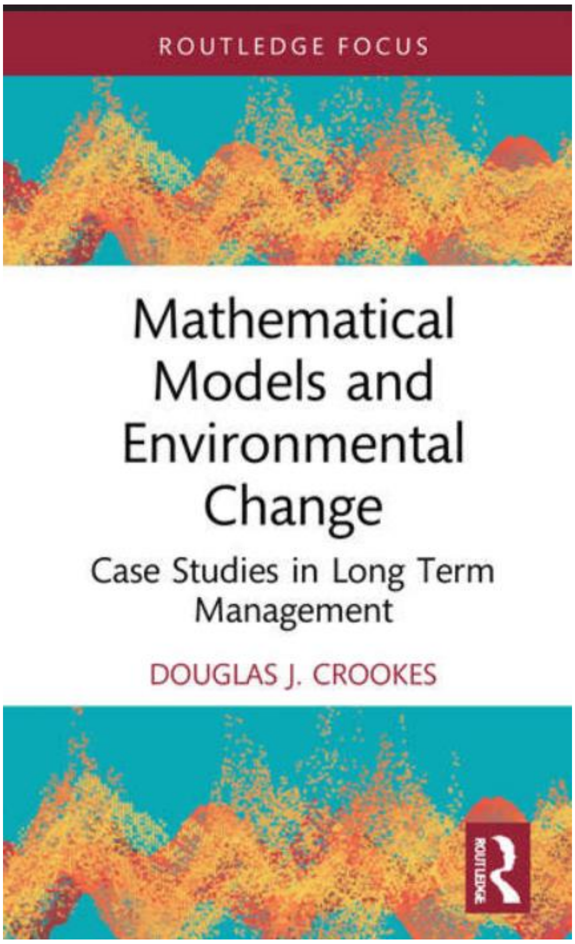

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5. Co-evolutionary models and rhino management

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Abstract

This chapter:

- Provides an example of how different co-evolutionary models provide different long term forecasts of the behaviour of systems
- Provides a comparison between least squares estimation technique and the numerical methods of MCMC
- Demonstrates the capabilities of these models to provide accurate long term (strategic) forecasts of natural resource phenomena (provided the correct model specification is selected)
- Highlights how different model specifications can provide insights into the behaviour of economic agents
- It uses a case study for rhinos, for which a long term dataset is available for both population abundance, as well as poaching effort

5.1. Introduction

Forecasting the future state of an entity is an important part of decision-making. For example, business managers need to forecast demand for their products, so that they can make informed decision on production. Economists forecast economic variables such as inflation, growth, in order to determine what macroeconomic policies are applicable. Environmental managers wish to know the future state of a biological population, in order to determine the extinction risk of a species. In all of these cases, forecasting can help inform decision-makers on how best to manage the resources available to them.

Sherden (1998) estimated that the forecasting industry, broadly defined, was worth US$200 billion, but these figures are dated. The weather services forecasting market (in other words, the sector that sells weather forecasting services) is expected to grow from $1.5 billion in 2020 to $2.3 billion in 2025, an annual growth rate of 9.3% (MarketsandMarkets™, 2020).

The fact that forecasting is a growth industry is highlighted by the consumer trends forecasting industry, which has grown from almost nothing to be worth GBP36 million in 2011 (The Telegraph, 2011), but this excludes the value of stock and market forecasts which are also likely to be sizeable. Based on these data, we can reasonably assume that the forecasting industry is worth at least $1550 billion in today's (2021) prices. The forecasting industry is indeed big business.

Why is this important? Because forecasting is crucial to the survival of many entities. It is crucial to the survival of businesses. For example, weather forecasting is vital for the agriculture sector, the fishing industry, the energy sector, and other industries dependent on the weather. It is crucial for consumers. For example, forecasting consumer trends help companies to deliver the right products at the right time (WGSN, 2021). It is crucial for the financial sector. For example, market forecasts are essential for making investment decisions, which could affect private individuals as well as pension funds, corporate investors, and governments. It is safe to assume that all sectors of the economy are reliant on some form of forecasting.

But not only is forecasting critical to the survival of markets and the economy, the survival of species is critically dependent on accurate forecasts of population trends. For example, the IUCN Red List uses historical population trends as one of the assessments of threat to a biological population. But, historical trends are not necessarily indicators of future biological populations. There is a need for models that provide accurate long term forecasts.

Lotka-Volterra (LV) models are utilized for a wide range of forecasting business, financial and microeconomic phenomena, including stock markets (Lee et al. 2005), competition between firms (Marasco et al. 2016), sales (Hung et al. 2017), revenue growth in the retail sector (Hung et al. 2014). The model has immense potential for modelling intersectoral dynamics where the resource from one sector is used as an input in another sector. For example, Crookes and Blignaut (2016) model the dynamics of vehicle manufacturing using steel as an input (the prey). In many cases, the LV model performs the same, or better, than other comparable models (such as the bass model, neural networks, see e.g. Hung et al. 2014, Crookes and Blignaut 2016). These models are also used to forecast macroeconomic phenomena. For example, Wu and Liu (2013) develop an LV model to forecast Gross Domestic product (GDP) and Foreign Direct Investment (FDI).

At the same time, although these models have been used to model aquaculture (Cacho 1997; Ponce-Marbán et al. 2006), Land use change (Castro et al. 2018; Paul et al. 2019), and the management of weeds (Jones et al. 2006; Grimsrud et al. 2008; McDermott et al. 2013), and many other applications, these types of models are underutilized tools for forecasting biological populations that are subject to exploitation, which is surprising given that these models largely emerged from the fisheries literature. A reason for these methods being less frequently used for forecasting bio-economic phenomena are that the biological growth parameters (intrinsic growth rate, carrying capacity of the population, or maximum population size) that are required for these models are frequently unknown in natural systems. The system dynamics modelling tool provides a means by which this limitation may be overcome. The unknown biological parameters may be estimated from trend data in biological populations, and effort data (if available). The system dynamics modelling software also provides a means for estimating these unknown parameters, and also validating these models. These two techniques (namely LV models coupled with the system dynamics (SD) modelling platform) provides an improved means of forecasting bio-economic phenomena.

This chapter provides an application of the coupled LV/SD technique for forecasting bio-economic phenomena. Rhino management is an important case study. Rhino poaching in South Africa has escalated enormously in the past 10 years, leading to concerns over the possible survival of rhino populations. A predator-prey simulation model was developed in 2015 (Crookes 2017) based on data collected up until 2012. Using estimates of population abundance subsequent to 2012 (up until 2019), it is possible to test the forecast accuracy of the model, particularly as it relates to rhino abundance, over the ensuing seven years.

The chapter is laid out as follows. First, compare the forecast of the Schaefer model with two other harvest functions, namely the Cobb-Douglas harvest function and the Baranov harvest function. These LV models are then compared with a least squares specification of the Schaefer logistic model. After that, the best model is then selected to forecast rhino abundance from 2012 to 2020 and compared with historical data on population and poaching data over that period.

5.2. The model

The equations of this LV model are based on Crookes' (2017) model of rhino population dynamics. The form of LV model is as follows:

$$\frac{dx}{dt} = F(x) - mh \qquad (1)$$

$$\frac{dE}{dt} = n(ph - cE) \qquad (2)$$

Where x is the prey species (in this case the rhino population) and E is the poaching effort (the predator). F(x) is the rhino growth function, p is the price of rhino horn, and c is the cost per unit capital, and h is the harvest function, assumed to follow the Cobb-Douglas production relationship:

$$h_t = aqE_t^{\alpha}x_t^{\beta} \qquad (3)$$

Where α and β are elasticities of substitution, q is the catchability coefficient which relates effort and stocks to harvests and a is a scaling parameter. If a=α=β=1, then the well-known Schaefer production function is obtained. In this example, if rhino populations are abundant, profits are positive and since open access prevails, poachers (E) enter the game reserve as long as ph exceeds cE, but as this occurs rhino populations decline, and h therefore declines, so that poachers exits the game reserve. With poachers exiting the game reserve, rhino populations recover, resulting in a dynamic system.

The basic model (Equations 1 and 2) also includes a number of other parameters such as the probability a poacher is detected and the magnitude of the penalty (Equation 4). F(x) follows the Pella and Tomlinson (1969) specification (see Equation 5) with density dependent term, and the Schaefer production function is assumed. In the present study we extend this analysis and model three harvest specifications in total: 1] the [original] Schaefer (S) function; 2] a

Cobb-Douglas (CD) function (Equation 9), and 3] a Baranov (BV) function (Equation 12) discussed above.

Poaching effort (E_t) evolves according to:

$$E_{t+1} = E_t + n'\left(h_t^* - \frac{c}{p}E_t - bE_t\frac{f+p}{p}\right) \quad (4)$$

Where n' is an adjustment coefficient, c and p is the cost of poaching and value of rhino horn sold, and f is the fine and b the probability of detection and conviction.

Rhino populations (x_t) evolve according to:

$$x_{t+1} = x_t + rx_t - \frac{rx_t^{z+1}}{k^z} - mh_t^* \quad (5)$$

Where r is the intrinsic growth rate, z is a Fowler density dependent term, k is the carrying capacity and m is the mortality coefficient. The values of the parameters are given in Crookes (2017). The harvest coefficient h_t^*varies depending on whether the Schaefer model, the Cobb-Douglas or the Baranov catch equation is used. More particulars are given in the next section when the estimation methodology is discussed.

5.3. Least squares estimation of production function

The first step is to estimate the values for a, α and β using the Cobb-Douglas production function (Equation 3). Historical estimates for rhino abundance, effort and harvests from 1990 to 2013 were employed for this purpose.

The OLS estimation gave the following results (Table 5.1):

Table 5.1: regression results for Cobb-Douglas specification

	Coefficient	T stat	Statistic/data	Sig
‘aq’	0.9944	-1.47984		n.s
α	0.002169	5.497837		***
β	-0.00016	-0.10389		n.s
Model F			34.49	***
Adj R^2			0.744	

n			24	

Notes: *** Significant at least at the 1 percent level; n.s= not significant

Given that aq and β are not significantly different from zero, we conclude that the least squares estimation of the production function results in a trivial solution such that a harvest function is not needed for the model. We model this for our forecast model (CD, a=0), however, we also model an alternative specification where a=1 in order to test the importance of the harvest function. Based on the results of the OLS estimation, the Cobb-Douglas harvest function is either:

$$h_t = qE_t^{\alpha} \qquad or \qquad h_t = 0 \qquad (6)$$

For the Baranov model (see equations 7 below), the abovementioned Cobb-Douglas production function is also utilised for F_t in, following Liu and Heino (2014). The rest of the parameter values for the model are reported in Crookes (2017). The models were constructed in Vensim which allows for simultaneous feedback between the parameters in the model.

5.4. Historical data replication

The model simulations from the LVs model are evaluated in two ways. Firstly, they are compared with a traditional econometric model of the Schaefer logistic model, and secondly they are compared with criteria proposed by Li et al (2017). These evaluation steps are given in more detail here.

5.4.1. Cobb-Douglas catch equation

The Cobb Douglas catch equation used in the model is given in Equation 6.

5.4.2. Schaefer production function

The Schaefer production function is a special case of the Cobb-Douglas catch equation, where α=β=1.

5.4.3. Baranov catch equation

Although the Cobb-Douglas production function is the most common in the open access literature, there are other important harvesting functions in the fisheries literature. One example is the Baranov catch equation. The harvest at the end of the season is:

$$h^b = \frac{F}{F+M}\left(1 - e^{-(F+M)T}\right)\bar{x}_0 \qquad (7)$$

Where $\bar{x}_0$ is the initial population abundance and F and M are the fishing and natural mortality rates, respectively, and T is usually 1 (Liu and Heino 2014). Liu and Heino (2014) assume a Cobb-Douglas production function for F of the form:

$$F_t = ah_t = aqE_t x_t^{\beta} \qquad (8)$$

Where a is a scaling parameter and β captures the potential of a non-linear response of harvests to changes in abundance. Catch h^b therefore becomes:

$$h_t^b = \frac{F_t}{F_t+M}\left(1 - e^{-(F_t+M)}\right)\bar{x}_0 \qquad (9)$$

5.4.4. Schaefer logistic model

Following Pella and Tomlinson (1969), the logistic growth model may be written in the form:

$$z_{t+1} = (1+r)z_t - \frac{r}{qk}z_t^2 - qh_t + u_t \qquad (10)$$

Where ut is an error term and zt is the catch per unit effort (CPUE). Under certain conditions this function may be estimated using Ordinary Least Squares (OLS) (Zhang and Smith, 2011). The model assumes a Schaefer production function. More advanced estimation methods have been proposed. For example, Zhang and Smith (2011) propose a “CPUE like” estimator using a Cobb-Douglas production function, which is then estimated using maximum likelihood methods. In this case, however, we are interested in the output of the Schaefer model in order to compare with our original model.

5.5. Adaptive expectations

The preceding discussion assumes that, as far as stocks are concerned, poachers are myopic, in other words that they only utilise current period information about abundance in order to determine their harvesting behaviour. Harvests under the adaptive expectations hypothesis are formulated based on expectations of future stock size.

$$H_t = A + \beta \hat{X}_{t+1} + u_t \quad (11)$$

Stocks adjust based on the following:

$$\hat{X}_{t+1} - \delta X_t = X_{t-1} - \delta X_{t-1} \quad (12)$$

Where δ is an adjustment coefficient relating actual change to desired change. Substituting $\hat{X}_{t+1}$ into H_t and rearranging gives an equation that is estimable, however estimating such an equation is problematic due to the presence of contemporaneous correlation between the lagged endogenous variable and the error term. A solution is to use the method of instrumental variables (IV) regression, however, a suitable instrument is needed. One method proposed by Liviatan involves using lagged values of an exogenous variable. From these values it is possible to compute long term values for α and β (see Gujarati 2003) and it is then possible to determine the value of scale variable a.

5.6. Implications for poaching behaviour

Two broad categories of harvesting behaviour are considered (Table 5.2): Firstly, harvesting decisions that are myopic versus those based on expectations of future prey abundance, and secondly, harvesting decisions that are based only on prey abundance versus those based on prey abundance and changes in poaching profitability. The myopic model simulates harvesting decisions based on constant effort focussed on prey abundance (model 1) as well as a variable effort based on profitability (model 2), while the adaptive expectations model (model 3) simulates the effect of harvesting decisions based on a variable effort and poaching decisions based on changes in profitability.

Table 5.2: Harvesting decisions modelled

		Constant Effort	Variable Effort
	Harvesting decisions …	… based on changes in stocks	… based on changes in stocks and profitability

Myopic	… based only on current stocks	Model 1	Model 2
Adaptive expectations	… based on expectations of future stocks	-	Model 3

5.7. Mean Absolute Percentage Error (MAPE)

The second stage of assessing the replication of the model with the historical data is conducted by comparing the LV and econometric model with data from 2010 to 2015 by calculating the Mean Absolute Percentage Error (MAPE). Although there are problems with using this measure to assess forecast accuracy (Tayman and Swanson 1999), it is still the most commonly used measure (Mentzer & Kahn, 1995; Armstrong 2001). This measure is calculated as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} | \frac{\hat{x}_t - x_t}{\hat{x}_t} | \; x \; 100 \qquad (13)$$

Where $\hat{x}_t$ is the actual data on rhino abundance in time t, and x_t is the simulated rhino abundance; n is the number of observations. The criteria for assessing the forecast accuracy based on the MAPE is given in Table 5.3.

Table 5.3: Forecast accuracy of the model based on MAPE

MAPE	Forecast accuracy
0-10%	Highly accurate
10-20%	Good
20-50%	Reasonable
50-100%	Poor

Source: Li et al. 2017

5.8. Forecast accuracy

The forecast accuracy of the model is then assessed through a visual plot of the 'best' model with the historical data, as well as comparing with other estimates in the literature.

In the next section, the results of the replication of the historical data and the forecast accuracy of the models are discussed, with reference to the econometric model, a visual plot and the MAPE measure.

5.9. Validation

Chapter 3 highlights the different ways in which an LV model may be validated. Here we validate the model by comparing it with the historical data. Three methods are employed. Firstly, we compare the model with actual data between 2010 and 2015 using the mean absolute percentage error (MAPE). Secondly, we compare the estimates with other models. Thirdly, we utilise a visual plot of the data to compare actual versus forecasted values. Error bars are calculated based on uncertainty over the area under rhino management. In this way, a coefficient of variation (CV) of 30% was calculated. In the absence of available data to estimate the CV for numbers killed, the same CV is assumed. The smaller the CV the greater weighting that data point and/or time series gets due to the higher precision associated with the data point. The CV for rhinos is relatively high, and indicates the uncertainty in the underlying spatial data and kill data rather than the population survey data, which is likely to be fairly accurate. In the next section, we use actual data to assess the forecast accuracy of the predator-prey model based on three different production functions.

5.10. Results

5.10.1. Parameter values

Most of the parameter values in the model are given in Crookes (2017), and are therefore not repeated here. The values obtained for a and β, for the different models, which are summarised in Table 5.4, indicate that the Schaefer and Baranov models produces similar estimates for β. The value of a is much lower under the adaptive expectations model, which one expects as harvests have time to adjust to changes in stocks. But the most significant result from the analysis is that, over time when expectations fully adjust, the value of β is 1, indicating that the model reverts to the standard Schaefer and Baranov production functions.

Table 5.4: Values of parameters under different harvesting functions

	'a'	β
A. Baranov production function		
Model 1: Myopic (constant E)	16.1	2.96
Model 2: Myopic (variable E)	15.55	2.96
Model 3: Adaptive expectations	1.33	1.00
B. Schaefer production function		
Model 1: Myopic (constant E)	13.33	2.96
Model 2: Myopic (variable E)	10.73	2.96
Model 3: Adaptive expectations	1.13	1.00

5.10.2. Model 1: Myopic: current stocks only

The stock flow diagram of model 1 (Figure 5.1) indicates that the myopic model is linear in the sense that there is no feedback between the different components of the model.

<Figure 5.1 here>

In spite of this, the model is able to reproduce the historic behaviour of the data extremely well. Projecting the model forward indicates that rhino stocks will recover to carrying capacity (Figure 5.2, top row, first column). Although hunting mortality and CPUE is reasonably well replicated, harvest rates are considerably less than 2012 values.

<Figure 5.2 here>

5.10.3. Model 2: Current stocks, future profitability

The myopic model considers dynamics based on only one system: stocks. The second model relaxes this assumption, and harvesting decisions are a function of both current stocks and expectations of future profitability. The stock flow diagram for the model in Figure 5.3 indicates that there is now feedback between three components in the models: stocks, poaching effort and profitability. In contrast to the myopic model presented above which was linear, this is a dynamic model. Effort influences both poacher profit as well as stocks, and while stocks influence poacher profit and profitability in turn influences changes in effort.

<Figure 5.3 here>

The fit of the model with the historical abundance data is as good as the myopic model (Figure 5.2, second row, first column), however the dynamics are significantly different. For the Baranov model, populations decline but stabilise at a long term equilibrium value, whereas for the Schaefer model populations with variable effort, rhino abundance declines to extinction (Figure 5.2, third row, column one). The difference is due to the density dependent term β which affects harvests in different ways in the model.

5.10.4. Model 3: Future stocks, future profitability

The third model simulates the effects of the adaptive expectations model, where harvesting decisions are based on both future stocks as well as future profitability (Figure 5.2, bottom row). It also replicates the historical data well, but harvests are significantly higher compared with the other two models (Figure 5.2). Once expectations fully adjust, stocks are more likely to be driven to extinction sooner, even compared with the Schaefer model (compare row three and row four of Figure 5.2, first column). The adaptive expectations model replicates the Crookes (2017) model.

5.10.5. Schaefer logistic regression results

The previous models all utilize numerical methods for estimating the value of the parameters in the model. We can now compare this method with the results obtained from the least squares method. The estimation results are given in Table 5.5. These show that the coefficients are highly significant ($p<0.01$) and the model fit reasonable (Adj. R^2=0.557). However, although the estimate for carrying capacity k is significant, it differs markedly from estimates from the LV model. Here k=0.16 individuals/km2, while the LV model using numerical methods to estimate produced an estimate for k=0.4 individuals/km2 (Crookes 2017). Clark (1990) note that bioeconomic models are often sensitive to changes in their underlying parameters. This suggests that forecasts of rhino abundance could differ markedly depending on the parameters employed. It is therefore necessary to assess forecast accuracy using a quantitative measure. Next, we will consider the results of the MAPE calculations.

Table 5.5: Least squares regression results for Schaefer logistic specification

	Coefficient	T stat	Statistic/data	Sig
K	0.1627	14.11		***
qk/r	14.9901	5.47		***
Model F			29.96	***
Adj R^2			0.557	
N			24	

Notes: *** Significant at least at the 1 percent level

5.10.6. MAPE calculation

Table 5.6 indicates that the LV models calibrated using numerical methods produced “highly accurate” calibration estimates of the historical data [based on MAPE]. This suggests that all three models could be used to make predictions of rhino abundance. By contrast, the LV model based on the least squares methodology provided a forecast that is “poor”. Although a limitation of the MAPE measure is that it overstates the error found in population forecasts (Tayman and Swanson 1999), the measure nonetheless indicates large discrepancies between the LV models based on numerical method calibration, and those using the least squares method. More advance econometric specifications are possible that may address some of the problems with the traditional Schaefer logistic model (e.g. Zhang and Smith, 2011), however this is beyond the scope of this study. The best model, according to the MAPE calculation, was the Schaefer LV model (which is the Cobb Douglas with adaptive expectations model), estimated using numerical methods (which is also the model used by Crookes (2017).

Table 5.6: Calculations of MAPE (%) for the three production functions (2010-2015)

Production function	MAPE (%)
LV: Cobb-Douglas (a=0;α=0.002; β=0)	8.76
LV: Cobb-Douglas (a=1;α=0.002; β=0)	7.95
LV: Schaefer (a=1; ;α=1; β=1)	5.55
LV: Baranov (a=1; α=0.002; β=0)	8.80
Econ: Schaefer logistic	101.75

LV= Lotka-Volterra; Econ= Econometric. Cobb-Douglas harvest function given in Equation 9

Source: Own calculations

In the next section, we consider some of the implications of this for conservation by comparing forecasts of the model forward from 2015 to 2020.

5.10.11. Forecast accuracy

The Schaefer LV model provided the best calibration of rhino abundance for the historical data to 2015 based on the MAPE measure. We compare forecasts from 2015 to 2020 through a visual plot of the data, as well as by comparing the forecasts of the LV Schaefer model with forecasts from Emslie and Adcock (2016).

Figure 5.4 summarises the results of the visual plots for both rhino abundance (Figure 5.4, top graph) and number killed (Figure 5.4, bottom graph). The results show that the data provide a reasonable fit with the historical data given the uncertainty associated with the data. Also, the forecasts are highly accurate over the short to medium term (2-3 years), but that the forecasts are still reasonably accurate over the seven years of the forecast, particularly as it pertains to rhino abundance.

<Figure 5.4 here>

Table 5.7 summarises the results of the comparison of the LV Schaefer model (for black and white rhino) with forecasts from Emslie and Adcock (2016, white rhinos only). The Table indicates that the forecasts by Emslie and Adcock (2016) and Crookes (2017) are remarkably similar, but both underestimate the actual number (in 2019). A reason for this is that neither model could anticipate the effects of the droughts that occurred in 2018/19 on rhino abundance. In spite of this, the forecast capability of both models is highly accurate. Given that Crookes' (2017) model is based on 2012 rhino abundance data, it means that this model has a forecast accuracy of at least seven years.

Table 5.7: Forecasts of rhino abundance: 2015 – 2020

Forecasts	Year	White rhino[1]	Annual. % change	White & Black Rhino[2]	Annual % change
Starting number (actual data)	2015	18489		20306	
Based on last 5+ years poaching data	2020	16277	-2.5%	16743	-3.8%
Actual population (2019) [3]				13206	

Source: [1] White Rhino estimates from Emslie and Adcock (2016); [2] White & black rhino estimates from Crookes (2017). [3] Actual data from annual reports from Department of Agriculture, Forestry and Fisheries (DEFF)

Notes: Emslie and Adcock (2016) uses a growth rate of 0.077 for white rhinos, Crookes (2017) models a growth rate of both black and white rhinos of 0.061. Assumes 100% detection rate. Crookes (2017) estimates based on the Schaefer LV model

5.11. Discussion

Crookes and Blignaut (2016) compare the forecasting capabilities of a simple LV system dynamics model modelling intersectoral dynamics with a forecast generated by Artificial Neural Networks (ANN). They demonstrate that these simple LV models based on the logistic model provide a comparable forecast to Neural Networks over a ten year period. More recently Li et al. (2017) found that the LV model provided 'highly accurate' forecasts of Battery Electric Vehicle (BEV) demand in China. In the present study, we assess forecast accuracy of the LV model using numerical methods to estimate the value of the parameters (MCMC). We compare three LV models based on different production functions, and assess the prediction accuracy high over the short to medium term using MAPE. This is compared with an LV model developed using the least squares method. The results showed that the LV model estimated using numerical methods produced better estimates for the unknown biological and harvest parameters compared with estimates derived from an LV model estimated using the least squares methodology.

Previous studies have found that the logistic model provides robust predictions in a variety of sectors. For example, Devezasa and Corredine (2001) found that "the simple logistic often outperforms more complicated parameterizations, which have the disadvantage of losing physical interpretations for their parameters." (p.28, see also Marchetti et al. 1996). In this assessment, the simple Schaefer production function (Cobb Douglas with Adaptive expectations) provided the best forecast of rhino abundance data. This again supports the assertion that "simple is better" in forecasting specifications. Although this is not an exhaustive evaluation of the forecasting capability of the predator-prey system, and there may be instances when other functional forms are preferable, it nonetheless indicates the potential of even these models to provide forecasts of different entities.

The modelling exercise also indicated that just because a model is validated according to statistical criteria it does not mean that it is suitable for forecasting. The time series regression model provided statistically significant parameter estimates (at least at the 1 percent level), yet the forecasting capabilities of the model were poor. Our results show that model validation should include an assessment of forecast accuracy by comparing model estimates with a segment of the historical data before it is used to forecast into the realm of the unknown. While forecasting remains a highly imprecise science, with many unknown factors and variables, these validation methods can improve the robustness of predictions.

Our study also sheds light on hunter behaviour. The adaptive expectations model was indicated as the best fit with the historical data. It shows that future stocks are the basis on which poachers form expectations of harvests, and that elasticities of substitution of stocks and effort are unity (Schaefer model). This means that harvests have fully adjusted to expectations around stocks and are thus higher than would be the case under a Cobb-Douglas specification (with $\alpha,\beta<1$). This was the most aggressive harvesting regime of the models considered. Poachers do appear to have revised their poaching behaviour downward as a result of declines in rhino abundance, which shows promise that rhino populations may rebound in the future.

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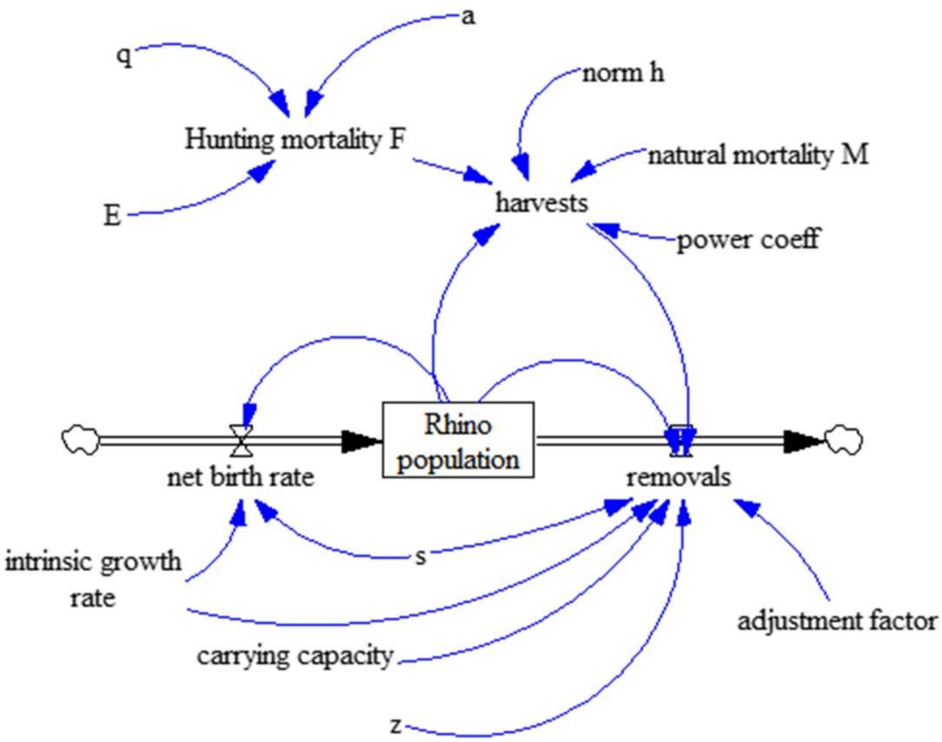

Figure 5.1: Stock flow diagram for constant effort model (harvesting function model 1)

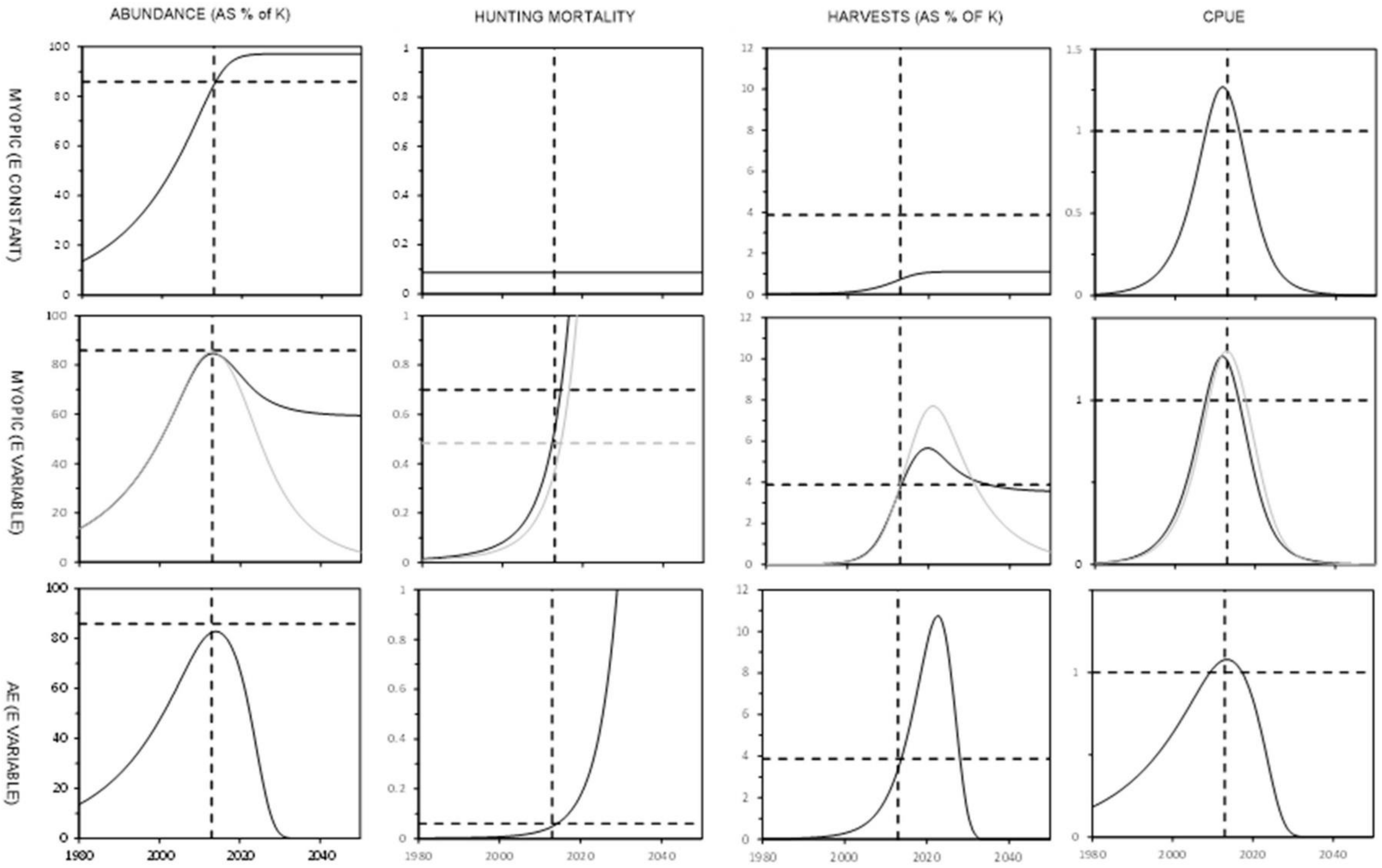

Figure 5.2: Dynamics over time of hunting from different harvesting functions. The intersection of the dashed lines indicate 2012 data. Therefore, values to the right of the vertical dashed lines are all projected values. The black lines are for the Baranov model, while grey lines are for the Schaefer model.

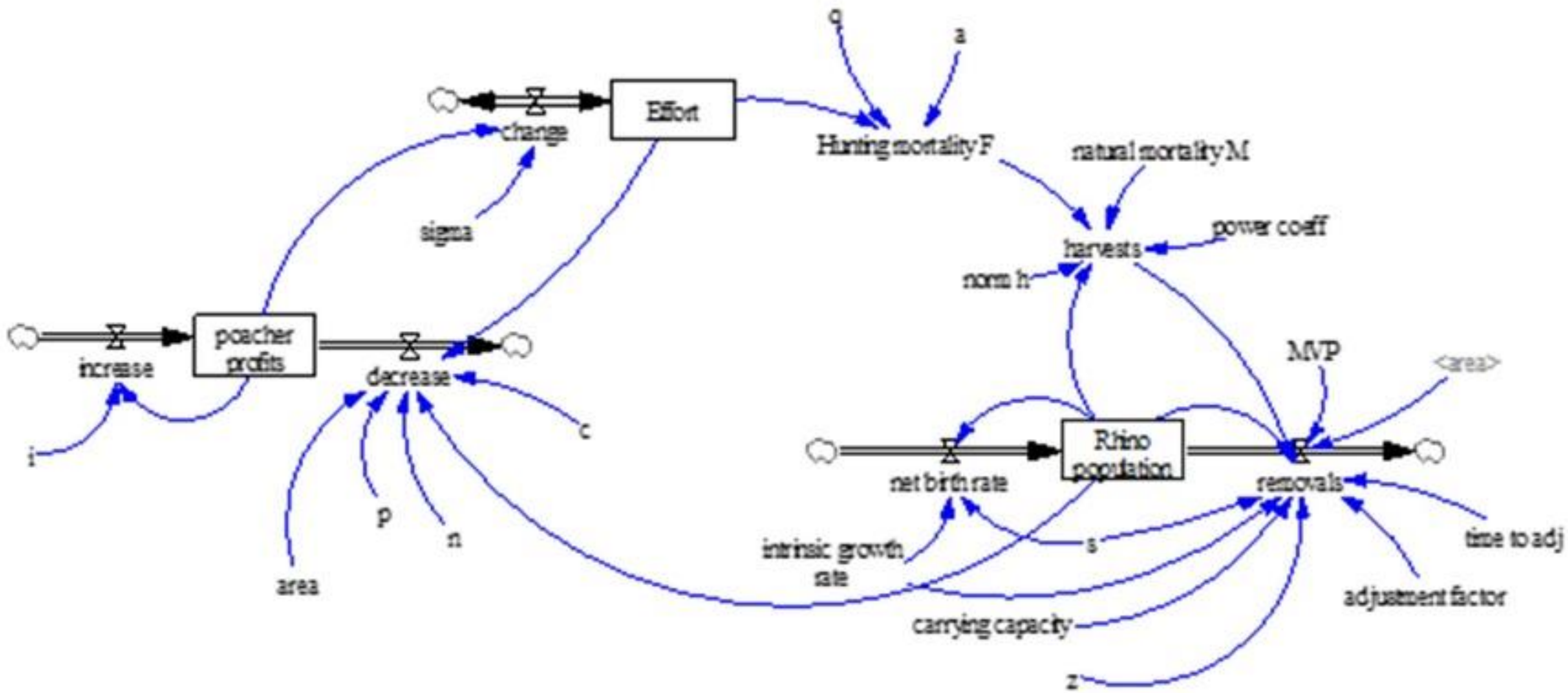

Figure 5.3: Stock flow diagram for variable effort models (harvesting function model 2 and 3)

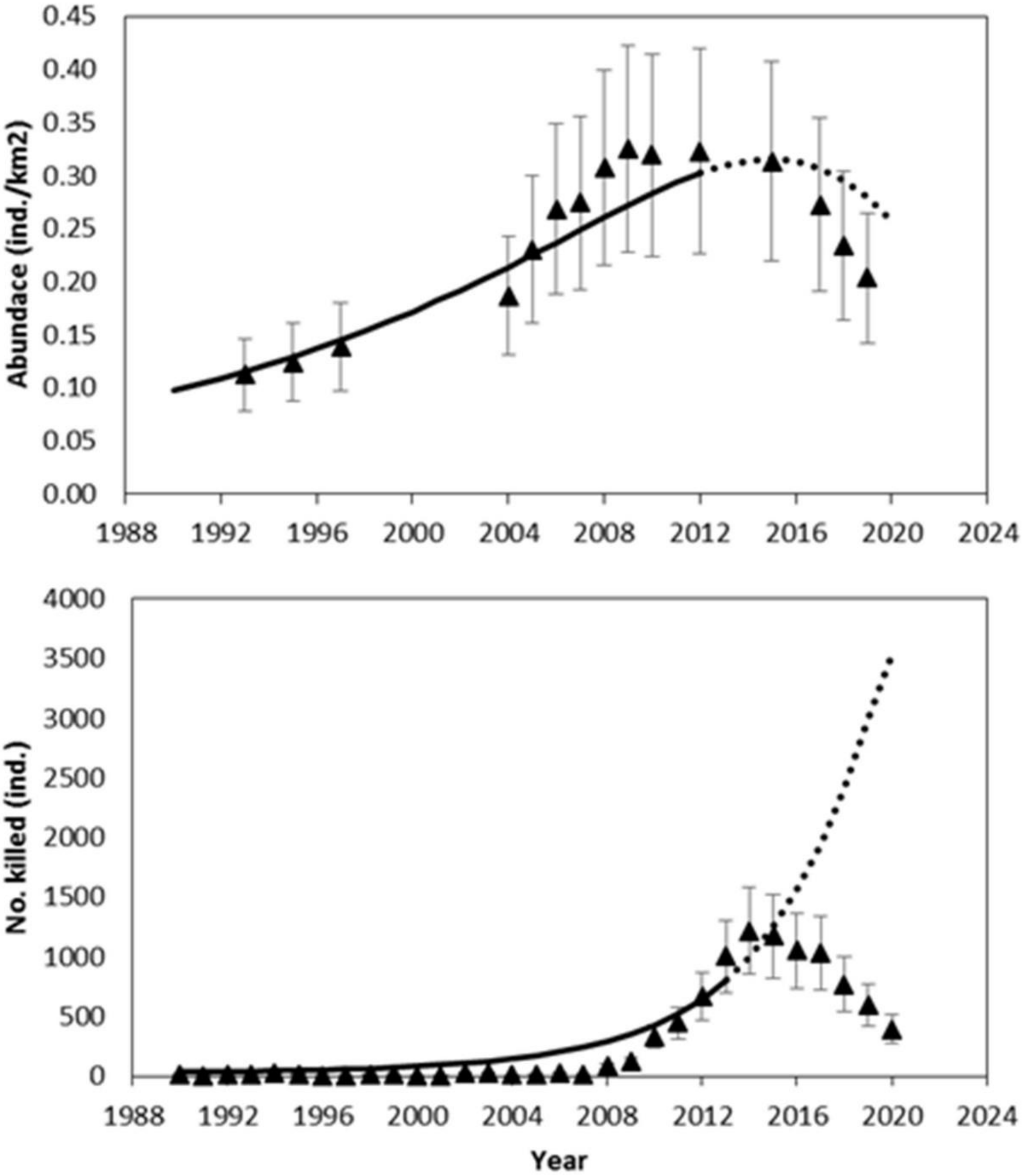

Figure 5.4: Visual plot of A. rhino abundance (top graph) and B. Number killed (bottom graph). The error bars represent coefficients of variation (CVs) and the triangles actual data. The solid line represents model simulations from the LV Schaefer model (a=1), and the dotted line represents forecasts from the same model.