Quantifying uncertainty in the HadCRUT4 near-surface temperature dataset

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1. Overview

Recent developments in observational near-surface air temperature (Jones et al., 2012) and sea-surface temperature (Kennedy et al., 2011a., 2011b) datasets have been combined to produce HadCRUT4 (Morice et al., 2012), an updated dataset of global and regional temperature evolution from 1850 to the present, based on in situ observations. This dataset update has been constructed using additional measurement data, new bias adjustments and a more comprehensive uncertainty model.

This poster provides an introduction to the uncertainty model of the HadCRUT4 near-surface temperature dataset. Areas in which further research would be beneficial to the dataset are also outlined.

2. Biases and uncertainty representation in HadCRUT4

Land air temperature and sea-surface temperature (SST) observations are subject to sources of potential bias. Changes in the observation network and motion of SST measurement platforms result in uncertainties with potentially complex correlation patterns, which may be important on different spatial and temporal scales.

1.Measurement biases specific to individual sensors reduce rapidly in averages of measurements from multiple sensors.

2.Uncertainty in large-scale biases, such as biases applying to all observations from a specific measurement technique do not cancel out when averaging spatially or temporally, so understanding these biases is highly important for climate studies.

3.Uncertainty arising from limited observational coverage of the globe remains the largest component of total uncertainty in the HadCRUT4 global record (Figure 1).

In HadCRUT4, an ensemble approach has been adopted. Uncertainties with spatial and temporal correlation structures have been encoded into 100 dataset realisations. This approach allows correlated uncertainties to be better taken into account by dataset users.

The following boxes provide an overview of the uncertainties represented in the HadCRUT4 uncertainty model.

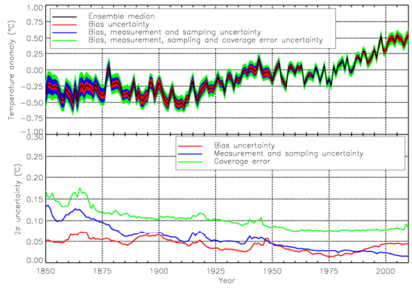

Figure 1 – Global average temperature time series with uncertainties according to the HadCRUT4 dataset (Morice et al., 2012).

3. Sea surface temperature data

In-situ measurements of sea-surface temperature (SST) are available from a number of different observation types: temperatures measured in buckets hauled out of the water; measured in ship engine room intakes and hull contact sensors; and measured by drifting buoys. The measurement types are subject to different biases and observe temperatures at different depths.

In HadSST3 (Kennedy et al., 2011a, 2011b), the ocean component of the HadCRUT4, SST measurement biases are separated into two forms:

1.Inter-platform biases unique to each type of measurement method.
2.Intra-platform biases unique to an individual ship or buoy.

Uncertainties in inter-platform biases can create complicated correlations between grid boxes in the gridded dataset because:

•The various measurement methods are biased relative to one another.
•Measurement platforms are typically mobile.
•The relative number of observations obtained by each method has changed over time.

In HadSST3 and HadCRUT4, bias adjustments are applied to the gridded dataset ensemble to account for inter-platform biases (Figure 2), with adjustment values chosen so to span the range of uncertainties in the required adjustments.

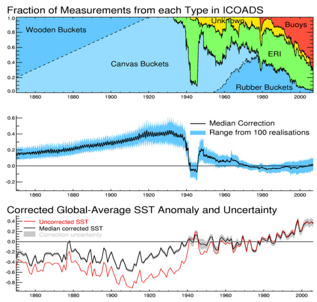

Figure 2 - Bias adjustments for inter-platform measurement biases in the HadSST3 dataset.

Estimates of the typical scales of persistent intra-platform biases (those biases unique to individual observing platforms), have been made through comparisons of in-situ measurements with satellite based SST retrievals (Kennedy et al., 2011c). A description of how these intra-platform biases map into correlated errors between grid boxes requires that observing platforms can be uniquely identified. However, this information is not always available in the historical records, which is a limiting factor in estimation of intra-platform biases in HadSST3 and HadCRUT4.

4. Land surface air temperature data

Sources of bias in Surface Air Temperature (SAT) include changes in instrumentation, local relocation of stations, changes in sensor shelters and encroachment of buildings and other artificial structures on observation sites. The methods used to identify biases in land records are typically very different to bias identification in sea-surface temperature records for two principle reasons:

1. Land stations are static, restricting studies using coincident observations to small-scale experiments at specially designed experimental sites.

2. Satellite instruments cannot directly observe near surface air temperatures.

Because coincident observations are not typically available, land station biases are commonly estimated through the study of time series of temperature differences between nearby or well correlated stations. Artefacts in these difference series can be identified and bias adjustments constructed in a process known as homogenisation.

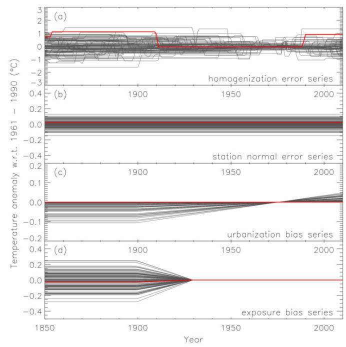

Figure 3 – 100 realisations of possible errors in surface air temperature station data arising from uncertainty components represented in the HadCRUT4 uncertainty model.

CRUTEM4, (Jones et al., 2012), the land component of the HadCRUT4 global temperature dataset, makes use of meteorological station data that has been homogenised in independent, regional homogenisation studies, for example performed by national meteorological services. The uncertainty model used for HadCRUT4 is an ensemble variant of the Brohan et al., (2006) uncertainty model, and models residual uncertainties remaining after homogenisation.

To generate the land ensemble, realisations of known uncertainties are drawn from the land station uncertainty model (Figure 3), and are then combined with temperature measurement series and gridded data. The resulting dataset realisations sample the distribution of likely surface temperature evolution given knowledge of uncertainties in the station data. To produce the global ensemble, these dataset realisations are combined with HadSST3 as one-to-one blends of the ensemble members of the two datasets.

5. Global and regional time series

Although the HadCRUT4 update includes many additional observations in previously poorly observed regions, the largest uncertainty in global average temperature estimates computed from HadCRUT4 is the uncertainty arising from incomplete spatial coverage of the globe in the observational network (Figure 1).

In HadCRUT4, estimates of uncertainty in global and regional time series arising from limited global coverage are made based on the study of the effects of limiting global coverage in time series computed for reanalysis data (see Morice et al., 2012). Unlike other global temperature datasets (Hansen et al., 2010; Lawrimore et al., 2011), no spatial infilling is employed to estimate temperature anomalies in unobserved regions in the HadCRUT4 dataset.

The agreement of derived climate diagnostics, such as annual global average temperature anomalies, between each near-surface temperature dataset is generally good (Figure 4). However, differences remain and are likely to be related to the use of different approaches to homogenisation, bias adjustments, gridding, data infilling methods, time series calculation and, to a lesser extent, differences in the underlying measurement data.

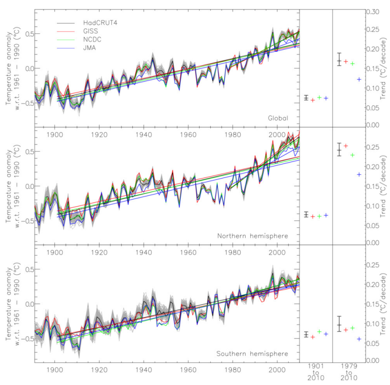

Figure 4 – Global and hemispheric series (left) and decadal temperature trends (right) for the HadCRUT4 ensemble and for other prominent surface temperature datasets.

6. Summary

This poster has presented a brief overview of the components of the HadCRUT4 uncertainty model. Further details can be found in Morice et al., (2012).

The following list presents some of the areas in which further work would be beneficial:

1.Independent assessments of SST biases are required to validate existing studies and better understand the uncertainties in the estimated biases.

2.Controlled studies of individual sources of measurement biases would help to refine the uncertainty model.

3.Further digitisation of SST observations and metadata.

4.The provision of additional homogenised land station data in poorly sampled regions.

5.The development of methods to reduce coverage biases, such as data infilling methods or additional data sources would also be greatly beneficial.

References

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