Mapping cumulative human impacts to California Current marine ecosystems

Benjamin S. Halpern[1], Carrie V. Kappel[1], Kimberly A. Selkoe[1,2], Fiorenza Micheli[3], Colin M. Ebert[1], Caitlin Kontgis[4], Caitlin M. Crain[5], Rebecca G. Martone[3], Christine Shearer[6], & Sarah J. Teck[7]

[1] National Center for Ecological Analysis and Synthesis, 735 State Street, Santa Barbara, CA 93101, USA
[2] Hawai'i Institute of Marine Biology, University of Hawai'i, Kaneohe, HI 97644, USA
[3] Hopkins Marine Station, Stanford University, Pacific Grove, CA 93950, USA
[4] School of Public Health, Division of Environmental Health Sciences, University of California, Berkeley, CA 94720, USA
[5] University of California, Santa Cruz and The Nature Conservancy Global Marine Initiative, Center for Ocean Health, 100 Shaffer Road, Santa Cruz, CA 95060, USA
[6] Sociology Department, University of California, Santa Barbara, CA 93106, USA
[7] Department of Ecology, Evolution, and Marine Biology, University of California, Santa Barbara, CA 93106, USA

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Correspondence
Benjamin S. Halpern, National Center for Ecological Analysis and Synthesis, 735 State Street, Santa Barbara, CA 93101, USA.
Tel: +805 892 2531; fax: +805 892 2510.
E-mail: halpern@nceas.ucsb.edu

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Abstract

Quantitative assessment of the spatial patterns of all human uses of the oceans and their cumulative effects is needed for implementing ecosystem-based management, marine protected areas, and ocean zoning. Here, we apply methods developed to map cumulative impacts globally to the California Current using more comprehensive and higher-quality data for 25 human activities and 19 marine ecosystems. This analysis indicates where protection and threat mitigation are most needed in the California Current and reveals that coastal ecosystems near high human population density and the continental shelves off Oregon and Washington are the most heavily impacted, climate change is the top threat, and impacts from multiple threats are ubiquitous. Remarkably, these results were highly spatially correlated with the global results for this region ($R^2 = 0.92$), suggesting that the global model provides guidance to areas without local data or resources to conduct similar regional-scale analyses.

Introduction

Recent calls for ecosystem-based management of the oceans have emphasized the fundamental need to assess and account for cumulative impacts of human activities (POC 2003; USCOP 2004; McLeod *et al.* 2005; Ruckelshaus *et al.* 2008). Management focused on impacts of a single stressor is inefficient and often ineffective because co-occurring human activities lead to multiple simultaneous impacts on communities and individual species (Halpern *et al.* 2008b). This shift in focus has gained particular traction on the West Coast of the United States, where the Pew and U.S. Ocean Commissions reports (POC 2003; USCOP 2004), three-state governors' agreement (WCGA 2006), and California Marine Life Protection Act (MLPA; http://www.dfg.ca.gov/mlpa) have all articulated the need to evaluate cumulative impacts in management. Consequently, there is a pressing need for high-resolution spatial information on cumulative impacts to provide an assessment of the state of the oceans within the California Current and help identify priority areas and issues for ongoing conservation and management.

A global map of the cumulative impact of human activities on marine ecosystems showed the California Current region to have many areas of high impact and few refuges of low impact (Halpern *et al.* 2008c). However, the reliability of the global results for local or regional use is unclear (Halpern *et al.* 2008c). When higher-quality data are available, updating the cumulative impact map for a focal region should give more accurate results that better inform regional management (Selkoe *et al.* 2008). Additionally, comparing a regional-scale analysis to the global results can address how well the global data sets and analysis predict regional and local cumulative impacts.

With this regional-scale focus, we address several questions for management action within the California Current: (1) Which are the most and least impacted areas? (2) What are the top threats to the region? (3) What is the relative contribution to the cumulative impact of different sets of drivers (e.g., land-based sources, climate change stressors, and fishing), and how does this vary between coastal and offshore areas? (4) Which ecosystems are most and least impacted? (5) How do the regional- and the global-scale results compare? The results also provide a comprehensive baseline of ocean condition against which future assessments can be compared.

Methods

The analytical framework for calculating cumulative impact scores (I_C) is described elsewhere (Halpern *et al.* 2008c). Briefly, I_C is calculated for each 1-km^2 pixel as $I_C = \sum_{i=1}^{n} \frac{1}{m} \sum_{j=1}^{m} D_i \times E_j \times \mu_{i,j}$, where D_i is the log-transformed and normalized value (scaled between 0 and 1) of intensity of an anthropogenic driver at location i, E_j is the presence or absence of ecosystem j, $\mu_{i,j}$ is the impact weight for anthropogenic driver i and ecosystem j, and $1/m$ produces an average impact score across ecosystems. We calculated the average here rather than the sum, as was done before (Halpern *et al.* 2008c; see Supporting Information), although we also calculated the sum for comparison.

Impact weights ($\mu_{i,j}$) were estimated using expert judgment to quantify vulnerability of ecosystems to human drivers of ecological change (Neslo *et al.* 2008; Teck *et al.* in review; see Table S1). We found or created spatial data sets for $n = 25$ drivers and $m = 19$ ecosystems (Table 1) from a comprehensive list of 53 potential drivers and 20 ecosystems relevant to the California Current identified by several regional experts. Cumulative impact to individual ecosystems (I_E) was calculated as $I_E = \sum_{i=1}^{n} D_i \times E_j \times \mu_{i,j}$, impact of individual drivers across all ecosystem types (I_D) was calculated as $I_D = \sum_{j=1}^{m} D_i \times E_j \times \mu_{i,j}$, and the footprint (unweighted by ecosystem vulnerability) of a driver (F_D) was calculated as $F_D = \sum_{i=1}^{n} D_i$. The sources and methods used to develop each data layer are detailed in the Supporting Information and briefly in Table 1. All major ecosystems and nearly all major human stresses to them are captured, including locations of positive "stresses" where extractive activities are prohibited (marine reserves).

We evaluated percent contribution of each individual driver and four categories of drivers (land, climate, fishing, and other) to I_C in each 1 km^2. We calculated the mean, variance, and maximum percent contribution values across all pixels for each driver. We correlated per-pixel values (pairwise linear regressions) to assess how well each component layer could predict overall spatial patterns. We did not test sensitivity of results to impact weights because previous Monte Carlo simulations showed the global results to be insensitive to the weights (Halpern *et al.* 2008c) and additional analyses have shown them to be robust (Teck *et al.* in review).

We also correlated I_C scores to results for the region from the global-scale analysis (Halpern *et al.* 2008c). A high correlation indicates that the relative magnitude of human impact among locations in the region is similar despite very different data sources, resolution, and quality.

Results

U.S. coastal and continental shelf areas had the highest impact scores, while coastal Baja California had some of the lowest (Figure 1). The highest scores are concentrated around areas of large human populations, such as Puget Sound and locations in Central and Southern California, and areas of heavily polluted watersheds such as Tijuana and southern Oregon. Offshore, I_C generally increased with latitude, peaking over Washington and Oregon's continental shelves. Spatial patterns of stressor subsets vary, highlighting intraregional variation in the relative importance of different stressors (Figure 1). Climatic stressors have the highest impacts in northern offshore waters. Impacts of land-based activities are concentrated not only in U.S. coastal waters but also in high-latitude offshore waters because of atmospheric pollution deposition. Fishing impacts are concentrated in coastal waters, but in contrast with most other stressor categories, also affect offshore waters in California and Baja California. Impacts from other commercial activities (e.g., shipping) are distributed throughout the region, except in northern Baja California.

Increased sea surface temperature (SST), ultraviolet radiation (UV), and atmospheric deposition best predict cumulative impact patterns, as indicated by high correlations with I_C values (Table 2). Per-pixel scores are mostly driven by these variables plus ocean acidification (Table 2) because of the widespread presence of these stressors (Figure 2). However, even stressors poorly correlated with I_C, such as organic pollution, increased sediment input, invasive species, and recreational and demersal destructive fishing, can contribute a relatively large fraction to the per-pixel scores ("Max" column in Table 2). Locally high impacts of these drivers contribute to high cumulative scores in coastal areas.

Table 1 Data details for anthropogenic drivers and ecosystems included in our analyses. Full descriptions, data sources (with expanded acronyms), and additional details and full references for sources are provided in the Supporting Information

	Code	Anthropogenic driver	Brief description	Source	Native resolution
Land-based	N	Nutrient input			
		Fertilizer and manure input	Fertilizer use for crops and confined manure (dairy farms)	USGS	1 km^2
		Atmospheric deposition of nitrogen	Wet deposition of ammonium and nitrate	NADP	Point, kriged to 1 km^2
	OP	Organic pollution	Pesticide use on agricultural land	Halpern *et al.* (2008c)	1 km^2
	IP	Inorganic pollution			
		Nonpoint source	Impervious surface area (urban areas)	NGDC	1 km^2
		Point source	Factories, mines, and other point sources	EPA	Point, converted to 1 km^2
	CE	Coastal engineering	Linear extent data on consolidated and riprap structures	ESI, Google	1 km^2
	DH	Human trampling	Modeled by beach attendance at each access point	MLPA, OGEO, WADOE	1 km^2
	PP	Coastal power plants	Cooling water entrainment from power plants	Platts	1 km^2
	SI	Sediment increase	Global warming caused increases in sediment runoff	SRTM60plus, PRISM, Syvitski *et al.* (2003)	1 km^2
	SD	Sediment decrease	Sediment captured by dams	SRTM60plus, PRISM, Syvitski *et al.* (2003)	1 km^2
	LP	Noise/light pollution	Satellite nighttime images of light intensity	NGDC	1 km^2
	AD	Atmospheric deposition of pollutants	Wet deposition of sulfate	NADP	Point, kriged to 1 km^2
	CS	Commercial shipping	Commercial shipping and ferry routes and traffic	CalTrans, WADOT, Halpern *et al.* (2008c)	1 km^2
	IS	Invasive species	Modeled as a function of ballast water release in ports	Modified from Halpern *et al.* (2008c)	Modeled to 1 km^2
	P	Ocean-based pollution	Pollution derived from commercial ships and ports	CalTrans, WADOT, Halpern *et al.* (2008c)	1 km^2
	MD	Marine debris (trash)	Coastline trash picked up by annual beach clean-up	CCCPEP	County level, modeled to 1 km^2
	AQ	Aquaculture	Salmon and tuna fish pens	Google	1 km^2
Fishing	RF	Recreational fishing	Number of recreational charter boat and private skiff trips	CRFS, CPFV	1′ microblocks
	PLB	Pelagic low bycatch	Total annual catch for all gear types in this class	CalDFG, SAUP	1/2 degree and 10′ blocks
	PHB	Pelagic high bycatch	Total annual catch for all gear types in this class	CalDFG, SAUP	1/2 degree and 10′ blocks
	DD	Demersal destructive	Total annual catch for all gear types in this class	CalDFG, SAUP	1/2 degree and 10′ blocks
	DNLB	Demersal nondestructive low bycatch	Total annual catch for all gear types in this class	CalDFG, SAUP	1/2 degree and 10′ blocks
	DNHB	Demersal nondestructive high bycatch	Total annual catch for all gear types in this class	CalDFG, SAUP	1/2 degree and 10′ blocks
	OR	Oil rigs	Offshore oil platforms	NGDC, MLPA	1 km^2
Climate	SST	SST	Recent anomalously high sea temperature	Halpern *et al.* (2008c)	21 km^2
	UV	UV	Recent anomalously high UV irradiance	Halpern *et al.* (2008c)	1 degree
	OC	Ocean acidification	Modeled patterns of change to ocean acidity	Guinotte *et al.* (2003)	1 degree

Continued

Table 1 Continued.

	Ecosystem	Brief description	Source	Native resolution
Intertidal	Beach	Sandy shoreline	ESI, TNC, Google	1 km^2
	Rocky intertidal	Hard-substrate shoreline	ESI, TNC, Google	1 km^2
	Mud flats	Tidal flats with mud and sand substrate	ESI, TNC, Google	1 km^2
	Salt marsh	Vegetated tidal flats	ESI, TNC, Google	1 km^2
Subtidal	Suspension-feeding reefs	Oyster reefs	Polson *et al.* (2009)	1 km^2
	Seagrass	Shallow, subtidal vegetated substrate	PSMFC	1 km^2
	Kelp forest	Canopy-forming kelp forests	CDFG, TNC, Broitman & Kinlan (2009)	1 km^2
	Rocky reef	Hard substrate <30 m depth	MLPA, TNC, Halpern *et al.* (2008c)	1 km^2
	Shallow soft-bottom	Soft sediment <30 m depth	MLPA, TNC, Halpern *et al.* (2008c)	1 km^2
	Hard shelf	Hard substrate 30–200 m depth	MLPA, TNC, Halpern *et al.* (2008c)	1 km^2
	Soft shelf	Soft sediment 30–200 m depth	MLPA, TNC, Halpern *et al.* (2008c)	1 km^2
	Hard slope	Hard substrate 200–2,000 m depth	MLPA, TNC, Halpern *et al.* (2008c)	1 km^2
	Soft slope	Soft sediment 200–2,000 m depth	MLPA, TNC, Halpern *et al.* (2008c)	1 km^2
	Hard deep benthic	Hard substrate >2,000 m depth	MLPA, TNC, Halpern *et al.* (2008c)	1 km^2
	Soft deep benthic	Soft sediment >2,000 m depth	MLPA, TNC, Halpern *et al.* (2008c)	1 km^2
	Canyons	Hard and soft substrate canyons across all depths	PSMFC	1 km^2
	Seamounts	Peaks with >1,000 m rise and circular or elliptical	Halpern *et al.* (2008c)	1 km^2
	Surface pelagic	All surface waters over areas >30 m depth	SRTM30 DEM data	1 km^2
	Deep pelagic	All waters >200 m depth	SRTM30 DEM data	1 km^2

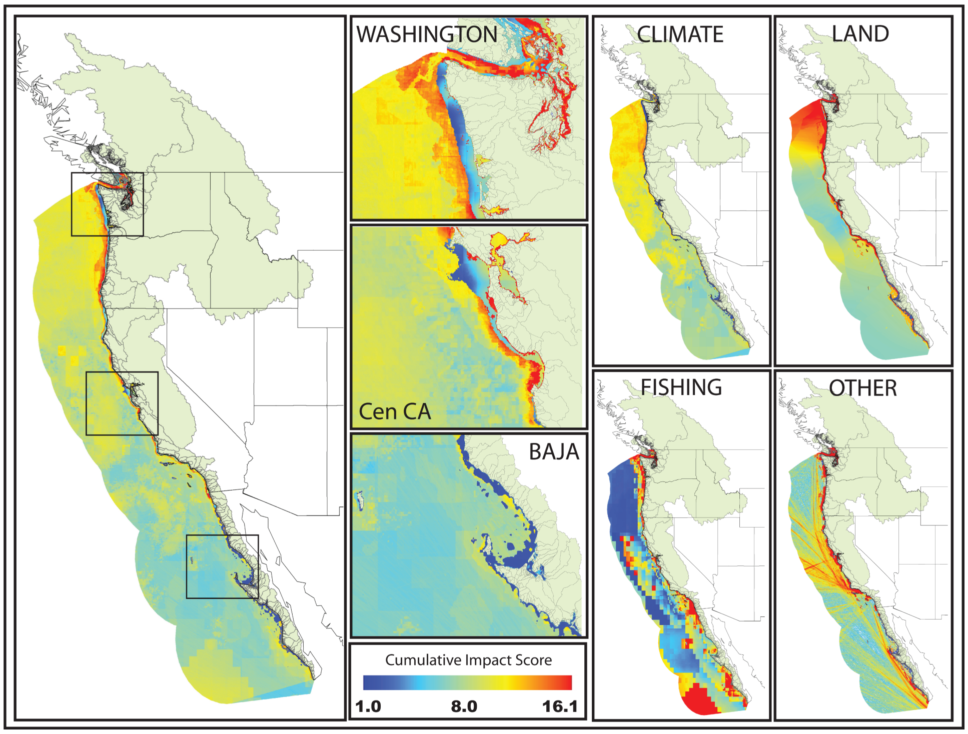

Figure 1 Cumulative impact map of 25 different human activities on 19 different marine ecosystems within the California Current with close-up views of three regions (Washington State, central California, and central Baja California), and impact partitioned into four sets of human activities of particular interest: climate change ($n = 3$ layers), land-based sources of stress ($n = 9$ layers), all types of fishing ($n = 6$ layers), and other ocean-based commercial activities ($n = 7$ layers). Puget Sound is the reticulated bay in Washington, San Francisco Bay is the large bay in Central California, and Tijuana is at the Mexican border with California.

Table 2 The influence of each driver layer and subsets of layers on cumulative impact maps. Spatial correlations (R^2) indicate how well each layer predicts overall patterns, while the values for "per-pixel fraction of the total" indicate the relative contribution of each layer to I_C on a per-pixel basis. Drivers ordered by R^2 values.

		Per-pixel fraction of total		
Layer	R^2	Average	SD	Max
Atmospheric deposition	0.68	0.0826	0.0257	0.2472
SST	0.66	0.0949	0.0989	0.3462
UV	0.62	0.1662	0.0419	0.3579
Ocean-based pollution	0.47	0.0112	0.0103	0.1267
Nutrient input	0.37	0.0015	0.0072	0.1263
Inorganic pollution	0.30	0.0008	0.0061	0.1301
Organic pollution	0.28	0.0021	0.0148	0.3349
Noise/light pollution	0.27	0.0004	0.0037	0.1466
Recreational fishing	0.27	0.0050	0.0182	0.3593
Invasive species	0.26	0.0031	0.0227	0.3352
Commercial shipping	0.25	0.0356	0.1279	0.1279
Ocean acidification	0.24	0.5313	0.0928	0.9941
Sediment decrease	0.24	0.0009	0.0083	0.1771
Demersal destructive	0.24	0.0097	0.0187	0.2805
Coastal engineering	0.20	0.0001	0.0035	0.2518
Demersal nondestructive high bycatch	0.16	0.0046	0.0094	0.0938
Sediment increase	0.16	0.0026	0.0193	0.3296
Marine debris (trash)	0.15	0.0001	0.0029	0.2258
Human trampling	0.13	0.0001	0.0022	0.1629
Demersal nondestructive low bycatch	0.07	0.0105	0.0192	0.1697
Pelagic high bycatch	0.06	0.0137	0.0394	0.2384
Coastal power plants	0.05	0.0000	0.0007	0.1273
Oil rigs	0.01	0.0000	0.0028	0.2230
Aquaculture	0.01	0.0000	0.0000	0.0202
Pelagic low bycatch	−0.09	0.0215	0.0261	0.1187
Climate	0.74	0.7933	0.0932	0.9941
Land-based	0.62	0.0902	0.0479	0.6977
Other	0.44	0.0496	0.0337	0.4825
Fishing	0.18	0.0654	0.0648	0.4503

I_C values are partly driven by ecosystem-specific impact weights; when weights are removed (i.e., footprints are mapped), all fishing types, commercial shipping, and ocean-based pollution emerge as key stressors (Figure 2). These results highlight how the distribution and magnitude of activities and relative vulnerabilities of affected ecosystems all contribute to cumulative impact patterns, which cannot be anticipated from independent components. No single pixel in the study region experiences fewer than five stressors, nearly all experience more than 10 (Figure 2, counts; mean = 10.1 ± 1.6 SE), and coastal areas experience up to 15–20 coexisting stressors (mean = 13.2 ± 3.1 SE, max = 23).

Marine ecosystems vary greatly in relative anthropogenic impacts (Figure 3). Intertidal ecosystems (salt marsh, mudflats, rocky intertidal, and beach) and nearshore ecosystems (rocky reefs, kelp forests, oyster reefs, and seagrass beds) are most impacted, with the highest average per-pixel I_C and most pixels with scores greater than 8.0 (Figure 3). Continental shelf and pelagic ecosystems also have relatively high average I_C. Least impacted ecosystems are shallow soft-bottoms and seamounts (Figure 3).

Spatial correlation between the regional and the global cumulative sum model results was remarkably high ($R^2 = 0.92$), despite only four full (and several partial) stressor data sets and one ecosystem map being shared between the models. Correlation was also high in coastal (<200 m) areas ($R^2 = 0.76$) where differences between data sets are greatest. Given this high correlation, we regressed the global cumulative impact (sum) model with the cumulative impact (average) model presented here and used the equation ($\mathrm{Score}_{\mathrm{Global}} = 2.217 \times (\mathrm{Score}_{\mathrm{Regional}}) - 3.683$) to translate global ocean condition category values into new values for the California Current that we used to color code pixels as nearly pristine (blue) to highly impacted (red; Figure 4).

Discussion

Quantifying ecosystem vulnerability is fundamental to understanding how oceans are affected by human activities (Halpern *et al.* 2007; Teck *et al.* in review). The distribution and relative vulnerability of marine ecosystems play a major role in producing observed spatial variation in cumulative impact. For instance, in both the global-scale and the present analysis, the relatively low vulnerability of soft-bottom ecosystems creates low impact in most places it is found, even where affected by multiple overlapping drivers (Figure 1) (Halpern *et al.* 2007, 2008c), but this blue band disappears in threat footprint maps unweighted by ecosystem vulnerabilities (Figure 2). Where cumulative impact scores are high over soft-bottom ecosystems, as in San Francisco Bay, the extremely high number and severity of drivers influence the scores. In contrast, other intertidal and continental (soft and hard) shelf ecosystems are some of the most vulnerable, producing bands of red (heavy impact) where these ecosystems exist (Figure 1).

The quality of ecosystem data is therefore important for evaluating the accuracy of these maps. Many ecosystem layers have been extensively vetted, but several highly vulnerable ecosystems have poorer data quality. Rocky reefs (especially smaller patches) are not well mapped along most of the coast (notable exceptions, Monterey Bay and the Channel Islands, California). These patches exist within the blue band of low impact described above,

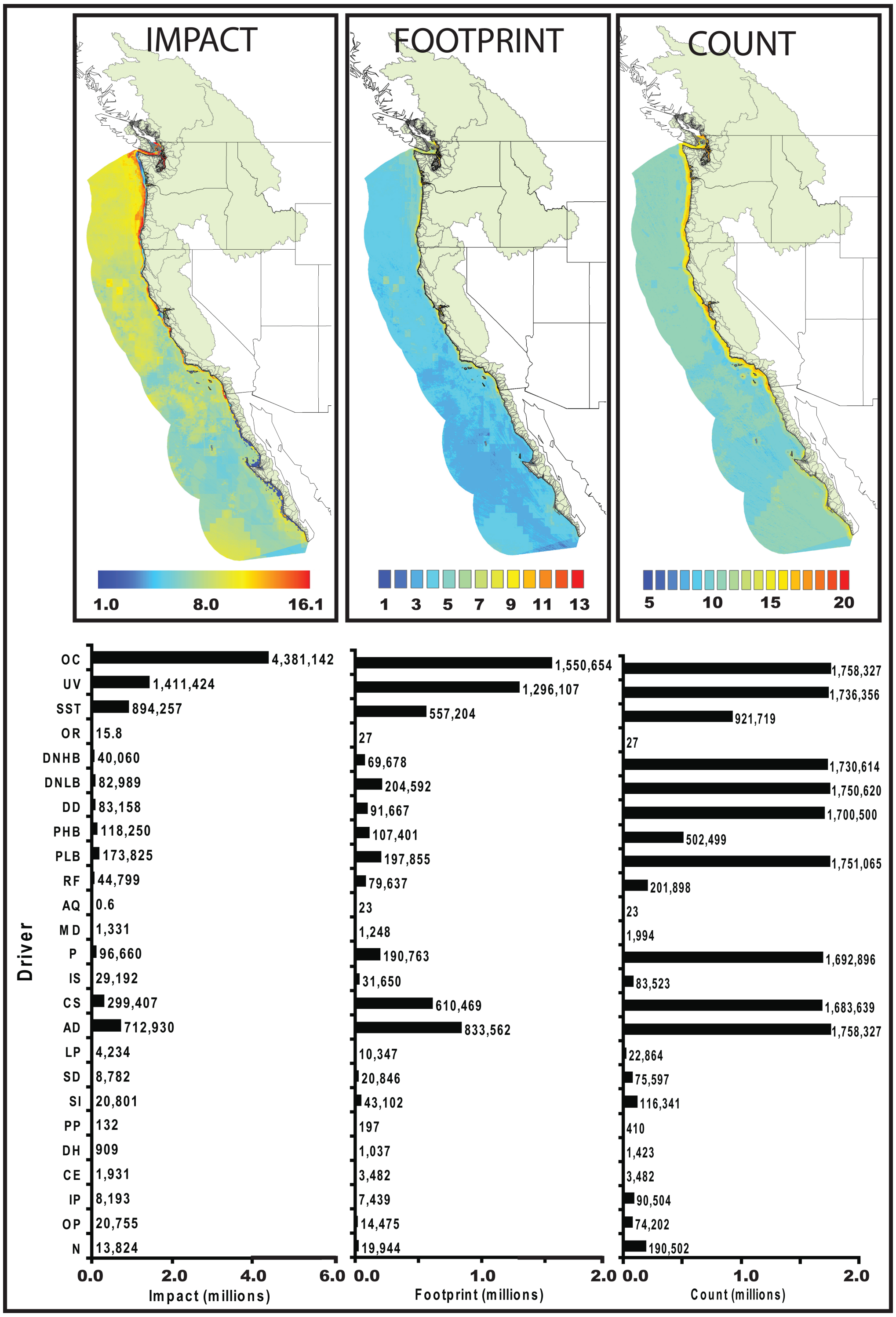

Figure 2 Cumulative impact scores (weighted values), footprint (unweighted values), and pixel count (presence/absence values) for each of the 25 human drivers used in our analyses. Inset maps show the summed output of the 25 layers; bar graphs show total values for each driver. Human stressors are abbreviated using labels from Table 1.

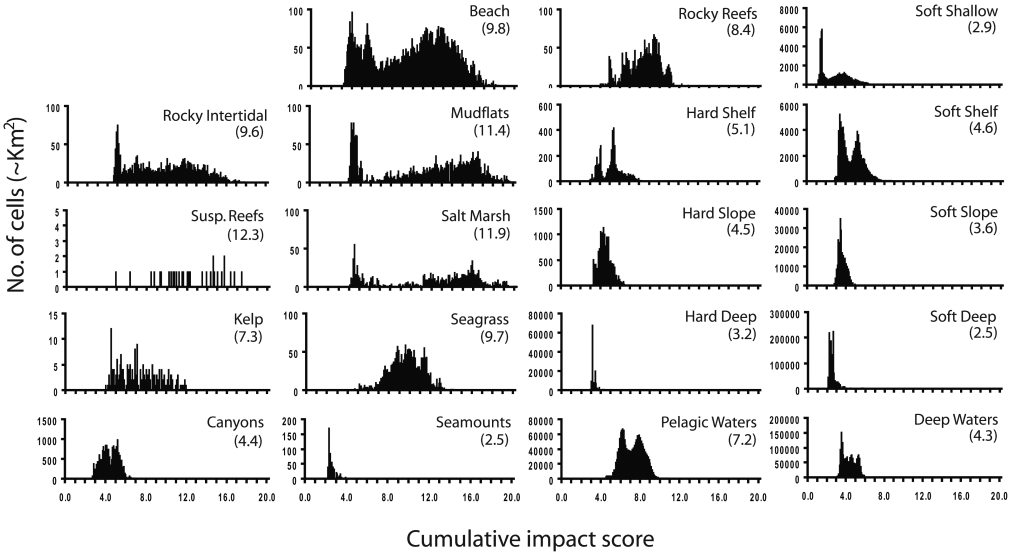

Figure 3 Histograms of per-pixel I_C calculated independently for each ecosystem. Mean scores for each ecosystem are provided in parentheses under the ecosystem name. Note the large differences in *y*-axes among ecosystem types.

warranting caution when assessing allowable levels of activities if local rocky reef data are of poor quality. The spatially modeled data used for deep hard-bottom ecosystems (Halpern *et al.* 2008c) likely underestimate the distribution of this ecosystem, so deep-water activities (such as bottom trawling) may have a larger impact than that estimated here. Suspension-feeding (oyster) reefs are also incompletely mapped. Finally, intertidal and nearshore

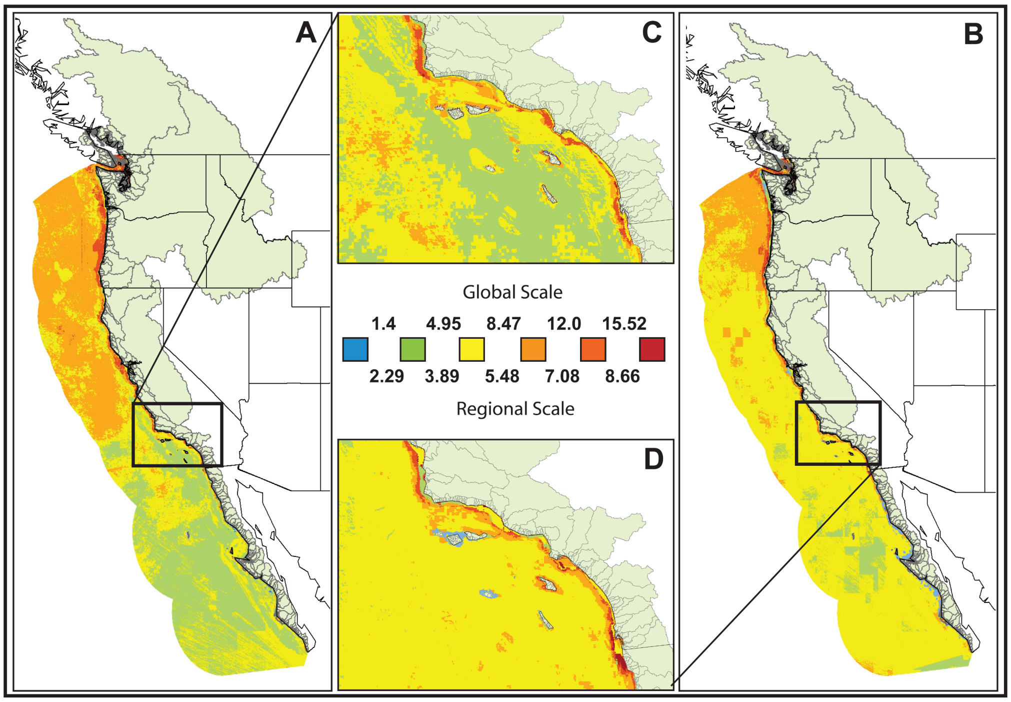

Figure 4 Maps of ocean condition for the California Current region based on (A) global results using ocean condition categories derived in (Halpern *et al.* 2008c) and (B) results from the analyses here binned into ocean condition categories based on the regression of the two models. Inset panels show a zoom-in view of the same region from the (C) global and (D) California Current model. Colors are designated uniquely for each map based on the impact scores indicated on the adjacent side of the color bar.

ecosystems are often patchy at scales smaller than 1 km^2, yet such data rarely exist, so we assigned these ecosystems as present or absent at a 1-km^2 scale. These ecosystems are some of the most vulnerable, so cumulative impact scores for some shoreline pixels may be slightly overestimated.

Not surprisingly, climate change drivers (SST, UV, and ocean acidification) exhibit the greatest impacts across the region (Figure 2) because of their widespread distribution and high vulnerability of many ecosystems to these stressors. Indeed, cumulative impact scores were highly correlated with individual climate drivers as well as with their sum, and these drivers contributed significantly to the values within each pixel (Table 2). However, these data may not accurately predict actual impacts of these stressors. Ocean acidification data were derived from a model that performs poorly for shallow coastal areas (Guinotte *et al.* 2003). Data on patterns of increased UV and SST came from remote satellite sensors that only capture ocean surface values. In addition, climate oscillations in the California Current region (Chavez *et al.* 2003) make it difficult to isolate the role of anthropogenic factors in climate change here. For these reasons, we also ran the model with climate layers removed. We found similar overall patterns in relative cumulative impact, but fishing and land-based stressors played a larger role in driving regional patterns and per-pixel values (Figure S2). Impacts from fishing peak not only in coastal areas from demersal fisheries but also offshore of northern and central California and southern Baja California where pelagic fisheries are intense.

Intertidal and nearshore ecosystems are most heavily impacted because of exposure to stressors from both land- and ocean-based human activities. Two of the top three most impacted ecosystems are mudflats and oyster reefs, which rarely receive management or conservation attention (Lenihan & Peterson 1998). Historic overharvesting of oysters and subsequent disease outbreaks that accompanied introduction of non-native species and expansion of invasive cordgrass, *Spartina alterniflora,* into mudflats have been identified as key threats to these ecosystems (Callaway & Josselyn 1992; Ruesink *et al.* 2005), neither of which were addressed well in our analyses, suggesting these ecosystems are likely even more impacted than shown here.

Observed low cumulative impacts to seamounts are, at first, puzzling. Yet, expert assessment revealed that seamounts are likely vulnerable to very few human activities (Teck *et al.* in review), although vulnerability to these few stressors (in particular, trawling and ocean acidification) is high. The small number of stressors with high impacts and limited overlap of these activities with seamounts in the region result in low cumulative impacts.

Replicating the framework from the global analysis (Halpern *et al.* 2008c) allowed a test of the usefulness of the global model at regional scales. Spatial correlation between the global model output for this same region and the results here was remarkably high ($R^2 = 0.92$), even when focused only on coastal areas (<200 m) where the number, quality, and sources of data are most different between the two analyses ($R^2 = 0.76$; Figure 4). This result suggests that the data-poorer global model can provide guidance on ocean condition for regional-scale management elsewhere in the world and is perhaps not surprising, as key groups of human stressors (land-based, climate, and fishing) tend to have similar spatial patterns across scales (e.g., land-based stressors are always greatest in nearshore waters). The global model is most reliable for regions where (1) the global ecosystem data are accurate and (2) the 17 global driver data sets represent well the top threats. A regional replication of the cumulative impact model for the Northwestern Hawaiian Islands produced lower correlation between the global and the regional models because of inaccuracies in global ecosystem data for this region (Selkoe *et al.* 2009). Once ecosystem data were updated, the correlation greatly improved, suggesting that adjustments and/or additions to the global model may be sufficient in many regions as an alternative to full replication (Selkoe *et al.* 2009).

For the global analysis, we groundtruthed cumulative impact scores with in situ measurements of ocean condition relative to a pristine baseline. Unfortunately, appropriate groundtruthing data do not exist for the California Current region. While ecotoxicology studies of shallow soft-bottom infaunal community composition or fish and water quality data (e.g., EPA 2005) are not uncommon, they are insufficient to groundtruth condition (relative to historic status) because they focus on a subset of stressors (pollution) in a single ecosystem. While the strong correlation between the global and the regional results can be used to extrapolate ocean condition cutoff values for this analysis (Figure 4), they require further testing.

Data do not exist for the full suite of 53+ potential stressors to the California Current system (Teck *et al.* in review), precluding a complete picture of cumulative impacts here. However, many missing stressors likely have minimal impacts at the regional scale, as most ecosystems have low impact weights for these stressors (e.g., scuba diving, kayaking, and scientific research; Teck *et al.* in review). However, missing stressors such as altered freshwater input, hypoxic zones, sea level rise, and disease likely have significant impacts on particular systems (e.g., salt marshes and seagrass beds) or locations (e.g., hypoxia in Oregon; Chan *et al.* 2008).

Our maps do not capture dynamic processes such as annual variation in vegetated ecosystems (e.g., kelp), dispersal and migration, or oceanographic currents, which may change a stressor's distribution and/or spread its impacts among locations. In some cases, the absence of dynamic processes may not affect the overall picture that emerges (Selkoe *et al.* 2008); in others, it may be fundamentally important (Halpern *et al.* 2008a). For example, high levels of land-based stressors caused large patches of high impact in Monterey Bay, yet known upwelling likely disperses and dilutes most input, thus reducing impacts (e.g., Chase *et al.* 2005). Incorporating dynamic realism to the model would greatly improve it.

Finally, our analyses capture the current status of the oceans without considering historical impacts, such as habitat loss and historical overfishing, or potential (near-term) future impacts, particularly from climate change and coastal development. An assessment of potential future impacts is critical for management planning efforts, but their absence should not affect our results. However, historical depletion of key species (e.g., sea otters, abalone, giant seabass, and some rockfish) and past coastal development that converted coastal habitat (e.g., estuaries) are unaccounted for in our maps. Consequently, cumulative impact is underestimated where these ecosystems and activities once existed.

Policy implications and policy limitations

The cumulative impact map and component ecosystem, stressor, and ecosystem vulnerability data sets can each be useful to management and conservation objectives and policy initiatives. Many data sets were developed for the first time in this study and are now freely available for management efforts aimed at addressing specific issues (http://www.nceas.ucsb.edu/GlobalMarine). For example, land-based pollution intensity and distribution data can be used in local- and regional-scale water quality management. In addition, the cumulative impact maps provide concrete guidance on where conservation action may be most critical (e.g., last remaining low-impact areas), where mitigation of key stressors is most needed, and where various activities are compatible. Our approach to assessing cumulative impacts allows one to decompose impact scores into component values for each ecosystem or stressor to assess the drivers of a particular score, and this in turn provides clear direction to management and conservation efforts on the most pressing needs. An interactive mapping website associated with this project can assist in this sort of usage (http://globalmarine.nceas.ucsb.edu/california_current.html).

Policy and management can be local to global in scale, and the scale of data used to guide those decisions should ideally match the scale of decisions. Our results are ideal for regional-scale (state and federal) decisions. For example, given the increased interest in ecosystem-based management and marine spatial planning within the California Current (Sivas & Caldwell 2008), these results provide key information for ranking management priorities and for the development of spatially explicit management plans such as comprehensive ocean zoning. Similarly, the West Coast Governors' Agreement on Ocean Health commits the states to implement ecosystem-based management (http://westcoastoceans.gov/), which will require consideration of cumulative impacts and may be informed by these results and maps. Data layers from our analyses can also be fed into optimization algorithms, such as MARXAN (Ball & Possingham 2000; Possingham *et al.* 2000), to identify efficient strategies for preserving and improving ocean health.

Our results may also be appropriate for some local-scale decisions, but could be made more useful by incorporating better high-resolution local data where they exist, as is being done for the MLPA Initiative in California because of known inaccuracies in the commercial fishing data (see Supporting Information). Ideally, such efforts would also gather higher-resolution data for all types of human activities so that marine protected area (MPA) planning could accurately consider fishing in the context of cumulative impacts.

Our results serve as a baseline against which to compare future ocean condition as well as a platform for forecasting future impacts and predicting costs and benefits of different management scenarios. As new data and ocean uses emerge, analyses can be repeated to assess how ocean health has changed. The framework can easily incorporate new data so that cumulative impact assessments can be updated quickly to evaluate and appropriately permit various uses of the ocean. For instance, our framework could assist siting of wave energy facilities by finding where they will have the least impact on overall ocean health while still meeting design needs.

We have presented a number of ways in which the results could inform several prominent ongoing and pending management activities within the California Current by showing where the most and least impacted areas are, which stressors are having the greatest impacts, and which ecosystems are most heavily impacted. These results do not prescribe particular actions, but instead provide information that can help improve the rationality, effectiveness, and efficiency of management decision making. The ubiquity of overlapping stressors shows that human impacts within the California Current go beyond any single sector, issue, or vulnerable species, and that addressing cumulative impacts is essential.

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Supporting Information

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

Figure S1 Subregion boundary delineations.

Figure S2 Cumulative impact scores for the California Current with the three climate variables removed.

Figure S3 Close-up views of three locations undergoing active assessments of management and conservation priorities: (A) Puget Sound, WA, (B) San Francisco Bay, CA, and (C) Santa Barbara Channel, CA.

Table S1 Ecosystem vulnerability weights for threats and ecosystems in our analyses for the whole region and for each subregion, taken from Teck *et al.* in review.

Table S2 Chemical pollutant relative toxicity weights.

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