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The legacy of a crowded ocean: indicators, status, and trends of anthropogenic pressures in the California Current ecosystem

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SUMMARY

As human population size and demand for seafood and other marine resources increase, understanding the influence of human activities in the ocean and on land becomes increasingly critical to the management and conservation of marine resources. In order to account for human influence on marine ecosystems while making management decisions, linkages between various anthropogenic pressures and ecosystem components need to be determined. Those linkages cannot be drawn until it is known how different pressures have been changing over time. This paper identifies indicators and develops time series for 22 anthropogenic pressures acting on the USA's portion of the California Current ecosystem. Time series suggest that seven pressures have decreased and two have increased over the short term, while five pressures were above and two pressures were below long-term means. Cumulative indices of anthropogenic pressures suggest a slight decrease in pressures in the 2000s compared to the preceding few decades. Dynamic factor analysis revealed four common trends that sufficiently explained the temporal variation found among all anthropogenic pressures. This reduced set of time series will be a useful tool to determine whether links exist between individual or multiple pressures and various ecosystem components.

Keywords: cumulative effects, energy development, human activities, marine ecosystems, multiple pressures, ocean management, pollution, stressors, transportation, toxics

INTRODUCTION

Human activities in, on and around the ocean are varied and growing. These activities generate many benefits, including production of food, employment, energy and livelihoods (Guerry *et al.* 2012). However, they are also associated with pressures on the ecosystem that have negative consequences, such as loss or modification of habitat, depletions and introductions of species, physical, visual and auditory disturbances, and toxic and non-toxic contamination (Eastwood *et al.* 2007). Despite the increasing urgency of these influences (Wilson *et al.* 2005; Halpern *et al.* 2007), full accounting of how anthropogenic pressures in the marine environment have changed over time is rare.

Importantly, these pressures do not act upon the ecosystem independently, but rather collectively. They are disparate and broadly based, ranging from terrestrial-based pollution, commercial shipping activities, and offshore energy development to fisheries and coastal development, all of which exert cumulative effects on the ecosystem and could benefit from a holistic management approach (Vinebrooke *et al.* 2004; Crain *et al.* 2008; Halpern *et al.* 2008). Quantifying the cumulative effects from multiple pressures is a challenging task, however, because there is a limited understanding of how pressures interact and whether the cumulative effects are additive, synergistic or antagonistic (Darling & Côté 2008; Hoegh-Guldberg & Bruno 2010). The strength and direction of these interactions may also have different consequences for different taxa or ecosystem components (Crain *et al.* 2008). Additionally, the intensity and trends of many anthropogenic pressures are likely correlated with each other due to ultimate drivers such as human population growth, seafood demand or economic conditions, and so are best understood in the context of one another (see for example Link *et al.* 2002).

Previous studies that aim to evaluate the effect of cumulative pressures on marine ecosystems have primarily focused on spatially-explicit analyses which have revealed pressures hotspots in ecosystems across the globe (Ban & Alder 2008; Halpern *et al.* 2008, 2009; Stelzenmüller *et al.* 2010; Hayes *et al.* 2012). These analyses are particularly useful for describing patterns of spatial variation among individual and cumulative pressures; they provide a framework for identifying vulnerable habitats or regions and focusing limited management resources on these regions of concern. These spatially-explicit analyses, however, generally provide only a 'snapshot' in time which can make it challenging to determine what management actions are necessary.

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Without an understanding of the legacy of anthropogenic pressures in an area, it is difficult to interpret current and potential future conditions. For instance, the ecological consequences of oil extraction in a previously untouched area like the North Slope of Alaska are likely to be very different than in a historically high-use environment such as the North Sea. Without a temporal reference of the current intensity of the pressures, it is unknown whether the intensities of these pressures are at levels of concern or whether these pressures are increasing, decreasing or remaining the same. Temporal analyses can provide this important context and help focus management actions on pressures that might be at unacceptable levels (Rockström *et al.* 2009) or that may exhibit unacceptable changes over time. Time series data for many human-related pressures are however, often buried in state and federal agency reports, described at small spatial scales, and measured inconsistently among local, state and federal entities. Thus, it is important to develop a standardized set of time series that reflect the current intensity and historical trends of these pressures that could also be used to evaluate the cumulative intensity of these pressures at scales appropriate for management.

Here, we developed standardized time series of indicators for 22 anthropogenic pressures acting across the entire USA's portion of the California Current Large Marine Ecosystem (hereafter, the California Current ecosystem [CCE]). These time series were used to quantify and evaluate the intensity and temporal trends of each pressure. We then used several approaches to describe the relative intensity and trends of these pressures as a whole. First, we used simple additive models to quantify the relative status and trends of cumulative pressures in the CCE. Second, we used multivariate models to determine (1) whether pressures were correlated, (2) how the composition of pressures changed over time, (3) whether there were shared trends in the time series of pressures, and (4) whether these trends were related to specific drivers such as coastal population abundance or economic activity. Our synthesis, and corresponding methodological approaches to quantify the intensity and trends of these pressures, provide a foundation for future integrative analyses on ecological components (such as risk analysis and management strategy evaluations) across the CCE.

METHODS

Indicators of anthropogenic pressures

We developed indicators for 22 anthropogenic pressures in the CCE. The pressures selected were derived primarily from those identified in spatially-explicit analyses by Halpern *et al.* (2009) and from vulnerability analyses by Teck *et al.* (2010); they ranged in scope from land-based pressures, such as inorganic pollution and nutrient input, to at-sea pressures, such as commercial shipping and offshore oil and gas activities. Ultimately, we evaluated 41 different indicators and selected the best indicator to describe the intensity and trends of each pressure. Indicators were evaluated (Appendix 1, Table S1, see supplementary material at Journals.cambridge.org/ENC) using the indicator selection framework developed by Levin *et al.* (2011), Kershner *et al.* (2011) and James *et al.* (2012). Briefly, we evaluated each indicator according to 18 criteria using the scientific literature to determine whether there was support for each criterion for each indicator. This resulted in a matrix of references and notes with a corresponding value of literature support (1 for 'support', 0.5 for 'ambiguous support', 0 for 'no support'; Appendix 1, Table S1, see supplementary material at Journals.cambridge.org/ENC). These values were summed across criteria for each indicator and the highest scoring indicator was chosen for each pressure.

Data for all indicators were compiled from state and federal reports and databases to create the longest possible time series (Table 1). Compatible data from the states of California, Oregon and Washington were pooled to characterize pressures at the scale of the CCE. For some land-based pressures (Appendix 2, see supplementary material at Journals.cambridge.org/ENC), data from other states were included if watersheds in these states drained into the Pacific Ocean (such as Idaho, Montana and Wyoming). The Fraser River in Canada drains into the upper reaches of the CCE and may contribute a significant amount of pressures associated with runoff and input of freshwater and sediments to coastal habitats. However, there were numerous complexities trying to combine datasets from the USA and Canada for nearly all relevant pressures. To reduce the effects of differences in the datasets, we limited our analysis to USA data.

The status of each indicator was evaluated against two criteria: recent short-term trend (increasing, decreasing or remaining the same over the last five years) and short-term status relative to the mean and variance of long-term conditions (higher than, lower than or within historic levels) (Levin & Schwing 2011). An indicator's trend was considered to have changed in the short term if the modelled trend over the last five years of the time series showed an increase or decrease of more than one standard deviation (SD) of the mean of the entire time series. An indicator's status was considered to be above or below historical levels if the mean of the last five years was greater than or less than one SD from the mean of the full time series, respectively. We used the mean and standard deviation of the entire series, as opposed to some earlier period of comparison (such as the first five years of the dataset), because there were no good temporal reference points for these pressures that made sense to compare the most recent five years of data against. The long-term mean and standard deviation of a time series serves as a 'moving window' temporal target that is widely used in marine management applications (Samhouri *et al.* 2012). Defining the 'short-term' as the last five years of the dataset is consistent with other management review processes that occur at the scale of large marine ecosystems (see for example Essential Fish Habitat reviews [National Marine Fisheries Service 2013] and National Oceanic and Atmospheric Administration's Integrated Ecosystem Assessments [Levin & Schwing 2011]).

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Table 1 Top indicators for anthropogenic pressures in the California Current ecosystem (CCE) (Appendices 1 and 2 provide evaluation and selection, source of data and calculations of indicators for each pressure, see supplementary materials at Journals.cambridge.org/ENC). *Pressures used in cumulative pressures index and principal components analysis, CA = California, OR = Oregon and WA = Washington.

Pressure	*Indicator*	*Definition*	*Time series*	*Sampling frequency*
*Aquaculture: finfish	Finfish production	Estimates of Atlantic salmon production in CCE waters	1986–2011	yearly
*Aquaculture: shellfish	Shellfish production	USA shellfish (clams, mussels and oysters) production	1985–2010	yearly
*Atmospheric pollution	Deposition of sulphate	Annual precipitation-weighted mean concentrations of sulphate measured at sites in CA, OR and WA	1994–2010	yearly
*Benthic structures	No. offshore oil and gas wells	Total number of offshore oil and gas wells in production	1981 - 2009	yearly
*Coastal engineering	Human coastal population	Population size of coastline counties in CA, OR, WA	1970–2012	yearly
Commercial shipping activity	Volume of water disturbed	Calculated using draft, breadth and distance travelled within CCE of domestic and foreign vessels	2001–2010	yearly
Dredging	Dredge volumes	Dredge volumes for individual private contracts and Army Corps operated dredge projects in WA, CA and OR	1997–2011	yearly
*Fishery removals	Total landings	Tonnes of all species landed by commercial and recreational fisheries in CA, OR and WA	1981–2011	yearly
*Freshwater retention	Impoundment storage volume	Total reservoir storage volume in CA and Pacific Northwest water resource regions	1900–2011	yearly
Habitat modification	Distance trawled	Kilometres trawled by the limited-trawl groundfish fishery in CA, OR and WA	1999–2004	yearly
*Inorganic pollution	ISA-toxicity-weighted chemical releases	Total pounds of inorganic pollutants disposed of or released on site to the ground or water for '1988 core chemicals' weighted by toxicity scores and impervious surface area (ISA) in the drainage watersheds of the CCE	1988–2010	yearly
*Invasive species	Tonnes of cargo	Tonnes of cargo moved through ports in CA, OR and WA	1993–2010	yearly
*Light pollution	Average night-time visible light	Data are cloud-free composites of average visible night-time lights made using all the available archived DMSP-OLS smooth resolution data for each calendar year	1994–2010	yearly
Marine debris	Predicted counts of debris	Estimates from the National Marine Debris Monitoring Program separated into north and south CCE estimates	1999–2007	yearly
*Nutrient input	Nitrogen and phosphorus input	Total farm and non-farm nitrogen and phosphorus input from fertilizer used in counties within CCE watersheds	1945–2010	yearly
Ocean-based pollution	Commercial shipping activity combined with tons of cargo	Combines 'Commercial shipping activity' and 'Invasive species' datasets	2001–2010	yearly
*Offshore oil activities	Offshore oil and gas production	Normalized sum of the number of barrels of oil and cubic feet of gas produced from offshore wells in CA	1970–2010	yearly
*Organic pollution	Toxicity-weighted concentrations	Toxicity-weighted concentrations of 16 pesticides measured in water samples from stream-water sites in WA, OR and CA	1993–2008	yearly
Power plants	Saline water withdrawal volumes	Average daily withdrawal volumes of saline water from thermoelectric power plants in the Pacific Northwest and California regions	1955–2005	Every 5 years
Recreational beach use	Beach attendance	Summed beach attendance from CA, OR and WA	2002–2011	yearly
*Seafood demand	Total consumption	Total consumption of edible and non-edible fisheries products in the USA	1962–2011	yearly
*Sediment retention	Impoundment storage volume	Same as 'Freshwater retention'	1900–2011	yearly

The historical status of each indicator should be placed in context with the amount of data available for each time series. For shorter time series, the mean of the last five years was not likely different from the mean of the entire time series; thus, the relative status for indicators with short time series was more closely related to the availability of data and not historic trends. However, indicators were chosen because they were the most fundamentally sound datasets (Appendix 1, Table S1, see supplementary material at Journals.cambridge.org/ENC) and most of the indicators chosen will continue to be measured, thus providing meaningful comparisons into the future.

Summarizing anthropogenic pressures as a whole

We employed three different methods to examine the status and trends of pressures as a whole. First, we calculated a cumulative pressures index using a subset of pressures. Second, we used principal components analysis to examine correlations and temporal shifts among pressures. Last, we used dynamic factor analysis to determine whether the 22 pressures could be reduced to a smaller number of common trends.

Cumulative pressures index

In order to calculate a cumulative pressures index, we determined the longest period for which there were the most pressures with continuous data available. For the years 1994–2008, we had annual data available for 15 of the 22 pressures (Table 1). Data from these time series were normalized (mean = 0, SD = 1) across the years 1994–2008 so that all pressures were on the same scale. We then used two methods to calculate a cumulative pressures index. The first method was an additive model in which all 15 normalized pressure values were summed for each year.

The second method weighted the relative importance of each pressure according to vulnerability scores determined by Teck *et al.* (2010). Briefly, vulnerability scores were developed through surveys of experts, in which experts estimated the value of five components of ecosystem vulnerability based on the relative exposure and sensitivity of a habitat to a specific pressure. These five values were then combined to create a single vulnerability score for each habitat to each pressure. In our analysis, we used the mean vulnerability scores for each pressure averaged across all habitat types ('Score mean' in table 6 of Teck *et al.* (2010)). We then normalized mean vulnerability scores of all pressures listed in Teck *et al.* (2010) to a scale of 0 to 1 and used the scores relevant to our 15 pressures as weightings. Mean vulnerability scores were averaged across pressure categories when more than one related to one of our 15 pressures (for example, four nutrient input pressures were identified in Teck *et al.* 2010). Finally, we multiplied each normalized pressure value in the time series by its respective weighting value and summed across all pressures for each year.

Correlations and temporal shifts among pressures

We used principal components analysis (PCA; PRIMER 6.0; Clarke & Gorley 2006) to identify correlations among pressures and to reduce the number of multivariate dimensions to a smaller set that explained most of the variance of the datasets. Because PCA cannot accommodate missing values, we used the same set of 15 pressures from 1994–2008 that we used above to get the greatest number of pressures across the longest period of time. Loadings greater than 0.30 were considered relevant for interpretation of the results (Tabachnick & Fidell 1996). We used the principal component scores across years to examine how the importance of each axis changed over time.

Common trends among pressures

We used dynamic factor analysis (DFA; Zuur *et al.* 2003*a*, *b*) to characterize underlying common trends among the time series of anthropogenic pressures. The objective of DFA is to reduce the number of multivariate dimensions needed to describe patterns in data, based on time series models that explicitly account for temporal autocorrelation common in time series data. The DFA framework consists of two models: it combines (1) a random-walk model that captures the underlying shared trends among a set of time series and any covariates, and (2) a model that describes how well each time series is described by each underlying trend.

In the DFA framework, a set of one or more hidden common trends (linear combinations of a set of random walks) shared by the time series data explains their temporal variations (Zuur *et al.* 2003*a*). DFA is particularly useful for our set of time series because it can account for missing values; thus, we can incorporate a larger number of pressures across a longer period than was possible for the cumulative pressures index or the PCA. Because DFA allows for the inclusion of covariates, we could also explore explanatory drivers of the pressures such as population size and economic growth.

Using the MARSS package in R (Holmes *et al.* 2012; R Development Core Team 2012), we tested models with 1–5 common trends and models including zero, one or two covariates (coastal human population abundance and gross domestic product of the USA's West Coast). Preliminary analyses tested five commonly used variance-covariance matrix structures available in the MARSS package and suggested 'diagonal and equal' was the most appropriate (Appendix 3, see supplementary material at Journals.cambridge.org/ENC). This model structure had observation variances (along the diagonal) that were equal and covariances that were equal to zero.

Prior to the analysis, time series of all 22 pressures (Table 1) were normalized across the period of interest (1985–2011). We limited the time series to this period because longer time series have proportionately greater influence than shorter time series in determining common trends and only a third of the indicators had longer time series (Table 1). We used Akaike's model selection criterion (AICc; Burnham & Anderson 1998) values to determine the fewest common trends and covariates

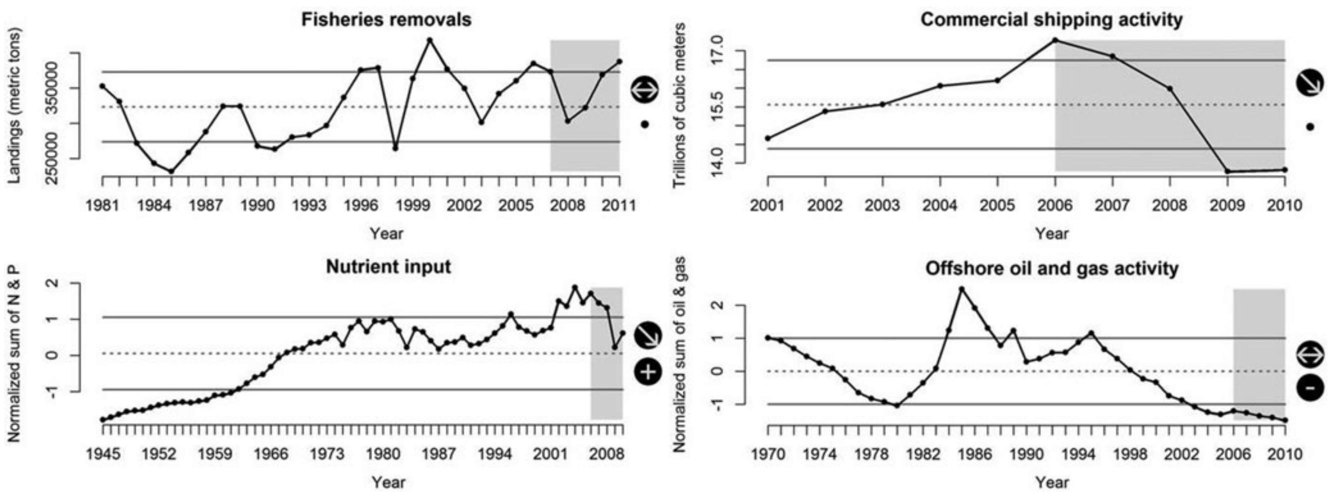

Figure 1 Examples of the status and trends of anthropogenic pressures in the California Current ecosystem. Each pressure is represented by specific indicator datasets (Table 1 and Appendix 2, see supplementary material at Journals.cambridge.org/ENC). Arrows to the right of each panel represent whether the modelled trend over the last five years (shaded) increased (↗) or decreased (↘) by more than 1 SD or was within 1 SD (↔) of the long-term trend. Symbols below the arrows represent whether the mean of the last five years was greater than (+), less than (-) or within (•) 1 SD of the mean of the full time series (dotted line). Solid lines are ±1 SD of the mean of the full time series.

required to explain the full set of time series. We used an oblique rotation method (promax) to calculate factor loadings as it helped separate factor loadings among trends better than the default orthogonal method (varimax). DFA factor loadings > 0.2 were considered relevant for interpreting whether pressures were represented by a specific trend (Zuur *et al.* 2003*b*). Loading values represent coefficient values that when multiplied by the respective trend value and summed across all trends produce fitted values for each year for each pressure (Appendix 3, Fig. S27, see supplementary material at Journals.cambridge.org/ENC).

For the covariate 'coastal population abundance', we used data from the USA Census Bureau (2010–2012: http://www.census.gov/popest/data/datasets.html) and the National Bureau of Economic Research (1970–2009: http://www.nber.org/data/census-intercensal-county-population.html). We limited data to 'coastal' counties in California, Oregon and Washington, as defined by National Oceanic and Atmospheric Administration (http://www.census.gov/geo/landview/lv6help/coastal_cty.pdf). For the covariate 'gross domestic product' (GDP), data were summed annually across the states of California, Oregon and Washington from 1963–2011 (Bureau of Economic Analysis; http://www.bea.gov/iTable/index_nipa.cfm) using 'Regional Data' by state across all industries.

RESULTS

Indicators of anthropogenic pressures

Indicators of anthropogenic pressures in the CCE (Table 1) were chosen based on rankings in the indicator evaluation matrix (Appendix 1, S1, see supplementary material at Journals.cambridge.org/ENC). Descriptions, status and trends of individual indicators are described in Appendix 2 (see supplementary material at Journals.cambridge.org/ENC), but examples of indicator time series show that the short-term status and trend of anthropogenic pressures in the CCE varied widely (Fig. 1). Most indicators showed either significant short-term trends or their current status was at historically high or low levels (Fig. 2). Indicators of inorganic, organic and ocean-based pollution, commercial shipping activity, recreational use, invasive species and habitat modification all weakened over the short-term, while indicators of dredging and marine debris (in the northern CCE) intensified; all of these pressures remained within historic levels. In contrast, indicators of seafood demand, sediment and freshwater retention, power plant activity and coastal engineering remained relatively constant over the short-term, but were above historic levels, while indicators of offshore oil and gas activity and related benthic structures were at historically low levels. Nutrient input and shellfish aquaculture were at historically high levels, but nutrient input weakened over the last five years of its time series (Figs 1 and 2), while shellfish aquaculture has continued to intensify (Fig. 2 and Appendix 2, Fig. S2, see supplementary material at Journals.cambridge.org/ENC).

Cumulative pressures index

The 'additive' and 'weighted' methods provided qualitatively similar estimates (Fig. 3). However, the additive index showed a positive trend (adjusted r^2: 0.51, $F_{1,13} = 15.7$, $p = 0.002$), whereas the weighted index showed no trend (adjusted r^2: 0.12, $F_{1,13} = 2.9$, $p = 0.110$) across the entire period. Using the same criteria to define the recent short-term status and trends of individual pressures, there was a short-term decrease in

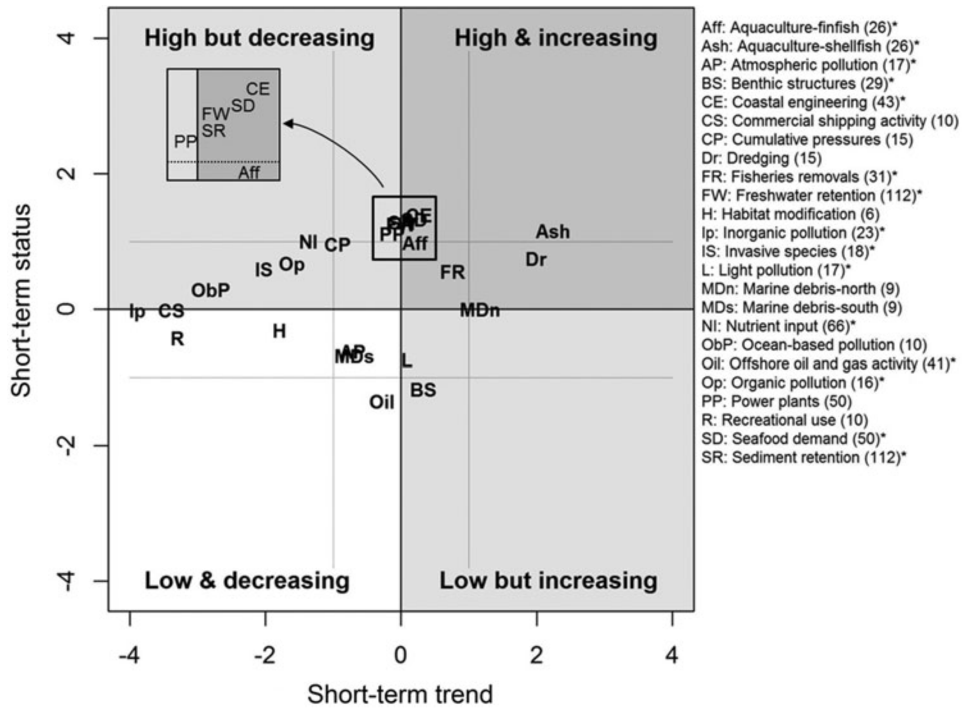

Figure 2 Short-term status and trends of anthropogenic pressures in the California Current ecosystem. The short-term trend indicates whether the indicator increased, decreased or remained the same over the last five years. The short-term status indicates whether the mean of the last five years was higher, lower, or within historical levels of the full time series. Data points outside the dotted lines (± 1.0 SD) are considered to be increasing or decreasing over the short term or the current status is higher or lower than the long-term mean of the time series. Numbers in parentheses in the legend are the number of years of data for each pressure. The 'Cumulative pressures' indicator (see Fig. 3) is the additive sum of 15 of these pressures, which had annual data from 1994–2008 (asterisks).

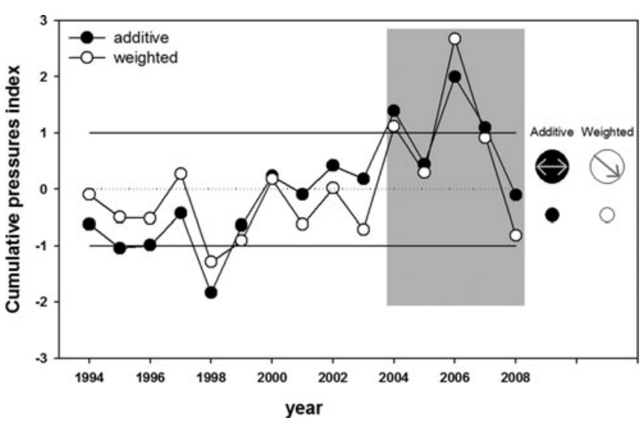

Figure 3 Indices of cumulative pressures from 1994–2008 using 15 anthropogenic pressures (asterisks in Fig. 2) which had data during this period. Each index was normalized prior to plotting to place them on the same scale. 'Additive' is the sum of all pressure values each year; 'Weighted' is the sum of pressure values multiplied by their respective weighting values (derived from Teck *et al.* 2010) (see Fig. 1 for description of symbols, lines, and shading).

cumulative pressures using the weighted index, whereas there was no significant change in the short-term trend using the additive index (Fig. 3). The short-term status for both indices was within historic levels of this time series.

Correlations and temporal shifts among pressures

The first two axes of the PCA explained *c.* 68% of the total variation in the same 15 1994–2008 time series used to calculate the cumulative pressures index, and the first four axes explained 86% (Appendix 3, Fig. S25, see supplementary material at Journals.cambridge.org/ENC). Plotting the scores of the first two principal components across time showed clear changes in the composition of pressures over this period (Fig. 4). In the 1990s, there was strong influence by oil and gas activities, light pollution and benthic structures, while coastal engineering, seafood demand, nutrient input, aquaculture and organic and inorganic pollution became more important to this multivariate measurement in the 2000s. The change in the position of the PCA score observed in 2002 can be attributed to a particularly large increase in atmospheric pollution that year and the abrupt change that occurred in 2006 was related to large increases of inorganic (Appendix 2, Fig. S12, see supplementary material at Journals.cambridge.org/ENC) and organic (Appendix 2, Fig. S20, see supplementary material at Journals.cambridge.org/ENC) pollution.

Sediment retention and freshwater input also loaded heavily on PC1, but in the complete time series for these pressures, they are relatively stable from 1994 to 2008 (Appendix 2, Figs S9 and S22, see supplementary material at Journals.cambridge.org/ENC) and thus would have little influence on any changes in cumulative pressure if the entire time series could have been used. 'Fisheries removals', which was quite variable during this time period, was the only pressure that did not load significantly on PC1 or PC2, but loaded heavily on PC3.

Common trends

Model selection criteria revealed a model with either four or five common trends with no covariates sufficiently explained the time series of pressure indicators (Table 2). Because the

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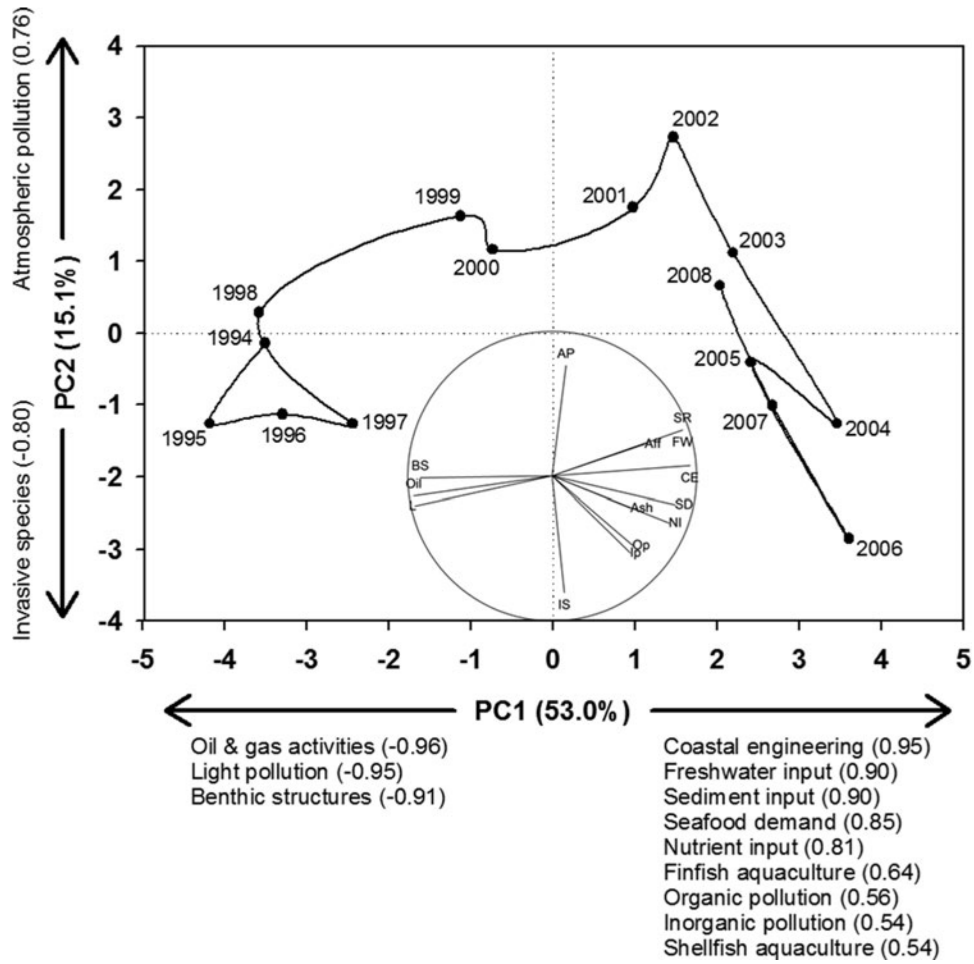


Figure 4 Principal components analysis using indicators of 15 anthropogenic pressures (asterisks in Fig. 2) that had data from 1994–2008. Pressures identified along each axis had eigenvectors > 0.3 for one of the first two principal components, while the values in parentheses are the loading values for the predominant principal component for each pressure (see Fig. 2 for abbreviations).

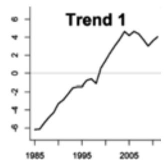
Table 2 Model selection criteria from the top ten dynamic factor analysis models using all 23 indicator time series from 1985 to 2011 and comparing among different variance-covariance structures (R matrix), 1–5 trends and with 0–2 covariates. K = number of parameters; AICc = Akaike information criterion corrected for small sample sizes; ΔAICc = difference between each model and the lowest AICc from all possible models; population = coastal population abundance estimate; GDP = gross domestic product of the USA's west coast states. (See Appendix 3, see supplementary material at Journals.cambridge.org/ENC for description of each R matrix structure.)

R matrix	*Trends*	*Covariate(s)*	*K*	*AICc*	*ΔAICc*	*Akaike weight*	*Cumulative Akaike weight*
Diagonal and equal	4	None	87	875.5	0.00	0.49	0.49
Equal variance-covariance	5	None	107	877.2	1.68	0.21	0.70
Diagonal and equal	5	None	106	877.4	1.89	0.19	0.89
Diagonal and equal	3	Population	90	879.6	4.12	0.06	0.95
Equal variance-covariance	4	None	88	881.9	6.42	0.02	0.97
Equal variance-covariance	3	Population	91	882.7	7.19	0.01	0.98
Diagonal and equal	2	Both	92	884.5	8.97	0.01	0.99
Diagonal and equal	4	Population	110	885.4	9.90	0.00	0.99
Diagonal and equal	3	GDP	90	885.8	10.30	0.00	1.00
Equal variance-covariance	2	Both	93	887.3	11.75	0.00	1.00

model with four trends was more than twice as likely to be the best model as the two models with five trends, we used the 4-trend model to describe the common trends below. The 4-trend model had tight fits with most of the indicator time series, though a notable exception was 'Fisheries removals' (Appendix 3, Fig. S27, see supplementary material at Journals.cambridge.org/ENC).

Trend 1 showed a relatively monotonic increase from 1985 to the early 2000s followed by a more variable period during the rest of the 2000s (Table 3). Eight pressures had their highest loadings on this trend and were not related to any other trend. These pressures were related to food supply, construction and energy production. Most of these pressures were positively correlated with trend 1,

Table 3 Common trends and factor loadings identified from the four-trend dynamic factor analysis model using 23 pressures and time-series data from 1985 to 2011. ‡Pressures related to each trend (absolute value of factor loadings > 0.2). *Trend most related to each pressure. Negative loadings mean that a pressure is related to the inverse of the trend shown above each column. Factor loadings are the coefficients that when multiplied by the trend value and summed across all trends produce predicted values for each pressure.

Broad category of pressures	*Pressures*				
Terrestrial pollutants	Atmospheric pollution	0.01	–0.53‡*	0.12	0.28‡
	Inorganic pollution	– 0.12	0.01	0.09	0.77‡*
	Organic pollution	– 0.19	– 0.01	0.00	1.02‡*
	Nutrient input	0.17	0.12	– 0.19	0.39‡*
Transportation	Dredging	0.05	– 0.03	0.14	– 0.58‡*
	Commercial shipping	– 0.01	0.27‡	– 0.43‡*	0.36‡
	Ocean–based pollution	– 0.01	0.47‡	– 0.48‡*	0.17
	Invasive species	– 0.08	0.60‡*	– 0.15	0.07
Coastal disturbance	Marine debris (south)	0.02	– 0.34‡*	– 0.11	– 0.13
	Marine debris (north)	0.00	0.38‡	– 1.36‡*	0.04
	Recreational use	0.26‡	0.05	– 0.89‡*	– 0.18
	Light pollution	– 0.10	0.08	– 0.41‡*	– 0.20
	Habitat modification	– 0.09	– 0.18	– 0.62‡*	– 0.14
Food	Fisheries removals	0.22‡*	– 0.01	– 0.19	– 0.14
	Shellfish aquaculture	0.15	0.22‡	0.25‡	– 0.31‡*
	Finfish aquaculture	0.29‡*	– 0.06	– 0.05	– 0.20
	Seafood demand	0.22‡*	0.11	0.06	– 0.01
Construction	Coastal engineering	0.27‡*	– 0.01	0.04	– 0.13
	Freshwater retention	0.28‡*	– 0.12	0.03	– 0.08
	Sediment retention	0.28‡*	– 0.12	0.03	– 0.08
	Benthic structures	– 0.27‡*	0.03	0.11	– 0.01
Energy	Oil and gas activities	– 0.26‡*	0.04	– 0.12	0.07
	Power plant activity	0.08	– 0.45‡	0.14	0.54‡*

but oil and gas activities and related benthic structures were negatively correlated (Table 3; Appendix 3, Fig. S28, see supplementary material at Journals.cambridge.org/ENC). Trends 2–4 showed a variety of peaks and valleys at various times throughout the period. Six of eight pressures that loaded heavily on trend 2 also loaded heavily on trend 3 or 4 (Table 3), suggesting some correlation among these three trends in certain periods. Pressures associated with transportation and coastal disturbance tended to have higher loadings on trend 3, while pressures associated with the input of terrestrial pollutants were generally related to trend 4 (Table 3).

Because all four trends were estimated simultaneously, we cannot statistically determine which trend was most important; however, comparing the results from models with one, two and three common trend(s) with the trends found in the 4-trend model (Zuur *et al.* 2003*a*) suggested that trend 1 was the most important as it was nearly identical to the trend found in the 1-trend model and other monotonic trends found in the 2- and 3-trend models (Appendix 3, Fig. S29, see supplementary material at Journals.cambridge.org/ENC).

The inclusion of covariates did not significantly increase the fit of the DFA model to the pressures time series data in the top three models, but trend 1 from the 4-trend model was highly correlated with both covariates (population abundance versus trend 1: $r = 0.98$; GDP versus trend 1: $r = 0.95$).

It is important to note that the strength of the relationship between each pressure and each common trend is a function of the length of each time series. For example, the time series for marine debris in the northern CCE was strongly related to the inverse of trend 3 and less positively related to trend 2 for only a short period of that trend (data for marine debris only available from 1999 to 2007; Tables 1 and 3). In contrast, the time series for seafood demand (data available from 1962 to 2011; Table 1) was related to trend 1 across the entire period from 1985–2011 (Table 3).

DISCUSSION

One central tenet of ecosystem-based management is to address the multiple activities occurring both on land (for example agricultural and industrial practices) and in the ocean (such as fishing and energy exploration) that affect various components of marine ecosystems (Leslie & McLeod 2007). Spatial analyses have quantified individual and cumulative

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pressures across the CCE (Halpern *et al.* 2009), but prior to this work there have not been companion analyses conducted to determine the temporal status and trends of these anthropogenic pressures.

In this study, most indicators of pressures showed either significant short-term trends or their current intensity was at historically high or low levels. Taken together, these results support two primary conclusions: (1) decreasing trends of several pressures (such as shipping related indicators, industrial pollution and recreational activity) potentially reflect slowing economic conditions during the economic recession that began around December 2007 (see Grusky *et al.* 2011), and (2) most pressures at historically high intensity levels have levelled off and are not continuing to increase. An exception to these general conclusions is shellfish aquaculture, which continues to increase despite being at historically high levels. The time series for seafood demand and dredging also suggest that these pressures will be increasing at historically high levels if current trends continue over the next few years. In addition, new pressures related to wind/wave/tidal energy will need to be incorporated into this framework as activities associated with these technologies will undoubtedly increase over the next several decades.

Since each of the catalogued pressures is associated with one or more human activities, the connotation of their status and trend depends on one's perspective. For example, a decreasing trend in fisheries removals may be positive for some conservation outcomes, while at the same time, it could be negative in the short term for human well-being in coastal communities (Levin *et al.* 2009). Understanding the trade-offs resulting from dynamic changes in these pressures for the social, economic and biological components of the ecosystem is essential for making informed management decisions (Link 2010; Kaplan & Leonard 2012). The time series developed here can be used to inform such decisions in the USA's portion of the CCE, and to populate science-based decision support tools that link biological components of marine ecosystems with human communities and economies.

In addition to quantifying the intensity and trends of individual pressures, the ultimate goal of this work was to reduce the large number of pressures to a manageable number of trends that could subsequently be used in integrative analyses that investigate linkages between pressures and state variables across the CCE. In our first method that calculated two indices of cumulative pressures across the CCE, we found statistical differences in the status and trends between the additive and weighted models, but they provided qualitatively similar results. These results suggest that, at the scale of the USA's portion of the CCE, either model could be useful for capturing the overall variation in cumulative pressures. The weighted model may be most useful when examining relationships between cumulative pressures and specific species where the sensitivity of each species to each pressure could be used as weightings (see Maxwell *et al.* 2013). For resource managers interested in the potential impacts of these pressures in specific habitats, habitat-specific vulnerability scores for each pressure (Teck *et al.* 2010) could be used instead of the average vulnerability score across all habitats. The habitat-specific vulnerability scores would be weighted by the proportion of area of each habitat within the region of interest in order to calculate the weighting for each pressure. In this application, the difference between additive and weighted models could be quite significant depending on the relative size of the habitats present in the region-of-interest and their relative vulnerability to various pressures.

A clear limitation of any analysis attempting to combine multiple pressures into a cumulative index is the lack of data on the strength and form of interactions between them (Halpern & Fujita 2013). Without a clear understanding of the potential synergistic and antagonistic interactions among multiple pressures (Crain *et al.* 2008; Darling & Côté 2008; Brown *et al.* 2013), an additive index can be used to describe the cumulative effect of multiple pressures acting on the system (Halpern *et al.* 2009). However, an increasing body of work has more realistically described effects of multiple pressures on fish populations, as well as on fisheries (Kaplan *et al.* 2010; Ainsworth *et al.* 2011; Brown *et al.* 2013), and there has been increasing effort to empirically evaluate the strength and direction of interactions among multiple pressures (Lefebvre *et al.* 2012; Lischka & Riebesell 2012; Sunda & Cai 2012). This research will help better understand cumulative effects of multiple pressures on various species, habitats and ecosystems, and reduce uncertainty in quantifying these effects.

Of the two multivariate approaches to reduce the number of pressures into a manageable number of trends, principal components analysis (PCA) allowed us to reduce a set of 15 pressures down to two principal components that explained 68% of the variation. The analysis showed large changes in the composition of pressures during the 1994–2008 period. The relative changes among pressures may reflect changes in regulatory actions, business practices, economic activity, technological advances and social norms over this period. The principal component score framework has been suggested as a way to measure the relative status of an ecosystem and to derive specific control rules, analogous to single species management (Link *et al.* 2002). As the PCA score moves around in multidimensional space, managers could determine whether this point falls outside of acceptable conditions (Rockström *et al.* 2009; Samhouri *et al.* 2011, 2012). Once this occurs or is approached, pressures that are correlated with the movement outside the acceptable range could be subject to regulatory actions or incentives to reduce these pressures on the marine ecosystem.

However, we caution against the use of PCA as a way to reduce or combine multiple variables when those variables are time series (see Link *et al.* 2002; Sydeman *et al.* 2013) for two primary reasons: (1) PCA assumes that each year is independent from the year before and after, thus it does not account for autocorrelation that is present in time series data, and (2) PCA does not allow for missing data, which are common in time series data, thus reducing the set of time series that can potentially be used or adding in uncertainty associated with using averaged or predicted data to fill in missing values. In contrast, DFA is an analogous dimension-reducing methodology that explicitly accounts for the nature of time series data and can explicitly account for missing data, as well as incorporate the effects of explanatory variables (Zuur *et al.* 2003*b*; Holmes *et al.* 2012).

Using DFA, we were able to include all pressure time series and increase the number of years in the analysis from 15 to 27 compared to the cumulative pressures index and the PCA. The DFA reduced the 23 pressure time series to four underlying common trends. Ideally, this analysis would remove the effects of assumed drivers (covariates) and then reveal correlations between each pressure and one common trend. In our analysis, the covariates did not help remove underlying variation, but only seven of the 23 pressures were related to multiple common trends, making interpretation of the results more reasonable. Despite its flexibility in dealing with missing data and autocorrelation within time series, the correlations of these seven pressures with multiple trends highlights a caution in over-aggregating pressures data into a single index or even into a few common trends, as highly-variable pressures can load significantly onto multiple trends. In addition, the pressures are only related to the specific period of the trend for which there are pressure data. Alternative nonlinear approaches for reducing the dimensionality of large data sets have shown promise, in some instances, of being able to explain more of the total variance in the data (for example Kenfack *et al.* 2014) or in estimating the true dimensionality of the data set (for example Tenenbaum *et al.* 2000) compared to the linear methods we used, but nonlinear methods have also been prone to detect nonlinearities and multi-modal trends where none exist (Christiansen 2005; Andersen *et al.* 2009).

A second goal of ecosystem-based management is to identify thresholds and/or reference points of pressures that affect ecosystem state variables. Recent studies have begun to identify thresholds for individual pressures on marine ecosystem components (Samhouri *et al.* 2010; Large *et al.* 2013), but there has been no attempt at identifying thresholds across multiple pressures. Reducing 23 pressure time series to four common trends provides a way forward to identify relationships, including thresholds, between pressures and ecosystem components. The trends presented here, for example, could be used by themselves or in conjunction with oceanographic indices to explore the parameter space which is favourable for the dynamics of specific ecosystem components or could be used as covariates in models to help account for 'unknown factors' that are not measured directly in most studies (see for example Auth *et al.* 2011).

Importantly, we do not fully understand the relationship between most ecosystem components and the intensity levels of these pressures, either individually or collectively; thus, it is difficult to predict whether changes in 'pressures' will translate to detectable changes in 'impacts' on an ecosystem component. Also, given that many of these pressures are correlated (such as pressures that load on the same DFA trend), it may be difficult to disentangle effects of individual pressures and appropriately identify management responses. Each of these concerns highlights the need for increased empirical testing of the effects of these pressures on ecosystem responses.

It was surprising that the covariates coastal population abundance and economic activity did not significantly improve the fit of DFA models to the time series of anthropogenic pressures. However, trend 1 appeared to explain the greatest amount of variation across the set of pressures and was highly correlated with both covariates. Coastal population abundance and gross domestic product may be drivers of anthropogenic pressures as a whole in the CCE but institutional controls (laws and governance), market forces, technological advances and/or cultural norms likely interacted with these drivers at various times during this period to modify the relationship between pressures and drivers. For example, implementation of the Clean Water Act (http://www.epw.senate.gov/water.pdf) over the years has provided incentives and regulations which reduced the magnitude of certain industrial pollutants (Adler *et al.* 1993; Houck 2002), even though it likely reduced profits in the short-term. Similarly, social norms have changed the way some people feel about littering our roadways and waterways (Lee & Kotler 2011; Naquin *et al.* 2011), thus reducing per person littering in some regions even though the numbers of humans and the amount of waste produced has continued to increase over time (USEPA [United States Environmental Protection Agency] 2011; Brogle 2012). At some point, we expect our governing institutions, technological capabilities and/or social awareness to modify the effects of pressures ultimately caused by increases in the number of humans on the planet.

CONCLUSIONS

Despite the uncertainties about the strength and direction of interactions among pressures, it is important to understand how the intensities of multiple pressures have been changing over time. The determination of common trends among pressures can help reduce the number of variables included in ecosystem assessments and may help identify common drivers for multiple pressures. Incorporating numerous anthropogenic pressures into the framework of ecosystem-based management is necessary to understand linkages between these pressures and various biological components, and more importantly, will allow identification of thresholds (Samhouri *et al.* 2010; Large *et al.* 2013) and consideration of trade-offs among socioeconomic, cultural and biological components of the ecosystem (Rosenberg & McLeod 2005; Link 2010). Combining spatial and temporal patterns of anthropogenic pressures will provide a better understanding of how pressures are changing over time and space and allow managers to make better use of limited funding and resources. Recently developed 'end-to-end' ecosystem models (such as Atlantis; Fulton *et al.* 2011) and coupled ecological/economic models (Kaplan & Leonard 2012) allow examination of the effects and interactions of anthropogenic, oceanographic and climatic pressures on multiple ecological components and human communities. Our analyses highlight the great variety of trends in anthropogenic pressures and may be useful for improving hindcasts of ecosystem dynamics in these end-to-end models. Now, marine ecologists, fisheries scientists, and social scientists need to develop creative methods to test the validity of model results in the field in order to increase resource managers' and stakeholders' confidence in their use as part of the decision-making process.

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Supplementary material

To view supplementary material for this article, please visit Journals.cambridge.org/ENC.

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