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Key Points:

- In situ profile observations suggest marine heatwave intensity has shown a suspicious outsized intensification globally over recent decades
- This is primarily an artifact caused by increasing amount of profiles with time from sparse to abundant
- Early sparsity of profiles underestimates the intensity while subsequent densification of profiles alleviates it, introducing the artifact

Supporting Information:

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

Correspondence to:

Z. Jing,
jingzhao@ouc.edu.cn

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Author Contributions:

Conceptualization: Zhao Jing
Formal analysis: Zhiqiao Wang
Funding acquisition: Zhao Jing
Methodology: Hao-xuan Sun, Zhao Jing
Resources: Zhao Jing
Supervision: Zhao Jing
Validation: Zhiqiao Wang, Zhao Jing
Visualization: Zhiqiao Wang
Writing – original draft: Zhiqiao Wang, Hao-xuan Sun, Zhao Jing
Writing – review & editing: Hao-xuan Sun, Zhao Jing

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Temporal Heterogeneity of In Situ Ocean Observing Capacity Could Cause an Artificial Intensification of Extreme Warm Water Events Globally

Zhiqiao Wang^{1,2,3} , Hao-xuan Sun⁴ , and Zhao Jing^{1,2} 

¹Frontiers Science Center for Deep Ocean Multispheres and Earth System and Key Laboratory of Physical Oceanography/Academy of Future Ocean, Ocean University of China, Qingdao, China, ²Department of Ocean Big Data and Prediction, Laoshan Laboratory, Qingdao, China, ³College of Oceanic and Atmospheric Sciences, Ocean University of China, Qingdao, China, ⁴School of Mathematics, Harbin Institute of Technology, Harbin, China

Abstract Extreme warm events in the ocean, known as marine heatwaves (MHWs), can have severe and even irreversible impacts on marine ecosystems, underscoring the imperative need to quantify their anthropogenic changes based on observations. In situ temperature profiles over the past three decades reveal an outsized global increase (over 10% per decade) in intensity of MHWs, whereas both ocean reanalysis and climate simulations suggest changes should be an order of magnitude smaller. Here we show that the paradox arises primarily from an artificial trend of MHWs caused by sparse-to-abundant temporal evolution of amount of temperature profiles. Sparsity of temperature profiles in the early period systematically underestimates intensity of MHWs, while subsequent densification of temperature profiles alleviates such underestimation, introducing an artificial positive trend of MHW intensity. Our findings indicate that temporal heterogeneity of in situ ocean observing capacity may severely contaminate the genuine response of extreme events to global warming.

Plain Language Summary One of the devastating effects of global warming is potentially more frequent and stronger extreme events. In particular, extreme warm water events, known as marine heatwaves (MHWs), can have severe and even irreversible impacts on marine ecosystems. Therefore, it is of imperative necessity to quantify their changes under global warming based on observations. In situ temperature profiles over the past three decades reveal an outsized global increase in the intensity of MHWs, whereas other data sets and climate simulation suggest the increase should be an order of magnitude smaller. Here we show that this paradox arises primarily from an artificial trend of MHWs caused by the increasing of amount of in situ profiles with time from sparse to abundant. Sparsity of profiles in the early period systematically underestimates the intensity of MHWs, while subsequent densification of profiles alleviates such underestimation, introducing an artificial intensification of MHWs. Our findings suggest that sparse-to-abundant increase of amount of profiles may severely contaminate the genuine response of extreme events to global warming so that careful handling of these observations is essential to reach valid conclusions.

1. Introduction

Global warming induced by increasing anthropogenic greenhouse gas emissions has been not only changing the climatological mean state of the Earth system but also increasing the intensity and frequency of many extreme events, such as extreme precipitation (Berg et al., 2013; Kharin et al., 2013; Myhre et al., 2019), wildfires (Brown et al., 2023; Cunningham et al., 2024), tropical cyclones (Emanuel, 1987; Landsea, 2005; Villarini & Vecchi, 2012) and extreme ice melting (Clarke et al., 2015; Hugonnet et al., 2021; Rounce et al., 2023). These events can impose devastating impacts on ecosystems, biodiversity and human societies (Arias-Ortiz et al., 2018; Field et al., 2012; González-Trujillo et al., 2023; Gruber et al., 2021; Intergovernmental Panel on Climate Change (IPCC), 2023b; Smale et al., 2019; Smith et al., 2021; Wernberg et al., 2025; Zhao et al., 2025). Therefore, it is imperative to have a comprehensive understanding of how these extreme events respond to ongoing anthropogenic climate changes.

Marine heatwaves (MHWs) are extreme warm events in the ocean that can cause severe impacts on marine ecosystem such as the reduction of ocean biodiversity (Gurgel et al., 2020; Smale et al., 2019; Starko et al., 2024), change in species behavior (Smith et al., 2023; Wernberg et al., 2016) and loss of fishery catch rates (Caputi

et al., 2016, 2019; Mills et al., 2013). MHWs at the sea surface have been extensively investigated based on the satellite observations. These observations have shown increasing intensity and frequency of surface MHWs during the past four decades in response to greenhouse warming (Frölicher et al., 2018; Oliver et al., 2018, 2019). However, MHWs are not confined to the surface layer. There are frequent MHWs in the subsurface ocean and their intensity can be even stronger than surface ones (Schaeffer & Roughan, 2017; Elzahaby & Schaeffer, 2019; Hu et al., 2021; Y. Zhang et al., 2023; Sun et al., 2023). Observations to these subsurface MHWs have to rely on in situ temperature profiles. A recent in situ observation-based study (He et al., 2024) revealed an outsized intensification ($\sim 10\%$ per decade) of subsurface MHWs induced by mesoscale eddies over the past three decades, although mesoscale eddies themselves do not show similar enhancement (Martínez-Moreno et al., 2021; Wang et al., 2024). Such an intensification trend raises concern because it is much stronger than that of surface MHWs (Oliver et al., 2018), in view that anthropogenic impacts on ocean temperature are generally more evident in the surface than the subsurface layer. As will be demonstrated below, the outsized intensification of subsurface MHWs estimated from in situ temperature profiles is not a genuine response to greenhouse warming. Instead, it is largely an artifact arising from the increase of amount of in situ observations from sparse to abundant during the past decades.

2. Data and Methods

2.1. Data

In situ temperature profiles: The World Ocean Database (WOD) by NOAA's National Centers for Environmental Information (NCEI), provides the largest uniformly formatted, quality controlled and publicly available collection of ocean profile data (Mishonov, 2024). It integrates diverse sources of profiles such as ship-based conductivity–temperature–depth (CTD), expendable bathythermograph (XBT), moored buoy, Argo float and glider, and covers global measurements spanning from the 18th century to the present. We use temperature profiles with quality control flags marked as ‘0’ (accepted) from all sources during 1993–2021.

Gridded monthly mean temperature data set: We use $1^\circ \times 1^\circ$ monthly mean ocean temperature data from the 4th version of the Institute of Atmospheric Physics (IAP) objective analysis product (Cheng et al., 2024). It is a global ocean temperature and ocean heat content objective analysis product from the Institute of Atmospheric Physics, with 119 vertical levels from 0 to 6,000 m and from 1940 to present.

Ocean reanalysis data set: The ocean reanalysis data used in this study are the GLORYS12V1 from the Mercator Ocean International operational system (Jean-Michel et al., 2021). It is a global ocean eddy-resolving reanalysis with a $1/12^\circ$ horizontal resolution and 50 vertical levels, covering from 1993 to the present. Observations are assimilated including satellites and in situ measurements such as Argo, CTD and XBT profiles.

Climate simulation: The climate simulation (Chang et al., 2020) used in this study is performed based on Community Earth System Model (CESM) version 1.3 (ref (Hurrell et al., 2013)). This model includes the atmospheric component of the Community Atmosphere Model version 5 (CAM5), the oceanic component of the Parallel Ocean Program version 2 (POP2), the sea-ice component of the Community Ice Code version 4 (CICE4) and the land component of the Community Land Model version 4 (CLM4). The POP2 has a nominal horizontal resolution of 0.1° and 62 vertical levels. The CAM5 has a nominal horizontal resolution of 0.25° and 30 vertical levels. The CESM consists of a 500-year-long pre-industrial control (PI-CTRL) simulation and a historical-and-future transient (HF-TNST) simulation from 1850 to 2100. The HF-TNST simulation is forced by the historical forcing from 1850 to 2005 and representative concentration pathway 8.5 (RCP8.5) forcing during 2006–2100. The daily temperature output during the 1993–2021 is used for analysis. Note that we also conduct the same filtering of profiles with He et al. (2024).

2.2. Definition of Extreme Events

Extreme warm (cold) events are defined when a temperature anomaly exceeds (falls below) the 95th (5th) percentile. Here the temperature anomaly of individual profiles is referenced to the gridded monthly mean temperature from IAP (Cheng et al., 2024). The percentile of the temperature anomaly is estimated from the empirical PDF of temperature anomalies collected over some neighboring spatio-temporal domain, that is, $10^\circ \times 10^\circ$ horizontally (Figure S1 in Supporting Information S2) and 1 month temporally. The intensity of MHWs I_{MHW} is defined as the mean value of temperature anomalies that exceeds the corresponding 95th

percentile, while intensity of extreme cold events is defined as the mean value of temperature anomalies falling below the corresponding 5th percentile. So is the case for MHWs based on ocean reanalysis GLORYS and CESM climate simulation.

We remark that the definition of MHW events in this study is generally consistent with that of He et al. (2024), although it is not identical to the more common MHW definition proposed by Hobday et al. (2016). The latter is not applicable to in situ temperature profiles as these profiles, moving with time, do not provide time series of temperature observations at fixed spatial locations.

2.3. Quantile Estimation With Finite Samples

According to the well-established order statistics theory (David & Nagaraja, 2003), the quantile estimates with finite sample number n are systematically biased low. Suppose that the temperature anomaly in the ocean at specific time and location follows a distribution with probability density function f . Let q_p denote the p -quantile ($p \in (0, 1)$) and $\hat{q}_p$ be a linearly interpolated estimator of q_p . Suppose that f is sufficiently smooth in a neighborhood of q_p and $f(q_p) > 0$. Then the bias of $\hat{q}_p$ can be approximated by

$$E[\hat{q}_p - q_p] \approx \left\{ \frac{1-2p}{f(q_p)} - \frac{f'(q_p)p(1-p)}{2\{f(q_p)\}^3} \right\} n^{-1} + O(n^{-2}), \quad (1)$$

where $E[\cdot]$ denotes expectation. A detailed derivation of Equation 1. is provided in Text S1 in Supporting Information S1. Equation 1 implies that the leading finite-sample bias of the sample quantile estimator is of order $O(n^{-1})$ (when the coefficient on the right-hand side of Equation 1 is non-zero), and such effect can get intensive especially when n is small. Specifically, for upper quantiles, it can be verified that the right-hand side of Equation 1 is negative for most distributions including the normal distribution and the exponential distribution. For example, if f is the standard normal distribution, for $p = 0.95$ we have $E[\hat{q}_{0.95} - q_{0.95}] \approx -5.05n^{-1} + O(n^{-2})$. Thus, the sample quantile estimator $\hat{q}_{0.95}$ underestimates the 95th percentile. In addition, since $E[\hat{q}_p] \rightarrow q_p$ when $n \rightarrow +\infty$, it shows that the sample quantile estimator is asymptotically unbiased. For a more general case, one can refer to Reiss (1976), which enables more accurate approximation to the asymptotic distribution of sample quantile estimator at arbitrary orders of n .

2.4. Calibration of MHW Intensity Bias Due To Insufficient Samples

The intensity of MHWs I_{MHW} biases low with insufficient samples. This may be calibrated at each $10^\circ \times 10^\circ$ box via the following steps. First, we construct an empirical probability density function (PDF) of temperature anomaly using data from the entire temporal period (1993–2021). The mean of temperature anomalies exceeding the 95th percentile of this PDF is taken as the true value of MHW intensity. Then, we establish a bias curve as a function of sample size. For a given sample size n , we randomly draw n samples from this PDF, estimate the I_{MHW} from these samples and repeat this procedure 1,000 times to obtain an average estimate. By comparing this average estimate with the true MHW intensity, we obtain the relative bias in percentage of true MHW intensity (denoted as $b\%$ with $b < 0$) for each n . Finally, for any given month with sample size n , we multiply the raw estimated I_{MHW} by $\frac{1}{1+b\%}$ corresponding to that n . This yields a first-order calibration of I_{MHW} .

3. Results

3.1. Outsized Intensification of MHWs Derived From In Situ Temperature Profiles

Intensity of MHWs I_{MHW} derived from in situ temperature profiles shows a positive trend over many parts of the global ocean during 1993–2021 (Figures 1a–1c). The trend is vertically coherent but geographically inhomogeneous, being strongest in the Southern Ocean where I_{MHW} increases at a rate of more than 40% per decade. The global mean trend is about 12% per decade, varying little from the sea surface to 200 m (Figure S2 in Supporting Information S2). Such an increase rate is comparable to the value reported by He et al. (2024). However, the global mean trend is on the order of 1% per decade, when applying the same computation to the GLORYS ocean reanalysis assimilating in situ temperature profiles and climate simulation based on a Community Earth System Model (Figures 1d–1i and Figure S2 in Supporting Information S2). It is noteworthy that such a large contrast of

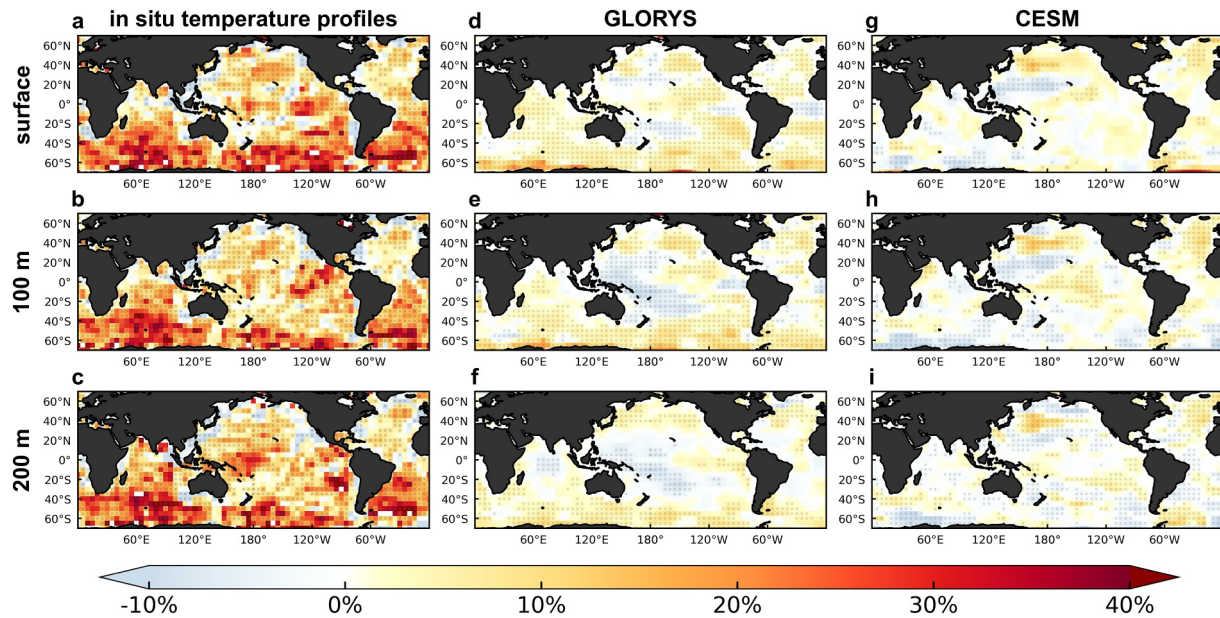


Figure 1. Geographical distribution of trend of intensity of marine heatwaves (MHWs) during 1993–2021. (a–c), Trend from in situ temperature profiles archived by the World Ocean Database (WOD) at the sea surface (a), 100 m (b), and 200 m (c). (d–f), and (g–i), Same as (a–c), but from the Copernicus global ocean physics reanalysis (GLORYS) and Community Earth System Model (CESM) simulation, respectively. Black dots represent regions where the trend is statistically significant at the 95% confidence level.

I_{MHW} trends between in situ temperature profiles and ocean reanalysis/climate simulation also holds for extreme cold water events. The global mean trend of intensity of extreme cold water events is about 15% per decade based on in situ temperature profiles but is on the order of 1% for the ocean reanalysis and climate simulation (Figure S2 in Supporting Information S2). In summary, in situ temperature profiles imply an outsized intensification of extreme temperature events during the past several decades that is absent in the ocean reanalysis and climate simulation.

3.2. Artificial Intensification of MHWs Caused by Temporal Heterogeneity of Amount of Profiles

The outsized intensification of MHWs estimated from in situ temperature profiles is not a genuine response to greenhouse warming. Instead, it is largely an artifact caused by the amount of in situ ocean observations increasing from sparse to abundant with time. It can be theoretically proved based on the order statistics theory that the estimated 95th percentile biases low when the number of samples used for estimation is insufficient, leading to underestimation of I_{MHW} (see Section 2.3). Figure 2b illustrates the estimated 95th percentile of temperature anomaly and I_{MHW} as a function of sample number used for estimation, where the samples are drawn randomly from an empirical probability density distribution (PDF) of temperature anomaly at 100 m within 60°S–50°S, 60°E–70°E during 1993–2021 obtained from the GLORYS reanalysis (Figure 2a). The estimated I_{MHW} biases low by 50% when the sample number is 5 and converges asymptotically to the true value as the sample increases. The bias becomes negligible, once the sample number exceeds 200.

During the past three decades, the number of in situ temperature profiles increases with time (Figure 2c). The global average number of in situ temperature profiles per $10^\circ \times 10^\circ$ area per month N_{prof} was approximately 10 in the 1990s. Since the beginning of the 21st century, the widespread deployment of profiling instruments across the global ocean, especially through the Argo project, has substantially increased the number of in situ observations, with N_{prof} reaching over 30 at the end of 2010s in terms of the global average. This increase of sample number alleviates the negative bias of MHW intensity, leading to an artificial positive trend of MHW intensity. It is noteworthy that the time series of I_{MHW} averaged over the global ocean closely follows that of N_{prof} with a correlation coefficient of 0.92 (Figure 2d). The value of I_{MHW} is characterized by a weak negative trend from 1993 to 2003, coinciding with the slight decrease in N_{prof} during that period. During 2003–2013, both N_{prof} and I_{MHW} increase rapidly with time. After 2013, both N_{prof} and I_{MHW} becomes relatively stable.

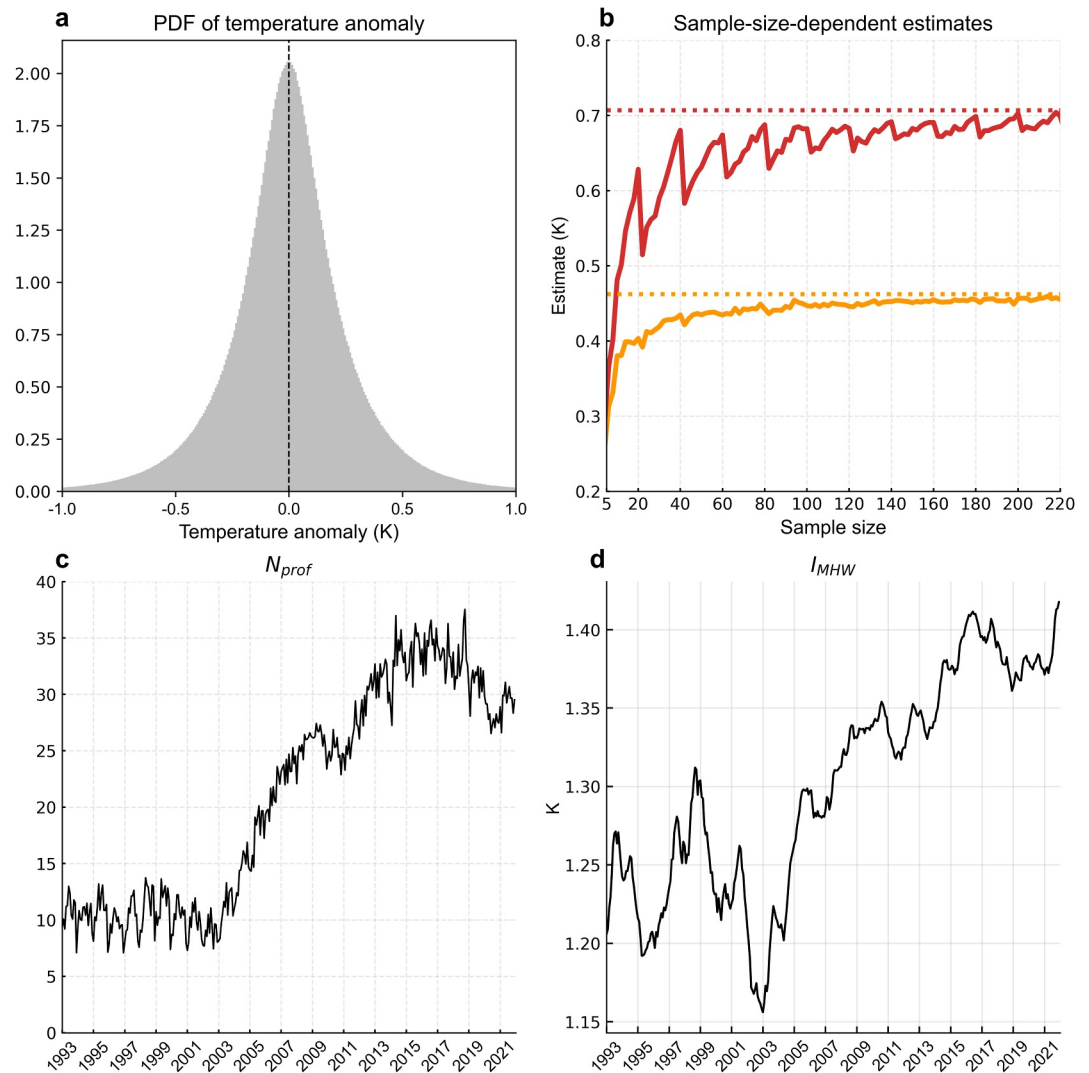


Figure 2. Effect of in situ temperature profile numbers on the bias of marine heatwave (MHW) intensity estimates. (a) Empirical probability density function (PDF) of temperature anomalies at 100 m within 60°S–50°S, 60°E–70°E during 1993–2021 obtained from the Copernicus global ocean physics reanalysis (GLORYS). (b) Estimates of 95th percentile temperature anomaly (orange solid line) and intensity of MHWs I_{MHW} (red solid line) as a function of sample number. Here the estimates are derived by randomly sampling from the empirical PDF in (a). For each sample number, 1,000 sampling experiments are repeated and the averages of 95th percentile and I_{MHW} among these experiments are computed and shown. The orange dotted and red dotted line represents value of 95th percentile estimated from PDF in (a) and mean value of temperature anomalies in PDF that exceeding the former, respectively. Note that the jagged feature in the red line occurs whenever n is a multiple of 20. (c) Time series of monthly number of in situ temperature profiles per $10^\circ \times 10^\circ$ area N_{prof} averaged over the global ocean. (d) Time series of I_{MHW} averaged over the global ocean.

The close relationship between I_{MHW} and N_{prof} implies that the trend of I_{MHW} might be dominated by the artificial trend of I_{MHW} caused by the increase of N_{prof} . To test this conjecture, we recompute the trend of I_{MHW} by calibrating the bias of I_{MHW} estimated from the insufficient samples (see Section 2.4), referred to as the calibrated trend of I_{MHW} henceforth. We remark that the genuine trend of I_{MHW} can be relatively weak and might be largely contaminated by other artifacts, such as those arising from time-varying bias of XBT measurements and from substantial changes in dominant type of measurement instrument (Levitus et al., 2009; B. Zhang et al., 2024). To minimize such artifacts, we only use Argo profiles during 2004–2021 here, during which Argo dominates (>80% in average) the in situ temperature profiles and also exhibits significant increase of N_{prof} (Figure S3 in Supporting Information S2).

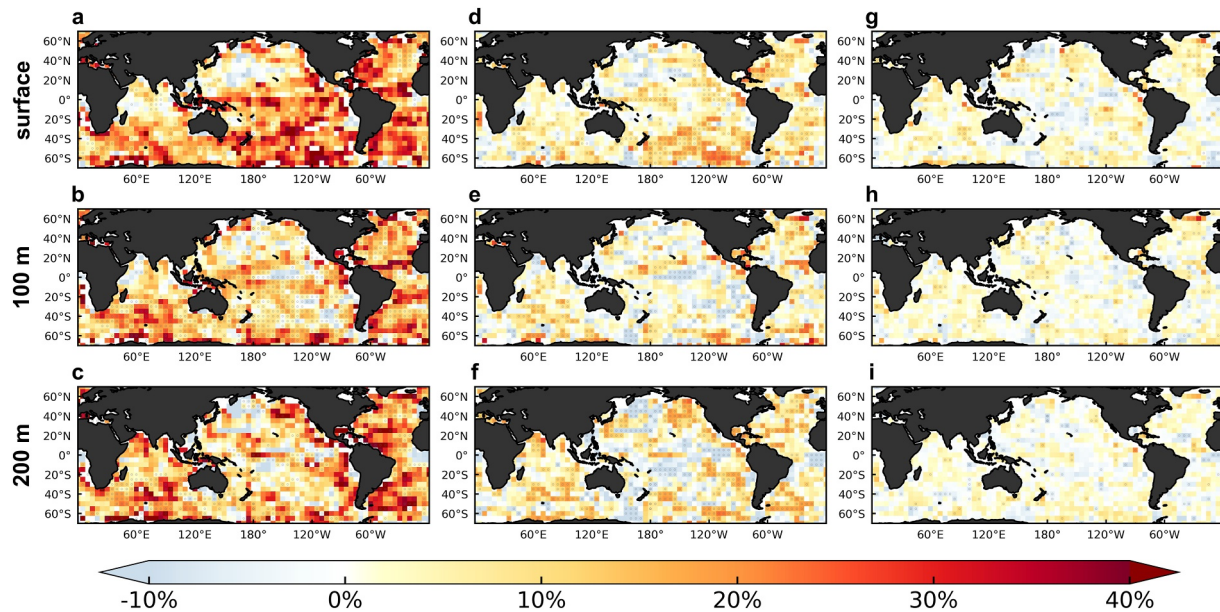


Figure 3. Geographical distribution of trend of intensity of marine heatwaves (MHWs) during 2004–2021 with the effect of insufficient sample number on intensity estimation removed. Trends of MHW intensity from Argo temperature profiles at the sea surface (a, d, g), 100 m (b, e, h) and 200 m (c, f, i) with the bias due to the insufficient profiles included (a)–(c), calibrated (d)–(f) and with the 95th percentile of temperature anomaly estimated from profiles during the entire period (g)–(i), respectively. Black dots represent regions where the trend is statistically significant at the 95% confidence level.

As shown in Figures 3d–3f, the calibrated trend of I_{MHW} from in situ temperature profiles is much weaker than the non-calibrated trend over most parts of the global ocean (Figures 3a–3c). Its global average is on the order of 1% per decade between 0 and 200 m (Figure S4 in Supporting Information S2). This is comparable to those derived from the GLORYS reanalysis and CESM simulation, but is an order of magnitude smaller than that from in situ temperature profiles without calibrating the bias (Figure S2 in Supporting Information S2). Our argument can be further supported by a control analysis in which profiles from later periods are subsampled to match the sample size of the early period, thereby keeping the sample size constant through time. The resulting global mean trend is also on the order of 1% per decade (Figure S5 in Supporting Information S2). In addition, the artificial trend of I_{MHW} caused by the increase of N_{prof} does not only dominate the global mean trend of I_{MHW} but also its geographical distribution. In particular, the strong trend of I_{MHW} in the Southern Ocean is largely due to the sparse in situ temperature profiles in the 1990s with N_{prof} less than 5 over most regions (Figure S1 in Supporting Information S2).

4. Discussion

In this study, we attempt to extract the genuine trend of I_{MHW} by calibrating the bias of I_{MHW} estimate from insufficient in situ temperature profiles. Another possible way is to adopt a temporally fixed threshold to define MHWs, in which case the 95th percentile of temperature anomaly should be computed based on in situ temperature profiles collected during the whole period rather than the individual months and thus has nearly no bias. It can be demonstrated that once the estimate of 95th percentile of temperature anomaly is unbiased, the estimate of I_{MHW} is unbiased regardless of the sample number (Figure S6 in Supporting Information S2). Setting aside the debate whether a temporally fixed or varying threshold is more appropriate to define MHWs (Chiswell, 2022; Oliver et al., 2019; Rosselló et al., 2023), adopting a temporally fixed threshold avoids the contamination of I_{MHW} trend by the increase of in situ temperature profile number. The trend of I_{MHW} with a fixed threshold is much weaker than that with a monthly threshold (Figures 3g–3i). Its global average is on the order of 1% per decade, qualitatively consistent with that of the calibrated trend of I_{MHW} (Figure S4 in Supporting Information S2). Moreover, it shows spatial variations that is similar to that of the calibrated trend of I_{MHW} , with a spatial correlation coefficient higher than 0.6. This lends support to the fidelity of our calibration. However, it should be noted that there are quantitative differences between the calibrated trend of I_{MHW} and the trend of I_{MHW} with a fixed threshold (Figure 3). This may reflect the difference of MHW definition (temporally fixed vs. varying threshold).

and the uncertainties in calibrating the effect of finite sample number on the 95th percentile estimate. In summary, the I_{MHW} has been intensifying under greenhouse warming, but with a trend of order of only 1% per decade instead of the outsized 10% per decade.

Accurate assessment of the response of Earth system to greenhouse warming is crucial for making sensible climate policy (Intergovernmental Panel on Climate Change (IPCC), 2023a, 2023b; Cologna et al., 2025) yet turns to be challenging. In addition to the difficulties in isolating the anthropogenic signals from the internal natural variability, this study, along with previous literature (Chan et al., 2019; Chen & Tung, 2024; Karl et al., 2015; Medhaug et al., 2017; Thompson et al., 2008), suggest that the evolution of ocean observation method and capacity may contaminate the anthropogenic ocean changes. In particular, our analysis demonstrates that the outsized intensification of MHWs derived from in situ temperature profiles during the recent three decades (He et al., 2024) is not a genuine response to global warming. Instead, it arises primarily from an artificial trend caused by the increasing number of in situ temperature profiles with time. Apparently, this artifact does not only contaminate the trend of MHW intensity but also any other types of extreme ocean events such as the extreme cold events and hypoxia. Without carefully addressing effects of temporal heterogeneity in ocean observations, there are risks of overstating the impact of greenhouse warming on marine ecosystems and taking improper management.

Here we also remark that our conclusions do not apply to the commonly used Hobday et al. (2016) framework as it relies on temporally uniform gridded data that are free from changes in sampling density. Moreover, our definition of MHWs is slightly different from that of He et al. (2024), which defines MHWs in various dynamical regions spatially and over each adjacent 5 months temporally when estimating recent trend of MHWs. This definition allows larger amount of in situ temperature profiles during the early 1990s, especially in basin-wide regions. However, over smaller regions of western boundary currents and observation-lacking Southern Ocean where the intensification of MHWs is more 'outsized', the sample sizes are still quite limited (all less than 50 per five months and even less than 20 per five months over Brazil-Malvinas Current during the early 1990s) (Figure S7 in Supporting Information S2). This issue is more pronounced at deeper levels as many profiling instrument (such as XBT) cannot reach deeper levels such as 1,000 m (Mishonov, 2024). To better highlight this artificial effect, we define MHWs in a different way in this study. In view of the severe impacts of MHWs, it is of imperative importance to carefully handling the ocean observations to reach an accurate assessment of their response to climate warming.

Conflict of Interest

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

Availability Statement

The WOD global historical in situ temperature-profile data can be downloaded from Mishonov (2024). The IAP global ocean temperature gridded product is available at Cheng et al. (2024). The GLORYS12V1 global ocean reanalysis product is available at European Union-Copernicus Marine Service (2018). The CESM climate simulation outputs can be downloaded from Chang et al. (2020).

Codes for the main results are available at Zenodo via Wang, Z. (2026).

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