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# Ecological Projection of Giant Kelp Presence

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## 1. ABSTRACT

Kelp forests are one of the most productive and biologically diverse ecosystems in the world, providing habitat for numerous species of marine plants and animals. Kelp forests face numerous threats, including rising ocean heat, overfishing, pollution, and invasive species. We analyze the relationship between quarterly kelp presence data from Kelp Watch and monthly sea surface temperature (SST) data from MUR, and other variables (coastal elevation and sunlight availability). Our study focuses on kelp between 27N and 37N along the coast of California because it is suspected to contain a single species of kelp, Macrocystis pyrifera i.e. giant kelp. We train various regression models with data from 2003 to 2023 to predict the abundance of kelp given the environmental factors. We find an inverse correlation between the change in kelp and sea surface temperature which also follows a seasonal cycle with most of the growth happening in the Spring and Summer quarters. We find the largest correlation between kelp presence and SST lagged by one quarter, corresponding to a kelp response timescale. We then use our resulting linear ecological model to project kelp presence in the future given downscaled SST from the global climate models under various emissions scenarios. the with temperature estimates from climate models to determine how the kelp will respond to heat waves and climate change.

## 2. INTRODUCTION

Biodiversity is essential to the existence and proper functioning of all ecosystems and the provision of ecosystem services that humans depend on for food, air, water, and other natural benefits. However, biodiversity loss has been accelerating globally (Butchart et al. 2010). Ecological projections on multi-decadal timescales and ecological forecasting on shorter timescales are increasingly important tools to understand the threats to biodiversity and inform ecosystem management. Following recommendations from the 2017 Earth Science Decadal Survey, NASA has made biodiversity a priority through current and upcoming remote sensing missions like ECOSTRESS, UAVSAR, and PACE. These missions will provide high-resolution time series of environmental variables related to ecological systems in the next few years. This presents a timely opportunity to advance ecological modeling by combining these new observations with numerical models. Here, we demonstrate a use case of EcoPro (Ecological Projection Analytic Collaborative Framework) to support multidisciplinary teams conducting ecological projection studies using cutting-edge data science methodologies. EcoPro will contain an analytic toolkit, a data gateway, and a web portal for publishing results and enabling collaboration. EcoPro will be demonstrated in three use cases: giant sequoia ecosystems (Sudip et al. in prep.), kelp forests (our study), and coral reefs (Kalmus et al. in prep.). By improving ecological projections and connecting researchers across disciplines, EcoPro will be an important resource for understanding biodiversity threats, informing ecosystem management, and exploring new observation strategies.

Kelp forests along the California coast provide habitat for diverse and economically important species and play a key role in coastal carbon cycling. However, these ecosystems have experienced declines due to marine heatwaves, urchin grazing, and disease outbreaks (Rogers-Bennett and Catton 2019). Bull kelp forests in northern California saw large declines during a 2014 marine heatwave, resulting in ecological impacts and fishery losses (Cavanaugh et al. 2019). As climate change increases future marine heatwave frequency and intensity, more regional kelp loss is expected. However, projections of climate change impacts on kelp distributions are lacking. We will use the EcoPro framework to relate future sea surface temperature and other environmental factors to

 

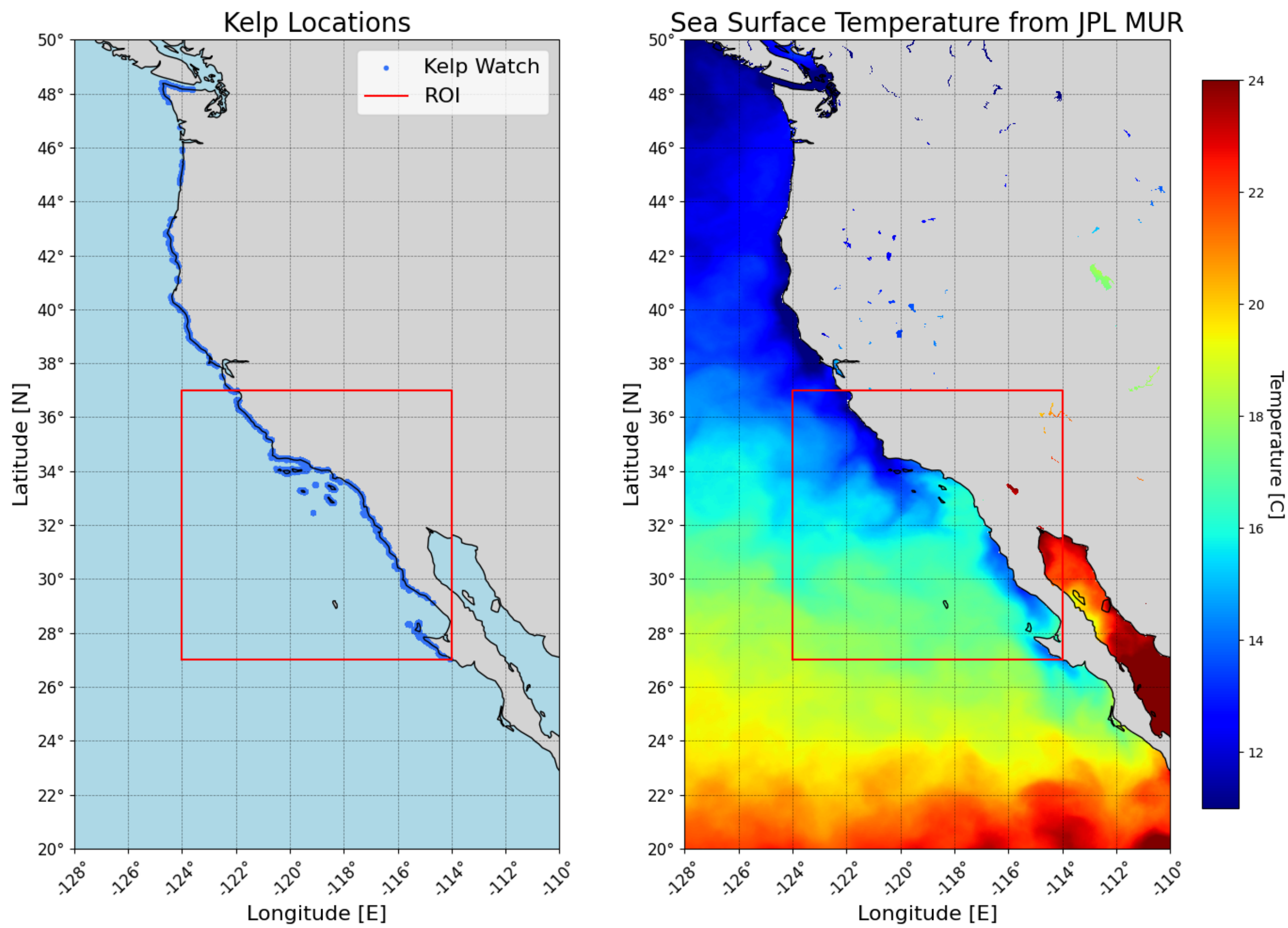


**Figure 1.** A map of locations along the west coast of the United States where the Kelp Watch project is monitoring over ∼550,000 stations with footprints of ∼30x30 $m^2$ and measurements spanning ∼20 years. The entire dataset spans from ∼27-49 N but for the purposes of our study we focus on a region between ∼27-37 N for two reasons; it's suspected to contain a single species of kelp and we have 1-km resolution sea surface temperatures from JPL MUR.

temperature thresholds associated with declines in giant kelp abundance. This suitability modeling will forecast climate impacts on key kelp species across the California coast this century.

Kelp forests are threatened by climate change and have experienced significant declines in recent decades in many regions globally (Krumhansl et al. 2016, Wernberg et al. 2016). Climate factors like marine heatwaves can cause abrupt kelp forest loss, facilitating phase shifts to turf-dominated systems (Filbee-Dexter and Wernberg 2018). Giant kelp in California saw declines during marine heatwaves and is projected to experience future habitat contraction under continued warming (Kavanaugh et al. 2018, Wilson et al. 2022). Threshold temperatures linked to kelp loss (∼24 C in southern California) have been estimated in prior work, providing an approach to model future climate suitability (Bartsch et al. 2016, Cavanaugh et al. 2019). However, kelp forests also have mechanisms that may confer resilience to climatic stress, such as the dispersal of detached macrophytes (Fujiwara and Caswell 2021). Our study will build on this prior research to project climate change impacts on key kelp species across the California coast this century using an ecological modeling framework relating future temperature projections to identified thermal thresholds.

Machine learning techniques like random forests and neural networks have shown promise for forecasting across a range of domains (Elith et al. 2008, LeCun et al. 2015). These methods can uncover complex nonlinear relationships between environmental predictors and ecological response variables making them a suitable algorithm for our kelp study. Machine learning has been applied to model giant kelp biomass in California using satellite data (Cavanaugh

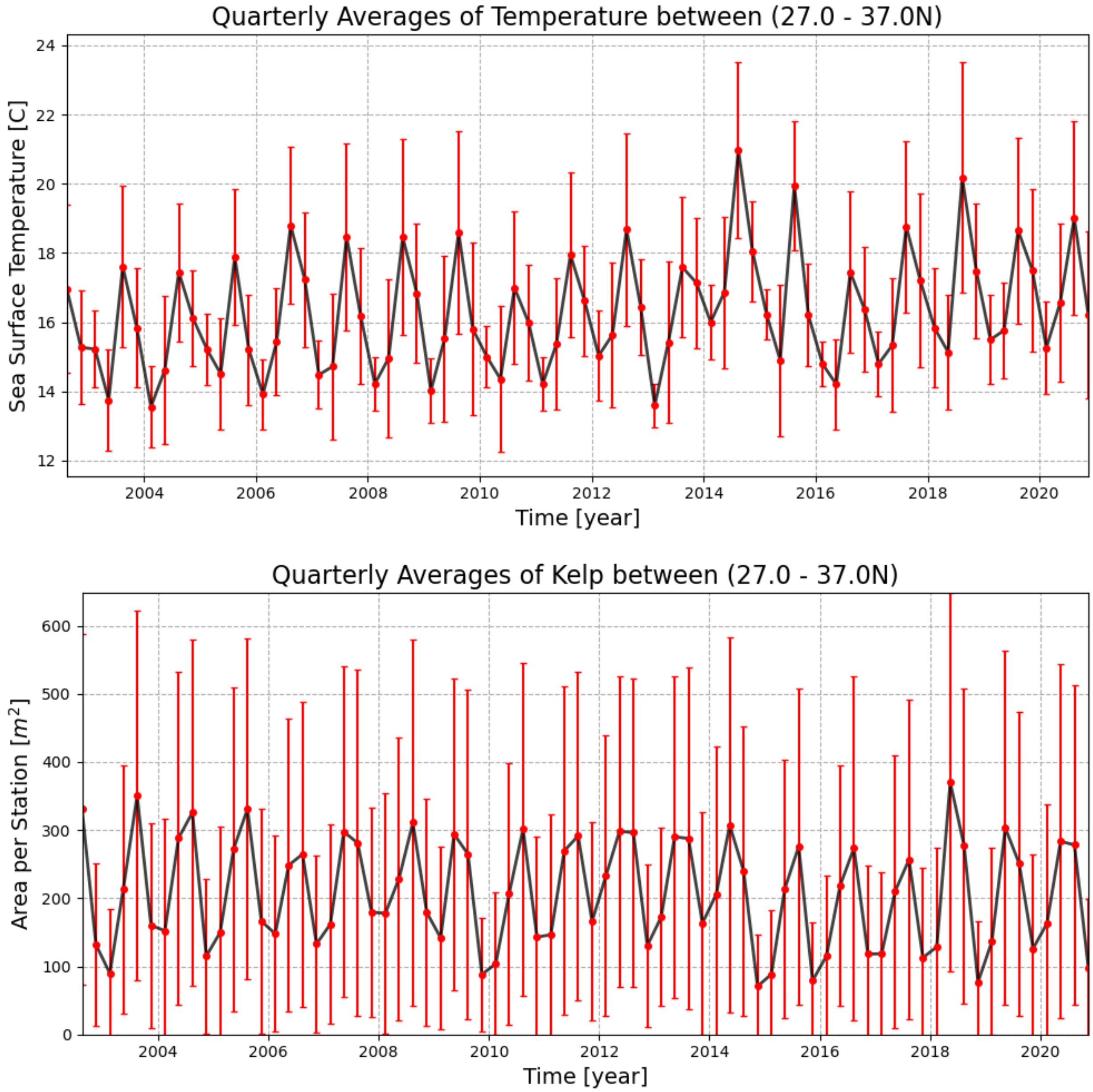


**Figure 2.** (Top) A time series of MUR sea surface temperatures averaged on a quarterly basis and over the region of 27 - 37N at locations with giant kelp along the west coast of the United States. (Bottom) A time series showing the average Kelp presence area at each Kelp Watch station between 27 - 37 N (∼550,000) and averaged every quarter.

et al. 2015?) and to predict future kelp habitat suitability in Australia under climate change (Young et al. 2022). However, forecasting future kelp dynamics along the California coast using machine learning and climate model projections has yet to be explored. Our study will test random forest and multi-layer neural network models to forecast giant kelp canopy biomass across the 21st century. We will integrate Earth system model outputs of future sea surface temperature, bathymetric depth, and other relevant environmental variables with historical kelp biomass data. This machine learning approach will enable nonlinear modeling of kelp dynamics under novel future climate conditions.

## 3. OBSERVATIONS

### 3.1. *Sea Surface Temperature*

The Multi-scale Ultra-high Resolution (MUR) Sea Surface Temperature (SST) Analyses is part of the NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Program[1]. MEaSUREs, de-

 

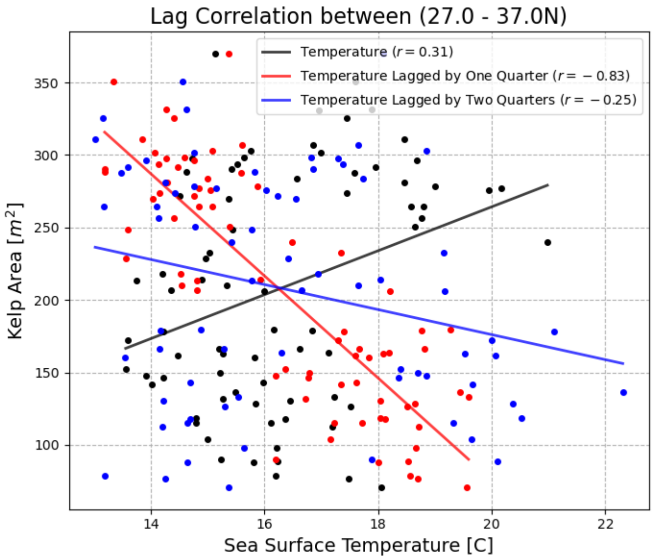


**Figure 3.** A correlation between the averages in Figure 2. The correlations are lagged by one and two quarters with the biggest correlation being at one quarter lag. The strong negative correlation means the Kelp takes roughly 3 months to respond to major heating events and does so in a negative way (i.e. if the temperature increases the kelp decreases). The correlation is likely tied to the availability of nutrients and sunlight which will inhibit the growth of kelp if diminished.

velops consistent global- and continental-scale Earth system data records. The MUR SST data produced by the NASA MEaSUREs program provides daily SST maps at $0.01^\circ$ resolution globally from 2002-present by combining observations from multiple satellite sensors. MUR analysis uses a multi-resolution variational approach to optimally blend complementary data from infrared and microwave sensors while preserving fine-scale spatial features. The result is an ultra-high resolution SST record revealing ocean processes down to 1 km scales. MUR adheres to community data standards and includes per-pixel uncertainty estimates, land masks, and sea ice data. With its unprecedented spatial detail, the freely available MUR SST dataset enables new insights into ocean circulation patterns, fronts, eddies, and other surface dynamics relevant to ecological forecasting.

### 3.2. *Kelp Watch*

The Kelp Watch program has generated an extensive time series of kelp canopy area and biomass along the US West Coast using Landsat satellite data spanning 1984-present (Bell et al. 2020). Kelp canopy area and biomass are estimated from surface reflectance and empirical relationships for giant kelp. The data provide quarterly 30m resolution maps of giant and bull kelp canopy area for California, Oregon, Washington, and Baja California. Multiple Landsat sensors have been cross-calibrated and synthesized to derive a continuous time series (Bell et al. 2020). This unique long-term kelp dataset enables analysis of kelp forest dynamics over recent decades in relation to climate variability and change. The open access Kelp Watch[2] data will be a valuable asset for ecological forecasting studies to understand and project climate change impacts on these critical nearshore ecosystems.

### 3.3. *Coastal Relief Model*

The National Centers for Environmental Information (NCEI) Coastal Relief Model (CRM) provides 90-meter resolution digital elevation models spanning onshore and offshore regions along U.S. coastlines by merging topographic data from the USGS with bathymetric soundings. The CRM offers researchers and managers a comprehensive elevation layer for GIS mapping and analysis in coastal areas. With elevations resolved to 0.1 meters, the CRM supports applications like modeling storm impacts, managing coastal development, and understanding sea level rise. The CRM uses a geographic NAD83 horizontal datum and an unspecified vertical datum, with elevations in meters. The large cell size results in $\sim$1 meter vertical uncertainty, exceeding differences between tidal datums, so no vertical datum transformation was performed. The CRM delivers key elevation information to study interconnected processes across the land-sea interface.

## 4. ANALYSIS

Our study focuses on the latitude band spanning $27^\circ$ N to $37^\circ$ N along the southern California coast (see Figure 1). This region encompasses the biogeographic range of giant kelp (Macrocystis pyrifera) as the dominant canopy-forming kelp species (?). Our analysis integrated time series of sea surface temperature and giant kelp canopy abundance from 2003-2023 (see Figure 2). Since the original SST and kelp data are on two different timescales, we downscale the temperature data using a spatial modeling code described in (Kalmus et al. 2022) such that we can have estimates on a quarterly basis to match the kelp time series. We first explore seasonal and lag correlations between SST and kelp changes. We then developed statistical models using ordinary least squares (OLS) regression, random forest, and multilayer perceptron neural networks to predict the kelp abundance based on SST, elevation data, and sunlight availability. This analytical approach elucidates temperature effects on giant kelp while leveraging machine learning techniques to uncover nonlinear relationships and enhance ecological forecasting capabilities for this foundation species.

### 4.1. *Seasonal Correlations*

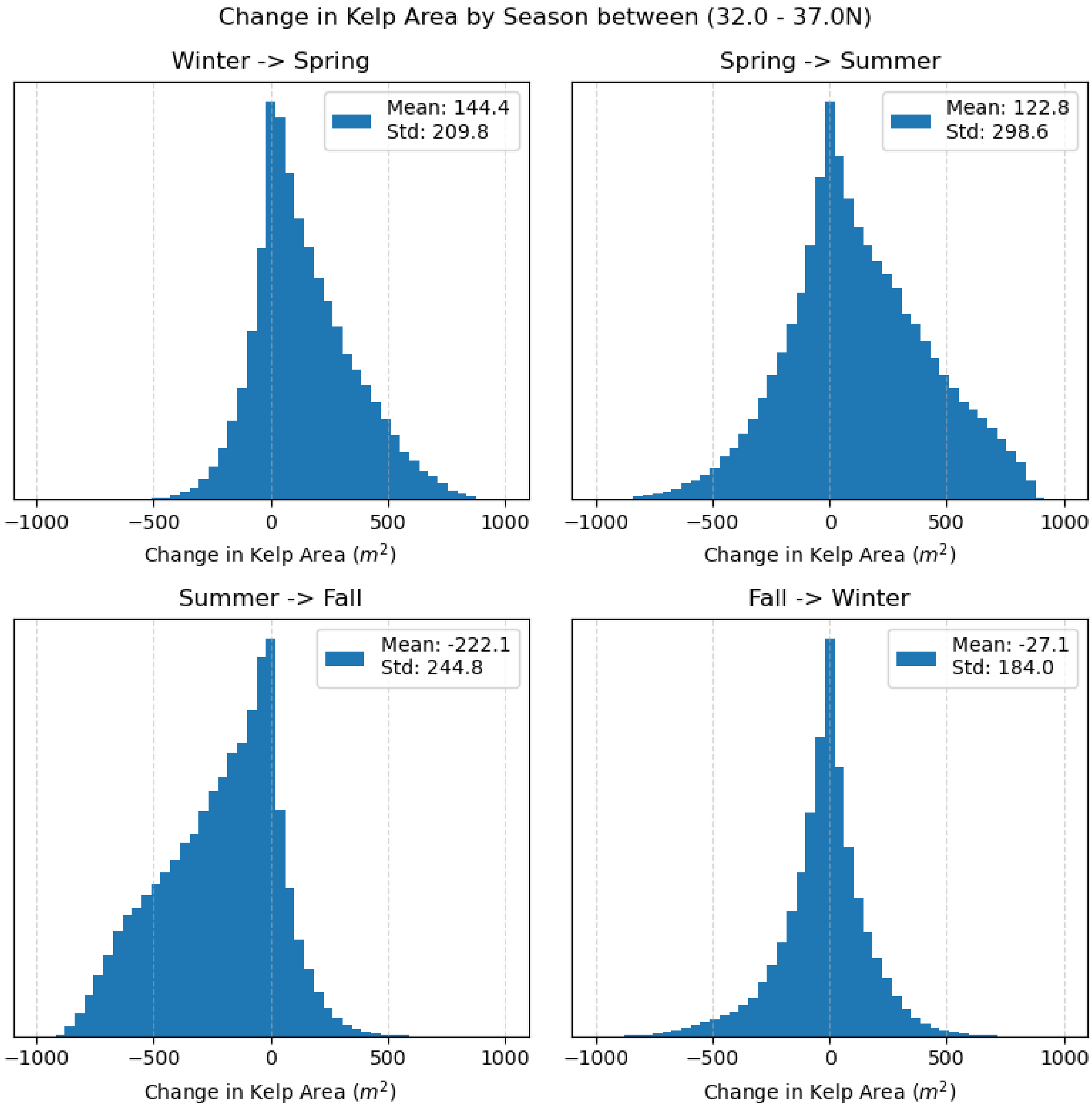


**Figure 4.** Seasonal histograms for change in abundance. The histograms indicate derivatives in kelp abundance between seasons listed in the title of each plot. We see the biggest growth between the winter and spring and the biggest decline in kelp from summer going into fall. Winter consists of January – March, spring is April – June, summer is July – September, and fall is October – December.

Figure 3 shows something similar to an autocorrelation function for giant kelp canopy area averaged along the California coast from 2003-2023. Autocorrelation quantifies the similarity between a time series and lagged versions of itself, revealing intrinsic dynamics. Kelp canopy area exhibits significant negative autocorrelation at a lag of one quarter (R=-0.79) and two quarters (R=-0.41). This indicates the kelp canopy in one quarter is strongly related to the temperature state in the previous quarter, and moderately related two quarters prior. The one-quarter lag likely reflects the resilience of individual kelp plants to heat waves and their ability to respond. Environmental fluctuations may also induce coherence over seasonal timescales. However, autocorrelation decays to near zero beyond two quarters. The positive correlation on a 0-quarter timescale represents the seasonal effects shown in Figure 4 and **??**. Essentially, the biggest growth occurs between winter to spring and spring to summer however after the hottest season, the kelp canopy area experiences its largest decline with not much change occurring between fall and winter. Quantifying these intrinsic lags provides insight into kelp population dynamics relevant for ecological forecasting.

The quarterly lag we identified in giant kelp canopy autocorrelation aligns with multiple previous studies. Reed et al.

 

(2011) found autocorrelation peaks at 3-4 month lags in California kelp biomass related to individual lifespan. Cavanaugh et al. (2011) reported ∼quarterly lags attributed to both lifespan and seasonal effects. Across California, Bell et al. (2015) noted persistent quarterly autocorrelation important for forecasting. Schroeter et al. (2015) identified maximum autocorrelation near a quarterly lag due to intrinsic and environmental drivers. Most recently, Wilson et al. (2022) confirmed distinct quarterly cycles in giant kelp linked to sporophyte longevity, recruitment, and seasonal dynamics. Our results agree with these analyses finding quarterly coherence as a robust feature of giant kelp time series. This intrinsic population driver should be considered in developing ecological forecast models.

### 4.2. *Future Projections*

We project giant kelp presence to 2100 using downscaled SST from global climate models in the region of our study.

These results suggest temperature trends over the next decade could significantly reduce giant kelp habitat suitability and distribution. In order to compare our measurements to climate simulation data it is first downscaled to match our kelp locations using the perscription in Kalmus et al. 2022. The authors employed a novel statistical downscaling method to project sea surface temperatures (SSTs) at a high spatial resolution of 1 km for coral reef locations worldwide. The standard downscaling approach used in ecological projection studies involves deterministically interpolating coarse-resolution climate model anomalies to a fine-scale observational grid, which assumes a homogeneous spatial dependence structure (e.g., Van Hooidonk et al., 2016). Instead, we adopted a bivariate Gaussian process model that jointly models the fine-scale observational SST data (NASA/JPL MUR) and the coarse-scale climate model output, enabling the spatial dependence structure to be learned from the data in a nonstationary manner (Ekanayaka et al., 2022). This novel method utilizes observational data more effectively in the downscaling process and allows for the quantification of uncertainties in the downscaled projections. Validation studies showed that this method outperformed the standard downscaling technique, particularly in near-coastal regions where many coral reefs are located, reducing the mean squared error by up to 31% compared to withheld test data (Kalmus et al. 2022).

Our study utilizes an ensemble of global climate model simulations from the Coupled Model Intercomparison Project Phase 6 (CMIP6). Specifically, one realization from each of 35 CMIP6 model groups providing monthly sea surface temperature (SST) output was included, encompassing the historical experiment from 1870-2014 and two future emissions scenarios (SSP1-2.6 and SSP5-8.5) from the Shared Socioeconomic Pathways spanning 2015-2100 (O'Neill et al., 2014). These two scenarios represent a range of potential future greenhouse gas emissions trajectories and associated radiative forcing levels. The high emissions SSP5-8.5 scenario could raise temperatures by $\sim 4^\circ$ C globally by 2100. The resulting temperatures are used in our regression model and shown in Figure 6. Under the extreme SSP5-8.5 warming trajectory where offshore SSTs increase by $\sim$ 20% or more by 2100, the downscaled projections indicate kelp forests along the California coast could experience sustained temperature increases beyond their thermal tolerance. Such chronic heat exposure may reduce canopy-forming kelp abundance by up to 50% in many areas, potentially causing fundamental regime shifts in these productive coastal ecosystems. The high-resolution projections can help identify potential climate refugia to prioritize kelp conservation efforts under future warming.

## 5. CONCLUSION

Kelp forests provide critical habitat along the California coast, but face threats from climate change and other anthropogenic stressors. We developed an ecological forecasting model to project giant kelp dynamics in relation to environmental drivers. Focusing on southern California, we found an inverse relationship between kelp abundance changes and sea surface temperature, following a seasonal cycle with peak growth in spring/summer. We identified a one-quarter lag as the dominant timescale linking kelp fluctuations to temperature due to intrinsic population processes. We designed a regression model using quarterly lagged-temperature and estimate kelp abundances using temperature data from climate models and satellite measurements. In the worst case scenario, one of the climate scenarios shows a ∼20% increase in temperature with a ∼50% decrease in kelp. Quantifying environmental effects and forecasting future kelp distributions will inform conservation strategies for this highly productive and biodiverse ecosystem. Going forward, incorporating additional stressors and higher-resolution data could further improve kelp projection capabilities.

## 6. ACKNOWLEDGEMENTS

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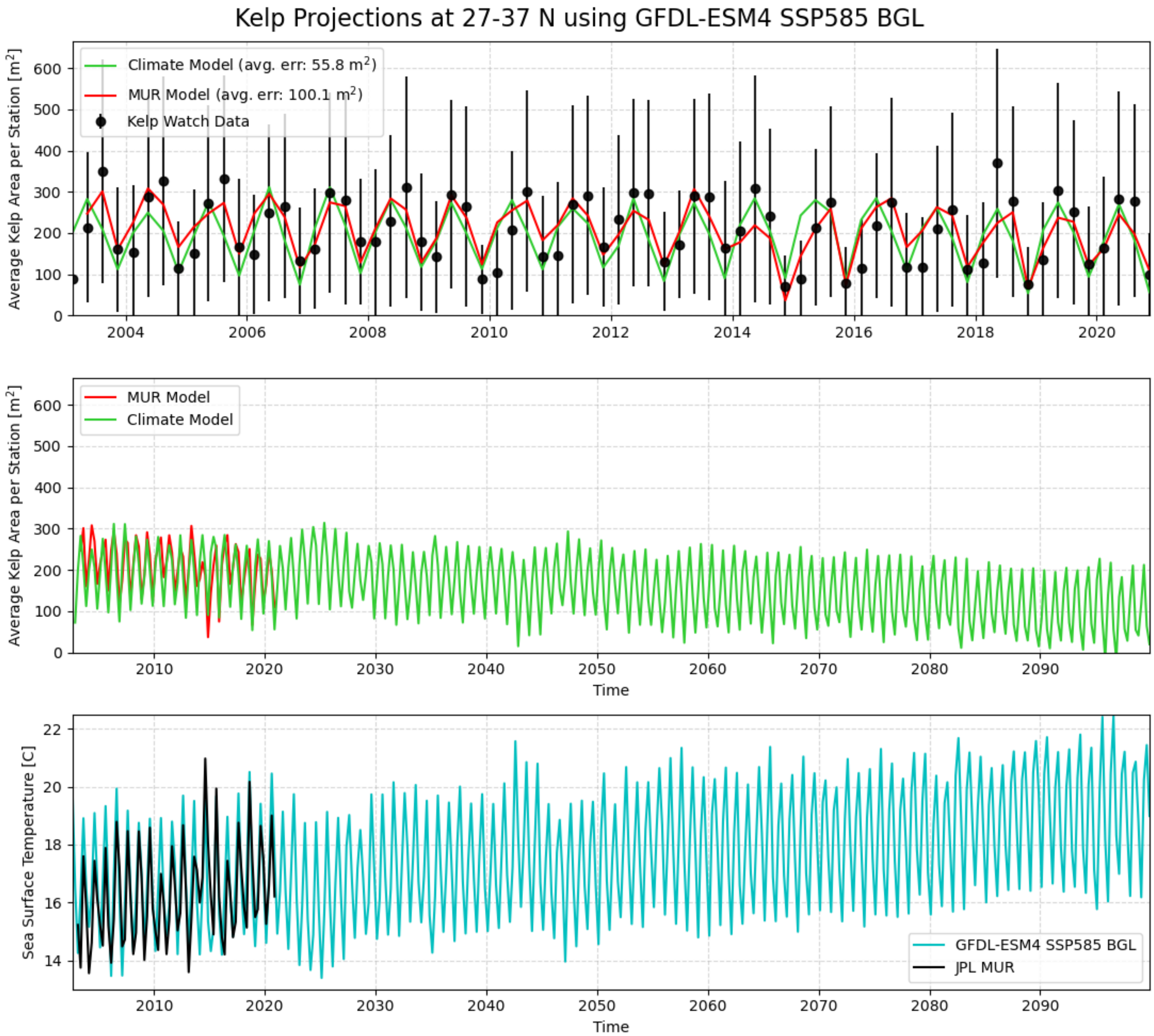


**Figure 5.** Top) Quarterly average of Kelp Watch data in comparison to our regression model with two different temperature inputs. The red line uses data from the JPL MUR mission while the green uses sea surface temperatures from the SSP5-8.5 climate model. Middle) Comparison of kelp projections using different temperatures. There is good agreement between JPL MUR and the climate model. The climate model extends to 2100 and shows the kelp decreasing up to $\sim$50% Bottom) Sea surface temperatures for JPL MUR data and climate model. The sinusoidal pattern corresponds to seasonal variations since this data is on a quarterly timescale.

## REFERENCES

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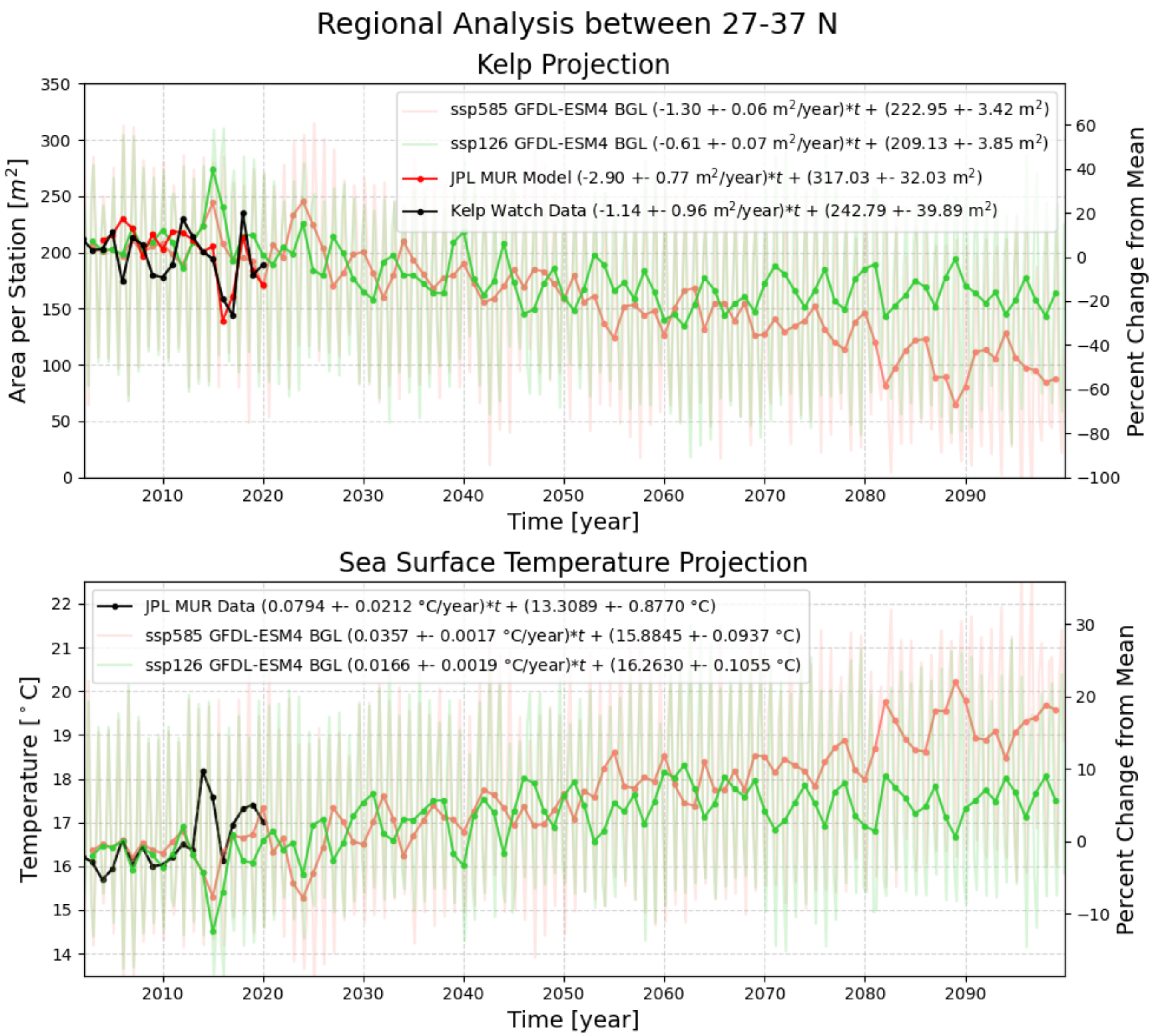


**Figure 6.** A comparison of projection results using different climate scenarios. Top) estimations of kelp with yearly averages. The legend shows results for a linear fit to the yearly averages along with uncertainties. The yearly projections are used to calculate a year in which the Kelp goes to 0 in Table 1. Bottom) Comparison of sea surface temperatures between the climate model and JPL MUR measurements. In the worst case scenario, when the temperature increases up to ∼20% it corresponds to a ∼50% loss.