



Rocky Reefs

BIGHT '13



Southern California Bight
2013 Regional Monitoring
Program
Volume II

SCCWRP Technical Report 932

Southern California Bight 2013 Regional Monitoring Program: Volume II. Rocky Reefs

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June 2016
SCCWRP Technical Report 932

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FOREWORD

The 2013 Southern California Bight Regional Monitoring Survey (Bight'13) is an integrated, collaborative effort to provide large-scale assessments of the Southern California Bight (SCB). The Bight'13 survey is an extension of previous regional assessments conducted every five years dating back to 1994. The collaboration represents the combined efforts of nearly 100 organizations. Bight'13 is organized into five elements: 1) Contaminant Impact Assessment (formerly Coastal Ecology), 2) Shoreline Microbiology, 3) Nutrients, 4) Marine Protected Areas, and 5) Trash and Debris. This assessment report presents the results of the Marine Protected Area portion of the survey. Copies of this and other Bight'13 reports, as well as workplans and quality assurance plans, are available for download at www.sccwrp.org.

ACKNOWLEDGEMENTS

The authors thank the scientists that collected the critical information in this report. Too numerous to count, these dedicated individuals spent thousands of hours underwater quantifying rocky reef ecosystems. Special gratitude is extended to the Partnership for Interdisciplinary Studies of Coastal Oceans (www.PISCOweb.org), the Vantuna Research Group (<http://www.oxy.edu/vantuna-research-group>), and the California Department of Fish and Wildlife (<https://www.wildlife.ca.gov>) for providing large portions of the data used in this report. And thanks to Jonathan Williams with the Vantuna Research Group for providing photos for the cover page.

EXECUTIVE SUMMARY

Background

About 25% of the Southern California Bight coastline is made up of shallow, subtidal rocky reef habitats, which are one of the most productive marine ecosystems on earth. Rocky reefs support extensive commercial and recreational fishing industries valued at an estimated \$400 million annually. Because of the reefs' proximity to the largest urbanized coastline in the nation, Bight rocky reefs are particularly vulnerable to the twin stressors of fishing extraction and land-based pollution loading. To mitigate the impacts of these stressors, regulations have been developed to restrict extraction practices in Bight rocky reefs, and best management practices have been implemented to lessen pollution loading.

At the same time, there has historically never been a study at a Bight-wide scale that offered insights into the relative contributions of fishing extraction and pollution loading on the overall ecological health of rocky reefs. Prior studies, which have been conducted at smaller spatial scales, have offered limited insights because of three main factors. First, many species, especially fished species, move at Bight-wide spatial scales. Second, natural biogeographic cycles at the Bight-wide scale can confound observations of presumed anthropogenic effects. Third, although individual stressors at low levels may not impact ecosystem function, low levels of multiple stressors in combination can exert cumulative impacts.

Goals of This Study

This study aimed to shed important new insights into the relative impacts of fishing extraction and pollutant discharges on the health of rocky reefs at the Bight-wide scale. Three key questions were asked:

- **What is the Bight-wide extent of fishing pressure on rocky reefs, and how does fishing pressure vary by individual reef?**
- **What is the Bight-wide extent of water quality pressure on rocky reefs, and how does water quality pressure vary by individual reef?**
- **What is the rocky reef biological response to fishing and water quality pressure?**

To answer these questions, three environmental scoring tools were developed: a fishing index to measure extraction density, a plume exposure index to measure pollutant loading and plume exposure, and a reef response index to measure biological impacts in rocky reefs.

Study Design and Findings

The three indices were used to illuminate the three stressor-response relationships outlined by the study's three key questions:

Fishing Pressure Index: GIS tools were used to map historical harvest rates for both commercial and recreational fishing across the Bight coast. The harvest rates, which came from the California Department of Fish and Wildlife and dated back as early as 1980, were adjusted in accordance with the amount of reef area available in 10-mi² fishing blocks. Commercial fishing pressure was greatest in a block south of Anacapa Island, and recreational fishing pressure was greatest in a Santa Monica Bay. Predictable patterns were identified from the GIS-based analysis, and there was confidence in the large-scale spatial findings. However, inferences at smaller spatial scales were limited as multiple reefs may be contained in a single fishing block. The magnitude of extraction was underreported, since not all extraction techniques are reported in this data set.

Plume Exposure Index: While pollutant loading from stormwater and wastewater effluent plumes to the ocean has already been examined, this index took analyses of Bight plumes to the next level by estimating the likelihood of plume exposure in any given area of the Bight. Probability of exposure was estimated using geostatistical tools and new technology to estimate advection of plumes away from wastewater outfalls and large rivers and streams. While plume exposure was estimated to extend across more than 2,400 km² of nearshore Bight ocean, the probability of exposure was frequently low, with just 200 km² having a probability of exposure greater than 50%. The analysis was limited for three reasons: Stormwater plume probability maps were not validated fully, minor pollutant inputs such as individual coastal storm drains and small wastewater discharges were not included, and pollution loading data for most Channel Islands locations were not available and thus they were assumed to have zero pollution loading.

Biological Reef Response Index: A multivariate model was developed to predict which species of fish, invertebrates and algae should be present at a given site under natural environment conditions; then, these data were compared to species that were actually observed. This so-called “observed-to-expected” index is already used to assess biological health in streams and marine soft-bottom habitats; the more these expected species are absent, the more the ecosystem is assumed to be impacted. In this study, fishing pressure influenced the Biological Reef Response Index more than plume exposure – an indication that some fish species are being extracted faster than they can be recruited. Although the Biological Reef Response Index was slightly more responsive to fishing pressures than plume exposure, water quality remains a significant concern of degradation for nearshore rocky reef habitats and, in fact, the twin stressors of fishing extraction and pollutant loading tend to co-occur and exert cumulative effects, especially across the highly urbanized portions of the Bight.

Next Steps

While this study sheds new insights into the relative contributions of fishing extraction and pollutant loading on overall ecological health, additional work is needed to address the study’s limitations and enhance its impactfulness. First, the Plume Exposure Index modeling should be improved upon, especially as more powerful computer models and validation data become available. Second, managers should continue to aim for integrated collaborations with regional monitoring programs focused on water quality and natural resources, including the Southern California Marine Protected Area Monitoring Enterprise and Areas of Special Biological Significance (ASBS).

CONTENTS

Technical Committee Members	i
Foreword	ii
Acknowledgements	ii
Executive Summary	iii
Background	iii
Goals of This Study	iii
Study Design and Findings	iii
Next Steps	iv
Synthesis	1
Introduction	1
General Approach	2
Fishing Pressure Index	2
Plume Exposure Index	3
Biological Reef Response Index	4
Future Directions	5
References	6
Chapter 1: Fishing Pressure Index	11
I. Abstract	11
II. Introduction	12
III. Methods	14
A. Study system	14
B. Data processing	14
C. Analyses	15
IV. Results	17
A. Summary Statistics	17
B. Processes of Spatial Structure	17
C. Corrected Fishing Distributions	17
V. Discussion	18
A. Conservation implications	19
B. Supporting Information	19
VI. References	20
VII. Tables	24
Chapter 2: Plume Exposure Index	35
I. Abstract	35
II. Introduction	36

A. The Southern California Bight is a valuable resource.....	36
B. Human influence in the region	37
C. Study Objective.....	37
III. Methods.....	39
A. Riverine pollutant loading.....	39
B. Riverine plume mapping	39
C. Treated Wastewater discharge pollutant loading.....	41
D. Treated wastewater plume mapping	42
E. Sensitivity analysis.....	43
IV. Results	44
A. Spatial extents of plumes.....	44
B. Pollutant loading and exposure.....	45
C. Plume Exposure Index.....	48
D. Sensitivity Analysis	49
V. Discussion.....	53
A. Benefits of using GIS to create a regional Plume Exposure Index	53
B. Extent of plumes and pollutant exposures.....	54
C. Comparison of relative risk from each source	54
D. Role of Plume Exposure Index in research and management.....	55
E. Future Directions	55
VII. Acknowledgements	56
VIII. References.....	57
Chapter 3: Biological Reef Response.....	61
I. Abstract	61
II. Introduction.....	62
III. Methods.....	64
A. Aggregation of Data.....	64
B. Designation of Reference and Stressed Sites.....	65
C. Development of the O/E Index	66
IV. Index Performance Evaluation.....	67
A. Relative Impacts of Fishing Pressure and Water Quality.....	67
V. Results	69
A. Reference Sites	69
B. Model Performance	69
C. Relative Impacts of Fishing Pressure and Water Quality.....	70
VI. Discussion.....	71

VII. Conclusions.....	73
VIII. References.....	73

SYNTHESIS

Introduction

The Southern California Bight (SCB) with its eight Channel Islands and biogeographic transition zone (Horn and Allen 1978, Pondella et al. 2005) is one of the most complex ecosystems in the world (Figure 1). Its scale is challenging, particularly from a research and monitoring perspective; the coastline is ~1200 km in length comprising as much coastline as the rest of the state. Twenty-five percent of coastline contains shallow (0-30m) subtidal rocky habitat, approximately 49,055 hectares (Pondella et al. 2015). These rocky reefs support the keystone species giant kelp (*Macrocystis pyrifera*), an indicator of highly productive temperate marine ecosystems and one of the most productive globally.

The well-chronicled, hallmark ecosystem of shallow subtidal rocky reefs faces critical sustainability challenges in the SCB. These reefs exist proximate to the largest urbanized coastline in the United States; over 20 million people live within an hours' drive of the coast. As a result, these reefs suffer from varying levels of fishing pressure and exposure to poor water quality. Thus, the primary management question posed for this study juxtaposes fishing pressure versus pollution pressure, and their relative roles in the health of rocky reef biological communities.

Due to its high productivity and accessibility, the SCB's rocky reefs support extensive commercial and recreational fishing industries valued at approximately \$400 million dollars annually (Gautam et al. 1996). This fishing pressure has caused ecosystem stress and multiple fisheries have collapsed or declined including abalone, bass, white seabass, giant seabass, rockfish etc. (Love et al. 1998, CDFG 2005, Allen et al. 2007, Pondella and Allen 2008, Erisman 2011). At the climax of this spectrum is white abalone (*Haliotis sorenseni*), now on the endangered species list.

Fishery declines have promulgated substantially increased regulations of the fishing industry. These regulations include fishing closures (both individual species and spatial closures) or restrictions on catch limits and increased size at capture (e.g., Rock Basses). More recently, California Department of Fish and Game (CDFG 2012) implemented Marine Protected Area networks (MPAs) that restrict extractive practices. Concurrent with the promulgation of new fishing regulations, is a debate about the impact of nearshore pollution and its deleterious effects on this habitat.

Poor water quality can lead to a number of potential rocky reef impacts including smothering and habitat loss from sedimentation, decreased water column clarity that limits light availability for plants, or toxic pollutants (i.e., trace metals, pesticides, and herbicides) that can cause detrimental acute or chronic effects on different life stages of endemic organisms. For example, sediment from runoff can scour or smother rocky substrate preventing settlement (Airolidi 2003). Runoff samples have proven toxic to purple sea urchins in the laboratory (Bay et al. 2003). Water quality effects may be exacerbated in locations such as the SCB, where this highly urban coastline generates sediment and potentially toxic pollutants from its 27,830 km² watersheds, nearly all which receives no treatment during infrequent, but often intense rainstorms (Ackerman and Schiff 2003).

The question of which stressor – fishing or water quality - presents a greater risk to rocky reef ecosystems has been asked for decades, but not well answered (Allen et al. 2004). This is partly because stress evaluations, and subsequent remediation strategies, are typically sector-based. For example, the State of California Department of Fish and Wildlife (CDFW) promulgated Marine Protected Areas (MPAs) as locations of harvest refugia in an effort to curb fishing pressure. In contrast, the State Water Resources Control Board promulgated Areas of Special Biological Significance (ASBS) as water quality protected areas where the discharge of pollutants is unlawful. Both agencies aim to “protect natural ecosystem

function”, but only address one-half of the fishing-water quality pressure conundrum, associated with their respective missions and legal authorities.

Regardless of whether fishing or water quality pressure presents the greater risk to natural ecosystem function, this question has never been answered at the scale of the entire SCB. This scale is important for several reasons. While many fish and invertebrate species can be sedentary or have a very small home range, many other species (especially fished species) move at spatial scales of the SCB. So, site-specific examinations may miss important confounding factors. Also, many oceanographic processes occur at SCB-wide scales, potentially confounding presumed anthropogenic effects with natural biogeographic cycles. Finally, while low levels of an individual stressor alone may not cause impacts, cumulatively low levels of multiple stressors may impact ecosystem function.

General Approach

The general approach to this element of the Southern California Bight Regional Monitoring Program was to address three questions:

- What is the bightwide extent of fishing pressure on rocky reefs and how does fishing pressure vary by individual reef?
- What is the bightwide extent of water quality pressure on rocky reefs and how does water quality pressure vary by individual reef?
- What is the rocky reef biological response to fishing and water quality pressure?

There are at least three unique features used in our approach to answering these questions. The first is the desire to work at SCB-wide scale, while attempting to provide data at individual rocky reef scale. The second unique feature is the stressor-response approach used in this the study design, which required the development of three new indices; one each to capture the complexity of fishing stress, water quality stress, and biological response. These generalized indices form their respective axis necessary for examining stress-response relationships. The third unique feature is the availability of new data sets for constructing the three indices at this wide range of spatial scales. These datasets include GIS maps of individual rocky reefs for the entire SCB, commercial and recreational fish and invertebrate extraction data from CDFW, and new remotely sensed data for measuring surface currents and detecting discharge plumes.

The following three sections represent the major chapters of the report, each designed to answer one of the primary monitoring questions.

Fishing Pressure Index

The Fishing Index assigned fishing pressure to individual reefs by extraction density (MT/yr/km²). The Fishing Index utilized historical catch data from Commercial landings receipts and from recreational fishers on Commercial Passenger Fishing Vessels (CPFVs or “party boats”) from the California Department of Fish and Wildlife, but examined it in a new geostatistical context. Although the historical data was collected in 10 mi² blocks, we were able to achieve the desired spatial resolution by focusing the species selection on rocky reef associated organisms and then using GIS to assign harvest data to rocky habitats. The key to unlocking this approach was the map of rocky reef habitat that was created during the Bight’08 Regional Monitoring Program (Pondella et al. 2015).

Commercial and recreational CPFV fishers extracted a recorded total of 2.04×10^5 MT for 68 shallow rocky reef species combined from the SCB during the period 1980-2009 (excluding 1985). The Red Sea Urchin (*Strongylocentrotus franciscanus*), primarily a commercially harvested species, dominated this total accounting for 76% of the total biomass harvested (1.55×10^5 MT). We attribute much of this extreme harvest size to the large amount of water contained within the body of the urchin when weighed, and thus to prevent any bias we removed this species from all further analyses. Recreational CPFV annual harvest rates (mean = 602.0 MT/yr) were only slightly, although significantly, lower than commercial harvest rates (mean = 771.9 MT/yr) on shallow rocky reefs in the SCB (Paired *t* test: $t = 3.15$, $p = 0.003$), with the exclusion of the Red Sea Urchin. While recreational CPFV fishers harvested primarily finfishes, commercial fishers harvested mostly invertebrates with some overlap between the two fisheries. Recreational and commercial harvest rates were not significantly correlated with one another (Spearman Rank Correlation: $S = 20554$, $p = 0.06$). While commercial harvest rates were greater in blocks around the Channel Islands, recreational harvest rates were greater in blocks along the mainland. For commercial fishers, harvest rates increased with increasing reef area and decreased with distance to the nearest port. Recreational harvest rates asymptotically decreased in more distant blocks. After correcting for the amount of reef area available in each block, both commercial and recreational CPFV harvest rates were randomly distributed across the SCB (Com: Moran's $I = -0.01$, $p = 0.41$; Rec: Moran's $I = 0$, $p = 0.05$). Commercial reef area-corrected fishing pressure was highest in block 707 (52.3 MT/yr/km², south of Anacapa Island), while recreational reef area-corrected fishing pressure was highest in block 701 (338.8 MT/yr/km², Marina del Rey).

Challenges remain with the Fishing Index. Due to the way data are reported, multiple reefs may be contained in large fishing blocks making inter-reef comparisons difficult or impossible. Similarly, it has been widely reported that not all fishers are submitting their fishing location data accurately. In addition, we found a substantial amount of nearshore reef data reported to fishing blocks that did not contain rocky reefs. The data that were inaccurately reported were removed from the analyses. Regardless, we identified predictable patterns within the data. Further, the Fishing Pressure Index does not include all fishing pressure. Non-CPFV fishing (from shore, private boaters, kayaks, piers etc.) was not quantified. Thus, while we have confidence in large-scale spatial patterns we report, inferences into smaller spatial scales are limited, and it is likely the magnitude of the extraction is undoubtedly higher.

Plume Exposure Index

The Plume Exposure Index (Schaffner et al. 2014) assigned relative plume exposure based on dose (pollutant load) and probability of plume exposure. Pollutant load information has been available for some time (Ackerman and Schiff 2003, Schiff et al. 2000), but new geostatistical tools were necessary to quantify probability of exposure. These new tools were built upon recent innovations that measure treated wastewater plume presence or absence (Nezlin et al., in prep), or advection of surface plumes away from major rivers and streams (Rogowski et al. 2015). Treated wastewater plume presence was detected using *in situ* sensors for Colored Dissolved Organic Matter (CDOM). Surface plume advection utilized the Southern California Ocean Observing System's new high frequency radar (HFRadar) network. Both CDOM and HFRadar needed algorithm development to process the dosing information utilizing a handful of representative pollutants (sediment/suspended solids, nutrients/nitrogen, trace metals/copper).

Results indicated that there was a gradient in plume exposure amongst rocky reefs in the region. Cumulatively, treated wastewater and untreated stormwater discharged an estimated 200,000 metric tons of suspended solids annually, accompanied by 1,000 metric tons of copper and 4,000 metric tons of dissolved nitrogen. The probability of plume exposure extended across more than 2,400 km² of nearshore

ocean in the SCB. However, the probability of plume exposure was frequently low, and approximately 200 km² had a plume probability greater than 50%.

There were also challenges and assumptions with the Plume Exposure Index. The first and largest of these assumptions was that the stormwater plume probability maps remain unverified. While the algorithms for making the maps were validated, the validation was conducted at a small number of site-specific locations. While the SCB-wide plume probability maps did match satellite images reasonably well, rigorous additional validation should occur when using this line of data. A second assumption for the Plume Exposure Index was a number of additional pollutant sources, albeit with exceedingly small doses, that were not included. These sources included individual coastal storm drains, small wastewater plumes, and small creeks. While not large contributors of pollutant inputs at the SCB-wide scale, each of these sources could have localized impacts at the individual reef scale. Finally, we did not examine pollutant sources at most Channel Islands because we had no information on source loading. Therefore, we assumed zero water quality pressure for these locations.

Biological Reef Response Index

The Reef Response Index used an “observed-to-expected” (O:E) ratio approach to defining biological expectations. This technique, commonly applied in streams and marine soft bottom habitats, has never been attempted in rocky subtidal reefs. This approach is based on the presence or absence of hundreds of fish, invertebrate, and algal species providing a mechanism to include fished and non-fished species, pollution tolerant and intolerant species, and a means to assess natural ecosystem function that is both fishery- and pollution-independent. Simply described, a multivariate model predicts which species should be present at a site based on natural environmental (i.e., depth, substrate, temperature) factors. Then, the observed species are compared to what is expected. O:E values near one indicate all of the expected species are present and values less than one indicate absent species. As more and more species are absent, the O:E values depart further and further from one, and ecosystem function is assumed to be impacted.

We found that the Reef Response Index was more responsive to the Fishing Pressure Index than the Water Quality Index. In the O:E analyses we observed that there was a significant reduction in the number of taxa present on a variety of nearshore rocky-reef in the bight, i.e. we are missing taxa where we expect taxa to be found. The Reef Response Index was sensitive to extractable resources (fishes and mobile invertebrates). Thus, it makes sense that fishing pressure was largely driving this conclusion. Benthic and encrusting invertebrates and algae, which are not as easily extracted but immobile and cannot escape plume excursions, are perhaps better indicators of pollution pressure. These results suggest that localized fishing mortality rates can approach 1.0 (100%), indicating that animals are extracted at rates exceeding recruitment resulting in their complete loss from reef habitats.

The challenges and assumptions with the Reef Response Index fell into two distinct categories. The first category was defining reference condition, which essentially sets the biological expectations for E as part of the O:E ratio (Ode et al. 2015). In a location like the SCB, however, there are likely no sites that have zero fishing pressure. So, the challenge is to include as many “best available” reference sites as possible to appropriately model E across all of the important biogeographic gradients, while at the same time minimizing fishing pressure index values. Our analysis indicated that all of the important biogeographic gradients were incorporated into the ecological models for E. However, this leads to our second challenge, whereby including some fishing pressure may reduce the O:E index responsiveness to stress (especially at low levels of fishing pressure). We evaluated this balancing act of covering biogeographic gradients while at the same time minimizing fishing pressure using sensitivity analysis, but the true answer may never be known since fishing has always occurred in the SCB.

Future Directions

Since the Reef Response Index was more responsive to the Fishing Index than the Plume Exposure Index, does that mean that pollution is not a problem for southern California nearshore reefs? Of course not. All three Indices had limitations and additional future work is recommended. Historically, water quality has been a significant cause for degraded nearshore rocky reef habitat (North 1964, Foster and Schiel 2010). What was clear from the detailed analysis was that the greatest urbanization leads to the greatest ocean access for fishing and the greatest potential for plume exposure. Thus, these stressors are not independent, and instead tend to co-occur at many locations throughout the SCB.

The Bight'13 Rocky Reef Element was a good step forward, but only a first step forward. There are a number of recommendations from the Bight'13 Planning Committee for topics to be explored for future Bight Programs. Here, we suggest integration among other Bight Elements that should prove fruitful in future regional surveys. The first recommendation is to improve upon the Plume Exposure Index modeling. As new, more powerful computer models become available, they can and should be adapted for applications such as this. One such model is being developed as part of the Bight'13 Nutrient Element; a predictive tool that links physical oceanography and biogeochemistry at a bightwide scale. The second recommendation is to improve upon the integration between the Bight Rocky Reef monitoring and the water quality conducted by Areas of Special Biological Significance (ASBS) Regional Monitoring. ASBS Regional Monitoring is specifically focused on small drain discharges and local water column chemistry, one of the primary data gaps identified in the Plume Exposure Index. The third recommendation is to improve the interaction between Bight Rocky Reef and Marine Protected Area (MPA) monitoring. The MPA monitoring, currently coordinated by the Ocean Science Trust, was an important collaborator with the Bight '13 Rocky Reef Element, helping create the Reef Response Index. We look to continue this collaboration, including enhancing the Reef Response Index or testing alternative indices. Using these opportunities to not just enhance coordination and reduce uncertainties, but to also generate positive momentum towards case studies and restoration opportunities, all of which provide a transition towards management.

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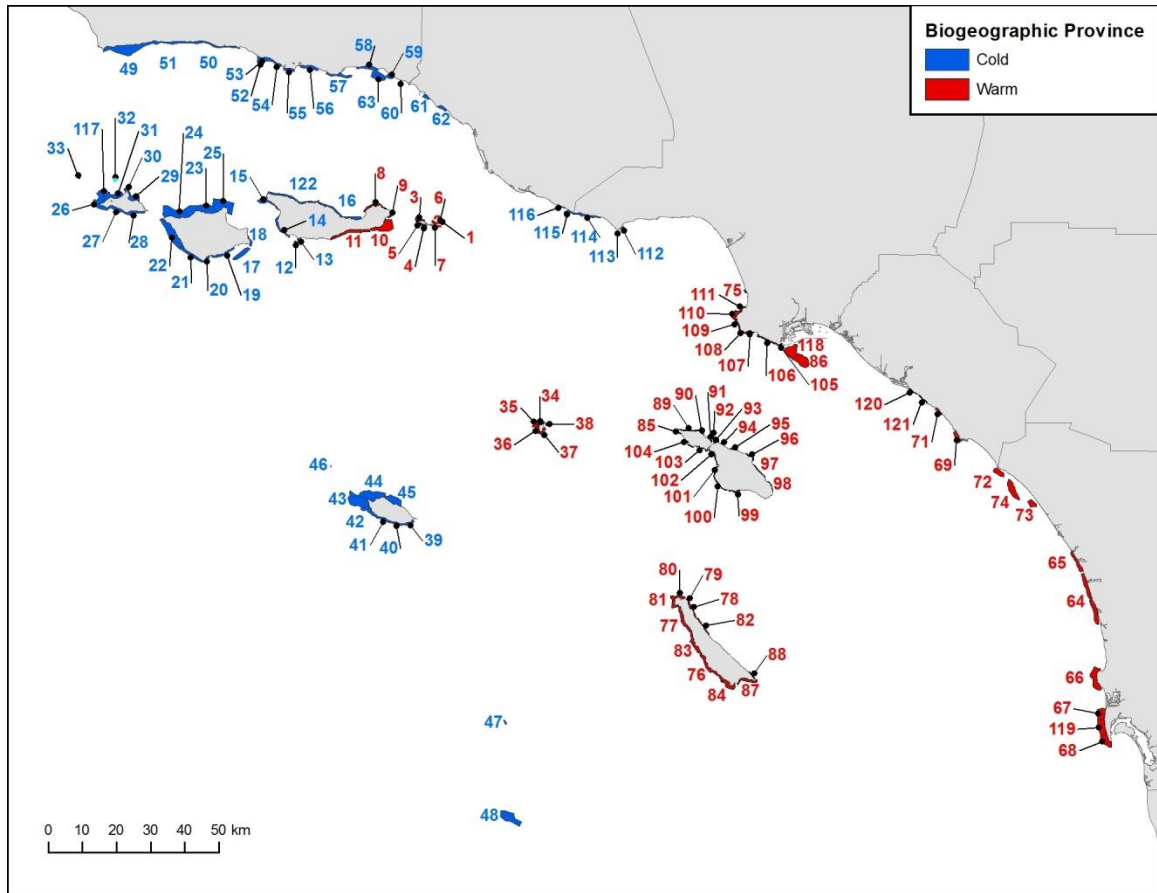


Figure 1. Map of the Southern California Bight and its 119 shallow (0-30m depth) rocky reefs (from: Pondella et al 2015).

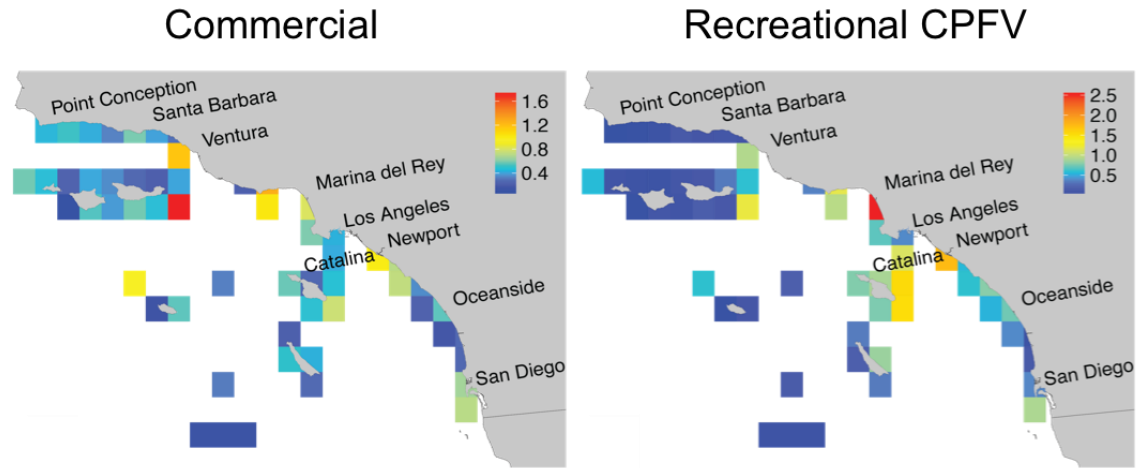


Figure 2. Average reef area-corrected harvest rates (MT/yr/km²) for Commercial and Recreational CPFV fishers in the SCB between 1980-2009.

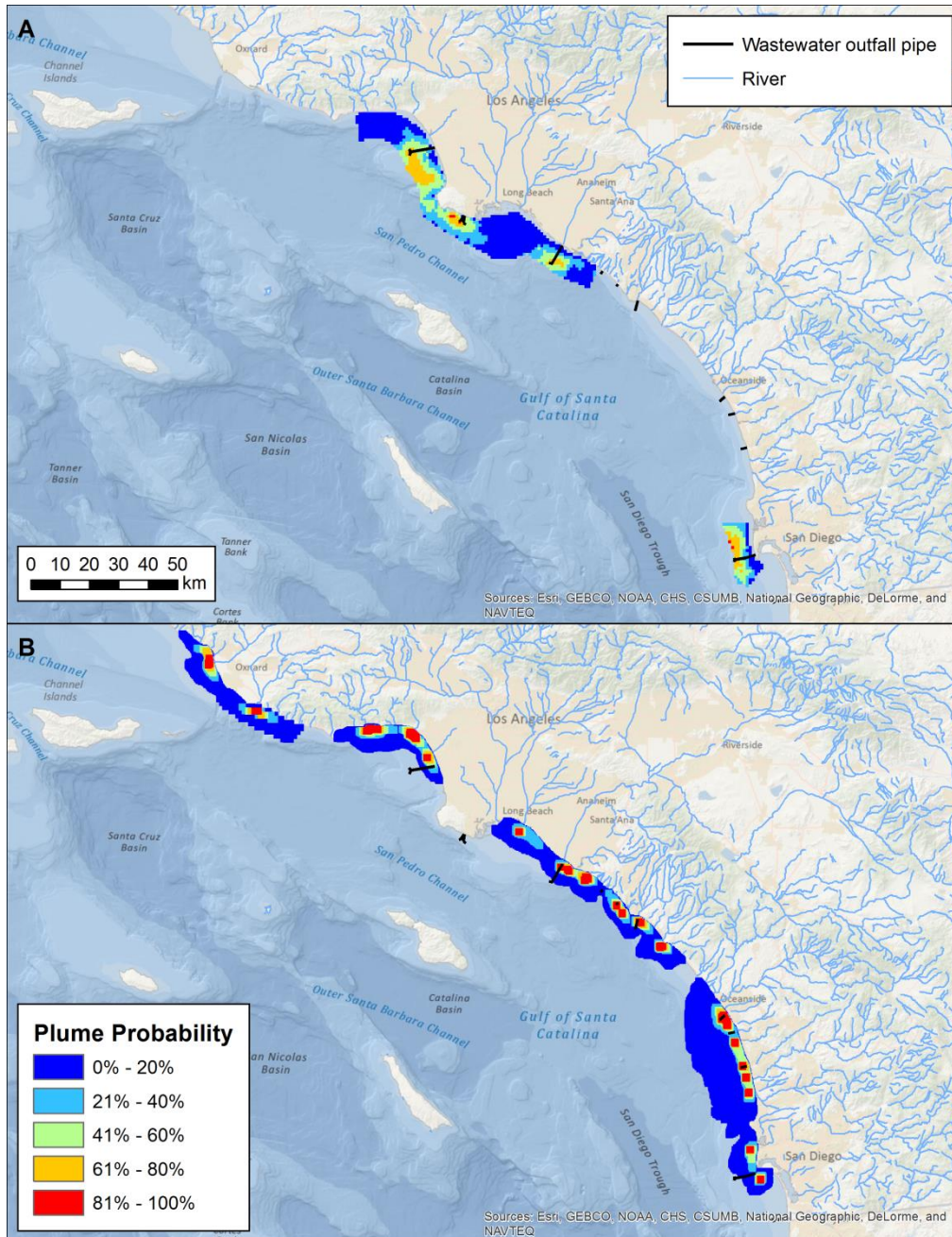


Figure 3. Maps illustrating plume exposure probabilities for (A) treated wastewater and (B) major creek and river storm discharges (from: Schaffner et al 2014).

CHAPTER 1: FISHING PRESSURE INDEX

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I. Abstract

Spatial conservation priorities are increasingly being utilized in ecosystem management, but our ability to accurately identify where these priorities should be located requires an understanding of the processes structuring human impacts. While the intensity of human activities may vary across space due to socio-economic processes, the structure of biological resources may also contribute. Here we use an extensive, spatially-explicit dataset with both commercial and recreational landings records collected by the California Department of Fish and Wildlife to evaluate the processes structuring harvest rates of shallow rocky reef marine species in southern California. While commercial harvest rates increase with greater reef area availability and the minimum distance to the nearest port, recreational harvest rates were only related to the minimum distance to the nearest port. Our results thus suggest that both biological and socio-economic processes are involved in the spatial structuring of fishing pressure across southern California. After correcting for the biological spatial structure, we identified new locations for conservation priorities, demonstrating the need to account for variation in biological structure when evaluating the spatial distribution of human impacts. The presence of significant spatial variation in fishing pressure highlights the importance of collecting georeferenced data on human impacts for development of spatially-informed conservation and resource management plans.

II. Introduction

Human-related activities now impact almost every part of the world, encompassing both terrestrial (Evans et al. 2011) and marine ecosystems (Halpern et al. 2008). However, across space, the extents of these impacts vary, with some regions incurring much higher levels of impact than others (Halpern et al. 2007). Mapping this variation in human impacts is crucial for identifying spatial conservation priorities (Crowder et al. 2006), which are increasingly being utilized by conservation practitioners in the development of spatially-based management plans (Margules & Pressey 2000). Yet, just knowing the patterns of spatial variation in human impacts provides limited information. It may help us identify areas that are exposed to greater levels of human activity, but our results will only be applicable locally. If instead we know what processes are responsible for generating that spatial structure, then we can potentially extrapolate to other ecosystems and create regulations that can be applied at broader spatial scales.

The main processes that explain spatial variation in the distribution of human impacts may be the biological processes that structure the resource itself. In the ecological literature, it is well known that predators concentrate in areas with high prey density (e.g., Sih 1984), and since humans often functionally fill this role as predator, we expect similar processes to occur in the anthropogenic use of biological resources. In other words, human impacts are likely to be greater in areas with more resources. Since these areas may be able to sustain greater levels of human activity, what we really want to know instead is where human impacts are expected to be the greatest after accounting for the underlying biological structure. After controlling for biological processes, we can then begin to investigate hypotheses about other processes that structure human impacts, such as socio-economic dynamics.

One of the biggest challenges to studying the processes structuring anthropogenic threats is the lack of georeferenced data. While a few studies have estimated or modeled the spatial distribution of human impacts (e.g., Halpern et al. 2008; Evans et al. 2011), collecting large-scale, georeferenced data on the intensity of human impacts remains a challenge. Not only is it difficult to collect these data, but also there is often disparate governance of the diverse set of users and stakeholders involved, resulting in incomplete datasets. Here we take advantage of a unique dataset with 29 years of spatially-explicit commercial and recreational landings data collected by the California Department of Fish and Wildlife (CDFW)* (Perry et al. 2010) in an effort to investigate the processes driving the spatial distribution of fishing across shallow rocky reefs in southern California. This dataset is not only extensive in spatial and temporal scales, but also includes all commercially and recreationally important species, allowing for multi-species assessment of the spatial distribution of fishing pressure. Ecosystem-based approaches to conservation are increasingly being favored to single-stock methods, due to inherent dependencies among species (Pauly et al. 2002; e.g., Browman et al. 2004). As a result, this data set provides an opportunity to evaluate the general processes that structure fishing rather than species-specific processes.

Overfishing remains one of the greatest pressures to marine ecosystems, especially in coastal regions (Jackson et al. 2001). Our ability to identify and predict where overfishing is the greatest is essential for successful conservation of marine ecosystems. Fishing intensity does in fact vary across the seascape (Ralston & O'Farrell 2008; Stelzenmüller et al. 2008a, 2008b; Stewart et al. 2010; Hunt et al. 2011), but marine habitats themselves are often highly structured (Margalef 1979; Wedding et al. 2011). So what are the processes that generate spatial variation in fishing? We tested two hypotheses – the amount of fish harvested may be affected by variation in biological productivity across the ocean (i.e., how many fish are available) and further may be affected by socio-economic factors driving the fishing industry (i.e., how many fishers are fishing). To test whether biological productivity influences the structure of fishing pressure, we tested for a relationship between harvest rates of reef-associated species and amount of reef habitat available, since larger reefs support greater biomass (Bohnsack et al. 1994). If biological productivity drives spatial structure in fishing, then we expect that harvest rates will be positively associated with habitat availability.

We also tested for an effect of socio-economic dynamics in driving the spatial structure of fishing. Specifically, we tested whether harvest rates were associated with the distance to the nearest port, since this provides a measure of the cost of fishing. More distant reefs incur greater travel costs on fishers. Additionally, we investigated differences between the commercial and recreational fishing industries since the socio-economic processes driving these fishers are different. While commercial fishers are driven by market demands for marine organisms (e.g., Purcell et al. 2013), recreational fishers are driven by demands for fishing opportunities (Dotson & Charter 2003; Figueira & Coleman 2010). Thus, similar distributions in these two fisheries would lend support to the hypothesis of biological productivity, whereas differences would indicate a role of socio-economic factors. By teasing apart the contributions of biological and socio-economic factors in generating fishing pressure, we will better be able to identify regions most at risk of overfishing and which spatial processes to target in conservation plans.

III. Methods

A. Study system

For this analysis, we focus specifically on fishing pressure of fish and invertebrate species associated with the shallow rocky reefs of the Southern California Bight (SCB). The SCB is a unique and increasingly critical stretch of California, encompassing 1197.2 km of coastline between the mainland and the islands (Pondella et al. 2015). Within the SCB, the extensive kelp beds that grow upon rocky substrates provide habitat for a wide array of species (Graham 2004; Stephens et al. 2006). The SCB is a transitional zone between the cold temperate (Oregonian) fauna fueled by the California current from the north and the warm temperate (San Diegan) fauna from the south. As a result, the SCB hosts an exceptionally biodiverse and productive community of subtidal rocky reef species (Hubbs 1960; Horn & Allen 1978; Pondella et al. 2005; Horn et al. 2006). However, being located off the coast of Los Angeles, the largest city in the western United States, the highly productive shallow rocky reefs of the SCB are of prime conservation concern due to intense commercial and recreational fishing pressure (Love 2006). Commercial fishing on reefs in southern California accounts for approximately \$12.2 million in US dollars per year (Perry et al. 2010). Similarly, in the recreational fishing market, total expenditures for charter and private boats alone in southern California have been estimated to average almost \$400 million US dollars annually (Gautam et al. 1996). The proximity of an ecologically diverse community next to such a large source of anthropogenic pressure makes the SCB an especially important region to closely monitor and manage for sustainability of marine populations.

B. Data processing

Commercial and recreational fishing records were downloaded from the Pacific Coast Fisheries GIS Resource Database (Perry et al. 2010; Original data source: State of California, The Resources Agency, Department of Fish and Wildlife (CDFW), USA). The commercial fisheries data come from monthly tabulations of landing receipts collected by the CDFW between 1972-2009 (Perry et al. 2010). The recreational fisheries data cover monthly harvests between 1980-2009 recorded in Commercial Passenger Fishing Vessel (CPFV) logbooks (Hill & Schneider 1999; Perry et al. 2010). While CPFVs constitute only part of the total recreational landings (~37%, Love 2006), the dataset provides a good comparison to the commercial data.

Since our primary interest was in conservation of shallow rocky reef species within the SCB, we filtered the data in R based on the following criteria. We included only landings records that occurred within blocks in the SCB (from the Mexican border to Point Conception). We limited the dataset to the years 1980-2009, because CPFV data were only reported back to 1980 in the dataset. We also removed data from 1985, since no spatially-explicit recreational data was available for this year. Additionally, we filtered the dataset for only shallow reef-associated species. We only included species that had been observed on shallow rocky reef habitats (above 30 m depth) during previous visual SCUBA based surveys across the region (Pondella et al. 2015). This list was then reduced further based on expert opinion, removing species that reside or are caught primarily in deeper (>30 m) or in pelagic habitats.

The data were additionally filtered to include only those blocks in which shallow rocky reefs, above 30m depth, are known to occur. These blocks were identified using a shapefile of reefs in the SCB, which outlines most of the known rocky reef habitat above the 30 m isobath (Pondella et al. 2015). By restricting the spatial analyses to only those blocks with known shallow rocky reefs, the analyses exclude any harvest of reef-associated species that occurs in blocks with no known shallow reef habitat. This non-reef harvest may occur because some species spend only part of their life cycle on reefs or migrate away from reefs for spawning aggregations, where they are likewise fished (Erisman & Allen 2006; Erisman et al. 2011; McKinzie et al. 2014). To confirm that exclusion of non-reef blocks did not significantly impact the results, we conducted the analyses with and without the Barred Sand Bass (*Paralabrax nebulifer*), a

shallow reef species known to be caught both on and off reefs (Erisman et al. 2011). The results remained the same regardless of whether this species was included in the analysis (Tables S2,S3).

Since the recreational data were reported in number of individuals harvested, while the commercial data were reported in pounds harvested, we used an estimate of the average weight of individuals caught to convert the numbers harvested in the recreational database to pounds. For each fish species and Red Sea Urchin, we calculated the mean weight observed on shallow rocky reefs across the SCB (Pondella et al. 2015) after excluding individuals below the minimum length catch limits, when applicable, or young-of-the-year for all other species. Observed fish lengths were converted to weights using standard species-specific weight-length relationships from the literature. For California Spiny Lobster (*Panulirus interruptus*) we used the mean weight caught in the recreational fishery (Neilson & Buck 2008), and for Rock Scallops (*Crassadoma gigantea*) we used a weight based on the average size sold in retail markets (CDFG 2001), because no other information was available. There were nine other species of invertebrates caught recreationally for which we could not determine a mean size at harvest and thus could not convert the landings from these species to pounds (Supporting Information). However, the total recreational landings of these species during the 29-year period was minimal and inconsequential to the dataset.

After combining the commercial and recreational datasets, all records were then converted into amount of metric tons harvested. While our calculations are dependent upon this conversion for the recreational fishing data, any biases should only affect biomass totals but not patterns of spatial distribution. Finally, harvest rates for each block were divided by the area of the block to account for variation in the size of each block.

C. Analyses

All analyses were completed in R v 3.0.1 (R Development Core Team 2013). We calculated summary statistics for both fisheries. To compare yearly harvest rates among commercial and recreational fisheries we conducted a Welch two-sample *t* test. To determine whether harvest rates were spatially structured, we calculated Moran's *I* statistic as a measure of spatial autocorrelation using the R package, *ape* (Paradis et al. 2004). Moran's *I* values that are significantly greater than zero indicate positive spatial autocorrelation, or a patchy distribution, while values significantly less than zero indicate negative spatial autocorrelation, or a uniform distribution. Values that are not significantly different from zero are expected when there is no spatial autocorrelation, or a random distribution. Moran's *I* was also calculated for the proportion of reef habitat within blocks to assess whether the underlying biological feature was spatially structured as well. We compared the distribution of fishing pressure between the fisheries by testing for an association in fishing pressure index values between commercial and recreational fishers using Spearman rank correlation.

To evaluate the role of biological and socio-economic factors in predicting harvest rates, we conducted an AIC_C model selection analysis (Burnham & Anderson 2002, 2004) using the R package, *AICcmodavg* (Mazerolle 2011). We compared 13 candidate models for harvest rates, including combinations of proportion of reef area per block, minimum distance to nearest port, and the interaction between reef area and port distance. Based on inspection of the data, we also evaluated a polynomial function for both reef area and minimum distance to port (Table 1). To fit the models, we used the Linear and non-linear mixed effects models (*nlme*) R package (Pinheiro et al. 2009), which allowed us to include a correction for the spatial location of blocks in each model to account for potential spatial autocorrelation in harvest rates. For each candidate model, we performed a linear regression analysis and calculated the second-order bias corrected Akaike's Information Criterion (AIC_C), a measure of the relative quality of a model based on the goodness of fit observed and the parsimony of that model. Akaike weights (ω_i) were calculated to assess the relative likelihood of each model in a set and were interpreted as a weight of evidence in favor of the hypothesis represented by the model (Burnham & Anderson 2002, 2004). Reef area was calculated in ArcGIS v. 10.1 (ESRI 2011) using the shapefile of known shallow rocky reefs in southern California

described above (Pondella et al. 2015). Models in each set were ranked according to the difference in AICc (Δ_i) and ω_i . A difference in AICc greater than 2 can be considered equivalent to a significant difference.

Since reef area was found to be a significant predictor of harvest rates, we calculated reef area-corrected harvest rates to account for the proportion of reef habitat within blocks. We calculated the reef area-corrected harvest rates by dividing harvest rates (MT/yr/km²) by the proportion of reef habitat within each block. We repeated the Moran's *I* spatial autocorrelation analyses on the reef area-corrected data to evaluate spatial structure of overfishing.

IV. Results

A. Summary Statistics

Commercial and recreational CPFV fishers extracted a total of 2.04×10^5 MT for 68 shallow rocky reef species combined from the SCB between 1980-2009 (Supporting Information). The Red Sea Urchin (*Strongylocentrotus franciscanus*), a primarily commercially harvested species, dominated this total accounting for 76% of the total biomass harvested (1.55×10^5 MT). Although this is one of the most important commercially harvested species in California (Rogers-Bennett 2013), the over-representation of Red Sea Urchin harvest in the dataset would swamp out any general patterns observed across each of the other species. We attribute much of this extreme harvest size to the large amount of water contained within the body of the urchin when weighed, and thus to prevent any bias we removed this species from all further analyses. Results including the Red Sea Urchin can be found in the online Supporting Information.

Recreational CPFV (mean = 602.0 MT/yr) annual harvest rates were only slightly, although significantly, lower than commercial harvest rates (mean = 771.9 MT/yr) on shallow rocky reefs in the SCB (Paired t test: $t = 3.15$, $p = 0.003$), with the exclusion of the Red Sea Urchin. While recreational fishers harvested primarily finfishes, commercial fishers harvested mostly invertebrates with some overlap between the two fisheries (Supporting Information). The proportion of reef habitat within blocks was not uniform (Moran's $I = 0$, $p = 0.39$, Supporting Information). Harvest rates similarly were not uniformly distributed across the bight, but instead were randomly distributed for commercial fishers (Moran's $I = -0.03$, $p = 0.72$; Figure 1a, Supporting Information) and clumped for recreational fishers (Moran's $I = 0.13$, $p = 3.56 \times 10^{-10}$; Figure 1b, Supporting Information). Recreational and commercial harvest rates were not significantly correlated with one another (Spearman Rank Correlation: $S = 20554$, $p = 0.06$). While commercial harvest rates were greater in blocks around the Channel Islands, recreational harvest rates were greater in blocks along the mainland (Figure 1).

B. Processes of Spatial Structure

Model selection analysis resulted in a single model with Δ_i score < 2 for both commercial and recreational harvest rates, however the best-fit model was different for each. The best-fit model for commercial harvest rates included the proportion of reef habitat within blocks and the polynomial of this variable, the minimum distance to the nearest port, and the interaction between reef proportion and minimum distance to port (Table 1). Further, the three models with the lowest Δ_i scores each included the proportion of reef, distance to port, and the interaction (combined $\omega_i = 0.90$). For commercial fishers, harvest rates increased with increasing reef area (Figure 2a) and decreased with increasing distance to the nearest port (Figure 2c). The relationship between reef area and harvest rates was less strong for more distant blocks. Only minimum distance to the nearest port and the polynomial function of port distance were included in the best-fit model of recreational harvest rates, and models that included minimum distance to port consistently ranked high in the analysis (Table 1). Recreational harvest rates asymptotically decreased in more distant blocks (Figure 2b).

C. Corrected Fishing Distributions

After correcting for the amount of reef habitat per block, the distribution of fishing pressure across the SCB differed qualitatively compared to the uncorrected harvest rates for both commercial and recreational fishers (Figure 1c,d). Corrected for reef area, commercial fishing pressure was highest in block 707 (52.3 MT/yr/km^2 , south of Anacapa Island), while recreational fishing pressure was highest in block 701 (338.8 MT/yr/km^2 , Marina del Rey). Commercial reef area-corrected harvest rates remained randomly distributed across the SCB (Moran's $I = -0.01$, $p = 0.41$), while recreational rates shifted from clumped before the correction to a random distribution after (Moran's $I = 0$, $p = 0.05$).

V. Discussion

Understanding the spatial distribution of human impacts is a crucial component of conservation, especially for identifying locations of spatial conservation priority. However, the success of these management plans is dependent upon our ability to correctly identify the areas that are most at risk. The amount of risk depends not only on the amount of human impact occurring but also the extent to which the environment can handle the pressure. Here we show that by incorporating underlying structure of the environment, we identify different patterns of spatial structure in fishing pressure on southern California shallow rocky reef species compared to analyses that do not include the underlying biological processes (Figure 1). As a result, we are able to identify new areas of spatial conservation priority where fishing pressure is greater than expected based on the amount of reef habitat available. For example, the blocks south of Anacapa Island, and south of Point Dume, and near the port of Newport had relatively low average annual commercial harvest rates; however, after correcting for relatively small reef area, these blocks had some of the highest harvest rates.

In addition, our results provide support for the role of socio-economic processes in structuring fishing pressure. Consistent with previous research we found comparable harvest rates among commercial and recreational fishers (Eggleston et al. 2003; Coleman et al. 2004; Birkeland & Dayton 2005; Erisman et al. 2011); however, our results also provide new evidence that the spatial structures of harvest in these fisheries vary significantly. Moreover, we found that harvest rates were associated with an indicator of cost, the minimum distance to the nearest port (Figure 2b). This relationship is consistent with previous studies that have found increased hunting and fishing closer to areas with dense human populations (Sirén et al. 2004). Further, we unexpectedly found that recreational CPFV fishing pressure was unrelated to the underlying spatial distribution of reefs (Table 1, Figure 2). This result suggests that socio-economic factors may be stronger for recreational fishers than biological ones, although it is possible that there are other biological factors that are more relevant to recreational fishing than reef area.

These results raise the question as to why the minimum distance to port, an indicator of socio-economic processes, impacts the structure of recreational fishing pressure more than for commercial fishers and why reef area, an indicator of biological processes, has such little impact on the structure of recreational fishing. One possibility may be that since commercial fishers generally tend to be more efficient harvesters than recreational fishers, they are able to shift to more productive locations when stocks become less profitable per amount of effort (Cooke & Cowx 2006). As a result, they may be able to better track the structure of biological resources. Moreover, since recreational fishing depends on maximizing fishing opportunities (Dotson & Charter 2003; Figueira & Coleman 2010), recreational fishers may be restricted to only the most accessible reefs, preventing them from optimizing for biological productivity in their choice of fishing locations. Remaining close to ports is especially important for CPFVs so that these vessels can operate multiple fishing trips per day and accommodate customers with more limited time available for fishing, further increasing profits. There is thus less incentive for recreational fishers to travel to more distant reefs, since they can afford to withstand lower catch rates (Crowder et al. 2008).

As an alternative hypothesis, these differences in the spatial distribution of commercial and recreational fishers could be the result of different distributions of the species targeted by each industry. In fact, we detected important differences, with commercial fishers targeting primarily invertebrates while recreational CPFV fishers target finfishes (Supporting Information). Regardless, when we look at species that are equally fished by both industries (e.g., California Sheephead, *Semicossyphus pulcher*), we find similar patterns to the full species dataset. Commercial fishing of California Sheephead increases with reef area, while there is little evidence to suggest that recreational harvest rates of this species are related to reef area (Supporting Information). This suggests that socio-economic factors play a significant role in structuring the spatial distribution of fishing pressure, despite biological influences. Moreover, these socio-economic processes are general and not just species-specific. For example, if we remove the most highly fished recreational species (Barred Sand Bass) from the dataset, the results remain the same.

Minimum distance to nearest port remains the best predictor of recreational harvest rates and we still identify the same blocks as the highest impacted regions (Supporting Information).

Blocks where fishing pressure is greater than expected based on amount of habitat available could alternatively be due to increased biological productivity, possibly as a result of upwelling or better conditions on reefs in those blocks (e.g., Wolanski et al. 1988). If this were the case, then we would expect both commercial and recreational fishing to be greater in these blocks. However, we did not detect a correlation in harvest rates between the two fisheries. Taken together, our results suggest that while biological processes are associated with patterns of fishing pressure across space, this relationship is dependent upon socio-economic processes affecting fishing.

A. Conservation implications

The spatial variation of human impacts observed in this study provides further evidence for the necessity of spatial conservation priorities. Fishing pressure was not consistent across blocks in the SCB, and thus different reefs will require various levels of attention in order to protect shallow rocky reef-associated marine species. As human impacts continue to intensify globally, it will become increasingly crucial to investigate spatial variation in order to prioritize our efforts for conservation (Brooks et al. 2006). With a detailed understanding of this variation we can identify ideal locations for implementing a suite of strategies to limit or mitigate human impacts, such as designation of reserves (e.g., Marine Protected Areas (MPAs)), habitat restoration, and pollution management, allowing for an ecosystem-based approach to conservation.

With an understanding of the processes generating structure in fishing, we can go beyond just identifying specific locations for spatial conservation priorities. Combined, the roles of biological and socio-economic processes in structuring spatial fishing pressure suggest that it is the smallest reefs that are easily accessible that are most at risk. Consequently, conservation efforts should be concentrated in these locations. Similarly, the differences between the commercial and recreational fisheries suggest that management and conservation may need to be specific to the socio-economic processes acting within each. By identifying general trends in the processes shaping the spatial structure of fishing, we can inform the development of spatially-explicit conservation and resource management plans that are applicable over broad scales (e.g., Hamilton et al. 2011), rather than applying on just a site-by-site basis. Further, these results provide important hypotheses to test in other coastal ecosystems, which may speed the process of developing conservation plans across the globe. Last, the use of broad-scale policies as opposed to site-specific designations will become increasingly useful with continued global climate change (Faleiro et al. 2013), as they allow for a more dynamic response to environmental changes.

B. Supporting Information

The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author. All scripts are available on Data Dryad.

VI. References

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VII. Tables

Table 1. Comparison of linear models for harvest rates (MT/yr/km²) for shallow rocky reef species¹ in the SCB using AIC_C analysis. The candidate models include the variables proportion of reef area per block (Reef), minimum distance to nearest port (Port), and the interaction between reef area and minimum distance to port (Int). Results are shown for both the commercial and recreational datasets. The results include: the parameter count, K; the AIC_C score; the change in AIC_C scores relative to the lowest AIC_C score, Δ_i ; the weight of each model, ω_i ; and the log-likelihood values, LL.

Fishery	Model	K ²	AIC _C	Δ_i	ω_i	LL
Commercial	Reef + Port + Int + Reef ²	8	-131.4	0.0	0.63	75.2
	Reef + Port + Int + Reef ² + Port ²	9	-129.1	2.3	0.20	75.6
	Reef + Port + Int	7	-126.9	4.4	0.07	71.7
	Reef + Port + Reef ²	7	-125.5	5.9	0.03	70.9
	Reef + Port + Int + Port ²	8	-124.5	6.9	0.02	71.8
	Reef + Port	6	-124.0	7.3	0.02	68.9
	Reef + Port + Reef ² + Port ²	8	-123.6	7.7	0.01	71.4
	Reef + Reef ²	6	-122.2	9.2	0.01	68.0
	Reef + Port + Port ²	7	-121.9	9.4	0.01	69.2
	Reef	5	-121.4	10.0	0.00	66.3
	Port	5	-92.8	38.6	0.00	52.0
	Null	4	-92.2	39.2	0.00	50.5
	Port + Port ²	6	-90.6	40.7	0.00	52.2
Recreational	Port + Port ²	6	-106.9	0.0	0.54	60.3
	Port	5	-104.3	2.6	0.15	57.8
	Reef + Port + Port ²	7	-104.3	2.6	0.15	60.3
	Reef + Port + Reef ² + Port ²	8	-102.0	4.9	0.05	60.6
	Reef + Port	6	-101.8	5.1	0.04	57.8
	Reef + Port + Int + Port ²	8	-101.6	5.4	0.04	60.3
	Reef + Port + Reef ²	7	-99.4	7.5	0.01	57.9
	Reef + Port + Int	7	-99.2	7.7	0.01	57.8
	Reef + Port + Int + Reef ² + Port ²	9	-99.2	7.8	0.01	60.6
	Reef + Port + Int + Reef ²	8	-96.7	10.2	0.00	57.9
	Null	4	-95.1	11.8	0.00	52.0
	Reef	5	-92.8	14.1	0.00	52.0
	Reef + Reef ²	6	-90.4	16.6	0.00	52.1

¹Excludes Red Sea Urchin

²Parameter count includes intercept and variance

Supplementary Table 3. Comparison of linear models for harvest rates (MT/yr/km²) for shallow rocky reef species¹ in the SCB using AIC_C analysis. The candidate models include the variables proportion of reef area per block (Reef), minimum distance to nearest port (Port), the interaction between reef area and minimum distance to port (Int). Results are shown for both the commercial and recreational datasets. The results include: the parameter count, K; the AIC_C score; the change in AIC_C scores relative to the lowest AIC_C score, Δ_i ; the weight of each model, ω_i ; and the log-likelihood values, LL.

Dataset	Fishery	Model	K ¹	AIC _C	Δ_i	ω_i	LL
All Species including Red Sea Urchin	Com	Reef + Reef ²	6	124.14	0.00	0.46	-55.19
		Reef + Port + Reef ²	7	125.46	1.33	0.24	-54.54
		Reef + Port + Reef ² + Port ²	8	125.96	1.82	0.19	-53.41
		Reef + Port + Int + Reef ²	8	128.19	4.05	0.06	-54.53
		Reef + Port + Int + Reef ² + Port ²	9	128.80	4.66	0.04	-53.40
		Reef	5	133.19	9.06	0.00	-60.98
		Reef + Port + Port ²	7	134.72	10.59	0.00	-59.17
		Reef + Port	6	134.94	10.80	0.00	-60.59
		Reef + Port + Int	7	137.25	13.12	0.00	-60.43
		Reef + Port + Int + Port ²	8	137.28	13.14	0.00	-59.07
		Null	4	143.81	19.67	0.00	-67.50
		Port	5	145.67	21.53	0.00	-67.22
		Port + Port ²	6	145.82	21.68	0.00	-66.04
	Rec	Port + Port ²	6	-106.93	0.00	0.54	60.34
		Port	5	-104.35	2.58	0.15	57.79
		Reef + Port + Port ²	7	-104.30	2.63	0.15	60.34
		Reef + Port + Reef ² + Port ²	8	-102.02	4.91	0.05	60.58
		Reef + Port	6	-101.82	5.11	0.04	57.79
		Reef + Port + Int + Port ²	8	-101.56	5.37	0.04	60.35
		Reef + Port + Reef ²	7	-99.39	7.54	0.01	57.89
		Reef + Port + Int	7	-99.21	7.72	0.01	57.80
		Reef + Port + Int + Reef ² + Port ²	9	-99.16	7.77	0.01	60.58
		Reef + Port + Int + Reef ²	8	-96.69	10.24	0.00	57.91
All Species excluding Red Sea	Com	Null	4	-95.14	11.79	0.00	51.97
		Reef	5	-92.79	14.14	0.00	52.01
		Reef + Reef ²	6	-90.35	16.58	0.00	52.05
	Com	Reef + Port + Int + Reef ²	8	-131.35	0.00	0.63	75.24
		Reef + Port + Int + Reef ² + Port ²	9	-129.10	2.25	0.20	75.55

Dataset	Fishery	Model	K ¹	AIC _C	Δ_i	ω_i	LL
Urchin and Barred Sand Bass		Reef + Port + Int	7	-126.94	4.41	0.07	71.66
		Reef + Port + Reef ²	7	-125.47	5.88	0.03	70.93
		Reef + Port + Int + Port ²	8	-124.48	6.87	0.02	71.81
		Reef + Port	6	-124.03	7.32	0.02	68.89
		Reef + Port + Reef ² + Port ²	8	-123.65	7.71	0.01	71.39
		Reef + Reef ²	6	-122.20	9.15	0.01	67.97
		Reef + Port + Port ²	7	-121.94	9.41	0.01	69.16
		Reef	5	-121.37	9.99	0.00	66.29
		Port	5	-92.79	38.56	0.00	52.01
		Null	4	-92.17	39.18	0.00	50.49
		Port + Port ²	6	-90.64	40.71	0.00	52.19
	Rec	Port	5	-308.08	0.00	0.39	159.65
		Port + Port ²	6	-306.54	1.54	0.18	160.15
		Reef + Port	6	-305.56	2.51	0.11	159.66
		Null	4	-305.26	2.82	0.10	157.03
		Reef + Port + Port ²	7	-304.01	4.07	0.05	160.20
		Reef + Port + Int	7	-303.68	4.40	0.04	160.03
		Reef + Port + Reef ²	7	-302.98	5.10	0.03	159.68
		Reef	5	-302.84	5.24	0.03	157.03
		Reef + Port + Int + Port ²	8	-302.22	5.85	0.02	160.68
		Reef + Port + Reef ² + Port ²	8	-301.37	6.71	0.01	160.25
		Reef + Port + Int + Reef ²	8	-300.93	7.15	0.01	160.03
		Reef + Reef ²	6	-300.35	7.73	0.01	157.05
		Reef + Port + Int + Reef ² + Port ²	9	-299.38	8.70	0.01	160.69
California sheephead	Com	Reef	5	-392.14	0.00	0.43	201.68
		Reef + Reef ²	6	-390.62	1.52	0.20	202.19
		Reef + Port	6	-390.00	2.15	0.15	201.87
		Reef + Port + Reef ²	7	-388.36	3.79	0.06	202.37
		Reef + Port + Int	7	-387.46	4.68	0.04	201.92
		Reef + Port + Port ²	7	-387.39	4.76	0.04	201.89
		Null	4	-386.15	6.00	0.02	197.47
		Reef + Port + Int + Reef ²	8	-385.94	6.20	0.02	202.54
		Reef + Port + Reef ² + Port ²	8	-385.60	6.55	0.02	202.36
		Reef + Port + Int + Port ²	8	-384.73	7.42	0.01	201.93

Dataset	Fishery	Model	K ¹	AIC _C	Δ_i	ω_i	LL
		Port	5	-384.02	8.13	0.01	197.62
		Reef + Port + Int + Reef ² + Port ²	9	-382.97	9.18	0.00	202.48
		Port + Port ²	6	-381.52	10.62	0.00	197.64
	Rec	Null	4	-467.25	0.00	0.33	238.02
		Port	5	-466.12	1.12	0.19	238.67
		Reef + Reef ²	6	-465.54	1.71	0.14	239.65
		Reef	5	-465.40	1.85	0.13	238.31
		Reef + Port	6	-464.06	3.19	0.07	238.90
		Reef + Port + Reef ²	7	-463.77	3.47	0.06	240.08
		Port + Port ²	6	-463.63	3.62	0.05	238.69
		Reef + Port + Port ²	7	-461.44	5.80	0.02	238.91
		Reef + Port + Reef ² + Port ²	8	-461.04	6.21	0.01	240.08
		Reef + Port + Int	7	-456.61	10.64	0.00	236.50
		Reef + Port + Int + Reef ²	8	-454.20	13.05	0.00	236.66
		Reef + Port + Int + Port ²	8	-453.98	13.27	0.00	236.56
		Reef + Port + Int + Reef ² + Port ²	9	-451.49	15.76	0.00	236.74

¹Parameter count includes intercept and variance

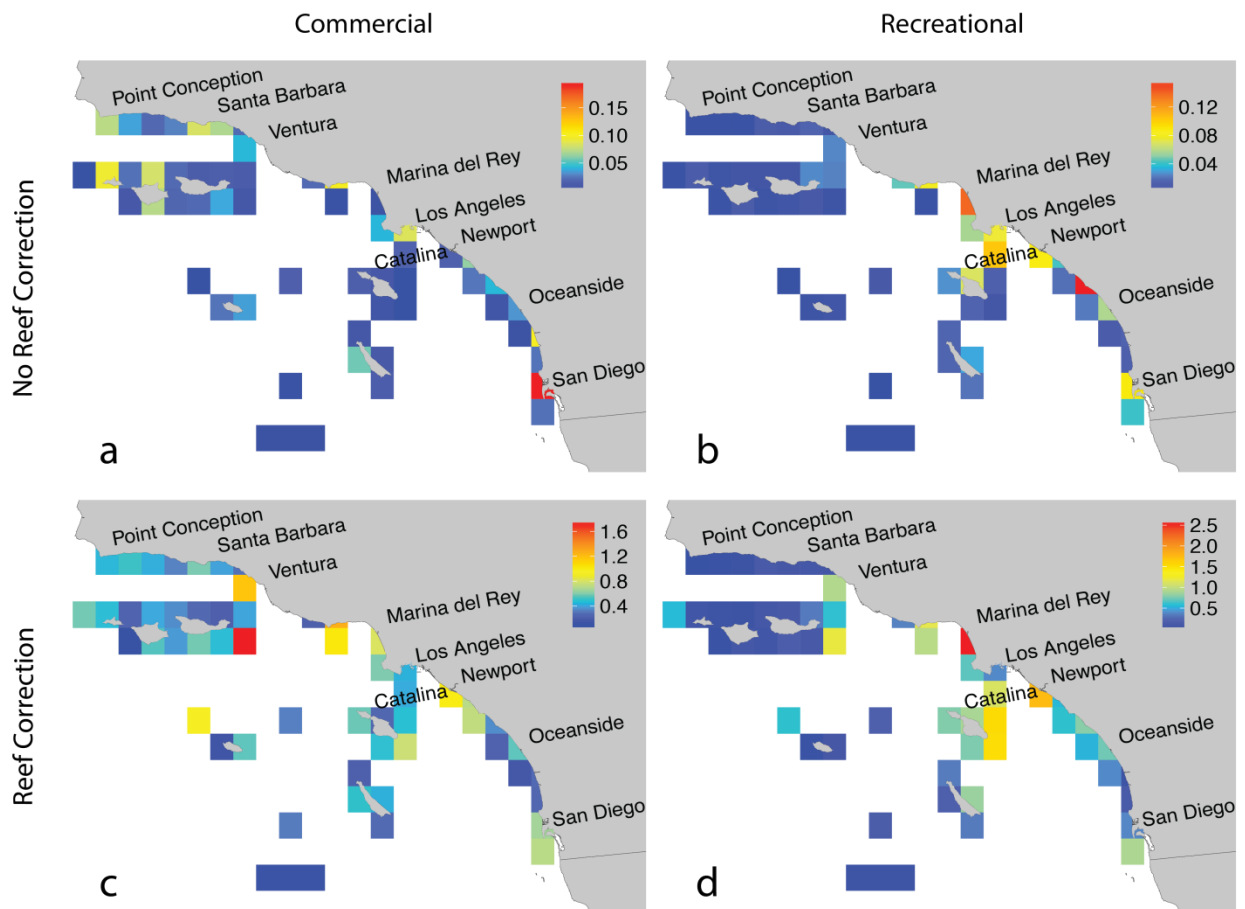


Figure 1. Distribution of harvest rates of 67 shallow rocky reef species in fishing blocks with known rocky reef habitat above the 30m isobath in the SCB. The average annual harvest rates (MT/yr/km²) and reef area-corrected harvest rates (MT/yr/km²), both with a $\log_{10}+1$ transformation, are shown for both commercial (a,c) and recreational (b,d) fishers.

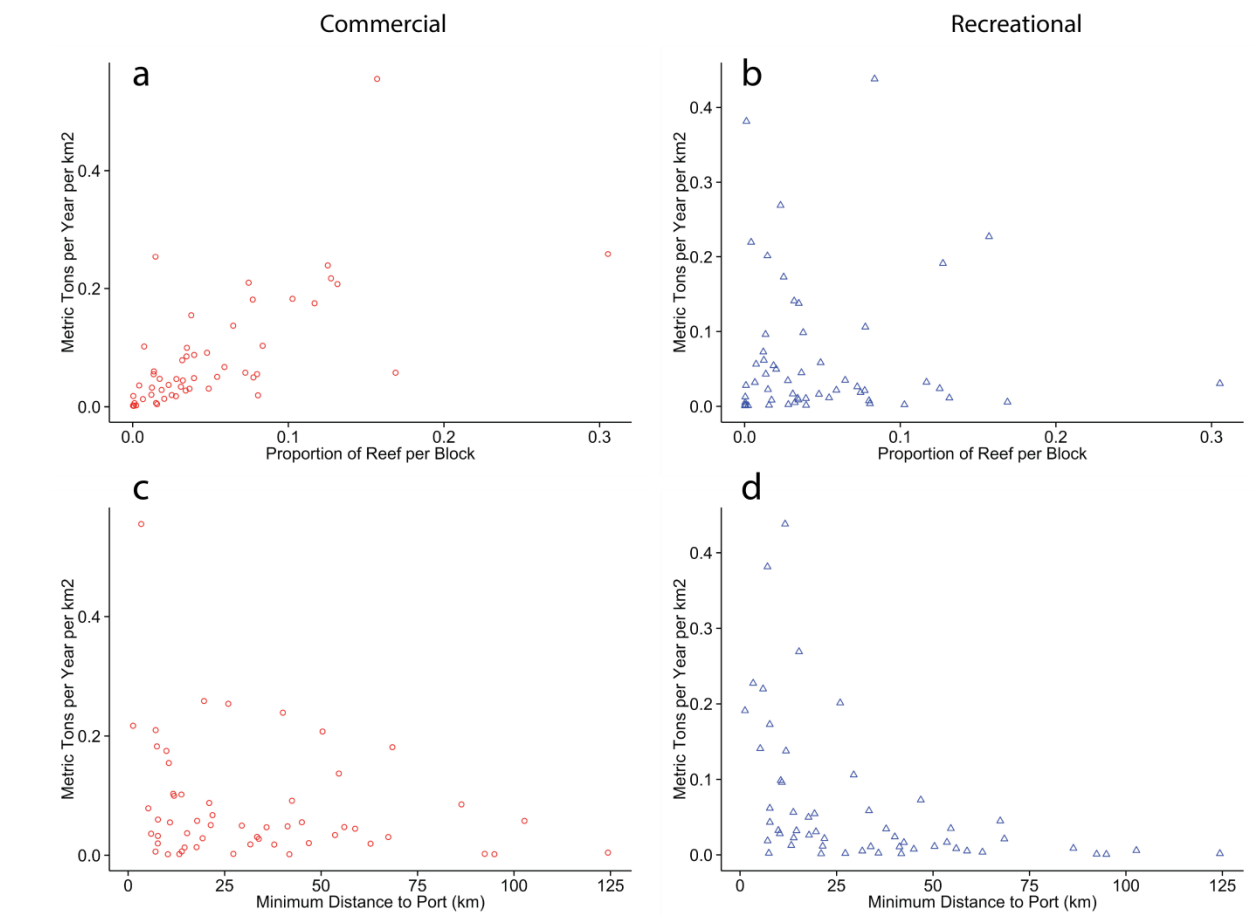


Figure 2. Predictors of harvest rates of shallow rocky reef species. Both commercial (a,c) and recreational (b,d) average yearly harvest rates (MT/yr/km²) are shown in relation to the proportion of reef habitat available within blocks (a,b) and the minimum distance to the nearest port for each block (c,d).

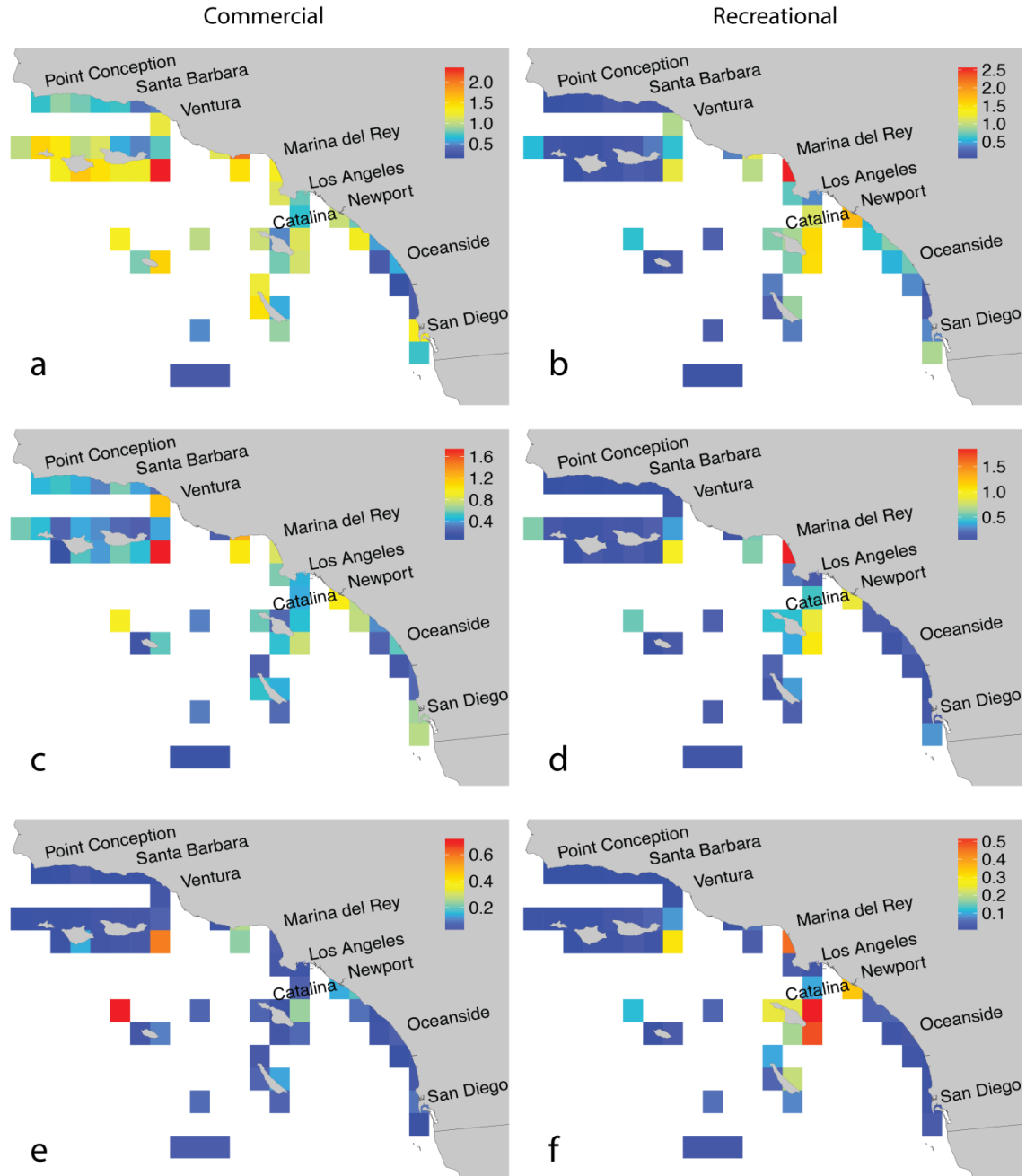


Figure S1. Distribution of harvest rates of shallow rocky reef species in fishing blocks with known reef habitat in the SCB. The average annual reef area-corrected harvest rates ($\text{MT}/\text{yr}/\text{km}^2$), with a $\log_{10}+1$ transformation, are shown for both commercial and recreational fishers. The distributions shown are for: all species including Red Sea Urchin (a-b), all species excluding Red Sea Urchin and Barred Sand Bass (c-d), and California Sheephead (e-f).

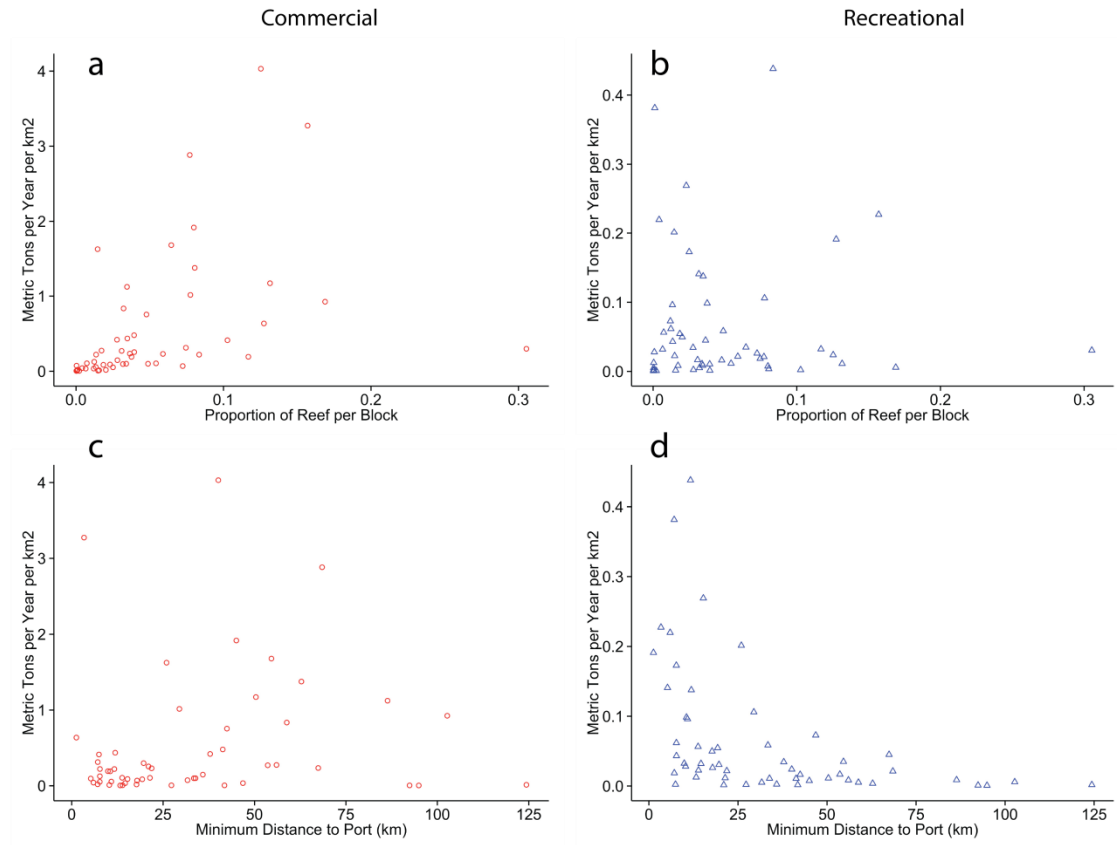


Figure S2. Predictors of harvest rates for all shallow rocky reef species including Red Sea Urchin. Both commercial (a,c) and recreational (b,d) average yearly harvest rates (MT/yr/km²) are shown in relation to the proportion of reef habitat available within blocks (a,b) and the minimum distance to the nearest port for each block (c,d).

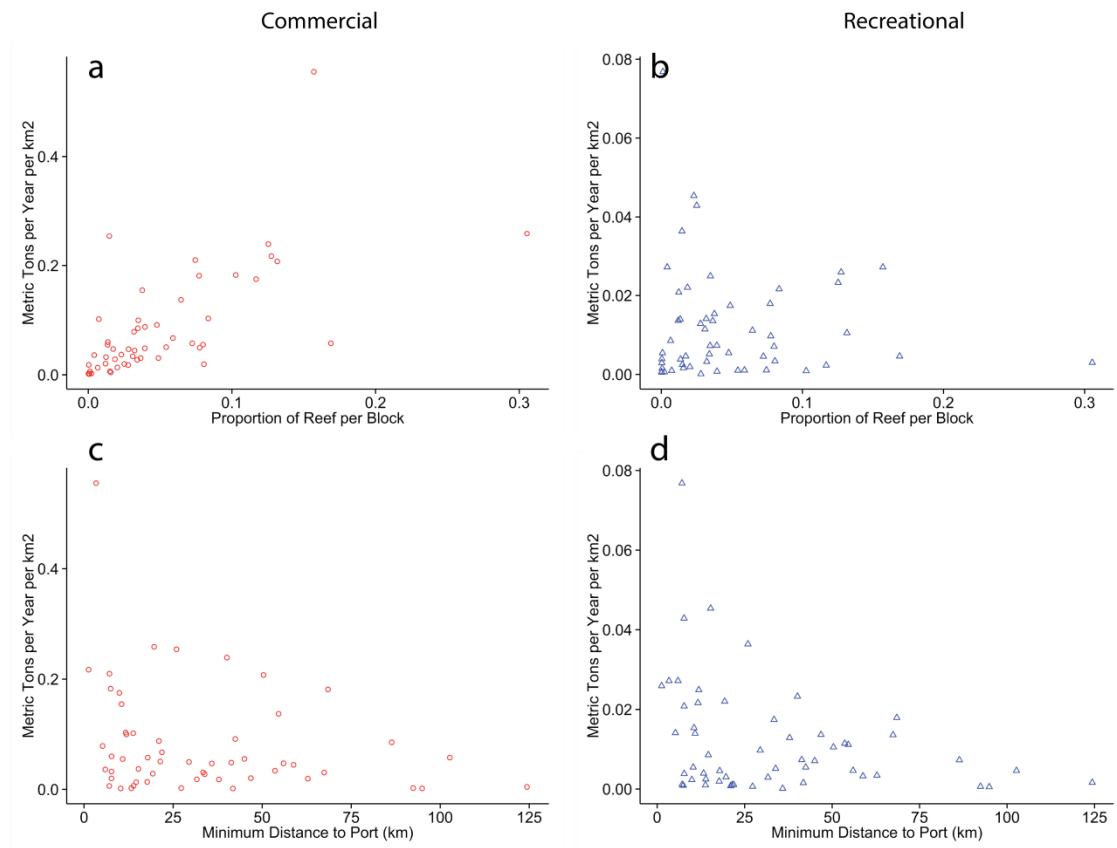


Figure S3. Predictors of harvest rates for all shallow rocky reef species excluding Red Sea Urchin and Barred Sand Bass. Both commercial (a,c) and recreational (b,d) average yearly harvest rates (MT/yr/km²) are shown in relation to the proportion of reef habitat available within blocks (a,b) and the minimum distance to the nearest port for each block (c,d).

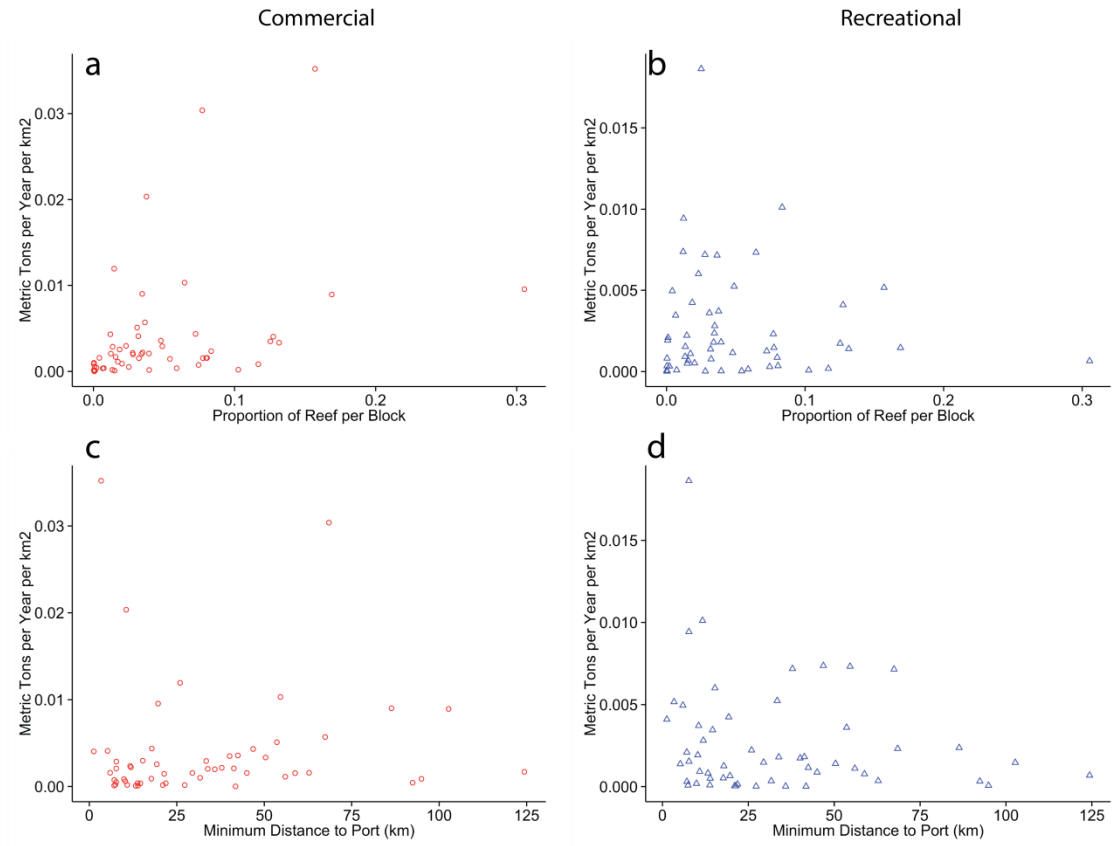


Figure S4. Predictors of harvest rates for California Sheephead. Both commercial (a,c) and recreational (b,d) average yearly harvest rates (MT/yr/km²) are shown in relation to the proportion of reef habitat available within blocks (a,b) and the minimum distance to the nearest port for each block (c,d).

CHAPTER 2: PLUME EXPOSURE INDEX

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I. Abstract

Southern California marine ecosystems face a variety of threats to their integrity and health as a result of their proximity to urbanized areas. These threats may be direct, through fishing and resource extraction, or indirect, through exposure to anthropogenic pollutants. Two primary sources of anthropogenic pollutants are treated wastewater, released by publicly owned treatment works (POTWs) through ocean outfalls, and stormwater runoff contained in urban river plumes. We developed a geospatial tool in ArcGIS to calculate a Plume Exposure Index (PEI) for the Southern California Bight (SCB). The PEI quantifies long-term exposure to potentially harmful pollutants emanating from these two sources. Recent studies on the dispersal of plumes have resulted in high quality spatial datasets that predict plume occurrence frequencies as point grids around POTWs and river mouths throughout the region. We multiplied the plume frequency values with data on average annual discharge rates, initial dilution factors, and concentration of chemicals in discharges to calculate total exposure to pollutants at each location. Using this approach, we developed maps of the distribution of three important plume constituents: dissolved inorganic nitrogen in the form of nitrate and nitrite (DIN), total suspended solids (TSS), and copper. A series of Python scripts were created to facilitate geoprocessing of the exposure data and to calculate the final PEI raster, including: 1) Creating exposure rasters for each pollutant and source using Inverse Distance Weighting; 2) Summing POTW and river plume exposure rasters for each pollutant and normalizing each raster to the maximum exposure value; 3) Creating the PEI by summing pollutant exposure rasters and normalizing again to provide values ranging from zero to one. The resulting georeferenced PEI raster may be used with other spatial data to examine relative pollution risk for any area of interest within the mapped region. The PEI will be incorporated into an ongoing study to examine relative risks posed to marine habitats by water quality and fishing pressure.

II. Introduction

A. The Southern California Bight is a valuable resource

The Southern California Bight (SCB) is an oceanographically defined region that extends from Point Conception in Santa Barbara County, California to Cabo Colnett, Mexico, including the Channel Islands (Figure 1). The SCB is a valuable natural resource that contributes to the regional economy and enhances quality of life for those who work in, live in or visit the area. Human uses of the coastline and ocean waters of the SCB include recreation, tourism, aesthetic enjoyment, sport and commercial fishing, coastal development, and industry. For example, ocean-dependent tourism contributed approximately \$41 billion to the economies of coastal communities surrounding the SCB and supported over 800,000 jobs in 2007 (NOEP 2008).

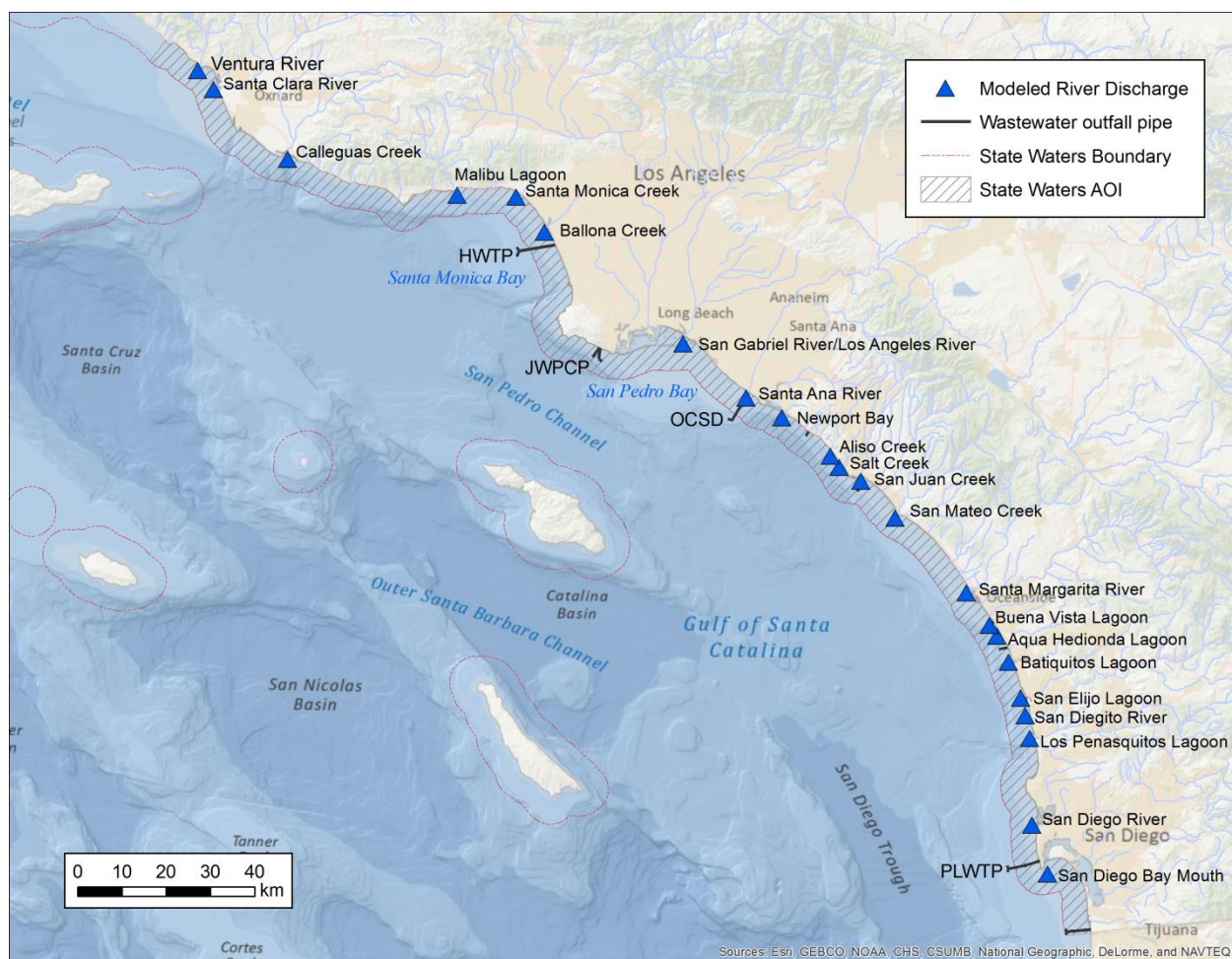


Figure 1: Map of the Southern California Bight showing the four major wastewater treatment plant outfalls: City of Los Angeles Hyperion Treatment Plant (HWTP); Los Angeles County Sanitation District Joint Water Pollution Control Plant (JWPCP), Orange County Sanitation District (OCSD), and the City of San Diego Point Loma Treatment Plant (PLWTP) and major river mouths draining to the Southern California Bight. Also shown are the state offshore jurisdictional boundary and the boundary encompassing the plumes analyzed in this study.

The SCB is a unique and highly diverse ecological resource (Schiff et al. 2000). For example, subtidal rocky reefs that support giant kelp (*Macrocystis pyrifera*) are amongst the most productive habitats in the world. The SCB is a primary stop along the Pacific Flyway, the major migration route for seabirds from North to South America. It also hosts a number of threatened and endangered species, including the Blue (*Balaenoptera musculus*) and humpback (*Megaptera novaeangliae*) whales, California least tern (*Sterna antillarum browni*), and least Bell's Vireo (*Vireo bellii pusillus*). Altogether, the SCB is home to over 5000 species of invertebrates, 480 species of fish, and 195 species of marine birds (Dailey et al. 1993).

B. Human influence in the region

Throughout the 20th century, significant population growth propelled the coastal community along the SCB from under 200,000 in 1900 to over 17 million (US Census 2010) making the region the largest metropolitan center in the United States. As a result of rapid urbanization, marine resources in the SCB have been placed under extreme pressure including loss of habitat and discharge of pollutants.

There are a variety of pollutant sources to the SCB including publicly-owned treatment works (POTWs), urban and agricultural runoff, industrial facilities, power generating facilities, boating and shipping, dredged material disposal, atmospheric deposition, amongst others (Schiff et al. 2000). Historically, the largest of these sources has been POTWs. With increased treatment, pre-treatment, and reclamation, both total discharge rates and pollutant inputs from POTWs have decreased over the last four decades, greater than 90% for some individual pollutant types. However, surface runoff generated by storm events that wash off the region's highly developed watersheds deliver large pulses of potential pollutants that enter the ocean without any treatment. Flows and pollutant inputs from surface runoff have generally increased over this same time period as impervious surfaces (roads, rooftops, etc.) have hardened coastal watersheds. As a result, pollutant inputs from runoff now rival those of POTWs.

Of the 17 POTWs in the SCB, four comprise the vast majority of the discharge flow and pollutant inputs (Schiff et al. 2000). These four POTWs are amongst the largest in the United States and include the City of Los Angeles, County of Los Angeles, County of Orange, and City of San Diego (Figure 1) cumulatively discharging over 800 million gallons of treated wastewater per day. These inputs remain relatively stable as flows are metered and treatment processes are engineered to maintain a consistent effluent quality, but there has been a gradual downward trend in total discharge rates due to improvements in treatment and in wastewater reclamation projects (Lyon and Sutula 2011).

There are 23 major watersheds in the SCB (Figure 1). Stormwater discharges are highly variable, with infrequent but intense storms capable of increasing streamflow three to four orders of magnitude in less than one hour (Schiff and Tiefenthaler 2011). Intensive stormwater discharge after rainstorms can produce plumes that are easily distinguished from ambient marine waters by their high concentration of suspended matter that changes the color of the ocean surface (Mertes et al. 1998, Sathyendranath 2000, Mertes & Warrick 2001). The movement and persistence of plumes may be influenced by a variety of factors, such as wind and ocean circulation, coastline shape and bathymetric variability which may cause resuspension of sediments, as well as the volume, timing and intensity of stormwater discharge (Nezlin et al. 2005).

C. Study Objective

To date, no study has effectively utilized a geospatial approach in assessing potential exposure to POTW effluent or stormwater plumes throughout the full extent of the SCB. Prior studies tended to focus on individual sources of pollution such as a single POTW outfall or an individual watershed (Bay et al. 2003, Warrick et al. 2004, Ahn et al., 2005). While these localized studies are valuable, they leave numerous gaps in both spatial and temporal coverage of the SCB making it impossible to develop a comprehensive understanding of conditions and potential water quality threats. Furthermore, since each study used independent data and methods to assess water quality at a specific time and location, study results are not

directly comparable. This variability results in a fragmented understanding of conditions in the SCB, making it difficult to understand how water quality conditions are changing over time as a result of management decisions or regulatory actions intended to protect and improve the water quality of the SCB.

To develop an accurate map of water quality conditions of the entire SCB requires data that is collected in a consistent manner and at an appropriate spatial scale. Such data have only recently become available through the efforts of coordinated regional monitoring programs such as those led by SCCWRP (<http://www.sccwrp.org/ResearchAreas/RegionalMonitoring>), and data obtained from regional efforts such as the Southern California Coastal Ocean Observing System (SCCOOS) or satellite imagery data collected by NOAA and NASA.

Our objective was to develop geospatial tools in ArcGIS to model ocean exposure to land-based sources of pollution. Combining sources of newly acquired spatial data for the SCB with information on locations of pollution sources and inputs, we developed a series of Python scripts to calculate a composite Plume Exposure Index (PEI) based on pollutant inputs from both POTWs and rivers. Developing tools like the PEI provide several important benefits. The ArcGIS scripts provide a mechanism to assess plume exposure throughout the SCB in a consistent and repeatable manner. Second, these scripts provide a documented methodology that may be readily adapted by other researchers. This allows for adjustments that may be useful to incorporate data for additional pollutants or to apply these methods in other locations.

For purposes of this study, we focused development of the PEI on three pollutants: dissolved inorganic nitrogen in the form of nitrate and nitrite (DIN), total suspended solids (TSS), and toxic trace metals (copper). Selection of pollutants for development and testing of the tool was based upon the following characteristics:

- The pollutant has known impacts on marine ecosystem health, either through direct toxicity or secondary effects by promoting growth of nuisance algal blooms;
- Data are available on the pollutant for both river and wastewater discharge sources;
- The pollutant is discharged frequently and in large enough quantities that it is likely to have significant and ongoing effects on marine ecosystems;
- The pollutant represents a range of sources such as urban, agriculture, or industrial activities.

Nitrate is a critical plant nutrient necessary for the growth of phytoplankton, seagrasses, kelp, and other macroalgae. However, in large concentrations nitrate can promote the growth of harmful algal species and cause phytoplankton blooms (Anderson et al. 2008). Recent studies have found that treated effluent may have nitrate concentrations equivalent to natural sources such as upwelled seawater (Howard et al. 2014).

Total suspended solids (TSS) can negatively impact nearshore subtidal communities, reefs, and kelp beds through reduction of light availability and, in large quantities, by smothering benthic organisms. Episodic riverine TSS inputs can be quite large in some regions such as the Santa Clara River (up to 5.5×10^7 kg/yr). Additionally, other toxic chemicals adsorb onto the surface of particulate matter, creating a large-scale transport mechanism between the water column and benthic substrates (Hart 1982).

In sufficiently large doses, copper is a trace metal that can cause both acute (lethal) and chronic (impaired growth, reproduction) effects in marine organisms. Copper is a by-product of some industrial activities and is a common contaminant found in stormwater. Its ubiquity in stormwater is due to its use in brake pads on vehicles, pesticides, building materials, and from atmospheric deposition (Davis et al. 2001). Copper toxicity to marine plants and invertebrates is so prevalent that it is often used as a biocide in paints used to coat the bottoms of boats and docks. Copper does not transform easily and can settle into ocean sediments, exerting long-term effects (Long et al. 1995).

III. Methods

We used a regional-scale risk-based approach to creating the PEI. The risk was estimated as a function of pollutant concentration, magnitude, and duration of exposure. Therefore, the primary factors for the index were pollutant loading and plume contact frequency. Pollutant loading was estimated for the SCB's two largest sources, POTWs and rivers. Spatial distribution of exposure duration was acquired from multiple sources that utilize advances in plume detection technology. Table 1 lists the sources of data used for the WQI. Many of the geoprocessing tasks were automated using ArcGIS Model Builder and Python scripts.

Table 1. Sources of spatial data and pollutant loading data for POTWs and river plumes.

Pollutant Source	Loading Data	Frequency Data	References
Wastewater Treatment Plants	Discharge Monitoring Reports; Bight '08 Water Quality Study	CDOM plume detection method	Lyon and Sutula, 2011 Howard et al., 2014 Nezlin et al., in prep
River plumes	Riverine loading model	HFR-based surface circulation models	Sengupta et al. 2013 Rogowski et al. 2014

A. Riverine pollutant loading

A rational model was developed that uses precipitation data, watershed size, and land cover to predict daily loads of chemicals from watersheds (Ackerman and Schiff 2003, Sengupta et al. 2013). For 23 rivers, we calculated average annual loads of DIN, TSS, and copper based on eleven years of data (2000-2010). Watershed sizes for these rivers range from 25 to 4486 km² and comprise a wide range of predominant land uses including urbanized (i.e. residential, commercial, and industrial areas), agricultural lands, and open space (i.e. largely undisturbed areas of wetlands, forest, or scrub/shrub vegetation) (Sengupta et al. 2013). The model ignores base flows that result from inland wastewater treatment plant discharges and general dry-weather run-off. For the purposes of this study, we assumed that base river flows are minor source of pollutants whose effects do not radiate far from river mouths.

Each river mouth was treated as a single point source. Pollutant loads were multiplied by a dilution factor of 1:100 to account for estuarine mixing processes and loss of the pollutant from the plume as it entered the ocean. This factor was selected based on studies showing that during storm events, only about 1% of the TSS originating from riverine inputs is found in the surface plume offshore of river mouths. The majority of sediment settles out in the estuarine mixing zone and within 1km of the river mouth (Mertes and Warrick 2001, Warrick et al. 2004).

B. Riverine plume mapping

Southern California river plumes have been mapped using several different methods, primarily satellite imagery in combination with in situ sampling of plume tracers (Otero and Siegel 2004, Nezlin and DiGiacomo 2005, Warrick and DiGiacomo 2007, Nezlin and DiGiacomo 2008, Reifel et al. 2009). These methods provide empirical data on plume locations and extents, but have several limitations. Generally, they focus on limited areas and individual storm events. Cloud cover can interfere with accurate imaging, preventing visualization of the plume during inclement weather when plumes are forming and dispersing. Remotely sensed plume indicators tend to correlate with the presence of suspended solids in surface waters, but may not always agree with concentrations of other dissolved pollutants. One alternative method of mapping plume probability is the utilization of High Frequency Radar (HFR) to model the dispersion of surface water tracers seeded into regions of river discharge. HFR-derived surface currents over a given temporal period are input into a random walk model. (Kim et al. 2009, Rogowski et al. 2014). Rogowski et al. (2014) used HFR surface current data to model the probability of plume exposure for twenty river discharges in southern California, based on two years of hourly surface current data. In Rogowski's model, fifty water tracers were released hourly at each source location (1km offshore) and

independently tracked for three days. A probability density function was used to compute the cumulative sum of water tracers that advected into predefined model grids surrounding each river mouth source location. These grids vary in point density, and may overlap (Figure 2).

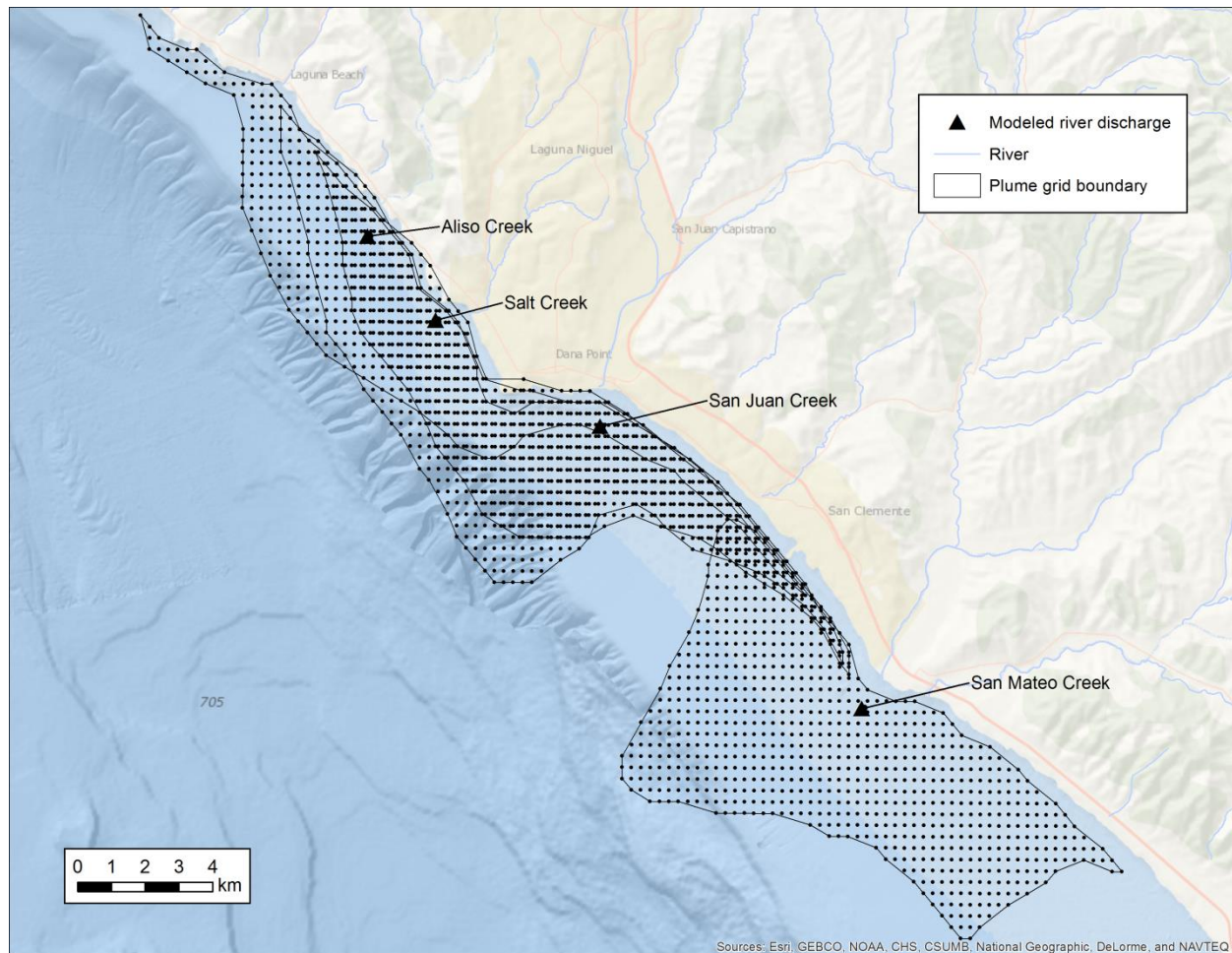


Figure 2. Four overlapping river plume grids in Orange County, CA.

Final river plume probability exposure maps used many realizations (with the number varying among the grids) of hourly water tracer trajectory estimates to determine statistical convergence over various time periods. We converted the model output for each river plume into a point feature class representing the centroid of each grid cell, with a river plume exposure probability (RPE) attribute field. The RPE was calculated for each cell based on the maximum number of particles observed at a single point within the grids. Probabilities ranged from 0 to 1, and in order to reduce noise and eliminate probable non-plume regions of the grids, only cells with a value of ≥ 0.01 were included in the spatial analysis. This value was also used to identify the maximum extent of each plume and to create individual plume boundary polygons for clipping interpolated raster layers.

To calculate the exposure for each cell, the riverine loading value for each constituent was multiplied by the dilution factor and the RPE (Equation 1):

$$\text{Exposure} = \text{Load} \times \text{Dilution} \times \text{Frequency}$$

We developed Python scripts to automate most of the subsequent geoprocessing tasks (Figure 3). For each river plume and parameter, exposure values were interpolated across each grid using Inverse Distance Weighting (IDW), an exact interpolator which assumes that the influence of a known point on an unknown location varies inversely with the distance between the points. It is a simple interpolator that ignores all factors other than distance between points. We selected IDW because sufficient data are not available to describe the complex variables affecting plume distributions at the scale of the study region and time period necessary to parameterize more sophisticated interpolators such as kriging. The twenty individual river plume exposure grids were interpolated to rasters using a power of two, a resolution of 250m² and a maximum search radius of 10km. The interpolated plumes were clipped by the corresponding plume boundary polygon, “No Data” values were converted to 0, and the spatial extent of the raster was set to the maximum extent of all plumes (river and POTW) to simplify integration of the various layers. The 23 plume rasters were then summed to create a single layer representing the bight-wide exposure for each chemical, and a plume boundary polygon that encompassed all 23 grids was created. Finally, the Zonal Statistics tool was used to calculate spatial statistics for the resulting pollutant exposure raster layers, including mean, median, and maximum values, using the bight-wide plume boundary polygon as the zone. This polygon exactly encompasses all points in the plume grids, and was created using the Aggregate Points tool in the Generalization section of the Cartography toolbox (Figure 1).

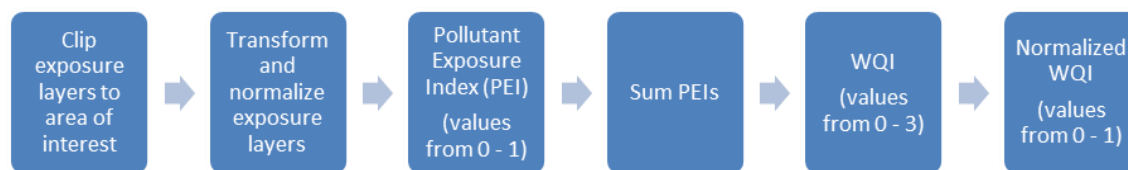


Figure 3. Workflow showing the geoprocessing steps used in the interpolation of pollutant exposure rasters and calculation of the PEI raster.

C. Treated Wastewater discharge pollutant loading

Data on monthly discharge flow rates and concentrations of copper and TSS from four major southern California wastewater treatment plants were obtained from Discharge Monitoring Reports each agency is required to submit to the United States Environmental Protection Agency (Lyon and Sutula 2011). Data on DIN concentrations in effluent were acquired from a recent study that directly measured nutrients in treated wastewater discharge (Howard et al. 2014). The four POTWs used for this analysis, City of Los Angeles Hyperion Treatment Plant (HWTP); Los Angeles County Sanitation District Joint Water Pollution Control Plant (JWPCP), Orange County Sanitation District (OCS), and the City of San Diego Point Loma Treatment Plant (PLWTP) are shown in Figure 1. The average annual load of each pollutant from each plant was calculated for the period 2003-2009. An instantaneous dilution factor was applied to the loading value to account for immediate dilution of discharged effluent in seawater before dispersal occurs. This dilution factor is calculated individually for each outfall as part of their permitting process, based on empirical data comparing concentrations in the undiluted effluent with concentrations in the seawater immediately adjacent to the outfall (Environmental Protection Agency 1985).

D. Treated wastewater plume mapping

Treated wastewater outfall plumes are typically modeled by measuring plume tracers such as salinity, ammonia, and bacteria at stations surrounding the outfall. These approaches can be time consuming and costly, so alternative methods of detecting plumes are being assessed. Nezlin et al. (in prep) used measurements of Colored Dissolved Organic Matter (CDOM) to rapidly measure and track plumes emanating from subsurface discharge outlets at the four large sewage treatment plants. Each POTW agency regularly samples water quality at a grid of stations surrounding their outfall pipes (Figure 4). CDOM data were collected at each station on a quarterly basis from 2004-2010. For each station, the percentage of sampling events when a plume was observed (at any depth between the outlet and below the mixed layer) was calculated (WPE). The four individual sampling grids were combined into a single point feature class, and each point was attributed with its associated WPE value.

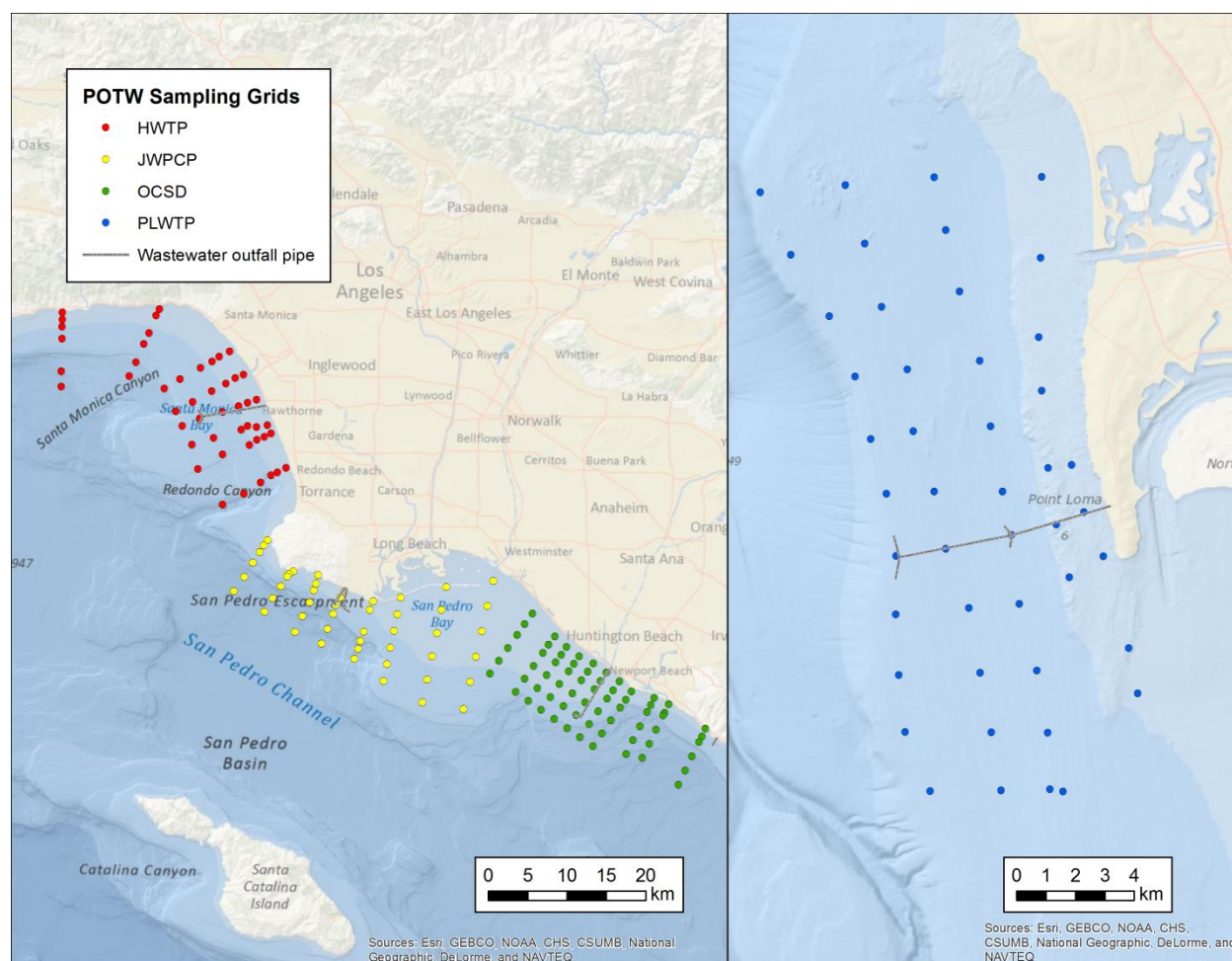


Figure 4. Grids of water quality stations sampled quarterly by each POTW agency. The distance between stations is variable.

We assumed that plume probability at a given grid point is directly equivalent to the dilution of the treated effluent as it is advected away from the source, and that dilution of each chemical within the outfall plume also varies in proportion. Pollutant exposure at each point was calculated using Equation 1. The

exposure values were interpolated across the grid using IDW with a power of two, a resolution of 250m², and a maximum search radius of 10km. A linear shoreline layer was used as a barrier to prevent interpolation of plumes over land areas. Merging the pollutant exposure layers and creating the PEI.

The above geoprocessing steps resulted in six rasters, representing the distribution of each of the three pollutants from both rivers and POTWs within the SCB. For each pollutant, we summed the river plume and wastewater discharge plume rasters to create a single total exposure raster. Each parameter was then normalized to the maximum value before integrating them into the single index. This was a two-step process. First, to reduce skewness for each individual parameter, we calculated the cube root of each raster cell. The cube root-transformed value of each raster cell was divided by the maximum value found in the grid, resulting in a Plume exposure index layer (PEI) with values ranging from 0 – 1 for each chemical. These three normalized PEIs were summed to create a new raster with potential value ranging between 0 – 3. Finally, the cells in this raster were divided by the maximum value in the raster to create the normalized PEI raster, with continuous values ranging between 0 and 1 (Figure 3.)

E. Sensitivity analysis

We conducted a sensitivity analysis to assess variability in riverine pollutant loadings and exposure between wet and dry years. Representative wet and dry years in our 10-year data set were based on long-term (63 year) rainfall records from three Southern California rain gauge stations (Los Angeles International Airport, Santa Ana Fire Station, and San Diego Lindbergh Field) downloaded from NOAA's National Climatic Data Center (<http://www.ncdc.noaa.gov/cdo-web/>). Total rainfall from 2007 (8.2cm) was less than the 10th percentile of the long-term average. Total rainfall from 2010 (51.3cm) was greater than the 90th percentile of the long-term average.

For 2007 and 2010, we calculated the total annual loads of each chemical, and compared the resulting range of values to the 10-year average annual loading value for each parameter and watershed. Exposure layers were created for both 2007 and 2010 using Equation 1 described above, and the total spatial variation in loading was mapped and analyzed. To examine spatial bias, the twenty river plumes assessed were grouped into four regions: Ventura County, Santa Monica Bay (SMB), Orange County, and San Diego County.

IV. Results

A. Spatial extents of plumes

By design, outfalls of wastewater treatment plants are located greater than eight kilometers offshore and at depths between 60-100m to inhibit effluent from recirculating back into surface and nearshore waters. By contrast, plumes emerging from river mouths are immediately subject to multiple nearshore processes, including estuarine mixing, entrainment in the surf zone, and exposure to surface currents. The resulting differences in the fates of riverine and wastewater plumes are shown in Figure 5. Wastewater plumes are observed most frequently in the immediate vicinity of the outfalls, and carried by prevailing subsurface currents either upcoast or downcoast of the pipe. They rarely reach shallow water, generally occurring within 2 km of shore less than 20% of the time. By contrast, riverine plumes tend to hug the shoreline, with the predominant direction depending on prevailing surface currents. Rapid settling and mixing processes prevent freshwater inputs from extending too far into the ocean except under extraordinary climatic conditions and flood events. As a result, the portion of river plumes with the greatest concentration of pollutants occurs within 2 km of shore.

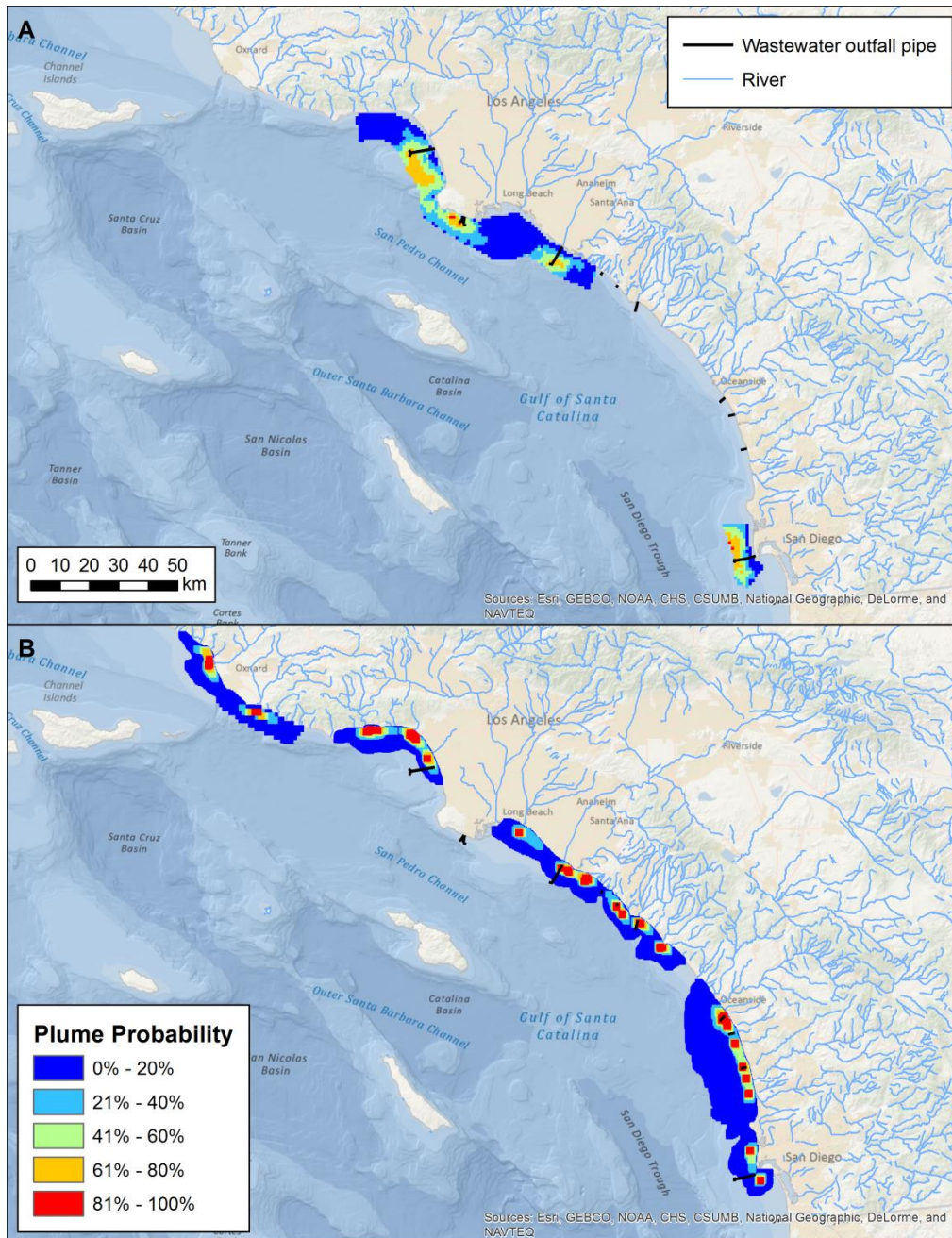


Figure 5: A) Wastewater treatment plant plume probability (WPE); B) River plume probability (RPE).

B. Pollutant loading and exposure

The relative loadings of the three pollutants vary between sources, and their spatial distributions within the area affected by plumes vary correspondingly. We calculated exposure statistics for individual and combined pollutants across the entire region, including the annual median, mean, and maximum exposure values (Table 2). For all pollutants, the median exposure is lower than the mean, and both values are very low compared to the maximum exposure value. This skewness reflects the fact that even within coastal waters impacted by plumes, exposures are generally low over much of the affected area. However, localized areas may be at risk where maxima occur.

Table 2: Spatial statistics for individual pollutants by source.

Source Parameter	Plume Area (km ²)	Average Annual Load (kg/yr)	Exposure (kg/yr)		
			Median	Mean	Max
POTWs					
Copper	1178.9	2.62×10^4	6.5	13.7	81.2
DIN		2.99×10^6	261.8	2813.9	25502.8
TSS		3.39×10^7	11183	171670	89800
Rivers					
Copper	1594.3	1.37×10^4	0.2	0.7	25.4
DIN		9.47×10^5	15.2	49.4	2070
TSS		1.72×10^8	2832	9478	505746
Combined					
Copper	2433.1	4.0×10^4	1.2	7.1	81.2
DIN		1.25×10^6	37.3	1396.9	25502.8
TSS		2.06×10^8	6163	14527	505746

Copper

Large POTWs contribute nearly twice as much copper to the SCB than the rivers considered in this study (Table 2). Maximum exposures occur near the HTP outfall, in Santa Monica Bay. Riverine exposure to copper is highest in the vicinity of the Los Angeles and San Gabriel River mouths, in San Pedro Bay. The Santa Clara River also contributes high loads of copper to the coast of Ventura County.

DIN

POTWs also contribute 3 times as much DIN as rivers (Table 2). This agrees with recent studies showing that wastewater discharge represents the dominant anthropogenic source of nitrogen to the SCB (Howard et al. 2014). As with copper, highest exposures from wastewater sources are found near the Hyperion Outfall. The small but highly urbanized Ballona Creek watershed also contributes relatively high amounts of DIN to Santa Monica Bay (Figures 4A and 4B). As with copper, the Los Angeles River and Santa Clara River contribute the most riverine DIN overall. The Los Angeles River is predicted to load an average of 219,524 kg/yr, and the Santa Clara River contributes 121,159 kg/yr.

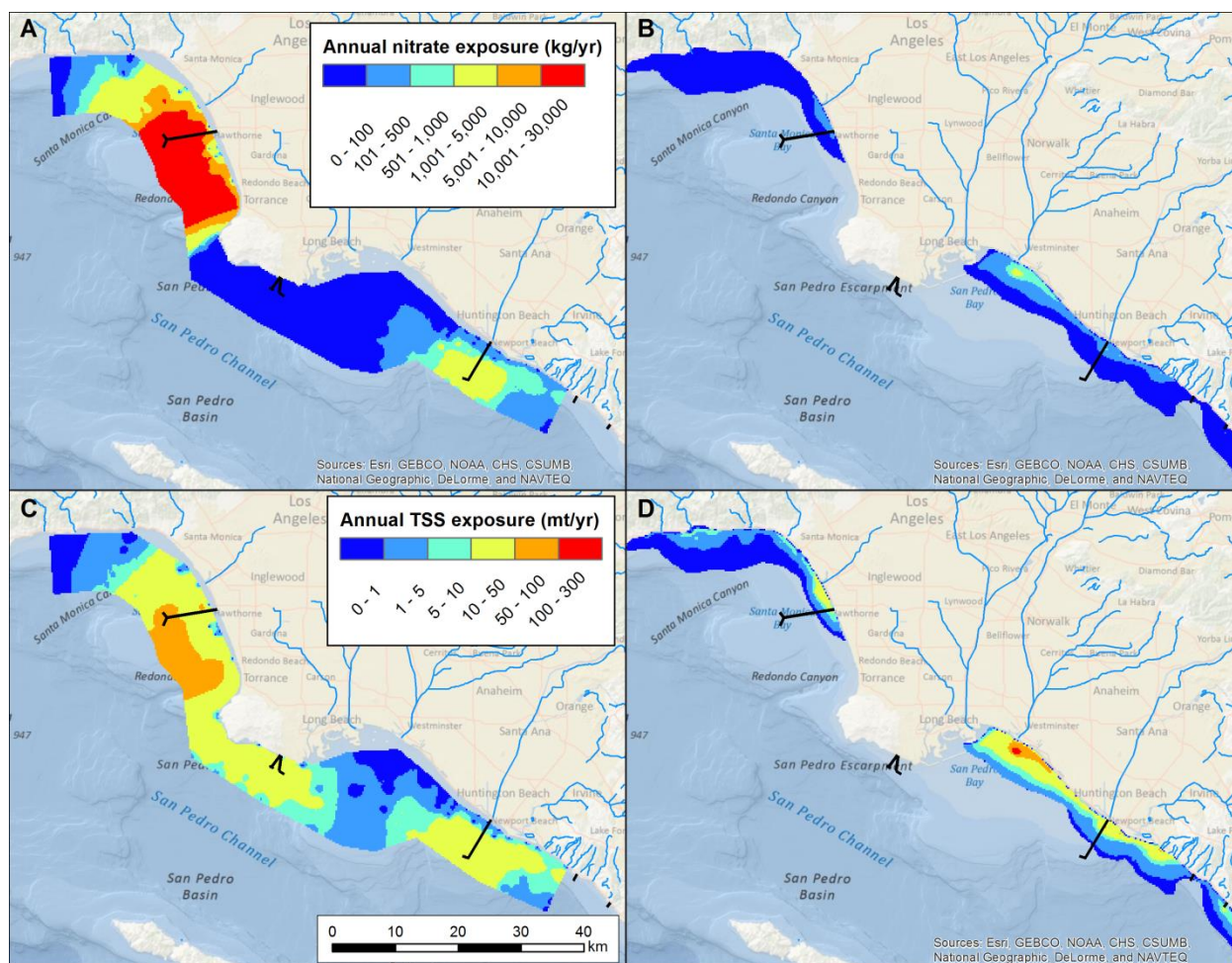


Figure 6: Comparison of pollutants by source in Santa Monica Bay/San Pedro Bay. A) DIN exposure from POTWs; B) DIN exposures from rivers; C) TSS exposure from POTWs; D) TSS exposure from rivers.

TSS

In contrast to copper and DIN, sediment inputs are dominated by riverine loading, which contributes five times the TSS of POTWs (Table 2). Three of the four POTWs employ secondary treatment (activated sludge or biological reactors), which reduces the amount of suspended solids discharged offshore. There are no such controls on the sediments that enter rivers via runoff, especially from watersheds where elevation gradients and land use contribute to high sediment levels. Thus, while offshore exposures from POTW discharges are highest in Santa Monica Bay (Figure 6C) and offshore of Point Loma, San Diego, they are low in comparison to riverine TSS exposures, particularly from the northernmost watersheds in this study (Ventura River, Santa Clara River and Calleguas Creek). These watersheds have the highest elevations, most erosion-prone soil types, and the greatest rainfall quantities, as well as large areas of agricultural land. As a result, the highest TSS loadings and exposures are found in the nearshore waters of Ventura County. Urbanized areas such as the watersheds emptying into San Pedro Bay also contribute high TSS loads (Figure 6D).

C. Plume Exposure Index

The PEI developed through this process is designed to be adaptable for use in comparing different polygonal areas of interest within the larger SCB. Figure 7 maps the combined PEI score across the Bight. For the purpose of this paper, the area of interest (AOI) is defined as California state waters inshore of the three nautical mile State Seaward boundary, and extending from the Mexico border to the northernmost extent of the mapped plumes (hatched area, Figure 7). Table 3 summarizes the percent area within the AOI found within each range of the normalized pollutant exposure indices, and the normalized PEI. Of the total AOI, over 45% of the AOI had a PEI score of $>0 - 0.3$. Another 24.2% is not covered by any mapped plume. The river plume model includes all major rivers, but omits some smaller coastal watersheds and catchments. However, most are relatively undeveloped, and unlikely to be major sources of pollutants.

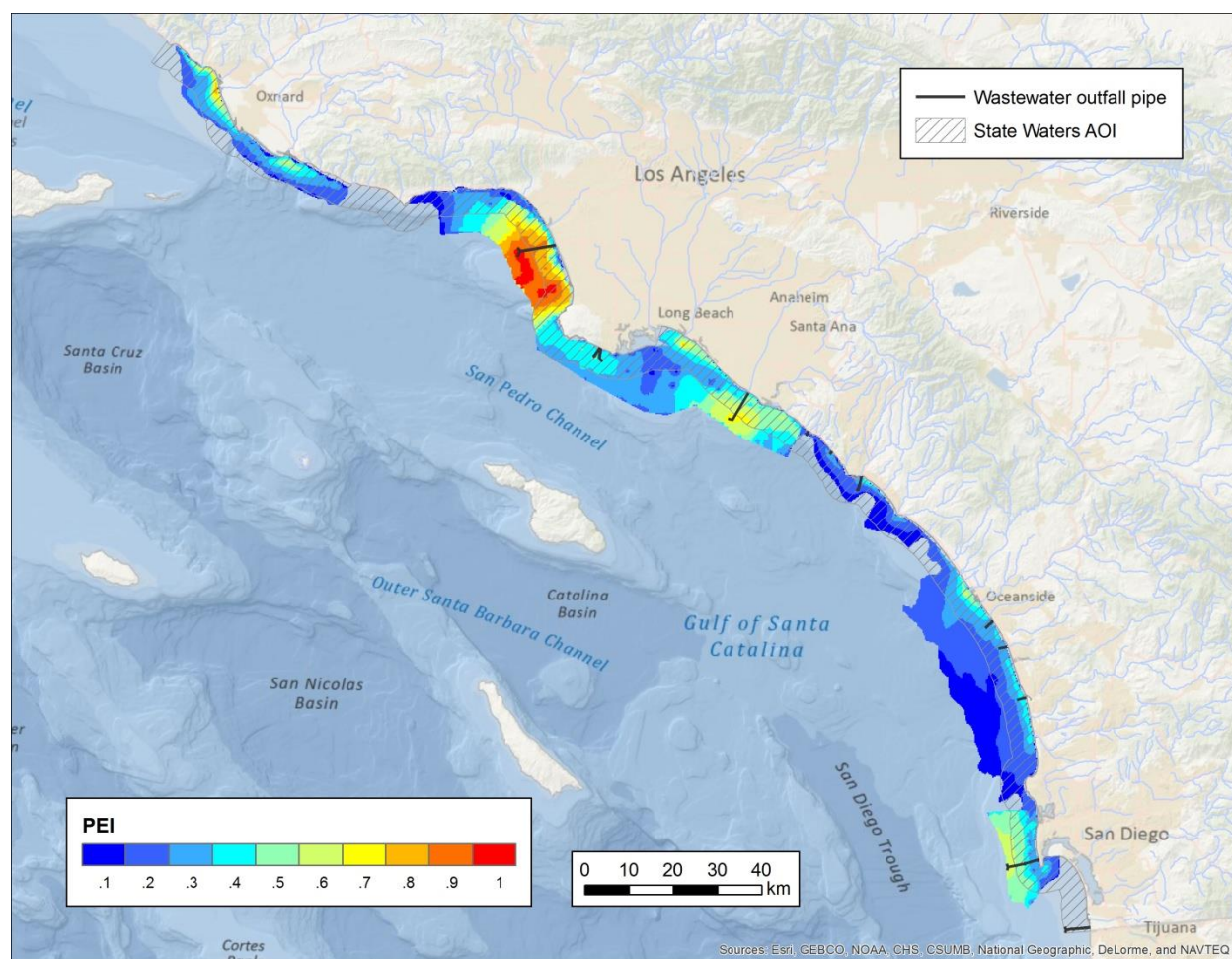


Figure 7: Map of Plume exposure index based on combined sources.

Table 3: Percent area of California State Waters (inside the 3nm limit) within each class of the Plume Exposure Index for individual parameters and the combined Plume Exposure Index (total area = 1986.7km²).

	Percent of SCB Area for each Plume Exposure Index Class										
	No Plume	>0-0.1	>0.1-0.2	>0.2-0.3	>0.3-0.4	>0.4-0.5	>0.5-0.6	>0.6-0.7	>0.7-0.8	>0.8-0.9	>0.9-1.0
Copper	24.2	8.2	20.6	15.9	10	8.2	4.6	3.7	3	1.4	0.2
DIN	24.2	28.9	25.5	10.2	3.4	1.2	1.1	1.3	2.4	1.5	0.3
TSS	24.2	4.6	20.2	22.1	19.2	7.3	1.5	0.4	0.2	0.1	0.1
All	24.2	6.5	19.5	19.3	13.4	7.8	3.2	1.8	2.6	1.4	0.3

D. Sensitivity Analysis

The interannual variability in precipitation is reflected in total riverine pollutant loading and the spatial extent of plumes (Figure 8). In dry weather, plumes are ephemeral and restricted to within a few kilometers of river mouths. With increasing precipitation, plumes extend both alongshore and offshore and plumes from adjacent river mouths may merge. Table 4 and Figure 9 compare the regional mean and maximum exposure values between dry, average, and wet years. In all regions, dry years produce about 20% of the total loads of wet years, while average years produce about 45% of the loads of wet years. Such interannual variability can play a large role in the integrity of coastal ecosystems. For example, several dry years in a row may allow the establishment of habitats and communities that may be severely impacted by heavy flows and pollutant inputs in a subsequent wet year.

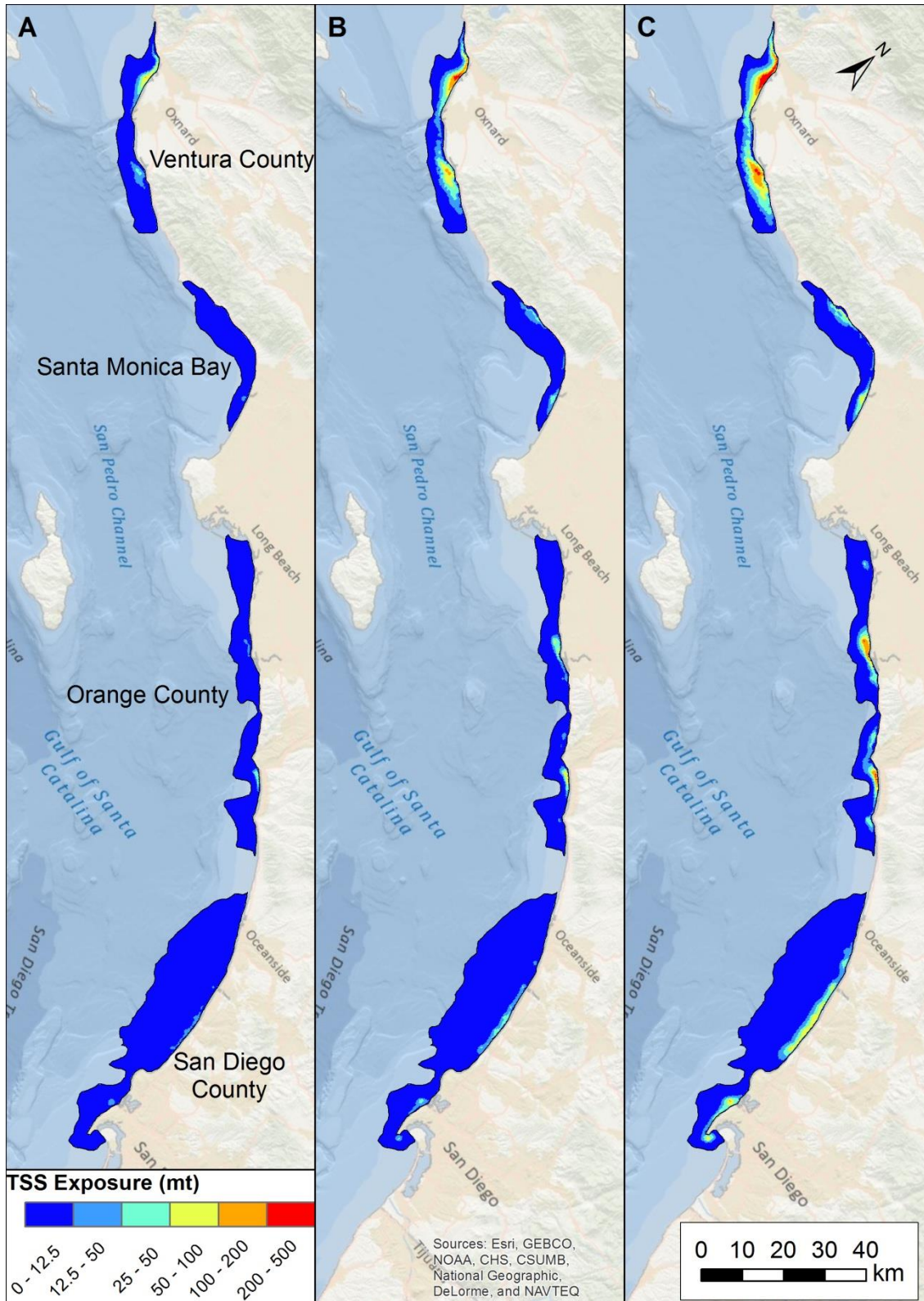


Figure 8: Maps comparing TSS exposures for A) dry, B) average, and C) wet years. The mapped plumes are grouped into four regions.

Table 4: Sensitivity analysis: summary statistics by pollutant and region

	Mean Exposure (kg/yr)			Maximum Exposure (kg/yr)		
	Dry	Average	Wet	Dry	Average	Wet
Copper						
Ventura	0.11	0.32	0.61	1.66	4.13	7.52
SMB	0.04	0.12	0.24	1.03	2.39	5.49
Orange	0.03	0.07	0.18	0.78	1.73	3.93
San Diego	0.16	0.29	0.80	2.84	4.61	14.19
Nitrate						
Ventura	7.2	21.5	40.6	109.7	273.7	498.4
SMB	3.1	9.0	18.2	82.2	190.1	439.9
Orange	1.8	4.6	12.3	52.7	116.8	265.1
San Diego	10.6	18.4	50.8	183.4	297.9	871.3
TSS						
Ventura	7070	21,013	39,643	107,267	267,515	487,234
SMB	1201	4527	7743	18,312	44,679	94,354
Orange	1501	3893	10,739	42,135	95,163	226,030
San Diego	1249	2178	6016	24,564	38,016	102,712

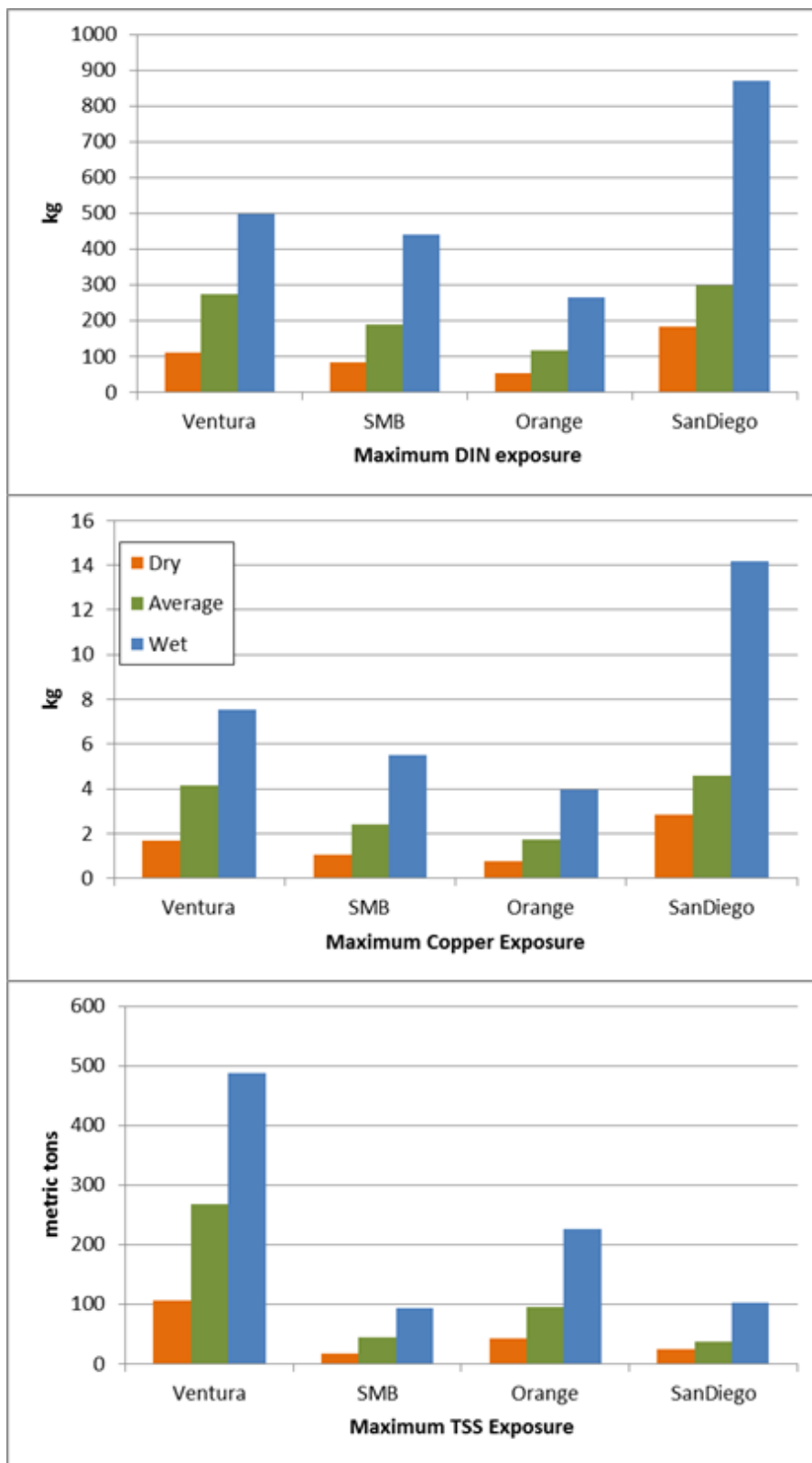


Figure 9. Comparison of pollutant exposure by region during dry, average, and wet years.

V. Discussion

As development and population growth continue within watersheds adjacent to the SCB, loads of potentially harmful chemicals may present a risk to the many valuable resources via both river run-off and treated wastewater. Little is known about the spatial extent of the relative and combined effects of these pollutant sources in different areas of the SCB. With new methods of plume detection, we can now more effectively map and analyze these data. Regional-scale spatial analysis of freshwater plumes and pollutant exposures in the marine environment is a relatively new and growing field. To date, few studies have been done to examine regional extents and effects of plumes (McLaughlin et al. 2003, Mertes and Warrick 2010, Alvarez-Romero et al. 2013). As consistent and comparable data become more readily available through advances in both *in situ* sampling instruments and remote sensing systems, in conjunction with increasing data processing power, the opportunity to conduct regional spatial analysis and modeling of these data is feasible. Satellite imagery allows us to distinguish plumes from ambient water over large areas and longer time scales. Technologies such as High-Frequency Radar aid in the localized prediction of currents and particle movement through surface water. New sensor applications, such as CDOM, now enable researchers to capture subsurface water quality information more quickly, consistently and economically than they could previously using traditional sampling techniques.

A. Benefits of using GIS to create a regional Plume Exposure Index

Our development of geoprocessing tools to spatially integrate these data with information on pollutant loads to create a regional PEI provides an important next step in mapping and understanding potential threats to water quality in the SCB. This index enables a consistent approach to quantify the spatial extent of exposure to these pollutants and to identify critical coastal habitats that may be affected. These tools encapsulate numerous geoprocessing steps into a documented, transferrable and modifiable package. Most of the repetitive steps of this analysis including the interpolation of the individual plume frequency grids, summing of rasters, and generation of spatial statistics, were quickly accomplished by creating models in ArcGIS Model Builder or developing Python scripts. These tools can be customized to accept different input variables rather than being hardcoded with set parameters, increasing their flexibility. The separate scripts may then be packaged into an ArcGIS toolbox, which is easily shared with others who wish to perform similar analyses.

GIS also allowed for spatial integration of datasets acquired through different methods and sources. Data from multiple studies and sources can be integrated as long as they have sufficient resolution and similar spatial referencing. In this study, we combined plume frequency data from the two primary sources, POTWs and rivers. The POTW plumes were empirically mapped using field sampling techniques (CDOM detectors), while river plume locations were modeled based on interpretations of surface current data. Despite these different approaches, both methods resulted in a simple grid of points attributed with a predicted plume frequency, enabling us to apply similar calculations and interpolation methods for both datasets.

Another advantage of using GIS to model plume exposures is that variables can be easily modified to reflect different environmental conditions and predict different outcomes. For example, the Southern California climate is characterized by high interannual variability in precipitation. This variability has significant effects on the annual loading of pollutants by river plumes. In some years (such as those when El Niño conditions prevail), this can result in massive inputs of sediment, nutrients, and metals; while in other years, the inputs barely rise above baseline. Fortunately, the loading model we used explicitly incorporates precipitation as a variable in predicting loads, and provides data on a daily basis enabling us to subset the data into years that reflect this natural climatic variability. These subsets provide representative end-members for our sensitivity analysis. Other variables that could be modified include the dilution factors used to represent initial loss of pollutants from the plume. Flexibility to adjust these

tools to match regional requirements provides a distinct advantage reducing the need for expensive, long-term empirical field-sampling efforts to capture natural variability.

These GIS-based index development tools do have some limitations. It is a 2-dimensional model that does not incorporate the dispersal of pollutants with depth, or reflect complex oceanographic mixing processes, and is therefore only applicable to nearshore shallow water. The strength of its predictive capabilities lie in the methods used to integrate plume effects over a large region and long timespan, providing for a relative ranking of pollution impacts on coastal areas. Clearly, site-specific or short-duration inputs will require dedicated, localized effort beyond this long-term, regional scale PEI approach.

B. Extent of plumes and pollutant exposures

In this study, we identified at least 2400km² of nearshore waters and approximately 320km of coastline between San Diego and Ventura County that could potentially be affected by discharge plumes emanating from either wastewater treatment plants or rivers. About 15% of this area experiences plumes from both sources, making cumulative impacts of anthropogenic influences an important management concern. As expected, areas where plumes overlap also tend to be some of the most highly populated, accessible, and utilized portions of the coastline. Santa Monica Bay and San Pedro Bay receive both treated effluent and riverine run-off from large urbanized areas of the greater Los Angeles Basin, making them two of the areas with the greatest PEI values in the SCB.

The distribution of PEI throughout the SCB indicates that the majority of California state waters within the SCB remain relatively unaffected by anthropogenic pollutants from these sources. Of the 1986 km² of state waters affected by plumes, 45% has a PEI less than three, while only 4.2% has a PEI greater of eight or higher. However, areas of higher PEI are generally closer to shore and, therefore, more likely to impact both sensitive habitats and areas used for human recreation.

C. Comparison of relative risk from each source

The risk from POTWs and rivers varies both temporally and spatially. Treated wastewater discharge from POTWs is a relatively continuous process that discharges pollutants to coastal waters. Conversely, the extent and volume of river discharge is directly proportional to precipitation events resulting in intermittent and somewhat unpredictable plume extent and duration. Subsequently, river plume extent was generally smaller than POTW plume extent. However, river plumes tend to remain inshore of the 30 meter isobath, while POTW plumes occur most frequently between the 30 and 60 meter contours. Therefore, pollutants from river plumes may be more likely to settle out into nearshore sediments or be retained within very shallow waters, potentially causing greater impacts on marine ecosystems (Bay et al., 2003). POTW plumes, though persistent and widespread, emerge from outfalls near the ocean bottom (approximately 60-100m), and tend to remain trapped below the upper mixed layer, mixing into larger volumes of water. Ultimately, this decreases the likelihood that POTW discharges will affect shallower habitats. However, treated wastewater plumes may be more likely to impact offshore ecosystems (Howard et al., 2014).

Our sensitivity analysis indicated that in wet years, river plumes can contribute up to five times the pollutant load of dry years and potentially impact 10 times the area, while inputs from treated wastewater discharge remain relatively similar from year to year. For this reason, it is important to use multiple years of run-off and loading data (at least ten, as in this study) to capture long-term patterns in pollutant exposure. While smaller time scales could be modeled using our approach, the accuracy of the model as a predictor of overall exposures would be limited.

D. Role of Plume Exposure Index in research and management

Our development of a spatially referenced PEI for the SCB provides a means to easily and rapidly compare relative anthropogenic exposure to a variety of ecosystems. It relies on underlying datasets that model the intrusion and dispersal of freshwater plumes and pollutants into the marine environment. The index provides a simplified, long-term average, and inherently loses some of the accuracy of intensive studies examining plumes over smaller areas and time scales. However, by integrating multiple sources of data, the PEI provides a synoptic look at coastal water quality providing environmental management agencies the ability to rank and prioritize affected habitats in terms of susceptibility and management opportunities.

The PEI has many implications for mitigation and management practices designed to protect both the integrity of coastal ecosystems and human health. Since enactment of the Clean Water Act in 1972 and subsequent environmental legislation explicitly recognizing the connections between anthropogenic pollutants and ocean health, our understanding of these connections has continually been strengthened by research. This PEI continues the trend by directly linking land-based loads of nutrients, metals, and sediments arising from multiple individual sources, to ocean circulation patterns. The links can be manipulated to model how upstream changes in land use, flood control and drainage infrastructure, and run-off mitigation attempts might affect loadings, on an individual parameter basis. For example, if new regulations require POTWs to change how they process effluent in order to meet new permitting standards, the downstream effects of those changes can be easily predicted using our tools.

E. Future Directions

We are aiming to use and modify the PEI in several aspects. The first direction is to examine PEI within a new AOI. There are 27 new or modified Marine Protected Areas (MPA), comprising approximately 15% of the SCB coastline (including the Channel Islands), that specifically limit fishing and other extractive activities (California Department of Fish and Wildlife, 2013). Little is known about the effect of water quality in these MPAs, and the new index is one avenue to ascertain risk and prioritize future resources for characterizing problems in MPA performance.

A second new direction is to examine additional sources of pollutants. Two potentially important sources are small POTWs and run-off from small urbanized coastal catchments. We examined the four largest POTWs in the SCB, but there are seven small POTW outfalls that, despite being only a fraction of the four large POTWs examined herein, may have discrete local impacts. Unfortunately, the plume mapping for these small POTWs is lacking (Jones et al., 2009) and we chose not to extrapolate limited results or large POTW plumes to unmapped small POTW outfalls. Similarly, urban run-off that directly enters the ocean through small creeks and coastal storm drains can be a major localized source of pollution. More storm drain water quality data is becoming available through municipal and volunteer monitoring programs (e.g. Los Angeles Department of Public Health, LA Waterkeeper, and City of San Diego all have regular storm drain monitoring projects). However, there is little available long-term data on the dispersal of these pollutants once they enter the ocean. With the advent of new plume monitoring methods such as gliders, it may become easier and less expensive to map the extent of these sources.

A third new direction is incorporating differential dispersal patterns in the modeled parameters (Reifel et al., 2009). We treated each of the three pollutants as though they are conservative tracers of the plume and, therefore, their concentrations decrease linearly with distance from plume source. However, it is likely that they are not true conservative tracers of freshwater transport. For example, TSS typically settles more rapidly than nitrate is diluted. The result would be a higher rate of TSS loss from the plume. Prediction of TSS exposure in the nearshore environment is also complicated by processes other than riverine and POTW discharges. In particular, the resuspension of sediments by high wave energy and currents near headlands can result in high TSS exposures that are not accounted for in this study. By

adjusting dilution factors for each pollutant to more accurately reflect true oceanographic conditions, accuracy of the model could be further improved for TSS. Likewise, nitrate is typically consumed relatively rapidly by phytoplankton and these dynamics are not intrinsic to the PEI. To enhance the plume extent portion of the PEI, additional dispersion, advection, or transformation models could be applied. This would allow for more accurate estimates of potential secondary effects, if necessary.

A fourth new direction is to determine not just potential exposure, but link to ecosystem risk. This will require evolving the dose information from the PEI into predicted responses from the marine ecosystem. For example, we estimated copper as one of the loading parameters in the PEI, but we did not create a threshold for when copper exposure was beyond a limit of concern. Thus, the PEI provides a tool for ranking exposure for different sources or locations, but does not provide managers an estimate if the highest ranked sources or locations should expect to see a biological response. It is possible that even the highest ranked locations may have little impact on biota. This will likely take many years of research to achieve, but several activities have started to tackle this challenge including development of a biological reef response index (next chapter), dedicated special studies to examine chemical-biological interactions in AOIs such as Areas of Special Biological Significance (Schiff and Brown 2015), and development of a linked physical oceanographic-biogeochemical response model to assess the anthropogenic impacts of nutrients in the Southern California Bight.

VII. Acknowledgements

The authors would like to thank Nikolay Nezlin and Peter Rogowski for assistance with interpreting their plume grid data; Dan Pondella, Julia Coates, and the members of the Bight '13 MPA Committee for assistance with manuscript development and review; and two anonymous reviewers for their helpful comments and suggestions.

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CHAPTER 3: BIOLOGICAL REEF RESPONSE

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I. Abstract

Quantitative biological assessment indices overcome many of the challenges faced when conveying the status or trends of complex biological communities with large natural variability, particularly when attempting to evaluate the impacts from human influences. In this paper, we developed a biological condition index for shallow (5-30 m) rocky reefs of the Southern California Bight, evaluate its performance to distinguish healthy from stressed sites, and then apply the index to quantify the relative effects of fishing and water quality as ecosystem stressors. We utilized a multivariate, predictive index based on the ratio of observed-to-expected taxa (O/E). O/E indices are relatively common in freshwater environments, but rarely utilized in marine systems and never before applied to rocky reefs. Based on expectations drawn from region-wide reference reefs with the least fishing or water quality stress, the O/E index predicts expected taxa at a new site based on environmental factors such as sea surface temperature, reef area, and slope, amongst others. The observed taxa at that site are then compared to the predicted taxa to generate index scores; values near unity indicate intact, reference-like communities. Overall, the accuracy of the index was high, with minimal bias, and precision exceeded the performance of an index based on null models (i.e., indices that did not account for natural gradients). Based on multiple lines of evidence, the index was more responsive to fishing pressure than water quality. This study demonstrates that a multivariate predictive index is feasible in rocky reef assessment.

Keywords: Bioassessment, Rocky reef, Water quality, Predictive Index, Ecosystem-based management

II. Introduction

The concept of measuring the health of whole ocean ecosystems is receiving increasing attention (Halpern et al. 2012, Halpern et al. 2014), yet the best biological characteristics for defining healthy marine ecosystems remain uncertain. The uncertainty arises from the complexity of ecosystem responses, which are not always monotonic often producing a complex mix of positive and negative effects on the number and abundance of species (Pearson & Rosenberg 1978). For example, complex trophic linkages can produce unexpected gains within one fishing sector resulting from overexploitation of another fishing sector (Andersen & Pedersen 2010, Steneck et al. 2013). Additionally, increased runoff from agriculture can serve as useful nutrient subsidy to some nearshore organisms (Page et al. 2008, Gorman et al. 2009, Russell et al. 2009), but smother others through sedimentation (Irving & Connell 2002, Airolidi 2003, Connell 2005, Schiel et al. 2006, Balata et al. 2007, Walker 2007). Determining ecosystem health in the context of these numerous and sometimes compound influences is not straightforward and requires a multivariate bioassessment approach that encompasses many ecosystem components.

California USA represents a good case study of the need for multivariate bioassessment indices. The state promulgated the Marine Life Management Act (CDFW 2014a) and the Marine Life Protection Act (CDFW 2014b) in 1999, which has resulted in a spatially integrated network of marine protected areas (MPAs). Historically, California has relied on changes in abundance and size structure of a series of target species (CDFW 2008, CalOST & CDFW 2013) to judge MPA performance. This approach requires contentious judgments among professionals, who must value certain species over others for assessment purposes, and there is currently little consensus on which taxa are most effective indicators of a healthy marine ecosystem. Moreover, MPAs are expected to differentially affect species occurring within their boundaries depending on their life history characteristics and dispersal capabilities. Thus, single species assessments of MPA impacts may be variable and not provide a complete picture of ecosystem status. Finally, the strength of interactions among species may change under MPA protection and therefore unexpected ecosystem changes may occur that are not detected in single species assessments. For these reasons, California is breaking away from traditional single species-based approach to marine resource management for MPAs and is embracing an ecosystem-based approach. The state's new holistic perspective includes attention to non-fisheries impacts from water quality, habitat loss or degradation, and climate change. The departure from single species marine resources management and the complexity of the multiple ecosystem stressor interactions clearly delineates the need for developing a multi-variate predictive bioassessment index of ecosystem status.

MPAs address resource depletion due to consumptive use, but often don't incorporate protections against non-consumptive uses or stressors such as water quality. The potential for non-consumptive impacts to marine resources is unclear. Many studies have demonstrated the effect of sedimentation on settlement and survival of rocky reef organisms (Irving & Connell 2002, Airolidi 2003, Connell 2005, Schiel et al. 2006, Balata et al. 2007, Walker 2007). However detection of ecosystem impacts due to storm water runoff (Ghedini et al. 2011) and treated wastewater discharge (Tegner et al. 1995, O'Connor 2013) has been difficult. Improved methods, including multi-variate based assessment tools for understanding impacts due to poor water quality are needed both in managing those impacts, and to aid in explaining inconsistencies in MPA performance.

Predictive bioassessment indices are increasingly used by the water quality management community as tools for assessing the ecosystem level impacts of anthropogenic pollutants in primarily fresh water or fresh water influenced ecosystems such as streams, wetlands, and estuaries (Yoder & Rakin 1998, Cao & Hawkins 2011). These indices typically establish an expected biological community composition within reference sites defined by a relative absence of anthropogenic stress (Hawkins 2006, Stoddard et al. 2006). Predictive models describe natural variability in biological communities due solely to environmental characteristics at these reference sites. Once natural environmental variability is taken into account with the predictive model, deviations in index scores among non-reference sites can then be

associated with gradients in anthropogenic influences, thus quantifying the direction and magnitude of those influences on ecosystems (Vander Laan et al. 2013). Similar indices have rarely been developed for marine ecosystems (Smith et al. 2001), perhaps because of a long tradition of single-species focus (Mace 2004, Guerry 2005), a lack of spatial management (Douvere 2008), or disagreement on the most important ecosystem components (de Jonge et al. 2012, Ward 2014).

In this paper, we developed a predictive multivariate index of ecosystem status for shallow rocky reefs of the Southern California Bight (SCB). This highly productive and diverse ecosystem supports intense consumptive and non-consumptive use and is represented within nearly all the region's MPAs. The effects of multiple stressors and management through MPAs are of particular interest in Southern California because of its dense coastal human population centers, which lead to particular concern about water quality. Our specific objectives were to 1) develop a multivariate bioassessment index, 2) assess its performance and ability to distinguish healthy from stressed sites, and 3) apply the index in an effort to distinguish the relative effects of fishing and water quality as ecosystem stressors.

III. Methods

We constructed an observed-to-expected (O/E) index to describe the condition of shallow-rock reef sites with the aim of using index scores to assess the relative impacts of fishing pressure and water quality on this ecosystem. The study habitat is defined as subtidal, generally kelp forested, with areas of hard substratum ranging from approximately 5 to 30 m depth. Geographic extent of our study covered the SCB, which ranges from Point Conception to the US/Mexico border including the Channel Islands. Approximately 49,000 hectares of shallow rocky reef area is distributed along the mainland and island coastlines in this region (Pondella et al., 2011).

A. Aggregation of Data

Biological data

Rocky reef biological data was aggregated from three separate monitoring programs conducted in four years: 1) the California Department of Fish and Wildlife's Cooperative Research and Assessment of Nearshore Ecosystems (CRANE) in 2004, 2) the Southern California Coastal Water Research Project's Bight Regional Monitoring Program in 2008, and 3) California Ocean Science Trust's South Coast Marine Protected Area Baseline Program in 2011 and 2012. These programs used nearly identical protocols and also to those used by the Partnership for Interdisciplinary Studies of Coastal Oceans (PISCO; <http://www.piscoweb.org/research/science-by-discipline/ecosystem-monitoring/kelp-forest-monitoring/subtidal-sampling-protocol>) and described by (Gillett et al. 2012). Briefly, three types of transect protocols were used to collect information on fish, invertebrates, benthic algae, and physical habitat characteristics. Transects were placed within four reef sections (inner, middle, outer, deep). Fish, as well as mobile macroinvertebrates and algae (swath), were counted along replicate 30 x 4-m bottom transects within those sections. Additional fish transects were performed midwater and immediately below the kelp canopy. The uniform point contact (UPC) method assessed percent cover of invertebrates and algae that are colonial or blanketing and physical habitat characteristics. Abundance on replicate transects for each survey method (fish, swath, UPC) were averaged within each site and sample year then converted to a presence/absence matrix. Therefore, a biological sample reflects a unique site-year combination. Monitoring was conducted at 140 unique reefs during one to four sample years, resulting in 299 biological samples.

Stressor data

We characterized two stressor gradients: water quality and fishing pressure. Each was described by an index that aggregated multiple years of local-scale stressor data into an SCB regional scale map.

We used a risk-based approach to create the water quality index (WQI) detailed within Schaffner et al. (2015). The risk was estimated as a function of pollutant concentration, magnitude, and duration of exposure. Pollutant loading was estimated for the SCB's two largest sources, publicly owned treatment works (POTWs) and rivers (Lyon & Stein 2009). Spatial distribution of exposure duration was acquired from multiple sources that utilize advances in plume detection technology including High Frequency Radar and optical sensors for Colored Dissolved Organic Matter (CDOM). Average annual loads of dissolved inorganic nitrogen (DIN), total suspended solids (TSS), and copper were calculated for twenty rivers based on eleven years of data (2000-2010; Howard et al. 2014) and four POTWs using seven years of data (2003-2009; Lyon & Stein 2009). Due to the absence of rivers and POTWs at the Channel Islands and because mainland plumes rarely if ever extend that far offshore, we assumed an absence of water quality pressure (WQI = 0) in that region of the SCB. Our WQI varied at spatial scales (250 m) finer than the biological sites (individual reefs from 6-5000 hectares). The WQI incorporated data over a similar time frame to biological data (2000-2010).

Data to describe fishing pressure was taken from a synthetic fishing pressure index derived for the SCB by Zellmer et al. (Chapter 1). Development of the fishing index involved additively combining California Department of Fish and Wildlife commercial fisheries data with commercial passenger fishing vessel (CPFV) recreational data after converting both to pounds taken. Both fisheries report take with reference to a spatial grid or “fishery blocks” approximately 10 minutes square. The data was filtered to include only rocky reef associated species and trimmed to the time period 1980-2009. Some alterations were made for the purpose of the present study including weighting take within fishery blocks by the length of ocean-facing coastline within that block, removal of urchins from the aggregate index, and trimming the data to biological transect sample dates. Fishery take to be associated with a given biological transect sample reflected the most recent possible fishing data, not extending past the transect sample date (e.g. transect data collected in 2004 was associated with fishing data up to and not past 2004, transect data collected in 2012 was associated with fishing data up to 2009). The spatial scale of commercial fishing blocks is generally greater than that of individual reefs; therefore, the index may not be able to distinguish fine variation in fishermen’s behavior. Because we chose to include historical fishing pressure back to 1980, catch during past decades tended to swamp smaller catch amounts during recent years. Thus, the index showed little effective temporal variation.

B. Designation of Reference and Stressed Sites

Reference sites were defined by the relative absence of stress, as measured by our two stressor indices. Therefore, our reference sites meet Stoddard’s (2006) criteria for best available sites experiencing the least human influence in the current [sea]scape. This designation represents an objective reference definition. Best professional judgements of high quality reef sites based on biological attributes like high species diversity were not considered, as they are subjective and perpetuate circular reasoning (i.e., using biology to define biology). Rather, this framework allows sites to be judged on their best achievable biological community based on their physical environmental characteristics and lack of human-induced stress.

Stress due to fishing was described in three ways: take within the 5 most recent years, within the 10 most recent years, and between 1980 and 2012. Stress due to water quality impacts was described using the synthetic water quality index (WQI) as well as each of its components (DIN, TSS, Copper) (Schaffner et al. 2015). Criteria for identifying reference sites were set at fisheries take below the 30th percentile of take among all sites, and an absence of water quality stress (WQI = 0). Our goal was to have a sufficient number and geographic distribution of reference sites to reflect the full spectrum of natural habitat gradients. To verify that reference sites could represent the environmental gradients at stressed sites, we visually compared probability density plots of the environmental gradients represented within reference sites that met these thresholds and each of the three fisheries take time periods with environmental gradients within non-reference sites (Ode et al. in press).

Reference sites were divided into calibration (80%) and validation (20%) sets. Models were trained on a single sample year at each reference calibration site, chosen at random for sites with multiple years of samples (later referred to as selected samples). This selection procedure was carried through validation and non-reference sites, as well for assessment of index performance in samples that are both replicated and unreplicated at the three site types (reference validation, reference calibration, non-reference).

Habitat data

Each sample site was attributed with a suite of variables describing its habitat characteristics generally not associated with anthropogenic influence (Table 1). These are factors expected to influence the biological community on rocky reefs and inform the expected taxa of the observed to expected index. Some of these variables are expected to vary spatially, temporally, or both. Bedrock and sand substrate categories may or may not be covered by biota, while bare rock and bare sand are separately measured cover categories

devoid of biota. Sea surface temperatures are averages of measurements taken at 15-day intervals over multiple (MeanSST) or single (SST, SST1, and SST2) year periods. Monthly El Niño Southern Oscillation (ENSO) index values were averaged within one year periods. The strength of settlement patterns was described using invertebrate settlement on artificial substrates at six Southern California sites collected by the Santa Barbara Coastal Long Term Ecological Research project (Schroeter et al. 2012). Values were averaged across all sites within one-year periods.

C. Development of the O/E Index

Degraded biological condition can be described as a loss of expected taxa, and quantified by the ratio of observed-to-expected taxa (O/E) (Wright 1995, Hawkins 2006). We developed the reef O/E index following methods described by Moss et al. (1987) and modified by Mazor et al. (in review). First, we used cluster analysis to identify biologically-homogeneous groups of sites within the reference calibration set. Second, we developed a random forest model to relate group membership to the habitat variables. Third, this model was used to predict group membership for test sites based on their habitat predictors, generating probabilities of taxa presence at those sites (capture probability). Fourth, the overall expected number of taxa at a site was calculated as the sum of the probabilities of observing each taxon, including only taxa with capture probabilities greater than 0.5.

In order to evaluate the relative improvement in index precision attributable to modeling reference site variability, an index based on a null model (wherein all reference sites belong to a single group) was calculated; the null index provides an estimate of the upper limit of precision attainable by a model. A theoretical lower limit of precision was calculated as the standard deviation of replicate samples (SDRS), as described by Van Sickle et al. (2005). Thus, the standard deviation of the index may be compared to the standard deviation of the null index and the SDRS to evaluate the improvement caused by modeling natural gradients

Five separate O/E indices were created using each of the three species assemblages (fish, swath and UPC), fish and swath combined, and all assemblages combined. Different clusters of reference calibration sites were derived based on each species assemblage. Individualized final random forest models with unique sets of habitat predictors were created for each species assemblage.

IV. Index Performance Evaluation

O/E index performance was assessed with regard to accuracy, precision and sensitivity. Accuracy was evaluated as the mean score of reference sites. Mean scores close to 1 indicate high accuracy. Accuracy was also evaluated as the number of validation reference sites with scores within one standard deviation of the reference mean. We assessed bias as a component of accuracy by regressing O/E scores with each continuously varying habitat variable at reference sites. Temporal bias with sample year was assessed using an ANOVA of scores at reference sites by year. Finally, we used random forest models to examine the percent variance in O/E scores explained by habitat variables at reference sites; an unbiased index will have low variability associated with natural gradients at reference sites.

Precision was evaluated as the standard deviation of scores at reference sites; low standard deviation among reference sites indicated high precision. Means close to one indicate accuracy and small standard deviations indicated precision (Ode et al. 2008). These were calculated for reference calibration and validation site sets. We also assessed precision by examining the within-site variability of index scores where sites were visited in multiple years.

Sensitivity was evaluated as the frequency of impairment among nonreference sites, and responsiveness was evaluated as a t-test comparing mean index scores at reference and non-reference sites. We further assessed responsiveness by regressing index scores against continuously varying stressor data; significant regression slopes indicated a responsive index.

Indices trained on different species assemblages (i.e., fish, swath, UPC, or combinations thereof) were first compared with regard to accuracy and precision as defined by the mean and standard deviation of scores. Sensitivity and responsiveness were then evaluated. Then, the index with best performing index based on these criteria was further evaluated for bias.

A. Relative Impacts of Fishing Pressure and Water Quality

Relationships between index scores and stressor levels were used to assess the relative impacts of stressors on site condition. A weight-of-evidence approach was taken to achieve confirmation of stressor patterns relative to an index performance threshold and to individual species abundances.

A threshold to identify degraded biological communities was defined as the lowest reference O/E (fish+swath) score (0.847). Samples above this threshold were considered within reference condition and samples below this threshold were considered degraded or in non-reference condition. We compared mean stress and habitat variables for samples above and below threshold using t-tests. Those stress and habitat variables showing significant differences in samples above and below the threshold were used as predictor variables in a multiple regression with OE (fish+swath) index scores as the response variable. A simplified model was produced using a step-wise procedure. Finally, a Chi squared analysis was used to further examine patterns relative to the threshold. Both the fishery and water quality indices were divided into high and low impact categories based on their median value. Impact intervals for the fishing index were set at low: 20,758 to 95,781 and high: 95,782 to 43,851,984. Impact intervals for the water quality index were low: 0 to 0.36 and high: 0.37 to 2.9. The proportion of all samples falling within those categories were used to generate an expected proportion of samples below threshold that should fall within those categories. A Chi squared test assessed differences in the expected and observed number of below-threshold index scores within the impact categories.

We examined the impact of stress on individual species in an effort to identify indicator species and their influence on the index. We identified the fish and swath species with probabilities of capture greater than 50% as those species having an influence on index scores and compared the abundance of those species in

samples above and below the index performance threshold. Those species with significant abundance differences between the sample groups were then tested in an ANOVA using abundance as the response variable and the log of the fishery index and TSS as random factors. The strength of main effects and their interaction was assessed to determine the relative influence of stressors on the individual species.

V. Results

A. Reference Sites

We identified a set of 41 reference samples with broad geographic distribution and representation of habitat variability in our non-reference sample set. Probability density plots for 29 different habitat variables demonstrated tremendous agreement in the relative range of natural gradients among the reference and non-reference sample distributions (Figure 1). These 41 reference samples included reefs that scored zero in the water quality index and reefs that scored below the 30th percentile in the fishing pressure index dating back to 1980. To evaluate the potential effect of fishing pressure on the reference sample population, this analysis was re-run by defining fishery stress by the most recent 5 and 10 years of fishing pressure data for each sample (data not shown). Many, but not all, of the same sites were found in this sensitivity analysis. However, the reference sample population dating back to 1980 provided the greatest coverage of natural gradients.

Flexible beta cluster analysis produced five dendrograms based on Bray-Curtis dissimilarity in species presence/absence data for each of the five species assemblages. We then chose five to six groups within those dendrograms. Sites within the same clusters grouped together geographically with some restricted to either island or mainland sites and others spanning both. For the fish+swath species assemblage, habitat features that differed most strongly among clusters included mean SST [$F(1, 30) = 45.68, p = 1.711 \times 10^{-7}$], reef area [$F(1, 30) = 13.43, p = 9.502 \times 10^{-2}$], and slope [$F(1, 30) = 9.00, p = 5.391 \times 10^{-3}$], while differences in relief and amount of bedrock were also observed (Figure 2). Samples with colder temperatures differentiated by reef area and samples with warmer temperatures differentiated primarily by slope.

B. Model Performance

The predictive model produced similar accuracy and precision across the five different species assemblages (Table 2). The UPC index produced the highest accuracy as measured by reference site scores closest to one. The indices using fish + swath and swath only were equally accurate as measured by each with only one reference validation sample falling outside one standard deviation of the reference calibration mean. The indices using fish, UPC, and all assemblages were less accurate with eight, three and two validation samples outside one standard deviation of the reference calibration mean, respectively. The index using all assemblages combined resulted in the highest precision as measured by the lowest standard deviations of scores. At calibration sites, improvement in precision over the null model was greatest for fish, fish+swath, and swath assemblage index scores. Performance through predictive modeling was only improved by 0.6% using the UPC assemblage in these samples. Reference site samples not used for model training showed the greatest index precision improvement when all assemblages were used. Finally, the greatest improvement in precision at test sites was achieved by the indices using swath and fish + swath assemblages. The majority of reef sites were sampled in multiple years. The median of within-site standard deviations of O/E (fish + swath) scores at reference and non-reference sites was 0.046 and 0.065 respectively.

Random forest models show that predictive modeling effectively reduced bias in selected calibration and validation samples by reducing the variance in fish + swath index scores explained by habitat (Table 3). Percent variance explained by habitat for unselected calibration and validation samples not used for model training was greatly reduced by predictive modeling but 20% variance was still explained by habitat in these samples (Table 3). Bias was also indicated in reference samples not used for model training by significant relationships between index (fish + swath) scores and bedrock, cobble, relief from

0-0.1 m and 0.1-1 m, site aggregation, and reef area (Table 4). There was no significant bias by sample year among reference samples [$F(1, 49) = 2.358, p = 0.131$].

Index sensitivity to stress was greatest for the fish + swath species assemblage and was more responsive to fishing than water quality. Differences between scores of reference (samples not used for model training) and nonreference samples were greatest for the fish + swath species assemblage [$t(130) = -2.882, p = 0.005$] (Figure 3). Differences in fish assemblage index scores were also significant [$t(125) = -2.626, p = 0.010$] and all other assemblage differences were nonsignificant. Regressions of index scores on stressor indices showed significant negative relationships with the log of the fishery index with each species assemblage, although the magnitude of these relationships was small (Table 5). Only one significant relationship was observed between O/E index scores based on each of the species assemblages and any of the water quality indices. The O/E index based on the UPC assemblage was significantly, positively related to the synthetic water quality index [$F(265) = 3.977, p = 0.047$]. Because sensitivity was greatest using the fish + swath species assemblage, and this assemblage's index performed well relative to its null model, we applied only this index to determining the relative impacts of fishing and water quality.

C. Relative Impacts of Fishing Pressure and Water Quality

The threshold for the O/E (fish + swath) index was set at the value for the lowest performing reference sample (0.847). Non-reference sample index scores ranged as low as 0.173. Some significant differences in means of habitat variables and stress indices in samples above and below the threshold showed that low performing samples were associated with more bare rock, less bedrock, more cobble, low relief, shallower water, more sand transport, greater invertebrate settlement, and higher fishing pressure (Table 6). Mean TSS was higher while DIN and Copper were lower at sites below threshold, though differences were nonsignificant.

Multiple regression identified both stress and habitat variability as important predictors of index scores. Stepwise variable reduction identified bare rock, bare sand, bedrock, sand transport, relief, cobble, fishing pressure and TSS as important predictors of O/E (fish + swath) scores (Table 7). While these results indicated that many habitat factors are important in dictating the biological community, the influence of fishing pressure was the strongest predictor.

Chi square analysis also indicated an influence of fishing pressure on index scores. Fewer low performing sites experienced low fishing impact than expected and more low performing sites experienced high fishing impact than expected [$\chi^2(1, 38) = 3.79, p = 0.052$]. The proportion of samples with low performing index scores did not differ from expected relative to the water quality index.

The abundance of species with high capture probabilities was not necessarily related to the position of index scores relative to the index threshold. Those species for which abundance was significantly different in samples with high index performance demonstrated influence of both fishing pressure and TSS. Of the 25 fish species with high capture probabilities, 15 had significantly greater abundance in samples with index scores above the index threshold. Seven of those were significantly related to fishing pressure and nine to TSS (Table SI1). Of the 31 swath species with high capture probabilities, 15 had significantly different abundance in samples with index scores above the index threshold. Means of all taxa except *Pterygophora californica* were higher above the index threshold. Four of those were significantly related to fishing pressure and 10 to TSS.

VI. Discussion

This is the first O/E index constructed for a marine rocky reef ecosystem and, while not intended to be the final assessment tool to be used by scientists or managers, this study illustrated initial concepts and demonstrated the utility of its application to scientists and managers who invest in this habitat. The benefits of an O/E index overcome at least three challenges that have presented roadblocks to scientists and managers in the past. The first challenge the O/E index overcomes is its ability to integrate across the entire biological community and not rely on single species (or groups of single species) assessments. Much research on marine community structure has focused on disentangling the effects of biotic or top down forces (often impacted by fishing pressure) from abiotic or bottom up forces (often impacted by water quality). Identification of the dominant force can be limited by ecological interactions and non-linear responses in single species assessments (Worm et al. 2000, Smith et al. 2004, Heck & Valentine 2007, Foster & Schiel 2010, Huntington et al. 2010, Sangil et al. 2013). Multivariate approaches are a common approach to multi-species assessments in rocky reef ecosystems (Smith & Simpson 1993, Smith et al. 1999, Hamilton et al. 2010, Sala et al. 2012, Sangil et al. 2013, Horta e Costa et al. 2014), but these studies are typically focused on single and spatially limited project issues. These single-focused multivariate approaches, unlike the O/E index, limit broader applicability such as when new sites or future time periods are sampled. In this paper, we trained five O/E models on five different species assemblages (including combinations of fish, invertebrates, algae) using data over a 10-year period, all of which performed similarly with regard to producing mean index scores close to one at reference sites (accuracy) and doing so consistently (precision). However, the O/E index achieved its greatest sensitivity to stress when fish and non-colonial/non-blanketing macroinvertebrates and algae were combined together (fish + swath). In freshwater habitats, the sensitivity of the O/E index to stress at the community level has been attributed to its ability to integrate differences in species tolerance and differences in life history strategies, while accounting for natural species replacement (Hawkins 2006). Clearly, the mix of rocky reef assemblages in the selected O/E has these important characteristics.

A second benefit of the O/E index is that it overcomes the challenges of natural variability that confound most attempts to draw out changes due to human-induced stress. The fact that rocky reef communities respond to differences in temperature, reef size, substrate, and other purely natural factors is not new (Dayton et al. 1984, Tegner & Dayton 1991, Torres-Moye et al. 2013). However, the ecological modeling in the O/E index that predicts taxa occurrence is a novel approach in this habitat to “normalize” these environmental gradients. The challenge of natural variability is perhaps maximized in California where the cold, sub-arctic California Current meets the warm, sub-tropical Davidson Counter-current, and rocky reef substrates range from low-lying cobbles with intermittent sand burial to tall pinnacles (Airame et al. 2003 and references therein). However, this challenge is no less than the dynamic freshwater habitat variability observed in California where O/E models have had to overcome natural gradients that range from the highest (Mt Whitney, 4,421 m) and lowest (Death Valley -86 m) elevations in the contiguous United States (Mazor et al. in review). The key to meeting the challenge of large natural variability is ensuring that our pool of reference sites captures the entire gradient of natural environmental conditions. In this study, we illustrated that our reference samples captured the same range of environmental gradients as was observed in our non-reference samples.

The third benefit of the O/E index was its ability to identify stressed sites once natural variability was accounted for. In this study, 13% of the samples in southern California were identified as non-reference or “stressed”. One advantage of the O/E index is its objective quantitative nature that can be used for ranking and prioritizing future activities. This allows scientists to focus their efforts on the most stressed sites, identifying site-specific causative factors, and for managers to focus their efforts on restoration and/or mitigation. Moreover, once a management action is taken, the O/E index can provide a quantitative tool for measuring and communicating progress towards agreed upon endpoints of success.

Application of the O/E index in this study identified that fishing was a more important stressor than water quality based on two lines of evidence. The first line of evidence was the step-wise regression of O/E scores versus stressor values. In this case, increasing fishing pressure index values was the single largest variable that correlated with decreasing O/E scores. While the slope of this regression was not large, there were no significant correlations with the water quality index score or any of its component metrics. The second line of evidence was the chi square analysis, where disproportionately low O/E scores occurred when the fishing pressure index scores were high. In contrast, there was no significant change in the proportion of O/E scores due to water quality index scores.

Unlike relationships between index scores and stressors, species specific responses to stressors showed a more complex mix of influence from fishing and water quality pressure. Many species of fish and invertebrates with significantly higher abundance (not frequency) in samples above threshold, experience little to no fishing pressure. Therefore, it is not surprising that more of these species show significant relationships between abundance and water quality stress than fishing pressure. Some interesting species responses, such as negative relationships between the abundance of unfished species like giant kelp and garibaldi with fishing pressure, illustrate the potential for species interactions to complicate understanding of ecosystem response to stress and thus the need for an index.

While the O/E index has many advantages, certain limitations need to be addressed before it is used. One limitation was the remaining influence of natural gradients, even after the ecological modelling was completed. This was most acutely observed during the step-wise regression analysis; increasing fishing pressure provided the strongest regression coefficients relative to decreasing O/E scores. However, some natural characteristic variables were also identified (e.g., bare rock, bare sand, bedrock, sand transport, relief, cobble). Two outcomes, equally challenging, could account for this potential bias in the O/E model. The first is that the O/E model was not adequately trained, most likely due to insufficient reference sites with these natural characteristics. As previously illustrated, our reference pool covered all of the major natural gradients in southern California rocky reefs found in our regionwide data set, and in the relative frequency of which they are found. However, the relative frequency of naturally occurring reefs with bare rock, bare sand, or bare cobble reefs with high sand transport is low and, as a result, the number of reference sites with these natural characteristics was also low. The second outcome that could account for this bias is the covariance of fishing pressure and reef characteristics. In essence, fishing pressure exerts a disproportionately large influence on reefs with these natural characteristics because resiliency is far less. Archaeological evidence at the Channel Islands for geographic continuity in kelp-forest associated red abalone populations suggests resilience of kelp forests to dramatic ecological change over long time scales (Braje et al. 2009). Southern California kelp forests are also thought to be particularly resilient due to resistance of urchin-mediated trophic cascades provided by a diverse suite of urchin predators (Steneck et al. 2002). Despite strong resilience at broad spatial and long temporal scales, local scale kelp forests and their associated organisms are more variable and subject to disturbance on unstable substrata (Dayton 1985, Edwards 2004).

A second limitation of the model is how reference sites were selected. We utilized a composite fishing pressure index and a composite water quality index as a screen for human influence. These were useful tools for us, since these were the two stressors we wished to evaluate, similar to how soft-bottom marine ecotoxicologists use sediment contamination as screens for reference sites for their quantitative condition assessment tool, the Benthic Response Index (Smith et al. 2001). However, the fishing pressure and water quality composite indices each had their own assumptions that could miss potential impacts to reef communities. For example, the water quality index captured the largest pollution discharges and representative chemicals of concern in southern California, but it did not capture every source and every chemical. Likewise, the fishing pressure index captured commercial fishing and CPFV recreational fishing, but it did not capture private vessel fishing effort (which remains unquantified in southern California). Finally, both the fishing pressure and water quality indices were based on long-term averages

of up to 10-30 years. However, the samples used for calibrating, validating, and applying the O/E index are single point-in-time measurements. Clearly, further work in the development of screening tools should be evaluated for building future O/E indices because the inclusion of non-reference sites in the reference pool will decrease sensitivity of the model and potentially lead to false negative conclusions (or type I error of identifying a test site as reference when it really isn't).

A third limitation of the O/E model is the basic construct of species presence or absence. While both fishing and water quality can lead to complete extirpation, this is usually far past the scientific concept of community alteration. For example, fishing pressure may vastly reduce the population and dramatically alter the size frequency distributions of an extracted species, but there still may be an individual(s) of that taxa residing at a reef. Similarly, water quality impacts may exert sublethal impacts on growth and reproduction that can be equally detrimental as fishing, but without complete loss of that taxa through acute mortality (Pearson & Rosenberg 1978). We would encourage future iterations of predictive rocky reef ecological modeling to consider weighting factors for key biological community factors including abundance, taxa functional groups, and/or diversity measures.

Our final evaluation of future O/E model needs is to further refine the thresholds index impact. Defining impact thresholds is partly technical, but also partly sociological. In the case of our study, we utilized a conservative index threshold, defined as the minimum reference pool O/E score. However, other quantitative indices have used other population based estimators (i.e., 1st percentile, 5th percentile, Mazor et al in review), two standard deviations below the mean of the reference population (Ode et al. 2005), or community-based ecological cutoffs (i.e., loss of taxa groups, Smith et al 2001). The statistical approaches lend themselves to objective and repeatable thresholds, but the magnitude of these changes (and the management reactions to them) are ultimately a sociological choice.

VII. Conclusions

Based on a multi-decadal data set of biological surveys, fishing pressure, and water quality exposure in southern California, we developed the first known O/E index for shallow, subtidal rocky reefs. This predictive model performed best using combined fish, invertebrate, and algal communities (fish + swath) based on accuracy and precision across a wide range of environmental gradients, and sensitivity to multiple stressors. The O/E index is a new approach for this habitat providing an objective, quantitative, and repeatable assessment tool for use by scientists and managers when ranking and prioritizing shallow, rocky reef sites for management action, and assessing the progress of sites once management action(s) is taken.

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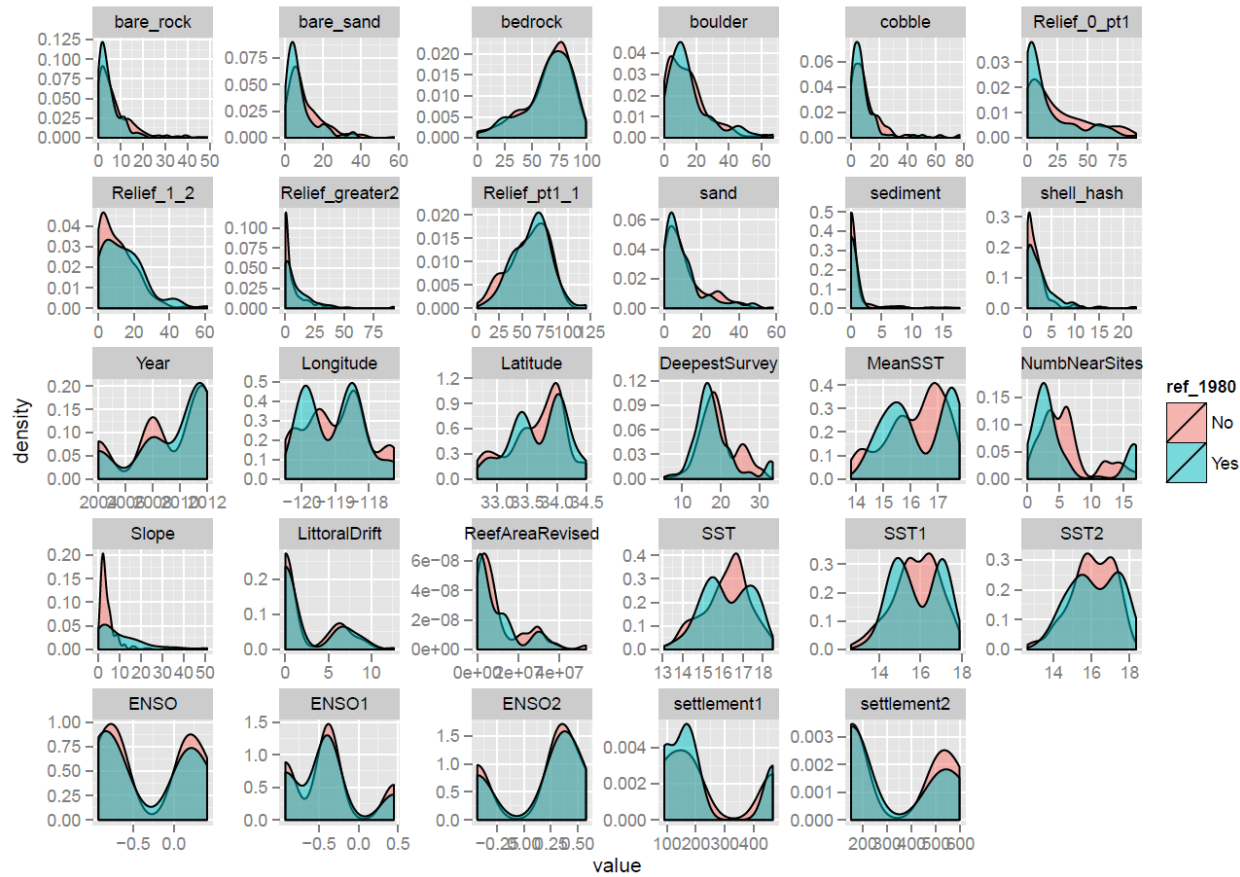


Figure 1: Probability density plots of habitat variable distributions in reference and non-reference samples. Overlaps in reference and non-reference distributions are an indicator of the scoring tools' ability to assess across natural gradients.

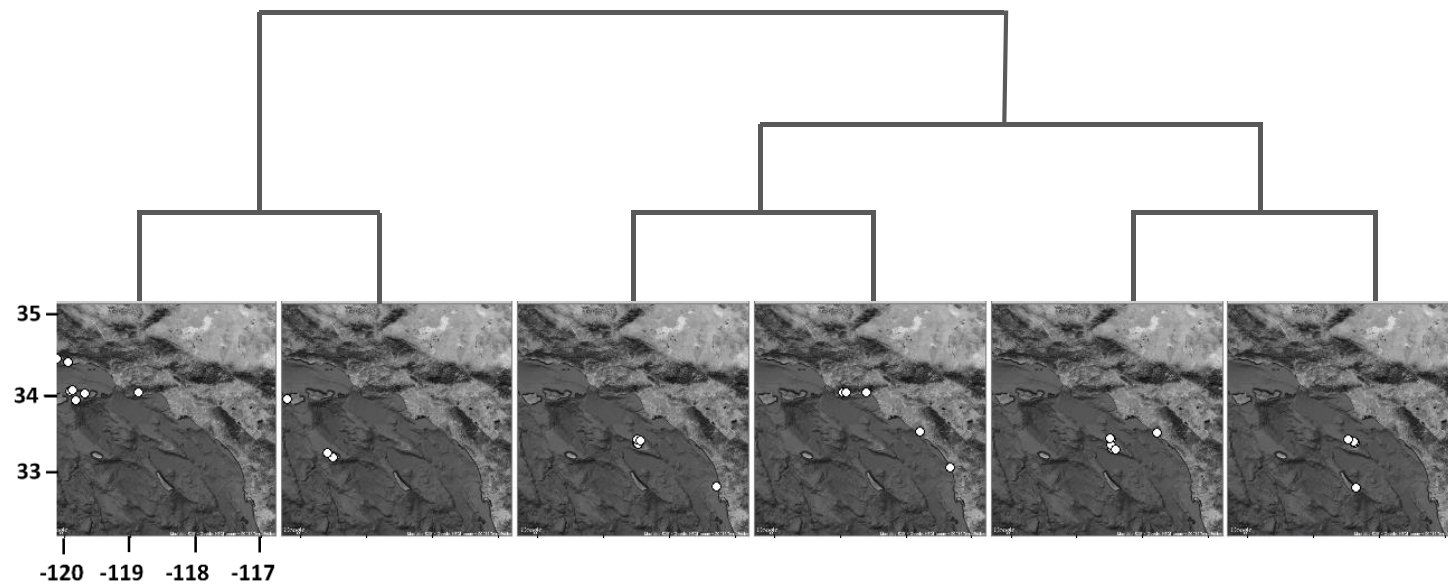


Figure 2: Dendrogram based on fish+swath community assemblages, with specific sites plotted in a map of the Southern California Bight.

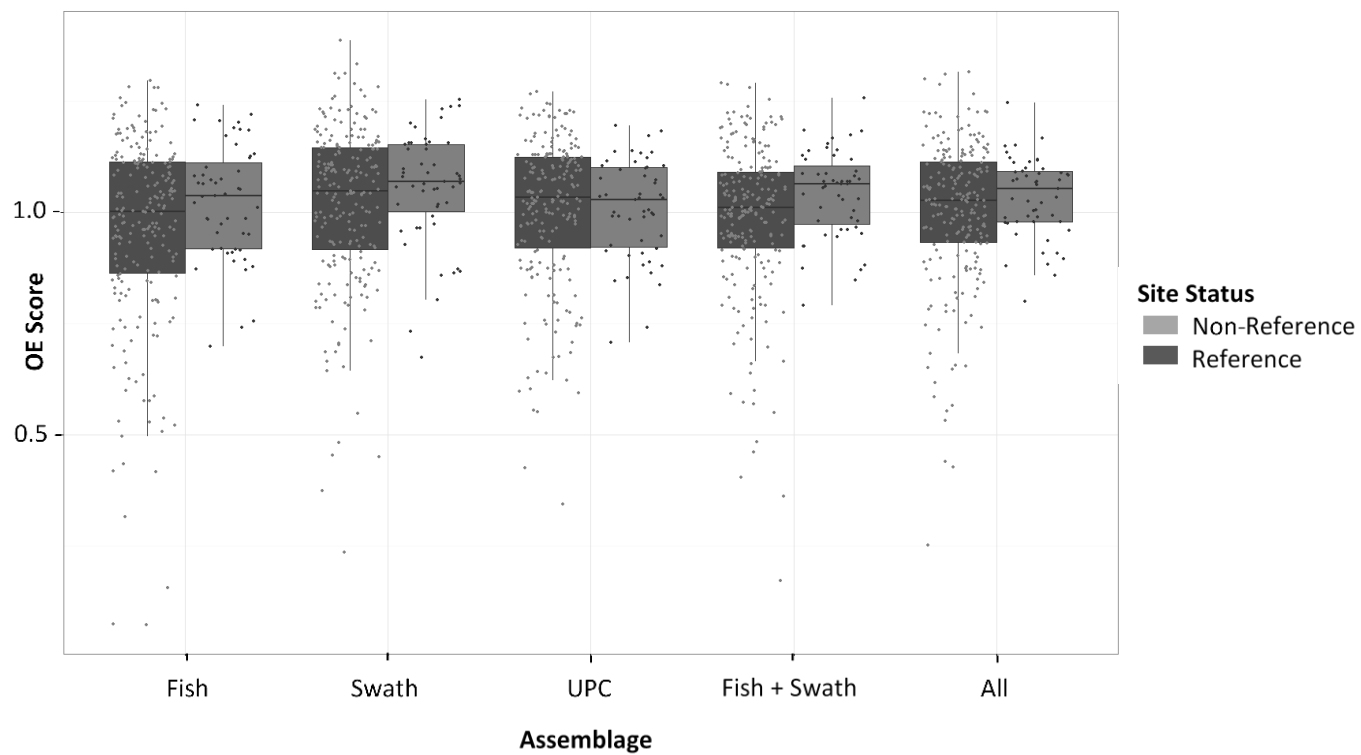


Figure 3. Boxplot of reference and nonreference sample index scores for each of five species assemblages.

Table 1. Habitat variables and their attribution to temporal or spatial variability

Habitat Gradient	Variability		Citation
	Spatial	Temporal	
Substrate (% Cover)			
Bare Rock	X	X	Pondella et al., 2001
Bare sand	X	X	Pondella et al., 2001
Bedrock	X	X	Pondella et al., 2001
Boulder	X	X	Pondella et al., 2001
Cobble	X	X	Pondella et al., 2001
Sand	X	X	Pondella et al., 2001
Sediment	X	X	Pondella et al., 2001
Shell harsh	X	X	Pondella et al., 2001
Relief (m)			
0-0.1	X	X	Pondella et al., 2001
0.1-1	X	X	Pondella et al., 2001
1-2	X	X	Pondella et al., 2001
>2	X	X	Pondella et al., 2001
Temperature (C)			
Mean Sea Surface Temperature (MeanSST)		X	
SST	X	X	
SST1	X	X	
SST2	X	X	
Longitude	X		
Latitude	X		
Island/Mainland	X		
Deepest Survey	X	X	
Site Clustering	X		
Reef Area	X		Pondella et al., 2001
Slope	X		
Littoral Drift	X		Patsch & Griggs, 2006
El Niño Southern Oscillation (ENSO) Index		X	Wolter, 2014; Wolter & Timlin, 1993, 1998
ENSO1		X	Wolter, 2014; Wolter & Timlin, 1993, 1998
ENSO2		X	Wolter, 2014; Wolter & Timlin, 1993, 1998
Settlement 1		X	Schroeter et al., 2012
Settlement 2		X	Schroeter et al., 2012

Table 2. Mean O/E Index score and standard deviations for five different species assemblages for reference or nonreference category using predictive and null models.

		Fish + Swath		Fish		Swath		UPC		All Assemblages	
O/E Scores		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Predicted Model											
Calibration	Selected	1.017	0.131	1.006	0.126	1.014	0.182	1.028	0.177	1.026	0.131
	Not Selected	1.048	0.105	1.041	0.118	1.061	0.138	1.010	0.121	1.038	0.098
	All	1.033	0.120	1.024	0.123	1.038	0.163	1.019	0.152	1.032	0.116
Validation	Selected	1.027	0.094	0.988	0.123	1.038	0.071	1.034	0.093	1.020	0.088
	Not Selected	1.032	0.059	0.988	0.143	1.049	0.122	0.979	0.075	1.023	0.046
	All	1.030	0.076	0.988	0.134	1.044	0.102	1.004	0.088	1.022	0.068
Test	Selected	0.952	0.187	0.923	0.227	0.988	0.198	0.976	0.183	0.966	0.179
	Not Selected	1.017	0.156	0.991	0.200	1.042	0.160	1.028	0.151	1.031	0.147
	All	0.987	0.174	0.960	0.216	1.017	0.181	1.004	0.168	1.001	0.166
All	Reference	1.032	0.112	1.016	0.127	1.039	0.152	1.015	0.140	1.030	0.107
No training	Reference	0.997	0.164	0.972	0.203	1.024	0.172	1.005	0.159	1.007	0.155
Null Model											
Calibration	Selected	1.000	0.156	1.000	0.159	1.000	0.206	1.000	0.178	1.000	0.134
	Not Selected	1.049	0.139	1.012	0.140	1.076	0.181	1.048	0.183	1.051	0.140
	All	1.025	0.149	1.006	0.150	1.039	0.197	1.024	0.182	1.026	0.139
Validation	Selected	0.995	0.151	0.956	0.201	1.024	0.148	1.081	0.125	1.009	0.111
	Not Selected	0.970	0.118	0.916	0.198	1.011	0.113	1.044	0.142	0.992	0.099
	All	0.981	0.135	0.934	0.201	1.016	0.130	1.060	0.136	0.999	0.105
Test	Selected	0.963	0.209	0.917	0.240	0.998	0.223	0.979	0.205	0.970	0.192
	Not Selected	1.023	0.195	0.968	0.221	1.065	0.203	1.057	0.155	1.039	0.166
	All	0.995	0.204	0.944	0.231	1.034	0.215	1.021	0.184	1.007	0.182
All	Reference	1.015	0.147	0.991	0.165	1.034	0.185	1.032	0.174	1.020	0.133
No training	Reference	1.001	0.194	0.952	0.221	1.038	0.207	1.027	0.182	1.012	0.203

Table 3. Variance in O/E Index scores trained on the fish + swath species assemblage explained by habitat variables.

	% Variance Explained	
	Predictive Model	Null Model
All reference samples	20.76	54.04
Reference (not for training)	20.59	44.38
Selected Validation	-36.77	2.56
Selected Calibration	-16.07	24.84

Table 4. Regression statistics for significant relationships between index (fish + swath) scores with habitat variables for reference samples.

		Estimate	t	p	r ²	F	df
Bedrock	Slope	0.001	2.086	0.042	0.082	4.353	49
	Intercept	0.952	21.501	<0.001			
Cobble	Slope	-0.003	-2.982	0.004	0.154	8.892	49
	Intercept	1.070	64.243	<0.001			
Relief 0-0.1 m	Slope	-0.002	-2.490	0.016	0.112	6.199	49
	Intercept	1.066	61.950	<0.001			
Relief 0.1-1 m	Slope	0.002	2.272	0.028	0.095	5.163	49
	Intercept	0.942	20.931	<0.001			
Aggregation	Slope	-0.005	-2.113	0.040	0.084	4.467	49
	Intercept	1.066	57.684	<0.001			
Reef Area	Slope	0.000	-1.861	0.069	0.066	3.464	49
	Intercept	1.062	58.272	<0.001			

Table 5. Regression statistics for O/E Index scores from each species assemblage with fishing pressure

		Estimate	t	p	r ²	F	df
Fish+Swath	Slope	-0.044	-3.820	0.000	0.052	14.590	265
	Intercept	1.504	11.290	<0.001			
Fish	Slope	-0.055	-3.897	0.000	0.054	15.190	265
	Intercept	1.613	9.766	<<0.001			
Swath	Slope	-0.047	-3.863	0.000	0.053	14.930	265
	Intercept	1.567	11.090	<0.001			
UPC	Slope	-0.027	-2.394	0.017	0.021	5.730	265
	Intercept	1.321	9.921	<0.001			
All Assemblages	Slope	-0.040	-3.694	0.000	0.049	13.640	265
	Intercept	1.474	11.591	<0.001			

Table 6. Statistics for t-tests comparing means of habitat and stress stress variables above and below the index performance threshold. Bold indicates statistically significant result at P< 0.05.

Habitat or Stress Variable	t	df	P	Mean Above	Mean Below
bare rock	-2.362	37.496	0.023	5.963	10.996
bare sand	-1.693	42.162	0.098	9.647	12.956
bedrock	3.164	41.371	0.003	66.565	51.842
boulder	-0.680	41.574	0.500	14.356	16.226
cobble	-2.573	37.153	0.014	8.803	16.853
Relief 0-0.1m	-5.135	41.329	0.000	19.892	45.949
Relief 0.1-1 m	3.981	41.352	0.000	60.619	42.704
Relief 1-2 m	5.880	61.369	0.000	12.796	4.781
Relief >2 m	0.280	37.188	0.781	7.115	6.103
sand	-1.899	40.277	0.065	10.278	15.080
sediment	-1.761	37.310	0.086	0.532	1.827
shell hash	-1.104	39.486	0.277	2.040	2.891
deepest survey	2.145	45.717	0.037	19.451	17.531
slope	1.620	46.001	0.112	6.008	4.148
reef area	-0.716	41.829	0.478	9834745	11632635
littoral drift	-4.164	40.253	0.000	1.660	4.708
settlement 1	-3.238	43.988	0.002	217.529	309.904
settlement 2	-2.999	48.922	0.004	322.114	419.603
mean SST	-0.002	43.278	0.999	16.179	16.179
SST	0.287	43.120	0.775	16.162	16.095
SST1	0.669	44.522	0.507	15.752	15.896
SST2	-0.798	42.417	0.429	15.985	16.181
ENSO	1.016	48.041	0.315	-0.275	-0.369
ENSO1	-1.406	49.505	0.166	-0.408	-0.299
ENSO2	-1.787	53.653	0.080	0.137	0.245
WQ Index	1.4944	65.012	0.140	0.537	0.436
TSS	-0.4349	48.845	0.666	1739.608	2092.972
Copper	0.3844	72.382	0.702	0.712	0.593
Nitrate	1.7692	255.242	0.078	96.637	19.006
log Fishery	-2.3996	38.974	0.021	4.957	5.221

Table 7. Results of multiple linear regression of stressors and habitat variables versus reef index scores.

	Estimate	StandardError	t	Pr(> t)
Intercept	1.464	0.127	11.567	<0.001
Barerock	-3.175x10 ⁻³	1.324x10 ⁻³	-2.397	0.017
Baresand	0.633x10 ⁻³	21.152x10 ⁻³	2.285	0.023
Bedrock	1.526x10 ⁻³	5.998x10 ⁻⁴	2.544	0.012
LittoralDrift	-8.410x10 ⁻³	2.974x10 ⁻³	-2.828	0.005
Relief0-0.1m	-2.595x10 ⁻³	4.404x10 ⁻⁴	-5.892	<0.001
LogFishery	-0.104	2.365x10 ⁻²	-4.392	<0.001
Cobble	2.237x10 ⁻³	1.239x10 ⁻³	1.806	0.072
TSS	3.812x10 ⁻⁶	1.863x10 ⁻⁶	2.046	0.042

Table SI1. ANOVA results for relationships between individual species (species with high capture probabilities and significant differences in abundance above and below the index performance threshold) abundance with fishing pressure and TSS as random factors.

Common Name	Scientific Name	Factor	D f	Sum Sq	Mean Sq	F value	Pr(>F)
Fishes							
Black perch	<i>Embiotoca jacksoni</i>	log_fishery	1	0.003662	0.003661 5	9.399 9	0.00237 2
		TSS	1	0.000146	0.000145 8	0.374 2	0.54119 3
		log_fishery:TSS	1	0.001692	0.001692 4	4.344 7	0.03798 8
			1	0.001692	0.000124 6	0.329 9	0.56618 4
Striped perch	<i>Embiotoca lateralis</i>	log_fishery	1	0.000125	0.000125 6	7.330 4	0.00717 7
		TSS	1	0.002769	0.002769 0	0.000 1	0.97660 9.71E-
		log_fishery:TSS	1	0	0.000000 33	0.000 9	0.97660 9
			1	0	0.000000 33	0.000 9	0.97660 9
Opaleye	<i>Girella nigricans</i>	log_fishery	1	0.00557	0.005570 2	0.769 0.792	0.09717
		TSS	1	0.00159	0.001593 0	0.792 1	0.37418
		log_fishery:TSS	1	0.03221	0.032211 16	.0125 7.	9.71E- 03
			1	0.03221	0.005473 2	8.505 5	0.00381 4
Garibaldi	<i>Hypsypops rubicundus</i>	log_fishery	1	0.005473	0.005473 2	8.505 5	0.00381 4
		TSS	1	0.000196	0.000196 2	0.305	0.5812

Common Name	Scientific Name	Factor	D f	Sum Sq	Mean Sq	F value	Pr(>F)
Halfmoon	Medialuna californiensis	log_fishery:T SS	1	0	0	0	0.99488 3
		log_fishery	1	0.000487	0.000487 01	1.349 8	0.24625
		TSS	1	0.001122	0.001121 86	3.109 4	0.07888
		log_fishery:T SS	1	0.000566	0.000565 62	1.567 7	0.21154
Painted greenling	Oxylebius pictus	log_fishery	1	0.000754	0.000753 66	5.114 8	0.02445 2
		TSS	1	0.002082	0.002082 27	14.13 15	0.00020 5
		log_fishery:T SS	1	0.00008	0.000080 44	0.545 9	0.46057 2
		Kelp bass	Paralabrax clathratus	log_fishery	1	0.03859	0.038594
TSS	1			0.00019	0.000185	0.082 5	0.7742
log_fishery:T SS	1			0.00319	0.00319	1.421 8	0.2341
Rubberlip	Rhacochilus toxotes			log_fishery	1	0.000506	0.000505 59
		TSS	1	0.001145	0.001145 48	2.726 6	0.09976
		log_fishery:T SS	1	0	0.000000 04	0.000 1	0.9919
		Blackeye goby	Rhinogobiops nicholsii	log_fishery	1	0.00001	1.03E-05
TSS	1			0.000243	2.43E-04	8	0.1404
log_fishery:T SS	1			0.000072	7.25E-05	0.651 4	0.4203
Kelp rockfish	Sebastes atrovirens			log_fishery	1	0.001772	0.001772 4
		TSS	1	0.003262	0.003262 1	6.467 0.753	0.0115
		log_fishery:T SS	1	0.00038	0.000379 9	0.753 2	0.38618
		Copper rockfish	Sebastes caurinus	log_fishery	1	0.000001 79	1.79E-06
TSS	1			0.000018 09	1.81E-05	9.619 1	0.00211 3
log_fishery:T SS	1			0.000001 2	1.20E-06	0.639 2	0.42465 9
Black & yellow rockfish	Sebastes chrysomelas			log_fishery	1	0.000006	6.43E-06
		TSS	1	0.000017	1.75E-05	8.86	0.00314 2
		log_fishery:T SS	1	0	4.67E-07	0.23	0.62658 3
		Blue rockfish	Sebastes mystinus	log_fishery	1	0.00148	0.001482 7
TSS	1			0.00914	0.009136 8	5.689 3	0.0177
log_fishery:T SS	1			0.00094	0.000942 7	0.587	0.4442
Juvenile rockfish	Sebastes YOY			log_fishery	1	0.000087	5 8.753e- 05
		TSS	1	0.000603	3 6.033e- 04	7.056 5	0.00832 9

Common Name	Scientific Name	Factor	D f	Sum Sq	Mean Sq	F value	Pr(>F)
		log_fishery:T SS	1 1	0.000002	5 2.470e- 06	0.028 9	0.86516 5
Invertebrates							
Sunburst anenome	<i>Anthopleura sola</i>	log_fishery	1	16404	16404.2	2.465 2	0.1175
		TSS	1	12773	12773.4	1.919 6	0.1669
		log_fishery:T SS	1 1	2870	2869.5	0.431 2	0.5119
							0.00781 3
Understory kelp	<i>Eisenia arborea</i>	log_fishery	1	5192	5191.8	7.174 4.745	0.03016 4
		TSS	1	3435	3434.5	8 0.213	0.64454 4
		log_fishery:T SS	1 1	154	154.4	3	
White urchin	<i>Lytechinus anamesus</i>	log_fishery	1	117.5	117.524	1.713 7	0.1915
		TSS	1	99.7	99.721	1.454 1	0.2288
		log_fishery:T SS	1 1	10.1	10.071	0.146 9	0.7018
Giant kelp	<i>Macrocystis pyrifera</i>	log_fishery	1	1101	1101.31	7.215 5	0.00763 9
		TSS	1	98	98.05	0.642 4	0.42348 5
		log_fishery:T SS	1 1	0	0.02	0.000 1	0.99090 7
Giant keyhole limpet	<i>Megathura crenulata</i>	log_fishery	1	19.2	19.189	1.512 4	0.21975
		TSS	1	84.3	84.304	6.644 6	0.01043
		log_fishery:T SS	1 1	1.1	1.097	0.086 5	0.76893
Tube dwelling anemone	<i>Pachycerianthus fimbriatus</i>	log_fishery	1	1533	1533.25	10.87 75	0.00109 3
		TSS	1	450	450.36	3.195 1	0.07489 1
		log_fishery:T SS	1 1	305	305.06	2.164 2	0.14232 6
California spiny lobster	<i>Panulirus interruptus</i>	log_fishery	1	17.74	17.7393	3.796 1	0.05232
		TSS	1	0.46	0.4637	0.099 2	0.75297
		log_fishery:T SS	1 1	2.34	2.3379	0.500 3	0.47993
Warty sea cucumber	<i>Parastichopus parvimensis</i>	log_fishery	1	64.1	64.1	0.726 6	0.39468 6
		TSS	1	783.7	783.7	8.883 3	0.00311 8
		log_fishery:T SS	1 1	0.5	0.45	0.005 1	0.94293
Bat star	<i>Patiria miniata</i>	log_fishery	1	2914	2914.4	1.566 5	0.21170 68
		TSS	1	27010	27009.5	14.51 82	0.00016 91
		log_fishery:T SS	1 1	1053	1052.8	0.565 9	0.45248 4
Giant spined star	<i>Pisaster giganteus</i>	log_fishery	1	82.4	82.41	1.378 8	0.24125

Common Name	Scientific Name	Factor	D f	Sum Sq	Mean Sq	F value	Pr(>F)
Understory kelp	<i>Pterygophora californica</i>	TSS	1	340.2	340.24	5.693	0.01767
		log_fishery:TSS	1	146.5	146.48	2.451	0.11853
		log_fishery	1	1374	1374.3	0.4169	0.519
		TSS	1	3125	3124.9	0.9479	0.3311
		log_fishery:TSS	1	4118	4117.9	1.2491	0.2646
Sunflower star	<i>Pycnopodia helianthoides</i>	log_fishery	1	0.01	0.008	0.0022	0.962295
		TSS	1	32.71	32.707	9.4678	0.002288
		log_fishery:TSS	1	0.38	0.375	0.1087	0.741892
Red urchin	<i>Strongylocentrotus franciscanus</i>	log_fishery	1	1508	1508	0.1092	0.7413
		TSS	1	373540	373540	27.0574	3.71E-07
		log_fishery:TSS	1	3359	3359	0.2433	0.6222
Purple urchin	<i>Strongylocentrotus purpuratus</i>	log_fishery	1	98261	98261	0.9303	0.3355659
		TSS	1	1564631	1564631	14.8141	0.0001456
		log_fishery:TSS	1	3887	3887	0.0368	0.8479976
Orange puffball sponge	<i>Tethya californiana</i>	log_fishery	1	1.4	1.363	0.0627	0.80251
		TSS	1	183.3	183.27	8.4256	0.00398
		log_fishery:TSS	1	7.5	7.502	0.3449	0.55748