MODELING THE NICHE SPACE OF CORAL ASSEMBLAGES ALONG THE
FLORIDA REEF TRACT

by

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A THESIS

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ABSTRACT

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Quantifying the niche space of organisms is critical for conservation and restoration purposes. Yet, with warming oceans, we cannot assume that the localities that were optimal for species in the past remain so today or will be optimal for that species in the future. Over the next century, the climate is predicted to drive sea-surface temperatures to even higher levels, consequently increasing the risk of mass coral bleaching and disease outbreaks, and potentially reducing the niche space available to corals. Yet, there is considerable temporal and spatial variation in coral bleaching, disease prevalence, and mortality. Using data collected from 2398 sites along the Florida reef tract from 2005-2015, this study examined the temporal and spatial patterns of coral bleaching and disease in relation to coral colony size, depth, temperature, and chlorophyll a concentration. The study also constructed a coral niche model for the threatened coral species *Acropora cervicornis* in Florida, to determine optimal environmental conditions for its survival. The niche model was developed at three spatial scales, 9 km, 4 km, and 1 km, using depth, wave exposure, irradiance, turbidity (Kd$_{490}$), sea-surface temperature, and chlorophyll-a concentration as predictive covariates.
The results of this study show that coral bleaching was most prevalent during the warmest years in 2014 and 2015, and disease was also most prevalent in 2010, 2014, and 2015. The majority of the coral colonies surveyed, independent of their size, were found in habitats with low chlorophyll-a concentrations, and high irradiance, and these same habitats showed the highest prevalence of coral bleaching and disease outbreaks during thermal stress events. The species distribution model indicated that the most optimal locations for *Acropora cervicornis* were in the upper and lower Florida reef tract. Although the geographical patterns of the model results did not vary with an increase in the resolution of the predictive variables, the highest resolution models predicted a higher latitudinal extent of *Acropora cervicornis* than the low-resolution (9 km) model, with favorable conditions extending up to 27-degrees north. The variable that best predicted *Acropora cervicornis* at 1 km was chlorophyll-a concentration, with colonies mostly supported in habitats with chlorophyll a concentration <1.25 mg m\(^{-3}\). At a 4-km resolution, chlorophyll a concentration had a negative relationship and irradiance had a positive relationship with *A. cervicornis* occurrence. The results show that well-lit habitats with low chlorophyll a concentrations favor *Acropora cervicornis* on the Florida reef tract. Yet, the results also suggest that directional selection in a warming ocean may favor corals able to tolerate inshore, shaded environments with high turbidity.
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DEDICATION

I dedicate this dissertation to my family.

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CHAPTER I INTRODUCTION, RESEARCH GOALS, RESEARCH QUESTIONS, AND HYPOTHESES

RATIONALE

Since the 1970s there has been a Caribbean-wide decline in live coral cover (Aronson and Precht 2001; Gardner et al. 2003). This decline has included unprecedented mortality of two reef-framework-building species, *Acropora palmata* and *Acropora cervicornis* (Aronson and Precht 2001). Both coral species have declined to the extent that they have been declared threatened under the U.S. Endangered Species Act (NMFS 2006), and critically endangered on the IUCN Red List (IUCN 2016). The Florida reef tract has been particularly affected by the region-wide coral loss. The death of historically dominant coral species, particularly the *Acropora* species, has resulted in a significant reduction in live coral cover that has dramatically altered the composition of reef assemblages (Burman et al. 2012; Ruzicka et al. 2013). There have been multiple causes linked to coral loss from Florida reefs including hurricanes (Aronson and Precht 2001; Gardner et al. 2003), coral disease (Aronson and Precht 2001; Porter et al. 2001; Gardner et al. 2003), and eutrophication (Gardner et al. 2003). However, the most significant coral mortality stems from thermal-stress events (Manzello 2015). The Florida reef tract has failed to recover from its coral loss (Aronson and Precht 2001; Burman et al. 2012; Ruzicka et al. 2013; van Woesik et al. 2014), and as thermal stress and storm events become more frequent through the effects of
climate change (Hoegh-Guldberg 1999; Baker et al. 2008) it is unlikely to recover without active restoration.

Current coral-restoration efforts in Florida focus mainly on *Acropora palmata* and *Acropora cervicornis*, although other framework-building coral species are also being considered. Restoration groups mainly use “coral-gardening” techniques, in which fragments are taken from healthy corals and grown in nursery settings. The goal of coral nurseries is to outplant nursery-grown fragments to degraded reef locations to stimulate reef recovery (Young et al. 2012). Although there are 13 coral nurseries in Florida, the restoration efforts lack a unified plan (Hunt and Sharp 2014), and nurseries often lack the proper funding to examine the suitability of outplant sites (Young et al. 2012). The lack of knowledge concerning ideal outplant locations leaves nursery workers with nothing more than a trial-and-error approach based on the knowledge gained from their own past successes and failures.

There is an increasing effort to identify locations where environmental conditions remain suitable for coral survival. One technique involves the use of species distribution modeling approaches, which predict the location of suitable habitat based on a suite of environmental parameters (Cacciapaglia and van Woesik 2015; Cacciapaglia and van Woesik 2016). Models have been created for coral on the Florida reef tract (Wirt et al. 2015; Ames 2016), but they considered a limited number of environmental parameters and studied only *Acropora* species. The
previous work also examined only species presence and not the condition of the corals, including bleaching and disease, at different reef locations.

Coral bleaching is a sign of physiological stress, and can result from a multitude of conditions, including increased nutrient concentrations (Wooldridge 2009; Wagner et al. 2010), cold-water events (Lirman et al. 2011; Ruzicka et al. 2013), and anomalously warm water (Wagner et al. 2010; Ruzicka et al. 2013). Stress caused by high temperatures can also lead to outbreaks of coral disease (Randall and van Woesik 2015), and in combination with high nutrients can increase the severity of coral diseases (Bruno et al. 2003; Voss and Richardson 2006). Additional data on coral bleaching and disease, which are available for locations throughout the Florida reef tract, can be used to identify locations in which corals might experience stress.

Different physiological tolerances of coral species result in the occupation of different niche spaces leading to different species distributions. These species distributions are most likely driven by nutrient concentrations (Tomascik and Sander 1987), temperature (Vega-Rodriguez et al. 2015), irradiance, turbidity, and the rates of water movement (van Woesik et al. 2012). Deriving accurate niche models for important framework-building species, in combination with data on coral ‘health’, will improve the accuracy of the prediction on the location of reef sites that are ideal for restoration efforts. It is important to accurately designate critical reef habitat to improve long-term outplant
survivorship, and increase the efficiency of coral restoration programs (Young et al. 2012).

RESEARCH GOALS

I used contemporary coral monitoring data in combination with high-resolution environmental data to create coral niche models for the common framework building coral, *Acropora cervicornis*, on the Florida reef tract. These niche models produced spatial outputs and probability maps, indicating which locations are most likely to support this coral species. The association between the prevalence of coral bleaching and disease, in *Acropora cervicornis* and other Florida coral species, with water-quality conditions was also examined and compared with the coral occurrence data. The results of this analysis, in combination with the coral niche models, were used to draw conclusions about where on the Florida reef tract corals are most likely to survive.

RESEARCH QUESTIONS

1. Where on the Florida reef tract are corals most likely to survive?
2. Which environmental and biological parameters will best predict coral survival on the Florida reef tract?
HYPOTHESES

The most important variables to predict the survival of corals on the Florida reef tract will include temperature, irradiance, water-flow conditions, and nutrient concentrations. Corals will be most likely to survive in (i) moderately turbid environments with reduced irradiance, (ii) where local temperatures are consistently low, and (iii) where there is moderate water flow.
CHAPTER II REPEATED THERMAL STRESS, SHADING, AND DIRECTIONAL SELECTION IN THE FLORIDA REEF TRACT

ABSTRACT

Over the last three decades reef corals have been subjected to an unprecedented frequency and intensity of thermal-stress events, which have led to extensive coral bleaching, disease, and mortality. Over the next century, the climate is predicted to drive sea-surface temperatures to even higher levels, consequently increasing the risk of mass bleaching and disease outbreaks. Yet, there is considerable temporal and spatial variation in coral bleaching and in disease prevalence. Using data collected from 2398 sites along the Florida reef tract from 2005 to 2015, this study examined the temporal and spatial patterns of coral bleaching and disease in relation to coral-colony size, depth, temperature, and chlorophyll-a concentrations. The results show that coral bleaching was most prevalent during the warmest years in 2014 and 2015, and disease was also most prevalent in 2010, 2014, and 2015. Although the majority of the corals surveyed, independent of their size, were found in habitats with low chlorophyll-a concentrations and high irradiance, these same habitats showed the highest prevalence of coral bleaching and disease outbreaks during thermal-stress events. These results suggest that directional selection in a warming ocean may favor corals able to tolerate inshore, shaded environments with high turbidity and productivity.
INTRODUCTION

Predicting and responding to the effects of climate change are critical if we wish to preserve marine life in the oceans. The global effects of climate change are becoming glaringly apparent on coral reefs, where repeated thermal anomalies are forcing temperatures beyond the physiological tolerance range of reef corals. These stress events are causing widespread coral bleaching and mortality (Loya et al. 2001; Baker et al. 2008). Yet, predicting where corals are less likely to bleach, and more likely to survive thermal-stress, is an important scientific endeavor that might redirect ocean conservation efforts at both local and regional scales (Cacciapaglia and van Woesik 2015). Here we use an 11-year dataset (from 2005–2015) to examine the spatial relationships between coral bleaching, coral disease, and environmental conditions at 2398 study sites along the Florida reef tract.

Coral bleaching is a combination of irradiance and temperature stress (Takahashi et al. 2004). High seasonal irradiance causes photoinhibition of the coral symbionts, from which they can recover, unless water temperatures are high. When irradiance and water temperature are both high, the symbiont’s photosystems are compromised, and nighttime recovery from daytime photoinhibition is minimal (Warner et al. 1999; Takahashi et al. 2004). Weeks of high water temperatures lead to chronic photoinhibition, or bleaching, that can lead to the expulsion of coral symbionts. This bleaching can be temporary and non-fatal for some coral species
(Goreau 1964; Loya et al. 2001), or fatal for other coral species that rely heavily on their symbionts as a food source (Grotelli et al. 2006).

Coral bleaching can also lower the tolerance of corals to pathogens, and bleaching can lead to disease (Muller et al. 2008; Brandt and McManus 2009; Randall et al. 2014). The causative agents of most coral diseases are still unknown, but laboratory and field studies have shown an influence from a variety of stressors in addition to temperature, including population density (Bruno et al. 2007), nutrient enrichment (Bruno et al. 2003; Voss and Richardson 2006), and light attenuation (Kuta and Richardson 2002). It is also likely that physiological and environmental parameters interact to influence the virulence of the pathogens, and the susceptibility of coral hosts (Randall and van Woesik 2015).

By contrast, reducing irradiance during temperature-stress events relieves stress on the symbiont’s photosystem, buffers corals from temperature stress, and reduces the likelihood of coral bleaching (Warner et al. 1999; Takahashi et al. 2004). Such reductions in irradiance are common on deep reef slopes (Smith et al. 2014), or nearshore, where turbidity and chlorophyll-a concentrations are high (Wagner et al. 2010; van Woesik et al. 2012). Yet, reef corals generally prefer low-nutrient waters (Tomascik and Sander 1987), and nearshore environments support high nutrient concentrations, which in combination with high temperatures are detrimental to reef corals (Wooldridge and Done 2009; Wagner et al. 2010; Wiedenmann et al. 2013). Still, if shading in nearshore, turbid environments
provides protection to corals under thermal-stress events, then the corals that can tolerate those nearshore conditions may be selected for when thermal-stress events become frequent. We hypothesize that although shading by high turbidity and high organics are less than optimal for reef-building corals, these conditions may be physiologically beneficial for corals under thermal stress. Indeed, the benefits of shading under extreme thermal stress may override the costs of living in these less suitable nearshore environments, with high thermal variation, low irradiance, and high nutrients. We question whether global warming is progressively driving reef corals away from clear, oligotrophic waters, to more nearshore, turbid habitats.

The present study uses an extensive dataset collected between 2005 and 2015 (http://www.frrp.org) at 2398 sites along the Florida reef tract to examine the spatial distribution of scleractinian corals and the environmental variables that cause and relieve stress. Specifically, the objectives of this study were to: (i) quantify the water-quality characteristics of the study sites, particularly temperature and chlorophyll-a concentrations, (ii) determine the spatial extent of bleaching and coral disease, and (iii) examine interactions between coral bleaching, coral disease, and water quality.
MATERIALS AND METHODS

WATER-QUALITY DATA

Water-quality data were obtained from the Southeast Environmental Research Center, Florida International University (http://serc.fiu.edu/wqmnetwork/). These data were collected at 215 sites along the Florida Keys sampled quarterly from January 2005 to December 2015. We were particularly interested in both the benthic water temperature that the corals experienced, hereinafter called temperature (Figure II.1, p. Error! Bookmark not defined.), and the chlorophyll-a concentrations, used as a proxy for primary productivity in the water column. To geographically align the water-quality data with the coral data, we spatially cropped the coral data to the same extent as the water-quality data, and then spatially interpolated the water-quality data using ordinary kriging with the R package ‘gstat’ (Pebesma 2004). The interpolated data were combined to reflect patterns (i) over the entire study period, (ii) from 2005-2009, and (iii) from 2010-2015, before and after the major coral bleaching event in 2010.
Figure II.1. Sea surface (red) and benthic (blue) temperatures (°C) along the Florida Keys from 2005 to 2015 (data from Southeast Environmental Research Center (http://serc.fiu.edu/wqmnetwork/) (n=6849).

CORAL SAMPLING

The study used data that stemmed from the Florida Reef Resilience Program (FRRP) (http://www.frrp.org), which was a two-stage stratified-random survey design to assess the condition of scleractinian corals along the Florida reef tract every summer from 2005 to 2015 (Smith et al. 2011; Wagner et al. 2010; Burman et al. 2012). The region was stratified into geographic sub-regions and habitats. To date the FRRP has surveyed 2398 sites, using replicated 10 m by 1 m belt transects. Along each transect each coral colony was identified to species, measured for diameter, and examined for bleaching and disease. The database is available from The Nature Conservancy upon request.
DATA ANALYSIS

We used semivariograms to estimate the extent of autocorrelation of the coral and water-quality data, and plotted the semivariance of each variable expressed as a function of distance across the spatial field. The semivariogram value $\gamma(d)$, or estimated semivariance, for lag distance $d$ was defined as:

$$\gamma(d) = \frac{1}{2N(d)} \sum_{i=1}^{N(d)} (z(x_i) - z(x_i + d))^2$$  (1),

where $N(d)$ is the number of pairs of points separated by $d$, $z(x_i)$ are the data values for points $x_i$, and $z(x_i + d)$ are the data at cells separated from $x_i$ by the lag distance $d$ in the chosen direction. The semivariogram estimates assumed that: (i) the process that generated the data was random, (ii) the variance of the process was constant and independent across space, and (iii) the process was only dependent on the separation distance $h$ between points. We examined the semivariogram estimates for inherent changes through time (i.e., stationarity), and for directionality (i.e., isotrophy).

We used generalized linear and non-linear exponential models to examine relationships between coral bleaching and the water-quality parameters of interest, in particular water temperature and chlorophyll-a concentration. All linear and non-linear models showed spurious results, with significant negative slopes, suggesting that high water temperature, for example, predicted low coral bleaching. We have long known that the opposite is true, because high-water temperatures cause coral
bleaching. Therefore, the linear and non-linear models provided misleading predictions. We suspect that the negative slope is, in part, related to the high density of data, particularly around the 29.5 °C, reducing the central tendency of the relationship. We instead considered using point pattern processes, which gain strength from high density data, because they utilize the intensity of spatially explicit geographic data as predictors. We therefore examined the coral responses as spatial point patterns and determined the dependence of those point patterns on environmental covariates (Baddeley et al. 2012), using the following:

$$\lambda(u) = \rho(X(u))$$  \hspace{1cm} (2),

where $$\lambda(u)$$ is an intensity function of a finite set of spatial data points of the coral localities ($$u$$), $$X(u)$$ is a spatial covariate (i.e., benthic temperature and chlorophyll-a in this study) at every locality. The data were modeled as a spatial point Poisson process, and $$\rho$$ was determined using a nonparametric estimator with the R package ‘spatstat’ (Baddeley et al. 2015). Although we analyzed the relationship between all stony corals present on the reefs and chlorophyll-a concentrations and temperature, we were also particularly interested in the corals Acropora cervicornis, which is a threatened species, and Orbicella annularis, which was common in the Florida reef tract in the past. We therefore further examined the relationship between these two species and chlorophyll-a concentrations and temperature. We also wanted to know whether the size of the coral colonies influenced the relationships with the environmental covariates, and therefore ran similar spatial point pattern analyzes.
after categorizing the coral colony diameters as either small (4-50 cm), medium (51-100 cm), or large (> 100 cm). All analyses were run in R (R Core Team, 2016).
RESULTS

WATER-QUALITY DATA

Over the 11-year study period within the study region, the benthic water temperature ranged from 13.4 °C to 37.6 °C, and chlorophyll-a concentrations ranged from 0.002 μg l⁻¹ to 12.29 μg l⁻¹. Sea surface temperatures (SSTs) were more variable than benthic temperatures (Figure II.1, pg. Error! Bookmark not defined.), ranging from 10.5 °C to 37.6 °C. The highest temperatures were recorded in 2010, and the lowest temperatures were recorded in 2009 (Figure II.1, pg Error! Bookmark not defined.). The extent of homogeneous patches of benthic temperatures, evident from the range in the semivariograms, averaged approximately 15 km (SD ± 9.9 km) for the time period from 2005-2009, and approximately 17 km (SD ± 12 km) for the time period from 2010–2015. The semivariogram range of chlorophyll-a concentrations averaged approximately 23 km (SD ± 16 km) for the time period from 2005–2009, and approximately 33 km (SD ± 18 km) for the time period from 2010–2015 (see Appendix A, pg. 69).

CORAL BLEACHING AND DISEASES

Coral bleaching was most prevalent in 2014 and 2015 (Figure II.2, pg. 17), with average bleaching around 45% and 33% respectively. Coral bleaching was recorded at depths between 2 and 28 m, although bleaching was most prevalent at depths between 6 and 8 m (Figure II.3, pg. 18).
bleached corals averaged at approximately 46 km (SD ± 47 km), although during extremely warm years the patch sizes were larger than in other years (see Appendix A, pg. 69). There was clear directionality (i.e., anisotropy) in the coral bleaching data, with most time periods showing east-west alignment along the geographic axis of the Florida Keys (see Appendix A, pg. 69).

Coral diseases were most prevalent in 2010, 2014, and 2015 (Figure II.2, pg. 17), with average disease prevalence at 7%, 5%, and 4%, respectively. Diseases were most common at depths between 2 m and 7 m (Figure II.3, pg. 18). The average range of homogenous coral disease patches was typically 5 km or less, except in 2005 and 2014, when the sea surface and benthic temperatures were high, and when the range of homogeneous coral-disease patches averaged 14 km (SD ± 19 km). As occurred with the coral bleaching data, there was clear directionality (i.e., anisotropy) in the coral disease data, with most time periods showing east-west alignment along the geographic axis of the Florida Keys (Appendix A, pg. 69).
Figure II.2. Time series of the percentage of coral bleaching (upper panel), and the prevalence of coral disease (lower panel) at 2398 sites along the Florida reef tract from 2005 to 2015. The longest horizontal line for each time period represents the yearly mean, and the dotted horizontal line displays the overall mean.
Figure II.3. The percentage of coral bleaching (upper panel), and the prevalence of disease (lower panel) across depth (m) at 2398 sites along the Florida reef tract from 2005 to 2015.
ENVIRONMENTAL RELATIONSHIPS

Most reef-building corals along the Florida reef tract were geographically located in habitats where the water temperatures were above 24 °C during the winter season, and below 30 °C in the summer season (Figure II.4, pg. 21). Similarly, most corals favored habitats with low chlorophyll-a concentrations, yet these same oligotrophic conditions increased the prevalence of coral bleaching and disease (Figure II.5, pg. 22). There was a considerable decline in coral bleaching and coral disease where chlorophyll-a concentrations were > 0.3 μg l⁻¹. The two main reef-building corals, *Acropora cervicornis* and *Orbicella annularis*, showed similar responses to chlorophyll-a concentrations and bleaching. Both coral species were most common in oligotrophic waters, with low chlorophyll-a concentrations, yet these same clear-water habitats were conducive to coral bleaching (Figure II.6, pg. 23). When we categorized the sizes of the coral colonies and analyzed each size-class separately, both species showed a similar response, with most colonies occurring in waters with low chlorophyll-a concentrations independent of size class (Figure II.7, pg. 24). By contrast, *Acropora cervicornis* colonies in localities with chlorophyll-a concentrations > 0.3 μg l⁻¹ were less susceptible to bleaching, and *Orbicella annularis* in localities with chlorophyll-a concentrations > 0.4 μg l⁻¹ were less susceptible to bleaching. Similarly, when summer temperatures and chlorophyll-a concentrations were considered together, as spatial covariates of the spatial-point-process-intensity estimates, the corals were most common at low
chlorophyll-a concentrations and at 27.5 °C. Bleached corals were most prevalent at low chlorophyll-a concentrations and at temperatures > 29 °C (Figure II.8, pg. 25).
Figure II.4. Occurrence of all recorded coral species relative to winter and summer benthic temperatures (°C) in the Florida reef tract at 2398 sites from 2005 to 2015. Kernel estimates of $\rho$ (equation 2) (solid lines), and two-standard deviation confidence limits (gray shading) for winter (blue) and summer (red) temperatures. The rug plot indicates the number of sites that supported corals.
Figure II.5. All coral colonies in the Florida reef tract from 2005-2009 (upper row), from 2010-2015 (middle row), and throughout the entire study period (2005-2015) (lower row). Kernel estimates of $\rho$ (equation 2) (solid black line), with two-standard deviation confidence limits (gray shading) for: (left column) the occurrence of all coral colonies as a function of chlorophyll-a concentrations ($\mu g \ l^{-1}$) in the water column, (central column) the prevalence of coral bleaching as a function of chlorophyll-a concentrations ($\mu g \ l^{-1}$), and (right column) the prevalence of coral disease as a function of chlorophyll-a concentrations ($\mu g \ l^{-1}$). The rug plots indicate the number of sites surveyed.
Figure II.6. *Acropora cervicornis* and *Orbicella annularis* from the Florida reef tract from 2005 to 2015. Kernel estimates of $\rho$ (equation 2) (solid black line), with two-standard deviation confidence limits (gray shading) for: (top left panel) the occurrence of *Acropora cervicornis* as a function of chlorophyll-a concentrations ($\mu$g l$^{-1}$), (top right panel) the prevalence of coral bleaching of *Acropora cervicornis* as a function of chlorophyll-a concentrations ($\mu$g l$^{-1}$), (lower left panel) the occurrence of *Orbicella annularis* as a function of chlorophyll-a concentrations ($\mu$g l$^{-1}$), (lower right panel) the prevalence of coral bleaching of *Orbicella annularis* as a function of chlorophyll-a concentrations ($\mu$g l$^{-1}$). The rug plot indicates the number of sites surveyed that supported the coral species.
Figure II.7. *Acropora cervicornis* colonies of three size classes, small (4-50 cm), medium (51-100 cm), or large (>100 cm), in the Florida reef tract from 2005 to 2015. Kernel estimates of $\rho$ (equation 2) (solid black line), with two-standard deviation confidence limits (gray shading) for the occurrence of *Acropora cervicornis* as a function of chlorophyll-a concentrations (µg L⁻¹). The rug plot indicates the number of sites surveyed that supported the coral species of the specific size class.
Figure II.8. *Acropora cervicornis* from 633 sites in the Florida reef tract from 2005-2015. Kernel intensity estimates of $\rho$ (equation 2) for all colony occurrences (left panel) and all bleached corals (right panel) against chlorophyll-a concentrations ($\mu$g l$^{-1}$) and benthic temperatures ($^\circ$C).
DISCUSSION

The analysis of this extensive dataset from the Florida reef tract suggests that thermal-stress events are responsible for coral bleaching and associated coral disease, but water clarity also plays an important role. We found that throughout the decade of observation, the clearer the water the more likely it was that corals bleached. Corals in general, and the two major reef-building corals, *Acropora cervicornis* and *Orbicella annularis*, in particular, occurred in greater numbers in habitats with low chlorophyll-a concentrations. Yet coral colonies in these low chlorophyll-a habitats showed more extensive bleaching during thermal stress events than coral colonies in high chlorophyll-a habitats. It is most likely that the high concentrations of chlorophyll-a acted as a thermal refuge for coral colonies because of the shading they provided to the corals.

Physiological studies have confirmed the benefits of reducing irradiance during temperature-stress events. Shading reduces stress on the symbiont’s photosystem, which in turn reduces the likelihood of coral bleaching (Warner et al. 1999; Takahashi et al. 2004). Notwithstanding the obviously adverse effects that poor-water quality, with high levels of pollutants and high nutrient concentrations, has on corals (Wooldridge 2009; Wagner et al. 2010; Weidenmann et al. 2013), some shading provided by high-primary productivity and high turbidity can benefit corals during thermal-stress events (Cacciapaglia and van Woesik 2016). Indeed, since coral bleaching is essentially extreme photoinhibition, and high temperatures
make that photoinhibition worse (Warner et al. 1999; Takahashi et al. 2004), high productivity and high turbidity during high temperature events should effectively reduce the probability of photoinhibition and coral bleaching.

Similarly, the results showed that corals in habitats with high water-column productivity had a lower prevalence of disease than elsewhere. Previously, Lesser et al. (2007) suggested that reducing chronic photoinhibition and bleaching reduces the likelihood of coral disease. Subsequent field studies have validated these observations. For example, Muller at al. (2008) showed that bleached *Acropora palmata* colonies were more likely to suffer disease than coral colonies that did not bleach.

Still, reducing irradiance can be detrimental to the calcification process, causing reductions in coral growth rates (Tomascik and Sander 1987). Moreover, high sedimentation environments can deplete coral resources and increase their susceptibility to disease (Sheridan et al. 2014). Therefore, reducing irradiance, through primary productivity in the water column and high turbidity, can have beneficial effects up to a point, beyond which the costs may override the benefits for reef corals. Indeed, high and persistent productivity and extremely high turbidity can reduce the capacity of corals to build reefs entirely, because the photic zone becomes so narrow that there is insufficient irradiance for photosynthesis and calcification (Tomascik et al. 1993; Kleypas 1996; Toth et al. 2012). Previously, Kleypas et al. (1999) showed that reef building is unlikely in habitats with an
average irradiance of < 250 $\mu$E m$^{-2}$ s$^{-1}$ (at a depth of 3 m). Therefore, locating optimal niches, where corals can survive through thermal-stress events, should be a research priority, to not only detect natural refuges, but also for the rapidly burgeoning coral restoration endeavor that is expanding throughout Florida and the Caribbean.

Ocean temperatures are clearly increasing globally (Hansen et al. 2010; IPCC 2013), and as the oceans continue to warm, thermal anomalies will most likely continue to cause coral bleaching and subsequent diseases (Hoegh-Guldberg 1999; Harvell et al. 2002; Donner et al. 2005; Hoegh-Guldberg et al. 2007; Muller and van Woesik 2012). Some researchers question the capacity of corals to adapt to rapid climate change (Hoegh-Guldberg 2006; Frieler et al. 2013), whereas other researchers suggest that adaptive radiations and directional selection of thermally tolerant genotypes are likely (Thompson 1998, Hoffmann and Sgro, 2011; Guest et al. 2012; Poloczanska et al. 2016). The present study suggests an additional, more nuanced, effect of ocean warming — causing geographical shifts of reef corals toward more turbid environments.

Adaptation, however, will occur only under persistent selective pressure. In the past, there may have been little selective pressure for corals to live in habitats with consistently high turbidity and high chlorophyll-a-concentrations, since reef-building corals grow best under moderate irradiance (Done 1982). Most recently however that selective pressure may have increased. The almost annual
reoccurrence of thermal-stress events and coral bleaching in the Florida reef tract, shown by this study, may be selecting for coral genotypes that can live in naturally shaded environments, with high primary productivity and turbidity. Corals in these shaded habitats are less likely to suffer thermal stress than elsewhere. Therefore, in a rapidly warming ocean, there is likely to be a fitness advantage for corals that can live in habitats with less than optimal irradiance, because those same environments shield corals from short-term temperature-stress events. This study suggests that directional selection in a warming ocean may favor corals that are able to tolerate inshore environments with high turbidity and productivity. Because of reduced thermal stress in those shaded environments, selection for colonies in these habitats may provide the genetic pool of corals needed to survive through climate change.
CHAPTER III  THE CHANGING NICHE SPACE OF *ACROPORA CERVICORNIS* ALONG THE FLORIDA REEF TRACT

ABSTRACT

Quantifying the niche space of organisms is critical for conservation and restoration purposes, yet with warming oceans we cannot assume that localities that were optimal for species in the past remain so today, nor will they be optimal in the future. This study constructed a coral-niche model for the threatened coral species *Acropora cervicornis* in Florida reef tract to determine optimal environmental conditions for its survival. We used data collected from 2398 sites along the Florida reef tract to construct and validate the niche model. We developed these models at three spatial scales, 9 km, 4 km, and 1 km, using depth, wave exposure, irradiance, turbidity (Kd_{490}), sea-surface temperature, and chlorophyll-a concentration as predictive covariates. The most optimal locations for *Acropora cervicornis* were the upper and lower Florida Keys. Although the geographical patterns did not vary with an increase in the resolution of the predictive variables, the highest resolution models predicted a higher latitudinal extent of *Acropora cervicornis*, with favorable conditions extending up to 27-degrees north. The variables that best predicted *Acropora cervicornis* at 1 km was chlorophyll-a concentration, with colonies mostly supported in habitats with chlorophyll a concentration <1.25 mg m$^{-3}$. At a 4-km resolution, chlorophyll a concentration had a negative relationship and irradiance had a positive relationship with *A. cervicornis* occurrence. Our results
show that some well-lit, low chlorophyll a concentration habitats favor *Acropora cervicornis* on the Florida reef tract.
INTRODUCTION

Since the 1970s there has been a Caribbean-wide decline in live coral cover (Aronson and Precht 2001; Gardner et al. 2003). This decline has included unprecedented mortality of two of the most important reef-building coral species in the Caribbean, Acropora cervicornis and Acropora palmata (Aronson and Precht 2001). Both coral species have been declared threatened under the U.S. Endangered Species Act (NMFS 2006), and critically endangered on the International Union for Conservation of Nature Red List (IUCN 2016). The most significant coral mortality in the Caribbean stems from thermal-stress events (Wagner et al. 2010; Lirman et al. 2011; Manzello 2015), and the coral populations, particularly along the Florida reef tract, have failed to recover (Schutte et al. 2010; Burman et al. 2012; Ruzicka et al. 2013; Toth et al. 2014). As thermal stress events become more frequent and intensive through the effects of climate change (Hoegh-Guldberg 1999; Baker et al. 2008), it is widely argued that these populations are unlikely to recover without active restoration efforts (van Oppen et al. 2015).

Coral nurseries have been established to facilitate the recovery of Acropora populations in the Florida reef tract. Although considerable effort has been spent on successfully growing corals at the nurseries, far less effort has been spent on understanding the characteristics of outplant-sites, and determining which reef features and environmental conditions might facilitate or deter coral survival (Young et al. 2012; Hunt and Sharp 2014; van Woesik et al 2017). One approach to
determine optimal sites to outplant nursery-reared corals is through the use of niche, or species distribution, models (Elith and Leathwick 2009). Niche models examine the spatial distributions of contemporary coral species at a number of sites, and use the environmental conditions at those sites to geographically predict where the species is likely to be found.

The concept of niche has changed from Elton’s (1927) time, when niche was considered as a species' exclusive place in the biological environment and its relationship with food and predators. Gause (1934) emphasized that niche overlap was dependent on the intensity of competitive interactions, and Hutchinson’s (1959) hyper-space environment delineated a species’ fundamental niche, where competitive interactions reduced that fundamental space to realized space. Early niche models implicitly assumed that two species could not coexist indefinitely on the same limiting resource, however Roughgarden’s (1994) work advanced niche theory to include coexistence, and low inter-species interactions, particularly in diverse systems. Similarly, Scheffer and van Nes (2006) showed that multiple species can coexist within any give niche, which arise from the potential coevolution of competitors and convergent evolution of look-a-likes. Multiple-species niches agree with Hubbell’s assumption of neutrality (2001), and is particularly applicable to branching reef corals, where tens of species can occupy the same reef slope (van Woesik 2002). Yet such neutrality may be less likely at
high latitudes where environmental constraints become more dominant than at benign, low latitudes.

Contemporary niche models characterize the environmental conditions at a subset of sites in which a species occurs to predict potential occupancy across a species’ geographic range. Potential distributions are identified when the characterized environmental envelope is projected back onto geographic space. We then evaluate the model by returning to the environmental space and assess how good the model was at predicting the occurrence of the species. Still, species distribution models suffer from incomplete geographic sampling, scale mismatches, and cause-versus-correlation effects (Sinclair et al. 2010), and these models do not capture local adaptation, but instead use phenotypic-space averaging. Furthermore, with increasing anthropogenic stressors species may not be always found in optimal environments. Nevertheless, previous studies have made useful contributions to species predictions (Franklin et al. 2016), which have global implications for conservation (Cacciapaglia and van Woesik, 2015).

Species distribution models also have been used to identify suitable habitat for *Acropora* species in the Florida Keys (Wirt et al 2013, Wirt et al. 2015; Ames 2016), and along the northern Florida reef tract (D’Antonio et al. 2016). Past models showed that *Acropora* species were most common on shallow reefs where temperatures were moderate (Wirt et al 2013, Wirt et al. 2015; Ames 2016). Along the northern Florida reef tract, colonies of *Acropora cervicornis* were found close
to reef ridges, and in shallow reefs where the topography was high (D’Antonio et al. 2016). These models made considerable progress toward characterizing suitable Acropora habitats.

Here we used data collected from 2398 sites along the Florida reef tract to construct a niche model, which we developed at three spatial scales of resolution, 9 km, 4 km, and 1 km, to examine the effect of scale on the model’s accuracy. We included information on the presence and absence of Acropora cervicornis at over 4500 sites along the Florida reef tract, and an array of physical covariates, including depth, wave-exposure, sea-surface temperatures, chlorophyll-a concentrations, irradiance, and turbidity. More specifically, the objectives of this study were to create a coral-niche model that accurately identifies the environmental conditions that are optimal for Acropora cervicornis along the Florida reef tract.
MATERIALS AND METHODS

We used benthic survey data from the Florida Reef Resilience Program (http://frrp.org) to create the *Acropora cervicornis* model. These data were collected using habitat-dependent stratified randomly sampling, with replicated belt transects of 10 m² (Smith et al. 2011; Wagner et al. 2010; Burman et al. 2012). Along each transect the coral species, colony size, and coral-colony condition (i.e., bleaching and disease prevalence) were recorded for each coral colony over 4 cm. A total of 2398 sites were surveyed from 2005-2015, over 17 sampling periods. We also used data on the presence and absence of *Acropora cervicornis* collected by Steven Miller and colleagues at 2141 sites along the Florida reef tract, collected from 1999 to 2015.

Benthic habitat data was obtained from the Unified Florida Reef Tract Map (v 1.3) created by the Florida Fish and Wildlife Conservation Commission’s (FWC) Fish and Wildlife Research Institute (FWRI) (http://ocean.floridamarine.org/IntegratedReefMap/UnifiedReefTract.htm). This map combines multiple sources of benthic habitat mapping of the Florida reef tract and merges the maps to a single unified classification scheme. Habitat classification data were used to examine reef zone as a categorical predictor, and to examine the impact of constraining the analysis to only coral reef and hard-bottom areas.
ENVIRONMENTAL DATA

Several water-quality datasets were used to create the coral niche models. Benthic- and surface-level *in-situ* water quality data were obtained from the South East Environmental Research Center (SERC) water quality monitoring network (http://serc.fiu.edu/wqmnetwork/). This network monitors 27 water quality parameters over 215 sites, along the Florida reef tract on rolling quarterly sampling schedule, from January 2005 to December 2015. We were particularly interested in the surface and benthic water temperature that corals experienced, hereinafter called temperature.

Depth data was obtained from the General Bathymetric Chart of the Oceans (GEBCO) website (http://www.gebco.net). A global gridded dataset at 30 arc-second resolution (about 1 km; GEBCO_2014 Grid) was obtained and clipped to the study area. To produce data for the coarser resolution models, the dataset was imported into R as a raster and transformed to 4 and 9 km resolutions using bilinear resampling in the R package ‘raster’. To detect artifacts in the raster dataset, the depth measurements were compared to in-situ depth measurements in the FRRP dataset. Areas where depth measurements were clearly errant were effectively removed by restricting the raster dataset to depths of less than 100 meters.

A suite of satellite data were obtained for (i) sea-surface temperature, (ii) chlorophyll-a concentrations, (iii) turbidity, and (iv) irradiance. Satellite products were obtained at 9 km, 4 km, and 1 km resolutions. All four variables were
available at 9 km and 4 km resolutions, and were obtained from the MODIS Aqua Satellite via NASA’s Ocean Color Web (https://oceancolor.gsfc.nasa.gov; OBPG 2015). All 9 km and 4 km products were obtained at a daily resolution from 2005 to 2016. Chlorophyll-a concentration data, at a spatial resolution of 250 m, were obtained from the Optical Oceanography Laboratory (http://optics.marine.usf.edu/) for the Florida Keys and Southeast Florida. These data were resampled to 1 km resolution in R using nearest-neighbor interpolation. Sea-surface temperature data at 1 km resolution were obtained from the AVHRR satellite via the NOAA CoastWatch East Coast Node (https://eastcoast.coastwatch.noaa.gov). A 1 km data product was not available for irradiance. Chlorophyll-a data were available from 2011-2015 and sea-surface temperature data were available from 2008-2015. All products were obtained at a daily temporal resolution. Sea-surface temperature (SST) data were provided in degrees Celsius, and chlorophyll-a concentrations were measured in milligrams per meter cubed (mg m$^{-3}$). Irradiance was measured as photosynthetically available radiation (PAR) between the wavelengths of 400 to 700 nm. Turbidity was assessed as the diffuse attenuation coefficient, Kd$_{490}$, using NOAA’s algorithm (Wang et al. 2009). Daily data files were imported into R (R Core Team 2017) as raster files using the package ‘raster’, where all values greater than zero were used to determine the range and mean of the variables for the time periods of interest.
Previous studies have shown that in-situ sea-surface temperature measurements were significantly different from benthic temperature measurements, which the corals experience, at the same locations (Wagner et al 2008). Furthermore, satellite sea-surface level measurements are likely to differ significantly from in-situ level measurements, especially at fine spatial and temporal scales of resolution (McClanahan et al. 2007, Castillo and Lima 2010). Indeed, MODIS satellites are known to be biased towards cooler temperatures at night and warmer temperatures during the day (Castillo and Lima 2010). To address these problems, the data were transformed using relationships defined by the generalized linear models. The transformation of the data followed the form:

\[ y_i = \beta_o + \beta_1 x_i + \text{error} \quad (1), \]
\[ z_i = \beta_2 + \beta_3 y_i + \text{error} \quad (2), \]

In equation 2, \( y \) is the in-situ sea-surface temperature measurement at site \( i \), \( \beta_o \) is the intercept of the model, \( x \) is the satellite sea-surface temperature measurement at site \( I \), \( \beta_1 \) is the slope representing the extent of the relationship between the satellite and in-situ measurements, and \( \text{error} \) represents the residual error term. In equation 3, \( y \) is again the in-situ sea-surface temperature measurement at site \( i \), \( z_i \) is the in-situ benthic temperature measurement at site \( i \), \( \beta_2 \) is the intercept of the model, \( \beta_3 \) is the slope representing the extent of the relationship between the in-situ surface and benthic measurements, and \( \text{error} \) represents the residual error term. Once the models were parameterized using
known data, satellite sea-surface temperature \( (x_i) \) data were transformed using the system of equations into a benthic temperature equivalent \( (z_i) \).

Wave exposure models were created following methods developed by Ekebom et al. 2003 and revised by Chollett and Mumby 2012. Fetch, which is the distance waves can travel unobstructed to a site of interest, in a specific direction, was calculated over a grid at 9, 4, and 1 km resolution using the R package ‘fetchR’ (Seers 2017). Fetch was calculated over 36 compass directions, with an angular width of 10° and a maximum distance of 2,000 km. The average, minimum, maximum, and standard deviation fetch were calculated for each study site. Wind data were obtained from the Cross-Calibrated Multi-Platform version 2.0 (CCMP V2.0) gridded surface-wind vectors via Remote Sensing Systems (http://www.remss.com/measurements/ccmp) (Wentz et al. 2015). Wind data were obtained over the study area in U and V component format at 0.25° resolution from 1987-2016. The data was converted to absolute speed and direction, and resampled to 1 km resolution using bilinear interpolation in the R package ‘raster’ (Hijmans 2016). A series of equations was then used to calculate wave-energy. The non-dimensional fetch \( (\xi) \) for each pixel was calculated as,

\[
\xi = \frac{gF}{U_{10}^2}
\]

where F is the previously calculated average fetch in meters, \( U_{10} \) is the wind speed at an elevation of 10 m in ms\(^{-1} \), and \( g \) is the acceleration due to gravity \( (9.81 \text{ ms}^{-2}) \).

A pixel was classified as fetch-limited when the values from equations (6) and (8)
are equal, or when the non-dimensional fetch ($\xi$) calculated by equation (4) was equal to 38,590 m. For fetch-limited pixels, wave height ($H_{mo}$) and wave period $T_m$ can be calculated with:

$$H_{mo} = 0.00082 \times U_{10}^{1.1} \times F^{0.45} \quad (4),$$

$$T_m = 0.087 \times U_{10}^{1.1} \times F^{0.27} \quad (5),$$

where $U_{10}$ is the wind speed at an elevation of 10 m in ms$^{-1}$, and $F$ is fetch in meters. If pixels were not fetch-limited, wave height and exposure were calculated by:

$$H_{mo} = 0.034 \times U_{10}^2 \quad (6),$$

$$T_m = 0.081 \times U_{10} \quad (7),$$

where $U_{10}$ is the wind speed at an elevation of 10 m (ms$^{-1}$). The total wave energy of the system, $WE$ (Joules), was calculated using:

$$WE = \frac{1}{16} \rho g H_{mo}^2 \quad (8),$$

where $\rho$ is the density of sea water (1,030 kgm$^{-3}$). These values were calculated for all pixels over the study area, at 9, 4, and 1 km resolution, at a daily resolution using the wind data from 1987 to 2015. The average wave energy, $E$, was found per pixel by taking the geometric mean of the daily energy estimates. Summary statistics were then calculated for reef zones.
THE CORAL-NICHE MODELS

Species distribution models were developed for *Acropora cervicornis* along the Florida reef tract at three spatial scales: 9 km, 4 km, and 1 km. Predictions were made as the probability of presence or absence of *Acropora cervicornis*, and whether the corals bleached or had disease using the environmental predictors. The relationship between the presence of *A. cervicornis* and the environmental variables of interest were examined using a suite of approaches, including a logistic regression and a logit-link function, generalized linear model, generalized additive model (Wood 2017). To train the models and test fit, we split the data into 5 partitions using the *k*-fold algorithm in the R package ‘dismo’ (Hijmans et al. 2017). Each model was run 5 times, where four of the five *k*-folds were used as training data, and the remaining *k*-fold was used as testing data. The best fitting models were selected by finding the average Akaike Information Criterion (AIC) and area under the receiver operating characteristic curve (AUC) for the five model runs. Raw model results were averaged per pixel, and a threshold was calculated as the greatest sum of sensitivity (i.e., the true positive fraction) and specificity (i.e., the true negative fraction) averaged over the five model runs was used to determine the probability of presence. We also examined the coral responses as spatial point patterns and determined the dependence of those point patterns on environmental covariates (Baddeley et al. 2012), using the following:

\[
\lambda(u) = \rho(X(u))
\]  \hspace{1cm} (10),
where $\lambda(u)$ is an intensity function of a finite set of spatial data points of the coral localities ($u$), $X(u)$ is a spatial covariate (i.e., benthic temperature and chlorophyll-a in this study) at every spatial locality (van Woesik and McCaffrey 2017). The data were modeled as a spatial point Poisson process, and $\rho$ was determined using a nonparametric estimator with the R package ‘spatstat’ (Baddeley et al. 2015).
RESULTS

*Acropora cervicornis* colonies were found between 2 and 17 m, with highest occurrences between 6-7 m. (Figure III.1, pg. 44). Of 366 records of *Acropora cervicornis* presence, 298 were found on coral reef and hard-bottom habitat (81%), 49 on seagrass (13%), 17 on unconsolidated sediment (5%) and 2 on unclassified areas (<1%). For our species distribution models, the potential range of *A. cervicornis* was not restricted to coral reef and hard-bottom areas, and when the species was restricted to those habitats the model fit was reduced considerably.

![Figure III.1. Acropora cervicornis from 633 sites in the Florida Keys from 2005 to 2015 (FRRP data). Kernel estimates of ρ (equation 2) (solid black line), with two-standard deviation confidence limits (gray shading) for the occurrence of Acropora cervicornis as a function of depth. The rug plot indicates the number of sites surveyed that supported the coral species.](image)
Acropora cervicornis was most frequently located in habitats where the modeled sea bottom temperatures were above 24°C during the winter season, and below 30°C in the summer season, with ‘preferable’ summer temperatures between 29°C and 30°C (Figure III.2, pg. 46). Model estimates of benthic temperature at 9, 4, and 1 km resolutions were generally similar and, to some extent, independent of resolution of observation. However, at 9 km and 4 km, satellite measurements generally overestimated sea-surface temperatures by more than 1 degree Celsius, and in-situ sea-surface temperature measurements underestimated benthic temperature by approximately 0.2 degrees Celsius (Table III.1, pg. 47). At 1 km resolution, satellite data underestimated sea-surface temperature by just 0.1 degree Celsius, and in-situ sea-surface temperature overestimated benthic temperature measurements by less than 0.1 degree Celsius (Table III.1, pg. 47).
Figure III.2. Colony frequency of *Acropora cervicornis* at 1 km resolution modeled sea-bottom temperatures. *A. cervicornis* colonies occurred where winter temperatures were above 24 °C and where summer temperatures were below 30 °C.
Table III.1. Summary table of temperature model results, to three significant digits. Satellite surface-temperature measurements over-predicted in-situ surface temperature measurements and in-situ benthic-temperature measurements over-predicted in-situ surface-temperature measurements at every scale.

<table>
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<td>1997</td>
<td>0.00001</td>
<td>0.444</td>
<td>0.986</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>4 km Model</td>
<td>1.001</td>
<td>0.195</td>
<td>1997</td>
<td>0.00001</td>
<td>0.444</td>
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<td>-0.052</td>
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<td>0.978</td>
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Table III.2. Summary table of the generalized additive species distribution models for *Acropora cervicornis* using different combinations of annual mean environmental variables at spatial resolutions of 9, 4, and 1 km. Model fit values are averaged over the $k$ model runs. Note that the best models have the lowest GCV (generalized cross validation) and the highest AUC (area under the receiver operating characteristic curve). Variable that were significant in at least one model run are in bold italics.

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<th>$R^2$</th>
<th>Deviance Explained</th>
<th>GCV</th>
<th>AUC</th>
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<td>3.63%</td>
<td>0.083</td>
<td>0.503</td>
</tr>
<tr>
<td>4 km</td>
<td>$SBT + Chla + PAR + Kd + Wave + Depth$</td>
<td>0.038</td>
<td>5.01%</td>
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<td>1 km</td>
<td>$SBT + Chla + Wave + Depth$</td>
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Mean wave energy (J) varied across reef zones, with the highest mean values in fore reef and back reef zones, and the lowest mean values in the bank and shelf, channel, and lagoon zones, with a difference between them of about 2.5 J (Figure III.3, pg. 49). These variations between reef zones were consistent across data scales, but were not significant due to a large amount of variation in the wave energy. *Acropora cervicornis* were primarily found at sites with an average wave energy of about 2-2.5 Joules, and did not occur where wave energy was high, about 7 Joules (Figure III.4, pg. 50). *A. cervicornis* were found at site with low concentrations of chlorophyll a (<1.5 mg m$^{-3}$), and although colonies were found at sites with high concentrations, densities were low (Figure III.5, pg. 50).

Figure III.3. Mean wave energy estimates in different reef zones at 9, 4, and 1 km. The differences between reef zones were not significant, due to large amounts of variation in the data. The highest mean values were found in fore reef and back reef zones, and the lowest mean values in the bank and shelf, channel, and lagoon zones.
Figure III.4. *Acropora cervicornis* from 80 sites in the Florida reef tract from 2005 to 2015 (FRRP data). Kernel estimates of $\rho$ (solid black line), with two-standard deviation confidence limits (gray shading) for the occurrence of *Acropora cervicornis* as a function of wave-exposure. The rug plot indicates the number of sites surveyed that supported the coral species.

Figure III.5. *Acropora cervicornis* from 76 sites in the Florida reef tract from 2005-2015. Kernel estimates of $\rho$ (solid black line), with two-standard deviation confidence limits (gray shading) for the occurrence of *Acropora cervicornis* as a function of chlorophyll a concentration. The rug plot indicates the number of sites surveyed that supported the coral species.
Different combinations of explanatory environmental variables were analyzed to create species distribution models at 9, 4, and 1 km using annual mean, annual range, seasonal mean, and seasonal range data. The generalized additive model performed best at all model scales, whether annual or seasonal mean or range data were used. Models using annual mean data out-performed models using annual range or seasonal data, and models at 4 and 1 km resolution performed better than those that used 9 km data. Variable importance varied depending on the data used and the scale of resolution (Table III.2, pg. 48). In general, models including all explanatory variables, except for reef zone, were among the best performing models. Chlorophyll a, Kd_{490}, and sea-bottom temperature were the most consistently significant variables across all model types, scales, and data summaries. Wave exposure was rarely a significant predictor (Table III.2, 48). Chlorophyll a was the only variable significant in both the 4 km and 1 km models, and showed the same trend at both scales, indicating that the probability of *A. cervicornis* presence decreased when chlorophyll a concentrations exceeded 1.25 mg m$^{-3}$ (Figure III.6, pg. 52).
Figure III.6. A plot of generalized additive species distribution model results for chlorophyll a concentration at 4 km (left) and 1 km (right) resolution. In each model, the probability of species occurrence trends downward after the chlorophyll a concentration surpasses approximately 1.25 mg m$^{-3}$.

Although the general geographical patterns of predicted $A. cervicornis$ presence did not vary with an increase in the resolution of the predictive variables, from 9 km to 4 km to 1 km, the higher resolution model predicted a higher latitudinal extent, showing favorable conditions for $Acropora cervicornis$ up to 27 degrees north. The area of the habitat that was predicted to be suitable for $A. cervicornis$ was found at each scale of resolution. At the 9 km resolution, an area of 2712.8 km$^2$ was predicted to be suitable, at 4 km resolution 1452.1 km$^2$ was predicted to be suitable, and at 1 km resolution 1595.9 km$^2$ was predicted to be suitable. Thus, the higher the scale of resolution of the species distribution models,
the less area was predicted to be suitable for *A. cervicornis* throughout the Florida reef tract (Figure III.7, pg. 53).

Figure III.7. Species distribution model for *Acropora cervicornis* at 9 km grid (left), 4 km grid (middle), and 1 km grid (right), where the scale is the predicted presence or absence as 1 or 0 using generalized additive models. For the environmental variables used in these models, see Table III.2, pg. 48. All models use average annual mean environmental variables.
DISCUSSION

The decline of the historically dominant coral species, particularly *Acropora cervicornis*, has resulted in a significant reduction in live coral cover on the Florida reef tract, which has dramatically altered the composition of coral reef assemblages (Burman et al. 2012; Ruzicka et al. 2013; Toth et al. 2014). In the present study, we quantified the niche space of the endangered species *Acropora cervicornis* to determine which environmental variables might serve as predictors of coral survival, and to identify niche space suitable for the growth of *Acropora cervicornis*. Our results indicate that data resolution matters a great deal, and that temperature, chlorophyll a concentration in the water column, irradiance, and water depth are all useful predictive variables of *Acropora cervicornis*.

Our sea-surface temperature models of satellite to in-situ values indicated that in-situ sea-surface temperature measurements over-estimated benthic temperature measurements by about 0.2 degrees Celsius. These results agree with previous work that found satellite data was biased towards warmer temperatures for daytime measurements (Castillo and Lima 2010). In general, sea-surface temperatures are greater than benthic temperatures. In the Florida reef tract, however, reverse thermoclines can cause sea-surface temperatures to be lower than benthic temperatures, or can be made equivalent by strong wind mixing the water column (Barnes et al. 2015). These sources of variation likely increased the variation present in our temperature model, but pooling of the data through time
and across the entire reef-tract effectively masked areas with reverse thermoclines. Yet, these reverse thermoclines may be important to coral distribution within certain habitats, particularly in areas where there is flow-through from the Florida Bay. We also did not incorporate depth into our benthic temperature model, which may improve model fit when covering a wide range of habitats. These additional considerations could improve the fit of surface to benthic temperature models for other applications.

In our species distribution models, more significant results were only consistently obtained when high-resolution (1 km) data were used, and when potential habitat area was not restricted to coral reef and hard-bottom areas. Previously, work on the Florida reef tract has shown that more than 90% of observations of *A. cervicornis* occur in coral reef and hard-bottom areas, and more than 99% were located within 100 m of those habitats. Our data indicated that 81% of *A. cervicornis* observations occurred in coral reef and hard-bottom areas and 13% of observations were within seagrass areas. Observations of *A. cervicornis* outside of mapped coral reef and hard-bottom areas may indicate that there is greater habitat area available than mapped coral reef and hard-bottom, or they could indicate that there are mapping errors in the current habitat data products (Wirt et al. 2013, Wirt et al. 2015). Our results, which showed that the models were poorly fit when limited to coral reef and hard-bottom areas, supports the ideas that
Acropora cervicornis presence is not restricted to these habitats, and is also more routinely occurring in other habitat areas.

Many current coral restoration efforts are focused in the Middle Keys, yet our models predicted less potential habitat in these areas relative to the lower and upper Keys, and relative to the the northern extent of the reef tract. These unfavorable predicted conditions are likely related to water flowing from the Florida Bay, which is often warmer and more saline than the surrounding waters and inhibits reef development in the area it flows (Ginsburg and Shinn 1964, Marszalek et al. 1977, Ginsburg and Shinn 1994). Previous species distribution modeling work on the Florida reef tract predicted the probability that Acropora cervicornis was (i) never present, (ii) transiently present, or (iii) continuously present along the reef tract (Ames 2016). Our predicted areas of suitable habitat in the lower and upper Keys roughly correspond to those predicted by Ames 2016 to be suitable for continuous presence of Acropora cervicornis between 1996-2013. The suitable habitat predicted by our models at the northern extent of the reef tract, however, corresponded to areas that were predicted to have a high probability of having never been occupied by Acropora cervicornis between 1996-2013 (Ames 2016). This is an important distinction between this work and the previous models. Though habitats close to 27 degrees North on the reef may have been unsuitable for occupation of Acropora cervicornis in the past, the northern extent of the reef tract may now be
suitable for the colonization of staghorn coral, as climate change forces species distributions to change their geographic preferences.

On the Florida reef tract, it may be that habitat suitable for adult *Acropora cervicornis* is not being occupied. While conditions are suitable for adult corals, they may not be suitable for the development of recruits into adult corals (van Woesik et al. 2014). Local adaptation to environmental conditions may be reducing the survival of coral recruits which stem from neighboring populations (Kenkel et al. 2015; Drury et al. 2016). Empty habitats may also be suitable for survival, but are ephemeral and unoccupied because of stochastic mortality, or may be unsuitable due to local conditions not currently captured in our models.

It is important to address the problem of identifying occupied and empty niche space at a variety of scales. This study was restricted to scales ≥ 1 km, yet features at scales < 1 km may also be influential (van Woesik et al. 2017). For example, the distance from the reef edge, where corals are outplanted, will likely influence water-flow rates and hence may influence coral growth and survival (D’Antonio et al. 2016). There may also be differences in microhabitats along the reef edge which influence survival and growth. At the scale of tens of meters, a data resolution not often use in species niche modeling, some microhabitats may be elevated from the reef base, which may also enhance water flow rates and improve colony survival (van Woesik et al. 2012). The dependence of our model on high-resolution environmental data shows that there is a need to study the niche
availability of corals at microhabitat scales, of less than one kilometer, to improve restoration outcomes.
LITERATURE CITED


The GEBCO_2014 Grid, version 20150318, [www.gebco.net](http://www.gebco.net).


Table A.1. The results of semivariogram analyses of monthly benthic temperature (°C) data. The autocorrelative patch size averaged 15.2 km (Standard Deviation ± 9.9 km) for the period from 2005-2009, and 17.4 km (Standard Deviation ± 12.3 km) for the period from 2010-2015.

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Table A.2. The results of semivariogram analyses of monthly chlorophyll-a (µg l⁻¹) water-quality data. The autocorreltive patch size averaged 23.0 km (Standard Deviation ± 16.0 km) for the period from 2005-2009, and 32.9 km (Standard Deviation ± 17.9 km) for the period from 2010-2015. No spatial autocorrelative structure was indicated by Moran’s I analyses for the time periods of March 2010-2015, March 2005-2015, June 2010-2015, August 2005-2009, November 2010-2015, and December 2010-2015. For these time periods, spatial interpolation was performed using Inverse Distance Weighting Interpolation.

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<td>0.03</td>
<td>NA</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>0.1</td>
<td>0.4</td>
<td>NA</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>35.3</td>
<td>13.2</td>
<td>NA</td>
<td>30.6</td>
</tr>
<tr>
<td></td>
<td>11.4</td>
<td>18.4</td>
<td>NA</td>
<td>11.4</td>
</tr>
</tbody>
</table>
Table A.3. The results of semivariogram analyses of bleaching percentages for the benthic sampling periods from 2005-2015. The autocorrelative patch size averaged 78.6 km (Standard Deviation ± 49.6 km) for the period from 2005-2009, and 23.8 km (Standard Deviation ± 20.8 km) for the period from 2010-2015.

<table>
<thead>
<tr>
<th>Time</th>
<th>Nugget</th>
<th>Psill</th>
<th>Range (km)</th>
<th>Anisotropy directionality (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>153.4</td>
<td>138.3</td>
<td>73.4</td>
<td>10.7</td>
</tr>
<tr>
<td>2006</td>
<td>20.0</td>
<td>20.0</td>
<td>84.5</td>
<td>57.9</td>
</tr>
<tr>
<td>2007</td>
<td>100.0</td>
<td>50.0</td>
<td>5.8</td>
<td>23.9</td>
</tr>
<tr>
<td>2008</td>
<td>25.0</td>
<td>10.0</td>
<td>161.5</td>
<td>57.5</td>
</tr>
<tr>
<td>2009</td>
<td>75.0</td>
<td>15.0</td>
<td>72.7</td>
<td>12.6</td>
</tr>
<tr>
<td>2010</td>
<td>54.7</td>
<td>52.0</td>
<td>57.6</td>
<td>288.0</td>
</tr>
<tr>
<td>2011</td>
<td>86.8</td>
<td>37.9</td>
<td>19.1</td>
<td>57.7</td>
</tr>
<tr>
<td>2012</td>
<td>15.0</td>
<td>10.0</td>
<td>30.0</td>
<td>51.1</td>
</tr>
<tr>
<td>2013</td>
<td>26.4</td>
<td>8.9</td>
<td>1.2</td>
<td>82.1</td>
</tr>
<tr>
<td>2014</td>
<td>300.0</td>
<td>250.0</td>
<td>39.3</td>
<td>358.7</td>
</tr>
<tr>
<td>2015</td>
<td>290.0</td>
<td>110.0</td>
<td>47.8</td>
<td>343.2</td>
</tr>
</tbody>
</table>
Table A.4. The results of semivariogram analyses of the prevalence of coral diseases for the benthic sampling periods from 2005-2015. The autocorrelative patch size averaged 9.7 km (Standard Deviation ± 13.2 km) for the period from 2005-2009, and 26.8 km (Standard Deviation ± 23.7 km) for the period from 2010-2015. Spatial autocorrelative structure was indicated by Moran’s I analyses for the time periods of 2006, 2009, 2010, 2012, 2013, and 2015. For these time periods, spatial interpolation was performed using inverse distance weighting interpolation.

<table>
<thead>
<tr>
<th>Time</th>
<th>Nugget</th>
<th>Partial sill</th>
<th>Range (km)</th>
<th>Anisotropy directionality (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>3.6</td>
<td>0.8</td>
<td>29.4</td>
<td>83.3</td>
</tr>
<tr>
<td>2006</td>
<td>0.5</td>
<td>1.1</td>
<td>4.8</td>
<td>56.7</td>
</tr>
<tr>
<td>2007</td>
<td>0</td>
<td>2.1</td>
<td>1.6</td>
<td>78.8</td>
</tr>
<tr>
<td>2008</td>
<td>1.3</td>
<td>0.3</td>
<td>3.0</td>
<td>44.3</td>
</tr>
<tr>
<td>2009</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>2010</td>
<td>9.3</td>
<td>19.8</td>
<td>5.3</td>
<td>49.5</td>
</tr>
<tr>
<td>2011</td>
<td>0.5</td>
<td>3.3</td>
<td>1.4</td>
<td>301.2</td>
</tr>
<tr>
<td>2012</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>2013</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>2014</td>
<td>10.0</td>
<td>20.0</td>
<td>41.0</td>
<td>NA</td>
</tr>
<tr>
<td>2015</td>
<td>8.9</td>
<td>3.9</td>
<td>29.1</td>
<td>342.2</td>
</tr>
</tbody>
</table>
###Calculating Fetch in the Florida Reef Tract###
###Kelly McCaffrey###
###October 2017###
#fetchR fetch calculation tutorial
#https://cran.r-project.org/web/packages/fetchR/fetchR.pdf

#load required libraries
library(rgdal)
library(raster)
library(rgeos)
library(fetchR)
library(maptools)

#load unified reef tract map from FWC - reef zone information
setwd("C:/Users/kmccaffrey2011/Desktop/Research/Unified Florida Reef Tract v 2.0 2017")
reef<-readOGR(".","UnifiedFloridaReefTract_poly")
#get only the reef crest form map
crest<-subset(reef, reef$Zone=="Reef Crest")
plot(crest)
rm(reef) #removing large spatial objects to save memory space

#Get world map at high resolution
library(rworldmap)
library(rworldxtra)
map<-getMap(resolution="high")
map<-spTransform(map, CRS(’+proj=longlat +south +ellps=WGS84 +units=m +no_defs’))
crest<-spTransform(crest, CRS(’+proj=longlat +south +ellps=WGS84 +units=m +no_defs’))
crest_poly<-SpatialPolygons(crest@polygons, proj4string=crest@proj4string)
shore_poly<-SpatialPolygons(map@polygons, proj4string=map@proj4string)
rm(map); rm(crest)
#put the separate shapes together to one object
map<-aggregate(rbind(crest_poly, shore_poly))

#To save memory, I crop by 2 different extents.
#The smaller area is the points for which I want to calculate fetch
#the larger area is to capture the surrounding land masses for the fetch calculation
e<-extent(-98, -66, 12, 40)
map1<-crop(map, e)

e2<-extent(-86, -76, 20, 32)
map2<-crop(map, e2)

rm(crest_poly); rm(shore_poly); rm(map)
#removing unused spatial objects to save space

#to calcualte fetch, coordinate system must be projected
map1<-spTransform(map1, CRS("+proj=merc +lon_0=0 +k=1 +x_0=0 +y_0=0
+ellps=WGS84 +datum=WGS84 +units=m +no_defs"))
map2<-spTransform(map2, CRS("+proj=merc +lon_0=0 +k=1 +x_0=0 +y_0=0
+ellps=WGS84 +datum=WGS84 +units=m +no_defs"))

#create a template raster – change res to km scale being used
r<-raster()
proj4string(r)<-proj4string(map2)
extent(r)<-extent(map2)
res(r)<-9000

#rasterize the map polugon to the template raster
maprast<-rasterize(map2, r)
maprast[!is.na(maprast)]<-1 #1 is land
maprast[is.na(maprast)]<-0 #0 is water

###These steps are meant to reduce memory required to run code ###
#crop raster points to FRRP data size, then extend with NA values
e2<-extent(-9250000, -8860000, 2700000, 3130000)
maprast<-crop(maprast, e2)
e3<-extent(map1)
maprast<-extend(maprast, e3, value=NA)

#convert maprast to points where fetch will be calculated
pts<-rasterToPoints(maprast, fun=function(x){x==0}, spatial=T, progress="text")
#points will be created in cells that = 0 (water)
SP<-SpatialPoints(pts@coords)
proj4string(SP)<-"+proj=merc +lon_0=0 +k=1 +x_0=0 +y_0=0 +ellps=WGS84 +datum=WGS84 +units=m +no_defs"

#calculate fetch at all locations for 36 compass directions
#to calculate fetch, at least one layer must be projected
#maximum fetch should be an estimate, based on the maximum expected distance to
#some landmass
my_fetch=fetch(map1, SP, n_directions=9, max_dist=2000)
my_fetch #check
summary(my_fetch) #check
plot(my_fetch, map1) #check

#back to original CRS, data frame
my_fetch2<-spTransform(my_fetch, CRS("+proj=longlat +south +ellps=WGS84 +units=m +no_defs"))
fetch_df<-as(my_fetch2, "data.frame")

#how many are within the max set distance? - a check of our estimate
nrow(fetch_df[fetch_df$fetch<2000,])/nrow(fetch_df)

#save results
# setwd("C:/Users/kmccaffrey2011/Desktop/Research/Exposure")
# write.csv(fetch_df, "fetch9km.csv")

#library(plotKML)
#kml(my_fetch, "fetch1km.kml", overwrite=T)
#plotKML(my_fetch)
R CODE: WAVE EXPOSURE

###Calculating wave exposure in the Florida Reef Tract using fetch and wind###
###Kelly McCaffrey###
###Based on Ekebom 2003 and Chollett and Mumby 2012###
###October 2017###

#load in required libraries
library(sp)
library(raster)
library(rgdal)
library(rgeos)

setwd("C:/Users/kmccaffrey2011/Desktop/Research/Exposure/Data")

#Daily fetch in 36 directions
fetch9km<-read.csv("fetch9km.csv")

#set our constants
g<-9.81 #gravity 9.81 ms-1
rho<-1030 #the density of seawater, kgm-3

directions<-seq(0, 350, 10) #0 to 350 degrees by 10

#wind data setup - data spans daily, 1987-2016
tmp_dir<"C:/Users/kmccaffrey2011/Desktop/Research/Wind CCMP v02.0/Processed/1987"
windfiles<-list.files(tmp_dir, full.names=T)

###equations used in wave exposure calculation - based on Ekebom 2003 and Chollett and Mumby 2012###

#non-dimensional fetch
nondimfetch<-function(x, y, na.rm=T){
  #x=fetch in m, y is wind speed at 10m in ms-1
  (g*x)/(y^2)
}

#fetch-limited significant wave height
Hmo<-function(x, y, na.rm=T){#Fe= fetch in m, U is wind at 10m in ms-1
  0.00082 * (y^1.1) * (x^0.45)
}

#fetch-limited wave period
Tm<-function(x, y, na.rm=T){ #x is Fe, y is U
  0.087 * (y^0.46)*(x^0.27)
}

#fetch-limited Wave energy (J), proportional to wave height
WE<-function(x, na.rm=T){ #x is Hmo
  (1/16)*rho*g*(x^2)
}

#fully-developed significant wave height
Hmofull<-function(x, na.rm=T){ # x is U
  0.034*(x^2)
}

#fully-developed wave period
Tmfull<-function(x, na.rm=T){ #x is U
  0.81*x
}

#Fully-developed wave energy (J), proportional to wave height
WEfull<-function(x, na.rm=T){ #x is Hmofull
  (1/16)*rho*g*(x^2)
}

#make progress bars to keep track of process
pb1<-txtProgressBar(min=0, max=length(windfiles), style=3)
pb2<-txtProgressBar(min=0, max=length(directions), style=3)

#Loop through wind files - change file save names based on what year you're
##running through
#Make sure resolution matches fetch resolution being used

for(k in 1:length(windfiles)){ #for wind file k
  removeTmpFiles(h=0) #remove the temporary files made by raster to save
  #computing space
  #make some empty stacks
  Hmo_stack<-stack()
Tm_stack<-stack()
WE_stack<-stack()

#load wind data
CCMP<-stack(windfiles[[k]]) #get kth wind file
CCMP<-projectRaster(CCMP, crs=CRS('+proj=longlat +south +ellps=WGS84 +units=m +no_defs')) #put in our CRS

for(i in seq_along(directions)) { #in fetch direction i
  removeTmpFiles(h=0)
  #get fetch in direction i
  fetch<-subset(fetch9km, fetch9km$direction==directions[i])
  coordinates(fetch)<-~lon+lat
  proj4string(fetch)<-"+proj=longlat +south +ellps=WGS84 +units=m +no_defs"
  #gridded(fetch)<-TRUE
  fetchrast<-SpatialPixelsDataFrame(fetch, tolerance=0.0220834, fetch@data)
  fetchrast<-raster(fetchrast, layer=3) #make fetch into a raster
  #plot(fetchrast)
  e<-extent(fetchrast) #grab extent of fetch

  #resample to same raster to match extent and origin
  e2<-extent(-88, -74, 21, 31)
  #make sure your resolution matches 9 km
  extentraster2<-raster(e2, resolution=c(0.08333334,0.08333334),
  crs="+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0")
  fetchrast<-resample(fetchrast, extentraster2, "ngb")
  #plot(fetchrast)
  CCMP<-resample(CCMP, extentraster2, "ngb")
  #plot(CCMP)

  Urast<-CCMP[[1]] #raster for wind speed
dirrast<-CCMP[[2]] #raster for wind direction
dirrast[dirrast<0]<-NA #I shouldn't have directional values <0

  #for each fetch direction i, I only want to use wind speed in that direction
  mask_rast<-dirrast
  mask_rast[mask_rast<(directions[i])]<-NA #if < the cutoff for this bin, set NA
  if(i <36){
    mask_rast[mask_rast>=(directions[i+1])]<-NA}
    #if >= the cutoff for the next bin, set NA
new_U <- mask(Urast, mask_rast)
# plot(Urast)
# plot(new_U)

# find nondim fetch in this direction
nondimfetchrast <- overlay(x=fetchrast, y=new_U, fun=nondimfetch)
# plot(nondimfetchrast)

# break into 2 version - subset raster if z<38590
nondim_fetchlim <- nondimfetchrast
nondim_full <- nondimfetchrast

nondim_fetchlim[nondim_fetchlim >= 38590] <- NA
nondim_full[nondim_full < 38590] <- NA

# plot(nondim_fetchlim)
# plot(nondim_full)

# crop wind data based on fetch limited or full seas
wind_fetchlim <- mask(new_U, nondim_fetchlim)
wind_full <- mask(new_U, nondim_full)
# plot(wind_fetchlim)
# plot(wind_full)

# crop fetch datat based on fetch limited or full seas
fetch_fetchlim <- mask(fetchrast, nondim_fetchlim)
fetch_full <- mask(fetchrast, nondim_full)

# for fetch-limited seas,
Hmo_lim <- overlay(x=fetch_fetchlim, y=wind_fetchlim, fun=Hmo, na.rm=T)
# plot(Hmo_lim)
Tm_lim <- overlay(x=fetch_fetchlim, y=wind_fetchlim, fun=Tm, na.rm=T)
# plot(Tm_lim)
WE_lim <- overlay(x=Hmo_lim, fun=WE, na.rm=T)
# plot(WE_lim)

# for fully-developed seas
Hmo_full <- overlay(x=wind_full, fun=Hmofull, na.rm=T)
# plot(Hmo_full)
Tm_full <- overlay(x=wind_full, fun=Tmfull, na.rm=T)
#merge fetch-limited and full seas IN THIS DIRECTION

#saving Hmo, Tm, WE in this fetch directio
#setwd("C:/Users/kmccaffrey2011/Desktop/Research/Exposure/TempRast")
Hmo_rast<-merge(Hmo_lim, Hmo_full)
#plot(Hmo_rast)
#make a stack
Hmo_stack<-stack(Hmo_stack, Hmo_rast) #should end up with 36 layers

Tm_rast<-merge(Tm_lim, Tm_full)
#plot(Tm_rast)
Tm_stack<-stack(Tm_stack, Tm_rast)

WE_rast<-merge(WE_lim, WE_full)
#plot(WE_rast)
WE_stack<-stack(WE_stack, WE_rast)

#update the progress bar
setTxtProgressBar(pb2, i)

} #repeat for all directions, stacks should have 36 layers

close(pb2)
#save the raster stacks for these directions on this day
#Now, let's find the average, min, and max wind energy for each day (k) in each
#pixel, over the fetch directions
WE_avg<-calc(WE_stack, fun=mean, na.rm=T)
WE_min<-calc(WE_stack, fun=min)
WE_max<-calc(WE_stack, fun=max)
WE_sd<-calc(WE_stack, fun=sd, na.rm=T)

Tm_avg<-calc(Tm_stack, fun=mean, na.rm=T)
Tm_min<-calc(Tm_stack, fun=min)
Tm_max<-calc(Tm_stack, fun=max)
Tm_sd<-calc(Tm_stack, fun=sd, na.rm=T)

WE_day_stack<-stack(WE_avg, WE_min, WE_max, WE_sd)
plot(WE_day_stack[[1]], main=paste(k))

Tm_day_stack<-stack(Tm_avg, Tm_min, Tm_max, Tm_sd)

# save the stack
writeRaster(WE_avg, paste(dir.out, "Average_WE_day_", k, ".asc", sep=""),
             format="ascii", overwrite=T)
writeRaster(Tm_avg, paste(dir.out, "Average_Tm_day_", k, ".asc", sep=""),
             format="ascii", overwrite=T)
writeRaster(WE_sd, paste(dir.out, "SD_WE_day_", k, ".asc", sep=""),
            format="ascii", overwrite=T)
writeRaster(Tm_sd, paste(dir.out, "SD_Tm_day_", k, ".asc", sep=""),
            format="ascii", overwrite=T)
writeRaster(WE_max, paste(dir.out, "Max_WE_day_", k, ".asc", sep=""),
            format="ascii", overwrite=T)
writeRaster(Tm_max, paste(dir.out, "Max_Tm_day_", k, ".asc", sep=""),
            format="ascii", overwrite=T)
writeRaster(WE_min, paste(dir.out, "Min_WE_day_", k, ".asc", sep=""),
            format="ascii", overwrite=T)
writeRaster(Tm_min, paste(dir.out, "Min_Tm_day_", k, ".asc", sep=""),
            format="ascii", overwrite=T)

# update the progress bar
setTxtProgressBar(pb1, k)
} # loop through all the wind file days
close(pb1)
### Satellite SST to in-situ SBT model ###
### October 2017 ###
### Kelly McCaffrey ###

# optics ascii projection:
# "+proj=eqc +lat_ts=0 +lat_0=0 +lon_0=0 +x_0=0 +y_0=0 +ellps=WGS84
#+datum=WGS84 +units=m +no_defs"

library(raster)

# pull in SERC table data
setwd("C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/SST Model/Output Files/NewSERCdf")

Jan<-read.csv("Jan.csv")
Feb<-read.csv("Feb.csv")
Mar<-read.csv("Mar.csv")
Ap<-read.csv("Ap.csv")
May<-read.csv("May.csv")
 June<-read.csv("June.csv")
July<-read.csv("July.csv")
Aug<-read.csv("Aug.csv")
Sept<-read.csv("Sept.csv")
 Oct<-read.csv("Oct.csv")
 Nov<-read.csv("Nov.csv")
Dec<-read.csv("Dec.csv")

# these files represent each measurement in a month at each station
# I want to find the average at each station, through time

# first, make files spatial
coordinates(Jan)<-~LONDEC+LATDEC
proj4string(Jan)<-CRS("+proj=longlat +datum=WGS84")
coordinates(Feb)<-~LONDEC+LATDEC
proj4string(Feb)<-CRS("+proj=longlat +datum=WGS84")
coordinates(Mar)<-~LONDEC+LATDEC
proj4string(Mar)<-CRS("+proj=longlat +datum=WGS84")
coordinates(Ap)<-~LONDEC+LATDEC
proj4string(Ap)<-CRS("+proj=longlat +datum=WGS84")
coordinates(May) <- ~LONDEC + LATDEC
proj4string(May) <- CRS("+proj=longlat +datum=WGS84")
coordinates(June) <- ~LONDEC + LATDEC
proj4string(June) <- CRS("+proj=longlat +datum=WGS84")
coordinates(July) <- ~LONDEC + LATDEC
proj4string(July) <- CRS("+proj=longlat +datum=WGS84")
coordinates(Aug) <- ~LONDEC + LATDEC
proj4string(Aug) <- CRS("+proj=longlat +datum=WGS84")
coordinates(Sept) <- ~LONDEC + LATDEC
proj4string(Sept) <- CRS("+proj=longlat +datum=WGS84")
coordinates(Oct) <- ~LONDEC + LATDEC
proj4string(Oct) <- CRS("+proj=longlat +datum=WGS84")
coordinates(Nov) <- ~LONDEC + LATDEC
proj4string(Nov) <- CRS("+proj=longlat +datum=WGS84")
coordinates(Dec) <- ~LONDEC + LATDEC
proj4string(Dec) <- CRS("+proj=longlat +datum=WGS84")

# subset by month and year
Jan05 <- subset(Jan, Jan$YEAR == 2005); Jan06 <- subset(Jan, Jan$YEAR == 2006); Jan07 <- subset(Jan, Jan$YEAR == 2007)
Jan08 <- subset(Jan, Jan$YEAR == 2008); Jan09 <- subset(Jan, Jan$YEAR == 2009); Jan10 <- subset(Jan, Jan$YEAR == 2010)
Jan11 <- subset(Jan, Jan$YEAR == 2011); Jan12 <- subset(Jan, Jan$YEAR == 2012); Jan13 <- subset(Jan, Jan$YEAR == 2013)
Jan14 <- subset(Jan, Jan$YEAR == 2014); Jan15 <- subset(Jan, Jan$YEAR == 2015)
Feb05 <- subset(Feb, Feb$YEAR == 2005); Feb06 <- subset(Feb, Feb$YEAR == 2006); Feb07 <- subset(Feb, Feb$YEAR == 2007)
Feb08 <- subset(Feb, Feb$YEAR == 2008); Feb09 <- subset(Feb, Feb$YEAR == 2009); Feb10 <- subset(Feb, Feb$YEAR == 2010)
Feb11 <- subset(Feb, Feb$YEAR == 2011); Feb12 <- subset(Feb, Feb$YEAR == 2012); Feb13 <- subset(Feb, Feb$YEAR == 2013)
Feb14 <- subset(Feb, Feb$YEAR == 2014); Feb15 <- subset(Feb, Feb$YEAR == 2015)
Mar05 <- subset(Mar, Mar$YEAR == 2005); Mar06 <- subset(Mar, Mar$YEAR == 2006); Mar07 <- subset(Mar, Mar$YEAR == 2007)
Mar08 <- subset(Mar, Mar$YEAR == 2008); Mar09 <- subset(Mar, Mar$YEAR == 2009); Mar10 <- subset(Mar, Mar$YEAR == 2010)
Mar11 <- subset(Mar, Mar$YEAR == 2011); Mar12 <- subset(Mar, Mar$YEAR == 2012); Mar13 <- subset(Mar, Mar$YEAR == 2013)
Mar14 <- subset(Mar, Mar$YEAR == 2014); Mar15 <- subset(Mar, Mar$YEAR == 2015)

May05<-subset(May, May$YEAR==2005); May06<-subset(May, May$YEAR==2006); May07<-subset(May, May$YEAR==2007)
May08<-subset(May, May$YEAR==2008); May09<-subset(May, May$YEAR==2009); May10<-subset(May, May$YEAR==2010)
May11<-subset(May, May$YEAR==2011); May12<-subset(May, May$YEAR==2012); May13<-subset(May, May$YEAR==2013)
May14<-subset(May, May$YEAR==2014); May15<-subset(May, May$YEAR==2015)

June05<-subset(June, June$YEAR==2005); June06<-subset(June, June$YEAR==2006); June07<-subset(June, June$YEAR==2007)
June08<-subset(June, June$YEAR==2008); June09<-subset(June, June$YEAR==2009); June10<-subset(June, June$YEAR==2010)
June11<-subset(June, June$YEAR==2011); June12<-subset(June, June$YEAR==2012); June13<-subset(June, June$YEAR==2013)
June14<-subset(June, June$YEAR==2014); June15<-subset(June, June$YEAR==2015)

July05<-subset(July, July$YEAR==2005); July06<-subset(July, July$YEAR==2006); July07<-subset(July, July$YEAR==2007)
July08<-subset(July, July$YEAR==2008); July09<-subset(July, July$YEAR==2009); July10<-subset(July, July$YEAR==2010)
July11<-subset(July, July$YEAR==2011); July12<-subset(July, July$YEAR==2012); July13<-subset(July, July$YEAR==2013)
July14<-subset(July, July$YEAR==2014); July15<-subset(July, July$YEAR==2015)


Sept05<-subset(Sept, Sept$YEAR==2005);Sept06<-subset(Sept, Sept$YEAR==2006);Sept07<-subset(Sept, Sept$YEAR==2007)
Sept08<-subset(Sept, Sept$YEAR==2008);Sept09<-subset(Sept, Sept$YEAR==2009);Sept10<-subset(Sept, Sept$YEAR==2010)
Sept11<-subset(Sept, Sept$YEAR==2011);Sept12<-subset(Sept, Sept$YEAR==2012);Sept13<-subset(Sept, Sept$YEAR==2013)
Sept14<-subset(Sept, Sept$YEAR==2014);Sept15<-subset(Sept, Sept$YEAR==2015)

Oct05<-subset(Oct, Oct$YEAR==2005);Oct06<-subset(Oct, Oct$YEAR==2006);Oct07<-subset(Oct, Oct$YEAR==2007)

Nov05<-subset(Nov, Nov$YEAR==2005);Nov06<-subset(Nov, Nov$YEAR==2006);Nov07<-subset(Nov, Nov$YEAR==2007)
Nov08<-subset(Nov, Nov$YEAR==2008);Nov09<-subset(Nov, Nov$YEAR==2009);Nov10<-subset(Nov, Nov$YEAR==2010)
Nov11<-subset(Nov, Nov$YEAR==2011);Nov12<-subset(Nov, Nov$YEAR==2012);Nov13<-subset(Nov, Nov$YEAR==2013)
Nov14<-subset(Nov, Nov$YEAR==2014);Nov15<-subset(Nov, Nov$YEAR==2015)

Dec05<-subset(Dec, Dec$YEAR==2005);Dec06<-subset(Dec, Dec$YEAR==2006);Dec07<-subset(Dec, Dec$YEAR==2007)
Dec08<-subset(Dec, Dec$YEAR==2008);Dec09<-subset(Dec, Dec$YEAR==2009);Dec10<-subset(Dec, Dec$YEAR==2010)
Dec11<-subset(Dec, Dec$YEAR==2011);Dec12<-subset(Dec, Dec$YEAR==2012);Dec13<-subset(Dec, Dec$YEAR==2013)
Dec14<-subset(Dec, Dec$YEAR==2014);Dec15<-subset(Dec, Dec$YEAR==2015)

#load in 9km SST satellite data
setwd("G:/Current Research/Data/MODIS Aqua/Mapped/Monthly/9km/processed_sst/tiff")
dir.in<-getwd()
list<-list.files(dir.in, full.name=T)
list<-list[31:162]
stack<-stack(list)

#clip smaller
e<-extent(-85, -78, 23, 28)
stack<-crop(stack, e)
proj4string(stack)<-"+proj=longlat +datum=WGS84"

#break up satellite data stack to months, years
Jan05_sat<-stack[[1]]; Jan06_sat<-stack[[13]]; Jan07_sat<-stack[[25]]
Jan08_sat<-stack[[37]]; Jan09_sat<-stack[[49]]; Jan10_sat<-stack[[61]]
Jan11_sat<-stack[[73]]; Jan12_sat<-stack[[85]]; Jan13_sat<-stack[[97]]
Jan14_sat<-stack[[109]]; Jan15_sat<-stack[[121]]

Feb05_sat<-stack[[2]]; Feb06_sat<-stack[[14]]; Feb07_sat<-stack[[26]]
Feb08_sat<-stack[[38]]; Feb09_sat<-stack[[50]]; Feb10_sat<-stack[[62]]
Feb11_sat<-stack[[74]]; Feb12_sat<-stack[[86]]; Feb13_sat<-stack[[98]]
Feb14_sat<-stack[[110]]; Feb15_sat<-stack[[122]]

Mar05_sat<-stack[[3]]; Mar06_sat<-stack[[15]]; Mar07_sat<-stack[[27]]
Mar08_sat<-stack[[39]]; Mar09_sat<-stack[[51]]; Mar10_sat<-stack[[63]]
Mar11_sat<-stack[[75]]; Mar12_sat<-stack[[87]]; Mar13_sat<-stack[[99]]
Mar14_sat<-stack[[111]]; Mar15_sat<-stack[[123]]


May05_sat<-stack[[5]]; May06_sat<-stack[[17]]; May07_sat<-stack[[29]]
May08_sat<-stack[[41]]; May09_sat<-stack[[53]]; May10_sat<-stack[[65]]
May11_sat<-stack[[77]]; May12_sat<-stack[[89]]; May13_sat<-stack[[101]]
May14_sat<-stack[[113]]; May15_sat<-stack[[125]]

June05_sat<-stack[[6]]; June06_sat<-stack[[18]]; June07_sat<-stack[[30]]
June08_sat<-stack[[42]]; June09_sat<-stack[[54]]; June10_sat<-stack[[66]]
June11_sat<-stack[[78]]; June12_sat<-stack[[90]]; June13_sat<-stack[[102]]
June14_sat<-stack[[114]]; June15_sat<-stack[[126]]

July05_sat<-stack[[7]]; July06_sat<-stack[[19]]; July07_sat<-stack[[31]]
July08_sat<-stack[[43]]; July09_sat<-stack[[55]]; July10_sat<-stack[[67]]
July11_sat<-stack[[79]]; July12_sat<-stack[[91]]; July13_sat<-stack[[103]]
July14_sat<-stack[[115]]; July15_sat<-stack[[127]]
Aug05_sat<-stack[[8]]; Aug06_sat<-stack[[20]]; Aug07_sat<-stack[[32]]
Aug08_sat<-stack[[44]]; Aug09_sat<-stack[[56]]; Aug10_sat<-stack[[68]]
Aug14_sat<-stack[[116]]; Aug15_sat<-stack[[128]]

Sept05_sat<-stack[[9]]; Sept06_sat<-stack[[21]]; Sept07_sat<-stack[[33]]
Sept08_sat<-stack[[45]]; Sept09_sat<-stack[[57]]; Sept10_sat<-stack[[69]]
Sept11_sat<-stack[[81]]; Sept12_sat<-stack[[93]]; Sept13_sat<-stack[[105]]
Sept14_sat<-stack[[117]]; Sept15_sat<-stack[[129]]

Oct05_sat<-stack[[10]]; Oct06_sat<-stack[[22]]; Oct07_sat<-stack[[34]]
Oct08_sat<-stack[[46]]; Oct09_sat<-stack[[58]]; Oct10_sat<-stack[[70]]
Oct14_sat<-stack[[118]]; Oct15_sat<-stack[[130]]

Nov05_sat<-stack[[11]]; Nov06_sat<-stack[[23]]; Nov07_sat<-stack[[35]]
Nov08_sat<-stack[[47]]; Nov09_sat<-stack[[59]]; Nov10_sat<-stack[[71]]
Nov11_sat<-stack[[83]]; Nov12_sat<-stack[[95]]; Nov13_sat<-stack[[107]]
Nov14_sat<-stack[[119]]; Nov15_sat<-stack[[131]]

Dec05_sat<-stack[[12]]; Dec06_sat<-stack[[24]]; Dec07_sat<-stack[[36]]
Dec08_sat<-stack[[48]]; Dec09_sat<-stack[[60]]; Dec10_sat<-stack[[72]]
Dec11_sat<-stack[[84]]; Dec12_sat<-stack[[96]]; Dec13_sat<-stack[[108]]
Dec14_sat<-stack[[120]]; Dec15_sat<-stack[[132]]

#extract satellite temperature values at in-situ locations by months, years

Jan05$SAT.TEMP<-extract(Jan05_sat, Jan05@coords); Jan06$SAT.TEMP<-extract(Jan06_sat, Jan06@coords)
Jan07$SAT.TEMP<-extract(Jan07_sat, Jan07@coords); Jan08$SAT.TEMP<-extract(Jan08_sat, Jan08@coords)
Jan09$SAT.TEMP<-extract(Jan09_sat, Jan09@coords); Jan10$SAT.TEMP<-extract(Jan10_sat, Jan10@coords)
Jan11$SAT.TEMP<-extract(Jan11_sat, Jan11@coords); Jan12$SAT.TEMP<-extract(Jan12_sat, Jan12@coords)
Jan13$SAT.TEMP<-extract(Jan13_sat, Jan13@coords); Jan14$SAT.TEMP<-extract(Jan14_sat, Jan14@coords)
Jan15$SAT.TEMP<-extract(Jan15_sat, Jan15@coords)

Feb05$SAT.TEMP<-extract(Feb05_sat, Feb05@coords); Feb06$SAT.TEMP<-extract(Feb06_sat, Feb06@coords)
Feb07$SAT.TEMP<-extract(Feb07_sat, Feb07@coords); Feb08$SAT.TEMP<-extract(Feb08_sat, Feb08@coords)
Feb09$SAT.TEMP<-extract(Feb09_sat, Feb09@coords); Feb10$SAT.TEMP<-extract(Feb10_sat, Feb10@coords)
Feb11$SAT.TEMP<-extract(Feb11_sat, Feb11@coords); Feb12$SAT.TEMP<-extract(Feb12_sat, Feb12@coords)
Feb13$SAT.TEMP<-extract(Feb13_sat, Feb13@coords); Feb14$SAT.TEMP<-extract(Feb14_sat, Feb14@coords)
Feb15$SAT.TEMP<-extract(Feb15_sat, Feb15@coords)

Mar05$SAT.TEMP<-extract(Mar05_sat, Mar05@coords); Mar06$SAT.TEMP<-extract(Mar06_sat, Mar06@coords)
Mar07$SAT.TEMP<-extract(Mar07_sat, Mar07@coords); Mar08$SAT.TEMP<-extract(Mar08_sat, Mar08@coords)
Mar09$SAT.TEMP<-extract(Mar09_sat, Mar09@coords); Mar10$SAT.TEMP<-extract(Mar10_sat, Mar10@coords)
Mar11$SAT.TEMP<-extract(Mar11_sat, Mar11@coords); Mar12$SAT.TEMP<-extract(Mar12_sat, Mar12@coords)
Mar13$SAT.TEMP<-extract(Mar13_sat, Mar13@coords); Mar14$SAT.TEMP<-extract(Mar14_sat, Mar14@coords)
Mar15$SAT.TEMP<-extract(Mar15_sat, Mar15@coords)

Ap05$SAT.TEMP<-extract(Ap05_sat, Ap05@coords); Ap06$SAT.TEMP<-extract(Ap06_sat, Ap06@coords)

May05$SAT.TEMP<-extract(May05_sat, May05@coords); May06$SAT.TEMP<-extract(May06_sat, May06@coords)
May07$SAT.TEMP<-extract(May07_sat, May07@coords); May08$SAT.TEMP<-extract(May08_sat, May08@coords)
May09$SAT.TEMP<-extract(May09_sat, May09@coords); May10$SAT.TEMP<-extract(May10_sat, May10@coords)
May11$SAT.TEMP<-extract(May11_sat, May11@coords); May12$SAT.TEMP<-extract(May12_sat, May12@coords)
May13$SAT.TEMP<-extract(May13_sat, May13@coords); May14$SAT.TEMP<-extract(May14_sat, May14@coords)
May15$SAT.TEMP<-extract(May15_sat, May15@coords)

June05$SAT.TEMP<-extract(June05_sat, June05@coords); June06$SAT.TEMP<-extract(June06_sat, June06@coords)
June07$SAT.TEMP<-extract(June07_sat, June07@coords); June08$SAT.TEMP<-extract(June08_sat, June08@coords)
June09$SAT.TEMP<-extract(June09_sat, June09@coords); June10$SAT.TEMP<-extract(June10_sat, June10@coords)
June11$SAT.TEMP<-extract(June11_sat, June11@coords); June12$SAT.TEMP<-extract(June12_sat, June12@coords)
June13$SAT.TEMP<-extract(June13_sat, June13@coords); June14$SAT.TEMP<-extract(June14_sat, June14@coords)
June15$SAT.TEMP<-extract(June15_sat, June15@coords)

July05$SAT.TEMP<-extract(July05_sat, July05@coords); July06$SAT.TEMP<-extract(July06_sat, July06@coords)
July07$SAT.TEMP<-extract(July07_sat, July07@coords); July08$SAT.TEMP<-extract(July08_sat, July08@coords)
July09$SAT.TEMP<-extract(July09_sat, July09@coords); July10$SAT.TEMP<-extract(July10_sat, July10@coords)
July11$SAT.TEMP<-extract(July11_sat, July11@coords); July12$SAT.TEMP<-extract(July12_sat, July12@coords)
July13$SAT.TEMP<-extract(July13_sat, July13@coords); July14$SAT.TEMP<-extract(July14_sat, July14@coords)
July15$SAT.TEMP<-extract(July15_sat, July15@coords)

Aug05$SAT.TEMP<-extract(Aug05_sat, Aug05@coords); Aug06$SAT.TEMP<-extract(Aug06_sat, Aug06@coords)
Aug07$SAT.TEMP<-extract(Aug07_sat, Aug07@coords); Aug08$SAT.TEMP<-extract(Aug08_sat, Aug08@coords)
Aug09$SAT.TEMP<-extract(Aug09_sat, Aug09@coords); Aug10$SAT.TEMP<-extract(Aug10_sat, Aug10@coords)
Aug11$SAT.TEMP<-extract(Aug11_sat, Aug11@coords); Aug12$SAT.TEMP<-extract(Aug12_sat, Aug12@coords)
Aug13$SAT.TEMP<-extract(Aug13_sat, Aug13@coords); Aug14$SAT.TEMP<-extract(Aug14_sat, Aug14@coords)
Aug15$SAT.TEMP<-extract(Aug15_sat, Aug15@coords)

Sept05$SAT.TEMP<-extract(Sept05_sat, Sept05@coords); Sept06$SAT.TEMP<-extract(Sept06_sat, Sept06@coords)
Sept07$SAT.TEMP<-extract(Sept07_sat, Sept07@coords); Sept08$SAT.TEMP<-extract(Sept08_sat, Sept08@coords)
Sept09$SAT.TEMP<-extract(Sept09_sat, Sept09@coords); Sept10$SAT.TEMP<-extract(Sept10_sat, Sept10@coords)
Sept11$SAT.TEMP<-extract(Sept11_sat, Sept11@coords); Sept12$SAT.TEMP<-extract(Sept12_sat, Sept12@coords)
Sept13$SAT.TEMP<-extract(Sept13_sat, Sept13@coords); Sept14$SAT.TEMP<-extract(Sept14_sat, Sept14@coords)
Sept15$SAT.TEMP<-extract(Sept15_sat, Sept15@coords)

Oct05$SAT.TEMP<-extract(Oct05_sat, Oct05@coords); Oct06$SAT.TEMP<-extract(Oct06_sat, Oct06@coords)
Oct07$SAT.TEMP<-extract(Oct07_sat, Oct07@coords); Oct08$SAT.TEMP<-extract(Oct08_sat, Oct08@coords)
Oct09$SAT.TEMP<-extract(Oct09_sat, Oct09@coords); Oct10$SAT.TEMP<-extract(Oct10_sat, Oct10@coords)
Oct11$SAT.TEMP<-extract(Oct11_sat, Oct11@coords); Oct12$SAT.TEMP<-extract(Oct12_sat, Oct12@coords)
Oct13$SAT.TEMP<-extract(Oct13_sat, Oct13@coords); Oct14$SAT.TEMP<-extract(Oct14_sat, Oct14@coords)
Oct15$SAT.TEMP<-extract(Oct15_sat, Oct15@coords)

Nov05$SAT.TEMP<-extract(Nov05_sat, Nov05@coords); Nov06$SAT.TEMP<-extract(Nov06_sat, Nov06@coords)
Nov07$SAT.TEMP<-extract(Nov07_sat, Nov07@coords); Nov08$SAT.TEMP<-extract(Nov08_sat, Nov08@coords)
Nov09$SAT.TEMP<-extract(Nov09_sat, Nov09@coords); Nov10$SAT.TEMP<-extract(Nov10_sat, Nov10@coords)
Nov11$SAT.TEMP<-extract(Nov11_sat, Nov11@coords); Nov12$SAT.TEMP<-extract(Nov12_sat, Nov12@coords)
Nov13$SAT.TEMP<-extract(Nov13_sat, Nov13@coords); Nov14$SAT.TEMP<-extract(Nov14_sat, Nov14@coords)
Nov15$SAT.TEMP<-extract(Nov15_sat, Nov15@coords)

Dec05$SAT.TEMP<-extract(Dec05_sat, Dec05@coords); Dec06$SAT.TEMP<-extract(Dec06_sat, Dec06@coords)
Dec07$SAT.TEMP<-extract(Dec07_sat, Dec07@coords); Dec08$SAT.TEMP<-extract(Dec08_sat, Dec08@coords)
Dec09$SAT.TEMP<-extract(Dec09_sat, Dec09@coords); Dec10$SAT.TEMP<-extract(Dec10_sat, Dec10@coords)
Dec11$SAT.TEMP<-extract(Dec11_sat, Dec11@coords); Dec12$SAT.TEMP<-extract(Dec12_sat, Dec12@coords)
Dec13$SAT.TEMP<-extract(Dec13_sat, Dec13@coords); Dec14$SAT.TEMP<-extract(Dec14_sat, Dec14@coords)
Dec15$SAT.TEMP<-extract(Dec15_sat, Dec15@coords)

# I want to aggregate by month and station, 2005-2015. Then, I want to put all of the # months together, and look for the overall relationships

Jan_comb<-rbind(Jan05, Jan06, Jan07, Jan08, Jan09, Jan10, Jan11, Jan12, Jan13, Jan14, Jan15)
Feb_comb<-rbind(Feb05, Feb06, Feb07, Feb08, Feb09, Feb10, Feb11, Feb12, Feb13, Feb14, Feb15)
Mar_comb<-rbind(Mar05, Mar06, Mar07, Mar08, Mar09, Mar10, Mar11, Mar12, Mar13, Mar14, Mar15)
May_comb<-rbind(May05, May06, May07, May08, May09, May10, May11, May12, May13, May14, May15)
June_comb<-rbind(June05, June06, June07, June08, June09, June10, June11, June12, June13, June14, June15)
July_comb<-rbind(July05, July06, July07, July08, July09, July10, July11, July12, July13, July14, July15)
Sept_comb<-rbind(Sept05, Sept06, Sept07, Sept08, Sept09, Sept10, Sept11, Sept12, Sept13, Sept14, Sept15)
Nov_comb<-rbind(Nov05, Nov06, Nov07, Nov08, Nov09, Nov10, Nov11, Nov12, Nov13, Nov14, Nov15)
Dec_comb<-rbind(Dec05, Dec06, Dec07, Dec08, Dec09, Dec10, Dec11, Dec12, Dec13, Dec14, Dec15)

#Jan
test<-aggregate(Jan_comb$TEMP.S, by=list(Jan_comb$STATION), FUN=mean, na.rm=T)
colnames(test)<-c("STATION", "TEMP.S")
test2<-aggregate(Jan_comb$TEMP.B, by=list(Jan_comb$STATION), FUN=mean, na.rm=T)
colnames(test2)<-c("STATION", "TEMP.B")
test3<-aggregate(Jan_comb$SAT.TEMP, by=list(Jan_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(Jan_comb, !duplicated(Jan_comb$STATION), select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Jansumm<-merge(m2, test3, by="STATION")

#Feb
test<-aggregate(Feb_comb$TEMP.S, by=list(Feb_comb$STATION), FUN=mean, na.rm=T)
colnames(test)<-c("STATION", "TEMP.S")
test2<-aggregate(Feb_comb$TEMP.B, by=list(Feb_comb$STATION), FUN=mean, na.rm=T)
colnames(test2)<-c("STATION", "TEMP.B")
test3<-aggregate(Feb_comb$SAT.TEMP, by=list(Feb_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(Feb_comb, !duplicated(Feb_comb$STATION), select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Febsumm<-merge(m2, test3, by="STATION")

#Mar
test<-aggregate(Mar_comb$TEMP.S, by=list(Mar_comb$STATION), FUN=mean, na.rm=T)
colnames(test)<-c("STATION", "TEMP.S")
test2<-aggregate(Mar_comb$TEMP.B, by=list(Mar_comb$STATION), FUN=mean, na.rm=T)
colnames(test2)<-c("STATION", "TEMP.B")
test3<-aggregate(Mar_comb$SAT.TEMP, by=list(Mar_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(Mar_comb, !duplicated(Mar_comb$STATION), select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Marsumm<-merge(m2, test3, by="STATION")
```r
# Ap
test <- aggregate(Ap_comb$TEMP.S, by=list(Ap_comb$STATION), FUN=mean, na.rm=T)
colnames(test) <- c("STATION", "TEMP.S")
test2 <- aggregate(Ap_comb$TEMP.B, by=list(Ap_comb$STATION), FUN=mean, na.rm=T)
colnames(test2) <- c("STATION", "TEMP.B")
test3 <- aggregate(Ap_comb$SAT.TEMP, by=list(Ap_comb$STATION), FUN=mean, na.rm=T)
colnames(test3) <- c("STATION", "SAT.TEMP")
# combine by station
m1 <- merge(stations, test, by="STATION")
m2 <- merge(m1, test2)
Apsumm <- merge(m2, test3, by="STATION")

# May

# June
```
test3<-aggregate(June_comb$SAT.TEMP, by=list(June_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(June_comb, !duplicated(June_comb$STATION), select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Junesumm<-merge(m2, test3, by="STATION")

#July
test<-aggregate(July_comb$TEMP.S, by=list(July_comb$STATION), FUN=mean, na.rm=T)
colnames(test)<-c("STATION", "TEMP.S")
test2<-aggregate(July_comb$TEMP.B, by=list(July_comb$STATION), FUN=mean, na.rm=T)
colnames(test2)<-c("STATION", "TEMP.B")
test3<-aggregate(July_comb$SAT.TEMP, by=list(July_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(July_comb, !duplicated(July_comb$STATION), select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Julysumm<-merge(m2, test3, by="STATION")

#Aug
test<-aggregate(Aug_comb$TEMP.S, by=list(Aug_comb$STATION), FUN=mean, na.rm=T)
colnames(test)<-c("STATION", "TEMP.S")
test2<-aggregate(Aug_comb$TEMP.B, by=list(Aug_comb$STATION), FUN=mean, na.rm=T)
colnames(test2)<-c("STATION", "TEMP.B")
test3<-aggregate(Aug_comb$SAT.TEMP, by=list(Aug_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(Aug_comb, !duplicated(Aug_comb$STATION), select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Augsumm<-merge(m2, test3, by="STATION")

#Sept
test<-aggregate(Sept_comb$TEMP.S, by=list(Sept_comb$STATION), FUN=mean, na.rm=T)
colnames(test)<-c("STATION", "TEMP.S")
test2<-aggregate(Sept_comb$TEMP.B, by=list(Sept_comb$STATION), FUN=mean, na.rm=T)
colnames(test2)<-c("STATION", "TEMP.B")
test3<-aggregate(Sept_comb$SAT.TEMP, by=list(Sept_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(Sept_comb, !duplicated(Sept_comb$STATION), select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Septsumm<-merge(m2, test3, by="STATION")

#Oct
test<-aggregate(Oct_comb$TEMP.S, by=list(Oct_comb$STATION), FUN=mean, na.rm=T)
colnames(test)<-c("STATION", "TEMP.S")
test2<-aggregate(Oct_comb$TEMP.B, by=list(Oct_comb$STATION), FUN=mean, na.rm=T)
colnames(test2)<-c("STATION", "TEMP.B")
test3<-aggregate(Oct_comb$SAT.TEMP, by=list(Oct_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(Oct_comb, !duplicated(Oct_comb$STATION), select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Octsumm<-merge(m2, test3, by="STATION")

#Nov
test<-aggregate(Nov_comb$TEMP.S, by=list(Nov_comb$STATION), FUN=mean, na.rm=T)
colnames(test)<-c("STATION", "TEMP.S")
test2<-aggregate(Nov_comb$TEMP.B, by=list(Nov_comb$STATION), FUN=mean, na.rm=T)
colnames(test2)<-c("STATION", "TEMP.B")
test3<-aggregate(Nov_comb$SAT.TEMP, by=list(Nov_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(Nov_comb, !duplicated(Nov_comb$STATION),
    select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Novsumm<-merge(m2, test3, by="STATION")

#Dec
test<-aggregate(Dec_comb$TEMP.S, by=list(Dec_comb$STATION), FUN=mean, na.rm=T)
colnames(test)<-c("STATION", "TEMP.S")
test2<-aggregate(Dec_comb$TEMP.B, by=list(Dec_comb$STATION), FUN=mean, na.rm=T)
colnames(test2)<-c("STATION", "TEMP.B")
test3<-aggregate(Dec_comb$SAT.TEMP, by=list(Dec_comb$STATION), FUN=mean, na.rm=T)
colnames(test3)<-c("STATION", "SAT.TEMP")
stations<-subset(Dec_comb, !duplicated(Dec_comb$STATION),
    select=c("BASIN", "SEGMENT", "ZONE", "STATION", "SITE", "DEPTH", "MONTH"))
#combine by station
m1<-merge(stations, test, by="STATION")
m2<-merge(m1, test2)
Decsumm<-merge(m2, test3, by="STATION")

#combine
SERC_comb<-rbind(Jansumm, Febsumm, Marsumm, Apsumm, Maysumm, Junesumm, Julysumm, Augsumm, Septsumm, Octsumm, Novsumm, Decsumm)

# setwd("C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/SST
Model/Output Files")
# write.csv(cbind(coordinates(SERC_comb), SERC_comb@data), "Data_9km.csv")
# I want to go from satellite to in-situ sst, in-situ sst to in-situ sbt

# first, y is serc sst, x is satellite
# then, y is sbt, x is sst serc

# First, see if the relationship between SST and satellite SST
t1<-t.test(SERC_comb$TEMP.S, SERC_comb$SAT.TEMP, paired=T) # sig diff
t2<-t.test(SERC_comb$TEMP.S, SERC_comb$TEMP.B, paired=T) # sig diff

lm1<-lm(TEMP.S~SAT.TEMP, data=SERC_comb)
lm2<-lm(TEMP.B~TEMP.S, data=SERC_comb)

newx<-seq(min(SERC_comb$SAT.TEMP, na.rm=T),
          max(SERC_comb$SAT.TEMP, na.rm=T))
newx2<-seq(min(SERC_comb$TEMP.S, na.rm=T),
           max(SERC_comb$TEMP.S, na.rm=T))
pred1<-predict(lm1, newdata=data.frame(SAT.TEMP=newx),
               interval=c("confidence"))
pred2<-predict(lm2, newdata=data.frame(TEMP.S=newx2),interval=c("confidence"))

plot(SERC_comb$TEMP.S~SERC_comb$SAT.TEMP, 
      # col=as.integer(new_SERC_comb$MONTH),
      pch=16, col="black", main="Satellite versus In-Situ Sea-Surface Temperature",
      xlab="Satellite SST (°C)", ylab="SERC SST (°C)"
      polygon(c(rev(newx), newx), c(rev(pred1[,3]), pred1[,2]), col="grey80",
             border=NA)
      abline(lm1, lwd=1)
      lines(newx, pred1[,2], col="black", lty="dashed")
      lines(newx, pred1[,3], col="black", lty="dashed")

plot(SERC_comb$TEMP.B~SERC_comb$TEMP.S, 
      # col=as.integer(new_SERC_comb$MONTH),
      pch=16, col="black", main="In-Situ Sea-Surface versus Sea-Bottom Temperature",
      xlab="SERC SST (°C)", ylab="SERC SBT (°C)"
      polygon(c(rev(newx2), newx2), c(rev(pred2[,3]), pred2[,2]), col="grey80",
             border=NA)
      abline(lm2, lwd=1)
      lines(newx2, pred2[,2], col="black", lty="dashed")
      lines(newx2, pred2[,3], col="black", lty="dashed")
### Transform Data ###

```r
lm1
transf <- function(x, na.rm = T) {
  -1.397 + (1.042 * x)
}

new_Jan05_sat <- calc(Jan05_sat, transf);
new_Jan06_sat <- calc(Jan06_sat, transf);
new_Jan07_sat <- calc(Jan07_sat, transf);
new_Jan08_sat <- calc(Jan08_sat, transf);
new_Jan09_sat <- calc(Jan09_sat, transf);
new_Jan10_sat <- calc(Jan10_sat, transf);
new_Jan11_sat <- calc(Jan11_sat, transf);
new_Jan12_sat <- calc(Jan12_sat, transf);
new_Jan13_sat <- calc(Jan13_sat, transf);
new_Jan14_sat <- calc(Jan14_sat, transf);
new_Jan15_sat <- calc(Jan15_sat, transf);

new_Feb05_sat <- calc(Feb05_sat, transf);
new_Feb06_sat <- calc(Feb06_sat, transf);
new_Feb07_sat <- calc(Feb07_sat, transf);
new_Feb08_sat <- calc(Feb08_sat, transf);
new_Feb09_sat <- calc(Feb09_sat, transf);
new_Feb10_sat <- calc(Feb10_sat, transf);
new_Feb11_sat <- calc(Feb11_sat, transf);
new_Feb12_sat <- calc(Feb12_sat, transf);
new_Feb13_sat <- calc(Feb13_sat, transf);
new_Feb14_sat <- calc(Feb14_sat, transf);
new_Feb15_sat <- calc(Feb15_sat, transf);

new_Mar05_sat <- calc(Mar05_sat, transf);
new_Mar06_sat <- calc(Mar06_sat, transf);
new_Mar07_sat <- calc(Mar07_sat, transf);
new_Mar08_sat <- calc(Mar08_sat, transf);
new_Mar09_sat <- calc(Mar09_sat, transf);
new_Mar10_sat <- calc(Mar10_sat, transf);
new_Mar11_sat <- calc(Mar11_sat, transf);
new_Mar12_sat <- calc(Mar12_sat, transf);
new_Mar13_sat <- calc(Mar13_sat, transf);
new_Mar14_sat <- calc(Mar14_sat, transf);
new_Mar15_sat <- calc(Mar15_sat, transf);

new_Ap05_sat <- calc(Ap05_sat, transf);
new_Ap06_sat <- calc(Ap06_sat, transf);
new_Ap07_sat <- calc(Ap07_sat, transf);
new_Ap08_sat <- calc(Ap08_sat, transf);
new_Ap09_sat <- calc(Ap09_sat, transf);
new_Ap10_sat <- calc(Ap10_sat, transf);
new_Ap11_sat <- calc(Ap11_sat, transf);
new_Ap12_sat <- calc(Ap12_sat, transf);
new_Ap13_sat <- calc(Ap13_sat, transf);
new_Ap14_sat <- calc(Ap14_sat, transf);
new_Ap15_sat <- calc(Ap15_sat, transf);

new_May05_sat <- calc(May05_sat, transf);
new_May06_sat <- calc(May06_sat, transf);
new_May07_sat <- calc(May07_sat, transf);
new_May08_sat <- calc(May08_sat, transf);
new_May09_sat <- calc(May09_sat, transf);
new_May10_sat <- calc(May10_sat, transf);
new_May11_sat <- calc(May11_sat, transf);
new_May12_sat <- calc(May12_sat, transf);
```
new_May13_sat<-calc(May13_sat, transf); new_May14_sat<-calc(May14_sat, transf)
new_May15_sat<-calc(May15_sat, transf)

new_June05_sat<-calc(June05_sat, transf); new_June06_sat<-calc(June06_sat, transf)
new_June07_sat<-calc(June07_sat, transf); new_June08_sat<-calc(June08_sat, transf)
new_June09_sat<-calc(June09_sat, transf); new_June10_sat<-calc(June10_sat, transf)
new_June11_sat<-calc(June11_sat, transf); new_June12_sat<-calc(June12_sat, transf)
new_June13_sat<-calc(June13_sat, transf); new_June14_sat<-calc(June14_sat, transf)
new_June15_sat<-calc(June15_sat, transf)

new_July05_sat<-calc(July05_sat, transf); new_July06_sat<-calc(July06_sat, transf)
new_July07_sat<-calc(July07_sat, transf); new_July08_sat<-calc(July08_sat, transf)
new_July09_sat<-calc(July09_sat, transf); new_July10_sat<-calc(July10_sat, transf)
new_July11_sat<-calc(July11_sat, transf); new_July12_sat<-calc(July12_sat, transf)
new_July13_sat<-calc(July13_sat, transf); new_July14_sat<-calc(July14_sat, transf)
new_July15_sat<-calc(July15_sat, transf)

new_Aug05_sat<-calc(Aug05_sat, transf); new_Aug06_sat<-calc(Aug06_sat, transf)
new_Aug07_sat<-calc(Aug07_sat, transf); new_Aug08_sat<-calc(Aug08_sat, transf)
new_Aug09_sat<-calc(Aug09_sat, transf); new_Aug10_sat<-calc(Aug10_sat, transf)
new_Aug11_sat<-calc(Aug11_sat, transf); new_Aug12_sat<-calc(Aug12_sat, transf)
new_Aug13_sat<-calc(Aug13_sat, transf); new_Aug14_sat<-calc(Aug14_sat, transf)
new_Aug15_sat<-calc(Aug15_sat, transf)

new_Sept05_sat<-calc(Sept05_sat, transf); new_Sept06_sat<-calc(Sept06_sat, transf)
new_Sept07_sat<-calc(Sept07_sat, transf); new_Sept08_sat<-calc(Sept08_sat, transf)
new_Sept09_sat<-calc(Sept09_sat, transf); new_Sept10_sat<-calc(Sept10_sat, transf)
new_Sept11_sat<-calc(Sept11_sat, transf); new_Sept12_sat<-calc(Sept12_sat, transf)
new_Sept13_sat<-calc(Sept13_sat, transf); new_Sept14_sat<-calc(Sept14_sat, transf)
new_Sept15_sat<-calc(Sept15_sat, transf)

new_Oct05_sat<-calc(Oct05_sat, transf); new_Oct06_sat<-calc(Oct06_sat, transf)
new_Oct07_sat<-calc(Oct07_sat, transf); new_Oct08_sat<-calc(Oct08_sat, transf)
new_Oct09_sat<-calc(Oct09_sat, transf); new_Oct10_sat<-calc(Oct10_sat, transf)
new_Oct11_sat<-calc(Oct11_sat, transf); new_Oct12_sat<-calc(Oct12_sat, transf)
new_Oct13_sat<-calc(Oct13_sat, transf); new_Oct14_sat<-calc(Oct14_sat, transf)
new_Oct15_sat<-calc(Oct15_sat, transf)

new_Nov05_sat<-calc(Nov05_sat, transf); new_Nov06_sat<-calc(Nov06_sat, transf)
new_Nov07_sat<-calc(Nov07_sat, transf); new_Nov08_sat<-calc(Nov08_sat, transf)
new_Nov09_sat<-calc(Nov09_sat, transf); new_Nov10_sat<-calc(Nov10_sat, transf)
new_Nov11_sat<-calc(Nov11_sat, transf); new_Nov12_sat<-calc(Nov12_sat, transf)
new_Nov13_sat<-calc(Nov13_sat, transf); new_Nov14_sat<-calc(Nov14_sat, transf)
new_Nov15_sat<-calc(Nov15_sat, transf)

new_Dec05_sat<-calc(Dec05_sat, transf); new_Dec06_sat<-calc(Dec06_sat, transf)
new_Dec07_sat<-calc(Dec07_sat, transf); new_Dec08_sat<-calc(Dec08_sat, transf)
new_Dec09_sat<-calc(Dec09_sat, transf); new_Dec10_sat<-calc(Dec10_sat, transf)
new_Dec11_sat<-calc(Dec11_sat, transf); new_Dec12_sat<-calc(Dec12_sat, transf)
new_Dec13_sat<-calc(Dec13_sat, transf); new_Dec14_sat<-calc(Dec14_sat, transf)
new_Dec15_sat<-calc(Dec15_sat, transf)

lm2
transf2<-function(x, na.rm=T){
  -0.1949+(1.0013 *x)
}

new_Jan05_sat<-calc(new_Jan05_sat, transf2); new_Jan06_sat<-calc(new_Jan06_sat, transf2)
new_Jan07_sat<-calc(new_Jan07_sat, transf2); new_Jan08_sat<-calc(new_Jan08_sat, transf2)
new_Jan09_sat<-calc(new_Jan09_sat, transf2); new_Jan10_sat<-calc(new_Jan10_sat, transf2)
new_Jan11_sat<-calc(new_Jan11_sat, transf2); new_Jan12_sat<-calc(new_Jan12_sat, transf2)
new_Jan13_sat<-calc(new_Jan13_sat, transf2); new_Jan14_sat<-calc(new_Jan14_sat, transf2)
new_Jan15_sat<-calc(new_Jan15_sat, transf2)
new_Feb05_sat<-calc(new_Feb05_sat, transf2); new_Feb06_sat<-calc(new_Feb06_sat, transf2)
new_Feb07_sat<-calc(new_Feb07_sat, transf2); new_Feb08_sat<-calc(new_Feb08_sat, transf2)
new_Feb09_sat<-calc(new_Feb09_sat, transf2); new_Feb10_sat<-calc(new_Feb10_sat, transf2)
new_Feb11_sat<-calc(new_Feb11_sat, transf2); new_Feb12_sat<-calc(new_Feb12_sat, transf2)
new_Feb13_sat<-calc(new_Feb13_sat, transf2); new_Feb14_sat<-calc(new_Feb14_sat, transf2)
new_Feb15_sat<-calc(new_Feb15_sat, transf2)
new_Mar05_sat<-calc(new_Mar05_sat, transf2); new_Mar06_sat<-calc(new_Mar06_sat, transf2)
new_Mar07_sat<-calc(new_Mar07_sat, transf2); new_Mar08_sat<-calc(new_Mar08_sat, transf2)
new_Mar09_sat<-calc(new_Mar09_sat, transf2); new_Mar10_sat<-calc(new_Mar10_sat, transf2)
new_Mar11_sat<-calc(new_Mar11_sat, transf2); new_Mar12_sat<-calc(new_Mar12_sat, transf2)
new_Mar13_sat<-calc(new_Mar13_sat, transf2); new_Mar14_sat<-calc(new_Mar14_sat, transf2)
new_Mar15_sat<-calc(new_Mar15_sat, transf2)
new_Ap05_sat<-calc(new_Ap05_sat, transf2); new_Ap06_sat<-calc(new_Ap06_sat, transf2)
new_Ap07_sat<-calc(new_Ap07_sat, transf2); new_Ap08_sat<-calc(new_Ap08_sat, transf2)
new_Ap09_sat<-calc(new_Ap09_sat, transf2); new_Ap10_sat<-calc(new_Ap10_sat, transf2)
new_Ap11_sat<-calc(new_Ap11_sat, transf2); new_Ap12_sat<-calc(new_Ap12_sat, transf2)
new_Ap13_sat<-calc(new_Ap13_sat, transf2); new_Ap14_sat<-calc(new_Ap14_sat, transf2)
new_Ap15_sat<-calc(new_Ap15_sat, transf2)
new_May05_sat<-calc(new_May05_sat, transf2); new_May06_sat<-calc(new_May06_sat, transf2)
new_May07_sat<-calc(new_May07_sat, transf2); new_May08_sat<-calc(new_May08_sat, transf2)
new_May09_sat<-calc(new_May09_sat, transf2); new_May10_sat<-calc(new_May10_sat, transf2)
new_May11_sat<-calc(new_May11_sat, transf2); new_May12_sat<-calc(new_May12_sat, transf2)
new_May13_sat<-calc(new_May13_sat, transf2); new_May14_sat<-calc(new_May14_sat, transf2)
new_May15_sat<-calc(new_May15_sat, transf2)
new_June05_sat<-calc(new_June05_sat, transf2); new_June06_sat<-calc(new_June06_sat, transf2)
new_June07_sat<-calc(new_June07_sat, transf2); new_June08_sat<-calc(new_June08_sat, transf2)
new_June09_sat<-calc(new_June09_sat, transf2); new_June10_sat<-calc(new_June10_sat, transf2)
new_June11_sat<-calc(new_June11_sat, transf2); new_June12_sat<-calc(new_June12_sat, transf2)
new_June13_sat<-calc(new_June13_sat, transf2); new_June14_sat<-calc(new_June14_sat, transf2)
new_June15_sat<-calc(new_June15_sat, transf2)
new_July05_sat<-calc(new_July05_sat, transf2); new_July06_sat<-calc(new_July06_sat, transf2)
new_July07_sat<-calc(new_July07_sat, transf2); new_July08_sat<-calc(new_July08_sat, transf2)
new_July09_sat<-calc(new_July09_sat, transf2); new_July10_sat<-calc(new_July10_sat, transf2)
new_July11_sat<-calc(new_July11_sat, transf2); new_July12_sat<-calc(new_July12_sat, transf2)
new_July13_sat<-calc(new_July13_sat, transf2); new_July14_sat<-calc(new_July14_sat, transf2)
new_July15_sat<-calc(new_July15_sat, transf2)
new_Aug05_sat<-calc(new_Aug05_sat, transf2); new_Aug06_sat<-calc(new_Aug06_sat, transf2)
new_Aug07_sat<-calc(new_Aug07_sat, transf2); new_Aug08_sat<-calc(new_Aug08_sat, transf2)
new_Aug09_sat<-calc(new_Aug09_sat, transf2); new_Aug10_sat<-
calc(new_Aug10_sat, transf2)
new_Aug11_sat<-calc(new_Aug11_sat, transf2); new_Aug12_sat<-
calc(new_Aug12_sat, transf2)
new_Aug13_sat<-calc(new_Aug13_sat, transf2); new_Aug14_sat<-
calc(new_Aug14_sat, transf2)
new_Aug15_sat<-calc(new_Aug15_sat, transf2)

new_Sept05_sat<-calc(new_Sept05_sat, transf2); new_Sept06_sat<-
calc(new_Sept06_sat, transf2)
new_Sept07_sat<-calc(new_Sept07_sat, transf2); new_Sept08_sat<-
calc(new_Sept08_sat, transf2)
new_Sept09_sat<-calc(new_Sept09_sat, transf2); new_Sept10_sat<-
calc(new_Sept10_sat, transf2)
new_Sept11_sat<-calc(new_Sept11_sat, transf2); new_Sept12_sat<-
calc(new_Sept12_sat, transf2)
new_Sept13_sat<-calc(new_Sept13_sat, transf2); new_Sept14_sat<-
calc(new_Sept14_sat, transf2)
new_Sept15_sat<-calc(new_Sept15_sat, transf2)

new_Oct05_sat<-calc(new_Oct05_sat, transf2); new_Oct06_sat<-
calc(new_Oct06_sat, transf2)
new_Oct07_sat<-calc(new_Oct07_sat, transf2); new_Oct08_sat<-
calc(new_Oct08_sat, transf2)
new_Oct09_sat<-calc(new_Oct09_sat, transf2); new_Oct10_sat<-
calc(new_Oct10_sat, transf2)
new_Oct11_sat<-calc(new_Oct11_sat, transf2); new_Oct12_sat<-
calc(new_Oct12_sat, transf2)
new_Oct13_sat<-calc(new_Oct13_sat, transf2); new_Oct14_sat<-
calc(new_Oct14_sat, transf2)
new_Oct15_sat<-calc(new_Oct15_sat, transf2)

new_Nov05_sat<-calc(new_Nov05_sat, transf2); new_Nov06_sat<-
calc(new_Nov06_sat, transf2)
new_Nov07_sat<-calc(new_Nov07_sat, transf2); new_Nov08_sat<-
calc(new_Nov08_sat, transf2)
new_Nov09_sat<-calc(new_Nov09_sat, transf2); new_Nov10_sat<-
calc(new_Nov10_sat, transf2)
new_Nov11_sat<-calc(new_Nov11_sat, transf2); new_Nov12_sat<-
calc(new_Nov12_sat, transf2)
new_Nov13_sat<-calc(new_Nov13_sat, transf2); new_Nov14_sat<-
calc(new_Nov14_sat, transf2)
new_Nov15_sat<-calc(new_Nov15_sat, transf2)

new_Dec05_sat<-calc(new_Dec05_sat, transf2); new_Dec06_sat<-calc(new_Dec06_sat, transf2)
new_Dec07_sat<-calc(new_Dec07_sat, transf2); new_Dec08_sat<-calc(new_Dec08_sat, transf2)
new_Dec09_sat<-calc(new_Dec09_sat, transf2); new_Dec10_sat<-calc(new_Dec10_sat, transf2)
new_Dec11_sat<-calc(new_Dec11_sat, transf2); new_Dec12_sat<-calc(new_Dec12_sat, transf2)
new_Dec13_sat<-calc(new_Dec13_sat, transf2); new_Dec14_sat<-calc(new_Dec14_sat, transf2)
new_Dec15_sat<-calc(new_Dec15_sat, transf2)

#save new rasters
# dir.out<"C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/SST Model/Output Files/AnnualSSTRasters/9km/
# writeRaster(new_Jan05_sat, paste0(dir.out, "Avg_SBT_equiv_Jan05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan06_sat, paste0(dir.out, "Avg_SBT_equiv_Jan06.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan07_sat, paste0(dir.out, "Avg_SBT_equiv_Jan07.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan08_sat, paste0(dir.out, "Avg_SBT_equiv_Jan08.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan09_sat, paste0(dir.out, "Avg_SBT_equiv_Jan09.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan10_sat, paste0(dir.out, "Avg_SBT_equiv_Jan10.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan11_sat, paste0(dir.out, "Avg_SBT_equiv_Jan11.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan12_sat, paste0(dir.out, "Avg_SBT_equiv_Jan12.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan13_sat, paste0(dir.out, "Avg_SBT_equiv_Jan13.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan14_sat, paste0(dir.out, "Avg_SBT_equiv_Jan14.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Jan15_sat, paste0(dir.out, "Avg_SBT_equiv_Jan15.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Feb05_sat, paste0(dir.out, "Avg_SBT_equiv_Feb05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Feb06_sat, paste0(dir.out, "Avg_SBT_equiv_Feb06.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Feb07_sat, paste0(dir.out, "Avg_SBT_equiv_Feb07.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Feb08_sat, paste0(dir.out, "Avg_SBT_equiv_Feb08.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Feb09_sat, paste0(dir.out, "Avg_SBT_equiv_Feb09.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Feb10_sat, paste0(dir.out, "Avg_SBT_equiv_Feb10.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Feb11_sat, paste0(dir.out, "Avg_SBT_equiv_Feb11.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Feb12_sat, paste0(dir.out, "Avg_SBT_equiv_Feb12.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Feb13_sat, paste0(dir.out, "Avg_SBT_equiv_Feb13.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Feb14_sat, paste0(dir.out, "Avg_SBT_equiv_Feb14.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Feb15_sat, paste0(dir.out, "Avg_SBT_equiv_Feb15.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar05_sat, paste0(dir.out, "Avg_SBT_equiv_Mar05.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar06_sat, paste0(dir.out, "Avg_SBT_equiv_Mar06.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar07_sat, paste0(dir.out, "Avg_SBT_equiv_Mar07.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar08_sat, paste0(dir.out, "Avg_SBT_equiv_Mar08.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar09_sat, paste0(dir.out, "Avg_SBT_equiv_Mar09.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar10_sat, paste0(dir.out, "Avg_SBT_equiv_Mar10.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar11_sat, paste0(dir.out, "Avg_SBT_equiv_Mar11.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar12_sat, paste0(dir.out, "Avg_SBT_equiv_Mar12.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar13_sat, paste0(dir.out, "Avg_SBT_equiv_Mar13.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar14_sat, paste0(dir.out, "Avg_SBT_equiv_Mar14.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Mar15_sat, paste0(dir.out, "Avg_SBT_equiv_Mar15.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Ap05_sat, paste0(dir.out, "Avg_SBT_equiv_Ap05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap06_sat, paste0(dir.out, "Avg_SBT_equiv_Ap06.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap07_sat, paste0(dir.out, "Avg_SBT_equiv_Ap07.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap08_sat, paste0(dir.out, "Avg_SBT_equiv_Ap08.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap09_sat, paste0(dir.out, "Avg_SBT_equiv_Ap09.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap10_sat, paste0(dir.out, "Avg_SBT_equiv_Ap10.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap11_sat, paste0(dir.out, "Avg_SBT_equiv_Ap11.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap12_sat, paste0(dir.out, "Avg_SBT_equiv_Ap12.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap13_sat, paste0(dir.out, "Avg_SBT_equiv_Ap13.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap14_sat, paste0(dir.out, "Avg_SBT_equiv_Ap14.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Ap15_sat, paste0(dir.out, "Avg_SBT_equiv_Ap15.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May05_sat, paste0(dir.out, "Avg_SBT_equiv_May05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May06_sat, paste0(dir.out, "Avg_SBT_equiv_May06.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May07_sat, paste0(dir.out, "Avg_SBT_equiv_May07.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May08_sat, paste0(dir.out, "Avg_SBT_equiv_May08.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May09_sat, paste0(dir.out, "Avg_SBT_equiv_May09.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May10_sat, paste0(dir.out, "Avg_SBT_equiv_May10.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May11_sat, paste0(dir.out, "Avg_SBT_equiv_May11.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May12_sat, paste0(dir.out, "Avg_SBT_equiv_May12.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May13_sat, paste0(dir.out, "Avg_SBT_equiv_May13.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May14_sat, paste0(dir.out, "Avg_SBT_equiv_May14.tif"), format="GTiff", overwrite=T)
# writeRaster(new_May15_sat, paste0(dir.out, "Avg_SBT_equiv_May15.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June05_sat, paste0(dir.out, "Avg_SBT_equiv_June05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June06_sat, paste0(dir.out, "Avg_SBT_equiv_June06.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June07_sat, paste0(dir.out, "Avg_SBT_equiv_June07.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June08_sat, paste0(dir.out, "Avg_SBT_equiv_June08.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June09_sat, paste0(dir.out, "Avg_SBT_equiv_June09.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June10_sat, paste0(dir.out, "Avg_SBT_equiv_June10.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June11_sat, paste0(dir.out, "Avg_SBT_equiv_June11.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June12_sat, paste0(dir.out, "Avg_SBT_equiv_June12.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June13_sat, paste0(dir.out, "Avg_SBT_equiv_June13.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June14_sat, paste0(dir.out, "Avg_SBT_equiv_June14.tif"), format="GTiff", overwrite=T)
# writeRaster(new_June15_sat, paste0(dir.out, "Avg_SBT_equiv_June15.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July05_sat, paste0(dir.out, "Avg_SBT_equiv_July05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July06_sat, paste0(dir.out, "Avg_SBT_equiv_July06.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July07_sat, paste0(dir.out, "Avg_SBT_equiv_July07.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July08_sat, paste0(dir.out, "Avg_SBT_equiv_July08.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July09_sat, paste0(dir.out, "Avg_SBT_equiv_July09.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July10_sat, paste0(dir.out, "Avg_SBT_equiv_July10.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July11_sat, paste0(dir.out, "Avg_SBT_equiv_July11.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July12_sat, paste0(dir.out, "Avg_SBT_equiv_July12.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July13_sat, paste0(dir.out, "Avg_SBT_equiv_July13.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July14_sat, paste0(dir.out, "Avg_SBT_equiv_July14.tif"), format="GTiff", overwrite=T)
# writeRaster(new_July15_sat, paste0(dir.out, "Avg_SBT_equiv_July15.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug05_sat, paste0(dir.out, "Avg_SBT_equiv_Aug05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug06_sat, paste0(dir.out, "Avg_SBT_equiv_Aug06.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug07_sat, paste0(dir.out, "Avg_SBT_equiv_Aug07.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug08_sat, paste0(dir.out, "Avg_SBT_equiv_Aug08.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug09_sat, paste0(dir.out, "Avg_SBT_equiv_Aug09.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug10_sat, paste0(dir.out, "Avg_SBT_equiv_Aug10.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug11_sat, paste0(dir.out, "Avg_SBT_equiv_Aug11.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug12_sat, paste0(dir.out, "Avg_SBT_equiv_Aug12.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug13_sat, paste0(dir.out, "Avg_SBT_equiv_Aug13.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug14_sat, paste0(dir.out, "Avg_SBT_equiv_Aug14.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Aug15_sat, paste0(dir.out, "Avg_SBT_equiv_Aug15.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept05_sat, paste0(dir.out, "Avg_SBT_equiv_Sept05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept06_sat, paste0(dir.out, "Avg_SBT_equiv_Sept06.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept07_sat, paste0(dir.out, "Avg_SBT_equiv_Sept07.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept08_sat, paste0(dir.out, "Avg_SBT_equiv_Sept08.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept09_sat, paste0(dir.out, "Avg_SBT_equiv_Sept09.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept10_sat, paste0(dir.out, "Avg_SBT_equiv_Sept10.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept11_sat, paste0(dir.out, "Avg_SBT_equiv_Sept11.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept12_sat, paste0(dir.out, "Avg_SBT_equiv_Sept12.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept13_sat, paste0(dir.out, "Avg_SBT_equiv_Sept13.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept14_sat, paste0(dir.out, "Avg_SBT_equiv_Sept14.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Sept15_sat, paste0(dir.out, "Avg_SBT_equiv_Sept15.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct05_sat, paste0(dir.out, "Avg_SBT_equiv_Oct05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct06_sat, paste0(dir.out, "Avg_SBT_equiv_Oct06.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct07_sat, paste0(dir.out, "Avg_SBT_equiv_Oct07.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct08_sat, paste0(dir.out, "Avg_SBT_equiv_Oct08.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct09_sat, paste0(dir.out, "Avg_SBT_equiv_Oct09.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct10_sat, paste0(dir.out, "Avg_SBT_equiv_Oct10.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct11_sat, paste0(dir.out, "Avg_SBT_equiv_Oct11.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct12_sat, paste0(dir.out, "Avg_SBT_equiv_Oct12.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct13_sat, paste0(dir.out, "Avg_SBT_equiv_Oct13.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct14_sat, paste0(dir.out, "Avg_SBT_equiv_Oct14.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Oct15_sat, paste0(dir.out, "Avg_SBT_equiv_Oct15.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Nov05_sat, paste0(dir.out, "Avg_SBT_equiv_Nov05.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Nov06_sat, paste0(dir.out, "Avg_SBT_equiv_Nov06.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Nov07_sat, paste0(dir.out, "Avg_SBT_equiv_Nov07.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Nov08_sat, paste0(dir.out, "Avg_SBT_equiv_Nov08.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Nov09_sat, paste0(dir.out, "Avg_SBT_equiv_Nov09.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Nov10_sat, paste0(dir.out, "Avg_SBT_equiv_Nov10.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Nov11_sat, paste0(dir.out, "Avg_SBT_equiv_Nov11.tif"), format="GTiff", overwrite=T)
# writeRaster(new_Nov12_sat, paste0(dir.out, "Avg_SBT_equiv_Nov12.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Nov13_sat, paste0(dir.out, "Avg_SBT_equiv_Nov13.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Nov14_sat, paste0(dir.out, "Avg_SBT_equiv_Nov14.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Nov15_sat, paste0(dir.out, "Avg_SBT_equiv_Nov15.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec05_sat, paste0(dir.out, "Avg_SBT_equiv_Dec05.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec06_sat, paste0(dir.out, "Avg_SBT_equiv_Dec06.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec07_sat, paste0(dir.out, "Avg_SBT_equiv_Dec07.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec08_sat, paste0(dir.out, "Avg_SBT_equiv_Dec08.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec09_sat, paste0(dir.out, "Avg_SBT_equiv_Dec09.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec10_sat, paste0(dir.out, "Avg_SBT_equiv_Dec10.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec11_sat, paste0(dir.out, "Avg_SBT_equiv_Dec11.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec12_sat, paste0(dir.out, "Avg_SBT_equiv_Dec12.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec13_sat, paste0(dir.out, "Avg_SBT_equiv_Dec13.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec14_sat, paste0(dir.out, "Avg_SBT_equiv_Dec14.tif"),
format="GTiff", overwrite=T)
# writeRaster(new_Dec15_sat, paste0(dir.out, "Avg_SBT_equiv_Dec15.tif"),
format="GTiff", overwrite=T)

###find seasonal averages, ranges

dir.in<"C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/SST Model/Output Files/AnnualSSTRasters/9km/
"
dir.out<"C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/SST Model/Result Raster Summaries/9km/
"

files05<list.files(dir.in, pattern="05", full.names=T)
files05
JFMAM05<files05[c(1, 4, 5, 8, 9)]
ASO05<files05[c(2, 11, 12)]
JFMAM05<-stack(JFMAM05)
ASO05<-stack(ASO05)
avg_JFMAM05<-mean(JFMAM05, na.rm=T)
range_JFMAM05<-(max(JFMAM05, na.rm=T)-min(JFMAM05, na.rm=T))
avg_ASO05<-mean(ASO05, na.rm=T)
range_ASO05<-(max(ASO05, na.rm=T)-min(ASO05, na.rm=T))

files06<-list.files(dir.in, pattern="06", full.names=T)
JFMAM06<-files06[c(1, 4, 5, 8, 9)]
ASO06<-files06[c(2, 11, 12)]
JFMAM06<-stack(JFMAM06)
ASO06<-stack(ASO06)
avg_JFMAM06<-mean(JFMAM06, na.rm=T)
range_JFMAM06<-(max(JFMAM06, na.rm=T)-min(JFMAM06, na.rm=T))
avg_ASO06<-mean(ASO06, na.rm=T)
range_ASO06<-(max(ASO06, na.rm=T)-min(ASO06, na.rm=T))

files07<-list.files(dir.in, pattern="07", full.names=T)
JFMAM07<-files07[c(1, 4, 5, 8, 9)]
ASO07<-files07[c(2, 11, 12)]
JFMAM07<-stack(JFMAM07)
ASO07<-stack(ASO07)
avg_JFMAM07<-mean(JFMAM07, na.rm=T)
range_JFMAM07<-(max(JFMAM07, na.rm=T)-min(JFMAM07, na.rm=T))
avg_ASO07<-mean(ASO07, na.rm=T)
range_ASO07<-(max(ASO07, na.rm=T)-min(ASO07, na.rm=T))

files08<-list.files(dir.in, pattern="08", full.names=T)
JFMAM08<-files08[c(1, 4, 5, 8, 9)]
ASO08<-files08[c(2, 11, 12)]
JFMAM08<-stack(JFMAM08)
ASO08<-stack(ASO08)
avg_JFMAM08<-mean(JFMAM08, na.rm=T)
range_JFMAM08<-(max(JFMAM08, na.rm=T)-min(JFMAM08, na.rm=T))
avg_ASO08<-mean(ASO08, na.rm=T)
range_ASO08<-(max(ASO08, na.rm=T)-min(ASO08, na.rm=T))

files09<-list.files(dir.in, pattern="09", full.names=T)
JFMAM09<-files09[c(1, 4, 5, 8, 9)]
ASO09<-files09[c(2, 11, 12)]
JFMAM09<-stack(JFMAM09)
ASO09<-stack(ASO09)
avg_JFMAM09<-mean(JFMAM09, na.rm=T)
range_JFMAM09<-max(JFMAM09, na.rm=T)-min(JFMAM09, na.rm=T)
avg_ASO09<-mean(ASO09, na.rm=T)
range_ASO09<-max(ASO09, na.rm=T)-min(ASO09, na.rm=T)

files10<-list.files(dir.in, pattern="10", full.names=T)
JFMAM10<-files10[c(1, 4, 5, 8, 9)]
ASO10<-files10[c(2, 11, 12)]
JFMAM10<-stack(JFMAM10)
ASO10<-stack(ASO10)
avg_JFMAM10<-mean(JFMAM10, na.rm=T)
range_JFMAM10<-max(JFMAM10, na.rm=T)-min(JFMAM10, na.rm=T)
avg_ASO10<-mean(ASO10, na.rm=T)
range_ASO10<-max(ASO10, na.rm=T)-min(ASO10, na.rm=T)

files11<-list.files(dir.in, pattern="11", full.names=T)
JFMAM11<-files11[c(1, 4, 5, 8, 9)]
ASO11<-files11[c(2, 11, 12)]
JFMAM11<-stack(JFMAM11)
ASO11<-stack(ASO11)
avg_JFMAM11<-mean(JFMAM11, na.rm=T)
range_JFMAM11<-max(JFMAM11, na.rm=T)-min(JFMAM11, na.rm=T)
avg_ASO11<-mean(ASO11, na.rm=T)
range_ASO11<-max(ASO11, na.rm=T)-min(ASO11, na.rm=T)

files12<-list.files(dir.in, pattern="12", full.names=T)
JFMAM12<-files12[c(1, 4, 5, 8, 9)]
ASO12<-files12[c(2, 11, 12)]
JFMAM12<-stack(JFMAM12)
ASO12<-stack(ASO12)
avg_JFMAM12<-mean(JFMAM12, na.rm=T)
range_JFMAM12<-max(JFMAM12, na.rm=T)-min(JFMAM12, na.rm=T)
avg_ASO12<-mean(ASO12, na.rm=T)
range_ASO12<-max(ASO12, na.rm=T)-min(ASO12, na.rm=T)

files13<-list.files(dir.in, pattern="13", full.names=T)
JFMAM13<-files13[c(1, 4, 5, 8, 9)]
ASO13<-files13[c(2, 11, 12)]
JFMAM13<-stack(JFMAM13)
ASO13<-stack(ASO13)
avg_JFMAM13<-mean(JFMAM13, na.rm=T)
range_JFMAM13<-max(JFMAM13, na.rm=T)-min(JFMAM13, na.rm=T)
avg_ASO13<-mean(ASO13, na.rm=T)
range_ASO13 <- (max(ASO13, na.rm = T) - min(ASO13, na.rm = T))

files14 <- list.files(dir.in, pattern = "14", full.names = T)
JFMAM14 <- files14[c(1, 4, 5, 8, 9)]
ASO14 <- files14[c(2, 11, 12)]
JFMAM14 <- stack(JFMAM14)
ASO14 <- stack(ASO14)
avg_JFMAM14 <- mean(JFMAM14, na.rm = T)
range_JFMAM14 <- (max(JFMAM14, na.rm = T) - min(JFMAM14, na.rm = T))
avg_ASO14 <- mean(ASO14, na.rm = T)
range_ASO14 <- (max(ASO14, na.rm = T) - min(ASO14, na.rm = T))

files15 <- list.files(dir.in, pattern = "15", full.names = T)
JFMAM15 <- files15[c(1, 4, 5, 8, 9)]
ASO15 <- files15[c(2, 11, 12)]
JFMAM15 <- stack(JFMAM15)
ASO15 <- stack(ASO15)
avg_JFMAM15 <- mean(JFMAM15, na.rm = T)
range_JFMAM15 <- (max(JFMAM15, na.rm = T) - min(JFMAM15, na.rm = T))
avg_ASO15 <- mean(ASO15, na.rm = T)
range_ASO15 <- (max(ASO15, na.rm = T) - min(ASO15, na.rm = T))

# writeRaster(avg_JFMAM05, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2005.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM06, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2006.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM07, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2007.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM08, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2008.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM09, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2009.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM10, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2010.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM11, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2011.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM12, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2012.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM13, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2013.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM14, paste0(dir.out, 
# "Avg_SBT_equiv_JFMAM_2014.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_JFMAM15, paste0(dir.out, "Avg_SBT_equiv_JFMAM_2015.tif"), format="GTiff", overwrite=T)
# writeRaster(range_JFMAM05, paste0(dir.out, "Range_SBT_equiv_JFMAM_2005.tif"), format="GTiff", overwrite=T)
# writeRaster(range_JFMAM06, paste0(dir.out, "Range_SBT_equiv_JFMAM_2006.tif"), format="GTiff", overwrite=T)
# writeRaster(range_JFMAM07, paste0(dir.out, "Range_SBT_equiv_JFMAM_2007.tif"), format="GTiff", overwrite=T)
# writeRasster(range_JFMAM08, paste0(dir.out, "Range_SBT_equiv_JFMAM_2008.tif"), format="GTiff", overwrite=T)
# writeRasster(range_JFMAM09, paste0(dir.out, "Range_SBT_equiv_JFMAM_2009.tif"), format="GTiff", overwrite=T)
# writeRasster(range_JFMAM10, paste0(dir.out, "Range_SBT_equiv_JFMAM_2010.tif"), format="GTiff", overwrite=T)
# writeRasster(range_JFMAM11, paste0(dir.out, "Range_SBT_equiv_JFMAM_2011.tif"), format="GTiff", overwrite=T)
# writeRasster(range_JFMAM12, paste0(dir.out, "Range_SBT_equiv_JFMAM_2012.tif"), format="GTiff", overwrite=T)
# writeRasster(range_JFMAM13, paste0(dir.out, "Range_SBT_equiv_JFMAM_2013.tif"), format="GTiff", overwrite=T)
# writeRasster(range_JFMAM14, paste0(dir.out, "Range_SBT_equiv_JFMAM_2014.tif"), format="GTiff", overwrite=T)
# writeRasster(range_JFMAM15, paste0(dir.out, "Range_SBT_equiv_JFMAM_2015.tif"), format="GTiff", overwrite=T)
#
# writeRaster(avg_ASO05, paste0(dir.out, "Avg_SBT_equiv_ASO_2005.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_ASO06, paste0(dir.out, "Avg_SBT_equiv_ASO_2006.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_ASO07, paste0(dir.out, "Avg_SBT_equiv_ASO_2007.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_ASO08, paste0(dir.out, "Avg_SBT_equiv_ASO_2008.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_ASO09, paste0(dir.out, "Avg_SBT_equiv_ASO_2009.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_ASO10, paste0(dir.out, "Avg_SBT_equiv_ASO_2010.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_ASO11, paste0(dir.out, "Avg_SBT_equiv_ASO_2011.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_ASO12, paste0(dir.out, "Avg_SBT_equiv_ASO_2012.tif"), format="GTiff", overwrite=T)
# writeRaster(avg_ASO13, paste0(dir.out, "Avg_SBT_equiv_ASO_2013.tif"),
# format="GTiff", overwrite=T)
# writeRaster(avg_ASO14, paste0(dir.out, "Avg_SBT_equiv_ASO_2014.tif"),
# format="GTiff", overwrite=T)
# writeRaster(avg_ASO15, paste0(dir.out, "Avg_SBT_equiv_ASO_2015.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO05, paste0(dir.out, "Range_SBT_equiv_ASO_2005.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO06, paste0(dir.out, "Range_SBT_equiv_ASO_2006.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO07, paste0(dir.out, "Range_SBT_equiv_ASO_2007.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO08, paste0(dir.out, "Range_SBT_equiv_ASO_2008.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO09, paste0(dir.out, "Range_SBT_equiv_ASO_2009.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO10, paste0(dir.out, "Range_SBT_equiv_ASO_2010.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO11, paste0(dir.out, "Range_SBT_equiv_ASO_2011.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO12, paste0(dir.out, "Range_SBT_equiv_ASO_2012.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO13, paste0(dir.out, "Range_SBT_equiv_ASO_2013.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO14, paste0(dir.out, "Range_SBT_equiv_ASO_2014.tif"),
# format="GTiff", overwrite=T)
# writeRaster(range_ASO15, paste0(dir.out, "Range_SBT_equiv_ASO_2015.tif"),
# format="GTiff", overwrite=T)

JFMAM_avg_All<-mean(avg_JFMAM05, avg_JFMAM06, avg_JFMAM07,
avg_JFMAM08, avg_JFMAM09,
  avg_JFMAM10, avg_JFMAM11, avg_JFMAM12, avg_JFMAM13,
  avg_JFMAM14, avg_JFMAM15, na.rm=T)
JFMAM_range_All<-mean(range_JFMAM05, range_JFMAM06,
range_JFMAM07, range_JFMAM08, range_JFMAM09,
  range_JFMAM10, range_JFMAM11, range_JFMAM12,
range_JFMAM13,
  range_JFMAM14, range_JFMAM15, na.rm=T)
ASO_avg_All<-mean(avg_ASO05, avg_ASO06, avg_ASO07, avg_ASO08,
avg_ASO09, avg_ASO10,
  avg_ASO11, avg_ASO12, avg_ASO13, avg_ASO14, avg_ASO15,
na.rm=T)
ASO_range_All<-mean(range_ASO05, range_ASO06, range_ASO07, 
range_ASO08, range_ASO09, range_ASO10, 
range_ASO11, range_ASO12, range_ASO13, 
range_ASO14, range_ASO15, na.rm=T)

# writeRaster(JFMAM_avg_All, paste0(dir.out, 
"Avg_SBT_equiv_JFMAM_2005_2015.tif"), format="GTiff", overwrite=T) 
# writeRaster(ASO_avg_All, paste0(dir.out, 
"Avg_SBT_equiv_ASO_2005_2015.tif"), format="GTiff", overwrite=T) 
# writeRaster(JFMAM_range_All, paste0(dir.out, 
"Avg_Range_SBT_equiv_JFMAM_2005_2015.tif"), format="GTiff", overwrite=T) 
# writeRaster(ASO_range_All, paste0(dir.out, 
"Avg_Range_SBT_equiv_ASO_2005_2015.tif"), format="GTiff", overwrite=T)

### find annual average, range 
dir.in<-"C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/SST 
Model/Output Files/AnnualSSTRasters/9km/" 
dir.out<-"C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/SST 
Model/Result Raster Summaries/9km/" 
files05<-list.files(dir.in, pattern="05", full.names=T) 
stack05<-files05[c(1:12)] 
stack05<-stack(stack05) 
avg05<-mean(stack05, na.rm=T) 
range05<-(max(stack05, na.rm=T)-min(stack05, na.rm=T))

files06<-list.files(dir.in, pattern="06", full.names=T) 
stack06<-files06[c(1:12)] 
stack06<-stack(stack06) 
avg06<-mean(stack06, na.rm=T) 
range06<-(max(stack06, na.rm=T)-min(stack06, na.rm=T))

files07<-list.files(dir.in, pattern="07", full.names=T) 
stack07<-files07[c(1:12)] 
stack07<-stack(stack07) 
avg07<-mean(stack07, na.rm=T) 
range07<-(max(stack07, na.rm=T)-min(stack07, na.rm=T))

files08<-list.files(dir.in, pattern="08", full.names=T) 
stack08<-files08[c(1:12)] 
stack08<-stack(stack08) 
avg08<-mean(stack08, na.rm=T) 
range08<-(max(stack08, na.rm=T)-min(stack08, na.rm=T))
files09 <- list.files(dir.in, pattern = "09", full.names = T)
stack09 <- files09[c(1:12)]
stack09 <- stack(stack09)
avg09 <- mean(stack09, na.rm = T)
range09 <- (max(stack09, na.rm = T) - min(stack09, na.rm = T))

files10 <- list.files(dir.in, pattern = "10", full.names = T)
stack10 <- files10[c(1:12)]
stack10 <- stack(stack10)
avg10 <- mean(stack10, na.rm = T)
range10 <- (max(stack10, na.rm = T) - min(stack10, na.rm = T))

files11 <- list.files(dir.in, pattern = "11", full.names = T)
stack11 <- files11[c(1:12)]
stack11 <- stack(stack11)
avg11 <- mean(stack11, na.rm = T)
range11 <- (max(stack11, na.rm = T) - min(stack11, na.rm = T))

files12 <- list.files(dir.in, pattern = "12", full.names = T)
stack12 <- files12[c(1:12)]
stack12 <- stack(stack12)
avg12 <- mean(stack12, na.rm = T)
range12 <- (max(stack12, na.rm = T) - min(stack12, na.rm = T))

files13 <- list.files(dir.in, pattern = "13", full.names = T)
stack13 <- files13[c(1:12)]
stack13 <- stack(stack13)
avg13 <- mean(stack13, na.rm = T)
range13 <- (max(stack13, na.rm = T) - min(stack13, na.rm = T))

files14 <- list.files(dir.in, pattern = "14", full.names = T)
stack14 <- files14[c(1:12)]
stack14 <- stack(stack14)
avg14 <- mean(stack14, na.rm = T)
range14 <- (max(stack14, na.rm = T) - min(stack14, na.rm = T))

files15 <- list.files(dir.in, pattern = "15", full.names = T)
stack15 <- files15[c(1:12)]
stack15 <- stack(stack15)
avg15 <- mean(stack15, na.rm = T)
range15 <- (max(stack15, na.rm = T) - min(stack15, na.rm = T))
# writeRaster(avg05, paste0(dir.out, "Avg_SBT_equiv_2005.tif"), format="GTiff", overwrite=T)
# writeRaster(avg06, paste0(dir.out, "Avg_SBT_equiv_2006.tif"), format="GTiff", overwrite=T)
# writeRaster(avg07, paste0(dir.out, "Avg_SBT_equiv_2007.tif"), format="GTiff", overwrite=T)
# writeRaster(avg08, paste0(dir.out, "Avg_SBT_equiv_2008.tif"), format="GTiff", overwrite=T)
# writeRaster(avg09, paste0(dir.out, "Avg_SBT_equiv_2009.tif"), format="GTiff", overwrite=T)
# writeRaster(avg10, paste0(dir.out, "Avg_SBT_equiv_2010.tif"), format="GTiff", overwrite=T)
# writeRaster(avg11, paste0(dir.out, "Avg_SBT_equiv_2011.tif"), format="GTiff", overwrite=T)
# writeRaster(avg12, paste0(dir.out, "Avg_SBT_equiv_2012.tif"), format="GTiff", overwrite=T)
# writeRaster(avg13, paste0(dir.out, "Avg_SBT_equiv_2013.tif"), format="GTiff", overwrite=T)
# writeRaster(avg14, paste0(dir.out, "Avg_SBT_equiv_2014.tif"), format="GTiff", overwrite=T)
# writeRaster(avg15, paste0(dir.out, "Avg_SBT_equiv_2015.tif"), format="GTiff", overwrite=T)

#
# writeRaster(range05, paste0(dir.out, "Range_SBT_equiv_2005.tif"), format="GTiff", overwrite=T)
# writeRaster(range06, paste0(dir.out, "Range_SBT_equiv_2006.tif"), format="GTiff", overwrite=T)
# writeRaster(range07, paste0(dir.out, "Range_SBT_equiv_2007.tif"), format="GTiff", overwrite=T)
# writeRaster(range08, paste0(dir.out, "Range_SBT_equiv_2008.tif"), format="GTiff", overwrite=T)
# writeRaster(range09, paste0(dir.out, "Range_SBT_equiv_2009.tif"), format="GTiff", overwrite=T)
# writeRaster(range10, paste0(dir.out, "Range_SBT_equiv_2010.tif"), format="GTiff", overwrite=T)
# writeRaster(range11, paste0(dir.out, "Range_SBT_equiv_2011.tif"), format="GTiff", overwrite=T)
# writeRaster(range12, paste0(dir.out, "Range_SBT_equiv_2012.tif"), format="GTiff", overwrite=T)
# writeRaster(range13, paste0(dir.out, "Range_SBT_equiv_2013.tif"),
format="GTiff", overwrite=T)
# writeRaster(range14, paste0(dir.out, "Range_SBT_equiv_2014.tif"),
format="GTiff", overwrite=T)
# writeRaster(range15, paste0(dir.out, "Range_SBT_equiv_2015.tif"),
format="GTiff", overwrite=T)

avg_all<-mean(avg05, avg06, avg07, avg08, avg09, avg10, avg11, avg12, avg13,
avg14, avg15, na.rm=T)

avg_range_all<-mean(range05, range06, range07, range08, range09, range10,
range11, range12, range13, range14, range15, na.rm=T)

# writeRaster(avg_all, paste0(dir.out, "Avg_SBT_equiv_2005_2015.tif"),
format="GTiff", overwrite=T)
# writeRaster(avg_range_all, paste0(dir.out,
"Avg_Range_SBT_equiv_2005_2015.tif"), format="GTiff", overwrite=T)
R CODE: RHOHAT ANALYSIS

###Niche Project Rhohat Analysis###
###Using satellite data and modeled sbt-equivalent###
###Kelly McCaffrey###
###October 2017###

```r
rm(list=ls())
#load necessary libraries
library(maptools)
library(dismo)
library(rgdal)
library(raster)
library(spatstat)
library(sp)

setwd("C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/Data/")

#load and subset data
AllCorals<-read.csv("AllCorals2016B.csv")
ACERV<-subset(AllCorals, AllCorals$Species==1)
All_Bleached<-subset(AllCorals, AllCorals$Bleaching >1)
ACERV_Bleached<-subset(ACERV, ACERV$Bleaching >1)
All_Diseased<-AllCorals[AllCorals$Disease!="",]
ACERV_Diseased<-ACERV[ACERV$Disease!="",]

#only go through 2015, to match rest of data
AllCorals<-subset(AllCorals, AllCorals$Batch<16)
ACERV<-subset(ACERV, ACERV$Batch<16)
All_Bleached<-subset(All_Bleached, All_Bleached$Batch<16)
ACERV_Bleached<-subset(ACERV_Bleached, ACERV_Bleached$Batch<16)
All_Diseased<-subset(All_Diseased, All_Diseased$Batch<16)
ACERV_Diseased<-subset(ACERV_Diseased, ACERV_Diseased$Batch<16)

#get rid of sites that aren't correctly geo-referenced
#L2150 & L2151
AllCorals<-subset(AllCorals, AllCorals$Code != "L2150" & AllCorals$Code != "L2151")
ACERV<-subset(ACERV, ACERV$Code != "L2150" & ACERV$Code != "L2151")
```

All_Bleached<-subset(All_Bleached, All_Bleached$Code != "L2150" & All_Bleached$Code != "L2151")
ACERV_Bleached<-subset(ACERV_Bleached, ACERV_Bleached$Code != "L2150" & ACERV_Bleached$Code != "L2151")
All_Diseased<-subset(All_Diseased, All_Diseased$Code != "L2150" & All_Diseased$Code != "L2151")
ACERV_Diseased<-subset(ACERV_Diseased, ACERV_Diseased$Code != "L2150" & ACERV_Diseased$Code != "L2151")

###Get a map of Florida###
library(rworldmap)
library(rworldxtra)
library(sp)
FLOutplantMap<-getMap(resolution="high")

#read in satellite data, 9km
#SBT equivalent
setwd("C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/SST Model/Result Raster Summaries/9km/")
setwd("C:/Users/kmccaffrey2011/Desktop/Research/Niche Project/SST Model/Result Raster Summaries/9km/")
ASO_Avg_SBT_2005_2015<-raster("Avg_SBT_equiv_ASO_2005_2015.tif")
JFMAM_Avg_SBT_2005_2015<-raster("Avg_SBT_equiv_JFMAM_2005_2015.tif")

Ann_Avg_SBT_2005_2015<-projectRaster(Ann_Avg_SBT_2005_2015, crs=’+proj=longlat +south +ellps=WGS84 +units=m +no_defs’)
ASO_Avg_SBT_2005_2015<-projectRaster(ASO_Avg_SBT_2005_2015, crs=’+proj=longlat +south +ellps=WGS84 +units=m +no_defs’)
JFMAM_Avg_SBT_2005_2015<-projectRaster(JFMAM_Avg_SBT_2005_2015, crs=’+proj=longlat +south +ellps=WGS84 +units=m +no_defs’)

#Chla
setwd("G:/Current Research/Data/MODIS Aqua Rasters/Annual 2005 to 2016/chlor_a/")
Ann_Avg_Chla_2005_2015<-raster("AnnualChlaMean2005_2015_9km.tif")
setwd("G:/Current Research/Data/MODIS Aqua Rasters/Seasonal 2005 to 2016/chla/")
ASO_Avg_Chla_2005_2015<-raster("ASOChlaAvg2005_2015_9km.tif")
JFMAM_Avg_Chla_2005_2015<-raster("JFMAMChlaAvg2005_2015_9km.tif")
Ann_Avg_Chla_2005_2015<-projectRaster(Ann_Avg_Chla_2005_2015, 
crs="+proj=longlat +south +ellps=WGS84 +units=m +no_defs")
ASO_Avg_Chla_2005_2015<-projectRaster(ASO_Avg_Chla_2005_2015, 
crs="+proj=longlat +south +ellps=WGS84 +units=m +no_defs")
JFMAM_Avg_Chla_2005_2015<-projectRaster(JFMAM_Avg_Chla_2005_2015, 
crs="+proj=longlat +south +ellps=WGS84 +units=m +no_defs")

#PAR
setwd("G:/Current Research/Data/MODIS Aqua Rasters/Annual 2005 to 
2016/PAR/")
Ann_Avg_PAR_2005_2015<-raster("AnnualPARMean2005_2015_9km.tif")
setwd("G:/Current Research/Data/MODIS Aqua Rasters/Seasonal 2005 to 
2016/PAR/")
ASO_Avg_PAR_2005_2015<-raster("ASOPARAvg2005_2015_9km.tif")
JFMAM_Avg_PAR_2005_2015<-raster("JFMAMPARAvg2005_2015_9km.tif")

proj4string(Ann_Avg_PAR_2005_2015)<- "+proj=longlat +datum=WGS84 
+no_defs +ellps=WGS84 +towgs84=0,0,0"

Ann_Avg_PAR_2005_2015<-projectRaster(Ann_Avg_PAR_2005_2015, 
crs="+proj=longlat +south +ellps=WGS84 +units=m +no_defs")
ASO_Avg_PAR_2005_2015<-projectRaster(ASO_Avg_PAR_2005_2015, 
crs="+proj=longlat +south +ellps=WGS84 +units=m +no_defs")
JFMAM_Avg_PAR_2005_2015<-projectRaster(JFMAM_Avg_PAR_2005_2015, 
crs="+proj=longlat +south +ellps=WGS84 +units=m +no_defs")

#Wave Exposure
setwd("G:/Current Research/Data/Wind_Summary_Rasters/9km/1987_2015/Wave 
Energy/")
Avg_Wave_Energy_1987_2015<-
  raster("Average_Wave_Energy_9km_1987_2015.tif")
proj4string(Avg_Wave_Energy_1987_2015)<- "+proj=longlat +datum=WGS84 
+no_defs +ellps=WGS84 +towgs84=0,0,0"
Avg_Wave_Energy_1987_2015<-projectRaster(Avg_Wave_Energy_1987_2015, 
crs="+proj=longlat +south +ellps=WGS84 +units=m +no_defs")

#make everything an image to match rhohat formatting
library(geostatsp)
ASO_Avg_SBT_2005_2015.img<-as.im(ASO_Avg_SBT_2005_2015)
JFMAM_Avg_SBT_2005_2015.img<-as.im(JFMAM_Avg_SBT_2005_2015)
ASO_Avg_Chla_2005_2015.img <- as.im(ASO_Avg_Chla_2005_2015)
JFMAM_Avg_Chla_2005_2015.img <- as.im(JFMAM_Avg_Chla_2005_2015)
ASO_Avg_PAR_2005_2015.img <- as.im(ASO_Avg_PAR_2005_2015)
JFMAM_Avg_PAR_2005_2015.img <- as.im(JFMAM_Avg_PAR_2005_2015)

#################################

All Corals

AllCorals$Date <- as.Date(AllCorals$Date, format = "%m/%d/%Y")
AllJFMAM <- subset(AllCorals, AllCorals$Date > ("2004-12-31"))
AllJFMAM <- subset(AllJFMAM, AllJFMAM$Month == "January" |
  AllJFMAM$Month == "February" |
  AllJFMAM$Month == "March" | AllJFMAM$Month == "April"|
  AllJFMAM$Month == "May")

AllASO <- subset(AllCorals, AllCorals$Date > ("2004-12-31"))
AllASO <- subset(AllASO, AllASO$Month == "August" |
  AllASOS$Month == "September" |
  AllASOS$Month == "October")

All_Bleached$Date <- as.Date(All_Bleached$Date, format = "%m/%d/%Y")
All_BleachedJFMAM <- subset(All_Bleached, All_Bleached$Date > ("2004-12-31"))
All_BleachedJFMAM <- subset(All_BleachedJFMAM,
  All_BleachedJFMAM$Month == "January" |
  All_BleachedJFMAM$Month == "February" |
  All_BleachedJFMAM$Month == "March" |
  All_BleachedJFMAM$Month == "April" |
  All_BleachedJFMAM$Month == "May")

All_BleachedASO <- subset(All_Bleached, All_Bleached$Date > ("2004-12-31"))
All_BleachedASO <- subset(All_BleachedASO,
  All_BleachedASO$Month == "August" |
  All_BleachedASO$Month == "September" |
  All_BleachedASO$Month == "October")

All_Diseased$Date <- as.Date(All_Diseased$Date, format = "%m/%d/%Y")
All_DiseasedJFMAM <- subset(All_Diseased, All_Diseased$Date > ("2004-12-31"))
All_DiseasedJFMAM <- subset(All_DiseasedJFMAM,
  All_DiseasedJFMAM$Month == "January" |
  All_DiseasedJFMAM$Month == "February" |
All_DiseasedJFMAM$Month=="March" | All_DiseasedJFMAM$Month=="April" | All_DiseasedJFMAM$Month=="May"

All_DiseasedASO<-subset(All_Diseased, All_Diseased$Date> ("2004-12-31"))
All_DiseasedASO<-subset(All_DiseasedASO,
All_DiseasedASO$Month=="August"|All_Diseased$Month=="September"| All_DiseasedASO$Month=="October")

#remove duplicated sites
AllJFMAM<-subset(AllJFMAM, !duplicated(AllJFMAM$Code))
AllASO<-subset(AllASO, !duplicated(AllASO$Code))
All_BleachedJFMAM<-subset(All_BleachedJFMAM,
!duplicated(All_BleachedJFMAM$Code))
All_BleachedASO<-subset(All_BleachedASO,
!duplicated(All_BleachedASO$Code))
All_DiseasedJFMAM<-subset(All_DiseasedJFMAM,
!duplicated(All_DiseasedJFMAM$Code))
All_DiseasedASO<-subset(All_DiseasedASO,
!duplicated(All_DiseasedASO$Code))

#crs then ppp
xy<-data.frame(AllJFMAM$Longitude, AllJFMAM$Latitude)
AllJFMAM<-SpatialPoints(coords=xy, proj4string=CRS("+proj=longlat +south
+ellps=WGS84 +units=m +no_defs"))
#AllJFMAMCRS<-spTransform(xy, CRS("+proj=utm +zone=17n ellps=WGS84"))

xy<-data.frame(AllASO$Longitude, AllASO$Latitude)
AllASO<-SpatialPoints(coords=xy, proj4string=CRS("+proj=longlat +south
+ellps=WGS84 +units=m +no_defs"))

xy<-data.frame(All_BleachedJFMAM$Longitude, All_BleachedJFMAM$Latitude)
All_BleachedJFMAM<-SpatialPoints(coords=xy, proj4string=CRS("+proj=longlat
+south +ellps=WGS84 +units=m +no_defs"))

xy<-data.frame(All_BleachedASO$Longitude, All_BleachedASO$Latitude)
All_BleachedASO<-SpatialPoints(coords=xy, proj4string=CRS("+proj=longlat
+south +ellps=WGS84 +units=m +no_defs"))

xy<-data.frame(All_DiseasedJFMAM$Longitude, All_DiseasedJFMAM$Latitude)
All_DiseasedJFMAM<-SpatialPoints(coords=xy, proj4string=CRS("+proj=longlat
+south +ellps=WGS84 +units=m +no_defs"))

xy<-data.frame(All_DiseasedASO$Longitude, All_DiseasedASO$Latitude)
All_DiseasedASO<-SpatialPoints(coords=xy, proj4string=CRS("+proj=longlat
+south +ellps=WGS84 +units=m +no_defs"))
```r
xy<-data.frame(All_DiseasedASO$Longitude, All_DiseasedASO$Latitude)
All_DiseasedASO<-SpatialPoints(coords=xy, proj4string=CRS('+proj=longlat +south +ellps=WGS84 +units=m +no_defs'))

All_JFMAM<-as.ppp(AllJFMAM)
All_ASO<-as.ppp(AllASO)
All_BleachedJFMAM<-as.ppp(All_BleachedJFMAM)
All_BleachedASO<-as.ppp(All_BleachedASO)
All_DiseasedJFMAM<-as.ppp(All_DiseasedJFMAM)
All_DiseasedASO<-as.ppp(All_DiseasedASO)

###rhohat analysis
###All Corals

#Wave Energy
All_Coral_ppp<-superimpose(All_JFMAM, All_ASO)
All_Coral_ppp<-All_Coral_ppp[!duplicated(All_Coral_ppp)]

All_Coral_Bleached_ppp<-superimpose(All_BleachedJFMAM, All_BleachedASO)
All_Coral_Bleached_ppp<-All_Coral_Bleached_ppp[!duplicated(All_Coral_Bleached_ppp)]

All_Coral_Diseased_ppp<-superimpose(All_DiseasedJFMAM, All_DiseasedASO)
All_Coral_Diseased_ppp<-All_Coral_Diseased_ppp[!duplicated(All_Coral_Diseased_ppp)]

Test1<-rhohat(All_Coral_ppp, Avg_Wave_Energy_1987_2015.img, smoother='kernel')
Test2<-rhohat(All_Coral_Bleached_ppp, Avg_Wave_Energy_1987_2015.img, smoother='kernel')
Test3<-rhohat(All_Coral_Diseased_ppp, Avg_Wave_Energy_1987_2015.img, smoother='kernel')

ylim=c(0, 1800),
xlim=c(0, 7),
par(mfrow=c(1, 3))
plot(Test1, main=expression(bold(Coral~Species~Occurence)),
     ylim=c(1,1700),
     xlim=c(0,8),
     col='blue')
```

cex.lab=1.4,
cex.axis=1.3,
xlab=expression(paste("Wave Energy (Joules)")),
ylab=expression(paste(rho, "(x)")),
legend=F)
plot(Test2, main=expression(bold(Coral~Bleaching)),
  ylim=c(1,1700),
  xlim=c(0,8),
  cex.lab=1.4,
  cex.axis=1.3,
  xlab=expression(paste("Wave Energy (Joules)")),
  ylab=expression(paste(rho, "(x)")),
  legend=F)
plot(Test3, main=expression(bold(Coral~Disease~Prevalence)),
  ylim=c(1,1700),
  xlim=c(0,8),
  cex.lab=1.4,
  cex.axis=1.3,
  xlab=expression(paste("Wave Energy (Joules)")),
  ylab=expression(paste(rho, "(x)")),
  legend=F)

#Chla
Test1<-rhohat(All_JFMAM, JFMAM_Avg_Chla_2005_2015.img,
  smoother='kernel')
Test2<-rhohat(All_BleachedJFMAM, JFMAM_Avg_Chla_2005_2015.img,
  smoother='kernel')
Test3<-rhohat(All_DiseasedJFMAM, JFMAM_Avg_Chla_2005_2015.img,
  smoother='kernel')

Test4<-rhohat(All_ASO, ASO_Avg_Chla_2005_2015.img, smoother='kernel')
Test5<-rhohat(All_BleachedASO, ASO_Avg_Chla_2005_2015.img, smoother='kernel')
Test6<-rhohat(All_DiseasedASO, ASO_Avg_Chla_2005_2015.img, smoother='kernel')

par(mfrow=c(1, 3))
#WINTER
plot(Test1, main=expression(bold(Winter~Coral~Species~Occurrence)),
  ylim=c(0,625),
  xlim=c(0,4.2),
  cex.lab=1.4,
cex.axis=1.3,
  xlab=expression(paste("Chlorophyll a (mg m"^"-3","")) ),
  ylab=expression(paste(rho, "(x)")),
  legend=F)
plot(Test2, main=expression(bold(Winter~Coral~Bleaching)),
  ylim=c(0,625),
  xlim=c(0,4.2),
  cex.lab=1.4,
  cex.axis=1.3,
  xlab=expression(paste("Chlorophyll a (mg m"^"-3","")) ),
  ylab=expression(paste(rho, "(x)")),
  legend=F)
plot(Test3, main=expression(bold(Winter~Coral~Disease~Prevalence)),
  ylim=c(0,625),
  xlim=c(0,4.2),
  cex.lab=1.4,
  cex.axis=1.3,
  xlab=expression(paste("Chlorophyll a (mg m"^"-3","")) ),
  ylab=expression(paste(rho, "(x)")),
  legend=F)

#SUMMER
plot(Test4, main=expression(bold(Summer~Coral~Species~Occurence)),
  ylim=c(0,625),
  xlim=c(0,4.2),
  cex.lab=1.4,
  cex.axis=1.3,
  xlab=expression(paste("Chlorophyll a (mg m"^"-3","")) ),
  ylab=expression(paste(rho, "(x)")),
  legend=F)
plot(Test5, main=expression(bold(Summer~Coral~Bleaching)),
  ylim=c(0,625),
  xlim=c(0,4.2),
  cex.lab=1.4,
  cex.axis=1.3,
  xlab=expression(paste("Chlorophyll a (mg m"^"-3","")) ),
  ylab=expression(paste(rho, "(x)")),
  legend=F)
plot(Test6, main=expression(bold(Summer~Coral~Disease~Prevalence)),
  ylim=c(0,625),
  xlim=c(0,4.2),
cex.lab=1.4,
cex.axis=1.3,
xlab=expression(paste("Chlorophyll a (mg m"^"-3","))",
ylab=expression(paste(rho, "(x)")),
legend=F)

#PAR
Test1<-rhohat(All_JFMAM, JFMAM_Avg_PAR_2005_2015.img,
smoother='kernel')
Test2<-rhohat(All_BleachedJFMAM, JFMAM_Avg_PAR_2005_2015.img,
smoother='kernel')
Test3<-rhohat(All_DiseasedJFMAM, JFMAM_Avg_PAR_2005_2015.img,
smoother='kernel')

Test4<-rhohat(All_ASO, ASO_Avg_PAR_2005_2015.img, smoother='kernel')
Test5<-rhohat(All_BleachedASO, ASO_Avg_PAR_2005_2015.img,
smoother='kernel')
Test6<-rhohat(All_DiseasedASO, ASO_Avg_PAR_2005_2015.img,
smoother='kernel')

#WINTER
plot(Test1, main=expression(bold(Winter~Coral~Species~Occurence)),
 ylim=c(0,1000),
 xlim=c(36, 46),
 cex.lab=1.4,
 cex.axis=1.3,
 xlab=expression(paste("PAR (Einstein m"^"-2"," d"^"-1","))",
ylab=expression(paste(rho, "(x)")),
legend=F)
plot(Test2, main=expression(bold(Winter~Coral~Bleaching)),
 ylim=c(0,1000),
 xlim=c(36, 46),
 cex.lab=1.4,
 cex.axis=1.3,
 xlab=expression(paste("PAR (Einstein m"^"-2"," d"^"-1","))",
ylab=expression(paste(rho, "(x)")),
legend=F)
plot(Test3, main=expression(bold(Winter~Coral~Disease~Prevalence)),
 ylim=c(0,1000),
 xlim=c(36, 46),
 cex.lab=1.4,
 cex.axis=1.3,
xlab=expression(paste("PAR \text{ (Einstein m}^{\text{-2}} \text{ d}^{\text{-1}}\)),
ylab=expression(paste(\(\rho\) \((x)\)));
legend=F)

#SUMMER
plot(Test4, main=expression(bold(Summer~Coral~Species~Occurence)),
     ylim=c(0,1000),
     xlim=c(36, 46),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("PAR \text{ (Einstein m}^{\text{-2}} \text{ d}^{\text{-1}}\)),
     ylab=expression(paste(\(\rho\) \((x)\)));
     legend=F)
plot(Test5, main=expression(bold(Summer~Coral~Bleaching)),
ylim=c(0,1000),
xlim=c(36, 46),
cex.lab=1.4,
cex.axis=1.3,
xlab=expression(paste("PAR \text{ (Einstein m}^{\text{-2}} \text{ d}^{\text{-1}}\)),
ylab=expression(paste(\(\rho\) \((x)\)));
legend=F)
plot(Test6, main=expression(bold(Summer~Coral~Disease~Prevalence)),
ylim=c(0,1000),
xlim=c(36, 46),
cex.lab=1.4,
cex.axis=1.3,
xlab=expression(paste("PAR \text{ (Einstein m}^{\text{-2}} \text{ d}^{\text{-1}}\)),
ylab=expression(paste(\(\rho\) \((x)\)));
legend=F)

#SBT
Test1<-rhohat(All_JFMAM, JFMAM_Avg_SBT_2005_2015.img, smoother='kernel')
Test2<-rhohat(All_BleachedJFMAM, JFMAM_Avg_SBT_2005_2015.img, smoother='kernel')
Test3<-rhohat(All_DiseasedJFMAM, JFMAM_Avg_SBT_2005_2015.img, smoother='kernel')
Test4<-rhohat(All_ASO, ASO_Avg_SBT_2005_2015.img, smoother='kernel')
Test5<-rhohat(All_BleachedASO, ASO_Avg_SBT_2005_2015.img, smoother='kernel')
Test6<-rhoHat(All_DiseasedASO, ASO_Avg_SBT_2005_2015.img, smoother='kernel')

"Temperature [°,degree,"C"]"

#WINTER
plot(Test1, main=expression(bold(Winter~Coral~Species~Occurence)),
     ylim=c(0,5500),
     xlim=c(24, 26),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("Modelled Sea Bottom Temperature (" , degree, "C")")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)
plot(Test2, main=expression(bold(Winter~Coral~Bleaching)),
     ylim=c(0,5500),
     xlim=c(24, 26),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("Modelled Sea Bottom Temperature (" , degree, "C")")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)
plot(Test3, main=expression(bold(Winter~Coral~Disease~Prevalence)),
     ylim=c(0,5500),
     xlim=c(24, 26),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("Modelled Sea Bottom Temperature (" , degree, "C")")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)

#SUMMER
plot(Test4, main=expression(bold(Summer~Coral~Species~Occurence)),
     ylim=c(0,5500),
     xlim=c(24, 26),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("Modelled Sea Bottom Temperature (" , degree, "C")")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)
plot(Test5, main=expression(bold(Summer~Coral~Bleaching)),
     ylim=c(0,5500),
     xlim=c(24, 26),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("Modelled Sea Bottom Temperature (" , degree, "C")")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)
xlim=c(24, 26),
cex.lab=1.4,
cex.axis=1.3,
xlab=expression(paste("Modelled Sea Bottom Temperature (", degree, "C"))),
ylab=expression(paste(rho, "(x)")),
legend=F)
plot(Ttest6, main=expression(bold(Summer~Coral~Disease~Prevalence)),
ylim=c(0,5500),
xlim=c(24, 26),
cex.lab=1.4,
cex.axis=1.3,
xlab=expression(paste("Modelled Sea Bottom Temperature (", degree, "C"))),
ylab=expression(paste(rho, "(x)")),
legend=F)

#~~~~~~~~~~~~~~~~~~~~~~~~ACERV~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
ACERVSDate<-as.Date(ACERV$Date, format="%m/%d/%Y")
ACERVJFMAM<-subset(ACERV, ACERVSDate>"2004-12-31")
ACERVJFMAM<-subset(ACERVJFMAM, ACERVJFMAM$Month=="January" | ACERVJFMAM$Month=="February" | ACERVJFMAM$Month=="March" | ACERVJFMAM$Month=="April" | ACERVJFMAM$Month=="May") #30
ACERVASO<-subset(ACERV, ACERV$Date>"2004-12-31")
ACERVASO<-subset(ACERVASO, ACERVASO$Month=="August" | ACERVASO$Month=="September" | ACERVASO$Month=="October") #578

ACERV_BleachedSDate<-as.Date(ACERV_Bleached$Date, format="%m/%d/%Y")
ACERV_BleachedJFMAM<-subset(ACERV_Bleached, ACERV_BleachedSDate>"2004-12-31")
ACERV_BleachedJFMAM<-subset(ACERV_BleachedJFMAM, ACERV_BleachedJFMAM$Month=="January" | ACERV_BleachedJFMAM$Month=="February" | ACERV_BleachedJFMAM$Month=="March" | ACERV_BleachedJFMAM$Month=="April" | ACERV_BleachedJFMAM$Month=="May")
ACERV_BleachedASO<-subset(ACERV_Bleached, ACERV_BleachedSDate>"2004-12-31") #0
ACERV_BleachedASO<-subset(ACERV_BleachedASO,
ACERV_BleachedASO$Month=="August" |
ACERV_BleachedASO$Month=="September" |
    ACERV_BleachedASO$Month=="October") #116

ACERV_Diseased$Date<-as.Date(ACERV_Diseased$Date, format="%m/%d/%Y")
ACERV_DiseasedJFMAM<-subset(ACERV_Diseased,
ACERV_Diseased$Date>("2004-12-31"))
ACERV_DiseasedJFMAM<-subset(ACERV_DiseasedJFMAM,
ACERV_DiseasedJFMAM$Month=="January" |
ACERV_DiseasedJFMAM$Month=="February" |
    ACERV_DiseasedJFMAM$Month=="March" |
ACERV_DiseasedJFMAM$Month=="April" |
ACERV_DiseasedJFMAM$Month=="May")
ACERV_DiseasedASO<-subset(ACERV_Diseased,
ACERV_Diseased$Date>("2004-12-31")) #no JFMAM
ACERV_DiseasedASO<-subset(ACERV_DiseasedASO,
ACERV_DiseasedASO$Month=="August" |
ACERV_DiseasedASO$Month=="September" |
    ACERV_DiseasedASO$Month=="October") #17

#remove duplicated sites
ACERVJFMAM<-subset(ACERVJFMAM, !duplicated(ACERVJFMAM$Code)) #15
ACERVASO<-subset(ACERVASO, !duplicated(ACERVASO$Code)) #144
#ACERV_BleachedJFMAM<-subset(ACERV_BleachedJFMAM,
#   !duplicated(ACERV_BleachedJFMAM$Code))
ACERV_BleachedASO<-subset(ACERV_BleachedASO,
!duplicated(ACERV_BleachedASO$Code)) #34
#ACERV_DiseasedJFMAM<-subset(ACERV_DiseasedJFMAM,
#   !duplicated(ACERV_DiseasedJFMAM$Code))
ACERV_DiseasedASO<-subset(ACERV_DiseasedASO,
!duplicated(ACERV_DiseasedASO$Code)) #8

#crs then ppp
xy<-data.frame(ACERVJFMAM$Longitude, ACERVJFMAM$Latitude)
ACERVJFMAM<-SpatialPoints(coords=xy, proj4string=CRS('+proj=longlat +south +ellps=WGS84 +units=m +no_defs'))
xy<-data.frame(ACERVASO$Longitude, ACERVASO$Latitude)
ACERVASO<-SpatialPoints(coords=xy, proj4string=CRS('+proj=longlat +south +ellps=WGS84 +units=m +no_defs'))
# xy<-data.frame(ACERV_BleachedJFMAM$Longitude, ACERV_BleachedJFMAM$Latitude)
# ACERV_BleachedJFMAM<-SpatialPoints(coords=xy, proj4string=CRS('+proj=longlat +south +ellps=WGS84 +units=m +no_defs'))
xy<-data.frame(ACERV_BleachedASO$Longitude, ACERV_BleachedASO$Latitude)
ACERV_BleachedASO<-SpatialPoints(coords=xy, proj4string=CRS('+proj=longlat +south +ellps=WGS84 +units=m +no_defs'))
# xy<-data.frame(ACERV_DiseasedJFMAM$Longitude, ACERV_DiseasedJFMAM$Latitude)
# ACERV_DiseasedJFMAM<-SpatialPoints(coords=xy, proj4string=CRS('+proj=longlat +south +ellps=WGS84 +units=m +no_defs'))
xy<-data.frame(ACERV_DiseasedASO$Longitude, ACERV_DiseasedASO$Latitude)
ACERV_DiseasedASO<-SpatialPoints(coords=xy, proj4string=CRS('+proj=longlat +south +ellps=WGS84 +units=m +no_defs'))

ACERVJFMAM<-as.ppp(ACERVJFMAM)
ACERVASO<-as.ppp(ACERVASO)
#ACERV_BleachedJFMAM<-as.ppp(ACERV_BleachedJFMAM)
ACERV_BleachedASO<-as.ppp(ACERV_BleachedASO)
#ACERV_DiseasedJFMAM<-as.ppp(ACERV_DiseasedJFMAM)
ACERV_DiseasedASO<-as.ppp(ACERV_DiseasedASO)

#rhohat

#Wave Energy
All_ACERV_ppp<-superimpose(ACERVJFMAM, ACERVASO)
All_ACERV_ppp<-All_ACERV_ppp[!duplicated(All_ACERV_ppp)]
All_ACERV_Bleached_ppp<-ACERV_BleachedASO
All_ACERV_Bleached_ppp<-All_ACERV_Bleached_ppp[!duplicated(All_ACERV_Bleached_ppp)]
All_ACERV_Diseased_ppp<-ACERV_DiseasedASO
All_ACERV_Diseased_ppp<-All_ACERV_Diseased_ppp[!duplicated(All_ACERV_Diseased_ppp)]

Test1<-rhohat(All_ACERV_ppp, Avg_Wave_Energy_1987_2015.img, smoother='kernel')
Test2<-rhohat(All_ACERV_Bleached_ppp, Avg_Wave_Energy_1987_2015.img, smoother='kernel')
Test3<-rhohat(All_ACERV_Diseased_ppp, Avg_Wave_Energy_1987_2015.img, smoother='kernel')

#ylim=c(0, 1800),
xlim=c(0, 7),

par(mfrow=c(1, 3))
plot(Test1, main=expression(italic(Acropora~cervicornis)~Occurence), ylim=c(0,200), 
xlim=c(0,8),
cex.lab=1.4, 
cex.axis=1.3, 
xlab=expression(paste("Wave Energy (Joules)")), 
ylab=expression(paste(rho, "(x)")),
legend=F)
plot(Test2, main=expression(italic(Acropora~cervicornis)~Bleaching), ylim=c(0,200), 
xlim=c(0,8),
cex.lab=1.4, 
cex.axis=1.3, 
xlab=expression(paste("Wave Energy (Joules)")), 
ylab=expression(paste(rho, "(x)")),
legend=F)
plot(Test3, main=expression(italic(Acropora~cervicornis)~Disease~Prevalence), ylim=c(0,200), 
xlim=c(0,8),
cex.lab=1.4, 
cex.axis=1.3, 
xlab=expression(paste("Wave Energy (Joules)")), 
ylab=expression(paste(rho, "(x)")),
legend=F)

#Chla
Test1<-rhohat(ACERVJFMAM, JFMAM_Avg_Chla_2005_2015.img, smoother='kernel')
#Test2<-rhohat(All_BleachedJFMAM, JFMAM_Avg_Chla_2005_2015.img, smoother='kernel')
#Test3<-rhohat(All_DiseasedJFMAM, JFMAM_Avg_Chla_2005_2015.img, smoother='kernel')

Test4<-rhohat(ACERVASO, ASO_Avg_Chla_2005_2015.img, smoother='kernel')
Test5<-rhohat(ACERV_BleachedASO, ASO_Avg_Chla_2005_2015.img, smoother='kernel')
Test6<-rhohat(ACERV_DiseasedASO, ASO_Avg_Chla_2005_2015.img, smoother='kernel')

#WINTER
plot(Test1, main=expression(Winter~italic(Acropora~cervicornis)~Occurence),
     ylim=c(0,625),
     xlim=c(0,4.2),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("Chlorophyll a (mg m"^"-3",")")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)
# plot(Test2, main=expression(bold(Winter~Coral~Bleaching)),
#     ylim=c(0,625),
#     xlim=c(0,4.2),
#     cex.lab=1.4,
#     cex.axis=1.3,
#     xlab=expression(paste("Chlorophyll a (mg m"^"-3",")")),
#     ylab=expression(paste(rho, "(x)")),
#     legend=F)
# plot(Test3, main=expression(bold(Winter~Coral~Disease~Prevalence)),
#     ylim=c(0,625),
#     xlim=c(0,4.2),
#     cex.lab=1.4,
#     cex.axis=1.3,
#     xlab=expression(paste("Chlorophyll a (mg m"^"-3",")")),
#     ylab=expression(paste(rho, "(x)")),
#     legend=F)
par(mfrow=c(1, 3))

#SUMMER
plot(Test4, main=expression(Summer~italic(Acropora~cervicornis)~Occurence),
     ylim=c(0,100),
     xlim=c(0,2.6),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("Chlorophyll a (mg m"^"-3",")")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)
plot(Test5, main=expression(Summer~italic(Acropora~cervicornis)~Bleaching),
ylim=c(0,100),
xlim=c(0,2.6),
cex.lab=1.4,
cex.axis=1.3,
lab=expression(paste("Chlorophyll a (mg m"^-3","")),
ylab=expression(paste(rho, "(x)")),
legend=F)
plot(Test6,
main=expression(Summer~italic(Acropora~cervicornis)~Disease~Prevalence),
ylim=c(0,100),
xlim=c(0,2.6),
cex.lab=1.4,
cex.axis=1.3,
lab=expression(paste("Chlorophyll a (mg m"^-3","")),
ylab=expression(paste(rho, "(x)")),
legend=F)

#SBT
Test1<-rhohat(ACERVJFMAM, JFMAM_Avg_SBT_2005_2015.img,
smoother='kernel')
#Test2<-rhohat(All_BleachedJFMAM, JFMAM_Avg_Chla_2005_2015.img,
smoother='kernel')
#Test3<-rhohat(All_DiseasedJFMAM, JFMAM_Avg_Chla_2005_2015.img,
smoother='kernel')
Test4<-rhohat(ACERVASO, ASO_Avg_SBT_2005_2015.img, smoother='kernel')
Test5<-rhohat(ACERV_BleachedASO, ASO_Avg_SBT_2005_2015.img, smoother='kernel')
Test6<-rhohat(ACERV_DiseasedASO, ASO_Avg_SBT_2005_2015.img, smoother='kernel')

#WINTER
plot(Test1, main=expression(Winter~italic(Acropora~cervicornis)~Occurrence),
ylim=c(),
xlim=c(),
cex.lab=1.4,
cex.axis=1.3,
lab=expression(paste("Modelled Sea Bottom Temperature (", degree, "C")),
ylab=expression(paste(rho, "(x)")),
legend=F)
#SUMMER
par(mfrow=c(1, 3))
#SUMMER
plot(Test4, main=expression(Summer~italic(Acropora~cervicornis)~Occurence),
ylim=c(0,600),
xlim=c(24,26),
cex.lab=1.4,
cex.axis=1.3,
xlab=expression(paste("Modelled Sea Bottom Temperature (", degree, "C"))),
ylab=expression(paste(rho, "(x)")),
legend=F)
plot(Test5, main=expression(Summer~italic(Acropora~cervicornis)~Bleaching),
ylim=c(0,600),
xlim=c(24,26),
cex.lab=1.4,
cex.axis=1.3,
xlab=expression(paste("Modelled Sea Bottom Temperature (", degree, "C"))),
ylab=expression(paste(rho, "(x)")),
legend=F)
plot(Test6, main=expression(Summer~italic(Acropora~cervicornis)~Disease~Prevalence),
ylim=c(0,600),
xlim=c(24,26),
cex.lab=1.4,
cex.axis=1.3,
xlab=expression(paste("Modelled Sea Bottom Temperature (", degree, "C"))),
ylab=expression(paste(rho, "(x)")),
legend=F)

#PAR
Test1<-rhohat(ACERVJFMAM, JFMAM_Avg_PAR_2005_2015.img,
smoother='kernel')
#Test2<-rhohat(All_BleachedJFMAM, JFMAM_Avg_Chla_2005_2015.img,
smoother='kernel')
#Test3<-rhohat(All_DiseasedJFMAM, JFMAM_Avg_Chla_2005_2015.img,
smoother='kernel')

Test4<-rhohat(ACERVASO, ASO_Avg_PAR_2005_2015.img, smoother='kernel')
Test5<-rhohat(ACERV_BleachedASO, ASO_Avg_PAR_2005_2015.img, smoother='kernel')
Test6<-rhohat(ACERV_DiseasedASO, ASO_Avg_PAR_2005_2015.img, smoother='kernel')
#WINTER
plot(Test1, main=expression(Winter~italic(Acropora~cervicornis)~Occurence),
     ylim=c(),
     xlim=c(),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("PAR (Einstein \(m^{-2} \cdot d^{-1}\))")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)

#SUMMER
par(mfrow=c(1, 3))

#SUMMER
plot(Test4, main=expression(Summer~italic(Acropora~cervicornis)~Occurence),
     ylim=c(0,200),
     xlim=c(35,46),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("PAR (Einstein \(m^{-2} \cdot d^{-1}\))")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)
plot(Test5, main=expression(Summer~italic(Acropora~cervicornis)~Bleaching),
     ylim=c(0,200),
     xlim=c(35,46),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("PAR (Einstein \(m^{-2} \cdot d^{-1}\))")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)
plot(Test6,
     main=expression(Summer~italic(Acropora~cervicornis)~Disease~Prevalence),
     ylim=c(0,200),
     xlim=c(35,46),
     cex.lab=1.4,
     cex.axis=1.3,
     xlab=expression(paste("PAR (Einstein \(m^{-2} \cdot d^{-1}\))")),
     ylab=expression(paste(rho, "(x)")),
     legend=F)
### Florida reef tract, SDM Models, 9 km Annual Mean Example ###
### Acropora cervicornis, building with FRRP and SCREAM data (Steven Miller) ###

```r
# load required libraries
library(dismo)
library(sp)
library(raster)
library(rgdal)
library(mgcv)

# read FRRP location data
FRRP <- read.csv("AllCorals2016B.csv")
# I only want 2005-2015
FRRP <- subset(FRRP, FRRP$Batch < 16)
ACERV_FRRP <- subset(FRRP, FRRP$Species == 1)
FRRP_back <- subset(FRRP, FRRP$Species != 1)

# Load in SCREAM data
SCREAM <- read.csv("SCREAM Data.csv")
# I want 2005-2015
SCREAM <- subset(SCREAM, SCREAM$Year > 2004)
ACERV_SC <- subset(SCREAM, SCREAM$Density..col.m2..ACRV > 0) # 209
SCREAM_back <- subset(SCREAM, SCREAM$Density..col.m2..ACRV == 0) # 1737

ACERV_FRRP <- ACERV_FRRP[, c("Latitude", "Longitude")]
FRRP_back <- FRRP_back[, c("Latitude", "Longitude")]

# remove duplicate points
coordinates(ACERV_FRRP) ~<~ Longitude + Latitude
coordinates(FRRP_back) ~<~ Longitude + Latitude
```

R CODE: NICHE MODEL EXAMPLE
proj4string(FRRP_back)<"+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0"
proj4string(SCREAM_back)<"+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0"
proj4string(ACERV_SC)<"+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0"
proj4string(ACERV_FRRP)<"+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0"

ACERVpres<-rbind(ACERV_FRRP, ACERV_SC)
backg<-rbind(FRRP_back, SCREAM_back)

ACERVpres<-remove.duplicates(ACERVpres) #366
backg<-remove.duplicates(backg) #3869

###load in environmental data###
#chla - annual
AnnAvgChla2005_2015<-raster("AnnualChlaMean2005_2015_9km.tif")
#PAR - annual
AnnAvgPAR2005_2015<-raster("AnnualPARMean2005_2015_9km.tif")
proj4string(AnnAvgPAR2005_2015)<"+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0"
#kd490 - annual
AnnAvgKd4902005_2015<-raster("AnnualKd490Mean2005_2015_9km.tif")
#SBT equivalent- annual
#wave energy 1987-2015 summaries
AvgWaveEnergy1987_2015<-
raster("Average_Wave_Energy_9km_1987_2015.tif")
proj4string(AvgWaveEnergy1987_2015)<"+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0 "

###load in habitat layer###
#took FWC habitat shapefile to R, made 9, 4, and 1km rasters of zone
#based on the max total area of the attribute values per each cell
#(may underestimate coral area)
reef_zone<--raster("ZoneRaster_9km.tif")
reef_zone[reef_zone==128]<-NA
reef_zone<--projectRaster(reef_zone, crs="+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0")
reef_zone_matrix<-as.matrix(reef_zone)
reef_zone_matrix<-round(reef_zone_matrix, 0)
rast<-raster(e=extent(reef_zone), res=res(reef_zone))
proj4string(rast)<-"+proj=longlat +datum=WGS84 +no_def +ellps=WGS84 
+towgs84=0,0,0"
values(rast)<-reef_zone_matrix
reef_zone<-rast

##use original FWC unified reef tract to clip to only CR and hardbottom
reef<-readOGR(".","UnifiedFloridaReefTract_poly")
reef<-spTransform(reef, "+proj=longlat +datum=WGS84 +no_def +ellps=WGS84 
+towgs84=0,0,0")

#load in raster to mask study area
Mask<-raster("Mask.tif")

###load in GEBCO Depth
Depth2<-raster("GEBCO2014_-90.0_12.0_-60.0_29.0_30Sec_Geotiff.tif")
Depth2[Depth2>0]<-NA
Depth2<-Depth2*(-1)

###resample depth to 9 km resolution
e2<-extent(AvgWaveEnergy1987_2015)
Depthm<-crop(Depth2, e2)
extentraster2<-raster(e2, resolution=c(0.08333334,0.08333334), crs="+proj=longlat 
+datum=WGS84 +no_def +ellps=WGS84 +towgs84=0,0,0")
Depthm2<-resample(Depthm, extentraster2, method="bilinear")
Depthm<-crop(Depthm2, e2)
Mask<-extend(Mask, e2)
Mask<-resample(Mask, extentraster2, method="bilinear")
Mask<-crop(Mask, e2)

#extend, and resample all rasters to match origins
pred1<-stack(AnnAvgChla2005_2015, AnnAvgKd4902005_2015, 
pred2<-reef_zone
extentraster3<-raster(e, resolution=c(0.08333334,0.08333334), crs="+proj=longlat 
+datum=WGS84 +no_def +ellps=WGS84 +towgs84=0,0,0")
pred1<-resample(pred1, extentraster3, method="bilinear") #because this data is 
continuous, I don't care if new values are created
pred2 <- resample(pred2, extentRaster3, method = "ngb") # this data is categorical, I don't want new values to be created
predictors <- stack(pred1, pred2, AvgWaveEnergy1987_2015)
pred <- mask(predictors, Depthm_K)
Depthm <- mask(Depthm, Depthm_K)
Depthm[Depthm > 100] <- NA
predictors <- stack(pred, Depthm)
AnnMeanPreds <- predictors

library(dismo)
# extract predictor values at presence locations and at absence locations (background)
presvals <- extract(AnnMeanPreds, ACERVpres)
backvals <- extract(AnnMeanPreds, backg)
# assign 1 = presence, 0 = background
pb <- c(rep(1, nrow(presvals)), rep(0, nrow(backvals)))
# combine presence and background
sdmdata <- data.frame(cbind(pa = pb, rbind(presvals, backvals)))
sdmdata[, "layer"] <- as.factor(sdmdata[, "layer")

pairs(sdmdata[, 2:8], cex = 0.1, fig = T) # make sure # columns of data is correct
x <- as.matrix(sdmdata[, c(2:5, 7:8)], head = T) # can't corr factor columns
y <- as.matrix(sdmdata[, c(2:5, 7:8)], head = T)
C <- cor(x, y, use = "complete.obs")

### where do corals occur relative to habitats, zones?
occurrence_habitat <- over(ACERVpres, reef)
summary(occurrence_habitat$ClassLv0)
nrow(occurrence_habitat)
summary(occurrence_habitat$Zone)

# subset sdmdata to only complete cases
new_sdmdata <- sdmdata[complete.cases(sdmdata),]
new_sdmdata$layer <- as.factor(new_sdmdata$layer)
colnames(new_sdmdata) <- c("pa", "Chla", "Kd", "PAR", "SBT", "Zone", "Wave", "Depth")

k <- 5
group <- kfold(new_sdmdata, k)

### Logistic Regression – example ###
### Generalized linear model – example ###

#1 \( \text{pa} \sim \text{SBT}+\text{Chla}+\text{PAR}+\text{Kd}+\text{Wave}+\text{Depth} \)

```r
log_mod1 <- list()
log_e1 <- list()
for(i in 1:k) {
  train <- new_sdmdata[group!=i,]
  test <- new_sdmdata[group==i,]
  log_mod1[[i]] <- glm(p ~ SBT + Chla + PAR + Kd + Wave + Depth,
                      family = binomial(link = "logit"), data = train)
  log_e1[[i]] <- evaluate(p = train[test$pa==1,], a = test[test$pa==0,], log_mod1[[i]])
}
```

### Generalized additive model – example ###

#1 \( \text{pa} \sim \text{SBT}+\text{Chla}+\text{PAR}+\text{Kd}+\text{Wave}+\text{Depth} \)

```r
gam_mod1 <- list()
gam_e1 <- list()
for(i in 1:k) {
  train <- new_sdmdata[group!=i,]
  test <- new_sdmdata[group==i,]
  gam_mod1[[i]] <- gam(p ~ s(SBT) + s(Chla) + s(PAR) + s(Kd) + s(Wave) + s(Depth),
                      family = gaussian(link = "identity"), data = train)
  gam_e1[[i]] <- evaluate(p = train[test$pa==1,], a = test[test$pa==0,], gam_mod1[[i]])
}
```

# how to find mean summary statistics

```r
auc <- sapply(gam_e1, function(x) {slot(x, 'auc')}); mean(auc)
aic <- c(gam_mod1[[1]]$aic, gam_mod1[[2]]$aic, gam_mod1[[3]]$aic, gam_mod1[[4]]$aic, gam_mod1[[5]]$aic); mean(aic)
```
spec<-sapply(gam_e1, function(x){x@t[which.max(x@TPR + x@TNR)]});
mean(spec)#threshold value
sum1<-summary(gam_mod1[[1]]); sum2<-summary(gam_mod1[[2]]); sum3<-summary(gam_mod1[[3]]); sum4<-summary(gam_mod1[[4]]); sum5<-summary(gam_mod1[[5]])
r2<-mean(sum1$r.sq, sum2$r.sq, sum3$r.sq, sum4$r.sq, sum5$r.sq)
dev<-mean(sum1$dev.expl, sum2$dev.expl, sum3$dev.expl, sum4$dev.expl, sum5$dev.expl)
GCV<-mean(gam_mod1[[1]]$gcv.ubre, gam_mod1[[2]]$gcv.ubre,
gam_mod1[[3]]$gcv.ubre, gam_mod1[[4]]$gcv.ubre, gam_mod1[[5]]$gcv.ubre)

###example – plot of GAM model results
names(AnnMeanPreds)<-c("Chla", "Kd", "PAR", "SBT", "Zone", "Wave", "Depth")
p1<-predict(AnnMeanPreds, gam_mod1[[1]])
p2<-predict(AnnMeanPreds, gam_mod1[[2]])
p3<-predict(AnnMeanPreds, gam_mod1[[3]])
p4<-predict(AnnMeanPreds, gam_mod1[[4]])
p5<-predict(AnnMeanPreds, gam_mod1[[5]])
predictions<-stack(p1, p2, p3, p4, p5)
gam_prediction<-mean(predictions)
plot(gam_prediction>mean(spec),
    main="9 km SDM, Presence",
    xlim=c(-84, -79),
    ylim=c(23, 28))
library(rworldmap)
map<-getMap(resolution="high")
plot(map, add=T, border="black", col="grey")
gam_prediction_9km<-gam_prediction

###find the predicted suitable habitat area
gam_prediction[gam_prediction<mean(spec)]<-NA
area<-area(gam_prediction, na.rm=T)
area<-as.vector(area)
area_9km<-sum(area, na.rm=T)

###plot the variable influence of chlorophyll a
fv<-predict(gam_mod1[[1]], type="terms")
prsd1<-residuals(gam_mod1[[1]], type="working")
plot(gam_mod1[[1]], select=2, xlab=expression(paste("Chlorophyll a concentration
    (mg m"^"^-3"",")"), cex=1.5),
    ylab="Coral Occurrence Relative Proportion",
    main="9 km SDM, Presence",
    xlim=c(-84, -79),
    ylim=c(23, 28))
library(rworldmap)
map<-getMap(resolution="high")
plot(map, add=T, border="black", col="grey")
gam_prediction_9km<-gam_prediction

###find the predicted suitable habitat area
gam_prediction[gam_prediction<mean(spec)]<-NA
area<-area(gam_prediction, na.rm=T)
area<-as.vector(area)
area_9km<-sum(area, na.rm=T)
main="4 km GAM Chlorophyll a",
shade=T)
ind<-sample(1:length(prsd1), 150)
points(new_sdmdata$Chla[ind], prsd1[ind], pch=19, col="grey")