

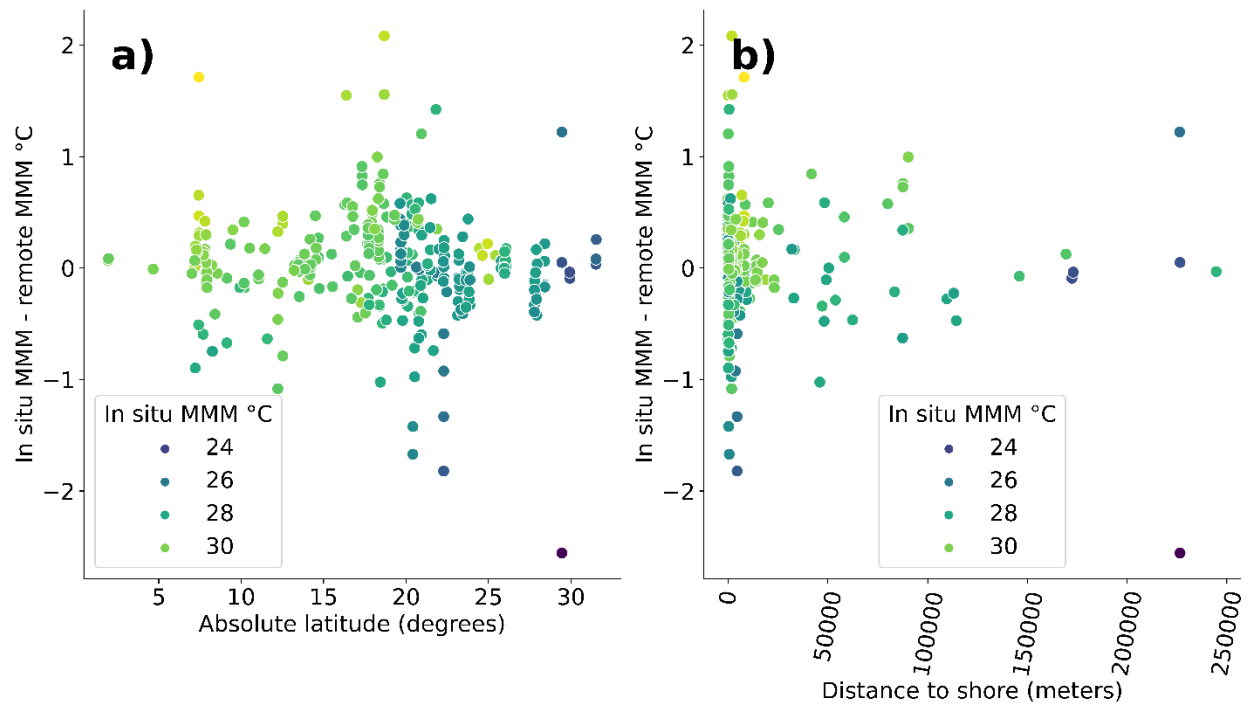
Supplementary information for
Fine resolution satellite sea surface temperatures capture the conditions experienced by corals at monthly
but not daily time scales.

Bos, J.T. & Pinsky, M.L.

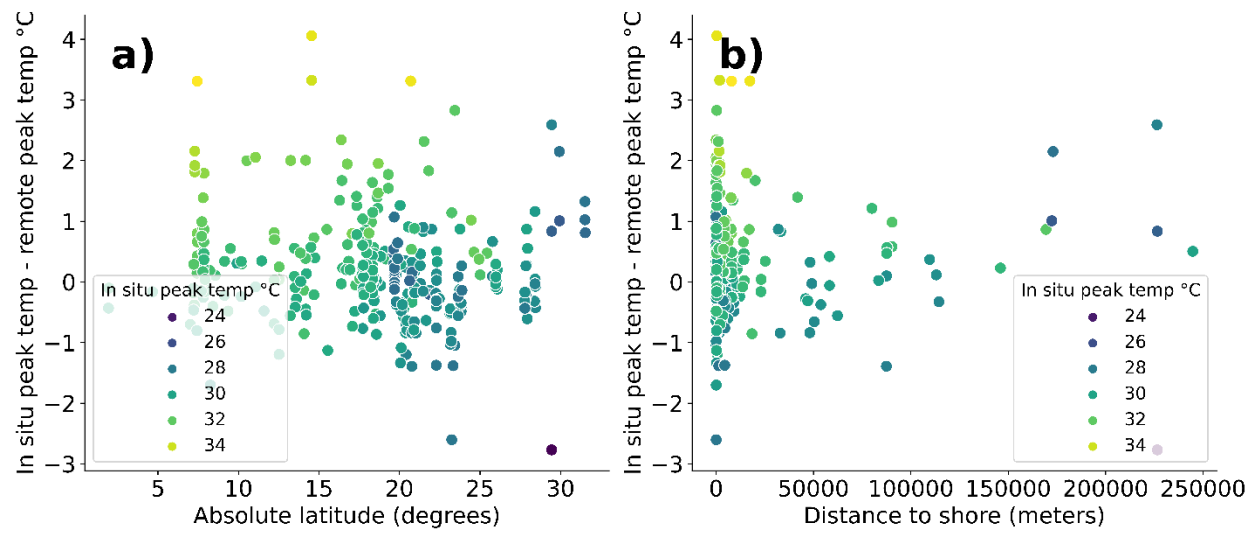
Jaelyn T. Bos. University of California, Santa Cruz, Department of Ecology and Evolutionary Biology,
Santa Cruz, California, USA. orcid.org/0009-0007-7877-3862. Corresponding author.
jaelynbos@gmail.com

Malin L. Pinsky. University of California, Santa Cruz, Department of Ecology and Evolutionary Biology,
Santa Cruz, California, USA. orcid.org/0000-0002-8523-8952.

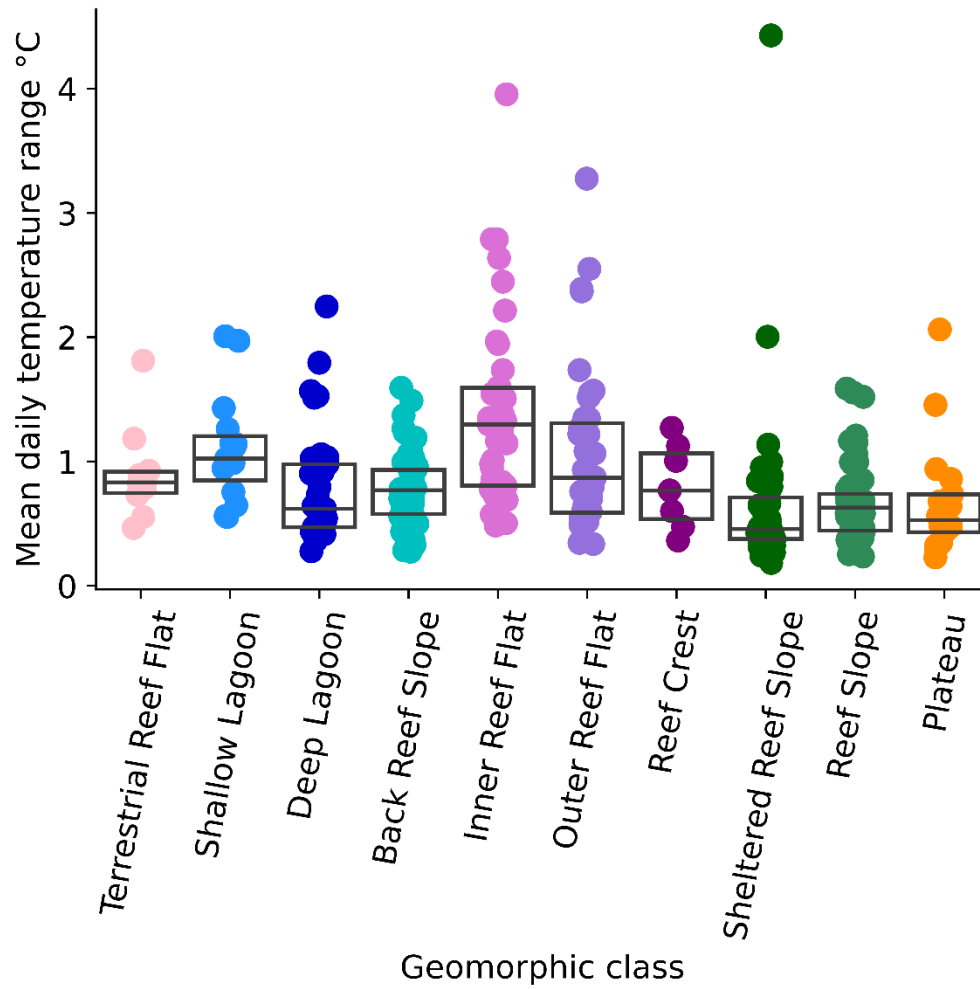
Supplemental figures



Supplemental Fig. 1. There was no clear linear relationship between the *in situ* vs. remotely sensed MMM differences and either latitude (A; Pearson's $r = -0.087$) or distance to shore (B; Pearson's $r = -0.063$).



Supplemental Fig. 2. There was no clear relationship between the *in situ* vs. remotely sensed peak temperature differences and either latitude (a; Pearson's $r = -0.101$) or distance to shore (b; 0.062).



Supplemental Fig. 3. Mean daily temperature range varied with remotely sensed geomorphic class (Kruskal-Wallis $H = 71.67$, $p = 7 \times 10^{-12}$, $n = 314$)

Supplemental Tables

Supplemental Table 1. Model parameters and cross-validated R^2 for *in situ* MMM temperatures. Each geomorphic class (e.g., “is outer reef flat”) is coded as 1 or 0 for whether a location is in that class or not (respectively).

Independent variable(s)	Model type	Mean cross-validated R^2
Remote MMM	Linear	0.8803
Remote MMM, latitude	Linear	0.8753
Remote MMM, log distance to shore	Linear	0.8803
Remote MMM, log distance to shore, interaction	Linear	0.8805
Remote MMM, log distance to shore, Remote MMM * log distance to shore, is outer reef flat	Linear	0.8844
Remote MMM * log distance to shore, is outer reef flat, is shallow lagoon	Linear	0.8846
Remote MMM, log distance to shore, each geomorphic class	Random Forest	0.8297
Remote MMM, log distance to shore, each geomorphic class	Linear	0.8780

Supplemental Table 2. Model parameters and results for *in situ* peak annual temperatures. Details as in Supplemental Table 1.

Independent variable(s)	Model type	Mean cross-validated R^2
Remote MMM	Linear	0.574
Remote peak temperature	Linear	0.629
Remote peak temperature, latitude	Linear	0.622
Remote peak temperature, log distance to shore	Linear	0.623
Remote peak temperature, is inner reef flat	Linear	0.649
Remote peak temperature, is inner reef flat, is outer reef flat	Linear	0.661
Remote peak temperature, is inner reef flat, is outer reef flat, is shallow lagoon	Linear	0.666
Remote peak temperature, each geomorphic class	Linear	0.644

Remote peak temperature, each geomorphic class	Random forest	0.650
Remote peak temperature, log distance to shore, each geomorphic class	Random forest	0.645

Supplemental Table 3. Model parameters and results for *in situ* mean DTR. Details as in Supplemental Table 1.

Independent variable(s)	Model type	Mean cross-validated R^2
Remote mean weekly temperature range	Linear	-0.355
Remote maximum monthly mean temperature	Linear	-0.387
Remote peak annual temperature	Linear	-0.349
Log distance to shore	Linear	-0.365
Each geomorphic class	Linear	-0.327
Each geomorphic class	Random forest	-0.326
Back reef slope	Linear	-0.438
Is reef slope	Linear	-0.277
Sheltered reef slope	Linear	-0.338
Deep lagoon	Linear	-0.388
Shallow lagoon	Linear	-0.333
Outer reef flat	Linear	-0.318
Inner reef flat	Linear	-0.343
Terrestrial reef flat	Linear	-0.360
Reef crest	Linear	-0.357
Plateau	Linear	-0.361

Supplemental text

Modeling *in situ* temperature metrics from remotely sensed data

Maximum monthly mean temperatures

We used multiple model types and remotely sensed variables to model and predict *in situ* MMMs. We selected models with the highest mean cross-validated R^2 , which involved iteratively fitting the model using a randomly selected 80% of the data, calculating the R^2 value of the same model on the remaining 20% of the data, repeating this procedure five times, then calculating the mean of all five R^2 values. This procedure helps avoid overfitting (Lever 2016). We specifically fit the models on independent variables that could be remotely sensed from space and for which datasets covering all or most of global coral reefs are publicly available. We fit both linear and random forest models. The input variables, model type, mean cross-validated R^2 value, and variable coefficients (where relevant) are reported in Supplemental Table 1. We created dummy variables for each geomorphic class, setting the variable equal to 1 if the point fell within that geomorphic class (for example, a shallow lagoon), and otherwise equal to zero.

We first fit each model using only remotely sensed temperature and reported the cross-validated R^2 (Supplemental Table 1). We then added other variables in a stepwise manner, selecting the best model using cross-validated R^2 . For geomorphic classes, we fit a model using the dummy variable for each individual geomorphic class in addition to the other parameters chosen in previous step(s). For any geomorphic class that improved the model, we then conducted an additional round of model fitting and evaluation adding each remaining geomorphic class one at a time. We also fit a random forest model using all of the potential dependent variables and reported the mean cross-validated R^2 value.

Peak annual temperatures

We repeated the same procedure described above to fit models with the 99th percentile annual *in situ* temperature (hereafter “peak annual temperature”) as the dependent variable (Supplemental Table 2).

Mean daily temperature range

Finally, we fit both linear and random forest models to predict mean daily temperature range (DTR). We found no models with positive predictive power in cross validation; in fact, all of the mean cross validated R^2 values were negative (Supplemental Table 3). While mean DTR appears somewhat related to geomorphic class (see Kruskal-Wallis test results in main text), we were unable to predict mean DTR from any remotely sensed variables.

References

Lever J, Krzywinski M, Altman N (2016) Model selection and overfitting. *Nat Methods* 13:703–704.