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From Space to the Rocky Intertidal: Using NASA MODIS Sea Surface Temperature and NOAA Water Temperature to Predict Intertidal Logger Temperature

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Abstract: The development of satellite-derived datasets has greatly facilitated large-scale ecological studies, as in situ observations are spatially sparse and expensive undertakings. We tested the efficacy of using satellite sea surface temperature (SST) collected by NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) and local water temperature collected from NOAA buoys and onshore stations to estimate submerged intertidal mussel logger temperatures. Daily SST and local water temperatures were compared to mussel logger temperatures at five study sites located along the Oregon coastline. We found that satellite-derived SSTs and local water temperatures were similarly correlated to the submerged mussel logger temperatures. This finding suggests that satellite-derived SSTs may be used in conjunction with local water temperatures to understand the temporal and spatial variation of mussel logger temperatures. While there are limitations to using satellite-derived temperature for ecological studies, including issues with temporal and spatial resolution, our results are promising.

Keywords: sea surface temperature; NASA MODIS; *Mytilus zonarius*; intertidal; Oregon; mussel

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1. Introduction

Development of satellite remote sensing has enhanced our ability to accurately map and analyze small and large-scale physical and biological phenomena. For example, satellite-derived products can be used to characterize bio-optical properties in coastal waters [1], better understand large-scale drought [2], monitor snow cover [3], estimate plant species richness [4], understand the relative abundance of disease vectors [5], and understand many other ecological processes [6]. While satellite-derived products cannot replace in situ observations, they can be used in conjunction with in situ observations for better understanding of small and large-scale processes. Furthermore, satellite-derived products can be used to fill gaps in spatially and temporally limited datasets. Satellite products can have either high spatial resolution (10–100 m) but limited temporal repetition (days), or low spatial resolution (>100 m) but frequent temporal repetition (hours, e.g., twice a day for sun synchronous satellites). For example, the Landsat 8 sensor has a 15 m spatial resolution (OLI panchromatic band) and global coverage, but temporal repetition every 16 days. In contrast, NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) provides two measurements per day but only at 250 m to 4 km spatial resolution (depending on the spectral band). Thus, the proper utilization of these satellite-derived products depends on their temporal and spatial resolution. Lastly, these remotely sensed products are publicly available through easy download and sub-setting options. This makes the datasets easily accessible to non-scientists and scientists alike.

In this paper, we decided to utilize sea surface temperature (SST) from NASA's MODIS sensor for the rocky intertidal ecosystem along coastal Oregon, USA. We chose MODIS Aqua and Terra SST (spatial resolution 4 km) over other satellite products because they sample daily, have global coverage, and offer more than a 10-year data set. Further, using SST from both the Aqua and Terra satellites provides two daytime surface temperature estimates.

We chose to work with the rocky intertidal ecosystem because it is a complex and dynamic system. For decades, marine intertidal ecosystems have served as a "model" system, contributing greatly to the conceptual and empirical development of ecology [7–9]. Intertidal habitats are considered to be one of the most sensitive systems to climate change because they are exposed to aerial conditions during low tide and to aquatic conditions during high tide [10–13]. As such, temperature is one of the most important physical factors influencing marine intertidal species [14,15]. Rapid changes in body temperature of intertidal species can cause stress and may result in changes in population distributions after repeated exposure to such extremes [11,14,16]. Since body temperature directly influences the growth [7,17], ecology [18], and the distribution of mussels [19] and other intertidal species [20], being able to map body temperature across varying temporal and spatial scales is essential [18]. However, collecting in situ body temperature data in order to understand long-term, regional-scale climate effects on intertidal species can be logistically challenging. Currently, the body temperatures of intertidal species are being collected using two main methods: (1) direct field measurements and (2) biomimetic temperature loggers [21,22]. Both methods can be time-consuming, expensive and geographically/spatially limited [19,23].

For several reasons, exploring alternatives to in situ temperature loggers or using other temperature measurements for gap-filling is worthwhile. First, localized in situ field deployments are relatively easy and inexpensive, but deployments at large scales (regional to global) are limited by personnel, travel, and equipment expenses. Second, depending on the frequency of sampling, loggers have limited storage capacity, are battery powered, need to be downloaded, recharged, and restarted at time scales of months to a year or two. Third, the likelihood of data stream interruption from human- or wave-caused loss will vary in time and space. For example, while mussel temperature mimics are relatively cryptic, they are still seen and, in many regions, can be vandalized. Wave disturbance can also cause losses, especially in strongly seasonal regions. Given these limitations, and the relatively inexpensive and easy access to satellite temperature data, it is worthwhile exploring alternative methods for measurement of body temperature for these intertidal organisms.

While several biophysical models can accurately estimate body temperature of terrestrial and intertidal organisms, they are typically complex and require several variables to provide accurate results [18]. Among the many variables used in these models are air or water temperature collected by weather stations, ocean buoys, or field observations. Temperatures collected by weather stations and ocean buoys are used because they provide accurate and reliable observations for specific locations. Buoy and stations collect data at varying temporal frequency and over multiple years. However, as they are sparsely distributed in space, buoys and stations cannot capture spatial variation in temperature and other physical properties [24,25].

It is for all of these reasons that we present a comparative study using satellite-derived SST from NASA MODIS and "local" water temperatures collected by NOAA buoys and stations to predict submerged mussel logger temperatures. We wanted to determine the temperature variable, satellite-derived SST or "local" water temperature, that could predict submerged mussel logger temperature. Additionally, we wanted to determine if better prediction of logger temperature resulted from water temperature measurements collected closer in distance from one another, during certain collection times, or using different sources of water temperatures.

2. Materials and Methods

2.1. Mussel Logger Temperature

We used data collected by the Partnership for Interdisciplinary Studies of Coastal Oceans (PISCO): a long-term ecological consortium funded by the David and Lucile Packard Foundation and the Gordon and Betty Moore Foundation (Table 1). Mussel logger temperatures were collected hourly at five study sites along the Oregon coastline (Figure 1) from 1 January 2003 to 31 December 2013. Study sites from north to south were Fogarty Creek (FC), Boiler Bay (BB), Yachats Beach (YB), Strawberry Hill (SH), and Tokatee Klootchman (TK) (Table 2).

Table 1. Information about the type, source, frequency, availability, and web site address of the datasets used in the study from the NASA Jet Propulsion Laboratory (JPL), Partnership for Interdisciplinary Studies of Coastal Oceans (PISCO), and NOAA National Data Buoy Center (NDBC).

Type of Data	Source	Frequency	Units	Availability
Aqua SST	JPL	Daily	°C	2002–present
Terra SST	JPL	Daily	°C	2000–present
Mussel logger temperature	PISCO	Hourly	°C	2000–2013
Local Water temperature	NDBC	Hourly	°C	Varies by location

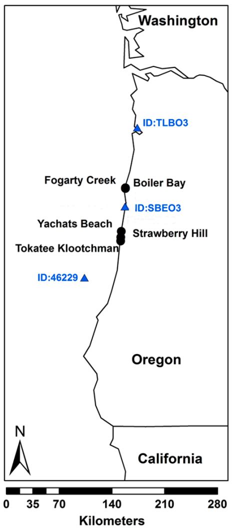

Figure 1. A map of the temperature collection locations and study sites along the Oregon coastline.

Table 2. Study site name, geographical location, and number of daily observations for each study site.

Study Site Name	ID	Northern	Southern	Western	Eastern	Number of Daily Observations
Fogarty Creek	FC	44.838°N	44.837°N	124.060°W	124.058°W	4018
Boiler Bay	BB	44.832°N	44.830°N	124.059°W	124.061°W	4018
Yachats Beach	YB	44.319°N	44.318°N	124.109°W	124.108°W	4018
Strawberry Hill	SH	44.250°N	44.249°N	124.114°W	124.115°W	3989
Tokatee Klootchman	TK	44.207°N	44.204°N	124.116°W	124.117°W	3944

Temperatures from each study site were then converted into daily exposed and submerged mussel logger temperatures using a de-tiding program written by the PISCO research team [7]. This research only used the submerged temperatures from the loggers to compare to the satellite SST and the local water temperatures. Temperature measurements were collected using micro-T Temperature Loggers (NexSens DS1921G). Mussel temperature loggers were embedded within an artificial mussel in the middle of the mid intertidal mussel bed. Each study site had three replicates, each containing several loggers. These replicates were then averaged so that there would be one temperature measurement per day.

2.2. Satellite Sea Surface Temperature

Remotely sensed sea surface temperature data were obtained from NASA's sun-synchronous Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Earth Observing System (EOS) Aqua (1:30 a.m. local standard time ascending overpass; n = 5023) and Terra (10:30 a.m. local standard time descending overpass; n = 5365) satellites (Table 1). Level-3 daytime Aqua and Terra SST were obtained from the Physical Oceanography Distribution Active Archive Center (PO.DAAC). MODIS satellites produce approximately four-kilometer spatial resolution SST.

Global Positioning System (GPS) coordinates of each study site corresponding to the location of the mussel loggers were used to determine the corresponding SST pixels for each study site. All SST pixels within 8 km of each study site were averaged together to get daily measurements of SST. Daily level-3 SSTs were downloaded, mapped, and analyzed using Marine Geospatial Ecology Tools (MGET), ArcGIS software, and the R statistical software. Days in which there were no temperature values due to uneven temporal sampling of SST by MODIS Aqua or Terra due to clouds were not included in the data analysis. This resulted in far fewer usable SST measurements than local water temperature measurements.

2.3. National Oceanic and Atmospheric Administration (NOAA) Local Water Temperature

NOAA National Data Buoy Center (NDBC) provided hourly local water temperature for three stations/buoys along the Oregon coast (Table 1). Hourly water temperature was collected from the NDBC stations/buoys (Table 3) and averaged to daily temperature values. Tillamook Bay water temperature (n = 14,230), South Beach water temperature (n = 13,860), and Umpqua Offshore water temperature (n = 14,745) observations varied in temporal availability. All available water temperature data corresponding to the study period were used in this paper regardless of whether datasets were continuous during 2003 to 2013. We chose these specific stations/buoys because they were close to the study sites with data available during the study period.

Table 3. The location name, ID, type, and geographical location of NOAA National Center Data National Data Buoy Center (NDBC) stations and buoys used in the study.

Location Name	ID	Type	Location
Tillamook Bay, OR	TLBO3	Station	45.555°N, 123.919°W
South Beach, OR	SBEO3	Station	44.625°N, 124.045°W
Umpqua Offshore, OR	46229	Wave rider buoy	43.767°N, 124.549°W

2.4. Statistical Analyses

We conducted statistical analyses on the data using several R packages [26]. All hourly data was averaged to daily observations for analysis. To understand the temporal and spatial variation of the data, identify any anomalies in the datasets, and to determine if the data met the assumptions of the statistical tests, we used univariate descriptive statistics, such as mean, variance, standard deviation, boxplots, and frequency distributions. To better understand the relationship between the different datasets and whether distance, type of temperature collection, or the time of temperature collection (month or season) had an impact on prediction of logger temperature, we conducted different bivariate statistical tests.

To determine how well temperature variables (satellite SSTs, water temperatures, and logger temperatures) correlated with one another, we used Pearson r correlation coefficients. Additionally, linear regression models were fit using daily observations to determine the relationship between mussel logger temperature and other temperature observations. All predictor variables used in the linear models were tested for multicollinearity using the variance-inflation factor (VIF) using the car package [27] in R. This helped to determine whether predictor variables should be used in fitting the models. Forward and backward step regressions were used to help fit the chosen model. Forward step regressions added a water temperature variable at each step. Whereas, backward step regressions removed a water temperature variable at each step. Additionally, to choose the best model, Akaike information criterion (AIC) values were calculated for each model in the forward and backward steps. Comparisons of the models were done using Taylor Diagrams. Taylor Diagrams graphically display the Pearson's r correlation coefficient, the root-mean-square error (RMSE), and the standard deviation of the models. Together, the lowest AIC, highest r-squared, strongest correlation, lowest root mean square error and standard deviation were used to help fit the best model. We used the plotrix package [28] in R. To determine the most important predictor variables, we used classification trees from the party package [29].

3. Results

The mussel logger temperatures, local water temperatures, and the remotely sensed SSTs varied in temporal availability with continuous and non-continuous records from 2003−2013 (Figure 2). Time series figures show the interannual and intrannual variation in daily temperatures from 2003−2013 was between 10 and 15 °C (Figure 2). However, there were some temperatures in 2006 at the South Beach location that were abnormally high (>25 °C) followed by no observations until 2007. These abnormally high temperatures followed by no observations suggest that the sensor was not recording correctly.

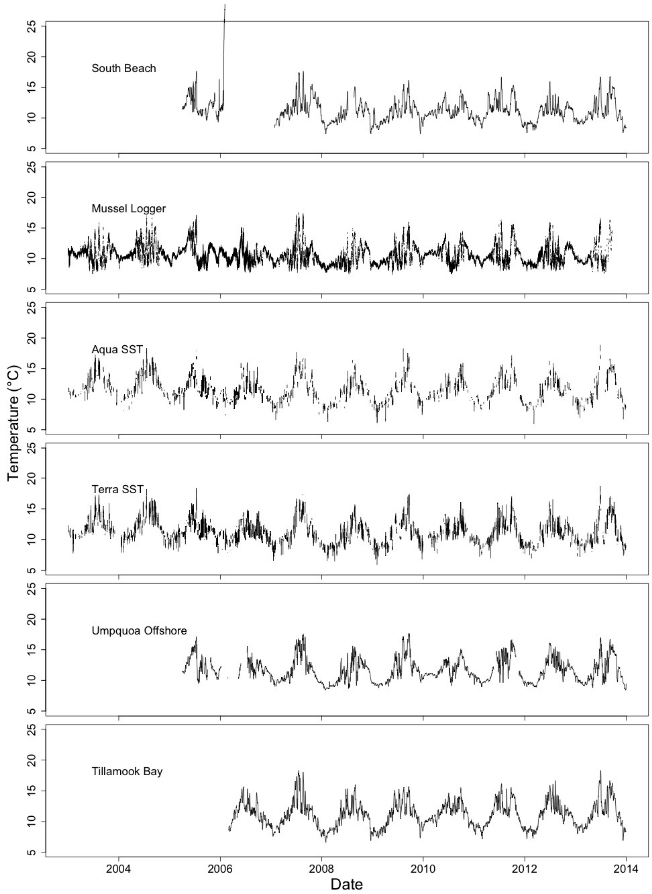

Figure 2. Time series graphs of daily logger temperatures, satellite-derived sea surface temperatures (SST), and local water temperatures from 2003−2013. The entire available data record from 2003−2013 for each location is shown above. The South Beach station, Umpquoa Offshore buoy, and Tillamook Bay station have many missing daily temperatures as shown by breaks in the time series.

3.1. Relationship between Temperature Variables

The strength of temperature correlations was highly dependent on the type of temperature collection (logger, local, or satellite) and the study site location. Mussel logger temperatures were very strongly linearly correlated (Pearson $r = 0.911$ to Pearson $r = 0.986$, p-value < 0.001) with each other as expected, with the strongest correlation being between the two closest study sites, Boiler Bay and Fogarty Creek (Figure 3). The next strongest correlation was between SSTs collected by the Aqua and Terra satellites (Pearson $r = 0.898$, $p < 0.001$). Local water temperatures collected at Tillamook Bay, South Beach, and the Umpqua Offshore buoy were also strongly correlated with each other as expected (Pearson $r = 0.786$ to Pearson r = 0.851, $p < 0.001$).

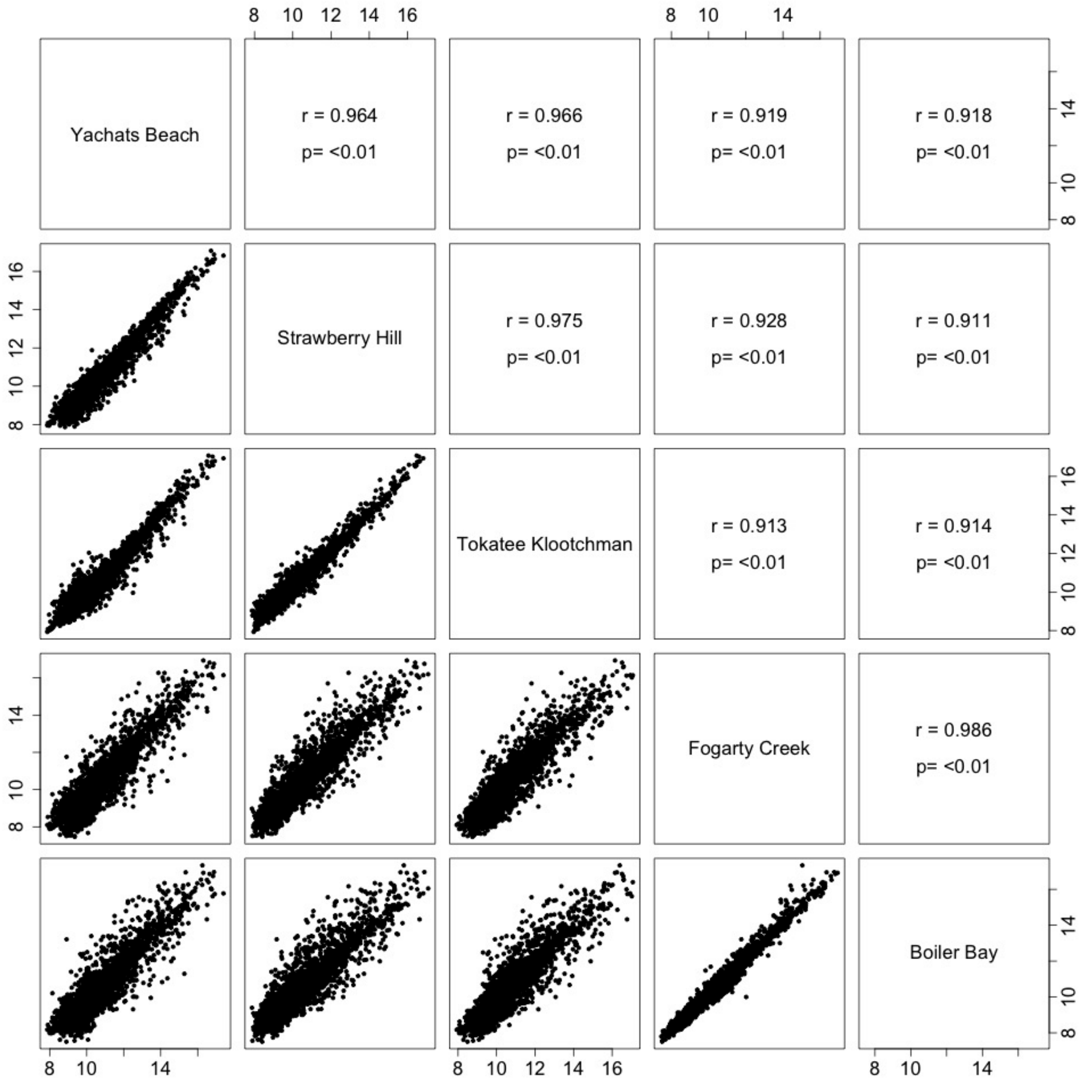

Figure 3. Correlation matrix of logger temperatures between each study site with the scatterplot shown in the bottom left and the Pearson r correlation coefficients shown in the top right of the figure. The study site names are shown in the middle diagonal boxes. The strongest correlation was between logger temperatures at Fogarty Creek and Boiler Bay, the two closest study sites. The weakest correlation was between logger temperatures at Boiler Bay and Strawberry Hill.

3.2. Estimation of Mussel Logger Temperature by Study Site

To understand if mussel logger temperature could be predicted accurately, we calculated Pearson r correlation coefficients and fit linear models for each study site. We compared the models using Taylor

Diagrams. Due to the large number of results, we only included one example Taylor Diagram, one correlation matrix, and combined the other results into one table (Table 4; Figures 4 and 5, respectively).

Table 4. Standard deviation (σ), root mean square error (RMSE), Pearson r correlation coefficient, and r-squared (r^2) are shown for each linear model used to predict submerged mussel logger temperature at each study site. The Taylor Diagram and correlation matrix output for every study site is shown in the table.

Study Site	Variable	σ	RMSE	Pearson r	r^2
Fogarty Creek	Aqua SST	2.16	1.52	0.78	0.61
	Terra SST	1.80	1.25	0.79	0.63
	South Beach	1.86	1.32	0.82	0.68
	Umquoa	2.05	1.86	0.74	0.55
	Tillamook Bay	2.23	1.68	0.74	0.54
Boiler Bay	Aqua SST	2.16	1.32	0.83	0.69
	Terra SST	1.53	1.09	0.77	0.59
	South Beach	1.87	1.17	0.85	0.72
	Umquoa	2.01	1.63	0.79	0.62
	Tillamook Bay	2.24	1.48	0.79	0.62
Tokatee Klootchman	Aqua SST	1.49	1.30	0.81	0.66
	Terra SST	2.06	1.28	0.82	0.67
	South Beach	1.82	1.13	0.84	0.71
	Umquoa	2.05	1.67	0.77	0.60
	Tillamook Bay	2.19	1.51	0.77	0.58
Strawberry Hill	Aqua SST	2.06	1.57	0.76	0.57
	Terra SST	2.02	1.52	0.75	0.56
	South Beach	1.87	1.34	0.81	0.65
	Umquoa	2.08	1.96	0.70	0.49
	Tillamook Bay	2.24	1.77	0.70	0.48
Yachats Beach *	Aqua SST	2.14	1.33	0.84	0.71
	Terra SST	2.23	1.39	0.82	0.67
	South Beach	1.89	1.06	0.88	0.77
	Umquoa	2.10	1.69	0.78	0.61
	Tillamook Bay	2.28	1.46	0.81	0.66

* The output for the two example figures shown in the text.

We found that correlation strength and the amount of variation explained by the water temperature measurements varied by site and by the water temperature measurement (Table 4). The strongest correlation between mussel logger temperature and one of the water temperature variables (satellite-derived SST or local water temperature collected from South Beach, Tillamook Bay, or Umpquoa Offshore) was found using the water temperature collected from the South Beach location (Table 4; Figure 4).

Strong correlations were found between mussel logger temperature and water temperature collected at South Beach (FC: Pearson r = 0.82; BB: Pearson r = 0.85; YB: Pearson r = 0.88; SH: Pearson r = 0.81; TK: Pearson r = 0.84). The water temperature collected at South Beach was able to explain 65% to 77% of the variation in mussel logger temperature depending on the study site (Table 4). Water temperature collected at South Beach was able to explain 77% of the variation in mussel logger temperature at Yachats Beach (Figure 4). The fitted linear model is shown below:

$$\text{Logger Temperature} = 2.05\ (\pm 0.25) + 0.77\ (\pm 0.02)\ \text{South Beach} \tag{1}$$

Whereas, satellite SST was able to explain 56% to 71% of the variation in mussel logger temperature depending on the study site (Table 4), Aqua SST was able to explain 71% of the variation in mussel logger temperature at Yachats Beach (Figure 4). The linear model is shown below:

$$\text{Logger Temperature} = 3.35\ (\pm 0.25) + 0.65\ (\pm 0.02)\ \text{Aqua SST} \tag{2}$$

We also compared these models using Taylor Diagrams and the associated output. Water temperature from the South Beach location was the best predictor of mussel logger temperature (Table 4; Figure 5). While satellite-derived SST was not as good at predicting mussel logger temperature as the water temperature collected at the South Beach location, it was a better predictor than the other local water temperatures from Tillamook Bay and Umpquoa Offshore.

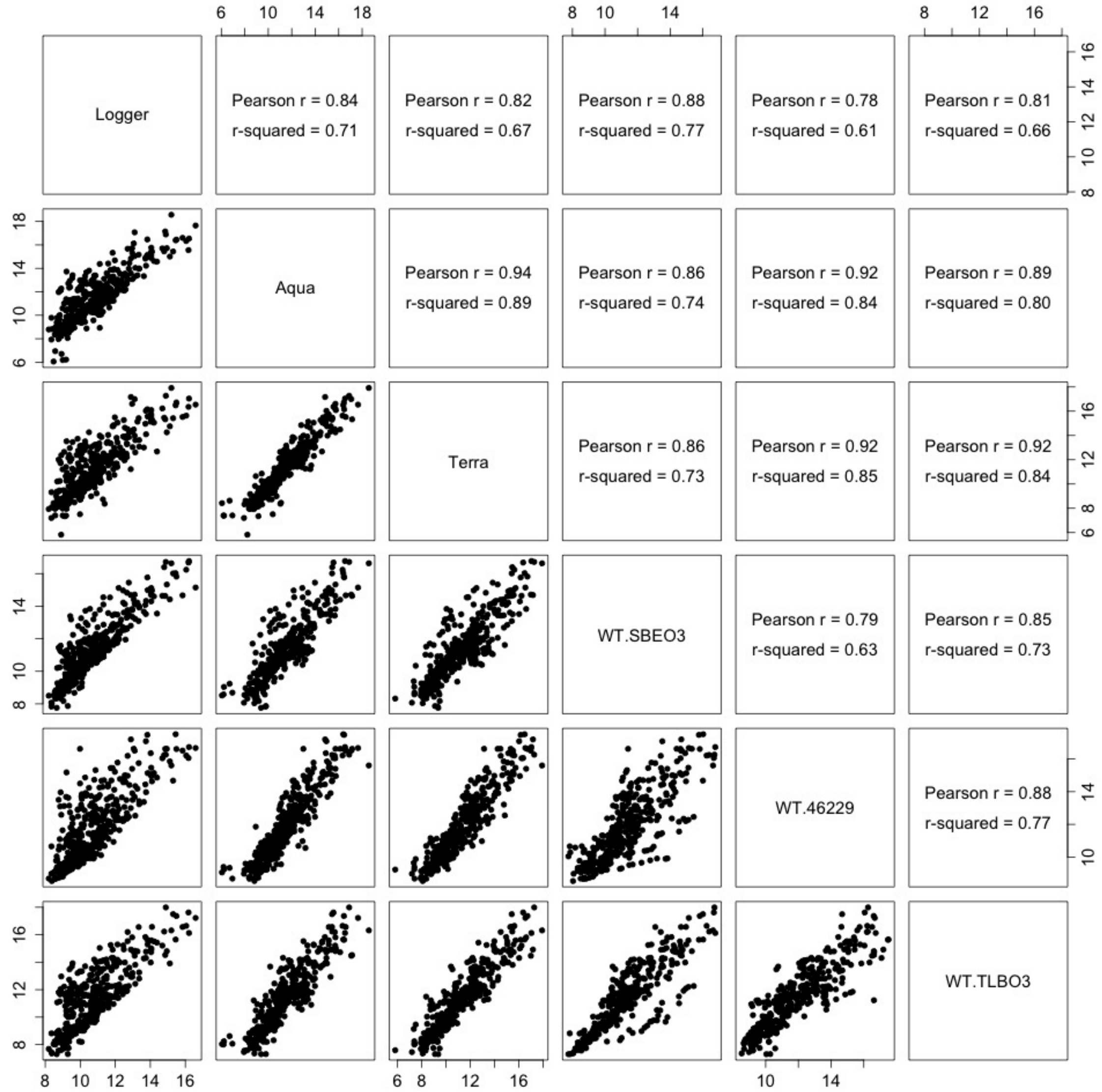

Figure 4. Correlation matrix with scatterplots showing the relationship between submerged mussel logger temperature and the water temperature estimate at the Yachats Beach study site. The scatterplots are shown in the lower left portion of the figure. The Pearson r correlation coefficients and r-squared values are shown in the upper right portion of the figure.

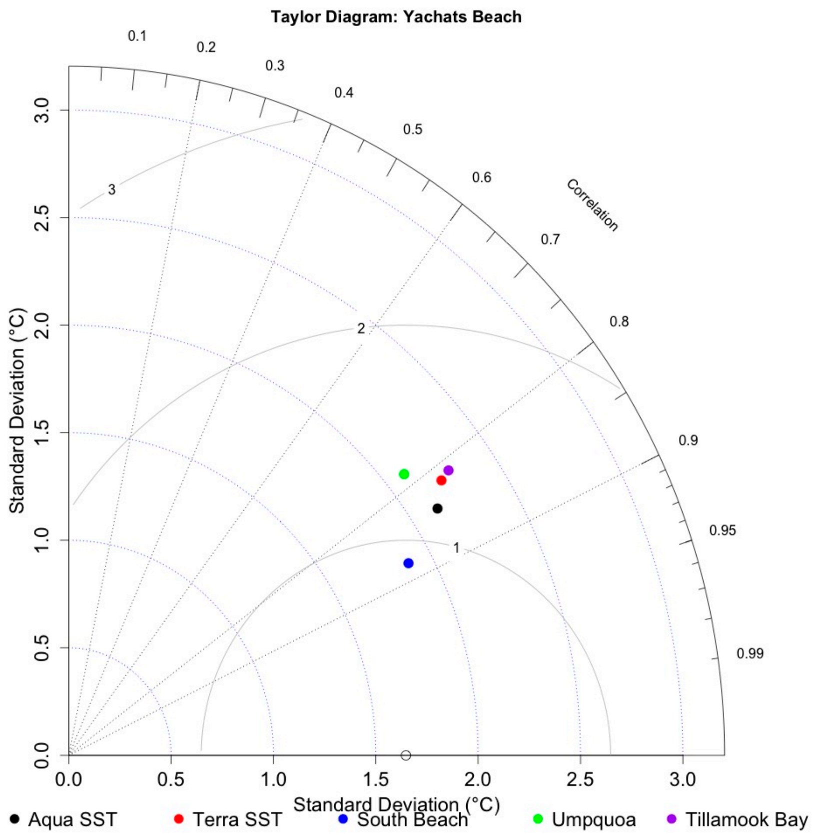

Figure 5. Taylor diagram for Yachats Beach where each water temperature estimate (Aqua SST, Terra SST, South Beach water temperature, Umpquoa Offshore water temperature, and Tillamook Bay water temperature) was used to predict daily submerged mussel logger temperature. South Beach water temperature was the best predictor of daily submerged mussel logger temperature when compared to the other water temperature estimates. The second-best predictor for logger temperature at Yachats Beach was Aqua SST.

3.3. Estimation of Overall Mussel Logger Temperature

We also wanted to determine if multiple water temperature estimates could be used to predict overall mussel logger temperature (not separated by study site). The Akaike information criterion (AIC) values from the forward stepwise regression suggest using all of the prediction variables to strengthen the quality of the model. We removed the water temperature collected at the Umpquoa Offshore buoy location because it was not a significant predictor of logger temperature (t-value = 1.541, p-value = 0.123).

We also removed study site as a predictor variable, because not all of the sites were significant predictors (TK: p-value = 0.621; YB: p-value = 0.932). After the removal of study site and the Umpquoa Offshore water temperature, we calculated the relative importance of each predictor variable to the model. Water temperature collected at the South Beach station contributed the most (33.15%) to the linear model than any of the other water temperatures. Aqua SST contributed 24.95%, Terra SST contributed 21.75%, and water temperature collected at Tillamook Bay contributed 20.14%. Including all of these predictor variables, the linear model explained 74.14% of the variation in mussel logger temperature (equation shown below).

$$\text{Overall Logger Temperature} = 2.163\ (\pm 0.127) + 0.229\ (\pm 0.026)\ \text{Aqua SST}$$

$$+ 0.088\ (\pm 0.025)\ \text{Terra SST} + 0.487\ (\pm 0.022)\ \text{South Beach} - 0.054\ (\pm 0.022)\text{Tillamook Bay} \quad (3)$$

The VIF for each predictor variable for the model was as follows: Aqua SST: VIF = 7.44; Terra SST: VIF = 6.14; South Beach: VIF = 4.23; and Tillamook Bay: VIF = 5.82. None of the VIFs for the predictor variables were higher than 10, so we did not exclude any of them.

3.4. Relationship between Distance, Sensor Type, Month, Season, and Logger Correlation

There was a strong positive relationship between logger temperatures correlation value and the distance between sites, with higher correlations for closer sites and lower correlations for sites farther from each other (r^2 = 0.934, *p*-value < 0.001) (Figure 6). However, this relationship between distance and temperature is not seen when local water temperatures or satellite temperatures were used (r^2 = 0.058, p = 0.172).

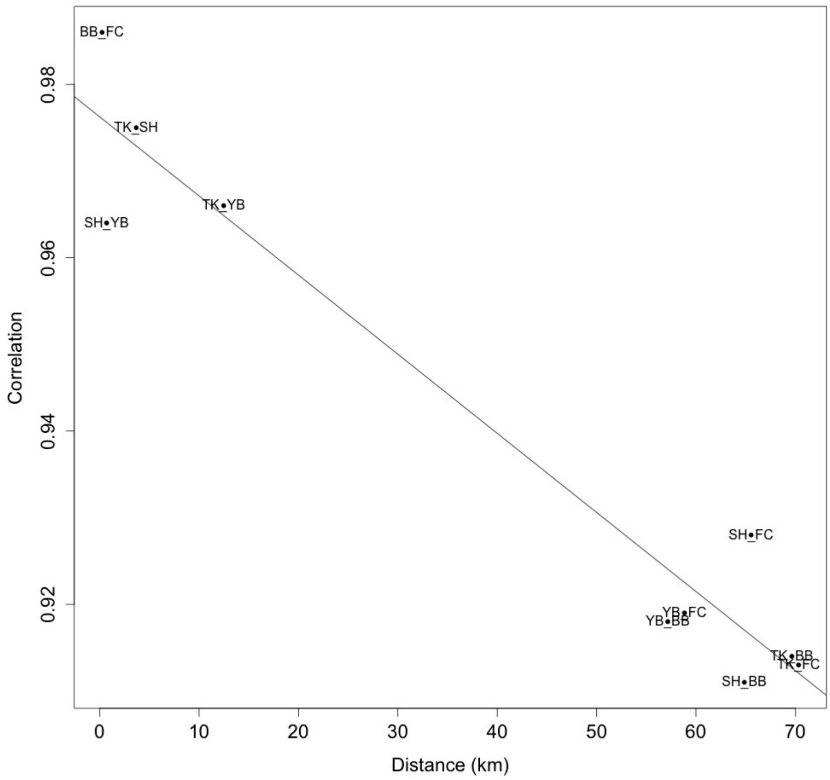

Figure 6. Relationship between the distance between study sites and logger temperature Pearson r correlation coefficient value. Closer study sites were more strongly correlated with each other than farther sites. The points are labeled with the abbreviation of each pair of study sites. Study sites shown are: Fogarty Creek (FC), Boiler Bay (BB), Strawberry Hill (SH), Tokatee Klootchman (TK), and Yachats Beach (YB). For example, SH_YB represents the relationship between the correlation strength of logger temperatures and the distance between Strawberry Hill and Yachats Beach.

A classification tree was used to determine whether distance between sites, type of temperature collection (logger, local water temperature, or satellite), or the time of temperature collection (month or season) was most important for predicting temperature correlation strength. Using classification trees, we determined that the type of data collection (satellite versus local) was the most important when predicting the strength of the relationship between logger and water temperature.

4. Discussion

Much of the research involving temperature and intertidal species focuses on developing a better understanding on the effects of temperature on species biology and ecology [30–32] and not actually measuring or predicting the temperature the species experience. We know from previous research that temperature influences intertidal species physiology [30], interactions [30,32], competitive advantage [30,31,33], fitness [34], abundance and geographic extent [35]. However, currently there are only a few accepted ways to estimate the body temperature of intertidal species in their natural habitat and not in a laboratory setting [36]. These include using biomimic temperature loggers, temperature models, and direct field observations. While all of these methods provide accurate (within ~1 °C) body temperature estimations, they are limited in spatial and temporal extent. Furthermore, the data associated with these methods are often difficult to find or access.

In this paper, we investigate whether satellite-derived SST can be used to predict daily submerged mussel logger temperature. While satellite-derived SST has limitations [37], it also offers many advantages over in situ and modeled temperature measurements. Satellite-derived SST from NASA MODIS Aqua and Terra provide two daily temperature measurements around the globe at a spatial resolution of 4 km^2. Additionally, these temperature measurements are publicly available from the year 2000, from the Terra satellite, and 2002, from the Aqua satellite.

Using linear models, we found that satellite-derived SST was a better predictor of daily submerged mussel logger temperature than two of the three local water temperature measurements used in our analyses. Additionally, satellite-derived SST only performed slightly worse than the best predictor, water temperature collected at South Beach. At Yachats Beach, satellite-derived SST explained 71% of the variation in submerged mussel logger temperature and 77% was explained by water temperature collected at South Beach. We expected the local water temperature from South Beach would be a better predictor of mussel logger temperature when compared to the other local water temperatures, because of its proximity to the study sites. However, both temperature measurements have limitations and advantages that have to be taken into account.

Within our study period, water temperature measurements collected at the South Beach location and satellite-derived SST raised some questions. The only usable water temperature measurements from the South Beach location started in 2007 after a long period of sensor malfunction, whereas, satellite-derived SST was collected from 2000 and 2002 depending on the satellite. This highlights a common issue that satellite remote sensing can help address. In our study, widely accepted and used water temperature measurements from NOAA still proved to have temporal limitations due to sensor malfunction. Fortunately, there were local water temperature measurements available for us to use, even though there were issues. In many study areas, there are no available local water temperature measurements for a comparison to be made. This further supports the use of remotely sensed SST.

However, water temperatures collected at South Beach were hourly in comparison to twice daily for satellite-derived SST. This means that daily temperature variations could be measured using local water temperature measurements, whereas satellite-derived SST can only provide a “snapshot” of the temperature in a given day. Furthermore, clouds and fog affect satellite-derived SST measurements. This means that the number of available SST measurements will be less in areas that have frequent clouds or fog, which can greatly affect our ability to predict temperature.

Based on these limitations, advantages, and our own results, we can make a few inferences. First, if there are water temperature measurements collected close to the study sites, they will likely offer the strongest prediction ability for daily submerged mussel logger temperature. Second, while local water temperature measurements collected close to the study sites might offer the best prediction, the sensors can malfunction just as sensors on biomimetic loggers or satellites. Third, if there are no local water temperature measurements available, satellite-derived SST may offer a good alternative to local water temperature measurements and will help fill gaps in areas lacking water temperature data. Lastly, limitations exist for every temperature collection method and must be taken into account depending on the research question.

5. Conclusions

In some ecological studies, remotely sensed satellite data could provide better estimates of organismal body temperature than in situ observations. Furthermore, the spatial and temporal limitations of in situ temperature observations make utilizing remotely sensed satellite data necessary in many ecological studies. However, caution must be exercised in the use of satellite-derived products when investigating processes at high temporal and spatial resolutions. While there are many limitations and advantages in utilizing remotely sensed satellite data to estimate organismal body temperature, using remotely sensed satellite observations can provide excellent spatial coverage to better understand spatial variability in temperature. Our results showed that satellite-derived SST was comparable to local water temperatures collected along the Oregon coastline when predicting daily-submerged mussel logger temperature. While temperature loggers and water temperatures measured close to the study sites provide the best results, remotely sensed satellite temperatures can help gap-fill in areas where there are no other or sparse temperature measurements.

Further research is needed to determine whether remotely sensed satellite data can be used in place of, or in conjunction with, in situ observations in heat budget models to accurately estimate organismal body temperature. To fully understand the effects of the changing climate on rocky intertidal ecosystems, we need to first be able to measure different biological and physical phenomena at varying spatial and temporal scales. This further strengthens the need for more studies focused on using satellite observations for these dynamic and vulnerable ecosystems.

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Author Contributions: Jessica Sutton and Venkat Lakshmi conceived the research; Jessica Sutton gathered and analyzed all the data; Jessica Sutton wrote the paper; Jessica Sutton and Venkat Lakshmi revised and edited the paper.

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Abbreviations

The following abbreviations are used in this manuscript:

NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
MODIS	Moderate Resolution Imaging Spectroradiometer
PISCO	Partnership for Interdisciplinary Studies of Coastal Oceans
SST	Sea Surface Temperature
NDBC	National Data Buoy Center
GPS	Global Positioning System
MGET	Marine Geospatial Ecology Tools
PO.DAAC	Physical Oceanography Distribution Active Archive Center

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