How do avoidance behaviours, monitor 'cheating' and individual heterogeneity affect individual incentives to comply with conservation rules?

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Abstract

Enforcement of rules is necessary for the effective conservation of natural resources, whether it is to be achieved through a command-and-control approach or alternative instruments. Using a simulated, mutually-enforced resource harvesting agreement this paper expands upon previous analyses of enforcement measures, exploring the importance of individual heterogeneity, costly avoidance behaviours and dishonest or incompetent monitoring of compliance. These novel features are found to significantly alter the model's predictions. Sensitivity analyses show how behaviourally heterogeneous groups within the resource user population can introduce non-linearities in the system's response to various policy levers, such as the level of fine or the fee paid for monitoring compliance with rules. Several possible objectives are considered for the resource manager, showing how biological and welfare-oriented goals might trade-off against one another. These findings suggest that the design and implementation of instruments for conservation should explicitly consider the behavioural complexity within heterogeneous socio-ecological systems.

Introduction

All models are by nature simplified representations of real-world processes, intended to allow specific properties of a system to be explored. A typical model of rule-enforcement in a conservation context include a representation of a harvested species' population dynamics and a payoff function for the resource-users (e.g. Milner-Gulland & Leader-Williams, 1992). The expected costs of enforcement are incorporated into this payoff function and individuals are assumed to act in a rational, profit maximising fashion. Some models have extended this framework to consider enforcement in the context of the household economy (Damania et al, 2005), by explicitly considering spatial dynamics (Clayton et al, 1997), or by incorporating moral and ethical considerations into an economic framework (Sutinen & Kuperan, 1999). However, the responses of individuals to interventions such as enforcement may be far more complex than such simple models allow. The aim of this study is to explore the possible implications of previously unconsidered aspects of this complexity for effective conservation management.

I take the model of Mesterton-Gibbons & Milner-Gulland (1998) as my starting point. Theirs was the first attempt to analyse the role of strategic behaviour in producing stable enforcement regimes for conservation using a game theoretic framework. The model consists of a small community of self-monitoring resource users who choose behavioural strategies from a set with options to poach, monitor, do both or do neither. A key result from this study was a series of conditions for a self-monitoring agreement to be stable, including the need for monitors to be paid whether or not poaching occurs and for the population to be over a minimum threshold. However, these results are sensitive to the exact specification of the model and different assumptions can produce very different outcomes.

Given the sensitivity of model outputs to their specification, it is useful to ask how robust models of enforcement might be to the omission of potentially important features. Here I focus on three such features which I consider to be plausible and potentially common aspects of rule-breaking/enforcement systems. The first of these is the inclusion of a 'cheating' strategy where individuals claim the fee for monitoring but do not report infractions, thereby avoiding the opportunity costs and social opprobrium of monitoring. Although the term cheating implies deliberate dishonesty, the 'cheating' strategy represents a broader set of behaviours which result in monitors not reporting rule-breaking effectively, whether due to dishonesty, laziness or a lack of the necessary skills (e.g. because of poor training). The second feature is individual heterogeneity. In many models of enforcement, individual actors are assumed to be identical but real people differ from one another in many respects, such as their skills, abilities and preferences. The final novel feature I consider is 'avoidance behaviour'. This represents a range of costly activities carried out by rule-breakers to diminish their chances of being punished. In the context of illegal hunting this might include bribing officials, using less conspicuous but less efficient technologies (e.g. bow hunting rather than gun hunting) or attempting to physically evade detection (e.g. detouring from the most efficient route in order to avoid ranger patrols). More generally, it applies to any process where a costly behavioural response to management actions feeds back to diminish the effect of management.

For managers, the most useful outputs from models of rule-breaking are those which predict the response of the system to 'policy levers' (i.e. targets for management actions). Several parameters of the model presented here represent potential policy levers but I focus my analyses on four: (1) the amount that individuals caught poaching are fined, (2) the opportunity costs of monitoring the compliance of others, (3) the fee paid to monitors, and (4) the amount that individuals caught cheating are fined. The most obvious of these is perhaps the first. A manager can reasonably expect that increasing the fine for poaching will reduce the number of poaching offences and therefore increase the animal population. Similarly, lowering the opportunity costs of monitoring or increasing the fee paid to monitors to compensate them for their opportunity costs, should make monitoring strategies attractive to a greater proportion of the population. Again this is expected to reduce poaching by increasing the chance that poachers are detected and punished. The fourth policy lever is the least direct. The fine for cheating is intended to deter potential monitors from adopting a cheating strategy and thereby increase the number of monitors.

The responses of the system to these policy levers must be measured in terms of the manager's goals. Many different goals are possible in conservation, and many initiatives may require a balance to be found between several different objectives. For highly threatened species a suitable biological goal might be to maximise the animal population. Managers of harvested resources might aim to maintain their population at around 50% of carrying capacity to produce the maximum sustainable yield (Clark, 1990) or to prevent the population from falling below 30% of carrying capacity, the United Nations Food and Agriculture Organisation threshold for 'overexploited' status in fisheries (see http://www.fao.org/fishery/). In other situations, managers might wish to maximise the average income per individual from a harvesting system, or to minimise inequalities in income. Clearly, it cannot be assumed that such different welfare-oriented and biologically-oriented goals will automatically coincide or there would be little need for conservation.

My analyses of the model fall into three groups. First I investigate how the choice of policy lever affects the optimal choice of management strategy, and show how this is linked to the reaction of different groups within the human population. Second, I explore how each of the novel features outlined above influences the model's predictions by comparing a set of simplified versions of the model. Finally, I consider how specifying different objectives affects the optimal choice of management strategy.

Methods

Model structure

I adopted an individual-based modelling framework which allows individual heterogeneity to be incorporated and has been used to study emergent properties of complex systems (Bousquet & Le Page, 2004). Individual-based models (IBMs) are "simulation models that treat individuals as unique and discrete entities which have at least one property in addition to age that changes during the life cycle" (Grimm, 1999) and have been widely applied in ecology. They are conceptually similar to agent-based models (ABMs) or multi-agent simulation (MAS) approaches which appear in the computer and social science literatures and which are more explicitly oriented towards the study of decision-making and social organisation (Bousquet & Le Page, 2004). Examples of IBMs include models of fish population dynamics (van Winkle et al, 1993), predator-prey interactions (e.g. Provencher & Riechert, 1995, Rice et al, 1993) and landscape structure (e.g. Shugart et al, 1988). IBMs have also been applied to species conservation to examine protected area design for migratory birds (Fahse et al, 1998). ABMs have been used to model various aspects of human behaviour, including the spread of agricultural innovations in Chile (Berger, 2000), hunting in rural Cameroon (Bousquet et al, 2001), the response of farmers to government policies in Vietnam (Castella et al, 2005) and the decision-making of pastoralists in Kazakhstan (Milner-Gulland et al, 2006).

The model presented here is of a small, self-monitoring community harvesting a natural resource (Figure 4.1). The prey species is treated as a homogenous, single-species population whose dynamics are described by a discrete logistic equation. The number of animals in round t, X_t, is given by

$$X_t = X_{t-1} + \rho X_{t-1}\left(1 - \frac{X_{t-1}}{K_{t-1}}\right) - H_{t-1} \qquad (1)$$

where ρ is the intrinsic growth rate, K_{t-1} is the environmental carrying capacity in the previous round and H_{t-1} is the number of animals hunted in the previous round.

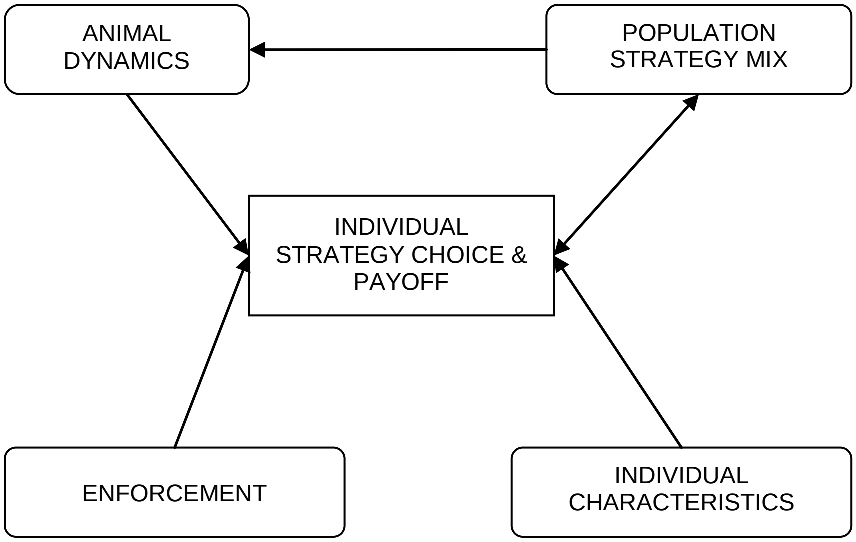

Figure 4.1: A simplified representation of the model structure

The human population is a community of n individuals with three characteristics: (1) an opportunity cost of monitoring, (2) a hunting 'effort' (including effort in the traditional sense of the word and other factors such as their equipment, innate skill and experience), and (3) their propensity to try to avoid punishment when they break rules. Individual opportunity costs and effort are sampled randomly from a normal distribution while avoidance behaviour is drawn from a uniform distribution. Individual characteristics are independent of one another and once assigned to an individual they are fixed.

Strategies

In any given round each individual adopts one of six strategies, combining poaching/not poaching and monitoring/cheating/neither components (Tables 4.1 & 4.2).

Component	**Description**
P	poach
N	do not poach
M	monitor
C	cheat
O	neither monitor nor cheat

Table 4.1: Strategy components

Strategy	**Description**
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 monitor nor cheat

Table 4.2: List of the six strategies individuals can adopt

Unlike an individual's other characteristics, their strategy may change from round to round as they copy strategies that have been used by more successful peers.

Community benefit

The community benefit in round t, B_t, is paid by the an external organisation to the community as an incentive not to poach. For the first 5 rounds it is fixed at its maximum amount so every individual receives a share of this sum given by the equation

$$B_t = \frac{B_{max}}{n} \tag{2}$$

After the initial five round grace period the actual amount paid is reduced in proportion to the number of individuals who were caught poaching in the previous round, $n_{P_{t-1}}\overline{D}_{t-1}$, where $n_{P_{t-1}}$ is the number of poachers in the previous round and $\overline{D}_{t-1}$ is the mean probability that a poacher is caught. The payment per individual is therefore

$$B_t = \frac{B_{max}\left(1 - \frac{n_{P_{t-1}}\overline{D}_{t-1}}{n}\right)}{n} \tag{3}$$

Payoff to poaching

Individual i's revenue from poaching in round t, $\Pi_{i,t}$, is a function of the size of the prey population in that round, X_t, the revenue from catching a single animal, v, and the focal individual's effort, e_i,

$$\Pi_{i,t} = e_i X_t v \tag{4}$$

Note that all the costs of hunting (except fines and the costs of trying to avoid punishment which are dealt with in subsequent paragraphs) are assumed to be a constant amount per animal caught and included in the revenue per animal, i.e. only the variable costs are considered in the analysis. Furthermore, the effect of local hunting on the market for bushmeat is assumed to be negligible so poachers face a constant price for each animal caught.

Hunting effort is directly linked to hunting mortality. The total hunting mortality experienced by the animal population in round t, H_t, is therefore the sum of each hunter's effort, e_i, multiplied by the size of the animal population in the previous round, X_{t-1}

$$H_t = \sum e_i X_{t-1} \tag{5}$$

Any individual who poaches faces the risk of being caught and punished. Punishment takes the form of a fixed fine per unit of hunting mortality, u. The expected fine that poacher i faces in round t, $U_{i,t}$, is therefore proportional to e_i, X_t, u and the overall probability that he will be detected poaching having adjusted for avoidance behaviour, $D_{i,t}$ (see eqn. 7),

$$U_{i,t} = uD_{i,t}e_i X_t \tag{6}$$

Poachers expend resources on avoidance in order to reduce the chance that they are detected while breaking rules. Avoidance behaviour has costs (e.g. time spent evading detection that is not spent hunting, the cost of using less noticeable but less efficient equipment or the payment of bribes to monitors for not reporting infractions). For simplicity avoidance cost is treated here as a fixed monetary amount with one unit of avoidance behaviour costing a. The cost of avoidance behaviour by individual i in round t, $A_{i,t}$, is also a function of the average chance that any poacher was caught in the previous round, $\bar{D}_{t-1}$ (reflecting a general perception of the risk involved in poaching at that time) and the focal individual's 'propensity to avoid', α_i, a measure of his willingness and ability to engage in avoidance behaviour,

$$A_{i,t} = a\alpha_i \bar{D}_{t-1} \tag{7}$$

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

$$D_{i,t} = 1 - \left(1 - \frac{p}{(\bar{D}_{t-1}\alpha_i) + 1}\right)^{n_{M_t}} \tag{8}$$

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.

Payoff to monitoring

Individuals who monitor the compliance of others receive a fee, f, each round but incur opportunity costs, o_i. In addition, monitors face resentment from the poachers who are reported which imposes an additional cost proportional to the number of poachers during round t, n_{P_t}, the average probability that a poacher is caught, $\overline{D}_t$, and the ‘unit cost of social opprobrium’, s. The expected net gain from monitoring, $Y_{i,t}$, is therefore

$$Y_{i,t} = f - \left(s n_{P_t} \overline{D}_t\right) - o_i \tag{9}$$

The average chance that any poacher is caught in round t, $\overline{D}_t$, is

$$\overline{D}_t = \frac{\sum_{i=1}^{n_{P_t}} D_{i,t}}{n_{P_t}} \tag{10}$$

The first individual to report a poaching incident is also paid a bonus, j, as an incentive to monitor effectively. The expected bonuses for any monitor, J_t, are therefore given by

$$J_t = \frac{j n_{P_t} \overline{D}_t}{n_{M_t}} \tag{11}$$

Payoff to cheating

An alternative to the monitoring strategy is ‘cheating’ where an individual pretends to monitor, claiming his fee, but does not do the work thereby avoiding the opportunity and opprobrium costs of monitoring. If caught, cheats are fined (see eqn. 13) and have their monitoring fee taken away from them for that round so the expected returns to cheating are given by

$$F_{i,t} = f(1 - G_{i,t}) \tag{12}$$

$G_{i,t}$ is the total chance that cheating individual i is detected in round t having taken into account his avoidance behaviour

$$G_{i,t} = 1 - \left(1 - \frac{q}{(\bar{G}_{t-1}\alpha_i) + 1}\right)^{n_{M_t}} \tag{13}$$

q is the baseline probability that a cheat is detected by any monitor in the absence of avoidance behaviour. $\bar{G}_{t-1}$ is the average probability that a cheating individual was detected in the previous round which feeds back to influence the amount cheats invest in avoidance in the current round. In addition to their fee being taken away, cheats who are caught are fined a fixed amount, k. The expected fine for cheating during any round, $K_{i,t}$, is therefore

$$K_{i,t} = kG_{i,t} \tag{14}$$

As in the case of illegal poaching, cheats invest in avoidance behaviour to lower their chances of being caught. The cost of avoidance by cheats, $Z_{i,t}$, analogous to that by poachers, is

$$Z_{i,t} = z\alpha_i\bar{G}_{t-1} \tag{15}$$

z is the unit cost of behaviour to avoid being detected cheating.

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

Table 4.3: Payoffs to each strategy component. An 'x' in one of the final six columns indicates that the strategy receives that row's payoff component.

Running the model

The model was implemented in R-2.6.0 (R Development Core Team, 2007). A model run lasts 250 rounds by which time the simulated population invariably reaches an equilibrium state. The human population size remains constant. At the end of every round individual payoffs are calculated, and the 30 people receiving the lowest payoff may change their strategy. 24 are randomly assigned the strategies adopted by the 24 most successful individuals while the remaining 6 choose a new strategy at random. This random element is intended to reflect imperfect knowledge about the most successful strategies and to prevent the population settling at local optima. The rate of turnover in the model is relatively high (~6%) but the mode of change is cultural, proceeding via learning rather than mutation as in genetic algorithms. There is little in the literature to guide the choice of learning rate in the situation modelled here so the figure of 6% was decided upon as practical level. Each run of the model is repeated 50 times and an average taken.

The paucity of information about many of the parameters in this model precludes its parameterisation with real-world data. The default values for the model parameters were therefore chosen to create a scenario in which moderate levels exploitation occur and, for the least complicated models explored, the strategy of not poaching and monitoring the compliance of others would be favoured. The strategy composition at the beginning of a run is an equal mixture of the six available options. Community size is set at 498 individuals. This number was chosen for convenience (as it is evenly divisible by six, the number of different strategies present in the model), is likely to be sufficiently large for by-product mutualism to be stable (Mesterton-Gibbons & Milner-Gulland, 1998) and is a realistic value for a small community. The parameter values chosen for the animal population model allow the population to be robust to high levels of hunting. When included, an individual's propensity to engage in avoidance behaviour is randomly sampled from a uniform distribution. Opportunity costs and hunting effort are drawn from normal distributions when individual heterogeneity is included, otherwise the values of these variables were fixed at the mean of their distributions. Values for other parameters (Table 4.4) were chosen following exploratory runs of the simulation (Keane, 2006).

Parameter	Description	Base value
ρ	Intrinsic growth rate	0.6
X_1	The initial number of individual animals present in the population	7,000
K_t	Environmental carrying capacity in round t	15,000
$B_{\max}$	Maximum community benefit	10,000
n	Size of hunter population	498
v	Returns to poaching per animal caught	180
j	Reward for being the first to report an incidence of poaching	340
p	The baseline probability that any individual monitoring detects a and incidence of poaching, before avoidance behaviour	0.008
q	The baseline probability that any individual monitoring detects a and incidence of pretending to monitor, before avoidance behaviour	0.002
u	Fine incurred if caught poaching	375
k	Fine incurred if caught pretending to monitor	225
f	Fee paid to monitors per round	80
O_i	Opportunity costs of individual i	40 or Normal distrib.
$\overline{O}_i$	Mean opportunity cost	40
$\overline{O}_\sigma$	Standard deviation of opportunity costs	15
s	Unit cost of social opprobrium incurred in response to monitoring	2
a	Cost of one unit of avoidance behaviour for poaching	30
z	Cost of one unit of avoidance behaviour for pretending to monitor	10
E_i	Effort	15×10^{-4} or Normal distrib.
$\overline{E}_i$	Mean effort	15×10^{-4}
E_σ	Standard deviation of effort	2×10^{-4}
α_i	Individual propensity to invest in avoidance behaviour	Uniform distrib., $0 \leq \alpha_i < 20$

Table 4.4: Default parameter values.

Results

Equilibrium behaviour of model variants

Eight variants of the model were studied, including different combinations of the novel components (Table 4.5). The simplest model, model 1, is comparable to that of Mesterton-Gibbons & Milner-Gulland (1998).

Model	Av	Ch	He
1			
2	X		
3		X	
4			X
5	X	X	
6	X		X
7		X	X
8	X	X	X

Table 4.5: A list of the components included in each of the eight model variants. Av = avoidance behaviour, Ch = cheating strategies, He = individual heterogeneity in opportunity costs of monitoring and hunting effort.

With the baseline parameter values, a reduced model in which individuals cannot adopt cheating strategies or invest in avoidance activities, and individuals have identical opportunity costs of monitoring and hunting effort produces an equilibrium human population dominated by the strategy 'don't poach but monitor the compliance of others' (NM) and an animal population close to carrying capacity (Figure 4.2, model 1). With these features excluded the model is comparable to that of Mesterton-Gibbons & Milner-Gulland (1998). By contrast, the full model, incorporating all three novel features together, makes very different predictions. At equilibrium a complex mixture of strategies is produced in the human population and the animal population is depleted to approximately 40% of carrying capacity (Figure 4.2, model 8).

The inclusion of avoidance behaviour produces the most striking differences between the eight models' equilibrium predictions. The four models which exclude avoidance behaviour (1,3,4 & 7) produce the same predictions as the base model suggesting that for the set of parameter values tested the incentives to play the NM strategy are strong, and that neither cheating strategies nor heterogeneity have a large effect. The predictions of the four models which include avoidance behaviour (2,5,6 & 8) differ in terms of the mixture of strategies present at equilibrium (Figure 4.3) but make similar predictions about the size of the animal population(Figure 4.2).

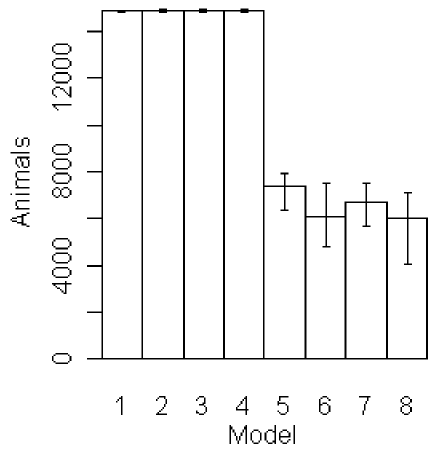

Figure 4.2: Predicted animal population size at equilibrium for the eight model variants. Lines show 95% confidence intervals calculated by bootstrapping.

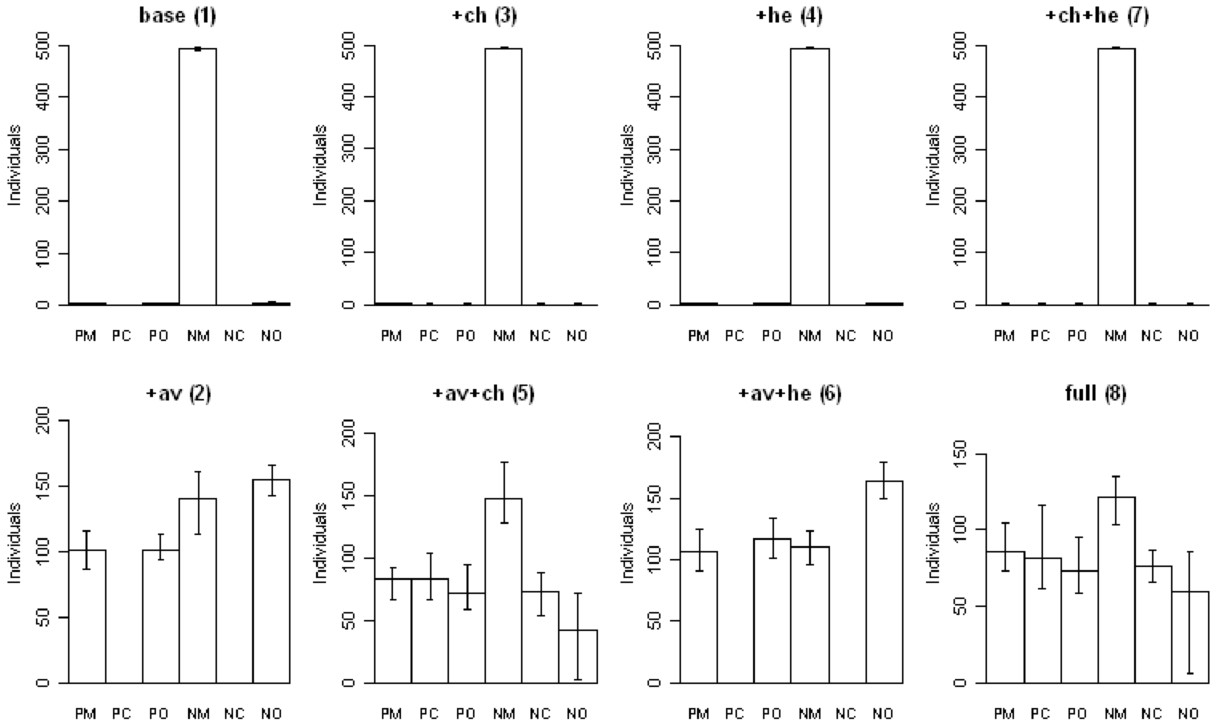

Figure 4.3: Predicted mix of strategies present in the human population at equilibrium for the eight model variants. Lines show 95% confidence intervals calculated by bootstrapping.

What is the predicted response of the animal population to the four 'policy levers'?

The response of the equilibrium animal population to changes in the four policy levers was tested using sensitivity analyses and was found to vary in shape from lever to lever (Figure 4.4). Increasing the probability of being caught poaching produces a monotonic increase in the animal population while increasing the opportunity costs of monitoring produces a monotonic decrease. The responses to increasing the fee paid to monitors and the fine imposed if monitors are caught cheating display local maxima.

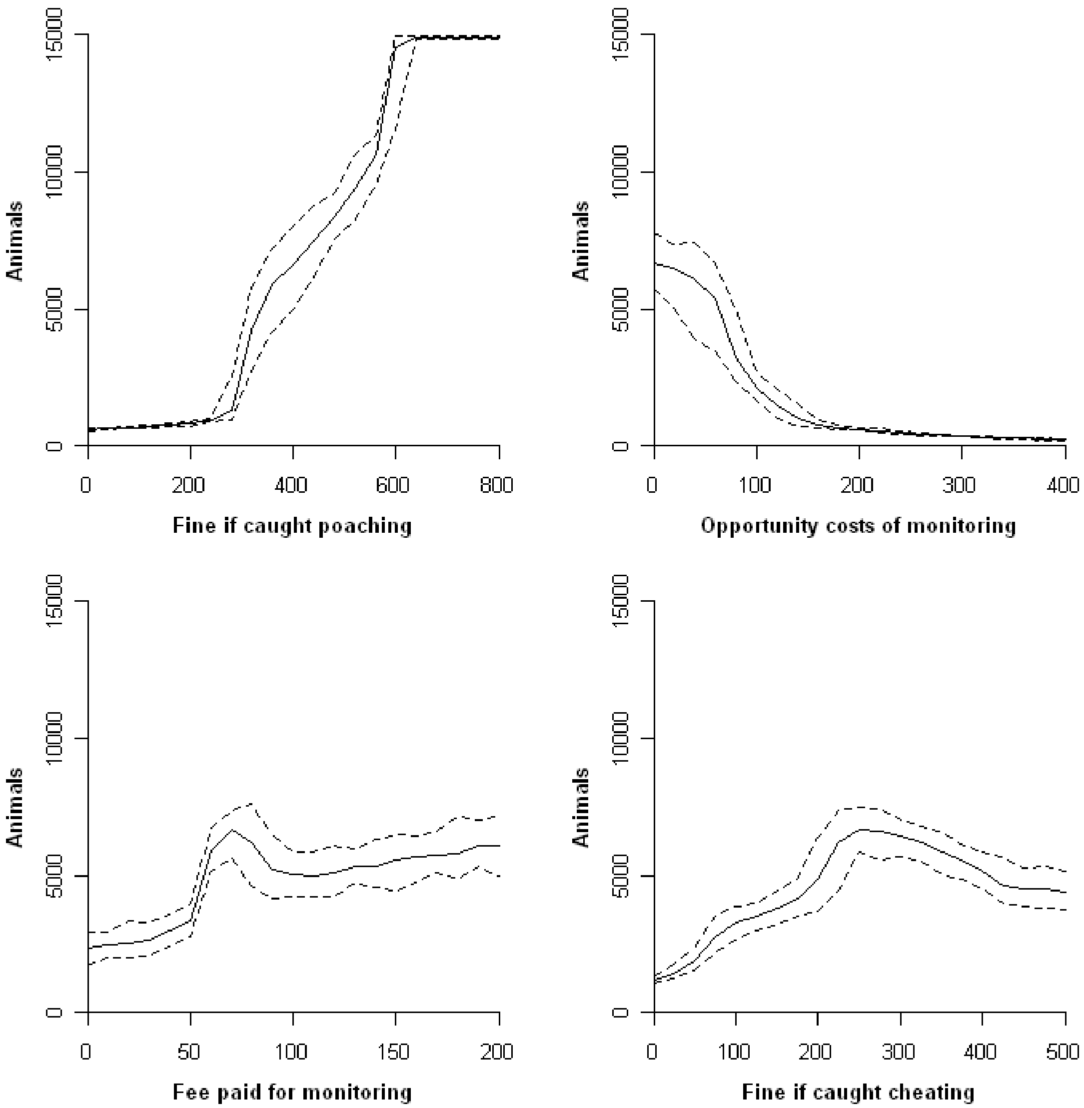

Figure 4.4: Modelled responses in the equilibrium animal population take on different shapes according to the parameter being varied. Broken lines indicate the upper and lower bounds of the 95% confidence interval calculated by bootstrapping.

In each case, the change in the equilibrium animal population varies in a non-linear manner with changes in the policy lever. This non-linearity arises from the heterogeneities in the human population

By what mechanism do changes to the policy levers produce changes in the animal population?

Although every individual in the model acts in their own self-interest the same parameter change affects their incentives differently because each one has different characteristics and can adopt different strategies. As the model is moved through parameter space, therefore, different groups within the population sequentially change their behaviour according to their individual characteristics and choice of strategies (Figures 4.5-4.8).

Not only do different groups within the modelled population react differently to management actions, they also produce different effects upon the rest of the model. For example, the prevalence of the three poaching strategies within the population directly affects the amount of hunting and therefore the number of animals. Monitors, on the other hand, only affect the animal population indirectly via their effects upon the incentives to poach. Similarly, if two individuals pursuing a poaching strategy differ in their hunting abilities, the more effective hunter will have a greater impact upon the animal population. The ultimate effect of changing one of the policy levers therefore depends on how it affects the incentives faced by key groups within the population.

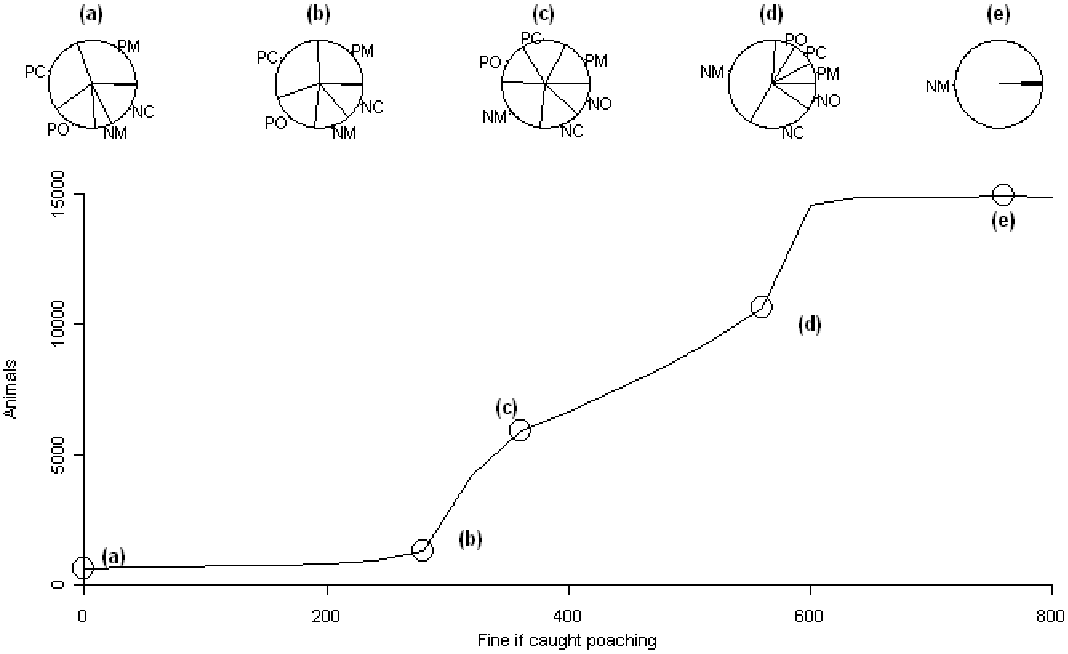

Figure 4.5: Changes in the equilibrium animal population (line chart) and prevalence of each strategy in the human population (pie charts) in response to changes in the fine if caught poaching.

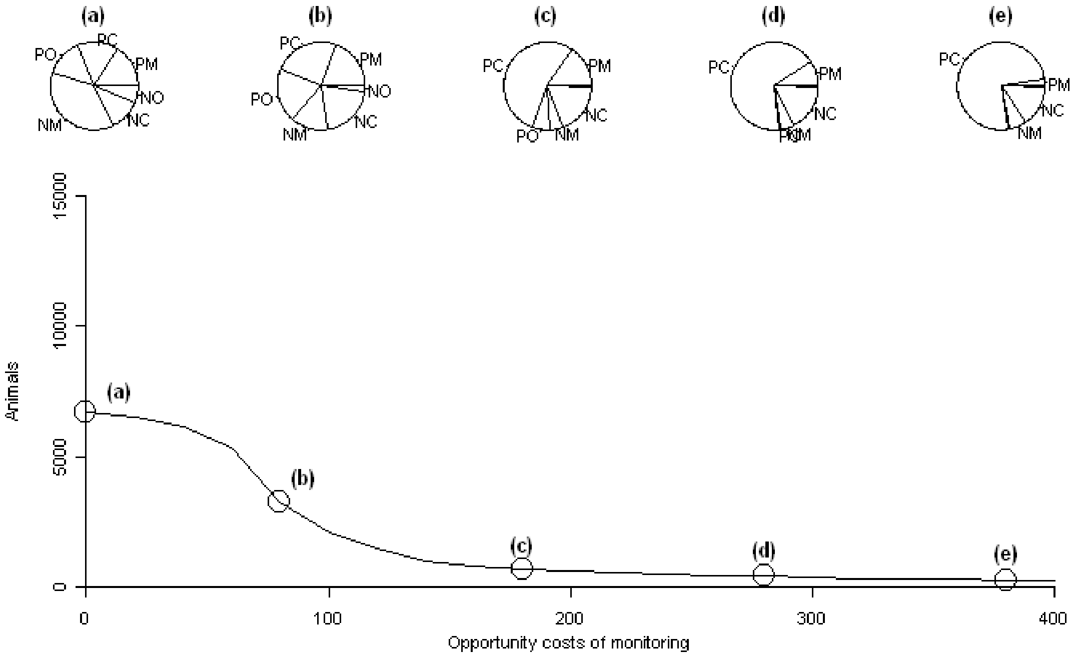

Figure 4.6: Changes in the equilibrium animal population (line chart) and prevalence of each strategy in the human population (pie charts) in response to changes in the opportunity costs of monitoring.

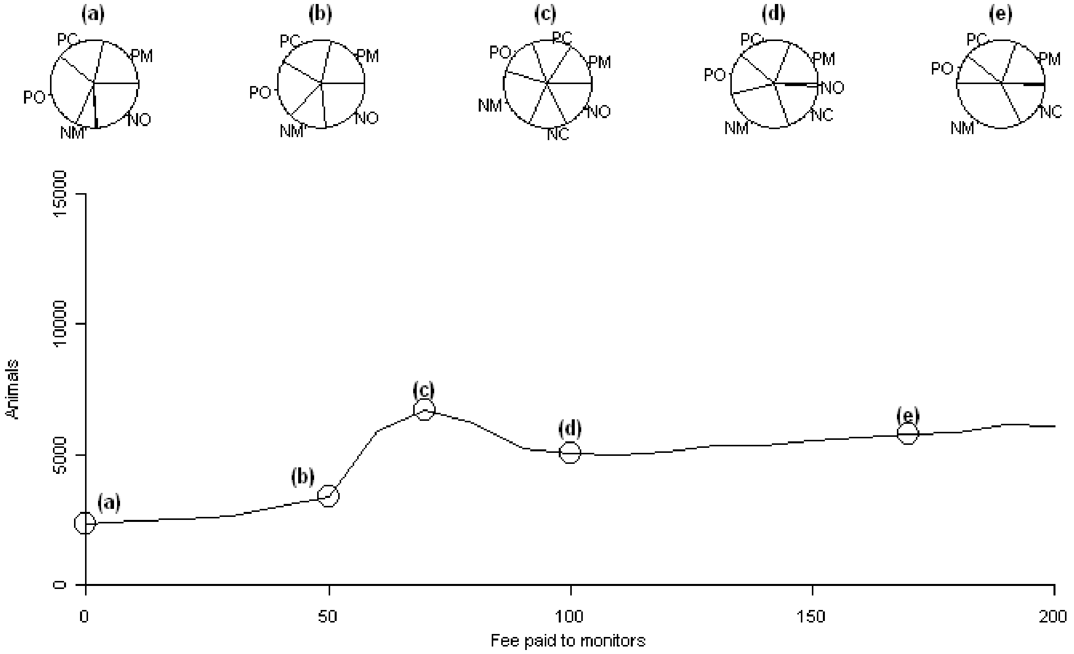

Figure 4.7: Changes in the equilibrium animal population (line chart) and prevalence of each strategy in the human population (pie charts) in response to changes in the fee paid to monitors.

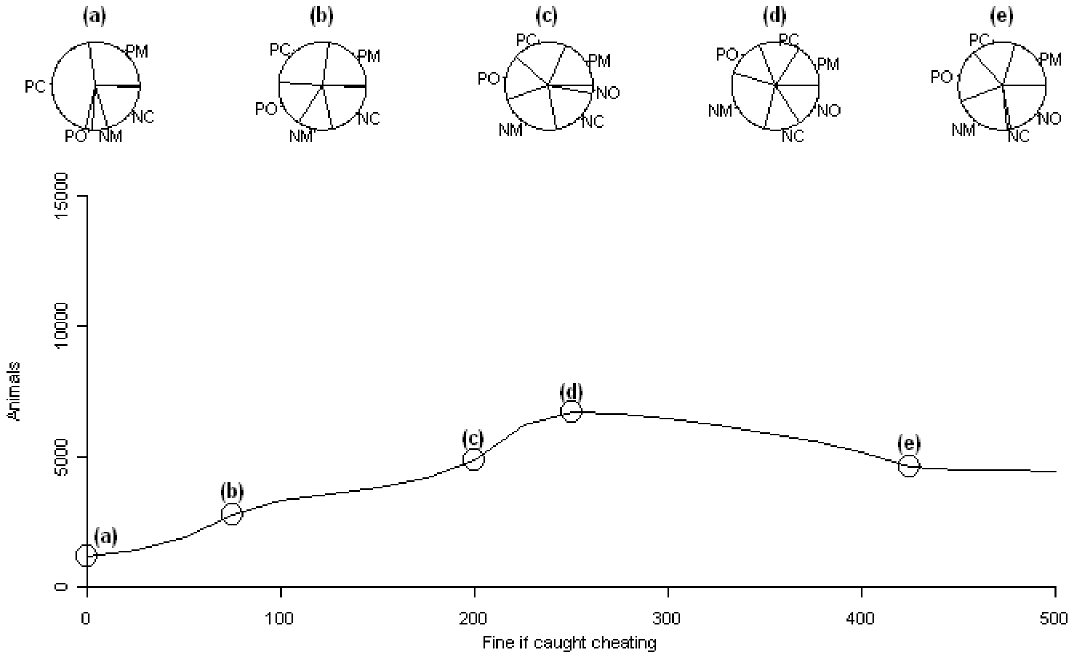

Figure 4.8: Changes in the equilibrium animal population (line chart) and prevalence of each strategy in the human population (pie charts) in response to changes in the fine imposed on monitors who are caught cheating.

Consider the level of the fine for cheating as an example (Figure 4.8). Increasing the fine from (a) to (b) causes a small increase in the animal population as the overall number of individuals adopting one of the three poaching strategies (PM, PC or PO) drops slightly. Most of this change in the number of poachers is due to a drop in PC, the strategy 'poach and cheat'. Interestingly, there is very little change in the number of individuals adopting the other cheating strategy, NC ('do not poach but cheat'). From (b) to (c) the number of poachers continues to drop as more individuals adopt the strategy NM ('do not poach but monitor the compliance of others'), accompanied by further small increases in the animal population. From (c) to (d) poaching decreases further and the numbers of NC begin to fall. Beyond (d), further increases in the fine for cheating actually produce a lower animal population as some of the individuals who were previously using the strategy NC change to use poaching strategies PM ('poach and monitor the compliance of others') and PO ('poach and neither monitor nor cheat').

How do the novel features included in the model affect responses to the policy levers?

The influence of each of the novel factors upon the outputs of the model can be understood by comparing a series of reduced models which systematically exclude avoidance behaviour, cheating strategies and individual heterogeneity (Figure 4.9).

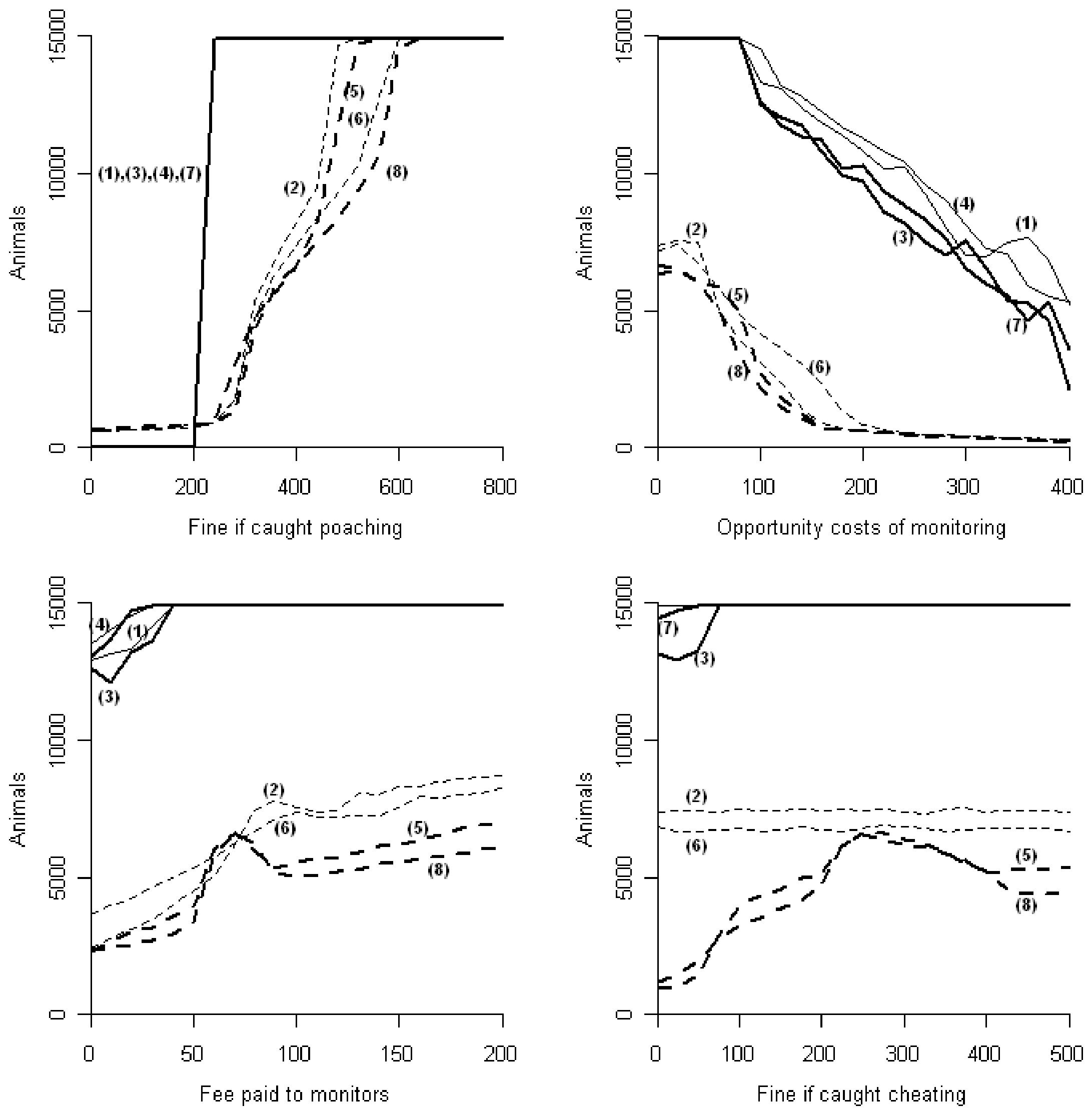

Figure 4.9: Sensitivity analyses demonstrating how the four policy levers affect the size of animal population for different reduced model configurations (see Table 4.5) for the components included in each model). The results from models which include avoidance behaviour are shown as dotted lines. Models which include cheating are drawn with heavy lines.

Their effects are complex and depend on each other's presence in the model, the choice of policy lever and the level at which it is set. For the range of parameter values (Figure 4.9 & Table 4.4) explored here, the presence or absence of avoidance behaviour produces the most significant changes. For example, the responses of models without avoidance to changes in the probability of being caught poaching (Figure 4.9, top left panel) are indistinguishable from one another, all displaying a clear threshold where the population jumps from one equilibrium to another. Models including avoidance behaviour (i.e. models 2,5,6 & 8) predict a more gradual change in the size of the animal population in response to a changing probability of being caught poaching.

The effect of individual heterogeneity and cheating are generally less marked than that of avoidance behaviour under the conditions examined here. Changing the fine for cheating (bottom right panel), as expected, has no effect upon the animal population if models do not include cheating strategies, such as model 2 and model 6. The difference between these two is the inclusion of individual heterogeneity in model 6 which results in a smaller equilibrium animal population. However, under different conditions the presence of individual heterogeneity in a model can produce different results. Comparing the responses of the same two models to changes in the fee paid to monitors (bottom left panel), there is a clear change. Below a fee of 70 model 2, in which individuals have homogenous opportunity costs and hunting effort, consistently predicts a smaller animal population than model 6. Above this level, model 6 predicts a smaller animal population.

How would the optimal strategy change if different objectives were considered?

Different measures of success – relevant to different objectives – suggest different optimal choices for each of the policy levers under consideration (Figures 4.4, 4.10 and 4.11). This is well illustrated by considering what the optimal fine for poaching is given different objectives.

A manager whose only goal was to maximise the number of animals in the population might choose to set the fine level at approximately 600, as the minimum necessary to maintain the population close to carrying capacity (Figure 4.4, top left panel). If, instead of having a pure conservation objective, the same manager wished to harvest the population at a level which produced the maximum sustainable yield, the relevant measure of success might be to find the minimum fine necessary to ensure that the probability of the population falling below 50% of carrying capacity is close to zero. Then, the appropriate fine would be approximately 500. (Figure 4.10, top left panel, heavy line). Alternatively, they might wish to ensure that the population does not fall below 30% of carrying capacity so set the fine around 400 (Figure 4.10, top left panel, broken line).

Looking at the same system, another manager whose objectives were welfare-oriented would reach very different conclusions. For example, in order to maximise the average payoff received by individuals the fine should be set at around 350 (Figure 4.11, top left panel, heavy line). However, if the equitable distribution of wealth in the community was seen as the more important goal, the manager might aim to minimise the standard deviation in the individual payoffs by setting the fine around 200 (Figure 4.11, top left panel, broken line).

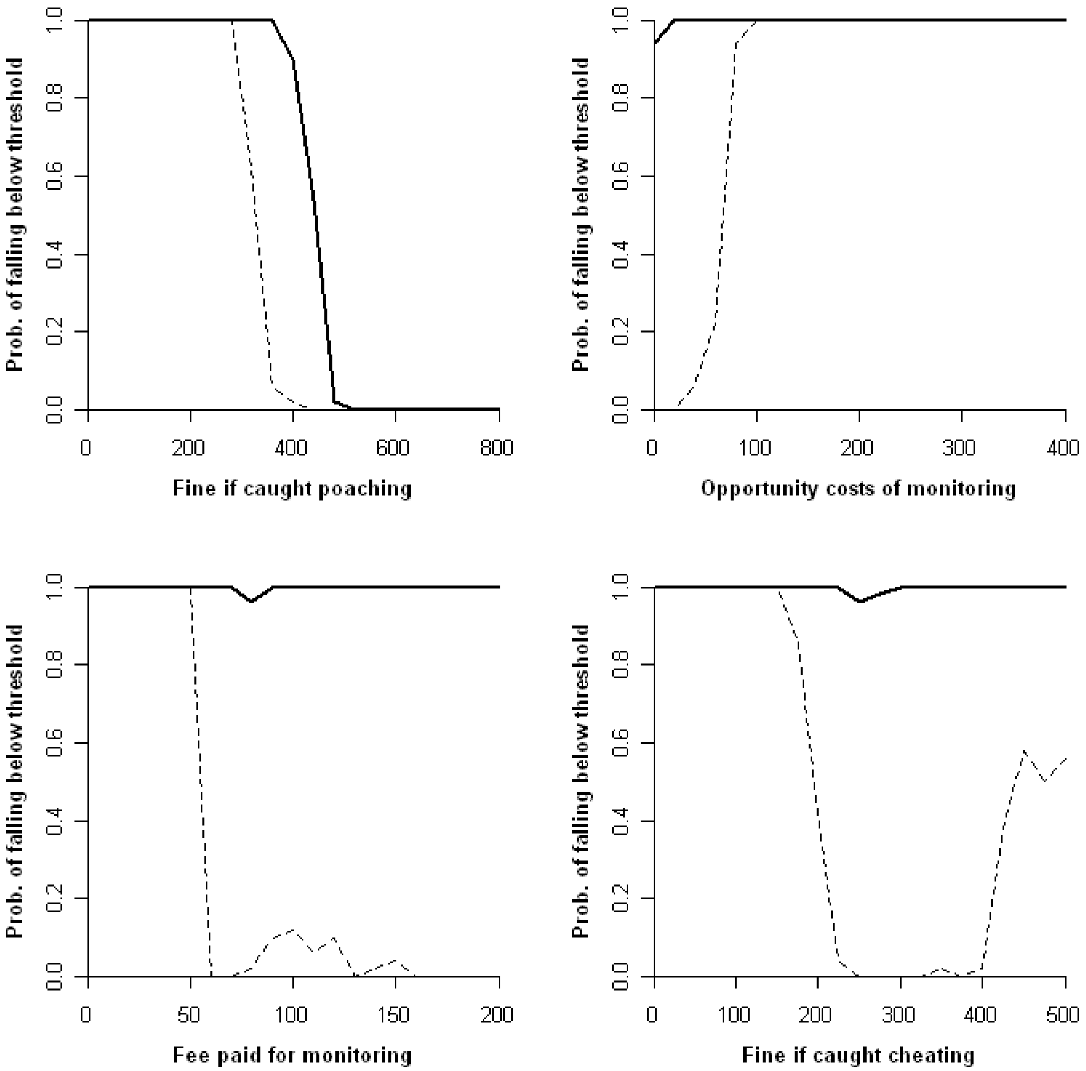

Figure 4.10: Comparison of two biologically-oriented measures of success: probability that the animal population falls below 50% of carrying capacity (heavy lines) and 30% of carrying capacity (broken lines).

In reality, a real manager might have to balance several of these different objectives. Table 4.6 compares the performance on other objectives when the fine for poaching is set near its optimal level for a given primary objective. Some objectives are compatible with others. For example, if a manager aims to maximise the animal population in this system he would clearly also minimise the probability that the population falls below thresholds set at 50% or 30% of carrying capacity. However, other objectives require trade-offs to be made. For example, minimising the standard deviation of payoffs in the community results in the mean payoff being approximately 28% of maximum. Conversely, inequality is about ten times greater than minimum achievable when mean payoff is maximised.

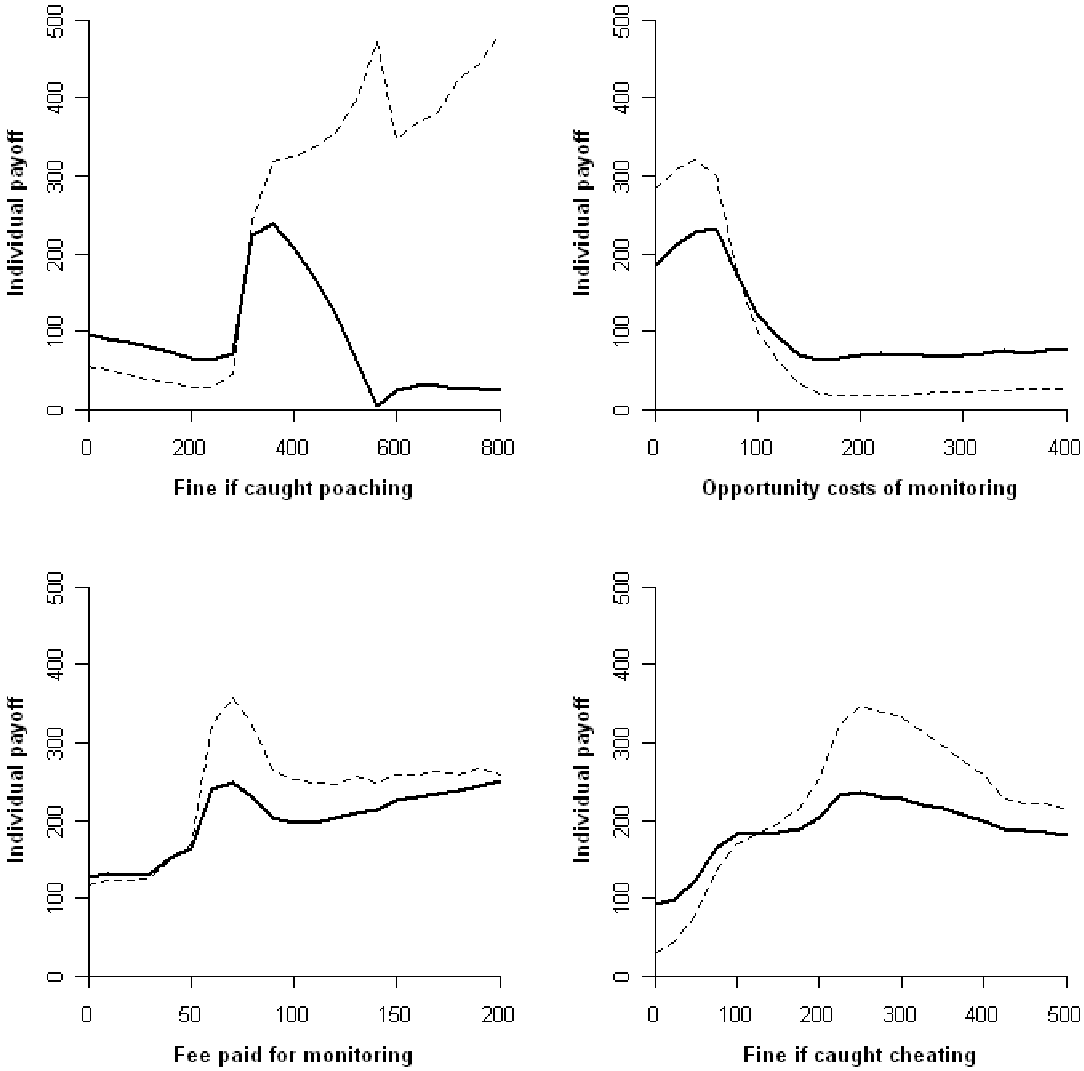

Figure 4.11: Comparison of two welfare-oriented measures of success: mean individual payoff (heavy lines) and equity, represented by the standard deviation in individual payoffs (broken lines).

OBJECTIVE	*Max. animals*	*Min. <50%K*	*Min. <30%K*	*Max. avg. pay*	*Min. SD pay*
Max. animals	100%	100%	100%	10%	1215%
Min. <50%K	65%	100%	100%	27%	1422%
Min. <30%K	45%	∞	100%	86%	1135%
Max. avg. pay	40%	∞	300%	100%	1115%
Min. SD pay	6%	∞	∞	28%	100%

Table 4.6: Comparison of objectives. The values indicate what percentage of the optimum value is achieved for each possible objective (columns) when the fine for poaching is set to optimise the primary objective (rows). Higher values are better for maximising objectives while lower values are better for minimising objectives.

Discussion

Although the goals of those who manage conservation initiatives may be expressed in terms of desired animal population size or human welfare, the tools available for achieving these goals do not always influence these things directly. In the case of enforcement measures, the link is normally indirect, with management actions (e.g. increasing the number of patrols to raise the probability that poachers are caught) designed to influence resource users' perceptions of the costs and benefits of different courses of action. Consequently, the application of policy levers may produce unexpected responses in a system and when human populations are behaviourally heterogeneous we should be wary of relying on predictions based on simple, linear responses to enforcement measures.

Models of natural resource management can be sensitive to the assumptions that underpin their design. For example, those which include avoidance behaviour produce very different predictions from those which do not. Although the model presented here is not intended to represent any specific place or system, the new features and processes incorporated are plausible representations of commonly observed behaviours. Systematically exploring areas of parameter space within the model illustrates how processes such as these could affect our ability to accurately predict the effects of enforcement measures.

When considering the output of models of enforcement, it is important to recognise that the action may have several goals. While previous models of enforcement in conservation have tended to focus upon biological goals, alternative measures of success may result in different optimal choices of enforcement strategy. For example, a manager seeking to maximise human welfare would aim to achieve a different probability of capturing poachers than one whose sole concern was for the size of animal populations. Five measures of success have been considered here, but others such as management efficiency (i.e. the increase in some measure per unit expenditure) could also be addressed.

Clearly, the lack of empirical data with which to parameterise more complex models of enforcement is a significant limitation upon their use but in the absence of suitable data theoretical models of behavioural processes may still provide useful insights. For example, this model suggests that the more direct the link between management goals and management actions, the greater the likelihood of success. Considering the goal of maximising animal numbers, one might *a priori* expect that increasing the chance that poachers are caught, raising the fine for monitors caught cheating, or increasing the fee paid to monitors would all result in a larger animal population. However, while increasing the probability of capture, which directly increases the expected costs of poaching, is matched by a monotonically (although not linearly) increasing animal population, changes in the fine for cheating and the fee paid to monitors can produce either increases or decreases in the animal population depending on the starting point.

Future research into the enforcement of conservation rules should aim to understand the behaviour of rule-breakers as part of a complex system. This may be particularly true for the conservation of harvested resources, where population dynamics and behavioural dynamics are interlinked. In order to manage such systems effectively it is necessary to have a good understanding of both the biological and the human components, and the processes which link them. Ultimately, our ability to design effective enforcement strategies would be greatly improved if discussions of enforcement, and other management activities which target human behaviour, were grounded in a framework of individual incentives. Such an approach would also allow the links with other conservation tools, such as education, alternative livelihood strategies and direct payment schemes, which also aim to produce conservation-friendly behaviour to be made explicit and addressed in a co-ordinated way. Achieving this will require a concerted effort to treat the study of enforcement, and other management tools in conservation, with scientific rigour.

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