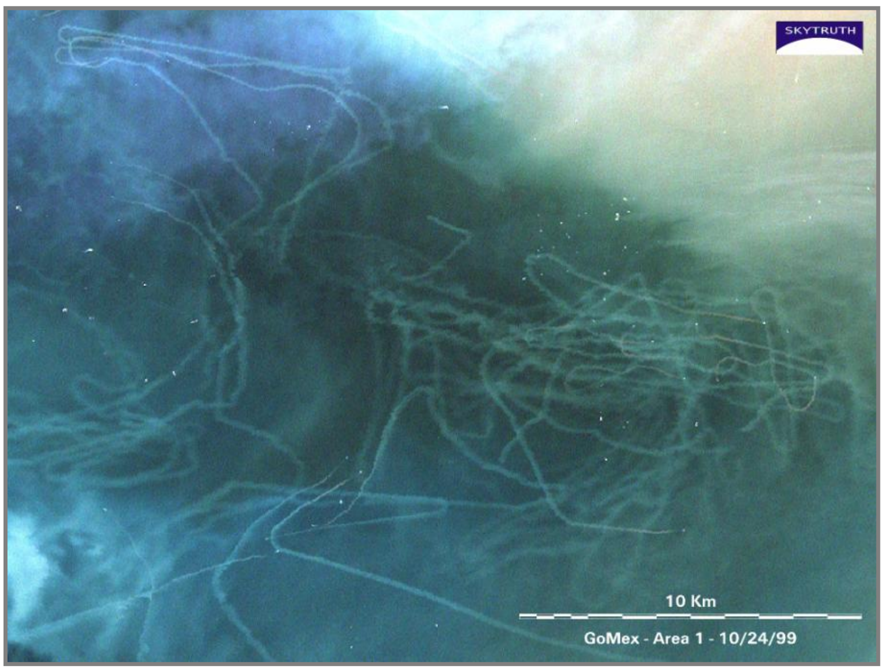
Global Biodiversity Indicators: scenario modelling for fisheries policy

Kathryn Sullivan

September 2010



Landsat satellite image of trawl sediment trails in an area of the Gulf of Mexico.

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science and the Diploma of Imperial College London

Abstract

The Convention on Biological Diversity set a target to reduce the rate of biodiversity loss by 2010. This target has not been met, and in the wake of this, scientists are looking at the suite of global biodiversity indicators developed to measure progress towards this target, to see how they can be improved and refined for use in the future. Adapting these indicators raises an opportunity to predict impacts of new environmental policies, and to assess the success of past management decisions. However, in order to do this the connection between different policy options and indicators needs to be fully understood. In this study, I look at potential of Marine ocean systems indicators to investigate this policy-indicator interface. Marine systems are an area of concern for conservation practitioners and policy makers alike, and so make an ideal test case. I use an ecosystem model, Ecopath, to model the outcomes of two marine fisheries policies on two well developed biodiversity indicators, the Red List Index and the Living Planet Index. I found that the indicators are able to detect policy change, but the more fine scale impacts of policy change are not well reflected in the indicators. A number of weaknesses in both the modelling process and the indicators were identified. The indicators need to be used in conjunction as their primary weakness is species composition. Without being fully representative of all species it is unlikely that one single indicator will provide a complete picture of biodiversity

Acknowledgements

Firstly, I would like to thank my supervisors, Dr. Ben Collen (Institute of Zoology) and Dr. Emily Nicholson (Imperial College), for their advice, suggestions and endless support over the past six months. I would also like to thank Imperial College for providing financial support for this project.

I would also like to express my gratitude to Alberto Barausse, for his exceptional work on the modelling component of this study. My thanks go to Louise McRae (Institute of Zoology), Julia Blanchard (Imperial College), Julia Jones (Bangor Unversity) and Hugh Possingham (Queensland University) for their advice and suggestions from the very beginning.

Thanks to everyone at the Institute of Zoology for their help and humour during the long write up. Thanks to my family and friends for their support and patience over the course of the last year.

A special thanks to Brendan for listening to every single problem I encountered, no matter what time of the day or night, and for sharing this experience with me.

Contents

List of Figures

List of Tables

Abbreviations

CBD: Convention on Biological Diversity

LPI: The Living Planet Index

RLI: The Red List Index

MTI: Marine Trophic Index

BAU: Business-as-Usual

CR: Critically Endangered

EN: Endangered

VU: Vulnerable

NT: Near Threatened

LC: Least Concern

DD: Data Deficient

Word count: 14,971

1 Introduction

The Convention on Biological Diversity target to "significantly reduce the rate of biodiversity loss by 2010" has not been met (Butchart *et al*. 2010). As a result, we are left with a selection of indicators in need of development, to allow continued, improved monitoring of the state of the world's biodiversity (Jones *et al.* In review). Biological diversity is defined by the CBD as, "the variability among living organisms from all sources including . . .terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part: this includes diversity within species, between species and of ecosystems" (Millennium Ecosystem Assessment, 2005). To assess the progress towards this target, a suite of indicators was developed, of which, only 9 of the 29 headline indicators are fully developed (Walpole *et al.* 2009). However, many of these indicators, were selected not for their relevance or rigour, but because the data are available (Mace *et al.* 2010). As we have reached 2010, the focus has now shifted to these indicators, and the conservation community is asking how these indicators can be used to assess global biodiversity. As a result, Jones *et al*. (In review) considered what the full role of these indicators is, and how best they can be utilised and improved.

No single indicator will be able to give a complete picture of biodiversity; however by using a number in conjunction, they may provide us with a representation of what is occurring. One important role of indicators highlighted by Jones *et al.* (In review) is improved understanding of how indicators will respond to policy change. This means using the indicators as a tool for predicting change as a result of new policy, and potentially auditing past conservation decisions, to assess their success. However, to do this successfully the gaps in our knowledge need to be filled. Even within a field as well studied as agriculture, which is vital for global food production, there are gaps and inconsistencies in the data and the way it is collected (Millennium Ecosystem Assessment, 2005). What is needed is a common protocol, enabling data collection for a suite of metrics (*Sachs* et al. 2010). As we develop similar metrics for biodiversity it is vital that they are statistically robust, and provide some insight into the mechanisms driving any changes (Dobson, 2005).

It is important for indicators to fulfil the roles outlined above. Firstly, knowing past successes and failures provides important information for the improvement of decision making (Sutherland *et al.* 2004). In addition, policy makers will work harder to meet commitments and targets if, in the future, there is the possibility that failure to do so will be detected (Jones *et al.* In review). If indicators can be used to audit policy decisions, it is logical for them to also be used proactively, to decide between competing policy options. However, the connection between policy decisions and global biodiversity indicators is still to be explored for most indicators (Jones *et al.* In review).

One system where the impact of policy upon indicators could be investigated is the marine ocean system. Marine systems are subject to much disturbance as a result of commercial fishing (Thrush and Dayton, 2002), while recent crashes in fish stocks mean that policies affecting them are up for revision (Caddy and Seijo, 2005). The extent and intensity of human disturbance to marine ecosystems is a significant threat to both structural and functional biodiversity, and in many cases it has virtually eliminated natural systems that might serve as baselines to evaluate fishing impacts (Thrush and Drayton, 2002). Of all fishing practises, bottom trawling is arguably the most destructive (Kaiser *et al*. 2006). Trawl gear affects the environment in both direct and indirect ways. Direct effects include scraping and ploughing of the substrate, sediment resuspension, destruction of benthos, and dumping of processing waste. Indirect effects include post-fishing mortality and long-term trawling induced changes to the benthos (Jones, 1992). It is understood that the greater the frequency of gear impacts on an area, the greater the likelihood of permanent change. In deeper waters (<1000m), where the fauna is less adapted to changes in sediment regimes, and disturbance from storm events the effects of fishing gear take longer to disappear, here recovery is probably measured in decades (Jones, 1992).

1.1 Aims

This project was developed from points raised in a recent study by Jones *et al.* (In review), that stressed the importance of understanding and developing Global Biodiversity Indicators, particularly in the wake of the failure to meet the CBD 2010 targets (Butchart et al 2010). Specifically, Jones *et al*. (In review) suggest that in order to maximise the utility of the current biodiversity indicator set, we must improve our understanding of how indicators will respond to changes in environmental policy. Given that the capability of the current set of CBD indicators to detect changes in policy is unknown, it is appropriate that they are evaluated against a range of policy scenarios. This involves a number of stages, from policy and indicator selection through to modelling and indicator analysis.

I model two policy scenarios to investigate their impact on two indicators. The policy scenarios being addressed in this project are:

- *Scenario 1:* A 50% reduction in bottom trawling effort within the selected study regions.
- *Scenario 2:* A 100% reduction (i.e. a total ban) in bottom trawling within the selected study regions.

The affects of these two policy scenarios were then tested to see how they impacted the two selected indicators; the Red List Index (RLI) and the Living Planet Index (LPI).

1.2 Objectives

- To model both the direct and indirect effects of the two scenarios using Ecopath with Ecosim software (Ecopath).
- To test the capabilities of two global biodiversity indicators (Living Planet Index and the Red List Index), to detect the effects of the chosen policy scenarios
- To assess the differences in the response of the indicators to the policies
- To compare the responses of the indicators between different regions
- To critically appraise the biodiversity indicators, and make recommendations for their improvement

1.3 Thesis Structure

Chapter 2 provides a background to the Global Biodiversity Indicators, and specifically the ones being assessed in this study. It also provides some context to the policies being investigated and why they are important. Finally, it describes the development and background of the models used to assess the impacts of the policies.

Chapter 3 describes the methods used in the study, starting with the selection of the scenarios and indicators to investigate. It then goes on to describe the modelling process in greater detail, and states the regions analysed. This is followed by the process used to project the results of the models with the two chosen indicators.

The results of the study are outlined in Chapter 4, starting with the aggregated results of the Indicator projections, and progressing to two regional case studies.

The final Chapter (5) suggests reasons and causes for the observed results, and then places them in the broader context of previous research. It then examines the limitations of both the indicators and the Ecopath modelling process, and identifies any gaps in the current knowledge or understanding.

2 Background

In the following sections, I discuss why indicators should be studied and tested, and outline the theory and background behind the project and the choices made. I start with a review of global indicators, in particular the indicators of interest: the Red list Index (RLI) and the Living Planet Index (LPI). I then describe the policy area of interest: bottom trawling, giving a brief background to commercial fishing and the problems inherent with bottom trawling. I then go on to briefly outline the models that will be used to complete this study.

2.1 CBD Indicators

In 2002 and 2003, at the World Summit on Sustainable development in Johannesburg, some significant political commitments towards the conservation of biodiversity were made (Mace and Baillie, 2007). 188 countries pledged to reduce the rate of biodiversity loss by 2010 (Walpole *et al*., 2009), and more recently, this target has been included in the Millennium Development Goals (Millennium Development Goal Indicators, 2008). As we have entered 2010, it is clear that the target has not been met, and that in fact, there are problems with the target itself being vague and hard to quantify (Mace *et al*. 2010).

In order to track progress towards this target, a headline set of indicators have been developed to gauge a range of measures of status of biodiversity, pressures causing biodiversity change and human responses to these changes (Jones *et al*. In review). The purpose of the CBD 2010 Biodiversity Indicators is to measure changes in biodiversity at a number of levels, from genes to ecosystems (Butchart et *al*., 2010). Once fully established, they should be able to quantify how habitats and populations react to changes in threat ranging from invasive species (McGeoch *et al.* 2010) to changes in freshwater ecosystems (Revenga *et al.* 2005). There is also potential for them to monitor the effectiveness of reactive measures, such as changes in legislation that are aimed at protecting biodiversity (Dobson, 2005). In order for indicators to achieve their potential, it is important that the manner in which they will respond to changes in biodiversity, and as a result of specific legislation, is fully understood (Jones *et al.* In review). However, only nine of the indicators within the CBD framework of 22 (headline) indicators are now considered to be completely developed, and have founded methods (Walpole *et al.* 2009), four of which are the indicators of biodiversity trends: RLI, LPI, protected area coverage and forest cover.

In order to refine and improve the indicators, it is vital that their aims and purposes are clear and understood. Jones *et al.* (In review) outline the main objectives of the current global indicator set, highlight the areas where improvement is needed and recommend how this can be achieved. The study also categorises the purposes of the indicators into two main groups: knowledge focused and action focused. This basically translates to collecting information without a direct link to management or policy action, and collecting information where it feeds directly in to management or policy action (Jones *et al.* In review). The CBD indicators were intended to promote more cohesion amongst disciplines, to encourage the use of a globally accessible format for environmental monitoring by conservation biologists and ecologists etc. (Dobson, 2005). However, so far this does not appear to have succeeded. Unfortunately the current set of indicators continues to suffer from gaps in coverage, both regionally and taxonomically. More effort is required to ensure those groups that underpin ecosystem function, although less charismatic, are included, e.g. fungi, nematodes and arthropods etc. (Dobson, 2005).

In other disciplines, better linked indicators have been established (Shin *et al.* 2010). For example, within fisheries science, ecosystem indicators have been developed that include and synthesise a range of information that underlies ecosystem status and how it responds to fishing pressure. These indicators are intended to serve as signals that something is happening, other than what is actually being measured. However, more emphasis of these is placed on assessing trends within ecosystems, rather than assessing the systems current ecological status (Shin *et al.* 2010). Within fisheries science, and indeed elsewhere, it is thought that for indicators to be of any use, they must be capable of summarising an array of complex processes in a single number, where otherwise the processes would be difficult to understand. Indicators must also be useful for communication and, where possible, policy and management (Pauly and Watson, 2005). For example, the Marine Trophic Index, has been adopted as the headline marine indicator by the CBD and describes complex interactions between ecosystems and fisheries, and communicates the effects of fisheries on species replacement (Pauly and Watson, 2005).

2.2 Living Planet Index Background

The LPI was started in 1997 as a WWF project to establish a measure of the changing condition of global biodiversity over time. The first index was published in 1998, in the

Living Planet Report (Loh *et al.* 1998) and has since been updated biennially. The aim of the LPI is to measure average population trends of vertebrates from across the globe since 1970.

Currently the index is based on nearly 11,500 time series of populations for more than 2,500 species (Collen *et al.* 2009; Global Biodiversity Outlook 3, 2010). The index is restricted to vertebrate species abundance trends from the year 1970 onwards due to data availability. Invertebrates are excluded from the index as there are very few time series available for them, and those that do exist are from geographically restricted locations (Loh *et al*., 2005).

In order for a series to be included it must meet the following criteria (Collen *et al.* 2009):

(1) Estimates available for at least two years from 1970 onwards.
(2) Estimates of population size, population density, biomass or number of nests. Numbers of densities of animals taken through harvest either by hunting or fisheries, although sometimes taken as indicative of population size or density, are not used.
(3) Survey methods and area covered are comparable throughout each survey of the series (as far as can be ascertained).
(4) Time series with little or no indication of how, where or when the data were collected are not used.
(5) The data source is referenced and traceable

Before any calculations are carried out, the data are divided up into biome depending on the species primary habitat. Within each biome, species are divided into either biogeographic realm, or to the ocean they inhabit. Each time-series is given a quality rating by combining several features of the study: source type, method type, and whether or not a measure of variation was calculated. Time series with scores four or below are considered to be poor quality, and those with a score of five or above are considered high quality (Collen *et al.* 2009). Multiple time-series for a single species within a realm or ocean, are treated as a single time-series, so that each species carries equal weight within each realm or ocean (Loh *et al.* 2005; Collen *et al. 2009)*.

When the LPI was first established the annual change in abundance by species was aggregated using a chain method (Loh *et al.* 1998), which was later complimented with a linear modelling method (Loh et al 2005). In 2009, Collen *et al.* reassessed these methods, and introduced a generalized additive modelling technique (GAM: Fewster *et al.* 2000, Buckland *et al.* 2005). A GAM framework is thought to be advantageous in long-term trend analysis, as it allows the change in mean abundance to follow a smooth curve, and not just a linear form. It also provides greater flexibility for drawing out the long-term trends (non-linear) that are generally not revealed by the chain method (Collen e*t al.* 2009; methods for calculation covered in detail in the method, section 3.4.3).

2.3 The Red List Index

The IUCN Red List of Endangered species has a long history dating back to the 1950s when IUCN began creating lists of species at risk of extinction. During the 1960s these became known as the international red data books for birds and mammals. Species coverage in the Red Data books increased in the 1970s as IUCN attempted to include all higher vertebrates and representative groups of plants, fishes, and invertebrates (Mace *et al.*, 2008). The initial categories developed were; endangered, vulnerable, rare and indeterminate, insufficiently known, and out of danger. The categories were developed to separate extinction risk, and expressed the degree of threat and levels of uncertainty. In the 1980s, the assessment criteria and categories for classifying species began to be questioned (Mace *et al.*, 2008). In 1984 a need for a more widely applicable system that was more robust and objective was called for (Fitter and Fitter, 1987). This led to the development of the IUCN Species Survival Commission (SSC) Steering Committee, which reviewed, revised and tested a new set of quantitative criteria and threat categories. New criteria were developed between 1991-1995, and in 1994 version 2.3 was accepted and published, with Mace and Lande's (1991) proposal providing the basis. During 1996-1999 these again went under a review process to produce the new criteria, version 3.01, which were formally adopted by IUCN's council in 2000, and first applied to species in 2002 (Mace *et al.* 2008).

The purpose of the Red Lists was to direct conservation action through raising awareness of the plight of declining species (IUCN 2010). The IUCN Red List is designed for application at the global level to taxonomic levels of the species and below. The goals of the IUCN Red List are to (IUCN 2010):

- Identify and document those species most in need of conservation attention if global extinction rates are to be reduced; and

- Provide a global index of the state of change of biodiversity.

Table 2.1: Simplified overview of the thresholds for the IUCN Red List Criteria (IUCN 2001)

Criterion	***Critically Endangered***	***Endangered***	***Vulnerable***	***Notes/ Qualifiers***
A1: reduction in population size	$\geq$ 90%	$\geq$ 70%	$\geq$ 50%	Over 10years/ 3 generations in the past, where causes are reversible, understood and have ceased.
A2-4: reduction in population size	$\geq$ 80%	$\geq$ 50%	$\geq$ 30%	Over 10 years/ 3 generations in past, future or a combination
B1: small range	<100 km^2	<5000 km^2	<20 000 km^2	Plus two of (a) severe fragmentation/ few localities, (b) continuing decline, (c) extreme fluctuation
B2: small range	<10 km^2	<500 km^2	<2000 km^2	Plus two of (a) severe fragmentation/ few localities, (b) continuing decline, (c) extreme fluctuation
C: small and declining population	<250	<2500	<10 000	Mature individuals. Continuing decline either (1) over specified rates and time periods or (2) with (a) specified population structure or (b) extreme fluctuation
D1: very small population	<50	<250	<1000	Mature indiduals
D2: very small range	N/A	N/A	<20km^2 or $\leq$5 locations	Capable of becoming critically endangered or extinct within a very short time
E: quantitative analysis	$\geq$50% in 10 years/3 generations	$\geq$20% in 10 years/3 generations	$\geq$10% in 10 years/3 generations	Estimated extinction-risk using quatitative models, e.g. population viability analysis

The current IUCN Red list criteria include 5 criteria with further sub-criteria which evaluate different symptoms of risk, detailed in Table 2.1. The three threat categories used by IUCN are *Critically Endangered, Endangered,* and *Vulnerable*, reflecting differing levels of risk over various timescales (Mace and Lande, 1991; Mace and Stuart, 1994).

I will now outline briefly the development of the Red List Index (RLI) from the IUCN Red List of Threatened Species. The RLI observes the movement of species through Red

List categories over time. The categories can be used to calculate the rate at which species under threat move to extinction (Butchart *et al.* 2004, 2007). The RLI is based on the number of species in each Red List category. Categories were each weighted, to make the index sensitive to not only the total number of threatened species, but also to the changes in category given to each species (Butchart *et al.*, 2004). The RLI is not just capable of tracking global trends. It can be disaggregated to show trends for species in different ecosystems, habitats, taxonomic groups etc., and for species relevant to different international law (Butchart *et al.*, 2007).

RLI has changed and improved since it was initially developed and tested in 2004 using bird data from 1988-2004. Three shortcomings in the original design were identified (Butchart *et al.* 2007) leading to the revision of the original formula. The first was that newly evaluated species may have introduced bias to the index. If a species was previously assessed as *Data Deficient* or was newly recognised taxonomically, they may introduce a “false” change to the index trend once their assessment is included (Butchart *et al.*, 2007). The second is that RLI values were affected by the frequency of assessments. Using the original formulation the RLI value is dependent on the number of assessments that precede it since the baseline year. The third shortcoming was that the RLI performs inappropriately when it reaches in zero. The 1988-2004 bird dataset used to develop the formula showed an important, but relatively small proportional decline in status over time. This did not prepare the formula for the problems that may arise when a group of species undergo a large proportional decline in status. If the RLI calculated declines to zero (by 100%) it subsequently cannot change, even if the species continued to decline (Butchart *et al.*, 2007). To address these outlined shortcomings, the original formula was revised, and subsequently became easier to interpret (Butchart *et al.*, 2007). For details of the formula please see Methods section 3.5.3.

Instead of measuring the state of biodiversity, the RLI measures the rate of biodiversity loss. The RLI is calculated from changes between the Red List categories, hence an RLI value is an index of the proportion of species expected to avoid extinction in the near future, without any conservation action (Butchart *et al.* 2007). If the rate of biodiversity loss is increasing it is shown by a downward trend in the RLI, whereas a decrease in the rate of biodiversity loss is shown by an upward trend. A horizontal line means the expected rate of species extinctions is remaining the same (Butchart *et al.* 2007).

The RLI has some shortcomings, which are currently being addressed by further research. These include taxonomic bias, documentation of reasons for change, and time lags and the resolution of changes (Butchart *et al.* 2005). The validity of the IUCN Red List Index as an indicator could be compromised by taxonomic bias. This problem is in part being addressed by expanding taxonomic coverage through the sampled approach to Red Listing (a random sample of 1,500 species from new taxonomic groups being assessed; (Baillie et al 2008; Collen et al. 2009). As the species are tracked over time and move between categories, it is important to have a good auditing system to allow documentation outlining the reasons for re-classification (IUCN 2001). These are currently classified as being "genuine" (e.g. due to change in species abundance) and "non-genuine" (e.g. due to change in knowledge). Due to the nature of the Red List categories, RLIs have a moderately course level of resolution of status changes. However, the disadvantages of this are potentially outweighed by the advantage of having a repeatable method to assess all the species within a taxonomic group, and not just a subset for which detailed information is available (Butchart *et al.* 2004). The index may also be insensitive to status changes as a result of time lags between changes in a species and changes in the RLI value. Work is being done to mitigate this latter problem, and a study completed addressing changing statuses of birds, found that the true index value may lie somewhere between 0.21%-0.37% of what had previously been estimated (Butchart *et al*., 2004).

2.4 Current and potential future uses of global biodiversity indicators

Currently the indicators developed by the CBD are not being used to their full potential i.e. to drive policy change and audit management decisions (Jones *et al.* In review). It is known that the world has not met the CBD 2010 target, and so has failed to reduce biodiversity loss (Mace *et al.* 2010). The LPI has fallen by about 30% since 1970 (The Living Planet Report, 2008). It is described as a "measure of global biodiversity only as far as trends in vertebrate species populations are representative of wider trends in all species, genes and ecosystems" (Loh *et al.* 2005). However, it is not known if trends in vertebrates would convey true trends of other taxonomic groups, and this needs to be investigated if the LPI is to be used successfully to assess the full impact of new environmental policy and to audit past management decisions. Currently, the Red List can be used to prioritize species for conservation action, and the RLI can be used to analyze trends in the few groups where species have been reassessed (Butchart *et al.* 2005; Butchart *et al.* 2007). However, it is yet to be used to assess the impact of specific policy (assuming that it is capable of detecting such trends). This is considered to be the future use of indicators in the wake of the CBD (Jones *et al.* In review).

The Marine Trophic Index is another of the headline CBD indicators. In the past it was used to identify what is now a widely known phenomenon called ‘fishing down marine food webs’ (Pauly *et al.* 1998). It has been developed to clearly describe and communicate the complex interactions between fisheries and marine ecosystems (Pauly and Watson, 2005). In the future, specific Marine Trophic Index values could be used as targets for management interventions, and so could be used to monitor the response of systems to policy interventions. However, our present knowledge of systems does not allow for critical trophic level threshold values to be indentified (Watson and Pauly, 2005).

2.5 Fisheries in Crisis

In recent years there has been a lot of focus on sustainable fisheries and fisheries management. Current global marine fisheries landing trends provide little evidence of sustainability of marine resources and suggest a number of them are in fact in decline (Caddy and Seijo, 2005). Sustainable target levels for managed fisheries in the past have focused on reaching the *maximum sustainable yield (MSY)*, however recent experience suggests that MSY is risky target for fisheries management (Caddy and Seijo, 2005). Not enough is known about stock status and fluctuations in productivity to accurately predict the MSY for a fishery (Larkin, 1977). Progress towards reducing overfishing is hampered by a reluctance to tolerate the inevitable short-term economic and social costs of doing so (Worm *et al.* 2009). In addition to this, government subsidies often encourage overfishing, and need to be urgently readdressed (Sumaila *et al*. 2007). Radical policies are needed to allow fisheries to recover, however the management of fisheries is a complex process and requires multidisciplinary integration between ecology, resource biology, economics and politics (Caddy and Seijo, 2005). The affect of these policies on biodiversity needs to be known, in order to monitor their success once enforced.

Briefly outlined next is the history of commercial sea fishing, which dates back centuries. At the end of the first millennium Europe was changing and developing. As the European economy emerged, many workers began specialising in trades such as metalwork, leather tanning and fishing (Roberts, 2007). Bottom trawling was first mentioned in 1376, in a complaint made to King Edward III. It was a request that he ban the use of this new and destructive fishing gear (Roberts, 2007). The complaints made in the late 14^{th} century included the decrease in captured fish size, the capture of non-target species, and the notion that fish were deteriorating (Jones, 1992). Bottom trawling remains the primary method of catching bottom-dwelling fish (Thurstan *et al.* 2010). Bottom trawlers were sail powered and fished close to the shore until the end of the nineteenth century. However, the development of steam trawlers in the 1880s resulted in the quick growth in fishing effort that continued throughout the twentieth century (Knauss, 2005). Steam trawlers were controversial in the United Kingdom, through their competition with line fishers for fish. This resulted in a government enquiry in 1885, examining claims that trawls were causing damage to habitats, and reducing fish stocks (Roberts, 2007). Due to the absence of any fishery data or statistics the enquiry could not reach any conclusions, and instead recommended that catch data should be collected. All major ports in England and Wales, as of 1889, began gathering fishery statistics. The data this provides about fleet composition and fish landings, allows the reconstruction of the changes in the commercial fishing industry over the last century (Roberts, 2007). Since the nineteenth century industrialisation of fishing, landings per unit of fishing power (LPUP) has reduced by 94% - 17 fold (Thurstan *et al.* 2010). This suggests a remarkable change in seabed ecosystems, and a decrease in the availability of bottom-living fish (Thurstan *et al.* 2010). This could be partly due to the setting of quotas by politicians 20-25% higher than advised by scientists since 1984, under the Common Fisheries Policy. This has kept landings constant, despite falls in spawning stocks (Thurstan *et al.* 2010).

In modern fisheries, towed bottom trawls are believed to be one of the biggest sources of global anthropogenic disturbance to the seabed and the species that inhabit it (Kaiser et al., 2006) (See Fig.1.1). Globally trawlers cover an area of 15 million km^2 of seabed per year. That equates to an area 150 times larger than that which is deforested annually (Malakoff, 1998). The design of trawl nets, is to catch species that are economically valuable, however, as they are a “mobile non-selective fishing gear” they collect every species they encounter (Kumar and Deepthi, 2006). This results in the catch of non-target species, known as ‘by-catch’. This by-catch, combined with the amount of ‘discarded catch’ (portion of catch returned to the sea), is a major concern associated with the practise of trawling (Kumar and Deepthi, 2006). The major reasons for discarding by-catch are (Kumar and Deepthi, 2006):

(1) Minimal commercial value,
(2) the costs of landing, and
(3) storage capacity of the vessel

There are also concerns about the effects of dumping substantial amounts of discards and waste, such as fish heads and frames, on the seabed (Jones, 1992). Commercial bottom trawling contributes approximately 27 million tonnes of discard per year. This is more than half of all fish captured from marine fisheries directly for human consumption annually (Kumar and Deepthi, 2006).

Figure 2.1: (a) Hexactinellid sponges are found only on deep-water reefs off the western coast of Canada, **(b)** The same area of sea floor after the trawl has gone. © Manfred Krauter 2007

In the North Sea alone, over the last decade trawlers have used heavier gears, and more than 90% of the seabed has been trawled at least once, and in a number of cases six times a year (Olsgard *et al.* 2008). Usually, the seabed is affected more when in contact with heavier gear. The damage varies with the amount of gear used, together with the structure and depth of the seabed and the strength of the currents (Jones, 1992). There are a number of direct and indirect effects from trawling. The direct effects include things such as sediment resuspension, ploughing and scraping of the substrate, and the dumping of discards and processing waste. Indirect effects are things such as long-term changes to the habitat as a result of trawling, and post-fishing mortality (Jones, 1992).

The indiscriminate nature of bottom trawls is one of the primary reasons for concern with regards to high by-catch levels, and unsustainable fishing, but there are a whole host of other effects, both direct, and indirect, that they can have on marine environments. Bobbins and chains attached to the gear can leave distinctive tracks in the seafloor, and potentially skim off the sediment on the surface. Otter boards leave imprints on the seabed, and can plough a groove, which can be between a few centimetres and 0.3m deep (Jones, 1992). The persistence of trawl tracks varies depending on the substrate and water movement. However, where seamounts are trawled, and deep-sea corals are damaged, the substrate could potentially take decades or even hundreds of years to recover (Althous *et al.* 2009). As trawls flatten the seafloor the habitat becomes more homogenous. This can be a significant factor in survival and recruitment for a variety of marine organisms, including some species of commercial importance (Kumar and Deepthi, 2006). Another effect of trawling is the resuspension of sediment. As the trawl gear passes over the seafloor it causes a disturbance in the surface sediment. It can result in damage and/ or removal of much of the resident biota. In addition, it can impact a number of ecosystem functions such as the remineralisation of organic matter and fluxes in nutrients (Olsgard *et al.*, 2008). These changes and alterations to ecosystems functioning are just some of the indirect results that bottom trawling can have on our global marine environments.

2.6 Ecopath Modelling

In fisheries science, a range of models are available to look at trends in fish populations due to changes in communities, ecosystems, and exploitation rates. Single-species models are commonly used to calculate the exploitation rate that provides the MSY for a specific stock (Worm *et al.* 2009). Multispecies models range from simpler community models to very complex ecosystem models. They can be used to predict the effects of exploitation on species composition, biomass, size structure and other ecosystem properties (Fulton *et al.* 2003). There has been a move towards the ecosystem approach to fisheries globally over the last decade. In order to do this, single-species models need to be integrated with ecosystem level assessments (Shin & Shannon, 2009).

Ecopath is one model that has been used often to assess the impact of protected areas (Pauly *et al*., 2000). It was developed in the early 1980's by Polovina (1984), and since then has been continuously developed. Ecopath is a static, mass-balanced snapshot of the system. Ecosim, a development of Ecopath, emerged in 1995, adding dynamic modelling capability. In 1998 Ecospace was developed and resulted in an integrated software package ‘Ecopath with Ecosim’ (Ecopath) (Christensen and Walters, 2004). It is based on a two master equations. The first describes the production term, and the second is the energy balance for each group of species (functional group) within the model (Christensen and Walters, 2004).

Although Ecopath has been used for over 20 years there are still some potential drawbacks to consider. Ecopath provides an ‘instantaneous estimate of biomasses, mortaility rates and trophic flows, for some reference period (usually a year). As biomass is generally at equilibrium the models assume no trends under constant fishing. To alter this, a rate of biomass ‘accumulation’ or ‘depletion’ can be entered into the model, however this can be difficult to paramaterise and can lead to misleading results (Christensen and Walters, 2004). Due to their complexity it is hard to quantify the uncertainty that is inherent in the models. It is important to recognise this when comparing policy comparisons within Ecopath (Christensen and Walters, 2004).

3 Method

This section describes the methods used to investigate the sensitivity of Global Biodiversity Indicators to changes in policy, and follows the steps outlined in Fig 3.1.

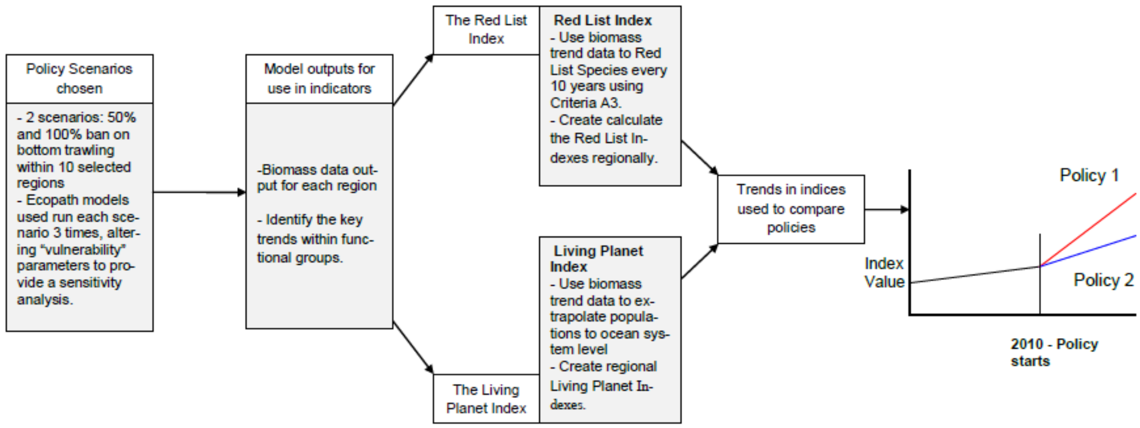


Figure 3.1: Schematic diagram, outlining the different stages of the method used to complete this analysis

3.1 Choosing Suitable Scenarios

In order to investigate the sensitivity of indicators to changes in global policy, I developed a set of scenarios, a means of modelling the potential policy outcomes and a set of existing biodiversity indicators. For this study I selected two scenarios:

- *Scenario 1:* A 50% reduction in bottom trawling effort within the selected study regions.
- *Scenario 2:* A 100% reduction (i.e. a total ban) in bottom trawling within the selected study regions.

These scenarios were selected because bottom trawling is acknowledged as one of the most destructive practises in the marine environment and has been likened to deforestation of rainforests (Malakoff, 1999). Bottom trawling occurs in all major ocean basins, and is destructive to species (indiscriminate catch) and ecosystems (destruction of habitats) (Jones, 1992).

Although the policy scenarios are likely too extreme to realistically come to fruition, they were designed to increase the likelihood of their detection by the indicators suite.

3.2 Indicator selection

Out of the 29 indicator measures outlined by the CBD, nine are now considered to be well-developed, and have well founded, peer reviewed methods (Walpole *et al.*, 2009). For this study, it was important to investigate how well these fully developed indicators perform, and whether they can actually fill their potential role, helping to inform policy decisions. I also considered how relevant the indicators were to the policy decision. Following a ban or reduction in bottom trawling, increases in abundance of commercial species and prominent by-catch species were expected. As a result of this, the extinction risk for many species was anticipated to decline. The indicators selected needed to be able to detect these changes, and any indirect changes as result of this, within the system in order to detect the policy. As the policies being studied were based in marine systems, and were based on fishing catch reduction some indicators would be more informative than others. For example, it is harder to study "Connectivity/ fragmentation of ecosystems" in marine systems than in many terrestrial systems.

I selected two indicators from the CBD set to study the effects of the policy scenarios: the Living Planet Index (Collen *et al.* 2009), and the Red List Index (Butchart *et al.* 2004), as they are capable of detecting changes in abundance and extinction risk, and so are relevant to the changes expected following enforcement of the policy scenarios. In addition, they are applicable to terrestrial, freshwater and marine systems, and so could be used in the future for a wider range of policy decisions. The Marine Trophic Index (Pauly and Watson, 2005) was another obvious choice to test the impact of policy change in the marine environment, however, data are not widely available so it was beyond the scope of this project.

3.3 Ecopath Modelling

In order to investigate whether Global Biodiversity Indicators are capable of detecting changes as a result of the policy scenarios, the first step was to model the effects of the policy change in different regions. To do this, Ecopath models were chosen. They were selected as they provide ecosystem level information in the form of biomass changes among species or groups of species (functional groups). In addition, due to the inclusion of non-catch species, they allow the investigation of the indirect effects of the bottom trawl reduction policy, such as changes in food-chain structure. Alternative models were

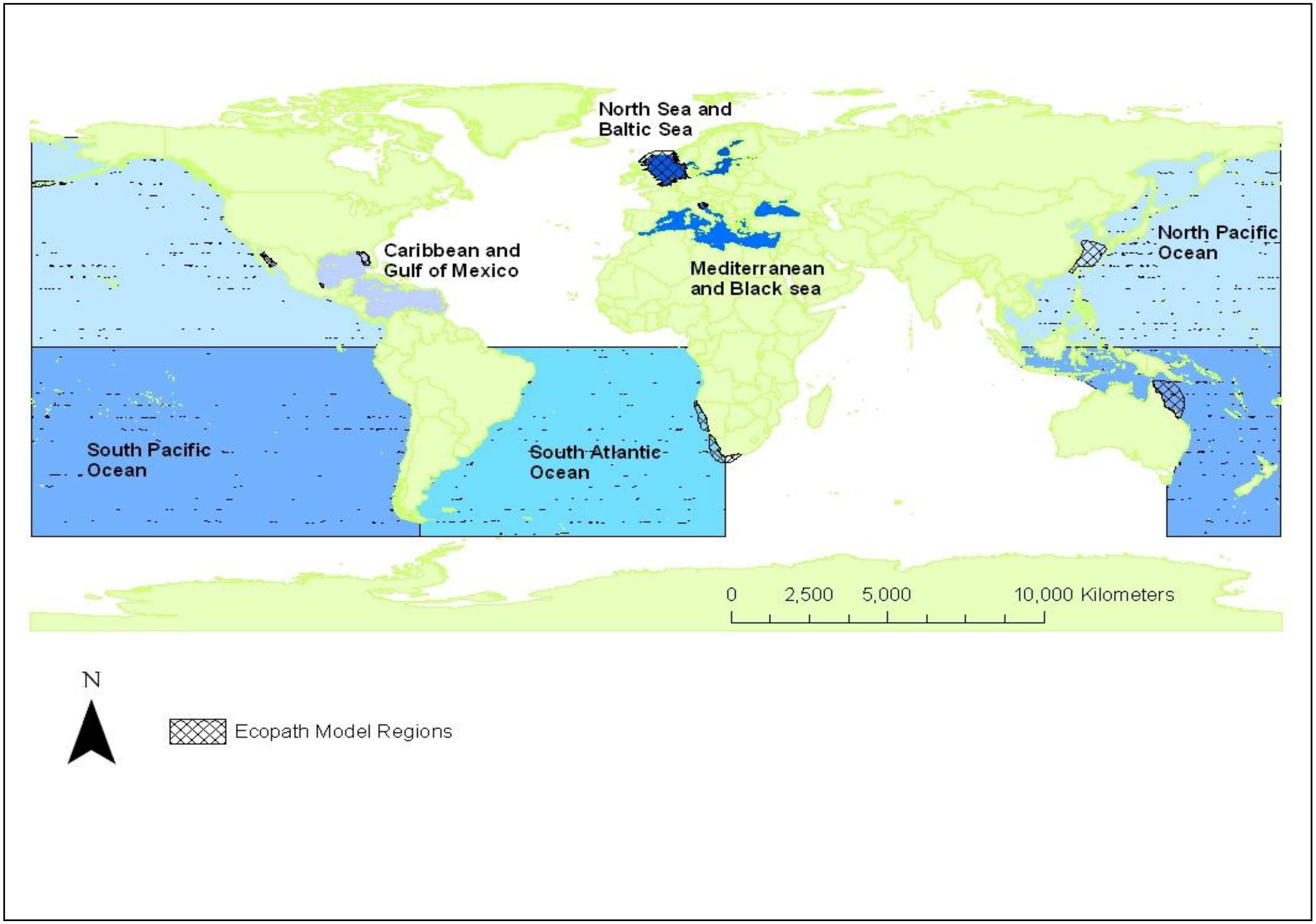


Figure 3.2: Global map showing the regional Ecopath models and the ocean systems they are in

considered, such as single-species models (Versteeg *et al.* 1999, Kinzey and Punt, 2009) and the multispecies models used by Worm *et al.* (2003) and Van Kirk *et al.* (2010). However, as they lacked inclusion of non-commercial species, such as non-target fish species, marine mammals etc. their capacity to detect indirect impacts of the removal of bottom trawling were limited.

From the 127 Ecopath models that are reportedly available (Ecopath, 2010) I selected 10 models to provide coverage of a range of marine environments (Figure 3.2, Table 3.1). The models were selected based on a range of criteria. The first consideration was ensuring fairly even coverage of models over tropical and temperate areas, as they may be impacted differently by the policy scenarios. Secondly, guaranteeing that each region was covered by the indicators, and contained functional groups (groups of species) that could be assigned to species in the two indicators. It was also important that the models ranged in their indicator coverage (based on the number of species included in both the model and indicators). This would allow inference of the power of each indicator to detect change in regions with strong coverage, and regions with weaker coverage.

In order to apply the scenarios to the models, it was necessary for them to contain individual fishing fleets, and not an aggregated fishing effort, to allow the isolation and alteration of fishing effort by bottom trawl fleets. This also contributed to limiting which regional models were selected for use.

Ecopath models are based on a two master equations. The first (Equation 1) describes the production term:

$$\text{Equation 1: } P_i = Y_i + M2_i \times B_i + E_i + \mathrm{BA}_i + M0_i \times B_i$$

Where Y_i is the total fishery catch rate of i, $M2_i$ is the instantaneous predation rate for group i, E_i the net migration rate, BA_i is the biomass accumulation rate for i, while $M0_i$ is the ‘other mortality’ rate for i. B_i is the biomass of i.

Table 3.1: The regional Ecopath models selected to form the basis of the analysis, the number of functional groups each model contained, and the ocean system they were grouped in for analysis. The number of fleets manipulated for the policy simulations

Model/ Region	***Number of Functional Groups***	***Fleets reduced from total fleets included***	***Tropical/ Temperate***	***Oceanic System***	**Reference**
Central Gulf of California	27	1 trawl reduced out of 4 fishing fleets	Temperate	North Pacific	**Arreguin-Sanchez *et al*. 2002**
Great Barrier Reef	32	1 out of 3	Tropical	South Pacific	**Gribble, 2005**
East China Sea	45	1 out of 6	Temperate	North Pacific	**Jiang *et al*. 2008**
North Sea	68	4 out of 12	Temperate	North Sea and Baltic Sea	**Mackinson and Daskalov, 2007**
Northern Adriatic Sea	34	2 out of 6	Temperate	Mediterranean and Black Sea	**Barausse *et al*. 2009**
Northern Benguela	26	1 out of 8	Tropical	South Atlantic	**Roux and Shannon, 2004**
Southern Benguela	27	1 out of 6	Tropical	South Atlantic	**Shannon *et al*. 2003**
West Florida Shelf	59	1 out of 11	Tropical	Caribbean and Gulf of Mexico	**Okey and Mahmoudi, 2002**
Gulf of Alaska, Eastern Aleutians	40	1 out of 6	Temperate	North Pacific	**Heymans *et al*, 2007**
Gulf of Mexico, Alvarado Shelf	40	1 out of 1	Tropical	Caribbean and Gulf of Mexico	**Cruz-Escalona (In preparation)**

And the second (Equation 2) is the energy balance for each group Equation 2:

Consumption = production + respiration + unassimilated food

In order to calculate trophic impacts of groups on all other groups in the model a *mixed trophic impact* analysis is included in the model software. It includes both direct and indirect impacts, e.g. competitive interactions and predatory interactions (Christensen and Walters, 2004). The data requirements for Ecopath are simple, and normally available from stock assessments, literature, or ecological surveys. Data include species biomass estimates, total mortality estimates, consumption estimates, diet compositions and fishery catches (Christensen *et al.* 2005). Once the data are input, the chosen scenarios can be run for a set number of years (in this case 50), and the output comes in the form of annual biomass data (t/km^2) for each functional group (species or group of species).

For the chosen regions (Table 3.1; Figure 3.2), the “static” mass-balanced representation of the trophic network of biomass flows in the ecosystem (i.e. the Ecopath model) were used. Ecopath models are capable of estimating parameters where data are not available using a number of algorithms included in the parametrisation routine (Christensen and Walters, 2004), therefore the data input varied for each region. This also impacts the accuracy of the various models (Christensen and Walters, 2004).
I did not collect simulation related data (i.e. Ecosim-related data), such as effort or catch or biomass time series. Such time series would have allowed better estimates of the parameters of the Ecosim scenario simulations, but were only available for a small number of the ecosystems; to enable a consistent approach I therefore did not use them. In order to set up an Ecosim simulation to evaluate the scenarios, I took the static Ecopath models and, for each one, created an Ecosim simulation with all the Ecosim parameters set to the default values.

For each of the 10 regional models, I ran the simulations for 20 years with no changes to fishing effort to enable the biomass trajectory to stabilise. I then ran each model for 50 years under each policy scenario. I chose 50 years as this allows sufficient time for longer lived species to recover or decline.

3.4 Indicator Analysis - Living Planet Index

Biomass data were used to predict trends in population size, as measured by the LPI. Each regional Ecopath model was allocated to an Ocean System. Species within this system were then be allocated to a functional group within the model. For example, in the North Sea model species *Clupea harengus* was allocated to the functional group ‘Herring’ and *Megaptera novaeangliae* to the group ‘Baleen whale’ (for further examples of functional groups see table 3.2). Each model within an ocean system was extrapolated to the level of ocean system, by not just allocating species from the model location to a functional group, but allocating all species within the system as a whole to a functional group. This assumes that a reduction in bottom-trawling would have the same effect across the entire system, and that fishing pressure was the same across the entire system.

3.4.1 Allocating models to ocean systems

Within the LPI there are a number of ocean systems used to classify the location of populations. Models were allocated to whichever of these systems they were found in (Figure 3.2; Table 3.1)

3.4.2 Allocating Species to functional groups

Species for each ocean system were allocated to a functional group within the model, unless there was no applicable group. Original authors of each of the regional Ecopath models set up functional groups. These ranged between models from groups of species such as “Marine Mammals” to single species groups such as “Atlantic Cod”. There were differences between the level of detail and number of functional groups per model. Some models used functional groups based on families and species (e.g. East China Sea; Jiang *et al.* 2008), where as others were more habitat focussed (e.g. West Florida Shelf model; Okey and Mamoudi, 2002). Species were allocated at a population level, as many regions contain numerous populations of the same species. Where there was more than one model for an ocean system (e.g. the North Pacific, which contains the ‘Aleutian Island’ (Heymans *et al*. 2007), ‘Central Gulf of California’ (Arreguin-Sanchez *et al*. 2002) and the ‘East China Sea’ (Jiang *et al.* 2008) models), species were allocated to a functional group within the model that best matched their actual distribution. For example, in the North Pacific *Fratercula cirrhata* was allocated to the functional group “seabirds” within the Aleutian Islands model over the Central Gulf of California, or the East China Sea, as this overlaps with more of their range than either of the other models.

In the ’Mediterranean and Black Sea’ ocean system for example, which contains the ‘Northern Adriatic Sea’ Ecopath model (Barausse *et al*. 2009), there was a possible 34 functional groups into which species could be allocated (including detritus and

Functional Group	***Number of Species***
Anchovy	1
Dolphins	2
European Hake	1
Flat fish	2
Other pelagics	2
Sardines	1
Sea birds	17
Sharks	3
Total	**29**

Table 3.2: The functional groups within the ‘Mediterranean and Black Sea’ System, and the number of LPI species in each.

zooplankton). However, only eight were applicable to the species present on the LPI (Table 3.2).

3.4.3 Calculating the LPI

Once all possible species were allocated a functional group, the raw population data was then extrapolated to 2010 from the end point of their time series using a linear projection of the average annual rate change in abundance over the course of each time series. Once all populations that were to be included in the models (all those within a functional group) had been extended to 2010, they were then extended for 30 years, using the annual rates of change calculated from the biomass results of the regional Ecopath models. This created an annual time series running from the start year of the population, up to 2040. These calculations assumed a 1:1 relationship between change in biomass and abundance.

Following Collen et al (2009) I calculated an aggregated trend in population abundance using a generalized additive modeling (GAM) framework. I implemented a GAM, specified with the mgcv package framework in R (Wood 2006). For each time series, I followed the method outlined by Collen *et al.* (2009). The Index value *(I)* was calculated in year *t* as:

$$I_t = I_{t-1} 10^{-d_t}$$

Where d_t is the mean value of species with multiple time series.

A GAM was fitted on observed values with $\log_{10}(N_t)$ as the dependent variable (where *N* is the population variable) and year (*t*) as the independent. Fitted GAM values were used to calculate predicted values for all years (including those with no real count data) and averaged and aggregated *d* values from the imputed counts. A bootstrap resampling technique was used to provide confidence limits around the index values. In order to calculate the bootstrap replicate, for each interval, *t-1* to *t* (where *t* is year), a sample of n_t, species specific values of d_t was selected at random with replacement from the n_t observed values (Collen *et al*. 2009).

3.4.4 Aggregating the LPI

An aggregated regional LPI was created by combining the six ocean system LPI's. The systems are: 'Caribbean and Gulf of Mexico', 'Mediterranean and Black Sea', 'North Pacific Ocean', 'North Sea and Baltic Sea', 'South Atlantic Ocean' and 'South Pacific Ocean'. As species are recorded in the LPI by population there were no concerns about duplication in the results.

3.5 Indicator Analysis – Red List Index

I extracted annual biomass data for every species or functional group from the regional Ecopath models. I investigated the effect of this data on the Red List Index (RLI) by matching Red Listed species to species within the model, or assigning them to functional groups where no match was available (not all species in the models have Red List assessments). For example, in the North Sea model species *Clupea harengus* was allocated to the functional group 'Herring' and *Megaptera novaeangliae* to the group 'Baleen whale' (Table 3.2). The Red Lists data were obtained from www.iucnredlist.org, or from unpublished assessments which are currently being added to the red list (Collen, In preperation). This data consisted of species assessments, the Red List criteria used for the assessments, distribution information and life history information such as generation length. Where life history data were unavailable from the Red List, it was gathered from FishBase (2010).

3.5.1 Allocating species to a model

For a species from the Red List to be allocated to a model, it was assumed that any species present in the same FAO Major Fishing Area (FAO, 2010) as the model had the potential to be included unless it was in a Red List threat category based on a range restriction (criterion D). For example, any species found in the Mediterranean and Black Sea FAO Major Fishing area was allocated to a functional or species group within the Northern Adriatic Sea Ecopath model, unless they were in a threat category using criterion D that stated it was exclusively found elsewhere, not included in the area of this model.

3.5.2 Allocating species to a functional group

Species on the Red List were allocated to functional groups in the models as outlined in section 3.4.2.

3.5.3 Determining projected Red List Status

Species were assigned a new projected Red List Status every 10 years for the 50 years of each regional Ecopath model run under the 2 scenarios, based on how trends in biomass triggered category listing under criterion A4 (IUCN, 2001), based on the trends in biomass for the functional group they were in (as produced by the regional Ecopath Models). This criterion specifies an "observed, estimated, inferred, projected or suspected population decline" (IUCN, 2001). If a species' decline is greater than 80% it is classed as Critically Endangered (CR), if it is between 80% and 50% it is Endangered (EN), and if it is between 30% and 50% it is Vulnerable (VU). Anything less than that, or a population increase, than it was classed as Least Concern (LC). The Near Threatened (NT) status could not be allocated, as that is ordinarily allocated to species where potential threats can be inferred, or the species has undergone declines that are close to reaching a threat category threshold and the threats facing it are likely to continue in the future. Data Deficient (DD) species were not allocated new Red List status as little information is known about them.

In order to calculate the Red List Status the average annual change in proportion of biomass over the 10 year period was calculated and projected forward over the longer of 3 generations or 10 years (IUCN 2001) for each species to give a trend in abundance over the period, using the equation:

$$N_t/N_0 = (1+y)^t$$

Where *t* is the number of years (either 3 generations or 10 years), y is the annual rate of change, N_t is the population size in year *t*, and N_0 is the current population size. Where generation length was not known for a species, the default value of ten years, given by IUCN, was used to assess their status. This was the case only for species of fishes. The estimated change in abundance over the assessment period for that species was then used to allocate a Red List status. During the analysis, a 1:1 relationship was assumed between biomass and abundance. I excluded species assessed as Data Deficient and species with restricted range, classified under Criterion D, as they are unlikely to benefit from the reduction in trawling, and could not be included in the model.

The RLI was calculated as follows, using the IUCN weighting system used outlined by Butchart *et al.*, (2004) and revised by Butchart *et al.* (2007):

$$RLI_t=(M-T_t)/M$$

Where each threat category is weighted and assigned a threat score, *M* is the "maximum threat score", i.e. the number of species multiplied by the maximum category weight, *T* is the "current threat score" and *t* is the year. The RLI for each region was then calculated for each year of assessments (2020, 2030, 2040 and 2050 - assuming the policy was implemented in 2010, first year of results 2011). The temporal trend generated was used to see if the effects of the ban could be detected in the RLI.

3.5.4 Allocating models to ocean systems

Models were allocated to the same ocean systems as for the LPI (Section 3.4.1; Table 3.1). This was to allow easy comparison of the results. They were allocated to ocean systems after the individual Red List statuses had been calculated however. This was because the models included in an ocean system could contain the same species, where this occurred, the population trends for those species were aggregated and the Red List status recalculated based on the aggregated trend data (IUCN 2001).

3.5.5 Aggregating Regional Red Lists

An aggregated RLI was compiled using the Red Lists created for the six ocean systems. Again, where there were duplicate species with potentially, differing Red List statuses, Red List status was calculated using the combined regional trends. The RLI was then calculated as previously outlined in section 3.5.3.

4 Results

4.1 Aggregated LPI and RLI for the Six Study Regions

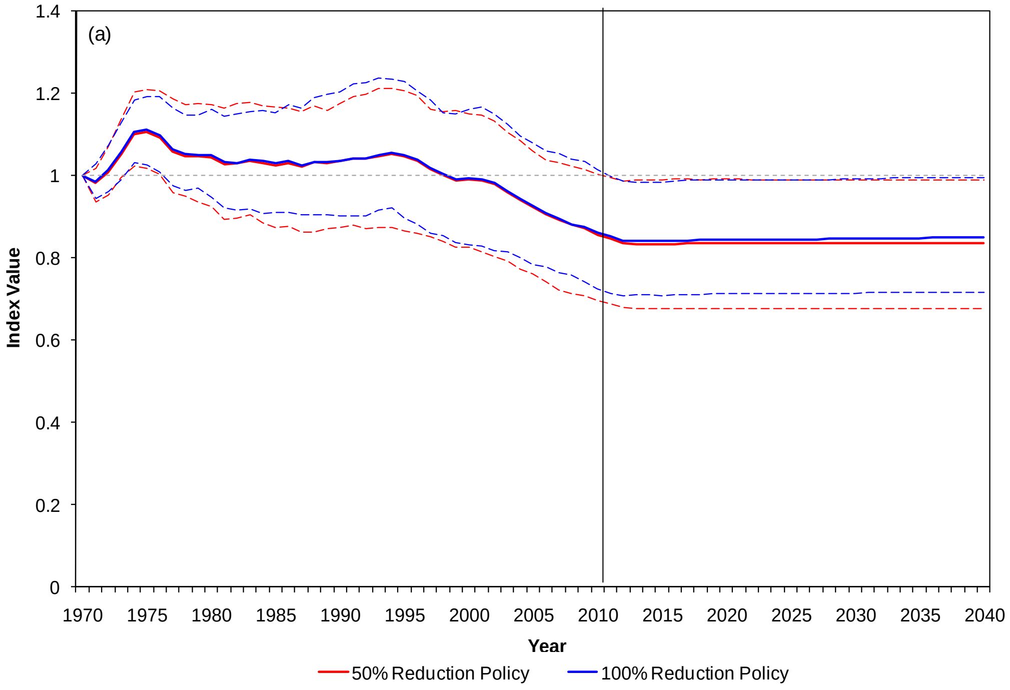
The aggregated LPI of the six ocean systems (‘Caribbean and Gulf of Mexico’, ‘Mediterranean and Black Sea’, ‘North Pacific’, ‘North Sea and Baltic Sea’, ‘South Atlantic’ and ‘South Pacific’) shows populations stabilizing but showing no signs of recovery (Fig 4.1, (a)). Following a 100% reduction in bottom trawling it stabilizes after a 16% decline from the start of the LPI in 1970, and 1% decline from the start of the policy in 2010. As a result of a 50% reduction, abundance trends are only 1% lower. The difference between the impacts of the two policies is much smaller than anticipated.

The Red List Index (Fig 4.1, (b)) shows after 10years a 1.3% decline in response to a 100% reduction in fishing effort and an increase of 3.4% in response to a 50% reduction. This means a complete halt to bottom trawling results in a short-term increase in the number of species in IUCN threat categories. However this decline is followed by a swift recovery and the index then stabilizes at 98%, which means 98% of species included in the index are in ‘non-threat’ categories. Following either a 100% or a 50% reduction in bottom trawling, the RLI shows all previously threatened species (except those categorized using criterion D) are downgraded to non-threat categories after 20 years of the policy being introduced.

Overall, initial observations appear to show that the two indicators being studied can detect the policy of halting bottom trawling: the LPI shows stabilization, although not a recovery in abundance, while the RLI shows species extinction risk decline, resulting in them being downgraded. The impacts of a 50% reduction policy are very similar, populations within the LPI stabilize, and extinction risk also declines. Analyzing the underlying regional patterns will give a better understanding of the aggregated results and what they mean, which we do below.

4.2 Regional LPI Results

One of the most notable things from the analysis is the small difference detected by the indicators between the two policies. The differences range from population trends being 0.3 % higher following a 100% reduction in bottom trawling over a 50% reduction (‘South Atlantic Ocean’), to 14% lower following a 100% reduction (‘North Sea and Baltic Sea’). It was anticipated that the two policies would have more differing effects for the indicators to detect. Within the regional results, the key trend within the LPI was rapid stabilization.



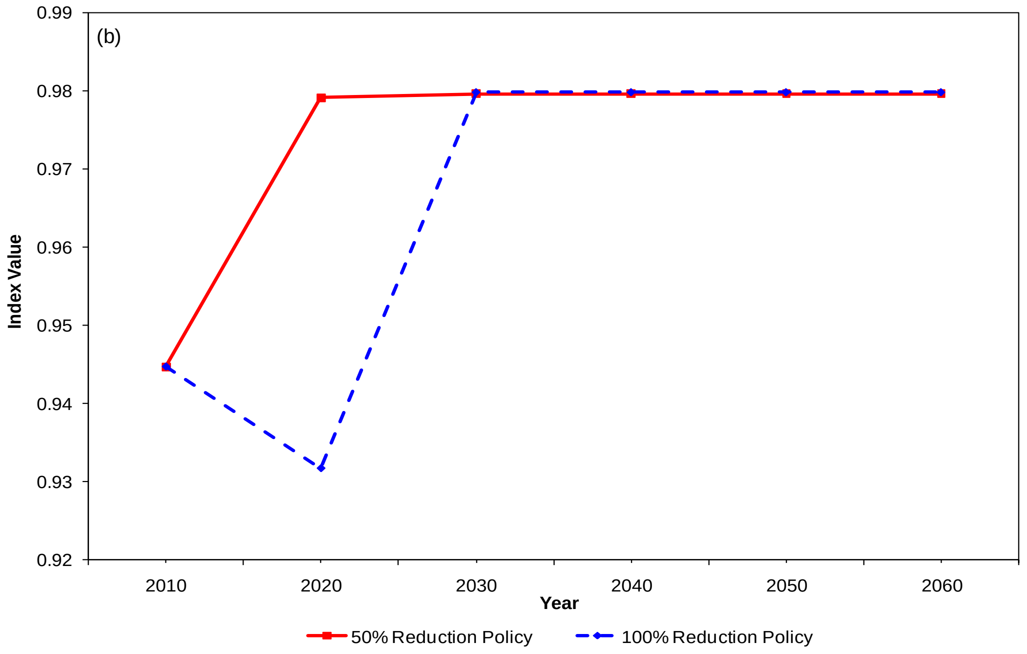


Figure 4.1: Aggregated across all six study regions, the LPI **(a)** and RLI **(b)** compare a 50% reduction in bottom trawling and 100% reduction. The dashed lines on **(a)** show the boot strapped confidence intervals, and the vertical line indicates the start of the policy in the 2010, with the first results of the policy in 2011.

All the regions in the LPI, under both policies showed population trends stabilizing within 10-15 years of the policy being enforced (Appendix 1.1). The LPI values for the two scenarios in each region were very similar, in most cases with the 100% reduction having a slightly higher LPI (i.e. relatively greater abundance).

The temperate regions appeared to be impacted differently to the tropical regions. In two cases, the LPI was higher for 50% reduction than 100% reduction after stabilisation: the ‘North Sea’ and the ‘Mediterranean and Black Sea’, though in the latter the initial impact of 100% was greater. Both showed increasing abundance trends prior to the policies. The ‘North Pacific Ocean’ system differs from the other two temperate systems as it is declining prior to the policy. It then stabilizes as the other two do, but abundance is 3% higher following the complete ban in bottom trawling than following the 50% reduction.

The tropical regions showed differing trends to those outlined for the temperate regions. The ‘Caribbean and Gulf of Mexico’ index was in decline prior to the policies. It stabilized as a result of the policies, with both policies showing very similar trends in abundance, with the difference between them being 1% in 2040 (100% reduction index higher than 50% index). The ‘South Atlantic Ocean’ was also declining before the policies were enforced and again showed very similar responses to both. The index is 0.3% higher in 2040 following the 100% reduction as opposed to the 50% reduction in bottom trawling. The ‘South Pacific Ocean’ index shows a bigger difference in its response to the two policy scenarios. The LPI is 4.3% higher in 2040 if bottom trawling is completely stopped, than if there is a 50% reduction. Before the policies are enforced the index trend was increasing.

It is initially unclear as to why there appear to be differences in the response of tropical and temperate systems. It could be a result of the data available for these regions, or as a result of true differences in the way these systems react to the policy. In two out of the three temperate systems (‘North Sea and Baltic Sea’ and the ‘Mediterranean and Black Sea’ systems) the 100% reduction in bottom trawling resulted in lower abundance than the 50% reduction. However, this was not the case in any of the tropical systems.

4.3 Regional RLI Results

When the RLI was looked at regionally, it could be seen that most regions showed almost no difference between the two policies. In three cases no differences were detected by the RLI (‘Mediterranean and Black Sea’, ‘Caribbean and Gulf of Mexico’ and ‘South Pacific Ocean’).

Those regions that did react differently to the two policies settled into the same values after 20 years (Appendix 1.2).

Similarly to the LPI, there was a difference between the way tropical and temperate systems performed. The ‘Mediterranean and Black Sea’ index shows no difference in the response to the two different policies. Both policies result in an increase in the index, which then remains stable. The two other temperate systems however both show declines in the index, after 10 years of the policy being enforced, following the 100% reduction in bottom trawling.

The tropical systems show a different response to the temperate ones. Both the ‘Caribbean and Gulf of Mexico’ and the ‘South Pacific Ocean’ indexes show the same response following both policies. They increase after 10 years of the policy, and then remain stable at that level. They show all species (except those classified using criterion D) move into ‘non-threat’ categories. The species showing this quick change between categories are generally short-lived fish species. If it were marine mammals, or other longer lived species, the changes between categories would be expected to take longer. The ‘South Atlantic Ocean’ index however takes longer to recover following the 100% reduction policy. After 10 years of the policy, the index increases by 4%, as species extinction risk declines, it then increases by 1% in the following 10 years, and then remains constant. They delay in stabilization is a result of all the species in the index becoming ‘non-threatened’ except for the ‘mesopelagic’ functional group species (and those threatened under criterion D), which declines (moves from ‘Least Concern’ to ‘Vulnerable’) in the ten years after the policy enforcement and then recovers to ‘Least Concern’ in the following ten years.

Due to the differences in the response of tropical and temperate systems seen in both the indicators, two regions were selected as case studies to investigate these effects in more detail: the temperate system of the ‘North Sea and Baltic Sea’, and the tropical ‘South Pacific Ocean’.

4.4 Case Study 1: The North Sea and Baltic Sea

Following a 50% reduction in bottom trawling both the LPI and RLI show a rapid stabilization (Fig 4.2). In the LPI there appears to be no recovery of populations, which one would expect to appear as an increasing trend in abundance. The index remains at a constant level over the 30 year period after the policy is enacted. The RLI shows species being downgraded to non-threat categories 10 years after the policy is enforced, and then remaining in those categories over the following 40 years. All species are down listed except those that are threatened and listed using criterion D. This downgrade occurs very quickly after the policy is enforced, and could be due to the short generation length of the species.

Both indices show a larger decline in index value following a complete reduction in bottom trawling than following a 50% reduction (Fig 4.2). This is an unexpected result, as it would be anticipated that the complete removal of a fishing pressure (especially one as destructive as bottom trawling) would cause greater increases in species abundance than a 50% reduction in fishing pressure. The LPI shows lower population abundance after the complete reduction policy, than after the 50% reduction policy, and the RLI shows some species become more threatened (and then recover) as a result, whereas after a 50% reduction they recover without a decline.

To investigate why the LPI may react to the policies in this way, I disaggregated the regional index into functional groups; the relative abundance of each group is shown in Figure 4.3. In total, 24 functional groups (two of which were predatory) from the Ecopath model were included. Of these, the single largest group contributing to the index was the ‘seabirds’ group which made up 47% of the species in the LPI for the region. The four next biggest contributors were ‘small demersal fish’ (10% of species in the regional LPI), ‘large demersal fish’ (8%), and ‘miscellaneous pelagic filter feeders’ and ‘small sharks’ (both 4%). All the other functional groups had only one or two species represented in the LPI. As Ecopath models are based on predator prey relations, the original biomass results of these top five contributing functional groups were compared to the biomass results of the predatory functional groups of the highest trophic levels (top of the food-chain) (Fig 4.3).

It is evident that the regional LPI response is driven by the relative increase in biomass of ‘top’ predators and with a corresponding decrease in prey groups and seabirds. These biomass trends are greater following the 100% reduction in bottom trawl fishing effort; hence the greater decline in the LPI, which is dominated by prey groups and seabirds (Fig 4.3, note differences in axis scale). Although one functional group included in the LPI did significantly increase in biomass (‘large demersal fish’) it appears that this increase was not large enough to outweigh the decrease in ‘seabird’ biomass, as seabirds accounted for 47% of the species included in the LPI in the region. These shifts in biomass may also account for the decline seen in the RLI after 10 years of the 100% reduction policy. The decline in the RLI is seen as ‘sandeels’ move from ‘Least Concern’ to ‘Vulnerable’. This could be the result of biomass declining in this functional group and increasing in a predatory functional group that predates sandeels (e.g. ‘Atlantic cod’). The one marine mammal group included is seen to take longer

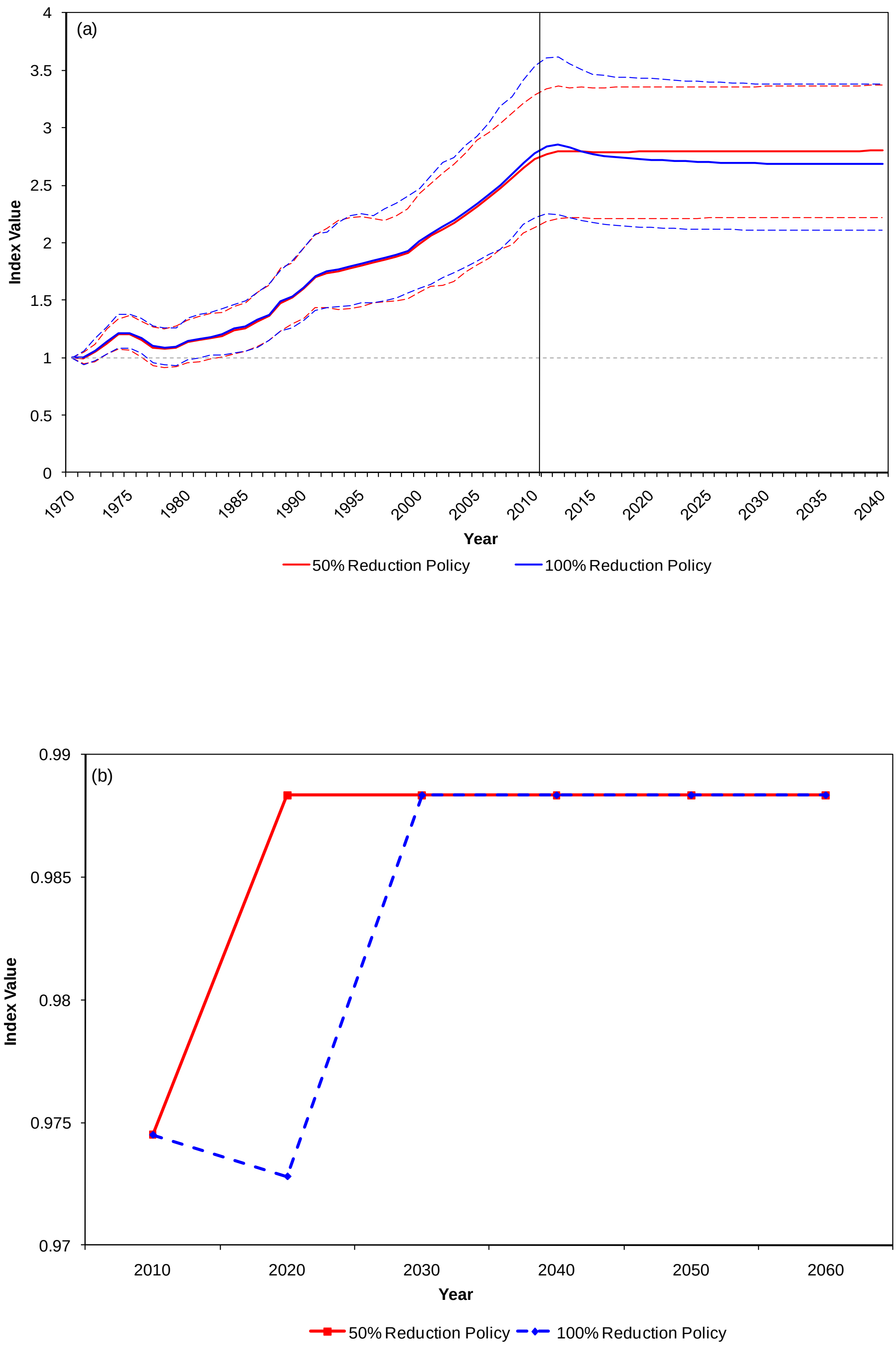


Figure 4.2: The 'North Sea and Baltic Sea' System LPI **(a)** and the RLI **(b)** compare a 50% reduction and 100% reduction in bottom trawling. The dashed lines on **(a)** show the boot strapped confidence intervals, and the vertical line indicates the start of the policy in the 2010, with the first results of the policy in 2011.

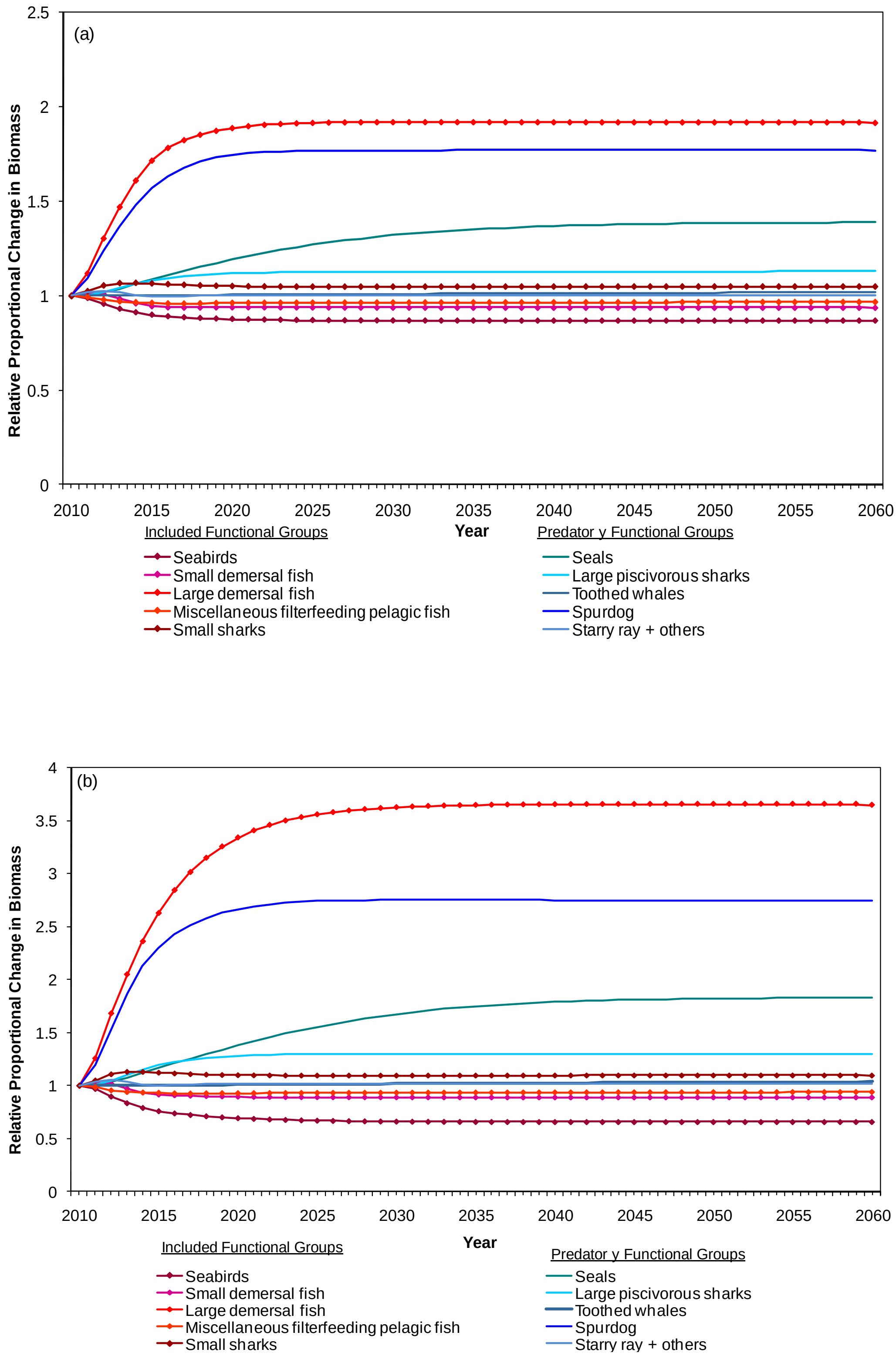


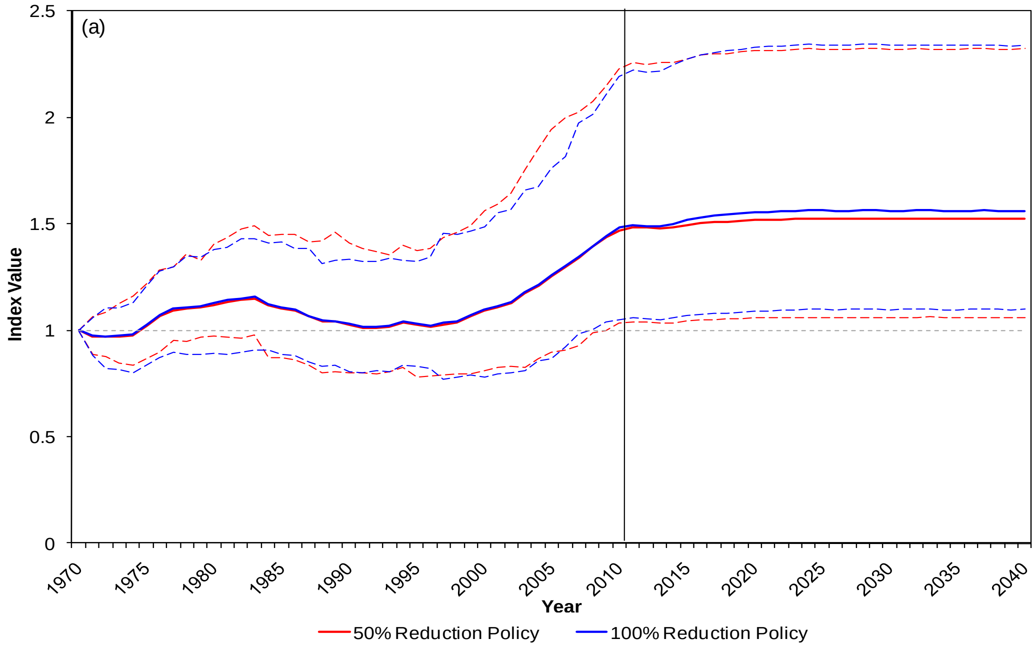
Figure 4.3: Comparison between the biomass, following a 50% reduction in bottom trawling **(a)** and a 100% reduction **(b)** results, of the five functional group contributing the majority of species to the LPI analysis, and the five predatory functional groups of the highest trophic level in the 'North Sea and Baltic Sea' ocean system

to recover from both policies. This is likely to be a result of its longer generation length.

4.5 Case Study 2: The South Pacific Ocean

In the ‘South Pacific Ocean’ system, both indicators display a more intuitive result. Regional abundance increases to around 50% more than the index value in 1970, following a complete regional ban in bottom trawling (Fig 4.4, a). The regional change in LPI in response to a 50% ban is qualitatively very similar though slightly less. This is different to what is seen in the majority of temperate systems studied (Appendix 1.1; 1.2). The RLI shows a reduction in extinction risk (number of species in threatened categories) as a result of both policies (Fig 4.4, b). Both policies result in a stabilised index very quickly after the enforcement. This is a trend seen throughout all the regions.

Typically the LPI stabilizes after only 10 years, whereas the RLI may take up to twenty years (Appendix 1.2). It can be seen in this example that not only does the LPI stabilise very quickly following the enforcement but that the difference between the index values for each policy are very small (4%) (Fig 4.4, a). To investigate why it stabilises so quickly, five functional groups were disaggregated from the index, and their individual LPI’s were analysed (Fig 4.5). The groups were: ‘small schooling fish’, ‘inshore finfish’, ‘large fish carnivores’, ‘seabirds’ and ‘sea turtles’. From this it can be seen that all the functional groups stabilize after 5 years, apart from ‘sea turtles’, which stabilize after about 15 years. The delay seen in the ‘sea turtles’ functional group could be the result of their longer generation lengths. This also shows that the low index values of three of the groups (‘small schooling fish’, ‘large fish carnivores’ and ‘inshore finfish’) do not greatly impact the overall index of the region (Fig 4.4). This is likely due to the ‘seabirds’ group containing 15 of the regions 42 LPI species, and so driving the trend of the index; as the other functional groups contain fewer species in this regional LPI.



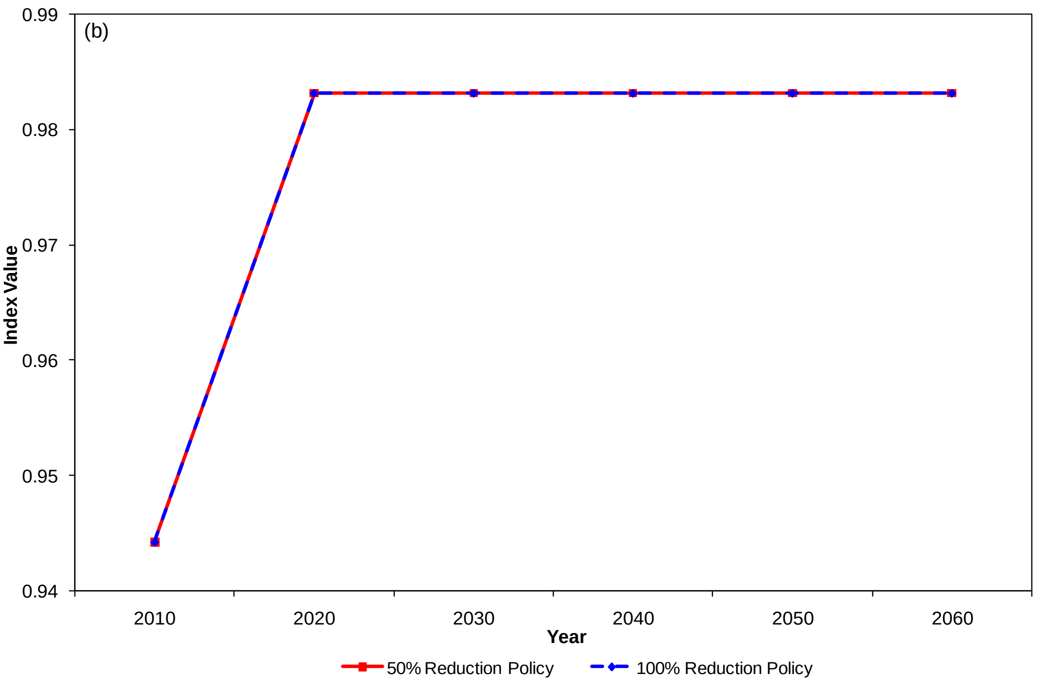


Figure 4.4: The 'South Pacific Ocean' System LPI **(a)** and the RLI **(b)** compare a 50% reduction and 100% reduction in bottom trawling. The dashed lines on the LPI show the boot strapped confidence intervals, and the vertical line indicates the start of the policy in the 2010, with the first results of the policy in 2011.

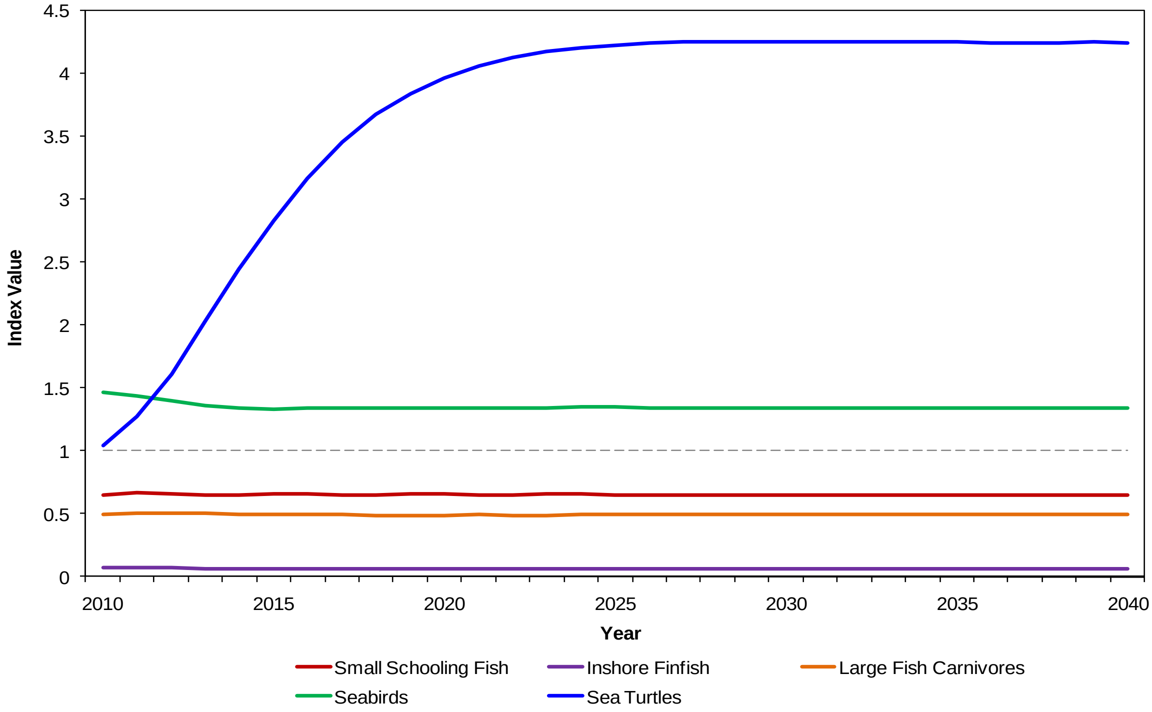


Figure 4.5: The Disaggregated LPI's for five functional groups from the 'South Pacific Ocean' system from the start of the 100% reduction in bottom trawling policy.

5 Discussion

5.1 Policy Results

The aggregated index produced for both the LPI and RLI suggests that the two indicators tested are capable of detecting changes in the status and trends of biodiversity, produced by the alternative fishing policies modelled in this study. However, the difference in response to the two policies is extremely small, a trend seen at the regional level too. Both indicators show populations and species stabilising after the policy and in the case of the RLI a reduction in extinction risk. In addition, the indicators behave differently to one another, which reflects the different aspects of biodiversity trends they represent: abundance and extinction risk.

The LPI shows populations stabilising after the policies in all regions, but does not increase, so species abundance does not increase after the policy. The aggregated index shows little or no recovery after the policies. If recovery continued at the slow rate suggested by the modelling, it would take over 100 years for populations to return to the levels they were in 1970. Similar patterns of slow recovery have been observed in marine systems off the East Coast of Canada. 15 years after the moratorium on fishing, and despite considerable conservation efforts, few demersal fish species showed any signs of recovery (Caddy and Seijo, 2005). In contrast to this, the invertebrates in the region showed huge increases in productivity, close to historical highs (Caddy and Seijo, 2005); such species are not included in either the LPI or RLI.

The aggregated RLI for all six ocean systems presents a different result to the LPI, and shows, a somewhat unexpected response to change in both fisheries policies. In the 10 years immediately after a 100% reduction in bottom trawling, many species appear to face a higher extinction risk than following a 50% reduction, which results in an index that declines after 10 years of policy enforcement and recovers in the proceeding 10 years. On further investigation this global acceleration in extinction risk is driven by species in temperate regions, which appear to be impacted differently to tropical regions. Within temperate regions some species moved into threat categories in the 10 years immediately after the policy, as a result of predator release following the alleviation of fishing pressure (e.g. the ‘North Sea and Baltic Sea’ system). The species in the tropics may have been less vulnerable to this affect due to naturally higher productivity in tropical regions (Bellwood and Hughes, 2001) allowing mid-trophic level prey species to recover. As criterion A was used to Red List the species, the decline in index value indicates that there was an increase in the number of species in the threatened categories (‘Critically Endangered’, ‘Endangered’, ‘Vulnerable’) as a result of population decline. By virtue of this, similar trends to those seen in the LPI would be anticipated.

There are three reasons why the indicators could be presenting different results. Firstly, the indicators detect different aspects of biodiversity change. The second is that different species contribute to the indicators, and indicators are bias towards temperate vertebrate species (Pereira & Cooper 2006); and the third is that the effects are due to community interactions between species that are being detected by the indicators. It is likely that all these reasons contribute to the results seen here, and being able to discern between them would improve our understanding of the indicators.

5.2 The different roles of the indicators

The RLI is regarded as a course resolution indicator, due to the broad nature of the Red List categories (Butchart *et al.* 2005). This means that populations have to undergo substantial changes in range, distribution or size before crossing the criteria threshold to qualify for either higher or lower Red List status (Butchart *et al.* 2005*).* This is unavoidable when using the Red List categories rather than more precise parameters such as population size estimates. This makes the RLI complimentary to the LPI, a population based index (Butchart *et al.* 2005). This was seen in the current project, when investigating the ‘South Pacific Ocean’ case study. The RLI presented both policies as being equally beneficial to the system, where as the LPI was capable of detecting the finer scale differences in the population abundance. A time-lag between changes in species populations or range, and the change being detected has been previously reported for the RLI (Butchart *et al.* 2005). This was not seen in the current study however, as there were no large declines of the monitored species, however, had the species coverage been more extensive, and more of the dynamics of the systems been detected, it is likely that this may have been an issue.

The response of the Red List to both policies was the same in the South Pacific Ocean system: an increase in index value, whereby all species that could be listed as Least Concern by 2040 were. On first appraisal this suggests that both policies deliver equal benefit to species, which is true, if you consider only extinction risk. Both policies do reduce extinction risk to species equally in that species are downgraded, however, they may do this to varying degrees which cannot be captured by the RLI as it has no way of distinguishing between levels of ‘non-threat’ category. This means that one species could be showing increasing trends in abundance and be listed in the same ‘non-threat’ category as a species that’s abundance is remaining constant over time, and is just outside a ‘threat’ category threshold. Although these species will both be classed as non-threatened, they are reacting very differently to the policies, and the latter is certainly more vulnerable to future potential threats than the other. The LPI detects a difference between the two policies (albeit small), because in population abundance data, it uses a more fine scale measure of biodiversity change (Loh *et al.* 2005; Collen *et al*. 2009). The RLI shows no difference between the two policies as once the more coarse measure of biodiversity change, extinction risk, is below a certain threshold (declines less than 30% over the longer of 10 years or 3 generations (IUCN, 2001)), no category change can take place (Butchart *et al.* 2004; Butchart *et al.* 2007). However, as the LPI gives all species equal weighting within the index (Collen *et al.* 2009), it is easily dominated by one 'functional group' of species, as seen in the North Sea and Baltic Sea system where seabirds appear to have dominate the index. One way to compensate for this would be to give different groups of species different weighting within the index to compensate for any taxonomic bias.

From a policy perspective, the value of modelling is the ability to identify differences between a range of alternatives (Mackinson *et al.* 2009); however the RLI is unable to do this after extinction risk is decreased past a critical threshold. This could be important in a system where a number of populations are close to the threshold and vulnerable to future threats. For example, if a species appears to have recovered as it is no longer classed as threatened, but in reality is close to the 'Vulnerable' criteria threshold of a 30% decline (IUCN, 2001). If fishing effort is increased, this could result in a population collapse and the species being up-listed back into a threat category.

5.3 Taxonomic Bias of the Indicators

As mentioned in previous studies (Butchart *et al.* 2005; Loh *et al.* 2005; Collen *et al.* 2009) the primary drawback of the indicators was the taxonomic coverage and representativeness of the population data. This was most striking in the LPI. The LPI contains time series for over 11,500 populations of 2,500 species (Collen *et al.* 2009), but it is not necessarily the lack of taxonomic diversity that is the problem, rather the uneven coverage of species across the world. Ideally, the perfect dataset would make significant steps to correct the current taxonomic bias, and would contain a higher proportion of diversity (Dobson, 2005) from every system on the planet.

Some regions in this analysis were dominated by seabird data (e.g. Northern Benguela regional model), whereas others were predominantly fish species (e.g. Great Barrier Reef). The effects of these species biases were evident in the way the indicators reacted to the policy change. The species coverage did not reflect the regions they were representing. To truly represent the regions the indicators need to contain a wider sample of species. It is unfeasible for them to contain all species, but they should aim to be a representative sample of what is present (Butchart *et al.* 2005). Typically, tropical regions are more species rich (Bergmann, 1847; Gaston, 2000), however the tropical regions only contained 152 species, in the LPI, where as the temperate regions contained 252. In addition, upwelling regions such as the Northern Benguela, should be areas of high fish productivity (Bianchi *et al.* 2000), and yet was dominated by species of seabird. It was only when combined with the Southern Benguela region that the coverage of species became more even.

Different functional groups of species were used in the two indicators, based on the different species they included. Neither indicator has complete coverage of all the species in a system, as the LPI does not contain any invertebrate species, and the RLI is limited the groups that have previously been assessed. This means that neither of them is likely to be a perfect tool for monitoring change. However, the knowledge of where there coverage varies allows for better interpretation of their results. Where the same functional group was used in both indicators, the number of species it was applied to differed within regions (Appendix 1.3, 1.4). This would impact the way the indicators responded to the policy. For example, if there was one functional group that was drastically reduced as a result of the policy, and that species was only included in one indicator, it would influence the response of that indicator and show a decline, whereas the other indicator would show an increase in abundance due to the exclusion of that species and the inclusion of others. This was shown to an extent in the RLI for the 'North Sea and Baltic Sea' region, which noticeably decreased as result of declines in functional group 'sandeels'. However, this effect was not detected by the LPI, which did not contain the 'sandeels' functional group. The effects of the policy on the indicators need to be discerned from the effects of their species composition.

In the North Sea and Baltic Sea system the majority of species in the LPI analysis were 'seabirds' and low- to mid-trophic species (that are typically preyed upon by other high-trophic species). The only predatory group included was 'small sharks'. Research by Petire *et al.* (2009) suggests that predator-prey interactions can be very important in temperate systems, and shows that a reduction in the fishing pressure on predator species does not necessarily result in a recovery of that species in the following decade. With a reduction in fishing effort modelled in this study, there appears to be a predatory release, with increases in the biomass of the predatory functional groups (Seals, Piscivorous Sharks, Toothed Whales, Spurdog and Starry Ray + Others). These seem to dominate the system resulting in reduced biomass in prey functional groups. This shows that the results are a product of the functional groups included in the analysis, and had the region contained alternative species the LPI trend observed would be different.

The quick recovery times observed in the RLI may be the result of short-lived species on the index, as it is short-lived fish species changing threat category. Had longer lived species contributed more than the recovery could have been prolonged. The reduction in the Red List Index in the North Sea and Baltic Sea system is due to declines in the prey-species functional group 'Sandeels'. The release of predatory species is much greater following a complete ban on bottom trawling, hence the lower abundance trends seen which lead to a decline in the RLI. However, this observed RLI decline may have been larger or more prolonged had other functional groups been included. This is also the case for the LPI. Out of the 63 functional groups in the Ecopath model, 24 were present in the species contained in the LPI. As 'Seabirds' was the applied to 39 species out of a possible 83 (Appendix 1.3) it is likely that they are heavily driving the decline.

In the South Pacific Ocean system the breadth of predator and prey species included is greater than in the North Sea and Baltic Sea. This means that more complex food-web interactions are included in the index, as opposed to just model responses from one group. Despite the inclusion of more functional groups from different trophic levels, it is unlikely that the wide reaching impacts of the policies throughout the ecosystem will be detected. This is because the species coverage of the indicators does not accurately reflect the species actually present (Pereira and Cooper. 2006), especially in the tropics, where biodiversity is greatest (Bergmann, 1947; Gaston 2000). Despite, the models featuring a wider variety of species in the indicators, the indicators themselves are limited by what species they contain.

Although the RLI shows comprehensive coverage within certain taxonomic groups, relatively few groups have been completely assessed. This is constantly improving, but the RLI is not representative of biodiversity as a whole (Butchart *et al.* 2005), and so is limited in what it can detect. The Sampled Red List Index (SRLI) is designed to address this problem. It aims to measure the changing relative extinction-risk of all species, major taxonomic groups, realms, and three primary ecosystems (Butchart *et al.* 2005; Baillie *et al.* 2008). However, this will be limited by the availability of data and resources. This sampling approach will include the assessment of invertebrate groups, and will begin to cover the taxonomic gaps inherent in the RLI.

5.4 Species community interactions

As the LPI only includes vertebrate species, it is likely that complex ecosystem dynamics are being missed. Practises like bottom trawling, change the structure of fish communities through not only direct mortality from fishing, but from the related destruction of large epibenthic organisms (Bianchi *et al.* 2000) and habitat alteration (Jones, 1992). If these are not monitored for recovery then vital information pertaining to the recovery of other species will be lacking. The 'patchy' coverage even of vertebrate species impacts on the results seen, as demonstrated in the North Sea and Baltic Sea case study. The North Sea is considered to be dominated by bottom-up control (Fredericksen *et al.* 2006), which implies the system is controlled by food abundance and the availability of prey. This has far reaching effects on the dynamics of marine top predators and seabirds. There have been documented cases, where crashes in prey species have resulted in the breeding failure of seabirds (e.g. Anker-Nilssen *et al*. 1997). It is possible that this is the cause of the biomass decrease in the 'Seabirds' functional group, and resulted in the severe decline seen in the LPI. By having data available predominantly for prey species, the increases in predator abundance were not seen. This is important when indicators are being considered for use as tools to audit management decisions and to predict the responses of specific policy changes. If they are not able to detect dynamics within ecosystems, they will never detect the full effects of the policy. This predatory release is similar to what has been seen in some Marine Protected Areas (Lamb and Johnson, 2010). Although fishing mortality rates are directly reduced by the ban in fishing, apex predators recover quickly and may have strong indirect effects on non-target species. Lamb and Johnson (2010) also found that the largest species in the systems increased in biomass, as seen in this study by the increase in predatory group biomass, intermediate-size species decreased in biomass, and small-size species showed variable responses. This suggests that significant reductions in fishing effort can substantially alter the composition and structure of fish communities.

It appears from the interaction between the 50% reduction and 100% reduction, that the ecological predator-prey relationships have remained intact (Petrie *et al.* 2009) within the South Pacific Ocean, and there has not been a sudden predatory release, resulting in depletion of a number of prey functional groups. As this is a tropical region, it is likely to be more species-rich than the temperate regions (Bergmann, 1847; Gaston, 2000). Species rich systems are more stable and resilient to changes in environmental factors such as reduction in fishing effort due to the stabilising role of alternate predators (Petrie *et al.* 2009). This too could account for the trends observed in the LPI. The response of the South Pacific Ocean LPI is more typical of what might be expected following the two policy scenarios, whereby a greater increase in overall population trend follows a complete ban in bottom trawling compared to that following a 50% reduction. This suggests the ecosystem improves more following a complete fishing ban, than from a reduction in fishing effort.

There are other dynamics at play in the marine system especially with regard to fish that it is possible our indicators may not be able detect. Fishing not only affects demersal fish through direct removal, but it also through habitat modification, and changes in species composition and size-structure (Bianchi *et al.* 2000). Bianchi *et al.* (2000) found that regional differences in size spectra of commercial fish are a result of different histories of fishing intensity, and so their interpretation of the spectra was not straightforward. The regional differences in exploitation history could also affect species recovery as a result of alleviating fishing pressure. Wide ranging changes in the demersal fish community in the Gulf of Thailand were linked to the rapid expansion of the trawl fishery after 1961 (Pauly, 1988). Size spectra differ between ecosystems and are affected by the histories of fishing intensity (Bianchi *et al.* 2000). During periods of heavy exploitation, there is a smaller range of sizes, whereas during periods of less exploitation the size range increases (Bianchi *et al*. 2000). These kinds of system specific dynamics will not be detected by global biodiversity indicators.

5.5 Limitations of Ecopath Modelling

One of the drawbacks of using Ecopath models is that they are mass-balanced models, which focus on the flow of biomass among trophic groups. The assumptions that all energy is cycled within the system, and that each species has an inflexible diet, are not always supported (Heithaus *et al.* 2007). In terms of the models used for this analysis, the mass-balance has the effect that biomass very quickly (generally within 10-15 years) stabilised as the models returned to equilibrium. This rapid stabilisation may be an accurate reflection of species recovery; however, it did appear to happen quicker than anticipated based on previous studies (Althous *et al.* 2009). This could also be an artefact of the species included in the indicators. It could be that the indicators, especially the LPI, did not include enough of the longer-lived species such as sea mammals, for the effects of their recovery to make a difference to the stabilisation period of the models. Long-Lived species require recovery periods of several decades (MacArthur and Wilson, 1967; Purvis *et al.* 2000; Purvis *et al.* 2005). It will be difficult to convey the interactions between the recovery times of the short- and long-lived species in one indicator such as the LPI. As a bias in species composition in favour of bigger, longer-lived, commercially important species, would result in slower recovery times.

Although ecosystem models have been used in the past to investigate the effects of fishing and trophic interactions between species, the results should always be treated cautiously, as other unknown or untested factors may be responsible for the resultant model trends (Mackinson *et al* 2009). The results demonstrated in this study could be the result of a whole host of changes in the ecosystem resulting from the policy change simulations. Trends predicted by food-web models are complex and often have poor data sources, as there are few fisheries independent data sets, making them open to questioning (Caddy and Seijo, 2005).

One major limitation of using these ecosystem models, is that due to the mass-balance assumptions of the models a ‘business-as-usual’ (BAU) scenario would give a flat line as the model is assumed to be in equilibrium. This is a problem, as the LPI data shows this is not the case, with populations changing abundance over time. This means no BAU scenario could be used for comparison with the indicator results.

5.6 Sensitivity analysis

In complex ecosystem models, with numerous parameters, such as Ecopath, it can be difficult to quantify uncertainty. Ecopath software has a resampling routine, Ecoranger, which can be included in the models. It calculates input probability distributions for the estimated parameters (Christensen and Walters, 2004). However, it was beyond the scope of this project to investigate the sensitivity of every parameter within the Ecopath models, due to the number of models used, and the number of parameters in each model.

Without any formal sensitivity analysis, it is important to consider which areas of the process could be affected by uncertainty. It is likely that the models are open to inaccuracy in the way they represent the biological systems being analysed, which will impact the validity of any results produced (Regan *et al.* 2002). In this study there is uncertainty in the representation of the systems by the models, as Ecopath models assume static mass-balance over the course of a year (Christensen *et al*. 2005), implying that they are modelling a closed systems, which they are not. Other areas of uncertainty could also impact the modelling process such as: systematic error, for example a bias in the measuring or sampling of species. This is likely to be having an effect on the modelling process as the majority of the model data came from fisheries estimates, but without sensitivity analysis it is difficult to quantify the size of this impact. Natural variation in systems is another area of uncertainty not accounted for in the Ecopath models, as they are deterministic. However, by ignoring stochasticity, temporal and spatial components of the system such as disease spread through communities and weather fluctuations are missed, and their impacts unknown (Regan *et al.* 2002). Additional issues of uncertainty lie with subjective judgement, and a host of linguistic uncertainties (Regan *et al.* 2002). These issues, could not only affect the Ecopath models, but are also applicable to the assemblage of the indicators themselves.

5.7 Concluding remarks

The modelling presented here suggests that it is too late for many marine species to rebuild stocks to previous levels. The models imply that bottom trawling has an impact on the environment, but these effects vary in duration and extent depending on locality. It would be an important next step to investigate the underlying socioeconomic and ecological variables that would enable some regions to conserve, restore and rebuild marine resources (Worm *et al,* 2009). In order to effectively reduce overfishing and to set sustainable goals policy makers and management authorities need to face the short-term economic and social costs of reducing fishing (Worm *et al.* 2009). Until this is done, there will be no enforceable effective fisheries policies that will reduce anthropogenic impact on marine environments. We have to link the conservation and sustainable use of biodiversity and the indicators to the development issues that policy-makers and the majority of the general public care about. It is important to develop agreed national or international indicators for biodiversity aspects of sustainable development that are also compatible with, and appropriate for, national sustainable development objectives (Watson, 2005).

Ultimately, what this study has shown is that although the two indicators explored here, the LPI and the RLI, are capable of detecting changes in policy, they cannot detect all the effects of the policy given their current taxonomic and global coverage. Until the gaps in coverage are filled, they are unlikely to be useful in decision making at a policy level. They will need further rigorous testing and refining to ensure key impacts of policy are detected, and that differences in policy results can be seen. It has also been demonstrated in this study that indicators are potentially strongest when used in conjunction and, the use of another system specific indicator such as the Marine Trophic Indicator may help in detecting changes missed by the LPI and RLI. Work still needs to be done, to ensure there is a strong understanding of how global biodiversity indicators and policy interact and can be used in the wake of 2010.

References

Althaus, F., A. Williams, T. A. Schlacher, R. J. Kloser, M. A. Green, B. A. Barker, N. J. Bax, P. Brodie, and M. A. Schlacher-Hoenlinger. 2009. Impacts of bottom trawling on deep-coral ecosystems of seamounts are long-lasting. Marine Ecology-Progress Series **397**:279-294.

Anker-Nilssen, T., R. T. Barrett, and J. V. Krasnov. 1997. Long- and short-term responses of seabirds in the Norwegian and Barents Seas to changes in stocks of prey fish. Pages 683-698. Forage Fishes in Marine Ecosystems.

Arreguin-Sanchez, F., E. Arcos, and E. A. Chavez. 2002. Flows of biomass and structure in an exploited benthic ecosystem in the gulf of California, Mexico. Ecological Modelling **156**:167-183.

Baillie, J. E. M., B. Collen, R. Amin, H. R. Akcakaya, S. H. M. Butchart, N. Brummitt, T. R. Meagher, M. Ram, C. Hilton-Taylor, and G. M. Mace. 2008. Toward monitoring global biodiversity. Conservation Letters **1**:18-26.

Barausse, A., A. Duci, C. Mazzoldi, Y. Artioli, and L. Palmeri. 2009. Trophic network model of the northern Adriatic Sea: analysis of an exploited and eutrophic ecosystem. Estuarine Coastal and Shelf Science **83**:577-590.

Bellwood, D. R., and T. P. Hughes. 2001. Regional-Scale Assembly Rules and Biodiversity of Coral Reefs. Science **292**:1532-1535.

Bergmann, C. 1847. Über die Verhältnisse der Wärmeökonomie der Thiere zu ihrer Grösse. Gottinger Studien **3**:595-708.

Bianchi, G., H. Gislason, K. Graham, L. Hill, X. Jin, K. Koranteng, S. Manickchand-Heileman, I. Paya, K. Sainsbury, F. Sanchez, and K. Zwanenburg. 2000. Impact of fishing on size composition and diversity of demersal fish communities. Ices Journal of Marine Science **57**:558-571.

Buckland, S. T., A. E. Magurran, R. E. Green, and R. M. Fewster. 2005. Monitoring change in biodiversity through composite indices. Philosophical Transactions of the Royal Society B-Biological Sciences **360**:243-254.

Butchart, S. H. M., H. Resit AkÃ§akaya, J. Chanson, J. E. M. Baillie, B. Collen, S. Quader, W. R. Turner, R. Amin, S. N. Stuart, and C. Hilton-Taylor. 2007. Improvements to the Red List Index. PLoS ONE **2**:e140.

Butchart, S. H. M., A. J. Stattersfield, J. Baillie, L. A. Bennun, S. N. Stuart, H. R. Akcakaya, C. Hilton-Taylor, and G. M. Mace. 2005. Using Red List Indices to measure progress towards the 2010 target and beyond. Philosophical Transactions of the Royal Society B-Biological Sciences **360**:255-268.

Butchart, S. H. M., A. J. Stattersfield, L. A. Bennun, S. M. Shutes, H. R. AkÃ§akaya, J. E. M. Baillie, S. N. Stuart, C. Hilton-Taylor, and G. M. Mace. 2004. Measuring Global Trends in the Status of Biodiversity: Red List Indices for Birds. PLoS Biol **2**:e383.

Butchart, S. H. M., M. Walpole, B. Collen, A. van Strien, J. P. W. Scharlemann, R. E. A. Almond, J. E. M. Baillie, B. Bomhard, C. Brown, J. Bruno, K. E. Carpenter, G. M. Carr, J. Chanson, A. M. Chenery, J. Csirke, N. C. Davidson, F. Dentener, M. Foster, A. Galli, J. N. Galloway, P. Genovesi, R. D. Gregory, M. Hockings, V. Kapos, J.-F. Lamarque, F. Leverington, J. Loh, M. A. McGeoch, L. McRae, A. Minasyan, M. H. Morcillo, T. E. E. Oldfield, D. Pauly, S. Quader, C. Revenga, J. R. Sauer, B. Skolnik, D. Spear, D. Stanwell-Smith, S. N. Stuart, A. Symes, M. Tierney, T. D. Tyrrell, J.-C. Vie, and R. Watson. 2010. Global Biodiversity: Indicators of Recent Declines. Pages 1164-1168.

Caddy, J. F., and J. C. Seij. 2005. This is more difficult than we thought! The responsibility of scientists, managers and stakeholders to mitigate the unsustainability of marine fisheries. Philosophical Transactions of the Royal Society B-Biological Sciences **360**:59-75.

Christensen, V., and C. J. Walters. 2004. Ecopath with Ecosim: methods, capabilities and limitations. Ecological Modelling **172**:109-139.

Christensen, V., C. J. Walters, and D. Pauly. 2005. Ecopath with Ecosim: a User's Guide. Page 154. Fisheries Centre, Univeristy of British Columbia, Vancouver.

Collen, B., N. Dewhurst, and M. Bohm. In Preparation. Global Status of Marine Fish. Assessments submitted to IUCN Red List v2010.4. www.iucnredlist.org.

Collen, B., J. Loh, S. Whitmee, L. McRae, R. Amin, and J. E. M. Baillie. 2009. Monitoring Change in Vertebrate Abundance: the Living Planet Index. Conservation Biology **23**:317-327.

Cruz-Escalana, V. H. In Preparation. Structure and function of the continental shelf ecosystem of the Northwest Gulf of Mexico

Dobson, A. 2005. Monitoring global rates of biodiversity change: challenges that arise in meeting the Convention on Biological Diversity (CBD) 2010 goals. Royal Society Philosophical Transactions Biological Sciences **360**:229-241.

Ecopath. 2010. http://ecopath.org/models. Ecopath with Ecosim.

FAO. 2010. FAO (Fisheries and Aquaculture Department) Major Fishing Areas; http://www.fao.org/fishery/area/search/en.

Fewster, R. M., S. T. Buckland, G. M. Siriwardena, S. R. Baillie, and J. D. Wilson. 2000. Analysis of population trends for farmland birds using generalized additive models. Ecology **81**:1970-1984.

Fitter, R., and M. Fitter. 1987. The road to extinction in R. Fitter, and M. Fitter, editors. IUCN, Gland, Switzerland.

Frederiksen, M., M. Edwards, A. J. Richardson, N. C. Halliday, and S. Wanless. 2006. From plankton to top predators: bottom-up control of a marine food web across four trophic levels. Journal of Animal Ecology **75**:1259-1268.

Froese, R., and D. Pauly. 2010. Fishbase, www.fishbase.org, version (05/2010).

Fulton, E. A., A. D. M. Smith, and C. R. Johnson. 2003. Effect of complexity on marine ecosystem models. Marine Ecology-Progress Series **253**:1-16.

Gaston, K. J. 2000. Global patterns in biodiversity. Nature **405**:220-227.

Gribble, N. A. 2001. A Model of the Ecosystem, and Associated Penaeid Prawn Community, in the Far Northern Great Barrier Reef. Pages 189-207 in E. Wolankski, editor. Oceanographic processes of coral reefs: physical and biological links in the Great Barrier Reef. CRC Press, Townsville.

Heithaus, M. R., A. Frid, A. J. Wirsing, and B. Worm. 2008. Predicting ecological consequences of marine top predator declines. Trends in Ecology & Evolution **23**:202-210.

Heymans, S. J. J. 2005. Ecosystem model of the eastern Aleutians and central Gulf of Alaska in 1963. University of British Columbia Fisheries Centre Research Reports **13**:83-105.

IUCN. 2001. IUCN Red List categories and criteria: version 3.1. IUCN, Gland, Switzerland, and Cambridge, United Kingdom.

IUCN. 2010. IUCN Red List of Threatened Species. Version 2010.2. http://www.iucnredlist.org.

Jiang, H., H.-Q. Cheng, H.-G. Xu, F. Arreguín-Sánchez, M. J. Zetina-Rejón, P. Del Monte Luna, and W. J. F. Le Quesne. 2008. Trophic controls of jellyfish blooms and links with fisheries in the East China Sea. Ecological Modelling **212**:492-503.

Jones, J., B. Collen, P. W. J. Baxter, P. Bubb, J. B. Illian, T. E. Katzner, A. Keane, J. Loh, E. McDonald-Madden, E. Nicholson, H. M. Pereira, H. P. Possingham, A. S. Pullin, A. S. L. Rodrigues, V. Ruiz-Gutierrez, M. Sommerville, and E. J. Milner-Gulland. In Review. The 'why', 'what' and 'how' of global biodiversity indicators beyond 2010.

Jones, J. B. 1992. Environmental impact of trawling on the seabed: a review. New Zealand Journal of Marine and Freshwater Research **26**:59-67.

Jones, J. B., J. Bielby, M. Cardillo, S. A. Fritz, J. O'Dell, C. D. L. Orme, K. Safi, W. Sechrest, E. H. Boakes, C. Carbone, C. Connolly, M. J. Cutts, J. K. Foster, R. Grenyer, M. Habib, C. A. Plaster, S. A. Price, E. A. Rigby, J.Rist, A.Teacher, O. R. P. B. Emonds, J. L. Gittleman, G. M. Mace, and A. Purvis. 2009. PanTHERIA: A species-level database of life-history, ecology and geography of extant and recently extinct mammals. Ecology **90**: 2648.

Kaiser, M. J., K. R. Clarke, H. Hinz, M. C. V. Austen, P. J. Somerfield, and I. Karakassis. 2006. Global analysis of response and recovery of benthic biota to fishing. Marine Ecology Progress Series **311**:1-14.

Kinzey, D., and A. E. Punt. 2009. Multispecies and Single-Species Models of Fish Population Dynamics: Comparing Parameter Estimates. Natural Resource Modeling **22**:67-104.

Knauss, J. M. 2005. The Growth of British Fisheries during the Industrial Revolution. Pages 1 - 11. Taylor & Francis.

Kumar, A. B., and G. R. Deepthi. 2006. Trawling and by-catch: Implications on marine ecosystem. Current Science **90**:922-931.

Lamb, R. W., and D. W. Johnson. 2010. Trophic restructuring of coral reef fish communities in a large marine reserve. Marine Ecology-Progress Series **408**:169-180.

Larkin, P. A. 1977. Epitaph for Concept of Maximum Sustained Yield. Transactions of the American Fisheries Society **106**:1-11.

Loh, J., R. E. Green, T. Ricketts, J. Lamoreux, M. Jenkins, V. Kapos, and J. Randers. 2005. The Living Planet Index: using species population time series to track trends in biodiversity. Philosophical Transactions of the Royal Society B-Biological Sciences **360**:289-295.

Loh, J., J. Randers, A. MacGillivray, V. Kapos, M. jenkins, B. Groombridge, N. Cox, and B. Warren. 1998. Living Planet Report. WWF, Gland, Switzerland.

MacArthur, R. H., and E. O. Wilson 1967. The equilibrium theory of island biogeography. Princeton University Press.

Mace, G. M., and J. E. M. Baillie. 2007. The 2010 Biodiversity Indicators: Challenges for Science and Policy. Pages 1406-1413.

Mace, G. M., N. J. Collar, K. J. Gaston, C. Hilton-Taylor, H. R. Akcakaya, N. Leader-Williams, E. J. Milner-Gulland, and S. N. Stuart. 2008. Quantification of Extinction Risk: IUCN's System for Classifying Threatened Species. Conservation Biology **22**:1424-1442.

Mace, G. M., W. Cramer, S. Díaz, D. P. Faith, A. Larigauderie, P. Le Prestre, M. Palmer, C. Perrings, R. J. Scholes, M. Walpole, B. A. Walther, J. E. M. Watson, and H. A. Mooney. 2010. Biodiversity targets after 2010. Current Opinion in Environmental Sustainability **2**:3-8.

Mace, G. M., and R. Lande. 1991. Assessing Extinction Threats - toward a Reevaluation of Iucn Threatened Species Categories. Conservation Biology **5**:148-157.

Mace, G. M., and S. N. Stuart. 1994. Draft IUCN Red List Categories, Version 2.2. Species 21-22: 13-24.

Mackinson, S., and G. Daskalov. 2007. An ecosystem model of the North Sea to support an ecosystem approach to fisheries management: description and parameterisation. Page 196. Science Series Technical Report. Cefas, Lowestoft.

Mackinson, S., G. Daskalov, J. J. Heymans, S. Neira, H. Arancibia, M. Zetina-Rejón, H. Jiang, H. Q. Cheng, M. Coll, F. Arreguin-Sanchez, K. Keeble, and L. Shannon. 2009. Which forcing factors fit? Using ecosystem models to investigate the relative influence of fishing and changes in primary productivity on the dynamics of marine ecosystems. Ecological Modelling **220**:2972-2987.

Malakoff, D. 1998. FISHERIES SCIENCE:Papers Posit Grave Impact of Trawling. Pages 2168b-.

McGeoch, M. A., S. H. M. Butchart, D. Spear, E. Marais, E. J. Kleynhans, A. Symes, J. Chanson, and M. Hoffmann. 2010. Global indicators of biological invasion: species numbers, biodiversity impact and policy responses. Diversity and Distributions **16**:95-108.

Millennium Ecosystem Assessment. 2005. Ecosystems and Human Well being. Millenium Ecosystem Assessment World Resources Institute, Synthesis Washington DC.

Okey, T. A., G. A. Vargo, S. Mackinson, M. Vasconcellos, B. Mahmoudi, and C. A. Meyer. 2004. Simulating community effects of sea floor shading by plankton blooms over the West Florida Shelf. Ecological Modelling **172**:339-359.

Olsgard, F., M. T. Schaanning, S. Widdicombe, M. A. Kendall, and M. C. Austen. 2008. Effects of bottom trawling on ecosystem functioning. Journal of Experimental Marine Biology and Ecology **366**:123-133.

Pauly, D., V. Christensen, J. Dalsgaard, R. Froese, and F. Torres, Jr. 1998. Fishing down marine food webs. Science (Washington D C) **279**:860-863.

Pauly, D., V. Christensen, and C. Walters. 2000. Ecopath, Ecosim, and Ecospace as tools for evaluating ecosystem impact of fisheries. ICES Journal of Marine Science **57**:697-706.

Pauly, D., and R. Watson. 2005. Background and interpretation of the 'Marine Trophic Index' as a measure of biodiversity. Royal Society Philosophical Transactions Biological Sciences **360**:415-423.

Pereira, H. M., and H. D. Cooper. 2006. Towards the global monitoring of biodiversity change. Trends in Ecology & Evolution **21**:123-129.

Petrie, B., K. T. Frank, N. L. Shackell, and W. C. Leggett. 2009. Structure and stability in exploited marine fish communities: quantifying critical transitions. Fisheries Oceanography **18**:83-101.

Polovina, J. J. 1984. Model of a Coral-Reef Ecosystem .1. the Ecopath Model and Its Application to French Frigate Shoals. Coral Reefs **3**:1-11.

Purvis, A., M. Cardillo, and R. Grenyer. 2005. Correlates of extinction risk: phylogeny, biology, threat and scale. Symposium of the Zoological Society of London. Phylogeny and Conservation, Conservation Biology Series, London.

Purvis, A., J. L. Gittleman, and G. M. Mace. 2000. Predicting extinction risk in declining species. Proceedings of the Royal Society B - Biological Sciences **267**:1947-1952.

Regan, H. M., M. Colyvan, and M. A. Burgman. 2002. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecological Applications **12**:618-628.

Revenga, C., I. Campbell, R. Abell, P. de Villiers, and M. Bryer. 2005. Prospects for monitoring freshwater ecosystems towards the 2010 targets. Philosophical Transactions of the Royal Society B-Biological Sciences **360**:397-413.

Roberts, C. 2007. The Unnatural History of the Sea. Island Press, Washington DC.

Roux, J. P., and L. J. Shannon. 2004. Ecosystem approach to fisheries management in the northern Benguela: The Namibian experience. African Journal of Marine Science **26**:79-93.

Sachs, J., R. Remans, S. Smukler, L. Winowiecki, S. J. Andelman, K. G. Cassman, D. Castle, R. DeFries, G. Denning, J. Fanzo, L. E. Jackson, R. Leemans, J. Lehmann, J. C. Milder, S. Naeem, G. Nziguheba, C. A. Palm, P. L. Pingali, J. P. Reganold, D. D. Richter, S. J. Scherr, J. Sircely, C. Sullivan, T. P. Tomich, and P. A. Sanchez. 2010. Monitoring the world's agriculture. Nature **466**:558-560.

Shannon, L. J., C. L. Moloney, A. Jarre, and J. G. Field. 2003. Trophic flows in the southern Benguela during the 1980s and 1990s. Journal of Marine Systems **39**:83-116.

Shin, Y.-J., A. Bundy, L. J. Shannon, M. Simier, M. Coll, E. A. Fulton, J. S. Link, D. Jouffre, H. Ojaveer, S. Mackinson, J. J. Heymans, and T. Raid. 2010. Can simple be useful and reliable? Using ecological indicators to represent and compare the states of marine ecosystems. Pages 717-731.

Shin, Y.-J., and L. J. Shannon. 2009. Using indicators for evaluating, comparing, and communicating the ecological status of exploited marine ecosystems. 1. The IndiSeas project. Pages 686-691.

Sumaila, U. R., A. Khan, R. Watson, G. Munro, D. Zeller, N. Baron, and D. Pauly. 2007. The World Trade Organization and global fisheries sustainability. Fisheries Research **88**:1-4.

Sutherland, W. J., A. S. Pullin, P. M. Dolman, and T. M. Knight. 2004. The need for evidence-based conservation. Trends in Ecology & Evolution **19**:305-308.

Thrush, S. F., and P. K. Dayton. 2002. Disturbance to marine benthic habitats by trawling and dredging: Implications for marine biodiversity. Annual Review of Ecology and Systematics **33**:449-473.

Thurstan, R. H., S. Brockington, and C. M. Roberts. 2010. The effects of 118 years of industrial fishing on UK bottom trawl fisheries. Nat Commun **1**:1-6.

Van Kirk, K. F., T. J. Quinn, and J. S. Collie. 2010. A multispecies age-structured assessment model for the Gulf of Alaska. Canadian Journal of Fisheries and Aquatic Sciences **67**:1135-1148.

Versteeg, D. J., S. E. Belanger, and G. J. Carr. 1999. Understanding single-species and model ecosystem sensitivity: Data-based comparison. Environmental Toxicology and Chemistry **18**:1329-1346.

Walpole, M., R. E. A. Almond, C. Besancon, S. H. M. Butchart, D. Campbell-Lendrum, G. M. Carr, B. Collen, L. Collette, N. C. Davidson, E. Dulloo, A. M. Fazel, J. N. Galloway, M. Gill, T. Goverse, M. Hockings, D. J. Leaman, D. H. W. Morgan, C. Revenga, C. J. Rickwood, F. Schutyser, S. Simons, A. J. Stattersfield, T. D. Tyrrell, J.-C. Vie, and M. Zimsky. 2009. Tracking Progress Toward the 2010 Biodiversity Target and Beyond. Pages 1503-1504.

Watson, R. T. 2005. Turning science into policy: challenges and experiences from the science-policy interface. Royal Society Philosophical Transactions Biological Sciences **360**:471-477.

Wood, S. N. 2006. Generalized additive models: an introduction with R. Chapman & Hall/ CRC, Boca Raton, Florida.

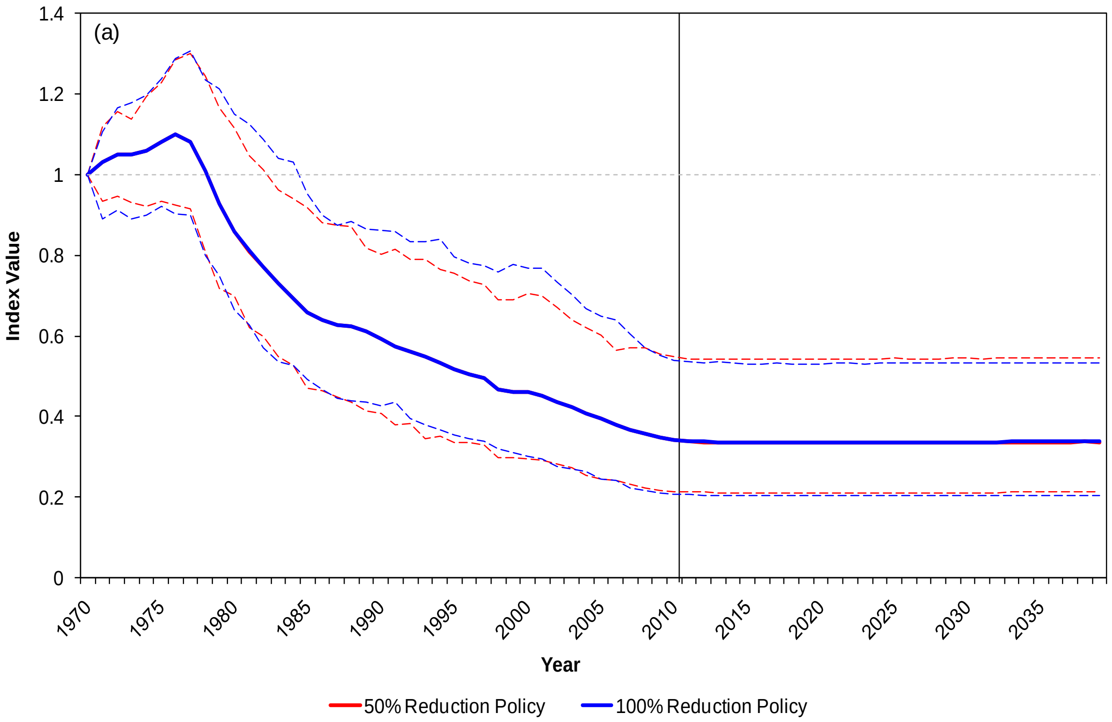
Worm, B., R. Hilborn, J. K. Baum, T. A. Branch, J. S. Collie, C. Costello, M. J. Fogarty, E. A. Fulton, J. A. Hutchings, S. Jennings, O. P. Jensen, H. K. Lotze, P. M. Mace, T. R. McClanahan, C. Minto, S. R. Palumbi, A. M. Parma, D. Ricard, A. A. Rosenberg, R. Watson, and D. Zeller. 2009. Rebuilding global fisheries. Science (Washington D C) **325**:578-585.

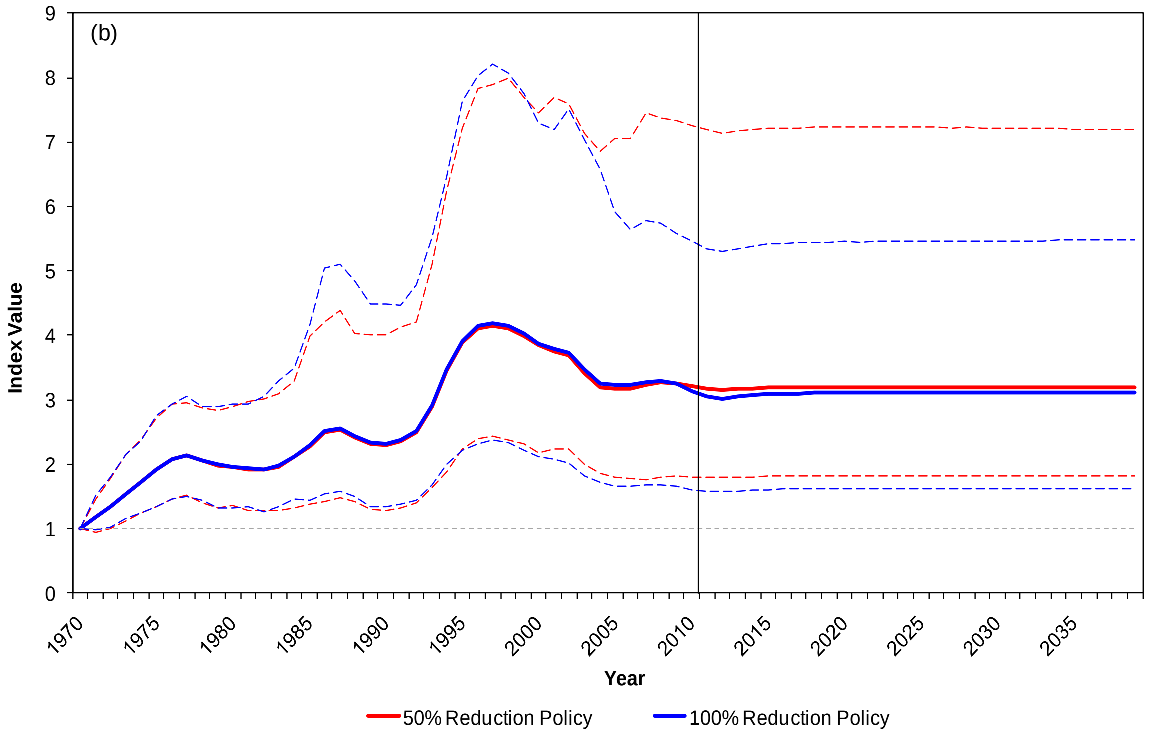
2008. The Living Planet Report in C. Hails, editor. WWF, Gland, Switzerland.

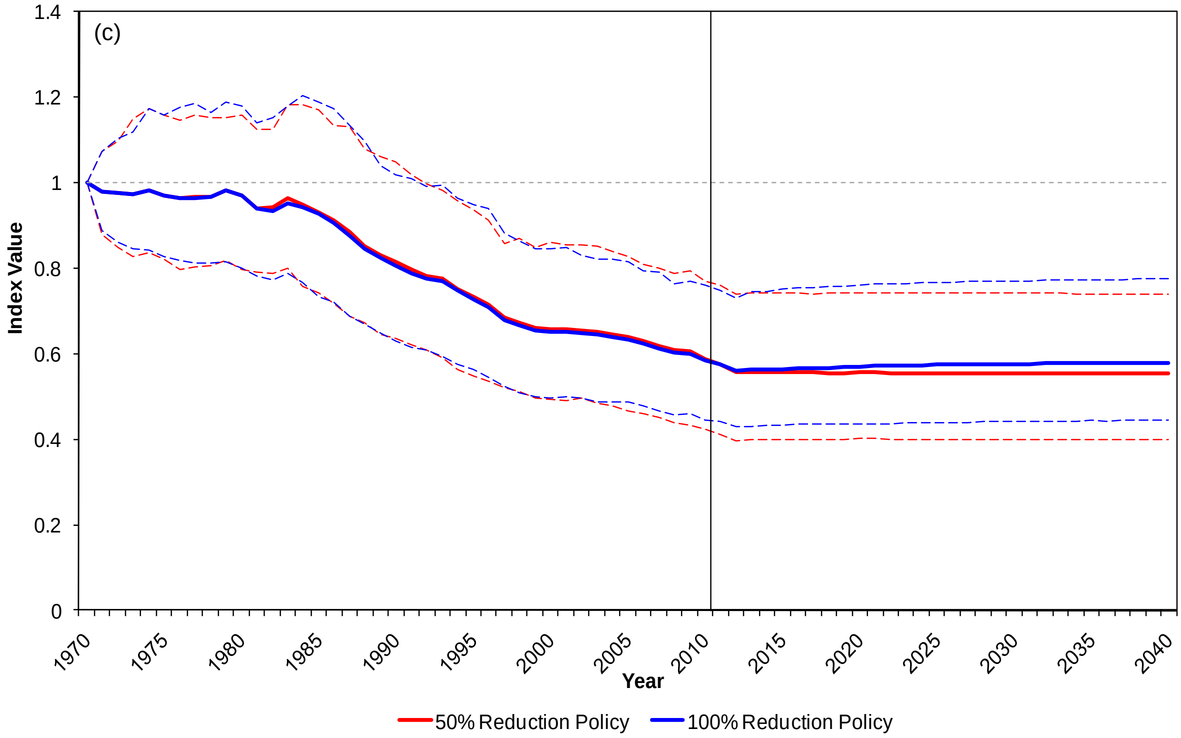
2010. Global Biodiversity Outlook 3. Page 94. Secretariat of the Convention on Biological Diversity, Montreal.

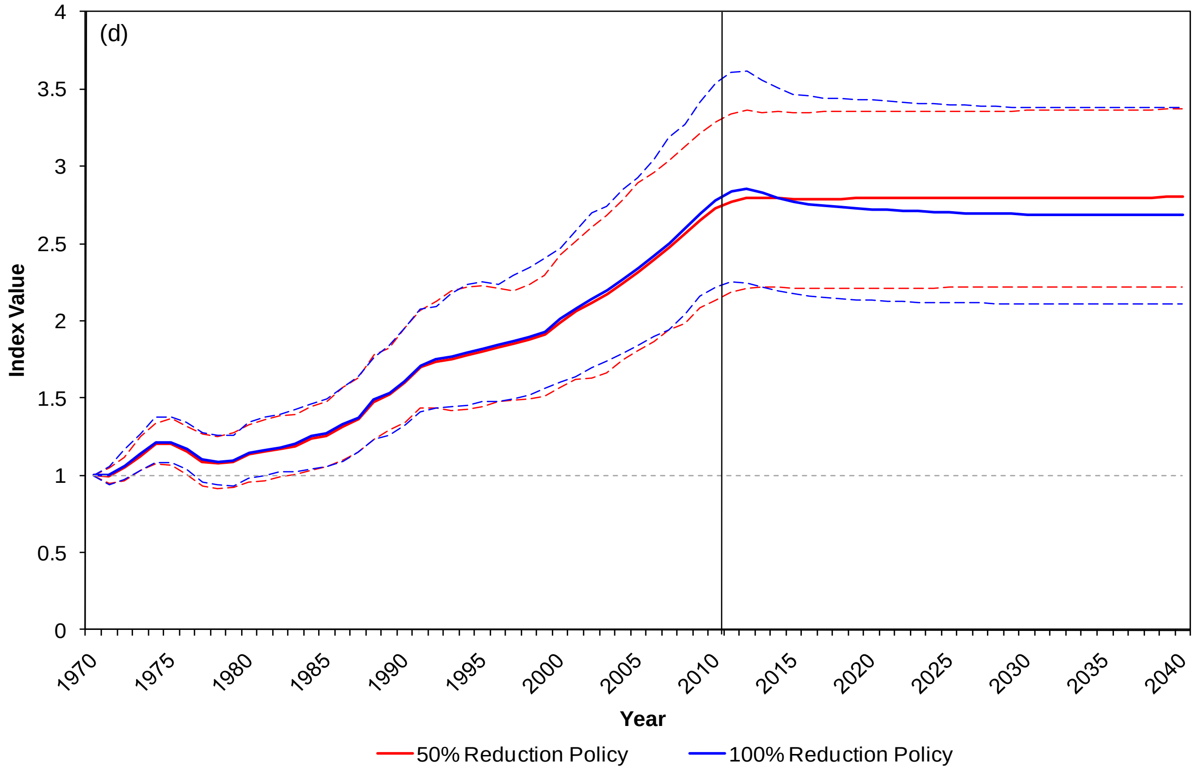
6 Appendix

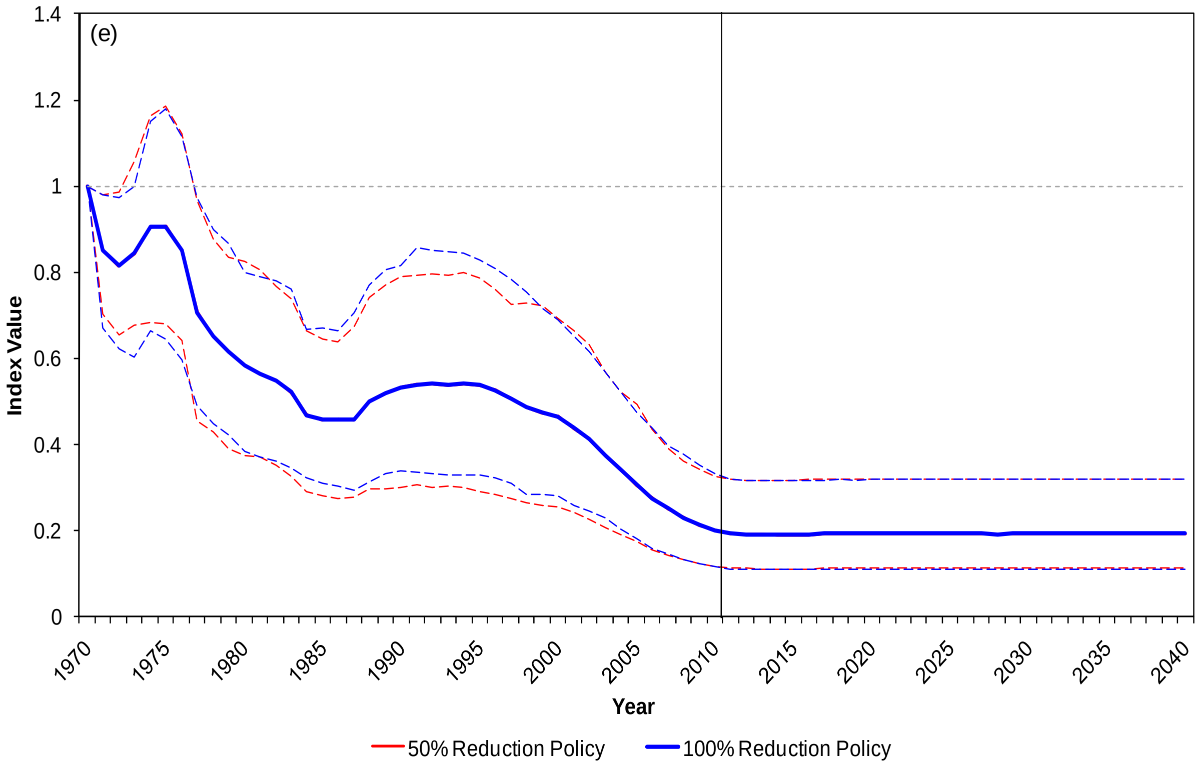
Appendix 1. 1: Comparisons of the LPI for both bottom trawl reduction policies, in all the ocean systems analysed: **(a)** Caribbean and Gulf of Mexico, **(b)** Mediterranean and Black Sea, **(c)** North Pacific Ocean, **(d)** North Sea and Baltic Sea, **(e)** South Atlantic Ocean, **(f)** South Pacific Ocean. The dashed lines indicate the boot strapped confidence intervals, and the vertical line indicates the start of the policy in the 2010, with the first results of the policy in 2011.

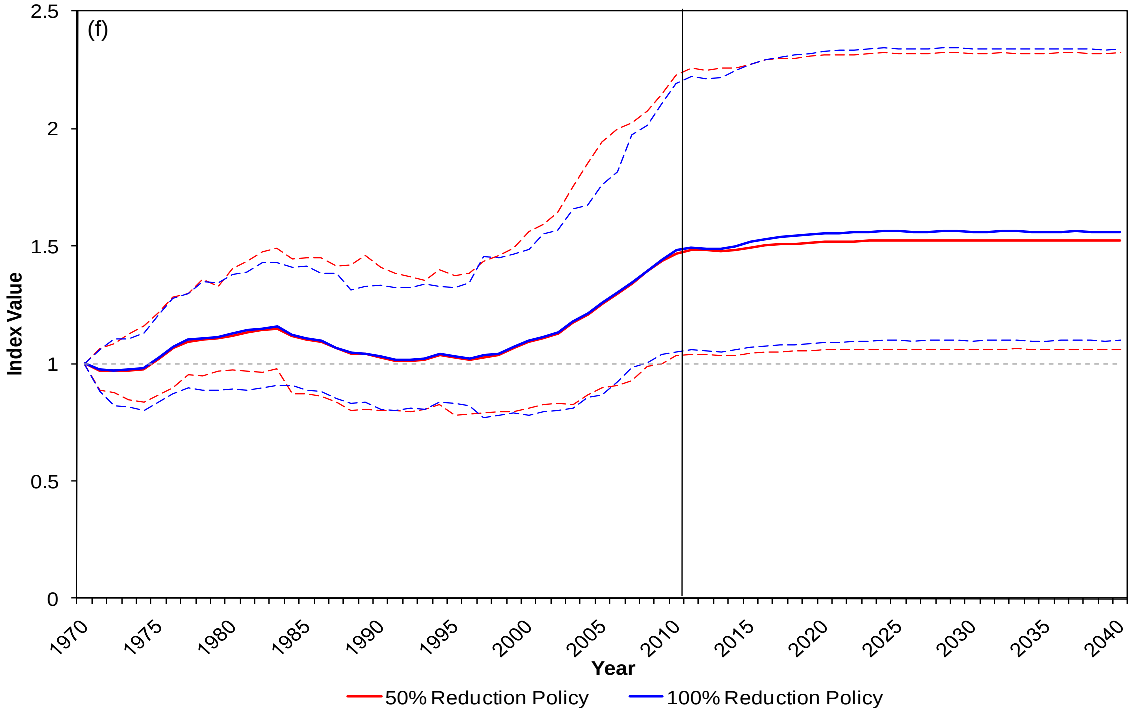



(b)
Index Value
0
1
2
3
4
5
6
7
8
9
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
2030
2035
Year
50% Reduction Policy
100% Reduction Policy

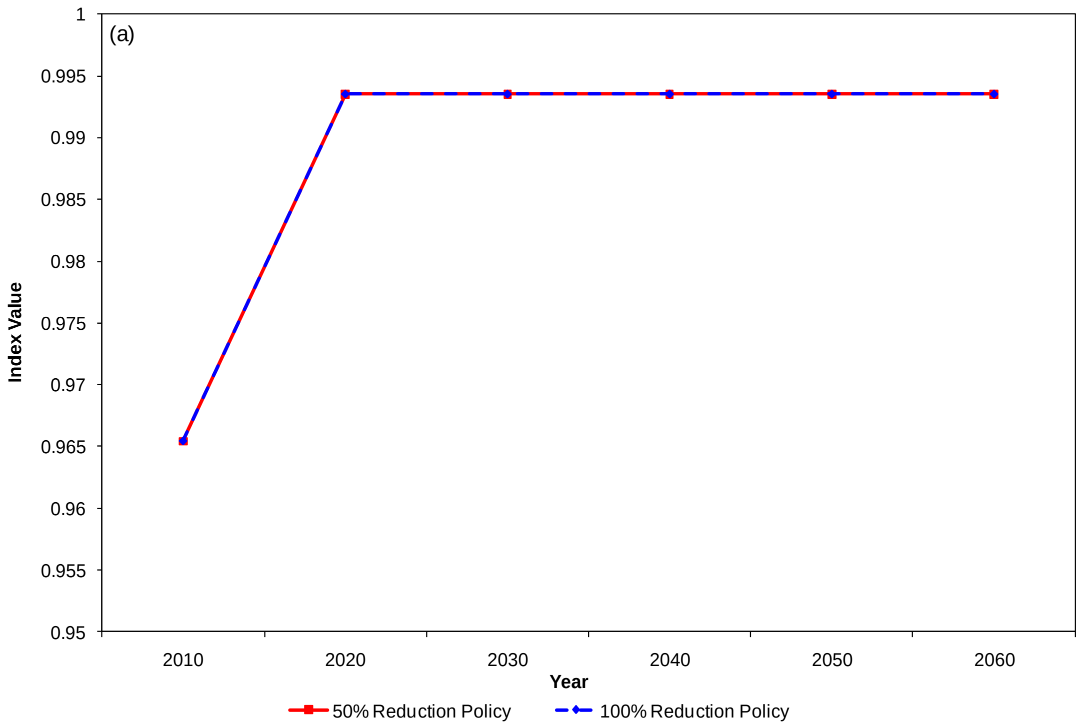

(c)
Index Value
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
2030
2035
2040
Year
50% Reduction Policy
100% Reduction Policy

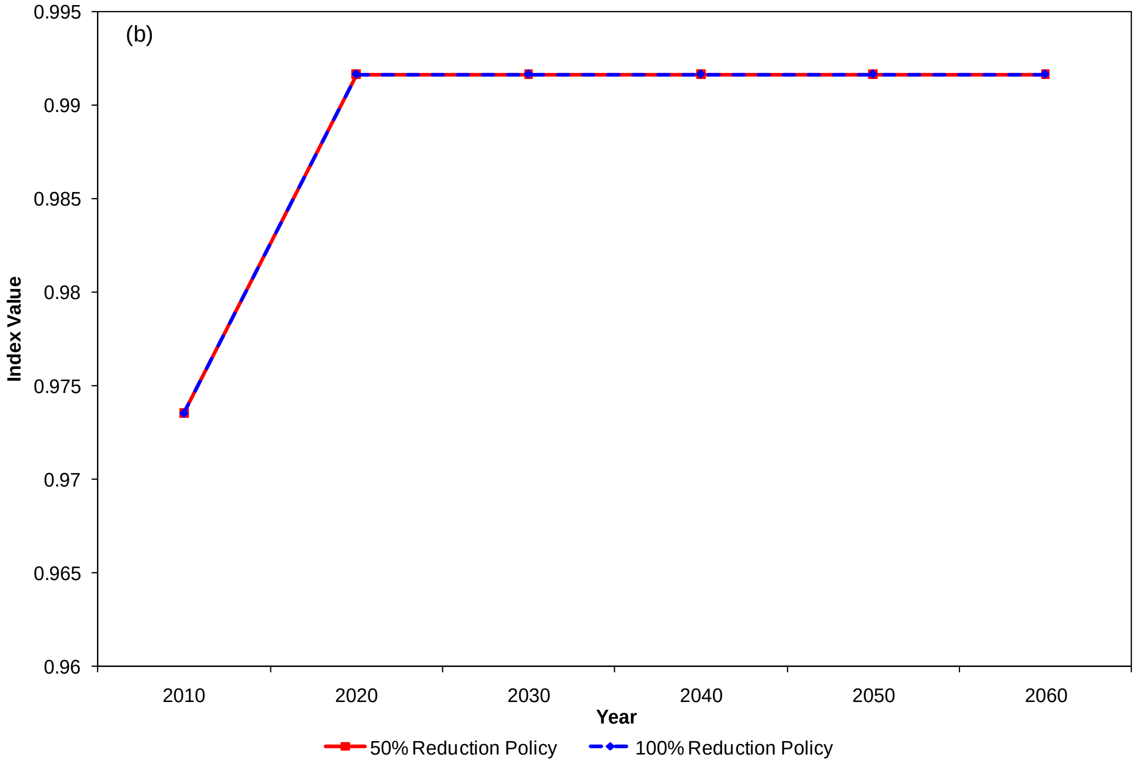

(d)
Index Value
Year
0
0.5
1
1.5
2
2.5
3
3.5
4
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
2030
2035
2040
50% Reduction Policy
100% Reduction Policy

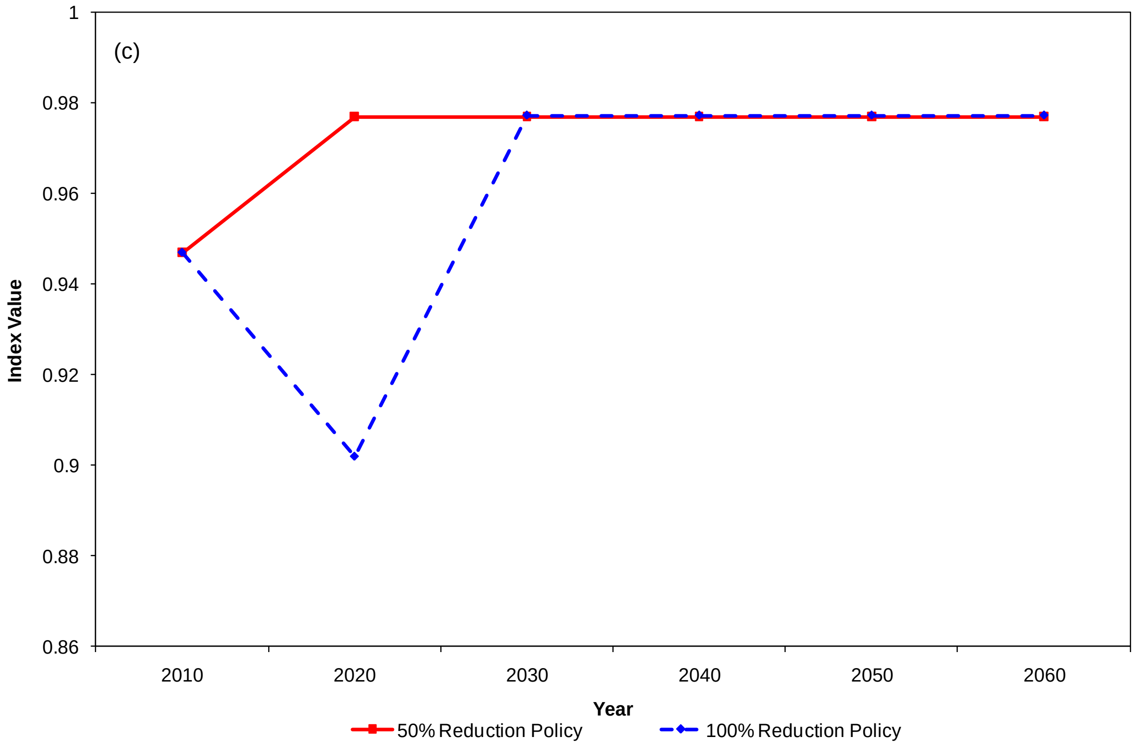

(e)
Index Value
Year
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
2030
2035
2040
50% Reduction Policy
100% Reduction Policy

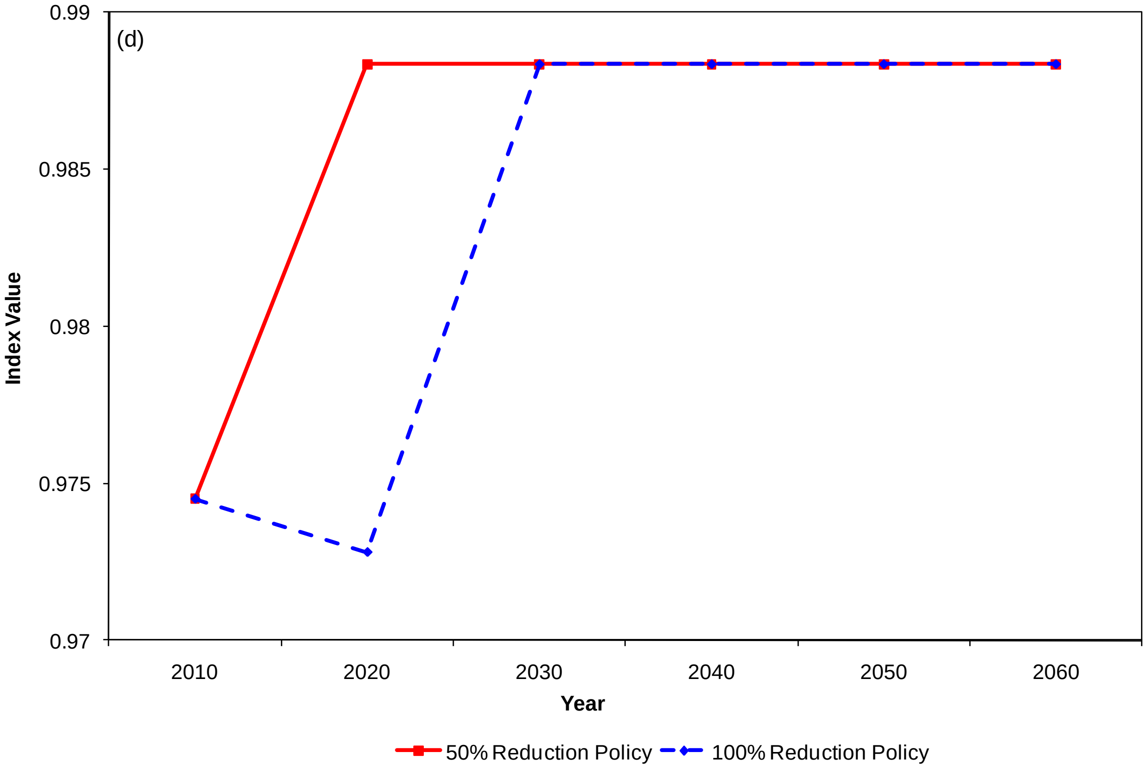


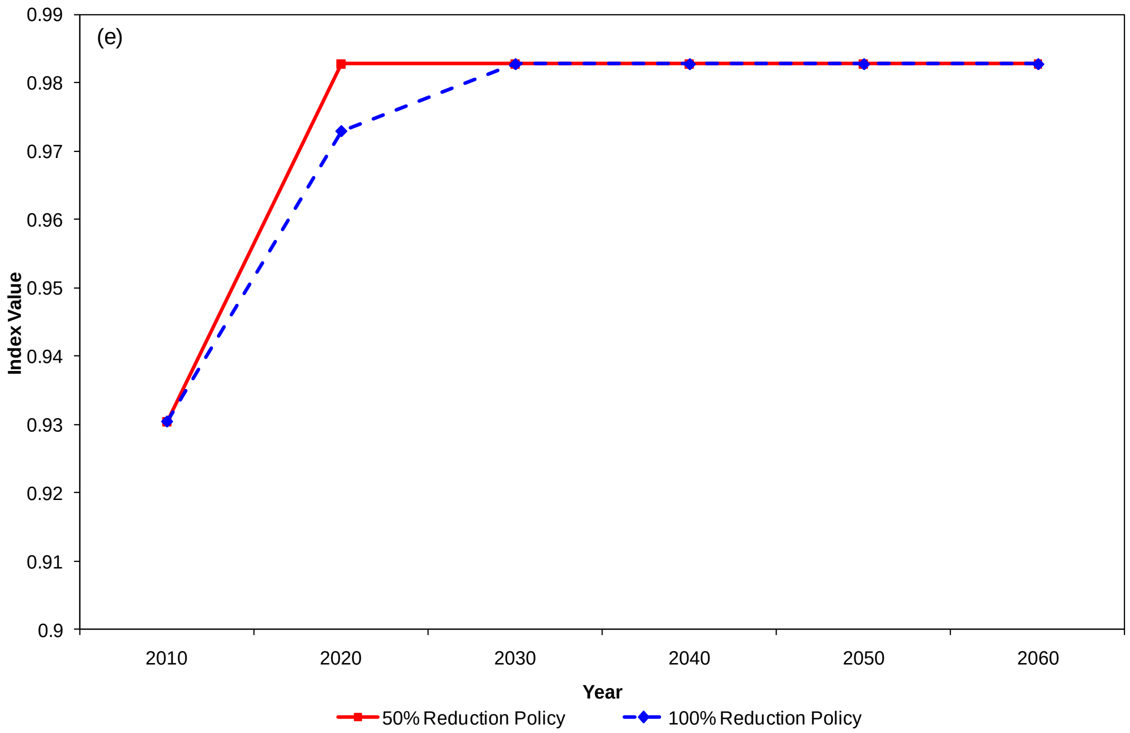
Appendix 1. 2: Comparisons of the RLI for both bottom trawl reduction policies, in all the ocean systems analysed: **(a)** Caribbean and Gulf of Mexico, **(b)** Mediterranean and Black Sea, **(c)** North Pacific Ocean, **(d)** North Sea and Baltic Sea, **(e)** South Atlantic Ocean, **(f)** South Pacific Ocean.

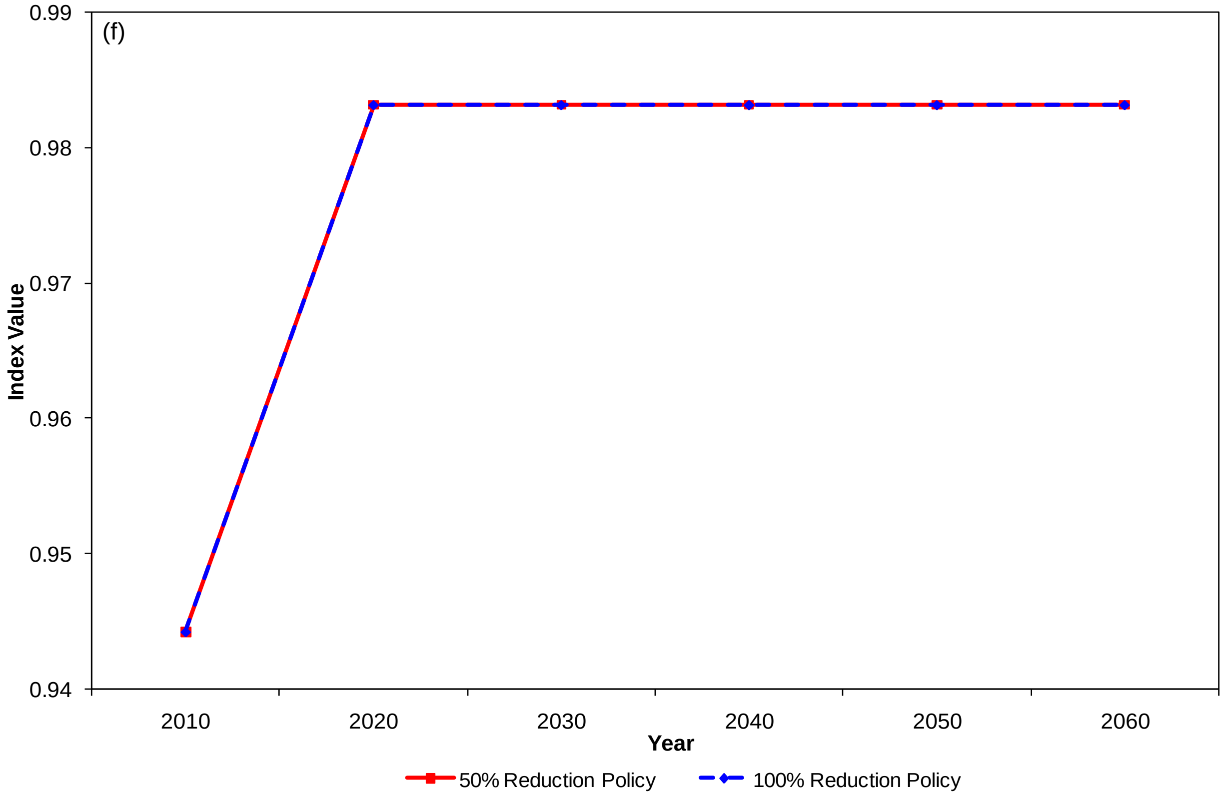



(b)
Index Value
0.995
0.99
0.985
0.98
0.975
0.97
0.965
0.96
2010
2020
2030
2040
2050
2060
Year
50% Reduction Policy
100% Reduction Policy


(c)
Index Value
1
0.98
0.96
0.94
0.92
0.9
0.88
0.86
2010
2020
2030
2040
2050
2060
Year
50% Reduction Policy
100% Reduction Policy


(d)
Index Value
0.99
0.985
0.98
0.975
0.97
2010
2020
2030
2040
2050
2060
Year
50% Reduction Policy
100% Reduction Policy


(e)
Index Value
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0.91
0.9
2010
2020
2030
2040
2050
2060
Year
50% Reduction Policy
100% Reduction Policy



Appendix 1. 3: The primary species groups in each ocean system and the number of species included in the LPI analysis for each group

	Caribbean	Mediterranean	North Pacific	North Sea	South Atlantic	South Pacific
Fish	8	7	66	41	44	23
Marine Mammals	1	2	24	0	4	1
Seabirds	9	17	42	39	36	15
Turtles	5	0	4	0	0	3
Sharks and Rays	3	3	4	3	1	
Total	**25**	**29**	**40**	**83**	**85**	**42**

Appendix 1. 4: The primary species groups in each ocean system and the number of species included in the RLI analysis for each group

	Caribbean	Mediterranean	North Pacific	North Sea	South Atlantic	South Pacific
Fish	106	31	241	29	54	152
Marine Mammals	16	7	25	20	20	1
Seabirds	59	31	126	54	89	80
Turtles	5	0	1	0	0	6
Total	**186**	**69**	**393**	**103**	**163**	**239**