Detecting marine heatwaves with sub-optimal data

Robert W. Schlegel1,2,\*,#, Eric C. J. Oliver1, Alistair J. Hobday3, Albertus J. Smit2

1Department of Oceanography, Dalhousie University, Halifax, Nova Scotia, Canada  
2Department of Biodiversity and Conservation Biology, University of the Western Cape, Bellville, South Africa  
3CSIRO Oceans and Atmosphere, Hobart, Tasmania, 7000, Australia

\_\_\*Correspondence:\_\_  
Robert Schlegel  
[robert.schlegel@dal.ca](mailto:robert.schlegel@dal.ca)  
# Currently based at the Department of Physical Oceanography, Woods Hole Oceanographic Institution, Woods Hole, Massachusetts, USA

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# Abstract

Marine heatwaves (MHWs), or prolonged periods of anomalously warm sea water temperature, have been increasing in duration and intensity globally for decades. However, there are many coastal, oceanic, polar, and sub-surface regions where our ability to detect MHWs is uncertain due to limited high quality data. Here we investigate the effect that short time series length, missing data, or linear long-term temperature trends may have on the detection of MHWs. We show that MHWs detected in time series as short as 10 years did not have durations or intensities appreciably different from events detected in a standard 30 year long time series. We also show that the output of our MHW algorithm for time series missing less than 25% data did not differ appreciably from a complete time series, and that the level of allowable missing data could cautiously be increased to 50% when gaps were filled by linear interpolation. Finally, linear long-term trends of 0.10°C/dec or greater added to a time series caused larger changes (increases) to the count and duration of detected MHWs than shortening a time series to 10 years or missing more than 25% of the data. The long-term trend in a time series has the largest effect on the detection of MHWs and has the largest range in added uncertainty of the results. Time series length has less of an effect on MHW detection than missing data, but is the most difficult to predict. We provide suggestions for best practices to improve the accuracy of MHW detection with sub-optimal time series and show how the accuracy of these corrections may change regionally.

# Introduction

The idea of locally warm seawater disrupting species distributions or ecosystem functioning is not a novel concept. We have known for decades that transient warm water occurrences in the ocean could result in major impacts on marine ecosystems (e.g. Baumgartner, 1992; Salinger et al., 2016). The study of the effects of anomalously warm seawater temperatures began in earnest in the early 1980’s when research into the ENSO phenomenon intensified (e.g. Philander, 1983). After the 1980’s, researchers began noticing that warm water events were becoming more frequent and with large ecosystem impacts (e.g. Dayton et al., 1992), but it was not until 2018 that this was demonstrated with global observations (Oliver et al., 2018).

In order to quantify the increased occurrence and severity of these events it was necessary to develop a methodology that would be inter-comparable for any location on the globe. This was accomplished in 2016 after the International Working Group on Marine Heatwaves (marineheatwaves.org) initiated a series of workshops to address this issue. This definition for anomalously warm seawater events, known as marine heatwaves (MHWs), has seen wide-spread and rapid adoption due to ease of use and global applicability (Hobday et al., 2016). One limitation with this algorithm that has not yet been addressed is the assumption that a researcher has access to the highest quality data available when detecting MHWs. In the context of MHW detection, a ‘high quality’ time series is spatio/temporally consistent, quality controlled, and at least 30 years in length (Table 3 in Hobday et al., 2016). While not stated explicitly in Hobday et al. (2016), a ‘high quality’ time series should also not have any missing days of data. To avoid contention on the use of the word ‘quality’, time series that meet the aforementioned standards are referred to here as ‘optimal’, whereas those that do not meet one or more of the standards are referred to as ‘sub-optimal’. Another unresolved issue with the Hobday et al. (2016) algorithm, which does not fall within the requirements for optimal data, is how much of an effect the long-term (secular) trend in a time series may have on MHWs detected in it when compared to that same time series when the trend has been removed.

Most remotely-sensed data, and more recently output from ocean models and reanalyses, consist of over 30 years of data and utilise statistical techniques to fill gaps in their time series from a number of environmental and technical sources. This means that these data are considered optimal for MHW detection. An excellent reference for the remotely-sensed products currently available, as well as their strengths and weaknesses, is provided by Harrison et al. (2019). Even though remotely-sensed data products are considered optimal, they still have other issues (e.g. land bleed, incorrect data flagging, spatial and temporal infilling) and so it may be necessary that for coastal applications researchers utilise sub-optimal data, such as sporadically collected *in situ* time series (Smit et al., 2013; Hobday et al., 2016).

This paper seeks to understand the limitations the use of sub-optimal data impose on the accurate detection of MHWs. Of primary interest are three key challenges:

1. The use of time series shorter than 30 years
2. The use of temporally inconsistent (missing data) time series
3. The use of time series in areas with large (steep) long-term sea surface temperature trends

We use a combination of reference time series from specific locations and a global dataset to address these issues. The effects of the three sub-optimal data challenges on the detection of MHWs are quantified in order to provide researchers with the level of confidence they may express in their results. Where possible, best practices for the correction of these issues are detailed.

# Defining marine heatwaves

The definition used in this paper for a MHW is “a prolonged discrete anomalously warm water event that can be described by its duration, intensity, rate of evolution, and spatial extent.” (Hobday et al., 2016). This qualitative definition is quantified with an algorithm that calculates a suite of metrics. These metrics may then be used to characterise MHWs and allow comparison with ecological impacts. The calculation of these metrics first requires determining the mean and 90th percentile temperature for each calendar day-of-year (‘doy’) in a time series. The mean ‘doy’ temperatures, which also represent the seasonal signal in the time series, provide the expected baseline temperature whose daily exceedance is used to calculate the local intensity of MHWs. The 90th percentile ‘doy’ temperatures serve as the threshold that must be exceeded for 5 or more consecutive days for the anomalously warm temperatures to be classified as a MHW and for the calculation of the additional MHW metrics.

In this paper we focus on the three metrics that succinctly summarise a MHW, of the set described in Table 2 of Hobday et al. (2016). The first metric, *duration*, is defined as the period of time that the temperature remains at or above the 90th percentile threshold without dipping below it for more than 2 consecutive days. The duration of an event may be used as a measurement of the chronic stress that a MHW may inflict upon a target species or ecosystem (e.g. Oliver et al., 2017; Smale et al., 2019). The second metric, *maximum intensity*, is the largest temperature anomaly during the event and is calculated by subtracting the climatological mean ‘doy’ temperature from the recorded temperature on that day. This metric may be used as a measurement of acute stress (e.g. Oliver et al., 2017; Smale et al., 2019). A third metric, *cumulative intensity*, is used to determine the ‘largest’ MHW in a time series (see Methods). This metric is the integral of the temperature anomalies of a MHW, and so has units of °C-days not °C, but represents the sum of temperature anomalies over the duration of the MHW, therefore; cumulative intensity is comparable to the degree heating days metric used in coral reef studies (Fordyce et al., 2019).

We used the R implementation of the Hobday et al. (2016) MHW definition, which is available in python (<https://github.com/ecjoliver/marineHeatWaves>), R (Schlegel and Smit, 2018), and MATLAB (Zhao and Marin, 2019). We compared the R and python default outputs, assessed how changing the arguments affected the results, and compared the other functionality provided between the two languages. While some style differences exist as a result of the functionality of the languages, the climatology outputs are identical to within < 0.001°C per ‘doy’. An independent analysis of the Python and MATLAB results also confirmed that they were functionally identical (pers. com. Zijie Zhao; MATLAB distribution author).

# What are optimal data for detecting marine heatwaves?

When working with extreme values in a time series, such as MHWs, it is important that the quality of the data are high (Hobday et al., 2016). Hobday et al. (2016) stated that high quality data, referred to here as ‘optimal’, used for the detection of MHWs should meet the following criteria:

1. A time series length of at least 30 years
2. Quality controlled
3. Spatially and temporally consistent
4. Be of the highest spatial and temporal resolution possible/available
5. *In situ* data should be used to compliment remotely sensed data where possible

Although the authors did not specifically state that time series must not contain large proportions of missing data, it can be inferred from the aforementioned requirements and the nature of the proposed algorithm. Another issue affecting the accurate detection of MHWs not discussed in Hobday et al. (2016) is the presence of long-term trends in a time series. Oliver et al. (2018) have shown how dominant the climate change signal can be in the detection of MHWs and we seek to quantify this effect here.

A time series with a sub-optimal length may impact the detection of MHWs by negatively affecting the creation of the daily climatology relative to which MHWs are detected in two primary ways. The first is that with fewer years of data to draw from, the presence of an anomalously warm or cold year will have a larger effect on the climatology than with a sample size of 30 years. The second cause is that because the world is generally warming (Pachauri et al., 2014), the use of a shorter time series will almost certainly introduce a warm bias into the results. This means, counterintuitively, that the MHWs detected in a shorter time series will appear to be cooler than the same MHWs detected in a longer time series. This is because the average temperature in a time series consisting of recent data will likely be warmer, which will raise the 90th percentile relative to the observed temperatures and the reported MHW metrics will appear to be less/lower.

The climatology derived from a time series serves two main roles (Organization, 2017); 1) it serves as a ‘benchmark’ relative to which past and future measurements can be compared, and against which anomalies can be calculated, 2) it reflects the typical conditions likely to be experienced at a particular place at a particular time. The WMO Guide to Climatological Practices (Organization, 2011) stipulate that daily climatologies (which they call ‘climate normals’) must be based on the most recent 30-year period that ends on a complete decade (currently 1981 – 2010). The suggested length of a time series for MHW detection was based on this WMO guideline (Hobday et al., 2016).

Some remotely sensed products suffer from ‘gappiness’ that result in missing data. This may be due to cloud cover, the presence of sea ice, unsuitable sea states, etc., which become more prevalent at smaller scales, particularly nearer the coast. Some products interpolate to fill missing data gaps, but this results in smoothed sea surface temperature (SST) fields that may mask small-scale spatial variations in surface temperatures. Remotely sensed products may also fill gaps by blending with data from other products, which may introduce other biases. It has been demonstrated that coastal SST pixels from remotely-sensed products may have biases in excess of 5°C from *in situ* collected data (Smit et al., 2013) however; there is also research that has shown there may be no bias between these different data types (Smale and Wernberg, 2009; Stobart et al., 2016). This is why the use of imperfect *in situ* collected time series may be needed for coastal MHW applications. These data are also prone to large gaps and so issues with regards to accurate MHW detection are also uncertain. It must be stressed here that the methods proposed in the Best Practices section for working with sub-optimal data do not address the issues that remotely-sensed data have near coastlines.

# Methods

To quantify the effects that time series length, missing data, and long-term trends have on MHW detection we compare the count, duration (days), and maximum intensity (°C) of MHWs from time series as they become increasingly sub-optimal. To ensure approximately equal sample sizes across all tests, only the results for MHWs in the final 10 years of data (2009 – 2018) are used for each test and are hereafter referred to as the ‘average MHWs’. The single largest MHW in each time series, as determined by cumulative intensity, is drawn from the same ten year sample and is referred to hereafter as the ‘focus MHW’.

The amount of uncertainty that the sub-optimal tests (see sub-sections below) introduce into the results is calculated by measuring the percent of change in the results from the control (optimal) time series as the data become more sub-optimal. No significance test is used here, rather the increasing uncertainty range in the results is shown so as to provide a benchmark against which one may decide how much uncertainty is too much depending on ones applications. Linear models are used to quantify the increasing rates of uncertainty that these sub-optimal tests introduce. These rates are analysed at a global scale to investigate spatial patterns before being discussed in more depth in the Best Practices section.

We use the remotely sensed NOAA OISST dataset (Reynolds et al., 2007; Banzon et al., 2016) in this study. This daily remotely-sensed global SST product has a 1/4 degree spatial resolution with 1982 the first full year of sampling. These data are interpolated and where possible verified against a database of *in situ* collected temperatures so that the final product does not have any spatial or temporal gaps. The NOAA OISST dataset was used during the creation of the MHW algorithm in Hobday et al. (2016) and is used here for consistency. Before being used in this study, the time series at each location (pixel) is de-trended by fitting a simple linear model and removing the residuals from the data. This must be performed so that we may control for the effects of time series length and long-term trends separately. Once de-trended, each time series is treated to the suite of sub-optimal controls (see following sub-sections) and the desired results itemised above are extracted.

The percent change in the average and focus MHW results from sub-optimal data is highlighted with the three reference OISST time series from Hobday et al. (2016). These time series are taken from the coast of Western Australia (WA; Figure 1A), the Northwest Atlantic Ocean (NWA; Figure 1B), and the Mediterranean Sea (Med; Figure 1C). These time series are used here for ease of reproducibility and because they each contain a MHW that has been the focus of multiple publications (e.g. Garrabou et al., 2009; Wernberg et al., 2012; Mills et al., 2013). The effect of the sub-optimal tests on these three time series are overlaid on 1000 randomly selected pixels from the global OISST dataset to show a range of results.

While not a specific focus in this study, the effects that the sub-optimal tests have on the seasonal mean and threshold climatologies have been included in the supplementary material (Figure S1).

The following three sub-sections describe how the three sub-optimal time series tests are implemented.

## Controlling for time series length

There are currently 37 complete years of data available in the NOAA OISST dataset (1982 – 2018). In order to determine the effect that time series length has on the focus output we systematically shorten each time series one year at a time from 37 years down to 10 years (2009 – 2018), before running the MHW detection algorithm. The MHW results for each one year step for each of the time series are then compared against the output from the 30 year (1989 – 2018) version of the same time series as the control.

In order to ensure equitable sample sizes we only compare the MHW metrics for events detected within the last 10 years of each test as this is the period of time during which all of the different tests overlap. This is also why we limited the shortening of the time series lengths to 10 years, so that we would still have a reasonable sample size to draw from for all of the other tests, too.

Because the lengths of the time series were being varied, and were usually less than 30 years in length, it was also necessary that the climatology periods vary likewise. To maintain consistency across the results we use the full range of years within each shortened time series to determine the climatology. For example, if the time series had been shortened from 37 to 32 years (1987 – 2018), the 32 year period was used to create the climatology. If the shortened time series was 15 years long (2004 – 2018), this base period was used. The control time series were those with a 30 year length ending in the most recent full year of data available (1989 – 2018). Note that due to necessity this differs from the climatology period of 1982 – 2011 that would most closely match the WMO standard. The effect of shifting the 30 year climatology base is shown in the supplementary material (Figure S2).

The *a-priori* fix proposed to address the issue of short time series length is to use a different climatology estimation technique. The option currently available within the MHW detection algorithm is to expand the window half width used when smoothing the climatology. Other techniques, such as harmonic regression/Fourier analysis, would have a similar effect but are not used here in favour of the Hobday et al. (2016) method. It is beyond the scope of this paper to compare every possible climatology calculation technique.

## Controlling for missing data

In order to determine the effect of random missing data on the MHW results, each time series has 0 – 50% of its data removed in 1% steps before running the MHW algorithm. The control time series are the complete versions.

The *a-priori* fix for missing data in the time series is to linearly interpolate over any gaps. There are many methods of interpolating (imputing) gaps in time series, such as spline interpolation, but we choose linear interpolation here due to its speed, simplicity, and the lack of assumptions it imposes on the data. It is beyond the scope of this paper to account for every possible method of interpolation.

## Controlling for long-term trend

To quantify the effect of a long-term (secular) trend on the MHW results we add linear trends of 0.00 – 0.30°C/dec in 0.01°C/dec steps to each time series. The control time series are those with no added trend (e.g. 0.00°C/dec).

There is no proposed *a-priori* method to correct for the added linear trend in these data as this would be simply not to add a trend. Rather it is proposed that the relationship between the slope of the added trend and the effect it has on the results be documented to determine if a predictable relationship may be used for any *post-hoc* corrections.

# Results

## Time series length

Shortening the length of a time series from 30 to 10 years had an unpredictable effect on the count of average MHWs (Figure 2A). At 10 years in length, 90% of the 1000 time series (pixels) tested had between 32% fewer to 85% more MHWs than the 30 year control. The overall increase or decrease in the count of average MHWs was close to linear, meaning that one may be able to say what the change in the count of MHWs may be as a time series is shortened, but it does not allow us to say if this change is positive or negative. The change in the sum of days of the durations of the average MHWs from a 10 year time series ranged from 41% fewer to 84% more than the 30 year control (Figure 2B). This change is slightly more linear than for the count of MHWs, but again, the values may increase or decrease. The mean of the maximum intensities of the average MHWs also either increase or decrease, with 10 year time series having mean maximum intensities anywhere from 16% less to 7% more than the 30 year control.

Increasing the climatology period longer than 30 years had almost as rapid an effect on creating dissimilar results as using fewer years of data. This result stresses the importance of adhering to the WMO standard as closely as possible to ensure the comparability of results. It also demonstrates the arbitrariness of the 30 year climatological base period.

Shortening time series length tended to decrease both the duration and maximum intensity of the focus MHW from each time series (Figure 3B and 3C), while the count of MHWs within the duration of the focus MHW increased (Figure 3A). This is because shortening a time series may increase the seasonal and threshold climatologies, so the shorter a time series becomes, the lower the maximum intensity and shorter the duration of the MHWs may become. MHWs with many spikes (Figure 1A), rather than a smooth hump (Figure 1C), will be particularly affected by this change in the climatology as it will more rapidly break the focus MHW into smaller events (Figure 3A).

There are clear global patterns in the changes in MHW results as time series are shortened from 30 to 10 years (Figure 4). The median change in the count of average MHWs due to changes in time series length is nearly 0, but much of the western Pacific and northern Atlantic oceans show large rates of increasing MHW counts as time series are shortened (Figure 4A). The rates of change in the eastern Pacific, southern Atlantic, and the Indian Ocean show a mix of both increasing and decreasing counts of MHWs as time series become shorter. The patterns of change in the sum of MHW days closely resemble the change in the count of MHWs (Figure 4B). The change in the maximum intensity of average MHWs from decreasing time series lengths occurred throughout most of the oceans at a median rate of -0.21% per year (Figure 4C) . This means that, on average, a MHW detected in a 10 year time series will have a maximum intensity about 4.2% cooler than a MHW detected in a 30 year time series (0.21%/year times 20 year difference). This small difference shows the robustness of the MHW detection algorithm. There are areas where decreasing a time series tends to increase the maximum intensities of the MHWs detected. These areas are roughly the same regions where the shortening of a time series causes a decrease in the count of MHW days detected. It is important to note that the long-term trends in these data were removed beforehand so the patterns observed in Figure 4 are due to the properties of the time series themselves and not the climate change signal that would otherwise be dominant in the results.

The same global patterns of the effect of shortened time series on the average MHWs are roughly seen in the effects on the focus MHW. Much of the ocean that shows a decrease in the count of MHWs as a time series is shortened (Figure 4A) also show an increase in the count of MHWs during the duration of the focus MHW at 0.1 additional MHWs per year the time series is shortened (Figure 4D). This may seem contradictory, but this increase in the count of MHWs during the focus MHW in a time series is due to it being broken into smaller events. When this occurs on the smaller MHWs they may be broken up enough to no longer be counted, and therefore the count of average MHWs decreases. The decrease in the durations of the focus MHWs are greater than the decreases for the average MHWs, but the spatial homogeneity of this pattern is more broken up (Figure 4B and 4E). The regions that show increasing durations in the focus MHW are spatially smaller than the average MHWs and the rates of increase are roughly one quarter of those for the average MHWs (Figure 4B and 4E). Finally, the increasing and decreasing maximum intensities were similar in scale, but differed somewhat in their spatial patterns. Whereas the average MHWs show clear warming trends in the northeast and south Pacific (Figure 4C), these features are much reduced for the focus MHWs (Figure 4F). The strong cooling signal in the average MHWs north of Europe is replaced by a spatially broad warming trend in the focus MHWs in the area. The minor warming trend in the average MHWs around the Kuroshio current is replaced by a spatially larger and more intense warming trend in the focus MHWs.

## Missing data

The effects of increasing missing data on MHW detection were more linear than the effects of time series length, with the exception of MHW count, which was the least linear effect of all tests (Figure 2). Up to 25% missing data, the count of average MHWs in a times series decreases by 45% or increases by 38% (Figure 2D). Past this point the count of MHWs falls at a roughly linear rate until there are 33 – 86% fewer MHWs when 50% data are missing. The effect of missing data on the sum of the average MHW days was linear at a rate of roughly 2% fewer MHW days in a time series for every 1% of missing data (Figure 2E). The effect of missing data on the maximum intensities of the average MHWs was also linear, but very noisy. The maximum intensities of average MHWs detected in time series missing 50% of their data could decrease by 33% or increase by 3%.

The effect of random missing data on the focus MHW in each time series was dramatic. As missing data in a time series increased, it becomes increasingly likely that the focus MHW is broken into multiple smaller events. It is not uncommon for this to begin with as little as 1% missing data, and increases in severity up to 25 – 30% (Figure 3D). From this point the number of separate events the MHW is broken into decreases as the smaller events are completely missed due to the loss of data. The duration of the focus MHW was almost always negatively impacted by missing data (Figure 3E). The decrease in duration follows a linear trend of a reduction ranging from 1 – 3% per 1% of missing data. At 26% missing data at least 5% of the time series had their focus MHW removed entirely from the time series, as seen by a reduction in maximum intensity of 100% (Figure 3F). At 41% missing data at least 25% of the time series had their focus MHW removed.

The effect of missing data on a MHW depends largely on their shape, which is the area above the threshold climatology and below the observed anomaly. The WA event has a very pronounced peak (Figure 1A), so when more data are missing we see how likely it becomes that this peak is not being recorded. The maximum intensity measured in the control time series is 6.5°C, but because very few days of this MHW were so intense, increases in missing data become more likely to remove these large values and the maximum intensity of the WA event begins to decrease more rapidly than either the NWA or Med MHWs.

The global patterns in missing data are unremarkable and generally consistent across the oceans. They may be seen in the supplementary material (Figure S3).

## Long-term trend

The effect of a long-term trend on MHW detection was the most linear of the three tests and resulted in the largest changes in the results. An added linear trend can lead to a reduction in the count of average MHWs in a time series, but generally it causes a linear increase at roughly 3% additional average MHWs detected for every 0.01°C/dec added (Figure 2G). The effect that these additional MHWs had on the sum of average MHW days was an increase, ranging from 1.7 – 11.5% for every 0.01°C/dec added (Figure 2H). This means that the average MHWs detected in a time series with a long-term trend of 0.30°C/dec could be anywhere from 48 – 347% longer than in the same time series with no long-term trend. The effect of linear trends on the maximum intensity of the average MHWs, though generally linear, could be either positive or negative at a rate of -0.1 – 0.6% per 0.01°C/dec added.

The focus MHW in each time series was never broken into multiple events due to the added long-term trend (Figure 3G) however; the duration of the focus MHWs were affected differently. The Mediterranean focus MHW showed practically no increase in duration due to an added long-term trend, the Western Australia MHW saw a large jump at 0.03°C/dec, and the Northwest Atlantic MHW had a dramatic jump at an added trend of 0.09°C/dec, followed by a few other increases at larger added trends (Figure 3H). Likewise, all of the other 1000 time series included in Figure 3 tend to jump up in dramatic steps, as seen by the very large range in the 90% and 50% confidence intervals (CI). These jumps in duration occur as the temperature anomalies increase more rapidly than the threshold and neighbouring MHWs in a time series connect into one event. The effect that the long-term trend had on the maximum intensity of focus MHWs was also linear and at an added trend of 0.30°C/dec the 90% CI was from 8 – 35% (Figure 3I).

The global patterns in added long-term trends generally show that MHW metrics increase. The patterns may be seen in the supplementary material (Figure S4).

# Best practices

There are many factors in the detection of MHWs that cannot be predicted due to the anomalous nature of these events. It is however possible to know how much confidence one may have in the results. In Table 1 the increasing rates of uncertainty per step in the sub-optimal tests for average MHWs is shown, while Table 2 shows the uncertainty for focus MHWs. From this information it is possible to say that, if we have a time series that is 20 years in length (10 years shorter than optimal), the median difference in the duration of average MHWs will be 3% lower, and the 90% CI will be +-27% around that median difference. These rates of uncertainty at the 90% CI are large, but if one knows where in the world one’s time series comes from it is possible to make a more accurate inference. For example, the change in the duration of average MHWs in the North Sea as the time series are shortened is very consistently positive and near the high end of the global distribution (Figure 4). This means that one can be more confident that the upper range of the 90% CI is an appropriate choice when estimating the possible change in ones results if they had been calculated with an optimal time series (30 years). One final point of consideration in the application of this information for judging uncertainty is to consider how linear the response of the results to the sub-optimal tests is. The values in both tables that are seen in parentheses show the R2 (coefficient of determination) for each linear model that was used to determine the change in uncertainty as time series become more sub-optimal. The closer the R2 value is to 1, the better of a predictor the slope is, with 0 meaning their is no clear response in the data to be modelled. In our previous example of calculating uncertainty for average MHW duration the R2 value is 0.65, which is not good. More examples, as well as a step-by-step walk through for how to use the numbers in these tables is provided in each sub-section below. The *a-priori* and *post-hoc* fixes proposed in the methods are also covered in more detail in the following sub-sections.

## Correcting for time series length

The *a priori* fix proposed for shorter time series, that of creating a smoother seasonal signal by expanding the window half width of the moving average, proved not to be a reliable option and it is advised to leave this at the default 5 days. Increasing the window half width to as much as 30 days has very little effect on the 50% (interquartile) and 90% CI ranges for the count of average MHWs, but looking at the reference time series we see how unpredictable the effect on individual time series may be (Figure 5, top row). The effect this change to the detection algorithm had on the duration of average MHWs was negligible at all window half widths tested (Figure 5, middle row). The effect of wider window half widths on the maximum intensity of the average MHWs was positive and may be a viable option to produce more accurate maximum intensities in shorter time series (Figure 5, bottom row), but it is the opinion of the authors that this is not a satisfactory trade-off with the other changes this introduces into the results to justify doing so. The effect of widening the window half widths was similar for the focus MHWs so is included in the supplementary material (Figure S5) in the interest of saving space. The widening of the window half widths effects MHW detection by flattening the shape of the roughly sinusoidal seasonal climatology. The overall mean value does not change, but the peaks and troughs are pulled closer to the mean while the slopes between them become more gradual. Because the mean of the seasonal signal doesn’t change, the total anomalous observation remain roughly constant, but where along the seasonal signal those anomalies are detected may shift dramatically. This is particularly noticeable for MHWs that occur at the peak of summer because the seasonal and threshold climatologies are lowered the most then, leading these events to appear more intense.

Knowing that the *a priori* fix for time series length is not effective, one must use the known rates of uncertainty to provide the *post-hoc* uncertainty to detected MHWs. We’ll use Table 2, the focus MHW uncertainty rates, as an example. The first six rows of this table show the rate of uncertainty introduced into results for a focus MHW for each year less or more than 30 years. The ‘range’ column in both tables indicates which direction from the 30 year control the slope in uncertainty is moving. The focus MHW detected in a 10 year time series will have a median (50th quantile) difference in maximum intensity of -3% from that same MHW in a 30 year time series (Table 2, row 5, column ‘q50’, value = -0.15%/year shorter than 30). This may be known by taking the value found in the corresponding cell of the table and multiplying it by the number of years shorter (or longer) than the 30 year optimal length that one’s time series is. Unfortunately it is unlikely that one’s results will match the median difference seen in the sub-sample of global results. It is more likely that the detected MHW will fall somewhere within the 50% CI (Table 1 and 2, column ‘q25’ to ‘q75’), or the 90% CI (Table 1 and 2, column ‘q05’ to ‘q95’) range. To determine these ranges in uncertainty one takes the slope found in the respective columns and multiplies them by the number of years one’s time series is shorter or longer than the 30 year control. This provides the full range of uncertainty within the 50% CI or 90% CI as well as the median change. For example, we may find the the 50% CI in the change in the maximum intensity of a focus MHW in a 10 year time series by multiplying the 25th and 75th quantiles of change. Going back to the 10 year time series example above, this means that the overall range of uncertainty around the median change is: 0.38% x 20 (difference in year) = 7.6%, the change in the 25th quantile is -0.36% x 20 = -7.2%, and the change in the 75th percentile is 0.02% x 20 = 0.4%. The final estimate of the 50 CI around the median change in maximum intensity is therefore: -7.2% – -3.8% – 0.4%. This means that in a 10 year time series one can assume that the focus MHW detected has a 50% chance of having a maximum intensity that is somewhere between -7.2% to 0.4% that the same MHW would be in a 30 year times series.

## Correcting for missing data

Linear interpolation was proposed as an *a priori* fix to address the issue of missing data and was surprisingly effective. This fix could hypothetically allow for the use of time series missing more than 50% of their data (Figure 6), assuming that there is not so much missing data that the period of time during a MHW that one may want to study is completely missing. The rates of uncertainty that missing data introduce into detected MHWs may be found in rows 7 – 10 of Tables 1 and 2, but we will focus on the use of the rates of uncertainty for interpolated data here as this is such an effective fix. Note that rows 7 and 8 of both tables show rates of change in count of MHWs for missing data between different ranges of missing data. This is because the change in the count of MHWs due to missing data is not linear. If one cuts the data at roughly 25% this provides the highest R2 values for the two slopes (most linear fit).

As an example for the use of linear interpolation over missing data in a time series we will look at how to calculate the 90% CI around the average MHW duration in a time series missing 30% data. The median rate of change in average MHW duration per 1% missing data after linear interpolation is 0.3% (Table 1, row 12, column ‘q50’), the rate of change for the 5th quantile is 0.09% (Table 1, row 12, column ‘q05’), and for the 95th quantile it is 0.85% (Table 1, row 12, column ‘q95’). At 30% linearly interpolated data one may assume a 90% CI around the average MHW duration to be 2.7% – -9.0% – 25.5%. In other words, their is a 90% chance that the average duration of the MHWs detected in a time series with 30% interpolated data are between 2.7% to 25.5% that of the MHWs detected in the same time series without any missing data.

## Correcting for long-term trend

There was no *a-priori* fix proposed for the correction of an added-linear trend. Rather, by knowing the trend in a time series *a-priori* we have been able to model the effect that it has on detected MHWs. The effect that long-term trends have on the results are much greater than the tests for time series length or missing data, and the effects are more linear, therefore; we can be more confident in the uncertainty we assign to the detected MHWs. That being said, the ranges of uncertainty introduced by long-term trends are also much greater than for the other two tests. As an example of how long-term trends affect MHW detection we will use a time series with a known linear trend of 0.25°C/dec. The median rate at which a long-term trend in a time series affects the count of average MHWs is 2.69% per 0.01°C/dec (Table 1, row 14, column ‘q50’), the 5th quantile is 0.71% (Table 1, row 14, column ‘q05’), and the 95th quantile is 7.44% (Table 1, row 14, column ‘q95’), therefore; the count of average MHWs detected in a time series with a long-term trend of 0.25°C/dec is likely (90% CI) 17.75% – 67.25% – 186%. This is a very large effect that supports the argument for using a 10 year long or 50% interpolated data time series. There are long-term trends present in most time series being used and these effects on the MHWs therein are almost certainly greater than using short time series with missing data. If one is comfortable detecting MHWs in a time series before detrending it, one should be comfortable with the use of time series shorter than 30 years or missing some data.

# Discussion

An investigation into the effects of sub-optimal data on MHW detection revealed that there are no clear statistical thresholds at which the outputs of the MHW algorithm become different than those from optimal data. The ranges/rates of uncertainty that sub-optimal data introduce into MHW results was able to be determined and it is up to the user to decide for themselves what an acceptable level of uncertainty may be. We discuss here what these uncertainties may mean for MHW research.

The MHW results from time series with 10 years of data are not appreciably different from the MHWs detected with 30 years of data. The rates at which the count, duration and maximum intensity of MHW change from year-to-year within a single time series may vary wildly, but a global sampling showed that the increasing range in the uncertainty of the results one may expect are roughly linear. The rates seen in Table 1 may therefore be applied *post\_hoc* to MHWs detected in shorter time series to provide the uncertainly range within which the results are comparable to those from an optimal time series.

An unexpected result was that increasing the base period used for climatology creation to longer than 30 years reduced the probability that the outputs would be comparable by as much as shortening the base period did. This means that the common (often unspoken) assumption that using 30 years of data is the same as using > 30 years of data for a base period is incorrect. In other words, a 30 year time series is often thought of as the minimum length needed to constrain the climatology but we have shown here that using a climatology period greater than 30 years may create outputs as different as using fewer than 30 years. This is due to the decadal and multi-decadal variability in an environmental time series. In time series with less interannual variability there will be no appreciable difference between results calculated with a 30 year base period versus the 30+ years. In a time series with large interannual variability, such as the Western Australia reference time series, a base period of 30 years is not yet enough to completely average out the variability. It is therefore important to stress the adherence to the WMO standards for climatology periods as closely as possible, should one want one’s results to be comparable to other studies. Increased smoothing of the climatologies derived from shortened time series was not an effective fix so it is recommend that the default climatology creation methodology in Hobday et al. (2016) be adhered to if one’s results are meant to be comparable to the growing body of literature that uses this methodology.

The MHW algorithm proved to be resilient to missing data. Time series missing as much as 25% of their data may be used if necessary as the effect this may have on the count of MHWs is comparable to using a 10 year time series and the rate of increase in uncertainty can be modelled with some accuracy. Over 25% missing data and the count of average MHWs in a time series is affected too much and too unpredictably for the results to be reliable, while the focus MHWs may begin to disappear at 26% or more missing data. That being said, the effect that missing data has on the duration of average MHWs in a time series is very predictable and can be corrected for rather easily as seen in Table 1. We showed here that a simple correction for missing data in a time series is to linearly interpolate over the gaps. Hypothetically this may be done for more than 50% missing data and the results will have less uncertainty in them than using a 10 year time series would. Should one choose to use linear interpolation to fill gaps in a time series missing more than 25% missing data one must be very cautious that the period of time one is interested in is not being heavily interpolated.

The long-term trends in times series have the largest potential effect on the MHWs detected. These effects are the most predictable of the three tests but also introduce the largest ranges of uncertainty. A concept to consider with the increase in duration from added long-term trends is that the temperatures in the time series usually increase “faster” than the 90th percentile threshold. So as the slope of the added trend increases, a given MHW effectively spreads outwards. If the rate of onset/decline for the MHW was more gradual (e.g. the NWA event) it will increase in duration more rapidly. If the rate of onset/decline was more rapid (e.g. the Med event), then the duration of the MHW won’t change much with a larger long-term trend. If MHWs have close neighbours then as they spread outward they may encounter one another and merge into a single much larger event, as the NWA event is prone to do. This reduces the overall count of the MHWs detected in a time series while increasing the mean duration of the events detected.

# Conclusions

The acceptable sub-optimal data limits, the amount of uncertainty they introduce into the results, and their proposed corrections are as follows:

1. Time series length:

* A length of 10 years produces acceptable MHW metrics that may be used with some caution
* The shortening of a time series introduced the largest uncertainty into the duration of average and focus MHW:
  + Average MHW duration changes by -1.62 – 3.8%/year shorter than 30 (90% CI)
  + Focus MHW duration changes by -2.16 – 1.05%/year shorter than 30 (90% CI)
* Smoothing the climatology before detecting MHWs does not improve the results and should not be done

1. Missing data:

* The effect of missing data up to 25% on MHW results was comparable to the effect of a 10 year time series
* Focus MHWs may begin to disappear from time series missing 26% or more data
* Linear interpolation is an excellent fix for missing data up to 50%, assuming that the time period of interest is not completely missing

1. Long-term trends

* Long-term trends had a greater effect on MHWs than the other two sub-optimal tests and had a greater range of uncertainty around those effects

In this manuscript we demonstrated why researchers must not shy away from the use of sub-optimal time series when the situation calls for it, such as coastal research or sub-surface analyses. Time series length may have an unpredictable effect on MHW results, but this may be corrected for within reason, and we have shown that time series lengths as short as 10 years are still useful for MHW research. Any shorter than 10 years however and the relationship between time series length and the effect on MHW metrics becomes too unpredictable to provide any corrections with confidence. Missing data has a larger effect on MHW detection, but is less of a concern as linear interpolation can apparently fix the challenges this creates up to and hypothetically in exceedance of 50% missing data. Lastly, the effect of long-term trends on MHW detection are the largest and most linear but also have the largest uncertainties. The MHW detection algorithm is very robust and we have shown here that one may be confident in the inter-comparability of one’s results when using time series within a generous range of sub-optimal data challenges.

# Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

# Author Contributions

The majority of the text and figures were produced by RWS. A large portion of an early version of the text and a number of initial figures were produced by AJS. AJH, ECJO, and AJS provided several rounds of comments on the manuscript as it was developed. RWS synthesised the comments and uploaded the manuscript.

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# Acknowledgements

The authors currently have no acknowledgements to make.

# Data Availability Statement

The code and datasets generated for this study may be found at <https://github.com/robwschlegel/MHWdetection>.

# Tables

best\_table\_average <- readRDS("../data/best\_table\_average.Rda")  
  
knitr::kable(best\_table\_average, caption = "Table 1: The rate of change in uncertainty as time series become increasingly sub-optimal. The columns containing numerical data show the slope (R^2^) of uncertainty for each step in the range column as percentages. Starting from the left, the 'test' column shows which of the three sub-optimal tests the results are for. The rows labelled 'interp' are for the interpolation fix for the missing data tests. The 'var' column shows the MHW metric that was focussed on in the sub-optimal tests and are seen the other figures in this paper. The 'range' column shows the range of values over which the various uncertainty rates were measured. Note that their are two entries for each variable in the length test. This is done to show the difference in the uncertainty that increasing OR decreasing a time series past the 30 year standard affects the results. The final five columns show the rate of uncertainty in each variable at the five different quantile steps used in the boxplot figures in this paper.")

Table 1: The rate of change in uncertainty as time series become increasingly sub-optimal. The columns containing numerical data show the slope (R2) of uncertainty for each step in the range column as percentages. Starting from the left, the ‘test’ column shows which of the three sub-optimal tests the results are for. The rows labelled ‘interp’ are for the interpolation fix for the missing data tests. The ‘var’ column shows the MHW metric that was focussed on in the sub-optimal tests and are seen the other figures in this paper. The ‘range’ column shows the range of values over which the various uncertainty rates were measured. Note that their are two entries for each variable in the length test. This is done to show the difference in the uncertainty that increasing OR decreasing a time series past the 30 year standard affects the results. The final five columns show the rate of uncertainty in each variable at the five different quantile steps used in the boxplot figures in this paper.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| test | var | range | q05 | q25 | q50 | q75 | q95 |
| length | count | 30 - 10 | -1 (0.76) | -0.39 (0.65) | 0.32 (0.65) | 1.39 (0.94) | 3.77 (0.93) |
| length | count | 30 - 37 | -2.89 (0.8) | -1.29 (0.87) | -0.35 (0.22) | 0.52 (0.31) | 1.97 (0.64) |
| length | duration | 30 - 10 | -1.62 (0.95) | -0.96 (0.89) | -0.29 (0.44) | 0.86 (0.87) | 3.8 (0.93) |
| length | duration | 30 - 37 | -2.86 (0.86) | -1.24 (0.83) | -0.33 (0.28) | 0.52 (0.43) | 1.67 (0.68) |
| length | intensity\_max | 30 - 10 | -0.72 (0.98) | -0.42 (0.99) | -0.23 (0.97) | -0.06 (0.4) | 0.21 (0.67) |
| length | intensity\_max | 30 - 37 | -0.45 (0.55) | -0.11 (0.33) | 0.1 (0.81) | 0.36 (0.95) | 0.83 (0.86) |
| missing | count | 0.00 - 0.25 | -1.45 (0.97) | -0.92 (0.95) | -0.44 (0.59) | 0.24 (0.15) | 1.53 (0.74) |
| missing | count | 0.26 - 0.50 | -1.67 (0.99) | -1.95 (1) | -2.16 (1) | -2.48 (1) | -3.1 (0.99) |
| missing | duration | 0.00 - 0.50 | -1.8 (0.97) | -1.81 (0.99) | -1.8 (0.99) | -1.76 (1) | -1.65 (0.99) |
| missing | intensity\_max | 0.00 - 0.50 | -0.6 (0.99) | -0.42 (0.98) | -0.31 (0.96) | -0.19 (0.89) | -0.01 (0) |
| interp | count | 0.00 - 0.50 | -0.17 (0.85) | 0 (1) | 0.17 (0.9) | 0.35 (0.98) | 0.7 (0.98) |
| interp | duration | 0.00 - 0.50 | 0.09 (0.83) | 0.19 (0.97) | 0.3 (0.99) | 0.44 (0.99) | 0.85 (0.99) |
| interp | intensity\_max | 0.00 - 0.50 | -0.22 (0.99) | -0.16 (1) | -0.12 (0.99) | -0.07 (0.91) | -0.02 (0.21) |
| trend | count | 0.00 - 0.30 | 0.71 (0.95) | 1.74 (1) | 2.69 (1) | 3.97 (1) | 7.44 (0.99) |
| trend | duration | 0.00 - 0.30 | 1.66 (1) | 2.87 (1) | 3.97 (1) | 5.66 (1) | 11.47 (1) |
| trend | intensity\_max | 0.00 - 0.30 | -0.12 (0.4) | 0.14 (0.79) | 0.29 (0.97) | 0.42 (0.99) | 0.61 (0.99) |

best\_table\_focus <- readRDS("../data/best\_table\_focus.Rda")  
  
knitr::kable(best\_table\_focus, caption = "Table 2: The rate of change in uncertainty in the measurements of the focus marine heatwave as a time series become increasingly sub-optimal. All elements of this table are the same as Table 1.")

Table 2: The rate of change in uncertainty in the measurements of the focus marine heatwave as a time series become increasingly sub-optimal. All elements of this table are the same as Table 1.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| test | var | range | q05 | q25 | q50 | q75 | q95 |
| length | focus\_count | 30 - 10 | 0 (1) | 0 (1) | 0 (1) | 3.51 (0.33) | 9.59 (0.78) |
| length | focus\_count | 30 - 37 | -8.93 (0.67) | 0 (1) | 0 (1) | 0 (1) | 0 (1) |
| length | focus\_duration | 30 - 10 | -2.16 (0.95) | -1.12 (0.94) | -0.34 (0.66) | 0 (1) | 1.05 (0.71) |
| length | focus\_duration | 30 - 37 | -2.58 (0.87) | 0 (1) | 0 (1) | 0 (1) | 2.06 (0.82) |
| length | focus\_intensity\_max | 30 - 10 | -0.65 (0.98) | -0.36 (0.98) | -0.15 (0.97) | 0.02 (0.23) | 0.29 (0.91) |
| length | focus\_intensity\_max | 30 - 37 | -0.4 (0.82) | -0.13 (0.66) | 0.04 (0.42) | 0.19 (0.89) | 0.44 (0.84) |
| missing | focus\_count | 0.00 - 0.25 | 0 (1) | 0 (1) | 5.23 (0.67) | 8.75 (0.78) | 19.12 (0.86) |
| missing | focus\_count | 0.26 - 0.50 | -0.85 (0.07) | -5.47 (0.7) | -5.64 (0.72) | -8.41 (0.81) | -12.12 (0.85) |
| missing | focus\_duration | 0.00 - 0.50 | -1.8 (0.81) | -2.17 (0.97) | -2.07 (0.99) | -1.95 (0.99) | -1.59 (0.93) |
| missing | focus\_intensity\_max | 0.00 - 0.50 | -2.66 (0.86) | -2.17 (0.74) | -0.7 (0.74) | -0.2 (0.54) | -0.01 (0.1) |
| interp | focus\_count | 0.00 - 0.50 | 0 (1) | 0 (1) | 0 (1) | 0 (1) | 0 (1) |
| interp | focus\_duration | 0.00 - 0.50 | -0.12 (0.91) | 0 (1) | 0.02 (0.32) | 0.2 (0.88) | 1.26 (0.97) |
| interp | focus\_intensity\_max | 0.00 - 0.50 | -0.31 (0.98) | -0.09 (0.81) | -0.01 (0.77) | 0 (0.02) | 0.01 (0.98) |
| trend | focus\_count | 0.00 - 0.30 | 0 (1) | 0 (1) | 0 (1) | 0 (1) | 0 (1) |
| trend | focus\_duration | 0.00 - 0.30 | 0 (1) | 0.35 (0.92) | 1.07 (0.98) | 2.7 (1) | 5.66 (0.98) |
| trend | focus\_intensity\_max | 0.00 - 0.30 | 0.27 (1) | 0.44 (1) | 0.59 (1) | 0.79 (1) | 1.19 (1) |

# Figure legends

Figure 1: The focus marine heatwaves (MHWs) shown in red for the three reference time series A) Western Australia (WA), B) Northwest Atlantic (NWA), and C) Mediterranean (Med). Other MHWs shown in salmon. Each panel is centred around the peak date of the focus MHW, which is highlighted by a dark green vertical segment. The beginning and end of each event are demarcated with light green vertical segments. The seasonal mean climatology for each time series is shown as a light blue line, while the threshold climatology is shown with a dark blue line. The observed temperatures are shown as a black line.

Figure 2: The effects of sub-optimal data on the average MHWs detected in 1000 randomly selected time series (pixels) from the OISST dataset. The columns show the results for each of the three sub-optimal tests: time series length (10 – 37 years), missing data (0 – 50%), and added long-term trends (0.00 – 0.30°C/dec). The rows show the results from the MHW detection output: the percent change in the count of MHWs, the percent change in the sum of the MHW days, and the percent change in the mean of the maximum intensities of the MHWs. The light grey vertical bars show the 5th and 95th quantiles of the values at each step along the x-axis. The dark grey boxplots within the light grey bars show the 25th, 50th, and 75th quantiles of the values at each step. The dashed black line highlights 0 on the y-axis, which denotes the where there has been no change from the control time series. The coloured lines show the effect of the sub-optimal tests on the three reference time series seen in Figure 1. Note that the y-axes differ between rows of panels.

Figure 3: The effects of sub-optimal data on the focus MHWs detected in 1000 randomly selected time series (pixels) from the OISST dataset. The columns and rows of this figure are laid out the same as Figure 2. The top row of panels, “Count (% n)”, shows the difference in the count of MHWs during the duration of the focus event from the control time series. A value of -100% means that no events were detected, and a value of 0 means that no additional MHWs were detected in addition to the focus MHW. Theoretically this value should remain at 0, when it increases that means that the focus event is being broken up into multiple smaller events. The bottom two rows of panels show percentage changes in the duration of the focus MHW and its maximum intensity. A value 0f -100% means that no MHW was detected. The 0 line on the y-axis is highlighted with a dashed black line and the effect of the sub-optimal tests on the three reference time series are shown in colour.

Figure 4: Global map showing changes in MHW detection as the time series at each pixel is shortened from 30 to 10 years. The left column shows the effect of time series length on the average MHWs detected, while the right column shows the effect on the focus MHW. Panels A and D show the change in count of MHWs as the time series are shortened, panels B and E show the change in the duration (days) of the detected MHW(s), and panels C and F show the change in the maximum intensities (°C). The labels on the colour bars at the bottom of each panel show what the values are at the 5th, 25th, 50th, 75th, and 95th quantiles of the data shown in the coloured pixels. Any values smaller/larger than the 5th/95th quantile were rounded to prevent the very long tails of the distribution from interfering with the visualisation of the results.

Figure 5: The effect of changing the window half widths used for seasonal and threshold climatology creation on average MHW detection. The left column (A, B, C) is reproduced from Figure 2 (A, B, C) and included here for ease of comparison to the effects of the three different window half widths tested: 10, 20, and 30 days. The default window half width, that used in the left column, is 5 days. All other elements are the same as Figures 2 and 3.

Figure 6: The effect of linear interpolation on the MHW results from time series with missing data. The left column (A, B, C) and right-centre column (H, I ,J) are reproduced from Figure 2 (D, E, F) and Figure 3 (D, E, F) respectively. They are included here for convenience of comparison against the other two columns that show the results from linearly interpolating missing data in 1000 randomly selected time series (pixels) from the OISST dataset before running the MHW algorithm. Note that the y-axes of the left two columns are not the same as the right two columns. A value of -100% along the y-axis means no MHWs were detected. All other elements are the same as Figures 2, 3, and 5.

Figure S1: The effect of the sub-optimal tests on the seasonal mean and threshold climatologies. These panels show the same information as Figure 2 except that the variables shown are the thresholds from the MHW detection output.

Figure S2: The effect of different 30 year climatology base periods on MHW results. The elements of this figure are the same as Figure 2.

Figure S3: The same global map as Figure 4, but with rates of change shown due to increasing missing data from 0 – 50%.

Figure S4: The same global map as Figure 4, but with rates of change shown due to increasing long-term trends from 0.00 – 0.30°C/dec.

Figure S5: The effect of increasing window half width on the focus MHWs. This figures contains the same information as Figure 5 but shows the focus MHW results rather than the average MHW results.

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