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UNIVERSITY OF CALIFORNIA SAN DIEGO

Modeling White Abalone Habitat in the Southern California Bight
to Inform Future Outplanting Efforts

A Thesis submitted in partial satisfaction of the requirements for the degree
Master of Science

in

Marine Biology

by

Jordan DiNardo

Committee in charge:

Brice Semmens, Chair
Marco Octavio Aburto Oropeza
Paul Parnell

2018

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The Thesis of Jordan DiNardo is approved, and it is acceptable
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Chair

University of California San Diego

2018

DEDICATION

I dedicate this body of work to the fishermen I interviewed for this research. Thank you for sharing your stories. To my parents, Leslie and Gerard, thank you for your patience, support, and love.

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LIST OF ABBREVIATIONS

AUC: Area under the curve

B.C.: Before Christ

BTM-Benthic Terrain Modeler

CalCOFI: California Cooperative Oceanic Fisheries Investigations

CC: California Current

CDFG: California Fish and Game

CINPS: Channel Islands National Park Service

CPDBs: Commercial Passenger Dive Boats

CPFVs: Commercial Passenger Fishing Vessels

CSUF: California State University: Fullerton

CU: California Undercurrent

ENFA: Ecological-Niche Factor Analysis

ESA: Endangered Species Act

GAM: Generalized Additive Model

GIS: Geographic Information Systems

GLM: Generalized Linear Model

kg: Kilogram

km: Kilometer

Lbs: Pounds

IDW: Inverse Distance Weighting

in: Inch

m: Meter

MaxEnt: Maximum Entropy

mm: Millimeter

m²: Square meter

MSE: Mean square error

n: Sample size, number

NMFS: National Marine Fisheries Service

NOAA: National Oceanic Atmosphere Administration

OC: Occidental University

psu: Practical Salinity Unit

RCP: Representative concentration pathway

RLP: Rickettsiales like prokaryote

RMSE: Root mean square error

ROC: Receiver operated characteristics

ROV: Remote Operated Vehicle

SBC-LTER: Santa Barbara Coastal: Long Term Ecological Research

SCB: Southern California Bight

SCC: Southern California Countercurrent

SDM: Species Distribution Model

SFML CSUMB: Sea Floor Mapping Lab at California State University: Monterey Bay

SWFSC: Southwest Fisheries Science Center

UCSD SIO: University of California: Scripps Institution of Oceanography

US: United States

VRM: Vector Ruggedness Measure

WS: withering syndrome disease

LIST OF SYMBOLS

$^{\circ}\text{C}$: degrees Celsius

\pm : plus-minus

$>$: greater than

$<$: less than

\geq : greater than or equal to

\leq : less than or equal to

\sim : about

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ABSTRACT OF THE THESIS

Modeling White Abalone Habitat in the Southern California Bight
to Inform Future Outplanting Efforts

by

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Master of Science in Marine Biology

University of California San Diego, 2018

Professor Brice Semmens, Chair

White abalone (*Haliotis sorenseni*) supported an intense commercial fishery in southern California during the 1970s, which closed in 1996. In 2001 white abalone was listed under the Endangered Species Act (ESA), and due to their high risk of extinction, National Oceanic Atmosphere Administration (NOAA) identified the species as a “Species in the Spotlight” in 2016. Efforts are underway to develop a conservation hatchery and outplanting program to recover the species. To inform outplanting efforts, I modeled broad-scale (17 km) historical (fishery-dependent) and contemporary (fishery-

independent) distributions of white abalone habitat using random forest and maximum entropy (MaxEnt), respectively. I projected models to future scenarios in 2050 and 2100 to assess the quality of habitat under climate change. Using MaxEnt, I developed fine-scale (10 m) models with fishery-independent data. I also conducted interviews with former abalone fishermen who observed white abalone during the fishery.

Fishery-dependent and -independent based models revealed differing outcomes of suitable habitat and ensuing effects of climate change. These differences in suitability resulted from differences in the spatial distribution of white abalone between the two data sets. Fine-scale fishery-independent data was limited in its spatial extent, yet in places with sufficient data, I generated high resolution suitability maps. These maps comported with oral histories from fishermen regarding fine-scale habitat, and can help guide site selection within broadly suitable geographic regions. This study provides managers with potential areas to outplant that are resistant to climate change and a framework to design experimental outplanting to adaptively manage a successful recovery effort.

CHAPTER 1 (INTRODUCTION)

1.1 Distribution and Ecology of White Abalone

1.1.1 Historical Distribution

White abalone historically inhabited coastlines found between Point Conception, California, United States (US) and Punta Abreojos, Baja California, Mexico (Cox 1960) (Figure 1.1). In the US, the species was common along the coast in the Santa Barbara county and along the coastlines of the Channel Islands. In Mexico, white abalone were common at the center of the Baja California Peninsula, as well as around Isla Cedros and Isla Natividad (Shepherd, Tegner, and Guzman Del Proo 1992).

1.1.2 Habitat

Thought to be the deepest-living of the west coast abalone species, white abalone occurred in high numbers at 30-70 meters (m) (Davis, Haaker, and Richards 1998; Butler et al. 2006), although both scientists and fishermen have observed them at depths as shallow as 10 m (Shepherd, Tegner, and Guzman Del Proo 1992).

White abalone occur in open low relief areas, amongst large rocks or boulders surrounded by sand (Davis, Haaker, and Richards 1996; Tutschulte 1977; Hobday and Tegner 2000; Hobday, Tegner, and Haaker 2000). Sand channels between rock structures are thought to facilitate movement and collection of macroalgae. Brown algae species, such as *Laminaria farlowii* and *Agarum fimbriatum*, as well as a variety of red algae species, are commonly found in white abalone habitat (Hobday and Tegner 2000; Hobday, Tegner, and Haaker 2000; Butler et al. 2006).

Preferences of microhabitat depend on life stages. Newly settled abalone are cryptic until they reach 75-100 millimeters (mm) (2-5 years old), when they become

emergent (Cox 1962). Juveniles tend to exploit small crevices and sometimes areas underneath adult *Strongylocentrotus franciscanus*, red sea urchin, to escape predation, while adults are found on exposed rock usually at the sand-rock interface (Hahn 1989). Amongst the west coast abalone species, white abalone tend to occupy the exposed habitat regardless of size.

1.1.3 Diet

Upon settlement juveniles feed on benthic diatoms, bacterial films, and encrusting coralline algae (Cox 1962). When juveniles reach ~10 (mm) in length, their diet shifts to attached or drifting macroalgae (Hahn 1989; Tutschulte 1977). Tutschulte (1977) observed wild adult white abalone feeding on dominant brown algae within their habitat. Laboratory observations have recognized *Macrocystis pyrifera* and *Pelagophycus porra* as other common food sources for white abalone although it is not as high in nutritional value as *Laminaria farlowii* or *Agarum fimbriatum* (Cox 1962).

1.1.4 Reproduction

White abalone are dioecious and exhibit broadcast spawning, directly releasing their gametes into the water column for external fertilization typically during the winter months. Temperature influences gonad development and at temperatures >16 degrees Celsius (°C) development ceases (Rogers-Bennett et al. 2010). Organism size and food availability are known factors to affect fecundity in abalone. Although white abalone have the highest fecundity of west coast abalone (Tutschulte 1977), successful fertilization of broadcast spawners requires individuals to be in close proximity, as well as in synchronization of gonadal maturation and spawning.

1.1.5 Larval Stage and Settlement

Larval settlement, survival, and growth are temperature dependent. Under laboratory conditions, white abalone larval settlement occurred at 9-10 days (Leighton 1972). Survival from fertilization to settlement was greatest at 12 °C (McCormick et al. 2016). Settlement was most successful at 15-16 °C (Leighton 1972) while survival and growth of newly settled larvae was best at 15 °C (McCormick et al. 2016). Larvae raised at extremes of 21 °C and 9 °C had 100% mortality (McCormick et al. 2016).

1.1.6 Growth

Information on growth rates of juveniles and adults is limited. Tutschulte (1977) conducted laboratory growth experiments and reported juvenile (sample size (n)=5) and adult (n=3) abalone had growth rates of 29.2 ± 15.0 mm/year and 16.4 ± 7.8 mm/year, respectively. White abalone reach sexual maturity after 4-6 years (Hobday and Tegner 2000). Temperature, salinity, and dissolved oxygen have been shown to influence growth rate and survival of juvenile abalone (Kong, N., et al. 2017). McCormick et al (2106) conducted growth experiments study the effect of temperature on growth of juvenile white abalone in the mariculture laboratory of the Channel Islands Marine Resource Institute and found juveniles exhibited fastest growth at 15 °C when fed *Macrocystis pyrifera*. White abalone can grow to a maximum size of 200-254 mm and weight of 0.771 kilograms (kg) (Cox 1960) and under optimal conditions, white abalone are estimated to live a maximum of 35-40 years (Tutschulte 1977).

1.1.7 Predators and Competitors

White abalone predators include sea otters, asteroids (*Pycnopodia* and *Astrometis*), octopuses (*Octopus bimaculatus* and *Octopus rubescens*), crustaceans

(*Panulirus Cancer* and *Loxorhynchus*), and fishes (*Scorpaenichthys*, *Myliobatis*, *Semicossyphus*, and *Heterodontus*) (Tutschulte 1977). Asteroids tend to feed on juvenile and stressed abalone, while fishes generally predate on adult abalone. Octopuses and crustaceans are perpetual predators, exploiting abalone at all life stages. Healthy adult abalone with thicker shells are less vulnerable to predation, even when completely exposed (Hahn 1989). Studies with restoration stocking experiments using red abalone, a common surrogate species, assessed the severity of mortality brought on by predation on outplanted juveniles, and identified *Octopus bimaculatus* as a prominent predator (Hofmeister et al. 2018).

Sea urchins (*Strongylocentrotus purpuratus* and *Strongylocentrotus franciscanus*) compete with white abalone for food and space. Laboratory studies demonstrated when drift algae is abundant, red abalone out compete red sea urchin and vice versa when drift algae abundance is low (Shepherd, Tegner, and Guzman Del Proo 1992; M. Tegner and Levin 1982). No field experiments investigating competition for space and food between abalone and sea urchins have been conducted. Sea urchins also have the potential of facilitating juvenile white abalone survival. Juvenile red abalone have been observed clustered under red sea urchin, using the physical protection from predators engendered from the sea urchin's large spin canopy (M. J. Tegner and Dayton 1977; Hahn 1989).

1.1.8 Disease

First detected in 1985, withering syndrome (WS) eradicated most of the remaining black abalone population, not exploited from the fishery and affected green, pink, red, and white abalone (Altstatt et al. 1996). A Rickettsiales like prokaryote (RLP) that infects the mucosal epithelium of the gastrointestinal tract is thought to cause WS. The prevalence of

WS is temperature dependent. In water $<18^{\circ}\text{C}$ RLP remains dormant while in temperatures $\geq 18^{\circ}\text{C}$ RLP is activated (Moore, Robbins, and Friedman 2000). WS has been observed in white abalone, but at a lower frequency compared to other west coast abalone species, possibly because white abalone tend to inhabit deeper depths and thus colder waters.

1.2 History of Fishery and Management of White Abalone

1.2.1 California White Abalone Commercial Fishery

Anthropological evidence, dating as far back as 7,500 years indicates that native peoples of the coastal regions of California and Channel Islands exploited west coast abalone species as a source of food, ornaments, and hunting, gathering, and bartering tools. In the early 1850s, Chinese immigrants began targeting abalone in the intertidal via skiffs, and gradually moved south along the northern California coastline (Cox 1962).

To impede overexploitation of west coast abalone populations, the state prohibited “shore-gathering” in many southern California counties in 1990 (Hobday and Tegner 2000). While this management measure curtailed further increases in fishing pressure from Chinese immigrants fishing skiffs, Japanese immigrants replaced them with hard-hat diving, a more efficient fishing method. This new method of catch, permitted access to offshore abalone populations at greater depths. In efforts to monitor the fishery, California Department of Fish and Game (CDFG) started to record abalone commercial and recreational catch landings in 1916. Japanese divers dominated the California abalone fishery from Monterey Bay to Point Conception until World War II, when the state relocated the Japanese immigrants inland. Although this change removed fishing pressure from Japanese fishermen, wartime demand for additional protein kept

exploitation of abalone high. The state opened waters between Point Conception and San Diego, including the Channel Islands, to fishing in 1943 to meet this local demand (Cox 1960).

Subsequent technology improvements in the 1950s, including lightweight dive suits and scuba, introduced even more efficient diving methods. Although CDFG named white abalone a species that could be harvested in 1955, the species did not appear in catch records until 1959. Reported white abalone catches increased substantially in 1968 after the steady overexploitation of shallower abalone species and improvement of nautical equipment (Figure 1.2; California Department of Fish and Game 2005). Fishermen and scientists believe white abalone may have been caught and mistakenly recorded under red or pink abalone prior to this time due to their similar physical features and habitat overlap (M. J. Tegner, Breen, and Lennert 1989; Dugan and Davis 1993; Davis, Haaker, and Richards 1998). White abalone landings peaked in 1972 at 65 metric tons, predominantly taken from San Clemente Island, followed by Tanner Bank and thereafter dramatically declined (Figure 1.3). Over 95% of the commercial white abalone catch occurred in 10 years (1968-1977). By 1978 white abalone catch declined so dramatically that mandatory reporting in fishing receipts was eliminated, until the closure of the fishery in 1996 (Hobday and Tegner 2000).

1.2.2 California White Abalone Recreational Fishery

The California recreational abalone fishery began in the 1860s, when CDFG prohibited the sale of commercially caught abalone collected from the littoral zone, consequently moving the commercial fishery offshore and opening shallow coastal waters to recreational fishing. Recorded recreational catch comes from specialized

Commercial Passenger Fishing Vessels (CPFVs), known as Commercial Passenger Dive Boats (CPDBs), which limit trips to skin and scuba diving. CPDB began operating for recreational divers, primarily in southern California, in the 1940s, but CDFG did not begin monitoring catch from these trips until 1958. Most of the CPDB effort included several day trips, concentrated around northern Channel Islands (Santa Rosa, Santa Cruz, and Anacapa) and southern Channel Islands (San Clemente, Santa Catalina, and Santa Barbara).

White abalone contributed 1.29% of the total and 2.89 % of identified recreational catch from 1971 through 1993 (Hobday and Tegner 2000). These percentages may not represent all of the white abalone exploited recreationally because reporting by species was voluntary and catch from private recreational divers (non-CPDB), while likely substantial, was never quantified. It is difficult to quantify recreational catch from CPDBs because catch values differ substantially in catch reports (Hobday and Tegner 2000). However, the majority of white abalone catch came from Santa Catalina and San Clemente Islands, followed by Santa Cruz and Anacapa Islands (Hobday and Tegner 2000). Catch declined sharply thereafter, and by 1986 white abalone were rarely harvested recreationally.

1.2.3 California Management Regulations and Status

The first abalone management regulation enacted by the state was instituted in 1901, which established a minimum size on all species of 15 inches (in) (381 mm) in circumference (4.75 in (120 mm) in diameter). CDFG established minimum size limits at sizes greater than size at sexual maturity, allowing abalone to spawn before being harvested. However, successful reproduction does not occur regularly, especially for

white abalone, which may have contributed to the species' reproduction and recruitment failure (Hobday and Tegner 2000). Additional regulations included the ban of spearing for subtidal abalone and the first bag limit of 10 abalone per day in 1913. In 1976, the bag limit decreased to 4 abalone of any species per day after it was evident populations were declining. (Cox 1962).

In 1939, CDFG required recreational divers to carry a measuring instrument to aid in the identification of legal size individuals. In an effort to reduce the fishing effort, CDFG required commercial fishermen to use surface-supplied air through a hose in 1954 and enforced catch seasons. To stem the further decline of abalone landings in the 1970s, CDFG required commercial fishermen to land at least 10,000 pounds (Lbs) of abalone annually to maintain their license. Despite these efforts landings continued to decline, and in 1990 the state modified its licensing rule requiring commercial fishermen to land at least 1,200 pounds or 320 abalone per year to keep their license (Lundy 1997).

CDFG closed the white abalone commercial and recreational fisheries in 1996, along with the green and pink fisheries throughout California (California Department of Fish and Game 2005; Hobday and Tegner 2000). Despite the closure of these fisheries white abalone populations continued to decline, and in 2001 became the first marine invertebrate to be listed as endangered under the ESA. Since the last recruitment pulse to the white abalone population was in the 1960s only a remnant population exists. Field monitoring surveys of the remnant populations conducted by NOAA since the species had been listed under the ESA indicate further population declines, confirming the species' collapsed status post fishery-closure (Stierhoff, Neuman, and Butler 2012).

National Marine Fisheries Service (NMFS) published a recovery plan in 2008 that identified goals and strategies to delist the species from the ESA and recover the white abalone population. Such strategies include field monitoring and protection of wild populations and their habitat, captive propagation for enhancement of wild populations, and development of an enforcement, public outreach, and education plan (The White Abalone Recovery Team 2008).

Due to the species' high risk of extinction in the very near future, NOAA recognized white abalone as a "Species in the Spotlight" in 2016, with the aim of applying its time, energy, and resources to meeting the goals identified in the recovery plan. NOAA Southwest Fisheries Science Center (SWFSC) continues to conduct regular remote operated vehicle (ROV) and scuba surveys to locate and monitor wild populations, characterize habitat, and collect individuals for broodstock, which helped to initiate the captive breeding program in 2011 at University of California Davis Bodega Marine Lab. This program has resulted in juvenile white abalone ready to be introduced into the wild, presenting a need for habitat modeling to identify areas of suitable habitat that can support survival and growth of outplanted populations in a variable environment.

1.2.4 Mexican White Abalone Commercial Fishery

The history of white abalone exploitation in Mexico is similar to that in California. Native peoples began harvesting abalone in 7000 before Christ (B.C.). The Chinese and Japanese immigrants began exploiting Mexican abalone populations in the 1860s and ceased when the Mexican government gave local villages exclusive control over the fishery in 1945. The government divided the coast of Baja California between the Coronado Islands and Margarita Island into cooperatives and larger zones for

management. In 1992 the government allowed additional fishing groups, not representative of cooperatives, to participate in the abalone fishery. The effects of these changes on abalone populations are unknown since the Mexican government did not establish the requirement of species identification in catch until 1984.

Reporting of white abalone catch data commenced in 1990, but these data are considered unreliable, patchy both spatially and temporally. Although the catch of each species varied between and within zones, the fishery was predominantly supported by pink and green abalone. While white abalone comprised only a few percent of the total catch throughout all of Baja California, in some months of the year white abalone represented a little over half the catch for particular zones. These occasional pulses are believed to represent either newly located populations or recruitment events, that were quickly harvested and no longer observed in the catch records.

1.2.5 Mexican Management Regulations and Status

Prior to 1972, Mexican abalone size limits were similar to those established in California. Unfortunately the Mexican government did not establish size limits specifically for white abalone and assumed fishermen captured white abalone at sizes greater than 135 mm, as required for pink abalone. Even with this assumed size limit, abalone were shelled at sea, conceivably producing a substantial proportion of abalone harvest at sublegal size (Hobday and Tegner 2000). Not until 1984 did the government introduce regulations that required in shell landings of abalone to verify size limits and identify catch by individual species.

The closed season which initially spanned winter months, changed in 1973 to summer months. Although this change in season closure protected spawning pink and green

abalone, it left winter-spawning white abalone vulnerable to exploitation. In 1981 the government established white abalone size limits and closed seasons by zones (Hobday and Tegner 2000).

The white abalone fishery supposedly closed in Natividad in 1995 (Shepherd, Turrubiates-Morales, and Hall 1998) and a petition to close the white abalone fishery, along with red and black abalone fisheries, throughout the entire Baja California coast was put forward in 1997. The government has yet to act on this petition. Given the lack of regulations and appropriate surveying, little information is available to assess the status of white abalone populations in Mexican waters.

1.3 Habitat Modeling

Species Distribution Models (SDMs) attempt to predict the potential species' distribution by modeling the relationship between locations of occurrences (or abundances) and associated environmental conditions, extrapolating inferred relationships in both time and space. SDMs are now widely used tools in the terrestrial, freshwater, and marine fields, demonstrating applications in conservation planning, ecology, evolution, invasive-species management, and biogeography (Phillips et al. 2006). The nature of species occurrences and quality of data determines the appropriate modeling method. Systematic surveys yield presence-absence data and motivate the application of familiar statistical methods, such as Generalized Linear Model (GLM), Generalized Additive Model (GAM) and Random Forest. However, when absences are difficult to obtain or unreliable due to insufficient field effort, modeling methods are constrained to BIOCLIM, DOMAIN, Ecological-Niche Factor Analysis (ENFA), and

MaxEnt. In this study I made use of MaxEnt, which utilizes presence-only data and Random Forest, which can leverage species abundance information (Phillips et al 2006).

Among the SDMs equipped to work with species occurrence data lacking true or pseudo absences, MaxEnt is one of the leading methods due to its efficiency with complex interactions between response functions and environmental predictor variables (continuous and categorical), as well as its low sensitivity to small sample sizes (Elith et al. 2006; Wisz et al. 2008; Monk et al. 2010). MaxEnt estimates the realized niche of a species by identifying the distribution with the maximum entropy, similar to the maximum likelihood in parametric instances, subject to constraints at locations of known occurrences (presence only data). These constraints are classified by environmental predictor variables and functions of them (Phillips., Mirosalv, and Schapire.2004, Phillips et al. 2017).

To offset the lack of absences, MaxEnt uses a sampled set of background points from the study area to compare against the distribution of species occurrences (presence only data) along environmental gradients and make inferences on selection of habitat. Selection of these background points can greatly influence model accuracy. By default, MaxEnt randomly selects background points, assuming sampling effort is uniform throughout the entirety of the study area. When sampling is biased, models based on a random sample of background points may reflect the sampling effort rather than the species' realized niche and environmental response curves may reflect underlying variation in sampling intensity rather than pure environment responses (Syfert, Smith, and Coomes 2013). By accounting for sampling bias, with an analogous biased sampling

of background points representative of actual sampling intensity across the study area, MaxEnt is more accurate in predicting species distribution.

Outputs of MaxEnt models include a map of relative likelihood of presence of a species, which can be interpreted as an measure of suitability of habitat along with metrics of environmental variable importance, including percent contribution and jackknife regularized gain (Kearney 2006). MaxEnt also provides response curves for the environmental variables included in modeling, which describe the effect each variable has on the prediction, which can then be applied to project to past or future conditions.

Random forest is a non-parametric algorithm derived from classification and regression trees, belonging to the machine learning methods. Due to its practicality in addition to its ability to handle data with non-linear or hierarchical interactions, the use of random forest in ecology and climate change research has gained momentum. By applying the general technique of bootstrap aggregation, random forest constructs a multitude of decision trees based on randomly selected subsamples of data and random subsets of environmental predictor variables. Species' observations that do not occur in the bootstrap sample are considered out-of-bag observations, which are predicted by each tree. The prediction for each observation is determined by the mode class (for classification) or average value (for regression) of the out-of-bag predictions for a particular observation (Beard 2007).

Outputs of random forest include a set of relative predictions, presence-absence (for classification) or abundance estimates (for regression), that represent a measure of habitat suitability of the species of interest, similar to that seen from MaxEnt. Random forest measures variable importance by the ratio of the improvement in error at each node

for each randomly selected variable to all nodes in the forest. Variables that greatly improve error are of more importance compared to those that do not. To explore the mechanistic relationships between predictor environmental variables and the response variable (relative abundance of the species) identified in the model, random forest produces “response curves” of each variable when all other variables are held at its average effect. These defined relationships can be applied to predict potential past and future species’ distributions similar to MaxEnt.

CHAPTER 2 (MATERIALS AND METHODS)

2.1 Study Areas

The SCB includes the coastline of southern California extending from Point Conception, California to the California-Mexico border, in addition to the Channel Islands and part of the Pacific Ocean. The waters within the SCB are characterized by complex circulation patterns (Figure 2.1, Hickey 1992). While the California Current (CC) flows towards the equator, it diverges shoreward and then poleward to form the SCC, which is found throughout all seasons, except Spring, when winds near the coast increase and cause surface currents to change direction (Brown 1991). The California Undercurrent (CU) flows along the continental slope transporting relatively warm, high-salinity, low-oxygenated water from the equator poleward. The Northern Channel Islands are found in the Santa Barbara Channel where a cyclonic eddy exists nearly year round due to the main coastline structure. The Southern Channel Islands experience the convergence of the CC and Southern California Countercurrent (SCC) (Dong, Idica, and McWilliams 2009).

(Rogers-Bennett et al. 2002) estimated spatial productivity estimates for white abalone from reported commercial catch and estimates of potentially suitable habitat throughout the SCB. In that study, researchers estimated productivity for each predefined region by dividing the catch (in metric tons) by the amount of potentially suitable habitat. To estimate potential suitable white abalone habitat, a two-step approach was employed. First the amount of shelf area was computed as the area of shelf within 25 to 65 m depths. Second, potential white abalone habitat was assumed to be 3% of the computed shelf area (Davis, Haaker, and Richards 1998; Rogers-Bennett et al. 2002).

These estimates relied on the assumption that effort and fishing efficiency were similar across all locations, allowing catch to represent abundance. Locations with similar productivity were assumed to exhibit similar dynamics.

I chose the SCB as the study area for broad-scale models because it covers the historical white abalone distribution within U.S. waters, as well as all recorded species data. The spatial resolution of broad-scale models is the size of the CDFG statistical fishing blocks (~17 kilometers (km)). The fine scale models differ in extent and geography. After examination of general ocean circulation patterns within the SCB, productivity of regions estimated from CDFG commercial catch data, and fishery-independent white abalone presence data, I developed 5 study areas, which included coastal waters of 1) San Clemente Island, 2) Tanner and Cortes Banks, 3) Santa Catalina and Santa Barbara Islands, 4) San Diego, and 5) Palos Verdes, all with spatial resolutions of 10 m.

2.2 Species Datasets

2.2.1 Fishery-Dependent

I acquired white abalone commercial and recreation catch data reported from CDFG fishing receipts and CPFV logs. Commercial catch were recorded by CDFG statistical fishing blocks in pounds from 1951 to 1993 (Figure 2.2). Recreational catch was recorded by CDFG statistical fishing blocks in number of abalone from 1980 to 1997.

2.2.2 Fishery-Independent

I acquired fishery-independent white abalone occurrence data from various surveys conducted in the SCB, from 1976 to 2017 (Table 2.1). Since sampling platforms varied

between surveys (scuba, manned submersible, ROV), spatial resolution of white abalone observations also varied.

Tutschulte (1977) reported the first fishery-independent density estimate for white abalone in 1971. He sighted 7 abalone in 3 quadrats (10 square meters (m^2) each) near the Isthmus region of Santa Catalina Island at 20-33 meters in depth, generating a density of 0.23 white abalone/ m^2 and 3 abalone in a $35m^2$ quadrat at 20 meters in depth, corresponding to a density of 0.0857 white abalone/ m^2 (Tutschulte 1977).

CDFG and Channel Islands National Park Service (CINPS) divers conducted surveys in 1980-81 and 1992-93 to describe the status and trends of white abalone at its historic center of abundance around the Channel Islands. In the 1980-81 survey, divers searched a total of 10,000 m^2 of suitable habitat at 10 locations (1,000 m^2 at each survey location) in depths of 24-30 meters. Divers observed a total of 21 live white abalone, yielding a mean density of .0021 white abalone/ m^2 . In the 1992-93 survey, divers searched a total of 30,600 m^2 of suitable habitat at 15 locations in depths of 25-35 meters, using transect (30-100 meters long along depth contours) and timed (30 minute periods) search methods. Divers sighted only 3 live white abalone, yielding a mean density of 0.0001 white abalone/ m^2 and 119 empty white abalone shells. All but one shell were adult size (>50mm), indicating recruitment had not occurred (Davis, Haaker, and Richards 1996; Hobday and Tegner 2000).

In 1996-97 and 1999 CDFG and CINPS researchers conducted surveys to locate remnant white abalone populations, lying below normal scientific scuba diving depths (~32 meters) using the DELTA manned submersible. During the 1996-97 survey, a total of 77,050 m^2 of suitable habitat in depths of 31-67 meters was surveyed. Researchers

observed a total of 9 live white abalone, yielding a mean density of 0.0001 white abalone/m². The survey also observed over 300 empty white abalone shells (Davis, Haaker, and Richards 1998; Hobday and Tegner 2000). The survey in 1999 covered a search area of 277,876m² of suitable habitat in depths of 19-72 m. Researchers sighted 157 live white abalone, yielding a mean density of 0.0006 white abalone/m² (K. Lafferty, personal communication, May 2017).

Between 2002 and 2004, Butler et al. 2006) used multibeam and side-scan sonar with a ROV to refine population estimates at several locations (Tanner and Cortes Banks and part of San Clemente Island) where white abalone historically occurred and were surveyed in the 90s. The use of advanced mapping technology improved search methods, spatial coverage, and consequently estimations of remnant populations and suitable habitat. Multibeam and side-scan sonar also made it possible to examine white abalone presence and microhabitat characteristics at Tanner Bank. Microhabitat analysis found white abalone closely associated with flat, moderately complex seafloor and close to sand at depths of 30-60 meters, and in close proximity to brown algae species (Butler et al. 2006).

Subsequent surveys conducted by scientists at NOAA SWFSC from 2005 through 2017 continued to (1) monitor previously identified populations, (2) survey for additional remnant populations and suitable habitat, and (3) in more recent years identify individuals for broodstock collection (Stierhoff et al. 2014; Stierhoff, Neuman, and Butler 2012). Researchers sighted a total of 398 white abalone throughout these surveys (2002-2017).

Scientific divers associated with NOAA, Occidental College (OC), and California State University, Fullerton (CSUF) conducted abalone surveys from 2010 through 2017, primarily in coastal waters along the southern California coast at depths where ROV could not operate due to the obstruction of kelp canopies and where previous surveys missed. A total of 47 white abalone were sighted in 40-91 m depths.

2.2.3 Species Data for Modeling

For fine-scale models, I included fishery-independent white abalone occurrences recorded from 1993 through 2017. While some white abalone observations (NOAA/Universities surveys in 2010-2012 at 35 m² and NOAA SWFSC surveys 2012-2017 at 2 m²) recorded during this period were not consistent with a 10m spatial resolution, I still included them into modeling to increase sample size across study areas. Because depth and habitat characteristics were fairly uniform throughout surrounding areas of white abalone occurrences, I assumed less accurate observations held the same relationship with environmental variables at a 10m spatial resolution (D. Witting, personal communication, November 2017). I addressed white abalone observations recorded at a finer resolution within MaxEnt by removing duplicates, which omitted any white abalone observations that occurred within the same pixel, and thus eliminated the risk of existing duplicates across surveys.

For broad-scale models, I included white abalone commercial catch data from 1951 to 1993 and fishery-independent observations from 1993 to 2017 into the fishery-dependent and -independent models, respectively. Raw recreational catch data was unavailable and therefore omitted from modeling. As commercial catch data are only available at the CDFG statistical fishing block (~17 km) resolution, I coerced fishery-independent data to

match the resolution of fishery-dependent data to compare models. After removing duplicates within MaxEnt, the fishery-independent species dataset consisted of a sample size of 20 white abalone occurrences while the fishery-dependent species dataset consisted of a sample size of 209 (the number of fishing blocks within the SCB).

2.3 Environmental Data

2.3.1 Depth

Depth represents the ocean's depth, in meters, relative to sea level. As depth increases, depth values become more negative. I obtained broad-scale (Shuman 2018) and fine-scale (Seafloor Mapping Lab of California State University Monterey Bay 2008) depth data at spatial resolutions of 200 m and 2 m, respectively. Depth values range from 0 to -4,000 m and 0 to -260 m for broad-scale and fine-scale data, respectively

The Marine Region Geographic Information System (GIS) lab at CDFG provides GIS data derived from remote sensing platforms and map based spatial analysis for California marine science and management. Seafloor Mapping Lab at California State University Monterey Bay (SFML CSUMB) specializes in high-resolution acoustic remote sensing for coastal habitats. The California Seafloor Mapping Project, one of the many projects SFML CSUMB is involved in, is a collaborative, multi-institutional operation creating high-resolution bathymetry data for use in ecological modeling, coastal conservation, baseline habitat maps, etc. Depth data was developed from analysis of hydrographic data, bathymetric contours, and digital elevation models, representative of terrain surfaces.

2.3.2 Vector Ruggedness Measure (VRM)

VRM measures the terrain roughness of the seafloor as the variation of grid cells in three-dimensional space within a predefined neighborhood. Unlike rugosity, VRM is based on a geomorphological method for measuring vector dispersion that is less correlated with slope. VRM values can range from 0 (flat, no terrain variation) to 1 (rough, complete terrain variation), while typical seafloor terrain ranges from 0 to about 0.4 (Sappington, Longshore, and Thompson 2007).

I obtained available fine scale VRM data (Seafloor Mapping Lab of California State University Monterey Bay 2008) at a spatial resolution of 2 m. For areas with missing data, I derived VRM from respective bathymetry data using ArcGIS extension Benthic Terrain Modeler (BTM) with a neighborhood size of 3. The methods executed to derive VRM from bathymetry data are comparable with methods taken by researchers at SFML CSUMB.

2.3.3 Slope

Slope is the incline or steepness of the seafloor and can be measured in degrees from a horizontal plain. Slope values are larger when an area of relief has a greater degree of slope. At a broad scale, areas of greater slope can be representative of continental shelves, while at a fine scale areas of greater slope may represent rock structures or ledges.

I derived broad scale slope data from respective bathymetry data using ArcGIS extension BTM. When available, I obtained fine scale slope data (Seafloor Mapping Lab of California State University Monterey Bay, 2008) at a spatial resolution of 2 m. For areas with missing data, I derived slope from bathymetry data using ArcGIS extension

BTM. The methods to derive slope from bathymetry data is comparable to methods executed by researchers at CSUMB SFML.

2.3.4 Substrate

Substrate is a classification of roughness (soft bottom (0) and rough bottom (1)), but can serve as a proxy for seafloor type: sand/sediment (0) and rock (1). I obtained available fine scale substrate data (Seafloor Mapping Lab of California State University Monterey Bay 2008) at a spatial resolution of 2 m. For areas where data is lacking, I derived substrate data from the interpretation of VRM data, using an appointed threshold to differentiate soft from rough substrate. VRM values equal to or above the selected threshold were categorized as “rough” while VRM values below were categorized as “smooth”. I selected site specific thresholds based on accuracy assessments that compared “supervised” classifications with visual classifications. Supervised classifications were based on interpretation of VRM values relative to a standardized set of appointed thresholds while visual classifications were based on visual interpretation of substrate from hillshade and shaded relief. I elected thresholds that minimized and balanced Type 1 and Type 2 errors amongst 100 randomly selected points for each site to be used to classify substrate. The methods executed to derive substrate from VRM data compares to methods executed by researchers at SFML CSUMB. I combined substrate data into study areas in ArcGIS.

2.3.5 Kelp Persistence Index

I defined kelp persistence as a measure of the binary maximum likelihood of *Macrocystis pyrifera* presence through time. Kelp persistence values range from 0 to 1, where small values represent low persistence and large values represent high persistence.

Because kelp experiences reduced or negative growth months in the summer, I focused my analysis on spring months (April through June), a period when cool, nutrient-rich bottom waters are brought to the surface through upwelling, thus providing an ideal environment for growth and an appropriate indicator of kelp presence (Kelp Forest-a Description).

I obtained data for the coastal areas of southern California, including northern and southern Channel Islands and banks that overlapped with fine-scale study areas from 1993 through 2017 (Bell, Cavanaugh and Siegel. 2017). Santa Barbara Coastal: Long Term Ecological Research (SBC-LTER) collects a time series of canopy biomass of *Macrocystis pyrifera* derived from Landsat 5 Thematic Mapper, Landsat 7 Enhanced Thematic Mapper Plus, and Landsat 8 Operational Land Imager satellite imagery. Wet biomass estimates are recorded in weight (kilogram) on a 16 day repeat cycle and at a spatial resolution of 30 m for coastal areas from Año Nuevo to San Diego, including Northern and Southern Channels Islands from 1984 to 2017.

I converted wet biomass estimates for each 30 m pixel to a binary classification of presence where if wet biomass was greater than 0 it was considered present and if wet biomass was 0 it was considered absent. If kelp was observed present at least once during these 3 months, kelp was considered present for that specific year. I calculated the binary maximum likelihood for each pixel by dividing the number of years kelp was present by the total number of years observed. In ArcGIS I used inverse distance weighting (IDW) spatial interpolation to develop kelp persistence estimates at a finer resolution (10 m) assuming spatially distributed objects are spatially correlated. Each measured point has a local influence that diminishes with distance, giving greater weights to points closest to

the prediction location and the weights diminish as a function of distance. I justified the use of spatial interpolation by assuming that kelp presence did not vary dramatically within 30 m. For IDW settings, I set the search radius to 3 nearest input sample points to be used to perform interpolation and kept the power at the default value of 2. Power controls the significance of surrounding points on the interpolated value. A higher power results in less influence from distant points. It can be any real number greater than 0, but the most reasonable results are obtained using values from 0.5 to 3. The default is 2.

2.3.6 Temperature and Salinity

Temperature and salinity are measured in °C and practical salinity unit (psu) respectively. I retrieved surface temperature and salinity data for time periods associated with fishery-dependent (1951-1993) and fishery-independent (1993-2017) white abalone occurrence data (NOAA NMFS SWFSC ERD 2017). California Cooperative Oceanic Fisheries Investigations (CalCOFI), a collaborative research effort with NOAA Southwest Fisheries Science Center (SWFSC), University of California San Diego, Scripps Institution of Oceanography (UCSD SIO), and CDFG, has and continues to conduct fisheries and oceanography surveys since 1951.

For both time periods, I averaged measurements over years at each sample site. In ArcGIS, I used IDW spatial interpolation to develop sea surface temperature and salinity estimates at spatial resolution of ~17km.

I acquired future sea surface temperature and salinity data for the SCB for 2040-2050 and 2090-2100 at a spatial resolution of 5 arcminutes (~9.2 km at the equator) (Assis et al. 2018; Tyberghein et al. 2012). Temperature is recorded in °C and salinity is recorded in psu. Bio-ORACLE is a team of marine researchers aiming to provide new ecologically

relevant layers tailored for ecological modeling. Researchers produced future estimates by averaging data from distinct atmosphere-ocean general circulation models provided by the Coupled Model Intercomparison Project. Future conditions are based on new representative concentration pathway (RCP) scenarios with varying CO² concentration levels: RCP26, a peak-and-decline scenario resulting in low concentration levels by the end of the 21st century, RCP45 and RCP60 where CO² levels stabilize, and RCP85 where emission increases over time, resulting in high concentration levels of greenhouse gases (Assis et al. 2018; Tyberghein et al. 2012).

The sources for physical oceanographic variables differed in collection and derivation methods. To assess the equivalency of these data sources and verify differences in collection and derivation did not bias estimates, I conducted a comparison test with the averaged sea surface measurements for overlapping years (2000-2014). I expected to get a 1:1 relationship, depicted by a diagonal line ($y=x$) through the origin when graphing. Although data sources did not exhibit a direct 1:1 relationship, they were comparable and assumed equivalent (Figure 2.3 and Figure 2.4).

2.3.7 Predator Diversity Index

Predator diversity is the average proportion of abalone predators present through time. Among the sweet of known predator species, I included *Octopus* Spp. (*Octopus bimaculatus* and *Octopus rubescens*), *Panulirus interruptus*, *Semicossyphus pulcher*, *Scorpaenichthys marmoratus*, *Myliobatis californica*, and *Heterodontus francisci* in the analysis. Predator diversity values range from 0 (no predators present) to 1 (high predator presence and diversity).

I acquired predator data (Reef Environmental Education Foundation 2017) for southern California from 1994 to 2017. Reef Environmental Education Foundation (REEF) is an active organization of divers and marine enthusiasts (researchers and citizen scientists) committed to ocean conservation. One of REEF's primary projects, the Volunteer Fish Survey Project, collects and reports information on marine fish populations as well as selected invertebrate and algae species in temperate reef areas, including the West Coast of the US and Canada, the South Atlantic States, and the Northeast US & Eastern Canada. Divers use a Roving Diver Technique, a visual survey method where divers swim freely throughout a 500 meter radius of a dive location and record every observed fish and invertebrate species that can be positively identified. Each recorded species is assigned one of four abundance categories based on how many were seen throughout the dive (single (1); few (2-10), many (11-100), and abundant (>100)).

In R, I converted species' abundance data for each survey to a binary classification of presence where if abundance was greater than 0 it was considered present (1) and if species were not detected in a survey it was considered absent (0). I derived predator diversity by first calculating the sighting frequency for each predator at each dive location (Equation 1) and then calculating the mean proportion of predators present for each dive site (Equation 2). Using the Buffer Tool in ArcGIS, I developed buffers around survey sites (600 meters in radius) that assumed its corresponding predator diversity values to mimic the search area of divers. Assuming similar habitat and thus similar predator abundances, the buffers were extended by 100 meters in radius around survey site to meet modeling requirements. In areas where buffers overlapped, the highest predator diversity value was adopted.

Equation 1 . Sighting Frequency

$$SF_p = \frac{n_p}{n_s}$$

Where n_p is the number of surveys where a predator species, p , was observed and n_s is the number of surveys conducted at location s .

Equation 2. Mean Proportion of Predators Present (Predator Diversity)

$$\frac{SF_1 + SF_2 + SF_3 \dots + SF_p}{N_n}$$

Where SF_p is the sighting frequency for each predator species, and N_n is the number of predator species (in this case 7 species).

2.3.8 Two Spot Octopus and Urchin (Purple and Red) Abundance Scores

Abundance score is an estimate of abundance for a species that accounts for non-sightings. Values range from 0 (no abundance) to 4 (high abundance) for Two Spot Octopus and 0 to 8 for urchin (because it represents a collective measure for Red and Purple Urchin). I calculated abundance scores (Equation 4) from species' density scores (Equation 3), derived from REEF's abundance category data and sighting frequency for each dive location. Density score is a weighted average index based on the frequency of observations in different abundance categories. Dive locations that included at least 5 conducted surveys were used in analysis to increase confidence in analysis results. I conducted similar methods from predator diversity analysis in ArcGIS.

Equation 3. Density Score

$$D = \frac{(nS \times 1) + (nF \times 2) + (nM \times 3) + (nA \times 4)}{nS + nF + nM + nA}$$

where nS , nF , nM , and nA represented the number of times each abundance category (Single, Few, Many, Abundant) was assigned for a given species.

Equation X. Abundance Score

$$A = D \times SF_p$$

2.3.9 Distance from Port

Distance from nearest port is defined as the shortest path between two points on a curved surface, in this case Earth, and is represented as geodesic distance in km. Using the Near tool in the ArcGIS Proximity toolset, I derived distance from closet CPFV port location to the center of each CDFG statistical fishing block. Distance values range from 0 to 240 km.

2.3.10 Length of Coastline

Length of coastline is defined as the distance in km of coastline within each CDFG statistical fishing block and ranges from 0 to 190 km.

2.3.11 Variable Preparation and Diagnostics

Using ArcGIS (version 10.15), I prepared (aggregated, clipped, and projected) rasters for corresponding environmental variables for broad-scale and fine-scale models at the appropriate spatial resolution, spatial extent, and projected coordinate system (WGS84 UTM Zone 11N) using the Aggregation, Extract by Mask, and Project tools, respectively. These files were then converted into ASCII files to be used in MaxEnt and dataframes to be used in Random Forest for broad-scale and fine-scale modeling.

I applied a suite of diagnostics to warrant the inclusion of variables in analysis for both broad-scale and fine-scale models, including an analysis of the relationship (in environmental space) between species occurrences and variables, Moran's I test, and

Pearson's correlation. Relationships between species occurrences and variables should not be truncated to make inferences of its effect on habitat suitability. Calculating the Moran's I for each variable using the species' occurrences can measure spatial autocorrelation. A lack of autocorrelation can be a result of local spatial patterns or the inclusion of a variable that is meaningless to the distribution of the species. Pearson's correlation is a measure of linear correlation between two variables. I calculated the Pearson's correlation coefficient for each environmental variable pair for each study area (fine-scale and broad-scale). When variables exhibited a correlation coefficient ≥ 0.75 , I assessed the information content of both variables to explain white abalone habitat and omitted the variable considered to be less informative.

All study areas passed the relationship test and Moran's I test. At the broad-scale temperature and salinity exhibited a correlation of 0.75 and so I omitted salinity and kept temperature because temperature is known to influence reproduction, growth, and survival. At the fine scale, slope and VRM exhibited a correlation > 0.75 at 2 out of the 5 study areas. Because study areas had very few variables, I used both variables in modeling at all study areas. The variables included in each fine-scale study area is listed in Table 2.2. I decided to omit substrate from fine-scale modeling because abalone are known to adhere to substrate and any discrepancy observed in the models is an artifact of misclassification (Type 1 or 2 error).

2.4 Species Distribution Models

2.4.1 Random Forest

To make the most of fishery-dependent catch data, I used random forest to develop the "historic" distribution of white abalone at a broad-scale. I then projected the

model to future climate change scenarios for two periods (2040-2050 and 2090-2100) based on RCP scenarios to assess potential impacts resulting from of climate change. Here I am assuming the fishery-dependent data are a reasonably exhaustive and standardized survey throughout the species' distribution within US waters, where areas with no catch recorded are assumed void of white abalone. With these assumptions in place, random forest was a strong method to develop SDMs using fishery-dependent data.

I used 'randomForest' package to fit random forest to fishery-dependent data. Outputs represent the mean catch averaged over 2000 trees. Because white abalone catch is right-skewed, more specifically zero-inflated, there were more observations in the lower tail, and therefore random forest tended to over predict lower tails and under predict the upper tails. I transformed the catch data to $\log x+1$ to alleviate the skewness. Despite this issue, in the context of species distribution modeling relative values, rather than actual values, are of more interest. Consequently, I converted predicted mean catch to relative mean catch, shifting the scale from 0 (low relative catch to 1 (high relative catch). By assuming catch as a proxy of abundance, I interpreted these outputs as a metric of suitability of habitat where probabilities represented relative habitat suitability. I also computed every SDMs associated 95% quantile range of predicted relative catch. I used root mean square error (RMSE), comparing predicted and actual catch values to evaluate model performances.

To assess the importance of each environmental predictor variable and compare with the broad-scale fishery-independent based SDM, I obtained random forest's measure of importance, which is known as the percent increases in mean square error (MSE), for each variable. Percent increase in MSE is the most robust and informative measure,

representing the increase in MSE of predictions for each variable if it were omitted from the model. Higher values correspond to variables of more importance.

Lastly, I developed response curves of the variables to examine and compare effects of each variable on the prediction of relative abundance. Response curves display how each variable included in the model affects the random forest prediction (feature contribution), while keeping all other environmental variables constant at their average sample values.

2.4.2 MaxEnt

I used MaxEnt to model the contemporary distribution of white abalone at both broad-scale and fine-scale resolutions using fishery-independent species occurrence data. I then projected the broad-scale model to future scenarios analogous to that done for fishery-dependent models to compare findings. Since fishery-independent surveys were conducted at specific locations within the SCB where white abalone were known to historically occur, it cannot be considered a standardized survey throughout the entirety of the SCB. Consequently, MaxEnt was the best method to develop SDMs using fishery-independent data. I developed these models in R (v 3.4.2) using the MaxEnt method implemented in 'dismo' package.

Every SDM developed from MaxEnt can be slightly different because results depend on the random selection of background points (S. B. Phillips et al. 2006), making it valuable to obtain a sample of SDMs. Thus, the final models and projections of white abalone were the averages of 100 model runs. MaxEnt outputs represent the relative likelihood of presence of white abalone, which can be interpreted as the relative habitat suitability ranging from 0 (very unsuitable) to 1 (highly suitable), similar to

interpretations of random forest SDMs. I also calculated every SDMs associated 95% quantile range of relative likelihood of presence.

By default MaxEnt runs with auto-features selecting at random 70 % of the species occurrences as training data and 30% as test data. However given the low sample sizes of species data in a majority of the study areas, I adopted bootstrapping. When bootstrapping, I used all species occurrences as training data and sampled background points with replacement for each model run.

One of MaxEnt's fundamental assumptions is that the study area has been systematically sampled, yet a majority of occurrence records are spatially biased towards better surveyed areas (Kramer-Schadt et al. 2013). To address this potential sampling bias, I developed a probability surface in ArcGIS, where cell values reflected sampling effort (prevalence of white abalone), giving weight to each background point. Sampling of background points was thus biased by these weights to mirror sampling effort.

SDMs are usually evaluated with area under the curve (AUC) of the receiver operating characteristics (ROC) curve. AUC is used to discriminate a species' model from a random model and is independent of prevalence (Raes and Ter Steege 2007). However AUC is sensitive to the proportion of species occurrences and the study area (background points); the larger the proportion, the larger the AUC value (Lobo, Jiménez-Valverde, and Real 2008). Due to this sensitivity, I conducted significance testing, similar to hypothesis testing, of SDMs' against null models' AUC values. Null models represent a null distribution based on, in this case, spatially bias sampling (Raes and Ter Steege 2007). I used a one-sided 95% confidence interval since I was only interested in whether an SDM performed significantly better than by chance, and interpreted

significant models to indicate that relationships between species' occurrences and associated environmental conditions were stronger than can be expected by chance.

To assess the importance of each environmental predictor variable in explaining species' distribution, I computed average percent contribution of each environmental variable and conducted a jackknife analysis of regularized training gain to the models. The average percent contribution is a metric that quantifies the relative contribution of each variable in developing the model and thus explaining presence of the species. The jackknife regularized gain is a statistic that measures how well a variable distinguishes locations where white abalone occur from the total area under study. By excluding each environmental variable in turn and developing models with the remaining variables, MaxEnt generates the regularized gain of the model in predicting species presence without the variable. A similar procedure is done to develop models with each variable alone to determine gain with only the respective variable. Due to the low sample sizes across study areas, I was unable to conduct a jackknife analysis test gain or AUC values.

Lastly, I developed response curves of the variables to examine the effect of each environmental predictor variable on the prediction of relative suitable habitat. Response curves displays how each variable included in the model affects the MaxEnt prediction (probability of presence), while keeping all other environmental variables constant at their average sample values.

2.5 Assessment of Climate Change

To assess the impact of climate change on habitat quality, I took the difference in habitat suitability values between future projected (2040-2050 and 2090-2100) and original (historical and contemporary) broad-scale SDMs based on fishery-dependent and

-independent data. Resulting maps capture persistence of suitable habitat, ranging from -1 (complete loss of suitable habitat in the future) to 1 (complete gain of suitable habitat in the future); 0 represents no change in habitat suitability through time.

2.6 Interviews with Former Abalone Fishermen

Fishery-dependent white abalone catch data, which temporally covers the species' presence when it was more prevalent, exists at a scale much larger than that which white abalone operate on. In effort to refine this spatial scale and gain more insight on white abalone habitat preferences, I conducted interviews with former abalone fishermen who observed white abalone during their fishing experience in the SCB. Using detailed nautical charts of the Channel Islands and the southern California coast, I asked each fisherman to identify locations where he or she observed white abalone.

For each identified location I asked for details on the catch history, fine-scale habitat characteristics, and population structure. I interviewed a total of 10 former abalone fishermen throughout the SCB and the Channel Islands and acquired 2 oral transcripts of interviews with former abalone fishermen conducted by David Kushner at CINPS.

CHAPTER 3 (RESULTS)

3.1 Broad-scale SDMs

3.1.1 Fishery-Dependent

The computed RMSE for the random forest model developed from fishery-dependent data was 42676.16. Based on fishery-dependent data, Depth exhibited the highest percent increase in MSE (45.34303), followed by Length of Coastline (41.9360), Distance from Port (37.8108), Slope (15.4483), and Sea Surface Temperature (16.2159) (Figure 3.1). The response curves of the variables included in the model indicated relative abundance and effectively relative probability of suitable habitat of white abalone suitable habitat increased as Length of Coastline increased (Figures 3.2). The response curve for Distance from Port suggests suitable habitat is offshore at varying distances. At greater depths, suitable habitat for white abalone decreased. Sea Surface Temperature and Slope had minimal effects on white abalone habitat, although these effects were highest when temperatures ranged from 14 to 18 °Celsius and slope was greater than 4°.

Random forest predicted the highest suitable habitat at San Clemente Island and Tanner and Cortes Banks as well as Anacapa, San Nicolas, and Santa Catalina at lower levels (Figure 3.3). Although random forest predicted suitable habitat in areas where white abalone were not as abundant in catch, areas of higher suitable habitat corresponded to areas of high catch.

3.1.2 Fishery-Independent

The MaxEnt model developed from fishery-independent data at the broad-scale obtained a high average AUC training value (0.8620). The pairwise comparison against a

null model's AUC value indicated that MaxEnt was significantly better in predicting suitable habitat ($p\text{-value} < 0.001$) than that predicted by chance ($\text{AUC} = 0.6149$).

Distance from Port had the highest average percent contribution (62.9922), followed by Length of Coastline (26.1954), Slope (4.3816), Depth (3.5131), and Sea Surface Temperature (2.9176). Jackknife analysis indicated Distance from Port was the most informative variable to the model, followed by Length of Coastline, shown by the consistency in rankings of importance in both jackknife metrics ("gain With only" and "gain Without") (Figure 3.9). The remaining variables exhibited inconsistent verdicts in ranking of importance from jackknife metrics. Sea Surface Temperature displayed the next highest gain when used by itself, followed by Slope and Depth. These rankings of variable importance differ from that seen when each variable was omitted from model development process. When omitted from model development, Slope displayed the next most loss in gain, followed by Depth and Sea Surface Temperature.

The response curves of each variable indicated that the probability of white abalone presence and thus suitability of habitat increased with Length of Coastline and Sea Surface Temperature (Figure 3.10). On the contrary, suitability of habitat decreased as Depth increased (became more negative) as well as when Distance from Port and Slope increased.

The MaxEnt model based on fishery-independent data predicted a larger suitable area than that occupied by white abalone from 1993 through 2017 (Figure 3.11). Suitable habitat were confined to areas along the southern California coast, particularly in the middle and the coastlines of immediate islands, closer to Port, specifically Anacapa, Santa Cruz, and Santa Catalina Islands.

3.2 Future Projections and Effects of Climate Change

Projected fishery-dependent SDMs of future scenarios differ slightly from the predicted model developed from fishery-dependent data at hand (Figure 3.4-Figure 3.7). Most areas along the southern California coast, where suitability was predicted to be low, remain unchanged through time. While areas of high suitability at the Channel Islands and northern region of the southern California coast exhibit a slight decreasing trend in habitat suitability through time (Figure 3.16 and Figure 3.17).

Projected fishery-independent SDMs for future scenarios (Figure 3.12-Figure 3.15) are partially different from the contemporary SDM, exhibiting a slight increase in suitability throughout the SCB (Figure 3.18 and Figure 3.19).

3.2 Fine-scale SDMs

MaxEnt models developed for each fine-scale study area had high average AUC training values (Table 3.1). Pairwise comparisons of AUC values against null models indicated that MaxEnt was significantly better in predicting suitable habitat at all study areas (p -value <0.001) than that predicted by chance. I obtained the percentage contribution of each variable used in the models (averaged over 100 model runs) and calculated the mean percentage contribution across all study areas (Table 3.2, Figure 3.20). Depth had the highest mean percentage contribution (57.82) across all study areas, followed by Kelp persistence Index (36.29), Two Spot abundance Score (22.14), Slope (10.64), Predator Diversity Index (10.35), VRM (9.38) and Urchin Abundance Score (5.67).

Jackknife analysis indicated that at three out of the five study areas, excluding San Diego and Santa Catalina, Depth contained the most information over all other variables,

shown by the consistency in ranking of importance in both jackknife metrics (gain With only and gain Without), followed by VRM and Slope (Table 3.3 and Figure 3.21). At San Diego, Kelp Persistence Index was the most important variable, followed by Slope, Depth, and VRM. At Santa Catalina where predator and competitor variables were included into analysis, jackknife metrics were inconsistent in ranking most variable's importance. When each variable was used exclusively to build the model, Depth was the most informative, followed by VRM, Two Spot Abundance Score, Predator Diversity Index, and Urchin Abundance Score. When excluded from model development, Depth exhibited the most loss in model performance, followed by Predator Diversity Index, Two Spot Abundance Score, VRM, Slope, and Urchin Abundance Score.

Response curves of these variables indicated that suitability of habitat was estimated highest at depths ranging from 30 to 70 m (3.22-Figure3.26). Suitability of habitat decreased as VRM, Slope, Predator Diversity Index, and Urchin Abundance Score increased. Habitat suitability was generally high at all levels of Two-spot Abundance Scores. Kelp persistence index exhibited conflicting results between the two study areas that included the variable. At San Diego, suitable habitat increased as Kelp Persistence Index increased, while at Palos Verdes the opposite relationship was detected. The fine-scale SDMs identified areas of high habitat suitability mostly on hard substrate at depth ranges of 30 to 70 m at the Channels islands and 15 to 30 m along the southern California coast (Figures 3.28-Figure 3.36). Not all areas of high suitability were occupied by white abalone, demonstrating the power of the model to detect suitable habitat in unsurveyed areas.

3.3 Fishermen Observations

Fishermen observations span areas along the Channel Islands, including Santa Cruz, Anacapa, Santa Barbara, Santa Catalina, San Clemente, in addition to the outer Banks, Tanner and Cortez, and along the coast of the Santa Barbara county and San Diego county. While white abalone were observed at depths ranging from 5-60 m, highest abundance was observed at 20-40 m, along or near the edge of the kelp bed, where the prevalent macroalgae species shifted from *Macrocystis* to *Nereocystis*. All fishermen identified preferred white abalone habitat to be small rock piles or boulders with low rugosity, scattered amongst sand channels. White abalone were most often observed exposed on boulders usually at the sand-rock interface located at the base of the boulder where drift macroalgae collected. Sometimes white abalone were seen under low ledges, but not generally on high reefs.

Fishermen observed white abalone along the entire west side of San Clemente Island from Cat Rock to China Point, at the edge of the kelp bed in 20-60 m of water (Figure 3.42). A majority of these observations came from depths of 20-40 m. At Anacapa Island, fishermen observed white abalone along the northwest side of the island, near Rat Rock and all along the edge of the kelp bed towards Cat Rock (Figure 3.37). Fishermen observed white abalone near the southeast end between Anacapa and Santa Cruz Islands. In both areas white abalone inhabited areas in 20-40 m depths, but predominantly in latter depths of this range. Fishermen observed white abalone along the west side of Santa Catalina from Whale Rock to Farnsworth Bank, near the edge of the kelp bed at 18-50 feet, with a majority of white abalone, occurring in 20-40 m (Figure 3.41). Some fishermen observed white abalone along the northwest side of the island from Black

Rock to Yellowtail Point as well as Little Farnsworth, located near the southeast edge of the island at similar depths. At Santa Barbara Island, white abalone inhabited deeper depths specifically at Arch Point and Landing Cove, on the northwest side of the island (Figure 3.39). Along the coast, fishermen observed white abalone near Santa Barbara county, from Gaviota to Camby's Reef in 5-25 m (Figure 3.40). In San Diego County, fishermen observed white abalone in San Onofre as well as in the La Jolla Canyon and South of Point Loma near the kelp bed edge at 20-30 m depths (Figure 3.44). Fishermen sighted white abalone in high numbers at the Coronado Islands in similar depths. At Cortes and Tanner, fishermen spotted white abalone at depths deeper than 25 m (Figure 3.43).

The amount of white abalone observed by fishermen at the Channel Islands and Tanner and Cortes Banks was much higher compared to that seen along the coast. Based on the interview results, fishermen identified fishing hotspots, areas where fishermen persistently observed white abalone of all size classes in high abundance over time. Identified hotspots (Nine Fathoms, Cat Rock, Yellow Banks, and Coronado Islands) were unanimously identified amongst all fishermen who fished at those locations. Only a few of the fishermen interviewed observed white abalone of all size classes, including juveniles because fishermen were targeting adults of legal size. When white abalone were observed in aggregations (two or more abalone in close proximity), they did not aggregate as tightly as other abalone species that usually stacked on top of each other. Many fishermen noted white abalone were most closely associated with pink abalone in depth. Consequently white abalone were recorded as pinks before white abalone became a species to catch in 1955, and often times mistakenly recorded as pinks thereafter.

When asked where one would outplant white abalone for conservation efforts, most fishermen identified locations where they persistently observed highest numbers of abalone. Interestingly, a majority of fishermen identified the coast as poor habitat for outplanting efforts due to the high risk of poaching and quality of water due to runoff.

CHAPTER 4 (DISCUSSION)

The goal of this research was to develop a SDM to inform future outplanting efforts and assess the effects of climate change on habitat. To facilitate these goals I applied random forest and MaxEnt models to fishery-dependent and independent data, respectively. These modeling platforms were the strongest methods that could accommodate the intricacies and nuances of each dataset. Given the spatial scale at which fishery-dependent data were recorded (fishing block), I developed SDMs at a broad-scale to compare historical and contemporary species distributions derived from each dataset. SDMs at this spatial scale allowed for the assessment of climate change at broad regional scales.

Because white abalone operate at a much finer spatial scale than CDFG statistical fishing blocks I developed fine-scale SDMs based on fishery-independent data using MaxEnt. While these models provide reasonable estimates of suitability, model performance was nevertheless constrained by data quality and quantity. In an effort to match fine-scale SDMs and gain knowledge of white abalone presence during the fishery, I also interviewed former abalone fishermen who consistently observed white abalone and could describe fine-scale habitat.

4.1 Broad-scale SDMs

Fishery-dependent and -independent based SDMs indicated differences between historic and contemporary white abalone distributions, and thus potential differences in suitable habitat. Although the rankings of variable importance in each model did not differ dramatically between models (Figure 3.1 and Figure 3.8), prediction of relative abundance or presence did differ in variable space across models (Figure 3.3 and Figure

3.11). Both models defined white abalone habitat to longer coastlines at shallow depths with a slight steepness in seafloor. However the fishery-dependent SDM described white abalone habitat to locations further from Port in temperatures ranging from 14-18 ° C while the fishery-independent SDM described habitat to locations closer to Port in warmer temperatures (≥ 16 ° C).

Random forest and MaxEnt predicted a larger suitable area than that occupied by white abalone during their respective time periods. Although the most suitable areas corresponded largely to the observed populations, there were other areas where habitat was suitable but the species was not recorded. The fishery-dependent based SDM identified the Channel islands, specifically San Clemente Island and Tanner and Cortes Banks, where catch was highest, to be highly suitable habitat, followed by Santa Catalina, San Nicholas and Anacapa Islands. The fishery-independent based SDM recognized the southern California coast, particularly the middle region in addition to the immediate Channel islands to be highly suitable, specifically Anacapa, Santa Cruz and Santa Catalina Islands. These inconsistencies in suitability across models likely resulted from data limitations/differences associated with the input data. Fishery-dependent data is distributed throughout the SCB at broad-scale resolutions while fishery-independent data are spatially-restricted and derived from a remnant post fishery populations. Additionally, the quantity of fishery-dependent data is significantly greater than fishery-independent data. These differences are significant and likely impact model performance and outcome in habitat associations and predicted suitable habitat.

4.2 Fine-scale SDMs and Fishermen Observations

At a fine-scale, Depth, VRM and Slope generally contributed the most to SDMs. Habitat was defined by low rugosity and relief across study areas. At the Channel Islands suitable habitat was found at deeper depths (30-70 m) while along the southern California coast suitable habitat was in shallower depths (<30 m). These associations were observed in past studies (Butler et al. 2006; Hobday and Tegner 2000) and from former abalone fishermen.

For study areas where I included biological data, inconsistencies amongst study areas and historical knowledge existed. San Diego and Palos Verdes define habitat to areas of most and least kelp persistence, respectively. Past studies (Butler et al. 2006; Tutschulte 1977) and former abalone fishermen identified brown algae species to be a staple food source for white abalone, suggesting habitat would be confined to areas of high kelp persistence like exhibited in San Diego. This inconsistency may be due to the small sample size or spatial resolution of satellite kelp estimates. For Santa Barbara and Santa Catalina Islands where predator and competitor data were included, habitat was identified as areas of low predator diversity and urchin abundance score, which holds true to past studies (Tutschulte 1977; Tegner, Breen, and Lennert 1989) and ecological theory of predator-prey and competitor dynamics. Although I expected suitable habitat would be confined to areas of low Two-spot octopus abundance Score, the model suggested white abalone suitable habitat occurs in all areas where Two-spot were found, irrespective of abundance level. This association may be representative of poor habitat or the high prevalence of Two-spot octopus within this study area, but without further investigation at other study areas, little can be concluded.

4.3 Future Projected SDMs and Effects of Climate Change

Since Sea Surface Temperature did not contribute a great deal to either of the broadscale models, future projected SDMs exhibited minimal deviations suggesting that the consequences of climate change will minimally impact habitat suitability.

Nonetheless, fishery-dependent and -independent SDMS told contradicting stories. Based on the fishery-dependent SDMs, areas of higher predicted suitability will decrease in suitability as temperatures rise in the future. On the contrary, fishery-independent based SDMs suggest a slight increase in suitability of habitat throughout the SCB in the future. Taking into consideration the temperature preferences and thresholds identified in historical laboratory experiments, the fishery-dependent SDMs convey a more likely story.

The cause of the differing model results stemming from fisheries dependent versus independent datasets is likely due to the different timeframes of the two datasets. Assuming fishermen focused their effort on highly productive areas, results derived from fishery-dependent data are likely more representative of white abalone habitat. On the other hand, the fishery-independent data, which exists as an artifact of the fishery, is representative of a vestigial population that reflects both habitat quality and a legacy of exhaustive fishing. Water temperatures exhibited in the SCB during the abalone fishery were much cooler than those seen in latter years during the fishery-independent studies (Di Lorenzo et al. 2005). Regarding the relationship between SST and habitat suitability results of the fishery-independent model are inconsistent with the thermal tolerances of white abalone (Leighton 1972; Tutschulte 1977) and thermal requirements of WS (Moore, Robbins, and Friedman 2000). As water temperatures in the SCB increase they

approach the thermal tolerance of white abalone and the activation temperature of WS, which decreases suitability.

Based on the assessment of asses impacts from climate change using outputs from the fishery-dependent model current areas of higher predicted suitability in the south will decrease in suitability as water temperatures increase. Conversely, the distribution of suitable areas will increase further north.

4.4 Limitations with Data and Modeling Methods

Given the long history of exploitation and lack of efficient management of white abalone, both datasets may be representative of previously impacted population with fishery-independent data most obviously so. In view of this, the SDMs I have developed with these data may not represent all suitable habitat. Also, because the fishery-dependent and –independent datasets do not represent standardized surveys throughout the SCB, they are not ideally suited to habitat assessment. On the other hand, such broad scale and long term surveys are very rare in practice, and the analytic methods I employed admit for and account for this lack in standardization.

While I made assumptions to address data limitations, data quality and quantity curtailed model performance and strength. Low sample size amongst the fishery-independent dataset was an issue at both spatial scales. The incorporation of fine-scale biological data proved challenging given the inconsistency in spatial resolution with white abalone occurrences data. Despite these limitations and associated assumptions, the data generated from the fishermen interviews largely comported with results produced from both the fine-scale and broad-scale habitat models. The agreement between these

information sources suggests habitat models are a reasonably accurate representation of suitable habitat, and should support an aggressive and effective outplanting effort.

4.5 Conservation Implications and Next Steps

The differing outcomes in broad-scale SDMs developed from fishery-dependent and -independent data pose challenges for managers when planning future recovery efforts. Managers should be wary of looking to the remaining white abalone population, notably represented by the fishery-independent studies, to inform outplanting. Instead, more focus should be directed to historical catch records captured in fishery-dependent data and fishermen observations. Fishery-dependent models suggest the Channel Islands, specifically San Clemente and Tanner and Cortes banks as strong candidates of potential outplanting sites, based on the high catch from those locations. Knowledge of the biology and ecology of the species as well as ensuing effects of climate change suggest efforts should be made at the northern Channel Islands, specifically Anacapa and Santa Cruz Islands. These islands were highly suitable in fishery-independent SDMs and suitable, although less than San Clemente and Tanner and Cortes Banks in fishery-dependent SDMs.

Temperature and nutrients influence the health and persistence of *Macrocyctis* populations in the SCB. Long periods of warmer temperatures observed in past El Nino events brought destruction of populations and deterioration of subsurface kelp canopies (M. J. Tegner et al. 1996). As temperatures increase in the future, the kelp forest will most likely exhibit similar patterns. Persistent warm temperatures will inhibit kelp forest recovery and persistence, starving future outplanted abalone populations of food. These potential conditions also will likely increase activation of RLP and thus prevalence of

WS disease. These locations present a natural experiment to assess the effects of temperature and climate change on the success of outplanting.

In addition to these areas suggested from the models, experimental outplanting based on a randomized block design can be set up in additional areas within the SCB, such as Santa Catalina, Santa Barbara, and Palos Verdes, and San Diego, which were identified as suitable in the fishery-independent and fishery-dependent, although less so for the southern California coast. Although more economically feasible to outplant and monitor, these locations come with a higher risk of poaching than more distant or protected locations (e.g. San Clemente Island), which managers should consider. Fine-scale models and fishermen observations can inform outplanting experiments with environmental variable space to test in. An outplanting approach that incorporates an experimental design to assess habitat performance has the potential to expedite recovery efforts. If such a approach is employed, I suggest efforts are made to collect the high resolution environmental and biological data at outplanting sites, such as temperature, dissolved oxygen, biological data (macroalgae, predator and competitor abundance). While the research presented is representative of habitat suitability for adult white abalone, the proposed experiment will provide greater insight on juvenile white abalone habitat preference and suitability, which has proven to be challenging to identify due to their cryptic behavior.

To further advance these efforts, fishery-independent surveys should continue to monitor existing populations and in addition begin to conduct a standardized survey of all coastlines within the SCB. These surveys will help to locate new potential habitat and

provide the necessary data to develop more reliable habitat models to better inform outplanting and recovery efforts.

APPENDIX

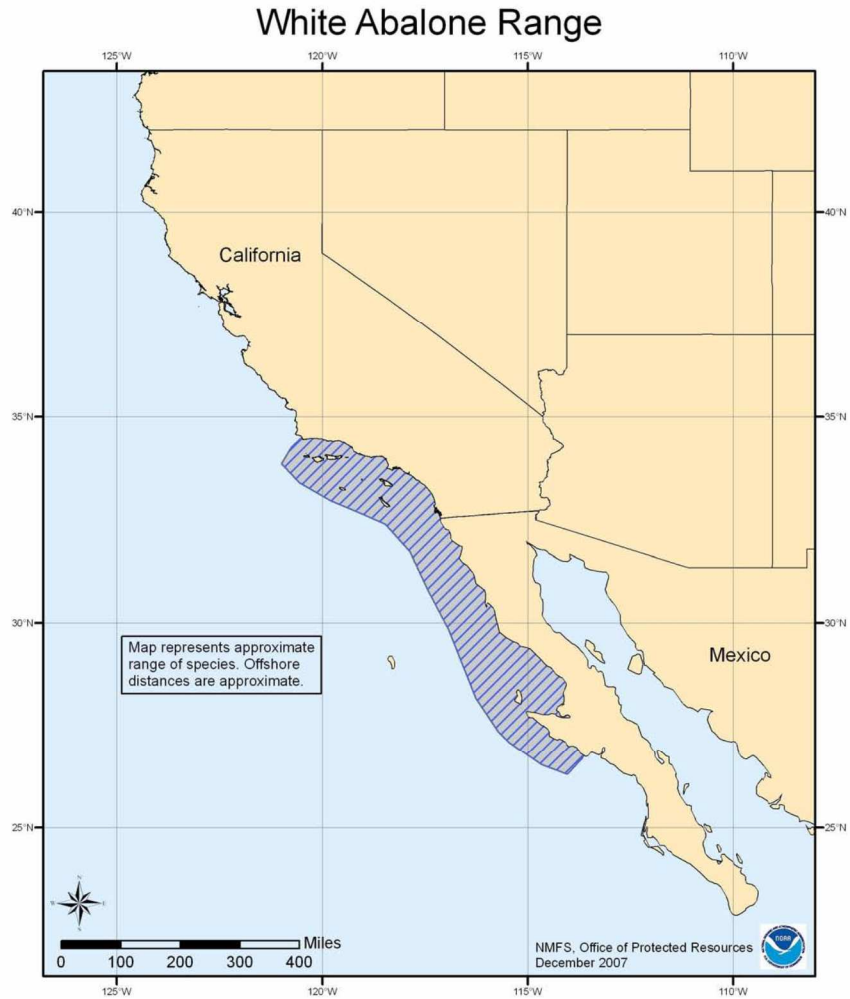


Figure 1.1: Historical white abalone distribution from Point Conception, California, US to Punta Abrejos, Baja California, Mexico.

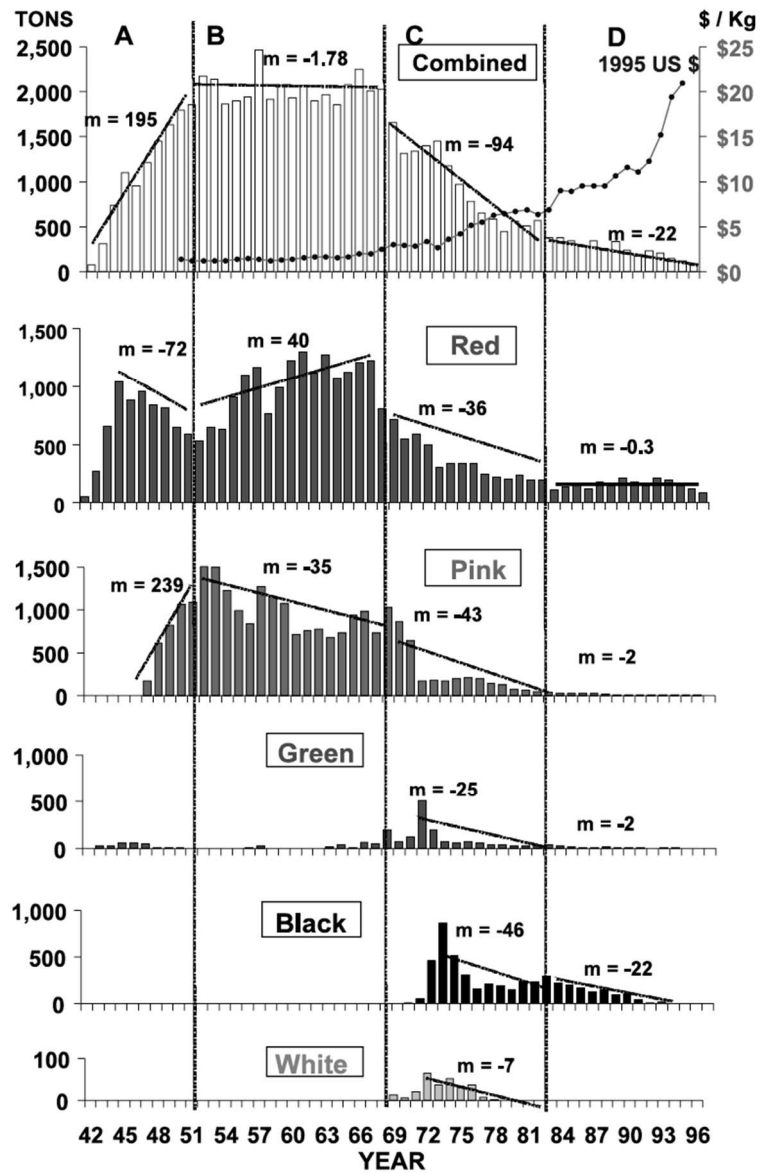


Figure 1.2: Time series of commercial landings (metric tons) of the California abalone fishery (bars), combined (top), and by red, pink, green, black, and white abalones. Landings are divided into periods (A-D) by trends in the total fishery landings, with regression (dotted) lines for each period (m =slope). Regressions are provided for individual species where sufficient data exists. The average annual value of all species (US \$ per kilogram) is represented by a solid line. Figure came from 2005 Abalone Recovery and Management Plan.

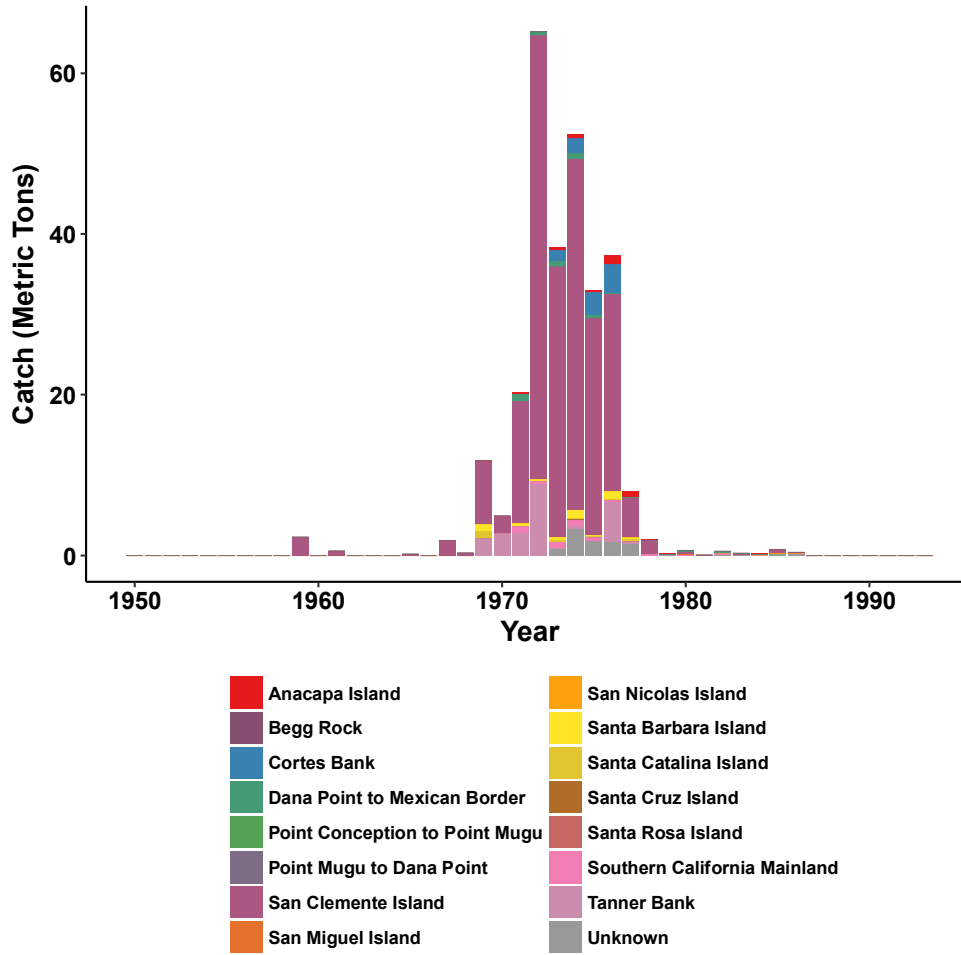


Figure 1.3: Time series of commercial white abalone catch (metric tons) by region from 1951 to 1993. Data provided by CDFG.

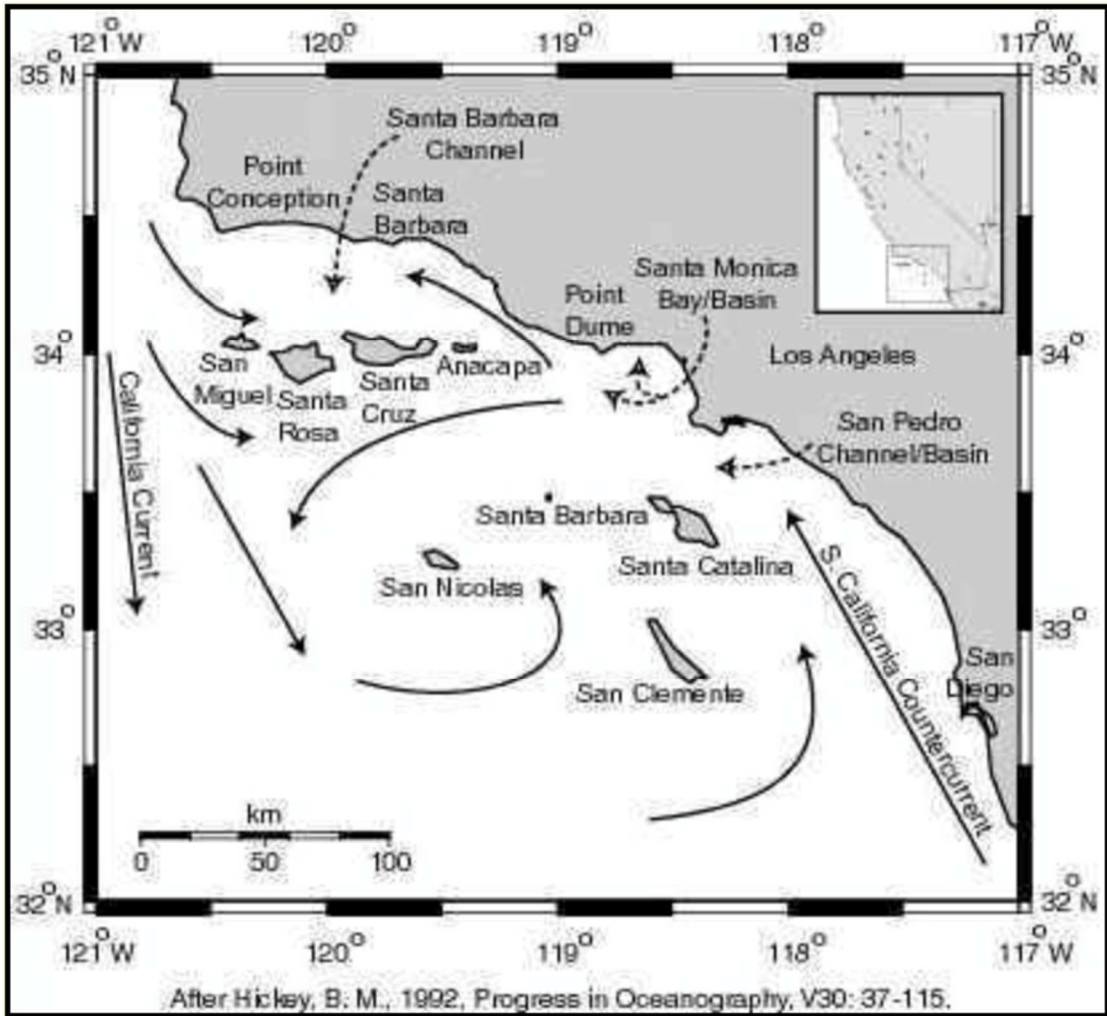


Figure 2.1: Ocean circulation patterns in the SCB.

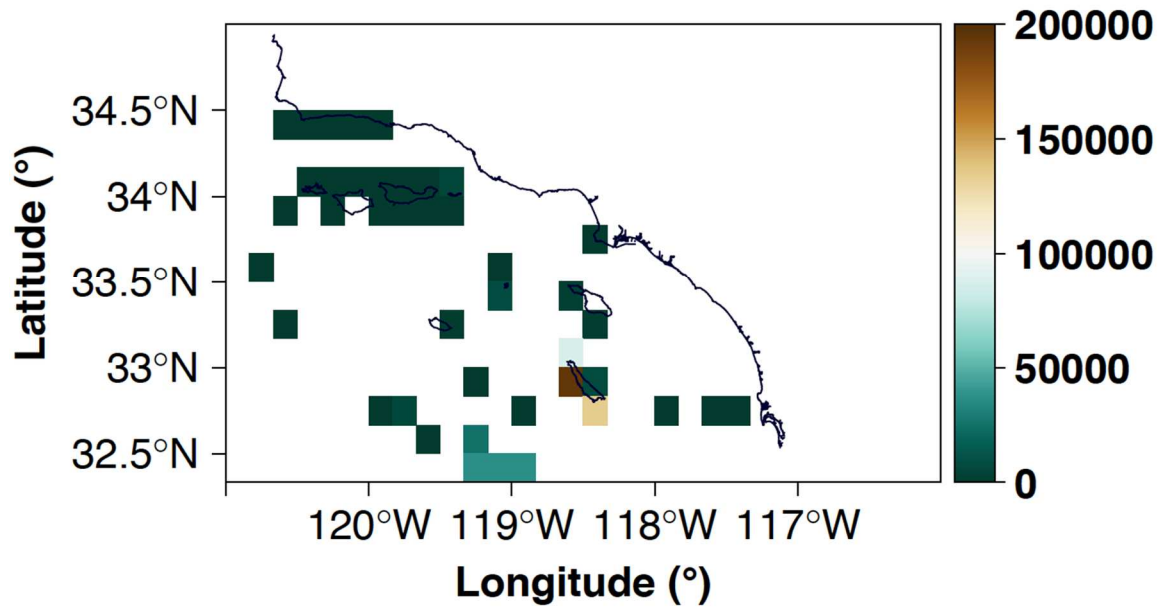


Figure 2.2: Total commercial landings (metric tons) of by CDFG statistical fishing block from 1951 through 1993. Data provided by CDFG.

Table 2.1: Fishery-independent white abalone surveys. Surveys are described by data, spatial resolution, method, and general location surveyed.

Survey	Date	Spatial Resolution (m)	Survey Method	Location
Tutschulte, 1976	1976	800	Scuba	Santa Catalina Island
Davis et al., 1996 (1)	1980-1981	100	Scuba	Anacapa, Santa Cruz, and Santa Barbara Islands
Davis et al., 1996 (2)	1992-1993	65 (1992); 10 (1993)	Scuba	Anacapa, Santa Cruz, San Clemente, Santa Catalina Islands
Davis et al, 1998	1996-1997	10	Submersible	Anacapa, Santa Cruz, and Santa Barbara Islands, and Osborn Bank
DELTA 1999	1999	10	Submersible	Anacapa, Santa Cruz, and Santa Barbara, San Clemente, Santa Catalina Islands, Tanner and Cortes Banks, Osborn bank
NOAA SWFSC	2002-2017	10 (2002-2010); 2 (2012-2017)	ROV	San Clemente, Santa Catalina, Tanner and Cortes Banks, and southern California coast
NOAA/Universities	2010-2017	35 (2010-2012); 10 (2013-2017)	Scuba	Santa Catalina Island, southern California coast

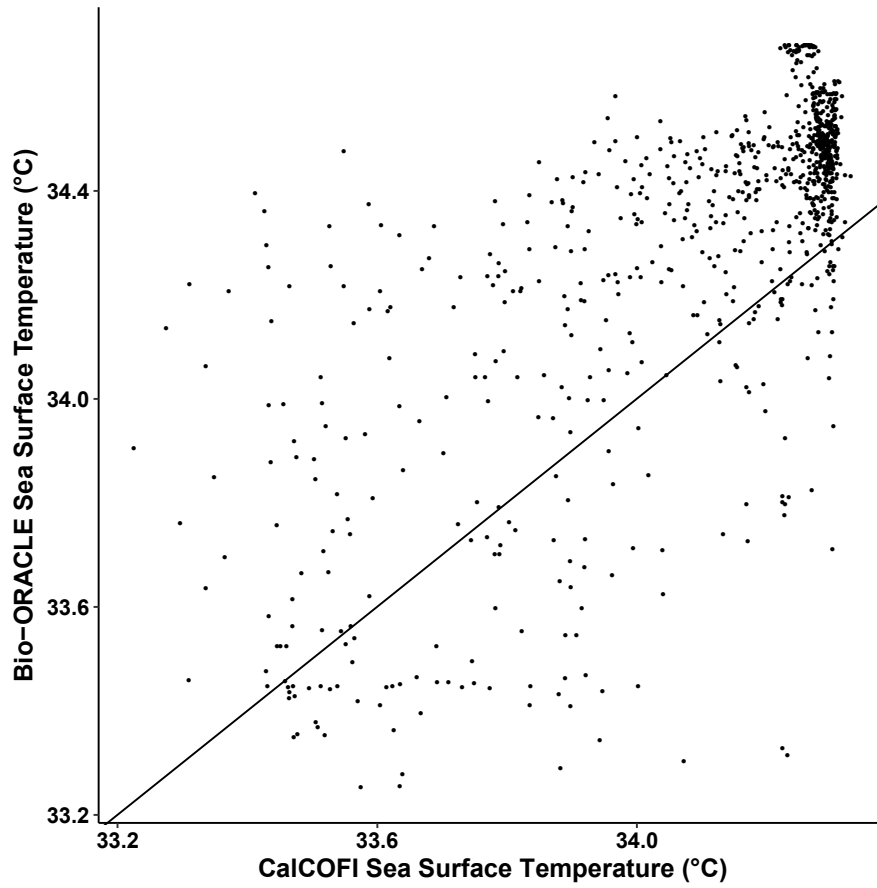


Figure 2.3: Comparison of data sources (CalCOFI versus Bio-ORACLE) for mean sea surface temperatures (averaged over 15 years; 2000-2014) throughout the SCB. The diagonal lines represents the $y=x$ line, which denotes a 1:1 relationship between the two data sources.

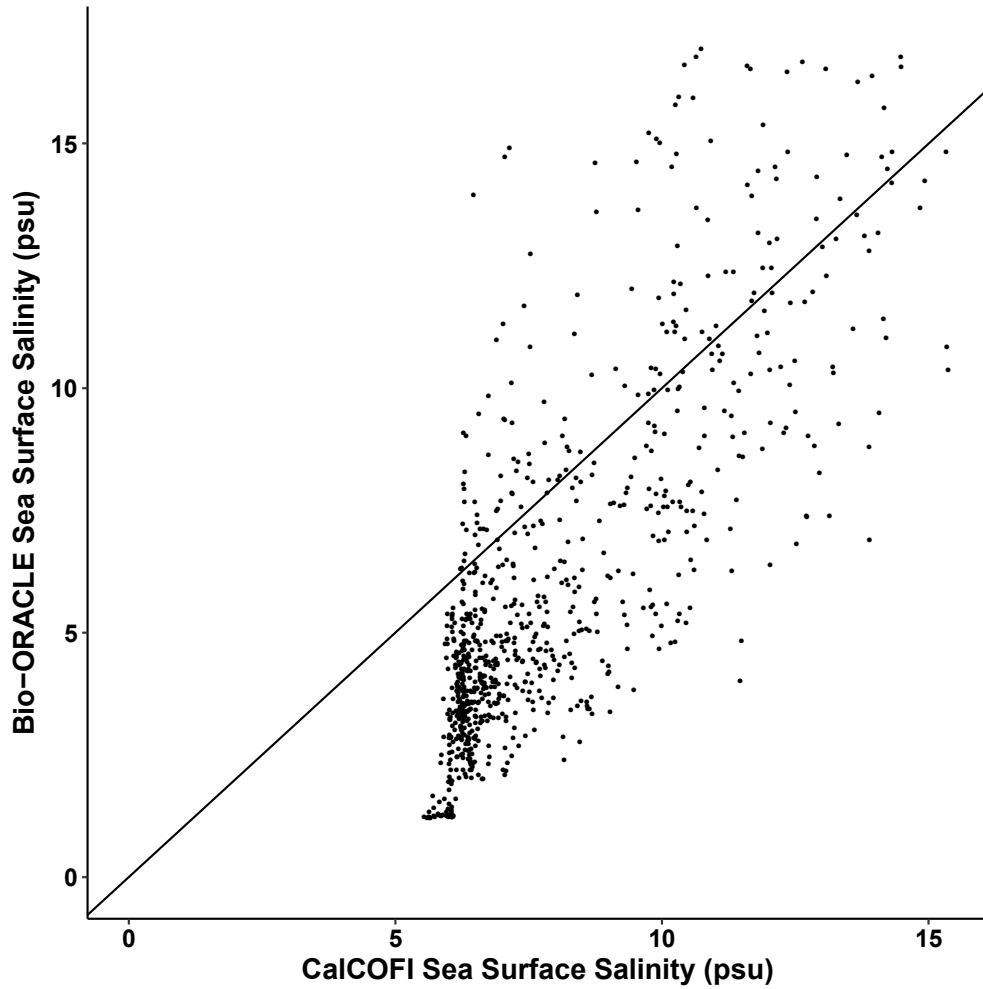


Figure 2.4: Comparison of data sources (CalCOFI versus Bio-ORACLE) for mean sea surface salinity (averaged over 15 years; 2000-2014) throughout the SCB. The diagonal lines represents the $y=x$ line, which denotes a 1:1 relationship between the two data sources.

Table 2.2: List of variables and sample sizes included in modeling by study area

San Clemente Island (n=26)	Tanner and Cortes Banks (n=359)	Santa Barbara and Santa Catalina Islands (n=16)	San Diego (n=19)	Palos Verdes (n=14)
Bathymetry	Bathymetry	Bathymetry	Bathymetry	Bathymetry
Slope	Slope	Slope	Slope	Slope
VRM	VRM	VRM	VRM	VRM
		Predator Diversity Index	Kelp Persistence Index	Kelp Persistence Index
		Two Spot Octopus Abundance Score		
		Urchin Abundance Score		

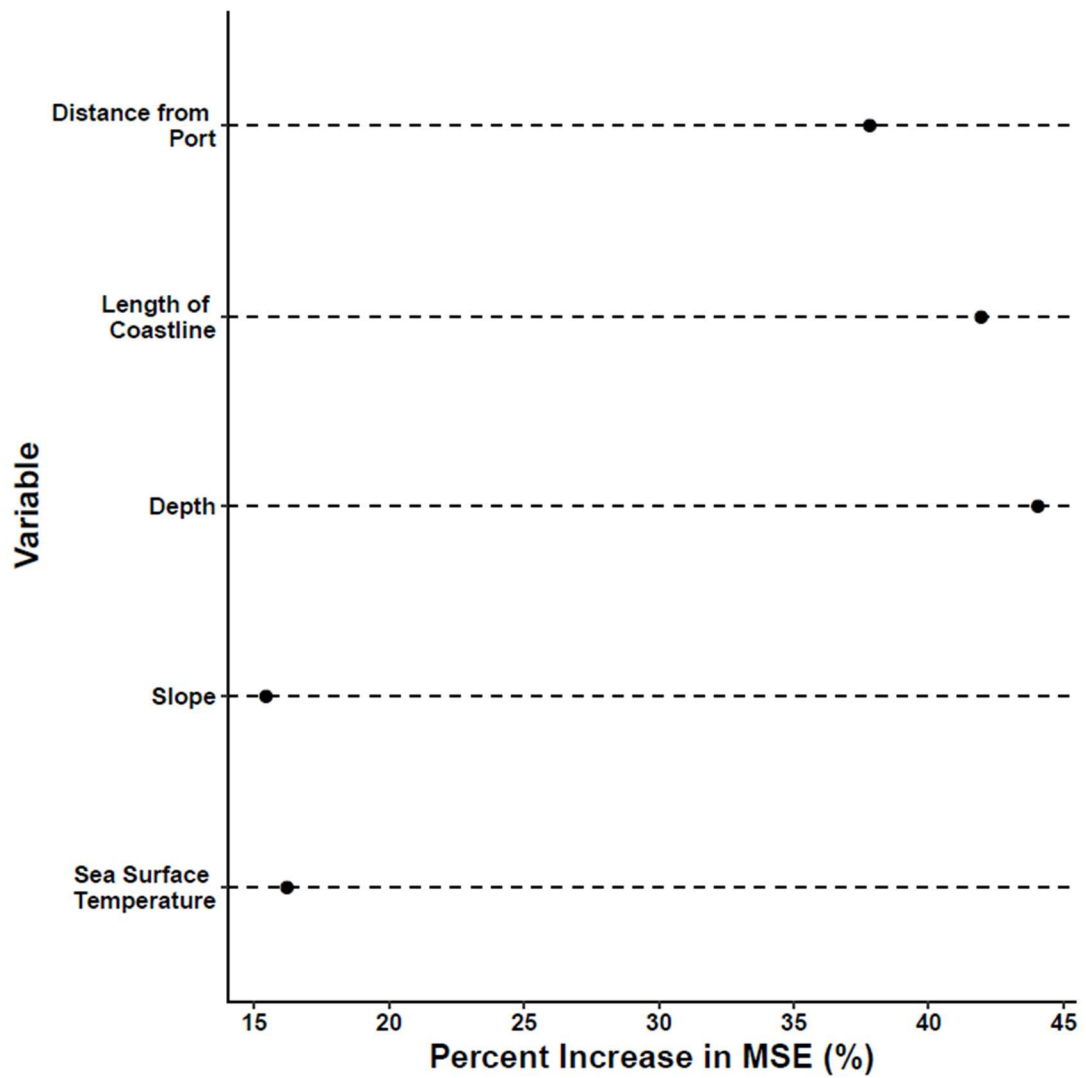


Figure 3.1: Variable importance (percent increase in MSE) developed by random forest using fishery-dependent data.

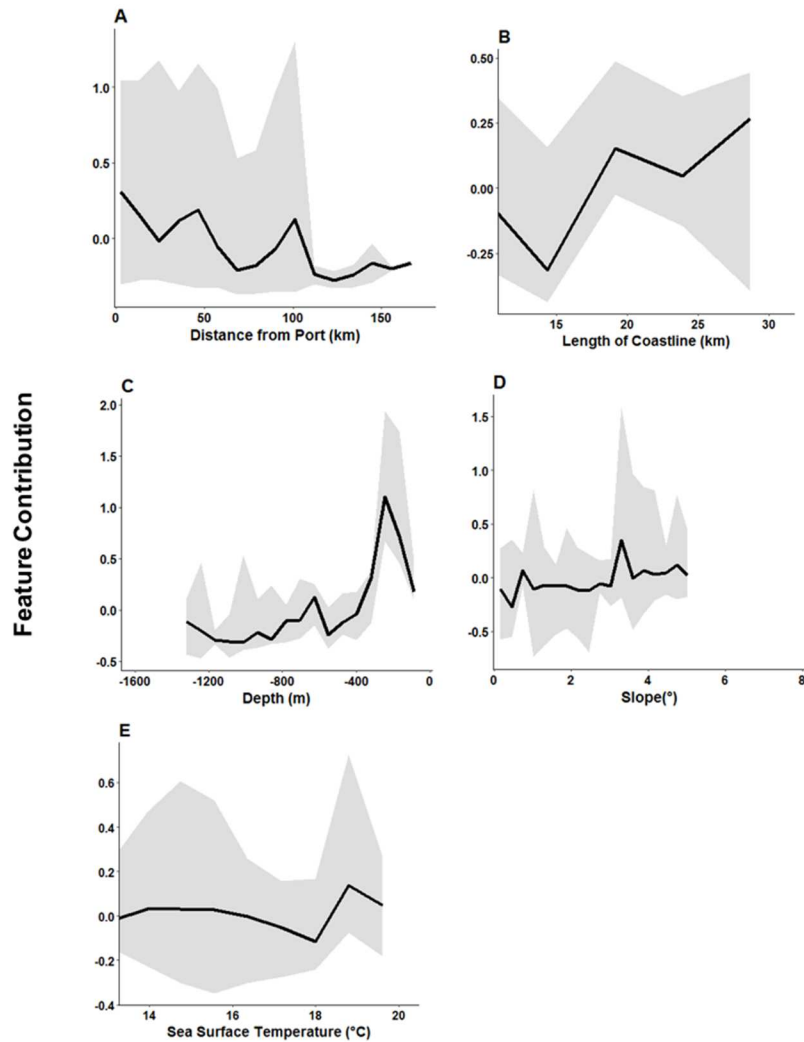


Figure 3.2: Response curves (feature contribution) for each predictor variable developed by random forest using fishery-dependent data. The black line represents the mean contribution to prediction and the grey shaded region represents the 95% quantile range of predictions in variable space.

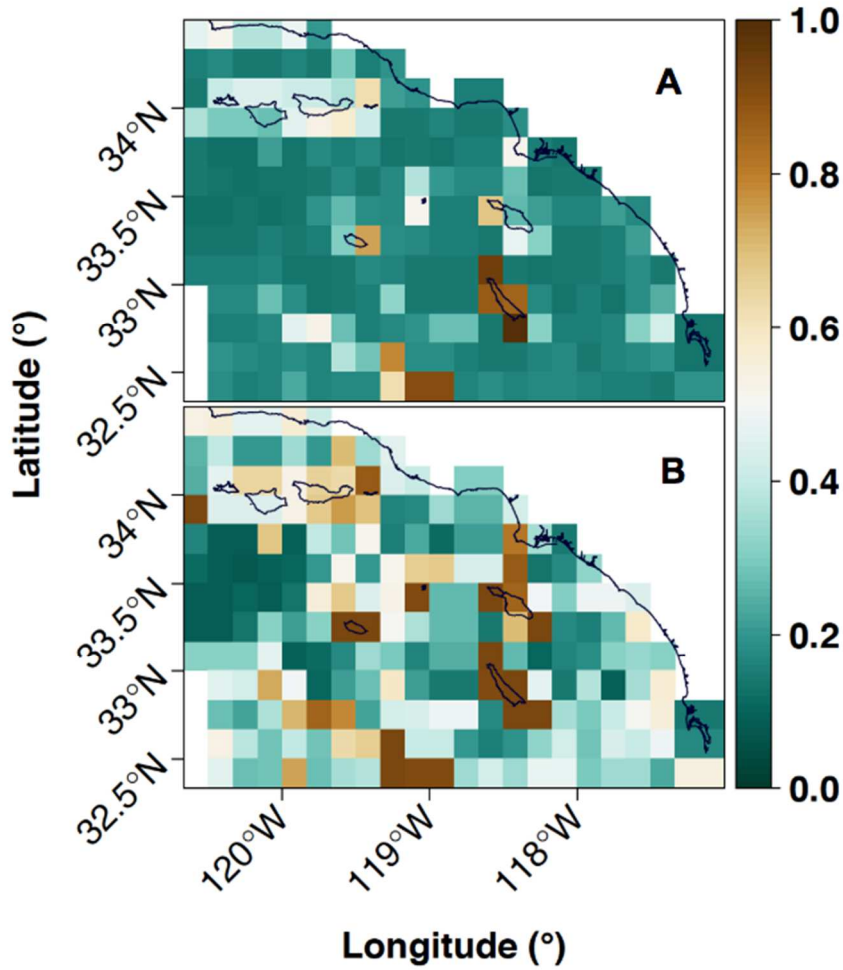


Figure 3.3: Projected historical distribution of white abalone developed by random forest using fishery-dependent data. A. Predicted relative mean abundance averaged over 2000 trees and B. Error in predicted relative abundance (represented as the 95% quantile range of predictions).

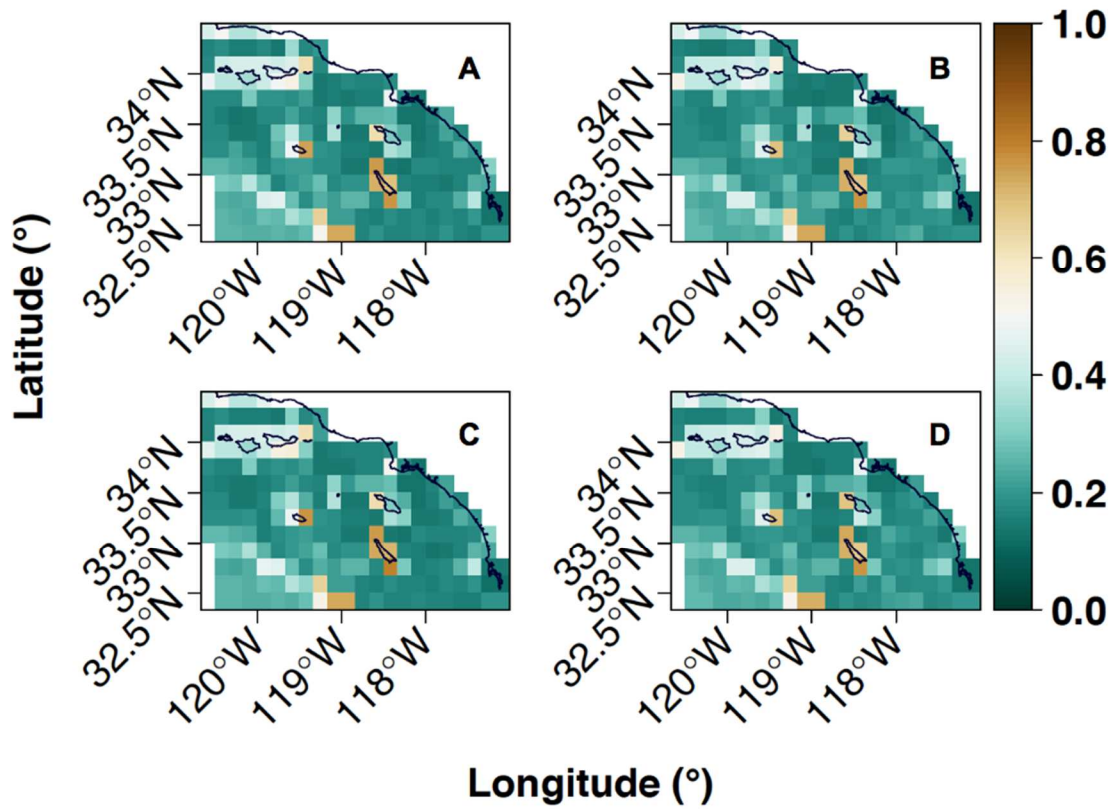


Figure 3.4: Projected relative mean abundance of white abalone for 2040-2050 developed by random forest using fishery-dependent data. Each map represents projected relative mean abundance for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios averaged over 2000 trees.

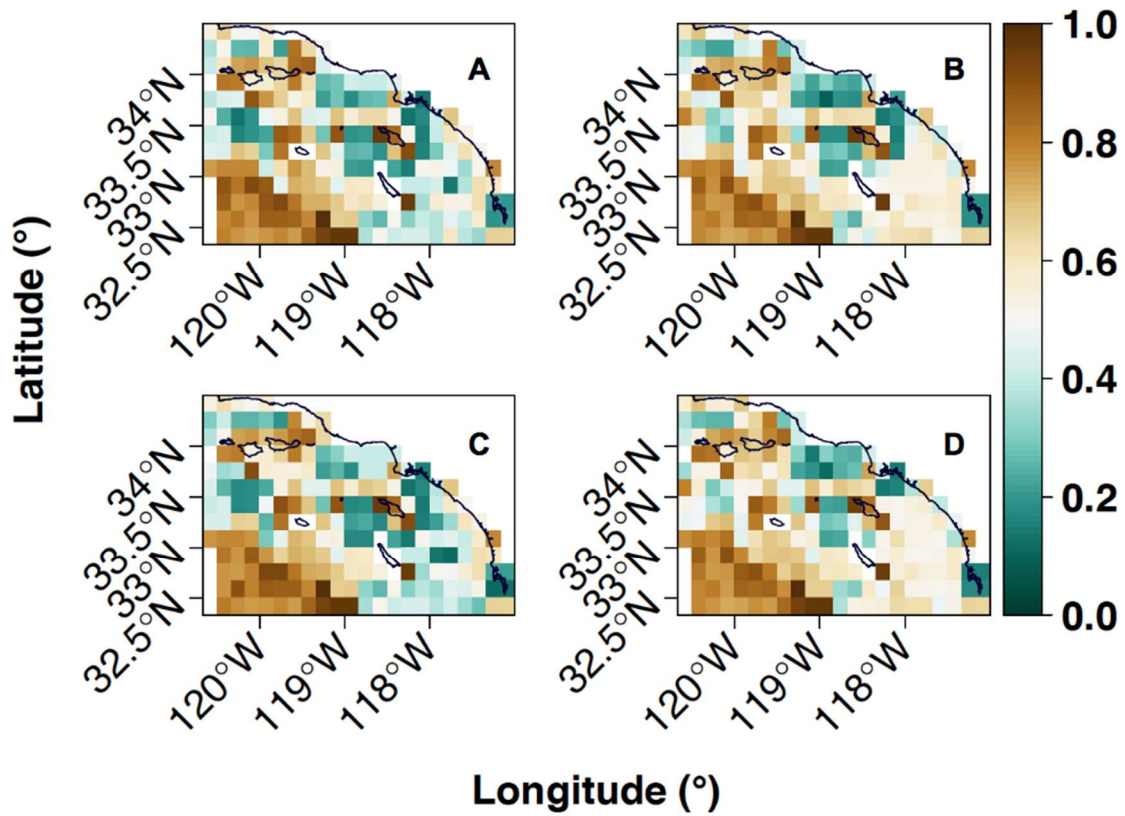


Figure 3.5: Error in projections for 2040-2050 based on random forest and fishery-dependent data. Each map represents 95% quantile range of predictions of relative abundance for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios.

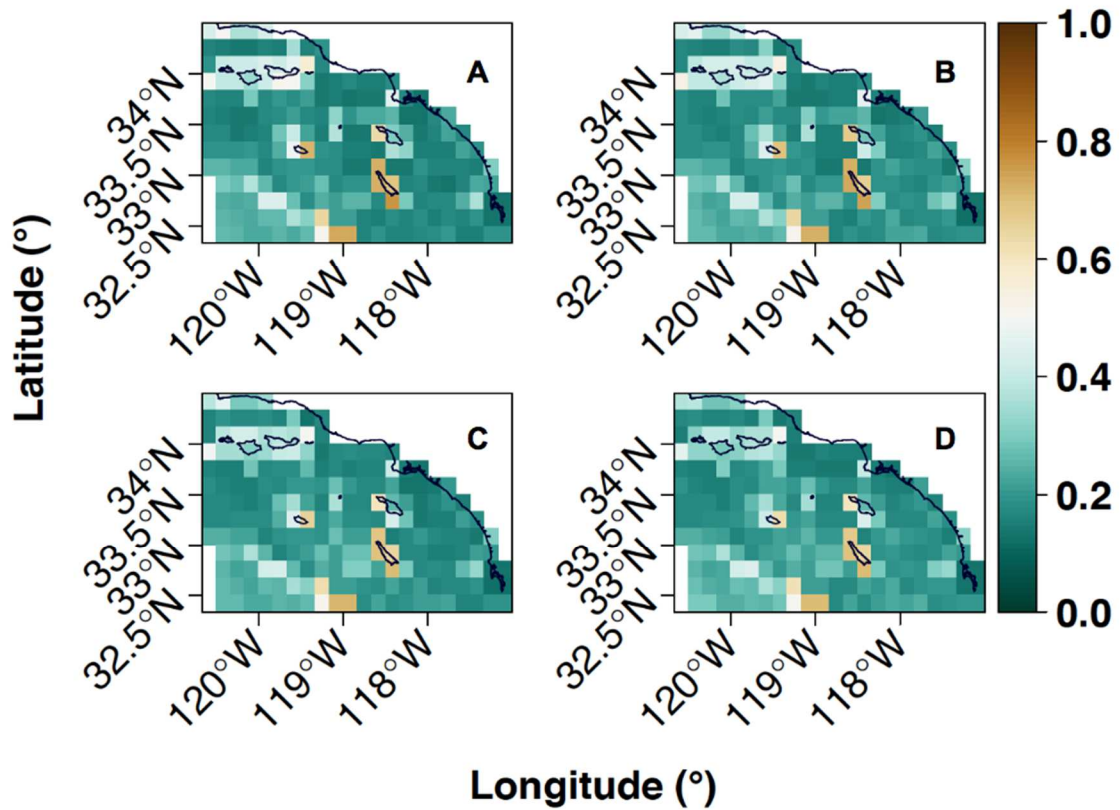


Figure 3.6: Projected relative mean abundance of white abalone for 2090-2010 developed by random forest using fishery-dependent data. Each map represents projected relative mean abundance for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios averaged over 2000 trees.

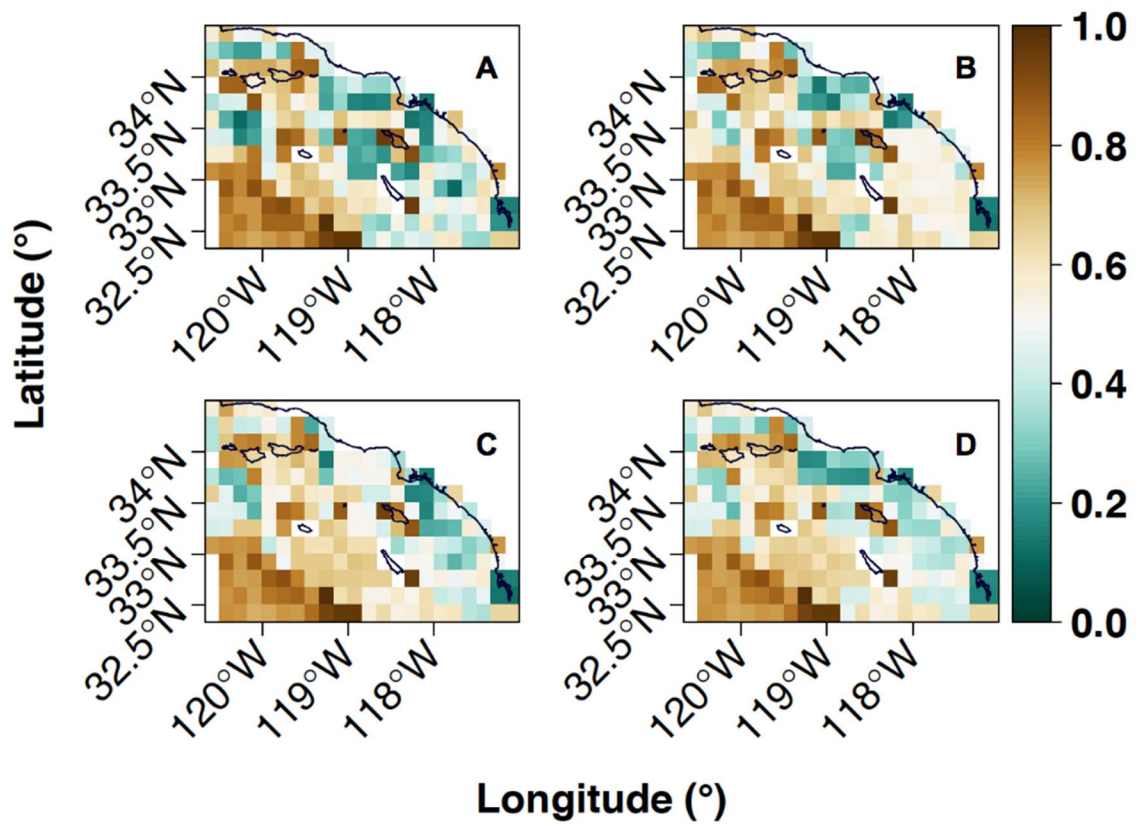


Figure 3.7: Error in projections for 2090-2010 based on random forest and fishery-dependent data. Each map represents 95% quantile range of predictions of relative abundance for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios.

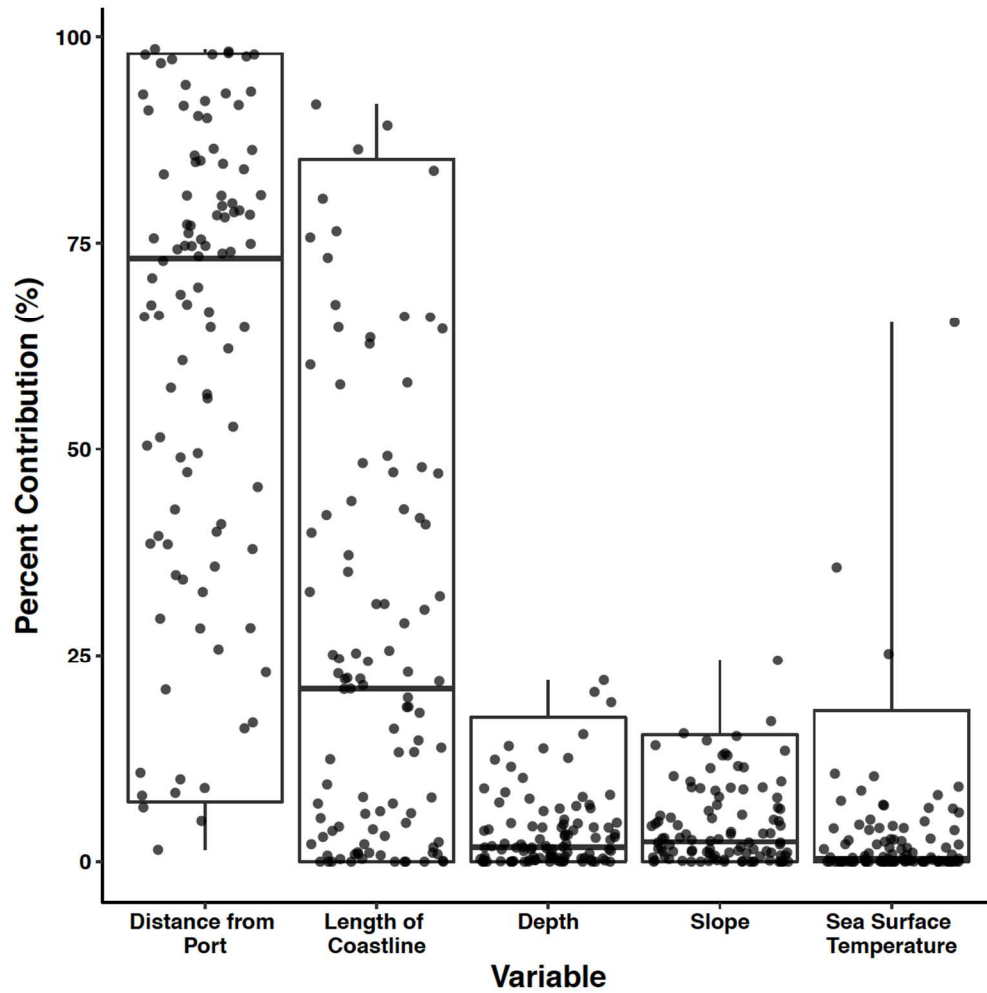


Figure 3.8: Variable importance (percent contribution) developed by MaxEnt using fishery-independent data at a broad-scale. The horizontal lines within each box and whisker plot represents the median of 100 model runs. The ends of the box represent the upper and lower quartiles. The whiskers that extend from the box represent minimum and maximum values of percent contribution. Each point represents a model run.

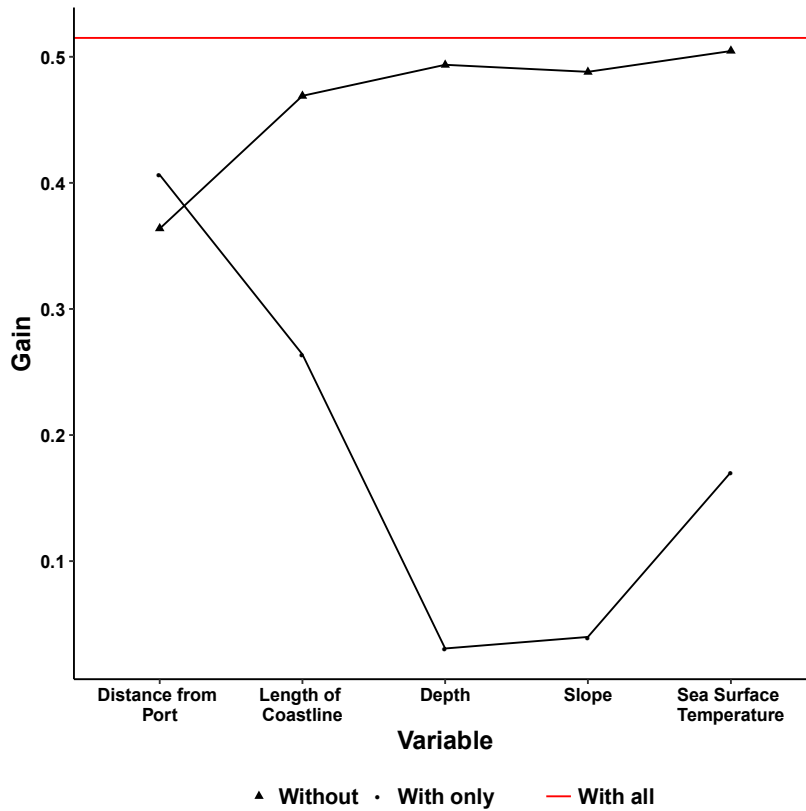


Figure 3.9: Variable importance (jackknife regularized training gain) developed by MaxEnt using fishery-independent data at a broad-scale. The red horizontal line (With all) represents the gain of the model developed with all variables included. The circle points represent the gain of a model when developed with each variable is used exclusively (With only). The triangle points represent the gain of a model developed when each variable is excluded and remaining variables are used (Without).

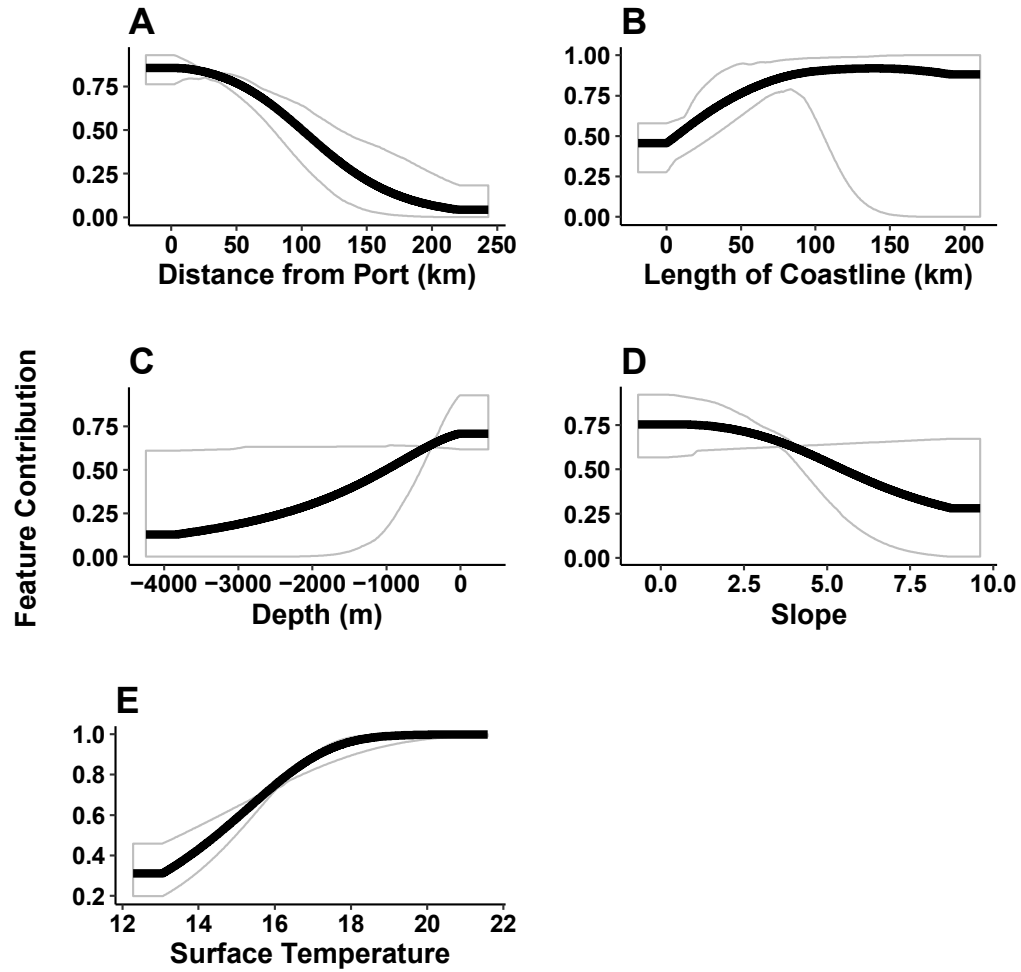


Figure 3.10: Response curves (log contribution to prediction) for each predictor variable developed by MaxEnt using fishery-independent data at a broad-scale. The black line represents the mean contribution to prediction and the grey shaded region represents the 95% quantile range of predictions in variable space.

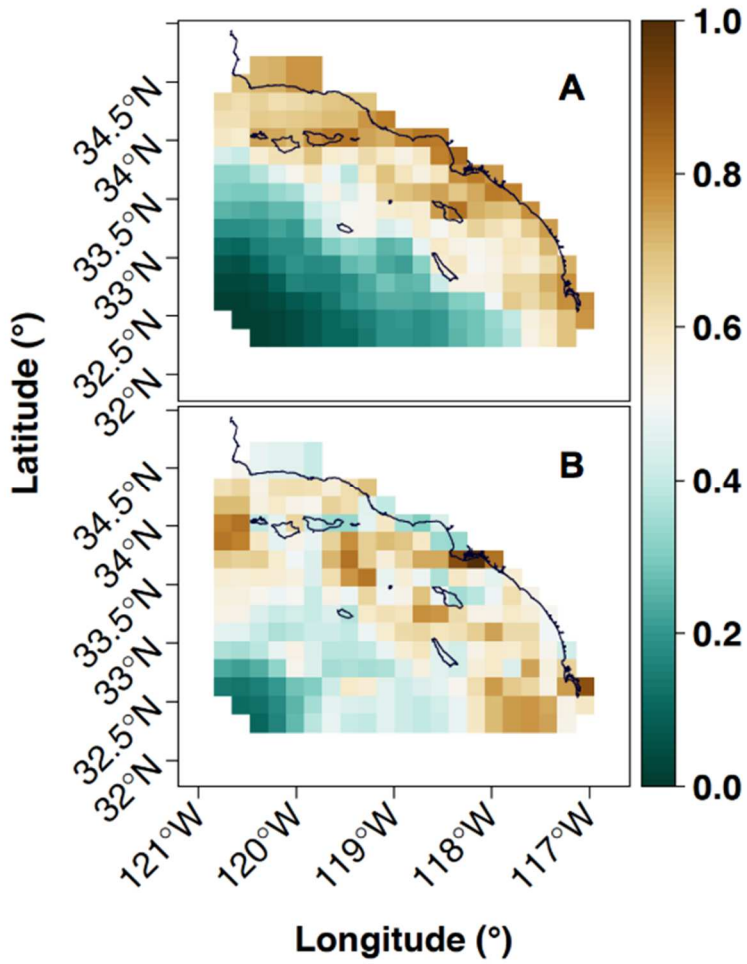


Figure 3.11: Projected contemporary distribution of white abalone developed from MaxEnt using fishery-independent data at a broad-scale. A. Predicted relative mean likelihood of presence averaged over 100 model runs and B. Error in predicted relative likelihood of presence (represented as the 95% quantile range of predictions).

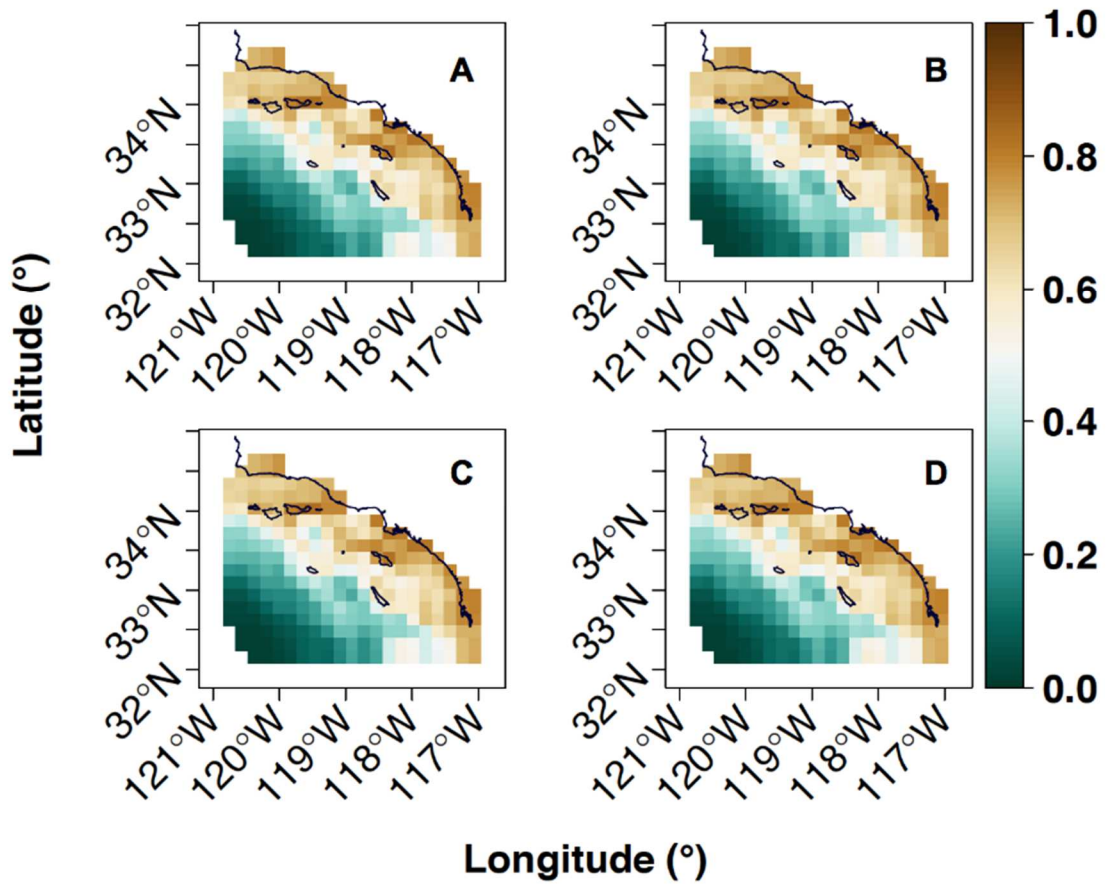


Figure 3.12: Projected relative mean likelihood of presence of white abalone for 2040-2050 developed by MaxEnt using fishery-independent data at a broad-scale. Each map represents projected relative mean likelihood of presence for A. RCP 2.6, B. RCP 4.5, C. RCP 6.0, and D. RCP 8.5 scenarios averaged over 100 model runs.

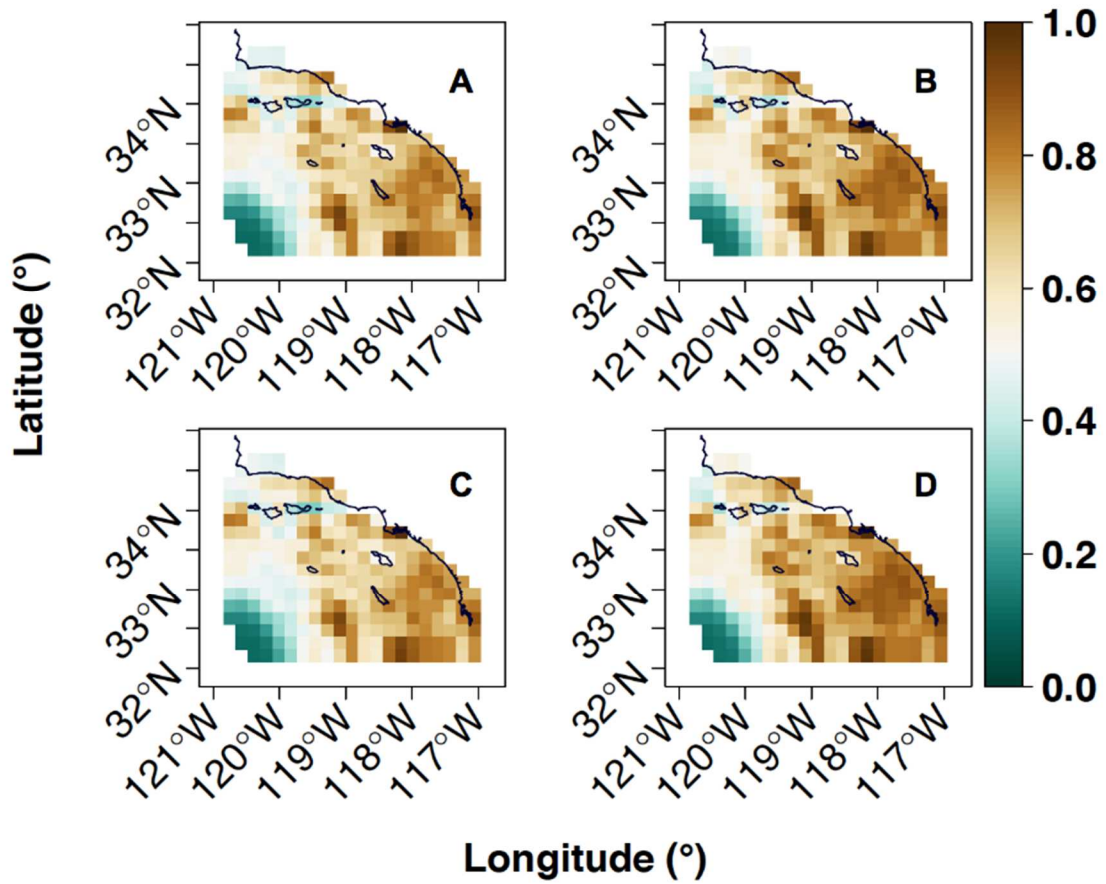


Figure 3.13: Error in projections for 2040-2050 based on MaxEnt and fishery-independent data at a broad-scale. Each map represents 95% quantile range of predictions of relative likelihood of presence for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios.

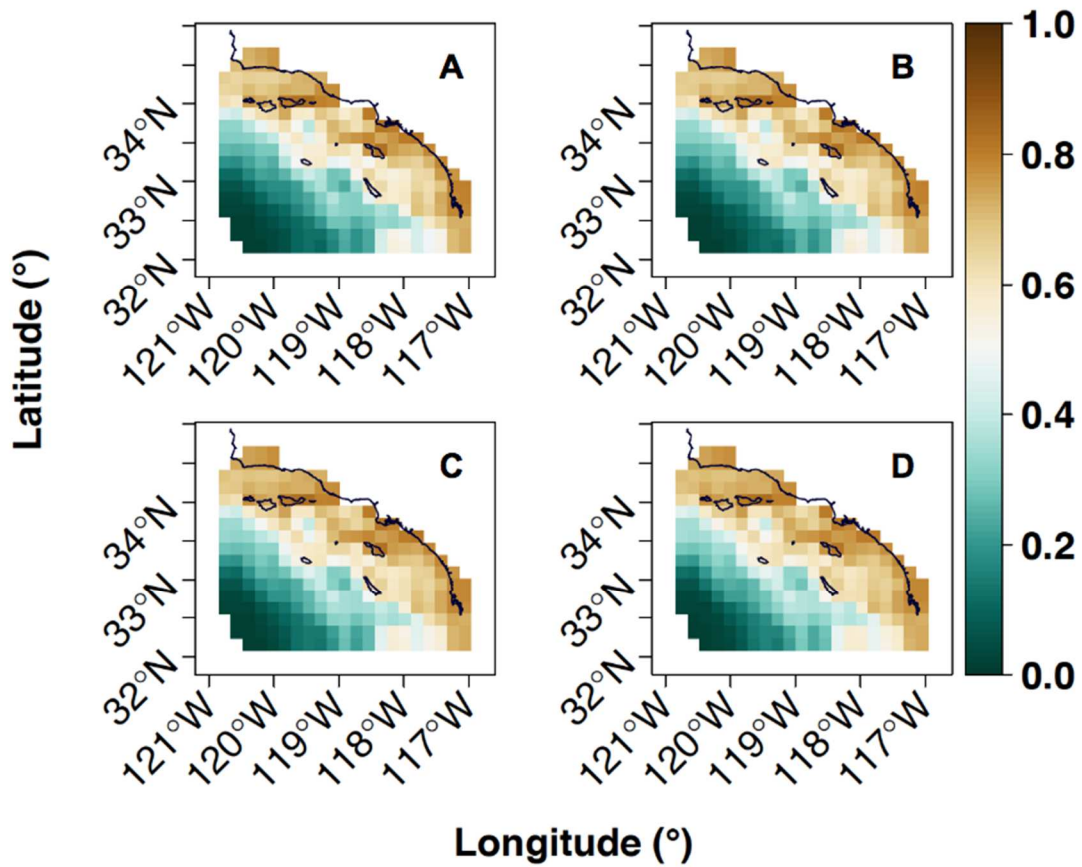


Figure 3.14: Projected relative mean likelihood of presence of white abalone for 2090-2100 using fishery-independent data at a broad-scale. Each map represents projected relative mean likelihood of presence for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios averaged over 100 model runs.

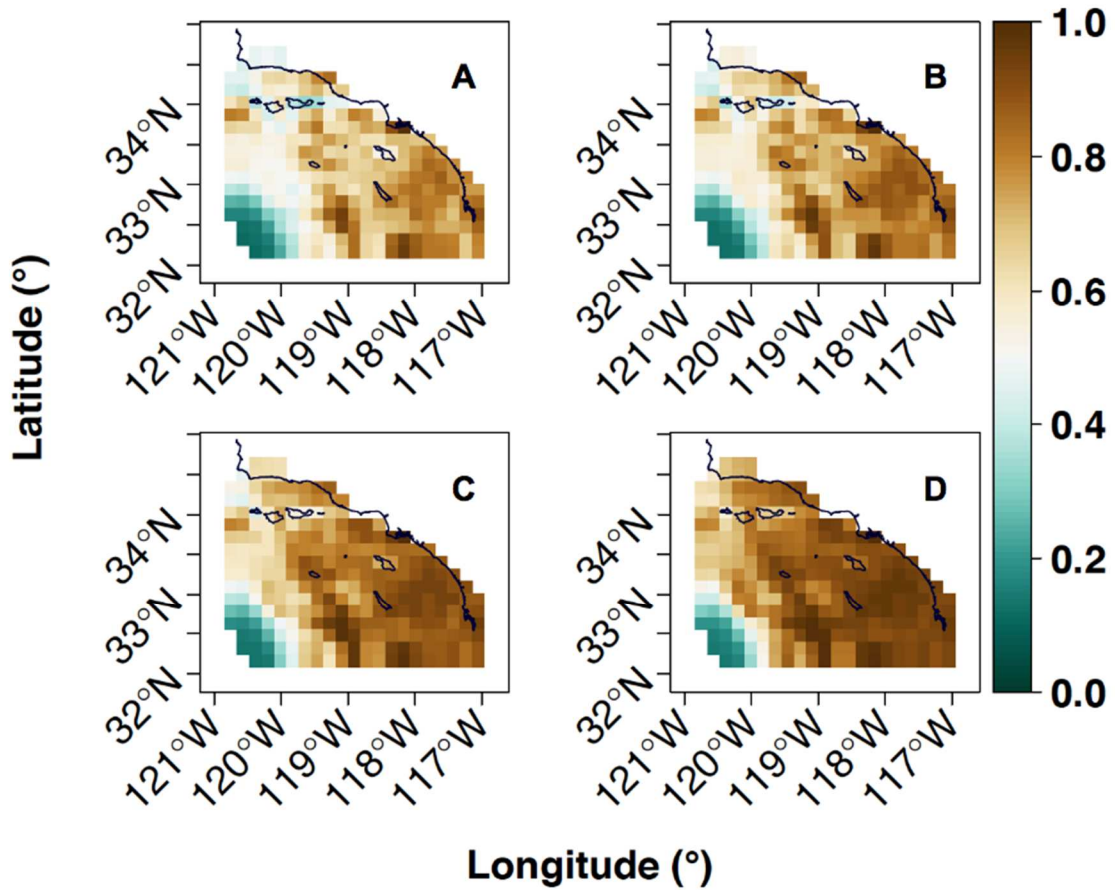


Figure 3.15: Error in projections for 2090-2100 based on MaxEnt and fishery-independent data at a broad-scale. Each map represents the 95% quantile range of predictions of relative likelihood of presence for A. RCP 2.6, B. RCP 4.5, C. RCP 6.0, and D. RCP 8.5 scenarios.

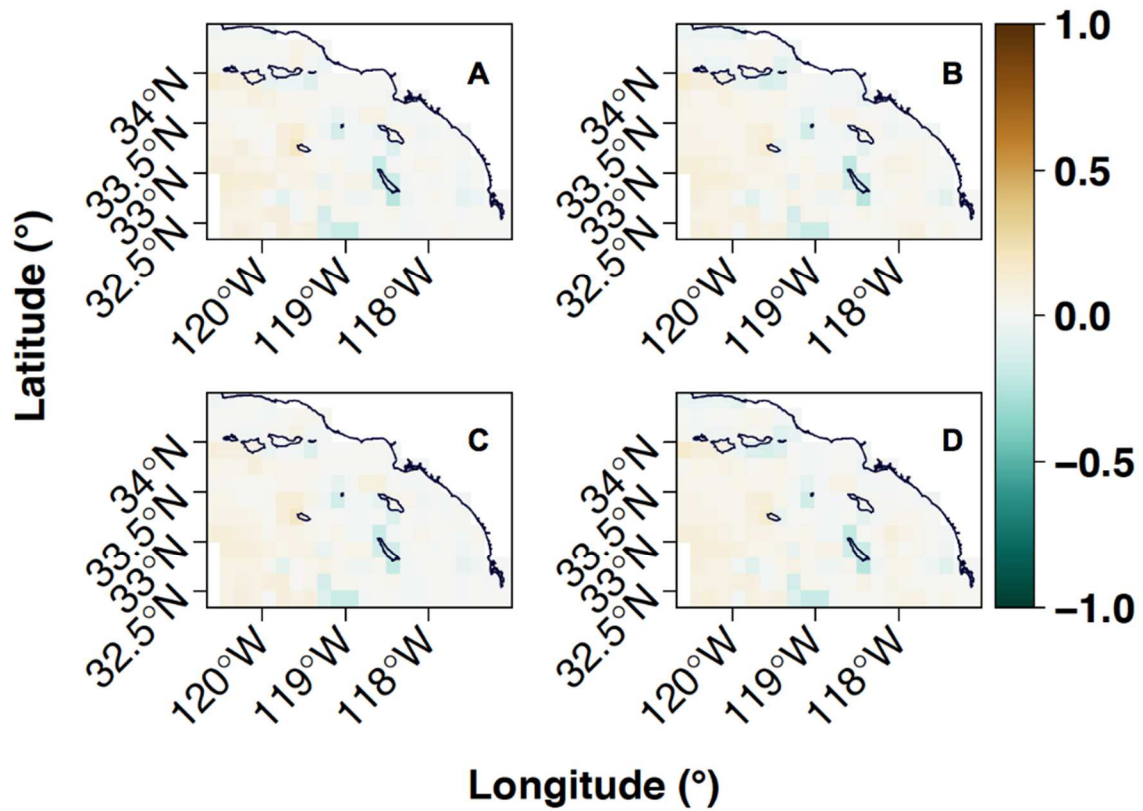


Figure 3.16: Change in relative mean abundance for white abalone in 2040-2050 from projected historic distribution based on fishery-dependent data. Each map represents change in relative mean abundance for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios.

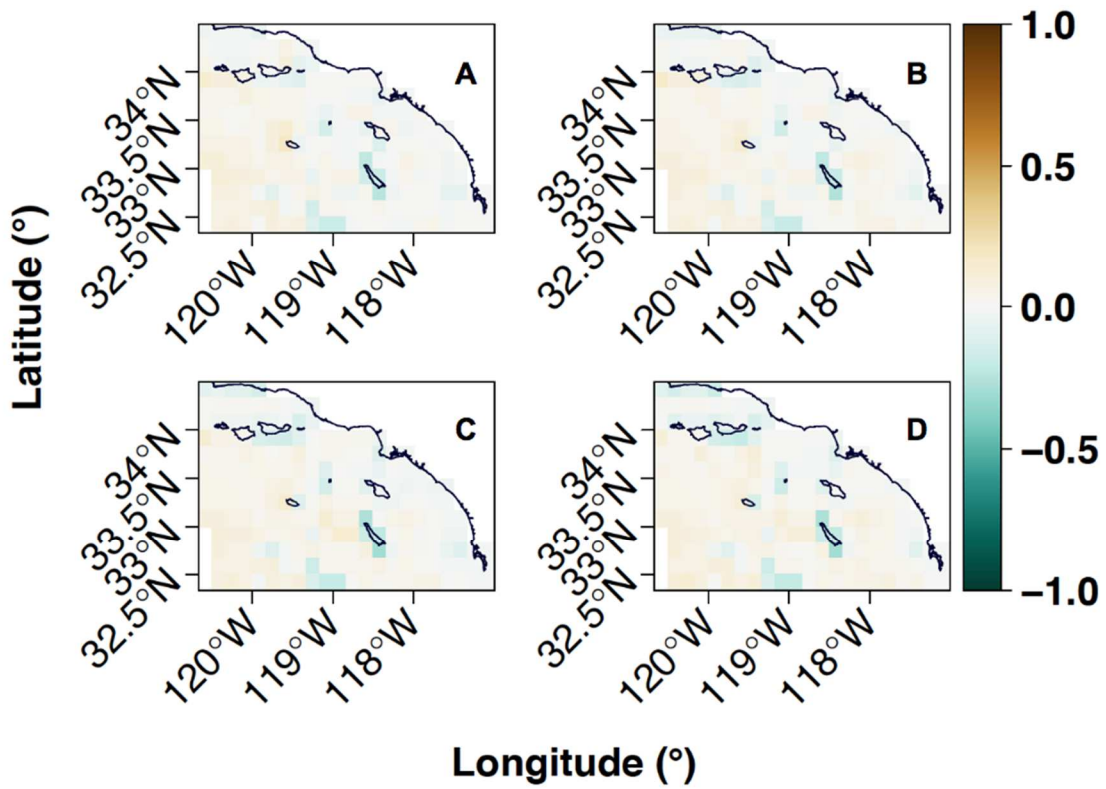


Figure 3.17: Change in relative mean abundance for white abalone in 2090-2100 from projected historic distribution based on fishery-dependent data. Each map represents change in relative mean abundance for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios.

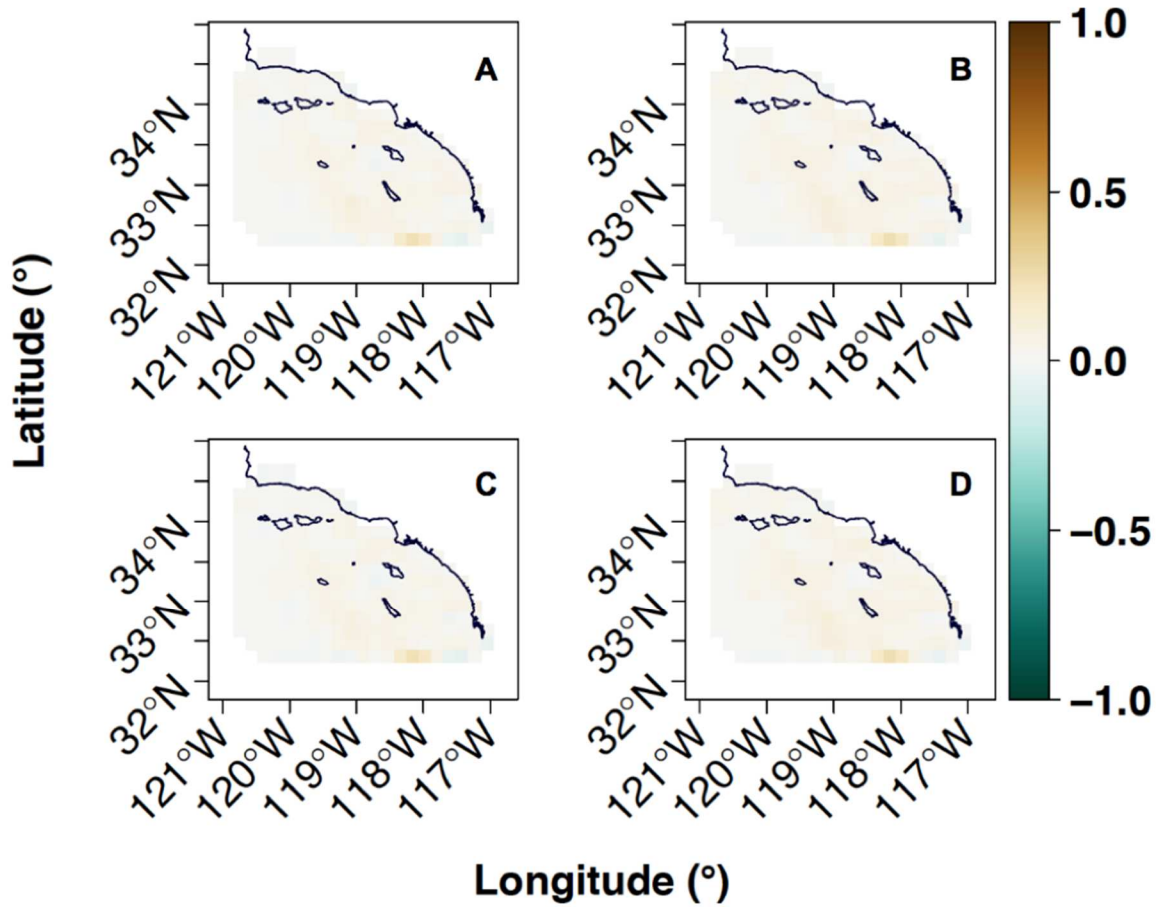


Figure 3.18: Change in relative mean likelihood of presence for white abalone in 2040-2050 from projected contemporary distribution based on fishery-independent data at a broad-scale. Each map represents change in relative mean likelihood of presence for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios.

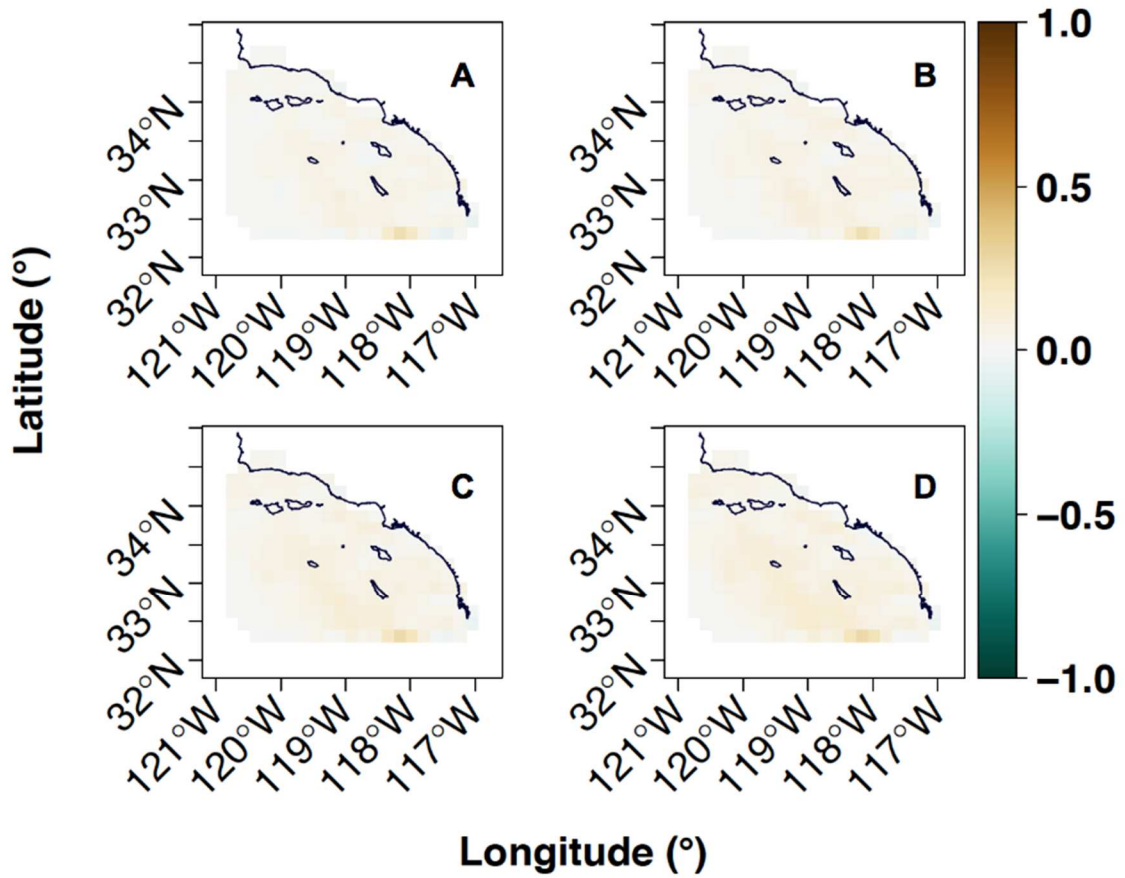


Figure 3.19: Change in relative mean likelihood of presence for white abalone in 2090-2100 from projected contemporary distribution based on fishery-independent data. Each map represents change in relative mean likelihood of presence for A. RCP 2.6, B. RCP 4.5, C. RCP6.0, and D. RCP8.5 scenarios.

Table 3.1: Results of one-sided significance test by study area (AUC values derived from null and MaxEnt fine-scale models). Values in parentheses represents the 95% CI intervals.

	San Clemente Island	Tanner and Cortes Banks	Palos Verdes	San Diego	Santa Barbara and Santa Catalina Islands
Null model mean	0.6954 ($-\infty, 0.7704$)	0.5420 ($-\infty, 0.8032$)	0.5706 ($-\infty, 0.8984$)	0.6918 ($-\infty, 0.7639$)	0.6840 ($-\infty, 0.9341$)
MaxEnt model mean	0.7763	0.8046	0.9042	0.7698	0.9370

Table 3.2: Variable importance (percent contribution) by study area developed by MaxEnt using fishery-independent data at a fine-scale. Values represent mean percent contributions averaged over 100 model runs.

	San Clemente Island	Tanner and Cortes Banks	San Diego	Palos Verdes	Santa Barbara and Santa Catalina
Bathymetry	81.96	81.96	16.93	71.25	26.36
VRM	15.76	15.76	0.18	7.84	16.47
Slope	2.27	2.28	28.14	3.05	10.35
Kelp Persistence Index	NA	NA	54.74	17.84	NA
Predator Diversity Index	NA	NA	NA	NA	10.35
Two-spot Abundance Score	NA	NA	NA	NA	22.14
Urchin Abundance Score	NA	NA	NA	NA	5.67

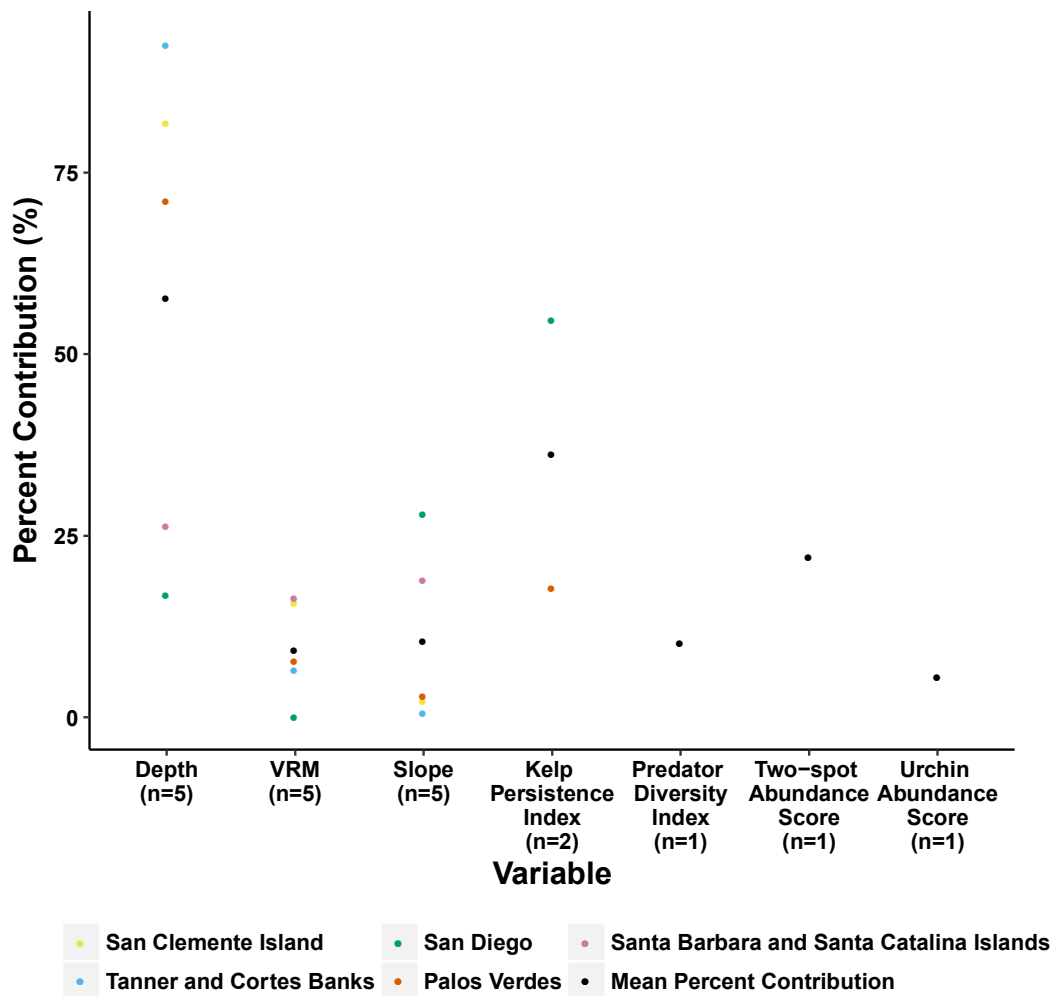


Figure 3.20: Variable importance (percent contribution) by study area developed by MaxEnt using fishery-independent data at a fine-scale. The black points represent mean variable importance (percent contribution) averaged over study areas and n represents the number of study areas used to derive mean contribution for each variable.

Table 3.3: Variable importance (jackknife regularized training gain) by study area developed by MaxEnt using fishery-independent data at a fine-scale. Values within parentheses next to the name of each study area represent the gain of the model when all variable are included in model development. Values under “With only” represent the gain of a model when developed with each variable is used exclusively. Values under “Without” represent the gain of a model developed when each variable is excluded and remaining variables are used.

San Clemente (0.1950)		
	With only	Without
Depth	0.1542	0.0554
VRM	0.0532	0.1732
Slope	0.0276	0.1929
Tanner and Cortes Banks (0.5855)		
Depth	0.5529	0.1226
VRM	0.1184	0.5627
Slope	0.0307	0.5818
San Diego (0.3037)		
Depth	0.0484	0.2642
VRM	0.0242	0.3035
Slope	0.0584	0.2473
Kelp Persistence	0.1704	0.1042
Palos Verdes (0.65555)		
Depth	0.5305	0.2499
VRM	0.1249	0.6268
Slope	0.1070	0.6473
Kelp Persistence	0.0914	0.6050
Santa Barbara and Santa Catalina Islands (0.9213)		
Depth	0.3430	0.6771
VRM	0.3354	0.8032
Slope	0.1830	0.8614
Predator Diversity	0.0700	0.7817
Two Spot Abundance	0.1752	0.7931
Urchin Abundance	0.0691	0.8678

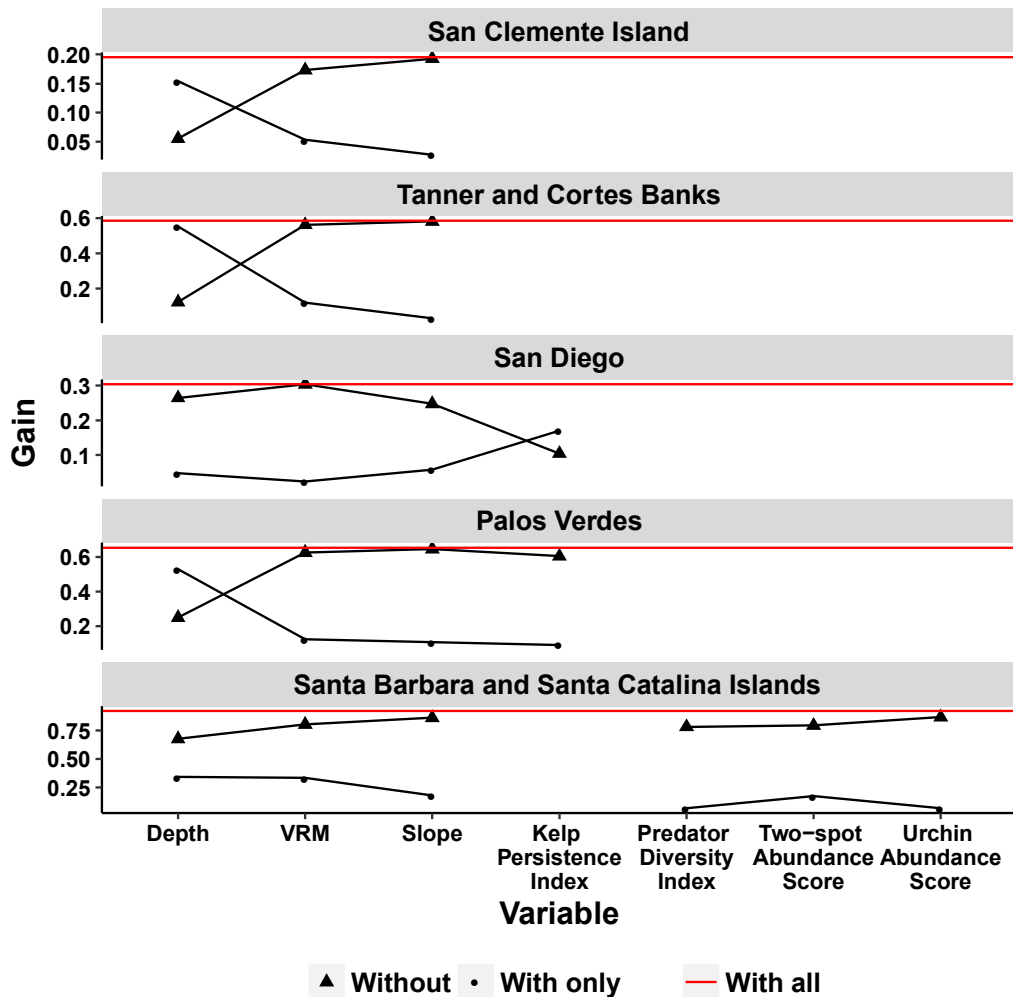


Figure 3.21: Variable importance (jackknife regularized training gain) by study area developed by MaxEnt using fishery-independent data at a fine-scale. The red horizontal line (With all) represents the gain of the model developed with all variables included. The circle points represent the gain of a model when developed with each variable is used exclusively (With only). The triangle points represent the gain of a model developed when each variable is excluded and remaining variables are used (Without).

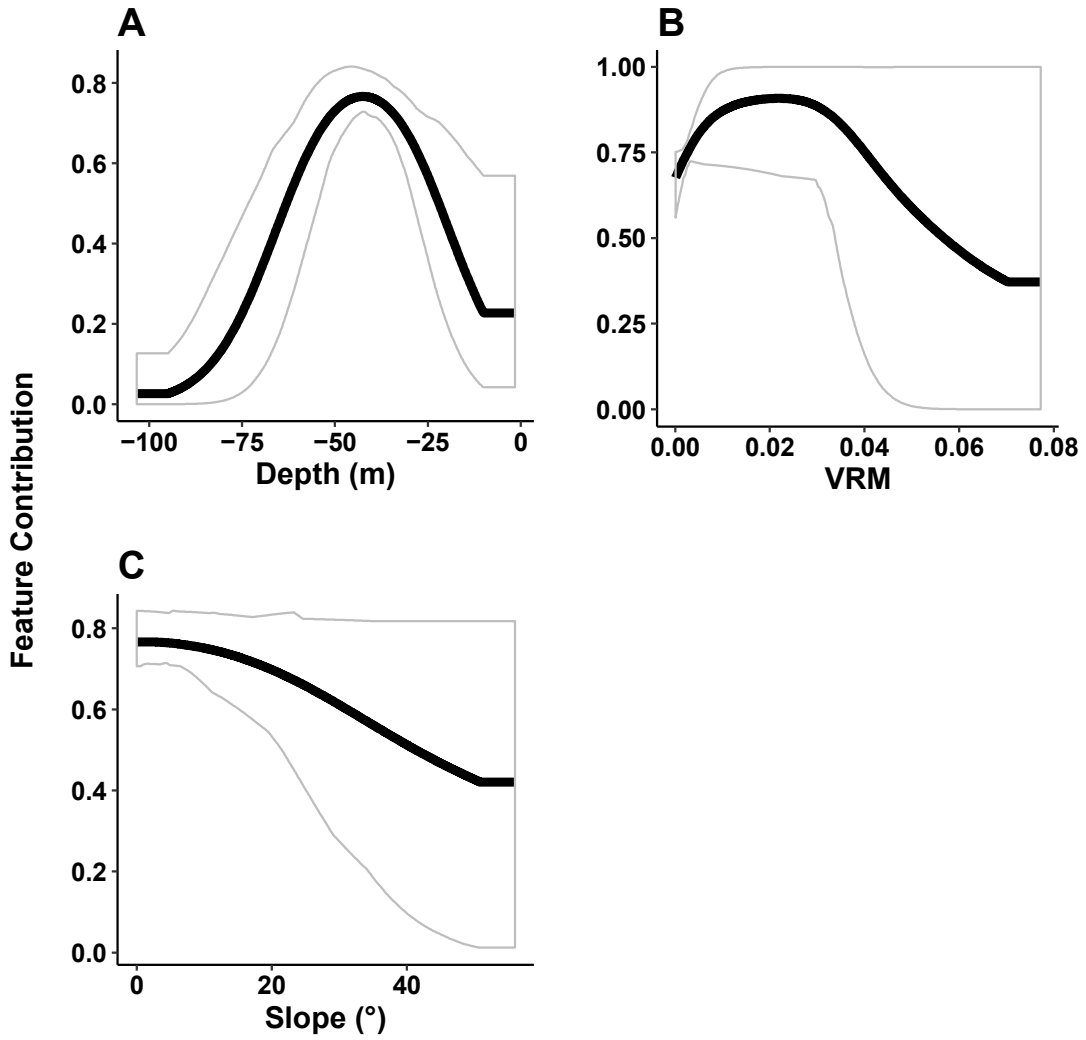


Figure 3.22: Response curves (log contribution to prediction) for each environmental predictor variable developed by MaxEnt at San Clemente Island. The black line represents the mean log contribution to prediction and the grey shaded region represents the 95% quantile range of predictions in variable space.

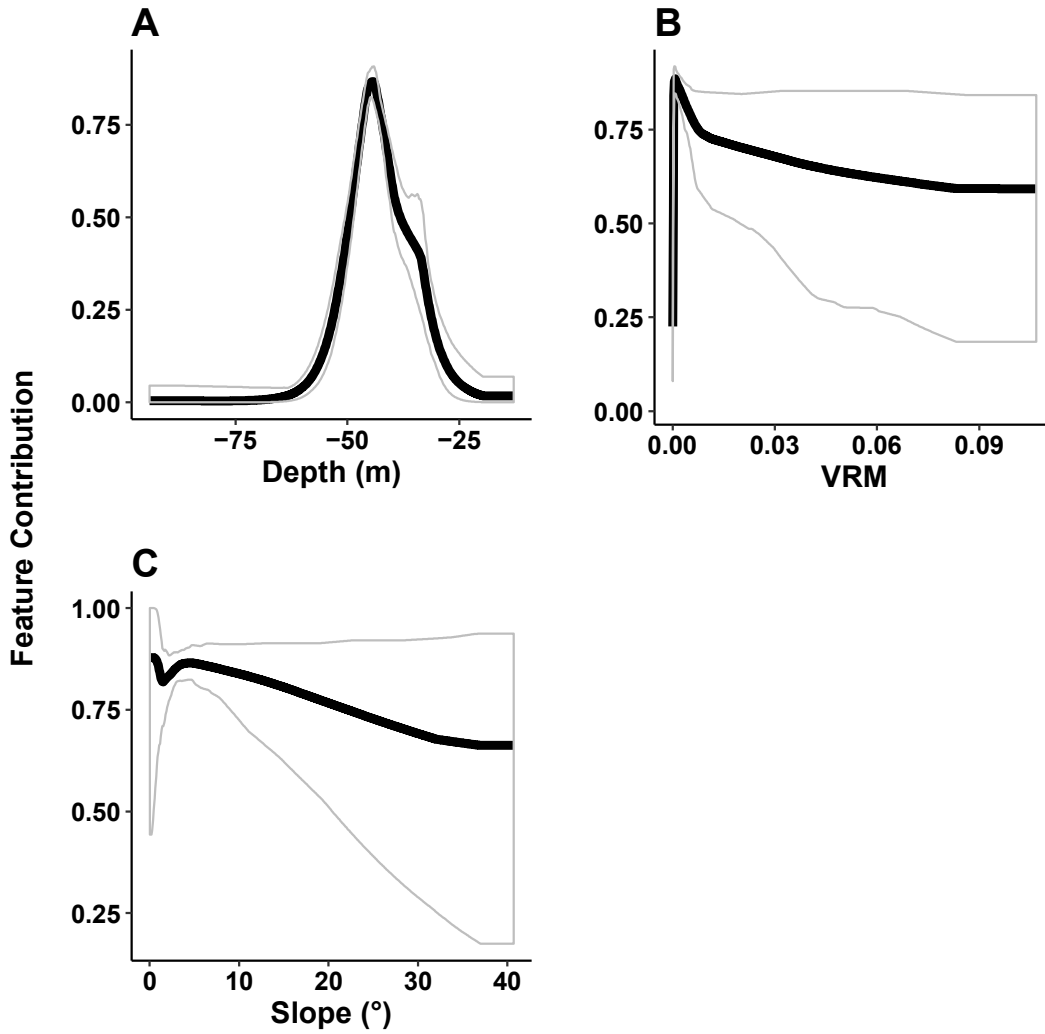


Figure 3.23: Response curves (log contribution to prediction) for each environmental predictor variable developed by MaxEnt at Tanner and Cortes Banks. The black line represents the mean log contribution to prediction and the grey shaded region represents the 95% quantile range of predictions in variable space.

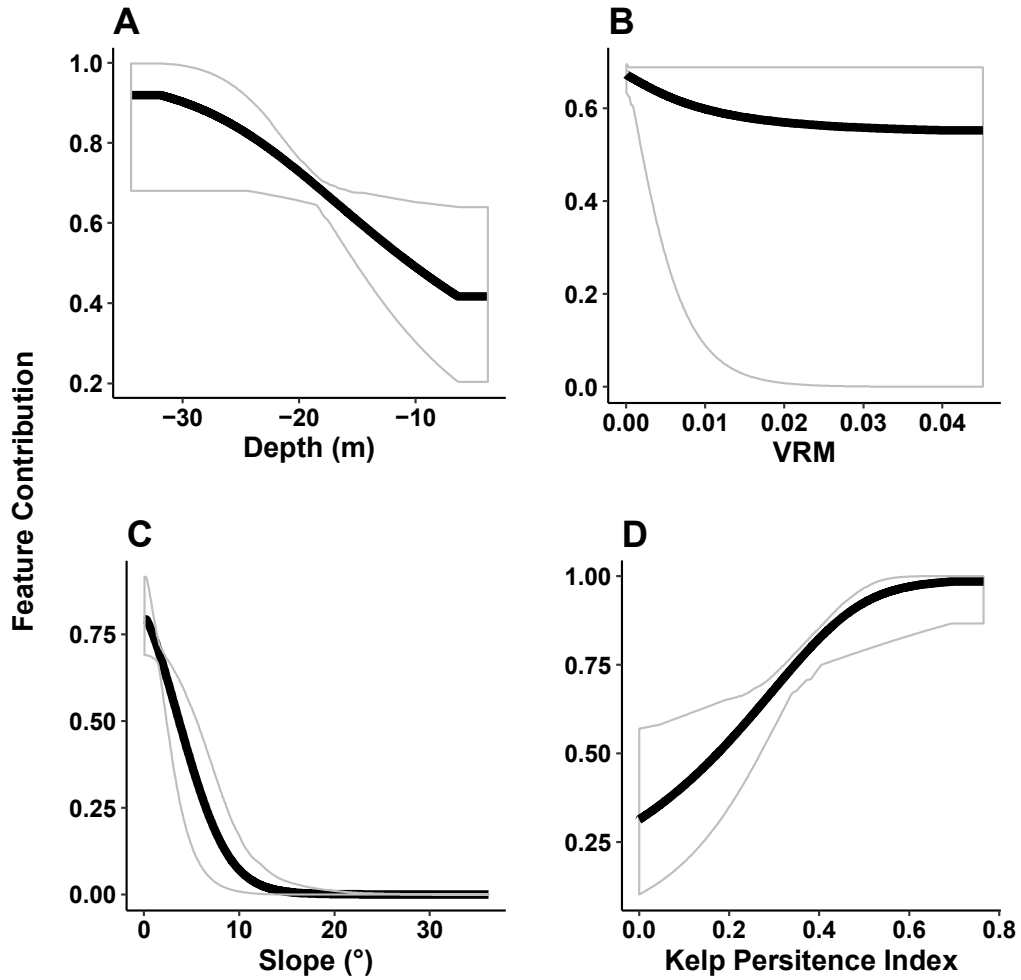


Figure 3.24: Response curves (log contribution to prediction) for each environmental predictor variable developed by MaxEnt at San Diego. The black line represents the mean log contribution to prediction and the grey shaded region represents the 95% quantile range of predictions in variable space.

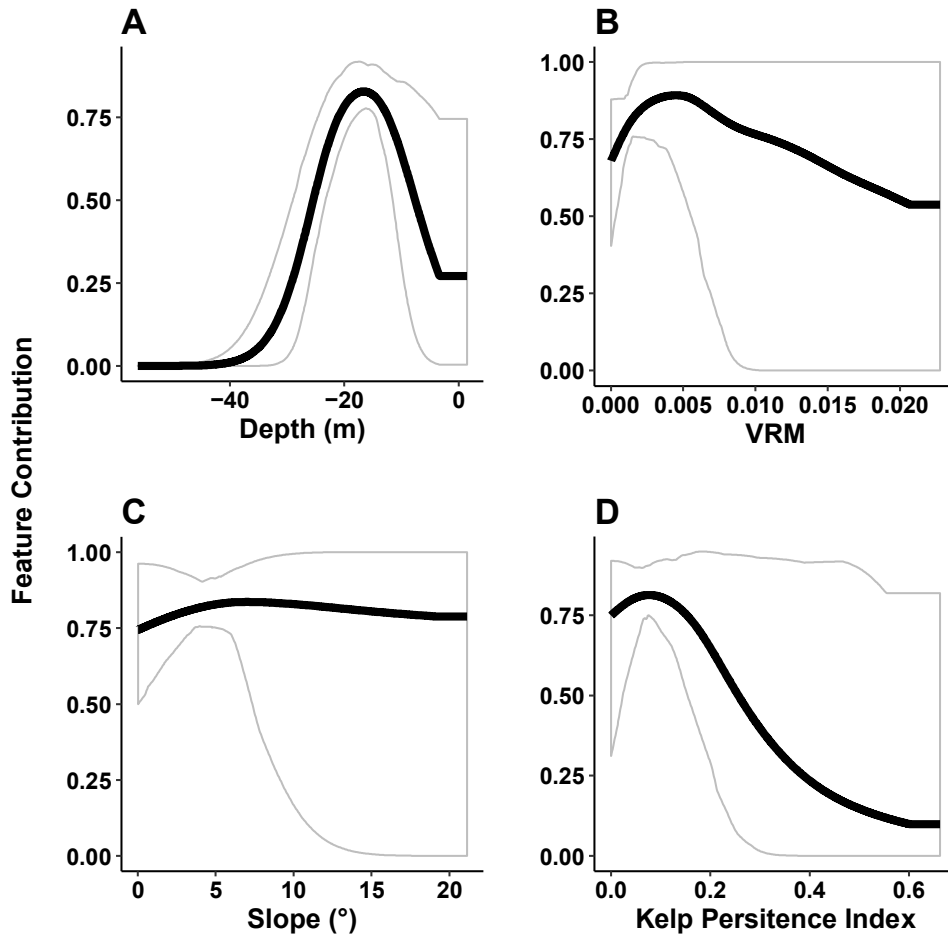


Figure 3.25: Response curves (log contribution to prediction) for each environmental predictor variable developed by MaxEnt at Palos Verdes. The black line represents the mean log contribution to prediction and the grey shaded region represents the 95% quantile range of predictions in variable space.

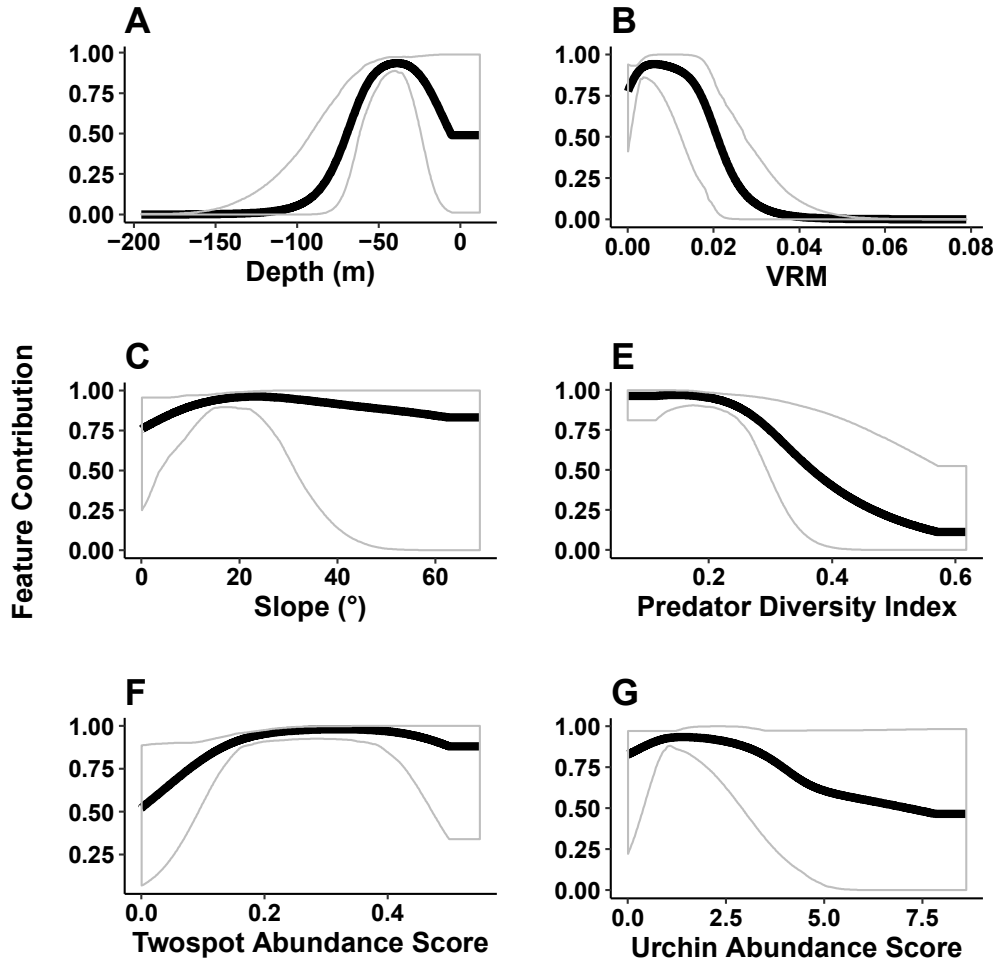


Figure 3.26: Response curves (log contribution to prediction) for each environmental predictor variable as generated by MaxEnt at Santa Barbara and Santa Catalina Islands. The black line represents the mean log contribution to prediction and the grey shaded region represents the 95% quantile range of predictions in variable space.

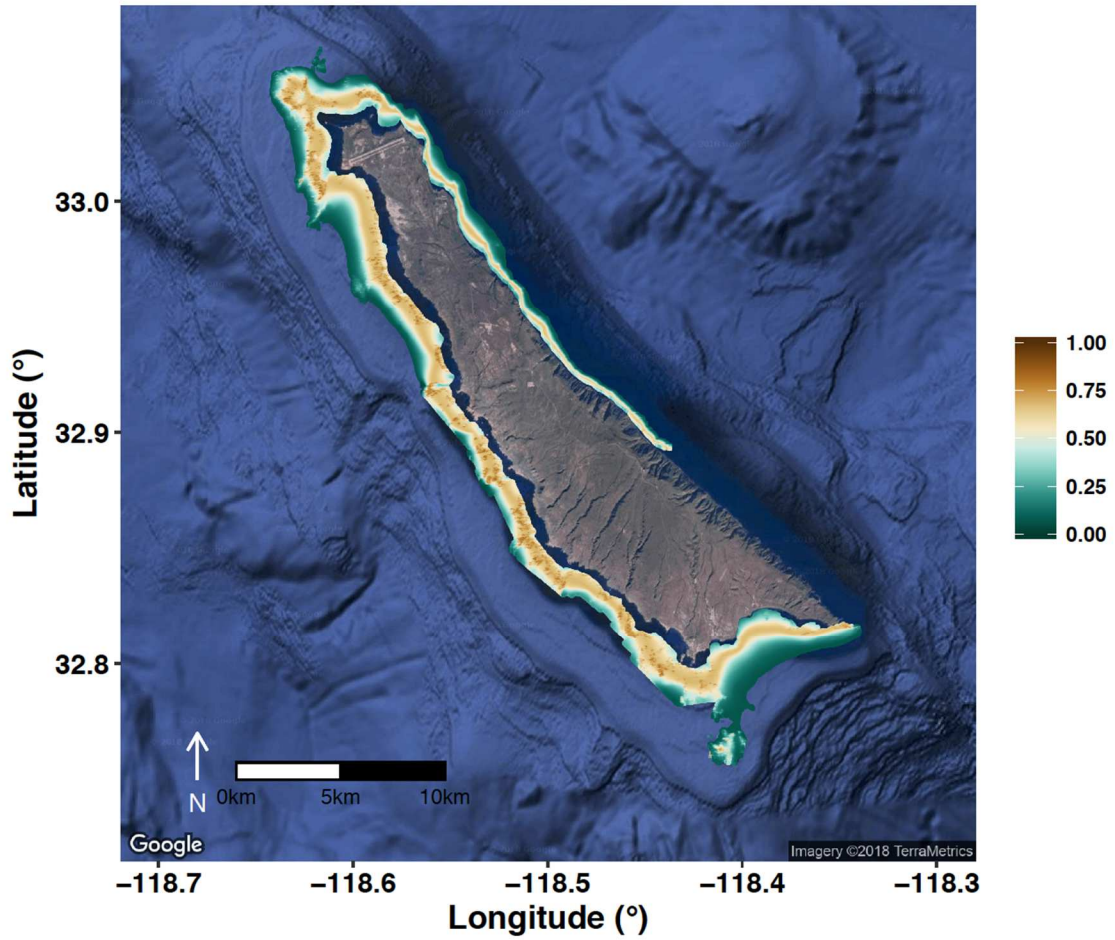


Figure 3.27: Projected relative mean likelihood of presence of white abalone at San Clemente Island. Values represent predicted relative mean likelihood of presence averaged over 100 model runs.

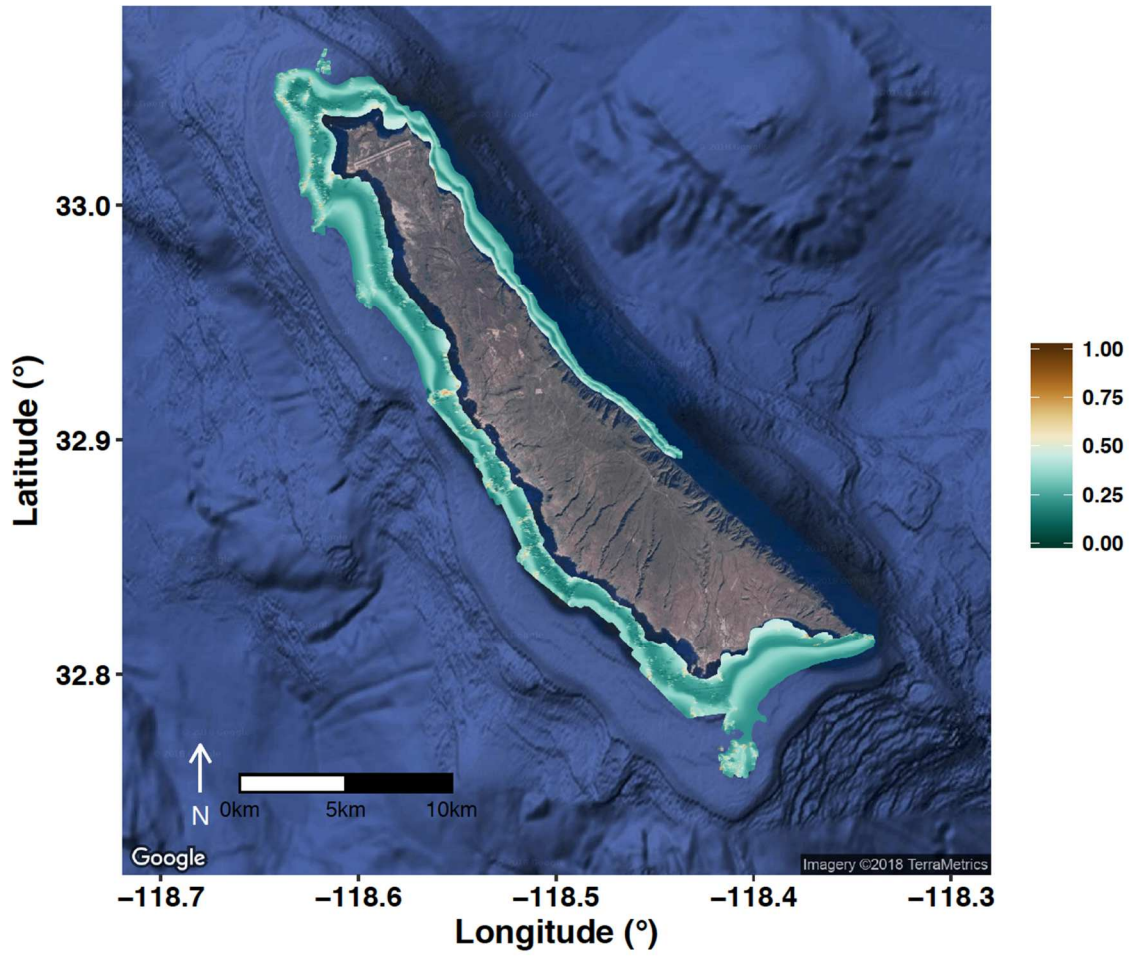


Figure 3.28: Error in projections of relative likelihood of presence at San Clemente Island represented as the 95% quantile range of predictions.

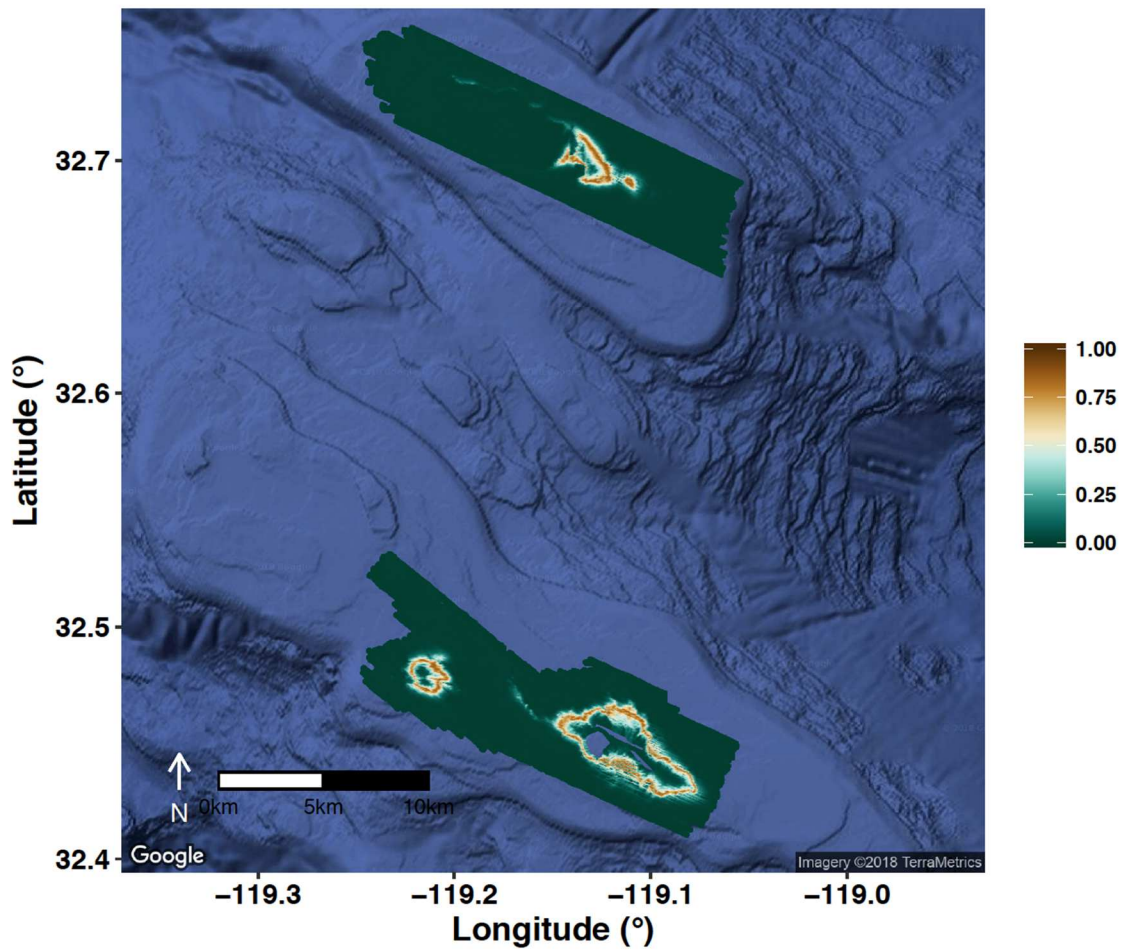


Figure 3.29: Projected relative mean likelihood of presence of white abalone at Tanner and Cortes Banks. Values represent predicted relative mean likelihood of presence averaged over 100 model runs.

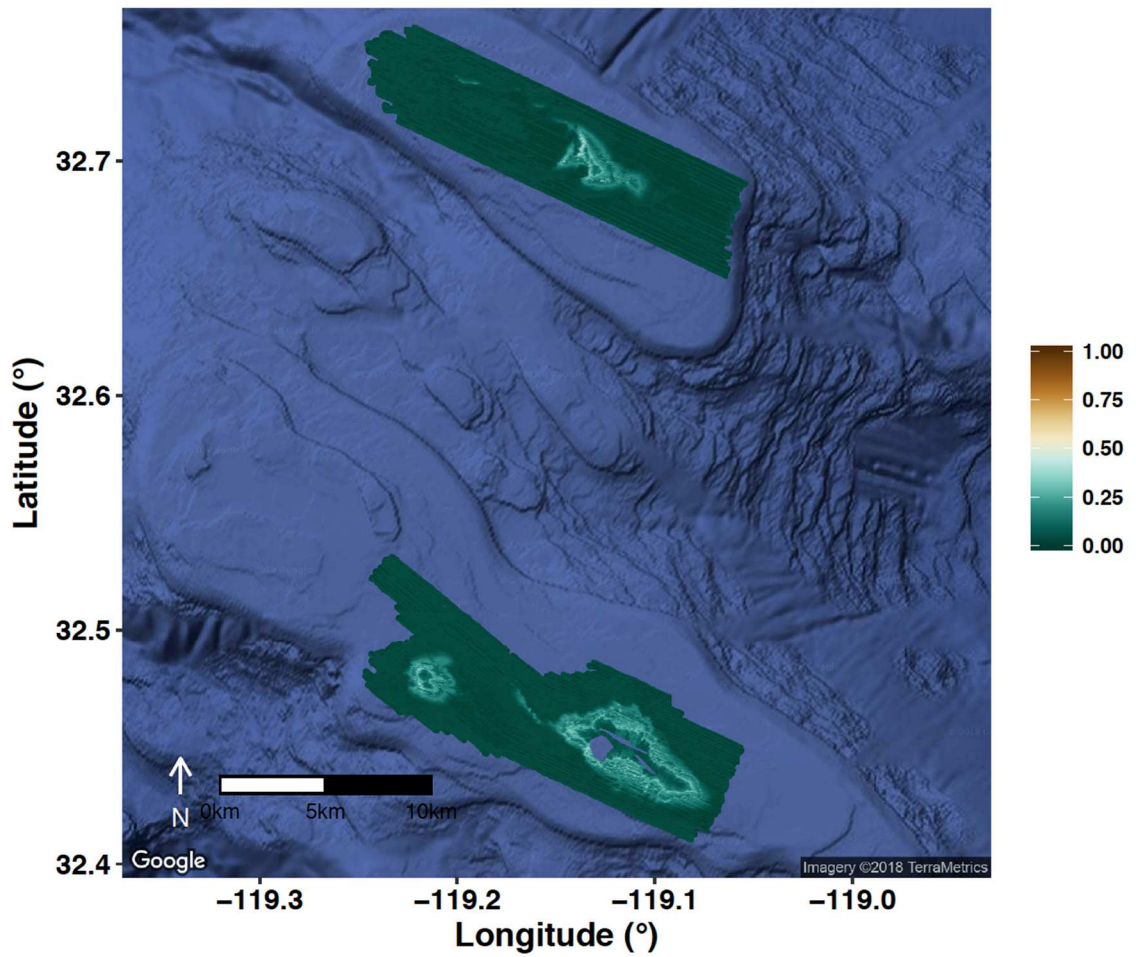


Figure 3.30: Error in projections of relative likelihood of presence at Tanner and Cortes Banks represented as the 95% quantile range of predictions.

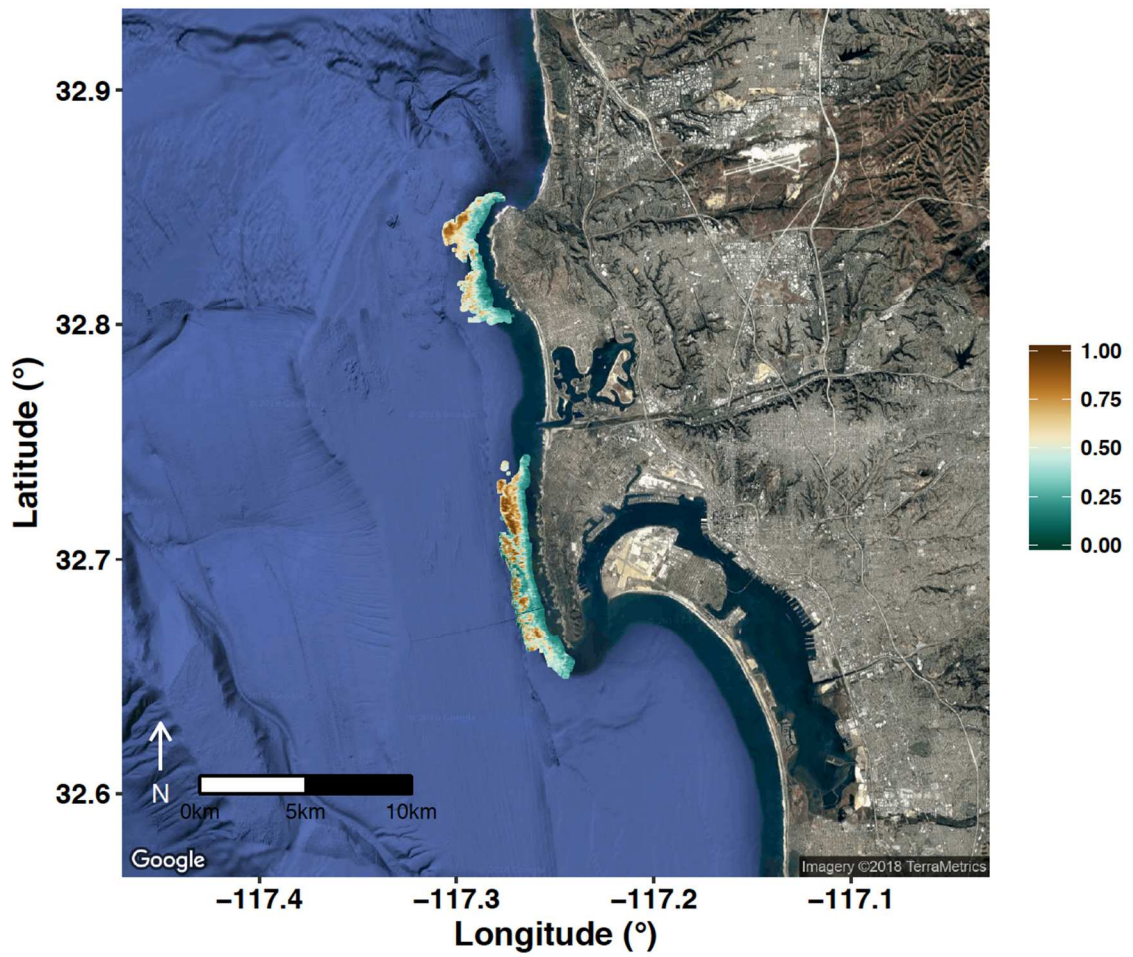


Figure 3.31: Projected relative mean likelihood of presence of white abalone at San Diego. Values represent predicted relative mean likelihood of presence averaged over 100 model runs.

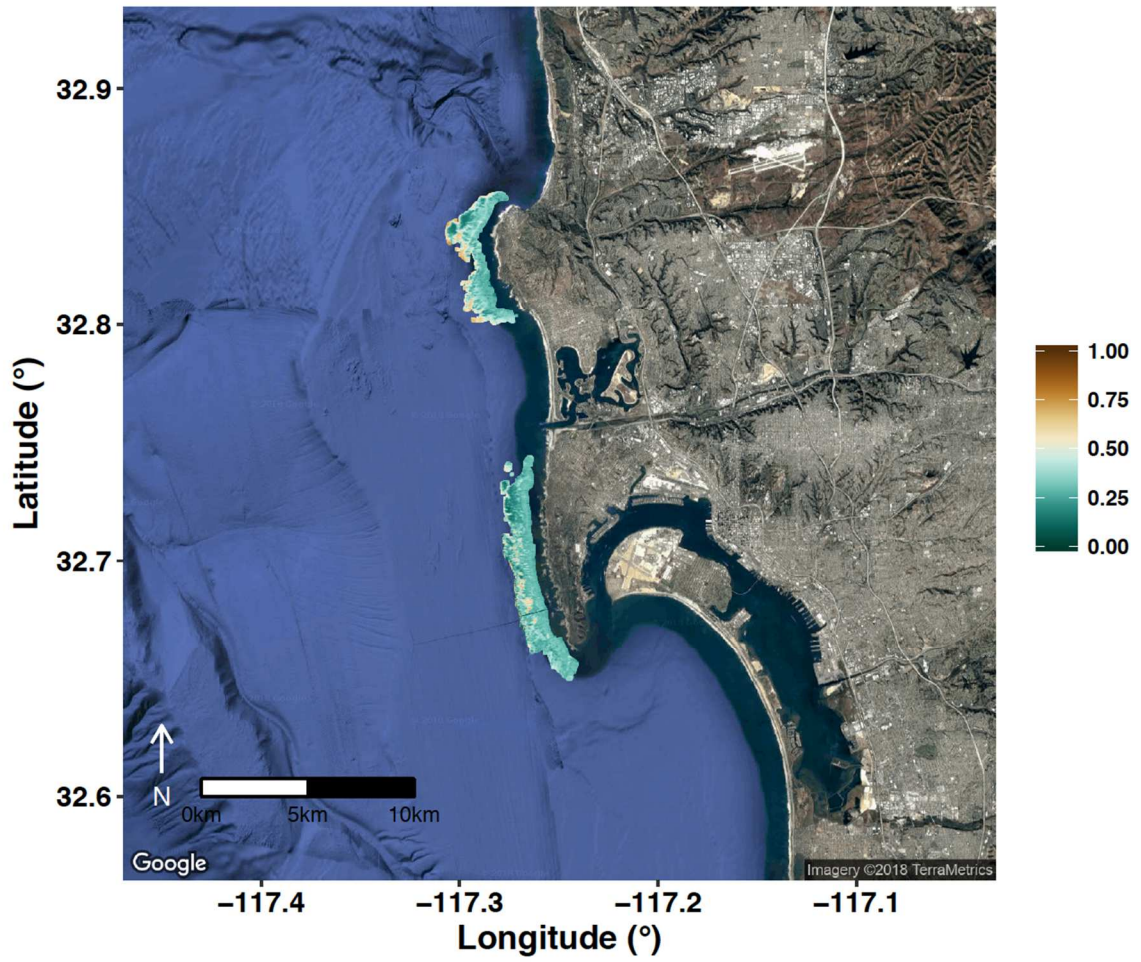


Figure 3.32: Error in projections of relative likelihood of presence at San Diego represented as the 95% quantile range of predictions.

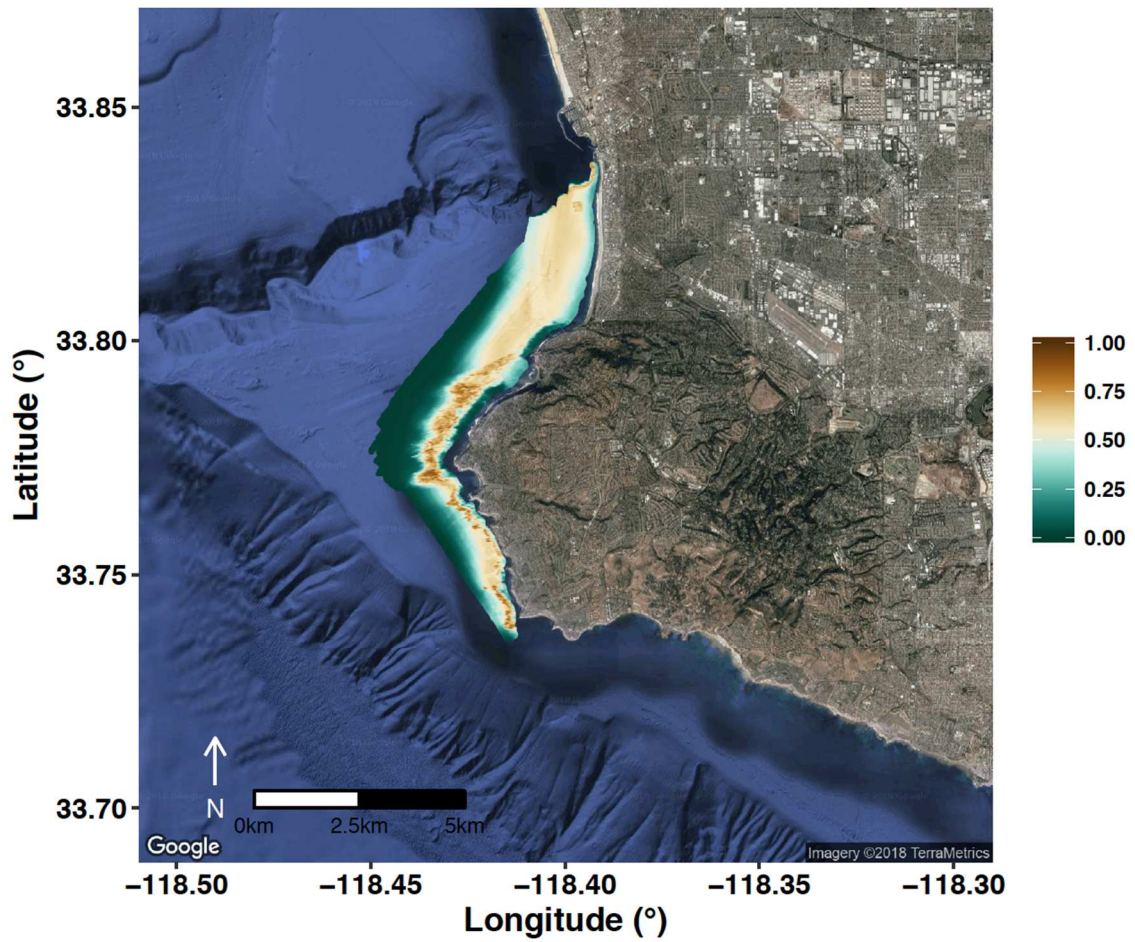


Figure 3.33: Projected relative mean likelihood of presence of white abalone at Palos Verdes. Values represent predicted relative mean likelihood of presence averaged over 100 model runs.

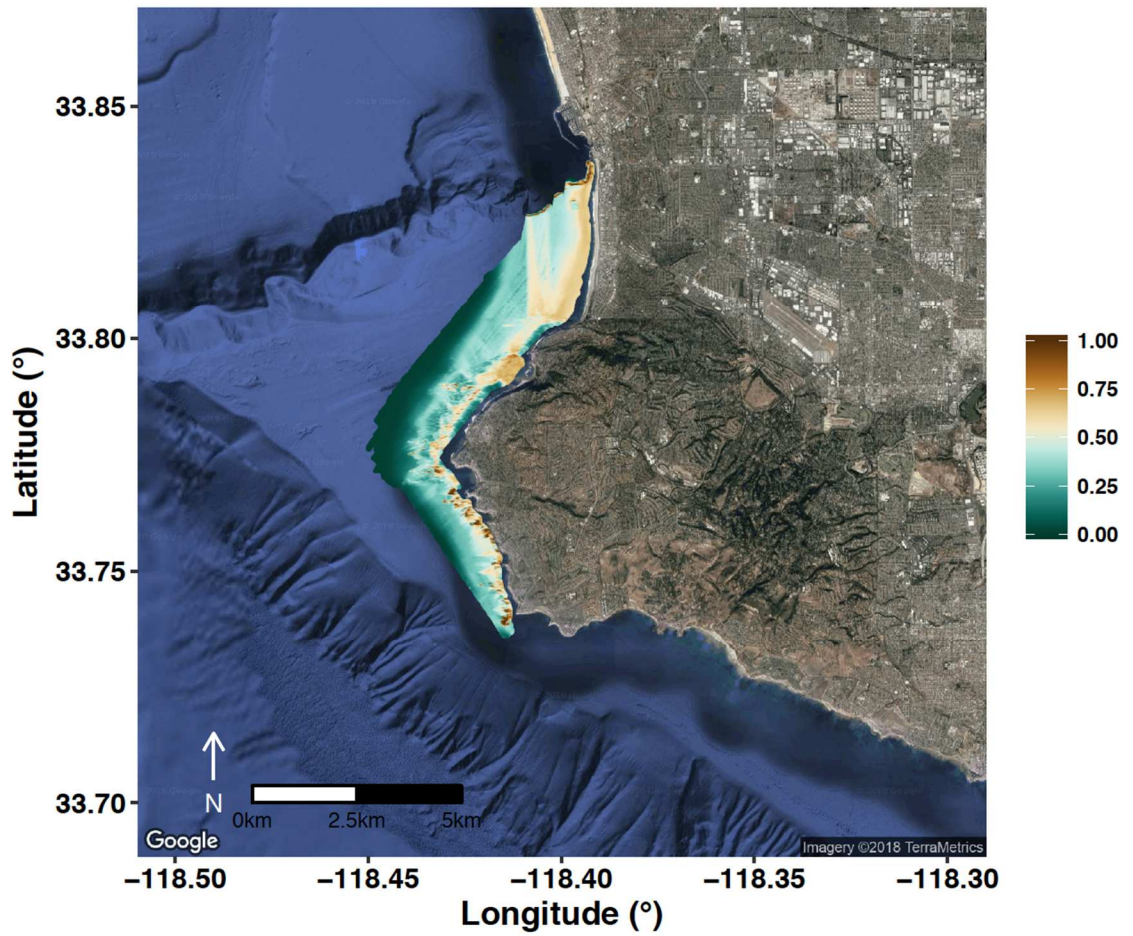


Figure 3.34: Error in projections of relative likelihood of presence at Palos Verdes represented as the 95% quantile range of predictions.

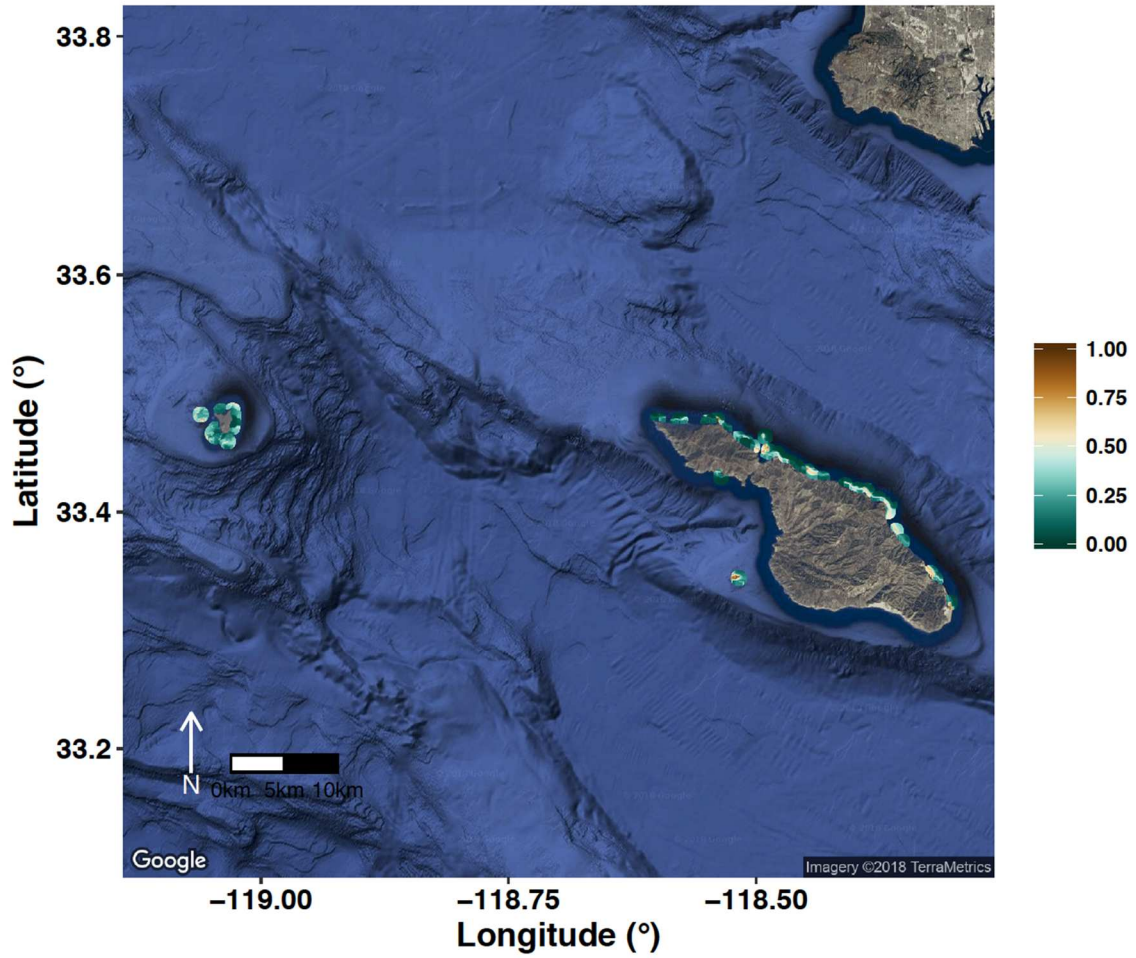


Figure 3.35: Projected relative mean likelihood of presence of white abalone at Santa Barbara and Santa Catalina Islands. Values represent predicted relative likelihood of presence averaged over 100 model runs.

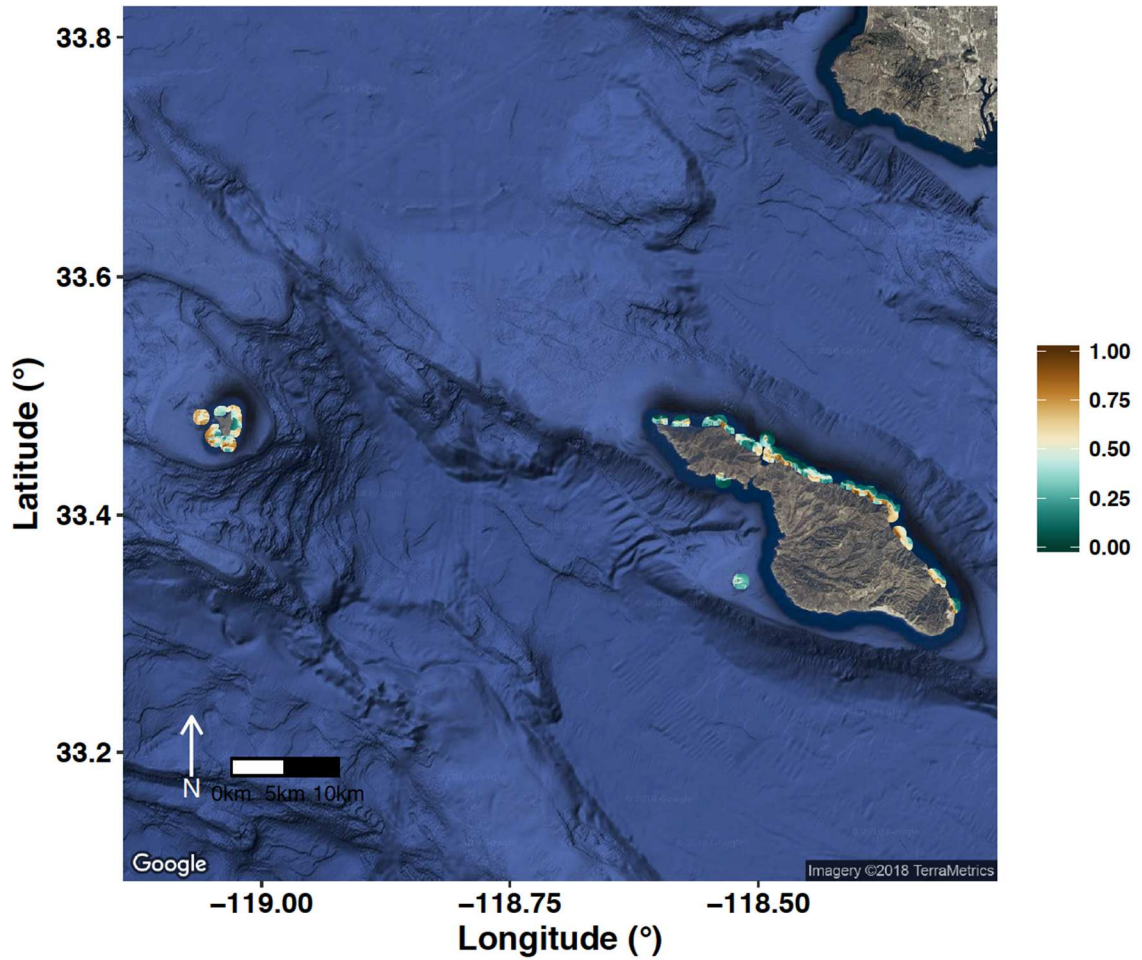


Figure 3.36: Error in projections of relative likelihood of presence at Santa Barbara and Santa Catalina Islands represented as the 95% quantile range of predictions.

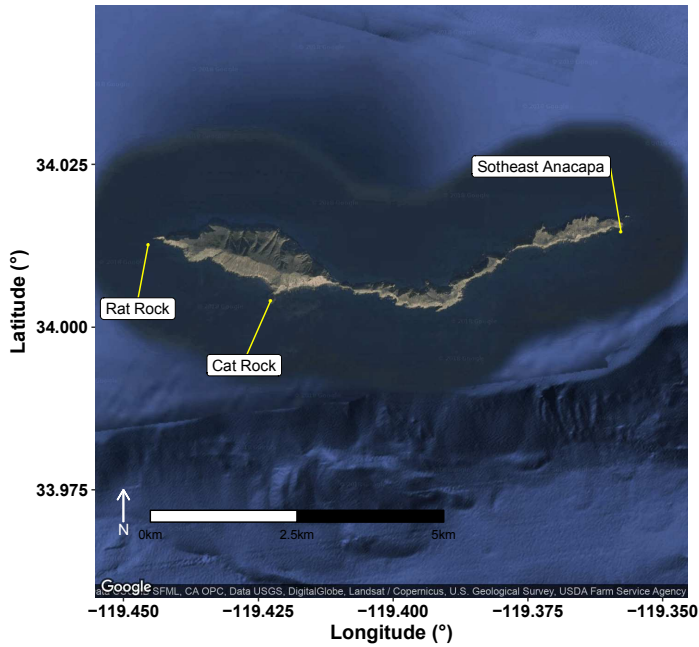


Figure 3.37: General locations where former abalone fishermen observed white abalone at Anacapa Island during the fishery.

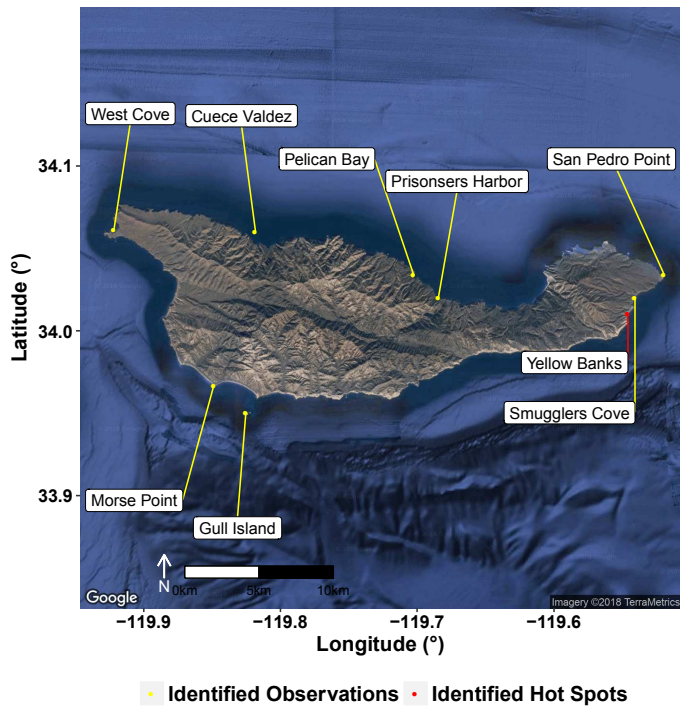


Figure 3.38: General locations where former abalone fishermen observed white abalone at Santa Cruz Island during the fishery.

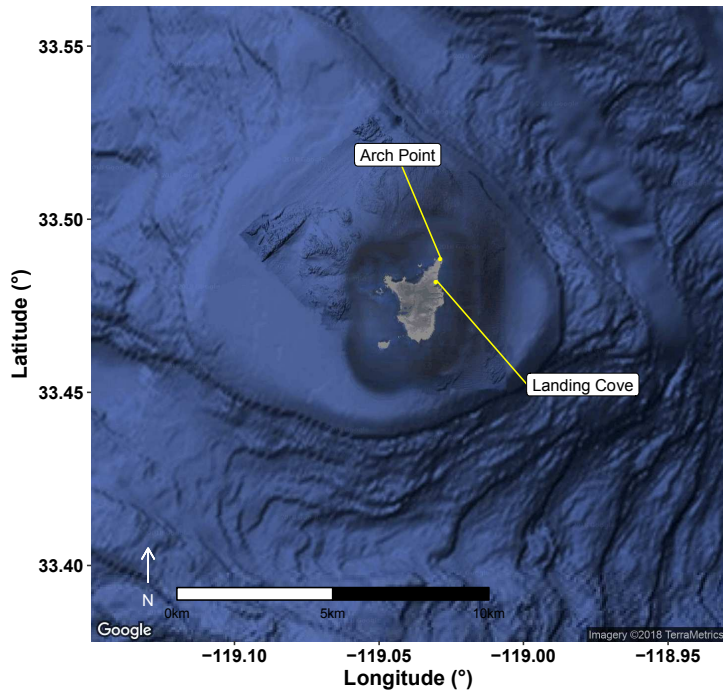


Figure 3.39: General locations where former abalone fishermen observed white abalone at Santa Barbara Island during the fishery.

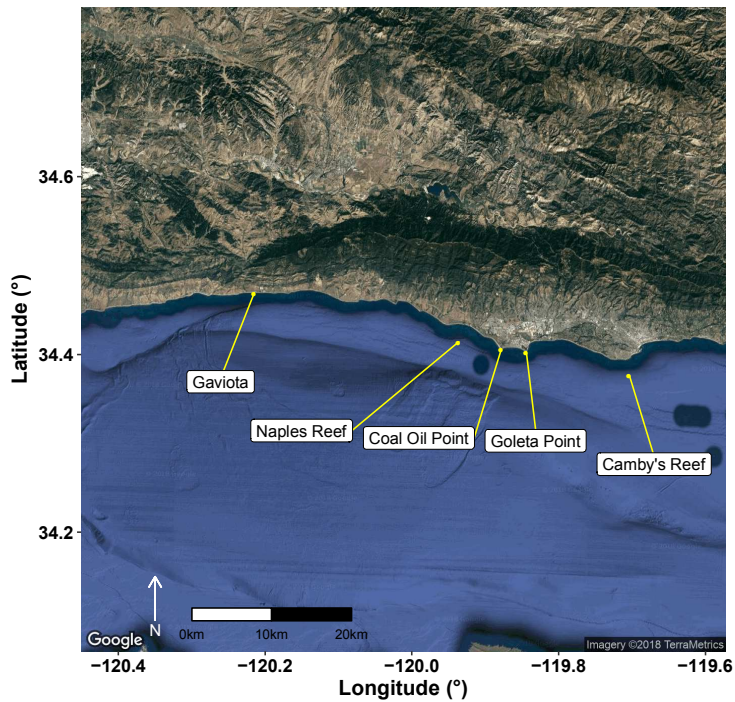


Figure 3.40: General locations where former abalone fishermen observed white abalone in the Santa Barbara area during the fishery.

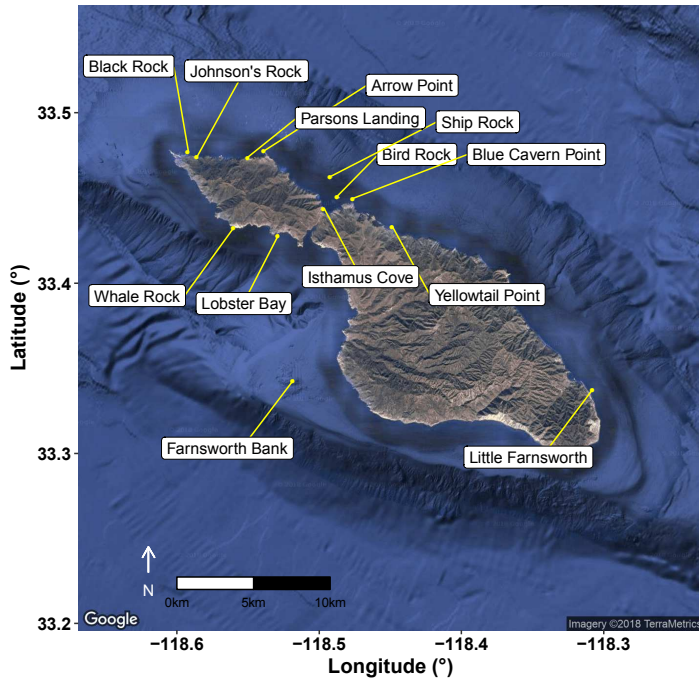


Figure 3.41: General locations where former abalone fishermen observed white abalone at Santa Catalina Island during the fishery.

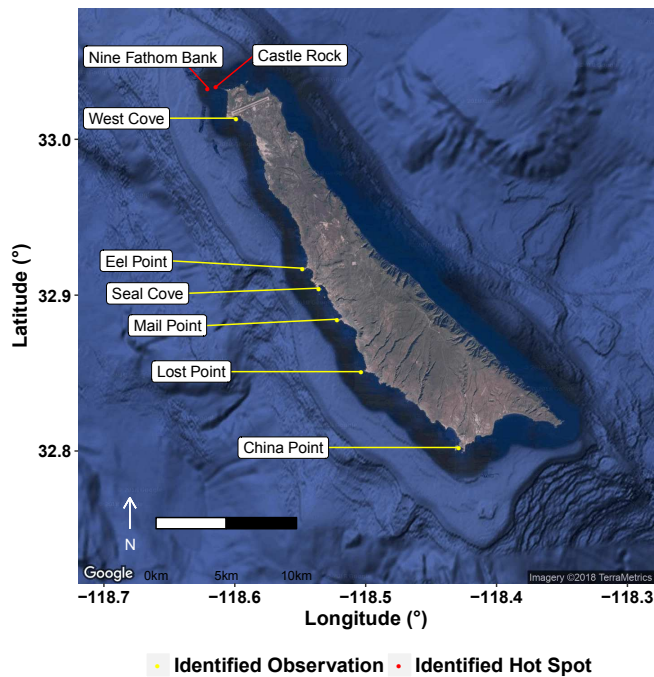


Figure 3.42: General locations where former abalone fishermen observed white abalone at San Clemente Island during the fishery.

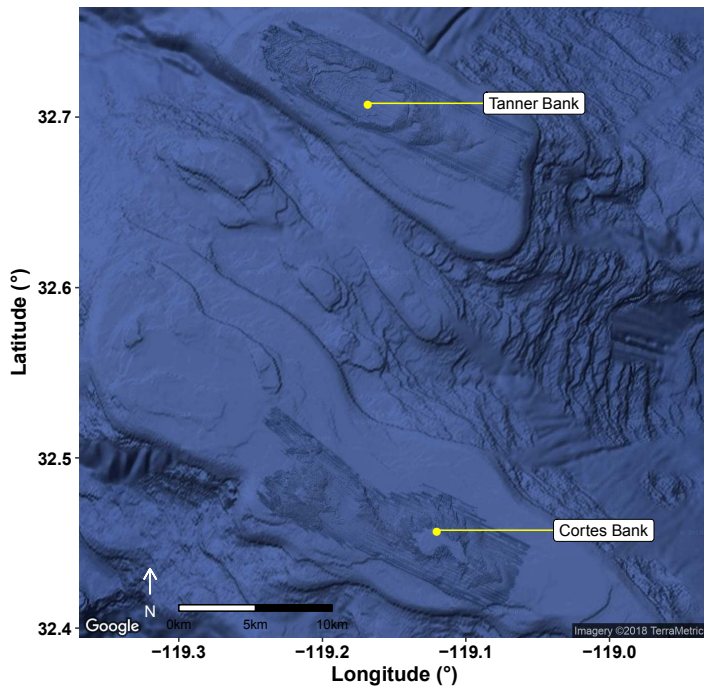


Figure 3.43: General locations where former abalone fishermen observed white abalone at the banks during the fishery.

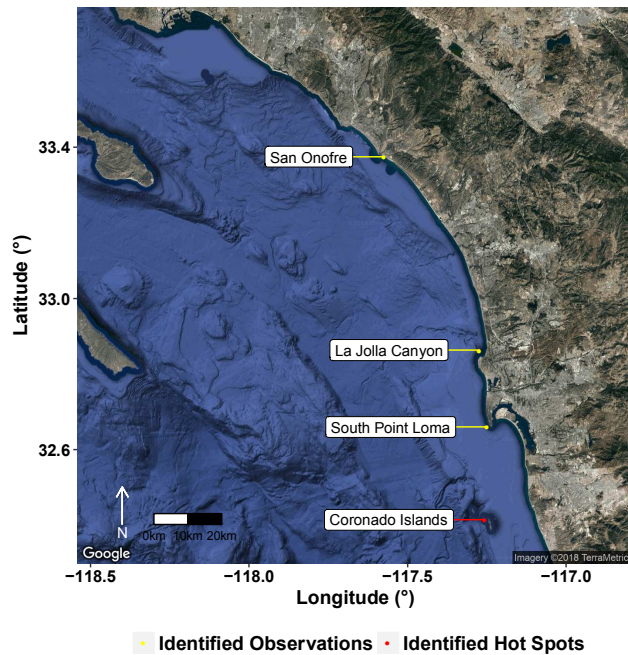


Figure 3.44: General locations where former abalone fishermen observed white abalone in the San Diego area during the fishery.

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