A Simple Statistical Model to Predict Fine Scale Spatial Urban Temperature Variability

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Urban Temperatures and Mortality

NYC MetNet data

Patrick Kinney, NYC ClimAID Report 2013

from "Forecasting the New York City urban heat island and sea breeze during extreme heat events". Meir, Orton, Pullen, Holt, Thompson and Arend in *Weather and Forecasting, 2013*
Field Campaigns

Temps, RH => dewpoint, Light

**High spatial resolution measurements:**
- 2 pm, ~ 40 minutes, 1.5 m AGL
  - 19 Simultaneous street walks (mainly in shade)
  - 13 Simultaneous avenue walks (mainly in sun)
  - Every 6 seconds, averaged to ~ 2 minutes; ~ 150 m

**High time resolution measurements:**
- Fixed Instruments, 10 locations
- 3 minute increments, 3 months
- ~ 3.5 m agl
## Walking Campaign Data Reduction

### Step 1: all walks divided into equal number of bins for spatial averaging

<table>
<thead>
<tr>
<th>Week 1</th>
<th>.................................................................</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week 2</td>
<td>........................................................................</td>
</tr>
</tbody>
</table>

### Step 2: **detrend**
- Temperature trend (fixed) subtracted from bin averages

### Step 3: **group statistics**
- For each day, Manhattan-wide average and standard deviation calculated ('daily avg' & 'daily SD') from detrended data

### Step 4: **Anomalies, scaling**
- 'Differences' = bin avgs - daily avg
- 'Deviations' = Differences/((daily SD)

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**MN**
<table>
<thead>
<tr>
<th>Color</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>&lt; -1.75 units</td>
</tr>
<tr>
<td>Blue</td>
<td>-1.25 to -1.75 units</td>
</tr>
<tr>
<td>Light blue</td>
<td>-0.75 to -1.25 units</td>
</tr>
<tr>
<td>Green</td>
<td>-0.25 to -0.75 units</td>
</tr>
<tr>
<td>Yellow</td>
<td>+/- 0.25 units; average</td>
</tr>
<tr>
<td>Orange</td>
<td>+0.25 to +0.75 units</td>
</tr>
<tr>
<td>Red</td>
<td>+0.75 to +1.25 units</td>
</tr>
<tr>
<td>Purple</td>
<td>+1.25 to +1.75 units</td>
</tr>
<tr>
<td>White</td>
<td>&gt; + 1.75 units</td>
</tr>
</tbody>
</table>

*Bluer is lower: Yellow is Average: Redder is higher*
Temp Avgs

In the shaded street data, low buildings are warmer, vegetation and higher elevations are cooler.

In the sunny avenues high buildings are warmer, proximity to water is cooler. There is also a patchwork effect between routes.

Bluer is lower: Yellow is Average: Redder is higher
DewPt Avgs

An increase with proximity to water and vegetation. Some patchwork effects very visible.
Surface Data Sets

**USGS survey** - 30 m resolution
- elevation
- water (elevation < 0.15 m)
- 1km² water fraction

**LandSat** - 30 m resolution
- Vegetation (NDVI)
- Albedo (narrow to broadband conversion)

**NYC mapPluto** - aggregated to 100 m resolution
- Building height
- Building area fraction
Viewing Vegetation/Albedo in Cities
Variable Modifications

Scaled Building Height $\Rightarrow 1 - \exp(-H/H_o)$
$H_o = 7.5 \text{ m}$
$(0 < SBH < 1)$

Scaled Building Volume $= SBH \times \text{Building Area Fraction}$

note that $1 - SBV \sim = \text{Sky View Fraction}$
Regression of local Temperature Anomalies to Surface Characteristics

Temperature Observed versus Regressed

\( T_{\text{dev observed}} \) vs. \( T_{\text{dev regressed}} \)

\( \text{mcorr} = 0.666 \)
Correlations and Coefficients
Temperature anomalies to Surface Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlation</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation</td>
<td>- 0.52</td>
<td>- 0.03 /m</td>
</tr>
<tr>
<td>NDVI</td>
<td>- 0.39</td>
<td>- 0.59</td>
</tr>
<tr>
<td>Build Volume</td>
<td>0.087</td>
<td>2.5</td>
</tr>
<tr>
<td>Build Area %</td>
<td>0.08</td>
<td>- 2.1</td>
</tr>
<tr>
<td>Albedo</td>
<td>0.06</td>
<td>- 0.70</td>
</tr>
<tr>
<td>Water %</td>
<td>0.02</td>
<td>- 0.81</td>
</tr>
<tr>
<td>Build Height</td>
<td>- 0.01</td>
<td>- 0.76</td>
</tr>
</tbody>
</table>

1 std dev ~ 1 degree C
When observations differ from the model predictions (1.5 m agl)

- Cool in downtown
- Warm in villages
- Unpredicted average
- Hot spot at piers
- Cool in the Park
- Cool in downtown
Observed Cool points in Central Park

Bluer is lower: Yellow is Average: Redder is higher
During 3 months the fixed instruments sample a wide range of meteorological conditions, reflected in the spread of temperatures between locations. The standard deviation is a measure of spatial variability.

Since our field campaigns are scaled to standard deviation, we can relate weather to the amplitude of temperature variation within the city.

(3.5 m agl)
Weather and Temperature Anomaly Amplitudes

A windy overcast day is expected to have less temperature variation within the city than a calm clear day.

![Graph showing observations versus NWP regression with a correlation of 0.52](image_url)
## Temperature Difference between Highest and Lowest Elevation Stations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlation</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temp</td>
<td>0.471</td>
<td>0.067</td>
</tr>
<tr>
<td>RH</td>
<td>-0.134</td>
<td>0.011</td>
</tr>
<tr>
<td>Northward Wind</td>
<td>0.186</td>
<td>0.012</td>
</tr>
<tr>
<td>Eastward Wind</td>
<td>0.278</td>
<td>0.025</td>
</tr>
<tr>
<td>CF</td>
<td>-0.047</td>
<td>-0.003</td>
</tr>
<tr>
<td>Mid Level LR</td>
<td>-0.106</td>
<td>-15.315</td>
</tr>
<tr>
<td>Low Level LR</td>
<td>-0.216</td>
<td>-41.859</td>
</tr>
<tr>
<td>V Total</td>
<td>0.018</td>
<td>-0.001</td>
</tr>
<tr>
<td>Evaporation Rate</td>
<td>0.076</td>
<td>0.024</td>
</tr>
</tbody>
</table>
Critique: is the anomaly function Separable?

Temperature Anomalies

\[ = \quad F(\text{surface, weather}) \]

\[ ?= \quad G(\text{surface}) \times K(\text{weather}) \]

\[ = \quad \text{(Anomaly map} \times \text{Amplitude)} \]

*Not rigorous; and yet…

…*simple approximate tools get more use.*
Testing the Model

If the model is correct, for a set of spatial observations

\[ \text{StdDev}(T_{\text{observed}} - T_{\text{uniform}}) > \text{StdDev}(T_{\text{observed}} - T_{\text{model}}) \]

3 months of observations with our 10 stations on Manhattan show an average reduction of 20% in standard deviation.

The model so far is only a moderate success. We are expanding testing to the rest of the city but the data quality is lower: greater variety may balance the quality.
Manhattan UHI Website

The site explains methods, provides images and data for download, and the paper describing the dataset. It hosts real time forecasts and nowcasts of the Manhattan UHI.

http://glasslab.engr.ccny.cuny.edu/u/brianvh/UHI

This data has been used by the urban WRF team at CCNY, testing output of a high resolution dynamical model with urban surface parameterizations (Guiterrez, Gonzalez, Arend).

http://air.ccny.cuny.edu/ws/wrfn/anibmaster.wrfmetnet.php
Summary

• A multivariable linear regression is used to model afternoon urban temperature anomalies from surface characteristics: buildings, vegetation, and elevation.
• The amplitude of the anomalies are predicted via regression of weather variables.
• Temperature dependence on elevation is super-adiabatic, perhaps linked to wind.
• This simple model is imperfect but easy to apply using data available to any municipality.

http://glasslab.engr.ccny.cuny.edu/u/brianvh/UHI

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