ESSAYS ON THE ECONOMICS OF POACHING

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ABSTRACT

Charismatic mega-fauna species such as elephants and rhinos have valuable tusks and horns that are sought after by opportunistic poachers. Poaching also assumes the form of subsistence hunting by households living in and around protected areas. The conservation of endangered animal species is important for the environmental sustainability of natural ecosystems. This dissertation consists of four separate essays on the economics of poaching and protection of endangered species.

The first essay examines the labor allocation problem of an opportunistic poacher harvesting an endangered species within a protected area. The labor allocation problem is coupled with the species' population dynamics to estimate how poaching responds to economic parameters over time. The model provides insight into the relationship between species population dynamics, economic parameters, and biological parameters. Interesting and counterintuitive results are observed for a wide range of economic and biological parameters.

Civil unrest and political instability have been associated with poaching. In the second essay I examine an empirical data set on rhino poaching in Assam, India.

Assam witnessed a prolonged period of civil unrest and political instability during which rhino poaching increased dramatically. The relationship between civil unrest and rhino poaching is identified through an econometric exercise. I factor in the relationship between poaching and other variables associated with it – including black-market rhino horn prices, potential size of black markets, and anti-poaching efforts. These variables are seen to have the predicted associations with poaching, and help identify the latter's relationship with civil unrest.

International criminal syndicates sponsor elephant poaching in Africa. The third essay develops a dynamic a model of organized criminal poaching. Under plausible conditions poaching is insensitive to black-market price of ivory, but changes dramatically with the probability of interception by anti-poaching patrols. Parameter space is analyzed extensively to ascertain the effect of economic parameters on elephant population sustainability. In the fourth essay I examine the strategic interaction between poachers and anti-poachers in a spatiotemporal setting. A space is conceptualized within which meta-populations of elephants disperse temporally. Optimal locational strategies of poachers and anti-poachers are solved for, and their effects on elephant population dynamics are examined.

Keywords: *Rhinoceros unicornis*; *Loxodonta africana*; poaching; stochastic population dynamics; bifurcation; deterministic chaos; civil unrest; strategic interaction.

BIOGRAPHICAL SKETCH

Adrian A. Lopes is a doctoral candidate in the Charles H. Dyson School of Applied Economics. Prior to the Ph.D. program he earned his Master of Science degree in Agricultural and Resource Economics at the University of Arizona, Tucson. He did his undergraduate education at the University of Delhi, India.

To my parents, for understanding my keenness to embark on this journey.

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CHAPTER 1

INTRODUCTION

The harvesting of endangered or protected species is a major concern for environmental conservation. Opportunistic poachers react according to economic incentives and disincentives underlying conservation policy. The sustainability of protected species population would depend on how poaching behavior is affected by changes in economic or policy parameters. The first essay (Chapter 2) develops a labor allocation model of an opportunistic poacher harvesting a protected species within a protected area. Economic or conservation policy parameters – such as fines for poaching, wage rates in and around the protected area, black market prices for the protected species, and anti-poaching enforcement – are fed into the model. The model frames the labor allocation problem in the context of the protected species' population dynamics. In this essay we will examine the effect of changing economic parameters on both the quantitative and qualitative aspects of harvesting behavior and the resultant species population dynamics.

In the next essay (Chapter 3) we will examine the effect that civil unrest and political instability in a region have on endangered species poaching. In particular we will consider the case of the Kaziranga National Park in Assam, India, which witnessed a marked increase in the poaching of Indian rhinos that coincided with a prolonged period of civil unrest, militancy, and political instability in the region. We will use estimates of rhino population and poaching data to econometrically estimate a harvest function. In this empirical exercise we will identify the relationship between civil unrest and rhino poaching.

The protection of elephants in Southern Africa has become more difficult and dangerous with the advent of international syndicates that use organized crime to sponsor elephant poaching in Southern Africa. In the next essay (Chapter 4) we will develop a dynamic model of organized poaching. We will examine how the opportunistic behavior of the leader of a poaching organization is affected by high-value returns of selling elephant tusks on the black market. We will factor in the cost of poaching effort and the probability of getting intercepted by anti-poaching patrols. This enables us to model the operating life of a poaching organization as a stochastic process over time. The economic decision-making process is coupled with the population dynamics of elephants in Southern Africa's range states. We will examine how poaching behavior is affected by economic parameters and the probability of interception by anti-poaching patrols. The model of elephant population dynamics will also enable us to examine the sustainability implications of changes in economic parameters.

With elephant poaching increasing markedly over the last decade and anti-poaching units having limited resources to protect them against poachers, anti-poaching units must act strategically in order to achieve effective protection. Elephants are distributed over wide geographic regions and thereby it becomes important for conservation policy to consider the spatial aspects of elephant population distribution. In the final essay (Chapter 5) we will develop a model that views poaching and protection as a repeated game between strategic opponents in space. A space is conceptualized within which meta-populations of elephants disperse via seasonal migration. Poaching and protection are introduced as strategic location-specific choices of the opponents in space. The conceptual model will enable us to develop insight into the effect of various location choice strategies of poachers and anti-poachers on elephant population dynamics.

CHAPTER 2

POACHING AND THE DYNAMICS OF A PROTECTED SPECIES

2.1 Introduction and Background

Poaching is a threat to the survival of protected species in low-income countries. Bio-economic models account for the economic parameters that drive the incentive to harvest or poach under open access conditions under which poachers myopically maximize short-run profit, and entry and exit occur until rents are dissipated. Such models predict equilibrium levels of endangered populations under various conservation policies such as trade bans (Bulte & van Kooten, 1999a; Bulte & van Kooten, 1999b; Burton, 1999), fines for poaching (Bulte & van Kooten, 1999a; Bulte & van Kooten, 1999b; Damania, Milner-Gulland, & Crookes, 2005; Damania, Stringer, Karanth, & Stith, 2003; Milner-Gulland & Leader-Williams, 1992; Skonhoft & Solstad, 1998), alternative livelihoods to resolve conflict between land use and species conservation (Fischer, Muchapondwa, & Sterner, 2011; Johannesen & Skonhoft, 2005; Skonhoft, 2007; Winkler, 2011), and black market price-control through supply restrictions (Brown & Layton, 2001; Kremer & Morcom, 2000; Mason C.F., Bulte E.H., & Horan R.D., 2012). Such models analyze steady states and the dynamics of open access resource systems using the Gordon-Schaefer framework, which essentially models a dynamic system with two differential or first-order difference equations representing harvest effort and species growth net of harvest (Bulte, 2003). Species growth is often modeled using a logistic function, and harvest is represented by a Schaefer or Cobb-Douglas production function. (Bulte, 2003) extends the Gordon-Schaefer framework by the accounting for the relationship between harvest and species population abundance. Harvest is determined by the abundance of species population and prey switching can take place at low prey densities. Bulte finds that the traditional result of a unique and stable steady state under open access in the long run might be misleading, and that multiple equilibria or steady states might exist that are driven by small changes in the underlying economic parameters used in the model.

Ecologists have noted that discrete-time models of species populations may exhibit seemingly random or chaotic behavior (Hastings & Powell, 1991; May RM, 1976) because the stability of steady states in such dynamical systems are dependent on the values of model parameters (Edelstein-Keshet, 1988; Hale, Jack K.,Koçak, Hüseyin., 1991). (May RM, 1976) first showed how parameter variation in a first-order difference equation may cause steady state values to become unstable. For some range of parameter values there may exist critical values at which a qualitative change in the behavior of the dynamical system occurs. Oscillatory and chaotic population behavior has been observed empirically. For instance ecologists have found, on examination of historical data on the fur trade of the Canadian lynx (*Lynx canadensis*), that increased trapping effort on the part of fur traders seemed to induce high-amplitude chaotic behavior in the lynx population (Gamarra & Ricard, 2000; Schaffer, 1985). These studies deduce that the amplitude of population cycles is affected by changes in pelt price for lynx and in some cases results in counterintuitive population dynamics. Ecologists find that dynamic natural systems are generally unstable over long time horizons (Gamarra & Ricard, 2000; Schaffer, 1985).

Predictions of species population behavior merit careful study. Abrupt qualitative changes in population behavior may come about by changes in economic and biological parameters. In this chapter we develop a model of poaching in a protected area that houses a protected species. We study the qualitative effects of economic and biological parameter changes on poaching behavior, as well as the resultant effects on protected species' population dynamics. The economic parameters that we examine include the black market price of the protected species, the fine for poaching, the wage rate from employment in and around the protected area, and anti-poaching enforcement. We also examine changes in the biological parameters that can be used to represent different types of species. We provide extensive numerical analyses of parameter space for both economic parameters and biological parameters. Our results serve as an extension of the findings of previous studies which deduce that dynamic natural systems are either unstable in the long run or have non-unique steady states driven by changes in the model's economic and biological parameters. The model reveals that policy parameter variations induce abrupt qualitative changes in poaching and population behavior.

In section 2.2 we present a model of illegal harvest or poaching based on a system of two first-order difference equations. We study the effects of poaching on population dynamics with the help of numerical comparative static exercises. The numerical results are presented in section 2.3. Section 2.4 provides a discussion of the numerical results and possible implications for conservation policy.

2.2 A Model of Risky Open Access

In this section we develop a bio-economic model of poaching to study its effects on species' dynamics and poacher utility. Let us consider a poacher living near a protected area (PA) who allocates time to poaching, non-poaching employment and leisure. The poacher accordingly derives utility from consumption of harvest, income from non-poaching employment and black market sales, and leisure time. The poacher maximizes a utility function subject to time and budget constraints in each time period for a finite time horizon. The protected species' population dynamics is modeled using a growth function and a poaching production function. Poaching is subject to risky open access, whereby a fine is incurred for being caught poaching by an anti-poaching patrol. The poacher solves for the optimal sequences of poaching time, non-poaching employment time and leisure time. We first provide the general mathematical form of the bio-economic model and the resulting constrained-maximization conditions. Later we use specific functional forms for utility, population growth, poaching production and probability functions.

We define $\mathrm{E}[U_t] = U(C_t, \mathrm{E}[I_t], T_t^L)$ as the poacher's expected utility in time period t, where C_t is the consumption of the endangered species from the preserve in period t, $\mathrm{E}[I_t]$ is the expected income in period t, and T_t^L is the leisure time in period t. We define T_t^H to be the time spent poaching and T_t^W to be the time spent in non-poaching employment in and around the PA in period t. Accordingly we define T to be the time constraint for each period as $T = T_t^L + T_t^H + T_t^W$.

We define a poaching production function as $H_t = H(T_t^H, X_t)$, where H_t represents the harvested amount from the PA and X_t is the protected species population in period t. The poacher consumes C_t out of H_t and sells the remainder $(H_t - C_t)$ at a price, P_t on the black market. The poacher also allocates time towards non-poaching employment (T_t^W) within the PA and earns a wage rate of W_t in period t. We define F_t to be the fine that the poacher pays for being caught by an anti-poaching patrol in period t. Since poaching is risky, we define $\phi(T_t^H)$ to be the probability of getting caught poaching. This implies that the expected fine in period t is given by $\phi(T_t^H)F_t$, and therefore the total expected income of the poacher is given by $E[I_t] = (H_t - C_t)P_t + W_t T_t^W - \phi(T_t^H)F_t$.

Given these definitions expected utility takes the form $U(C_t, E[I_t], T_t^L) = U(C_t, (H_t - C_t)P_t + W_t T_t^W - \phi(T_t^H)F_t, T - T_t^W - T_t^H)$ where we assume that $H_t \geq C_t \geq 0$. The protected resource is assumed to evolve as per the iterative map: $X_{t+1} = X_t + F(X_t) - H(T_t^H, X_t)$ i.e. generations of the protected species or the renewable resource are assumed to overlap. The utility maximizing poacher views X_t as given and does not know or concern himself with how his actions will affect X_{t+1}. The poacher solves a static time allocation problem in each period t, given the level of resource stock and the risk of a fine. The constrained-optimization problem is set up as follows:

$\max_{\{C_t, T_t^H, T_t^W\}_{t=0}^N} \sum_{t=0}^N \rho^t U(C_t, E[I_t], T_t^L)$ subject to:

$T_t^L = T - T_t^W - T_t^H$,

$E[I_t] = (H_t - C_t)P_t + W_t T_t^W - \phi(T_t^H)F_t$, and $X_{t+1} = X_t + F(X_t) - H(T_t^H, X_t)$.

ρ is the discount factor and N is the finite time horizon in this time allocation problem. The Lagrangean ($\mathcal{L}$) is set up as follows:

$$\mathcal{L} = \sum_{t=0}^{N} \rho^t \{U(C_t, (H_t - C_t)P_t + W_t T_t^W - \phi(T_t^H)F_t, T - T_t^W - T_t^H) + \rho\lambda_{t+1}(X_t + F(X_t) - H(T_t^H, X_t) - X_{t+1})\}$$

With the assumption that the poacher is myopic and does not account for the future value of the stocks we set $\rho\lambda_{t+1} = 0$. The resulting first-order constrained-optimization conditions are as follows:

$$\left\{\frac{\partial U(.)}{\partial C_t} - \frac{\partial U(.)}{\partial I_t} P_t\right\} C_t = 0,\ H_t \geq C_t \geq 0 \tag{2.1}$$

$$\left\{\frac{\partial U(.)}{\partial I_t}\left[\frac{\partial H(.)}{\partial T_t^H} P_t - \phi'(T_t^H)F_t\right] - \frac{\partial U(.)}{\partial T_t^L}\right\} T_t^H = 0,\ T_t^H \geq 0 \tag{2.2}$$

$$\left\{\frac{\partial U(.)}{\partial I_t} W_t - \frac{\partial U(.)}{\partial T_t^L}\right\} T_t^W = 0,\ T_t^W \geq 0 \tag{2.3}$$

$$E[I_t] = (H_t - C_t)P_t + W_t T_t^W - \phi(T_t^H)F_t \tag{2.4}$$

$$T_t^L = T - T_t^W - T_t^H \tag{2.5}$$

Equations (2.1) through (2.5) can be solved simultaneously for C_t, T_t^H, T_t^W, I_t and T_t^L given $X_t \geq 0$ and parameter values for P_t, W_t and F_t. Once we solve for T_t^H we can use the iterative map $X_{t+1} = X_t + F(X_t) - H(T_t^H, X_t)$ to calculate the next period's renewable resource stock, X_{t+1}. Then we use Equations (2.1) through (2.5) to solve for C_{t+1}, T_{t+1}^H, T_{t+1}^W, I_{t+1} and T_{t+1}^L given $X_{t+1} \geq 0$. From the iterative map we will have $X_{t+2} = X_{t+1} + F(X_{t+1}) - H(T_{t+1}^{H}, X_{t+1})$. This process is continued until the finite time horizon, N. A steady state is reached if C_t, T_t^H, T_t^W, I_t and T_t^L are unchanging, i.e. where net growth equals harvest: $F(X_t) = H(T_t^H, X_t)$.

We specify functional forms for poacher utility, the harvest function, species population growth, and the probability of getting caught poaching. The poacher's utility is represented by a Cobb-Douglas utility function specified in Equation (2.6), where $\alpha > 0, 1 \geq \beta > 0, 1 > \gamma > 0, \eta > 0, 1 > \omega > 0$. Note that $C_t > 0$ is not necessary for a positive level of utility.

$$U_t = \alpha E[I_t]^{\beta} (T_t^L)^{\gamma} (1 + \eta C_t^{\omega}) \tag{2.6}$$

A Schaefer production function is specified in Equation (2.7) for the poaching production function, where $q > 0$ is a poaching technology or efficiency parameter.

$$H(T_t^H, X_t) = q T_t^H X_t \tag{2.7}$$

We use a modified logistic population growth function from previous studies (Cromsigt, Hearne, Heitkonig, & Prins, 2002; Milner-Gulland & Leader-Williams, 1992). r represents the intrinsic growth rate of the protected species, K is the carrying capacity of the protected area and z is a skew parameter in the growth function; a value of $z > 1$ causes the population level supporting peak growth to lie to the right of $K/2$. (Cromsigt et al., 2002; Milner-Gulland & Leader-Williams, 1992) discuss how different values of z can be used to represent different species.

$$F(X_t) = r X_t (1 - (X_t/K)^{z}) \tag{2.8}$$

As we mentioned previously poaching is a risky activity for the individual, whereby a fine is incurred for being caught poaching by an anti-poaching patrol. Probability functions can be formulated to include the property that the probability of getting caught increases with the proportion of time spent poaching or harvesting (see: (Copeland, Brian Richard., Taylor, M. Scott,National Bureau of Economic Research., 2004; Damania et al., 2005). We model riskiness with a probability function specified in Equation (2.9), which satisfies this property; when $T_t^H = 0$ we have $\phi(T_t^H) = 0$, and when $T_t^H = T$ we have $\phi(T_t^H) = 1$.[1] Note that as κ declines the probability of being caught while poaching increases. In this probability function The parameter κ can be taken to represent the effectiveness of anti-poaching enforcement within the PA; the more effective the anti-poaching patrols are in apprehending the poacher, the lower would be the value of κ.

$$\phi(T_t^H) = (T_t^H/T)exp\left(-\kappa(T - T_t^H)\right) \tag{2.9}$$

Using Equations (2.6) – (2.9), we derive the first order constrained-optimization conditions. We evaluate the first-order conditions in steady state by setting $X_t = X_{t+1} = X$, dropping the t subscripts from the choice variables C, T^H and T^W, and deriving the following expressions:

$$\eta\omega I - \beta C^{1-\omega}(1 + \eta C^{\omega})P = 0 \tag{2.10}$$

$$\beta T^L\left(qK(1 - 2qT^H/r)P - (1 + \kappa T^H)\mathrm{e}^{-\kappa(T-T^H)} F/T\right) - \gamma I = 0 \tag{2.11}$$

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[1] We use the simplifying assumption that the probability of getting caught poaching and the probability of paying the fine are the same. While we can include a joint probability of getting caught poaching and paying the fine, no additional insight would be garnered from the model.

$$\beta W T^{L} - \gamma I = 0 \tag{2.12}$$

We note that $X = K(1-(q/r)T^{H})$ in steady state and that therefore we derive $\partial H(\cdot)/\partial T_{t}^{H} = qK(1-2qT^{H}/r)$. Equations (2.10) – (2.12) can be numerically solved for the steady state values of the decision variables C, T^{H} and T^{W}. We can use these values to derive the steady state value of the resource stock, X. This is done for a set of base-case parameter values, which are listed in Table 2.1.

Table 2.1: Steady state values of the Risky Open Access model under base-case model parameters.

Parameters	**Values**	**Decision variables**			
r=	1	$C =$	0.0316	Maximized utility=	1.5046
K=	1	T^{H}=	0.5892		
q=	1	T^{W}=	0.1634		
α=	1				
β=	1	*Steady state values*:			
γ=	0.3	$X =$	0.4108	Equation (2.10)=	1.23E-06
η=	5	$H =$	0.2420	Equation (2.11)=	1.78E-07
ω=	0.3	$I =$	0.8246	Equation (2.12)=	-1.00E-07
P=	5	$T^{L} =$	0.2474		
W=	1	$\phi(T^{H}) =$	0.3907		
F=	1				
T=	1				
κ=	1				
z=	1				

2.3 Numerical Analyses

Table 2.1 shows the steady state values of the resource stock and the decision variables. We can numerically solve for the optimal sequence of $\{C_t, T_t^H, T_t^W\}_{t=0}^{N-1}$ for a given initial value for the resource stock, X_0. Let us consider an initial value of $X_0 = 0.5$. We numerically solve for C_0, T_0^H, T_0^W using Equations (2.1) – (2.3). Then we use the iterative map $X_1 = X_0 + F(X_0) - H(T_0^H, X_0)$ to calculate X_1 and numerically solve for C_1, T_1^H, T_1^W in the next time period $t = 1$. The simulation exercise is conducted for one hundred time periods i.e. $N = 100$ to check for convergence to a steady state value of the population over time.

Figure 2.1 depicts a simulation of the risky open access model using the base-case parameter values listed in Table 2.1 for the time horizon $t = 0$ to 100 with initial stock $X_0 = 0.5$. The plots for the resource stock (X_t) and the time spent poaching (T_t^H) show convergence to the steady state values of 0.4108 and 0.5892 respectively via *damped overshoot* after $t = 10$. We note that the steady state values correspond to those listed in Table 2.1.

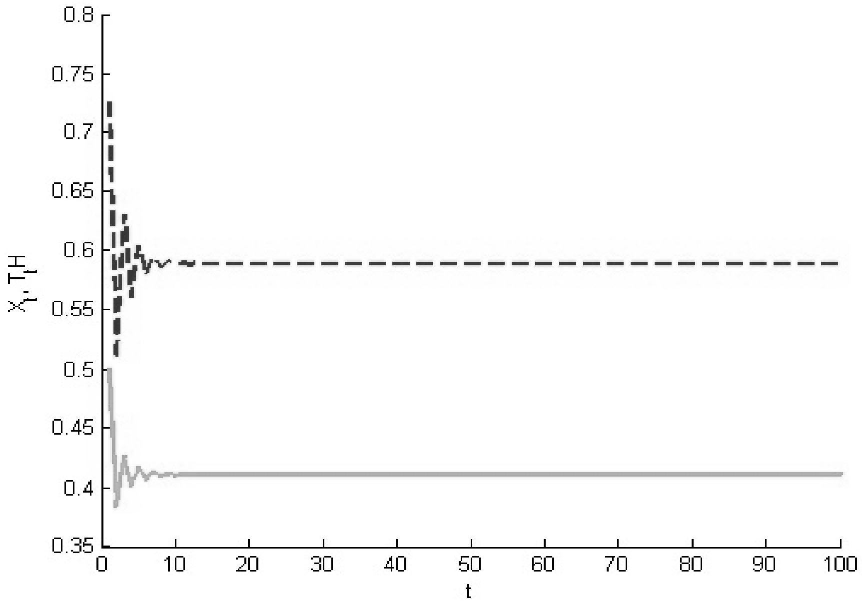

Figure 2.1: Approach dynamics of the resource stock, X_t (solid line) and poaching time, T_t^H (dashed line) using base case parameter values of Table 2.1.

From Figure 2.1 it is evident that when the stock level is high the time spent poaching is also high, and when the stock declines, so does the poaching time. Thus the changes in poaching time follow the changes in the abundance and scarcity of the resource stock. In Figure 2.1 we see that the stock converges to the previously calculated steady state and $X_0 = 0.50$ lies in the "basin of attraction". [2]

We noted earlier that for a certain range of parameter values there may exist critical values or "bifurcation points," for which we observe abrupt changes in the qualitative behavior of the dynamical system being modeled. Bifurcation diagrams can be used to show the values of the parameter at which the dynamical system moves

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[2] The steady state value of $X = 0.4108$ is locally stable, because $|G'(X)| \leq 1$ where $G(X) = X + rX(1 - (X/K)^z) - qT^H X$; $|G'(X)| = 0.5892$ when evaluated at $X = 0.4108$, i.e. the steady state.

from steady state to period-doubling bifurcation, and then eventually to "deterministic chaos"; deterministic because the parameters are not random variables in our model.

The parameters in our risky open access model include the wage rate (W_t) for employment in and around the PA, the fine (F_t) imposed for being caught poaching and the effectiveness of anti-poaching enforcement (κ). The price of the species sold on the black-market (P) can be considered as an indirect policy parameter, i.e. confiscated harvest by anti-poaching patrols can be dumped on local markets causing the black-market price to fall, and thereby create a disincentive to poach. These parameters can be referred to as policy parameters in that they might be directly or indirectly controlled by the manager of the PA. Changes in the values of policy parameters may facilitate a renewal of population from low levels, but with the possibility of chaotic behavior, policy may well induce widely oscillating population trends over time. The biological parameters in our model are the intrinsic growth rate (r) of the protected species, the skew parameter (z) in the logistic growth function, and the size of the PA or the carrying capacity (K). We can represent different species in our model with different values of r and z. Small mammals would have higher reproductive rates (i.e. higher values of r in the model) compared to large or mega-fauna species; the latter can be represented by lower values of r (Eberhardt, 1987). The modified logistic growth function with the skew parameter (z) allows for non-linearity in the relationship between X_t and the strength of population density-dependence $(1 - X_t/K)$. For modeling mega-fauna there is empirical evidence for values of $z > 1$; density-dependence becomes more important for large mammals when their population is closer to the environmental carrying capacity (K) (Cromsigt et al., 2002; Eberhardt, 1987).

In the analysis of our bio-economic model we shall study the changes in qualitative behavior of the protected population dynamics and poaching time for changes in the economic parameters, which include the wage rate (W), the poaching fine (F), the black-market price (P), and the effectiveness of anti-poaching enforcement (κ), as well as for different values of the biological parameters, which include the intrinsic growth rate (r), and the skew parameter (z). Bifurcation diagrams of X for different combinations of κ, r, and z could provide insight on the effectiveness of anti-poaching policy in conserving populations of different species. This has the potential of providing an integrative analysis of the economics and the ecology of species conservation policy.

We begin our comparative static exercises by changing the wage rate W from its base case value of 1 to a value of 1.5 (i.e. a fifty percent increase in wage rate from its base-case value). All other parameter values retain the same values of Table 2.1. The resulting simulation is shown in Figure 2.2. What we observe is that X_t and T_t^H oscillate with increasing amplitude until $t = 30$ and afterwards they both oscillate within a two-point cycle with $X_t = \{0.3915, 0.5859\}$ and $T_t^H = \{0.1120, 0.7458\}$. When $X_t = 0.3915$ the stock is so low as to only induce a $T_t^H = 0.1120$ from the expected utility-maximizing poacher. When $X_t = 0.5859$ poaching is more attractive and poaching effort increases to $T_t^H = 0.7458$, i.e. by a factor of 6.67. Given this observed two-point cycle pattern when $W = 1.5$, we suspect that further increases in W will lead to cycles of 2^n and ultimately deterministic chaos in the evolution of the resource stock X_t. Figure 2.3 plots the bifurcation points for changes in the parameter values of W- it shows the resource stock, X_t, for increments of 0.005 in the interval $W \in [0.5, 2]$. The critical values, or "bifurcation points," occur in the range $W \in [1.4, 2]$. Bifurcation diagrams, like in Figure 2.3, provide us with information about the qualitative dynamics of the resource stock for a given range of parameter values. For instance in Figure 2.3 in the interval $W \in \{1.5, 2\}$ we note that when $X \in \{0.37, 0.68\}$ the lower bound of which is smaller than the resource stock levels when $W \in \{0.8, 1.4\}$. This result shows that policy aimed at increasing the wage rate might have unintended consequences of a lower resource stock level.

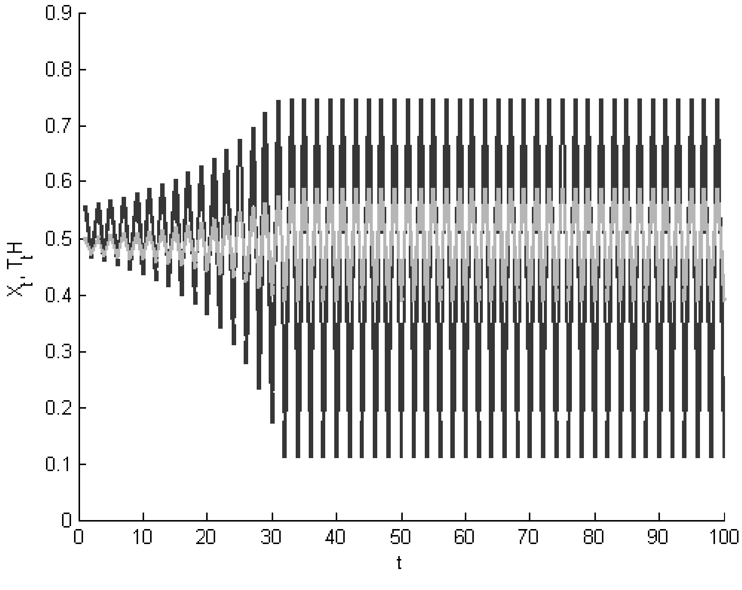


Figure 2.2: Dynamics of the resource stock, X_t (light) and poaching time, T_t^H (dark) when W increases to 1.50

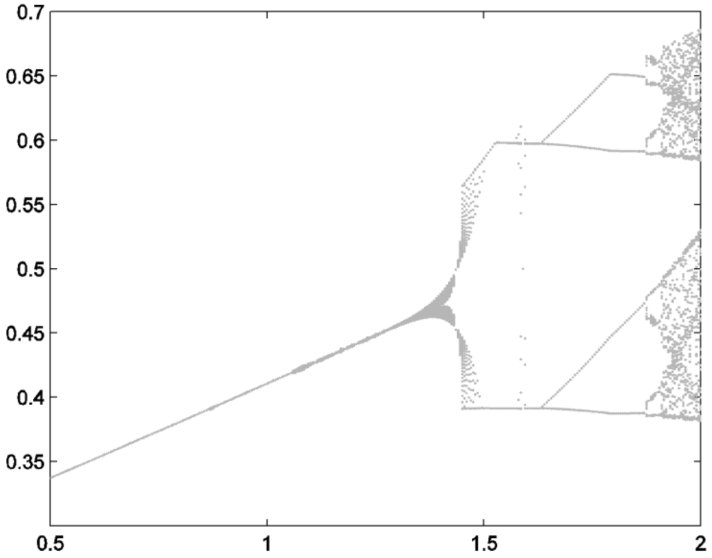


Figure 2.3: Bifurcation points and steady state values in the dynamics of $\mathrm{X_t}$ (vertical axis) for increments of 0.005 in values of $\mathrm{W} \in [0.5, 2]$ (horizontal axis)

Next we study the effects of changes in the fine (F) for getting caught poaching. Figure 2.4 plots the bifurcation points for increments of 0.005 in the parameter values of F in the interval $[0, 2]$. The critical values (bifurcation points) occur approximately at $F = 0.3$ and 0.47. This tells us that when the fine is reduced from its base-case level of 1 to a little below 0.50 (i.e. half the base-case level) we observe a period-doubling bifurcation in the resource stock dynamics. Chaotic behavior in the resource stock dynamics occurs when $F \leq 0.3$ and the resource stock attains steady state values in the range with no bifurcations in the resource stock. The level of the steady state values is seen to increase when the fine is increased, which serves intuition since an increasing poaching fine would lower the marginal productivity of the time spent poaching T_t^H. It is interesting to note that when the level of the fine is reduced to zero the resource stock value does not decline to zero.

This is because the marginal product of the time spent poaching T_t^H goes to zero as $X_t \to 0$, while at the same time the marginal product of wage labor time remains at $W = 1 > 0$ (remember in these comparative static numerical exercises we change one parameter at a time while maintaining the other parameters at their base-case values listed in Table 2.1).

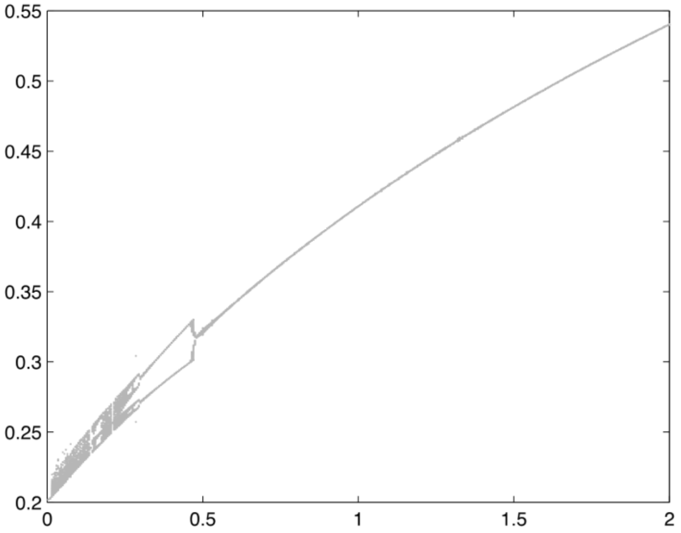


Figure 2.4: Bifurcation points and steady state values in the dynamics of X_t (vertical axis) for increments of 0.005 in values of $F \in [0, 2]$ (horizontal axis).

We now examine the bifurcation points in the third economic parameter- the black market price P- for the range $P \in [2, 5]$ as shown in Figure 2.5. Period-doubling bifurcation begins to occur in the resource stock values when the black market price is lowered to the range of $[2, 3]$. When the value of P increases above this range we note that the resource stock attains steady state values with no bifurcation occurring. The resource stock steady state level does decline, which serves intuition since an increasing black market price would increase the marginal productivity of the time spent poaching T_t^H. This tells us that increasing black market prices might tend to reduce the resource stock to lower levels that are locally stable, unique, steady state values.

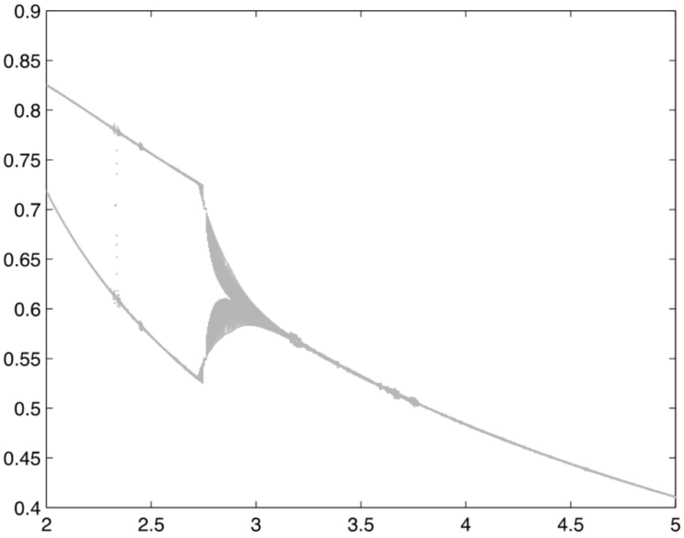


Figure 2.5: Bifurcation points and steady state values in the dynamics of X_t (vertical axis) for increments of 0.005 in values of $P \in [2, 5]$ (horizontal axis).

The last policy parameter that we examine is the effectiveness of anti-poaching enforcement (κ). Figure 2.6 plots the bifurcation points for increments of 0.005 in the parameter values of κ in the interval $[0, 5]$. Recall from Equation (2.9) that a higher value of κ result in a lower probability of capture, and so would imply a reduced level of effectiveness of anti-poaching patrols. For $\kappa \in (0.75, 5]$ we note that the resource stock attains unique, locally stable, steady state values with no bifurcation occurring. The resource stock steady state level does decline, which serves intuition since lowering the effectiveness of anti-poaching enforcement lowers the probability of detection. Therefore the poacher would spend relatively more time poaching compared to other activities; in other words the marginal productivity of the time spent poaching, T_t^H, increases for the poacher. For $\kappa \in [0, 0.75]$ we observe two-point cycles. This tells us that increasing the effectiveness of anti-poaching patrols (lowering the value of κ) does not always lead to higher steady state levels in the resource stock, i.e. the lower limit of the bifurcation or critical values are lower than some range of steady state values. Next we show that counterintuitive dynamics can emerge from our comparative static numerical exercise when modeling different type of protected species.

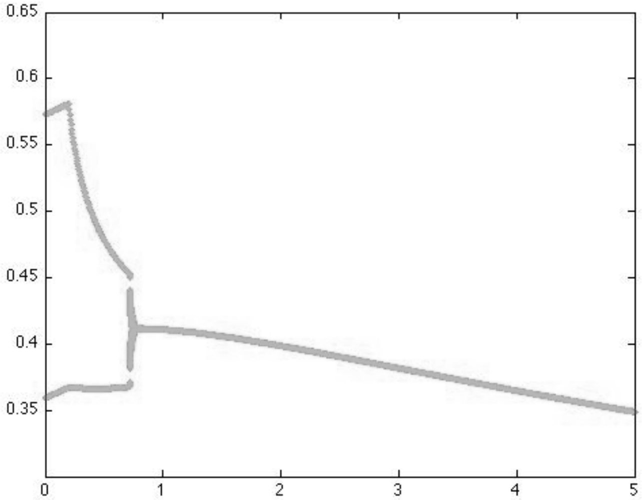


Figure 2.6: Bifurcation points and steady state values in the dynamics of X_t (vertical axis) for increments of 0.005 in the interval $\kappa \in [0, 5]$ (horizontal axis).

We turn our attention to the qualitative dynamics when we model different types of species. Different values of biological parameters in the logistic growth function have been used to study he population dynamics of different types of species. Values of $z > 1$ are used to model population dynamics of large mammal species

(Cromsigt et al., 2002). Different values of the net intrinsic growth rate (r) in the logistic growth function can represent different species. Empirical estimates find small values of r (low reproductive rates) for large mammals and high values of r for small mammals (Eberhardt, 1987). First we change the value of the skew parameter z to represent different mammal species being modeled. Figure 2.7 plots the bifurcation points for increments of 0.005 in the parameter values of κ in the interval $[0, 5]$, but this time when we change the value of z to 2. Note that when the anti-poaching effectiveness increases (i.e. the value of κ reduces, which then increases the probability of anti-poaching patrols intercepting the poacher) the resource stock attains locally stable, unique, steady state values. However for κ in the range $[0, 3]$ we note that the steady state stock levels reduce. In Figure 2.6 we saw that increasing the effectiveness of anti-poaching patrols beyond a critical value leads to bifurcations in the stock level. This comparative static exercise reveals that it is possible to have *counterintuitive* results when one increases the effectiveness of anti-poaching patrols, particularly when different species are being modeled with different skew parameter values.

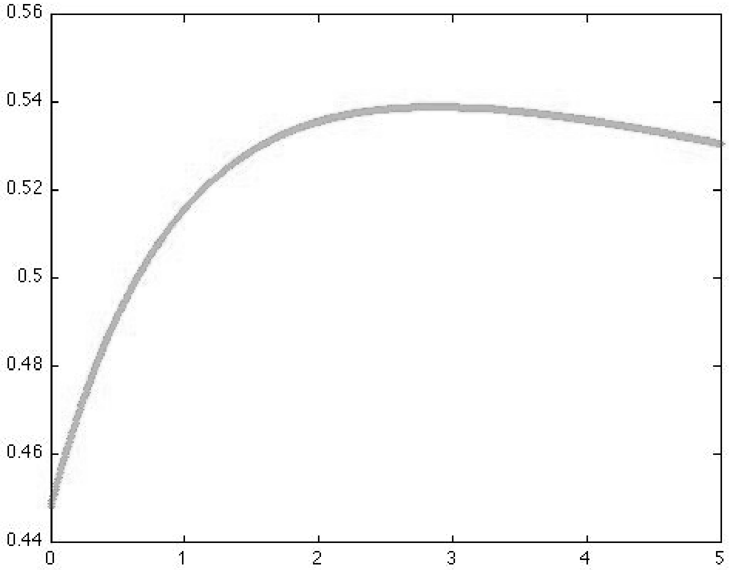


Figure 2.7: Steady state values in the dynamics of X_t (vertical axis) for increments of 0.005 in the interval $\kappa \in [0, 5]$ for a variation in the skew parameter from its base-case value, i.e. $z = 2\ (> 1)$.

We use these comparative static numerical exercises to derive combined insight on the effects of changing levels of both biological and economic parameters on the qualitative population dynamics. First we examine the effects of changing levels of the intrinsic growth rate (r) in conjunction with different levels of anti-poaching enforcement effectiveness (κ). We do this by simulating the time paths of the resource stock, X_t, for combinations of values of $r \in \{0.15, 0.20, 0.25, \dots, 1.00\}$ and $\kappa \in \{0, 1, 2, \dots, 10\}$. Once we derive the time paths for each combination of r and κ, we record the points in the time paths of X_t at which the qualitative behavior changes from steady state to period-doubling bifurcation. In Figure 2.8 we record the qualitative behavior of the resource stock's equilibrium points for the values of r (along the horizontal axis) in conjunction with values of κ (along the vertical axis). The legend on the right hand side in Figure 2.8 indicates the qualitative behavior of species dynamics: convergence to steady state shown in dark blue, two-point cycles shown in light blue/green, four-point cycles shown in yellow, eight-point cycles shown in orange/red, and finally "deterministic" chaos shown in dark red.

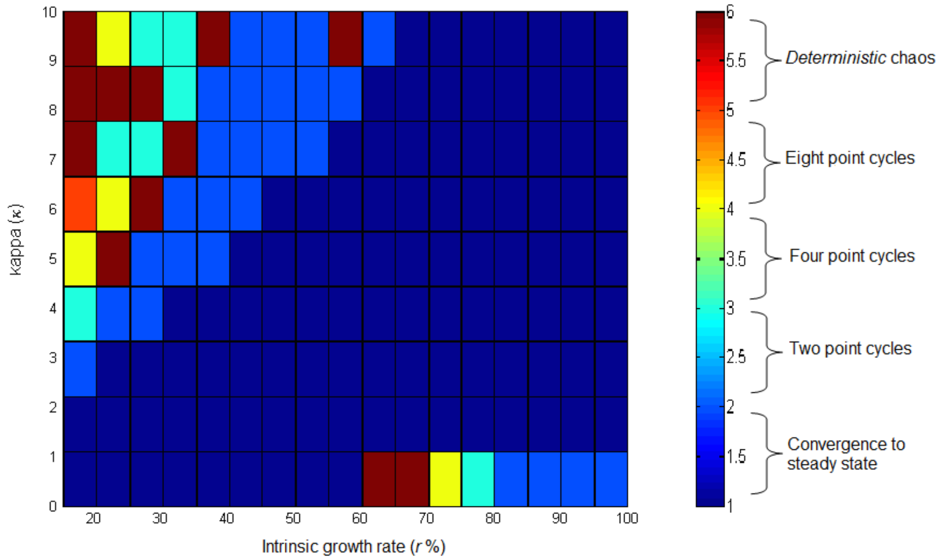
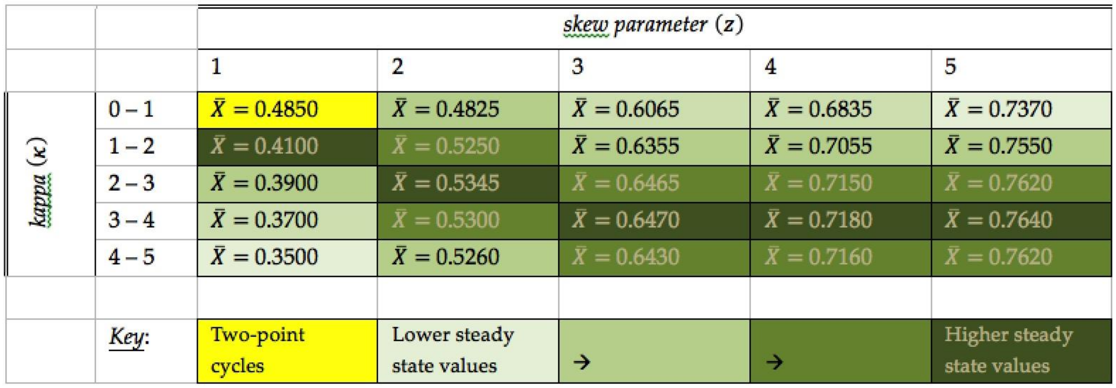


Figure 2.8: Qualitative behavior of the resource stock, X_t, for combinations of values of the intrinsic growth rate $r \in \{0.15, 0.20, 0.25, \dots, 1.00\}$ (horizontal axis), and the anti-poaching effectiveness parameter $\kappa \in \{0, 1, 2, \dots, 10\}$ (vertical axis).

For any given value of κ on the vertical axis as we move across the grid (i.e. left to right) we have color-coded cells depicting the qualitative features of the equilibrium points for different values of r on the horizontal axis. Figure 2.8 tells us how the changing effectiveness of anti-poaching enforcement affects the stability characteristics of the equilibria for different species represented by different intrinsic growth rates, r. Conversely for any given value of r (i.e. any one particular species being modeled) as we move from bottom to top in Figure 2.8 we see how the changing effectiveness of anti-poaching enforcement affects the qualitative dynamics of a particular species. From Figure 2.8 we observe that for smaller values of r, we have locally stable, unique, steady states of the resource stock for low values of κ. For those same values of r, as we move up the vertical axis, we are seeing a slackening in the effectiveness of anti-poaching enforcement, and the resource stock begins to give way to two-point cycles, four-point cycles, eight-point cycles and eventually to *deterministic* chaos. For high values of r on the horizontal axis, low values of κ do not always produce locally stable, unique, steady state values. However for those high values of r, it appears that as the effectiveness of anti-poaching enforcement slackens, we begin to observe unique, locally stable, steady state values of the resource stock. Another result we found from this numerical exercise, which is not depicted in Figure 2.8, was that for all values of r increasing the value of κ led to declining average values of the resource stock – in terms of average steady state values or average values of the bifurcation points.

In essence what Figure 2.8 tells us is that different levels of anti-poaching enforcement have variable effects on the qualitative aspects of population dynamics for different species as represented by different intrinsic growth rates. As far as policy insight that can potentially be garnered from Figure 2.8 our results suggest that if policy makers wish to avoid chaotic population dynamics for mega-fauna species with low-r values, the effectiveness of anti-poaching patrols/enforcement needs to be relatively better than in the case of protecting high r species or small mammals. In Figure 2.8 we see that for high-r species (i.e. $r > 0.60$) increasing the effectiveness of anti-poaching enforcement (reducing κ from the range $[2, 10]$ to the range $[0, 1]$) results in period doubling bifurcation in the resource stock.

Lastly we examine the effects of changing levels of the skew parameter (z) in conjunction with different levels of anti-poaching enforcement effectiveness (κ). Recall from Figure 2.7 that increasing the anti-poaching effectiveness (i.e. lowering the value of κ) gave us counterintuitive results for some range of κ values: for values of the skew parameter $z > 1$ the steady state stock levels began to decline when anti-poaching enforcement was made more effective. In figure 2.9 we use a color-coded grid to depict at what combinations of κ and z the resources stock, X, goes from steady state to two-point cycles. Two-point cycles are shown in yellow, and the steady states are shown in different shades of green- darker green indicates higher average steady state resource stock values for the range of κ values, and lighter green indicates lower average steady state values. For any given z value as we move down the grid we have increasing values of κ (i.e. lower levels of anti-poaching effectiveness). For $z = 1$ when κ increases from 1 through 5 we observe decreasing steady state X values. This serves intuition because as the effectiveness of anti-poaching enforcement decreases, the marginal product of poaching time (T_t^H) would increase, and we would expect lower stock values. Recall that higher values of z are used to model larger mammals (Cromsigt et al., 2002). So as we move across the grid in Figure 2.9 we are modeling the population dynamics of larger mammals. The counterintuitive results seen in Figure 2.7 are also noted here in Figure 2.9 for larger z values: i.e. increasing the effectiveness of anti-poaching patrols leads to decreasing steady state values of the resource stock, X. This is consistent for values of $z \in [2, 5]$ for decreasing κ values in the range $[3, 0]$. We provide a summary of the key results from our numerical analysis in Table 2.2 for each of the economic and biological parameters in our model.



		skew parameter (z)				
		1	2	3	4	5
kappa (κ)	$0-1$	$\bar{X} = 0.4850$	$\bar{X} = 0.4825$	$\bar{X} = 0.6065$	$\bar{X} = 0.6835$	$\bar{X} = 0.7370$
	$1-2$	$\bar{X} = 0.4100$	$\bar{X} = 0.5250$	$\bar{X} = 0.6355$	$\bar{X} = 0.7055$	$\bar{X} = 0.7550$
	$2-3$	$\bar{X} = 0.3900$	$\bar{X} = 0.5345$	$\bar{X} = 0.6465$	$\bar{X} = 0.7150$	$\bar{X} = 0.7620$
	$3-4$	$\bar{X} = 0.3700$	$\bar{X} = 0.5300$	$\bar{X} = 0.6470$	$\bar{X} = 0.7180$	$\bar{X} = 0.7640$
	$4-5$	$\bar{X} = 0.3500$	$\bar{X} = 0.5260$	$\bar{X} = 0.6430$	$\bar{X} = 0.7160$	$\bar{X} = 0.7620$
	Key:	Two-point cycles	Lower steady state values	→	→	Higher steady state values

Figure 2.9: Qualitative behavior of the resource stock, X_t, for combinations of values of the skew parameter $z \in \{1, 2, \dots, 5\}$ and the anti-poaching effectiveness parameter $\kappa \in \{0, 1, \dots, 5\}$. $\bar{X}$: average value of resource stock.

Table 2.2: Summary of key numerical results.

Parameter	**Effect of increasing parameter value on time spent poaching (T_t^H)**	**Effect of increasing parameter value on resource stock (X_t)**	**2^n-point cycles observed?**	**Additional comments**
Wage rate (W)	$-$	$+$	High-amplitude dynamics for $W > 1.40$[a]	Deterministic chaos for $W > 1.80$
Fine (F)	$-$	$+$	Low-amplitude dynamics for $F < 0.50$	Deterministic chaos for $F < 0.25$
Black market price (P)	$+$	$-$	High-amplitude dynamics for $P < 3$.	Deterministic chaos for higher values of z (> 1), when $P < 3$
Intrinsic growth rate (r)	n.a.	n.a.	High-amplitude dynamics for low-r values when $\kappa > 5$.	Greater anti-poaching effectiveness needed to protect low-r species if steady state preferred to high-amplitude, chaotic, population dynamics by policy maker.
Anti-poaching effectiveness (κ)	$-/+$	$+/-$	Bifurcation when $z = 1$ and $\kappa \in [0, 1]$.	For $z > 1$ low κ values (i.e. $\kappa < 3$) reduce steady state X values.

[a] Refer to Table 2.1 for the set of base-case parameter values.
$+$ indicates an increase; $-$ indicates a decrease; $+/-$ indicates an ambiguous effect.

2.4 Conclusion

Robert (May RM, 1976) introduced the idea of how small parameter changes in a logistic growth equation leads to very complicated dynamics or 2^n-point cycles in the evolution of resource stocks. In discrete-time models of single species ecologists have shown how dynamical systems can exhibit seemingly random or chaotic behavior, which results when the stability of steady states are dependent on the values of model parameters (Edelstein-Keshet, 1988; Hale, Jack K.,Koçak, Hüseyin., 1991; Hastings & Powell, 1991). Erwin (Bulte, 2003) shows that multiple equilibria or steady states might exist in open access systems, and that equilibria are affected by small changes in the underlying economic parameters. The analysis and results of our chapter serves as an extension of previous studies of ecological-economic dynamic systems. We have shown, through extensive comparative static exercises, how small changes in both economic parameters and biological parameters can lead to complicated dynamics in the behavior of a protected species' population.

Given the nature of Equations (2.7) and (2.8) – a Schaefer production function and a logistic growth function – in our open access model, bifurcation diagrams reveal important behavioral aspects of poaching and its effects on population or renewable resource stock dynamics. Bifurcation diagrams have the potential to provide insight to policy makers who are considering changes in parameters as part of conservation policy. Simply increasing the wage rate, W, or lowering the black market price, P, might not always lead to higher steady state stock levels of a protected species. The resource stock can exhibit high-amplitude chaotic dynamics for even small changes in policy parameters. The economic and ecological aspects of our bio-economic model are readily apparent when we record the bifurcation points of the resource stock, X, for combinations of values of r (intrinsic growth rate) and κ (effectiveness parameter of anti-poaching enforcement), as well as for combinations of values of κ and z (skew parameter in logistic growth function). The results in Figures 2.8 and 2.9 suggest that there is no "one-size-fits-all" conservation policy when it comes to protecting species, as represented by different intrinsic growth rates and skew parameters. When protecting large mammal species with high z values, lowering the effectiveness of anti-poaching enforcement leads to decreasing steady state resource stock levels. However we found that increasing the effectiveness of anti-poaching enforcement beyond a certain critical point could result in counterintuitive dynamics wherein the steady state stock value declines. The relevance of policy-induced bifurcation in the long-term behavior of renewable resources subject to opportunistic harvest merits careful consideration in the design or the study of conservation policy.

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CHAPTER 3

CIVIL UNREST AND THE POACHING OF RHINOS IN THE KAZIRANGA NATIONAL PARK, INDIA

3.1 Introduction

The Kaziranga National Park (KNP), spread over an area of three hundred and seventy eight square kilometers, is located in the north-eastern state of Assam in India. The state of Assam shares international borders with Bangladesh and Bhutan, and is geographically close to Myanmar. A flagship species of the KNP is the greater one-horned rhinoceros (*Rhinoceros unicornis*) – also known as the Indian rhinoceros. Concerns over rhino poaching led to the declaration of Kaziranga as a national park in January of 1974 in accordance with the Assam National Park Act, 1968 (Saikia, 2011). Rhino poaching increased significantly in the 1980s through the mid-1990s in the state of Assam (refer to Table 3.1). This time period coincided with extensive civil unrest in Assam. The war of independence of Bangladesh (East Pakistan until March 1971) from West Pakistan in 1971 led to an exodus of ten million refugees to neighboring parts of India, including the state of Assam (UNHCR, 2012). The large influx of refugees changed the demographics of Assam and made the task of identifying illegal residents difficult (ICM, 2012). In 1979 mass movements led by native Assamese separatists campaigned for the detection of illegal migrants, for their removal from state voter lists, and for their deportation to Bangladesh (Thakur & Pandey, 2009).

Secessionist tendencies began to form amongst the native Assamese in the late 1970s and a militant organization called the United Liberation Front of Assam was established with the goal of separation from the Indian state (ICM, 2012). This network of militant separatists was speculated to have carried out rhino poaching in Assam during the period of civil unrest in order to fund arms purchases through the illicit sale of rhino horn (Agarwal, Narain, & Sen, 1999; Menon, 1996)

During the late 1970s the Assam state government, led by the Congress (I) party, was more favorable to illegal immigrants because the immigrants formed a significant electoral voting block (Thakur & Pandey, 2009). Disagreement between the native Assamese separatists and the state government led to a breakdown of state administration, and Assam was brought under President's rule in December of 1979 (ICM, 2012). In 1980 the Indian Army was deployed in the state to maintain law and order. Talks between the separatists and the central government made no progress between 1980 and 1983. Elections were imposed by the Indian central government in 1983 despite opposition by the Assamese separatists. The Congress (I) party came back to power, but the election result was deemed unacceptable by the separatists. Attempts to force the separatists to accept the election result led to a breakdown of the state administration, and violence led to the deaths of over three thousand people (Thakur & Pandey, 2009).

A peace accord was signed between the separatists and the central government in 1985, which led to the dissolution of the Congress (I) state government, and the agreement to deport illegal immigrants. A new regional political party, the Asom Gana Parishad (AGP), came to power after the signing of the peace accord. Secessionist sentiments remained strong despite the peace accord and new political leadership, which led to the continuation of civil unrest and armed conflict. A lack of clearly defined rules to identify illegal immigrants meant that the provisions of the peace accord were not implemented meaningfully, and this only strengthened the secessionist sentiment. In 1990, President's rule was once again enforced and the Indian Army was used to subdue the militant separatists (Thakur & Pandey, 2009). In 1993 another peace accord was signed between the state government (under the Congress (I) party) and the separatists, wherein army operations were suspended and amnesty was granted to surrendering militants. The remaining militant separatists moved across the international border to Myanmar and Bhutan (ICM, 2012).

This chapter studies an important but inadequately understood relationship between civil unrest and endangered species protection. Animal species in tropical countries have been subject to poaching in regions that have witnessed political instability and civil unrest. For instance, the Central African region has seen a prolonged period of civil strife along with escalated levels of poaching in the elephant range states (UNSC, 2013). Civil unrest in the Democratic Republic of Congo is associated with gorilla poaching (WWF, 2014). Given the political nature of extensive civil unrest in Assam during the 1980s and 1990s and the associated increase in rhino poaching, this chapter attempts to identify this relationship. In the next section I describe the data on which the empirical analysis is based. Section 3.3 discusses a suitable biological model of population dynamics of the Indian rhinoceros. Section 3.4 presents an identification strategy for quantifying the relationship between rhino poaching and civil unrest, while accounting for several other variables that are probably associated with poaching – including black market rhino horn prices, the potential size of black markets, and anti-poaching efforts in the KNP. The predicted associations of these variables with rhino poaching are described in Section 3.4. Section 3.5 provides a discussion of the regression results, and section 3.6 concludes.

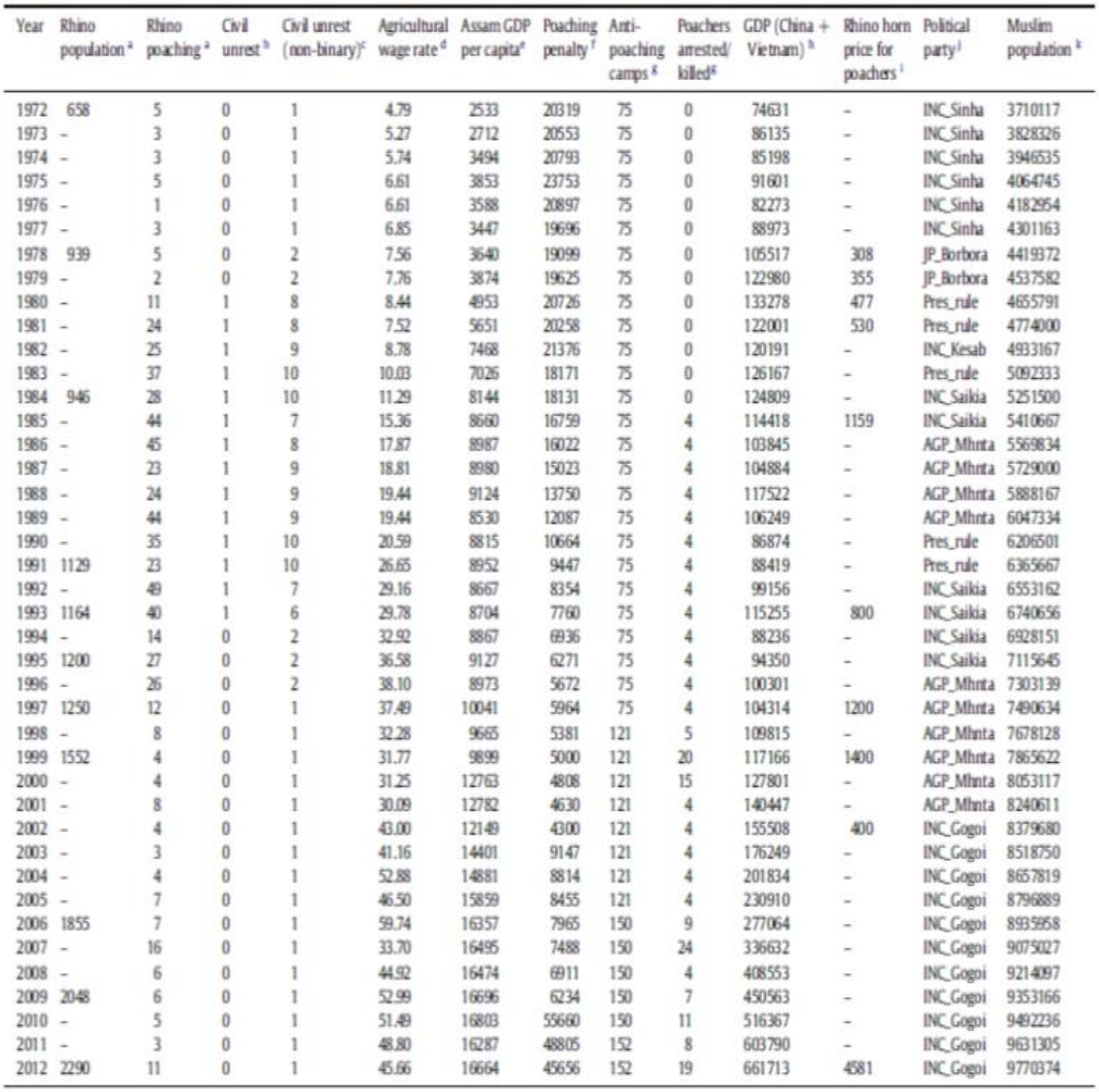
3.2 The Data

Census enumerations of the rhino population have been carried out by Assam's State Forest Department every few years since the declaration of Kaziranga as a national park. These data are listed in Table 3.1. Civil unrest in Assam is indicated as a binary variable assuming a value of 1 in periods of extensive unrest and political instability, and a value of 0 in other time periods. In addition I define an alternative variable representing civil unrest in Assam, which assumes integer values between 1 and 10 – with higher values representing periods of greater political instability, unrest, and militancy. Rhino poaching incidents in the KNP are regularly recorded every year by Assam's Forest Department. The mean poaching level during the extensive civil unrest period (1980–1993, i.e. 14 periods) is 32 rhinos per year compared to an average of 8 rhinos per year in the other time periods (1972–1979; 1994–2012, i.e. 27 periods). The difference in means of rhino poaching per year in these two periods (samples) is 24. A t-test of this difference derives a t-statistic of 7.62, which is statistically significant at the 99% confidence level.

As a measure of the opportunity cost of poaching in Assam I consider two variables: agricultural labor wage rates and gross state domestic product per capita. Data on wage rates, gross state domestic product, and Assam's human population are made available from various economic and population census reports. A penalty or fine is imposed by Assam's Forest Department for poaching. The penalty as per the Indian Wildlife (Protection) Act (1972) and its subsequent amendments are listed in Table 3.1. Assam's Forest Department employs anti-poaching staff or armed forest guards who regularly patrol the KNP to intercept and apprehend poachers (AFD, 2008). The Forest Department has a de facto shoot-to-kill policy, and more than one hundred poachers have been killed or arrested by forest guards since 1985 (Dutta, 2013). At present there are one hundred and fifty two anti-poaching camps in the KNP with approximately six armed forest guards in each camp (Gray, 2013). In earlier time periods there were fewer anti-poaching camps and forest guards in the KNP. Moreover, the anti-poaching camps' infrastructure – including communication, anti-poaching equipment, and staff survival kits – has improved significantly in the 2000s (AFD, 2008; Mathur, Sinha, & Mishra, 2005). Table 1 lists the political party and chief minister in power in Assam. Different categorical values are assigned to the political parties under the different chief ministers in order to account for variation in state policy over time. I also note when President's rule was enforced in the state. The Muslim population is listed as per census reports and (Sachar et al., 2006).

There is evidence of organized crime in the supply side of the rhino horn black market. Crime syndicates coordinate rhino horn supply through a network of poachers and middlemen who source horns from national parks in South Asia and South Africa, and ship them to China and Vietnam (Dutta, 2013; Sas-Rolfes, 2012; Somerville, 2012). Table 3.1 lists the gross domestic products of China and Vietnam as a measure of the external market demand. The few data of rhino horn price that poachers receive are listed in Table 3.1. Given that there are no regular time-series estimates of horn prices, I consider two such measures. As a *first measure* I assume a linear trend in the available information on horn prices to estimate the missing data points in Table 3.1. As a *second measure* I estimate a horn price index using a structural model of horn supply and demand through an organized crime network (see APPENDIX 3.1). Demand is assumed to be a function of horn price and income in China and Vietnam. Supply is a function of horn price. Given that crime syndicates source horns from South Africa and South Asia, I use time-series data on rhino poaching in South Africa as an instrument for index estimation. Supply and demand functions are calibrated based on the assumption that the crime syndicate seeks to minimize the difference between supply and demand. This presumably ensures that horns move as quickly as possible from poacher to end consumer, and lowers the risk of getting caught by authorities (for instance, poachers are known to sell horns as quickly as possible to smugglers to avoid interception by authorities (Sas-Rolfes, 2012)). The index increases over time (see Table 3A.1) – reflecting the trend in the limited data on horn prices available to poachers.

Table 3.1: Empirical data



Year	Rhino population [a]	Rhino poaching [a]	Civil unrest [b]	Civil unrest (non-binary)[c]	Agricultural wage rate [d]	Assam GDP per capita[e]	Poaching penalty [f]	Anti-poaching camps [g]	Poachers arrested/ killed[g]	GDP (China + Vietnam) [h]	Rhino horn price for poachers [i]	Political party[j]	Muslim population [k]
1972	658	5	0	1	4.79	2533	20319	75	0	74631	-	INC_Sinha	3710117
1973	-	3	0	1	5.27	2712	20553	75	0	86135	-	INC_Sinha	3828326
1974	-	3	0	1	5.74	3494	20793	75	0	85198	-	INC_Sinha	3946535
1975	-	5	0	1	6.61	3853	23753	75	0	91601	-	INC_Sinha	4064745
1976	-	1	0	1	6.61	3588	20897	75	0	82273	-	INC_Sinha	4182954
1977	-	3	0	1	6.85	3447	19696	75	0	88973	-	INC_Sinha	4301163
1978	939	5	0	2	7.56	3640	19099	75	0	105517	308	JP_Borbora	4419372
1979	-	2	0	2	7.76	3874	19625	75	0	122980	355	JP_Borbora	4537582
1980	-	11	1	8	8.44	4953	20726	75	0	133278	477	Pres_rule	4655791
1981	-	24	1	8	7.52	5651	20258	75	0	122001	530	Pres_rule	4774000
1982	-	25	1	9	8.78	7468	21376	75	0	120191	-	INC_Kesab	4933167
1983	-	37	1	10	10.03	7026	18171	75	0	126167	-	Pres_rule	5092333
1984	946	28	1	10	11.29	8144	18131	75	0	124809	-	INC_Saikia	5251500
1985	-	44	1	7	15.36	8660	16759	75	4	114418	1159	INC_Saikia	5410667
1986	-	45	1	8	17.87	8987	16022	75	4	103845	-	AGP_Mhnta	5569834
1987	-	23	1	9	18.81	8980	15023	75	4	104884	-	AGP_Mhnta	5729000
1988	-	24	1	9	19.44	9124	13750	75	4	117522	-	AGP_Mhnta	5888167
1989	-	44	1	9	19.44	8530	12087	75	4	106249	-	AGP_Mhnta	6047334
1990	-	35	1	10	20.59	8815	10664	75	4	86874	-	Pres_rule	6206501
1991	1129	23	1	10	26.65	8952	9447	75	4	88419	-	Pres_rule	6365667
1992	-	49	1	7	29.16	8667	8354	75	4	99156	-	INC_Saikia	6553162
1993	1164	40	1	6	29.78	8704	7760	75	4	115255	800	INC_Saikia	6740656
1994	-	14	0	2	32.92	8867	6936	75	4	88236	-	INC_Saikia	6928151
1995	1200	27	0	2	36.58	9127	6271	75	4	94350	-	INC_Saikia	7115645
1996	-	26	0	2	38.10	8973	5672	75	4	100301	-	AGP_Mhnta	7303139
1997	1250	12	0	1	37.49	10041	5964	75	4	104314	1200	AGP_Mhnta	7490634
1998	-	8	0	1	32.28	9665	5381	121	5	109815	-	AGP_Mhnta	7678128
1999	1552	4	0	1	31.77	9899	5000	121	20	117166	1400	AGP_Mhnta	7865622
2000	-	4	0	1	31.25	12763	4808	121	15	127801	-	AGP_Mhnta	8053117
2001	-	8	0	1	30.09	12782	4630	121	4	140447	-	AGP_Mhnta	8240611
2002	-	4	0	1	43.00	12149	4300	121	4	155508	400	INC_Gogoi	8379680
2003	-	3	0	1	41.16	14401	9147	121	4	176249	-	INC_Gogoi	8518750
2004	-	4	0	1	52.88	14881	8814	121	4	201834	-	INC_Gogoi	8657819
2005	-	7	0	1	46.50	15859	8455	121	4	230910	-	INC_Gogoi	8796889
2006	1855	7	0	1	59.74	16357	7965	150	9	277064	-	INC_Gogoi	8935958
2007	-	16	0	1	33.70	16495	7488	150	24	336632	-	INC_Gogoi	9075027
2008	-	6	0	1	44.92	16474	6911	150	4	408553	-	INC_Gogoi	9214097
2009	2048	6	0	1	52.99	16696	6234	150	7	450563	-	INC_Gogoi	9353166
2010	-	5	0	1	51.49	16803	55660	150	11	516367	-	INC_Gogoi	9492236
2011	-	3	0	1	48.80	16287	48805	152	8	603790	-	INC_Gogoi	9631305
2012	2290	11	0	1	45.66	16664	45656	152	19	661713	4581	INC_Gogoi	9770374

[a] Talukdar (2000, 2002, 2003, 2006), Vigne & Martin (1998), and various Forest Department Annual Reports.

[b] (Agarwal et al., 1999; Thakur & Pandey, 2009)

[c] Integer variable indicating extent of civil unrest based on Assam's history. Higher values indicate periods of President's rule, Indian Army deployments, and civilian deaths due to unrest. Lower values (1 – 2) indicate time periods of relative political stability in Assam.

[d] Real daily agricultural wage rate in 2005 Indian Rupees (INR); time-series data on wage rates are available from various census reports for Assam. Conversion to real rates using consumer price indices (CPI) for Assam (Directorate of Economics and Statistics, Various years; Jose, 1988; Rao, 1980).

[e] GDP per capita (2005 INR; sources – various Assam state population and economic census reports). With no population census conducted in 1981 the population estimates are interpolated using growth rates between the 1971 and 1991 Census.

[f] Poaching penalties (2005 INR) as per Indian Wildlife Protection Act (1972) Section 51 and its Amendments in 2003 and 2010 (MoEF, 2013).

[g] Assam's Forest Department set up 152 anti-poaching camps in KNP by 2012 (Gray, 2013) and 121 camps during the late 1990s and early 2000s (Mathur et al., 2005). In the 2000s there were improvements made to the anti-poaching camps' infrastructure and equipment; additional staff/guards were also employed – this doubled from three armed guards per camp in earlier periods to six armed guards per camp in the 2000s (sources: (AFD, 2008;

Gray, 2013), and author's personal communication with Principal Chief Conservator of Forests (Wildlife) Assam office). Given this doubling of number of armed guards per camp the number of anti-poaching camps in earlier periods is taken to be half of that in the 2000s to reflect the improvement in KNP's anti-poaching efforts. In 2006 KNP was declared a tiger reserve, which facilitated additional staff employment (Dutta, 2013). Information on poachers arrested/killed based estimates from (AFD, 2008; Dutta, 2013; Gray, 2013; Talukdar, 2000).

[h] GDP ('0,000,000s US$) of China and Vietnam in 2005 CPI prices: http://www.ers.usda.gov/datafiles/International_Macroeconomic_Data/Historical_Data_Files/HistoricalCPIsValues.xls (accessed September 2013).

[i] Reports of rhino horn prices (US$/kg) available to poachers: 1978-1981, 1985 (Sas-Rolfes, 1997); 1993 (Milliken, Nowell, & Thomsen, 1993); 1997 (Vigne & Martin, 2000); 2002 (Talukdar, 2002); 2012 (Eustace, 2012; Sas-Rolfes, 2012). Missing data interpolated using linear trends. US$ converted to 2005 INR using exchange rates (http://fx.sauder.ubc.ca/etc/USDpages.pdf (accessed September 2013)).

[j] Political party ruling Assam; INC_Sinha: Congress (I) under S.Sinha; JP_Borbora: Janata Party under G.Borbora; INC_Kesab: Congress (I) under K.Gogoi; INC_Saikia: Congress (I) under H.Saikia; AGP_Mhnta: Asom Gana Parishad under P.Mahanta; Pres_rule: President's rule; INC_Gogoi: Congress under T.Gogoi.

[k] Assam census reports and (Sachar et al., 2006).

3.3 A Population Model of Rhinos in the KNP

Using the limited data on rhino census numbers I adopt the methodology of (Cromsigt et al., 2002) to estimate rhino population for the intervening years during which no census was conducted. I estimate a rhino population model that best fits the observed data. The approach adopted by (Cromsigt et al., 2002) is to assume the relationship between the modeled population, X_t, and the observed census population, P_t, as Equation (3.1), where ϵ_t is the error term with an assumed expected value of zero, and a variance of σ^2. For a given initial population size, P_{1972}, the best possible estimates of the population model parameters can be computed by minimizing the sum of squared errors, $\sum \epsilon_t^2$ (for the years when census data is available, i.e. $t =$1972, 1978, 1984, 1991, 1993, 1995, 1997, 1999, 2006, 2009, 2012). A non-linear solver was used to find the parameters of the population model that minimized the sum of squared errors.

$$P_t = X_t + \epsilon_t \tag{3.1}$$

For a population growth function (Cromsigt et al., 2002) find that the modified logistic growth function gives the best fit to population data on South African black rhinos (*Diceros bicornis*). Their modified logistic growth function fit observed black rhino population data better than other growth functions such as the exponential growth function, which has a constant specific growth rate r, and the ordinary logistic growth function. The modified logistic growth function assumes the form: $F(X_t) = rX_t(1 - (X_t/K)^z)$, where K is the carrying capacity and $z\ (> 1)$ is a skew parameter that allows for non-linearity in the relationship between X_t and the strength of density-dependence $(1 - X_t/K)$. When modeling mega-fauna there is empirical support for $z > 1$ because density-dependence becomes more important when the population is closer to carrying capacity (Cromsigt et al., 2002). I use the time series data on poaching levels, H_t, to account for harvest subtracted from yearly growth, $F(X_t)$. The iterative map (3.2) describes rhino population dynamics in the KNP: [3]

$$X_{t+1} = X_t + rX_t(1 - (X_t/K)^z) - H_t \tag{3.2}$$

---

[3] Alternatively one can consider another growth function:

$$X_{t+1} = X_t + r(X_t - H_t)(1 - ((X_t - H_t)/K)^z)$$

Harvest, H_t, is not just a deductible term, as in Equation (3.2), and influences both r and z. This is plausible when poaching takes place before species reproduction, or when poachers target only mature rhinos with larger horns for instance. Calibrated values for this growth function are: $r = 0.03132$, $z = 109.795$. The two estimated populations have a correlation coefficient = 0.9921.

Table 3.2: Population model's parameter calibration

Census populations $(\boldsymbol{P_t})$	***Initial value guesses***	***Calibrated values***
$P_{1972} = 658$, $P_{1978} = 939$	$r = 0.10$	$r = 0.0484$
$P_{1984} = 946$, $P_{1991} = 1129$,	$z = 1$	$z = 7.5676$
$P_{1993} = 1164$, $P_{1995} = 1200$,	$K = 2400$	$K = 2420$
$P_{1997} = 1250$, $P_{1999} = 1552$,	$\sum \epsilon_t^2 = 24{,}300$	$\sum \epsilon_t^2 = 3{,}752$
$P_{2006} = 1855$, $P_{2009} = 2048$,		
$P_{2012} = 2290$		

I use the given initial population level, P_{1972}, as the starting value for the iterative map, i.e. $X_{1972} = 658$. I then assign initial guesses for the demographic model's parameters $r, z,$ and K as per Table 3.2. The optimized values for the parameters are reported in Table 3.2. The best-fit value I obtain for $r = 0.0484$. Other studies – (Mason C.F. et al., 2012; Milner-Gulland & Leader-Williams, 1992)– have used an intrinsic growth rate of $r = 0.06$ to model population dynamics of African black rhinos. The best-fit skew parameter value I obtain for $z = 7.5676$. (Mason C.F. et al., 2012; Milner-Gulland & Leader-Williams, 1992)use a skew parameter value of $z = 7$; (Cromsigt et al., 2002) estimate a z value between 10 and 28. Rhino population estimates derived using the method of least squared errors are plotted in Figure 3.1. These data are used to estimate a poaching model in the next section.

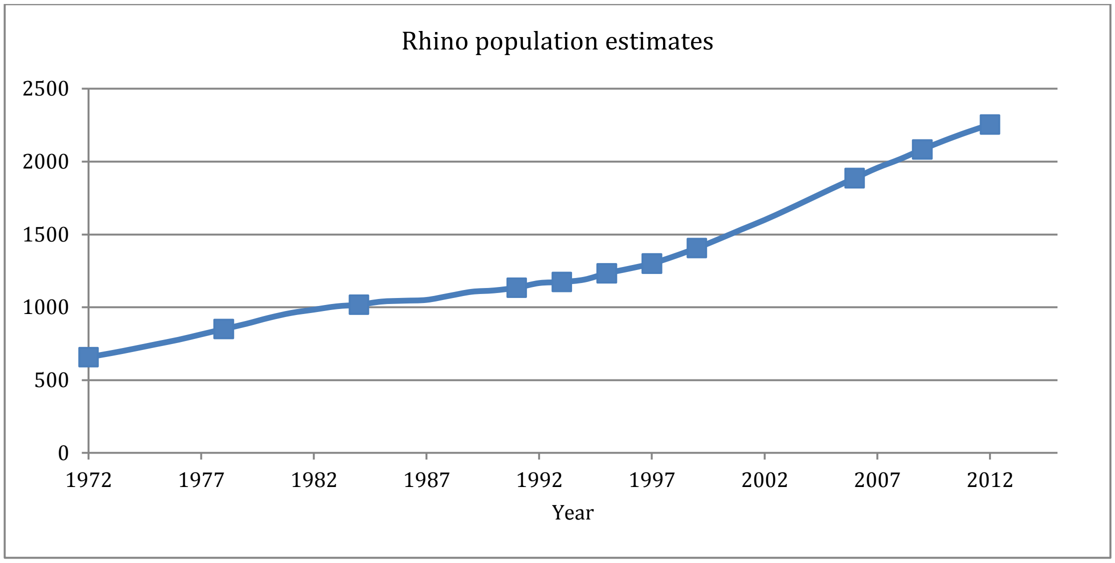


Figure 3.1: Estimated rhino population for $r, z,$ and K that minimizes $\sum_t \epsilon_t^2$. The square blocks on the trend line indicate the census enumeration years.

3.4 Estimating a Harvest Function and Identifying the Relationship between Civil Unrest and Rhino Poaching

I assume an exponential harvest function (Spence, 1973) to model poaching, Y_t:

$$Y_t \equiv Y_t(X_t, E_t) = X_t\big(1 - \exp(-qE_t)\big) \tag{3.3}$$

X_t: rhino population in year t

E_t: harvesting effort ($E_t = 0 \Rightarrow Y_t = 0$; as $E_t \to \infty$, $Y_t \to X_t$)

q: catchability parameter ($q > 0$)

Poudyal et al., (2009) use time-series data on rhino poaching in Nepal to estimate a reduced-form harvest function under the assumption of zero-profits with *de facto* open access. The variables they consider in the profit function are the price received by local poachers for rhino horn (p), quantity of horns harvested $\big(h(\cdot)\big)$, and anti-poaching effort (B). Harvest, $h(\cdot)$, is a function of the anti-poaching effort, poaching effort (E), and the rhino population (X). They net out both the expected poaching fine $(\theta(B,E)[F+ph])$, where $\theta(\cdot)$ is the probability of getting caught, and the cost of poaching $(c(A)E)$, where $c(\cdot)$ is a function of the opportunity cost of poaching such as local wage rates (A). Under the assumption of zero profits, they solve for the reduced-form equilibrium poaching effort, E^*, which is a function of $B, X, A, F,\ p$. There are other characteristics that might be pertinent to estimating poaching effort, for which one must rely on proxy information. Poudyal et al. proxy the fines imposed on convicted poachers by poaching fines set as per Nepalese law. They proxy the international demand for rhino horn by East Asian gross domestic product, given that an inverse demand relationship determines black market horn price.

I assume aggregate harvesting effort to be represented by a composite term $E_t = (1 + \beta_1 R_t + \beta_2 A_t + \beta_3 P_t + \beta_4 G_t + \beta_5 W_t + \beta_6 C_t + \beta_7 B_t + \beta_8 I_t + \varepsilon_t)$, which is estimated econometrically using the data in Table 1 and the estimated rhino population from the previous section. I define the individual terms of E_t:

R_t: civil unrest in Assam (binary and discrete [1, 10])

A_t: number of anti-poaching camps in KNP (or number of armed forest guards)

P_t: poaching penalty in Assam

G_t: gross domestic product (GDP) per capita in Assam

W_t: agricultural labor wage rate in Assam

C_t: GDP of China/Vietnam

B_t: black market horn price for poachers

I_t: estimated price index (see Appendix)

ε_t: error term

Rearranging the terms of Equation (3.3) yields an estimable Equation (3.4):

$$ln[1 - Y_t/X_t] = -q(1 + \beta_1 R_t + \beta_2 A_t + \beta_3 P_t + \beta_4 G_t + \beta_5 W_t + \beta_6 C_t + \beta_7 B_t + \beta_8 I_t + \varepsilon_t) \tag{3.4}$$

The natural log term on the left-hand side of Equation (3.4) is taken to be the dependent variable in the regression models. The exponential harvest function, Equation (3.3), requires that the constant term, q, be greater than zero. Given the observed increase in rhino poaching during the period of extensive civil unrest in Assam, I predict that the coefficient of R_t will be positive $(\beta_1 > 0)$. The presence of more anti-poaching camps and armed forest guards would increase the likelihood that poachers get caught and thereby reduce poaching ($\beta_2 < 0$). Poaching is predicted to decrease with the poaching penalty $(\beta_3 < 0)$. I expect that Assam GDP per capita (G_t) would have a negative effect on poaching ($\beta_4 < 0$). Similar to (Poudyal, Rothley, & Knowler, 2009) I predict that since income of China and Vietnam would have a positive effect on poaching ($\beta_6 > 0$). Higher black market horn prices would create additional incentive to poach ($\beta_7 > 0$). Alternatively the horn price index, I_t, is predicted to be positively related to E_t, i.e. $\beta_8 > 0$. I_t should be used as a covariate in regression models without C_t and B_t to avoid the problem of multi-collinearity because C_t is used to estimate I_t. Since $-q$ is multiplied through the parenthesis in

Equation (3.4) the regression coefficient estimates should be the opposite of the signs predicted: $-q\beta_1 < 0$, $-q\beta_2 > 0$, $-q\beta_3 > 0$, $-q\beta_4 > 0$, $-q\beta_5 > 0$, $-q\beta_6 < 0$, $-q\beta_7 < 0$, $-q\beta_8 < 0$.

Since poaching was higher during civil unrest one might encounter omitted variable bias in the regression coefficient estimates. Such bias might occur when there is some variable that is correlated with both the dependent and the independent variables, and for which there are usually no data available (Angrist & Pischke, 2009). To provide an unbiased estimate of the effect of the independent variable of interest (civil unrest) on the dependent variable (rhino poaching) an econometric model should include any determinants of the dependent variable that are also correlated with the independent variable of interest (Angrist & Pischke, 2009). I consider two instrumental variables to identify the relationship between civil unrest and rhino poaching: “ruling political party in Assam,” and “Muslim population in Assam”. Given Assam’s historical context these instruments are probably associated with civil unrest, but not correlated with other independent variables that affect rhino poaching.

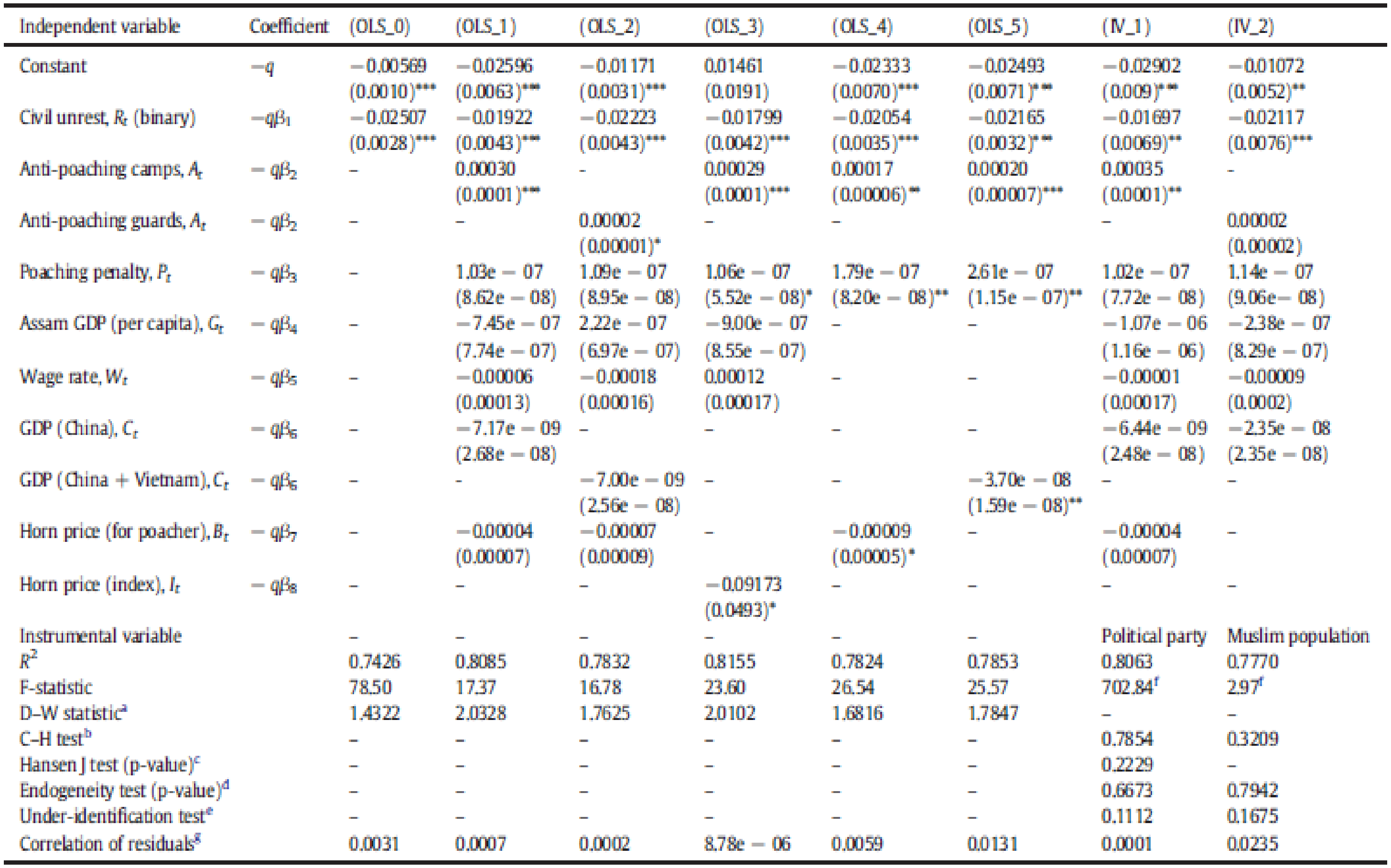
3.5 Results and Discussion

Equation (3.4) is econometrically estimated and the results are listed in Table 3.3. In the first model, (OLS_0), ordinary least squares (OLS) is used to examine the relationship between civil unrest and poaching. The catchability coefficient, q, estimated at 0.0056, has the expected positive sign and is statistically significant. The civil unrest coefficient, β_1, has the predicted positive sign and is statistically significant. The regression coefficients, β_i, are calculated by dividing $-q\beta_i$ by $-q$, $i = 1,\ldots,8$. I calculate $\beta_1 =$ -0.025/-0.006 $=$ 4.46, which suggests that the unrest period in Assam was associated with at least four times more poaching effort per year as compared to the non-unrest time period. This interpretation of β_1 follows from the binary definition of civil unrest, R_t, in Equation (3.4). One needs to consider additional covariates; this is done in model (OLS_1). A higher number of anti-poaching camps in the KNP appear to significantly reduce poaching. Poaching penalty has an expected negative effect but is not statistically significant. Other controls of GDP per capita and agricultural wages in Assam are not statistically significant. The external demand for rhino horn appears to rise with income in China as predicted, but the coefficient (β_6) is not statistically significant. Similarly horn price coefficient (β_7) is positively related to poaching. I find that the relationship between unrest and rhino poaching is positive $(\beta_1 > 0)$ and significant. The Durbin-Watson statistic indicates that the error terms are not serially correlated.

In model (OLS_2) I consider different covariates and again find the relationship between unrest and poaching to be positive and significant: $\beta_1 =$ -0.022/-0.0117 $=$ 1.89, i.e. the unrest period is associated with nearly twice as much poaching effort per year. A higher number of armed forest guards in KNP's anti-poaching camps appear to significantly reduce poaching. I also consider the GDP of both China and Vietnam, C_t, and find that income in these two countries is positively associated with poaching. Similar to OLS_1 horn price, B_t, is positively related to poaching effort. The poaching penalty coefficient (β_2) has the predicted negative sign but is not statistically significant. In model (OLS_3) I consider the effect of the horn price index, I_t, which is estimated using the income of China and Vietnam. The effect of the price index has the predicted positive effect and is significant. Poaching penalty and anti-poaching camps reduce poaching significantly. The catchability coefficient, q, is however not statistically significant. In models (OLS_4) and (OLS_5) I note that B_t and C_t significantly increase poaching. I check for endogeneity in the regression results by calculating the correlation between the error terms from the biological parameter calibration, ϵ_t (equation (1)), and the regression residuals, ε_t. The R^2 value (last row of Table 3.3) indicates very low correlation between these error terms.

I now check for endogeneity caused by omitted variable bias. Model (IV_1) uses the instrumental variable indicating the category of the political party ruling Assam. The argument for using this instrument is that civil unrest was political in nature and there is no correlation between political parties and the other independent variables affecting rhino poaching. The signs and statistical significance of the coefficients are similar to model (OLS_1). Civil unrest and the catchability coefficients are positive and significant. The test of the null hypothesis of over-identifying restrictions is satisfied, given that there are more instruments (eight categories of political parties) than the endogenous variable. The first stage F-statistic exceeds the benchmark of 10, which indicates a strong instrument (Stock, Wright, & Yogo, 2002). Including additional covariates appears not to change the magnitude of the civil unrest coefficient by much, which implies the instruments aren't correlated with the covariates – a condition that satisfies the exclusion restriction in instrumental variable regression (Angrist & Pischke, 2009). The endogeneity test reports a probability value of 0.6673 – indicating that civil unrest is not endogenous. Model (IV_2) uses the instrument indicating population of Muslims in Assam. The argument for using this instrument is that since unrest was the response of Assamese separatists to the illegal immigration of Muslims from neighboring Bangladesh, this population presumably affected poaching effort only indirectly through the unrest variable, and is not correlated with the other independent variables. The results suggest that civil unrest was associated with twice as much poaching on average (i.e. $\beta_1 =$ -0.021/-0.011 $\approx$ 2). The first stage F-statistic is less than 10, which suggests that the instrument of Muslim population is not strong. The Cumby-Huizinga test statistic produces a probability value of 0.321 suggesting that the error terms are not serially correlated.

Table 3.3: Regression estimates with dependent variable = $ln[1 - Y_t/X_t]$



Independent variable	Coefficient	(OLS_0)	(OLS_1)	(OLS_2)	(OLS_3)	(OLS_4)	(OLS_5)	(IV_1)	(IV_2)
Constant	$-q$	−0.00569 (0.0010)***	−0.02596 (0.0063)***	−0.01171 (0.0031)***	0.01461 (0.0191)	−0.02333 (0.0070)***	−0.02493 (0.0071)***	−0.02902 (0.009)***	−0.01072 (0.0052)**
Civil unrest, R_t (binary)	$-q\beta_1$	−0.02507 (0.0028)***	−0.01922 (0.0043)***	−0.02223 (0.0043)***	−0.01799 (0.0042)***	−0.02054 (0.0035)***	−0.02165 (0.0032)***	−0.01697 (0.0069)**	−0.02117 (0.0076)***
Anti-poaching camps, A_t	$-q\beta_2$	-	0.00030 (0.0001)***	-	0.00029 (0.0001)***	0.00017 (0.00006)**	0.00020 (0.00007)***	0.00035 (0.0001)**	-
Anti-poaching guards, A_t	$-q\beta_2$	–	–	0.00002 (0.00001)*	–	–		–	0.00002 (0.00002)
Poaching penalty, P_t	$-q\beta_3$	–	1.03e − 07 (8.62e − 08)	1.09e − 07 (8.95e − 08)	1.06e − 07 (5.52e − 08)*	1.79e − 07 (8.20e − 08)**	2.61e − 07 (1.15e − 07)**	1.02e − 07 (7.72e − 08)	1.14e − 07 (9.06e− 08)
Assam GDP (per capita), G_t	$-q\beta_4$	–	−7.45e − 07 (7.74e − 07)	2.22e − 07 (6.97e − 07)	−9.00e − 07 (8.55e − 07)	–	–	−1.07e − 06 (1.16e − 06)	−2.38e − 07 (8.29e − 07)
Wage rate, W_t	$-q\beta_5$	–	−0.00006 (0.00013)	−0.00018 (0.00016)	0.00012 (0.00017)	–	–	−0.00001 (0.00017)	−0.00009 (0.0002)
GDP (China), C_t	$-q\beta_6$	–	−7.17e − 09 (2.68e − 08)	–	–	–	–	−6.44e − 09 (2.48e − 08)	−2.35e − 08 (2.35e − 08)
GDP (China + Vietnam), C_t	$-q\beta_6$	–	-	−7.00e − 09 (2.56e − 08)	–	–	−3.70e − 08 (1.59e − 08)**	–	–
Horn price (for poacher), B_t	$-q\beta_7$	–	−0.00004 (0.00007)	−0.00007 (0.00009)	–	−0.00009 (0.00005)*	–	−0.00004 (0.00007)	–
Horn price (index), I_t	$-q\beta_8$	–	–	–	−0.09173 (0.0493)*	–	–	–	–
Instrumental variable		–	–	–	–	–	–	Political party	Muslim population
R^2		0.7426	0.8085	0.7832	0.8155	0.7824	0.7853	0.8063	0.7770
F-statistic		78.50	17.37	16.78	23.60	26.54	25.57	702.84[f]	2.97[f]
D–W statistic[a]		1.4322	2.0328	1.7625	2.0102	1.6816	1.7847	–	–
C–H test[b]		–	–	–	–	–	–	0.7854	0.3209
Hansen J test (p-value)[c]		–	–	–	–	–	–	0.2229	–
Endogeneity test (p-value)[d]		–	–	–	–	–	–	0.6673	0.7942
Under-identification test[e]		–	–	–	–	–	–	0.1112	0.1675
Correlation of residuals[g]		0.0031	0.0007	0.0002	8.78e − 06	0.0059	0.0131	0.0001	0.0235

Observations = 41; robust standard errors in parentheses; statistical significance at 1% (***), 5% (**), 10% (*) error levels.

[a] Durbin-Watson test statistic for auto-correlation.

[b] Cumby-Huizinga chi-square test statistic's p-value; null hypothesis: error terms not serially correlated at order one.
[c] Hansen's J-statistic for test of over-identifying restrictions when there are more instruments than endogenous variables.
[d] Durbin-Wu-Hausmann test of endogeneity (p-value reported); null hypothesis: variables are exogenous.
[e] Kleibergen-Paap LM test statistic for under-identification under null hypothesis (p-value reported).
[f] First stage F-statistic of instrumental variable regression.
[g] Correlation between residuals (ϵ_t) from equation (1) and regression residuals.

I conduct robustness checks using the alternative (non-binary) definition of civil unrest (see Table 3.1), and the alternative rhino population estimates (using growth equation in footnote 3). In Table 3.4 under model (OLS_ 6) I use the same covariates as model (OLS_1) except that the unrest variable is non-binary. Unrest is still positively and significantly associated with poaching except that the magnitude of β_1 is lower because of the non-binary definition. I note that the coefficients of catchability, anti-poaching, income in China, and horn prices have the same signs and magnitudes as those in OLS_1. Model (OLS_7), which uses the alternative rhino population estimates and the same covariates as model (OLS_2), yields similar signs and magnitudes of the regression coefficients as the other models. In model (IV_3) I use the political party instrument to check for omitted variable bias. The results are similar to those in model (IV_1). In model (OLS_8) I find no significant effect of the number of poachers arrested/killed by forest guards on reducing poaching. Model (OLS_9), using the same covariates as model (OLS_5), shows that the difference between external GDP and domestic GDP (i.e. China+Vietnam–Assam) has a positive and significant effect on rhino poaching. In model (OLS_10) I consider interactive terms of unrest with anti-poaching camps, GDP of China, and horn price for poachers. The interactive terms show the effect of these variables on poaching during civil unrest. GDP of China is a significant determinant of poaching. The poaching penalty coefficient is negative and significant. The coefficient ($\beta_1\beta_7$) of the interactive term, unrest × horn price, is positive and significant, thus suggesting that price had a stronger effect on poaching during the civil unrest period.

Table 3.4: Robustness checks for regression estimates

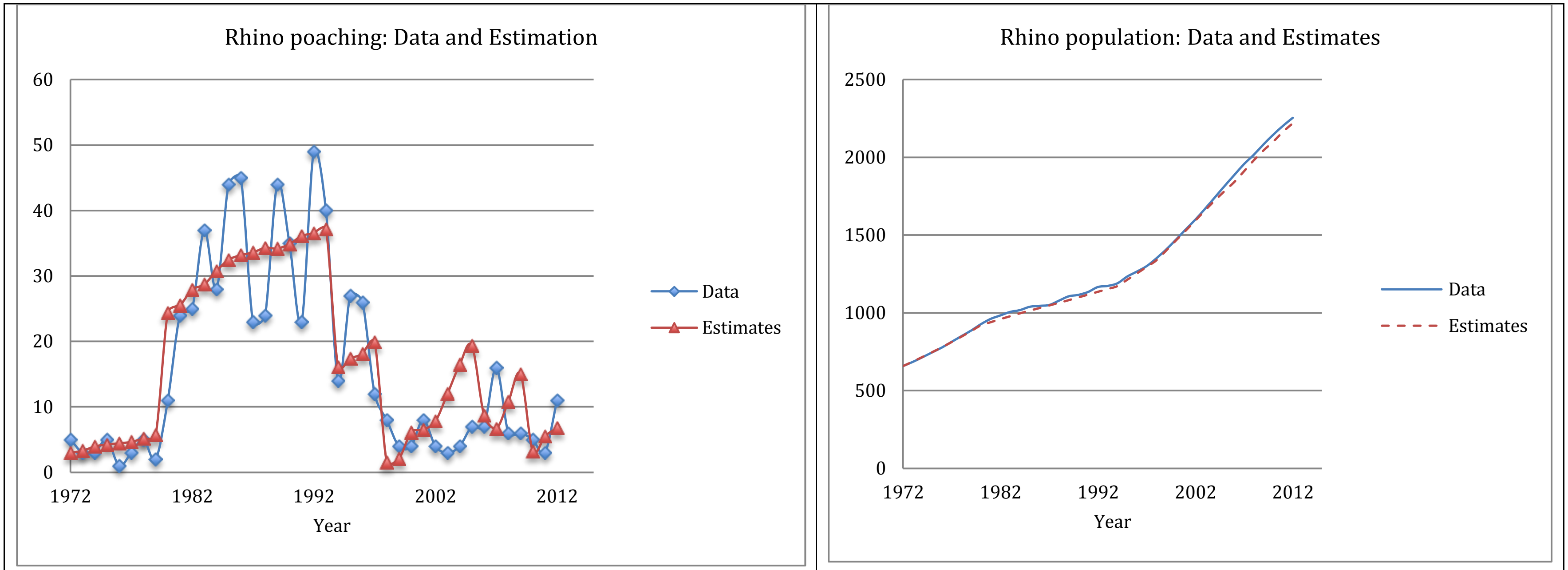
Independent variable	Coefficient	(OLS_6)	(OLS_7)[a]	(IV_3)	(OLS_8)	(OLS_9)	(OLS_10)
Constant	$-q$	−0.02593 (0.0080)***	−0.00933 (0.0040)**	−0.03071 (0.0098)***	−0.00515 (0.0026)*	−0.02020 (0.0061)***	−0.02269 (0.0057)***
Civil unrest (non-binary)	$-q\beta_1$	−0.00223 (0.0006)***	−0.00274 (0.0006)***	−0.00183 (0.0007)**	−0.00334 (0.0005)***	−0.00290 (0.0004)***	–
Anti-poaching camps	$-q\beta_2$	0.00034 (0.0001)***	–	0.00041 (0.0001)***	–	0.00018 (.00006)***	0.00023 (0.00008)***
Anti-poaching guards	$-q\beta_2$	–	0.00003 (0.00001)*	–	–	–	–
Poachers arrested/killed	$-q\beta_2$	–	–	–	−0.00033 (0.00027)	–	–
Poaching penalty	$-q\beta_3$	1.04e − 07 (9.63e − 08)	9.80e − 08 (9.55e − 08)	1.03e − 07 (8.59e − 08)	2.07e − 10 (1.04e − 07)	2.24e − 07 (9.96e − 08)**	1.87e − 07 (1.87e − 07)**
Assam GDP (per capita)	$-q\beta_4$	−1.05e − 06 (8.72e − 07)	−1.04e − 07 (7.65e − 07)	−1.50e − 06 (1.02e − 06)	1.03e − 06 (7.62e − 07)	-	1.59e − 08 (7.28e − 07)
Wage rate	$-q\beta_5$	−0.000017 (0.00015)	−0.00009 (0.00016)	0.00005 (0.0001)	−0.00028 (0.00019)	–	−0.00016 (0.00016)
GDP (China)	$-q\beta_6$	−7.16e − 09 (3.25e − 08)	-	−6.02e − 09 (2.92e − 08)	2.97e − 08 (4.28e − 08)	–	−4.38e − 08 (1.81e − 08)**
GDP (China + Vietnam)	$-q\beta_6$	–	−1.99e − 09 (3.06e − 08)	–	–	–	–
GDP (China + Vietnam–Assam)	$-q\beta_6$	–	–	–	–	−3.37e − 08 (1.36e − 08)**	–
Horn price (for poacher)	$-q\beta_7$	−0.00004 (0.00009)	−0.0001 (0.0001)	−0.00005 (0.00008)	−0.00007 (0.00012)	–	0.000069 (0.00005)
Unrest × anti-poaching camps	$-q\beta_1\beta_2$	–	–	–	–	–	-0.00041 (0.0003)
Unrest × GDP of China	$-q\beta_1\beta_6$	–	–	–	–	–	1.64e − 07 (2.02e − 07)
Unrest × Horn price for poacher	$-q\beta_1\beta_7$	–	–	–	–	–	−0.00033 (0.00018)*
Instrumental variable		–	–	Political party	–	–	–
R^2		0.7612	0.7471	0.7576	0.7220	0.7446	0.8313
F-statistic		13.31	12.87	267 (First stage)	9.99	20.93	13.17

[a] Rhino population estimated using alternative growth function (see footnote 3 in the rhino population model section).

The main result of this chapter is that civil unrest is positively and significantly associated with rhino poaching in Assam – the unrest period is associated with up to four times more poaching effort per year compared to other time periods. The results in this chapter are similar to those of (Poudyal et al., 2009) who find that civil unrest (defined as Maoist insurgency in Nepal) led to significantly higher rhino poaching; that anti-poaching by the Nepalese Forest Department significantly reduces poaching; that GDP in East Asia has a positive but insignificant effect on poaching; and that poaching penalty insignificantly reduces poaching. In this chapter I find that anti-poaching efforts of the Assam Forest Department significantly reduce poaching; poaching penalty reduces poaching (significantly in OLS models 3,4,5,9,&10); Chinese and Vietnamese GDP are positively associated with poaching (significantly in OLS models 5,9,&10); and that both measures of horn price are positively associated with poaching (significantly in OLS models 3,4,&10).

Having estimated Equation (3.4) I now fit the data on rhino poaching and population to the estimated trend to examine the goodness of fit of the regression results. The coefficients of the regression models (q & β_i, $i = 1,\ldots,8$) can be used to estimate rhino poaching levels, Y_t, as given by Equation (3.3): $Y_t = X_t(1 - e^{-qE_t})$, where $E_t = (1 + \beta_1 R_t + \beta_2 A_t + \beta_3 P_t + \beta_4 G_t + \beta_5 W_t + \beta_6 C_t + \beta_7 B_t + \beta_8 I_t + \varepsilon_t)$. Given that the actual rhino poaching data (H_t) is econometrically estimated as Y_t, the rhino population estimates can now be calculated using Equation (3.2): $X_{t+1} = X_t + rX_t(1 - (X_t/K)^z) - Y_t$. This provides estimates of rhino population and poaching levels from 1972 through

2012. I examine the goodness of fit between the data and estimates from models (OLS_1), (OLS_2), (IV_1), and (IV_3). I plot the data and the estimates of poaching and population as per these regression models in Figures 3.2, 3.3, 3.4, and 3.5 respectively, and list the correlation coefficients between the data and the estimates. I find that the ordinary least squares regression model, (OLS_1), suggests a correlation coefficient of 0.8668 between the poaching data and their estimates, which is higher than that in the instrumental variable regression models (IV_1) and (IV_3). Model (OLS_2) does not appear to provide as good a fit in the poaching data and their estimates as the other models. The correlation coefficient between the poaching data and their estimates from model (IV_2) that uses the Muslim population instrument is 0.7800; this is lower than 0.8636 – the corresponding correlation coefficient in model (IV_1) that uses the political party instrument. This suggests that the model using the political party instrument yields better explanatory power than that using the Muslim population instrument.



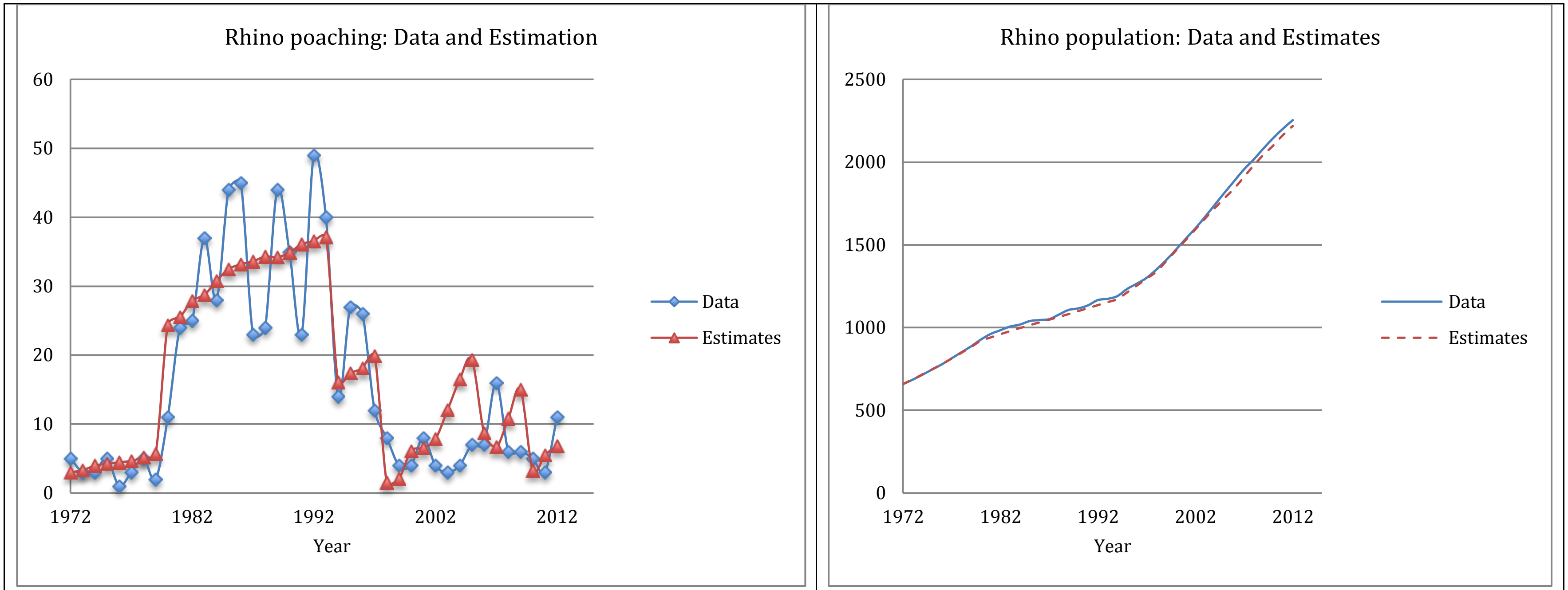
Rhino Poaching: Data (blue line) & Estimation (red line)

Correlation = 0.8668

Rhino Population: Data (blue line) & Estimation (red line)

Correlation = 0.9997

Figure 3.2: Rhino poaching and rhino population fit between data and estimates (*model OLS_1*).


Rhino poaching: Data and Estimation

Rhino population: Data and Estimates

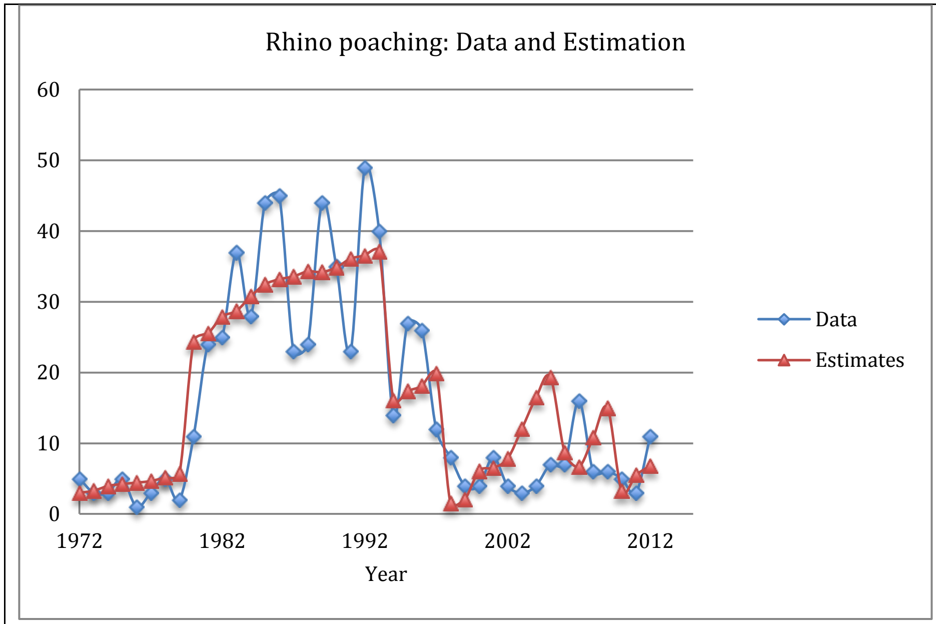
Rhino Poaching: Data (blue line) & Estimation (red line)

Correlation = 0.8018

Rhino Population: Data (blue line) & Estimation (red line)

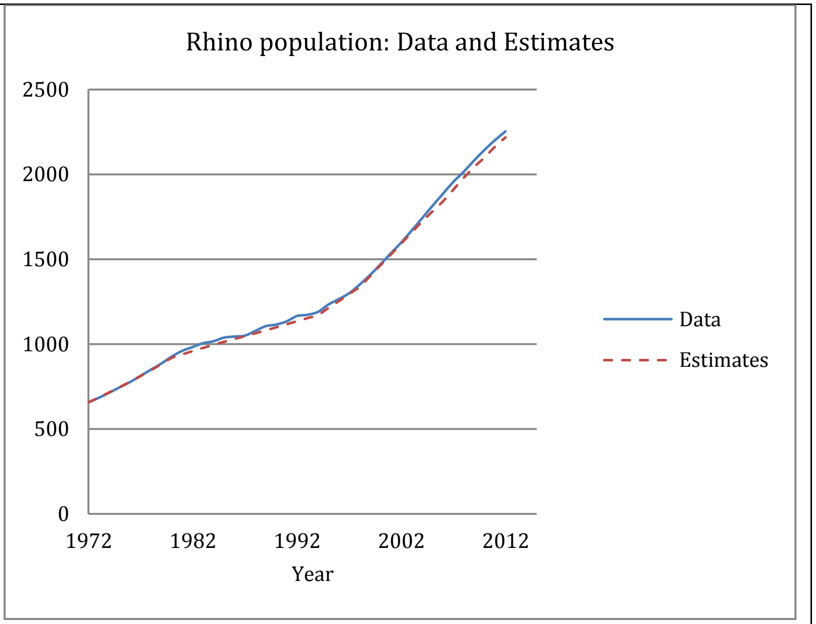
Correlation = 0.9994

Figure 3.3: Rhino poaching and rhino population fit between data and estimates (*model OLS_2*).



Rhino Poaching: Data (blue line) & Estimation (red line)

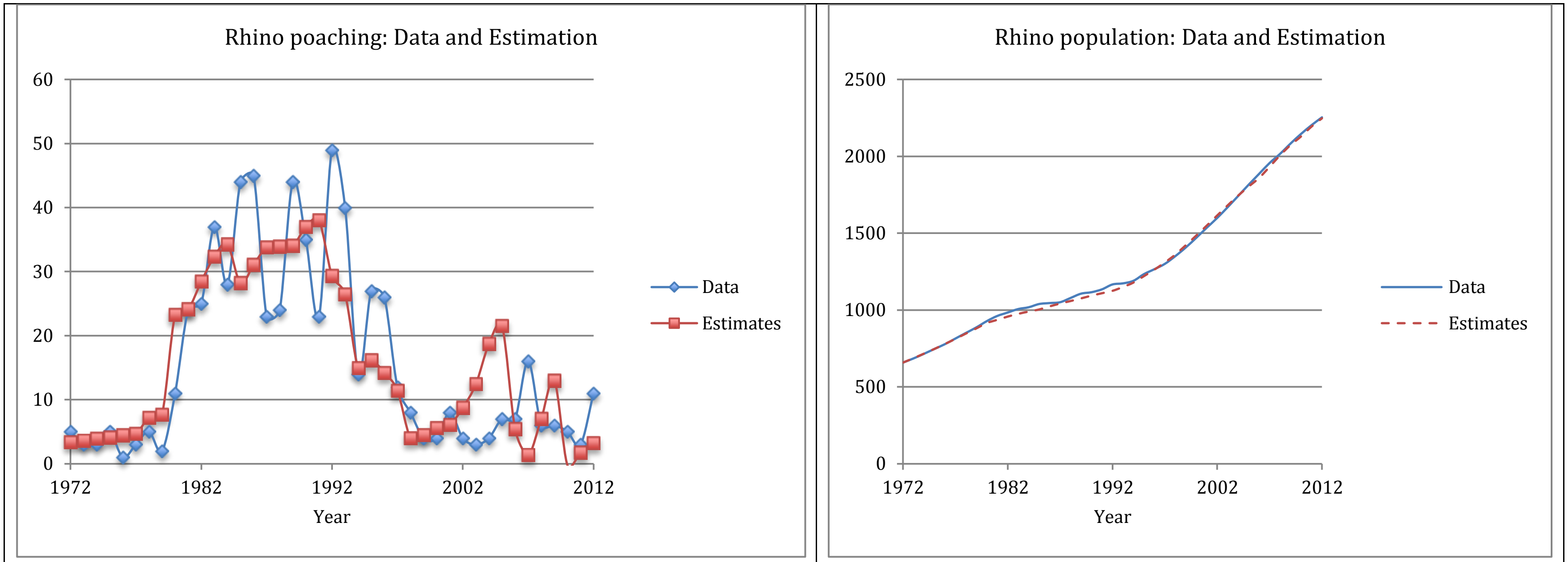
Correlation = 0.8636



Rhino Population: Data (blue line) & Estimation (red line)

Correlation = 0.9997

Figure 3.4: Rhino poaching and rhino population fit between data and estimates (*model IV_1*); instrument = political party



Rhino Poaching: Data (blue line) & Estimation (red line) Correlation = 0.8033	Rhino Population: Data (blue line) & Estimation (red line) Correlation = 0.9994

Figure 3.5: Rhino poaching and rhino population fit between data and estimates as per (*model IV_3*); instrument = political party

3.6 Conclusion

In this chapter I have examined the historical context of extensive civil unrest in Assam and the concurrent increase in rhino poaching. Using data on rhino poaching in the Kaziranga National Park I have undertaken two exercises. The first exercise is a calibration of the biological parameters of a rhino population growth function. Given that animal census enumerations are expensive and not undertaken regularly in Assam, I have adopted the methodology of previous studies to estimate rhino population levels for time periods in which data aren't available. The empirically calibrated parameters are similar to those derived in other studies of rhino populations.

In the second exercise this chapter identifies the relationship between extensive civil unrest and rhino poaching in Assam. Given the illicit nature of rhino poaching one would encounter the problem of missing relevant data – such as regular time-series data on black market rhino horn prices and international market demand for rhino horn. Data unavailability could lead to omitted variable bias in econometric estimations. In this chapter I have estimated proxies of such data. Incomes of China and Vietnam, which proxy the market demand for rhino horn, are positively associated with poaching. Both measures of horn prices (one being a linear trend in the limited data on horn prices, and the other being a novel index estimated using a structural model of supply and demand through an organized crime network) are also positively related to poaching. In addition to including several covariates in the regression analyses – poaching penalties, Assam's GDP, and agricultural wages – I have considered anti-poaching policy of Assam’s Forest Department, which is seen to significantly reduce poaching. Given that civil unrest is associated with political instability in Assam, and an unchecked influx of Muslim refugees from Bangladesh, I have accounted for probable endogeneity in the regression results by using two instruments – political party and Muslim population. I find no evidence to suggest that the OLS models are endogenous. This chapter finds that civil unrest in Assam is positively and significantly associated with rhino poaching in the KNP. The results are robust to different specifications of the civil unrest variable, alternative rhino population estimates, and to the inclusion of several additional covariates. This chapter studies an important and inadequately understood relationship between civil unrest, political instability, and the conservation of endangered species.

APPENDIX 3.1

Estimating a Rhino Horn Price Index:

Given the presence of organized crime networks in the supply of rhino horn from South Africa and Asia, and that demand comes primarily from China and Vietnam, I define the following terms:

$D_t(C_t, I_t) =$ Demand for Indian rhino horn; C_t: income in China and Vietnam; $I_t > 0$ is the estimable horn price index.

$S_t(R_t, I_t) =$ Number of Indian rhinos killed by poachers in year t; R_t represents civil unrest in Assam.

$J_t =$ Total number of rhinos killed by poachers in South Africa.

$I_t = I_t(J_t)$ Horn price index. I treat J_t as an instrument for I_t because I assume that black market price is a function of poaching in South Africa.

$V_t =$ Unobservable inventory of Indian rhino horn held by the crime syndicate.

$V_{t+1} - V_t =$ $S_t(R_t, I_t) - D_t(C_t, I_t)$: change in Indian rhino horn inventory held by the syndicate over time.

I assume the following functional forms for supply, S_t, and demand, D_t:

$$S_t(R_t, I_t) \equiv S_t(I_t(J_t), R_t) = \alpha J_t^{-\beta} R_t, \quad \alpha > 0, \beta > 0 \tag{3A.1}$$

$$D_t(C_t, I_t) \equiv D_t(I_t(J_t), C_t) = \gamma J_t^{\eta} C_t, \quad \gamma > 0, \eta > 0 \tag{3A.2}$$

As noted in The Data section the crime syndicate presumably has an incentive to maintain as low a difference between horn supply and demand levels. This could ensure that horns move as quickly as possible from poacher to end consumer – presumably lowering the risk of getting caught by authorities. Function parameters are calibrated by minimizing the sum of squared differences between $S_t(\cdot)$ and $D_t(\cdot)$:

$$\underset{\alpha,\beta,\gamma,\eta}{\text{minimize}} \sum_{t=0}^{T} \left(\alpha J_t^{-\beta} R_t - \gamma J_t^{\eta} C_t\right)^2 \tag{3A.3}$$

Time-series data on rhino poaching in South Africa's national parks, J_t, are listed in Table 3A.1 (Knight & Emslie, 2012; Milliken & Shaw, 2012). Data on GDP of China and Vietnam, C_t, and civil unrest in Assam, R_t, are listed in Table 3.1. These data are used in a non-linear solver to yield the calibrated values as per (3A.3): $\alpha = 1.04418$, $\beta = 2.03751$, $\gamma = 4.58\text{e-}08$, $\eta = 0.05082$. These values are used to derive the market price index for rhino horn as: $I_t \equiv I_t(J_t) = \gamma J_t^{\eta}$ by using Equation (3A.2).

Table 3A.1: Data on rhino poaching in South Africa, J_t, as an instrument for horn price index, I_t

Year	Rhino poaching in South Africa, J_t	Estimated Price index, $I_t = \gamma J_t^{\eta}$
1990	14	0.5240481540
1991	5	0.4973286495
1992	18	0.5307850539
1993	14	0.5240481540
1994	27	0.5418372794
1995	14	0.5240481540
1996	6	0.5019587467
1997	6	0.5019587467
1998	12	0.5199582682
1999	13	0.5220779407
2000	12	0.5199582682
2001	9	0.5124107389
2002	25	0.5397219137
2003	22	0.5362264970
2004	12	0.5199582682
2005	17	0.5292452588
2006	36	0.5498182454
2007	13	0.5220779407
2008	83	0.5736644738
2009	122	0.5850060943
2010	333	0.6156377863
2011	448	0.6249906309
2012	455	0.6254833376

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CHAPTER 4

ORGANIZED CRIMES AGAINST NATURE: ELEPHANTS IN SOUTHERN AFRICA

4.1 Background and Overview

In early 1981, the elephant population in Africa was estimated at 1.2 million animals. There are two subspecies of elephant on the African continent; the forest elephant (*Loxodonta cyclotis*), predominantly found in the forested areas of Central Africa, and the savanna elephant (*Loxodonta africana*), found primarily in Eastern and Southern Africa. During the 1980s an estimated 675,000 elephants were poached and by 1989 the elephant population had declined to just over 600,000 animals (Barbier, Burgess, Swanson, & Pearce, 1990). In 1989 the African elephant was listed as an Appendix I (endangered) species by the Convention on International Trade in Endangered Species (CITES) and a ban was placed on the trade of elephant products. Recent estimates place the total elephant population in African range states at 423,000 in the year 2012 (IUCN, 2012).

There is considerable evidence to suggest that the poaching of elephant tusk and rhino horn in Africa is planned and financed by international syndicates using organized crime as a business model. These syndicates sponsor poaching gangs with aircraft and high-powered weapons, and also arrange for rapid shipment of tusk and horn to markets in Asia (Mullen & Zhang, 2012; Sas-Rolfes, 2012; Shukman, 2013; Wassener, 2013; S. K. Wasser et al., 2008). Based on data from seizures of illegal ivory shipments amounting to roughly 24 tons in the year 2006 Wasser *et. al.* (2007) use DNA analysis to estimate that approximately 23,000 savannah elephants were illegally harvested from the southern African range states. In June 2002 authorities in Malawi seized a shipment of 6.5 tons of ivory that was bound for Hong Kong; (S. K. Wasser et al., 2008) estimate that approximately 6,500 elephants were illegally harvested for that shipment alone. Based on the evidence from the ivory seizures (S. K. Wasser et al., 2008) suggest that at least two syndicates were associated with poaching at the time in different regions of the African range states.

The change in elephant populations has varied widely by country. Government corruption and the number of armed anti-poaching patrols have been considered important variables when explaining country-level changes in elephant populations. Balmford et al. (2003) use ordinary least squares to regress the change in elephant populations in 20 African countries on a subjective index of corruption. They show that a higher index of corruption had a significant negative effect on the change in a country's elephant population between 1987 and 1994. Frank & Maurseth (2006) find that there are significant “neighborhood effects” that may reduce the size of the coefficient on corruption. Corruption still causes a significant negative effect, but neighborhood effects may also influence the change in a country’s elephant population. Neighborhood effects account for the migration of elephants between countries, and the presence or lack of poaching in a neighboring country.

In a provocative article Messer (2010) plots the estimated elephant populations in Kenya and Zimbabwe after those countries adopted a “shoot-on-sight” policy when dealing with poachers going after elephant ivory or rhino horn. For the period 1984 through 2002, elephant populations increased in countries that adopted the shoot-on-sight policy, and declined in countries that did not. The decline of elephant populations in countries not adopting a shoot-on-sight policy continued even after 1989, when CITES listed *Loxodonta africana* in Appendix I. Messer contends that low wages in developing countries impose limits on the potential economic costs for poachers of fines and imprisonment.

In a model where elephant ivory is a storable commodity Kremer & Morcom (2000) show that rational expectations may lead to multiple equilibria in a dynamic open-access model. There could be equilibria where elephant are driven to extinction. In their model, the cheapest way for a government to eliminate extinction equilibria may be to commit to tough anti-poaching measures if the population falls below some threshold. For governments without a credible anti-poaching threat, the cheapest way to eliminate extinction equilibria may be to accumulate a sufficient stockpile of ivory and threaten to sell it should the elephant population fall below some threshold. Their analysis assumes that the black-market price would fall when a government sells a large amount of stockpiled ivory.

While strategic selling of accumulated stockpiles of ivory might seem rational to economists, it has been opposed by many African leaders and conservation organizations. On July 18th 1989, then President Daniel Arap Moi of Kenya ignited twelve tons of ivory, much of it confiscated from poachers, as a gesture in support of the Appendix I listing of *Loxodonta africana* by CITES (Perlez, 1989). In 1997, CITES voted to down-list elephant populations in Botswana, Namibia, and Zimbabwe to Appendix II (Burton, 1999). Down-listing to Appendix II allows these countries to engage in a tightly monitored sale of stockpiled ivory. In 2010 a similar request by Tanzania and Zambia was denied (IUCN, 2013). These two countries had accumulated approximately one hundred and twelve tons of ivory. The majority of CITES members, and most conservation groups opposed the change to Appendix II for Tanzania and Zambia on the grounds that it would "flood the ivory market," increase the use ivory, and make the detection of illegally poached ivory more difficult. The effectiveness of the CITES ban in the recovery of elephant populations has been questioned by several other studies, including (Barbier et al., 1990; E. Bulte & Van Kooten, 1996; Kreuter & Simmons, 1995; Sugg & Kreuter, 1994). For the CITES ban to be effective it would have to stigmatize the trade and use of ivory so that demand and the black-market price fall (Burton, 1999). The lack of time-series data on black-market prices and the volume of ivory traded make it impossible to develop accurate estimates of the price flexibility of ivory. Burton (1999) is skeptical that either the stigma created by the CITES ban or the sale of government stockpiled ivory would lower the black-market price sufficiently to reduce poaching. According to Burton's open-access simulations, the price of ivory on the black market would have to fall by ninety percent for elephant populations to increase under open-access equilibrium. The model in this chapter identifies why the sale of stockpiled ivory may not reduce poaching.

The incentive to poach has been studied under various conservation policies including trade bans (E. H. Bulte & van Kooten, 1999a; E. H. Bulte & van Kooten, 1999b; Burton, 1999), fines for poaching (E. H. Bulte & van Kooten, 1999a; E. H. Bulte & van Kooten, 1999b; Damania, Milner-Gulland, & Crookes, 2005; Damania, Stringer, Karanth, & Stith, 2003; Milner-Gulland & Leader-Williams, 1992; Skonhoft & Solstad, 1998), alternative livelihoods when there is conflict between land use and species conservation (Fischer, Muchapondwa, & Sterner, 2011; A. Johannesen & Skonhoft, 2005; Skonhoft, 2007), and price-control through supply restrictions (Brown & Layton, 2001; Kremer & Morcom, 2000; Mason C.F., Bulte E.H., & Horan R.D., 2012). Models of poaching assume open access harvest conditions where, with imperfect property rights, poachers myopically maximize short-run profit, and entry/exit occurs until rents are dissipated. Economic models of poaching predict how the steady-state equilibrium stock, harvest, and enforcement levels change with economic parameters such as price, poaching cost, and detection probability (E. H. Bulte & van Kooten, 1999b; A. Johannesen & Skonhoft, 2005; A. B. Johannesen & Skonhoft, 2004; Milner-Gulland & Leader-Williams, 1992; Skonhoft & Solstad, 1998). In linking economics and ecological theory (E. Bulte, Damania, Gillson, & Lindsay, 2004; Skonhoft, 2007) have noted that models should expand their scope beyond the notion of steady state equilibrium by incorporating uncertainty, ecological variability, complexity, scale.

In this chapter I introduce uncertainty through stochastic poaching, and study its effects on elephant population dynamics. In the next section I construct a biomass (lumped-parameter) model of the elephant population in Southern African range states. In section 4.3 I focus on the optimization problem for the leader of a poaching organization (gang). I identify the plausible conditions under which the number of planned poaching expeditions will be insensitive to the black-market price of ivory. I also identify a critical value for the annual number of poaching expeditions. If this number is consistently exceeded, the elephant population will slowly decline to extinction. Section 4.4 reports on the stochastic implications of poaching by more than one gang with free entry/exit under open access until profits are driven to zero. I also conduct a sensitivity analysis of our results by changing the values of economic parameters including the probability of interception by an anti-poaching patrol, the cost of poaching expeditions, and the black market price of ivory. Section 4.5 concludes.

4.2 An Aggregate Model of Elephant Poaching in Southern Africa

Let X_t denote the number of elephants in the population in Southern Africa and H_t the number killed by poaching organizations, both in year t. The dynamics of the elephant population will be described by the iterative map (4.1):

$$X_{t+1} = (1 - m)X_t + F(X_t) - H_t \tag{4.1}$$

$1 > m > 0$ is an average annual mortality rate, and $F(X_t)$ is a purely compensatory growth function. An age-structured model, or a model with delayed recruitment to an adult population might be more appropriate, but this biomass (lumped-parameter) model has been used in previous studies (E. H. Bulte & van Kooten, 1999b; Cromsigt, Hearne, Heitkonig, & Prins, 2002; Milner-Gulland & Leader-Williams, 1992), and has the advantage of providing analytic benchmarks for stochastic poaching.

The number of elephant killed by poachers in any year is determined in part by the number of poaching expeditions planned by the leaders of the various poaching gangs. In deciding the likely number of poaching expeditions, a leader must balance expected net revenue with the probability that members of a unit might be captured, plea-bargain, and provide information leading to the destruction of the organization. The details of this optimization problem will be presented in the next section. For now, I simply note that if poachers are intercepted by an anti-poaching unit, our model assumes that the organization is "decommissioned" for the rest of the year. Early detection and dismantling of the poaching organization will reduce the number of elephant killed in that year. However, I assume that poaching can never be eliminated entirely, and that a new poaching organization reappears at the start of the next year, with a new leader who again optimizes the number of planned poaching expeditions.

At the start of year t the organization leader gathers information on the size of the elephant herd as well as the number of anti-poaching units. Let P_t denote the average value of two ivory tusks from a single elephant when sold on the black market. The kill rate of a poaching unit for a single expedition is assumed proportional to the elephant population and is given by $q_t X_t$, where $1 > q_t > 0$ is an efficiency parameter for hunters in a poaching expeditions deployed in year t. The value of q_t has likely increased in the last decade given reports (Mullen & Zhang, 2012; Shukman, 2013; Wassener, 2013; S. K. Wasser et al., 2008) of poaching organizations using high-tech equipment like aircraft, darting guns, and knock-down drugs for their operations.

To make the biomass model more concrete, I specify a form for the growth function in Equation (4.1) and calibrate its parameters. Following (Milner-Gulland & Leader-Williams, 1992) I adopt a skewed logistic where $F(X_t) = rX_t[1 - (X_t/K)^z]$. Because the average survival rate of the elephant population is given by $(1 - m)$, I treat $r > 0$ as the pregnancy rate of adult females giving birth to approximately one offspring every third year. This implies $r = 0.33$. The average mortality rate varies across countries and depends on the abundance of water and forage. Under normal years, the average mortality rate (including juveniles) has been estimated at $m = 0.27$ (Armbruster & Lande, 1993). These values would imply a net intrinsic growth rate of $(r - m) = 0.06$, a value very close to the estimate used by (Calef, 1988). A skew parameter greater than one $(z > 1)$ will cause the population level supporting peak growth to lie to the right of $K/2$. (Milner-Gulland & Leader-Williams, 1992)set $z = 7$. With mortality occurring after growth, the parameter $K > 0$ will influence the steady-state elephant population in the absence of poaching, but it should not be interpreted as environmental carrying capacity.

The no-poaching, steady-state population can be shown to equal $X = K[(r - m)/r]^{1/z}$. This steady-state population will be locally stable provided $|1 - z(r - m)| < 1$. If $K = 500{,}000$ elephants for all of Southern Africa, $r = 0.33$, $m = 0.27$, and $z = 7$, the no-poaching, steady-state elephant population is calculated to be $X = 391{,}926$; this value is locally stable since $|1 - z(r - m)| = 0.58 < 1$. According to (Blanc, 2007), the combined elephant population in the Southern African range states (i.e. Angola, Botswana, Mozambique, Namibia, South Africa, Zambia, and Zimbabwe as shown in Figure 4.1) in 2006 was approximately 297,718. If this number represented the steady-state elephant population with poaching ($X_P = 297{,}718$) then $H = [r - m - r(X_P/K)^z]X_P = 15{,}256$ would be the steady-state number of elephants killed by poachers. In reality, the elephant population in Southern Africa will never be in steady state because of stochastic poaching and droughts. However these "counterfactual" steady-state values, $X_P = 297{,}718$, and $H_P = 15{,}256$ are useful because they give us a benchmark from which to assess the consequences of organized, stochastic, criminal poaching. As mentioned earlier in this chapter Wasser *et. al.* (2007) estimated that approximately 23,000 savannah elephants were illegally harvested from the Southern African range states in the year 2006. These results are summarized in Table 4.1.

Figure 4.1: Southern African elephant range states.

Table 4.1: Population dynamics, biological parameters, steady-state, and stability.

Parameter		**Value**
Intrinsic growth rate	$r =$	0.33 (Armbruster & Lande, 1993)
Natural mortality rate	$m =$	0.27 (Armbruster & Lande, 1993)
Logistic growth skew parameter	$z =$	7 (Bulte & van Kooten, 1999b; Milner-Gulland & Leader-Williams, 1992)
Initial elephant population in 2006	$X_0 =$	297,718 in the Southern African range states (Blanc, 2007)
Carrying capacity	$K =$	500,000

Iterative map (4.1): $X_{t+1} = (1-m)X_t + rX_t[1-(X_t/K)^z] - H_t$

Steady-state elephant population with no poaching ($H_t = 0$): $X = K[(r-m)/r]^{1/z} = 391{,}926$

Elephant population in Southern African range states in 2006: $X_P = 297{,}718$ (i.e. steady-state elephant population with deterministic poaching)

Steady-state elephant population killed by poachers: $H = [r - m - r(X_P/K)^z]X_P = 15{,}256$

Approximately 23,000 savannah elephants illegally harvested in Southern African range states in 2006 (Wasser *et. al.* 2007).

4.3 Optimal Poaching

Let us now develop the optimization problem for the leader of a poaching organization and show how it leads to a target number of planned poaching expeditions. Let $a_t \geq 0$ denote the number of anti-poaching units that the leader of a poaching organization thinks will be deployed in year t. Let $\pi_t = \pi(a_t)$ be the subjective, Bernoulli probability, held by the leader of the poaching organization, that any single poaching expedition will be intercepted by a government anti-poaching unit. Let us assume that $\pi_t = \pi(a_t)$ is identical and independent for all poaching expeditions in a given year.[4]

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[4] It would be possible to allow the probability of interception by an anti-poaching unit to increase with each completed (i.e. successful) poaching expedition. One would then need a model of how the conditional probability of success for the next poaching expedition depends on the fact that all previous

Let $c_t > 0$ denote the cost of deploying a single poaching expedition in year t. This would be the cost of gasoline, food, ammunition, and other supplies. The poaching unit is comprised of hunters, carriers, drivers, and perhaps pilots. Assume that these individuals collectively receive the net revenue from a poaching expedition, provided that it has not been intercepted by an anti-poaching unit. At the beginning of each year the gang leader determines the number of planned poaching expeditions, n_t^*, a non-negative integer, as per Equation (4.2):[5]

$$n_t^* = \underset{n_t \in \{0,1,2,\dots\}}{\operatorname{argmax}} \left\{ \left(1 - \pi(a_t)\right)^{n_t} P q X_t n_t - c n_t \right\} \tag{4.2}$$

One can think of the poaching expeditions as being sent out sequentially during a given year. If the gang leader sets a target of n_t^* expeditions in year t, then $\left(1 - \pi(a_t)\right)^{n_t^*}$ would be the probability that none of the expeditions will be intercepted by an anti-poaching unit. The actual number of poaching expeditions "successfully" completed in year t will be less than or equal to n_t^*. The number of elephants killed by poaching units in year t is thereby a random variable given by

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poaching expeditions were successful.

[5] The non-linear nature of equation (4.2) does not permit the derivation of an analytical expression for n_t^*. The optimal number of planned expeditions n_t^* can be numerically solved for a positive integer value. The first-order condition of the maximization process is implicit in a numerical solution of the optimal number of planned poaching expeditions, n_t^*, in time period t.

$H_t = n_t q_t X_t$, where $n_t \leq n_t^*$ is the "realized" number of successful poaching expeditions in year t.

The gang leader's decision-making process can be summarized with the help of the schematic in Figure 4.2. At the beginning of time period t the gang leader forms an assessment of the elephant population (X_t). Given the parameters of black-market price (P), probability of interception $\left(\pi(a_t)\right)$, cost per expedition (c) and the poaching technology or catchability coefficient (q), the leader maximizes the expected profit expression, Equation (4.2), by numerically solving for the optimal number of planned poaching expeditions (n_t^*). With a given probability of interception $(\pi(a_t))$, one can simulate for a resulting number of realized poaching expeditions, denoted by $n_t \in [0, n_t^*]$. The elephant population in the next time period, $t + 1$, will evolve as per the iterative map (4.1), after a realization of poaching/harvest, $H_t = n_t q_t X_t$, in time period t.

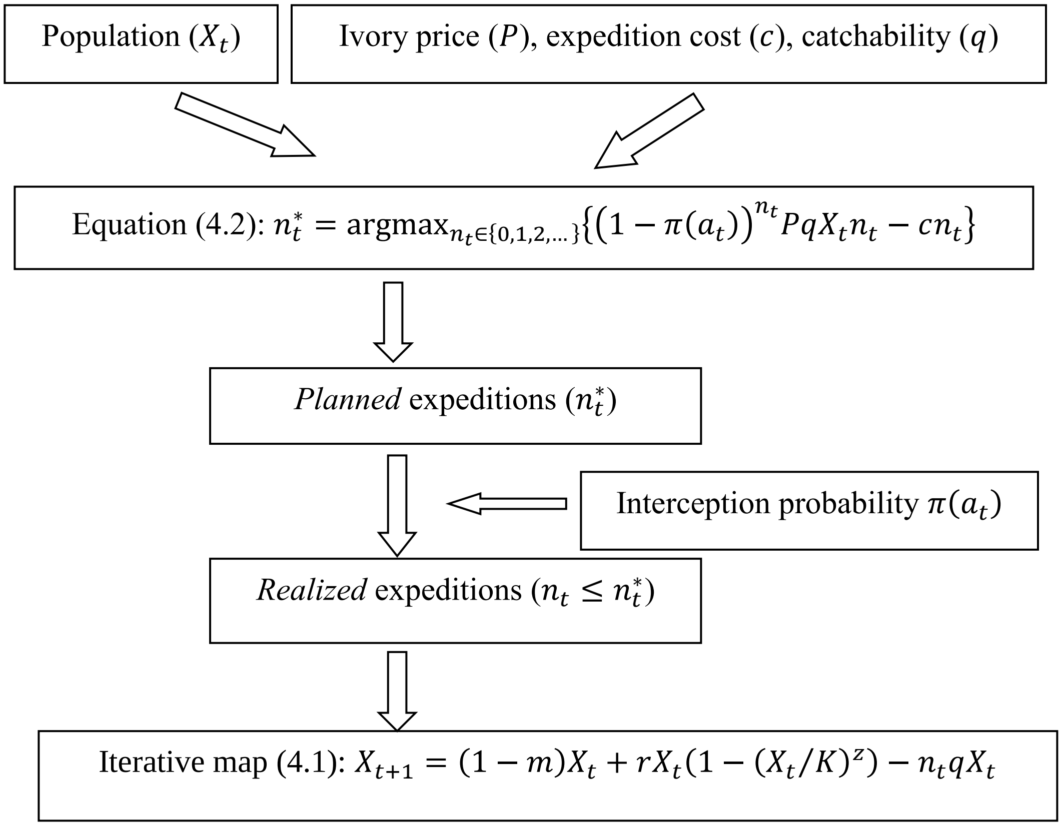


Figure 4.2: Poaching gang leader's decision process of planned expeditions (n_t^*).

Having laid out the theoretical optimization process, I now turn to numerical simulations using parameter values from the literature. (Milner-Gulland & Leader-Williams, 1992) estimated an average "detection rate" for poaching expeditions in Zambia for the period 1980 to 1983 to be $\pi(\cdot) = 0.05$. It is difficult to determine whether this probability is appropriate for our model of organized poaching *circa* 2013. Assuming that the investment in the number of anti-poaching units in the Southern Africa range states has significantly increased since the early 1980s I set a base-case probability of $\pi(a_t) = 0.10$. However, the use of high-tech equipment by poaching organizations might also result in a lower probability of detection by anti-poaching patrols. In the next section the dynamic consequences of more sophisticated, high-tech poaching with lower probabilities of detection will be examined.

The black-market price for two ivory tusks, weighing twenty kilograms, may be as high as $P_t = \$3{,}000$ (Messer, 2010). The cost of outfitting a single poaching expedition will be set at $c_t = \$2{,}000$. The efficiency of a poaching unit, as measured by q_t, was estimated by (Milner-Gulland & Leader-Williams, 1992) to be $2.56 * 10^{-4}$ for organized gangs in Zambia in 1985. Given the technology available today I multiply this efficiency parameter by a factor of ten and set $q_t = 2.56 * 10^{-3}$.

If $X_t = 297{,}718$ and $\pi(a_t) = 0.10$, then $n_t^* = \text{argmax}_{n_t \in \{0,1,2,\ldots\}} \left\{ \left(1 - \pi(a_t)\right)^{n_t} PqX_{\square} n_t - cn_t \right\} = 9$. If $\pi(a_t) = 0.05$, $n_t^* = \text{argmax}_{n_t \in \{0,1,2,\ldots\}} \left\{ \left(1 - \pi(a_t)\right)^{n_t} PqX_t n_t - cn_t \right\} = 19$.

With $\pi(a_t) = 0.10$, $n_t^* = 9$. If all 9 expeditions were completed without interception by an anti-poaching unit, net revenue accruing to “management” of the poaching organization would be $7,158,998 from the killing of 6,859 elephants. With $\pi(a_t) = 0.05$, $n_t^* = 19$. If all 19 expeditions were completed without interception, a single poaching organization would kill 14,481 elephants for a profit of $14,719,839. These results are summarized in Table 4.2.

Table 4.2: Economic parameters and optimal poaching when $\pi(a_t) = 0.10$ and 0.05

Parameter		**Value**
Black market ivory price	$P =$	\$3,000 per set of two tusks (Messer, 2010)
Harvest efficiency	$q =$	$2.56 * 10^{-3}$ (Milner-Gulland & Leader-Williams, 1992)
Detection probability	$\pi(a_t)$=	0.10; 0.05 (Milner-Gulland & Leader-Williams, 1992)
Expedition cost	$c =$	\$2,000

For $X_0 = 297{,}718$:

If $\pi(a_t) = 0.10$, then $n_t^* = \text{argmax}_{n_t \in \{0,1,2,\ldots\}} \{(1-\pi(a_t))^{n_t} PqX_t n_t - cn_t\} = 9$

Expected net revenue of poaching gang = \$7,158,998 from harvest of 6,859 elephants.

If $\pi(a_t) = 0.05$, then $n_t^* = \text{argmax}_{n_t \in \{0,1,2,\ldots\}} \{(1-\pi(a_t))^{n_t} PqX_t n_t - cn_t\} = 19$

Expected net revenue of poaching gang = \$14,719,839 from harvest of 14,481 elephants.

While Equation (4.2) would imply that $\pi(a_t)$, P_t, c_t, q_t, and X_t would all play a roll in determining n_t^*, the sensitivity of n_t^* to these parameters is not uniform. In fact, Equation (4.2) has an interesting property.

Proposition: If $\{(1-\pi(a_t))^{n_t} PqX_t n_t - cn_t\} > 0$ and $c_t/(PqX_t) > 0$ *but sufficiently small*, then n_t^* *only* depends on $\pi(a_t)$.

Proof: Define the expected net revenue from n_t planned poaching expeditions as $\text{E}[NR_t] = \{(1-\pi(a_t))^{n_t} PqX_t n_t - cn_t\}$. Divide both sides by $PqX_t > 0$ so that $\text{E}[NR_t]/[PqX_t] = (1-\pi(a_t))^{n_t} n_t - [c_t/(PqX_t)]n_t$. Then, if $c_t/(PqX_t) \approx 0$, the integer value of n_t which maximizes $\text{E}[NR_t] = \{(1-\pi(a_t))^{n_t} PqX_t n_t - cn_t\}$ is the integer that maximizes $(1-\pi(a_t))^{n_t} n_t$ and n_t^* *only* depends on $\pi(a_t)$.

For the parameter values in Table 4.2, $c_t/(PqX_t) = 0.000874$, which is sufficiently small so that changes in P_t, c_t, q_t, and X_t may not change n_t^*. Specifically, a drop in P_t from \$3,000 to \$1,000 will not change the optimal number of planned poaching expeditions. If $\pi(a_t) = 0.05$ and X_t falls from $X_t = 297{,}718$ to $X_t = 14{,}000$, poaching still generates a positive profit and the number of planned poaching expeditions remains at $n_t^* = 19$. The relative insensitivity of n_t^* to changes in the black-market price of ivory or to the elephant population will have important implications for system dynamics and anti-poaching policy.

With poaching the dynamics of the elephant population are determined by:

$$X_{t+1} = (1-m)X_t + rX_t(1-(X_t/K)^z) - n_t q X_t \tag{4.3}$$

Insight can be gleaned on the behavior of elephant population with stochastic poaching from the deterministic case where $n_t = n$, and $n > 0$ is a constant. Equation (4.3) can be solved for a steady state at $X = K[(r-m-nq)/r]^{1/z} > 0$ (provided $r - m - nq > 0$). This steady state locally stable if and only if $|1 - z(r-m-nq)| < 1$. If $n > (r-m)/q$, we would have $X < 0$, and the elephant population will ultimately become extinct as a result of poaching. With stochastic poaching, if n_t is frequently above $n_c = (r-m)/q$, the population may go to extinction as $t \to \infty$; this may however take a long time to occur. For $r = 0.33$, $m = 0.27$, and $q = 2.56 * 10^{-3}$ we calculate $n_c = 23.4375$. Because I restrict the realized number of poaching expedition to be a non-negative integer, if $n_t > 24$ is frequently above n_c, the elephant population will ultimately go extinct. In Figure 4.3 I show the elephant population starting from $X_0 = 297{,}718$ when $K = 500{,}000$, $r = 0.33$, $m = 0.27$, $q = 2.56 * 10^{-3}$, $z = 7$, and $n_t = \{0, 50\}$ with equal probability, $\Pr(n_t = 0) = \Pr(n_t = 50) = 0.5$, ultimately goes extinct over 500-time periods. In this case the expected value for n_t is 25, which exceeds $n_c = 23.4375$.

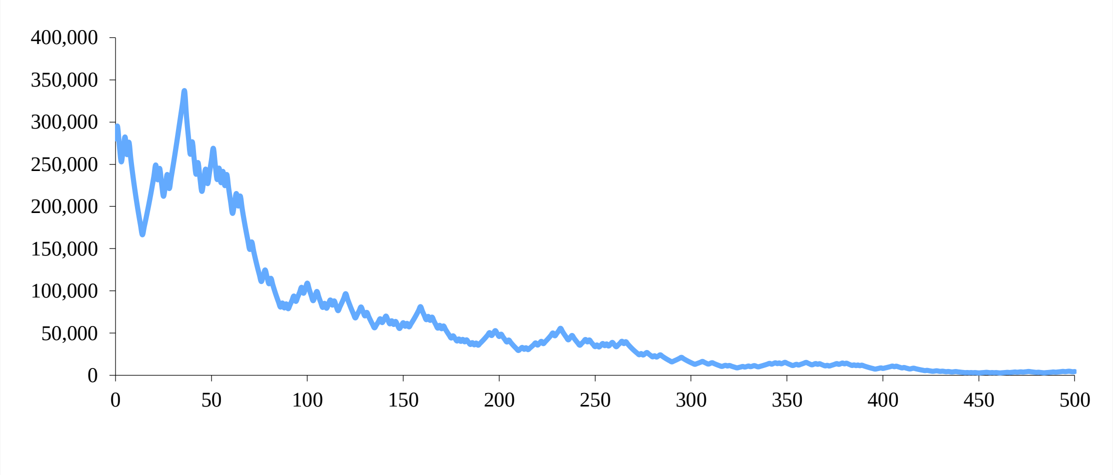


Figure 4.3. A single realization depicting extinction of elephant population with $\mathrm{E}[n_t] = 25$, which exceeds the *critical value*, $n_c \equiv (r - m)/q = 23.4375$. Time period shown on the horizontal axis, and elephant population shown on the vertical axis.

I now examine the dynamics of the elephant population in Southern Africa with multiple poaching gangs where under open access conditions there is free entry/exit until profits are driven to zero. I examine the dynamics of elephant population and the economic choices of the poaching organizations when the probability of interception/detection by an anti-poaching unit on any particular expedition is initially set at the base-case value of $\pi(a_t) = 0.10$. I also examine the dynamics of elephant population and economic choices when, because of more evasive, high-tech poaching, the probability of interception assumes lower values.

4.4 The Elephant Population with Multiple Poaching Organizations

Recall that at the start of each year, the leader determines n_t^*, the optimal number of planned expeditions. The number of elephant killed in year t becomes the realization $H_t = n_t q X_t$, where $0 \leq n_t \leq n_t^*$ is a random variable. I consider now the possibility of additional poaching gangs operating independently in the Southern African range states. Each gang to carry out the same maximization process, as determined by equation (4.2). I examine the possibility of multiple gangs under the open access conditions of myopic poaching, and free entry/exit until profits are driven to zero for the poaching industry. Accordingly, each gang leader chooses his/her own optimal planned number of expeditions $n_{t,g}^*$, where g denotes the gang. Expeditions are sent out by each gang leader independently and sequentially. The probability of interception of any expedition of any gang remains $\pi(a_t)$. In this event the total realization of harvest or poached elephants will be the sum $\sum_{g=1}^{G} H_{t,g}\big(n_{t,g}, q, X_t\big)$, where G is the total number of operating gangs in time period t. This sum is subtracted from the growth of elephant population as per the modified iterative map (4.4):

$$X_{t+1} = (1-m)X_t + rX_t(1-(X_t/K)^z) - \sum_{g=1}^{G} n_{t,g} q X_t \tag{4.4}$$

Numerical simulations are carried out for time periods $t = 0,1,\ldots,999$ according to Equations (4.2) and (4.4). I report the relevant economic and population statistics of the simulation exercises for one, two and three operating gangs. In addition I determine the number of poaching gangs that would operate under open access conditions when the elephant population settles into a low-population-level steady state, or goes to extinction, and it is no longer profitable for more gangs to operate. The simulated elephant population of the first 100 years is disregarded to eliminate the influence of the initial condition, $X_0 = 297{,}718$. Each of the one thousand time period simulations are iterated one thousand times and the average number of realized poaching expeditions is calculated as $\overline{n_t} = (1/1000)\sum_{j=1}^{1{,}000} n_{j,t}$ for $\mathrm{t} = 0{,}1, \dots, 999$. Also calculated is the average elephant population in year t, that is $\overline{X_t} = (1/1000)\sum_{j=1}^{1{,}000} X_{j,t}$ for $t = 100, \dots, 999$. These averages are plotted in Figures 4.4 through 4.9.

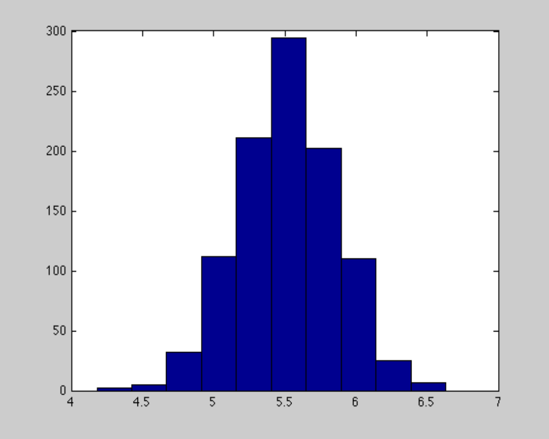
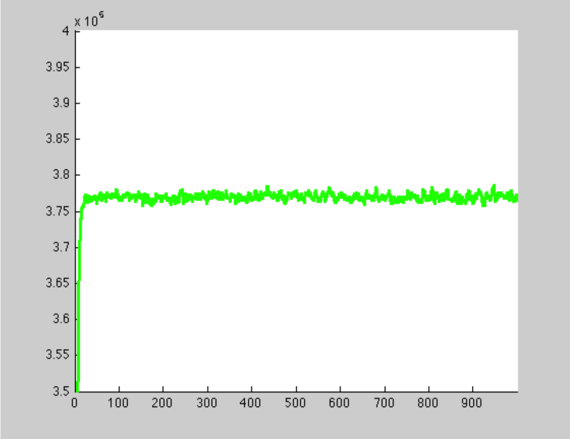
Distribution of realized number of trips: $\overline{n_t} = (1/1000)\sum_{j=1}^{1,000} n_{j,t}$ for $t = 0,1,\dots,999$. Mean = 5.5179 Variance = 0.1181 Minimum Value = 4.18 Maximum Value = 6.63	Distribution of realized population: $\overline{X_t} = (1/1000)\sum_{j=1}^{1,000} X_{j,t}$ for $t = 100,\dots,999$. Mean = 376,975 Variance = 205,145 Minimum Value = 375,790 Maximum Value = 378,522
	

Figure 4.4: Summary statistics for one poaching gang; $\pi(a_t) = 0.10$, $n_t^* = 9$

Over the one thousand iterations of the one thousand year realization time period I find that for the one poaching gang, with $\pi(a_t) = 0.10$ and $n_t^* = 9$, the mean number of realized poaching expeditions is 5.51 with a variance of 0.118. The elephant population, for the interval $t = 100,\dots,999$, is centered at a mean of 376,975 with a variance of 205,145. None of the one thousand iterations resulted in elephant population extinction.

The corresponding descriptive statistics and distributions with two poaching gangs are shown in Figure 4.5. I note that the mean and variance of the number of realized poaching expeditions approximately double while the average elephant population declines to 357,384. The variance of the elephant population more that doubles to 451,586. The planned poaching expeditions remains at $n_t^* = 9$, and the average number of realized expeditions increases to 11. Similar to the case with one gang none of the 1,000 simulations resulted in extinction.

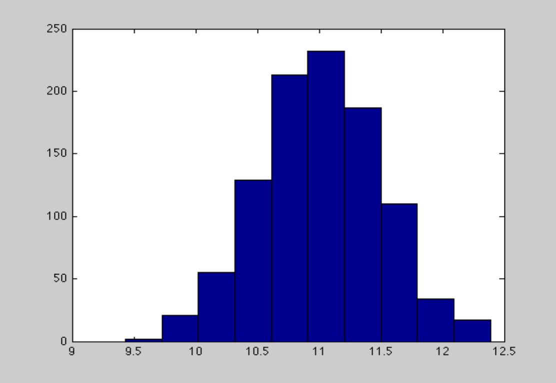
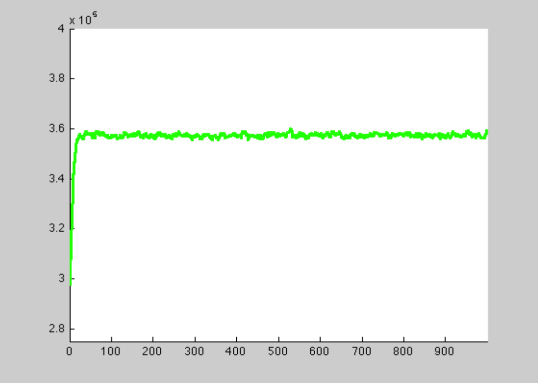
Distribution of realized number of trips: $\overline{n_t} = (1/1000)\sum_{j=1}^{1,000} n_{j,t}$ for t $= 0,1,\ldots,999$. Mean = 11.014 Variance = 0.2383 Minimum Value = 9.43 Maximum Value = 12.39	Distribution of realized population: $\overline{X_t} = (1/1000)\sum_{j=1}^{1,000} X_{j,t}$ for t $= 100,\ldots,999$. Mean = 357,384 Variance = 451,586 Minimum Value = 355,413 Maximum Value = 359,969
	

Figure 4.5: Summary statistics for two poaching gangs; $\pi(\mathrm{a_t}) = 0.10$, $n_t^* = 9$

The results with three poaching gangs are shown in Figure 4.6. The distribution of poaching expeditions shifts to the right (it is now centered at a mean of 16.53 realized expeditions). The elephant population shifts downward to a time series with a mean of 327,857 a variance of 1,025,570. With the detection probability set at its base-case value of $\pi(a_t) = 0.10$, the qualitative behavior of the system remains similar for one, two, and three gangs; each gang attempts $n_t^* = 9$ planned poaching expeditions over the one thousand year time horizon. With three poaching gangs operating the average number of realized expeditions increases to 16.53. I note that this is lower than the critical value of expeditions, $n_c = 23.4375$. This provides insight into why the elephant population does not result in extinction for any of the simulations with the base-case parameter values.

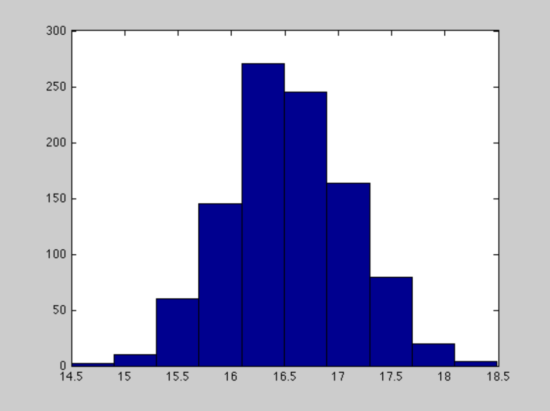
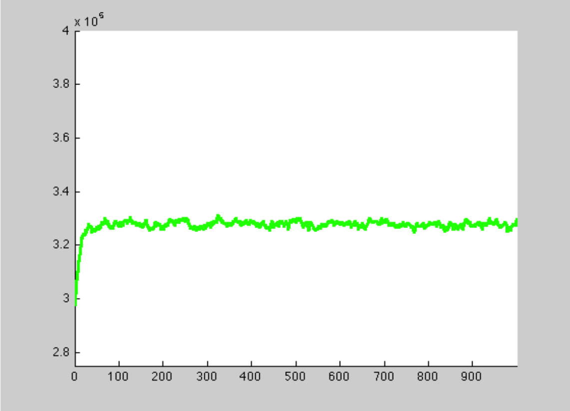
Distribution of realized number of trips: $\overline{n_t} = (1/1000)\sum_{j=1}^{1,000} n_{j,t}$ for $t = 0,1,\dots,999$. Mean = 16.53 Variance = 0.3466 Minimum Value = 14.50 Maximum Value = 18.49	Distribution of realized population: $\overline{X_t} = \left(\frac{1}{1000}\right)\sum_{j=1}^{1,000} X_{j,t}$ for $t = 100,\dots,999$. Mean = 327,857 Variance = 1,025,570 Minimum Value = 324,805 Maximum Value = 331,049
	

Figure 4.6: Summary statistics for three poaching gangs; $\pi(a_t) = 0.10$, $n_t^* = 9$

I now examine how the dynamics of elephant population and the poaching organizations' economic decision-making change as a result of more high-tech poaching. More high-tech poaching is represented by a lower probability of detection given the use of modern equipment by the poaching gangs. One can also argue that more high-tech poaching would increase the cost of poaching expeditions from the base-case value listed in Table 4.2. In this chapter I examine this in a sensitivity analysis of the results where the economic parameters are varied.

Reducing the interception probability to $\pi(a_t) = 0.05$ causes the optimal number of planned poaching expeditions to increase to $n_t^* = 19$ as noted in Table 4.2. As more poaching gangs participate in the illegal business of elephant poaching, the frequency with which $n_t > n_c$ increases, and so does the likelihood that the population is driven to extinction. In Figure 4.7 I show the distributions of average realized poaching expeditions and average elephant populations with just one poaching gang. The annual average of the realized number of poaching expeditions is 11.79, which is below the critical value, $n_c = 23.4375$. Thus here again I note that the elephant population does not decline to extinction, and attains a stationary distribution much like the previous three cases. The average elephant population fluctuates around a mean of 353,456 with a variance of 1,057,366.

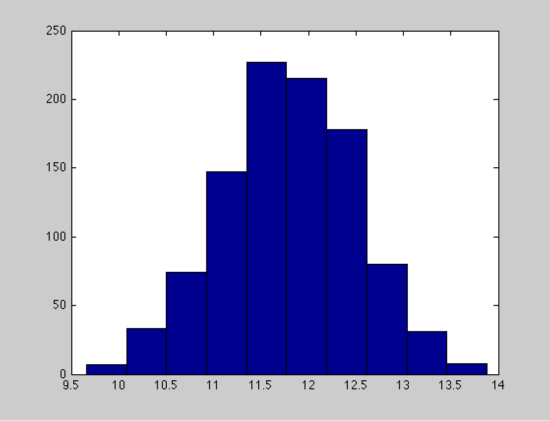
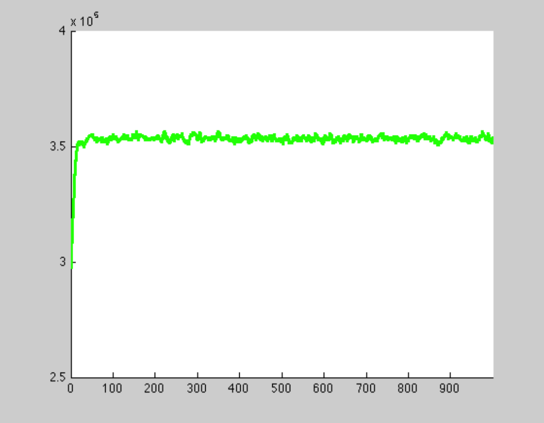
Distribution of realized number of trips: $\overline{n_t} = (1/1000)\sum_{j=1}^{1,000} n_{j,t}$ for $t = 0,1,\dots,999$. Mean = 11.79 Variance = 0.501 Minimum Value = 9.66 Maximum Value = 13.88	Distribution of realized population: $\overline{X_t} = (1/1000)\sum_{j=1}^{1,000} X_{j,t}$ for $t = 100,\dots,999$. Mean = 353,456 Variance = 1,057,366 Minimum Value = 350,782 Maximum Value = 356,553
	

Figure 4.7: Summary statistics for one poaching gang; $\pi(a_t) = 0.05$, $n_t^* = 19$

An interesting mathematical phenomenon occurs when one considers the addition of a second poaching gang when $\pi(a_t) = 0.05$. The results are shown in Figure 4.8 where a *stochastic bifurcation* seems to occur causing a change in the stochastic behavior of the resource system. One way to analyze a stochastic bifurcation is through the statistical analysis of the time to cross a critical value for the state variable (Diks and Wagener, 2006). I assume a critical value for the state variable (elephant population) of $X_c = 150{,}000$. Then I examine the number of simulations (realizations) out of 1,000 where the elephant population drops below $X_c = 150{,}000$, and the median time to drop below $X_c = 150{,}000$. Figure 4.8 is one such realization out of 1,000. In this realization the elephant population undergoes a steep decline but appears to stabilize at a new stationary distribution for $500 \leq t \leq 1{,}000$ centered at a mean of 105,067 with a standard deviation of 15,359. Due to the insensitivity of n_t^*, the optimal number of planned poaching expeditions remains at 19 for both gangs.

A more detailed analysis of the crossing statistics reveals that the median time for the elephant population to drop below $\mathrm{X_c} = 150{,}000$ is $t_{\pi(a_t)=0.05}^{two\ gangs} =$□224. Only three out of the one thousand stochastic simulations remained above $X_c = 150{,}000$ for $500 \leq t \leq 1{,}000$. In contrast, when $\pi(a_t) = 0.10$ *none* of the stochastic simulations, with one, two, or three poaching gangs, caused the elephant population to drop below $X_c = 150{,}000$. This was also true for $\pi(a_t) = 0.05$ when there was only one poaching gang (see Figure 4.7).

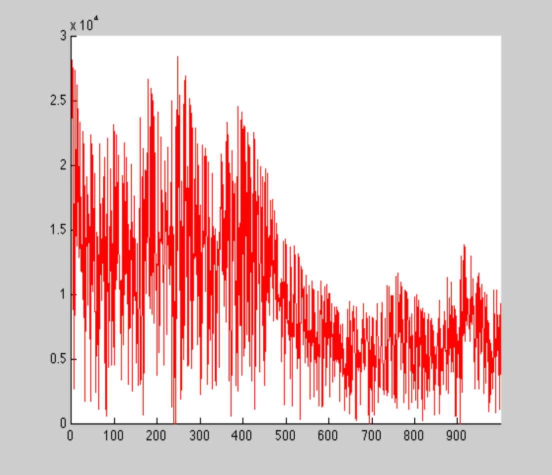
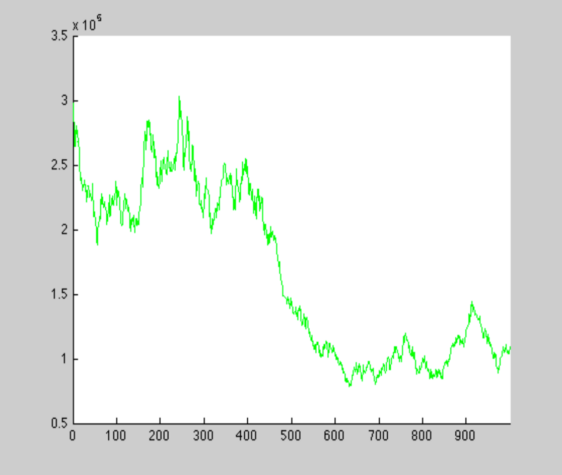
Harvest: Mean = 9,926 St. Dev. = 5,954 Minimum Value = 0 Maximum Value = 28,367	Elephant population: Mean = 166,013 St. Dev. = 65,602 Minimum Value = 78,600 Maximum Value = 303,163
	

Figure 4.8: Harvest and elephant population with two poaching gangs (single simulation; $\pi(a_t) = 0.05$).

To continue our line of analysis adopted for the previous cases, we plot the average of 1,000 simulations for the case of two gangs operating under $\pi(a_t) = 0.05$. One sees a mean average for realized poaching expeditions increase to 23.63, which is higher than the critical value, $n_c = 23.4375$. The variance of the average elephant population is split into two parts: 432,267,466 for t = 100 to 500, and 121,045,740 for t = 501 to 1000. The results are shown in Figure 4.9. This difference in the variance for the two time periods shows that the initial decline is steeper than the latter. The frequency with which $n_t > n_c$ is such that the elephant population exhibits a slow decline toward extinction although none of the 1,000 realization resulted in extinction before $t = 1{,}000$. The stochastic nature of realized poaching expeditions, where in some years $n_t < n_c$, can significantly slow the descent toward extinction. In years where $n_t < n_c$ the elephant population may increase in the following year. The average harvest of the two poaching organizations combined is estimated to be 8,896 elephants over the 1,000 year time horizon. A maximum average harvest of 23,932 occurs at the starting period in the simulations, which corresponds to the year 2006. I note that this average maximum realized harvest of 23,932 is close to the estimated 23,000 elephants killed in the empirical study of Wasser *et. al.* (2007).

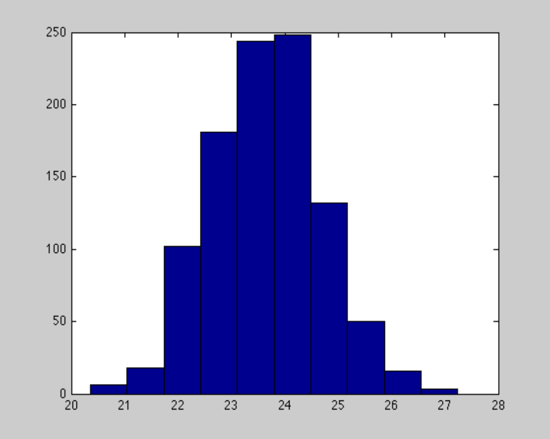
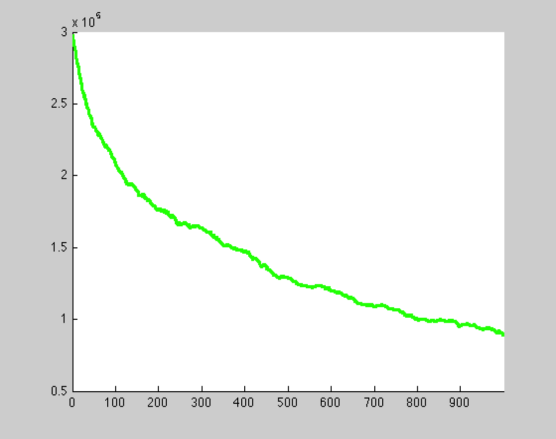
Distribution of realized number of trips: $\overline{n_t} = (1/1000)\sum_{j=1}^{1{,}000} n_{j,t}$ for $t = 0,1,\ldots,999$. Mean = 23.63 Variance = 1.039 Minimum Value = 20.36 Maximum Value = 27.24	Distribution of realized population: $\overline{X_t} = (1/1000)\sum_{j=1}^{1{,}000} X_{j,t}$ for $t = 100,\ldots,999$. Mean = 131,872 Variance (t = 100 to 500) = 432,267,466 Variance (t = 501 to 1000) = 121,045,740 Minimum Value = 88,922 Maximum Value = 208,919
	

Figure 4.9: Summary statistics for two poaching gangs; $\pi(a_t) = 0.05$, $n_t^* = 19$

When the number of poaching gangs increases to three, the descent to low population levels is much more rapid. Here too I note the occurrence of a stochastic bifurcation. The median crossing time occurs sooner when there are three gangs as opposed to two gangs, given a probability of detection and interception of $\pi(a_t) =$□0.05. For all 1,000 simulations, the median crossing time is $t_{\pi(a_t)=0.05}^{three\ gangs}$ =182, and the elephant population dropped below the chosen critical value of X_c =150,000 in all simulations.

In Figure 4.10 most of realized poaching expeditions are above $n_c = 23.4375$ with a maximum annual average of $\overline{n_t} =$ 39.26. The elephant population goes into an immediate and steep decline and by period $t =$ 200, the population has declined below 14,000 elephants and the three poaching gangs have reduced their number of planned poaching expeditions to between $n_t^* =$ 10 and 12. This alters the dynamics of the elephant population. A reduction in the planned poaching expeditions by all three gangs may stabilize the population at a low steady-state level of 1,497 after $t =$ 150. The variance of the average elephant population for the years $t =$ 100 to 150 is 7,664,541, while for the years $t =$ 151 to 1,000 the variance is much lower at 130,024. The average harvest level with three poaching organizations is estimated to be 897 elephants over the time period t =151 to 1,000. The maximum average harvest was estimated to be 26,806 elephants at the beginning time period of these simulations. This is higher than the corresponding 23,932 elephants killed under the previous case of two gangs, each facing $\pi(a_t) =$ 0.05.

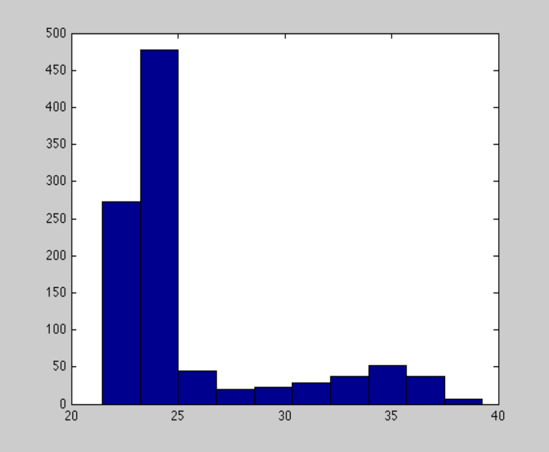
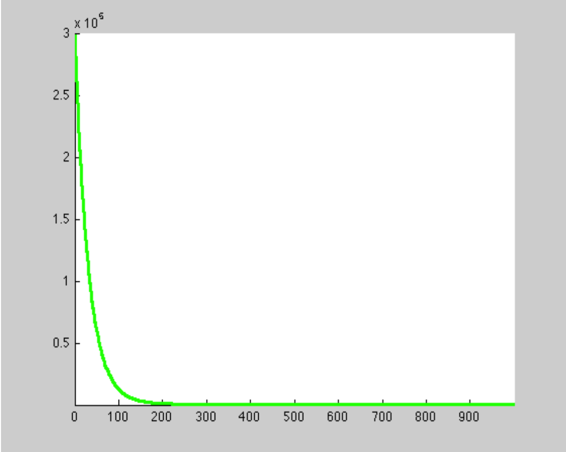
Distribution of realized number of trips: $\overline{n_t} = (1/1000)\sum_{j=1}^{1,000} n_{j,t}$ for $t = 0,1,\ldots,999$. Mean = 25.54 Variance = 17.14 Minimum Value = 21.46 Maximum Value = 39.26	Distribution of realized population: $\overline{X_t} = (1/1000)\sum_{j=1}^{1,000} X_{j,t}$ for $t = 100,\ldots,999$. Mean = 1,497 Variance (t = 100 to 150) = 7,664,541 Variance (t = 151 to 1000) = 130,024 Minimum Value = 1,001 Maximum Value = 13,540
	

Figure 4.10: Summary statistics for three poaching gangs; $\pi(a_t) = 0.05$, $n_t^* = 19$

Given the dramatic changes in system dynamics with additional gangs in operation under different levels of detection and interception probability, I summarize the qualitative dynamic behavior of the above six cases in Table 4.3.

Table 4.3: Stochastic Behavior of the Elephant Population with One, Two, and Three Poaching Gangs when $\pi(a_t) = 0.10$ and $\pi(a_t) = 0.05$

	One Gang	**Two Gangs**	**Three Gangs**
$\pi(a_t) = 0.10$	Stationary distribution	Stationary distribution	Stationary distribution
$\pi(a_t) = 0.05$	Stationary distribution	Apparent stochastic bifurcation	Stochastic bifurcation

One can potentially determine the number of poaching organizations that might operate under “open access” conditions with our base-case set of model parameter values. Despite the small population levels with three gangs in operation, poaching is still profitable with median net revenue of \$26,295 per year. With the lure of profits additional organizations may enter the illegal business of elephant poaching in the Southern African range states. This would occur until it is no longer profitable for additional organizations to operate, or the elephant population goes extinct. It was noted in Figure 4.10 that the minimum population was 1,001 over the time period $t =$ 151 to 1,000. There might still exist economic incentive for additional poaching organizations to enter the illicit poaching market. This might happen even though the elephant population settles into a low steady state value. Poaching gangs might target smaller sub-populations of elephant, and this would potentially lead to extinction.

In Table 4.4 I report the average statistics from simulation exercises with an increase in the number of poaching gangs in operation to ten, fifteen, and twenty gangs. This is done for the two values of the probability of detection, $\pi(a_t) = 5\%$ and 10%. I note that extinction of the elephant population in the Southern African range states occurs in each of the scenarios considered. The number of planned poaching trips/expeditions drops down to 3, 2, and 1 when the number of gangs increases to 10, 15, and 20. However in the beginning time periods of the simulation when the population is high the total harvest increases to as much as 166,226 by 20 gangs. As a result of high harvest levels initially, the total harvest by these poaching gangs eventually declines to 14 for 20 gangs under $\pi = 5\%$. The total number of realized poaching trips/expeditions declines to little as 17, which implies that for 20 gangs the average is less than 1 poaching expedition per year. With the possibility of elephant populations settling into low levels, it may be unviable to support high-tech, organized poaching, and there might be an evolution back to small-scale, local, low-tech, gangs operating under open access conditions.

Table 4.4: Elephant extinction under open access in the Southern African range states

	10 gangs		**15 gangs**		**20 gangs**	
	$\pi = 5\%$	$\pi = 10\%$	$\pi = 5\%$	$\pi = 10\%$	$\pi = 5\%$	$\pi = 10\%$
Population (median)	363	680	324	417	318	405
Total Harvest (minimum)	18	33	14	20	14	17
Total Harvest (median)	21	41	19	25	19	24
Total Harvest (maximum)	92,144	43,519	131,396	65,164	166,226	90,468
Total Poaching trips (minimum)	22	21	18	20	18	17
Total Poaching trips (median)	26	26	25	25	24	24
Total Poaching trips (maximum)	131	61	184	90	243	118
Profit minimum (per gang)	984	5,097	406	1,024	315	847
n^*	3	3	2	2	1	1
Elephant extinction	Yes	Yes	Yes	Yes	Yes	Yes

Lastly, in Table 4.5 I consider changing the economic parameter values in our model to analyze how they affect the key results of this chapter. The economic parameters include the black market ivory price, P, the cost per poaching expedition, c, and the catchability coefficient, q. The sensitivity analysis is conducted for a single poaching gang. For the black market price I consider an increase and a decrease from the base-case value of $P = \$3{,}000$ for a pair of ivory tusks in Table 4.2. I note that the number of planned poaching expeditions does not change for either of these cases, and remains at $n^* = 9$. Only the profit increases significantly when the price is raised to \$4,000. Changing the cost parameter also does not affect the key results of this chapter. The planned number of poaching expeditions remains at $n^* = 9$. I also examine what happens when the catchability coefficient doubles from $q = 2.56*10^{-3}$ to $5.12*10^{-3}$. The median harvest increases to 10,035 and the median population declines to 356,849 compared to their respective base-case values. However there is no change in the planned poaching expeditions. When the catchability coefficient decreases from $q = 2.56*10^{-3}$ to $2.56*10^{-4}$ I note that median harvest declines dramatically to 550. Again there is no change in the planned poaching expeditions, and it remains at $n^* = 9$.

Table 4.5: Sensitivity analysis of model parameters for the case of one poaching gang.

	Base case parameters [a]	$P = 500$	$P = 4{,}000$	$c = 3{,}000$	$c = 500$	$q = 5.12*10^{-3}$	$q = 2.56*10^{-4}$
Population (minimum)	375,790	371,920	372,448	373,296	373,638	348,187	390,205
Population (median)	376,975	376,948	376,741	377,005	376,921	356,849	390,586
Total Harvest (minimum)	1,637	2,024	2,021	2,305	1,910	3,413	270
Total Harvest (median)	5,307	5,304	5,412	5,364	5,330	10,035	550
Total Harvest (maximum)	8,028	8,107	8,075	8,105	8,513	15,770	889
Total Poaching trips (minimum)	4	2	2	2	2	1	2
Total Poaching trips (median)	5	5	5	5	5	5	5
Total Poaching trips (maximum)	6	8	8	8	8	8	9
Profit minimum (per gang)	8,982,000	1,478,000	12,091,000	9,108,200	8,895,000	16,716,000	924,480
n^*	9	9	9	9	9	9	9
Elephant extinction	No	No	No	No	No	No	No

[a] Refer to Table 4.2 for the base-case values of the economic parameters of the model.

4.5 Conclusions and Caveats

This chapter has developed a model of high-tech, stochastic poaching where the number of elephant killed by poachers is a random variable determined by the realized number of completed poaching expeditions. Stochastic poaching induces a stochastic evolution in the elephant population. The salient results of this chapter are as follows. First, the optimal number of planned poaching expeditions may be relatively insensitive to the black-market price for ivory and the elephant population, but quite sensitive to the probability of detection and interception by anti-poaching patrols. Second, increasing the number of poaching gangs not only lowers the mean of the elephant population but also increases the variance of its stationary distribution, when a stationary distribution exists. Third, if poaching gangs were to become more high-tech and thereby lower the probability of detection by anti-poaching patrols, the number of planned poaching expeditions increases and the frequency with which realized expeditions exceed the critical value, $n_c = (r - m)/q$, may increase. This may cause the elephant population to start a slow descent toward extinction. Fourth, when the probability of interception is low (i.e. $\pi(a_t) = 0.05$), the addition of a third, high-tech poaching gang results in a stochastic bifurcation where the elephant population permanently drops below a critical threshold. This can cause the poaching gangs to lower the number of planned poaching expeditions to below the critical threshold of $n_c = 23.4375$, and thereby allow the elephant population to stabilize at a low level.

Under open access conditions there is incentive for additional poaching gangs to operate as long as positive profits are expected, or the elephant population is not extinct. I examined this possibility for up to twenty poaching gangs. The planned number of poaching expeditions declines to one trip per year when twenty gangs operate. There are high levels of poaching in the beginning time periods of our simulations, and this causes the population to rapidly decline towards extinction. With rapidly declining elephant populations the planned expeditions eventually begin to decline. The expected profits also decline and this decreases the incentive for additional gangs to operate.

The simulated estimates of poaching or illegal harvest levels are corroborated by anecdotal evidence and reports of elephant poaching in the Southern African range states. I noted earlier in this chapter that Wasser *et. al*. (2007) estimated that approximately 23,000 savannah elephants were illegally harvested from the southern African range states in 2006. The closest simulated result that I derived was an average of 23,932 elephants killed per year across the Southern African elephant range states. This was the scenario of two poaching gangs that became more high-tech, thereby lowering the probability of detection to $\pi(a_t) = 0.05$. The planned number of expeditions increased to $n_t^* = 19$ from the base-case value of 9. In this scenario I also noted that the elephant population begins a slow descent towards extinction.

The model in this chapter has no spatial dimension; more realistic models should incorporate spatial differences between the range states in Southern Africa, including suitable habitat, the current size of elephant populations in those countries, the migration of elephant between countries, and most importantly, the country-specific investment to prevent poaching. Based on the location of elephant and the expected number of anti-poaching patrols, a poaching gang would need to determine not only the number of planned expeditions but their location. The resulting model might be viewed as a repeated game between poachers and anti-poaching patrols with sub-game strategies that would depend on the location of elephant herds and the expected deployment of anti-poaching patrols. High-tech poaching will require a high-tech, game-theoretic strategic response. In the next chapter of this dissertation I develop a model of strategic interaction between poachers and anti-poachers in terms of their location choices in space.

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CHAPTER 5

POACHING AND THE PROTECTION OF AN ENDANGERED SPECIES: A GAME-THEORETIC APPROACH

5.1 Introduction

As noted in Chapter 4 the poaching of endangered species has increased significantly over the last decade. Species such as elephants and rhinos have been subject to increasing levels of poaching, which pose a significant threat to their sustainability (Sas-Rolfes, 2012; Wasser et al., 2007; Wasser et al., 2008). Endangered species are often distributed over large areas of Africa and Asia. Anti-poaching or protection units have limited resources at their disposal, which makes it unlikely that they can choose to simultaneously protect all areas inhabited by the endangered species. Anti-poaching units would have to behave strategically by choosing where to devote patrolling activities so as to increase the chances of intercepting and destroying poaching units. Poaching units might also behave strategically by choosing where to poach so as to increase the chances of avoiding anti-poaching units. In this chapter we propose a novel theoretical framework to examine such strategic interaction and relate it to the ecological aspects of endangered species – including population growth over time and population dispersal over space. This chapter asks the following questions: (1) “What anti-poaching strategy can best combat the best strategy of a poaching unit in terms of location choices?” and (2) “How do these strategies affect the population sustainability of an endangered species?”

The biological literature provides interesting insight into strategic interaction between opposing entities. For instance, in host-parasite systems such interactions have been modeled as zero-sum games, which provide a framework to study the evolutionary fitness of strategies for hosts and parasites (Adami, Schossau, & Hintze, 2012; Cohen & Newman, 1989; Kerr et al., 2002; Kirkup & Riley, 2004). A parasite may favor one distribution of possible strategies so as to maximize the mean change in its net reproductive rate. The host, in defending itself from the parasite, will favor a different distribution, one that minimizes the net reproductive rate of the parasite (Cohen & Newman, 1989). The value of the host-parasitic interaction may be defined as the mean change in net reproductive rate when evolutionary fitness forces the parasite to maximize the mean change in its net reproductive rate, given that the host is evolving (choosing strategies) by minimizing the net reproductive rate that the parasite can achieve. Cohen & Newman (1989) find that the best mean change in the parasite's net reproductive rate results from the randomization of strategies from stable distributions for parasites and hosts. In the context of this chapter we provide a framework to examine the strategic, antagonistic interaction between opposing units – poachers and anti-poachers.

Economists usually model poaching as optimal harvesting decisions under open access, steady-state equilibrium i.e. species population growth is exactly offset by species population harvest in bio-economic models. Such models predict how steady-state levels of endangered species populations respond to conservation policies and changes in economic parameters.[6] Other studies note that ecological systems are often in a state of flux and therefore models should extend their scope beyond steady-state equilibrium

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[6] A number of studies analyze how poaching is affected by various conservation policies – including trade bans (Bulte & van Kooten, 1999, Burton, 1999), fines for poaching (Bulte & van Kooten, 1999, Damania, Milner-Gulland, & Crookes, 2005, Damania et al., 2003, Milner-Gulland & Leader-Williams, 1992, Skonhoft & Solstad, 1998), alternative livelihoods options when there are conflicting land use and species conservation priorities(Fischer, Muchapondwa, & Sterner, 2011, Johannesen & Skonhoft, 2005, Skonhoft, 2007), price-control through supply restrictions(Brown & Layton, 2001, Kremer & Morcom, 2000, Mason, Bulte, & Horan, 2012), and the controversial shoot-poachers-on-sight policy (Messer, 2010).

(Barrett & Arcese, 1998; Skonhoft, 2007). Moreover species populations are known to disperse over large areas by virtue of population movements or migration. When studying ecological systems that have resources distributed heterogeneously in space (Sanchirico & Wilen, 1999a) note that a considerable amount of economic behavior of resource harvesters is unaccounted for when a model ignores such heterogeneity. Bulte et al. (2004) and Skonhoft (2007) note that models linking ecology and economics should incorporate variability, complexity, scale, and uncertainty; thereby emphasizing the need for further research on the interaction between ecological variability and the economic behavior of individuals. With ecosystems continually changing models should incorporate ecological variability of interconnected habitats and the opportunity costs of protecting them (Bulte et al., 2004). For instance, in a spatial econometric study Frank & Maurseth (2006) find that elephant population changes in one country positively affect population changes in neighboring countries or habitats. Frank & Maurseth (2006) hypothesize that poachers account for variations in anti-poaching enforcement in different habitats; thereby emphasizing that economic behavior is dependent on the spatial aspects of resource distribution. Natural resource models allow for spatial heterogeneity of the resource and connectivity between meta-populations through population dispersal (Conrad & Smith, 2012; Sanchirico & Wilen, 1999a; Skonhoft, 2007).[7]

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[7] (Sanchirico & Wilen, 1999a) show how the dispersal of meta-populations can be modeled in several ways – such as fully integrated systems, closed systems, sink-source systems, and spatially linear systems. In a fully integrated system biomass disperses directly from one patch to any other patch in the system. In a closed system the maintenance of biomass density within each region is only determined by its own production and no dispersal occurs anywhere in the system. In a sink-source system one or more patches provide unidirectional biomass movement to other patches. In a spatially linear system one can have dispersal in a pairwise fashion between adjacent patches. Animal population dispersal is often observed as being of the sink-source variety – for instance the African savannah elephant (Muchapondwa & Ngwaru, 2010; Van Aarde et al., 2008), the wildebeest (Johannesen & Skonhoft, 2004), reindeer and moose (Skonhoft, 2007) usually migrate seasonally depending on food availability in different climatic regions.

In this chapter we do not examine resource harvesting and protection decisions in terms of their optimal magnitudes or levels (since this has been dealt with extensively by previous studies as noted). Instead we focus on the strategic interaction between poachers and anti-poachers in terms of choosing locations (i.e. patches or habitats) to poach and protect respectively in the presence of a spatially distributed resource. Successful poaching (unsuccessful protection) versus unsuccessful poaching (successful protection) will be the stochastic outcome of a repeated game. Using insights from the biological literature on antagonistic interactions, we will consider how randomization might lead to higher evolutionary fitness, or higher payoffs, for both poaching units as well as anti-poaching units. We will also examine the effects of different location choice strategies on species population dynamics and sustainability. In section 5.2 we lay out the components of the game, the payoffs and potential strategies of the opponents, a solution for a Nash equilibrium, and simulations of the model. In section 5.3 we provide a discussion of the model's simulation results, some caveats, and a conclusion.

5.2.1 A Model of Poaching and Protection

Consider a "space" represented by a three-by-three grid as shown in Figure 5.1. The protected species population is distributed spatially and temporally across the nine patches or cells as and when seasonal migration takes place. In season one of the first year the population is distributed over seasonal patches 1, 2, & 3 in the row denoted season $s = 1$. In season two migration of the meta-populations in the three seasonal patches takes place from row $s = 1$ to row $s = 2$, when the meta-populations flow to the subsequent three seasonal patches. Migration routes follow a northward direction from season one through season three, and then turn southward in season four, returning to the seasonal patches 1, 2, & 3 at the beginning of season one in the subsequent year. Migration coefficients determine the population distribution across the grid, over the four seasons, in each year. Thereby the meta-populations are distributed in the seasonal patches 1, 2, & 3 in seasons one, two, three, and four in the rows denoted by season $s = 1$, $s = 2$, $s = 3$, and $s = 4$ respectively. The migration cycle continues year after year.

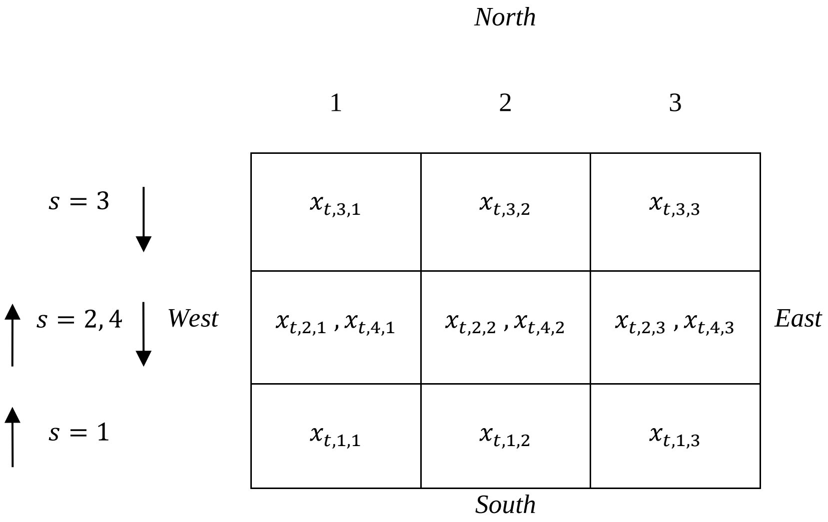

Figure 5.1: Space within which seasonal migration, poaching and anti-poaching patrolling take place.

A poaching unit and an anti-poaching unit choose patches to operate in each season. The poaching unit wants to choose a patch that has no anti-poaching unit in it in order to successfully harvest the patch population. At the same time the anti-poaching unit wants to choose the same patch as the poaching unit in order to intercept it, and thereby successfully preserve the resident patch population. If the poaching unit selects a different patch from the anti-poaching unit , the poaching unit kills some proportion of the resident patch's animal population. If both choose the same patch then the poaching unit is decommissioned for the rest of that year, and a new poaching unit forms in season one of the following year. In each season both units know the population distribution in the three seasonal patches. We use the following notation for our model:

$i, j = 1, 2, 3$: seasonal patch index,

$\mathrm{s} = 1, 2, 3, 4$: number of seasons within a year,

$t = 1, 2, \dots, T$: year index,

$x_{t,s,i}$: species meta-population in time period t, in season s, in patch i.

$m_{s,j,i}$: migration coefficient for meta-population flowing from patch j in season s, to patch i in season $s+1$; $0 \leq m_{s,j,i} \leq 1$, $\sum_{i=1}^{3} m_{s,j,i} = 1$,

$0 < q \leq 1$: kill rate of the poaching unit,

$k_{t,s,i} = q x_{t,s,i} \geq 0$: population lost to poaching in year t, in season s, in patch i,

$x_{t,s+1,i} = m_{s,i,i}\left(x_{t,s,i} - k_{t,s,i}\right) + \sum_{j \neq i} m_{s,j,i}\left(x_{t,s,j} - k_{t,s,j}\right)$: species meta-population in year t, in season $s+1$, in patch i,

$x_{0,1,i}$: initial population distribution in $t = 0$, in $s = 1$, in patch i,

In season one of each year the population is augmented by the offspring of population that survives poaching and natural mortality in the previous year. The surviving meta-populations in season one of the next year, $t+1$, can be denoted as per the iterative map (5.1), with $F(\cdot)$ being a population growth function:

$$x_{t+1,1,i} = \left\{m_{4,i,i}\left[x_{t,4,i} + F(\cdot) - k_{t,4,i}\right] + \sum_{j \neq i} m_{4,j,i}\left[x_{t,4,j} + F(\cdot) - k_{t,4,j}\right]\right\} \tag{5.1}$$

Given the seasonal location of the species' meta-populations, the poaching unit and the anti-poaching unit must make binary decisions $G_{t,s,i} = \{0, 1\}$ and $P_{t,s,i} = \{0, 1\}$ in season $s =$ 1, 2, 3, and 4, in patch i =1, 2, and 3. With only one patch chosen by the poaching unit and the anti-poaching unit we impose the restriction that $\sum_i G_{t,s,i} = 1$ and $\sum_i P_{t,s,i} = 1$.

5.2.2 Payoffs and Strategies

Location or patch choice strategies could potentially depend on the population distribution in the seasonal patches. We assume the poaching unit is myopic and maximizes the *expected* payoff in each season given the chosen strategy of the anti-poaching unit. With myopic poaching in each season the anti-poaching unit maximizes its own *expected* payoff, or equivalently minimizes the *expected* loss to poaching for a given population distribution. Similar to how hosts and parasites choose to randomize strategies for their own evolutionary fitness (as noted in section 5.1) we will now consider whether randomization of patch choice strategy by poaching and the anti-poaching units lead to higher payoffs when the game is repeated. The poaching unit might consider randomizing using the population in the seasonal patches to generate a discrete distribution for selecting a patch in which to poach. The anti-poaching unit similarly generates a discrete distribution for selecting a patch to patrol. For ease of notation we can ignore the season (s) and time (t) subscripts of the meta-populations in the seasonal patches and refer to $x_{t,s,1}$, $x_{t,s,2}$, and $x_{t,s,3}$ simply as x_1, x_2, and x_3.

As payoffs let us consider the following. If, for instance, in a given season the poaching unit chooses seasonal patch 1 and the anti-poaching unit chooses another seasonal patch j ($\neq 1$) then the poaching unit achieves a payoff of qx_1, which is the population killed since the poaching unit would have successfully evaded the anti-poaching unit. The anti-poaching unit therefore loses qx_1 of the population to poaching. If however both choose the same patch then the poaching unit is destroyed and there is no loss of that patch's resident population to poaching. Consequently the poaching unit is destroyed and there are no gains for the poaching unit.[8] We assume that the cost of choosing a patch is zero for both the poaching unit and the anti-poaching unit. We further assume that the gain to the anti-poaching unit when choosing the same patch as the poaching unit is only the amount of the resident species population that is not lost to poaching, i.e. zero. We can thereby formulate the payoffs and losses, to the poaching unit and anti-poaching unit respectively, as a zero-sum game. Since the kill rate of the poaching unit (q) is a common term we can ignore it in the payoff matrix shown in Figure 5.2.

		Anti-poaching unit		
		Patch 1 (p_1)	Patch 2 (p_2)	Patch 3 (p_2)
Poaching unit	Patch 1 (g_1)	$0, 0$	$x_1, -x_1$	$x_1, -x_1$
	Patch 2 (g_2)	$x_2, -x_2$	$0, 0$	$x_2, -x_2$
	Patch 3 (g_3)	$x_3, -x_3$	$x_3, -x_3$	$0, 0$

Figure 5.2: Payoff matrix of the seasonal game.

We denote the set of possible actions (patch choices of the poaching unit and the anti-poaching unit) as $L = \{1, 2, 3\}$. We denote $\Delta G = \{(g_1, g_2, g_3) \in \mathbb{R}^3 | (g_1, g_2, g_3) \geq 0 \,\&\, \sum_{i=1}^{3} g_i = 1\}$ as the set of probability distributions of the poaching unit on L. Similarly we denote $\Delta P = \{(p_1, p_2, p_3) \in \mathbb{R}^3 | (p_1, p_2, p_3) \geq 0 \,\&\, \sum_{i=1}^{3} p_i = 1\}$ as the set

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[8] We ignore any monetary cost (such as poaching fines) to the poaching unit when decommissioned since this could be considered as a transfer from the poaching unit to the patrol with the same property of a zero-sum payoff in the game.

of probability distributions of the anti-poaching unit on L. $\pi_G(l_G, l_P)$ is the poaching unit's payoff associated with the action pair $(l_G, l_P) \in L \times L$. The poaching unit's expected payoff for a pair of mixed strategies $(g, p) \in \Delta G \times \Delta P$ would equal $E[\pi_G(g,p)] = \sum_{(l_G,l_P)\in L\times L} g(l_G)p(l_P)\,\pi_G(l_G, l_P)$. Similarly the anti-poaching unit's expected payoff for a pair of mixed strategies $(p, g) \in \Delta P \times \Delta G$ would equal $E[\pi_P(p,g)] = \sum_{(l_P,l_G)\in L\times L} p(l_P)g(l_G)\,\pi_P(l_P, l_G)$.

The payoff matrix in Figure 5.2 shows that there are no dominant strategies for either the poaching unit or the anti-poaching unit. We use the property that any two-player game must have at least one Nash equilibrium (Gibbons, 1992) to derive a solution to the game. With no dominant strategies for either player the solution is that of a mixed strategy Nash equilibrium. We list the associated Nash equilibrium probabilities over the action spaces for the poaching unit and the anti-poaching unit. The derivation of the mixed strategy Nash equilibrium and a proof of its uniqueness are provided in Appendix 5.1.

$$g_1^* = \frac{x_2x_3}{x_1x_2+x_2x_3+x_1x_3}\,,\; g_2^* = \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}\,,\; g_3^* = \frac{x_1x_2}{x_1x_2+x_2x_3+x_1x_3}\,,$$

$$p_1^* = \frac{x_1x_2+x_1x_3-x_2x_3}{x_1x_2+x_2x_3+x_1x_3}\,,\; p_2^* = \frac{x_1x_2+x_2x_3-x_1x_3}{x_1x_2+x_2x_3+x_1x_3}\,,\; p_3^* = \frac{x_1x_3+x_2x_3-x_1x_2}{x_1x_2+x_2x_3+x_1x_3}\,.$$

In a system with *two seasonal patches* we can similarly derive the associated mixed strategy Nash equilibrium probabilities over the action spaces of the poaching unit and the anti-poaching unit. The derivation and the uniqueness proof are provided in Appendix 5.1.

$$g_1^* = \frac{x_2}{x_1+x_2}\,, g_2^* = \frac{x_1}{x_1+x_2}\,,$$

$$p_1^* = \frac{x_1}{x_1+x_2}\,, p_2^* = \frac{x_2}{x_1+x_2}\,.$$

In order to derive the intuition behind this result we turn to the two-player game of rock-paper-scissors. In the two player zero-sum game of rock-paper-scissors Nouweland (2007) analytically proves that, with equal payoffs for each of the three actions, the unique mixed strategy Nash equilibrium is to play each action with equal probability, i.e. one-third each. If however one were to modify the game of rock-paper-scissors with unequal payoffs then it can be shown that on average the players will each choose an action depending on the chances of that action defeating their opponent's chosen action in such a way that expected payoffs for each action tend towards zero in equilibrium.[9] Drawing from the zero-sum game of rock-paper-scissors with uneven payoffs we can infer an interpretation of the mixed strategy Nash equilibrium $\left((g_1^*, g_2^*, g_3^*), (p_1^*, p_2^*, p_3^*)\right)$ in the economic game of poaching and protection. The poaching unit's probability of choosing a location depends on how often he expects the anti-poaching unit to choose the other location(s), given the seasonal population distribution. The anti-poaching unit's probability of choosing a location to patrol depends on how often it expects the poaching unit to choose that location, thereby minimizing the expected loss of population to poaching given the seasonal population distribution. We note that if the meta-populations were to be evenly distributed in a season then the mixed strategy Nash equilibrium values would be exactly $((1/3, 1/$

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[9] For example if the wining payoffs to rock, paper, and scissors are 1, 3, and 5 (i.e. rock beating only scissors with a payoff of 1, paper beating only rock with a payoff of 3, and scissors beating only paper with a payoff of 5), then it can be shown that players would choose to play rock with 5/9th probability, paper with 1/9th probability, and scissors with 3/9th probability.

$3,1/3),(1/3,1/3,1/3))$ in the three seasonal patches system, and $((1/2,1/2),(1/2,1/2))$ in the two seasonal patches system.

5.2.3 Simulations of the Game

Having derived a mixed strategy Nash equilibrium in our game of poaching and protection we proceed to study the effect of this strategy on the population dynamics of an endangered species. The model is applied to the case of the migratory savannah elephant (*Loxodonta africana*). The logistic growth function is often used to model elephant population dynamics (Bulte & van Kooten, 1999; Milner-Gulland & Leader-Williams, 1992). Following Milner-Gulland & Leader-Williams (1992) we adopt a skewed-logistic specification for the population growth function $F(x) = x + rx(1 - (x/c)^z)$. x is the population, r is the intrinsic net growth rate of population, c is the habitat carrying capacity, and z is a skew parameter. The surviving adult population at the end of season four of year t is augmented by the birth of juveniles in season one of the next year $t + 1$ as per the *iterative map* previously defined in (5.1):

$$x_{t+1,1,i} = \Big\{ m_{4,i,i} \left[x_{t,4,i} \left(1 + r\big(1 - (x_{t,4,i}/c_i)^z\big)\right) - k_{t,4,i} \right] + \sum_{j \neq i} m_{4,j,i} \left[x_{t,4,j} \left(1 + r\big(1 - (x_{t,4,j}/c_j)^z\big)\right) - k_{t,4,j} \right] \Big\}$$

Adult female elephants give birth to approximately one offspring every three years, which implies a population pregnancy rate of approximately 0.33 per year (Armbruster & Lande, 1993). The average natural mortality rate of elephants has been estimated at 0.27, which implies a net intrinsic growth rate of $r = 0.06$ (Armbruster & Lande, 1993). A skew parameter greater than one ($z > 1$) is used to model population dynamics of large mammals (Cromsigt et al., 2002); Bulte & van Kooten (1999) and Milner-Gulland & Leader-Williams (1992) set $z = 7$. We normalize the carrying capacity of the seasonal "space" to one (i.e. $\sum_i c_i = 1$), and assume it to be equally divided between the seasonal patches.

Using the data of Bulte & van Kooten (1999) on illegal off-take of elephants in African range states we calculate the off-take rates as varying between 0.03% and 3.8% of the resident elephant population in the mid-1990s. Noting the reports of organized criminal syndicates involved in elephant and rhino poaching in African range states (Mullen & Zhang, 2012; Sas-Rolfes, 2012; Shukman, 2013; Wassener, 2013; Wasser et al., 2008) it is likely that the scale and intensity of poaching has increased since the 1990s. Blanc (2007) estimates the savannah elephant population in Southern Africa as approximately 300,000 individuals. Based on data from seizures of illegal ivory shipments amounting to roughly 24 tons in the year 2006. Wasser *et. al.* (2007) use DNA analysis to estimate that approximately 23,000 savannah elephants were illegally harvested from the southern African range states. This evidence suggests an illegal off-take rate of approximately 7% to 8% in the year 2006. For the base-case set of parameters in the model we assume a poaching off-take/kill rate of $q = 0.07$. Table 5.1 lists the base-case values of the model's parameters.

Table 5.1: Model base-case parameter values

Parameter		Value	Source
Intrinsic growth rate	$r =$	0.06	(Armbruster & Lande, 1993)
Logistic growth skew parameter	$z =$	7	(Bulte & van Kooten, 1999; Milner-Gulland & Leader-Williams, 1992)
Poaching/off-take rate	$q =$	0.07	Based on data from Wasser *et. al.*(2007)
Initial meta-populations	$x_{0,1,i} =$	0.15 $(i = 1,2,3)$	
Carrying capacity	$\sum_i c_i =$	1	
Number of time periods	$T =$	100	

We assume an evenly distributed initial elephant population of $E_{0,1,1} = 0.15$, $E_{0,1,2} = 0.15$, and $E_{0,1,3} = 0.15$. Table 5.2 lists the migration coefficients for the spatial-temporal dispersal of the meta-populations in our space (Figure 5.1). For simplicity these migration or dispersal coefficients are held constant over time.

Table 5.2: Seasonal migration coefficients

$s = 1$:	$m_{1,1,4} = 0.4$	$m_{1,1,5} = 0.3$	$m_{1,1,6} = 0.3$
	$m_{1,2,4} = 0.3$	$m_{1,2,5} = 0.5$	$m_{1,2,6} = 0.2$
	$m_{1,3,4} = 0.1$	$m_{1,3,5} = 0.3$	$m_{1,3,6} = 0.6$
$s = 2$:	$m_{2,4,7} = 0.2$	$m_{2,4,8} = 0.5$	$m_{2,4,9} = 0.3$
	$m_{2,5,7} = 0.1$	$m_{2,5,8} = 0.4$	$m_{2,5,9} = 0.5$
	$m_{2,6,7} = 0.1$	$m_{2,6,8} = 0.4$	$m_{2,6,9} = 0.5$
$s = 3$:	$m_{3,7,4} = 0.5$	$m_{3,7,5} = 0.3$	$m_{3,7,6} = 0.2$
	$m_{3,8,4} = 0.4$	$m_{3,8,5} = 0.5$	$m_{3,8,6} = 0.1$
	$m_{3,9,4} = 0.2$	$m_{3,9,5} = 0.3$	$m_{3,9,6} = 0.5$
$s = 4$:	$m_{4,4,1} = 0.6$	$m_{4,4,2} = 0.2$	$m_{4,4,3} = 0.2$
	$m_{4,5,1} = 0.4$	$m_{4,5,2} = 0.5$	$m_{4,5,3} = 0.1$
	$m_{4,6,1} = 0.1$	$m_{4,6,2} = 0.2$	$m_{4,6,3} = 0.7$

As noted previously in the setup of the game the poaching unit wants to choose a patch with no anti-poaching unit, and the anti-poaching unit wants to choose the same patch. If different patches are selected the poaching unit kills some proportion (q) of the resident population. If both choose the same patch then the poaching unit is "decommissioned" for the rest of that year, but a new poaching unit forms in season one of the next year. Given initial conditions, the model parameters in Table 5.1, and the set of migration coefficients in Table 5.2, the random process of poaching and protection will cause the elephant population to evolve stochastically over T years. We simulate approach paths for a period of $T = 100$ years (i.e. 400 seasons) to garner insight of the long-term effects of location strategies on species population dynamics. Qualitatively different approach paths would arise depending on the type of strategy chosen by the poaching unit and anti-poaching unit.

We first study the effect on elephant population dynamics when the poaching unit and the anti-poaching unit randomize their seasonal location choices based on their respective mixed strategy Nash equilibrium probabilities.

Mixed strategy Nash equilibrium randomness:

$$\big((g_1, g_2, g_3), (p_1, p_2, p_3)\big) = \big((g_1^*, g_2^*, g_3^*), (p_1^*, p_2^*, p_3^*)\big)$$

Next we study the effect on elephant population dynamics when the poaching unit and the anti-poaching unit randomize their location choices uniformly with equal probability of choosing any of the seasonal locations.

Mixed strategy uniform randomness:

$$\big((g_1, g_2, g_3), (p_1, p_2, p_3)\big) = \big((1/3\,, 1/3\,, 1/3), (1/3\,, 1/3\,, 1/3)\big)$$

Given the previous two sets of strategies we consider two possible combinations of them. This can be used to determine if there is incentive for either the anti-poaching unit or the poaching unit to deviate from the Nash equilibrium. In the first combination the anti-poaching unit chooses the mixed Nash equilibrium strategy and the poaching unit deviates by choosing the uniform mixed strategy. In the second combination we look at the opposite case where the anti-poaching unit deviates by choosing the uniform mixed strategy and the poaching unit plays the Nash mixed strategy.

Mixed strategy: *Uniform and Nash equilibrium randomness*

$$\big((g_1, g_2, g_3), (p_1, p_2, p_3)\big) = \big((1/3\,, 1/3\,, 1/3), (p_1^*, p_2^*, p_3^*\,)\big)$$

or

$$\big((g_1, g_2, g_3), (p_1, p_2, p_3)\big) = \big((g_1^*, g_2^*, g_3^*\,), (1/3\,, 1/3\,, 1/3)\big)$$

Lastly we consider the effect on population dynamics when the strategy of the anti-poaching unit is to patrol the patch with the highest species meta-population. The strategy of the poaching unit is to select in the patch with the next highest meta-population.

Non-random strategy:

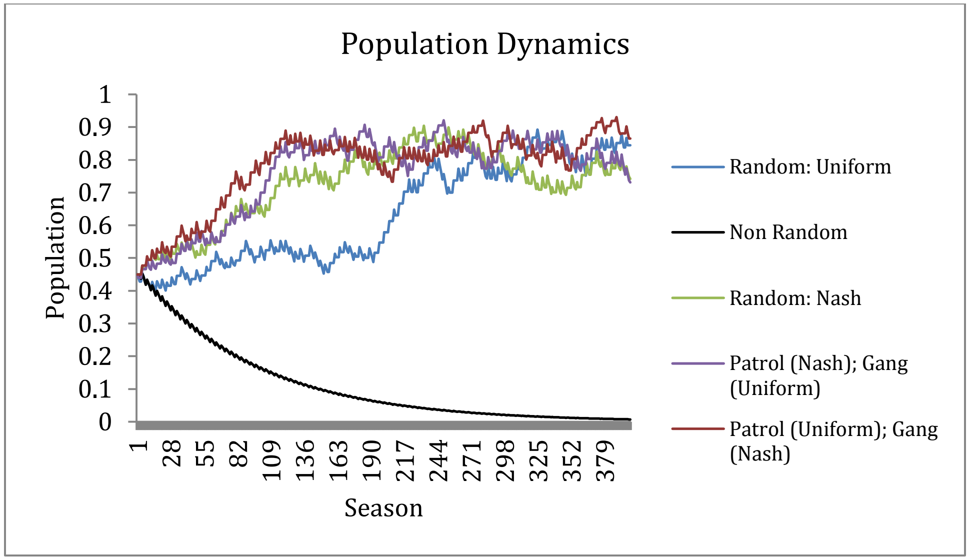
$$l_P = i, \qquad E_{t,s,i} \geq E_{t,s,j}\ (i \neq j)$$

$$l_G = j, \qquad E_{t,s,i} \geq E_{t,s,j} \; (i \neq j)$$

Population dynamics and the average payoffs to the anti-poaching unit and poaching unit under the different strategies as listed are compared with that of the mixed strategy Nash equilibrium. Figure 5.3 charts the results of a single simulation for each of the strategy sets over the one hundred year time horizon for the set of base-case model parameters. The simulations are repeated one thousand times and the average population and poaching levels are reported on the right-hand side panel of Figure 5.3. The mixed Nash strategy is shown in green; the uniform random strategy is shown in blue; the combination of the anti-poaching unit playing the Nash mixed strategy and the poaching unit playing the uniform random mixed strategy is shown in purple; the combination of the poaching unit playing the Nash mixed strategy and the anti-poaching unit playing the uniform random mixed strategy is shown in red; and finally the non-random strategy is shown in black. Each of the random strategies appear to have the effect of leading to higher elephant population over time when compared with the non-random strategy. For each of the strategy sets we list the average values of population and poaching from season two hundred to season four hundred, or the period of time when a stable distribution of population is attained. This reduces the effect of the initial conditions on the average values.

Let us study the average values of population and poaching of Figure 5.3 a little more closely. The average values of population and poaching are 0.82516 and 0.00745 in the mixed strategy Nash equilibrium. This is what the anti-poaching unit and the poaching unit can expect on average. Now we ascertain if there is incentive for either party to deviate from playing the Nash mixed strategy. If the poaching unit deviates by playing the uniform strategy while the anti-poaching unit continues playing the Nash strategy we note that the average poaching level declines to 0.00739 and the average population increases to 0.82657 which is statistically greater than the Nash equilibrium value at the ten percent error level. There is therefore no incentive for the poaching unit to deviate from playing the Nash strategy. If the anti-poaching unit deviates from playing the Nash strategy by playing the uniform random strategy, while the poaching unit continues to play the Nash strategy the anti-poaching unit is better off since the average population increases to 0.83374 and the average poaching level declines to 0.00724. The average population level is also statistically greater than the Nash equilibrium value at the one percent error level. Since the poaching unit is worse off it will consider playing the uniform random strategy as well and increase its average payoff- poaching value- to 0.00761. The average population value declines to 0.81551, which is statistically lower than the Nash equilibrium value at the one percent error level. This creates a disincentive for both the anti-poaching unit and the poaching unit to deviate from playing the mixed strategy Nash equilibrium.

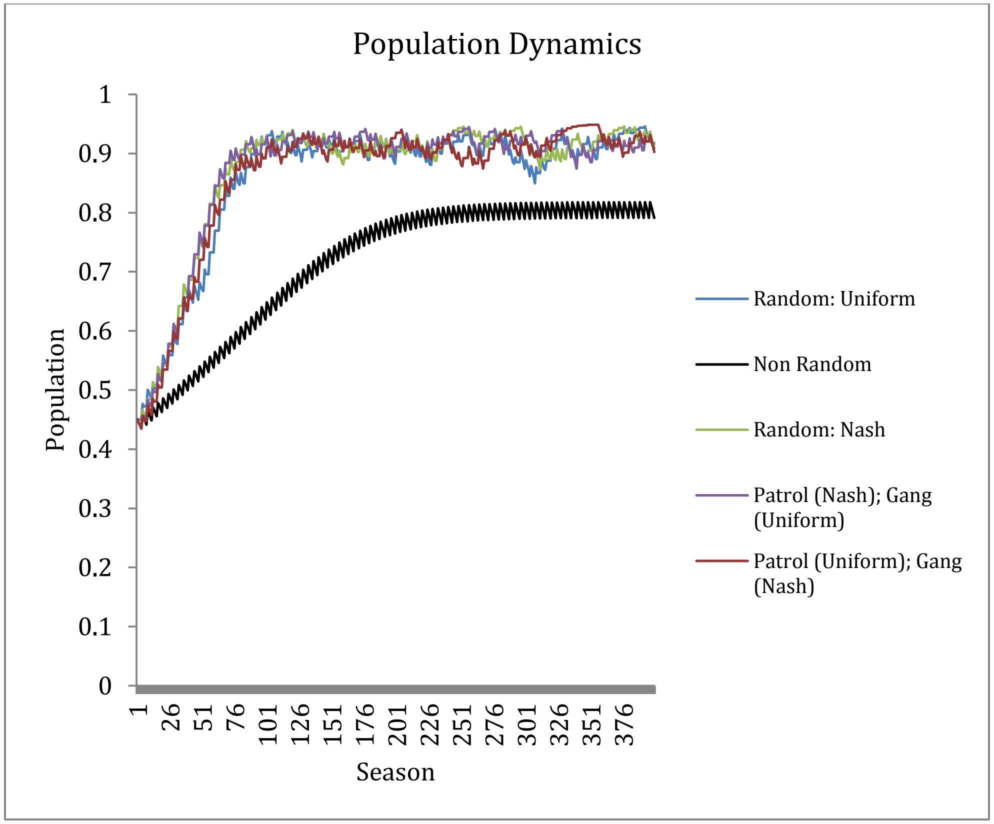
We carry out further numerical analyses by varying the poaching unit's kill rate, q, between 3% and 12% to account for a wide range of poaching efficiency rates. The simulation results are plotted in Figures 5.4 through 5.8 for $q =$ 3%, 5%, 8%, 10%, and 12%. We note that for q between 3% and 8% the broad results are similar to the base-case when $q =$ 7%. The differences in average population levels are statistically different from the Nash equilibrium average values. Apart from $q =$ 3% we note that the random strategies achieve higher average payoffs for both the anti-poaching unit and the poaching unit . Similar to the results in Figure 5.3 the simulated average values of population and poaching in Figure 5.4, Figure 5.5, and Figure 5.7 suggest that the Nash mixed strategy is a unique equilibrium on average. When the poaching off-take/ kill rate is increased to $q \geq 10\%$ we begin to notice that the differences in average poaching become statistically significant when compared with the average Nash equilibrium values. The population distributions are no longer stable and the variance increases dramatically. One thing that we do note is that the uniform random strategy does worse than the Nash for both units. In Figure 5.8 when $q = 12\%$ we note that the elephant meta-populations begin a slow decline towards extinction for each of the random location choice strategies. The non-random location choice strategies always result in very quick declines towards the meta-populations' extinction.



	Average Population $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=200}^{400}E_s}{400-200}\right)_n}{1000}$	**Average Poaching** $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=200}^{400}K_s}{400-200}\right)_n}{1000}$
Random: Uniform	0.81551 (9.0997)***	0.00761 (-0.4540)
Random: Nash	0.82516	0.00745
Anti-poaching unit (Nash); Poaching unit (Uniform)	0.82657 (-1.3756)*	0.00739 (0.1409)
Anti-poaching unit (Uniform); Poaching unit (Nash)	0.83374 (-8.4142)***	0.00724 (0.5557)
Non Random	0.02395 (649.97)***	0.00059 (26.89)***

Figure 5.3: Population and poaching dynamics with initial population set at 0.45, and poaching off-take set at $\boldsymbol{q = 0.07}$

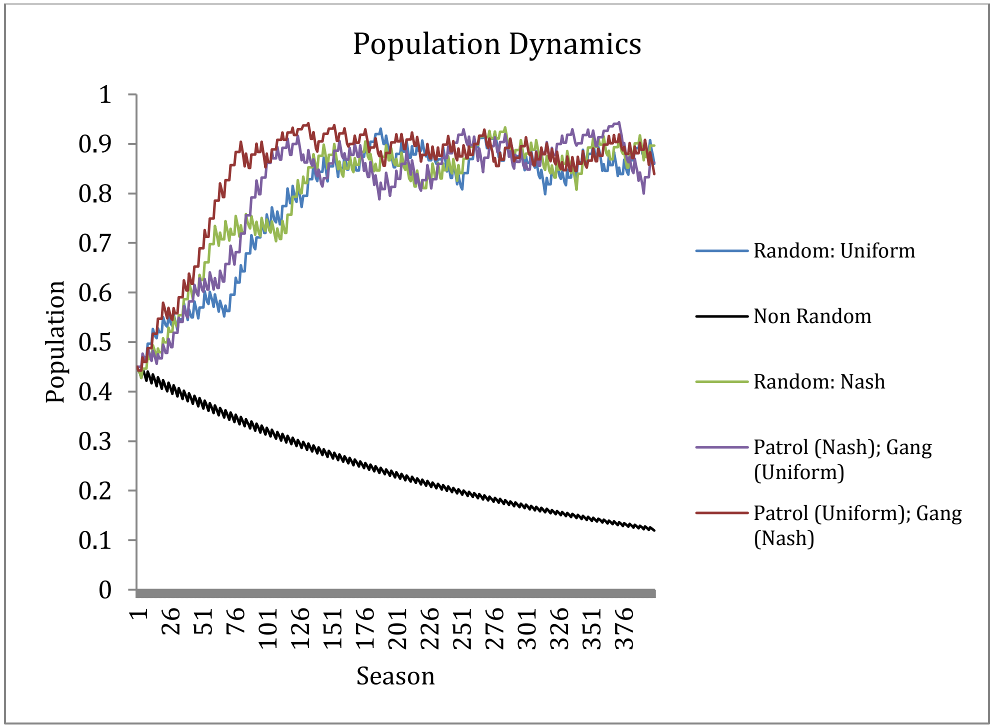
t-statistics of difference of means between Nash equilibrium value and other strategy's equilibrium value in (parentheses). *** statistically significant mean difference at 1% error level; ** statistically significant mean difference at 5% error level; * statistically significant mean difference at 10% error level.



	Average Population $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=200}^{400} E_s}{400-200}\right)_n}{1000}$	**Average Poaching** $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=200}^{400} K_s}{400-200}\right)_n}{1000}$
Random: Uniform	0.91152 (1.7298)**	0.00363 (-0.4554)
Random: Nash	0.91234	0.00355
Anti-poaching unit (Nash); Poaching unit (Uniform)	0.91317 (-1.7636)**	0.00350 (0.2926)
Anti-poaching unit (Uniform); Poaching unit (Nash)	0.91349 (-2.4717)***	0.00346 (0.5369)
Non Random	0.80046 (123.8)***	0.00856 (-35.94)***

Figure 5.4: Population and poaching dynamics with initial population set at 0.45, and poaching off-take set at $\boldsymbol{q = 0.03}$

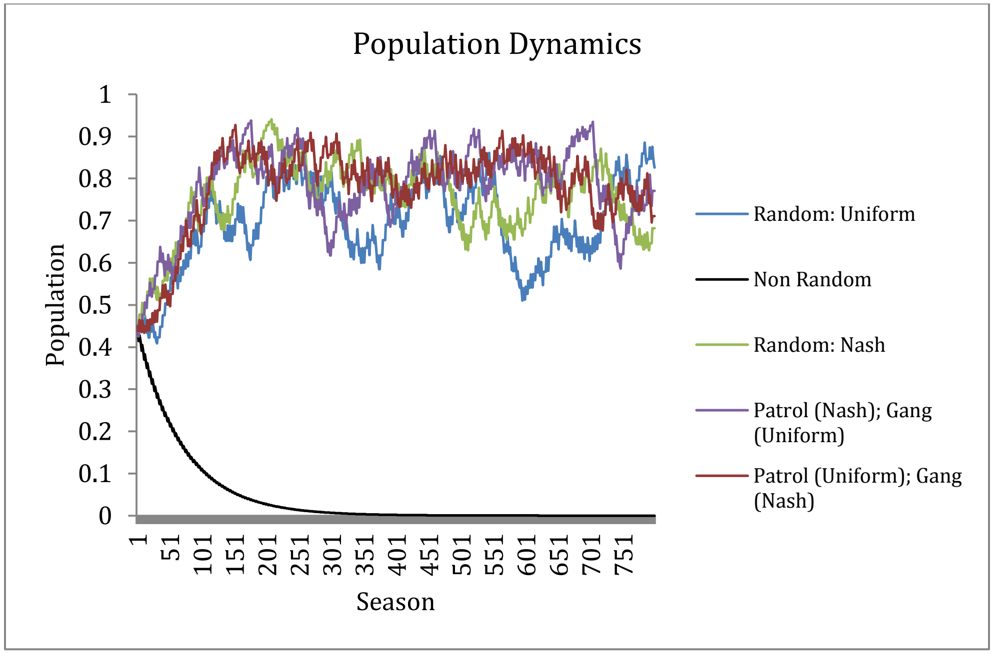
t-statistics of difference of means between Nash equilibrium value and other strategy's equilibrium value in (parentheses). *** statistically significant mean difference at 1% error level; ** statistically significant mean difference at 5% error level; * statistically significant mean difference at 10% error level.



	Average Population $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=200}^{400} E_s}{400-200}\right)_n}{1000}$	**Average Poaching** $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=200}^{400} K_s}{400-200}\right)_n}{1000}$
Random: Uniform	0.87432 (4.3353)***	0.00582 (-0.5483)
Random: Nash	0.87764	0.00568
Anti-poaching unit (Nash); Poaching unit (Uniform)	0.87913 (-1.9778)**	0.00559 (0.3412)
Anti-poaching unit (Uniform); Poaching unit (Nash)	0.88081 (-4.2492)***	0.00551 (0.5989)
Non Random	0.17331 (298.3)***	0.00309 (13.22)***

Figure 5.5: Population and poaching dynamics with initial population set at 0.45, and poaching off-take set at $\boldsymbol{q = 0.05}$

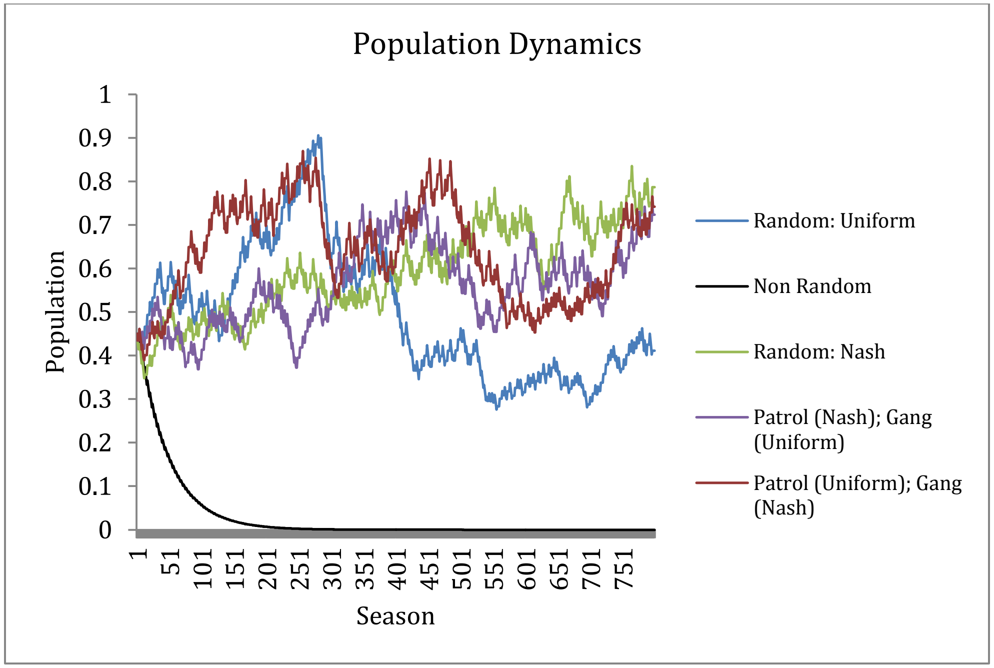
t-statistics of difference of means between Nash equilibrium value and other strategy's equilibrium value in (parentheses). *** statistically significant mean difference at 1% error level; ** statistically significant mean difference at 5% error level; * statistically significant mean difference at 10% error level.



	Average Population $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=800}^{1000} E_s}{1000-800}\right)_n}{1000}$	**Average Poaching** $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=800}^{1000} K_s}{1000-800}\right)_n}{1000}$
Random: Uniform	0.7786 (8.4741)***	0.00819 (-0.0535)
Random: Nash	0.7879	0.00817
Anti-poaching unit (Nash); Poaching unit (Uniform)	0.7918 (-3.6103)***	0.00806 (0.2664)
Anti-poaching unit (Uniform); Poaching unit (Nash)	0.7998 (-10.998)***	0.00799 (0.4408)
Non Random	0.0000 (1030.9)***	0.0000 (29.41)***

Figure 5.6: Population and poaching dynamics with initial population set at 0.45, and poaching off-take set at $\boldsymbol{q} = \mathbf{0.08}$

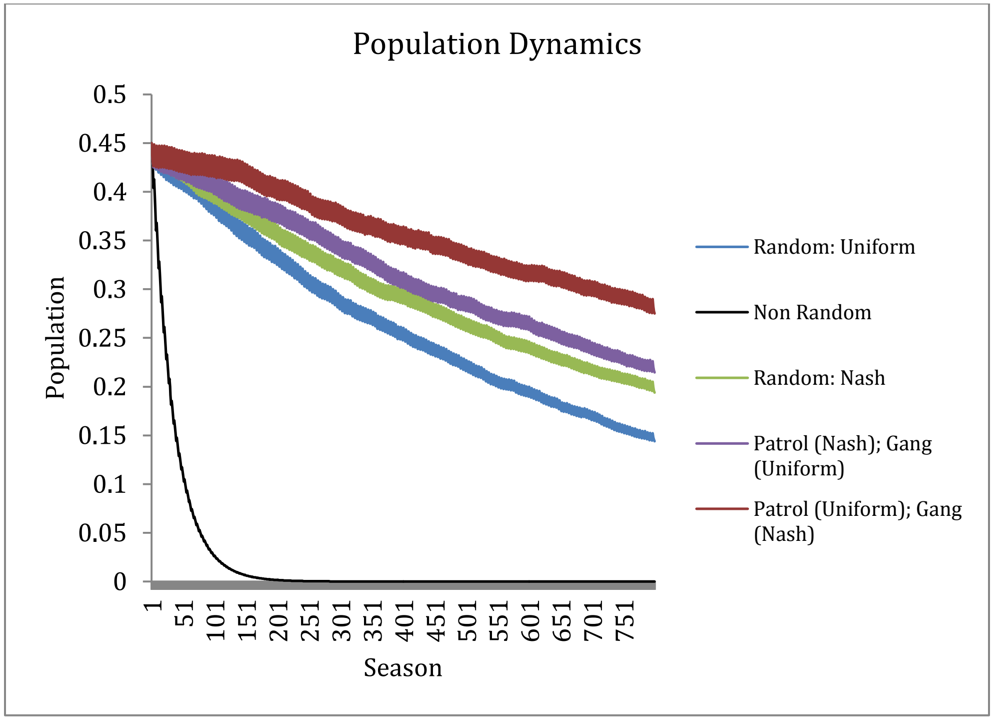
t-statistics of difference of means between Nash equilibrium value and other strategy's equilibrium value in (parentheses). *** statistically significant mean difference at 1% error level; ** statistically significant mean difference at 5% error level; * statistically significant mean difference at 10% error level.



	Average Population $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=800}^{1000} E_s}{1000-800}\right)_n}{1000}$	**Average Poaching** $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=800}^{1000} K_s}{1000-800}\right)_n}{1000}$
Random: Uniform	0.56298 (59.032)***	0.00746 (1.6930)**
Random: Nash	0.62530	0.00809
Anti-poaching unit (Nash); Poaching unit (Uniform)	0.63735 (-10.923)***	0.00816 (-0.1502)
Anti-poaching unit (Uniform); Poaching unit (Nash)	0.66922 (-39.65)***	0.00838 (-0.6697)
Non Random	0.00000 (825.1)***	0.00000 (29.0)***

Figure 5.7: Population and poaching dynamics with initial population set at 0.45, and poaching off-take set at $\boldsymbol{q} = \mathbf{0.10}$

t-statistics of difference of means between Nash equilibrium value and other strategy's equilibrium value in (parentheses). *** statistically significant mean difference at 1% error level; ** statistically significant mean difference at 5% error level; * statistically significant mean difference at 10% error level.



	Average Population $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=800}^{1000} E_s}{1000-800}\right)_n}{1000}$	**Average Poaching** $\frac{\sum_{n=1}^{1000}\left(\frac{\sum_{s=800}^{1000} K_s}{1000-800}\right)_n}{1000}$
Random: Uniform	0.13063 (50.05)***	0.00205 (6.013)***
Random: Nash	0.18026	0.00279
Anti-poaching unit (Nash); Poaching unit (Uniform)	0.20532 (-25.22)***	0.00310 (-2.036)**
Anti-poaching unit (Uniform); Poaching unit (Nash)	0.26669 (-82.98)***	0.00398 (-6.512)***
Non Random	0.00000 (243.6)***	0.00000 (28.18)***

Figure 5.8: Population and poaching dynamics with initial population set at 0.45, and poaching off-take set at $\boldsymbol{q = 0.12}$

t-statistics of difference of means between Nash equilibrium value and other strategy's equilibrium value in (parentheses). *** statistically significant mean difference at 1% error level; ** statistically significant mean difference at 5% error level; * statistically significant mean difference at 10% error level.

5.3 Discussion and Conclusion

The model simulation exercises provide some key results in this chapter. We observe that when both the anti-poaching unit and the poaching unit play their mixed strategy Nash equilibrium strategies they achieve higher payoffs on average as compared with the uniform random strategy. This holds true for a wide range in values for the poaching efficiency parameter, q. The numerical analysis also reveals that on average there is no incentive for either the anti-poaching unit or the poaching unit to deviate from the Nash equilibrium. This occurs in the range $3\% \leq q \leq 8\%$, i.e. when we observe stable distributions of population over a long time horizon. This corroborates the analytical proof of the uniqueness of the mixed strategy Nash equilibrium. The base-case value of $q = 7\%$ is estimated from secondary data in the literature. We have considered what would occur if q were to increase i.e. poaching units become more effective. The population distributions are no longer stable, the variances in the distributions increase significantly, and the meta-populations start to descend towards extinction over time.

The different random strategies achieve higher payoffs for both the units compared to the non-random strategy. This result mirrors findings from other studies on evolutionary fitness of strategies in zero-sum antagonistic games between strategic opponents (Adami et al., 2012; Cohen & Newman, 1989; Kerr et al., 2002; Kirkup & Riley, 2004). The numerical results also suggest that non-random strategies lead to extinction of meta-populations when q increases. The incentive for both the anti-poaching unit and the poaching unit to deviate from playing the Nash strategy is stronger once the poaching off-take rate increases beyond eight percent. The differences in average payoffs between the Nash strategies and other random strategies become statistically significant. At the same time however we observe that the population stocks decline rapidly, and that population distributions are no longer stable.

We noted earlier that the mixed strategy Nash equilibrium probabilities would be identical to those of the uniform random strategy if the meta-populations were evenly distributed across seasonal patches in the conceptual space. The probabilistic nature of choosing patches by both the anti-poaching unit and the poaching unit, in conjunction with the set of migration coefficients, leads to uneven seasonal population distributions in our numerical analyses. We have confirmed that the Nash strategy is superior to the uniform random strategy for both the anti-poaching unit and the poaching unit. The superiority of the Nash strategy stems from the nature of the game of poaching and protection, in that the players behave strategically with each other. Deviations from the Nash for either player would merit careful consideration.

This chapter has considered the theoretical implications of optimal strategies on the population dynamics of an endangered species. The model is generally applicable to other species, and it can also be scaled up for more realistic analysis. Different growth functions and biological parameters can be used in the model to better suit the modeling of different species' population dynamics. The set of migration coefficients in Table 5.2 can be modified to reflect different proportions of the meta-populations that migrate from one patch to another. For simplicity we assumed a costless choice of patch to poach and patrol in the conceptual space. The model can be modified to account for heterogeneity in patrolling and poaching costs in the different seasonal patches. The model can be applied to an empirical setting if data were to be made available on poaching and patrolling. In scaling up this model one could think about adding more seasonal patches in the space, adding more anti-poaching units, and adding more poaching units to reflect a more realistic setting.

As we noted earlier Bulte et al., (2004) state that models which link ecological theory and natural resource economics should expand their scope beyond the notion of steady state equilibrium by incorporating variability, complexity, scale, and uncertainty into economic models. This chapter has considered purely the strategic aspects of poaching and protection when smart opponents face each other. We introduced uncertainty into our model through the strategic location choices of a poaching unit and an anti-poaching unit. Spatial-temporal strategic decisions by the poaching unit and the anti-poaching unit caused the number of elephants killed to become a stochastic process. The model provides insight into the effects of different strategies on the long-term population dynamics of an endangered species, and thereby links the spatial-temporal dynamics of species migration with the economic game of poaching and protection.

APPENDIX 5.1

Derivation of the mixed strategy Nash equilibrium, and a proof of its uniqueness:

Nouweland (2007) lists three conditions for the existence of a mixed strategy Nash equilibrium in two-player zero-sum games. We adapt the definition for the game in this chapter.

Condition 1: A pair of mixed strategies (g, p) is a mixed Nash equilibrium if and only if the strategy of one player (poaching unit) is a best response to the strategy of the other player (anti-poaching unit) and vice-versa.

Condition 2: If (g, p) $\big((p, g)\big)$ is a strategy profile and every action $l_G \in L$ $(l_P \in L)$ that the poaching unit (anti-poaching unit) plays with positive probability $g(l_G) > 0$ $(p(l_P) > 0)$ is at least as good a response to p (g) as every other action, then g (p) is a best response to p (g). For the poaching unit (anti-poaching unit) this would mean $E[\pi_G(l_G, p)] \geq E[\pi_G(l'_G, p)]$ $(E[\pi_P(l_P, g)] \geq E[\pi_P(l'_P, g)])$ for all $l'_G \in L$ $(l'_P \in L)$.

Condition 3: If $g \in \Delta G$ $(p \in \Delta P)$ is a best response to $p \in \Delta P$ $(g \in \Delta G)$ and the poaching unit (anti-poaching unit) plays action $l_G \in L$ $(l_P \in L)$ with a positive probability, i.e. $(l_G) > 0$ $(p(l_P) > 0)$, then l_G (l_P) is at least as good a response to p (g) as every other action. For the poaching unit (anti-poaching unit) this would mean $E[\pi_G(l_G, p)] \geq E[\pi_G(l'_G, p)]$ $(E[\pi_P(l_P, g)] \geq E[\pi_P(l'_P, g)])$ for all $l'_G \in L$ $(l'_P \in L)$.

Using *Condition 1* we can state that a pair of mixed strategies (g, p) is a mixed strategy Nash equilibrium if, for the poaching unit (anti-poaching unit) and every alternative mixed strategy $g' \in \Delta G$ ($p' \in \Delta P$) of the poaching unit (anti-poaching unit) , it holds that $E[\pi_G(g',p)] \leq E[\pi_G(g,p)]$ ($E[\pi_P(p',g)] \leq E[\pi_P(p,g)]$). This entails that at a Nash equilibrium a player in the game will be indifferent between the action choices when the expected payoffs from these actions are equal to each other i.e. $E[\pi_G(i,p)] = E[\pi_G(j,p)]$ and $E[\pi_P(g,i)] = E[\pi_P(g,j)]$ where $i,j = 1,2,\dots,n$ and $i \neq j$. Given the payoff matrix in Figur we can define the associated expected payoffs to the poaching unit and the anti-poaching unit for the individual location choices or actions. When there are two seasonal patches i.e. $n = 2$, we have the expected payoffs for the poaching unit of choosing patches 1 and 2.

$$\mathrm{E}[\pi_G(1,p)] = p_1.0 + p_2.x_1 \tag{1}$$

$$\mathrm{E}[\pi_G(2,p)] = p_1.x_2 + p_2.0 \tag{2}$$

Similarly we define the expected payoffs for the anti-poaching unit of choosing patches 1 and 2.

$$\mathrm{E}\left[\pi_p(g,1)\right] = g_1.0 - g_2.x_2 \tag{3}$$

$$\mathrm{E}[\pi_P(g,2)] = g_2.0 - g_1.x_1 \tag{4}$$

Setting (1) = (2) and (3) = (4) we solve for the Nash equilibrium values of the system with *two* seasonal patches.

$g_1^* = \frac{x_2}{x_1+x_2}$, $g_2^* = \frac{x_1}{x_1+x_2}$, $p_1^* = \frac{x_1}{x_1+x_2}$, and $p_2^* = \frac{x_2}{x_1+x_2}$.

When there are three seasonal patches i.e. $n = 3$, we have the expected payoffs for the poaching unit of choosing patches 1, 2, and 3.

$$E[\pi_G(1,p)] = p_1.0 + p_2.x_1 + p_3.x_1 \tag{5}$$

$$E[\pi_G(2,p)] = p_1.x_2 + p_2.0 + p_3.x_2 \tag{6}$$

$$E[\pi_G(3,p)] = p_1.x_3 + p_2.x_3 + p_3.0 \tag{7}$$

Similarly we define the anti-poaching unit's expected payoffs for its actions of choosing seasonal locations a, b, & c.

$$E[\pi_P(g,1)] = -g_2.x_2 - x_3 + g_1.x_3 + g_2.x_3 \tag{8}$$

$$E[\pi_P(g,2)] = -g_1.x_1 - x_3 + g_1.x_3 + g_2.x_3 \tag{9}$$

$$E[\pi_P(g,3)] = -g_1.x_1 - g_2.x_2 \tag{10}$$

Setting (5) = (6) = (7), and (8) = (9) = (10), and using that $g_3 = 1 - g_1 - g_2$ and $p_3 = 1 - p_1 - p_2$ we solve for the Nash equilibrium values of the system with *three* seasonal patches.

$$g_1^* = \frac{x_2x_3}{x_1x_2+x_2x_3+x_1x_3}\,, g_2^* = \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}\,, g_3^* = \frac{x_1x_2}{x_1x_2+x_2x_3+x_1x_3}\,,$$

$$p_1^* = \frac{x_1x_2+x_1x_3-x_2x_3}{x_1x_2+x_2x_3+x_1x_3}\,, p_2^* = \frac{x_1x_2+x_2x_3-x_1x_3}{x_1x_2+x_2x_3+x_1x_3}\,, p_3^* = \frac{x_1x_3+x_2x_3-x_1x_2}{x_1x_2+x_2x_3+x_1x_3}\,.$$

First we prove the uniqueness of the Nash equilibrium for the system with *two* seasonal patches. We use the approach followed by (Nouweland, 2007) who uses *Condition 2* and *Condition 3* to show that a mixed strategy, which is not the Nash equilibrium, cannot be a best response to any strategy that is a best response to it. We derive the following useful identities, which equal zero at the Nash equilibrium values.

Any deviations from the Nash equilibrium values would mean that the identities would no longer equal zero.

(1) – (2): $E[\pi_G(1,p)] - E[\pi_G(2,p)] = p_2.x_1 - p_1.x_2$

(3) – (4): $E[\pi_P(g,1)] - E[\pi_P(g,2)] = g_1.x_1 - g_2.x_2$

Consider the first case of the poaching unit deviating from the Nash equilibrium: $g_1 > \frac{x_2}{x_1+x_2}$, $g_2 < \frac{x_1}{x_1+x_2}$. We will accordingly have (3) – (4) $>$ 0, and by *Condition 2* we know that $p_2 = 0$. But if $p_2 = 0$ then we will have (1) – (2) $<$ 0, and by *Condition 3* we know that $g_1 = 0$, which contradicts $g_1 > \frac{x_2}{x_1+x_2}$ for x_1, $x_2 > 0$. In the second case of the poaching unit deviating from the Nash equilibrium we consider $g_1 < \frac{x_2}{x_1+x_2}$, $g_2 > \frac{x_1}{x_1+x_2}$. We will accordingly have (3) – (4) $<$ 0, and by *Condition 2* we know that $p_1 = 0$. But if $p_1 = 0$ then we will have (1) – (2) $>$ 0, and by *Condition 3* we know that $g_2 = 0$, which contradicts $g_2 > \frac{x_1}{x_1+x_2}$ for x_1, $x_2 > 0$. The other two cases of the poaching unit deviating from the Nash equilibrium i.e. $g_1 > \frac{x_2}{x_1+x_2}$ & $g_2 > \frac{x_1}{x_1+x_2}$, and $g_1 < \frac{x_2}{x_1+x_2}$ & $g_2 < \frac{x_1}{x_1+x_2}$ are mathematically not feasible since $g_1 + g_2 = 1$ by definition, and the latter two cases violate this condition.

Let us now consider the first case of the anti-poaching unit deviating from the Nash equilibrium: $p_1 > \frac{x_1}{x_1+x_2}$, $p_2 < \frac{x_2}{x_1+x_2}$. We will accordingly have (1) – (2) $<$ 0, and by *Condition 2* we know that $g_1 = 0$. But if $g_1 = 0$ then we will have (3) – (4) $<$ 0, and by *Condition 3* we know that $p_1 = 0$, which contradicts $p_1 > \frac{x_1}{x_1+x_2}$ for x_1,

$x_2 > 0$. In the second case of the anti-poaching unit deviating from the Nash equilibrium we consider $p_1 < \frac{x_1}{x_1+x_2}$, $p_2 > \frac{x_2}{x_1+x_2}$. We will accordingly have (1) – (2) > 0, and by *Condition 2* we know that $g_2 = 0$. But if $g_2 = 0$ then we will have (3) – (4) > 0, and by *Condition 3* we know that $p_2 = 0$, which contradicts $p_2 > \frac{x_2}{x_1+x_2}$ for x_1, $x_2 > 0$. The other two cases of the anti-poaching unit deviating from the Nash equilibrium i.e. $p_1 > \frac{x_1}{x_1+x_2}$ & $p_2 > \frac{x_2}{x_1+x_2}$, and $p_1 < \frac{x_1}{x_1+x_2}$ & $p_2 < \frac{x_2}{x_1+x_2}$ are mathematically not feasible since $p_1 + p_2 = 1$ by definition, and the latter two cases violate this condition. This proves that a mixed strategy other than the Nash equilibrium is not a best response to any mixed strategy that is a best response to it. Using *Condition 1* we have shown that there is no mixed strategy Nash equilibrium in which the anti-poaching unit and poaching unit plays a strategy that is different from $\left((g_1^*, g_2^*), (p_1^*, p_2^*)\right)$ in a system with *two* seasonal patches. ■

Now we prove the uniqueness of the Nash equilibrium for a system with *three* seasonal patches. Again we make use of the following identities that equal zero at the Nash equilibrium values.

(5) – (6): $E[\pi_G(1,p)] - E[\pi_G(2,p)] = x_1 - x_2 - p_1.x_1 + p_2.x_2$

(5) – (7): $E[\pi_G(1,p)] - E[\pi_G(3,p)] = x_1 - p_1.x_1 - p_1.x_3 - p_2.x_3$

(8) – (9): $E[\pi_P(g,1)] - E[\pi_P(g,2)] = g_1.x_1 - g_2.x_2$

(8) – (10): $E[\pi_P(g,1)] - E[\pi_P(g,3)] = g_1.x_1 - g_3.x_3$

Consider the first case of the poaching unit deviating from the Nash equilibrium: $g_1 > \frac{x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $g_2 > \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$, & $g_3 < \frac{x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$. The sign of (8) – (9) is ambiguous, while the sign of (8) – (10) is unambiguously greater than zero. Suppose (8) – (9) ≥ 0 and (8) – (10) > 0. Then by *Condition 2* we know that $p_2 = 0$ and $p_3 = 0$. This would imply that (5) $= 0$, (6) > 0, & (7) > 0. This in turn would imply that (5) – (6) < 0 and (5) – (7) < 0. Using *Condition 3* we know that $g_1 = 0$, which contradicts $g_1 > \frac{x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$. Now suppose (8) – (9) < 0 and (8) – (10) > 0. By *Condition 2* we know that $p_1 = 0$ and $p_3 = 0$. This implies that (5) > 0, (6) $= 0$, & (7) > 0. This would imply that (5) – (6) > 0, and using *Condition 3* we would have $g_2 = 0$, which contradicts $g_2 > \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$.

The proof by contradiction in the case of $g_1 > \frac{x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $g_2 < \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$, & $g_3 > \frac{x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$ holds by symmetry. The case of $g_1 > \frac{x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $g_2 < \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$, & $g_3 < \frac{x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$ is straightforward since the signs of (8) – (9) and (8) – (10) would be unambiguously greater than zero.

Consider next the case of $g_1 < \frac{x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $g_2 > \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$, & $g_3 < \frac{x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$. The sign of (8) – (9) is unambiguously less than zero, but the sign of (8) – (10) is ambiguous. Suppose (8) – (9) < 0 and (8) – (10) ≥ 0. Then by *Condition 2* we know that $p_3 = 0$ and $p_1 = 0$. This would imply that (5) > 0, (6) $= 0$, & (7) > 0. This in turn would imply that (5) – (6) > 0, and by *Condition 3* $g_2 = 0$, which contradicts $g_2 > \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$. Now suppose (8) – (9) < 0 and (8) – (10)

< 0. By *Condition 2* this implies $p_1 = 0$ and $p_2 + p_3 = 1$, and thereby (5) $= p_2.x_1 + p_3.x_1 = x_1$. We also derive (6) $= p_3.x_2 \geq 0$, and (7) $= p_2.x_3 \geq 0$.[10] Thereby we derive (5) – (6) $= 0$,[11] and we can infer from *Condition 3* that $g_2 = 0$, which contradicts $g_2 > \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$.

The proof by contradiction in the case of $g_1 < \frac{x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $g_2 < \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$, & $g_3 > \frac{x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$ holds by symmetry. The case of $g_1 < \frac{x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $g_2 > \frac{x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$, & $g_3 > \frac{x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$ is straightforward since the signs of (8) – (9) and (8) – (10) would be unambiguously less than zero. We have shown that $(g_1, g_2, g_3) \neq (g_1^*, g_2^*, g_3^*)$ is not a best response to (p_1^*, p_2^*, p_3^*). Next we prove that any deviation from (p_1^*, p_2^*, p_3^*) is not optimal for the anti-poaching unit.

Let us begin with the case of $p_1 > \frac{x_1x_2+x_1x_3-x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $p_2 > \frac{x_1x_2+x_2x_3-x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$, $p_3 < \frac{x_1x_3+x_2x_3-x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$. The sign of (5) – (7) is unambiguously less than zero while the sign of (5) – (6) is ambiguous.[12] Suppose (5) – (6) ≥ 0 and (5) – (7) < 0. Then by *Condition 2* we know that $g_2 = 0$ and $g_1 = 0$. This would imply that (8) $= -z$, (9) $= -z$, and (10) $= 0$. This is turn implies that (8) – (10) ≤ 0 and (9) – (10) ≤ 0. Using *Condition 3* we can infer that $p_1 = 0$ and $p_2 = 0$, which contradicts $p_1 > \frac{x_1x_2+x_1x_3-x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$ and $p_2 > \frac{x_1x_2+x_2x_3-x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$. Now suppose (5) – (6) < 0 and (5) – (7) $<$

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[10] Note that since $p_1^* = \frac{x_1x_2+x_1x_3-x_2x_3}{x_1x_2+x_2x_3+x_1x_3} = 0$ is only possible when $x_1x_2 + x_1x_3 = x_2x_3$, we will have $p_3.x_2 = \frac{x_1x_3+x_2x_3-x_1x_2}{x_1x_2+x_2x_3+x_1x_3}.x_2 = \left(\frac{x_1x_2+x_1x_3+x_1x_3-x_1x_2}{x_1x_2+x_2x_3+x_1x_3}\right).x_2 = \frac{2x_1x_2x_3}{x_1x_2+x_2x_3+x_1x_3} \geq 0$.

[11] (5) – (6) $= x_1 - \frac{2x_1x_2x_3}{x_1x_2+x_2x_3+x_1x_3} = \frac{x_1(x_1x_2+x_2x_3+x_1x_3)-2x_1x_2x_3}{x_1x_2+x_2x_3+x_1x_3} = \frac{x_1(x_2x_3+x_2x_3)-2x_1x_2x_3}{x_1x_2+x_2x_3+x_1x_3} = 0$ (see footnote 10).

[12] Note that the sign and magnitude of p_3 does not matter since it drops out of identities (5) – (6) and (5) – (7).

0. Then by *Condition 2* we know that $g_1 = 0$ or that $g_2 + g_3 = 1$. This would imply that (8) $= -g_2.x_2 - x_3 + g_2.x_3$, (9) $= -x_3 + g_2.x_3$, and (10) $= -g_2.x_2$. Therefore (8) – (9) < 0, and (8) – (10) < 0. Using *Condition 3* we can infer that $p_1 = 0$, which contradicts $p_1 > \frac{x_1x_2+x_1x_3-x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$. In the case of $p_1 > \frac{x_1x_2+x_1x_3-x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $p_2 < \frac{x_1x_2+x_2x_3-x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$ and $p_3 < \frac{x_1x_3+x_2x_3-x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$, we note that (5) – (7) < 0 always and that since p_2 enters as a positive term in (5) – (6) we have the same case of ambiguity in the sign of (5) – (6).

Next we consider the case of $p_1 < \frac{x_1x_2+x_1x_3-x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $p_2 > \frac{x_1x_2+x_2x_3-x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$ and $p_3 < \frac{x_1x_3+x_2x_3-x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$. The sign of (5) – (6) is unambiguously greater than zero while the sign of (5) – (7) is ambiguous. Suppose (5) – (6) > 0 and (5) – (7) ≥ 0. Then by *Condition 2* we know that $g_2 = 0$ and $g_3 = 0$ or that $g_1 = 1$. This in turn implies that (8) $= 0$, (9) $= -x_1$, and (10) $= -x_1$. Therefore we would have (8) – (9) $= x_1 \geq 0$, and (10) – (9) $= x_1 \geq 0$. Using *Condition 3* we can infer that $p_2 = 0$, $p_3 = 0$, and $p_1 = 1$. Now suppose (5) – (6) > 0 and (5) – (7) < 0. Then by *Condition 2* we know that $g_2 = 0$ and $g_1 = 0$ or that $g_3 = 1$. This in turn implies that (8) $= x_3$, (9) $= -x_3$, and (10) $= 0$. Therefore we would have (8) – (10) ≤ 0 and (10) – (9) ≥ 0. Using *Condition 3* we can infer that $p_2 = 0$.

Finally we consider the case of $p_1 < \frac{x_1x_2+x_1x_3-x_2x_3}{x_1x_2+x_2x_3+x_1x_3}$, $p_2 < \frac{x_1x_2+x_2x_3-x_1x_3}{x_1x_2+x_2x_3+x_1x_3}$ and $p_3 > \frac{x_1x_3+x_2x_3-x_1x_2}{x_1x_2+x_2x_3+x_1x_3}$. The signs of both (5) – (6) and (5) – (7) are unambiguously greater than zero. By *Condition 2* we know that $g_2 = 0$ and $g_3 = 0$ or that $g_1 = 1$.

This implies (8) $= 0$ and (10) $= -g_1.x_1$. We now have (8) – (10) > 0 and by *Condition 3* we know that $p_3 = 0$. ■

We have shown that a mixed strategy other than the Nash equilibrium is not a best response to any mixed strategy that is a best response to it. Using *Condition 1* we have shown that there is no mixed strategy Nash equilibrium in which the anti-poaching unit and poaching unit plays a strategy that is different from $\left((g_a^*, g_b^*, g_c^*), (p_a^*, p_b^*, p_c^*)\right)$ for the system with *three* seasonal patches.

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CHAPTER 6

SUMMARY

This dissertation has attempted to provide the reader with insights into the economics of endangered species harvesting and protection. In the first essay (Chapter 2) the integrated economic and ecological model facilitated a numerical estimation of changes in poaching effort and protected population levels over time. The Schaefer harvest function and the modified logistic growth function allow for both oscillatory convergence to steady state and period-doubling bifurcation. The model reveals that the protected population dynamics goes through bifurcation for changes in both economic and biological parameters, and in some cases gives way to "deterministic" chaos. We find that the economic or policy parameters – wage rates in and around the PA, fines for poaching, and black market prices – have qualitatively different effects on the protected species' population dynamics. The effectiveness of anti-poaching enforcement has different qualitative effects on population dynamics depending on the biological parameters. The model reveals interesting and sometimes counterintuitive results for the economic and biological parameters, driven largely due to changing marginal products of harvest.

In Chapter 3 we examined the relationship between civil unrest and rhino poaching. We found the relationship to be positive and statistically significant. The analysis factored in the relationship between poaching and several additional variables that are probably associated with it – including black market rhino horn prices, potential size of black markets, and anti-poaching efforts. These variables are seen to have their predicted associations with poaching in the regression models. They also help to isolate and identify the relationship between poaching civil unrest. We find reasonably good fits between the rhino population data, poaching data, and the model's estimates of the same.

In Chapter 4 we examined an economic model of organized crime in elephant poaching in the Southern African range states. We have seen that under plausible economic and biological parameters, the number of planned poaching expeditions is insensitive to the black-market price of ivory, but quite sensitive to the probability that a poaching expedition will be intercepted. We ascertained a critical value for the number of poaching expeditions as approximately twenty-three per year, above which the elephant population may exhibit a slow decline to extinction. The presence of multiple poaching organizations leads to a decline in elephant population and increased variance in the distribution. The mathematical phenomenon of stochastic bifurcations occurs for the case of two or more poaching gangs operate with higher technology (as represented by lower probabilities of interception by anti-poaching patrols).

In Chapter 5 we examined the effects of different location choice strategies on elephant population dynamics over time. It is seen that random location choice strategies that account for spatial population distribution are superior to non-random location choice strategies for both poachers and anti-poachers. We derived a mixed strategy Nash equilibrium in location choice strategies, and also provided an analytical proof of optimality and uniqueness of this strategy.