A Simple Statistical Model for Predicting Fine Scale Spatial Temperature Variability in Urban Settings

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Abstract: Given that mortality rates during a heat wave are a sensitive function of temperature, forecast maps of temperature anomalies within cities should be useful to the health community. An empirically based approach for predicting daily spatial variations in the Urban Heat Island has been developed for New York City. Our technique is derived from two data sets: high spatial resolution temperature data collected by multiple synchronized traverses of Manhattan by foot; and several months of high temporal resolution data collected at 10 fixed locations by instruments mounted on lamp posts. The high spatial resolution data is regressed against local characteristics such as vegetation, albedo and building height to produce a statistical model of relative temperature anomalies. The fixed instruments show local temporal variability attributed to convection, and spatial variability between instruments attributed to local surface characteristics. The magnitudes of both types of variability are regressed against weather conditions such as cloud cover, wind speed, lapse rate and humidity. When applied to the average spatial anomaly map, the amplitude of the temperature variations within the city each day can be predicted based on a weather forecast. A working model is online, predicting temperature variations within the city 24 hours in advance, and is currently undergoing testing. The technique should be easily portable to other similar cities.

Introduction

The varying surface characteristics inside a city means that the urban heat island is best characterized as an archepelago [Grimmond, 2007], with temperatures changing on the neighborhood scale. Once temperatures climb above a certain threshold the health impacts become a sensitive function of temperature [Kinney et al, 2008] complicating the influence of neighborhood demographics and the response to heat events. Given the difficulties of modeling microclimate on this scale it is unlikely that the health community will have access to the physical modeling they need to predict impacts within a city. We have therefore worked to create a much simpler statistical model based on surface characteristics and weather that can be used to estimate temperature variability within large cities such as New York.

Dataset

Data collection was focussed on Manhattan, and consisted of a series of 19 walking campaigns during the summers of 2012 and 2103 along 8 fixed routes with measurements at a uniform 1.5 meters above the ground, and a set of 10 fixed instruments set up for a 3 month period during the summer of 2013 set between 3.2 and 3.9 meters above the ground [Vant-Hull et al, 2014]. All instruments measured temperature, RH and visible light; though this paper concerns only the temperature.

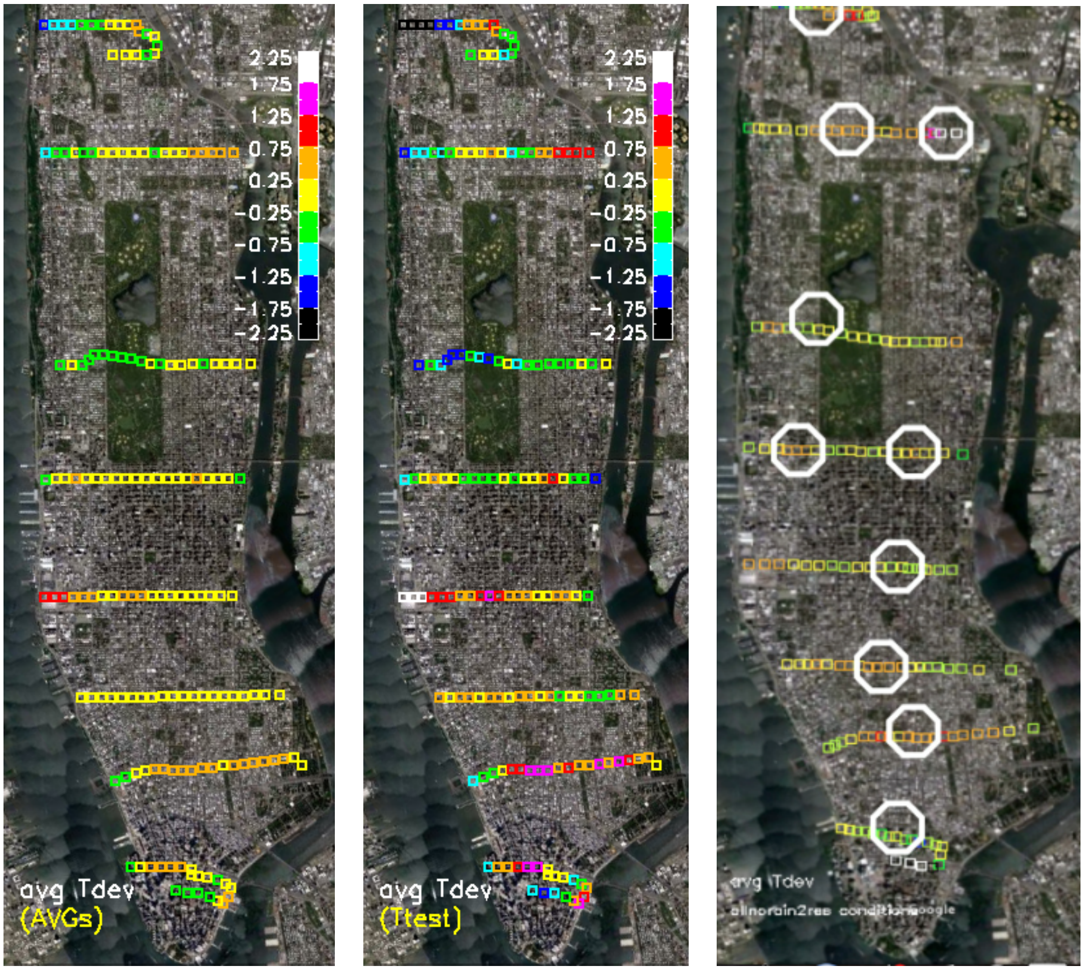


Figure 1: Dataset locations. Left: averaged temperature deviations, in units of standard deviations. Middle: Student T values for the walking campaigns. Right: fixed instrument locations superimposed on walking route examples. Yellow is within 1/4 standard deviation of average. The red end of the scale is above average, the blue end of the scale is below average.

The walking campaigns consisted of 8 field agents starting simultaneously on the western eadge of Manhattan at 2 pm, predominantly walking in shadow. Data was collected every 6 seconds but aggregated into 20 segments, each roughly 150 meters in length. Each day the standard deviation of all these segments was calculated, the average temperature was subtracted and the residuals scaled by the standard deviation. These scaled residuals were averaged together to produce the left panel of Figure 1. These variations should be due to surface characteristics. These variations were compared to an average point by the Student T test, and in the middle panel the results show that deviations from the average tend to be significant, as red and blue values indicate the 90% confidence level.

As the walking campaigns are episodic, they are accompanied by fixed instruments with locations shown on the right of Figure 1. These instruments were measuring every 3 minutes to capture not only the diurnal cycle and range of weather conditions, but convective variability.   Hourly averages were used to filter out temporal variability, and the differences between hourly averages at different locatons reflect the spatial variability.

This data set is publicly available, described in detail [Vant-Hull et al, 2014] and accessible at http://glasslab.engr.ccny.cuny.edu/u/brianvh/UHI/ .

Model Development

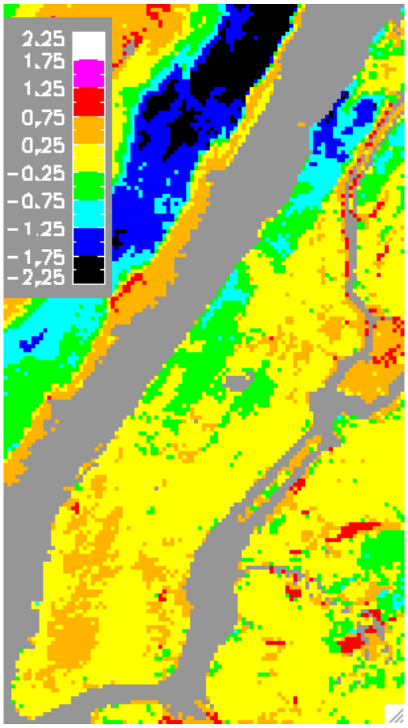
The goal is to extend the results shown in the middle of Figure 1 throughout Manhattan for any summer day.   The first step is to extend the results spatially by regressing the local averages of the temperature variations against local characteristics that might affect temperature. The following variables were used:

Variable	**Source**	**comments**
Elevation	US Geological Survey	1 m vertical resolution regridded to 50 m horizontal resolution
Water fraction	Based on elevation	Fraction of sea level within a 1 km square centered on each point
Vegetation	LandSat	Normalized Vegetation Index regridded to 50 m resolution
Albedo	LandSat	Narrow to broadband conversion regridded to 50 m resolution
Building Fraction	New York City Tax Lot database (mapPluto)	Regridded to 100 m resolution
Building Height	MapPluto	Regridded to 100 m resolution

Table 1: Surface variables regressed against local observations of temperature variations.

Multivariable linear regression was applied, with the results shown in Figure 2 below. For those who are familiar with Manhattan it should be immediately obvious that elevation is a key variable, and it had the heighest correlation to street level temperature. In fact the relationship is super-adiabatic, indicating that the effect is not due to air temperature variation with altitude alone. We hypothesize that since these air temperatures are measured in the afternoon when surface temperatures are generally much warmer than air temperature, exposure to wind causes less equilibration at high elevations compared to sheltered lower elevations. This has been tested by Karimi et al [2015] by regressing the difference in temperature between two elevations to weather variables, and finding wind is the most significant factor after temperature itself.

The regressed and observed temperature variations are compared on the left of Figure 2, and we see the multivariable correlation of 0.67, with an average deviation of 0.2.



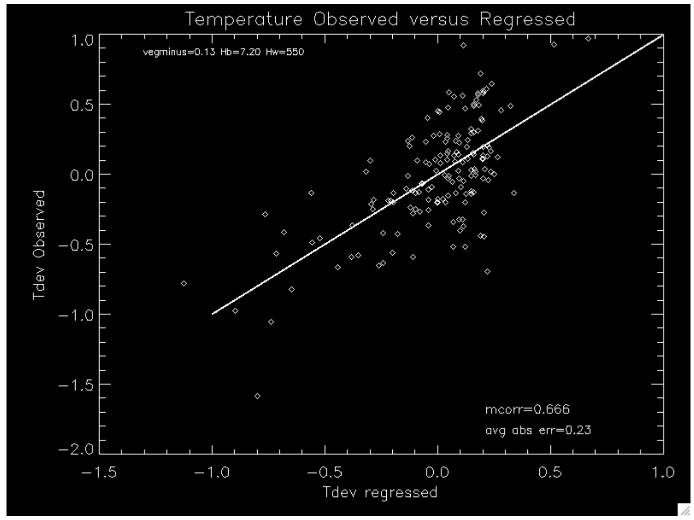


Figure 2: Results of the regression of the observations of Figure 1 against local surface characteristics. Left: extending the observations across Manhattan based on the local characteristics. Same color scale as Figure 1. Right: comparison of observations to regressed values.

The map shown in Figure 2 shows temperature in terms of number of standard deviations from the average. In order to get temperature itself we need both the average and the standard deviation for each day. The average temperature is easily obtained by observation or weather forecast; to find the standard deviation we must turn to the set of fixed instruments.

The spatial standard deviation in temperature at 2 pm each afternoon for 3 months was calculated from the set of 10 station hourly averages. These daily standard deviations were regressed against weather variables taken from the North American Model Regional Reanalysis (NARR, National Climatic Data Center). The variables used appear in Table 2.

Weather Variable	**Description**
Temperature	2 meters above ground
Relative Humidity	2 meters above ground
North, West Wind	10 meters above ground
Wind Speed	10 meters above ground
Evaporation Potential	(Wind speed)*(1 – RH)
Cloud Fraction	Total column
Downwelling shortwave	Watts/m^2
Downwelling longwave	Watts/m^2
Low level lapse rate	$(T_2 - T_1)/(H_2 - H_1)$ 1: 975 mb 2: 950 mb
Low level lapse rate	$(T_2 - T_1)/(H_2 - H_1)$ 1: 950 mb 2: 925 mb

Table 2: NWP analysis variables regressed against surface temperature variability.

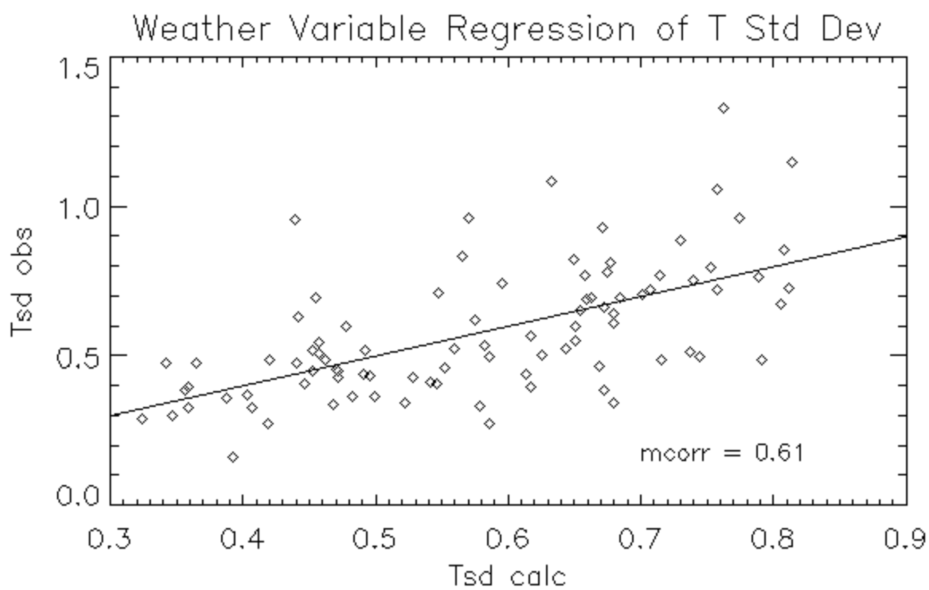


Figure 3: Regression of Weather Variables against Temperature variability. Observations versus regressed results.

Figure 3 demonstrates moderate skill when weather variables are used to predict the magnitude of temperature variations within an urban environment. This means weather forecasts can be used to predict not just the average temperature, but the spread of temperatures as shown on the left of Figure 2. Predicting the temperature pattern throughout a city proceeds in two steps:

1. Calculate the pattern of temperature variations based on surface characteristics, in units of standard deviations from the average each day
2. Use the weather forecast to predict the temperature average and standard deviation for the day. Use this to convert the scale of Figure 2 to actual temperature.

This has been done, and is running routinely for the city of New York. Nowcasts and forecasts are available at
http://glasslab.engr.ccny.cuny.edu/u/brianvh/UHI/modelpage.html

Concluding Remarks

This model is meant to be simple, and is easily criticized on physical grounds; for example assuming that the effects of weather and surface variables are separable. But the simplicity means that ease of applicability is being traded for accuracy. The surface variable coefficients should largely be transferable to city centers that resemble Manhattan, though the dependence of variability on wind components suggest that different topographies may respond differently. We would recommend that cities set up individual instrument arrays that will reflect characteristic variability.

References

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