Sustainable management of fisheries

3.1 Introduction

Sustainable management of a resource was the theme of Chapter 2, with specific reference to agriculture, but there is obviously much more to this topic. We specifically explored production as well as some of the underlying biological principles of relevance. Thus we looked at the link between the biodiversity of agricultural systems and output, including the importance of system resilience and what farmers are trying to achieve. Farmers in many countries look to crop diversity as an insurance policy against crop failure, especially as they may lack access to inputs such as fertiliser, pesticide and irrigation. Underlying this is the concept of the niche and compatibility of crops.

But agriculture is only one source of food, albeit the most important one on a global scale. In this chapter we will continue the production theme, but look instead at the management of a wild animal resource, notably fish stocks. Fish farming aside, people manage fish stocks primarily through the means by which they harvest them. Wild fish stocks are not directly replenished by people in the same way that farmers plant crops or breed farm animals. Instead, the management is by controlling the rate of extraction of the stock or by the size (equates to age) of the animals which are removed. Thus, the management regime is more one dimensional than that of the systems we discussed in Chapter 2. Allied to this is the fact that many fisheries are not ‘owned’ by one person or even by one country. Instead they are regarded as common property resources, with access open to anyone with the means to harvest the population (Gordon, 1954). This results in what has been called ‘The tragedy of the commons’ which was mentioned in Chapter 1; a virtual decimation of many fish stocks as a result of over-fishing.
One of the central tenets in fishery management has been the concept of **maximum sustainable yield** (MSY; Ostrom, 2001), and the MSY will be the main focus of this chapter. The idea behind the MSY is straightforward in biological terms:

Given a population of a species what is the number or biomass of individuals that can be removed without reducing the population?

The idea applies, of course, to any harvested population, be it animal or plant. However, perhaps the strongest association is with wild fish populations. MSY builds upon some of the central ideas in ecology, notably population growth and carrying capacity, and thus has held an almost mythical place in fishery management. Indeed, while it may be rare to come across biographies of economic concepts such as total factor productivity, it is even rarer for ecological concepts to be the subject of a prayer, but Peter Larkin (1924 to 1996), a Canadian fisheries biologist based at the University of British Columbia, Vancouver, published a now famous paper entitled ‘An epitaph for the concept of maximum sustained yield’. Why he uses the term ‘epitaph’ we will see later in the chapter, but in his paper we have the prayer:

\[
\text{Any species each year produces a harvestable surplus,}
\]
\[
\text{and if you take that much,}
\]
\[
\text{and no more,}
\]
\[
\text{you can go on getting it forever and ever.}
\]
\[
\text{(Amen)}
\]

Larkin (1977)

Amen indeed!

The chapter will begin by setting out the theoretical basis for the MSY and thus provide the rationale as to the popularity of the concept. From here we will explore some of the limitations of the MSY when applied in practice, along with examples of fishery collapse when managed with incomplete knowledge. Indeed, this chapter will highlight the importance of good knowledge (data and models) for the sustainable management of animal populations.

### 3.2 The enticing concept of maximum sustainable yield

The MSY was developed in the 1930s as the rational (scientific) basis for fisheries management strategy and, if anything, increased in popularity during the 1950s (Ostrom, 2001). Its promise of being able to
manage a resource so that the best yield could be obtained indefinitely has always been an alluring one, and it can be argued that this same ethos rests at the very heart of our current enthusiasm for sustainable development.

But what is the theory behind MSY? To set this out we need to go back in time to some of the original work on population dynamics. Population growth is a function of birth rate, death rate, immigration and emigration. Birth and immigration increase the population, while death and emigration reduce population size. In populations that are growing it is clear that the combination of birth rate and immigration is greater than the combination of mortality rate and emigration. In such populations we can regard the excess as an ‘interest’; if we can harvest that excess and no more then we have a sustainable yield. It is akin to living off the interest on your bank account. As long as you don’t eat into your capital then you are fine. Maximum simply refers to removing the excess at the time when the population growth rate is at its highest; thus we are living off the interest when the rate is at its highest. Sounds straightforward in theory, but, as anyone who has tried to live off interest on capital will acknowledge, much depends upon the size of the capital and the interest rate, and the latter can fluctuate wildly. So how can we set this out in biological terms?

The key to all this is knowledge of the population growth rate, but how can we determine this? Some of the earliest (and simplest) approaches were based on the fundamental idea that at each time \( t \) one individual in a population (represented by \( N \)) becomes two or more. Note that here we are assuming that the ‘parents’ at each generation do not live to the next. The population at time 1 \( (N_1 = 4) \) are the offspring of the two individuals living at time 0 and not the sum of both \( (2 + 4) \). Thus the population progresses from 2 to 4 to 8 to 16 to 32 and so on. We can present this change as a graph (Figure 3.1), and what we see is an example of organic (exponential) growth. The trend shown in Figure 3.1 is a curve with an increasing rate of ascent, as distinct from a linear growth with a constant rate of ascent. Population growth rate is the change in the number of individuals over a time period, and is represented by the slope of the line in the graph. Note how the population growth rate is greater for larger populations. In our example (where one ‘parent’ reproduces to give two offspring) the overall effect will be an acceleration of population increase with time. The increase over time 1 to 2 is 4 individuals, while the increase over time 4 to 5 is 32 individuals. In other words, population growth rate is a function of population size, which in this
model is a function of time. Note that an assumption here is the constancy of multiplication rate over all the generations. Thus at a ‘generational’ scale we can find the population at $N_{t+1}$ provided we know $N_t$ and the multiplication rate (often abbreviated as $\lambda$, which equals 2 in the above example). Higher values of $\lambda$ will give population curves of increasing steepness, but it can be surprising how sensitive the curves are to $\lambda$. Figure 3.2 shows four populations with values of $\lambda$ ranging from 2 to 5. The resulting curves are markedly different, even over just six generations.

The same curve can also be explored mathematically using differential calculus. We can start by making the reasonable assumption that change in population over a time period (growth rate) is a function of the population size at the start of that time and a multiplication constant which is related to the number of offspring that individuals produce. In the above we were looking at change over a generation
(t to t + 1), but this is somewhat 'lumpy'. We can smooth out the change by bringing the time intervals down to very short periods, so that population growth rate becomes:

\[ \frac{dN}{dt} = \frac{\text{difference in } N \text{ over time } dt}{\text{very small change in time } (dt)} \]

Where ‘d’ is a mathematical term meaning ‘a very small change in’ or perhaps more accurately ‘an instantaneous change in’. Please note that dt is not d multiplied by t (d × t), but instead is a mathematical shorthand. Thus given the assumption above, we can say:

\[ \frac{dN}{dt} = \text{population size } (N) \times \text{constant} \]

This might seem rather simplistic, and indeed it is as we will discuss later, but it does succeed in allowing us to model the curves in Figures 3.1 and 3.2. By convention, the constant is given the symbol r and is referred to as the intrinsic (or innate) rate of population increase. Hence:

\[ \frac{dN}{dt} = rN \]

The maximum value of r for a particular environment is called the maximum intrinsic or innate rate of increase, or sometimes the biotic
potential (abbreviated as $r_m$). While $r$ is operating over instantaneous time scales and $\lambda$ operates over generations, there has to be a relationship between them. Indeed, the value of $r$ can be found by taking the natural logarithm of the number of individuals produced by one individual at generational time scales.

$$r = \ln(\lambda)$$

In our example where one individual has two offspring in each generation:

$$r = \ln(2) = 0.6931$$

While this approach of exploring instantaneous population growth rate for each value of $N$ might be mathematically elegant, it doesn’t seem to be of much practical use. We need to modify this equation by bringing it up to more intuitive timescales; in other words changing $dt$ to $t$ and $dN$ to $N$. Fortunately, the differential equation can be ‘rearranged’ and we can solve the differential equation using the method of separation of variables:

$$\frac{dN}{dt} = rN$$

and

$$\frac{dN}{N} = rdt$$

To get this equation away from $dN$ and $dt$, we need to integrate both sides and there are rules for integration which simplify matters. The ones which apply here are:

Rule 1: Integration of $dN/N$ is given by $\ln(N) + C_1$
Rule 2: Integration of $rdt$ is given by $rt + C_2$

The terms $C_1$ and $C_2$ are integration constants.

Thus:

$$\ln(N) + C_1 = rt + C_2$$

Let’s simplify this by renaming the difference of the two constants $(C_2 - C_1)$ as a single constant $C$. 

$$\ln(N) = rt + (C_2 - C_1)$$
\[ \ln(N) = rt + C \]

To get \( \ln(N) \) back to \( N \) we need to take its exponent and we also need to do that for both sides of the equation. The exponent of natural logarithms is \( e \) (2.71828 etc.), and therefore:

\[ e^{\ln(N)} = e^{rt+C} \]

which is the same as:

\[ N = e^{rt} e^C \]

The \( e^C \) component of the equation is a constant given that both \( e \) and \( C \) are constants, but what is it exactly? We can answer this question by making the \( e^{rt} \) component equal to one and we can achieve that by assuming that \( t=0 \). This makes the product \( rt \) equal to zero and \( e^0 \) is equal to 1. Therefore \( e^C \) is the value of \( N \) at time zero and we can re-label it as \( N_0 \). To avoid confusion we can also re-label \( N \) as \( N_t \) (the population at time \( t \)). The result is:

\[ N_t = N_0 e^{rt} \]

This equation can give us the population at any time (\( N_t \)) by knowing the size of the starting population (\( N_0 \)), the value of \( r \) and the time (\( t \)) which has elapsed. For example, if \( N_0 \) is set at one individual (as in the above example) and \( r = 0.6932 \) then we can find the number of individuals at each generation, as shown in Table 3.1. The derivation of the population growth rate given here is intended to illustrate a number of key points that will emerge throughout this chapter. The population growth rate (\( dN/dt \)) is dependent on just one variable, the size of the population. Therefore the population growth is density dependent (i.e. population growth rate depends on the size (density) of the population). As \( r \) is a constant, it is density independent (i.e. its value does not depend on the size of the animal population). The validity of these assumptions will be discussed later, but there is a problem in all of this. In reality, populations do not increase to infinity as limitations of space and food usually become apparent. A population tends to increase up to a certain point, but then these limitations (space and food) start to operate and the growth rate slows down. Eventually the growth rate (\( dN/dt \)) becomes zero (i.e. the population is static). Fortunately this can be easily accommodated in the basic population growth curve already described.
by introducing a ‘correction’ depending upon how close the population is to this limit.

\[
\frac{dN}{dt} = r \left( \frac{K - N}{K} \right) N
\]

or

\[
\frac{dN}{dt} = r \left( 1 - \frac{N}{K} \right) N
\]

This is called the logistic model of population growth, and \( K \) is yet another constant commonly referred to as ‘carrying capacity’. Population growth rate \( (dN/dt) \) changes depending on how close the population is to \( K \). As \( N \) approaches the value of \( K \), the \( (K - N)/K \) part of the equation becomes closer to zero and hence the growth rate also gets closer to zero. One way of regarding the \( (K - N)/K \) element is to think of it as providing a density-dependent correction for the value of \( r \) so that as \( N \) gets closer to \( K \) the adjusted value of \( r \) declines. Eventually when \( N = K \) the value of \( r \) becomes zero and the population stays at \( K \):

\[
\frac{dN}{dt} = r \left( \frac{K - K}{K} \right) K = 0
\]

As before, the differential form of the equation can be altered to provide

### Table 3.1 Calculation of population size at time \( t \) based upon a starting population \( (N_0) \) of one individual and an intrinsic population growth rate \( (r) \) of 0.6931.

<table>
<thead>
<tr>
<th>Time (t)</th>
<th>Calculation (integral form)</th>
<th>Estimated population at time ( t ) ( (N_t) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>( 1 \times e^{(0.6932 \times 1)} )</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>( 1 \times e^{(0.6932 \times 2)} )</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>( 1 \times e^{(0.6932 \times 3)} )</td>
<td>8</td>
</tr>
<tr>
<td>4</td>
<td>( 1 \times e^{(0.6932 \times 4)} )</td>
<td>16</td>
</tr>
<tr>
<td>5</td>
<td>( 1 \times e^{(0.6932 \times 5)} )</td>
<td>32</td>
</tr>
</tbody>
</table>

e = the exponential constant (2.71828 etc.)

Note how \( N_t \) is set as a function of \( t \) and not the population size in the proceeding generation.
an integral form. I will not go into that detail here, but the result is:

\[ N_t = \frac{K}{1 + e^{a r_t}} \]

The new term in the denominator, \( a \), is another integration constant. For example, if we use values for \( K = 100 \) and \( r = 0.6931 \) (as before), and \( a \) arbitrarily set at 4.6 to give an intercept \((N_0)\) of approximately 1, the result is the curve shown in Figure 3.3. The growth rate per individual of the population is shown plotted against population size in Figure 3.4. As the population increases in size towards \( K \) then the growth rate per individual declines.

It is possible to find the value of \( r \) in logistic curves, although this is more complex than with the simple exponential equation. We need to have a reasonable idea as to the value of \( K \), and we also need to know the values of \( N \) for various times \((t)\). We can plot the value of \( \log ((K/N_t) - 1) \) against \( t \), and a declining straight line indicates logistic growth, with the slope of the line providing an estimate of \( r \) (Figure 3.5).

What do these theoretical equations and graphs have to do with sustainable yield? Even simple equations such as these provide the basis for an understanding of the meaning and indeed complexities of sustainable yield. In logistic population growth, the MSY corresponds to the point on the graph where there is a maximum surplus of births over deaths; in other words where the population growth rate is the highest. Taking the logistic curve presented earlier and plotting population growth rate against population size, as shown in Figure 3.6,
the maximum growth rate occurs once the population reaches 56 individuals. At this point of inflexion the population growth rate is 17 individuals per time period. Provided we only begin harvesting at this point and provided we only remove 17 individuals in each time period and don’t become greedy then the population will remain static and the yield will be sustainable. This point corresponds to the MSY. What can
be considered the intuitive answer – harvesting the population when it is at carrying capacity ($K$) – will reduce the size of the population as at $K$ there is no excess of births over deaths. This is an example of a surplus yield model or more precisely as a biomass dynamics model, and in theory provides the scientific basis for a sustainable management regime (Gause, 1934).

However, in practice the logistic equation would be difficult to use for sustainable management of a renewable resource in the form given here. To begin with we would need to know the values of $r$ and $K$, and this requires a very detailed biological knowledge of the population. However, there are deeper concerns to do with the relative simplicity of these equations and the assumptions upon which they are built. First, there is the focus on change over very short periods of time ($dN/dt$), which implies an instantaneous change in $N$ that does not seem to be logical. In ‘real’ populations there is a time lag for this density-dependent influence. Second, Secondly we can question whether the assumed constants really are constants. There are two main constants included in the above equations (not including the integration constant $a$): $r$ and $K$. Is it realistic to assume that carrying capacity is a constant? After all, real environments fluctuate greatly from year to year, or even day by day, and hence the value of $K$ may also fluctuate. Also, what about $r$? Real populations are made up of two groups:
(1) Individuals which can contribute to population growth (i.e. reproductively active)
(2) Individuals (too young or too old) which cannot add to population increase.

It is the first group that contributes to population growth and hence would have an influence on \( r \); the second group would have no influence. Figure 3.7a is an example of an age distribution, with 10 categories based on age and the proportion of that category in the total population. Perhaps only categories 3 to 7 are reproductively active, and they make up 46% of the population. The remaining 44% are not reproductively active. In this example there is a steady mortality operating through all of the age groups, but there can, of course, be a higher rate of mortality operating on younger age groups, as shown in Figure 3.7b. In this case there is greater mortality operating between age groups 1 and 2 than others, perhaps because they are more vulnerable to predation or disease. This may be more realistic for wild populations of animals, where the young are not protected and hence are more vulnerable. Categories 3 to 7 make up 40% of this population. The species relies on high multiplication rates to ensure its survival (so-called ‘r-selected’ species). The other extreme would be a high survival through early age groups (Figure 3.7c), which can happen if the young are protected in some way by older age groups. Mortality rates get higher for older age groups perhaps because of increased vulnerability to disease or loss through predation. This species relies less on high multiplication rates, but on better survival (so-called ‘K-selected species’), and humans are an example. For our model, the shape of the curves is immaterial. What does matter is the consistency of the shape over time. The assumption that \( r \) is a constant will only be true if the proportion of reproductively active individuals in the population remains stable. However, in practice, age distributions may not be stable over time as a result of natural or indeed human-induced pressures.

### 3.3 Managing with the logistic curve: the Schaefer model

While the logistic curve highlights the theory behind MSY, it is of little practical use. However, it can be modified to produce an equation that is of more use. If we take the logistic equation as our starting point:
Figure 3.7 Theoretical examples of age distributions within a population: (a) equal mortality rate with increasing age category from 1 (youngest) to 10 (oldest); (b) mortality rate is higher for younger age categories; (c) mortality rate is higher for older age categories.
\[ \frac{dN}{dt} = r \left( 1 - \frac{N}{K} \right) N \]

and make the logical assumption that catch will be related to how much fish is present \((N)\) and the fishing mortality rate (proportion of the population we catch, \(F\)):

\[ \text{Catch} \ (Y_e) = FN \]

The yield being taken over a time period will need to be subtracted from the population growth over that same time period to give a net growth:

\[ \frac{dN}{dt} = r \left( 1 - \frac{N}{K} \right) - Y_e \]

According to this equation, net population growth (\(dN/dt\)) would become zero when catch equals population growth, and thus the population would reach equilibrium. At this point:

\[ Y_e = r \frac{N_{\text{equil}}}{K} \left( 1 - \frac{N_{\text{equil}}}{K} \right) \]

\(N_{\text{equil}}\) (rather than \(N\)) has been used here as a reminder that this is the point where \(N\) is in equilibrium i.e. the 'special case' when \(dN/dt = 0\). As \(Y_e\) will be equal to \(FN_{\text{equil}}\) at this point then we can substitute as follows:

\[ FN_{\text{equil}} = rN_{\text{equil}} \left( 1 - \frac{N_{\text{equil}}}{K} \right) \]

Divide both sides by \(N_{\text{equil}}\) to simplify:

\[ F = r \left( 1 - \frac{N_{\text{equil}}}{K} \right) \]

and rearrange:

\[ \frac{F}{r} = \left( 1 - \frac{N_{\text{equil}}}{K} \right) \]

\[ \frac{N_{\text{equil}}}{K} = \left( 1 - \frac{F}{r} \right) \]

and therefore:

\[ N_{\text{equil}} = K \left( 1 - \frac{F}{r} \right) \]

If we substitute this for \(N\) in the yield equation given above \((Y_e = FN)\) and remind ourselves that we are looking for the catch we can take so as to leave the population in equilibrium \((Y_{\text{equil}})\) then the equation becomes:
\[ Y_{\text{equil}} = FK \left( 1 - \frac{F}{r} \right) \]

This can be rearranged as:
\[ Y_{\text{equil}} = FK - \frac{F^2 K}{r} \]

Assuming \( K \) and \( r \) are constants (as before) then this equation has the general form of a quadratic curve:
\[ Y_{\text{equil}} = aF - bF^2 \]

Where \( a = K \) and \( b = (K/r) \). A plot of yield (when population is assumed to be in equilibrium) against fishing mortality rate generates a curve with a maximum. If the fishing mortality rate exceeds this point then yield will decline. Time-series yield data are available for many fisheries, even sub-divided into different species, but how can we find values for \( F \)? The fishing mortality rate will depend upon a number of factors, but at a basic level we could deconstruct \( F \) into two components:

1. Fishing effort (number and size of trawlers, how many days they spend at sea etc., \( U \))
2. Catchability (quality of the fishing gear, skill of the fishers, how easy the fish are to catch etc., \( q \)). This can be be thought of as efficiency.

such that \( F = Uq \) (effort \( \times \) efficiency). Then the equation becomes:
\[ Y_{\text{equil}} = UqK \left( 1 - \frac{Uq}{r} \right) \]

This also has the generic form of a quadratic equation if we assume that \( q, K \) and \( r \) are constants:
\[ Y_{\text{equil}} = aU - bU^2 \]

Where \( a \) in this case is shorthand for \( (qK) \) and \( b \) is shorthand for \( (q^2 K/r) \). Thus, when using this equation to manage fish stocks we don’t need \( q, K \) and \( r \) but just \( a \) and \( b \). We can now plot yield against fishing effort (\( U \)), as shown in Figure 3.8a, and the latter can in turn be proxied by available data, such as the size of the fleet and how many days they spend at sea. This equation is referred to as the Schaefer model and the graph in Figure 3.8a as the Schaefer curve after its creator (Schaefer, 1954, 1957). Yield per unit of fishing effort (\( Y_{\text{equil}}/U \)), at equilibrium can be found by:
Multiplying out the right-hand side gives:

\[
\frac{Y_{\text{equil}}}{U} = qK \left( 1 - \frac{Uq}{r} \right)
\]

which is a linear equation of the form:

\[\text{CPUE} = a - bU\]

where CPUE is ‘catch per unit of fishing effort’, \(a\) is shorthand for \((qK)\) and \(b\) is shorthand for \((\frac{Kq^2}{r})\). The equation tells us that CPUE will
decline with increasing fishing effort as shown in Figure 3.8b. CPUE has similarities with Total Factor Productivity (output/input), discussed in Chapter 2.

It is also possible to combine the catch-based Schaefer curve with economic considerations such as the cost of fishing (i.e. the cost of $F$) and the revenue obtained for the yield. An example is the maximum economic yield (MEY) shown in Figure 3.9. The graph shows the same curve as that of Figure 3.8a only with yield changed to revenue (yield $\times$ price). In Figure 3.9 there is yet another simplifying assumption that price remains constant, whereas in reality of course it is likely that price will change according to the law of supply and demand. Also shown is a plot of expenditure, in this case given by fishing effort $\times$ cost of each unit of that effort (assumed to be a constant). Gross margin = revenue − expenditure.

Economic over-fishing

Biological over-fishing

Figure 3.9 Maximum economic yield (MEY) for a fishery. Revenue is determined by yield (catch) $\times$ price (assumed to be a constant). Expenditure is given by fishing effort $\times$ cost of each unit of that effort (assumed to be a constant). Gross margin = revenue − expenditure.

Thus an economically rational management of the fishing effort would suggest that it be kept at MEY. Where the resource is subject to a less controlled fishing effort then it is quite possible for MEY to be exceeded. It is, after all, an economic threshold and not a biological one and its placement on the fishing effort axis will depend upon the relative balance of price for the fish and cost of fishing, and these will
vary over time. While the model suggests that exceeding MEY will not be detrimental to the fish population, the gross margins of those fishing the resource will be lowered. However, once the uncontrolled fishing effort exceeds MSY then the model predicts that the fish stock will go into decline.

The above derivation of the Schaefer model from the logistic may have been somewhat protracted, but was not meant to be mathematically exhaustive. My aim has been to highlight the many assumptions that have been made in its creation. The model uses the logistic equation as a starting point and builds from there. A surplus-production model such as the one given here does have the significant advantage of being easy to fit to data that are often readily available (Prager, 1994). The calculation of the model parameters can be readily achieved with a spreadsheet or even a calculator. However, the edifice is built upon a number of key assumptions and unfortunately these are all too readily ignored. To begin with it assumes that the population remains in equilibrium when we are taking our catch; hence, we purposely employed the terms $N_{\text{equil}}$ and $Y_{\text{equil}}$ to remind us of this. Thus, we are attempting to take the excess of births over deaths without driving the population down. It also assumes that values of $r$ (growth rate) and $K$ (carrying capacity) are constant, but as we have already seen in reality it is unlikely that they will be. Similarly is it reasonable to assume that $q$ is also a constant? Indeed what does 'catchability' really mean in practice? Here, it can be regarded as a measure of the efficiency of the fishing effort so that fishing mortality is a simple product of fishing effort (hours spent fishing by a number of boats) multiplied by how effective each of those boats is at catching fish. Effectiveness could be a complex measure of a number of influences such as how good the equipment, captain and crew are, the weather conditions, decisions over where they fish (the distribution of fish in three dimensions will not be even) and so on. As with the TFP discussion in Chapter 2, it does not seem reasonable to assume that all of these will remain constant over time. Thus, we are trying to manage a complex resource with a rather simplistic tool.

### 3.4 Applying the Schaefer model

As already mentioned, one of the major advantages of the Schaefer model is that it can readily be estimated from data on fishing effort and catch, and such data are available for a number of important fisheries, although quality of the data may be variable (Watson and Pauly, 2001). As a result of this relative ease of use, the Schaefer model has proved to
be highly popular in fisheries management. Four examples have been chosen here and I in no way wish to imply that these are the only such examples that could have been selected. Instead, the examples have been chosen to illustrate different aspects of the use of scientific knowledge to sustainably manage fisheries.

The first is for cod in the North Sea and is employed here merely to illustrate how easy it is to fit a Schaefer model to a set of data. Catches of cod from 1906 to 1959, spanning two World Wars, are shown in Figure 3.10a. There is a data gap for the First World War, while data are available for the Second World War, although note how the catches declined. Fishing in the North Sea has its dangers at the best of times, but is far riskier during a war. A Schaefer model can be readily fitted to these catches and corresponding effort data which are also available, and the results are shown in Figure 3.10b. The curve which can be seen in the graph is a quadratic ‘least squares’ fit to the data using the model:

\[ Y_{\text{equil}} = aU - bU^2 \]

There is no need for any specialised software to achieve this. The estimated MSY is around 500 units and only a few data points are above that. The relationship between catch per unit effort (CPUE) and fishing effort is shown in Figure 3.10c.

The second example is the South Atlantic Albacore (\textit{Thunnus alalunga}) fishery. The Albacore is a type of tuna found in many oceans. North Atlantic stocks of the species are now regarded as critically endangered by the IUCN as a result of over-fishing and are listed in their ‘Red Book’ of populations and species at risk. Indeed both the South and North Atlantic Albacore fisheries are regarded as being ‘data deficient’ by IUCN. A graph of catch and fishing effort for the North Atlantic Albacore is provided in Figure 3.11 (covers 1967 to 1989; the source of data is Polacheck \textit{et al}., 1993). There are three separate curves in the graph giving three different estimations of the MSY. MSY (1) is akin to a simple ‘least squares’ quadratic curve fitted for cod in Figure 3.10a. It provides an estimation of the MSY as approximately 50,000 tonnes per annum, although it should be noted that this is well above any of the data points. The other two curves to the left-hand side of the graph are based upon estimated values for \( q \), \( K \) and \( r \) rather than a simple ‘least squares’ fit to the data. These two curves are constructed in a ‘bottom up’ fashion using the equation we derived earlier:
Figure 3.10 Estimation of the MSY using a Schaefer model, cod in the North Sea (1906 to 1959): (a) catches of cod; (b) fitting of a Schaefer model to catch and fishing effort data; (c) catch per unit fishing effort (CPUE) as a function of fishing effort.
\[ Y_{\text{equil}} = U q K \left( 1 - \frac{Uq}{r} \right) \]

But the curves differ in their assumptions and values for \( q, K \) and \( r \) also end up being different. The details need not be discussed here, but it should be noted that MSY(2) and MSY(3) are much lower than MSY(1); figures are approximately 20 000 and 24 000 tonnes per annum, respectively. MSY(1) and MSY(2) have been generated from a more sophisticated process than has MSY(1) and the outcomes are quite different. If MSY(1) is taken as the target, then clearly none of the data points are even close to exceeding it. A manager might therefore assume based upon this evidence that fishing effort can be increased rather than reduced, although it should be noted that Figure 3.11 does not have values of the MEY. On the other hand, both MSY(2) and MSY(3) are much lower than MSY(1) and there are some data points which have exceeded the MSY. Based upon these estimates, it might be reasonably assumed that fishing effort needs to be controlled rather than increased. The result is a set of mixed messages leading to quite different recommendations for management, depending upon the basis employed to find the MSY.
A third example of a Schaefer model is provided by the Peruvian Anchovy fishery, and, indeed, this is perhaps one of the most spectacular examples of the collapse of a fishery we have witnessed to date (Boerema and Gulland, 1973; Idyll, 1973; Laws, 1997; Ibarra et al., 2000). The fishery was established in the 1950s and at one time accounted for almost a quarter (22%) of all fish caught throughout the world. The Anchovy were converted to fishmeal for animal consumption as this increased the commercial value by some 300%. Indeed, sale of this product accounted for 25 to 30% of Peru’s foreign exchange in the 1970s. The fishery exists largely because of the combination of various currents along the coast resulting in deep water bringing nutrients to the surface. These nutrients encourage the growth of phytoplankton which in turn provides a source of energy for the whole ecosystem (Espinoza and Bertrand, 2008). Such upwellings occur throughout the world, but the Peruvian upwelling has been shown to be three to ten times more productive than others and the reasons why this is so are still under some debate (the so-called ‘Peruvian Puzzle’; Cury et al., 1998). Anchovy (Engraulis ringens) lives in shallow-water ecosystems off the Western coast of South America, but the Peruvian fishery is especially productive. The fish can live up to four years and reach reproductive age after only six months. Catch and effort data for the Peruvian fishery were readily available in the 1960s and a Schaefer model can be used to estimate the MSY, as in the case of the previous two examples. The result is shown in Figure 3.12, where it can be observed that the MSY is just over 10 million tonnes, and occurs at a fishing effort of about 30 million gross registered tonnage (GRT, referring to the size of the fishing fleet). In this case the curve is a simple ‘least squares’ fit to the data akin to the MSY(1) of Figure 3.11 and the MSY for cod in Figure 3.10b. While some of the data points are near to the MSY there is no evidence from the graph that the MSY was being exceeded and fishing effort was consistently below 30 million GRT.

However, the Anchovy fishery collapsed in dramatic fashion in 1972 and the niche left behind was occupied by the less profitable Sardine (Sardinaps sagax). Both species feed on the same organisms, but Anchovy and Sardine larvae are normally separated in space and hence there is little competition between them. The two species appear to follow an inverse cyclic behaviour in many fisheries (Al-Jufaili, 2007), such that as one increases the other declines. The collapse of the Anchovy population occurred for two main reasons. Firstly, despite the reassuring picture provided by Figure 3.12, the extraction was especially heavy between 1967 and 1970, and this hit recruitment
hard. In effect, the value of $r$ had been reduced. Secondly, the fishery was subject to a natural oscillation in the Pacific every two to ten years; the El Niño event. In the early 1970s, an El Niño occurred which brought warmer water into the fishery, and with it came increased numbers of predators of Anchovy which placed further pressure onto the Anchovy population. The warm water also reduced the upwelling and the flow of nutrients to surface waters. El Niño does seem to have a significant impact on the ecosystem off the Peruvian coast (Niquen and Bouchon, 2004). The combination of increased predation, fewer nutrients, continued fishing effort and a fall in recruitment resulted in the collapse. This was a biological disaster, but one which had a number of important social and economic consequences (Glantz, 1990). The industry was nationalised by the military government of Peru and effectively reduced to half its size. The number of boats was cut from 1 500 to 800, the number of fishmeal plants was reduced from 100 to 50 and the number of people employed was reduced from 25 000 to 12 000. The Anchovy has recovered since then, and Figure 3.13 shows landings of the Anchovy and Sardine from the 1950s to 2006, as well as the timing of some strong El Niño events. The El Niño of 1997–98 clearly had an impact on the fishery, but recovery was good.

Sadly, the Peruvian Anchovy is far from being the only example of over-fishing as a result of our poor knowledge of ecosystems or unwillingness to act. The fourth example to be discussed here, albeit
one that contrasts with the Peruvian Anchovy in a number of regards, is provided by the New Zealand Orange Roughy Fishery. Unlike Anchovy, the Orange Roughy (*Hoplostethus atlanticus*) is a deep-water species and for understandable reasons it is difficult to study the biology of such fish and their ecosystems, and this does not aid management (Pankhurst, 1999). What is known is that such deep-water species tend to be long-living. The Orange Roughy, for example, can live to 100 years of age and reach sexual maturity between 23 and 31 years of age. The fish has firm flesh that produces a white boneless fillet which has proved to be highly palatable to consumers. Indeed the original name of ‘slimeheads’ was changed to ‘roughy’ to make the species more marketable. New Zealand is the main supplier in the world today and the USA is the main consumer. The New Zealand roughy fishery has only recently been exploited and catches are shown in Figure 3.14. The
1980s were a main period of activity, with a peak catch of 55 000 tonnes in 1988. It was initially thought that the Orange Roughy had a relatively short lifespan and bred relatively quickly, hence the stock could recover quickly from exploitation, but this was not the case and catches declined dramatically in the early 1990s. By 1994 the catch levels had already declined to around 25% of the original level. Clearly the exploitation had a major impact on the population of the species and also on the genetic diversity of the surviving population, which had significantly narrowed (Smith et al., 1991). We now know that such deep-sea species are slow to recover from exploitation (Clark and Tracey, 1994). Controls on catches were quickly changed and at present the total catch of the species is set at roughly 30% of what is assumed to be the pre-exploitation biomass levels. For example, in the 2008/09 fishing season, the total allowable commercial catch was set at 12 532 metric tonnes. But even so, the sustainability of this resource has been questioned, given how little we know about it, the low reproduction rate and ease of capture (Francis and Clark, 2005). Others have argued that, given the gaps in our knowledge, it should be assumed that current exploitation of this resource is already optimal and we are taking the MSY (Hilborn et al., 2006).

### 3.5 Sustainability, Chaos and Strange Attractors

The examples given in the previous section reinforce what we know; nature is complex and can be unpredictable. Founding a management regime on wrong assumptions and far from complete knowledge of what is in an ecosystem and how the components interact over time and space is a recipe for disaster. The smooth logistic and Schaefer curves in the previous sections are aesthetically attractive and, while useful in a theoretical sense for illustrating the biological logic which rests behind management of a dynamic resource, they are misleading in their simplicity when it comes to practical management. Indeed, it doesn’t take much to change the equations to reflect what we often see in practice and thereby illustrate the problems of achieving MSY. Instead of relating population size \((N)\) to time \((t)\), what happens if it is related to the size of the population in the previous generation? After all, this seems a more logical stance to take. Population growth will obviously be directly related to the population size of the previous generation more than to some absolute notion of time.
population this year \( (t + 1) \) = population last year \( (t) \) \times\) number of offspring per individual

or

\[ N_{t+1} = N_t \lambda \]

where

\[ N_{t+1} = \text{population in generation } t+1 \]
\[ N_t = \text{population in generation } t \]
\[ \lambda = \text{multiplication rate (number of offspring/individual between time } t \text{ to } t+1) \]

Allowing for ‘carrying capacity’ \( (K) \) limitations, as in the logistic equation:

\[ N_{t+1} = N_t \left( \frac{K - N_t}{K} \right) \lambda \]

This seems to be straightforward, but unfortunately such a logical starting point can generate very complex population curves as they incorporate the notion of feedback. Indeed it can produce chaotic behaviour, especially with higher values of the multiplication rate. The graphs in Figure 3.15 illustrate what happens when \( \lambda \) increases from 2 to 4 (starting population is 1 and \( K = 100 \)). With a \( \lambda \) of 2, the picture is reminiscent of the logistic curve with a steady increase in population towards a plateau, but note that the population does not reach carrying capacity. With a value of \( \lambda \) equal to 3 there is some evidence of instability. The population reaches 75 and then begins to oscillate, although as time progresses the degree of oscillation dampens. With a \( \lambda \) of 4 there is apparent chaos with no clear pattern in the population curve over time. Don’t forget that these three quite different patterns have come from the same equation, and one that on the surface does not look all that different from the logistic. The difference has been brought about by linking population at one generation to the population of the previous generation and not simply to time. There is a feedback process at play.

What about predictions of MSY in such populations? As might be expected, this becomes problematic when values of \( \lambda \) are high. When \( \lambda \) equals 2 the curve is ‘well behaved’ and a MSY of approximately 12 seems appropriate, and even with a \( \lambda \) of 3 there is a discernible point of inflection (this time suggesting an MSY of approximately 30). However, once \( \lambda \) becomes 4 the possibility of finding an MSY disappears. The result is a wild circularity with no clear single point of inflection;
instead there are many! Don’t forget that with all these graphs the value of $\lambda$, as well as $K$, are held constant over the generations. There is no fluctuation in environmental conditions built into these graphs.

A simple rearrangement of the basic population growth equation allows us to estimate the population increase per individual:

![Growth curves](image)
\[ N_{t+1} = N_t \left( \frac{K - N_t}{K} \right) \lambda \]
\[ \frac{N_{t+1}}{N_t} = \left( \frac{K - N_t}{K} \right) \lambda \]
\[ \frac{N_{t+1}}{N_t} = \lambda - \left( \frac{\lambda}{K} \right) N_t \]

Given that \((\lambda/K)\) is itself a constant, this equation is equivalent to \(y = a - bx\), the equation for a straight line, and that is indeed what we see when \(\lambda\) equals 2 (Figure 3.16a). However, note how this ‘straight line’

![Graph](image1)

![Graph](image2)

Figure 3.16 Population growth rate per individual: (a) multiplication rate of 2 (solid line) and 3 (dashed line); (b) multiplication rate of 4.
prediction breaks down once $\lambda$ is increased to 3 and disappears altogether once $\lambda$ reaches 4, as shown in Figure 3.16a and 3.16b. The same chaos occurs when we plot population growth rate against population size (Figure 3.17), the relationship we used to derive the MSY earlier in the chapter. The smooth curve we observed with the differential equations breaks down once $\lambda$ is greater than 2. Unfortunately for sustainable management, chaotic patterns such as those of Figure 3.15b are often what we see with animal populations in

Figure 3.17 Population growth rate as a function of population: (a) growth rates of 2 (solid line) and 3 (dashed line); (b) growth rate of 4.
practice (Fielding, 1991). Wild populations do fluctuate widely (an effect caused by an array of environmental and biotic factors) and don’t just increase smoothly to a maximum before levelling. Finding an MSY for such populations based on the equations given here seems impossible.

However, isn’t there another way to proceed rather than try and make fixed predictions based on simple models as we have done here? Given the complexity we expect to see in nature, surely it makes more sense to constantly monitor the population and set our fishing effort relative to the density of the population that we find. This sounds like an intuitively obvious thing to do, and in fact is practiced in fisheries such as the Orange Roughy where populations are monitored. In effect, we make the removal from fishing a density-dependent relationship to the size of the fish population rather than have a single figure for an MSY applied each year. This approach is referred to as a ‘state-dependent strategy’ (SDS; Hunter and Runge, 2004). We can model removal from fishing easily enough by allowing for a loss from the basic population growth equation used earlier:

\[ N_{t+1} = \left( N_t \left( \frac{K - N_t}{K} \right) \right) - F \]

where \( F \) is the number removed by fishing between \( t \) and \( t+1 \). As we discussed earlier, \( F \) is a function of fishing effort \( (U) \) and ‘catchability’ \( (q) \). The value of \( F \) can be made density dependent so that the rate will vary as the fish-population varies. As fish-population increases, so will the fishing effort, and vice versa. But much depends on the time delay of the density dependence. For example, using the same starting conditions as before \( (N_0 = 1 \text{ and } K = 100) \) and a multiplication rate of 2 we can easily build-in a fish catch per fishing vessel (and make it a constant), but assume that the number of fishing vessels will be positively density dependent. For the sake of simplicity, if we set our fish catch at 2.2 individuals/vessel (please forgive the decimal point) and our density dependence at 7 (for every seven fish in a generation there is one fishing vessel) the result is shown in Figure 3.18a. Note that I have also built in a delay at the start to give the fish population a chance to get going. As we would perhaps expect, as the fish population increases, so do the number of vessels, and both populations level off at exactly the same time (the response is instantaneous). For the 150 generations of this graph the two populations are in complete harmony; we have reached sustainability.
We can also include a delay factor in the density dependence. After all, monitoring will need to take place some time prior to the fishing fleet setting sail and with current technology it may be unrealistic to expect that fishing effort can be set at the same time as monitoring. But between monitoring and decisions made over the number of vessels to send out, the fish population may well change. In that case, the fishers are

Figure 3.18 Number of fishing vessels as a function of fish density: (a) no time delay in the response; (b) with a delay in the response.
responding to what is perceived to be the fish population some time ago, and not what it may be at the time of fishing. The outcome is still sustainability, but the means by which the fish and fisher populations get there is different. Figure 2.18b is based on exactly the same parameters as before, but this time there is time delay in the density-dependency relationship of four fish generations (vessel numbers reflect the size of the fish population four generations ago). Note that the two populations have offset responses. At times the fish population will be declining while the fishing boat population is increasing and vice versa. But the end result is still a dampening down of the fluctuations and eventually a pair of parallel lines emerges as before. Plotting the two populations against each other yields the graph in Figure 3.19. The line winds into itself until eventually a single point – sustainability – is reached, where fisher and fish numbers remain at the point. This sort of behaviour has long been observed with systems having feedback relationships, and the central point in the graph has been given the enticing name of ‘strange attractor’. In this case it represents the Holy Grail that we have strived for throughout this chapter – sustainability.

So what are lessons here for the fishing industry? The obvious utopian answer is to make fishing effort and efficiency density dependent so that at any one time the number of fishing vessels and the catch of each vessel are kept set in such a way as to create a balance.
But the problem, yet again, is that we are dealing with something far more complex than our simple models allow. To begin with, the regular and detailed monitoring which is being advocated here would be very expensive and who is going to pay for it, even if it was technically feasible? The obvious answer might be to tax the fishers and let them pass that cost on to the consumer, but prices may rise as a result and that may not be popular. Secondly, what about the fishers told to stay in port while others fish? While these are not insurmountable problems given enough will and, more important of all, resources, they do seem to be well beyond our reach at the time of writing. In the previous section we heard about the ‘data deficiency’ surrounding the North and South Atlantic populations of Albacore and also the difficulty of monitoring deep-sea fish such as the Orange Roughy.

We still continue to hear of problems of over-fishing, even with relatively well-monitored stocks such as those in the North Sea. Time and time again the issue appears to come down to economics and politics and the trade-offs which take place rather than biology. Economics has not featured all that much in this chapter, but will be the focus of Chapter 5.

3.6 Conclusion

The concept of a fixed MSY for fish stocks assumed to be at equilibrium has proved to be popular and resilient (Larkin, 1977; Jennings et al., 2001). However, as a result of the issues raised above, the use of MSY, at least as defined and set out in this chapter, in order to manage fisheries has been heavily criticised. Instead, a more flexible approach is adopted to managing such a dynamic resource and fisheries scientists and managers aim for a maximum average yield (MAY; Mace, 2001). Thus the MSY applied to fish stocks provides a further affirmation, if one were needed, that sustainability is complex and in order to best be able to achieve it in practice we need much good quality data, as well as good theories. But obtaining such data on a routine basis does not come cheaply and what we are often left with is a compromise: a rough rule of thumb that we hope allows us to utilise a resource without driving it to extinction. In the case of the Orange Roughy the allowable commercial catch is set at 30% of what is thought to be the natural equilibrium population, but this is based on current knowledge and perhaps can be seen as no more than a best guess! In other cases, such as the Peruvian Anchovy, the influence of El Niño on the fishery was not known and neither was the event anticipated. Thus, we have a conundrum; we know that we are dealing with complex systems, yet
we all too often try to manage those systems with highly simplified tools, even when we know that the assumptions behind those tools may not apply.

It is true, of course, that our knowledge is improving and the previous paragraph and indeed the chapter should certainly not be read as a message of hopelessness; that we should give up any attempt to unravel this complexity. We are somewhere in between a mechanistic view of populations, where knowledge of parameters such as growth rates, recruitment, age structure and so on can be used to model change, and a chaotic view of nature (Gaichas, 2008). There is a need to re-think fishery management and MSY and MEY in less absolute terms and take on board this fusion of the mechanistic with chaos (Mous et al., 2005; Gaichas, 2008). Some have suggested that a new emphasis should be upon on a more ecosystems-based approach (Garcia et al., 2003) and the ecologically sustainable yield (ESY), the yield an ecosystem can sustain without shifting to an undesirable state (Katz et al., 2001). More on this later in the book, but all too often we do ignore the extent of our ignorance and that can have devastating effects. Even recent reports on the state of the world’s fisheries produced by the FAO have contradictions as to whether we are more or less fishing at the MSY for most of them, whether many are seriously depleted and in danger or whether there is scope for enhancing the fishing effort as we are not yet at the MSY (Holt, 2009). So how does biological knowledge and indeed the uncertainty which is present in most cases regarding fish-stock dynamics translate to management and policy? The policies employed to manage fish stocks are varied and are typically the setting of a constant catch, fishing mortality rate and/or escapement (fish not caught), all based on various degrees of knowledge and uncertainty. Indeed there has been surprisingly little research on the comparative effectiveness of these tools (Deroba and Bence, 2008) or indeed on the institutional landscapes which are charged with governance (Young, 1998). This is a point that will be returned to later. The danger is that while many may espouse the need for sustainable management of fisheries, the implementation may not be so apparent (Corten, 1996; Shelton and Sinclair, 2008), and even when clear plans are put in place for recovery there can be problems in reducing exploitation (Rosenberg et al., 2006). ‘The tragedy of the commons’ does unfortunately mean that unregulated exploitation is more the norm than the exception (Hilborn et al., 1995) and regulation in itself is not enough unless there is rigorous enforcement and closing of loopholes.

3.6 Conclusion