Influence of Urban Heating on the Global Temperature Land Average Using Rural Sites Identified from MODIS Classifications

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Abstract

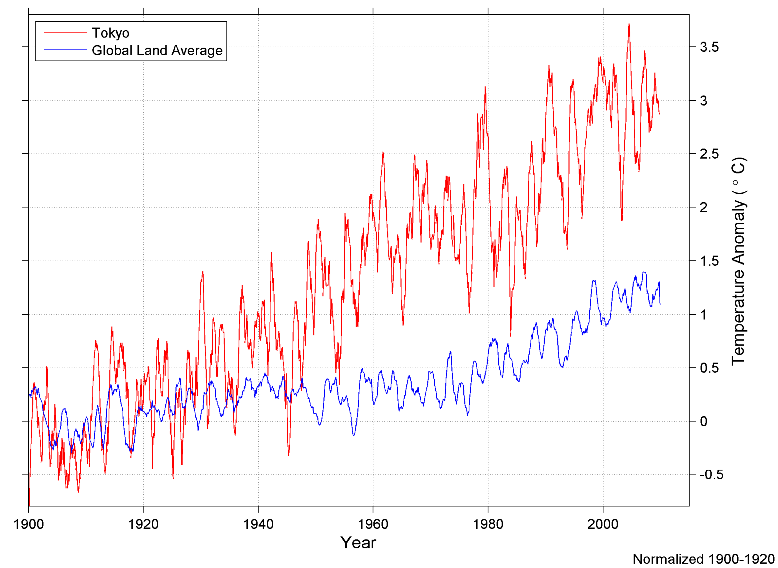
The effect of urban heating on estimates of global average land surface temperature is studied by applying an urban-rural classification based on MODIS satellite data to the Berkeley Earth temperature dataset compilation of 39,028 sites from 10 different publicly available sources. We compare the distribution of linear temperature trends for these sites to the distribution for a rural subset of 16,132 sites chosen to be distant from all MODIS-identified urban areas. While the trend distributions are broad, with one-third of the stations in the US and worldwide having a negative trend, both distributions show significant warming. Time series of the Earth's average land temperature are estimated using the Berkeley Earth methodology applied to the full dataset and the rural subset; the difference of these shows a slight negative slope over the period 1950 to 2010, with a slope of -0.19°C ± 0.19 / 100yr (95% confidence), opposite in sign to that expected if the urban heat island effect was adding anomalous warming to the record. The small size, and its negative sign, supports the key conclusion of prior groups that urban warming does not unduly bias estimates of recent global temperature change.

1. Introduction

The Urban Heat Island (UHI) effect describes the observation that temperatures in a city are often higher than in its rural surroundings. London was the first urban heat island to be documented (Howard ,1833) but since then many cities have been identified as urban heat islands (see Chandler,1976; Oke, 1974, 1979 and Arnfield , 2003). A well-known example is Tokyo where the temperature has risen much more rapidly in the city than in nearby rural areas: Fujibe (2011) estimates excess warming of almost 2^{o}C/100yr compared to the rest of Japan. The warming of Tokyo is dramatic when compared to a global average as seen in Fig.1. The UHI effect can be attributed to many physical differences between urban and rural areas, including absorption of sunlight, increased heat storage of manmade surfaces, obstruction of re-radiation by buildings, absence of plant transpiration, differences in air circulation, and other phenomena (Oke, 1982).

Urban areas are heavily overrepresented in the siting of temperature stations: less than 1% of the globe is urban but 27% of the Global Historical Climatology Network Monthly (GHCN-M) stations are located in cities with a population greater than 50,000. If the typical urban station exhibited urban heating of the magnitude of Tokyo this could result in a severe warming bias in global averages using urban stations. To avoid this bias the urban heating contribution to global temperature change should be isolated to the greatest extent possible.

Figure 1 Annual running mean of monthly temperatures at Tokyo compared to a global land average for 1900-2010



Detailed analyses of average land temperature time series of the Earth's surface (T_{avg}) have been reported by three major teams: the National Oceanographic and Atmospheric Administration (NOAA), the NASA Goddard Institute for Space Science (GISS), and the collaboration between the Hadley Centre of the UK Met Office and the Climatic Research Unit of the University of East Anglia (HadCRU). They differ in the methods used to account for the effect of urban heating on their global averages.

The approach of the GISS team is to identify urban, "peri-urban" (near urban) and rural stations using satellite images of nighttime lights (Hansen et al., 2010). Urban and peri-urban stations are then adjusted by subtracting a two-part linear trend based on comparison to an average of nearby rural stations. The result of the adjustment on their global average is a reduction of about 0.01°C in warming over the period 1900 - 2009.

The NOAA group does not perform a specific urban adjustment in their most recent analysis, GHCN-M version 3. They use an automated procedure (Menne & Williams, 2005) to make adjustments for documented and undocumented changes in station records, and expect that this process will remove most urban warming. When applied to the United States Historical Climatology Network, Menne et al. (2009) report that the average minimum temperature of the 30% most urban stations (based on population metadata) rises 0.06°C per century more than the more rural locations between 1895 – 2007.

The HadCRU group does not specifically model or adjust for urban warming because of the absence of relevant historical metadata for the HADCRUT dataset. Instead, they include an estimate for the UHI effect when they give their uncertainty statement. In a recent analysis, (‘HadCRUT3’, Brohan et al. 2006) they add a one-sided one sigma uncertainty starting in 1900 and increasing linearly by 0.055°C per century. This value is based on a previous analysis of urban heating by Jones (1990).

The conclusion of the three groups is that the urban heat island contribution to the global average is much smaller than the observed global warming. Support is provided by the studies of Karl et al. (1988), Peterson et al. (1999), Peterson (2003) and Parker (2004) who also conclude that the magnitude of the effect of urban heating on global averages is small.

There has been further discussion about the possibility of large non-climactic contamination in global temperature averages, particularly due to local effects of urbanization, development, and industrialization (see, for example, McKitrick & Micheals 2004, 2007; De Laat & Maurellis 2006; Schmidt 2009; and McKitrick & Nierenberg 2010.) Here we present an approach that uses rural sites to build a global average that can be compared to an average that includes possibly UHI contaminated sites.

We consider two sets of stations, a complete set and a set restricted to sites that are far from urban regions. To accomplish this we use the MODIS urban classification map (Schneider et al. 2009, 2010; described below) combined with our large collection of temperature stations. This is a larger set of stations than previous analyses have included. We first describe the datasets, and place the problem of estimating urban heating in context by conducting an investigation of the linear trends in this large set of temperature stations. Our primary analysis of the significance of site selection restricted to non-urban stations is then performed with the Berkeley Earth Temperature averaging procedure.

2. Data

The analysis presented here is based on merged monthly average temperatures from the Berkeley Earth Surface Temperature Study dataset. This dataset consists of measurements from 39,028 unique stations, which are merged from 10 preexisting data archives (Rohde et al., 2011). We classify these stations as rural or non-rural by comparing their locations with the MODIS 500m Global Urban Extent classification map (MOD500) of Schneider et al. (2009, 2010). Schneider et al. used Collection 5 MODIS 500-m resolution satellite imagery to classify land use as urban using supervised decision trees, a statistical learning algorithm that they trained using a set of sites with known land cover type. They define urban areas to be “places that are dominated by the built environment”. Urban heat islands are primarily a result of replacing the natural (soil, vegetation, etc.) surface of the land with buildings and manmade ground surfaces, which makes the MOD500 dataset potentially quite helpful in identifying built-up regions that may be subject to urban heating. It may provide a criterion that is less socio-economically biased than night lights data, therefore it offers an alternative to the approach used by GISS. The MOD500 map is available as a raster image, providing a binary classification (*urban* or *not urban*) for a global grid with pixels of size 15 arc-seconds. According to Potere et al. (2009) the MOD500 map outperforms other global urban maps in terms of predicting city size and per pixel agreement on a sample of known cities with population greater than 100,000.

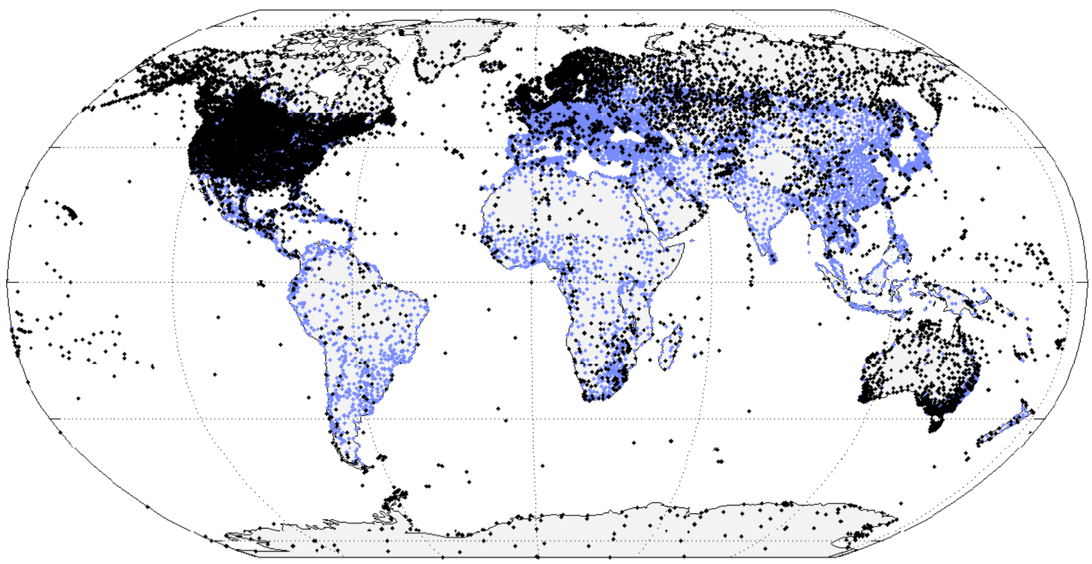
Unfortunately, a portion of station locations in the Berkeley Earth merged dataset are reported only to the nearest tenth of a degree in latitude and longitude. This makes it impossible to identify each station as definitively urban or rural using the fine resolution MOD500 map. This imprecision in site location could yield a site which is urban being labeled as rural. An alternative, which we adopt here, is to analyze the urban-rural split in a different way. Rather than compare urban sites to non-urban, thereby explicitly estimating UHI effects, we split sites into very-rural and not very-rural. We defined a site as “very-rural” if the MOD500 map showed no urban regions within one tenth of a degree in latitude or longitude of the site. We expect these very-rural sites to be reasonably free from urban heating effects. Of the 39,028 sites, 16,132 were classified by this method as very-rural.

The station locations and their classifications are displayed in Figure 2. Although the continental USA looks saturated with very-rural sites this is due to the density of stations in the USA and overplotting of points. In actuality 18% of the stations in the USA are classified as very-rural by our method.

We note that the imprecision in station locations also affects the GISS night lights analysis, with approximately 1/8th of the stations in their study also being positioned to only the nearest tenth of a degree. The GISS analysis (Hansen et al., 2010) does not explicitly address the possibility that station types might be misclassified due to geolocation uncertainties that far exceed to the 30 arcsecond resolution of the night lights maps.

The MOD500 map identifies urban areas circa 2001. It seems reasonable that an area that is rural in 2001 has been so for the past century, but the same isn't true for urban areas in 2001. Some stations labeled urban could have urbanized prior to the start of their record and while they may be hotter than nearby rural area they may not necessarily show excess warming trends. The not very-rural sites are a mix of sites, including some which are truly urban and exhibit urban heating, others that are truly urban but do not exhibit urban heating (or that warmed due to urbanization prior to the start of their temperature record) and, also, rural sites located near urban regions. Examining the temperature record of very-rural sites allows us to estimate the global average based on sites well removed from sources of urban heating.

Figure 2 Locations of the 39,028 stations in the Berkeley Earth data set



3. Station Trend Analysis

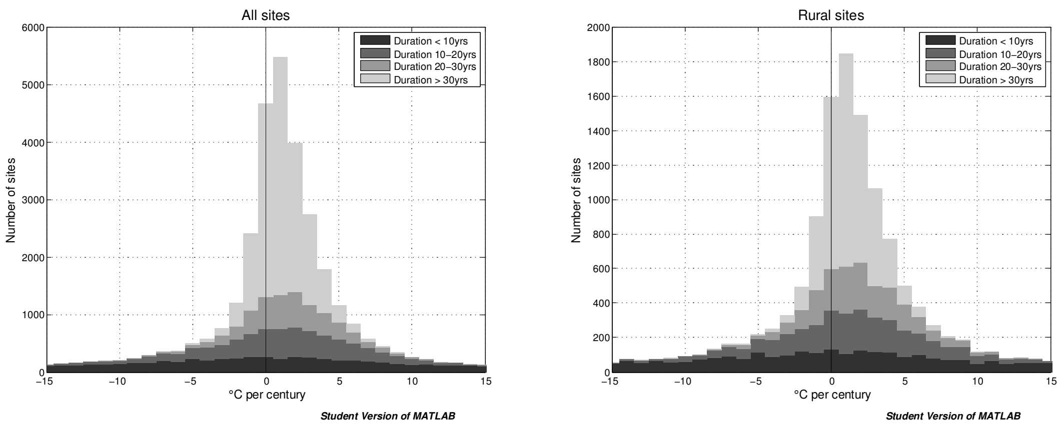
A straightforward way to gain insight into the temperature trends associated with the stations in very-rural locations is a station trend analysis. We apply a very simple procedure in which a straight line is fit (using least squares minimization) to the temperature record for each station; the slope of this line is called the temperature trend for that station. The distribution of these trends can then be examined. For the purposes of this simple analysis, we do not consider whether any individual trend is statistically significant. In fact, we expect many trends are driven primarily by statistical fluctuations and noise, but by looking at such trends in the aggregate we can yield some basic insights about the population of station time series from which they are derived. A primary limitation of the trend analysis is that it is an average over stations and time, not an average over the true land distribution of the Earth or the distribution of recording stations though time. Nevertheless, this technique has the advantage of simplicity, and it illustrates important features of the temperature record.

For the station trend analysis, we used the data set of the Berkeley Earth project consisting of the raw data for each of 39,028 sites with seasonality removed. (The data had cycles with one year periods and harmonics of that period subtracted; that reduces errors from end effects; see Rohde et al. 2011.)

A histogram of the station trends is shown in Figure 3a, categorized by station record length. The distribution is broad with a width substantially larger than the mean; 67% of the slopes are positive, i.e. there are about twice as many warming stations as cooling stations. The dispersion is larger in the records of short duration, but even in the stations with records longer than 30 years 23% have negative trends.

The reason the records with the shortest duration (< 10 years) have the broadest distribution is that short term variations in individual time series are typically several degrees C, so a 2 degree fluctuation during a 10 year period could yield an apparent "trend" of 20 degrees per century. There were other causes for spuriously large trends; for example, in some samples there is a gap in the data lasting for years or decades, with a large jump in the value of the average temperature when the data resumes. This is likely due to undocumented station changes and/or the reuse of an existing site identifier. Very large trends are largely non-physical and trends more extreme than $\pm 15\,^{o}$C/100yr are excluded from the histogram but not the following calculations; this excludes about 21% of all sites but only 1.4% of sites with records longer than 10 years. To avoid the outliers unduly influencing of estimates of the center of the distributions we compare medians rather than means.

Figure 3 Temperature trends



The median trends with standard errors are given in Table 1.

Table 1. Estimates for the median trends for all and rural stations[2]

Station characteristic	Median trend in °C/100yr	
	Sites with ≥ 2 months	*Sites with >30 years*
all	0.98 ± 0.04 (n = 38898)	0.97 ± 0.03 (n = 14950)
very rural	1.08 ± 0.08 (n = 16068)	1.09 ± 0.05 (n = 4791)
	Difference in median trend in °C/100yr	
all – very rural	-0.10 ± 0.06	-0.12 ± 0.04

[2] The number of stations in each group is shown in brackets. Stated errors are 2σ uncertainty estimated from interpenetrating samples.

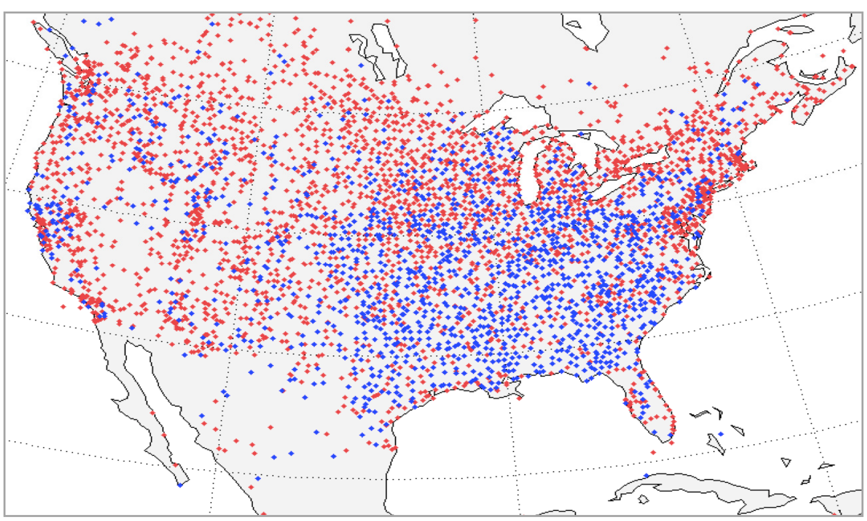
The standard errors were obtained by randomly assigning each station to one of 50 roughly equal sized groups, calculating the median trend in each group, and using the standard error of the group medians to estimate the standard error in the overall median.

In this table we see evidence of “global warming.” Using all the records there is a median warming trend of 0.98 ± 0.04 ^{o}C/100yr. There is a statistically significant difference between the median of the complete data set and the very rural subset. The value for the difference, -0.10 ± 0.06 ^{o}C/100yr, is in the opposite direction expected from urban heating. In part, the difference observed in this simple analysis may simply reflecta different spatial and temporal distribution of rural and nonrural sites rather than an indication of rural heating. We emphasize that this section presents only a rough analysis, since there is no accounting for station density and different stations reporting during different time periods.

Although trend analysis is a very crude way to look at global temperature change, it illustrates important features of the data. The histograms show that the global warming is in some ways a subtle effect compared to the weather and instrumental noise that can affect individual stations. The distribution of trends in the station data is so broad that many simultaneous measurement sites are necessary in order to properly characterize the effect; a handful is not enough. With a full width at half max of about 5 ^{o}C per century, the trend histogram suggests that averaging one hundred independent stations would yield a 1σ trend uncertainty of about $5/\sqrt{100} = 0.5$ ^{o}C/century – just barely enough to resolve the collective temperature trend. With over 30,000 stations, we do much better. The trend analysis also supports the view that the spurious contribution of urban heating to the global average, if present, is not a strong effect; this agrees with the conclusions in the literature that we cited previously.

The positive and negative sloped stations are mixed together, even though some light clumping related to underlying climate patterns also occurs. This is seen in Figure 4, a map of the stations in the United States with at least a 70 year duration, with red + signs indicating stations that showed net warming over their record, and blue circles showing stations with net cooling. As with the world sample, the ratio of warming sites to cooling ones was in the ratio of 2:1. Though some clumping is present, it is nonetheless possible to find long time series with both positive and negative trends from all portions of the United States. This reemphasizes the point that detection of long-term climate trends should never rely on individual records.

Figure 4. Map of stations in and near the United States

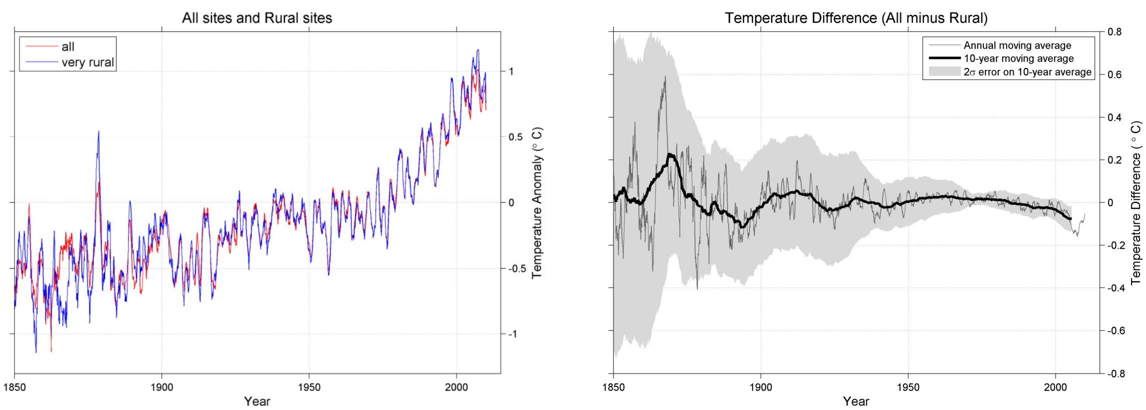


4. Berkeley Earth Surface Temperature Global Average

For a more rigorous estimate of the urban heat island effect, we performed a complete global land temperature record reconstruction using the Berkeley Earth Surface Temperature averaging methodology (Rohde et al., 2011). Briefly, this includes the following steps. Metadata, when available, are used to break records at changes in time of observation, station moves, and at gaps in station data to avoid systematic biases. Stations are weighted according to their spatial distribution, taking into account their spatial correlation, so that regions with a high density of stations are not overweighted. Statistical uncertainty in monthly averages is produced by a standard technique relying on repeated recalculations of the temperature time series using random subsamples of the temperature stations. The temperature averages from these subsamples can also be used to estimate uncertainties on other statistical quantities such as, linear trends. We evaluate the effect of very-rural station siting on the global average by applying the Berkeley Earth Surface Temperature averaging procedure to the very-rural stations. By comparing the resulting average to that obtained by using all the stations we can quantify the impact of selecting sites not subject to urbanization on the estimated average land temperature.

In the full averaging procedure sites have their weights adjusted via an iterative procedure which compares their time series to the reconstructed T_{avg}; sites that deviate substantially from the group behavior have their weights reduced for the next iteration (see Rohde et al. (2011) for details). Thus, the influence of sites with anomalous trends, such as urban heat island effects, should be reduced by the averaging procedure even when sites with spurious warming are part of the dataset being considered. In Figure 5A we show the comparison of the temperature estimate for all the land sites (in red) with the temperature trend for the very rural land sites (blue). The difference between the two plots is shown in Figure 5B. An urban heat island bias would be expected to show itself as an upward trend in 5B; none is seen.

Figure 5. A. Berkeley Earth global temperature averages, normalized to zero mean for 1950-1980. **B** is the difference between the two curves in **A**.



Over the bulk of the record, the difference between the two calculations is consistent with zero within 2 standard errors (shown as the grey area on Figure 5B). However, at late times a slight downward trend is observed. Over the period 1950 to 2010 (covering most of the data in Fig 3, and during which anthropogenic interference with climate is considered most acute) the temperature difference (Fig 5B) had a slope of -0.19 ± 0.19 °C/100yr, broadly consistent with the trend of -0.10 ± 0.06 °C/100yr obtained from the crude station slope analysis (95% confidence intervals). This value is less than the urban heating effect estimated by the prior groups of +0.01 to +0.1°C per century.

5. Discussion

We observe the opposite of an urban heating effect over the period 1950 to 2010, with a slope of -0.19 ± 0.19 °C/100yr. This is not statistically consistent with prior estimates, but it does verify that the effect is very small, and almost insignificant on the scale of the observed warming (1.9 ± 0.1 °C/100yr since 1950 in the land average from figure 5A).

Only during the very recent period does the difference between the very-rural station average and the average from the complete data set become statistically significant. This would suggest the existence of a residual urbanization bias in the Berkeley Earth averaging technique, albeit one whose sign is contrary to the traditional expectation. We hesitate to offer any explanation for this specific difference given the relatively short interval of deviation until a more detailed investigation has been made. The natural explanations might require some recent form of “urban cooling”and/or “rural warming”. Alternatively, the effect might be related to some subtle difference in the spatial coverage of rural and non-rural sites at recent times; however, preliminary analysis tends to make this latter suggestion appear unlikely.

The stations we identified as “very rural” provide good spatial coverage of the land surface of the globe and an average based solely on these stations provides a reconstruction robust to urban heating. Our conclusion that the effect of urban heating on the global trends is nearly negligible agrees with that obtained by Parker (2010) in his review of methods for avoiding, assessing and mitigating the influence of urban heat islands on global trends. Our value is smaller than that HadCRU, who estimated a rise of 0.05 °C per century (Brohan et. al. 2006); however, their estimate refers to uncorrected effects in homogenized data, whereas ours applies a difference process to raw data. Similarly for NOAA; their procedures are meant to eliminate urban heat effects, and they estimate residual urban heating of 0.06 °C per century (Menne et al., 2009). GISS applies a correction to their data of 0.01 ^{o}C per century, but the important fact is that this correction is small on the scale of global warming.

The huge effects seen in prominent locations such as Tokyo has caused concern that the T_{avg} estimates might be unduly affected by the urban heat effect; yet we find that was not true. This is not surprising; the fraction of the Earth's land area denoted as urban by the MOD500 analysis is only 0.5%. Even if all these urban areas had a heat island effect as large as that of Tokyo, roughly 3^{o}C per century, the contribution to the world average once properly weighted for land area would be only 0.5% of that, or 0.015 ^{o}C per century. The station slope analysis shows that there are also a large number of sites with negative trend lines. Some of these are due to microclimate, but others could be due to various biases, including urban and rural cooling effects. For example, if an asphalt surface is replaced by concrete, we might expect the solar absorption to decrease, leading to a net cooling effect. Rural areas could show temperature biases due to anthropogenic effects, for example, changes in irrigation.

We note that our averaging procedure uses only land temperature records. Inclusion of ocean temperatures will further decrease the influence of urban heating since it is not an ocean phenomenon. Including ocean temperatures in the Berkeley Earth reconstruction is an area of future work.

6. Acknowledgements

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8. Figure Captions

Figure 4 Annual running mean of monthly temperatures at Tokyo compared to a global land average for 1900-2010. (Tokyo station id: wmo_47662).

Figure 5 Locations of the 39,028 stations in the Berkeley Earth data set, plotted in blue. Stations classified as rural, at least 0.1° from an urban area in the MOD500 map (Schneider et al. 2009, 2010), are plotted on top in black.

Figure 6 Temperature trends. A histogram of the trends is shown in (a) for all land stations in the Berkeley Earth data set of 39,028 records, and (b) only rural stations, defined as those that are at least 0.1 degrees in latitude and longitude from a MOD500 urban region. The x-axis limits are chosen to include the central 80% of trends in (a).

Figure 4. Map of stations in and near the United States with at least 70 years of measurements; red stations are those with positive trends and blue stations are those with negative trends.

Figure 5. A. Berkeley Earth global temperature averages, normalized to zero mean for 1950-1980. The dotted (blue) estimate is based on all sites; the solid (red) estimate is based on the very rural sites (those more than 0.1 degrees distant from a MOD500 urban region). B is the difference between the two curves in A. The thin line shows a one-year running

average; the thicker line shows the 10-year running average. The grey area shows twice the standard error on the 10-year running average.