

## **Reviewer 1**

**1. The biggest issue is not one of the authors own making, but rather indicative of renewed interests in surface temperatures and a proverbial race by dataset producers to create new and improved versions of products, presumably for inclusion in the upcoming IPCC assessment report. The implications are two fold for the present study as follows.**

**Firstly, the Hadley Centre have recently updated their SST product to HadSSTv4 which builds upon the new ICOADS R3.0 which has considerably better coverage in several critical periods. It also does a better job of handling modern era biases. The dataset is available from <https://www.metoffice.gov.uk/hadobs/hadsst4/> and my feeling is that it would future proof the current analysis to use the HadSSTv4 product rather than HadSST3 as the marine basis. I am assuming that updates to HadSSTv3 will stop when HadCRUTv5 becomes operational so this decision will be enforced onto the team sooner or later. Changing now would save the need for another paper / the situation where there is a mismatch between the paper and the operational product. Changing would also, presumably improve coverage in the historical eras and thus improve the analyses. Unless there is a compelling technical impediment to doing so I would urge the authors to switch over SST source to HadSSTv4 now.**

We are well aware of HadSSTv4 and are planning to incorporate it into the Berkeley Earth product when it is operational. Currently HadSSTv4 is not updated monthly (it only runs through December 2018), so it is not a good fit for a monthly-updated product like Berkeley Earth until it is made operational (which we suspect will occur in early 2021).

We have had conversations with John Kennedy about when this will occur and are preparing to make any needed tweaks based on (minor) changes in data format. Aside from certain minor changes in the communicated data format, HadSSTv4 can be used identically to HadSSTv3 in our analysis and should provide a drop-in replacement whenever the new version becomes operational.

[As an aside, we are also aware that HadCRUTv5 will be including a new interpolation of both CRUTEM and HadSST. In the future, we may choose to discontinue our own interpolation and replace it with the HadCRUTv5 approach. However, as the next version of HadCRUT is not yet published, we can't yet evaluate whether that course of action is desirable.]

We have updated the manuscript to read (lines 51-52):

“The ocean component of the land/ocean product uses an interpolated variant of HadSST v3, whose construction is described below. ... Lastly, we note that HadSST v3 will be replaced with HadSST v4 once that product becomes operational (Kennedy et al. 2019). Aside from minor

differences in the way data is communicated and formatted, HadSST v4 should be usable following the same steps described here.”

**Secondly, the new versions of datasets and presence of new products means updates are likely warranted to the comparisons section. These include: • HadCRUTv5 (in final review) – contact Colin Morice for details •**

**<https://essd.copernicus.org/articles/11/1629/2019/essd-11-1629-2019.pdf> - the Chinese merged product recently extended back to 1850 •**

**<https://www.nature.com/articles/s41561-020-0582-5> which provides spatially complete estimation based upon HadCRUTv4 •**

**[https://journals.ametsoc.org/bams/article/doi/10.1175/BAMS-D-19-](https://journals.ametsoc.org/bams/article/doi/10.1175/BAMS-D-19-0095.1/348446/The-EUSTACE-project-delivering-global-daily-new-global-surface-air-temperature-estimates)**

**[0095.1/348446/The-EUSTACE-project-delivering-global-daily](https://journals.ametsoc.org/bams/article/doi/10.1175/BAMS-D-19-0095.1/348446/The-EUSTACE-project-delivering-global-daily-new-global-surface-air-temperature-estimates) - new global surface air temperature estimates •**

**<https://journals.ametsoc.org/jcli/article/33/4/1351/346368/UncertaintyEstimates-for-Sea-Surface-Temperature> - substantially updated uncertainty estimates on the NOAA product**

**Not all these need be used but clearly the HadCRUTv5 and updated NOAA estimates are key to include in revisions to at a minimum figure 7.**

While we agree with the reviewer’s suggestions that HadCRUTv5 should be used if possible in Figures 3 and 7, we reached out to Colin Morice and he indicated that their paper will likely not be out before ours, and would prefer we not release their results before they do. We do not feel that excluding this yet-to-be-released dataset from our comparisons should be a reason to delay publication.

We have updated Figure 7 to include NOAA’s revised uncertainty estimates. We have also changed references in the text from ERSSTv4 to ERSSTv5 to reflect the latest version of that dataset.

**2. I am not entirely convinced there is merit in persisting with a version that uses SST under sea-ice as this clearly is not a surface temperature. The true surface temperature in such regions is either the ice (near-)skin temperature or the air temperature at some nominal height above the surface. There is a potential risk of mis-use of a product that considers sea surface temperature under ice as a reasonable estimate of a true surface temperature. It would possibly be better to discuss this but provide only the air temperature over ice version as this is the only realistic product over these regions. It would be good to back up with references the contention made line 277-281 in this regard.**

We agree with the reviewer that the use of water temperatures in sea ice regions is not a natural way to think about global temperature changes, and we have now try to de-emphasize it for that reason. However, we believe that it remains a useful comparison for a variety of reasons.

For one, ERSST (e.g. Huang et al. 2017) continues to have an adjustment that shifts SST estimates towards the freezing point of ocean water (-1.8 C) in regions of high sea ice concentration. Functionally, this is analogous to using ocean temperature in these sea ice regions. If one is specifically working with ERSST, then a treatment of SST under sea ice is a natural comparison.

However, one must also acknowledge that ERSST's adjustment has only a minimal impact on NOAA GlobalTemp since one of the final steps in constructing NOAA GlobalTemp is to mask all cells with a high sea ice concentration as missing (e.g. Vose et al. 2012).

Similarly, HadSST will only use SST values in partial sea ice regions (when data exists), though the availability of such measurements is relatively rare.

It is a limited audience, but people working specifically with ERSST or HadSST may naturally want to make comparisons with ocean temperature in the sea ice region.

A more important point is that this analysis allows us to call out the role of warming in sea ice areas on the overall global warming trend.

As the reviewer knows, there are important differences in how global averages consider the sea ice region. NASA GISTEMP uses air temperature extrapolation, similar to our preferred method. NOAA GlobalTemp simply omits missing values (including all regions with high sea ice concentrations) in performing their averages. Similarly, HadCRUT omits missing values in their averages, which will include most of the cells in sea ice areas. Omission of missing cells will in effect treat those regions as having an average equivalent to the global average of non-missing cells. Given the large role of Arctic amplification, omission of Arctic cells is likely to underestimate the true extent of global warming. While not exactly equivalent to omitting sea ice cells, the extrapolation of SST values into the sea ice regions also removes most of the effect of warming in these regions. Thus comparing the averages resulting from SST interpolation to that involving air temperatures helps to characterize the magnitude of the missing warming.

To summarize, we think the SST interpolation is somewhat informative and useful, though primarily of specialist interest. However, for most applications, the air temperature interpolation in the sea ice regions is the more applicable tool.

We have now added multiple comments to the paper to emphasize that the analysis using air temperatures over sea ice is the result that should be preferred in most applications.

**3. The discussion in ln 30 to ln 34 is dated. The ICOADS release 3.0 is described in a newer manuscript (Freeman et al., 2017, doi:10.1002/joc.4775) and forms the basis for HadSSTv4 and ERSSTv5. The GHCN dataset has been updated in Menne et al., 2019**

**(<https://doi.org/10.1175/JCLI-D-18-0094.1>) and now includes very many more stations arising from the efforts of Rennie et al to improve land holdings. NASA don't, any longer, therefore use additional stations. This whole passage could be expanded and made a little more clear to provide a better and more accurate context for the reader here. More generally the discussion of others efforts is somewhat perfunctory and in several aspects significantly dated. The whole introductory section requires substantive updates including several additional new products and new versions of products as noted in major comment 1. In particular, with the move to HadCRUT5 all products will employ some form of interpolation.**

We agree with the author that a number of these references are dated and reflect developments in the time between when this portion of the manuscript was originally written and ultimately submitted.

We have updated lines 26-43 to read:

“A number of prior groups have developed global land/ocean surface temperature indexes, including NASA's GISTEMP (Hansen et al., 2010; Lenssen et al 2019), Hadley/UEA's HadCRUT4 (Morice et al., 2012), NOAA's GlobalTemp (Smith et al., 2008; Vose et al., 2012; Huang et al 2020), and the Japan Meteorological Agency (JMA) (Ishihara 2006). Additionally, Cowtan and Way (2014) provide a spatially-interpolated variant of HadCRUT4 featuring greater spatial coverage. These series differ in a number of respects. They all largely utilize the same set SST measurements drawn from the ICOADS database (Freeman et al., 2017) and most of the same land temperature records contained in the Global Historical Climatological Network monthly database (GHCNm) (Lawrimore et al., 2011), though HadCRUT4 (and by extension Cowtan and Way) includes a more modest number of land stations than GISTEMP and GlobalTemp, which recently transitioned to using the much larger GHCNm v4 database (Menne et al 2018).

Both GISTEMP and GlobalTemp utilize NOAA's pairwise homogenization algorithm to detect and correct inhomogenities such as station moves or instrument changes in land stations (Menne and Williams 2009), though NASA applies an additional satellite nightlight-based urbanity correction (Hansen et al., 2010). GISTEMP and GlobalTemp both use NOAA's Extended Reconstruction Sea Surface Temperature (ERSST) version 5 (Huang et al., 2017) for SSTs, HadCRUT4 and Cowtan and Way use HadSST3 (Kennedy et al., 2011), and JMA uses COBE-SST (Ishii et al., 2005). HadCRUT4 and JMA include no spatial interpolation outside of 5-by-5 latitude/longitude grid cells, while GlobalTemp includes some interpolation over land but has nearly complete ocean temperature fields with the primary exception that sea ice regions are masked as missing. GISTEMP and Cowtan and Way spatially interpolate temperatures out to regions with no direct station coverage (GISTEMP using a simple linear interpolation technique, while Cowtan and Way uses Kriging). The upcoming HadCRUT5 will transition to HadSST4 and include spatial interpolation (Morice et al, submitted).”

Menne et al 2018 GHCNv4 paper:

<https://journals.ametsoc.org/jcli/article/31/24/9835/90961/The-Global-Historical-Climatology-Net-work-Monthly>

Huang et al 2017 ERSSTv5 paper:

<https://journals.ametsoc.org/jcli/article/30/20/8179/33181/Extended-Reconstructed-Sea-Surface-Temperature>

Morice et al 2020, submitted.

**4. The temperature to distance correlation assumption in the ocean interpolation step is probably reasonable in ocean interior gyres. But it presumably breaks down in vicinity of upwelling, downwelling, coastal shelf seas and boundary currents. A little more justification / discussion is required than is given in ln 77-79. I suspect that you will need to provide a specific caveat about likely location-specific performance in such regions.**

The reviewer is correct that the use of a uniform correlation structure is an imperfect assumption.

Central ocean basins will actually have a longer average correlation than indicated, with polar regions, geographically complex basins, and regions of variable currents having a shorter average correlation.

On the monthly time scale, interpolation across these areas may be less reliable, and we have added a caveat to this effect.

“This treatment, using a single scale length for the whole ocean, simplifies the analysis; however, it does ignore some of the real variations across the oceans. For example, in regions with boundary currents, upwelling/downwelling, or complex ocean to land geographies, the scale length of monthly average temperature variations may be smaller than suggested here. In practice, the 5x5 degree gridding of HadSST already precludes a detailed analysis of most small features. The interpolation presented here primarily serves to improve the representation by smoothing over noise and filling gaps, but it won’t necessarily capture the smallest features.”

While not discussed in this paper, on longer timescales, higher resolution models seem to suggest that temperatures in areas of boundary currents still tend to evolve at a similar rate to larger regional trends (with a few exceptions). So, while failure to resolve small scale processes does reduce the utility of our local fields, it might not matter very much in the estimation of long-term trends in most cases.

#### **Minor comments**

**1. It feels dangerous to claim on ln 11 of the abstract that the product is more homogeneous. Without an absolute benchmark it is impossible, sadly, to say whether**

**any given product is more homogeneous than another and aspects such as spatial smoothness can be misleading as pointed out in Sherwood et al., 2009 (<https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/joc.1825>). I don't see an explicit justification for such a statement from the underlying text.**

We agree that this language is too strong, and have revised the line to avoid the impression that the dataset is more spatially complete or homogenous than existing datasets:

"It agrees quite well with records from Hadley's HadCRUT4, NASA's GISTEMP, NOAA's GlobalTemp, and Cowtan and Way, and provides a spatially complete and homogeneous temperature field."

**2. There are several newer analyses than Cowtan et al. 2015 on Ln 25 regarding SST/SAT. Richardson et al., 2018 plus newer in press papers by Lea Beusch, Nathan Gillett, Gareth Jones and others. It would also be worth being explicit how these measures may be expected to differ with time e.g. that SAT would be expected to warm / cool a little more than the underlying SST were to warm or cool.**

We have revised line 25 to read:

"..though it is only an imperfect proxy and may be subject to slightly slower warming rates than marine air temperatures in recent decades (Cowtan et al., 2015; Richardson et al 2016; Jones 2020)."

Richardson et al 2016: <https://www.nature.com/articles/nclimate3066>

Jones 2020: <https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.3871>

**3. Ln 28 the product is a joint effort between the Hadley Centre and UEA's CRU**

We have revised this to read "Hadley/UEA's HadCRUT4".

**4. Ln 28 Note newer references exist for the NOAA product and its uncertainty estimation (see major comments)**

Updated to read "NOAA's GlobalTemp (Smith et al., 2008; Vose et al., 2012; Huang et al 2020)"

**5. Please double check with GISS colleagues whether they continue to apply an additional night-lights based adjustment as my reading of Lenssen et al ended up ambiguous in this regard.**

Our understanding is that night lights still play a minor role though it has been reduced with the introduction of the homogenized station data from NOAA.

**6. Both NOAA and NASA have switched to using ERSSTv5 so the text and reference in 38-39 needs changing accordingly.**

ERSSTv4 had been changed to ERSSTv5 there and on line 297.

**7. Globaltemp (ln40) does include some limited interpolation over land and is complete over the oceans. This needs to be corrected accordingly.**

The reviewer's caveat is partially incorrect. ERSST is complete over the oceans, but GlobalTemp masks as missing all cells with a sea ice concentration over 50% (Vose et al. 2012) so GlobalTemp has missing cells in both land and ocean areas.

We've updated this to read: "HadCRUT4 and JMA include no spatial interpolation outside of 5-by-5 latitude/longitude grid cells, while GlobalTemp includes some interpolation over land but has nearly complete ocean temperature fields with the primary exception that sea ice regions are masked as missing."

**8. Ln 47-49 NOAA and NASA now use closer to 20 thousand stations following the GHCNv4 update and this should be reflected here.**

We've update this to include the proper GHCNv4 number. The sentence now reads:

"The land data utilizes significantly more land station data (over 40,000 stations) compared to the ~10,000 land stations used by some of the other groups (though GISTEMP and GlobalTemp have both recently updated their records to include a larger number of land stations, including more 20,000 sites in GHCNv4)."

**9. Ln 233-236 makes little sense as written. I think you mean to say that in the more recent past coverage uncertainty diminishes in importance and bias uncertainty becomes increasingly important?**

We've rewritten this paragraph to make the intention clearer.

"Over all time periods, we find that interpolation does reduce the uncertainty associated with missing coverage. In the early period, this results in an appreciable reduction in total uncertainty. However, the total uncertainty in the global average is little changed in the recent period. This is because bias and measurement uncertainties play a dominant role in the recent period, and the impact of these uncertainties on the global average are little changed as a result of the interpolation. However, even if the ocean-average uncertainty is not changed during the recent period, the interpolation may still aid in the interpretation of local to regional-scale features."

**10. Ln 273-274 or Antarctic coastal stations, surely? There are two hemispheres with sea-ice ...**

We've added mention for Antarctica.

**11. Can a reference be given e.g. to the ERSSTv5 paper to back up the assertion on Ln296-298? Note also that NASA and NOAA use ERSSTv5 and not v4 as noted in a prior comment.**

We have added a references to Huang et al 2017, Kennedy et al 2019, and Cowtan et al 2017, which examines these issue in depth:

Differences around World War 2 relate primarily to differences in adjustments to ERSST v5 and HadSST3 sea surface temperature records during that period (Huang et al 2017; Kennedy et al 2019; Cowtan et al 2017).

Huang et al 2017 ERSSTv5 paper:

<https://journals.ametsoc.org/jcli/article/30/20/8179/33181/Extended-Reconstructed-Sea-Surface-Temperature>

Kennedy et al 2019: [https://www.metoffice.gov.uk/hadobs/hadsst4/HadSST4\\_accepted.pdf](https://www.metoffice.gov.uk/hadobs/hadsst4/HadSST4_accepted.pdf)

Cowtan et al 2017: <https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.3235>

**12. In figure 3 are the trends OLS fits? You need to be explicit not just about the ARMA model applied but also the trend calculation method.**

We've clarified the caption to indicate that:

"The bottom panel shows trends calculated via an OLS fit and two-sigma trend uncertainties (calculated using an ARMA[1,1] approach to account for autocorrelation) for various starting dates through the end of 2019 based on monthly anomalies."

Similar approaches (central trend estimate from OLS, uncertainties from ARMA model) have been used in other papers, e.g. Hausfather et al 2017:

<https://advances.sciencemag.org/content/3/1/e1601207>

**13. As noted in a prior comment NOAA is interpolated to an extent so Ln 307 and Ln313-314 require revision accordingly.**

Line 307 has been revised to "... (which are more limited in both the NOAA and Hadley records)."



Lines 313-314 have been revised to “This contrasts with HadCRUT4 which exclude any grid cells lacking station coverage or SST measurements, or and NOAA GlobalTemp where interpolation is more limited.”

#### **14. HadCRUT and not HadCRU in In 338**

Fixed.

#### **Reviewer 2**

**1) As one of the other reviewers comments, the use of HadSST3 rather than HadSST4 is not ideal, although I appreciate that the HadSST3 version has been available for some time. I suspect the authors will also want to use HadSST4 (and will have to soon), but as long as the methods don't change when swapping for HadSST4 then this paper sufficiently describes the approach to creating the overall dataset.**

As discussed in our response to Reviewer 1, we are preparing to switch to HadSST4 once that dataset is operational and updated monthly (likely early in 2021). We have updated the manuscript to read (lines 51-52):

“Lastly, we note that HadSST v3 will be replaced with HadSST v4 once that product becomes operational (Kennedy et al. 2019). Aside from minor differences in the way data is communicated and formatted, HadSST v4 should be usable following the same steps described here.”

**2) I also agree with one of the other reviewers when they question the use of a version of the dataset that uses SSTs under ice. Is this appropriate as a measure of global temperature change? But, if the authors want to include it then that should be their Choice.**

Please see our response to the other reviewer. While we agree that extending the SST field under the sea ice is not a good measure of global temperature change, we do think it has some utility for making comparisons to other datasets that do this (e.g. ERSST) and for helping to characterize the effects of Arctic Amplification.

#### **Minor comments:**

**1) Abstract: 'agrees quite well' is not very precise and could be expanded.**

These comparisons are expanded later in the text, but we have changed it to “It provides a global mean temperature record quite similar to records from...” to be more precise in the abstract.

**2) I23 - there are more observations of MATs than SSTs before around 1900 so this sentence could be edited slightly. There is a new NMAT dataset - Cornes et al. (in press) - for example.**

We have changed it to “Sea surface temperatures are used in lieu of marine air temperatures due to relative scarcity post-1900 and...” to reflect this.

**3) I338 - typo 'ot' -> 'to'**

Fixed.

**4) Is it worth adding ERA5 to the post-1979 trends?**

While ERA5 is quite a useful dataset, it is substantially different in its construction from instrumental surface temperature records that we think its inclusion here is probably not warranted (though comparisons are certainly useful in other contexts!). The long length of other records would also make ERA5 difficult to see in the top panel of Figure 3.

# The Berkeley Earth Land/Ocean Temperature Record

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**Abstract.** A global land/ocean temperature record has been created by combining the Berkeley Earth monthly land temperature field with spatially-kriged version of the HadSST3 dataset. This combined product spans the period from 1850 to present and covers the majority of the Earth’s surface: approximately 57% in 1850, 75% in 1880, 95% in 1960, and 99.9% by 2015. It includes average temperatures in 1°x1° lat/lon grid cells for each month when available. It provides a global mean temperature record quite similar to records from Hadley’s HadCRUT4, NASA’s GISTEMP, NOAA’s GlobalTemp, and Cowtan and Way, and provides a spatially complete and homogeneous temperature field. Two versions of the record are provided treating areas with sea ice cover as either air temperature over sea ice or sea surface temperature under sea ice, the former being preferred for most applications. The choice of how to assess the temperature of areas with sea ice coverage has a notable impact on global anomalies over past decades due to rapid warming of air temperatures in the Arctic. Accounting for rapid warming of Arctic air suggests ~0.1 °C additional global-average temperature rise since the 19<sup>th</sup> century than temperature series that do not capture the changes in the Arctic. Updated versions of this dataset will be presented each month at the Berkeley Earth website (<http://berkeleyearth.org/data/>), and a convenience copy of the version discussed in this paper has been archived and is freely available at <https://doi.org/10.5281/zenodo.3634713> (Rohde & Hausfather, 2020).

## 1 Introduction

Global land-ocean temperature indices combining 2-meter surface air temperature over land with sea surface temperatures (SST) over oceans are commonly used to assess changes in the Earth’s climate. While it is a less physically meaningful metric than earth system total heat content, it is well-measured with reliable data extending back to c.1850 for oceans (Kennedy et al., 2011) and as far back as c.1750 for land (Rohde et al., 2013a) and is the part of the Earth system most relevant for impacts on human civilization. Sea surface temperatures are used in lieu of marine air temperatures due to scarcity and inhomogeneity of marine air temperature data (Kent et al., 2013), though it is only an imperfect proxy and may be subject to slightly slower warming rates than marine air temperatures in recent decades (Cowtan et al., 2015; Richardson et al 2016; Jones 2020).

A number of prior groups have developed global land/ocean surface temperature indexes, including NASA’s GISTEMP (Hansen et al., 2010; Lenssen et al 2019), Hadley/UEA’s HadCRUT4 (Morice et al., 2012), NOAA’s GlobalTemp (Smith et al., 2008; Vose et al., 2012; Huang et al 2020), and the Japan Meteorological Agency (JMA) (Ishihara 2006). Additionally, Cowtan and Way (2014) provide a spatially-interpolated variant of HadCRUT4 featuring greater spatial coverage. These series differ in a number of respects. They all largely utilize the same set SST measurements drawn from the ICOADS database (Freeman et al., 2017) and most of the same land temperature records contained in the Global Historical Climatological Network monthly database (GHCNm) (Lawrimore et al., 2011), though HadCRUT4 (and by extension Cowtan and Way) includes a more modest number of land stations than GISTEMP and GlobalTemp, which recently transitioned to using the much larger GHCNm v4 database (Menne et al 2018).

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Both GISTEMP and GlobalTemp utilize NOAA's pairwise homogenization algorithm to detect and correct inhomogeneities such as station moves or instrument changes in land stations (Menne and Williams 2009), though NASA applies an additional satellite nightlight-based urbanity correction (Hansen et al., 2010). GISTEMP and GlobalTemp both use NOAA's Extended Reconstruction Sea Surface Temperature (ERSST) version 5 (Huang et al., 2017) for SSTs, HadCRUT4 and Cowtan and Way use HadSST3 (Kennedy et al., 2011), and JMA uses COBE-SST (Ishii et al., 2005). HadCRUT4 and JMA include no spatial interpolation outside of 5-by-5 latitude/longitude grid cells, while GlobalTemp includes some interpolation over land but has nearly complete ocean temperature fields with the primary exception that sea ice regions are masked as missing. GISTEMP and Cowtan and Way spatially interpolate temperatures out to regions with no direct station coverage (GISTEMP using a simple linear interpolation technique, while Cowtan and Way uses Kriging). The upcoming HadCRUT5 will transition to HadSST4 and include spatial interpolation (Morice et al., submitted).

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Here we describe the global land/ocean surface temperature product from Berkeley Earth that combines the Berkeley Earth land temperature data (Rohde et al 2013a; Rohde et al 2013b) with SST data from HadSST3 (Kennedy et al., 2011). It uses a Kriging-based spatial interpolation to provide an extensive spatial coverage for the period from 1850 to present. The land data utilizes significantly more land station data (over 40,000 stations) compared to the ~10,000 land stations used by some of the other groups (though GISTEMP and GlobalTemp have both recently updated their records to include a larger number of land stations, including more 20,000 sites in GHCNv4). The land component also includes the novel homogenization technique of the Berkeley Earth temperature record that detects breakpoints through neighbor difference series comparisons, cuts land stations into fragmentary records at breakpoints, and combines these fragmentary records into a temperature field. The ocean component of the land/ocean product uses an interpolated variant of HadSST v3, whose construction is described below. A version of the Berkeley Earth interpolated dataset has been publicly available for some time, but has not been formally described. Lastly, we note that HadSST v3 will be replaced with HadSST v4 once that product becomes operational (Kennedy et al. 2019). Aside from minor differences in the way data is communicated and formatted, HadSST v4 should be usable following the same steps described here.

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## 2 Methods

The Berkeley Earth Land/Ocean temperature record combines the Berkeley Earth land record (Rohde et al 2013a) with SST data from HadSST3 (Kennedy et al. 2011a, Kennedy et al. 2011b). The HadSST3 data is adjusted in several ways. The primary manipulation is to replace the gridded data with an interpolated field using a Kriging-based approach. The HadSST3 data set provides grid cell averages on a 5° by 5° grid and only reports monthly averages for cells where data was present during the month in question. HadSST3 often reports no data for ~40% of ocean grid cells. As described below, the interpolation produces a more complete field and reduces the component of uncertainty associated with incomplete coverage. While providing a more complete field, the interpolation does not materially change the apparent rate of warming in the oceans.

After interpolation, the ocean temperature anomaly field is merged with Berkeley Earth land anomaly field using the fraction of land / water in each grid cell (typically reported with a 1° by 1° latitude/longitude resolution). As described below, two versions are considered with respect to the role of sea ice. The version using air temperature above sea ice is recommended for most users, though the other version may be useful for certain specialists and diagnostic purposes.

## 2.1 Interpolation Method

The HadSST3 gridded fields provide several critical components, the temperature anomaly, the number of observations, and several estimates of the uncertainty (Kennedy et al. 2011a, Kennedy et al. 2011b). The grid cell uncertainties and observation counts allow one to treat some grid cells as having greater confidence than others. Unlike land surface station data, where each monthly average represents many temperature observations, the ocean observation counts are a true measure of the number of instantaneous SST measurements.

Analogous to Rohde et al 2013a, the core of the interpolation approach is to generate a Kriging-based field using an assumed distance-based correlation function. As with Rohde et al 2013a, a correlation-based approach is used rather than the more common covariance-based approach to simplify the computational considerations, and should be adequate as long as the variance changes relatively slowly with changes in position. A review of both the HadSST data and climate model outputs suggested that the temperature to distance correlation function could be modeled effectively via the same spherical correlation function approach used for land surface temperatures:

$$R(d) = R_0 \left(1 - \frac{d}{d_{max}}\right)^2 \left(1 + \frac{d}{2d_{max}}\right), \quad d < d_{max} \quad (1)$$
$$R(d) = 0, \quad d \geq d_{max}$$

The empirically estimated distance parameter  $d_{max}$  was found to have a value of 2,680 km based on the spatial variance of the HadSST monthly averages. This is similar to, though somewhat smaller than, the 3,310 km scale adopted in the land surface temperature study (Rohde et al. 2013a). By contrast, the local correlation parameter  $R_0 = 0.47$  was estimated to be much lower in the oceans (compared to 0.86 on land). This is due to two factors. Firstly, ocean observations are individual measurements whereas land observations reflect monthly averages. Secondly, the typical monthly fluctuations in the oceanic environment are much smaller in than on land, causing a reduced signal-to-noise ratio. The estimation of  $R_0$  was based on a comparison of the variance in HadSST grid cells with a single measurement to those with  $> 100$  observations. The latter condition provides a proxy for cells where the random portion of measurement and sampling uncertainty could plausibly be neglected.

Figure 1 shows an empirically estimated average correlation versus distance between HadSST grid cells. This shows the empirical length scale, though a larger intercept is used ( $\sim 0.75$ ) reflecting the fact that the average HadSST grid cell incorporates many observations. The lower value for  $R_0$  represents the typical relationship between a single measurement and the monthly average.

This treatment, using a single scale length for the whole ocean, simplifies the analysis; however, it does ignore some of the real variations across the oceans. For example, in regions with boundary currents, upwelling/downwelling, or complex ocean to land geographies, the scale length of monthly average temperature variations may be smaller than suggested here. In practice, the 5x5 degree gridding of HadSST already precludes a detailed analysis of most small features. The interpolation presented here primarily serves to improve the representation by smoothing over noise and filling gaps, but it won't necessarily capture the smallest features.

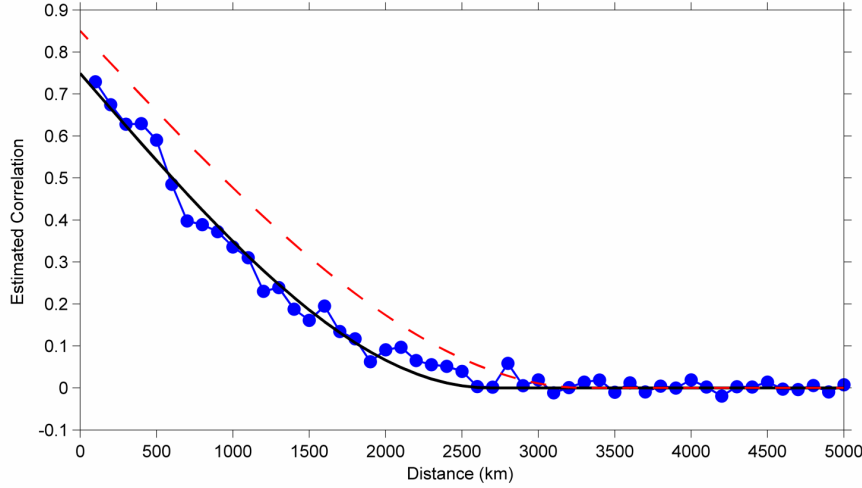


Figure 1: Empirically estimated correlation versus distance for monthly average sea surface temperatures. Correlation was estimated by comparing root-mean-square differences for all possible pairs of HadSST grid cells and all months, and binning the population by distance. The black curve reflects a best fit for the spherical correlation function model. The red dashed curve shows the corresponding correlation model derived for land-based measurements (Rohde et al. 2013a).

The distance correlation function gives rise to a Kriging formulation that:

$$T(x, t) = \theta_t + \sum_j (K(x_j, x, t)(SST(x_j, t) - \theta_t)) \quad (2)$$

$$\begin{pmatrix} K(x_1, x, t) \\ \vdots \\ K(x_N, x, t) \end{pmatrix} = \begin{pmatrix} D(x_1, t) & R(\|x_1 - x_2\|) & \cdots & R(\|x_1 - x_N\|) \\ R(\|x_2 - x_1\|) & D(x_2, t) & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ R(\|x_N - x_1\|) & \cdots & D(x_{N-1}, t) & R(\|x_{N-1} - x_N\|) \\ & & R(\|x_N - x_{N-1}\|) & D(x_N, t) \end{pmatrix}^{-1} \begin{pmatrix} R(\|x_1 - x\|) \\ \vdots \\ R(\|x_N - x\|) \end{pmatrix} \quad (3)$$

$$D(x_j, t) = \frac{1 + (N_{eff}(x_j, t) - 1)R_0}{N_{eff}(x_j, t)} \quad (4)$$

$$N_{eff}(x_j, t) = \frac{s_m^2}{(\sigma_m(x_j, t))^2}, \text{ minimum value of } 1 \quad (5)$$

Where  $t$  is the current month,  $T(x, t)$  is the interpolated temperature at a general location  $x$ ,  $SST(x_j, t)$  is the HadSST anomaly value in the grid cell centered at location  $x_j$ , and  $\sigma_m(x_j, t)$  is the measurement uncertainty associated with location  $x_j$ , and  $s_m$  is the average measurement uncertainty of a single measurement.  $N_{eff}(x_j, t)$  is then an effective number of independent measurements associated with the grid cell. Though HadSST provides the true number of observations per cell,  $N(x_j, t)$ , we found that  $N_{eff}(x_j, t)$ , which incorporates the measurement uncertainty appeared to give superior results than simply relying on the reported number of observations. The incorporation of  $N_{eff}(x_j, t)$  into the determination of the Kriging coefficients  $K$  has the

effect of giving greater weight to grid cells with less uncertainty. For integer values of  $N_{eff}(x_j, t)$ , the formulation of  $D(x_j, t)$  is mathematically equivalent to having  $x_j$  appear  $N_{eff}(x_j, t)$  independent times in the correlation matrix. Note also that any empty HadSST grid cells at time  $t$  are omitted from the matrix formulation for  $K$ .

$\theta_t$  is a free parameter at each time  $t$  and effectively represents the global ocean average temperature anomaly. Its value is found iteratively by insisting that the spatial average of  $T(x, t) - \theta_t = 0$ .

It is instructive to note that this Kriging formulation has the property that  $T(x_j, t) \rightarrow SST(x_j, t)$  in the limit that  $N_{eff}(x_j, t) \rightarrow \infty$ , but will ordinarily produce a temperature estimate based on a weighted average of multiple HasSST grid points in the case that  $N_{eff}(x_j, t)$  is small or moderate. The latter property can be useful in suppressing noise at grid locations with high uncertainty and/or very few measurements.

It is also important to recognize that though the correlation function  $R(d)$  has a very long tail, this does not mean that average necessarily extends over a large area. In general, the Kriging coefficients  $K(x_j, x, t)$  constructed in this way will heavily favor the nearest several data points. As long as nearby data is available, little weight will be given to distant grid cells. However, the long-tail of the correlation function means that the Kriging will attempt to fill large holes using distant data if no nearby data is available.

An absolute value field was also created by applying a similar interpolation to the HadSST climatology.

$$C(x, m) = P(x, m) + \sum_j (K_B(x_j, x, m)(SSTCLIM(x_j, m) - P(x, m))) \quad (6)$$

$C(x, m)$  is the interpolated climatology for month  $m$ ,  $SSTCLIM(x_j, m)$  is the reported climatology,  $K_B(x_j, x, m)$  is a set of Kriging parameters, which are the same as  $K(x_j, x, m)$  except that  $R_0$  and  $D(x_j, t)$  are both replaced with 1, effectively treating the  $SSTCLIM(x_j, m)$  as if it has no uncertainty.  $P(x, m)$  a background prediction function dependent only on the month and the latitude of  $x$ . It is described as a piece-wise cubic spline with 11 knots as free parameters equally spaced in the cosine of latitude. These free parameters are chosen to minimize the spatial average of  $C(x, m) - P(x, m)$ . By construction,  $C(x_j, m) = SSTCLIM(x_j, m)$  for all  $x_j$ , and this construction merely provides a way of interpolating between grid cell centers.

In addition to the above description, a physical cutoff was applied to the absolute temperature  $C(x, m) + T(x, t)$  at a fixed minimum temperature of -1.8 C, which is freezing temperature of seawater. If the interpolation would suggest a value lower than this,  $T(x, t)$  was adjusted accordingly to maintain the minimum value of -1.8 C. Such adjustments are rare.

Finally, one last interpolation is performed using an assumption of temporal persistence. Unlike land temperature anomalies, where the temporal correlation is often only a couple weeks, ocean temperature anomalies typically have a temporal correlation measured in months. This can be exploited to estimate ocean temperatures based on adjacent months when no other information is available.

Analogous to Rohde et al. 2013a, a diagnostic criterion can be constructed  $V(x, t) = \sum_j K(x_j, x, t)$ . Because of the nature of the Kriging coefficients,  $V(x, t) \rightarrow 1$  in the presence of dense data and  $V(x, t) \rightarrow 0$  if there is no HadSST data in the neighborhood of  $x$ .

The final estimate of the SST, including a temporal persistence adjustment for regions of low  $V(x, t)$  is then

$$T_{final}(x, t) = T(x, t) + (1 - V(x, t)) \left( \frac{V(x, t+1)T(x, t+1) + V(x, t-1)T(x, t-1)}{V(x, t+1) + V(x, t-1)} - \theta_t \right) \quad (7)$$

Here,  $t-1$  and  $t+1$  refer to the temperature field one month earlier and one month later, respectively. This adjustment allows for a modest reduction in uncertainty at early times when data is temporally sparse.

As described, this analysis is agnostic about the resolution used to sample the final temperature field. In practice, we generally use the same 15984-element equal-area grid as Rohde et al. 2013a to calculate  $T_{final}(x, t)$ , though with non-ocean elements masked out.

## 2.2 Ocean Uncertainty

The ocean-average uncertainty in our ocean reconstruction is estimated following essentially the same model as adopted by HadSST3. HadSST3 estimates the total reconstruction uncertainty as the combination of measurement uncertainty, coverage uncertainty, and bias uncertainty (Kennedy et al. 2011a, Kennedy et al. 2011b). Bias uncertainty,  $\sigma_{bias}$ , which reflects biases created due to variations over time in the ways that SST has been measured, is brought forward essentially unchanged by our analysis process (Figure 2). Due to its slowly varying nature, this uncertainty remains the most important limitation of the detection of long-term averages.

The coverage uncertainty,  $\sigma_{coverage}$ , is the uncertainty in the large-scale average arising due to incomplete sampling of the spatial field. As with HadSST3, our estimate of the coverage uncertainty is constructed by sampling a known field, applying our interpolation procedure, and seeing how well we reproduce the underlying average of the known field. Following HadSST3, we used the SST fields provided by HadISST v2 as our target. The HadISST fields are spatially complete, observation-based historical reconstructions of SST and sea ice concentration (Titchner and Rayner 2014). To estimate the coverage uncertainty associated with a specified HadSST sampling field, we mask every month of the HadISST dataset using that sampling field, interpolate the remaining data, and measure the error in the interpolated average relative to the true ocean-average of the whole HadISST field. The deviations in the ocean-average are then collected across all HadISST months and the uncertainty for that coverage mask is reported as the root-mean-square average of the deviations. Using this technique, which is directly analogous to the HadSST3 coverage assessment technique, we estimate that the application of our interpolation approach typically reduces the coverage uncertainty by 20-40% (Figure 2).

Lastly, we consider the impact of our interpolation on the measurement and sampling uncertainty. Measurement uncertainty essentially captures the errors in individual observations, while sampling uncertainty reflect the fact that water temperatures can vary on timescales shorter than a month and spatial scales smaller than a grid box. Though interpolation does not change the



underlying uncertainty associated with individual measurements, by adjusting the weight of individual observations in the overall average, we affect the way that individual measurement errors propagate into the global average. In particular, in the presence of sparse data, limited measurements may be extrapolated over a large area. In some circumstances, this can cause the effective uncertainty in the global average due to these uncertainties to increase. In essence, the interpolation may trade improvements in coverage uncertainty against a greater impact for measurement uncertainty. This largely limits our ability to reduce the overall uncertainty by interpolation.

The impact of measurement uncertainty on a large-scale average depends on the error correlation. If the measurement uncertainties were uncorrelated, then the error would generally be expected to decline with the square root of the number of measurements. In actuality, the measurement uncertainties are frequently correlated. In most cases, single ships report many measurements per month. Each of those measurements can have both random errors and a potential for systematic bias. For a single ship, we cannot expect this bias component of a measurement error to be reduced by increasing the number of observations. In their analysis HadSST3 models the entire error correlation matrix to understand the effect of measurement errors on the global average uncertainty.

For HadSST3, the error correlation matrices were not published. As a result, it is not possible to exactly determine the effect of our interpolation procedure on the measurement uncertainty. However, we can make a reasonable estimate. Since HadSST3 releases both the per grid cell measurement uncertainties and the global average measurement uncertainty, we can compare the expected measurement uncertainty treating all grid cell as independent to what is actually observed by HadSST3 using the whole error correlation matrix (Kennedy et al. 2011b).

$$\sigma_{uncorrelated} = \sqrt{\sum_j \left( A(x_j) \sigma_m(x_j, t) \right)^2} \quad (8)$$

Where  $A(x_j)$  is the fraction of the Earth's oceans represented by grid cell  $x_j$  and  $\sigma_{uncorrelated}$  is the measurement uncertainty resulting from assuming that the measurement errors in individual grid cells are uncorrelated with other grid cells.

We find that the measurement uncertainty reported by HadSST3 in the ocean-average is typically ~2.1 times larger than  $\sigma_{uncorrelated}$ , with some variation over time.

We use this estimate as a benchmark to approximate the effect of error correlation on our analysis of measurement uncertainty.

$$\sigma_{interpolated, measurement} = \frac{\sigma_{HadSST, measurement}}{\sigma_{uncorrelated}} \sqrt{\sum_j \left( K(x_j, t) \sigma_m(x_j, t) \right)^2} \quad (9)$$

$$K(x_j, t) = (\iint K(x_j, x, t) dx) / (\iint 1 dx) \quad (10)$$

Where the double integral denotes the integral over the surface of the ocean. Thus  $K(x_j, t)$  is effectively the weight of the  $x_j$  grid point in the global average.

260 The total uncertainty in the ocean-average is then found by assuming the components are independent.

$$\sqrt{\sigma_{bias}^2 + \sigma_{coverage}^2 + \sigma_{interpolated, measurement}^2} \tag{11}$$

265 Over nearly all time periods, we find that interpolation does reduce the uncertainty associated with missing coverage. In the early period, the interpolation results in an appreciable reduction in total uncertainty. However, the total uncertainty in the global average is little changed in the recent period. This is because the bias and measurement uncertainties play a dominant role in the recent period, and the impact of these uncertainties on the global average is little changed as a result of the interpolation. However, even if the ocean-average uncertainty is not changed during the recent period, the interpolation may still aid in the interpretation of local to regional-scale features.

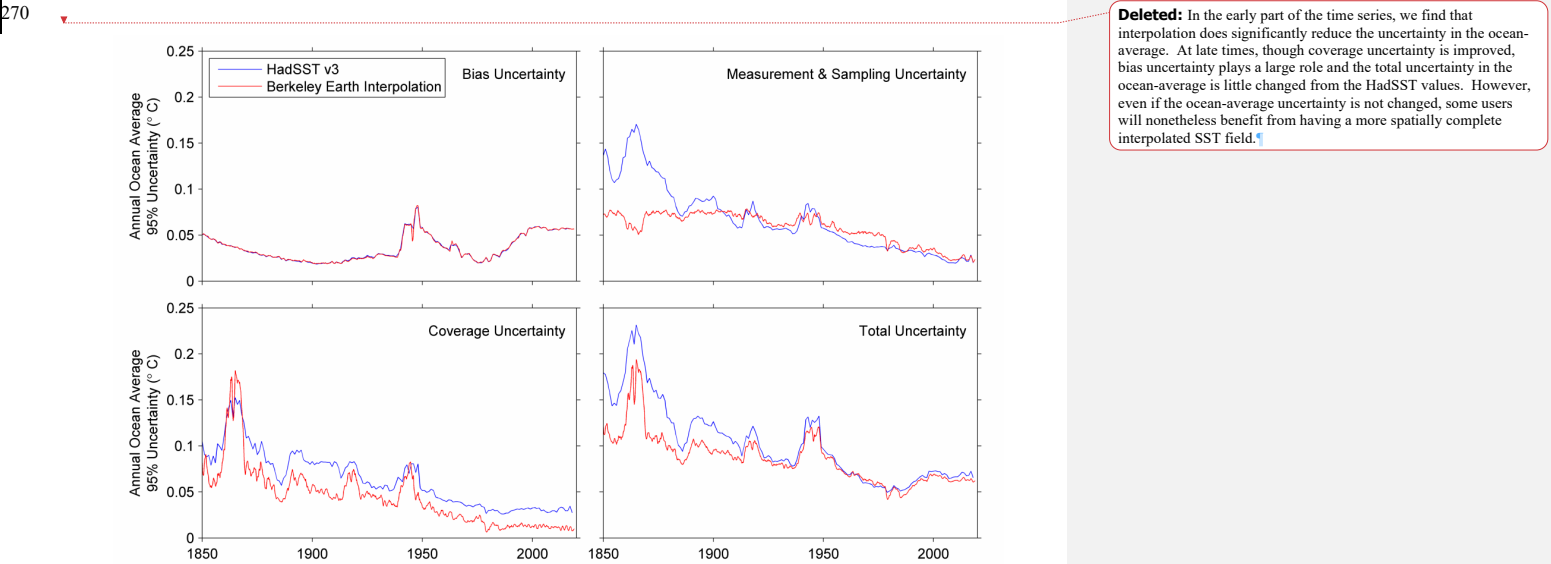


Figure 2: Component uncertainties for the ocean-average of HadSST v3 and the corresponding transformed forms of those components after the application of the interpolation scheme described in the text. All uncertainties are expressed as appropriate for 95% confidence intervals on annual ocean-averages.

275 **2.3 Land and Ocean Combination**

The combined field is constructed by merging the Berkeley Earth Land Surface temperature with the interpolated SST field described above. Two versions are considered that differ only in their treatment of sea ice, using either the land air temperature (LAT) or the SST field to estimate the temperature anomaly at sea ice locations. From 1850 to near-present, the sea ice locations are estimated using the ice concentration fields in HadISST v2 (Titchner and Rayner 2014).

280 To combine LAT and SST data, both data sets are expressed on the same grid. To simplify the combination at cells that are part-land and part-ocean, we have taken to adding in the spatial climatology and doing the combination in absolute temperatures.

In the case where sea ice areas are represented by SST, the combination is straightforward:

$$T_{combined}(x, t) = L(x) T_{LAT}(x, t) + (1 - L(x)) T_{SST}(x, t) \quad (12)$$

Where  $L(x)$  is the fraction of the grid cell at location  $x$  that is land, and  $T_{LAT}$  and  $T_{SST}$  are respectively the LAT as estimated by Rohde et al. 2013a and the interpolated SST as described above.

In the case where sea ice regions are treated as land:

$$T_{combined}(x, t) = L^*(x, t) T_{LAT}(x, t) + (1 - L^*(x, t)) T_{SST}(x, t) \quad (13)$$

$$L^*(x, t) = L(x) + (1 - L(x)) I(x, t) \quad (14)$$

Where  $I(x, t)$  is the ice fraction at location  $x$  at time  $t$  as reported by HadISST v2 (Titchner and Rayner 2014). For this purpose, HadISST is also regridded on to the same grid as LAT and SST. As HadISST is frequently delayed by a few months compared to other climate data, it is necessary to supplement this data set when producing near real-time estimates. For this purpose, the Sea Ice Index of the National Snow and Ice Data Center (Fetterer et al. 2017) is used for months that are not yet available in HadISST. The modern ice distribution in both HadISST and the Sea Ice Index are based on satellite observations; however, we found that the Sea Ice Index tended to have systematically more partial melting than HadISST. To maintain consistency, a distribution transform was applied to the sea ice fractions provided in the Sea Ice Index based on comparing the 2014-2018 ice fields in each dataset.

It is useful to note that regardless of whether one is using SST or LAT to estimate temperatures in association with sea ice, most such estimates involve a considerable extrapolation. In the case of LAT, for example, conditions over sea ice in the Arctic will usually be extrapolated from Greenland, Canada, Scandinavia and Russia. Similarly, in the Antarctic, coastal stations will be extrapolated outward over the ice. By contrast, when using SST, one extrapolates from rare SST measurements that may be far removed from the sea ice edge. Or, in the case that analysis of the sea ice regions is excluded entirely, averaging methods are effectively substituting the ocean or global average temperature anomaly.

It is our belief that the anomaly field generated by extrapolating air temperatures over sea ice locations is a more sensible approach to characterizing climate change at the poles. The air temperature changes over the sea ice can be quite large even while the water temperatures underneath are not changing at all. In particular, over the last decades Arctic air has shown a very large warming trend during the winter.

Regardless of the approach used, the spatial climatology can then be calculated and removed (differing from the original only in cells with a mix of land and water/sea ice). Then the long-term trend in the climate can be computed using the spatial average of the anomaly fields.

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335      Uncertainties for the combined record are calculated by assuming the uncertainties in LAT and SST time series are independent and can be combined in proportion to the relative area of land and ocean. In the case that LAT is used over sea ice, the uncertainties for both LAT and SST have to be slightly recalculated by assuming that the time varying mask  $L^*(x, t)$  is applied the relevant spatial averages in the uncertainty estimations described in Rohde et al. 2013a and in the SST section above. Doing this adjustment causes a slightly increase in LAT uncertainty (due to the extrapolation over sea ice), and similar small decrease in SST uncertainty.

**3 Results and Conclusions**

340      The global mean anomalies obtained from the Berkeley Earth land/ocean temperature record are quite similar to other published records, as shown in Figure 3. With the exception of some short periods prior to 1880 and before and after World War 2, all four other temperature records examined lie within the uncertainty envelope of the Berkeley Earth record. Differences around World War 2 relate primarily to differences in adjustments to ERSST v5 and HadSST3 sea surface temperature records during that period (Huang et al 2017; Kennedy et al 2019; Cowtan et al 2017).

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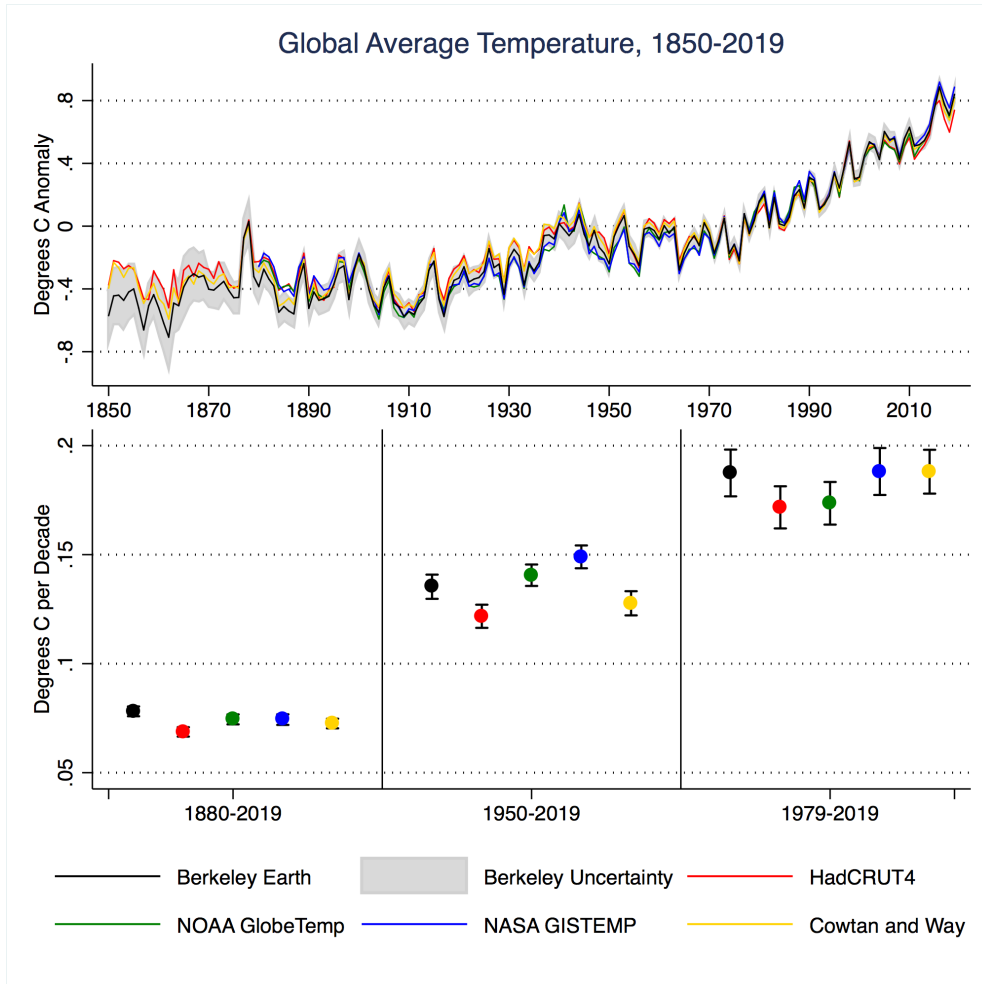
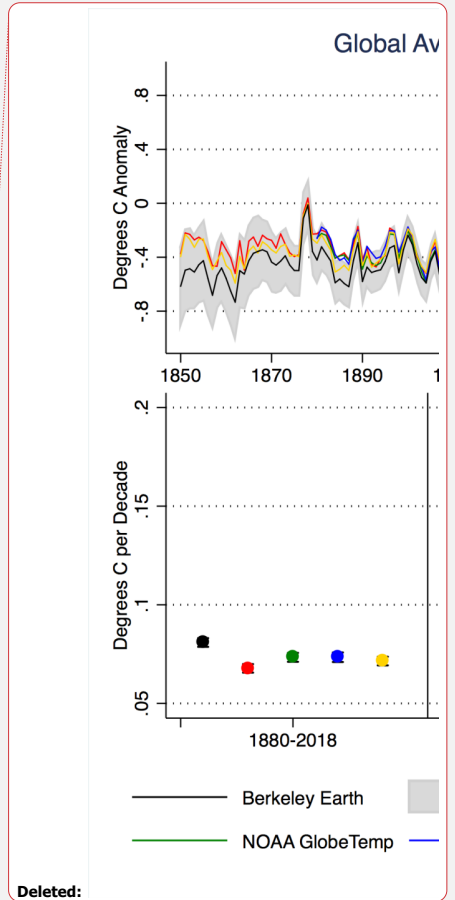


Figure 3: Comparison of published global surface temperature records. The top panel shows annual anomalies (relative to a 1961-1990 baseline period), with the Berkeley Earth uncertainty as a shaded area. The bottom panel shows trends and two-sigma trend uncertainties (calculated using an ARMA[1,1] approach to account for autocorrelation) for various starting dates through the end of 2015 based on monthly anomalies.

Berkeley Earth has the highest trend of any temperature record examined for the period from 1880 to 2015, largely due to lower surface temperature estimates prior to 1900. These differences are driven both by increased spatial coverage from the inclusion of additional land records and the spatial interpolation of both land and ocean records (which are more limited in both the NOAA and Hadley records). Similarly, Berkeley Earth has among the highest warming rates in the recent period (1979-2015) due primarily to greater Arctic coverage (where warming was unusually rapid during that period). The other records that provides robust arctic interpolation, Cowtan and Way and NASA GISTEMP, also shows higher trends during this period.



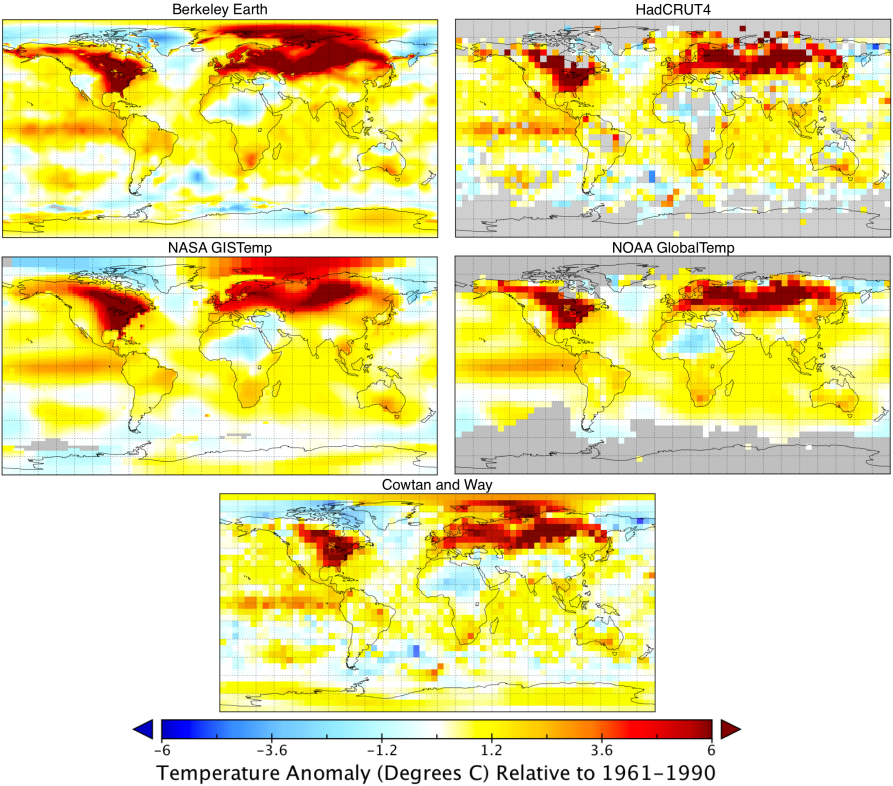
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From 1955 to present (after the availability of data in Antarctica), Berkeley Earth provides globally complete coverage via spatial interpolation, similar to NASA's GISTEMP and Cowtan and Way. This contrasts with HadCRUT4 which exclude any grid cells lacking station coverage or SST measurements, or NOAA GlobalTemp where interpolation is more limited. As shown in Figure 4, the patterns of spatial anomalies between the different groups tend to be quite similar, apart from differences due to spatial coverage or gridded field resolution.

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**Figure 4:** Global gridded temperature anomalies for December 2015 relative to a 1961-1990 baseline for each global temperature dataset. Grid resolution is based on the highest resolution dataset provided by each group; 1x1 lat/lon for Berkeley Earth, 5x5 for HadCRUT4, 1x1 for NASA GISTEMP, 5x5 over land and 2x2 over oceans for NOAA GlobalTemp, and 5x5 for Cowtan and Way.

When constructing a global surface temperature record, sea ice produces a challenging edge-case. The water temperature under sea ice is tightly constrained by the freezing point of water, and can only change with changes in sea ice cover. Air temperatures over sea ice are less well constrained, and can vary significantly over time. Whether areas with sea ice coverage are estimated using sea surface temperatures or surface air temperatures will have a notable result on the record. While most groups (GISTEMP, Cowtan and Way) that interpolate temperatures over areas with sea ice cover use air temperatures, Berkeley Earth has provided both variants to allow researchers to select the series that best supports their needs. We consider the variant using air temperature above sea ice to be a better description of global climate change, but the ocean temperature variants may be useful for comparison and for certain specialists. Both variants of the Berkeley Earth record are shown in Figure 5 as well as the HadCRUT temperature

series for comparison. When SSTs under sea ice are used the apparent warming trend in recent years is lower than when air temperatures are used. Comparing these versions helps to reveal the contribution of sea ice areas to the overall global warming rate.

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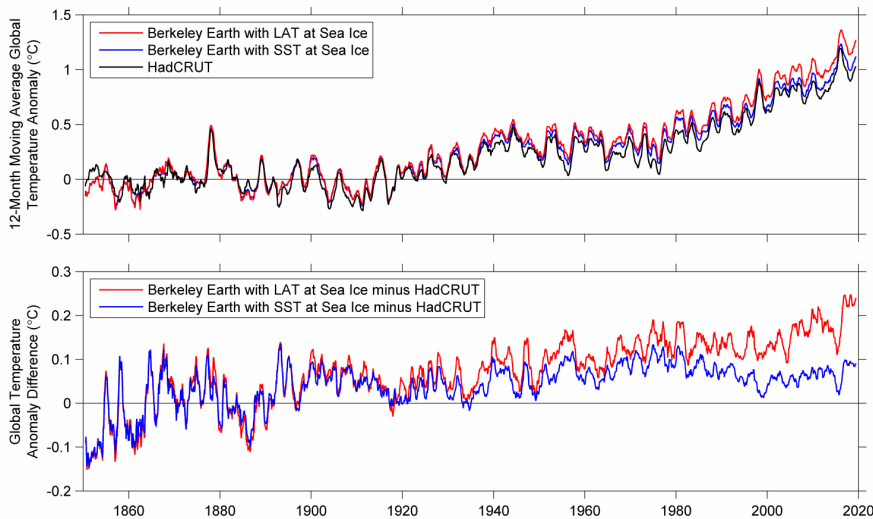


Figure 5: (Top) Two variants of the Berkeley Earth global surface temperature product estimating temperatures under sea ice based on SSTs (red) or proximate air temperature measurements (blue), as well as the HadCRUT temperature series for comparison. (Bottom) The same two versions of the Berkeley Earth data set with the HadCRU time series subtracted.

Figure 5 also aids in understanding the difference between Berkeley Earth and HadCRUT. The interpolated SST field adopted here has a nearly identical trend to the HadSST field, differing by less than  $0.01^{\circ}\text{C} / \text{century}$ . Part of the difference between Berkeley Earth's global temperature series and HadCRUT is due to differences in the amount of warming estimated to have occurred over land. This is the primary source of difference when comparing the Berkeley Earth series with SST at sea ice to the HadCRUT series (blue line in Figure 5). While this difference is not insignificant, the larger overall difference is due to the incorporation of air temperature warming in sea ice regions, especially in the Arctic (red line in Figure 5). Inclusion of the rapid warming above Arctic sea ice suggests the global average has increased an additional  $\sim 0.1^{\circ}\text{C}$  during the last 100 years compared to estimates that do not include the changes in this region.

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In addition to monthly temperature anomalies, Berkeley Earth produces monthly absolute temperature fields. A climatology field is estimated via Kriging observations, using elevation as a factor in the kriging process over land. Both absolute temperature variants with air temperature over sea ice and water temperature under sea ice are available, as shown in Figure 6. Absolute temperatures are created by adding the climatology field to monthly anomalies.

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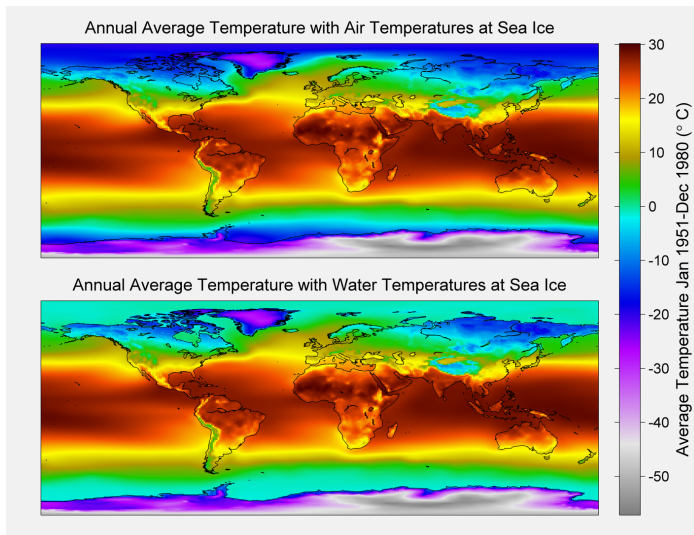


Figure 6: Berkeley Earth average absolute climatology for the period from 1951-1980 with the air temperature at sea ice (top panel) and ocean temperature under sea ice (bottom) variants shown.

Figure 7 provides a comparison between published uncertainties (two sigma) for each of the major global land/ocean temperature series. The Berkeley Earth, GISTEMP, and Cowtan and Way records have the lowest uncertainty of the groups providing annual values, in part due to their spatial interpolation reducing the uncertainty associated with coverage.

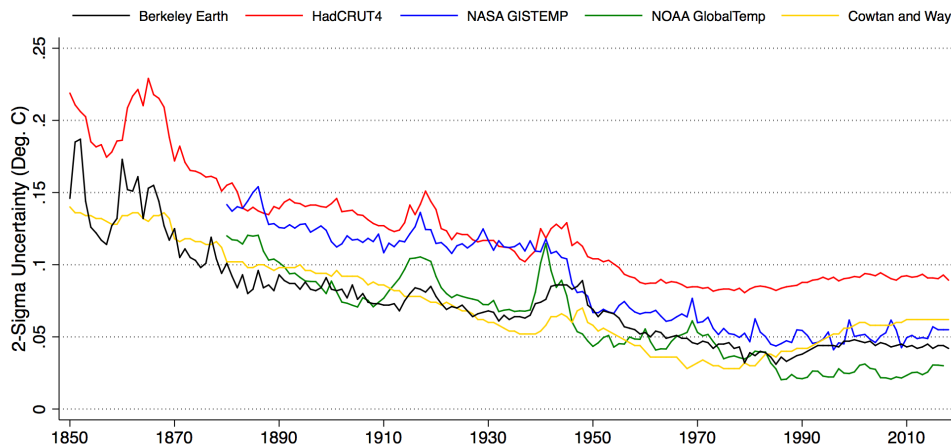
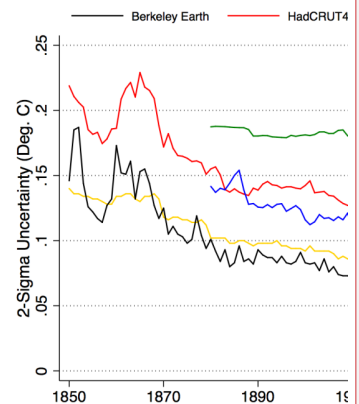


Figure 7: Comparison of published annual uncertainty estimates (two sigma) for Berkeley Earth, HadCRUT4 (Morice et al 2012), GISTEMP (Lenssen et al 2019), GlobalTempv5 (Vose et al 2012), and Cowtan and Way (2014).

The Berkeley Earth Land/Ocean surface temperature record presented here has already been used by a number of publications (e.g. Jones 2015; Thorne et al 2016; Sutton et al 2015). It joins a number of existing land/ocean surface temperature products that help



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provide a diverse examination of the Earth's changing climate since 1850, and can be used for diverse applications including climate model validation, estimating transient climate response, examining changes in extreme events, and other research areas.

**Data Availability**

The Land/Ocean temperature product will be updated monthly on the [berkeleyearth.org](https://berkeleyearth.org) website, and is freely available for use to all interested researchers. A convenience copy of the dataset available at the time this paper was created has been registered with Zenodo and is available at DOI:10.5281/zenodo.3634713 (Rohde & Hausfather 2020).

**Author contribution**

RR designed and implemented the data set construction. ZH provided feedback, graphics, and analysis. RR and ZH jointly prepared the manuscript.

**Competing interests**

The authors declare that they have no conflict of interest.

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