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1 Marine Heat waves – Multiple Analysis / 2 Definitions (MHW-MAD): A Multi-Definition 3 Global Marine Heatwave Dataset from 4 Satellite Sea Surface Temperature data

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24 Abstract

25 Marine heatwaves (MHWs) are prolonged anomalies of warm sea surface temperature
26 (SST) that can disrupt marine ecosystems, physical climate processes, and human coastal
27 activities. MHW definitions vary due to different stakeholders requirements, such as
28 ecological scientists and climate scientists having differing yet specific thresholds and
29 metrics. Here we introduce a new global dataset of daily MHW metrics: climatological
30 baselines, threshold exceedances, SST anomalies, and categorical event classifications of
31 severity, derived from the European Space Agency SST Climate Change Initiative (ESA SST
32 CCI) climate data record (CDR; 1982-2021) version 3.0 and an extension from 2022-2024
33 provided as an interim climate data record (iCDR). Building on the widely used definition of
34 MHWs, periods in which SST exceeds the local 90th percentile for 5 or more days, our
35 dataset extends this framework by incorporating multiple baseline climatologies (including
36 fixed 30-year periods and rolling 30-year windows, as well as the period for reanalysis 1993 -



2016), varied percentile thresholds (90th, 95th, 99th), and both raw and linearly detrended SST anomalies. We also implement alternative event duration criteria (minimum 10-day and 30-day persistence) to classify longer-lasting warm events. All data products are provided at daily resolution on a 0.05° (~ 5 km) grid, with outputs including daily climatological percentiles, SST anomalies and binary MHW flags with severity category indices. This comprehensive dataset provides a consistent foundation for detecting and analysing MHWs across time and space, enabling researchers to assess how methodological choices affect MHW characterisation. By offering multiple definitions in parallel, the dataset facilitates intercomparison studies and supports applications from climate monitoring and model evaluation to marine ecological impact assessment, thereby providing users with pre-made indices for extremes.

1. Introduction

Marine heatwaves (MHWs) are discrete, prolonged periods of abnormally high ocean temperatures relative to typical local conditions (Hobday et al., 2016). They often persist for days to months and can extend over vast regions (>1000 km). MHWs can have important ecological and socioeconomic impacts. For example, extreme warming events have caused mass mortalities of marine organisms and biodiversity loss, including coral bleaching events (Garrahou et al., 2019; Hsu et al., 2025), harmful algal blooms (Roberts et al., 2019), shifts in species distributions (Lonhart et al., 2019), and declines in fisheries (Wernberg et al., 2016; Smale et al., 2019; Gonzalez et al., 2025). Demonstrating these effects, an intense MHW off Western Australia in 2011 removed ~ 100 km of kelp forests ($\sim 90\%$ of the region's kelp), leading to a regime shift in the local ecosystem (Wernberg et al., 2016). Such events threaten the resilience of marine ecosystems and the services they provide to coastal communities.

There is clear evidence that the frequency and intensity of MHWs are increasing under climate change (Frolicher et al., 2019; Lien et al., 2023). Long-term analyses indicate that from 1925 to 2016, the average annual number of MHW days has increased globally by over 50% (Oliver et al., 2018). In recent decades, many MHW events have been attributed to anthropogenic warming (Oliver et al., 2018; Smale et al., 2019), and are expected to increase in frequency by the end of the century (Frolicher et al., 2019). In particular, the duration and spatial extent of MHWs have expanded, coincident with the rise in baseline ocean temperatures. These trends underscore the urgency of monitoring MHWs as well as understanding their drivers.

Despite growing research, there is still ongoing debate on how best to define and detect MHWs across different studies (Farchadi et al., 2025; Smith et al., 2025), with the most common definition taken from Hobday et al., (2016). How MHWs are identified depends on methodological choices including the baseline climatology period, threshold percentiles, and minimum duration, among other factors. Some studies use a fixed historical baseline (e.g. 30-year climatology) whereas others use a shifting baseline that moves with each year. In a warming climate, a fixed baseline (such as the standard World Meteorological standard 30-year baseline between 1991 to 2020) will likely label more recent warm events as extreme (Oliver et al., 2018) compared to a moving baseline (or periodically updated “normal”). A shifting baseline effectively raises the threshold over time, filtering out the



warming (or cooling) trend and highlighting interannual variability. Similarly, choosing a 90th percentile threshold versus a more extreme 95th or 99th percentile can substantially change which events qualify as MHW. The required duration matters as well too; the original Hobday et al. (2016) definition requires ≥ 5 consecutive days, but some applications consider longer minima (e.g. 10 days or more) to isolate only the most persistent events. Due to the vast array of methodological differences, recent studies have called for clearer and more standardised MHW definitions to aid comparisons and decision-making (Amaya et al., 2023; Farchadi et al., 2025).

To address these differences, we present a “multi-definition” global MHW dataset that allows users to examine events under a suite of definitions within a single, consistent framework. We derive this dataset from the European Space Agency SST Climate Change Initiative (ESA SST CCI) Climate Data Record (CDR) v.30 (Embury et al., 2024), which combines data from different satellite sensors into a daily 0.05° gridded gap-free SST product (in the future we plan to incorporate more SST products).

The MHW dataset provides multiple climatological baselines (both a fixed 30-year baseline and rolling 30-year windows) so that users can explore the influence of baseline period on detected MHWs. We include both raw and detrended SST anomaly fields, enabling analysis of MHWs with and without the long-term warming signal. Furthermore, we provide event detections based on the standard 90th-percentile/5-day definition, but also on more stringent threshold exceedances (95th and 99th percentiles) and longer minimum durations (10-day and 30-day). By offering these options side-by-side, the dataset facilitates comparative studies of how MHW properties change under different definition choices. In the following, we describe the data sources and processing methods, present example results comparing definitions including a case study of the 2014 “Blob” event in the Northeast Pacific (Bond et al., 2014), an unusually large and persistent MHW (2013-2016) that disrupted ecosystem processes, causing mass mortalities (Renner et al., 2024). Further to this, we detail data availability and potential uses, and examine the broader implications of this multi-definition approach.

2. Sea Surface Temperature Data

The ESA SST CCI CDR v3.0 CDR and ICDR are based on the same software and systems, which ensures a consistent and uninterrupted daily global SST time series covering the years 1982 through 2025. In this study, the Level 4 (L4) analysis product is used, which combines SST observations from multiple satellite instruments into a daily gridded gap-free product at $0.05^\circ \times 0.05^\circ$ resolution. The L4 analysis product integrates infrared and microwave sensor SST retrievals from 22 different satellite missions (Embury et al., 2024). The infrared and microwave signals were collected from the following four series of sensors: 15 Advanced Very High Resolution Radiometers (AVHRRs), three Advanced Along-Track Scanning Radiometers ((A)ATSR), two Sea and Land Surface Temperature Radiometer (SLSTR) and two Advanced Microwave Scanning Radiometers (AMSRs). The L4 analysis product is produced using the climate configuration of the Operational Sea Surface Temperature and Ice Analysis (OSTIA) system (Donlon et al., 2012; Good et al., 2020), which blends the input SST data from multiple satellite sensors and corrects for diurnal warming and depth-based temperature gradients, by standardising SST values to ~ 20 cm



depth. Unlike the OSTIA reprocessed L4 dataset (Good et al., 2020), the ESA SST CCI system does not assimilate in situ data into its L4 product, thereby preserving satellite-derived trends.

The ESA SST CCI CDR v3.0, is specifically designed for robust climate research through rigorous inter-sensor calibration and bias corrections (Embury et al. 2024). As a result, the physics-based retrieval algorithms generate a stable, low-bias SST dataset that is largely independent of in situ observations. The CCI SST L4 SST product adheres to Group for High Resolution SST (GHRSSST) standards, delivering daily, gap-free global SST fields ideal for the assessment of MHWs (Yang et al., 2021). Furthermore, the SST CCI v3.0 has been proven as a suitable product for long-term ocean climate studies, including the detection and characterisation of MHWs (Yang et al., 2021). This being said, the approach taken can be implemented on different SST products and algorithms, and we hope to explore this in the future.

3. Marine Heatwave Definitions and Framework

Definitions of MHWs were selected and assessed, based on percentiles, baselines, persistence, and detrended data. All data processing was performed using Python and Climate Data Operators (CDO) software 2.1.1, with some of the post-processing also done with the help of NCO 5.2.1. We first computed long-term climatologies for each grid cell and day-of-year (DOY) using multiple baseline definitions (Fig. 1). We then calculated daily SST anomalies relative to those climatologies and identified MHW events by applying threshold criteria to the anomaly time series, as in Hobday et al., (2016). We then categorised the intensity of detected events using the severity index of Hobday et al., (2018) and organised all output variables into CF compliant NetCDF files, for 10 different sets of definitions (Fig. 1; Table. 1). All the framework steps are described in detail in the following paragraphs.

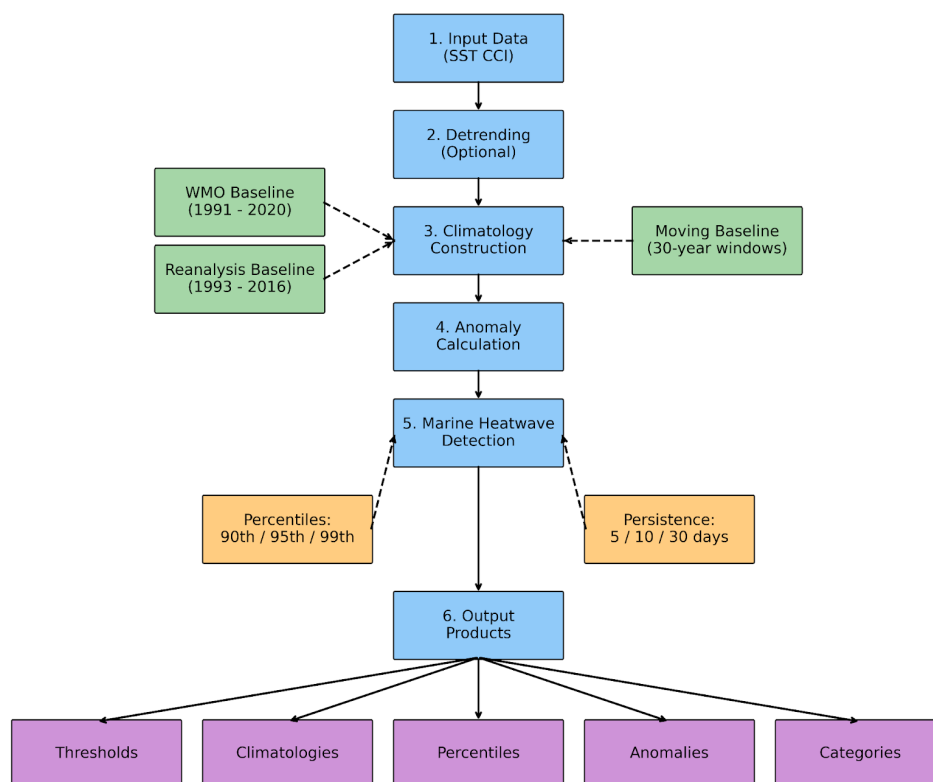
Table 1. Definitions used to build the MHW-MAD dataset

Definitions	Baseline Period	Percentiles	Min. Duration (days)	Notes
WMO (percentiles)	1991-2020	90th, 95th, 99th	5	
Reanalyses period	1993-2016	90th, 95th, 99th	5	
Persistence	1991-2020	90th	10, 30	
Detrended	1991-2020	90th	5	Detrend SST (calendar day)
Moving	30 year moving*	90th	5	*MHWs starting from



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	From 1982-2011 1995-2024	to		2011
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150 **Figure 1:** Workflow for creating daily MHW metrics based on different definitions.

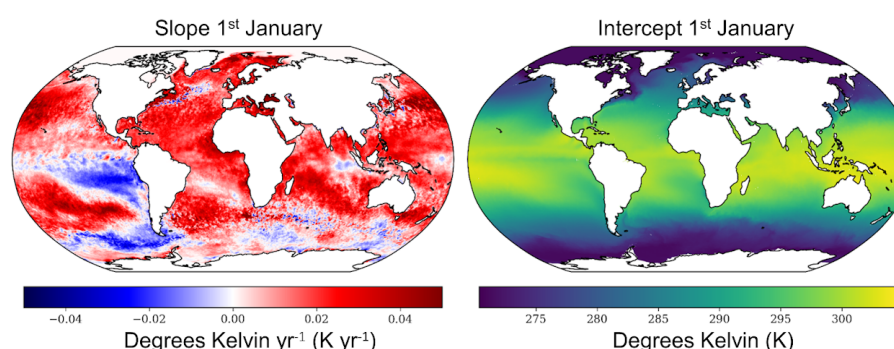
151 3.1 Detrending of SST Time Series

152 Long-term ocean warming elevates the baseline SST over time for most areas, causing
153 more frequent MHW events in later years if the baseline remains static. To allow users to
154 separate the effect of global warming from natural variability, we created a detrended version
155 of the SST record. In areas without strong decadal variability, removing the trend ensures
156 that the baseline climatology represents the stationary seasonal cycle, so that anomalies
157 and MHW detections reflect short-term fluctuations rather than the slowly shifting mean
158 (Schlegel et al., 2019). This approach can be useful for attribution studies, as MHW
159 occurrence after detrending can be interpreted as the portion driven by natural variability
160 without the influence of long-term climate warming.

161 We applied a grid-point-specific linear detrending to the SST time series for each calendar
162 day-of-year. For each grid cell, all SST values corresponding to the same calendar date



across 1982–2024 were collated (e.g., all January 15 values over the 44-year span). We then performed an ordinary least squares linear regression of SST against the year for each calendar date at each grid cell. This yields a linear warming (or cooling) rate for that date and location (Fig. 2). The linear trend component for a given day was then subtracted from the original SST value. Detrending was applied at all grid cells regardless of statistical significance to ensure the dataset remained gap-free. The result is a parallel SST dataset where each grid cell's time series has no linear trend over 1982–2024. It is important to note that the detrending was only undertaken for the standard Hobday MHW definition of exceedance of the 90th percentile, 5-day persistence, and WMO climatology (1991–2020).



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173 **Figure 2.** The slope and intercept used for detrending SST CCI data. The example shown is
174 for the first of January.

175 3.2 Climatology Construction

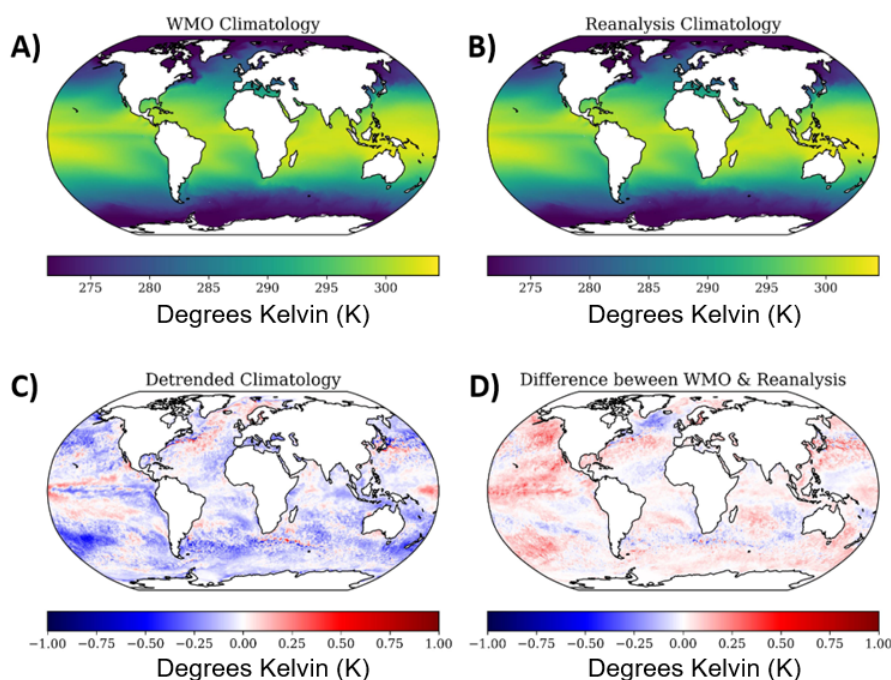
176 We defined the climatological baseline as the distribution of SST for each DOY at each grid
177 point, against which anomalies and extremes are measured. Two approaches were used to
178 construct climatologies:

179 **(a) Fixed 30-year climatology and reanalysis:** We adopted the 30-year period 1991–2020
180 as a representative modern baseline, consistent with WMO-recommended climate normal
181 periods - and hereby refer to this as the 'WMO baseline' (Fig. 3). For day (DOY 1–366) in all
182 baseline periods, we aggregated all SST values for that same DOY, including the 29th
183 February across the 30 years. This yielded, for each grid cell and each DOY, a distribution of
184 30 values (one from each year). From this distribution, we computed the 10th percentile,
185 50th percentile, 90th percentile, and additionally the 95th and 99th percentiles of SST. To
186 ensure smoother day-to-day continuity in the climatology while retaining sensitivity to
187 short-term extremes, we applied a 21-day moving average (wrapped from 31st December to
188 1st January, when required) to the percentile time series as a function of DOY, instead of the
189 30-day window used by Hobday et al. (2016). This shorter smoothing window preserves
190 more of the variability associated with extreme events, which may otherwise be weakened
191 by a longer averaging period. This moderate temporal smoothing (± 10 days around each
192 date) reduces sampling noise and prevents abrupt jumps in the threshold from one day to
193 the next, at the cost of slightly blunting the most short-lived seasonal extremes. The same



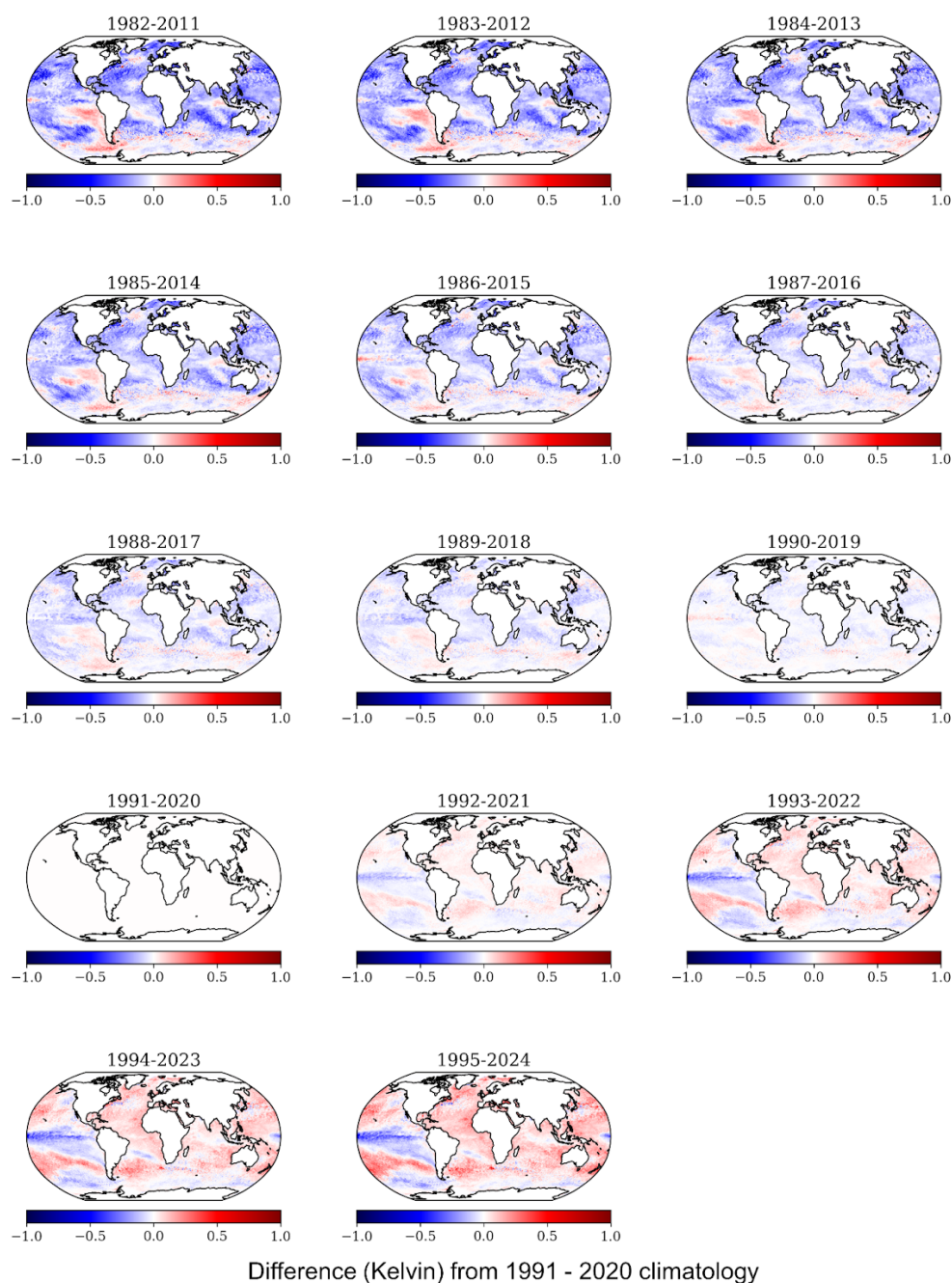
approach was taken for the reanalysis period, however the baseline was instead between 1993–2016.

(b) Moving 30-year climatology: As the ocean's climate is non-stationary, and warming has been prevalent over the past decades, we computed a series of moving-window climatologies. Starting with the earliest period of 1982–2011, we then advanced the 30-year window by one year at a time (i.e. 1983–2012, 1984–2013... up to 1995–2024). For each window, we calculated daily percentiles using the same method detailed above. The result is a time-evolving climatology that gradually warms (or cools) in most areas over time (Fig. 4). As a consequence of a shifting baseline, extreme anomalies are measured relative to the local contemporary climate for each year, rather than a historical reference period.



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Figure 3: Different climatologies, including: A) WMO climatology (1991–2020), B) Climatology based on the reanalysis period (1993–2016), C) Climatology based on detrended data for the WMO period, and D) Difference between the WMO climatology and the climatology based on the reanalysis period.



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Figure 4: 30-year moving climatologies from 1982-2011 to 1995-2024, based on the WMO definition. Each panel shows the difference to the WMO 1990-2021 climatology for the 1st January for each respective period.



213 3.3 Anomaly Calculation

214 For each day in the record, we calculated SST anomalies as the deviation from the
215 climatology on that DOY. Let SST_x denote the daily sea surface temperature (SST) at a
216 given DOY (x), and M_x the 50th percentile climatology for that DOY. The anomaly is then
217 defined as: $\text{anomaly} = SST_x - M_x$.

218 In the anomaly calculations, we used a 366-day reference that explicitly includes 29
219 February. To ensure consistency in non-leap years, all days after 28 February were shifted
220 forward by one in their day-of-year index (i.e. 1 March becomes DOY 61, 2 March DOY 62,
221 and so on). This adjustment preserves the one-to-one correspondence between calendar
222 days and the 366-day climatological reference, ensuring that anomalies for non-leap years
223 are correctly aligned with those from leap years, while avoiding any artificial discontinuities
224 around late February and early March. Anomalies were calculated independently using the
225 fixed-baseline, moving-baseline, and also for the raw and detrended SST data records.
226 These daily anomaly fields form the basis for MHW detection. Positive anomalies indicate
227 warmer-than-normal conditions; negative anomalies indicate colder-than-normal conditions
228 (i.e. used to detect cold spells).

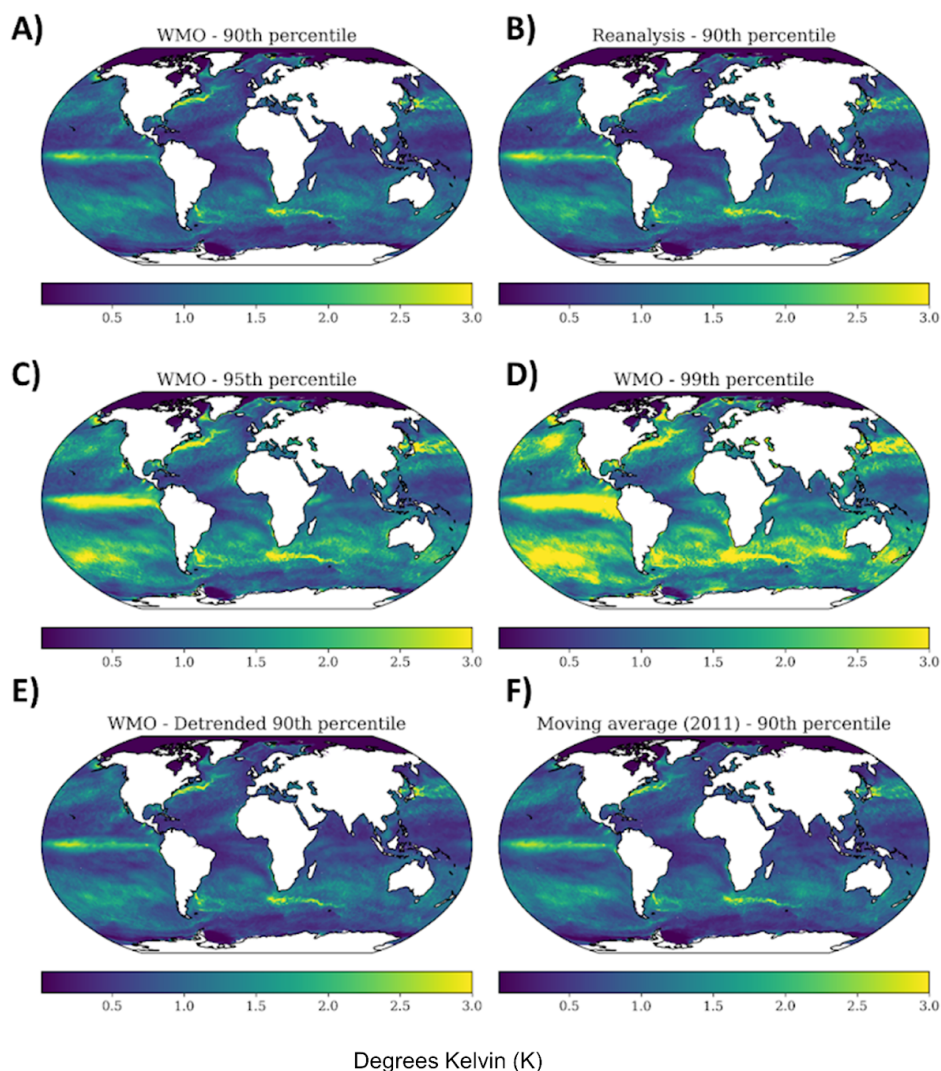
229 3.4 MHW Event Detection

230 MHW events were identified by applying the threshold criteria to the SST anomalies.
231 Following the framework of Hobday et al. (2016), an MHW is detected at a given grid cell
232 whenever the SST (anomaly) exceeds a threshold (90th, 95th or 99th) for a minimum
233 duration of five days (or more). This yields a binary MHW mask indicating the
234 presence/absence of an MHW at each grid cell each day. We implemented multiple
235 threshold and duration combinations:

236 **Extended thresholds:** In addition to the 90th percentile from Hobday's definition, we also
237 used 95th and 99th percentile thresholds (Fig. 4). These higher thresholds capture the more
238 extreme temperature anomalies. Using the 95th or 99th percentile substantially reduces the
239 number of events detected, focusing on the upper tail of extreme warm events. By
240 comparing results from 90th vs. 95th vs. 99th percentile criteria, users can gauge the
241 sensitivity of MHW statistics to the extremeness of the threshold.

242 **Extended persistence criteria:** We also include longer minimum durations for MHWs. We
243 required events to last at least 10 consecutive days above the threshold (instead of 5). We
244 also created another more extreme criteria, where 30 days of consecutive exceedance were
245 required. Naturally, imposing a longer duration criterion filters out shorter temperature
246 anomalies. The 30-day criterion is more restrictive and captures only the most prolonged
247 marine heatwave episodes. These longer-duration definitions can be useful for focusing on
248 events likely to have consequential physical or ecological impacts.

249 **Event metrics:** We have provided the day-by-day anomaly values and threshold
250 exceedance status (Fig. 4), along with severity category (see section 2.5), so users can
251 examine the temporal evolution of each event. Here, we do not assign spatial extents or
252 track contiguous areas of MHW, though such analyses could be done using this dataset.



253

254 **Figure 5:** Marine heat wave anomaly threshold values (DOY=1) based on different criteria
 255 using for the first January. A) the WMO climatology and 90th percentile threshold, B) the
 256 reanalysis period (1993 - 2016) and a 90th percentile threshold, C) the WMO climatology
 257 with the 95th percentile threshold, D) the WMO climatology with the 99th percentile
 258 threshold, E) the detrended data with a 90th percentile threshold, and F) the moving average
 259 centred at 2011, with the 90th percentile threshold.

260 **Ice-covered regions:** In areas of sea ice cover, the SST-CCI product provides a value
 261 corresponding to the assumed freezing point of sea water of about -1.8°C (assuming
 262 salinities of $\sim 33\text{PSU}$). As a result, areas of multi-year sea ice cover have threshold values of
 263 0 (Fig. 4). As both the Arctic and Antarctic have witnessed pronounced sea ice loss in recent
 264 times (Stroeve et al., 2007; Purich and Doddridge., 2023), new areas of open water would



be classified as marine heat wave hot spots due to their low thresholds, making ecological assessments of SST in polar regions challenging (Hayward et al., 2025, Pecuchet et al., 2025). To study polar regions, we suggest using targeted products such as the dedicated Arctic product produced in Copernicus Marine Service (CMEMS), L4 Arctic Ocean - Sea and Ice Surface Temperature Analysis (SST/IST; Nielsen-Englyst et al. 2023) or for Antarctic applications the C3S global L4 SST/IST product produced by the Danish Meteorological Institute (DMI), which in both cases provide satellite-observed sea-ice surface temperatures in sea ice covered areas, and blends the SST and IST observations in the marginal ice zones. MHW analyses based on these products have not been included here.

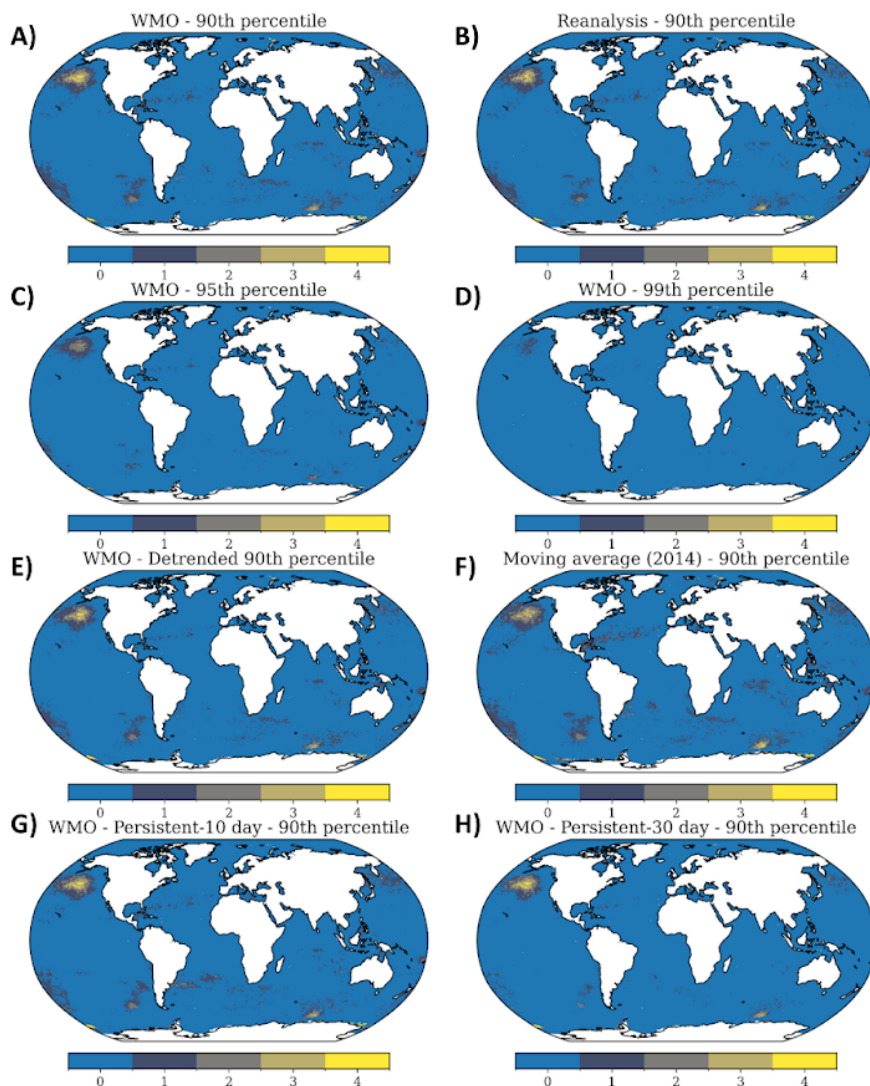
3.5 Categorical Severity Index

In addition to the binary identification of MHW days, we also provide a categorical severity index following the approach of Hobday et al. (2018) for classifying MHW intensity levels. Specifically, we define four categories of MHW intensity at each grid cell and day by comparing the SST anomaly to the local threshold difference.

1. Category 1 (“moderate”) corresponds to anomalies just above the threshold (anomaly $\geq$ threshold and < 2 times threshold difference),
2. Category 2 (“strong”) for anomalies 2-3 times the threshold difference,
3. Category 3 (“severe”) for 3-4 times, and
4. Category 4 (“extreme”) for anomalies ≥ 4 times the threshold difference.

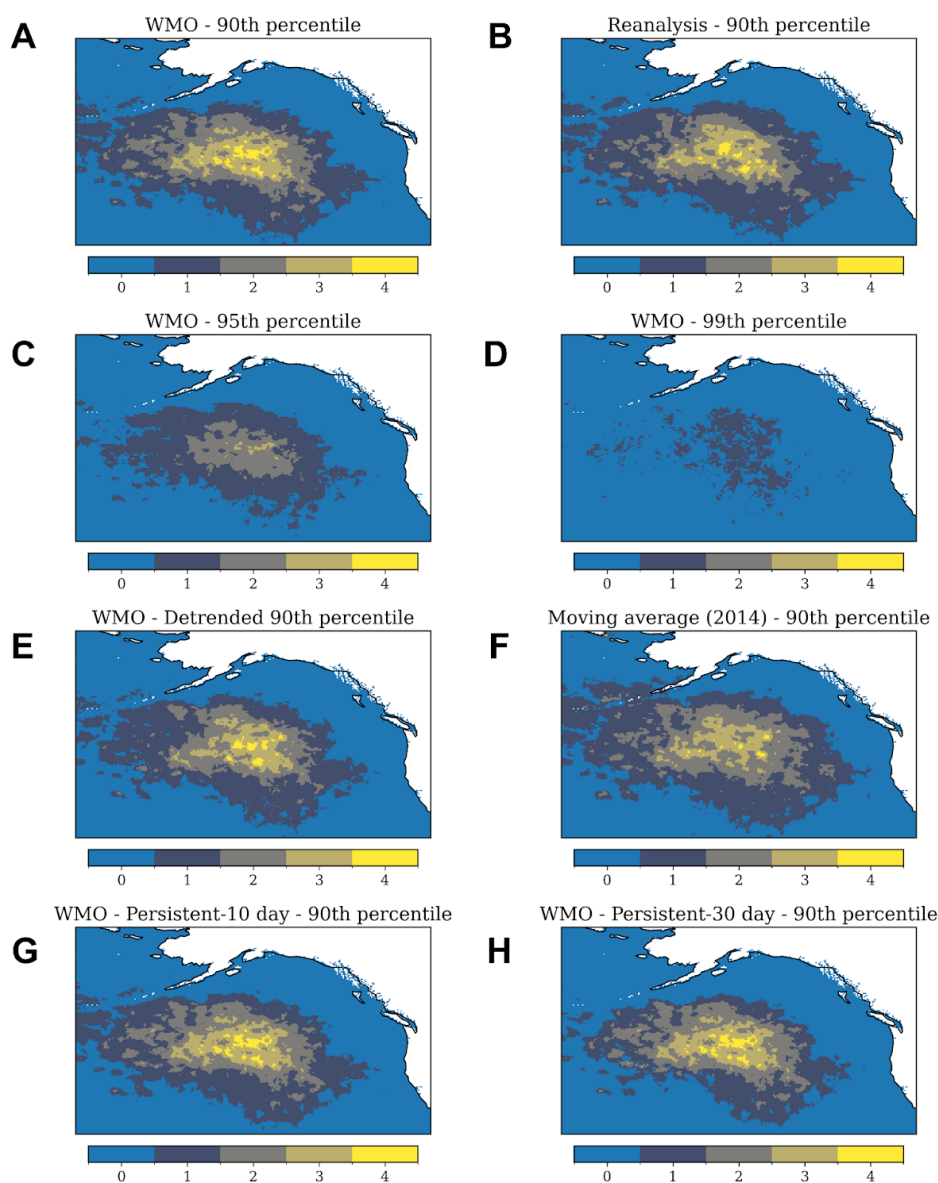
These provide a simplified way to communicate the severity of an ongoing MHW. We compute such categories for each threshold definition (e.g., 90th, 95th, or 99th percentile) as separate files; a category 4 event for the 99th percentile threshold would only capture very extreme events, indicating using severity indices could also be a good way to track more extreme events instead of higher percentile thresholds.

In the dataset, days with no MHW are given a category value of 0. We note that cold spells are not explicitly categorised in this study, however, using this dataset it is possible to classify cold extremes below the 10th percentile.



292

Figure 6: Categories of marine heat waves on 1st January 2014 (during ‘the Blob’ event) using different definitions. Where A) uses the WMO climatology (1991 to 2020) and the 90th percentile, B) uses the reanalysis period (1993 - 2016) and the 90th percentile, C) uses the WMO climatology and the 95th percentile, D) uses the WMO climatology and the 99th percentile, E) uses the WMO climatology and the 90th percentile with detrended data, F) uses a climatological period between 1985 and 2014, and the 90th percentile, G) uses the WMO climatology and the 90th percentile with a 10 day persistence window, and H) uses the WMO climatology and the 90th percentile with a 30 day persistence window.



301

Figure 7: The Pacific Blob on the 1st January 2014 using various definitions. Where A) uses the WMO climatology (1991 to 2020) and the 90th percentile, B) uses the reanalysis period (1993 - 2016) and the 90th percentile, C) uses the WMO climatology and the 95th percentile, D) uses the WMO climatology and the 99th percentile, E) uses the WMO climatology and the 90th percentile with detrended data, F) uses a climatological period between 1985 and 2014, and the 90th percentile, G) uses the WMO climatology and the 90th percentile with a 10 day persistence window, and H) uses the WMO climatology and the 90th percentile with a 30 day persistence window.



4. Results

Below we briefly discuss the effect of each MHW definition based on data from the 1st January 2014, during the event of the Pacific Blob (Fig. 6), we however note that our descriptions are only from a single day, and may not represent longer term trends.

4.1 Baselines / climatologies

Baseline effect – Using the fixed WMO baseline yields lower percentile thresholds than a climatology using later years (e.g. 1995 - 2024). As such, recent anomalies are more frequently flagged as MHWs events, and with higher severity than when using warmer climatological periods from later years, as evidenced from the Pacific Blob (Fig. 6,7).

Detrended effect – Removing each grid-cell's linear trend before building the climatology reduces the warming signal embedded in the thresholds, as also discussed in Schlegel et al., (2019). Globally, the share of MHWs was reduced when detrended SST is used, compared to its non-detrended counterpart (Fig. 6), however, the effect was very minor for the Pacific Blob (Fig. 7), indicating that the event was not attributed to long-term warming.

	No MHW (%)	MHW (%)	Category 1 (%)	Category 2 (%)	Category 3 (%)	Category 4 (%)
WMO90	93.4	6.6	5.2	0.9	0.3	0.2
Rean	93.8	6.2	5.0	0.7	0.3	0.1
WMO95	97.5	2.5	2.1	0.3	0.0	0.0
WMO99	99.5	0.5	0.5	0	0	0
detrended	94.6	5.4	4.3	0.7	0.3	0.1
Moving	91.3	8.7	6.9	1.2	0.3	0.2
Persisten-10	93.8	6.2	4.9	1	0.3	0.1
Persistent-30	97.4	2.6	1.6	0.7	0.3	0.1

Table 2: Summary statistics for area of oceans covered by MHWs alongside categories for different experiments.

4.2 Sensitivity to Threshold, Persistence and Detrending

Raising the percentile threshold or minimum duration acts as an increasingly strict filter on detections (Fig. 5/6). Generalised by assessing the 1st January 2014, we find that:



- 331 • **Percentile effect** – Moving from the 90th to the 95th or 99th percentile progressively
 332 screened out moderate anomalies and highlighted only the strongest warm events
 333 (Fig. 6,7), and reduced the spatial extent and severity of events (Fig. 7C-D; Tab. 2).
- 334 • **Duration effect** – Requiring 10 consecutive days (instead of 5) removed shorter
 335 MHWs, however only reduced MHW globally by 0.5% (Tab. 2). A 30-day minimum
 336 isolated only the most persistent basin-scale events globally (Fig. 6), and reduced the
 337 extent of MHWs by 4%. However, for the Pacific Blob there was little effect other than
 338 a slight reduction in the spatial extent of low-intensity areas (Fig. 7).
- 339 • **Detrending effect** – After detrending, some events disappeared on a global scale
 340 (1.2% Tab. 2), making the threshold for MHW detection higher (Fig. 6). However,
 341 there was little effect on the Pacific Blob, which highlighted that the event was not
 342 due to long-term warming (Bond et al., 2014).
- 343 • **Baseline choice (WMO vs Reanalysis)** – There was little difference on the global
 344 scale between the WMO and reanalysis baselines (0.4%, Tab. 2). However, the
 345 severity index for the Pacific Blob was generally higher for the WMO baseline than
 346 the reanalysis, with a greater extent of category 3 and 4 events (Fig. 7).
- 347 • **Moving baseline (moving-average)** – A rolling 30-year climatology increased the
 348 occurrence of MHWs globally by 2.1% (Tab. 2). As the thresholds climb with time. As
 349 2014 is closer to the start of the rolling window, comparatively lower thresholds lead
 350 to greater MHW occurrences (Fig. 6).

351 Together, the panels show that the Blob's existence is robust across definitions, but its
 352 spatial extent and intensity category vary depending on baseline, threshold and persistence
 353 parameters.

354 5. Data Records and Access

355 All data described in this paper are archived in CF-compliant NetCDF format to facilitate
 356 ease of use across programming languages and compliance with community standards. The
 357 dataset is structured into several components:

- 358 • **Daily Climatology files:** These files contain the daily climatological percentiles for
 359 each grid cell under each baseline, each containing p10 and p50, and one of p90,
 360 p95, p99, depending on the experiment. The daily climatology files are also provided
 361 with threshold values for MHWs and MCSs. Each file is named by corresponding
 362 day-of-year, e.g. 362_Raw_90p_1991-2020_SSTCCI.nc.
- 363 • **Anomaly files:** We provide daily global maps of SST anomalies (difference above
 364 threshold), for both raw and detrended data, relative to both the fixed and moving
 365 climatologies. Daily files are provided for the entire data record, except for the
 366 moving averages and for p95 and p99 of the reanalysis period 1993-2016. For the
 367 moving averages, daily files are provided for only the last year in each window. Each
 368 file is named by corresponding date, e.g.
 369 20161227_Raw_5d_90p_1991-2020_anomalies_SSTCCI.nc.
- 370 • **Category files:** Categorical severities are provided for each day, encoding the MHW
 371 category (0 for none, 1–4 for moderate to extreme) based on the highest percentile
 372 threshold. In most of the experiments this is the 90th percentile threshold, though in
 373 select experiments we have computed categories based on the 95th and 99th



percentile thresholds. (These latter thresholds often have many days of zero severity value since events are rarer at those levels). Daily files are provided for the entire data record, except for the moving averages and for p95 and p99 of the reanalysis period 1993-2016. For the moving averages, daily files are provided for only the last year in each window. Each file is named by corresponding date, e.g. 20161227_Raw_5d_90p_1991-2020_categories_SSTCCI.nc.

- The folders are organised by input data source (in this case, only SSTCCI), whether the raw input has been used or it has been detrended first, the climatological period, the highest percentile used, and the duration of an event. E.g., the anomalies and categories for 10-day persistent events, calculated using the WMO climatological period with threshold p90, can be found at the path SSTCCI/Raw/WMO_Climatology/90p/duration/10_days/.

Each NetCDF file is accompanied by metadata attributes describing the variables, units, and conventions, following CF (Climate and Forecast) standards. The data is publicly available at <https://download.dmi.dk/public/MHW> and can also be accessed from the same location using tools such as curl and wget.

6. Usage Notes

6.1 Potential Applications

This dataset is intended as a resource for a broad range of studies in oceanography, climatology, and marine ecology. A few key applications include:

- **Ecosystem impact studies:** Researchers examining biological responses to ocean warming events can use the various MHW definitions to test sensitivity. For example, one could correlate coral bleaching occurrences or fishery yields with MHWs defined by the standard vs. a longer-duration criterion. If an impact (such as a coral bleaching event) correlates only with the longer, more intense MHWs, that insight could inform management, for example focusing on multi-week thermal stressors. Our detrended anomalies could also help separate impacts due to anomalous variability from those simply due to overall warming (Amaya et al., 2023).
- **Climate model evaluation:** Climate modellers can use the observational MHW statistics provided here to assess model skill. By applying the same algorithm to SST output from models (historical or future simulations), one can directly compare frequencies, durations, and intensities of MHWs between models and observations under consistent definitions. This is particularly useful given that different modeling studies have sometimes used different MHW thresholds; our dataset offers a common reference.

6.2 Code Availability

We aim to make this code available as a python package, for users to create their own satellite-based MHW indicators, as such the code is currently under embargo.



414 7. Summary and Outlook

415 Here we have presented a comprehensive dataset that provides a flexible toolkit for studying
416 MHWs at the global scale. As this dataset enables direct comparisons of MHW
417 characteristics under different definitions, we address a critical need in the field, as divergent
418 definitions have made it difficult to compare results across studies. With our multi-definition
419 framework, researchers can now assess how much of the discrepancy between studies is
420 simply due to the choice of MHW definitions.

421 Through a brief analysis of our data, we showed that a short or moderate warming event
422 might be classified as an MHW under the less restrictive standard definition of a 90th
423 percentile and 5-day requirement, but would not register under a stricter definition (99th
424 percentile or 30-day minimum). Conversely, what we consider an “extreme” MHW under the
425 standard definition might be fairly routine under a shifting baseline in a warming climate. This
426 has implications for how we interpret long-term trends. Under a fixed baseline, there were
427 more MHWs than with a detrended baseline, consistent with the effect of climate change
428 driving more frequent extremes. Both fixed, moving, and detrended baselines are valid: the
429 fixed highlights the change relative to past climate, and the others highlights deviations from
430 the contemporary climate or long term warming. The dataset provides both views, and the
431 reality of ocean warming means users should be mindful of which dataset is most
432 appropriate for their studies. For example, whether the biological response of interest is
433 more sensitive to absolute temperatures or to deviations from a shifting mean, or whether an
434 event can truly be considered extreme if its occurrence has become increasingly frequent?

435 It is worth noting that while our dataset focuses on surface waters (being SST-based),
436 subsurface MHWs can also occur and may not always align with surface events. Our use of
437 SST CCI means areas of the ocean below the mixed layer are not directly assessed here.
438 Future efforts could merge this with subsurface temperature data or model output to
439 examine the vertical dimension of MHWs. Additionally, the framework here could be applied
440 to other variables (such as marine cold spells). The general approach of multi-definition
441 analysis is broadly applicable to extreme events research.

442 Looking ahead, we anticipate updating and expanding this dataset, adding new products and
443 definitions such as non-linear detrending as well as extending persistence thresholds for
444 detrended data. As new SST reanalysis products or satellite data become available, they
445 can be incorporated to extend the record and possibly improve accuracy in certain regions,
446 for example in coastal and sea ice covered areas. By embracing the complexity of definitions
447 rather than choosing a single metric, it enables a more nuanced understanding of extreme
448 ocean warming events under climate change.

449 8. Conclusions

450 Our global MHW dataset offers, in a single resource, daily data that span the spectrum of
451 commonly used definitions. As our dataset includes both fixed (1991-2020) and moving
452 30-year baselines, users can analyse how a warming-adjusted threshold reshapes event
453 counts relative to a historical climate normal. Parallel streams of raw and linearly detrended



454 SST anomalies further allow researchers to disentangle MHWs driven by natural variability
455 from those amplified by the long-term warming trend, an essential capability for attribution
456 studies. Event masks are provided at three intensity thresholds (90th, 95th and 99th
457 percentiles) and at three minimum-duration criteria (5, 10 and 30 consecutive days),
458 capturing everything from moderate, short-lived anomalies to the most persistent and
459 extreme episodes. By packaging these options side-by-side, the dataset becomes both a
460 practical tool for climate monitoring, ecosystem-impact assessment and model evaluation,
461 and a conceptual lens through which to examine how methodological choices alone can alter
462 our perception of ocean extremes. In short, the multi-definition design promotes transparent,
463 apples-to-apples comparisons across studies and supplies a robust foundation for deeper,
464 more nuanced understanding of MHWs in a rapidly changing climate.

465 Author contributions

466 All authors contributed to guiding the research process and provided scientific input
467 throughout. A.H., N.D., and M.R.P. generated the code and processed the data. A.H. wrote
468 the main manuscript text and prepared the figures. All authors (A.H., N.D., R.M., M.R.P.,
469 R.R., G.B., S.C., V.C., D.D., P.E., V.H., P.H., J.H., A.J.K., B.L., A.O., J.P., F.D.R., K.v.S., F.S.,
470 S.S., A.Z.R., S.O.) contributed to discussions, reviewed the manuscript, and provided
471 comments and revisions.

472 Disclaimer

473 NA

474 Competing Interests

475 There are no competing interests

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