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Improved Characterization of Coral Bleaching Patterns From a Percentile-Based Threshold Model

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Key Points:

- Percentile-based thresholds in temperature accumulation metrics have higher explanatory power for estimates of coral bleaching risk
- Percentile thresholds reflect the local temperature variances which vary spatially
- The 90th percentile represents the present-day optimal threshold for coral bleaching risk

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract

Tropical corals are increasingly threatened by anthropogenic global warming and marine heatwaves. However, questions remain about how to best characterize potential heat stress relevant to coral bleaching. The degree heating week (DHW) metric has guided bleaching risk assessments for ~25 years. Here, we compare the DHW approach, which uses a static anomaly threshold, with a percentile-based approach developed from a widely used marine heatwave definition. We find that the explanatory power of coral bleaching risk—measured by the equitable threat score—is higher for the percentile-based approach compared to the DHW, with improvements of up to 41%. This is likely because percentile thresholds better reflect spatiotemporal temperature variability. We further demonstrate how the weather-forecasting framework can help identify current optimal adapting baselines, a key step toward evaluating ecological risks as global warming challenges the use of fixed versus shifting baselines.

Plain Language Summary

This study compares the utility of the traditional degree heating week metric—the definition that has been central to studying heat stress induced coral bleaching likelihood—against an approach that uses a percentile-based thermal threshold. Our findings indicate that the percentile-based framework is better at characterizing severe coral bleaching globally because it accounts for the local temperature variance that differs spatially. We also illustrate how a weather-forecasting framework can help identify the most appropriate baselines for assessing temperature extremes under climate change. This is an essential step for evaluating ecological risks as global warming challenges the use of fixed versus shifting baselines.

1. Introduction

Biologically relevant heat stress can be measured in several ways, including temperature exceeding a fixed threshold (Glynn & D'Croz, 1990), maximum temperatures (Berkelmans et al., 2004), or anomalies relative to a local climatology (Wernberg et al., 2013). Among the most widely used approaches is the degree heating week (DHW) metric developed by the U.S. National Oceanic and Atmospheric Administration (NOAA) to monitor coral bleaching (Liu et al., 2003, 2014). The DHW is an example of a cumulative measure of the potentially harmful temperature intensity: temperature anomalies over a 12-week period are summed relative to a local climatology (the maximum monthly mean, or MMM) when they exceed an anomaly threshold of MMM + 1°C. Historically, a cumulative heat stress—measured in terms of Degree Heating Weeks (DHWs: °C-weeks)—of 4 DHWs (Level 1) has indicated that significant coral bleaching is likely, while 8 DHWs (Level 2) has been associated with coral mortality (Liu et al., 2014). However, NOAA recently expanded its official alert levels, which now include Levels 3–5, to keep pace with the increasingly severe bleaching events (NOAA Coral Reef Watch, 2024). While the DHW metric has served as a reliable indicator of coral bleaching and associated mortality over the past ~25 years (e.g., Hughes et al., 2017; Hughes, Kerry, et al., 2018; Kayanne, 2017), recent research suggests that this framework may be usefully revised to further improve bleaching predictions (DeCarlo, 2020; van Hooidonk & Huber, 2009; Whitaker & DeCarlo, 2024).

An alternative to the DHW metric for quantifying temperature extremes is the widely used marine heatwave (MHW) definition developed by Hobday et al. (2016). Unlike the DHW, which employs a time-invariant (fixed) anomaly threshold of 1°C above the MMM, the Hobday et al. definition uses a seasonally varying 90th percentile threshold relative to a climatological baseline (typically, an average seasonal cycle based on temperature data over a selected 30-year period). Although both frameworks define temperature extremes relative to the local climatology and are therefore region-dependent, the percentile-based method for computing the threshold likely better reflects the biological threshold of species (Benthuysen et al., 2021; Ferris et al., 2025) because temperature variances vary significantly in different regions (Hobday et al., 2016; Li Shing Hiung et al., 2024) and marine species (including tropical corals) adapt to their local temperature variability (Carilli et al., 2012; Fordyce et al., 2019). Therefore, refining the threshold calculation method in the DHW framework holds strong potential for improving coral bleaching predictions.

However, it is also notable that with future increases in global mean temperatures expected under different Intergovernmental Panel on Climate Change anthropogenic CO_2 emissions scenarios (Fox-Kemper et al., 2021), the use of a climatological baseline that remains fixed can lead to some regions approaching a permanent MHW state (Chiswell, 2022). While the use of a shifting baseline (Amaya et al., 2023) ensures MHWs remain infrequent events and can be valuable to understand the dynamics of variability and extremes, using a fixed baseline (Sen Gupta, 2023) or adaptation-adjusted baseline (Li et al., 2023) provides greater connection with potential impacts to marine species in a warming ocean climate. Ultimately, the choice of baseline depends on the research question (see Smith et al. (2025) for a set of recommendations on the choice of MHW baseline). To better understand ecological impacts in a warming climate, the use of an "adaptation-adjusted baseline"—an approach where the threshold is updated at the same rate that marine organisms can adapt to warmer temperatures—is appropriate for species or ecosystem risk and vulnerability assessments (Smith et al., 2025). Yet, before future adapting baselines can be determined in a world that is likely to keep warming (Oliver et al., 2019), we must establish the current baseline from which species may adapt.

In this study, our first objective is to compare global coral bleaching expectations based on the general DHW and Hobday et al. frameworks (N.B.: we focus on the latter definition, as opposed to other analogous frameworks (e.g., Richards et al., 2024), given its widespread application). Building on previous work that explored various aspects of the DHW metric (DeCarlo, 2020; Whitaker & DeCarlo, 2024), we conduct these comparisons using weather-forecasting statistics and by varying elements of both frameworks, such as the length of the warm-season windows. The standard Hobday et al. definition identifies MHWs year-round, accumulating heat-stress anomalies when temperatures exceed a percentile-based threshold (the 90th percentile) for at least 5 consecutive days. Here, we adapt this definition to align more closely with DHW by removing the 5-day duration criterion and summing anomalies only during a common summer warm-season window. After these adjustments, one of the main distinctions lies in how thresholds are computed: the DHW approach uses a time-invariant anomaly threshold—an Anomaly-Based Definition (ABD)—while the Hobday et al. approach relies on a seasonally varying percentile threshold—a Percentile-Based Definition (PBD). Our next objective is to employ DHW with a percentile threshold to determine whether the observed differences in coral bleaching explanatory power arise from the temporal structure of the threshold (time-invariant vs. seasonally varying) or from the threshold formulation (anomaly vs. percentile). Previous research has shown that coral thermal thresholds can exhibit some degree of seasonal variability (Berkelmans & Willis, 1999), potentially explaining why a seasonally varying threshold improves the relationship between bleaching severity and accumulated temperature anomalies (Weeks et al., 2008). Third, we explore whether there is an optimal window for defining heat stress accumulation events by identifying the window that results in the highest coral bleaching explanatory power. Our final and fourth objective is to estimate the present-day optimal adapting baselines for coral reefs globally.

2. Data and Methods

2.1. Data Sets

Sea surface temperature (SST) data were obtained from the NOAA Optimum Interpolation Sea Surface Temperature (OISST) (version 2.1) data set (Huang, Liu, Banzon, et al., 2021; Huang, Liu, Freeman, et al., 2021; Reynolds et al., 2007). We selected OISST because it is among the most reliable SST products for examining global coral bleaching events dating back to 1982 (DeCarlo, 2020). We use three global coral bleaching data sets (the Hughes, Anderson, et al. (2018), Hughes, Kerry, et al. (2018), and Donner et al. (2017), and the Reef Check (reefcheck.org) data sets) to verify that our results are robust irrespective of the data set used. All three data sets contain data on the presence and absence of bleaching which makes them appropriate for our analysis. However, they also contain some major differences (Table S1 in Supporting Information S1, discussed further in Text S1 in Supporting Information S1) that hinder compilation of all three data sets into a single analysis. For instance, the Hughes, Anderson, et al. (2018) and Hughes, Kerry, et al. (2018) data set defines the occurrence of "severe bleaching" when the coral bleaching percentage is >30% of the reef area, while the Donner et al. (2017) data set defines it above 50%. We mostly focus our analysis on the Hughes, Anderson, et al. (2018) and Hughes, Kerry, et al. (2018) data set since it provides a uniform global distribution of data both spatially and temporally (Figure S14 in Supporting Information S1). Thus, although its sampling density is lower, it is better suited to the present analysis because its global sampling coverage better matches the gridding interval of the SST product used here (Text S1 in Supporting Information S1). All analyses use the corrected Hughes, Anderson, et al. (2018) and Hughes, Kerry, et al. (2018) data set updated by DeCarlo (2020), which addresses errors present in the original data set.

2.2. Weather-Forecasting Framework

We use a weather-forecasting framework which has previously been used to improve understanding of coral bleaching (DeCarlo, 2020; van Hooidonk & Huber, 2009; Whitaker & DeCarlo, 2024). Using binary data based on a contingency table (Table S2 in Supporting Information S1), different event detection metrics can be computed to evaluate model performance (see examples in Table 2 of DeCarlo (2020)). We use the equitable threat score (ETS) because, unlike other metrics that change monotonically with varying levels of the accumulated heat stress, the ETS integrates multiple aspects of the forecast that allows an optimal cumulative heat stress level to be determined (this occurs at maximum ETS, DeCarlo, 2020). We compute the ETS according to:

$$\mathrm{ETS} = (H - H_{\mathrm{random}})/(H + \mathrm{FA} + M - H_{\mathrm{random}}) \tag{1}$$

where H, FA, and M represent the *Hits*, *False Alarms*, and *Misses*, respectively, as defined in the contingency table (Table S2 in Supporting Information S1), and H_{random} accounts for hits due to random chance and is given by $(H + \mathrm{FA}) * (H + M)/n$. The number of samples (summed across both space and time) is given by n. Despite known limitations of ETS regarding equitability (Hogan et al., 2010), these issues are unlikely to affect our conclusions because ETS becomes "asymptotically equitable" for $n > 30$ and our analyses are based on a large sample size (in the order of thousands). We also compute the standard error of the ETS using a bootstrapping procedure (Wilks, 2011, p. 185). Thus, we extend DeCarlo (2020)'s analyses by using a two-sample t-test at the maximum ETS values to evaluate whether the coral bleaching explanatory power of the two heat stress metrics are statistically different from each other.

Bleaching observations are binned into "presence" or "absence" of bleaching when a certain *bleaching level* (*BL*) is crossed (Figure 1). A BL of 30% is chosen for the Hughes data set based on its bleaching classification (Table S1 in Supporting Information S1). Bleaching predictions are determined from the accumulated extreme temperatures relative to a climatology (which represents a proxy of the biologically experienced thermal stress) that is computed using both the ABD and PBD (N.B.: under both frameworks, extreme temperatures are defined above the *threshold* but summed relative to the *climatology*). We use a *warm-season window* (Figure 1) ranging from 6 to 15 weeks (at 1-week intervals) that is common to both frameworks. Finally, we also define an *impact window* (Figure 1) that ranges from 60 to 150 days (with 30-day increments) for data sets that allowed it (i.e., only for the Reef Check and Donner data sets—noting that an impact window could not be determined for the Hughes data set because the data are annual). Further discussions regarding the BL, warm-season window (including computation of integrated anomalies), and the impact window are provided in Texts S2–S4 in Supporting Information S1, respectively. We perform sensitivity tests to confirm the robustness of our results to all of the above choices; these are presented in Supporting Information S1 (Figures S3–S13 in Supporting Information S1).

The ETS is computed iteratively for a range of values of the *minimum cumulative heat stress*, which is the minimum heat stress value at which corals are assumed to bleach (Text S3 in Supporting Information S1). Furthermore, variations in the ABD and PBD thresholds are tested. The ABD (based on DHW) uses a threshold of 1°C above the MMM, but here thresholds of MMM + β_{ABD} are tested, where β_{ABD} is in the range 0°C–2°C, at increments of 0.1°C. The seasonally varying PBD threshold is computed as the 90th percentile of the 1983–2012 baseline period. We also test variations in the amplitude of the PBD threshold, but here the method for varying the threshold is motivated by the *severity index* (Sen Gupta et al., 2020). This is a measure of the SST anomaly relative to the local difference between the threshold and climatology. We shift the threshold (hereafter referred to as the *severity threshold*) as determined by:

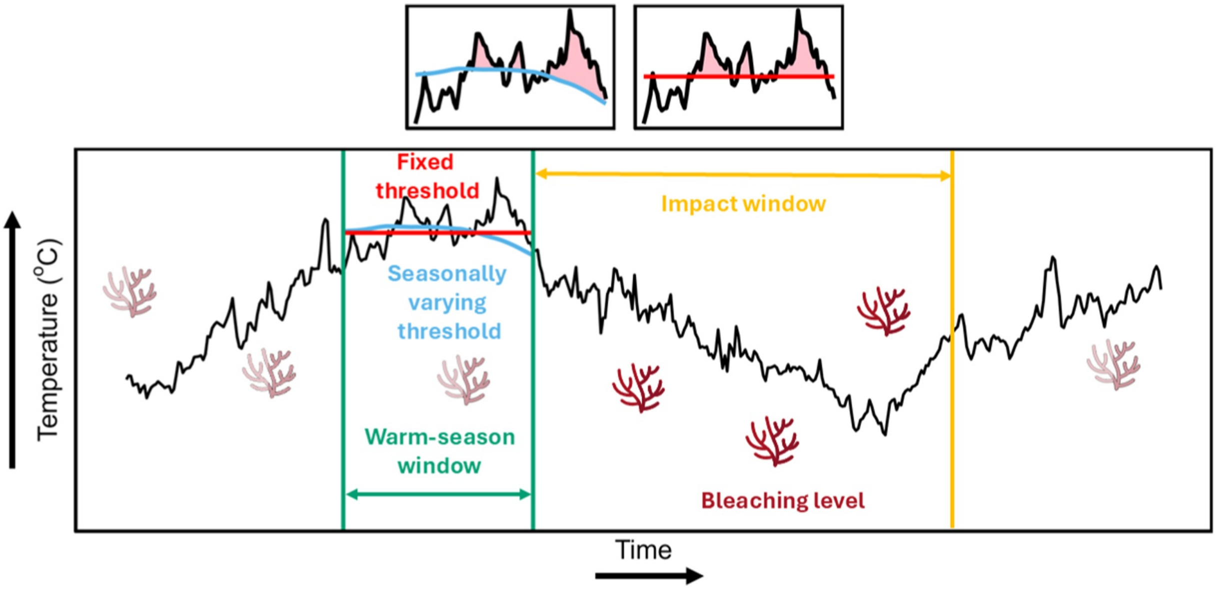

Figure 1. Schematic diagram of the methodology used to compare severe coral bleaching explanatory power using two heat stress frameworks: an Anomaly-Based Definition (ABD) and a Percentile-Based Definition (PBD). A temperature time series is shown in black. The ABD underpins degree heating week, and its threshold is shown by the red line (fixed—time-invariant), while the PBD is modified from the Hobday et al. (2016) marine heatwave definition and its threshold is shown by the blue line (seasonally varying). Under both the ABD and PBD, cumulative intensities are computed by integrating the "extreme" temperature anomalies—values above each framework's threshold (shaded in the top subpanels)—relative to their respective climatologies across the same warm-season window (green vertical bars). The impact window (beginning at the end of the warm-season window and ending with the yellow vertical bar) is the window in which coral bleaching surveys are considered (only for the Reef Check and Donner data sets due to their higher survey resolutions, Table S1 in Supporting Information S1). The choice of bleaching level is also central to the analyses for the Reef Check data set (Table S1 in Supporting Information S1).

$$\text{Threshold}_{i,d}^{n} = \alpha_{\text{PBD}} \cdot \left(\text{SST}_{i,d}^{\text{PC90}} - \text{SST}_{i,d}^{\text{clim}}\right) + \text{SST}_{i,d}^{\text{clim}} \tag{2}$$

where α_{PBD} is in the range 0–2 at increments of 0.1, $\text{SST}_{i,d}^{\text{clim}}$ is the long-term (climatological) average of SST on the dth day of the year at location i, and $\text{SST}_{i,d}^{\text{PC90}}$ is the 90th percentile SST value (computed in the climatological period) on the dth day of the year at location i. For $\alpha_{\text{PBD}} = 1$, the typical 90th percentile threshold (i.e., the threshold for Category 1 (Moderate) MHWs (Hobday et al., 2018)) is recovered, for $\alpha_{\text{PBD}} = 0$ it is the climatological mean, and for $\alpha_{\text{PBD}} = 2$ it equates to the threshold for Category 2 (Strong) MHWs (Hobday et al., 2018).

To identify the factor causing most of the difference in coral bleaching explanatory power between the two frameworks, we modify the way the threshold is originally computed in the DHW definition, from a MMM + β_{ABD} (temperature anomaly) to a MMM + β_{PBD} (percentile) threshold. The means and percentiles at each grid point are computed using all temperature values over summer months only (i.e., during the warm-season window) using the same baseline period from the PBD (i.e., 1983–2012). Thus, this modified DHW metric (pDHW) is more similar to the PBD, with the only difference being the temporal structure of the threshold; pDHW is time-invariant while PBD is seasonally varying. Variations in the pDHW threshold are tested using continuous multiples of the difference between the 90th percentile and the mean, similar to the PBD.

2.3. Statistical Significance

We use two different approaches to test whether the difference in coral bleaching explanatory power between the two temperature-extreme accumulation (as a proxy for implied accumulated heat stress) frameworks is statistically significant. Both approaches use two-sample t-tests, but their standard errors are obtained in different ways: the first via cross-validation and the second through bootstrapping, as detailed in Text S5 in Supporting Information S1.

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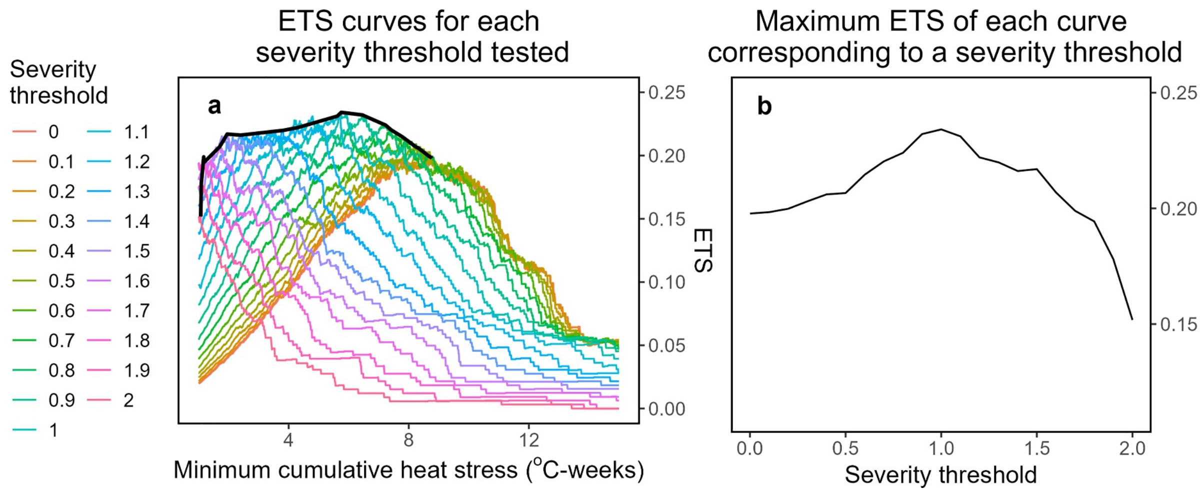

Figure 2. Equitable threat score (ETS) plotted against the minimum cumulative heat stress for each severity threshold from 0 to 2, with a 0.1 increment, using the Percentile-Based Definition (PBD) applied to the Hughes data set (a). The same is done for Anomaly-Based Definition and for the other data sets—see Section 3.2 and Figure S2 in Supporting Information S1. The thick black line connects the maxima of each of these curves. Panel (b) (which is the same as Figure 3a for PBD) is then obtained by taking the maximum ETS of each individual curve from panel (a) and matching it to its respective severity threshold.

2.4. Determination of Present Optimal Adapting Baselines

To address our fourth objective, we define the optimal "adapting baseline" as the severity threshold (see Equation 2) that yields the highest ETS for the respective period of analysis of each data set. This approach—which employs a fixed climatological baseline alongside severity thresholds that can be updated as (or if) organisms adapt in the future—follows the recommendations of Smith et al. (2025). It helps to not only keep studies comparable (with a fixed baseline period) but can also prevent the accumulation of biologically irrelevant temperature anomalies. This mirrors the phenomenon of MHW "saturation," where long-term warming combined with a fixed baseline results in a permanent marine heatwave state (Oliver et al., 2021), making such MHWs ecologically uninformative.

3. Results

3.1. Estimation of Optimal Thresholds

To estimate the optimal severity (α^*_{PBD}) and anomaly (β^*_{ABD}) thresholds for both PBD and ABD, we first compute the ETS curves for different threshold values (Figure 2a is an example for the Hughes data set using PBD). Then, plotting the maximum ETS of each individual curve against its respective threshold results in another non-monotonic curve that can be used to inform the choice of the optimal threshold (Figure 2b), which in this case is 1 at the maximum ETS value of 0.234.

3.2. Comparison of the Frameworks Under a 12-Week Warm-Season Window

The optimal PBD and ABD thresholds are very close to the respective thresholds of their original definitions (Hobday et al. (2016) MHW threshold of 1 and DHW threshold of MMM + 1°C) for all 3 data sets (Figure S2 in Supporting Information S1, first column), except for the optimal anomaly threshold in the Donner data set which deviates to a larger extent from the original threshold at +1.5°C. For the Hughes data set, an optimal severity threshold of 1 and anomaly threshold of 1°C are obtained for both metrics (Figure 3a).

As an objective comparison of ABD and PBD, we analyzed and compared the maximum ETS of the two frameworks at their optimal thresholds (Figure 3b). The maximum ETS for PBD (0.234) is greater than that of ABD (0.185). A similar conclusion is reached for the other two data sets (Figure S2 in Supporting Information S1). The results of the two-sample t-test indicate that the differences are statistically significant at the 5% confidence level (i.e., $p \leq 0.05$) for the Hughes data set ($p = 0.04$). For the other two data sets, the results were either significant or marginally significant at the 10% level ($p = 0.10$ for the Reef Check data set; $p = 0.05$ for Donner). To provide a more robust assessment, we performed cross-validation analysis on the data (McDonnell &

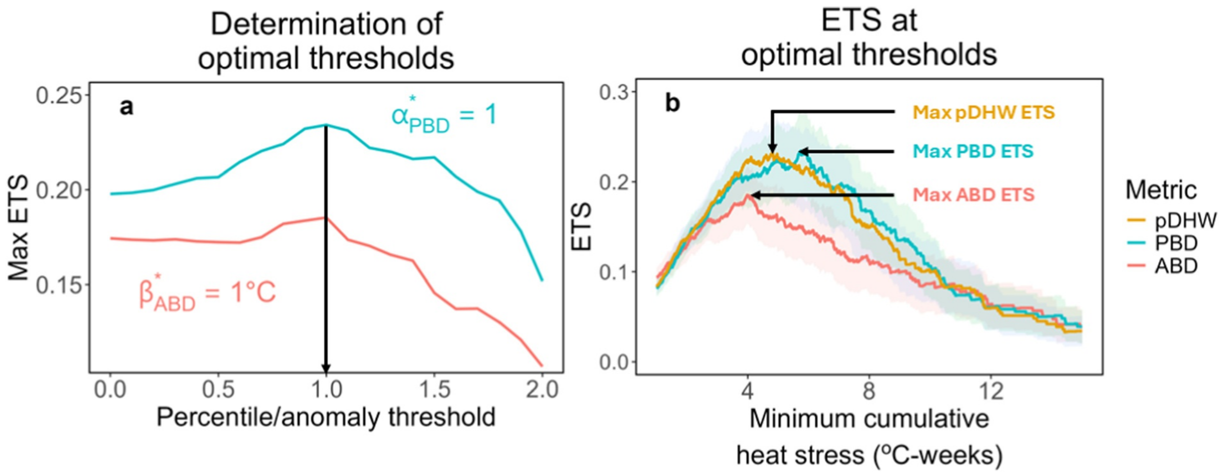

Figure 3. Comparison of coral bleaching explanatory power of degree heating week (DHW) (original (Anomaly-Based Definition) and modified definition (pDHW)) and Percentile-Based Definition (PBD) (modified from the Hobday et al. (2016) marine heatwave definition) applied to the Hughes data set. After obtaining the optimal thresholds (panel (a)), the equitable threat score (ETS) curves for the metrics at those thresholds (i.e., $\alpha_{PBD} = 1$ and $\beta_{ABD} = 1°C$) are plotted and compared (panel (b)). The modified DHW (pDHW) is similar to the original DHW framework, but its threshold is changed from MMM + β_{ABD} to MMM + β_{PBD}. Thus, pDHW is more similar to the PBD, with the only difference being the temporal structure of the threshold; pDHW is time-invariant while PBD is seasonally varying. The light shaded regions represent the 95% confidence interval of the computed ETS, obtained through bootstrapping (Wilks, 2011, pp. 185).

Holbrook, 2004; Whitaker & DeCarlo, 2024), by randomly splitting the data sets 100 times into an 80% training and 20% testing set and tallying the number of times the PBD approach overperformed ABD at the 5% and 10% statistical significance levels (Table S3 in Supporting Information S1). Among the 3 data sets, the statistical significance level of 5% is crossed in 10%–50% of those 100 splits, being marginally significant (i.e., at the 10% level) in 40%–80% of the splits. Moreover, PBD performs better in all of these 100 splits for all 3 data sets, with an average improvement of 26%, 20%, and 16% relative to ABD for the Hughes, Reef Check, and Donner data sets, respectively (Table S3 in Supporting Information S1). An overall maximum of 41% improvement in explanatory power was recorded for the Hughes data set (Table S3 in Supporting Information S1), under a 12-week warm-season window and an optimal severity threshold of 1.0.

After modification of the ABD threshold from MMM + β_{ABD} to MMM + β_{PBD}, the maximum ETS between PBD and pDHW become more similar (Figure 3b), showing that the threshold computation method (anomaly vs. percentile) is the major cause of the difference in model performance. The temporal structure of the threshold (time-invariant vs. seasonally varying) seems to make little difference. To confirm these results, we repeated the cross-validation procedures above after modifying the DHW threshold (Table S4 in Supporting Information S1). For all 100 splits from the cross-validation analysis for the 3 data sets, the differences in coral bleaching explanatory power between PBD and pDHW were found to be non-significant at both the 5% and 10% levels (Table S4 in Supporting Information S1).

An alternative approach to calculating the standard error of the ETS (in contrast to the bootstrapping method used previously) is to compute the variance of the ETS from the 100 ETS curves obtained from the above cross-validation analysis, before subsequently deriving the standard error from the variance (Text S5 in Supporting Information S1). Here again, our results (Tables S5–S7 in Supporting Information S1) confirm that the performance of the ABD is improved when modified to pDHW and becomes comparable to that of the PBD.

3.3. Sensitivity Tests and Optimal Warm-Season Windows

We have shown that accumulated extreme temperatures based on PBD performs better at characterizing severe coral bleaching globally than ABD under a 12-week warm-season window when applied to the Hughes data set. The other two data sets incorporate additional variables—such as impact window length and bleaching levels (Figure 1)—which provide opportunities to further explore the robustness of our findings. To assess this, we repeated the analysis for varying heat stress and impact window durations, as well as bleaching levels (Figures S4 and S5 in Supporting Information S1: Hughes, Figures S6–S11 in Supporting Information S1: Reef Check, and Figures S12 and S13 in Supporting Information S1: Donner data set). We found that in most cases, the PBD outperforms the ABD. However, the most notable exceptions occur for the Reef Check data set under both a BL of 50% and for longer impact window lengths of 120 and 150 days (Figure S11 in Supporting Information S1).

The PBD was also found to perform better at characterizing coral bleaching than the ABD when considering an optimal warm-season window. For both the Reef Check and Donner data sets, the ETS curves indicate that an optimal window exists (Figure 4) (N.B.: This pattern is less evident for the Hughes data set (Figure S5 in Supporting Information S1)). For impact windows of 120 days or less, the optimal warm-season window was found to be typically between 10 and 12 weeks for both the PBD and the ABD.

4. Discussion

In this paper, we compared the ability to characterize severe coral bleaching across the globe based on the commonly used DHW approach (an ABD, or ABD) for coral bleaching risk against a warm temperature extreme accumulation metric modified from a widely used marine heatwave definition from Hobday et al. (2016) (a PBD, or PBD). By systematically varying different components of both frameworks while holding them otherwise comparable (e.g., testing warm-season window lengths of 10, 11, and 12 weeks), we found that the PBD outperforms the ABD in characterizing severe coral bleaching events, estimated from analysis of satellite SST data (OISST) (with a maximum ETS improvement of 41%). This conclusion is based on our assessment of three coral bleaching data sets using both cross-validation and sensitivity tests. We found that the better representation of spatiotemporal temperature variability by the PBD against the ABD is important, likely because reefs in highly variable environments are more resistant to bleaching (Carilli et al., 2012), making percentile thresholds more biologically relevant (Ferris et al., 2025)—at least for the historical period examined here, prior to further coral adaptation. However, for the Reef Check data set, coral bleaching explanatory power between the PBD and ABD converges for extreme bleaching (≥50%) and long impact windows (120–150 days, Figure S11 in Supporting Information S1). This likely reflects two factors: extreme bleaching usually coincides with extreme heat stress, where the cumulative intensity overshadows the threshold choice, and longer windows decouple bleaching observations from thermal stress, reducing the framework differences. Thus, threshold type may matter less for extreme bleaching events surveyed more than 4 months after heat stress.

Based on our findings, we provide a few recommendations. First, if DHW is used to gauge coral bleaching likelihood, we suggest that its original threshold be changed from an anomaly (e.g., +1°C) to a 90th percentile threshold (which maximizes coral bleaching explanatory power for pDHW). This would allow the DHW metric to capture spatiotemporal temperature variability that is biologically relevant. Alternatively, if the measure of accumulated warm temperature extreme based on the percentile-based Hobday et al. (2016) MHW definition is used, it would be important to restrict its window to summer months. This is because, although negative impacts on corals were first reported under extreme cold water events rather than warm water events (Glynn & D'Croz, 1990), summer MHWs are becoming increasingly significant under global warming (Eakin et al., 2010) but the original Hobday et al. framework computes MHWs all year round. A warm-season window of 10, 11 or 12 weeks (centered on the month of maximum monthly mean) seems appropriate if this framework is used for coral bleaching studies. For non-coral contexts (e.g., kelps and seagrass meadows), optimal parameters remain uncertain; however, until further research is carried out, adopting the same summer-focused window is a reasonable starting point, given the increasing importance of hot temperature extremes under global warming. For bleaching data sets that record the date of surveys, it also seems reasonable to use impact window lengths of 90–120 days (Figure S3 in Supporting Information S1), balancing between sample size and temporal coupling. Although shorter than 30-day windows are recommended for capturing bleaching linked to acute thermal stress (Diaz-Pulido & McCook, 2002), corals may remain stressed for up to 6 months after a MHW (Thomas & Palumbi, 2017), supporting the use of longer windows. Still, longer windows introduce decoupling between stress and impact, resulting in a trade-off for increasing sample size.

Our findings build on recent work refining the DHW metric for coral bleaching characterization. Whitaker and DeCarlo (2024) tested 1,080 combinations of anomaly thresholds, minimum cumulative heat stress, and warm-season windows, finding that a +0.4°C anomaly threshold, a DHW value of 3, and an 11-week window improved the ETS from 0.098 to 0.167. Optimal ETS values from our analyses are overall higher, perhaps due in part to Whitaker and DeCarlo (2024)'s choice of lower BL (5%), as severe bleaching is easier to discriminate (DeCarlo, 2020). We also find that 10–12-week windows generally maximize ETS, though our optimal thresholds are higher (~+1°C for Reef Check (Figures S6–S8 in Supporting Information S1) and ~+1.5°C for Donner data

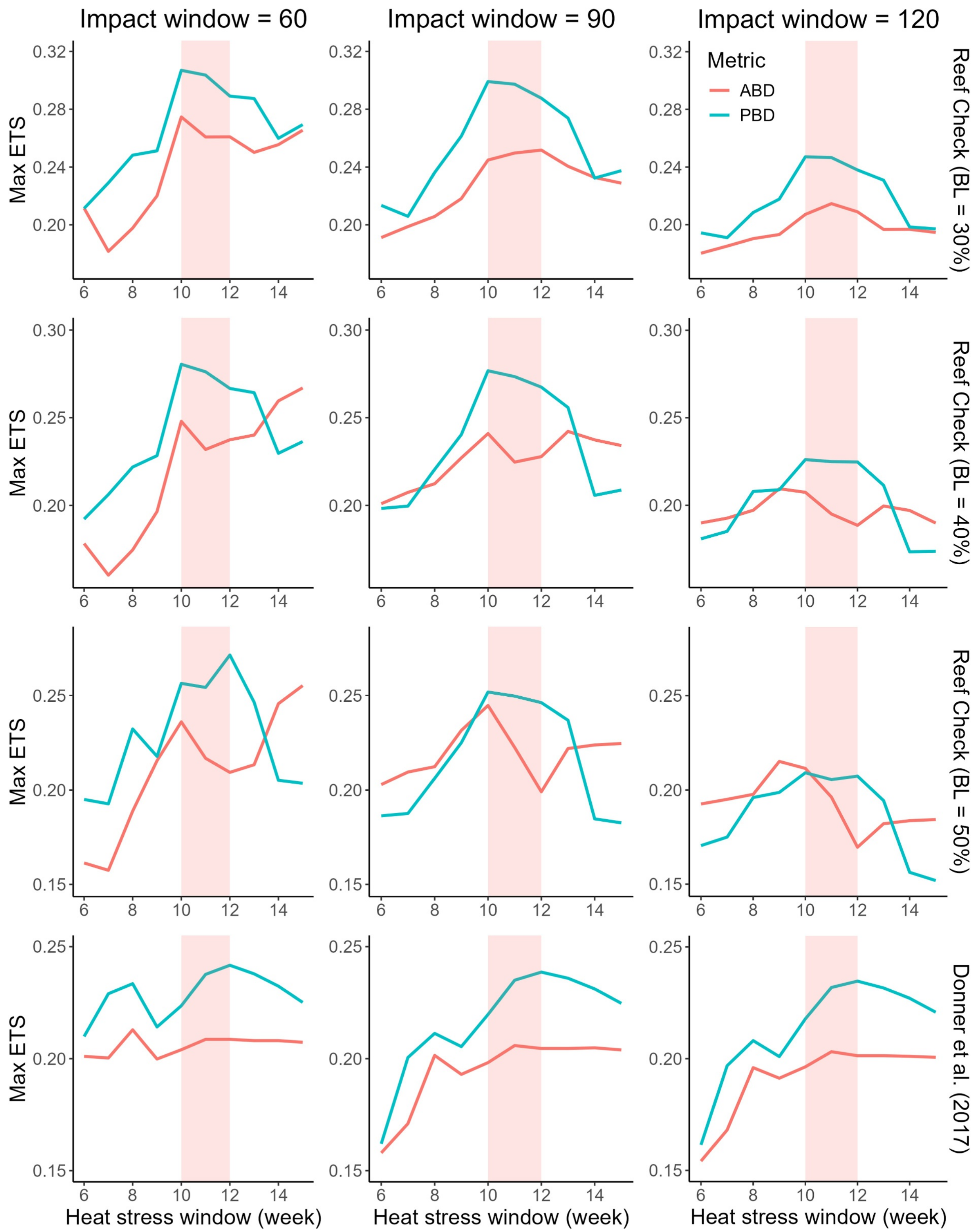

Figure 4. Maximum equitable threat score (ETS) at the optimal severity and anomaly thresholds, plotted against warm-season window length, for the different sensitivity tests performed on the Reef Check and Donner coral bleaching data sets. The shaded region (pink) represents the most likely optimal window range, based on the overall maxima of the maximum ETS at the optimal severity/anomaly thresholds. BL = Bleaching Level.

sets (Figure S12 in Supporting Information S1)). This could be due to different data sets and bleaching levels used. Nonetheless, when using a 60-day impact window and 12-week warm-season window, the Reef Check data set yields a lower threshold (+0.3°C) (Figures S6–S8 in Supporting Information S1). Overall, an anomaly threshold near +1°C appears most robust for general analyses; however, for more targeted applications, the DHW metric can be further refined through regional analyses (DeCarlo, 2020; Whitaker & DeCarlo, 2024).

Finally, our findings indicate that for the period between 1980 and 2020, coral reefs experience stress when the severity threshold reaches approximately 1.0—corresponding to the 90th percentile threshold defined by Hobday et al. (2016). While uncertainties remain around how fast adapting baselines should be updated (Smith et al., 2025), this study provides a foundational first step toward defining future adapting baselines for corals in a warming climate. Here, we did not investigate how the choice of the climatology baseline period affects coral bleaching explanatory power. Whitaker and DeCarlo (2024) have already demonstrated that, for DHW, the optimal historical baseline was 1985–2012. This period is nearly identical to the baseline adopted here for the PBD based on the Hobday et al. MHW definition (1983–2012), eliminating the need for further baseline testing. Accordingly, we follow Smith et al. (2025) in recommending a fixed climatological baseline combined with severity thresholds that can be revised as (or if) organisms adapt. Our results also help bridge the gap between the statistical Hobday et al. (2016) definition and observed ecological impacts, supporting the development of "adaptation-adjusted baselines" (Bailey & van de Pol, 2016; Li et al., 2023; Smith et al., 2025). We demonstrated how a weather-forecasting framework can serve as a useful statistical tool for identifying optimal adaptation-adjusted baselines for ecological risk assessment. Alternatively, experimental approaches—such as determining thermal thresholds (e.g., Beaty et al., 2023) for marine species using specific MHW definitions (e.g., Hobday et al., 2016)—offer another potential pathway for establishing adapting baselines for a period of interest.

As global warming causes more frequent and prolonged marine heatwaves that threaten marine ecosystems (Frölicher et al., 2018; Laufkötter et al., 2020; Oliver et al., 2019), it is crucial to refine heat stress metrics such that they can better reflect the physiology of marine species. Here, we have shown that percentile thresholds improve explanatory power of coral bleaching and likely better represent corals' thermal limits, and possibly those of other ectotherms. Thus, our findings may be beneficial in helping improve the prediction and assessment of the risks that marine heatwaves pose to underwater ecosystems.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

All data sets used in this study are open-source and available to be downloaded online. The OISST data set is available from NOAA at https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.highres.html. Coral bleaching data sets used in this study were sourced from published literature, including Hughes, Anderson, et al. (2018) and van Woesik and Kratochwill (2022). The latter is a compilation of multiple data sets, from which we specifically used data from Donner et al. (2017) and the Reef Check data set (available at reefcheck.org). We used the R programming language (R Core Team, 2024) to perform most of our analyses, which can be accessed from: https://github.com/DarrenLCY/mhw-vs-dhw-paper. The equitable threat score (and its standard error) was computed using the verification package version 1.44 (Gilleland, 2024). Marine heatwaves (as defined under Hobday et al. (2016)) were computed using heatwaveR version 0.4.6 (Schlegel & Smit, 2018). Figures were made with ggplot2 version 3.5.1 (Wickham, 2016) and other supporting packages (gridExtra v2.3 (Auguie, 2017) and grid v4.4.1 (R Core Team, 2024)). Other packages used include: ncdf4 v1.23 (Pierce, 2024), RSQLite v2.3.9 (Müller et al., 2024), rworldmap v1.3.8 (South, 2011), pheatmap v1.0.12 (Kolde, 2019), ggmap v4.0.0 (Kahle & Wickham, 2013), plyr v1.8.9 (Wickham, 2011), and dplyr v1.1.4 (Wickham et al., 2023).

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