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New surface temperature analyses for climate monitoring

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[1] Global surface temperature is a critical measure of climate variation. Here the averages of a new surface-temperature analysis are compared to an estimate of the global average which has been used for monitoring surface-temperature variations at NOAA's National Climatic Data Center (NCDC) since 1998. As a replacement to the existing method, this new analysis uses improved methods that provide error estimates as well as the ability to perform analyses on finer spatial scales. Comparisons show only minor global-average differences, and the two estimates indicate essentially the same trend over the historical record, beginning in 1880. The two are most similar after about 1970, a period with a large change in the global-average temperature. The uncertainty estimates computed here account for changes in sampling and for systematic bias uncertainties. The means of the different analyses generally fall within the uncertainty estimates. The uncertainty computed here indicates that anomalies in the 19th century may not be significant, but the 20th century trends are significant. **Citation:** Smith, T. M., T. C. Peterson, J. H. Lawrimore, and R. W. Reynolds (2005), New surface temperature analyses for climate monitoring, *Geophys. Res. Lett.*, *32*, L14712, doi:10.1029/2005GL023402.

1. Introduction

[2] Change in the global-average surface temperature is an important indicator of climate change [e.g., *Hansen et al.*, 1999; *Folland et al.*, 2001a, 2001b; *Jones and Moberg*, 2003; *Levinson and Waple*, 2004]. Much of the same basic data are used for different analyses, but differences in averages may occur because of differences in data quality control and in the analysis procedures. Here the results of two very different analyses are compared. One is an analysis that has been produced at NOAA's National Climatic Data Center (NCDC) since 1998, and has been used for climate monitoring since then. The other is an analysis incorporating improved analysis methods and uncertainty estimates, which is replacing the older analysis. The objective of this comparison is to show users of the older index what changes may be caused in the global average by switching to the new method.

2. Data and Analyses

[3] The two time series of global annual temperature anomalies being compared are both produced at NOAA's NCDC. Both begin in 1880 and are operationally updated through the present. The older operational surface temperature index was developed by *Quayle et al.* [1999] (hereinafter referred to as the Quayle index). The new analysis is an average of merged extended and reconstructed land-surface air temperature (LST) anomalies and sea-surface temperature (SST) anomalies [*Smith and Reynolds*, 2005, hereinafter referred to as SR05]. All anomalies discussed here are with respect to the 1961–1990 climatology.

2.1. The Quayle Index

[4] The Quayle index uses SSTs from two sources. For regular monthly updating purposes, it uses a merged satellite and in situ analysis developed by *Reynolds and Smith* [1994]. However, since those data only go back to 1982, they were merged with the in situ SST data of *Bottomley et al.* [1990] with updates through 1996, which are available beginning in the mid-19th century. For the overlap period of 1982–1996, the in situ averages are regressed against averages of the *Reynolds and Smith* [1994] analysis. The resulting regression coefficients are applied to averages of the in situ data over the historical period to produce a globally averaged SST time series beginning in 1880.

[5] The land surface temperature (LST) component of the Quayle index is an average of surface air-temperature station data from the Global Historical Climate Network (GHCN [*Peterson and Vose*, 1997]). Globally averaged LST time series were produced using an approach which sums the year to year change (First Difference) at all the stations [*Peterson et al.*, 1998]. This maximizes the number of stations that can contribute to the analysis because the standard anomaly approach requires station data to be available during a base period while the First Difference approach does not. A few stations have long records before the base period, but are not available for the base period. Some newly digitized time series from European colonial-era archives, which end with the countries' independence, would fill in data sparse regions with a First Difference approach but may not be available for an anomaly analysis [*Peterson and Griffiths*, 1997].

[6] To form the global index these two components are merged, weighting ocean data by 0.7 and land by 0.3. The Quayle index gives a global average that correlates well with comparison analyses. For example, interdecadal variations of the index are similar to those produced by *Hansen et al.* [1999], who used land station data, and *Folland et al.* [2001b], who used land and ocean data. All show temperature increasing by roughly 0.3° to 0.4°C from 1900 to about 1940, followed by a slight decrease from 1940 to 1970, then pronounced warming over the rest of the 20th century.

2.2. The SR05 Analysis

[7] The SR05 analysis merges a new analysis of in situ SST anomalies [*Smith and Reynolds*, 2004] with an analysis

of LST anomalies from a gridded version of GHCN [*Peterson and Vose*, 1997]. The LST analysis is produced using the same methods as the SST analysis. Here the analysis method is briefly discussed. Interested readers should see *Smith and Reynolds* [2004, 2005] for details.

[8] Both the SST and LST components of the SR05 are created by separately analyzing the low- and high-frequency anomalies. Low-frequency anomalies are analyzed by spatial and temporal filtering when enough data are available. Spatial filtering is done by averaging anomalies over 10°–15° latitude-longitude regions, and temporal filtering is done by averaging and median filtering over 15 year running periods. Separate low-frequency analysis is done to minimize the damping of those signals. Damping of the low-frequency may occur if it is analyzed by projecting it onto a set of stationary modes that do not fully resolve all of its variations.

[9] The high-frequency residuals from this low-frequency analysis are analyzed separately by fitting them to a set of screened covariance modes representing large-scale monthly temperature patterns. It is assumed that the base period for the modes is long enough to resolve the high-frequency variations. The sum of the low- and high-frequency anomalies gives the total anomaly. In addition to the anomaly, an error estimate is also computed for the merged analysis.

[10] Although the SR05 analysis is spatially complete, regions such as the Polar Latitudes are nearly always sampled poorly and the anomalies there are damped toward zero in the SR05 analysis. As expected, the SR05 sampling-error estimate is large for the poorly-sampled regions. To prevent poorly-sampled regions from damping the global average, regions with large sampling errors are excluded from the global average. Sampling error, normalized by anomaly standard deviation, is used to define excluded regions. After testing several cut offs, it was decided to exclude regions with a normalized sampling error of 0.5. The amount of global area excluded is greatest in the 19th century, when it is 20%–30%. For the 20th century the area excluded is 20% or less, and after 1950 it is less than 15%.

2.3. Differences in Analysis Methods and Data

[11] There are several important differences between the Quayle index and SR05. The SST component of the Quayle index is based on observations compiled at the U.K. Meteorological Office, which uses the historical bias adjustments of *Folland and Parker* [1995] before 1941. After 1981 the Quayle index is merged with the *Reynolds and Smith* [1994] in situ and satellite blended analysis. The SR05 SST is based on the International Comprehensive Ocean Atmosphere Data Set (ICOADS [*Woodruff et al.*, 1998]). It uses different, though similar, historical bias adjustments to account for the change from bucket measurements to engine intake SSTs [*Smith and Reynolds*, 2002]. In addition, SR05 is based on in situ data. For the LST component, both estimates are based on the GHCN temperatures, although the Quayle index also incorporates some additional colonial era data, noted above. The major difference in the LST component is that SR05 performed a statistical analysis similar to the SST analysis to interpolate temperature anomalies, while the Quayle index ignored grid boxes without observations. Besides analysis differences, SR05 also includes error estimates for all gridded temperature values. The SR05 analysis will replace the Quayle index, which has been widely used for climate monitoring. Therefore, the effects of these differences on the annual and global averages need to be documented.

3. Comparisons of Global Averages

[12] To more clearly illustrate differences between the old and new analysis, the averages of SST and LST anomalies are first discussed separately. Comparisons of the merged ocean and land averages are then considered.

3.1. Comparison of SST Anomalies

[13] For SST anomalies, the two estimates clearly represent the same major variations over the historical period (Figure 1). The two SST estimates are similar throughout the analysis period, but they are most similar after 1970 when there is almost no difference. For much of this time, 1982-present, the Quayle analysis directly incorporated satellite-derived SSTs while SR05 was computed consistently throughout its analysis period. The slight systematic difference between about 1910 and 1970, less than 0.04°C on average, may be caused by the slight damping of the anomalies by the Quayle regression. Although the SR05 SST anomalies are also damped in periods with sparse sampling, their analysis methods are designed to minimize that damping [see *Smith and Reynolds*, 2004]. In addition, differences in the historical bias adjustments before 1942 can contribute to the systematic differences.

[14] Although systematic differences in the SST anomalies occur between about 1910 and 1970, they are minor and have little effect on the overall trend estimates. For 1880–2004, the Quayle index trend is 0.68°C/century, while for SR05 it is 0.65°C/century. The correlation between them is 0.98, and the SR05-Quayle mean difference is −0.01°C. In addition, the Quayle index estimate is within the confidence intervals for the SR05 estimates. Considering all the differences in these two SST estimates, their similarity is remarkable.

3.2. Comparison of LST Anomalies

[15] The two estimates of global LST anomalies are also similar (Figure 2). As with the SST anomalies, the LST anomalies are most similar after 1970. The difference in the amplitude of the variability in the early period is likely due to sparse sampling in the period. The SR05 LST estimate is produced using the same methods used to produce its SST estimate, which damps anomalies toward zero when sampling is sparse. By contrast, the Quayle approach only averages grid boxes with data, and as the number of grid boxes with data decreases, the variability tends to increase. Early in the 20th century the LST data used for the Quayle index is much less spatially complete than later in the century. With sparse sampling, the Quayle index method can allow isolated anomalies to effectively represent regions much larger than their true influence regions. Filling of LST anomalies by SR05 limits the influence of isolated anomalies to their influence regions, as defined by the spatial covariance functions, which gives it more stability when sampling is sparse. Before 1950 the SR05 LST confidence intervals are much wider than later, due to sparser sampling

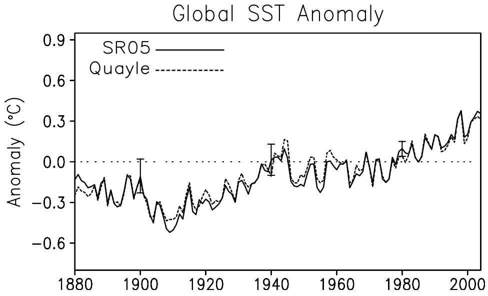

Figure 1. Global and annual average SST anomalies with respect to the 1961–1990 base using the Quayle index method (dashed line) and the SR05 method (solid line). The SR05 1 standard error confidence intervals are plotted for 1900, 1940, and 1980. Units are °C.

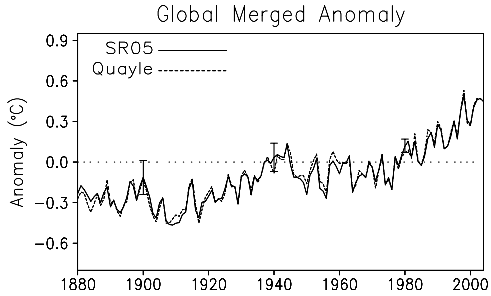

Figure 3. Global and annual average merged SST and LST anomalies with respect to the 1961–1990 base using the Quayle index method (dashed line) and the SR05 method (solid line). The SR05 1 standard error confidence intervals are plotted for 1900, 1940, and 1980. Units are °C.

for that period. The Quayle index LST tends to stay within the confidence intervals produced for the SR05 average, and the overall trend for both time series is the same, at 0.42°C/century. Their correlation is 0.97, and the SR05-Quayle mean difference is 0.01°C.

[16] The similarity of the two LST estimates is consistent with the work presented by *Peterson et al.* [1999]. In that work it was found that the global average LST was rather insensitive to variations in the network, and an average made with the full GHCN data set of 7,280 stations produced essentially the same global-mean temperature time series as that produced from a subset of 2,290 rural stations.

3.3. Comparison of Merged Anomalies

[17] The merged anomalies are more alike than either the SST or LST components (Figure 3) despite differences in the merging techniques. As discussed above, the Quayle index for SST is over damped toward zero anomaly, compared to SR05. Its simple method of estimating the historical SST anomaly can not resolve those variations as well as the SR05 method, leading to the SST damping. The Quayle index for LST is computed differently from its SST component. Their LST component is produced by simple averaging of the available data with no damping. However, when sampling is sparse simple averaging can cause errors because it effectively extrapolates variations from the sampled regions into unsampled regions. This may cause problems in the 19th and early 20th century. The SR05 method minimizes this problem by using spatial covariance to better estimate variations in unsampled regions. For times

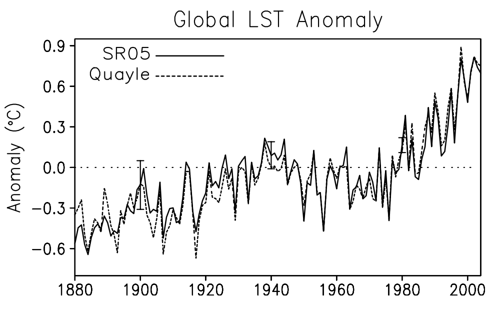

Figure 2. Global and annual average LST anomalies with respect to the 1961–1990 base using the Quayle index method (dashed line) and the SR05 method (solid line). The SR05 1 standard error confidence intervals are plotted for 1900, 1940, and 1980. Units are °C.

and places where the covariance can not reliably be used for interpolation, the SR05 anomaly is damped towards zero. Thus, the SR05 LST anomaly tends to me more damped than the Quayle index LST anomaly in periods when sampling is sparse.

[18] Because of these differences in the Quayle index SST and LST methods, their anomalies tend to have small systematic differences of opposite sign compared to SR05. When merged the differences tend to cancel. The trends from these two merged analyses are very similar, with an overall trend of 0.50°C/century for the Quayle index and 0.48°C/century for SR05. Their correlation is 0.99 and there is no mean difference between them.

4. Error Estimates

[19] Unlike the Quayle index, SR05 provides estimates of the errors in the global mean temperature analysis. Error estimates include the effects of both sampling and systematic data-bias errors. Random data errors are effectively removed by the SR05 analysis methods. Details of the error-estimation methods are given by *Smith and Reynolds* [2004] and SR05. Systematic errors reflect uncertainty in adjustments of systematic data biases. Sampling errors are separated into high- and low-frequency components. High-frequency sampling errors reflect the inability of the covariance modes to completely describe high-frequency variations with the given sampling. Because the low-frequency analysis is computed without using large-scale modes, the low-frequency sampling errors are often the largest component of the total error.

[20] For SR05, the low-frequency (interdecadal and longer) anomalies are assumed to have spatial scales of approximately 10°–15°, while in the works by both *Jones et al.* [1997] and *Folland et al.* [2001b] somewhat larger spatial scales are used for analysis. Because the spatial scales they used are larger, they require fewer data to sample the low-frequency anomalies and their sampling errors are smaller. It is desirable to use the largest spatial scales that can be justified to minimize the sampling needed. However, the larger scales are based on more recent data or models, and those larger scales may not be stationary over the entire analysis period. The SR05 method uses a non-parametric analysis of the low-frequency anomaly, which ensures that its signal is not over interpolated in the earlier decades. This more conservative approach produces standard errors that

are as much as twice as large as the *Jones et al.* [1997] and *Folland et al.* [2001b] estimates for the late 19th and early 20th century. Scales of the low-frequency anomaly may actually be larger than those assumed by SR05, but it is difficult to show that for the 19th and early 20th century when sampling is too sparse to estimate them. The true low-frequency error is likely to be somewhere within this range of estimates. In any case, all of the estimates give similar interdecadal variations regardless of the analysis techniques. Also, the errors of the decadal means are about half those of the annual means for the SR05 error estimates, indicating increased confidence in the interdecadal signal.

5. Conclusions

[21] A great deal of work has recently been done to improve the accuracy of NCDC's surface temperature analyses. These comparisons show that the new analysis has essentially the same interannual to interdecadal variations in global averages. Where differences do occur they are primarily confined to the early years, when sampling is more sparse. An advantage to the new analysis is the availability of uncertainty estimates. The addition of more observational data could reduce these uncertainty estimates and make regional analyses more accurate, but these results suggest that more data would be unlikely to greatly change the average global temperatures over most of the analysis period. Besides uncertainty estimates, the new analysis also makes it easier to develop a wide variety of regional analyses because it produces an intermediate gridded analysis that can be averaged for any region.

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