Uncertainty in models for decision making in Conservation

"To know one's ignorance is the best part of knowledge"

Loa tzu

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1. Abstract

Uncertainty is a central constraint to decision making. Decision makers depend on the reliability of scientific knowledge to make informed and well-guided decisions, however uncertainty exists within both scientific knowledge and the implementation of decisions. Across disciplines uncertainty is termed and treated differently. In this thesis, I review climate change, social-ecological systems, fisheries and applied ecology and conservation due to their active interactions with decision makers. In these and other fields, models are often used to assist decision making, and are inevitably affected by the fundamental uncertainties that surround modelling complex life systems. I investigated model uncertainty and parameter uncertainty by manipulating different structures and parameters of a harvest-household management strategy evaluation model, keeping other aspects constant, to examine the impacts on model outcomes. I found that applied ecology and conservation has the largest number of terms to describe the same uncertainties compared to climate change that has the most specific definition usage. Climate change has the clearest guidelines addressing uncertainty compared to fisheries, social-ecological systems and applied ecology and conservation. When assessing the impacts of uncertainty I found that when a population model differs in structure a cumulative effect of uncertainty occurs from the inclusion of stochasticity, logistic growth, density dependence functions and parameter differences. Similarly in the harvester model, structure differences highlighted the cumulative effects of uncertainty from the inclusion of stochasicity and differing utility equations. Parameter uncertainty of high and low juvenile mortality highlighted how one parameter can affect model outcomes. The exploration into model uncertainty is a research importance as many decision makers are reliant on tested and well communicated certainties of model outputs. A unified framework for dealing with uncertainty is particularly necessary for conservation in the context of the formation of the intergovernmental science-policy platform on biodiversity and ecosystem services, which aims to join the scientific community and decision makers and as uncertainty awareness climbs the research agenda.

Keywords: Uncertainty; Model uncertainty; Decision making; Conservation

2. Introduction

Uncertainty exists everywhere; the predictability of the effectiveness of different conservation management strategies is uncertain. Conservation is an interdisciplinary field which draws from many disciplines which deal differently with uncertainty. Conservationists have to make decisions quickly and effectively upon which species survival is often dependent and therefore they need to be aware of the uncertainty that surrounds the outcomes of making different decisions.

Across disciplines models have proven to be extremely useful assisting in the understanding of dynamics, predictive forecasts and applied to decision making (Perry & Millington 2008; Thomas et al. 2004; Drechsler 2000). Models are diverse in their application, for example from providing an open fishing season for the maintenance of spiny lobster (*Panulirus argus L.*) populations (Medley 1998) to combining with decision analysis to conserve orange-bellied parrots (*Neophema chrysogaster*) in Australia (Drechsler 2000) to the guiding management strategies for the Bonelli's eagle (*Aquila fasciata*) in Spain (Soutullo et al., 2008). When modelling, uncertainty is one element that is certain: a model is a representation of the real world; thus when models are used to simplify and untangle real world complexity uncertainty must be present (Kokko 2005). At least 97% of ecological models consider uncertainty in some way (Drechsler et al. 2007) .The presence of uncertainty in conservation management is a critical constraint; understanding and planning for uncertainty when making decisions will provide greater resilience to unexpected scenarios (Brugnach et al., 2006; Rowell, 2009). Brewer & Gross (2003) recommends that by cultivating a society who has a better grasp of uncertainties and its effects on prediction will benefit all. Ludwig et al. (1993) in lessons from history highlighted that confronting uncertainty is an effective principle for decision making.

Uncertainty is defined as the "incomplete information about a particular topic" (AscoughII, et al., 2008). Many disciplines have classified uncertainty but communication across disciplines is sparse (Harwood & Stokes 2003; Walker et al. 2003; Regan et al. 2002; Charles 1998; Morgan & Henrion 1990). There is a great potential for interdisciplinary learning from well established fields that deal with uncertainty such as engineering and economics. Uncertainty classification structures vary within ecology (AscoughII et al. 2008). For example Walker et al. (2003)

expressed uncertainty classification as the location and level of uncertainty types and produced an uncertainty matrix. AscoughII et al. (2008) classified uncertainty into process understanding, variability, decision making and linguistic uncertainty. The classification of uncertainty by Regan et al.'s (2002) for ecology and conservation is widely referenced, separating uncertainty into epistemic and linguistic uncertainty (Table 1).

Table 1. Definitions of sources of uncertainty

Sources of uncertainty	Definitions (Regan,et al., 2002)
Epistemic Uncertainty	The uncertainty of knowledge or understanding, arising due to insufficient data, extrapolation and the limitations of measurement devices and the variability in time or space. Epistemic uncertainty includes parameter, model and subjective uncertainty. Ambiguity as well as being classified within linguistic uncertainty can also be included within epistemic uncertainty as knowledge becomes uncertain if words used are ambiguous.
Parameter uncertainty	Measurement error (error due to measurement techniques and random variation in measurement) and systemic error (non random error due to bias in measuring procedure due to the judgement of the applier).
Model uncertainty	The inherent misrepresentation and misunderstanding due to the simplification of complex systems.
Ambiguity	When words have more than one meaning and therefore can be misinterpreted.
Subjective uncertainty	The uncertainty that arises due to the interpretation of data; due to the empirical lack of data expert judgement is used in its place.
Linguistic Uncertainty	Uncertainty derived from communication and definitions, where scientific terminologies are vague, context-dependent or has theoretical indeterminacies which include uncertainties such as numerical and non-numerical vagueness, context dependence, underspecificity and ambiguity.
Ontological Uncertainty	Uncertainty associated with processes including natural variation, inherent randomness and dynamical uncertainty.

Epistemic and Linguistic uncertainty both exist when modelling living systems (Elith et al.,2002) .There are four main sources of uncertainty when modelling (figure 1). Parameter uncertainty emerges due to model input variables. Model uncertainty occurs within the model due to the model being a representation of a biological system. This also includes model ontological uncertainty. Subjective uncertainty occurs from the interpretation of outputs affected already by parameter, model and ontological uncertainty. The communication of the model outputs for decision making purposes linguistic uncertainty occurs, due to the failure to apply clear, concise, defined, context of the inputs, model and outputs.

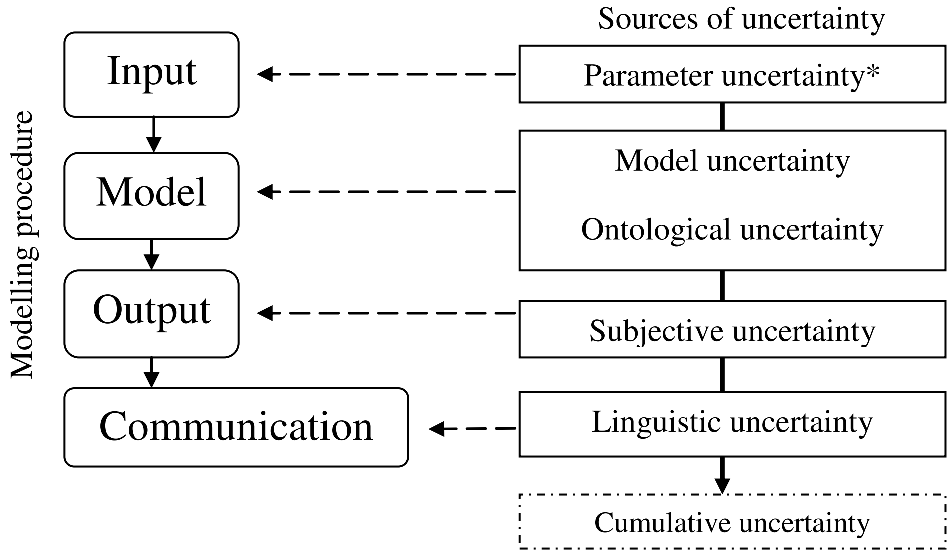


Figure 1. Schematic diagram of different uncertainties as they occur at different of stages in the modelling procedure, as uncertainty accumulates to produce cumulative uncertainty.

**parameter uncertainty is also involved in validating model s with empirical data, highlighting imperfections in observation and measuring techniques as well as bias in the sampling process however will not by highlighted in the conceptual model investigation as there is not empirical observation of a true system.*

This project aims to review uncertainty considered and dealt with across disciplines. Fisheries, climate change, social-ecological systems and applied ecology and conservation were chosen to be investigated due to active interactions with decisions makers. The types of uncertainty considered and defined within each discipline were examined to compare how definition and classification differ between fields. The disciplines' treatments of different sources of uncertainty were examined to see how different fields deal with uncertainty in addition to whether the methods available were widely applied within the discipline.

Decision-makers often use models to inform decisions. To explore the impacts of model uncertainties a harvest-household management strategy evaluation model (Milner-Gulland 2011) was used, as it includes harvester and management decision behaviour. The model does not represent a true system, but allows the interaction of harvester, resource and management dynamics to be explored and model outputs could be applied to evaluate management strategies impacts on the resource harvester utility. The model represents the interactions between management, resource populations and harvesters. The management splits the allocation of their budget between monitoring the resource and protecting the resource from illegal hunting. In addition the management sets a legal harvest control rule. The harvester hunts the resource dependant on household utility and may choose to harvest illegally to increase utility but this is dependent on the cost of being caught and whether it's worth harvesting the resource compared to farming. The resource population depends on the number being harvested by the harvester. The difference between what the management thinks is being harvest, the harvest control rule, may actually be very different if the harvester decides to illegally hunt. The difference between the truth and management highlighted by this model emphasizes its application into investigating real world disparity for maintaining resource populations. Therefore it is useful to know how model uncertainty could affect model outcome and decisions made from the application of this model.

As a conceptual exploration into model uncertainty the results are interpreted qualitatively rather that quantitatively as the results are not validated or calibrated by the observation of a real system. The results cannot be applied to inform real life decisions but can be used to highlight how model output can be affected by modelling uncertainty. Model structure uncertainty was examined by comparing a single age class population model to an age structured population model within the harvest-household management strategy model. The use of the age structure within the management strategy evaluation (MSE) model has not been widely used (excluding Myrseth et al. 2011) and has been shown to be a way of assessing management strategies by including uncertainty as a fundamental component(Bunnefeld et al. 2011; Milner-Gulland 2011).Lindstrom & Kokko (1998) investigated the behaviour of two density dependant population model, one being an age structured, showing that models come to similar conclusions but they highlighted, in the single structured model, the complicated relationship between density dependence and reproductive rate. In addition, differing harvester decision models were investigated to examine the driving uncertainty mechanisms affecting the models population size and harvest numbers. Parameter uncertainty was examined by comparing the influence of one parameter's on the model outputs of population size and harvest numbers. By defining and quantifying uncertainties, the impacts of different uncertainties impacts can be clearly presented to decision makers. Improved representation of uncertainty to decision makers will allow better decisions to be made.

Objectives

- To identify the types and sources of uncertainty recognized in different disciplines.
- To review how different disciplines address and treat uncertainty.
- To examine to what extent uncertainty is dealt with in each discipline.
- To explore conceptually how model uncertainty affects model outcomes.

3. Methods

3.1 Methods for the review of uncertainty in four environmental disciplines

I investigated the fields of applied ecology and conservation, climate change, fisheries and social-ecological systems, each of which are applied disciplines where models are used to help make management. Uncertainty is importance and fundamental in all these disciplines from the uncertainty in fish stock number to the prediction of our future climate. We need to try and understand the uncertainty that surrounds our world to better predict the future outcomes of our action.

The search engine science direct was used to review of the four disciplines (http://www.sciencedirect.com/). The key words used to search the literature included decision making, modelling, and uncertainty for each discipline. 180 papers and books were examined for applied ecology and conservation. 46 articles and books were examined for fisheries. 28 articles in addition to the intergovernmental panel on climate change reports on uncertainty were examined for climate change. 24 papers on social-ecological systems were examined but many papers were overlapping with applied ecology and conservation but they were also included within social-ecological systems.

For each discipline, the use and meaning of different types of uncertainties and terms used to describe those uncertainties were recorded. For each type of uncertainty, the ways in which they were acknowledge and dealt with was collated for each discipline, in addition to examples in which the application of model findings was applied to decision making. The aim is to look at what uncertainties exist in different fields and how the disciplines work with uncertainty whether it is avoided or addressed and how. Do disciplines rank uncertainty as an important element of research? Interestingly is there vagueness in the way we express uncertainty i.e. what words we use to describe uncertainty.

3.2 Age structured model uncertainty investigation

Firstly I converted Milner-Gulland(2011) harvest-household MSE model from C to R version 2.11.1 (2010-05-31) of which the code is available in the appendix. The model represents a discrete time single population using parameters in appendix 9.2.6. The population is harvested legally due to a harvest control rule set by the managers and illegally harvested dependant on household utility and hunting penalty. As many resource populations are overexploited this model captures the harvester behaviour as well as the management and resource population. It model has widely been applied to fisheries but Milner-Gulland (2011) and Bunnefeld et al. (2011) have highlighted its terrestrial application.

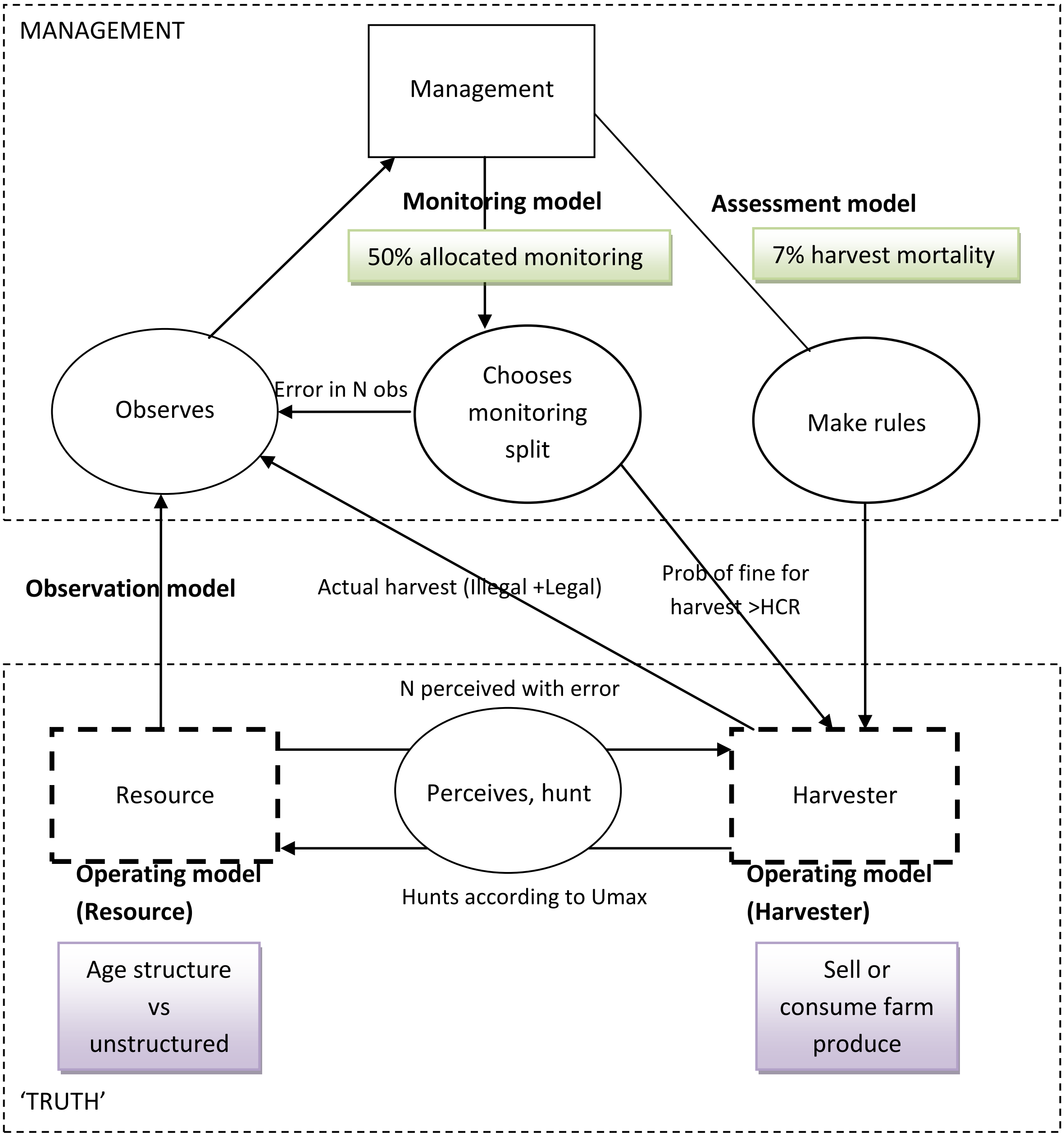


Figure 2. Schematic diagram of the integrated harvest-household management strategy evaluation model (Milner-Gulland 2011).The management was set with 50% of managers time allocated to monitoring and the harvest control rule of 7% mortality (shaded thin rectangles). Within the resource and harvester operating model (bold dashed lines) the utility of the household decision and the population were manipulated to examine model uncertainties impacts on the model outputs (shaded wide rectangles).

The model is made up of an observation, assessment, monitoring and operating models (Figure 1). The resource and harvester operating models capture the true resource population and harvester behaviour. The harvester aims to optimise its utility by calculating whether it is worth illegally harvesting the resource or instead allocate more labour to farming. The resource density dependant population initially starts at 500 and is harvested by the harvester which include illegal and legal harvest. The observed population and the illegal and legal harvest values are used by the management to use to set the harvest control rule and allocation the budget to monitoring and anti poaching. The management allocated its budget between monitoring the population number and catching illegal hunters. For this investigation the management sub model allocates a fixed 50% of the budget to monitoring and 50% to detecting poachers. The legal harvest rate of the population was fixed at 7% of the population. The metric performance values produced by the model include population, actual harvest, and legal harvest mean simulated from 2 to 50 years of management, with an initial population size of 500, and looped for 100 simulations within R version 2.11.1 to find the mean and co-efficient variation of each output. The actual harvest mean is the illegal harvest and legal harvest mean.

To examine the effects of uncertainty in model structure, I developed two versions of the population model: a single population (Milner-Gulland 2011) and an age structured model, and ran 100 simulations keeping all other aspects the same. I compared the model mean outputs of the population size, the legal and actual harvest to assess how different sub model structures affect estimates of the population and harvest I varied the penalty of the harvester being caught illegally hunting from no penalty to high to assess the impact on harvest and population means. Because different types of uncertainty may interact and cumulate, I ran several versions varying harvester behaviour, represented by changing the utility model for the decision of whether the harvester sells or consume his farm produce to examine how additional differences in the harvester sub model structure affects estimates of the population and harvest. To assess the impact of parameter uncertainty I used the age structured population and added the addition parameter of mortality. The mortality was varied for juvenile mortality and kept constant for the other two age classes to assess the impact of one parameters effect on harvest and population means. I varied the penalty of the harvester from no penalty to high to assess the impact of the cumulative effect of differing juvenile mortality had on harvest and population means.

3.2.1 Single structure population

I investigated the behaviour of two different density dependant resource operating models. These models describe the discrete time demography of the population. The single structured model is a simple discrete time logistic population model (Milner-Gulland 2011) :

$$\mathcal{N}(t+1) = \mathcal{N}(t)\ exp^{r\left(1-\frac{\mathcal{N}(t)}{\kappa}\right)} + \varepsilon \qquad (1)$$

The population, $\mathcal{N}(t)$ is the dependant the intrinsic rate of increase, r, is 0.2 and the carrying capacity, κ, of 500 produces the single structured population size next year, $\mathcal{N}(t+1)$. ε is represents the stochastic term

$$\varepsilon = \sum_i \delta_N \qquad (2)$$

which is the standard deviation of the population, δ , 40 multiplied by the random number taken from a normal distribution$\sum_i$ with mean 0 and standard deviation of 1.

3.2.2 Age structured population

The discrete time simple age structured model represents juvenile,$\mathcal{N}_J(t)$, young adult,$\mathcal{N}_Y(t)$ and adult, $\mathcal{N}_A(t)$, age classes.

$$\begin{aligned} \mathcal{N}_J(t+1) &= \varphi\mathcal{N}_A(t) + \varphi\mathcal{N}_Y(t) + \varepsilon \\ \mathcal{N}_Y(t+1) &= \mathcal{N}_J(t) + \varepsilon \\ \mathcal{N}_A(t+1) &= \mathcal{N}_A(t) + \mathcal{N}_Y(t) + \varepsilon \end{aligned} \qquad (3)$$

The juvenile population in the next year is dependent on the number of adults and young adults that reproduce plus stochasticity. The birth rate,φ, for each reproductive age class is 0.1. The numbers of young adults in the next year is dependent on the number of juveniles in the current year plus stochasticity. The numbers of adults in the next year is dependent on the number of adults and number of young adults. To achieve a density dependant structure, like the single structured model, the total population $\mathcal{N}(t)$,

$$\mathcal{N}(t) = \mathcal{N}_A(t) + \mathcal{N}_J(t) + \mathcal{N}_Y(t) \tag{4}$$

which is the total number of juveniles, young adults and adults in the current year when the population is more than the carrying capacity, the number of adults and young adults that are allowed to reproduce is halved which continues until the total population is below carrying capacity and equation 3 is used again.

$$\mathcal{N}_J(t+1) = \varphi\frac{A(t)}{2} + \varphi\frac{Y(t)}{2} + \varepsilon$$

$$\mathcal{N}_Y(t+1) = \mathcal{N}_J(t) + \varepsilon \tag{5}$$

$$\mathcal{N}_A(t+1) = \mathcal{N}_A(t) + \mathcal{N}_Y(t) + \varepsilon$$

To makes the age structured model have an intrinsic rate of increase the same as the single structured model the birth rate 0.1 was used for each of the reproductive age classes meaning that 20% of the population reproduced.

I used the single and age structured models to investigate model structural uncertainty. 100 simulations of each model within the integrated model over differing penalties so that differences between the model structures impacts on the mean population size, legal and actual harvest can be examined.

3.3 Harvester behaviour: consume or sell

I investigated how the behaviour of two different decisions made by the harvester, within the harvester operating model affected model uncertainty so that both components of the operating model; the resource and harvester model structures are examined. The choice of the harvester is whether to consume or sell farm produce, causing a difference in model structure due to a difference in how the optimal utility is calculated. I have used Milner-Gulland(2011) equations below to highlight the structural differences in calculation of making either the decision to sell or eat the farmed produce.

Firstly the perceived population, N_p, comes from the true population plus a random error in observation. The standard deviation of the perceived population δ_P, is 10.

$$N_p = \mathcal{N}(t) + \sum_i \delta_P \tag{6}$$

To find the optimal utility, the allocation of labour to hunting was looped from 1 to 50. The allocation of labour to hunting, h, and the allocation of labour to farming, $(1-h)$, was used to calculate farming production, $\mathrm{Q_f}$, and hunting production, $\mathrm{Q_h}$. Hunting production is dependent on catching, q, the perceived harvest and the labour allocation to hunting to the power of the hunting return coefficient, bh.

$$\mathrm{Q_h} = qN_p h^{bh} \tag{7}$$

The return hunting coefficient is the maximum return value, z_h, 1.2 when there is a high population. This is multiplied by the perceived population divides by the carrying capacity times the maximum return value minus the minimum return value, z_l, 0.4 when the population is low.

$$bh = z_h \frac{N_p}{\kappa(z_h - z_l)} \tag{8}$$

The farming production is dependent on the amount of land, L, (50) available to the harvester for farming and the labour allocation to farming to the power of the farming return coefficient, bf, which is 0.8.

$$\mathrm{Q_f} = L(1-h)^{bf} \tag{9}$$

The amount of illegal hunting, ω, is dependent on the difference between the legal harvest rule $H(t)$ and the hunting production.

$$\omega = \mathrm{Q_h} - H(t) \tag{10}$$

If illegal harvesting more than 0 detectability, D, is 1. These ten equations are the foundation equations used to calculate optimal utility for the harvester. The differing 11-14 equations highlight the difference model structure of the harvester making a decision o of either selling or consuming farm produce.

3.3.1 Harvester behaviour: Consume farm produce

If the harvester decides to consume the farm produce, the goods, $\mathcal{G}$, that the harvester has to sell is the hunted product worth which is the hunted production times the price of the hunted product, $\mathrm{P_h}$. The cost of hunting is the value cost of hunting, $\mathrm{C_h}$,(0.2) times the labour of hunting minus the risk and penalty for getting caught which is the detectability times the proportion of illegal hunters being caught, $(1-\theta)$, times the amount of illegal hunting, ω,times the penalty, λ, for getting caught. The overall risk worth of hunting is divided by the price of goods, P_G, (1).

$$\mathcal{G} = \frac{Q_h P_h - C_h h - D(1-\theta)\omega\lambda}{P_G} \tag{11}$$

The household goods is used to find the utility by which the elasticity of goods , α, (0.5), multiplied by the log of the goods plus the elasticity of farming, (1 − α, multiplied by the log of the farm production.

$$\mathcal{U} = \alpha \log \mathcal{G} + (1-\alpha) \log Q_f \tag{12}$$

3.3.2 Harvester behaviour: Sell farm produce

If the harvester decides to sell the farm produce, the goods calculation includes the farm production multiplied by the price of the farm produce,P_f , (1).

$$\mathcal{G} = \frac{Q_h P_h - C_h h + Q_f P_f - D(1-\theta)\omega\lambda}{P_G} \tag{13}$$

Therefore the utility is the elasticity of the log of the goods.

$$\mathcal{U} = \alpha \log \mathcal{G} \tag{14}$$

Both harvester decisions models were simulated 100 times in the integrated model to find assess the impact of differing decisions on the model outputs of population size and actual harvest mean.

3.4 Juvenile mortality: Parameter uncertainty

As models gain more reality, they gain complexity and addition uncertainty. This is a simple test of the parameter uncertainty. The age structured model was used and all three age classes have the same mortality rate, μ, of 10% affecting the survival of the population. However juveniles, more realistically, have a higher infant mortality rate, μ_J, compared to adults. The mortality rate for the juveniles was simulated at the same as the adults 10% and higher than the adults 50%. The number of juvenile becoming young adults is significantly fewer when juvenile mortality is high which should cause a difference the future population size. The replacement of the juvenile mortality rate in the age structure model, highlighted in bold, is to examine the affect of one parameter differences impacts on the mean population, actual and legal harvest.

$$\mathcal{N}_J(t+1) = \varphi \mathcal{N}_A(t)(1-\mu) + \varphi \mathcal{N}_Y(t)(1-\mu) + \varepsilon$$

$$\mathcal{N}_Y(t+1) = \mathcal{N}_J(t)\big(1-\boldsymbol{\mu_J}\big) + \varepsilon \tag{15}$$

$$\mathcal{N}_A(t+1) = \mathcal{N}_A(t)(1-\mu) + \mathcal{N}_Y(t)(1-\mu) + \varepsilon$$

The differ juvenile mortalities within the age structured models is simulate 100 times keeping all other aspects constant, apart from the penalty which was values changed from 0 to 5 to highlight how at different penalty values the harvest and population interact. I compared the mean population and harvest values at the low penalty (1) for illegal hunting to assess the different juvenile mortalities affect estimates of the population and harvest.

Summary table 2 summaries the methods used to examine uncertainty including the mechanism that might be driving differences between model outputs.

Table 2. Summary table of how model structure uncertainty and parameter uncertainty were investigated. Manipulations made for each investigation, the constants and differences in model settings, the mechanisms driving the uncertainty and the figure.

Uncertainty investigated (Model investigated in)	Manipulations made	Settings	Mechanisms driving the uncertainty	Figure
Model uncertainty (Resource operating model)	Single structure or 3 age class structures differing in structures and parameters to produce logistic growth of the population in resource operating model.	**Constants:** Consume farm produce; stochasticity, initial population 500 and carrying capacity 500. **Differences:** Differing carrying capacity structure and equations of logistic growth (see methods for details).. intrinsic rate of increase 20% (Single structure model), birth rate 10% (Age structure model), penalty varies 0-5,	Stochasticity, model structure, parameter difference between birth rate and intrinsic of rate increase, penalty values varies 0-5.	3
Model uncertainty (Harvester operating model)	Consume or sell farm produce decision made by harvester differing in structure to produce optimal utility affecting harvest rates in harvester operating model.	**Constants:** Stochasticity, initial population 500, carrying capacity 500 and penalty 1. Both single and age structured resource operating models used. **Differences:** consume or sell farm produce structures, same parameter values but different inclusion with goods and utility equations (see methods for details).	Stochasticity, model structure and differing uses of parameter values.	4
Parameter uncertainty (Mortality)	50% or 10% juvenile mortality rate used in age structured resource operating model.	**Constants:** Consume farm produce, stochasticity, initial population 500,carrying capacity 500 and 10% adults and young adults mortality **Differences:** 50% or 10% juvenile mortality	Stochasticity and parameter uncertainty.	5

4. Review of uncertainty in four environmental disciplines

To explore uncertainty I examined four disciplines applied ecology and conservation, social-ecological systems, fisheries and climate change which all fundamental interact with decision makers. Each discipline uses terms of uncertainty but some use more terms than others to describe different types of uncertainty (Table 3). Each discipline has different ways of dealing with each uncertainty (Table 4). In addition a general summary (Table 5) of whether, within each discipline for each type of uncertainty, terms of uncertainty were few or many and how well they dealt with different types of uncertainty, with darker shading representing gaps in which uncertainties are not treated.

Applied ecology and conservation has the widest range of terms used for different types of uncertainty; for example see different reviews and interpretation in (Elith et al. 2002; Regan et al. 2002; Harwood & Stokes 2003; AscoughII et al. 2008; Brugnach et al. 2008); The variation in terms and definitions causes more confusion and uncertainty in interpretation. Measurement error has eleven different terms in table S1, from data uncertainty to estimation error all meaning the same thing: the uncertainty that is found in a measured value. Applied ecology and conservation has a high number of terms for subjective uncertainty which is important when making decisions. Decision makers depend on the interpretation of data to be correctly presented to make decisions allow suitable actions to be taken. Especially in cases of endangered and rare species, which often have insufficient and error prone data, expert judgement is used but even ecologist cannot anticipate behaviour of ecological systems (Regan et al. 2002; Doak et al. 2008).

Applied ecology and conservation uses a wide range of strategies to treat uncertainty (Table 1), which could mean that this discipline regards the treatment of uncertainty as case-dependant. Individual studies chose to incorporate different uncertainties. Holland et al. (2009) modelled wild boar dynamics looking at parameter and model structure uncertainty. Gusset et al. (2009) discussed the robustness of parameter uncertainty on their individual based model on Africa wild dog's dynamics. Drechsler (2000) used plausible population parameters on orange bellied parrots to investigate scenario uncertainty to rank management actions. Parameter uncertainty is

Table 3. Types of uncertainty terms used across the different disciplines of applied ecology and conservation, fisheries, climate change and social-ecological systems. (Reference numbers in appendix 9.1)

	Type of uncertainty (Regan et al. 2002)	Terms	Applied ecology and conservation	Fisheries	Climate Change	Social-ecological systems
Epistemic- of knowledge	**Epistemic – of knowledge**	Epistemic uncertainty	✓ (7,65,69,98,113,122)			✓ (12,64,96,101)
		Metrical uncertainty	✓ (99)			
		Ignorance (inadequate understanding)	✓ (12,87)			✓ (12,64,87)
		Inadequate modelling of system(structural/ epistemic uncertainty)	✓ (118)			
		Forcing uncertainty			✓ (33)	
		Incomplete knowledge				✓ (13)
		Epistemic indeterminism				✓ (112)
	Measurement error (parameter uncertainty)	Approximation uncertainty	✓ (74)			
		Estimation error	✓ (39)	✓ (66)		
		Data uncertainty	✓ (6,30,6297)		✓ (123)	✓ (64)
		Parameter uncertainty	✓ (7,15,30,42,46,55,57,62,67)	✓ (79,53,82)	✓ (61,124)	
		Measurement error	✓ (3,17,30,44,49,89)	✓ (47, 50, 66,91, 104,105)	✓ (123)	✓ (12)
		Measurement uncertainty	✓ (125)			

	Sampling uncertainty	✓ (29)			
	Observer error Imperfect observation	✓ (44,118)	✓ (47,50,53,92)		
	Identification error	✓ (44)			
	Error in empirical observation	✓ (12)			
	Observational uncertainty	✓ (70)	✓ (82)		✓ (119)
	Parameter error		✓ (116)		
	Uncertainty about values			✓ (61)	
	Value uncertainty			✓ (71)	
	Input error				✓ (12)
	Partial observability				✓ (4,28,84)
Systematic error/bias (parameter uncertainty)	Statistical variation Random error	✓ (74)			
	Systematic errors	✓ (9)	✓ (25,45,91)		
	Systemic bias	✓ (89)	✓ (88)		
	Statistical uncertainty	✓ (17,67)		✓ (22)	✓ (64)
Model uncertainty	Model uncertainty	✓ (7,30,49,62,76,122)	✓ (41, 47, 53,56)	✓ (33,123)	✓(120)

	Structural uncertainty	✓ (6,17,99,122)	✓ (25)	✓ (61,71,80)	✓ (28,75, 84,87,121,119, 101)
	Model misspecification	✓ (30)			
	Model error	✓ (62)	✓ (50,66)		
	Model selection error	✓ (112)			
	Interpretation	✓ (12)			
	Implementation error		✓ (5,50,66,92)		
	Implementation uncertainty		✓ (56, 82,104,116)		
Ambiguity	Ambiguity	✓ (11,12,14)		✓ (81)	✓ (11,12,13,34)
Subjective uncertainty (interpretation of data)	Subjective judgement	✓ (39,69,74)		✓ (115)	
	Subjectivity			✓ (111)	✓ (12)
	Volitional uncertainty	✓ (7)			
	Uncertainty due to choices	✓ (55)			
	Translational uncertainty	✓ (99)			
	Subjective belief	✓ (125)			
	Disagreement (between expert uncertainty)	✓ (32)			

		Self assessment imprecision (within expert opinions)	✓ (32)			
Ontological-of processes	**Natural variation & inherent randomness**	Inherent randomness	✓ (74)			
		Randomness	✓ (74)			
		Aleatory/ irreducible uncertainty	✓ (7,29)			
		Random error	✓ (16)			
		Stochasticity Stochastic uncertainty	✓ (16,32,65)		✓ (24, 61,123)	
		Natural variation/variability	✓ (3,17,69,118)	✓ (25, 53,66,92,104)	✓ (33)	✓ (119)
		Variability	✓ (49,74)			
		Pattern-based surprises	✓ (35)			
		Unpredictability of ecological systems	✓ (74,87)			
		Environmental and demographic uncertainty	✓ (122)			
		Random fluctuations		✓ (25)		
		Natural stochasticity	✓ (17)			
		Internal variability			✓ (33)	
		Random effects			✓ (123)	
		Unpredictability			✓ (71)	✓ (13,87)

		Environmental variation				✓ (4,28,84,119)
		Ontological uncertainty				✓ (64,96,113)
		Aleatory indeterminism				✓ (112)
	Dynamics	Process uncertainty	✓ (6,30,70)	✓ (47,53,56)		✓ (4)
		Dynamics surprises	✓ (35)			
		Temporal uncertainty	✓ (99)			
		Complex dynamics	✓ (12)			
		Process error		✓ (66,105)		
		Process stochasticity		✓ (51)		
Linguistic- of communication and definitions	**Vagueness/ fuzziness, Context dependence, Ambiguity, Underspecified, Indeterminacy of theoretical terms**	Linguistic imprecision	✓ (74)			
		Ambiguity	✓ (7,11,87,125)			✓ (64,87,96,101)
		Language-based uncertainty	✓ (16)			
		Semantic uncertainty	✓ (3)			
		Underspecified	✓ (32)			
		Communication of uncertainty sources and lack of clarity		✓ (92)		

		Fuzzyness or vagueness			✓ (80)	
		Linguistic indeterminism				✓ (112)
Other	**Other**	Human uncertainty	✓ (76)			
		Intervention based surprises	✓ (35)			
		Categorization	✓ (39)			
		Lack of information Abundance of information Conflicting evidence	✓ (125)			
		Conflicting knowledge	✓ (12)			
		Limitation of management (part controllability)	✓ (118)			
		Disagreement	✓ (74)			
		Assessment error		✓ (5)		
		Mild and severe uncertainty			✓ (22)	
		Upstream and downstream uncertainty			✓ (89)	
		Court pseudo-certainty				✓ (84)
		Partial controllability				✓ (4,28,84)
		Scenario uncertainty				✓ (64)

Table 4. Ways of dealing with different type of uncertainty used in the different disciplines of applied ecology and conservation, fisheries, climate change and social-ecological systems.(Reference numbers in appendix 9.1)

	Type of uncertainty (Regan et al. 2002)	Analysis	**Applied ecology and conservation**	**Fisheries**	**Climate change**	**Social-ecological systems**
Epistemic- of knowledge	**Epistemic – of knowledge**	Additional knowledge and research	✓ (3,20,85,95)		✓ (48)	✓ (12, 87,96,101,109)
	Measurement error (parameter uncertainty)	Sensitivity analysis	✓ (26,31,37,38,78,109)		✓ (61)	✓ (13, 15, 54,90)
		Different types of confidence intervals, Error bands, Intervals and sure bounds, Widen bounds	✓ (15,19,31,38,109,122)	✓ (52)		✓ (1,13)
		Scenario analysis		✓ (52)	✓ (61,93)	✓ (13,96)
		Statistics, distributions and probabilistic modelling	✓ (30, 49, 52, 60, 73,85)	✓ (49)	✓ (28,71, 106)	✓ (1,13,98,)
		Likelihood methods/profiles		✓ (52,91)		
		Observers estimate uncertainty around point estimates	✓ (44)			
	Systematic error/bias (parameter uncertainty)	Bayesian analysis /network/inference for parameter values	✓ (21,30, 69,77,100)	✓ (52,79)		✓ (103)
		Bootstrap and Jack knife technique		✓ (52,79)	✓ (71)	
		Monte Carlo techniques	✓ (26,58)	✓ (52)		
		Recognize and remove bias	✓ (23)			
		Info-gap analysis			✓ (115)	✓ (8)
		Bayesian analysis for model structures and parameter values	✓ (18,51, 58,71,107)		✓ (115)	

Model uncertainty	Sensitivity analysis	✓ (28, 57,78)			✓ (13,15,102,100)
	Elasticity analysis		✓ (52)		
	Probability	✓ (18,122,)	✓ (52)		
	Model fitting/Checking -Least square residual error approach -Maximum likelihood -Bayesian statistics -Choice of criterion -Testing the predictions against independent data	✓ (18,38,122)	✓ (52,47)		
	Bayesian model averaging Continuous and discrete model averaging	✓ (36,38,122)			
	Uncertainty analyses	✓ (58,114)		✓ (24, 61,123)	✓ (13)
	Monte Carlo techniques	✓ (38,122)	✓ (52,53)	✓ (123)	
	Competing models and compare the outcome with data	✓ (18,27,51, 57,83,86, 98,122)		✓ (71)	✓ (100)
	Judgment of confidence by weight or credibility measure that reflects the degree of faith in that model.			✓ (84,106)	
Ambiguity	Group-decision-making, Communication, Calibrated language and participatory management -Rational problem solving -Persuasive communication -Dialogical learning -Negotiation -Opposition modes of action			✓ (71)	✓ (10,11,13)
	Clarify meaning/definition/terms and assumptions Specify context	✓ (3, 20,38, 63)		✓ (71)	✓ (98)

Ontological- of processes	**Natural variation & inherent randomness**	Probability distribution Statistical distributions Frequency distributions	✓ (3,38)		✓ (28)	✓ (12, 84,98)
		Scenario			✓ (71)	✓ (13)
		Recognized, measure and sometimes estimate	✓ (68)			
	Dynamics	More analysis and long-term data collection	✓ (35)			
Linguistic- of communication and definitions	**Linguistic – of communication and definition** Includes: vagueness, context dependence, under-specificity etc.	Communication and awareness of uncertainty cooperative research efforts Appropriate levels of precision Clear statements and explicit time frames	✓ (20,76)	✓ (92)	✓ (71)	✓ (96,111)
		Phrasing questions as frequencies	✓ (69)	✓ (43,110)		
		Using Sharp boundaries to define terms	✓ (38)			
		Define categories	✓ (20)			
		Calibrated language Qualitatively defined levels of understanding Calibrated levels of confidence			✓ (71)	
	Vagueness/ fuzziness	Use of Fuzzy sets Fuzzy logic	✓ (2,3,38,98)		✓ (94)	
		Supervaluational approach	✓ (40,98)			
	Other	Multi-criteria decision analysis			✓ (80)	✓ (101)

Table 5. Summary table across the different disciplines, applied ecology and conservation, fisheries, climate change and social-ecological systems, generally is uncertainty discussed, acknowledged and dealt with. ☑represents dealt with the uncertainty, ✓represents dealing with the uncertainty, % represent uncertainty is sometimes dealt with and ✖ represents that the uncertainty is not dealt with. The darker shading highlights the gaps in dealing with uncertainty.

	Applied ecology & conservation		***Fisheries***		***Climate change***		***Social-ecological systems***	
	Terms of uncertainty	Dealt with	Terms of uncertainty	Dealt with	Terms of uncertainty	Dealt with	Terms of uncertainty	Dealt with
Epistemic – of knowledge								
Measurement error (parameter uncertainty)	Lots of different terms	✓	Some different terms	☑	Some different terms	☑	Some different terms	☑
Systematic error/bias (parameter uncertainty)	Lots of different terms	✓	Specific terms	☑	Few terms	☑	Specific term	☑
Model uncertainty (at a smaller level)	Lots of different terms	✓	Some different terms	%	Specific terms	%	Specific terms	%
Ambiguity(multiple meanings)	Little discussed	%	Not discussed	✖	Little discussed	☑	Little discussed	☑
Subjective uncertainty (interpretation of data)	Lots of different terms	✖	Not discussed	✖	Specific terms	✓	Specific term	✖
Ontological – of processes:								
Natural variation & inherent randomness	Lots of different terms	☑	Very few terms	✓	Some different terms	☑	Some different terms	☑
Dynamics	Lots of different terms	✓	Very few terms	✓	Not discussed	✓	Little discussed	✖
Linguistic – of communication and definition								
Includes: vagueness, context dependence, under-specificity etc.	Lots of different terms	✓	Not discussed	%	Little discussed	%	Some different terms	%

the one that many ecologists concentrated on, despite acknowledging the impact of other uncertainties on model outcomes.

Social-ecological systems have many overlaps with applied ecology and conservation in the terms and ways in which different uncertainties are dealt with. There are intrinsic uncertainties in the dynamics and behaviour of the complex interactions of social-ecological systems (Allen et al. 2011). Few papers deal with the treatment of uncertainty in modelling social-ecological systems (Schlueter, pers. com.). Tyre & Michaels (2011) highlighted three case studies with uncertainty in social-ecological systems. One example, Slooten et al. (2001) examined the effects of gillnet on Hector's Dolphins (*Cephalorhynchus hectori*) used a subjective probability distribution of juvenile survival, the social conflict in opinion between fisheries and conservationist on the effect of gillnet on mortality due to the subjective probability Tyre & Michaels (2011) highlighted could be either pessimistic or optimistic. Acknowledging socially generated subjective uncertainty is important for decision making (Tyre & Michaels 2011).

Fisheries have classified uncertainty by random fluctuations, uncertainty in parameter estimates and states of nature and structural uncertainty (Charles 1998). Classification was an important development for the management of uncertainty as it provides a platform from which the treatment of defined uncertainties can begin, so that fishery managers can be best prepared to make decision under uncertainty (Gray et al. 2010). Fisheries have more terms for parameter and model uncertainty that the other types of uncertainty suggesting that these types of uncertainty are more widely discussed than areas such as subjective and linguistic uncertainty, for which there appears to be no term of reference (Table S1). Ambiguity and subjective uncertainty not treated and barely discussed, possible due to the strategy for dealing with uncertainty by concentrating on extensive data collection to reduce inherent uncertainty in parameter values and states of nature (Table 3) (Doyen 2003; Halpern et al. 2006).

There has been limited treatment of uncertainty within marine management and fisheries (Halpern et al. 2006). This is re-enforced by the methods for dealing with uncertainty, which are for mainly parameter and model uncertainty, for example model checking and different types of confidence intervals (Hilborn & Walters 1992; Haddon 2001). The communication of research by fishery scientists to fishery managers and stakeholders could be misinterpreted due to misunderstanding of probability (Peterman 2004). Teigen (1994) found that probaility can be intrepreted in six different ways from 'chance' to 'confidence'; to alleviate this issue frequency values are used instead (Gigerenzer & Hoffrage 1995; Peterman 2004).

Addressing uncertainty is becoming an important element of decision making in fishery management (Patterson et al. 2001) The development of the management strategy evaluation (MSE) framework within fisheries allows many management strategies under a range of alternative objectives and circumstances to be simulated to be compared scenarios (Bunnefeld et al. 2011). Management strategy evaluation incorporates implementation uncertainty, which is the uncertainty surrounding executing management rules and maintaining stocks (Fulton et al. 2011), as well as parameter uncertainty. In addition resource user and fisherman behaviour are included within models by using for example fleet dynamic modelling of fishing boats (Fulton et al. 2011).

Within climate change science the largest number of similar terms used are associated with natural variation and inherent randomness (stochasticity, natural variation internal variability, random effects unpredictability shown in Table S1). This discipline has ways of dealing with epistemic uncertainty and even clear guidelines set by the intergovernmental panel on climate change to communicate uncertainty using a calibrated language (however these guidelines were intended to assist lead authors of the fourth assessment report to deal with uncertainty but a wider application of guidance notes could benefit both scientist communication of understand but also assist policy makers understanding) (Manning et al. 2005). Unpredictability, structural and value uncertainty provide basic classification of the types of uncertainty (Manning et al. 2005). Working Group III from the Intergovernmental Panel on Climate Change (IPCC) 2007 qualitatively defined levels of understanding, based on levels of agreement of findings in concurrence with present literature and the amount of evidence from the number and quality of independent sources (Barker et al. 2007). In addition the guidance of calibrated language of three forms qualitatively defined levels of understanding, quantitatively calibrated levels of confidence and a likelihood scale to provide consistency (Manning et al. 2005). They emphasize that the future is uncertain and that scenarios are not prediction of the future, as well as highlighted that there are gaps in available knowledge particularly from developing countries. To reduce these uncertainties by addressing these gaps and thus facilitating improved decision-making for mitigating climate change. The positive approach to developing guidelines and frameworks for tackling uncertainty seen in climate change research to address uncertainty to facilitate improvements in decision making should be more widely applied to address uncertainty in other disciplines.

The future priority for scientists is to improve uncertainty acknowledgement, evaluation and communication to improve decision making (Hill et al. 2007; Tyre & Michaels 2011). Uncertainty may be seen as an impossible burden to try to deal with but by viewing uncertainty as 'information about information' makes the problem of removal turn into a task of discovery (Borchers 2005).

5. Model results

5.1 Model uncertainty: Single versus age structured model

Figure 3a illustrates that as the penalty for illegal hunting increases the actual and legal harvest means changes in relation to one another correlated also with the mean population size in Figure 3b. As the penalty increases the differences between the actual harvest and the legal harvest narrows, the single structured model actual and legal harvests means match after the penalty of 3. However the age structured model harvests narrows but the legal and actual means do not match. Figure 3a highlights that the age structure model behaved similarly in harvesting compared to the single structured model in relations to the affect of penalty. However the age structured model has a lower legal and actual harvest mean as well as a lower population size compared to the single structure model. In addition the age structured model has more fluctuation compared to the single structured model in both legal and actual harvest means and population mean. The differences between the single and age structured model results are driven by the stochastic term, model structure and the parameter differences between birth rate and intrinsic rate of increase. This highlight to that structural difference in population models can have an impact on population means and harvest means suggestion that caution should be taken when applying results of models to real life systems as how the model is structured impacts can impact model conclusions.

Figure 3a

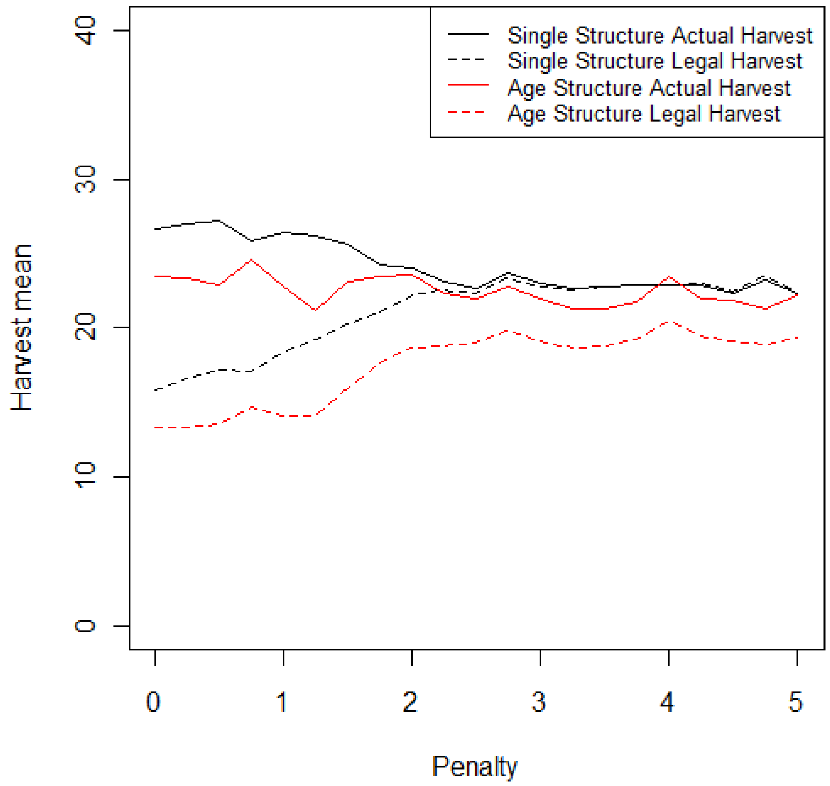


Figure 3b

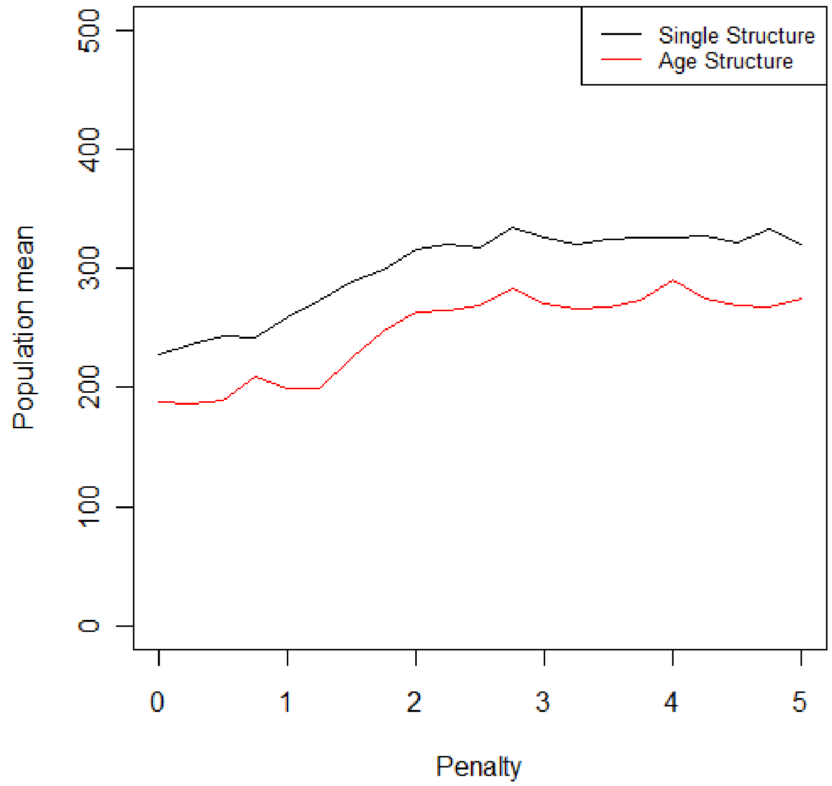
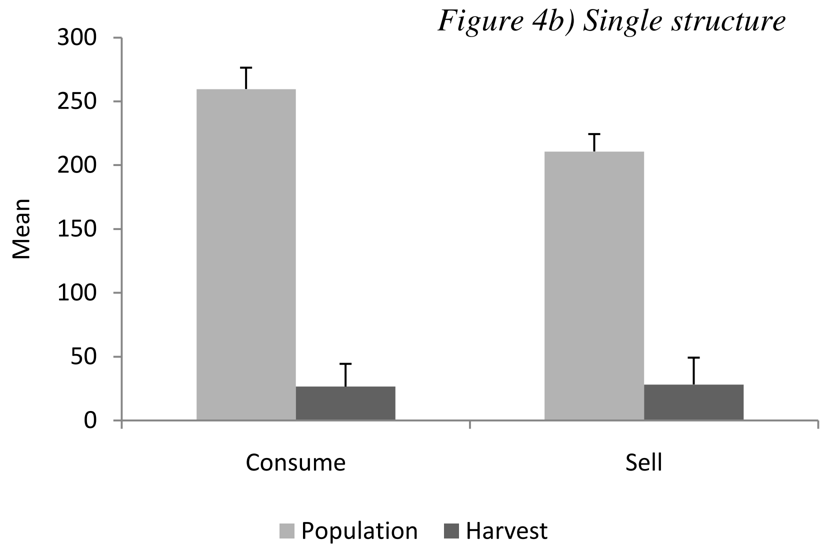


Figure 3: a) The single structure compared with the age structured resource operating model showing how model uncertainty, focusing on capturing structural differences, effects population and harvest means over varying penalty values a) represents the mean actual and legal harvest dynamics as the penalty for illegal harvesting increases changing harvester behaviour for single structured and age structured resource operating model. b) represents the mean population dynamics as the penalty for illegal harvesting increases changing harvester behaviour for single structured and age structured resource operating model.

5.2 Household decisions structural uncertainty

Figure 4 represents the differences between the harvester behaviour, whether to sell or consume farm produces, effects on population and harvest due to the different equations used to calculate goods and utility values affecting optimal utility. The actual harvest is dependent on the optimal utility which affects the population. The mean number of individuals actually harvested when the harvester decided to sell farm produce was higher than the mean harvest of 26 individuals when the farm produce was consumed when the single structured model was used (figure 4a). Similarly when the age structured model was used, the harvest mean number of individuals was 24 for when the harvester decided to sell farm produce which was higher compared to when the farm produce was consumed of which the mean harvest was 22 (figure 4b).

The population mean for selling compared to consuming farm produce is correlated with the harvest mean. The single structured model, the selling population mean is lower at 210 compared to the consuming population mean of 259. Similarly the age structure model the selling population mean is lower at 161 compared to the consume population mean of 199. The error bars represent the co-efficient variation highlighting that the single structured model has a lower co-efficient variation showing less dispersion around variables to age structured model population and actual harvest mean. The differences between the two harvester decisions are driven by the stochastic term and model structure.



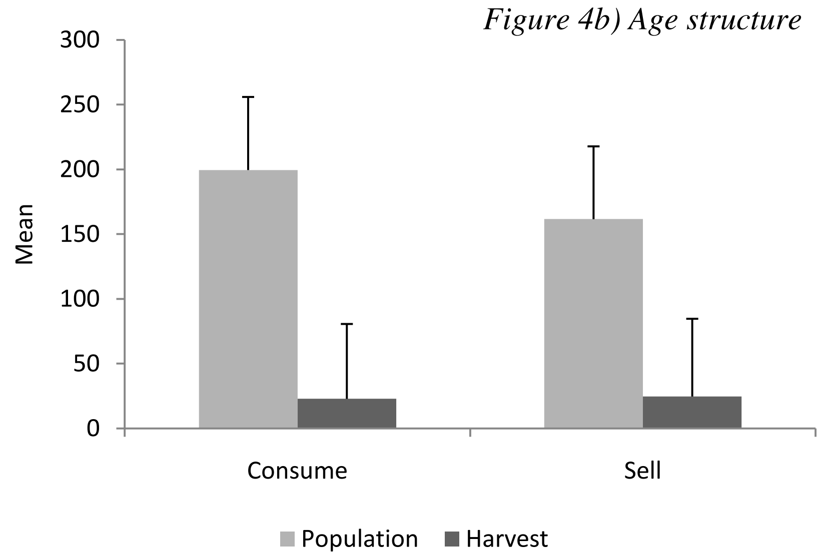


Figure 4: The harvester decision whether to sell or consume farm produces, in the harvester operating model within the integrated model, affects on the population and harvest means. Both structures, single and age population models outputs are shown a) represents the mean population and harvest for the single structure resource operating model and b) represents the mean population and harvest for the age structured resource operating model.

5.3 Parameter uncertainty

Figure 5 shows the effect of parameter uncertainty on model outputs. Figure 5a shows that higher juvenile mortality reduces the number of individuals harvested both the legal and actual harvest means. Figure 5b shows the effect of juvenile mortality on population mean over increasing penalty from 0 to 5. The 50% juvenile mortality mean

Figure 5a

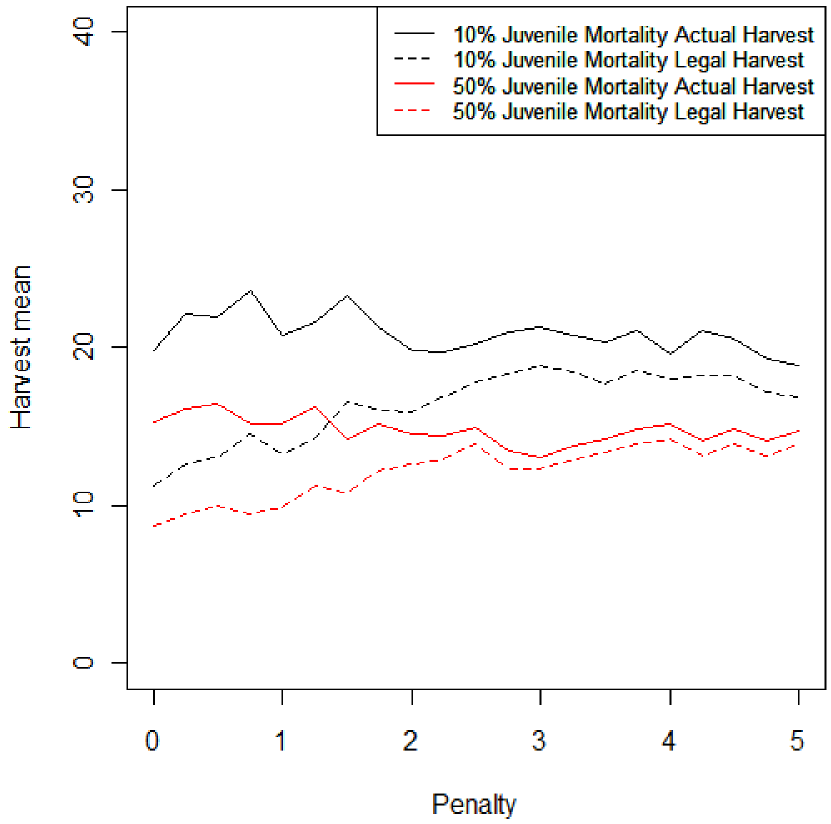


Figure 5b

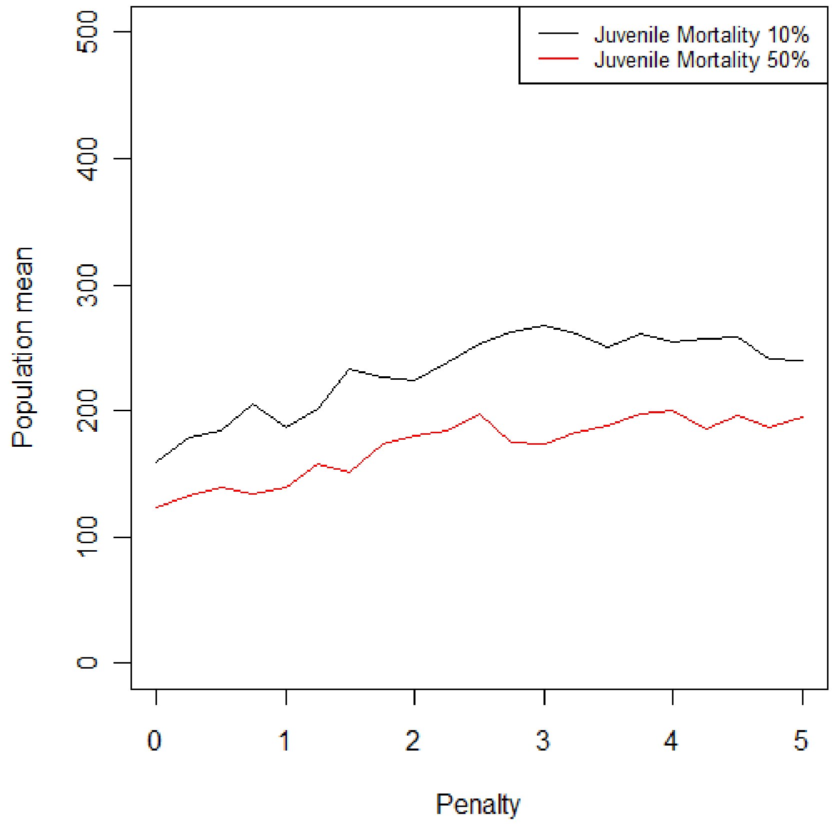


Figure 5: Representation of parameter uncertainty using the age structured resource operating model in integrated model with varying juvenile mortality of 50% or 10% over varying penalty values a) represents the mean actual and legal harvest dynamics as the penalty for illegal harvesting increases changing harvester behaviour. b) represents the mean population dynamics as the penalty for illegal harvesting increases changing harvester behaviour.

population is lower compared to the 10% juvenile mortality. The differences in the results are solely driven by the parameter juvenile mortality effect and the stochastic term.

When the penalty value is set at 1 the difference between the population mean for the 50% juvenile mortality is 139 compared to the 186 population mean when there is 10% juvenile mortality. The difference between the actual harvest mean for the 50% juvenile mortality is 15 compared to the 20 actual harvest mean when there is 10% juvenile mortality. The difference between the legal harvest mean for the 50% juvenile mortality is 9 compared to the 13 legal harvest mean when there is 10% juvenile mortality.

6. Discussion

Across environmental disciplines, climate change, social-ecological systems, fisheries and applied ecology and conservation, all vary in how they term and treat uncertainty. Applied ecology and conservation has many terms for the same uncertainty types compared to climate change that has a more frequent use of the same terms for uncertainty types. Fisheries lack terms for definition for linguistic uncertainty, ambiguity and subjective uncertainty.

There are many techniques that are used by scientists across the four disciplines to address uncertainty types. Commonly subjective uncertainty, which is the interpretation of data uncertainty, across disciplines, is not dealt with effectively suggesting a new area of uncertainty research. Linguistic uncertainty is sporadically examined between disciplines but is more often dealt within applied ecology and conservation; even through equally the other discipline rely on effective communication to decision makers. Interestingly parameter uncertainty was best treated for across disciplines which could be due to the ease of identification compared to other uncertainty types such as model uncertainty that has a combined cumulative effect from other uncertainties.

Although the majority of studies within applied ecology may consider uncertainty (Drechsler et al. 2007), it is clear from investigating the literature that few attempt to deal with it thoroughly some uncertainty types are easier to treat as they are easier to identify. Many identify parameter uncertainty and investigate the effects of different parameters on model outcomes (Wallach 1998; Drechsler 2000; Clancy et al. 2010; White 2010; McGowan et al. 2011). Model uncertainty however is often used to describe the cumulative uncertainty, including model structure and parameter uncertainty (Holland et al. 2009), rather than investigate the structure differences caused by modelling techniques and modellers themselves. This review has highlighted that as uncertainty is universal across disciplines; interdisciplinary communication between disciplines would be highly beneficial as some areas have dealt more effectively with certain uncertainties where others lack definition and treatment.

This investigation has emphasised the difficulty in acknowledging and representing uncertainty within modelling; when aiming to study one specific uncertainty other uncertainty are also involved in driving the differences between model outcomes. In the single and age structured models and age structured more than just model structure uncertainty was driving differences. The stochastic term, logistic growth and density dependence functions forms differed as well as parameter differences between birth rate and intrinsic rate of increase. This cumulative uncertainty resulted in the age structured model having a lower population, actual and legal harvest means. In addition the legal and actual harvest dynamics, unlike the single structured model, narrowed but did not match this could be due to the three age classes having differ harvests rates due to a proportion of the total population in each age class were harvested.

The harvester decision to consume farm produce resulted in a higher population mean when simulated in both the single and age structured models. When the harvester sold the farm produce the harvest mean was higher for both the single and age structured models. By comparing the age and single structured models differences in the model outputs of the actual harvest mean emphasises the differing effect between the single and age structure to the due to the differ structural outcome caused by the harvester decision making. Model complexity comes from representing complex systems. The decision of a harvester whether to sell or consume farm produce, within the integrated MSE model, highlights the cascade that model differences from functional forms and parameter uses drive model population and harvest mean differences.

Parameter uncertainty highlighted by the effect of 50% to 10% juvenile mortality within the resource operating model identified that higher juvenile mortality results in a smaller population mean and lower actual and legal harvest mean. In addition the effect of differing penalty values also highlighted differing harvest and population dynamics. Parameter uncertainty has a clear effect on model simulations and results and therefore exploring parameter space with differing parameters generated with real life systems in mind helps validate the models application.

Uncertainty is an integral component of modelling within the input, model and outputs, even in the interpretation of results subjective uncertainty exists humans are pattern recognizing facilitators (Doak et al. 2008). We have to live with the fact that irreducible uncertainty will always be there, but the way we attempt to recognise and eliminate reducible uncertainty is critical. This investigation has highlighted that conceptual model uncertainty is difficult to quantify compared to parameter uncertainty. There is a priority, as a modeller, to not only identify easily accessible parameter uncertainty but also recognise the importance of model uncertainty existence.

Burgman et al. (1993) emphasised that models fail if the uncertainties that surround them are not communicated. Communicating uncertainties in model outputs comprehensively to policy makers is essential for the information to be of value and application particularly in interdisciplinary research of conservation (Rae et al. 2007; Nicholson et al. 2009) Research lacks applicability if uncertainty estimates are not applied (Liu et al. 2008). However decision makers often want clear cut answers, not uncertainty in estimates and probabilities, to enforce fixed unchangeable management rather than appreciating that most management strategies wouldn't work as planned and therefore need to be flexible and adaptive (Doak et al. 2008). By using approaches such as the management strategy evaluation, uncertainty in intrinsically involved within the model from observation uncertainty to implementation uncertainty (Milner-Gulland 2011).

Many uncertainties are irreducible but we can't measure all the uncertainty of a system as some uncertainty might exist that we don't know about (Regan et al. 2002; Harwood & Stokes 2003; Borchers 2005). We can attempt to quantify uncertainty within modelling for example by providing interval, fuzzy number or probability distribution around a best estimate but information with high uncertainty could be disregarded (Burgman et al. 2005). In addition to obtaining more data and research, investigating uncertainty propagation and the use of expert opinions may give a better understanding of epistemic uncertainty (Brugnach 2005; Opdam et al. 2009). The difference between disciplines in addressing uncertainty can be highlighted by the acceptance of uncertainty within the discipline of climate change, emphasised by the IPCC guidance notes on the consistent treatment of uncertainty aiming to communicate uncertainty with a calibrated language for findings and describing evaluation of evidence (Mastrandrea et al. 2010), which even discusses the differences (see Annex A) in the guidance notes for addressing uncertainty between assessment report 3 and 4. In addition Hawkins & Sutton (2009; 2010)communicate decadal mean surface air temperature uncertainty, in a way that would appeal to decision makers in its visualisation of uncertainty, using fraction of total uncertainty represented as colour on world maps to represent uncertainty in predictions. An available interface of their results, of the regional variations in sources of uncertainty for precipitation and surface air temperatures, where uncertainty, year, type of plot and temporal meaning can be manipulated to examine and visually illustrate uncertainty (http://climate.ncas.ac.uk/research/uncertainty/).

There will always be a level of uncertainty that must be confronted when studying complex life systems. The lack of certainty when facing decision making creates a great challenge for conservationists (Schultz 2008).Decision makers faced with uncertainty and the lack of information have to decide whether to and how to act (Evans & Klinger 2008). Adaptive management strategies may allow flexibility in decision making, under uncertainty and unforeseen scenarios (Doak et al., 2008; Pahl-Wostl, 2007). Allen et al. (2010) illustrated in their ‘learn by doing’ figure of resource management’s interaction between uncertainty and management objectives as a structured feedback process of adaptive management emphasising that by enhanced learning through management experiments reduction of uncertainty is a key focus.

With the establishment of the intergovernmental science-policy platform on biodiversity and ecosystem services (IPBES) bringing together governments and organizations to act as a global mechanism of recognition of science-policy interface on biodiversity and ecosystem services (IPBES 2011). The aim of joining the scientific community and decision makers is to strengthen the use of science in decision making

(IPBES 2011). The IPBES's priorities include identifying scientific information needed for decision makers and identifying tools and methodologies relevant to decision makers (IPBES 2011). A unified framework and guidance for uncertainty would be greatly beneficial science-policy tool as uncertainty awareness across disciplines climbs the research agendas (Doyen 2003; Brugnach et al. 2007; Hill et al. 2007; Nicholson et al. 2009; Isendahl et al. 2010, IPBES 2011).

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9. Appendix

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9.2 Model code

9.2.1 Main model

```
####MSE #####
rm(list = ls()) #REMOVE other listed items
Util<<-0;

#The source () opens up the different parts of the code which are used
within the main model. Ideally the other models need to be saved
within the same directory and named within source(''). Allowing the
main model to go globally between functions and also allow the main
function to be used as an easier interface to explore the combined
harvest household management strategy model.

# Open up other model files saved
source('variables.r')
source('pop.r')
source('manage.r')
source('util.r')
source('house.r')

main<-function ()
{
#Set parameters
OM<<-1;       #OM is the observation model representing the resource
stock dynamics: 0=adaptive monitoring, 1=constant allocation to
monitoring resource stock, 2=prior OM knowledge of resource stock
decn<<-1;     # Managers choice: If OM is 0 or 2, 0=managers ignore
harvestor/hunters decisions/behaviour in budget decisions, 1= managers
include harvestor/hunters decisions/behaviours in budget decisions
check<<-1;    # Model choice: REAL 0= harvestor/hunter decisions
decisions/behaviour not included in model, 1 = harvestor/hunter
decisions included in model
HR<<-0;       # Managers set harvesting rate : 0=fixed harvest
mortality (hm); 1= maximized yeild (maxH) ; 2= maximized Utility
(maxU)  (both s.t. cons thresh)
det1<<-0;       # Stochasticity: 0=stochastic 1=deterministic

#Things to loop - choose which to comment out below:
#Dependant on penalty if caught for illegal harvesting
Pen<<-1;          #Penalty: if check=1 (that harvestor behaviour
included in model) penalty if caught 0= no penalty,1= low penalty,5=
high penalty
PMalloc<<-0.5;  # Population monitoring allocation: if OM=1 (constant
allocation to monitoring), allocation to population monitoring, 0= no
monitoring, all budget antipoaching,0.5= half time spend monitoring,
half on antipoaching,1= all budget allocation to monitoring
sdN<<-40;       #Standard deviation of resource stock dynamics

        Ploop<<-1;
    for (PenL in 0:PenLoop)  #Loop through penalties loop from 0 to 20
        {
#highlight in and out to explore population monitoring or penalty or
standard deviation
          #PMalloc<-PenL/PenLoop;  #Population monitor allocation
          Pen<<-PenL/PenLoop*PenMax; #Penalty if caught 0= no
penalty,1=low penalty,5=high penalty
          #sdN<-PenL/PenLoop*sdNmax; #Standard deviation of resource
population
```

```
          print(cbind(Pen)) #Print Penalty/population
monitoring/standard deviation loop


          OMon<<-0; #Resource population monitoring: OMon= 0 is the
True population size, OMon= 1 is the observed population size by
managers
          HRon<<-0;                  #Number of harvest individuals
from the resource population: HRon= 0 is the True harvest rate, HRon=
1 is the observed harvested population by managers
          testhm<<-0;

          hm<<-HCR();#Set hunting mortality rate

          if (OM>0) #If OM is constant or prior, allocation of
monitoring is set prior for the observation of the population
          {propB<<-budget(OM,decn);}

          loop<<-1
          for (loop in 1:no_loops) #Loop
          {

           J[1]<<-Jstart;         #Set J true population start value
           Y[1]<<-Ystart;         #Set Y true population start value
           A[1]<<-Astart;         #Set A true population start value
           Jobs[1]<<-Jstart;      #Set Jobs observed population start
value
           Yobs[1]<<-Ystart;      #Set Yobs observed population start
value
           Aobs[1]<<-Astart; #Set Aobs observed population start value
           Umax<<-0;
           OMon<<-0;

              i<<-2
              #Start the for loop through years at year 2 as first
vector values if [1]
             for (i in 2:finish)              #Year 2 to finish year
             {
                rule(hm) #Managers set Harvest Rule (HCR) either true
(Hrule[i]) or observed (omHrule[y])

                 if  (OM==0)  #OM=0 adaptive management best guess of
population size from previous year
                  {propB<<-budget(OM,decn);}   #Manager allocates
monitoring budget

                  AA[i-1]<<-propB  #A is the proportion of budget
allocated to monitoring

                  hunt(check,testhm); #Locals perception and hunting

                  logistic();#Resource population updates

                  observe(propB);  #Manager observation of population
dependant on budget allocation

                  if (U[i-1] > Umax)          # If Optimal Utility of
the household is more than the maximised Utility the Optimal utility
becomes the maximum utility
```

```
                  {Umax<<-U[i-1];}            #store maximum Utility
for this run

                 i<<-i+1

               } #end year=i

               chk<<-0;
               metric(chk);         #Metric works out means and co-
efficient of variation

           loop<<-loop+1

           } #end loop

           chk<<-1;
         metric(chk);     #Metric works out means, proportion and co-
efficient of variation
         Ploop<<-Ploop+1;
       } #end penalty bracket

} #end main bracket

main()   #RUN
```

9.2.2 Population model

```
#Save as 'pop.r'############################
#Population model####
#Logistic function - Age structure model
logistic<-function ()
{
    z_N<-0
    if (OMon==0 || OM>0&& det1==0)  #If operating model is true
population OM is constant monitoring or prior OM and stochastic
            { z_N<-rnorm(1,0,1) }

    Nstoch<<-z_N*sdN;  #Stochastic process error-random number from a
normal distribution times by the standard deviation of the population
size
      N<<-A[i-1]+J[i-1]+Y[i-1];

    if (OMon==0)  #True population
          {
            if (N<K)
            {
            J_i<<-Nstoch + ((A[i-1]*(1-mort))*birthrate) + ((Y[i-
1]*(1-mort))*birthrate)
            Y_i<<-Nstoch + J[i-1]*(1-Jmort)
            A_i<<-Nstoch + A[i-1]*(1-mort)+Y[i-1]*(1-mort)
            }

          if (N>K)
          {
            J_i<<-Nstoch + ((A[i-1]*(1-mort)/2)*birthrate) + ((Y[i-
1]*(1-mort)/2)*birthrate)
            Y_i<<-Nstoch + J[i-1]*(1-Jmort)
            A_i<<-Nstoch + A[i-1]*(1-mort)+Y[i-1]*(1-mort)
```

```
          }

          if (N<=0)
          { J_i<<-0; Y_i<<-0; A_i<<-0;}
          }

    if (OMon==1)  #Observed population
          { J_i<<-Nstoch + (omA[y-1]*birthrate + omY[y-
1]*birthrate)*(1-mort)
            Y_i<<-Nstoch + exp(rmax)*omJ[y-1]*K/(K+(exp(rmax)-
1)*omJ[y-1])
            A_i<<-Nstoch + exp(rmax)*omA[y-1]*K/(K+(exp(rmax)-
1)*omA[y-1]) + exp(rmax)*omY[y-1]*K/(K+(exp(rmax)-1)*omY[y-1])
          }

         if (J_i <0){ J_i<<- 0}
         if (Y_i <0){ Y_i<<- 0}
         if (A_i <0){ A_i<<- 0}#correction term population can't be
below 0

    if (OMon==0)   #True population
         {
           if (N>0)
           {
            J_ii<<- J_i-H[i-1]*(J[i-1]/N)-H[i-1]*(A[i-1]/N)-H[i-
1]*(Y[i-1]/N);#(1-propJ)
            Y_ii<<- Y_i-H[i-1]*(Y[i-1]/N);#*(1-propY)
            A_ii<<- A_i-H[i-1]*(A[i-1]/N);
            }
            if(N<=0)
            {J_ii<<-0;
             Y_ii<<-0;
             A_ii<<-0;}
         }  #True population minius hunting/harvest from previous time
step

    if (OMon==1)  #Observed population
         {  J_ii<<- J_i - JomH[y-1]
            Y_ii<<- Y_i - YomH[y-1]
            A_ii<<- A_i - AomH[y-1]
            }  #Observed population minius hunting/harvest from
previous time step

    if (J_ii <0){ J_ii<-0}
    if (Y_ii <0){ Y_ii<-0}
    if (A_ii <0){ A_ii<-0}#correction term population can't be below 0

    if (OMon==0) #True population
         { J[i]<<-J_ii
           Y[i]<<-Y_ii
           A[i]<<-A_ii }


    else if (OMon==1) #Observed population
         {  omJ[y]<<-J_ii
           omY[y]<<- Y_ii
           omA[y]<<- A_ii }
}
```

9.2.3 Harvest control model

Saved within 'pop.r'

```
#####################################################
#Set harvest rule
#setHR function  return offtake number of individuals harvested
setHR<<-function(testhm)  #input harvest mortality
{
    z_N<-0;
    if (det1==0)           #stochastic
    { z_N<-rnorm(1,0,1) }

    Nstoch<<- z_N*sdN  #Stochastic process error-random number from a
normal distribution times by the standard deviation of the population
size

    hrA[1]<<-Astart;   #Harvesting population start value
    hrJ[1]<<-Jstart;
    hrY[1]<<-Ystart

    J_i<<-Nstoch +((A[i-1]*(1-mort))*birthrate) + ((Y[i-1]*(1-
mort))*birthrate)   #Juveniles

    Y_i<<-Nstoch + J[i-1]*(1-Jmort)#  #young adults

    A_i<<-Nstoch +  A[i-1]*(1-mort)+Y[i-1]*(1-mort)  # adults

    if (A_i < 0){A_i <- 0}  #correction term
    if (Y_i < 0){Y_i <- 0}
    if (J_i < 0){J_i <- 0}

    offtake<<-testhm*A_i;   #management offtake of harvesting
population of Adults only

    A_ii<<-A_i-offtake;     #Harvested population of adults

    if (A_ii <0) {A_ii<-0}  #correction term

    hrA[t1]<<-A_ii;          #Harvest rule managed population
    hrJ[t1]<<-J_i;
    hrY[t1]<<-Y_i;
    ##print(cbind(setHR,t,A_i,A_ii,offtake))
    return (offtake)
}
###############################################
```

9.2.4 Household model

```
#Save within 'house.r'######################
######################################################
#Household model
hunt<-function (check,testhm)  #input whether harvester decisions
included and optimal harvest mortality
{
  #set parameters
  sdPerc<-10      #Variation in perceived N
  Lloop<-50       #Labour optimization loop
  betaF<-0.8      #0.8 return coefficient, farming
  betaH<-0.8      #0.8 return coefficient, hunting
```

```
  land<-50        #Amount of land available
  pG<-1           #Price of goods - keep at 1
  pF<-1           #Price of farm products
  pH<-2           #2 price of hunted products
  cH<-0.2         #Cost of hunting
  q1<-0.2         #Catchability coefficient
  alphaG<-0.5     #Elasticity of G (or farmed) consumption - low = H
pref
  sell<-0;        #Sell farm produce (1) or consume it (0)
  bvar<-1         #0=beta const, 1=beta dep on N
  minbeta<-0.4    #Beta when N is high
  maxbeta<-1.2    #Beta when N is low

   z_P<-0; #Set to 0

   if (OMon==0 || OM>0 && det1==0)     #If operating model is true
population OM is constant monitoring or prior OM and stochastic
   { z_P<-rnorm(1,0,1) }              #stochastic term

   if (OMon==0 && HRon==0)            #True population and not
harvested
   {  Nperc<- A[i-1]+ Y[i-1]+ J[i-1]+ sdPerc*z_P   } #perceived
population size

   if (OMon==1 && HRon==0)            #Observed population and not
harvested
   {  Nperc<- omN[y-1] + sdPerc*z_P } #perceived population size

   else if (HRon == 1)                #Harvested population
   { Nperc<- hrA[t1]+hrJ[t1]+hrY[t1] + sdPerc*z_P  } #perceived
population size

   if (HRon == 1)  #If harvest population
   {  hrH<- testhm * hrA[t1]+hrJ[t1]+hrY[t1];   }#number of harvest
individuals

  #
   if (check==0)  #Harvesting/hunter behaviour/decision not included-
just follow the HCR
   {
      if (OMon==0 && HRon==0)       #True population and not harvested
        { H[i-1]<<- Hrule[i-1] }    # harvest rule population equals
harvested population

      else if (OMon==1 && HRon==0)  #If operating model is observed
population and not harvest?
        { omH[y-1]<<- omHrule[y-1]}  # observed rule population equals
observed harvested population
    }

   else if (check==1) #Harvesting/hunter behaviour/decision included
   {
    L<<-1;
    for (L in 1:Lloop)          #For labour optimization loop
        {
          Lhunt<-L/Lloop;       #Allocation of labour to hunting
          Lfarm<-1-Lhunt;       #Allocation of labour to farming
        if (bvar==0)          #If bvar==0 means beta constant
             { betaHN<-betaH}   #Hunting return co-efficient
```

```
          if (bvar==1) #If bvar==1 means beta is dependent on
population N
             { betaHN <- maxbeta - Nperc/K*(maxbeta-minbeta)} #Hunting
return co-efficient dependant on maxbeta - perceive population/
carrying capacity* maxbeta-minbeta

            Qf<-land*(Lfarm^betaF); #Farming production- area*farm
labour* farm return coefficient
            Qh<-q1*Nperc*(Lhunt^betaHN); #Hunting production -
catchability*hunt labour* hunting return coefficient

             if (OMon==0 && HRon==0) #True population and not harvested
                { illegal<-Qh-Hrule[i-1];}   #Hunting production -
harvested individuals equals the amount of illegal hunting

             if (OMon==1 && HRon==0) #Observed population and not
harvested
                { illegal<-Qh-omHrule[y-1];}  #Hunting production -
harvested individuals equals the amount of illegal hunting

              if (HRon==1)    #Harvested population
                { illegal<-Qh-hrH;} #Hunting production minus number
of harvested individuals equals illegal


              if (illegal > 0)    #if illegal more than 0
d=detectability of harvesters
                { d<-1 }       #illegal harvester caught

              if (illegal < 0)  #if illegal less than 0
                {d<-0}         #illegal harvester escape

              if (sell==1)      #if sell=1 sell farm product
                    { goods<-(Qh*pH - cH*Lhunt + pF*Qf - d*(1-
theta)*Pen*illegal)/pG; }
              #Goods equals the hunting production* price of hunting
products -cost of hunting + price of farm products* farming production
-detectabiltiy*proportion illegal hunters caught*Penalty* amount
illegally harvested/ the price of goods

              if (sell==0)      #if sell=1  don't sell farm product
                     {goods<-(Qh*pH - cH*Lhunt - d*(1-
theta)*Pen*illegal)/pG;}
              #Goods equals the hunting production* price of hunting
products -cost of hunting -detectablity*proportion illegal hunters
caught*Penalty* amount illegally harvested/ the price of goods

              if (goods > 1)   #if goods>1
                   {
                   if (sell==1) #Sell everything
                       { Util<- alphaG*log(goods); }  #Utility equals
the elasticity of goods* log of goods

                   if (sell==0 && Qf>1) #Eat farmed product if sell= 0
and farm production is more than 1
                       { Util<- alphaG*log(goods) + (1-
alphaG)*log(Qf);} #Utility equals the elasticity of goods* log of
goods plus elasticity of farmed* log of farming production
```

```
                    }

                   #If Utility is more than or equal to Optimal Utility
                   if (Util >= OptUtil)
                       {lastOpt<-OptUtil; #Last optimal= Optimal
utility
                        OptUtil<-Util;    #Optimal utility = current
utility
                        OptQh<-Qh;        #Optimal hunting production =
hunting production
                        OptL<-Lhunt; }     #Optimal labour = Allocation
of labour to hunting

                   else
                     {L<-Lloop;} #labour optimization finished

          L<<-L+1
         # print(cbind(illegal,d,goods,Util,sell,lastOpt,OptUtil,Qh))
         #print(cbind(L,Qh,goods,Util,OptUtil,OptL)
         } #Lloop

              if (OMon==0 && HRon==0) #True population and not
harvested
                    {
                    if(OptQh>0)
                    {H[i-1]<<-OptQh;}  # Hunt/harvest population number
= optimal hunting production
                    else{H[i-1]<<-0;}
                    if(OptUtil>0)
                    {U[i-1]<<-OptUtil;} # Utility= optimal utility
                    else{U[i-1]<<-0;}
                    if(OptL>0)
                    {Lh[i-1]<<-OptL; }# Hunting labour = optimal labour
                    else{Lh[i-1]<<-0;}
                    }



                  else if (OMon==1 && HRon==0)
              #Observed population and not harvested
                     {
              omH[y-1] <<- OptQh;# Observed hunt/harvest population
number = optimal hunting production
              omU[y-1] <<- OptUtil;#Observed utility = optimal utility
              omLh[y-1] <<- OptL;
                     }    # Observed hunting labour = optimal labour


                 else if (HRon==1)           #Harvest population
             { HRutil <<- OptUtil;}#Harvest Utility = optimal utility


     #print
     #if (OMon==0)
     #    {print(cbind(Hrule,OptQh,OptUtil,OptL)); }
     #if (OMon==1)
     #    {print(cbind(omHrule,OptQh,OptUtil,Optl));}
     # if (HRon==1)
```

```
    # {   {print(cbind(testhm,OptQh,OptUtil,OptL));}

    } #end hunter decisions
}
```

9.2.5 Management model

```
#Save as 'manage.r'###################################
##Management sub model ################################
#HCR Function   setting the harvest rate HR =0 FIXED ,1 MAXMISE
HAREVEST/ YIELD ,2= MAXIMISE UTILITY
HCR<-function()
 {
     hmL<- 20;          #Harvest mortality loop ends
     hmMax<- 0.2;       #Maximum harvest mortality
     probT<-0.1;        #probability threshold: that the harvest is
less than population threshold* the carrying capacity

#////////////////////////fixed harvest mortality (hm)
    if (HR==0)
     { mort<<-Fixedhm }

#/////////maximize Harvest/yield subject to constant threshold
    if (HR==1)
    {
    for (hmloop in hmloop:hmL)
      { testhm<-hmloop/hmL*hmMax; #testhm increases
        hrN[1]<-Nstart;   #hrN- Harvesting population starting value
        meanBio<-0;               #set mean biomass to 0
        meanT<-0;                 #set mean threshold to 0

      for (t1 in 1:HRlength) #HRlength is the number of years manager
looks forward
      {
        biomass<-setHR(testhm); #biomass is the offtake of harvest
taken from the hrN harvesting population
          if(t1>start1)             #if t is more than start
            {
              if(hrN[t1]<Nthresh*K) # if the harvest population size
is more than the population threshold*the carrying capacity
                {
                 meanT<-meanT+1; #mean threshold plus 1
                 ##print(meanBio)
                 meanBio<-meanBio+biomass; #mean biomass plus offtake
                 }
            }
      }

      meanBio<-meanBio/(HRlength-start1); #mean biomass is the mean
biomass divided by the number of years the managers look forward minus
by the start value
      meanT<-meanT/(HRlength-start1); #mean threshold is the mean
threshold divided by the number of years the managers look forward
minus by the start value

      if (meanT<probT && meanBio>maxBio) #If the mean threshold is
less than the probability threshold and the mean biomass is more than
the maximum biomass
```

```
	{
	opthm<<-testhm; # The test harvest mortality rate equals the optimal harvest mortality rate
	maxBio<<-meanBio; # The mean Biomass equals the maximum biomass
	}

	#print(meanT)
	#print(cbind(meanBio,meanT,maxBio,opthm));

	}
	mort<<-opthm;  #optimal harvest mortality equals mortality
	}

#/////////////////////////////////maximize Utility (maxU)
  if (HR==2)
  {
  maxUtil<-0;    #set maximum utility to 0
  opthm<-0;      #set optimal harvest mortality to 0
  HRon<<- 1;      #check the Number of harvest individuals from the resource population HRon= 1 is the observed harvested population
  HRutil<-0;     #set Harvest rate utility to 0

  HRchk<<-1;      # include hunters make decisions

 for (hmloop in hmloop:hmL)
	{
	testhm<-hmloop/hmL*hmMax;  #testhm increases
	hrA[1]<-Astart;            #Harvesting population starting value
	hrY[1]<-Ystart
	hrJ[1]<-Jstart
	HRutil<-0;                 #Harvest rate Utility set to 0
	meanUtil<-0;               #set mean utility to 0
	meanT<-0;                  #set mean threshold to 0

    for (t1 in 1:HRlength) #HRlength is the number of years manager looks forward
      {
	biomass<-setHR(testhm);    #biomass is the off take of harvest taken from the hrN harvesting population
	hunt(HRchk,testhm);   #include harvester decisions for HRon == 1 check =1 for optimal utility (HRutility)
	if (t1>start1)              #if t is more than start
	  {
	  hrN[T1<<-hrA[t1]+hrJ[t1]+hrY[t1]
	    if (hrN[t1]>Nthresh*K)  #if the harvest population at time t is more than the population threshold times the carrying capacity
	    {
	      meanT<-meanT+1 # mean threshold equals mean threshold add one
	      meanUtil<-meanUtil+HRutil; # mean utility equals mean utility plus harvest rate utility
	    }
	  }
      }

   meanUtil<-meanUtil/(HRlength-start1); #mean utility is the mean utility divided by the number of years the managers look forward minus by the start value
```

```
   meanT<-meanT/(HRlength-start1); #mean threshold is the mean
threshold divided by the number of years the managers look forward
minus by the start value

   if (meanT < probT && meanUtil>maxUtil)   #if the mean threshold is
less the the probability threshold and the mean utility is more than
the maximum utility
   {  opthm<<-testhm; # the test harvest mortality is the optimal
harvest mortality
      maxUtil<<-meanUtil;  }# the mean utility is the maximum utility

      } #end hm loop

      #print(meanT)
      #print(cbind(meanUtil,meanT,maxUtil,opthm));

  mort<<-opthm;  #optimal harvest mortality equals mortality

  HRon<<-0;      #reset

  } #end HR2

 return(mort)
}


# Rule Function
rule<-function(hm)
 {
  if (OMon==0)  #if Monitoring is true population size
  { Hrule[i-1]<<-(Aobs[i-1]+Yobs[i-1]+Jobs[i-1])*hm;
    if(Hrule[i-1]<=0){Hrule[i-1]<<-0}
  }        #The previous population size Nobs times the harvest
mortality equals the harvested population at the current time step

  if (OMon==1)     #if Monitoring is observed population size
   {  omHrule[y-1]<<-(omAobs[y-1]+omYobs[y-1]+omJobs[y-1])*hm;
      if(omHrule[y-1]<=0){omHrule[y-1]<<-0;}}    #The previous
population size omNobs times the monitored harvest mortality equals
the harvest monitored/observed population at the current time step

 }
```

9.2.6 Monitoring model

#Saved in `'manage.r'`

```
#Budget function
 budget<-function(OM,decn) #input type of monitoring and whether to
include harvester behaviour
 {
 #/////////////////////////////////////////////////////
  if (OM == 0 || OM == 2)    #if monitoring model monitoring is
adaptive monitoring=0 and prior monitoring=2
    {
    OMon<-1; # monitoring model used for observed monitoring of the
population
    alloc<<-0;   #all funding allocated to antipoaching

    B<<-1;
```

```
    for (B in 1:Bloop)  #Budget allocated to population monitoring
        {
        pB<<-1-B/Bloop;  #pB increases, pB allocation to monitoring
        detn<-(1 - pB)*TotBudget;    #money to patrols
        theta<<-(1 - Detect)^detn; #theta = proportion escaping from
detection

        if (OM==2 || i==2) #Prior monitoring model on dynamics of
resource stock
        {
        omA[1]<<-Astart;
        omAobs[1]<<-Nstart;
        omY[1]<<-Ystart;
        omYobs[1]<<-Ystart;
        omJ[1]<<-Jstart;
        omJobs[1]<<-Jstart;
        }


        if (OM==0 && i>2)                #Adaptive monitoring
        {omA[1]<<-A[i-1];#monitored Observed population initial value
is the previous time step population
        omAobs[1]<<-Aobs[i-1];#true Observed population initial is the
previous time step population
        omY[1]<<Y[i-1];
        omYobs[1]<<-Yobs[i-1];
        omJ[1]<<-J[i-1];
        omJobs[1]<<-Jobs[i-1];
        }
        omUmax<<-0;     #observed population maximum utility =0
        omHav<<-0;      #observed harvest population =0

        y<<-2;
        for (y in 2:OMlength) # monitoring model number of years
manager looks forward
        {
        rule(hm);              # gives harvest population number
        hunt(decn,testhm);     # gives optimal utility
        logistic();            # gives population update
        observe(pB);           # gives observed population

            if (omU[y-1] > omUmax)  # If the observed monitored
Utility in this time step is more than the observed monitored maximum
utility
            { omUmax<<-omU[y-1]; }  #current utility equals maximum
utility
        y<<-y+1
        #print(cbind(y,pB,omA,omY,omJ,omH,omU,omUmax))
        }

        chk<<-2;           #gets the correct metrics/matrices
        metric(chk);                  #get observed harvest
        Hexcess[B]<<-omHav;

        if (Hexcess[B] >= Hthresh)    #If the observed harvest is less
or equal to the harvest threshold
           {
           alloc<<-pB;  #proportion of budget equals allocation
           B<<-Bloop;   #optimize allocation found
```

```
            }
         #B<<-B+1
         } # end B

      OMon<<-0;#end of monitoring model
     }

#////////////////////////////////////////////
    if (OM==1)       # monitoring model monitoring is constant
threshold
     {
    alloc<<-PMalloc;  #Constant allocation for monitoring
     }
#///////////////////////////////////////////
    detn<-(1 - alloc)*TotBudget; #Money to patrols to detect
population
    theta<<-(1 - Detect)^detn; #Proportion escaping from detection

    #if (OM>0)
    #{print(cbind(alloc))}

 return (alloc);  # return the allocation to monitoring

} #Budget
```

9.2.7 Observation model

```
#Saved in 'manage.r'
####
#Observation function
 observe<-function(alloc)  #input allocation to monitoring
 {
 a<-0.5    #parameters of detection f
 b<-0.018  #parameters of detection f

 Budget<-alloc*TotBudget;  #budget depends on allocation on monitoring
times  total budget

 z_N<-0;                         #set to 0
 if (OMon==0 || OM>0 && det1==0)  #If operating model is true
population OM is constant monitoring or prior OM and stochastic
 { z_N<-rnorm(1,0,1) }           #stochastic term

 if (OMon==0)             #True population
 { JPop<-J[i];          #Current J is the population size
   YPop<-Y[i];          #Current Y is the population size
   APop<-A[i];  }        #Current A is the population size


 else if (OMon==1)        #Observed population
 {  JPop<-omJ[y];         #Current J is the population size
    YPop<-omY[y];         #Current Y is the population size
    APop<-omA[y]; }       #Observed A is the population size

 CV<-1-(exp(a + b*Budget)/(1+exp(a + b*Budget)));
 sdJ<-CV*JPop;
 sdY<-CV*YPop;
 sdA<-CV*APop;
```

```
 if (OMon==0)  #True population
 {Jobs[i]<<-JPop+sdJ*z_N;
  Yobs[i]<<-YPop+sdY*z_N;
  Aobs[i]<<-APop+sdA*z_N;
   # Correction term a population can't be less than 0}
  if (Jobs[i]<=0)   { Jobs[i]<<-0; }
  if (Yobs[i]<=0)   { Yobs[i]<<-0; }
  if (Aobs[i]<=0)   { Aobs[i]<<-0; }}

 if (OMon==1)                #Observed population
 {omJobs[y]<<-JPop+sdJ*z_N;
  omYobs[y]<<-YPop+sdY*z_N;
  omAobs[y]<<-APop+sdA*z_N;
 if (omJobs[y]<=0) { omJobs[y]<<-0;}
 if (omYobs[y]<=0) { omYobs[y]<<-0;}
 if (omAobs[y]<=0) { omAobs[y]<<-0;}}
} #end observe
```

9.2.8 Variables

```
#Save as 'variables.r'###############################
#MSE variables
  finish<<-50     #where years finish
  start1<<-1      #where stats start being calculated from
  no_loops<<-100 #Number of loops - e.g 20
  OMlength<<-10  #Monitoring number years managers looks forward
  HRlength<<-50 #Harvesting rule length number of years manager looks
forward
  HRstart<<-20   #where harvesting rule is calculated from
  Bloop<<-20     #Monitoring budget loop increments
  PenL<<-0;       #where penalty loop start
  PenLoop<<-20;    #20 number of loops for exploration
  PenMax<<-5      #Maximum penalty
  sdNmax<<-200    #Maximum Standard deviation of population N

  mort<<-0.1;     #Mortality
  Jmort<<-0.5;    #Juvenile mortality
  birthrate<<-0.1 #population birth rate per adult
  Astart<<-166    #Population starting value
  Ystart<<-166    #Population starting value
  Jstart<<-166    #Population starting value
  TotBudget<<-100 #Total budget
  Detect<<-0.03   #Hunter/harvester delectability
  K<<-500         #Carrying capacity
  rmax<<-0.2      #Intrinsic rate of increase
  Nthresh<<-0.3   #Proportion of Carrying capacity above threshold
  Uthresh<<-0.5   #Proportion of maximum Utility above threshold
  Hthresh<<-0.1   #Illegal hunting as proportion of legal
  Fixedhm<<-0.07  #0.07 fixed hm throughout

  OptUtil<<-0;

 #Create empty vectors for numerical storage
  J<<-c()# True population size   (found in pop model)
  Y<<-c()
  A<<-c()
  H<<-c() # Actual hunting  (found in pop model) optimal hunting
(found in the household model)
  U<<-c() # optimal utility   (found in the household model)
```

```
  AA<<-c()# proportion of budget allocated to monitoring (found in
MSE)
  Jobs<<-c()
  Yobs<<-c()
  Aobs<<-c()
  Lh<<-c()  # optimal labour            (found in the household model)
  Hrule<<-c()
  omJ<<-c()
  omY<<-c()
  omA<<-c()  # Observed monitoring population   (found in pop model)
  omH<<-c() # optimal hunting          (found in the household model)
  omU<<-c() # optimal utility          (found in the household model)
  omLh<<-c() # optimal labour          (found in the household model)
  omYobs<<-c()
  omJobs<<-c()
  omAobs<<-c()   # observed population      (found in management model)
  AomHrule<<-c()#harvest rule set
  YomHrule<<-c()
  JomHrule<<-c()
  hrY<<-c()# Harvested population
  hrJ<<-c()# Harvested population
  hrA<<-c()# Harvested population
  Hexcess<<-c()#Observed harvest population
#########################################METRIC N
  Nav<<-c()  Hav<<-c()  Uav<<-c()  Ncv<<-c()  Hcv<<-c()  Ucv <<-c()
  Nt<<-c()  Ut<<-c()  Lav<<-c()  Lcv <<-c()  Aav<<-c()  Acv <<-c()
  Lhav<<-c()  Lhcv <<-c()  Np<<-c()  Hp<<-c()  Up<<-c()  Ncvp<<-c()
  Hcvp<<-c()  Ucvp <<-c()  Ntp<<-c()  Utp<<-c()  Lp<<-c()  Lcvp <<-c()
  Ap<<-c()  Acvp <<-c()  Lhp<<-c()  Lhcvp <<-c()
```

9.2.9 Metric model

```
#Save as 'util.r'#############################################
#Utilities  model
#Metric function
metric<-function(chk)  #input chk 0,1,2
{
if (chk==0 || chk==1)
{ Uthr<-Uthresh*Umax;  #Utility threshold
  Nthr<-Nthresh*K;  }   #Population threshold

#Mean
if (chk==0)
{
Nmean<<-mean(A+J+Y)            #True Population mean
Hmean<<-mean(H)             #Actual Harvest mean
Umean<<-mean(U)             #Utility mean
Amean<<-mean(AA)             #Mean proportion of budget allocated to
monitoring
Lhmean<<-mean(Lh)           #Hunting labour mean
Hlegalmean<<-mean(Hrule)    #Harvest legal mean
Nprop<<-length((A+J+Y)>Nthr);      #Proportion population above the
population threshold
Uprop<<-length(U>Uthr);      #Proportion utility above the utility
threshold
}

if (chk==1)
{
```

```
Nmean1<<-mean(Nav)                #True Population mean
Hmean1<<-mean(Hav)                #Actual Harvest mean
Umean1<<-mean(Uav)                #Utility mean
Amean1<<-mean(Aav)                #Mean proportion of budget allocated
to monitoring
Lhmean1<<-mean(Lhav)              #Hunting labour mean
Hlegalmean1<<-mean(Lav)           #Legal harvest mean
Nprop1<<-mean(Nt)
Uprop1<<-mean(Ut)
}

if (chk==2)
{
Hmean2<<-mean(omH);             #Observed harvest mean
Hlegalmean2<<-mean(omHrule);    #Observed legal harvest mean
}

#//////////////////////////////
#Co-efficient of Variation
C_V <- function(x) {100*sqrt(var(x))/mean(x)}
if (chk==0)
{
  if (Nmean > 0)   {N_cv <<- C_V(A+J+Y);}          #Population co-
efficient of variation
  if (Hmean > 0)   {H_cv <<- C_V(H);}          #Actual harvest co-
efficient of variation
  if (Umean > 0)   {U_cv <<- C_V(U);}          #Utility co-efficient
of variation
  if (Amean > 0)   {A_cv <<- C_V(AA);}          #co-efficient of
variation Proportion of budget allocated to monitoring
  if (Lhmean > 0)  {Lh_cv <<- C_V(Lh);}         #Hunting labour co-
efficient of variation
  if (Hlegalmean > 0) {L_cv <<- C_V(Hrule);}   #Legal harvest mean co-
efficient of variation
}
if (chk==1)
{
  if (Nmean1 > 0)   {N_cv1 <<- C_V(Nav);}          #Population co-
efficient of variation
  if (Hmean1 > 0)   {H_cv1 <<- C_V(Hav);}          #Actual harvest co-
efficient of variation
  if (Umean1 > 0)   {U_cv1 <<- C_V(Uav);}          #Utility co-
efficient of variation
  if (Amean1 > 0)   {A_cv1 <<- C_V(Aav);}          #co-efficient of
variation Proportion of budget allocated to monitoring
  if (Lhmean1 > 0)  {Lh_cv1 <<- C_V(Lhav);}        #Hunting labour co-
efficient of variation
  if (Hlegalmean1 > 0) {L_cv1 <<- C_V(Lav);}        #Legal harvest
mean co-efficient of variation
}
if (chk==2)
{
  if (Hmean2 > 0) {omH_cv <<-C_V(omH);}      #Observed harvest co-
efficient of variation
  if (Hlegalmean2 > 0) {omL_cv <<-C_V(omHrule);}   #Observed legal
harvest co-efficient of variation
}

if (chk==0) #Results of the mean and co-efficient of variation
```

```
 {
 Nav[loop]<<-Nmean
 Hav[loop]<<-Hmean
 Uav[loop]<<-Umean
 Lhav[loop]<<-Lhmean
 Lav[loop]<<-Hlegalmean
 Aav[loop]<<-Amean
 Ncv[loop]<<-N_cv
 Hcv[loop]<<-H_cv
 Ucv[loop]<<-U_cv
 Lcv[loop]<<-L_cv
 Acv[loop]<<-A_cv
 Lhcv[loop]<<-Lh_cv
 Nt[loop]<<-Nprop
 Ut[loop]<<-Uprop
 }
  if (chk==2 && Hlegalmean2>0)
  {omHav<<-(Hmean2-Hlegalmean2)/Hlegalmean2;}
  if (chk==2 && Hlegalmean2<0)
  { omHav<<-Hmean2;}

if(chk==1)
{
 Np[Ploop]<<-Nmean1
 Hp[Ploop]<<-Hmean1
 Up[Ploop]<<-Umean1
 Lhp[Ploop]<<-Lhmean1
 Lp[Ploop]<<-Hlegalmean1
 Ap[Ploop]<<-Amean1
 Ncvp[Ploop]<<-N_cv1
 Hcvp[Ploop]<<-H_cv1
 Ucvp[Ploop]<<-U_cv1
 Lcvp[Ploop]<<-L_cv1
 Acvp[Ploop]<<-A_cv1
 Lhcvp[Ploop]<<-Lh_cv1
 Ntp[Ploop]<<-Nprop1
 Utp[Ploop]<<-Uprop1
 }

 }   #end metric(chk)
```