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Relationships among fisheries exploitation, environmental conditions, and ecological indicators across a series of marine ecosystems

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Abstract :

Understanding how external pressures impact ecosystem structure and functioning is essential for ecosystem-based approaches to fisheries management. We quantified the relative effects of fisheries exploitation and environmental conditions on ecological indicators derived from two different data sources, fisheries catch data (catch-based) and fisheries independent survey data (survey-based) for 12 marine ecosystems using a partial least squares path modeling approach (PLS-PM). We linked these ecological indicators to the total biomass of the ecosystem. Although the effects of exploitation and environmental conditions differed across the ecosystems, some general results can be drawn from the comparative approach. Interestingly, the PLS-PM analyses showed that survey-based indicators were less tightly associated with each other than the catch-based ones. The analyses also showed that the effects of environmental conditions on the ecological indicators were predominantly significant, and tended to be negative, suggesting that in the recent period, indicators accounted for changes in environmental conditions and the changes were more likely to be adverse. Total biomass was associated with fisheries exploitation and environmental conditions; however its association with the ecological indicators was weak across the ecosystems. Knowledge of the relative influence of exploitation and environmental pressures on the dynamics within exploited ecosystems will help us to move towards ecosystem-based approaches to fisheries management. PLS-PM proved to be a useful approach to quantify the relative effects of fisheries exploitation and environmental conditions and suggest it could be used more widely in fisheries oceanography.

Highlights

► We quantified the effects of fishing and environment on two groups of indicators. ► There were consistencies across 12 ecosystems in the association among indicators. ► We derived commonalities in the links among indicators, fishing and environment.

Keywords : ecological indicators, environmental conditions, fisheries exploitation, marine ecosystems, partial least squares path modeling

1. Introduction

There are two main mechanisms controlling the trophodynamics of marine ecosystems: (1) bottom-up control from plankton species that are directly influenced by ocean climate (e.g., Richardson & Schoeman, 2004; Ware and Thomson, 2005; Conti and Scardi, 2010); and (2) top-down control from upper-level predators and fisheries exploitation (e.g., Jennings et al., 2001) that directly impact fisheries production. In the past few decades, ecosystems globally have witnessed climate regime shifts (e.g., Gedalof and Smith, 2001) and boom-bust fisheries exploitation (e.g., Jennings et al., 2001). The difficulty of disentangling cumulative effects of fishing from ocean climate processes poses problems in the management of marine living resources (Kirby et al., 2009; Conti and Scardi, 2010). Analyzing patterns of community and ecosystem variations across a number of ecosystems with contrasting anthropogenic pressures and environmental conditions should provide new insights into how these factors interact and influence the structure and functioning of marine ecosystems (Rouyer et al., 2008; Link et al., 2010). This will help inform ecosystem-based approaches to fisheries management (Sissenwine and Murawski, 2004; de Young et al., 2008; Link, 2011).

Ecosystem indicators are quantitative physical, chemical, biological, social, or economic measurements that serve as proxies for ecosystem attributes and are increasingly used to inform ecosystem status (e.g., Rochet and Trenkel, 2003; Cury and Christensen, 2005; Shannon et al., 2010; Shin et al., 2010b; Shin and Shannon, 2010). Multiple indicators are needed to reflect the complexity of ecosystems, effects of different drivers, and management objectives (Jennings 2005; Fulton et al., 2005; Rochet and Trenkel, 2009). Hundreds of ecosystem indicators have been proposed, including environmental, species-based, size-based, trophic-based, and integrated indicators (Rochet and Trenkel, 2003; Fulton et al., 2004, 2005; Cury and Christensen, 2005; Shin et al., 2010b).

However, the application of multiple indicators presents two major challenges: (1) interpreting different or even conflicting signals from different ecosystem indicators; and (2) understanding potential correlations among indicators either through functional or sampling dependencies (Cotter et al., 2009; Petitgas and Poulard, 2009). Principal component analysis (PCA), dynamic factor analysis (DFA), and partial least squares regression (PLSR) approaches have been used to combine different ecosystem indicators (Cotter et al., 2009; Petitgas and Poulard, 2009; Fu et al., 2012). These approaches are useful when indicators refer to a single dimension, such as one facet of the ecosystem functioning, which has been termed the latent concept (Trinchera and Russolillo, 2010). When indicators cover different dimensions, each referring to a different latent concept, then single dimension approaches are difficult to interpret. The framework of partial least squares path modeling (PLS-PM, Esposito Vinzi et al., 2010) is more suited to these problems and allows investigation of relationships among latent concepts and their relationships with their corresponding indicators.

The basic idea behind PLS-PM (Fig. 1) is that the complexity inside a system can be addressed through a relational network among latent concepts, called Latent Variables (LVs), each measured by several observed variables defined as Manifest Variables (MVs) (Wold, 1980; Esposito Vinzi et al., 2010; Sanchez, 2013). Here we defined external pressure LVs for fisheries exploitation and environmental conditions. We explored how these LVs are related to the ecological LVs represented by various ecological indicators.

Each ecological indicator responds differently to fishing and environmental pressures (Link et al., 2010). Consequently, we considered a suite of seven ecological indicators that were divided into two groups (catch-based and survey-based indicators) to represent two LVs, reflecting trophic and community structure of landed fish and of surveyed fish, respectively. We investigated how the two ecological LVs were connected with fishing and environmental variables. As a further step, we explored how these two ecological LVs were related to the resource potential reflected by total system biomass. While we do not claim to achieve causal relationships, we quantified trelationships among the LVs through correlations (i.e., path coefficients) provided by PLS-PM.

Here we analyze 12 exploited marine ecosystems using the PLS-PM approach. These data form part of the IndiSeas collaborative program (Shin et al., 2012; www.indiseas.org) developed under the auspices of EUROCEANS and IOC/UNESCO. The aim of IndiSeas is to perform comparative analyses of ecosystem indicators for quantifying the impact of fishing on marine ecosystems and providing useful information in the context of decision support for ecosystem-based approaches to fisheries management. The aim of the comparative analysis was to contribute to an improved understanding of fishing and climate impacts on the structure and functioning of exploited marine ecosystems.

2. Methodology

2.1 Ecosystems and indicators

The 12 marine ecosystems that we explored were the Barents Sea, Gulf of Cadiz, eastern English Channel, Guinean EEZ, Ionian Sea Archipelago, New Zealand Chatham, North Sea, Portuguese EEZ, eastern Scotian Shelf, western Scotian Shelf, Northeast USA and West Coast Canada. These ecosystems have different species compositions, fishery exploitation histories, and environmental influences (Shin et al., 2010b; www.indiseas.org). The period covered by the data for each ecosystem was listed in Table 1. They all have the complete set of indicator time series (>10 years duration) described below. An example of the data time series is provided in Table A.1 of Appendix A to show how data were structured. Environmental variables both at local (e.g., sea surface temperature) and basin scales (e.g., Pacific Decadal Oscillation (PDO), Atlantic Multidecadal Oscillation (AMO)) can be important drivers of ecosystem dynamics (e.g., Hare and Mantua, 2000; Wells et al., 2008; Link et al., 2010; Molinero et al., 2013; Alheit et al., 2014). For each ecosystem, regional experts were asked to provide two global and up to three local environmental indices that were considered important to biological production and ecosystem processes, based on published and unpublished information. These local- and basin-scale environmental indices (Table 1) were used for the environmental latent variable (LV), provided that there was at least 10 years of data that overlapped with the ecological indicator data. Total landings and exploitation rate (defined as the ratio of total landings to biomass of all landed species) were used for the exploitation LV.

A list of indicators was selected during the first phase of the IndiSeas project (Shin and Shannon. 2010) based on a set of criteria adapted from Rice and Rochet (2005). These indicators included annual time series of mean length of fish in the community, trophic level of landings, proportion of predatory fish biomass, and mean life span in the community (Shin et al., 2010b). During the second phase of the IndiSeas project, additional indicators were selected, relating to biodiversity and conservation, including annual time series of intrinsic vulnerability index of the catch, marine trophic index, trophic level in the community (Shin et al. 2012). These ecological indicators are assumed to decrease under increased fishing pressure (Rochet and Trenkel, 2003; Shin et al., 2010b). However, these theoretical reference directions of change depend strongly on which trophic levels and size of fish have been targeted, i.e., they depend on exploitation histories (Shannon et al., 2014). We explored annual time series of these ecological indicators (Fig.C.1 in Appendix C) and categorized them into two groups: catch-based and survey-based. Catch-based indicators (marine trophic index (MTI), mean trophic level of landings (TLc), and intrinsic vulnerability index of landed fish (IVI)) contributed to the LV fisheryS that reflects the trophic structure and vulnerability of landed fish. Survey-based indicators (mean length (MLength), mean life span (MLife), trophic level of the surveyed fish community (TLco), and the proportion of predatory fish (%pred)) contributed to the LV communityS for the surveyed fish community that reflects the trophic and size-based structure and the species composition of the surveyed fish community. Our focus was on exploring the relationship between fisheries exploitation and environmental LVs with fisheryS and communityS. We then further explored how fisheryS and communityS were associated with the LV of the system resource potential (denoted as resourceP) measured by total system biomass.

We used lagged variables as covariates to include the temporal dependence within the times series of fisheries exploitation, environmental conditions, and ecological indicators (Zuur et al., 2010). Comparisons among 12 exploited Northern Hemisphere ecosystems revealed that the time lag of the environmental variables was usually <3 to 4 years (Bundy et al., 2012). Therefore, time lagged data were produced by lagging time series by 1 to 3 years. As a consequence, we defined four LVs for external pressures LVs: Env0L for environmental conditions, Exp0L for fisheries exploitation, and their associated time lagged variables, EnvLag and ExpLag, respectively. Applying an appropriate transformation in PLS-PM analyses is essential for improving their performance (Sanchez, 2013). In this study, time series data were transformed using the cumulative sum (Cusum) transformation, by summing deviations over time (Ibañez et al., 1993). This transformation tends to cancel out random variations in time series, but preserves consecutive temporal changes. Consequently, the method preferentially identifies correlations between time series with similar temporal trends. For comparative purposes, we also produced results from the non-Cusum transformed data.

2.2 Partial Least Squares Path Modeling framework

Partial Least Squares Path Models (PLS-PM) have two sub-models: the structural (inner) model, showing relationships among LVs, and the measurement (outer) model, showing relationships between MVs and the corresponding LV.

Following Esposito Vinzi et al. (2010), the structural model is:

$$\xi_j = \beta_{0j} + \sum_q \beta_{qj}\xi_q + \varsigma_j ,$$

where ξ_j is the generic endogeneous (dependent) LV, β_{0j} is the intercept term, β_{qj} is the generic path coefficient interrelating the q^{th} exogenous (independent) LV(ξ_q) to the j^{th} dependent one, and ς_j is the error in the inner relation.

There are two main types of measurement model formulation, depending on the direction of relationships between the LV and the corresponding MVs: the reflective (or outwards directed model) and the formative model (or inwards directed model). In a reflective model, each MV reflects the underlying LV, playing the role of an endogenous variable, and all MVs should co-vary. For example, ecological indicators should reflect their underlying LV and co-variation among these is an important characteristic. By contrast, in a formative model, each MV is an exogenous variable and may have a different effect on the underlying LV and the MVs do not need to co-vary. For instance, environmental indices (such as wind stress and river discharge measured in North East USA, Table 1) often have different effects on the underlying environmental LV, therefore, the environmental LV is formative. PLS-PM is implemented through an iterative algorithm that separately estimates the various measurement models, and then in a second step estimates the path coefficients in the structural model (Fig. 1).

2.3 Scenarios of the structural model

Outcomes of PLS-PM depend on how we construct the structural model. As a first step, we defined a PLS-PM structural model (denoted as Scenario 1) that consisted of four formative LVs (Exp0L, ExpLag, Env0L, EnvLag) and two reflective LVs (fisheryS and communityS). An example of the structural model is shown in Fig.A.1 of Appendix A for the purpose of investigating the relationships among fisheries exploitation, environmental conditions and ecological indicators.

Ecological indicators include ecosystem attributes such as system productivity (e.g., Samhouri et al., 2009; Shin et al., 2010a). We thus expanded the PLS-PM structural model to include a third reflective LV resourceP for investigating its connections with the ecological LVs. Two possible pathways were explored: i) assuming no direct connections between resourceP and the LVs of fisheries exploitation and environmental conditions in the structural model (Scenario 2; refer to Fig. A. 3i as an example of the path diagram); ii) assuming direct connections existed (Scenario 3; refer to Fig. A. 3ii as an example of the path diagram). Essentially, in Scenario 2, the LVs fisheryS and CommunityS had a direct effect on resourceP; the LVs of fisheries exploitation and environmental conditions (EnvLag, Env0L, ExpLag, and Exp0L) had an indirect effect on resourceP through fisheryS and communityS. In Scenario 3, on the other hand, the LVs EnvLag, Env0L, ExpLag, and Exp0L not only had an indirect effect on resourceP through fisheryS and communityS, as in Scenario 2, but also a direct effect on resourceP, an assumption that would be closer to reality.

2.4 Evaluation of PLS-PM

We assessed three aspects of the robustness of the PLS-PM model: (1) the quality of the measurement model; (2) the quality of the structural model; and (3) the validation of the PLS-PM (Esposito Vinzi et al., 2010). The measurement model specifies the relationship between MVs and the underlying LV. To determine the quality of the measurement model, the determination of suitable reflective MVs for each underlying LV is an important step. This step is achieved through theoretical considerations and correlation analyses. Each MV should only be strongly related to its own LV, but not to other LVs, implying correlations of each MV to its intended LV (i.e., loadings) should be sufficiently large (> 0.7, Götz et al., 2010) and should always be larger than those with all other LVs (i.e., cross loadings). Validity is examined using the average variance extracted, with a value > 0.5 deemed acceptable (Sanchez, 2013); implying more than half of the variance is explained by the MVs. The quality of the measurement model can also be assessed by average communality ($\overline{Com}$) that measures how much of the variability in MVs is explained by its LV scores, and is calculated as the average of all squared correlations between each MV and its underlying LV scores (Esposito Vinzi et al., 2010).

The quality of the structural model is primarily evaluated based on the predictive power of the model, the R^2, which depicts the amount of variance in the endogenous LV explained by its independent LVs (Götz et al., 2010). Overall model performance is measured by the goodness of fit (GoF) value that is obtained as the geometric mean of $\overline{Com}$ and the average R^2 value: $GoF = \sqrt{\overline{Com} \times \overline{R^2}}$ (Esposito Vinzi et al., 2010). GoF value > 0.7 is considered very good (Sanchez, 2013).

The quality of the structural model is also evaluated based on path coefficients, and their directions (i.e., negative or positive) and significance levels. The path coefficient measures the direct effect of an independent LV (e.g., Env0L) on its dependent LV (e.g., resourceP). In addition to path coefficients, PLS-PM also estimates the indirect effect (e.g., the indirect effect of Env0L on resourceP through either fisheryS or communityS). The total effect of an independent LV on its dependent LV is the sum of all indirect and direct effects.

Model validation and assessment of statistical significance of important parameters such as path coefficients were carried out by a non-parametric bootstrap procedure (Sanchez, 2013). The bootstrap 95% confidence interval was generated to evaluate if the parameters were significantly different from zero. All analyses were conducted using R version 3.0.1 (R Development Core Team, 2013) and the PLSR-PM package (Sanchez, 2013). For those who want to find out more about the PLS-PM approach, the Appendix (A) provides more detail on the approach through application to the West Coast of Canada, and addresses sensitivity of the results to different model formulations.

3. Results

3.1 Model evaluations

Under Scenario 1 of the PLS-PM structural model, we compared the goodness of fit values between data with or without Cusum-transformation and with different time lags for the fisheries exploitation and environmental condition MVs for the 12 ecosystems. When the data were Cusum-transformed, most ecosystems had GoF values > 0.7, indicating very good model performances (Table 2). By contrast, non-Cusum transformed data resulted in much lower GoF values, with only two ecosystems (Gulf of Cadiz and New Zealand Chatham) having GoF > 0.6. Cusum-transformation thus produces a model more sensitive to consecutive temporal changes, and more robust to random variations. Hereafter we only present results based on Cusum-transformed data. Lagged time series of one to three years yielded similar GoF values, indicating the number of years lagged in the time series did not play a critical role in determining model performances. We chose a three-year time lag for the rest of analyses, as this produced highest GoF values for 9 of the 12 ecosystems (Table 2).

With the Cusum-transformed data and three-year time lag for the fisheries exploitation and environmental condition MVs, we assessed the measurement models for the LVs of fisheryS and communityS using loadings (correlations between MVs and their underlying LV) and cross-loadings. Loadings of the seven MVs for the two ecological LVs (fisheryS and communityS) were generally higher than the cross loadings (Tables D.1, D.2 in Appendix D). This indicated that the LV fisheryS, consisting of the three catch-based indicators, was inherently different from the LV communityS, based on the four survey-based indicators. Loadings of fisheryS on its MVs were generally > 0.7 (see Tables D.1). Three loadings were < 0.7, but still > 0.4.This indicated that the variances of the catch-based MVs were well explained by fisheryS. While most loadings of communityS on its MVs were > 0.7, there were five loadings < 0.4 (Table D.2). The MVs associated with the low loadings included MLife in Guinean EEZ, MLength in North Sea, MLength in Portuguese EEZ, and MLength and %pred in Northeast USA. Removing these five MVs improved the GoF by about 3 – 5% in each of the four ecosystems; on the other hand, the estimates of path coefficients only changed slightly (Table D.3). Values of the average variance extracted were generally > 0.5 (Table 3), implying that more than half of the variances in MVs were explained by their corresponding LVs. The R^2 values were generally > 0.7 (Table 3), suggesting that all models had high predictive power.

The addition of the third latent variable resourceP under the structural model Scenario 2 (assuming no direct links with the LVs of fisheries exploitation and environmental conditions) resulted in only slight changes to the R^2 values (Table 4) and the average variance extracted (results not shown) for fisheryS and communityS. However, the R^2 values for resourceP were < 0.5 in seven ecosystems, which indicated that the amount of variance in resourceP was not well explained by fisheryS and communityS in these ecosystems. However, by assuming that direct links existed between resourceP and the LVs EnvLag, Env0L, ExpLag, and Exp0L in Scenario 3, we obtained higher R^2 values for 11 ecosystems (Table 4). The assumption of direct links between resourceP and the LVs of fisheries exploitation and environmental conditions allowed more variance in resourceP to be explained by its independent LVs and thus produced higher predictive power. This may imply that it is important to account for direct connections when these direct connections exist. The GoF values were higher for 10 ecosystems under Scenario 3, although differences were small (Table 5).

3.2 Direct linkages among the LVs

Under the structural model Scenario 1, we examined the relationships between the independent LVs (EnvLag, Env0L, ExpLag, Exp0L) and the two dependent LVs (fisheryS and communityS). We focused on the significant correlations. Correlations between fisheryS and the fisheries exploitation LVs (ExpLag and Exp0L) were either positive (five ecosystems) or negative (six ecosystems) (Fig. 2, left panel). Positive correlations may imply that periods of higher fisheries exploitation coincided with periods of fishing at higher trophic levels. In the eastern Scotian Shelf, exploitation lagged by three-years negatively impacted fisheryS. This result implied that the higher exploitation three years prior to the indicator response could have resulted in a shift in fisheries to target species of lower trophic levels or lower vulnerability. In five ecosystems (Barents Sea, Gulf of Cadiz, Ionian Sea Archipelago, western Scotian Shelf and West Coast Canada), Exp0L was negatively correlated with fisheryS. These negative correlations indicated that a period of higher fisheries exploitations coincided with the period of targeting species of lower trophic level or less vulnerable species. Effects of environmental conditions on fisheryS were more likely to be negative (seven ecosystems) than positive (four ecosystems). In the eastern English Channel and West Coast Canada, both Env0L and EnvLag were negatively associated with fisheryS; in Northeast USA, both Env0L and EnvLag were positively correlated with fisheryS.

Significant effects of fisheries exploitation on communityS were caused predominantly by ExpLag and primarily negative (Fig. 2, right panel). This implies that the negative fishing effects on the trophic structure and species composition of the surveyed fish community takes three years to be tracked by ecological indicators. Effects of environmental conditions on communityS were negative in the Ionian Sea Archipelago, North Sea, eastern Scotian Shelf, western Scotian Shelf and West Coast Canada. This result suggests that environmental conditions in these five ecosystems had either negatively affected the whole community, especially the high trophic level and/or vulnerable species, or had favored species at lower trophic levels in the past few decades. On the other hand, effects of environmental conditions on communityS were positive in the Barents Sea, eastern English Channel, New Zealand Chatham, western and eastern Scotian Shelf.

As we extended the structural model to include the third LV resource in Scenario 2 and Scenario3, we focused comparisons on path coefficients without considering significant levels for clearer presentation. Under Scenario 2, previous model diagnoses have indicated that the R^2 values were barely changed for fisheryS and communityS compared with Scenario 1 (Table 4 vs. Table 3). The estimated path coefficients for fisheryS between Scenario 1 and 2 were identical in terms of direction (i.e., negative or positive) with the exception of Guinean EEZ where the effect of EnvLag changed from negative in Scenario 1 to positive in Scenario 2 and that of Env0L changed from positive to negative (Fig. 3). All other differences were minor in the strengths of the correlations (Fig. 3). Similarly, the direction (i.e., negative or positive) of the estimated path coefficients for communityS between Scenario 1 and 2 were only different in Northeast USA, where the effect of Exp0L changed from negative in Scenario 1 to positive in Scenario 2 (Fig. 4). All other differences between Scenario 1 and 2 were minor in the strengths of the correlations.

Under Scenario 3 assuming direct links between resourceP and the LVs of fisheries exploitation and environmental conditions, estimated path coefficients were different for some ecosystems compared to Scenario 2 (Fig. 3). The effect of Exp0L changed from positive in Scenario 2 to negative in Scenario 3 in Northeast USA; the effect of ExpLag changed from negative to positive in western Scotian Shelf and it changed from positive to negative in Barents Sea. Similarly, the estimated path coefficients for communityS were different for some ecosystems between Scenario 2 and 3. Nevertheless, the general patterns of the path coefficients remained consistent (Fig. 4).

3.3 Indirect linkages among the LVs

In addition to path coefficients measuring the direct effects of independent LVs on their dependent LV, PLS-PM also estimates the indirect effect (e.g., the indirect effect of Env0L on resourceP through either fisheryS or communityS). Fig. A. 4 in Appendix A shows the dissected total effects EnvLag, Env0L, ExpLag, and Exp0L on resourceP for both Scenario 2 (Fig. A.4i) and Scenario 3 (Fig. A.4ii) from where a better understanding of the total effects can be obtained. Fig. 5 shows the total effects of all independent LVs on resourceP for Scenario 2 (left panel) and Scenario 3 (right penal) for the 12 ecosystems. While the total effects of the fisheries exploitation LVs (ExpLag and Exp0L) were accounted for as indirect in Scenario 2, they were less prominent. On the other hand, the total effects of ExpLag and Exp0L on resourceP consisted of both direct and indirect effects in Scenario 3; they became more prominent for all ecosystems. Similarly, effects of the environmental conditions LVs (EnvLag and Env0L) were more outstanding in Scenario 3 compared to those in Scenario 2 for most ecosystems (Fig. 5). This implies that it is important to account for direct effects when there are direct connections between the independent and dependent LVs, and the indirect effects may not be sufficient to measure the overall connections. As a result of accounting for the direct connections between resourceP and the LVs of fisheries exploitation and environmental conditions, the estimated direct effects of fisheryS or communityS on resourceP in Scenario 3 were smaller than those in Scenario 2 for most ecosystems (Fig. 5), which suggested weak direct linkages between resourceP and the ecological LVs of fisheryS and communityS in most ecosystems. Based on Scenario 3, we found that resourceP was more likely to be associated with communityS than with fisheryS (Fig. 5, right panel), and the correlations tended to be negative (in eight ecosystems).

4. Discussion

4.1 Structural model configurations

In this study we have presented a novel application of the Partial Least Squares Path Modeling approach (PLS-PM) to compare 12 exploited marine ecosystems. This approach enabled us to quantify the relative effects of fisheries exploitation and environmental and conditions on ecological indicator responses and explore relationships between indicators and biomass (i.e., system resource potential).

We investigated three configurations of the structural model: Scenario 1 only including paths between the LVs of fisheries exploitation and environmental conditions and the ecological

LVs (fisheryS and communityS); Scenario 2 adding the LV of system resource potential (resourceP) to relate to fisheryS and communityS but assuming no direct effects from the LVs of fisheries exploitation and environmental conditions on resourceP; and Scenario 3, as an alternative to Scenario 2, assuming the existence of direct effects of the fisheries exploitation and environmental conditions on resourceP.

Estimated effects of fisheries exploitation and environmental conditions on fisheryS and communityS in Scenario 1 barely changed with the addition of resourceP in Scenario 2 where there were no direct paths from fisheries exploitation and environmental conditions to resourceP. However, the R^2 values for resourceP were poor (< 0.5) for seven ecosystems, suggesting the variance in resourceP was not well explained by its independent LVs. Allowing resourceP to be directly influenced by the LVs of fisheries exploitation and environmental conditions in Scenario 3 resulted in higher R^2 values in 11 ecosystems. This indicated that the direct effects of fisheries exploitation and environmental conditions on resourceP were common across the ecosystems and they should be explicitly modeled if resourceP was to be included in the PLS-PM structural model. By accounting for these direct connections with fisheries exploitation and environmental conditions, the direct effects of fisheryS or communityS on resourceP became smaller, which suggested weaker direct linkages between resourceP and the ecological LVs of fisheryS and communityS than what were perceived in Scenario 2. In addition, the result also suggested that the variance in resourceP was better explained by the LVs of fisheries exploitation and environmental conditions.

In general, comparisons of the estimated effects of fisheries exploitation and environmental conditions on fisheryS and communityS across the three scenarios revealed that these path coefficient estimates were consistent and thus robust to the assumptions pertaining to the structural model. As more dependent LVs were added to the structural model for deriving relationships on a higher order (e.g., resourceP in this case), the estimates of these higher-order relationships can become sensitive to the configuration of the structural model. Ideally, all potential configurations of the structural model should be considered and diagnosed in terms of their predictive power, and the resultant estimates of path coefficients should be compared.

4.2 Grouping ecological indicators

While ecosystem indicators are generally accepted tools for evaluating ecosystem status and trends (e.g., Shin and Shannon 2010; Shin et al., 2010b; ICES, 2012), it is still unclear how they can be collectively used for management purposes. With hundreds of ecosystem indicators having been proposed (Cury and Christensen, 2005; Rochet and Trenkel, 2003; Piet et al., 2008), the emphasis more recently has been to develop approaches to evaluate and select the most useful indicators to characterize and monitor ecosystem status in a context of increasing anthropogenic pressure and climate change (Shannon et al., 2014). Previous work by Shin et al. (2010b), based on data quality and availability, public awareness and theoretical rationale, identified the suite of ecological indicators we analyzed here. Shin et al. (2012) recognized that important selection criteria, such as sensitivity to fishing pressure, time of response, and specificity of the response to fishing versus climate variability, needed further empirical and modeling work to assess the usefulness of indicators for ecosystem-based fisheries management. The current study brings new results to assess these three properties for a set of IndiSeas indicators across a range of ecosystems.

An earlier study by Link et al. (2010) showed some significant correlations between individual indicators and environmental and fishing drivers. Here, we used a more complete suite of seven indicators and purposely aggregated them into two groups, reflecting whether they were catch-based (fisheryS) or survey-based (communityS). The PLS-PM analysis has shown that loadings from the seven indicators and their specific LVs were generally larger than cross loadings for the other LVs, indicating that catch-based and survey-based indicators were inherently different; and in some ecosystems these two groups of indicators changed in opposite directions, which is consistent with Shannon et al. (2014). Therefore each group deserved independent investigation, and both are complementary in terms of quantifying association of environmental conditions and fisheries exploitation and their subsequent association with the resource potential. Further, this result indicates that great care should be taken if relying upon a set of ecological indicators that is derived from one data type only (either catch-based or survey-based) to characterize ecosystem state.

The grouping of ecological indicators within the PLS-PM provided several valuable insights: it highlighted associations between groups and relationships among indicators within each group; it allowed easier interpretation of impacts from environmental and fishing pressures; and it facilitated connections between indicators and ecosystem attributes, such as biomass (i.e., resource potential). This study highlights the utility of the PLS-PM approach in providing a platform for integrating and simplifying a range of indicators from multiple sources. As recognized by Murawski (2000), additional sources of indicators (e.g., social and economic) can provide useful information to evaluate and modify management guidance for important fisheries. While only two sources of indicators (landings and surveys) have been analyzed here, as a greater number of indicators are recognized from new sources, additional groupings can be explored to reflect additional ecosystem attributes.

4.3 Impacts of fisheries exploitation and environmental conditions

For the effects of fisheries exploitation and environmental conditions on fisheryS and communityS, we based our comparisons of the 12 ecosystems on Scenario 1, paying special attention to those that are statistically significant. These estimated effects varied among the ecosystems both in terms of direction (i.e., negative or positive) and strength, suggesting no overarching patterns across the ecosystems. Significant correlations between fisheries exploitation and fisheryS were more common across ecosystems (9 of 12) than those between fisheries exploitation and communityS. Positive relationships between fisheries exploitation and fisheryS found in five ecosystems may be interpreted that periods of higher fisheries exploitation coincided with periods of fishing at higher trophic levels and on more vulnerable species; as ecosystems were fished down the cascade of trophic levels (Pauly et al., 1998), lower trophic levels were targeted. Intensive fishing at lower trophic levels is detrimental to an ecosystem, directly reducing the system biomass (Fu et al., 2013) and increasing ecosystem overexploitation (Coll et al., 2008), although balanced harvesting, where moderate fishing effort is balanced across trophic levels or size classes has been shown to maintain ecosystem structure and productivity (Bundy et al. 2005; Garcia et al., 2012). Therefore, when combined with an analysis of the historical fishing strategy in an ecosystem, the decreasing trends in these catch-based indicators could provide warning signs of ecosystem deterioration. However, a keen knowledge of fisheries management and food web interactions of an ecosystem must be present before a true warning signal can be recognized since decreasing trends in fisheries exploitation and FisheryS may also be due to other causes such as redistribution of fishing effort to a more moderate levels across trophic levels, or to environmental impacts, such as periodically high abundances of lower trophic level fish, which are known for naturally large stock fluctuations, and reduced allowable catch on higher trophic level fish species, as experienced in the Barents Sea from 2002-2010 (Johannesen et al., 2012).

It should be noted that the three catch-based MVs were positively correlated only in half of the 12 ecosystems (Table D.1 in Appendix D). In the other half, one of the three MVs was negatively correlated with the other two. For instance, IVI was negatively correlated with MTI and TLc in three ecosystems (eastern English Channel, Ionian Sea Archipelago, and eastern Scotian Shelf); negative correlations were also observed for MTI in Guinean EEZ, and TLc in North Sea and Northeast USA. Removing these negative MVs only resulted in slight changes in estimates of path coefficients (results not shown), thus it would not change the interpretation of the results. However, the inconsistent correlations between the catch-based indicators for half of the ecosystems suggested that the assumption of increased fishing pressure resulting in declines in ecological indicators (Rochet and Trenkel, 2003; Shin et al., 2010b) does not hold universally (Shannon et al., 2014). How the ecological indicators would change in response to fisheries exploitation depends on how fisheries operate over time, targeting high or low trophic levels. For a more complete picture of fisheries exploitation on ecosystem structure and functioning, more measurements of fishing pressure are needed, although there is no scientific consensus what these measurements should be. While using component-specific fisheries drivers such as catch and catch percentage of planktivores and zooplanktivores, Fu et al. (2012) found that these drivers produced significant responses across all ecosystems and indicators studied. Travers et al. (2006) also showed that because of indirect effects of fishing on different ecosystem components, indicators may vary counterintuitively. This is exemplified in various studies examining trophic level-based indicators, where seemingly unusual trajectories of these indicators have been observed over time, depending on the historical fishing strategy, often in accordance with ecosystem type (Cury et al., 2005; Shannon et al., 2010; Shannon et al., 2014), Therefore, we advocate that fishing configuration (species targeted as well as fishing intensity) should be incorporated into the development and evaluation of ecological indicators.

Significant effects of fisheries exploitation on communityS were less prevalent in comparison with fisheryS. It is worth noting that the survey-based MVs of communityS were not as tightly associated with each other as the catch-based MVs of fisheryS. In particular, there were five loadings < 0.4 (Table D. 2). This could be due to the survey-based indicators not only being subject to fisheries exploitation and environmental conditions, but also sampling errors and ecosystem-specific species composition. The ecosystem-specific species composition may result in different fishing strategies and subsequently different responses to fisheries exploitation. This also suggests that exploitation rate and total catch, as measures of fishing pressure, are insufficient to understand fully the impacts of fisheries exploitation on the ecosystems. Again, we assert that the fishing configuration should be incorporated into the development and evaluation of ecological indicators.

Effects of environmental conditions on the ecological LVs were predominantly significant, and tended to be negative, suggesting that in the recent period, indicators accounted for changes in environmental conditions and the changes were more likely to be adverse. However, results presented here might change if we were to apply the approach to different time periods or to incorporate different environmental variables. In the future, it will be possible to break down longer times series into periods of sufficient length so that the different impacts of fisheries exploitation and environmental conditions can be examined and compared between different time periods for a particular ecosystem.

4.4 Advantages of PLS-PM

To support the implementation of ecosystem-based approach to fisheries management, it is important to develop and monitor appropriate indicators of ecosystem status and the effectiveness of management strategies (Cury and Christensen, 2005; Shin et al., 2010b). It is challenging to apply traditional statistical approaches such as multiple linear regressions to the multitude of indicators that are not independent and may contain different or even conflicting signals and non-linear patterns (Cotter et al., 2009; Petitgas and Poulard, 2009). Our results clearly show that catch-based and survey-based indicators were inherently different and sometimes display opposite directions of change. Integrating these two groups of indicators without careful differentiation will inevitably result in confusing messages when investigating their responses to environmental changes and fisheries exploitation.

The - PLS-PM approach provides an effective way to separate a multitude of ecosystem indicators into meaningful groups, each relating to a latent concept. This approach allows the exploration of the relationships specified between the groups of LVs and their MVs, as well as relationships among the LVs through an iterative algorithm (Trinchera and Russolillo, 2010). As we separated ecological indicators into two groups and explored them via the PLS-PM, we were able to observe relationships of each LV represented by each group of ecological indicators with fisheries exploitation and environmental conditions. The separation of the catch-based and survey-based indicators showed that each group related to the resource potential of the ecosystem differently. Future applications of PLS-PM in fisheries could provide the possibility of further relating these ecological LVs to management goals through the construction of management LVs comprised of socio-economic indicators. The advantages and results derived from our study illustrated the usefulness of PLS-PM for compartmentalizing the multitude of ecosystem indicators that researchers and managers have been using and for identifying relationships among them. Information derived from these studies will improve our understanding of ecosystem dynamics and support an ecosystem-based approach to fisheries management.

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Table 1. Local- and basin-scale environmental variables analyzed in the 12 ecosystems for the given periods: NAO (North Atlantic Oscillation index), AMO (Atlantic Multidecadal Oscillation index), EAP (East Atlantic Pattern), MOI (Mediterranean Oscillation Index), SST (Sea Surface Temperature), SAM (Southern Annular Mode), SOI (Southern Oscillation Index) and PDO (Pacific Decadal Oscillation).

Ecosystems	Start year	End year	Local 1	Local 2	Local 3	Basin 1	Basin 2
Barents Sea	1983	2010	Ice cover	Average temperature at 50-200 m	-	NAO	AMO
Gulf of Cadiz	1993	2010	River discharge	-	-	NAO	AMO
Eastern English Channel	1988	2010	SST	-	-	NAO	AMO
Guinean EEZ	1985	2009	SST	-	-	NAO	AMO
Ionian Sea Archipelago	1964	2007	SST	-	-	MOI	-
New Zealand Chatham	1993	2010	-	-	-	PDO	SAM
North Sea	1983	2010	SST	-	-	NAO	AMO
Portuguese EEZ	1980	2010	-	-	-	NAO	EAP
Eastern Scotian Shelf	1970	2010	SST	Stratification index	Temperature at 100m	NAO	-
Western Scotian Shelf	1970	2010	SST	Stratification index	Temperature at 100m	NAO	-
Northeast USA	1964	2010	Wind stress	River discharge	-	NAO	AMO
West Coast Canada	1980	2010	Upwelling index	Transport index	SST	SOI	PDO

Table 2. Goodness of fit values under four scenarios: time series were Cusum transformed and the time lagged latent variables (LVs) of fisheries exploitation and environmental conditions have lags of one to three years, as well as a fourth scenario without the Cusum transformation and with a lag of three years. The highest goodness of fit value is in bold for each ecosystem.

Ecosystems	Lag 1 Yr	Lag 2 Yrs	Lag 3 Yrs	Lag 3 Yrs, no Cusum
Barents Sea	0.617	0.626	**0.637**	0.587
Gulf of Cadiz	0.750	0.757	**0.765**	0.616
Eastern English Channel	0.762	**0.763**	0.760	0.492
Guinean EEZ	0.568	0.541	**0.573**	0.415
Ionian Sea Archipelago	0.743	0.762	**0.785**	0.567
New Zealand Chatham	0.651	0.669	**0.685**	0.608
North Sea	**0.756**	0.753	0.744	0.473
Portuguese EEZ	0.782	**0.789**	0.785	0.548
Eastern Scotian Shelf	0.768	0.769	**0.773**	0.542
Western Scotian Shelf	0.728	0.745	**0.753**	0.494
Northeast USA	0.665	0.673	**0.678**	0.488
West Coast Canada	0.567	0.596	**0.612**	0.414

Table 3. Values of R^2 (representing predictive power of the model) and average variance extracted (AVE) for the two latent variables (fisheryS: structure of landed fish, communityS: structure of the surveyed fish community) under structural model Scenario 1 for the 12 ecosystems.

Ecosystems	LVs	R^2	AVE
Barents Sea	fisheryS	0.720	0.972
	communityS	0.736	0.767
Gulf of Cadiz	fisheryS	0.856	0.895
	communityS	0.819	0.602
Eastern English Channel	fisheryS	0.735	0.559
	communityS	0.868	0.690
Guinean EEZ	fisheryS	0.800	0.691
	communityS	0.556	0.592
Ionian Sea Archipelago	fisheryS	0.945	0.828
	communityS	0.951	0.767
New Zealand Chatham	fisheryS	0.570	0.701
	communityS	0.850	0.812
North Sea	fisheryS	0.807	0.567
	communityS	0.726	0.563
Portuguese EEZ	fisheryS	0.970	0.936
	communityS	0.693	0.501
Eastern Scotian Shelf	fisheryS	0.845	0.899
	communityS	0.882	0.894
Western Scotian Shelf	fisheryS	0.946	0.803
	communityS	0.888	0.770
Northeast USA	fisheryS	0.656	0.899
	communityS	0.877	0.374
West Coast Canada	fisheryS	0.786	0.964
	communityS	0.600	0.720

Table 4. Comparisons of R^2 values (representing predictive power of the model) and average variance extracted (AVE) for the three latent variables (fisheryS: structure of landed fish, communityS: structure of the surveyed fish community, and resourceP: resource potential reflected by total biomass) under Scenario 2 of the structural model (without direct link between resourceP and the LVs of fisheries exploitation and environmental conditions) and Scenario 3 (with direct link) for the 12 ecosystems.

		R^2	
Ecosystems	LVs	Scenario 2	Scenario 3
Barents Sea	fisheryS	0.719	0.530
	communityS	0.737	0.682
	resourceP	0.256	0.664
Gulf of Cadiz	fisheryS	0.856	0.840
	communityS	0.820	0.820
	resourceP	0.808	0.863
Eastern English Channel	fisheryS	0.740	0.762
	communityS	0.868	0.834
	resourceP	0.023	0.160
Guinean EEZ	fisheryS	0.786	0.737
	communityS	0.438	0.384
	resourceP	0.214	0.579
Ionian Sea Archipelago	fisheryS	0.945	0.926
	communityS	0.951	0.958
	resourceP	0.799	0.863
New Zealand Chatham	fisheryS	0.571	0.573
	communityS	0.848	0.821
	resourceP	0.701	0.840
North Sea	fisheryS	0.783	0.744
	communityS	0.725	0.695
	resourceP	0.248	0.434
Portuguese EEZ	fisheryS	0.967	0.940
	communityS	0.604	0.695
	resourceP	0.332	0.517
Eastern Scotian Shelf	fisheryS	0.843	0.938
	communityS	0.880	0.740
	resourceP	0.317	0.289
Western Scotian Shelf	fisheryS	0.946	0.938
	communityS	0.887	0.873
	resourceP	0.723	0.800
Northeast USA	fisheryS	0.683	0.791
	communityS	0.874	0.792
	resourceP	0.807	0.836
West Coast Canada	fisheryS	0.786	0.769
	communityS	0.600	0.635
	resourceP	0.371	0.552

Table 5. Goodness of fit values for the 12 ecosystems under Scenario 2 of the structural model (without direct link between resourceP and the LVs of fisheries exploitation and environmental conditions) and Scenario 3 (with direct link).

Ecosystems	Scenario 2	Scenario 3
Barents Sea	0.585	0.632
Gulf of Cadiz	0.778	0.782
Eastern English Channel	0.638	0.662
Guinean EEZ	0.507	0.562
Ionian Sea Archipelago	0.788	0.794
New Zealand Chatham	0.703	0.724
North Sea	0.663	0.679
Portuguese EEZ	0.696	0.720
Eastern Scotian Shelf	0.699	0.657
Western Scotian Shelf	0.747	0.756
Northeast USA	0.706	0.706
West Coast Canada	0.583	0.614

Figure Captions

Figure 1. Diagram of the partial least squares path model, showing in dashed arrows relationships among latent variables (LVs) of environment (Env) and fisheries exploitation (Exp), trophic structure and species composition of landings (fisheryS) and of the surveyed fish community (commnityS), as well as system resource potential. Each of the LVs is related to its own manifest variables (MVs) shown as solid arrows: the LV Env is related to three local variables (LI1, LI2, and LI3) and two basin-scale variables (BS1 and BS2), and the LV Exp is related to total landings (totalC) and exploitation rate (exp); fisheryS is reflected by marine trophic index (MTI), mean trophic level of landings (TLc), and intrinsic vulnerability index of landings (IVI), and communityS by mean length (MLength), mean life span (MLife), trophic level (TLco) and proportion of predatory fish (%pred) in the community; system resource potential is represented by the total biomass time series (totalB). For simplicity, LVs with lagged times series are not shown.

Figure 2. Path coefficients for the latent variables (LVs) fisheryS (representing the structure of landings, left panel) and communityS (the structure of the surveyed fish community, right panel) in relation to the LVs of fisheries exploitation and environmental conditions without time lags (Env0L and Exp0L) and with time lags of three years (EnvLag and ExpLag). Statistically significant (p<0.05) path coefficients are shown in bright colors and non-significant ones in grey.

Figure 3. Estimated path coefficients for the eight pathways of the latent variable fisheryS that are common to the three scenarios of the structural model: (1) Scenario 1 does not have the LV resourceP (representing resource potential); (2) Scenario 2 has the LV resourceP but assumes no direct links between resourceP and the LVs of fisheries exploitation and

environmental condition; (3) Scenario 3 has resourceP and assumes direct links between resourceP and the LVs of fisheries exploitation and environmental conditions.

Figure 4. Estimated path coefficients for the eight pathways of the latent variable communityS that are common to the three scenarios of the structural model: (1) Scenario 1 does not have the LV resourceP (representing resource potential); (2) Scenario 2 has the LV resourceP but assumes no direct links between resourceP and the LVs of fisheries exploitation and environmental condition; and (3) Scenario 3 has resourceP and assumes direct links between resourceP and the LVs of fisheries exploitation and environmental condition.

Figure 5. Total effects on the latent variable (LV) resourceP (representing resource potential) from the LVs fisheryS and communityS and the environmental and fisheries exploitation LVs (EnvLag, Env0L, ExpLag, Exp0L) under two scenarios: (1) Scenario 2 assumes no direct links between resourceP and the LVs of fisheries exploitation and environmental condition; and (2) Scenario 3 assumes direct links between resourceP and the LVs of fisheries exploitation and environmental condition. Notice the scale differences between Scenario 2 and Scenario 3.

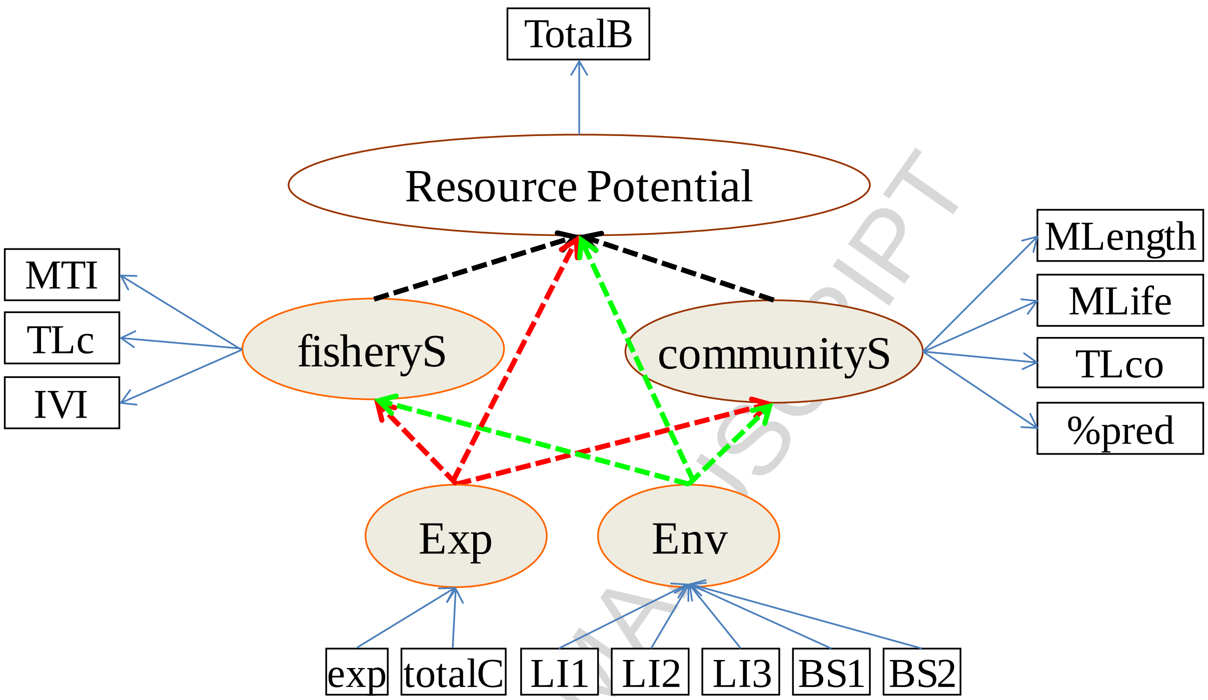
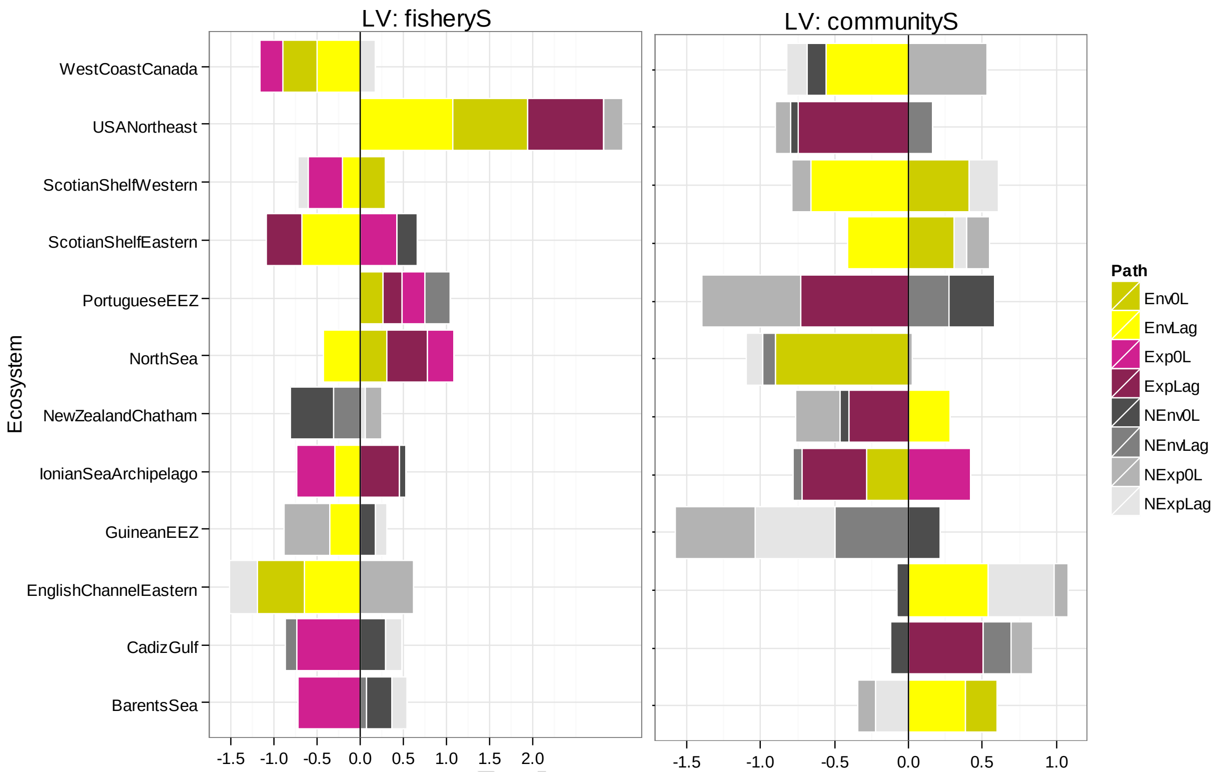

TotalB
Resource Potential
MTI
TLc
IVI
fisheryS
communityS
MLength
MLife
TLco
%pred
Exp
Env
exp
totalC
LI1
LI2
LI3
BS1
BS2

Fig. 1



LV: fisheryS
LV: communityS
Ecosystem
WestCoastCanada
USANortheast
ScotianShelfWestern
ScotianShelfEastern
PortugueseEEZ
NorthSea
NewZealandChatham
IonianSeaArchipelago
GuineanEEZ
EnglishChannelEastern
CadizGulf
BarentsSea
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5
2.0
Path
Env0L
EnvLag
Exp0L
ExpLag
NEnv0L
NEnvLag
NExp0L
NExpLag

Fig. 2


Scenario 1
Scenario 2
Scenario 3
Ecosystem
WestCoastCanada
USANortheast
ScotianShelfWestern
ScotianShelfEastern
PortugueseEEZ
NorthSea
NewZealandChatham
IonianSeaArchipelago
GuineanEEZ
EnglishChannelEastern
CadizGulf
BarentsSea
-1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 2.0
-1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 2.0
-1.0 -0.5 0.0 0.5 1.0 1.5
Path
Env0L
EnvLag
Exp0L
ExpLag

Fig. 3

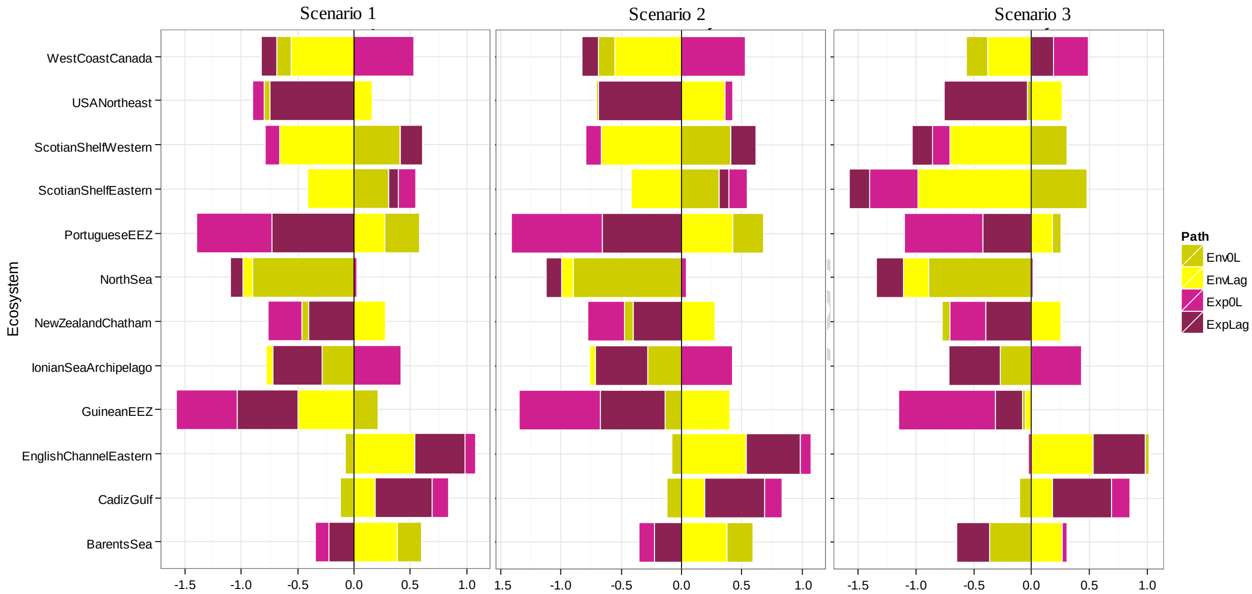

Scenario 1
Scenario 2
Scenario 3
Ecosystem
WestCoastCanada
USANortheast
ScotianShelfWestern
ScotianShelfEastern
PortugueseEEZ
NorthSea
NewZealandChatham
IonianSeaArchipelago
GuineanEEZ
EnglishChannelEastern
CadizGulf
BarentsSea
-1.5
-1.0
-0.5
0.0
0.5
1.0
Path
Env0L
EnvLag
Exp0L
ExpLag

Fig. 4

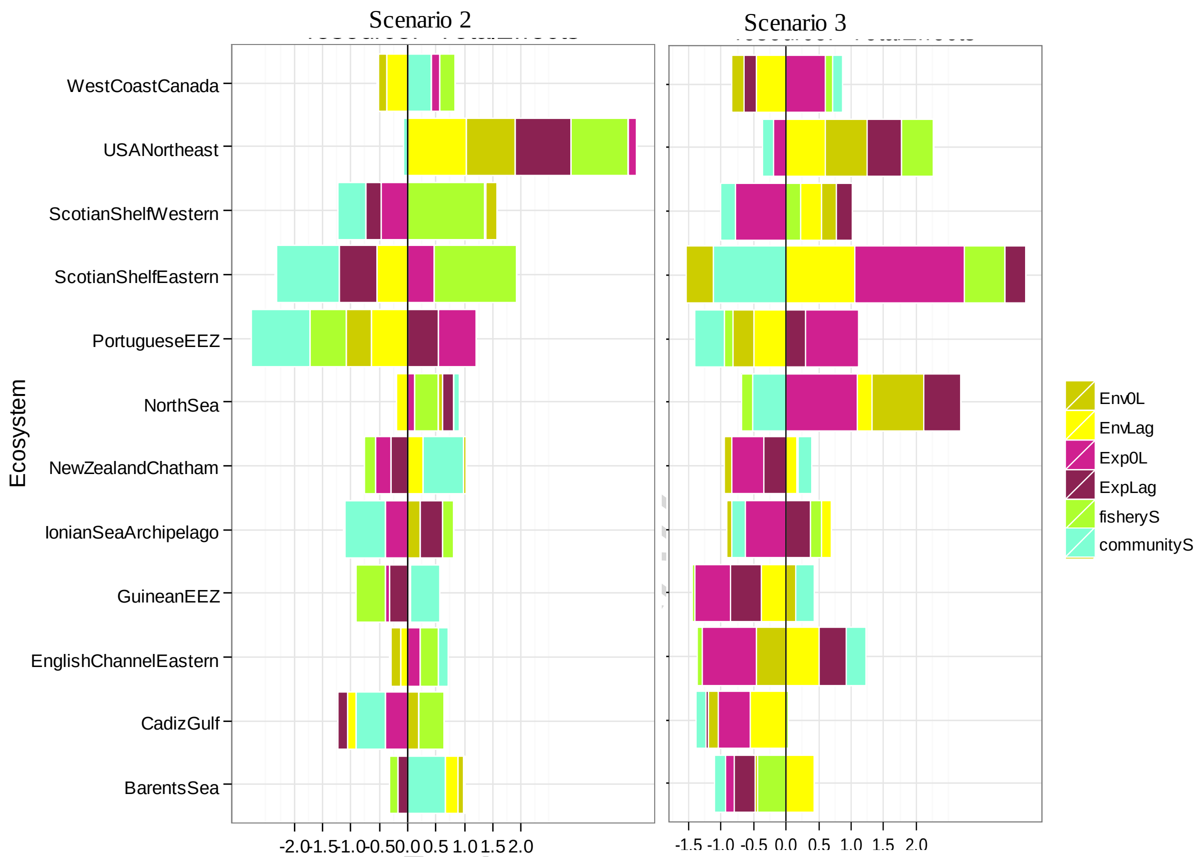

Scenario 2
Scenario 3
WestCoastCanada
USANortheast
ScotianShelfWestern
ScotianShelfEastern
PortugueseEEZ
NorthSea
NewZealandChatham
IonianSeaArchipelago
GuineanEEZ
EnglishChannelEastern
CadizGulf
BarentsSea
Ecosystem
-2.0 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 2.0
-1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 2.0
Env0L
EnvLag
Exp0L
ExpLag
fisheryS
communityS

Fig. 5