North Central Coast State of the Region Assessment (2010-2015) Portfolio Product

Document Title: North Central Coast MPA Baseline Program Integration: Filling in the nearshore "White Zone"

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Report to California Ocean Science Trust
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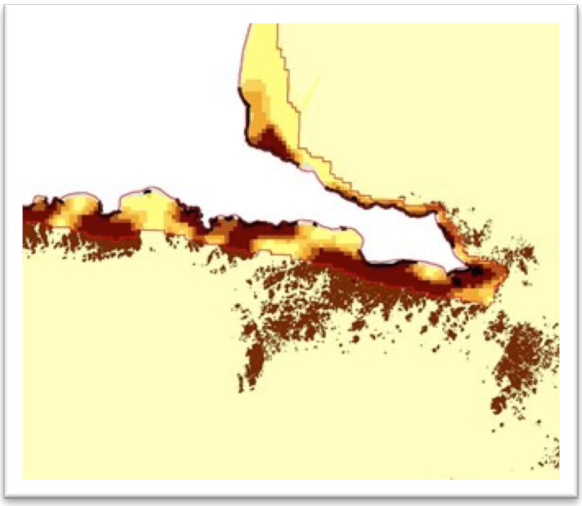 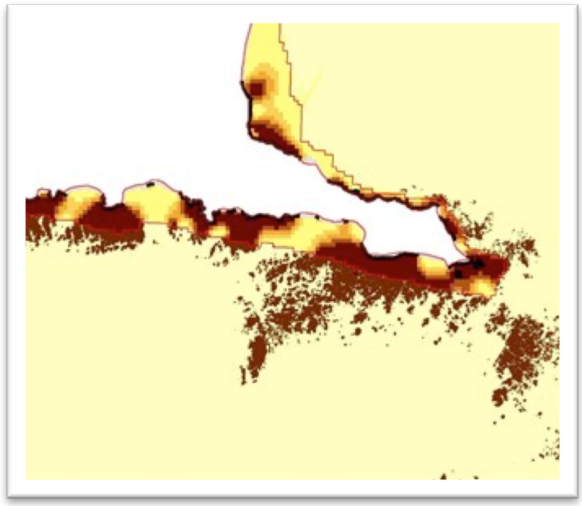

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Summary

State and federal agencies recently invested nearly thirty-five million dollars to collect and ground-truth seafloor data within California's state waters to create bathymetric, geologic, and habitat maps for a large portion of its nearshore marine habitats. These datasets were essential for the design of California's marine protected area (MPA) network, and are currently informing ongoing management. However, the existing seafloor maps contain a critical gap—the shallow, very nearshore zone, where navigation hazards and technical limitations prevented ship-board mapping, and turbid water or obstructions prevent successful remote sensing or aerial techniques. This 50-500m wide band of unmapped seafloor, a data gap known as the "white zone", extends from shore to 10-15m depth along the length of the California coast, encompassing much of the state's kelp forests and essential habitat for commercially and recreationally important species. Improved mapping of the white zone has been repeatedly identified as an area of critical data need, yet the costs and labor associated with empirically mapping this zone statewide are prohibitive.

We leveraged the wealth of seafloor and shoreline mapping data available through the California's Seafloor Mapping Program (CSMP) and the National Oceanic and Atmospheric Administration (NOAA) Environmental Sensitivity Index (ESI) shoreline habitat categorizations, to develop predictive maps of substrate characteristics in the white zone through interpolation (a mathematical technique to predict missing values in data). In order to determine an optimal method of interpolation, we used geographic information systems software (ArcGIS) to create artificial white zones within the CSMP substrate maps, and tested ten ArcGIS interpolation techniques, crossed by five resampled pixel sizes, crossed by four artificial white zone widths, to test which combination of interpolation methods and pixel size generated the most accurate and precise prediction of rock versus sand substrate across the variety of white zone widths that occur along the North Central Coast. We chose three of the methods with the highest precision and accuracy across multiple white zone widths, and used them to generate predictive substrate maps of rock versus soft bottom within the white zone of the North Central Coast.

These maps are available to stakeholders through the California Department of Fish and Wildlife (CDFW) web mapping and GIS data distribution platform, MarineBIOS (http://www.dfg.ca.gov/marine/gis/viewer.asp). They can be used for a range of management applications, such as population modelling for key species, setting expected rates of population change within MPAs to better evaluate MPA conservation performance, and setting guidelines for scientific collection permits.

Introduction

The substantial investments in mapping a majority of California's seafloor are a tremendous resource for marine resource managers and researchers. These data have been applied to conservation and management mandates, such as developing the MPA network, managing fisheries and endangered species (such as abalone), and assessing essential habitats (Butler et al. 2006, Young et al. 2010, Young 2014, Young and Carr 2015, Merrifield et al. 2013, Saarman et al. 2013). Unfortunately, monitoring and management of the critical nearshore regions is limited by the data gap known as the "white zone", which extends from shore to 10-15m depth along the entire California coast (Figure 1). Rife with navigation hazards such as shallow rocky shoals, this zone is rarely accessible by mapping vessels, and aerial remote sensing techniques are generally infeasible due to turbid water and dense kelp canopies. The Seafloor Mapping Lab at California State University, Monterey Bay (CSUMB) developed a hybrid JetSki/air boat shallow-water mapping vessel, the R/V Kelp Fly (Kvitek 2015), which can map this region on a small scale. While this vessel is uniquely able to operate in the white zone, the effort and funds necessary for this technique make it unlikely that it will be applied across the state's 1770 km of coastline in the near future.

Although in most locations, the white zone is a relatively narrow (50-500m wide) band along the coast, this zone supports rich kelp forest and dynamic soft-bottom ecosystems, and provides critical habitat for a variety of recreationally and commercially important species (such as red abalone, lobster, sea urchins, and nearshore fishes).

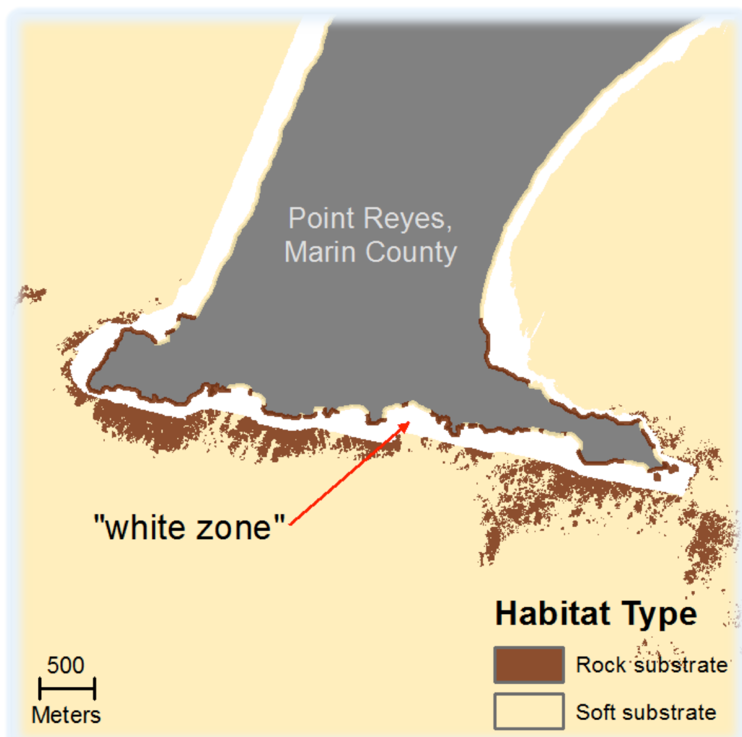


Figure 1. Example of white zone, showing the offshore CSMP substrate layer, the onshore rock versus soft bottom ESI shoreline categorization, and the "white zone" of missing data in between the two.

The distributions and productivity of these ecosystems and species are dictated by the geologic substrate, categorized at the most basic level into rock versus soft bottom habitats (Schiel and Foster 1986, Graham *et al.* 2008, Hamilton *et al.* 2010, Carr and Reed *in press*). These categories explain much of the coarse distribution of marine life, including the locations of critical ecosystems such as kelp forests, rocky reefs, and seagrass beds. Maps of the distributions of these rock versus soft bottom habitats would enhance understanding of the distribution of marine organisms, and inform adaptive management of these vital ecosystems.

A recent NOAA and U.S. Geological Survey (USGS) sponsored CSMP needs assessments workshop, which hosted almost 100 managers, policy makers, and research scientists from across California, found that an emerging and pressing topic of interest was to "fill in" the white zone with critical data for the nearshore regions (CSMP 2014). Given the high priority of these data needs, we developed methods to predict rock versus soft bottom substrates in the white zone for the North Central Coast, as a test case for methods to eventually cover the entire coast of California. These maps will allow for refined population estimates of marine life, which is useful across a suite of management mandates, from MPA monitoring and fishery assessments, to the new CDFW effort to assess the biological impacts of scientific collection in MPAs.

Methods

Spatial interpolation is a mathematical procedure used to predict values in unsampled areas, based on data attributes from neighboring sampled areas. It is increasingly tested and applied across multiple disciplines where data acquisition is too expensive or not technologically feasible (Sanchez-Carnero et al 2012). To explore the utility of spatial interpolation in shallow seafloor habitats, we compiled seafloor data collected through CSMP and simple shoreline classification data available from NOAA's Environmental Sensitivity Index (ESI) maps. We used ten standard spatial interpolation methods using geographic information system software (ArcGIS, Esri Industries, Redlands, CA). We examined the effects of crossing three main factors (further described in the following sections): 1) four on-offshore white zone widths, 2) ten interpolation methods, and 3) five pixel sizes. These combinations produced 200 models that were tested for their accuracy and precision in estimating substrate coverage in the white zone.

To test these 200 methods, we withheld areas of the mapped substrate, predicted the cover of these areas using each method (measured as the proportion of rock substrate), and then compared real and predicted substrate composition. In a hypothetical scenario of perfect prediction, the predicted substrate composition at each pixel would be exactly equal to the real substrate at that pixel. Thus, we calculated the difference between real and predicted substrate composition (real minus predicted proportion of rock substrate) for each pixel in each of our 200 models. By comparing the mean of this difference across different spatial scales, we were able to compare predictive power among models and choose the models with the greatest predictive power.

Creation of artificial white zones (AWZ) of varying widths

In order to test the accuracy and precision of the interpolation models, the predicted substrate must be compared with actual substrate measures. There are currently four areas with bathymetric data in the white zone, collected by the R/V KelpFly at CSUMB (Kvitek 2015). However, due to the intensive nature of shallow water bathymetric mapping, very few areas have been mapped, and all are within the Central Coast. Therefore, we created artificial white zones (AWZ) by whiting out (i.e. masking) areas of mapped seafloor within nearshore regions adjacent to the actual white zone (Figure 2).

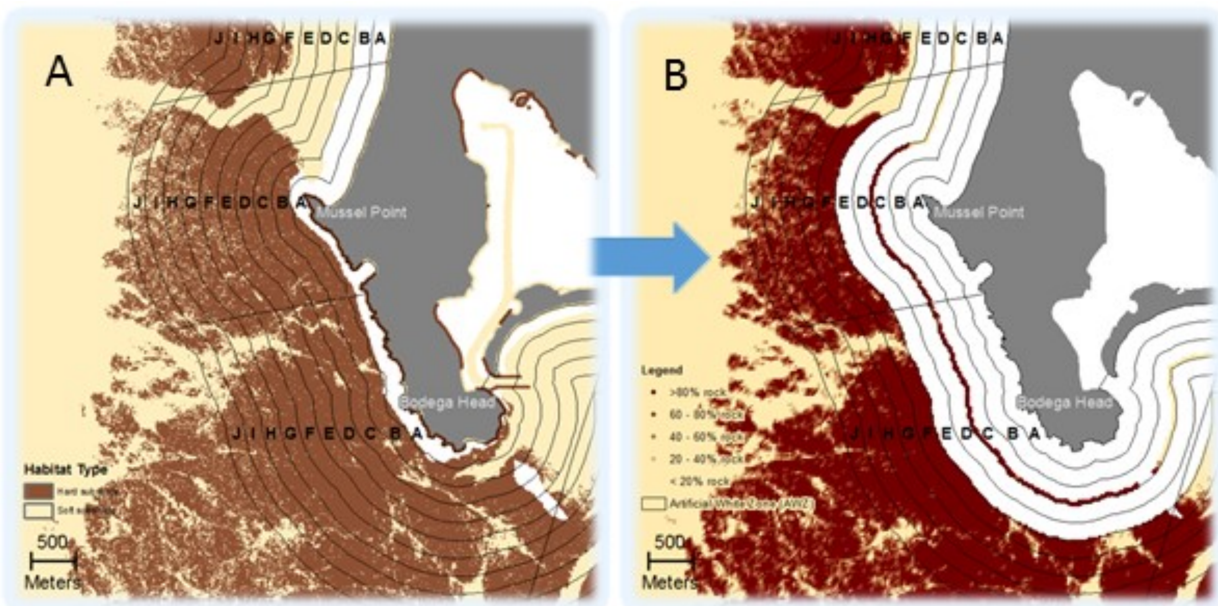


Figure 2. Map of AWZ creation and data exclusion. Gray areas are land, brown and tan areas are underwater rock and soft bottom substratum, respectively. **A**) The nearshore substrate was first divided into 200m wide strips labeled A through J, and divided into segments roughly 2.5 km **B)** Data were selectively filtered out for iterative testing of interpolation methods in AWZs at various sizes and geographies. Map B shows the input data used to test a 400m wide AWZ (segments D + E), using the simulated "inshore" line of rock versus sand data on one side (between segments C and D), and the seafloor data on the other (offshore of segment E). The source data to the left (offshore) of the AWZ is the original 2m pixel classified data. The derivative on the right is a line of 30m pixels with the proportion of hard substrate in each pixel.

Interpolation techniques

We tested ten standard interpolation methods available within the Esri ArcGIS software package, including ordinary kriging with 5 different semivariogram models (linear, circular, spherical, exponential, and Gaussian), inverse distance weighting (IDW) with three different powers (0.5, 1, and 2), natural neighbor method, and tensioned spline with a weight of 0.5. Variations on these methods are documented as among the most accurate for interpolating digital elevation modeling (Chaplot et al. 2006, Erdogan 2009), and thus were considered as the most appropriate methods to test for the substrate predictions as well.

Effects of pixel size

The substrate maps created through CSMP are high resolution, providing substrate information at a 2m pixel resolution (i.e. 2m x 2m pixel size = $4m^2$ area), however it is not possible to interpolate wide swaths of missing data accurately at that scale. Therefore, we tested a set of pixel sizes that would balance high prediction accuracy (larger pixels) with the most management relevance for estimating population abundances (smaller pixels). To test the most appropriate size, balancing accuracy and utility, pixels from the CSMP substrate maps were resampled using block statistics to calculate the proportion of rocky substrate at five resolutions: 30m, 60m, 90m, 120m, and 240m square pixels.

Decision framework and methods choice

The approach of looking at the mean difference between real and predicted substrate composition within each of the forty 2.5 km AWZ segments enabled us to visualize both the accuracy (mean difference across all segments), and the precision (variability across all segments) of the interpolations across real world segments of the coast that differed in substrate composition. Graphing these two pieces of information enabled us to choose a subset of the tested methods with the greatest predictive accuracy (lowest mean difference), and precision (smallest variability) across all 200 trial interpolation models (Figure 3).

To rank the candidate treatments and choose the three best combinations of interpolation method and pixel size, we calculated the product of the mean difference and the variability measure, and ranked these products. Using this ranking system, the top four interpolation method/pixel size combinations were variations on kriging, followed by spline and IDW techniques. We selected a kriging method (linear with 30m pixel size), an IDW method (power 0.5 with 30m pixel size), and a tensioned spline method (weighting of 0.5 and 60m pixel size) for final comparative interpolations across the real white zone.

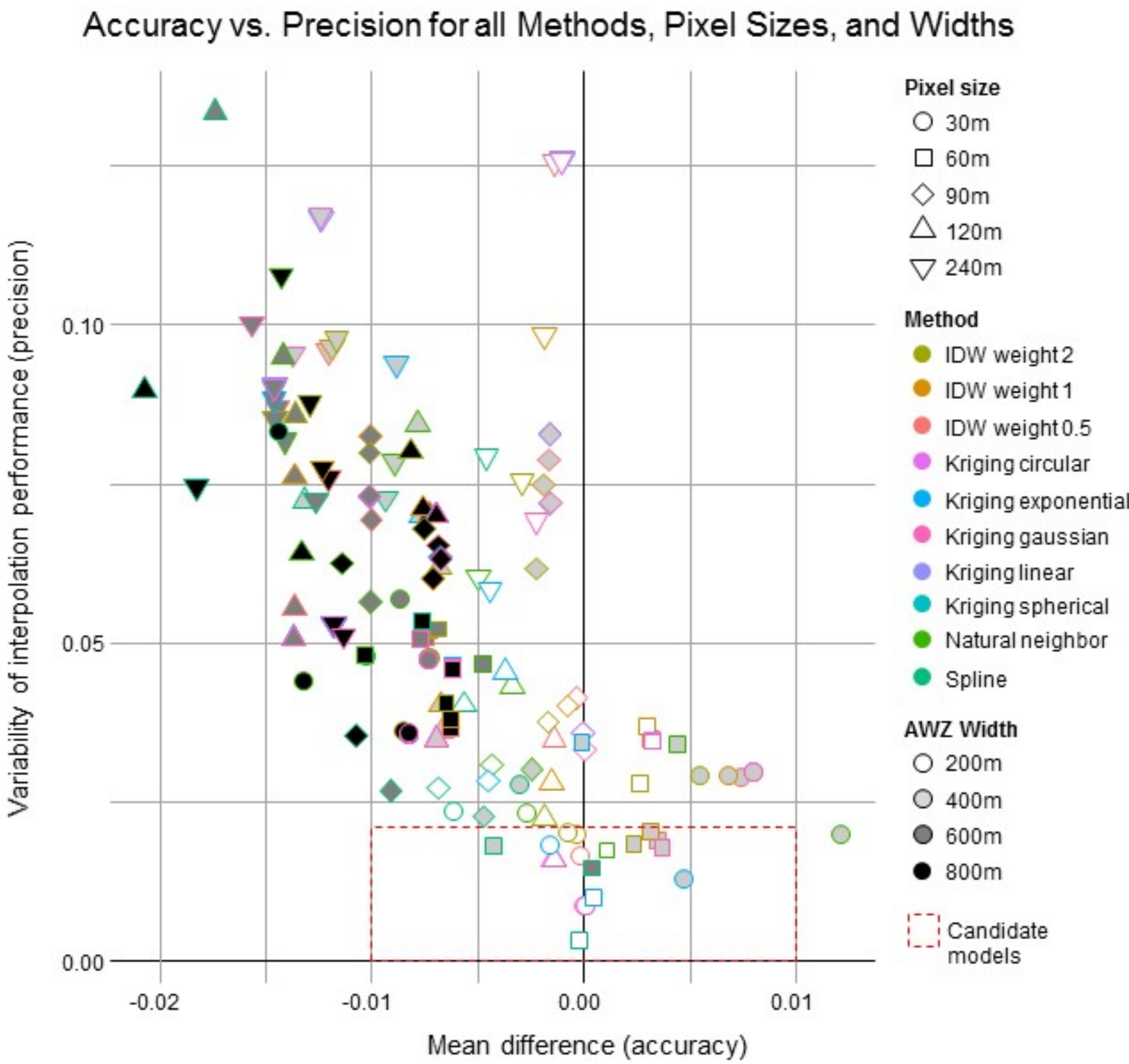


Figure 3. Comparison of accuracy and precision for all tested methods across all pixel sizes and all AWZ widths. Accuracy (x-axis) is assessed as the mean of the difference between real and predicted substrate across the study region. Precision is represented by the variability of interpolation performance across 40 segments of the coast (y-axis) and measured as the range between non-outliers. Candidate models (outlined with a red dashed line) were investigated further, and a subset was chosen for interpolation across the white zone.

Results and Discussion

Comparison of interpolated maps using three methods

We created three sets of interpolations of the white zone across the North Central Coast, using three high ranking methods: 1) Kriging using a linear semivariogram with 30m pixels, 2) IDW with a power of 0.5 with 30 m pixels, and 3) tensioned spline with a weighting of 0.5 with 60 m pixels (Figure 4). All three of these methods fulfilled our requirements for both accuracy and precision, and generate visually reasonable and extremely similar predictions across a variety of locations within the North Central Coast. Therefore, we chose the IDW method for the final map set, as it was the most time efficient and simple, while still providing all necessary information.

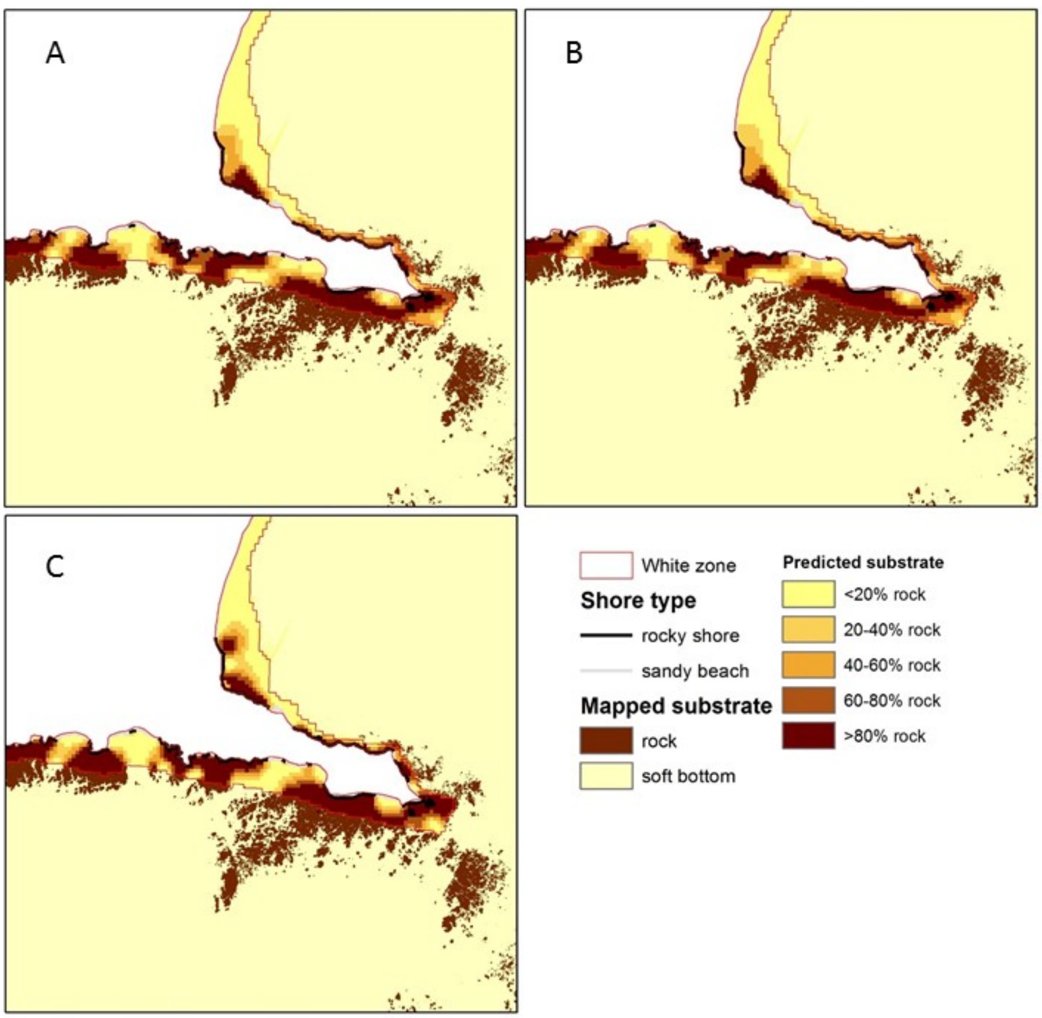


Figure 4. Visual comparison of interpolation results from three high ranking interpolation models at Point Reyes headland: (**A**) IDW, (**B**) kriging, and (**C**) spline methods.

Impacts of external factors on prediction accuracy

We tested the effects of interpolation methods and pixel size, both of which are within our control to choose for the best possible substrate prediction, however we also wanted to understand the impacts of varying white zone sizes on interpolation accuracy and precision. Though we can't control that factor, we can use the tests of various white zone sizes to understand the impact on the width of the white zone on the interpolation, and thus our interpretation of the results. In general, all interpolation methods showed lower mean differences when tested across narrower AWZs. While most of the region is within the typical range of 50–500m, there are a few areas that extend beyond this range. None of the interpolation methods tested are likely to generate accurate substrate predictions across such a broad swath of unknown substrate.

Interpretation of interpolated maps

The interpolation method we chose for filling in the white zone (IDW with a power of 0.5 and 30m input pixel size) showed variable predictive performance across different AWZ widths in our trials (Figure 5). Predictive accuracy was the highest for a narrow (200m wide) AWZ, which matches the width of the white zone along roughly 50% of the north central coast region. For a 200m wide white zone, predicted substrate composition was very similar to real, and there was comparatively little variability in the accuracy of these estimates across the forty 2.5 km alongshore segments used in the trials. To put this in perspective, the IDW method used for final interpolation overestimated the area of rock substrate in the 200m wide AWZ trials by 0.02% or ~350 m² over the 2.2 million m² (2.2 km²) of interpolation area. As AWZ width was increased in our trials, the accuracy of substrate composition estimates decreased and the variability of performance across segments increased. At the 400m width, there was a tendency to underestimate

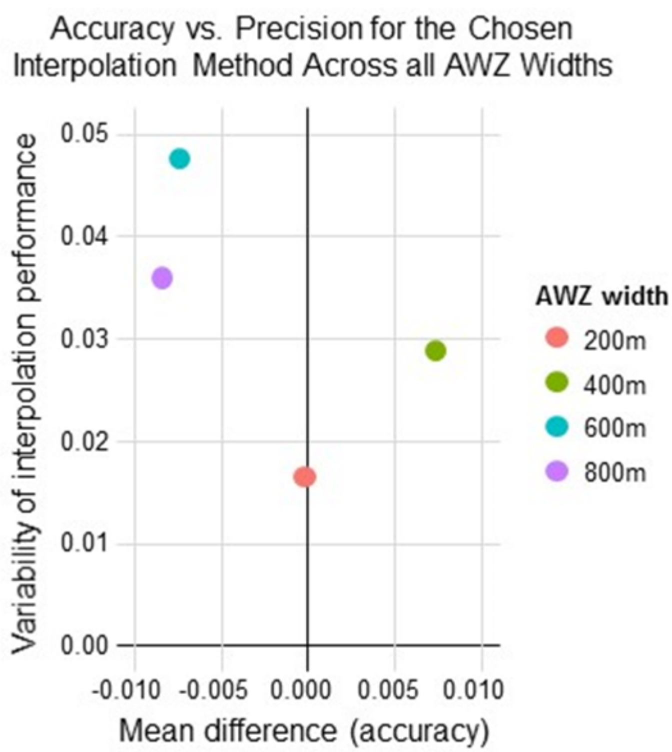


Figure 5. Accuracy vs. precision of substrate estimates derived using the chosen interpolation model (IDW power 0.5 and 30m pixel size) across different AWZ widths.

the proportion of rock with an overall underestimate across the study region of 0.7%, while at the 600m and 800m widths, there was a tendency to overestimate the proportion of rock with overall overestimate of 0.7% and 0.8% respectively. These tendencies toward over or under-estimation of the proportion of rock substrate at different white zone widths is likely a function of the distribution of substrate in the specific areas tested, not an inherent quality of the interpolation model.

The inverse relationship between substrate prediction accuracy and AWZ width indicate that white zone interpolation methods have the greatest utility and accuracy for areas with a narrow white zone, and are unlikely to generate accurate predictions where the white zone is extremely wide, for example Bolinas Point. This information may help direct future empirical mapping efforts to target areas with a particularly wide white zone, where the application of interpolation techniques is limited.

Applications of interpolated maps

The high resolution mapping information generated by the California Seafloor Mapping Project provided (among other things) a binary substrate classification where each 2m x 2m pixel could be classified as either rock or soft bottom. In contrast, the interpolation methods employed in this study use larger pixels and predict the proportion of rock substrate in each pixel. This decision to use larger pixels allowed us to dramatically increase computing efficiency, while also generating an output that is necessarily "blurry" relative to the empirically mapped substrate. This blurriness makes it apparent, even to the untrained eye, that the interpolations are not intended to precisely predict the locations of specific reef features, but rather to provide a general estimate of the amount of rock versus soft bottom that is likely to be present in a given area. To use these proportional substrate composition pixels for calculations of substrate area, one must calculate the mean proportion of rock vs. soft substrate across the area of interest, and then multiply that by the white zone size in the area of interest.

Despite the inevitable blurriness and the prediction's inability to pick up isolated features such as rocky reefs entirely within the white zone, interpolation across the white zone has a number of practical applications. These white zone interpolations can provide a dramatic improvement of estimates of nearshore habitat availability compared to the complete lack of information previously available. These improved habitat availability estimates are likely to be applied to numerous scientific and management questions, including predicting populations of nearshore species (e.g. abalone, sea urchins, lobster, fishes) inside and outside of MPAs, helping to set expected patterns of population changes within MPAs, and understanding geographic patterns of nearshore marine communities. In the near term, CDFW will use the improved habitat availability estimates to estimate the populations of a wide variety of marine species in MPAs statewide, in order to assess the potential impacts of scientific research activities on populations within MPAs.

The white zone interpolations created by this project will be stored and made available to the public, including management and scientific communities, through CDFW's MarineBIOS platform (http://www.dfg.ca.gov/marine/gis/viewer.asp). From this platform, users are able to view the data (along with a wide variety of other marine habitat data) in an interactive online mapping tool, as well as download it in several formats with associated metadata and information about appropriate data usage.

Limitations

The maps created by the interpolation method described in this report have several important limitations. Although our extensive testing showed that the interpolation method chosen (IDW with a power of 0.5 using 30m input pixels) generates relatively accurate and precise predictions of substrate composition at the scale of the test segments (2.5 km coastal length), the maps generated with this method do not predict the precise location of rocky reef features. Instead, the interpolations should be viewed as a probability surface that indicates where rock is more or less likely to occur and the likely proportion of rocky vs. soft substrate in each pixel of the white zone. As such, these maps are unlikely to be useful for selection of monitoring sites, fishing areas, or any other purpose where precise location of substrate features at scales less than 100's of meters is required.

Another important factor to consider when using the interpolated white zone maps, is the inverse relationship between interpolation accuracy and white zone width. As predicted, interpolation accuracy declined across all methods as white zone width increased in our test cases. Therefore, in areas where the white zone extends particularly far offshorethe accuracy of our interpolations is likely to be quite low.

Given the limitations of the spatially interpolated white zone maps, their most likely utility is for extrapolating and estimating species and community distribution and abundance at spatial scales of 100's of meters. Such scales are relevant for population modeling and evaluating MPA effects for shallow-water species. As such, they represent a marked improvement over the lack of information available in the white zone previously. However, this approach is not a substitute for empirical characterizations of seafloor features like those generated by the California's Seafloor Mapping Program. Rather, they provide researchers and managers with a temporary solution to the current gap of critical information.

Next Steps

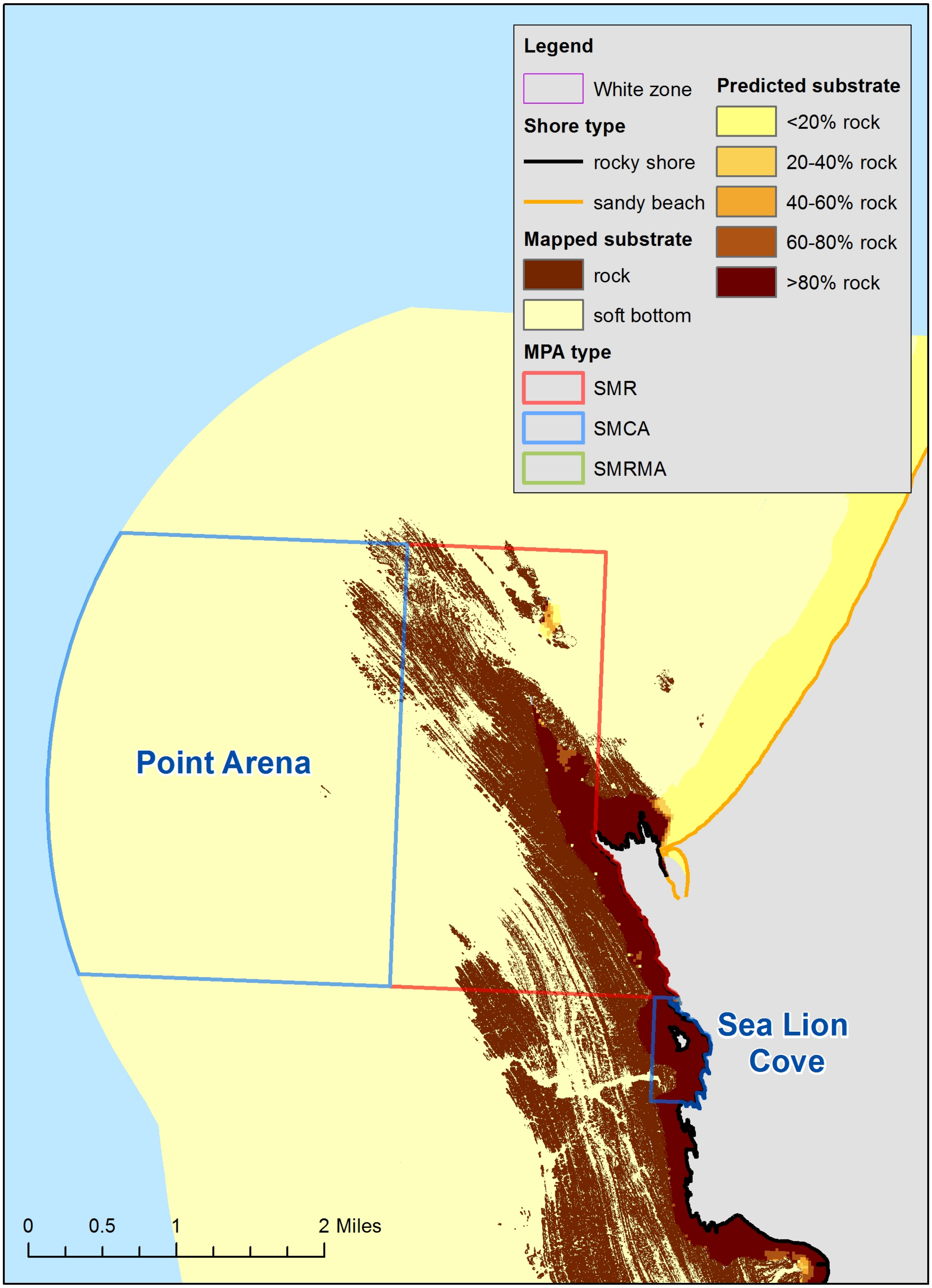
These interpolation methods allow for a relatively efficient prediction of substrate when data are missing, but all predictions are improved by more data. We aim to assess the potential for including a set of USGS onshore-offshore geologic maps where available, and to collect more empirical data in small portions of the white zone, to further interpret and potentially constrain the interpolations.

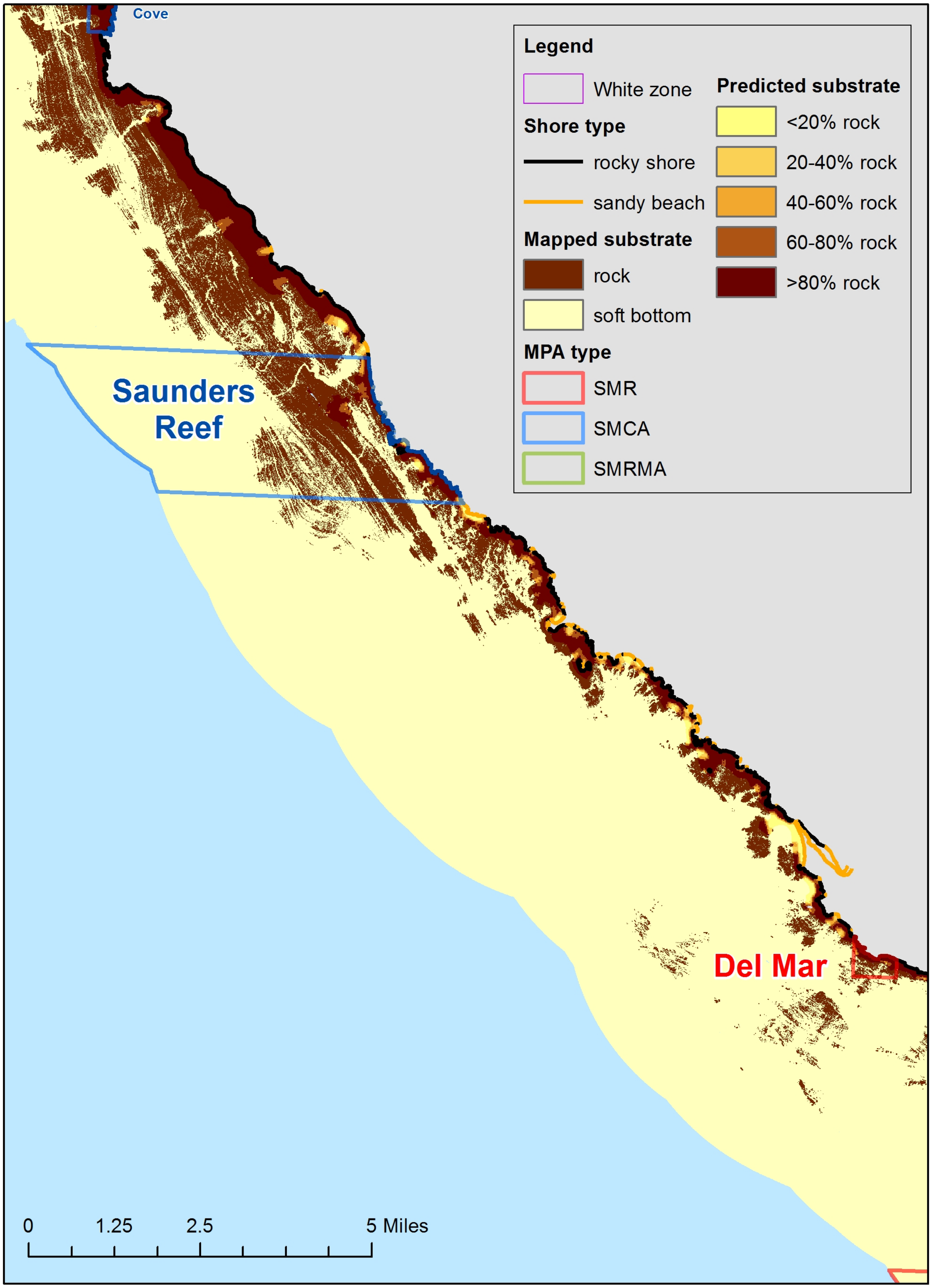
We hope to leverage these methods, designed and calibrated for the North Central Coast, to interpolate the white zone along the entire coast of California, so that the data are available for management across all four MLPA regions. We also aim to work further to employ these maps in population modelling for key marine species and to assist the scientific collections permitting process.

Additionally, a manuscript for publication (with more detailed methods descriptions) is currently under development. Please feel free to contact the lead author, Emily Saarman, with any questions at: esaarman@ucsc.edu.

Map set using the inverse distance weighting interpolation method

The following maps display the white zone interpolation using Inverse Distance Weighting (power of 0.5 with 30 m pixels) and a scale of 1:125,000, across a set of State Marine Reserves (SMRs), State Marine Conservation Areas (SMCAs), and State Marine Recreational Management Areas (SMRMAs). The large scale shown here allows a visualization of patterns along the coast, but the product on MarineBIOS (http://www.dfg.ca.gov/marine/gis/viewer.asp) will allow for interactive exploration of the predicted maps.


Legend
White zone
Shore type
rocky shore
sandy beach
Mapped substrate
rock
soft bottom
MPA type
SMR
SMCA
SMRMA
Predicted substrate
<20% rock
20-40% rock
40-60% rock
60-80% rock
>80% rock
Point Arena
Sea Lion Cove
0
0.5
1
2 Miles


Cove
Legend
White zone
Shore type
rocky shore
sandy beach
Mapped substrate
rock
soft bottom
MPA type
SMR
SMCA
SMRMA
Predicted substrate
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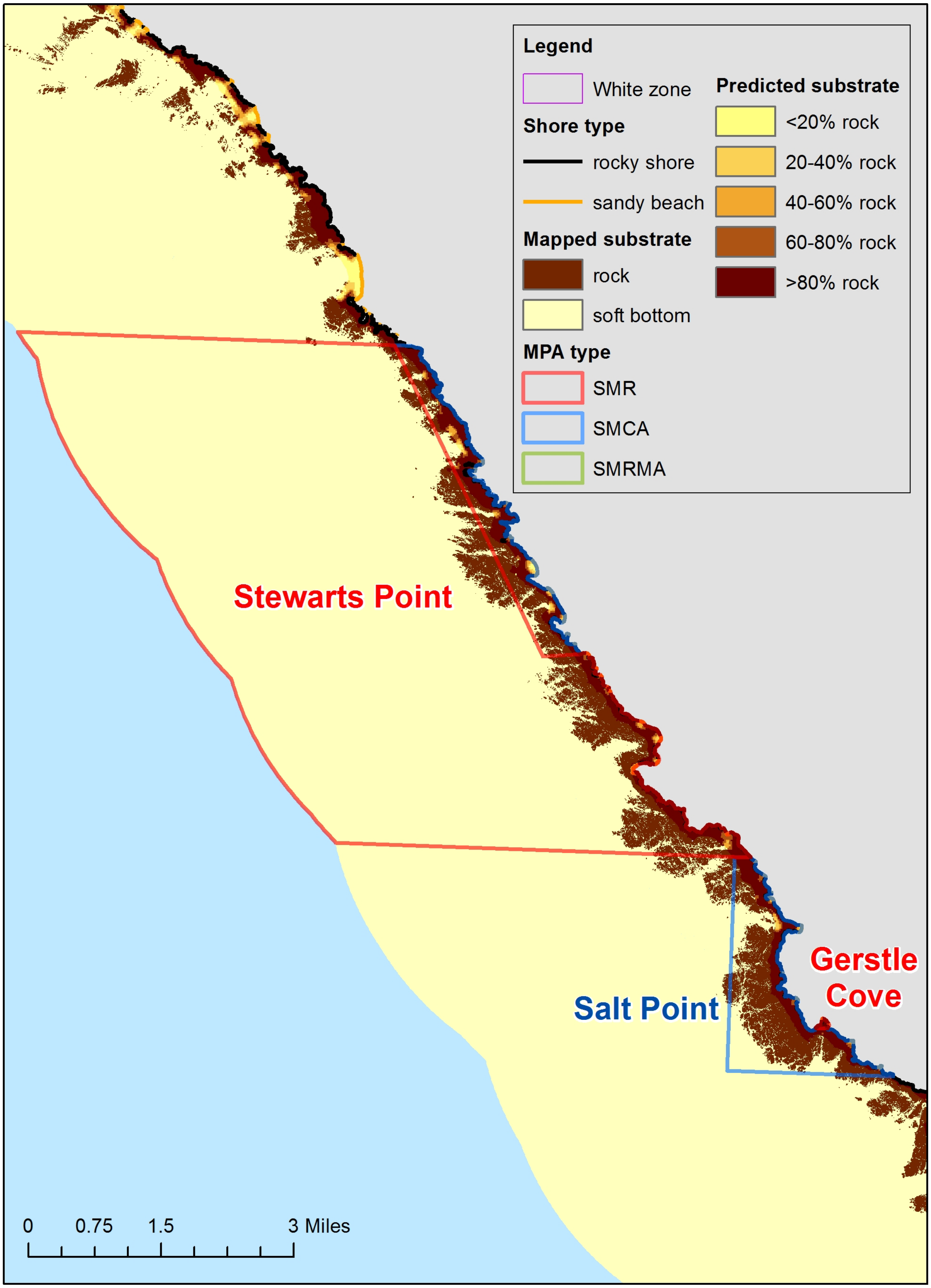
20-40% rock
40-60% rock
60-80% rock
>80% rock
Saunders Reef
Del Mar
0
1.25
2.5
5 Miles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White zone
Shore type
rocky shore
sandy beach
Mapped substrate
rock
soft bottom
MPA type
SMR
SMCA
SMRMA
Predicted substrate
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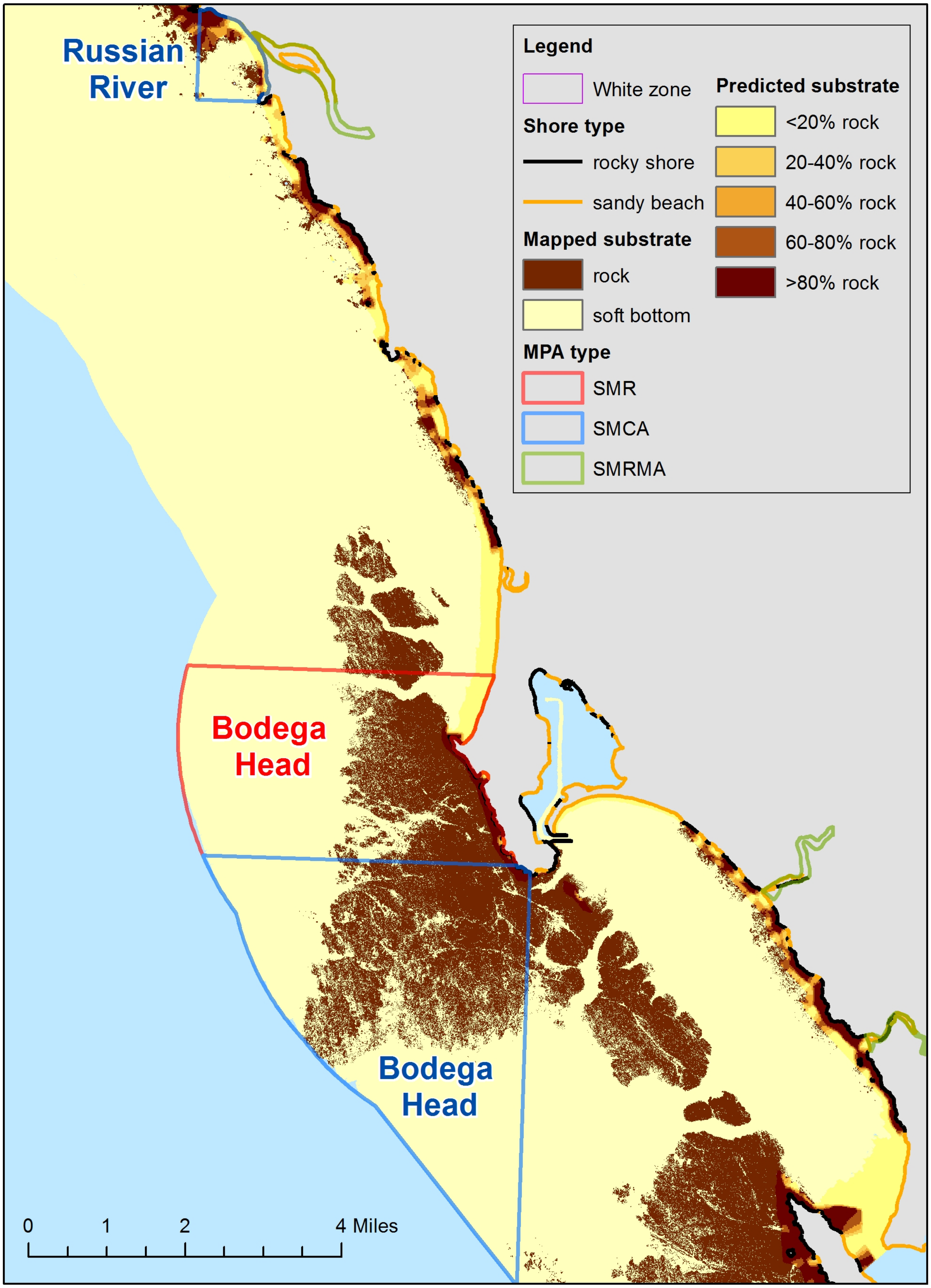
Stewarts Point
Salt Point
Gerstle Cove
0
0.75
1.5
3 Miles


Russian River
Legend
White zone
Shore type
rocky shore
sandy beach
Mapped substrate
rock
soft bottom
MPA type
SMR
SMCA
SMRMA
Predicted substrate
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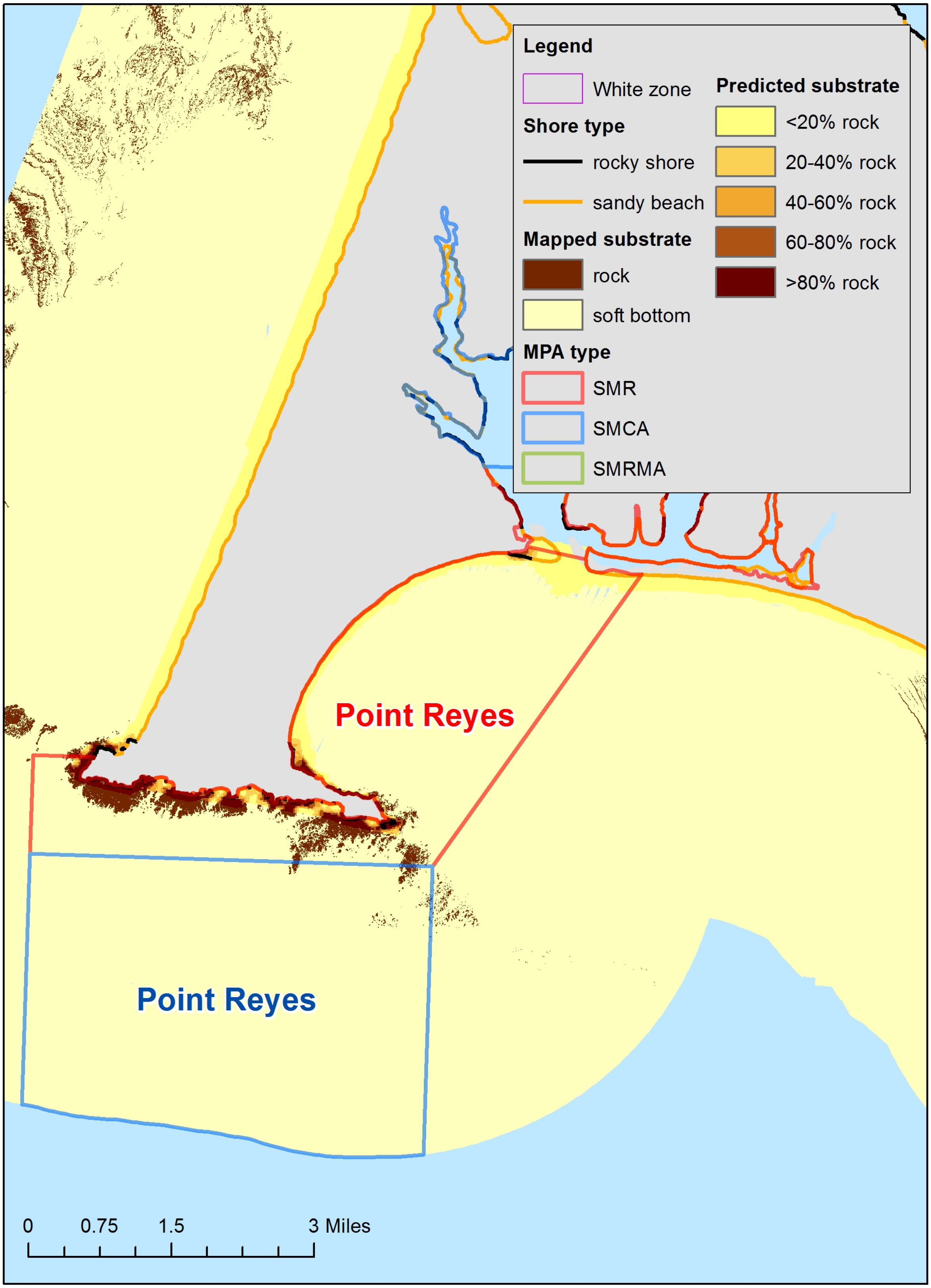
60-80% rock
>80% rock
Bodega Head
Bodega Head
0
1
2
4 Miles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Shore type
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Mapped substrate
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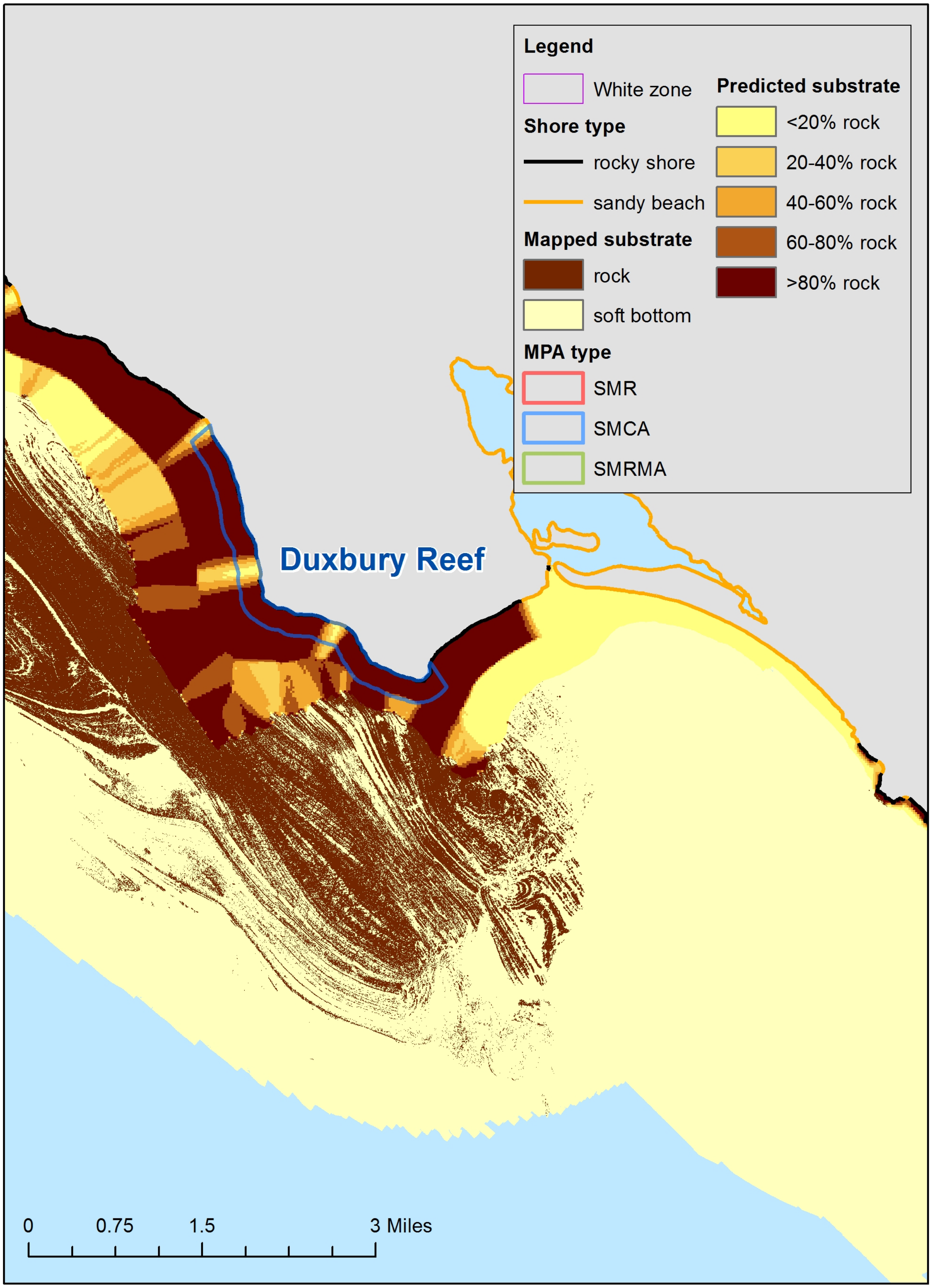
Point Reyes
Point Reyes
0
0.75
1.5
3 Miles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Duxbury Reef
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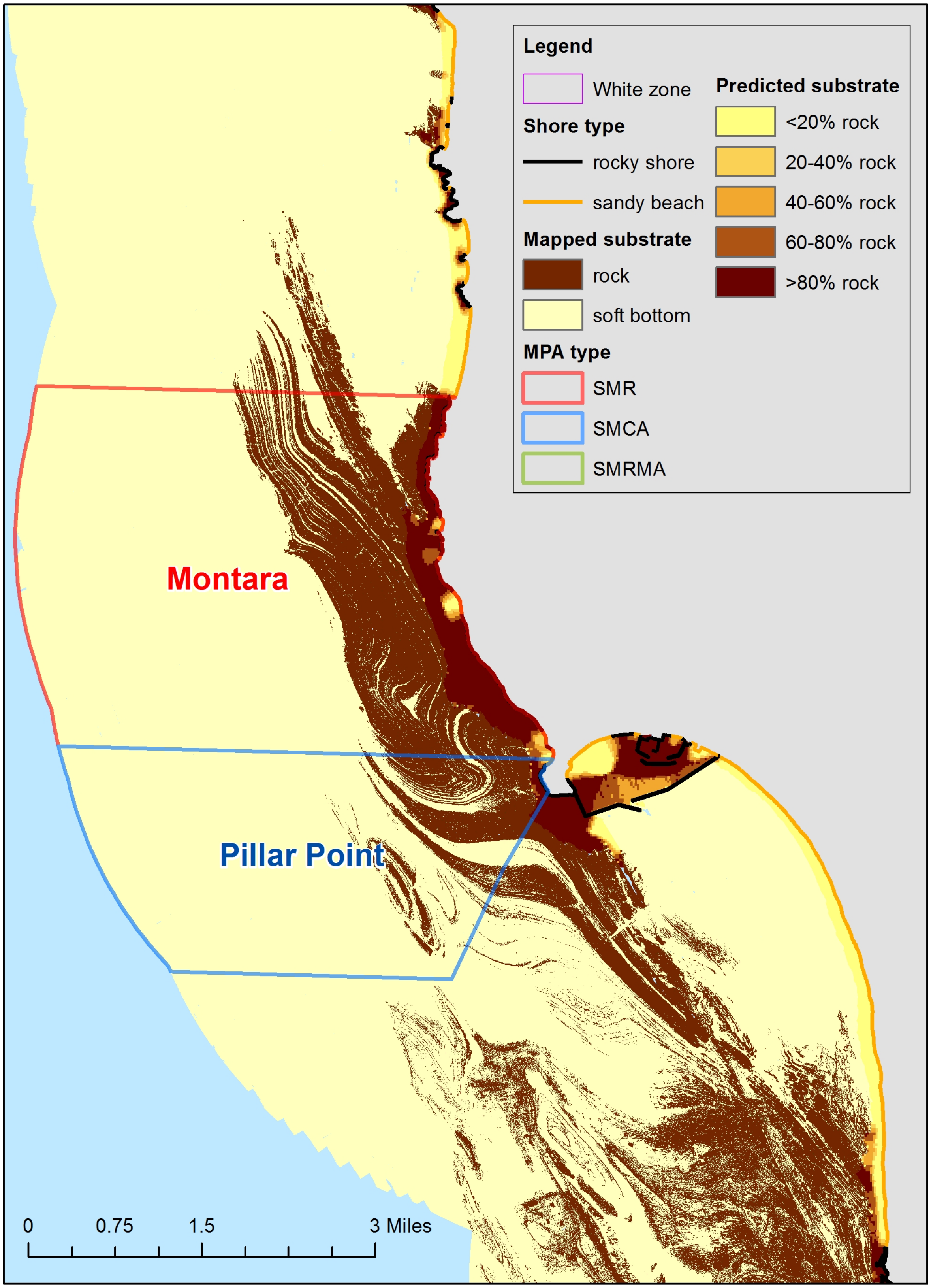
0.75
1.5
3 Miles


Legend
White zone
Shore type
rocky shore
sandy beach
Mapped substrate
rock
soft bottom
MPA type
SMR
SMCA
SMRMA
Predicted substrate
<20% rock
20-40% rock
40-60% rock
60-80% rock
>80% rock
Montara
Pillar Point
0
0.75
1.5
3 Miles

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