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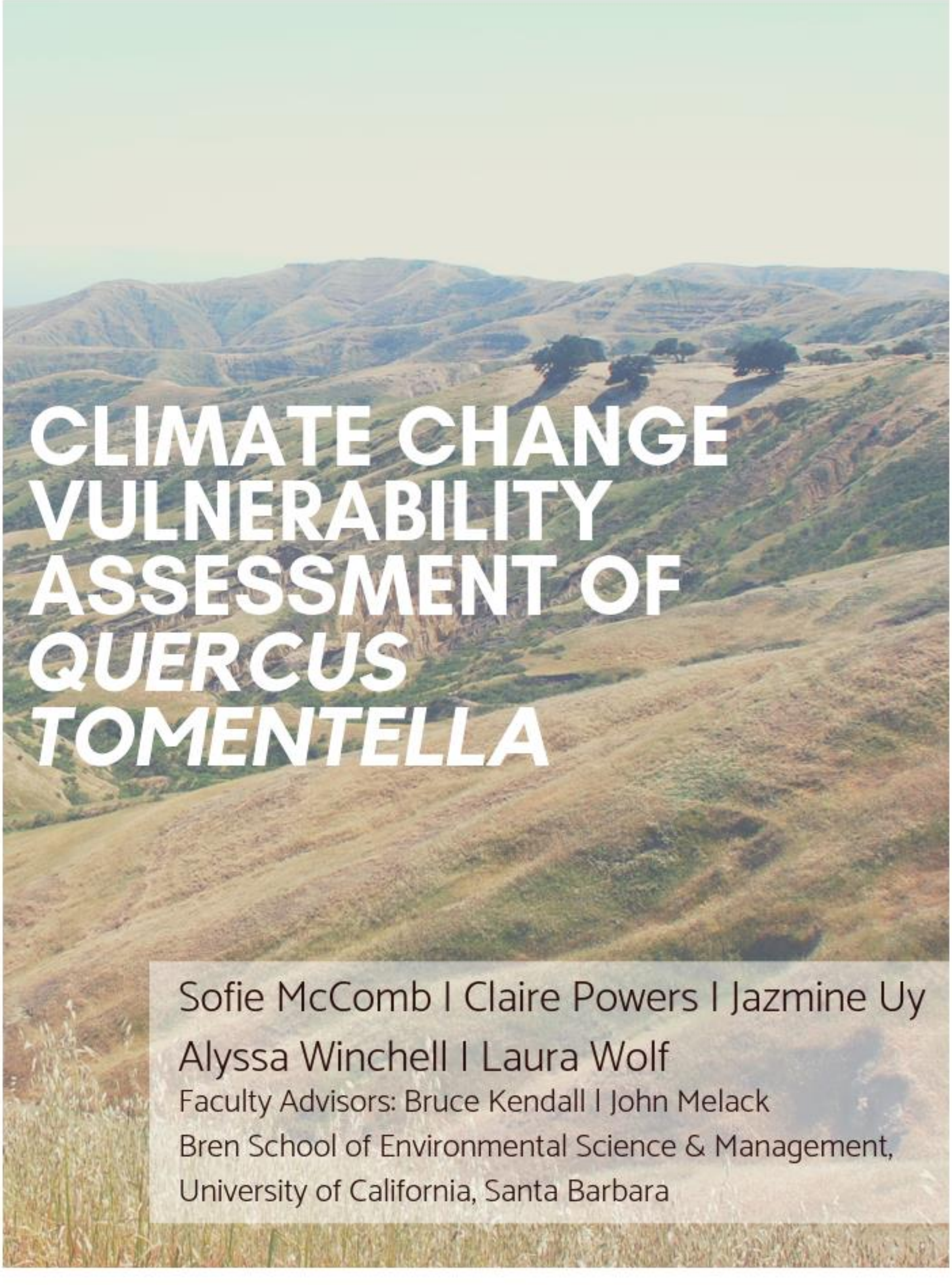

# CLIMATE CHANGE VULNERABILITY ASSESSMENT OF *QUERCUS TOMENTELLA*

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# Signature Page

## OAKOLOGY

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The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

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# Abstract

Island oak (*Quercus tomentella*) is a rare oak species endemic to six islands in the California Island Archipelago (CAIA). Over a century of farming and grazing on the islands degraded core habitat and reduced island oak seedling recruitment. The species was listed as endangered by the IUCN in 2016. Most historical threats have been removed, though island oak regeneration is still restricted and there is concern that impending climate change poses an additional threat that may ultimately lead to extinction. Spatially constrained, if the island oak's range shifts or further deteriorates, alternative options are limited. We used MaxEnt, a species distribution model, to identify island oak's bioclimatic niche on Santa Cruz, Santa Rosa, and Santa Catalina Islands and then predicted where that niche would exist through the end of the century, under four climate change scenarios. Model outputs supported three main findings: (1) Island oak's predicted bioclimatic niche was largely driven by soil moisture availability; (2) Santa Rosa Island had the most predicted suitable habitat under each climate change scenario, while predicted suitable habitat on Santa Cruz and Santa Catalina Islands was minimal; and (3) the bioclimatic habitat occupied by island oak varies substantially between the three islands studied. Improvements in life history information, legacy grazing patterns, and more finely downscaled climate data would substantially increase model validity. Research should focus on identifying mechanisms driving the variation in habitat occupied on each island, while restoration should prioritize habitat augmentation and seedling recruitment, to increase island oak's resiliency to climate change.

# Executive Summary

Islands in the California Island Archipelago (CAIA) off the coast of California and the Baja California Peninsula (BCP) are home to an abundance of rare and endemic flora (California Islands Biosecurity Program Subcommittee, 2013). One species endemic to the CAIA is *Quercus tomentella*, California's rarest oak. *Q. tomentella*, or island oak, lives on only six islands in the CAIA: Anacapa, Guadalupe, San Clemente, Santa Catalina, Santa Cruz, and Santa Rosa (Pavlik, 1991). Islands oaks are a foundation species in the CAIA's oak woodlands, where they provide forest litter, protective habitat for other species, and most importantly, soil moisture through fog drip (McCune, 2005; K. McEachern, Personal comm., 2019).

Unfortunately, *Q. tomentella* is currently threatened due to human activity on the islands over the last two centuries (Moody, 2000). European-American settlers arrived in the 19th century, transforming the majority of land on the islands to livestock farming and ranching. Grazing by introduced livestock left lasting impacts on the island oaks' ability to successfully establish and disperse, as direct predation, uprooting by feral pigs, soil erosion, and trampling eliminated seedling recruitment and survival (Kindsvater, 2010). Though grazers have been removed from or controlled on the six islands in recent years as ownership has shifted to conservation-focused organizations, many island oak populations are still declining. Impacts of human land use on *Q. tomentella* are magnified by their isolated, narrow range on the islands (Morrison, Parker, Collins, Funk, & Sillett, 2014; Riley & McGlaughlin, 2016). Observation of *Q. tomentella* suggests that it may prefer habitat with relatively cool temperatures and consistently moist soil, further limiting suitable habitat for the species. Climate change has the potential to further reduce the extent and connectivity of island oak habitat across the islands.

Human-driven climate change is rapidly shifting climate patterns away from historic natural norms and modifying ecological systems worldwide (Parmesan, 2006). Climate change has altered species ranges and community composition at a rate faster than many species can disperse and move, particularly less mobile plant species (Lovejoy & Hannah, 2005; Parmesan & Yohe, 2003). Species that are already habitat-limited due to niche preferences, fragmentation, or small ranges, such as those in the CAIA, are particularly vulnerable to changes in climate. Although cooling from the surrounding ocean may slow the effects of a warming global climate on island communities, these species are often adapted to a narrower range of environmental conditions than continental species, making them more vulnerable to climate change. In the California Floristic Province (CA-FP), climate change is predicted to cause an 80% reduction in the range size of 66% of species by the end of century, if no further protections or interventions are implemented (Loarie et al., 2008).

As the effects of climate change intensify, island ecologists and managers would like to develop management practices that ensure survival of *Q. tomentella* as the species recovers from grazing impacts while simultaneously facing a changing climate.  In collaboration with

The Nature Conservancy and the Santa Barbara Botanic Garden, this study investigates the preferred bioclimatic niche of *Q. tomentella* and how climate change may affect the species' future distribution. This project aims to provide information that will help ecologists and island managers develop climate change resilient adaptive management practices to increase the likelihood of *Q. tomentella* persistence. Development of reproducible methodology will allow for application of this analysis to other endemic CAIA species. Using a species distribution model (SDM), we modeled potential future changes in the distribution of island oak habitat, taking into account climate uncertainty. Predictions of suitable climate habitat were summed across future scenarios to develop an integrated outlook that quantifies long-term habitat suitability on each island analyzed. A comparison between the habitat that island oaks currently occupy and the complete range of conditions available on each island further explores the factors that may influence species presence. This comprehensive analysis in conjunction with prior known information about the species can inform adaptive management planning to restore and protect the island oak under climate change.

Our analyses required island oak presence points, present climate data, future climate projections, and data for additional environmental variables relevant to *Q. tomentella* habitat suitability. Island oak presence points were obtained from The Nature Conservancy, the National Park Service (NPS), the Catalina Island Conservancy (CIC), and Laura Kindsvater. Current and projected future climate data came from the Basin Characterization Model (BCM), a regional hydrologic climate model statistically downscaled for California to 270-meter resolution (Flint, Flint, Thorne, & Boynton, 2013). BCM provides climate data as averaged 30-year summaries for the current time period (1981 – 2010) and three future time periods (2010 – 2039, 2040 –2069, 2070 – 2099). We selected four future climate scenarios that capture climate projections most likely to occur in California: MIROC RCP8.5 ("hot-dry"), MIROC RCP4.5 ("warm-dry"), CCSM4 RCP4.5 ("hot-wet"), and MPI RCP4.5 ("warm-wet"). BCM provides precipitation and temperature-based climate variables, but does not have data available for fog, an important variable for coastal oak species. We obtained data depicting the current probability of fog inundation on Santa Rosa and Santa Cruz Islands from Rastogi et al., 2016. Using this data, we developed simulations of four future fog scenarios by adjusting historic trends: constant fog, decreasing fog, increasing fog, and change in fog based on an elevation threshold. We used these fog scenarios with the future climate scenarios. We obtained island outlines and elevation layers from NPS and CIC, soil data from the U.S. Geologic Survey (USGS), and vegetation community shapefiles from the Nature Conservancy, NPS, and CIC. All layers were resampled to the resolution of the coarsest data, 270 meters, and projected into the NAD83 Teale-Albers coordinate system. Sufficient data was only available for three of the six islands that contain the island oak (Santa Cruz, Santa Catalina, and Santa Rosa) so analyses were performed for only these three islands.

For our analyses we used MaxEnt, a SDM, to characterize the current distribution of *Q. tomentella* and predict future changes in its distribution as a result of climate shifts. SDMs are widely used to determine probable species distributions and inform conservation management strategies, often for endangered and endemic species (Phillips, Dudík, &

Schapire, 2004). MaxEnt performs presence-only species distribution analyses and identifies potential suitable habitat for a species in an area (Phillips, Anderson, & Schapire, 2006). We input *Q. tomentella* presence points and influential environmental layers into MaxEnt to perform a habitat suitability analysis under current and future climate conditions. We determined that the most influential variables for predicting island oak presence are maximum summer temperature, minimum winter temperature, annual precipitation, climate water deficit, and probability of fog inundation. Fog data was only available for Santa Cruz and Santa Rosa, so it was not included in the Santa Catalina analyses.

A total of 255 combinations of geographic extents, future climate change scenarios, time periods, fog scenarios, and island oak demographic information were input into MaxEnt to evaluate habitat suitability for island oaks. Scenarios included running the model for each island individually, all three islands combined, and for the entire extent of California. We also ran the model for two earlier twentieth century time periods to compare past oak-climate relationships to current oak-climate relationships. Additionally, we ran MaxEnt for available age data on Santa Rosa to explore the different niche requirements of seedlings and adults.

The results of our habitat suitability analyses revealed substantial variability in the location and amount of suitable habitat predicted depending on the model extent, climate change scenario, and time period. When each island was run separately, future predictions of suitable habitat were most optimistic for Santa Rosa, wet climate change scenarios, and fog scenarios of increasing fog or fog changing based on elevation. Results changed when all islands were run together, particularly for Santa Cruz Island. Santa Cruz retained virtually no predicted suitable habitat into the future when run individually but maintained suitable habitat through the end of century when all islands were run together. Similar to the individual island analyses, all islands analyses predicted the highest suitable habitat in the wet future scenarios, stressing the importance of moisture for island oak into the future.

In addition to analyzing predicted habitat suitability for individual model scenarios, we used an integrated outlook approach to identify locations that were consistently predicted as suitable through different time periods, climate change scenarios, and fog scenarios. We summed suitability across all possible climate change futures and all time periods for a given extent. In these analyses, Santa Rosa retained the greatest percent of suitable habitat, followed by Santa Catalina, with Santa Cruz retaining essentially no suitable habitat through all scenarios. We analyzed oak-climate relationships and found that for the model runs that included fog it was consistently the most important predictor of island oak presence, with other climate relationships varying by island. Furthermore, analysis of each island's climate in relation to island oak presence revealed distinct climate niches for island oaks by island.

Overall, the results emphasize that precipitation and fog are essential for maintaining suitable climate habitat for *Q. tomentella* into the future. More broadly, the results stress the importance of understanding the relationships between island oak presence and climate niche, and how presence is likely influenced by factors other than climate. Given the wide variety of predicted habitat suitability results across scenarios, and uncertainty in non-climate drivers of the species current distribution, additional research is necessary to determine causal island oak-climate relationships. The distinct climate niches found for island oaks on each island possibly explains the difference in results by extent, as MaxEnt utilizes the current climate range of the species to make species distribution predictions and treats novel values outside the current range as extremes of its current range. Therefore, an individual island analysis uses the current climate range of the population on that specific island, while an all island analysis uses the much broader climate niche occupied by the entire species across the various islands. From this analysis, it is unclear whether the modeled oak-climate relationships are the driving factors of current island oak distribution. Parsing out non-climate and climate drivers of the species' distribution is essential for accurately interpreting the habitat shifts and variability under different climate scenarios.

Potential non-climate drivers of island oak presence include past grazing impacts and human influences, as well as abiotic and biotic interactions. These dynamic and historic factors should be explored for better understanding of the underlying causes of current island oak distribution, and how these factors influence future predictions. Furthermore, island oaks live in microclimates, which were masked out by the resolution of our analyses; exploration of oak microclimates would further clarify climate preferences of the species. Lastly, more demographic and life history information of the oaks would provide further insight into dynamic changes and potential future suitability for seedling recruitment.

Even with variations in future predictions and model limitations, our analyses highlight potential recommendations for adaptive climate-resilient management of the island oak that hold across future scenarios. We recommend augmentation of current island oak groves in areas that will remain suitable in the future for greater climate change resiliency. Management recommendations also include prioritization of moisture related restoration efforts through fog nets, native species planting, and erosion control. Common garden plots should be established to explore the island oaks' climate niche and the species' adaptive ability. Additionally, enhancement of demographic studies of the species would provide information regarding its life history, acorn dispersal, seedling recruitment, and age structure. Recommendations vary for each island due to the differing climates and oak-climate relationships; for example, island oaks on Santa Catalina would benefit from close monitoring and moisture-promoting restoration due to its hotter and drier climate than the northern islands and the continued presence of nonnative herbivores. Island managers should consider outlining a systematic approach to human assisted-migration of island oaks across and between islands should the worst-case scenario projections become more likely.

Our clients and other island managers can use our framework to perform climate vulnerability assessments of other endemic species in the CAIA and rerun this analysis upon the availability of updated climate change information. Adaptive climate change management will prove increasingly important for the persistence of these endemic and rare species, as well as for biodiversity and ecosystem functioning across the islands.

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# List of Abbreviations

| | |
|---|---|
| AUC | Area under the receiver operating curve |
| BAU | Business as usual |
| BCSD | Bias correction spatial downscaling |
| BCM | Basin Characterization Model |
| BCP | Baja California Peninsula |
| CA-FP | California Floristic Province |
| CAIA | California Island Archipelago |
| CCSM | Community Climate System Model |
| CIC | Catalina Island Conservancy |
| CUSP | Channel Islands Continually Updated Shoreline Products |
| CWD | Climate water deficit |
| DEM | Digital elevation model |
| ENSO | El-Niño-Southern Oscillation |
| GCM | General circulation model or global climate model |
| GECI | Grupo de Ecología y Conservación de Islas |
| GLM | Generalized linear model |
| GUI | Graphical user interface |
| IPCC | Intergovernmental Panel on Climate Change |
| IUCN | International Union for Conservation of Nature |
| NOAA | National Oceanic and Atmospheric Administration |
| NPS | National Park Service |
| Max SSS | Maximum training sum of sensitivity plus specificity |
| MIROC | Model for Interdisciplinary Research on Climate |
| MPI | Max Planck Institute |
| PPT | Precipitation |
| PRISM | Parameter-elevation Relationships on Independent Slopes Model |
| SCA | Santa Catalina Island |
| SCR | Santa Cruz Island |
| SMI | Santa Miguel Island |
| SRI | Santa Rosa Island |
| RAWS | Remote Automatic Weather Stations |
| RCP | Representative concentration pathway |
| ROC | Receiver operating curve |
| SDM | Species distribution model |
| SERG | Soil and Ecology Research Group |
| SST | Sea surface temperature |
| TMN | Maximum winter temperature |
| TMX | Maximum summer temperature |
| USGS | United States Geological Survey |

# Significance

Human-induced climate change is increasing average temperatures and modifying many ecological systems worldwide (Parmesan, 2006). Many species vulnerable to the impacts of climate change have been forced to geographically or behaviorally adapt, and some have been pushed to extinction (Carroll, Lawler, Roberts, & Hamann, 2015; Pacifici et al., 2015). The effects of climate change can be particularly influential to island communities. Island ecosystems typically have lower diversity than mainland communities, making them more vulnerable to species loss and climate change pressure (Harter et al., 2015). On islands, when a subpopulation is near extinction it is less likely that it will experience the 'rescue effect' from adjacent ecosystems, whereby immigration from source populations counteracts high death rates in the threatened population (Moody, 2000; Whittaker & Fernandez-Palacios, 2007). The lack of 'source' populations on islands, or populations that contribute immigrating individuals, makes threatened island subpopulations at higher risk of extinction, which in turn threatens island-wide biodiversity. High levels of biodiversity contribute to increased productivity of a given ecosystem and species richness is often associated with an increase in temporal stability for ecosystems as a whole (Tilman, Reich, & Knops, 2006; Tilman, Wedin, & Knops, 1996). Additionally, ecosystems with higher diversity can provide protections against invasive species and drought (Kennedy et al., 2002; Tilman & Downing, 1994). On islands in particular, loss of biodiversity from climate change induced extinctions may increase the susceptibility of other species' populations to the same fate.

As climate changes, species range shifts tend to correspond with a species' bioclimatic envelope, so those that prefer cool temperatures shift towards higher latitudes or higher elevations, tracking cooler conditions (Chen, Hill, Ohlemüller, Roy, & Thomas, 2011; Lovejoy & Hannah, 2005; Parmesan & Yohe, 2003). On islands, the potential for these types of shifts are limited (Harter et al., 2015). Islands are spatially-constrained by surrounding ocean, so if an island species' habitat shifts or becomes damaged or fragmented to the point of being unsuitable, alternative habitat options are extremely limited; often, habitat contracts or disappears altogether. As a result, species survival on islands is becoming more dependent on restoration of damaged habitat or assisted migration to more suitable habitat (Hoegh-Guldberg et al., 2008; Mair et al., 2018).

Islands in the California Island Archipelago (CAIA) off the coast of California and the Baja California Peninsula (BCP) are home to an abundance of rare and endemic flora (California Islands Biosecurity Program Subcommittee, 2013). The California Floristic Province (CA-FP), which includes the CAIA, is one of the most biodiverse ecoregions in the world, hosting more than 5,500 native plant species, 40% of which are endemic to the province (Calsbeek, Thompson, & Richardson, 2003).

The CA-FP contains uniquely complex topography and isolated geographical regions propelling divergent evolution and thus leading to its remarkable biodiversity (Baldwin, 2014). Scientists believe islands in the CA-FP have been separated from Mainland California and Mexico for nearly one million years, but that during the last ice age they were close enough to the mainland to have higher rates of biological interaction and more similar flora (Rick et al., 2014). When sea level began to rise substantially around 20,000 years ago in an era of naturally-occurring climate change, the islands became more isolated, and species began evolving to unique island conditions. Now more than 20% of species on the islands are narrow endemics, evolved to only one or more of the islands. A number of these endemic species are threatened or endangered, and are already vulnerable given their isolated, confined ranges (Morrison, Parker, Collins, Funk, & Sillett, 2014; Riley & McGlaughlin, 2016). Unfortunately, the islands are increasingly threatened by climate change and legacy human and grazers impacts. Loarie et al. (2008) predict that over the next century, the range size of 66% of species in the CA-FP will shrink by at least 80% if those habitats are not carefully protected.

Nearly all islands in the CAIA have been greatly impacted by human activity over the last two centuries, leading to extirpation and extinction of some species, and threatening many others (Moody, 2000). Though most direct threats from human activity have been removed from the islands in recent years, legacy impacts from grazing livestock are widespread, and native plants are still encumbered by damaged and fragmented habitat. Spatially-constrained species, like those in the CAIA, are particularly susceptible to extinction from habitat loss or fragmentation, as they have limited opportunity to re-establish in more suitable regions. As the total area of a species' habitat decreases and individual patches become smaller and farther apart, their chance of survival declines rapidly (Harter et al., 2015). Despite substantial disturbance from introduced flora and fauna over the last several centuries, many endemic plant species on the islands have survived and the region remains a biodiversity hotspot. However, island species face a relatively new threat in the form of anthropogenic climate change (Kelly & Goulden, 2008). Habitat of endemic flora on the CAIA that has already been damaged and fragmented by past grazing and anthropogenic pressures is likely to be further negatively impacted by changing climate in the region. Conservation managers need to adopt adaptive management strategies and practices to account for changing climate and its potential impacts (Hopkins, McKellar, Worboys, & Good, 2015; Wilke & Rannow, 2014).

*Quercus tomentella* (island oak) is one of 20 oaks native to California and will likely be impacted by climate change. It is a paleoendemic living on six islands across the CAIA, which include Anacapa, San Clemente, Santa Catalina, Santa Cruz, and Santa Rosa Islands off California's southern coast as well as Guadalupe Island off the BCP. Island oak is a canopy dominant species in island woodland communities, where their canopies serve as fog and moisture collectors, habitat for insects, animals, and other plants, and form substrate (K. McEachern, Personal comm., 2018). As one of the CAIA's few tall trees, they provide a substantial amount of soil moisture through fog drip, which is especially important for understory plants and animals during summer droughts in the CAIA. Regeneration is limited across most of the island oak's range due to impacts from European-American settlers, introduced grazers, and invasive species, essentially eliminating seedling establishment over the last century (Kindsvater, 2006; D. A. Knapp, 2014). Pressures from introduced animals have been reduced on Guadalupe and Santa Catalina Islands, and completely removed from the other islands. Select *Q. tomentella* populations on Santa Cruz and Santa Rosa are recovering where seedling recruitment is more successful, but the species as a whole is struggling to rebound (D. A. Knapp, 2014; Pesendorfer, Baker, & Bode, 2018; Woolsey, Hanna, McEachern, Anderson, & Hartman, 2018). Human impacts of the last several centuries have altered *Q. tomentella*'s current distribution, which is likely smaller than its fundamental niche (Kindsvater, 2006). Slowed reproduction due to trampling and browsing of seedlings has restricted *Q. tomentella*'s ability to rebound from ranching and farming threats and has resulted in decreased numbers of individuals and an artificially-confined distribution. In 2016, the species was listed as endangered by the International Union for Conservation of Nature (IUCN), though its status has not been recognized as endangered under the U.S. Endangered Species Act (Beckman & Jerome, 2017).

Climate change may further impact *Q. tomentella*'s limited reproduction and shrinking populations and inhibit its ability to rebound from human impacts over the last two centuries. Substantial information about *Q. tomentella*'s current distribution, genetic variation, and soil preferences exist, but to date there has been minimal analysis of its bioclimatic envelope or response to climate change. Island oaks are typically observed in areas with cooler than average island-wide temperatures (Franklin & Knapp, 2007). They grow at a range of elevations, frequently on north- and northwest-facing slopes and in shaded drainages (Kindsvater, 2006). With current climate change trends, island ecologists are concerned that warming air temperatures and potentially drier conditions on the islands may change the distribution of island oaks, pushing them to higher elevations or restricting them to north-facing aspects and the shadiest canyons. As a species spatially-constrained by island boundaries, mountain tops, and bioclimatic preferences, climate change could significantly reduce island oak habitat across the islands (Harter et al., 2015).

Prediction of species range shifts through species distributions models (SDMs) is increasingly common as the effects of climate change become more apparent and pressing (Elith, Kearney, & Phillips, 2010). SDM outputs can be carefully employed to determine a species' current and future potential distribution based on its environmental and bioclimatic niche preferences. This project uses MaxEnt, a commonly used SDM software, to describe *Q. tomentella*'s bioclimatic envelop and predict how the species' range may change under different climate change scenarios (Elith et al., 2010). Based on results from this analysis, we provide research and conservation management recommendations for application by The Nature Conservancy and the Santa Barbara Botanic Garden to help ensure the persistence of *Q. tomentella.* This project also aims to serve as a reproducible methodology for studying climate change impacts on other endemic plants across the islands.

# Objectives

The objectives of this project are to:

1. Estimate *Q. tomentella*'s climate niche preferences, then use the modeled niche to predict the location and extent of current and future suitable climate habitat under four climate change scenarios on Santa Rosa, Santa Cruz, and Santa Catalina Islands.
2. Evaluate the likelihood of species persistence on each island based on quantitative changes in predicted suitable habitat using both individual scenario and integrated outlook perspectives.
3. Recommend restoration options for *Q. tomentella* taking into consideration findings from our analyses, impacts of grazers and ranching, supplementary *Q. tomentella* research findings, feasibility of restoration techniques in remote regions, and future research needs.
4. Develop reproducible methodology with refined data sets to facilitate future analyses of changes in species distribution under climate change on the CAIA.

# Background

## Climate Change and Species Modeling

*Quercus tomentella* is a paleoendemic that was once widespread in the southwestern United States. Researchers believe that naturally changing climatic factors restricted the species to its current range in the CAIA (Baguskas, Peterson, Bookhagen, & Still, 2014; Biondi, Cayan, & Berger, 1997; Mann & Gleick, 2015). Ecologists working with *Q. tomentella* are concerned that anthropogenically-driven climate change will threaten the persistence of the species in its already limited habitat. This section gives an overview of climate change in the modern era to provide context for the potential implications of climate change on *Q. tomentella* and its preferred habitat.

### Climate Change

Anthropogenically-driven climate change is rapidly shifting climate patterns away from historic natural norms. A majority of climate models predict that average global temperatures will increase at least 2 °C by 2100, with little hope of more moderate warming (Thomas et al., 2004). More recent climate projections based on current emissions rates show a high likelihood that temperatures will exceed a 4 °C increase by end of century (Brown & Caldeira, 2017). Large scale changes in precipitation patterns have also been predicted, although the directionality and magnitude of these shifts is highly uncertain and region-specific (Neelin, Langenbrunner, Meyerson, Hall, & Berg, 2013). In addition to warming temperatures and changes in precipitation, climate change is expected to alter discrete climate and weather processes including the timing of winter snowmelt, rates of severe weather events, and intensity and frequency of natural disasters (Levine, McEachern, & Cowan, 2011). Changes in climate will not be distributed uniformly across the globe as some regions are more sensitive to a changing climate than others; some areas will experience more extreme variations, while others may not see much change (Watson, Zinyowera, & Moss, 1998).

In California, projected temperature increases are all but guaranteed, while potential changes in precipitation are more unpredictable. This uncertainty could have drastic consequences in a region where variations in water-availability already result in water scarcity challenges. In the future, precipitation may have more extreme interannual behavior, with extended droughts and periods of intense storms (Berg & Hall, 2015). Global climate models, also referred to as general circulation models, regionally downscaled for California diverge in their predictions of whether California will experience an increase or decrease in precipitation, producing high precipitation projection uncertainty (Neelin et al., 2013). This uncertainty is a result of California's geographic and latitudinal location, as it lies directly between regions of opposing predictions: increases in precipitation are predicted for mid to high latitudes while decreases are projected for the subtropics (Meehl et al., 2007). Furthermore, large-scale climate events such as the Pacific decadal oscillation and El-Niño-

Southern Oscillation (ENSO) largely influence precipitation projections for California, but current predictions of how these particular events will change in the future are highly uncertain (Neelin et al., 2013).

Regardless, extreme interannual variation in precipitation levels is expected to continue, potentially increasing in severity by the end of the century (Berg & Hall, 2015). In combination with predicted temperature increases, drier wet seasons will be exacerbated by increased evapotranspiration, which will in turn escalate water stress in natural vegetation and agriculture (Mann & Gleick, 2015). If dry years are followed by years with high levels of precipitation, water-stressed soils lacking the capacity to retain extra water could be overwhelmed, leading to soil instability, erosion, and debris flows.

For California island and coastal ecosystems, another important climate consideration is the influence of climate change on fog formation. Fog occurrence in southern California is most commonly a result of advective fog formation in the marine boundary layer, which occurs when warm, wind-driven air parcels move across a colder surface, causing condensation (Filonczuk, Cayan, & Riddle, 1995). Stratus clouds in the marine boundary layer are promoted by a combination of wind driven-upwelling of cold oceanic water and the subsidence of warm air and often intersect with the land, especially in mountainous coastal areas (Rastogi et al., 2016; Williams et al., 2015). Many climate models predict warmer air temperatures and intensified upwelling near the CAIA, possibly resulting in an increase in fog occurrence in the future (Williams et al., 2015). According to readings from airfields on San Clemente Island and San Nicolas Island off the coast of southern California, the overall frequency of fog occurrence in the CAIA has already significantly increased from 1948 to 2014, particularly over San Nicolas Island (Williams et al., 2015). However, predictions of future fog inundation are highly uncertain as many of the patterns that influence local fog formation occur at global or regional scales (Filonczuk et al., 1995).

Given the highly uncertain predictions of fog by GCMs, historic trends of cloud cover and oceanic patterns can provide helpful insights (Williams et al., 2015). Trends in stratus cloud height indicate that the cloud base has descended in the CAIA, likely influenced by a local decrease in the depth of the marine boundary layer (Williams et al., 2015). Another possible cause for this trend is the major influence of ENSO and fluctuations of the Inter-Tropical Convergence Zone on trade wind inversion height and occurrence (Harter et al., 2015). If this trend continues, it could mean that areas at higher elevations on the CAIA could also be come free of fog and remain above the cloud layer. Additionally, as ENSO events increase in duration, intensity, and frequency, southern California is expected to experience increased periods of warmer water temperatures, potentially decreasing dense fog formation (LaDochy & Witiw, 2012; Perkins, Alexander, & Nairn, 2012).

## Impact of Climate Change on Species

Anthropogenic climate change has already directly impacted species biodiversity, distribution, and function (McCarthy & Intergovernmental Panel on Climate Change, 2001; Parmesan, 2006). Effects of climate change on species diversity and function have been recorded across the globe and for most taxonomic groups (McCarthy & Intergovernmental Panel on Climate Change, 2001; Sparksa & Menzelb, 2002). Additionally, the influence of climate change on species distribution and community composition has been well documented over the past century in both mechanistic and observational biological research studies (Lovejoy & Hannah, 2005; Parmesan, 2006).

Further projected changes in climate are expected to severely alter suitable habitat for species, limit their distribution, and majorly increase extinction risk (Moritz et al., 2008; Serra-Diaz, Scheller, Syphard, & Franklin, 2015). To adapt to changes in climate, species often migrate to higher elevations and latitudes exhibiting climate conditions that fulfill their niche requirements (Moritz et al., 2008; Parmesan, 2006). Species' range shifts in the Northern Hemisphere have moved significantly by an average of 6.1 km higher in latitude and 6.1 meters upslope per decade (Parmesan & Yohe, 2003). Range-restricted species, including island, endemic, mountaintop, and polar species are especially vulnerable as they display severe climate-induced range contractions and are some of the first species groups to become extinct under climate-induced range restrictions (Parmesan, 2006). Current human-induced changes in the environment are exacerbating species extinction at rates up to 1,000 times the background rate (Brooks et al., 2006). This rate is expected to continue to increase, possibly up to 10,000 times the background rate as climate change intensifies (Pimm, Russell, Gittleman, & Brooks, 1995).

While climate change affects all species, responses to climate change are species specific, as individual species move at different rates and in different directions (Hannah, Roehrdanz, Soong, Ikegami, & Tyner, 2013; Lovejoy & Hannah, 2005). Historically, plant communities have often maintained a particular species composition for prolonged periods, though species-specific responses to climate change indicate that new assemblages of plants and animals are likely to occur in the future (Walther, 2003). These new community assemblages would result in changes to ecosystem function including interspecific competition for limited resources due to more species having overlapping niches (Hannah et al., 2013). Widespread alterations in the phenology, or the natural calendars of plants and animals, is already underway, with potential large-scale repercussions for community interactions and threshold changes in ecosystems (Lovejoy and Hannah, 2005). These substantially novel ecosystems will require major modifications in current conservation practice (Root et al., 2003). Differences in species' reactions highlight the importance of modeling their responses to climate change individually rather than at the community level (Hannah et al., 2013).

# Impact of Climate Change on Plants

Plants face unique challenges that increase their vulnerability to climate changes due to their limited mobility and dependence on discrete climate and weather events (Hannah et al., 2013). Individual plants cannot move and must rely on seed dispersal for expansion and establishment in new locations. Seed dispersal and establishment is a slow process that occurs over the span of generations. Subsequently, many generations are required for an entire plant population to move to higher altitudes and latitudes compared to the shorter timespans required for mobile organisms (Hannah et al., 2013). This delayed, generational movement can have dire consequences if a species is not able to keep up with the movement of preferred environmental conditions due to climate change (Malcolm, Markham, Neilson, & Garaci, 2002). Furthermore, even if adult plants are able to survive climate change conditions, seedlings and saplings have narrower niche requirements that make establishment in a changing climate more difficult (Davis et al., 2016). When seedlings cannot successfully establish, population growth and movement are severely limited. Additionally, changes in phenology will further restrict plant movement if pollinators and dispersers are not present when and where plants need them, making the movement to new environments more difficult (Forrest, Inouye, & Thomson, 2010).

Changes to discrete weather events may have larger impacts on plants than changes to season-long variables like temperature (Levine et al., 2011). The timing of discrete weather events, such as storms and snowmelt, are critical for demographic transitions including germination, seed dispersal, and pollination, which are important variables in the movement and establishment of plant populations (Forrest et al., 2010). If these essential processes affecting the movement of plants are hindered, keeping pace with climate change will be even more difficult. As of yet, it is unclear how climate change will alter these specific weather events, making predictions of how climate change will affect plants more difficult.

Trees in island communities face unique pressures as climate change progresses. While the response of trees to climate change is already constrained by their limited mobility, they are further confined in island environments due to restricted area for dispersal. Island area has a negative correlation with the vulnerability of its plant species to climate change, which is particularly true for island endemics (Harter et al., 2015). As climate change pushes a species towards wetter, cooler areas usually at higher elevations, the size of the island determines its options for dispersal. A reduction in suitable habitat in island communities results in either retreat into refugia, rapid adaptation, or extinction (Harter et al., 2015). Sea level rise also contributes to a decrease in habitat in coastal ecosystems through temporary or permanent inundations and erosion. However, the islands in the CAIA have relatively high elevations, making them more resilient than lower elevation islands to climate change threats and allowing for more migration upslope (Ross, Lambdon, & Hulme, 2008).

Endemism and the genetics of island trees are also expected to play a major role in species persistence. Certain genetic traits that are typically present in island populations predispose island species to vulnerability in a changing climate. Colonization of an island by a tree species often encourages loss of mechanisms for wide-spread dispersal due to habitat constraints (Cody & Overton, 1996). While the relative stability of island climates compared to continental environments may shield island trees from experiencing some climate change effects, the reduction in dispersal ability further inhibits adaptability to changes in climate. Furthermore, limited resources and restrictive environmental processes that limit potential habitat on islands, particularly water availability, have promoted evolution in island trees to conserve resources through decreased dispersal and genetic homogeneity (Cody & Overton, 1996). Climate change is expected to alter some of these limiting resources and environmental processes at a faster rate than tree genetics can adapt to, resulting in species that are ill adapted to their present location. It is possible that some individuals within a population will adjust more readily to climate change due to certain genetic traits, while other genetic characteristics may disappear if they are inhibiting adaptation to a changing climate (Jump & Peñuelas, 2005).

## Human Disturbance and Climate Change Response

A number of factors complicate predictions of how climate change will impact the natural world, including human disturbance, threshold changes, species-specific movements, and large-scale earth process system changes (Lovejoy & Hannah, 2005). Human disturbance and landscape modification have created obstacles for species migration responses, which then further constrain the ability of species to adapt to climate change. The additive effects of anthropogenic land cover impacts with large scale climatic shifts will require species to adapt and migrate to suitable habitat more rapidly than in the past (Alley, 2003; Root et al., 2003).

Specifically, human disturbance on islands can have more severe repercussions than on mainland environments. For example, human introduced invasive or predatory species can have particularly detrimental impacts on native island species, especially native vegetation, as they tend to be especially poor competitors of invasives (Harter et al., 2015). When plants have evolved without the pressures of herbivory for thousands of years, their defenses against predation are less effective once they encounter introduced herbivores as compared to mainland plants (Vourc'h, Martin, Duncan, Escarré, & Clausen, 2001).

## Climate Change Management of Species

Based on the potential for dramatic impacts on organisms, future conservation targets and management strategies should incorporate climate change into decision-making processes. Historically, established protected areas, habitat refugia, and species corridors were created to cover the current distribution of species, communities, or ecosystems of interest. As the climate changes, the niches and distributions of organisms will shift and previously formed protected areas may fail to protect these species (Tanner-McAllister, Rhodes, & Hockings, 2017). Therefore, conservation managers need to establish adaptive management strategies and practices to account for potential impacts of climate shifts (Wilke & Rannow, 2014). Adaptive management strategies include establishment of climate refugia corridors between intact habitat areas to facilitate climate-induced migration and the selection of new protected areas that will maintain species diversity and functioning under forecasted climate changes (Hopkins et al., 2015). Climate uncertainty further complicates management decision making. Managers need to consider a wide range of possibilities, particularly with regard to precipitation variability. It is essential that managers integrate resiliency into their decision-making by planning for worst case scenarios.

Protected areas and adaptive management strategies can help safeguard plants against climate change, but additional strategies may be necessary to help plants keep pace. Habitat restoration, maintenance of population connectivity, and replanting after disasters like fire are some of the more straightforward management strategies. Assisted migration and translocation are more controversial and require more human effort and forethought to ensure successful establishment. For instance, when introducing a species to new environments, it is important to consider the risks and consequences that a new species can have on an existing community. It is critical to ensure that an introduced species will not displace or outcompete existing species. Extensive research into the species and ecosystem functioning of the proposed site is required, otherwise unintended ecosystem transformation can occur due to invasion and hybridization (Ewel et al., 1999). However, the pace of climate change and its potential impact on species diversity at large may require the use of more controversial assisted migration and translocation practices to maintain community biodiversity and ecosystem functionality (Courchamp, Hoffmann, Russell, Leclerc, & Bellard, 2014; Dawson, Jackson, House, Prentice, & Mace, 2011; Moir et al., 2012).

## Modeling Species Range Shifts under Climate Change

One way to incorporate climate change into the adaptive management of a species is through the use of species distribution models (SDMs). SDMs are common tools used to guide conservation of species habitat and ranges (Elith et al., 2010, 2011; Merow, Smith, & Silander, 2013). They estimate a species' fundamental niche, or the full range of biotic and abiotic conditions in which they can survive and reproduce, as opposed to their realized niche, or the actual range of conditions in which they exist. SDMs can also be useful when making spatial decisions about which portion of a species fundamental niche should be prioritized for protection. A species' fundamental niche refers to all locations with suitable environmental habitat, while a realized niche is all places that a species actually exists with biological and environmental dynamics acting as limitations. With climate change, species' fundamental niches are changing as environmental variables changes, and realized niches are also changing as species communities and competition dynamics change. As climate change-induced pressure on species increases, SDMs are becoming a more common tool to evaluate how changing climate will impact habitat and ranges and ultimately where to focus conservation efforts.

To maximize the efficacy of SDM outputs, users need to consider the large uncertainty associated with these models, especially when projecting into the future (Elith et al., 2010; Pearson & Dawson, 2003). First, weather predictions are highly uncertain. Human-induced climate change is increasing annual average temperatures globally, but it is unclear how changes in climate will alter short- and long-term weather patterns, and subsequently how these pattern alterations will impact fundamental climate niches of species (Berg & Hall, 2015; Pacifici et al., 2015; Swain, Langenbrunner, Neelin, & Hall, 2018). Increasing resolution of climate data requires modelers to make added assumptions about environmental dynamics and model parameters. Furthermore, future species distributions are often projected into novel environments (Elith et al., 2010). Models of future species distributions can approach novel environments by either 1) using known relationships between the species and environmental covariates to extrapolate into unobserved ranges or 2) treating values outside of a species' observed range as one extreme value. Additionally, Elith et al. (2010) also note that most current species distributions have been altered by human activity, so relationships between species presence and environmental variables may be in flux and inherently unstable. Lastly, the use of SDMs to predict species distribution assumes that species presence relies on a fundamental bioclimatic niche, and that the relationships between the species and climate variables are driving its presence. The lack of understanding of the species-climate relationship could result in increased uncertainty in the model inputs and outputs.

To make appropriate use of SDM outputs, users need to consider the uncertainty inherent in each data source, methodology, and assumption, and attempt to control for each when possible. When projecting species ranges into the future, SDM outputs must be interpreted with a clear understanding of the implications of uncertainty in future climate variable and species distributions. Likewise, results should be interpreted within the context of all that is known about the species rather than in isolation, and conservation decisions should be made with all available information in mind (Guisan et al., 2013; Villero, Pla, Camps, Ruiz-Olmo, & Brotons, 2017).

# California Island Archipelago

The current status of *Q. tomentella* is a product of long-term climate-driven range shifts and human land use over the last few centuries. Paleological records indicate that *Q. tomentella* was once widespread across the southwestern United States, but was restricted to the CAIA due to natural caused changes in climate (Baguskas et al., 2014; Biondi et al., 1997; Mann & Gleick, 2015). The island oak's range is now limited to just six islands including Anacapa, Guadalupe, San Clemente, Santa Catalina, Santa Cruz, and Santa Rosa, and human land use on those islands has damaged much of its habitat. It is suspected that in the past the species was located on San Miguel Island but has since been extirpated. The following section provides historical context about geologic and human history relevant to the current status and range of *Q. tomentella*.

## Geologic History

About 20 million years ago, the CAIA was formed by the northward movement of the Pacific Plate along the San Andreas Fault, which rotated and pushed areas of the California coast outwards into the Pacific Ocean (U.S. National Park Service, "Geologic Formations", 2016). During the Ice Age, the single land mass Santarosae separated through tectonic uplift and rising sea levels to become the present-day islands of Anacapa, Santa Cruz, Santa Rosa, and San Miguel Islands (Atwater, 1998). These tightly clustered northern islands are separated from the mainland by the Santa Barbara Channel. The southern islands include Santa Barbara, Santa Catalina, and San Clemente islands located in the San Pedro Channel and Guadalupe Island off the coast of the BCP (Moody, 2000).

Islands in the CAIA are home to an abundance of rare and endemic flora (California Islands Biosecurity Program Subcommittee, 2013). The CA-FP, which includes the CAIA, is one of the most biodiverse areas in the world, but is also one of the most threatened ecoregions (Calsbeek et al., 2003). The CA-FP contains uniquely complex topography that isolates geographical regions, encouraging divergent evolution and thus leading to remarkable biodiversity (Baldwin, 2014). The islands in the CA-FP is not believed to have ever been connected to Mainland California and Mexico, but in the last ice age were close enough to mainland to have more similar flora (Rick et al., 2014). When sea level began to rise substantially around 20,000 years ago in an era of naturally-occurring climate change, the islands became more isolated, and species began evolving to unique island conditions (U.S. National Park Service, "Geologic Formations", 2016). Now approximately 20% of species on the islands are narrow endemics, existing on only one or more of the islands (Baldwin, 2014). However quite a few of these endemic species are threatened or endangered, which are especially vulnerable given their isolated, narrow ranges (Morrison et al., 2014; Riley & McGlaughlin, 2016).

## Climate

Unless otherwise noted, climate information about the Channel Islands in this section comes from the NPS (U.S. National Park, "Weather", 2016). The CAIA generally experiences a Mediterranean dry summer subtropical climate. With a Mediterranean climate, the islands have mild temperatures throughout the year that is moderated by the presence of a large body of water, which in this case is the Pacific Ocean. A dry summer subtropical climate refers to low precipitation during the summer months caused by seasonally shifting wind patterns, with drought being a common occurrence. Compared to the mainland, the CAIA has milder summers, higher humidity, and more frequent nocturnal fog due to a stronger influence by the Pacific Ocean. The coolest temperatures occur from December to March on the islands while the hottest temperatures occur from July through October. The CAIA experiences cool days and warm nights, showing little difference in diurnal temperatures and the central valley of Santa Cruz Island is the only CAIA location with conditions suitable for frost. Overall, humidity varies most diurnally, with early mornings reaching 100% humidity and afternoons reaching 60%. Occasionally in the fall, Santa Ana wind conditions lower the humidity and increase temperatures. As is the case on the mainland, the Santa Ana winds in Southern California are the main driver of the fire regime on the CAIA. Though the severity is much lower than on the mainland for the northern islands, the southern islands may experience just as intense winds as the Los Angeles basin.

Wind patterns on the islands generally move in a west to northwest direction, with stronger winds occurring during the day. Wind patterns known as “sundowners” are downslope winds commonly experienced in Santa Barbara that play a large role in the occurrence of wildfires, although they infrequently reach the CAIA.

Most rainfall in the CAIA occurs between November and April, with January and February making up an average of 45% of total annual rainfall. Most of the precipitation comes as large storms rather than daily drizzles, and long periods without rain are common. The dry season occurs from May through October, with precipitation minima occurring from June through August. Regional rainfall and drought periods are highly variable and unpredictable, and multi-year droughts are possible. Average annual rainfall ranges from 25 cm to 50 cm, depending on an island’s topography. Since rainfall in the CAIA is infrequent and mostly in the winter, fog plays a large role in providing year-round soil moisture for island vegetation (Williams et al., 2015). Fog occurs often, especially from May through September, with maxima in July and August (Rastogi et al., 2016).

Fog formation is not uniform across all of the islands, in part because the islands exist within the transition zone between two biogeographic and coastal oceanic provinces: the colder Oregonian and the warmer Californian provinces (Santa Barbara Coastal LTER, 2006). CAIA islands typically found in the Oregonian province include San Miguel, Santa Rosa, and part of northern Santa Cruz Island, while Anacapa and eastern Santa Cruz Island are positioned more in the Californian province (U.S. Department of Commerce, National Oceanic and Atmospheric Administration, & National Marine Sanctuary Program, 2008). These differences in water temperature could account for some inter-island variation in fog formation since colder waters and warmer air promote advection fog (B. Kendall, Personal comm., 2019).

According to a cloud cover model by Rastogi et al. 2016, higher elevation areas further inland on Santa Cruz and Santa Rosa Islands are more likely to experience fog. However, on Santa Cruz Island, the highest parts of the east-west range are above the cloud layer, resulting in low probability of fog inundation in these areas. Fog on Santa Cruz Island is most likely to occur on windward ridge slopes on east-west gradient. On Santa Rosa Island, fog is often able to surpass the highest elevations, resulting in fog inundation on the leeward side of the island.

## Human History

There is a long history of human presence in the CAIA that has shaped the habitat and species assemblages we see today. Long before European colonization severely degraded habitat and species on the islands, indigenous Californian tribes frequented the islands for its rich supply of resources. Records indicate that the Chumash and Tongva lived in the CAIA up to approximately 10,000 – 13,000 years ago (U.S. National Park Service, "Native Inhabitants", 2016). The Chumash first arrived on the northern islands forming at least 148 villages, while the Tongva inhabited the southern islands, though they did not build any permanent establishments due to lack of freshwater (U.S. National Park Service, “Native Inhabitants,” 2016). These tribes hunted the fauna on the islands, formed a robust economy based on maritime goods, and are thought to have introduced some flora and fauna from the mainland (J. Knapp, Personal comm., 2018).

Upon the arrival of Europeans in the 19th century, the introduction of diseases, exploitation of resources, and alteration of native economies uprooted the Chumash and Tongva (U.S. National Park Service, “Native Inhabitants,” 2016). Many of the Channel Islands were then privately owned and managed by European-American ranchers (Kindsvater, 2006; Moody, 2000). The majority of land on the islands became dedicated to livestock farming and ranching, which significantly deteriorated native habitats across the islands and increased rates of herbivory of native flora. Though many of the islands have since removed the nonnative herbivores, programs to restore island communities resembling the pre-ranching era continue to take place.

## Individual Islands

### *Santa Cruz Island*

Santa Cruz Island is the largest of the Channel Islands, with an area of 250 km$^2$. It is home to 16 distinguished native plant communities, including grassland, coastal scrub, chaparral, and island woodland (Miller, 1985). Of all the Channel Islands, Santa Cruz has the most plant and animal species, with over 60 endemics (U.S. National Park Service, "Island Facts: Santa Cruz Island", 2016). A large central valley runs through the island bordered by relatively gentle slopes on the north and south sides (Van Vuren & Bowen, 2012). Diablo Peak is the highest peak on the islands at 740 meters (U.S. National Park Service, "Island Facts: Santa Cruz Island", 2016).

Spanish settlers arrived on the island in 1852 bringing domestic pigs that eventually became feral, with populations on the island remaining in the few thousands until the 2000s (U.S. National Park Service, "Santa Cruz Island History and Culture", 2016). The island was sold to a private party in 1857 as a sheep ranch. Ranchers brought cattle and horses to the island by 1869. Ranching operations were expanded and continued under various private owners until the 1980s.

Feral sheep were removed from the island as early as 1978 by The Nature Conservancy. Since their removal, native grasses dramatically increased in biomass and frequency (Van Vuren & Bowen, 2012). Other native vegetation had mixed responses to the removal, but exotic species overall showed a significant decrease in population (Van Vuren & Bowen, 2012). Feral pigs were eradicated from the island in 2007. While The Nature Conservancy and the National Park Service (NPS) have seen some success in minimizing the damages from non-native herbivores, invasive plants continue to be a significant problem for the island. Removal of invasive fennel through controlled fires and herbicide has been proposed, but the weed is still prominent across the island (U.S. National Park Service, "Santa Cruz Island History and Culture", 2016).

After The Nature Conservancy acquired the property in 1987, ranching operations completely ceased with the death of the last ranch owner. The NPS acquired 10% of the island in 1997 and was later given jurisdiction over another 12% of Santa Cruz by The Nature Conservancy. The goals of The Nature Conservancy are to conserve lands and water through a non-confrontational and collaborative approach. On Santa Cruz Island, this entails prioritizing weed and invasive management and restoration activities to repair the damages caused by ranching and other human activities.

## Santa Rosa Island

Santa Rosa Island has an area of about 214 km$^2$ and is currently home to 18 distinct vegetation communities (Miller, 1985). The island has a large fault that runs through it, creating distinct differences in vegetation on different facing slopes (U.S. National Park Service, “Geological Formations,” 2016). As a result of past geologic activity, Santa Rosa has an east to west trending highland with lateral canyons running north and south, sandy beach dunes prominent along the north and south coast, and rocky intertidal areas surrounding the island border (Lombardo & Faulkner, 1999). Historically, the island was covered in oak woodlands along with coastal sage scrub and chaparral communities extending into coastal grasslands (Anderson, Starratt, Jass, & Pinter, 2009).

According to Frisch et al. (2014), Spanish ranchers arrived on Santa Rosa Island in the early 19th century and began sheep ranching operations in 1843. In 1902, a private company purchased Santa Rosa and established cattle ranching and recreational hunting of deer and elk. Feral pigs were also present on the island, although the origin and timeframe of their introduction is uncertain.

After the island was deemed integral to the overall conservation of the Channel Islands, the private owners reluctantly sold Santa Rosa to the NPS in 1986. Ranching and hunting operations continued on the island for the next 5 years by a company under a special federal permit while the NPS developed park research, infrastructure, and general public use. Private use of the island for ranching continued until park biologists conducted surveys that made the detrimental effects of the non-native herbivores apparent. In 1995, the U.S. Fish and Wildlife Service submitted a proposal claiming 11 endemic species were eligible for the Endangered Species Act and cited ranching and hunting as threats. In 1997, a settlement prevented the renewal of the federal permit for private use and required the removal of the cattle, deer, and elk by 2011 (Frisch, Faulkner, & Wakelee, 2014). Feral pigs were successfully eradicated by 1993 (Lombardo & Faulkner, 1999).

The NPS aims to protect and conserve the unique ecosystems of Santa Rosa Island. Part of this goal includes consistent monitoring of environmental conditions, such as examining the changes in soil deposition and locating effective areas for erosion control structures (Perez, McEachern, & Niessen, 2017). The NPS has also worked to restore the cloud forests, which are still struggling after removal of invasive herbivores despite the recovery of other of vegetation types. High levels of erosion from intense herbivory has reduced the regeneration and establishment of oak woodland species. The NPS is combating this through implementation of erosion control structures that slow wind and water degradation, trapping of leaf litter and seeds near oaks, collection and propagation of seeds in nurseries, assistance of seedling root establishment, creation of fog fences that capture fog drip, and monitoring.

## Santa Catalina Island

Santa Catalina has a relatively large size at 194 $km^2$ (Miller, 1985). The island boasts a complex vegetative structure. Though coastal sage scrub is one of the dominant vegetation alliances found, it also has arborescent chaparral (Diamond, 1969). The island contains a north-west to south-east trending mountain range with steep canyons (Franklin & Knapp, 2007). Additional island features include an arid climate, mountains, and shallow soils.

Spanish settlers arrived on the island in the early 1800s, and the island was used as a pit stop for smugglers and other illegal activities until the mid-1800s, when the island became a private cattle ranch (Williamson, 1903). During the late 1800s, the city of Avalon developed as a resort and private baseball training grounds (Catalina Island Chamber of Commerce & Visitors Bureau, "Catalina Island History", 2018). The Catalina Island Conservancy (CIC) took control of 90% of the island in 1975, with the remaining 10% under the jurisdiction of the Santa Catalina Island Company, which oversees the recreational and resort operations on the island (Catalina Island Chamber of Commerce & Visitors Bureau, "Catalina Island History", 2018).

Since its occupation by European-America settlers, ranchers introduced feral goats, feral pigs, American bison, mule deer, domestic sheep, and cattle on Santa Catalina. Rats and cats have also invaded the island. Sheep were eradicated by the 1920s and the cattle were removed by the 1950s (Knapp, 2014). Under the CIC, feral pigs and feral goats have been removed. The mule deer and bison remain as a part of a hunting program operated by the CIC, which controls their populations. The CIC cannot entirely remove the mule deer population from the island, as jurisdiction over the species lies with the California Department of Fish and Wildlife, despite their tendency to graze native plants (Knapp, 2014). Although bison also feed on native flora, they remain on the island due to their contribution to the island's ecotourism.

Non-native ungulates damage to native plants has significantly impacted the island's ecosystems. Some areas of shrubland have been converted to grassland by invading non-native grasses. These invasive annual grasses suppress the growth of multiple natives and discourage the regeneration of woody trees. They also facilitate the start and spread of fire, alter the water regime, and reduce food sources for native animals (Knapp, 2014). Unfortunately, these grasses are near impossible to completely remove from the island and are at best only kept in control in certain areas (Knapp, 2014). Currently, game management is overseen in partnership with the California Department of Fish and Wildlife under a Private Lands Management agreement and views hunters as “conservation partners”  (Catalina Island Conservancy, "Game Management", 2018).

Current management practices for damaged vegetation communities include facilitation of island scrub oak regeneration by planting scrub oaks in sects with varying degrees of herbivory exposure (Catalina Island Conservancy, "Island Scrub Oak Regeneration", 2018). Generally, the CIC is conducting extensive monitoring, outplanting, surveying, and research concerning rare and endemic island species. This is part of a larger objective to maintain or restore vegetation alliances on the island.

## Anacapa Island

One of the smallest landmasses of the CAIA, Anacapa consists of three separate islands with a total area of 2.9 $km^2$ (Miller, 1985). Before the introduction of invasives, Anacapa was home to thousands of sea birds due to high cliffs and the absence of predators. Vascular flowering plants are dominant on the island, but there are a few tree groves. Despite its small size, Anacapa has a higher floral diversity than the much larger San Miguel Island (Junak & Philbrick, 2018).

Anacapa was also used for ranching operations beginning in the late 19th century. Due to the limitation of freshwater and vegetation, ranchers introduced plants as a food source (U.S. National Park Service, "Anacapa Island History and Culture", 2016). By the 1930s, sheep ranching completely ended due to overgrazing of both the exotic and native species(U.S. National Park Service, "Anacapa Island History and Culture", 2016). Anacapa was the first Channel Island acquired by the NPS in 1938 (U.S. National Park Service, "Anacapa Island History and Culture", 2016). In the 1940s, rats were accidentally brought to the island by visiting ships, leading to the decimation of reptile and bird populations due to egg predation. Additionally, the U.S. Coast Guard introduced ice plant for landscaping and erosion control in the 1940s and 1950s (U.S. National Park Service, "Restoring Anacapa Island: Native Plants", 2016). Since then, disturbances from non-native rabbits and the construction of an island-wide road system have contributed to the spread of ice plant, overwhelming many native plants.

Currently, the restoration of sea bird habitat and the removal of ice plant to conserve wildflower populations rank highly on the priority list for management of Anacapa. The NPS hosts programs to remove the plants mechanically and by hand, facilitate solarization, and apply herbicides (U.S. National Park Service, "Restoring Anacapa Island: Native Plants", 2016). Areas where the weeds are removed are then planted with native seeds collected from within the island.

## San Miguel Island

San Miguel is the westernmost of the northern islands and has an area of 37 km$^2$ (Miller, 1985). This island in particular bears the brunt of the sea and wind due to its location, making its landscape sandier and more weathered than the other northern islands. The most prominent feature of San Miguel is its caliche forests, or areas where root systems from hundreds of years ago formed into caliche casts and root sheaths (U.S. National Park Service, "Geologic Formations," 2016). Caliche is a calcium-carbonate cemented soil, which forms due to the sandiness of the island. Important vegetation communities include the coastal sage scrub that occupies most of the island (Diamond, 1969). As one of the islands that collectively formed Santarosae, island oak is thought to have historically inhabited this island.

As with the rest of the CAIA, ranchers arrived in the 1800s with invasive herbivores, which reduced the island to barren sand. After the island was bought and resold by a series of private owners, the Department of the Navy and the Department of the Interior acquired it in 1963 with the intent to protect its scientific and historic value (U.S. National Park Service, "Establishing Channel Islands National Park", 2016). By 1966, the NPS removed the non-native sheep, and removed the feral burros by 1977. However, damage from herbivory had already severely reduced the cover of native vegetation in sand dunes and open habitats (Corry & Mceachern, 2009). Native plant species continue to decline from competition for resources with invasive plants, possibly due to the lower salt tolerance of native species (Corry & Mceachern, 2009).

Though no prominent restoration programs on San Miguel are currently implemented, aside from continuous monitoring and research, soil moisture and invasive plant management are recommended by Corry and McEachern (2009).

## San Clemente Island

San Clemente Island is 147 km$^2$ and currently has the highest number of endemic plant species in the CAIA (Moody, 2000). San Clemente's high level of endemism could be due to its isolation relative to the northern islands (Moody, 2000).  Native vegetation includes coastal sage scrub and several oaks, toyon, and ironwood (Diamond, 1969).

Many of the native endemic plant species were negatively impacted by the arrival of invasive goats, sheep and pigs from Spanish ranchers from the 1840s (Wylie, 2012). Even after ranching operations ceased in 1934 and the island was acquired by the U.S. Navy, feral goats continued to roam. For conservation purposes, the Navy fully eradicated the goats and pigs by 1992 (Wylie, 2012).

Grazing significantly altered the number and distribution of native flora; historically, the island were thought to have coastal sage scrub with woodlands in its canyons (Wylie, 2012). In addition to lower population numbers of natives, the number of invasive plants has increased enough to significantly alter the landscape (Wylie, 2012). Non-native vegetation, particularly non-native grasses, have been outcompeting native species since herbivore removal. Native sage scrub, however, has significantly increased after the release of grazing pressures. From 2003 to 2004, the Native Habitat Restoration Program sought to increase sage scrub in order to provide more habitat for the endangered endemic shrike. Efforts included seed collection, use of native plant nurseries for a living collection, and outplanting to areas of suitable habitat.

The Soil and Ecology Research Group (SERG) at San Diego State University oversees conservation projects for the Navy on San Clemente Island. Current management objectives prioritize the conservation of suitable habitat for its native species in accordance with the Endangered Species Act. Research focuses on 17 of the island's endemic plant species, with a particular emphasis on the potential for invasives on other CAIA islands to spread to San Clemente. Monitoring plant and animal populations is also emphasized by island management, as San Clemente's species composition is more unstable than the other islands' (Wylie, 2012).

## Guadalupe Island

Guadalupe Island is 260 km$^2$ and lies off the coast of the BCP. Historically, the island was covered by shrubland, oak and pine woodlands, and cypress, juniper, and palm forests. These ecosystems have been mostly reduced to a desert-like vegetative state, with only pockets of native habitat remaining in areas inaccessible to the invasive ungulates (Keitt, Junak, Luna-Mendoza, & Aguirre-Muñoz, 2005).

Guadalupe Island is the only island with island oaks that is not under United States jurisdiction. The island remained unowned until 1839, when the Mexican government acquired it for its cloud forests and seal trade (Horizon Charters, "Guadalupe Island History", n.d.). In 1870, the United States privatized the island as a sheep and goat ranch and contracted deforestation on the island for lumber before the island's return to the Mexican government in 1885 (Horizon Charters, "Guadalupe Island History", n.d.). Nine years later, the first conservation efforts started with protection of the remaining fur seals (Horizon Charters, "Guadalupe Island History", n.d.). After the establishment of a tuna fishing industry near the island, Guadalupe Island was declared a pinniped sanctuary in 1975 (Horizon Charters, "Guadalupe Island History", n.d.).

Invasives introduced by ranching and overharvesting pushed many native species to extinction, creating a more desert-like landscape (Keitt et al., 2005). Furthermore, domestic cats decimated native bird populations, integral to the vegetated ecosystems (Keitt et al., 2005). Efforts to control the goat population and study their impacts only began in 2001. After 2001, fencing was transported to the island in a collaborative effort between Grupo Ecología y Conservación de Islas, Island Conservation, the Santa Barbara Botanic Garden, and the Instituto Nacional de Ecología (Keitt et al., 2005). Fenced areas showed significantly higher numbers of native species, including a 20% increase in pines (Keitt et al., 2005). The return of native species in these areas drove the removal of the entire goat population from

2004 to 2005. Recovering the pine and cypress populations is expected to increase the amount of fog capture, as the island is considerably drier than its northern counterparts (Keitt et al., 2005).

Currently, conservation efforts on the island are led by a collaboration between Island Conservation and Grupo de Ecología y Conservación de Islas (GECI). The Mexican federal government, the Mexican Navy, and the fishing community on the island created the Guadalupe Island Biosphere Reserve, which is currently overseen by the Mexican Natural Protected Areas system (Keitt et al., 2005). Conservation objectives now prioritize controlling the cat population and creating a buffer zone for the marine life around the island.

# Island Oaks

The island oak, *Quercus tomentella*, is one of 20 oaks native to California, and is endemic to six islands across the CAIA. In 2016, the species was listed as endangered by the IUCN, although its status has not been recognized as threatened or endangered under the Endangered Species Act (Beckman & Jerome, 2017). Its reproduction is limited across most of its range due to impacts from European-American settlers, grazing by introduced livestock, and competition with non-native plant species. Slowed reproduction has resulted in an overall decrease in the number of individuals and a constrained distribution.

*Q. tomentella* is a true evergreen that keeps its leaves for at least a year, and potentially up to three years. Mature trees take various forms depending on the environment. On ridge tops where wind exposure is high, *Q. tomentella* grows as a round, shrub-like tree. In areas without significant exposure to wind, like protected drainages, the trees grow tall and straight, and can reach up to 20 meters (Kindsvater, 2006). Island oaks on Guadalupe Island are shorter and have trunks seven to eight times wider than those on other islands (J. Knapp, Personal comm., 2018).

## Ecological Importance

*Q. tomentella* is a foundation species that plays an important role in a selection of oak woodlands and cloud forests across the islands it occupies (Franklin & Knapp, 2007; Kindsvater, 2006). It supports a wide array of insect populations, has a mutualistic relationship with the endemic island scrub jay (*Aphelocoma insularis*), and through fog capture, provides a significant amount of moisture to surrounding soil (Bernard, McEachern, & Niessen, 2016; Kindsvater, 2006; D. A. Knapp, 2014; Pesendorfer et al., 2018; Woolsey et al., 2018). In certain parts of its range, *Q. tomentella* is a canopy dominant, providing shade and moisture to other endemic islands plants in its understory. In other areas, the species is an important part of cloud forests, which have adapted to rely on fog capture as their primary water source. *Pinus muricata* (bishop pine) and *Pinus torreyana subsp. torreyana* (Torrey pine) are also foundational to CAIA cloud forests and augment soil moisture through fog capture. However, both pine species are subject to periodic large-scale die-offs, especially during drought periods, which are expected to become more frequent and severe with climate change (Baguskas et al., 2014; Berg & Hall, 2015; Biondi et al., 1997). These patterns of drought-induced die-offs have not been observed in mature *Q. tomentella*, so as drought frequency and intensity increase, its relative contribution to fog capture in cloud forests is also likely to increase.

## Legacy of Past Human Land Use

It is unknown whether the Chumash or Tongva specifically made use of *Q. tomentella*, though acorns were a staple of the plant-based portion of their diets (Moody, 2000). Fire use by native people may also have affected island oaks. Land clearing through fire may have removed former *Q. tomentella* populations and opened habitat to more competitive non-native species, potentially changing plant community structures across the islands. However, middens are commonly seen in coastal areas outside of current island oak habitat, indicating that island oak populations and areas most densely populated by native people did not significantly overlap. Additionally, ranchers may have used island oaks for fire wood and fence building (Kindsvater, 2006). Island oaks were also harvested from the islands and then towed by boat across the Santa Barbara Channel for use as building material on mainland California (J. Knapp, Personal comm., 2018).

## Current and Past Distribution

*Q. tomentella* currently lives on Guadalupe Island off the west coast of the BCP in Mexico and five of California's Channel Islands, though this is a relic distribution. Fossil records from the late Tertiary Period show that the species is a paleoendemic and was once widespread in the southwestern United States. Researchers presume it was restricted to its current range on the CAIA by naturally changing climatic factors (Baguskas et al., 2014; Biondi et al., 1997; Mann & Gleick, 2015). *Q. tomentella* became less adapted to mainland environments as inland conditions became warmer and drier, pushing it to more temperate and mesic environments. On the islands, the species faced less competition for resources, and had access to more summer fog (Kindsvater, 2006).

*Q. tomentella*'s current realized niche on the islands is more confined than previous studies of the species predicted (Kindsvater, 2006). According to Kindsvater, Santa Cruz and Santa Rosa Islands contain much more habitat with suitable soil and vegetation types than the tree occupies. The restricted distribution is likely a result of grazing impacts from herbivores introduced by ranching and livestock farming activity across all six islands. For example, Minnich (1980) observed that on Santa Catalina Island goats preferentially graze on chaparral communities which do sometimes contain *Q. tomentella*. Minnich found that chaparral abundance declined by up to 30% in the mid-20th century as a result of grazing.

In addition to the species not occupying the full extent of its range, there are also large generation gaps in many populations. Introduced grazers directly and indirectly reduced seedling recruitment through seed predation and habitat degradation. Pig rooting, for example, involves the consumption of acorns through digging, and is known to have severely impacted seedling establishment (Franklin & Knapp, 2007; Kindsvater, 2006). Scientists have not been able to acquire tree ring data to make accurate age estimates, but they presume that trees are either at least 100 years old and established in the 19th or early 20th century or in the last several decades since grazing livestock were removed (J. Knapp, Personal comm., 17 November, 2018).

## Associated Plant Communities

According to two island oak experts, Kathryn McEachern and John Knapp, *Q. tomentella* is a foundational species in island oak stands and oak-woodland alliances (Personal comm., 2018). Other dominant species in island woodland communities include *Lyonothamnus floribundus* subsp. *Floribundus* (Santa Cruz Island Ironwood) and *Prunus ilicifolia* subsp. *Lyonii* (Catalina Cherry). Kindsvater (2010) found that plant communities containing *Q. tomentella* on Santa Cruz and Santa Rosa Islands included other species that typically occur in mixed chaparral, mixed woodland, closed-cone pine forest, and Torrey pine forest communities. Mature *Q. tomentella* can successfully exist amongst many types of native and non-native flora. However, non-native annual grasses may be contributing to poor seedling recruitment by reducing soil moisture more than native grasses do (Kindsvater, 2010; Meehl et al., 2007; Neelin et al., 2013). On Santa Catalina Island, Franklin and Knapp (2007) found that predicted *Q. tomentella* where found most frequently in coastal sage scrub, grassland, and island chaparral communities. Variation is associated plant communities may be the result of each island's vegetative cover, past impacts on each island, and unique niche preferences of island oak and other plants' subpopulations.

## Environmental Niche Preferences

### *Soil Characteristics*

Kindsvater (2006) found that *Q. tomentella* grows in a wide variety of soil classes and associations derived from sedimentary and igneous parent material. Soil samples acquired from *Q. tomentella* sites on Santa Rosa and Santa Cruz Islands in 2006 found A horizon depths from 3 – 50 cm, 4 – 55% clay content, and pH from 4 – 6.7, and lower bulk density in the B horizon than in surrounding sites (Kindsvater, 2006). They were also found in rocky substrate, and generally seemed to grow in a wide variety of mesic soil conditions. The study also explored soil characteristics for sites where *Q. tomentella* was regenerating on Santa Rosa Island. In those plots soil had significantly higher average pH, exchangeable potassium, lower percent clay, higher percent sand, and lower phosphorus.

On Santa Catalina Island, Franklin and Knapp (2007) found that island oak tends to exist on soil substrate derived from igneous and sedimentary bedrock, and as on the two northern islands, prefers gravelly soil.

## *Fog and Soil Moisture*

Fog drip is an essential source of water for island oaks and other island vegetation (Williams et al., 2015). As the scientific name implies, island oak leaves are tomentose, meaning they are covered in a dense mat of short hairs that increase the leaves' surface area and their ability to collect fog (Rosatti & Tucker, 2014). Additionally, many species of lichen live on branched in the upper canopy of mature *Q. tomentella*, which increases fog capture through increased surface area (Kindsvater, 2006). Oak sapling germination requires fog drip to maintain steady moisture in the soil surrounding saplings' shallow roots because the embryo will die if it dries out (Rastogi et al., 2016). Fog plays an essential role in delivering this moisture to the saplings as it condenses on the canopy above them (Rastogi et al., 2016).

The patterns of fog inundation on the CAIA are essential for the estimation of the amount of fog drip that oak woodland communities receive seasonally (Rastogi et al., 2016). Fog inundation was found to be a strong predictor for fog drip and therefore is critical in determining potential shifts in suitable habitat for cloud forest communities (Rastogi et al., 2016). Tall trees like *Q. tomentella* play an important functional role in the collection of soil moisture as they intersect the fog layer. Changes in fog inundation patterns could exacerbate the species' vulnerability, making them more susceptible to extinction. The thinned canopy that could result from any loss of tall tree species would mean less fog drip for both the trees that make up the canopy and those in the understory below (Rastogi et al., 2016).

Although past trends in cloud cover suggest that fog occurrence is increasing significantly on average in the CAIA since 1948, the inversion layer has been sinking (Williams et al., 2015). If climate change shifts potentially desirable oak habitat upslope tracking cooler temperatures, and if the base of the inversion continues to sink, habitat at higher elevations could become less suitable (Harter et al., 2015).

## *Temperature and Elevation*

Island oaks are typically observed in areas with cooler than average temperatures (Franklin and Knapp, 2007). On Santa Catalina, populations are densest where solar radiation is low in the summer and high in the winter. They grow at a range of elevations, frequently on north- and northwest-facing slopes and in shaded drainages (Dahlin, Asner, & Field, 2014; Kindsvater, 2006). With current climate change trends, ecologists are concerned that warming air temperature and drier conditions on the islands may change the distribution of the island oaks, pushing them to higher elevations or restricting them to north-facing aspects and the shadiest canyons. As a species that is already spatially-constrained by both island boundaries and mountain tops, climate change could significantly reduce available habitat across the islands (Harter et al., 2015).

# Life History

## *Dispersal and Reproduction*

*Q. tomentella* reproduces both clonally and sexually (Ashley, Backs, Kindsvater, & Abraham, 2018). Clones are usually found in tight rings but are sometimes spatially separated enough that clonality is not apparent. Genetic variability studies of the species on Santa Rosa and Santa Catalina have illustrated that underground vegetative growth explained genetically identical trees, demonstrating that clones sprout from the roots of mature trees. Ashley et al. 2018 attribute *Q. tomentella*'s relatively high rates of clonal reproduction on the two islands to grazing pressure and soil erosion. Kindsvater (2010) also suggested that competition with non-native flora contributes to environmental stress and the species' tendency towards clonal reproduction. Clonal reproduction was detected at lower rates on the other California islands and not on Guadalupe Island.

*Q. tomentella* pollen is wind-dispersed in April and May (Baldwin et al., 2012; Kindsvater, 2006). After pollination, acorns take 13 — 18 months to mature and are typically dispersed by gravity, water, and sometimes the endemic deer mouse (*Peromyscus maniculatus).* On Santa Cruz Island, the endemic scrub jay also might contribute to acorn dispersal. Acorn masting events are thought to occur approximately every 5 – 8 years, though this behavior has not been explicitly validated in the field (Kindsvater, 2006). For the closely related species *Q. chrysolepis,* acorn production was highest one to two years after relatively wet rainy seasons (Koenig et al., 1996).

*Q. tomentella* acorns germinate in moist, nutrient rich topsoil. Kindsvater's 2006 study found that the soil at regenerating sites, or sites where trees are sexually reproducing, had more total nitrogen, more total carbon, lower phosphorus, more exchangeable potassium, lower bulk density, higher pH, lower percent clay, higher percent sand, and lower percent silt. Though this study was isolated to Santa Rosa Island, it indicates the sensitivities of island oak seedling recruitment.

## *Dispersal and Reproduction Challenges*

Soil degradation and the absence of acorn dispersers in many island oak populations has inhibited acorn germination and seedling establishment. The island scrub jay and acorn woodpecker are the only suspected avian dispersers of *Q. tomentella* acorns (Pesendorfer et al., 2018; Woolsey et al., 2018). Acorn woodpeckers (*Melanerpes formicivorus*) are widespread across California, including the California Islands, but the details of island oak-woodpecker interactions are unclear (Standiford & Purcell, 2015). Santa Cruz Island is currently the only island with scrub jays, and similarly, the degree of their island oak acorn dispersal is still being determined (Pesendorfer et al., 2018). A lack of common and frequent dispersal agents for larger seeds on the islands has reduced seedling recruitment in suitable areas both within and away from current oak stands. Formerly, the jay lived on more of the Channel Islands but was pushed to extinction on all but Santa Cruz, likely by ranching activity (Pesendorfer et al., 2018). A simulation of jay reintroduction on Santa Rosa Island saw more rapid spread of island scrub oaks (*Quercus pacifica*), covering four times that of the area simulated without jays after 200 years (Pesendorfer et al., 2018). Even on Santa Cruz Island, scrub jays are rarely observed carrying *Q. tomentella* acorns, possibly because of the seed size or because they are less common than the other acorns stored by scrub jays (McEachern, 2018). However, according to John Knapp (The Nature Conservancy; Island Ecologist), the existence of saplings located above mature *Q. tomentella* suggests that scrub jays are significantly involved in their dispersal (Personal comm., 2018). Kindsvater (2006) also reported that ravens may disperse island oak acorns.

Pigs specifically have a significant impact on *Q. tomentella* seed dispersal. Before they were removed from Santa Rosa and Santa Cruz Islands, rooting and seed predation likely contributed to limited seedling establishment. Grazing by invasive herbivores and the trampling of acorns and seedlings have also limited growth and survival (Kindsvater, 2006). Climate change may further impact *Q. tomentella*'s limited reproduction and shrinking populations. A recent study developed establishment niche models for two California oak species (*Quercus douglasii* and *Quercus kelloggii*) using climate variables (Davis et al., 2016). The model projected the distribution of the trees' establishment niches into the future under moderate and extreme climate change model projections. The study found that the opportunities for seedling establishment would shrink spatially and temporally with climate change. Based on *Q. tomentella's* similar seedling establishment preferences, it is likely to experience comparable restrictions.

## Genetic Diversity

Ecologists have been concerned that *Q. tomentella* may have experienced a genetic bottleneck in the last century due to human and grazing impacts which increased rates of clonal reproduction (Ashley, Abraham, Kindsvater, Knapp, & Craft, 2007). High rates of clonality may cause lower pollen production and limit sexual reproduction potential. Ashley et al. (2007) found that several populations on Santa Catalina Island relying primarily on clonal growth had very low genetic diversity. Though oaks are not known to have self-incompatibility, self-fertilization, even when hand pollinated, is rarely successful (Fernández-M. & Sork, 2005). Additionally, sterile acorns sometimes result from successful self-fertilization (Kindsvater, 2006). Consequently, in stands with a significant amount of clonal growth, pollen production is low. This is potentially because clones produce less pollen, since self-fertilization is not a viable reproductive option. Lower pollen production limits those population's ability to outcross with other local individuals or with other nearby populations.

However, a recent study revealed that the species still contains significant genetic diversity (Ashley et al., 2018). Each island's populations are genetically distinct and contain unique alleles not observed on other islands; Guadalupe Island is the most genetically distinct of the six (Ashley et al., 2018). Outcrossing potential, which would support *Q. tomentella'*s ability to adapt to changing conditions while maintaining viable populations, remains high (Awad, Gallina, Bonamy, & Billiard, 2014).

## Hybridization

*Q. tomentella* belongs to the *Protobalanus* (intermediate) section of the *Quercus* genus (Nixon, 2002), which also contains *Q. chrysolepis, Q. vaccinifolia,* and *Q. palmeri.* Intermediate oaks have features similar to both white and red oaks, though morphological and molecular studies have shown they are more similar to white oaks. Oaks within the *Protobalanus* section hybridize when they occur in the same location, but not with oaks from different sections. *Q. chrysolepis* and *Q. tomentella* have overlapping ranges and the two commonly hybridize. A genetic study of *Q. tomentella* found that where its range overlaps with *Q. chrysolepis,* it can be difficult to assign individuals to either species, and that the two are not well-differentiated in some areas, especially Santa Catalina Island (Ashley et al., 2018).

# Current Status

Though most historical threats have been removed from the islands in recent years, legacy impacts from grazers are still widespread, and *Q. tomentella* is still encumbered by damaged and fragmented habitat. In response, restoration programs such as the construction of fog fences to increase fog capture and erosion control, have been implemented on some islands (Kindsvater, 2006). Island ecologists have observed population increases on Santa Cruz. Santa Rosa Island is thought to have an overall declining population with the exception of some groves, such as those on Black Mountain, that are experiencing an increase in seedling establishment (Woolsey et al., 2018). The continued presence of non-native herbivores on Santa Catalina Island continues to contribute to the decline of the island's *Q. tomentella* populations. The remaining ungulates hinder island oak seedling establishment and growth (Knapp, 2014). Anacapa has seen the extirpation of a grove of the island oak during the 1980s (K. McEachern, Personal comm., 2019). Island oaks on San Clemente are thought to be declining as well (J. Knapp, Personal comm., 2018). The single grove on Guadalupe Island is not expected to survive under current climate trends (J. Knapp, Personal comm., 2018).

In summary, *Q. tomentella* is at risk of being highly susceptible to climate change. The species tends to exist in relatively cool places on the islands, and those places are likely to shift. However, so much of the islands have been damaged by land use and grazing, available island oak habitat is more limited than it otherwise would be, so shifting will be particularly challenging or impossible. That challenge paired with a lack of seedling establishment and regeneration due to degraded habitat where subpopulations currently exist make *Q. tomentella* habitat and population restoration necessary, in order to increase the species' resistance and resilience to climate change. This project aims to provide more information that will help island ecologists and managers develop adaptive, climate change resilient *Q. tomentella* restoration strategies to help the species recover from past impacts and successfully adjust to climate change.

# Methods

## Conceptual Overview

To assess the vulnerability of *Quercus tomentella* (island oak) to future changes in climate, we performed presence-only species distribution modeling for the species across a selection of its range on the Channel Islands under current and projected future climate conditions. Species distribution models (SDMs) provide statistical estimates of the relationship between recorded species presence points and the environmental and spatial characteristics at those locations that significantly influence species distribution (Franklin, 2010). SDMs are widely applied modeling tools for determining probable species distributions to inform conservation management strategies, particularly for endangered and endemic species that are otherwise difficult to fully model (Elith et al., 2010, 2011; Franklin et al., 2013; Guillera-Arroita et al., 2015; Guisan et al., 2013; Riordan, Montalvo, & Beyers, 2018).

Figure 1 gives a conceptual overview of our analytical approach. We gathered necessary species presence points and environmental layers for modeling the distribution of the island oak. Environmental layers include non-climate island-specific variables, climate layers, and fog layers. The project approach and extent of analysis is based in part on data availability and quality. We successfully acquired all necessary data for Santa Cruz, Santa Rosa, and Santa Catalina Islands, so these islands were the focus of our analysis. All available data was processed into a format compatible with species distribution modeling, which requires extremely precise extent and projection alignment across layers. The SDM was calibrated based on environmental layer contribution to model fit. We selected environmental layers that best contributed to model fit and predictive power as variables for final SDM iterations. We chose model parameters and settings that maximize the validity of the results. Finalized iterations were run across current and future scenarios of climate change to explore the climate niche of the island oak and to model predicted habitat distribution, which was interpreted as the probability of presence of the island oak under various climate change scenarios. Lastly, we analyzed results to assess the climate vulnerability of island oaks across the area of study.

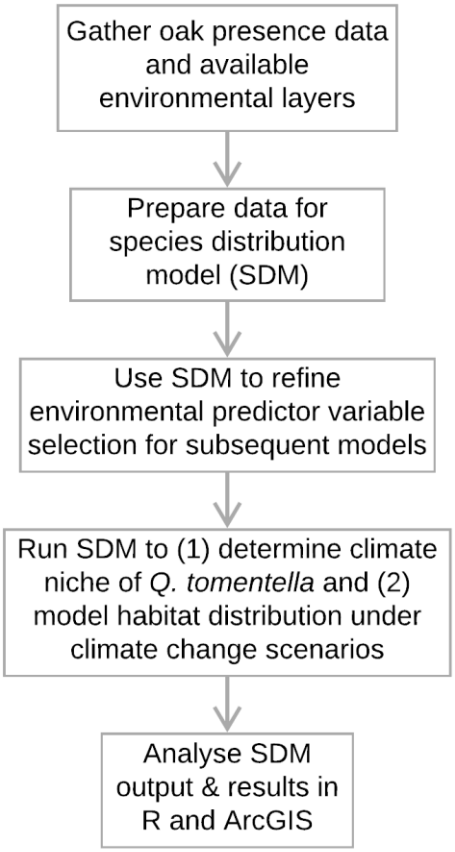
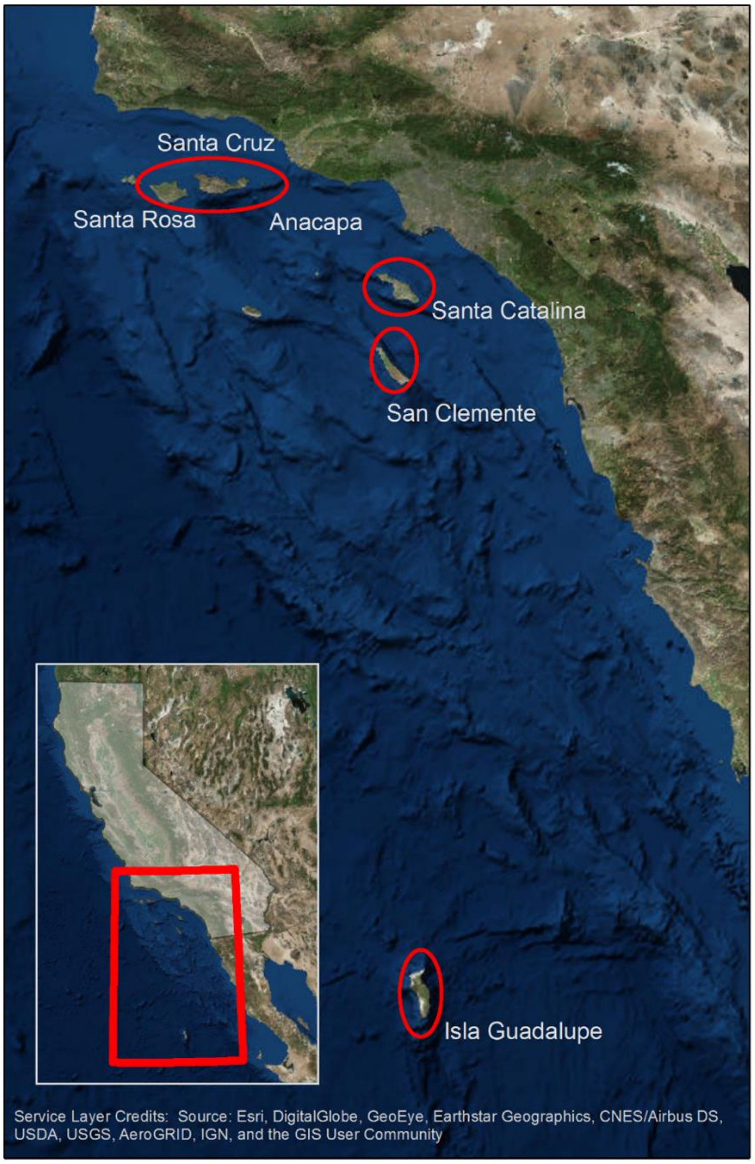


**Figure 1. Conceptual overview of analysis.** We first acquired and prepared all necessary data. Preliminary model runs determined variables used in the final iterations. Final analyses were performed after running the SDM to determine species niche and predicted habitat distribution.

# Data

## Presence Points

Presence points for species distribution modeling were compiled for three islands where the species currently resides: Santa Cruz, Santa Rosa, and Santa Catalina. These islands were the focus of the analysis because they have the three largest island oak populations and had the most complete presence point data available (Figure 2). In total, our analysis identified 1001 island oak points on Santa Rosa Island, 271 points on Santa Cruz, and 163 points on Santa Catalina. Current rough estimates of island oak numbers on the other three islands are 36 to 56 individuals on Guadalupe, at least 78 on San Clemente with limited information on an upper range, and less than about 20 trees total on Anacapa. These rough estimates were derived from the limited point data we received from island managers, which is incomplete and often lacked useful spatial information. This, combined with limited or no environmental layer information for these islands, prevented their inclusion in the analysis. While the presence data we have available for Santa Cruz, Santa Rosa, and Santa Catalina is not a full enumeration of presence, we do believe that the datasets include the majority of island oak presences on these islands. Although there is uncertainty in the possibility of missing points due either to systematic sampling bias or random sampling absences, we did not include any sampling bias layers in our analysis. The comprehensiveness of the available island oak presence data, its consistency with other analyses of the species, and direct contact with data sources minimized our concern that sampling biases would substantially impact our results (Ashley et al., 2007, 2018; Kindsvater, 2006; Pesendorfer et al., 2018). We recommend including a bias layer in future analyses if systematic sampling bias becomes more evident.



Service Layer Credits: Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community

**Figure 2. Extent of *Q. tomentella* range.** Extent of *Q. tomentella* range in the California Island Archipelago (California and Baja, Mexico). Red circles and labels indicate the six islands where the species currently exists.

Presence point data of island oaks on Santa Cruz, Santa Rosa, and Santa Catalina Islands were provided by The Nature Conservancy, the NPS and Laura Kindsvater, and the CIC, respectively. Presence points represent a mixture of individual trees, multiple individuals, and entire groves. Though the data does not account for every individual, it likely accounts for most locations where island oaks are found on these three islands. Presence data for Santa Rosa includes some demographic information, including seedling, sapling, and adult designations for a subset of data points. This allowed for stage-specific analyses of the population on this island.

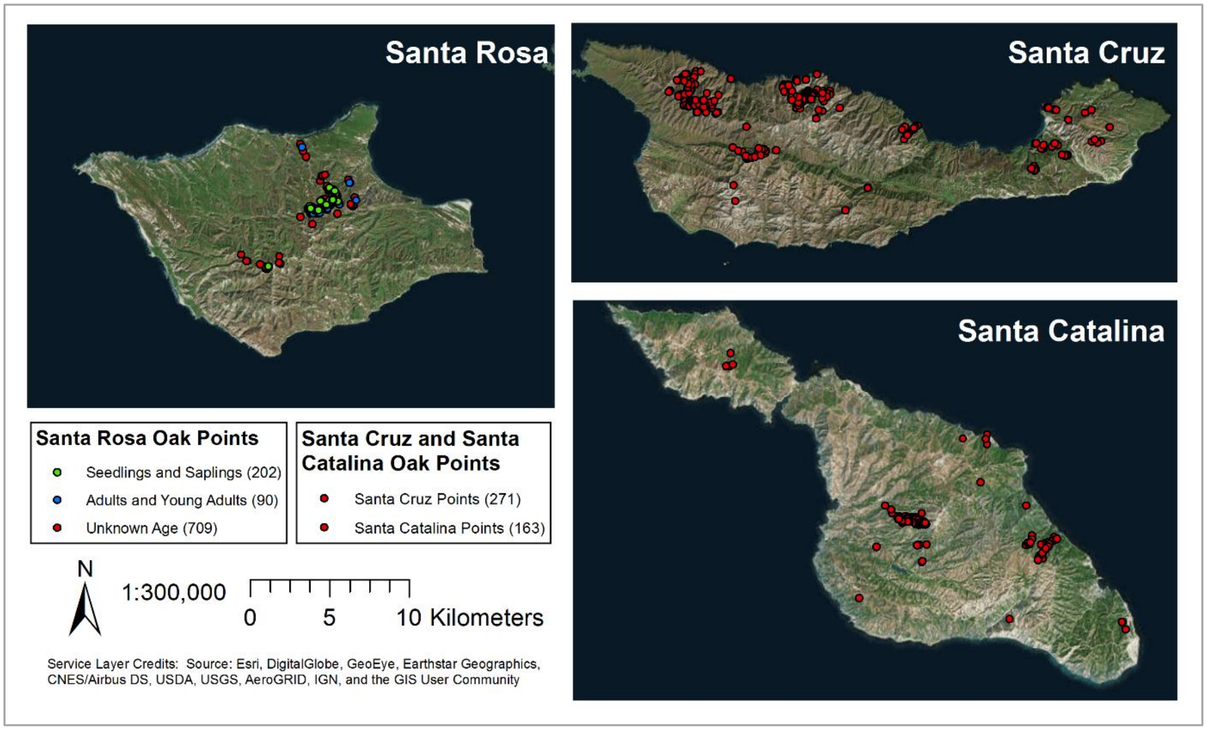
Presence data for both Santa Cruz and Santa Rosa were collected from 2003 – 2004, 2006 – 2007, and in 2018 by multiple researchers and compiled by Laura Kindsvater. Data was recorded either with satellite imagery or from GPS coordinates recorded in the field. Oak points for Santa Cruz were updated in 2018 by Wildlands Conservations Science using aerial surveys to estimate GPS coordinates. Original data for both islands was received from the National Park Service as a shapefile of points containing all of the data compiled from Laura Kindsvater's dissertation (2006). Wildlands Conservation Science provided the updated presence locations for Santa Cruz Island. The original layer contained GPS coordinates of other plant species, such as *Quercus pacifica,* and soil samples. Points containing information on anything other than island oak were manually filtered out line-by-line, as the compilation of data from multiple researchers led to a non-uniform data structure and formatting.

Santa Cruz Island required no additional data cleaning other than eliminating oak points that were recorded on Santa Rosa but were included in the Santa Cruz oak point layer. This was completed within ArcGIS and resulted in 271 total oak points on Santa Cruz. For Santa Rosa Island, Laura Kindsvater provided additional oak points to those provided by the NPS, which were originally sent as circular polygons. The latitude and longitude coordinates for these points were derived as the center value of each circle. Stage information was provided for a selection of these points in the shapefile attribute table. In total, there were 1,001 points on Santa Rosa, and from those, 90 were identified as adults or young adults and 202 as seedlings or saplings.

Santa Catalina presence points were collected and recorded in the field from 2001 – 2007 by Denise Knapp, John Knapp, Bill Thorne, Steve Junak, and other CIC researchers using a trimble GPS device. The shapefile provided with the point information contained information for other species in addition to the island oak. Each point was individually assessed and filtered from the shapefile, as the underlying dataset was compiled from multiple researchers without a consistent overarching structure, which made it difficult to filter iteratively. The process resulted in a total of 163 island oak presence points on Santa Catalina.

We were unable to acquire or utilize point location data for the oaks on Anacapa, San Clemente, and Guadalupe Island due to several island-specific challenges. Channel Islands National Park ecologists could not provide oak point data for Anacapa Island. San Clemente is owned and operated by the U.S. Navy, which was not able to provide the data necessary to perform these analyses in a timely manner. Guadalupe Island is owned by the city of Ensenada in Baja California, Mexico, and our primary contact organization was the conservation group Grupo de Ecología y Conservación de Islas (GECI). However, GECI has been preoccupied with more urgent conservation issues on the island and could not provide all of the necessary data.

Figure 3 displays the island oak presence points found on each island. On Santa Rosa the oaks are distributed in two large subpopulations near the center of the island, with the larger cluster to the northeast and the smaller cluster southwest of center. Santa Rosa oak points with known stage structure data are mainly located in the Black Mountain area in the northeastern portion of the island, as indicated by the multicolored points. Santa Cruz populations are more spread out, with two larger clusters on the north slope of the northern range on the western side of the island. There is another cluster along the Santa Cruz Island Fault towards the western side of the island. There are also scattered groves on and east of the isthmus. Most of Santa Catalina's oak points are located in two main clusters that are smaller than any of the large clusters on the other two islands. Smaller groups are scattered across the island, with several in more coastal areas.


Santa Rosa

Santa Cruz

Santa Catalina

Service Layer Credits: Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community

**Figure 3. Current distribution of island oak presence points for three Channel Islands.** Oak presence points are displayed for Santa Rosa (farthest west), Santa Cruz (middle), and Santa Catalina (farthest south). Red points indicate island oaks points without known stage information. Green points on Santa Rosa represent island oak seedlings and saplings while blue points represent adults.

## Environmental Layers

### *Non-Climate*

We obtained non-climate environmental layers including elevation, vegetation, and soil layers for potential use in the SDM as well as for understanding and interpreting oak presence. We acquired Channel Islands Continually Updated Shoreline Products (CUSP) from the National Oceanic and Atmospheric Administration (NOAA) National Geodetic Survey. This data acted as the extents used for cropping all environmental layers used in the SDM. These outlines are downloadable from https://www.ngs.noaa.gov/CUSP/. More detailed information on the non-climate environmental layers can be found in Appendix A.

Elevation layers were received for Santa Cruz, Santa Rosa, and Santa Catalina from The Nature Conservancy, the National Park Service, and the CIC respectively. Elevation layers were provided as digital elevation models (DEMs) in raster format, from which we calculated slope and aspect. DEMs for Santa Cruz and Santa Rosa were provided by The Nature Conservancy and NPS and were created at a 1-meter resolution by the United States Geological Survey (USGS) National Geospatial Program using LiDAR to create hydroflattened DEMs. The DEM for Santa Catalina was provided by the CIC and was at a 5-foot resolution and was created by EagleView Technologies, Inc. for LARIAC using LiDAR data.

The vegetation layers for each island were provided by the same sources as the DEM layers, and were available as multipolygon shapefiles. The vegetation layers for Santa Cruz and Santa Rosa were created by Aerial Information Systems, Inc., contracted by the NPS through the Santa Barbara Botanic Garden to create a detailed vegetation map. The vegetation map was created from digital orthophoto imagery from 2012 used as a base for georeferencing and photo interpretation. Vegetation classifications and descriptions for mapping were based on the National Vegetation Classification Standard floristic vegetation classification system. The application of the classification to the islands utilized standards taken from the Channel Islands National Park Floristic Vegetation Descriptions, the Floristic Vegetation Key, and data sampled from the field. For Santa Catalina Island, aerial photographs and contact prints were obtained by the CIC from I.K. Curtis Services Inc. and the prints were spatially referenced through ER Mapper software. ArcMap was then used to mosaic and digitize the vegetation polygons. The vegetation polygons were validated from over 600 points randomly sampled in 2006. The classification scheme implemented for Santa Catalina is similar to the one used for Santa Cruz and Santa Rosa, although there are inconsistences between the two. For species distribution modeling, vegetation information is needed in a more generalized and distinct categorical raster format; therefore, we classified the vegetation cover layers for all islands into seven categories in R based on a species-to-vegetation class table developed by referencing similar studies (methods in Appendix A).

Soil maps and relevant soil tables for each of the islands were obtained from the U.S. Department of Agriculture National Resources Conservation Service Web Soil Survey, accessible and downloadable at:

https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx (Soil Survey Staff, NRCS, USDA). For the Channel Islands, the digital soil surveys were developed by the National Cooperative Soil Survey. The soil layers were prepared by digitizing and georeferencing data from detailed field verified soil inventory across the island landscape. Unique soil polygons were given soil map units, which are linked to attributes in the National Soil Information System relational database. Unfortunately, soil information was provided for vertical layers within these large and unique soil polygons, so changes in soil across the horizontal landscape were both difficult and meaningless to calculate.

## Climate

Downscaled current and projected future climate data was sourced from the Basin Characterization Model (BCM) (Flint et al., 2013). The climate layers are available for download from CalCommons at http://climate.calcommons.org/dataset/2014-CA-BCM (The Climate Commons). To develop the current and projected grid-based climate information, BCM simulates hydrologic responses to climate changes based on a monthly regional water-balance model. The model incorporates landscape-level attributes including topography, soils, and geology to perform water balance calculations for 159 watersheds across California. The individual watersheds are used to define sub-regions for model calibration. Santa Cruz and Santa Rosa Islands are in the Santa Barbara Channel Islands watershed, and Santa Catalina Island is in the San Pedro Channel Islands watershed. This climate model is appropriate for studying the Channel Islands as it provides valuable historical parameter data potentially affecting island oak distribution and is relatively high resolution for climate data at 270 meters.

The BCM model spatially downscales PRISM data at 800 meters to 270-meter gridded spatial resolution using the gradient-inverse distance squared approach (GIDS). The PRISM datasets were created by using a “Parameter-elevation Relationships on Independent Slopes Model” interpolation method and are available at http://www.prism.oregonstate.edu/. This methodology calculates climate-elevation regressions for each DEM grid cell on the basis of interpolated regional and local weather station information, with stations weighted based on physiographic similarity between each station and the grid cell (Daly et al., 2008). Physiographic similarity factors include elevation, location, topographic position, coastal proximity, orientation, terrain, and vertical atmospheric layer. Station data is accumulated from a variety of available sources, including National Weather Service Cooperative Observer Program, Weather Bureau Army Navy stations, and USDA Forest Service and Bureau of Land Management Remote Automatic Weather Stations (RAWS) (Daly et al., 2008). PRISM layers assume that elevation is the most important variable for determining localized temperature and precipitation.

The coverage of BCM climate layers limited the extent of our analyses. Full coverage was available for Santa Cruz and Santa Rosa Islands and partial coverage of a large portion of Santa Catalina was available. However, BCM data was not available for Guadalupe Island and was sparse for Anacapa and San Clemente Islands. Alternate climate data sources are available for these islands but are at courser resolution not suitable for this analysis. Due to the partial coverage on Santa Catalina we extrapolated the available climate layers to the full extent of the island using universal co-kriging, and then performed our SDM analysis for the island using both extrapolated and non-extrapolated data. Elevation from the island's DEM served as the co-kriging variable. Further information on the kriging methodology is available in Appendix A and the R script performing the extrapolation is available in Appendix C. All BCM data is in the NAD 83 Teale Albers Conical projection, which is the projection used throughout our analysis.

These climate data are available for download as 30-year averages for annual, monthly, and seasonal time steps for three historical time periods and projected to three future time periods using various GCMs with a range of emissions scenarios. Nine variables are available as averages, standard deviations, and detrended standard deviations: precipitation, maximum temperature, minimum temperature, climatic water deficit, potential evapotranspiration, actual evapotranspiration, April 1st snowpack, recharge, and runoff. Of these variables, we downloaded annual averages of all variables except April 1st snowpack, which is irrelevant for the Channel Islands. Additionally, we downloaded average winter minimum temperature and average maximum summer temperature, as these are better predictors for western tree species distributions than annual averages (Sork et al., 2010). We selected the historic time period 1981 – 2010 to represent current climate, and the projected time periods 2010 – 2039, 2040 – 2069, and 2070 – 2099 for future climate representations. We also used early 20th century time periods 1921 – 1950 and 1951 – 1980 to examine past climate range. Throughout the paper, the baseline time period for comparison is the 1981 – 2010 climate data. This time period will be referred to as "historic" in relation to the three future climate projections and is the representation of the "current" climate.

As there is inherent uncertainty in modeling future climate, we included multiple climate projections to account for the variability of predicted future climate ranges. BCM has datasets for 18 future climate scenarios based on various combinations of GCMs and representative concentration pathway emission scenarios (RCPs). GCMs are numerical models that simulate Earth's climate system based on atmospheric processes and vary based on how atmospheric processes are modeled. RCPs are greenhouse gas emissions scenarios adopted by the Intergovernmental Panel for Climate Change (IPCC) to represent future possible climate pathways. We selected four future scenarios from the 18 available to represent the potential spectrum of future climate ranges in California, as is common practice for similar climatic niche species modeling (Davis et al., 2016). The four scenarios chosen to represent the variance of future climate were two RCP4.5 projections—MPI for warm-wet and MIROC for warm-dry—and two RCP8.5 projections—CCSM for hot-wet and MIROC for hot-dry.

The four climate scenarios were developed from a variety of originating groups, but all four assessments were included in the 5th IPCC Assessment report and were downscaled using bias correction spatial downscaling (BCSD) methodologies (Flint & Flint, 2012). MPI RCP4.5 was developed by the Max Planck Institute (MPI) for Meteorology, while CCSM4 RCP8.5 was developed by the U.S. National Center for Atmospheric Research, with funding from the National Science Foundation, Department of Energy, and NASA, as the fourth version of the Community Climate System Model by the agency. MIROC RCP4.5 was developed from a combined effort by The University of Tokyo Center for Climate System Research, the Japan National Institute for Environmental Studies, and the Frontier Research Center for Global Change. MIROC RCP8.5 was developed by the Japan Agency for Marine-Earth Science and Technology and the Atmosphere and Ocean Research Institute at The University of Tokyo. MIROC stands for the Model for Interdisciplinary Research on Climate developed by the collaborators on both MIROC projections. The four projections differ in how the model coupling processes define ocean-land-atmospheric interactions, which results in varied predictions of future climate.

These four scenarios were chosen based on their use in previous species distribution modeling studies in California and on expert opinion (Davis et al., 2016). We believe that the chosen scenarios encapsulate variations in climate projections most likely to be seen in California based on current emissions projections and climate analysis models. We chose four scenarios that are relatively biased toward hotter and drier predictions to represent the more likely cases for California if we continue on our current trajectory of warming (Figure 4). An RCP of 4.5 represents greenhouse gas concentrations leveling off by about 2050 and RCP8.5 illustrates business as usual (BAU), with global carbon concentrations continuing to increase into the future. Therefore, temperature increases in the 8.5 scenarios are generally greater than the 4.5 scenarios, but temperature is increasing relative to the current climate under all scenarios. Changes in precipitation are more uncertain, so the wet and dry scenarios represent deviations from the current climate, represented as the origin in Figure 4, but also in relation to the climate projection ensemble mean. For the wet scenarios we chose scenarios with relatively conservative increases in precipitation. While RCP2.6 is often the standard “best case” scenario used, it is exceptionally optimistic with regard to climate emission reductions in the next century and is highly unlikely given current emission projections and climate policy inaction. Therefore, in our analysis RCP4.5 serves as the “best case” scenario. Furthermore, in our analysis the MPI RCP4.5 is often referred to as the “best-case scenario” of the four as it predicts the lowest temperature increase and the highest precipitation increase, while MIROC RCP8.5 serves as the “worst-case” due to high predicted temperature increases and precipitation decreases.

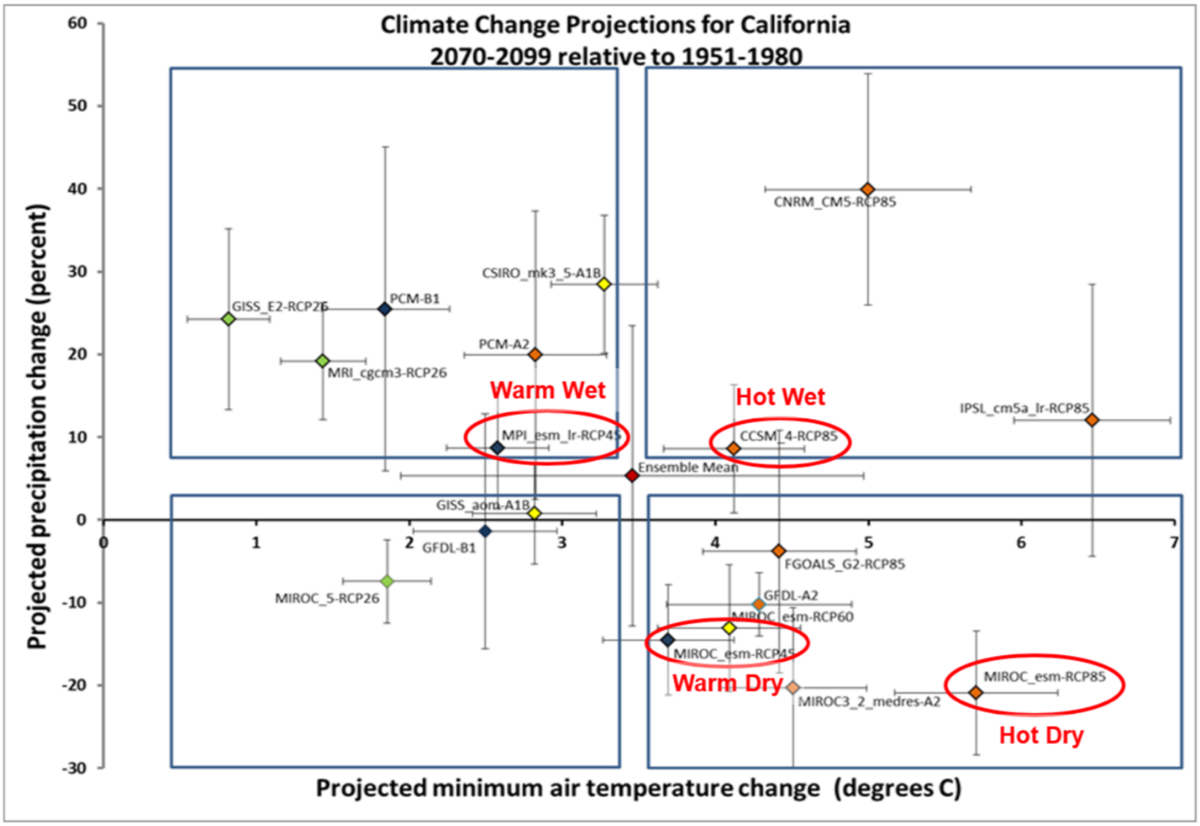


**Figure 4. BCM climate change projections for California.** Values represent projected temperature and precipitation changes in the 2070 – 2099 time period relative to the 1951 – 1980 time period for 30-year water means for 18 future climate projections. Bars represent the range of potential values in the California region. The projections that we chose for our analysis are circled in red. Figure sourced from the USGS California Basin Characterization Model page (Flint and Flint 2014).

From the available BCM layers, we selected climate water deficit, annual precipitation, maximum summer temperature, and minimum winter temperature as potential environmental variables for use in our analysis. Actual and potential evapotranspiration are encapsulated in climate water deficit while recharge, runoff, and snow pack were all deemed irrelevant for our analysis, so these variables were not included. We selected maximum and minimum temperatures because they are believed to have a larger impact on oak presence than averaged annual temperatures. The current (1981 – 2010) distributions of these climate variables across the extent of our analysis are shown in Figure 5. Santa Rosa and Santa Cruz are considered part of the northern islands and have climates more similar to each other than to Santa Catalina, which is about 150 km to the southeast and is warmer and drier.

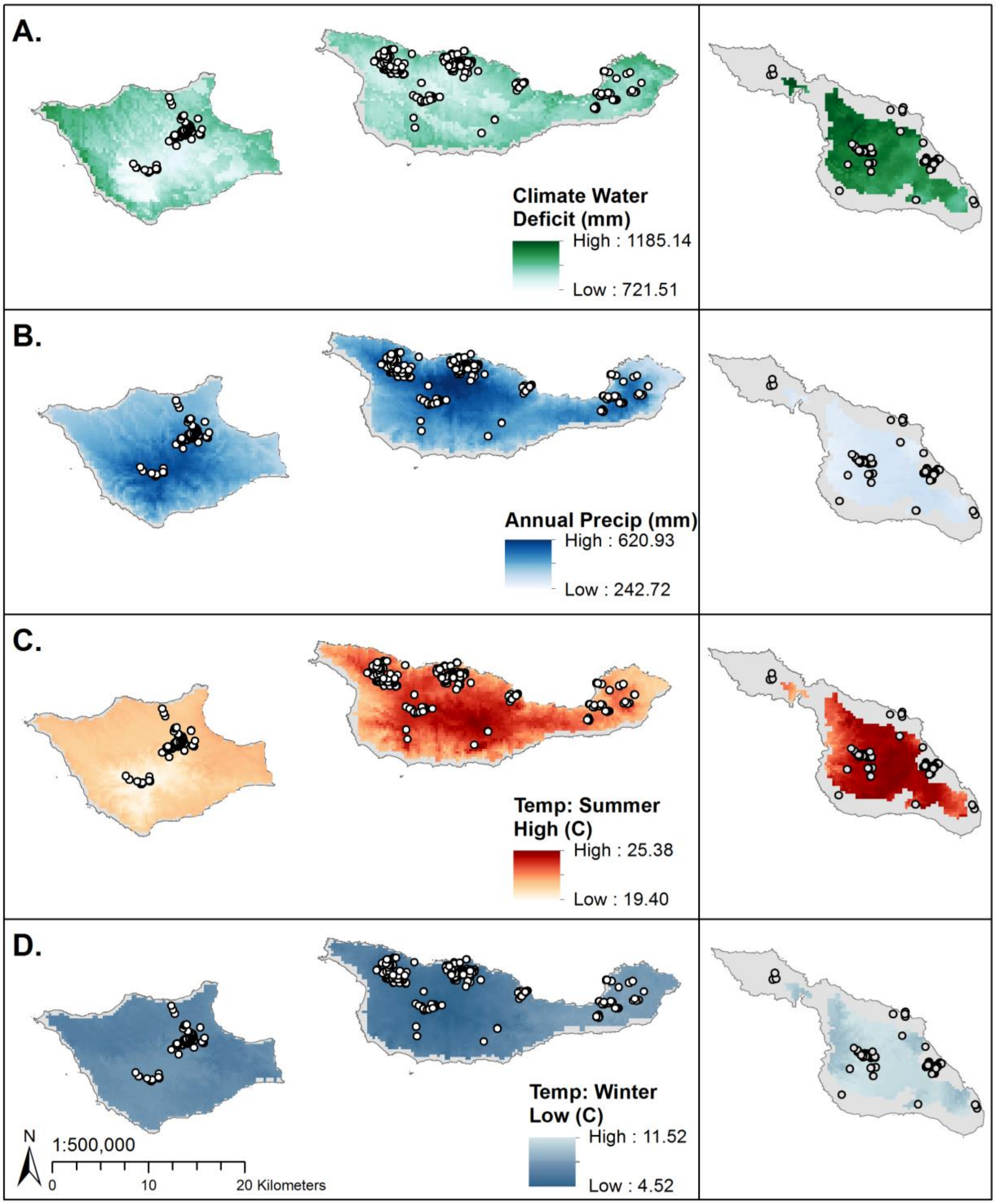


Figure 5. BCM climate variables for the three islands under current climate conditions (1981-2010). The variables from top to bottom: A) climate water deficit, B) annual precipitation, C) maximum summer temperature, and D) minimum winter temperature. White circles represent oak presence points.

The current climate conditions indicate that climate water deficit varies between 722 – 1185 mm, with Santa Catalina having the highest climate water deficit and Santa Rosa and Santa Cruz having much lower climate water deficit values (Figure 5). Annual precipitation varies from 243 – 621 mm and is much higher on the northern islands than Santa Catalina. Maximum summer temperature ranges across the islands from 19 – 25 °C, with the highest temperatures on Santa Cruz and Santa Catalina. Minimum winter temperatures range from 4 – 12 °C, with the northern islands having much lower values than Santa Catalina. Future projections of these four BCM climate variables are displayed in Figure 6 compared to the four climate projections to the current (1981 – 2010) climate distributions found on each of the three islands.

Figure 6 illustrates the changes in each environmental layer in the 2070 – 2099 time step in the four projections that we chose for each island as compared to the historic conditions (1981 – 2010). Different projections correspond to approximately uniform shifts in each climate variable range for all islands. For example, in the MIROC RCP8.5 projection, temperature increases from the historic value by about 5 °C on each island, shifting the temperature range on each island hotter by about 5 °C. This indicates that we will see the same relative differences in climate between the islands as we see currently, shown in Figure 5 above. Although the shift in range on each island is uniform, the distribution of climate values within each island may change as seen in the changes in shape of some of the curves in Figure 6. This is most visually apparent in the climate water deficit graph for Santa Catalina. In the historic time period, the island's distribution has a relatively smooth curve, while the distributions for the wet scenarios (CCSM and MPI) have a dip in the middle of the curve and the dry scenarios (MIROCs) have a sharper peak in their curves.

Furthermore, Figure 6 allows for the comparison of climate variable values between different climate projections on each island. For each climate variable, the MIROC RCP8.5 projection exhibits the most extreme changes in relation to current climate. When compared to current climate, the MIROC RCP8.5 scenario has a greater decrease in precipitation, increase in climate water deficit, and increase in maximum and minimum seasonal temperatures than the other three projections. Additionally, changes in predicted temperature and precipitation vary more clearly across projections than climate water deficit, which changes more subtly.

The hot scenarios (RCP8.5) have noticeably higher increases in minimum winter temperature than the warm scenarios (RCP4.5), and the drier scenarios (MIROCs) have larger magnitudes of decrease in precipitation than the magnitude of increase in precipitation for the wet scenarios (MPI and CCSM). The dry projections (MIROCs) have larger changes than the wet scenarios, with increased climate water deficit and decreased precipitation; the wet scenarios have relatively similar climate water deficit and precipitation to the current climate distribution. Furthermore, for the wet scenarios, differences in climate water deficit are hard to detect, but the distribution of values does change within each island. Climate water deficit increases for CCSM and MPI, even though both are wet projections, indicating that even though these are 'wet' projections, increases in temperature are driving an increase in climate water deficit. This is especially apparent for CCSM, as it is the hotter scenario experiencing a greater increase in temperature, therefore experiencing a greater shift in climate water deficit.

Additionally, Santa Catalina has much clearer shifts than the other two islands across the climate variables, as it has an overall more restricted climate distribution across variables, particularly for precipitation. Santa Cruz and Santa Rosa have broader climate distributions that are more subtly impacted by predicted climate variable change. Santa Cruz in particular has the widest distribution across most variables.

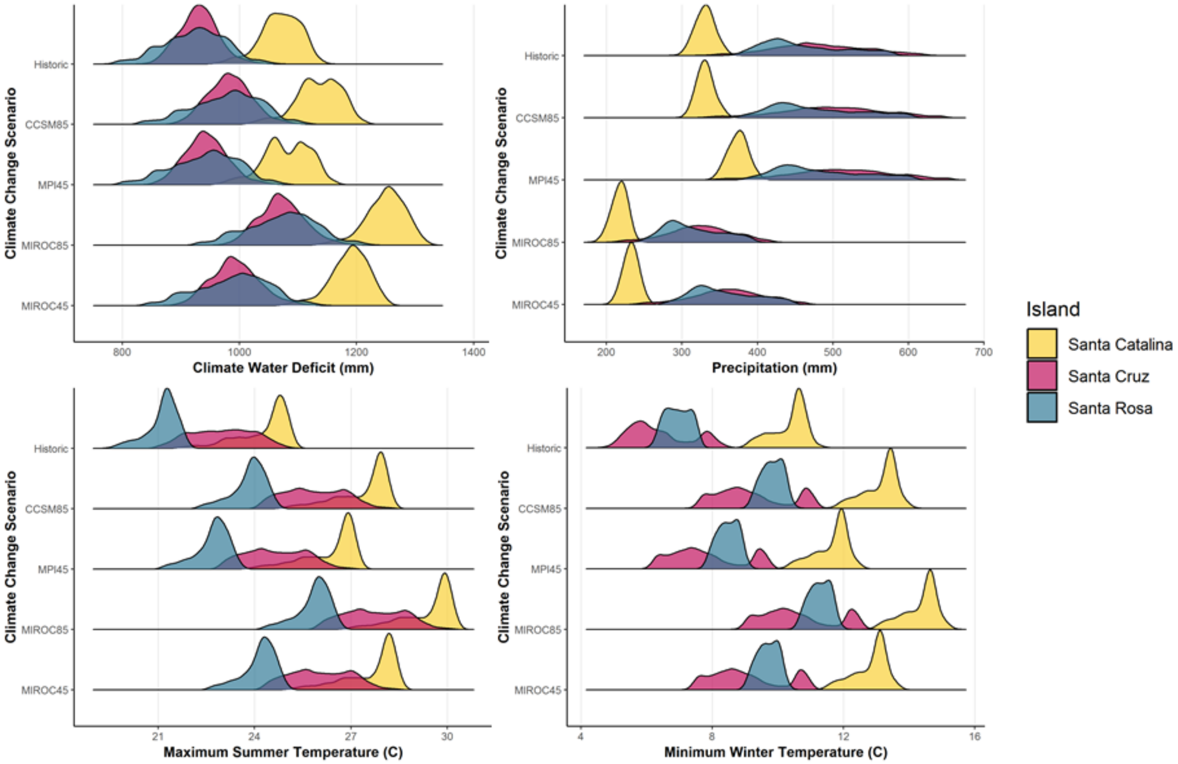


**Figure 6. BCM climate variables for the three islands comparing projected climate conditions (2070 – 2099) to historic (1981 – 2010).** The historic BCM layer represents current climate conditions. The variables from top left to bottom right: A) climate water deficit, B) annual precipitation, C) maximum summer temperature, and D) minimum winter temperature. The different colors represent each island: Santa Catalina is yellow, Santa Cruz is pink, and Santa Rosa is blue.

## *Fog*

The layers depicting probability of fog inundation for Santa Cruz and Santa Rosa Islands were acquired from Rastogi et al. (2016), in which fog is defined as cloud intercepted by the land. In the paper, probability of fog inundation in a given 100-meter pixel was calculated by multiplying the probability of cloud cover by the probability of that pixel being at a higher elevation than the cloud base, with values ranging from 0 – 1. Overall, current fog patterns are highly related to elevation. Fog inundation probabilities were averaged over May through September from 2001 to 2012, and rely on a downscaled spatial and temporal model of cloud cover and past fog patterns. We selected this data to approximate fog on the islands as no direct measurements or models of fog distribution are available for the CAIA. After processing (Appendix A1), this probability of fog inundation layer was used to represent current fog conditions on Santa Cruz and Santa Rosa Islands. No fog data was available for Santa Catalina Island.

Four future fog scenarios were created for Santa Cruz and Santa Rosa by modifying the current fog layer based on historic trends of fog occurrence cited in the literature (LaDochy & Witiw, 2012; Perkins et al., 2012; Williams et al., 2015). These scenarios include: 1) fog remaining constant, 2) fog decreasing overall, 3) fog increasing overall, and 4) fog increasing below an elevation threshold of 255 meters and decreasing above it. Figures 7 and 8 display the probability of fog inundation in the four fog scenarios for Santa Rosa and Santa Cruz Islands at the end of the century (2070 – 2099). Current fog conditions are the same as the constant fog scenario in the top left of each figure. Increasing, decreasing, and elevation threshold fog predictions were calculated based on a 9% change every 30 years, resulting in a 27% change by the end of the century. For increasing and decreasing scenarios this translates to a 27% increase or decrease in probability of fog inundation by end of century. For the elevation threshold scenario this translates to a 27% increase in probability of fog inundation by end of century for elevations below the threshold, and a 27% decrease above that threshold by 2099. These values were derived from historic trends measured on San Nicolas Island and San Clemente Island and are described in detail below (Williams et al., 2015).

Since no measurements of fog are available from the northern islands and fog occurrence patterns can be highly variant at the high resolution of our analysis, the constant, increasing, decreasing, and elevation threshold scenarios approximate the trends measured at nearby stations. The measured trends of each fog scenario are as follows:

1. Constant fog: no significant change in fog occurrence was observed at either San Clemente Island (1960 – 2014) or coastal Santa Barbara (1948 – 2014), both of which are located near the Northern Channel islands (Williams et al, 2015);
2. Increasing fog: a significant 60% increase in fog was observed from 1948 – 2014 when observations from San Clemente Island and San Nicolas Island are averaged (Williams et al., 2015);
3. Decreasing fog: significant reductions in dense fog frequency have been documented near coastal Los Angeles during ENSO events (LaDochy and Witiw, 2012); and
4. Fog with an elevation threshold: a significant 40% increase in fog on San Nicolas Island was observed as a decrease in cloud base height but overall no significant change in stratus frequency (Williams et al., 2015).

All observations reported by Williams et al. (2015) define fog as the lowest 25% of stratus, with 255 meters set as the boundary height for fog on San Nicolas.

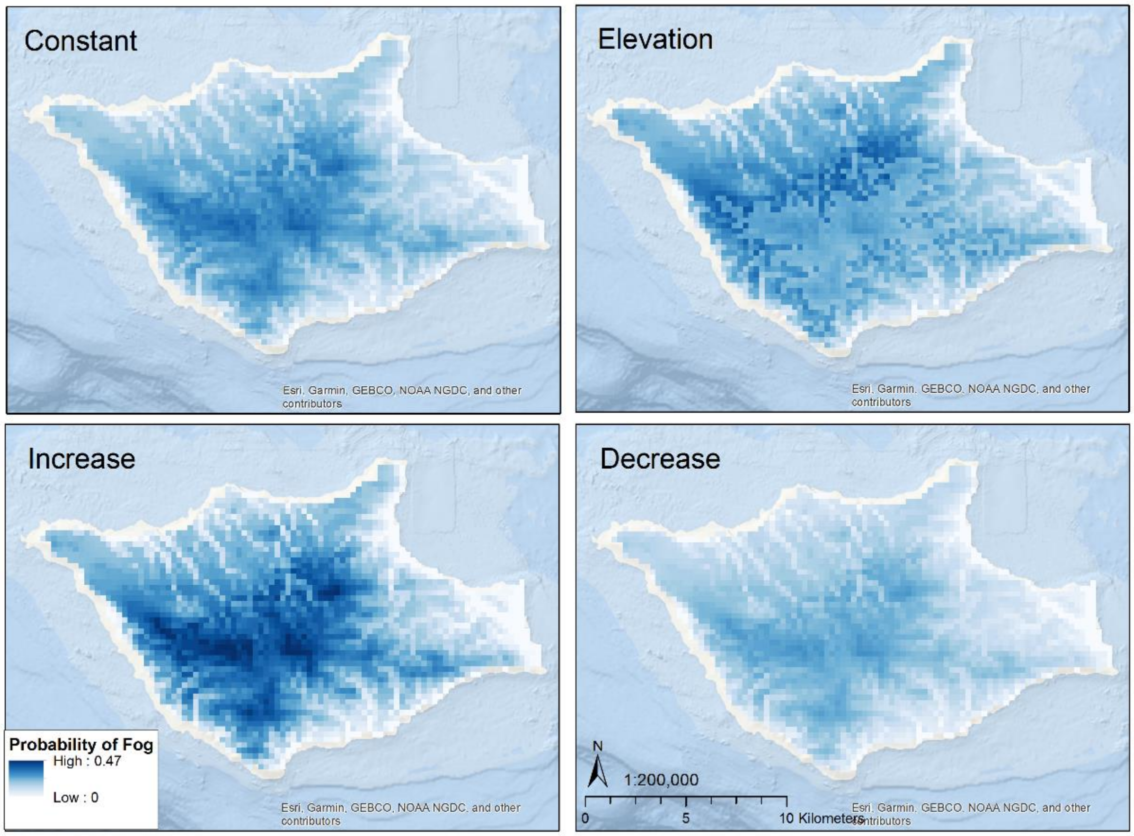


**Figure 7. Projected changes in fog inundation on Santa Rosa Island (2070 – 2099).** Constant fog (top left) is the same as current fog. Increasing, decreasing, and elevation threshold fog projections were calculated based on a 9% change every 30 years, resulting in a 27% change by the end of the century. The elevation threshold in the top right panel is 255 meters, above which fog decreased and below which fog increased. Darker blues indicate higher probability of fog inundation, with a maximum of 47%.

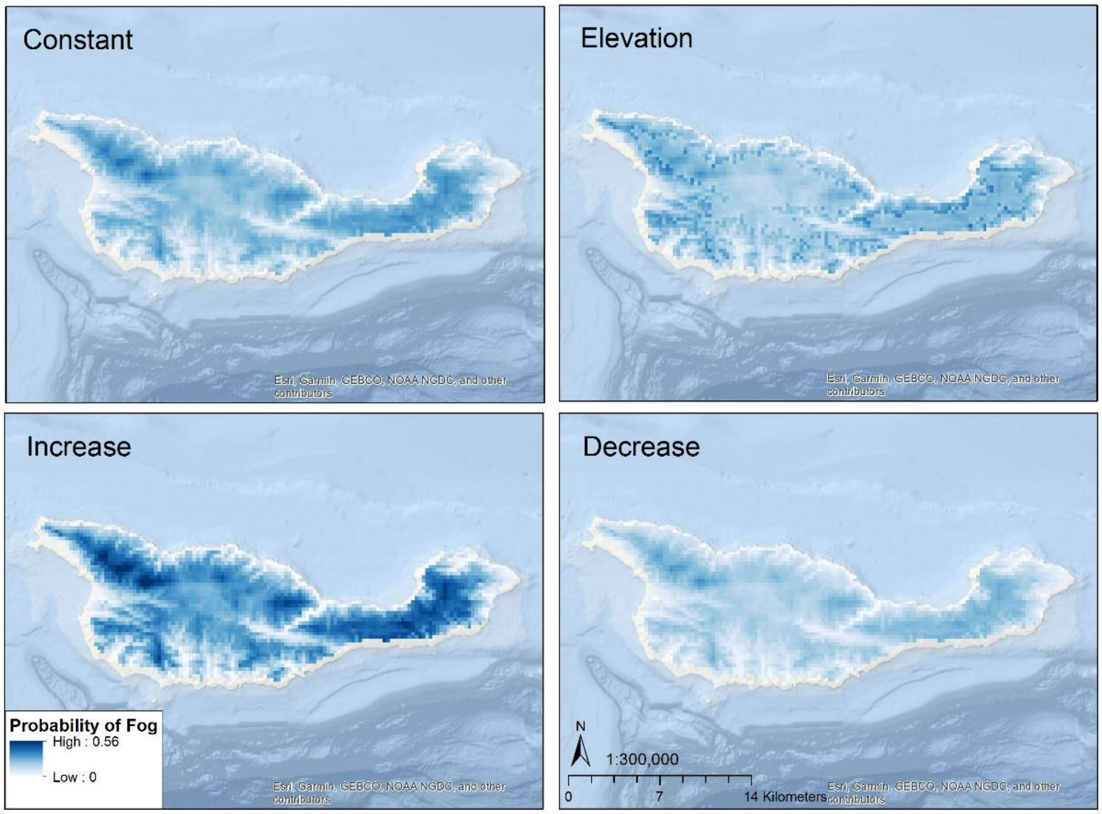


**Figure 8. Projected changes in fog inundation on Santa Cruz Island (2070 – 2099).** Constant fog (top left) is the same as current fog. Increasing, decreasing, and elevation threshold fog projections were calculated based on a 9% change every 30 years, resulting in a 27% change by the end of the century. The elevation threshold in the top right panel is 255 meters, above which fog decreased and below which fog increased. Darker blues indicate higher probability of fog inundation, with a maximum of 56%.

The four fog scenarios attempt to account for some of the uncertainty in how future climate and oceanic changes will likely impact the formation and distribution of fog. The constant fog scenario acts as a control, as it keeps the current probability of fog inundation values constant across all future time periods. This scenario also corresponds to historic trends measured at Santa Barbara and San Clemente Island individually (Williams et al., 2015). The decreasing fog scenario accounts for possible reductions in fog formation that may occur during the increasing intensity, frequency, and duration of ENSO events (Perkins et al., 2012; LaDochy and Witiw, 2012). Even if fog formation increases under non-ENSO periods, the significant decrease in fog levels during ENSO periods could substantially impact island oaks and should be considered when predicting their future distribution. The increasing fog scenario augments fog probability based on the assumption that the historic trend of increasing fog averaged over San Nicolas and San Clemente islands continues through all time steps. More specifically, this increase is largely attributed to an increase in fog at San Nicolas, while San Clemente saw no significant change individually. When considering only data from San Nicolas, the station spatially and climatically closest to Santa Rosa and Santa Cruz, its significant 40% increase in fog appears as a lowering of the cloud base height, concentrating stratus into the lower elevations. The elevation threshold scenario approximates this trend by increasing fog below an elevation threshold and decreasing fog above the threshold.

Although historic observations in fog inundation were available for two weather stations within the CAIA, the value of the percent change for the increase, decrease, and elevation scenarios was developed from only the San Nicolas station. We focused on the trends from San Nicolas rather than San Clemente because they are more likely to be similar to those on the northern islands; of the two stations, San Nicolas is located closer to Santa Rosa and Santa Cruz than San Clemente is. Also, San Nicolas, Santa Rosa, and part of Santa Cruz are located in the biogeological Oregonian province, which has a colder water regime than the Californian province that contains San Clemente (Pondella, Gintert, Cobb, & Allen, 2005). Although the other part of Santa Cruz is also in the Californian province, more area of the islands of interest are in the Oregonian province (Pondella et al., 2005). From 1948 – 2014, stratus above 255 meters decreased by 55% on San Nicolas, while stratus below 255 meters increased by 40% (Williams et all, 2015). The elevation threshold scenario was developed to account for these changes in cloud height that impact fog occurrence trends on San Nicolas. The relative spatial and oceanic similarity between San Nicolas and the northern islands makes the elevation threshold scenario the most robust prediction of fog on Santa Rosa and Santa Cruz out of the four fog scenarios, given that current trends continue into the future. The changes in fog for the increasing and decreasing scenarios were then derived from values used in the elevation threshold scenario.

To account for further variation in local fog observed at high resolution, we did not apply the exact elevation threshold changes seen on San Nicholas to our scenarios for Santa Cruz and Santa Rosa. The large difference in fog trends between San Nicolas and San Clemente likely means substantial differences in fog trends found on the more northern islands compared to San Nicolas. Specifically, San Nicolas saw a 28% higher increase in fog occurrence than San Clemente over the 67-year period. Since San Nicolas is approximately as far from the northern islands as it is from San Clemente, fog trends are also likely to differ notably on Santa Rosa and Santa Cruz. Additionally, the importance of fog drip for island oak populations means that overestimating future fog could result in significantly more projected habitat suitability than is accurate. Therefore, we determined that reducing the percentage of fog change was a more conservative decision for approximating future fog and appropriately incorporating fog in the SDM.

For the approximated future fog layers, the 40% increase in fog observed below 255 meters over 67 years on San Nicolas was halved to 20% over 67 years as a conservative value for calculating both decreases above the 255-meter threshold and increases below the threshold. The same number was also chosen as the change in fog probability for the increasing fog and decreasing fog scenarios to keep values and comparisons more consistent across fog scenarios. A 20% change over 67 years corresponds to approximately a 9% change over 30 years, which is the time increment of our climate projections. This change becomes

4.5% when averaged over one entire 30-year time period, resulting in a 4.5% change for 2010 – 2039, 13.5% change for 2040 – 2069, and 22.5% change for 2070 – 2099. We applied these incremental changes in fog for each time step across the different fog scenarios. By end of century, these changes accumulate to the 27% change in probability of fog inundation predicted across the various scenarios seen in Figures 7 and 8 and mentioned above.

# Analysis

R scripts and ArcGIS Toolboxes were built to prepare data for species distribution modeling and analyzing outputs in a systematic and reproducible manner. A flowchart of the methodology, more detailed methods, and descriptions of the various processes can be found in Appendix A. All R Scripts can be found in Appendix C.

## MaxEnt

We used MaxEnt (Maximum Entropy Modeling) version 3.3.3k to perform species distribution modeling for the island oak (Phillips et al., 2006). MaxEnt is an open-source java tool that performs presence-only SDM analyses and identifies habitat suitability for a species over a landscape (Phillips et al., 2006). It is one of the most commonly used modeling methods for SDM analyses (Elith et al., 2006, 2010, 2011). The MaxEnt graphical user interface (GUI) was used for running the processed data through MaxEnt. The model requires user inputs for species presence points and environmental variables of interest, and also allows inputs for a bias layer to correct for sampling bias. User-defined parameters, model validation methods, and various output settings make MaxEnt a flexible tool for application to a broad range of SDM scenarios. We selected MaxEnt over other SDM tools due to its flexibility and relatively low data requirements that matched the data we were able to acquire.

To develop probability of presence estimates, MaxEnt extracts a set of randomly distributed background points over the defined range and contrasts those points with presence points (Elith et al., 2011; Merow et al., 2013). The model develops two sets of covariate probability densities across the entire region, one using background points and the other using presence points. A maximum entropy-based comparison minimizes the relative entropy between the null covariate probability densities and those developed from presence points and allows the model to make estimates about relationships between species presence and environmental variables. Those relationships define which areas within the region of study satisfy a species' ecological niche, or the species' environmental requirements for survival (Hutchinson, 1957; Phillips, Anderson, Dudík, Schapire, & Blair, 2017; Phillips et al., 2004). The output presents a suitability raster layer that predicts the probability of species presence from 0 to 1, or low to high. Our MaxEnt analysis both determines the island oak's ecological niche, or climate envelope, in the current time period and predicts how the species distribution is likely to change in the future based on potential future changes in its niche.

## Environmental Layer Selection

We used MaxEnt to determine which of the available environmental variables were the most influential for predicting the island oak's niche. We ran analyses with present species observations and various combinations of the available environmental layers. The potential environmental layers considered included: climate water deficit, annual precipitation, maximum summer temperature, minimum winter temperature, probability of fog inundation (Santa Cruz and Santa Rosa), elevation, slope, aspect, vegetation classes, and soil classes. We assessed collinearity between variables and selected those that were unique, independent, and increased the model's predictive power while reducing uncertainty. Measures of temperature and precipitation were vital to include; previous work with oaks has noted that conditions that induce high stress levels are better predictors of western tree species distributions (Rehfeldt, Crookston, Warwell, & Evans, 2006). Therefore, we used summer maximum temperature and winter minimum temperature instead of annual averages (Sork et al., 2010). Since most of the precipitation occurs in the winter months in coastal California, annual averages and averages of the wettest months are essentially the same, so we used average annual precipitation. Although climate water deficit is correlated to some extent with other climatic variables, it was necessary in the analysis due to the importance of soil moisture to both the life history of island oak specifically and plant biology in general (Stephenson, 1998).

For selecting other variables and assessing the model fit of temperature and precipitation variables, we performed sensitivity analyses of the environmental variables by determining how much the model output changed when different variables and variable combinations were selected. MaxEnt determines how individual environmental variables influence overall model prediction and fit by identifying the marginal and independent importance of each environmental variable included. Jackknife and area under the curve (AUC) analyses were performed during initial MaxEnt runs to select the environmental variables that maximize predictive capacity and minimize correlation between predictor variables. Jackknife analysis calculates the relative increase of gain, or goodness of fit, that each variable adds to the model, by removing them one at a time and running a training model with each individually. AUC represents the number of omission and commission errors in the training model. An AUC close to 1 means that both types of errors are minimized. An AUC close to 0.5 indicates that there are the same number of the two error types in presence points and the randomly selected background data and that the model cannot distinguish between the two types of points.

Sensitivity analyses resulted in the selection of four variables across all islands: maximum summer temperature, minimum winter temperature, annual precipitation, and climatic water deficit. All four of these BCM climate layers were deemed influential indicators of the climatic niche of the island oak based on their contribution to MaxEnt model output and to establishing the best model fit. They were selected as the main environmental layers for input into MaxEnt for all model runs. Elevation, slope, aspect, vegetation, and soils were not selected for final model runs as they were too heavily correlated with climate variables, did not augment model fit, or did not substantially improve the predictive power of the model.

Probability of fog inundation was included as a fifth environmental layer for individual runs of Santa Cruz and Santa Rosa Islands. In addition to the four BCM climate variables, we determined that fog is an influential indicator of the climatic niche of the island oak based on its contribution to MaxEnt model output and to establishing the best model fit. It was selected as a main environmental layer for input into MaxEnt for Santa Cruz and Santa Rosa. More detailed information on selected environmental layers, MaxEnt model parameters, and selected settings, including number of training runs, test samples, and iterations can be found in Appendix A2.

## Model Runs

Species presence points and selected environmental layers were input into Maxent to perform ecological niche and habitat suitability analysis for *Q. tomentella* under current and projected future climate conditions. We built several R scripts to process the data for entry into MaxEnt. Detailed descriptions, figures, and R scripts of the pre-MaxEnt processing of data layers and all potential environmental layers into MaxEnt are listed in Appendix A1 – A2. In brief, environmental layers from each island were projected to NAD 83 California Teale Albers (meters), masked to the same extent, resampled to 270-meter resolution if necessary, and written to an ASCII file. An oak point .csv was created from island oak presence points that included species name and projected coordinates.

We analyzed a combination of climate scenarios, time periods, and spatial extents (Table 1). Climate scenarios included three historic time periods (1921 – 1950, 1951 – 1980, 1981 – 2010) and three future time periods (2010 – 2039, 2040 – 2069, 2070 – 2099). We treated the 1981 – 2010 climate data as current climate conditions for model training. We used all available future time periods for the four selected climate change scenarios. Spatial extents for individual island analyses and all islands combined were both explored. For all scenarios, cross validation was used for model training and 100 bootstrap replicates were used for finalized model runs. Greater detail on MaxEnt settings and the scenarios run are available in Appendix A.

Additionally, some island managers believe it is likely that San Miguel Island recently supported the oaks due to its shared geologic history with the other northern islands and that they could be successfully reintroduced there. Therefore, we used oak point data from Santa Rosa and Santa Cruz and environmental layers from Santa Rosa, Santa Cruz, and San Miguel in order to analyze current and future suitable island oak habitat on San Miguel. Furthermore, since island managers are interested in potential suitability of the species on Mainland California, we performed a similar analysis for all of California, using all available presence points.

**Table 1. List of scenarios.** The scenarios ran in MaxEnt based on data availability and extent. Islands analyzed include Santa Catalina (SCA), Santa Cruz (SCR), Santa Rosa (SRI), and San Miguel (SMI).

| | Extent | Oak Points | Climate Scenarios | Fog Scenarios |
|---|---|---|---|---|
| **Individual Islands** | SCA, SCR, SRI | Presence points for each individual island | Historic and future time periods; all climate scenarios. SCA BCM non-kriged and kriged | NA |
| **Individual Islands with Fog** | SCR, SRI | Presence points for just SCR and SRI individually | Historic and future time periods; all climate scenarios | Constant, decreasing, increasing, elevation threshold |
| **All Islands Combined** | SCA, SCR, SRI | Presence points for all islands combined | Historic and future time periods; all climate scenarios | NA |
| **Age Classes** | SRI | Presence points separated by stage | Historic and all future time periods; all climate scenarios | NA |
| **Other Locations** | SCA, SCR, SRI, SMI, Mainland California | Presence points for all islands (SCA, SCR, SRI) combined | Historic and future time periods; all climate scenarios | NA |

## Model Output Analysis

We used R to perform spatial and statistical analyses of MaxEnt outputs to:

1. Determine current and future predicted habitat suitability on the islands and examine changes in predicted suitability across scenarios and time periods;
2. Evaluate whether each island will provide long-term suitable habitat for Q. tomentella under various climate change scenarios; and
3. Explore Q. tomentella's modeled climate niche across islands.

The R scripts used to perform these analyses are available in Appendix C.

To address our first objective, ArcGIS was used to display current and future predicted habitat suitability outputs and examine visual changes in habitat suitability for each scenario and time period. Current and future predicted habitat suitability were mapped using the maximum sensitivity plus specificity (max SSS) value as the threshold, masking out all predicted suitability values below the threshold. Max SSS values are automatically calculated by each MaxEnt model and differ from one to another, but all values represent the same threshold qualitatively – the predicted probability of presence that corresponds to the place on the receiver operating curve (ROC) where the slope of the tangent line is equal to one. Regardless of the numerical value, at this threshold the false negative and false positive predictions are simultaneously minimized. A higher threshold value would disproportionally exclude true presences from suitable habitat, while a lower value would disproportionally introduce false positives into areas of predicted suitable habitat. Use of the max SSS value as a binary threshold has been thoroughly compared to both quantitatively reasoned and arbitrarily chosen threshold value options and is the recommended binary threshold value for presence-only species distribution models (Liu, Newell, & White, 2016; Liu, White, & Newell, 2013). Therefore, the scenario-specific max SSS values are used as the metric for binary suitability threshold for all current and future projections

To meet the second objective, the binary suitability outputs of each model run were summed across climate scenarios and time periods for a given spatial extent to create an integrated outlook map. The integrated map of summed values represents the number of times a cell was deemed suitable in all model runs for a given extent. The integrated outlook is used as a proxy for capturing the likelihood of species persistence across the wide variation of potential futures and future fog scenarios.

For the third objective, we explored the relationships between island oak presence and each climate variable, to better understand the species' climate niche. R was used to visualize the climate conditions found across the islands and in current island oak point locations, and how these climate conditions are changing in the future. The two environmental variables that contributed most to each MaxEnt model were plotted against each other for each island individually. Convex hull graphs were created to visualize the climate envelope of these variables across the islands for the historic climate as well as for two future climate scenarios: MIROC RCP8.5 and MPI RCP4.5. We selected these two future scenarios as the "best case" (MPI) and "worst case" (MIROC) scenarios. Current oak points were plotted according to the oak distribution among climate envelopes. These were then overlaid on the associated convex hull representing the historic climate. Additionally, density contour lines were overlaid on each climate envelope to indicate the distribution of available climate conditions. Density plots illustrating the range and frequency of current oak points over each climate variable were constructed to examine differences between the distributions on each island.

# Results

## Climate Suitability

Our first research objective was to determine the current climate niche for *Q. tomentella* on each of the three analyzed islands and to assess how predicted climate suitability changes across projected future climate change scenarios. The current predicted climate niche was described through each model's predicted probability of presence and the maximum sum of sensitivity plus specificity (max SSS) as the binary threshold value for suitability. After determining the island oak's current climate niche, we assessed future climate suitability by analyzing how the extent and location of suitable island oak habitat changed from the historic time period (1981 – 2010) through the end of the century across the combined climate change projections and fog scenarios. Results discussed in the climate suitability section are presented in the following order: Santa Cruz, Santa Rosa, Santa Catalina, All Islands, Fog Scenarios, and Additional Climate Suitability Analyses.

In this section, results for Santa Cruz and Santa Rosa Islands are presented for the fog elevation threshold scenario, in which probability of fog inundation decreases above elevations of 255 meters and increases below 255 meters. The fog elevation scenario was determined to be the most likely future scenario based on past trends in cloud stratus height on San Nicolas, the closest island in location and oceanic patterns with available fog observations (Williams et al., 2015). For Santa Catalina Island we discuss both the results from the model runs that used original climate data as obtained from BCM (non-kriged) as well as model runs that used the universally co-kriged version of this climate data (kriged). The original BCM data covers approximately 64% of the island, while the kriged data covers the full extent of the island. Probability of fog inundation was not available for Santa Catalina Island. Furthermore, we discuss results for the 'All Islands' model in which all three islands' presence points and climate layers were combined to determine the current and predicted future island oak niche distribution found across islands. Additionally, we provide selected results for auxiliary analyses, including model runs for the additional fog scenarios, for extents beyond the three islands, and for stage structure data on Santa Rosa.

### Santa Cruz Island

Results for Santa Cruz Island are presented for the fog elevation threshold scenario across climate projections and time periods. The area under the receiver operating curve, or area under the curve (AUC), a model performance metric, is 0.79 for the Santa Cruz Island fog elevation threshold training model. This AUC value is the average of 100 bootstrap replicates and is an estimate of the model's predictive accuracy. Possible values range from 0 to 1, and values above 0.5 represent better than random accuracy with distinguishing true presence from background points. Receiver operating curve (ROC) figures for all models included in the results section can be found in appendix B.

Table 2 reports the percent contribution of each environmental layer to overall model gain and the sensitivity of the finalized training model to adjustments in the value of a specific variable while holding other variables constant. These values help describe the training model development and sensitivities. In particular, values for the variable percent contribution can have notable differences between individual model runs as there is stochasticity inherent to training model development, given the software's intentionally randomized process of increasing model fit. All reported values are averages from the 100 bootstrapped replicates.

Probability of fog inundation had the highest contribution to model gain, followed by annual precipitation, maximum summer temperature, minimum winter temperature, and climate water deficit, respectively. The training model was most sensitive to changes in the probability of fog inundation values. Metrics of moisture availability, which are fog and precipitation, accounted for over 70% of model fit, highlighting the importance of these layers for predicted habitat suitability on Santa Cruz Island.

**Table 2. Santa Cruz predictor variables.** Percent contribution of predictor variables to model fit in the Santa Cruz Island fog elevation threshold model.

| Variable | Percent Contribution to Model Gain | Sensitivity to Variable Permutations |
|---|---|---|
| Fog | 47.3% | 48.5% |
| Annual Precipitation | 24.2% | 18.1% |
| Maximum Summer Temperature | 15.3% | 16.7% |
| Minimum Winter Temperature | 8.9% | 16.2% |
| Climate Water Deficit | 4.4% | 0.5% |

Figure 9 displays the marginal response curves for the predictor variables included in the Santa Cruz Island fog elevation threshold scenario. Marginal response curves display the relationship trend of each predictor variable to the predicted probability of presence in the training model. Figures are presented in order of importance as defined by their percent contribution to the model. MaxEnt was set to develop training models using any combination of linear, quadratic, and product functions, making model coefficients difficult to interpret and compare. With these combined function settings and correlation between the four to five covariates, most model coefficients were either product (interaction) or quadratic (squared) terms. Additionally, with 100 bootstrapped replicates, training models were developed 100 times for each scenario, each with a unique set of coefficients and values due to the stochasticity of training model development. In an attempt to simplify the MaxEnt output and coefficients, we experimented with only allowing the use of linear functions and reducing the number of environmental variables included, but model fit significantly decreased in both cases.

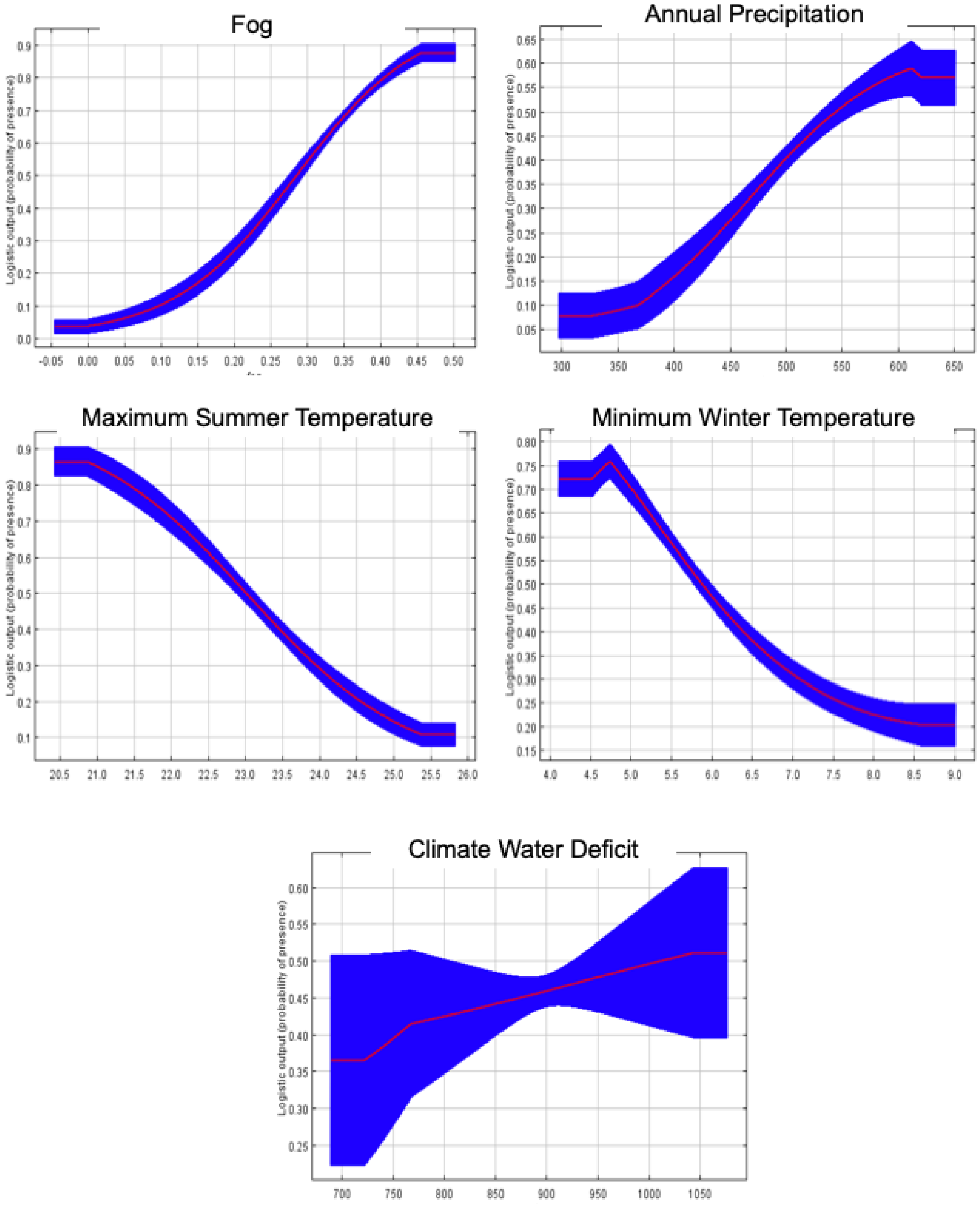


**Figure 9. Santa Cruz response curves.** Marginal response curves for predictor variables in the Santa Cruz Island fog elevation threshold model. Figures are in order of importance as defined by their percent contribution to the model. Covariate values are on the x-axis and probability of presence values are on the y-axis. Red lines indicate correlation trends between each covariate and probability of presence. Blue ribbons are +/- one standard deviation around the trend line, based on the average standard deviation of 100 bootstrap replicates.

Regardless of function complexity, response curves offer clear insights into covariate-predicted probability of presence relationships. Response curves for the Santa Cruz Island fog elevation threshold scenario reveal that maximum summer temperature and minimum winter temperature are negatively correlated with predicted probability of presence while annual precipitation, fog probability, and climate water deficit have positive correlations with predicted probability of presence. It is also notable that climate water deficit has a wide error bar around the response curve, which is likely due to its strong correlation with fog and precipitation and moderate correlation with temperature variables. This wide confidence interval implies that the correlation between climate water deficit ranged from slightly positive to slightly negative in the replicate model runs.

Detailed results for current and future predicted habitat suitability for the Santa Cruz Island fog elevation threshold scenario across all time steps and climate projections are in Table 3, including the predicted maximum suitability score, average suitability score, percent suitable area, and percent change in suitable area compared to the baseline for each combination. For the historic time period (1981 – 2010), which corresponds to the baseline scenario, the maximum predicted suitability score is 0.94 for the current distribution, and average score is 0.5. Using the model's maximum training sum of sensitivity plus specificity (max SSS) of 0.35 as the binary threshold for determining climate suitability, predicted suitable habitat covers approximately 25% of the island.

Future predicted suitability scores in all climate projections decrease through time for the Santa Cruz Island fog elevation threshold scenario. Within each time period, predicted suitability scores are higher for the two wet scenarios than for the two dry scenarios. All future predicted maximum and average suitability scores are much lower than the current predicted average suitability score of 0.50 and maximum suitability score of 0.94, especially for later time periods. Maximum suitability scores were derived from all outputs of predicted suitability values, while average suitability scores were calculated once unsuitable areas were masked out by the binary threshold. Both values offer useful perspectives on changes of predicted habitat through time, and the average suitability score is also a useful metric for comparing the relative quality of predicted suitable habitat. Furthermore, projections with NAs for average suitability scores represent scenarios in which there was no suitable area predicted after applying the binary threshold, which is the case for most of the dry future projections with 0% predicted suitable area. Due to the highly spatial nature of the results, the summary statistics will be discussed more in depth below in combination with the mapped results of the projections.

**Table 3. Santa Cruz summary statistics.** Summary statistics for predicted future species distribution on Santa Cruz Island under each climate projection and time step. All values are from model iterations with fog changing around an elevation threshold through time. Summary statistics include maximum predicted habitat suitability, average predicted suitability score, percent suitable area, and percent change in suitable area compared to the present as defined by binary suitability threshold value (maximum sum of sensitivity + specificity value from MaxEnt output). NAs for average suitability score indicate where there was no suitable habitat on the island.

| Years | Projection | Name | Maximum Suitability Score | Average Suitability Score | % Suitable Area | % Change in Suitable Area |
|---|---|---|---|---|---|---|
| 1981 – 2010 | Historic | Current | 0.94 | 0.50 | 25.29% | NA |
| 2010 – 2039 | MPI 4.5 | Warm-Wet | 0.75 | 0.45 | 4.97% | -80.36% |
|  | CCSM4 8.5 | Hot-Wet | 0.75 | 0.45 | 5.16% | -79.59% |
|  | MIROC 4.5 | Warm-Dry | 0.58 | 0.40 | 0.42% | -98.32% |
|  | MIROC 8.5 | Hot-Dry | 0.51 | 0.45 | 0.07% | -99.74% |
| 2040 – 2069 | MPI 4.5 | Warm-Wet | 0.48 | 0.43 | 0.16% | -99.35% |
|  | CCSM4 8.5 | Hot-Wet | 0.28 | NA | 0.00% | -100.00% |
|  | MIROC 4.5 | Warm-Dry | 0.10 | NA | 0.00% | -100.00% |
|  | MIROC 8.5 | Hot-Dry | 0.04 | NA | 0.00% | -100.00% |
| 2070 – 2099 | MPI 4.5 | Warm-Wet | 0.52 | 0.42 | 0.20% | -99.22% |
|  | CCSM4 8.5 | Hot-Wet | 0.40 | 0.38 | 0.10% | -99.61% |
|  | MIROC 4.5 | Warm-Dry | 0.07 | NA | 0.00% | -100.00% |
|  | MIROC 8.5 | Hot-Dry | 0.05 | NA | 0.00% | -100.00% |

Figure 10 displays the probability of *Q. tomentella* presence on Santa Cruz Island for the fog elevation threshold model using the historic climate data and four climate projection scenarios. Unsuitable areas were determined using the max SSS value (0.35) and are displayed in light grey, while predicted suitable habitat is displayed with a color gradient. Cool colors represent low probability scores while warm colors represent high probability scores. The current time step seen in the top left box of Figure 10, denoted 1981 – 2010, indicates that the majority of the predicted suitable area on Santa Cruz (25.29%) occurs in higher elevations in the northwest region of the island. There are other small sections with high predicted suitability scores, but most of the other locations have scores at the lower end of the suitable range.

The top two long panels in the figure show the spatial results of the wet climate change scenarios, or those that predict slightly increasing annual precipitation with increasing temperatures relative to the 1981 – 2010 time step. In both scenarios, total suitable area constricts by approximately 80% in the first time step (2010 – 2039) relative to the historic time step. Approximately 5% of the island is predicted to be suitable, mostly in the northwest portion of the island. In all other wet scenario time steps, there is effectively no predicted suitable island oak habitat remaining at the 270-meter resolution.

The bottom two panels show the dry climate change scenarios, in which the associated climate models predict declines in annual precipitation in combination with increasing temperatures relative to the present. MaxEnt output for the dry scenario projections predict an effectively complete loss of suitable habitat in all time steps; even in the first time step, less than 1% of the island is predicted as suitable.

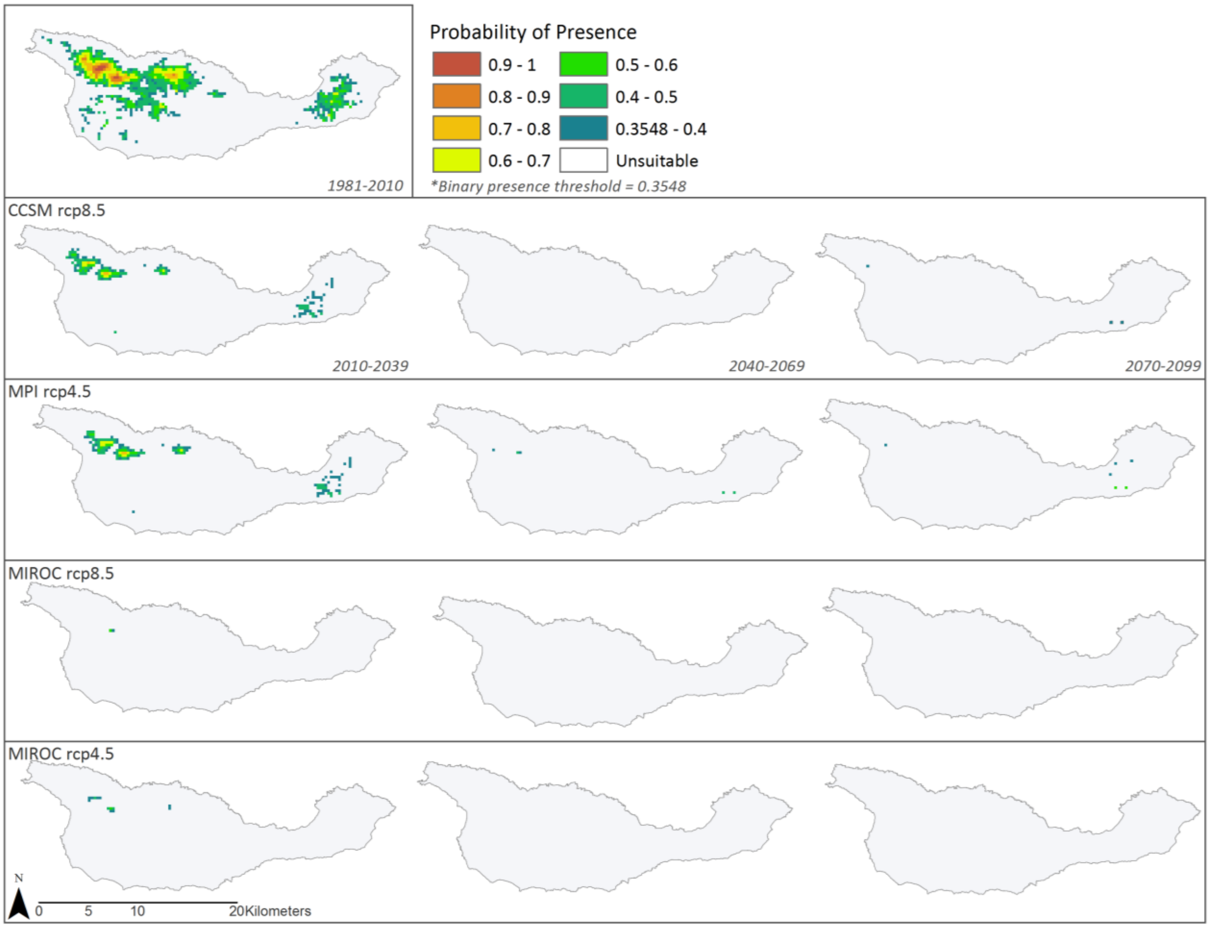


**Figure 10. Santa Cruz probability of presence predictions.** Probability of presence of island oak across Santa Cruz Island for the fog elevation threshold scenario. The top panel shows probability of presence with current climate conditions. The next four panels show the probability of presence for the four climate projections through time. Warmer colors indicate higher probabilities of presence. Grey indicates areas below the suitability threshold (max SSS) of 0.3548.

In all four climate change scenarios, by the mid-century time period, there is little to no predicted suitable habitat at the 270-meter resolution. The significant loss or complete absence of predicted future suitable habitat on Santa Cruz Island can be explained by the model response curves (Figure 9). Habitat suitability on the island has a strong positive correlation with precipitation and fog, and negative correlations with the two temperature variables. However, the magnitude of change in precipitation is less than the magnitude of change in maximum summer temperature and minimum winter temperature (Methods Figure 6). Therefore, change in precipitation has a weak positive effect on predicted habitat suitability in the two wet scenarios and a negative effect in the two dry scenarios. Meanwhile, the two temperature predictor variables have distinct negative effects on predicted probability of presence, as their values significantly increase with time in all climate change scenarios.

MaxEnt results for the Santa Cruz Island fog elevation threshold scenario are fairly representative of all individual models for the island. Output figures illustrating the spatial distributions of predicted probability of presence under other Santa Cruz Island fog scenarios are discussed later in the results and are also in Appendix B. In summary, at a 270-meter resolution, the area of predicted suitable habitat on Santa Cruz progressively decreases with time in all climate change scenarios and is miniscule or absent by the mid-century time period. The strong negative correlations between predicted probability of presence and increasing temperature are likely driving the sharp decline in suitability observed in Santa Cruz Island MaxEnt models, since both temperature values—minimum winter and maximum summer—increase in all climate change scenarios.

The range of values present in the historic climate data substantially influences model results, as MaxEnt uses the current climate range occupied by the species to predict probability of presence and is restricted in predicting outside these value ranges. MaxEnt only uses species presence data and current environmental covariates to produce a suitability distribution over an area. However, climate projections may introduce novel climate conditions that are not present in the current climate range. To deal with climate variable values outside of the current range, MaxEnt uses "clamping," a process by which the model treats values outside the current training range as extreme values. For example, the range of maximum summer temperature on Santa Cruz in the hot-dry projection is 25.8 – 30.2 °C, but the range of maximum summer temperature in the current time step is 20.87 – 25.37 °C. Through clamping, the model treats every projected value in the training range above 25.37 °C as if it were 25.37 °C, the highest maximum summer temperature value.

MaxEnt output includes spatial figures that demonstrate the degree to which clamping may be influencing model results. Figure 11 is an example of these produced from the Santa Cruz Island fog elevation model for the warm-dry climate scenario in the first future time step (2010 – 2039). In the left panel, warmer colors correspond to locations where the future projected climate data is significantly different from the training data, and cool colors show locations where the two climate data sets are similar. The right panel shows which variable is furthest outside the training range in specific places. In combination, these figures help assess the magnitude of the effect of clamping, and which variables are contributing most to that effect, increasing our ability to interpret predicted probability of presence outputs.

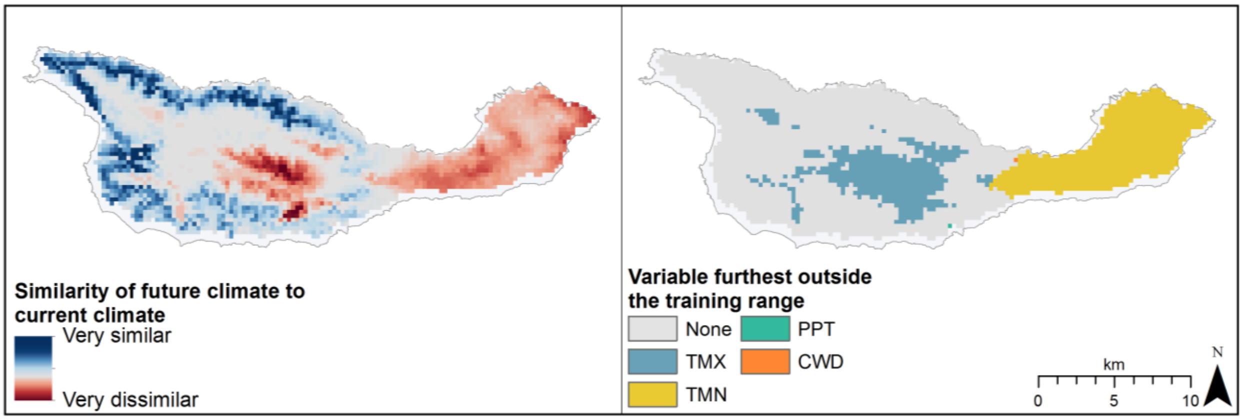


**Figure 11. Santa Cruz clamping impacts.** The degree and source of the effects of clamping on predicted probability in the MIROC RCP4.5 2010 – 2039 time period. The left panel shows the relative difference of future projection climate layers to current climate layers, in which cool colors show areas where the two are similar and warmer colors showing areas where they are different. The right panel shows which variable in the future projection layers is most different from the training range in each cell across the island.

## Santa Rosa Island

Results for Santa Rosa are presented for the fog elevation threshold scenario across climate projections and time periods. The average training AUC value for the Santa Rosa Island fog elevation model is 0.89, which is a slightly higher model performance and fit than for analogous Santa Cruz Island scenario. Table 4 indicates that fog and maximum summer temperature account for 75% of training model gain followed by annual precipitation, climate water deficit, and finally minimum winter temperature. The finalized training model was most sensitive to adjustments in precipitation followed by the probability of fog inundation, maximum summer temperature, climate water deficit, and minimum winter temperature, respectively. Compared to the 70% contribution for Santa Cruz, fog and annual precipitation still contributed about 60% of the model gain for Santa Rosa, illustrating the importance of moisture availability.

**Table 4. Santa Rosa predictor variables.** Percent contribution of predictor variables to model fit in the Santa Rosa Island fog elevation threshold model.

| Variable | Percent Contribution to Model Gain | Sensitivity to Variable Permutations |
|---|---|---|
| Fog | 49.7 % | 21.2% |
| Maximum Summer Temperature | 24.6% | 13.3% |
| Annual Precipitation | 11.7% | 49.8% |
| Climate Water Deficit | 10.5% | 8.2% |
| Minimum Winter Temperature | 3.6% | 7.5% |

Figure 12 shows the marginal response curves for predictor variables in the Santa Rosa Island fog elevation scenario. Predicted probability of presence is positively correlated with probability of fog inundation, maximum summer temperature, and annual precipitation, and negatively correlated with minimum winter temperature. Predicted probability of presence and climate water deficit are slightly positively correlated, but high error bars indicate that this is not a strong or consistent relationship.

The biggest difference compared to Santa Cruz's response curves is that probability of presence is positively correlated with maximum summer temperature, for Santa Rosa, while the correlation was negative with both temperature variables for Santa Cruz. This could be because Santa Rosa has cooler temperatures than Santa Cruz overall. Additionally, there may be interactions between climate variables that are not apparent in our analysis.

Predicted habitat suitability results for the Santa Rosa Island fog elevation threshold scenario across all time steps and climate projections are displayed in Table 5. The highest current (1981 – 2010) predicted suitability score is 0.91, and approximately 25% of the island currently contains predicted suitable habitat, as defined by the max SSS value of about 0.14. The maximum future predicted probability of presence ranges from 0.79 – 1.00, with some scenarios having higher predicted suitability scores than are found in the present.

In the first future time step (2010 – 2039) the percent of predicted suitable habitat on Santa Rosa Island increases by at least 73% across projections, with the two wet projections increasing by approximately 160%. In the second future time step (2040 – 2069), predicted suitable habitat covers a larger portion of the island than the current time period for all projections except the hot-dry scenario, in which it decreases. In the end-of-century time period (2070 – 2099) predicted suitable habitat decreases for both dry scenarios, while for the two wet scenarios predicted suitable habitat covers substantially more of the island than in the current time period. The statistics will be discussed more in depth below with regard to the observed spatial trends.

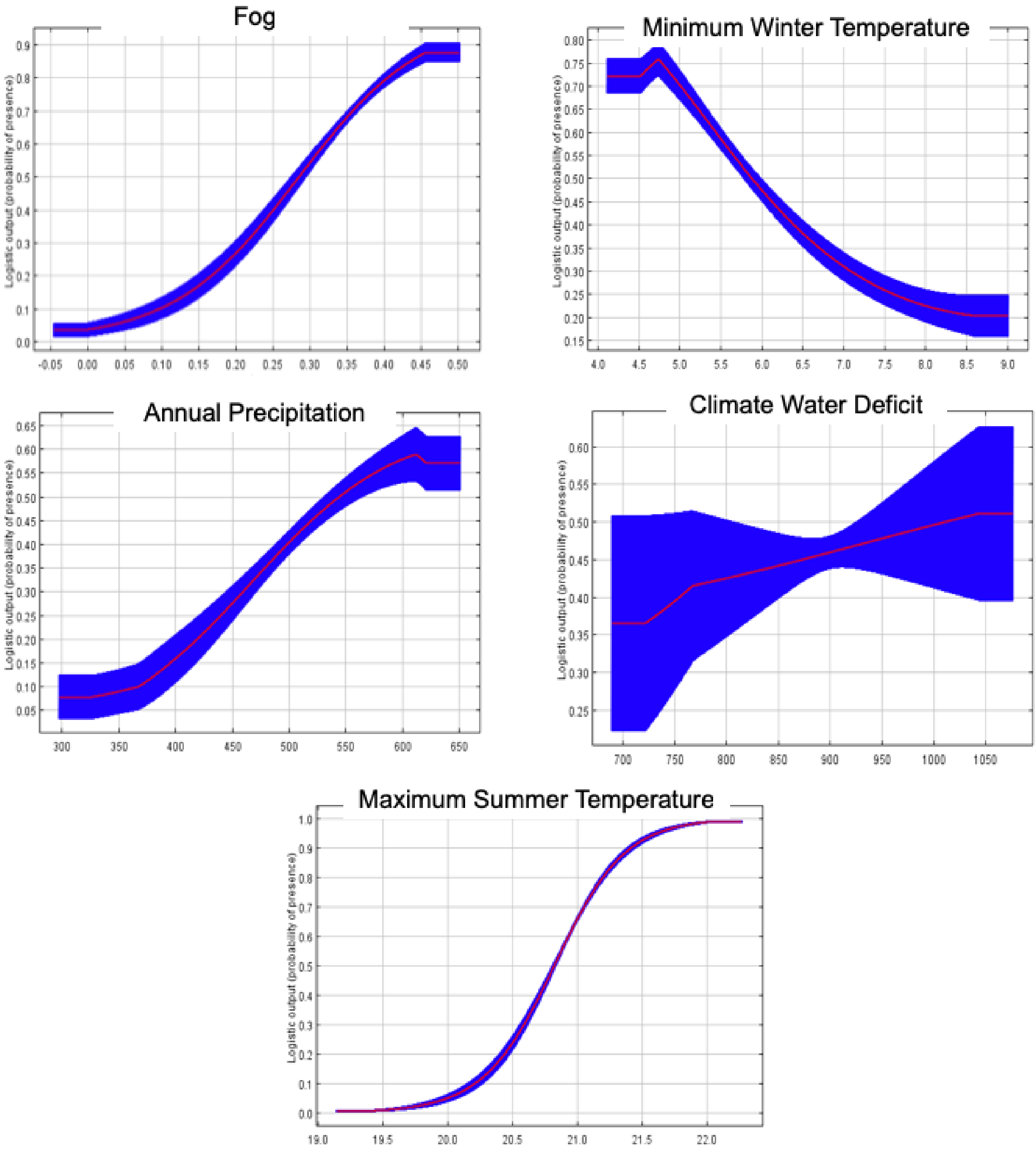


**Figure 12. Santa Rosa response curves.** Marginal response curves for predictor variables in the Santa Rosa Island fog elevation threshold model. Figures are presented in order of importance as defined by their percent contribution to the model. Covariate values are on the x-axis and probability of presence values are on the y-axis. Red lines show correlation trends between each covariate and probability of presence. Blue ribbons are +/- one standard deviation around the trend line, based on the average standard deviation of 100 bootstrap replicates.

**Table 5. Santa Rosa summary statistics.** Summary statistics for predicted future species distribution on Santa Rosa Island under each climate projection and time step. All values are from model iterations with fog changing around an elevation threshold through time. Summary statistics include predicted maximum future habitat suitability, average suitability score, percent suitable area, and percent change in suitable area compared to the present as defined by binary suitability threshold value (maximum training sensitivity + specificity value from MaxEnt output).

| Years | Projection | Name | Maximum Suitability Score | Average Suitability Score | % Suitable Area | % Change in Suitable Area |
|---|---|---|---|---|---|---|
| **1981 – 2010** | Historic | Current | 0.91 | 0.37 | 25% | NA |
| **2010 – 2039** | MPI 4.5 | Warm-Wet | 1.00 | 0.71 | 90.99% | 260.55% |
| | CCSM4 | Hot-Wet | 1.00 | 0.74 | 92.34% | 265.90% |
| | MIROC 4.5 | Warm-Dry | 1.00 | 0.60 | 66.12% | 161.99% |
| | MIROC 8.5 | Hot-Dry | 1.00 | 0.65 | 60.47% | 139.60% |
| **2040 – 2069** | MPI 4.5 | Warm-Wet | 1.00 | 0.80 | 91.83% | 263.87% |
| | CCSM4 | Hot-Wet | 1.00 | 0.69 | 58.10% | 130.20% |
| | MIROC 4.5 | Warm-Dry | 0.98 | 0.63 | 37.16% | 47.25% |
| | MIROC 8.5 | Hot-Dry | 0.87 | 0.38 | 21.99% | -12.86% |
| **2070 – 2099** | MPI 4.5 | Warm-Wet | 1.00 | 0.84 | 92.67% | 267.20% |
| | CCSM4 | Hot-Wet | 1.00 | 0.83 | 92.01% | 264.60% |
| | MIROC 4.5 | Warm-Dry | 0.99 | 0.54 | 34.06% | 34.97% |
| | MIROC 8.5 | Hot-Dry | 0.79 | 0.34 | 12.73% | -49.57% |

Figure 13 spatially illustrates the probability of *Q. tomentella* presence on Santa Rosa in the fog elevation threshold scenario for the four climate projections through the end of the century. Predicted suitable habitat was determined using the model's max SSS value of about 0.14. Compared to Santa Cruz, Santa Rosa has a more optimistic future outlook for total island area with predicted suitable habitat. Current suitable habitat, seen in the top left box denoted 1981 – 2010, is similar to that of Santa Cruz (25%). Current predicted habitat is found mostly in the center of the island at higher elevations, and predicted habitat suitability scores are mostly below 0.5, represented by the cooler colors, though there are several small regions with scores above 0.7, indicated by the warmer colors.

The top two full panels illustrate the results for the two wet scenarios. In the warm-wet climate change scenario, predicted suitable habitat expands throughout all time steps, and habitat suitability scores are high on average. In the hot-wet scenario, the area of suitable habitat substantially increases in the first-time step from 25% to 90%, contracts slightly in the midcentury time step to 60%, and then expands in the last time step to cover approximately 100% of the island. The contraction in habitat suitability in the hot-wet scenario may be the result of opposing responses in predicted habitat suitability to increasing minimum winter temperature compared to fog, annual precipitation, and maximum summer temperature. Increasing minimum winter temperature in the second time step may have the strongest impact on predicted habitat suitability, reducing the area of total suitable habitat, while in the first and third timesteps those variables that increase habitat suitability must have the strongest effect.

The bottom two panels display the results for the dry scenarios. In both scenarios predicted suitable habitat expands in the first-time step. Predicted suitable habitat contracts through the rest of the century in the hot-dry scenario, while it remains relatively constant through time in the warm-dry scenario, in which the highest suitability scores are centered around the current *Q. tomentella* population near Soledad Peak in the southern part of the island. However, predicted suitable habitat is still present in the final time step in both dry scenarios. Based on the training model response curves, the decline in total predicted suitable habitat in the two dry climate change scenarios is driven by reduced precipitation and increasing minimum winter temperature. As shown in Table 5, the Santa Rosa Island fog elevation threshold training model is sensitive to changes in precipitation, and the response curve indicates that reductions in precipitation would correspond to proportionally large reductions in predicted probability of presence.

The predictions of future habitat suitability differ significantly between Santa Rosa Island and Santa Cruz Island. In contrast to Santa Cruz, all projection scenarios for Santa Rosa have at least some predicted suitable habitat left on Santa Rosa. In all modeled futures for the fog elevation threshold scenario, a minimum of 13%, and in many cases greater than 50%, of the island is predicted suitable. By the end of century, the suitability predictions in the wet scenarios predicted suitable habitat remains on the majority of the island (about 90%), and much of that area has a predicted suitability score above 0.7. In the warm-dry climate change scenario the model predicts about 34% of the island to be suitable at the end of the century, and a large proportion of the suitable area has high predicted suitability scores. In the hot-dry scenario, approximately 13% of the island area is predicted to be suitable in the end-of-century time period, and the predicted suitability scores are relatively low.

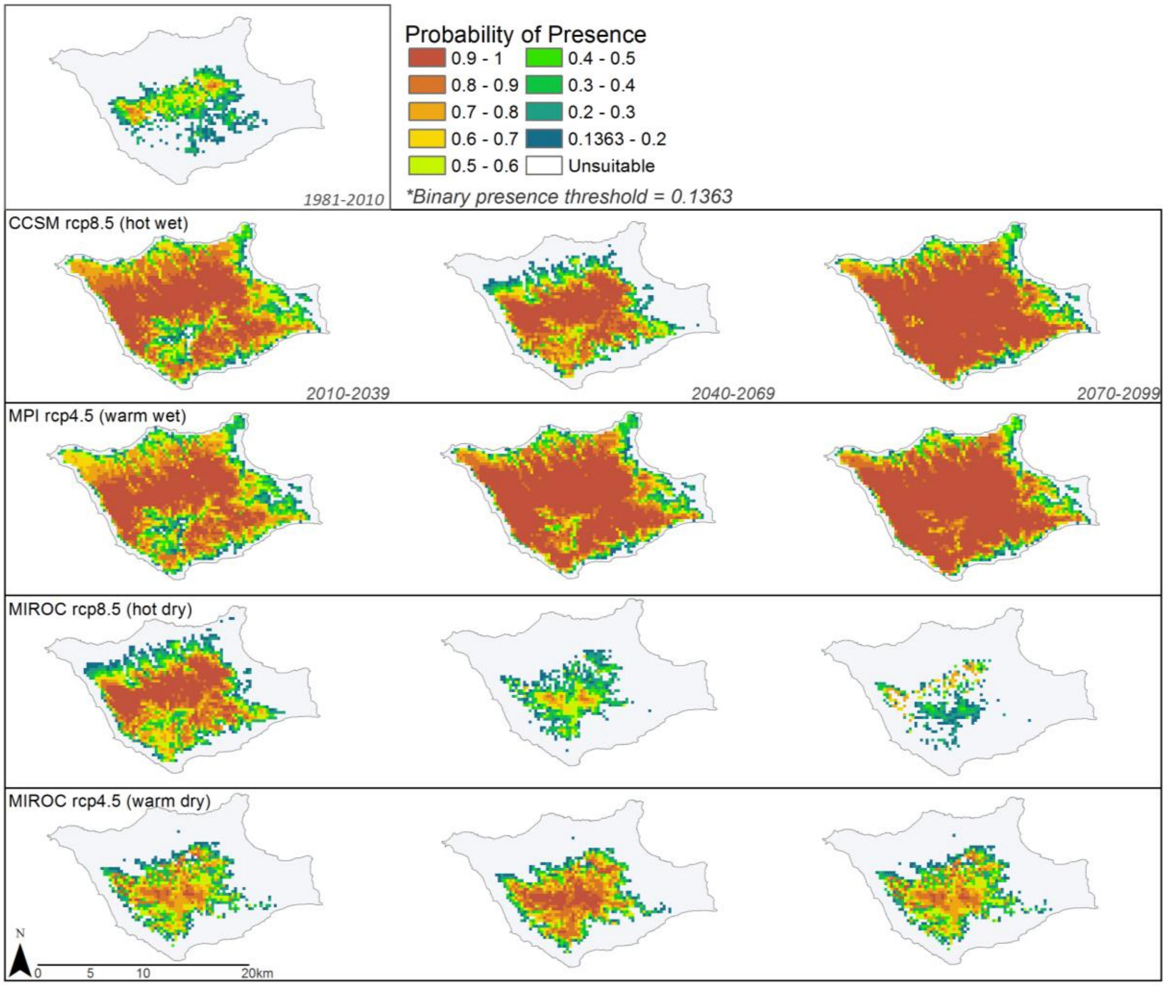


**Figure 13. Santa Rosa probability of presence predictions.** Probability of presence of island oak across Santa Rosa Island for the fog elevation threshold scenario. The top panel shows probability of presence with current climate conditions. The next four panels show the probability of presence for the four climate projections through time. Warmer colors indicate higher probability of presence. Grey indicates areas below the suitable habitat threshold of 0.1363.

## Santa Catalina Island

Results for Santa Catalina are presented for both the non-kriged and kriged model runs across climate projections and time periods, without any fog inclusion (Table 6). The average training AUC value is 0.84 for the current predicted distribution of *Q. tomentella* on Santa Catalina Island using non-kriged climate data. In comparison, the average training AUC is 0.78 for the current predicted distribution of island oaks on Santa Catalina using the universally co-kriged climate data. In contrast to the non-kriged data, the kriged model results have a lower model fit, lower maximum predicted suitability value, and greater percent predicted suitable area.

With non-kriged climate data, minimum winter temperature contributes most to model fit at 61.1%, followed by climate water deficit, maximum summer temperature, and annual precipitation. The finalized training model was most sensitive to changes in minimum winter temperature, followed by climate water deficit, annual precipitation, and maximum summer temperature. In the model with kriged climate data, maximum summer temperature was responsible for 70.8% of model gain, followed by climate water deficit, minimum winter temperature, and annual precipitation. The model was most sensitive to changes in maximum summer temperature, then climate water deficit, minimum winter temperature, and annual precipitation. Compared to the other two islands, precipitation has a much lower contribution to either of the models. Furthermore, contribution of temperature variables is substantially higher; one temperature variable in each model has a similar percent contribution to model gain as fog and precipitation combined have for the other two islands. The change in variable importance illustrates the higher influence of temperature on the probability of oak presence on Santa Catalina compared to the northern islands, which have relatively cooler climates.

**Table 6. Santa Catalina predictor variables.** Percent contribution of predictor variables to model fit for Santa Catalina. Values for non-kriged climate data are on the left and kriged climate data are on the right.

| | Non-kriged Climate Data | | Kriged Climate Data | |
|---|---|---|---|---|
| Variable | Percent Contribution to Model Gain | Sensitivity to Variable Permutations | Percent Contribution to Model Gain | Sensitivity to Variable Permutations |
| Minimum Winter Temperature | 61.1% | 51.6% | 8.1% | 11.6% |
| Climate Water Deficit | 16.9% | 29.4% | 16.5% | 21.7% |
| Maximum Summer Temperature | 16% | 1.6% | 70.8% | 56.2% |
| Annual Precipitation | 6% | 17.4% | 4.6% | 10.5% |

With non-kriged climate data, predicted probability of presence is positively correlated with maximum summer temperature and minimum winter temperature, negatively correlated with climate water deficit, and has a parabolic relationship with precipitation (Figure 14). The error bars around precipitation suggest notable uncertainty in those trends. Very similar relationships exist between predictor variables and predicted probability of presence in the Santa Catalina model with kriged climate data, except the minimum winter temperature, trends have higher uncertainty, as indicated by the large error bars (Figure 15).

These response curves vary significantly from the other two islands. For Santa Catalina, both temperature variables have a positive correlation between probability of presence and temperature, while both have a negative correlation for Santa Cruz and only maximum summer temperature has a positive correlation for Santa Rosa. Climate water deficit has a large negative correlation with probability of presence for Santa Catalina, while this trend on the other two islands is highly uncertain but weakly positive. Furthermore, while both the northern islands have a strong positive correlation between precipitation and probability of presence, probability of island oak presence on Santa Catalina has a parabolic relationship, suggesting a strong positive correlation with precipitation values from 300 – 324 mm followed by a strong negative correlation with values ranging from 325 – 360 mm. This is a difficult relationship to interpret, particularly over such a small range of precipitation values compared to the range available on the northern islands. These substantial changes in response curves have large impacts on habitat suitability predictions for the island.

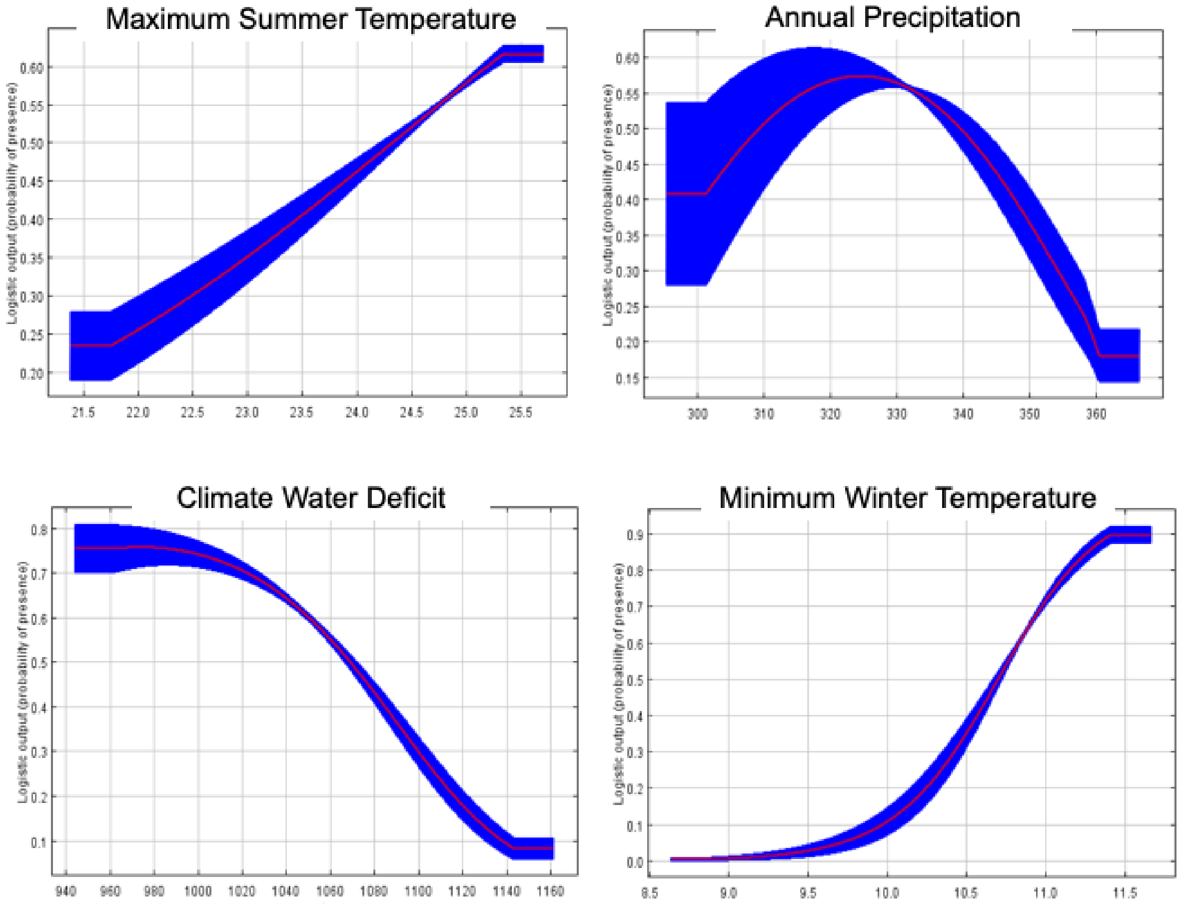


**Figure 14. Santa Catalina non-kriged response curves.** Marginal response curves for predictor variables in the Santa Catalina non-kriged model. Figures are presented in order of importance as defined by their percent contribution to the model. Predictor variable values are on the x-axis and predicted probability of presence values are on the y-axis. Red lines show correlation trends between each variable and predicted probability of presence. Blue ribbons are +/- one standard deviation around the trend line, determined by 100 bootstrap replicates.

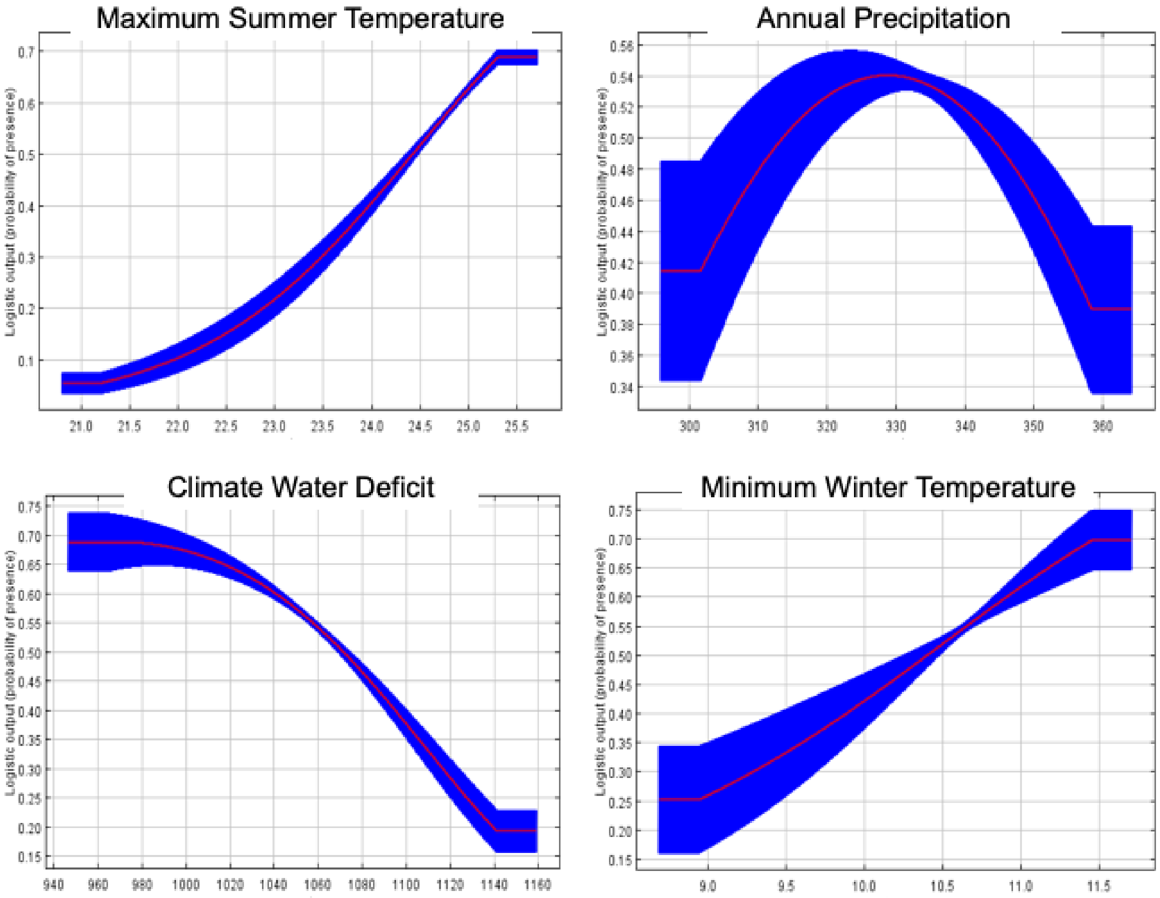


**Figure 15. Santa Catalina kriged response curves.** Marginal response curves for predictor variables in the Santa Catalina kriged model. Figures are presented in order of importance as defined by their percent contribution to the model. Predictor variable values are on the x-axis and predicted probability of presence values are on the y-axis. Red lines show correlation trends between each variable and predicted probability of presence. Blue ribbons are +/- one standard deviation around the trend line, determined by 100 bootstrap replicates.

Results for future predicted habitat suitability for non-kriged and kriged data across all climate scenarios and time steps are displayed in Table 7. With non-kriged climate data, the highest present predicted suitability score is 0.85 and current percent of suitable area is about 17%. The highest future predicted habitat suitability scores across projections range from 0.12 to 1.00. The percent of the island with predicted suitable area ranges from 0% to 97%, and the percent change in suitable area ranges from a 461% increase to a 100% decrease.

Overall, there are few distinguishable trends between future projections with respect to temperature or precipitation. The hot-wet scenario maintains at least 17% predicted suitable area within the modeled region that increases to 97% predicted suitable area by the end of century. In contrast, for the warm-wet scenario, the total predicted suitable habitat in the modeled area decreases to 0% in the first time step and never increases. Predicted suitable area in the two dry climate change scenarios increases in the first time step from 17% to 52%

in the warm-dry scenario and to 37% in the hot-dry scenario. They both decrease substantially in mid-century and are effectively 0% in the end-of-century time step.

For the kriged climate model, the maximum predicted present suitability value is 0.78 and the current percent of predicted suitable area across Santa Catalina Island is 29%. The highest future maximum predicted suitability scores across all projections range from 0.18 to 1.00. The percent of the island with predicted suitable area ranges from 0% to 61%, and the percent change in predicted suitable area ranges from a 114% increase to a 100% decrease.

**Table 7. Santa Catalina summary statistics.** Summary statistics for predicted species distribution on Santa Catalina Island for each climate projection and time step. Summary statistics include highest future habitat suitability, percent suitable area, and percent change in suitable area compared to the present as defined by binary suitability threshold value (maximum training sensitivity + specificity value from MaxEnt output).

| | | Non-kriged Climate Data | | | | Kriged Climate Data | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Years** | Projection | Max Suit. Score | Avg. Suit. Score | % Suitable Area | % Change in Suitable Area | Max Suit. Score | Avg. Suit. Score | % Suitable Area | % Change in Suitable Area |
| **1981–2010** | Historic | 0.85 | 0.60 | 17.33% | NA | 0.78 | 0.58 | 28.57% | NA |
| **2010–2039** | MPI 4.5 | 0.47 | 0.00 | 0.00% | -100.00% | 0.71 | 0.64 | 56.28% | 96.97% |
| | CCSM4 8.5 | 0.86 | 0.61 | 24.23% | 39.82% | 0.78 | 0.65 | 54.40% | 90.39% |
| | MIROC 4.5 | 1.00 | 0.78 | 52.22% | 201.33% | 1.00 | 0.68 | 46.50% | 62.76% |
| | MIROC 8.5 | 1.00 | 0.75 | 37.35% | 115.49% | 1.00 | 0.66 | 30.04% | 5.13% |
| **2040–2069** | MPI 4.5 | 0.62 | 0.57 | 0.61% | -96.46% | 0.74 | 0.65 | 61.09% | 113.82% |
| | CCSM4 8.5 | 1.00 | 0.71 | 17.25% | -0.44% | 0.99 | 0.62 | 15.26% | -46.58% |
| | MIROC 4.5 | 0.92 | 0.68 | 4.29% | -75.22% | 0.82 | 0.60 | 2.67% | -90.66% |
| | MIROC 8.5 | 0.66 | 0.56 | 0.61% | -96.46% | 0.50 | 0.50 | 0.08% | -99.74% |
| **2070–2099** | MPI 4.5 | 0.37 | 0.00 | 0.00% | -100.00% | 0.70 | 0.66 | 43.61% | 52.63% |
| | CCSM4 8.5 | 0.90 | 0.64 | 97.24% | 461.06% | 0.88 | 0.65 | 35.79% | 25.26% |
| | MIROC 4.5 | 0.74 | 0.59 | 1.00% | -94.25% | 0.58 | 0.52 | 0.49% | -98.29% |
| | MIROC 8.5 | 0.12 | 0.00 | 0.00% | -100.00% | 0.18 | 0.00 | 0.00% | -100.00% |

Climate trends between future projections for the kriged model are clearer than trends for the non-kriged model. The total area on Santa Catalina Island with suitable habitat increases in the first time step with all climate change scenarios, though the magnitude of increase is larger for the two wet scenarios, and smallest for the hot-dry scenario. In the mid-century time step, the wet and dry scenarios begin to diverge. Total suitable habitat expands to 61% in the warm-wet scenario, while it contracts in the hot-wet scenario, although 15% of the island remains predicted suitable habitat. Both dry scenarios contract mid-century, with the total predicted suitable habitat decreasing to 0% for the hot-dry scenario and 2% for the warm-dry scenario. In the last time step, 44% of the island is predicted suitable in the warm-wet scenario and 36% is predicted suitable in the hot-wet scenario. The dry scenarios have effectively no predicted suitable habitat by the end of the century. These statistics will be discussed more in depth below with regard to the observed spatial trends for both non-kriged and kriged models.

Figure 16 displays the probability of *Q. tomentella* presence on Santa Catalina for the four climate projections with the original BCM climate data. The data displayed in Figure 17 only varies from Figure 16 in that it uses the kriged climate data instead of the original. Both models for Santa Catalina had higher binary suitability max SSS thresholds than the other two islands, with values of about 0.49 for the non-kriged scenario and about 0.47 for the kriged scenario.

Spatial patterns and predicted suitability trends associated with non-kriged and kriged climate data for Santa Catalina are similar for some climate change scenarios but very different for others. The general trends for the dry scenarios are consistent, with suitable habitat increasing in the first future time period and decreasing thereafter; however, model predictions have large differences in the two wet climate change scenarios. For the non-kriged model, the warm-wet scenario has effectively no predicted suitable habitat through all time steps, but for the kriged model, the warm-wet scenario has the most predicted suitable habitat in all time steps. Based on other model outputs, and well-known oak biology, it is illogical that the warm-wet scenario would be the worst of all four climate change scenarios. A significant number of island oak presence points are omitted when using the non-kriged model, particularly those in lower elevations, which may be the cause of unusual results produced in those model runs. The predictions resulting from the kriged models seem to better represent the current climate occupied by island oaks and may present more accurate futures of island oaks on Santa Catalina.

Additionally, a majority of the suitable habitat in both non-kriged and kriged models is found on the southeastern portion of the island at high elevations where many of the oaks are presently located. However, the coverage of the original BCM data is highest in the southern portion of the island, so there is higher uncertainty associated with the kriged climate data on the northwestern portion of the island. For the kriged model in particular, the location of predicted suitable habitat expansion in the first time step for all four climate projections varies by climate change scenario, but all scenarios gain predicted suitable habitat in the northwest segment of the island. While the kriged scenario may provide potentially more accurate projections of predicted future suitable habitat, areas on the island with kriged climate data should be analyzed more critically and treated as more uncertain.

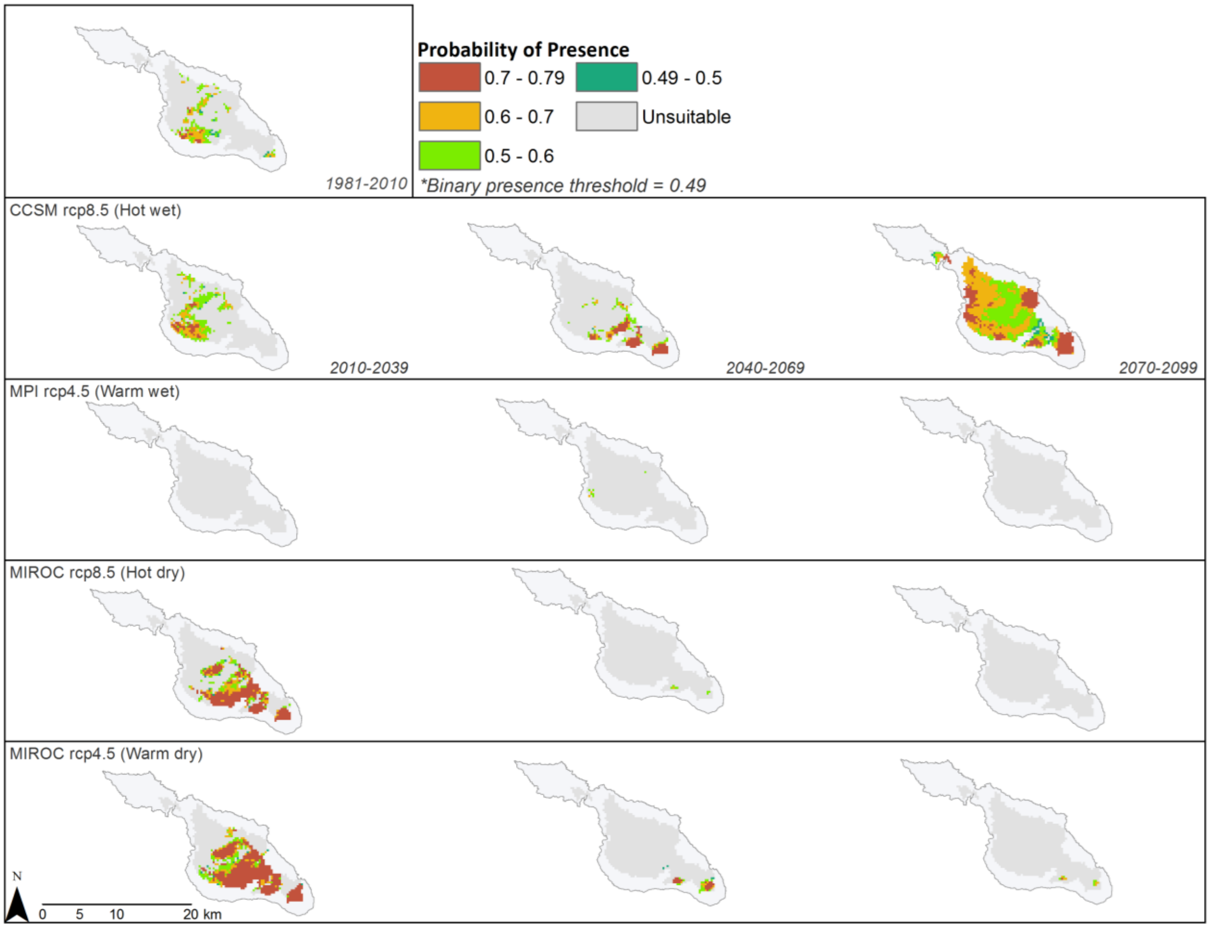


**Figure 16. Santa Catalina non-kriged probability of presence predictions.** Probability of presence of island oak across Santa Catalina Island using non-kriged climate data. The top panel shows probability of presence with current climate conditions. The next four panels show the probability of presence for the four climate projections through time. Warmer colors indicate higher probability of presence. The darker grey indicates areas below the suitable habitat threshold of 0.49 that are within the extent of the non-kriged climate data.

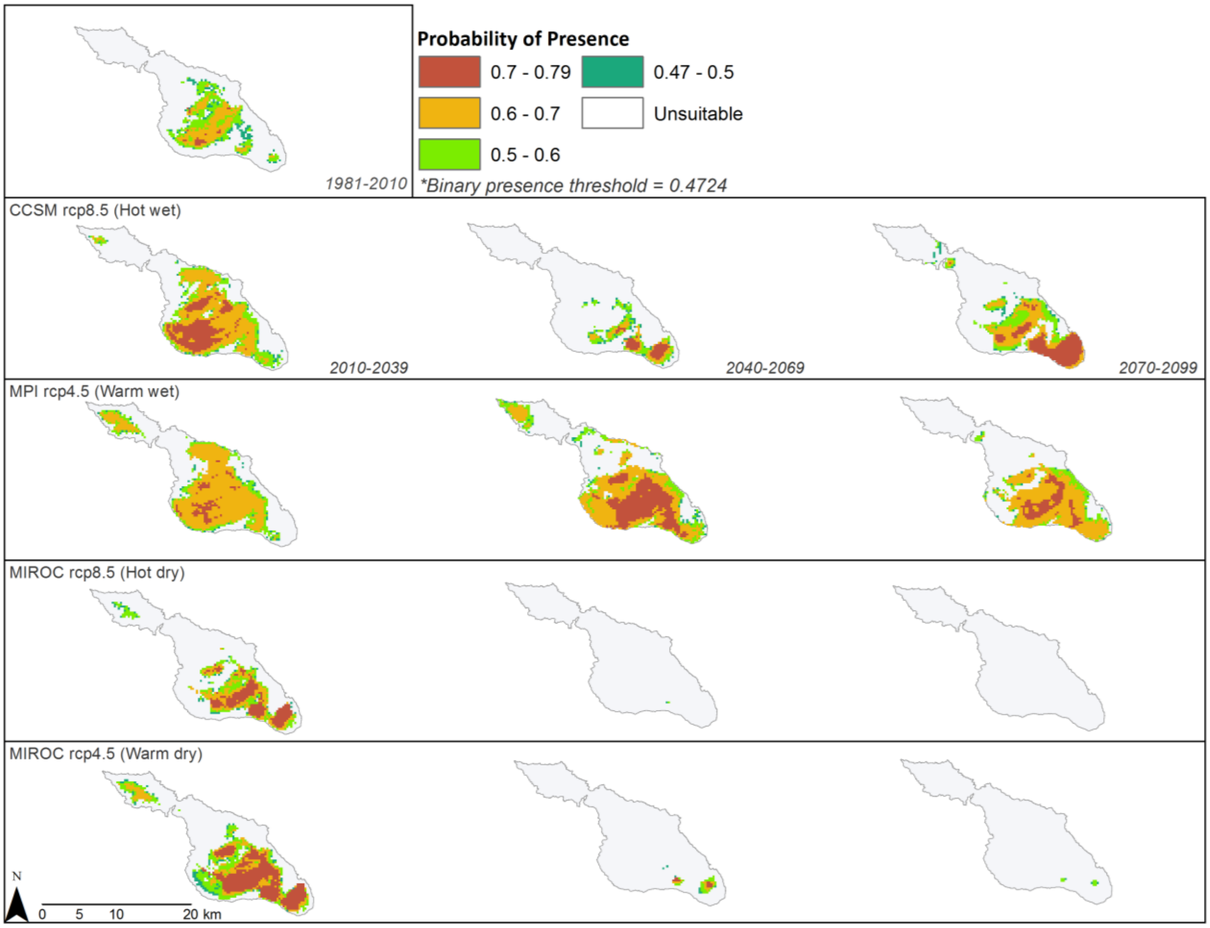


**Figure 17. Santa Catalina kriged probability of presence predictions.** Probability of presence of island oak across Santa Catalina Island using the kriged climate data. The top panel shows probability of presence with current climate conditions. The next four panels show the probability of presence for the four climate projections through time. Warmer colors indicate higher probability of presence. Light grey indicates areas below the suitable habitat threshold of 0.4724.

## All Islands

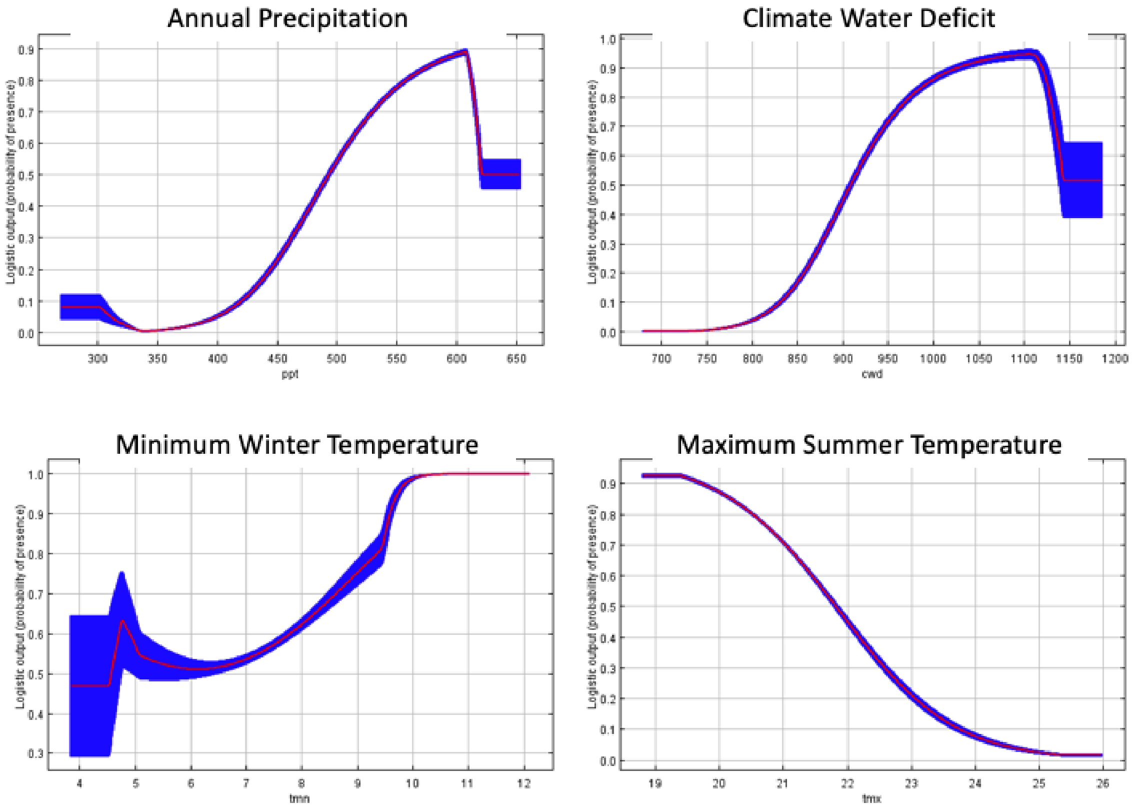
Results for the 'All Islands' models are presented for all three islands combined across climate projections and time periods. These models were created from the original BCM data without any fog inclusion and without the kriged Santa Catalina data. Analyzing all islands together produces very different predicted suitable habitat outcomes than individual island models using the same climate data. When predictions are made for each island separately, the species niche is derived from *Q. tomentella*'s current climate range on the specific island analyzed. However, when predictions of probability of presence are made for all islands together, then the defined climate niche of the species is derived from the much broader climate range of oak presences across all three islands. In this 'All Islands' scenario, MaxEnt treats the populations on each island as one uniform species that can live in a wider range of climate conditions.

The AUC value for the all islands model for the historic time period (1981 – 2010) is 0.87, and the maximum predicted suitability score is 0.93. Using the model's max SSS of 0.47 as the binary threshold, predicted suitable habitat covers 13% of all the islands. Table 8 demonstrates that precipitation has highest percent contribution to model gain followed by minimum winter temperature, climate water deficit, and maximum summer temperature, respectively. The finalized training model was most sensitive changes in annual precipitation, then maximum summer temperature, minimum winter temperature, and climate water deficit, respectively. Across all islands, precipitation contributes the most to model gain at 45.3%, which is similar to the importance of moisture variables seen in the individual Santa Cruz and Santa Rosa runs.

**Table 8. All Islands predictor variables.** Percent contribution of predictor variables to model fit in the all islands model.

| Variable | Percent Contribution to Model Gain | Sensitivity to Variable Permutations |
|---|---|---|
| Annual Precipitation | 45.3% | 43.3% |
| Minimum Winter Temperature | 20.4% | 15.1% |
| Climate Water Deficit | 19.1% | 12.4% |
| Maximum Summer Temperature | 15.2% | 29.2% |

Figure 18 presents marginal response curves for the predictor variables in the all islands scenario. These response curves cover a larger range of values than the response curves for the individual island analyses based on the inclusion of all three islands' environmental variables. Some of the relationships in these response curves are unexpected, specifically for climate water deficit. Based on reports of *Q. tomentella's* observed niche, climate water deficit was expected to have a negative correlation with probability of presence due to increased water stress, but the response curves have the opposite trend. This unusual relationship is likely due to the interaction of variables in training model coefficients as well as the wider range of values occupied by the oaks across the three islands. The other curves align more with what would be expected from the observed island oak niche: maximum summer temperature has a negative correlation with probability of presence, minimum winter temperature has a mostly positive correlation with probability of presence, and annual precipitation has a mostly positive correlation with probability of presence, except in the upper range of precipitation where the correlation becomes sharply negative. This drop is similar to what occurs with climate water deficit, suggesting an interaction between these variables.



Annual Precipitation

Climate Water Deficit

Minimum Winter Temperature

Maximum Summer Temperature

**Figure 18. All Islands response curves.** Marginal response curves for predictor variables in scenarios modeling joint habitat suitability for all three islands. Figures are presented in order of importance as defined by their percent contribution to the model. Covariate values are on the x-axis and probability of presence values are on the y-axis. Red lines show correlation trends between each covariate and probability of presence. Blue ribbons are +/- one standard deviation around the trend line, based on the average standard deviation of 100 bootstrap replicates.

Running all islands together results in different response curves for some variables in comparison to running islands individually (Figure 19). Higher maximum summer temperature has a negative relationship with probability of island oak presence for Santa Cruz Island individually and for all islands run together. In contrast, for Santa Rosa Island this relationship is positive, most likely due to the cooler range of temperatures MaxEnt uses to extrapolate information. On Santa Rosa, island oaks were found clustered around maximum temperature values of 21° C, which is on the higher side of available temperature on Santa Rosa but on the lower side of temperature on Santa Cruz. Santa Catalina also has a positive relationship between maximum temperatures and probability of presence, although it is a weaker relationship than that for Santa Rosa. However, these positive relationships are inconsistent with what is known about oak biology; therefore, the response curves for Santa Cruz and for all islands together may be more reflective of oak distribution in the future, while the future distribution of habitat suitability of Santa Rosa and Santa Catalina should be considered with caution.

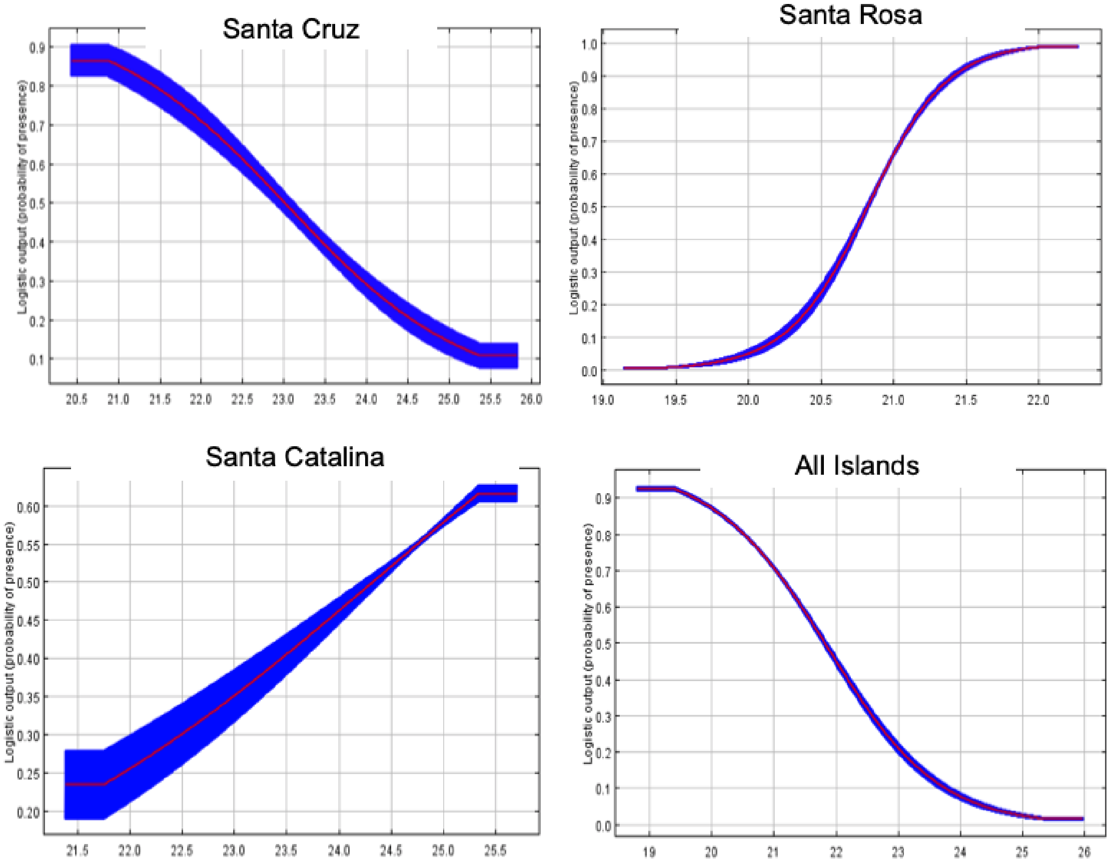


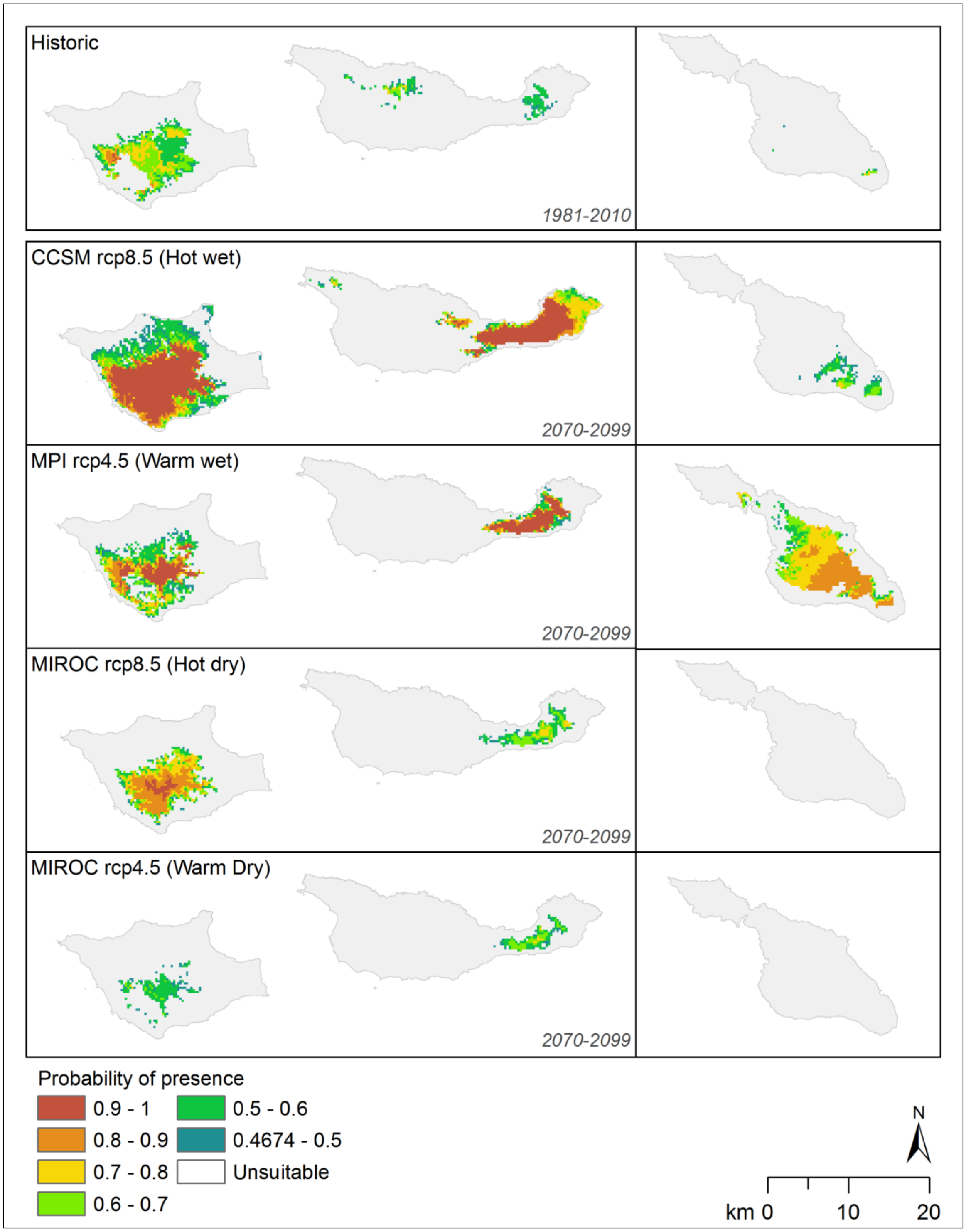
**Figure 19. Scenario response curves of maximum summer temperature.** Response curves for maximum summer temperature on Santa Rosa, Santa Cruz, Santa Catalina (kriged), and for all islands run together. Comparison between model versions demonstrates how the logistic prediction changes as maximum summer temperatures vary. The y-axis represents oak presence and the x-axis represents maximum summer temperatures (°C), and blue ribbons represent one +/- standard deviation in curves from 100 bootstrap replications.

Table 9 displays the differences in percent predicted suitable area calculated when running the models with climate and island oak presence data for the three islands combined versus each island individually. The 'All Islands' columns state the percent predicted suitable area found on all islands combined as well as on each individual island within the all islands scenario, for each projection and time step. The 'Individual Island' columns are based on the model runs where each island was run individually with only the island oak points and climate data found on that specific island, excluding probability of fog inundation and using non-kriged climate data for Santa Catalina for ease of comparison. These columns give the percent predicted suitable area for each island run individually across projections and time steps. The all islands model had a threshold of 0.47, Santa Catalina individually had a value of 0.49, Santa Cruz had 0.47, and Santa Rosa had 0.23. Some predictions do not change between all islands and individual island analyses, particularly several of the predictions with 0% suitable area, while other predictions vary substantially. The results for Santa Catalina are the most varied between the all islands analysis and the individual island analysis, further complicating interpretation of the island oak's climate niche on this island. Overall, the all islands analysis compared to the individual island analysis predicts more suitable habitat on Santa Cruz, less suitable habitat on Santa Rosa, and mixed results on Santa Catalina.

**Table 9. Scenario comparison summary statistics.** Percent predicted suitable area on each island with all islands analyzed together versus each island analyzed separately. Values are from models without probability of fog inundation on Santa Cruz and Santa Rosa and with non-kriged climate data for Santa Catalina. Percent predicted suitable area is defined by the binary suitability threshold value (maximum training sensitivity + specificity value from MaxEnt output). The all islands threshold is 0.4674, Santa Catalina (SCA) is 0.49, Santa Cruz (SCR) is 0.4659, and Santa Rosa (SRI) is 0.2296.

| | | | All Islands Model | | | | Individual Island Models | | |
|---|---|---|---|---|---|---|---|---|---|
| **Years** | Projection | Name | Combined | SCA | SCR | SRI | SCA | SCR | SRI |
| **1981 – 2010** | Historic | Current | 13% | 1% | 6% | 28% | 17% | 26% | 24% |
| **2010 – 2039** | MPI 4.5 | Warm-Wet | 22% | 64% | 6% | 22% | 0% | 2% | 91% |
| | CCSM4 8.5 | Hot-Wet | 20% | 54% | 7% | 19% | 24% | 2% | 93% |
| | MIROC 4.5 | Warm-Dry | 1% | 3% | 0% | 1% | 52% | 0% | 42% |
| | MIROC 8.5 | Hot-Dry | 1% | 1% | 0% | 1% | 37% | 0% | 40% |
| **2040 – 2069** | MPI 4.5 | Warm-Wet | 28% | 78% | 11% | 26% | 1% | 0% | 92% |
| | CCSM4 8.5 | Hot-Wet | 1% | 1% | 0% | 2% | 17% | 0% | 39% |
| | MIROC 4.5 | Warm-Dry | 1% | 0% | 0% | 3% | 4% | 0% | 16% |
| | MIROC 8.5 | Hot-Dry | 2% | 0% | 1% | 6% | 1% | 0% | 0% |
| **2070 – 2099** | MPI 4.5 | Warm-Wet | 31% | 81% | 12% | 33% | 0% | 0% | 93% |
| | CCSM4 8.5 | Hot-Wet | 39% | 14% | 27% | 66% | 97% | 0% | 90% |
| | MIROC 4.5 | Warm-Dry | 5% | 0% | 5% | 8% | 1% | 0% | 8% |
| | MIROC 8.5 | Hot-Dry | 14% | 0% | 8% | 28% | 0% | 0% | 0% |

Figure 20 illustrates the predicted suitable habitat for all islands in each climate scenario for the 2070 – 2099 time period. For the all islands analysis, Santa Rosa and Santa Cruz have the highest percent predicted suitable area in the hot-wet, end of century scenario, while Santa Catalina has the highest percent predicted suitable area in the warm-wet, end of century scenario. Santa Rosa and Santa Cruz have predicted suitable climate habitat across all climate projections, with more predicted suitable area in the wetter projections and the lowest predicted suitable area in the hot-dry scenario. Santa Catalina, on the other hand, only has predicted suitable habitat in the wet scenarios and has no predicted suitable oak habitat in the end of century dry scenarios. Additionally, in the All Islands scenario, Santa Catalina only has 1% predicted suitable area under current conditions, which seems odd given that there are island oaks currently surviving on the island, though not necessarily thriving.


Historic

1981-2010

CCSM rcp8.5 (Hot wet)

2070-2099

MPI rcp4.5 (Warm wet)

2070-2099

MIROC rcp8.5 (Hot dry)

2070-2099

MIROC rcp4.5 (Warm Dry)

2070-2099

**Figure 20. All Islands probability of presence predictions.** Probability of presence of island oak across Santa Rosa, Santa Cruz, and Santa Catalina Islands for all climate scenarios for the historic and 2070 – 2099 time periods. Warmer colors indicate higher probability of presence. Light grey extent indicates areas below the suitable habitat threshold of 0.4674.

## Fog Sensitivity Analysis

Of the four adjusted fog scenarios, the elevation threshold scenario most closely matches the historic trends of fog occurrence observed at San Nicolas, which is the weather station with the most spatial and oceanic similarities to the northern islands (Williams et al., 2015). Therefore, our analysis focuses on the elevation threshold scenario when including fog as a predictor variable. Given the high uncertainty in future fog trends, we analyzed sensitivity of the results to the fog scenario by comparing general observed trends in probability of presence when all variables are held constant except for the fog scenario selected. When compared to output from the same climate scenario and time step with no fog layer included, inclusion of any fog scenario increased model fit and concentrated predicted suitable habitat more closely around where *Q. tomentella* are currently found.

MaxEnt output across fog scenarios for Santa Cruz (Figure 21) and Santa Rosa (Figure 22) are compared for the end of century (2070 – 2099), warm-wet climate projection (MPI RCP4.5) as an example of the sensitivity analysis. We selected this example because general patterns in sensitivity are similar for all climate scenarios and time steps but are most obvious under these conditions. While the patterns between fog scenarios are obscured on Santa Rosa due to very high predicted suitability scores across the majority of the island, the general trends between fog scenarios are more visible on Santa Cruz.

On Santa Cruz, the increasing fog scenario predicts substantially higher percentage of suitable habitat across the island and higher probability of presence values compared to the constant fog scenario, particularly in the northwest and eastern sections of the island. Compared to the constant scenario, the decreasing fog scenario predicts reductions in suitable areas across the island. The elevation threshold scenario results for Santa Cruz has both increases and decreases in predicted suitable area that are location specific following elevation trends. Increases are significantly smaller in area than the decreases, which is especially notable since much of the current suitable oak habitat tends to be at mid to high elevations. Generally, patterns for this scenario appear as a reduction in predicted suitable habitat in the more central and elevated areas of the islands and an increase in more low elevation coastal areas. Elevational changes in fog could potentially have huge ramifications for island oak habitat suitability, as currently a large percentage of island oaks are found at higher elevations. If future fog decreases at higher elevations where many oaks are currently found and increases at lower elevations where there are fewer oaks, substantial impacts on the population at high elevations could occur.

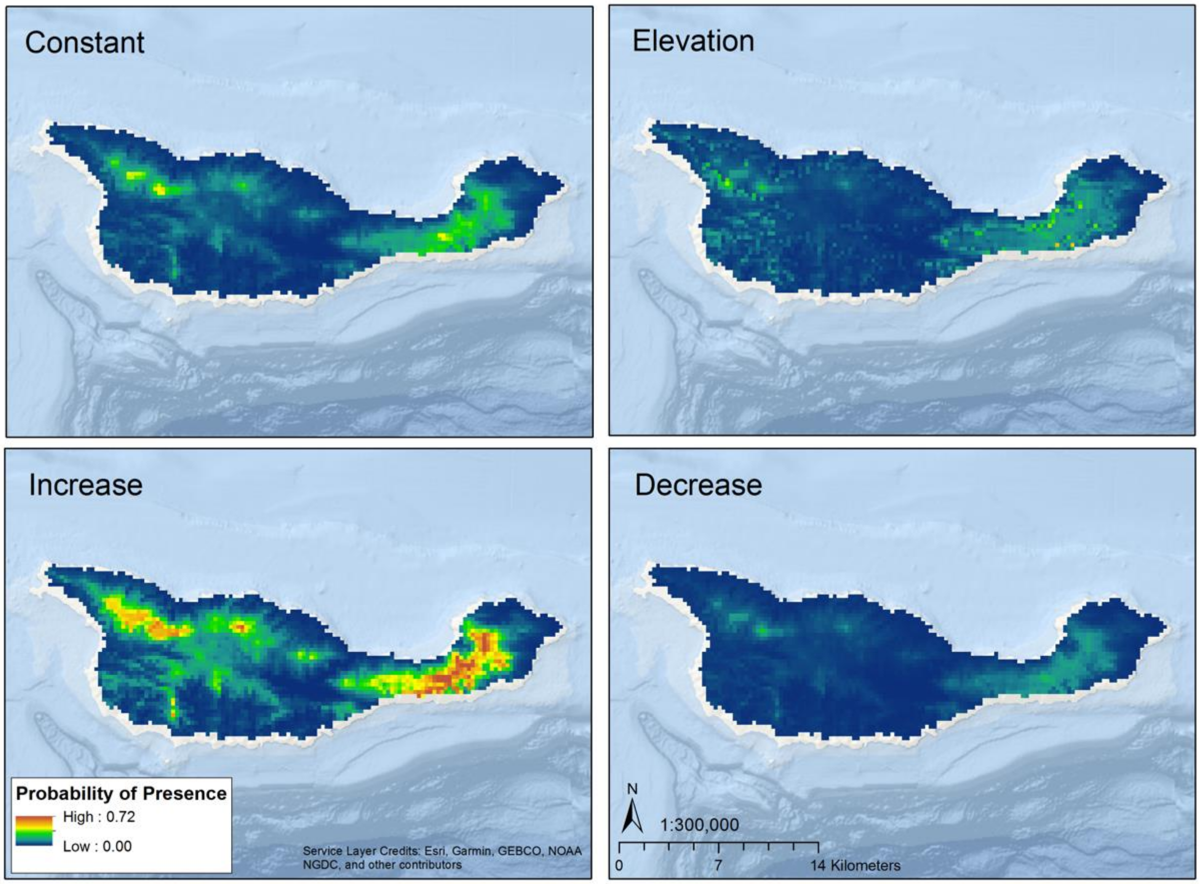


**Figure 21. Santa Cruz probability of presence predictions for fog scenarios.** Predicted probability of presence for *Quercus tomentella* in the MPI RCP4.5 climate scenrio from 2070 – 2099 under each fog scenario on Santa Cruz Island. In the elevation threshold scenario, shown in the top right panel, input probability of fog inundation was decreased above 255 meters and increased below 255 meters. Warmer colors indicate higher probability of presence, with a maximum of 72%.

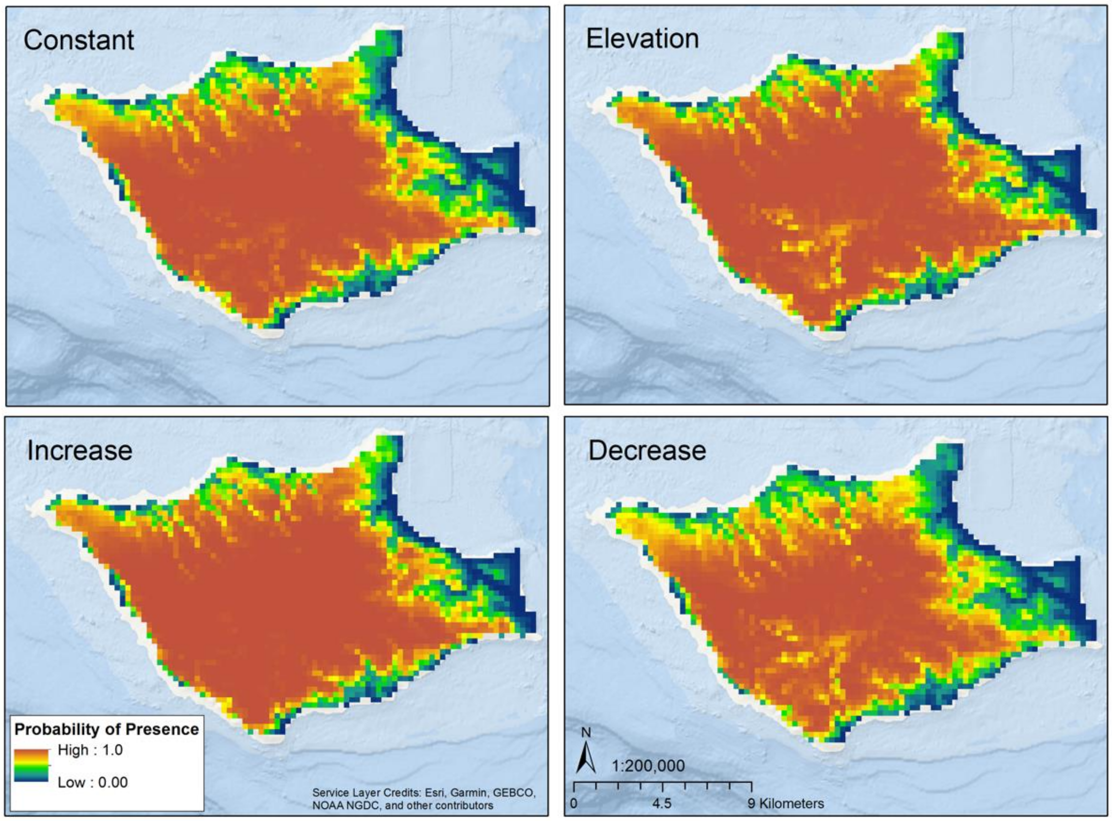


**Figure 22. Santa Rosa probability of presence predictions for fog scenarios.** Probability of presence for *Quercus tomentella* in the MPI RCP4.5 climate scenrio from 2070 – 2099 under each fog scenario on Santa Rosa. In the elevation threshold scenario, shown in the top right panel, input probability of fog inundation was decreased above 255 meters and increased below 255 meters. Warmer colors indicate higher probability of presence, with a maximum of 100%.

## Additional Climate Suitability Analyses

We briefly discuss results for additional climate suitability analyses here, but more in-depth figures are available in Appendix B. In addition to the results presented above, we ran analyses at larger extents to explore island oak suitability beyond its current range. We explored the potential for *Q. tomentella* habitat on San Miguel Island, directly west of Santa Rosa, as well as on mainland California. Our analyses showed no suitable habitat on San Miguel across all climate projections and time periods. San Miguel is the westernmost of the Channel Islands and is windier, flatter, and sandier (U.S. National Park Service, "San Miguel Island", 2016). Given these conditions, the habitat on San Miguel is very different compared to the habitat that the oaks currently occupy on Santa Rosa and Santa Cruz. In the analysis of mainland California, suitable habitat in coastal areas for all climate projections and time steps moves farther north through time to areas surrounding to the San Francisco Bay area. We also performed analyses on the stage structure data available for Santa Rosa, with separate analyses for recruits (seedlings and saplings) and adults. The results indicate that seedlings tend to have more restricted climate preferences and fare worse than adults through each climate projection over time. Known stage structure information was limited, so these results should be considered with caution.

## Integrated Outlook

Our second research objective was to evaluate the integrated outlook of *Q. tomentella* for each island across all climate and fog scenarios through the end of the century, with respect to climate-driven probability of presence. We integrated, or summed, the number of times a cell was predicted as suitable habitat across all potential future scenarios for that specific island. 'All island' model results were not included in the summed value. In Figures 23 – 25, each 270-meter cell indicates the number of times it was deemed suitable climate habitat for the oak across all combinations of future scenarios.

For Santa Rosa and Santa Cruz, the maximum possible score is 49, as there are four fog scenarios that each have suitable predictions for the current time step and four future climate projections for each of the three future time steps (Figures 23 – 24). Cells with a value of 49 are predicted as suitable habitat both currently and for every future climate and fog scenario across all time steps. In the figures, the darkest green represents a higher number of "suitable scenarios," while yellow depicts areas that were rarely deemed suitable habitat. The output on the top left of the Santa Cruz and Santa Rosa figures illustrates this cumulative, all time step integration. The row below shows a similar result, but with each individual time step separated out, so the maximum number of summed scenarios is 16.

For Santa Catalina, the maximum score across all time steps is 13 because fog scenarios were not an available option (Figure 25). Pixels with a value of 13 are suitable currently and across all climate projections and time steps. Summed values for individual time steps are not illustrated for Santa Catalina since there are fewer scenarios to integrate.

Figure 23 shows the integrated outlook results for Santa Cruz. Santa Cruz Island has no cells that are suitable across all scenarios and time steps. The maximum integrated value is 27 for a few sparse cells, almost half of the potential maximum value of 49. Overall, Santa Cruz has the lowest values, with a majority of cells with values of 0 or 1, in which 1 represents area that is currently predicted suitable habitat. In the first time step, there are a few pixels with the maximum number of 16 on the northwestern portion of the island where a large number of oaks are currently present; these suitable pixels disappear in the next two time steps. Overall, the lack of suitable habitat in all predicted futures suggests that island oaks on Santa Cruz may struggle to persist into the future, regardless of the uncertainty in future climate and fog variability. However, it should be noted that the current derived relationships been oak presence and climate layers on Santa Cruz, described by the response curves in the previous section, could be highly influencing the projected outlook of the species.

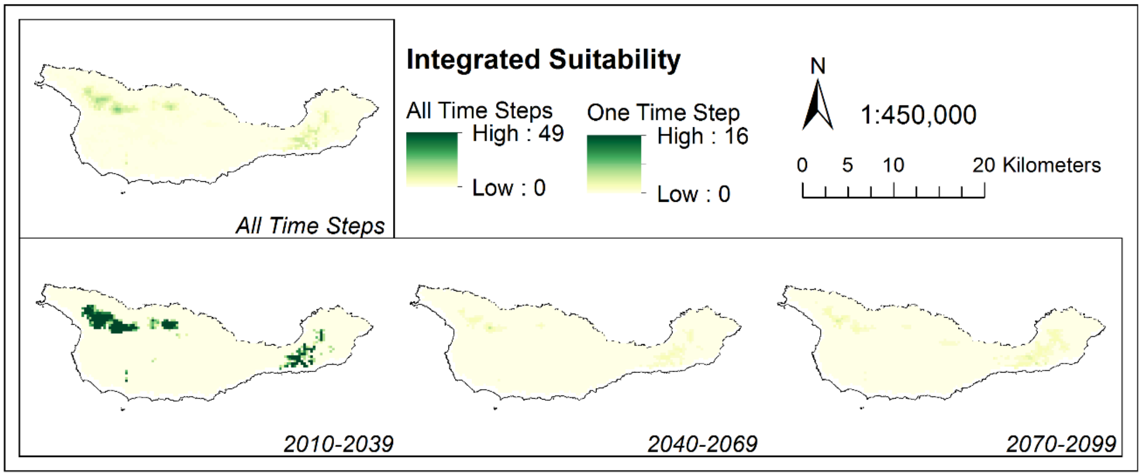


**Figure 23. Santa Cruz integrated outlook.** Integrated climate suitability for island oaks on Santa Cruz Island across all climate and fog scenarios. The top panel shows the integrated suitability across all time steps, while the bottom panel shows across three future time steps. Darker green indicates the pixel is suitable in a higher number of scenarios: 49 is the highest possible value for all scenarios and 16 for each time step.

Figure 24 shows the integrated outlook results for Santa Rosa Island, which is the only island to have cells suitable across all projections and time periods, with the maximum value of 49. The integrated outlook shows a general contraction of suitable range summed across scenarios through time, focused around areas that currently have high island oak presence. Overall, Santa Rosa has many cells deemed suitable across most of the predicted future scenarios, as indicated by the relatively dark green color across the island for all time steps and for each time step. These results suggest that there will be suitable climate for the island oak on Santa Rosa through the end of the century even for the worst-case scenarios. However, due to the questionable positive correlation of probability of presence with maximum summer temperature, these results could be an overestimation.

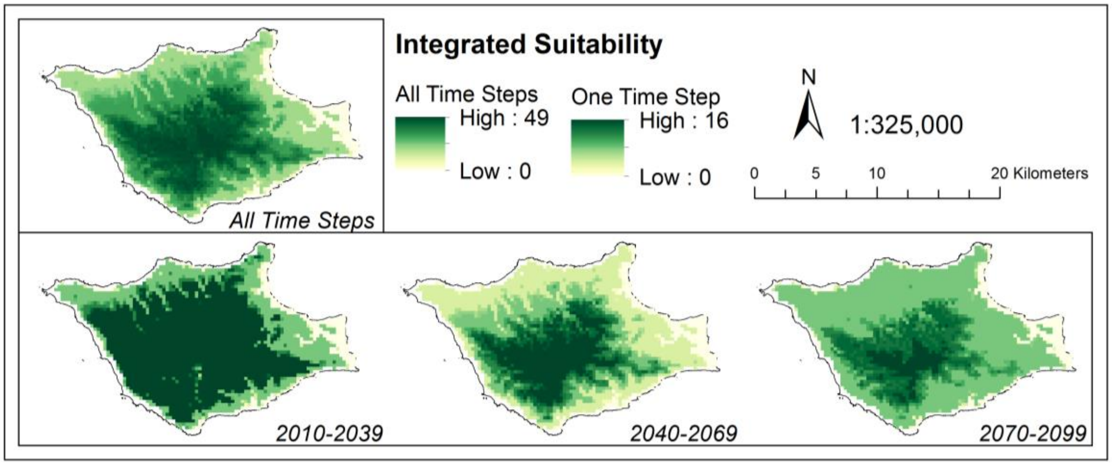


**Figure 24. Santa Rosa integrated outlook.** Integrated climate suitability for island oaks on Santa Rosa Island across all climate and fog scenarios. The top panel shows the integrated suitability across all time steps, while the bottom panel shows across three future time steps. Darker green indicates that the pixel is suitable in a higher number of scenarios: 49 is the highest possible value for all scenarios and 16 for each time step.

Figure 25 shows the integrated outlook results for Santa Catalina summed across all time steps and climate projections for non-kriged and kriged scenarios respectively. The maximum possible value is 13. For Santa Catalina, the changes in suitability in the wet scenarios drive predictions for which areas will be suitable across scenarios through the end of century (Figure 25). The non-kriged outcome has suitable area remaining in fewer scenarios than the kriged data, mainly for the wetter projections. The kriged scenario has a large proportion of cells that remain suitable through 10 – 12 of all projections and time periods (including historic), while the non-kriged scenario has the majority of its area remaining suitable in only 3 – 4 projections and time periods. The kriged climate data and the inclusion of additional oak presence points that were excluded in the non-kriged scenario seem to widen the range of potential climate niches considered for the species by the model. This results in greater suitability across a wider range of climate projections in the future.

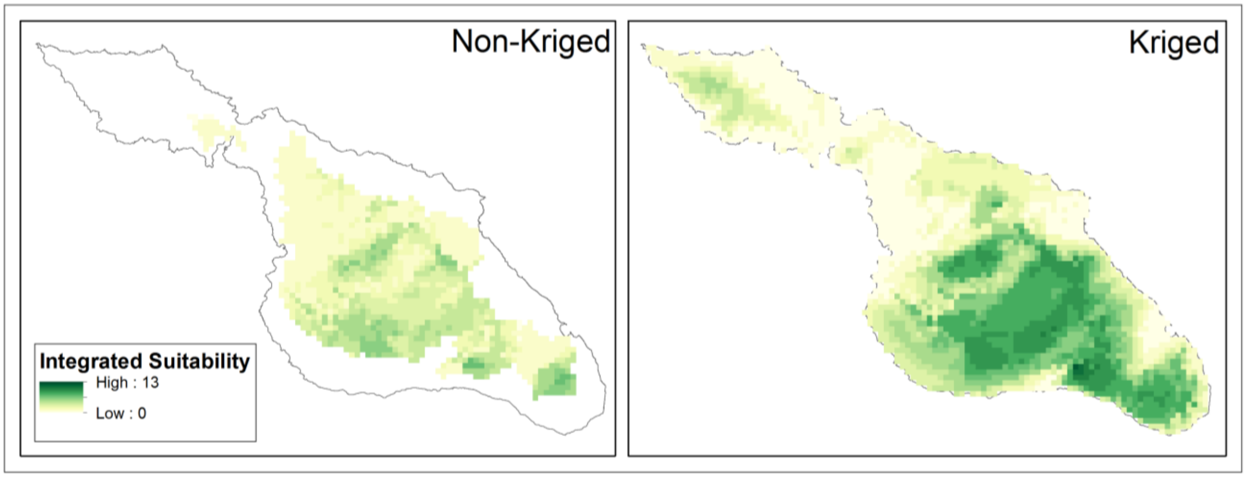


**Figure 25. Santa Catalina integrated outlook.** Integrated climate suitability for island oaks on Santa Catalina Island across all climate scenarios. Integrated suitability with non-kriged data is presented on the left and kriged data on the right. Darker green indicates that the pixel is suitable in a higher number of scenarios, with 13 as the highest possible value.

# Oak-Climate Niche Relationships

Our third research objective was to examine the relationships between *Q. tomentella* presence and climate variables to increase our understanding of the species climate envelope on each island. We examined how climate niches for the species varied across the islands to inform the degree of local adaptation the oak may have on each island and to better understand the potential full range of the species niche. This section focuses on the current range of climate types occupied by the species and explores how the climate range on each island may shift in the future. In order to compare the climate niches on all three islands, fog was not a focus of this analysis since probability of fog inundation data was unavailable for Santa Catalina.

## Current Oak-Climate Ranges

*Q. tomentella* exists in a wide range of climate conditions found across the islands. On Santa Cruz, island oaks occupy a large spread of the temperature and precipitation conditions present on the island (Table 10). The trees are present at maximum summer temperatures of 21.60 – 24.72 °C out of the full island climate range of 20.87 – 25.37 °C, and are found at precipitations from 391 – 616 mm out of the full climate range of 327 – 621 mm. Overall, Santa Cruz oaks are found in areas of higher precipitation levels on average and occupy a relatively narrow range of available climate water deficit values.

**Table 10. Santa Cruz climate values.** Range of available climate values on Santa Cruz Island (Island) and climate values where island oaks are present on Santa Cruz Island (Oak). Environmental variables include climate water deficit (CWD), maximum summer temperature (TMX), minimum winter temperature (TMN), annual precipitation (PPT), and probability of fog inundation (Fog).

| Environmental Variable | Range | Minimum | Maximum | Average |
|---|---|---|---|---|
| CWD (mm) | Island | 721.51 | 1043.56 | 930.40 |
| | Oak | 856.47 | 969.66 | 911.39 |
| TMX (°C) | Island | 20.87 | 25.37 | 23.01 |
| | Oak | 21.60 | 24.72 | 23.17 |
| TMN (°C) | Island | 4.52 | 8.59 | 6.45 |
| | Oak | 4.82 | 8.44 | 6.06 |
| PPT (mm) | Island | 327.20 | 620.93 | 483.49 |
| | Oak | 391.05 | 616.60 | 526.48 |
| Fog (Probability) | Island | 0.00 | 0.46 | 0.20 |
| | Oak | 0.00 | 0.42 | 0.27 |

Similar to Santa Cruz, Santa Rosa island oaks are found in a wide range of climate values available on the island (Table 11). Santa Rosa island oaks are located between maximum summer temperatures of 19.4 – 21.5 °C out of the island's climate range of 19.4 – 22 °C. For precipitation, island oaks on Santa Rosa are found from a range of 405 – 581 mm of out of the island's total range of 368 – 585 mm. On average, *Q. tomentella* is found in locations of higher precipitation levels, lower climate water deficit, lower maximum temperature values, and higher minimum temperature values.

**Table 11. Santa Rosa climate values.** Range of available climate values on Santa Rosa Island (Island) versus climate values where island oaks are present on Santa Rosa Island (Oak). Environmental variables include climate water deficit (CWD), maximum summer temperature (TMX), minimum winter temperature (TMN), annual precipitation (PPT), and probability of fog inundation (Fog).

| Environmental Variable | Range | Minimum | Maximum | Average |
|---|---|---|---|---|
| CWD (mm) | Island | 787.25 | 1062.94 | 924.14 |
| | Oak | 835.91 | 974.40 | 902.84 |
| TMX (°C) | Island | 19.40 | 22.01 | 21.13 |
| | Oak | 19.40 | 21.54 | 20.86 |
| TMN (°C) | Island | 6.07 | 7.71 | 6.96 |
| | Oak | 6.69 | 7.61 | 7.20 |
| PPT (mm) | Island | 368.31 | 585.63 | 460.93 |
| | Oak | 405.88 | 581.83 | 514.86 |
| Fog (Probability) | Island | 0.00 | 0.38 | 0.19 |
| | Oak | 0.07 | 0.38 | 0.29 |

Santa Catalina oaks tend to be found in a smaller range of the available summer maximum temperatures (23.4 – 24.9 °C out of the full climate range of about 21.2 – 25.3 °C) and climate water deficit values (988 – 1108 mm out of the full climate range of 964 – 1141 mm), as shown in Table 12. Island oaks on Santa Catalina generally have similar average climate variable values to the island as a whole.

**Table 12. Santa Catalina climate values.** Range of available climate values on Santa Catalina Island (Island) versus climate values where island oaks are present on Santa Catalina Island (Oak). Environmental variables include climate water deficit (CWD), maximum summer temperature (TMX), minimum winter temperature (TMN), annual precipitation (PPT), and probability of fog inundation (Fog).

| Environmental Variable | Range | Minimum | Maximum | Average |
|---|---|---|---|---|
| CWD (mm) | Island | 964.39 | 1141.11 | 1074.70 |
| | Oak | 988.31 | 1108.01 | 1061.74 |
| TMX (°C) | Island | 21.21 | 25.30 | 24.02 |
| | Oak | 23.38 | 24.94 | 24.58 |
| TMN (°C) | Island | 8.94 | 11.45 | 10.27 |
| | Oak | 9.73 | 11.17 | 10.57 |
| PPT (mm) | Island | 301.60 | 358.42 | 329.73 |
| | Oak | 315.19 | 352.34 | 334.26 |

## Current Oak-Climate Distributions

Climate conditions in confirmed oak locations varied by island (Figure 26). Since Santa Rosa has overall cooler temperatures than the other two islands, island oaks on Santa Rosa tend to be in areas with relatively lower maximum summer temperatures, with the majority found in locations maximum summer temperatures around 21 °C. Island oaks on Santa Cruz are present in areas with slightly higher maximum temperatures, with most oaks found between temperatures of 22.5 °C to 24.5 °C. Santa Catalina oaks withstand the highest temperatures of all three islands, with most oaks living in areas with a summer maximum temperature of about 25 °C, which is also approximately the upper limit for the island as a whole. Santa Catalina oaks also experience the highest average minimum winter temperature, while this value is lowest for Santa Cruz oaks at a lower limit of 5 °C for the island. Climate water deficit is the highest for Santa Catalina Island oaks, as Santa Catalina generally experiences hotter and drier conditions than the other islands, with most oaks occupying a deficit of 1050 mm. Oaks on Santa Rosa and Santa Cruz experience similar levels of climate water deficit, up to 250 mm less than those on Santa Catalina. Similarly, precipitation is lowest on Santa Catalina with most oaks experiencing about 330 mm of rain per year. Santa Rosa and Santa Cruz oaks have similar precipitation ranges, with values often double that found on Santa Catalina. The probability of fog inundation for both Santa Cruz and Santa Rosa oaks peak around 20 – 37%, but Santa Cruz oaks are often in areas with higher maximum probability of fog inundation than oaks on Santa Rosa. The differences in distributions on each island concerning climate variable values further support the potential for the existence of distinct preferred climate niches by island oaks across the islands.

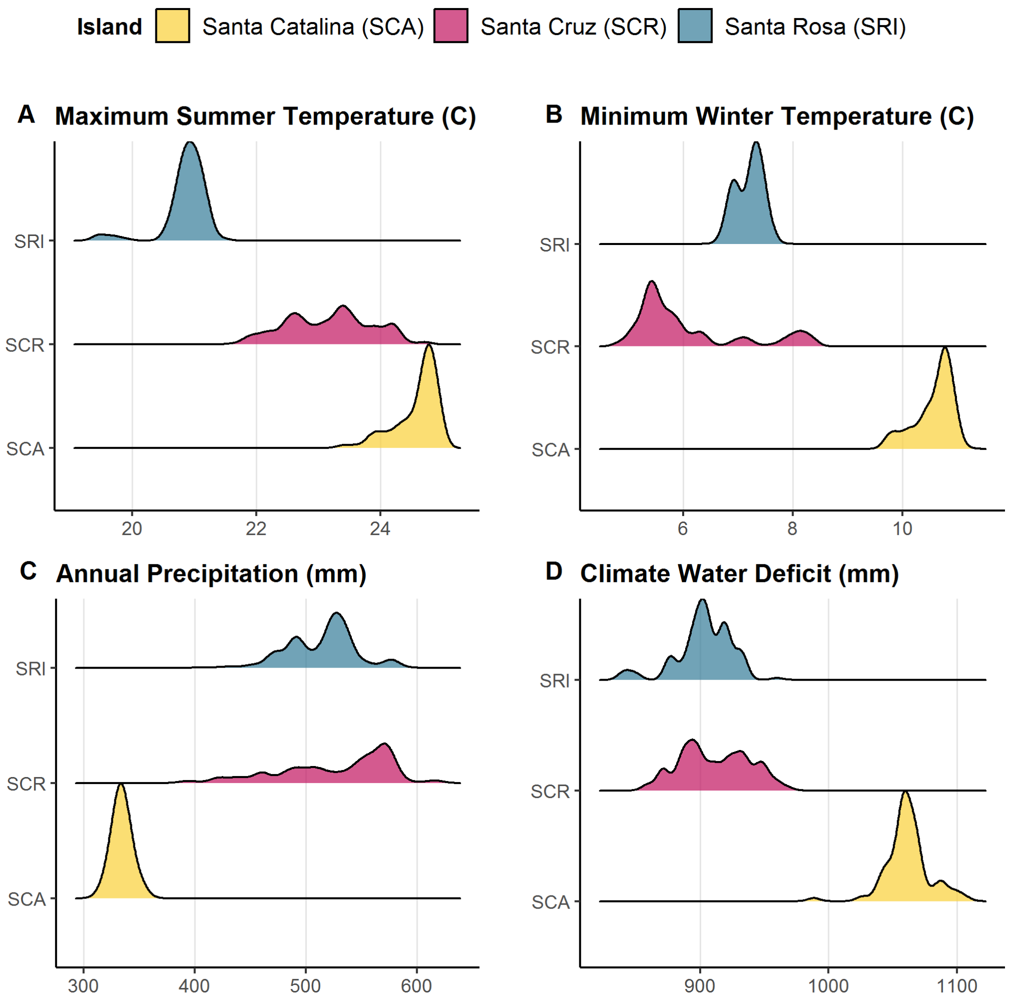


**Figure 26. Presence curves for climate variables.** *Quercus tomentella* presence counts across climate conditions on each island. Kriged climate layers were used for Santa Catalina. Values on the y-axis represent the kernel density, while values on the x-axis represent the range of climate conditions in confirmed island oak presence locations on each island.

## Potential Future Oak-Climate Relationships

Figure 27 compares the current and projected climate conditions for each island for the two climate layers that had the highest contribution to model gain for that island, excluding probability of fog inundation for ease of comparison. The climate projections visualized are for the warm-wet and hot-dry future climate scenarios at end of century shown by the polygons representing the full range of climate variables on the island. The contour lines on the polygons represent the density of locations found on each island that fall in that particular climate space combination. For the current climate conditions, current oak point locations overlay the climate polygons based on where they fall in the climate space. Larger points indicate a higher density of oak points found in the climate space. The axes of Santa Cruz and Santa Rosa are precipitation and maximum summer temperature, while Santa Catalina has climate water deficit and maximum summer temperature.

Under the “best-case” warm-wet scenario, maximum summer temperature shifts 2 °C warmer (upward) on each island. For Santa Cruz and Santa Rosa, precipitation shifts 10 mm higher (right) for both islands. For Santa Catalina, climate water deficit does not distinctly shift in this scenario. In comparison, for the “worst-case” hot-dry scenario, maximum summer temperature shifts about 5 °C warmer (upward) for each island. For Santa Cruz and Santa Rosa, precipitation shifts 200 mm lower (left), a more substantial shift in precipitation than under the warm-wet scenario. For Santa Catalina, climate water deficit shifts about 180 mm higher (right) under the hot-dry scenario, which is a substantial shift.

In the hot-dry scenario, summer maximum temperature shifts completely out of the current climate range of the island oaks on Santa Cruz. However, the upper range of precipitation in the projected climate overlaps with the lower range of the current precipitation values. There are a few island oaks in this overlapping range at about 400 mm of rainfall. Considering the importance of maximum summer temperature on the model’s prediction of oak presence, oaks on Santa Cruz in this scenario may not persist despite overlapping precipitation. In the warm-wet scenario for Santa Cruz, there are temperature and precipitation values that overlap with current oak climate ranges, although only for a small number of oaks. Precipitation in this scenario is predicted to fall completely within current oak ranges by the end of the century, while maximum summer temperatures are predicted to increase, overlapping with oaks currently withstanding higher temperatures.

Conversely, island oaks on Santa Rosa will not find precipitation and maximum summer temperature values similar to where they are currently located in the hot-dry scenario, as both variables shift completely out of the current range where oaks are currently situated. In the warm-wet scenario for Santa Rosa, some parts of the island will maintain similar temperature ranges in the current oak distribution. However, there are currently not many oaks found at these higher maximum summer temperatures where there is overlap. On the other hand, precipitation in this scenario is predicted to cover the entire current range of rainfall where oaks are situated.

Similarly, Santa Catalina has no range overlap with climate water deficit and summer maximum temperature in the hot-dry scenario. In the warm-wet scenario, a majority of island oaks on Santa Catalina are located in a climate well within both their current range of climate water deficit and maximum summer temperature values.

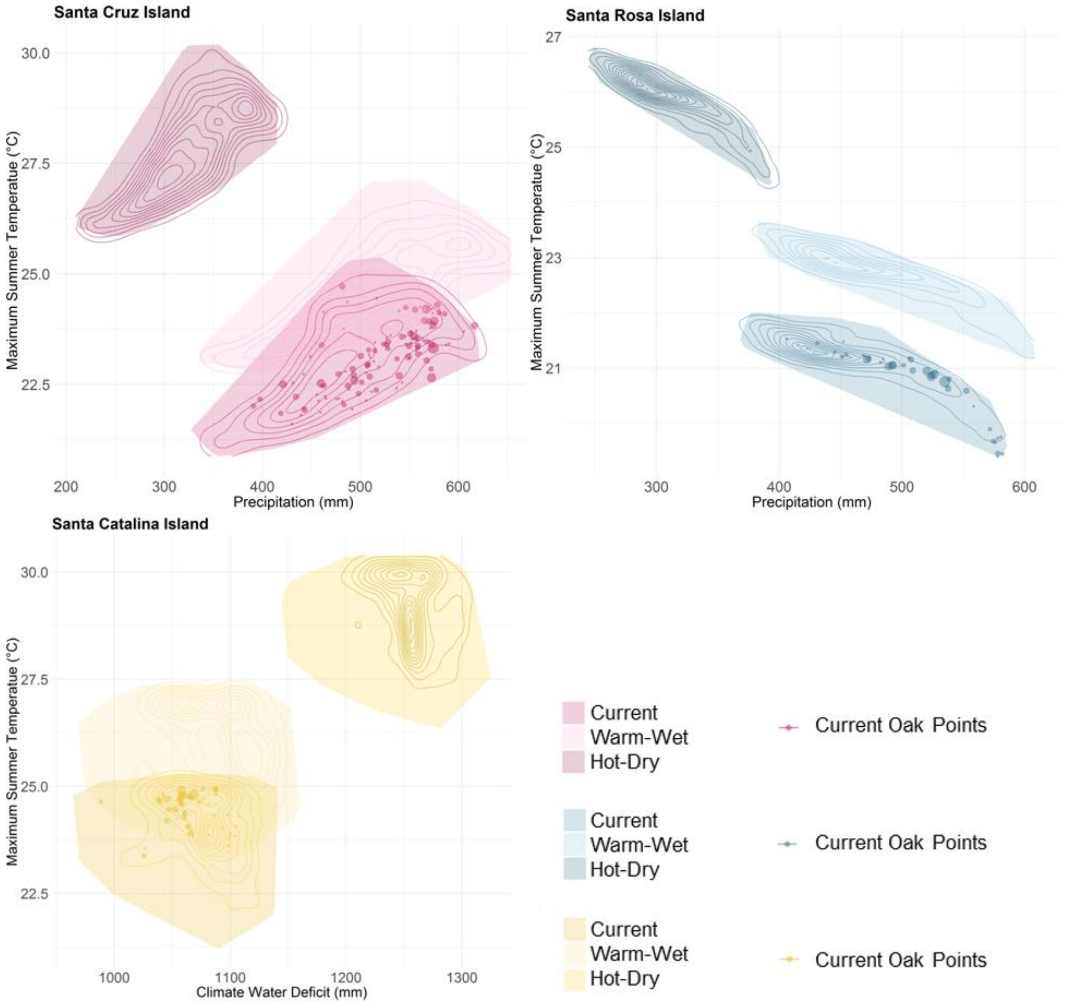


Figure 27. Current and projected climate niche comparisons. Comparisons of current and projected climate conditions for the two variables with the highest model contribution for each island. Projected climate projections are displayed for MPI RCP4.5 (warm-wet) and MIROC RCP8.5 (hot-dry) for the 2070 – 2099. The most important variables for both Santa Cruz (pink) and Santa Rosa (blue) are precipitation and maximum summer temperature, while for Santa Catalina (yellow) it is maximum summer temperature and climate water deficit. Contour lines represent the density of locations with that climate variable combination, while polygons represent the full range of climate variables on the island. Current island oak point locations are overlaid on current climate polygons, with larger sizes indicating a higher number of island oak points present at that climate location.

Overall, in the hot-dry scenario, climate conditions do not overlap with current conditions where oaks are currently found on any of the islands. In the warm-wet scenario, Santa Catalina has a substantial portion of island oaks remaining in conditions within the current range of oak climate conditions, Santa Cruz has a small proportion, and Santa Rosa has none.

# Discussion

## Main Findings

### Summary

1) Climate Suitability: The distribution of predicted suitable habitat in the future varies by island and climate change scenario, implying that additional research and adaptive management will be essential for managing the persistence of *Q. tomentella* while accounting for uncertainty in these analyses.
    a) Expansions or contractions of suitable habitat around areas of current island oak suitability are predicted, rather than habitat shifts in elevation or latitude.
    b) Precipitation and fog are influential predictors of island oak presence on Santa Cruz and Santa Rosa, while temperature is most influential on Santa Catalina.

2) Integrated Outlook: The extent and quality of predicted suitable habitat, as determined by predicted habitat suitability scores, is greatest on Santa Rosa Island and lowest on Santa Cruz Island in both individual island and all island analyses.
    a) Out of the three islands, Santa Rosa has the highest certainty of maintaining predicted suitable habitat across a wide spectrum of potential future scenarios.
    b) Santa Cruz's sparse predicted suitable habitat and Santa Catalina's uncertain total predicted suitable habitat may be influenced by the coarse resolution of analysis.

3) Oak-Climate Niche: The modeled bioclimatic niche for island oaks was significantly different on each island.
    a) Future suitability is largely dependent on whether the species' climate niche is island-specific or island-wide.
    b) Non-climate influences of oak presence are likely in part driving the differences in bioclimatic niches seen across islands.

### Climate Suitability

Our results predict wide variation in total area of future suitable habitat on each island across time steps and climate change scenarios. However, several consistencies in model output offer useful insight about the current and future extent and location of the modeled bioclimatic niche of *Q. tomentella* on Santa Cruz, Santa Rosa, and Santa Catalina. These consistencies center around the manner in which predicted suitable habitat distribution is likely to change across islands and the role climate variables play in these predicted distributional changes.

In both individual and all islands scenarios, there does not appear to be latitudinal or elevational shifts in suitable habitat through the three projected time periods, which is often found with climate change-induced range shifts (Lovejoy and Hannah, 2005; Parmesan and Yohe, 2003). Changes in total area of predicted suitable habitat are characterized by expansions and contractions around areas that are either consistently predicted as suitable on each island or that are relatively close to or centered around current presence points of the species. When islands are predicted to have more substantial losses of suitable habitat, such as on Santa Cruz, our model indicates locations of predicted habitat contracting through time rather than shifting. Therefore, establishment of entirely new populations in different locations on the island may not be necessary or useful. Focusing on existing populations and ensuring these locations will have suitable microclimates into the future is important for validating our predictions of future suitable oak habitat on each island.

When exploring the effects of climate variables on predicted climate suitability, we found that probability of fog inundation is the most important predictor variable for Santa Cruz and Santa Rosa Islands. It is the highest contributing variable to model gain, and models for both islands are highly sensitive to changes in its value. When fog is not included as a covariate for these two islands, precipitation is the most important predictor variable. This demonstrates the importance of water availability to *Q. tomentella*. Given that *Q. tomentella*'s modeled bioclimatic niche is strongly influenced by precipitation or fog, and that fog occurs throughout the year while precipitation primarily occurs in the winter, we can conclude that fog is extremely important to this species' success. This is apparent when considering the adaptation of *Q. tomentella*'s leaves to maximize fog capture with tomentum, small, dense woolly hairs across the leaves' surface.

In contrast to Santa Rosa and Santa Cruz Islands, the probability of island oak presence on Santa Catalina Island is most impacted by temperature. With both non-kriged and kriged climate data, the predicted distribution of island oaks is largely driven by minimum winter temperature and maximum summer temperature, respectively. However, fog data is not available for Santa Catalina. Since fog is likely a significant influence on island oak presence, its exclusion from Santa Catalina's model could mean that the actual distribution of suitable habitat will differ from our predictions. In the non-kriged scenarios, island oaks do very well in the hot, wet scenario and extremely poorly in the warm, wet scenario. Although this could be due to the island oaks having a very highly adapted climate niche on Santa Catalina, this unusual outcome indicates the need for running the model with more complete data. This is especially important when considering the importance of moisture, especially from fog, to island oak biology and the relatively dry and hot climate of the island.

## Integrated Outlook

Overall, Santa Rosa has the most optimistic outlook, with a higher proportion of the island predicted to remain or become suitable habitat across various scenarios into the future. In many cases, the total area of predicted suitable habitat expands on the island by the end of the century. In all scenarios and time steps, Santa Rosa has far more predicted suitable habitat than on the other two islands. The integrated outlook for Santa Rosa suggests that the island oaks will fare best in the southern portion of their range on the island, centered around the existing grove on Soledad Peak. Since the predicted suitability is robust to variability in model parameters, this area will likely support island oaks in the future. Currently, a grove of more than 35 oaks occupy this area. The impact of grazers in this region has been severe, and conditions are unfavorable for seedling establishment (Woolsey et al., 2018). The area is so degraded that most of the island oaks' roots are exposed from top soil loss, which has also contributed to low soil moisture and nutrient levels. To ensure seedling survival, restoration programs should consider procedures outlining soil restoration or using plant nurseries instead of hand-planting acorns. A recently published paper also detailed success in island oak cloud forest habitat restoration on Santa Rosa Island (Woolsey, et al., 2018). Restoration strategies have focused on improving island oak habitat and increasing population sizes and have included erosion control, leaf litter capture, fog capture, and reforestation. There is also potential for scrub jay reintroduction on Santa Rosa, which would further facilitate island oak recovery through the distribution of acorns (J. Knapp, Personal comm., 2018). These management efforts would be highly supportive for restoration of the Santa Rosa population, which has the most optimistic predictions for future suitable habitat.

Based on integrated model predictions, bioclimatic island oak habitat on Santa Cruz Island will be substantially negatively impacted by climate change, regardless of its intensity. However, our analysis is performed at a relatively course resolution of 270 $m^2$. This resolution masks the impacts of microclimates and could be influencing the response curves defining oak-climate relationships for all islands. For example, many of the island oaks currently exist in narrow drainages that have distinct microclimates, but many of those ecosystems are too small for representation in 270 $m^2$ model outputs. It is also likely that microclimates influence where island oaks can establish; for example, they have managed to survive on Soledad Peak due to exploitation of moisture trapped within saprolite bedrock on the mountain (K. McEachern, Personal comm., 2019). Based on previous island oak research, topography on Santa Cruz Island, and well-known oak biology, we believe microclimates with adequate soil moisture will exist on Santa Cruz Island and provide continued habitat for island oaks into the future. Suitable habitat is likely to remain in the northwestern portion of island oak's current range on Santa Cruz, as well as the eastern portion of its current range near the isthmus. However, it is likely that those locations will become sparser and more isolated in the future.

Santa Catalina Island has highly variable predictions of suitable habitat integrated across possible futures. Nonetheless, in the majority of kriged and half of the non-kriged scenarios run for Santa Catalina, predicted suitable habitat appears to be shifting to the southern end of the island. This indicates that this area is somewhat robust to variations in the model and is more likely to contain suitable habitat for a longer period than other areas of the island. The trees currently situated on the southern tip of Santa Catalina may survive into the future, and this area may be a strong choice for grove augmentation. Bolstering groves in this general area or establishing structures to help capture soil moisture will encourage island oak survival on the island.

## Oak-Climate Niche Relationships

*Q. tomentella* occupies a wide range of climate niches across the islands studied. Santa Catalina island oaks are found in areas with lower precipitation and higher climate water deficit than the wetter and cooler northern islands. Even on the northern islands where more similar environmental conditions exist, substantial differences in the temperature ranges exist between islands. For example, Santa Rosa island oaks experience maximum summer temperatures from 19.4 – 22 °C, while those on Santa Cruz experience temperatures from 20.87 – 25.37 °C. The large difference in maximum summer temperature between the islands is similar to the magnitude of temperature changes projected to occur in the future on the islands. This disparity brings into question the degree of local adaptation and the theoretical climate niche in which these oaks are able to establish and survive.

Substantial differences are found when all islands are run together, compared to scenarios in which all islands are modeled individually. These differences appear in the percentage of suitable habitat predicted, variable contribution percentages, and response curves. For example, Santa Cruz has predicted suitable habitat throughout all climate projections for the all islands analysis but has almost none when modeled on its own. Furthermore, the response curves provide conflicting information, such as the positive response of predicted probability of presence on Santa Rosa and Santa Catalina to maximum summer temperature versus the negative response to maximum summer temperature for Santa Cruz and All Islands analyzed together. These discrepancies in island oak-climate relationships when examining individual island and all islands analyses imply that there is a difference in occupied climate niches between islands, and that the oaks may have a wider range of climate variables across all islands than their local climate envelopes. The distinctly different available climate niches found on the different islands may partly explain the differences in predicted suitable habitat results seen for individual islands compared to all islands.

MaxEnt uses the extreme values of the current oak's distribution to inform the oaks' response to novel climate conditions. It is likely that variation in occupied climate niches per island influenced how projected climates were incorporated in the model and how response curves were calculated. Together, the response curves and the treatment of extreme values using clamping may explain why the islands have such different outcomes. In particular, Santa Rosa Island is predicted to have more suitable habitat throughout all climate projection scenarios than the other islands. The response curves reveal that island oaks on Santa Rosa are more likely to be present at high temperature values. Since clamping treats all temperature values above 22 °C the same as 22 °C, the highest observed value in the training model, higher maximum summer temperatures across all climate projections support the prediction of oak presence. Biologically, it would make more sense for values above 22 °C to follow a parabolic shape, where very high summer temperature values are negatively correlated with predicted probability of presence. Unlike on Santa Rosa, Santa Cruz island oaks have a highly negative response to high temperatures in the summer causing MaxEnt to predict very low suitability in the future. Santa Catalina island oaks do show a generally positive response to higher temperatures, but to a smaller degree than Santa Rosa island oaks. This is reflected in the distribution of predicted suitable habitat in the future, where patches of the island still remain suitable for island oaks.

Considering these relationships, the individual island versus all island analyses, and the comparison of island-specific bioclimatic conditions for island oak, it is ambiguous whether the species' actual niche is island-specific or island-wide. It is possible that island oaks on the different islands have genetically evolved over time to be locally adapt to the climate ranges found on each specific island, subsequently supporting the results found in the individual island analyses. A number of prior *Q. tomentella* studies support and are consistent with these findings. Kindsvater (2006) developed GIS models to predict habitat suitability across Santa Cruz and Santa Rosa Islands using vegetation classes, elevation, slope, aspect, soil, and geology. Franklin and Knapp (2007) predicted *Q. tomentella* habitat suitability across Santa Catalina Island using a wide variety of environmental variables as covariates in a generalized linear model (GLM). The characteristic vegetation classes and geology of predicted suitable habitat in these two studies varied by island, especially when comparing Santa Rosa and Santa Cruz Islands to Santa Catalina. In 2018, Ashley et al. found significant genetic variation in island oak populations with and between islands, another potential justification for distinct local climate adaptations.

It is also possible, however, that subpopulations of the species have not genetically adapted to local island conditions over time, and instead the species as a whole has a broad potential niche range across all islands. The species is believed to have high phenotypic plasticity, which is exemplified by the stout trees on Guadalupe Island, the relatively short trees on the more exposed, windy areas on Santa Rosa Island, and the tall, straight trees in drainages on Santa Cruz Island (K. McEachern, Personal comm., 2019). Current oak presence on each island could simply be a result of establishing in available climate habitat, and phenotypically adapting to that area without evolving for a distinct climate niche. Furthermore, there could be other non-climate drivers impacting the current island oak climate niche and influencing derived climate responses. The apparent bias towards certain values of climate suggests the distribution of island oak is attributed to a number of factors, including but not limited to: grazing pressures, limited dispersal ability, and geologic suitability. Understanding whether island oaks are sensitive specialists uniquely adapted to narrow climate niches found on each island or are robust generalists adaptable to a wide range of potential climates is imperative to managing the island oak.

Additional research and field experiments are necessary to understand both the island oak climate niche and the relationship between underlying climate and non-climate drivers of island oak presence. Further understanding of this topic has critical implications for making clear and impactful decisions about managing island oak populations, especially considering the variation within our results. For example, Santa Catalina island oaks, currently situated in a relatively hot, dry environment, could potentially be better adapted to future projected climate change conditions if each island population has evolved its own niche. Under this assumption, augmenting groves on more northern islands using Santa Catalina acorns could be successful, even if highly controversial, given that the current climate of Santa Catalina is similar to the projected future climates of the northern islands. However, if island oaks on Santa Catalina do not have higher adaptive capacity to future climate conditions than oaks found on the northern islands, than assisted migration would be meaningless, as the island oaks found on the northern islands would have as much adaptive capacity and likelihood of survival as the Santa Catalina island oaks. Furthermore, the degree of urgency for implementing a management program depends on whether *Q. tomentella* has a narrow or broad range of climate adaptability and sensitivity to climate variables. More drastic and rapid action is necessary for the species if it is highly climate sensitive and only exists in narrow, locally-adapted climate ranges.

Regardless of defined climate niches, climate envelopes are projected to move outside the current climate ranges found on each island. It is likely that all island oaks will be exposed to novel climate conditions that they may not be fully capable of adapting to quickly enough, particularly on Santa Catalina where the climate is hotter and drier. This implies that the island oaks are predicted to experience a future with less suitable habitat, especially if they have narrow ranges of tolerable climates. Adult oaks are highly resilient and will likely survive changes in climate; however, seedlings are much more sensitive to climate variability and losing suitable habitat for seedling establishment is a larger future concern. Water availability, in particular, will be critical, as consistent soil moisture is one of the known requirements for island oak seedling establishment. It is likely that facilitating fog capture through apparatuses such as fog fences and fog nets can greatly enhance seedling survival (K. McEachern, Personal comm., 2019).

Although our analysis implies that suitable habitat for island oaks will likely disappear well before the end of the century, resisting the possible extinction of the species is still possible. Continuing to research the island oak's climate niche and understanding its relationship with other factors in the environment can greatly bolster programs for managing the species. Using adaptive management, in which conservation plans change as new technologies and information arise, the island oak can live to see the end of the century.

# Limitations

MaxEnt is a useful tool for modeling ecological niches and species distributions. However, careful consideration of model outputs is required due to data and software limitations and assumptions inherent to this type of analysis. Several of these limitations and assumptions impact the interpretation of our results and are necessary to keep in mind when applying the results to management practices.

## Climate-Only Predictor Variables

In an effort to identify characteristics of the bioclimatic niche for *Q. tomentella*, we specifically input climate variables to predict the probability of presence. This method assumes that the distribution of island oak is entirely controlled by climate variables, though we know that is not the case. Exclusion of additional variables introduces the potential for omitted variable bias and endogeneity, whereby the included predictor variables account for the impact of variables not included or the model error is correlated with predicted probability of presence. In both cases, model outputs are biased, and model coefficients may not accurately reflect the interaction between climate variables and predicted probability of presence. We justify our choice to use only climate variables in two ways. First, based on what is known about the species, it does not experience intra- or interspecific competition that would significantly impact its distribution (K. McEachern, Personal comm., 2019). Second, paleoecological records suggest that island oak was forced onto the islands by a warming climate in the southwestern United States (Heusser, 1978; Kindsvater, 2006; Moody, 2000). This indicates that the species' distribution has been significantly impacted by climate in the past, and that it is reasonable to assume the same trend will continue into the future.

## Species Distribution Prediction in Novel Environments

SDMs develop an initial training model that defines relationships between covariates and species points to predict species distributions. In many cases, especially when the current range of a species is narrow, SDMs must make predictions about species distributions in novel environments, outside the range used in the training model. This is especially common when using SDMs to make predictions about the impact of climate change on species distributions, as climate conditions in the future are often predicted to extend beyond the bounds of current conditions. This limitation requires users to decide what extrapolation method to use, if any. For our analyses, all climate data for future predictions contained at least some if not all novel climate values. We used a setting in MaxEnt called 'clamping', which treats all values outside of the training range the same as the most extreme value within the training range. For example, if the current maximum summer temperature is 22 °C, then for future predictions all values above 22 °C will have a constant effect on predicted probability of presence that is the same as 22 °C. The alternatives are to allow the model to use the determined coefficients for novel values or to inhibit the model from extrapolating, which would defeat the purpose of our project.

## Past Human Impact on Current Oak Distribution

Our analysis implicitly assumes *Q. tomentella* presence is based solely on climate variables, though studies have shown this is an incomplete floristic niche assessment (Hijmans & Graham, 2006; Pearson & Dawson, 2003). Human-introduced grazers have restricted oak regeneration and affected the current species distribution, which biases MaxEnt output. In the absence of grazers, we expect that island oaks would have a wider distribution that would in fact be primarily dictated by climate. More information about the distribution of livestock grazing and logging on the islands would help define *Q. tomentella*'s realized and fundamental niches. This could also identify spatial grazing and logging patterns, which could then be incorporated into MaxEnt as a bias layer, thus accounting for this limitation. For increased ecological niche model accuracy, it is essential to develop a spatial data layer that represents patterns of 19th and 20th century grazing on each island to more accurately distinguish climate influences on the island oak's realized niche from grazing impacts on the species' current distribution.

## Lack of Stage Structure Information

The available oak point data included sparse information about stage structure for Santa Rosa Island only, which limits our understanding of establishment-specific climate variable preferences. Since seedling establishment requires more specific conditions than adult persistence, particularly regarding soil moisture, differences in habitat suitability for population expansion by seedlings may be masked by the broader climate conditions tolerated by adult oaks (Serra-Diaz et al., 2016).

The available data allowed for two preliminary analyses of niche requirements for island oak establishment on Santa Rosa Island, where we were able to run MaxEnt for a small number of seedling points. The results of these analyses suggest that the probability of presence for seedlings is more confined than when all oak points are considered regardless of life stage, but much of the island remains suitable for seedlings through the end of the century for all climate change scenarios. However, the small number of seedling points often located in close proximity to the adult points limited the robustness of the model output, so that both the adult and seedling suitability distributions appear largely similar given the 270-meter resolution. From the limited resolution and number of seedling points, we determined that running the seedling analysis a second time including fog would not be worthwhile. In future studies of stage structure environmental preferences, and with more thorough demographic stage data, fog should be included because it will likely have a significant impact on seedling presence, given its known importance to oak establishment.

The majority of living island oaks are mature and established before the 1981 – 2010 time period. To learn more about *Q. tomentella*'s current distribution as it relates to climate conditions closer to when many mature trees were seedlings or juveniles, we explored predicted species distributions using climate data from the 1921 – 1950 and 1951 – 1980 time periods. We found that the predicted species distribution in both the early 20th century and mid-20th century time periods were nearly identical to the current predicted species distribution using the 1981 – 2010 climate data. The negligible differences between current and earlier 20th century predicted species distributions imply that at a spatial scale of 270-meters and temporal scale of 30-year averages, climate conditions are still conducive to seedling establishment. These spatial and temporal scales of course mask out the resolution at which seedlings establish, and more research is needed to determine if shorter term weather and climate patterns that support island oak seedling establishment are changing.

Davis et al. (2016) found that those ‘windows of opportunity’ that allow for seedling establishment are changing for *Quercus doulasii* and *Quercus kelloggii*, two other California oaks.

## Climate Models

Due to significant and complex stochasticity of weather and climate, climate models are inherently inaccurate and contain substantial uncertainty. Climate data in this study was downscaled through two different methods by two different climate groups. First, the PRISM Climate Group statistically downscaled data from GCMs to 800-meter resolution. The layers were further downscaled by the California Landscape Conservation Cooperative Climate Commons to 270 meters (Flint et al. 2013). PRISM downscaling incorporated weighted coastal proximity interpolation, but did not include additional coast-specific variables, such as sea surface temperature (SST). The second statistical downscaling was based on unimpaired watersheds in California. There were unique watersheds used for the Channel Islands, but the BCM model also did not incorporate climate variables unique to coastlines or islands. One potential method of cross-checking the climate data for the CAIA is to explore projected spatial shifts in SST around the CAIA. GCMs tend to converge on an increase in the intensity of cold upwelling in coastal southern California (Williams et al., 2015). If cold oceanic influences are able to increase advection fog formation and attenuate increasing air temperatures, perhaps lower SSTs can mitigate the extremity of air temperature changes seen in the BCM climate data for some or all of the islands.

## Microclimates

Another challenge in modeling species’ responses to climate change is accounting for the sensitivity of species to microclimates (Hannah et al., 2013). Climate models are often too coarse to adequately capture microclimate dynamics, but they are still useful for informing a species’ response to climate change (Franklin et al., 2013). Our analyses were completed at a 270-meter resolution, and therefore mask out microclimates. Likewise, 270 $m^2$ is larger than the extent of many island oak subpopulations. Island oaks exist in known micro-climates, like narrow drainages and ridge tops, so this resolution masks out the scale at which the species functionally occupies habitat. As such, our results should be used to identify island oak-climate variable relationships and broad regions with suitable habitat, not as high-resolution depictions of all available island oak habitat.

## Fog

The incorporation of fog data into the analysis is limited in its accuracy by the available data. Current GCMs vary greatly on which climate conditions will drive regional future changes in fog and how these drivers may either promote or inhibit fog formation (Williams et al., 2015). Due to this uncertainty, no projected fog layers are available for the CAIA from other peer-reviewed sources. To fill this informational gap, we created our own by applying historic fog occurrence and cloud height trends to modeled current fog inundation probability (Williams et al., 2015; Rastogi et al., 2016). This methodology assumes that fog and stratus trends will continue into the future as they have in the past, although the four different fog scenarios included in our analysis attempt to account for future variation in these trends. Additionally, we could not account for changes in global weather patterns that influence local fog in the CAIA, or the influence of long-term patterns like the Pacific Decadal Oscillation.

Although the decreasing fog scenario attempts to predict fog occurrence under ENSO conditions, it is likely overestimating the decrease in fog probability. Rather than only decreasing fog during predicted ENSO years, this scenario applies the decrease continuously. Since we are not able to more accurately include ENSO years in a prediction, the decreasing fog scenario acts more as a worst-case scenario for fog occurrence, allowing island managers to plan for possible reductions in fog due to the influence of ENSO in the absence of projected fog models.

A study on the influence of ENSO events on rainfall in southern California from 1950 – 1982 indicates that years with heavy rainfall are often also consistently ENSO years (Schonher & Nicholson, 1989). Another study investigating rainfall trends in Santa Barbara, California found that while ENSO years did not increase the probability that the year would also be wetter than average, wet ENSO years were frequently extremely wet (Haston & Michaelsen, 1994, 1997). Both of these studies were of coastal Californian patterns rather than the CAIA directly, but based on these nearby trends, it is likely that ENSO events often result in increased rainfall, possibly counteracting any soil moisture stress that may occur due to concurrent decreased fog.

# Conclusions

## Study Relevance

Human population growth in the past several centuries has magnified our impact on natural and developed ecosystems around the world, and there is virtually no place on earth that we have not altered in some capacity (Walther et al., 2002). Human influence has prompted and accelerated rates of climate change, species habitat loss and degradation, natural resource exploitation, and introduction of non-native species to ecosystems around the world, all of which have been linked to higher extinction rates than the natural historic trend (Ceballos et al., 2015). Specifically, human-induced climate change is shifting and shrinking species ranges and distributions globally and is the known cause of several flora species-level extinctions, and a likely cause of others (Thomas et al., 2004; Tilman & Lehman, 2001). In the United States, several tree species are experiencing alarming range shifts that have been definitively attributed to climate change (Staudinger et al., 2013). In the California Floristic Province, at least 66% of endemic plant taxa are expected to experience range reductions in the next 90 years (Loarie et al., 2008). Increasing anthropogenic pressure is amplifying the need for robust, comprehensive adaptive restoration and conservation plans.

In the California Island Archipelago, grazers and human activity have fragmented and severely damaged *Quercus tomentella* habitat. Though these threats have largely been eliminated, their effects are still felt, and island oak populations are in initial recovery stages (Kindsvater 2006). A large generation gap in *Q. tomentella* populations suggests minimal regeneration through most of the 20th century, and reproduction is still limited on all islands except Santa Cruz (J. Knapp, Personal comm., 2018). Additionally, island ecologists worry that the species may have a narrow climate envelope that climate change is likely to affect (Kindsvater 2006). Our analysis provides insights into *Q. tomentella'*s bioclimatic niche and variation in currently occupied habitat on each island, which inform management of the species.

## Further Research

Our study has identified some potential impacts of climate change on *Q. tomentella,* filling an information gap important to the successful restoration and management of the species. Our results can be synthesized with existing studies regarding the species to create a more complete picture of *Q. tomentella*'s survival potential and to reduce uncertainty. Existing studies include an assessment of the soil preferences of regenerative *Q. tomentella* populations, a thorough study of the species' genetic diversity within and across islands, and previous studies of island-specific restoration strategies (Kindsvater 2006; Ashley et al. 2018; Woolsey et al. 2018). Our results and understanding of *Q. tomentella* could be improved with further collection of relevant biotic and abiotic information. Suggested biotic information includes data on comprehensive island oak locations, population stage structure and life history, disperser agents, and grazer impacts. Suggested abiotic information includes expanded climate data coverage, more detailed soil data, and models predicting future fog trends. Additionally, a combination of these types of data would allow for dynamic modeling. The diagram below details the workflow of our project with emphasis on analysis and interpretation of results in the broader context of how to manage *Q. tomentella* (Figure 28).

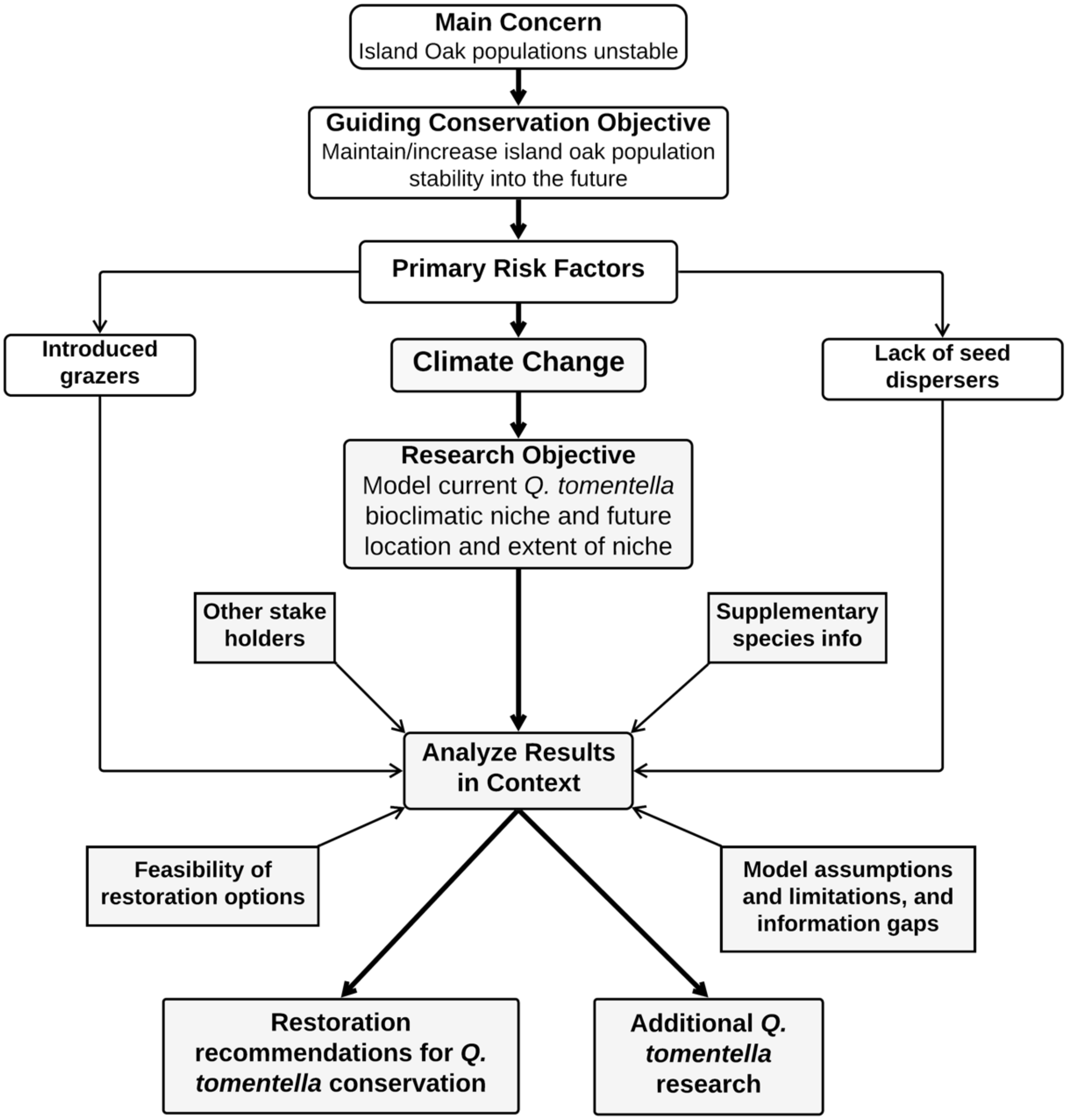


Figure 28. Workflow diagram. Project flow diagram with emphasis on analysis and interpretation of model results in the broader context of *Q. tomentella* information and management.

## Biotic Data

At the time of this study, sufficient *Q. tomentella* presence data was not available for Anacapa, Guadalupe, or San Clemente Islands, which are the islands with the fewest island oaks. Climate data is also lacking for the majority of Anacapa and San Clemente Islands, and the entirety of Guadalupe Island. If possible, it would be important to include these islands in future analyses, as the populations on each island have been isolated for thousands of years and have likely adapted to unique climate conditions (Morrison et al., 2014; Riley & McGlaughlin, 2016). Partial oak point data for Guadalupe and San Clemente were acquired near the end of this project, and could be included in future SDM projects. Acquisition of more complete presence data and climate data for the islands not considered in this study would broaden ecologists' understanding of *Q. tomentella's* species-level and island-level climate tolerances, and could inform potential translocation options.

Collection of stage structure and life history information for oak presence points would greatly enhance understanding of the species' stage-specific climate envelopes, individual population viability, and future reproductive potential. For example, information about seedlings' climate preferences would increase success of *Q. tomentella* hand-planting through more robust site selection criteria. A 2018 study by Woolsey et al. investigated some non-climate variables that may influence the successful expansion of *Q. tomentella* groves on Santa Rosa's Black Mountain, such as presence and species of nurse-plants, which could be integral to site selection for hand-planting. Stage structure information would also inform island managers on the life span, current levels of senescence, and reproductive capacity of the aging individuals. This information would help managers prioritize conservation action in aging populations. Filling information gaps on the longevity, age of sexual maturation, and masting patterns of *Q. tomentella* could also help guide conservation prioritization.

Island ecologists currently debate whether mutualism between scrub jays and island oaks exists on Santa Cruz Island. If the relationship exists, then scrub jays would play an integral role in dispersal of island oaks across the island. Implementation of acorn monitoring on Santa Cruz could validate the hypothesized role of scrub jays as island oak acorn dispersers. This knowledge would inform conservation tactics and help forecast the survival of the *Q. tomentella.* Although island oaks face little competition for resources, seedlings that germinate underneath the canopy of the parent trees have a lower survival rate than those on the outskirts of groves (Woolsey et al., 2018; K. McEachern, Personal comm., 2019). An avian seed disperser can facilitate movement of the seeds farther than gravity or rodent dispersal to areas where the seeds may have a higher chance of establishing and surviving, potentially expanding the current distribution of island oak (Pesendorfer et al., 2017).

As the impact of grazers on *Q. tomentella* likely introduces significant bias to our analysis, future research should further investigate this bias through both qualitative and quantitative assessments of the theoretical historic extent of the island oaks. Explorations of past land use influences on native vegetation would help establish the scale of human impacts on island oak distribution, and how these human impacts potentially change current modeling efforts of the species under climate change. Maps of past ranching activity and human structures would aid understanding of where grazing has likely impacted island oak distribution. Distances from these features from georeferenced historic documents can be included as an environmental variable in species distribution modeling. Comparison of outputs from models with and without human influences could help clarify grazer impacts on the island species.

## Abiotic Data

Climate data limitations greatly restricted the scope and accuracy of our analysis, particularly because there are so few weather stations on or near the islands. For the islands with sufficient climate data, resolution limitations decreased the specificity of model results and increased uncertainty. Additional weather stations and climate monitoring would facilitate the development of higher resolution climate models for the CAIA, and could also allow for the expansion of climate data coverage for the islands that had little to no climate data. Furthermore, statistical downscaling of the BCM data specifically for the CAIA to an even finer resolution could substantially improve climate envelope modeling of the species. More island-specific downscaling could better include and represent coastal factors and processes in the layers, and could exist at a finer resolution that may better capture some of the microclimate features that are so important for oak presence. Additional weather stations and monitoring on the islands would improve and facilitate this downscaling.

The low horizontal resolution of soil data prevented its inclusion in our model. The creation of smaller polygons with only one type of soil per polygon would allow for the inclusion of soil in future modeling studies and increase understanding of the island oak's geological niche. The same process for bedrock data is also recommended, since the taproots of adult island oaks have allowed them to grow in certain types of bedrock like saprolite (K. McEachern, Personal comm., 2019). Specifically, useful soil layers should include fine-resolution soil chemistry and texture information at horizons influential to seedling establishment.

Additionally, fog is the main year-long source of soil moisture on the islands (Fischer & Still, 2007; Fischer, Still, & Williams, 2009). Though we were able to incorporate fog into our analysis for Santa Cruz and Santa Rosa, data for probability of fog inundation is not available for the other islands. Increased monitoring of fog-related weather data across the islands, such as stratus frequency and cloud height, would improve the ability of researchers to both track changes in island-specific fog occurrence and create more comprehensive models of fog inundation. Furthermore, as of yet there is no model projecting fog into the future. However, Charles Jones at the University of California, Santa Barbara is currently developing a downscaled 30-year regional model of fog including the CAIA (C. Jones, Personal Comm., 2018). Once completed, this model could provide fog layers for MaxEnt using our methods alongside our other collected layers and presence point data.

## Dynamic Modeling

The collection of both additional biotic and abiotic variables would not only increase overall understanding of the island oak, but would also allow for further modeling of the species. Along with demographic data and dispersal agents, if more information were collected about the disturbance regimes that interact with *Q. tomentella,* dynamic modeling with programs like LANDIS could explore how non-static variables affect island oak distribution in future climate scenarios. Higher resolution climate data would also allow for meaningful results from dynamic models like BioMove.

# Recommendations

In addition to the suggestions for future research outlined above, we have several conservation management recommendations to help ensure persistence of island oaks into the future. Ecologists on Santa Rosa Island have already begun to implement successful restoration strategies that we have considered in our recommendations (Woolsey et al., 2018). These strategies should be tailored to each island and should consider how climate is likely to change on that island. Likewise, given the uncertainty surrounding alteration of hydrologic climate patterns by increasing global temperature, adaptive management strategies that consistently assess island oak's response to climate will increase the species' resilience to climate change (Heller et al., 2015). As new information becomes available, conservation plans can change to become more suited to support island oak populations.

Our MaxEnt results and analyses can be used to characterize island oak-climate variable relationships and identify broad regions with suitable habitat in which to focus restoration. However, our results should not be used as high-resolution depictions of all available island oak habitat due to the coarse climate data and uncertainty in drivers of the species current distribution. Below we outline the major recommendations developed from our analyses that apply both across islands and for each island specifically.

## All Islands

Many restoration practices that would support *Q. tomentella* populations under any future climate scenario are already in place across some of the islands as strategies for recovery from past human pressures. These include native plant population restoration, erosion control, fog capture, and soil restoration. Expansion of these activities to more *Q. tomentella* groves would improve their resilience to potential climate shifts. Additionally, we suggest the initiation of several strategies to incorporate climate change adaptation into current management, including common garden plots and grove augmentation, as well as an increased focus on certain habitat restoration practices.

## Grove Augmentation

For current island oak groves, we recommend augmentation, or the intentional addition of individuals to existing populations. Areas of predicted suitable habitat most vulnerable to climate change impacts are not expected to shift, but rather to contract. Therefore, we suggest identifying core populations of *Q. tomentella* and hand-planting within and near these areas, as this is where habitat is predicted to remain suitable for longer periods of time. We recommend supporting established groves in favor of planting around solitary trees; increasing the density of island oaks may provide a synergistic effect for increasing fog capture, which would assist in seedling establishment and soil moisture. Furthermore, higher densities of oaks increase the rate of pollination for oaks and by extension increases genetic mixing (Sork et al., 2002). Woolsey et al. (2018) offers specific suggestions for the biotic conditions and relative locations within a given grove that could promote successful sapling growth during grove augmentation.

## Common Garden Plots

Common garden plots are experimental gardens in which seeds are sown in plots along an environmental gradient. They allow for the observations of seedling establishment and growth without the confounding effects of other site-specific environmental variables. We propose using this approach to identify the degree of local adaptation and the range of conditions the island oak can survive.

We recommend a method similar to Davis et al., (2016) in creating and analyzing these plots. To begin, a common garden plot for an inter-island study would need to locate and reserve multiple areas with climate profiles representative of the range of climates in which island oaks are found on other islands. Ideally, various plots would represent the average and extreme temperatures of each island of interest. These areas should be large enough for the monitoring and growth of many trees. Each acorn sown should have its parentage recorded, including the local population and island, and then be hand-planted in each of the reserved plots. Observing which oaks are able to germinate, establish as seedlings, and survive into adulthood can reveal the degree of local adaptation from each island's tree population. For example, if seedlings from Santa Rosa Island are unable to survive in temperatures similar to that of Santa Catalina and the seedlings do more poorly than all other island oaks in the same garden plot, then this indicates there may be a strong local adaptation of Santa Rosa oaks to cooler climates and they are unlikely to survive hotter temperatures. If there are no significant differences among the germination and establishment of seedlings across the islands, then there is strong evidence that island oaks are able to survive in climate conditions outside their current island-specific ranges. Additionally, common garden plots can be done for island oaks on an intra-island scale in order to find the degree of local adaptation per island. Increased understanding of the oak-climate relationship can provide inferences on the potential impacts of grazing and other potential climate drivers on *Q. tomentella*'s current and future distribution.

### *Assisted Migration*

Assisted migration is an aggressive and controversial management option, often seen as a last resort strategy. Island oak populations on Guadalupe and Anacapa Islands are suffering to an extent that may necessitate assisted migration if preserving the genetic strains on those islands is a priority(McLachlan, Hellmann, & Schwartz, 2007). The genetic study of the species by Ashley et al. (2018) can serve as a reference for issues regarding inter-island translocation. Especially considering the uncertainty in the specificity of the island oak's climate niche, we recommend performing common garden experiments before resorting to assisted migration. Understanding the true climate envelope in which these trees operate would better inform the details of this approach, such as specifying which acorns to collect and to which groves to plant individuals. In general, we recommend considering translocation to alternative locations on the same island before considering assisted migration to other islands. We also do not recommend prioritizing the reintroduction of island oaks to San Miguel Island, as our findings indicate that there is not suitable climate habitat for island oak and the species is unlikely to establish in the sandy soil that dominates the island. However, if additional stage-structure information shows that some populations are in need of more aggressive restoration strategies, we suggest considering inter-island translocation.

We recommend the following approach to assisted migration:

1. Use acorns collected from oaks that reliably mast in a given time period, such as those from Black Mountain on Santa Rosa.
2. Identify locations suitable for intra-island translocation, which should have similar bioclimatic niches to the origin of individuals that will be moved and are expected to be habitable for oaks in the future.
    a. At each of these sites, assess ecological costs and benefits of island oak introduction.
    b. This includes understanding how they will affect biotic and abiotic factors, such as the degree to which native flora may be displaced by island oak introduction, and which will benefit from increased fog capture.
3. Outline criteria and a systematic approach for human assisted-migration of island oaks between islands, addressing feasibility, genetic implications, island-specific costs and benefits, and detailing a methodical procedure for acorn collection and planting.

## Island-Specific

Though each island would benefit from restoration of any kind, model results suggest specific areas on which to focus conservation efforts for Santa Rosa, while spatial patterns of suitability are less consistent for Santa Cruz and Santa Catalina. Our results also suggest several restoration techniques that, if prioritized, could substantially benefit the island oaks. We are not suggesting any new techniques, but are basing our recommendations on successful techniques already implemented on some of the islands.

## Santa Rosa

1. Restore habitat in the southern part of the island near Soledad Peak, which remained suitable through all projected scenarios and therefore may be a climate refuge.
    a. Restore the soil quality in this area, which has been greatly degraded, to increase the possibility of natural establishment.
2. Augment existing populations in the southern part of the island near Soledad Peak, where suitable habitat seems to be robust to the variability of results between scenarios.

## Santa Cruz

1. Complete a more comprehensive survey of island oak locations on the southern half of the island to account for any potential sampling bias towards oak points in the northern half of Santa Cruz.
2. Monitor acorns and scrub jays to determine their role in facilitating dispersal.

## Santa Catalina

1. Prioritize habitat restoration prior to planting, as the continued presence of grazers on Santa Catalina complicates conservation and will likely increase expenses.
    a. Construct fog fences near both established oaks and planted seedlings to reduce stress from Santa Catalina's high climate water deficit and increase soil moisture.
    b. Restore soil to further reduce the moisture stress indicated by the high climate water deficit values on this island.
2. If planting becomes feasible and necessary, protect planted seedlings from non-native fauna.

Overall, ensuring the survival of *Quercus tomentella* in turn ensures the survival of other species in the California Island Archipelago and protects California's unique biodiversity. This project aims to provide some of the tools necessary to help accomplish this as climate change progresses.

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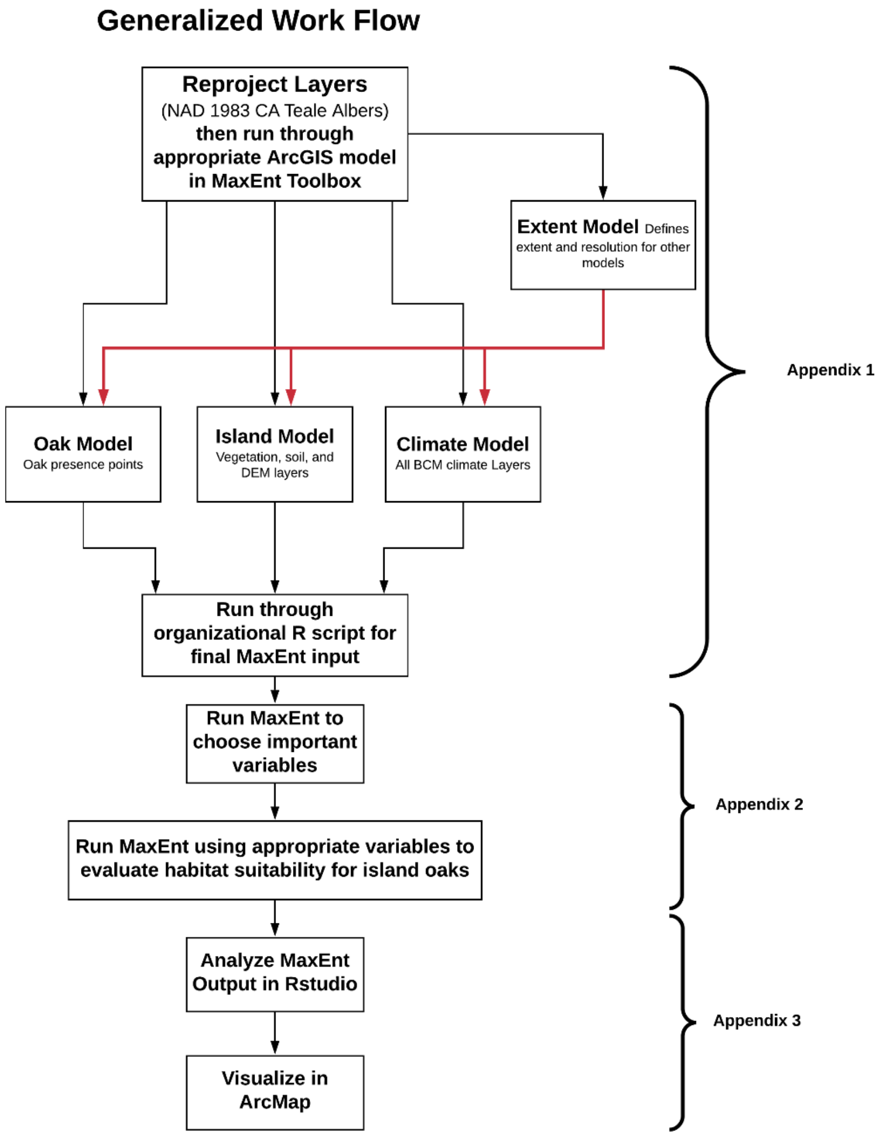
Wylie, J. (2012). *Vegetation change on San Clemente Island following the removal of feral herbivores*. San Diego State University, San Diego, CA. Retrieved from http://sdsu-dspace.calstate.edu/bitstream/handle/10211.10/2205/Wylie_Douglas.pdf;sequence=1

# Appendix

## Appendix A: Additional Methodology

The methodology chart below documents our entire workflow, in an effort to make our analysis procedure reproducible. Specific methods can be found in the following detailed Appendix sections, which expand upon data processing for MaxEnt input (Appendix A1), running MaxEnt (Appendix A2), and analyzing MaxEnt output (Appendix A3).



# Appendix A1: MaxEnt Input Data Processing

## *Initial Data Wrangling*

### Vegetation Cover Reclassification

Vegetation communities and alliances were highly varied and inconsistent across islands. Each island's vegetation communities were normalized by dominant species in the classification using the system shown in the table below, and assigned to tables of shapefiles and geodatabase files using an R script (Vegetation R Markdown Script in appendix C). We projected the Catalina Vegetation shapefile, the shapefile containing the vegetation maps for San Miguel, Santa Rosa, and Anacapa, and the shapefile for Santa Cruz Island into NAD 83 California Teale Albers.

**Table A1.** Vegetation Reclassification Table.

| Vegetation Cover | Value |
|---|---|
| Woodland | 1 |
| Chaparral | 2 |
| Coastal Shrub | 3 |
| Grassland | 4 |
| Riparian | 5 |
| Dune | 6 |
| Developed/Water | 7 |

### DEM Processing

We converted the Santa Catalina Island DEM from feet to meters and brought all DEM files into the correct projection: NAD 83 California Teale Albers.

### Soil Data Management

SSURGO soil data came in tabular file formats accessible through Microsoft Access and shapefiles compatible with ArcGIS. Most relevant information was in the tabular files. We generated an .xls soil classification report using Microsoft Access, then joined that data with spatial polygons by a map unit identifier from the main SSURGO shapefile in ArcGIS. The resulting shapefile was set to NAD 83 CA Teale Albers and then used as input in an ArcGIS model described below.

### Climate Processing

We downloaded the current and future projected climate data .tif files directly from the CalCommons website, and the files were already in NAD 83 California Teale Albers projection. The files were sorted into appropriate raw data input folders to run through ArcGIS Model processing for MaxEnt. For Santa Catalina Island we performed universal cokriging to extend the available climate data to the extent of the island for all current and future projected data with DEM as the covariate (Kriging BCM Data for Santa Catalina R

Markdown Script in Appendix C). These data layers were used when examining only Santa Catalina Island, but not for the analyses with all islands together.

## Fog Processing

Santa Cruz and Santa Rosa fog probability layers were received from Bharat Rastogi as NetCDF files with 100-meter resolution. These files originally appeared inverted upside down and without spatial referencing. The five values of the time dimension corresponded to months, starting with 0 as May and ending with 4 as September. The following tools were used to process the NetCDF files into a useable format:

- Make NetCDF Raster Layer: Raster layers were created with easting as the x dimension, northing as the y dimension, seasonal fog as the variable, and time in months as the dimension value.
- Flip: For each dimension value 0 – 4 for both Santa Cruz and Santa Rosa, the raster layer was flipped and then saved as a .tif.
- Define Projection: For Santa Cruz, the projection was defined as UTM11 (1983) and for Santa Rosa, the projection was defined as UTM10 (1983).
- Project: All .tifs were projected into NAD 83 California Teale Albers.

Cell Statistics: For both Santa Cruz and Santa Rosa, the output .tifs from the project tool for months 0 – 4 were averaged (mean) and saved as a tif. Points with no data were excluded.

The below tools modify the 1981 – 2010 historic fog layers as .tifs into three of the different fog scenarios: overall increase, overall decrease, and fog changing with an elevation threshold. The fourth fog scenario layers, fog held constant, are not changed from the 1981 – 2010 historic layers. The historic layers were already resampled to 270 meters and extracted by mask to the Santa Cruz and Santa Rosa extents using the Maxent Toolbox fog model discussed in the below section.

The model developed to create .tif files for multiple fog layers with a decrease or increase is illustrated in Figure A1. The tools used and their functions include:

- Raster Calculator: For increasing fog scenarios, increases all values in the fog layer by the percent indicated by the parameterized double variable. For decreasing fog scenarios, decreases all values in the fog layer by the percent indicated by the parameterized double variable. The equation input is: Input Later +/- (Input Layer * float(%double%)).

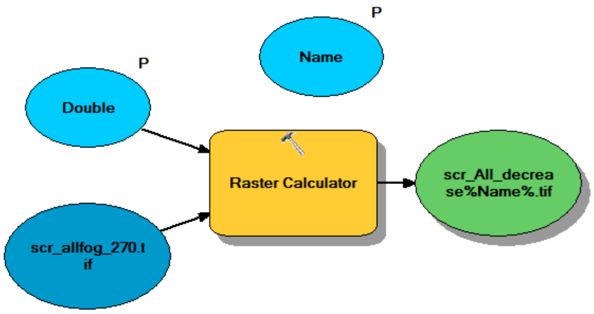


Figure A1. ArcGIS Model to Create Fog Layers for Projected Data with a 20% Increase or Decrease in Fog Inundation.

The model developed to create .tif files for multiple fog layers with an elevation threshold is illustrated in Figure A2. The tools used and their functions include:

- Reclassify: Reclassifies all values in the DEM layer above 255 meters as 0 and all values below 255 as 1.
- Extract by Attributes: The unnumbered extract by attributes selects only the DEM values set at 1; extract by attributes (2) selects only DEM values set at 0.
- Extract by Mask: Extracts the historic fog .tif by the mask created with the extract by attribute tool. Extract by mask (2) selects only the fog values that exist at or above 255 meters while the unnumbered extract by mask selects fog values corresponding to below 255 meters.
- Raster Calculator: For locations below 255 meters elevation, this step increases all values in the fog layer by the percent indicated by the parameterized double variable. For locations above 255 meters elevation, this step decreases all values in the fog layer by the percent indicated by the parameterized double variable. The equation input is: Input Later +/- (Input Layer * float(%double%)).
- Mosaic to New Raster: Creates a new raster layer by merging the two outputs from raster calculator. [Single band, 32-bit float, mosaic operator: last, mosaic colormap mode: first].

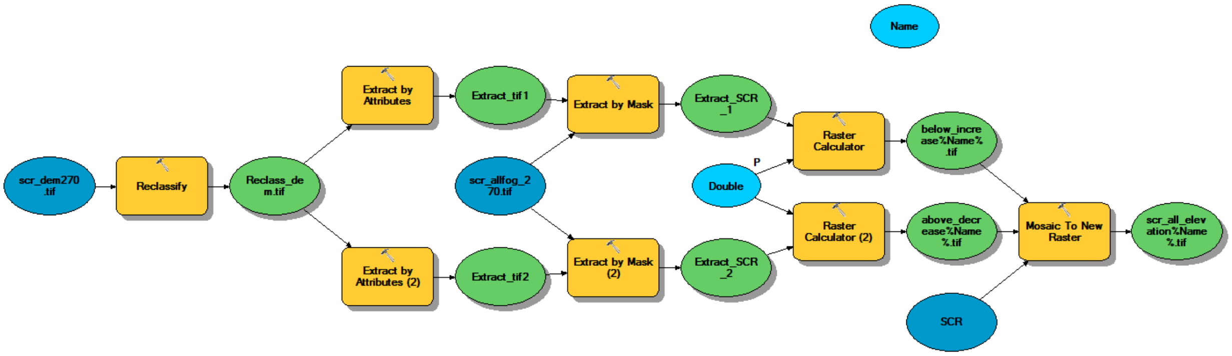


Figure A2. ArcGIS Model to Create Fog Layers for Projected Data with an Elevation Threshold.

## *ArcGIS Models*

Once data was prepared via methods described above, we worked both in ArcMap/ArcGIS ModelBuilder and R to process data and make it compatible for use in MaxEnt. We created the "MaxEnt Toolbox" in both ArcGIS and R in order to provide a tool in both systems. Projections for all data was verified as NAD 83 CA Teale Albers before the layers were run through the models. Our general objectives with these tools were to:

- Ensure all data was in rasterized format and compiled across the islands.
- Extract all data to the same extent layer, also defined as processing and raster analysis extent in model properties.
- Change the cell size of raster data to 270 meters x 270 meters, our selected resolution for the analysis.
- Export environmental variables as ASCII files, the preferable file type for use in MaxEnt.

The following are specific methods and models we used to prepare environmental layers and species presence data for our initial MaxEnt runs. The MaxEnt ArcGIS toolbox is outlined below, and the R script that performs the equivalent analysis is in Appendix C as the MaxEnt Toolbox RMarkdown script. The R script performs the same basic functions as the GIS toolbox detailed below, except that it also performs the organization of the data and renaming function.

### Set Model Properties

Model properties for all models described below were set to ensure that all output files had the same extent and cell size. To set model properties:

1) Go to 'Environments'

2) Check boxes for 'Processing Extent', 'Raster Analysis', and 'Output Coordinates', then select 'Value'.

3) In 'Processing Extent' set:

- 'Extent' = 'Same as variable extent'
- 'Snap raster' = 'extent'

4) In 'Raster Analysis' set:

- 'Cell size' = 'Same as variable extent'

### Extent

We used ArcGIS ModelBuilder to create an extent mask raster to be used as a mask in other data processing models (Figure A3). The extent was derived from the most restricted environmental layer and masked to the extent of the Channel Islands or the island of interest. We then resampled the extent to 270 x 270 meters and saved a new extent shapefile to be used as the extent parameter in all other models. A cell size of 270 meters was determined an appropriate extent for analysis of the oak species given the combination of coarse and fine resolution data and the need for maximizing processing power for the extent. Furthermore, it was the coarsest resolution of all the data sources (BCM data) and so to mitigate uncertainty inherent with resampling to finer resolutions, all data sources were set to the coarsest dataset resolution.

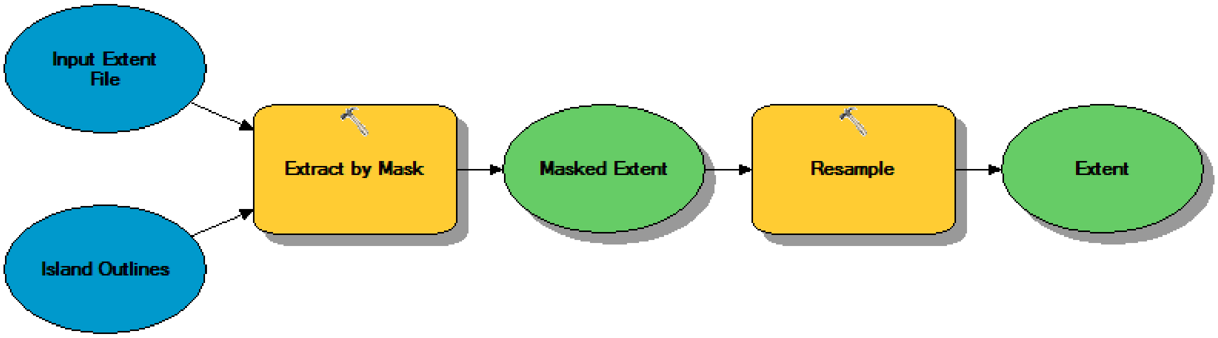


**Figure A3.** ArcGIS Model to Create Extent Layer.

## Oak Points

The model developed to create a csv of oak point presence data is illustrated in Figure A4. The tools used and their functions include:

- Merge: Combined oak points for Santa Cruz, Santa Rosa, and Santa Catalina Islands.
    - If only single island or within island points run, then merge is not run and the oak shapefile is run through the rest of the process. The OakIndividual submodel can be used for this purpose.
- Add XY Coordinates: Added XY coordinates to the merged shapefile.
- Add Field: Add Column to include species name information
- Calculate Field: Populate new column with “quercus_tomentella” in each row
- Table to Table: Create and save csv file to be used in MaxEnt

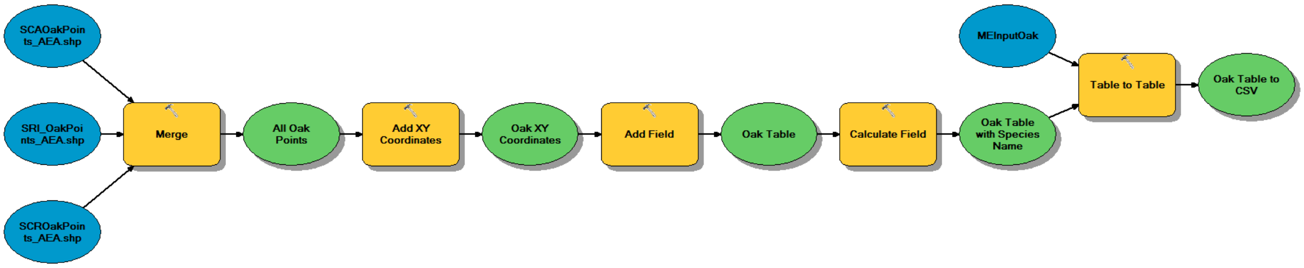


**Figure A4.** ArcGIS Model to Create Island Oak Presence Point CSV File.

## Island::Vegetation

The Island model contains the model workflows to develop the environmental layers for vegetation, DEM, and soils, or the island-by-island environmental variables. The model workflow developed to create a vegetation ASCII file is illustrated in Figure A5. The tools used and their functions include:

- Polygon to Raster: Convert Santa Cruz (SCR), North Islands without SCR (NI: San Miguel, Santa Rosa), and Santa Catalina (SCA) vegetation shapefiles to rasters. Build rasters by Value (the common 7 group values described in 'vegetation reclassification' above).
- Mosaic to New Raster: Combine the three vegetation rasters. [Cell center, no priority field, cell size 270 x 270 rasters, single band, 32-bit signed unit, mosaic operator: last, mosaic colormap mode: first]
- Extract by Mask: Extract by mask this new mosaiced raster using the mask created with the Extent mask tool.
- Raster to ASCII: Convert raster to an ASCII file and save it in a folder for MaxEnt input variables.

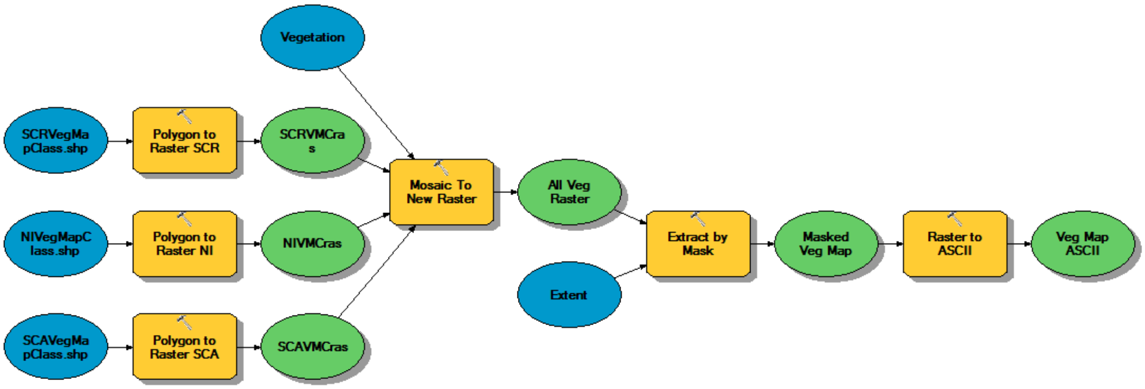


**Figure A5.** ArcGIS Island Model to Create Vegetation Layer.

## Island::DEM

The model workflow developed to create a DEM ASCII file is illustrated in Figure A6. The tools used and their functions include:

- Mosaic to New Raster: Combine the five DEM rasters and assign them the name DEM. [Cell center, no priority field, cell size 270 x 270 rasters, single band, 32-bit signed unit, mosaic operator: last, mosaic colormap mode: first]
- Extract by Mask: Extract by mask this new mosaiced 'All DEM' raster using the mask created with the extent mask tool.
- Raster to ASCII: Convert 'Masked All Dem' raster to an ASCII file and save it in a folder for MaxEnt input variables.

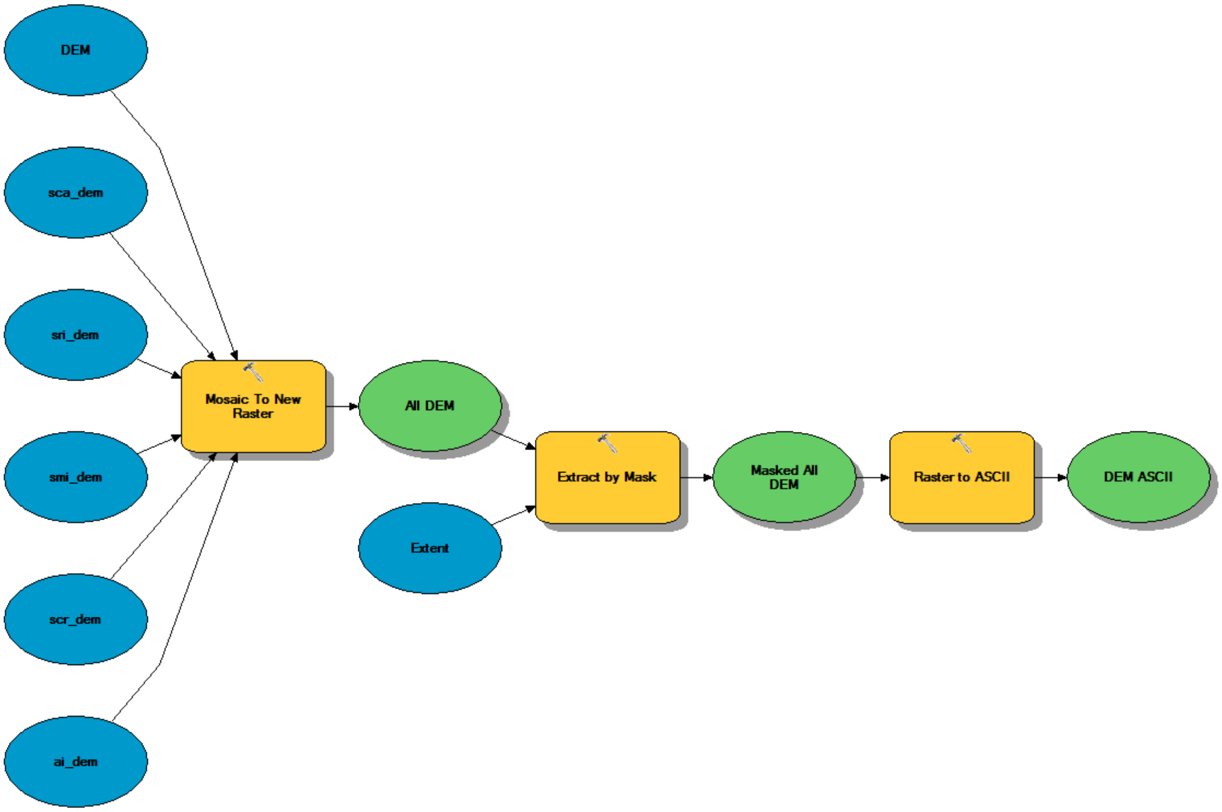


**Figure A6.** ArcGIS Island Model to Create DEM Layer.

## Island::Soil

The model developed to create a soil ASCII file is illustrated in Figure A7. The tools used and their functions include:

- Polygon to Raster: Convert 'Soils Data' shapefile to a raster, assigning cell values based numeric values in the 'MapUnit' field, a unique identifier for each soil classification.
- Extract by Mask: Extract by mask this new soil raster using the mask created with the extent mask tool.
- Raster to ASCII: Convert 'Masked Soils' raster to an ASCII file and save it in a folder for MaxEnt input variables.

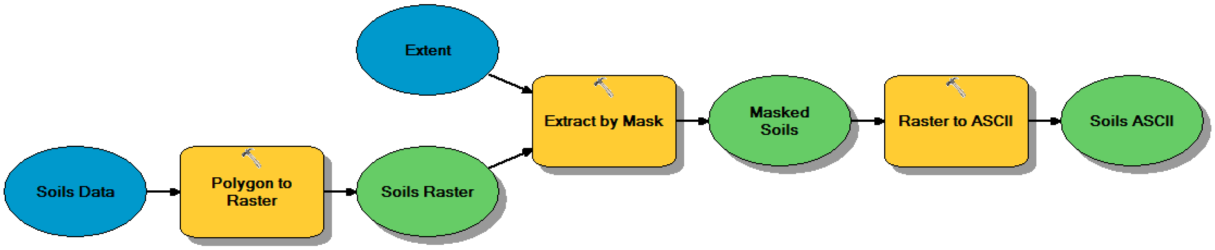


**Figure A7.** ArcGIS Island Model to Create Soils Layer.

## Climate

The model developed to create multiple current and future climate ASCII files is illustrated in Figure A8. The tools used and their functions include:

- Iterate rasters: 'BCM Data' is a folder of climate data layers. The iterate tool ensured that all rasters in the 'BCM Data' folder were processed through the model.
    - Iterator model conditions were set in addition to model properties, by right clicking iterator and setting the same model properties values based on extent as for the general model properties. The BCM Data folder was also set as an iterator precondition.
- Extract by Mask: Extract by mask the climate raster of the current iteration using the mask created with the extent mask tool.
- Raster to ASCII: Convert climate raster to an ASCII file and save it in a folder for MaxEnt input variables.

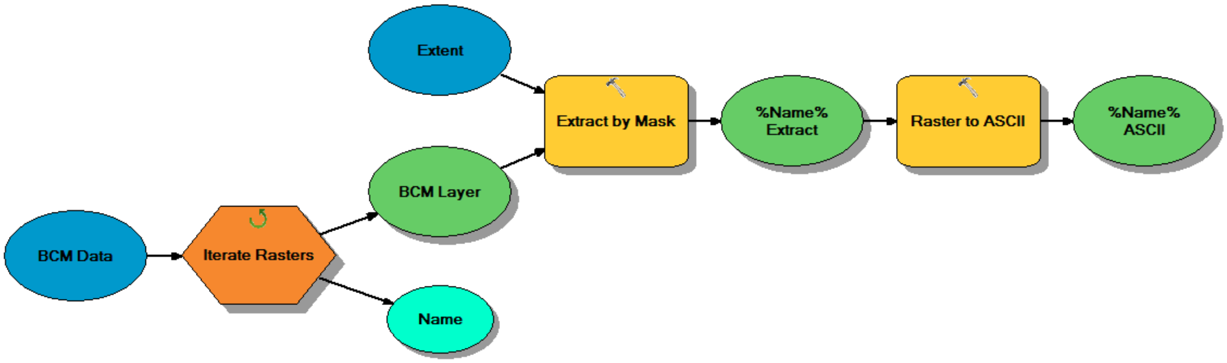


**Figure A8.** ArcGIS Model to Iteratively Create Climate Layers for Historic Data.

### Fog

The model developed to create current fog ASCII files for SCR and SRI is illustrated in Figure A9. The tools used and their functions include:

- Extract by Mask: Extracts the fog raster of the historic layer to the extent of only SCR or only SCI by the mask created with the extent mask tool.
- Raster to ASCII: Converts fog raster to an ASCII file and saves it in a folder for MaxEnt input variables.

Fog scenario layers also used the output from this model as base and were saved as .tifs after processing. R code selected the .tif files and sorted them into the appropriate file structure for MaxEnt.

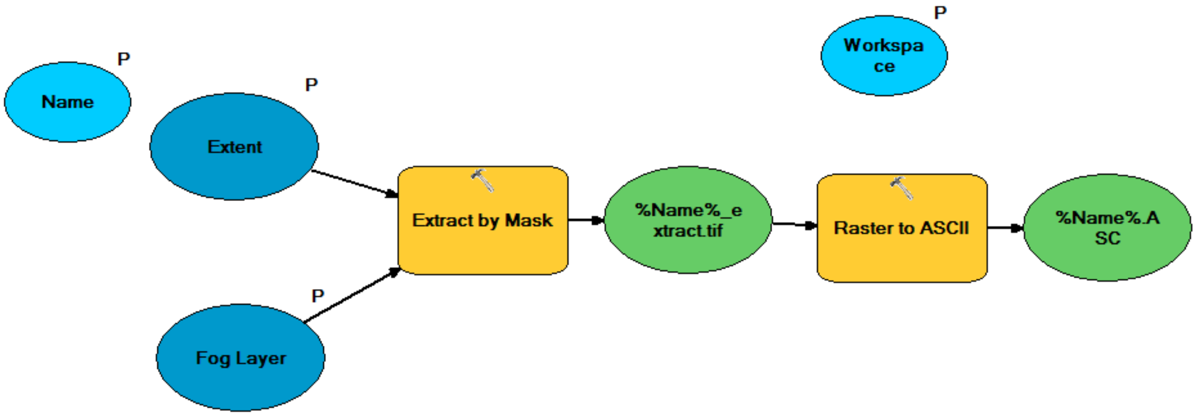
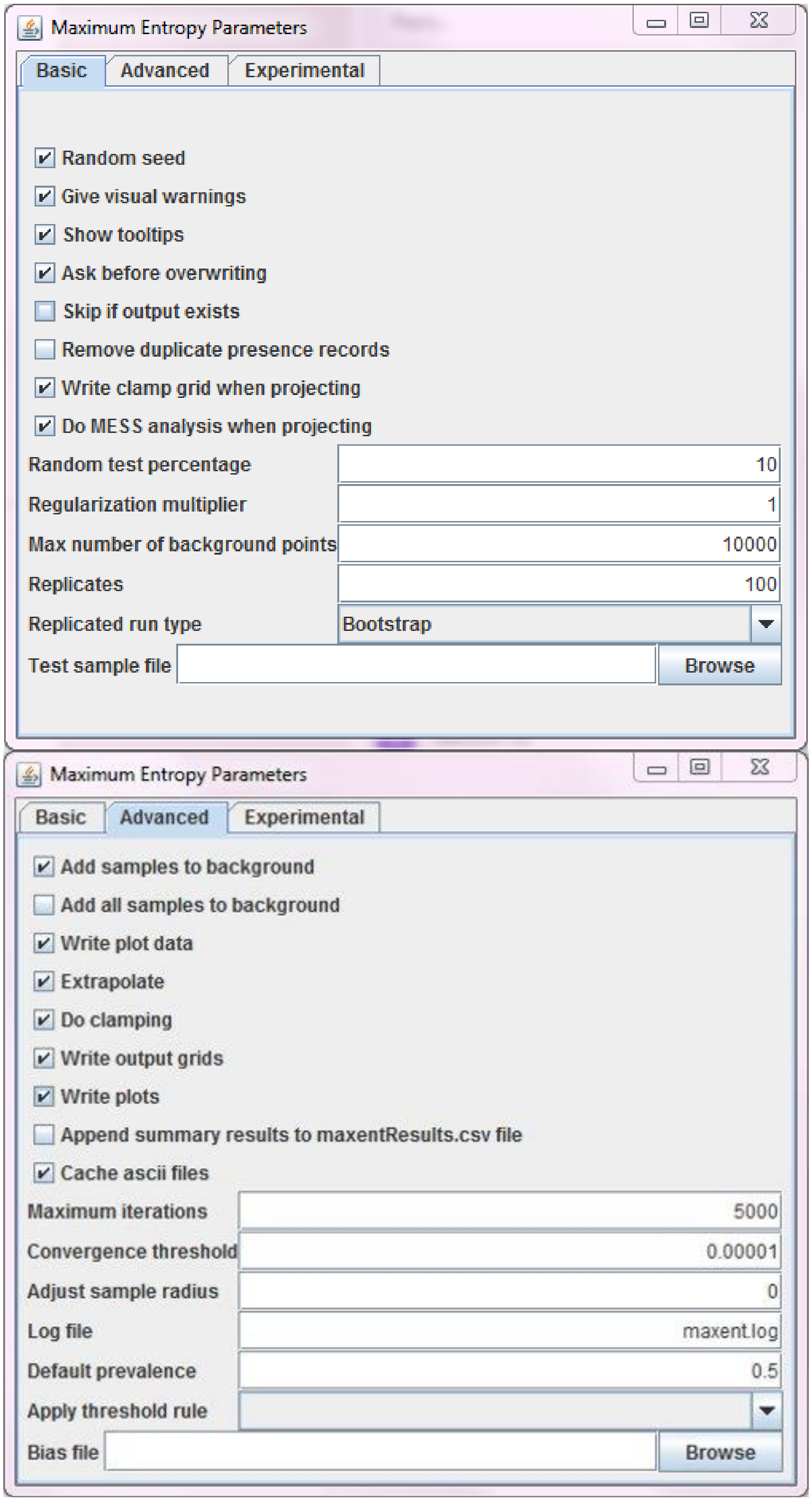


**Figure A9.** ArcGIS Model to Create Fog Layers for Historic Data.

## Appendix A2: MaxEnt

The presence sample.csv and environmental layer ASCII file outputs from the ArcGIS processing models serve as inputs into MaxEnt. The files were moved into the appropriate folders for MaxEnt analyses, ensuring the same file structure and file names and no NaNs in the ASCII (Organization section of the MaxEnt Toolbox R Script in Appendix C). For MaxEnt model parameters, linear, quadratic, and product features were selected, while hinge and threshold features were disabled, and all plots and analyses run for each scenario. The current parameters are shown in Figure A10 below. Random test percentage set to 10%. Replicates were set to 100 and run for all historic climate scenarios using Bootstrapping as the replicated run type. When running the model with Mainland California, the number of replicates was set to 1. Iterations were set to 5000 to ensure model convergence.



☑ Random seed
☑ Give visual warnings
☑ Show tooltips
☑ Ask before overwriting
☐ Skip if output exists
☐ Remove duplicate presence records
☑ Write clamp grid when projecting
☑ Do MESS analysis when projecting

| | |
|---|---|
| Random test percentage | 10 |
| Regularization multiplier | 1 |
| Max number of background points | 10000 |
| Replicates | 100 |
| Replicated run type | Bootstrap |
| Test sample file | |

☑ Add samples to background
☐ Add all samples to background
☑ Write plot data
☑ Extrapolate
☑ Do clamping
☑ Write output grids
☑ Write plots
☐ Append summary results to maxentResults.csv file
☑ Cache ascii files

| | |
|---|---|
| Maximum iterations | 5000 |
| Convergence threshold | 0.00001 |
| Adjust sample radius | 0 |
| Log file | maxent.log |
| Default prevalence | 0.5 |
| Apply threshold rule | |
| Bias file | |

**Figure A10.** Current MaxEnt Model Parameter Settings.

## *MaxEnt Input Considerations*

We determined the environmental layers to be used to create our final species distribution models through initial trial MaxEnt runs using all historic climate variables and island variables. We included the variables which were most important for augmenting model fit without increasing uncertainty through independent variable collinearity. Tested environmental variables are listed in Table A2, along with whether or not they were used in the final model. Additionally, when we analyzed habitat suitability for island oak seedling recruitment and establishment, we isolated representative points in the oak presence data for Santa Rosa Island and created new shapefiles.

**Table A2.** Environmental variables considered and selected for MaxEnt.

| Environmental Layers | Reference | Source | Included |
|---|---|---|---|
| Maximum annual temperature | tmx | BCM | Yes |
| Minimum annual temperature | tmn | BCM | Yes |
| Annual precipitation | ppt | BCM | Yes |
| Climate water deficit | cwd | BCM | Yes |
| Probability of Fog Inundation (May- September) | fog | Rastogi et al., 2016 | Yes |
| Potential evapotranspiration | pet | BCM | No |
| Actual Evapotranspiration | aet | BCM | No |
| Recharge | rch | BCM | No |
| Runoff | run | BCM | No |
| Digital Elevation Models | all_dem | Island Managers | No |
| Vegetation classes | veg_map | Island Managers | No |
| Soil Classes | soil_classes | USDA | No |

# Appendix A3: MaxEnt Output

After running MaxEnt, the output species distribution prediction ASCII files were compared spatially and statistically for visualization in ArcGIS and to create summary statistic data tables (MaxEnt Analysis and Integrated Outlook in Appendix C). Current and future climate distributions were compared to determine changes in oak habitat suitability across projections. At minimum, for each scenario summary statistics were calculated for the AUC of each model, the highest suitability value for each projection, the mean change in suitability, and percent change in suitable area and overall percent suitable area as defined by set binary threshold values. Rasters were created for each current, future, comparison, and binary habitat suitability distribution for visualization in ArcGIS.

# Appendix B: Additional Results

Expanded methods and results figures are provided in this section, including additional projected climate figures, the receiver operator curves for all scenarios shown in the results, and the most important figures for the additional climate suitability analyses section in the results.

## Appendix B1: Climate

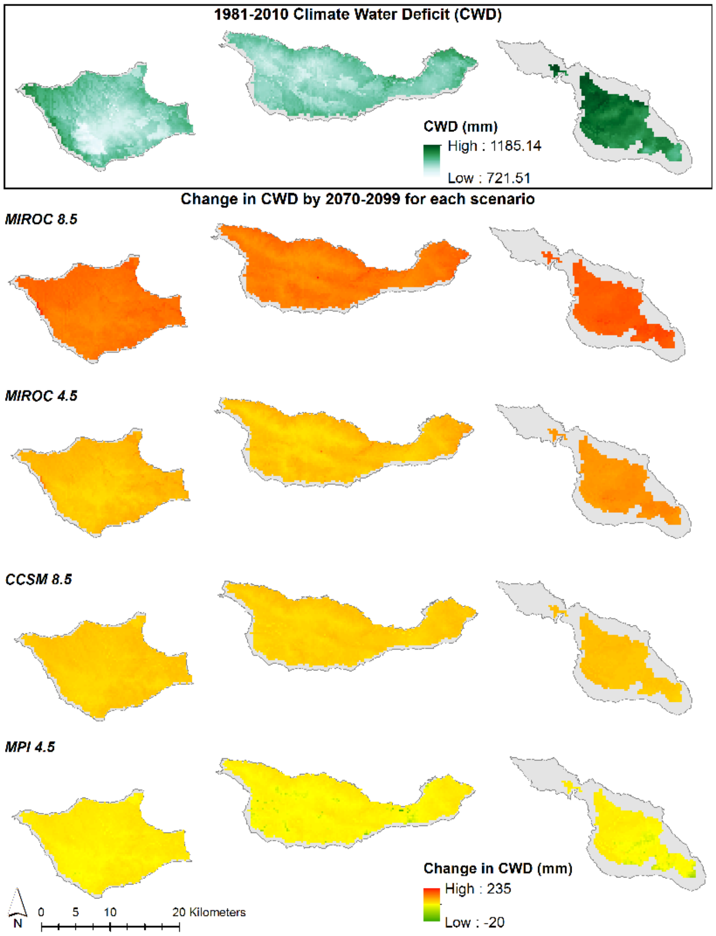


**Figure B1.** Change in climate water deficit (mm) on Santa Rosa, Santa Cruz, and Santa Catalina Islands from 1981 – 2099 for four climate models.

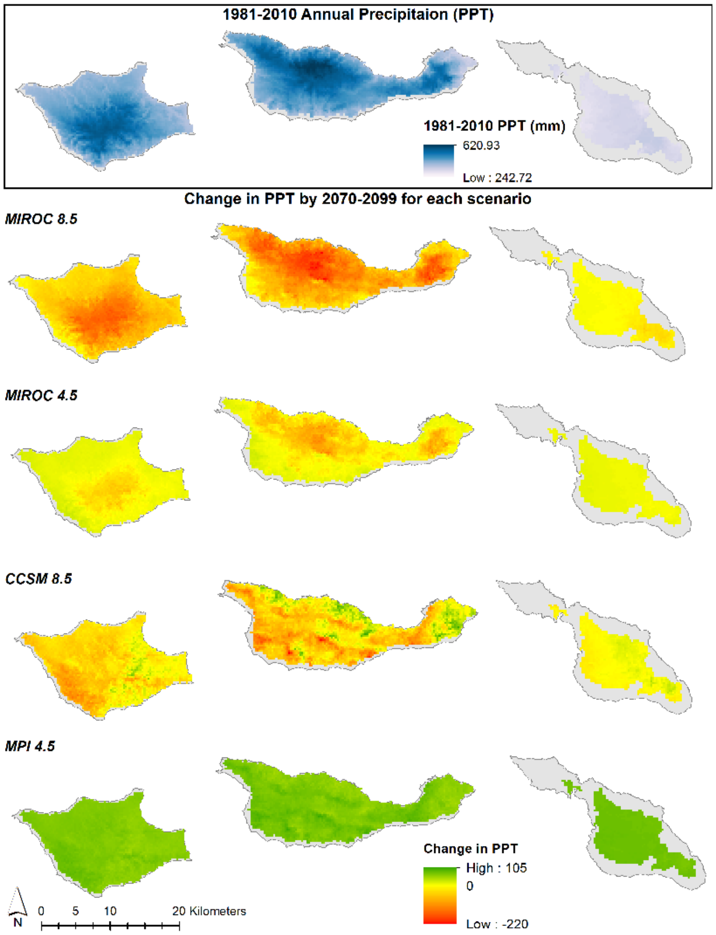


**Figure B2.** Change in annual precipitation (mm) on Santa Rosa, Santa Cruz, and Santa Catalina Islands from 1981 – 2099 for four climate models.

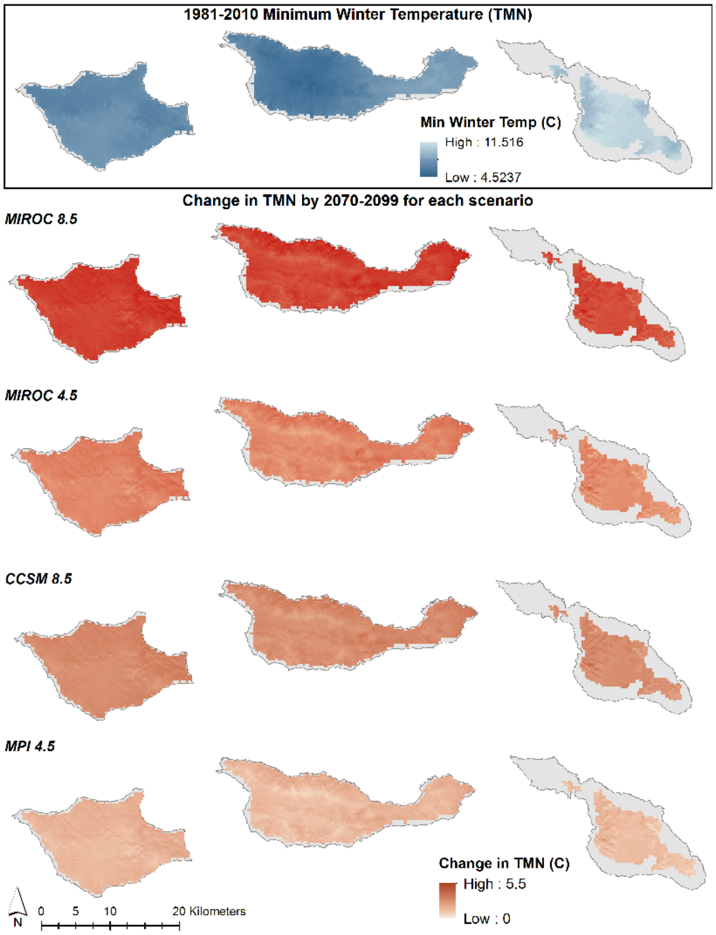


**Figure B3.** Change in minimum winter temperature (°C) on Santa Rosa, Santa Cruz, and Santa Catalina Islands from 1981 – 2099 for four climate models.

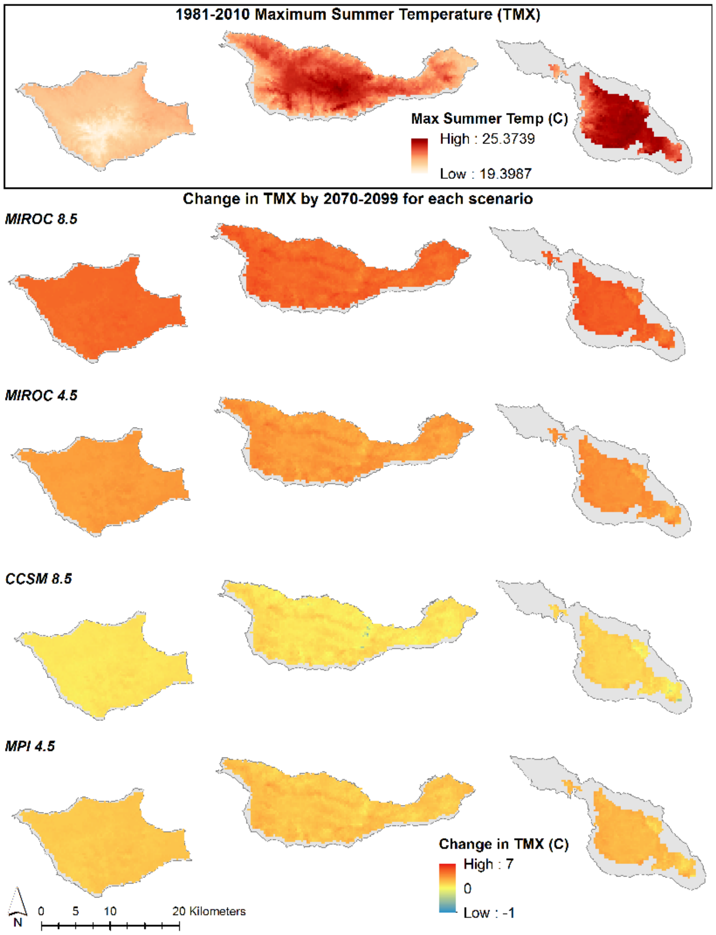


**Figure B4.** Change in maximum summer temperature (°C) on Santa Rosa, Santa Cruz, and Santa Catalina Islands from 1981 – 2099 for four climate models.

# Appendix B2: Receiver Operating Curves

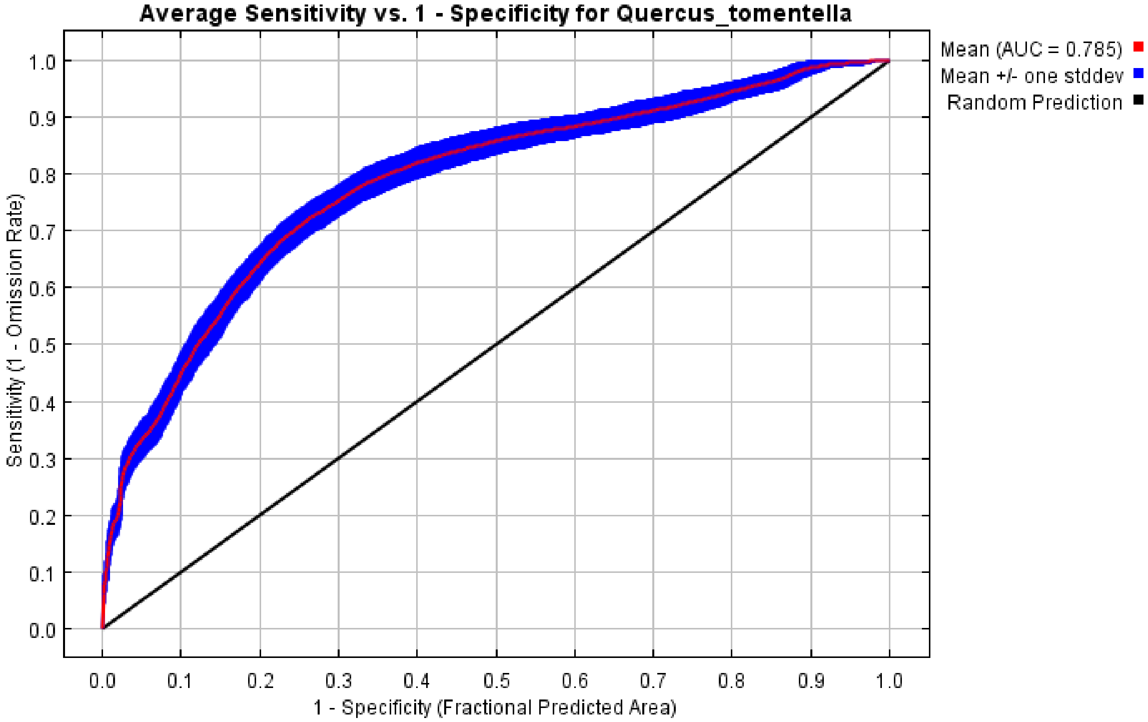


**Figure B5.** ROC for Santa Cruz Island fog elevation threshold scenario.

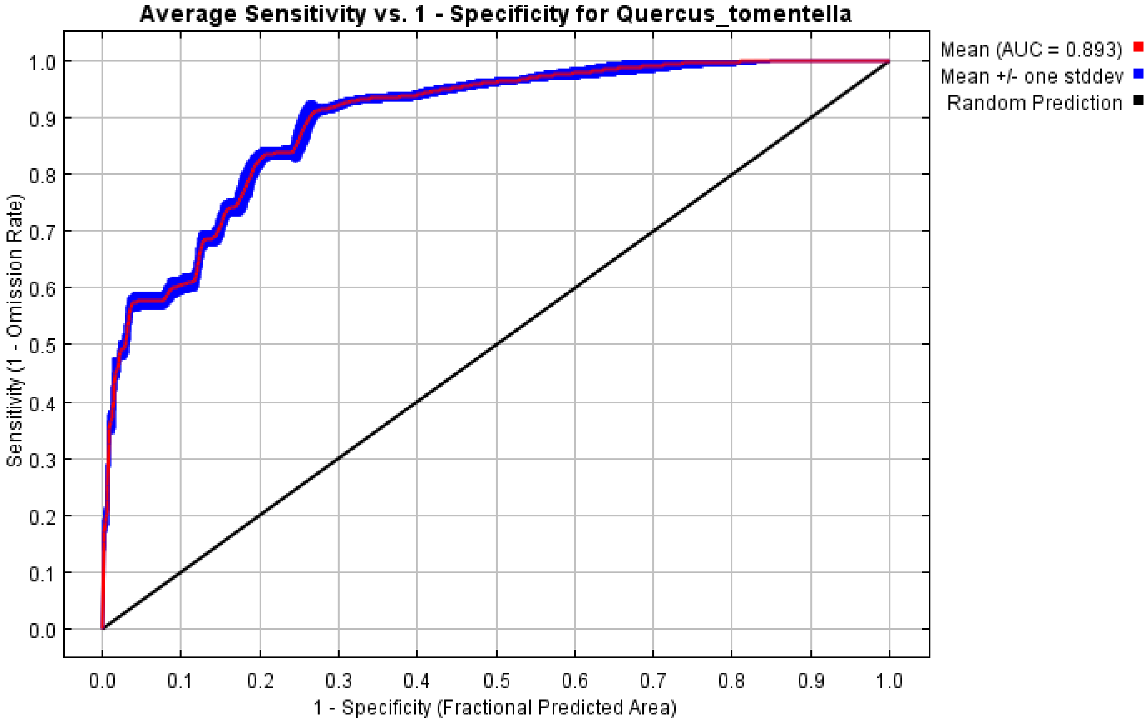


**Figure B6.** ROC for Santa Rosa Island fog elevation threshold scenario.

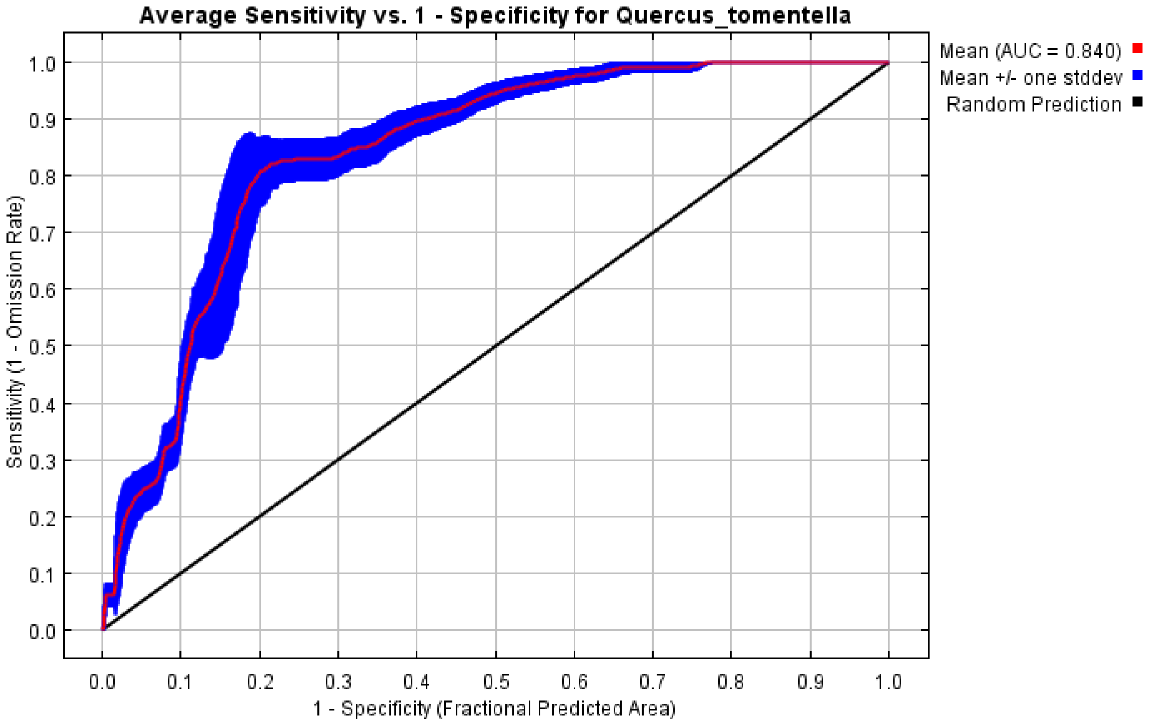


**Figure B7.** ROC for Santa Catalina Island non-kriged climate data.

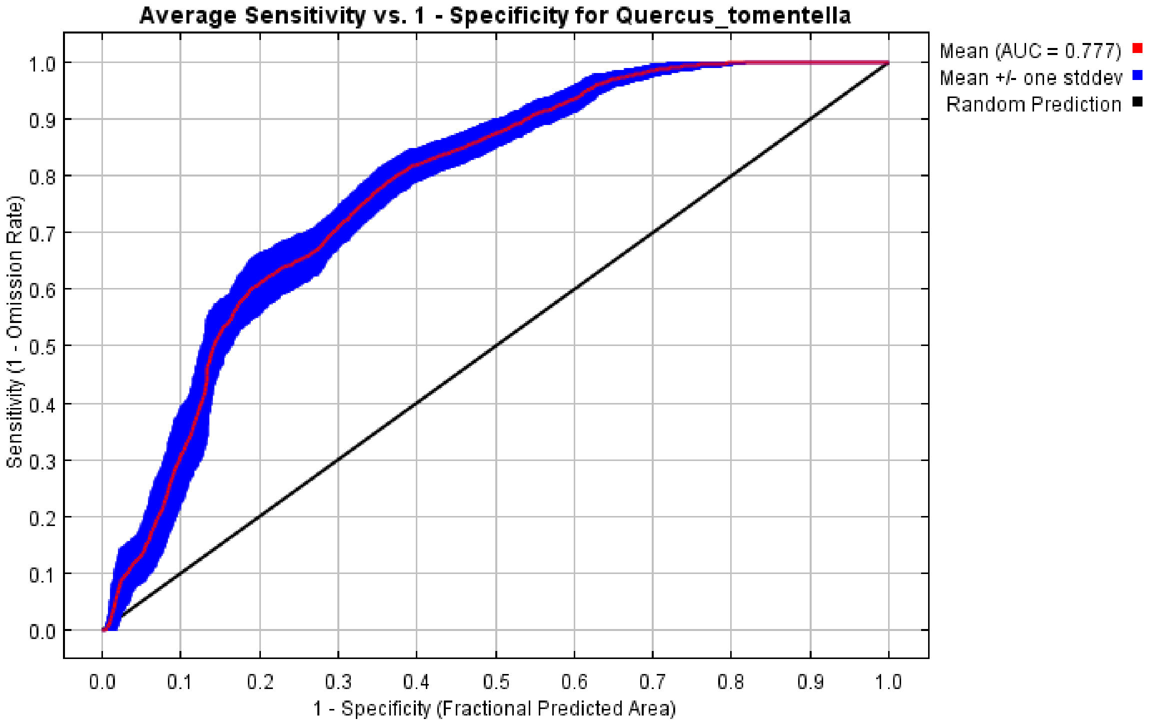


**Figure B8.** ROC for Santa Catalina kriged climate data.

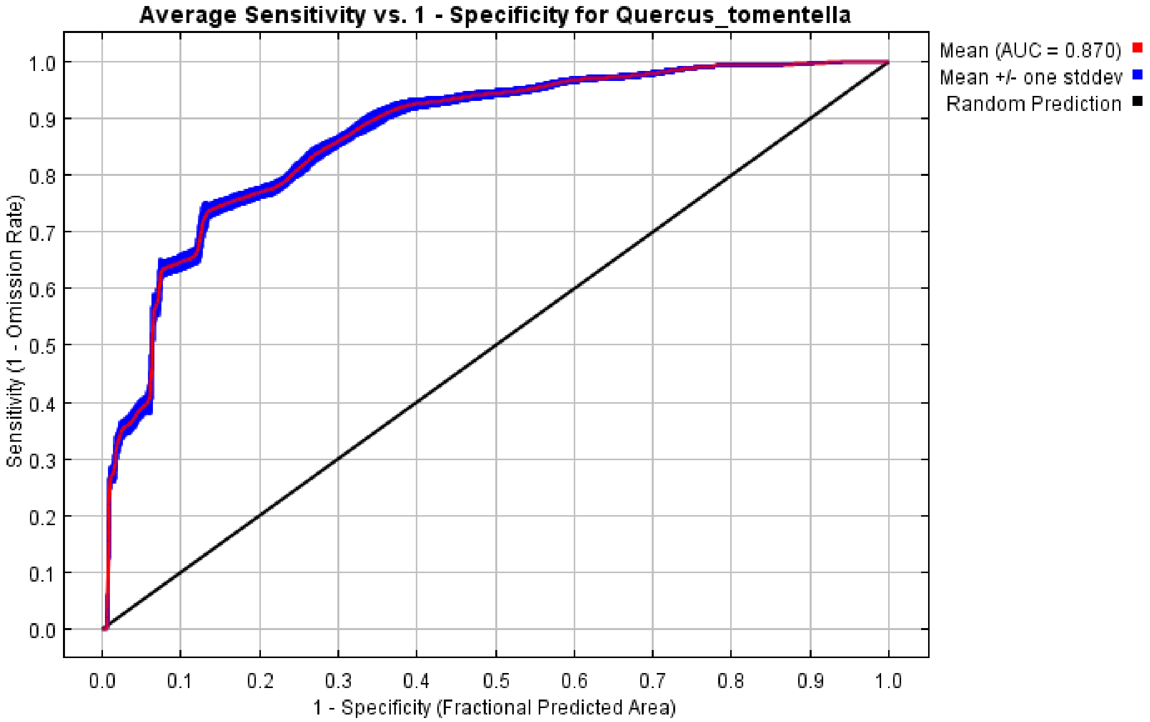


**Figure B9.** ROC for All islands scenario – non-kriged Santa Catalina climate data and no fog included for Santa Rosa and Santa Cruz islands.

# Appendix B3: Additional Climate Suitability Analyses

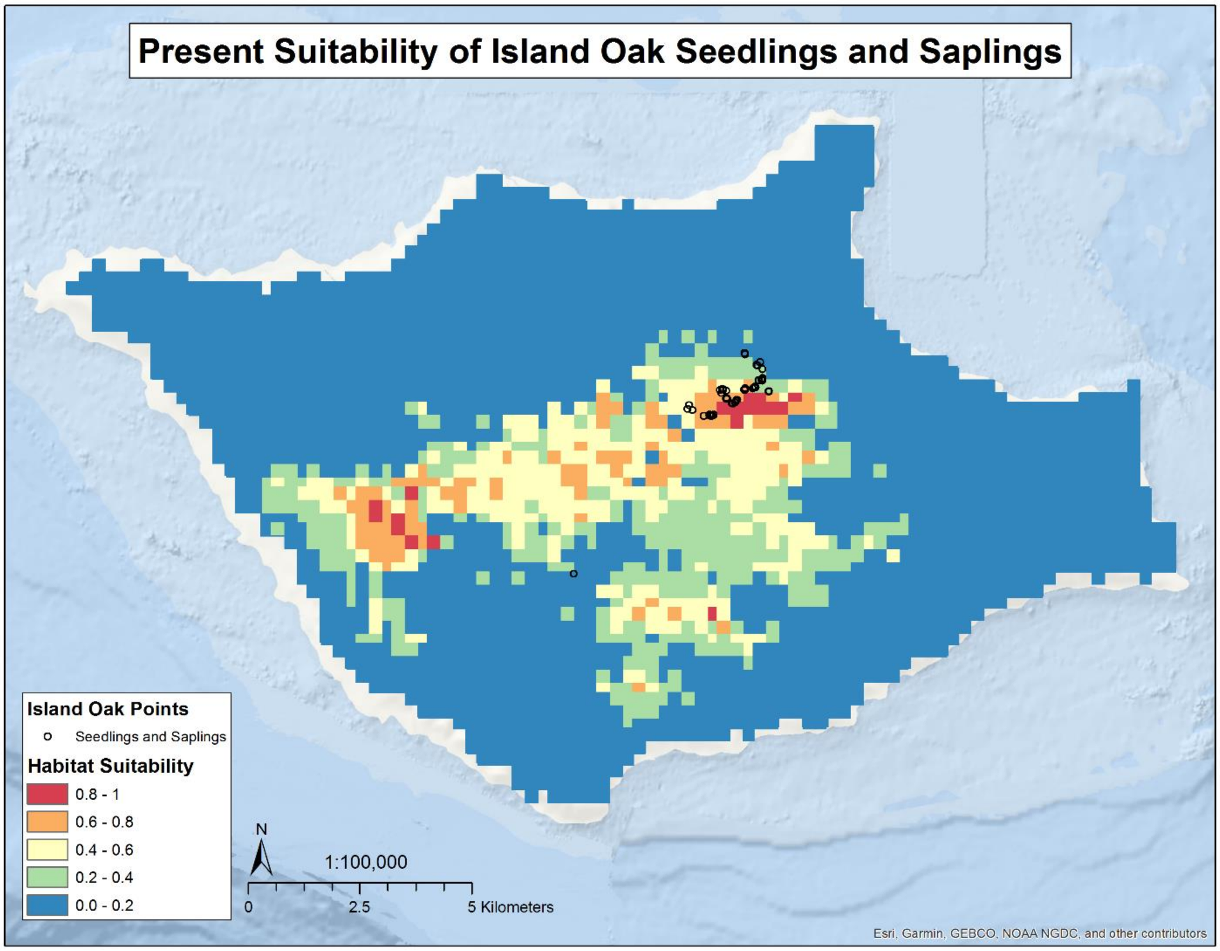


Figure B10. Predicted distribution of current habitat suitability of island oak seedlings and saplings on Santa Rosa Island utilizing only Santa Rosa oak seedling and sapling presence points and climate layers masked to the extent of the island.

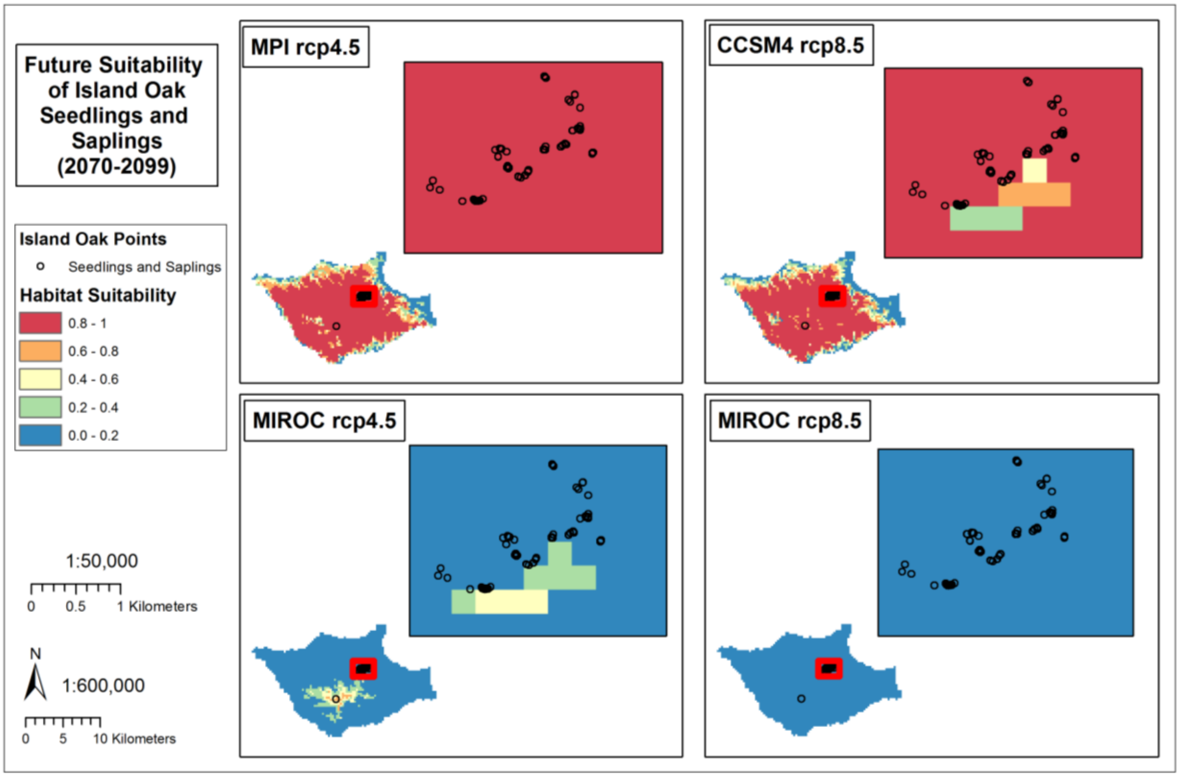


Figure B11. Predicted future distribution of habitat suitability for islands oak seedlings and saplings on Santa Rosa Island under four future climate projections for 2070-2099: MPI RCP4.5 (warm-wet), CCSM4 RCP8.5 (hot-wet), MIROC RCP4.5 (warm-dry), and MIROC RCP8.5 (hot-dry). Suitability determined from only Santa Rosa oak seedling and sapling presence points and climate layers masked to the islands' extent.

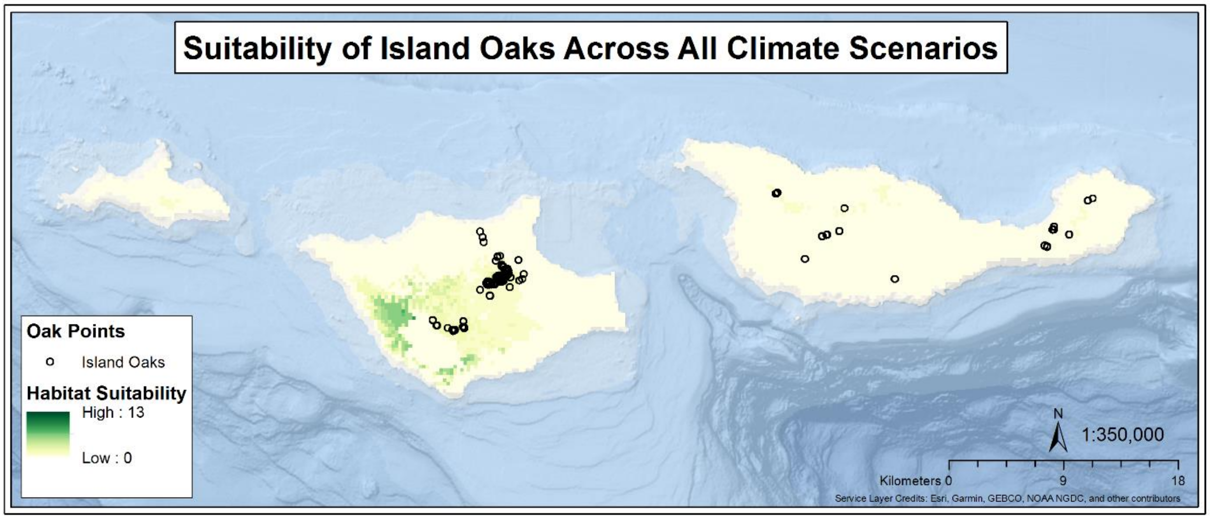


**Figure B12.** Predicted distribution of area considered suitable for island oaks across all current and future climate scenarios for all time-periods for San Miguel (left), Santa Rosa (center), and Santa Cruz (right).

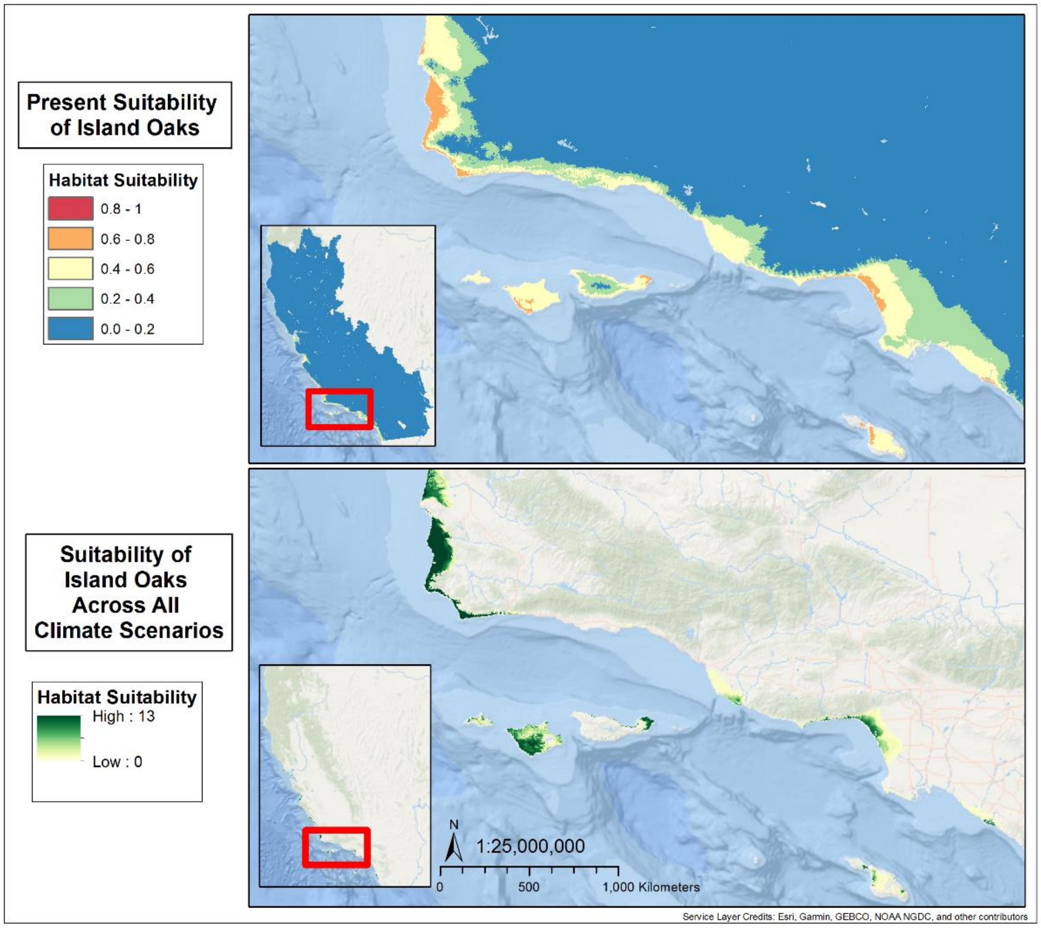


Figure B13. Current and predicted habitat suitability for Santa Barbara, Ventura, and Los Angeles counties. Predicted distribution of current habitat suitability for islands oaks on Mainland California (top panel). Predicted distribution of area considered suitable for island oaks across all current and future climate scenarios for all time-periods for Mainland California (bottom panel).

# Appendix C: R Scripts

These are the R scripts we used for our analysis mentioned throughout the paper.

## Vegetation

This R Markdown script can be used to classify the broad island-by-island vegetation types into more specific vegetation classification schemes that can be used to merge all the islands together and create a systematic raster of vegetation types to be input into MaxEnt.

This is an interactive script where you need to input your selected vegetation classifications in the middle. It makes an output halfway that needs to be corrected in excel on the basis of selected broad vegetation classification schemes (user decided), and then brought back in to make the final shapefile that is joined with the vegetation classification information.

1. Load “necessary”" packages

2. Load in data
   - Vegetation Map Shapefile including Santa Rosa, San Miguel, and Anacapa
   - Vegetation Map Shapefile of Santa Catalina -Current 2007 Santa Cruz Vegetation Map

## Vegetation Maps

```
#Read in the northern Channel Islands Veg Map which is in a geodatabase

require(rgdal)

# The input file geodatabase
vegni_gdb <- "G:/data/islands/all_islands/Channel_Islands_Veg_Map_2017/ChannelIslands_Veg_201
7.gdb"

# List all feature classes in a file geodatabase
subset(ogrDrivers(), grepl("GDB", name))

vegni_list <- ogrListLayers(vegni_gdb)


# Read the feature class
vegni_fc <- readOGR(dsn=vegni_gdb,layer="ChannelIslandsVegetation",stringsAsFactors = FALSE)

#Read in SCA veg map
vegsca<-readOGR("G:/data/islands/sca/veg_2000/veg_2000.shp", stringsAsFactors = FALSE)
```

```
#Read in SCR veg map
vegscr<-readOGR("G:/data/islands/scr/scr_veg_aea/scr_veg_aea.shp", stringsAsFactors = FALSE)
```

## Vegetation Communities

Determine unique vegetation community names for each shapefile and export table of the names with numbers

```
#Create table of unique veg names and numbers for northern islands
vegni_uniqnum<-unique(vegni_fc@data$All_Equiv)
vegni_uniqname<-unique(vegni_fc@data$AllCommon)

vegni_table<-data.frame(vegni_uniqnum, vegni_uniqname)


#Create table of unique veg names and numbers for sca
vegsca_uniqnum<-unique(vegsca@data$ID)
vegnsca_uniqname<-unique(vegsca@data$COMMUNITY)

vegsca_table<-data.frame(vegsca_uniqnum, vegnsca_uniqname)


#Create table of unique veg names and numbers for scr
vegscr_uniqnum<-unique(vegscr@data$MapCode_05)
vegnscr_uniqname<-unique(vegscr@data$Common_05)

vegscr_table<-data.frame(vegscr_uniqnum, vegnscr_uniqname)


#Export tables as csv to Vegetation in Working All Folder to Make Excel Tables to Join

#write.csv(vegni_table, file="G:/working/all/Vegetation/vegni.csv")
#write.csv(vegsca_table, file="G:/working/all/Vegetation/vegsca.csv")
#write.csv(vegscr_table, file="G:/working/all/Vegetation/vegscr.csv")
```

## Match-up Tables

In excel create match up table, or a master table that establishes the major vegetation groups and numbers. And then in the exported table make a new column where you put this new number as well as the vegetation associated name (for loop through to add)

This was performed by looking at the tables and creating overarching categories based on NLCD and Calscape.

Used papers to define between Chaparral and Coastal Shrub:
https://escholarship.org/uc/item/9rj6r9f1
http://rangelandarchive.ucdavis.edu/Annual_Rangeland_Handbook/Ecology/Calscape

VegCover Value Definitions:

Woodland 1 Chaparral 2 Coastal Shrub 3 Grassland 4 Riparian 5 Dune 6 Developed/Water 7

## Join Tables

Join finished table with shapefiles (in R but GIS style join)

```r
#Reading in the veg map connecting tables we designed to implement broader veg map groupings
vegni_csv<-read.csv("G:/working/all/Vegetation/vegni_class.csv", stringsAsFactors = FALSE)
vegsca_csv<-read.csv("G:/working/all/Vegetation/vegsca_class.csv", stringsAsFactors = FALSE)
vegscr_csv<-read.csv("G:/working/all/Vegetation/vegscr_class.csv", stringsAsFactors = FALSE)

require(sp) # the trick is that this package must be loaded!

vegni_join <- sp::merge(vegni_fc,vegni_csv, by="All_Equiv")
vegsca_join<-sp::merge(vegsca,vegsca_csv, by="ID")
vegscr_join<-sp::merge(vegscr,vegscr_csv, by="MapCode_05")
```

## Create Vegetation Shapefiles

Export new updated shapefiles to same location where veg shapefiles originally exist

```r
#Project spatial data frames into California Teale Albers

ctalbers<-"+proj=aea +lat_1=34 +lat_2=40.5 +lat_0=0 +lon_0=-120 +x_0=0 +y_0=-4000000 +ellps=GRS80 +datum=NAD83 +units=m +no_defs"
vegni_prj <- spTransform(vegni_join, CRS(ctalbers))
vegsca_prj<- spTransform(vegsca_join, CRS(ctalbers))
vegscr_prj<- spTransform(vegscr_join, CRS(ctalbers))


#Write SPDF as shapefile under veg folders

#writeOGR(vegni_prj, dsn = "G:/data/islands/all_islands/Channel_Islands_Veg_Map_2017/NIVegMapClass", layer = "NIVegMapClass", driver="ESRI Shapefile")
#writeOGR(vegsca_prj, dsn = "G:/data/islands/sca/SCAVegMapClass", layer = "SCAVegMapClass", driver="ESRI Shapefile")
#writeOGR(vegscr_prj, dsn = "G:/data/islands/scr/SCRVegMapClass", layer = "SCRVegMapClass", driver="ESRI Shapefile")
```

## Kriging BCM Data for Santa Catalina

This R Markdown script can be used to extrapolate the climate variables for Santa Catalina to the entire extent of the island, as the island is missing BCM climate data for some of its extent. The island DEM was used for universal co-kriging. The model for loops through the climate layers for current climate and all future climate projections and time periods, and saves the kriged climate layers in a new folder for input into the ArcGIS data processing model. The layers were resampled to 270 meters, which can be selected in the script.

A big thanks to Allison Horst and her ESM 244 Data Analysis class for teaching us kriging.

### Kriging Santa Catalina

```r
#Make sure all packages installed before running- use install.packages("packagename") if necessary
library(tidyverse) #datascience package

library(raster) #raster library

library(sf) #spatial

library(sp) #more spatial

library(gstat) #For geospatial statistics

library(rgdal) #spatial library

library(dplyr) #data wrangling

library(rgeos) #open source

#Define directories and files and pre-processing
################################################################################
#Bring in extent data to create spatial grid for Catalina
dsn_extent="G:/data/islands/sca/sca_extent"
layer_extent="sca_extent"
CI_extent<-st_read(dsn = dsn_extent, layer = layer_extent)

#DEM in correct projections
DEM_sca<-raster("G:/data/islands/sca/DEM/sca_dem_alb/sca_dem_alb.tif")

#Make CI extent into spatial points (Outline to raster to points for what to interpolate to)
ras <- raster()
extent(ras) <- extent(CI_extent)
CI_ras <- rasterize(CI_extent, ras, 'ShpAreaSqM')
proj4string(CI_ras)<-CRS("+proj=aea +lat_1=34 +lat_2=40.5 +lat_0=0 +lon_0=-120 +x_0=0 +y_0=-4000000 +ellps=GRS80 +datum=NAD83 +units=m +no_defs")
```

```r
CI_ras_res<-raster("G:/data/islands/sca/sca_extent/scaext_alb270.tif")#resample for cell size 270x270
CI_resamp<-raster::resample(CI_ras, CI_ras_res)


CI_extent_points<-rasterToPoints(CI_resamp, spatial=FALSE)
CI_extent_points<-as.data.frame(CI_extent_points)

Grid <- subset(CI_extent_points, select=c(x,y))
colnames(Grid)<-c("Long", "Lat")
coordinates(Grid) <- ~ Long + Lat

# Make predictions over pixels (not single points)
gridded(Grid) = TRUE
proj4string(Grid) <- CRS("+proj=aea +lat_1=34 +lat_2=40.5 +lat_0=0 +lon_0=-120 +x_0=0 +y_0=-4000000 +ellps=GRS80 +datum=NAD83 +units=m +no_defs")

#Extract from DEM for the GRID
Grid_DEM<-raster::extract(DEM_sca, Grid)
Grid_sp<-Grid
Grid_sp$DEM<-Grid_DEM


#Time to For Loop through BCM variables
############################################################

# dsn_bcm="G:/data/climate/GISModel_Input/historic/"
# files <- list.files(path = dsn_bcm, pattern = "\\.tif$")#From before f for loop-if only want to run one folder

folders<-list.dirs(path="G:/data/climate/GISModel_Input", recursive=FALSE)
for (f in folders){
dsn_bcm<-f
files <- list.files(path = dsn_bcm, pattern = "\\.tif$")
 for (c in files){
 BCM_ras <- raster(paste0(dsn_bcm,"/", c))
 BCM_ras_clip <- mask(BCM_ras, CI_extent) #Cut raster to bbox extent of islands

 BCM_points<-rasterToPoints(BCM_ras_clip, spatial=TRUE)#Create points from raster (using defined cell size)
 BCM_points<-as.data.frame(BCM_points)
 colnames(BCM_points)<-c("Avg", "lat", "long") #change x to long and y to lat
 coordinates(BCM_points) <- ~ lat + long #turns data int spatial points df
 proj4string(BCM_points) <- CRS("+proj=aea +lat_1=34 +lat_2=40.5 +lat_0=0 +lon_0=-120 +x_0=0 +y_0=-4000000 +ellps=GRS80 +datum=NAD83 +units=m +no_defs") #basically doing the same thing that crs did before

 BCM_DEM<-raster::extract(DEM_sca, BCM_points) #Pull DEM points using the raster BCM points
```

```
 BCM_sp<-BCM_points
 BCM_sp$DEM<-BCM_DEM

 BCM_vg <- variogram(Avg ~ DEM, BCM_sp)#Create a variogram

 vg_fit <- fit.variogram(BCM_vg, vgm(c("Exp","Sph","Gau")))#Fit a variogram model

 BCM_krige <- krige(Avg ~ DEM, BCM_sp, newdata = Grid_sp, model = vg_fit)#Krige

 proj4string(BCM_krige)<-CRS("+proj=aea +lat_1=34 +lat_2=40.5 +lat_0=0 +lon_0=-120 +x_0=0 +y_0
=-4000000 +ellps=GRS80 +datum=NAD83 +units=m +no_defs")

 writeGDAL(BCM_krige, fname=paste0("G:/data/climate/GIS_Input_SCAInterpolated/", basename(f),
"/", c), drivername="GTiff")

 }#end c for loop
} #end f for loop
```

# MaxEnt Toolbox

This R Markdown Script performs all the pre-processing of the data files for input into MaxEnt. Choose a scenario to run all the data processing for that scenario. Also be sure to turn on (remove the #) for a writing of rasters, csvs, or shapefiles, in order to have them run and saved. They are currently coded out so that they will not continuously overwrite previously compiled scenarios. Also if creating a new scenario, be sure to add it to the scenario options below and to add the appropriate folder structure for that scenario for where all outputs are to be written.

## Scenario Selection

```
#Change scenario
scenario<-"sca_270m"

#Options:
#allislands_270m
#ni_270m
#sca_270m
#sca_int_270m
#scr_270m
#sri_270m
#sri_adultyoung_270m
#sri_seedsap_270m
#scr_foginc_270m
#scr_fogdec_270m
#sri_foginc_270m
#sri_fogdec_270m
#scr_fogelev_270m
#sri_fogelev_270m
#scr_fogconstant_270m
#sri_fogconstant_270m
#MainlandCA
```

## Load Packages

```
#If packages missing use install.packages("packagename")
library(tidyverse)
library(sf)
library(raster)
library(sp)
library(rgdal)
library(tools)
```

## Extent

```
#Create scenario extent that will be used throughout the rest of the processes, based off the minimum BCM data available as well as the Channel Island CUSP outlines
```

```
#If else statements for scenarios: read in the correct data for each scenario
if (scenario=="allislands_270m"){
 #All Islands
 scenario_extent<-read_sf("G:/data/islands/all_islands/extent/allislandsoutline.shp")
 min_data<-raster("G:/data/climate/GISModel_Input/historic/cwd1981_2010_ave_HST_1539127145.tif")
}else if (scenario=="ni_270m"){
 #Northern Islands
 scenario_extent<-read_sf("G:/data/islands/all_islands/ni_outline/ni_outline.shp")
 min_data<-raster("G:/data/climate/GISModel_Input/historic/cwd1981_2010_ave_HST_1539127145.tif")
}else if (scenario=="scr_270m"|scenario=="scr_foginc_270m"|scenario=="scr_fogdec_270m"|scenario=="scr_fogelev_270m"|scenario=="scr_fogconstant_270m"){
 #Santa Cruz
 scenario_extent<-read_sf("G:/data/islands/scr/scr_extent/scr_extent.shp")
 min_data<-raster("G:/data/climate/GISModel_Input/historic/cwd1981_2010_ave_HST_1539127145.tif")
}else if (scenario=="sri_270m"|scenario=="sri_adultyoung_270m"|scenario=="sri_seedsap_270m"|scenario=="sri_foginc_270m"|scenario=="sri_fogdec_270m"|scenario=="sri_fogelev_270m"|scenario=="sri_fogconstant_270m"){
 #Santa Rosa
 scenario_extent<-read_sf("G:/data/islands/sri/sri_extent/sri_extent.shp")
 min_data<-raster("G:/data/climate/GISModel_Input/historic/cwd1981_2010_ave_HST_1539127145.tif")
}else if (scenario=="sca_270m"){
 #Santa Catalina
 scenario_extent<-read_sf("G:/data/islands/sca/sca_extent/sca_extent.shp")
 min_data<-raster("G:/data/climate/GISModel_Input/historic/cwd1981_2010_ave_HST_1539127145.tif")
}else if (scenario=="sca_int_270m"){
 #Santa Catalina Interpolated
 scenario_extent<-read_sf("G:/data/islands/sca/sca_extent/sca_extent.shp")
 min_data<-raster("G:/data/climate/GIS_Input_SCAInterpolated/historic/cwd1981_2010_ave_HST_1539127145.tif")
}else if (scenario=="MainlandCA"){
 #Mainland CA
 scenario_extent<-raster("G:/data/climate/GISModel_Input/historic/cwd1981_2010_ave_HST_1539127145.tif")
 min_data<-raster("G:/data/climate/GISModel_Input/historic/cwd1981_2010_ave_HST_1539127145.tif")
}else
 print ("No Scenario Selected")

#Turn the below on if you want to rewrite the extent rasters
# cropped <- crop(min_data, extent(scenario_extent)) #Crop to extent of outlines
# scen_extent <- mask(cropped, scenario_extent) #Mask to the exact island outline(s)
```

```
# extent(scen_extent)<-round(extent(scen_extent),1) #Rerun with rounded extent so extents same dec
imal amount
# writeRaster(scen_extent, filename=paste0("G:/data/islands/MaxEnt/Extent/", scenario, ".tif"), over
write=TRUE)#write extent raster


#Extent will be used throughout Script. Will call in the extent each time just to be careful.
```

## Oak Combined and Individual

```
#Read in Oak Points
sca_oaks<-read_sf("G:/data/islands/sca/Quertome/SCAOakPoints_AEA.shp")
sri_oaks<-read_sf("G:/data/islands/sri/OakPoint/SRI_OakPoints_Updated.shp")
scr_oaks<-read_sf("G:/data/islands/scr/OakPoint/SCR_OakPoints_Updated.shp")


#If else statements for scenarios: read in the correct data for each scenario
if (scenario=="allislands_270m"|scenario=="MainlandCA"){
  #All Islands or Mainland CA
  sca_xy<-st_coordinates(sca_oaks)
  sri_xy<-st_coordinates(sri_oaks)
  scr_xy<-st_coordinates(scr_oaks)
  all_oaks<-rbind(sca_xy[,1:2],sri_xy[,1:2],scr_xy[,1:2])
}else if (scenario=="ni_270m"){
  #Northern Islands
  sri_xy<-st_coordinates(sri_oaks)
  scr_xy<-st_coordinates(scr_oaks)
  all_oaks<-rbind(sri_xy[,1:2],scr_xy[,1:2])
}else if (scenario=="scr_270m"|scenario=="scr_foginc_270m"|scenario=="scr_fogdec_270m"|scenari
o=="scr_fogelev_270m"|scenario=="scr_fogconstant_270m"){
  #Santa Cruz
  scr_xy<-st_coordinates(scr_oaks)
  all_oaks<-scr_xy[,1:2]
}else if (scenario=="sri_270m"|scenario=="sri_foginc_270m"|scenario=="sri_fogdec_270m"|scenario
=="sri_fogelev_270m"|scenario=="sri_fogconstant_270m"){
  #Santa Rosa
  sri_xy<-st_coordinates(sri_oaks)
  all_oaks<-sri_xy[,1:2]
}else if (scenario=="sca_270m"|scenario=="sca_int_270m"){
  #Santa Catalina and Santa Catalina Interpolated
  sca_xy<-st_coordinates(sca_oaks)
  all_oaks<-sca_xy[,1:2]
}else if (scenario=="sri_adultyoung_270m"){
  #Santa Rosa Adult and Young
  sri_ay<-subset(sri_oaks, sri_oaks$Age=="adult"|sri_oaks$Age=="young") #Fix this so it works
  sri_xy<-st_coordinates(sri_ay)
  all_oaks<-sri_xy[,1:2]
}else if (scenario=="sri_seedsap_270m"){
```

```
 #Santa Rosa Seedling and Saplings
 sri_ay<-subset(sri_oaks, sri_oaks$Age=="seedling"|sri_oaks$Age=="sapling") #Fix this so it works
 sri_xy<-st_coordinates(sri_ay)
 all_oaks<-sri_xy[,1:2]
}else
 print ("No Scenario Selected")

#Make Oak Point CSV based on selected oak points
alloaks<-as.data.frame(all_oaks)
alloaks$Species<-"Quercus tomentella"
Oaks<-alloaks[,c(3,1,2)]
oak_fn<-paste0("G:/data/islands/MaxEnt/MEInputOak/", scenario,"/OakPoints.csv")
#Turn on write csv to write out the oak points
#write.csv(Oaks, oak_fn, row.names=FALSE)
```

## Climate

```
if (scenario=="sca_int_270m"){
 #Santa Catalina Interpolated: Made by KrigingCatalina_AllBCM.Rmd
 clim_dirs<-list.dirs(path="G:/data/climate/GIS_Input_SCAInterpolated", full.names=T, recursive=F)
}else
clim_dirs<-list.dirs(path="G:/data/climate/GISModel_Input", full.names=T, recursive=F)

#Call in appropriate extent
scen_extent<-raster(paste0("G:/data/islands/MaxEnt/Extent/", scenario, ".tif"))
crs(scen_extent)<-CRS('+init=epsg:3310')

for (clim in clim_dirs){
 #print (clim) #For loop through climate projections
 clim_vars<-list.files(clim, pattern='tif$', full.names=TRUE )
 for (climvar in clim_vars){
  #print (climvar)#For loop through climate variables
  clim_ras<-raster(climvar)
  crs(clim_ras)<-CRS('+init=epsg:3310')

  if(scenario=="MainlandCA"){
   climate_new<- resample(clim_ras, scen_extent, "ngb")
  }else
   climate_new<-clim_ras

  clim_crop <- crop(climate_new, extent(scen_extent)) #Crop to extent of outlines
  climate <- mask(clim_crop, scen_extent) #Mask to the exact island outline(s)
  extent(climate)<-round(extent(climate),1) #Rerun with rounded extent so extents same decimal am
ount
  clim_name<-file_path_sans_ext(basename(climvar))
  fn <- paste0("G:/data/climate/MEInput/", scenario, "/", basename(clim), "/", clim_name, ".asc")
  #Uncode write raster if you want the raster to be written
  #writeRaster(climate,fn,format="ascii",overwrite=T)
```

```
  }#End for loop through climate variables
}#End for loop through climate projections
```

## Island

```
if (scenario!="MainlandCA"){

  #Set final directory
island_fn<-paste0("G:/data/islands/MaxEnt/MEInput/", scenario, "/")
#Call in appropriate extent
scen_extent<-raster(paste0("G:/data/islands/MaxEnt/Extent/", scenario, ".tif"))
crs(scen_extent)<-CRS('+init=epsg:3310')


#Soils
  soilshp<-read_sf("G:/data/islands/all_islands/Soil/soils_AEA.shp")
  ext<-extent(scen_extent)
  gridsize <- 270
  soilr <- raster(ext, res=gridsize)
  soilras <- rasterize(soilshp, soilr, field = 'MapUnit')
  crs(soilras)<-CRS('+init=epsg:3310')
  soil_crop <- crop(soilras, extent(scen_extent)) #Crop to extent of outlines
  soils <- mask(soil_crop, scen_extent) #Mask to the exact island outline(s)
  extent(soils)<-round(extent(soils),1)
  #Uncode write raster if you want the raster to be written
  #writeRaster(soils,paste0(island_fn, "soilclasses.asc"),format="ascii",overwrite=T)


#Vegetation: Made by VegetationMapGrouping.Rmd
  #SCR
    scr_vegpshp<-read_sf("G:/data/islands/scr/SCRVegMapClass/SCRVegMapClass.shp")
    scr_vegr <- raster(extent(scen_extent), res=270)
    scr_vegras <- rasterize(scr_vegpshp, scr_vegr, field = 'Value')
    crs(scr_vegras)<-CRS('+init=epsg:3310')
  #NI
    ni_vegpshp<-read_sf("G:/data/islands/all_islands/Channel_Islands_Veg_Map_2017/NIVegMapClass/NIVegMapClass.shp")
    ni_vegr <- raster(extent(scen_extent), res=270)
    ni_vegras <- rasterize(ni_vegpshp, ni_vegr, field = 'Value')
    crs(ni_vegras)<-CRS('+init=epsg:3310')
  #SCA
    sca_vegpshp<-read_sf("G:/data/islands/sca/SCAVegMapClass/SCAVegMapClass.shp")
    sca_vegr <- raster(extent(scen_extent), res=270)
    sca_vegras <- rasterize(sca_vegpshp, sca_vegr, field = 'Value')
    crs(sca_vegras)<-CRS('+init=epsg:3310')
  #Merge to New Raster
    all_veg<-merge(scr_vegras, ni_vegras, sca_vegras)
    veg_crop <- crop(all_veg, extent(scen_extent)) #Crop to extent of outlines
```

```
   veg <- mask(veg_crop, scen_extent) #Mask to the exact island outline(s)
   extent(veg)<-round(extent(veg),1)
  #Uncode write raster if you want the raster to be written
   #writeRaster(veg,paste0(island_fn, "veg.asc"),format="ascii",overwrite=T)



#DEM
  ai_dem<-raster("G:/data/islands/all_islands/DEM/ai_dem270.tif")
  scr_dem<-raster("G:/data/islands/all_islands/DEM/scr_dem270.tif")
  sri_dem<-raster("G:/data/islands/all_islands/DEM/sri_dem270.tif")
  smi_dem<-raster("G:/data/islands/all_islands/DEM/smi_dem270.tif")
  sca_dem<-raster("G:/data/islands/sca/DEM/sca_dem_alb/sca_dem_alb270.tif")
  all_dem<-merge(ai_dem, scr_dem, sri_dem, smi_dem, sca_dem, tolerance=0.5)#Accepts different origins
  #all_dem<-raster("G:/data/islands/all_islands/DEM/all_dem270.tif") #Combined all DEMS at 270 in GIS with mosaic to new raster because much quicker and save across all projects
  all_dem_new <- resample(all_dem, scen_extent, "ngb")
  #Figure out cropping and masking issue
  dem_crop <- crop(all_dem_new, scen_extent) #Crop to extent of outlines
  dem <- mask(dem_crop, scen_extent) #Mask to the exact island outline(s)
  extent(dem)<-round(extent(dem),1)
#Uncode write raster if you want the raster to be written
  #writeRaster(dem,paste0(island_fn, "DEM.asc"),format="ascii",overwrite=T)

  #Slope and Aspect
  all_terrain<-terrain(dem, opt=c('slope', 'aspect'), unit='degrees')
  slope<-all_terrain$slope
  aspect<-all_terrain$aspect
#Uncode write raster if you want the raster to be written
  #writeRaster(slope,paste0(island_fn, "slope.asc"),format="ascii",overwrite=T)
  #writeRaster(aspect,paste0(island_fn, "aspect.asc"),format="ascii",overwrite=T)

}else
  print ("Mainland CA needs data") #data not currently available for Mainland
```

## Fog

```
scen_extent<-raster(paste0("G:/data/islands/MaxEnt/Extent/", scenario, ".tif"))
crs(scen_extent)<-CRS('+init=epsg:3310')

#If else statements for scenarios: read in the correct data for each scenario
if (scenario=="scr_foginc_270m"){
  #Future fog changed by a percent (20%) Inc/Dec for SRI and SCR
  current_fog<-raster("G:/data/climate/Fog/Fog_270/Historic/scr_allfog_270.tif")
  future_fog_10_40<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SCR/scr_All_increase045.tif")
  future_fog_40_70<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SCR/scr_All_increase135.tif")
```

```
 future_fog_70_100<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SCR/scr_All_increase225.tif")

}else if (scenario=="scr_fogdec_270m"){
 #Future fog changed by a percent (20%) Inc/Dec for SRI and SCR
 current_fog<-raster("G:/data/climate/Fog/Fog_270/Historic/scr_allfog_270.tif")
 future_fog_10_40<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SCR/scr_All_decrease045.tif")
 future_fog_40_70<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SCR/scr_All_decrease135.tif")
 future_fog_70_100<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SCR/scr_All_decrease225.tif")

}else if (scenario=="sri_foginc_270m"){
 #Future fog changed by a percent (20%) Inc/Dec for SRI and SCR
 current_fog<-raster("G:/data/climate/Fog/Fog_270/Historic/sri_allfog_270.tif")
 future_fog_10_40<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SRI/sri_All_increase045.tif")
 future_fog_40_70<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SRI/sri_All_increase135.tif")
 future_fog_70_100<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SRI/sri_All_increase225.tif")

}else if (scenario=="sri_fogdec_270m"){
 #Future fog changed by a percent (20%) Inc/Dec for SRI and SCR
 current_fog<-raster("G:/data/climate/Fog/Fog_270/Historic/sri_allfog_270.tif")
 future_fog_10_40<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SRI/sri_All_decrease045.tif")
 future_fog_40_70<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SRI/sri_All_decrease135.tif")
 future_fog_70_100<-raster("G:/data/climate/Fog/Fog_270/PercentChange/SRI/sri_All_decrease225.tif")

}else if (scenario=="scr_fogelev_270m"){
 #Future Fog Elevation (+-20%): SRI and SCR
 current_fog<-raster("G:/data/climate/Fog/Fog_270/Historic/scr_allfog_270.tif")
 future_fog_10_40<-raster("G:/data/climate/Fog/Fog_270/Elevation/SCR/scr_all_elevation045.tif")
 future_fog_40_70<-raster("G:/data/climate/Fog/Fog_270/Elevation/SCR/scr_all_elevation135.tif")
 future_fog_70_100<-raster("G:/data/climate/Fog/Fog_270/Elevation/SCR/scr_all_elevation225.tif")

}else if (scenario=="sri_fogelev_270m"){
 #Future Fog Elevation (+-20%): SRI and SCR
 current_fog<-raster("G:/data/climate/Fog/Fog_270/Historic/sri_allfog_270.tif")
 future_fog_10_40<-raster("G:/data/climate/Fog/Fog_270/Elevation/SRI/sri_all_elevation045.tif")
 future_fog_40_70<-raster("G:/data/climate/Fog/Fog_270/Elevation/SRI/sri_all_elevation135.tif")
 future_fog_70_100<-raster("G:/data/climate/Fog/Fog_270/Elevation/SRI/sri_all_elevation225.tif")
```

```
}else if (scenario=="scr_fogconstant_270m"){
 #Current fog level constant across all future projections
 current_fog<-raster("G:/data/climate/Fog/Fog_270/Historic/scr_allfog_270.tif")
 future_fog_10_40<-raster("G:/data/climate/Fog/Fog_270/Historic/scr_allfog_270.tif")
 future_fog_40_70<-raster("G:/data/climate/Fog/Fog_270/Historic/scr_allfog_270.tif")
 future_fog_70_100<-raster("G:/data/climate/Fog/Fog_270/Historic/scr_allfog_270.tif")

}else if (scenario=="sri_fogconstant_270m"){
 #Current fog level constant across all future projections
 current_fog<-raster("G:/data/climate/Fog/Fog_270/Historic/sri_allfog_270.tif")
 future_fog_10_40<-raster("G:/data/climate/Fog/Fog_270/Historic/sri_allfog_270.tif")
 future_fog_40_70<-raster("G:/data/climate/Fog/Fog_270/Historic/sri_allfog_270.tif")
 future_fog_70_100<-raster("G:/data/climate/Fog/Fog_270/Historic/sri_allfog_270.tif")

}else
 print ("No Fog Data Available")

if (scenario=="scr_foginc_270m"|scenario=="scr_fogdec_270m"|scenario=="sri_foginc_270m"|scenario=="sri_fogdec_270m"|scenario=="scr_fogelev_270m"|scenario=="sri_fogelev_270m"|scenario=="scr_fogconstant_270m"|scenario=="sri_fogconstant_270m"){

#Goes through the climate folders and inserts current into historic and future into different climate projections

 #Resample
 current_fog_new <- resample(current_fog, scen_extent, "ngb")
 future_fog_1040_new <- resample(future_fog_10_40, scen_extent, "ngb")
 future_fog_4070_new <- resample(future_fog_40_70, scen_extent, "ngb")
 future_fog_70100_new <- resample(future_fog_70_100, scen_extent, "ngb")
 #Crop and Mask
 current_fog_crop <- crop(current_fog_new, scen_extent) #Crop to extent of outlines
 current_fog_mask <- mask(current_fog_crop, scen_extent) #Mask to the exact island outline(s)
 future_fog_1040_crop <- crop(future_fog_1040_new, scen_extent) #Crop to extent of outlines
 future_fog_1040_mask <- mask(future_fog_1040_crop, scen_extent) #Mask to the exact island outline(s)
 future_fog_4070_crop <- crop(future_fog_4070_new, scen_extent) #Crop to extent of outlines
 future_fog_4070_mask <- mask(future_fog_4070_crop, scen_extent) #Mask to the exact island outline(s)
 future_fog_70100_crop <- crop(future_fog_70100_new, scen_extent) #Crop to extent of outlines
 future_fog_70100_mask <- mask(future_fog_70100_crop, scen_extent) #Mask to the exact island outline(s)
 #Extent
 extent(current_fog_mask)<-round(extent(current_fog_mask),1)
 extent(future_fog_1040_mask)<-round(extent(future_fog_1040_mask),1)
 extent(future_fog_4070_mask)<-round(extent(future_fog_4070_mask),1)
 extent(future_fog_70100_mask)<-round(extent(future_fog_70100_mask),1)
```

```
 clim_dirs<-list.dirs(path="G:/data/climate/GISModel_Input", full.names=T, recursive=F)
  for (clim in clim_dirs){
   #print (clim) #For loop through climate projections
   if(basename(clim)=="historic"|basename(clim)=="historic_1921_1950"|basename(clim)=="historic_1951_1980"){

    current_fog_fn <- paste0("G:/data/climate/MEInput/", scenario, "/", basename(clim), "/fog.asc")
   #Uncode write raster if you want the raster to be written
    #writeRaster(current_fog_mask,current_fog_fn,format="ascii",overwrite=T)

   }else if (basename(clim)=="CCSM4_rcp85_2010_2039"|basename(clim)=="MIROC_rcp45_2010_2039"|basename(clim)=="MIROC_rcp85_2010_2039"|basename(clim)=="MPI_rcp45_2010_2039"){

    future_fog_fn <- paste0("G:/data/climate/MEInput/", scenario, "/", basename(clim), "/fog.asc")
   #Uncode write raster if you want the raster to be written
    #writeRaster(future_fog_1040_mask,future_fog_fn,format="ascii",overwrite=T)

   }else if (basename(clim)=="CCSM4_rcp85_2040_2069"|basename(clim)=="MIROC_rcp45_2040_2069"|basename(clim)=="MIROC_rcp85_2040_2069"|basename(clim)=="MPI_rcp45_2040_2069"){

    future_fog_fn <- paste0("G:/data/climate/MEInput/", scenario, "/", basename(clim), "/fog.asc")
   #Uncode write raster if you want the raster to be written
    #writeRaster(future_fog_4070_mask,future_fog_fn,format="ascii",overwrite=T)

   }else if (basename(clim)=="CCSM4_rcp85_2070_2099"|basename(clim)=="MIROC_rcp45_2070_2099"|basename(clim)=="MIROC_rcp85_2070_2099"|basename(clim)=="MPI_rcp45_2070_2099"){

    future_fog_fn <- paste0("G:/data/climate/MEInput/", scenario, "/", basename(clim), "/fog.asc")
   #Uncode write raster if you want the raster to be written
    #writeRaster(future_fog_70100_mask,future_fog_fn,format="ascii",overwrite=T)

   }else
   print ("No fog for this projection")
  }#End for loop through climate projections
}else
 print ("No Fog Data Available")
```

## Organization

```
#Move files over to correct layer for MaxEnt and name them correctly

 clim_dirs<-list.dirs(path="G:/data/climate/GISModel_Input", full.names=T, recursive=F)
  for (clim in clim_dirs){
   #print (clim) #For loop through climate projections
   #Select files to pull from due to names set above
   #Which folders to pull from and send to for climate and fog variables
   clim_from<- paste0("G:/data/climate/MEInput/", scenario, "/", basename(clim), "/")
   clim_to<-paste0("G:/data/tools/MaxEnt/Input/", scenario, "/", basename(clim), "/layers/")
```

```
   #Which folders to pull from and send to for oak csv-just send to historic samples folders
   oak_from<-paste0("G:/data/islands/MaxEnt/MEInputOak/", scenario, "/OakPoints.csv")
   oak_to<-paste0("G:/data/tools/MaxEnt/Input/", scenario, "/historic/samples/OakPoints.csv")

   #Which folders to pull from and send to for island information-coded out because not sending unle
ss needed
   #island_from<- paste0("G:/data/islands/MaxEnt/MEInput/", scenario, "/")
   #island_to<-paste0("G:/data/tools/MaxEnt/Input/", scenario, "/", basename(clim), "/layers/")

   files <- list.files(path = clim_from, pattern = ".asc$")
   for (i in files){
   var<-substr(i, 1, 3)
  #Uncode file copy if you want the files to be moved
   #file.copy(from=paste0(clim_from, i), to=paste0(clim_to,var, ".asc"), overwrite=TRUE)
   }#End climate move

   #Turn on if want to move over island variables
   #files <- list.files(path = island_from, pattern = ".asc$")
   #for (i in files){
   #file.copy(from=paste0(island_from, i), to=paste0(island_to,var, ".asc"), overwrite=TRUE)}

  }#End per climate
 #Oak points, because not dependent on climate projections
#Uncode file copy if you want the files to be moved
 #file.copy(from=oak_from, to=oak_to, overwrite
```

## MaxEnt Analysis

This R Markdown Script can be used to take the MaxEnt outputs and perform spatial and statistical analyses on the files for visualization in ArcGIS. The only variable you have to change is the scenario to the current scope of analysis being run. The script then for loops through all the current and projected climate file outputs for the scenario and performs the specified analyses for each and writes the appropriate raster tiff files to the correct folders. The entire process is automated so that a new scenario can be input and the all the same calculations and rasters can be created rapidly. Then the files can be visualized in ArcGIS using predesigned templates for each analysis type that we created. Ensure that there is appropriate file structure to run analysis.

## Scenario-Based MaxEnt Analysis

```
#Change the Scenario and the run the analysis

scenario<-"allislands_270m"

#Options:
#allislands_270m
#ni_270m
#sca_270m
#sca_int_270m
#scr_270m
#sri_270m
#sri_adultyoung_270m
#sri_seedsap_270m
#scr_foginc_270m
#scr_fogdec_270m
#sri_foginc_270m
#sri_fogdec_270m
#scr_fogelev_270m
#sri_fogelev_270m
#scr_fogconstant_270m
#sri_fogconstant_270m
#MainlandCA

#Filename options:
filename<-"final2"

#Packages
library(tidyverse)#data rearrangement
```

```
library(raster)#rasters

#Note that rasters will overwrite themselves so run with caution or code them out
################################################################################
```

```
#Grab model statistic values: Get AUC value from each climate run, but get threshold value from historic only

#Read in the csvs with the model statistics for that scenario for all climate projections
historic<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/historic/final2/maxentResults.csv"))
hist_2150<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/historic_1921_1950/final2/maxentResults.csv"))
hist_5180<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/historic_1951_1980/final2/maxentResults.csv"))

mpi45_1039<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/MPI_rcp45_2010_2039/final2/maxentResults.csv"))
mpi45_4069<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/MPI_rcp45_2040_2069/final2/maxentResults.csv"))
mpi45_7099<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/MPI_rcp45_2070_2099/final2/maxentResults.csv"))

ccsm485_1039<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/CCSM4_rcp85_2010_2039/final2/maxentResults.csv"))
ccsm485_4069<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/CCSM4_rcp85_2040_2069/final2/maxentResults.csv"))
ccsm485_7099<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/CCSM4_rcp85_2070_2099/final2/maxentResults.csv"))

miroc45_1039<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/MIROC_rcp45_2010_2039/final2/maxentResults.csv"))
miroc45_4069<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/MIROC_rcp45_2040_2069/final2/maxentResults.csv"))
miroc45_7099<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/MIROC_rcp45_2070_2099/final2/maxentResults.csv"))

miroc85_1039<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/MIROC_rcp85_2010_2039/final2/maxentResults.csv"))
miroc85_4069<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/MIROC_rcp85_2040_2069/final2/maxentResults.csv"))
miroc85_7099<-read.csv(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/MIROC_rcp85_2070_2099/final2/maxentResults.csv"))

#Select AUC values
hist_auc<-historic[101,] %>%
  dplyr::select(Test.AUC)
hist_2150_auc<-hist_2150[101,] %>%
  dplyr::select(Test.AUC)
hist_5180_auc<-hist_5180[101,] %>%
  dplyr::select(Test.AUC)
```

```
mpi45_1039_auc<-mpi45_1039[101,] %>%
  dplyr::select(Test.AUC)
mpi45_4069_auc<-mpi45_4069[101,] %>%
  dplyr::select(Test.AUC)
mpi45_7099_auc<-mpi45_7099[101,] %>%
  dplyr::select(Test.AUC)

ccsm485_1039_auc<-ccsm485_1039[101,] %>%
  dplyr::select(Test.AUC)
ccsm485_4069_auc<-ccsm485_4069[101,] %>%
  dplyr::select(Test.AUC)
ccsm485_7099_auc<-ccsm485_7099[101,] %>%
  dplyr::select(Test.AUC)

miroc45_1039_auc<-miroc45_1039[101,] %>%
  dplyr::select(Test.AUC)
miroc45_4069_auc<-miroc45_4069[101,] %>%
  dplyr::select(Test.AUC)
miroc45_7099_auc<-miroc45_7099[101,] %>%
  dplyr::select(Test.AUC)

miroc85_1039_auc<-miroc85_1039[101,] %>%
  dplyr::select(Test.AUC)
miroc85_4069_auc<-miroc85_4069[101,] %>%
  dplyr::select(Test.AUC)
miroc85_7099_auc<-miroc85_7099[101,] %>%
  dplyr::select(Test.AUC)

#AUC Values for scenario
histTestAUC<-rbind(hist_auc, hist_2150_auc,hist_5180_auc) %>%
  mutate(Projection=c("Historic", "Historic 1921_1950", "Historic 1951_1980")) %>%
  dplyr::select(Projection, everything())

projTestAUC<-rbind(mpi45_1039_auc,mpi45_4069_auc,mpi45_7099_auc,
                   ccsm485_1039_auc,ccsm485_4069_auc,ccsm485_7099_auc,
                   miroc45_1039_auc,miroc45_4069_auc,miroc45_7099_auc,
                   miroc85_1039_auc,miroc85_4069_auc,miroc85_7099_auc) %>%
  mutate(Projection=c("MPI 4.5 2010-2039", "MPI 4.5 2040-2069", "MPI 4.5 2070-2099", "CCSM4 8.5 2010-2039", "CCSM4 8.5 2040-2069", "CCSM4 8.5 2070-2099",
"MIROC 4.5 2010-2039", "MIROC 4.5 2040-2069", "MIROC 4.5 2070-2099",
"MIROC 8.5 2010-2039", "MIROC 8.5 2040-2069", "MIROC 8.5 2070-2099")) %>%
    dplyr::select(Projection, everything())

#Threshold value for scenario
#Threshold is the Binary threshold values:#Reclassify matrix based on replicates average of the maximum training sensitivity + specifitiy (Liu 2013)
```

```
threshold<-historic[101,] %>%
  dplyr::select(Maximum.training.sensitivity.plus.specificity.logistic.threshold)
threshold<-as.double(threshold)

#All statistic values gathered

########################################################
########################################################
########################################################
#Run the Analysis (should run smoothly based on inputs above)

#############################################################
#First part of analysis focused on raster analysis between historic and future projections
#############################################################
rclmat<-c(-Inf,threshold,0, threshold,1,1)#Actual reclassify matrix based on threshold
rclmat_grad<-c(-Inf,threshold,0)#Actual reclassify matrix based on threshold

#Run analysis on historic projections
historics<-c("historic", "historic_1921_1950", "historic_1951_1980")
histhighmat<-NULL
phistsuitmat<-NULL

histmeanmat<- NULL

for (h in historics){
  #Read in historic information
if (scenario=="MainlandCA"){
  hist<-raster(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/", h, "/", filename,"/Quercus_tomentella.asc"))
}else
  hist<-raster(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/", h, "/", filename,"/Quercus_tomentella_avg.asc"))


proj4string(hist) <- CRS("+proj=aea +lat_1=34 +lat_2=40.5 +lat_0=0 +lon_0=-120 +x_0=0 +y_0=-4000000 +ellps=GRS80 +datum=NAD83 +units=m +no_defs")
writeRaster(hist, filename = paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/", h, ".tif"), format="GTiff", overwrite=TRUE)
histhigh<-cellStats(hist, max)
histhighmat<-rbind(histhighmat,histhigh)
histrc <- reclassify(hist, rclmat) #Threshold used here
writeRaster(histrc, filename = paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/", h, ".tif"), format="GTiff", overwrite=TRUE, datatype="INT1U")
histrc_grad <- reclassify(hist, rclmat_grad) #Threshold used here

histrc_grad_df<-as.data.frame(histrc_grad)

histrc_grad_df<-na.omit(histrc_grad_df)
```

```
histrc_grad_dfnonz<-as.data.frame(histrc_grad_df[histrc_grad_df$layer>=0.00001,])

colnames(histrc_grad_dfnonz)<-c("layer")

histrc_grad_df_mean<-mean(histrc_grad_dfnonz$layer)
writeRaster(histrc_grad, filename = paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary_g
radient/", h, ".tif"), format="GTiff", overwrite=TRUE)
histfq<-as.data.frame(freq(histrc, 1))
histsuit<-histfq[2,2]
histnosuit<-histfq[1,2]
phistsuit<-histsuit/(histsuit+histnosuit)
phistsuitmat<-rbind(phistsuitmat, phistsuit)

histmeanmat<-rbind(histmeanmat, histrc_grad_df_mean)
} #end historic for loop

###Create historic summary table
histhighsuit<-as.data.frame(histhighmat,row.names = FALSE)
perchistsuit<-as.data.frame(phistsuitmat,row.names = FALSE)

meanhistsuit<-as.data.frame(histmeanmat,row.names = FALSE)
histtable<-cbind(histTestAUC, histhighsuit, perchistsuit, meanhistsuit)
colnames(histtable)<-c("Projections", "Avg Test AUC", "Highest Present Suitability", "Percent Suitable
Area", “Average Suitability”)


#Run analysis on future projections
#Set historic for comparison code
if (scenario=="MainlandCA"){
  histpr<-raster(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/historic/", filename,"/Quercus_to
mentella.asc"))
}else
  histpr<-raster(paste0("G:/data/tools/MaxEnt/Output/", scenario, "/historic/", filename,"/Quercus_to
mentella_avg.asc"))

proj4string(histpr) <- CRS("+proj=aea +lat_1=34 +lat_2=40.5 +lat_0=0 +lon_0=-120 +x_0=0 +y_0=-400
0000 +ellps=GRS80 +datum=NAD83 +units=m +no_defs")
histprrc <- reclassify(histpr, rclmat) #Threshold used here
histfq<-as.data.frame(freq(histprrc, 1))
histsuit<-histfq[2,2]
histnosuit<-histfq[1,2]



proj_nam<-as.matrix(c("MPI_rcp45_2010_2039", "MPI_rcp45_2040_2069", "MPI_rcp45_2070_2099"
,"CCSM4_rcp85_2010_2039", "CCSM4_rcp85_2040_2069", "CCSM4_rcp85_2070_2099", "MIROC_rc
p45_2010_2039", "MIROC_rcp45_2040_2069", "MIROC_rcp45_2070_2099", "MIROC_rcp85_2010_2
039", "MIROC_rcp85_2040_2069", "MIROC_rcp85_2070_2099"))
```

```r
highmat<-NULL
diffmeanmat<-NULL
diffmaxmat<-NULL
diffminmat<-NULL
pcsuitmat<-NULL
percsuitmat<-NULL

meanmat<- NULL

for (p in proj_nam){
print (p)
if (scenario=="MainlandCA"){
  proj<-raster(paste0("G:/data/tools/MaxEnt/Output/",scenario,"/",p,"/",filename,"/Quercus_tomentella_layers.asc"))
}else
  proj<-raster(paste0("G:/data/tools/MaxEnt/Output/",scenario,"/",p,"/",filename,"/Quercus_tomentella_layers_avg.asc"))

proj4string(proj) <- CRS("+proj=aea +lat_1=34 +lat_2=40.5 +lat_0=0 +lon_0=-120 +x_0=0 +y_0=-4000000 +ellps=GRS80 +datum=NAD83 +units=m +no_defs")
writeRaster(proj, filename = paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/", p, ".tif"), format="GTiff", overwrite=TRUE)
high<-cellStats(proj, max)
highmat<-rbind(highmat,high)
diff<-proj-histpr
writeRaster(diff, filename=paste0("G:/data/tools/MaxEnt/Analysis/", scenario, "/", p, ".tif"), format="GTiff", overwrite=TRUE)
diffmean<-cellStats(diff, mean)
diffmeanmat<-rbind(diffmeanmat, diffmean)
diffmax<-cellStats(diff, max)
diffmaxmat<-rbind(diffmaxmat, diffmax)
diffmin<-cellStats(diff, min)
diffminmat<-rbind(diffminmat, diffmin)
projrc <- reclassify(proj, rclmat) #Threshold value used here
writeRaster(projrc, filename=paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/", p, ".tif"), format="GTiff", overwrite=TRUE, datatype="INT1U")
projrc_grad <- reclassify(proj, rclmat_grad) #Threshold value used here

projrc_grad <- reclassify(proj, rclmat_grad) #Threshold value used here

projrc_grad_df<-as.data.frame(projrc_grad)

projrc_grad_df<-na.omit(projrc_grad_df)

projrc_grad_dfnonz<-as.data.frame(projrc_grad_df[projrc_grad_df$layer>=0.00001,])

colnames(projrc_grad_dfnonz)<-c("layer")
```

```
projrc_grad_df_mean<-mean(projrc_grad_dfnonz$layer)
writeRaster(projrc_grad, filename=paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary_gradient/", p, ".tif"), format="GTiff", overwrite=TRUE)
projfq<-as.data.frame(freq(projrc, 1))
projnosuit<-projfq[1,2]

if (nrow(projfq)==2){
  projsuit<-0
}else
  projsuit<-projfq[2,2]

###
pcsuit<-(projsuit-histsuit)/histsuit
pcsuitmat<-rbind(pcsuitmat, pcsuit)
percsuit<-projsuit/(projsuit+projnosuit)
percsuitmat<-rbind(percsuitmat, percsuit)

meanmat<-rbind(meanmat, projrc_grad_df_mean)

}#End proj names for loop

#Create projected summary table
highsuitdf<-as.data.frame(highmat,row.names = FALSE)
meandiffdf<-as.data.frame(diffmeanmat,row.names = FALSE)
gaindf<-as.data.frame(diffmaxmat,row.names = FALSE)
lossdf<-as.data.frame(diffminmat,row.names = FALSE)
pcsuitdf<-as.data.frame(pcsuitmat, row.names = FALSE)
percsuitdf<-as.data.frame(percsuitmat, row.names = FALSE)

meandf<-as.data.frame(meanmat, row.names = FALSE)

projtable<-cbind(projTestAUC, highsuitdf, meandiffdf, gaindf, lossdf, percsuitdf, pcsuitdf, meandf)
colnames(projtable)<-c("Projections", "Avg Test AUC", "Highest Future Suitability", "Mean Change in Suitability", "Highest Gain", "Highest Loss","Percent Suitable Area", "Overall Percent Change of Suitable Area", “Average Suitability”)


#Export tables for histtable and projtable
write.csv(histtable,file=paste0("G:/data/tools/MaxEnt/Analysis/", scenario, "/summarytables/historicsummarytable.csv"),row.names = FALSE)
write.csv(projtable,file=paste0("G:/data/tools/MaxEnt/Analysis/", scenario, "/summarytables/projectionssummarytable.csv"),row.names = FALSE)

##################################################################
#Second part of analysis focused on raster analysis between all stacked rasters
##################################################################

#Read in all rasters and create summed raster (ignoring other historic options here)
```

```r
histrc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/historic.tif"))
projA1rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/MPI_rcp45_2010_2039.tif"))
projA2rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/MPI_rcp45_2040_2069.tif"))
projA3rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/MPI_rcp45_2070_2099.tif"))
projB1rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/CCSM4_rcp85_2010_2039.tif"))
projB2rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/CCSM4_rcp85_2040_2069.tif"))
projB3rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/CCSM4_rcp85_2070_2099.tif"))
projC1rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/MIROC_rcp45_2010_2039.tif"))
projC2rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/MIROC_rcp45_2040_2069.tif"))
projC3rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/MIROC_rcp45_2070_2099.tif"))
projD1rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/MIROC_rcp85_2010_2039.tif"))
projD2rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/MIROC_rcp85_2040_2069.tif"))
projD3rc<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/", scenario, "/binary/MIROC_rcp85_2070_2099.tif"))

  #Sum across scenarios and write raster
Asum<-sum(histrc, projA1rc, projA2rc, projA3rc)
writeRaster(Asum, filename=paste0("G:/data/tools/MaxEnt/Analysis/", scenario, "/percentchange/MPI_rcp45.tif"), format="GTiff", overwrite=TRUE)
Bsum<-sum(histrc, projB1rc, projB2rc, projB3rc)
writeRaster(Bsum, filename=paste0("G:/data/tools/MaxEnt/Analysis/", scenario, "/percentchange/CCSM4_rcp85.tif"), format="GTiff", overwrite=TRUE)
Csum<-sum(histrc, projC1rc, projC2rc, projC3rc)
writeRaster(Csum, filename=paste0("G:/data/tools/MaxEnt/Analysis/", scenario, "/percentchange/MIROC_rcp45.tif"), format="GTiff", overwrite=TRUE)
Dsum<-sum(histrc, projD1rc, projD2rc, projD3rc)
writeRaster(Dsum, filename=paste0("G:/data/tools/MaxEnt/Analysis/", scenario, "/percentchange/MIROC_rcp85.tif"), format="GTiff", overwrite=TRUE)

#Sum all and write raster
Allsum<-sum(histrc, projA1rc, projA2rc, projA3rc, projB1rc, projB2rc, projB3rc, projC1rc, projC2rc, projC3rc, projD1rc, projD2rc, projD3rc)
writeRaster(Allsum, filename=paste0("G:/data/tools/MaxEnt/Analysis/", scenario, "/percentchange/ALLScenarios.tif"), format="GTiff", overwrite=TRUE)
```

## Integrated Outlook

Creating Integrated Outlook across all fog and climate scenarios, both for separate time periods and across time periods.

```
#Packages
library(tidyverse)#data rearrangement

library(raster)#rasters

#Options:
#Keeping separate and noc including
#allislands_270m
#ni_270m
#sca_270m
#sca_int_270m
#MainlandCA
#sri_adultyoung_270m
#sri_seedsap_270m

#Keep separate for now
#scr_270m
#sri_270m

#So currently making SCR integrated and SRI integrated

#scr_foginc_270m
#scr_fogdec_270m
#sri_fogelev_270m
#scr_fogconstant_270m

#sri_foginc_270m
#sri_fogdec_270m
#scr_fogelev_270m
#sri_fogconstant_270m

#Combining All SRI Fog Scenarios
#A is MPI and B is CCSM4 and C is MIROC 45 and D is MIROC 85
#Read in all rasters to create summed raster

#Rasters were intentionally treated individually rather than in a list format or loop to reduce potential error in the integration process.
```

```
##########################################################
#Santa Rosa
##########################################################

#sri_fogelev_270m
srifogelev_hist<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/historic.tif"))
srifogelev_projA1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/MPI_rcp45_2010_2039.tif"))
srifogelev_projA2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/MPI_rcp45_2040_2069.tif"))
srifogelev_projA3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/MPI_rcp45_2070_2099.tif"))
srifogelev_projB1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/CCSM4_rcp85_2010_2039.tif"))
srifogelev_projB2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/CCSM4_rcp85_2040_2069.tif"))
srifogelev_projB3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/CCSM4_rcp85_2070_2099.tif"))
srifogelev_projC1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/MIROC_rcp45_2010_2039.tif"))
srifogelev_projC2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/MIROC_rcp45_2040_2069.tif"))
srifogelev_projC3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/MIROC_rcp45_2070_2099.tif"))
srifogelev_projD1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/MIROC_rcp85_2010_2039.tif"))
srifogelev_projD2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/MIROC_rcp85_2040_2069.tif"))
srifogelev_projD3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogelev_270m/binary/MIROC_rcp85_2070_2099.tif"))

#sri_foginc_270m
srifoginc_hist<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/historic.tif"))
srifoginc_projA1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/MPI_rcp45_2010_2039.tif"))
srifoginc_projA2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/MPI_rcp45_2040_2069.tif"))
srifoginc_projA3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/MPI_rcp45_2070_2099.tif"))
srifoginc_projB1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/CCSM4_rcp85_2010_2039.tif"))
srifoginc_projB2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/CCSM4_
```

```
rcp85_2040_2069.tif"))
srifoginc_projB3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/CCSM4_rcp85_2070_2099.tif"))
srifoginc_projC1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/MIROC_rcp45_2010_2039.tif"))
srifoginc_projC2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/MIROC_rcp45_2040_2069.tif"))
srifoginc_projC3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/MIROC_rcp45_2070_2099.tif"))
srifoginc_projD1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/MIROC_rcp85_2010_2039.tif"))
srifoginc_projD2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/MIROC_rcp85_2040_2069.tif"))
srifoginc_projD3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_foginc_270m/binary/MIROC_rcp85_2070_2099.tif"))

#sri_fogdec_270m
srifogdec_hist<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/historic.tif"))
srifogdec_projA1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/MPI_rcp45_2010_2039.tif"))
srifogdec_projA2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/MPI_rcp45_2040_2069.tif"))
srifogdec_projA3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/MPI_rcp45_2070_2099.tif"))
srifogdec_projB1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/CCSM4_rcp85_2010_2039.tif"))
srifogdec_projB2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/CCSM4_rcp85_2040_2069.tif"))
srifogdec_projB3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/CCSM4_rcp85_2070_2099.tif"))
srifogdec_projC1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/MIROC_rcp45_2010_2039.tif"))
srifogdec_projC2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/MIROC_rcp45_2040_2069.tif"))
srifogdec_projC3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/MIROC_rcp45_2070_2099.tif"))
srifogdec_projD1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/MIROC_rcp85_2010_2039.tif"))
srifogdec_projD2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/MIROC_rcp85_2040_2069.tif"))
srifogdec_projD3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogdec_270m/binary/MIROC_rcp85_2070_2099.tif"))

#sri_fogconstant_270m
srifogconstant_hist<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/historic.tif"))
```

```
srifogconstant_projA1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/MPI_rcp45_2010_2039.tif"))
srifogconstant_projA2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/MPI_rcp45_2040_2069.tif"))
srifogconstant_projA3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/MPI_rcp45_2070_2099.tif"))
srifogconstant_projB1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/CCSM4_rcp85_2010_2039.tif"))
srifogconstant_projB2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/CCSM4_rcp85_2040_2069.tif"))
srifogconstant_projB3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/CCSM4_rcp85_2070_2099.tif"))
srifogconstant_projC1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/MIROC_rcp45_2010_2039.tif"))
srifogconstant_projC2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/MIROC_rcp45_2040_2069.tif"))
srifogconstant_projC3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/MIROC_rcp45_2070_2099.tif"))
srifogconstant_projD1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/MIROC_rcp85_2010_2039.tif"))
srifogconstant_projD2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/MIROC_rcp85_2040_2069.tif"))
srifogconstant_projD3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/sri_fogconstant_270m/binary/MIROC_rcp85_2070_2099.tif"))




##############################################################
#Santa Cruz
##############################################################

#sri_fogelev_270m
scrfogelev_hist<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/historic.tif"))
scrfogelev_projA1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/MPI_rcp45_2010_2039.tif"))
scrfogelev_projA2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/MPI_rcp45_2040_2069.tif"))
scrfogelev_projA3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/MPI_rcp45_2070_2099.tif"))
scrfogelev_projB1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/CCSM4_rcp85_2010_2039.tif"))
scrfogelev_projB2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/CCSM4_rcp85_2040_2069.tif"))
scrfogelev_projB3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/CCSM4_rcp85_2070_2099.tif"))
```

```r
scrfogelev_projC1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/MIROC_rcp45_2010_2039.tif"))
scrfogelev_projC2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/MIROC_rcp45_2040_2069.tif"))
scrfogelev_projC3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/MIROC_rcp45_2070_2099.tif"))
scrfogelev_projD1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/MIROC_rcp85_2010_2039.tif"))
scrfogelev_projD2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/MIROC_rcp85_2040_2069.tif"))
scrfogelev_projD3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogelev_270m/binary/MIROC_rcp85_2070_2099.tif"))

#scr_foginc_270m
scrfoginc_hist<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/historic.tif"))
scrfoginc_projA1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/MPI_rcp45_2010_2039.tif"))
scrfoginc_projA2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/MPI_rcp45_2040_2069.tif"))
scrfoginc_projA3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/MPI_rcp45_2070_2099.tif"))
scrfoginc_projB1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/CCSM4_rcp85_2010_2039.tif"))
scrfoginc_projB2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/CCSM4_rcp85_2040_2069.tif"))
scrfoginc_projB3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/CCSM4_rcp85_2070_2099.tif"))
scrfoginc_projC1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/MIROC_rcp45_2010_2039.tif"))
scrfoginc_projC2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/MIROC_rcp45_2040_2069.tif"))
scrfoginc_projC3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/MIROC_rcp45_2070_2099.tif"))
scrfoginc_projD1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/MIROC_rcp85_2010_2039.tif"))
scrfoginc_projD2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/MIROC_rcp85_2040_2069.tif"))
scrfoginc_projD3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_foginc_270m/binary/MIROC_rcp85_2070_2099.tif"))

#scr_fogdec_270m
scrfogdec_hist<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/historic.tif"))
scrfogdec_projA1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/MPI_rcp45_2010_2039.tif"))
scrfogdec_projA2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/MPI_r
```

```
cp45_2040_2069.tif"))
scrfogdec_projA3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/MPI_rcp45_2070_2099.tif"))
scrfogdec_projB1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/CCSM4_rcp85_2010_2039.tif"))
scrfogdec_projB2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/CCSM4_rcp85_2040_2069.tif"))
scrfogdec_projB3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/CCSM4_rcp85_2070_2099.tif"))
scrfogdec_projC1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/MIROC_rcp45_2010_2039.tif"))
scrfogdec_projC2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/MIROC_rcp45_2040_2069.tif"))
scrfogdec_projC3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/MIROC_rcp45_2070_2099.tif"))
scrfogdec_projD1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/MIROC_rcp85_2010_2039.tif"))
scrfogdec_projD2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/MIROC_rcp85_2040_2069.tif"))
scrfogdec_projD3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogdec_270m/binary/MIROC_rcp85_2070_2099.tif"))

#scr_fogconstant_270m
scrfogconstant_hist<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/historic.tif"))
scrfogconstant_projA1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/MPI_rcp45_2010_2039.tif"))
scrfogconstant_projA2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/MPI_rcp45_2040_2069.tif"))
scrfogconstant_projA3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/MPI_rcp45_2070_2099.tif"))
scrfogconstant_projB1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/CCSM4_rcp85_2010_2039.tif"))
scrfogconstant_projB2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/CCSM4_rcp85_2040_2069.tif"))
scrfogconstant_projB3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/CCSM4_rcp85_2070_2099.tif"))
scrfogconstant_projC1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/MIROC_rcp45_2010_2039.tif"))
scrfogconstant_projC2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/MIROC_rcp45_2040_2069.tif"))
scrfogconstant_projC3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/MIROC_rcp45_2070_2099.tif"))
scrfogconstant_projD1<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/MIROC_rcp85_2010_2039.tif"))
scrfogconstant_projD2<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/MIROC_rcp85_2040_2069.tif"))
```

```r
scrfogconstant_projD3<-raster(paste0("G:/data/tools/MaxEnt/Output_tiff/scr_fogconstant_270m/binary/MIROC_rcp85_2070_2099.tif"))

#Sum across scenarios and across scenarios/timeperiods and write raster
#For each time period
#Santa Rosa
#Historic-All historic the same
srihist<-srifogelev_hist

#2010-2039
sri_2010_2039<-sum(srifogelev_projA1,srifogelev_projB1,srifogelev_projC1,srifogelev_projD1,srifoginc_projA1,srifoginc_projB1,srifoginc_projC1,srifoginc_projD1,srifogdec_projA1,srifogdec_projB1,srifogdec_projC1,srifogdec_projD1,srifogconstant_projA1,srifogconstant_projB1,srifogconstant_projC1,srifogconstant_projD1)

#2040-2069
sri_2040_2069<-sum(srifogelev_projA2,srifogelev_projB2,srifogelev_projC2,srifogelev_projD2,srifoginc_projA2,srifoginc_projB2,srifoginc_projC2,srifoginc_projD2,srifogdec_projA2,srifogdec_projB2,srifogdec_projC2,srifogdec_projD2,srifogconstant_projA2,srifogconstant_projB2,srifogconstant_projC2,srifogconstant_projD2)

#2070-2099
sri_2070_2099<-sum(srifogelev_projA3,srifogelev_projB3,srifogelev_projC3,srifogelev_projD3,srifoginc_projA3,srifoginc_projB3,srifoginc_projC3,srifoginc_projD3,srifogdec_projA3,srifogdec_projB3,srifogdec_projC3,srifogdec_projD3,srifogconstant_projA3,srifogconstant_projB3,srifogconstant_projC3,srifogconstant_projD3)

#Santa Cruz
#Historic
scrhist<-scrfogelev_hist

#2010-2039
scr_2010_2039<-sum(scrfogelev_projA1,scrfogelev_projB1,scrfogelev_projC1,scrfogelev_projD1,scrfoginc_projA1,scrfoginc_projB1,scrfoginc_projC1,scrfoginc_projD1,scrfogdec_projA1,scrfogdec_projB1,scrfogdec_projC1,scrfogdec_projD1,scrfogconstant_projA1,scrfogconstant_projB1,scrfogconstant_projC1,scrfogconstant_projD1)

#2040-2069
scr_2040_2069<-sum(scrfogelev_projA2,scrfogelev_projB2,scrfogelev_projC2,scrfogelev_projD2,scrfoginc_projA2,scrfoginc_projB2,scrfoginc_projC2,scrfoginc_projD2,scrfogdec_projA2,scrfogdec_projB2,scrfogdec_projC2,scrfogdec_projD2,scrfogconstant_projA2,scrfogconstant_projB2,scrfogconstant_projC2,scrfogconstant_projD2)

#2070-2099
scr_2070_2099<-sum(scrfogelev_projA3,scrfogelev_projB3,scrfogelev_projC3,scrfogelev_projD3,scrfoginc_projA3,scrfoginc_projB3,scrfoginc_projC3,scrfoginc_projD3,scrfogdec_projA3,scrfogdec_projB3,scrfogdec_projC3,scrfogdec_projD3,scrfogconstant_projA3,scrfogconstant_projB3,scrfogconstant_
```

```
projC3,scrfogconstant_projD3)

#All Time Periods Together
sri<-sum(srifogelev_hist,srifogelev_projA1,srifogelev_projB1,srifogelev_projC1,srifogelev_projD1,srifoginc_projA1,srifoginc_projB1,srifoginc_projC1,srifoginc_projD1,srifogdec_projA1,srifogdec_projB1,srifogdec_projC1,srifogdec_projD1,srifogconstant_projA1,srifogconstant_projB1,srifogconstant_projC1,srifogconstant_projD1,srifogelev_projA2,srifogelev_projB2,srifogelev_projC2,srifogelev_projD2,srifoginc_projA2,srifoginc_projB2,srifoginc_projC2,srifoginc_projD2,srifogdec_projA2,srifogdec_projB2,srifogdec_projC2,srifogdec_projD2,srifogconstant_projA2,srifogconstant_projB2,srifogconstant_projC2,srifogconstant_projD2,srifogelev_projA3,srifogelev_projB3,srifogelev_projC3,srifogelev_projD3,srifoginc_projA3,srifoginc_projB3,srifoginc_projC3,srifoginc_projD3,srifogdec_projA3,srifogdec_projB3,srifogdec_projC3,srifogdec_projD3,srifogconstant_projA3,srifogconstant_projB3,srifogconstant_projC3,srifogconstant_projD3)

scr<-sum(scrfogelev_hist,scrfogelev_projA1,scrfogelev_projB1,scrfogelev_projC1,scrfogelev_projD1,scrfoginc_projA1,scrfoginc_projB1,scrfoginc_projC1,scrfoginc_projD1,scrfogdec_projA1,scrfogdec_projB1,scrfogdec_projC1,scrfogdec_projD1,scrfogconstant_projA1,scrfogconstant_projB1,scrfogconstant_projC1,scrfogconstant_projD1,scrfogelev_projA2,scrfogelev_projB2,scrfogelev_projC2,scrfogelev_projD2,scrfoginc_projA2,scrfoginc_projB2,scrfoginc_projC2,scrfoginc_projD2,scrfogdec_projA2,scrfogdec_projB2,scrfogdec_projC2,scrfogdec_projD2,scrfogconstant_projA2,scrfogconstant_projB2,scrfogconstant_projC2,scrfogconstant_projD2,scrfogelev_projA3,scrfogelev_projB3,scrfogelev_projC3,scrfogelev_projD3,scrfoginc_projA3,scrfoginc_projB3,scrfoginc_projC3,scrfoginc_projD3,scrfogdec_projA3,scrfogdec_projB3,scrfogdec_projC3,scrfogdec_projD3,scrfogconstant_projA3,scrfogconstant_projB3,scrfogconstant_projC3,scrfogconstant_projD3)
#Write Rasters
# writeRaster(srihist, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/srihist.tif"), format="GTiff", overwrite=TRUE)
# writeRaster(sri_2010_2039, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/sri_2010_2039.tif"), format="GTiff", overwrite=TRUE)
# writeRaster(sri_2040_2069, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/sri_2040_2069.tif"), format="GTiff", overwrite=TRUE)
# writeRaster(sri_2070_2099, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/sri_2070_2099.tif"), format="GTiff", overwrite=TRUE)
#
# writeRaster(scrhist, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/scrhist.tif"), format="GTiff", overwrite=TRUE)
# writeRaster(scr_2010_2039, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/scr_2010_2039.tif"), format="GTiff", overwrite=TRUE)
# writeRaster(scr_2040_2069, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/scr_2040_2069.tif"), format="GTiff", overwrite=TRUE)
# writeRaster(scr_2070_2099, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/scr_2070_2099.tif"), format="GTiff", overwrite=TRUE)
#
# writeRaster(sri, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/sri.tif"), format="GTiff", overwrite=TRUE)
# writeRaster(scr, filename=paste0("G:/data/tools/MaxEnt/Analysis/Integrated/scr.tif"), format="GTiff", overwrite=TRUE)
```