

## Assessment of Urban Versus Rural In Situ Surface Temperatures in the Contiguous United States: No Difference Found

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### ABSTRACT

All analyses of the impact of urban heat islands (UHIs) on in situ temperature observations suffer from inhomogeneities or biases in the data. These inhomogeneities make urban heat island analyses difficult and can lead to erroneous conclusions. To remove the biases caused by differences in elevation, latitude, time of observation, instrumentation, and nonstandard siting, a variety of adjustments were applied to the data. The resultant data were the most thoroughly homogenized and the homogeneity adjustments were the most rigorously evaluated and thoroughly documented of any large-scale UHI analysis to date. Using satellite night-lights–derived urban/rural metadata, urban and rural temperatures from 289 stations in 40 clusters were compared using data from 1989 to 1991. Contrary to generally accepted wisdom, no statistically significant impact of urbanization could be found in annual temperatures. It is postulated that this is due to micro- and local-scale impacts dominating over the mesoscale urban heat island. Industrial sections of towns may well be significantly warmer than rural sites, but urban meteorological observations are more likely to be made within park cool islands than industrial regions.

### 1. Introduction

#### *a. Impetus for this analysis*

As just about every introductory course on weather and climate explains, urban areas are generally warmer than nearby rural areas. Often referred to as the urban heat island (UHI) effect, urbanization has long been regarded as a serious contamination of the climate signal (e.g., Landsberg 1956). Those of us working with century-scale instrumental climate data strive to remove all sources of artificial biases from the data. So the UHI contamination is one aspect dataset creators seek to address. For example, the Global Historical Climatology Network (GHCN; Peterson and Vose 1997) consists of over 7500 temperature stations around the world that were identified as rural, urban, or an in-between class of small town using information on operational navigation charts and a variety of different atlases. A rural station was any station not associated with a town of over 10 000 population.

However, there were problems with the operational navigation charts. Much of the information going into the charts was over a decade old. Some towns that were rural a decade or two ago have since been engulfed by sprawling urban centers. Therefore, another approach to identifying which stations were rural and which were

urban was sought. A good current source of information is night-lights data from the Defense Meteorological Satellite Program (DMSP). Owen et al. (1998) developed an approach to identify locations as urban, rural, or suburban using night-lights data as have other researchers (e.g., Hansen et al. 2001). These night-lights rural/urban metadata avoid some of the shortcomings of the map-based metadata.

To find out how contaminated global temperature trends were from the UHI, Peterson et al. (1999) identified each station in GHCN using both the map-based and the satellite-based metadata. Two time series were then created. One was the time series from the full dataset, the one used routinely to determine global temperature trends over land areas at the National Climatic Data Center (e.g., Lawrimore et al. 2001), and another one produced using only data from stations that were identified as rural by both techniques. The two time series were very similar. The linear trend from 1880 to 1998 was  $0.65^{\circ}\text{C century}^{-1}$  for the full dataset and the slightly higher  $0.70^{\circ}\text{C century}^{-1}$  for the rural-only subset. The resulting conclusion was that the well-known global temperature time series from in situ stations was not significantly impacted by urban warming.

The research presented here attempts to unravel the mystery of how a global temperature time series created partly from urban in situ stations could show no contamination from urban warming. This is important to improving our understanding of the UHI contamination

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of in situ temperature observations and therefore the fidelity of the climate change measurements. This point is highlighted by the fact that some “greenhouse skeptics” continue to argue that a significant portion of the observed warming is only an urban effect (Hansen et al. 2000).

#### *b. The central problem with in situ data*

The central problem with any long-term analysis of climate data is that the data are unlikely to be homogeneous. Indeed, some researchers, such as I. Auer [quoted in Peterson et al. (1998)], believe that all long-term time series are inhomogeneous. This agrees with the experience in the United States with the stations in the U.S. Historical Climatology Network (USHCN; Easterling et al. 1996). This dataset of the most homogeneous long-term U.S. stations has an average of six discontinuities per century and not a single station is homogeneous for its full period of record. A wide variety of factors can cause inhomogeneities in long-term time series. These primarily are as follows:

- 1) changes in location (station moves that involve changes in latitude, longitude, or elevation);
- 2) changes in observing practices (of particular concern are changes in the time of once-daily observing and resetting of maximum and minimum thermometers);<sup>1</sup> and
- 3) changes in instrumentation. (Not all thermometers are created equal, and even equal thermometers give different readings in different housings. Therefore, the change from one type of thermometer to another can cause an artificial warming or cooling in the data.)

Many international researchers have expended a great deal of effort to adjust climate data to account for these inhomogeneities [see Peterson et al. (1998) for a review]. GHCN is no different. Using statistical approaches described in Peterson and Easterling (1994) and Easterling and Peterson (1995), GHCN station data were adjusted to compensate for all the inhomogeneities that could be detected. This presents an interesting problem for the assessment of the effects of urbanization. The data are inhomogeneous so they need to be adjusted. Yet if the adjustment technique can successfully identify and account for a discontinuity caused by changing from one thermometer to another, the techniques may well identify and compensate for abrupt changes associated with urbanization such as paving nearby grass. There-

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<sup>1</sup> In the United States, mean daily temperature is the average of maximum temperature ( $T_{max}$ ) and minimum temperature ( $T_{min}$ ). If a station observes in the afternoon, and day 2 is colder than day 1, then the maximum temperature of day 2 may well be the temperature from the afternoon of day 1 when the maximum/minimum temperatures were reset. This gives a warm bias to the data. Conversely, if the observations are in the early morning near the coldest time of the day, the effect on minimum temperature observations can impart a cold bias.

fore, the inhomogeneity of the data and the approaches to compensate for the inhomogeneities can have strong impacts on assessments of the UHI's effect on in situ observations.

#### *c. Previous research into UHI*

This section of the article is a standard review of the literature on the subject, which has been extensively studied, but with a distinct purpose. The focus will not only briefly describe the results of previous research on the subject of UHI contamination of in situ observations, but will also focus on how the authors dealt with the confounding influences of data inhomogeneity. Literature that reports on remote sensing data analyses (e.g., Akbari et al. 1999) or urban transects (e.g., Melhuish and Pedder 1998) that do not measure the temperature at in situ weather observing sites will not be evaluated. Satellite observations of very warm rooftops or highway intersections are likely accurate measurements of these parts of the UHI but are unlikely to accurately indicate the magnitude of the UHI effect at meteorological observing stations. As urban heat island literature is an extensive body of work, to limit the review, it starts in 1980.

An analysis of the Minneapolis–St. Paul urban heat island was made by Winkler et al. (1981) using both unadjusted and adjusted data. They report that the mean annual urban–rural difference was  $0.5^{\circ}\text{C}$  with unadjusted data and  $1.0^{\circ}\text{C}$  based on adjusted data. The authors used the mean of 10 yr of data from 21 stations in an  $\sim 18\,000\text{-km}^2$  area and then analyzed them spatially. The data were adjusted for time of observation biases and the effect of latitude. Stations that moved during this period had their time series adjusted for the effect of the move, but no adjustments were made to make the 21 stations homogeneous with respect to the effect of elevation. And no efforts were made to account for the effect of differences in instrumentation or rooftop siting. Contours of mean temperature were drawn on a map. The rural/urban classifications were then made based on analysis of the temperature, with stations outside the closed contours around the city classified as rural.

Cayan and Douglas (1984) found urban-affected heat island temperature increases of  $1^{\circ}\text{--}2^{\circ}\text{C}$  common when comparing linear trends over three to five decades of urban stations with trends at nonurban sites, 700-hPa radiosonde-derived temperatures, and sea surface temperatures. The authors made an attempt to identify station moves, but no effort was made to account for inhomogeneities in the data. In fact, the authors admit that they “experienced rather severe changes in location” (Cayan and Douglas 1984).

One study acknowledged that “the large differences of our individual station pairs demonstrate that isolation of the urban warming effect from other inhomogeneities is a complicated task” (Kukla et al. 1986). They looked at the difference in trends between rural and urban data

over a 40-yr period for 34 station pairs and concluded that the urban contamination amounted to about  $0.12^{\circ}\text{C}$  decade<sup>-1</sup>. In their analysis, Kukla et al. (1986) adjusted the data to address the biases caused by changes in the time of observation and one part of their analysis carefully isolated subsections of the record of eight station pairs to eliminate the effect of changes in instrument locations. However, no effort was made to account for changes in the instrumentation itself.

Two different approaches were used by Karl et al. (1988) in an attempt to determine the effect of urbanization on the U.S. climate record. One approach, the time rate of change method, looked at differences in temperature time series between urban and rural. The results of this method indicated that the warming rate of maximum temperature was inconsistent from time period to time period, that the approach was vulnerable to imperfect adjustments, and that it was adversely impacted by undocumented local changes in the landscape. Therefore, the authors preferred an approach that analyzed mean urban-rural differences for two 9-yr periods of urban-rural pairs. These data were then regressed against the metropolitan population to the 0.45 power [many different options were tested with (population)<sup>0.45</sup> having the best fit]. Average annual temperature was found to be  $0.11^{\circ}\text{C}$  warmer in cities of 10 000 people,  $0.32^{\circ}\text{C}$  warmer in a 100 000 population city, and  $0.91^{\circ}\text{C}$  warmer in a 1 000 000 population city. All of the warming in average temperature comes from minimum temperature as their annual assessment of daily maximum temperature indicates that urban sites tend to be cooler than rural during the warmest part of the day. The time series analyses had adjustments for changes in station location, time of observation, and instrumentation reported in the metadata. The spatial analysis had homogeneity adjustments for elevation, time of observation, and latitude but not for instrumentation or non-standard siting. More discussion about these results is in section 5c.

Jones et al. (1990) determined that the impact of urbanization on hemispheric temperature time series was, at most,  $0.05^{\circ}\text{C}$  century<sup>-1</sup>. This result was based on the work of Karl et al. (1988) for the United States and further analysis of three other regions: European parts of the Soviet Union, eastern Australia, and eastern China. "In none of these three regions was there any indication of significant urban influence in either of the two gridded time series relative to the rural series" (Jones et al. 1990). The homogeneity assessments varied with regions. The data for one region "were assessed for artifacts due to factors such as site moves or changing methods used to calculate monthly mean temperatures." Another region used data from stations "with few, if any, changes in instrumentation, location or observation times." The homogeneity of data used in the third region was not discussed. Their results showed that the urbanization influence "is, at most, an order of magnitude less than the warming seen on a century scale."

Nasrallah et al. (1990) used data from four stations to examine Kuwait City's urban heat island. Their analysis revealed a lack of well-developed heat island with no statistically significant temporal trends in the differences in minimum temperatures between desert and urbanized locations. No homogeneity issues were addressed for this analysis.

Using 42 pairs of urban-rural stations in China, Wang et al. (1990) found an average urban heat island of  $0.23^{\circ}\text{C}$  "despite the fact that the rural stations were not true rural stations." "Multiple regression techniques" were used "to minimize the effects of differences in altitude, latitude and longitude." No details or additional information were provided on this or any other aspect of homogeneity.

Gallo et al. (1993) looked at clusters of stations and compared the relationship between the difference in rural and urban temperatures and a vegetation index. Most but not all of their rural-urban differences showed urban stations as warmer. Elevation effects were addressed by running a second analysis limited to "only those cities with weather stations that exhibited less than 500-m elevation differences." Latitude and time of observation effects were not addressed. They acknowledge that rooftop observations were included in their analysis. Also, they cite a different paper indicating that one type of thermometer used in their study averaged  $0.3^{\circ}\text{C}$  warmer during the summer months than others, yet they made no adjustments for instrumentation.

China's northern plains were the subject of a UHI analysis by Portman (1993). Using data from 1954 to 1983 and examining how the differences of residuals between each urban station and every rural station changed, the author determined that the mean annual urban warm bias increased  $0.19^{\circ}\text{C}$  during these 30 yr. Homogeneity issues were addressed by statistically comparing time series of all the stations and removing stations with "large potential discontinuities" from the analysis. However, this region has warmed during this period (Wang and Gaffen 2001) and no effort was made to address the potential trend-damping influence that proximity to a large body of water might provide. This could be a confounding factor as analysis of a map in Portman (1993) revealed that 38% of the rural stations were within 15 km of the Yellow Sea and 63% within 50 km, while only 19% and 29%, respectively, of the urban stations were that close.

An analysis of the Barcelona heat island is presented in Moreno-Garcia (1994). In addition to transects, the author examined data from two stations. On an annually averaged basis, the urban site was  $0.2^{\circ}\text{C}$  cooler for daily maximum temperatures and  $2.9^{\circ}\text{C}$  warmer on minimum temperatures. It was noted that the two stations had the same instrumentation, similar elevations, and "similar" distances from the sea (the map indicated  $\sim 0.6$  km for the urban and  $\sim 1.8$  km for the rural).

The San Antonio, Texas, heat island was assessed by Boice et al. (1996) using 45 yr of data from one San

Antonio station and three stations from surrounding small towns. The results indicate that San Antonio's minimum temperature increased at an average rate of  $0.3^{\circ}\text{C}$  relative to the other stations. No effort was made to assess the homogeneity of the data.

Todhunter (1996) determined that the Minneapolis–St. Paul mean urban heat island in 1989 was  $2.1^{\circ}\text{C}$ . This value was determined based on data from one station at the local National Weather Service (NWS) forecast office, one university station, 11 NWS cooperative network stations, and 13 weather stations organized by a local television station. In order to make the UHI analysis, the author developed “a high-density, homogeneous, daily maximum and minimum air temperature dataset” (Todhunter 1996). This “homogeneous” dataset was created using only homogeneity adjustments for the time of observation biases. No adjustments were made for latitude. No effort was made to account for the effect of differences in elevation apparently “because of its modest local relief ( $<90$  m),” although information from a table in Todhunter (1996) indicates that the greatest difference in elevation between two stations was 119 m. And despite using data from several different sources, no adjustments were made to account for the effects of differences in instrumentation or non-standard siting.

Using data from three different parts of the world, Camilloni and Barros (1997) determined that the urban–rural temperature difference decreases during periods when rural temperatures are increasing and increases when rural temperatures are decreasing. Some of the data they used had been adjusted for all known inhomogeneities and some of their data had no homogeneity assessments or adjustments.

Böhm (1998) used data from three urban, three suburban, and three rural stations to examine the Vienna, Austria, urban heat island. He found that the urban effect is strongly influenced by local surroundings and therefore could not be regarded for the city as a whole, with the magnitude varying from  $0.2^{\circ}$  to  $1.6^{\circ}\text{C}$ . The trend in urban warming varied as well, with two central city stations showing no increase in urban warming while the third had  $0.6^{\circ}\text{C}$  warming in 45 yr. In Vienna, the average urban heat island effect was found to be strongest in winter. The data were rigorously tested for inhomogeneities from a time series perspective and the data for all nine stations were adjusted to a constant elevation. No comment was made as to whether the instruments and shelters were the same for all stations or not.

Data from two stations were used by Magee et al. (1999) to determine that the effect of the Fairbanks, Alaska, urban heat island grew by  $0.4^{\circ}\text{C}$  over a 49-yr period, with winter months experiencing a more significant increase of  $1.0^{\circ}\text{C}$ . Nothing was done to the data to account for any potential inhomogeneities, though the authors did document that the Fairbanks station

moved twice and used three different types of thermometers during this period.

An analysis of surface air temperature compared to 0.91-m-deep soil temperature indicated an urban heat island increase of  $0.2^{\circ}\text{C}$  over the period 1889–1952 for Urbana–Champaign, Illinois (Changnon 1999). The land air temperatures were adjusted for all temporal inhomogeneities in the station history archives. The soil temperature record “is considered an unbiased measure of the natural temperature trend in this region.” Implicit in this assumption is that soil temperature records are not biased by long-term changes in factors other than temperature, such as snow cover. However, an increase in winter snow cover can cause markedly warmer soil temperatures even during colder than normal winters (DeGaetano et al. 1996). Therefore, if snow cover decreased during this period, which is likely considering that the temperature has warmed and the amount of snowfall reported by the Urbana station was about 20% less in the latter part of the study period than the earlier part, soil temperature time series would likely have a cold bias.

Gallo and Owen (1999) identified clusters of stations in the contiguous United States and compared the relationship between the difference in rural and urban temperatures and a vegetation index. They found seasonal changes in the urban–rural differences that tracked changes in the vegetation index. Most, but not all, of their rural–urban differences showed urban stations as warmer with urban stations averaging  $0.38^{\circ}\text{C}$  warmer than rural. The effects of elevation were addressed by requiring the difference between lowest and highest stations in each cluster to be less than 500 m. Latitude, time of observation, differences in instrumentation, and siting were not addressed.

Two different approaches were used to examine the urban heat island of Lodz, Poland (Klysiak and Fortuniak 1999). The approach that used in situ stations compared three years of early 1990s data between an airport station and a station located in a big downtown square as well as three years of data during the 1930s between the airport station and a meteorological station operating in the city center at the edge of a small park. The results indicate “that the UHI intensity reached fairly similar dimensions” in the 1930s, when the built-up area of the town was four times less, as in the 1990s. No homogeneity adjustments were made to the data.

One city, Tucson, Arizona, was the subject of several different analyses by Comrie (2000), including transects by vehicle-mounted thermistors, spatial examination of in situ data, and comparison of rural and urban temperature time series. The results indicated that Tucson's urban heat island warming was  $\sim 3^{\circ}\text{C}$  over the last century and  $>2^{\circ}\text{C}$  of this occurred in the last 30 yr. No homogeneity assessments or adjustments were made and Comrie (2000) did not reference Gall et al. (1992), which looked at then-current measurements at the National Weather Service Office in Tucson and found “daytime temperatures that are two to three degrees too high.”

Using 20 yr of data from one urban station and three rural airport stations, Morris et al. (2001) determined that Melbourne's nocturnal urban heat island was 1.13°C. Potential time of observation differences were addressed by only using the 0600 LT observations and the effects of differences in elevation were not addressed because the mean rural–urban elevation difference was only 20.7 m. There was no discussion about other potential homogeneity issues such as instrumentation.

One rural and one urban station were used by Kim and Baik (2002) to determine that Seoul warmed 0.56°C relative to its rural neighbor during the 24-yr period 1973–96. The authors showed time series of Seoul and five neighboring stations but made the comparison only to the one neighbor that had the least warming during this period because it had “the largest temperature difference between Seoul and any rural observatories.” There was no discussion or assessment of data homogeneity.

Kalnay and Cai (2003) compared data from 775 urban contiguous U.S. (CONUS) stations with 167 rural stations and found that the urban warmed 0.18°C more than the rural during the 1980s and 1990s. In situ data homogeneity was not addressed at all.

#### *d. The approach used in this analysis*

The main insight from the literature review is that most assessments of urban heat island contamination do not rigorously deal with potential inhomogeneities in the data. When inhomogeneities have not been fully dealt with, it is impossible to have confidence that the analyses correctly determined the impact of urbanization on the temperature record. However, when adjusting long time series for inhomogeneities due to factors such as station moves and changes in observing practices, the effect of urbanization may be inadvertently compensated for as well. Thus, it is doubtful that these two intertwined issues can ever be 100% successfully separated. The work presented here, therefore, will not look at differences in trends. Instead, the approach used will evaluate the effect of urban warming in a subset of the U.S. network by comparing temperatures of nearby rural and urban stations.

“Unquestionably, many towns and cities are so located that even if we eliminated the man-made features, a microclimatic gradient would still exist between the city and the airport. Differences in elevation, river valleys, and proximity to lake and sea shores or mountains would introduce many well-known temperature differences, inversions, and local wind flow patterns” (Landsberg 1970). However, one can adjust the data to account for some natural and most artificial inhomogeneities. Specifically, careful attention will be paid to adjusting the data to account for the natural effects due to differences in elevation and latitude as well as the artificial effects due to differences in time of observations, differences in instrumentation, and the effects of non-standard siting practices, namely, rooftop installations. Once

the data are adjusted for these factors, it will be possible to accurately assess the impact of urbanization on the climate record.

## **2. Data and rural/urban metadata**

Quality-controlled mean monthly temperature data for U.S. in situ stations were obtained from the National Oceanic and Atmospheric Administration/National Environmental Satellite, Data, and Information Service/National Climatic Data Center (NOAA/NESDIS/NCDC) archives. The analysis period selected was the same one used by Gallo and Owen (1999), the three years 1989–91. Ending the period in December 1991 allowed the analysis to avoid the confounding influence of the Automated Surface Observing System (ASOS) deployment, which started in 1992. Three years is long enough to produce robust means. A longer period would increase the problem of missing data.

Due to the innate variability in climate, it was important not to bias the analysis with incomplete data. For example, if a station was missing an unusually warm or cold month, the average for the three years could be inappropriately cold or warm. Therefore, the first criterion was that the station have complete data for the analysis period.

Satellite night-light data are the latest tool used for determining which stations are rural and which are urban. For example, while Hansen et al. (1999) use map-derived rural/urban metadata in their global temperature analyses, Hansen et al. (2001) moved up to satellite-derived night-lights rural/urban metadata. The rural/urban classification metadata used in the analysis presented here was developed by Owen et al. (1998) using night-light data from the Defense Meteorological Satellite Program-Operational Linescan System. Their methodology divided 1-km<sup>2</sup> grid boxes throughout the United States into urban, suburban, and rural classifications. Figure 1 shows how their metadata compare with other approaches. Advantages of the Owen et al. metadata include that they are objective (while map based is often subjective) and that night-lights, in the United States at least, are good indicators of urbanization whether residential or industrial. Owen's et al.'s urban grid boxes had an 84.4% agreement with data from the U.S. Bureau of the Census (1997).

These metadata were available for the station locations that went into the analysis of Gallo and Owen (1999). The stations consisted of 40 clusters of stations well distributed around the country with a total of 289 stations (see Fig. 2). The Owen et al. (1998) methodology classified 85 of these stations as rural, 191 as urban, and 13 as suburban. A significant percentage of these stations required careful assessment of the hard-copy station history metadata to determine their true instrumentation and siting characteristics. For example, digital metadata often listed instrument type as unknown or would list many stations as rooftop observations

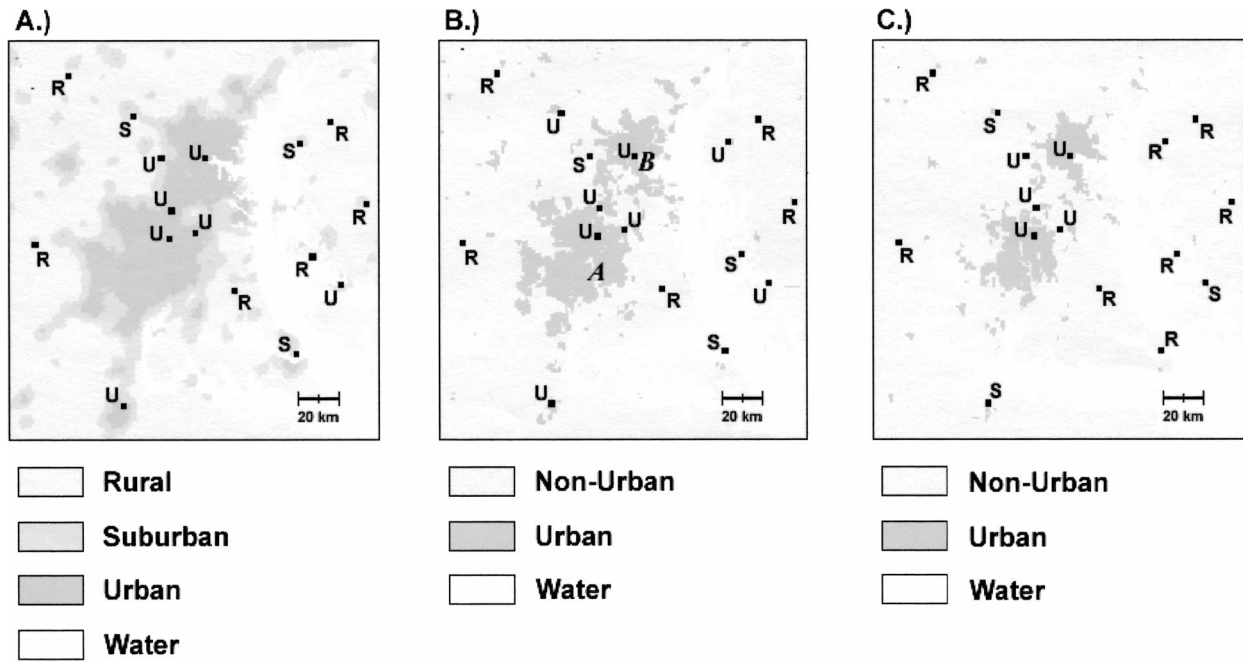


FIG. 1. Rural and urban stations identified by three techniques: (a) the night lights-derived metadata used in this analysis; (b) based on U.S. Census Bureau data; and (c) rural/urban metadata derived from maps. Figure from Owen et al. (1998).

while careful analysis of the full station history archive revealed that the rooftop installation was only for the back-up instrumentation. Therefore, 289 was a reasonable number of stations to evaluate.

### 3. Methods

There are two parts to this analysis. The first part applies adjustments to the data to account for all five

of the different bias-inducing factors impacting analyses of the data: elevation, latitude, time of observation, instrumentation, and nonstandard siting. The adjustment approaches used methodologies similar to those widely applied to time series (Peterson et al. 1998). The second part evaluates the impact of the UHI on in situ temperature observations and whether each adjustment has a statistically significant impact on the assessment. Because there are numerous inhomogeneities to address



FIG. 2. Locations of stations and clusters used in the analysis.

TABLE 1. Evaluation of elevation adjustment. Results of analysis dividing each cluster into two groups depending on whether the station elevation was above (high elevation) or below (low elevation) the mean elevation for the cluster are presented. The temperature difference is mean annual temperature for low-elevation stations minus high-elevation stations. There are fewer stations above the mean (89) than below it (114), indicating that lower-elevation stations tend to be closer in elevation than the high-elevation stations. Since the effect of, e.g., the time of observation could bias the results, values are provided for the original data, for data after all the other homogeneity adjustments except elevation have been applied, and for fully adjusted data, which includes the elevation adjustment. An MRPP (Mielke 1991) was used to determine the probability that, given all of the data points, two groups more different could occur by random chance alone. Values with probabilities less than 10% are given in **bold** and less than 5% are **bold\***. This analysis used data from 36 clusters.

	Original (°C)	All adjustments except elevation (°C)	Full adjusted (°C)
Mean temperature difference	<b>1.13*</b>	<b>1.12*</b>	0.10

and because part of the purpose of this paper is to evaluate their importance, the adjustments are discussed in detail.

#### a. Elevation

Most U.S. cities are located on coasts (e.g., Boston, Seattle), lakes (e.g., Milwaukee, Salt Lake City), or rivers (e.g., Cincinnati, Waterloo) and therefore tend to be at lower elevations than nearby rural stations (though exceptions, such as Flagstaff, Arizona, do exist). Therefore, rural stations in this analysis, not unexpectedly, tend to be at higher elevations than nearby urban stations, but only 20 m higher on average. However, the average is only a small part of the problem as some stations can be significantly higher or lower than the average for the group. The adjustment values for the effect of elevation on temperature,  $-5.3^{\circ}\text{C km}^{-1}$  of elevation, were taken from Landsberg (1945). Local terrain features that can impact the effect of nocturnal drainage flow influences on minimum temperature could not be addressed by this adjustment. As Table 1 indicates, this elevation adjustment removes the majority of the bias that elevation has on the mean annual temperature at the stations.

#### b. Latitude

Perhaps the most dominant feature of the temperature in the United States is that it varies with latitude. The effects of latitude need to be taken into consideration because a single cluster can span as much as  $0.97^{\circ}$  of latitude, though, on average, rural stations were only slightly farther south than urban ( $0.02^{\circ}$ ).

To determine the magnitude of this gradient, 1989–

91 average temperature were calculated at all U.S. cooperative stations. The United States was then divided into  $2^{\circ}$  latitude by  $1^{\circ}$  longitude grid boxes. Station latitudes and temperatures were converted to anomalies from the means of all the stations in their grid boxes. A linear regression on all of these annual mean temperature anomaly data points provided the adjustment factor of  $-0.90^{\circ}\text{C}$  per degree of latitude.

Table 2 indicates that this approach removes almost all of the bias that differences in latitude imparts. Unfortunately, the gradients of temperature are not uniform around the country, so it can not be completely accurate at each cluster. Interestingly, in Table 2, there is a decrease in the north–south (N–S) bias when adjustments for other factors are applied. It turns out that the elevation factor was aliased to N–S, as the average elevation of the more northerly half of the stations was significantly higher than the southern half.

#### c. Time of observation bias

The time that an observer reads and resets maximum and minimum thermometers can cause biases as high as  $2^{\circ}\text{C}$  in monthly temperatures (Karl et al. 1986). Using hourly station data, Karl et al. (1986) developed a model to account for time of observation (TOB) bias. The model adjusts all observations to be equivalent to midnight readings. As one would expect, these adjustments are regionally and seasonally varying. The percentage of stations reading in the afternoon is about the same for rural (33%) as urban (35%). However, rural stations have a higher percentage of a.m. readers (53% versus 37%) and a lower percentage of midnight readers (14%

TABLE 2. Evaluation of latitude (lat) adjustment. Results of analysis dividing each cluster into two groups, depending on whether the station lat was above or below the mean lat, for the cluster are presented. The temperature difference is the mean annual temperature of the southern stations minus the northern stations. This analysis involved data from 36 clusters with 94 stations in the southern half and 110 stations in the northern sections. Bold type has same meanings as in Table 1.

	Original (°C)	All adjustments except latitude (°C)	Fully adjusted (°C)
Mean temperature difference	<b>0.72*</b>	<b>0.43*</b>	0.05

TABLE 3. Assessment of time of observation adjustments. Results of analysis of mean annual temperature of morning reading stations minus the rest of the stations and afternoon reading stations minus the rest of the stations. No adjustments were made in the data used in “unadj analysis,” all of the data in “adj except TOB” analysis has all the adjustments except TOB; and “fully adjusted” uses only data with all of the adjustments. Also shown are the number of station clusters used, the number of stations in the first category listed in column one, and then the number of stations in the second category that went into the analysis. Note that unadjusted A.M. (P.M.) readers have a cold (warm) bias as expected. Bold type has same meanings as in Table 1.

	Unadj (°C)	Adj except TOB (°C)	Fully adjusted (°C)	Number of groups	Number of stations in first category	Number of stations in second category
A.M.-rest	<b>-0.70*</b>	<b>-0.49*</b>	-0.11	30	85	98
P.M.-rest	<b>0.46*</b>	<b>0.57*</b>	-0.03	30	67	113

versus 27%) than urban stations. This difference in observation times would add a cold bias to rural data.

TOB adjustments can be quite large, so using an incorrect time of observation can create some significant outliers in the adjusted data. Applying TOB adjustments using existing electronic NCDC metadata did, in fact, produce some significant outliers. Therefore, rather than rely on incomplete or occasionally erroneous station history metadata, the time of observation metadata used in these adjustments were derived from analysis of the daily data using the methodology described in De-Gaetano (2000).

Evaluations of the TOB adjustments are shown in Table 3. As expected, in the raw data and the data with all adjustments except TOB, morning observers have significant cold biases and afternoon observers have significant warm biases. After the adjustments, some bias still remained but they were no longer significant at the 90% level.

#### d. Instrumentation

Different instruments have significantly different biases. The effectiveness of the solar radiation shield varies with the type of shield, with the cotton region shelter (CRS) being more effective at shielding out solar radiation than the maximum–minimum temperature system (MMTS) shield (Hubbard et al. 2001). Also, the airflow characteristics for the different shields also vary with shield design, with the MMTS design having higher airflow efficiency than the CRS (Lin et al. 2001a).

The data from the 289 stations used in this analysis come from a variety of instrumentation: 106.9 liquid-in-glass (LiG) maximum and minimum thermometers in CRS, 142.8 thermistor-based MMTSs, 35.0 hygrothermometers, 2.3 hygrothermographs, and 2.0 “other.” The fractional instrumentation numbers are due to instruments changing during the 1989–91 period and one station used MMTS during the week and a hygrothermograph on weekends. Rural and urban stations had about the same percentage of LiG/CRS (35.5% rural, 36.0% urban). Rural had a higher percentage of MMTS (55.1% versus 49.7%), hygrothermographs (1.2% versus 0.6%) and “other” (1.2% versus 0%), while urban stations had the highest percentage of hygrothermometers (13.6% versus 7.1% for rural). Biases produced

by these different methods in observing temperature would impact any rural/urban analysis.

#### 1) HYGROTHERMOMETERS

The hygrothermometer in use during this period was the HO-83, which has been the focus of several investigations. In Albany, New York, a “warm bias, amounting to as much as 1°–2°C, could be identified in all seasons” in the HO-83 data (Kessler et al. 1993). While the HO-83 has a small aspirated shield (see Fig. 3a), Gall et al.’s (1992) examination of the HO-83’s warm bias in Tucson, Arizona, found that “the ventilation rate of its aspiration system at the entrance aperture of the housing . . . was observed to be in the range of 0.1 to 0.2 m s<sup>-1</sup>, about a factor of 5 less than other temperature sensors with housings of similar design.” They also noted that the “HO-83 contains a Peltier cooled dew-point system, which also emits heat within the cylinder containing the temperature sensor.” Once these deficiencies in the instrumentation were noted, the NWS moved quickly to improve the ventilation of the HO-83. Therefore, any study relevant to the data from 1989 to 1991 needs to have used data from the HO-83 prior to any modification.

The data Jones and Young (1995) used were collected starting in October 1991 from 15 side-by-side HO-83 and the new ASOS thermometer and continued until December 1992. They report that some changes were made during this time to the HO-83 but they were minor. These data did not include maximum and minimum temperature but instead compared hourly observations. However, C. Jones (2000, personal communication) reprocessed the data with extreme daily maximum and minimum hourly temperatures as surrogates for maximum and minimum temperature. The mean temperature adjustment is the average of the maximum and minimum since mean temperature in the U.S. cooperative network is the average of the maximum and minimum daily temperature. The annual mean temperature adjustment that results from this methodology,  $-0.62^{\circ}\text{C}$ , is in keeping with the “approximately  $0.6^{\circ}\text{C}$  warmer” value determined by Jones and Young (1995). This value is added to the data from the HO-83 to make them comparable to the ASOS instrument. This adjustment to the ASOS standard essentially removes the HO-83 bias because



(a)



(b)



(c)



FIG. 3. (a) The HO-83 housing includes a small fan. (b) The painted wood CRS houses liquid-in-glass thermometers. (c) MMTS on a pole; this unspirated plastic shield is 24 cm tall. Photos courtesy of the NWS.

when McKee et al. (1997) took “a field standard temperature system to three ASOS instruments for a side-by-side comparison” they determined that “ASOS has no temperature bias.”

## 2) LIQUID-IN-GLASS THERMOMETERS

CRSs are the old traditional white-slatted wooden instrument shelters (see Fig. 3b) that house LiG thermometers. The mean bias caused by stations changing from LiG thermometers in CRS to MMTS has been documented by Quayle et al. (1991) using data from 424 MMTSs and 675 CRSs that had no changes in observation times. This is by far the largest study of the difference between these two observing systems. While the introduction of the MMTS caused a significant decrease in maximum temperatures and increase in minimum temperatures, its effects on mean temperatures was small with the MMTS mean annual temperatures found to be only 0.06°C cooler than LiG in CRS. Quayle et al. (1991) combined data from all parts of the contiguous United States even though there are certainly regional differences due to regional variation in the strength of nocturnal longwave radiational cooling, the strength of incoming solar radiation, and the solar radiation angle, all of which can impact the observed temperatures inside the shelters (Lin et al. 2001b). Two side-by-side comparisons of individual MMTS and LiG thermometers in Minnesota and New Jersey indicated similar results (Baker and Ruschy 1989; Croft and Robinson 1993). However, one side-by-side comparison of an MMTS to two LiG thermometers in Illinois reported similar changes in maximum temperature but very little differences in minimum temperature (Wendland and Armstrong 1993). The Quayle et al. (1991) adjustments were applied to the liquid-in-glass temperature data to make them compatible with MMTS data.

## 3) HYGROTHERMOGRAPHS

Hygrothermographs are another type of thermometer that are housed in cotton region shelters. These instruments are calibrated with LiG thermometers and therefore should have the same biases that LiGs in CRSs have. The Quayle et al. (1991) bias adjustments were therefore applied to hygrothermograph data as well to make them comparable to MMTS.

## 4) MAXIMUM-MINIMUM TEMPERATURE SYSTEMS

The MMTS has an electronic thermistor inside a small unspirated housing (see Fig. 3c). While several studies compared the MMTS to the CRS, no studies could be located that compared the MMTS in the field to the ASOS instrument or a field standard. Since the MMTS and CRS can be adjusted to make their data equivalent, which instrument is closest to having no bias? When that question was posed to M. Sturgeon (2001, personal

communication) of the NWS Sterling Test Facility, he indicated that, in his opinion, the MMTS was more precise. This sentiment was also echoed by Quayle et al. (1991). Part of the difference between CRS and MMTS “is most likely due to the tendency for the CRS to overheat during sunny, quiet weather” (Chenoweth 1993). The MMTS does not have that problem as much because the “ventilation of the MMTS shelter is better than that of the CRS” (Wendland and Armstrong 1993). Quayle et al. (1991) suggest two possible causes for the CRS having lower minimum temperatures. The first is that column separation in the LiG maximum thermometer (which sometimes occurs near the constriction in the bore that prevents the mercury from re-entering the bulb when the temperature begins to drop) causes erroneous high readings. The second is radiation loss to the cool ground at night from the CRS through its single slatted bottom (the MMTS has a double bottom). The implication clearly is that the MMTS is likely to have less bias. Therefore, the differences between MMTS and LiG in CRS were applied to LiG in CRS data to make them comparable to MMTS. No adjustments could be identified that would make the MMTS more similar to ASOS.

The final step in the instrumentation adjustments was to remove data from the two nonstandard instrument stations from the analysis. Table 4 shows how well the instrumental biases were removed. The biggest impact was the change in HO-83. It was reading 0.7°C warmer than the other stations and that has been cut to 0.14°C. The bias for the LiG in the CRS went from a very small bias in the original data to a fairly high but statistically insignificant 0.2°C. The MMTS bias was cut from reading 0.44° too cool to 0.24°C too cool but still has a statistically significant bias. However, since the MMTS temperatures were not adjusted, the change in its bias was probably due to the large HO-83 adjustment and the small CRS adjustment. When comparing LiG in CRS directly with MMTS it was found that after all the adjustments there is still a significant difference, with the MMTS data being 0.27°C cooler than the LiG.

The adjustments that Quayle et al. (1991) identified are based on nationally averaged data. However, if the differences are largely due to the effect of radiation, there should be significant regional variations in this adjustment. It is possible that this regional variation is a cause for the residual MMTS/LiG bias. It is also possible that the bias is related to changes to the instrument over time as the Quayle et al. (1991) assessment examined the effect of installing new MMTS.

The warm residual bias in hygrothermometers could be removed by simply adding the residual bias to the adjustment. However, since hygrothermometers are twice as likely to be in urban locations, such manipulation of the adjustments may inappropriately remove the UHI signal that one is trying to identify. Therefore, these imperfect adjustments are the best possible based on the available information. Fortunately, a bias in the

TABLE 4. Assessment of instrument adjustments. Results of analyses of mean annual temperature of different categories based on the stations' instrumentation are presented. No adjustments were made to data used in the "unadj analysis," all of the data in "adj except instrument" analysis has all the adjustments except instrumentation; and "fully adjusted" uses only data with all of the adjustments. In the unadjusted data, HO-83 hygrometers had a warm bias during this period as expected. Bold type has same meanings as in Table 1.

	Unadj (°C)	Adj except instrument (°C)	Fully adjusted (°C)	Number of groups	Number of stations in first category	Number of stations in second category
HO-83-rest	<b>0.70*</b>	<b>0.71*</b>	0.14	26	29	117
LiG in						
CRS-rest	-0.02	0.10	0.20	28	70	102
MMTS-rest	<b>-0.32*</b>	<b>-0.44*</b>	<b>-0.24*</b>	31	97	90
LiG in						
CRS-MMTS	-0.23	<b>-0.32*</b>	<b>-0.27*</b>	25	78	63
Lig in						
CRS-HO-83	<b>-0.85*</b>	<b>-0.60*</b>	-0.05	20	50	23
MMTS-HO-83	<b>-0.83*</b>	<b>-0.68*</b>	<b>-0.24*</b>	23	67	26

LiG in CRS observations should not dramatically impact UHI analysis, as the percentage of stations with LiG in CRS is approximately the same for rural and urban classifications (35.5% versus 36.0%). The MMTS differ more (55.1% for rural, 49.7% for urban) but are still fairly similar.

#### e. Siting

Microscale siting characteristics can produce biases in the temperature measurements. Assessing these characteristics can be both extremely difficult, given the level of available metadata, and is part of the essential rural/urban question this analysis seeks to address. However, one siting characteristic that is not part of the rural/urban question and that can impart a large bias is non-standard siting, particularly rooftop observations. Rooftop observations tend to be warmer at night due to being higher in the stably stratified nocturnal boundary layer and warmer during the day due to less thermal mass below them being warmed by the sun and less available water to be converted into latent heat.

This problem has been known for decades. Indeed, Landsberg (1942) states that the differences between rooftop and ground-based observations "indicates clearly that conclusions on climate derived from records of roof stations may by no means be representative of those at the ground level . . . Stations located at roof level and on tall buildings have been used in the past. Most of their observations are hard to interpret . . . They are certainly of little value in a full assessment of the climatic changes brought about by urbanization" (Landsberg 1970). In 1994 R. Leffler (2002, personal communication) of the NWS documented one example of the rooftop bias by installing a new station on the ground within a few hundred meters of the rooftop station that he intended to close. Both the new and the old station were definitely urban stations located near the center of Baltimore. During this overlap period, the rooftop station had 13 days above 100°F (37.8°C) and 81 days above 90°F (32.2°C) while the nearby ground station had no days above 100° and only 38 days above 90°F.

The Baltimore–Washington International airport also reported 38 days above 90° and no days above 100°F during this period. For minimum temperatures, the rooftop station reported 12 minimum temperatures above 80°F (26.7°C) while the nearby ground-level station and the airport reported no minimums above 80°F. Parallel observations like these during site moves are the exception rather than the rule. Leffler's addressing the effects of site changes before the move was made resulted in some valuable site-specific information.

The results of the Davey et al. (2002) analysis of rooftop stations indicated that rooftop sites are usually warmer than nearby ground-based observations. Davey et al. (2002) also concluded that, due to building and site-specific features, no widely applicable formula to adjust rooftop observations to be equivalent with surface observations was able to be determined. Yet it is clearly important to remove this source of bias from the data. Fortunately, only 2 of the 289 stations had metadata indicating nonstandard siting during this period, which in both cases were rooftop locations. One was urban and the other was classified as suburban. Data from rooftop stations were removed from further analysis.

#### f. Analysis methodology

The first step in determining the difference between rural and urban stations was to convert each station's original and adjusted temperatures to anomalies from its respective cluster mean value. To have its data used in the analysis, a cluster needed to have both rural and urban stations with complete data. The station anomaly data were then put into two groups depending on whether they were rural or urban. The null hypothesis that these two groups were not significantly different was tested using a multiresponse permutation test (MRPP; Mielke 1991), which returned the probability that, given all the data points, two groups more different could occur only by random chance.

# Unadjusted Data

## Annual Temperature Anomalies

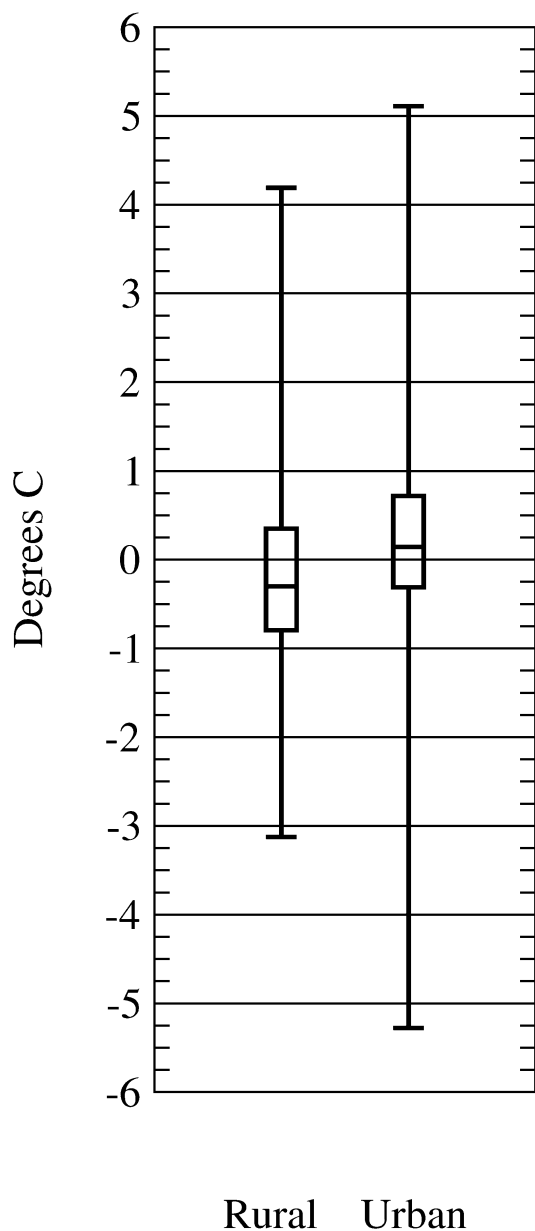


FIG. 4. Rural and urban mean annual temperature anomalies relative to each cluster's mean temperature using original unadjusted data. The box and whiskers used in this article indicate the median value (centermost line), the 25th and 75th percentiles (edges of the box), and extreme values (end of the whiskers).

### 4. Results

The box and whisker plot in Fig. 4 shows that for mean annual unadjusted temperature anomalies, rural temperatures tended to be cooler than the urban temperatures. As indicated in Table 5, the mean urban minus

TABLE 5. Impact of inhomogeneities on UHI assessment. Assessment of mean annual UHI (urban minus rural temperatures) using datasets with different homogeneity adjustments (adj.). Bold type has same meanings as in Table 1.

	Urban-rural ( $^{\circ}\text{C}$ )
No adjustments	<b>0.31*</b>
Fully adjusted data	0.04
All adj. except elevation	0.15
All adj. except latitude	-0.02
All adj. except TOB	<b>0.21*</b>
All adj. except instrumentation	0.09
Number of groups	31
Number of urban stations	116
Number of rural stations	66

rural temperature difference was  $0.31^{\circ}\text{C}$  and the difference between the two groups was significant at better than the 5% level. But even with this significant difference between the urban and rural stations, examination of Fig. 4 reveals considerable variability in the temperature anomalies, with some urban sites reporting colder temperature anomalies than many rural stations.

Once the homogeneity adjustments were made (Fig. 5), the situation changes dramatically. Note that the scale on Fig. 5 is less than that of Fig. 4. With the spread from highest to lowest anomaly going from  $10.4^{\circ}$  to  $5.2^{\circ}\text{C}$  with adjustments, it is clear that some of the variability in a cluster was due to biases that the adjustments removed. The mean difference between urban and rural dropped to  $0.04^{\circ}\text{C}$  and was not significant at the 90% level (Table 5). Therefore, inhomogeneities, which had already been indicated as not being random with regard to urban and rural stations, accounted for almost all of the apparent urban heat island in the raw data.

To determine which inhomogeneities had the greatest impact, the same analysis was run on data that were adjusted for all but one source of bias (Table 5). The magnitude of the urban minus rural difference listed in Table 5, less the residual in the fully adjusted results, indicates how much of a difference each source of inhomogeneity made in assessment of urbanization. In declining order, the time of observation accounted for  $0.17^{\circ}\text{C}$  of the bias (as rural stations had a higher percentage of morning readers, which have a cold bias), differences in elevation accounted for  $0.11^{\circ}\text{C}$  (in keeping with rural stations tending to be at higher elevations than nearby urban stations), instrumentation  $0.05^{\circ}\text{C}$  (which is in keeping with urban stations having a higher percentage of hygrothermometers that had a well-documented warm bias during this period), and latitude turned out to be a negative  $0.06^{\circ}\text{C}$  (meaning that the differences in latitude actually made the perceived unadjusted urban heat island assessment less due to the urban stations tending to be a little farther north than the nearby rural stations).

Two tests were conducted to assess the robustness of the analysis. The first addressed the homogeneity adjustments. The quality of the adjustments was assessed

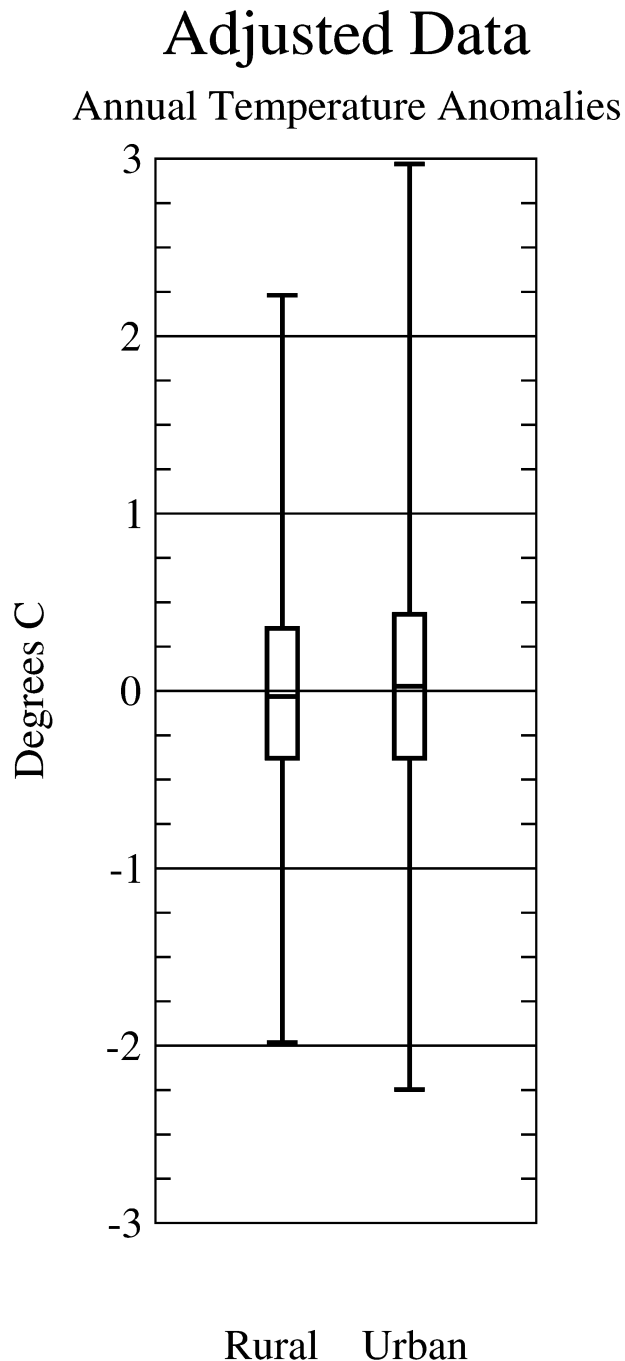


FIG. 5. Rural and urban mean annual temperature anomalies as in Fig. 4, but for data that have been adjusted to account for the effects of differences in elevation, latitude, time of observation, instrumentation, and nonstandard siting. Note that Figs. 4 and 5 have different scales.

in section 3, and residuals for each adjustment were presented. Tweaking the adjustments to make all of the residuals equal to zero and then readjusting the data makes the small and insignificant difference between urban and rural stations even smaller, thereby indicating

that the adjustments not removing 100% of the biases did not significantly impact the results. The second test was with the analysis approach. There are two possible approaches for calculating the mean temperature at each cluster: the mean of all the stations (presented earlier) and one-half the mean of the urban stations plus one-half the mean of the rural stations. Also, there are two ways to evaluate the differences between rural and urban stations: treat each station individually (presented earlier) or address only the mean rural temperature and the mean urban temperature at each cluster. These different approaches required four different analyses. The results of all four analyses agreed that the difference between rural and urban stations was small ( $0.01^{\circ}$ – $0.06^{\circ}\text{C}$ ) and very insignificant (the probability that more dissimilar groups could be caused by random chance alone varied from 0.77 to 1.00).

Some of the largest cities in the United States were not represented in the 40 clusters. Could the large cities be showing urban warming while the smaller ones do not? To answer that question, the mean urban minus rural temperature difference was calculated for each cluster. An assessment of five of the largest cities—Boston, Massachusetts; Dallas, Texas; Detroit, Michigan; Salt Lake City, Utah; and Seattle, Washington—found that one (Detroit) did not have adequate rural and urban data to be analyzed while all of the rest had homogeneity-adjusted urban temperatures that were cooler than the homogeneity-adjusted temperatures of their rural neighbors.

Analyses were also performed separately on each of the three years of data used in this study. As with the 3-yr results, the results for each year indicated a small and statistically insignificant difference between rural and urban temperatures. The variability in each year's data was quite similar to the variability of the 3-yr analysis shown in Fig. 5 in both the interquartile range (96%–114%) and extreme values (98%–123%). This indicates that the analysis is robust with respect to interannual variability of weather and climate.

## 5. Discussion

### a. Competing micro-, and local-, and mesoscale influences

In a recent talk at the World Meteorological Organization, T. Oke (2001, personal communication) stated that there has been considerable advancement in the understanding of urban climatology in the last 15 years. He went on to say that urban heat islands should be considered on three different scales. First, there is the mesoscale of the whole city. The second is the local scale on the order of the size of a park. And the third scale is the microscale of the garden and buildings near the meteorological observing site. Of the three scales, the microscale and local-scale effects generally are larger than mesoscale effects.

The reasons, in part, are because vegetation is responsible for distinct meteorological and climatic effects at all scales in the city (Oke 1989). "Research in the past decade has demonstrated that cities are not the 'deserts' they were once thought to be. The urban forest, together with other greenspace (some irrigated) and a variety of smaller sources, provides a significant flux of water and latent heat into the urban boundary layer" (Oke 1989).

Gallo et al. (1996) examined the effect of land use/land cover on observed diurnal temperature range and the results support the notion that microscale influences of land use/land cover are stronger than mesoscale. A metadata survey provided land use information in three radii: 100 m, 1 km, and 10 km. The analysis found that the strongest effect of differences in land use/land cover was for the 100-m radius. While the land use/land cover effect "remains present even at 10,000 m," this weaker relationship may actually be an artifact of the 100-m influence as, for example, the majority of sites with farmland listed for the 10 000-m radius also have farmland listed as the land use/land cover for the 100-m radius.

On the local scale, Böhm (1998) also found that, for maximum temperatures, local factors such as the annual leaf cycle in a city park can overwhelm other urban heat factors and "create thereby a much higher degree of thermal comfort right in the city center during summer." Recent research by Spronken-Smith and Oke (1998) also concluded that there was a marked park cool island effect within the UHI. They report that under ideal conditions the park cool island can be greater than 5°C, though in midlatitude cities they are typically 1°–2°C. In the cities studied, the nocturnal cooling in parks is often similar to that of rural areas. They reported that the thermal influence of parks on air temperatures appears to be restricted to a distance of about one park width.

The gradients of temperature within a city can be quite steep. Examining UHI using a radiosonde mounted to a car, Klyzik and Fortuniak (1999) found "permanent existence of heat cells" during the night in which "each housing estate placed on the outskirts of the city distinguished itself very sharply from surroundings in terms of its thermal structure. Open areas (gardens, parks, railway yards) were then sharply separated regions of cold air. Thermal contrast at the border between the housing estates and the fields covered with snow (horizontal gradients of temperature) reached several degrees centigrade per 100 m."

"The well known change in air temperature at screen-level . . . has a steep gradient at the edge of the city, but the distribution is much flatter over most of the rest of the urban area except for relatively 'hot' and 'cool' spots in particularly densely built-up (high rise, narrow canyons) or open and/or vegetated (parks, vacant land) areas, respectively. Again, one must remember that the nature of the urban canopy layer climates is dominated

by the immediate surroundings, not distance from the edge or the centre" (Oke 1998).

Figure 6 visually portrays the geographic nature of the local effect within a mesoscale urban environment. While just one snapshot in time—about 1100 local time (LT) in August—the analysis shown in Fig. 6 provides a very good qualitative representation of the scales described by the research cited earlier. S. Stetson (2003, personal communication) compared Figure 6, which he created, to similar images from different seasons and times and concluded that while the absolute temperatures will vary from hour to hour, day to day, and season to season, the spatial distribution of surface temperature classes—the relative position of the hot and cold spots—remains the same. Therefore, if a station is located within a park, it would be expected to report cooler temperatures than the industrial sections experience. But do the urban meteorological observing stations tend to be located in parks or gardens? The official National Weather Service guidelines for nonairport stations state that an observing shelter should be "no closer than four times the height of any obstruction (tree, fence, building, etc.)" and "it should be at least 100 feet from any paved or concrete surface" (Observing Systems Branch 1989). If a station meets these guidelines or even if any attempt to come close to these guidelines was made, it is clear that a station would be far more likely to be located in a park cool island than an industrial hot spot.

Park cool islands are not the only potential mitigating factor for in situ urban temperature observations. Oceans and large lakes can have a significant influence on the temperature of nearby land stations whether the station is rural or urban. The stations used in this analysis that were within 2 km of the shore of a large body of water disproportionately tended to be urban (5.8% of urban were coastal versus 2.4% of rural).

Clouds can also have a great impact on the radiation budget at the surface of the earth, both urban and rural. However, an analysis of clouds in the Atlanta area found "that there always tend to be more clouds over the urban area than over a ring of surrounding rural area" (Kidder and Hafner 2001). The authors go on to say that "this is consistent with the urban warming effect, which would produce rising air and more clouds over the city and subsidence and fewer clouds over the surrounding area" and that the "clouds tend to counteract the warming effect of urbanization," though only warming in the maximum temperature. Therefore, the warm industrial parts of town may, via cloud effects, contribute to further cooling of park cool islands.

Another factor that can influence urban temperatures is the ruralization of urban areas. The urbanization of rural areas is widely recognized as new housing developments being built on farmland or forests. The new subdevelopments will typically have hectares of asphalt and rooftops exposed to the sun with young trees planted in the yards. However, trees grow and eventually shade some or all of the asphalt. If, from a meteorological



FIG. 6. Temperature data derived from the Landsat thermal band from about 1100 LT in Aug are overlaid on a detailed base map of Washington, D.C. Red, yellow, purple, and light blue illustrate temperature variations over the hottest surface areas. The National Mall's grass and trees appear in more natural colors. This figure illustrates the local-scale variability of the UHI and how the specific location of a station within a city can greatly alter the UHI contamination of its temperature observations. Figure created by and provided courtesy of S. Stetson, Global Environmental Management, Inc., and published in Tomerlin (1999).

standpoint, paving a street is urbanization, then trees growing and increasingly shading the asphalt must be ruralization. Some residential urban areas with mature trees can look like a forest from the air.

One unequivocal feature of rural and urban temperatures (Figs. 4, 5) is that whether adjusted for biases or not, there is considerable variability. In the adjusted data the fairly large whiskers are probably due to the local- and microscale impacts, which can easily cause a station to be  $1^{\circ}$  or  $2^{\circ}\text{C}$  warmer or colder than a neighboring station, with neighboring often defined as several tens of kilometers away. Site-specific impacts of nearby bodies of water, differences in topography's effect on nocturnal drainage flow, and exposure to the prevailing wind can have a real and significant impact on a station's temperature observations that have nothing to do with whether a station is urban or rural. Therefore, accurate

site-specific adjustments—which, unfortunately, may not actually be possible—might be required to decrease the noise for more precise quantification of the impact of urbanization at each location. As examination of Figs. 4 and 5 indicates, site-specific local- and microscale effects will make some urban stations genuinely warmer than nearby rural stations and will also make some of them colder. It is interesting to note, however, that in the literature review, while there were many articles reporting comparisons of two or three sites, none of these articles reported urban sites as cooler than rural despite most multistation assessments indicating locations where urban sites were cooler. Since it seems unlikely that researchers just never happened to select two stations to compare where urban sites were cooler, this publication record would indicate a bias in the literature.

The bias is certainly not intentional but it impacts our

perceptions of the urban heat island phenomena. The cause of the bias may be that inhomogeneities are selectively ignored. Whenever one is using inhomogeneous data, the results are always suspect. If data produce an unexpected result, such as an urban station being cooler than nearby rural stations, the homogeneity of the data would probably be questioned, thereby discouraging the article from being published. However, if the results are what is expected, namely, that urban stations are warmer than rural, then, as section 1c indicates, the potential effects of inhomogeneities and biases in the data may not even come to mind, thereby allowing these articles to be published.

While analyses of inhomogeneous data cannot accurately assess the magnitude of urban heat islands, there are other types of accurate measurements of the real UHI phenomenon that also bias our expectations. These are analyses of in situ transects of urban areas and high-resolution IR satellite data. These data will accurately reveal that major urban highway intersections, industrial areas, and rooftops are indeed hot. But unless the meteorological station is located in an intersection, industrial area, or on a rooftop, the analyses should not be used to guide our expectations of urban biases at in situ observation sites.

#### *b. Rural stations are not pristine*

Any article comparing urban and rural temperatures would be remiss if it did not discuss factors that can cause rural stations not to be pristine. Indeed some of the factors that cause warming in parts of an urban area are also present at rural sites. While climatologists most often think of anthropogenic influences in terms of man-made structures, such as building a new house or paving a driveway, there are more subtle aspects as well. One of the causes of the nighttime urban warming signal is urban canyon geometry limiting “sky view factors for long-wave radiative cooling” (Oke 1976, 1981). A station on a flat savannah can radiate IR out to the sky at night from horizon to horizon. In an urban canyon, the sky view is greatly diminished and therefore IR radiative cooling at night is limited.

The change in sky view angle may have the potential to cause systematic biases at rural stations in some regions. For example, many farms in Australia were established in grassland. But once wells were put in, farmers planted and cared for trees around their dwellings. Therefore, among the huge expanses of open farmland, most of the long-term observing sites are now surrounded by trees (N. Nicholls 1998, personal communication). Although the growing trees’ IR effect may have some similarities to that of an urban canyon, the shade and evapotranspiration that the trees provide are also likely to introduce a cool bias during the day. The potential, nearly worldwide, artificial impact on observed temperatures caused by tree growth near observing sites

deserves to be thoroughly researched and quantified if possible.

#### *c. Comparison with other results*

As indicated in the literature review, the vast majority of analyses of UHI’s impact on in situ observations use inhomogeneous data and therefore are not appropriate for comparison purposes. Only two large-scale studies were found that used homogeneous data. These are the time series analyses of Peterson et al. (1999) and the Russian and Chinese regions of the analyses presented in Jones et al. (1990). These analyses found no indication of significant urban influence on the temperature signal. However, the results of two additional large-scale analyses deserve further discussion and perhaps reinterpretation in light of the results presented in this paper. The first is Hansen et al. (2001), which adjusts the trends in urban stations around the world to have the same mean trends as the rural stations in their regions. The data they used were not adjusted for inhomogeneities. But it is still interesting to note that of all their urbanization adjustments, 42% warm the urban trend, indicating that nearly half the urban stations are experiencing urban cooling relative to nearby rural sites. This agrees with and is fairly similar to the analysis presented in Fig. 4 but from a time series rather than spatial perspective.

The second analysis that could be reinterpreted is Karl et al. (1988). As mentioned in Section 1c, Karl et al. (1988) found a relationship between the urban–rural difference and the population of the metropolitan area. A linear regression slope is used to determine the urban heat island adjustment applied to USHCN stations (Easterling et al. 1996). Figure 7 shows the data points used and the regression line determined for annual average temperatures by Karl et al. (1988). Note that temperature was actually regressed against  $(\text{population})^{0.45}$ , as that was determined to have the strongest relationship. While  $(\text{population})^{0.45}$  can explain 32% of the urban–rural temperature differences, the bulk of that signal comes from the limited number of data points where urban populations exceeds 100 000. Though Karl et al. (1988) state “that urban effects on temperature are detectable even for small towns with populations under 10,000” and that there is a “positive urban bias . . . even at very low urban populations,” the regression-based urbanization adjustment for towns under 10 000 explains less than 2% of the variance, and for towns with populations from 10 000 to 100 000, it only explains 4% of the variance. While the regression explains 50% of the variance for cities over 100 000 population, the data used in this analysis were not adjusted for differences in instrumentation or for rooftop sitings and, as presented earlier, instrumentation and siting characteristics have distinct urban/rural biases. Despite not adjusting for these two important factors, examination of Fig. 7 also indicates



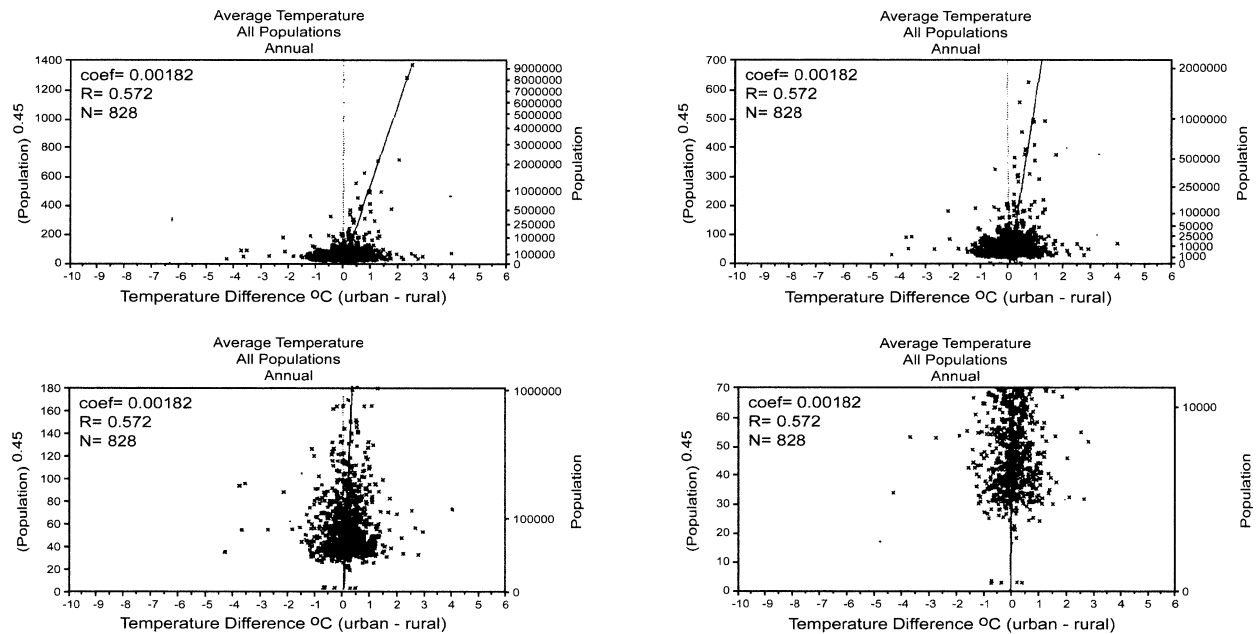


FIG. 7. Karl et al.'s (1988) scatterplots of urban minus rural temperatures vs (population)<sup>0.45</sup> along with a population-based UHI temperature effect regression line. To better reveal the observational values, the results are shown in four different scales on the y axis.

that many urban CONUS sites are cooler than their rural neighbors.

## 6. Summary and conclusions

All analyses of the impact of urban heat islands on in situ temperature observations suffer from inhomogeneities or biases in the data. The data used in this analysis were the most thoroughly homogenized and the homogeneity adjustments were the most rigorously evaluated and thoroughly documented of any large-scale UHI analysis to date. Using satellite night-lights-derived urban/rural metadata, urban and rural temperatures from 289 stations in 40 clusters in the CONUS were compared using data from 1989 to 1991. Once biases caused by differences in elevation, latitude, time of observation, instrumentation, and nonstandard siting were adjusted out of the data, contrary to generally accepted wisdom, no statistically significant impact of urbanization over the contiguous United States could be found in the existing in situ temperature observation network.

It is postulated that the reason for this is due to micro- and local-scale impacts dominating over the mesoscale urban heat island. Industrial sections of towns may well be significantly warmer than rural sites, but urban meteorological observations are more likely to be made within park cool islands than industrial regions.

There are several clear implications from this research. The first is that ensuring that the observational data that one uses in a variety of analyses are homogeneous is often crucial to getting an answer regarding which one has substantial confidence. The homogeneity adjustments, therefore, need to be very carefully applied

and documented. Simply saying that the dataset is homogeneous after addressing only one of several problems is not sufficient. Toward that end, this analysis suggests that the Quayle et al. (1991) adjustment for the transition from liquid-in-glass thermometers in cotton region shelters to the MMTS should be reevaluated.

The second implication has to do with adjustments to time series to account for the effects of urbanization. In the past, U.S. time series have been adjusted to account for conditions other than different instrumentation, elevation, rooftop siting, etc., that were thought to cause urban stations to be warmer than rural. However, since analysis of carefully homogenized data indicates that CONUS urban in situ stations are not warmer than nearby rural stations, adjustments to account for urbanization in CONUS in situ time series are not appropriate. How widely this finding should be interpreted cannot be determined by the research presented here, as it focused solely on CONUS data. Urban design and station siting criteria are different in other parts of the world. However, these results are in keeping with long-term global analyses of homogeneity adjusted GHCN data that found century-scale global temperature time series from only the rural GHCN stations warming at a slightly higher rate than a time series from the full GHCN dataset of both rural and urban stations (Peterson et al. 1999).

Additionally, as a community, we need to update our understanding of urban heat islands, to realize that this phenomenon is more complex than widely believed by those not immersed in the field. We should not view all oddly warmer stations as indications of UHI. Some urban stations are indeed warmer than nearby rural stations but almost the same number are colder.

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