

CS293S: Internet of Things

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

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# Outline

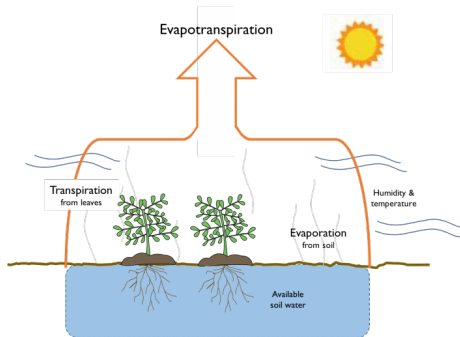
- 1 Introduction
- 2 Data Collection
- 3 Data Overview
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# Introduction: Evapotranspiration (ET)

- 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

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# Data Collection

- Publicly available API
- Reports both hourly and daily data
- A record contains 16 different features
- Current working dataset: data of last one year
- Working dataset will be extended to multiple years:
  - better for capturing seasonal variations

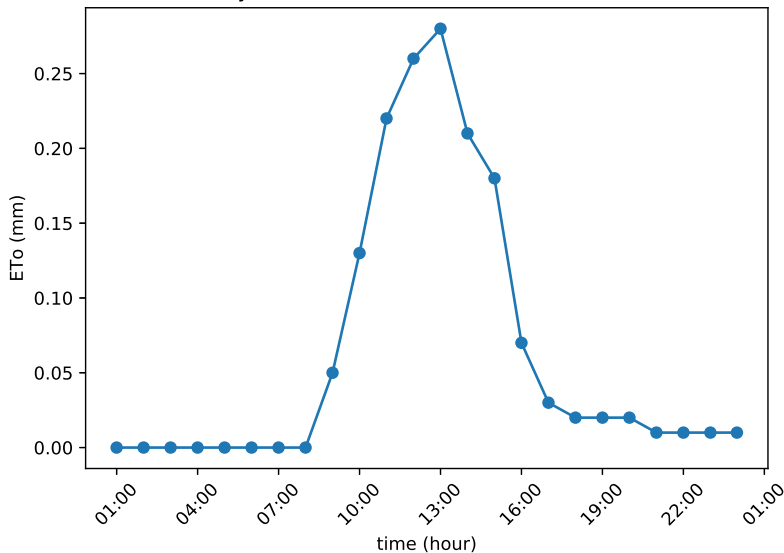
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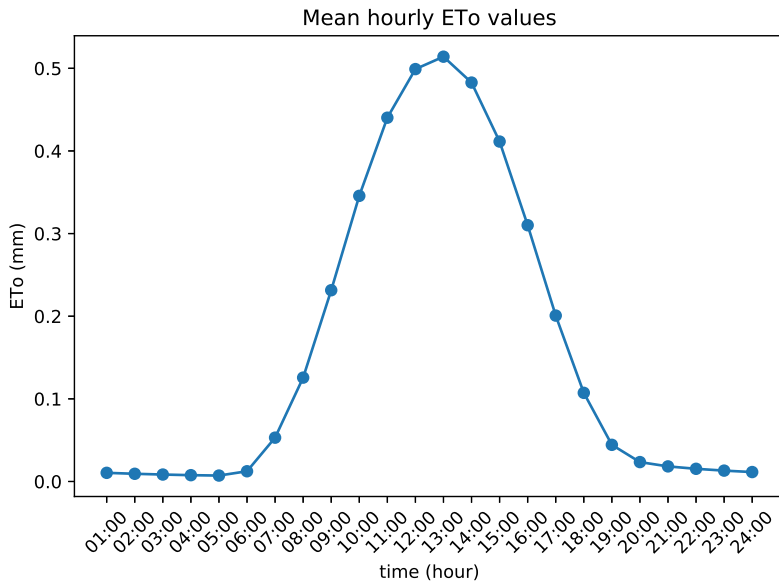


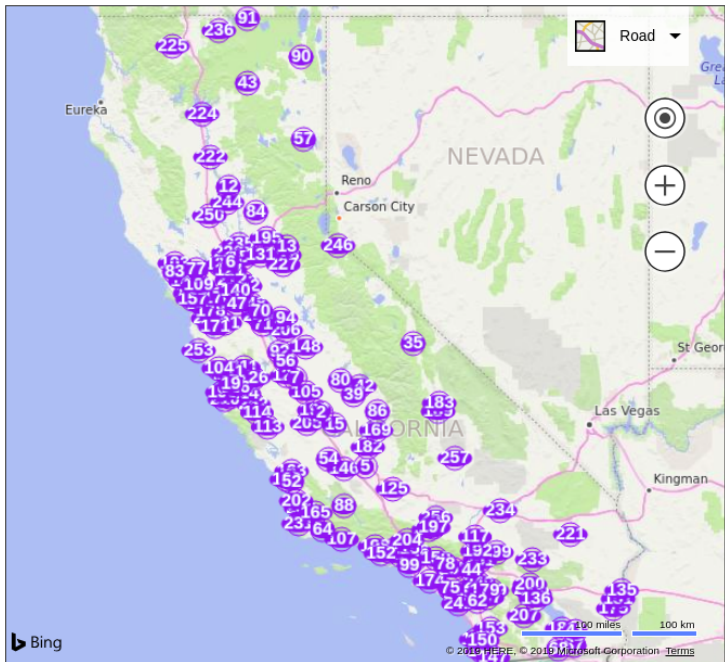
# Sample Hourly ET Values

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



# Mean Hourly ET Values

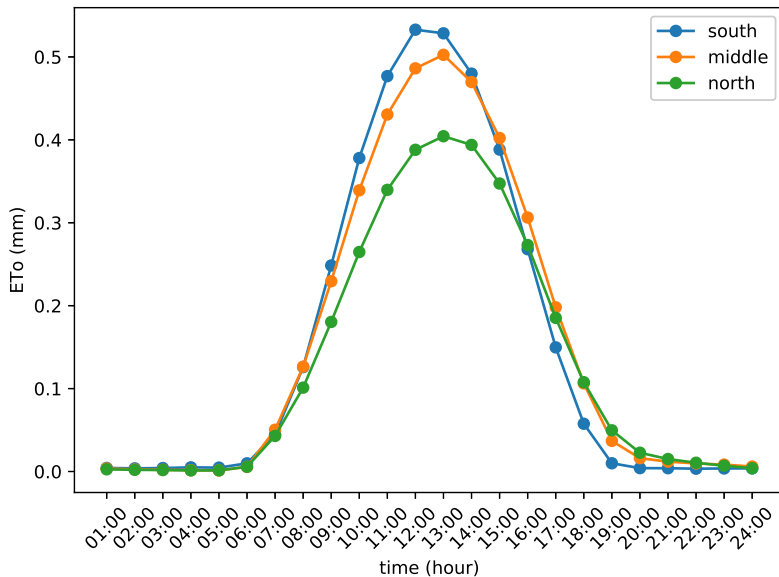




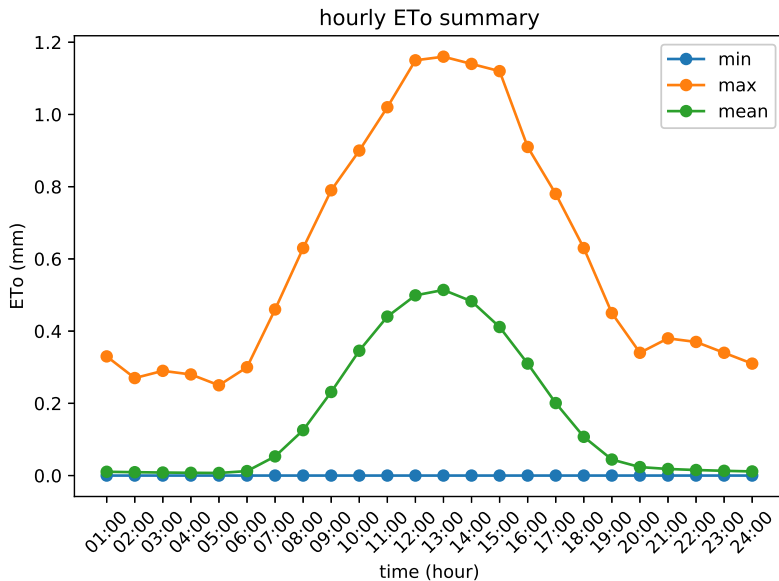
# Stations of Interest

- 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)

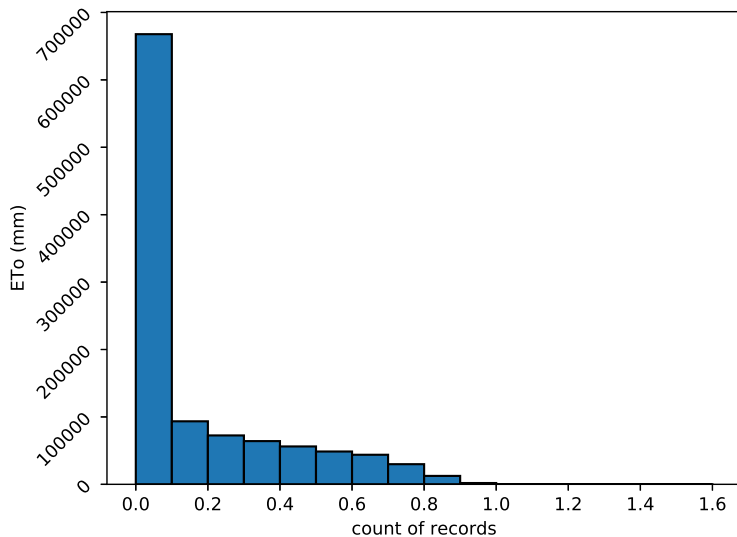
# Mean Hourly ET Values of Stations of Interest



# Min/Mean/Max Hourly ET Values



# Histogram of ET Values



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# Estimation of ET Values

Given a set of features, can we estimate ET?

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

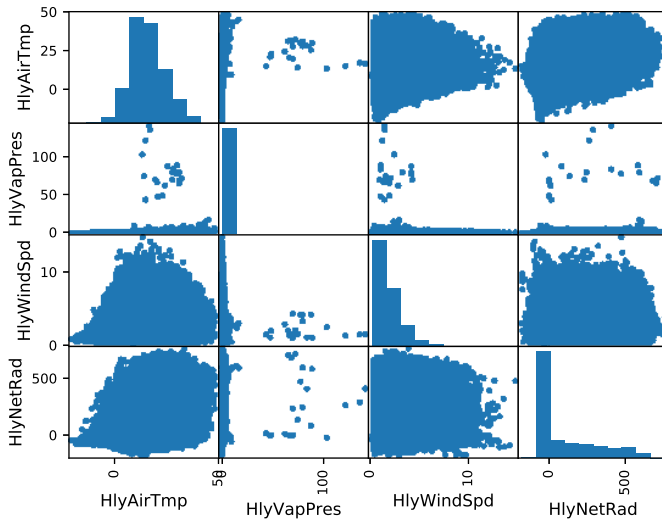
# (CIMIS) Penman Monteith Equation for Calculating ET

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

Ultimately depends on four weather features

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

# Scatterplot Matrix of Features of Interest



# 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

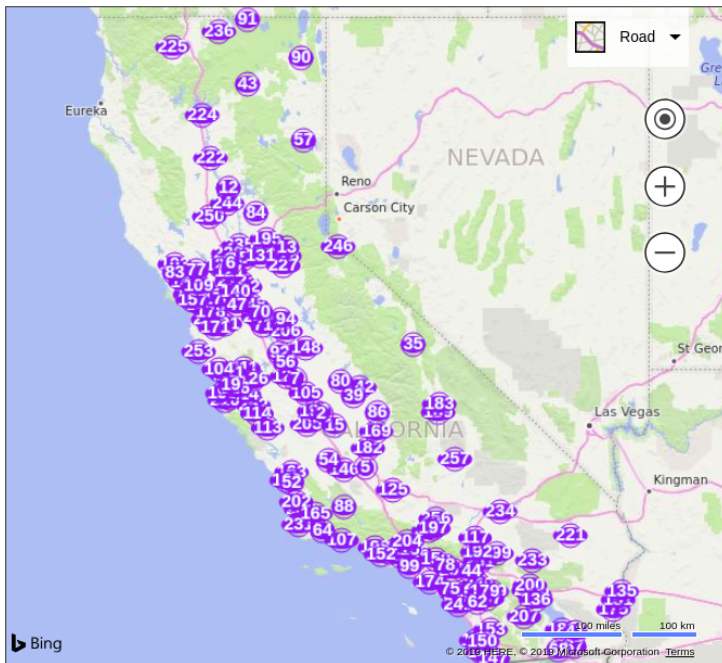
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# Nearest Neighbor Analysis

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



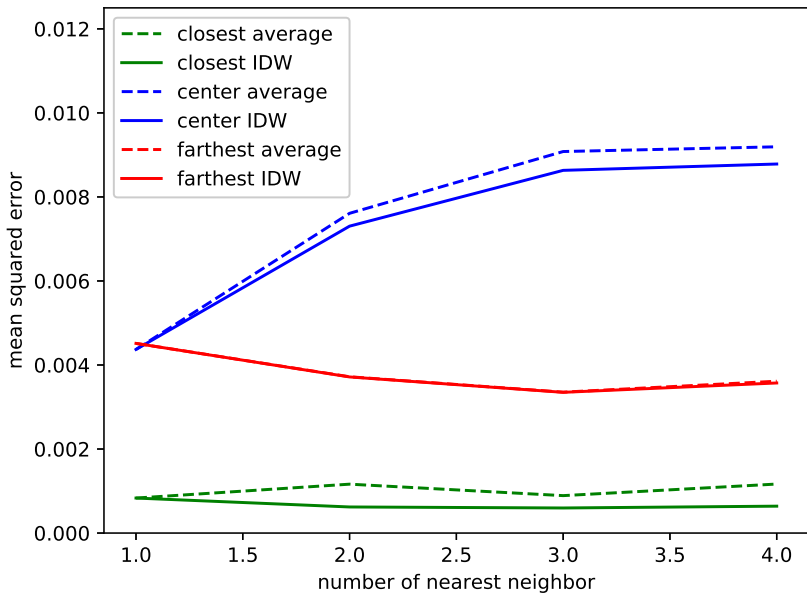
# Stations of Interest

- 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



# A Different Approach to Nearest Neighbor

- Some stations are sparsely located, some are densely located
- Distance to  $n$ th nearest station for different stations might vary widely

What is an optimal value of  $R$  such that  $k$  stations within that radius gives best overall estimates?

future work ...

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- 4 features used in equation, do the other 12 have significant effect on ET?
- Can the dimensionality of dataset be reduced using PCA/LDA?
- Given one (or more, but not all) sensor value at a particular place, how well can we estimate ET by taking into account other sensor values for nearby stations?
- Integrate web interface for analysis.
- Cross check with ground truth value of other sources (*Problem: features seem to be different?*)

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# Questions?