Relating marine ecosystem indicators to fishing and environmental drivers: an elucidation of contrasting responses

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Link, J. S., Yemane, D., Shannon, L. J., Coll, M., Shin, Y-J., Hill, L., and Borges, M. F. 2010. Relating marine ecosystem indicators to fishing and environmental drivers: an elucidation of contrasting responses. – ICES Journal of Marine Science, 67: 787–795.

The usefulness of indicators in detecting ecosystem change depends on three main criteria: the availability of data to estimate the indicator (measurability), the ability to detect change in an ecosystem (sensitivity), and the ability to link the said change in an indicator as a response to a known intervention or pressure (specificity). Here, we specifically examine the third aspect of indicator change, with an emphasis on multiple methods to explore the "relativity" of major ecosystem drivers. We use a suite of multivariate methods to explore the relationships between a pre-established set of fisheries-orientated ecosystem status indicators and the key drivers for those ecosystems (particularly emphasizing proxy indicators for fishing and the environment). The results show the relative importance among fishing and environmental factors, which differed notably across the major types of ecosystems. Yet, they also demonstrated common patterns in which most ecosystems, and indicators of ecosystem dynamics are largely driven by fisheries (landings) or human (human development index) factors, and secondarily by environmental drivers (e.g. AMO, PDO, SST). How one might utilize this empirical evidence in future efforts for ecosystem approaches to fisheries is discussed, highlighting the need to manage fisheries in the context of environmental and other human (e.g. economic) drivers.

Keywords: climate change, ecosystem approaches to fisheries, ecosystem dynamics, fisheries, indicators, multivariate analyses.

Received 11 June 2009; accepted 2 October 2009; advance access publication 4 December 2009.

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Introduction

Ecosystems are fundamentally dynamic. Their dynamics are an integrated response of the various ecosystem components (species groups) to several drivers that act independently but coincidentally (though often synergistically or even antagonistically). This presents major challenges for fisheries managers attempting to make the most appropriate decisions regarding fishing strategies, particularly as the world moves towards an ecosystem approach. Calls for an ecosystem approach to fisheries (EAF; Link, 2002; Garcia *et al*., 2003; Pikitch *et al*., 2004; Garcia and Cochrane, 2005; Hall and Mainprize, 2005) have noted the need to account simultaneously for social, economic, and ecological objectives. Such calls have explicitly noted the need to examine the wide range of ecosystem drivers concurrently in terms of how they influence ecosystem dynamics.

Initiated under the auspices of the European Network of Excellence Eur-Oceans (http://www.eur-oceans.eu), the IndiSeas working group was tasked with identifying and applying a suite of ecosystem indicators that would capture the effects of fishing on exploited marine ecosystems worldwide (Shin and Shannon, 2010). Several analyses have been performed to categorize and rank ecosystems in terms of fishing effects (Rochet *et al*., 2005; Bundy *et al*., 2010; Coll *et al*., 2010). Coll *et al*. (2010) considered a small set of "abiotic" indicators that may potentially have accounted for some of the similarities (or differences) found among all the ecosystems examined, as well as "human-induced" indicators, including fishing and socio-economic factors. The IndiSeas collective results confirm that non-fishing drivers or pressures can indeed have notable large-scale effects on ecosystems, so the interpretation of our suite of ecosystem indicators should take these external factors into consideration along with the measures of fishing.

Ecosystem models have been used as a means to explore fishing, environmental, and internal (i.e. interactions, usually trophic, among species) drivers of ecosystem dynamics (Fulton *et al*., 2004, 2005; Shannon *et al*., 2008; Coll *et al*., 2008a, 2009; Mackinson *et al*., 2009). Fishing is the most important driver in many marine ecosystems, but environmental drivers can more strongly impact other types of ecosystem (Mackinson *et al.*, 2009), and the combined effects of the various drivers are often non-additive (Shannon *et al.*, 2008). Using a more empirical approach, Link *et al.* (2002) and Frank *et al.* (2007) similarly found the same outcome for Northwest Atlantic ecosystems, ecosystems previously thought to be dominated by fishing effects. Therefore, it is important to examine the effect of non-fishing drivers on our comparative results of the impacts of fishing across ecosystems.

Given the recognized need, the empirical evidence, and the modelling outcomes that hint at the need for some form of simultaneous examination of both environmental and human drivers, our objectives were to elucidate relatively how much the main anthropogenic and environmental drivers can influence the major indicators of ecosystem structure and function (i.e. the IndiSeas suite of indicators; Shin *et al.*, 2010). The aims of this paper were therefore specifically to partition explainable variance between fishing and other (i.e. environmental) drivers and to explore further empirical evidence for the need to develop thresholds of ecosystem overfishing (while accounting for other drivers). We do so by assessing potential drivers of ecosystem dynamics from a multivariate and multi-ecosystem perspective.

Methods

The data sources have been described in other sister papers in this suite (Coll *et al.*, 2010; Shin *et al.*, 2010). In all, 19 exploited ecosystems were included in the analysis (Table 1), corresponding to upwelling, high latitude, temperate, and tropical marine ecosystems and covering a range of low- to high-productive areas that have been fished at different levels (generally, Pitcher *et al.*, 2009; Worm *et al.*, 2009; these specific ecosystems, Blanchard *et al.*, 2010; Coll *et al.*, 2010; Shannon *et al.*, 2010; Shin *et al.*, 2010). These ecosystems are variously located in the Atlantic and Pacific Oceans and the Mediterranean Sea. Here, we primarily examine what we term response (or more classically, species) indicators that include total biomass, proportion of exploited biomass, mean trophic level (TL) of landings, mean length of the (fish) community, proportion of predators, inverse fishing pressure (1/landings/biomass), and mean lifespan. Shin *et al.* (2010) provide fuller descriptions of these metrics. We also examine what we term explanatory (or more classically, environmental) indicators that include total landings and a human development index, HDI [United Nations Development Program (UNDP), http://hdr.undp.org], both of which we classify as human drivers. The HDI is an index used to rank countries by the level of human development according to the UNDP. It combines normalized measures of life expectancy, literacy, educational attainment, and the standard of living as measured by the gross domestic product *per capita* for each country worldwide. In addition to the human drivers, we also examined a set of environmental drivers including annual mean sea surface temperature (SST, °C; Smith and Reynolds, 2004), and some form of broad-scale climate forcing, i.e. *El Niño*–Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) index, or the North Atlantic Oscillation (NAO) and Atlantic Multidecadal Oscillation (AMO) index, depending on which ocean an ecosystem is in. We note that while the explanatory variables listed here are not *sensu strictu* drivers in the technically causal sense of the term, they are indeed a subset of ecosystem processes (or more accurately, indices thereof) that drive ecosystem dynamics.

Multivariate methods: BV-STEP

The multivariate non-parametric technique BV-STEP, implemented in the software PRIMER-E (Clarke and Gorley, 2006; http://www.primer-e.com), was applied for each ecosystem to assess the potential drivers of ecosystem dynamics. In this approach, a resemblance matrix was first created for each ecosystem using time-series of normalized data and Euclidean distance. The distance matrix was converted to a lower triangular distance matrix and imported to PRIMER-E for BV-STEP analysis.

Initially, BV-STEP was a method developed for assessing matches between environmental variables and the species composition of sampling sites (time or distance). Specifically, it attempts to find the best combination of environmental (or driver) variables that maximize the match, measured using Spearman rank correlation (ρ) between sites in terms of their species composition and environmental gradient (Clarke and Gorley, 2006; Clarke *et al.*, 2008). Although here we are not exactly tackling the same problem, the concept is sufficiently general for the test to be reasonably applied to our case. The aim is to arrive at the best combination of the subset of the environmental variables (in this case, the environmental drivers PDO, ENSO, SST, AMO, and normalized values of the human drivers total landings and HDI) that maximize the match (higher rank correlation, ρ) between the temporal pattern in these drivers and the temporal pattern in the ecosystem response indicators to indicate the best explanatory variables. A resemblance matrix of inter-year distance was created for each ecosystem based on the indicator time-series. This resemblance matrix represented the response matrix, whereas the corresponding time-series of landings and environmental variables represented the drivers' data matrix. Significance of the rank correlation was determined using permutation testing. Once a first BV-STEP procedure had been applied, it was iterated another 999 times, using successive permutations of the sample labels of one of the two sets (in this case, driver indicators or ecological indicators) and recording the value of ρ for each run. The p-value of the test was determined by taking the ratio of the number of ρ values computed under the null hypothesis that they are greater than or equal to the actual ρ values computed initially and the total number of permutations.

Most datasets are characterized by large numbers of missing values for some or all the indicators. To address this, we employed two approaches for this method by either applying row-wise deletion of all time-series with missing data, or in cases where there were only one or few datapoints (mainly total landings for the Bay of Biscay in 1999 and for Portugal in 1985), the average of the series was used to fill in the missing values.

Multivariate methods: canonical correlation

Multivariate analysis was also undertaken using the method of canonical correlation (CanCorr) in the SAS statistical package. This approach seeks to find linear combinations of explanatory (i.e. SST, HDI, climate-forcing, and landings) and response (various measures of biomass or proportions thereof) variables along canonical axes. It is a similar technique to PCA and factor analysis, but it attempts to relate the canonical variates between response and explanatory factors. It also provides a mechanism to partition explainable variance and, in so doing, provides an assessment of the relative importance of key processes or drivers (explanatory indicators) as they influence ecosystem structure and function (response indicators). The method also provides

Table 1. Ecosystems considered in the comparative approach, ancillary summary information, and the extent of the data time-series used in the analyses.

Coastal ecosystem	Geographic area	Type of ecosystem	Surrounding countries	Large marine ecosystem	Extent of catch time-series	Extent of survey time-series
Adriatic Sea (North Central)	Central Mediterranean	Temperate	Italy, Slovenia, Croatia, Bosnia-Herzegovina, Montenegro	Mediterranean	1975–2006	1976–2006
Baltic Sea (Central)	NE Atlantic	Brackish temperate	Germany, Estonia, Sweden, Poland, Russia, Lithuania, Latvia, Finland, Denmark	Baltic Sea	1974–2005	1974–2005
Barents Sea	NE Atlantic	High latitude	Norway	Barents Sea	1984–2006	1984–2006
Bay of Biscay	NE Atlantic	Temperate	France	Iberian Coastal	1993–2005	1994–2005
Benguela (Southern)	SE Atlantic	Upwelling	South Africa	Benguela Current	1980–2006	1986–2006
Bering Sea, Aleutian Islands	NE Pacific	High latitude	Alaska, USA	E Bering Sea	1977–2006	1977–2006
Canada coast (West)	NE Pacific	Seasonal upwelling	Canada	Gulf of Alaska	1980–2005	1980–2007
Catalan Sea (Southern)	NW Mediterranean	Temperate	Spain	Mediterranean	1976–2006	1978–2003
Guinean EEZ	E Central Atlantic	Upwelling	Guinea	Guinea Current	1985–2006	1985–2000–2001–2006
Humboldt (Northern)	SE Pacific	Upwelling	Peru	Humboldt Current	1983–2006	1983–2006
Humboldt (Southern)	SE Pacific	Upwelling	Chile	Humboldt Current	1993–2005	1993–2005
Irish Sea	NE Atlantic	Temperate	Ireland, UK	Celtic–Biscay Shelf	1973–2003	1980–2005
Mauritanian EEZ	E Central Atlantic	Upwelling	Mauritania	Canary Current	1990–2005	1982–2007
Morocco (Sahara Coastal)	E Central Atlantic	Upwelling	Morocco	Canary Current	1993–2005	1998–2005
North Sea	NE Atlantic	Temperate	UK, Norway, Denmark, Germany, Netherlands, Belgium	North Sea	1963–2003	1983–2006
Portuguese EEZ	NE Atlantic	Upwelling	Portugal	Iberian Coastal	1981–2006	1981–2006
Scotian shelf (Eastern)	NW Atlantic	Temperate	Canada	Scotian Shelf	1960–2006	1970–2006
Senegalese EEZ	Eastern central Atlantic	Upwelling	Senegal	Canary Current	1981–2005	1981–2000; 2001–2005
US coast (Northeast)	NW Atlantic	Temperate	USA	NE US continental shelf	1964–2005	1963–2007

Table 2. Importance of ecosystem drivers across the 19 ecosystems resulting from the BV-STEP analysis. Black boxes are significant, grey boxes marginally significant. Blank cells indicate that an indicator was either not applicable to the particular ecosystem or did not emerge as having detected a relationship with the response indicators. AMO, Atlantic Multidecadal Oscillation Index; PDO, Pacific Decadal Oscillation; ENSO, *El Niño* – Southern Oscillation; SST, sea surface temperature; HDI, Human Development Index.

Drivers	Adriatic Sea	Baltic Sea	Barents Sea	Southern. Benguela	Bering	Biscay	Chile	Eastern Scotian Shelf	Guinea	Irish Sea	Mauritania	Morocco	North Sea	Peru	Portugal	Southern Catalan Sea	Senegal	US northeast	West coast Canada
AMO		■				▒			▒	■		■	■				■		
PDO					■														
ENSO							▒							■					■
Landings	■		■	■	■			■			▒				■		■	■	
SST		■	■			▒					▒		■			■			
HDI			■	■	■					■		■	■	■	■		■	■	

Ecosystems

Table 3. Summary metadata of the CanCorr approach for the 19 ecosystems examined.

Of the 19 ecosystems	
Five had insufficient data or time-series that were too short	26.3%
Three had insignificant results	15.8%
Four had significant CanCorrs on the first axis only	21.1%
Seven had significant CanCorrs	36.8%
Of the 11 significant CanCorr ecosystems	
Seven had canonical axes explaining >90% of the explainable variances	63.6%
Ten had canonical axes explaining >80% of the explainable variances	90.9%

Those ecosystems retained in the analysis are shown in Table 4.

some measure of statistical significance in terms of the canonical relationships among variables.

Owing to the nature of this approach and unlike BV-STEP, those ecosystems for which there were insufficient data (time-series shorter than the number of variables, or time-series with many missing years; more than one quarter of the time-series) were not analysed. Therefore, of the 19 ecosystems posited throughout this suite (Table 1), we were only able to analyse 14 using this statistical method. Here, we only plot and present results for the first two canonical axes, noting those instances where the second axis was marginally significant.

One of the advantages of using multiple statistical tools is that it helps one to place more weight on the results and conclusions drawn. Although the two methods here have some structural differences, differences in assumptions, and differences in underlying approach, they have different methods of exploring and elucidating the data, which seemed reasonable, and the two methods are complementary given their different underlying methodologies. BV-STEP is more simple (non-parametric) than CanCorr, and it is basically a multiple correlation between explanatory and predicted variables. CanCorr also assesses the relationship between variables, but also allows for partitioning of the explainable variables to be obtained, along with the importance of each driver. There is a notable precedent of utilizing multimodel inference in the fields of ecology, oceanography, and fisheries science. Moreover, some methods are good at identifying relationships from time-series of any length, whereas others are severely constrained by the length of the time-series; some have non-parametric assumptions, others do not, etc. Therefore, in cases where both statistical methods concur, credence is lent to the results and conclusions drawn.

Results

BV-STEP

Overall when comparing across ecosystems, HDI is the most important ecosystem driver in most ecosystems, followed by total landings as the next most important (Table 2). Of the environmental variables, AMO and SST were most important, followed by ENSO and PDO. In some ecosystems, the relationship between the response and the drivers was not significant, and the rank correlation (ρ) was generally low [e.g. Biscay, Southern Humboldt (Chile), Guinea, and Mauritania]. That these ecosystems displayed non-significant results might be an indication of the limited temporal extent of the data (Table 1; cf. Blanchard *et al*., 2010; Coll *et al*., 2010; Shin *et al*., 2010), rather than a

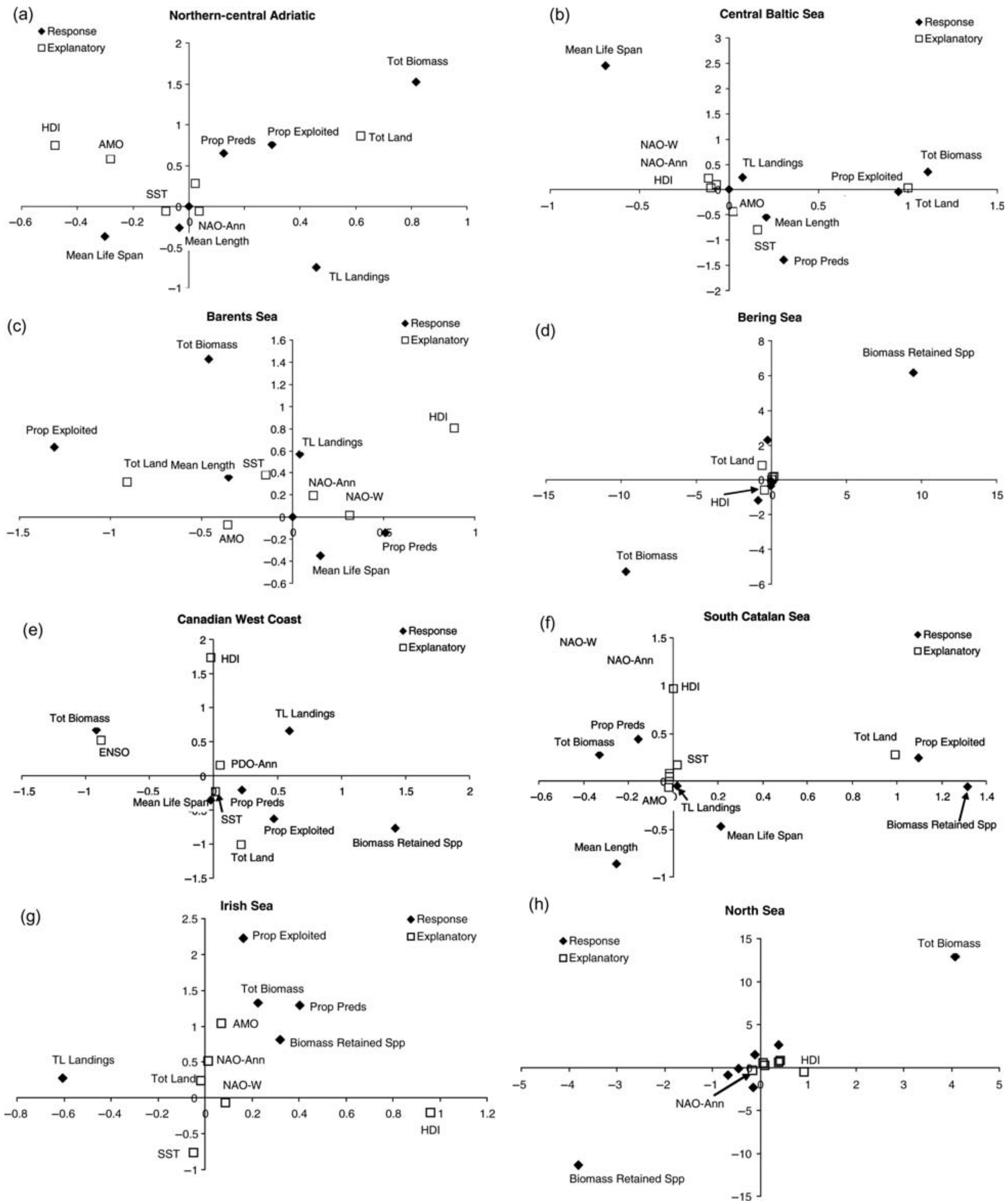

Figure 1. CanCorr biplots for ecosystems with sufficient data. The response (black diamonds) and explanatory metrics (open squares) are plotted on the same axes to demonstrate comparability of scale. HDI, human development index; SST, sea surface temperature; NAO-W, winter North Atlantic oscillation index; NAO-Ann, annual NAO index; AMO, Atlantic Multidecadal Oscillation index; Tot Land, total landings; ENSO, *El Niño*–Southern Oscillation; PDO, Pacific Decadal Oscillation; Prop Preds, proportion of predator biomass; TL, trophic level of landings; Tot Biomass, total surveyed biomass; Prop Exploited, proportion of exploited biomass. (a) North–central Adriatic, (b) central Baltic Sea, (c) Barents Sea, (d) Bering Sea, (e) Canadian West Coast, (f) Southern Catalan Sea, (g) Irish Sea, (h) North Sea, (i) Portugal, (j) eastern Scotian Shelf, and (k) Northeast US shelf. Note that for ecosystems (g)–(j), only the first canonical axis is statistically significant.

(*Continued on next page*).

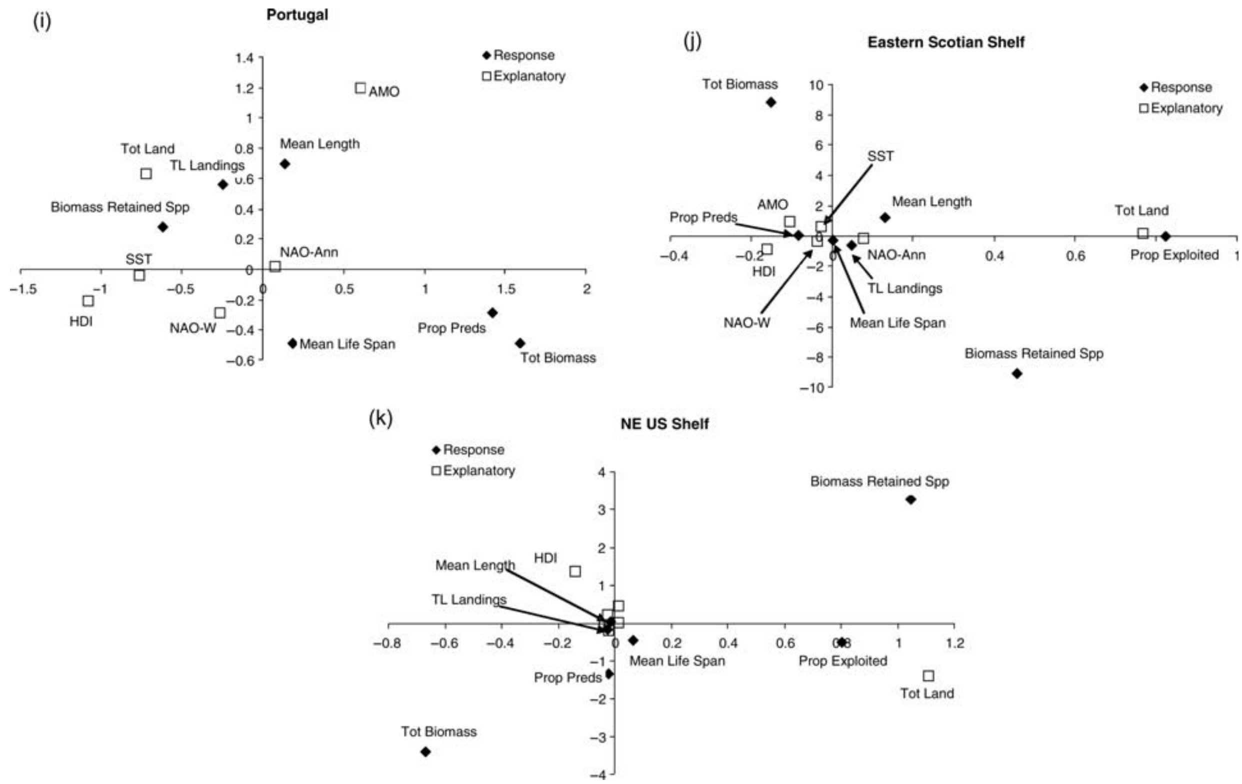

Figure 1. Continued.

Table 4. Summary of CanCorr results for all 11 ecosystems that were significant.

	Explainable variance (%)			Highest absolute value weighted variable	
System	Axis 1	Axis 2	Cumulative	Response	Explanatory
Adriatic Sea (NC)	82.2	13.3	95.5	Tot Biomass	Tot Land
Baltic Sea (Central)	93.2	4.8	98.0	Tot Biomass	Tot Land
Barents Sea	74.1	15.5	89.6	Prop Exp	Tot Land, HDI
Bering Sea	65.3	30.9	96.2	Tot B, Inv F Pressure (B/Y)	Tot Land
Canada, West Coast	63.9	19.1	83.0	Inv F Pressure	ENSO
Catalan Sea (S)	72.4	24.6	97.0	Inv F Pressure, Prop Exp	Tot Land
Irish Sea	94.1	–	94.1	TL Landings	HDI
North Sea	68.6	–	68.6	Tot Biomass	Tot Land, SST
Portugal	81.1	–	81.1	Tot Biomass, Prop Preds	HDI
Scotian Shelf (E)	97.0	–	97.0	Prop Exp	Tot Land
US Shelf (NE)	95.2	3.6	98.9	Inv F Pressure	Tot Land

Tot Land, total landings; HDI, human development index; SST, sea surface temperature; ENSO, *El Niño*–Southern Oscillation; Prop Preds, proportion of predator biomass; TL Landings, trophic level of landings; Tot Biomass, total surveyed biomass; Prop Exp, proportion of exploited biomass, Inv F Pressure, inverse fishing pressure.

minimal or absent relationship between the driver and the ecosystem response indicators.

Collectively all ecosystems showed a range from low to high susceptibility to drivers, six showing only one or no important driver, nine showing two important drivers, and four showing more than two drivers as important. Interestingly, ecosystems with a higher response to the drivers were ranked as less heavily impacted by fishing in terms of recent states (i.e. 2003–2005; cf. Blanchard *et al*., 2010; Coll *et al*., 2010; Table 2). This may be because historically these systems have already experienced notable exploitation and more recently are more responsive to other drivers.

Canonical correlation

A summary of the major CanCorr results is provided in Table 3. From the 19 ecosystems initially included in this study, there were sufficient data to execute CanCorr on just 14 ecosystems, and significant results were obtained for only 11. If one looks at the biplots for those ecosystems with significant CanCorr, the general pattern is that there are typically one or two explanatory indicators (on the first axis) that produce the spread in the data, with one or two response indicators similarly spreading the data, and most other indicators clumped near the origin (Figure 1). Some ordinations did a better job than others in terms of spreading the indicators across multivariate space (cf. Figure 1d, h, j, k),

Table 5. Comparison of the importance of ecosystem drivers (anthropogenic and environmental) as indicated by BV-STEP and CanCorr.

Ecosystems	CanCorr	BV-STEP
Barents sea	Total landing, HDI	Total landing, HDI, SST
Bay of Biscay	–	SST, AMO[a]
Bering Sea, Aleutian Is.	Total landing	Total landing, HDI, PDO
Central Baltic Sea	Total landing	SST, AMO
Eastern Scotian shelf	Total landing	Total landing
Guinea	–	AMO[a]
Irish Sea	HDI	HDI, AMO
Mauritania	–	Total landing, SST[a]
North Central Adriatic Sea	Total landing	Total landing
Northeast United States	Total landing	Total landing, HDI
North Sea	Total landing, SST	IHD, SST, AMO
Northern Humboldt	–	HDI, ENSO
Portugal	HDI	HDI, Total landing
Morocco (Coastal Sahara)	–	HDI, AMO
Senegal	–	HDI, AMO, Total landing
Southern Benguela	–	Total landing, HDI
Southern Catalan Sea	Total landing	SST
Southern Humboldt	–	ENSO[a]
West coast Canada	ENSO	ENSO

"–" denotes either lack of data or a lack of a significant correlation between drivers and response.
[a]A lack of a significant rank correlation (ρ) between selected drivers and the response matrix.

particularly with respect to the second axis. Yet despite this clumping of data, the pattern described above generally held.

Almost two-thirds of the canonical relationships explained more than 90% of the variance, and 10 of 11 explained more than 80% of the variance (Tables 3 and 4). Additionally, when one examines those indicators that had the highest weightings, they were usually total biomass or the proportion of exploited biomass as the most prominent response indicators, and total landings or HDI as the most prominent explanatory (i.e. driver) indicators (Table 4). Total landings constituted the main explanatory variable for the Mediterranean case studies, central Baltic Sea, Bering Sea, eastern Scotian Shelf, and Northeast US shelf system. HDI was the main factor for the Irish Sea and Portugal, whereas the ENSO index was the most important driver for Canada West Coast. HDI and Landings were often on opposites sides of an ordination. The most straightforward interpretation we can provide is that the landings from a fishery often decline as the country develops, as measured by the HDI. This development provides both the capital investment and fishing know-how to fish new fishing grounds and previously unfished stock/species, hence normally resulting in declining catch rate and ultimately sequential overexploitation/depletion of incumbent stocks.

Therefore, similar to the BV-STEP results, collectively these results demonstrate the overriding prominence of human-induced drivers on these ecosystems relative to climate drivers. It is not that climate drivers do not show up as important or secondary factors in many ecosystems, but rather that the landings and HDI indicators were almost always one of the most highly weighted indicators in all these ecosystems.

Comparison of the two methods

Comparing the outcomes of the two methods (Table 5), it is apparent that despite the caveats among the two, overall both multivariate methods detect similar drivers. However, owing to the nuances among the methodology, BV-STEP tended to highlight more explanatory variables than CanCorr. Except the Baltic and southern Catalan Seas, all ecosystems at least shared a major driver (environmental or anthropogenic) in the analyses. Moreover, both methods showed that human drivers (HDI or Landings) were the most prominent explanatory factors.

Discussion

Collectively our results confirm that the dominant drivers in a wide range of ecosystems are human-related, usually to fishing, but also more generally to human development (see HDI indicator and related discussion in Coll *et al.*, 2010). That fishing can impact marine ecosystems is not surprising (Pauly *et al.*, 1998, 2002; Jackson *et al.*, 2001; Worm *et al.*, 2009). What is intriguing is that this pattern generally holds across such a wide array of ecosystems with very different dynamics, exploitation histories, environmental contexts, and socio-economic realities (including low- to high-income countries). We admit that basically all the ecosystems here have undergone fisheries exploitation, but the range has varied considerably (Bundy *et al.*, 2010; Coll *et al.*, 2010). Given the types of ecosystem response indicators we selected, it is logical that fishing in particular will have a primary effect, as modulated by local conditions. This is in line with a ranking of the ecosystems from lesser to more strongly impacted by fishing (Coll *et al.*, 2010), but understanding the degree of modulation merits further consideration.

Our results also confirm the need to examine simultaneously a broad suite of ecosystem drivers. As in other modelling and empirical studies (Link *et al.*, 2002; Fulton *et al.*, 2004, 2005; Frank *et al.*, 2007; Coll *et al.*, 2008a, 2009; Shannon *et al.*, 2008; Mackinson *et al.*, 2009), it was apparent from these analyses that both environmental and human drivers influence marine ecosystems. The relative importance of both types of driver, as briefly elucidated here, also remains an important topic to examine as we move towards the implementation of an EAF. Claiming that only one or other type of driver is the only thing to worry about (or to ignore as the case may be) in a management context seems imprudent.

Our results confirm that the set of response variables we used are both sensitive and relatively specific to fishing (i.e. using landings as a proxy). The results support selection of indicators *a priori* to assessing the ecosystem effects of fishing (Shin *et al.*, 2010), with sensitivity and specificity as the two major properties desired (Rice, 2003; Rochet and Trenkel, 2003). Apart from considering fishing effects, this set of indicators is also meant to track changes in ecosystem structure and functioning. For example, fish length is related to many physiological and ecological processes (Shin *et al.*, 2005), and the total length of the fish in landings and the proportion of predators are related to the trophic structure (Cury *et al.*, 2005).

The importance of environmental relative to human drivers was variable across ecosystems, ranging from very minor through about equal to dominant. It is important to note that our analyses can help either to quantify the contributions of different drivers on ecosystems dynamics or to define in which cases environmental drivers cannot be ignored in an EAF. The situations where some form of environmental drivers seemed to be equal or more prominent were usually located in eastern ocean boundary ecosystems. The role of upwelling as a dominant feature has been well-documented for such ecosystems (Shannon *et al.*, 2008, 2010). That said, even in those ecosystems that are understood to be primarily dominated by fishing (e.g. the Northeast Unites States, eastern Scotian Shelf, and North Sea), it is clear that there is some degree of environmentally driven change (see discussion in Coll *et al.*, 2010). However, in those systems, it is currently not driving more than 35% of the variability, so they do not dominate to the same extent as in eastern ocean boundary systems (e.g. Portugal, Bering Sea, southern Humboldt, and West Coast Canada). This distinction across the types of ecosystems (Coll *et al.*, 2010) will remain important because not all processes have the same relative prominence in all marine ecosystems.

In the Baltic and southern Catalan Sea, BV-STEP identified environmental drivers as more important, whereas human drivers appeared to be more important in the CanCorr analyses. Therefore, it is possible to see differences between the two methods in the prominence of the type of driver selected for some ecosystems. For some ecosystems, the CanCorr analysis does not produce results because of an insufficiency of data (Tables 3 and 5), whereas BV-STEP does produce a result with some of the drivers selected as most important (e.g. the southern Benguela) or indicative that the relationships are not significant (e.g. Mauritania, Guinea, southern Humboldt). However, in most instances, similar results emerge from using both methods. This does not mean that one method is better than the other, though each has its strengths and drawbacks. Both methods are similar in the sense that they are both multivariate, but one elucidates linear relationships between response and drivers (CanCorr), whereas the other looks for a driver or group of drivers that maximize the association between the response matrix and the environmental matrix using non-parametric rank correlation. Despite such methodological differences, they were both generally able to capture the prominence of the same major drivers when examined across all ecosystems, i.e. overall both methods indicated the importance of Landings and HDI as human drivers and SST/AMO as environmental drivers.

Other studies that have examined human (mainly fishing) and environmental drivers simultaneously for a subset of the ecosystems we examine here have found similar outcomes. For instance, using a trophic modelling approach, Mackinson *et al.* (2009) generally found that the North Sea, the southern and northern Benguela, and the southern Catalan Sea were all mainly driven by fishing, although the internal trophic-flow dynamics were implicitly considered in their analyses of fishing. Our results confirm the importance of fishing as an ecosystem driver, but with the caveat that we seemed also to detect some (though a smaller percentage of explainable variance) response to environmental drivers. Also, in Mackinson *et al.* (2009), the southern Humboldt and Irish Sea were driven by environmental factors, which our results confirm. Additionally, Shannon *et al.* (2008) found a similar outcome for the Humboldt and Benguela ecosystems, though with the recognition that fishing was secondary but also important in those locales. Therefore, exploitation is modulated by the environmental conditions in which it operates, as seen in these upwelling situations. That there are subtle distinctions among various studies using different methods is to be expected. That there are more general similarities than distinctions demonstrates the power of such a comparative approach and confirms the prominence of major processes in an ecosystem. We support the principle of simultaneous examination of multiple drivers, but also suggest the use of multiple model or multiple (statistical) method inference when determining the relative prominence of human and environmental drivers. It may be that some methods are more appropriate for a given ecosystem given the type and extent of data available and that such considerations should be denoted explicitly. Yet, despite all the nuances noted here, the general patterns found in our work and those of other studies generally concur that across a wide range of ecosystems, fishing is a prominent driver and environmental drivers can also be important, depending on local conditions.

After accounting for environmental conditions, careful attention needs to be paid to the development of ecosystem overfishing definitions (Jennings, 2005). In other words, we need to develop indicators of ecosystem overfishing that are conditioned upon environmental factors. Several attempts to develop such system-wide indicators of overfishing are ongoing (Murawski, 2000; Link, 2005; Coll *et al.*, 2008b; Libralato *et al.*, 2008). The indicators in this suite could, among many others, serve as the basis for such overfishing definitions. However, there remains the need to identify regions or points of inflection in our suite of ecosystem indicators relative to these external pressures. Preliminary work using logistic and probit-type approaches (DY, unpublished data) proved elusive given the complexities of such a wide array of collinear drivers and responses. Clearly, further work to establish such thresholds, both empirically and via modelling, remains an important challenge.

One of the key challenges we are facing when implementing EAF (from a systems perspective) is how to document the relative importance of concurrent drivers, and subsequently how to deal with managing fisheries in the context of these multiple drivers. We trust that the approach presented here serves as one feasible, extant example of how one could evaluate the relative importance of ecosystem drivers simultaneously. We also affirm the need to do so. Even after fulfilling this observed need, one of the next challenges will be what to do with such information. Therein lies great opportunity.

Acknowledgements

We thank the Euroceans IndiSeas Working Group, funded by the European Network of Excellence EUR-OCEANS (FP6, contract 511106), IRD (l'Institut de Recherche pour le Développement, France), and the European collaborative project MEECE—Marine Ecosystem Evolution in a Changing Environment (FP7, contract 212085), plus in-kind contributions from the institutes of the various authors for funding this project. We also acknowledge all participants at the IndiSeas workshops for their inputs, ideas, and access to data. During part of the work, MC was partially supported financially by PFI and post-doctoral fellowships from the Spanish Ministry of Science and Technology, by the European Community Marie-Curie Post-doctoral Fellowship through the International Outgoing Fellowships (IOF; Call: FP7-PEOPLE-2007-4-1-IOF) and by Dalhousie University (Halifax, Canada). LJS was supported financially by the MEECE project and Astrid Jarre's South African Research Chair in Marine Ecology and Fisheries.

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doi:10.1093/icesjms/fsp258