FISH and FISHERIES

Using scenarios to project the changing profitability of fisheries under climate change

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Abstract

Over-exploitation and economic underperformance are widespread in the world's fisheries. Global climate change is further affecting the distribution of marine species, raising concern for the persistence of biodiversity and presenting additional challenges to fisheries management. However, few studies have attempted to extend bioclimatic projections to assess the socio-economic impacts of climate-induced range shifts. This study investigates the potential implications of changes in relative environmental suitability and fisheries catch potential on UK fisheries by linking species distribution modelling with cost-benefit analyses. We develop scenarios and apply a multimodel approach to explore the economic sensitivity of UK fisheries and key sources of uncertainty in the modelling procedure. We projected changes in maximum potential catch of key species and the resulting responses in terms of net present value (NPV) over a 45-year period under scenarios of change in fuel price, discount rate and government subsidies. Results suggest that total maximum potential catch will decrease within the UK EEZ by 2050, resulting in a median decrease in NPV of 10%. This value decreases further when trends of fuel price change are extrapolated into the future, becoming negative when capacity-enhancing subsidies are removed. Despite the variation in predictions from alternative models and data input, the direction of change in NPV is robust. This study highlights key factors influencing future profitability of UK fisheries and the importance of enhancing adaptive capacity in UK fisheries.

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Introduction

The global fishery sector employs almost half a billion people (FAO 2010) and provides over 20% of the per capita animal protein to 1.5 billion people (FAO 2009). In the United Kingdom and Ireland, commercial fishing continues to be an important socio-economic activity, directly employing approximately 12 000 people. However, many commercially important fish species have been over-exploited, and while total landings into the United Kingdom peaked at 1.1 million tonnes in 1930, by 2010 they had decreased to 600 000 tonnes (Cheung *et al.* 2012a).

Over-capacity has encouraged the development of suboptimal fishing and the economic underperformance of global fisheries (Sumaila *et al.* 2011), with estimated annual losses on the order of $50 billion in the world's fisheries (WorldBank and FAO 2008). Many EU fleets have been facing economic problems since 1995–2000, exacerbated by decreasing availability of resources and almost constant fish prices (Abernethy *et al.* 2010). Recent increases in fuel prices have further reduced economic benefits (COM 2006).

The decline in profitability of global fisheries is masked by technological creep and fishery subsidies, allowing vessels to exploit new fishing grounds in areas progressively deeper and further from shore (Morato *et al.* 2006; WorldBank and FAO 2008). Fishery subsidies may be defined as financial transfers, direct or indirect, from public entities to the fishing sector, enabling the sector to make more profit than would otherwise be feasible and significantly enhancing the decline of fishery resources due to overfishing (Sumaila *et al.* 2010). Global fishing subsidies have been estimated at US $ 25–29 billion, 15–30% of which are fuel subsidies (Sumaila *et al.* 2010). Europe provides US$ 4.7 billion in subsidies, second only to Asia (Sumaila *et al.* 2010). Capacity-enhancing subsidies artificially increase profits, promoting development of fishing capacity and effort allocation to a point where resources are over-exploited and long-term maximum sustainable benefits are unachievable (Milazzo 1998). These subsidies include capital inputs from public sources that reduce costs or enhance revenues, such as subsidies on fuel, boat construction and modernization (Sumaila *et al.* 2010). However, subsidies that promote fishing resource conservation and management may also be beneficial and necessary (Milazzo 1998).

Added to the challenges of over-capacity and marginal profitability in the world's fisheries, marine fisheries productivity will be affected by the changing ocean conditions associated with climate change (Bakun 1990; IPCC 2007). Theoretical and empirical studies have shown that life history, productivity and distributions of marine ectotherms to be strongly dependent on oceanic variables such as temperature (Pauly 1980; Perry *et al.* 2005; Cheung *et al.* 2012b) with a shift in stock distribution being the most commonly reported ecological response of marine species to climate change (Poloczanska *et al.* 2013). In the North Sea, marine species have been observed to have been moving polewards by 22 km per decade in relation to climate (Perry *et al.* 2005) and also deepening by 3.6 m per decade (Dulvy *et al.* 2008). Distribution shifts such as these are predicted to result in local extinctions and invasions worldwide (Cheung *et al.* 2010).

In addition to wider ecological effects, distribution shifts will likely have important consequences for the livelihoods of the world's 36 million fisherfolk (Dulvy *et al.* 2010) as well as food security and national economies (Sumaila *et al.* 2011). The effects of El Niño Southern Oscillation (ENSO) events on fisheries may provide insights into the possible effects of climate change. For example, during the 1997–1998 El Niño event, landings in Chilean and Peruvian pelagic fisheries declined by around 50%, resulting in a drop in fishmeal exports by approximately US$ 8.2 billion, negative economic effects and hardship due to lost jobs and income (Caviedes and Fik 1992). Ocean warming is linked to a shift in species composition of fisheries catch being increasingly dominated by warm-water-adapted species since the 1970s (Cheung *et al.* 2013). Thus, further large-scale shifts in marine species' distributions due to climate change are expected to result in the redistribution of global catch potential, a proxy for potential fisheries productivity which takes into account primary productivity and species distributions (Cheung *et al.* 2010). For example, despite a projected increase in global primary productivity of 0.7–8.1% by 2050 (Sarmiento *et al.* 2004), large regional differences lead to predictions of increases in maximum catch potential (MCP) of 30–70% in high-latitude countries but declines of up to 40% in tropical nations (Cheung *et al.* 2010). Changes such as these will bring increased challenges to long-term fisheries management. As fish stocks shift their distributions across jurisdictional boundaries, management policies and quota allocations may become outdated or contested (Miller and Munro 2004; Miller *et al.* 2013). Furthermore, the economic consequences of climate change for fisheries may manifest themselves through changes in the price and value of catches, fishing costs, fishers' incomes, earnings to fishing companies, discount rates and economic rents.

It is clear that there will be winners and losers with respect to fisheries and climate change. For example, while climate change is predicted to have a positive effect on the fisheries of Iceland and Greenland (Arnason 2007), earnings to the European sardine (*Sardina pilchardus*, Clupeidae) fishery are estimated to decrease by up to 1.4% on average per year with rising temperatures (Garza-Gil *et al.* 2010). Whether a fishery 'wins' or 'loses' will depend not only on the location of the country or region, but also on their vulnerability and ability to adapt, for example by switching target species, gear types or moving to more marginally productive areas, or even leaving to find employment in other sectors (Sumaila *et al.* 2011).

Here, we investigate the potential implications of climate-induced shifts in species' distributions and fisheries catch potential for UK fisheries by linking species distribution modelling with cost-benefit analyses. As it is difficult to predict the complex interaction of changes in fishers' behaviour (decision-making), fisheries governance and broader social-economic development, we focus on a set of likely consequences for the profitability of fisheries using alternative scenarios. A scenario is described as a narrative or storyline which provides a powerful tool in developing an understanding of a range of options or plausible alternative futures (Haward *et al.* 2012). Rather than focusing on accurate prediction, they enable a variety of futures to be considered, thereby allowing uncertainties to be explored (Peterson *et al.* 2003). Due to imperfect knowledge of the consequences of climate change in many contexts, scenarios aid decision-making and strategic formulation of policy under social and environmental change. The scenarios applied here include a range of alternative responses to shifts in species' potential catch in terms of fishing costs, fuel price, discount rates and government subsidies. The sensitivity of results to changes in discount rates and predictions of change in primary production is also investigated. Investigations such as this might thus provide the foresight necessary for adapting and coping with some of the effects of climate change on fisheries.

Methods

Prediction of species' relative environmental suitability

Maps of species' relative environmental suitabilities (RES) were generated using the three species distribution models (SDMs) AquaMaps (Kaschner *et al.* 2006; Ready *et al.* 2010), Maxent (Phillips *et al.* 2006) and the dynamics bioclimate envelope model (DBEM; Cheung *et al.* 2011). Maxent and AquaMaps use a statistical approach to associate species' occurrence data with averaged 'current' environmental data (1971–2000), thereby obtaining a bioclimatic envelope for each species. The bioclimatic envelope may then be projected under future scenarios of climate change for the set of environmental predictors. The dynamic bioclimatic envelope model (DBEM) and associated *Sea Around Us Project* (SAUP) model (Close *et al.* 2006) instead uses a discriminative approach (Jones *et al.* 2012), applying a set of 'filters' of known geographical or tolerance limits to delimit a species' current distribution (Close *et al.* 2006; Jones *et al.* 2012). The DBEM then simulates the change in a species' relative abundance following changing environmental conditions by incorporating a population growth model and ecophysiological parameters (Cheung *et al.* 2011). Cell values for the predicted distributions from each model represent the relative suitability of each cell for a species. These approaches are described in greater detail in the Supporting information.

Species' occurrence data

A set of 31 species of commercially exploited fish and invertebrates were selected for distribution modelling (Table 1). These species comprised 90% of demersal and 93% of pelagic species by weight, and 94 and 98% by value, respectively, of species landed by UK vessels into the United Kingdom in 2010 (MMO 2011). The crustacean Norway lobster was selected as representing the largest catch by value of shellfish by UK fleets into the United Kingdom, at 38% (MMO 2011). Additional species were selected that might provide new fishing opportunities following shifts in distribution in response to climate change (Cheung *et al.* 2012a). Species occurrence data were obtained from global online databases: the International Council for Exploration of the Sea (ICES) EcoSystemData database (http://ecosystemdata.ices.dk); the Ocean Biogeographic Information System (OBIS; OBIS 2011) and the Global Biodiversity Information Facility (GBIF; http://data.gbif.org), all last accessed in August 2011. Occurrence records for each species were spatially aggregated at the level of 0.5° latitude × 0.5° longitude and cleaned as described in the Supporting Information (Jones *et al.* 2012). This gave a binary value of presence or absence for each cell and species.

Environmental predictors and climate models

Oceanographic variables for predicting species distributions using Maxent and AquaMaps were: bathymetry, sea surface temperature (SST), sea bottom temperature, salinity, ice, primary productivity and distance to coast. Two sets of oceanographic variables were obtained, from Geophysical Fluid Dynamics Laboratory's Earth System Model (GFDL ESM2.1, Dunne *et al.* 2010) and physical climate data from an ensemble of 12 different models obtained from the World Climate Research Program (WCRP) Coupled Model Intercomparison Project phase 3 multimodel data set [http://esg.llnl.gov:8080 (last accessed August 2011)] (CMIP3).

As no primary productivity data were available for CMIP3 that from GFDL ESM2.1 was used in calculating MCP for both climate data sets. Both data sets represented the A2 climate scenario, thus being characterized by a heterogenous world with a continuously increasing global population and regionally orientated economic development and with expected atmospheric CO_2 concentration being around 575 and 870 ppm by mid and end of twenty-first century, respectively (IPCC 2000). Oceanographic variables were interpolated onto a 0.5° latitude × 0.5° longitude global grid using the nearest-neighbour method. Models were trained on climatic data averaged over a 30-year period centred on 1985 and subsequently projected into the future using a 30-year average centred on 2050.

Table 1 Commercially targeted fish and invertebrates selected for the study and their landed value in 2010.

Species name, family name	Common name	Value (£ million) 2010 (MMO 2011)
Clupea harengus, Clupeidae	Atlantic herring	10.3
Dicentrarchus labrax, Moronidae	European seabass	4.8
Engraulis encrasicolus, Engraulinae	European anchovy	–
Glyptocephalus cynoglossus, Pleuronectidae	Witch flounder	1.2
Gadus morhua, Gadidae	Atlantic cod	28.6
Hippoglossus hippoglossus, Pleuronectidae	Atlantic halibut	1.3
Limanda limanda, Pleuronectidae	Common dab	–
Lophius piscatorius, Lophiidae	Angler/Monkfish	38.5
Lepidorhombus whiffiagonis, Scophthalmidae	Megrim	10.1
Melanogrammus aeglefinus, Gadidae	Haddock	36.2
Microstomus kitt, Pleuronectidae	Lemon sole	6.3
Merlangius merlangus, Gadidae	Whiting	9.4
Merluccius merluccius, Merlucciidae	European hake	10.2
Molva molva, Lotidae	Ling	5.7
Micromesistius poutassou, Gadidae	Blue whiting	1.0
Mullus surmuletus, Mullidae	Surmullet	–
Nephrops norvegicus, Nephropidae	Norway lobster	95.3
Platichthys flesus, Pleuronectidae	Flounder	–
Pleuronectes platessa, Pleuronectidae	European plaice	3.3
Pollachius pollachius, Gadidae	Pollack	3.5
Pollachius virens, Gadidae	Saithe	12.4
Psetta maxima, Scophthalmidae	Turbot	3.4
Sardina pilchardus, Clupeidae	European pilchard	0.6
Scophthalmus rhombus, Scophthalmidae	Brill	1.6
Scomber scombrus, Scombridae	Atlantic mackerel	82.0
Solea solea, Soleidae	Common sole	14.0
Sprattus sprattus, Clupeidae	European sprat	–
Trisopterus esmarkii, Gadidae	Norway pout	–
Trisopterus luscus, Gadidae	Pouting	–
Trachurus trachurus, Carangidae	Atlantic horse mackerel	1.8
Zeus faber, Zeidae	John Dory (Atlantic)	–

Calculating MCP

Two sets of MCP for the current period were calculated from time series of catch data that came from two sources: ICES and the SAUP. As data on marine species abundance are seldom available, the maximum catch of each species over a time series was obtained to use as a proxy for maximum sustainable yield (MSY; Srinivasan *et al.* 2010; Froese *et al.* 2012). Firstly, ICES Catch Statistics (1950–2010) were used to calculate the mean maximum catch for the highest 10 years, thus accounting for some interannual variation. Secondly, maximum catch data for the UK EEZ were extracted from a database collated by the SAUP [www.seaaroundus.org (last accessed March 2014)]. This database presents a time series of landings data at a range of spatial scales formed by applying a rule-based approach to spatially distribute global landings statistics to a grid of 0.5° latitude × 0.5° longitude (Watson *et al.* 2004). The 10 years of highest catch within the UK EEZ were again averaged for the available years (1950–2006). The two sets of MCP estimates were then compared with assess the sensitivity of results to variation in these data.

The MCP in the future time period (t) was then calculated for each species as a function of the change in primary productivity and the maximum catch in the reference time period (t_0; Cheung *et al.* 2008b) (Algorithm MCP1, Equation 1). This methodology is supported by both modelled and empirical work which shows potential marine fisheries production to be significantly related to available primary productivity (Cheung *et al.* 2008a; Chassot *et al.* 2010; Blanchard *et al.* 2012). Specifically, change in MCP from current to the future period was projected from the change in primary productivity between reference (1985) and projection (2050) time periods within the study area, the UK Exclusive Economic Zone (EEZ):

$$\text{Maximum Catch Potential}_t = \text{Maximum Catch}_{t0} \times \frac{\Sigma(P)_{i,t} \times A_{i,t}}{\Sigma(P)_{i,t0} \times A_{i,t0}} \quad (1)$$

where P is the primary productivity in each 0.5° latitude × 0.5° longitude cell (i) of a species' exploitable range, and A is the area of each cell within that range.

The total future MCP for each species was re-distributed over the study area using the specific predictions of relative environmental suitability (Equation 2).

$$\text{Maximum Catch Potential}_{i,t} = \frac{\text{Maximum Catch Potential}_t}{\text{RES}_t} \times \text{RES}_{i,t} \quad (2)$$

where RES is the relative environmental suitability for a species, using a particular SDM model and set of climate data.

The annual percentage difference between estimated maximum catch in 1985 and MCP in 2050 for each cell of a species' distribution was calculated, assuming a linear change over time. These values were then associated with the Fisheries Activity Database of Defra/Cefas, a location-specific data set of catch weight and value for UK fishing fleets in the UK EEZ, to undertake a cost-benefit analysis.

To test the sensitivity of results to the MCP algorithm, a second method of calculating Maximum Catch Potential (MCP2) was implemented (Equation 3).

$$\text{Maximum Catch Potential}_t = \text{Maximum Catch}_{t0} \times \frac{\Sigma(P \times \text{RES})_{i,t}}{\Sigma(P \times \text{RES})_{i,t0}} \quad (3)$$

This method does not re-distribute values over all cells in the study area according to their relative environmental suitability value, instead incorporating aggregate values of future MCP for each species into the cost-benefit analysis.

As there are large uncertainties in the response of primary productivity to climate change and variations between alternative model simulations (e.g. Sarmiento *et al.* 2004; Steinacher *et al.* 2010), the sensitivity of the MCP algorithm to variation in primary productivity projections was explored using Equation (3) and data from the Medusa model (Yool *et al.* 2011). This model differs from the GFDL ESM2.1 in terms of model structure, such as the number of phytoplankton groups incorporated, initial parameter values, resolution and physical model coupling. Annual estimates from the Medusa model were averaged as above to obtain average predictions in 1985 and 2050.

Cost-benefit analysis

Cost-benefit analyses were conducted to assess the financial implications of climate-induced changes in catches of UK fisheries fishing within the UK EEZ between 2005 and 2050 under three scenarios, described below.

Catches by weight and ex-vessel price by year, gear and species from 2001 to 2010 were obtained from the Fisheries Activity Database of Defra/Cefas. Catches were recorded by 11 gear types: Bottom trawl, mid-water trawl, bottom seine, mid-water seine, drift nets, fixed nets, pots, lines, picking, dredge and other nets. Total average annual value of catch (V) for each year (y) between 2001 and 2010 was calculated as:

$$V = \frac{\sum_y^Y = w_{s,g} \times p_{s,g}}{10} \quad (4)$$

where w is the weight of catch and p is the price of species s using gear g. Values were averaged over the 10-year period to account for interannual variability. To calculate the total annual value following species' distribution shifts, species-specific percentage changes in MCP (calculated as described in Calculating MCP) were re-projected from the original 0.5° latitude × 0.5° longitude onto the ICES statistical rectangles (0.5° latitude × 1.0° longitude) by averaging the summed catch from both 0.5 × 0.5 degree cells within each ICES rectangle. We assumed a linear change in MCP from 1985 to 2050. The percentage change in MCP was then used to calculate the total catch value at each year from year = 1985–2050 for each species and gear using Equation (5):

$$V_{\text{year}} = V - \sum_{j=1}^{J} V_j \times \frac{\text{pMCP}_j}{(2050 - 1984)} \times (\text{year} - 1984) \quad (5)$$

where pMCP is the percentage difference in MCP at ICES rectangle j between 1985 and 2050. We therefore assumed that the percentage change in

MCP between 1985 and 2050 changed in equal increments for each of the 65 years, that all gears would remain constant in their catchability of each species and that vessels would not alter their fishing grounds during this time, although the distribution of effort could change. Ex-vessel price of fish was assumed to be constant because of the difficulty in predicting its changes (Swartz *et al.* 2012).

Annual costs of fishing by gear types were extracted for the United Kingdom from a global cost of fishing database (Lam *et al.* 2011). This database comprised costs for fuel, repair, labour, depreciation, interest and running costs. Values were converted from US dollars to Great Britain pounds sterling, using the 2005 average exchange rate, 0.55 (World Bank, 2012) [http://data.worldbank.org/indicator/PA.NUS.FCRF (last accessed January 2013)], thereby corresponding to the time period for which the data had been corrected to account for inflation, thus being converted to real values (Lam *et al.* 2011). Fishing costs in this database were expressed per unit weight of catch for each gear type. As with annual value of catch (V, Equation 4), the average annual costs excluding fuel (other costs, O) for each year between 2001 and 2010 was calculated as:

$$O = \frac{\sum_{y}^{Y} = w_g \times o_g}{10} \tag{6}$$

where o is the cost of fishing, excluding the cost of fuel, per unit weight of catch for each gear. Likewise, average annual cost of fuel (F) was calculated using Equation (7)

$$F = \frac{\sum_{y}^{Y} = w_g \times f_g}{10} \tag{7}$$

where f is the cost of fuel per unit weight of catch for each gear, g. Total number of gear types is 11. Net potential catch values for each year were subsequently calculated as the catch values predicted for each year minus total costs. Conventional and intergenerational discounting (Sumaila and Walters 2005) was then applied to calculate the Net Present Value (NPV) of benefits from 2005 to 2050.

Discounting

The choice of discount rate may have considerable effect on the NPV of a project or assessment. The discount rate recommended by HM Treasury for appraisal and evaluation of long-term projects (between 31 and 75 years long) is 0.03 (3%) (HM Treasury, 2011), while 0.05 represents the average discount rate for 2012 [www.bankofengland.co.uk/boeapps/iadb/ (last accessed 5 October 2012)] as well as the current official Bank Rate of the Bank of England [www.bankofengland.co.uk/boeapps/iadb/Repo.asp?Travel=NIxIRx (last accessed 5 October 2012)]. These rates were applied as conventional discount rate (r) = 0.03 and future discount rate (r^{fg}) = 0.05 under the intergenerational discounting method (Sumaila and Walters 2005, see Supporting Information). To investigate the effect of varying discount rates on NPV, a sensitivity analysis was also carried out, using both conventional and intergenerational discounting. Detailed methodology on the discounting method applied is given in the Supporting Information.

Scenario development

Socio-economic scenarios were developed to assess the potential financial implications of climate-induced changes in catch potential for UK fleets fishing in the UKEEZ. Three scenarios were designed based on narratives from the Alternative Future Scenarios for Marine Ecosystems scenarios (Pinnegar *et al.* 2006), from which alternative trajectories of changes in total catch, potential catch and fishing cost were developed.

Scenario 1: Increased costs for industry (baseline)

This scenario depicts a future in which the costs of fishing will increase according to historical trends. Specifically, fuel costs will increase while annual levels of catch value and weight remain constant at 2005 levels for every year between 2005 and 2050, therefore giving a baseline estimate of profitability. The effect of removing capacity-enhancing subsidies (Sumaila *et al.* 2010) on profitability is also investigated. Capacity-enhancing subsidies have been estimated at £8 331 694 per year for the United Kingdom (Sumaila *et al.* 2010).

Two assumptions of fuel price change were calculated to reflect average long-term and short-term rates of increase using a time series of diesel retail prices from the UK Department of Energy and Climate Change [DECC; www.decc.gov.uk/en/content/cms/statistics/energy_stats/prices/prices.aspx (last accessed 5 October 2012)]. To extrapolate the historical trend, we corrected for inflation using a Consumer Price Index obtained from the

Office for National Statistics [www.ons.gov.uk/ons/rel/cpi/consumer-price-indices/July-2011/tsd-June-2011.html (last accessed 5 October 2012)]. This annual corrected value may be described as the real price of diesel in each year between 1988 and 2011. Having been converted to base year 2011, real values expressed the value of diesel in each year in prices of 2011. Linear models were run to obtain trends of fuel price increase in the long term (1988–2011) and the short term (2005–11).

Alternative models were fit using linear, quadratic and polynomial terms and selected according to *R*-squared and adjusted *R*-squared values. The best model fit was achieved using a linear term ($R^2 = 0.92$ and 0.65 for the long term and short-term trend, respectively) (Figure S1). Equations obtained to increase fuel costs for each year of the study period (1:45) were as follows:

$$\text{Long-term trend: Fuel price}_{\text{year}} = 0.027 \cdot (\text{year} + 17) + 0.55 \tag{8}$$

$$\text{Short-term trend: Fuel price}_{\text{year}} = 0.041 \cdot \text{year} + 0.96 \tag{9}$$

To increase the average total cost of fuel (*F*, Equation 7) in each year according to the long-term and short-term trends, the number of gear units of fuel consumed per year (*U*) were back-calculated from the total annual cost of fuel consumed using Equation (10):

$$U = \frac{F}{\text{Unit price of fuel}} \tag{10}$$

where the unit price of fuel is $1.006\ \text{L}^{-1}$, the 2005 diesel price from the time series of diesel retail prices described above. The estimate of number of gear units was then used to calculate the impact of increases in fuel costs for each year using Equation (11).

$$\text{Fuel cost}_{\text{year}} = \text{Fuel price}_{\text{year}} \cdot U \tag{11}$$

Scenario 2: Climate change impacts catch

This scenario explores the impact of climate change on catch value. As described in Calculating MCP, the annual percentage change in MCP under climate change was incorporated into the Fisheries Activity Database (Defra/Cefas), recorded by species, gear and location. This was used to project the annual catch value for each species in each cell of the UK EEZ for each year of the study period. Scenario 2 thus assumes that catch changes proportionally to projected change in future MCP and that effort may be re-distributed amongst cells already fished for a particular species. It was also assumed that fisheries would not change their distribution to target locations that had not been targeted in the initial time period (2001–50). As this scenario aimed to focus on the influence of climate change on catch value, the former assumption allowed a moderate level of adaptation, while the later enabled the effect of shifting species' distributions and the potential need for further adaptation to be explored. For example, further adaptation might involve a change in distribution of fisheries, adequate analysis of which would require data on distance to ports, length of trips and boat capacity, which was thus outside the scope of this study. In this scenario, the increase in costs that would have resulted from rising fuel costs are compensated by an increase in government subsidies, thus ensuring that fuel costs to the fisher remain constant. This scenario thus also explores the increase in cost to the UK's public due to increasing fuel price.

To investigate the assumption used here and the effect of a change in fishery distribution on results for Scenario 2, the analyses were rerun for predictions from each model combination, accounting for catch in areas that had no catch in the initial time period. This was carried out in the following way:

Cells with no catch for a particular species in the database but with a predicted catch potential >0 under climate change were identified. The specific value of relative habitat suitability at that cell for each SDM-GCM combination was used to find the mean catch value across other cells with similar relative habitat suitability values. The mean future catch value under climate change was then attributed to the cell of interest. This method assumes that absence of catch value data for the cells recorded as 0 were due to the absence of the particular species at that location, rather than reasons that would continue to prevent catch under altered species' distribution.

Scenario 3: Sustainable future

This scenario reflects the introduction of management measures to ensure that stocks can continue to be exploited at current levels of fishing effort and furthermore, that stocks have been rebuilt to levels approximating their MSY. As MSY has not been estimated for many species in the UK EEZ, the maximum catch for each species, calculated as described above using ICES Catch Statistics, was again used as a proxy. The percentage difference between maximum catch and catch averaged for 2005 was calculated and used to adjust predicted future catch for each species under climate change, thereby reflecting the rebuilding of stocks. We therefore assume that catch potential will be proportional to fish abundance (as demonstrated by Fernandes *et al.* 2013). Summing these adjusted catches for each species allowed an estimation of the future potential catch if current stocks were allowed to rebuild to MSY levels. The scenario was also run using the baseline catch rates of *Increased costs for Industry* to estimate the implications of rebuilt stocks on current catches. Because fishing effort remains constant, this scenario assumes that fishing costs will not change in the future and catch per unit effort (CPUE) increase.

Both the *Climate Change Impacts Catch* and *Sustainable Future* scenarios were run for each of the SDM-GCM model combinations and variation between projected NPVs were compared.

Results

Relative environmental suitability and MCP

The majority of species investigated in this study are predicted to experience a decrease in median relative environmental suitability by 2050 within the UK EEZ (median = −4.66%; Fig. 1). However, environmental suitability is predicted to increase for a few species under some SDM-GCM combinations. In particular, European sea bass is predicted to experience a median increase in RES of 24%, while those for John Dory, sardine and monkfish are predicted to increase by 8.01, 9.32 and 5.73%, respectively.

Between 2000 and the 2050, primary productivity across all 0.5° latitude × 0.5° longitude grid cells of the UK EEZ is estimated to decrease by a median of 5% and a mean of 6% (range: 20% decrease to 7% increase) using the Geophysical Fluid Dynamics Laboratory's Earth System Model (GFDL ESM2.1; Dunne *et al.* 2010). Using the Medusa model (Yool *et al.* 2011), primary

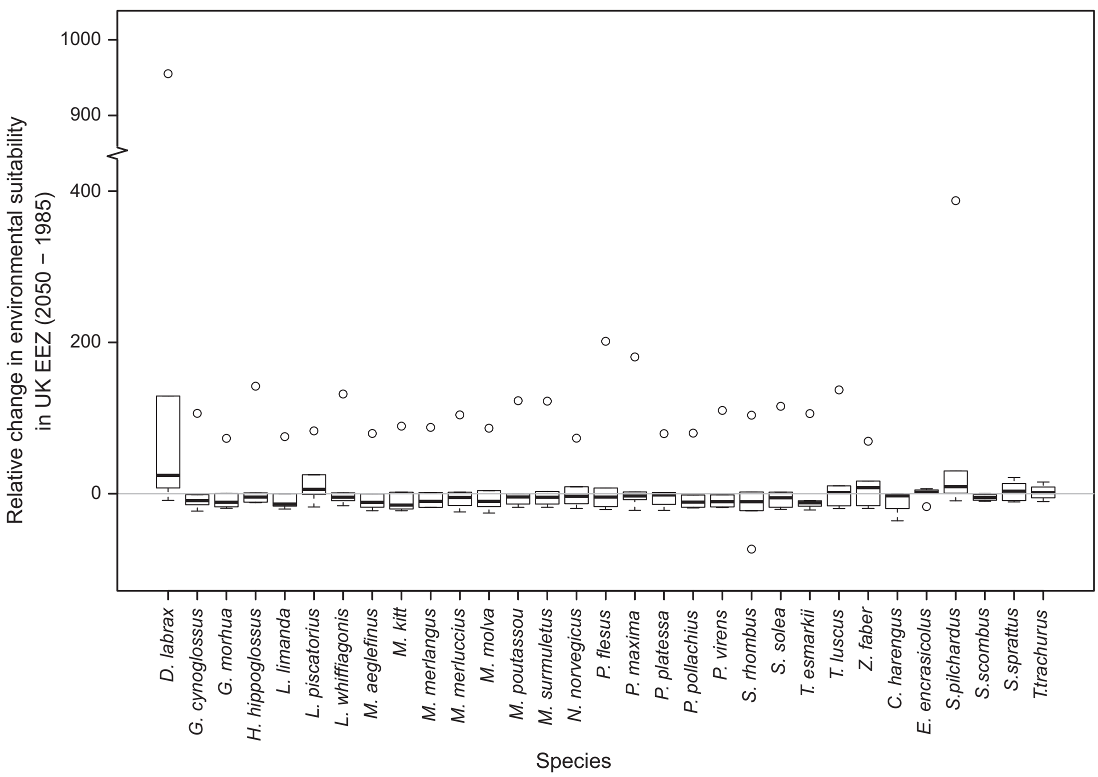

Figure 1 The percentage difference in total relative environmental suitability within the UK EEZ, for each species across GCMs and species distribution models (SDMs). Thick bars represent median values, the upper and lower ends of the box the upper and lower quartiles of the data, and the whiskers datapoints no >1.5 times interquartile range from the box. Points that are more extreme than whiskers are represented as circles.

productivity across the UK EEZ is predicted to decrease by a median of 44% and a mean of 39% (range: 70% decrease to 0.4% increase).

Overall, the annual MCP for this set of species is predicted to decrease between 1985 and 2050 in the UK EEZ using algorithm MCP1 (Equation 1; mean total decrease = 8.3%).

Cost-benefit analysis

Scenario 1: Increased costs for industry

The total NPV of benefits from the UK fishing fleet over 46 years (2005–50), assuming constant fuel prices, no change in catch or fishing location, and intergenerational discounting with a conventional discount rate of 0.3% and a future discount rate of 0.05% is estimated at £2.6 billion. This value decreases to £1.5 billion, using a discount rate of 0.3% under conventional discounting methods (Table S1). This represents an overall profitability of 36.2 and 21.2% using intergenerational and conventional discounting, respectively, for the baseline scenario. Increasing fuel prices according to a long-term (1988–2011) and short-term (2005–11) trend causes the net profitability of annual catch value to fall by 4.5 and 6.4%, respectively, between 2005 and 2050. It further increases the cost of fuel as a proportion of the total costs over the 45-year period (assuming no change in the latter) from 13.8 to 20.7 and 23.30% for long-term and short-term trends, respectively. In 2050, fuel price increases result in annual fuel accounting for 26.2 and 30.9% of total costs, respectively, also reflected in the percentage fuel cost as a proportion of total value. Higher fuel prices reduce overall profitability over 46 years to 31.7% for the long-term fuel price trend and 29.7% for the short-term one, using intergenerational discounting. The substantial contribution of subsidies to the profitability of the fishing industry is shown when they are removed from the cost-benefit analysis, causing profitability to become negative, at −13.09%.

Scenario 2: Climate change impacts catch

This scenario predicts climate change to have a negative impact on catch value, assuming the area targeted remains constant but allowing catch, and thus effort to change in proportion to the MCP (Fig. 2). Although the direction of change in NPV of benefits is consistent across predictions using different SDMs and climate data sets, the magnitude of this decrease varies. The majority of variation is spread evenly around a central tendency (e.g. median decrease in profitability for Scenario 2 = 10%), with outlying predictions from AquaMaps-GFDL presenting a best case scenario (3% decrease) and those from DBEM-GFDL presenting a worst case scenario (19% decrease).

This decrease in profitability results in a proportional increase in fuel costs relative to total profits, from 8.5% at the baseline scenario to a projected median of 9.1% under climate change across model combinations. Fuel cost would further increase to 14.7 and 17.2% of profits if fuel price were to increase by the long-term and short-term trends, respectively. To prevent this further decrease in profitability, subsidies would need to increase, representing a societal cost of climate change impacts on the fishing industry. In this scenario, by 2050, subsidies must increase by an additional £16.1 million per year for long-term trends, and £23.8 million per year for short-term trends, or at a rate of 19 and 29% per year, respectively, to compensate for the loss in profits.

Results from analyses investigating the potential impact of changing the distribution of fisheries according to species are shown in Table 2. Allowing species to be fished in cells where they had previously been unexploited results in a median

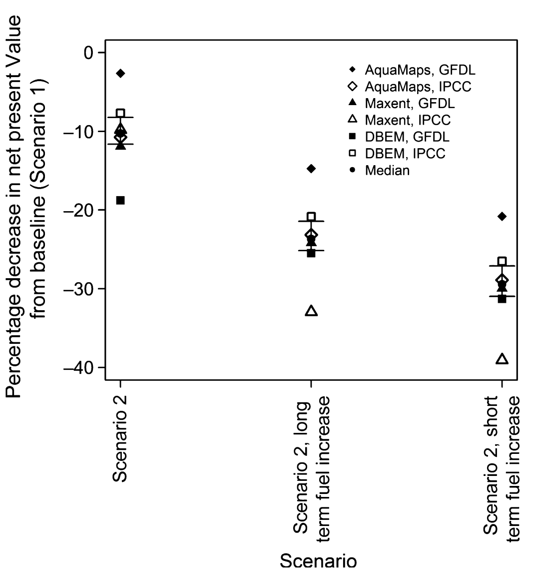

Figure 2 Percentage decrease in Net Present Value of Scenario 2 from Scenario 1 current catch values (baseline). Results are shown with no increase in fuel price and with fuel price increasing according to long-term and short-term trends.

Table 2 Percentage profitability for all model combinations under Scenario 2, with and without the assumption of no alteration of distance travelled.

Model combination	Percentage profitability, Scenario 2	Percentage profitability, Scenario 2 accounting for distance travelled
AquaMaps, GFDL	35.22	35.80
Maxent, GFDL	31.87	32.31
DBEM, GFDL	29.38	29.56
AquaMaps, CMIP3-E	32.29	32.91
Maxent, CMIP3-E	32.63	33.10
DBEM, CMIP3-E	33.39	33.52

increase in profitability of 2.0%, across all model combinations.

Scenario 3: Sustainable future

When all costs are assumed to remain constant and catches reflect the rebuilding of stocks to their maximum levels, a large increase in profitability is observed. Using $d = 0.03$ and $d_{fg} = 0.05$, the NPV over 45 years, assuming no climate change effects on catch (at *Increased costs for Industry* levels), is estimated at 61.7 and 25.5% higher than that currently. When NPV calculations made under Scenario 2 (*Climate Change Impacts Catch*), are also re-calculated to reflect the rebuilding of stocks, there is a comparable increase in profitability (median = 59.4%).

Sensitivity analysis

The choice of maximum catch data set (ICES or SAUP) used to calculate maximum catch makes no difference to the percentage change in MCP (Figure S2a). Although using SAUP data to calculate the actual MCP values gives a greater spread of results, when tested within SDM and GCM, the difference between the two maximum catch data sets was not significant [Figure S2b; Kruskal–Wallis test, $P \geq 0.01$, using species as replicates (n = 31)]. The SDM used did not have a significant effect on either the difference or value of MCP using both sources of maximum catch data, tested within each climate dataset [Kruskal–Wallis test, $P \geq 0.01$, using species as replicates (n = 31)]. Although all species reflect the decreasing trend in total MCP in the UK EEZ, there are variations in species-specific changes in MCP across SDM-GCM model combinations (Figure S3a).

The decrease in total MCP predicted using MCP1 (Equation 1) is mirrored using MCP2 (Equation 3), which predicts a mean total decrease in 10.2% across model combinations. More variation between the algorithms is seen for individual species. For example, MCP1 predicts a median decreases in MCP for all species, whereas introducing environmental suitability into the algorithm (MCP2) produces a wider range of predictions across model combinations (Figure S3b). Specifically, sea bass and sardine are predicted to show median increases in MCP of 19.2 and 4.2%, respectively.

The effect of variation in the MCP algorithm on NPV is shown in Figure S4. In general, MCP2 results in higher values of percentage profitability. When the effect of different model combinations has been accounted for, this difference is significant ($P < 0.05$, df = 5). Furthermore, the variation resulting from different scenarios is strongly significant ($P < 0.01$, df = 5). Despite variation between MCP algorithms, both predict decreases in NPV from the baseline scenario for Scenario 2 and predict increases for Scenario 3 (Table 3).

In UK waters, primary productivity is predicted to decrease by an average of 39% using data from the Medusa model, compared with 5% using data from GFDL ESM2.1. Primary productivity thus contributes a large source of uncertainty to model

Table 3 Median net present values across model combinations using MCP1 (Equation 1) and MCP2 (Equation 2) algorithms.

	Scenario 1: Increased costs for industry	Scenario 2: Climate change impacts catch	Scenario 3: Sustainable future, current fuel	Scenario 3: Sustainable future, future fuel
MCP1	36.18	32.46	59.39	54.19
MCP2, GFDL data	n/a	34.84	60.89	55.98
MCP2, Medusa data	n/a	32.03	59.72	54.58

MCP, maximum catch potential.

projections. The greater decrease indicated by Medusa data is reflected in projections for each species (using MCP2). Thus, all species are predicted to show a median decrease in MCP (Figure S3c). However, although using Medusa primary productivity data resulted in consistently lower median predictions of MCP, this was not always the case for predictions from each model combination. For example, while the total median percentage changes in MCP using GFDL and Medusa data are predicted at −5.3 and −34.5%, respectively, using CMIP3-E data, median total decreases are greater using GFDL PP (−11.3%) than Medusa (−5%) data. This pattern is consistent across MCP predictions for individual species (Table S2). Furthermore, the direction of difference is not consistent across model combinations (Figure S5).

Results detailed in the Supporting Information also show that the choice of discount rate can have a substantial effect on conclusions made if the actual NPV and profitability values are assessed. However, their impact is minimized when comparing results across scenarios, for the same discount rate. Although general conclusions concerning the impact of specific scenarios are robust to the discount rate chosen, the magnitude of variation across models and thus the differences between prediction of profitability using different scenarios increases with lower discount rates.

Discussion

Projected changes in MCP are driven by the predicted decrease in primary productivity across UK waters, using GFDL data. Change in MCP is determined by area and primary productivity, thus presenting the biomass production sustainable by predicted lower trophic level production. This reflects previous findings indicating primary productivity to be one of the key drivers of production at higher trophic levels (Chassot *et al.* 2010; Ottersen *et al.* 2010; Blanchard *et al.* 2012). Explicitly, considering primary productivity when making predictions under climate change is thus crucial if a study aims to predict changes in relative abundance in addition to environmental suitability. Although primary productivity was included as an environmental predictor in projections of environmental suitability, its effect may be diluted by the inclusion of other variables, or, in the case of Maxent, down-weighted in its impact on distribution in favour of key variables influencing distribution, such as temperature.

Cost-benefit analysis

The cost-benefit analysis presents an initial attempt at combining predictions made using species distribution models with economic data and spatially explicit records of catch weight and value. Although the approach developed here is simplistic, it allows an exploration of how key factors will impact fishery profitability.

Scenario 1: Increased costs for industry

The calculation of profitability here aimed to explore the potential effects of realistic changes in fuel price and catch potential of key targeted species, rather than provide accurate absolute values of NPV. The operating profit for 2005, as an average of catch between 2000 and 2010 is estimated at 38.9%. This is higher than the operating profit of the UK fleet calculated by Seafish in 2009, at 25% of total fleet earnings (Curtis and Brodie 2011). However, the result lies within the wider range calculated for different fleet segments, which varied between 3 and 41% (Curtis and Brodie 2011), although these profits decreased in 2010 (Curtis and Anderson 2012). Variability between operating profit estimated here and that calculated by Seafish could be due to a range of factors. For example, as this study aimed to make future projections specific to particular species, it focussed on a set of key species, rather than calculating total profitability. If this set of species represented greater value by weight, estimated profitability would be higher. Opportunity costs are also not accounted for here and labour costs do not include those of the skipper, which can account for a high proportion of costs.

The substantial impact of removing capacity-enhancing subsidies, resulting in negative profitability (−13.1%), agrees with findings and predictions for fisheries worldwide. In 2004, for example, global fisheries were estimated to have a profitability deficit of \$5 billion, compared to the operating profit of \$5.5 billion before subsidies were subtracted (WorldBank and FAO 2008).

Fuel price is estimated to account for 13.8% of the total costs calculated here for the 45 year period. Although fuel costs can represent up to 60% of the cost of fishing for purse seine fisheries in NW Africa (Sumaila *et al.* 2008), this result compares well to values for the SE Australian fishery, calculated at 10–25% of total operating costs (Sumaila *et al.* 2008). However, despite this relatively low percentage, European fisheries are still experiencing difficulties in the face of increasing fuel costs (COM 2006). The influence of fuel cost on profitability is highlighted by the trend of fuel price increase, which with a more conservative long-term price trend, will decrease overall profitability over the whole-study period (2005–50) by 4.5%. Although the increases in fuel price over time seem large in comparison with their effect on overall profitability, this results from the relative contribution of different fishing costs to the overall cost. For example, while fuel accounts for only 10.9% of the costs per unit weight of catch, labour accounts for 37.8%. Although this study does not take into account the potential change in fish price, predictions by the International Energy Agency suggest continued rising fuel prices over the next three decades (IEA 2010), compared with relatively little or no significant increase at the first point of sale for catches (Abernethy *et al.* 2010). For example, although fuel prices for fishers in Cornwall, UK, increased by 359% from 1998 to 2008, fish prices remained relatively stable and failed to balance this increased cost (Abernethy *et al.* 2010). Growth in aquaculture production in the last few decades has also increased consumption of fish from this source which were once wild-caught, thereby further reducing prices relative to the cost of fuel inputs (Sumaila *et al.* 2007). The price fluctuations of aquaculture production as well as supply and demand are thus likely to impact the price of fish in the future and its value at first point of sale (FAO 2012).

Scenario 2: Climate change impacts catch

Future predictions of MCP are estimated to decrease the profitability of UK fisheries irrespective of the modelling procedure or discount rate used. If fishers are to maintain profitability, they must be able to adapt and cope with this change, increasing the value of their catch relative to the costs of obtaining it. The simplest method of doing this would be to increase catch value by improving fish prices at the first point of sale. However, as mentioned above, stagnancy of the price of fish has prevented fishers passing the increased costs of fishing down the market chain and has also stopped them benefitting from times of reduced fish supply, when retail prices have not risen as would be expected (Abernethy *et al.* 2010). In this event, fishers must act to prevent decreases in marine production resulting in a drop in profitability. This may be performed in one of several ways.

Fishers may attempt to increase their catch by increasing fishing effort. They may thus explore potential new locations for particular species and stocks further from port or fish for longer. However, results for Scenario 2 that included distance did not show a great difference in profitability from those assuming no change in distribution, the former showing an increase in median profitability of only 2% across all model combinations. Although the incorporation of distance here presented a simplistic initial assessment and failed to account for altered fuel costs with distance, these results agree with what would be expected in a widely fished area, such as the UK EEZ. The assumption of no change in distribution was chosen to focus the analysis and explore the incentive to change. However, we consider the analysis of changes in distribution to be an important component of adaptation to climate change, which would benefit from a greater depth of understanding and further work. For example, the low profitability resulting from altered marine production presented here is enhanced by rising fuel prices. As the cost of fuel increases with steaming time, both distance and time will be limited by costs. For example, Abernethy *et al.* (2010) found rapidly increasing fuel price influenced how skippers fished and the amount they caught in 2008. They employed methods that would reduce fuel consumption, such as fishing closer to port or only in fine weather (Abernethy *et al.* 2010). Anticipated travel costs due to increased SST and consequential changes in squid distribution have also been observed to decrease the number of boats targeting squid in fisheries off Monterey Bay, California (Dalton 2001).

Fishing behaviour is likely to be modified by long-term changes in MCP and short-term changes in fuel prices. Findings elsewhere suggest that fishers respond rapidly to increased fuel costs (Dalton 2001; Abernethy *et al.* 2010; Tidd *et al.* 2011). Moreover, catch rate has been found to be significant in influencing fishing location choice in the subsequent year (Hutton *et al.* 2004). Particularly, if the profit margins are tight enough for fishers to show behavioural responses to increasing fuel prices, any further decrease in profitability is likely to have severe consequences on the long-term economic viability of the fleets. In contrast, if fuel price is low, fishers may be able to adapt to future changes in MCP by fishing for longer and further away.

An alternative strategy for an individual skipper or fishing vessel to address both rising fuel costs and altered fishing patterns of marine production would be to change fishing gears and target species to respond to changes in species relative abundance. Gears/segments vary considerably in the amount of fuel consumed by a vessel, with towed gears being more consumptive. For example, of the 11 gear types looked at here (bottom trawl, mid-water trawl, bottom seine, mid-water seine, drift nets, fixed nets, pots, lines, picking, dredge and other nets), dredging was most expensive in terms of fuel use, while fixed nets were the least expensive. Choice of gear will thus depend on its relative fuel consumption as well as the relative value, abundance and catchability of target species. However, as results here suggest that overall MCP within the UK EEZ will decrease, a complete shift in species targeted may not sufficiently reverse falling profitability. Diversifying in terms of gears and species targeted would thus seem an optimal adaptation strategy. However, although this study indicates a negative trend in profitability overall, the extent or direction of this trend may vary between fleets and individual fishing vessels. Thus, while the profitability of larger vessels with higher fixed costs (such as fuel) and lesser flexibility may become prohibitively low, smaller vessels may experience constant, or even improved profitability. The frequent shifts to smaller vessels following resource declines (Cheung and Sadovy 2004) reflect the great flexibility of these boats to adapt, potentially benefitting from the reduced capacity elsewhere in the fleet.

It should also be noted here that the need to adapt to altered patterns of fishing and potentially increasing costs may in part be mitigated by increases in fishing efficiency, here assumed to remain constant. As efficiency increases over time, catches per unit effort will improve, thereby increasing profits relative to costs (not including any initial capital costs of improved efficiency) and reducing any projected decrease in profitability and thus the economic impact of climate-induced shifts in species' distributions. Although the potential interaction between increasing efficiency across gears and fleets and the variation in flexibility is complex, it is clear that fishing fleets must improve resilience to uncertain changes in marine production and input costs. Vessels thus need to be efficient, adaptable in terms of gears deployed and species targeted, and resilient to weather and increasing costs.

Scenario 3: Sustainable future

Fishing has affected the population size and structure of many commercially targeted species in the UK EEZ. Results presented here show that although climate change will still have a negative effect on profit following the rebuilding of fish stocks to sustainable levels, this profit remains higher than that estimated for current catch levels. The impact of climate change on future fish populations will therefore depend on how other anthropogenic threats have been managed and mitigated.

Although results here show the impact of climate change additional to that of current fishing pressure, they do not account for potential interactions between these factors. A population with lowered growth rates, weight-at-age and reproductive outputs due to living in suboptimal environmental conditions is less likely to provide the surplus production necessary to sustain fishing pressure, resulting in declining biomass (Cheung *et al.* 2005). Sustainably harvested populations will therefore not only be beneficial in terms of resilience to future climate change and potentially suboptimal environmental conditions, but also in terms of biomass and surplus production, which may lead to increased CPUE and thus a reduction in relative fishing costs.

Despite predictions of decreasing profitability for the UK fishing fleet within its EEZ, analyses undertaken here suggest that the realized impacts of climate change on the UK fishing industry will depend on the capacity to adapt. Results presented here highlight that the key to ensuring adaptation and resilience to climate change in marine fisheries is to ensure adaptive capacity at all levels (Allison *et al.* 2009). Adaptation to climate change has been defined as involving an adjustment in ecological, social or economic systems in response to observed or expected changes in climate stimuli and their effects, to alleviate adverse impacts of change or take advantage of new opportunities (IPCC 2001).

Households within the EU have been found to have higher than average levels of social and economic flexibility (MacNeil *et al.* 2010). This may allow some North Sea fishers to leave the industry during periods of low catches and reduced quotas. However, the historical support of the Common Fisheries Policy (CFP) in the region through subsidies has enabled fleets to be technologically advanced and allowed marginal profitability to develop in overexploited stocks (Hentrich and Salomon, 2006). These assets have given fishers the flexibility to respond to decreased catches by spatial movement and gear changes (Catchpole *et al.* 2005). Despite enhancing fishery flexibility, the complexity surrounding this issue is reflected in discussions surrounding the EU Maritime and Fisheries Fund of the CFP. Although this fund aims to help the CFP towards its targets of sustainability and profitability in EU fisheries, there is also concern that subsidies will increase fleet capacity without sufficient assessment of whether available fisheries resources might support them (OCEAN2012 2013). Although recent decisions of the CFP reform have accepted some capacity increasing subsidies, proposals for subsidizing new vessels have been rejected and those funding data collection and monitoring have been increased (European Commission 2013). Furthermore, the substantial cost to society of artificially maintaining profits through subsidies, thereby buffering the effects of changing economic and ecological conditions has been highlighted here. If efforts are made to support the fishing industry by absorbing rising costs through increased subsidies, this cost to society will increase and the incentive to adapt decrease. The challenge under climate change is therefore to achieve adaptive capacity without increasing subsidies. Reducing subsidies would encourage energy efficiency and contribute towards reducing overcapacity, for example through reducing vessel number or fishing effort. This may in turn encourage the rebuilding of fish stocks and biological resilience (Pauly *et al.* 2002; Sumaila *et al.* 2008), with the potential to improve CPUE. This is corroborated by Arnason (2007), who predicted that a long term reduction in fishing effort could lead to increased sustainable yield and less chance of stock collapse. However, restructuring fisheries may result in short-term impacts on fishers' livelihood. It therefore brings challenges in providing appropriate alternative livelihood strategies in coastal communities which have high dependencies on the fishing sector.

Sensitivity analysis

The algorithm applied here to predict future changes in MCP depends on the assumption that the dominant influence on marine productivity is bottom up, determined by primary productivity. This assumption may not hold if the ecosystem is more strongly controlled by predator or fishing. Whether marine production will follow predictions made using MCP1 or MCP2 will thus depend on this assumption. However, although incorporating relative environmental suitability in the calculation of maximum catch potential (MCP2) results in greater variation in predictions from alternative SDM-GCM combinations, median predictions of change for the majority of species remain negative. This similarity is reflected in calculations of NPV for different scenarios. Thus, although results show that predictions of NPV are sensitive to the MCP algorithm used, the direction of change for each scenario is robust.

Furthermore, predictions of MCP made using each MCP algorithm are predominantly determined by primary productivity. Models projecting the biological response to climate change are less well developed than their physical counterparts, and there is much uncertainty surrounding how primary productivity will respond (Hinder *et al.* 2012). For example, although the temperature sensitivity of primary productivity for a given chlorophyll content may be the most critical factor determining oceanic response of PP to climate, there are further large differences between the coupled atmospheric-ocean global circulation model simulations and thus uncertainties in the predicted biological response (Sarmiento *et al.* 2004). Differences in modelling primary productivity are likely responsible for the disparity between predictions of higher trophic level productivity made here and those elsewhere, which predict slight increase in future productivity and potential catch in UK waters (Cheung *et al.* 2010; Blanchard *et al.* 2012). This study thus highlights the high uncertainty in projections of primary productivity under climate, and it's influence on resulting outputs. Additional sources of variability in the biological input data not addressed here may result from seasonal changes in distribution and species composition at lower trophic levels. While this uncertainty in the biological response remains, this study would benefit from inclusion of a wider range of primary or lower trophic level productivity predictions, enabling the relative uncertainty and range of results stemming from these data to be assessed.

General conclusions regarding the impact of specific scenarios were also found to be robust to the discount rate chosen. Applying a set of conventional and future discount rates provides a useful way of exploring the effect of possible changes in discount rate on the NPV of a resource. For example, it has been suggested that low discount rates favour environmentally sustainable behaviour (Cline 1992), but also that uncertainty might increase discount rates, increasing the preference for money now rather than in an uncertain future. If the added uncertainty imposed by climate change on resource use and stock persistence increase discount rates, any tendency to fish sustainably might be reduced, with implications for management.

Key assumptions

As the MSY was not available for several species investigated here, two estimates of maximum catch were used as proxies to estimate the abundance of each species within the study area. Although averaging maximum catch values over 10 years attempted to take account for interannual variation, estimates of the proxy maximum catch may underestimate MSY for species that are historically under-exploited, whereas those for commercially targeted species which have been unsustainably harvested may be over-estimated. Despite this weakness in assessing the actual magnitude of maximum catch for each species, it is the difference between primary productivity per unit area and habitat suitability in each time period that influences the future calculated value of MCP, and subsequently, the percentage change in MCP that feeds into the cost-benefit analysis. These inaccuracies should not therefore affect the direction or magnitude of the percentage change in MCP.

The cost-benefit analysis undertaken here aimed to explore the effect of specific factors on profitability and was limited in its scope to estimate factors such as when profitability might decrease below minimum viable levels or how fishers might respond. An important factor influencing this is opportunity cost. If profits reduce below those to be made in alternative employment, fishers may leave the fishery. For fishermen whose salary is determined as a proportion of profits, opportunity costs are particularly important in influencing individual decisions on whether to leave the fishery. However, adaptation strategies might also involve temporality switching to alternative occupations when fishing becomes less profitable, such as during winter and bad weather.

Furthermore, 'other costs' in this analysis (including repair costs and labour costs) were assumed not to change by 2050. Although this is unlikely, predicting their change is difficult. Added to these uncertainties are those caused by changing environmental phenomena, which may incur substantial capital costs. For example, the growing frequency of natural disasters such as floods and storms will increase the vulnerability of fishing communities through damage to gear and infrastructure and threat to human health (Allison *et al.* 2009). Increased risk of accidents and damage will push up insurance and likely cause more fishing days at sea to be lost to bad weather (Lane 2010). Furthermore, this analysis did not account for any strategies aimed at decarbonizing the fishing industry in line with commitments to climate change mitigation for increases in marine areas where sulphur-oxide emission levels are controlled. These factors are likely to further add to the cost of fuel of influence fishing location.

Conclusions

Climate change may influence the profitability of UK fisheries either directly, by altering the availability of fish to fishers, or indirectly, by altering the costs of inputs to a fishery, such as fuel and gear maintenance, or the time spent fishing. The response of primary productivity within the UK EEZ to climate change is found to be highly uncertain and further work should explore the impacts of alternative primary productivity projections on outputs. The decrease in marine productivity due to climate change projected here will likely lead to future decreases in total catch value and weight. Thus, although environmental suitability within the UK EEZ may decrease for some species and increase for others, this is not translated to fishery productivity. The degree to which fishery profitability will decrease will further depend on changes in factors such as fuel price and subsidies. Furthermore, it will depend on the price paid for fish, as well as human behaviour and the opportunity costs of fishing. To minimize projected decreases in profitability, fisheries need to build adaptive capacity and diversify, ideally without incurring additional societal costs.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Changes in retail price of diesel between 1988 and 2011 (DECC) with long-term and short-term trends fit using linear models according to time values from a) 1988 and 2011 and b) 2005 and 2011 respectively.

Figure S2. Change in Maximum Catch Potential using MCP1. a) Percentage Change in maximum catch potential between 1985 and 2050 and b) MCP values in the UK EEZ for each time period across all species, using GFDL and CMIP3-E data and maximum catch values obtained from ICES and SAUP.

Figure S3. Change in maximum catch potential in the UK EEZ. Percentage change in maximum catch potential for each species in the UK EEZ between 1985 and 2050 using a) MCP1 (eq. 1) b) MCP2 (eq. 2) c) MCP2 using Medusa primary productivity data.

Figure S4. Percent profitability of Net Present Values for each SDM-GCM combination using the two algorithms for calculating Maximum Catch Potential (MCP1 and MCP2) and Scenario 1: Increased Costs for Industry, Scenario 2: Climate Change Impacts Catch, and Scenario 3: Sustainable Future.

Figure S5. Percent profitability of Net Present Values for each SDM-GCM combination using the MCP2 algorithm with primary productivity data from GFDL and Medusa for Scenario 1: Increased Costs for Industry, Scenario 2: Climate Change Impacts Catch, and Scenario 3: Sustainable Future.

Figure S6. Change in annual net profits between 2005 and 2050 using different conventional and intergenerational discount rates.

Figure S7. Mean changes in percentage profitability of the Net Present Value over a 45 year period using different conventional (r) and future (rfg) discount rates for Scenario 1, 2 and 3.

Data S1. Supplementary Methods and Results.

Table S1. Net Present Value (NPV) and profitability of catch value under different scenarios and using standard discount rate 0.03 and future discount rate 0.05.

Table S2. Change in maximum catch potential (2050–1985) using GFDL ESM2.1 and CMIP3-E climatic datasets, GFDL ESM2.1 and Medusa projections of primary productivity and two algorithms for maximum catch potential.

