Urban heat islands: Global variation and determinants in hot desert and hot semi-arid desert cities

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ABSTRACT

The urban heat island (UHI) phenomenon affects local, as well as regional and global climates, yet most of what is known about UHI comes from local case studies using methodologies that vary considerably from case to case. We present the first global examination of UHI for hot desert and hot semi-arid desert cities using data and methodology consistent across 159 cities. By using a global approach it is apparent that desert cities cluster at the edges of climate zones. As suggested in the case-study literature, the majority, but not all, desert cities have negative UHI during the daytime, but positive at night. Vegetation in the cities, compared to bare ground in the rural buffer is an important contributor to the negative daytime UHI. But there are a variety of other biophysical factors including nearness to an ocean, the Humboldt current, elevation, and the Indian monsoon, that are important. Even after all the biophysical factors are controlled, development, whether measured by GDP, energy consumed or electricity consumed, reduces the size of the oasis UHI effect, confirming that anthropogenic effects go beyond planting and irrigating vegetation.

INTRODUCTION

The urban heat island phenomenon (UHI) is well-known, with urban areas warmer than their surrounding rural countryside. Cities produce their own microclimates, affecting local behavior, health, and economies as well as regional and global climates. The reasons for UHI include building and road materials absorbing radiant heat in the daytime, slowly releasing it at night; HVAC systems and motor vehicles generating heat; lower proportion of surface area covered in water; manufacturing activities releasing heat; and human metabolism itself. And there is a positive feedback loop as temperatures increase more energy is used to cool workplaces and dwelling units.

Most of what is known about the UHI effect comes from case studies of a single city, with regional and global relationships resulting from literature reviews of case studies[1]. Most case studies are in temperate zones, with even less known about cities in the (sub)tropics (Roth

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[1] An exception is the analysis by Ping and coauthors (2011) of 419 global cities with populations larger than 1,000,000 using MODIS data. But they did not examine the difference in land surface temperatures (LST) between the urban area and the surrounding rural buffer, as is common in UHI studies. Rather they compared the LST of the urban core with the suburban ring.

2007) and/or desert cities. Among the few reports available for desert cities are hints that desert urban areas may be *cooler*, rather than warmer, than their rural surroundings, especially during the daytime with the suggestion that vegetation patterns are likely responsible (Bounoua et al. 2009; Imhoff et al. 2010; Jenerette et al. 2010; Jin, Dickinson and Zhang 2005; Lazzarini et al. 2013; Roth 2007; Saaroni and Ziv 2010). Relying on case studies, especially the few that exist for desert cities, has the drawback that the few cities studied are not globally representative and temperature measurement procedures vary across cases (Santamouris 2015; Stewart 2011; Wienert and Kuttler 2005). Further, case studies allow one to see the effect of factors that vary within the case site, but not the effects of factors that vary across cities but are constant within the case; you can see the tree, but not the forest.

Understanding the anomalous negative UHI, or oasis effect, for desert cities is important from several perspectives. Desert cities are already hot and projected to get hotter. The availability of water is a critical issue in arid climates. One fifth of the global land area is arid or hyperarid. U.S. desert cities are growing faster than cities in other climate zones (Sutten and Day 2004). And since more than 90% of the global population residing in the desert are in developing countries with high rates of rural to urban migration, rapid growth in desert cities is likely (United Nations Environment Programme 2006).

Here we present the first systematic, global investigation of urban heat index (UHI) variation across 159 desert cities in the hot desert and hot semi-arid climate zones – BWh and BSh zones respectively in the Köppen-Geiger climate classification (Peel et al. 2007). We use MODIS and GRUMP data which provides comparable global data across cities (Balk 2009; Jin 2012). Not only do our results show that vegetation differences are crucial in determining desert UHIs, but also that a range of additional biophysical and socioeconomic factors are also important determinants. Further, using globally consistent land surface measurements and demographic data, our method shows how global UHI studies are possible without resorting to aggregating a set of idiosyncratic case studies.

CITIES AND DATA

Two data sources are used to create UHIs for 159 desert cities. The location of urban areas, as well as their population counts, come from GRUMP, which uses the 1994-95 stable city-lights data set from NOAA's nighttime lights satellite data, census data from the national statistical offices of countries (2000-4 where available, and earlier if necessary), and a wide assortment of maps and gazetteers (http://sedac.ciesin.columbia.edu/data/collection/grump-v1). See Balk et al. 2005 and Balk 2009 for GRUMP construction details, and Dorelien et al 2013 for a cross-check of locational and boundary quality against an international survey effort. GRUMP's raster data provides global population information, with a rural-urban classification, for 30 arc-second (1km) pixels. We examine cities with a population of 50,000 or more. Because night-lights data can "overglow" into the surrounding rural areas, especially in developed countries, thus creating ambiguity about the urban extent boundaries[2] (Dorelein et al. 2013; Zhang and Seto

[2] Boundary definition is a general problem in UHI research (e.g., Balk 2009; Chow and Svoma 2011).

2013), we set urban boundaries with GRUMP urban pixels containing a population of 500 or more.

We obtained year 2000 land surface[3] temperature (LST) from the EOS-Terra-MODIS V5 (MOD11C3) composite product. The MODIS V5 LST product is monthly composited and averaged based on clear-sky observations at a spatial resolution of 0.05° (~5600 m). The MODIS V5 LST is well-validated. For example, Wan (2008) reported a high consistency between MODIS V5 LST product and in situ measurements with a less than 0.5 K RMS difference. To insure temperature measurement stability across pixels for a city, we choose cities that contain a minimum of 5 MODIS Terra LST pixels. We use both daytime, 10:30, and nighttime, 22:30, temperature data, summer (July 1-31 in the Northern Hemisphere and December 1-31 in the Southern Hemisphere) and winter.

Since MODIS is an optical instrument, clear-sky observations are necessary, and that is why a 31-day composite is used. For 17 cities in India there were one or more MODIS pixels for which for the entire month of July clear-sky observations were not available. For these pixels with missing data, we used a simple interpolation technique by iteratively applying a 7 × 7 MODIS pixel low-pass filter over the missing data pixels to obtain LST estimates from neighboring MODIS pixels.

The geographical location of the 159 cities examined is shown in Figure 1, along with the spatial extent of the BWh and BSh climate zones. Desert cities cluster on the edges of the BWh and BSh zones, rather than being dispersed evenly across the zones. This edge clustering has not been previously reported and presumably is related to the location of available water – both ground and atmospheric. It indicates the potential fragility of desert cities to climate change.

<Figure 1 about here>

The urban heat index is defined as: UHI = urban LST – rural buffer LST. Because cities typically have a transition zone where some urban features are mixed with rural land use, it is important for the rural buffer to be located some distance from the urban boundary. We use a rural buffer of 30-35 km around the urban boundary. Figure 2 shows the urban extent and rural buffer for Khartoum, Sudan. In cases where the buffer intersects a large water body, the part of the buffer over water is not included in the calculation of the buffer's temperature. To minimize the effect of substantial elevation differences between a city and its rural buffer, for each city, we calculated the difference between the elevation of each pixel in the rural buffer and the mean elevation of the city. This generates an elevation difference buffer (EDB). If a pixel in the EDB has an elevation value more than two standard deviations below or above the urban mean, the temperature for the pixel encompassing that particular elevation pixel is not included in the calculation of the UHI index for that city. We calculate UHIs for summer and winter, daytime and nighttime, providing seasonal and diurnal variability. For daytime, we expect oasis-cooling effects (negative UHIs) due to more vegetation/shading in built-up areas;

[3] Many case studies use air temperature; there is a high correlation between air and surface temperatures (Arnfield 2003; Mallick et al. 2013; Song et al. 2015).

whereas, during nighttime, heat storage of the city's impervious covers would induce classic heat island formation (positive UHI). In addition, the role of coastal location, terrain, elevation, and rural land conditions are expected to moderate dimension of UHI.

<Figure 2 about here>

URBAN COOLING

Table 1 shows the number of negative (the city is cooler than its rural buffer) and positive UHIs for our 159 desert cities for 4 combinations of summer/winter and day/night. As the few scattered case studies suggested, negative UHIs are common. During the daytime the majority of desert cities globally are cooling sinks. The contrast between daytime and nighttime is as expected, with fewer negative UHIs as impervious surfaces in the cities are still radiating heat, motor vehicles are still running, and HVAC units generating heat.

<Table 1 about here>

Figure 3 shows the UHI distributions across 159 cities ranked from most negative to most positive for summer daytime (Figure 3a), summer nighttime (3b), winter daytime (3c) and winter nighttime (3d). Variation is considerable for all four season/time combinations, but especially so for summer daytime. The UHI is between -1.0 and +1.0 for only 47% of the cities in summer daytime; for comparison, the comparable percentages for summer nighttime, winter daytime and winter nighttime are 72%, 70% and 60% respectively. With respect to the extremes, during the summer Aden, Yemen has the lowest daytime UHI (-8.38) and Ta'izz, Yemen the lowest summer nighttime (-2.15), Sawai Madhopur, India has the highest daytime (10.16) and Dehli, India the highest nighttime (6.56). In the winter, Lima, Peru is the lowest both daytime (-3.37) and nighttime (-7.38), and Basra, Iran/Iraq is the highest both daytime (3.68) and nighttime (3.81).

<Figure 3 about here>

Determinants – the variables

What explains the wide variation seen in Figure 3? The main factor suggested in the case-study literature is the amount of vegetative cover in the desert city relative to its rural buffer. But there are other biophysical and socio-economic factors that could influence a city's UHI.

Vegetation, or green cover, is measured by the Normalized Difference Vegetation Index, or NDVI, from MODIS. NDVI is calculated as follows: NDVI = (NIR-*red*)/(NIR+*red*) Due to a strong energy absorption by vegetation in the red visible portion of the electromagnetic spectrum and a strong reflection by vegetation in the near-infrared (NIR) portion of the spectrum the NDVI using the above formula can effectively identify green vegetation biomass (Jensen, 1996; Zhang et al., 2009). NDVI varies between -1.0 and +1.0. We then take the difference between urban and rural NDVI, NDVI-DIF = $NDVI_{urban}$- $NDVI_{rural\ buffer}$, as our measure of vegetative difference. NDVI-DIF ranges from -0.47 to +0.37 in the summer, and -0.42 to +0.42 in the winter.

We examine 6 other biophysical variables. First, we obtained the ASTER Global DEM V2 product for our elevation data and calculated the average elevation for each city. Higher elevation should lead to a cooler city. For our 159 cities, elevation ranges from -5m (Al'Amarah, Iraq) to 1,920m (Aguascolientes, Mexico). The second biophysical variable is the percent of rural buffer pixels that are below the mean elevation for the city, ranging from 5 to 99 percent, and influencing wind patterns for the city. Elevation range in the rural buffer, in kilometers, is also included. The larger the rural elevation range, the more likely the city is surrounded by mountains bringing cooling wind patterns.

Another biophysical variable is whether the rural buffer intersects with a major water body, which is the case for 49 cities. Figure 4 maps the water and non-water cities. Being near the ocean is expected to cool the city relative to its rural buffer. Eight of the water cities are on the Peruvian coast[4] where they are cooled by the Humboldt Current, especially in the winter when offshore winds are stronger. These eight cities are represented by a Humboldt Current dummy variable.

<Figure 4 about here>

The final biophysical variable is a set of dummy variables representing the location of the rural buffer pixels relative to the Köppen-Geiger climate zones: Only BWh, combination of BWh and BSh, and a mix including other Köppen-Geiger climate zones, with OnlyBSh as the reference category.

Demographic variables include population and density, both obtained from GRUMP. Other things being equal, a large population should lead to more heat build-up during the daytime. Higher density should lead to taller structures and more energy use per square meter. But, somewhat surprisingly, density was never significant across multiple model specifications, and so was dropped from the analyses reported below. Three country-level[5] socio-economic variables were used: GDP per capita (http://data.worldbank.org/indicator/NY.GDP.PCAP.CD?page=2), energy use measured as kg of oil equivalent per capita (http://data.worldbank.org/indicator/EG.USE.PCAP.KG.OE) and electric power consumption per capita (http://data.worldbank.org/indicator/EG.USE.ELEC.KH.PC). All three are right-skewed and were logged to adjust for the right-skew. All three are highly correlated with one another and sensitivity tests showed that they tend to have the same effect

[4] One is on the border with Ecuador and one on the border with Chile.

[5] The following cities sit on the border of two+ countries: Yuma (USA/Mexico), Brownsville (USA/Mexico), Faisalabad (Pakistan/India), Ghazzah (Israel/Egypt/Occupied Palestinian Territory), Basra (Iran/Iraq), Ad Dammam (Saudi Arabia/Bahrain), N'Djamena (Chad/Cameroon), Machala (Ecuador/Peru). For these countries, the socio-economic variables were averaged from the 2 or 3 countries with whom they share a border.

Energy and electricity data was not available for 3 sub-Saharan countries: Burkina Faso, Chad, and Mauritania. For these 3 countries we averaged values from neighboring countries, excluding those where the main population settlements were above the Sahara desert.

on UHI. Below, we report results for energy use (logged) because it is most clearly tied to urban heat generation, and broader than electric power consumption.

Finally, to control for unmeasured country-level factors, we created dummy variables for all countries for whom we had 8 or more cities in our set of cities: India, Iraq, Mexico, Pakistan, South Africa, and the United States. In a wide variety of preliminary analyses, only India was consistently significant, and is included in the regression results presented below.

Regression Results

To what extent does the vegetation difference between desert cities and their rural buffers explain variation across 159 desert cities? Put differently, is it just vegetation or are other factors also part of the explanation. Table 2 shows the variance explained (adjusted R-square) for an OLS regression model that just contains NDVI-difference and a full model that also contains all the other variables.

<Table 2 about here>

Clearly the urban-rural buffer vegetation difference is important in explaining UHI differences across desert cities. It explains more variance during the day than at night, as would be expected, with the most variance explained during winter daytime when desert cities are greener resulting from cooler temperatures producing less vegetative evapotranspiration. Adding the other social and biophysical variables increases the variance explained in all four season-diurnal combinations, arguing that global desert city UHI variation is not simply a vegetation story. It is not just that people planted and irrigated grasses, trees and shrubs. Adding the other variables has a larger impact at night than during the day, especially in the winter[6]. Further note that even the best fitting model (winter nighttime) explains only 35% of the variance, suggesting that there are important, unmeasured variables. Likely candidates would include albedo[7], building materials, roof aspect, roof slope, soil type, materials used for roads, pervious surface types, water elements within the city and the rural buffer, electricity generation, transportation systems, and wind direction/velocity,

[6] With respect to the large winter nighttime increase in variance explained when other variables are added to the model, in the winter the surrounding environment is very cold, and so there is little nighttime impact from vegetation. Hence, other variables that cool faster and more effectively or store colder temperatures longer (e.g., metal features) play a stronger role in lowering surface temperatures.

[7] Although albedo data is available from MODIS, we do not use it because the albedo of build structures and road surfaces operates differently than albedo of vegetation, open soil, and water surfaces, and these land use/land cover types were not available at a sufficiently fine grain to distinguish among them. On building surfaces (roofs and outer walls) and road surfaces, lower albedo means less reflectance and thus higher surface heat build-up. But lower albedo in dark vegetation and water surfaces provides cooling, compared, for example, to sand. And so without distinguishing surface type, albedo can provide confusing signals.

The results (coefficients) from OLS regressions for the 4 season-diurnal combinations are shown in Table 3. Given the relatively small N, a 0.10 statistical significance threshold is used.

The NDVI difference measure is always significant and negative as expected. When there is more vegetation in the urban area relative to the rural buffer, the city has a lower UHI. The effects are strong. Further, the coefficient is substantially stronger in the daytime compared to nighttime, likely due to the shade component of the NDVI-difference effect and because the rural buffer is hotter during the day. Further, results from sensitivity tests (not shown) indicate that this NDVI difference measure does not mediate the effects of the other variables which thus are capturing something distinct from greenness.

Elevation has a consistent negative effect on UHI at night in both summer and winter, but not during the daytime. The nighttime UHI decreases by 0.51 to 0.53 for every kilometer of elevation increase. At higher elevations, man-made features cool faster than man-made features at lower elevations, especially for features made of metal and similar materials. Also at higher elevations, in the rural buffer the ground is less likely to be composed of sand, a material that cools faster than rock or soil. Thus the city cools faster and the rural buffer retains heat as elevation increases. The percent of rural pixels below the city increases UHI by 0.01 for every percentage point increase in the summer daytime. And in winter nighttime, every kilometer increase in the rural buffer elevation range decreases UHI by 0.30, reflecting the cooling effect of being surrounded by mountainous terrain.

Having a portion of the rural buffer intersect a large water body has a negative effect on UHI at night in the summer, but not during summer daytime or in winter. The reason for this summer pattern involves the differential rate of diurnal temperature gain on land and sea, the pattern of sea breezes as a result, and the fact that on average the rural buffer is further from the sea than the urban area. Consider the last point first, using Port Sudan, Sudan as an illustrative city (Figure 5). The red line marks the point of the city furthest from the Red Sea and extends north and south to intersect the rural buffer. Most of the rural buffer is further from the Red Sea than the city. Land warms faster during the day and cools faster during the night than the ocean. This difference leads to an onshore breeze during the day and an offshore breeze at night. The evening offshore breeze helps dissipate heat from the land, cooling the land closest to the sea the most. In the cooler winters, having a portion of the rural buffer intersect a large water body is not significant, but for the 8 Peruvian cities near the Humboldt Current there is a large and significant winter nighttime cooling effect as expected.

<Figure 5 about here>

The final biophysical variables is the Köppen-Geiger climate zones for the rural buffer pixels. The only significant contrast involves winter nighttime, when having only BWh pixels in the rural buffer compared to only BSh pixels results in a higher UHI, likely due to less vegetation in the BWh zone than in the BSh zone.

Cities in India have a higher UHI in the summer, day and night, and winter nighttime, than cities elsewhere. This India effect is larger during the summer day than at night and consistent with a case study of Delhi (Pandey et al. 2014) and consistent with results by Oleson and colleagues (2011) using a completely different methodology to examine the effect of urban UHIs in global climate models. While there are a number of possible factors, the most likely for the summer effects are the timing of the summer monsoon, which begins in May and peaks in July[8]. As a result of the monsoon, the rural countryside has high soil moisture, cooling the rural buffer. Further, some of the Indian cities, such as Jodhpur, have considerable agriculture in the rural buffer; to the extent that it is greening up in July that could also have a cooling effect in the rural buffer leading to a higher UHI. To further test this explanation, we deleted 8 Indian cities with the highest percentage of "black" pixels and re-ran the analyses. Even though there were 9 Indian cities remaining in the analysis the Indian coefficient was no longer statistically significant. The winter nighttime positive effect is likely related to agricultural factors in the rural buffer. While the monsoon is no longer present in December, Indian desert cities have considerable agricultural land in the rural buffer and a second crop is planted in November such that the rural area in evenings cools faster than the city[9].

Energy logged has a positive impact on three seasonal/diurnal combinations, and it is stronger during the day than at night. It is not significant winter nighttime. We also examined GDP and electricity used, both of which are highly correlated with the energy measure and both of which also positively affect a city's UHI. All three variables are indicators of economic development. This relationship is as expected. With economic development comes higher anthropogenic heating due to increased use of motor vehicles, air conditioning (or heating depending on season/location), and manufacturing, all of which generate heat in the urban area relative to the rural buffer.

The final variable in Table 3 is city population size. It is not significant in any of the season/diurnal combinations. In some preliminary model specifications it was negatively significant for summer daytime, but this effect disappears once NDVI difference is controlled. This suggests that more people leads to more green grasses, shrubs and trees, presumably enabled by irrigation.

SENSITIVITY TESTS

We conducted a wide range of sensitivity tests to check the robustness of our results. We tested for plausible statistical interactions between the various predictor variables, and there is no evidence of significant interactions. Put differently, the additive models in Table 3 are sufficient. We also checked the functional form for the continuous variables, and the linear forms in Table 3 are appropriate, after energy (as well as GDP and electricity) are logged. We also removed 8 cities that lie on the border of 2 or more countries, and the results were fairly robust with and without these 8 cities. One summer-day, one summer-night, and one winter-

[8] For example, during July 2000, the average daily rainfall for Jodhpur, one of the Indian desert cities, was 0.20 inches (www.cpc.ncep.noaa.gov/products/assessments/assess_94/india.html). Also see Mitra et al. 2012.

[9] The desert cities in the Sahel have a monsoonal rain pattern similar to India, and so we tested a Sahel dummy variable. It was not significant, likely because it is a weaker monsoon (c.f., Oleson et al. 2011)

night coefficient that were marginally significant became marginally not significant. In a different sensitivity test, we removed 6 cities that were outliers in scatter plots of UHI and NDVI difference; one previously significant summer-night coefficient became marginally insignificant.

GRUMP data has three measures of quality. First, the resolution of the census polygons for which population counts are available. The finer the resolution of these census polygons, the better the population resolution across the GRUMP pixels. Second, there is a more impresionistic measure of quality that ranges from 1 (lowest) to 4. Finally, there is a variable indicating the year of the most recent census from which the population data were obtained. Most (79%) are within 4 years +/- of the year 2000, but some are older. At the extreme, there are 4 cities in Libya for which the data had to be extrapolated from 1984. Controlling for these variables, one at a time, does not alter the fundamental story in Table 3.

CONCLUSION

In both summer and winter daytime, the majority of desert cities experience the oasis effect of negative UHIs. At night, summer and winter, far fewer, but some, have negative UHIs. The vegetation planted in desert cities relative to the bare soil in the rural countryside plays an important role in creating the oasis effect, as was expected from a few case studies. But our findings suggest that there are a wide variety of other factors also responsible, including being near a large water body, being at higher elevations, not having experienced a rainy monsoon, and not having a highly developed economy.

As the first study to examine UHI at a global scale without resorting to using idiosyncratic case studies with inconsistent measurement approaches, the methodology used in this study –LST from MODIS and urban extent/population data from GRUMP – permits global examination of UHI phenomena and allows other socio-economic and biophysical variables to be brought into the analysis. As such, it opens the possibility of examining UHI distributions and correlates for a wide variety of variables. And it does so with consistent measurement of LST and obtains temperature measurement for all pixels in the rural land buffer rather than just a few points.

To what extent should desert cities be encouraged to take steps to lower LST, thus moving to lower UHIs? Given that higher urban temperatures are associated with elevated health risks (e.g., Patz et al. 2005), the answer would be yes. If lower urban LSTs could be accomplished with building and road materials which strongly reflect solar radiation, with cooling devices which minimize heat build-up, and motor vehicles which emit less heat, then such policies should be encouraged. If the approach is by having more trees and shrubs that are irrigated, then caution needs to be exercised. Of greatest concern would be the source of water and its abundance, with worries involving the nature of underground aquifers and locations downstream from rivers.

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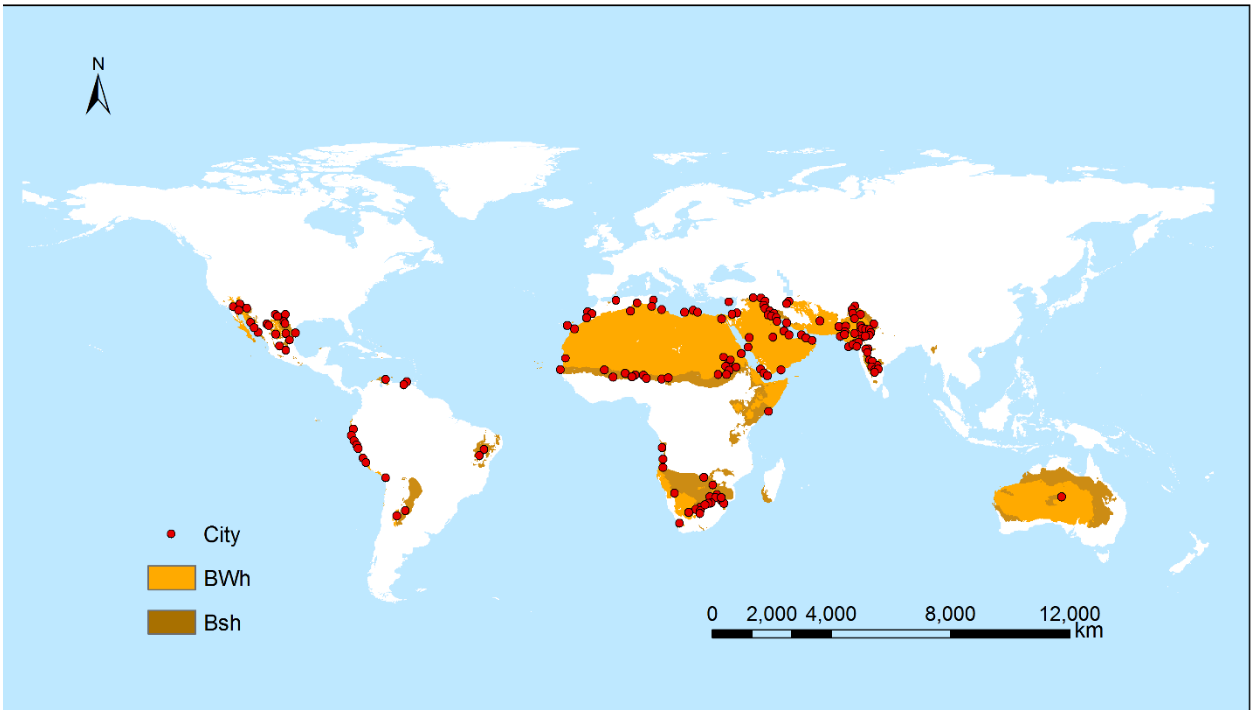

Figure 1. Geographic location of the 159 desert cities.

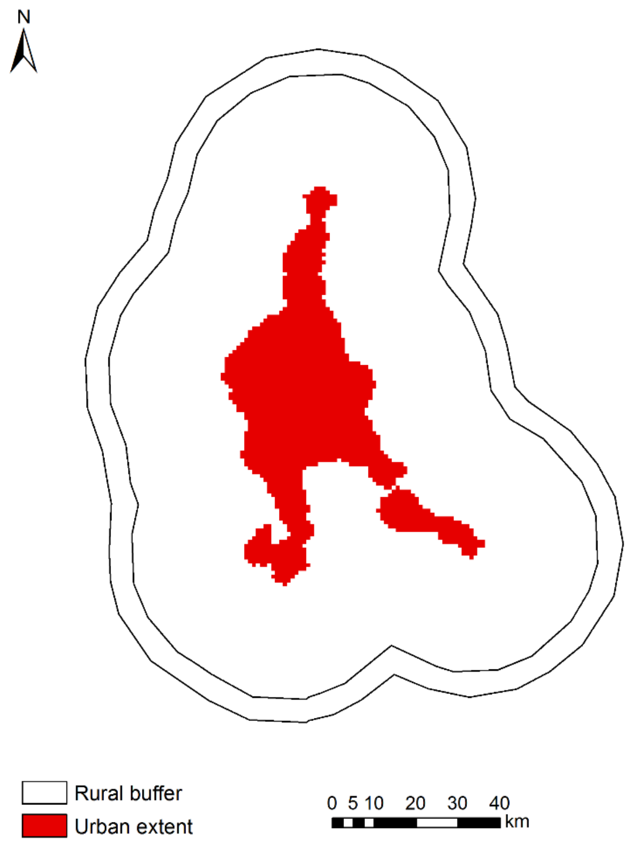

Figure 2. Urban extent and rural buffer for Khartoum, Sudan.

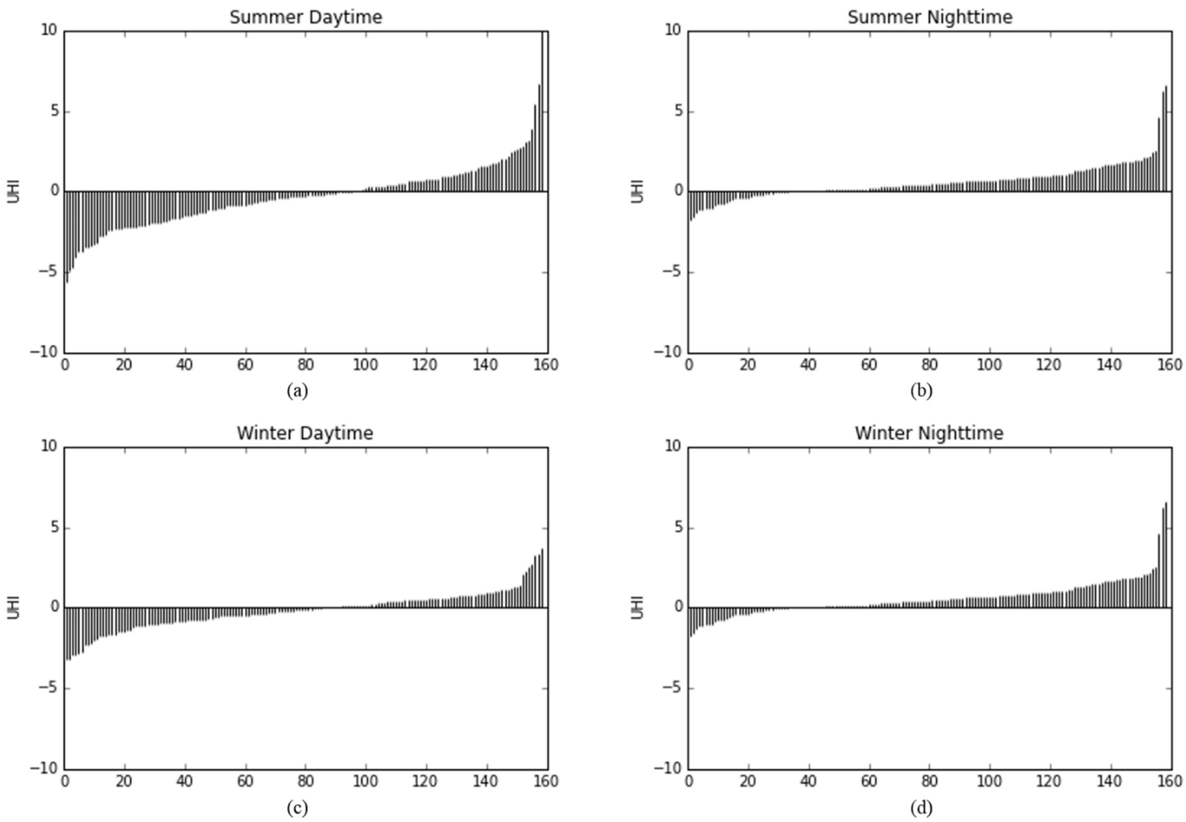

Figure 3. UHI values (in degrees C) across the 159 cities ranking from most negative to most positive for (a) summer daytime, (b) summer nighttime, (c) winter daytime, and (d) winter nighttime.

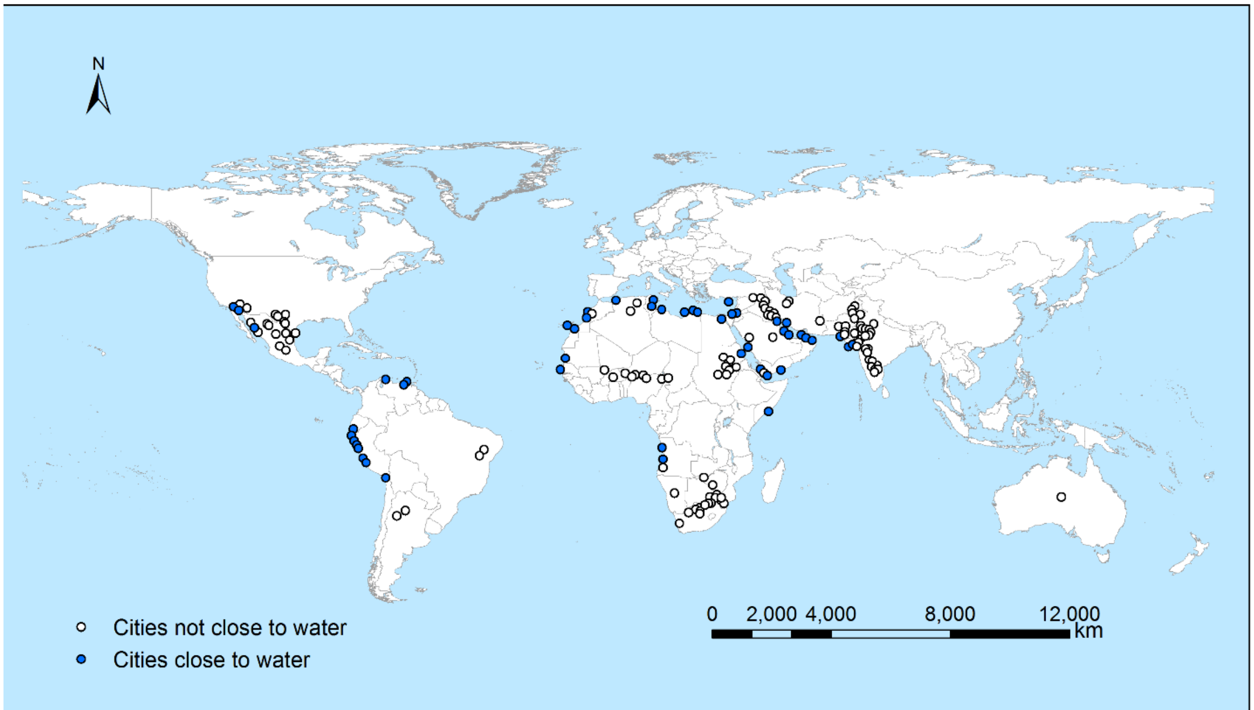

Figure 4. Map of water cities and non-water cities.

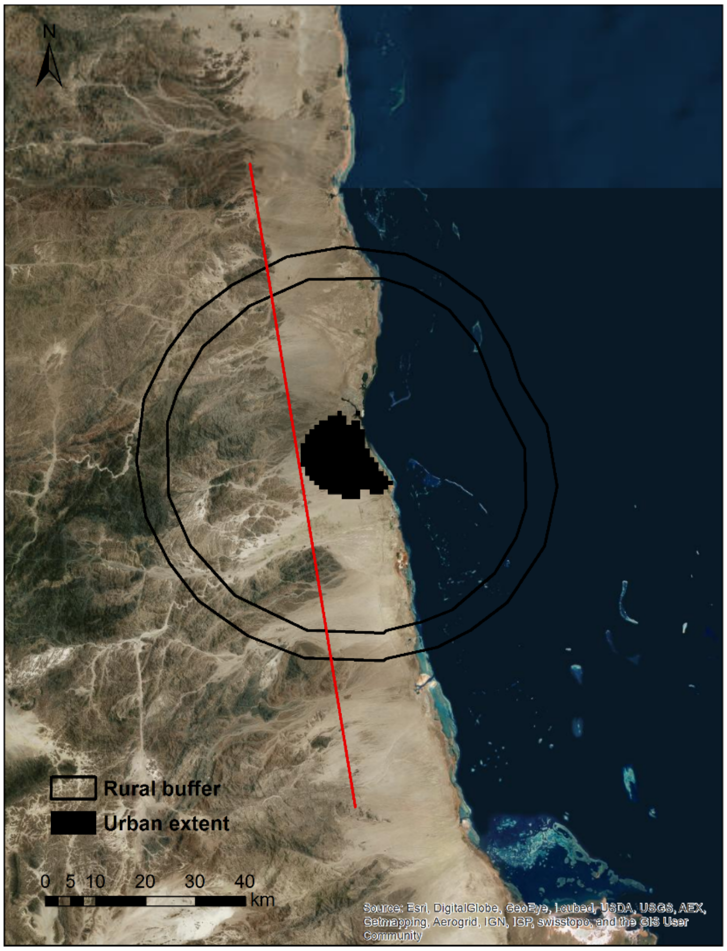

Figure 5. Urban extent and rural buffer for Port Sudan, Sudan.

Table 1. Number of negative and positive UHIs by season and time of day, year 2000.

Season/time	negative	positive	total
Summer day UHI	96	63	159
Summer night UHI	35	124	159
Winter day UHI	87	72	159
Winter night UHI	49	119	159

Table 2. Variance explained, excluding and including variables in addition to NDVI-difference.

	Summer		Winter	
	daytime	nighttime	daytime	nighttime
Just NDVI-difference	.09	.04	.19	.01
Additional variables added	.15	.16	.27	.35
Difference between models	.06	.12	.08	.34

Table 3. Results from OLS regression analysis of UHI.

Variable	Day	Night	Day	Night
Intercept	-2.92*	-0.86	-2.75*	-0.22
NDVI difference	-7.11*	-3.82*	-6.38*	-2.05*
Elevation[a]	0.28	-0.51*	0.33	-0.53*
Percent of rural pixels below city	0.01*	-0.01	0.00	0.00
Range in elevation[a]	0.09	0.21	0.03	-0.30*
Water	-0.34	-0.66*	0.07	0.02
Humboldt Current cities	0.18	0.14	-0.29	-2.21*
Climate zone[b]				
BWh only	-0.69	0.30	0.13	0.72*
BWh & BSh	-0.52	0.40	-0.12	0.33
Other zones	-0.52	0.19	0.05	0.27
India	0.95*	0.84*	-0.16	0.42*
Energy logged	0.34*	0.22*	0.35*	0.11
Population	-0.04	0.03	0.01	0.02

* Significant at 0.10

[a] In kilometers

[b] BSh only is the reference category