Marine heatwaves in global sea surface temperature records since 1850

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Abstract
The adverse impacts of marine heatwaves (MHWs) on marine ecosystems and human activities are well-documented, yet observational studies tend to largely rely on recent records. Long-term records of MHWs can put the recent increase in frequency and intensity of MHWs in the context of past variability. We used long-term monthly sea surface temperature (SST) data and night marine air temperatures to characterise past MHW activity. A persistent increase in the global extent of MHWs is demonstrated, beginning around 1970. The average annual MHW extent post-2010 is estimated to be increased at least four fold compared to that pre-1970. A strong correlation between spatial variance of recorded average monthly SSTs and the average inverse number of monthly observations implies both frequency and amplitude of MHWs is overestimated when the number of monthly observations is low. Nevertheless, many identified early MHWs appear genuine, such as a multi-month event in the North Atlantic in 1851–1852. MHWs are also affected by poorer sampling during the world wars. The most extensive MHW years globally coincide with El Niño years, and MHW extent in the North Atlantic is correlated with the Atlantic Multidecadal Oscillation.

1. Introduction
Marine heatwaves (MHWs) can be qualitatively described as 'discrete prolonged anomalously warm water events in a particular location' [1]. There have been a number of well-documented high-intensity MHWs in the past decade, such as in the Northwest Atlantic in 2012 [2], the multi-year 'blob' in the North Pacific 2014–16 [3], the 2011 ‘Ningaloo Niño’ in the Eastern Indian Ocean [4], and the 2012, 2015 and 2017 MHWs in the Mediterranean Sea [5]. These events have repeatedly broken records for intensity and duration of MHWs.

The profound impact of such high-temperature events on marine flora and fauna has been extensively documented. Fordyce et al [6] provide a review of the effect of MHWs on coral reefs, describing how discrete high-intensity events can lead to accelerated bleaching (and subsequent habitat destruction), overwhelming mechanisms for mitigation and recovery from gradual temperature increases. Multiple studies have demonstrated MHW-driven damage to habitat-forming kelp species, including in the California Current System 2014–16 [7, 8], local extinction of bull kelp in New Zealand 2017–18 [9], and in experiments on two common species from the North Atlantic [10].

MHWs also have strong impacts on human activities, most notably fisheries. The 2011 Ningaloo Niño resulted in fisheries closures and stock reduction across multiple invertebrate species, with only partial recovery by 2018 [11]. The 2012 Northwest Atlantic MHW caused commercially valuable species to change their seasonal migration patterns, or shift their geographic distribution entirely [2]. Sillago schomburgkii, a commercially fished species known as yellowfin whiting in English, accelerated a multi-decadal migration in response to brief intense temperatures [12]. A review of the socioeconomic ramifications of MHWs also included negative effects on
tourism and carbon sequestration as well as food security [13].

In addition to studies on the impact of MHWs, understanding of their past and future trends is also growing. Using a suite of proxies for MHW properties from historical data, Oliver et al [14] found that global MHW average duration and frequency increased by 17% and 34% respectively between 1925 and 2016, in response to increased ocean temperatures. The trend for high-intensity MHWs is more extreme: the frequency of MHWs above the 99.5th percentile of seasonal sea surface temperatures (SSTs) has already increased over 20-fold due to anthropogenic global warming [15]. The response of MHW characteristics to long-term warming was probed with a statistical model based on satellite observations of SSTs, used to simulate SST time series [16]. Changes in mean SST, not SST variance, were the primary driver of changing MHW frequency over approximately 2/3 of the ocean, suggesting recent increases in MHW frequency are directly attributable to long-term warming.

Global climate models have been used to make predictions about the future progression of MHWs. A suite of Earth system model simulations predicted the probability of MHW occurrence to increase by a factor of 16 for 1.5 °C warming relative to preindustrial levels, a factor of 23 for 2.0 °C and a factor of 41 for 3.5 °C [17]. Another set of global climate simulations predicts a ‘permanent MHW state’ over many parts of the ocean by the end of the 21st century [18]. Based on these projections, MHW impacts on marine ecosystems are expected to be widespread, significant and persistent throughout the 21st century.

While the impact of MHWs in the present and future is incontestable, the majority of studies of past MHWs rely on daily gridded satellite data (available 1980s onwards). Where the record has been extended, the focus has been on contextualising recent extremes, with studies relying on proxy data [14] or historical simulations [15] outside of the satellite record. One study analysed an infilled record of historical measurements, and used early extremes as a baseline for a marine heat index [19], an approach which we show is problematic.

Patterns in past MHW occurrence can bring insight into what conditions lead to extremes, and guide future work on their drivers. A spatially and temporally resolved record of historical MHWs is a worthwhile goal, which provides a robust context for studies of current and projected extremes. The availability of monthly, gridded historical SST data presents an opportunity to create such a record, but comes with unique challenges. With this analysis, we aim to extend the historical record of MHWs using observational data beginning in 1850, and describe the spatial and temporal distribution of MHWs in that record. In doing so, we will highlight the advantages and issues in searching for extremes in monthly historical data.

2. Materials and methods

2.1. Temperature datasets

The main dataset studied was HadSST4 [20]. It consists of monthly SST anomalies on a grid of 5° × 5° cells from 1850 to 2020. The anomalies are relative to a 30 year climatological average (1961–1990). The primary input data are from ICOADS release 3.0 [21]. ICOADS SST data originate primarily from bucket or engine room intake observations from ships, and moored and floating buoys. Data availability is therefore much better along major shipping routes, especially early in the record. The ICOADS SST data have been adjusted for systematic bias arising from changing measurement methods.

To validate results found from HadSST4, some results were repeated using data from CLASSnmat [22]. CLASSnmat consists of monthly night marine air temperatures (NMATs) from 1880 to 2019, on a 5° × 5° grid similar to HadSST4. The observations again originate from ICOADS release 3.0 [21]. These temperatures are expressed as anomalies relative to a 1961–1990 climatological average, and measurements taken at different heights are adjusted to a reference height of 10 m. Again, this dataset aggregates temperatures into monthly mean values in each grid cell. Data from CLASSnmat are used for cross-comparison with HadSST4. Any results/methods discussed below relate to HadSST4 unless specified otherwise.

To limit the effect of early inhomogeneous data coverage, cells where HadSST4 data was available for less than 30% of the total time period 1850–2020 were discarded from all further analysis. This proportion reflects a subjective balance between using all available data and avoiding systematic bias in the results. Data was also discarded from CLASSnmat where no data was available in HadSST4, to ensure a like-for-like comparison. Some coastal cells have a low percentage of water cover, resulting in a slightly higher weighting of coastal areas in the final analysis.

2.2. Definitions

Hobday et al [1] give a quantitative framework for defining MHWs based on daily SST records, which has been used extensively where daily records are available [14, 15, 18, 23]. In extending the MHW record using observational data, it is impossible to rely solely on daily records as this data is not available. In using monthly data, it is necessary to adapt the standard MHW definition. Typical MHW mean durations are 5–15 d [24], with some regional exceptions where mean duration can be up to 60 d [25]. There is limited use in implementing a duration-based definition when typical MHW duration falls below the data’s time resolution.

Since SST data tend to show larger persistence than surface air temperature over land [26], a monthly diagnostic should capture larger MHWs...
reasonably well. A MHW was defined to be occurring where the SST in a given grid cell exceeded the 90th percentile of SSTs for that cell and month in the baseline period 1951–2020. This local monthly value is hereafter referred to as a ‘threshold’. This definition based on monthly data follows the classical definition [1] in implementing a local, seasonal, percentile-based MHW threshold, but is based on monthly mean data and therefore does not impose a minimum duration. A percentile-based definition was chosen to align with existing MHW literature, despite known issues with discontinuities in exceedance rates at the beginning and end of the baseline period [27].

The baseline period is longer than the minimum of 30 years suggested by Hobday et al [1], which was done to avoid local decadal trends affecting MHW frequency. For example, the period 1961–1990 would artificially increase MHW frequency in the North Atlantic outside this period, which was anomalously cold in this region. An even longer baseline could lead to bias due to data coverage, e.g. cells with data available only in recent decades would have higher temperatures due to global warming, and thus higher MHW thresholds. The baseline period 1951–2020 thus reflects a subjective balance between the two considerations. Changing the baseline period to 1900–2020 resulted only in a very slight increase in MHW occurrence towards the end of the period studied (see figure S3 and video S7, supplementary information), which does not affect our conclusions.

The normalised spatial extent of MHWs \( A_{\text{MHW}} \) was defined as the spatial extent of all MHWs, divided by the total spatial extent where data was available. \( A_{\text{MHW}} \) was calculated globally for each month, from CLASSnmat data as well as HadSST4 to compare their long-term behaviour. The normalised frequency of MHWs \( f_{\text{MHW}} \) for a given cell was defined as the number of months that cell experienced a MHW, divided by the number of months data was available for that cell—analogously to \( A_{\text{MHW}} \).

3. Results

3.1. Spatial extent and frequency
\( A_{\text{MHW}} \) from both datasets is plotted in figure 1. The 10% of years with the highest average Niño 3.4 index [28] are also shown for comparison—this record only extends back to 1856.

This plot summarises the general variation of MHW extent over the past 170 years. Most obvious is the clear upward trend from 1970 onward. Before 1970, the average global \( A_{\text{MHW}} \) is 0.06, while after 2010, it is 0.28: more than a four-fold increase. The \( A_{\text{MHW}} \) record contains a number of short-timescale spikes—many of these occur in conjunction with strong El Niño events. Broad peaks coinciding with the world wars are also visible. The two datasets broadly follow similar long-term trends, and have similar peaks for individual events. However, CLASSnmat shows more MHWs in the early record. \( f_{\text{MHW}} \) was calculated decade-by-decade, and is visualised for selected decades in figure 2 (and all decades in video S2, see supplementary information). The decades in figure 2 were chosen to highlight noteworthy features across the period studied: locally frequent MHWs in the North Atlantic pre-1900, high MHW frequency in the northern hemisphere in the 1940s, the impact of strong El Niños in the 1980s and 1990s, and unprecedented frequency of MHWs globally in the 2010s.

3.2. Variability

Many record temperature anomalies are recorded pre-1900 in both HadSST4 and CLASSnmat, particularly in the North Atlantic and West Pacific (see figure S1, supplementary information). This is surprising in the context of recent increases in MHW frequency and spatial extent. How trustworthy are such early extremes? It is plausible that early MHWs are observed due to increased variability in monthly SSTs, potentially due to data issues rather than physical differences. One explanation is that the observed variability is driven by fewer monthly observations per cell, i.e. poorer sampling.

The variability of observed SSTs can be quantified by the spatial variance of monthly SST anomalies, \( \sigma^2_{\text{SST}} \). In the following analysis, \( \sigma^2_{\text{SST}} \) was calculated only across those cells with at least 80% data coverage over the entire record, to limit the effect of changing number of cells with data. Figure 3 compares \( \sigma^2_{\text{SST}} \) with the average inverse of the number of monthly observations per cell, \( n_{\text{obs}} \). This comparison is motivated by Kennedy et al discussion of sampling errors in SST observations [29]. For the monthly average of multiple observations within a cell, the excess variance due to sampling is given by \( \sigma^2_{\text{sampling}} = \frac{\sigma_s^2}{n_{\text{obs}}} (1 - \bar{r}) \), where \( \sigma_s^2 \) is the standard deviation of the SST anomalies at a fixed point, and \( \bar{r} \) is the average correlation of the SST anomalies measured at any pair of points within the cell. Ignoring the variation of \( \sigma_s^2 \) and \( \bar{r} \) across cells and time, the average of \( \frac{1}{n_{\text{obs}}} \) should be roughly proportional to the excess variance due to sampling. Figure 3 shows a strong correlation (\( r = 0.78 \)) between global \( \sigma^2_{\text{SST}} \) and \( \frac{1}{n_{\text{obs}}} \), where the overline indicates a spatial average. Only after 1970 does the spatial variance increase due to large-scale anomalous heat, while sampling error diminishes further. This relationship is also seen if we restrict the analysis to the North Atlantic (see figure S2, supplementary information).

3.3. North Atlantic
The North Atlantic was chosen as a key area to study in more detail. This was motivated by several factors: the apparent higher occurrence of early MHWs (see figure S1, supplementary information), the excellent data availability compared with other regions, and the
Figure 1. The normalised MHW spatial extent $A_{\text{MHW}}$ over time, calculated from both CLASSnmat and HadSST4 datasets. The 10% of years with the highest Niño 3.4 index (record begins 1856) are shown in green for comparison, and the world wars shown in red.

Figure 2. A map of the normalised MHW frequency $f_{\text{MHW}}$ is shown for individual decades. For cells where data was available for less than 30% of the decade, the cell is shaded in white.
The spatial variance of monthly SSTs $\sigma_{SST}^2$ over time, compared to the spatial average of the inverse number of monthly observations per cell, $\frac{1}{n_{\text{obs}}}$. Values of $\frac{1}{n_{\text{obs}}}$ above the 60th percentile are shaded in grey. The $r$ value given is the Pearson correlation coefficient between the two timeseries.

The normalised MHW spatial extent for the NA region, and AMO (1856 onwards) as a function of time. The $r$ value given is the Pearson correlation coefficient between the two timeseries.

existence of other studies on MHWs in this region for comparison [2, 30]. The area studied (and hereafter referred to as 'NA') was defined as the area between the 30th parallel North and 60th parallel North, and the prime meridian and 60th meridian West.

The normalised MHW spatial extent, $A_{\text{MHW}}$, is shown for the NA in figure 4, together with the average yearly value of the Atlantic Multidecadal Oscillation (AMO) [31]—the AMO data begins in 1856. The AMO is an index of North Atlantic mean SSTs—the timeseries used is unsmoothed and not detrended. Figure 4 shows that while the two quantities scale differently, their overall shape is remarkably similar, with positive AMO anomalies leading to higher occurrence of MHWs. This observation is confirmed by a value of Pearson’s $r = 0.72$. Note that like in the global case, $A_{\text{MHW}}$ may be biased towards higher MHW extent where sampling is low.

From figures 4, 1851/52 was singled out as an early period of interest, as it saw remarkably high
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4. Discussion

The record of $A_{\text{MHW}}$ singles out 1970 as the start of a persistent increase in MHW extent. This provides a clear indication that MHWs are getting more frequent and cover a larger spatial extent globally, as discussed in [14, 15]. The estimate of a four-fold increase in global MHW spatial extent between pre-1970 and 15 months. The spatial and temporal coherence of the 1851/52 warm anomaly suggest it is unlikely to be observed due to the sampling bias only (uncorrelated errors due to low sampling would result in more randomly distributed hot and cold anomalies).
post-2010 is quite a rough measure, as it is impacted by factors including increasing geographical data coverage and changing number of monthly observations. Nevertheless, it adds to the quantitative evidence of increasing MHW frequency due to global warming. The real increase may be larger due to overestimated early MHW occurrence caused by sampling issues, as discussed. The map of $f_{MHW}$ 2010–2019 provides a graphical illustration of how consistent this increase is in almost all areas of the global ocean. The discrepancies between datasets pre-1900 may be explained by outstanding, uncorrected biases in CLASSnmat related to recording practices or to incorrectly attributed observation times [32].

The importance of El Niño in driving the most extensive MHWs globally is highlighted by the coincidence of many of the strongest El Niño years with prominent peaks in $A_{MHW}$. Particularly noteworthy are the exceptionally powerful El Niño events in 1877–78 [33] and 1997–98 [34]. These events are also clearly visible in the decadal maps of $f_{MHW}$. This demonstrates ENSO is a globally important driver of MHWs on inter-annual timescales. In the North Atlantic, the correlation between $A_{MHW}$ and the AMO shows the frequency of extreme events follows the decadal evolution of SSTs as characterised by the AMO.

The decadal maps of $f_{MHW}$ show the spatial distribution of MHWs to a high degree of detail over the past 170 years. However, the accuracy of finding early MHWs in monthly data is called into question by the link between the spatial standard deviation of SSTs and average number of monthly observations per cell. The correlation between $\sigma^2_{SST}$ and $\frac{\text{obs}}{\text{m}}$ implies much of the increased variability of early SSTs is due to a lower sampling rate. This increased variability would increase both $A_{MHW}$ and $f_{MHW}$, where $\frac{\text{obs}}{\text{m}}$ is high, and lead to overestimates of MHW intensity. Figure 3 illustrates the times when such overestimates are particularly likely: 1940–1950, 1915–1920, and any time before 1905.

Much of the early variation in the observed $A_{MHW}$ is likely driven by this sampling error. The peaks in $A_{MHW}$ during the world wars are also likely influenced by this increased variability, in addition to a warm bias due to changing shipping fleet distribution during World War 2 [35]. The early occurrence of the most anomalous temperatures both in HadSST4 and CLASSnmat may also be explained by this effect. Such overestimates of the frequency and magnitude of extreme events are likely to be inherent to the use of monthly data in which the average number of monthly observations varies. Some credibility to the observed early events is restored by the case study of the 1851/52 North Atlantic MHW. As it is contiguous in time and space, it is likely a real event rather than a product of random sampling errors. The similarity to the 2012 episode demonstrates that MHWs on a similar scale to recent high-impact events can be identified in the early data. The approach then should be not to disregard any MHWs where $\frac{\text{obs}}{\text{m}}$ is large, but be aware that their frequency and amplitude is likely overestimated and it is difficult to make quantitative comparisons between areas and times with differing number of monthly observations. This highlights problems with using early extremes as a baseline to define later MHWs, such as in [19]; it is difficult to judge to what extent such extremes are impacted by low sampling rate. The broad conclusions of the analysis remain robust: MHWs have increased in extent and frequency since 1970 (the four-fold increase is likely an underestimate), the most extreme events coincide with El Niño globally and the AMO in the North Atlantic, and early examples of high-impact MHWs can be identified from reconstructions of monthly temperature observations.

5. Conclusions

The use of a MHW definition based on monthly data, along with the availability of comprehensive historical temperature datasets (HadSST4 and CLASSnmat), enables the creation of an extensive record of historical MHWs. This record aids the analysis of the spatial and temporal distribution of MHWs since 1850. There is a persistent increase in the global extent of MHWs since 1970, with at least a four-fold increase post-2010 compared to pre-1970. The frequency of MHWs globally correlates with known modes of variability: the most extensive MHW events globally coincide with the strongest El Niño years, and MHW extent in the North Atlantic is correlated with the AMO.

A difficulty in comparing MHW amplitude frequency across different locations and periods is presented by varying number of monthly observations. The demonstrated inverse relationship between variability of recorded monthly SSTs and number of monthly observations implies both frequency and amplitude of MHWs is overestimated when the number of monthly observations is low. Examples of genuine MHW events early in the record do exist, such as one in the North Atlantic in 1851–1852. The monthly definition is therefore of use in identifying MHWs from historical observations. However, care should be taken when comparing MHWs across locations and periods when the number of monthly observations varies.

Data availability statements

The data that support the findings of this study are openly available at the following URL/DOI: www.metoffice.gov.uk/hadobs/hadsst4/.
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