



# Surface Energy Balance Study and Temporal and Spatial Downscaling of Surface Temperature in Urban Area

**Hamid Norouzi**  
**Brian Vant-Hull**  
**Satya Prakash**  
**Prathap Ramamurphy**

New York City College of Technology, CUNY  
The City College of New York  
New York City College of Technology, CUNY  
The City College of New York

**NOAA-Cooperative Remote Sensing Science and Technology Center (CREST)**

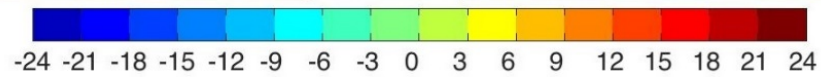
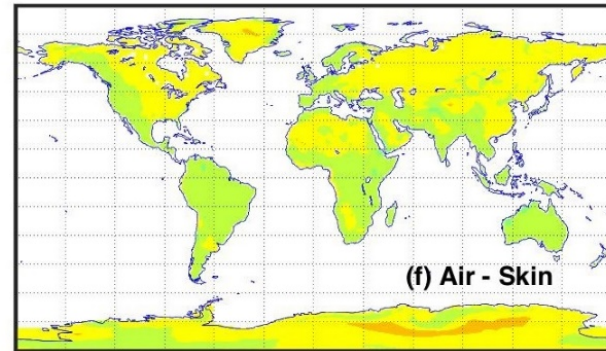
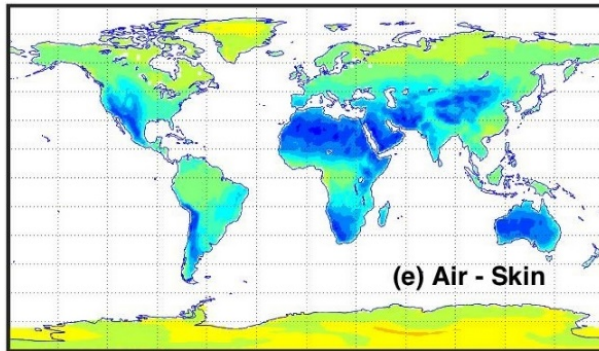
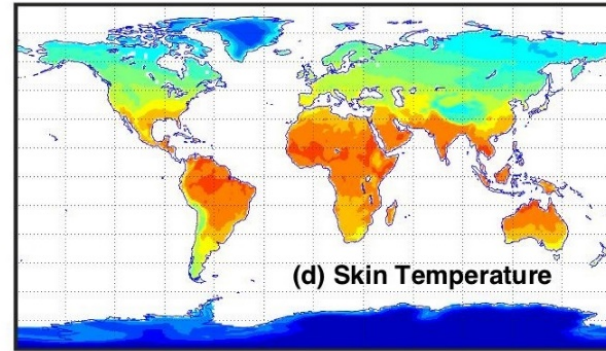
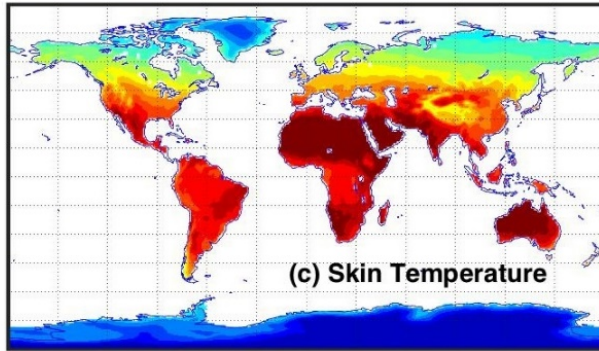
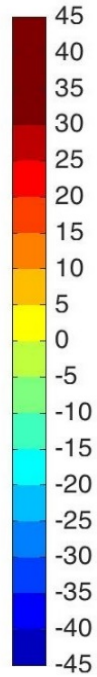
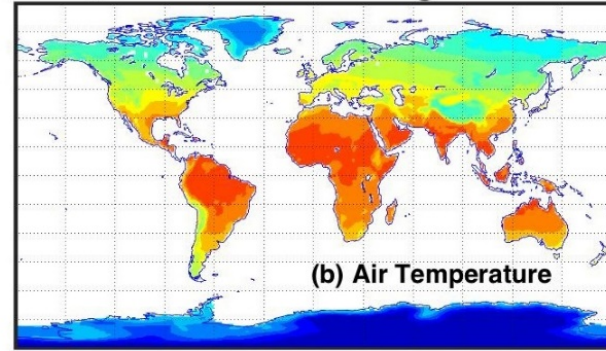
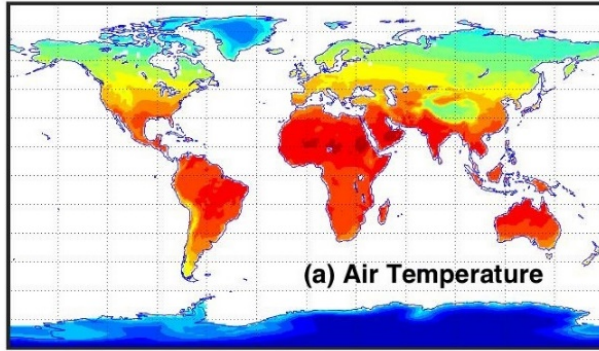
Rossow Symposium

June 7th, 2017

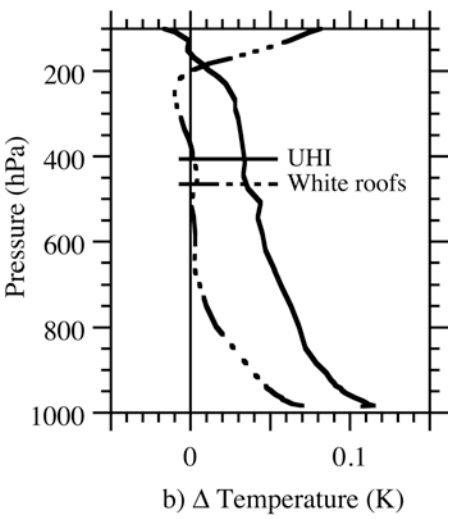
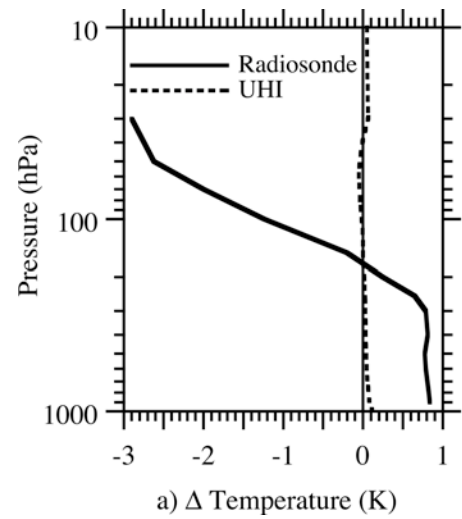
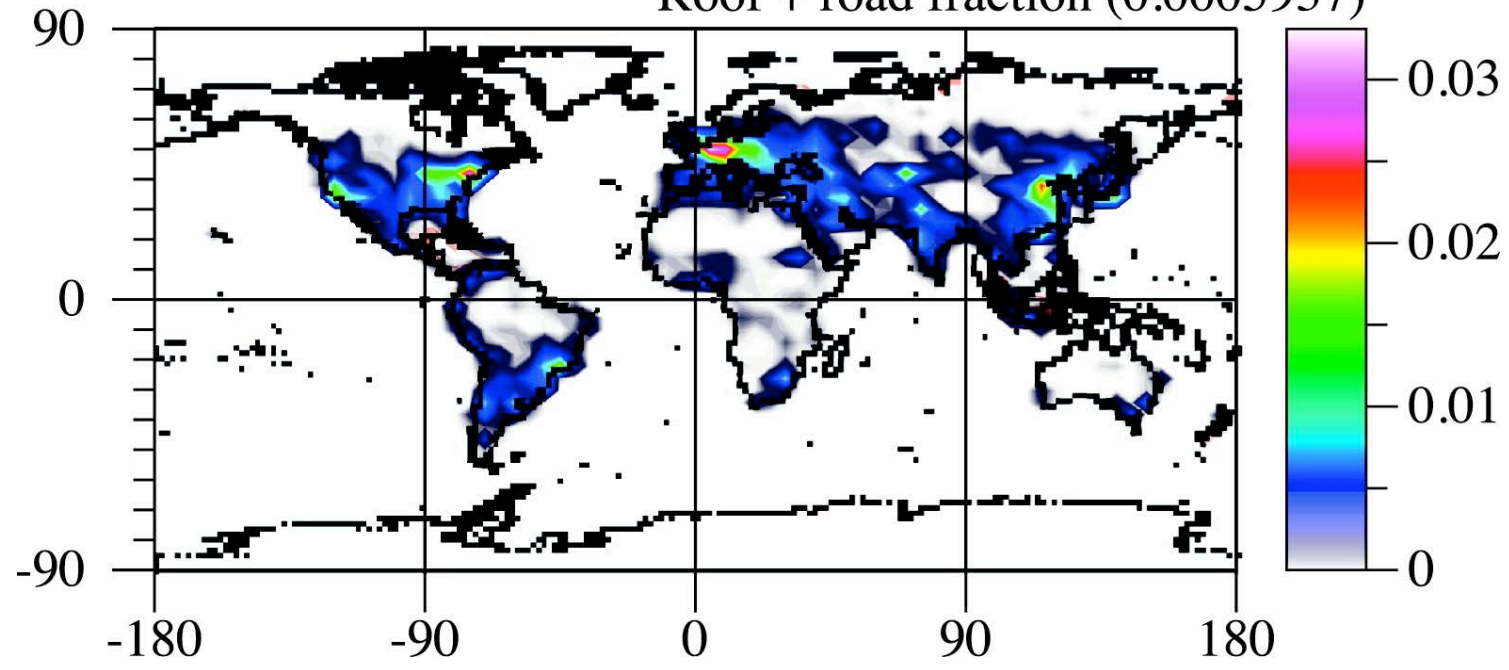
**Ascending**

**[Jan 2003 - Dec 2015]**

**Descending**



Roof + road fraction (0.0005937)



Jacobson, M.Z. and J.E. Ten Hoeve, 2012:  
*J. Climate*

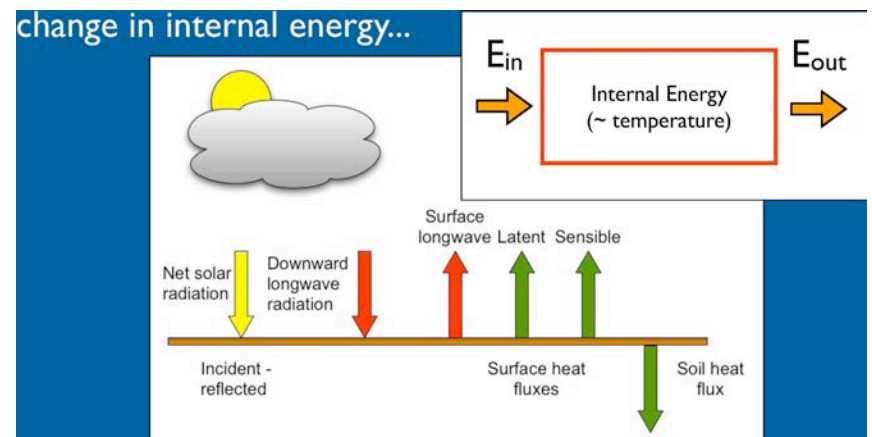




# Urban Surface Energy Balance

- Heavy rainfall often occurs around cities. In fact, cities themselves can affect the weather.
- Air is unstable when it is warmer than the air around it. The warm, unstable air starts to rise. The air cools as it rises, which allows water vapor within it to condense and form clouds.
- The goal is to develop a frame to address urban heterogeneity surface energy balance
- Developing air temperature maps with high temporal and spatial resolutions.

$$R_n = (1 - r) S_{\downarrow} + (L_{\downarrow} - L_{\uparrow}) = H + \lambda E + G$$



Schematic energy fluxes components at the surface  
(From Hahmann, NCAR)



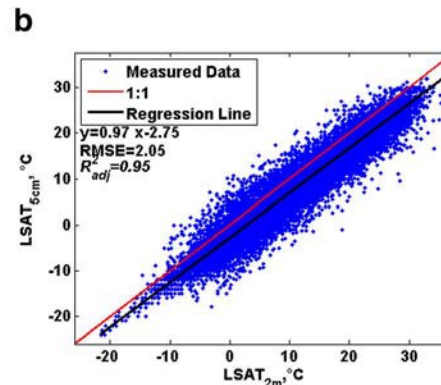
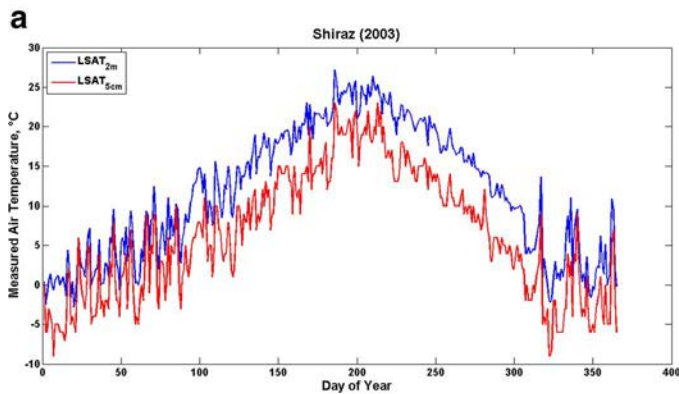
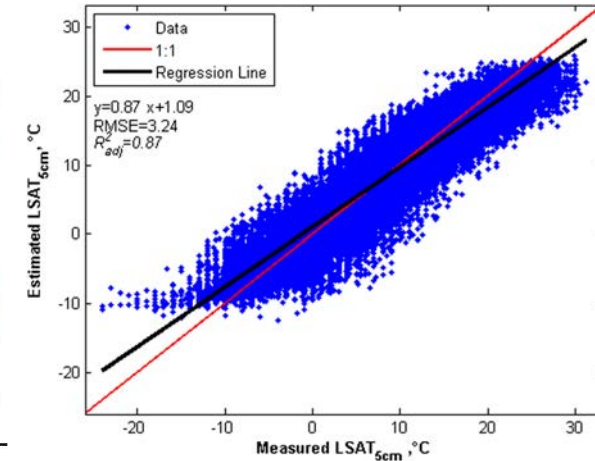
# Linking Satellite and Ground Observations

**Table 2** Statistical comparison between stepwise linear model-predicted  $LSAT_{5cm}$  and station-observed  $LSAT_{5cm}$  and their coefficients for all stations during 2003–2011

Used data	RMSE (°C)	MAD (°C)	$R^2_{adj}$ (%)	Coefficient						
				Intercept	Daytime LST (°C)	Nighttime LST (°C)	$T_{geom}$ (°C)	Elevation (m)	NDVI	
A										
Current day Aqua nighttime	4.38	3.54	74.82	-0.16	-	0.84	-	-	-	-
Current day Aqua daytime	6.02	4.91	53.96	-11.82	0.51	-	-	-	-	-
Current day Terra nighttime	4.35	3.51	75.29	-1.85	-	0.81	-	-	-	-
Current day Terra daytime	5.77	4.69	57.37	-10.58	0.53	-	-	-	-	-
B										
Current day Aqua nighttime	3.4	2.69	84.78	5.29	-	0.22	0.77	-4.07E-03	3.74	
Current day Aqua daytime	3.4	2.69	85.24	7	0.01	-	1	-5.16E-03	N. S	
Current day Terra nighttime	3.4	2.69	84.84	5.12	-	0.2	0.78	-4.19E-03	3.45	
Current day Terra daytime	3.4	2.68	85.17	6.55	0.03	-	0.97	-5.12E-03	0.57	
Current day Aqua daytime and nighttime	3.27	2.58	85.97	5.89	-0.03	0.21	0.85	-4.15E-03	2.7	
Current day Terra daytime and nighttime	3.27	2.59	85.93	5.36	-0.04	0.22	0.84	-4.14E-03	2.9	
C										
Previous day Aqua nighttime	3.24	2.56	86.56	4.19	-	0.27	0.75	-3.79E-03	4.73	
Previous day Aqua daytime	3.44	2.72	84.76	5.79	0.06	-	0.92	-5.12E-03	1.78	
Previous day Terra nighttime	3.3	2.61	86.01	4.19	-	0.24	0.75	-3.96E-03	4.28	
Previous day Terra daytime	3.44	2.72	84.65	5.81	0.07	-	0.9	-5.10E-03	1.65	
Previous day Aqua daytime and nighttime	3.2	2.53	86.79	4.01	0.01	0.24	0.77	-4.00E-03	4.9	
Previous day Terra daytime and nighttime	3.24	2.57	86.26	4.1	0.01	0.22	0.78	-4.12E-03	4.28	

$$T_{geom} = a \times \cos\phi - b \times (1 - \cos\theta) \sin|\phi|$$

$$\theta = (\text{calendar day} - 18) \frac{2\pi}{365} + 2^{(1 - \text{sign}(\phi))} \pi$$

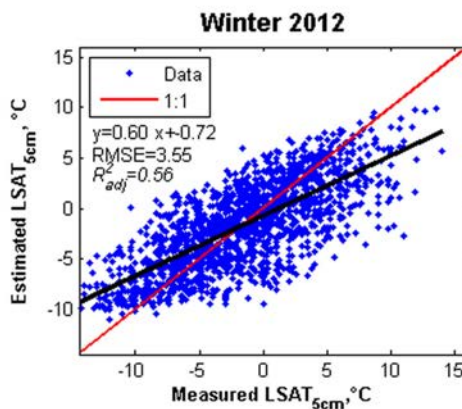
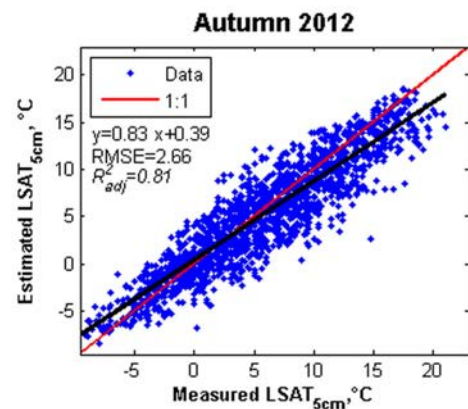
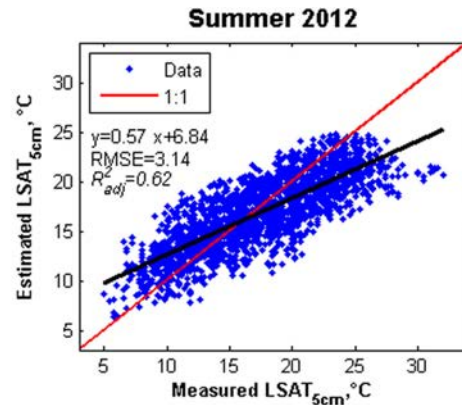
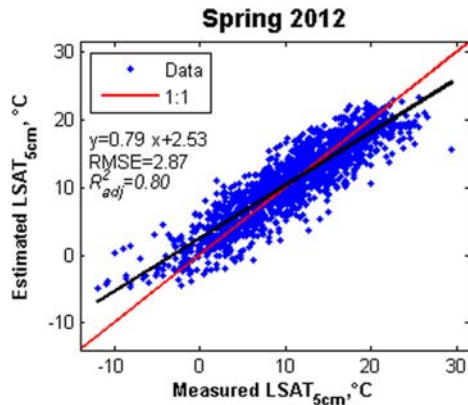


Comparison of measured minimum  $LSAT_{5cm}$  and its estimated values based on linear regression model for Aqua LST nighttime, NDVI data of the previous day,  $T_{geom}$ , and elevation during the years 2003–2011. Estimation of daily minimum land surface air temperature

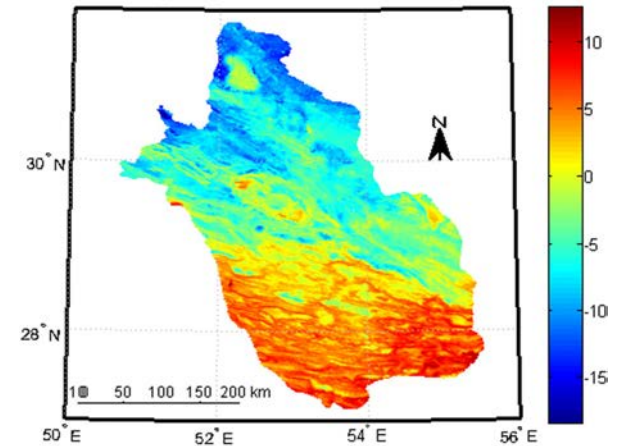
(Didari et al, TAC, 2016)



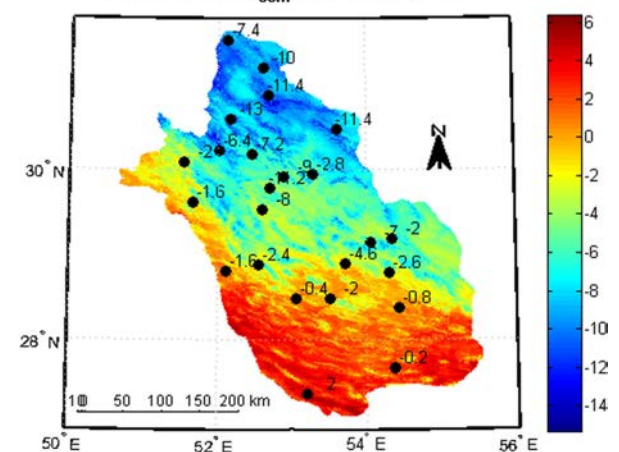
# Spatio-Temporal Regression



MODIS Aqua Nighttime LST at 30 January 2012



Estimated LSAT<sub>5cm</sub> at 30 January 2012



**Table 3** The statistic of estimated coefficients using stepwise linear regression model with Aqua LST nighttime and NDVI data of the previous day,  $T_{geom}$ , and elevation during the years 2003–2011

Coefficient	Estimated	Standard error	tStat
Intercept	4.19	7.77E-02	53.85
LST (°C)	0.27	4.11E-03	65.38
$T_{geom}$ (°C)	0.75	4.77E-03	157.07
Elev (m)	-3.79E-03	3.35E-05	-113.09
NDVI	4.73	2.29E-01	20.62

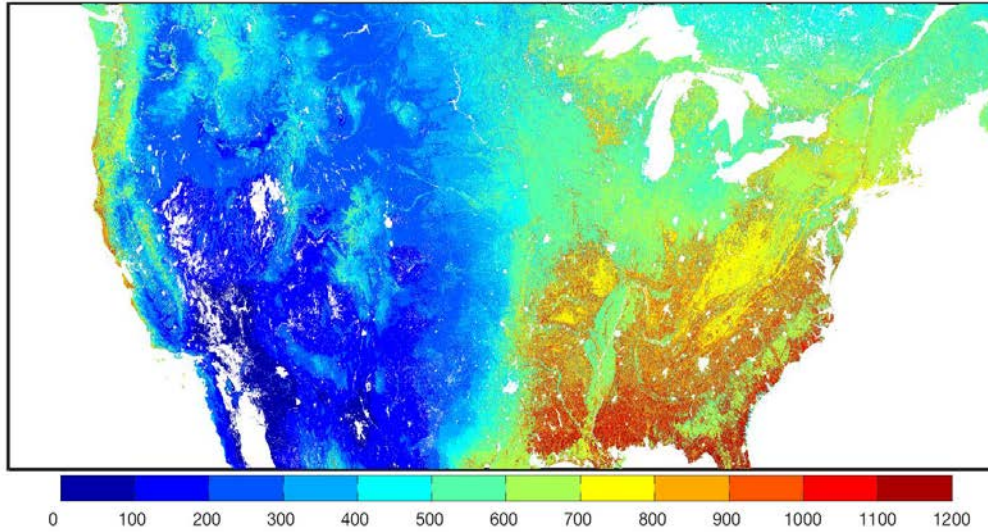
## Spatio-Temporal Regression-Kriging

$$Z(s, t) = m(s, t) + e'(s, t) + e''(s, t)$$

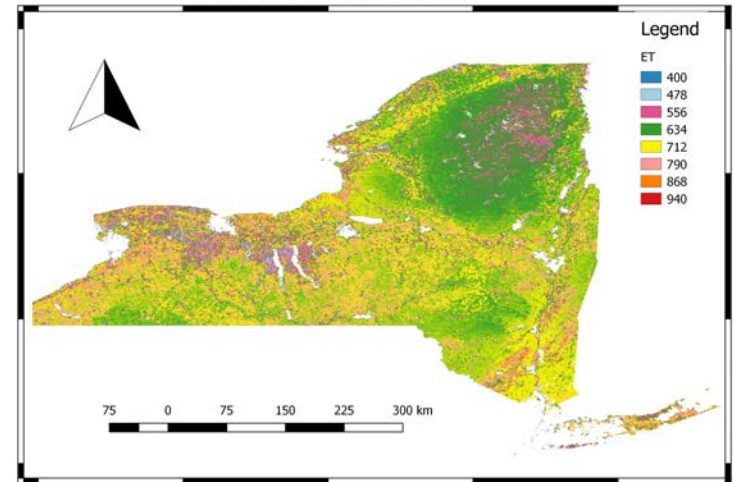
(Didari et al, TAC, 2016)



MODIS Mean ET [2000-2013]

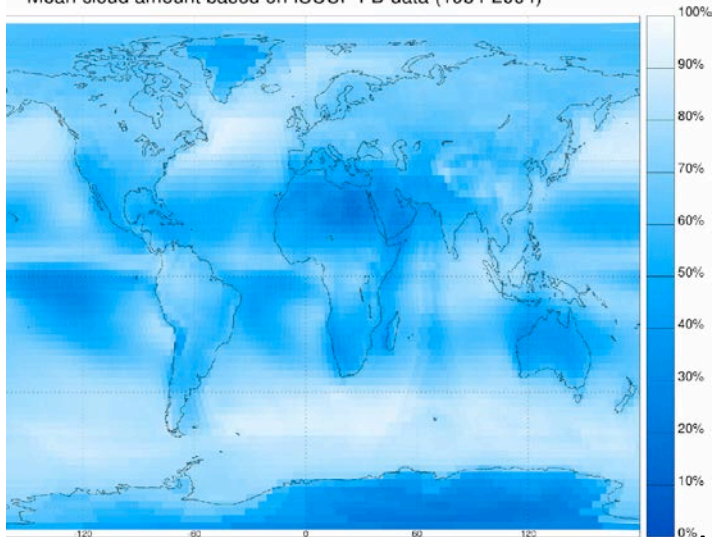


MODIS MEAN ET [2000 - 2013]

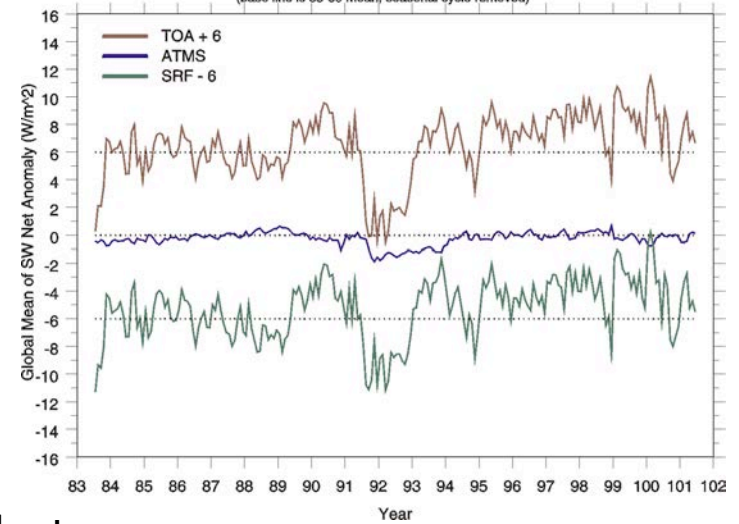


*Mu et al., 2011, RSE*

Mean cloud amount based on ISCCP FD data (1984-2004)

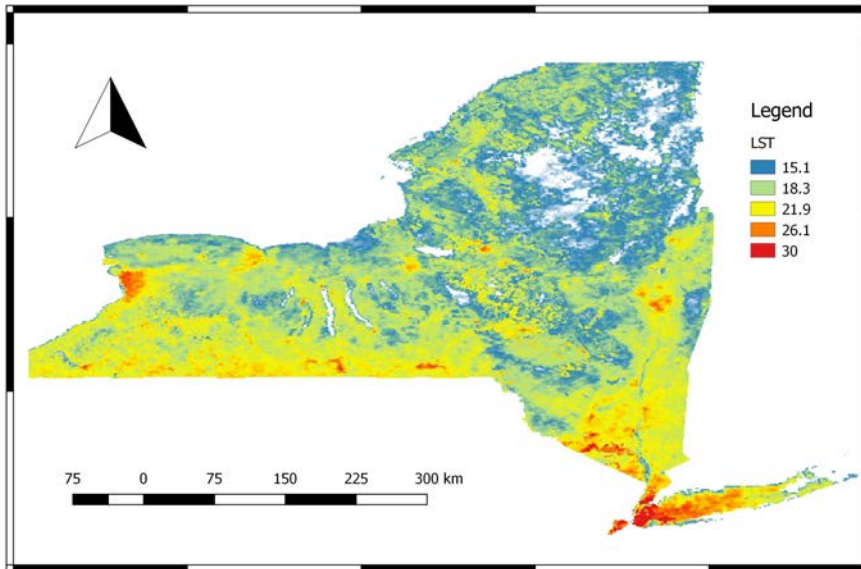


Global Mean Anomaly of SW Net from ISCCP FD Data  
(base line is 85-89 mean, seasonal cycle removed)

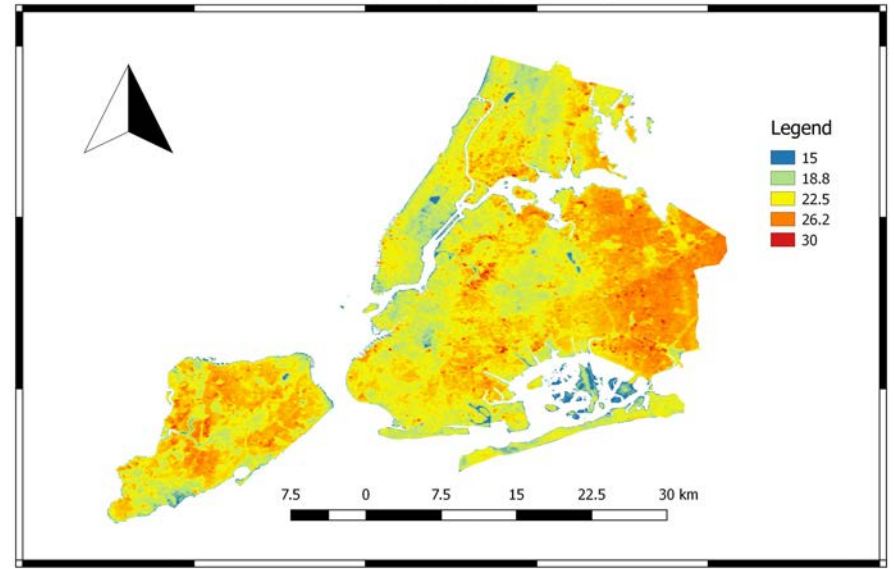


ISCCP-FD data product

MODIS: LST [Celsius] [Apr 22, 2016]



LANDSAT 8 : LST [Celsius] [ Apr 22, 2016]







# Flux Tower Observations

$$R_n = (1 - r) S_{\downarrow} + (L_{\downarrow} - L_{\uparrow}) = H + \lambda E + G$$

- **LI-7500A Open Path CO<sub>2</sub>/H<sub>2</sub>O Analyzer from LI-COR:**
- **Gill WindMaster Sonic Anemometer**
- **7900-300 Tripod**
- **7900-101 Biomet**
  - 7900-144 Net Radiometer (Kipp & Zonen CNR4).
  - 7900-130 Humidity and Temperature sensor (Vaisala HMP155).
  - 7900-135 Radiation Shield (RM Young 41005-5) for above.
  - 7900-150 Soil Heat Flux sensors (Hukseflux HFP01).
  - 7900-180 Soil Temperature thermistors (LI-COR).
  - 7900-170 Soil Moisture probes (Delta-T ML2x).
  - 7900-190 Quantum Sensor (LI-COR LI-190SL-50).
  - 7900-160 Rain/Precipitation gauge (Texas Electronics TR-525USW).
  - 7900-120 Data logger (Sutron Xlite 9210) with (2) 7900-124 Modules (10-channel).
  - 7900-125 Pre-configured Biomet Enclosure 36 x 41 cm (LI-COR)
- **7550-200 SMARTFlux**





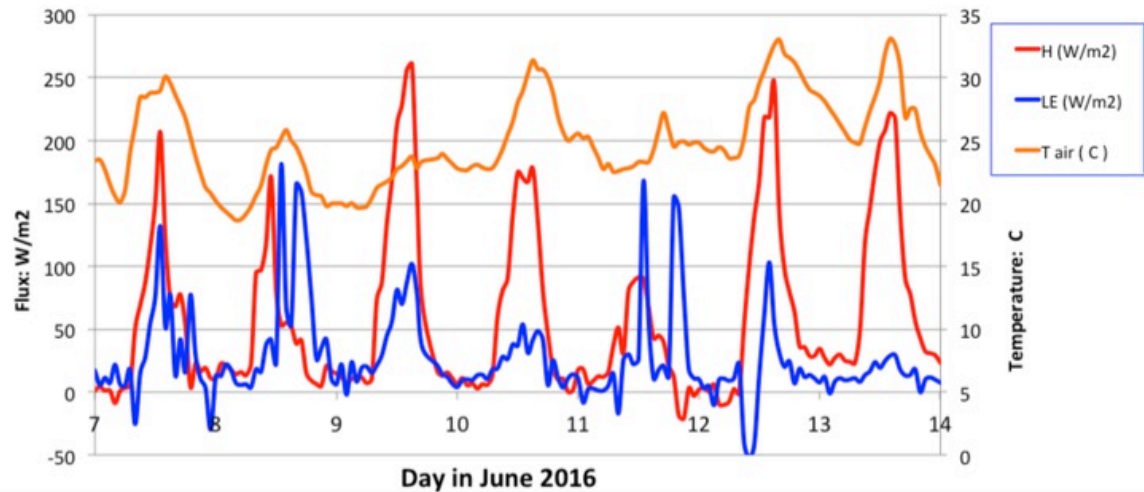
# Flux Tower Observations

Measurements are taken from following surfaces:

- Concrete
- Porous concrete
- Asphalt
- Black roofs
- White roofs
- vegetation



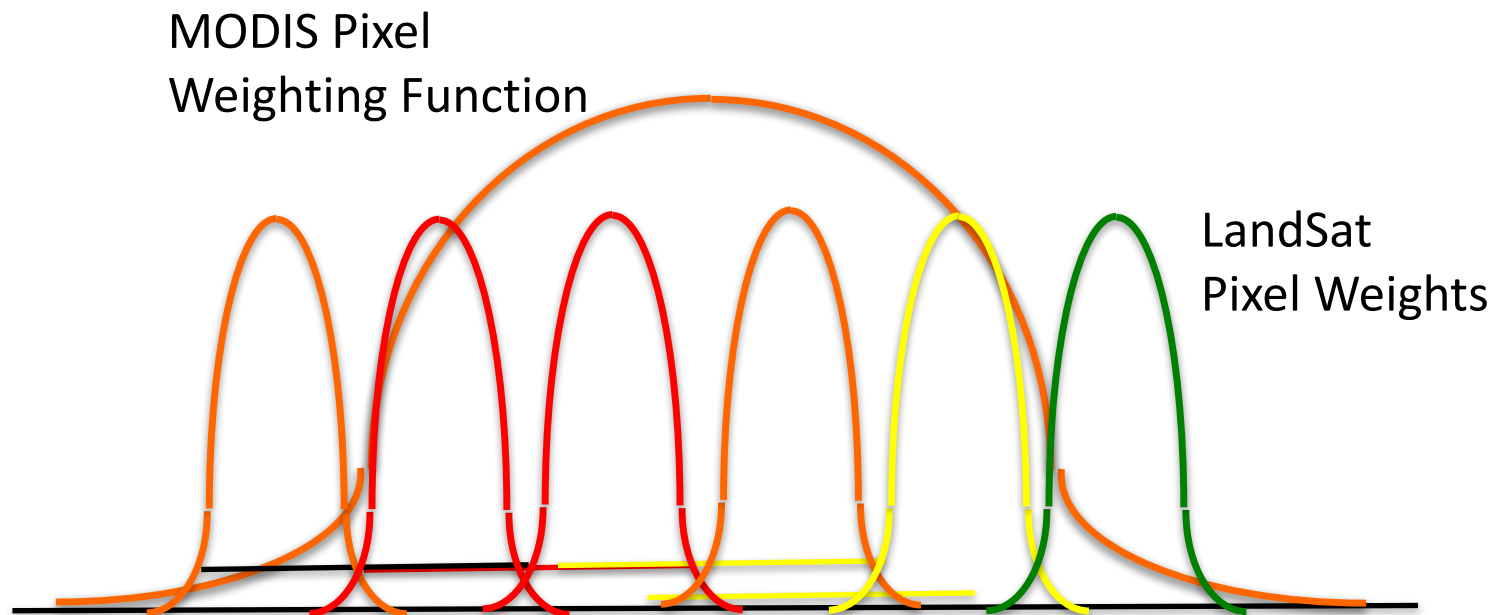
Flux towers installed at Manhattan College. Left: Asphalt. Right: Concrete.



Vertical fluxes of sensible and latent heat for the week of June 7-14, 2016.



# Satellite "Pixel" Cross-Sections

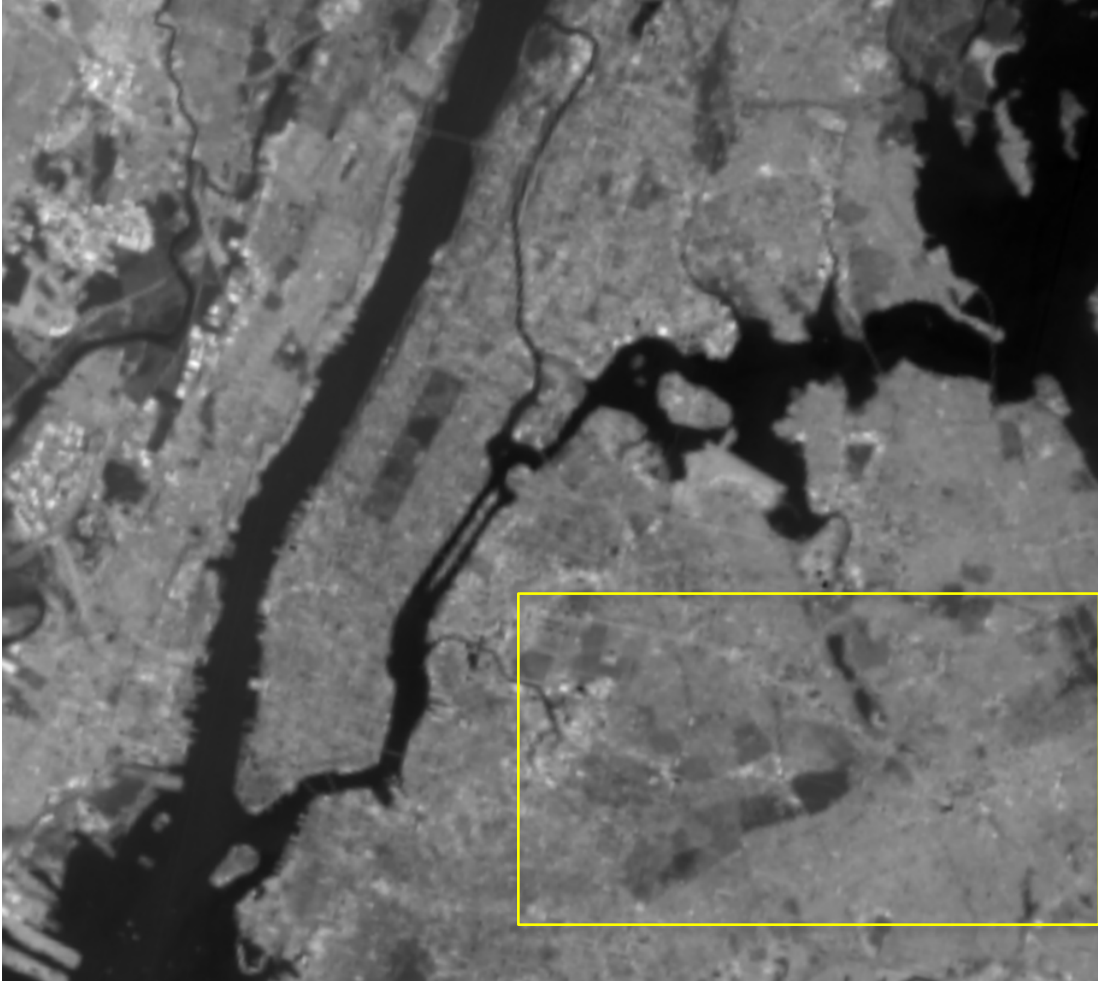


MODIS Pixels do not have uniform radiance weighting across the pixel area. The LandSat sub-pixel temperatures can not be weighted equally; an effect that varies with pixel position in the swath.





# Temperature Downscaling



The grayscale LandSat temperature image shows variability in East River versus Hudson river water temps.

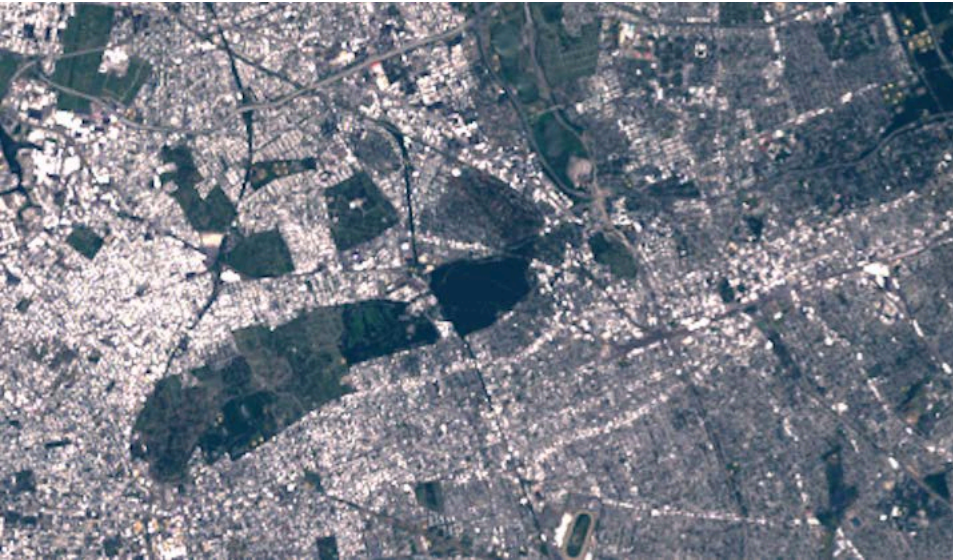
We choose a subset area of Queens & Brooklyn to avoid large water bodies on this first attempt.

Preliminary Downscaling of MODIS Temperature based on Surface Classifications

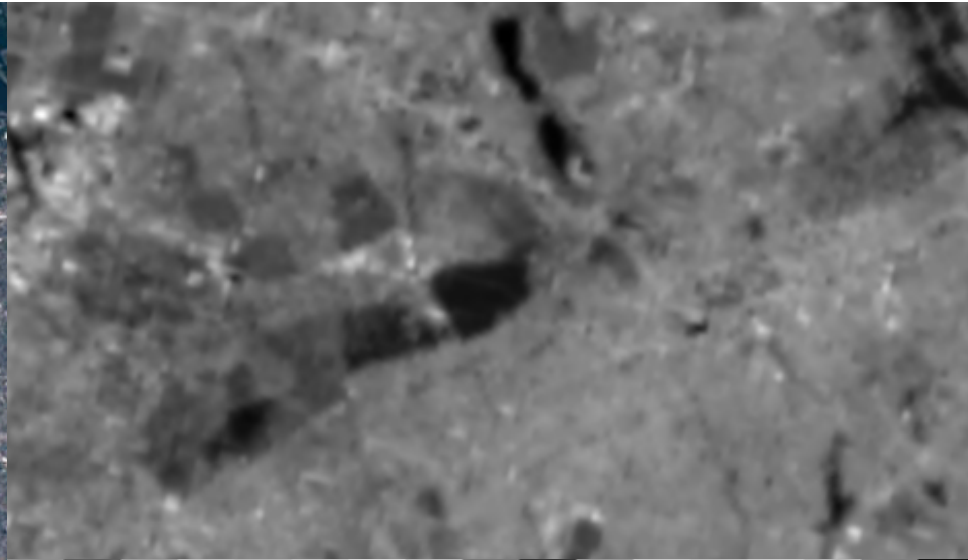


# Temperature Downscaling

**RGB Image**



**BT Image**

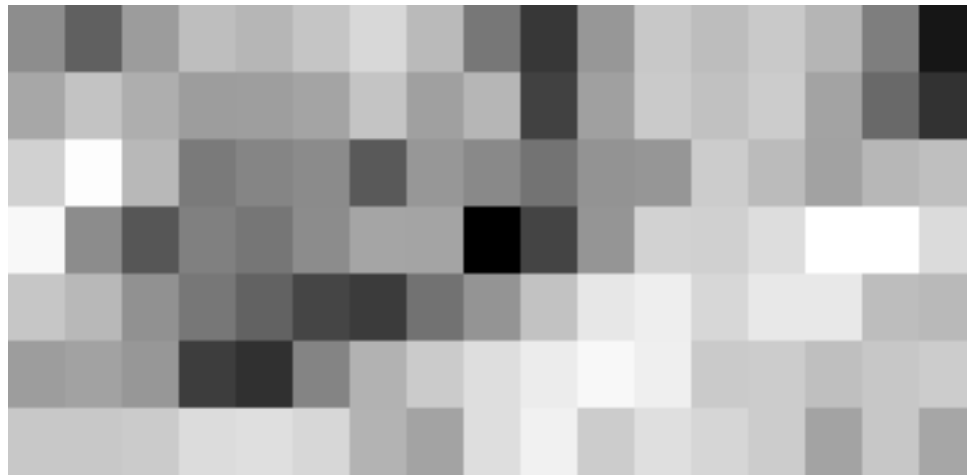


The Landsat Hi-Res BT image is regrided to match that of MODIS as a testbed for the downscaling technique.



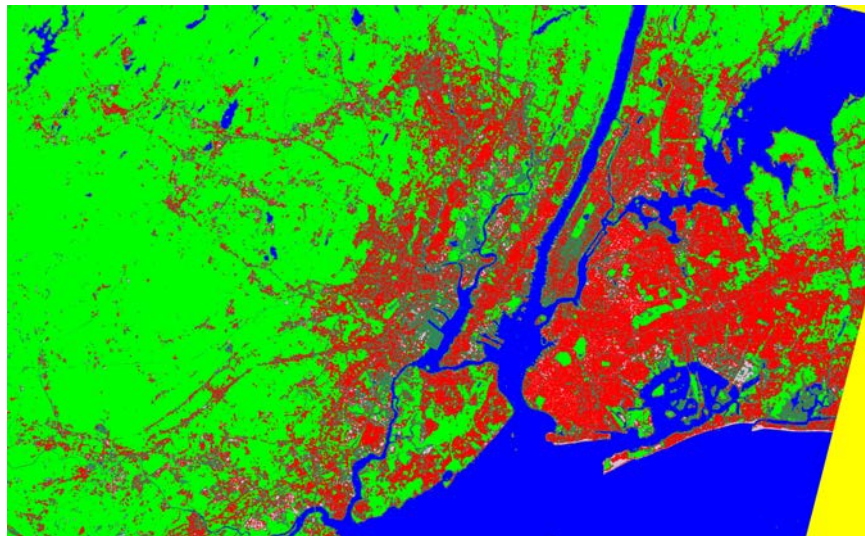
0.001 degree (1km) BT image

# Downscaling Technique



30% Veg  
20% water  
40% building  
10% road

15% Veg  
0% water  
65% building  
20% road



Each 1 km<sup>2</sup> bin has an average temperature  $T_i$  and a mix of  $k$  surface component fractions  $F_{ki}$  with coefficients  $C_k$  TBD. Coordinates in 3 dimensions were included to capture weather gradients.

$$T_i = T_o + \sum_{ik} C_k F_{ik}$$

$C_k$  and  $T_o$  found by regression.





# Surface Coefficients are Not as Expected

$$T_i = T_o + \sum_{ik} C_k F_{ik}$$

F = surface fraction

C = coefficient

$$T_o = -119 \text{ C}$$

*(expected close to average T!)*

## Coefficient

Water	111 C
Veg	144 C
Build 1	146 C
Build 2	152 C
Road	157 C
Elevation	-0.026 C/m
WtoE	0.032 C/km
StoN	-0.027 C/km

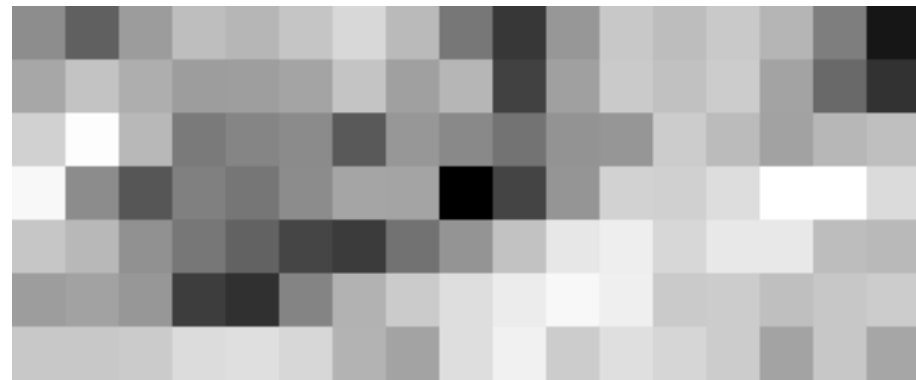
We expected fractional coefficients to be on the order of a few degrees to modify the average temperature.

Geographical coefficients will change daily, seasonally.

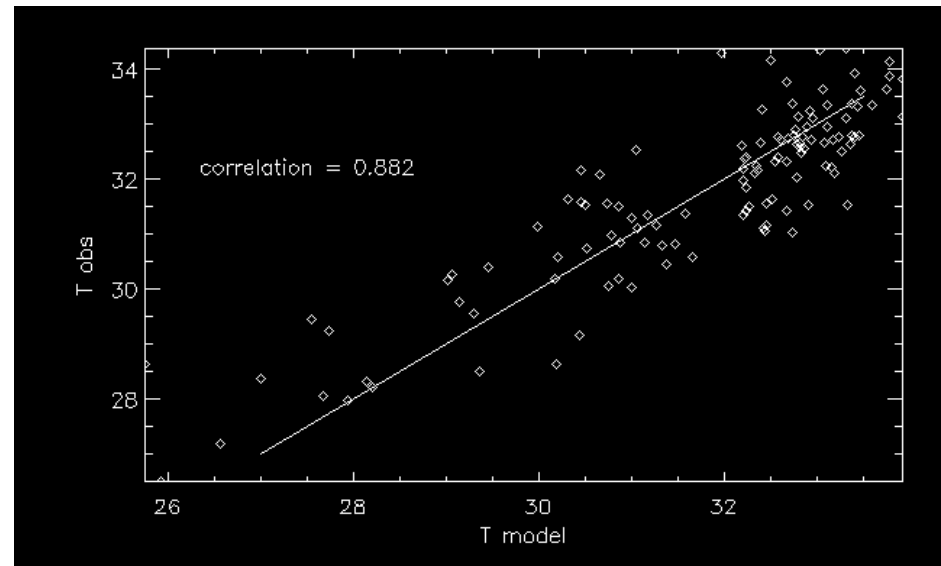


# Does Statistical Model Reproduce 1 km Temperatures?

## Observed Average Temperatures



## Modeled average Temperatures Based on Surface Classification





# Same Coefficients Used to Downscale



LandSat Scale  
Observations of  
Temperature

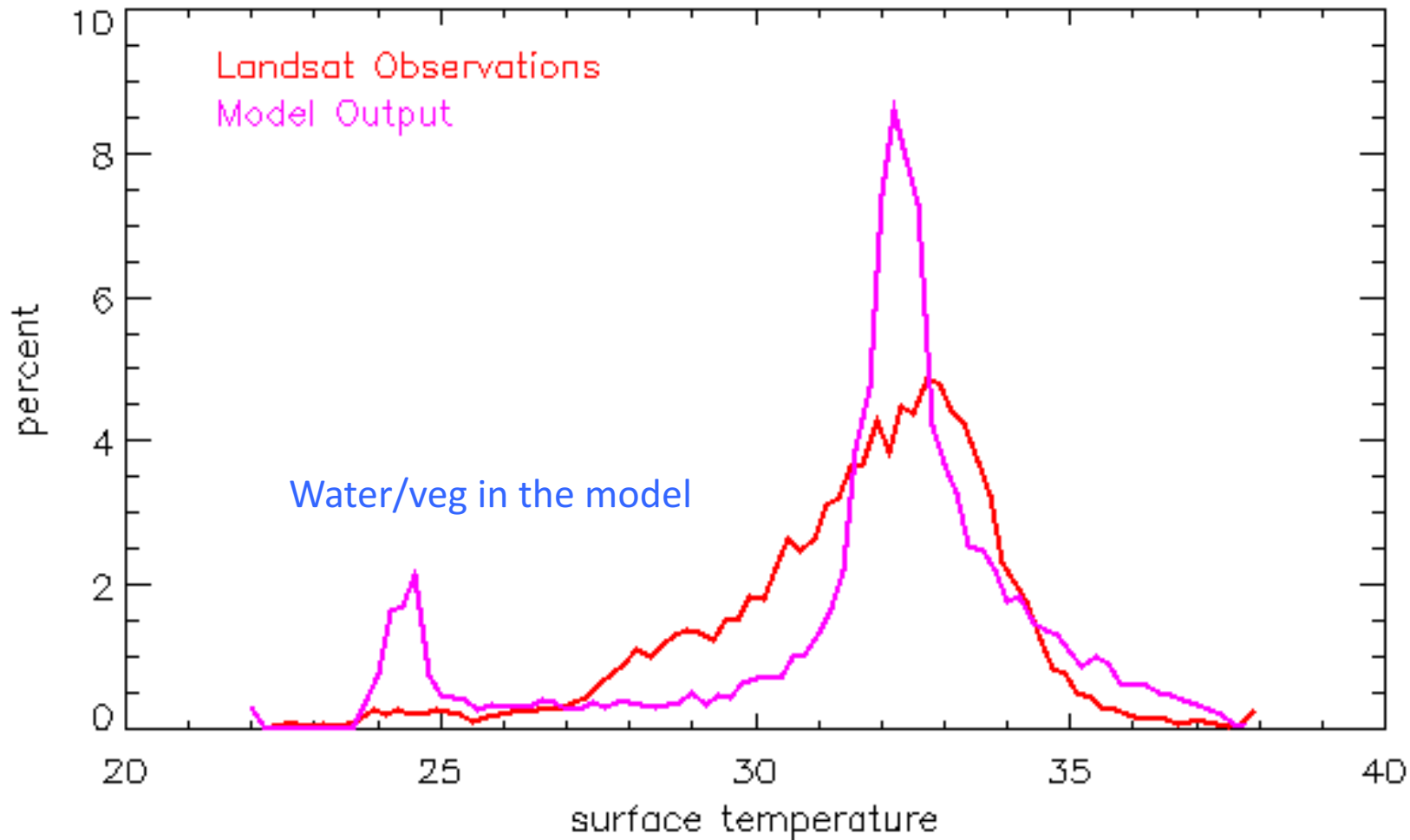


Downscaled From  
MODIS scale  
Observations plus  
Surface Classification





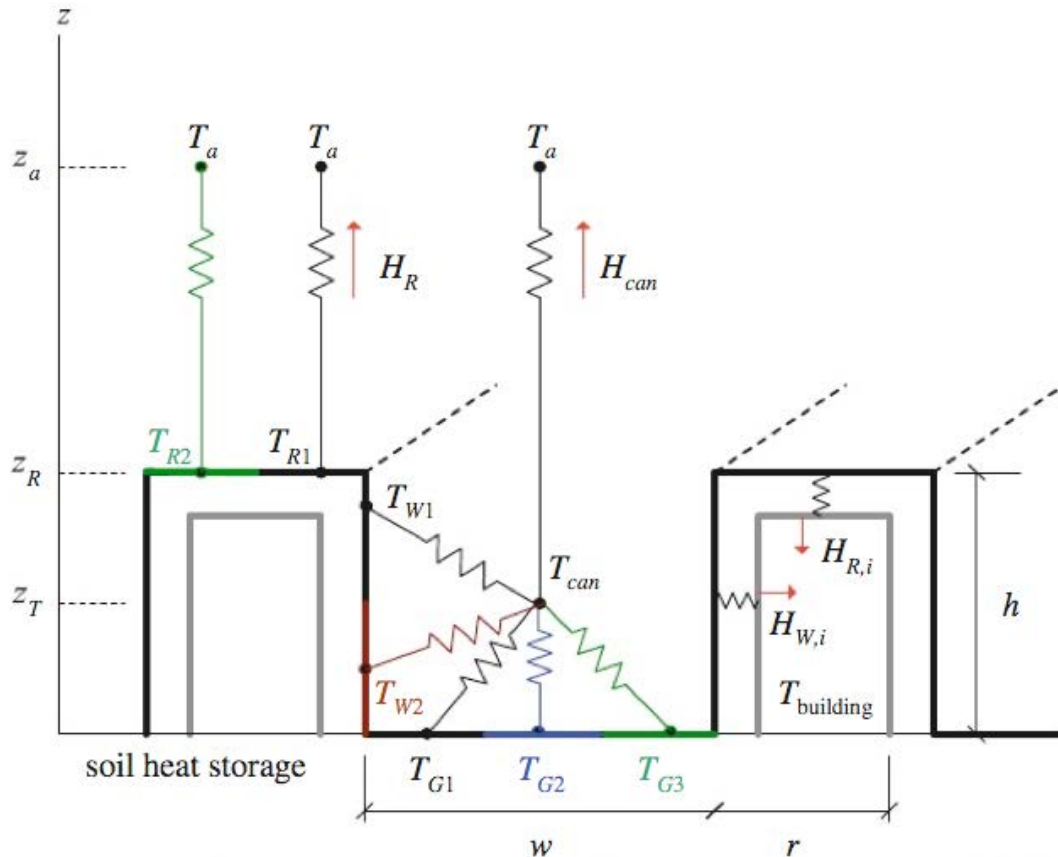
# Water/Vegetation Problem with Downscaling



Histograms of Observed and Modeled Temperature



# Urban Canopy Model



- Urban facets with multiple thermal properties
- Coupled with a Hydrological model
- Analytical solution for heat conduction

## Princeton Urban Canopy Model

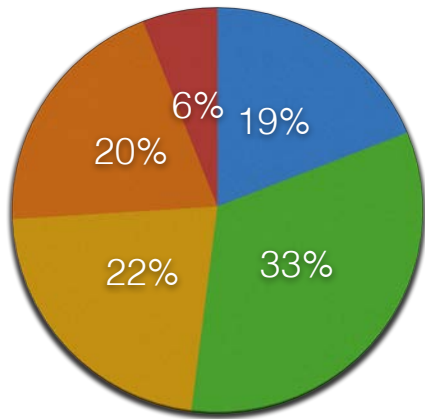
Based on *Kusaka's(2001)* energy exchange framework

(Wang et. al., 2013)



# Urban Canopy Model

## UMBC STUDY SITE



- CONCRETE
- GREEN
- ASPHALT
- WHITE ROOF
- BLACK ROOF



Average Footprint for the study period (July 2009)

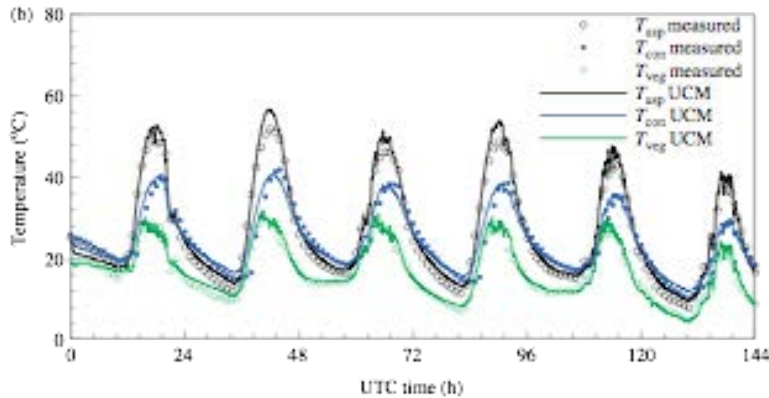
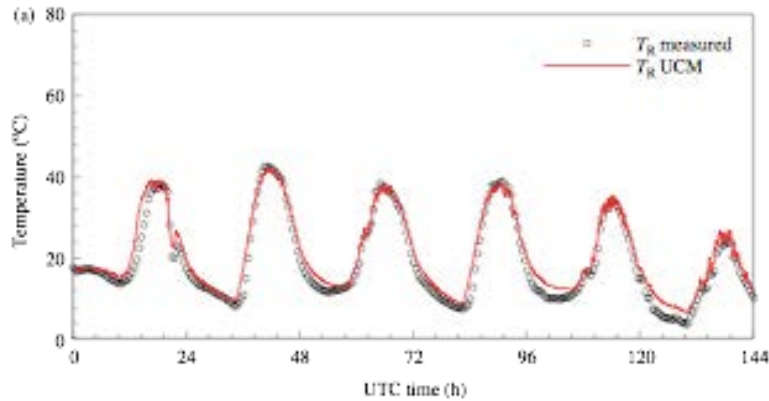
Data from the UMBC flux tower was used to calculate the footprint



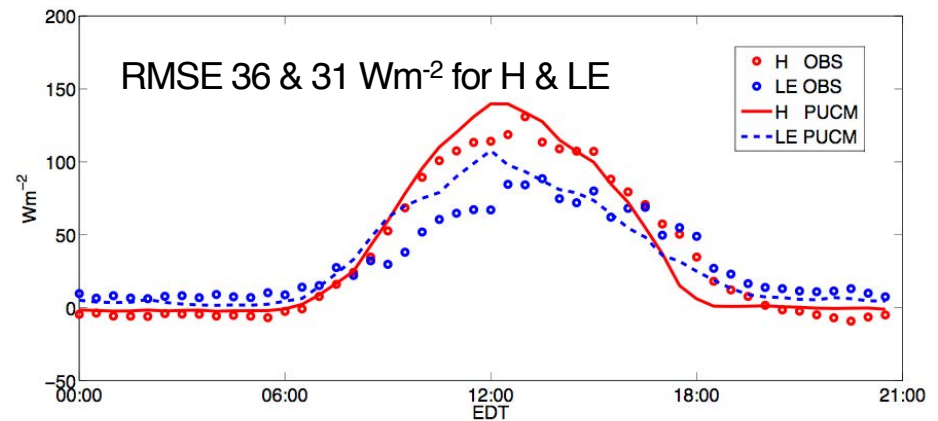


# Urban Canopy Model

## Validation



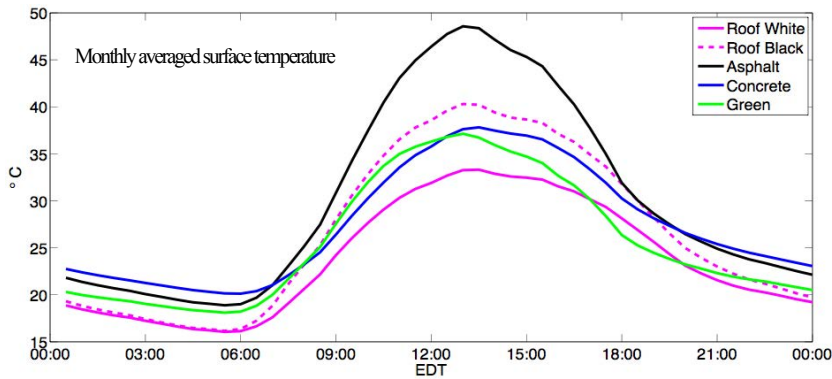
Air Temperature	Vaisala HMP45
Specific Humidity	Vaisala HMP45
Wind Speed	Campbell CSAT3
Pressure	Licor 7500
Incoming Longwave	Kipp & Zonen CNR1
Incoming Shortwave	Kipp & Zonen CNR1
Precipitation	All Weather Inc. Raingauge 6011-A





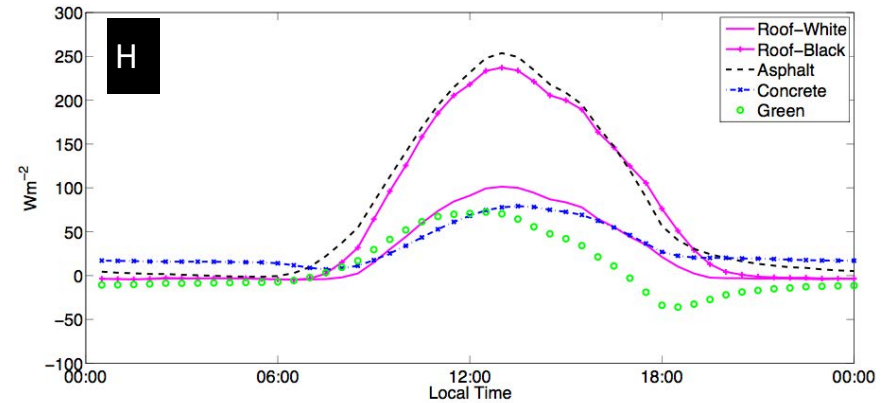
# Urban Canopy Model

## SURFACE/SKIN TEMPERATURE



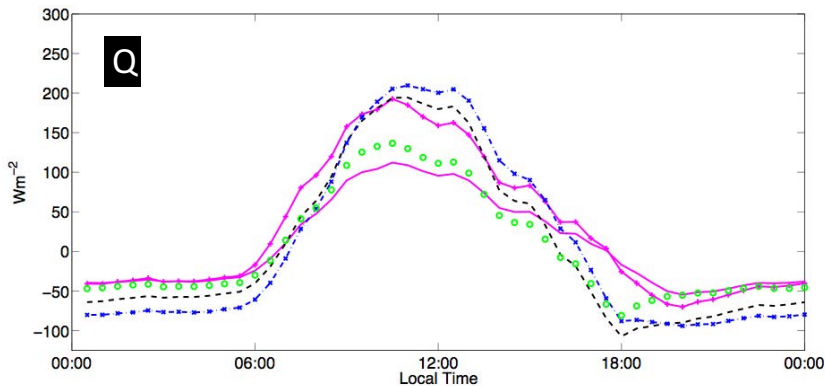
- ~10°C difference between black ( $\alpha=0.05$ ) and white roof ( $\alpha=0.50$ )
- Concrete warmest during night & early morning periods

## SENSIBLE HEAT FLUX



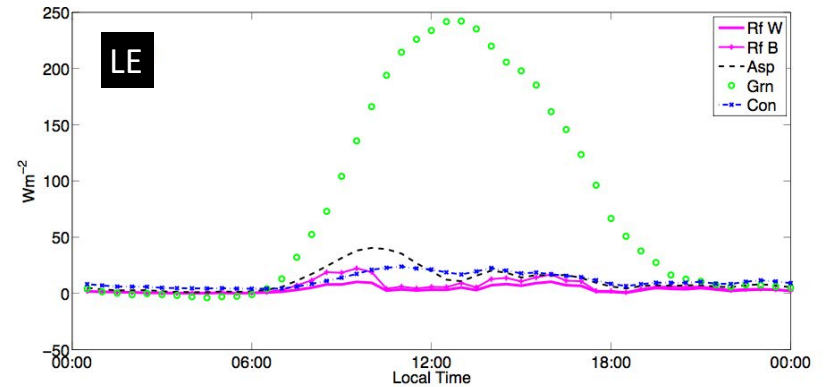
- Peak time lag between built and green surfaces
- Contributions from Concrete high at night
- Asphalt and Black roof contributions high during daytime

## STORAGE HEAT FLUX



- Substantial contribution in urban areas

## LATENT HEAT FLUX



- While LE from green surfaces dominate, evaporation from built surfaces visible
- Intermittency in LE from built surface due to precipitation being the primary driver

(Ramamurthy et. al., 2014)



# Conclusions & Future Work

- What will be the effect of clouds? And how the coarser satellite observation can be included in the model.
- What will be the effect of the Urban Areas on regional scale and global scale?
- Use more frequent MODIS or GEO satellites to get coarse-scale average temperatures
- Flux towers can help to understand the variability of surface energy parameters at each urban surface type
- Urban Canopy modeling can benefit from satellite and ground observations to produce surface energy components in heterogeneous urban areas.
- Use Regression coefficients from Coarse Scale to Produce downscaled Temperatures based on surface classification
- GOES-R satellite capabilities to enhance our understanding about the urban surface energy balance.



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[hnorouzi@citytech.cuny.edu](mailto:hnorouzi@citytech.cuny.edu)