Climate Change and Coastal Ecosystems: A Case Study on Sea Level Rise in San Diego

Connor Mack
Master of Advanced Studies
Climate Science & Policy
2022

Acknowledgements

Not only this project, but my entire experience as a Climate Science & Policy Student at Scripps would not have been possible without the people listed here, along with many who are not. My heartfelt gratitude and appreciation go out to all of them. First and foremost, to Corey Gabriel for his unwavering support and mentorship. His willingness to advocate for my place in this program altered the course of my life in more ways than I can count. To Mark Merrifield for his endless patience and generosity, for giving me the chance to participate in the scientific process, and for the countless doors of opportunity he has opened for me. To Bill O'Reilly for his overall brilliance, his time, and remarkable MATLAB prowess. His guidance, expertise and encouragement were the unequivocal driving forces behind this project. To Michele Okihiro for her kindness and generosity in welcoming me into the Coastal Process Group. To the rest of the CPG for their thoughtful advice and for showing me what it means to see the world like a scientist. To the endlessly talented and brilliant CSP cohort of 2022, it was an absolute honor to share this experience with each and every one of you.

Advisory Committee

Mark Merrifield Ph.D.
Director, Center for Climate Change Impacts and Adaptation
Scripps Institution of Oceanography

Bill O'Reilly Ph.D.
Coastal Process Group
Scripps Institution of Oceanography

Corey Gabriel Ph.D.
Executive Director, Climate Science & Policy MAS Program
Scripps Institution of Oceanography

Table of Contents

Abstract

The nearshore rocky reef environment is an ecosystem of great ecological and economic importance. Rocky reefs are hotspots of biodiversity and many marine food webs around the world rely on primary producers that reside on rocky, or hard-bottom substrate. Along the west coast of North

America, the presence of rocky reefs can be considered the first order control for the existence and distribution of marine biota. Like all ecosystems on our planet, rocky reefs face disruptions due to continued changes in the climate over the coming decades. Understanding the response of these ecosystems to climate stressors is crucial for informing management and restoration policies on local, regional, and national scales. Creating an accurate inventory of existing reefs is a crucial first step in quantifying the potential impacts of climate change on these habitats. Advances in remote sensing techniques, specifically airborne LiDAR survey methods provide an opportunity for scientists to quantify nearshore habitats at previously unachievable scales. This paper presents both a methodology for mapping the spatial distribution of rocky reefs, as well as an example of the climate impact assessments that can be conducted once these areas are accurately quantified. The study is therefore divided into two parts. First, a methodology is presented for mapping the extent of rocky reef habitats at high resolutions, using bathymetric measurements from airborne LiDAR surveys. The proposed algorithm extracts roughness values from topo-bathymetric LiDAR data, compares results to existing in situ surveys and classifies substrate as rocky or sandy at 1x1 meter resolution. Second, the effects of different sea level rise (SLR) scenarios on the distribution of rocky reef habitats are explored. After mapping the rocky substrate at two study sites in the San Diego region, a range of SLR scenarios were applied to a depth-stratified ecological model of the local nearshore ecosystems to assess changes in the spatial distribution of key primary producers. This analysis showed a loss in overall habitat area and a shoreward shift in the distribution of rocky nearshore habitats especially in the intertidal zone and in shallow waters populated by surfgrass. The outcomes of this study include both a viable methodology for creating inventories of nearshore rocky reefs at large scales, along with the results of the subsequent SLR assessment. Both avenues of inquiry explored in this study can be expanded upon by future research.

1. Introduction

Coastal ecosystems are some of the most productive and economically important habitats on the planet, providing food, income, coastal protection, and other benefits to billions of people around the world. Increased environmental stressors due to climate change pose an existential threat to the long-term survival of these habitats. Understanding the adaptive capacity of coastal ecosystems to climate driven changes in their environment is crucial for informing future management and restoration policies. Researchers estimate that coastal habitats overall are disappearing at a rate between 1.2% and 9% per year and are now the most endangered ecosystems on the planet, with loss rates 4-10 times greater than those of tropical rainforests [1]. Such losses underscore the urgent need for not only meaningful climate action and deep decarbonization, but also for direct, data driven policies and programs to protect and restore coastal habitats. Sea level rise, warming water temperatures, ocean acidification and increases in storm frequency and intensity are just a subset of the climate stressors that threaten the long-term health of these valuable ecosystems [2]. Research into the impacts of climate change on coastal habitats has increased substantially in recent years. At the same time, a growing number of papers have been published on the potential for strategically restoring and utilizing coastal ecosystems as climate solutions that contribute to both mitigation and adaptation [3,4,5]. Active enhancement and restoration of coastal ecosystems has the potential to reduce coastal erosion due to SLR while also preserving biodiversity, sequestering carbon, and providing other local co-benefits. Thus, coastal ecosystems pose both an urgent need for conservation and an opportunity for impactful climate action. The long-term viability and efficacy of these projects depends on a robust, empirical understanding of the controls acting on these habitats as well as their responses to climate stressors. Much of the literature on this topic thus far focuses on mangroves, wetlands, coral reefs, and seagrass beds [6,7,8]. Despite being a very common and extremely productive ecosystem with significant ecological and economic importance, nearshore rocky reefs are not as frequently discussed in the context of climate impacts or potential adaptation. While there is also potential for artificial structures that mimic rocky reefs to play a role in adaptation strategies by reducing wave stress along the coastline, that application is not explored in detail here. This paper focuses primarily on the identification and quantification of existing natural reefs, and then explores the potential impacts of climate change, specifically SLR, on these ecosystems.

The scope of this project was defined as such for multiple reasons. First, there is a paucity of information on the overall spatial distribution of rocky reefs at large scales. The methodology developed here for identifying rocky substrate using airborne LiDAR surveys can be used to map the rocky nearshore at a high resolution and at previously unachievable scales. Furthermore, by isolating SLR as our climate stressor of interest, we were able to demonstrate a direct application and concrete example of the spatial analysis made possible by the proposed LiDAR processing methodology. Rocky nearshore habitats are based around an array of foundational, photosynthetic primary producing species. As sea levels rise, the depths at which existing rocky substrate is found will increase, altering the availability of light for these primary producers and affecting the distribution of the different habitats they create. The methodology presented here for identifying and mapping nearshore rocky areas allows these changes to be quantified at high resolutions.

This paper begins with a description of the algorithm used for extracting rocky substrate locations from airborne topo-bathymetric LiDAR surveys. This algorithm is then applied to two study sites of interest: the Cardiff reef in Encinitas, CA and La Jolla Cove, CA. The second part of the paper describes the results obtained from applying different sea level rise scenarios at each location in the context of a depth-stratified model, based on the common depth ranges of key primary producers and ecological zones. By assuming a relatively stable bathymetric profile, we quantified the SLR driven shoreward displacement and subsequent change in total area for each of these depth ranges of interest. Overall, this project takes a key first step towards generating large scale inventories of nearshore rocky areas while also demonstrating an example of the kinds of analyses that can be performed once these habitats are mapped and accounted for.

2. Methodology

The first step for this project was to develop a means of extracting information on the location of rocky substrate using airborne topo-bathymetric LiDAR. An airborne LiDAR data set collected by the US Army Corps of Engineers (USACE) was the primary data set of interest for this effort. The USACE has conducted multiple airborne LiDAR surveys as part of a project known as the Scanning Hydrographic Operational Airborne LiDAR Survey (SHOALS) system [9]. The SHOALS system is still in operation and surveys have been flown across nearly the entire coastline of the United States. These surveys are therefore ideal candidates for the mapping of rocky nearshore areas at magnitudes relevant for policymakers and government agencies at local, state and federal levels. The topo-bathymetric SHOALS data was used in combination with in-situ multibeam echo sounding (MBES) substrate surveys conducted by the San Diego Association of Governments (SANDAG). The SANDAG data was collected using MBES and verified by on-site scuba surveys and is thus considered to be highly accurate. The SANDAG data consists of discrete substrate classifications which were used to inform a roughness threshold for the SHOALS data set that accounted for variability in the density of LiDAR returns with increasing water depth. The proposed methodology for extracting rocky substrate classifications from the SHOALS airborne LiDAR data could then be verified using the SANDAG surveys as a ground truth comparison. The data sources and analysis methods applied to the SANDAG and SHOALS datasets, as well as the classification algorithm itself are expanded upon in the following sections of this report.

2.1 The SHOALS System

The Scanning Hydrographic Operational Airborne Lidar Survey (SHOALS) system was developed in 1994 by the US Army Corps of Engineers to monitor nearshore bathymetry along US coastlines [9]. The SHOALS system has allowed for order of magnitude increases in survey speed, collecting highly dense and accurate data at rates of over 25 km^2/hour at relatively low costs [10]. SHOALS missions have been conducted for a wide variety of purposes including navigation, shore protection, shoreline structure evaluation, emergency responses, and coastal process monitoring [9]. The data used for this project was collected during separate topo-bathymetric surveys of the California coastline in 2009 and 2014. Data for specific locations typically consists of multiple flights within each year, done days or weeks apart to capture the roughness and bathymetry of substrate with low mobility that show no changes across these time scales. Both the 2009 and 2014 data consisted of multiple flights over the same areas, which were subsequently combined to increase the accuracy of the data. The SHOALS system is still in operating, and ongoing flights and monitoring can be used for the furthering of this research in the future.

2.1.1 SHOALS Data Collection and Processing

The SHOALS system uses Light Detection and Ranging (LiDAR) technology to measure nearshore bathymetry and coastal topography simultaneously. This paper focuses on the bathymetric application of the SHOALS system which is measured using a laser transmitter and receiver mounted underneath the aircraft [9]. The laser consists of collimated red (1064 nm) and green (532 nm) light emitted in pulses at a rate of 400 Hz [11]. The laser pulses are partially reflected by the surface of the water (surface return) while the remaining energy penetrates the water and reflects off the seafloor (bottom return) [9]. The water depth can then be calculated as a function of the difference between the surface and bottom return times. The intensity of the bottom return signal is a function of both the bottom type and the water clarity [9]. LiDAR is therefore less effective in areas with low water clarity or particularly absorptive substrate and returns generally diminish as water depths increase. Typically, measurements can be made up to approximately three times the Secchi depth, up to a max depth of about 60 m in very clear waters [10].

During surveys, measurements are georeferenced using real time differential or kinematic GPS measurements [9]. Once the raw pulse and GPS data are collected, post processing is done to extract accurate depth measurements by correcting for surface waves and water level fluctuations. After post processing, the data has a vertical accuracy of ±15 cm and a horizontal accuracy of ± 1-3 m depending on the GPS method used. Spacing of data points varied at the study sites in question for this project but were typically a fraction of a meter to a few meters apart with an expected trend towards wider spacing at greater depths. Patches of shallow water without returns were somewhat common due to water clarity issues (surfzone bubbles) and kelp coverage. To create a bathymetry grid for our study sites, data from intra-annual flights were combined to make two composite data sets for 2009 and 2014 respectively. When creating these composite data layers, higher density areas at submeter resolutions were reduced to a 1-

meter spatial average. Finally, the two composite layers were combined to create a single set of bathymetry data, merging the 2009 and 2014 surveys. If both years' surveys had data in the same 1x1 meter bin, the deeper value was retained as it is more likely to represent the true elevation of the substrate at that location.

2.1.2 Extracting Roughness Values from Bathymetry

By spatially averaging intra-annual flights and merging the resulting data sets into one bathymetry layer, a robust representation of sea floor elevation and shape was derived from the 2009 and 2014 SHOALS surveys. From this bathymetry layer, roughness measurements were extracted using a scanning 11x11 meter, two-dimensional spatial filter window. Within the filter window, localized mean depth and standard deviation were calculated on the condition that at least five data points be present within the 11x11 meter grid. The standard deviation of the depth within the filter was retained as the roughness value for the center point. The filter was then moved across the entire study area, calculating roughness values for each cell

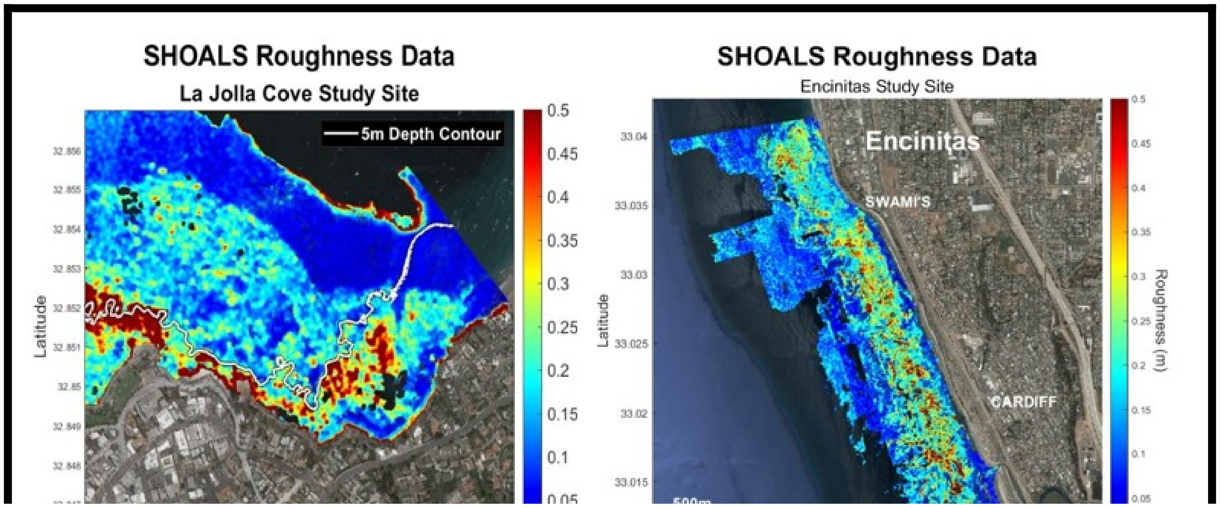


Figure 1: SHOALS roughness grids at La Jolla Cove (left) and Encinitas (right)

across the entire grid. The resulting roughness values were gridded back into 1x1 meter resolution using Delaunay Tessellation, omitting any gaps in the data exceeding 250 meters. The resulting roughness grids are shown in Figure 1 for both the Encinitas and La Jolla study sites with the color bar indicating the local roughness calculated for each 1x1 meter point. After extracting roughness grids from the SHOALS LiDAR data, a method for substrate classification was developed by relating SHOALS roughness values to the substrate data collected by SANDAG at the same location in Encinitas. While the La Jolla study site was not included in the SANDAG surveys, it was used to demonstrate potential for extrapolating this methodology to any locations where SHOALS LiDAR data has been collected.

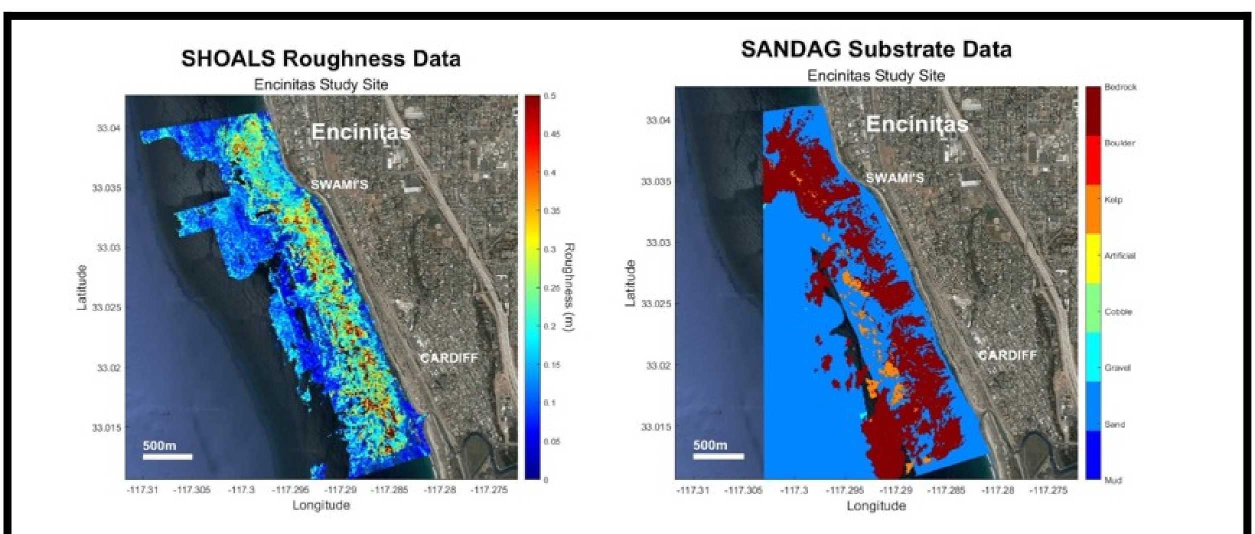
2.2 The SANDAG Substrate Data

The second data set that was used in this study was collected by the San Diego Association of Governments (SANDAG) Nearshore Habitat Mapping Program. This data was presented as part of the San Diego region's Coastal Regional Sediment Management Plan (RSM), a project that was developed by SANDAG to inform policy makers and researchers on sand and sediment deficits in the region. To evaluate the potential impact of beach nourishment undertakings on nearby habitats, the SANDAG RSM plan compiled and collected data on nearshore and coastal habitat occurrence in the region, creating a repository of figures, tables and GIS shapefiles describing nearshore substrate [12]. The data was collected and compiled for the purposes of informing the RSM plan's recommendations while also providing an important resource for future environmental assessments, scientific research, and coastal management applications [12].

Substrate data in the San Diego nearshore zone was measured using multibeam echo sounding (MBES) technology. MBES systems, mounted on small research boats, emit multiple beams of sonar, recording the time delay and intensity of the returning signals. The time delay between pulse emission and return detection can be used to map bathymetry, while the intensity of the return provides information on the reflectivity of the ocean floor. This is known as backscatter imaging, and it can be done across a range of frequencies to create detailed classifications of seafloor composition [13]. Multispectral camera data was also collected by in situ divers to supplement and confirm backscatter measurements. The resulting data sets provide detailed information of substrate type around the SANDAG region, classifying the seafloor as bedrock, boulder, cobble, kelp canopy, sand, mud, pebble/gravel, or artificial substrate at 5x5 meter resolutions [12].

2.3 SHOALS/SANDAG Comparison

The SHOALS and SANDAG datasets both contain high quality, rigorously obtained data on the nearshore environment in the San Diego region. By comparing the two surveys at the Encinitas study site, we were able to determine a roughness threshold value for the SHOALS data set that best aligned with the SANDAG substrate data in terms of classification as rocky (rough) or presumed sandy (smooth) substrate. This project compares



the two datasets in only one location, so similar comparisons should be made in future research to verify the methodology presented here and to further confirm the accuracy of using SHOALS LiDAR as a nearshore mapping tool. Figure 2 shows the data from each source at the Encinitas study site. The SHOALS data is displayed with a color bar indicating the local roughness as discussed previously. The SANDAG data is divided into discrete classification bins as determined and verified by the surveyors.

To compare the two datasets of interest, the SANDAG data was resampled to 1x1 meter resolution using nearest neighbor interpolation. The criteria used to determine a roughness function that best aligned the data sets was in terms of fractional or "percent rocky" coverage within discrete 1 m depth increments. The nearshore reef at Encinitas is a complex combination of rocky outcroppings and narrow sand channels, and precise alignment of the two datasets is beyond the scope of the spatial fidelity of the two surveys. As water depth increases, the density of the SHOALS returns diminishes, warranting a depth-dependent adjustment in the roughness cutoff value. Thus, a roughness threshold, (R) was determined as a function of the SHOALS depth value that led to percent coverage results most consistent with the areas defined as bedrock, boulders, or kelp in the SANDAG survey.

Figure 2: SHOALS and SANDAG data at the Encinitas study site

Only points where both surveys have valid data were used to define R values within each depth bin from -1 to -15 meters relative to MSL. Figure 3 shows the values of R that best align the SANDAG and SHOALS data in terms of percent rocky coverage within each depth bin. Beyond 15 meters of

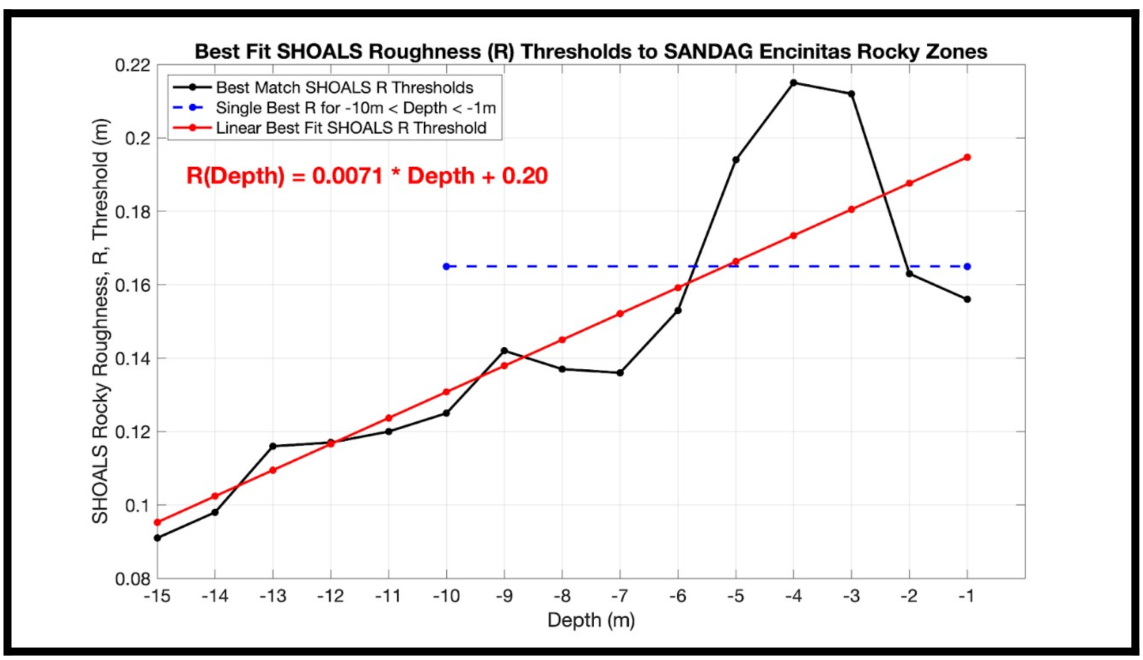


Figure 3: Roughness cutoff function (R)

depth, the density of the SHOALS returns drops off significantly, so those values were omitted from this analysis. Finally, a generalized, depth-dependent roughness threshold equation was defined using the linear best fit of the optimal R values by depth:

$$R(Depth) = 0.0071*Depth + 0.20$$

Using this equation for R, we were able to make binary substrate classifications of the SHOALS data. Any 1x1 meter point with a roughness value greater than R was classified as rocky, allowing us to quantify the total amount of rocky substrate in the area, as well as the percent coverage within certain depth ranges. This methodology allows for the mapping of nearshore rocky substrate at 1x1 meter resolution across large areas covered by aerial LiDAR flights. The limitations and opportunities for refinement of this methodology are discussed in the concluding sections of this paper. This methodology represents a critical first step towards the important, and to this point underdeveloped, work of creating an inventory of nearshore rocky habitats. After applying this method to the study sites of interest, further analyses were conducted by applying different SLR scenarios to each area. By integrating this substrate classification method with a depth-range based model of rocky nearshore ecology, we were able to estimate and quantify the potential spatial impacts of sea level rise on rocky nearshore habitats.

3. Rocky Nearshore Habitats

Identifying and mapping rocky nearshore areas is important primarily because of the extremely productive habitats that exist in these locations. Rocky nearshore habitats host a wide range of economically and ecologically important species. Many marine plants, algae and other organisms that support surrounding ecosystems are adapted to live exclusively on hard-bottom substrates. This includes various species of macroalgae and seagrass, foundational primary producers that are considered to be ecosystem engineers [8, 14]. These primary producers are photosynthetic, they require certain light levels in order to survive and are thus constrained within particular depth ranges. As sea levels rise, the availability of rocky substrates at appropriate depths and light levels will change, potentially impacting the habitat and distribution of key primary producers. By using the methodology for rocky substrate identification in conjunction with a simple model of local rocky nearshore habitats, we were able to quantify these potential changes due to sea level rise within depth ranges relevant to primary producers of interest.

3.1 Macroalgae

The primary species of macroalgae considered in this model is *Macrocystis Pyrifera,* commonly known as giant kelp. *Macrocystis* is a widely distributed canopy forming species of kelp that grows in nearshore rocky environments and makes up the bulk of kelp forest habitats along the west coast of North America. It is generally found between 5-30 meters of depth and can grow up to 60 meters in size [15]. Giant kelp can also be found in the intertidal and shallow subtidal zones as a recruit although it does not grow to adulthood in shallower depths [16]. Macrocystis is one of the most productive photosynthesizers on the planet and can grow up to 50 cm per day under ideal conditions [17]. The remarkable productivity of Macrocystis makes kelp forests some of the most dynamic and diverse ecosystems in the world. Kelp forests provide food, shelter, and habitat for a wide variety of marine mammals, invertebrates, seabirds, and commercially relevant fish [18]. Kelp forests also generate a range of other ecosystem services including coastal protection, mitigation of eutrophication and acidification, tourism, recreation, and carbon sequestration [19]. Because kelp grows on rocky substrate, it does not accumulate sediment on site and its contribution to carbon sequestration is an area of active study. Ongoing research efforts have identified kelp biomass sequestered in coastal marine sediment as well as the deep sea, fueling interest in macroalgae's role as a significant contributor to global sequestration [20]. Due to the variety of ecosystem services provided by *Macrocystis Pyrifera* and the subsequent kelp forests it creates, the global Total Economic Value (TEV) of these rocky nearshore habitats is on the order of hundreds of billions of USD [21]. While there are a multitude of smaller, understory algae species that reside under the canopy formed by giant kelp, Macrocystis plays the most significant role in the formation of kelp forests, so it is the primary species considered in this model.

3.2 Seagrass

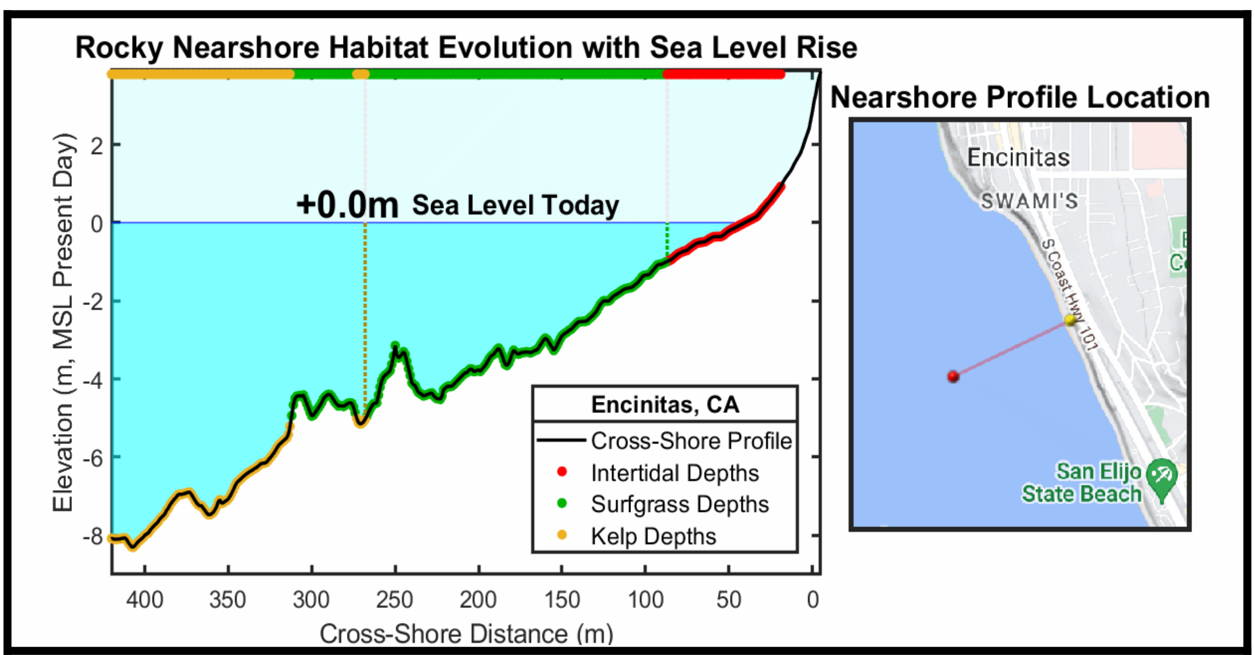
The primary species of seagrass considered in this study is *Phyllospadix Torreyi,* commonly known as surfgrass. Surfgrass is a perennial angiosperm that can be found along the west coast of North America, ranging from Vancouver Island to Baja California [15org]. Unlike the more widely ranging *Zostera* seagrass species that take root in soft-bottomed, and wave protected environments, *Phyllospadix* grows on rocky substrate and thrives in wave-exposed areas [22]. It is generally found between 0-5 meters of depth and can grow up to 2 meters in height [23]. Surfgrass also ranks among the most productive of marine primary producers and provides habitat for many species of fish and invertebrates [24]. Though surfgrass does not directly accumulate sediment like soft-bottom seagrasses, surfgrass canopies enhance the sedimentation of suspended particles and mitigate resuspension rates, thus stabilizing the surrounding seafloor [25]. Surfgrass beds also provide a similar range of economic and ecosystem benefits to kelp forests, including commercial fishery support, carbon sequestration, coastline stabilization, wave attenuation, direct food provision and general biodiversity support. Like kelp forests, these benefits make surfgrass beds extremely valuable, though historic coverage areas have been reduced by as much as 30%, driven primarily by human activities [26]. Though other species of seagrass have greater areas of coverage worldwide, surfgrass was included in this model because it takes root on rocky substrate and is one of the key foundational producers that makes the rocky nearshore extremely valuable both economically and ecologically.

3.3 Rocky Intertidal Zone

The rocky intertidal zone was the final habitat included in the model for this project. This habitat consists of rocky substrate found between low and high tide water levels, generally 1 meter above and below mean sea level [27]. This area consists of a unique set of organisms, specially adapted to survive both underwater and exposed to the air. The rocky intertidal zone will be one of the first marine habitats affected by sea level rise, and understanding future impacts is a developing area of active research [28]. Habitat loss rates due to SLR vary according to local geomorphology, erosion rates and sediment processes but the current level of understanding is limited [28]. When intertidal areas are backed up against steep cliffs or anthropogenic structures, they are likely to experience "coastal squeeze," a general narrowing of the habitat's cross shore width [28], as well as an overall steepening of the coastal profile [29]. The unique ecology of the intertidal zone also makes it particularly vulnerable to changes in sea level. The ecological functions of this habitat are stratified into (sometimes strict) bands along the tidal elevation gradient so changes in overall sea level will likely have significant impacts on abundance, distribution, and competition among intertidal species [28].

4. Rocky Nearshore Model

To quantify the effects of SLR on the rocky nearshore, each study area was divided into different depth zones corresponding to the depth ranges of giant kelp, surfgrass and the intertidal zone. For purposes of this analysis, each ecological zone was considered to be a discrete depth range, divided at specific boundaries. In this model, the kelp zone was determined to be anything below 5 meters of depth, while the surfgrass zone ranged from 5 meters of depth up to mean sea level (MSL). These ranges were chosen



based on the most common distribution of these producers by depth according to the relevant literature [15, 23, 27]. The intertidal zone was also included in the model and was demarcated as one meter above and below MSL. While there are various species of understory and other kinds of algae present, giant kelp and surfgrass are the key ecosystem engineers in the rocky nearshore, so other algal species were omitted from the model for clarity. Figure 4 shows an illustration of the model using a cross shore profile

from the Encinitas study site as an example. The bathymetrical variations of this profile are due to the presence of rocky reef at this location. As sea levels rise, each of the depth zones of interest in our model will change in overall size and relative location to shore. As these depth ranges are pushed shoreward, the amount of rocky substrate within each zone will change, affecting the distribution of the key primary producers in our model that are controlled by the availability of rocky substrate at appropriate light levels for photosynthesis. The intertidal zone will also be acutely affected as rising sea levels will push this area shoreward, potentially disrupting the ecology of the rocky intertidal zone. The overall goal of this analysis was to quantify the change in rocky coverage in each depth range of interest to better understand how sea level rise will affect both the size and distribution of rocky nearshore habitats.

5. Results

By applying the roughness threshold function to the SHOALS data at the Encinitas study site, we were able to quantify the amount of rocky

Figure 4: Rocky nearshore habitat model, illustrating changes due to SLR

coverage according to both datasets, compare the results and evaluate them within the context of the previously outlined nearshore rocky habitat model. Then, different sea level rise scenarios were applied to determine the effects of SLR on the presence of rocky substrate within the intertidal, surfgrass and kelp zones. The same process was then applied to the SHOALS data in La Jolla Cove to demonstrate the potential for extrapolating this technique to other areas.

5.1 Encinitas

To quantify the effects of SLR on the areas of interest outlined by our rocky nearshore model, the primary signal of interest was the percentage of rocky coverage within each depth range. Using both datasets in Encinitas, the percentage of rocky coverage was calculated within each depth range of the habitat model, along with the total area in hectares. Successive SLR scenarios were then applied, with the assumption of no radical changes in nearshore or beach topography. Figure 5 shows the change in both rocky coverage percentage and total rocky area within each depth range in response to changes in sea level. The results show a significant effect on the amount of rocky area in the intertidal zone (+1-1 meter depths), as rocky coverage in this area is essentially eliminated within the first meter of sea level rise. As sea level rises and MSL moves shoreward, the intertidal area will shift as well. At this particular stretch of coastline, the subaerial region is composed primarily of sand with little to no exposed bedrock present. Thus, the upper and middle intertidal zones will be pushed shoreward onto sandy substrate, while portions of the lower intertidal zone will become subtidal,

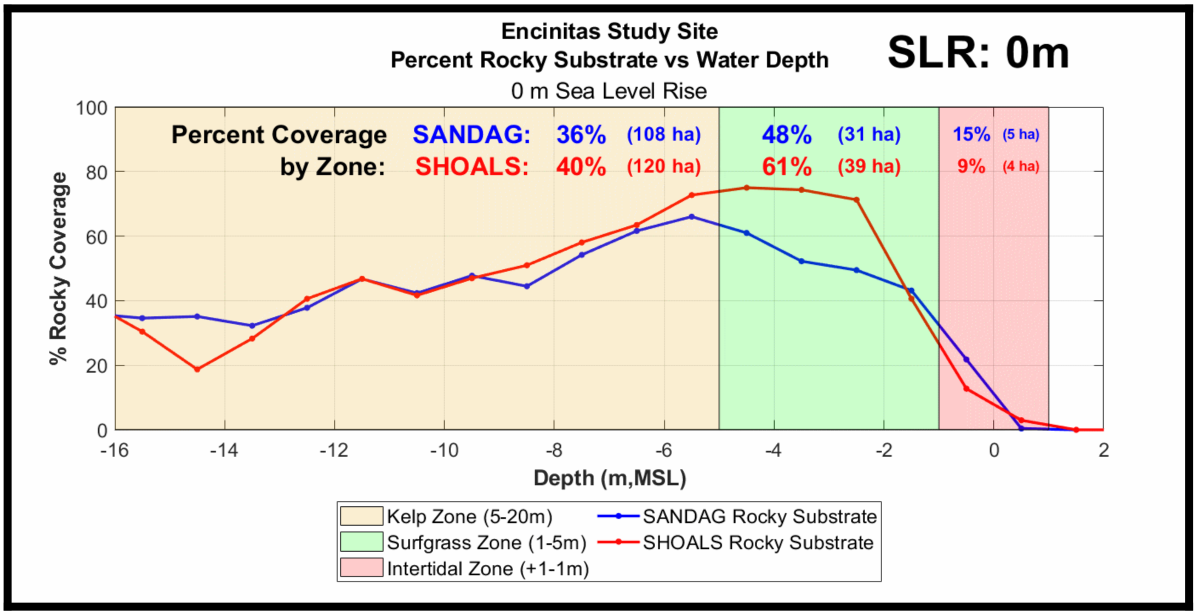


Figure 5: Percent rocky coverage under various SLR scenarios at Encinitas study site

significantly shifting the makeup of the intertidal ecosystem. The results also show a decrease in rocky coverage in the surfgrass zone (0-5 meter depths*), as areas currently dominated by surfgrass will potentially become too deep for adequate light penetration as water levels rise. While surfgrass is not actually constrained absolutely by the 5-meter depth boundary, deeper waters will favor understory algae and giant kelp, allowing them to encroach on surfgrass habitat and reducing the overall coverage of this key producer. The giant kelp depth range shows a slight increase in coverage under this analysis as it potentially overtakes some of the area allotted to surfgrass in this model. It is important to note that the depth range of giant kelp extends far deeper (30+ meters) than the rocky reef at this location, so there are no losses measured due to SLR induced changes in depth and light levels. However, giant kelp populations are extremely vulnerable to other impacts of climate change such as rising water temperatures and increases in storm surge intensity and frequency. While the quantitative analysis presented in this paper focuses specifically on sea level rise, the effects of other climate stressors will be considered qualitatively in greater detail during the discussion of these results. There is also the limitation of using discrete 1-meter bins for percent coverage calculations despite applying fractional SLR scenarios. While this causes some variation in the shape of the curve shown in Figure 5, the integrity of the calculations for percent coverage within each depth range is maintained.

Figure 6 shows the trends in percent rocky coverage for each of the areas of interest across a range of SLR scenarios from 0-2 meters. Some variation is present between the SHOALS and SANDAG datasets, especially in the surfgrass zone where the linear R function generally underestimates the optimal roughness threshold. However, the overall trends shown in Figure 6 as well as the total distribution shown in Figure 5 are reasonably similar between the two data sets, demonstrating the viability of the roughness threshold function that was developed to make classifications from the SHOALS data.

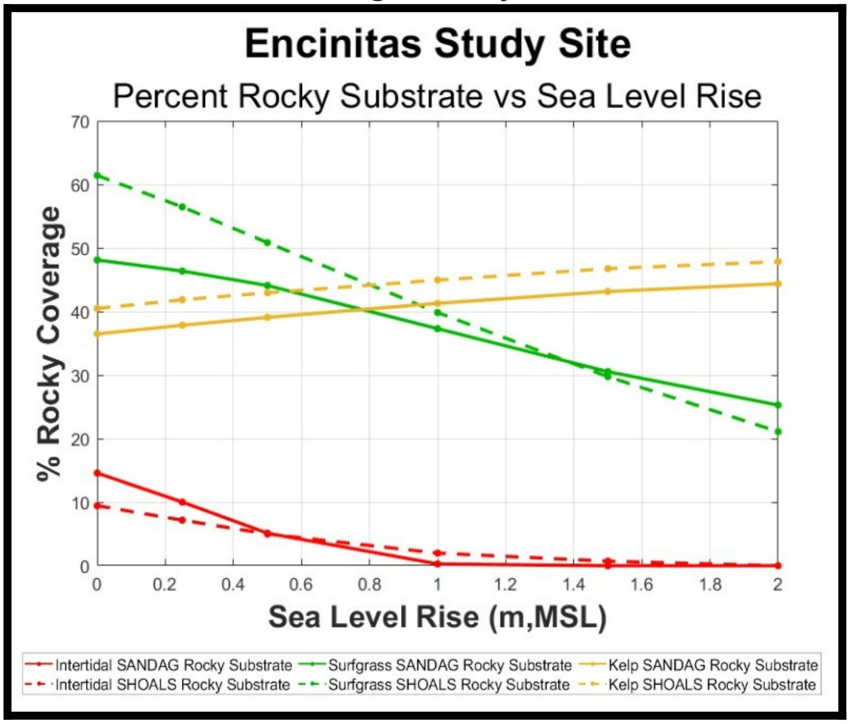


Figure 6: Trends in coverage for each data set & depth zone

5.2 La Jolla Cove

This methodology Cove. La Jolla Cove was chosen as the second study site due to the presence of a large surfgrass bed in the shallow areas of the cove. The cove is also lined by steep rocky cliffs, in contrast to the sloping sandy beach at Encinitas. Using the same approach as Encinitas, the R threshold function was applied to quantify percent coverage and total rocky area within each depth range of interest. Figure 7 shows the distribution at present day and under future SLR scenarios. The results found in La Jolla Cove are consistent with those measured in Encinitas, showing a decline in rocky coverage for the intertidal and surfgrass zones along with a slight increase in rocky substrate in the kelp zone. The shape of the curve in Figure 7 gives some insight into the physical makeup of the seascape of La Jolla Cove; the large surfgrass bed can be seen as the shallow peak, followed by a sandy gap until a deeper reef appears, primarily dominated by kelp forest. This creates an interesting stage for the encroachment of macroalgae into the surfgrass zone across two somewhat separate reef systems.

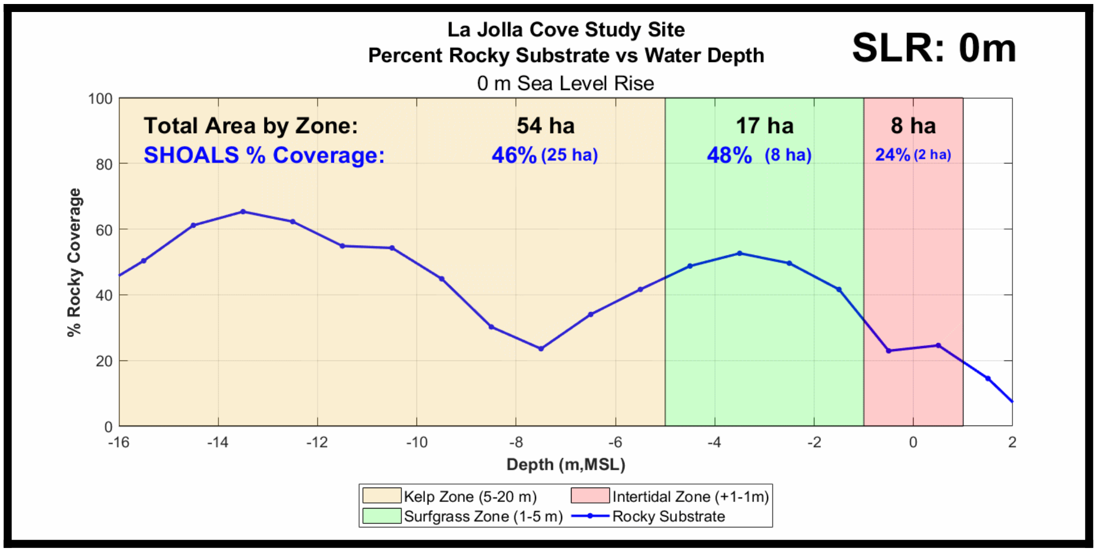


Figure 7: Percent rocky coverage under various SLR scenarios at La Jolla Cove study site

Figure 8 shows the trends in fractional rocky coverage in each zone at both locations under SLR scenarios from 0-2 meters. The steeper decline in percent coverage at Encinitas in the surfgrass and intertidal zones can be attributed to the presence of the cliffs in La Jolla Cove. The steep barrier created by the cliffs prevents MSL from moving shoreward as sea levels rise, leading to a phenomenon known as coastal squeeze [30]. Coastal squeeze is defined as the general narrowing of the intertidal zone, and a subsequent steepening of the coastal profile [29]. Areas lined by steep cliffs or anthropogenic structures such as sea walls are expected to experience significant amounts of coastal squeeze as sea levels continue to rise, prompting various recent studies on potential ecological impacts [28, 31, 32]. As the intertidal zone and shallow surfgrass depths in La Jolla Cove are compressed against the cliff faces, the total area of these depth ranges represented in the model declines significantly. The decline in total area subsequently lessens the loss of rocky coverage in terms of percentage. By contrast, in Encinitas, MSL migrates shoreward up the beach face. While the profile of the intertidal zone steepens in this case, it has moved onto a primarily sandy are and the amount of total area loss is

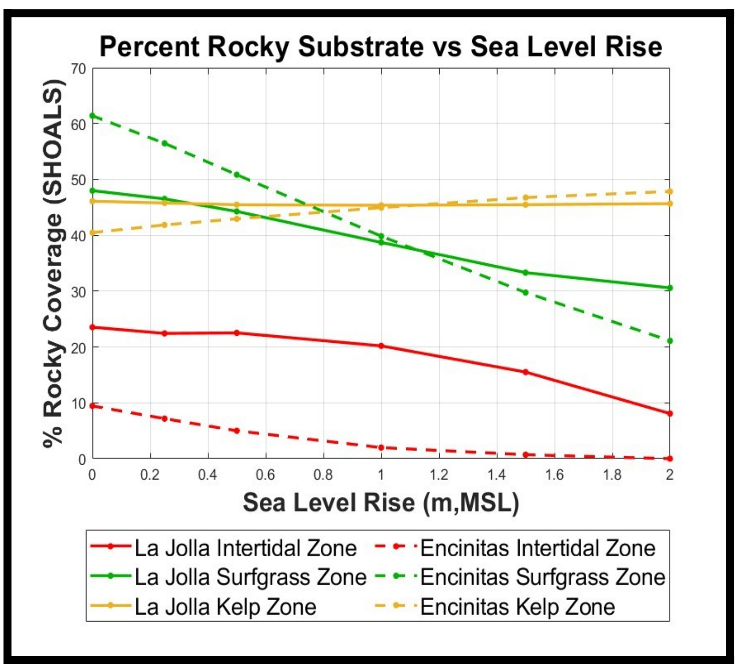


Figure 8: Trends by zone at each study site

not as extreme, corresponding to the sharper drop in percent rocky coverage shown in Figure 8. While the overall trends are similar between the two study sites, the coastal squeeze phenomenon, driven by the cliffs in La Jolla Cove, creates a significant difference in the predicted changes at the shoreline itself. Figure 9 shows the potential future impacts of coastal squeeze on both the surfgrass and intertidal depth ranges in La Jolla Cove.

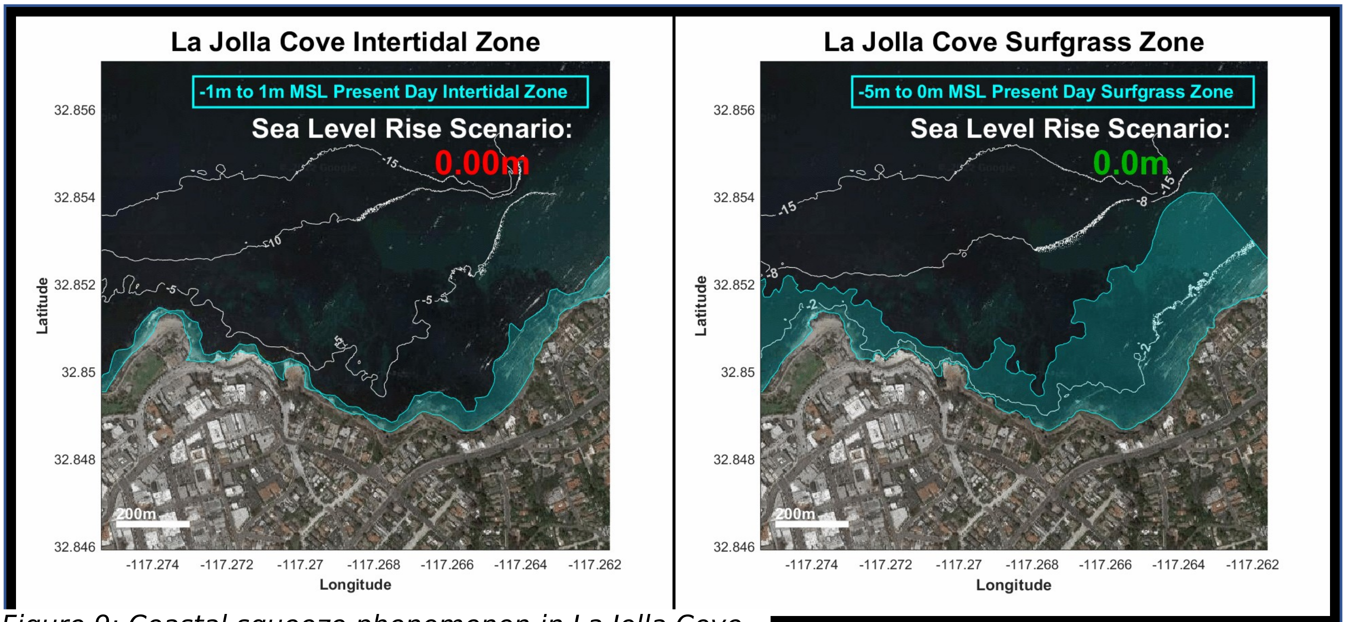


Figure 9: Coastal squeeze phenomenon in La Jolla Cove

Assuming the topography of the cliff dominated coastline remains relatively constant, the 5-meter bathymetry contour, defining the lower end of the surfgrass zone in our model, was found to shift 50 meters shoreward for every 1 meter of sea level rise. This value is a function of seafloor slope and will vary in practice at most locations due to ongoing coastal erosion, especially where sandy beaches are present. However, in this location, the back beach is essentially fixed by the vertical cliffs, so the 50-meter shoreward shift shown in Figure 8 is likely an accurate estimate. The changes predicted here will be transformative for both the physical and biological processes of the study sites in question.

6. Discussion

This project met both the stated goals of developing an algorithm for identifying nearshore rocky areas using airborne LiDAR surveys and demonstrating an application of said algorithm in the context of climate change. It represents an important first step towards accurately mapping and quantifying rocky nearshore areas at large scales. Before accomplishing this goal, more research is needed to assess the transferability of the methodology we have developed to other locations. The linear cutoff function accounts primarily for the reduction in LiDAR returns with increasing depth, which will be a relatively consistent phenomenon across all areas that have been surveyed. However, verification at other sites and with other external data sources is an important next step to increase the robustness of this approach. In terms of forecasting ecosystem response to climate change, the second goal of this project was pursued primarily for the purposes of demonstration. While the SLR scenarios applied to each location are accurate representations of impending changes in the physical seascape, a complete assessment of ecosystem responses to climate stressors would involve a myriad of other environmental factors. The SLR analysis was not mean to be strictly predictive, rather an illustration of the powerful monitoring and management tool that high resolution LiDAR based maps of the rocky nearshore can be. The limitations of the progress made towards both stated goals are further explored in the following sections.

6.1 Ecological Limitations

As mentioned previously, a major limitation of this work in terms of forecasting ecosystem responses to climate change is that only sea level rise was considered. This was an intentional choice based on the scope of the project and for purposes of demonstrating the potential for high resolution spatial analysis using this mapping technique. However, SLR alone clearly does not provide a complete picture of the changes that these coastal habitats will undergo due to climate change.

For example, our model showed kelp slightly overtaking some of the area currently dominated by surfgrass as water levels increase. This is not to suggest that in practice, macroalgae will thrive under higher SLR scenarios, as other climate induced stressors are already posing problems to the long-term survival of macroalgae and kelp forests. For example, rising water temperatures caused by a marine heat wave in 2013 reduced bull kelp canopy coverage by over 90% along more than 350 km of California coastline, turning extremely productive forests into urchin barrens [33]. Higher water temperatures in general also mean less nutrients are available in the water column, limiting macroalgae populations that are dependent on nitrate concentrations [34]. High wave stress due to storm surges can also dislodge kelp holdfasts and can disrupt large swaths of kelp forest all at once [35]. All of these phenomena will become increasingly more frequent as the climate continues to warm, posing multiple threats to the future of macroalgae forests.

Surfgrass is also sensitive to changes in ocean temperatures, although they can withstand warmer water than their macroalgal counterparts [36]. Wave stress is not as concerning for surfgrass as they are adapted specifically for life in areas with high wave energy and bottom shear stress. However, research has shown increasing water temperatures coupled with lower levels of light exposure (a likely outcome due to climate change), cause significant decreases in daily productivity, growth rates and overall health of surfgrass plants [36].

Of the three habitats discussed in this paper, rocky intertidal habitats will face the most disruption directly due to SLR. The phenomenon of coastal squeeze that was observed in La Jolla Cove is an actively researched area of concern for ecologists in this field. SLR will upset the balance struck by evolution in the intertidal zone's depth-defined ecological niches, leading to significant disruption and loss of biodiversity [28]. Current research methods include more localized LiDAR imaging of intertidal pools, although plane mounted LiDAR could potentially be used for this purpose as well. Intertidal ecosystems are also further threatened by rising temperatures, both in the sea surface temperatures and the air itself. Many intertidal species are sensitive to warmer water temperatures and struggle to survive marine heat waves [37]. At low tide, many of these creatures are also exposed to the air, and studies have documented potentially fatal increases in organism body temperatures due to higher ambient air temperatures [37].

The threat from climate change across all these ecosystems is both existential and uncomfortably imminent. A variety of climate change driven changes to the environment threaten the long-term survival of these habitats. In the face of these challenges, mapping and monitoring of these areas is vitally important. Spatial analyses like the one demonstrated here, in combination with temperature, salinity, wave, and other climate indicators could provide scientists and policymakers with the knowledge and tools to effectively conserve and protect these habitats to the greatest extent possible over the coming decades.

6.2 Data Limitations

In addition to the ecological limitations outline above, there are some important caveats to note regarding the rocky area identification algorithm itself. Further research is undoubtedly needed to verify and test the methodology discussed here before it can be confidently applied at large scales. The greatest limitation to this work so far is that only the Encinitas site was used for verification purposes. The value of the R function would likely change at other locations and understanding this variability would be crucial for creating a transferable method of identifying rocky areas. Verified transferability is the major key for deploying this technique at all locations where LiDAR surveys have been flown and data is publicly available. This would be the next step in furthering this work towards the end goal of creating a regional, state, or nationwide inventory of nearshore rocky habitats.

There are also various sources of errors within the data collection itself, as well as decisions made throughout the processing steps that can examined. Surface waves and bubbles in the surf zone create some inconsistencies with airborne LiDAR surveys; and although they are addressed in the post-processing steps, the methods used by USACE to remove these errors are not publicized alongside the final data itself. Another source of error is the resolution of the SANDAG data which was divided into a 5x5 meter grid. To match up the two data sets, the SANDAG data was resampled to 1x1 meter resolution which creates opportunities for error. Ideally, to verify the proposed mapping technique, data would be collected in situ with this goal in mind, so that the resulting ‘ground truth’ data would be high resolution and focused specifically on the identification of rocky substrate. Data collection of this rigor was beyond the scope of this project but could be done in the future as a continuation of this work. The biggest question moving forward will be the evolution of the roughness cutoff function as more study sites are considered. Rather than potentially fitting a higher order polynomial to other noise in the data, a linear function was chosen on the assumption that the loss of LiDAR return density with depth is roughly linear. This can be revisited and refined at future sites that have uniquely shaped reefs at different depths and may produce variations in the optimal roughness cutoff values. For this work to move forwards, the most important challenge will be establishing the transferability of this methodology across variable coastal seascapes.

6.3 Policy and Economic Implications

Developing this research with the end goal of quantifying and mapping nearshore rocky areas across California would create an important tool for policymakers. As previously mentioned, this resource could be extremely valuable for informing conservation decisions, resource allocation, and identifying new areas of interest for scientific inquiry. A statewide inventory could also be used as a foundation on which to calculate and quantify the total economic value (TEV) of the state’s nearshore rocky habitats. Valuation of ecosystems is an inexact science, though it is critical for making the economic and policy case for conservation. The different habitats examined in this study (the intertidal zone, surfgrass beds and macroalgae forests) all provide varying degrees of both use and non-use value. With regional or statewide inventories of the rocky nearshore, total area could be used to inform TEV estimations that impact policy outcomes. In general, a data set of this scale and resolution would be an enormously useful tool for groups like the California Coastal Commission, The Ocean Protection Council, CA State Parks, researchers, conservationists, and other stakeholders. Airborne LiDAR surveys are still being conducted by USACE, so the quality and accuracy of the data will most likely continue improving in the future.

California’s coastal management policies have been shaped largely by the landmark Coastal Act, enacted in 1976 which established the Coastal Commission as a permanent agency with the authority to regulate coastal management and development [38]. The mission of the Coastal Commission is stated to “protect, maintain and where feasible enhance and restore the overall quality of the coastal zone environment and its resources” [38]. The jurisdiction of the Coastal Commission extends past the coastline itself, to about three miles offshore. This makes the Coastal Commission the primary regulatory body is charge of managing, protecting and potentially restoring nearshore coastal habitats. The Coastal Act also includes provisions on taking technical advice and recommendations from the scientific community, acknowledging that “scientific recommendations are necessary for many coastal planning, conservation, and development decisions and that the commission should...interact with members of the scientific and academic communities in the social, physical, and natural sciences...especially with regard to issues such as coastal erosion and geology, marine biodiversity, wetland restoration and sea level rise” [39]. Further extrapolation of this research falls squarely into the language of the Coastal Commission’s mission, making a strong case for applying future rocky nearshore inventories towards the informing of state and regional policies. California has largely served as a model for the effective collaboration between policymakers and scientists for purposes of coastal management. Continuing this research to create a high resolution, accurate inventory of nearshore rocky habitats can help advance this mission in the face of ongoing and impending climate stressors. This research, and subsequent collaboration with policymakers is an important piece of the work needed to understand and monitor these crucial ecosystems, protecting them to the greatest extent possible so that the economic and ecological value they provide is not lost to climate change and destroyed for future generations.

Sources

1. BBVA Foundation. "Coastal Habitats Are The Biosphere's Most Imperiled Ecosystems." ScienceDaily. ScienceDaily, 21 October 2007.

2. Environmental Protection Agency, “Climate Impacts on Coastal Areas.” *EPA*, 6 Oct. 2016.
3. Narayan, Siddharth et al. “The Effectiveness, Costs and Coastal Protection Benefits of Natural and Nature-Based Defences.” (2016): n. pag. Web.

4. Pontee, Nigel et al. “Nature-Based Solutions: Lessons from Around the World.” *Proceedings of the Institution of Civil Engineers. Maritime engineering* 169.1 (2016): 29–36. Web.
5. Temmerman, S et al. “Ecosystem-Based Coastal Defence in the Face of Global Change.” *NATURE* 504.7478 (2013): 79–83. Web.
6. Montgomery, J.M., K.R. Bryan, and G. Coco. “The Role of Mangroves in Coastal Flood Protection: The Importance of Channelization.” *Continental shelf research* 243 (2022): 104762–. Web.
7. Borchert, Sinéad M. et al. “Coastal Wetland Adaptation to Sea Level Rise: Quantifying Potential for Landward Migration and Coastal Squeeze.” *The Journal of applied ecology* 55.6 (2018): 2876–2887. Web.
8. Ondiviela, Barbara et al. “The Role of Seagrasses in Coastal Protection in a Changing Climate.” COASTAL ENGINEERING 87 (2014): 158–168. Web.
9. Irish, J L, J K McClung, and W J Lillycrop. Airborne Lidar Bathymetry: The SHOALS System. N.p., 2016. Print.
10. Jennifer M. Wozencraft, and W. Jeff Lillycrop. “SHOALS Airborne Coastal Mapping: Past, Present, and Future.” Journal of coastal research (2003): 207–215. Print.
11. Wozencraft, Jennifer M, W J Lillycrop, and Nicholas C Kraus. SHOALS Toolbox: Software to Support Visualization and Analysis of Large, High-Density Data Sets. N.p., 2002. Print.
12. Final Coastal Regional Sediment Management Plan for the San Diego Region. Long Beach, Calif: Moffatt and Nichol, 2009. Print.
13. Costa, Bryan. “Multispectral Acoustic Backscatter: How Useful Is It for Marine Habitat Mapping and Management?” Journal of coastal research 35.5 (2019): 1062–1079. Web.
14. Rocchio, Laura. “Monitoring the Collapse of Kelp Forests.” *NASA*, NASA, earthobservatory.nasa.gov/images/148391/monitoring-the-collapse-of-kelp-forests.
15. O'Clair, R.M. 2000. North Pacific Seaweeds. Plant Press, Auke Bay, Alaska. 162 p.
16. Ricketts, E. F., J. Calvin, and J.W. Hedgpeth. 1985. Between Pacific tides. Stanford University Press, Stanford, CA. 652 p.
17. Mondragon, J. 2003. Seaweeds of the Pacific Coast: common marine algae from Alaska to Baja California. Sea Challengers, Monterey, CA. 97 p.
18. Graham, Michael H. “Effects of Local Deforestation on the Diversity and Structure of Southern California Giant Kelp Forest Food Webs.” Ecosystems (New York) 7.4 (2004): 341–357. Web.
19. Filbee-Dexter, Karen et al. “Leveraging the Blue Economy to Transform Marine Forest Restoration.” Journal of phycology 58.2 (2022): 198–207. Web.
20. Krause-Jensen, Dorte, and Carlos M. Duarte. “Substantial Role of Macroalgae in Marine Carbon Sequestration.” Nature geoscience 9.10 (2016): 737–742. Web.
21. Eger, Aaron & Marzinelli. (2021). The economic value of fisheries, blue carbon, and nutrient cycling in global marine forests. 10.32942/osf.io/n7kjs.
22. Phillips, Ronald C, and Ernani G Meñez. Seagrasses. Washington, D.C: Smithsonian Institution Press, 1988. Print.
23. MARINe. 2004 (Updated 12/09/04). Multi-Agency Rocky Intertidal Network. World Wide Web electronic publication, http://www.marine.gov.

24. Duarte, Carlos M, and Carina L Chiscano. “Seagrass Biomass and Production: a Reassessment.” Aquatic botany 65.1 (1999): 159–174. Web.
25. Ruiz-Montoya, Leonardo et al. “Ecophysiological Responses and Self-Protective Canopy Effects of Surfgrass (Phyllospadix Torreyi) in the Intertidal.” Marine environmental research 172 (2021): 105501–105501. Web.
26. Orth, Robert J et al. “A Global Crisis for Seagrass Ecosystems.” BioScience 56.12 (2006): 987–996. Web.
27. Largier, J.L, Cheng, B.S., and Higgason, K.D., editors. 2010. Climate Change Impacts: Gulf of the Farallones and Cordell Bank National Marine Sanctuaries. Marine Sanctuaries Conservation Series ONMS-11-04. U.S. Department of Commerce, National Oceanic and Atmospheric Administration, Office of National Marine Sanctuaries, Silver Spring, MD. 121 pp.
28. Kaplanis, Nikolas J. et al. “Future Sea-Level Rise Drives Rocky Intertidal Habitat Loss and Benthic Community Change.” *PeerJ (San Francisco, CA)* 8 (2020): e9186–e9186. Web.
29. Vaselli S, Bertocci I, Maggi E, Benedetti-Cecchi L. Assessing the consequences of sea level rise: effects of changes in the slope of the substratum on sessile assemblages of rocky seashores. Marine Ecology Progress Series. 2008
30. Pontee, Nigel. “Defining Coastal Squeeze: A Discussion.” Ocean & coastal management 84 (2013): 204–207. Web.
31. Doody, J. Patrick. “Coastal Squeeze and Managed Realignment in Southeast England, Does It Tell Us Anything About the Future?” Ocean & coastal management 79 (2013): 34–41. Web.
32. Martinez, Ma. Luisa et al. “Land Use Changes and Sea Level Rise May Induce a ‘coastal Squeeze’ on the Coasts of Veracruz, Mexico.” Global environmental change 29 (2014): 180–188. Web.
33. Rogers-Bennett, L, and C A Catton. “Marine Heat Wave and Multiple Stressors Tip Bull Kelp Forest to Sea Urchin Barrens.” Scientific Reports 9.1 (2019): 15050–9. Web.
34. Parnell, P. Ed et al. “The Response of Giant Kelp (Macrocystis Pyrifera) in Southern California to Low-Frequency Climate Forcing.” Limnology and oceanography 55.6 (2010): 2686–2702. Web.
35. Harris, L G et al. “Community Recovery after Storm Damage: A Case of Facilitation in Primary Succession.” Science (American Association for the Advancement of Science) 224.4655 (1984): 1336–1338. Web.
36. Vivanco-Bercovich, Manuel et al. “Combined Effects of Marine Heatwaves and Reduced Light on the Physiology and Growth of the Surfgrass Phyllospadix Torreyi from Baja California, Mexico.” Aquatic botany 178 (2022): 103488–. Web.
37. Gilman, Sarah E, David S Wethey, and Brian Helmuth. “Variation in the Sensitivity of Organismal Body Temperature to Climate Change over Local and Geographic Scales.” Proceedings of the National Academy of Sciences - PNAS 103.25 (2006): 9560–9565. Web.
38. Diamond, Jordan et al. “The Past Present and Future of California’s Coastal Act” Coastal Act Issue Brief – UC Berkeley School of Law. Aug 24, 2017.

39. California, State of. *The California Coastal Commission's Legal Authority to Address Climate Change*, 2019, State of CA. Web.