

CS293S: Internet of Things

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

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Outline

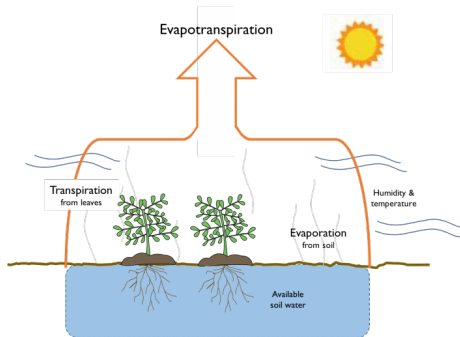
- 1 Introduction
- 2 Data Collection
- 3 Data Overview
- 4 Feature Selection
- 5 Regression Analysis
- 6 Nearest Neighbor Analysis
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Introduction: Evapotranspiration (ET)

- 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

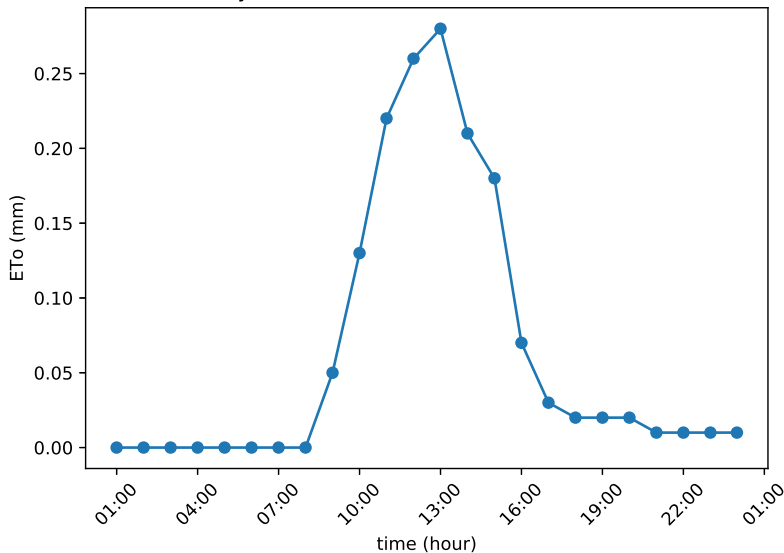
- Publicly available API
- Reports both hourly and daily data
- A record contains 16 different features
- Current working dataset: data of last one year
- Certain analysis uses data from multiple years to capture seasonal variations

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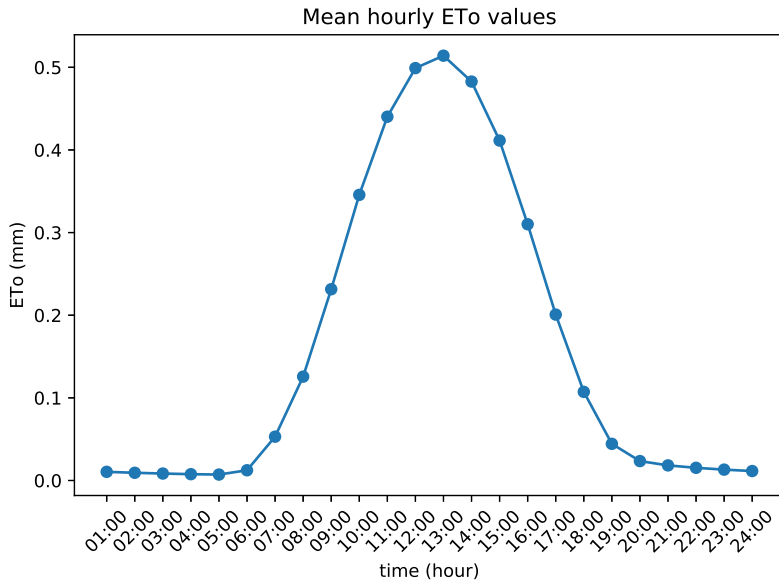
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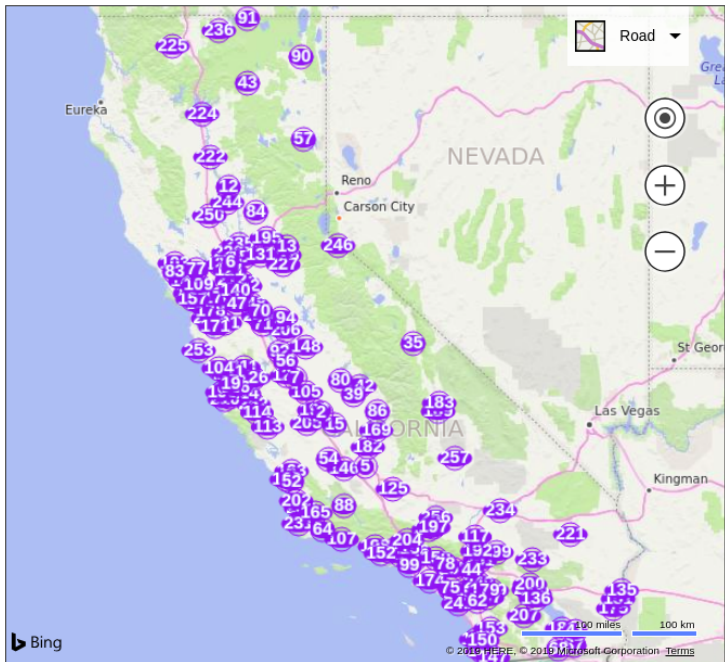
Sample Hourly ET Values

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



Mean Hourly ET Values

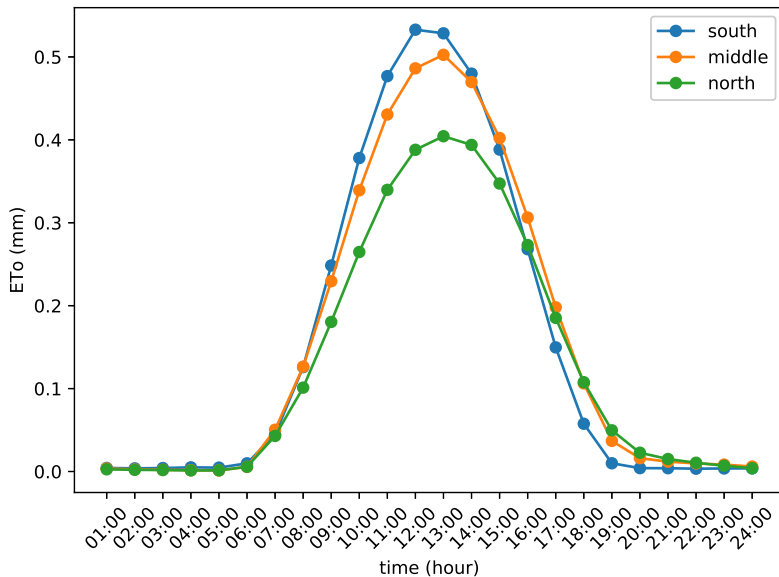




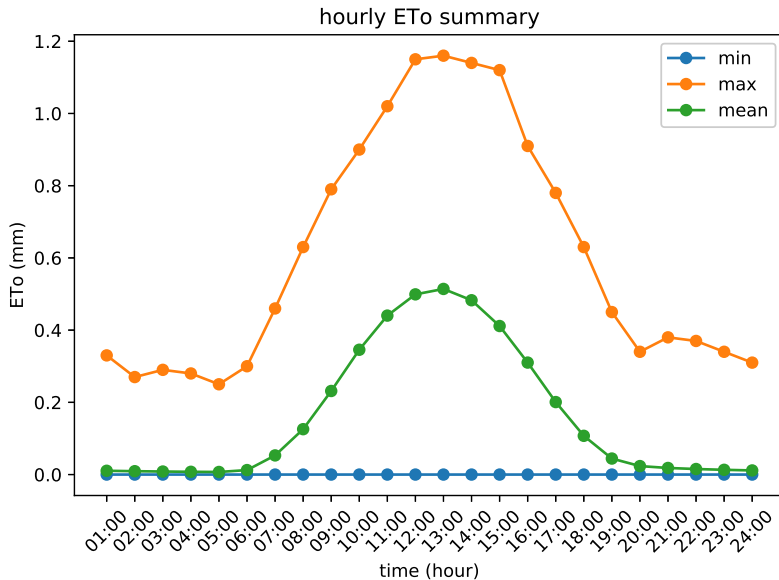
Stations of Interest

- 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)

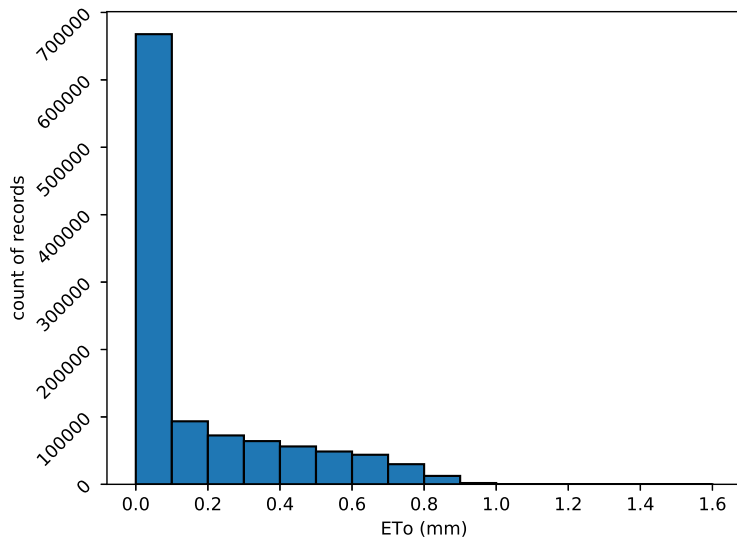
Mean Hourly ET Values of Stations of Interest



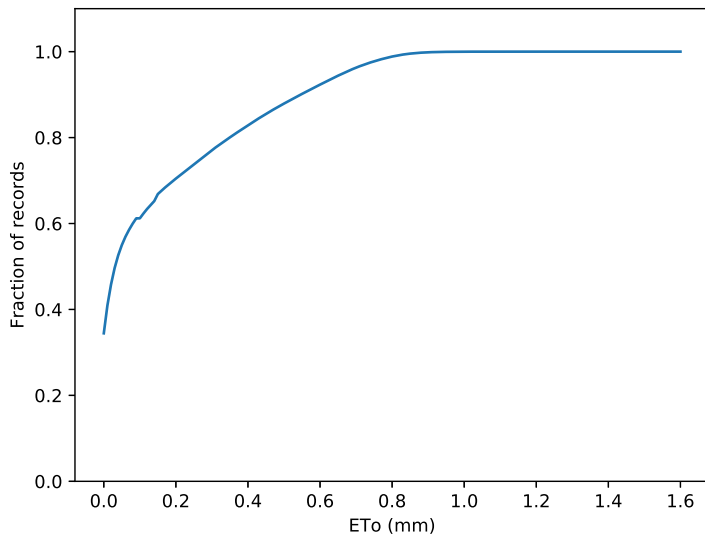
Min/Mean/Max Hourly ET Values



Histogram of ET Values



Empirical CDF 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?

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(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

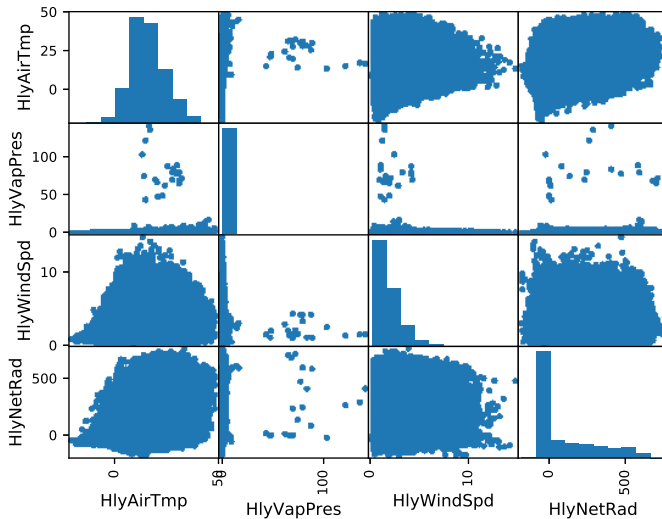
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Scatterplot Matrix of Features of Interest



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

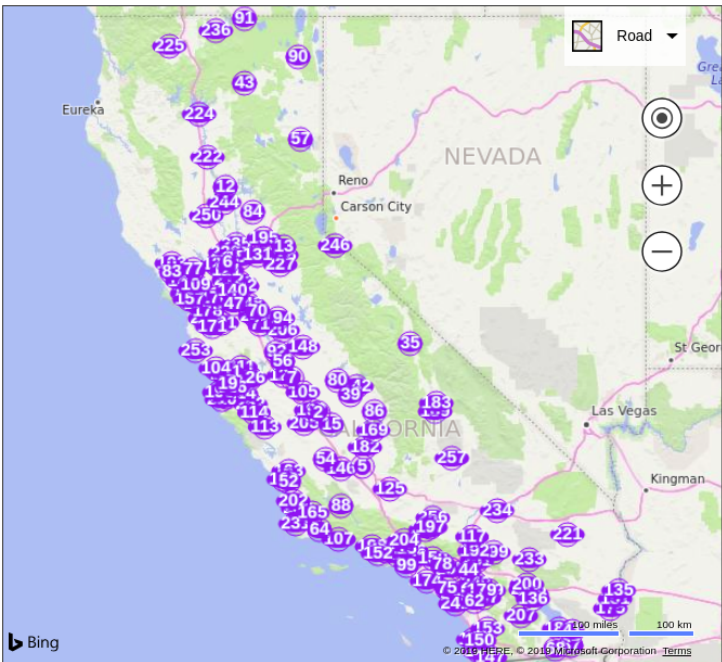
Given the ET value of k nearest stations of a place, can we estimate ET?

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

Nearest Neighbor Analysis

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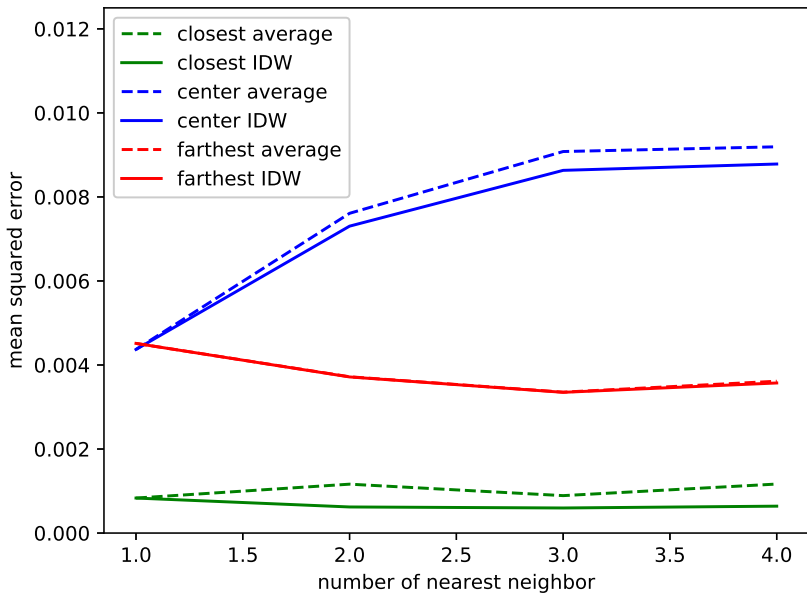


Stations of Interest

- 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

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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 |

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 radius R such that k stations within that radius gives best overall estimates?

Future Work...

A Different Approach to Nearest Neighbor

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Future Work...

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DEMO

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Questions?