Ocean Acidification Monitoring Network Design and Hotspot Mapping in the California Current System

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As authors of this Group Project report, we archive this report on the Bren School's website such that the results of our research are available for all to read. Our signatures on the document signify our joint responsibility to fulfill the archiving standards set by the Bren School of Environmental Science & Management.

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Abstract

Ocean acidification (OA) is a global issue with particular regional significance in the California Current System, where social, and economic, and ecological impacts are already occurring. Though OA is a concern that unifies the entire West Coast region, managing for this phenomenon at a regional scale is complex and further complicated by the large scale and dynamic nature of the region. Currently, OA-relevant data collected on the West Coast is inconsistent and cannot create a complete picture of the state of ocean acidification through time and across the region. Furthermore, marine managers do not currently have a framework to assess the risk OA may pose to the resources they manage. We developed tools to analyze gaps in the West Coast ocean acidification monitoring network and evaluate the spatial extent of OA hotspots—defined by biologically-relevant thresholds—with existing marine protected areas. The result is a framework that can be used to strategically fill OA monitoring gaps across the West Coast region and to identify the state of OA levels within West Coast marine protected areas. These two tools will enable scientists and marine managers in the California Current System to address the regional problem of ocean acidification through the implementation of management solutions at the local level.

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List of Abbreviations

OA - Ocean Acidification
WCODP - West Coast Ocean Data Portal
WCRPB (or RPB) - West Coast Regional Planning Body
WCOP - West Coast Ocean Partnership
SCCWRP - Southern California Coastal Water Project
IWG-OA - Interagency Working Group on Ocean Acidification
MPA - Marine Protected Area
OAH - Ocean Acidification Hypoxia
OST - Ocean Science Trust
PCC - Pacific Coast Collaborative
CCS - California Current System
NOAA - National Oceanic and Atmospheric Administration
GIS - Geographic Information System
WCGAOH - West Coast Governor's Alliance on Ocean Health
ROMS - Regional Ocean Monitoring System
SAV - Submerged Aquatic Vegetation
GOA-ON - Global Ocean Acidification Observing Network
C-CAN - California Current Acidification Network

Client Introduction

The West Coast Ocean Data Portal (WCODP) is a project to increase discovery and connectivity of ocean and coastal data and people to better inform regional resource management, policy development, and ocean planning. The Portal informs priority West Coast ocean issues such as tracking sources and patterns of marine debris, adaptation to sea-level rise, understanding impacts of ocean acidification on our coasts, and marine planning.

The West Coast Ocean Data Portal was originally established in concert with the West Coast Governors Alliance on Ocean Health (WCGAOH), now the West Coast Ocean Partnership (WCOP). More recently, the Portal has become associated with other large regional planning efforts like that of the National Ocean Policy. In accordance with this mandate for coordinated marine spatial planning and priority setting at the regional level, partners from the three West Coast states organized the West Coast region's effort and has recently adopted the Data Portal under one of its primary objectives.

Established in 2015, the West Coast Regional Planning Body (RPB) is a partnership between federally-recognized tribes, federal government agencies, and the states of Washington, Oregon and California focused on enhanced coordination and communication around planning and management of current and emerging ocean uses, as well as information and data-sharing on the West Coast of the U.S.

Executive Summary

Ocean acidification (OA), which results largely from atmospheric CO_2 emissions (Doney et al. 2009) is a problem of increasing concern along the West Coast of the United States. Ocean dynamics in the region are driven by the California Current System, which creates conditions that are naturally more acidic relative to global coastlines (Feely et al. 2012). OA is accelerated relative to global averages in this system via upwelling currents, coastal erosion, and runoff, which contribute CO_2 and nutrients to surface waters (Ekstrom et al. 2015). However, the intensity of acidification varies across time and space; some areas of the ocean are changing at faster rates than others, creating “hotspots” (Chan et al. 2017). These hotspots are a product of both physical oceanographic processes and anthropogenic inputs, but the precise location of hotspots is not well-understood. While OA has been modeled for the West Coast, it is not clear how accurate the models are for predicting hotspot formation or to what extent the modeled hotspots vary in space and time.

The West Coast also has a history of strong marine conservation policies. In this region, a network of marine protected areas (MPAs), including marine reserves, sanctuaries, and other classifications, has been established in state and federal waters. The objectives of MPAs can vary, including biodiversity conservation, protecting fisheries, and preserving educational and cultural resources (Airamé et al. 2003). However, West Coast MPAs were largely established without accounting for the effects of ocean acidification. It is not yet known whether OA hotspots coincide with MPAs and how these protected areas will respond to intensifying OA.

To begin to uncover the answers to these unknowns, marine managers along the West Coast convened to form the West Coast Ocean Acidification and Hypoxia Monitoring Taskforce, a joint project of the Pacific Coast Collaborative and the Interagency Working Group on OA. The Taskforce began compiling a monitoring inventory (OAH Inventory) to bridge ocean acidification monitoring efforts from a multitude of research, agency, and nonprofit monitoring projects to establish a more cohesive network. The OAH Inventory, while still in progress, has already revealed gaps in monitoring for acidification parameters along the West Coast. Managers and researchers must fill critical knowledge gaps to better understand the co-occurrence of OA hotspots and MPAs and the response of MPAs to these threats.

Thus, the West Coast Ocean Data Portal, which serves the West Coast Regional Planning Body and marine scientists and managers, tasked our team with analyzing gaps in ocean acidification monitoring efforts using the OAH inventory. In addition, we assessed spatial and temporal trends in OA hotspotting and the relationship between hotspots and marine spatial management via MPAs. These analyses will ultimately help the WCODP accomplish its goals to: provide access to valuable datasets in a way that is useful for data managers; and advance quantitatively informed management decisions when planning for MPA resilience to OA.

We obtained the latest data in OA monitoring inventory efforts through WCODP partners to analyze data collection gaps in the monitoring network. Our team developed a methodology to identify gaps based on spatial coverage, temporal frequency, and adequacy for calculating aragonite saturation state ("carbonate completeness"). We incorporated oceanographic variability into our analysis, acknowledging that the spatial coverage and frequency of monitoring should be higher where the ocean dynamics are more variable. We ran a preliminary analysis with the most updated version of the OAH inventory and identified severe and moderate gaps along the coast in parts of Northern California, Central Oregon, the Columbia River estuary, and Puget Sound.

We used cruise data from 2013 to generate an interpolation of aragonite saturation state "hotspots" along the West Coast, from Central California to Washington, based on biologically-relevant thresholds. Aragonite saturation state was used specifically because it is a biologically-relevant form of calcium carbonate which provides insight into potential impacts on foundational species and fisheries (McLaughlin et al. 2015). Our team combined this hotspot analysis with a map of MPAs to obtain a snapshot of where hotspots might coincide with protected areas for a given season. We compared this with hotspot maps from 2007, 2011, and 2012 and observed some change in hotspot location between years. Particular locations, such as the Columbia River estuary, showed consistent hotspotting over multiple years. We then calculated the mean aragonite saturation state and percent hotspot coverage of each MPA and generated a list of the top 10 MPAs with the lowest aragonite saturation state, all of which fall within Oregon's coastline. While the results from our analysis are limited by data constraints, we provide an example of how regional ocean acidification data can be used to assess impacts to MPAs. This framework can be re-produced with more robust OA models as they become available.

The results of our analyses lead to a summary of strategies for effective spatial management of coastal ecosystems to enhance resilience to OA. The preliminary gap analysis shows locations along the coast where monitoring could be enhanced by adding a sensor or increasing the frequency of observations for existing monitoring assets, which are potentially lower cost alternatives to deploying additional buoys or other assets. Our hotspot analysis can provide marine managers a method for assessing acidification impacts to MPAs and developing a prioritization for management actions based on the goals, habitat types, and acidification threat level for each MPA. Our team also outlined a number of management strategies that marine managers can leverage to ameliorate acidification impacts. Supporting policies to reduce coastal erosion and riverine nutrient inputs can prevent the exacerbation of acidification and hotspots. Identifying appropriate areas for vegetation (kelp and seagrass) restoration can reduce heightened levels of CO_2 and dampen acidification.

Ocean acidification is a global problem that also has very localized effects on marine ecosystems. By identifying gaps in OA monitoring, researchers and managers can make informed decisions for maximizing monitoring efforts with limited funding. Further, our project provides a method to assess OA impacts on MPAs. Our team hopes that our analyses provide a useful framework for researchers and managers working to better understand the implications of OA on the West Coast.

Objectives

Our team worked with the West Coast Ocean Data Portal and West Coast natural resource managers to assess the spatial coverage of the existing monitoring network. This assessment describes spatial patterns in OA, as well as the relationship of OA patterns to spatial management via marine protected areas (MPAs). Specifically, the project:

- created a methodology to analyze gaps in OA monitoring efforts using the recent West Coast Ocean Acidification and Hypoxia Monitoring Inventory (joint project of the Pacific Coast Collaborative and the Interagency Working Group on OA)

- assessed the spatial resolution of OA hotspotting, and evaluated the spatial relationship between OA hotspots and MPAs

- summarized strategies for effective spatial management of coastal and marine ecosystems to enhance ecosystem resilience to OA in reference to economically important representative species

Project Significance

As ocean conditions change, one of many issues of concern is ocean acidification. Changing seawater chemistry presents environmental, ecological, and economic consequences for the West Coast of the United States, where regional ocean circulation patterns heighten the effects of OA. While the primary driver of OA - carbon dioxide emissions - is global in nature, additional parameters are locally influential (Gruber et al. 2012). There are multiple factors which may affect OA conditions locally, including ocean circulation and upwelling, coastal erosion, and runoff. These factors, combined with seasonal upwelling, create hotspots of OA along the coast (Hauri et al. 2013). These relative influences are modeled, mapped, and understood to varying degrees, but still not at a comprehensive regional level.

Responding to OA and its effects requires a concerted management focus throughout the West Coast, where MPAs were established under various policy tools and approaches (Chan et al. 2016). While the specific structure, purpose, and framework of these protective policies vary, the overarching objectives are similar—to protect and sustain a variety of marine resources (Klein 2008). In some cases, the system of protected locations was developed with a holistic view of how they might form a network. Other MPAs were developed independently in time and space to protect specific resources of interest (Airamé et al. 2003). The result is a patchwork of protections, governed by multiple layers of jurisdiction and policies. It is not well-understood whether West Coast MPAs will provide adequate resilience of protected resources to OA. Since little was known about OA processes or effects when many MPAs were established, design and management decisions were not made with regard to their vulnerability to OA impacts (Chan et al. 2016).

Addressing the impacts of OA on these large MPA networks requires a multi-state effort, particularly for the West Coast where the California Current is a regional driver of acidification conditions for Washington, Oregon, and California together. This regional style of resource management is echoed by the National Ocean Policy, an Executive Order implemented during the Obama administration in 2010. In line with the goals of the National Ocean Policy to ensure the health of ocean and coastal resources, the three states and several tribal nations convened to form the RPB. To promote robust planning and decision-making, the WCODP supports the RPB.

The target audiences for the project are: the WCOP, a collection of tribal, state, and federal government representatives with a focus on ocean health, and the RPB, a formal body of tribal, state, and federal government representatives with a focus on marine planning to address ocean management challenges. The WCODP serves the WCOP and RPB as a data-providing and decision-making platform across the West

Coast region. An additional target audience is the West Coast Ocean Acidification and Hypoxia Science Panel (OAH Panel). This project is significant to our clients because of the WCOP and RPB's identification of OA as a priority issue that connects the entire region around a planning and management challenge.

This project will help marine policy makers and managers understand how well multiple layers of management address OA. Through mapping OA hotspots with MPAs, this project will allow MPA managers to better assess OA impacts on a more local scale, while also providing a regional context for which areas within the California Current System may be more impacted than others. By analyzing gaps in monitoring data and summarizing effective monitoring strategies, this project also assists regional planners in improving how the West Coast assesses ocean health. By better assessing, documenting, and integrating the policy and scientific frameworks, this project has the potential to contribute to the collective understanding of opportunities to improve resource planning and management frameworks The goal is that the project can inform adaptive management strategies for responding to changing ocean conditions. Acquired data, maps, and deliverables will be accessible on the data portal to ensure public access to project findings. This improved understanding will inform policy and decision-making by ocean managers.

Literature Review

Ocean Acidification and "Hotspots"

Ocean Acidification

Anthropogenic activities, primarily the burning of fossil fuels, have caused a nearly 40% increase in atmospheric carbon dioxide (CO_2) levels since the Industrial Revolution (Solomon et al. 2007). However, this rate of increase has been tempered by the world's oceans acting as a natural carbon sink. It is estimated that the ocean absorbs about 30% of all anthropogenic carbon emissions (Sabine and Feely 2007). Though this reduces the level of emissions that remain in the atmosphere, this increased carbon input is not without consequence for the world's oceans.

Ocean acidification, like climate change, is caused by anthropogenic carbon dioxide emissions, and has been called "the other CO_2 problem" (Henderson 2006, Doney et al. 2009). When the ocean absorbs carbon dioxide from the atmosphere, seawater chemistry is altered, resulting in decreased pH and increased acidity. On average, there has been a global decline in pH of 0.1 units, from 8.2 to 8.1 since pre-industrial times (Orr et al. 2005, Rhein et al. 2013). Although this change may seem insignificant, given the log scale of pH, this decrease is correlated with a 26% increase in hydrogen ion concentration in seawater. In the future, it is projected that pH could decrease even further, an additional 0.3-0.4 units under the IPCC "business as usual" trajectory (Orr et al. 2005).

Increased acidity in seawater is caused by the dissolution of carbon dioxide, which forms carbonic acid (H_2CO_3), a weak acid. With increased CO_2 inputs and thus increased acid formation, both ocean pH and the concentration of spare carbonate ions (CO_3) decrease (Rhein et al. 2013). When carbonate concentrations decrease, the saturation of calcium carbonate ($CaCO_3$), and its more soluble form, aragonite, also decrease. Traditionally, pH, and more recently, aragonite saturation state, are monitored as indicators for changing ocean chemistry conditions. Aragonite is the form most widely used by many calcifying organisms on the West Coast, and thus serves as an appropriate and informative monitoring parameter.

Decreased calcium carbonate saturation in coastal waters has potential consequences for marine organisms that rely on calcium carbonate ions. Calcifying organisms use $CaCO_3$ to produce their shells and skeletons. Thus, organisms such as crustaceans, corals, echinoderms, molluscs, and planktonic calcium carbonate producers, like foraminifera and coccolithophores, respond negatively to decreases in aragonite saturation state (Fabry et al. 2008, Kroeker et al. 2010). These effects vary across species, but include shell dissolution, reduced growth rates, reduced fertility, or even mortality for some plankton (Fabry et al. 2008).

Recently, attention and concern has turned toward the susceptibility of the California Current System to future changes in ocean acidification. As an Eastern Boundary Upwelling System, the California Current displays low pH and undersaturation with respect to aragonite (Hauri et al. 2009). This is due largely to the upwelling zones along the West Coast that seasonally create high levels of nutrients and dissolved carbon dioxide in surface waters, thereby decreasing carbonate saturation state, pH and oxygen levels. Upwelling results from the strengthening of northwesterly winds in the early spring, and lasts until late summer or early fall, creating a predictable seasonality to high OA levels (Feely et al. 2008). Due to its naturally low carbonate saturation state, models predict that the California Current System could be more susceptible to future changes in ocean acidification sooner, relative to other areas of the global ocean (Hauri et al. 2009, Gruber et al. 2012).

Further, variability of acidification is high in coastal regions due to the confounding factors that contribute to OA and their difference in spatial and temporal scales. Duarte et al. (2013) found that the annual variation in pH of coastal waters can be as much as 1 unit, altering local acidity by up to a factor of ten. This underscores the importance of accounting for temporal variation in the consideration of where and when OA impacts might be greatest in an ecosystem.

Hotspots

"Hotspots" are spatial areas that represent a characteristic anomaly or rapid change in a parameter of environmental quality (Reid 1998). In spatial planning, hotspots are used to identify priorities for conservation due to their high level of threat or importance for ecosystem services, as in the case of a "biodiversity hotspot" (Myers et al. 2000). The context of this term is crucial to understanding its application in a particular subject, as hotspots can imply superior quality or elevated degradation.

In regard to changing ocean conditions, hotspots are generally defined as areas where ocean conditions have deteriorated, often along multiple ocean health indicators. These departures from normal conditions are measured in two primary ways - either relative to historical observations or relative to spatial surroundings (Hobday and Pecl 2013, Kelly et al. 2011). For example, when examining global change of sea surface temperature, Hobday and Pecl (2013) chose to define the top 10% of areas of most rapid change as "hotspots".

While a formal definition for hotspots of ocean acidification does not yet exist, these zones typically represent areas of the ocean where pH has decreased significantly relative to historic baselines (Kelly et al. 2011). Likewise, specific boundary conditions have not been set for defining hotspots, however there is consensus that a long-term time component is crucial for distinguishing hotspots from seasonal or other short-term variations (Hofmann et al. 2014, Kelly et al. 2011).

Nearshore coastal waters are particularly susceptible to becoming hotspots of ocean acidification. Strong upwelling currents bring CO_2-rich waters to the surface, exacerbating the uptake of CO_2 at the surface through air-sea gas exchange (Ekstrom et al. 2015). In addition, most rivers have lower aragonite saturation states relative to the ocean, reducing aragonite saturation in estuarine waters (Duarte et al. 2013). Rivers also deposit nutrients from onshore anthropogenic sources into the ocean, contributing further to acidification. The coastal waters of California and the Pacific Northwest are areas of rapid acidification, where OA hotspots are concerning for biodiversity and fisheries (Ekstrom et al. 2015). Additionally, Feely et al. (2008) identified several places with increasingly shallow saturation horizons along the West Coast, particularly in Northern California and Southern Oregon.

Indicators of Ocean Acidification - Aragonite Saturation State

Given the importance of understanding how ocean acidification hotspots could intensify and change, researchers have increasingly focused on how OA is monitored and which metrics are its most appropriate indicators. Although acidity (i.e. the presence of hydrogen ions) in seawater is measured by pH, scientists often use different metrics to capture and analyze changes within the ocean carbonate system. Particularly for OA, saturation state (often expressed as "omega") is used to measure how saturated, and thus how available, calcium carbonate is within seawater. Research has shown that although changes to ocean conditions are cumulative, it is the calcium carbonate saturation state that has the greatest singular influence on shell production and growth (for that of bivalves, snails, etc.), more so than pCO_2 or pH (Waldbusser et al. 2015).

Due to the increasing evidence of the biological importance of calcium carbonate saturation state and its connection to biomineralization processes, recent research has begun to focus on this measure, particularly of the more soluble $CaCO_3$ polymorph - aragonite. Because this form of calcium carbonate is more soluble, organisms are more likely to build their shells with aragonite, but also more vulnerable to acidification conditions compared to organisms that build shells with other polymorphs, such as calcite (Feely et al. 2012). Saturation state of aragonite is also predicted to decline at a more rapid rate than that of calcite (McCoy et al. 2018). Thus, aragonite saturation state is emerging as the "gold standard" indicator for ocean acidification observation and research (McLaughlin et al. 2015). Instead of using more traditional measurements of acidification levels through pH observations, the metric of saturation state provides a more direct indication of how conditions may affect the biological response to an acidification event.

Due to the seasonality of upwelling, which transports subsurface CO_2-rich waters to the surface, observations of aragonite saturation state on the West Coast of the U.S. show variation from as low as 0.69 to as high as 3.9 (Feely et al. 2008, Harris et al. 2013). Mean saturation state was 2.2 in a study on coastal Oregon waters for 2007-2011 (Harris et al. 2013). Alin et al. (2012) found that aragonite saturation state varied from 1 to 2.88 in a study of the southern California Current System.

Several factors contribute to the variability in aragonite saturation state, including upwelling, net community production, and air-sea gas exchange. As a result, aragonite saturation state varies on multiple time scales. In instances of strong upwelling, surface aragonite saturation state can vary by as much as 3 units in one day (Harris et al. 2013). There is also a strong seasonal component to variability in aragonite saturation state. Values of aragonite saturation state tend to be highest in the summer and lowest in the winter, where biological productivity reduces seawater CO_2 (Alin et al. 2012, Pelletier et al. 2018). However, variability within seasons tends to be highest in the summer due to the combination of biological activity that coincides with the spring and summer upwelling season (Pelletier et al. 2018, Harris et al. 2013, Alin et al. 2012). Depending on the strength of upwelling influence in coastal areas, aragonite saturation state can also be driven to annual lows during the spring and summer upwelling season (Hauri et al. 2013). In more sheltered coastal areas, biological activity tends to drive variability in aragonite saturation state (Pelletier et al. 2018).

Thus far, anthropogenic CO_2 inputs have reduced aragonite saturation state by approximately 0.2-0.5 units since pre-industrial levels (Juranek et al. 2009, Hauri et al. 2009, Harris et al. 2013). Values of aragonite saturation state are expected to continue to decline and become more variable. Currently, upwelling brings waters to the surface that were in contact with the atmosphere on the order of decades ago (Feely et al. 2008). Because of steadily increasing atmospheric CO_2, it is expected that future upwelled waters will have even higher CO_2 concentrations leading to the positive feedback of reductions in aragonite saturation state.

Variability within the carbonate system as a whole has also increased over time. Between 1982 and 2015, seasonal differences in sea surface pCO_2 rose by 2.3 uatm per decade (Landschutzer et al. 2018). This effect could have negative consequences for marine biota, as they are exposed to more acidified waters earlier in a season, and annual peak acidity is more likely to cross critical thresholds for marine organisms (Landschutzer et al. 2018). Increased variability in seawater carbonate chemistry, continued rise in CO_2 emissions, and predicted strengthening of upwelling currents necessitate long-term, high-resolution monitoring of aragonite saturation state (Harris et al. 2013, Barton et al. 2012).

Additional OA stressors - Hypoxia and Rising Temperatures

In addition to ocean acidification, hypoxic events threaten the health of coastal ecosystems. Hypoxia occurs when coastal waters are deprived of oxygen throughout the water column. It can stress marine biota, often resulting in large die-offs of fish and other organisms (Chan et al. 2008). The leading cause of coastal hypoxia is eutrophication; however, coastal ecosystems with strong eastern boundary currents, such as the California Current System, are also subject to hypoxic conditions resulting from upwelling (Chan et al. 2008). Hypoxia is heightened in the summer and fall seasons when stratification of the water column prevents mixing and re-oxygenation (Melzner et al. 2013). Particularly, the coupling of dissolved oxygen and carbon dioxide through biological processes can lead to low oxygen conditions that intensify ocean acidification (Hales et al. 2015). Strong relationships between dissolved oxygen and carbonate system parameters, namely pCO_2, support this biological coupling (Borgesa and Gypensb 2010, Melzner et al. 2013). CO_2 produced during the decomposition of organic matter elevates total dissolved inorganic carbon and pCO_2, further exacerbating acidification conditions (Melzner et al. 2013). This positive relationship has implications for predicting aragonite saturation state declines under hypoxic conditions since eutrophication exacerbates acidification conditions (Pelletier et al. 2018).

Chan et al. (2008) also report the recent emergence of anoxic conditions, along with the increased severity of hypoxic events in nearshore environments within the California Current System. Rising ocean temperatures are also expected to exacerbate anoxic and hypoxic conditions in coastal waters through intensified and prolonged stratification of the water column (Melzner et al. 2013, Hales et al. 2015).

Impacts of Ocean Acidification

Ecological Effects

Changes in ocean chemistry, specifically the carbonate system, will likely impact marine species and communities. Projected changes to species abundance and distribution could spread through many trophic levels of marine food webs (Doney et al. 2009, Kroeker et al. 2013). Although the ecosystem effects of ocean acidification are difficult to predict, large impacts are anticipated in the California Current System due to the wide range of species that build shells from calcium carbonate, which are particularly vulnerable to acidified conditions (Guinotte et al. 2006).

The increase of CO_2 in the ocean alters the balance of carbonate and bicarbonate, which are physiologically important compounds in many marine organisms for photosynthesis. As their concentrations increase, so does primary productivity. However, altered carbonate concentrations negatively affects organisms that require a particular carbonate mineral for calcification. For many species, ocean acidification depresses calcification rates or creates an energy tradeoff to calcification, increasing physiological stress (Kroeker et al. 2010).

Impacts to individual organisms are variable, and some species are more vulnerable to OA than others (Table 1). Vulnerable species include pteropods, mollusks, coccolithophores, echinoderms, and corals. Many of these have already showed reduced calcification and growth rates under high CO_2 conditions in laboratory experiments (Doney et al. 2009). Sensitivity differs between organisms and some species may be able to control internal pH and cope with OA stress better than others (Kroeker et al. 2010). In fact, some species have actually shown increased calcification under OA conditions; however this is usually accompanied by a tradeoff to other physiological processes (Iglesias-Rodriguez et al. 2008). For example, species that are unable to compensate for changes in pH experience lower rates of metabolism and growth, as well as decreased fitness; this is due to changes in energy allocation under OA conditions (Kroeker et al. 2010).

Aragonite saturation state is often used to predict biological and ecological effects. Thus, its observation can help identify the correlation between ocean acidification and a particular species response. The aragonite saturation state of seawater is the product of the concentrations of dissolved calcium and carbonate ions divided by their product at equilibrium. When aragonite saturation state is 1, seawater is in equilibrium with respect to aragonite. When aragonite saturation is <1, aragonite is undersaturated and calcifying organisms can potentially enter a state of dissolution (McLaughlin et al. 2015). However, many calcifying organisms experience detrimental effects of OA at aragonite saturation states under 2. Additionally, there have been recorded incidents of die-off and shell dissolution tipping points at hatcheries along the West Coast at a saturation state of 1.7 (Barton et al. 2012, Chan et al. 2017).

Calcareous bivalves, including mussels, oysters, and clams respond negatively to low carbonate mineral saturation states, even when saturation state is above 1 (Barton et al. 2012). For example, studies of the California mussel show alterations in shell structure, including increased disorder between shells of mussels from 2010 compared to historical mussels from decades to centuries ago (McCoy et al. 2018). Greater variability in traits between current and historic mussel populations indicate that present-day mussels are undergoing increased environmental stress (McCoy et al. 2018). Oysters are also particularly vulnerable to ocean acidification because they use aragonite to build their shells (Barton et al. 2012). The larval stage is expected to be particularly susceptible to negative effects of acidification (Barton et al. 2012).

Acidified conditions can disrupt interspecific interactions amongst species, leading to cascading effects within ecological communities. In rocky intertidal ecosystems, OA can alter predator-prey interactions; for example, observed reductions in the escape response of black turban snails to the predatory sea stars affects algae (Jellison et al. 2016). These changes to predator-prey interactions are another confounding factor that results in reorganization or shifting of marine community structures in response to OA.

Table 1. Expected vulnerability of marine organisms to OA. Table from Fabry et al. (2008).

	Vulnerability	Level of Understanding	Comment	References
Diatoms	Low	High	Increased productivity, smaller or larger chain-forming species (?)	Tortell et al., 1997, 2008; Hare et al., 2007
Coccolithophorid	Medium	Low	Species specific response in calcification, increased photosynthesis	Iglesias-Rodriguez et al., 2008; Engel et al., 2005
Kelp	Medium	Medium	Species specific response in photosynthesis	Swanson and Fox, 2007
Copepods	Medium	Low	Shallow water copepods showed less tolerance to high pCO_2 than deep water copepods	Watanabe et al., 2006
Noncalcifying tunicate	Low	Medium	Increased growth, development, and fecundity	Dupont and Thorndyke, 2009
Shelled pteropod	High	Low	Shell dissolution	Orr et al., 2005; Fabry et al., 2008
Foraminifera	High	Medium	8–14% reduction in shell mass	Spero et al., 1997; Bijma et al., 1999, 2002; Moy et al., 2009
Sea urchin	Medium	Medium	Species specific, lack of pH regulation, decreased fertilization success	Burnett et al., 2002; Dupont and Thorndyke, 2008
Mussel	High	High	Decreased calcification in saturated water; dissolution and mortality in undersaturated water	Gazeau et al., 2007
Oyster	Medium	High	Decrease in calcification rate, highly vulnerable larval stage	Gazeau et al., 2007; Lee et al., 2006
Dungeness crab	Low	Low	Capable of pH regulation during 24 h	Pane and Barry, 2007
Cold water corals	High	Low	Experimental results only for warm water corals	Guinotte and Fabry, 2008
Coralline algae	High	Medium	Decrease in calcification rate, net dissolution, disappearance	Martin and Gattuso, 2009

Adaptive capacity of species to ocean acidification

The fate of species under acidified conditions is still largely unknown. Species response can vary between shifting distribution, phenotypic plasticity, or genetic modification and evolutionary adaptation (Hoffmann and Sgrò 2011). Without at least one of these strategies in place, species run the risk of extinction (Foo et al. 2012). The response that will most likely sustain a species for the long-term over changing ocean conditions is evolutionary adaptation (Hoffmann and Sgrò 2011).

There is evidence to suggest that species will be able to adapt to higher seawater acidity. This ability to adapt is known as ‘adaptive capacity’ (Foo et al. 2012). Adaptive capacity generally refers to the likeliness of a species to adapt to increased stress and changing environmental conditions. Adaptive capacity is supported by heritable genetic variance; genetic variation within a population provides a means for selection of traits suited to varying environmental conditions via evolution (Foo et al. 2012). Higher genetic variability is indicative of greater adaptive capacity within a population (Kelly et al. 2013). This variability differs between species and populations; however, it is likely that species exposed to higher environmental variation possess a greater capacity for evolutionary adaptation (Kelly et al. 2013).

The global gradient of pH is approximately 0.3 units, which is relatively small compared to the projected change in pH before the end of the century, which is also 0.3 units (Orr et al. 2005). This could present challenges for species living within ranges of relatively low pH variability. In the California Current System, pH variability is naturally relatively high from seasonal and latitudinal gradients (Kelly et al. 2013). In a study by Kelly et al. (2013) on the purple urchin along the California coast, larval urchins were smaller in size under elevated pCO_2 conditions; however, the researchers found that larval body size was highly variable within the population under the acidic scenario. Thus, there is potential for larval body size to rapidly evolve in response to different pCO_2 levels. This study supported the hypothesis that species occupying habitats with higher environmental variability are less sensitive to acute changes in conditions. Parker et al. (2011) also found evidence for evolutionary adaptation via carry-over effects in the Sydney oyster under acute acidification. Adults that were exposed to higher pCO_2 conditions reared larvae that increased in size and developed faster than larvae reared from adults exposed to the ambient control seawater when both larvae were exposed to acidic conditions. Thus species could potentially benefit from maternal and carry-over effects when adults respond to acute stressors.

Species responses to chronic elevated pCO_2 conditions are not well documented (Parker et al. 2011, Fabry et al. 2008). Studying chronic impacts is more difficult and requires long-term coupled biological and chemical monitoring. However, some evidence suggests that chronic stressors could lead to significant shifts in ecosystems and changes in dominant species (Fabry et al. 2008). Additionally, chronic elevated pCO_2 could lead to metabolic suppression, which reduces an organism's growth and reproductive potential (Fabry et al. 2008). While these effects are not lethal, they could impact a species survival over longer time scales.

Economic and Social Impacts

Beyond the ecological impacts of ocean acidification on calcifying organisms and their related food webs, ocean acidification may have significant economic impacts by placing additional pressures on fished species. The exact impacts to the fisheries can be difficult to estimate, since not all impacts of ocean acidification have been quantified. However, OA impacts have been estimated for several important fishery species. For example, molluscs are both globally significant in commercial market value and suffer impacts from OA. Global costs of OA impacts on the mollusc market is estimated at over $100 billion, assuming increasing demand and income growth (Narita et al. 2012).

Economic impacts of OA are also reaching a broader public understanding at the regional level. For example, the Pacific Northwest region relies on high productivity to support its seafood industry. In 2012, the National Marine Fisheries Service (NMFS) reported that the commercial seafood industry on the West Coast provided around 220,000 jobs and $32.7 billion in commercial sales (Alin et al. 2015). Calcifying organisms comprise four of the ten most valuable West Coast commercial fisheries (Table 2, Alin et al. 2015). A 2007 report of fisheries revenue found that 96% of commercial fishing ex-vessel revenue on the West Coast was attributed to species affected by ocean acidification (Hauri et al. 2009). Furthermore, NMFS reported in 2014 that recreational fishing was estimated to support 18,800 jobs and $2.5 billion in sales. Threats to the West Coast commercial and recreational fishing industry due to OA could impact a wide variety of stakeholders.

The Pacific Northwest is home to productive shellfish fisheries, in part, due to some of the same physical processes that drive OA: upwelling of nutrient-rich waters. OA has already begun to impact these coastal economies; the Pacific Northwest oyster industry has already experienced $110 million in economic loss and impacts to 3,200 jobs (Ekstrom et al. 2015). Larval production at oyster hatcheries on the West Coast have suffered significant impacts due to declines in growth and survival resulting from acidified waters (Barton et al. 2012). On a smaller statewide scale, impacts to marine food webs could influence the state of Washington's seafood industry, estimated to contribute $1.7 billion to the state economy and to generate over 40,000 jobs (Washington Blue Ribbon Panel on OA). These estimates do not account for the benefits healthy marine ecosystems have on West Coast for tourism and other industries that rely on the aesthetic value of biodiversity.

Shellfish fisheries also represent an important part of cultural heritage for many Native American tribes of the Northwest (Washington Blue Ribbon Panel on OA). Beyond coastal economies, OA threaten the cultural heritage and traditional food sources of many Native American tribes on the Pacific Coast. Specifically, impacts to shellfish may impact the culture, economy, and diets of Native Americans (Lynn et al. 2013). Due to the diverse impacts OA may have on Native American tribes, adaptation strategies within these communities are multifaceted and complex. Social and cultural impacts of OA on Native American tribes should be considered in management decisions regarding OA (Lynn et al. 2013).

Table 2. Commercial landings for invertebrates with calcium carbonate shells, tests, or exoskeletons that are within the most valuable fisheries on the West Coast (CA, OR, WA) from 2003 to 2012. Data was taken from NMFS commercial landings data, table adapted from Alin et al. (2015).

Species	**Total Value (2003-2012)**
Dungeness crab	$1,312,233,926
Pacific oyster	$411,768,620
Pacific geoduck clam	$400,817,096
Manila clam	$199,346,707
Ocean shrimp	$152,899,359
California spiny lobster	$86,553,611
Sea urchin	$75,240,059

Predicting Ocean Acidification in the California Current

Current Data Monitoring of OA on the West Coast

Given the pertinence of understanding how OA levels trigger these biological and socioeconomic impacts, streamlined conduits for data and analysis is crucial. Monitoring networks can provide organization for collection and synthesis of data across an entire region. Real time, in situ data collection allows researchers to monitor and track changes in ocean conditions over time. Combining data from monitoring assets across space can inform regional scale patterns. Monitoring data also validates oceanographic models, which are useful for predicting patterns in OA broadly across time and space, outside the scope of physical monitoring. Models can provide more precise predictions and forecasts that inform decision-making by coastal and marine managers, policy makers, and fishermen.

Along the West Coast, various federal and state agencies, research organizations and universities are monitoring biological and physical ocean conditions related to OA. As a joint project of the Pacific Coast Collaborative and the Interagency Working Group on OA, the OAH Monitoring Task Force created a comprehensive inventory of OA-relevant monitoring assets from California to Alaska. The inventory includes static monitoring locations (e.g. moorings and buoys) and cruise transects that collect OA data. Each monitoring asset includes information on its location (nearshore, estuarine, intertidal, offshore, open ocean), frequency of data observations, biogeochemical characteristics (salinity, temperature, pressure, turbidity, nutrients), whether monitoring pairs with biological data collection, and which parameters of the carbonate system are collected (Appendix 1).

Ideal OA Monitoring Network

Marine managers and researchers are coming to a consensus around what characteristics define an optimal OA monitoring network to optimize its efficiency and robustness on a regional scale. An ideal monitoring network includes monitoring assets that collect parameters to calculate aragonite saturation state ("carbonate complete"). The scientific community acknowledges this metric as a key indicator for assessing OA and comparing acidification conditions at varying spatial and temporal scales. (Doney et al. 2009, McLaughlin et al. 2015, Waldbusser et al. 2015).

The Global Ocean Acidification Observing Network (GOA-ON) was established to integrate OA monitoring networks across the globe. GOA-ON guidelines can shape regional OA monitoring networks, which may adapt data requirements based on stakeholders and information needed for decision support (Alin et al. 2015). The California Current Acidification Network (C-CAN) has created a list of the ideal characteristics of an OA monitoring network for the California Current, which includes using aragonite saturation state as indicator data for the current state of OA in the California Current (McLaughlin et al. 2015). To assess aragonite saturation state accurately and relate changes in ocean chemistry to ecosystem impacts, C-CAN has established a maximum of 0.2 units of deviation in uncertainty in the calculation of aragonite saturation. This is similar to GOA-ON's uncertainty levels, which allow for 10% uncertainty.

Since a variety of agencies with varying resources manage data monitoring, it is important to establish a minimum standard for datasets. This means establishing the highest priority data as a minimum standard and then encouraging agencies with more resources to expand monitoring capabilities. C-CAN recommends prioritizing the measurements needed to determine aragonite saturation state: temperature, salinity, dissolved oxygen (DO), and two of the four carbonate parameters (pH, total alkalinity, pCO_2, dissolved inorganic carbon). Agencies with more resources are encouraged to collect other helpful data, such as more carbonate parameters, atmospheric pCO_2, and nutrient concentrations (McLaughlin et al. 2015). Linking biogeochemical monitoring to biological monitoring networks will allow for better understanding of how OA affects ecosystems. A variety of temporal scales and high spatial coverage is best for monitoring changing ocean conditions in the California Current System. Continuous high frequency data is imperative for understanding daily and seasonal patterns; this is best accomplished using fixed monitoring assets such as buoys. To fill gaps of spatial coverage, cruises should be used in areas lacking continuous monitoring (McLaughlin et al. 2015). Lastly, an ideal monitoring network must have accessible data that is easily shared. Existing data should be used to guide objectives and methods of field and laboratory experiments to support marine managers and coastal policy decision makers (McLaughlin et al. 2015).

Since the California Current System includes coastal and estuarine ecosystems, monitoring here should reflect the diverse habitats and stakeholders within the region. Key resources of the California Current System include shellfish, benthic fish, nurseries for many fish species, seagrasses, and kelps, which impact a large number of stakeholders invested in OA conditions. Stakeholders concerned with monitoring networks and OA modeling include the recreational fishermen, tourism industries, fisheries managers, public health agencies, and government agencies. An ideal monitoring network will apply to the varied needs of these stakeholders (Avin et al. 2015).

Finally, because the ocean is such a variable and dynamic environment, oceanographic conditions such as ocean acidification change across space and time. It is important to capture these changes in a monitoring network, which means that it is necessary to have more monitoring where there is more variability (Halpern, personal communication, 2017). High resolution regional data on aragonite saturation is not available at this time. However, sea surface temperature and dissolved oxygen have been identified as the strongest correlators of aragonite saturation state (Juranek et al. 2009). By determining spatial and temporal variation of these variables, a proxy can be developed for the variability of aragonite saturation.

Current OA Modeling on the West Coast

As OA worsens globally, regional models are imperative for understanding localized conditions of OA. There are presently three OA models which predict OA in the California Current. These models vary temporally, spatially, and in utility. Coastal policy makers and MPA managers can use models to decide how to best manage in the face of the changing OA conditions. This is discussed in further detail in the Methodology section (Appendix 12).

Marine Protected Areas (MPAs)

Marine protected areas are discrete spatial locations within oceans, seas, and estuaries that are established to protect natural or cultural resources. Marine Protected Areas can be established and managed by all levels of government, including federal, state, local and tribal governments (Wenzel and D'Lorio 2011). Goals of MPAs vary, but include conservation of biodiversity, protection of fisheries or other goods of economic value, protection of resources with educational value, and the preservation of cultural heritage (Airamé et al. 2003). MPAs can be categorized by their focus, their level of protection, or their permanence. There are many different kinds of MPAs with different levels of restrictions, but most MPAs are multi-use (Wenzel and D'Lorio 2011). Many MPAs aim to conserve fisheries through establishing no-take marine reserves, which have been shown to be as effective as traditional fisheries management techniques (such as setting a catch limit) for managing yield (Botsford et al. 2003).

When the first MPAs were established in the twentieth century in the United States, many were created in isolation to serve a specific purpose. Scientists and managers now have greater interest in creating networks of ecologically connected networks of MPAs (Gleason 2010). The planning process of creating networks can be enhanced by strong legislation that allows for funding and enforcement of MPAs, and agency commitment to implementation. Managers can also include a mechanism to gauge the effectiveness of MPAs within the design, as it may be necessary to act under uncertainty (Halpern and Warner 2003).

West Coast MPAs

There are approximately 400 different marine protected areas, parks, and management zones currently established on the West Coast, all of which vary in size, goals, and jurisdictional agency. The Marine Life Protection Act, which passed in 1999, mandated and established a network of California MPAs through a community and scientifically driven process. Similarly, a series of State House bills created the original set of marine reserves in Oregon (CDFW 2012, Oregon State Legislature 2012). Marine protected areas and no-take reserves have been established extensively throughout Washington on a piece-by-piece basis since the state's first reserve was established for recreational divers in the 1970s (WDFW). Recently, scientists fear that new climate-induced threats are challenging the effectiveness of the current network of MPAs. When many MPAs were established, their spatial extent and management plans were created without taking into account future climate projections (CDFW 2012). However, through advanced modeling and strategic monitoring, it is becoming easier to evaluate the effectiveness of MPAs and to prioritize new areas for protection that are adaptive to changing conditions.

Assessing the Impacts of Climate Change on MPAs

Threats of climate change on marine ecosystems highlight the need for MPA planners and managers to address impacts on marine biodiversity and ecosystem services. First, managers must understand how climate change threats, such as sea level rise and ocean acidification, impact an MPA and its specific goals. Although climate change is a global phenomenon, localized regions relative to the scale of MPAs may experience intensified effects due to local stressors, such as nutrient inputs (Gruber et al. 2012). Second, managers should consider how some of these climate change threats may be addressed through different protective policies, replicating habitat types, and ensuring that MPAs are adequately spaced. Furthermore, it is important to protect functional groups of species, which serve similar ecological roles within an ecosystem, while strategizing how to support ecosystem functions and services (McLeod et al. 2009).

Direct climate impacts to MPAs may start at a more cellular level, such as when warming waters alter metabolic rates at an individual or population-wide scale. On a population level, changes in oceanographic processes may also affect species abundance and interspecific interactions. MPA planners should assess the biotic impacts along with abiotic alterations to marine ecosystems from climate change, such as sea level rise, changes to upwelling patterns, and intensifying storms. The cumulative effects of these climate change impacts could lead to serious impacts on ecosystem productivity or services (Bernardt 2013).

MPAs and Ecological Resilience

Ecological resilience refers to the ability of an ecosystem to resist frequent or severe disturbances, recover from these disturbances, and adapt to new changes. Typically, this breaks down into two broad categories of resilience: resistance to change and the capacity for recovery (Levin and Lubchenco 2008). Managing for resilience involves an ecosystem-based management approach, in which it is necessary to prioritize diversity, connectivity and adaptive capacity (Bernardt 2013). These prioritizations are not vastly different from the goals of traditional MPA planning. However, climate change will most likely increase the frequency and severity of disturbances and there is uncertainty about how quickly species and communities will be able to adapt to changing conditions (Hoegh-Goldberg and Bruno 2010).

Managing for resilience through ensuring diversity increases the ability of a functional group of species to respond to disturbance within an ecosystem; species with higher resilience may be able to compensate for less resilient species. For example, an increase in the numbers of species that contribute to the same ecosystems function leads to higher response diversity (Elmqvist et al. 2003). Additionally, connectivity among populations and ecosystems allows for recovery from major disturbances by ensuring a refuge of sources of nutrients and propagules (Bernhardt and Leslie 2013). Managing for adaptive capacity requires planning and forethought about how species' ranges or behavior shifts in response to disturbances and how to protect refuge areas to accommodate future shifts (Bernhardt and Leslie 2013).

Management Options for Ocean Acidification

The impacts of intensifying ocean acidification on individual species and entire communities challenge the objectives of MPAs. Many coastal communities are working to strategically change management plans to address ocean acidification and support ecosystem resilience. The West Coast Ocean Acidification and Hypoxia Science Panel has recommended strategies to coastal conservation planners and managers for MPAs, despite uncertainties about the impacts of OA in the California Current System. Recommendations include incorporating OA into MPA selection and networks, updating management goals to promote ecological resistance, supporting the advancement of OA models, conserving habitat that sequesters carbon, and integrating

OA into coastal management frameworks (Chan et al. 2016).

Reduce CO_2 Emissions

The root cause of ocean acidification is the ocean's absorption of CO_2 caused by increased atmospheric CO_2 due to anthropogenic emissions (Doney et al. 2009). Thus, to truly prevent future ocean acidification, CO_2 emissions must decrease. Model projections demonstrate that if CO_2 emissions increase at their current rate, the ocean's acidity will increase by 100% or more by 2100 (Orr et al. 2005).

CO_2 emissions are mostly regulated by federal authorities; federal air quality managers have the most regulatory power to introduce policy to reduce greenhouse gas emissions. Air quality and marine managers should recognize the impacts of CO_2 emissions on marine environments and coastal communities as they assess climate change damages of CO_2. Initiatives to reduce CO_2 emissions include pricing carbon through cap-and-trade programs or taxes, setting emission standard for new motor vehicles, emissions reporting, or expanding renewable fuel targets (Boehm et al. 2015).

Blue Carbon

Although some marine organisms are negatively impacted by OA, both calcifying and non-calcifying organisms have shown an increase in photosynthesis rates under increased CO_2 conditions (Doney 2009). Acidification conditions are closely linked, spatially and temporally, with biotic processes, namely photosynthesis and respiration (Silbiger and Sorte 2018). Marine vegetation, such as seagrasses, salt marshes and mangroves, has been estimated to capture 70% of organic carbon in marine environments (Duarte et al. 2005). Using vegetation as a technique for sequestering carbon has been named "blue carbon." Submerged aquatic vegetation (SAV) can take up carbon through photosynthesis, minimizing changes to pH within the surrounding habitat (Duarte et al. 2005). For this reason, blue carbon through SAV has become a large topic of research, especially in the California Current System.

SAV ecosystems sequester carbon in a few different manners. They can sequester carbon with their underlying sediments, underground through their root structures, and within aboveground biomass of leaves, stems and branches. Sedimentary sequestration can store carbon for long timescales, sometimes millenia, while SAV biomass sequesters carbon for a shorter time period, usually a decennial scale (McLeod et al. 2011). Because mangroves, salt marshes, and seagrass meadows do not become saturated with carbon, sediments can accrete vertically as sea level rises; this means carbon sequestration capacity through ocean sediments may increase over time (McLeod et al. 2011). Beyond vertical accretion, SAV ecosystems are also able to trap sediment efficiently, from both ocean and river sources. This is referred to as "laterally imported carbon." Estimates of global carbon burial through sediment vary, but seagrasses have been estimated to bury 48-112 Tg of carbon per year, compared to salt marshes, estimated at 4.8-87.2 and mangroves, estimated to between 31.1-34.1 Tg of carbon per year (McLeod et al. 2011). Threats to salt marshes, mangroves, and seagrass meadows may have serious impacts to current global carbon sinks (Waycott 2009). Recent studies estimate about 1/3 of these ecosystems have been lost in the past decades (McLeod et al. 2009).

Although there is variability in estimates of seagrass' ability to sequester carbon, most studies find the amount of sequestration to be relatively high; estimates of carbon storage vary between seagrass species and seasonal time scales (Macreadie et al. 2014). Seagrass meadows have been estimated to bury carbon 35 times faster than many terrestrial forests (McLeod et al. 2011). Furthermore, they can bury large amounts of carbon while covering minimal space. Seagrass meadows occupy less than 0.2% of global ocean areas, however they account for approximately 10% of the carbon buried in oceans (Fourqurean et al. 2012). In a 2012 survey of seagrass carbon stocks, it was estimated seagrasses can store from 4.2-8.4 Pg of carbon, although developing carbon budgets for seagrasses is quite complex (Fourqurean et al. 2012).

Since seagrasses are typically autotrophic, they can sequester carbon through biomass on seasonal timescales, and on longer timescales in below-ground sediment retention (Hendriks 2014). A few seagrass species have shown great potential to produce short-term changes to carbonate chemistry through biomass sequestration, reducing local impacts of OA. One case study in Padilla Bay in Washington assessed the ability of Zostera marina, a native seagrass, and Zostera japonica, a non-native seagrass, to lessen ocean acidification. Both seagrasses are known to provide habitat for bivalves and other OA-impacted species in the Pacific Northwest and both are found in soft-sediment habitats (Harrison 1982). Results of this lab experiment showed that Z. japonica could take up more TCO_2 than Z. marina, highlighting the differences in carbon uptake between species (Miller 2017).

Update Water Quality Criteria

Outside of CO_2 emissions, other anthropogenic inputs, such as land-based nutrient, sediment, and contaminant inputs, to waterways have the ability to alter the severity of OA (Breitburg et al. 2015). Updating water quality criteria through the Clean Water Act (CWA) may be an option for regulating OA in coastal waters, specifically permitting sources of pollution. The Clean Water Act (CWA) is intended to "restore and maintain the chemical, physical, and biological integrity of the Nation's waters" (33 U.S.C. §1251 Section 101). The CWA uses water quality criteria to assess the conditions of bodies of water, which determines limits of discharge into respective waters. Changing OA parameters of the CWA is the first step water quality managers can stake to addressing OA; secondly, appropriate thresholds should be set (Boehm et al. 2015). The CWA is a federal law, however state governments manage the regulation of this law. Section 303(d) specifically assesses whether a body of water is "impaired", which may be used to regulate OA. Currently the CWA uses pH as a parameter to assess ocean acidification and impaired waters. States each have their individual 303(d) lists which list polluted waters that do not meet water quality standards and then prioritize and rank these waters to develop Total Maximum Daily Loads (TMDL) (US EPA 2010).

The West Coast Ocean Acidification and Hypoxia Science Panel recommends including biologically relevant criteria, such as aragonite saturation state, to assess water quality. Current pH standards in California, Oregon, and Washington (Table 3) include static ranges and refer to “natural conditions” of pH, which can be difficult to define. By using aragonite saturation state as a parameter and establishing a better defined and measurable threshold, the CWA would be more effective in regulating OA (Boehm et al. 2015). It is imperative to ensure there is an adequate monitoring network to measure changes in ocean condition in regards to regulating the CWA. By advancing monitoring technology and networks, water quality managers can improve their understanding of historical conditions and how water quality is changing to better manage OA (Boehm et al. 2015).

Table 3. US EPA water quality for pH levels for West Coast states (US EPA 2010).

State	**Water Classification**	**pH Standards**
California	All water bodies	No more than 0.2 units from that which occurs naturally.
Oregon	Marine waters	Must fall between 7.0 - 8.5
	Estuarine waters	Must fall between 6.5 - 8.5
Washington	Exceptional waters	Between 7.0 - 8.5 with a human caused variation of less than 0.2 units.
	Excellent or good waters	Between 7.0 - 8.5 with a human caused variation of less than 0.5 units.
	Fair waters	Between 6.5 - 9.0 with a human-caused variation of less than 0.5 units.

Data Portals

One critical component of managing for natural resources, particularly on a regional level, is information and data sharing. This aggregation is known as “big data” and tools such as online data portals present an opportunity to facilitate more widespread sharing of big data to maximize its usability and value for managers. The benefits of sharing data include the incorporation of the results of small research projects, which represent a large portion of scientific output, and the acceleration of the pace of science by increasing opportunities for collaboration (Hampton et al. 2013, Michener 2015). However, technical improvements to data storage and support are necessary to realize the full potential of big data (Manyika et al. 2011, Chun et al. 2010). This is where the value of data portals is realized.

Here, we examine the functionality of data portals through the lens of ocean planning. Common characteristics of data portals for marine planning include: ocean-focused, map-based, and publicly accessible (Longley-Wood 2016). SeaPlan identifies several best practices for ocean-based data portals. Portal design should accommodate a wide range of users, enable data vetting and peer review, and integrate data with planning efforts. The data portal must also then be able to host and store data while ensuring that the data are functional and usable. User interface design is necessary to make the data user-friendly. Lastly, outreach and communications help keep users aware of updated data and tools (Longley-Wood 2016).

Marine spatial planning efforts have turned to the use of data portals to provide open access to a wide range of scientists and managers working within a region. This is stimulated by the National Ocean Policy, a 2010 executive order by President Obama which promotes coastal resilience, safety, and productivity through a collaborative regional framework (The White House 2015). The Implementation Plan for the National Ocean Policy provides freedom to regional, state, and local communities based on their specific needs in implementing new ocean and coastal planning initiatives. The West Coast Regional Planning Body was established through the National Ocean Policy and subsequently adopted the West Coast Ocean Data Portal to provide a platform for data access and sharing for scientists, managers, and policymakers on the West Coast. The West Coast Ocean Data Portal focuses on data connectivity for priority issues for the West Coast region, which includes ocean acidification impacts. Similar measures have been implemented in other marine planning regions. The Northeast Ocean Plan instigated the creation of a data portal for the Northeast to be used for policy and management decision-making. The Northeast Ocean Data Portal’s data integration has supported local and statewide planning initiatives, assessments for offshore aquaculture, and siting of monitoring equipment (Northeast Ocean Data 2018).

Dealing with OA Uncertainty

OA science is still a developing field with many uncertainties, however the need for OA science to inform marine management decisions is urgent. This provides a unique opportunity to shape research objectives by management needs. The IPCC 2014 report stated high confidence that OA will increase and impact marine ecosystems if CO_2 emissions continue. Furthermore, it has characterized the effects of OA as "high impact---high uncertainty." Marine managers and policymakers are most concerned with how OA and changing ocean chemistry impact marine systems, and ultimately how it may harm humans, which is a difficult concern to address under uncertainty. Two types of uncertainty make estimating OA impacts difficult: reducible uncertainty that comes from lack of knowledge and research, and irreducible uncertainty that stems from the complexity of the ocean and its natural ecosystems (Busch et al. 2015). Increased efforts in data monitoring and modeling are increasing certainty about how ocean chemistry is changing, but these uncertainties make predicting the exact spatial and temporal conditions of OA very difficult. Further uncertainties include future CO_2 emissions and the ecological and socioeconomic impacts of OA.

Despite uncertainty, communication about the threat of OA is vital to effectively expanding research to decrease uncertainty and to alert marine managers of potential impacts of OA. In communicating the threat of OA, it is important to report research with strong evidence, backed by long-term monitoring and strong data, though transparency about uncertainty is equally important (Busch et al. 2015). Communicating risks associated with OA is one way to acknowledge that no future impacts are entirely certain; instead, uncertainty can be part of the decision-making conversation. This means communicating OA risk through a wide range of impacts, even those with low probability. By presenting risks through ranges of likelihood of occurrences and consequences of each outcome, scientists can synthesize understanding across disciplines to better prepare marine managers for future decision making and planning (Busch et al. 2015). Uncertainties can be diverse in nature, especially within ecosystem-based management.

Link et al. (2012) identify sources of uncertainty in the specific case of ecosystem-based marine management: natural variability; observation error; inadequate communication among scientists, decision-makers, and stakeholders; the structural complexity of the model(s) used; outcome uncertainty; and unclear management objectives. Dealing with each of these uncertainty factors can be done in a unique way.

- Natural Variability: probabilistic reasoning and adaptive management can mitigate natural variability. Probabilistic reasoning involves creating a distribution of outcomes with estimated occurrences, and adaptive management means developing management strategies that are relatively insensitive to natural variability.
- Observation Error: increased sampling intensity can mitigate observation error.

- Structural Complexity: this can be addressed through the acknowledgement that several model alternatives are likely, and the use of model averaging as a way to address this.
- Inadequate Communication: increased stakeholder participation can lessen this.
- Unclear Management Objectives: the most significant way to improve this problem is to ensure that there is enough time for scoping, iterations, and discussions.
- Outcome Uncertainty: improved monitoring can mitigate this problem.

Communicating OA through the evaluation of the current state of knowledge can help inform stakeholders of what is known; this can be done through meta-analyses and literature reviews, for example. Using conceptual models can also help stakeholders understand the interdisciplinary nature of OA. Developing consistent terminology can help to communicate scientific understanding across disciplines, especially for policy-relevant science (Busch et al 2015).

Methods

In order to analyze the way OA is monitored and evaluated at the regional level, our team completed a series of analyses: OA monitoring data exploration, an OA monitoring network gap analysis, an OA hotspot and thresholds analysis, and an MPA and habitat analysis. We also assessed the suitability of future OA models and summarized management options based on the results of our analyses. We began our analyses by exploring the various ocean acidification datasets accessible through the West Coast Ocean Acidification and Hypoxia (OAH) Monitoring Inventory (Appendix 1). Doing so allowed us to analyze initial gaps within the monitoring system. Our monitoring network gap analysis created a spatial estimation of where high priority data gaps exist at the regional level. Our exploration of the inventory also allowed us to identify which datasets were appropriate to use in an aragonite saturation model to identify OA hotspots. In lieu of access to robust and formal OA model outputs, our hotspots and thresholds analysis created an aragonite saturation state model based on interpolation of monitoring data, from which we defined and identified hotspot thresholds on the West Coast. This analysis allowed us to determine which MPAs were of the highest risk and which habitats may be suitable for future management and restoration actions. Ultimately, our hotspot interpolation is a placeholder for more robust model outputs that could use our framework to identify changing locations of hotspots in the future and MPAs that may be at risk. Because of this, we also explored the suitability of existing OA models and models in development for a more robust hotspot and MPA analysis in the future.

Throughout this entire analysis we focus and frame our work under the assumption that aragonite saturation state is the ideal monitoring parameter for addressing OA at the regional scale. It is the most appropriate metric to use when considering management implications for MPAs that protect biological resources that respond to changes in aragonite saturation state.

Data Exploration and Wrangling

Our team began our analysis of the distribution of ocean acidification and hotspots by using data to create a continuous prediction layer of ocean acidification trends across space. As mentioned above, several models (for aragonite saturation state or pH) exist or are currently in development, at varying temporal and spatial scales. Though model outputs may be the ideal data input to use for predicting patterns in OA in the future, these outputs were not available for use in our project. Thus, our team created an interpolated estimate of aragonite saturation state for the purposes of this project based on data accessible in the West Coast OAH Monitoring Inventory.

We downloaded and explored publicly available data based on assets identified in the

West Coast OAH inventory. We evaluated datasets based on their spatial and temporal coverage, consistency, and carbonate completeness (i.e. ability to calculate aragonite saturation state from observed parameters). Aragonite saturation state was selected as the appropriate monitoring parameter for this analysis because it is recognized as the "gold standard" for modern ocean acidification monitoring and prediction; saturation state has been found to have the most effective predictive power for biological species response to OA conditions (McLaughlin et al. 2015, Waldbusser et al. 2015). Thus, the selection of aragonite saturation state for this analysis allows for a clear linkage between the physical oceanographic trends and the management evaluation tool we wanted to provide.

When looking to explore how OA trends change within our study region, we selected several mooring buoy sites that calculate aragonite saturation state based on in situ carbonate parameter measurements. These datasets were used to perform sample time series analyses which examine daily and monthly averages and temporal trends. Values of aragonite saturation state were plotted for two sites: one in the Santa Barbara Channel and one from Hog Island Oyster Company in Tomales Bay. Based on correspondence with the researchers from Hog Island, we excluded data points with salinity values less than 15 from our analysis due to data quality concerns. Monthly, weekly, and daily values of aragonite saturation state were plotted for January, February, June, and July based on data availability and to compare seasonal differences in saturation state mean and variability. The mean value and difference of one standard deviation were plotted with the raw data to compare aragonite saturation state over different time scales (see Results and Appendix 2).

Gap Analysis

The gap analysis was completed using data from the West Coast OAH Monitoring Inventory, a list of monitoring assets. Monitoring assets include survey areas, cruise stations, gliders, sample sites, shoreside sensors, and moorings. This inventory is an ongoing project led by the Interagency Working Group on Ocean Acidification and the Pacific Coast Collaborative and includes information on ocean acidification parameters collected, the frequency and duration of collection, and the monitoring locations. Ocean acidification parameters collected include pCO_2 of surface water, pCO_2 of air, pH, DIC (dissolved inorganic carbon), TA (total alkalinity), carbonate ion, and DO (dissolved oxygen). Of special note are monitoring locations which are "carbonate complete", meaning the asset collects two of the parameters needed to determine aragonite saturation state: pH, TA, DIC, and pCO_2. Managers along the West Coast are interested in quantitatively assessing gaps in this monitoring network. It is important to incorporate both geographic distance into this gap analysis, as well as variability in oceanographic conditions (Halpern, personal communication, 2017). The following analysis was completed using R (Version 3.4.3) and utilizes these parameters to locate where the existing West Coast ocean acidification monitoring network could be improved in the future (Appendix 3).

Data Exploration

The most recent version of the West Coast OAH Inventory was shared as a csv file by the partners at Oregon Department of Fish and Wildlife and the California Ocean Protection Council, both members of the Pacific Coast Collaborative OA Task Force. From this inventory, we reviewed the Field and Classification descriptions document to familiarize ourselves with each field and possible range of entry values. We examined each field (column) and determined that the following fields were relevant to our analyses: temporal frequency, carbonate completeness, and latitude and longitude. We noted that the significant digits of the latitude and longitude vary greatly, which affects the spatial resolution of monitoring sites. We acknowledge this as a limitation of the dataset, since coordinates were provided by researchers or directly from their data sources, and we left the coordinates as is. We noted a few gaps in latitude and longitude data and found that these are for either gliders or cruise stations.

Creating an Ocean Variability Raster

Sea surface temperature and dissolved oxygen have been identified as the strongest correlates of aragonite saturation (Juranek et al. 2009). Thus, in order to identify places in the ocean where aragonite saturation state is changing on a spatial scale or on a temporal scale, changes in these variables can be used as a proxy as they are much more commonly measured (and even measured through satellite imagery) than aragonite saturation.

We acquired mean and range rasters for sea surface temperature and dissolved oxygen to serve as ocean dissimilarity layers. The rasters are from the Bio-ORACLE global dataset and represent monthly averages over a 15-year period, 2000-2014 (Appendix 4) (Assis et al. 2017). Rasters were loaded into R (Version 3.4.3) using the 'smdpredictors' package (Assis et al. 2017), projected to North American Datum 83 California Teale Albers, and cropped to our study region, identified by the bounding box of NAD 83 coordinates (-670000, 340000, -650000, 1210000). We used voronoi polygons to divide the ocean into regions based on spatial proximity to each monitoring asset. We assigned a polygon ID to each polygon and rasterized the voronoi polygons by gridding the study region and the polygon ID associated with each individual cell. For each dissimilarity layer (sea surface temperature mean, sea surface temperature range, dissolved oxygen mean, dissolved oxygen range), we assigned the parameter value of all raster cells with the same polygon ID to the measured value of the cell containing the monitoring asset associated with that same polygon ID. We determined the oceanographic difference of each cell as compared to the cell containing the nearest monitoring asset with the following formulas:

$$Spatial\ Dissimilarity = (\Delta\ Normalized\ Mean\ SST)^2 + (\Delta\ Normalized\ Mean\ DO)^2$$

$$Temporal\ Dissimilarity = (\Delta\ Normalized\ SST\ Range)^2 + (\Delta\ Normalized\ DO\ Range)^2$$

$$Oceanographic\ Dissimilarity = \sqrt{(Spatial\ Dissimilarity + Weighted\ Temporal\ Dissimilarity)}$$

$$Temporal\ Weight = 10$$

Euclidean distance is a well-established method of combining variables and allows this analysis to combine sea surface temperature mean, sea surface temperature range, dissolved oxygen mean and dissolved oxygen range into a single “oceanographic difference” layer (Appendix 5).

In the future, when aragonite saturation state models are available on a regional scale, this oceanographic variability layer could be replaced with outputs from a model. The employment of Euclidean distance would still be relevant, but instead of using means and ranges of sea surface temperature and dissolved oxygen to create spatial and temporal dissimilarity, the difference in mean aragonite saturation would replace the spatial dissimilarity equation, and the difference in mean (or ideally the difference in standard deviation) of aragonite saturation would replace the temporal dissimilarity equation.

Performing the Gap Analysis in R

We observed discrepancies in the measurement frequency entries and standardized this column by converting frequency of measurement to a number representing the amount of measurements collected in one year. We created a new column for this conversion in the original inventory in R.

The variability raster was used in combination with the distance from each cell to its nearest monitoring asset with the formula:

$$\boldsymbol{Gap} = \sqrt{((\boldsymbol{Oceanographic\ Dissimilarity})^2 + (\boldsymbol{Weighted\ Geographic\ Distance})^2)}$$

$$Distance\ Weight = 10^{-11}$$

Once again, Euclidean distance is a well-established method of combining variables, and allows this analysis to combine oceanographic dissimilarity and geographic distance into a single “gap” layer.

We repeated this analysis with subsets of the inventory to examine different types of gaps. Gaps based on temporal frequency were examined by subsetting the inventory for assets where measurements are collected at least once per day. Carbonate complete gaps were analyzed by subsetting the inventory according to assets that collect data for a minimum of 2 of the carbonate complete parameters.

In order to effectively visualize the gaps in West Coast ocean acidification monitoring, the results from this analysis were separated by a ranking system based on percentiles. The top 0.1% of cell values were ranked as severe gaps, the top 1% of cell values were high priority gaps, the top 25% were low priority gaps, and the rest of the cell values were identified as adequately monitored.

Choosing Weights and a Sensitivity Analysis

In determining the weighting factors in this analysis, we decided to weight temporal dissimilarity over spatial dissimilarity. Weighting the ranges (temporal dissimilarity) rather than the means (spatial dissimilarity) allows the model to capture and emphasize the extreme values of sea surface temperature and dissolved oxygen. Ocean acidification is highly variable and in order to understand the biological impacts, it is necessary to consider these extremes. We decided to weight dissimilarity over distance because the dissimilarity raster was normalized while the distance raster was not normalized. We chose not to normalize the distance raster because we want the distances in all three analyses to be based off the initial, raw values. Thus, by weighting dissimilarity on an order that allows normalized dissimilarity to be comparable to distance in meters, we create a balance between these two components of the analysis.

A sensitivity analysis was performed on the weighting factors used in the gap analysis. This sensitivity analysis was done by running the gap analysis with ten different values for each weighting factor. These weighting factors ranged from 10^{-5} to 10^{-14} for the distance weight and from 2 to 20 for the temporal weight. These combinations were used to create 100 different raster layers representing the top 0.1%, 1% and 25% of gap values. The sum of these values was calculated to determine where the generated outputs of gap predictions overlapped over all 100 combinations of weighting values.

Hotspot Interpolation and Thresholds Analysis

Hotspot Interpolation

After extensively exploring the inventory, cruise datasets from the NOAA Ocean Acidification Program were selected for use in a spatial interpolation analysis due to their region-wide spatial coverage. We used point observations from four cruises that took place in 2007, 2011, 2012, 2013, each with different spatial extents and cruise stations along the West Coast (Appendix 6). This series of cruises provides the most spatially comprehensive and precise measurements of ocean carbonate system metrics within the region (Feely and Sabine 2011, Feely et al. 2014 a, Feely et al. 2014b, Feely et al. 2015).

For each cruise, surface observations were selected by excluding measurements with a pressure greater than or equal to 5 db. Surface observations of total alkalinity (TA) and pH from each cruise station were input into the program CO2SYS Version 25b, (Lewis and Wallace 1998), which estimates aragonite saturation state based on other measured values within the carbonate system. To calculate aragonite saturation state values, we used carbonate system parameters (TA and pH) and four carbonate constants appropriate to the Eastern Pacific as inputs into CO2SYS (Table 4).

Table 4. The sources for parameter constants used as inputs for CO2SYS Version 25b (Lewis and Wallace 1998), which is used to calculate aragonite saturation state values.

Parameter	**Source**
Carbonate	Lueker et al. 2000
KSO_4	Dickson 1990
Total Boron	Lee et al. 2010
Pressure Effect	Mucci 1983

Ordinary kriging, based on discrete point data, was performed in R (Version 3.4.3) to create a continuous spatial interpolation of aragonite saturation state in the California Current System (Appendix 7). As a part of the kriging calculations, directional variograms were created for each cruise to determine how aragonite saturation varies with distance and direction. A Gaussian model type was used to fit the variogram to point observations and determine the nugget, sill and range of each cruise's points and their predictive extent based on their spatial dependence or correlation.

The variogram showed that in the east-west direction, aragonite saturation varies with distance four times faster than in the north-south direction. To account for this difference, anisotropy was incorporated into the exponential model. The extent of the interpolation was set to include the entire area of the cruise as well as one degree of latitude and longitude beyond the furthest cruise station in each direction (see details of each cruise in Appendix 6). The grid was determined such that latitudinal and longitudinal grid dimensions were equal, each grid box being 0.16 degrees tall and 0.16 degrees wide.

Because of the different physical forces and conditions in estuaries, we were not able to assume that our spatial interpolation of aragonite saturation state could be extended into estuarine areas. A shapefile of estuaries on the West Coast was obtained from the Pacific States Marine Fisheries Commission and used to mask aragonite saturation state values in these areas (TerraLogic GIS, Inc 2005). This interpolation was duplicated for each set NOAA OA cruise observation points (see Results and Appendix 8).

Hotspot Thresholds Analysis

For the purpose of this analysis, we defined ocean acidification hotspots as areas where surface waters meet critical thresholds of aragonite saturation state. When aragonite saturation is <1, water is chemically undersaturated, meaning that the formation of shells by calcifying organisms is not energetically favored and can cause organisms to enter a state of dissolution. However, many calcifying organisms have shown detrimental effect of OA at aragonite saturation states under 2 (McLaughlin et al. 2015). Additionally, there have been recorded incidents of die-off and shell dissolution tipping points at hatcheries along the West Coast at a saturation state of 1.7 (Barton et al. 2012, Chan et al. 2017). These thresholds were used to repeat the analysis with each year and dataset of the NOAA OA cruises (see Results and Appendix 9).

MPA Analysis

The MPA analysis aims to develop a framework for considering impacts that OA hotspots may have on MPAs using various types of spatial analysis. Shapefiles for selected marine managed areas from Washington, Oregon, and California were obtained from the Anthropocene Institute's (2016) MPA Database (Appendix 10). These included all state reserves, conservation areas, and marine parks as well as federal National Marine Sanctuaries.

Because the goal of this project was to provide evaluation metrics for marine protected areas that were actively managed and established for long term ecosystem protections, the larger Anthropocene Institute database was subsetted for the purposes of this analysis. The database contains all marine managed areas - including vessel speed reduction management areas, water quality testing areas, catch reporting units, and seasonal and temporary closures as well. Within this large variety of management areas, seasonal protections, temporary closures, as well as single-species protection listings such as Essential Fish Habitats were excluded. This was due to their management framework's lack of relevance to the potential OA evaluation criteria and management options. Short term closures do not operate on the timeframe necessary for OA mitigation and management and the spatial area of Essential Fish Habitats are not actively managed or directed toward a species that is impacted by OA levels.

Next, each MPA's exposure to OA hotspots was evaluated in two ways: the mean aragonite saturation state across the spatial extent of the MPA, and the percent of the MPA covered by a hotspot (based on the 2.0 aragonite saturation state threshold). MPAs were ranked in order of lowest mean aragonite saturation state to highest. This analysis was repeated with each of the four NOAA OA Cruises (see Results and Appendix 11).

Model Suitability Analysis

To better understand the current state of OA modeling on the West Coast, a list of existing and underway models was compiled. Information sheets were developed to keep track of the goals, components, and resolution for each model (Appendix 12). Where available, online model simulations were observed. Contact was made through phone calls and emails with the modelers and their partner organizations to build a comprehensive list of characteristics for each model. Primary literature was also referenced. The characterization of each model included:

- Goals
- Sponsor institution
- Extent
- Domain
- Resolution and temporal scale
- Model forcing
- Validation
- Data access and availability

Results

Data Exploration and Wrangling

After downloading numerous datasets listed in the West Coast OAH Monitoring Inventory and contacting researchers and data managers to inquire about data access, we found that nearly all of the several hundred monitoring asset inventories were nullified or unusable for analysis due to the conditions of our evaluation. We did identify monitoring assets with available continuous aragonite saturation state data, however the data did not coincide temporally, and the spatial coverage was sparse. Thus, it was not feasible to use continuous data for a spatial interpolation of aragonite saturation state hotspots. This demonstrated some fundamental gaps in the accessibility and usefulness of the inventory catalog, explored in further detail in the Discussion section below.

Even though we could not use this continuous data to generate a map of hotspots, we plotted the data and calculated simple summary statistics (mean and standard deviation) to get a sense of aragonite saturation state observations within two sites of our study areas: an LTER site in the Santa Barbara Channel, CA and Hog Island in Tomales Bay, CA (Figure 1, Figure 2, Appendix 2).

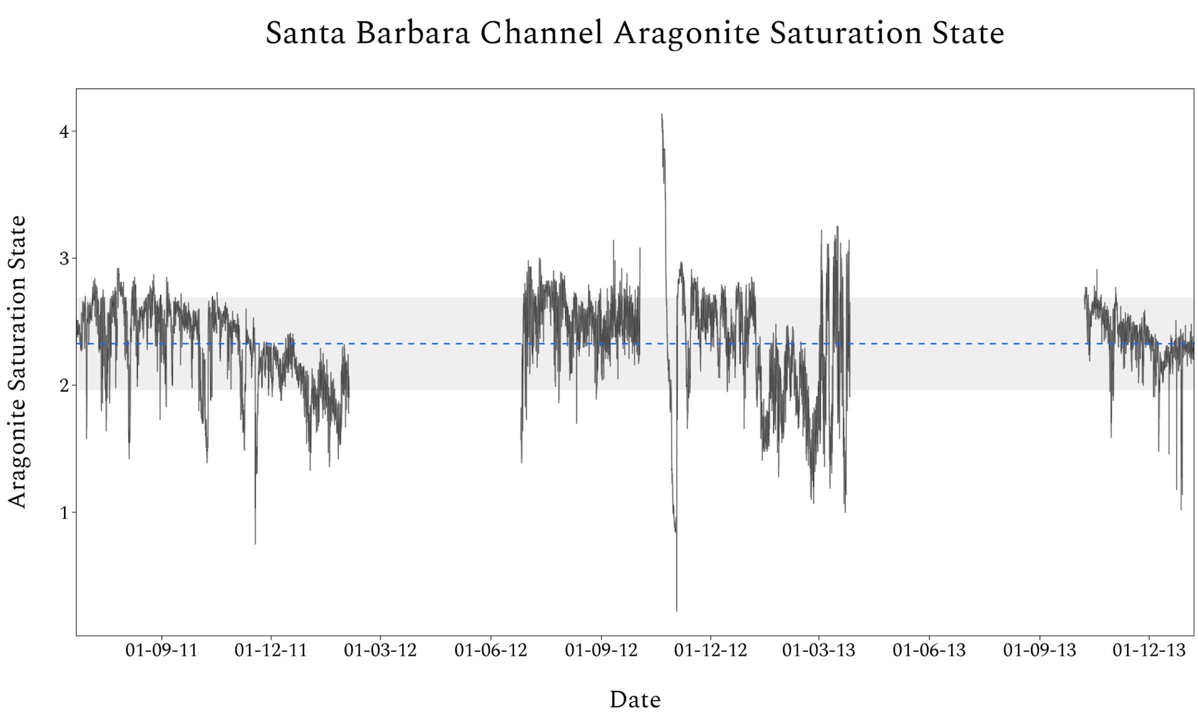

Figure 1. Time series of aragonite saturation state at Alegria Reef (ALE) in the Santa Barbara Channel for June 2011 - January 2014. Blue line represents the mean (2.32),

grey bar represents 1 standard deviation (0.36) above and below the mean. Data provided by Santa Barbara Coastal Long Term Ecological Research.

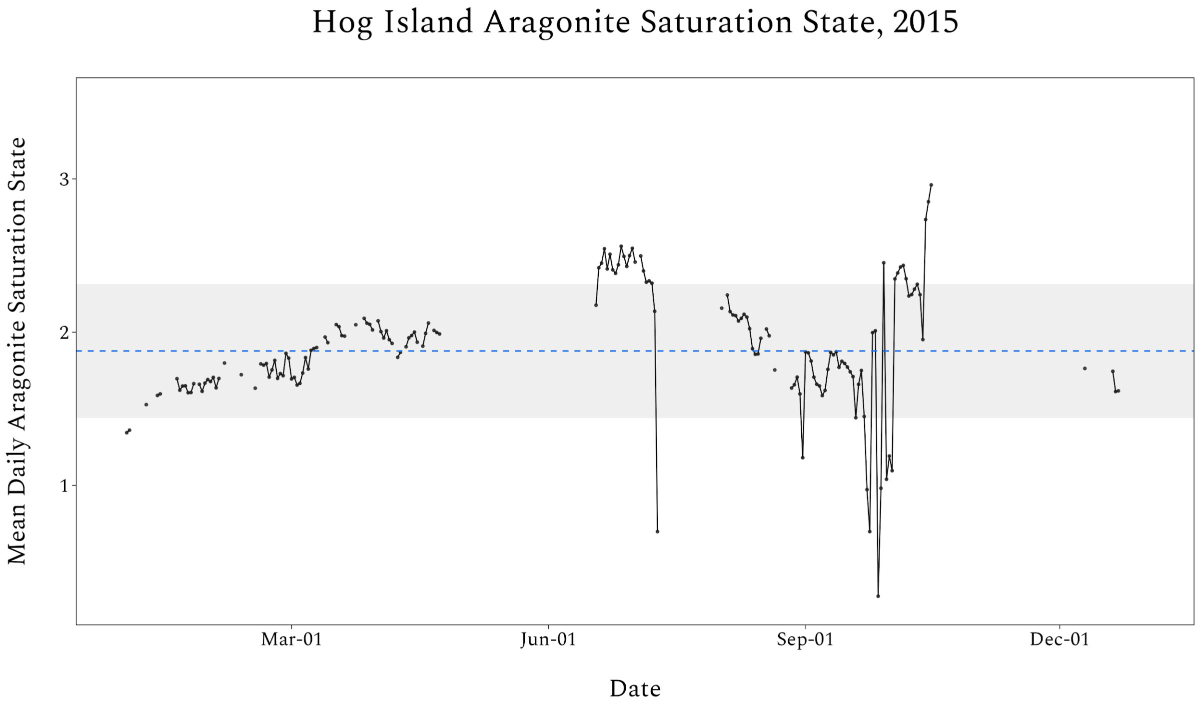

Figure 2. Time series of mean daily aragonite saturation state at Hog Island Oyster Company in Tomales Bay, CA in 2015. Blue line represents the mean (1.88), grey bar represents 1 standard deviation (0.44) above and below the mean. Data provided by Hog Island Oyster Company and managed by UC Davis Bodega Marine Laboratory.

Gap Analysis

The results of the gap analysis revealed severe gaps (top 0.1%) off the coast of Florence, Oregon, at the mouth of the Columbia River, and in the Straight of Juan de Fuca. High priority gaps (top 1%) throughout the southern coast of Oregon, The Straight of Juan de Fuca, and in the California Bight (Figure 3).

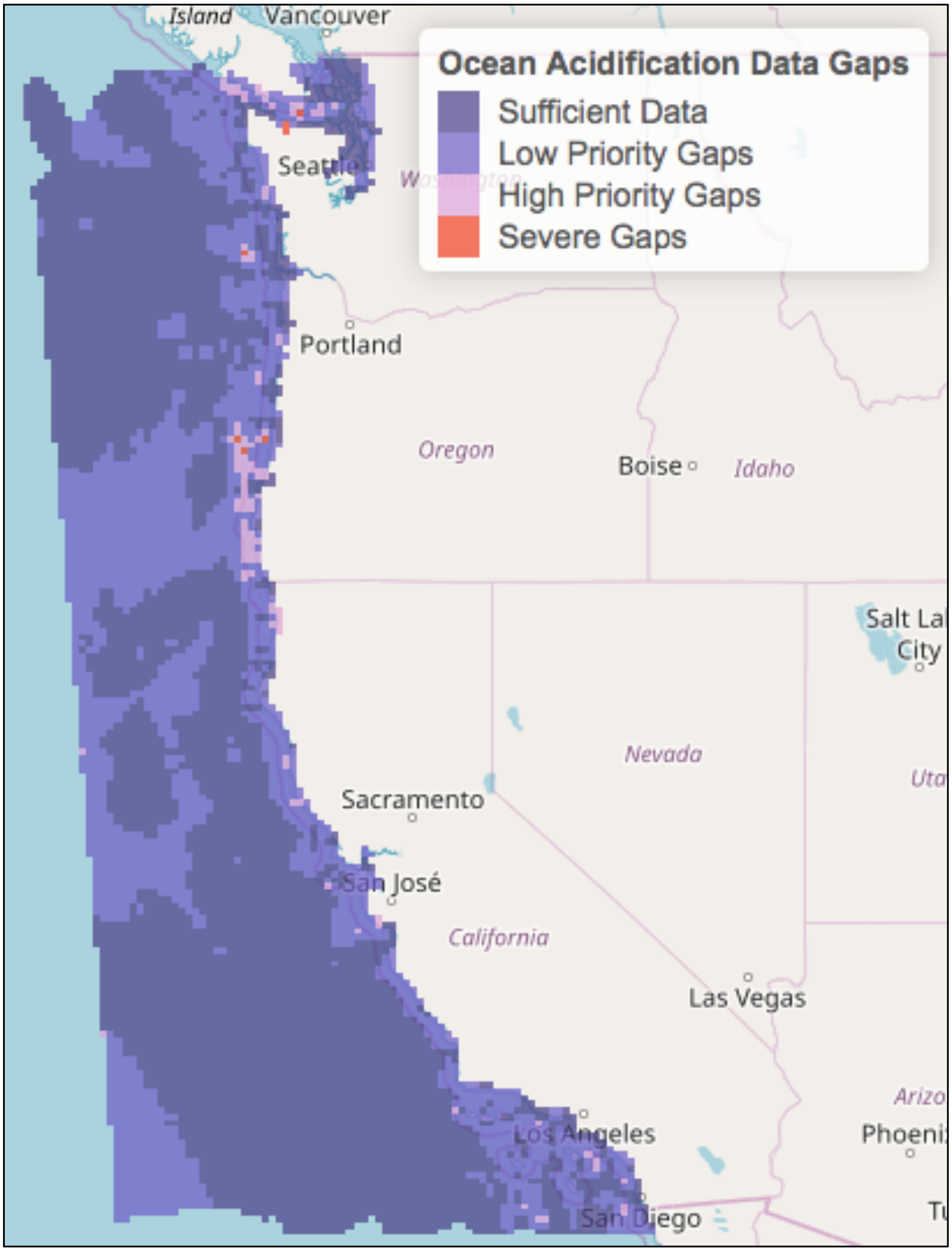

Figure 3. Results from a gap analysis of all ocean acidification-related monitoring.

The analysis of gaps in carbonate complete monitoring reveals severe gaps in the San Juan Islands and in the waterways of Vancouver Island. High priority gaps also exist along the Southern Oregon coast (Figure 4).

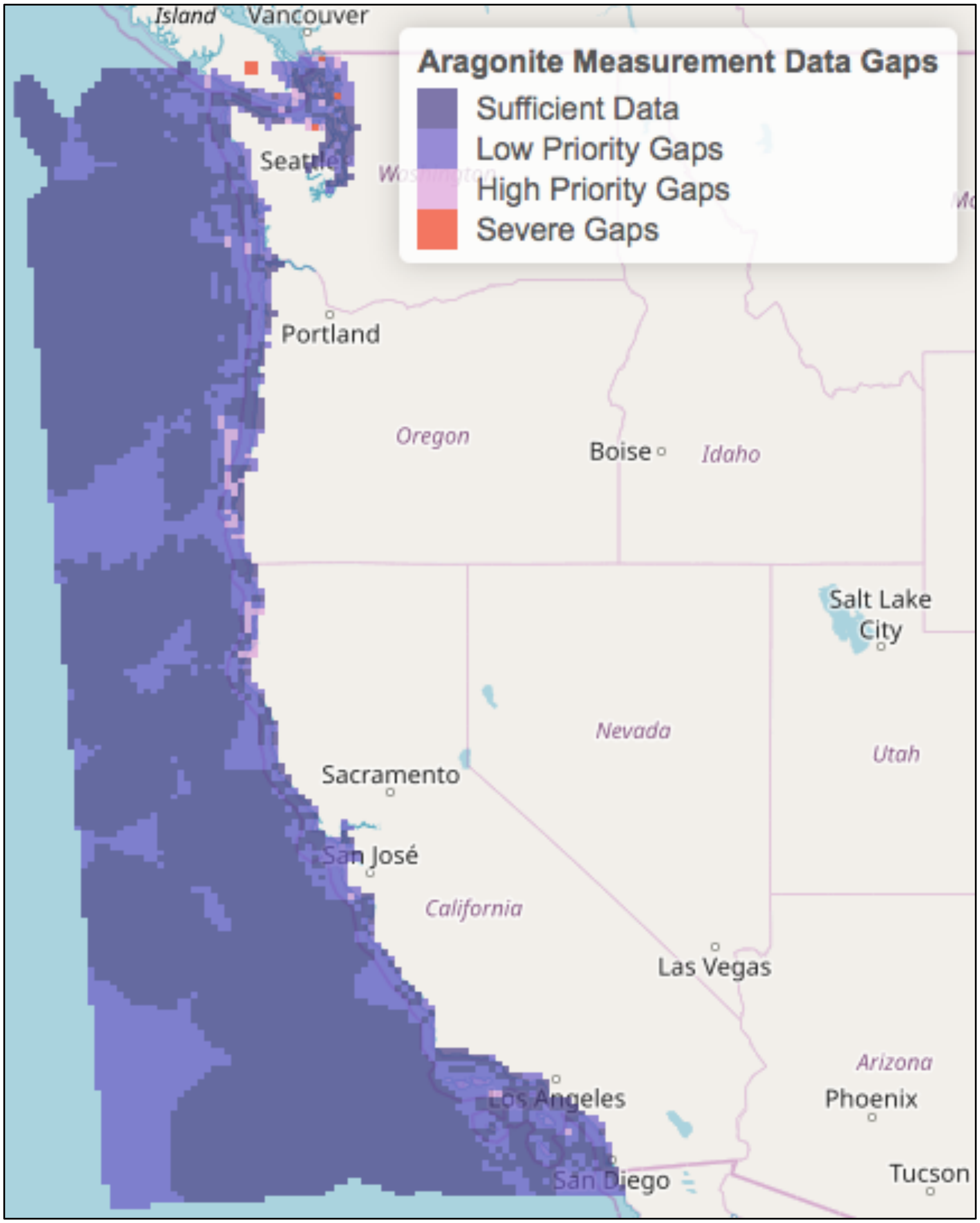

Figure 4. Results from a gap analysis of carbonate complete ocean acidification monitoring.

The analysis of gaps in daily monitoring reveal severe gaps offshore from Bellingham, Washington and Coos Bay, Oregon. High priority data gaps also exist offshore from the Columbia River mouth in the Salish Sea. (Figure 5).

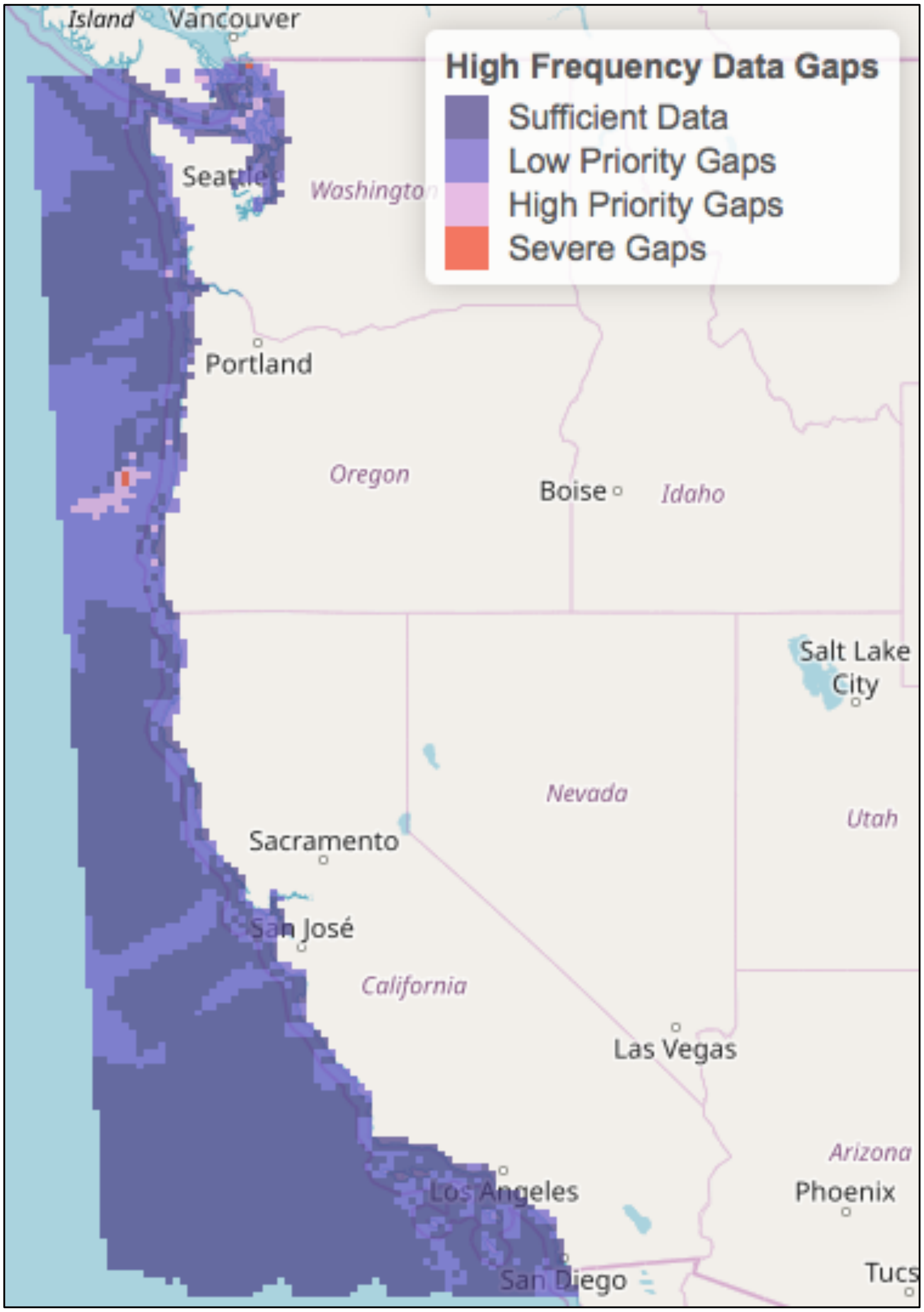

Figure 5. Results from a gap analysis of monitoring with a frequency of at least once a day.

The primary result from this section of the project is a finalized and polished script that is publicly accessible through GitHub in R. This product is still in progress, but will be complete in the coming weeks.

The results of the sensitivity analysis on the weighting factors used in the gap analysis on the full inventory reveal that between 100 different combination of weights ranging from 10^{-5} to 10^{-14} for the distance weight and 2 to 20 for the temporal weight, the top 0.1% and the top 1% of the gap values were completely insensitive. Under this range the top 25% of gap values were 8.4% sensitive (calculations available in Appendix 3).

Hotspot Interpolation and Thresholds Analysis

The results of our ordinary anisotropic kriging created a continuous layer of aragonite saturation state predictions across our study region, revealing areas of both under-saturation and supersaturation along the coast. Expectedly, our prediction is strongest when cruise observation points are closely clustered together. The standard error associated with our kriging predictions increases at an increasing rate as spatial dependence amongst predictions decreases away from the center of the observation point (Figure 6). Noticeably, there are areas in the southern region of our study in which observation points are almost too far apart to generate a reasonable prediction, at the limit of our observation points' spatial correlation.

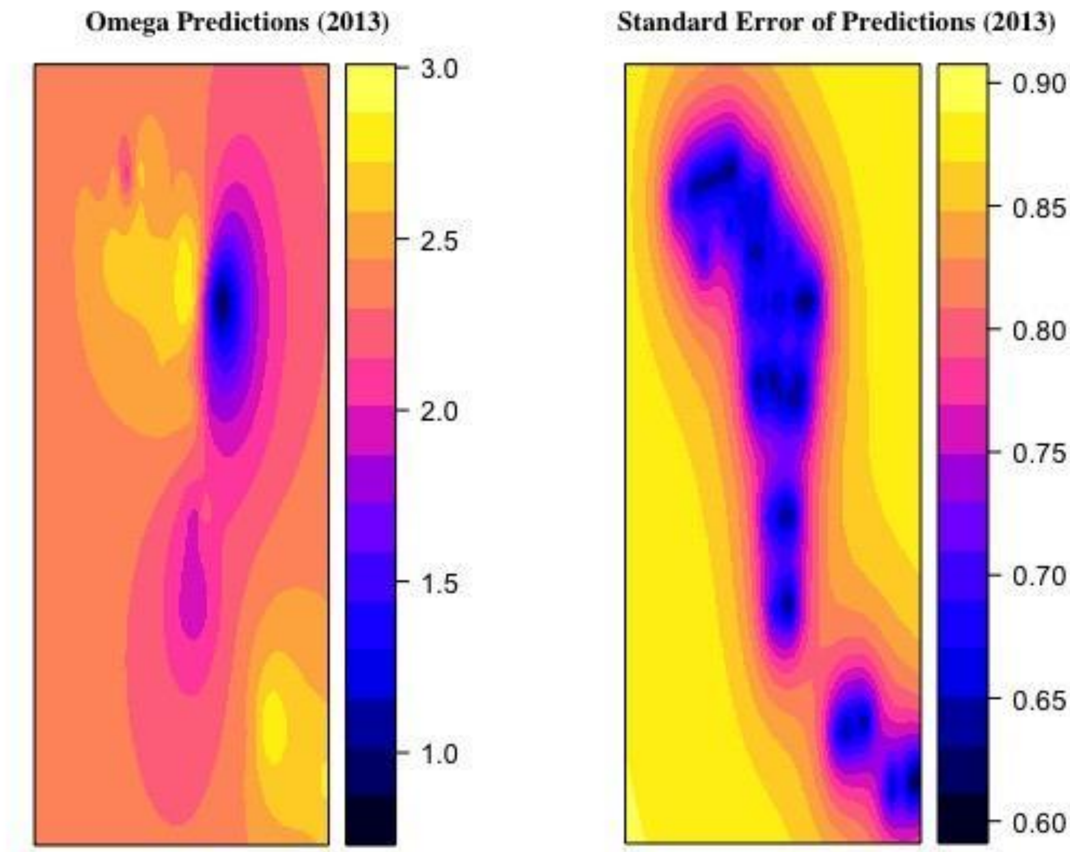

Figure 6. Raw kriging prediction outputs and standard error of predictions for aragonite saturation state based off of surface level observations in the 2013 NOAA OA Cruise (Feely et al. 2013). See outputs for each cruise in Appendix 8.

These raw interpolation predictions allow us to identify where OA hotspots may be occurring at distinct snapshots in time based on data from the NOAA West Coast Ocean Acidification cruises (2007, 2011, 2012, 2013). Data from the 2013 cruise shows hotspots that fall below the 2.0, 1.7, and 1.0 aragonite saturation state thresholds at the mouth of the Columbia River and off Cape Mendocino, while "cold spots" appear outside of San Francisco Bay and the coast Washington (Figure 7, Figure 8). Each cruise revealed different hotspots and relative "cold spots" that varied in both size and location over output. This variation could be due to annual variability of saturation state, but also could be an artifact of the different sampling locations used on each cruise (Appendix 6).

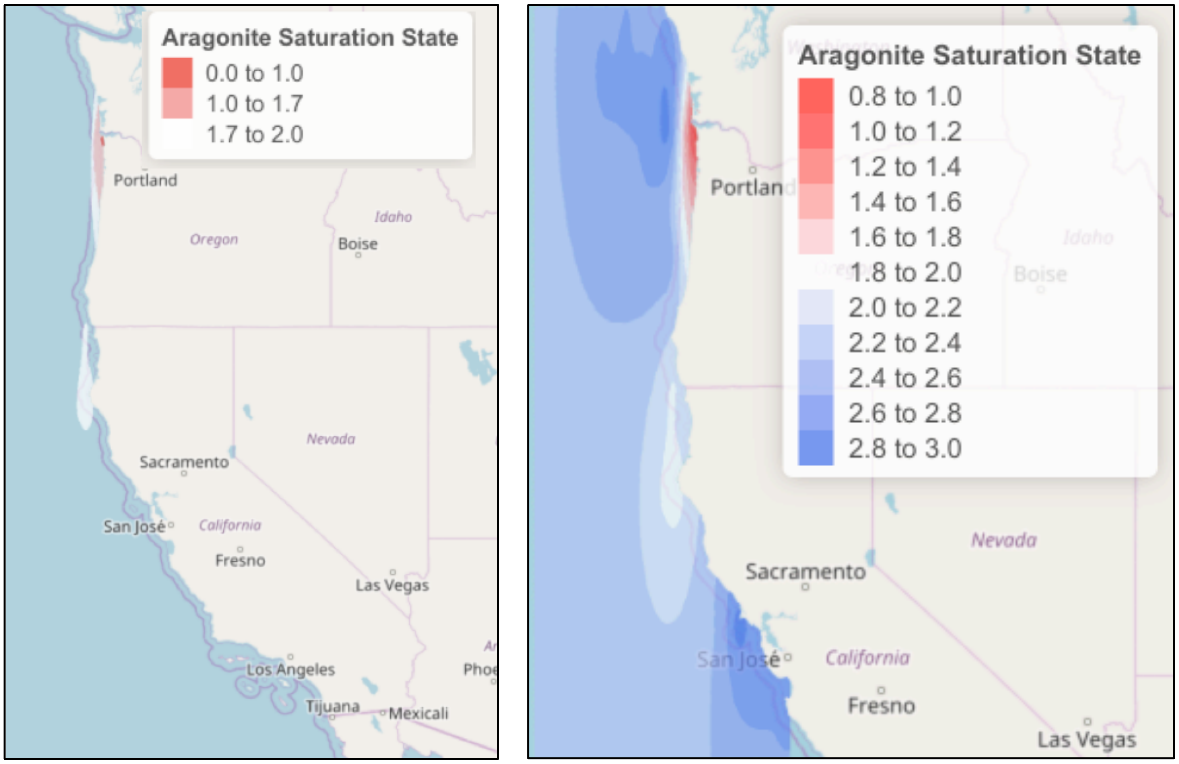

Figure 7. The map on the left shows the interpolated aragonite saturation state values for the West Coast produced using data from the 2013 NOAA West Coast Ocean Acidification Cruise. The map on the right shows hotspots of ocean acidification, defined as areas where aragonite saturation is below a biologically significant threshold of 2.0. Areas with aragonite saturation below 1.7 or 1.0 are also visualized. (Also see Appendix 9).

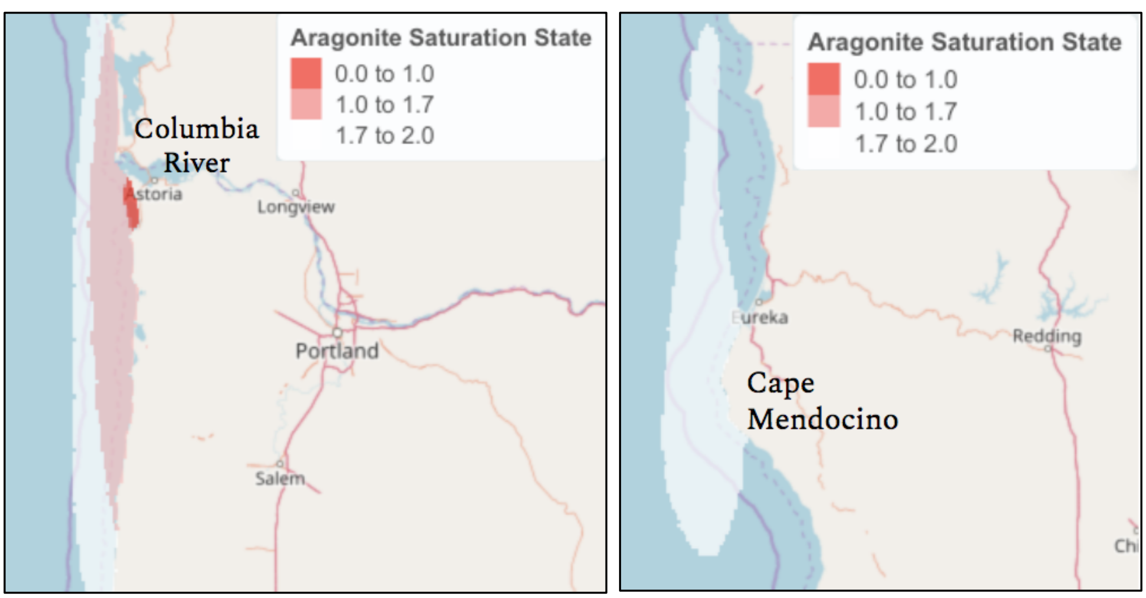

Figure 8. These maps display the two hotspots identified by by our analysis of the 2013

NOAA West Coast Ocean Acidification Cruise. The first hotspot shown on the left is located near the mouth of the Columbia River; the second hotspot is located near Cape Mendocino.

Due to the wide spatial extent of the cruise stations, the predictive capacity of our kriging outputs decreases at a relatively fast rate north to south away from each point. However, despite using different prediction methods, we found that our results were similar to results previously published by Dr. Richard Feely who created similar continuous predictions from each cruise (Appendix 13).

MPA and Habitat Analysis

We used the interpolation of aragonite saturation values from the 2013 NOAA West Coast Ocean Acidification Cruise and resulting hotspots of ocean acidification to evaluate the risk imposed to marine protected areas on the West Coast (Figure 9). Threat to marine protected areas was evaluated based on the mean saturation state in the geographic extent of the MPA and the percent of the MPA covered by a hotspot zone (Figures 9, 10 and Table 5).

The ten marine protected areas with the lowest mean aragonite saturation state were found in Oregon (Table 5).

The results for our MPA analysis also includes the percent of each MPA covered by one of three essential fish habitat types: kelp, seagrass, or rocky reefs. Figure 10 displays the percent coverage for each MPA.

The process of this analysis is systemized in a completed R code that is publicly accessible through GitHub. This analysis can be customized not only by the aragonite saturation state input used, but also by the relevant hotspots that may pertain to certain ecosystems and species of concern. With this in mind, we analyzed the suitability of various existing OA models to inform this type of MPA analysis.

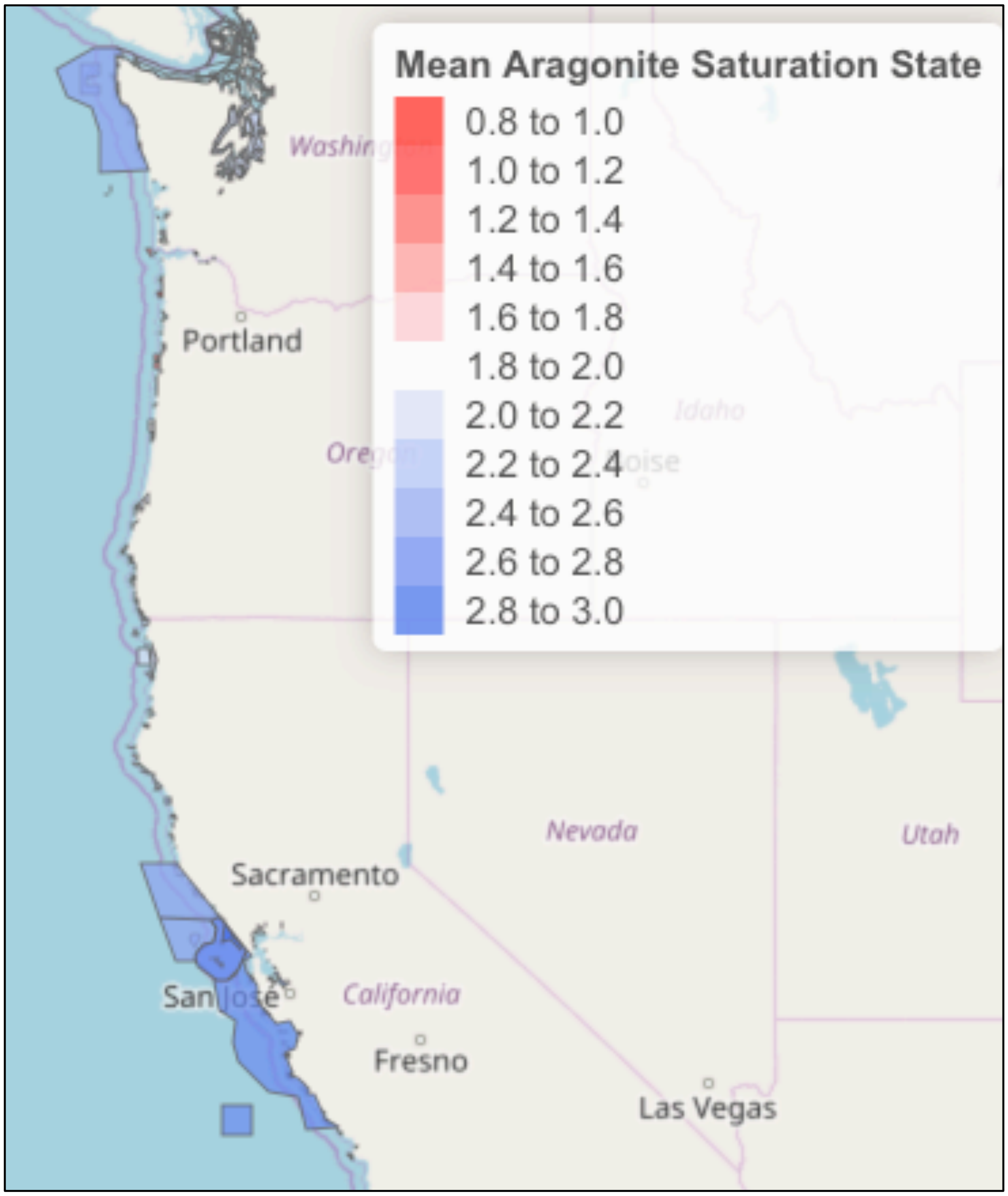

Figure 9. Marine protected areas on the West Coast where infill color represents the mean aragonite saturation state within the geographical extent of the MPA. The map on the right displays the percent of each MPA's area covered by an ocean acidification hotspot.

Table 5. The ten marine protected areas with the lowest mean aragonite saturation state. The list shows MPAs in the California Current system where MPAs co-occur with ocean acidification hotspots, determined by critical thresholds of aragonite saturation state. MPAs are ranked by the lowest aragonite saturation state. Across all three West Coast states, 21 MPAs were 100% covered by an ocean acidification hotspot.

Marine Protected Area	**Mean Aragonite Saturation State**	**Area of MPA (km^2)**
Haystack Rock Marine Garden, OR	1.04	0.34
Cape Falcon Shoreside Marine Protected Area, OR	1.11	0.61
Cape Falcon Marine Reserve, OR	1.15	32.04
Saltwater Salmon Angling Closure - Columbia River, OR	1.20	15.97
Cape Falcon West Marine Protected Area, OR	1.21	19.10
Cape Meares National Wildlife Refuge, OR	1.28	0.62
Netarts Bay Shellfish Preserve, OR	1.33	1.41
Columbia River Salmon Conservation Zone, OR	1.50	47.48
Cascade Head North Marine Protected Area, OR	1.54	31.55
Cascade Head Marine Reserve, OR	1.56	25.09

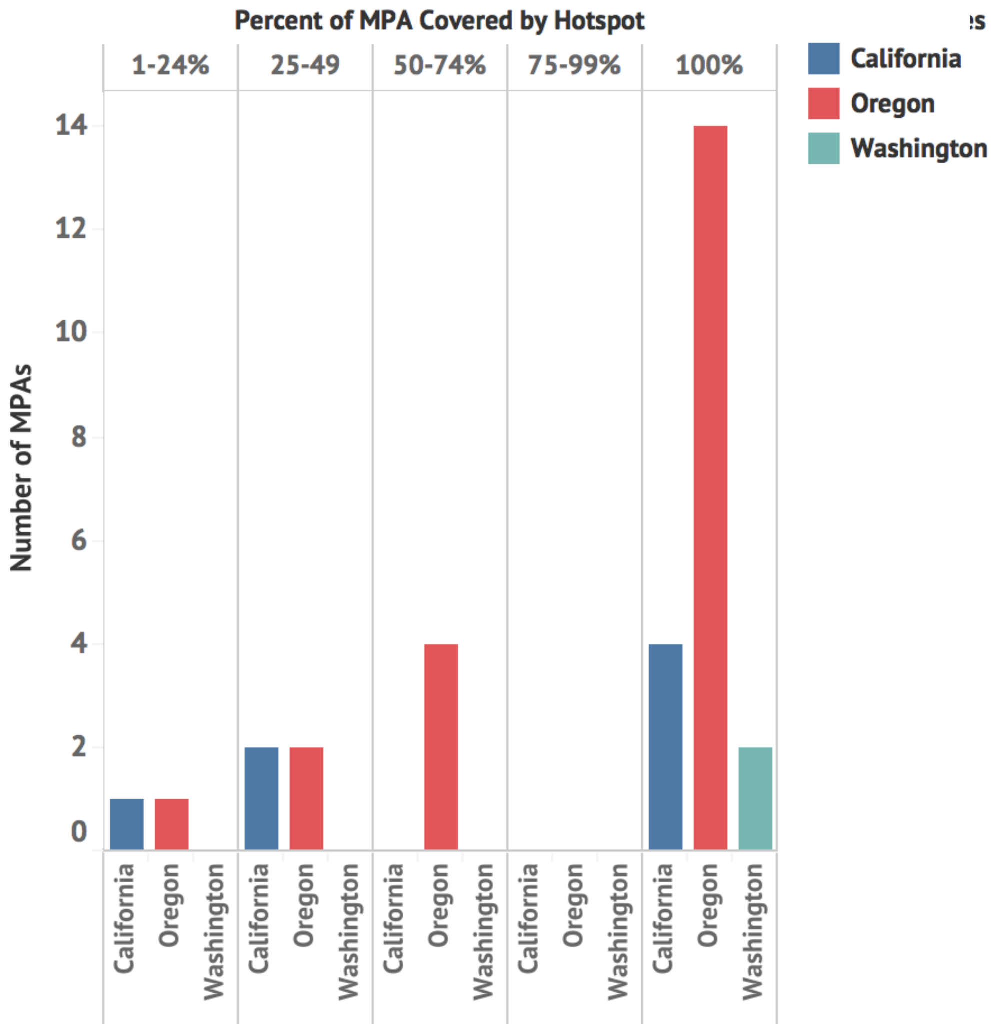

Figure 10. The number of marine protected areas by state (Washington, Oregon and California) that have a certain area covered by an ocean acidification hotspot (defined earlier in our analysis as having an aragonite saturation state below 2).

Model Suitability Analysis

Here, we analyze the three OA models for the California Current System to compare their spatial extents, temporal scales, forecasting abilities, and limitations, in order to summarize how to best use these models. Furthermore, we can assess how to improve models moving forward.

Temporal scales

Aragonite saturation states can vary widely on daily, seasonal, and annual scales. For this reason, using a variety of OA models to predict variability in aragonite saturation state is necessary for understanding management concerns. The J-SCOPE model, for example, biannually forecasts OA parameters 6-9 months in the future, whereas the

LiveOcean model provides outputs for OA parameters every 1.5 hours and can show 3-day hindcasts and forecasts. This may be especially useful for shellfish farmers to understand and plan for upcoming growing seasons. It also identifies "short-term" OA hotspots that may occur in the near future. The ROMS-BEC model will forecast OA conditions 5-10 years in the future in areas of low-resolution (1 km resolution), and forecast a few months in the future for high-resolution grids (<300 m). Annual predictions will help inform long-term OA hotspots where managers may expect long-term changes to aragonite saturation state. Ideally, models will continue to expand their temporal extents to include more certain predictions of daily, seasonal, annual, and long-term predictions years into the future.

Spatial Extent

The J-SCOPE and LiveOcean models visualize the same spatial extent from 43°N to 50°N including Puget Sound, whereas the ROMS-BEC model ranges from British Columbia, Canada to Baja, Mexico. The resolution of OA models has previously been a large limitation in understanding the current state of OA in the California Current due to the variability in nearshore environments. The ROMS-BEC model will be the first model to predict high-resolution conditions in nearshore environments, in some areas at less than 300-meter resolution. The ROMS model, however, varies in spatial resolution by region, using nested models. The model provides 1 km resolution data for a distance of 500 km area offshore of Washington, Oregon and California. A 300 m resolution model covers the Southern California bight, and a 100 m resolution model includes the Channel Islands and the greater Los Angeles region. The entire California Current System is predicted at a 4 km resolution. The J-SCOPE and LiveOcean models have a resolution of 1.5 km on the coast and 4.5 km in offshore environments. Fine resolution in highly variable areas is important to understand and predict biological impacts. As we begin to learn more about species response to OA, we want to understand how OA variability impacts the resiliency of OA vulnerable species. For example, the impact of high variability of aragonite saturation state on a diurnal scale in a small tidal area may differ from the impact of changes in aragonite saturation state that is widespread in area and occurs over long temporal scales. Similarly, some marine organism may be more or less resilient to acute versus chronic OA stress. We can only measure this variability with fine resolution models. Fine resolution models will also inform MPA managers of aragonite saturation state values and variability within an MPA.

The above models and their forecasting abilities of aragonite saturation state in the California Current System provide insight into future abiotic conditions. By coupling these models with ecological and human system models, the ecological and social impacts may be better understood (Busch et al. 2015). The coupling of models may be the most effective way to communicate knowledge from OA researchers to motivate policy changes (Boehm et al. 2015).

Discussion

Data Wrangling and Exploration

Though not an expected formal component of our analysis, we found interesting trends in the monitoring inventory when attempting to collect publicly available OA data. The West Coast OAH Monitoring Inventory contains the full listing of monitoring assets and, when available, links to online resources that can be used to access the data holdings. The purpose of the inventory is to build a collective knowledge about the state of ocean acidification and to inform West Coast managers about what is needed to build a more comprehensive monitoring network moving forward. Thus, the success of the inventory relies on the ability of collaborators to integrate the data being collected by assets in the inventory.

However, in our exploration of the inventory's assets and their consistency, we found several aspects of the inventory that may inhibit its usefulness in the future. Although many of the monitoring assets have an associated website and person of contact to facilitate obtaining this data, the data itself it not publicly available. When we reached out to the listed contacts to ask for the data listed in the inventory, we had limited success. If future researchers and managers are not able to easily obtain the data listed in the inventory, this limits its contribution to understanding ocean acidification on the regional scale. Additionally, we found that there is a lack in temporal overlap in data collection, making the comparison between datasets difficult. Many monitoring resources do not have consistent monitoring during the time frame that they have listed in the inventory, so finding data from the same time intervals that can be used to compare different spatial areas is rare. Large inconsistencies in how long each asset has been collecting monitoring data make it difficult to find time-series data from various locations that can be compared. More inconsistencies exist between the inventory's report of the types of data a monitoring asset is collecting and the availability of access to that data. Lastly, we found that many assets are not collecting carbonate complete data as stated, or they are collecting carbonate complete data, but for a shorter time span than described in the inventory.

Gap Analysis

It must be noted that the categorical severity of data gaps for each subset of this analysis are based off percentiles of that specific subset. This gives the appearance that carbonate complete monitoring and high frequency monitoring have no more data gaps than does the entire inventory. We considered creating categorical severities for the subsets based off percentiles of the whole, which would show that these subsets of the inventory have more gaps than the inventory as a whole. This, however, should be naturally inferred because the analysis is inherently being performed on fewer data points with each subset. We thought that using categorical severity based off subset percentiles creates a more actionable and relevant outcome; in order to fill gaps in high frequency data collection, managers need to know where the highest priority gap is in high frequency data collection may be, rather than where gaps in high frequency data collection exceed some set value relative to the inventory as a whole.

A major conclusion from the gap analysis is the importance of an international effort to conduct an inventory of monitoring assets throughout Canada, the United States, and Mexico. International borders are irrelevant to marine chemistry, revealing the need for international cooperation to better understand and monitor changing ocean chemistry.

Assuming that all existing monitoring assets are currently included within the inventory, results from the gap analysis reveal several possible actions that can be taken to fill priority areas for additional monitoring. To decrease data gaps, additional monitoring infrastructure can be established off the coast of Southern Oregon, which has the highest oceanographic difference, or variability, of any location on the West Coast. This makes the Southern Oregon Coast a priority area for additional monitoring infrastructure. It is recommended that any additional monitoring in that region should collect data at daily frequency or greater, and should collect carbonate complete data. High frequency data collection in this region will provide information on short-term changes, such as within diurnal or tidal cycles (McLaughlin et al. 2015). Understanding diurnal and seasonal patterns can better help managers and fisheries predict future impacts of OA on biological activity. As the shellfish industry prepares for OA, understanding the variability of the carbonate system can serve useful in planning for OA, for example, through developing water treatment systems that have mitigation potential (Barton et al. 2015). Additional monitoring infrastructure is also recommended offshore from the Columbia River Mouth, in the Straight of Juan de Fuca, and in Puget Sound. These locations repeatedly appear as the top 1% of gap values. By simply adding additional instrumentation to existing infrastructure at monitoring sites off the Oregon Coast, locations that currently only collect pH or pCO_2 can become carbonate complete monitoring assets. An ideal monitoring network will contain carbonate-complete monitoring assets to allow users to calculate aragonite saturation state from the data collected at each asset. Researchers have prioritized using aragonite saturation state to represent ocean acidification over other measurements, such as pH. Adding high temporal frequency instruments to the existing infrastructure off the Oregon Coast, and in the San Juan Islands in Washington can close severe data gaps.

Several factors limit our analysis. The existing monitoring inventory does not include information about the depths of data collection. Seawater in the California Current is most undersaturated at depth, making it important to monitor at a variety of depths in addition to the surface. Currently, there are significant gaps in assets that are monitoring at depth, but this analysis does not reflect these gaps due to data limitations. Additionally, this analysis does not address potential monitoring gaps in areas with specific management implications, such as marine protected areas or essential fish habitat. Managers have indicated the importance of having monitoring in and outside of these managed areas.

Assumptions made about oceanographic variability affect the sensitivity of our analysis. The backbone for this analysis is the Bio-ORACLE oceanographic parameter raster layers. Other oceanographic parameter rasters are available, but we chose to use Bio-ORACLE because it works well with our goal of developing a package in R. Our results are dependent on the raster layers we used, and it could be valuable to repeat these analyses with alternative underlying oceanographic parameter rasters. This analysis assumes that ocean acidification and its variability can be predicted by sea surface temperature and dissolved oxygen (Lee et al. 2006, Juranek et al. 2009, Alin et al. 2012). If other parameters are identified as equally or more relevant to ocean acidification, this analysis could be repeated to include additional oceanographic parameters. In the future, depth and essential fish habitat should be included in this analysis and the monitoring inventory should be expanded to include Canada and Mexico.

Hotspot Interpolation and Thresholds Analysis

Our analysis of where hotspots of ocean acidification occur on the West Coast is limited in the sense that it is based on a “snapshot” view of ocean acidification conditions. By using the NOAA West Coast Ocean Acidification cruises, our analysis output layer is discrete in time and space. The layers showing hotspots created by these cruise outputs give us an idea of how we might begin to think about aragonite saturation state relative to MPA location, though the resolution of the information these data are giving us may not be refined enough to influence management decisions as it currently stands.

However, based on our understanding of the research and trends on OA within the California Current System and based on the choice of a conservative interpolation method that suits our data, we are confident that the major hotspot we identify is chronic in the region. The Columbia River estuary shows chronic undersaturation in various model predictions and is highly influenced by nutrient loading from runoff. Additionally, all cruises occur during summer months, relatively central within the general upwelling season which begins in early spring and extends into late summer (Feely et al. 2008, Hauri et al. 2013). This suggests that the trends displayed by the cruise outputs may be reflective of the most severe or important trends in OA hotspots.

Because OA trends are so variable - changing within seasons, in response to acute forcings, and increasing largely over climatological time - an ideal spatial prediction for this type of analysis would be malleable to changing conditions and temporally robust (see Model Suitability Analysis below). We defined hotspots of ocean acidification as areas where aragonite saturation state fell below a threshold where biologically significant impacts begin to occur. However, additional criteria may be needed to define hotspots, such as the persistence of low aragonite saturation values over time.

MPA and Habitat Analysis

The objective of this analysis is to consider how a spatially fluid and dynamic problem like OA can be accounted for and incorporated into spatially explicit management zones like marine protected areas. Although the goals of each marine protected area may differ, their management generally focuses on an ecosystem-based approach and provides an accessible way to approach controlling for ocean acidification on a local, spatial scale. However, time and other resources are limited, so it may not be feasible to address ocean acidification in every marine protected area on the West Coast. Our spatial analysis evaluated which marine protected areas were most at risk based on the values of aragonite saturation produced by our spatial interpolation from the 2013 NOAA West Coast Ocean Acidification Cruise. Therefore, our analysis of which marine protected areas are most at-risk is limited by the aragonite saturation data available. In the future, this same methodology can be used with other datasets of aragonite saturation produced from ocean acidification models.

Once MPAs have been identified as threatened based on their average aragonite saturation state and amount of area covered by a hotspot, it is also important to consider what ecosystem type is found in the MPA. Considering the ecosystem type or habitat protected by MPAs can help identify areas where crucial species are found that are most vulnerable to MPAs. The management options described below describe different methods being developed to increase local ecosystem resilience to ocean acidification.

Model Suitability Analysis

Suitability of the ocean acidification models was analyzed based on their capacity to provide high-resolution information for MPA planning and management considerations. Models that are acceptable for MPA planning should have fine-scale resolution for small managed areas, capture seasonal variation, and make strong predictions with low uncertainty in nearshore areas, where biodiversity concerns are high and MPAs are most likely to be sited.

LiveOcean is currently the highest spatial resolution model and most appropriate for assessing impacts to MPAs on a spatial scale. Improved resolution for this model to a 500 m scale will improve its utility for protected area planning. However, this model is spatially-limited in the context of our study area. Another limitation of using this model for MPA decision-making is the short-term predictions considering policies for MPAs are often developed and implemented on the timescale of months to years. MPA managers will likely benefit from models that can make long-term predictions. J-SCOPE is equipped to make these types of predictions; however, the spatial resolution is coarser which limits the certainty of predictions at the scale of MPAs. The ROMS-BEC model is a work in progress and is slated for release in 2019. This model presents fine-scale resolution for coastal waters in southern California, which will be more useful for management of southern California MPAs.

There is a large gap in the spatial extent of these three acidification models. These models do not currently resolve acidification parameters for nearshore and offshore waters along the central and northern California coastlines or southern Oregon. Improved spatial extent of modeling and higher resolution will improve understanding of specific acidification threats at the scale of MPAs. In turn, this will provide more options for managers and policymakers to make decisions at the local scale, where decision-making is relatively simple compared to changing state or region-wide policies. The utility of these models will be further improved if they can be integrated with ecological models to improve understanding of abiotic and biotic coupling.

Management Options

Our discussion identifies feasibility of management options and outlines the barriers to implementing various techniques. These may include financial or technological barriers. We will discuss the degree to which each is being pursued or implemented.

Expand West Coast OA Monitoring Network

The gap analysis of the West Coast OA Monitoring network aims to identify opportunities to improve current data monitoring. Reducing gaps in spatial and temporal understanding of OA is integral for prioritizing areas of concern due to the high variability of OA. This will allow for more efficient use of management resources. The gap analysis can inform improvements to the existing network to provide more congruent and cohesive OA baseline monitoring and ensure adequate distribution of carbonate complete datasets.

The gap analysis ranks high to low priority data gaps. High priority gaps demonstrate areas where a lot of valuable information can be gained by updating or adding to the current monitoring network. Some data gaps may be easier to close than others. The gap analysis identifies existing monitoring assets that are not carbonate complete; by updating these monitoring assets through adding OA specific sensors, data gaps can be more efficiently closed.

The West Coast OAH Monitoring Inventory also identifies areas where biological monitoring is occurring. Pairing biological monitoring with physical monitoring assets can increase understanding of how changing ocean chemistry is impacting local marine communities.

Further, monitoring of MPAs could be expanded to track changing ocean chemistry and attribute ecosystem impacts. While this type of monitoring was recently instigated for a handful of MPAs in California through a partnership between the California Ocean Protection Council and Reef Check, assets can be added to additional MPAs. This will allow for a development of methods to monitor ecosystem resilience and better assess adaptive capacity.

Reduce Local Water Pollutants that Intensify OA

One option to reduce localized exacerbation of OA is to minimize the input of local water pollutants, such as nitrogen, phosphorus, and organic carbon into coastal watersheds. Nutrients in the form of nitrate and phosphate can lead to eutrophication of nearshore coastal waters, creating hypoxic conditions. Similarly, organic carbon is consumed by bacteria in the water column, which respire and create low oxygen conditions. Hypoxia typically coincides with high seawater pCO_2 and increased acidity. Thus, by reducing the drivers of localized hypoxic events, communities can also minimize exacerbations to OA. Communities can implement nutrient reduction programs by prioritizing subwatersheds with high nutrient-loading and working with landowners to achieve reduction goals. Cities can reduce nutrient inputs through upgrades to wastewater treatment facilities, or by incorporating water reuse technologies. Cities can also incorporate low-impact development to minimize the impacts of urban runoff. Estuarine environments are a particular priority area for nutrient reduction since localized processes have a relatively high influence on coastal water quality. The incorporation of runoff and terrestrial processes into OA models is critical to understanding their relative contributions to hypoxic and acidic conditions, which can lead to more informed policy to regulate local source pollution.

Expand Water Quality Criteria to Incorporate OA Parameters

At the state level, water quality criteria can also be updated to address OA. The standards for pH have remained unchanged since the Clean Water Act was written and could be fine-tuned to a narrower range based on biological thresholds. This could potentially increase the amount of coastal waters listed as “impaired” on the Clean Water Act 303(d) list, which would raise awareness of acidic conditions to managers and local decision-makers while opening up sources of funding to ameliorate OA stress. However, there are substantial hurdles to changing water quality criteria, namely funding and an arduous bureaucratic process.

Reduce CO_2 in Seawater through “Blue Carbon” Mitigation

Aquatic vegetation presents a mitigation tool for decreasing CO_2 in local waters, which can ameliorate stressful conditions for OA-vulnerable marine organisms. The basis of this method is to protect habitats which sustain ecological and biogeochemical functions. Thus, kelp forests and seagrass beds can be protected, specifically in places where they may ameliorate local pH through carbon sequestration. This strategy addresses the ecological and biological concerns of OA; it can also serve to promote the goals of an MPA that might be threatened by acidification. Conservation of existing seagrass and kelp habitats will be important for maintaining naturally occurring OA mitigation. Furthermore, finding suitable areas for the restoration of seagrass and kelp will benefit OA vulnerable species and communities.

Strengthen Resilience and Adaptive Capacity of Marine Ecosystems
MPAs were established before much was known about OA or its impacts. Our MPA analysis demonstrates MPAs that co-occur with hotspots and areas that may face lesser exposure to OA stress. Co-occurrence with hotspots and away from hotspots may both be beneficial in protecting OA vulnerable ecosystems. MPAs that co-occur with hotspots may promote adaptive capacity; marine organisms may be able to develop genetic tolerances or adaptations to OA which will be preserved in these MPAs. Conversely, MPAs with lesser OA exposure may prepare marine communities to better cope with future OA impacts by strengthening communities through increased diversity, productivity, and larval dispersion. Both of these environments are crucial to maintaining adaptive capacity, especially in light of the uncertainty and variability of responses of ecosystems to OA exposure.

Build Decision Maker Understanding of OA Processes and Impacts
Because ocean acidification impacts are experienced regionally, it is important that key fisheries, decision-makers and regulators in the public and private sectors are given the necessary tools to understand the processes and impacts of the issue. This can be done through increased communication about OA processes, impacts, and responses. As predictive tools are developed and fine-tuned and forecasts of OA conditions should be provided to decision-makers and end-users at geographic scales and time frames that are relevant to their management needs.

Continue Development of West Coast Ocean Data Portal to Inform Policy
As monitoring networks expand and OA modeling advances, it is important that this data is used to inform policy. By keeping data publicly accessible through data portals such as the West Coast Ocean Data Portal, marine managers can be more effective in their management strategies. Open communication between researchers and policy makers can ensure that OA studies and modeling efforts are policy-driven to the needs of OA stakeholders.

Conclusion

Ocean Acidification in the California Current System is a seemingly intractable issue that unites stakeholders across a variety of ecosystems along the West Coast. Though the root cause of this problem is much larger than the scale of the California Current System itself, there are many avenues through which the effects of this issue may be mitigated or ameliorated.

Primarily, greater coordinated information gathering at the regional scale can lead to more effective development and implementation of regional management. Analyzing the gaps within the existing monitoring network and the network's suitability for identifying important OA trends highlights the potential for improvement and coordination across the region. Improved coordination on the regional scale will lead to more accurate modeling and predictive abilities. Moving forward, it should be a regional priority to make ocean acidification data available to public. This is a goal of the West Coast Ocean Data Portal, which plans to host the results of the West Coast Ocean Acidification and Hypoxia Monitoring Inventory when it is complete. Public data accessibility will enable communication with a wide range of stakeholders, which is necessary to tackle this diffuse and regional problem.

Analyzing trends in OA through the lens of discrete spatial units (such as the co-occurrence of hotspots and marine protected areas) creates a tangible management interface for an otherwise spatially diffuse and elusive problem. Using marine protected areas as a metric of analysis improves our understanding about the severity of threat to already identified crucial locations within our coastal region. It also readily offers a platform by which to incorporate adaptive management and restoration strategies in the face of acidification conditions. With this threat level information in hand, MPA managers will be able to pursue local mitigation efforts to increase ecosystem resilience to ocean acidification. Courses of action include but are not limited to reducing nutrient input through stakeholder involvement, implementing blue carbon techniques through seagrass and kelp restoration, and, on a broader scale, encouraging community reduction of greenhouse gas emissions. Ultimately, the scale of this issue requires a robust contingency of stakeholders working in unity toward common efforts and integrated approaches at the ecosystem and regional scale.

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Appendix 1. OAH Monitoring Inventory Metadata.

Priority Fields in orange, Descriptive Fields in green.

CATEGORY	FIELD	CLASSIFICATIONS	DESCRIPTION
Project Background	**ProjectID**	*<name>*	Name of monitoring project
	AssetID	*<name>*	Name of particular monitoring asset (e.g. site name)
	AreaID	*<name>*	Name of a bounding area that a sampling effort falls in, for instance a marine reserve. Used to merge line multiple entries to one polygon geometry. Please provide a shapefile with bounding geometries if you use this field.
	Region	*California; Oregon; Washington*	Denotes the jurisdiction that collected an asset's information not necessarily the geographic region where a asset is located. If information was reported to Sara Briley / COPC the region is California. If information was reported to Daniel Sund/ODFW the region is Oregon.
	DataFormat	*Point*	Points are entries that are represented by a fixed location in space throughout time.
		Polyline	Polylines are entries that represent an asset that makes measurements while underway. The position for a polyline effort is not fixed.
		Polygon	Polygon entries represent projects that utilize a systematic method to assess information within an area.
	Orgniztion	*<name>*	List, separated by";", of institutions conducting a product
	URL	*<URL>*	Website where data and/or project information is stored
	Notes	*<notes>*	Notes provided with responses on additional details of project
	Contact	*<name>*	Name of the point person for a given project.
	Email	*<email>*	email/contact information for primary contact
Funding and Operational Security	**FundType**	*External Funds*	Currently funded by external grants, donations, or endowments. Includes volunteer efforts.
		Limited Duration Program Funds	Currently funded by short term (two years or less) non-renewable program funds.
		Dedicated Program Funds	Currently funded by dedicated program funds that are not expected to expire or reduce significantly.
	FunderName	*<Name>*	Name of funding source (optional)
	FundEnd	*<Month-Year>*	The Month and Year (i.e. June 2016) that the current funding cycle ended / will end for a specific project.

		Indefinite	No end date
	FundSecurity	*Funding is continued for the forseeable future*	Funding for the project is continued and sustained.
		Current funding has option for renewal	The current funding source has an option to apply for a renewal or extension of funding at the same or increased levels.
		Continued funding is likely from the same source	Funding source has shown an interest in or history in funding this project of analogous projects.
		Continued funding is likely from other sources	Other funding sources have shown an interest in or history in funding this project of analogous projects.
		Continued funding is unlikely but desired	PI's would like to continue project but are unable to secure reliable and sustained funding.
		Not pursuing continued funding	PI's are not pursuing funding for the project or the project has been discontinued.
Study Type	**ProjFocus**	*Physical/Biogeochemical*	Project's main aim is to characterize features of the physical environment or biogeochemistry.
		Biological	Project's main aim is to characterize biological features with no direct examination of the physical environment
		Physical/Biogeochemical & Biological	Project main aim incorporates both physical/biogeochemical information as well as biological (including chlorophyll). Both types of data are in reference tied together to inform the same question.
	PhysFocus Optional descriptive classificiation of focus of physical/biogeochemical studies. If study looked at more than one of these focus areas enter all that apply separated by a "/".	*Environmental Characterization*	If project focuses on either physical characterization or biological and physical characterization then this clarifies that the general goal was to generally characterize features of the environment that did not include oceanographic or seawater chemistry. Examples are spot measurements of temperature and DO used to provide reference to characteristics.
		Oceanographic Characterization	If project focuses on either physical characterization or biological and physical characterization then this clarifies that the general goal was to characterize oceanographic aspects of the environment, such as wind shear, seawater chemistry, salinity, etc. outside of the estuarine environment.
		Estuarine Environmental Monitoring	If project focuses on either physical characterization or biological and physical characterization then this clarifies that the general goal was to generally characterize environmental features related to the estuarine seawater chemistry, hydrography or other estuarine specific parameters.
	BioFocus Optional descriptive classification of focus for biological studies. If study looked at more than one of these focus areas enter all that apply separated by a "/".	*classification is determined study, examples include:*	
		Plankton Distribution	Study focused on examining the distribution, abundance, and/or community composition of plankton. Examples are projects focusing on characterizing prey availability for oceanic salmon.
		Shellfish Population Assessment	Study characterized the population, distribution, and/or abundance of shellfish
		Benthic Community	Study explicitly examined the community structure of benthic in-fauna

		Structure and Abundance	and/or meiofauna. May include shellfish but the purpose was general characterization of community structure.
		Water Quality	Study focused on characterizing the bacterial presence or loading within discrete samples. Examples include enterococcus assays.
		Habitat Characterization	Main purpose of the study was to characterize the structure, function, or physical characteristics of habitat within an area. Examples include seagrass surveys.
	InstiType	*Agency*	Lead institution is affiliated with federal, state, county, or city agencies.
		Academic	Lead institution is affiliated with an academic institution (i.e. research institute, university, etc.)
		Tribal	Lead institution is affiliated with a tribal government or natural resource program.
		Non-profit	Lead institution is affiliated with a non-profit organization.
		Academic/Agency	Project is a collaborative effort lead by academic institutions and agency(ies)
		Academic/Non-profit	Project is a collaborative effort lead by non-profit and academic institutions
		Agency/Tribal	Project is a collaborative effort lead by agency(ies) and tribal partners
		Tribal/Academic	Project is a collaborative effort lead by tribal and academic institutions
	AssetType	*Survey Area*	The asset is a represented by a polygon. Generally represents an area where survey efforts is concentrated. Indicative of systematic survey efforts that characterize more than the single points where samples are collectected.
		Cruise Station	The asset is represented by discrete point locations visited by a cruise. Cruise stations are generally a single part of a broader segment or leg. Locations are generally at sea or in estuarine settings that allow for visit by a research vessel.
		Cruise	The asset is represented by a polyline. Data were collected continuously while underway and are not represented by point locations.
		Glider	The asset is represented by a polyline/ Data was collected continuously by a remotely operated or autonomous glider.
		Sample Site	The asset is represented by point. Represents an area where data were collected in a discrete fashion such as with bacterial monitoring sites. Generally indicates that site was returned to at some frequency.
		Shoreside sensor	The asset is represented by a point. Indicates an in situ sensor that is mounted shoreside in either the intertidal, a flow through seawater system, or dock side.
		Mooring	The asset is represented by a point. Indicates an in situ sensor moored in the open ocean, nearshore, or estuarine environment.
	StudyType	*Cruise*	Study was part of a research cruise.

		Field Survey	Study was part of a survey that was collecting data or samples in the field that was not a cruise. Generally indicates that the samples collected were discrete. May include studies that characterize habitat, water quality, population assessments, etc.
		In Situ	Information collected by study was collected by in situ measurements.
	OAHFocus	*Ocean acidification*	Asset measured at least one parameter of ocean acidification (pH, pCO2, TA, DIC) but not Hypoxia (DO)
		Ocean acidification & hypoxia	Asset measured at least one parameter of ocean acidification (pH, pCO2, TA, DIC) AND Hypoxia (DO)
		Hypoxia	Asset measured DO but no other OA parameters.
		None	Asset did not measure OA (pH, pCO2, TA, DIC) or H (DO), but was including in the inventory for another reason (e.g. monitoring program represents a key monitoring asset, likely to expand OAH monitoring at sites)
Location Characteristics	**TidalExp**	*Yes or No*	Indicates whether the sensor is exposed on low tide or not. Denotes the shore zone and general habitat type a asset in located in. Is relative to both depth and habitat characteristics.
	EcoType	*Nearshore*	Asset collected information from the marine environment within an area 30m water depth.
		Offshore	Asset collected information from the marine environment within an area with greater than 30m water depth.
		Estuarine	Asset was deployed in an estuarine setting.
		Estuarine Aquaculture	Asset was deployed in an estuarine bivalve aquaculture setting. May be in either hatchery or on active aquaculture facility.
	Latitude	*Location <latitude>*	Cartesian latitude of a point asset. Reported in decimal degrees. Data stored as geographic/unprojected decimal degrees in the WGS 1984 datum.
	Longitude	*Location<longitude>*	Cartesian longitude of a point asset. Reported in decimal degrees. Data stored as geographic/unprojected decimal degrees in the WGS 1984 datum.
Depth of Measurements	**Depth_m_**	*<number>*	The fixed depth (meters) that measurements are recorded at an asset. If there are multiple discrete depths that measurements are made at separate depths using the ";". Do not use if information was recorded as a profile across multiple depths.
	ProfileMin	*<number>*	The shallowest depth (meters) that a profile starts to record measurements at. If multiple profiles are made by an asset use the shallowest depth.
	ProfileMax	*<number>*	The deepest depth (meters) that a profile recorded measurements at. If multiple profiles are made by an asset use the deepest depth.
Temporal Characteristics	**MeasType**	*Spot*	An asset collected discrete measurement on OAH parameters
		Continuous	An asset collected measurements on OAH parameters continuously for a high frequency of time, in situ
		NA	An asset does not collect OAH parameters

	MeasFreq **How often are measurements collected during the measurement period?** **Please use the most frequent interval for your answer. (i.e. if pH sampled at 30 and pCO2 sampled every 60 minutes then enter 30 minutes)**	*<number> units:minutes, decimal*	If asset records more frequently than every 6 hours please record the interval (minutes) as a continuous values. i.e. hourly would equal 60 (minutes), twice every minute would be 0.5 minutes.
		> 6 hours	measurements collected more than once a day but less frequently than every 6 hours
		Daily	measurements collected once a day
		Bi-monthly	measurements collected every other month
		Semi-monthly	measurements collected twice a month
		Annual	measurements collected once a year
		Semi-annual	measurements collected twice a year
		Biannual	measurements collected every other year
		Triannual	measurements collected every three years
		5 years	measurements collected every 5 years
		Once	measurements collected only once during the measurement period.
	MeasPeriod **The period during any given year that an instrument or project was recording measurements or collecting information.**	*Year-round*	Measurements are collected year round, not including sensor failure or short gaps.
		<month - month>	Measurements are collected during certain months of the year
	DataFreq	*<frequency>*	Frequency at which data is uploaded to a publically available website
	ProgDur	*<number> unit: year, integer*	Whole number of years that monitoring program collected measurements. Values >= 1.
	StartYr	*<year>*	Year that monitoring program began
	EndYr	*present*	Year that monitoring program ended/Will end
		<year>	Year that monitoring program ended/Will end
	YearSamp	*<year - year>*	range of years asset is actively collecting data. If asset is still collecting data, range goes to "present"
	Ongoing	*Yes or No*	Yes: project is currently active. No: project has ended.
OAH Parameters	**DiscSWpCO2**	*Yes or No*	Discrete seawater pCO2 measurements measured in a laboratory.
	ATMpCO2	*Yes or No*	Discrete atmospheric pCO2 measurements measured using laboratory equipment.
	DiscSWpH	*Yes or No*	Discrete pH measurement made using laboratory methods or instruments.

	DiscTA	*Yes or No*	Discrete measurement of Total Alkalinity.
	DiscDIC	*Yes or No*	Discrete measurement of Dissolved In Organic Carbon using laboratory instruments.
	SatSt	*Yes or No*	Study included a calculation of carbonate ion concentration.
	DiscDO	*Yes or No*	Discrete measurement of dissolved oxygen using laboratory instruments or methods.
	isSWpCO2	*Yes or No*	in situ measurement of seawater pCO2
	isSWpH	*Yes or No*	pH was measured under in situ conditions
	isDIC	*Yes or No*	Dissolved inorganic carbon was measured under in situ conditions.
	isDO	*Yes or No*	Dissolved oxygen was measured under in situ conditions.
	CalcPmtrs **If more than one is calculated separate using ";".**	*pH*	pH is calculated rather than measured at this assset.
		pCO2	pCO2 is calculated rather than measured at this assset.
		DIC	DIC is calculated rather than measured at this assset.
		TA	TA is calculated rather than measured at this assset.
	Methods	*<methods>*	Method used to measure discrete parameters
	Instrument	*<instruments>*	Manufacturer and model of in situ instruments used to measure in situ parameters.
	DisCrbPmtr	*<number>*	Number of carbonate parameters (pH, pCO2, TA, DIC) measured at an asset using discrete sampling techniques.
	ISCrbPmtr	*<number>*	Number of carbonate parameters (pH, pCO2, TA, DIC) measured at an asset regardles of sample type using in situ sensors.
Other Water Quality Parameters	**Temp**	*Yes or No*	Denotes whether or not temperature was recorded by a project.
	Salinity	*Yes or No*	Denotes whether or not salinity was recorded by a project.
	Pressure	*Yes or No*	Denotes whether or not pressure was recorded by a project.
	Turbidity	*Yes or No*	Denotes whether or not Turbidity was recorded by a project.
	DOC	*Yes or No*	Denotes whether or not dissolved organic carbon was recorded by a project.
	OtherPhys	*<parameters>*	Additional physical or biogeochemical parameters measured
	Chlorophyl	*Yes or No*	Denotes whether or not chlorophyll was recorded by a project.
Nutrients	**Nutrients**	*Yes or No*	Denotes whether or not nutrients were measured by a project.

	Nitrate	*Yes or No*	Denotes whether or not nitrate concentration was determined by a project.
	Ammonium	*Yes or No*	Denotes whether or not ammonium concentration was determined by a project.
	Phosphate	*Yes or No*	Denotes whether or not phosphate concentration was determined by a project.
	Silicate	*Yes or No*	Denotes whether or not Silicate concentration was determined by a project.
	Iron	*Yes or No*	Denotes whether or not iron concentration was determined by a project.
Biological Parameters	**BioSamples**	*None*	Project did not collect any biological samples.
		Phytoplankton	Project collected measurements on phytoplankton.
		Zooplankton	Project collected measurements on zooplankton.
		Invertebrates	Project collected measurements on invertebrates (not including shellfish)
		Shellfish	Project collected measurements on shellfish (e.g. oysters, mussels)
		Fish	Project collected measurements on fish
		Macrophytes	Project collected measurements on aquatic plants, including seagrass and algae
		Coral	Project collected measurements on coral
	BioAbund	*Yes or No*	Project examined the number of organisms in the environment, the relative abundance (% cover), or assessed the population size.
	BioAdapt	*Yes or No*	Project explictly examined the ability for an organism to adapt to changing environmental or ecological conditions.
	BioBiomass	*Yes or No*	Project examined or determined the biomass of an organism relative to environmental conditions or assessed the population of an organism.
	BioCalc	*Yes or No*	Project explcitly examined the rate of calcification of an organism relative to environmental conditions.
	BioComm	*Yes or No*	Project explcitly examined the community composition or structure.
	BioDistr	*Yes or No*	Project examined the distribution or population change of an organism in space or time.
	BioDiv	*Yes or No*	Project examined biodiversity of ecological community.
	BioEvol	*Yes or No*	Project examined the ability of an population to respond to changing environmental conditions.
	BioFoodweb	*Yes or No*	Project examined the structure and function of the foodweb.
	BioGrRate	*Yes or No*	Project examined the change in mass, size, or volume overtime.

	BioPhtosyn	*Yes or No*	Project examined the rate, efficiency, or mechanism of photosynthesis relative to OAH conditions.
	BioRecr	*Yes or No*	Project examined the addition of organisms to a population.
	BioSurv	*Yes or No*	Project examined the survival or organisms relative to environmental conditions or predation.
	BioMovmnt	*Yes or No*	Project examined the movement of organisms in space and time.
	BioBehvor	*Yes or No*	Project described the behavior of organisms.
	OtherBio	*<other>*	Additional biological parameters measured

Appendix 2. Data exploration for Hog Island in Tomales Bay, CA.

Time series plots represent data collected by a Burkeolator deployed by CeNCOOS in 2015.

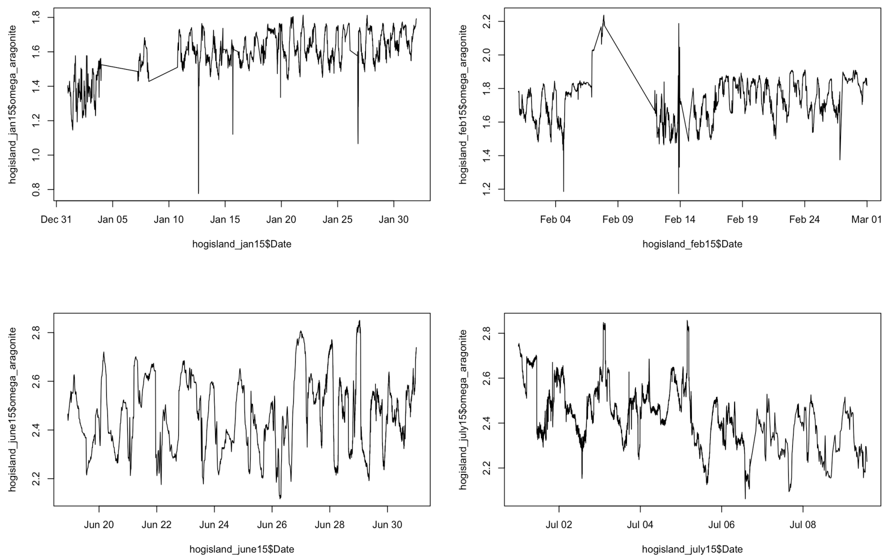


Figure 1. Monthly Aragonite Saturation State at Hog Island for select months.

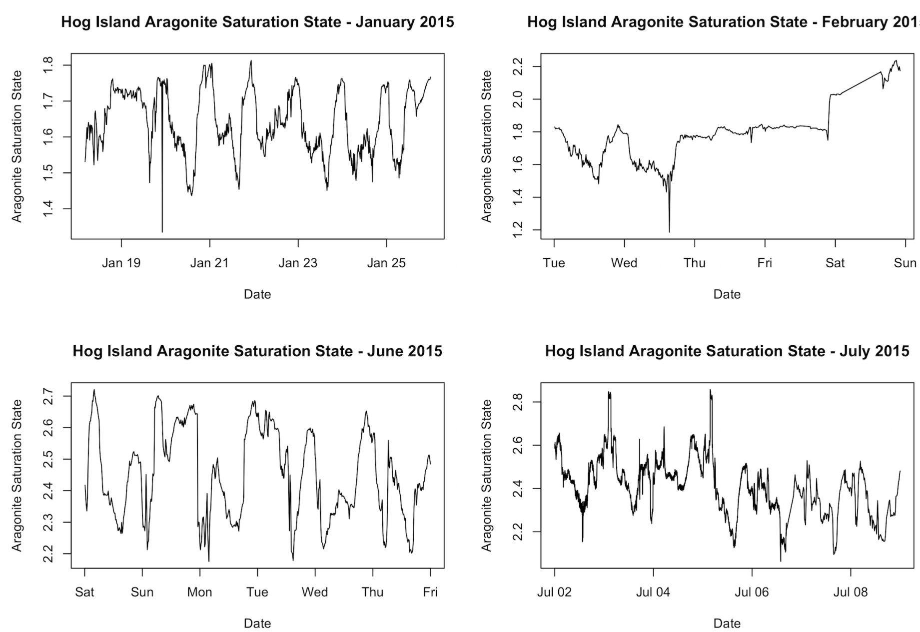


Figure 2. Weekly Aragonite Saturation State at Hog Island for select weeks.

Appendix 3. Monitoring Inventory Gap Analysis R Code

Ocean Acidification Monitoring Inventory Gap Analysis

Step 1. Manipulate sea surface temperature and dissolved oxygen as proxies for ocean acidificiation change

Load packages

```
if (!require(pacman)) install.packages("pacman")
library(pacman)
p_load(
  tidyverse, here, glue,
  raster,
  sdmpredictors, dismo,
  deldir,
  mapview,
  tmap)

devtools::load_all(here("../oatools"))
```

Set paths and variables

```
dir_data        <- here("data")
dir_sdmdata_old <- here("data/sdmpredictors")
dir_cache       <- here("cache")
dir_sdmdata     <- here("cache/sdmpredictors")

SST_tif <- here("data/sst_mean.tif")
DO_tif  <- here("data/do_mean.tif")
```

Set cache

```
if (!dir.exists(dir_data))    dir.create(dir_data)
if (!dir.exists(dir_cache))   dir.create(dir_cache)
if (!dir.exists(dir_sdmdata) & dir.exists(dir_sdmdata_old))
  file.rename(dir_sdmdata_old, dir_sdmdata)
if (!dir.exists(dir_sdmdata)) dir.create(dir_sdmdata)
```

Set extent and coordinate reference system

```
ext_study <- extent(-670000, 350000, -885000, 1400000)
crs_study <- '+init=EPSG:6414'
```

Create sea surface temperature layer (mean and range)

```
r_sst_mean_nofill <- lyr_to_tif(
  lyr = "BO_sstmean",
  tif = here("data/sst_mean.tif"),
  crs = crs_study,
  dir_sdm_cache = dir_sdmdata,
  extent_crop = ext_study,
  redo=T, fill_na=FALSE)

r_sst_mean <- lyr_to_tif(
  lyr = "BO_sstmean",
  tif = here("data/sst_mean.tif"),
  crs = crs_study,
  dir_sdm_cache = dir_sdmdata,
  extent_crop = ext_study,
  redo=T, fill_na=TRUE, fill_window=11) #caclulate mean

n_na_nofill <- sum(is.na(raster::getValues(r_sst_mean_nofill)))
n_na        <- sum(is.na(raster::getValues(r_sst_mean)))

r_sst_range_nofill <- lyr_to_tif(
  lyr = "BO_sstrange",
  tif = here("data/sst_range.tif"),
  crs = crs_study,
  dir_sdm_cache = dir_sdmdata,
  extent_crop = ext_study,
  redo=T, fill_na=FALSE)

r_sst_range <- lyr_to_tif(
  lyr = "BO_sstrange",
  tif = here("data/sst_range.tif"),
  crs = crs_study,
  dir_sdm_cache = dir_sdmdata,
  extent_crop = ext_study,
  redo=T, fill_na=TRUE, fill_window=11)
```

Create dissolved oxygen layer (mean and range)

```
r_do_mean_nofill <- lyr_to_tif(
  lyr = "BO_dissox",
  tif = here("data/do_mean.tif"),
  crs = crs_study,
  dir_sdm_cache = dir_sdmdata,
  extent_crop = ext_study,
  redo=T, fill_na=FALSE)

r_do_mean <- lyr_to_tif(
```

```r
  lyr = "BO_dissox",
  tif = here("data/do_mean.tif"),
  crs = crs_study,
  dir_sdm_cache = dir_sdmdata,
  extent_crop = ext_study,
  redo=T, fill_na=TRUE, fill_window=11) #calculate mean

r_do_range_nofill <- lyr_to_tif(
  lyr = "BO2_dissoxrange_bdmin",
  tif = here("data/do_range.tif"),
  crs = crs_study,
  dir_sdm_cache = dir_sdmdata,
  extent_crop = ext_study,
  redo=T, fill_na=FALSE)

r_do_range <- lyr_to_tif(
  lyr = "BO2_dissoxrange_bdmin",
  tif = here("data/do_range.tif"),
  crs = crs_study,
  dir_sdm_cache = dir_sdmdata,
  extent_crop   = ext_study,
  redo=T, fill_na=TRUE, fill_window=11)
```

Step 2. Relate SST and DO trends to each monitoring site

Load and clean monitoring inventory

```r
inventory <- read_csv(here("data/inventory.csv"))

oahfocus <- subset(inventory, OAHFocus == "OA" | OAHFocus == "H" | OAHFocus == "OAH") # remove non-OAH focus entries

unique(oahfocus$MeasFreq) # quantify frequencies

oahfocus$MeasFreq[oahfocus$MeasFreq =="Once"] <- 0
oahfocus$MeasFreq[oahfocus$MeasFreq == 10] <- 52560
oahfocus$MeasFreq[oahfocus$MeasFreq =="< 6 hours"] <- 1460
oahfocus$MeasFreq[oahfocus$MeasFreq == 60] <- 8760
oahfocus$MeasFreq[oahfocus$MeasFreq =="Daily"] <- 365
oahfocus$MeasFreq[oahfocus$MeasFreq ==30] <- 17520
oahfocus$MeasFreq[oahfocus$MeasFreq == 20] <- 26280
oahfocus$MeasFreq[oahfocus$MeasFreq == 15] <- 35040
oahfocus$MeasFreq[oahfocus$MeasFreq =="Quarterly"] <- 4
oahfocus$MeasFreq[oahfocus$MeasFreq =="Annual"] <- 1
oahfocus$MeasFreq[oahfocus$MeasFreq =="Monthly"] <- 12
oahfocus$MeasFreq[oahfocus$MeasFreq == 5] <- 105120
oahfocus$MeasFreq[oahfocus$MeasFreq == 6] <- 87600
oahfocus$MeasFreq[oahfocus$MeasFreq =="Semi-annual"] <- 2
```

```
oahfocus$MeasFreq[oahfocus$MeasFreq == 180] <- 2920
oahfocus$MeasFreq[oahfocus$MeasFreq == 2] <- 262800
oahfocus$MeasFreq[oahfocus$MeasFreq == 0.25] <- 2102400
oahfocus$MeasFreq[oahfocus$MeasFreq == 3] <- 175200
oahfocus$MeasFreq[oahfocus$MeasFreq == 1] <- 525600
oahfocus$MeasFreq[oahfocus$MeasFreq == 120] <- 2920
oahfocus$MeasFreq[oahfocus$MeasFreq =="Bi-weekly"] <- 26
oahfocus$MeasFreq[oahfocus$MeasFreq == 360] <- 1460

oahfocus$MeasFreq[oahfocus$MeasFreq == 720] <- 730
oahfocus$MeasFreq[oahfocus$MeasFreq =="Seasonally"] <- 1
oahfocus$MeasFreq[oahfocus$MeasFreq =="1/4 second"] <- 126144000
oahfocus$MeasFreq[oahfocus$MeasFreq =="Bi-monthly"] <- 6
oahfocus$MeasFreq[oahfocus$MeasFreq =="5  Years"] <- 0.2
oahfocus$MeasFreq[oahfocus$MeasFreq =="Bi-weekly"] <- 26
oahfocus$MeasFreq[oahfocus$MeasFreq =="Variable"] <- 0
oahfocus$MeasFreq[oahfocus$MeasFreq =="Decadal"] <- 0.1
oahfocus$MeasFreq[oahfocus$MeasFreq =="Biennial"] <- 0.5
oahfocus$MeasFreq[oahfocus$MeasFreq =="Weekly"] <- 52
oahfocus$MeasFreq[oahfocus$MeasFreq =="Triennial"] <- 0.33333
oahfocus$MeasFreq[oahfocus$MeasFreq =="Trimester"] <- 3

oahfocus <- oahfocus[!is.na(oahfocus$Latitude), ] # remove N/A coordinates
oahfocus <- oahfocus[!is.na(oahfocus$Longitude), ]

gsub(" ", "", oahfocus$Latitude) # remove spaces and transform to numeric
gsub(" ", "", oahfocus$Longitude)
gsub("'<ca>'", "", oahfocus$Longitude)
oahfocus$Longitude <- as.numeric(oahfocus$Longitude)
oahfocus$Latitude <- as.numeric(oahfocus$Latitude)

carbcomplete <- subset(oahfocus, DisCrbPmtr>1 | ISCrbPmtr > 1) # create subsets
incomplete <- subset(oahfocus, DisCrbPmtr<2 & ISCrbPmtr < 2)
highfrequency <- subset(oahfocus, MeasFreq > 364)
highfreqcarbcomplete <- subset(oahfocus, MeasFreq > 364 & DisCrbPmtr>1 |
        MeasFreq > 364 & ISCrbPmtr > 1)
lowfrequency <- subset(oahfocus, MeasFreq < 365)
```

Transform subsets into spatial data

```
coords <- cbind.data.frame(oahfocus$Longitude, oahfocus$Latitude) #isolate coordinate columns
carbcompletecoords <- cbind.data.frame(carbcomplete$Longitude, carbcomplete$Latitude)
incompletecoords <- cbind.data.frame(incomplete$Longitude, incomplete$Latitude)
highfrequencycoords <- cbind.data.frame(highfrequency$Longitude, highfrequency$Latitude)
lowfrequencycoords <- cbind.data.frame(lowfrequency$Longitude, lowfrequency$Latitude)
highfreqcarbcompletecoords <- cbind.data.frame(highfreqcarbcomplete$Longitude, highfreqcarbcomplete$Latitude)
```

```
deduped.coords <- unique(coords) # remove duplicate locations
deduped.carbcomplete <- unique(carbcompletecoords)
deduped.incomplete <- unique(incompletecoords)
deduped.highfrequency <- unique(highfrequencycoords)
deduped.lowfrequency <- unique(lowfrequencycoords)
deduped.highfreqcarbcomplete <- unique(highfreqcarbcompletecoords)

inventorycoords <- SpatialPoints(deduped.coords, CRS("+proj=longlat +ellps=WGS84"))
inventorycoords <- spTransform(inventorycoords, CRS('+init=EPSG:6414')) # create spatial poi
nts objects

carbcompletecoords <- SpatialPoints(deduped.carbcomplete, CRS("+proj=longlat +ellps=WGS8
4"))

carbcompletecoords <- spTransform(carbcompletecoords, CRS('+init=EPSG:6414'))

incompletecoords <- SpatialPoints(deduped.incomplete, CRS("+proj=longlat +ellps=WGS84"))

incompletecoords <- spTransform(incompletecoords, CRS('+init=EPSG:6414'))

highfreqcoords <- SpatialPoints(deduped.highfrequency, CRS("+proj=longlat +ellps=WGS84"))

highfreqcoords <- spTransform(highfreqcoords, CRS('+init=EPSG:6414'))

lowfreqcoords <- SpatialPoints(deduped.lowfrequency, CRS("+proj=longlat +ellps=WGS84"))

lowfreqcoords <- spTransform(lowfreqcoords, CRS('+init=EPSG:6414'))

highfreqcarbcompletecoords <- SpatialPoints(deduped.highfreqcarbcomplete, CRS("+proj=lon
glat +ellps=WGS84"))

highfreqcarbcompletecoords <- spTransform(highfreqcarbcomplete, CRS('+init=EPSG:6414'))
```

Create voronoi polygons

```
vor <-voronoi(inventorycoords)

carbcompletevor <- voronoi(carbcompletecoords)

incompletevor <- voronoi(incompletecoords)

highfreqvor <- voronoi(highfreqcoords)

lowfreqvor <- voronoi(lowfreqcoords)

vorraster<- rasterize(vor, r_sst_mean, "id") #rasterize

carbcompletevorraster<- rasterize(carbcompletevor, r_sst_mean, "id")

incompletevorraster<- rasterize(incompletevor, r_sst_mean, "id")
```

```r
highfreqvorraster<- rasterize(highfreqvor, r_sst_mean, "id")

lowfreqvorraster<- rasterize(lowfreqvor, r_sst_mean, "id")
```

Extract SST mean and range for each monitoring site cell and substitute value for each voronoi polygon

```r
sitesst<- raster::extract(r_sst_mean, inventorycoords, method='simple', df=TRUE) # extract SST value for each monitoring site cell
carbcompletesitesst<- raster::extract(r_sst_mean, carbcompletecoords, method='simple', df=TRUE)
highfreqsitesst<- raster::extract(r_sst_mean, highfreqcoords, method='simple', df=TRUE)

colnames(sitesst)<- c("id", "SST") #rename column names of site SST
colnames(carbcompletesitesst)<- c("id", "SST")
colnames(highfreqsitesst)<- c("id", "SST")

polygonsst <- subs(vorraster, sitesst, by="id", which="SST", subsWithNA=FALSE) # substitute polygon ID for monitoring site SST of that polygon
carbcompletepolygonsst <- subs(carbcompletevorraster, carbcompletesitesst, by="id", which="SST", subsWithNA=FALSE)
highfreqpolygonsst <- subs(highfreqvorraster, highfreqsitesst, by="id", which="SST", subsWithNA=FALSE)

sitesstrange<- raster::extract(r_sst_range, inventorycoords, method='simple', df=TRUE) # repeat with SST range
carbcompletesitesstrange<- raster::extract(r_sst_range, carbcompletecoords, method='simple', df=TRUE)
highfreqsitesstrange<- raster::extract(r_sst_range, highfreqcoords, method='simple', df=TRUE)

colnames(sitesstrange)<-c("id", "SSTrange")
colnames(carbcompletesitesstrange)<- c("id", "SSTrange")
colnames(highfreqsitesstrange)<- c("id", "SSTrange")

polygonsstrange<-subs(vorraster, sitesstrange, by="id", which="SSTrange", subsWithNA=FALSE)
carbcompletepolygonsstrange <- subs(carbcompletevorraster, carbcompletesitesstrange, by="id", which="SSTrange", subsWithNA=FALSE)
highfreqpolygonsstrange <- subs(highfreqvorraster, highfreqsitesstrange, by="id", which="SSTrange", subsWithNA=FALSE)
```

Repeat with DO

```r
sitedo<- raster::extract(r_do_mean, inventorycoords, method='simple', df=TRUE) # extract DO value for each monitoring site cell
carbcompletesitedo<- raster::extract(r_do_mean, carbcompletecoords, method='simple', df=TRUE)
highfreqsitedo<- raster::extract(r_do_mean, highfreqcoords, method='simple', df=TRUE)
```

```
colnames(sitedo)<-c("id", "DO") # rename column names of site DO

colnames(carbcompletesitedo)<- c("id", "DO")
colnames(highfreqsitedo)<- c("id", "DO")

polygondo<-subs(vorraster, sitedo, by="id", which="DO") # substitute polygon ID for monitorin
g site DO of that polygon
carbcompletepolygondo<-subs(carbcompletevorraster, carbcompletesitedo, by="id", which="D
O")
highfreqpolygondo<-subs(highfreqvorraster, highfreqsitedo, by="id", which="DO")

sitedorange<- raster::extract(r_do_range, inventorycoords, method='simple', df=TRUE) # repea
t with DO range
carbcompletesitedorange<- raster::extract(r_do_range, carbcompletecoords, method='simple',
df=TRUE)
highfreqsitedorange<- raster::extract(r_do_range, highfreqcoords, method='simple', df=TRUE)

colnames(sitedorange)<-c("id", "DOrange")
colnames(carbcompletesitedorange)<- c("id", "DO")
colnames(highfreqsitedorange)<- c("id", "DO")

polygondorange<-subs(vorraster, sitedorange, by="id", which="DOrange")
carbcompletepolygondorange<-subs(carbcompletevorraster, carbcompletesitedorange, by="id
", which="DO")
highfreqpolygondorange<-subs(highfreqvorraster, highfreqsitedorange, by="id", which="DO")
```

Step 3. Create “oceanographic variability” layer relative to monitoring asset

Normalize values

```
r_sst_mean_nofill_norm <- r_sst_mean_nofill/maxValue(r_sst_mean_nofill)
r_sst_range_nofill_norm <- r_sst_range_nofill/maxValue(r_sst_range_nofill)
r_do_mean_nofill_norm <- r_do_mean_nofill/maxValue(r_do_mean_nofill)
r_do_range_nofill_norm <- r_do_range_nofill/maxValue(r_do_range_nofill)

polygonsst_norm <- polygonsst/maxValue(r_sst_mean_nofill)
carbcompletepolygonsst_norm <- carbcompletepolygonsst/maxValue(r_sst_mean_nofill)
highfreqpolygonsst_norm <- highfreqpolygonsst/maxValue(r_sst_mean_nofill)

polygonsstrange_norm <- polygonsstrange/maxValue(r_sst_range_nofill)
carbcompletepolygonsstrange_norm<-carbcompletepolygonsstrange/maxValue(r_sst_range_n
ofill)
highfreqpolygonsstrange_norm <- highfreqpolygonsstrange/maxValue(r_sst_range_nofill)

polygondo_norm <- polygondo/maxValue(r_do_mean_nofill)
```

```
carbcompletepolygondo_norm <- carbcompletepolygondo/maxValue(r_do_mean_nofill)
highfreqpolygondo_norm <- highfreqpolygondo/maxValue(r_do_mean_nofill)

polygondorange_norm <- polygondorange/maxValue(r_do_range_nofill)
carbcompletepolygondorange_norm <- carbcompletepolygondorange/maxValue(r_do_range_
nofill)
highfreqpolygondorange_norm <- highfreqpolygondorange/maxValue(r_do_range_nofill)
```

Create spatial and temporal variation values

```
# variation = (imean - amean) + (imean - amean)*(irange – arrange)
where i = cell in raster of study area and a = cell containing nearest monitoring site

sstmeandiff <- abs(r_sst_mean_nofill - polygonsstnorm) # SST mean
carbcompletesstmeandiff <- abs(r_sst_mean_nofill - carbcompletepolygonsstnorm)
highfreqsstmeandiff <- abs(r_sst_mean_nofill - highfreqpolygonsstnorm)

sstrangediff <- abs(r_sst_range_nofill - polygonsstrangenorm) # SST range
carbcompletesstrangediff <- abs(r_sst_range_nofill - carbcompletepolygonsstrangenorm)
highfreqsstrangediff <- abs(r_sst_range_nofill - highfreqpolygonsstrangenorm)

domeandiffnorm <- abs(r_do_mean_nofill - polygondonorm) # DO mean
carbcompletedomeandiff <- abs(r_do_mean_nofill - carbcompletepolygondonorm)
highfreqdomeandiff <- abs(r_do_mean_nofill - highfreqpolygondonorm)

dorangediff <- abs(r_do_range_nofill - polygondorangenorm) # DO range
carbcompletedorangediff <- abs(r_do_range_nofill - carbcompletepolygondorangenorm)
highfreqdorangediff <- abs(r_do_range_nofill - highfreqpolygondorangenorm)
```

Step 4. Identify gaps

Identify gaps based on distance between monitoring points, qualified by strength of variability

```
distanceweight = 10^-11
temporalweight = 10

dissimilarity <- sqrt((sstmeandiff^2 + domeandiff^2) + temporalweight * (sstrangediff^2 + dora
ngediff^2)) # Oceanographic dissimilarity

carbcompletedissimilarity <- sqrt((carbcompletesstmeandiff^2 + carbcompletedomeandiff^2)
+ temporalweight * (carbcompletesstrangediff^2 + carbcompletedorangediff^2))

highfreqdissimilarity <- sqrt((highfreqsstmeandiff^2 + highfreqdomeandiff^2) + temporalweig
ht * (highfreqsstrangediff^2 + highfreqdorangediff^2))
```

Sensitivity analysis

```
# Create matrix of weights

distanceweight = c(10^-5, 10^-6, 10^-7, 10^-8, 10^-9, 10^-10, 10^-11, 10^-12, 10^-13, 10^-14)

temporalweight = c(2, 4, 6, 8, 10, 12, 14, 16, 18, 20)

# Create list of 100 rasters of top 1% of gaps

rastersensitivity <- list()

for(i in 1:length(distanceweight)){

 for(j in 1:length(temporalweight)){

   dissimilarity <- sqrt((sstmeandiff^2 + domeandiff^2) + temporalweight[j]*(sstrangediff^2 + d
orangediff^2))

   distance <- distanceFromPoints(dissimilarity, inventorycoords) * distanceweight[i]

   gap <- setValues(distance, sqrt((getValues(distance)^2 + (getValues(dissimilarity)^2))))

   highprioritygaps <- setValues(distance, sqrt((getValues(distance)^2 + (getValues(dissimilarit
y)^2)))) > quantile(gap, (.99))

   name = paste(temporalweight[j], distanceweight[i], sep = "_")

   rastersensitivity[[name]] = highprioritygaps

 }

}

# Transform to RasterStack

sensitivitystack <- stack(rastersensitivity[[1]])

for(i in 2:length(rastersensitivity))
        sensitivitystack <- addLayer(sensitivitystack, rastersensitivity[[i]])

# Add up values

sum <- sum(sensitivitystack)

plot(sum)

freq(sum)

overlap <- setValues(sum, getValues(sum == 100))

plot(overlap)
```

```r
freq(overlap)
```

Visualize gaps along the West Coast

```r
poly_coast <- readOGR(dsn=path.expand("Export_Output_2"), layer="Export_Output_2")

poly_coast <- spTransform(poly_coast, crs(gaps))

gaps_clipped <- mask(gaps, poly_coast, inverse = TRUE, progress='text')
```

Map final gaps

```r
tm_shape(finalgaps) +
 tm_raster(palette = pal(4), colorNA = NULL, breaks = c(-0.5, 0.5, 1.5, 2.5, 3.5), title = "Ocean Ac
idification Data Gaps", labels = c("Sufficient Data", "Low Priority Gaps", "High Priority Gaps", "S
evere Gaps")) +
 tm_layout(main.title = "Data Gap Severity", main.title.size = 1, bg.color = "white", main.title.p
osition = c("center", "top"), legend.show = TRUE, legend.position = c("right", "center"), fontfami
ly = "serif", fontface = "bold") +
 tm_layout(basemaps = c('OpenStreetMap')) +
 tm_legend() +
 tm_shape(inventorycoords) +
 tm_dots(col = "black")
```

Appendix 4. Sea Surface Temperature and Dissolved Oxygen Layers

Layers used to account for oceanographic variability as part of the Gap Analysis. Raster layers are from the Bio-ORACLE dataset (Assis et al. 2017, Tyberghein et al. 2012). Rasters for the mean and range of each parameter represent data from 2000-2014 based on monthly averages. The data are derived from satellite and in situ observations and downscaled to a common spatial resolution using kriging. The default projection is Behrmann cylindrical equal-area and the resolution is 5 arcmin (~9.2 km at the equator).

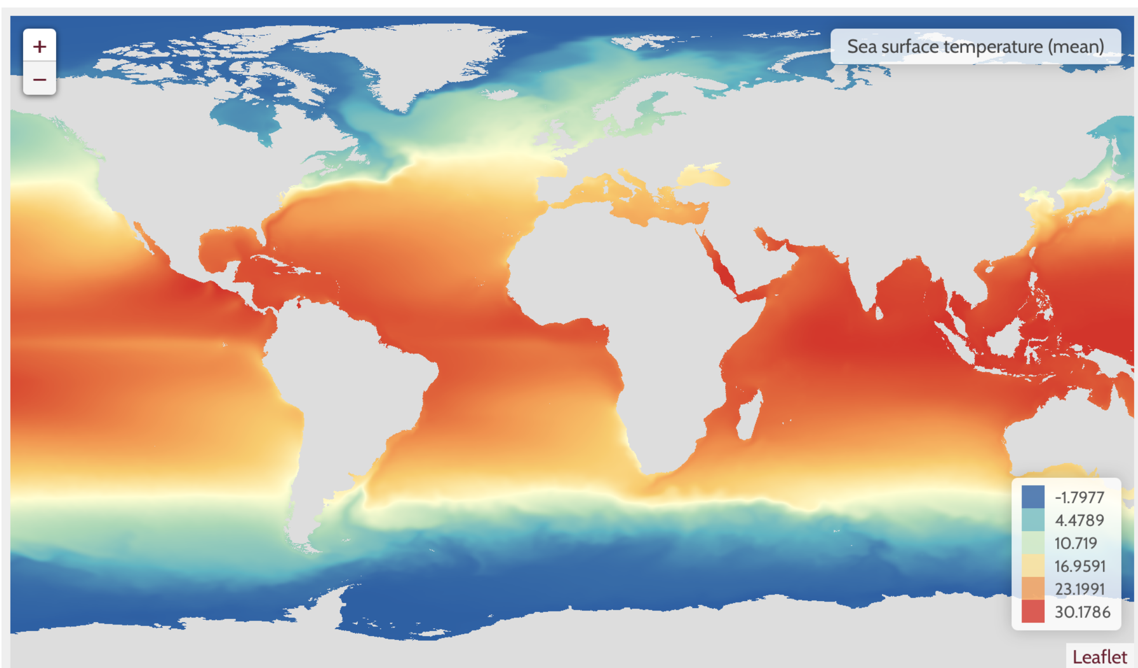


Figure 1. Mean Sea Surface Temperature

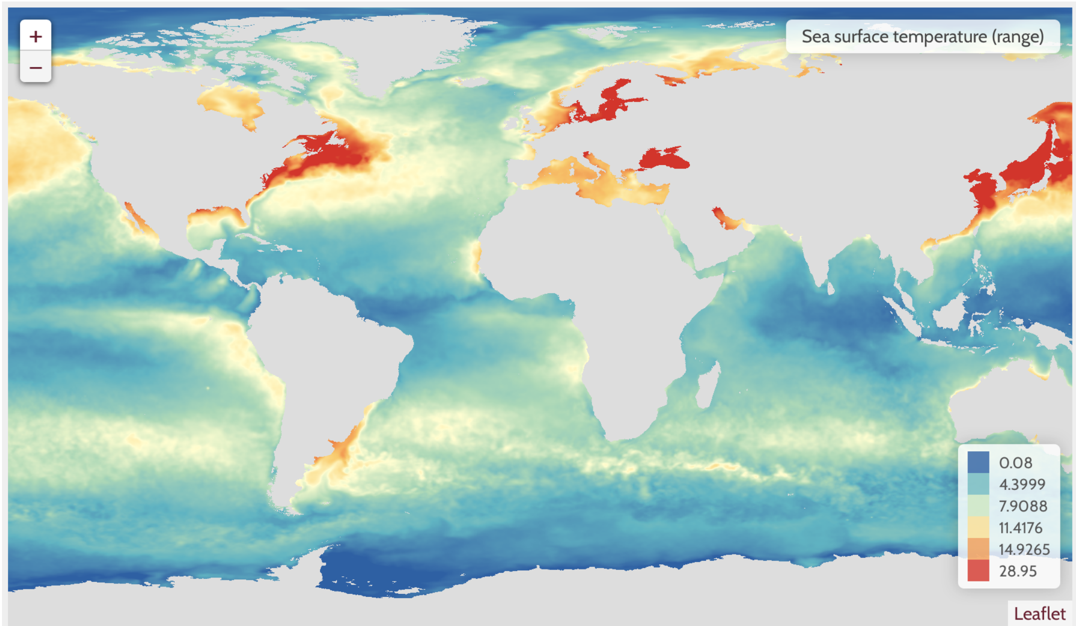


Figure 2. Range Sea Surface Temperature

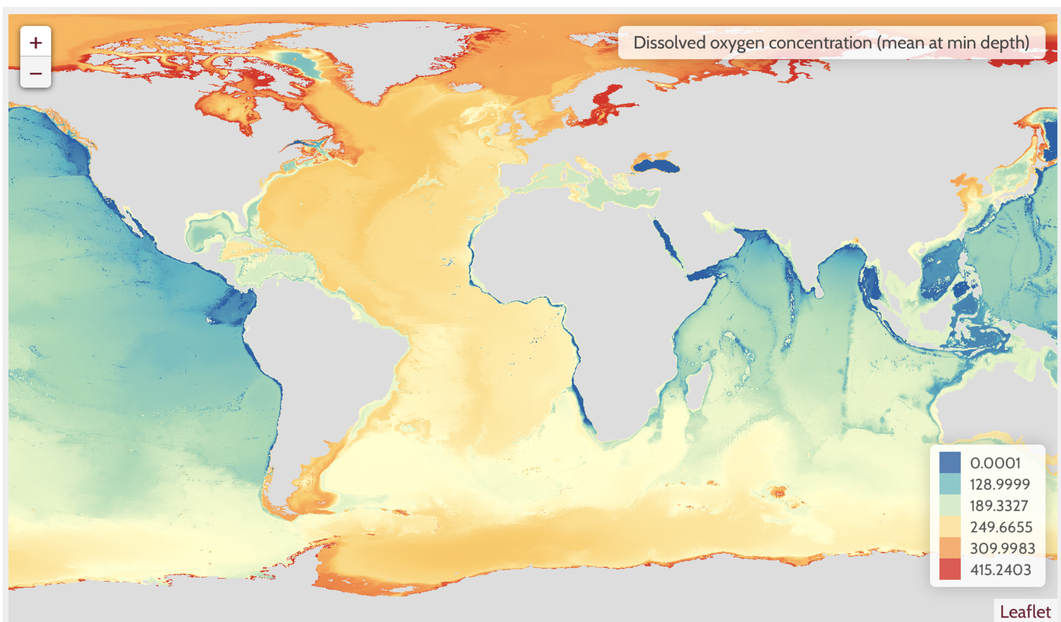


Figure 3. Mean Surface Dissolved Oxygen Concentration

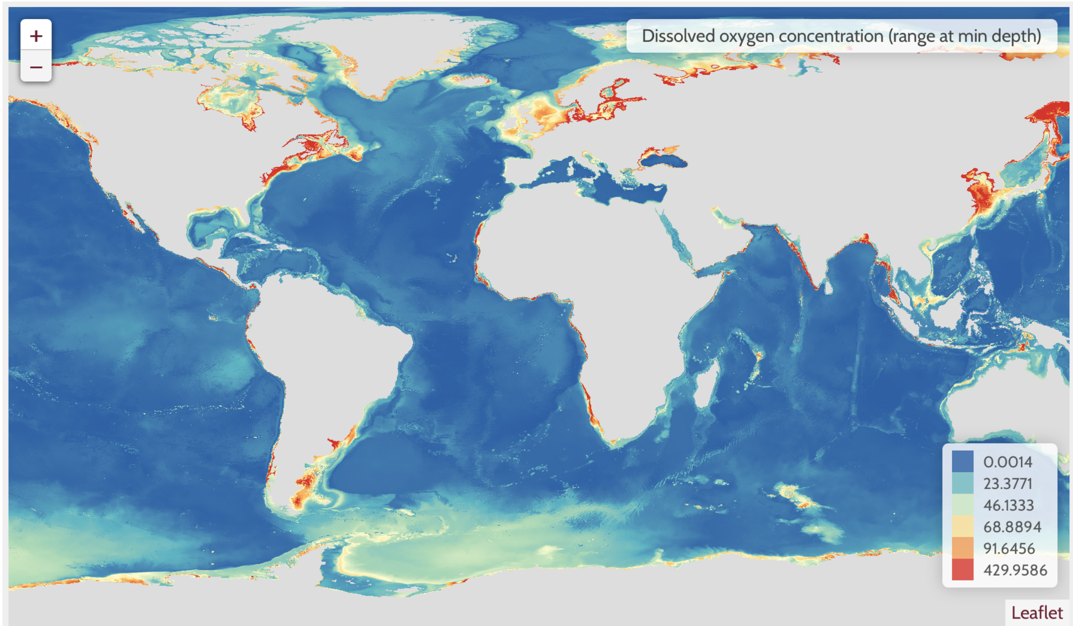
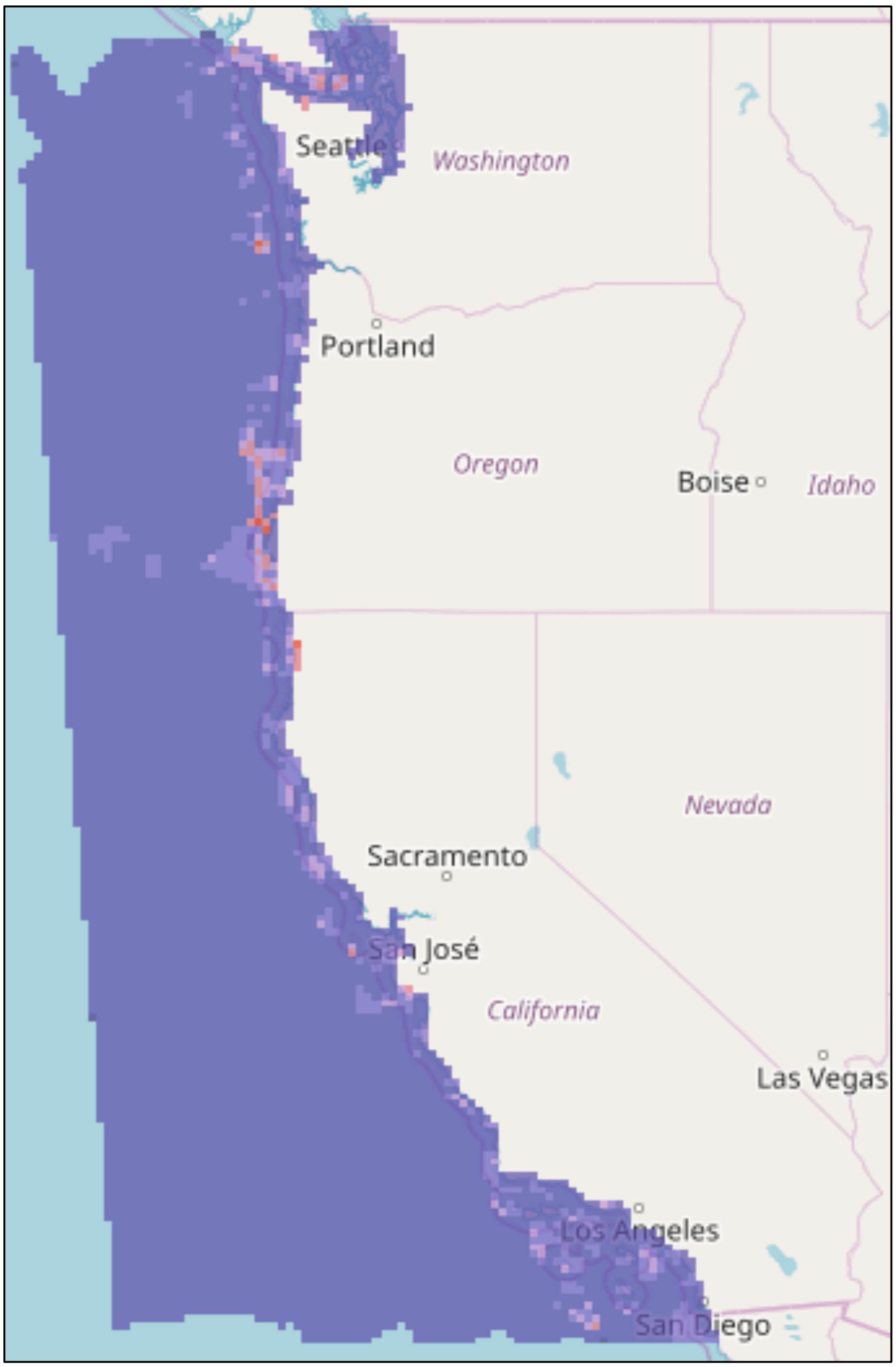


Figure 4. Range Surface Dissolved Oxygen Concentration

Appendix 5. Oceanographic Dissimilarity

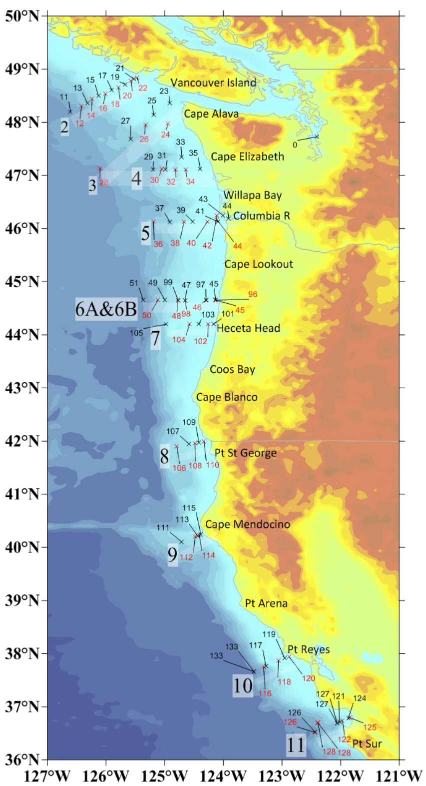
Generated with the layers from Bio-ORACLE. The visualization shows high variability off the coast of southern Oregon as well as in the Straight of Juan De Fuca.



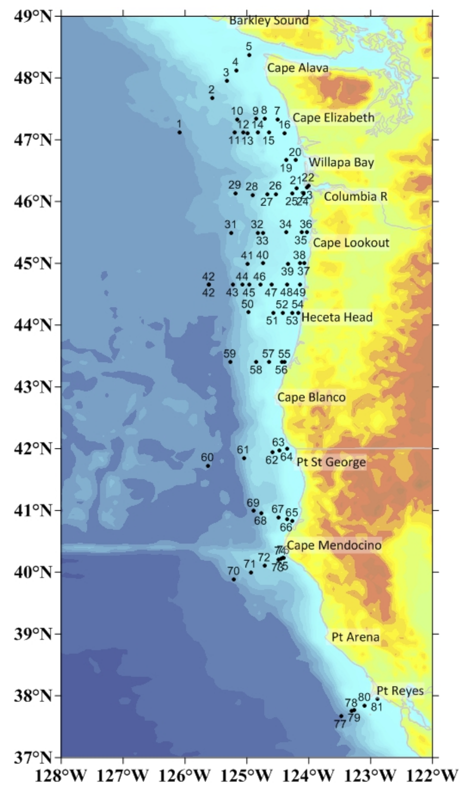
Appendix 6. Metadata and sampling locations for each NOAA West Coast Ocean Acidification Cruise

Title	Dates	Geographic Boundaries	Range	Cruise Stations	Transect lines
2013 West Coast Ocean Acidification Cruise	August 3-10, 21-29, 2013	36.52°N to 48.84°N by 126.61°W to 121.85°W	Vancouver Island, CAN to Point Sur, CA	76	10
2012 West Coast Ocean Acidification Cruise	September 4-17, 2012	37.67°N to 48.38°N by 126.09°W to 122.89°W	Olympic Coast, WA to Point Sur, CA	77	14
2011 West Coast Ocean Acidification Cruise	August 12-30, 2011	31.95°N to 48.38°N by 127.55°W to 117.75°W	Olympic Coast, WA to San Diego, CA	90	13
2007 West Coast Ocean Acidification Cruise	May 11 - June 14, 2007	24.92°N to 52.23°N by 112.82°W to 132.82°W	Bella Bella, CAN to Baja California, MX	115	13

2013 Cruise Stations

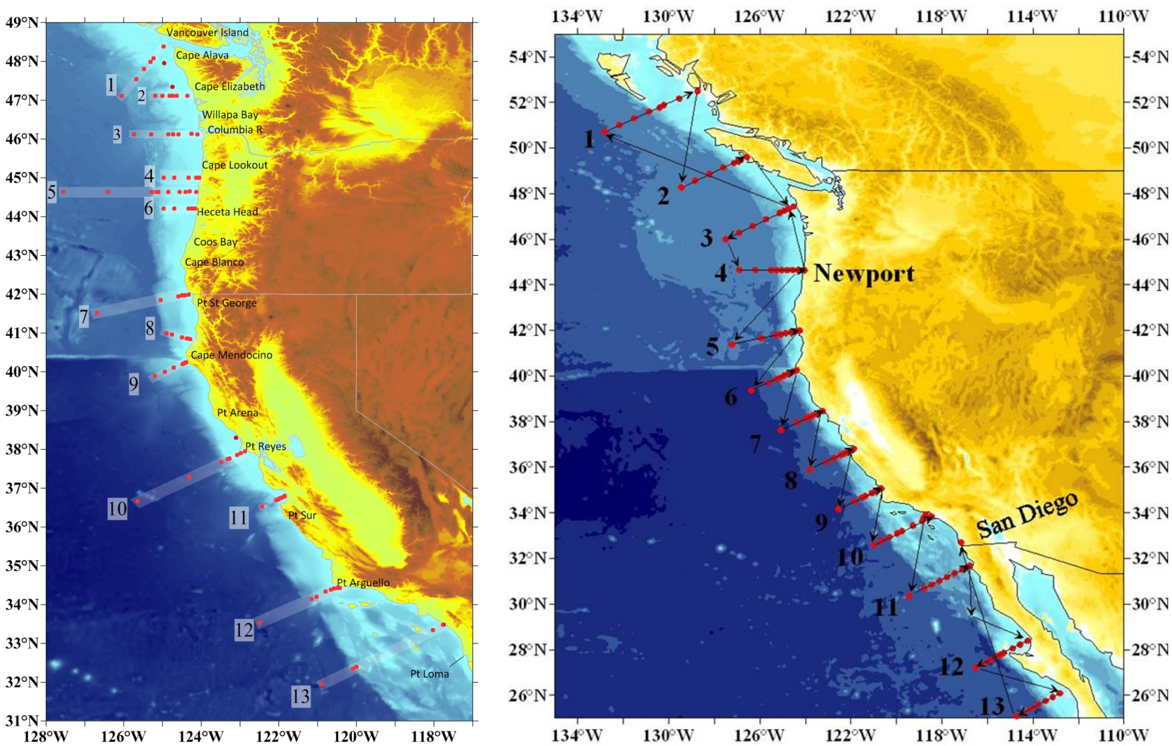


2012 Cruise Stations



2011 Cruise Stations

2007 Cruise Stations



Vancouver Island
Cape Alava
Cape Elizabeth
Willapa Bay
Columbia R
Cape Lookout
Heceta Head
Coos Bay
Cape Blanco
Pt St George
Cape Mendocino
Pt Arena
Pt Reyes
Pt Sur
Pt Arguello
Pt Loma
Newport
San Diego

Appendix 7. OA Hotspots and MPA Analysis R Code

Ocean Acidification Hotspot and MPA Analysis

Part 1. Create Predicted Aragonite Saturation State Surfaced via Kriging

Load packages

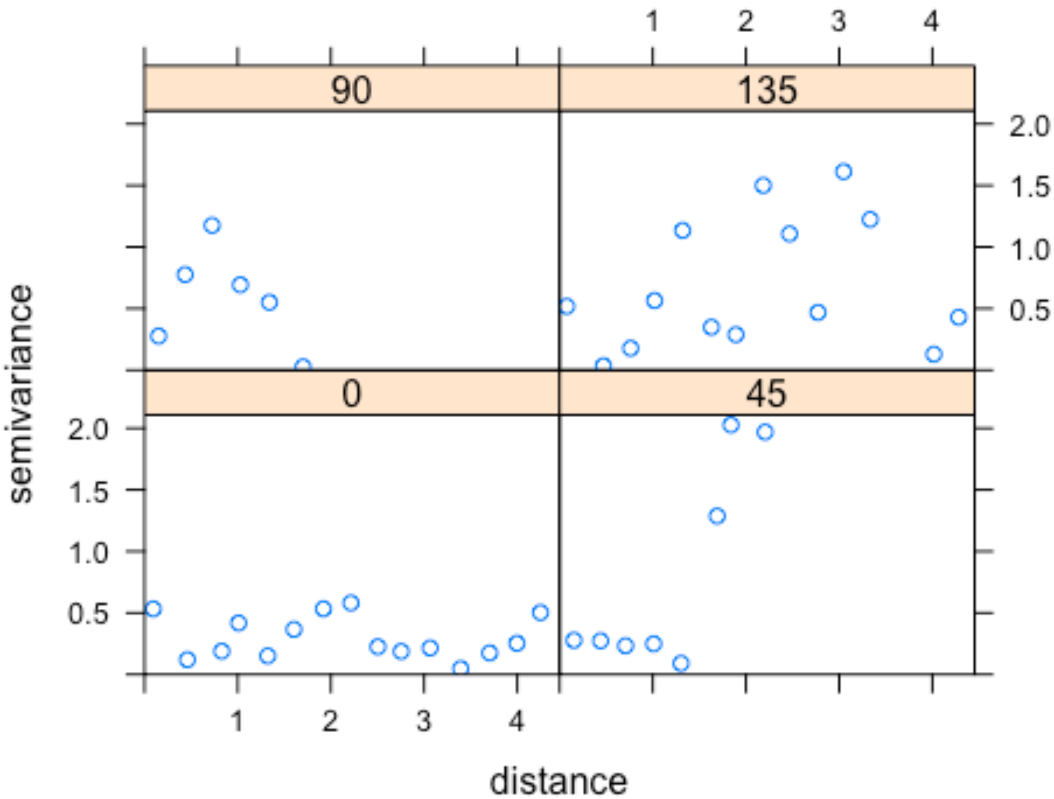
```
if (!require(pacman)) install.packages("pacman")
library(pacman)
p_load(
  tidyverse, here,
  sp, rgdal, gstat, raster,
  mapview)
```

Prepare cruise data set

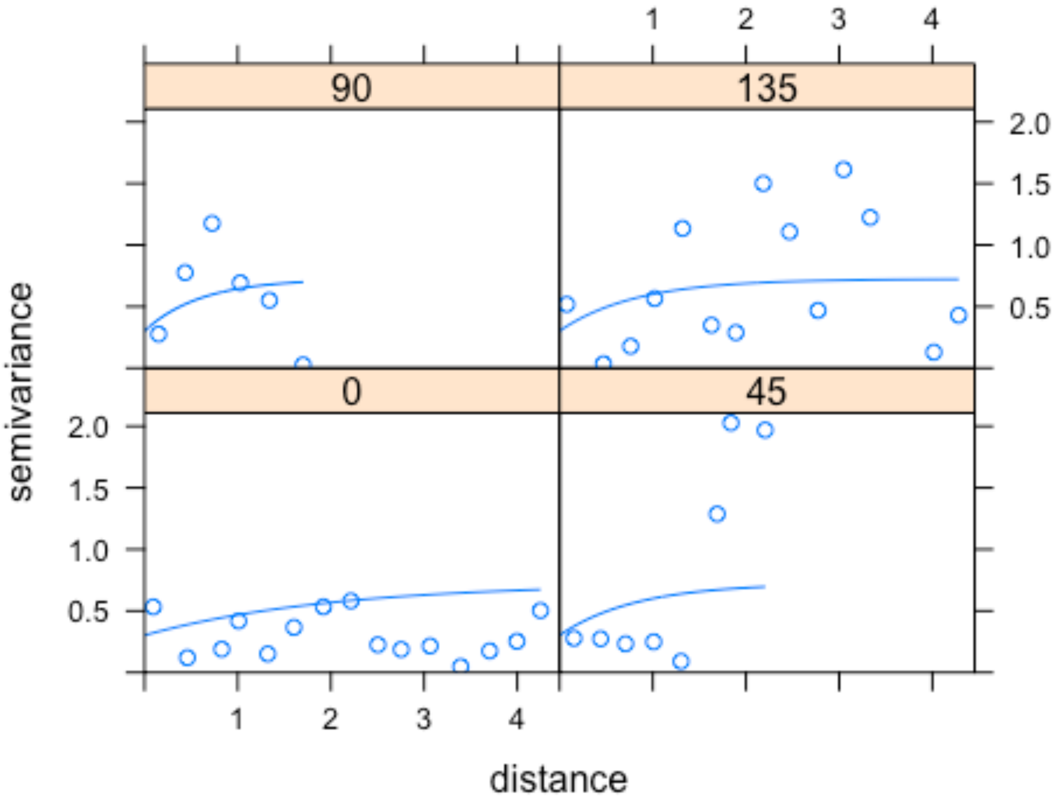
```
aragonite_data <- read_csv(here("data/WCOAC_2013_test.csv")) #load data
colnames(aragonite_data) <- c("Date", "Time", "Lat", "Long", "Pressure", "OmegaAr") #rename c
olumns in dataframe

aragonite_data <- aragonite_data %>% #remove N/A values
  mutate(OmegaAr=replace(OmegaAr, OmegaAr==-999.000, NA)) %>%
  na.omit(aragonite_data)

aragonite_data<- aragonite_data[aragonite_data[, 5]<5,] #filter for surface observations

coordinates(aragonite_data)<-  ~ Long + Lat #transform into spatial points

zd<-zerodist(aragonite_data)
aragonite_data<-aragonite_data[-zd[,2],] #remove observations taken at same coordinate point
```

Interpolation via simple kriging

```
aragonite_var<-variogram(OmegaAr ~1, data=aragonite_data, alpha=c(0, 45, 90, 135))
plot(aragonite_var) #look for anisotropy and create variogram of aragonite values
```




```
aragonite_fit<-fit.variogram(aragonite_var,model=vgm(nugget=0.2,psill=1,range=2,model="Exp", anis=c(0, 0.3))) #fit a model to the values based on estimated nugget, sill, and range, and anisotropy
plot(aragonite_var,aragonite_fit)
```




```
extent <- bbox(aragonite_data) #get extent of cruise observations
long<-seq(extent[1,1],extent[1,2],length=388) #increase ROI by one degree in each direction
lat<-seq(extent[2,1],extent[2,2],length=1000)

aragonite_grid<-expand.grid(long,lat) #create grid for interpolation surface
colnames(aragonite_grid)<- c("long", "lat")
coordinates(aragonite_grid) <- ~ long + lat
gridded(aragonite_grid)=TRUE

aragonitekrige<-krige(OmegaAr ~ 1, aragonite_data, newdata=aragonite_grid, model=aragonit
e_fit) #run kriging on interpolation grid, based on best fit model
```

Create continuous raster

```
aragonite_raster<-raster(aragonitekrige, layer=1, values=TRUE) #transform krige object to rast
er
projection(aragonite_raster) <- CRS("+proj=longlat +datum=WGS84") #set CRS
aragonite_raster_proj <- projectRaster(aragonite_raster, crs=CRS('+init=EPSG:6414'),method="
ngb") #re-project to California Teale Albers Equal Area
```

Part 2. Create hotspot thresholds mask

```
thresholds <- c(0,1,1, 1,1.7,1.7, 1.7,2,2, 2,10,NA)
thresholdsmatrix <- matrix(thresholds, ncol=3, byrow=TRUE)
hotspotmask <- reclassify(aragonite_raster_proj, thresholdsmatrix)
```

Part 3. Compare predicted aragonite saturation state and hotspots to MPA Location

Load shapefiles

```
poly_MPA <- readOGR(dsn=path.expand("/Users/Madi/Documents/UCSB Bren/ResilienSeas/al
l_mpas_update"), layer="all_mpas_update") #load MPAs

poly_MPA <- spTransform(poly_MPA, crs(aragonite_raster_proj)) #assign same CRS as aragon
ite layer

poly_coast<- readOGR(dsn=path.expand("/Users/Madi/Documents/UCSB Bren/ResilienSeas/Ex
port_Output_2"), layer="Export_Output_2") #load coast

poly_coast <- spTransform(poly_coast, crs(aragonite_raster_proj)) #assign same CRS

Canada  <- readOGR(dsn=path.expand("/Users/courtneycochran/Downloads/Canada"), layer="
Canada") # load Canadian coast file

Canada <- spTransform(Canada, crs(aragonite_raster_proj)) #assign same CRS

estuary  <- readOGR(dsn=path.expand("/Users/courtneycochran/Downloads/estuaries"), layer
="altb02") # load estuaries

estuary <- spTransform(estuary, crs(aragonite_raster_proj)) #assign same CRS

pugetsound <- readOGR(dsn=path.expand("/Users/courtneycochran/Downloads/hotspot_squa
re"), layer="hotspot_square") #load Puget Sound shape

pugetsound <- spTransform(pugetsound, crs(aragonite_raster_proj)) #assign same CRS
```

Clip rasters to coast

```
aragonite_clipped <- mask(aragonite_raster_proj, poly_coast, inverse = TRUE) #clip continuou
s raster
aragonite_clipped <- mask(aragonite_clipped, estuary, inverse= TRUE, progress='text') #remov
e nearshore estuaries from analysis
aragonite_clipped <- mask(aragonite_clipped, Canada, inverse= TRUE, progress='text') #clip to
Canadian coast

hotspot_clipped <- mask(hotspotmask, poly_coast, inverse = TRUE) #clip hotspot mask
hotspot_clipped <- mask(hotspot_clipped, estuary, inverse=TRUE) #remove nearshore estuarie
s from analysis
hotspot_clipped <- mask(hotspot_clipped, Canada, inverse=TRUE) #clip to Canadian coast
```

Zonal statistics - mean saturation state

```
aragonite_mean<- raster::extract(aragonite_clipped, poly_MPA, fun=mean, na.rm=TRUE, df=
TRUE) #calculate mean aragonite saturation state from continuous layer and export as datafra
me
colnames(aragonite_mean) <- c("OBJECTID", "ARAGONITE_MEAN")

poly_MPA@data[,1] <- seq(1, length(poly_MPA@data[,1])) #Replace "OBJECTID" with sequenc
ed list to remove duplicates and change from factor to integer form
poly_MPA@data <- poly_MPA@data %>%
 left_join(aragonite_mean, by = 'OBJECTID')
```

Zonal statistics - percent cover of hotspot

```
pctcover <- raster::extract(hotspot_clipped, poly_MPA, fun=function(x, ...) length(na.omit(x))
/length(x), df=TRUE) #calculate percentage of total MPA area covered by threshold of concern
colnames(pctcover) <- c("OBJECTID", "PCT_HOTSPOTCOVER")

poly_MPA@data <- poly_MPA@data %>%
 left_join(pctcover, by = 'OBJECTID')
```

Part 4. Visualize MPAs and hotspots

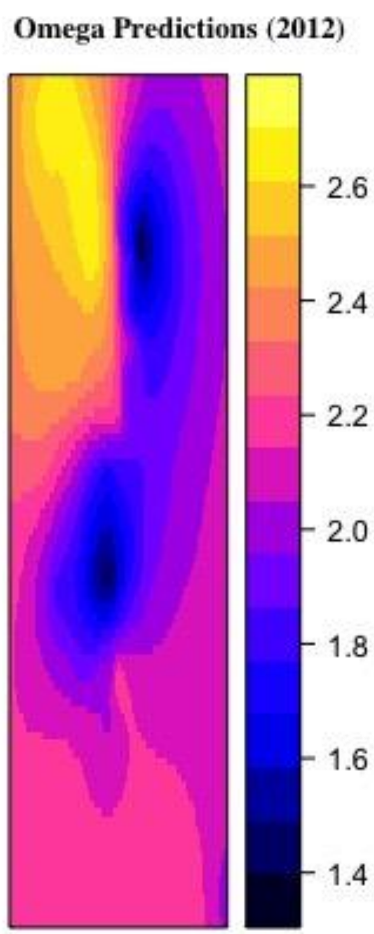
Zonal statistics - percent cover of hotspot

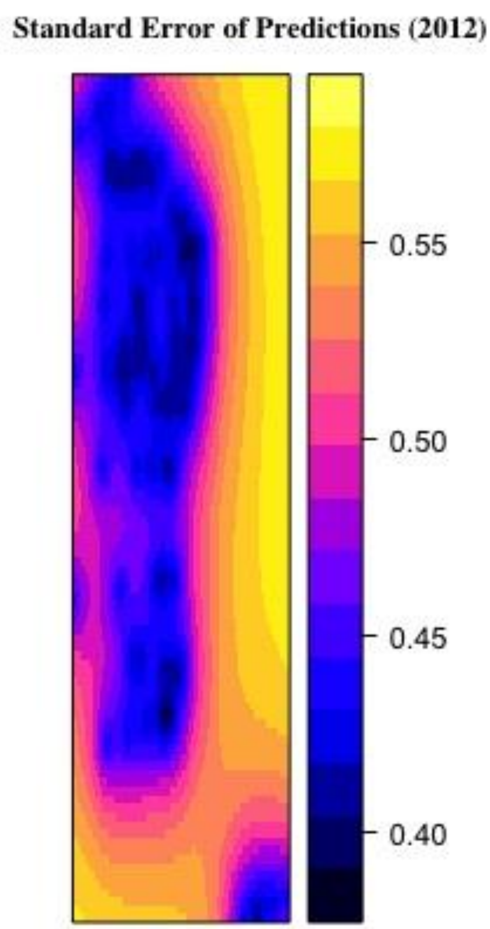
```
pal <- colorRampPalette(c("red", "white", "royalblue2"))

tm_shape(aragonite_clipped_2) +
 tm_raster(palette = pal(3),  breaks = seq(0.8,3, by=0.2),
          title="Aragonite Saturation State") +
 tm_layout(basemaps = c('OpenStreetMap'))


tm_shape(poly_MPA) + tm_polygons("ARAGONITE_MEAN", palette=pal(3), colorNA=NULL,
     breaks = seq(0.8,3, by=0.2),
     title="Mean Aragonite \nSaturation State") +
 tm_layout(basemaps = c('OpenStreetMap'))
```

Appendix 8. Raw Kriging Output and Standard Error of Predictions for NOAA OA Cruises

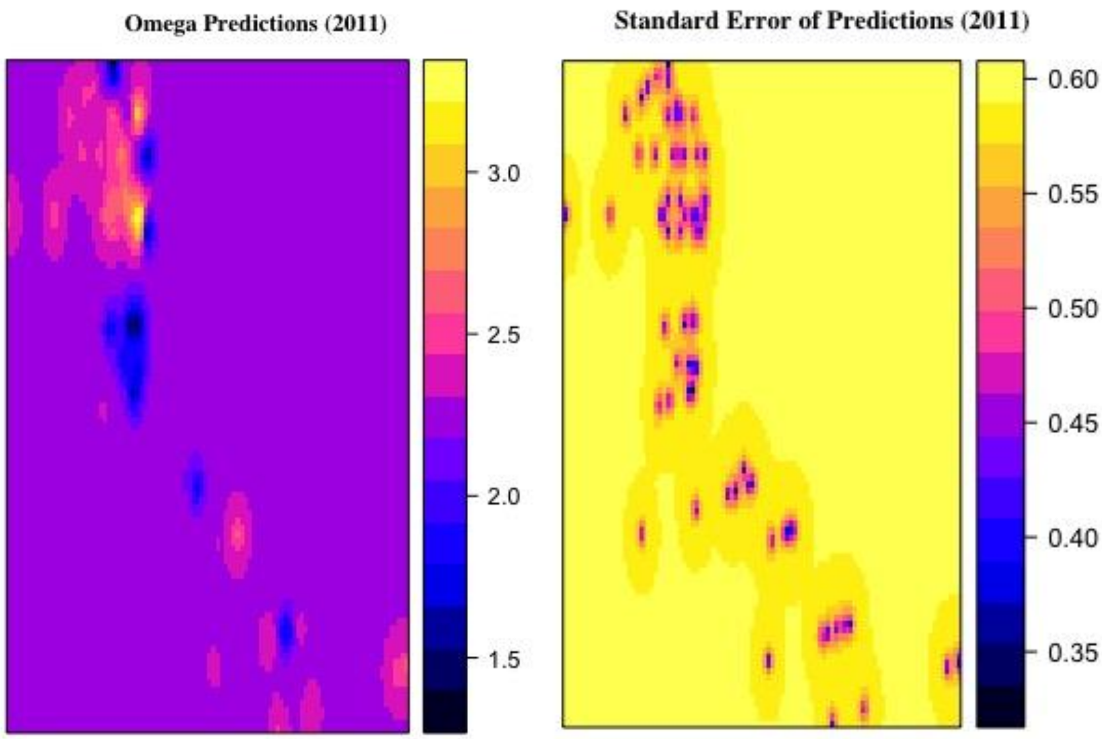
Kriging output and standard error of predictions for each NOAA OA Cruise (2012, 2011, 2007). The visualizations on the left show that the predictive power of our interpolation degrades quickly over the longshore direction. The visualization on the right demonstrates the standard error of our interpolation. Lower standard error values co-occur with our identified locations of hotspots.

2012 Cruise

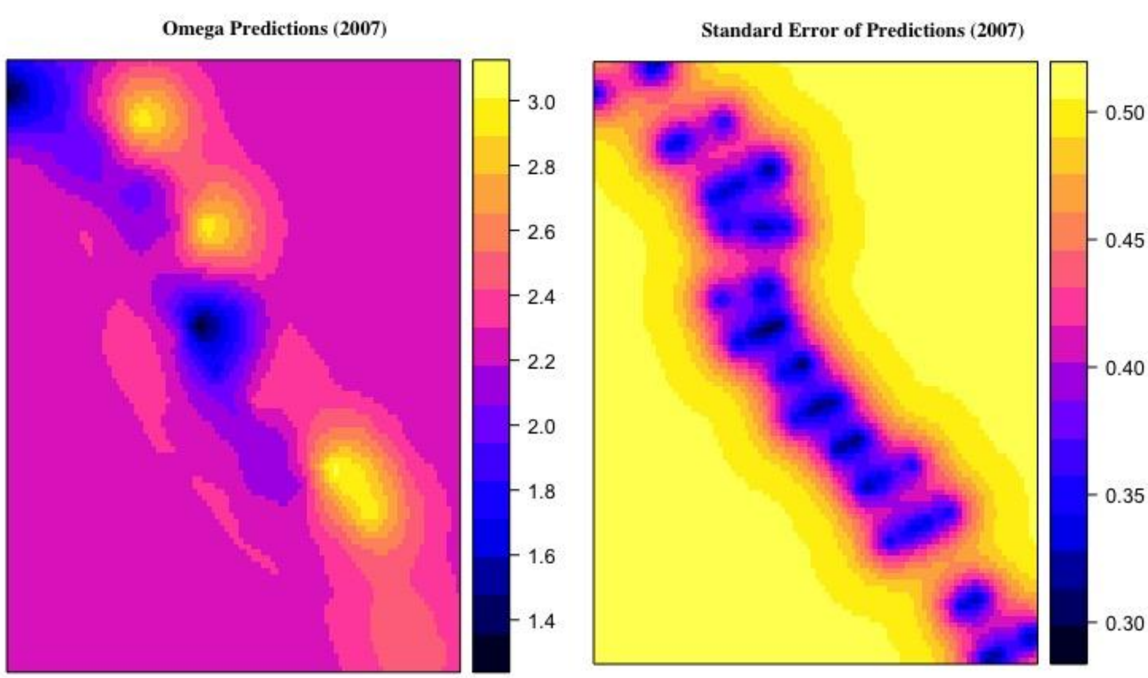




2011 Cruise



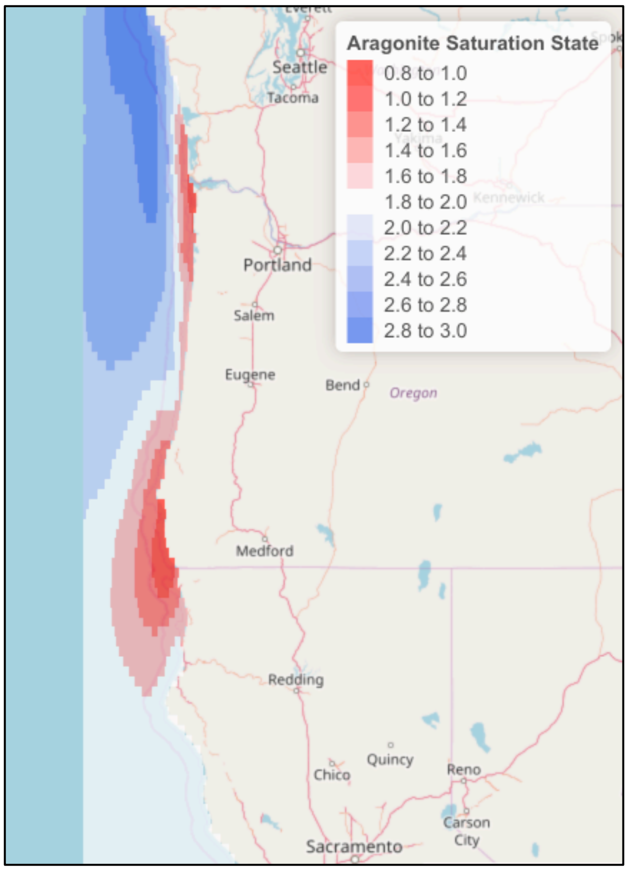
2007 Cruises



Appendix 9. Aragonite Saturation State Interpolation Outputs for NOAA OA Cruises

Continuous aragonite saturation state interpolation and ocean acidification hotspot raster for 2007, 2011, and 2012 NOAA West Coast Ocean Acidification Cruise.

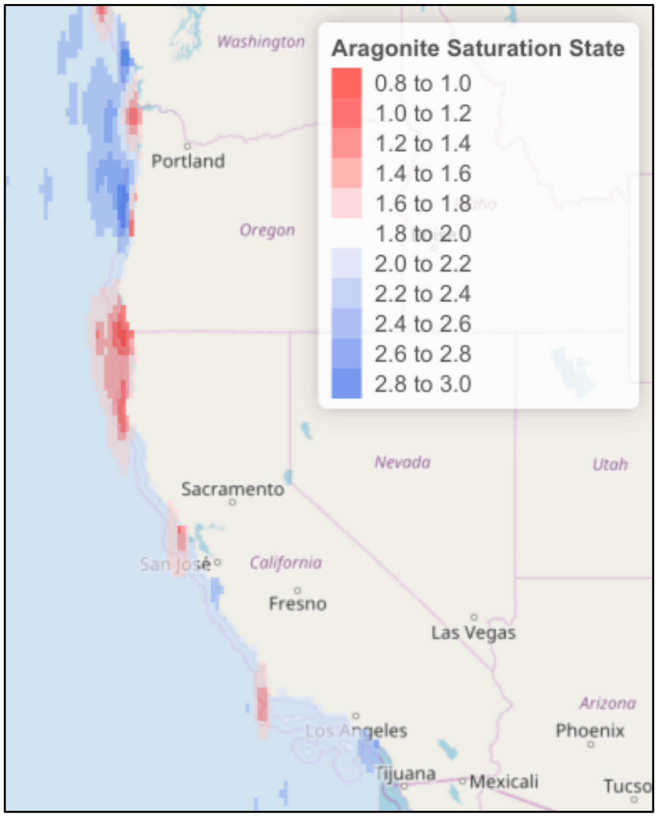
2012 Cruise



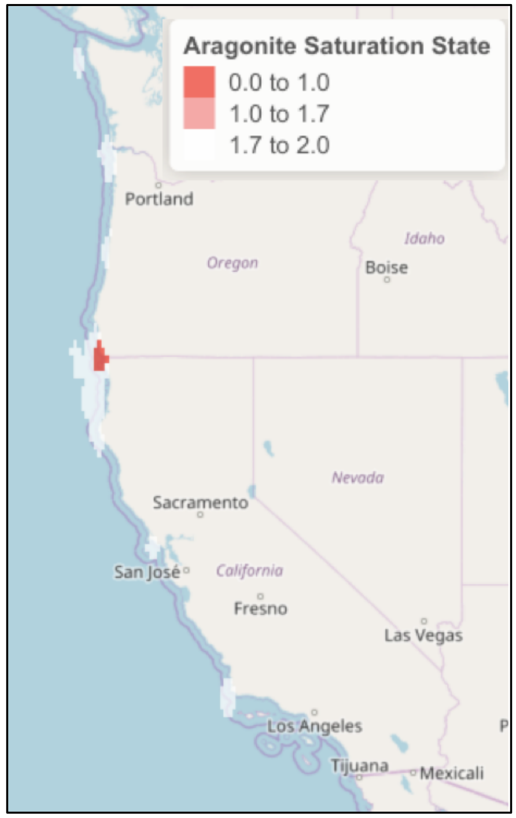
Aragonite Saturation Layer

OA Hotspots

2011 Cruise

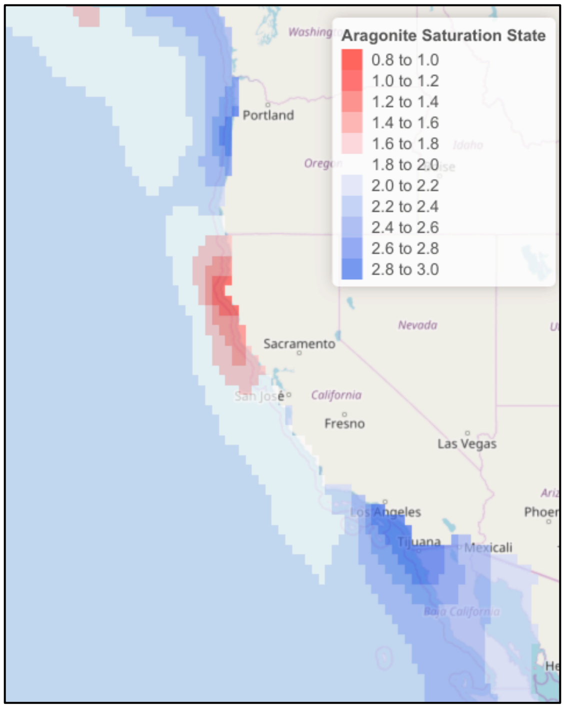


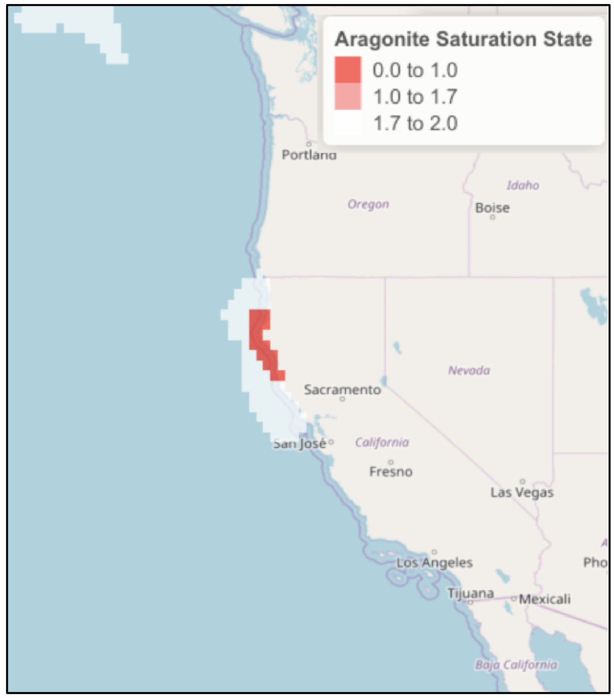
Aragonite Saturation Layer



OA Hotspots

2007 Cruise





Aragonite Saturation Layer

OA Hotspots

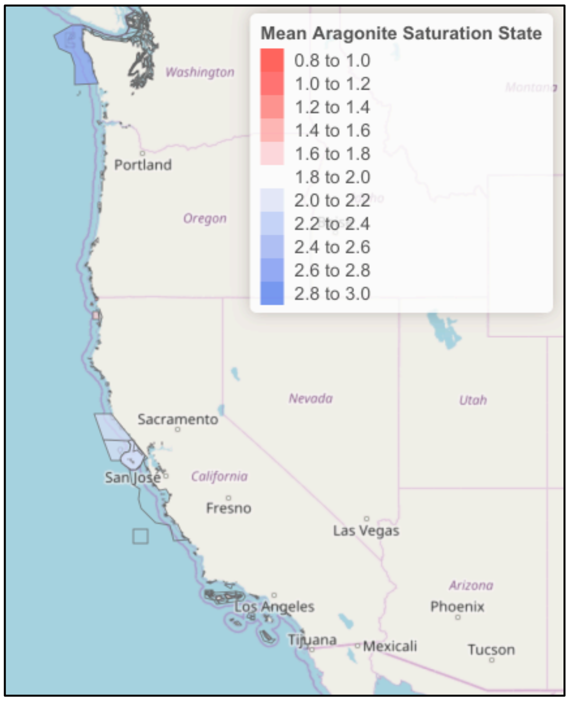
Appendix 10. Marine Protected Area Metadata from Anthropocene Institute

Data Source:	Anthropocene Institute (AI)
Name:	U.S. Marine Protected Areas Boundaries: MPA Inventory
Shapefile Names:	mpa_wa_shp, mpa_ca_shp, mpa_or_shp
Publication Date:	2016
Website:	http://www.anthropoceneinstitute.com/oceans/overfishing/mpa/
Extent:	150° West to 110° West, 48° North to 20° North
File Type:	Shapefile
GCS:	WGS_1984
Classifications of Managing Authority:	Agency with presiding jurisdiction over marine area
Classifications of Purpose:	2-4 sentences explaining what is special about this marine areas; number of habitats and endangered species
Classifications of Restrictions:	Lists prohibited or entirely banned marine-related activities (fishing, dumping, pollution, anchoring, boating) and outlines restricted commercial and/or recreational fishing activities

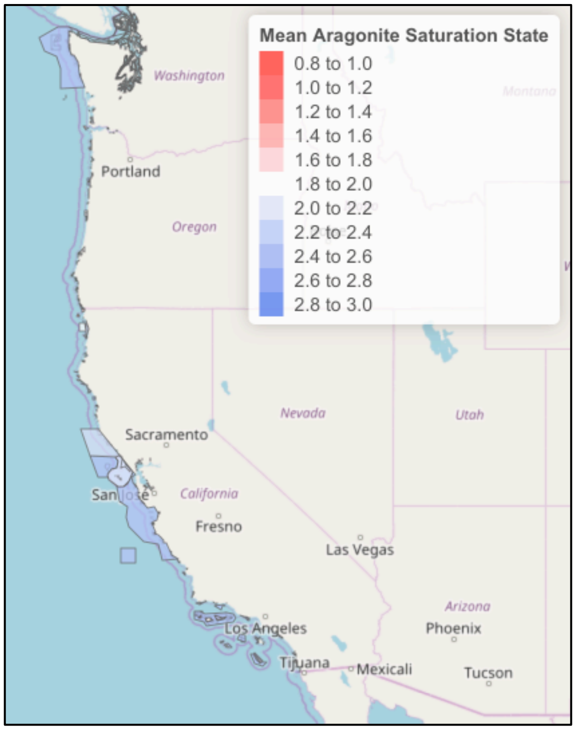
Appendix 11. MPA Analysis Outputs

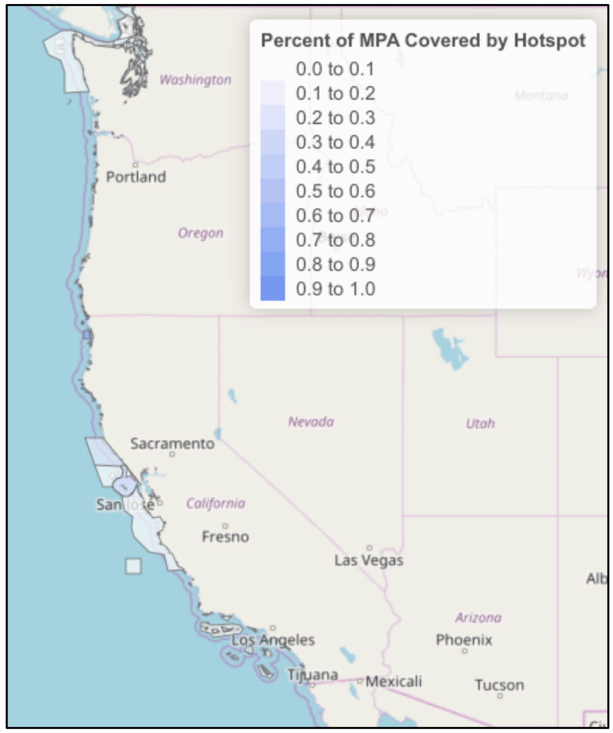
Mean aragonite saturation state and percent hotspot cover for West Coast MPAs based on each year of the NOAA OA Cruise (2007, 2011, 2012).

2012 Cruise

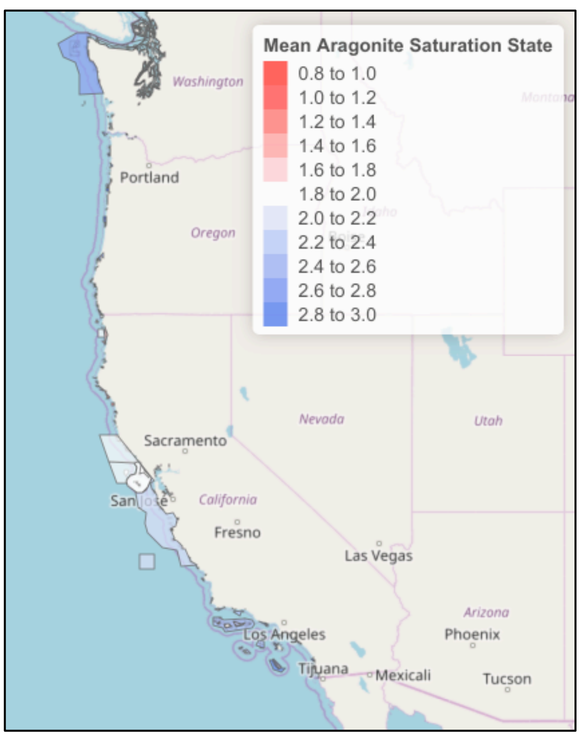


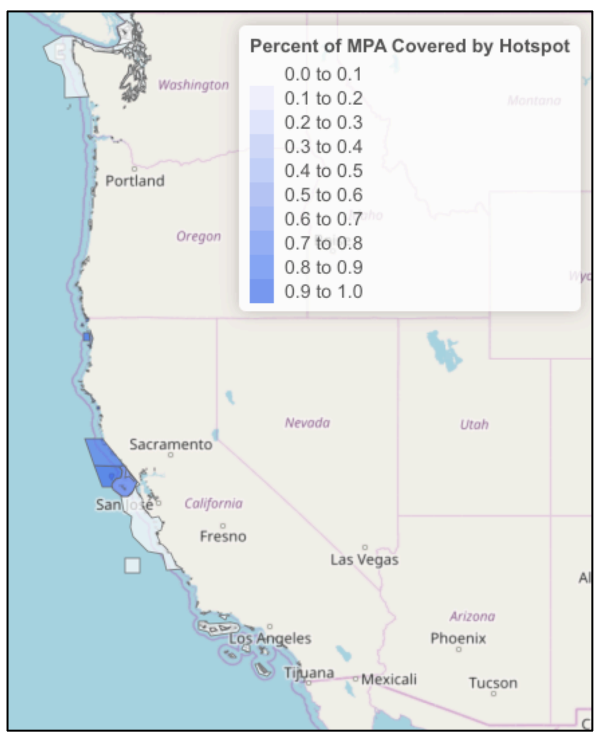
2011 Cruise





2007 Cruise





Appendix 12. Model Comparison Analysis

West Coast Ocean Acidification Models			
Model Name	LiveOcean	J-SCOPE	ROMS coupled to BEC
Working Group	UW Coastal Modeling Group	JISAO of UW with NOAA's NW Fisheries Science Center	SCCWRP, UCLA Institute of the Environmental and Sustainability Coastal Center, NOAA PMEL, UW
Goal	Provide 3-7 day forecasts of aragonite saturation state and pH of waters entering shellfish growing areas on the coast. Focused on making high-quality short-term forecasts	Provide seasonal (6-9 month) forecasts of oceanic properties, including aragonite saturation state and oxygen. Forecasts are available twice per year (January and April)	Understand large-scale changes in climate on small regions and the effects of localized nutrient inputs on acidic and hypoxic conditions.
Extent	43°N to 50°N including Puget Sound (OR-WA-BC Coast and Salish Sea)	43°N to 50°N including Puget Sound	Baja to British Columbia
Spatial Resolution	Horizontal- 1.5km on coast, 4.5 km offshore; 40 vertical layers	Horizontal- 1.5km; 40 vertical layers	Variable (4 km, 1 km, 300 m, 100 m)
Temporal Scale	Runs daily on 72 cores, takes 1.5 hours for 3 days of model time; model has been running continuously since January 2013	Runs daily on 72 cores, takes 1.5 hours for 3 days of model time	Variable; we represent the recent 20 years for the 4 km resolution run, 5-10 years for the 1 km grid, and a few months for the very high-resolution grids (<300 m).
Public Availability	Available on NANOOS NVS	Available on NANOOS NVS	Pending– will be made publicly available at later date

Appendix 13. Agreement of Findings with Previous Studies

Analysis from Feely et al. 2016 shown on the left and our interpolation analysis shown on the right. Using the same data set and aragonite state calculation methods but different interpolation tools, our analysis reveals a similar trend of aragonite saturation state based on the 2013 Ocean Acidification cruise. Hotspots (i.e. areas of undersaturation with respect to aragonite) are shown offshore from the Columbia River and along the Northern coast of Oregon. Similarly cold spots can be seen emerging near the San Francisco Bay area.