Changing perspectives: Significance of long-term temperature observations in major cities

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1. Introduction

Urban areas cover barely 1 % of the earth's surface. Yet, almost a quarter of the world's population lives in cities. Although welfare is more accessible in urban areas over rural areas, vulnerability is high in cities because of its dense artificial configuration. Specifically, warmth is detrimental to a city's sustainability and function. Uncomfortable atmosphere is brought about synoptically and locally. Two fields have emerged in the past decades to understand the urban atmospheric environment, urban climatology and climate change; where the former deals specifically from within, whereas the latter focuses on the global change in climate. Unfortunately, a gap remains between implementation of both studies. . For climate change experts, urban heating has minimal contribution to the global average temperature and trend, largely triggered by human-induced changes in the atmosphere composition (Karl and Trenberth, 2003). Due to the local influence of urban surroundings, temperature observations from weather stations at urban areas are considered noise in the estimation of global surface temperature (Hansen et al., 2010). For urban climatologists, it is difficult to generalize the influence of climate in cities due to the lack in historical temperature data in most cities of various socio-demographic and climatic backgrounds. Although synoptic condition influences the evolution of urban heat island (UHI) (Oke, 1982), the atmospheric feedback of urban areas to climate change is unclear insofar. As such, climate mitigation strategies in developing countries rely on generalized methods which may not necessarily be applicable for all cities. An alternative to observation is mesoscale modelling. However, setting up urban parameters is loosely assumed in most cases although recent improvements have been done. The potential for using mesoscale models is high but may take a little more time for preparation. Here, we focus purely on observations.

This study aims to utilize common tools from climate change studies, specifically global surface temperature datasets, and understand the UHI trends and its dependence to climate. Gridded global surface temperature datasets are initially used to estimate the anomalies relative to a base period, commonly from 1960s. After adjustments, the sources to create these datasets are observation networks of surface temperature. Adjustments are necessary to filter out inhomogeneity, discontinuities, and unrealistic observation. For example, the Goddard Institute for Space Studies (GISS) dataset (Hansen et al., 2010) adjusts stations based on its land classification (urban, peri-urban, and rural) by nigh-light images. The Berkeley Earth Surface Temperature (BEST) dataset uses automated process to identify dubious raw data and conduct a series of adjustments to include short and discontinuous records via weighting process (Rohde et al., 2013). In the present analyses, BEST dataset is used to estimate the UHI trend.

2. Data and Methodology

Data used in the analyses are:

1. Monthly BEST land gridded and quality-controlled source data for minimum temperature (T_{min}), maximum temperature (T_{max}), and average temperature (T_{avg}) (Rohde et al., 2013);
2. World map of Köppen-Geiger climate classification (Rubel and Kottek, 2010)
3. LandScan (2013)™ High Resolution global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy; and
4. Total Primary Energy Consumption (2012) from the International Energy Agency.

BEST was used to estimate UHI trend, while the rest are used to analyze the datasets. The reason for selecting BEST apart from other global surface temperatures is due to its up-to-date implementation and release of gridded absolute temperature data, unlike GISS which only provide gridded anomalies. Traditional method of measuring UHI is through observed temperature differences between urban and rural stations. However, this approach is slightly modified by assigning gridded surface temperature data as substitute to surrounding rural stations. Furthermore, temperatures are not directly subtracted but rather the temperature trends coming separately from the station and its bounding grid; this is similar to climate change studies wherein specific temperature values of periods are of less significance compared to the long-term trend. Three intermediate sources are provided by BEST, namely: raw data (multi-valued and single-valued), quality controlled, and breakpoint adjusted. BEST grids

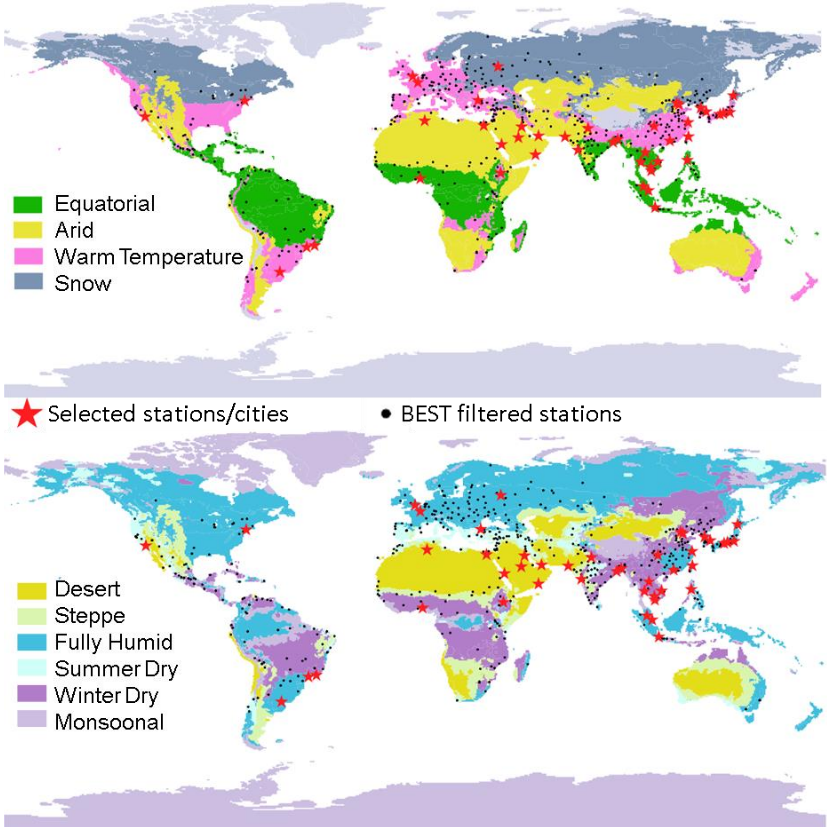

Fig. 1 Selected BEST stations used in this study overlaid on Köppen-Geiger climate classification (1976 – 2000) by Rubel and Kottek (2010) by main classes (above) and precipitation classes (below)

were estimated from breakpoint adjusted data which smoothed out urban stations. To get rid of unrealistic values from the raw data, here, we use the quality controlled station data.

In summary, procedure to estimate the UHI trend is as follows:

1. Acquire quality-controlled station and grid data for T_{min}, T_{max}, and T_{avg} for selected stations (fig. 1). The target period selected was from 1960 to 2010 (study period) when anthropogenic contribution to climate change was high.
2. Select stations situated within the top 30 list of megacities in World Population Prospects (2012) of the United Nations, and a few Southeast Asian cities and Middle Eastern cities (red stars in fig. 1). Unfortunately, a few cities rely on airport data were used on the condition that they are within city boundaries.
3. Using simple least-squares regression of year fraction (independent) and temperature (dependent), the slope (fig. 2) calculated for both stations and grids are multiplied by 100. The resulting product is assumed in this study as the 100-yr trend of T_{min}, T_{max}, and T_{avg}.

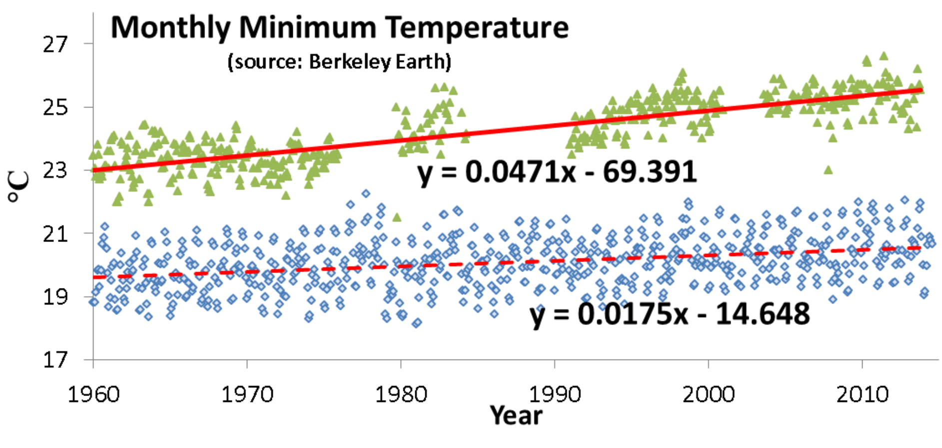

Fig. 2 Jakarta station temperature trends and its bounding grid trend.

4. To estimate the UHI trend, we subtracted the trends estimated from the station to that of the grid containing the station (fig. 3).

Not all stations in BEST were used since the stations comprised of both rural and urban stations, as well as observations taken from sea. Only observations on land were considered. Rural stations were filtered out based on population. Sum of population within a 5-km buffered region surrounding each station were calculated (fig. 3). Only stations with calculated sum greater than 200,000 remained. Also, stations with less than two-thirds of monthly values and station temperature trends exceeding ±10°C/century within the target period were assumed to provide unrealistic estimates and ignored in the analyses. Eventually, only 626 stations out of approximately 40,000 stations were found surrounded by the assumed population threshold (black dots in fig. 1).

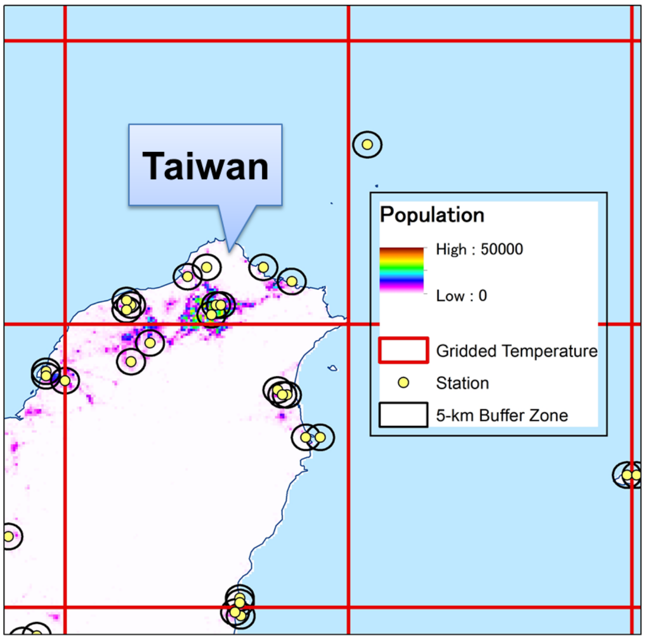

Fig. 3 Example of the stations used in BEST and its bounding temperature grids. Circles represent the 5-km buffer zones. Colored contours represent the LandScan population data.

The trends of UHI were later grouped based on the two types of climate zone classifications: main class, and precipitation class (Rubel and Kottek, 2010). Additionally, consumption with a 10-km buffer region for the selected megacities was estimated based on equation,

$$En = \left(\frac{pop_{10km}}{pop_{country}}\right)\left(En_{country}\right) \tag{1}$$

where En refers to the energy consumed annually by the populace surrounding the station. pop_{10km} and $pop_{country}$ refers to the population of the surrounding station and the country it belongs, respectively. $En_{country}$ refers to the total annual primary energy consumption of the country in which the station belongs provided by the International Energy Agency. The estimated energy consumption of the surrounding station is later used to compare with the UHI trends.

3. Results and Discussion

A limitation of this approach was the utilization of airport-acquired data. Some cities in the analyses only have reliable stations in airports within the city. Nevertheless, the trend can be determined. Since the focus was on the determination of trends, the selection was based only on one deciding factor, the quantity of monthly observed values.

The discussion will be divided in two. The first part will focus on selected cities (fig. 4) to provide an overview of the range of UHI trends by targeting stations within megacities and cities of different climates. The second part considers BEST stations following the population criteria (see fig. 1 and methodology) and the climate zones.

For the first part, only one station was used to represent each city. Some cities contain multiple stations. Furthermore, some selected stations have starting periods after 1960s, such as: Karachi (since 1991), London (1988), Sao Paulo (1973), Rio de Janeiro (1973), Calcutta (1991), and Taipei (1973). Height adjustments were not conducted in this study due to uncertainty in the observation heights and the ground topography.

The BEST grid is assumed to represent the temperature in synoptic scale. Figure 4 shows the trend differences between the station and the grid for all selected cities. More than 80 % of the average temperature trends estimated from the selected stations exceed that of its bounding grids. T_{min} trends have the largest differences, while T_{avg} trends had the least. Common understanding is that nighttime is usually the period of peak UHI due to the trapping of heat in urban areas and nocturnal anthropogenic activity. This phenomenon indirectly explains the larger UHI trend measured from the T_{min}, usually a measure of nighttime temperatures. In climate change studies, the difference between T_{max} and T_{min} will decrease in the future. In terms of positive T_{max} trend differences

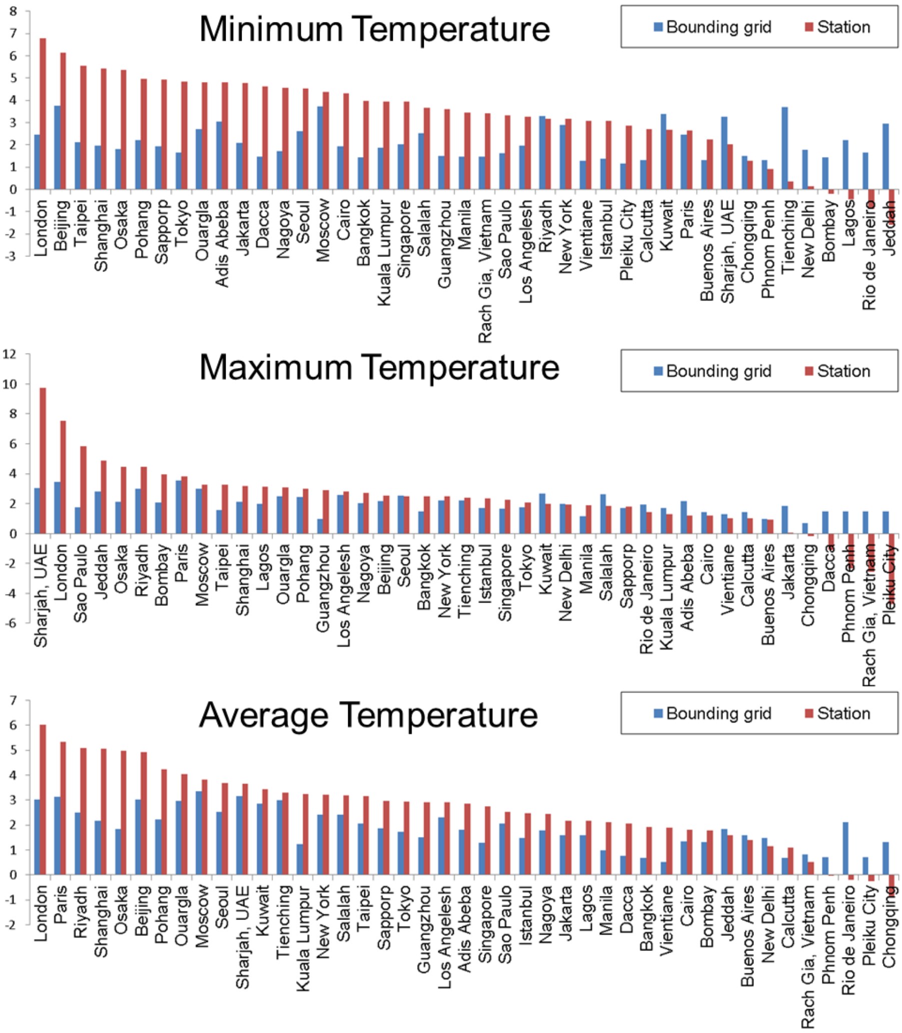

Fig. 4 Differences between the surface temperature trends of the station (designated by the city it belongs) and its bounding grid for the selected BEST stations shown in fig. 1. Cities are sorted based on the station's T_{min} trend.

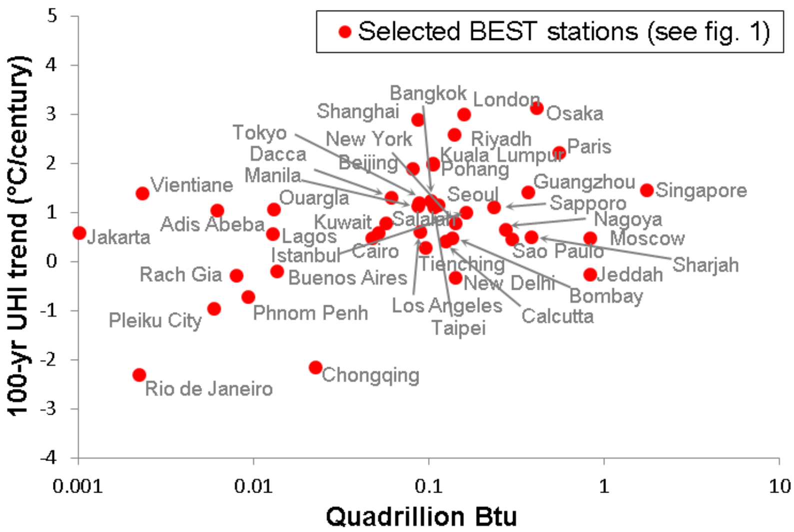

Fig. 5 Estimated UHI trend (from average temperature trend differences) vs. proportion of energy consumed by the population surrounding the station (see methodology) for selected BEST stations shown in fig. 1

between station and its bounding grid, peak daytime temperatures in urban areas, represented by T_{max}, appear to have lower differences with the grids than the differences in T_{min}. Furthermore, it seems more stations have slightly lower T_{max} trends than that of its bounding grids.

Being able to estimate the UHI trend is not the ends but rather an opportunity to understand the difference in thermal behavior among cities/stations. One possible explanation for the lower differences in T_{max} trends is the larger incoming shortwave radiation in daytime over nighttime which is equally distributed throughout the region.

It is difficult to validate the estimated UHI trend in London without looking into the local condition surrounding the representative station. A possible reason is the different analyses period of station representing London compared to other stations. The rate of urbanization varies on every period and every country – Calcutta has relatively lower trend in spite having 1991 as the starting period. Also, the cities listed at the right-side of fig. 4 seem to indicate cooling in city rather than warming. To explain this further would require detailed understanding of the local and synoptic conditions surrounding the station; other datasets (e.g. other parameters aside from temperature, socio-economic characteristics) can be tested for its relationship with the UHI trend. Here, we show test our estimated trends relationship with anthropogenic energy consumption and the climate zone of the stations.

One common predictor for anthropogenic heating is energy consumption (Allen et al., 2011). Figure 5 shows the relationship between the total annual energy consumption (calculated using eqn. 1) of a buffered region surrounding the selected stations in fig. 4 and the UHI trend estimated from the T_{avg}. Although statistically has a positively low coefficient of determination (R^2=0.1725), a logarithmic relationship can be deduced between variables. Low consuming stations can have below UHI trends. On the other hand, high energy consuming stations have a tendency for UHI to be much higher in the future. A possible extension to this approach is to replace the energy consumption to its estimated trend.

After analyzing individual stations, Statistical values of the UHI trends were calculated from all filtered BEST stations. Each station is assigned with one climate zone and one precipitation class. Fig. 9 shows the statistics of UHI trends by climate. For UHI trends estimated using T_{min}, equatorial and arid regions have higher mean/median UHI trends than regions classified with warm temperature and snow. Grouped in precipitation class, deserts tend to have the highest UHI trends estimated by T_{min}. On the contrary, stations with dry summer have least values. For UHI trends estimated using T_{max}, more stations were found to exceed whisker limits (i.e. more outliers than the T_{min}). Furthermore, arid and desert regions show negative mean/median values, opposite from UHI trends estimated from T_{min}. UHI trends estimated from T_{min} and T_{max} could mean nighttime or daytime UHI trend, respectively. Separating nighttime and daytime show more significant UHI trend values than the average UHI trend (via T_{avg}). Average UHI trend shows little variation among climate zones. Although median/mean UHI trends have lower than 1°C/century values, a few stations manifested large UHI trends. Further analysis is to be conducted to explain the differences in UHI trends temporally and spatially.

4. Conclusion and Recommendation

Smoothing out stations within urban areas in the construction of gridded global surface temperature datasets can be a useful procedure to rapidly estimate the trend of UHI in a global scale. In this study, we conduct the first attempt to examine the potential of global surface temperature dataset (Berkeley Earth Surface Temperature, Rohde et al., 2013) and its intermediate source to estimate the UHI trend of cities, assumed in this study to be equal to the absolute temperature trend difference between the station and its bounding grid. Three values of UHI were acquired based on the three available temperature statistics: minimum temperature, maximum temperature, and average temperature. UHI trends of selected megacities, Asian, and Middle Eastern cities were selected for testing. Differences were found with varying intensities for each available temperature statistics and city. A weak logarithmic relationship was found between the trend and energy consumption.

After filtering out the stations used to derive the global surface temperature dataset, only less than 2 % of the stations were detected to represent highly populated areas. These stations were grouped based on climate classifications. Stations in arid (desert) regions were found to have the highest nighttime UHI trend but with a negative daytime UHI trend. Stations in equatorial regions also have relatively higher nighttime UHI trends than that of warm temperature and snowy regions.

Statistical significance tests are to be conducted to validate the derived trends and to explain the extremely large UHI trends of a few stations. The methodology can also be applied to other global surface temperature datasets with available absolute temperature data. Other meteorological datasets can also be compared with the derived UHI trends, such as measured wind velocity, precipitation, or humidity from synoptic reports.

The results can also be calibrated or confirmed with mesoscale models, as long as acceptable initial surface boundary is acquired for all cities. The current methodology is a simple method which needs further developments. Nevertheless the results in this study can be useful for researchers who wish to determine future areas of UHI study and possibly contribute to the linking of the fields, urban climatology and climate change studies.

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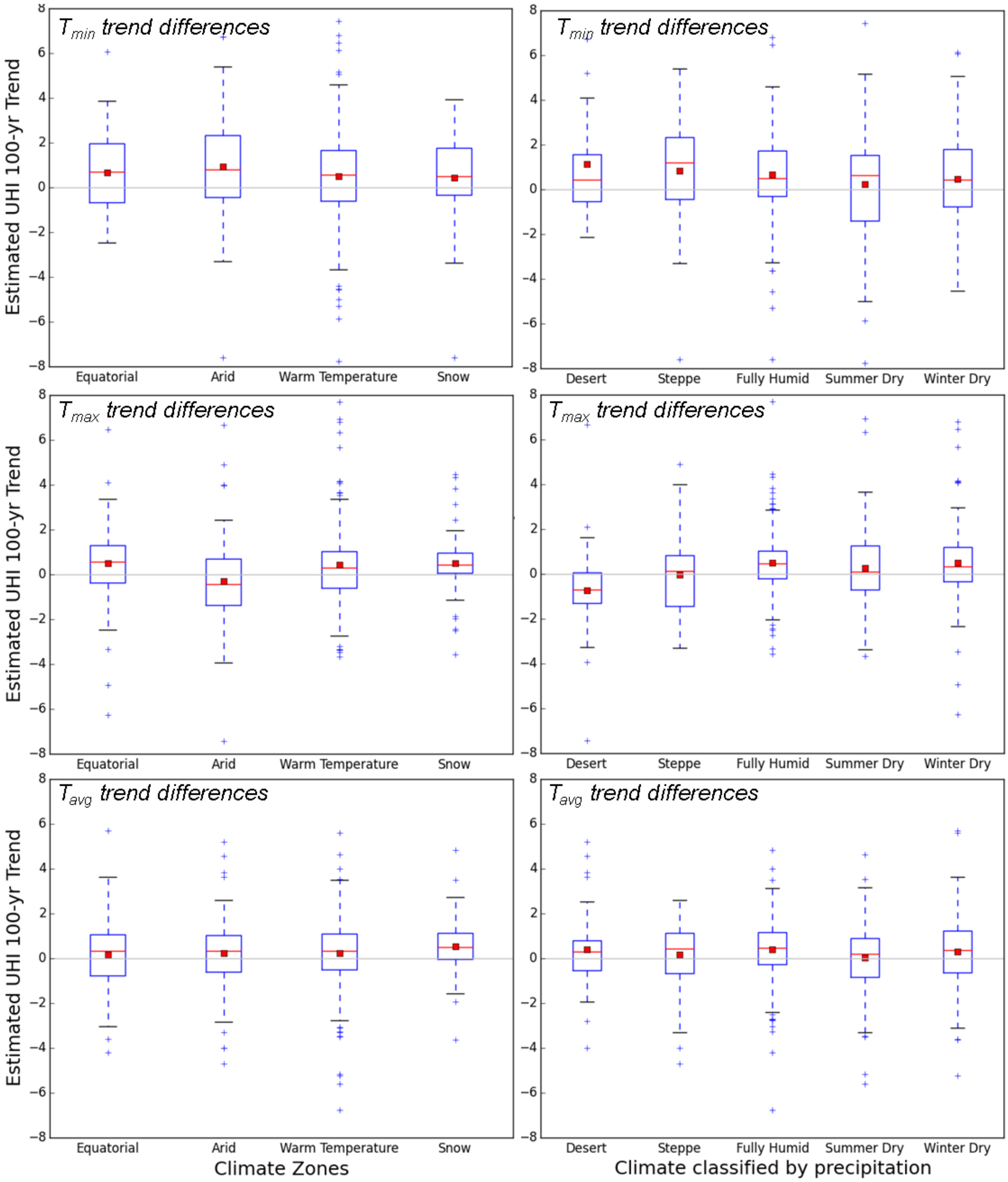

Fig. 6 Box-whisker of estimated UHI 100-yr trend grouped per Köppen-Geiger climate classification classes. Whiskers were limited up to 1.5×(Interquartile Range) beyond the first and third quartiles.