# INVESTIGATING THE RESPONSE OF STREET-LEVEL TEMPERATURE TO CITY MORPHOLOGY USING MOBILE MEASUREMENT METHOD

## 利用移动观测研究近地表气温对城市形态的响应

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# INTRODUCTION

- As a result of urbanization, anthropogenic climate change in urban areas has become one of the major climatic crises mankind must face besides global climate change [IPCC (2014) Climate change 2014 ].
- Actions to mitigate UHI intensity have become urgent, which should be based on profound understanding of UHI mechanism. However, our understanding of how the UHI comes into being is still insufficient, especially in the thermal process underlying the formation of Urban Heat Island (UHI).

# INTRODUCTION

- To measure the intensity UHI, the in-situ measurement and the satellite remote sensing technology are widely used because of satisfying spatial and temporal representativeness [Peng S , 2012]. However, both of the methodologies are not capable of capturing the details of temperature at the street floors.
- Why is the street-level UHI so important?
  - Prominent change of building geometry, vegetation fraction, underlying material, and illumination can create several distinct microclimates even within a small area [Oke T R , 1991]. As a result, the street-level UHI at local scale is more sensitive to the surrounding environment and is controlled by a more complicated mechanism than a larger scale.
  - On top of this, the air temperature is a more unpredictable variable compared to surface temperature because it has to do with the ambient thermodynamic condition, and is scale-dependent at street-level [Carly D. Ziter, 2019]. Therefore, the street-level Air Urban Heat Island (AUHI) is a key to the profound understanding of how microclimate change impacts UHI intensity.

# INTRODUCTION

- To acquire high-resolution data of AUHI intensity at street-level, mobile measurement plays a key role here. Mobile measurement is using a car or a bike as the platform for the sensors to collect data along the transect of the city [Yokoyama H, 2017; Ooka R, Kikumoto H., Busato F, 2014].
- Dry bulb temperature is used widely in UHI studies because it's a straight representative of urban climate. However, for comprehensive consideration which seeks to model the exposure of real human skin to urban climate, more complicated thermal comfort indices should be considered (Francisco Gomez). For example, wet bulb temperature is a good proxy of thermal comfort because it describes how the sweating human skin responds to urban heat by combining the dry bulb temperature with air humidity.

# RESEARCH QUESTIONS

- How does the street-level AUHI vary spatially and temporally in terms of both dry bulb temperature and wet bulb temperature? How does the distribution of wet bulb temperature differ from that of dry bulb temperature?
- How does the street-level AUHI relate to the microclimate changes (e.g., tree canopy cover, impervious surface cover, and building geometry). How different are the relations between dry bulb temperature and wet bulb temperature?
- What's the underlying thermal mechanism that controls these relations?

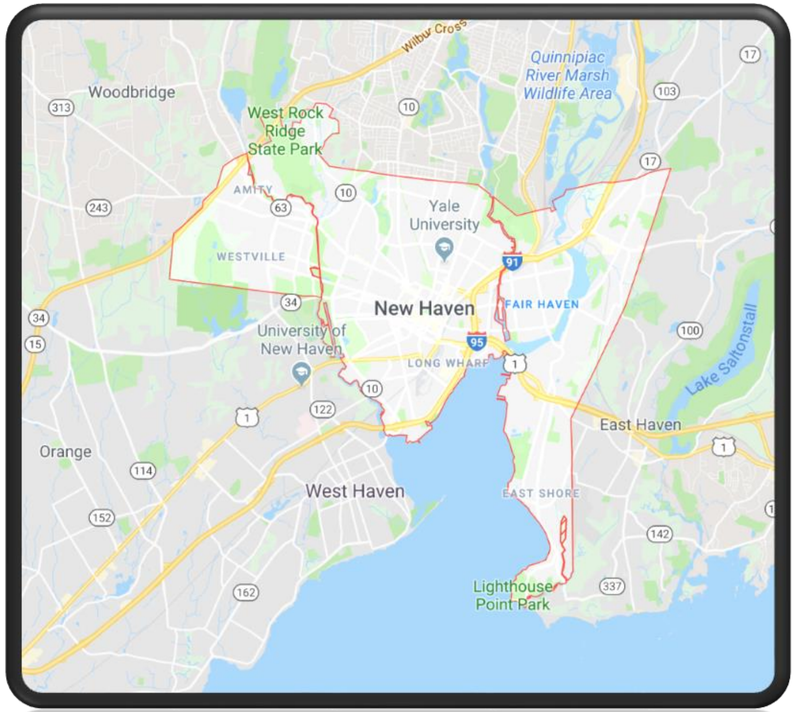
# SOME SIMPLE HYPOTHESES

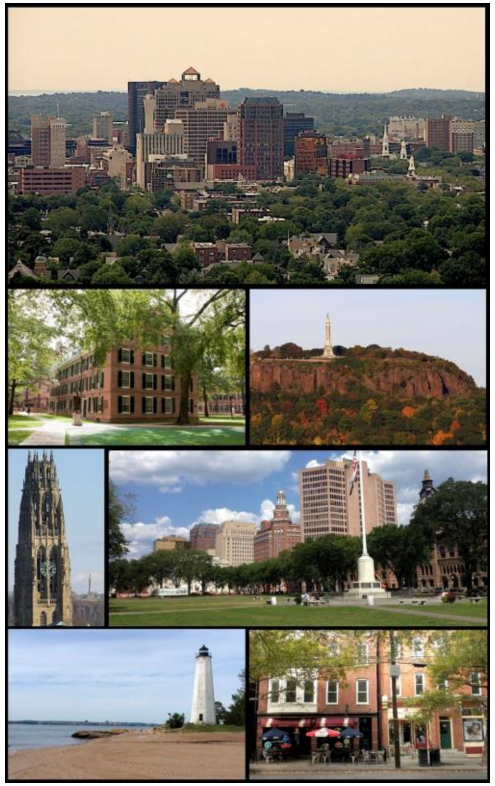
- The central area of the city is warmer than the off-center area. The spatial distribution of street-level AUHI changes with weather condition. Wet bulb temperature is less spatially variable than dry bulb temperature.
- The more tree canopy cover, the weaker the street-level AUHI. The more impervious surface cover, the stronger the street-level AUHI. The built-up area doesn't have the strongest AUHI because the building shadow.
- The street-level AUHI is dominated by the cooling effect of tree canopy cover via evapotranspiration, the warming effect of impervious surface cover via constraining the evaporation, and the cooling effect of building shadow via blocking the incoming solar radiation.

# METHODOLOGY

- Study Area

This research will be carried out in New Haven (41°18’36”, 72°55’25”), Connecticut, U.S. This city is selected because its surrounding typical rural area is located within 3 miles of the heavily built-up region. The contrast of land cover and city geometry is distinct. A single mobile measurement along the finally determined city transect, from the urban core to the typical rural environment, can be done in 20 minutes.



- Building up the network of mobile measurement

## Background: collaborating with the MODs!

Three sets of biking measurements were planned to take place on August 5, 12, and 19. For each set of measurements, about 15 volunteers were recruited in advance from the Summer Orientation Modules (MODs) of Yale School of Forestry & Environmental Studies (https://environment.yale.edu/mods). Significant data loss was found in the dataset of August 5, so one extra set of measurements was done immediately on the next day, August 6. The data were subject to different weather conditions, with clear sky for Aug 5, overcast for Aug 6, clear sky for Aug 12, and cloudy sky for Aug 19.

## Instruments: Smart-T sensor for biking measurement


| | Ta Sensor | RH Sensor |
|---|---|---|
| **Range** | -40 - 60°C | 10-90% |
| **Accuracy** | ±0.3°C | ±2% |
| **Response Time** | ~8s | |
| **Standby power consumption** | 0.06 mW | |
| **Typical power consumption** | 0.36 mW | |
| **Max power consumption** | 1.38mW | |
| **Operating temperature range** | -20 - 60°C | |
| **Ingress Protection Rating** | IP65 | |
| **Weight with batteries** | 63g | |
| **Height** | 85mm | |
| **Radiation** | ABS-like resin | |

## ▪ Instruments: HOBO sensor for background measurement


Tree Shade


Open Area

Building Shade

The three HOBO sensors are set in different typical urban environments but still close enough to represent the same region.

## ▪ Biking Route

① Built-up area

② New Haven Green

③ DeGale Field

④ Wooster Square

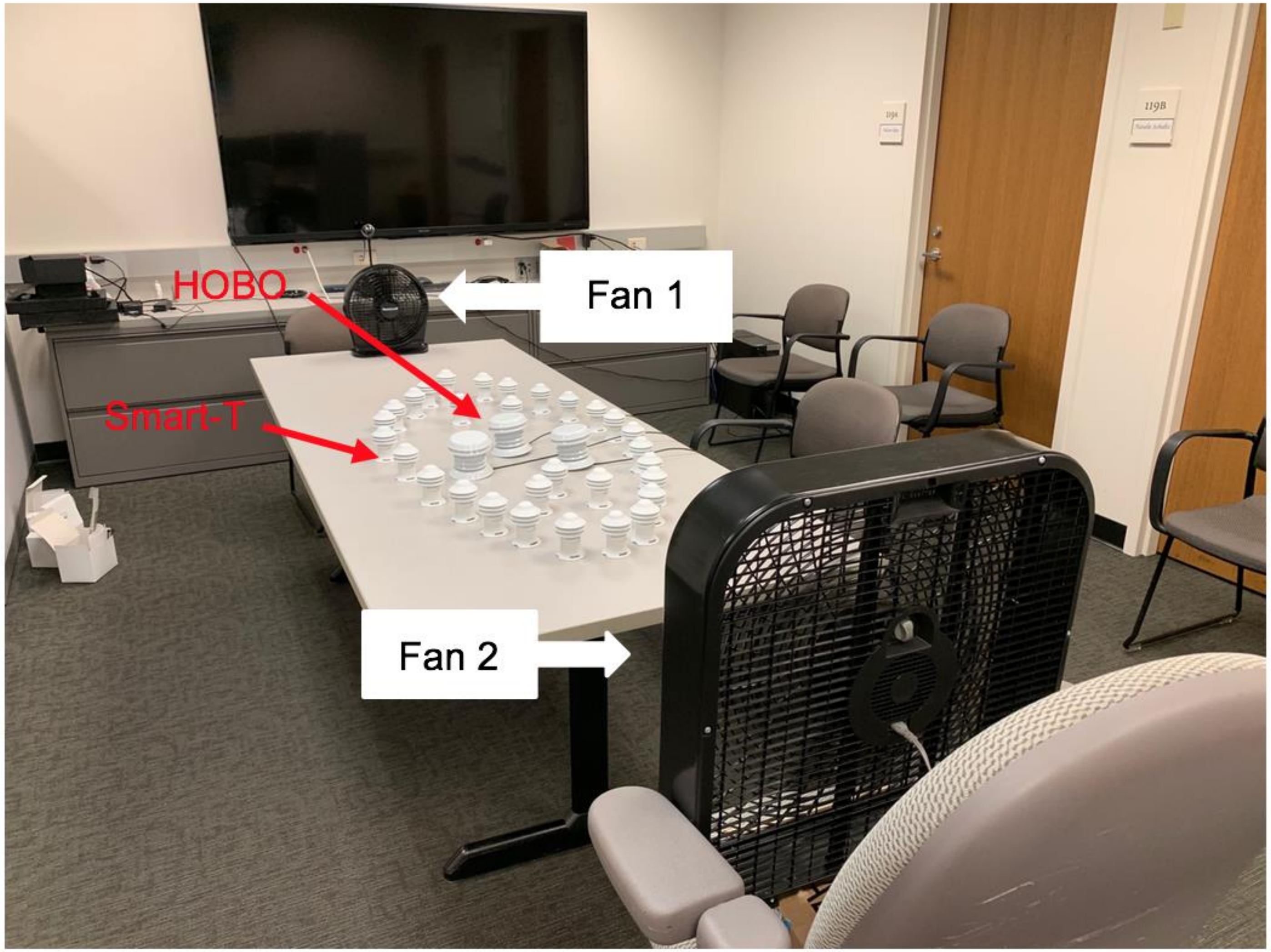
⑤ Criscuolo Park

⑥ Jocelyn Square Park

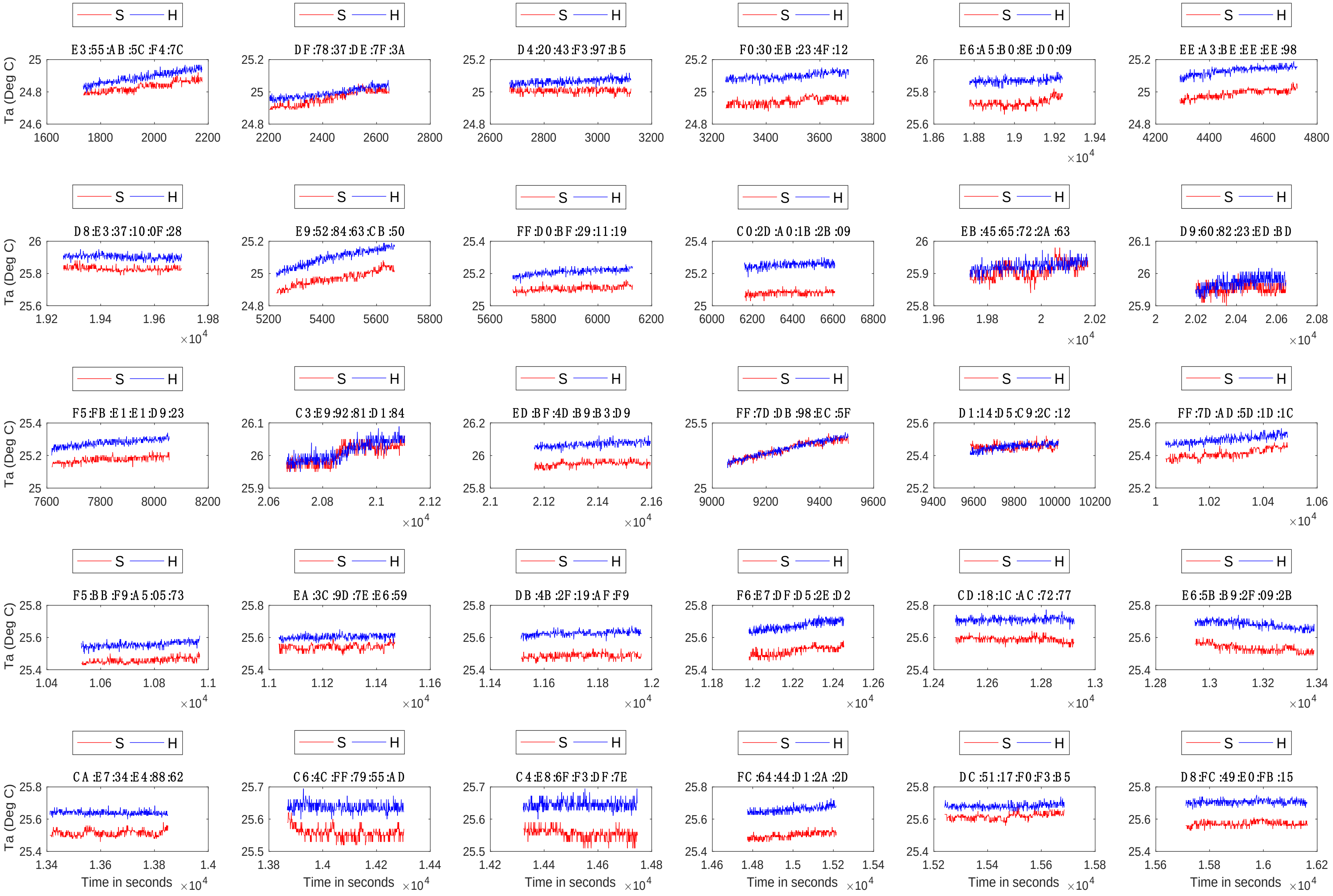
⑦ Dover Beach.

S region is the starting point of all the measurements.

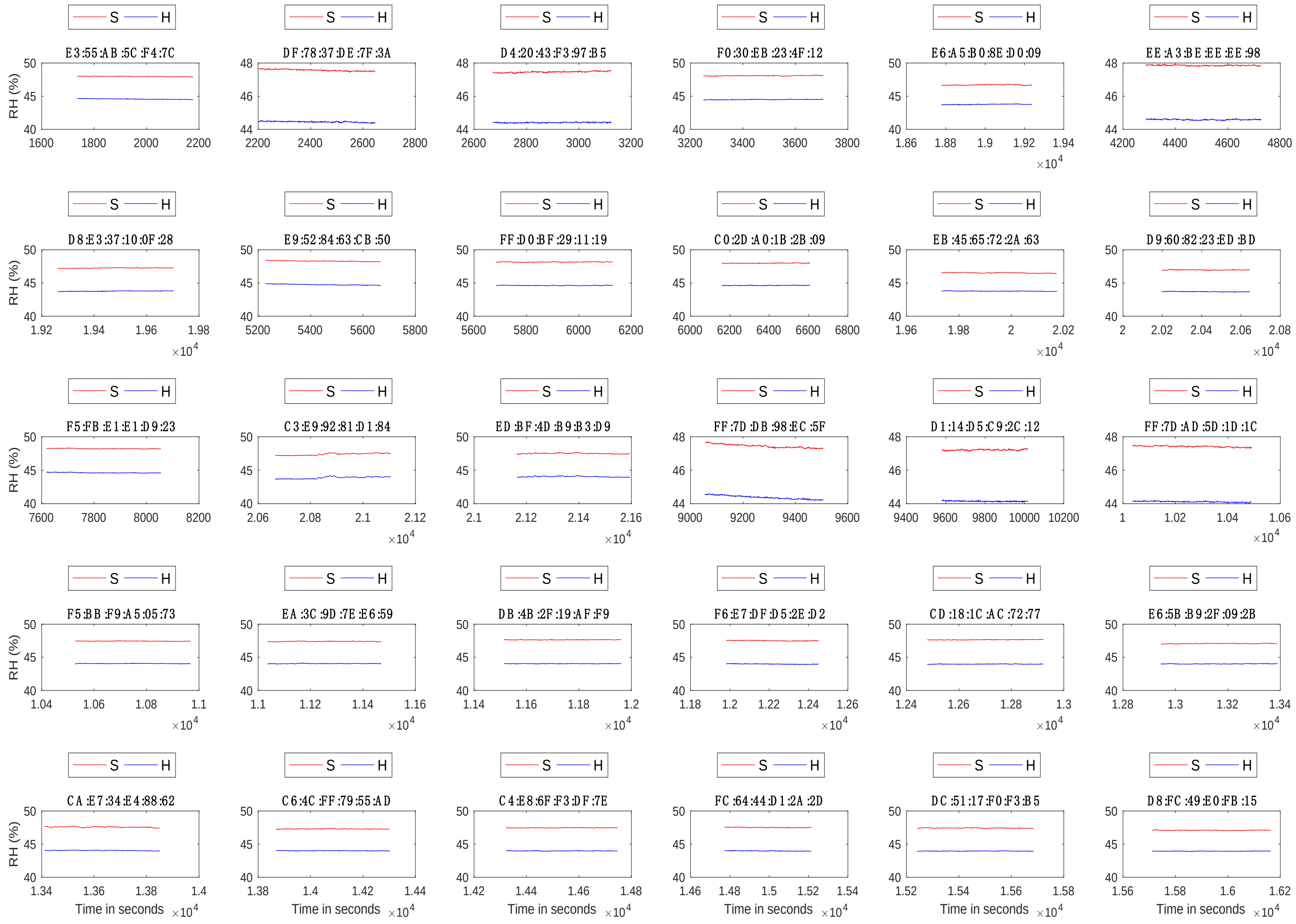
- **Sensor Calibration: Fan Test**



# Air Temperature



# Relative Humidity



$$\mathrm{RMS} = \sqrt{\frac{1}{n}\sum(V_H - V_S)^2}$$

$$\mathrm{Offset} = \frac{1}{n}\sum(V_H - V_S)$$

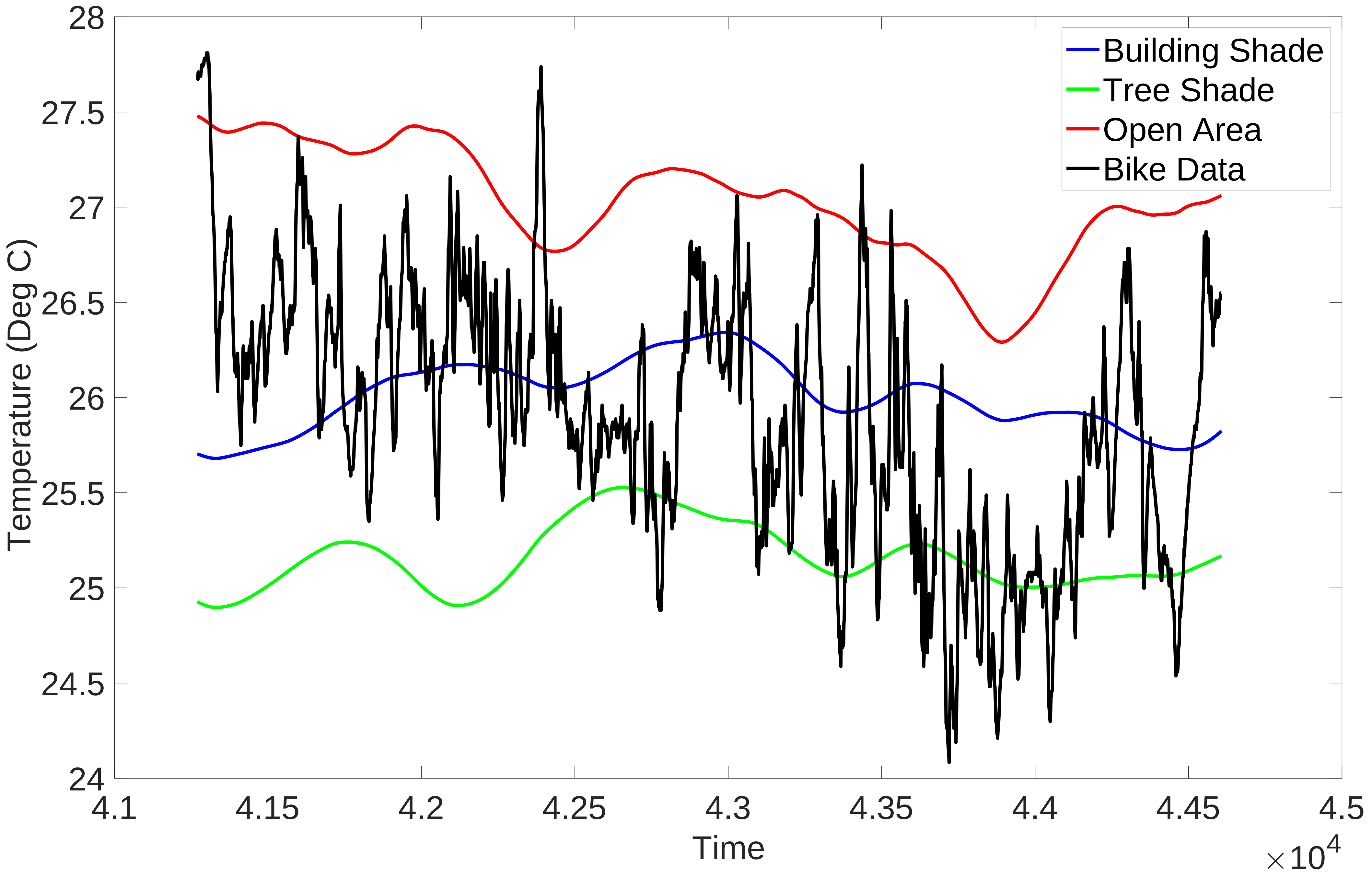
$$\mathrm{H} = \mathrm{S} + \mathrm{Offset}$$

| Device Name | RMS (Ta) | Offset (Ta) | RMS (RH) | Offset (RH) |
|---|---|---|---|---|
| **F47C** | 0.06 | 0.06 | 3.41 | -3.41 |
| **7F3A** | 0.04 | 0.03 | 3.12 | -3.12 |
| **97B5** | 0.06 | 0.06 | 3.05 | -3.05 |
| **4F12** | 0.16 | 0.16 | 3.60 | -3.60 |
| **D009** | 0.14 | 0.14 | 2.93 | -2.93 |
| **EE98** | 0.14 | 0.14 | 3.27 | -3.27 |
| **0F28** | 0.08 | 0.07 | 3.48 | -3.48 |
| **CB50** | 0.13 | 0.13 | 3.55 | -3.55 |
| **1119** | 0.10 | 0.10 | 3.54 | -3.54 |
| **2B09** | 0.18 | 0.17 | 3.36 | -3.36 |
| **2A63** | 0.03 | 0.01 | 2.75 | -2.75 |
| **EDBD** | 0.03 | 0.02 | 3.28 | -3.28 |
| **D923** | 0.10 | 0.10 | 3.59 | -3.59 |
| **D184** | 0.02 | 0.01 | 3.51 | -3.51 |
| **B3D9** | 0.12 | 0.12 | 3.46 | -3.46 |
| **EC5F** | 0.02 | 0 | 3.07 | -3.06 |
| **2C12** | 0.03 | 0 | 3.06 | -3.06 |
| **1D1C** | 0.09 | 0.09 | 3.30 | -3.30 |
| **0573** | 0.10 | 0.10 | 3.38 | -3.38 |
| **E659** | 0.07 | 0.06 | 3.34 | -3.34 |
| **AFF9** | 0.14 | 0.14 | 3.60 | -3.60 |
| **2ED2** | 0.16 | 0.16 | 3.52 | -3.52 |
| **7277** | 0.12 | 0.12 | 3.68 | -3.68 |
| **092B** | 0.15 | 0.15 | 3.06 | -3.06 |
| **8862** | 0.13 | 0.13 | 3.53 | -3.53 |
| **55AD** | 0.08 | 0.08 | 3.28 | -3.28 |
| **DF7E** | 0.09 | 0.09 | 3.48 | -3.48 |
| **2A2D** | 0.16 | 0.16 | 3.53 | -3.53 |
| [illegible] | [illegible] | [illegible] | [illegible] | [illegible] |

- **Deriving the important thermal indices**

**Dry Bulb AUHI Intensity**

$$\Delta T_d = T_{dS} - \underbrace{(T_{dH83} + T_{dH84} + T_{dH85})}_{\text{Averaging with a 5-min window}}/3$$



Building Shade
Tree Shade
Open Area
Bike Data
Temperature (Deg C)
Time
28
27.5
27
26.5
26
25.5
25
24.5
24
4.1
4.15
4.2
4.25
4.3
4.35
4.4
4.45
4.5
$\times 10^4$

- **Deriving the important thermal indices**

**Wet Bulb AUHI Intensity**

$$\Delta T_w = T_{wS} - \underbrace{(T_{wH83} + T_{wH84} + T_{wH85})}_{\text{Averging with a 5-min window}}/3$$

**Wet Bulb Temperature?**

# Wet Bulb Temperature?

Theoretical Method
(Lee 2018)

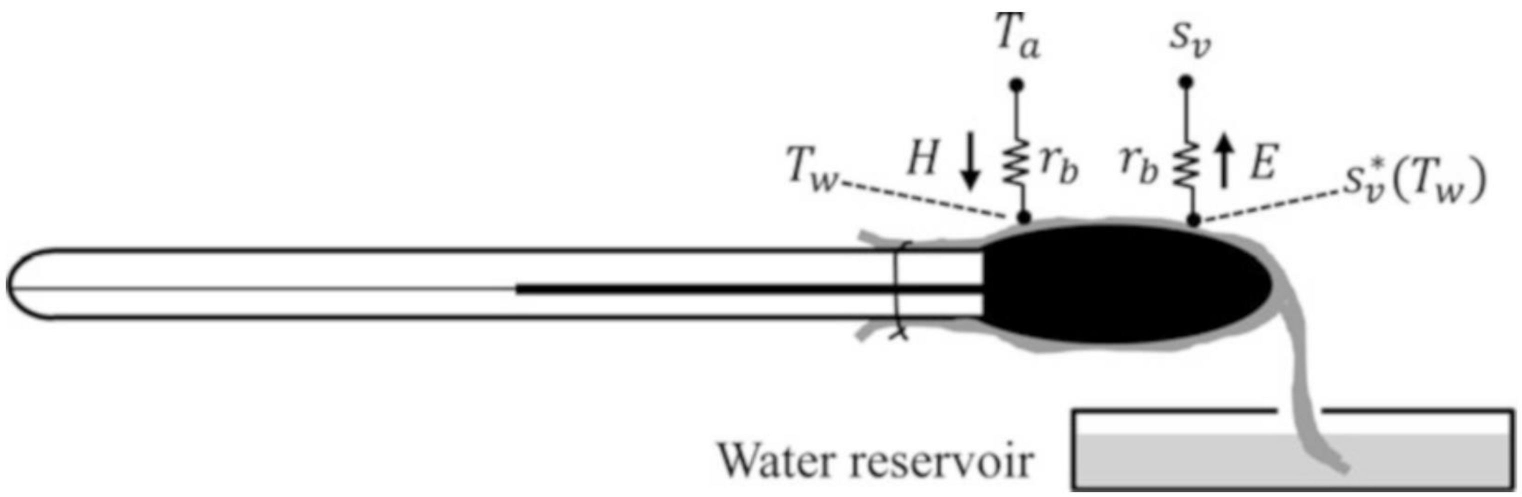
$$T_w = T_d - \frac{D}{\Delta+\gamma}$$

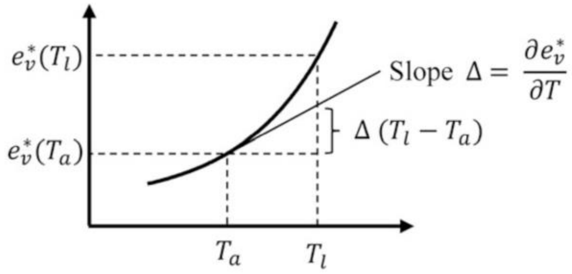
$$D = e_v^*(T_d) - e_v$$

$$\Delta = \frac{\partial e_v^*}{\partial T}$$

$$e_v^* = 6.11 \times 10^{\left(\frac{7.5\times T_d}{237.3+T_d}\right)}$$

$$e_v \;\; = e_v^* \times RH$$




$$e_v^*(T_l) \simeq e_v^*(T_a) + \Delta(T_l - T_a)$$

# Wet Bulb Temperature?

Empirical Method
(Stull 2011)

$$C_p \cdot (T - T_w) = -L_v \cdot (r - r_w)$$

$$r = r_w - \beta \cdot (T - T_w)$$

where

$$r_w = \frac{\varepsilon}{b \cdot P \cdot \exp\left(\frac{-c \cdot T_w(°C)}{T_w(°C) + \alpha}\right) - 1}$$

$$\varepsilon = 622 \text{ g kg}^{-1}, \quad b = 1.631 \text{ kPa}^{-1},$$
$$c = 17.67, \quad \alpha = 243.5°C,$$
$$\beta = 0.40224 \text{ (g kg}^{-1})/°C.$$

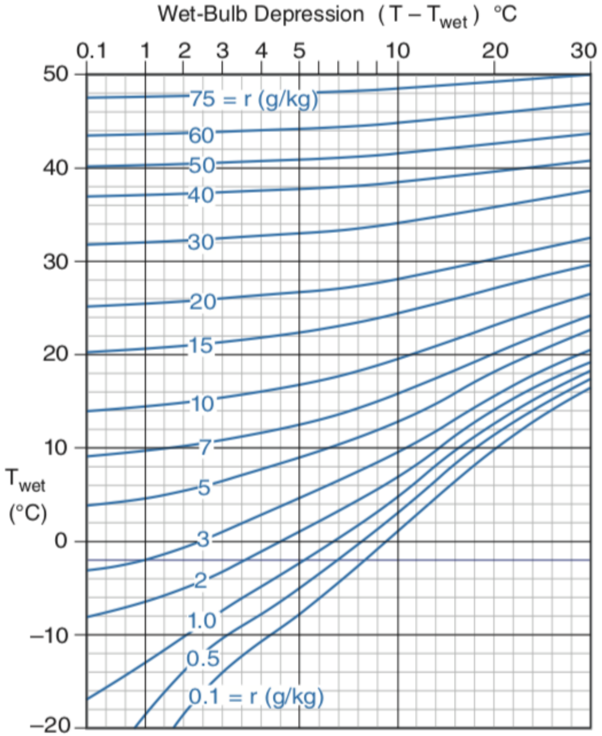



**Figure 4.4**
*Psychrometric graph, to find mixing ratio r from wet and dry-bulb temperatures. Based on P = 101.325 kPa. Caution, the darker vertical lines mark scale changes along the abscissa.*

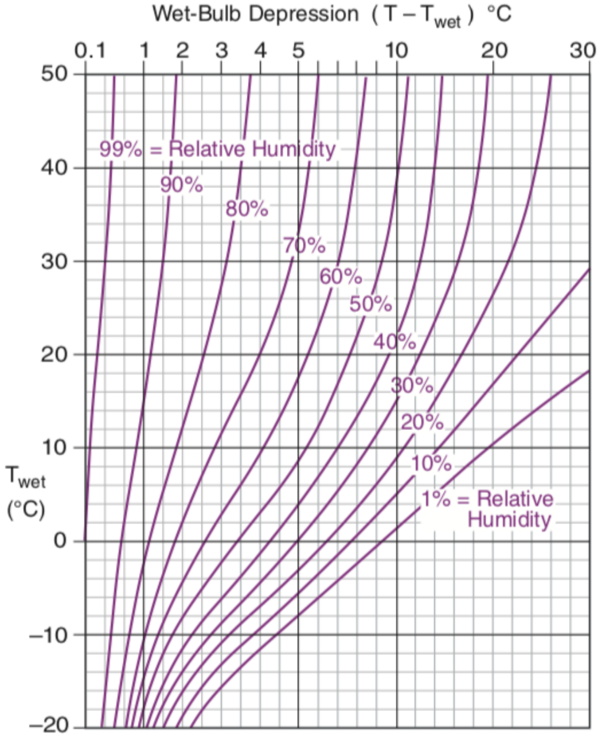
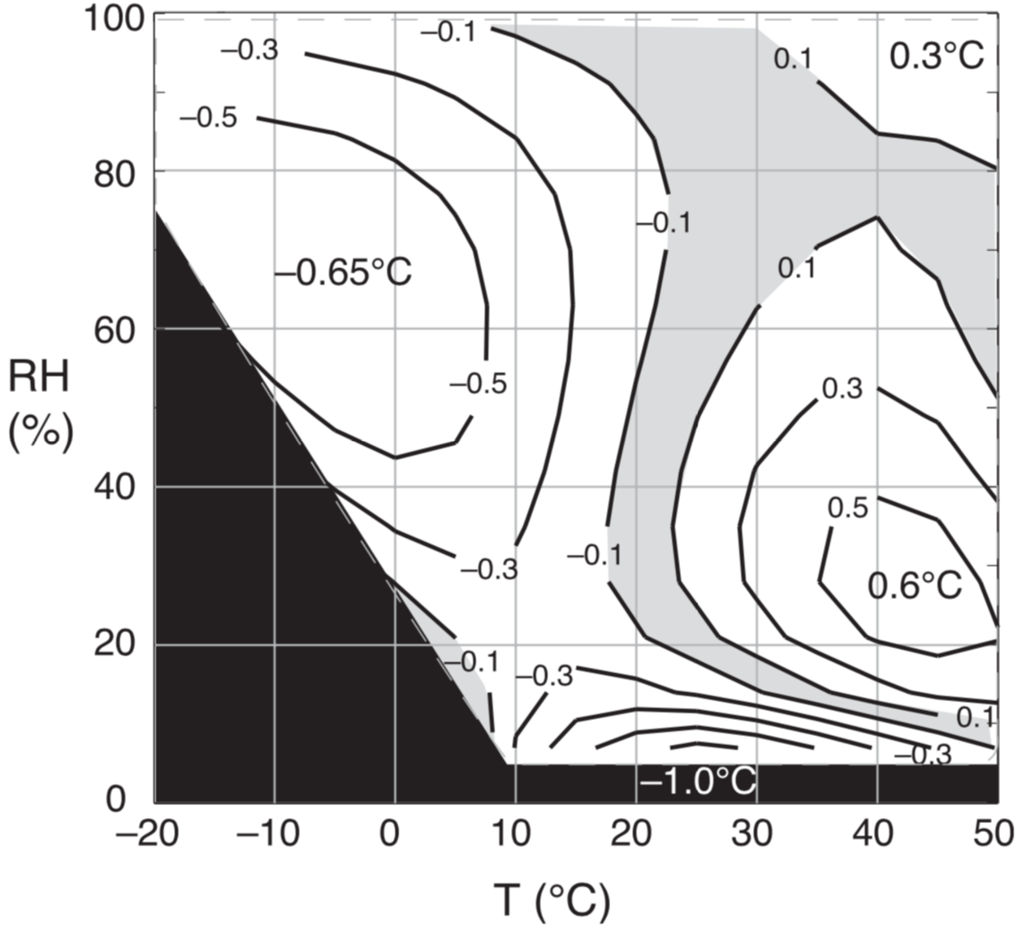


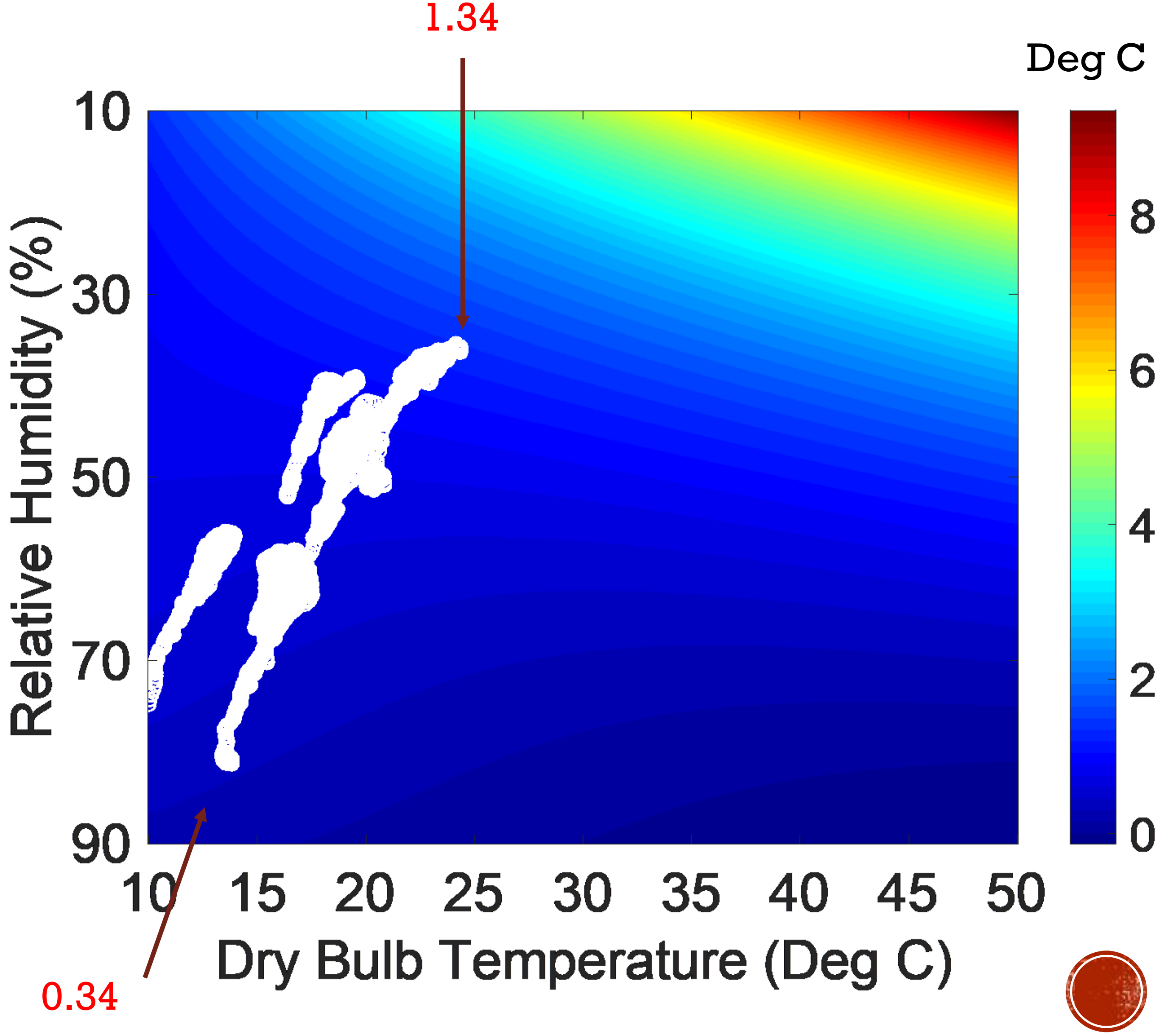

**Figure 4.5**
*Psychrometric graph, to find relative humidity from wet and dry-bulb temperatures. Based on P = 101.325 kPa. Caution, the darker vertical lines mark scale changes along the abscissa.*

$$T_w = T \operatorname{atan}[0.151977(RH\% + 8.313659)^{1/2}] + \operatorname{atan}(T + RH\%) - \operatorname{atan}(RH\% - 1.676331)$$
$$+ 0.00391838(RH\%)^{3/2} \operatorname{atan}(0.023101 RH\%) - 4.686035.$$

# Comparing the methods

Tw(theoretical) – Tw(empirical)

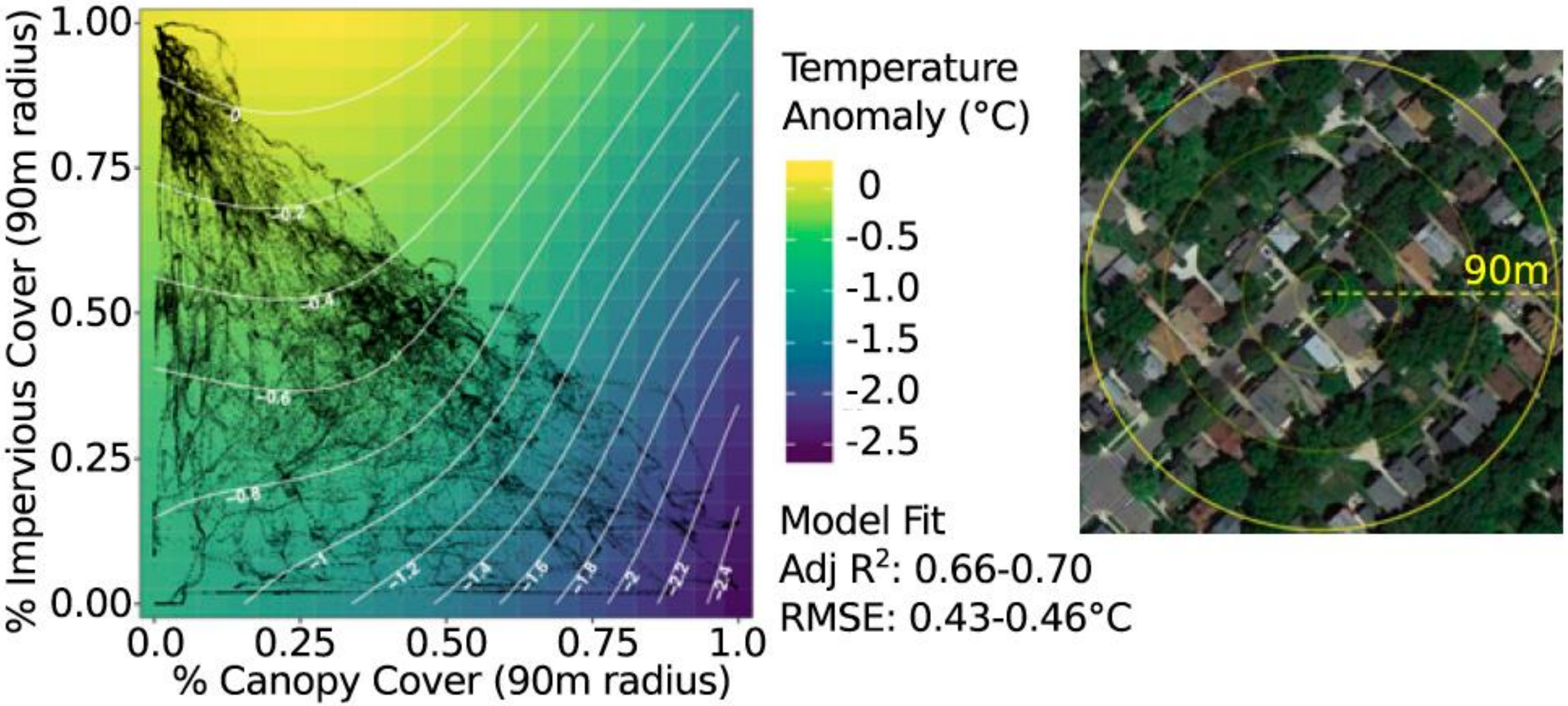


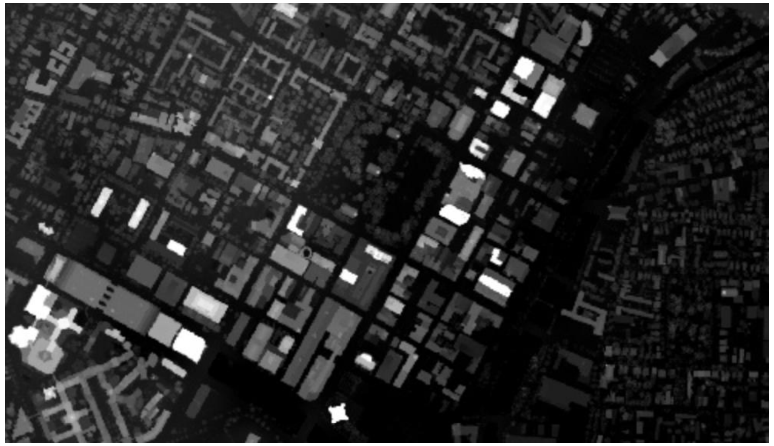
# AUXILIARY DATASET

- Landcover data and the method of scale-dependency
  - The tree canopy/classification data of New Haven County (Jarlath P. M. O'Neil-Dunne) is a GIS raster layer (3-feet resolution) with several landscape categories including tree canopy, grass/shrub, bare soil, water, buildings, roads/railroads, and other paved areas. It is classified using the Connecticut 2016 LiDAR/orthoimagery data.

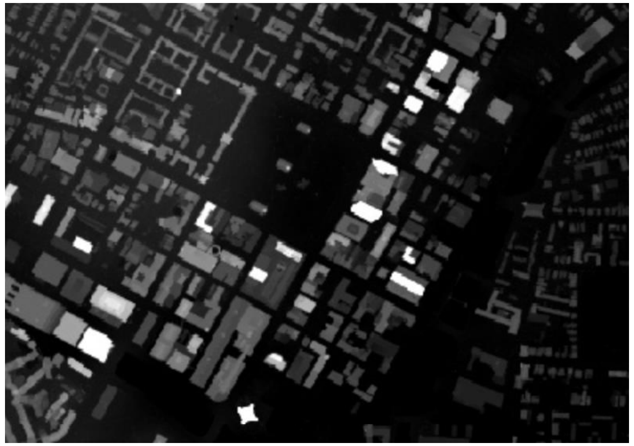
- Scale-dependent method (Ziter, 2019), 90-meter buffer is used.



- City morphology data
  - Connecticut 2016 LiDAR (1-meter resolution DSM)
    - Ground-class points to build bare earth (DTM)
    - Using building pixels to extract the building elevation, then overlay the building elevation on the DTM. The output is a building-only DSM layer.
  - Building Shadow: generated using the building-only DSM via Hillshade in ArcMap.



Original DSM

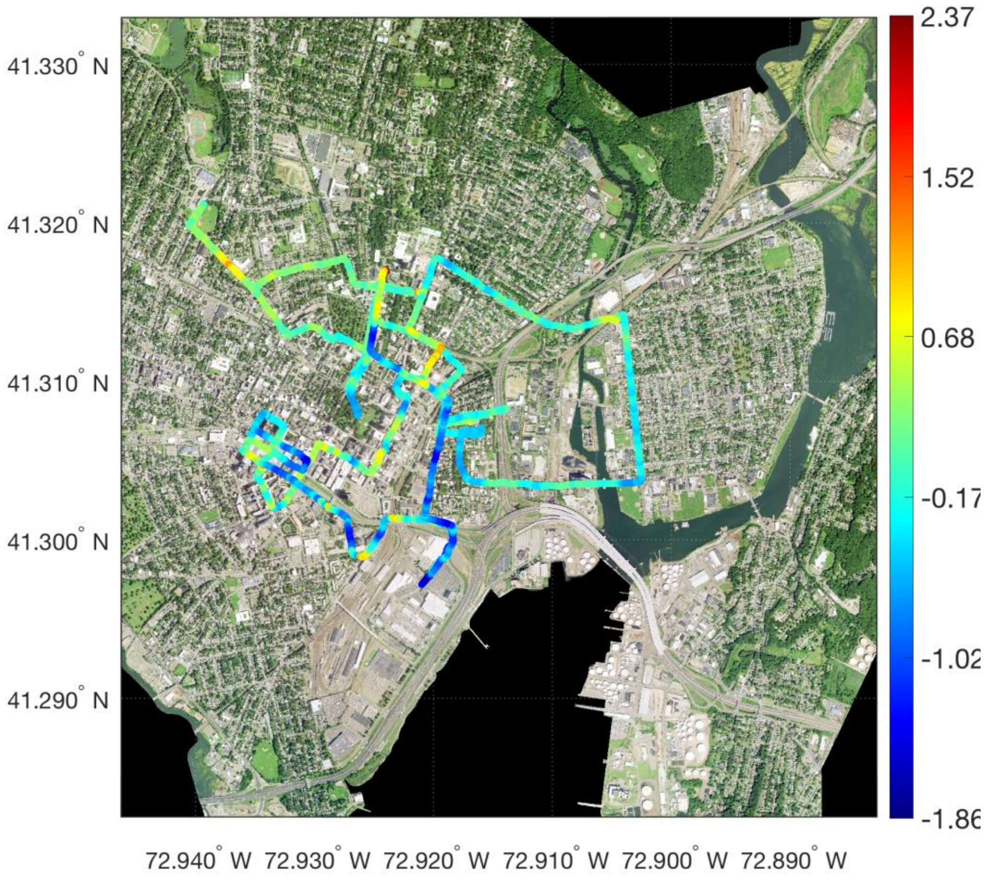


Only Building

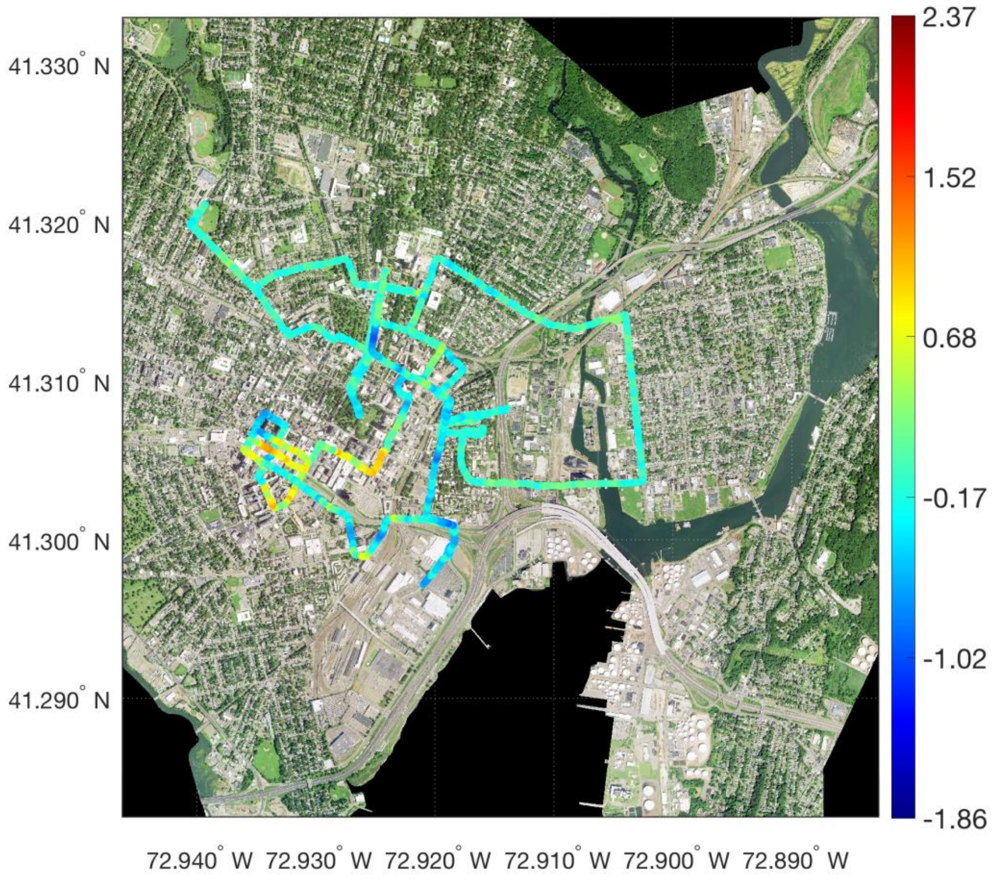
Shadow Pattern

# RESULTS AND PRELIMINARY ANALYSIS: SUMMER TEST

## WEEK1: DATA MISSING (CLEAR + OVERCAST)

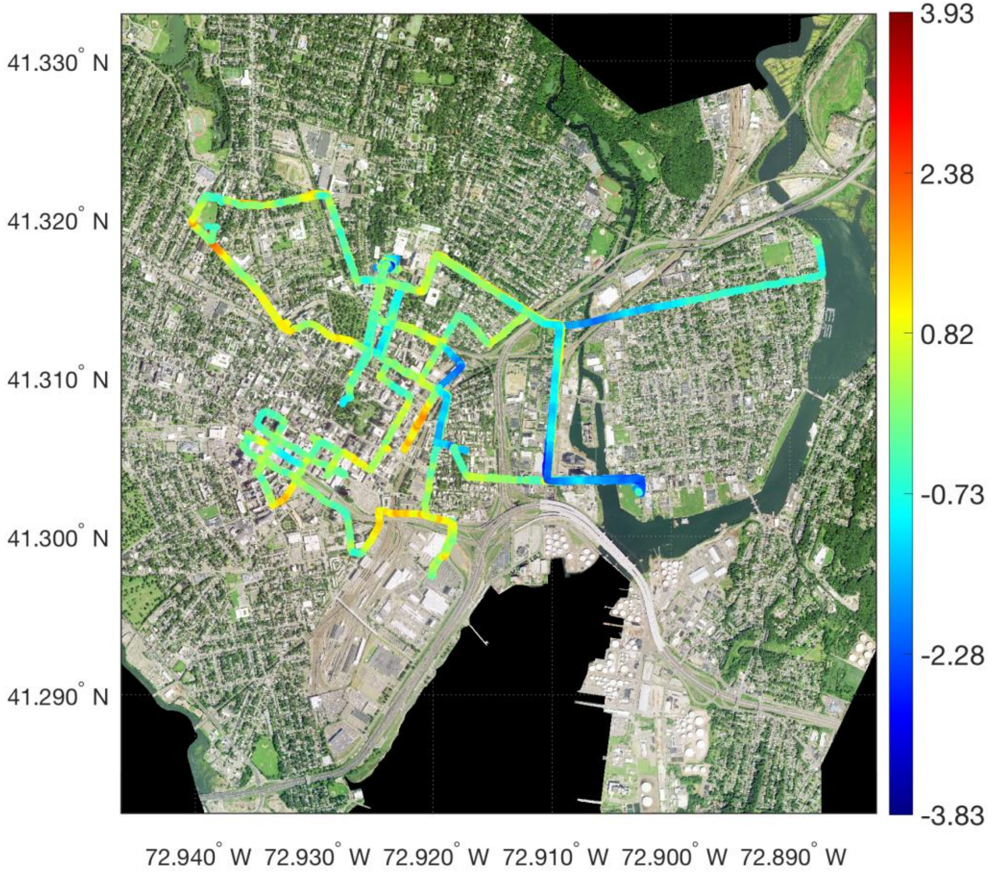



Dry Bulb Temperature

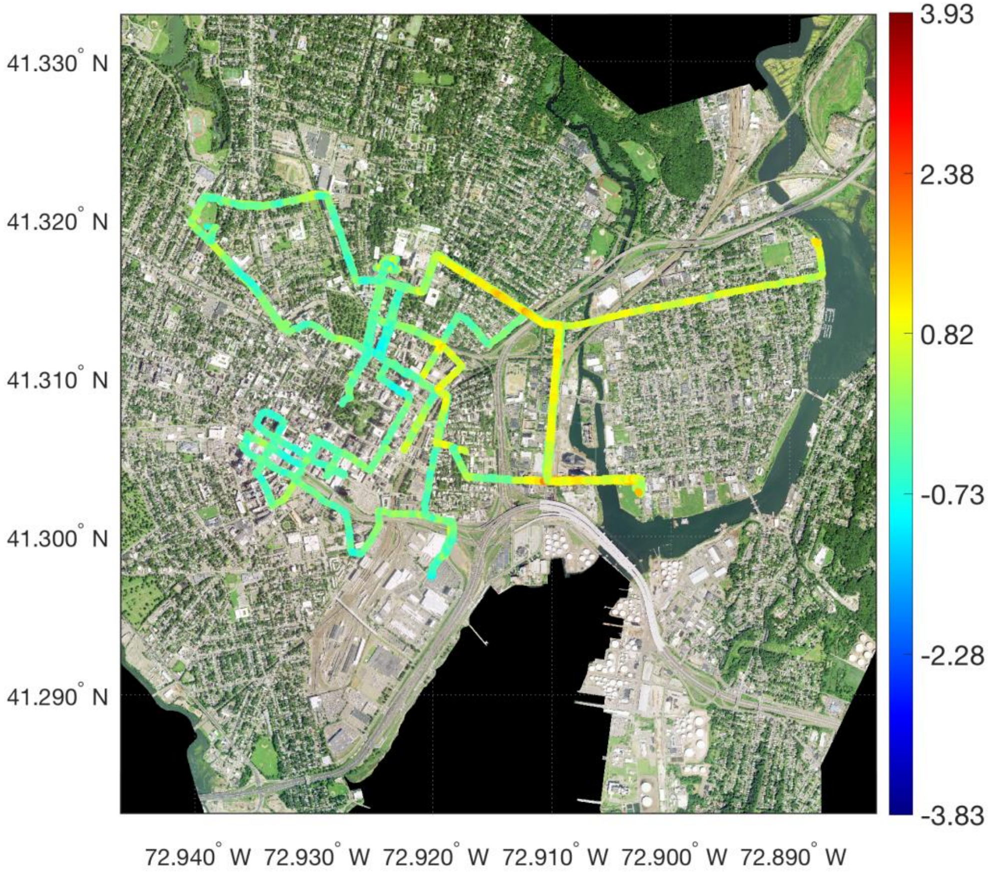



Wet Bulb Temperature

# WEEK2: CLEAR DAY

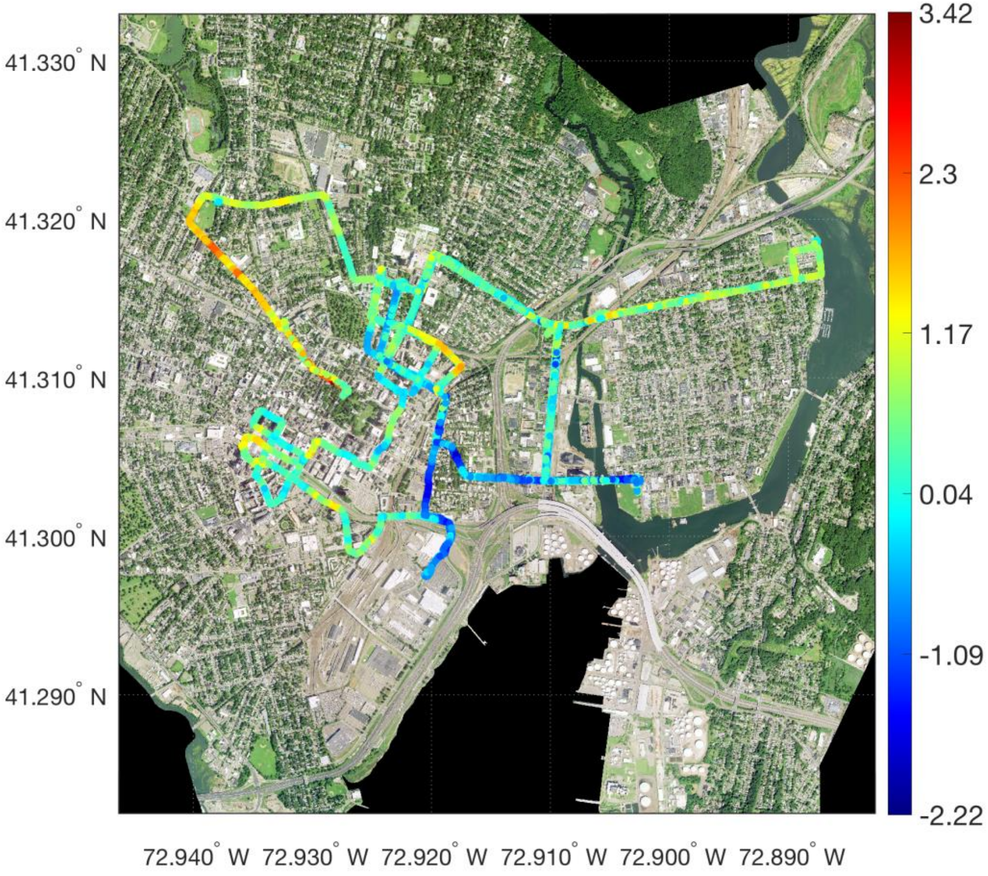



Dry Bulb Temperature

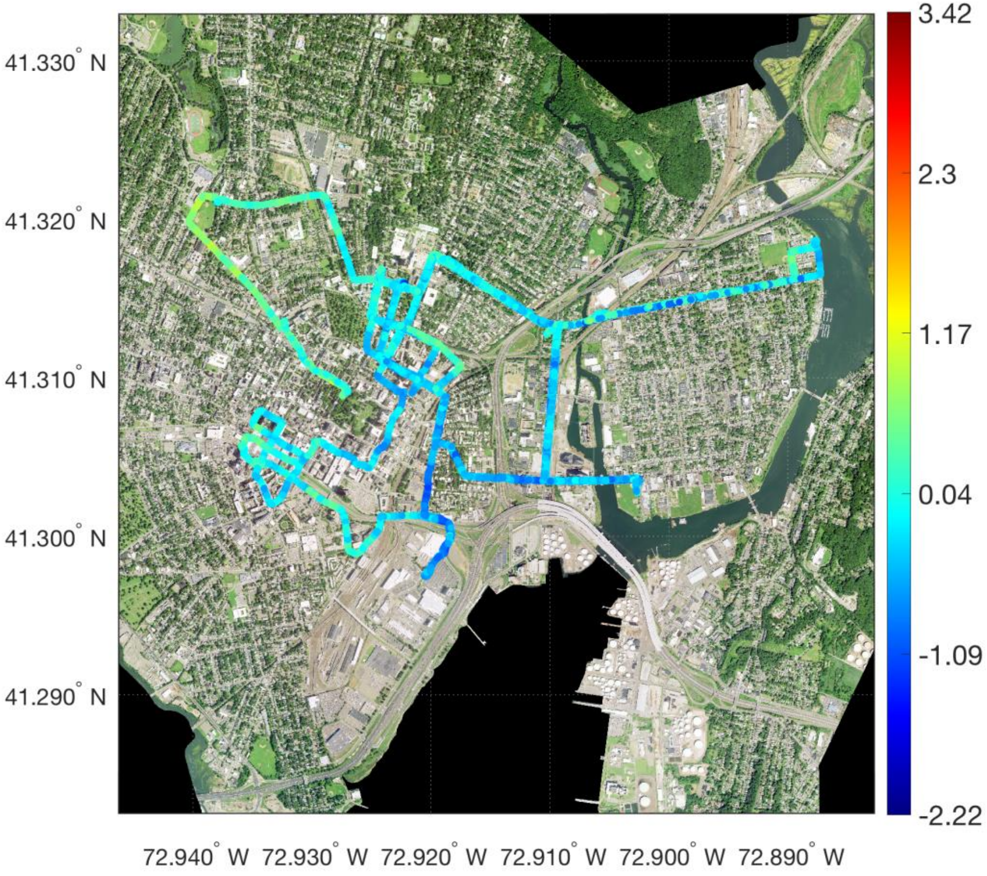



Wet Bulb Temperature

# WEEK3: CLOUDY DAY

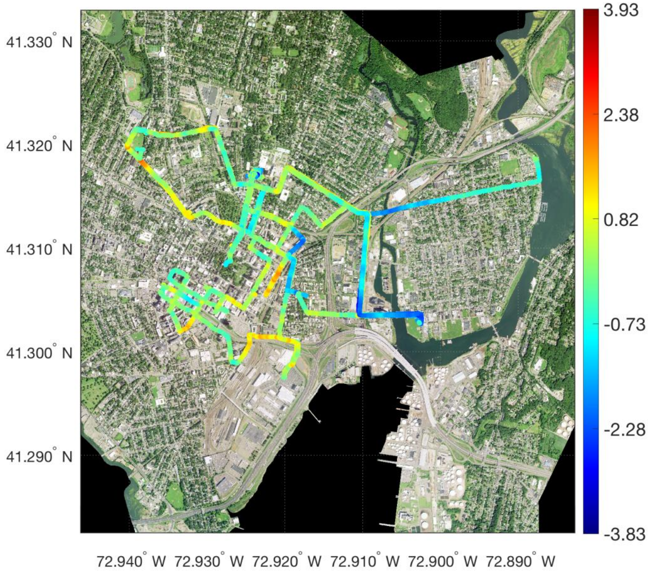


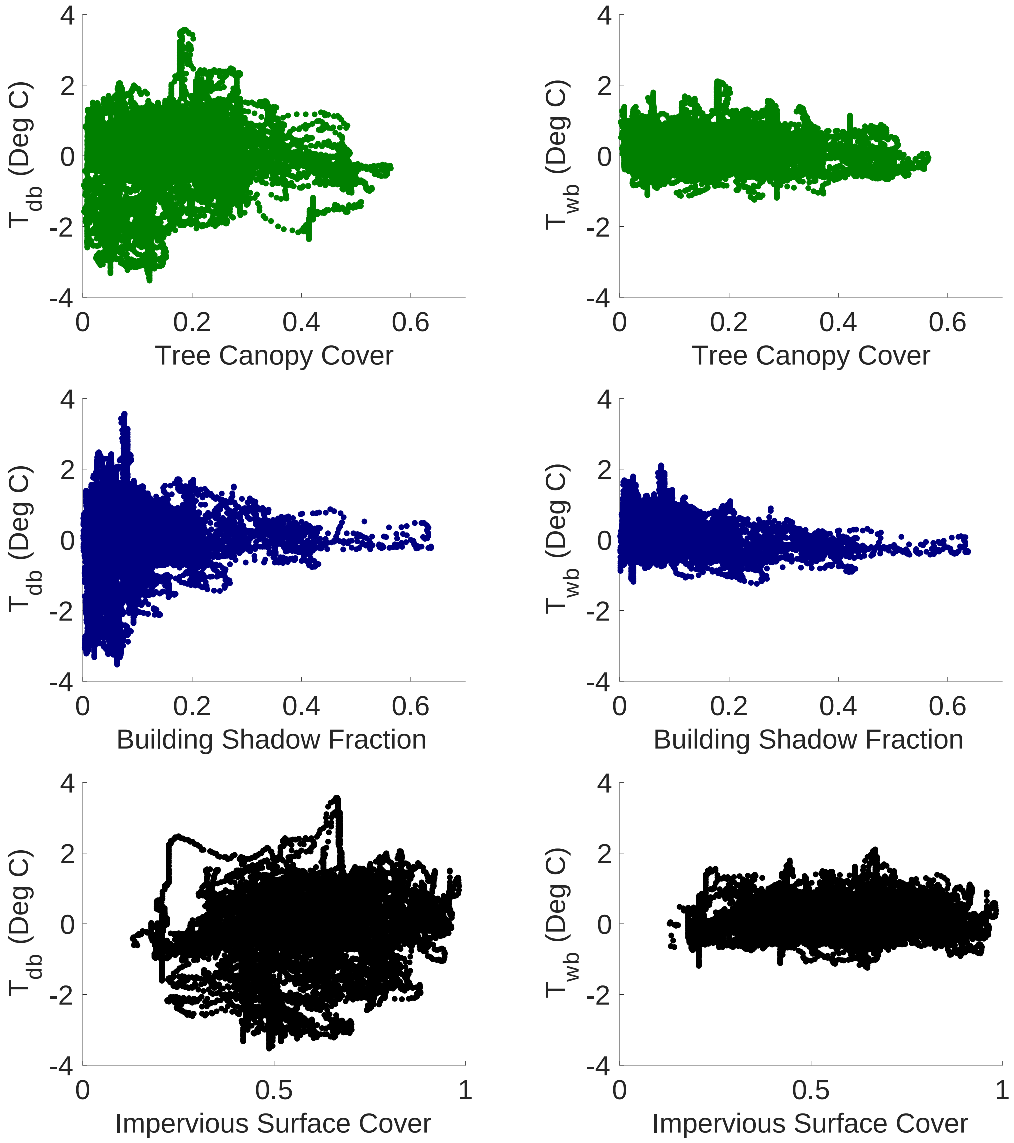

Dry Bulb Temperature

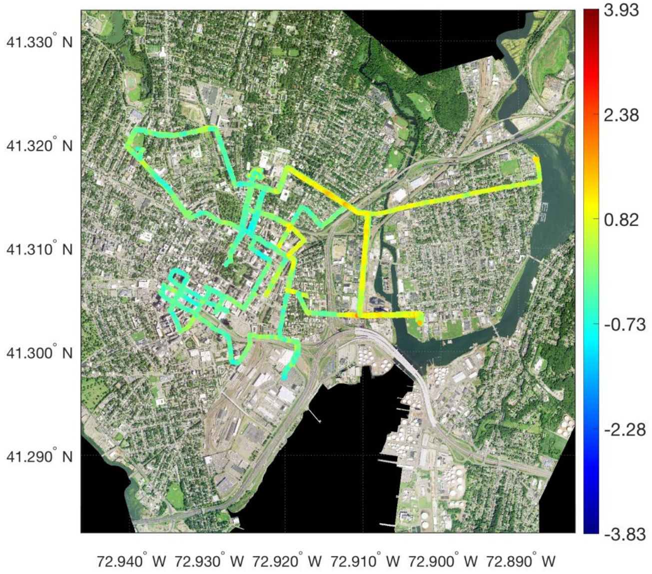



Wet Bulb Temperature

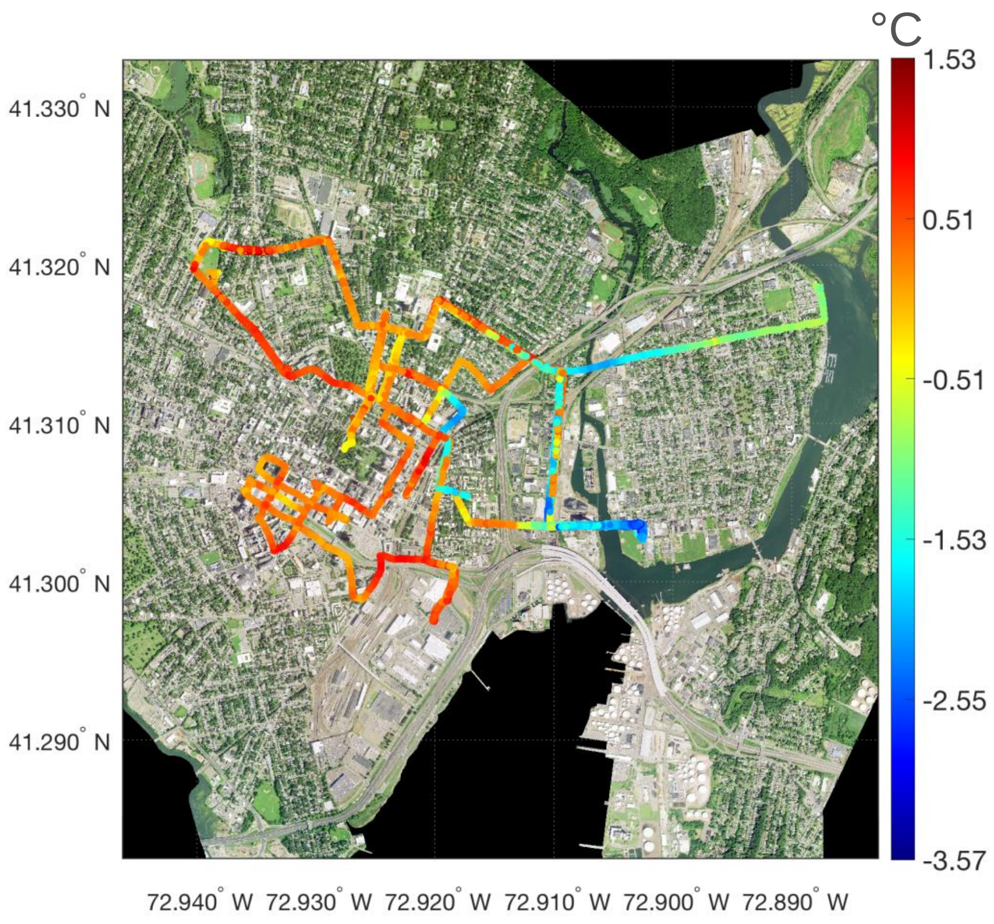
# ▪ Inspecting the Week 2 Data (Clear day)



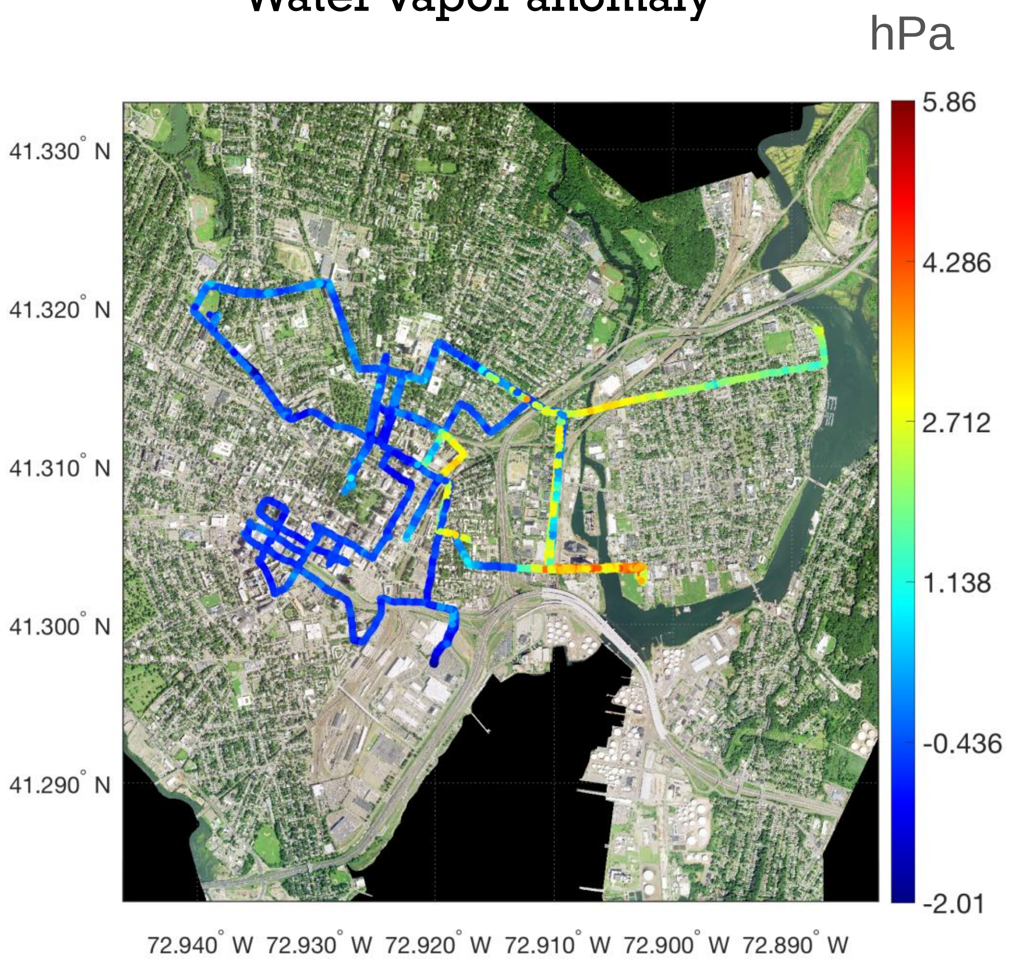



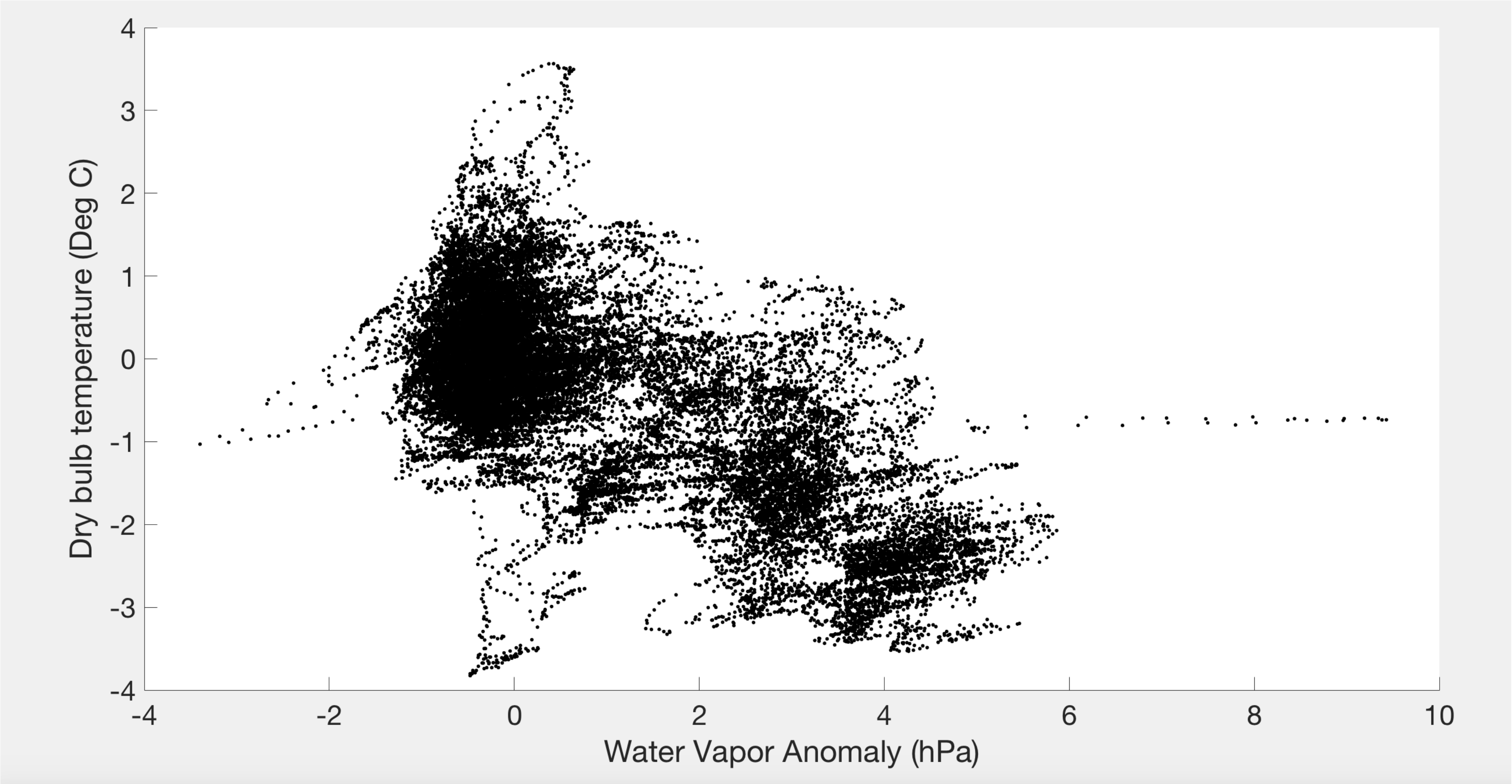



## Tdb anomaly – Twb anomaly

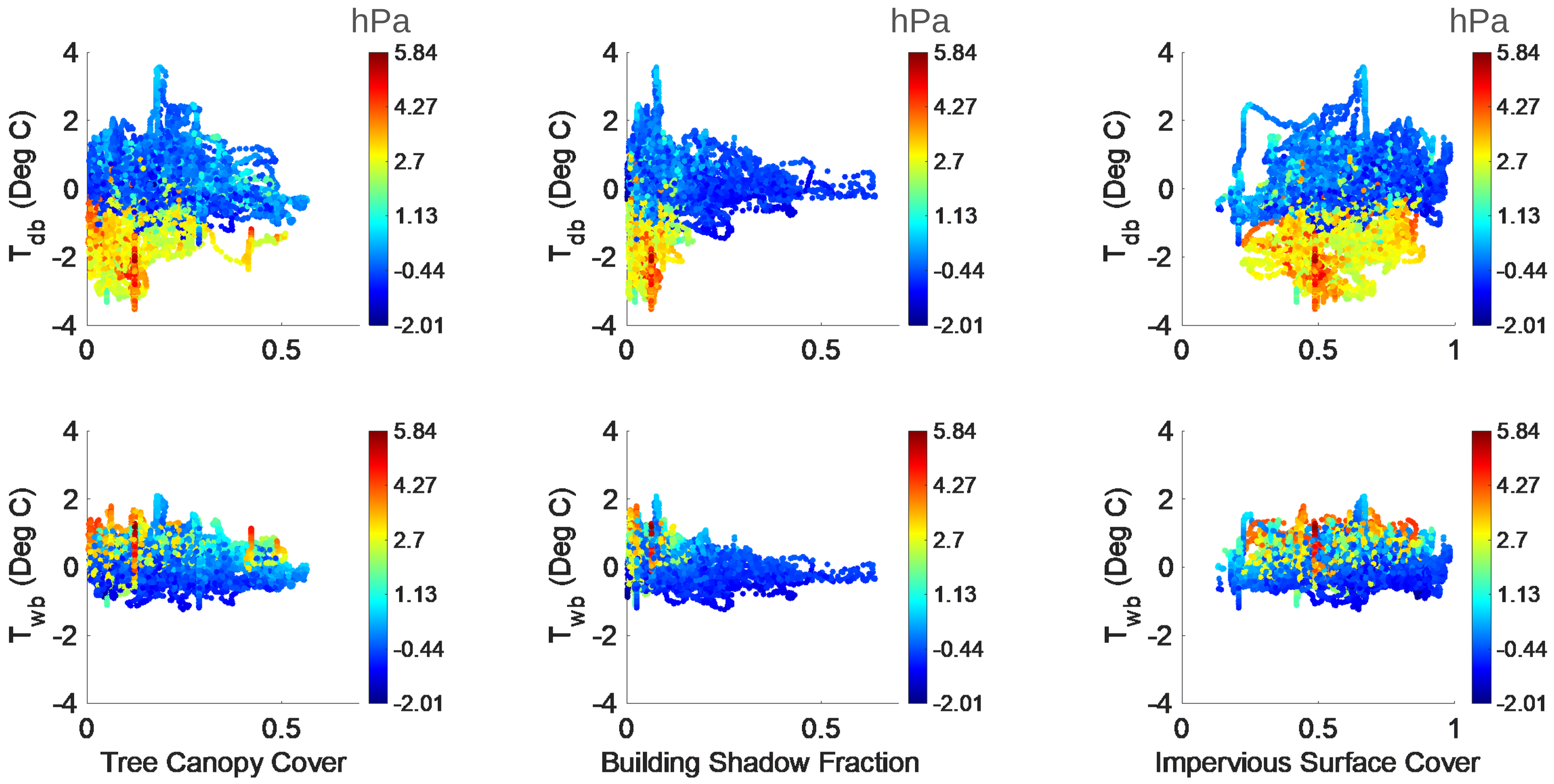



## Water Vapor anomaly

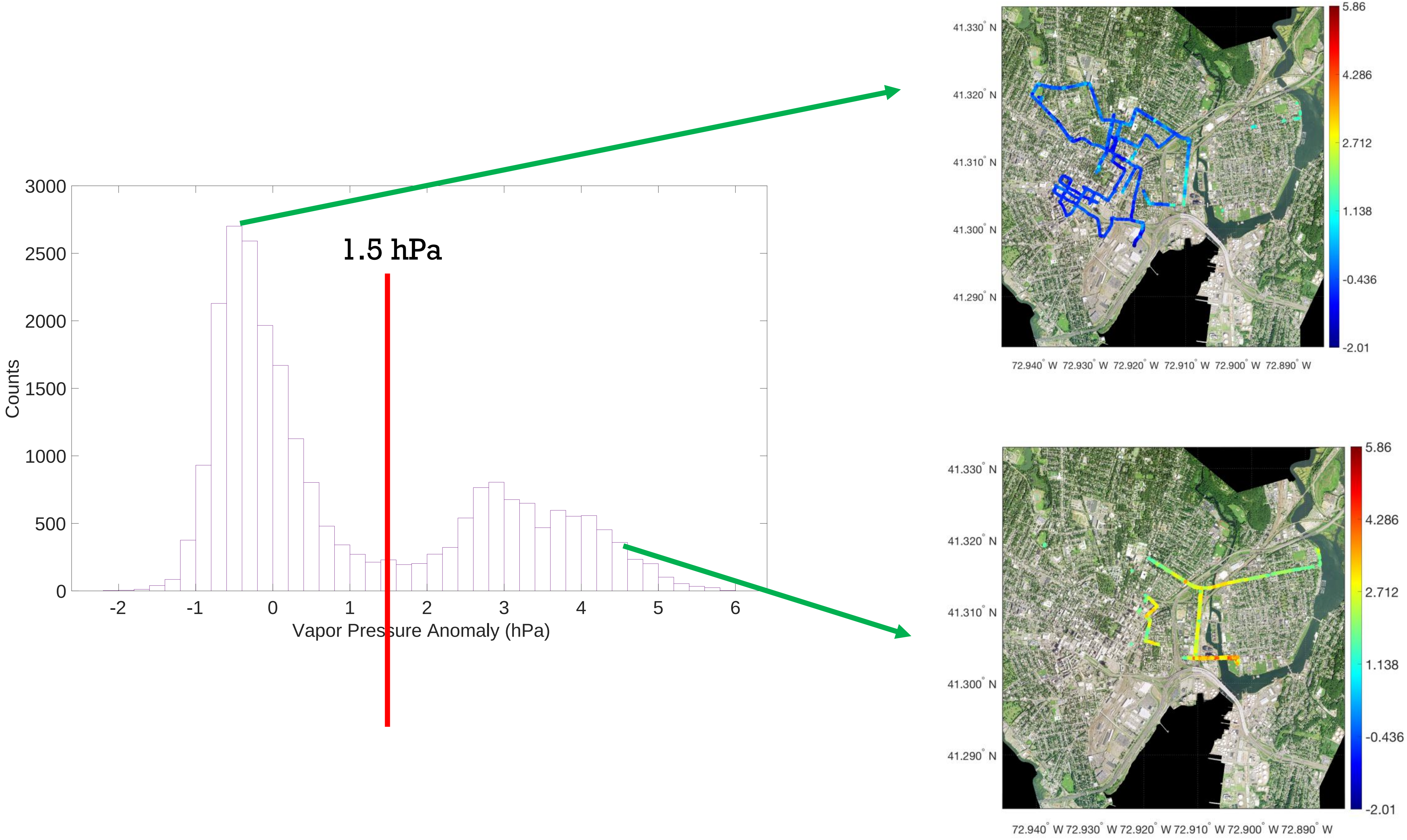




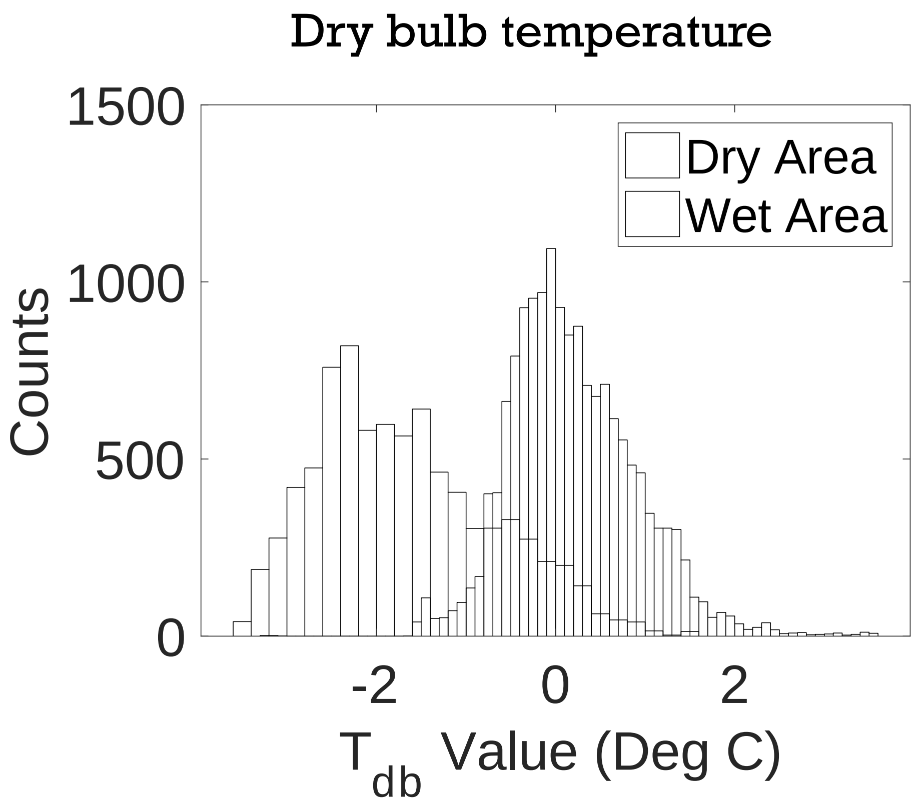
Dry bulb temperature (Deg C)
Water Vapor Anomaly (hPa)
4
3
2
1
0
-1
-2
-3
-4
-4
-2
0
2
4
6
8
10

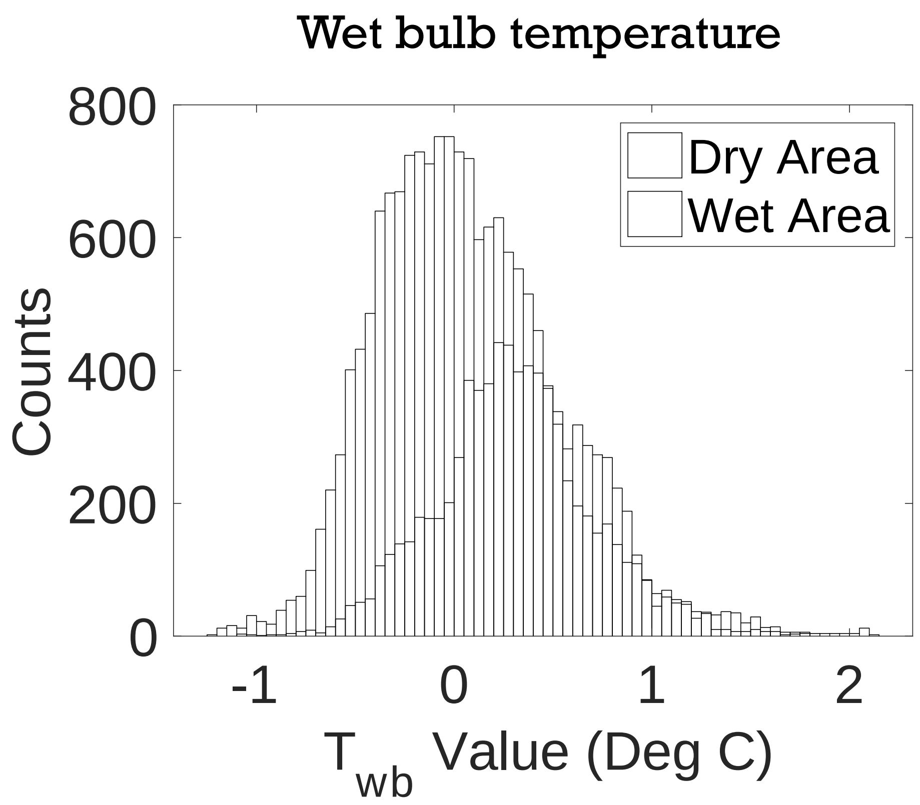


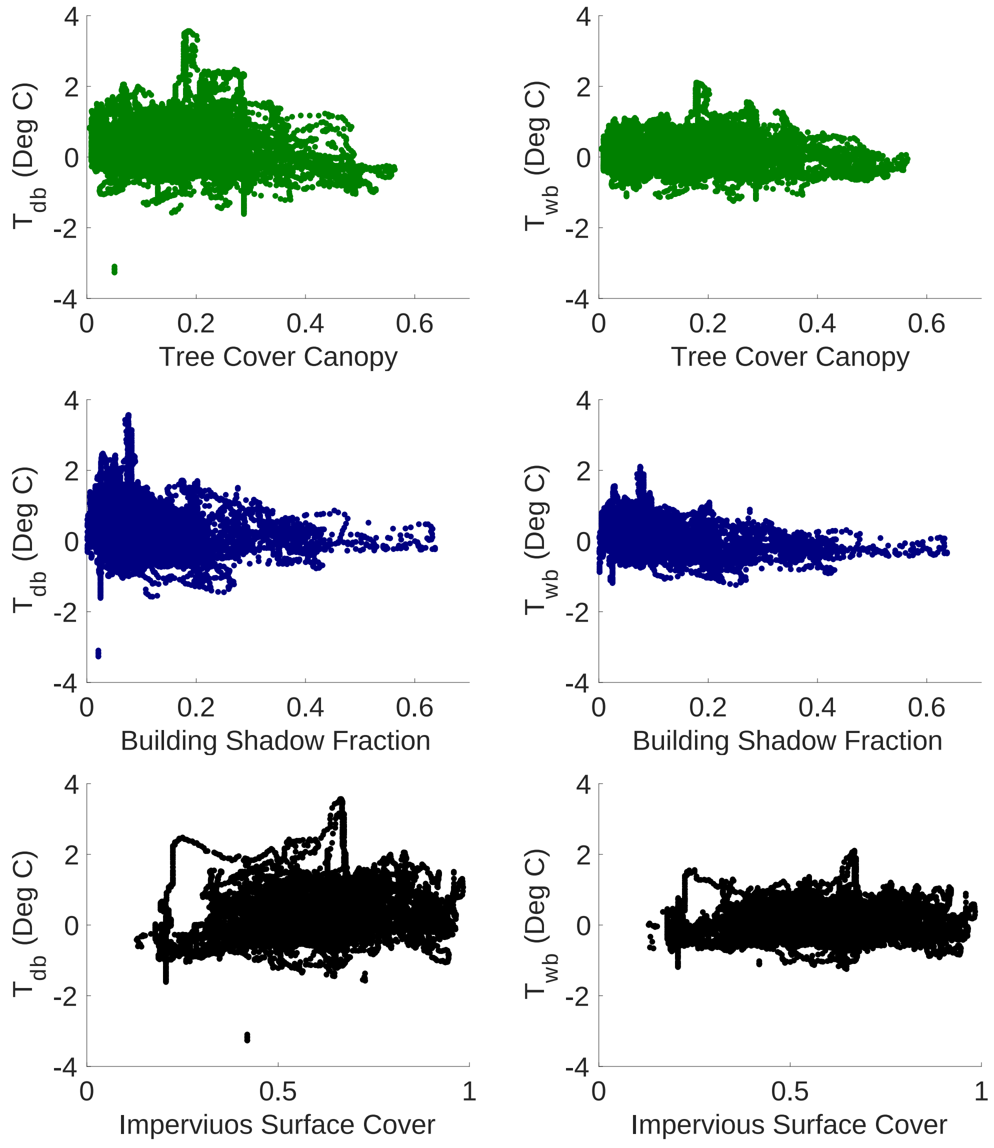
hPa
5.84
4.27
2.7
1.13
-0.44
-2.01
$T_{db}$ (Deg C)
$T_{wb}$ (Deg C)
Tree Canopy Cover
Building Shadow Fraction
Impervious Surface Cover



1.5 hPa
Counts
Vapor Pressure Anomaly (hPa)
3000
2500
2000
1500
1000
500
0
-2
-1
0
1
2
3
4
5
6
41.330° N
41.320° N
41.310° N
41.300° N
41.290° N
72.940° W 72.930° W 72.920° W 72.910° W 72.900° W 72.890° W
5.86
4.286
2.712
1.138
-0.436
-2.01

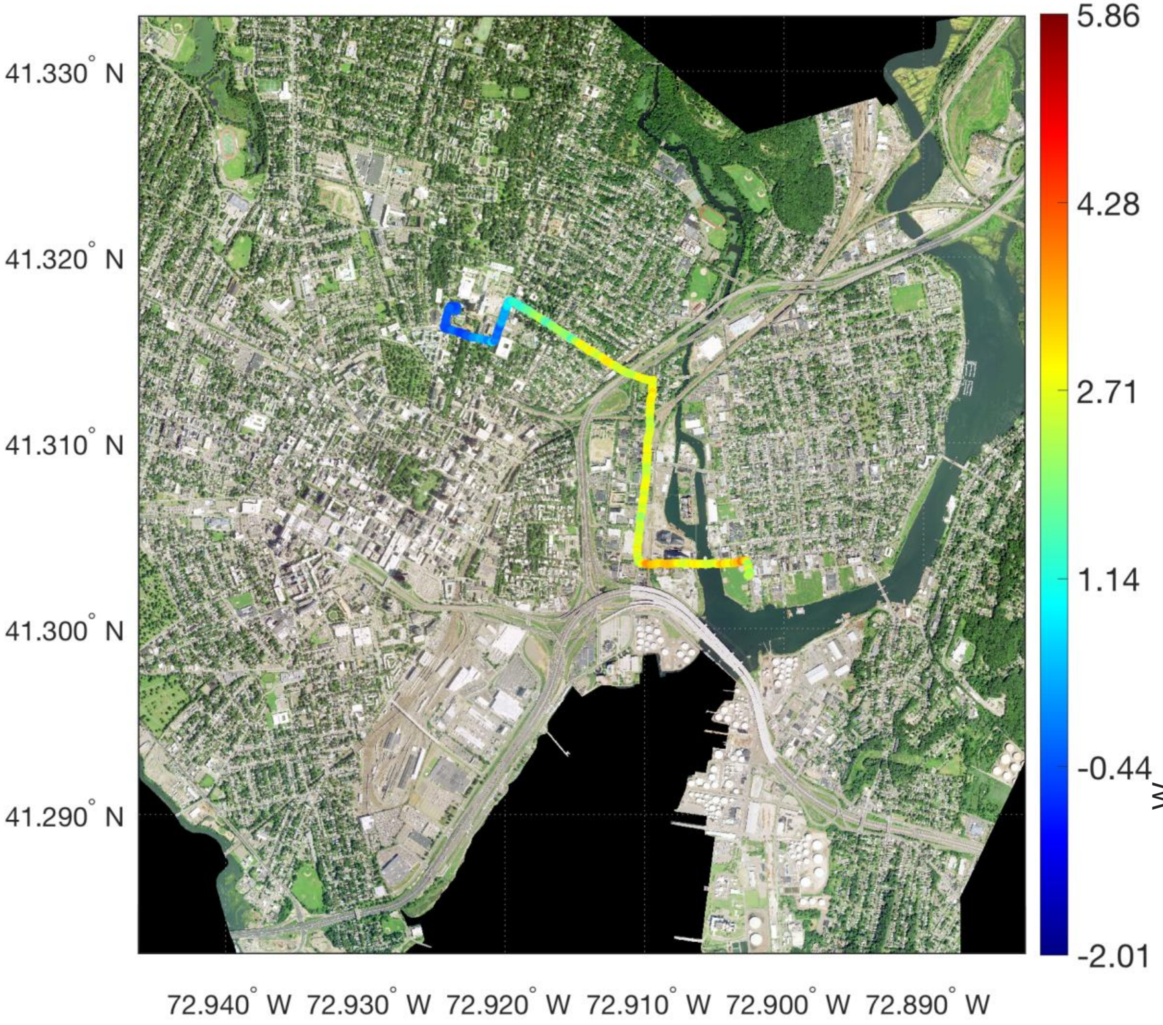

Dry bulb temperature
1500
1000
500
0
Counts
Dry Area
Wet Area
-2
0
2
$T_{db}$ Value (Deg C)


Wet bulb temperature
800
600
400
200
0
Counts
Dry Area
Wet Area
-1
0
1
2
$T_{wb}$ Value (Deg C)

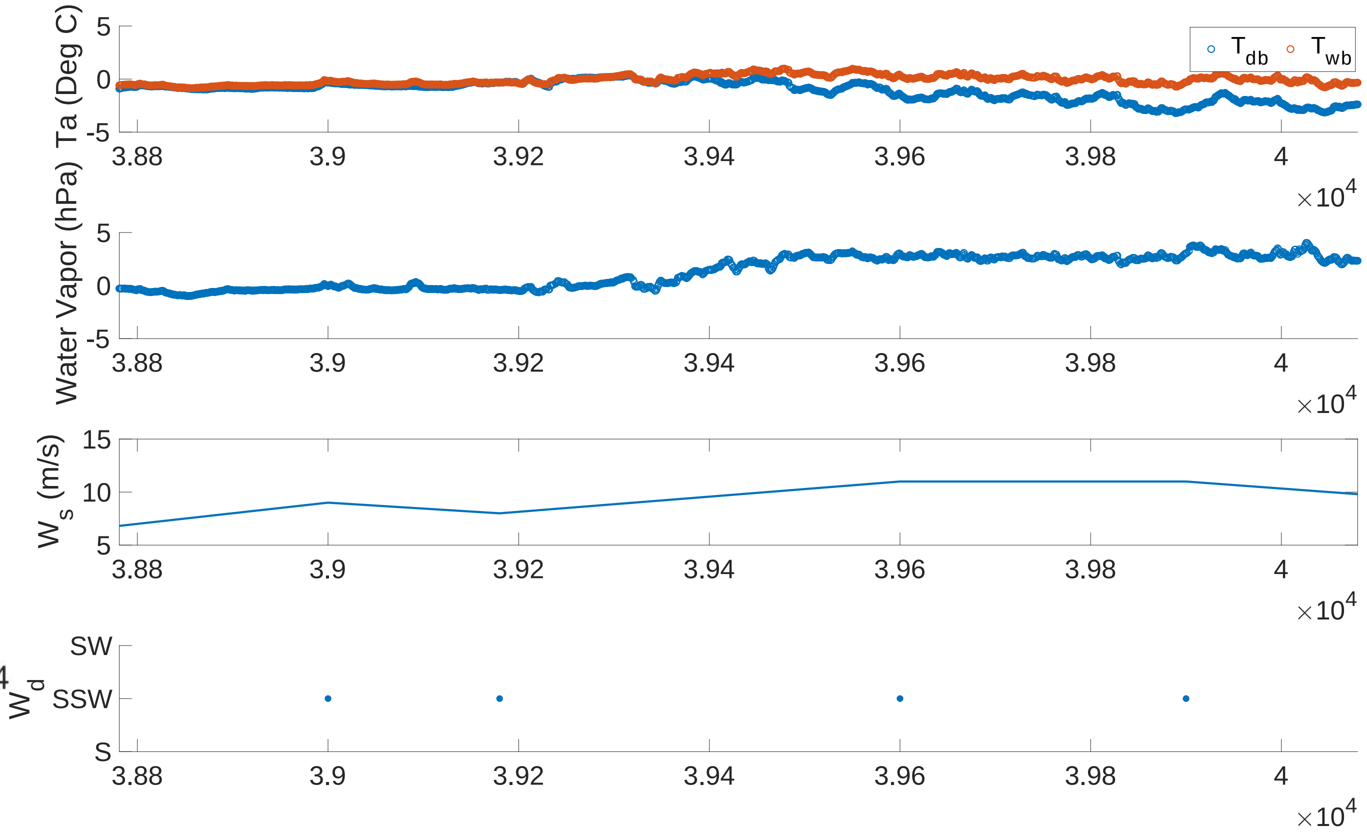


$T_{db}$ (Deg C)
Tree Cover Canopy
$T_{wb}$ (Deg C)
Tree Cover Canopy
$T_{db}$ (Deg C)
Building Shadow Fraction
$T_{wb}$ (Deg C)
Building Shadow Fraction
$T_{db}$ (Deg C)
Imperviuos Surface Cover
$T_{wb}$ (Deg C)
Impervious Surface Cover

# Water Vapor



5.86
4.28
2.71
1.14
-0.44
-2.01
41.330° N
41.320° N
41.310° N
41.300° N
41.290° N
72.940° W 72.930° W 72.920° W 72.910° W 72.900° W 72.890° W

Ta (Deg C)
$T_{db}$ $T_{wb}$
Water Vapor (hPa)
$W_s$ (m/s)
$W_d$
SW
SSW
S
3.88 3.9 3.92 3.94 3.96 3.98 4
$\times 10^4$

# Ta ~ Tree, Shadow, IMP

Dry Bulb Temperature

```
Coefficients:
                     Estimate        Std. Error   t value    Pr(>|t|)
(Intercept) -0.68782526319411  0.03266611528772 -21.05623 < 2.22e-16 ***
SHD         -3.17848183601928  0.06720499266609 -47.29532 < 2.22e-16 ***
Tree         0.19921199681431  0.06416943696801   3.10447  0.0019096 **
IMP          2.14178544712391  0.04178838086159  51.25313 < 2.22e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6081547337576 on 15859 degrees of freedom
Multiple R-squared:  0.2639923400175,   Adjusted R-squared:  0.2638531116311
F-statistic: 1896.110030719 on 3 and 15859 DF,  p-value: < 2.2204460493e-16
```

Wet Bulb Temperature

```
Coefficients:
                     Estimate        Std. Error   t value Pr(>|t|)
(Intercept) -0.20019929220370  0.02158452215114  -9.27513  < 2e-16 ***
SHD         -2.06348481428087  0.04440649401044 -46.46809  < 2e-16 ***
Tree        -0.03409029904033  0.04240071466909  -0.80400  0.42141
IMP          0.83515664381398  0.02761216705515  30.24597  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4018454354456 on 15859 degrees of freedom
Multiple R-squared:  0.151434982887,    Adjusted R-squared:  0.1512744623591
F-statistic: 943.3994823306 on 3 and 15859 DF,  p-value: < 2.2204460493e-16
```

# Best Subset Regression: using BIC

When fitting models, it is possible to increase the likelihood by adding parameters, but doing so may result in overfitting. Both BIC and AIC attempt to resolve this problem by introducing a penalty term for the number of parameters in the model; the penalty term is larger in BIC than in AIC.

## Do the suggested best model: Ta ~ Shadow + IMP

```
Coefficients:
                 Estimate       Std. Error  t value   Pr(>|t|)
(Intercept) -0.59505436752212  0.01319753744502 -45.08829 < 2.22e-16
SHD         -3.14812397140370  0.06650785317451 -47.33462 < 2.22e-16
IMP          2.04320140192522  0.02717088331269  75.19820 < 2.22e-16

(Intercept) ***
SHD         ***
IMP         ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6083203188196 on 15860 degrees of freedom
Multiple R-squared:  0.2635450583946,  Adjusted R-squared:  0.263452188919
F-statistic: 2837.800651474 on 2 and 15860 DF,  p-value: < 2.2204460493e-16
```

```
Coefficients:
                 Estimate         Std. Error   t value   Pr(>|t|)
(Intercept) -0.216074779756006  0.008717958123267 -24.78502 < 2.22e-16 ***
SHD         -2.068679826125122  0.043933399034423 -47.08672 < 2.22e-16 ***
IMP          0.852026910841916  0.017948395591149  47.47092 < 2.22e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4018409560947 on 15860 degrees of freedom
Multiple R-squared:  0.1514003949553,   Adjusted R-squared:  0.1512933836558
F-statistic: 1414.807554538 on 2 and 15860 DF,  p-value: < 2.2204460493e-16
```

## Do Ta ~ Tree + Shadow

### Dry Bulb Temperature

```
Coefficients:
                 Estimate       Std. Error   t value   Pr(>|t|)
(Intercept)  0.83862418009195  0.01448753070408  57.88593 < 2.22e-16 ***
SHD         -1.51277949014533  0.06350748230889 -23.82049 < 2.22e-16 ***
Tree        -2.30005398687941  0.04503256938258 -51.07534 < 2.22e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6565723776066 on 15860 degrees of freedom
Multiple R-squared:  0.1420800825233,   Adjusted R-squared:  0.1419718959006
F-statistic: 1313.286976392 on 2 and 15860 DF,  p-value: < 2.2204460493e-16
```

### Wet Bulb Temperature

```
Coefficients:
                  Estimate          Std. Error    t value   Pr(>|t|)
(Intercept)  0.395016440407802  0.009118747250198  43.31916 < 2.22e-16 ***
SHD         -1.413969531299925  0.039972904389304 -35.37320 < 2.22e-16 ***
Tree        -1.008641038351306  0.028344417459024 -35.58517 < 2.22e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4132600430777 on 15860 degrees of freedom
Multiple R-squared:  0.1024859381539,   Adjusted R-squared:  0.1023727585748
F-statistic: 905.5161630431 on 2 and 15860 DF,  p-value: < 2.2204460493e-16
```

# FINDINGS AND FUTURE STEPS

- The cooling effect of Tree Canopy Cover is seen, and the cooling effect of Building Shadow is proved. The impervious layer has warming effect. However, the landcover dataset constrains the method, indicating that only one of the inter-correlated tree and impervious indices should be used.
- Wet bulb AHUI is narrower in the range of variation. Dry bulb AUHI has stronger variability. The spatial pattern of wet bulb AHUI is smoother than that of dry bulb AHUI. Cold and humid spots in a dry bulb AUHI transect can become hot spots in it's corresponding we bulb AUHI transect. The cooler isn't always more comfortable!

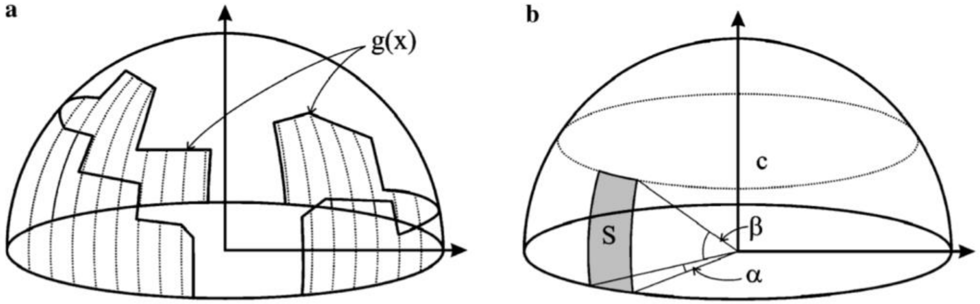
- To investigate the sea-breeze-related pattern, more cyclist volunteers were recruited. They encouraged to spread out their biking routes.
- Some interesting ideas about the shadow pattern will be tested in the future:
  - Shadow gradient pattern: how different times of a day alter the Shadow-Ta correlation. A guess is that the correlation is more negative in the afternoon than in the morning.
  - How the Shadow-Ta relationship changes with weather condition (Clear-Overcast).
  - How SVF gets involved.

# SOME NEW PLANS

Tree Shade

Open Area

# GIS-based SVF computation



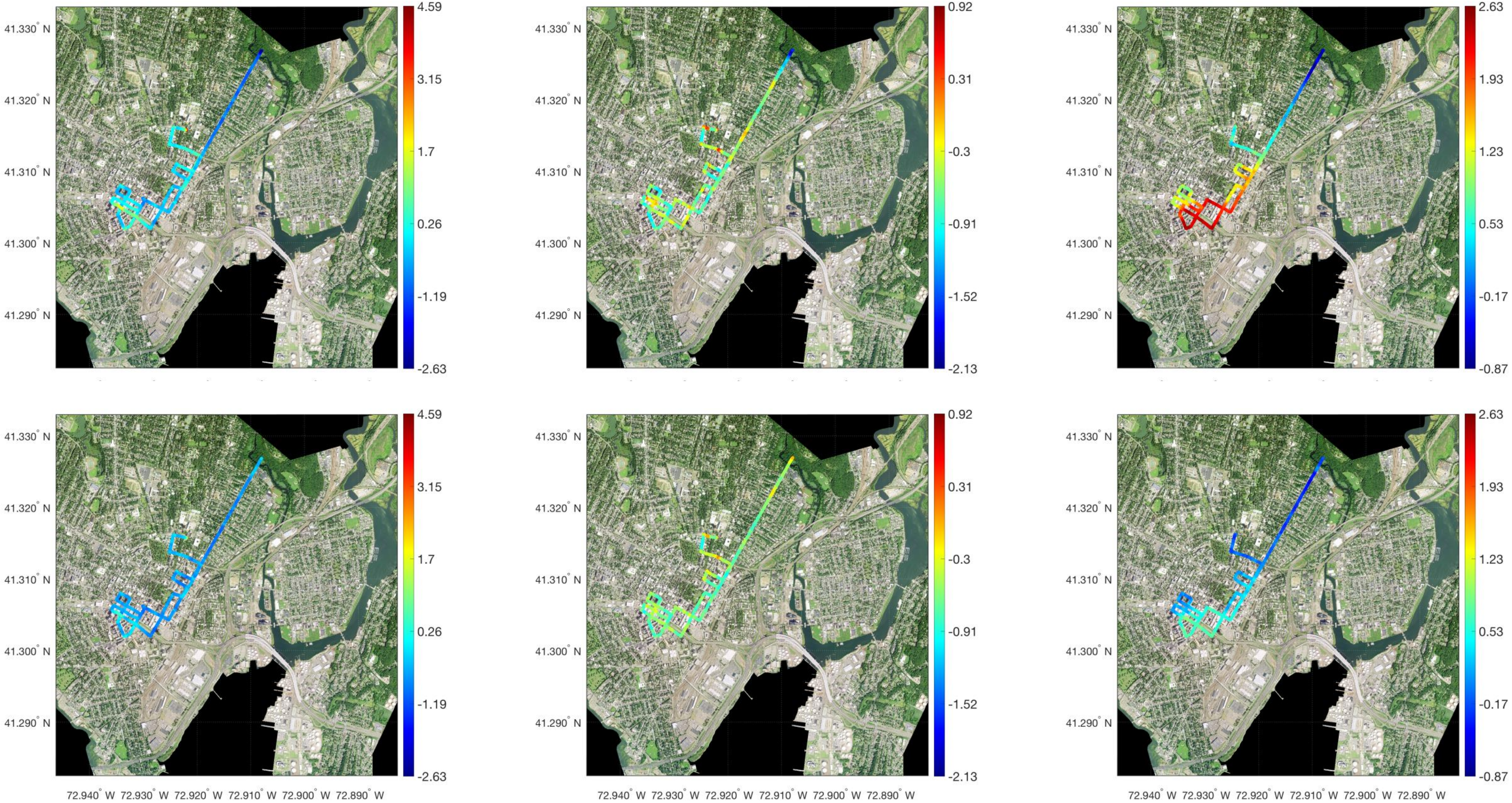

$$VF_S = \sin^2\beta \cdot (\alpha/360)$$

360*90 = 32400 individual shadow graphs were generated

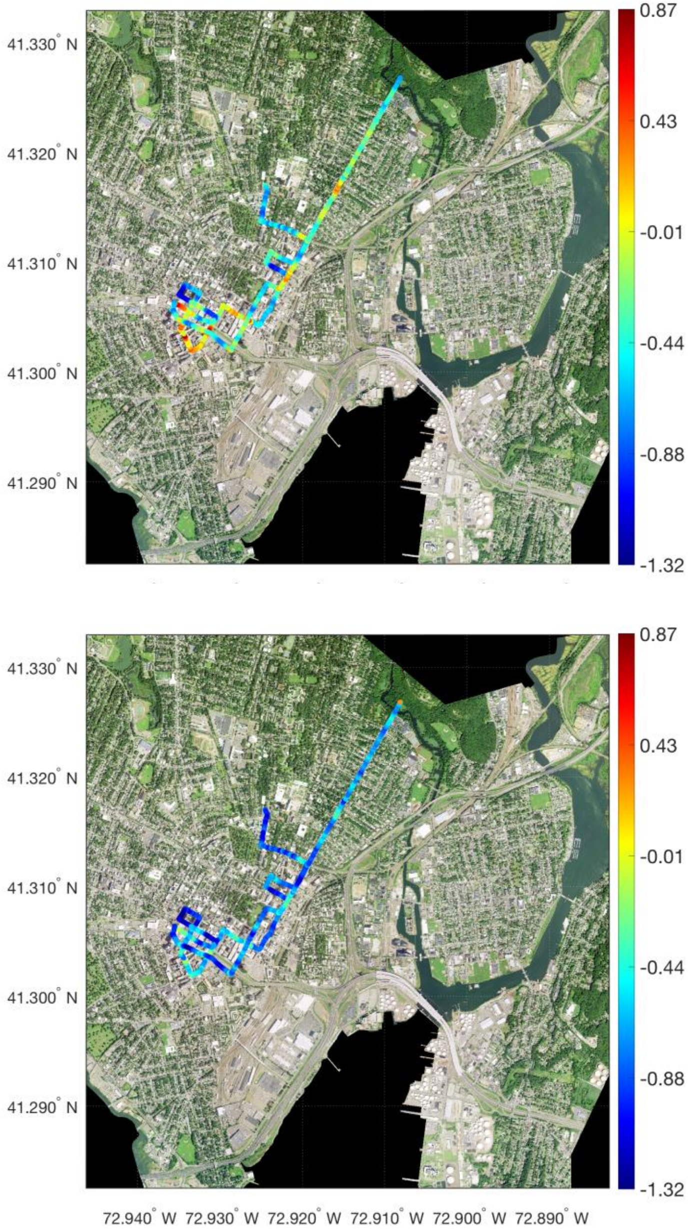
0917 9-10 am

0917 5-6 pm

0917 10-11 pm



0918 9-10 am

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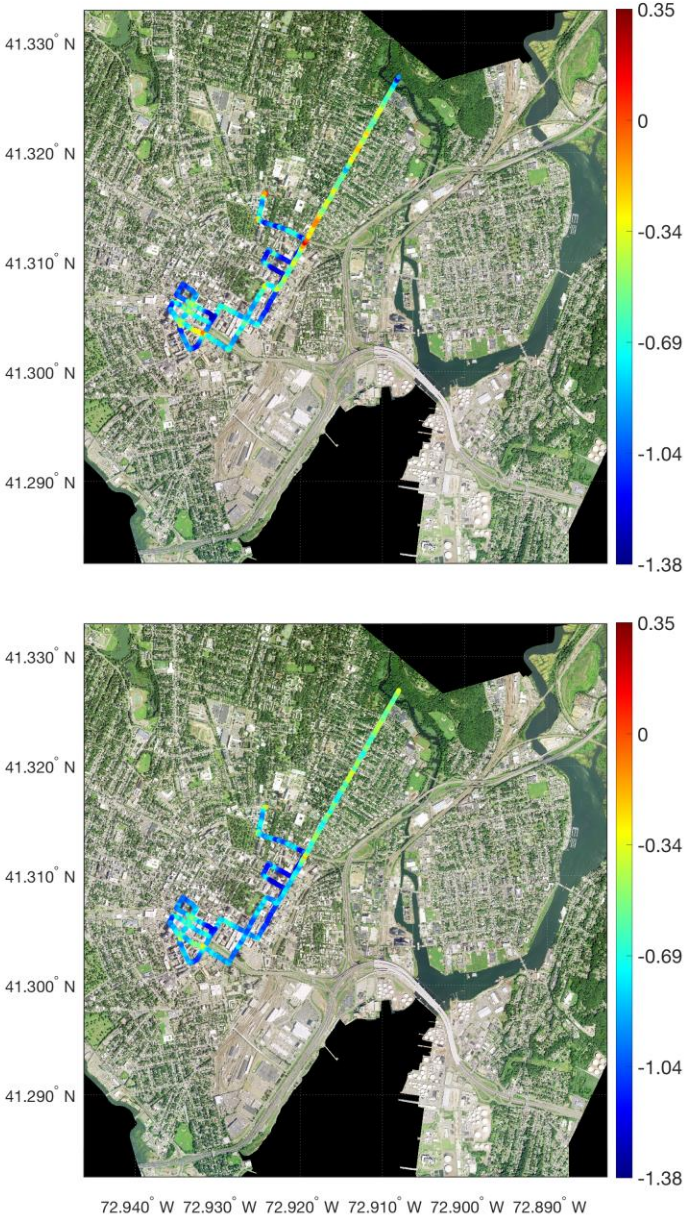
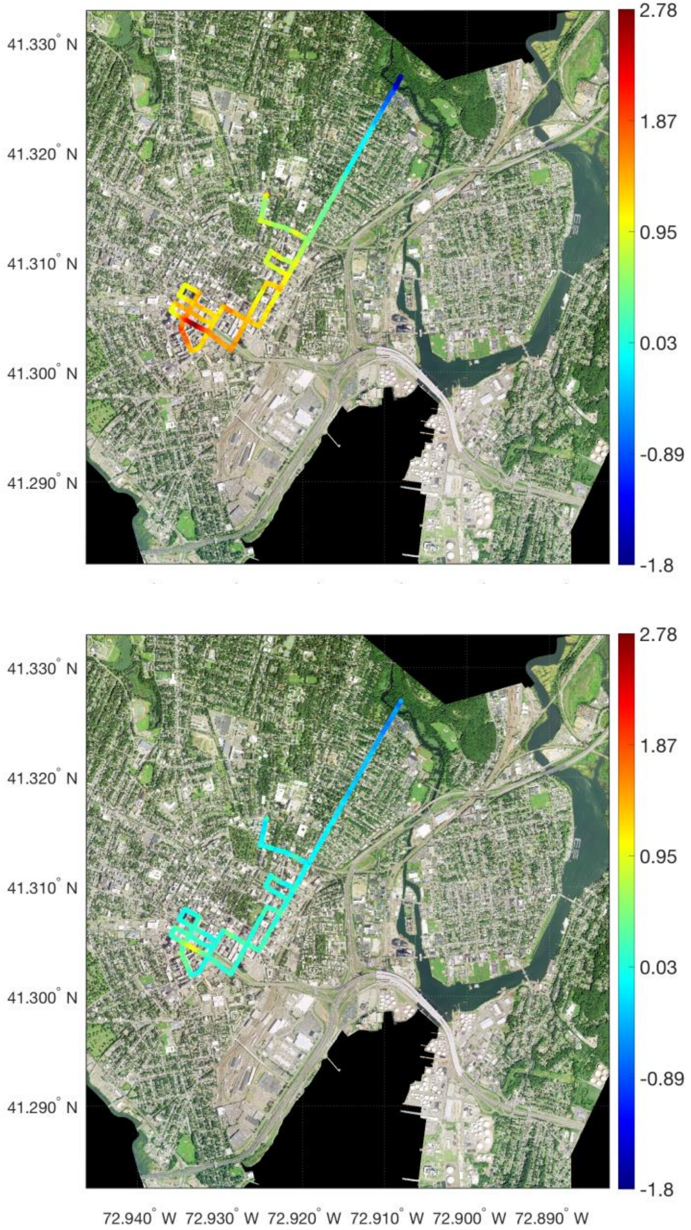


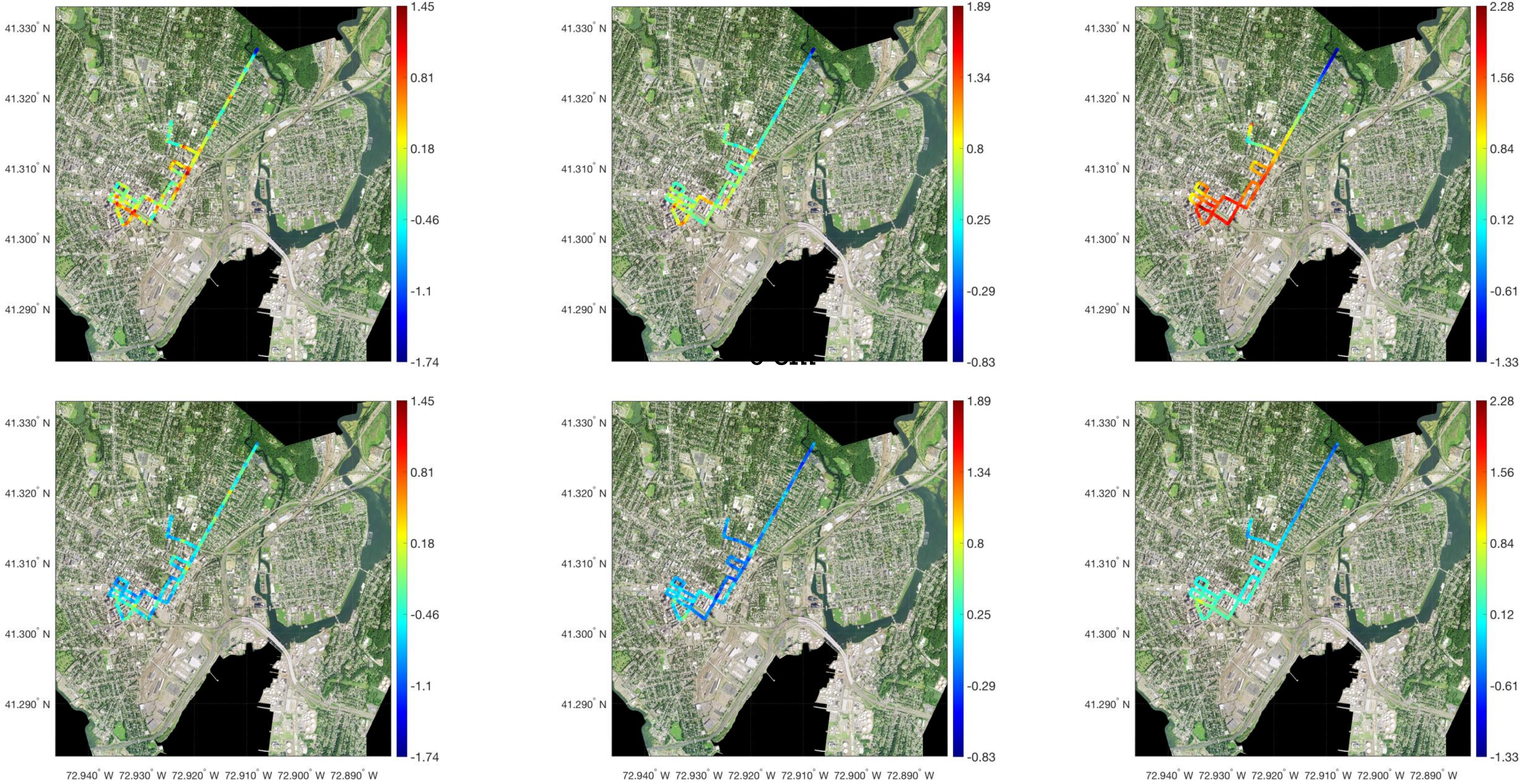

0918 10-11 pm



0924 9-10 am

0924 5-6 pm

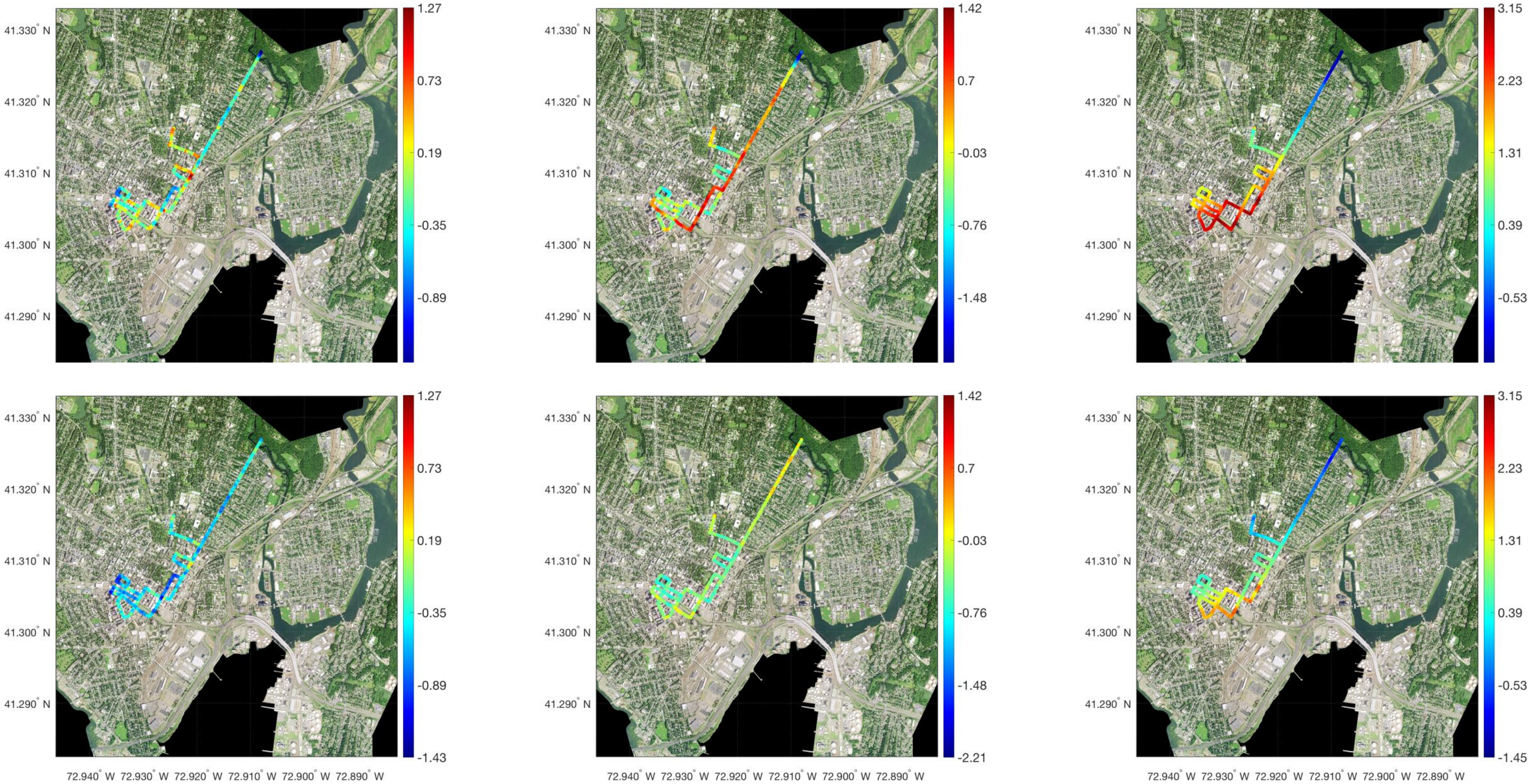
0924 10-11 pm



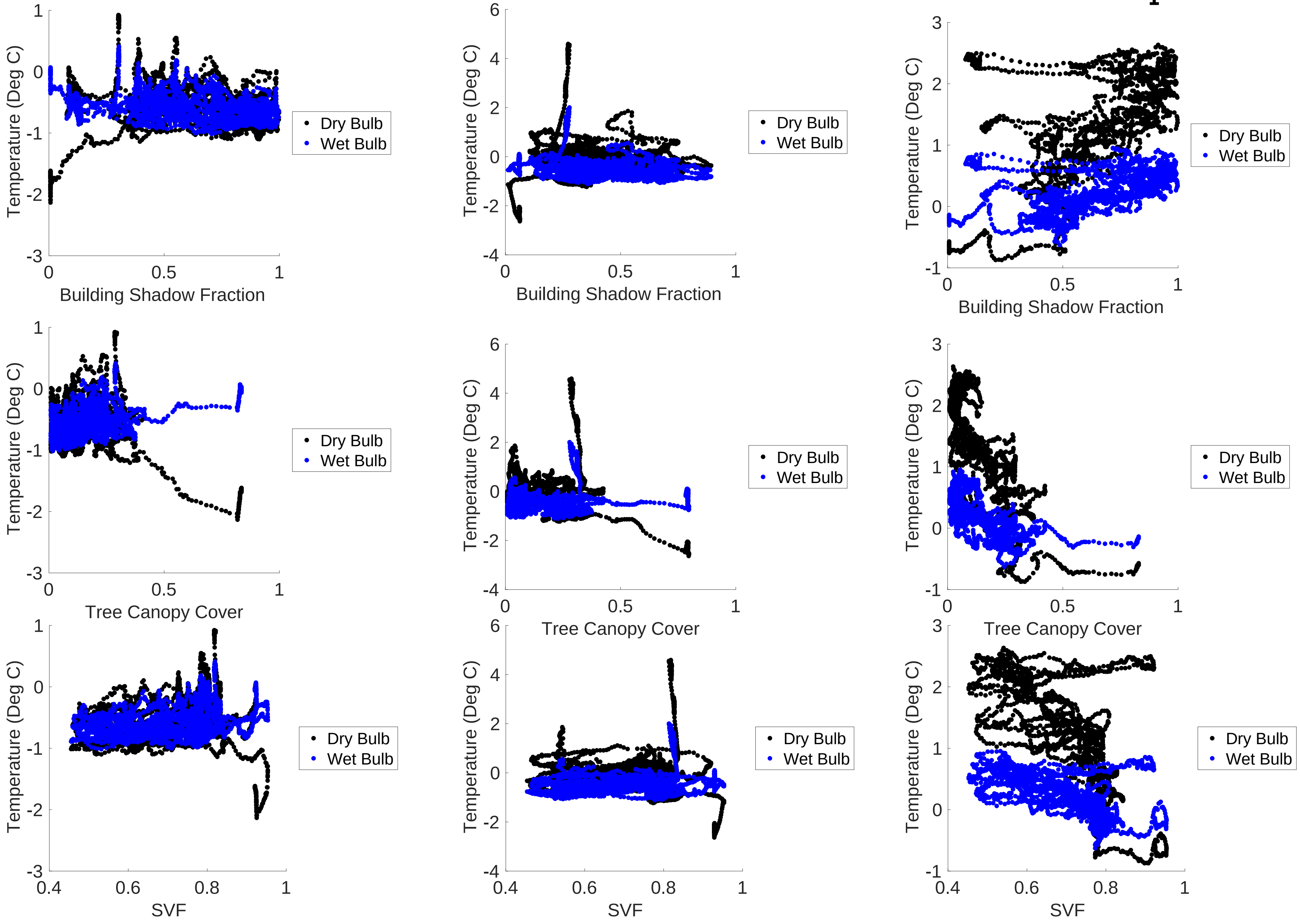
0925 9-10 am

0925 5-6 pm

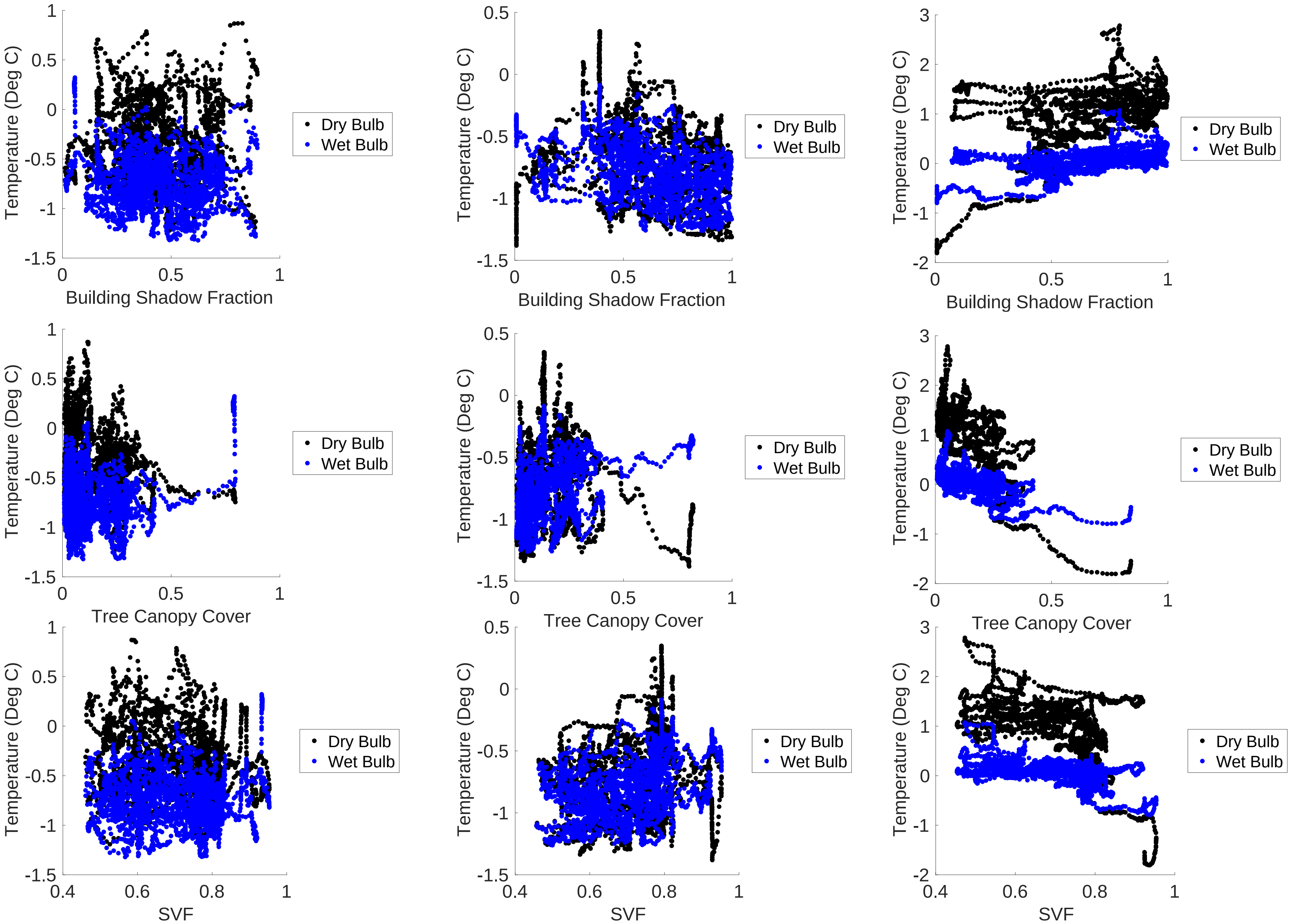
0925 10-11 pm

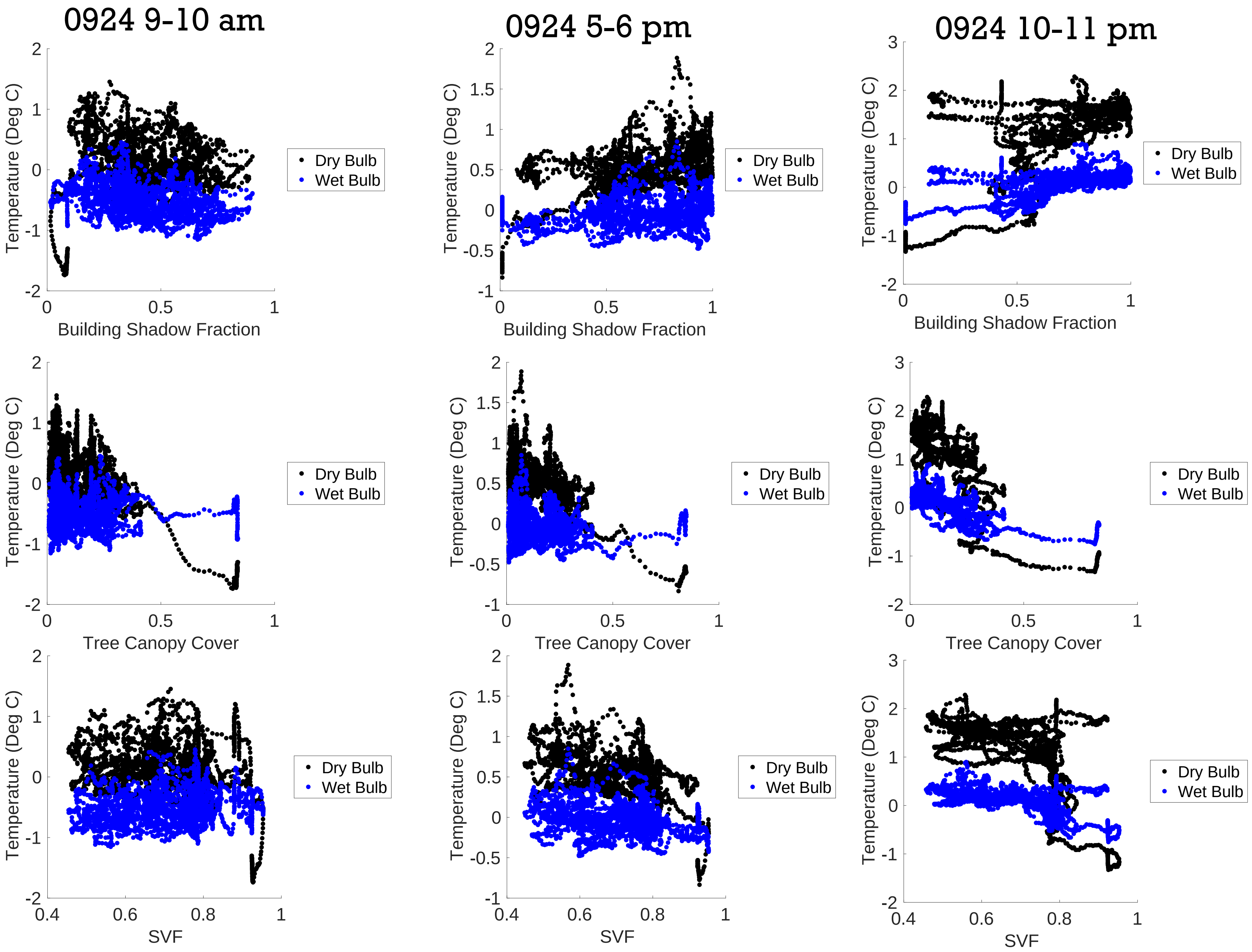


# 0917 9-10 am 0917 5-6 pm 0917 10-11 pm



0918 9-10 am | 0918 5-6 pm | 0918 10-11 pm

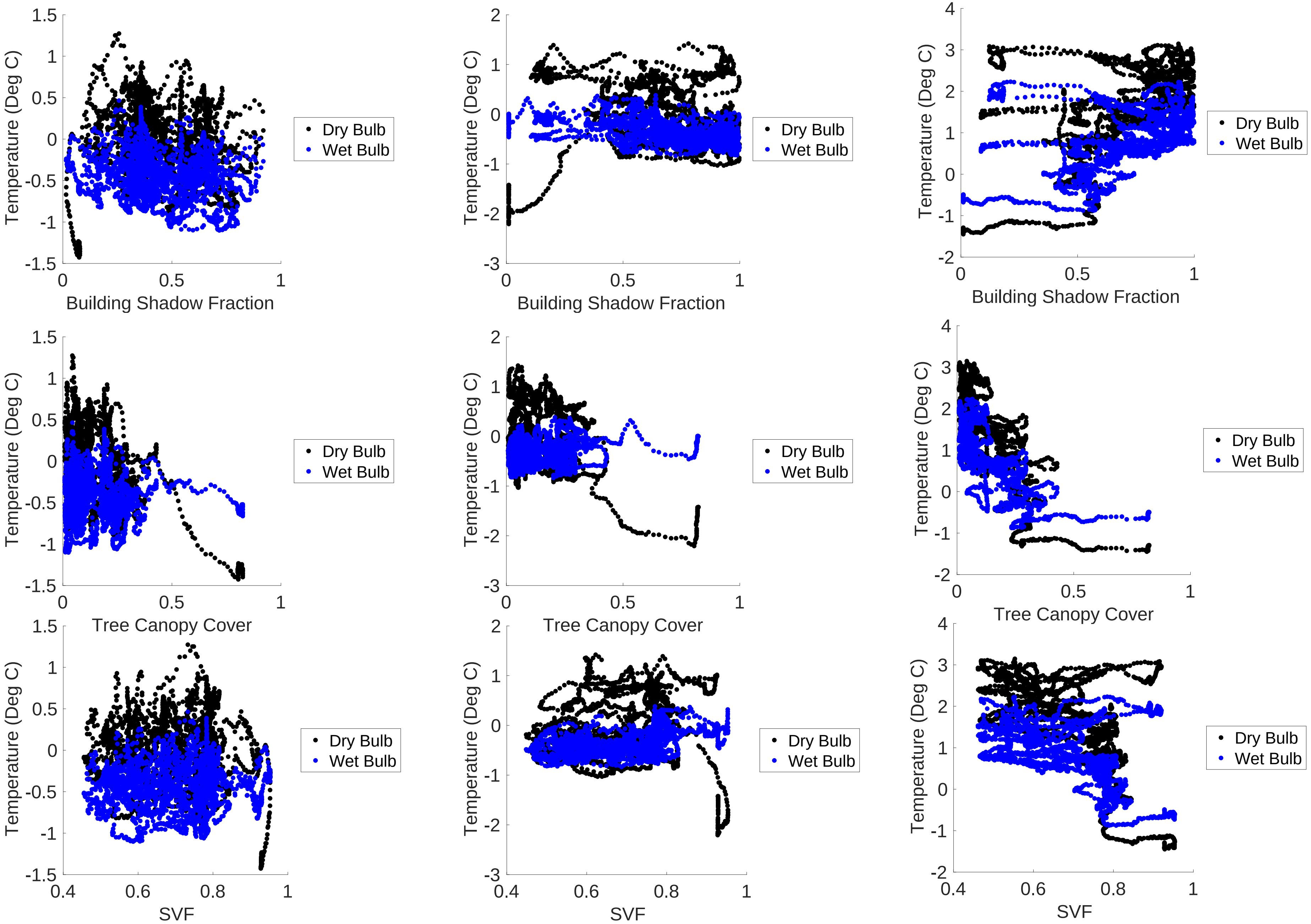



0924 9-10 am
0924 5-6 pm
0924 10-11 pm
Temperature (Deg C)
Building Shadow Fraction
Tree Canopy Cover
SVF
Dry Bulb
Wet Bulb

0925 9-10 am

0925 5-6 pm

0925 10-11 pm



Thank you!