A Spatial Resampling Perspective on the Depiction of Global Air Temperature Anomalies

Abstract

Networks of near-surface climate stations often produce samples of air temperature that are spatially uneven and sparse. Spatial samples of air temperature, as a result, affect both the regional depiction of air temperature anomalies and large-scale spatial averages. A resampling procedure is used here to illustrate the general problem of how spatially variable station networks can influence estimates of climatic change. As an example, the warm air temperature anomalies that occurred during 1988 are resampled using station networks from other years.

During 1988, areas in North America and northern Asia experienced very warm conditions, producing a terrestrial averaged air temperature anomaly of over 0.4°C. If the 1988 air temperature anomalies were resampled using the 1981 station network, the warm event in northern Asia would not have been detected due to missing air temperatures over northern Russia during 1981. As a result, the 1981 station network would have estimated the 1988 terrestrial air temperature anomaly to be 0.25°C. Alternatively, the station network of 1988 was biased toward areas that had warm 1988 air temperatures and would estimate the 1988 air temperature anomaly to be 0.52°C. In addition to problems in estimating the terrestrially averaged air temperature anomaly, regional climatic variability is altered by resampling the 1988 anomalies with other networks.

The sampling problems illustrated here also show the importance of having free and open exchanges of data worldwide. National networks of climatic stations are crucially important not only in the analysis of regional climatic variability, but also in the detection of global-scale climatic change.

1. Introduction

Estimating large-scale air temperature anomalies from networks of surface stations is an important component of climatic change research (e.g., Hansen and Lebedeff 1987; Jones et al. 1986). Near-surface air temperature data, however, are subject to a number of observational biases (e.g., Edwards 1987; Karl et al. 1986; Karl and Jones 1989; Mitchell 1953; Schaal and Dale 1977) that limit the accuracy of climatic change estimates.

Changes in the near-surface environment of the observing station have large potential for biasing air temperature records, as nearly all aspects of human settlement (e.g., paving, soil compaction, energy consumption, etc.) act to warm the near-surface environment (Oke 1982). Another observational problem involves the effects of variable space–time sampling of air temperature fields. Station networks have changed through time, in both the number and spatial distribution of stations (Fig. 1), possibly influencing estimates of climatic change. Some of these changes simply are a result of reporting problems and/or missing data.

Century-long trends in global air temperature anomalies have been estimated to be approximately 0.5°C (100 yr)⁻¹ (Houghton et al. 1990). While long-term global trends appear to be fairly robust with respect to spatial sampling problems (Karl et al. 1994; Robeson 1995), both regional climatic trends (Robeson 1994) and trends over decadal timescales (Karl et al. 1994) appear to contain network-induced variability. Although long-term global trends are robust with respect to spatial sampling, any given year’s average air temperature anomaly may have 95% (pseudo) confidence limits with ranges of nearly 0.4°C, depending on how the confidence limits are estimated (e.g., Hansen and Lebedeff 1987; Robeson 1995).

The portrayal of observed air temperature change, however, goes well beyond the estimation of large-scale averages (e.g., Jones and Kelly 1983; Jones et al. 1991b). Globally averaged air temperature anomalies provide statistical evidence of planetary-scale changes in the atmosphere, but many scenarios can be imagined where vastly different spatial patterns of air temperature anomalies produce the same global average. From the perspective of applied climatology, the depiction of regional-scale climatic variability and change is more important than the much smaller global-scale changes.

As an example of how spatially uneven air temperature networks can affect both large-scale averages...
and regional depiction of climate, the air temperature anomaly patterns of 1988 are reexamined. With a terrestrially averaged air temperature anomaly of over 0.4°C, 1988 is one of the warmest years on record. To examine how large-scale air temperature patterns may be biased by irregular spatial sampling, historical station networks are used to resample the 1988 air temperature anomalies.

2. Resampling methods

A number of resampling procedures can be used to estimate the reliability of statistical estimators. Random resampling or “bootstrapping” (Efron and Gong 1983) is perhaps the most widely used, but other resampling methods, such as cross validation, have been applied to climatological problems (Michaelson 1987; Robeson 1994).

A nonrandom or systematic resampling procedure that attempts to reproduce a fixed air temperature field is used here. Using this approach, historical station networks have been used to resample both general circulation model output (Hansen and Lebedeff 1987; Trenberth and Olson 1991) and long-term averages of air temperature and precipitation fields (Willmott et al. 1991, 1994). Nonrandom resampling can depict how well variable space–time samples represent a known field, both in terms of large-scale averages and spatial patterns. As implemented here, nonrandom resampling uses overlays of historical station networks onto a fixed, known field to generate point estimates of the known field at the historical station locations. After an air temperature anomaly field is resampled, the point estimates of the anomalies are interpolated to a grid to avoid uneven spatial weighting.

Comparison of various spatial interpolation methods has shown that large-scale averages of air temperature anomalies are not very sensitive to the choice of interpolation method (Robeson 1994). Spatial patterns of climatic change, however, can depend on how the anomalies are interpolated. Both spherical thinplate splines (Wahba 1981) and spherical inverse-distance weighting (Willmott et al. 1985) are used below to interpolate the resampled values.

3. Resampling of air temperature anomalies

Air temperature station networks often vary considerably from year to year; both the number of stations (without missing data) and their spatial distribution have changed through time (Fig. 1). To illustrate how spatially and temporally variable station networks can affect spatial averages and spatial representations of air temperature anomalies, a nonrandom (or systematic) resampling procedure is used with the well-documented station data from Jones et al. (1991a). Air temperature anomalies were created following the procedures of Jones et al. (1986), whereby the 1951–70 station mean was subtracted from the actual air temperatures at each station.

a. Terrestrial averages

As an illustration of the effects of irregular spatial sampling, the station distribution of every year from 1881 to 1987 is used to resample the 1988 air temperature anomaly field. An example of this resampling process is shown graphically in Fig. 2a, where the 1981 station network is overlaid on the 1988 anomaly field. The 1988 air temperature anomalies then are 1) resampled at the 1981 station locations, 2) interpolated to a terrestrial grid, and 3) spatially averaged. If network bias is small, then other station networks should reproduce the 1988 terrestrial average air temperature anomaly $\Delta T_{1988} = 0.42^\circ C$ as well as the
duce nearly the same resampled estimate of $\Delta T_{1988}$ for every year (Fig. 3). Given 1) the similar time series produced by the two interpolation methods and 2) that terrestrial averages of air temperature anomalies typically do not contain large interpolation errors (Robeson 1994), it is likely that only a small amount of the variability in these time series results from spatial interpolation errors. Most of the variability in the estimates of $\Delta T_{1988}$ therefore, is due to the inability of historical station networks to depict the 1988 air temperature anomalies accurately.

b. Spatial depiction

To examine how the spatial variability of climate can be altered by changing station locations, it is useful to examine maps of resampled air temperature anomalies. Since the 1981 station network produced the most biased estimate of $\Delta T_{1988}$, the 1981 station network is shown overlaid on a map of the 1988 air temperature anomaly field (Fig. 2a).

Land areas in the Northern Hemisphere, especially northern Asia and North America, experienced large air temperature anomalies during 1988 (Fig. 2a). The station network of 1981, however, would have completely missed the large anomalies in northern Asia. When resampled by the 1981 station network, the spatial depiction of 1988 air temperature anomalies is vastly changed by the lack of sampling in northern Asia (Fig. 2b). Spatial patterns and averages are altered whether the gridpoint values in northern Asia are interpolated or just not used. In either case, both the spatial variability and the terrestrial average would be unrepresentative of what actually occurred during 1988.

4. Summary and conclusions

Irregular spatial samples produced by air temperature networks can affect both the spatial patterns of air temperature anomalies and large-scale spatial aver-
Fig. 3. Estimates of the terrestrially averaged air temperature anomaly (°C) for 1988 after resampling the 1988 anomaly field with every other year's station distribution. The results using two different spherical interpolation methods are shown: thin-plate splines (TPS, dash-dotted line) and inverse-distance weighting (IDW, solid line). The terrestrial average air temperature anomaly using the original 1988 network also is shown (dashed line). If spatial sampling is adequate, every station network should reproduce the 1988 estimate.

ages. By using historical station networks to resample a given climatological field, the effects of irregular sampling can be estimated. Using 1988 air temperature anomalies as an example, the station networks of all other years were used to estimate the 1988 terrestrial average air temperature anomaly and the spatial patterns of anomalies during 1988.

Uncertainty from spatial sampling problems can be reduced only by improving national networks and by the free and open exchange of climatic data. Data quality issues also are of utmost importance.

During 1988, areas in northern North America and northern Asia experienced unusually warm conditions. If the station network of 1981 had been used with the 1988 air temperature anomaly field, however, a very warm event in northern Asia would have been undetected. As a result, the 1981 station network would have underestimated the 1988 terrestrial air temperature anomaly by 0.17°C. Alternatively, the station network of 1888 was biased toward areas that had warm 1988 air temperatures and would have overestimated the 1988 air temperature anomaly by 0.1°C. In addition to the network-induced variability in the average air temperature anomaly, the spatial depiction of climatic variability is altered by irregular and changing station networks.

In the context of climatic change, therefore, spatial sampling problems add uncertainty to estimates of global- and regional-scale change. Uncertainty from spatial sampling problems can be reduced only by improving national networks and by the free and open exchange of climatic data. Data quality issues also are of utmost importance. Unlike many data quality issues, however, network-induced variability appears to be unsystematic and can lead to either underestimation or overestimation of climatic change. Since network-induced uncertainty can push current estimates of air temperature change in either direction, problems with spatial sampling of air temperature do not provide arguments for or against global warming. Problems with spatial sampling, nonetheless, do provide limits on our ability to detect small climatic changes within the air temperature record.

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References


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