

CS293S: Internet of Things

# An In-Depth Analysis on Weather Data from CIMIS: Estimating Evapotranspiration (ET) Values

Nazmus Saquib   Udit Paul   Alex Ermakov   Santha Ramamoorthy

Graduate Students  
Department of Computer Science  
University of California Santa Barbara

March 11, 2019



# Outline

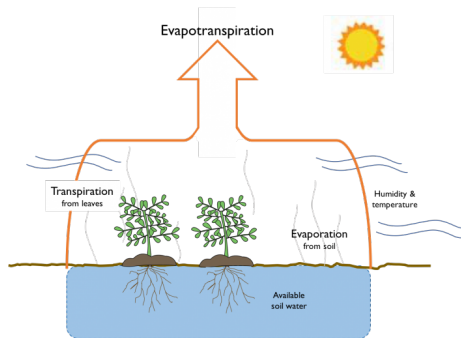
- 1 Introduction
- 2 Data Collection
- 3 Data Overview
- 4 Feature Selection
- 5 Regression Analysis
- 6 Nearest Neighbor Analysis
- 7 Demo
- 8 Questions

# Outline

- 1 Introduction
- 2 Data Collection
- 3 Data Overview
- 4 Feature Selection
- 5 Regression Analysis
- 6 Nearest Neighbor Analysis
- 7 Demo
- 8 Questions

# Introduction: Evapotranspiration (ET)

- Loss of water through:
  - 1 Evaporation and
  - 2 Transpiration
- Applications:
  - Irrigation scheduling
  - Water resource planning, etc.



# Introduction: CIMIS Weather Stations

- *California Irrigation Management Information System*
- 257 CIMIS stations all through California
  - 136 actively reports ET values
- Measures various weather parameters
- some directly influence ET
- Also measures (*calculates?*) ET

# Outline

- 1 Introduction
- 2 Data Collection**
- 3 Data Overview
- 4 Feature Selection
- 5 Regression Analysis
- 6 Nearest Neighbor Analysis
- 7 Demo
- 8 Questions

# Data Collection

- Publicly available API
- Reports both hourly and daily data
- A record contains 15 different features
- Current working dataset: data of last one year
- Certain analysis uses data from multiple years to capture seasonal variations

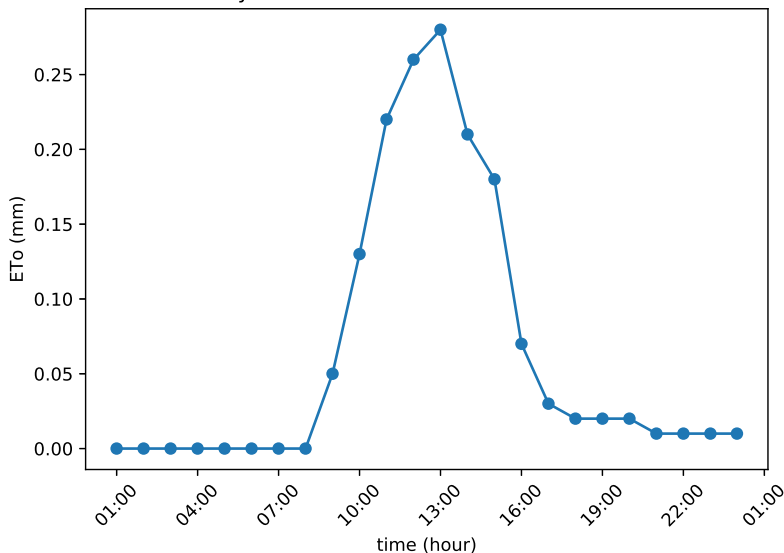
# Outline

- 1 Introduction
- 2 Data Collection
- 3 Data Overview**
- 4 Feature Selection
- 5 Regression Analysis
- 6 Nearest Neighbor Analysis
- 7 Demo
- 8 Questions

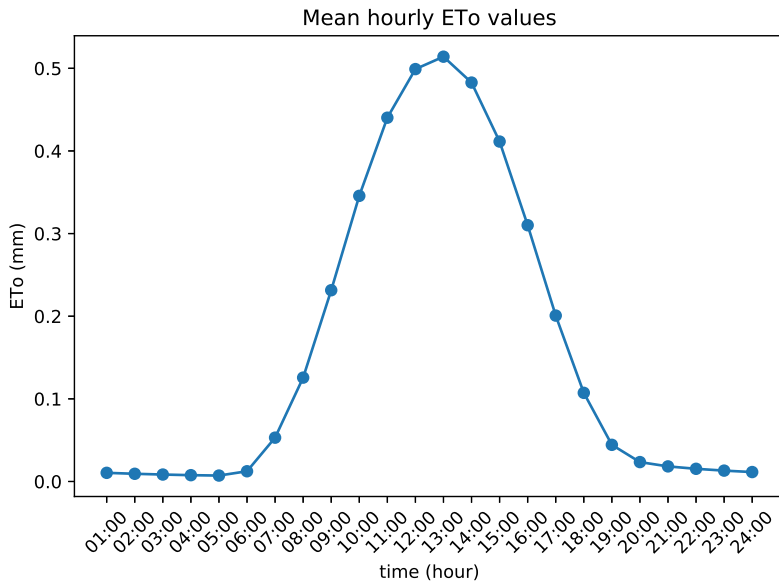


# Sample Hourly ET Values

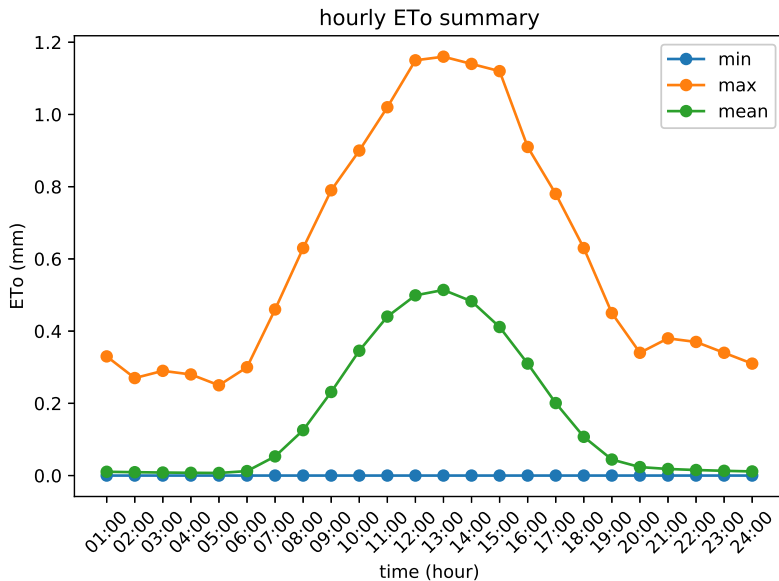
Hourly ETo values for station 2 on 2018-01-01

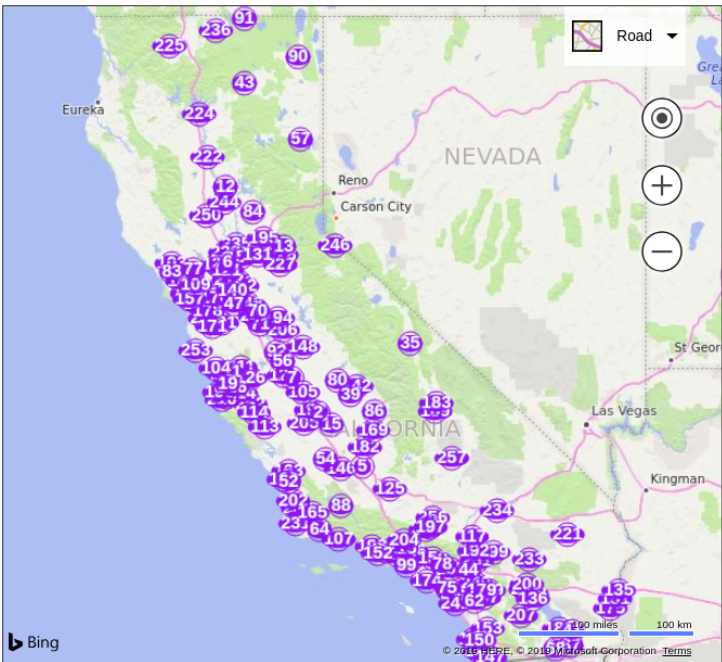


# Mean Hourly ET Values



# Min/Mean/Max Hourly ET Values

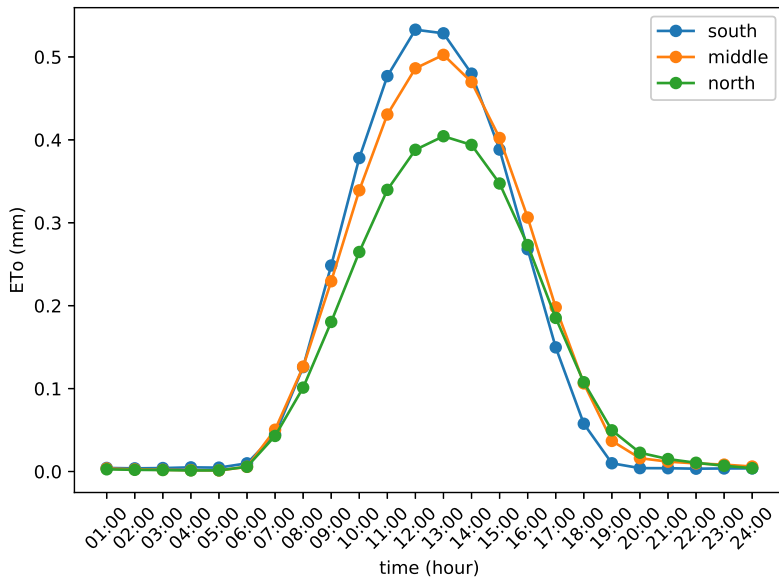




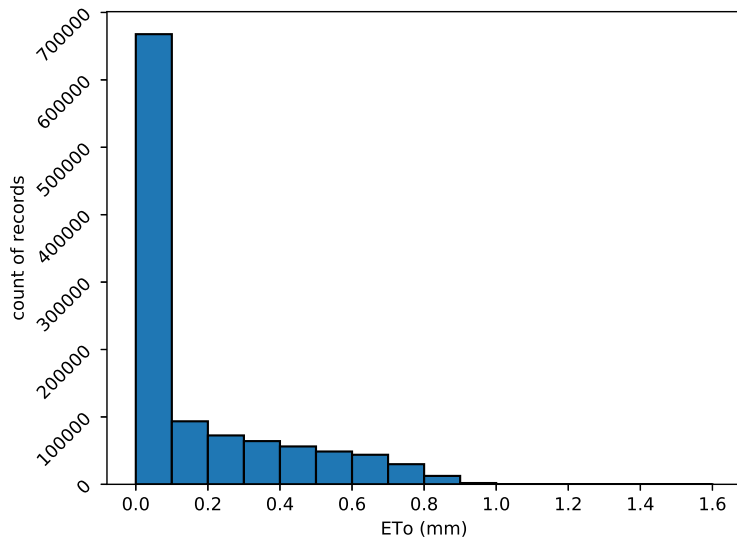
# Stations of Interest

- Station with lowest latitude  $LAT_{MIN}$  (south)
- Station with highest latitude  $LAT_{MAX}$  (north)
- Station with latitude closests to  $\frac{LAT_{MIN} + LAT_{MAX}}{2}$  (middle)

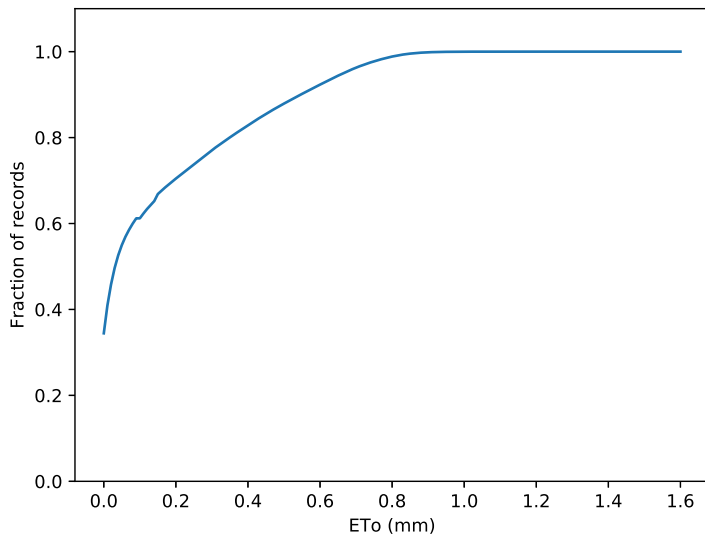
# Mean Hourly ET Values of Stations of Interest



# Histogram of ET Values



# Empirical CDF of ET Values



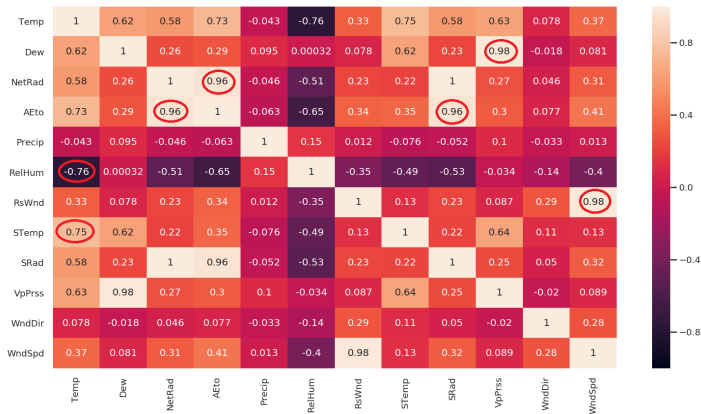


# Outline

- 1 Introduction
- 2 Data Collection
- 3 Data Overview
- 4 Feature Selection**
- 5 Regression Analysis
- 6 Nearest Neighbor Analysis
- 7 Demo
- 8 Questions

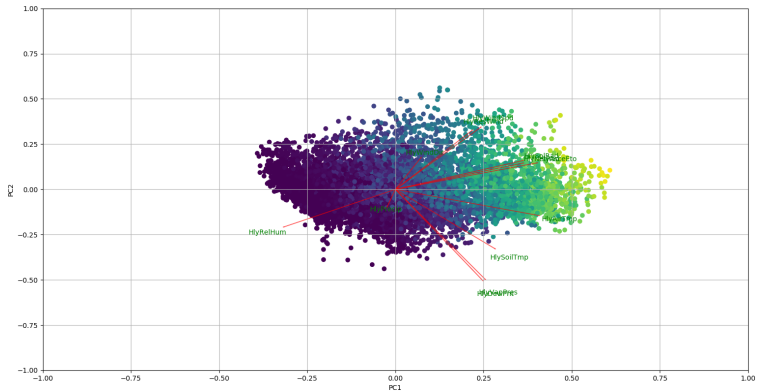
# Correlation Analysis

Correlation between the parameters



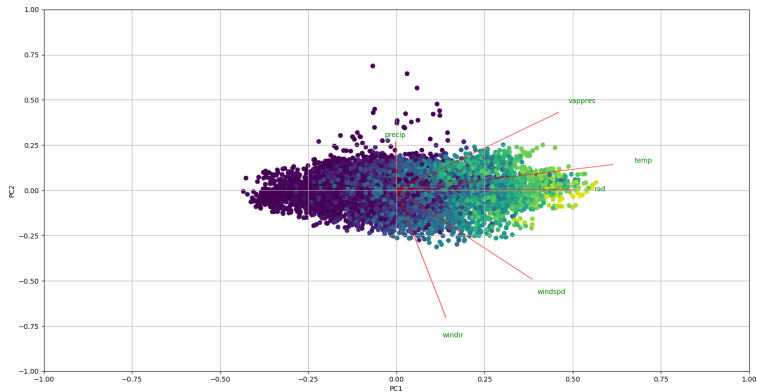
# Biplot-all

Biplot for all parameters



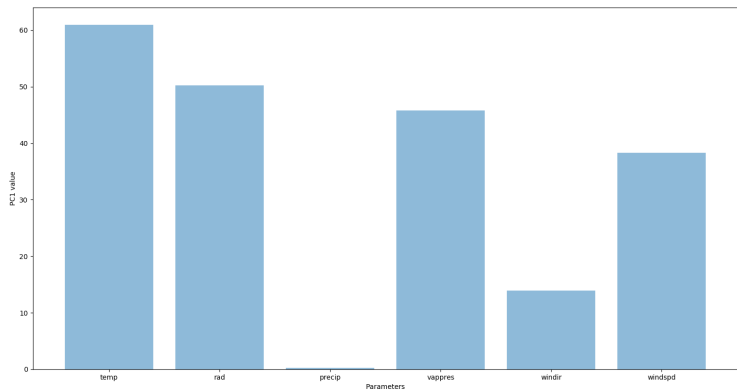
# Biplot-selected

Biplot for the selected parameters



# PC1 values

First order principal component values



# Outline

- 1 Introduction
- 2 Data Collection
- 3 Data Overview
- 4 Feature Selection
- 5 Regression Analysis**
- 6 Nearest Neighbor Analysis
- 7 Demo
- 8 Questions

Given a set of features, can we estimate ET?

- Which features to choose?
- *How well* is our estimate?

Given a set of features, can we estimate ET?

- Which features to choose?
- *How well* is our estimate?



# (CIMIS) Penman Monteith Equation for Calculating ET

$$ET_o = \frac{\Delta(R_n - G)}{\lambda[\Delta + \gamma(1 + C_d u_2)]} + \frac{\gamma \frac{37}{T_a + 273.16} u_2 (e_s - e_a)}{\Delta + \gamma(1 + C_d u_2)}$$

Ultimately depends on four weather features

- Solar net radiation
- Vapor pressure
- Air temperature
- Wind speed

# (CIMIS) Penman Monteith Equation for Calculating ET

$$ET_o = \frac{\Delta(R_n - G)}{\lambda[\Delta + \gamma(1 + C_d u_2)]} + \frac{\gamma \frac{37}{T_a + 273.16} u_2 (e_s - e_a)}{\Delta + \gamma(1 + C_d u_2)}$$

Ultimately depends on four weather features

- Solar net radiation
- Vapor pressure
- Air temperature
- Wind speed

# Regression Results

| Features                                  | Mean Squared Error | $R^2$ Value  |
|---|--------------------|--------------|
| HlyAirTmp,HlyNetRad,HlyVapPres,HlyWindSpd | 0.000970123960314  | 0.9812940161 |
| HlyAirTmp,HlyNetRad,HlyVapPres            | 0.00130358866256   | 0.9747612206 |
| HlyAirTmp,HlyNetRad,HlyWindSpd            | 0.00131186536214   | 0.9745279825 |
| HlyAirTmp,HlyNetRad                       | 0.00173654973306   | 0.9665370047 |
| HlyNetRad,HlyVapPres,HlyWindSpd           | 0.00248645097725   | 0.9520098573 |
| HlyNetRad,HlyWindSpd                      | 0.0024909080494    | 0.9516599092 |
| HlyNetRad,HlyVapPres                      | 0.00302176798112   | 0.9410658003 |
| HlyNetRad                                 | 0.00304665078019   | 0.9409558541 |
| HlyAirTmp,HlyVapPres,HlyWindSpd           | 0.0236668111725    | 0.540318481  |
| HlyAirTmp,HlyWindSpd                      | 0.0242823252297    | 0.5285606181 |
| HlyAirTmp,HlyVapPres                      | 0.026563048828     | 0.4850281600 |
| HlyAirTmp                                 | 0.0278295291341    | 0.4597101537 |
| HlyVapPres,HlyWindSpd                     | 0.0407552684279    | 0.2088275258 |
| HlyWindSpd                                | 0.0412914020576    | 0.1961185540 |
| HlyVapPres                                | 0.0510006461517    | 0.0128578989 |

# Regression Results

| Features   | Mean Squared Error | $R^2$ Value  |
|--|--------------------|--------------|
| HlyAirT <sub>mp</sub> ,HlyNetRad,HlyVapPres,HlyWindSpd | 0.000970123960314  | 0.9812940161 |
| HlyAirT <sub>mp</sub> ,HlyNetRad,HlyVapPres            | 0.00130358866256   | 0.9747612206 |
| HlyAirT <sub>mp</sub> ,HlyNetRad,HlyWindSpd            | 0.00131186536214   | 0.9745279825 |
| HlyAirT <sub>mp</sub> ,HlyNetRad                       | 0.00173654973306   | 0.9665370047 |
| HlyNetRad,HlyVapPres,HlyWindSpd                        | 0.00248645097725   | 0.9520098573 |
| HlyNetRad,HlyWindSpd                                   | 0.0024909080494    | 0.9516599092 |
| HlyNetRad,HlyVapPres                                   | 0.00302176798112   | 0.9410658003 |
| HlyNetRad  | 0.00304665078019   | 0.9409558541 |
| HlyAirT <sub>mp</sub> ,HlyVapPres,HlyWindSpd           | 0.0236668111725    | 0.540318481  |
| HlyAirT <sub>mp</sub> ,HlyWindSpd                      | 0.0242823252297    | 0.5285606181 |
| HlyAirT <sub>mp</sub> ,HlyVapPres                      | 0.026563048828     | 0.4850281600 |
| HlyAirT <sub>mp</sub>                                  | 0.0278295291341    | 0.4597101537 |
| HlyVapPres,HlyWindSpd                                  | 0.0407552684279    | 0.2088275258 |
| HlyWindSpd   | 0.0412914020576    | 0.1961185540 |
| HlyVapPres   | 0.0510006461517    | 0.0128578989 |

# Outline

- 1 Introduction
- 2 Data Collection
- 3 Data Overview
- 4 Feature Selection
- 5 Regression Analysis
- 6 Nearest Neighbor Analysis**
- 7 Demo
- 8 Questions

# Nearest Neighbor Analysis

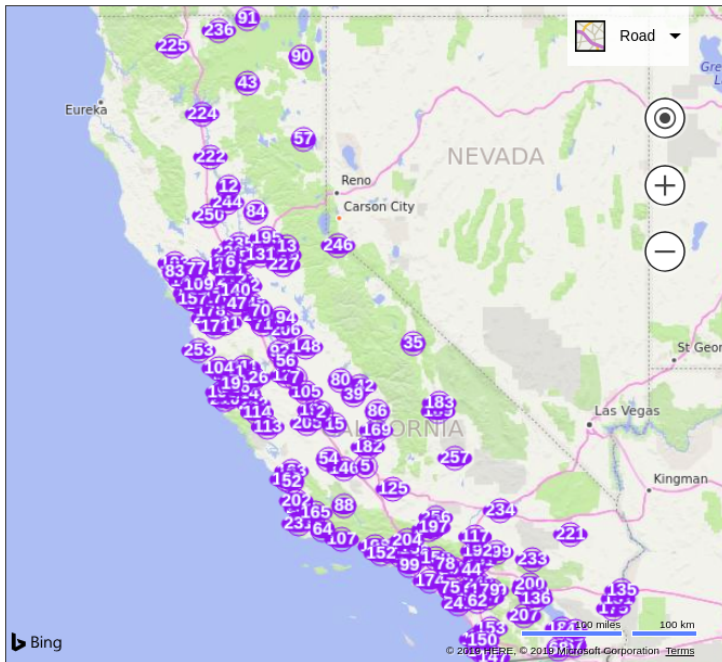
Given the ET value of  $k$  nearest stations of a place, can we estimate ET?

- Arithmetic mean of  $k$  values
- Inverse Distance Weighted (IDW) average of  $k$  values

# Nearest Neighbor Analysis

Given the ET value of  $k$  nearest stations of a place, can we estimate ET?

- Arithmetic mean of  $k$  values
- Inverse Distance Weighted (IDW) average of  $k$  values



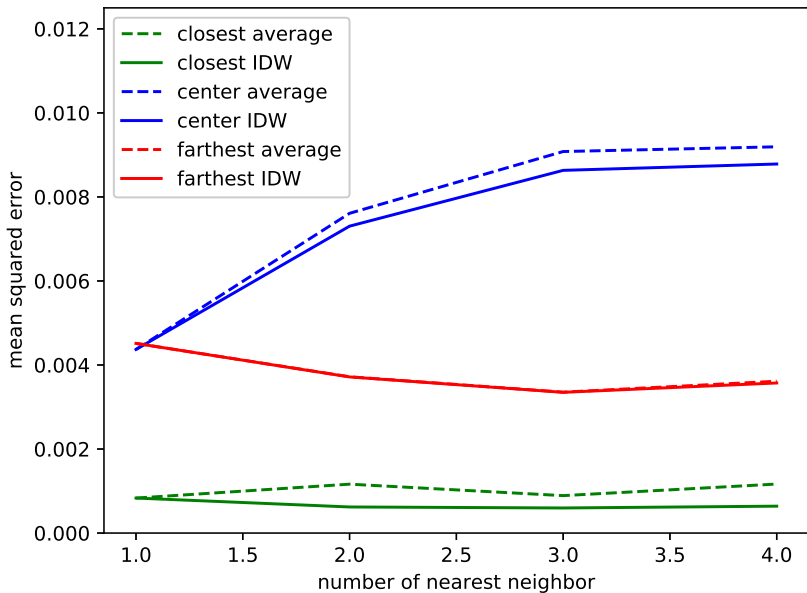


# Stations of Interest

- Station with lowest distance  $D_{MIN}$  to nearest neighbor
- Station with highest distance  $D_{MAX}$  to nearest neighbor
- Station with nearest neighbor at a distance closest to  $\frac{D_{MIN} + D_{MAX}}{2}$

# Nearest Neighbor Results

| Station Number | Num of Neighbors | MSE for Average   | MSE for IDW       |
|----------------|------------------|-------------------|-------------------|
| 129            | 1                | 0.000832971114168 | 0.000832971114168 |
| 234            | 1                | 0.00437018526497  | 0.00437018526497  |
| 57             | 1                | 0.00451400872516  | 0.00451400872516  |
| 129            | 2                | 0.00116361600992  | 0.000620877927137 |
| 234            | 2                | 0.00761026004119  | 0.00730456269316  |
| 57             | 2                | 0.00371994564336  | 0.0037154634375   |
| 129            | 3                | 0.000890784115612 | 0.000596760525931 |
| 234            | 3                | 0.00908058999082  | 0.00863260116925  |
| 57             | 3                | 0.00335367604618  | 0.00334925237208  |
| 129            | 4                | 0.00116647617403  | 0.00063999172153  |
| 234            | 4                | 0.00919325287807  | 0.00878339044833  |
| 57             | 4                | 0.00361403432169  | 0.00357201358681  |



# Nearest Neighbor with Sensor Values

What if we have sensor values from nearby stations instead of only ET values?

MSE decreases according to CIMIS Penman Equation

What if we have sensor values from nearby stations **along with local air temperature?**

MSE decreases even further

# Nearest Neighbor with Sensor Values

What if we have sensor values from nearby stations instead of only ET values?

MSE decreases according to CIMIS Penman Equation

What if we have sensor values from nearby stations **along with local air temperature?**

MSE decreases even further

# Nearest Neighbor with Sensor Values

What if we have sensor values from nearby stations instead of only ET values?

MSE decreases according to CIMIS Penman Equation

What if we have sensor values from nearby stations **along with local air temperature?**

MSE decreases even further

# Nearest Neighbor with Sensor Values

What if we have sensor values from nearby stations instead of only ET values?

MSE decreases according to CIMIS Penman Equation

What if we have sensor values from nearby stations **along with local air temperature?**

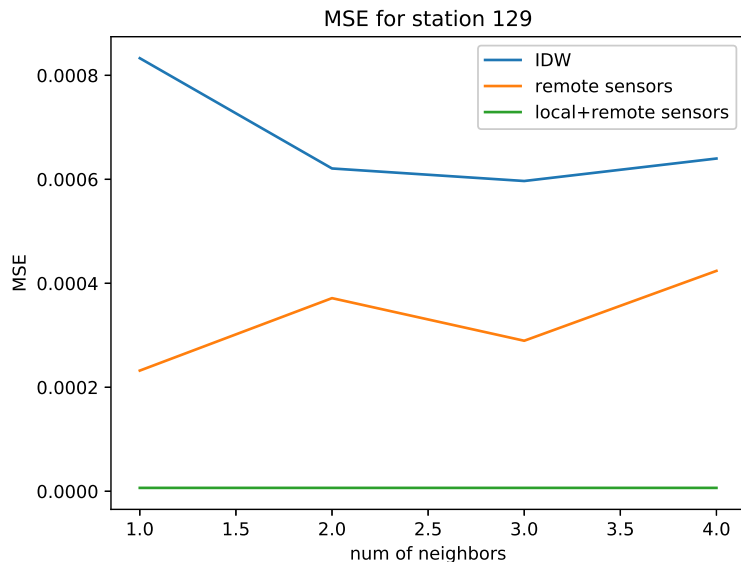
MSE decreases even further

# Nearest Neighbor with Sensor Values (*Cntd.*)

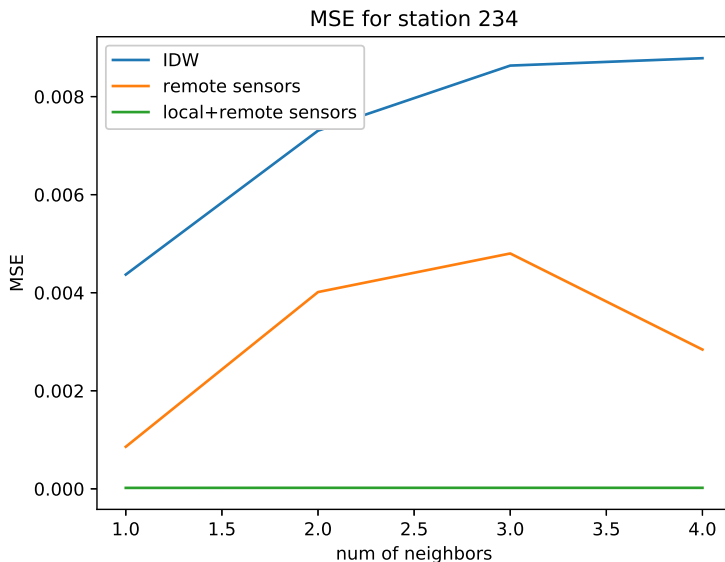
| Stn No | Num of Nbrs | MSE IDW    | MSE        | MSE Local  |
|--------|-------------|------------|------------|------------|
| 234    | 1           | 0.00437018 | 0.00085818 | 0.00001899 |
| 234    | 2           | 0.00730456 | 0.00401320 | 0.00002029 |
| 234    | 3           | 0.00863260 | 0.00480052 | 0.00002029 |
| 234    | 4           | 0.00878339 | 0.00284048 | 0.00002034 |
| 129    | 1           | 0.00083297 | 0.00023209 | 0.00000650 |
| 129    | 2           | 0.00062087 | 0.00037144 | 0.00000649 |
| 129    | 3           | 0.00059676 | 0.00028950 | 0.00000649 |
| 129    | 4           | 0.00063999 | 0.00042391 | 0.00000650 |
| 57     | 1           | 0.00451400 | 0.00044228 | 0.00000982 |
| 57     | 2           | 0.00371546 | 0.00051686 | 0.00000982 |
| 57     | 3           | 0.00334925 | 0.00031521 | 0.00000982 |
| 57     | 4           | 0.00357201 | 0.00042077 | 0.00000983 |



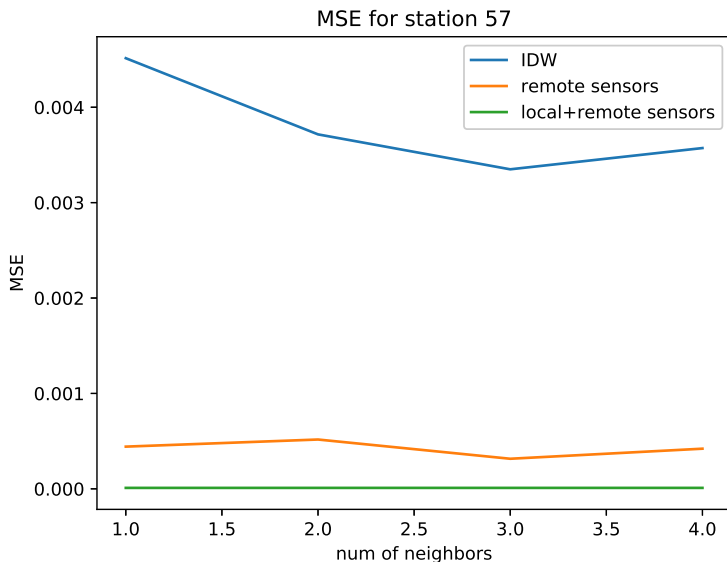
# Nearest Neighbor with Sensor Values (Cntd.)



# Nearest Neighbor with Sensor Values (Cntd.)



# Nearest Neighbor with Sensor Values (*Cntd.*)

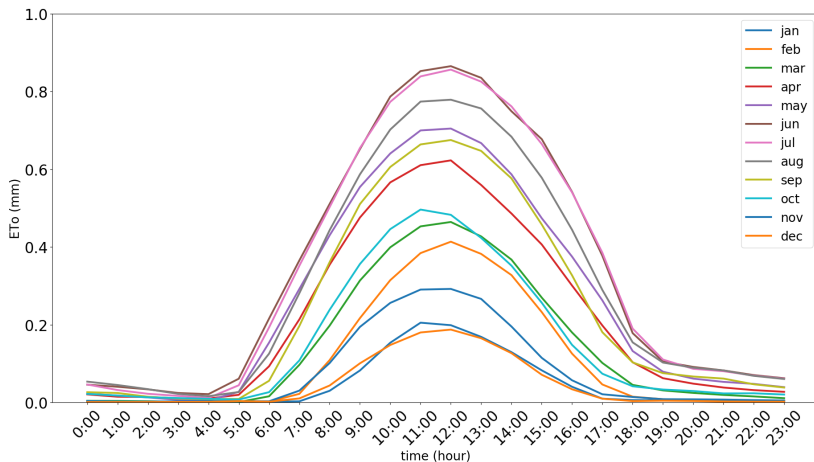


# Outline

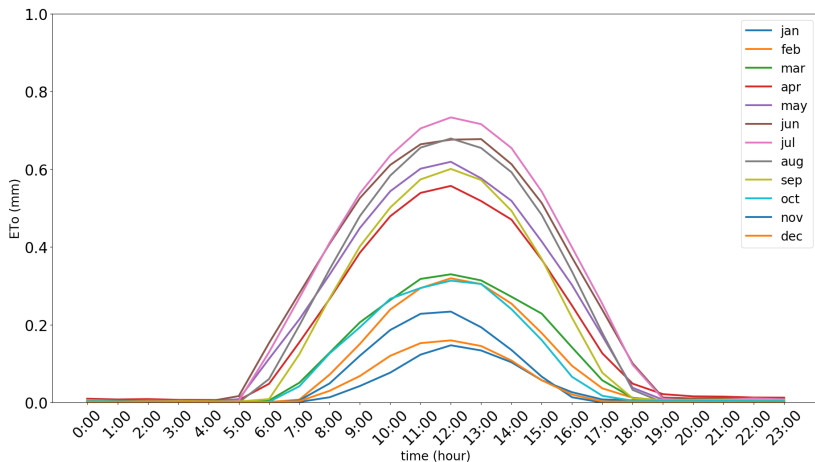
- 1 Introduction
- 2 Data Collection
- 3 Data Overview
- 4 Feature Selection
- 5 Regression Analysis
- 6 Nearest Neighbor Analysis
- 7 Demo**
- 8 Questions

# DEMO

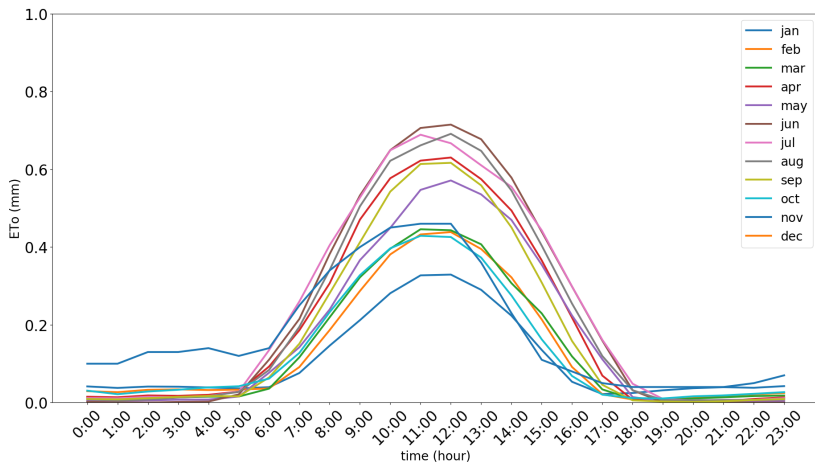
# Normal 12-month Graph for Station 2 in 2016



# 12-month Graph for Station 12 in 2016

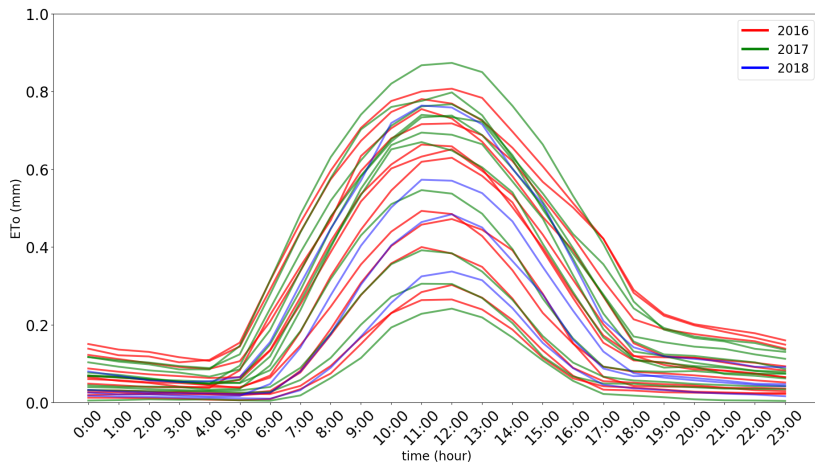


# 12-month Graph for Station 62 in 2018

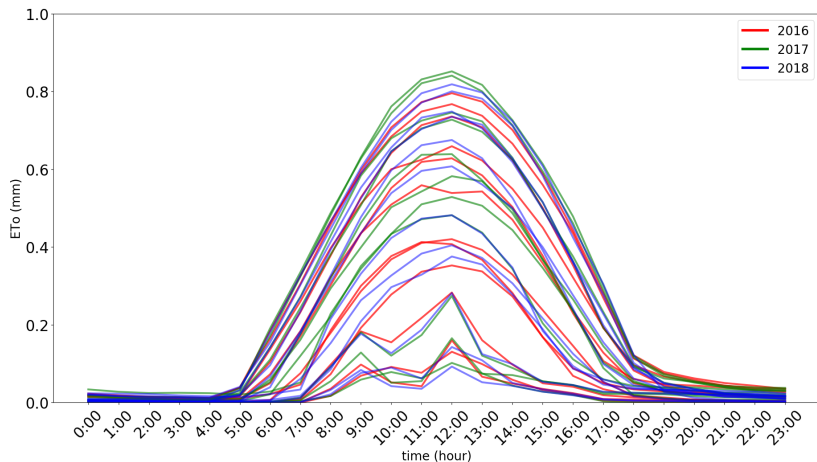




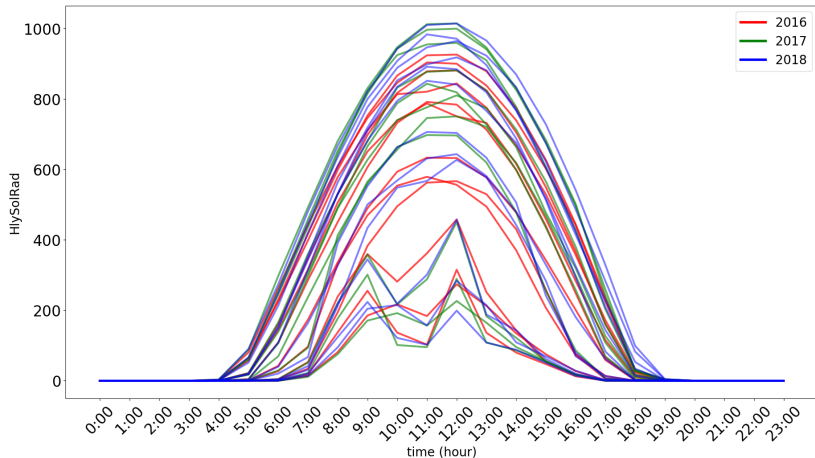
# 36-month Graph for Station 2



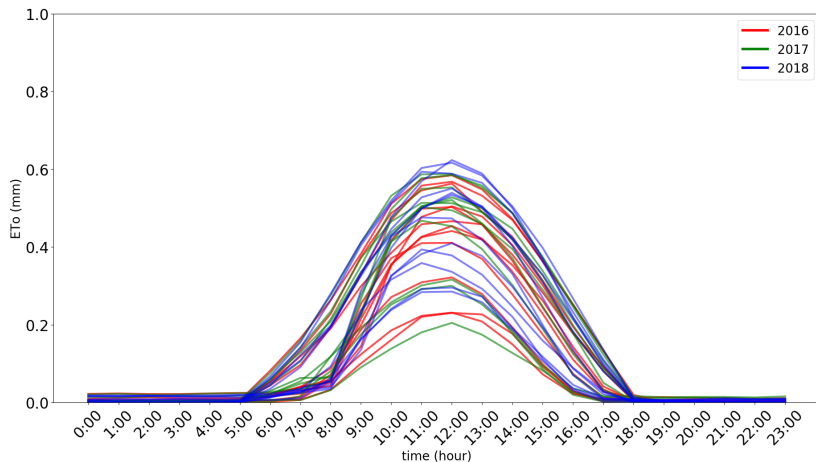
# 36-month Graph for Station 7



# 36-month Solar Graph for Station 7



# 36-month Graph for Station 202



# Outline

- 1 Introduction
- 2 Data Collection
- 3 Data Overview
- 4 Feature Selection
- 5 Regression Analysis
- 6 Nearest Neighbor Analysis
- 7 Demo
- 8 Questions**

# Questions?