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

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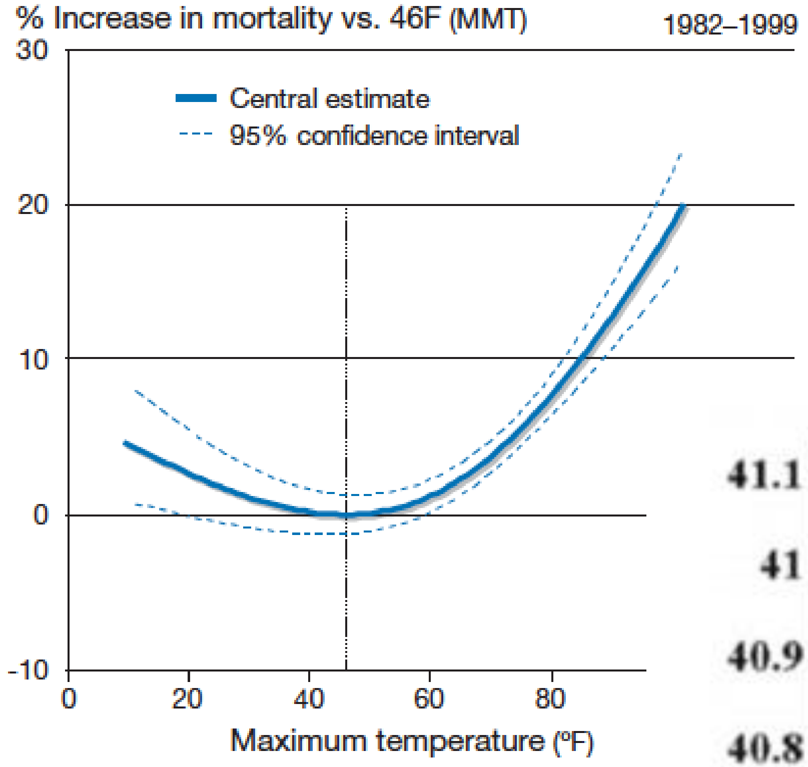
Funded in part by the Consortium for Climate Risk in the Urban Northeast

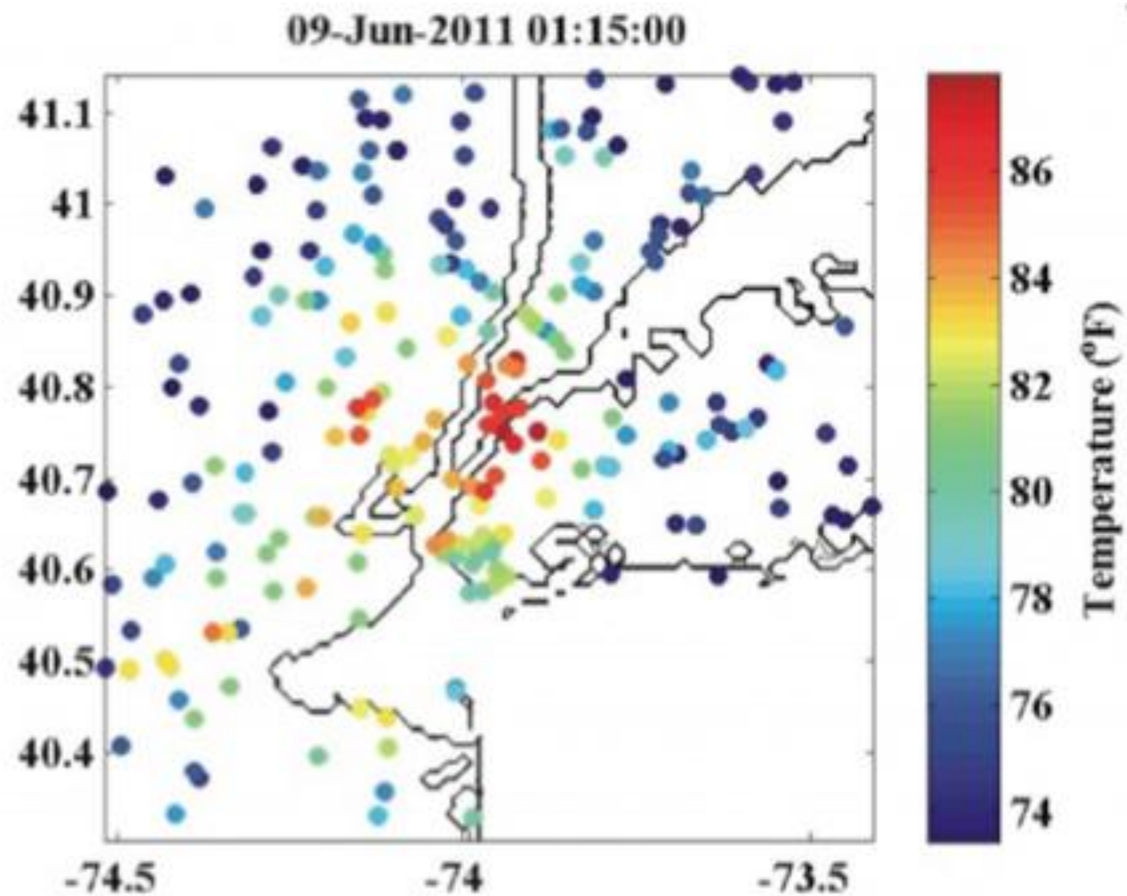
International Conference on Urban Climate, Toulouse, July 2015

Urban Temperatures and Mortality



Patrick Kinney, NYC ClimAID Report 2013

NYC MetNet data



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*


3.5 M
1.5 M

Field Campaigns

Temps, RH => dewpoint, Light

High spatial resolution measurements:
2 pm, ~ 40 minutes, 1.5 m AGL

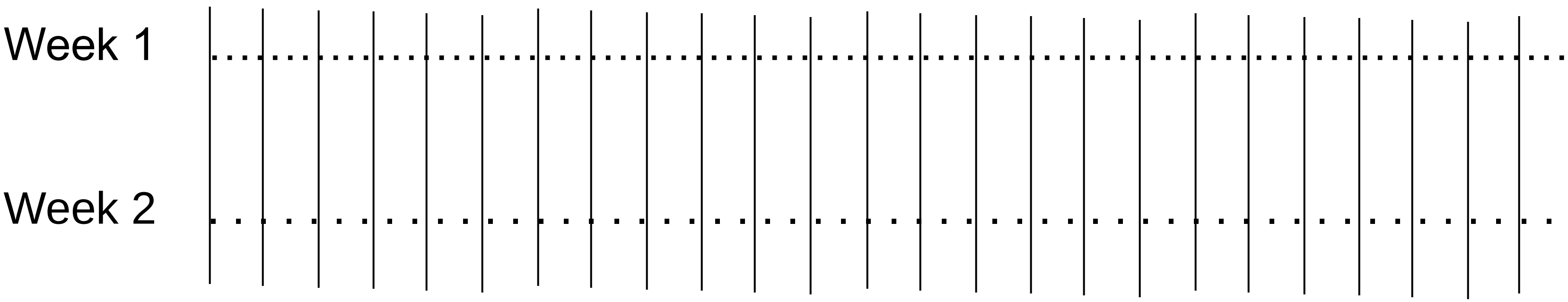
- 19 Simultaneous street walks (mainly in shade)
- 13 Simultaneous avenue walks (mainly in sun)
- Every 6 seconds, averaged to ~ 2 minutes; ~ 150 m

High time resolution measurements:

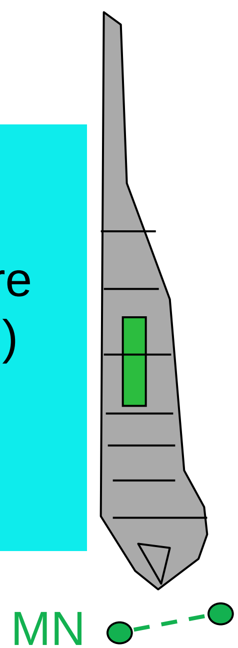
- Fixed Instruments, 10 locations
- 3 minute increments, 3 months
- ~ 3.5 m agl

Walking Campaign Data Reduction

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



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)

Color Scheme for all Measurement Units

Black	< -1.75 units
Blue	-1.25 to -1.75 units
Light blue	-0.75 to -1.25 units
Green	-0.25 to -0.75 units
Yellow	+/- 0.25 units; average
Orange	+0.25 to +0.75 units
Red	+0.75 to +1.25 units
Purple	+1.25 to +1.75 units
White	> + 1.75 units

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

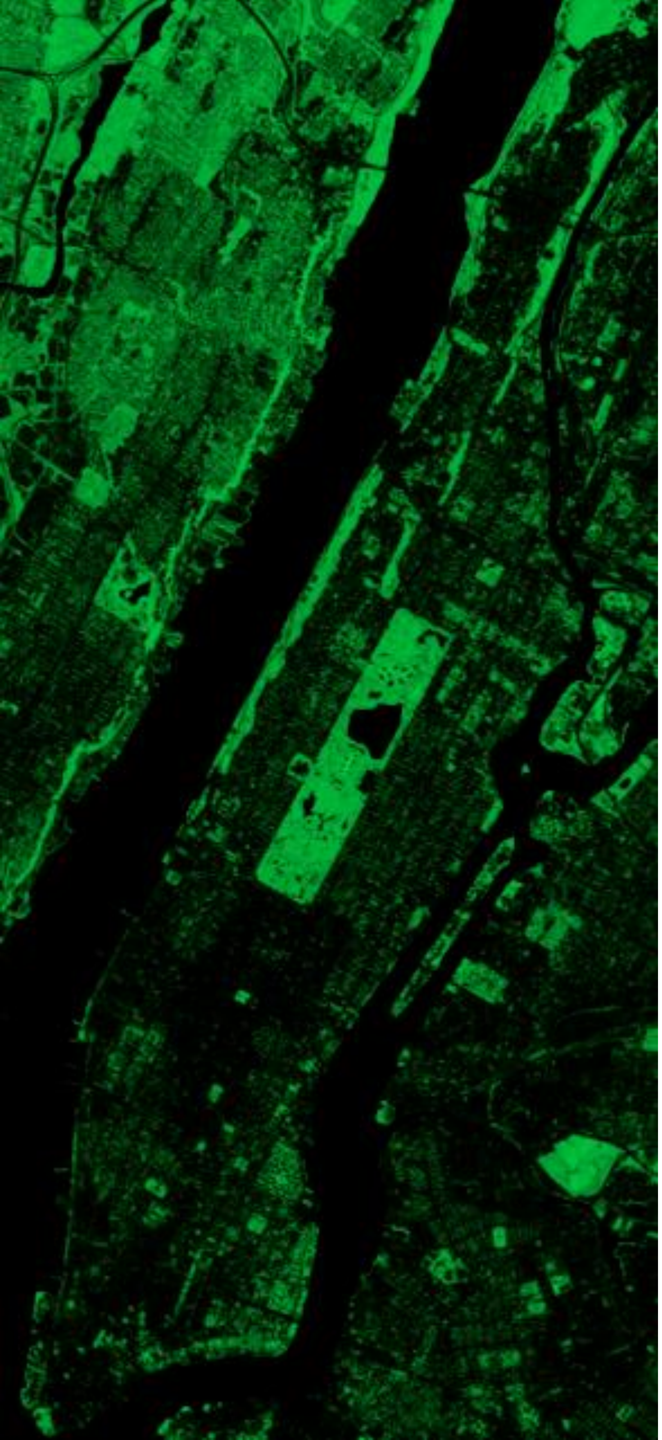
- elevation
- water (elevation < 0.15 m)
- 1km^2 water fraction

LandSat - 30 m resolution

- Vegetation (NDVI)
- Albedo (narrow to broadband conversion)

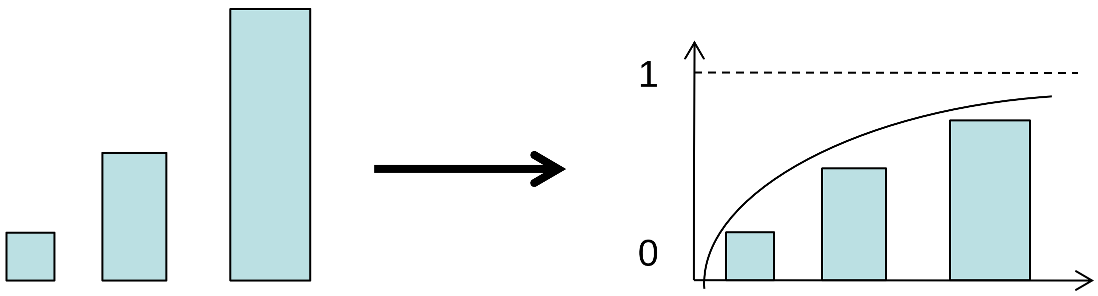
NYC mapPluto - aggregated to 100 m resolution

- Building height
- Building area fraction



Viewing Vegetation/Albedo in Cities

Variable Modifications

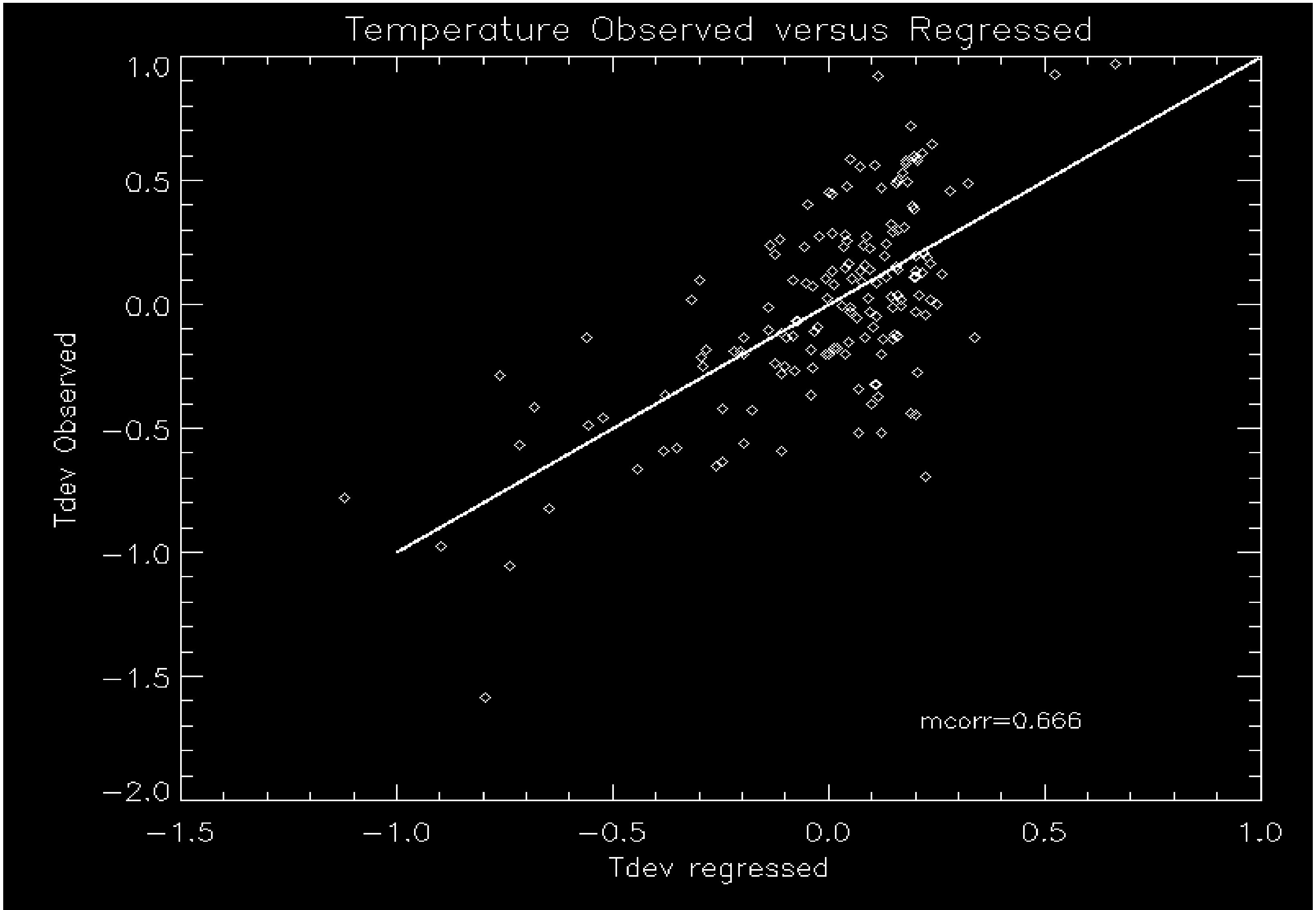


Scaled Building Height => 1 - exp(-H/Ho)
Ho = 7.5 m *(0 < SBH < 1)*

Scaled Building Volume = SBH x Building Area Fraction

note that 1 - SBV ~= Sky View Fraction

Regression of local Temperature Anomalies to Surface Characteristics



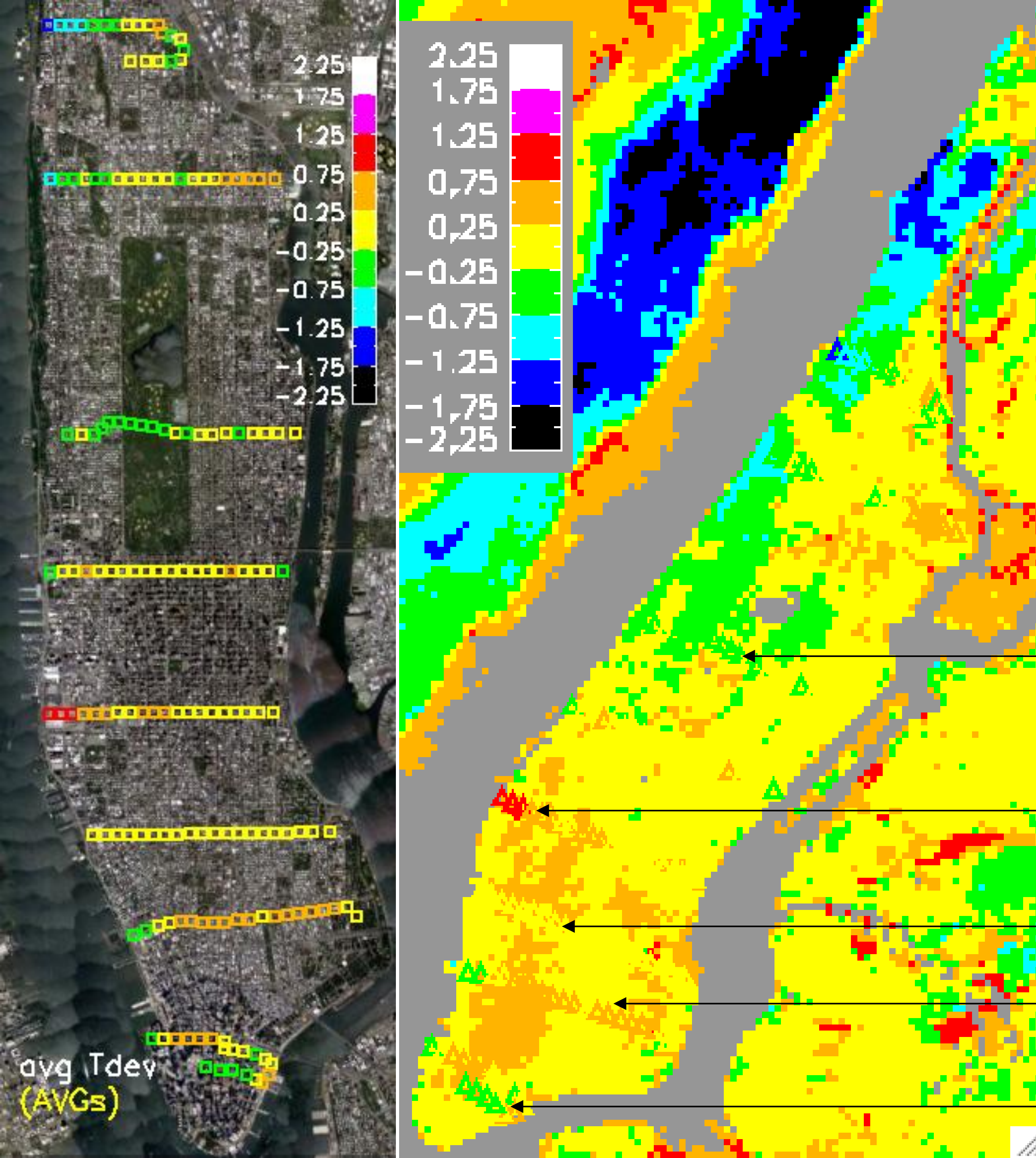
Correlations and Coefficients
Temperature anomalies to Surface Variables

Variable	Correlation	Coefficient
Elevation	- 0.52	- 0.03 /m
NDVI	- 0.39	- 0.59
Build Volume	0.087	2.5
Build Area %	0.08	- 2.1
Albedo	0.06	- 0.70
Water %	0.02	- 0.81
Build Height	- 0.01	- 0.76

0 to 1

1 std dev ~ 1 degree C

When observations differ from the model predictions (1.5 m agl)



Cool in the Park

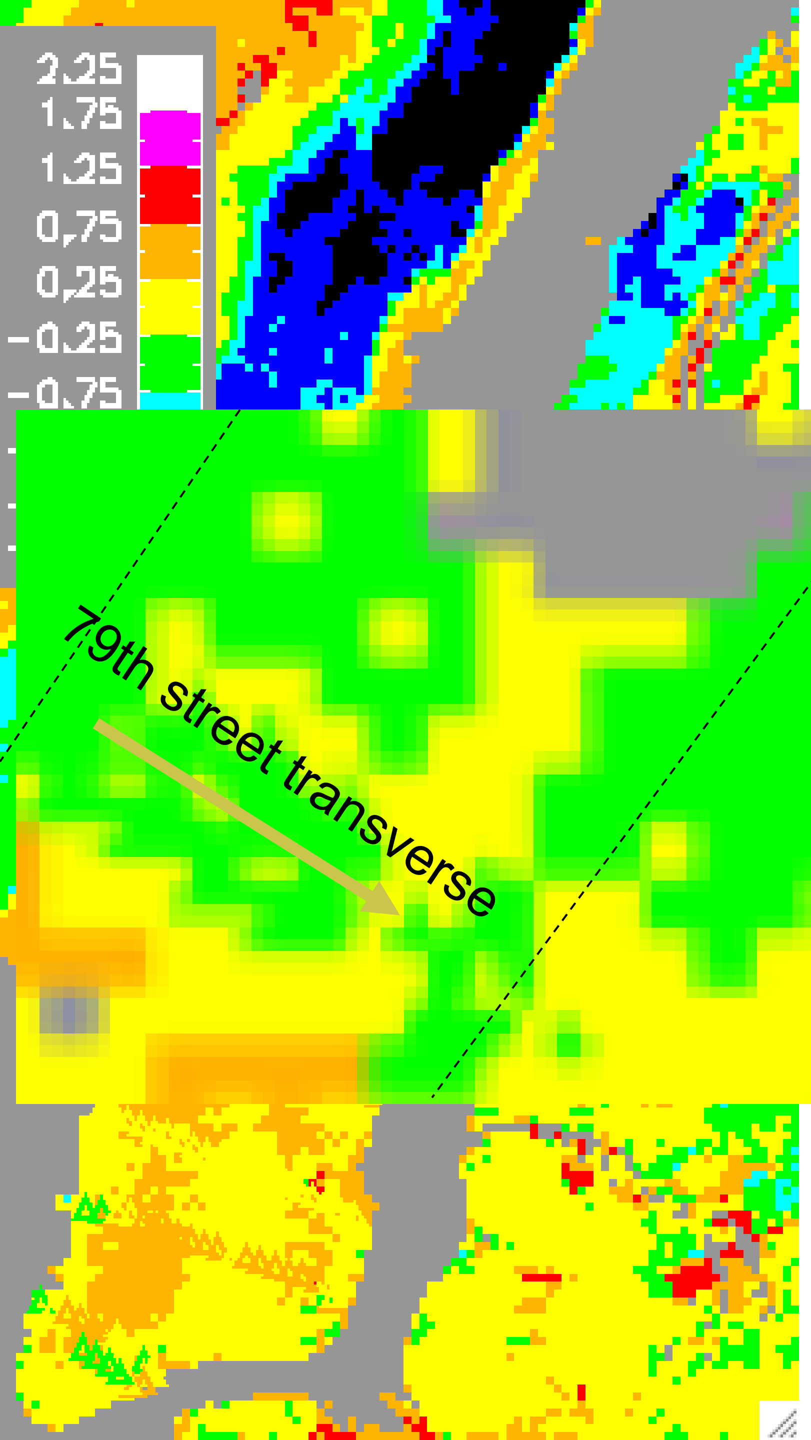
Hot spot at piers

Unpredicted average

Warm in villages

Cool in downtown

Observed Cool points in Central Park



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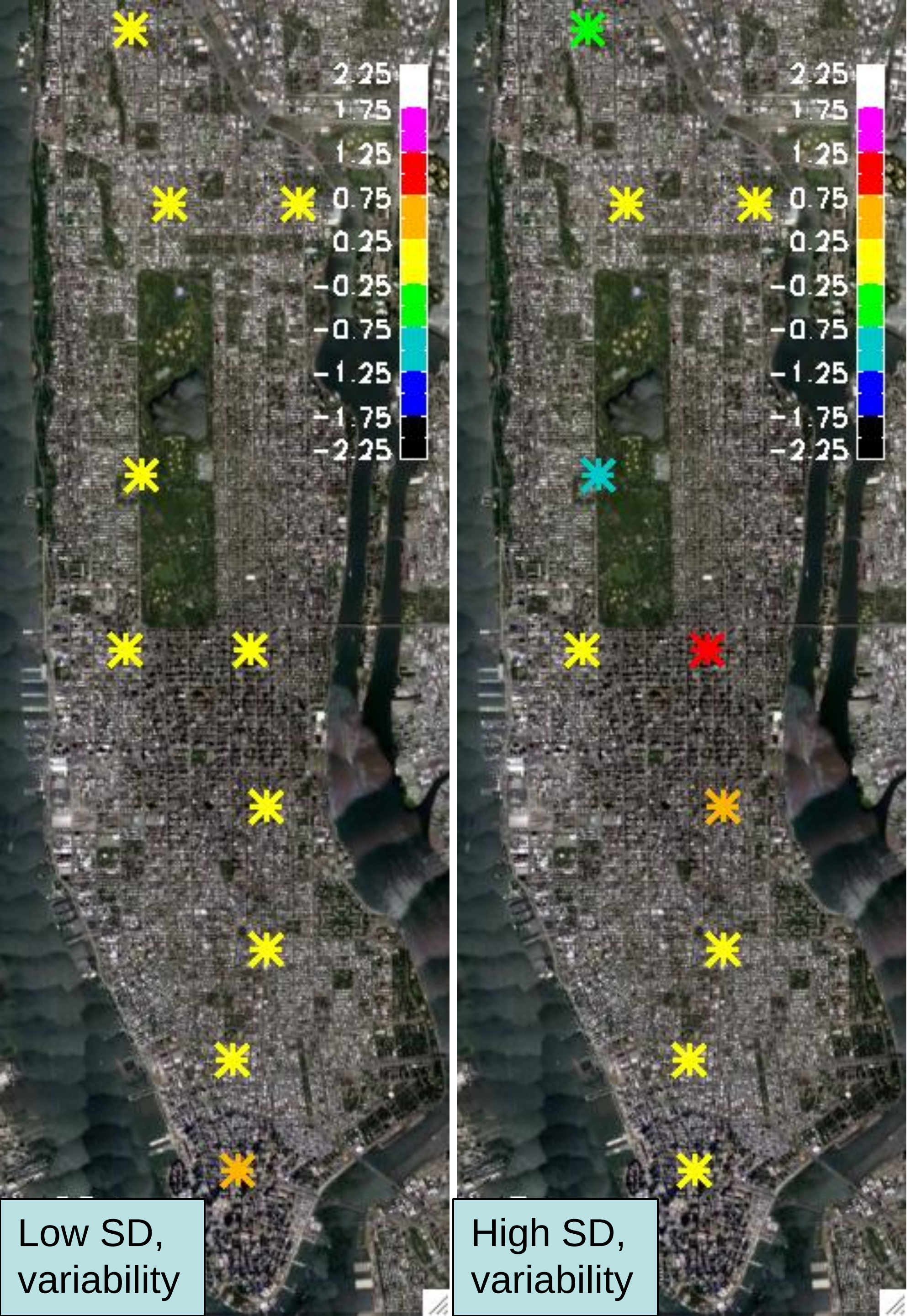


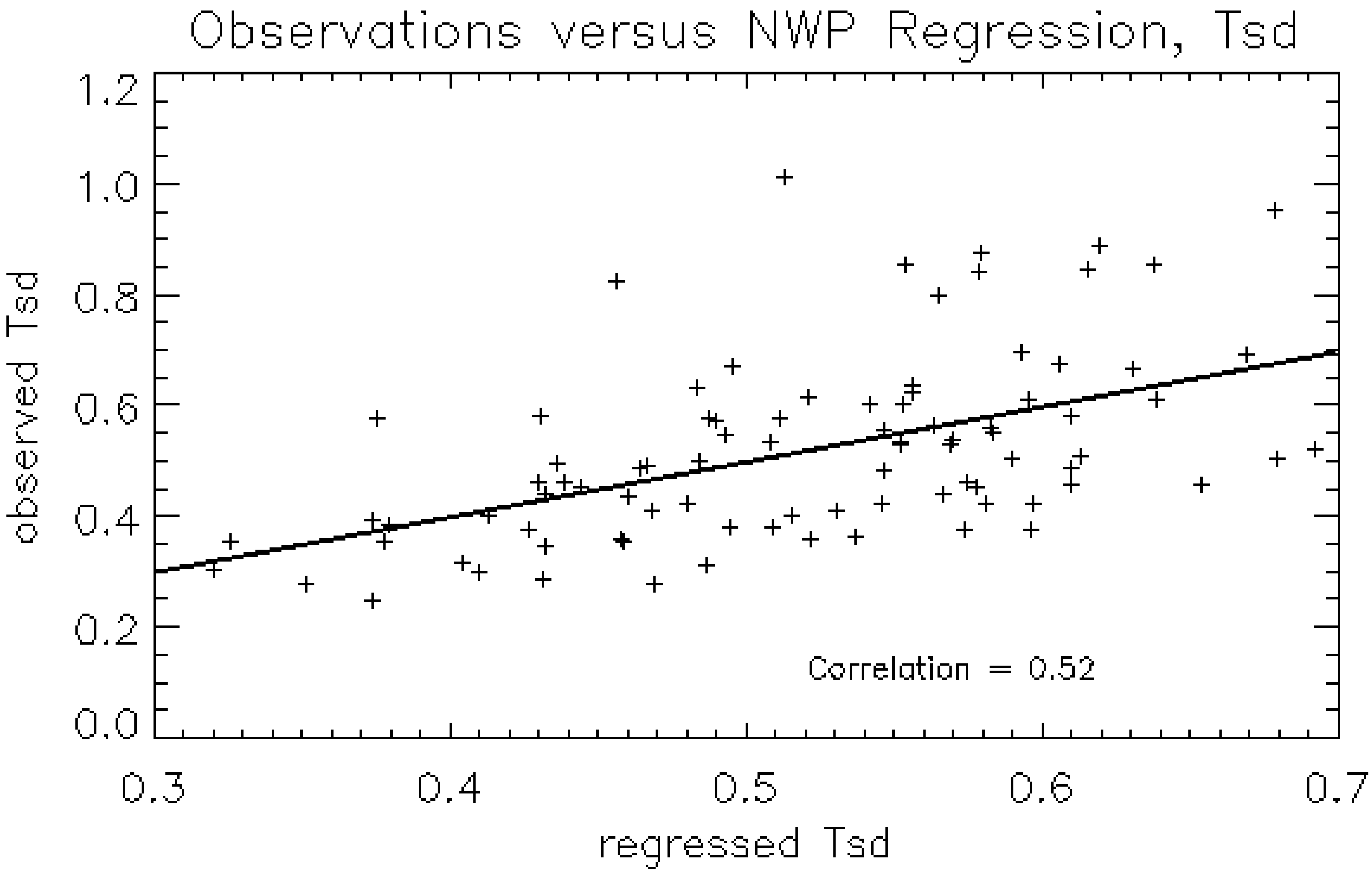
During 3 months the fixed instruments sample a wide range of meteorological conditions, reflected in the spread of temperatures between locations. The standard deviation is a measure of spatial variability.

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)

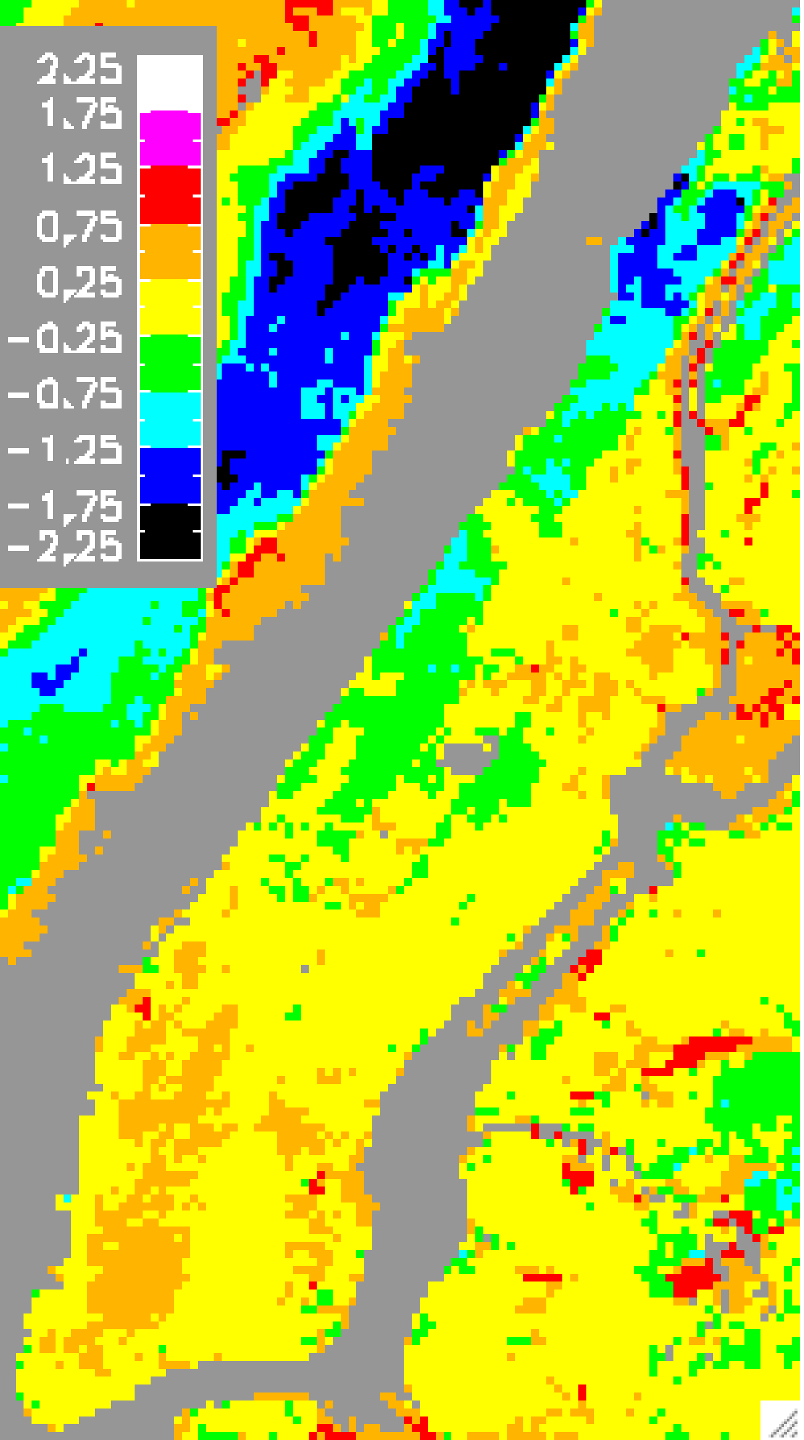
Weather and Temperature Anomaly Amplitudes

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



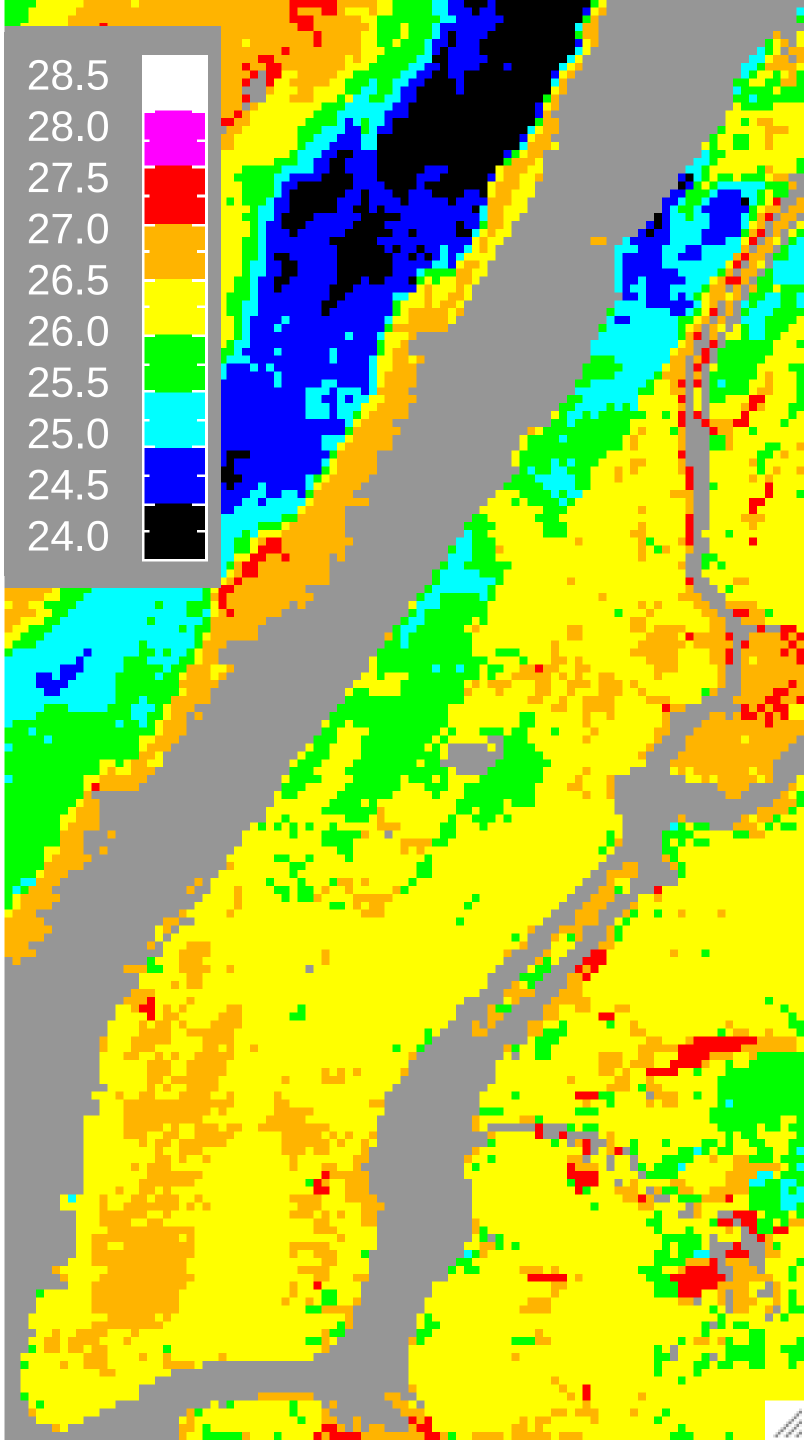
Temperature Difference between Highest and Lowest Elevation Stations

Variable	Correlation	Coefficient
Temp	0.471	0.067
RH	-0.134	0.011
Northward Wind	0.186	0.012
Eastward Wind	0.278	0.025
CF	-0.047	-0.003
Mid Level LR	-0.106	-15.315
Low Level LR	-0.216	-41.859
V Total	0.018	-0.001
Evaporation Rate	0.076	0.024



Actual degrees

Weather forecast



Critique: is the anomaly function Separable?

Temperature Anomalies	=	F(surface, weather)
	?=	G(surface) * K(weather)
		(Anomaly map * 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

$$\mathrm{StdDev}(T_{\mathrm{observed}} - T_{\mathrm{uniform}}) > \mathrm{StdDev}(T_{\mathrm{observed}} - T_{\mathrm{model}})$$

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

This work was funded by NOAA grants to the CREST Institute and CCRUN RISA