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A framework for comparing coral bleaching thresholds

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Abstract. Coral reefs are highly vulnerable to bleaching under elevated temperature. Since 2002, NOAA Coral Reef Watch has used a bleaching threshold based on global sea surface temperatures to provide operational bleaching warnings. Recent studies suggest that modifications to the current global bleaching prediction method may result in higher predictive power. Here, we present a method for comparing four bleaching prediction methods at different spatial and temporal resolutions, each calibrated against the global bleaching observational dataset from ReefBase between 1985 and 2005. We identify one method ("MMMmax") that consistently gives the highest predictive power at all spatial and temporal resolutions examined. An improved bleaching threshold will refine future bleaching projections under climate change and provide more reliable real-time bleaching alerts to international coral reef managers.

Key words: Coral Bleaching, Prediction, Variability, Sea surface temperature.

Introduction

Coral reefs are among the most biologically diverse and economically valuable ecosystems on earth, supporting coastal protection, tourism, and fisheries (Roberts et al. 2002). When corals are exposed to unusually warm temperatures, they expel their photosynthetic endosymbiotic algae ("coral bleaching"). Since these endosymbionts provide corals up to 95% of their metabolic requirements, bleaching significantly compromises coral health. Severe bleaching can lead to mortality (Jokiel and Coles 1977). Scientists' use bleaching algorithms to assess levels of thermal stress experienced on reefs, and to predict bleaching events into the future under different climate change scenarios (Parry et al. 2007; Donner et al. 2005; Donner 2009, 2011; Teneva et al. 2012). Bleaching algorithms can be used to trigger bleaching response plans and support appropriate management decisions, but their effectiveness depends critically on their accuracy.

The widely employed NOAA Coral Reef Watch Program (CRW) bleaching prediction method uses a thermal stress algorithm based on satellite-derived sea surface temperature (SST). This method is based on empirical data that corals bleach at ~1°C above their historical summertime maximum SST (Glynn and D'Croz 1990; Atwood et al. 1992; Gleeson and Strong 1995). Weekly thermal anomalies greater than 1°C above a climatology (maximum monthly mean SST) are summed over a 12 week period, resulting in the "Degree Heating Week" (DHW) metric (Eakin et al. 2009); a DHW > 4°C-weeks predicts a "likely bleaching event". A modified metric, the "Degree Heating Month" (DHM), was developed for monthly SST generated by historical and projected datasets; a DHM > 1°C-months predict a "likely bleaching event" (Donner et al. 2005).

Global bleaching prediction power (probability of predicting a bleaching event when one was observed) ranges from 13.7-40% compared to the best global observational bleaching database (ReefBase; Boylan and Kleypas 2008; Donner 2011). Power varies depending on spatial and temporal resolution, climatology, and observational time period. This relatively low predictive power could also be attributed to: 1) the large mismatch in scale that exists between in situ reef temperatures and satellite SSTs (Selig et al. 2010); 2) species specific thermal stress responses (e.g., Grottoli et al. 2006); 3) other factors influencing mass bleaching besides SST (e.g. PAR/UV) an imperfect bleaching database missing many bleaching events (Oliver et al. 2009; 5) an insufficient bleaching prediction method. A "static" thermal stress threshold (e.g., 1°C above a summertime maximum) may not be appropriate for corals acclimatized to more/less thermally variable environments (e.g., McClanahan et al. 2007, Oliver and Palumbi 2011).

We compare alternative global bleaching prediction methods at different spatial and temporal resolutions against historical bleaching observations to determine the most skillful algorithm. In addition to the standard CRW method, we examine three other methods that incorporate historical thermal variability (Donner

2009, 2011). To address potential mismatches in spatial and temporal resolution, we examine 3 SST datasets at different spatial resolutions (4km, 0.5° x 0.5° and 1° x 1°) and assess the 0.5° x 0.5° dataset at both biweekly and monthly temporal resolutions. Importantly, we implement a novel, quantitative framework in which to compare these different methods. Each algorithm is normalized to a fixed nominal bleaching frequency to objectively compare relative statistical fidelity between methods based on global bleaching observations.

Material and Methods

Reef Locations and Observational Sea Surface Temperatures

Reef locations were extracted from the Millennium Coral Reef Mapping Project website (UNEP-WCMC, 2010) and re-gridded 4km x 4km, 0.5° x 0.5°, and 1° x 1° degree spatial resolutions. This resulted in 63,838, 3,812 and 1,672 reef-containing grid cells, respectively. We used three SST datasets of differing spatial and temporal resolution. Our coarse resolution dataset was the 1° x 1° monthly HadISST1 dataset (Rayner et al. 2003). Historical SST datasets and global climate models often employ this resolution. Second, a 0.5° x 0.5° twice-weekly nighttime-only SST dataset was obtained from the Advanced Very High Resolution Radiometer (AVHRR) Pathfinder satellite. NOAA CRW uses this dataset for real-time bleaching predictions (Eakin et al. 2009) and future bleaching prediction studies have used this dataset to create baseline climatologies (Donner et al. 2005; Donner 2009, 2011). Third, the 4km CorTAD dataset served as our high-resolution SST dataset (Selig et al. 2010).

MMM and MMMmax Climatology

Several recent studies have shown that corals living in more thermally variable environments may be more resistant to bleaching than those in more stable environments due to acclimatization or shifts in community structure over time (McClanahan et al. 2007, Thompson and van Woesik 2009, Oliver and Palumbi 2011). To incorporate these findings into a new threshold, two climatologies were calculated for each of the three SST datasets. The CRW Maximum Monthly Mean (MMM) climatology is the mean of the average warmest month during the climatological time period (e.g., all Septembers from 1985-2000), whereas MMMmax is the mean of the warmest month of each year (MMMmax) (e.g., Jul. in 1985, Sept. in 1986, Aug. in 1987) (Donner 2009, 2011). MMMmax better characterizes thermal extremes in regions where the timing of the seasonal peak in SST varies from year to year (e.g. the equatorial Pacific), providing a more robust estimate of recent thermal history assuming corals living in more variable thermal environments will bleach less frequently than in more seasonally synchronized thermal environment

Variability Based Bleaching Alert Threshold

In addition to the standard CRW static bleaching threshold (Control), a second variability based threshold method (Variability) was tested using both climatologies described above. This Variability method accounted for historical variability in interannual maximum temperatures, as described by Donner (2009, 2011). Briefly, instead of using a static threshold (i.e., where a Bleaching Alert threshold of DHW=4°C-weeks or DHM=1°C-months generates a "likely" bleaching event), we re-calculated the Bleaching Alert threshold to incorporate thermal variability using the standard deviation of SSTs in each reef cell (Donner 2009, 2011). The initial average of the bleaching thresholds in all reef cells globally was still 1°C but the threshold varied from cell to cell. The combination of two climatologies and two Bleaching Alert thresholds resulted in a total of four prediction methods: 1) MMM + Control, 2) MMM + Variability, 3) MMMmax + Control, and 4) MMMmax + Variability.

Normalization of the Four Prediction Methods

As illustrated in Donner (2011), different bleaching prediction methods result in vastly different numbers of global bleaching events. Thus comparing predictive power between methods is not a fair assessment because higher false positive rates (type I error) are associated with higher predictive power as total events increase (also see Hooidonk and Huber 2009). To address this, we employed a normalization scheme that resulted in similar false positive rates among all four bleaching prediction methods to allow us to directly compare predictive power between methods.

Given that the number of bleaching observations in ReefBase is thought to be an order of magnitude smaller than the actual number of bleaching events that have occurred over this time period (Oliver et al., 2009; Donner, 2011), the typical type I error rate of $\alpha = 0.05$ is probably too low. Nevertheless, an unreasonably high α could greatly overpredict bleaching and "false alarms" would eventually lead to mistrust in any prediction method. ReefBase observations indicate a bleaching frequency of 1.3% per year over 1985-2005. To set a reasonable α value, we estimated a higher, perhaps more realistic value for bleaching frequency of 10% (i.e., bleaching once every ten years at each location, or 10% of reefs bleaching each year). We then normalized each of the four prediction methods to this nominal bleaching frequency. As a sensitivity test, we also examined the effect of assuming a bleaching frequency of 20%, and obtained similar results (not presented here). Indeed, the frequency itself is somewhat arbitrary for this analysis; a full sensitivity analysis using the range of conceivable bleaching frequencies would be required to test the relative predictive power of each method.

To normalize each prediction method, we increased or decreased the Bleaching Alert threshold to achieve bleaching frequency of 10%. For the Control methods, a value was added to the standard 1°C-month DHM or 4°C-week DHW Bleaching Alert threshold. For the Variability methods, a value was added to change the median global standard deviation of all reef cells to be greater to or less than 1°C (see Methods in Donner 2011).

Bleaching Observations

ReefBase bleaching observations were used to calibrate bleaching prediction methods with observations at a global scale (Tupper et al. 2012). Despite many biases in this database (Oliver et al. 2009, Donner 2011), it is the best currently available. ReefBase bleaching observations were gridded at the spatial resolution of each SST dataset. Observations over 1985-2005 were vetted for spatial and temporal duplicates and "no bleaching events" as in Donner (2011).

Results

Pre-normalized Bleaching Predictions

We compared results for each of the four bleaching prediction methods applied to the 1° x 1°, 0.5° x 0.5°, and 4 km monthly SST data, as well as the 0.5° x 0.5° biweekly SST data (Table 1, left). The number of ReefBase bleaching events varied by spatial resolution, resulting in a total of 815, 1010, and 2105 events at the 1° x 1°, 0.5° x 0.5°, and 4 km resolutions, respectively. Bleaching frequency increased with SST variability at higher spatial and temporal resolutions (Table 1, left). Using the MMM + Control method with the 1° x 1° SST dataset, 10.4% of reefs bleach each year, resulting in a predictive power of 31.4% and a false positive rate of 8.3%. In the 4 km monthly case, bleaching frequency increases to 30.9% with a predictive power of 62.6% with a higher false positive rate of 22%. The MMM + Variability method biweekly 0.5° x 0.5° dataset resulted in the highest predictive power (76.8%), but it also had the highest false positive rate at 42%. As discussed in Donner (2011), lack of consistency between the statistical weightings makes absolute comparison among algorithms difficult.

Normalized Bleaching Predictions

After normalizing to a common global bleaching frequency of 10% (Table 1, right), three results stood clear. Firstly, the Control + MMMmax algorithm performed superior to the other prediction methods for all data sets. Secondly, Variability + MMMmax did not perform better than the Control + MMMmax. Thirdly, the highest overall predictive power (43.2%) was achieved using the monthly 0.5° x 0.5° data set, indicating that enhancement of neither spatial (4 km) nor temporal (biweekly) resolution actually degraded the fit. The geographical distribution of bleaching events varied for each prediction method. Fig. 1 compares observational ReefBase events with each of the four prediction methods at the 0.5° x 0.5° spatial scale using monthly SSTs. Relative to the MMM + Control method, the MMM + Variability method

Table 1 Global bleaching predictions and statistical comparison to ReefBase bleaching events between 1985-2005. The best prediction methods following normalization to a 10% bleaching frequency are highlighted in bold.

Prediction Method *1° x 1° - monthly*	DHM Bleaching Alert Level	Bleaching Frequency (% Global Reefs / Year)	% Predicted but not Observed (alpha)	% Observed but not Predicted (beta)	Predictive Power (%)	DHM Bleaching Alert Level	Bleaching Frequency (% Global Reefs / Year)	% Predicted but not Observed (alpha)	% Observed but not Predicted (beta)	Predictive Power (%)
MMM + Control	1	10.4	8.3	68.6	31.4	1.0	10.0	8.0	69.0	31.0
MMM + Variability	1	10.0	8.0	71.7	28.3	1.0	10.0	8.1	71.6	28.4
MMMmax + Control	1	5.1	4.3	77.6	22.4	***0.7***	***10.0***	***8.1***	***64.9***	***35.1***
MMMmax + Variability	1	4.3	3.6	79.6	20.4	0.7	10.0	8.2	65.2	34.8
0.5° x 0.5° - monthly										
MMM + Control	1	22.1	16.5	44.3	55.7	1.6	10.0	8.2	64.1	35.9
MMM + Variability	1	22.5	16.5	47.7	52.3	1.6	10.0	8.0	71.3	28.7
MMMmax + Control	1	9.4	7.9	58.4	41.6	***1.0***	***10.0***	***8.3***	***56.8***	***43.2***
MMMmax + Variability	1	8.8	7.3	61.2	38.8	0.9	10.0	8.2	58.1	41.9
4km2 - monthly										
MMM + Control	1	30.9	22.0	37.4	62.6	2.1	10.0	8.6	73.2	26.8
MMM + Variability	1	31.0	22.0	39.8	60.2	1.5	10.0	8.5	75.3	24.7
MMMmax + Control	1	10.5	9.3	61.9	38.1	***1.0***	***10.0***	***8.9***	***63.4***	***36.6***
MMMmax + Variability	1	9.9	8.8	64.0	36.0	1.0	10.0	8.8	63.6	36.4
0.5° x 0.5° - biweekly	**DHW**					**DHW**				
MMM + Control	4	35.6	24.3	37.4	62.6	7.7	10.0	8.4	65.1	34.9
MMM + Variability	4	89.0	42.0	23.2	76.8	11.0	10.0	8.3	73.2	26.8
MMMmax + Control	4	18.8	14.9	48.1	51.9	***5.6***	***10.0***	***8.5***	***61.6***	***38.4***
MMMmax + Variability	4	68.3	37.0	26.4	73.6	8.5	10.0	8.4	66.1	33.9

shows higher thermal stress in the Western Pacific as opposed to the Red Sea. The MMMmax + Control method shows highest thermal stress in the Caribbean. Scaled histograms on the right side of each subplot show how the distribution of predicted bleaching events varied with latitude for each method after normalization. With the MMM + Variability method, bleaching events were most severe in equatorial regions where less interannual variability occurs (e.g., Micronesian islands in the West Pacific Warm Pool). With the MMMmax + Control method, thermal stress events were most severe in higher latitude reef regions (e.g. Caribbean, Red Sea, and Australia), where the hottest month of the year is fairly consistent year to year. The warmest month varies more year to year in equatorial regions, leading to a higher MMMmax and results in less overall bleaching.

Discussion

We attempted to address incompatibilities between previous analyses of coral bleaching through the use of a common framework to globally compare both bleaching algorithms and sea surface temperature datasets. Through this effort, we found the Control + MMMmax method (maximum normalized power 43.2%) superior at the global scale to either the Control + MMM method (maximum normalized power 35.9%) currently used operationally by Coral Reef Watch, or the Variability + MMM method (maximum normalized power 28.7%) proposed by Donner (2009, 2011).

Nevertheless, when the prediction methods were examined spatially, it is difficult to interpret the reliability of the global statistics. Because ReefBase observations are biased towards regions with active communities of divers, like the Caribbean and the Great Barrier Reef (Fig. 1A), global predictive power in this study is mostly based statistical comparisons to these locations. By normalizing to a common bleaching frequency, we effectively set the false positive value for all the methods (percentage of predicted events that were not observed) in an attempt to directly compare methods, despite the uncertainty in the actual bleaching frequency. We plan to conduct further analyses at the regional scale to assess the relative strength of each algorithm compared to the most intensely observed regions such as the Caribbean, Great Barrier Reef, Western Indian Ocean, and Eastern Equatorial Pacific. In addition, as more “bleaching” and “no bleaching” observations are recorded in ReefBase; we suggest this normalization framework for comparing alternative prediction methods should become even more useful.

Despite the limitations of a statistical analysis against the

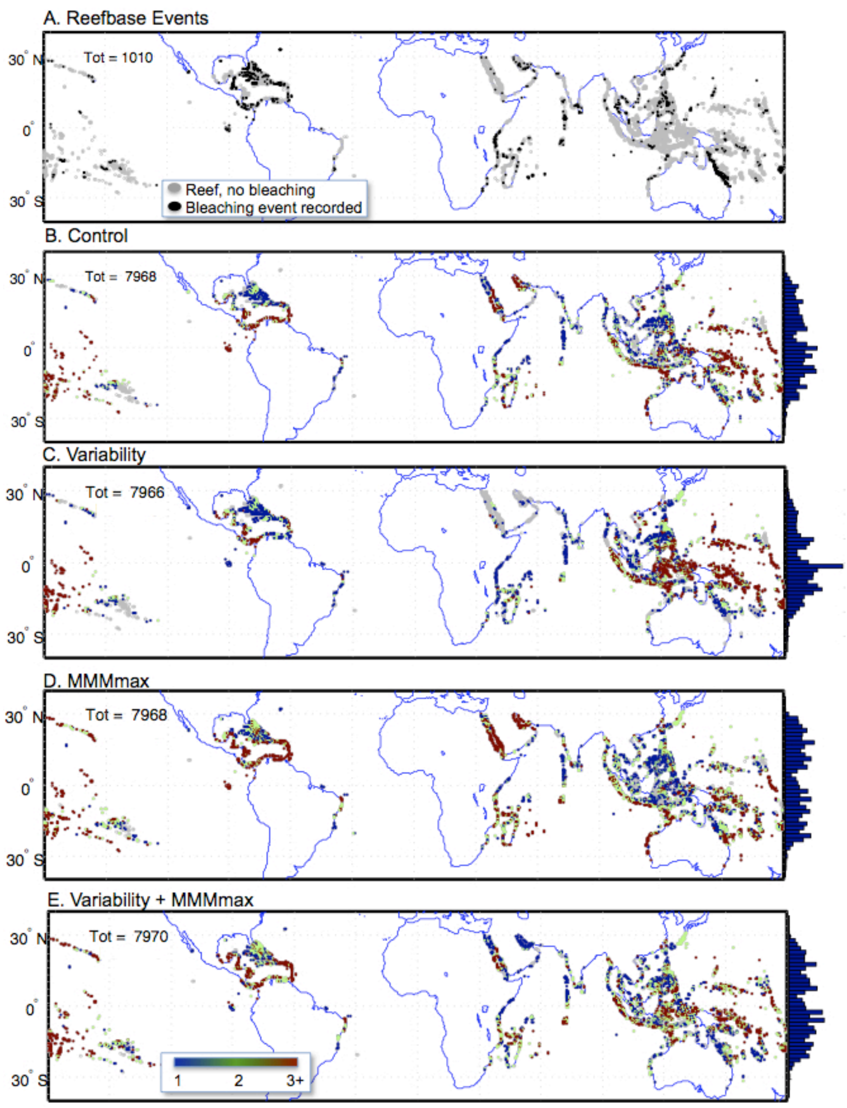

Fig. 1: Maps of bleaching events observed and predicted during the 1985-2005 time period (50km SST resolution, monthly timestep) after normalizing all methods to a bleaching frequency of 10%. Summary histograms (right) show the latitudinal distribution of bleaching events for each method.

ReefBase observations, we suspect that the reason for the relative success of the MMMmax + Control method related to its lack of statistical dependence of this climatology on a fixed seasonal cycle and partially incorporates variability. Thus, the MMMmax climatology had greater robustness in the context of the very brief temperature record (1985-2000) at our disposal for the characterization of variability statistics. We suspect that given a much longer dataset, we should be able to build a more robust algorithm characterizing both MMMmax climatology and the Varibility-based Bleaching Threshold, but unfortunately could not test this hypothesis given the lack of high quality data.

Our results did not support the hypothesis that high spatial and temporal SSTs would improve predictive power. However, we suspect that the observed degradation of fit when moving to high temporal or spatial resolution was related to the need for gap filling in these high resolution datasets (to account for clouds and other factors) that may extend these datasets beyond the limits of their practical utility. The fact that the monthly dataset at 0.5° x 0.5° spatial resolution resulted in the highest predictive power, is "good news" for future modeling work given the lower spatial and temporal resolution output of most global climate models.

An additional limitation of this statistical analysis was that satellite-era observations required the use of a climatological period that was nearly the same as the analysis period. We tried using the historical HadISST1 record to get around this constraint, but the data quality was found to be insufficient at the reef scale. In future work, we plan to utilize GFDL Earth System Model simulations to create a longer, rolling climatology at the reef scale to avoid this problem and to implement this normalization framework to directly compare mechanistic models of coral adaptation and acclimatization under future climate change scenarios.

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