule-breaking (Chapter 2). So far, however, only a small proportion of this research has been applied to the study of rule-breaking in conservation. There is much to be gained from further exploration of this literature, but in many cases existing theory does not translate directly to situations commonly encountered in conservation (e.g., Robinson et al., 2010). In the literature on the economics of crime and its applications to resource management, a great deal of effort has been devoted to understanding how optimal enforcement can be achieved; that is, from the point of view of a policy maker and given that enforcement is a costly activity, determining how many resources should be invested in enforcement (Chapter 2). The models developed to study these questions provide a number of insights into the efficiency of enforcement measures at producing compliance under different conditions. However, such models are generally based on the assumption that individuals act rationally to maximise their utility. This assumption is known often to be flawed (McFadden, 1999).

Currently, little is known about the decision rules that are used by local people affected by conservation interventions. However, there are indications that the framework of utility maximisation may not be appropriate. For example, different models of subsistence in the field of human behavioural ecology have used short-term maximisation of gain (e.g., Hill et al., 1987), short-term minimisation of risk (e.g., Kaplan et al., 1990) or long-term household survival (e.g., Mace, 1993) as the currencies of decision-making. It has repeatedly been shown that humans are not consistent in their decision-making when faced with sets of mathematically equivalent decisions framed in differing manners (e.g., Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). It has also been argued that humans are boundedly, rather than strictly, rational and may aim to satisfy their immediate needs rather than achieve truly optimal outcomes (see Conlisk, 1996). For example, Gadgil et al. (1993) report that the behaviour underpinning traditional resource management systems in tribal societies is often based upon rules of thumb for harvesting decision-making. The relevance of such issues for environmental problems has been recognised, but their practical significance for the design of successful conservation interventions remains very poorly explored (Penn and Mysterud, 2007).

Where decision-making is found to be strongly dependent upon the an individual's stage in life, it may be necessary to modify the models used to explore the effects of conservation interventions to take this into account. Incorporating this sort of heterogeneity is a logical extension of the individual modelling approach I adopted in Chapter 4 and has also been suggested to solve similar problems in related fields. For example, the decision-making of farmers is known to depend on factors such as their age, education, attitudes to risk and personality, and one solution has been to model their decisions using 'frame-based' models, a type of individual based model structured around the differing frames of reference of individuals at different stages in life (Edwards-Jones, 2006).

Modelling approaches could also be deployed more widely to study other aspects of rule-breaking and enforcement. The nature of rules and enforcement imposes serious practical and ethical limits on the types of studies which can be carried out; in reality it would never be possible systematically to vary the severity of punishments handed out for a particular infraction over large ranges (as is done in Chapter 4) or to know precisely the behaviour of both rule-breakers and enforcement agents (as is possible in Chapter 5). The use of models as virtual environments in which different conservation strategies can be explored, and where the experimenter has perfect information about their effects on different actors' behaviour, holds considerable promise. As in this thesis, applications of these approaches could include exploring both the robustness of management approaches to changing behaviour under different levels of uncertainty and variability (cf. Chapter 4) and the suitability of existing data sources for learning about the state of managed systems. (cf. Chapter 5).

In order to explore these questions further, new empirical approaches are required. A limitation of the modelling approaches employed in this thesis has been the lack of suitable data for their parameterisation and validation. While models have a valuable role to play in the study of rule-breaking, their potential can only be realised if their predictions can be rigorously tested with suitable data. As models become more sophisticated and complex, and better able to account for the range of behavioural interactions that drive systems of enforcement and compliance, their information requirements increase (Chapter 2). The development of new models of rule-breaking in conservation must therefore go hand in hand with efforts to devise novel methods, and novel applications of existing methods, for gathering data on rule-breaking in conservation.

One promising avenue is the adoption of experimental economics techniques which aim to test hypotheses about human behaviour within a controlled experimental framework (Carpenter et al., 2005). For example, Sirén et al. (2006) used an experimental lottery to explore the relationship between income and preferences for wild meat in Ecuador. Winners of the lottery were given a choice between prizes, some of which were intended to be used for either hunting (e.g., a shotgun) while others were for alternative foodstuffs (e.g., chicken wire for farming poultry). The study interpreted their decisions as indications of how marginal increases in wealth might affect hunting. Similar approaches could readily be adopted for the study of enforcement. For example, Travers (2009) conducted a series of experimental games with villagers in Cambodia to examine how levels of extraction from a common resource varied with the imposition of different institutional arrangements. One was designed to mimic external enforcement and others mimicked direct payment schemes, distributed by an external authority or by the villagers themselves. This study was one of the first in which several different approaches to changing behaviour were compared within a common framework and found that the extent to which they encouraged self-organisation and group decision-making strongly influenced their effectiveness. It also found evidence that externally imposed interventions can undermine inherent compliance with rules if the incentives they create are not sufficiently strong, emphasising the need to ensure that incentive-based approaches to conservation are carefully designed to meet the needs of specific situations (cf. Chapter 4).

7.3.1 Recommendations for practitioners

Although there is a clear need for further research into problems of enforcement and compliance in conservation, this thesis also suggests a number of practical measures that could be adopted immediately by managers. For example, Chapter 3 suggests that more attention should be given to the differences in knowledge of conservation laws that exist between local people. Armed with such information, conservation practitioners might carry out targeted awareness campaigns to supplement traditional enforcement measures. In designing enforcement strategies, care must be taken to ensure that enforcement agents are sufficiently motivated to carry out the duties effectively (Jachmann, 2008a). Furthermore, encouraging rangers and park guards to collect a greater variety of data during their patrols and, where possible, assessing the viability of alternative data sources as means of validating patrol data will help to establish whether patrol data will play a useful role in the study of enforcement.

7.4 Conclusions

Rules, and measures to enforce them, are at the heart of conservation. As such they should be important topics for research, but they remain seriously understudied. This thesis has laid out the basis for a theoretical framework for understanding these issues, based upon a foundation of incentives and individual decision-making. In the past, the study of enforcement may have suffered from the focus placed on developing alternative approaches to changing behaviour. However, enforcement measures have remained key components of many types of conservation intervention and share considerable common ground with approaches such as community-based benefit sharing and payments for environmental services, in that they all aim to provide incentives for local people to behave in ways which are compatible with conservation. To achieve this aim, there is an urgent need for conservation to recognise these similarities, to think in a more unified way about approaches to changing behaviour, and take a more active interest in developing an understanding of human behaviour in conservation interventions (Mascia et al., 2003; Chan et al., 2007). It is therefore vital that enforcement seen as part of a broader toolkit of approaches to changing behaviour in conservation, and established as an essential subject for research in conservation.

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