
Smoke, Clouds, and Clear Skies

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Background:

Location

- SB experiences seasonal fires, cloudy days, and fog
- Coal Oil Point radiometer has been able to measure data during two of the largest fires in the SB area: Thomas & Jesusita

Clouds

- Cloudiest days begin in early November and last through late April
- Lots of rain during this times

Thomas Fire

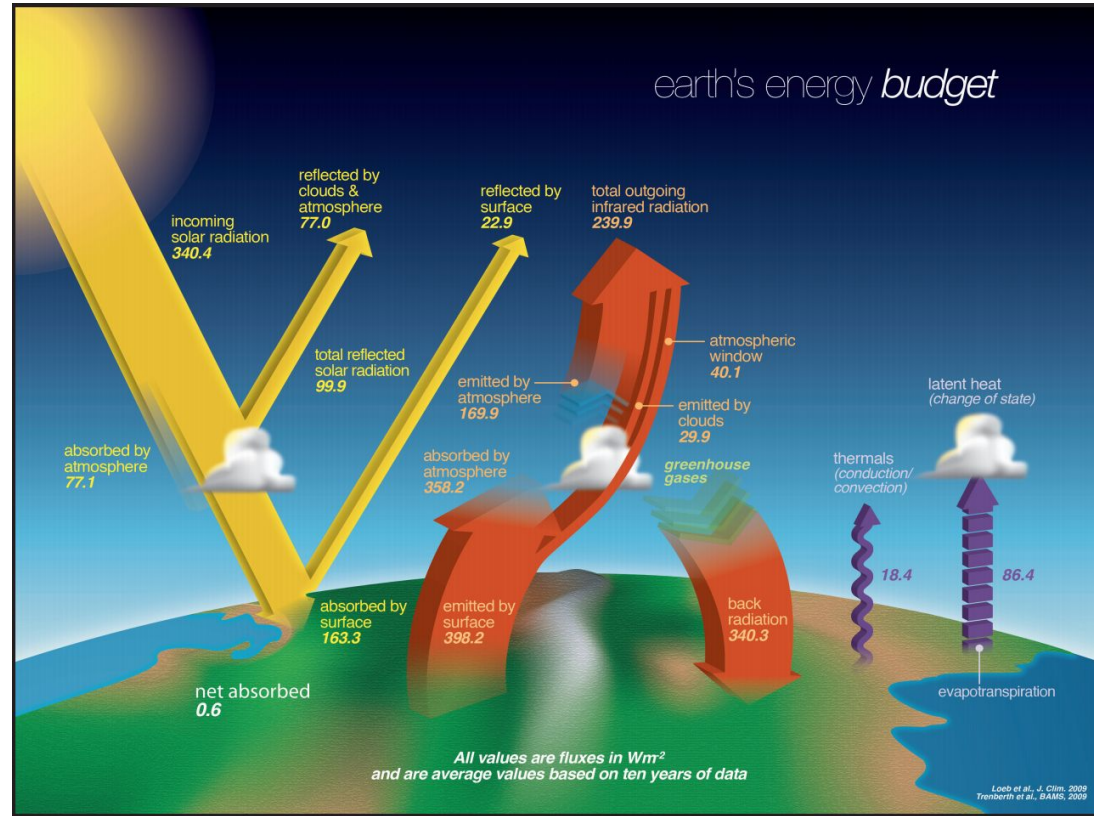
- December 2017 through March 2018
 - Started near Santa Paula
 - Active wildfire only in December
- Large rainstorm followed the fire and caused a debris flow

Jesusita Fire

- May 5 through May 18, 2009
 - Started near Mission Canyon
 - Much closer than Thomas Fire
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Theory:

- Net radiation budget = incoming - outgoing
- Clouds block shortwave radiation and re-emit longwave radiation
 - Act as blackbodies
- Smoke changes the radiation budget → scattering and absorbing effects
 - Re-emits longwave radiation
 - Similar effect to greenhouse gas



Research Question:

Can longwave insolation determine
if the skies are cloudy, smokey, or
clear?

By using monthly data from Coal Oil Point we will be able to distinguish between cloudy, smokey, and clear skies.

Cloudy and smokey days will have more longwave insolation, while clear days will have less longwave insolation.

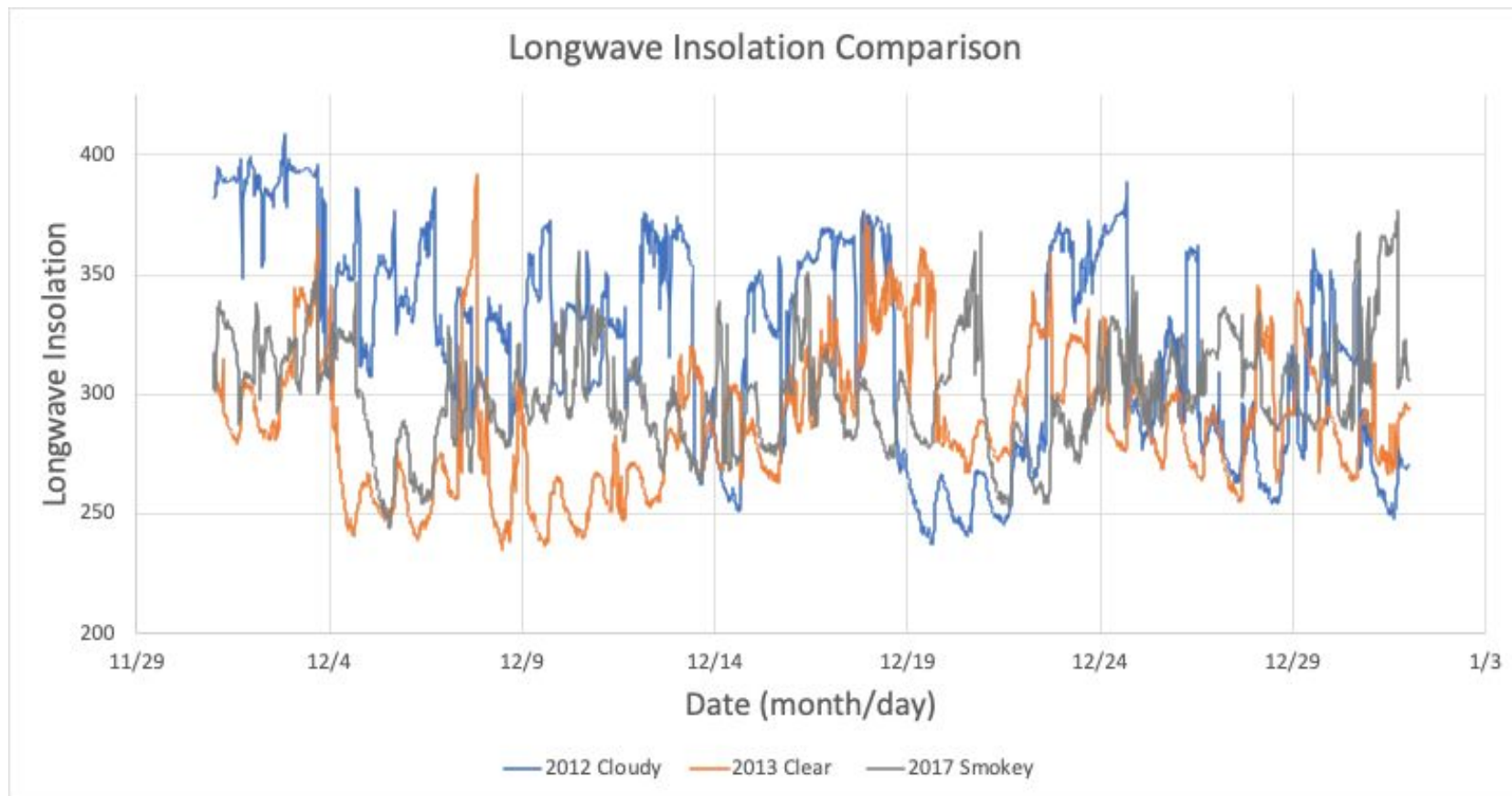
Experiment 1:

Data comparison of
clear, cloudy, and
smokey months

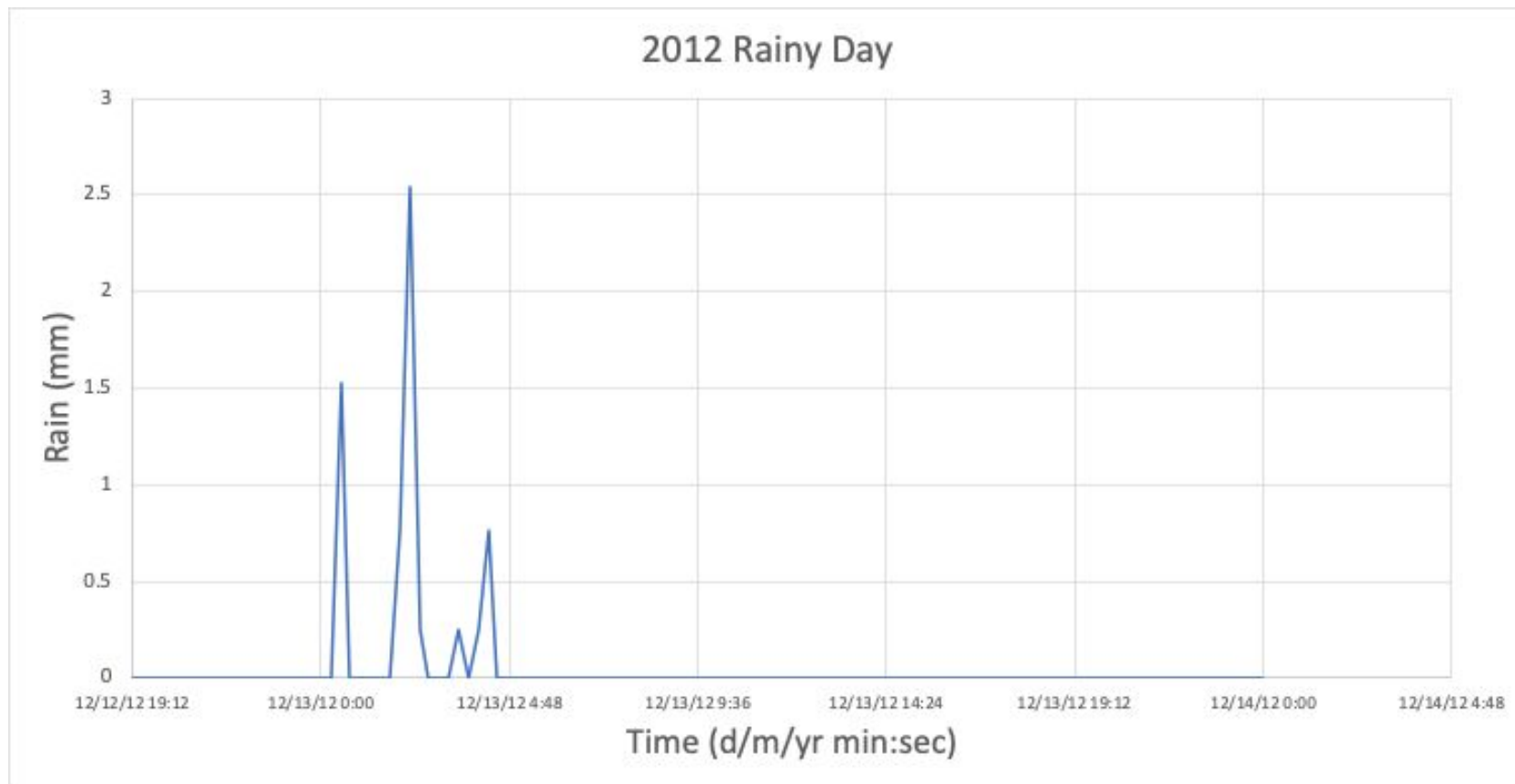
Experiment Design:

- Comparing longwave/shortwave insolation time series graphs from the same month throughout three years
 - **1st year:** clear skies
 - **2nd year:** cloudy
 - **3rd year:** smokey
- Using two different comparison months and fires
 - **Thomas Fire:** December
 - **Jesusita Fire:** May
- Comparing data to determine if the longwave incoming radiation can show the difference between clouds, smoke, and clear skies

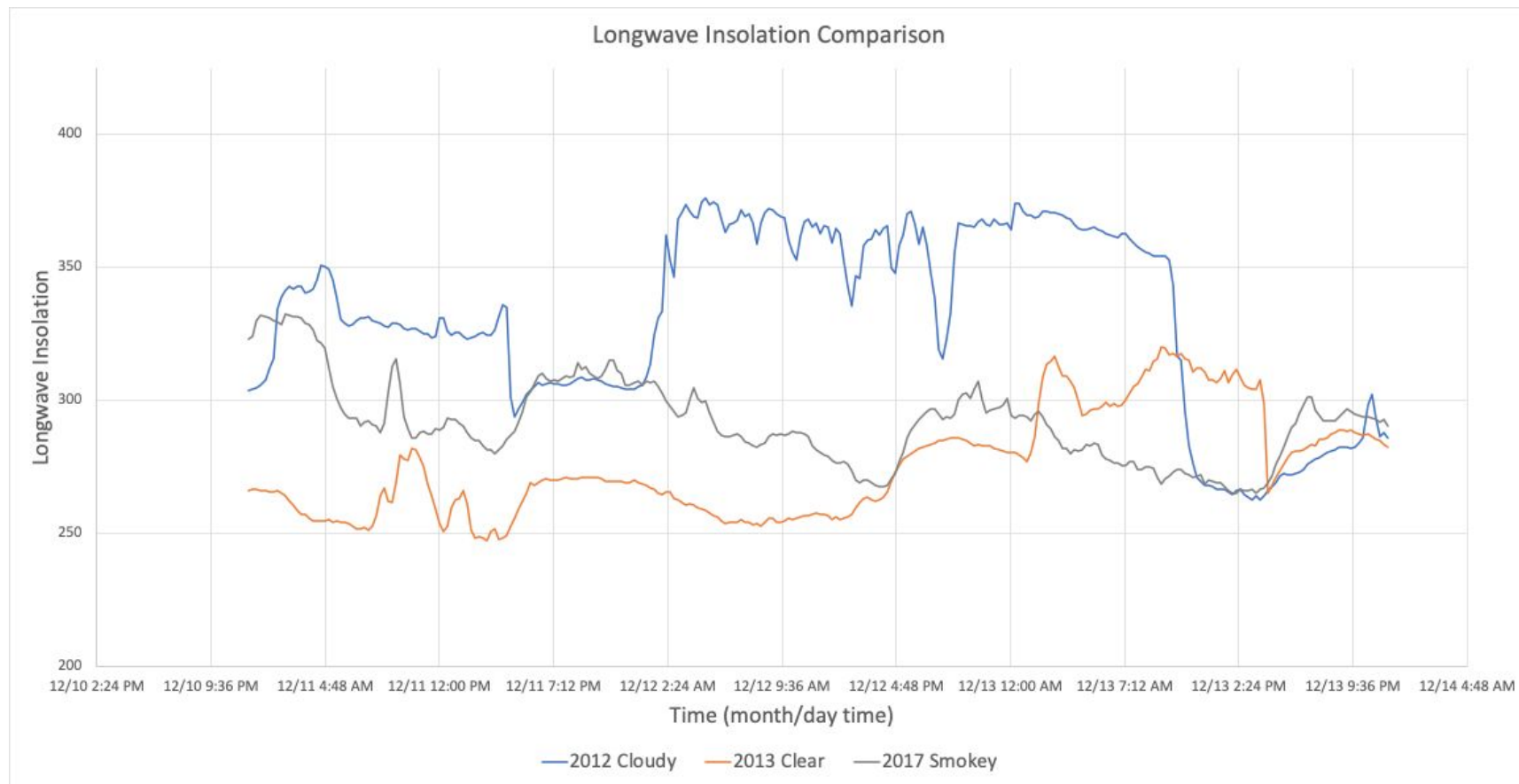
Results: December



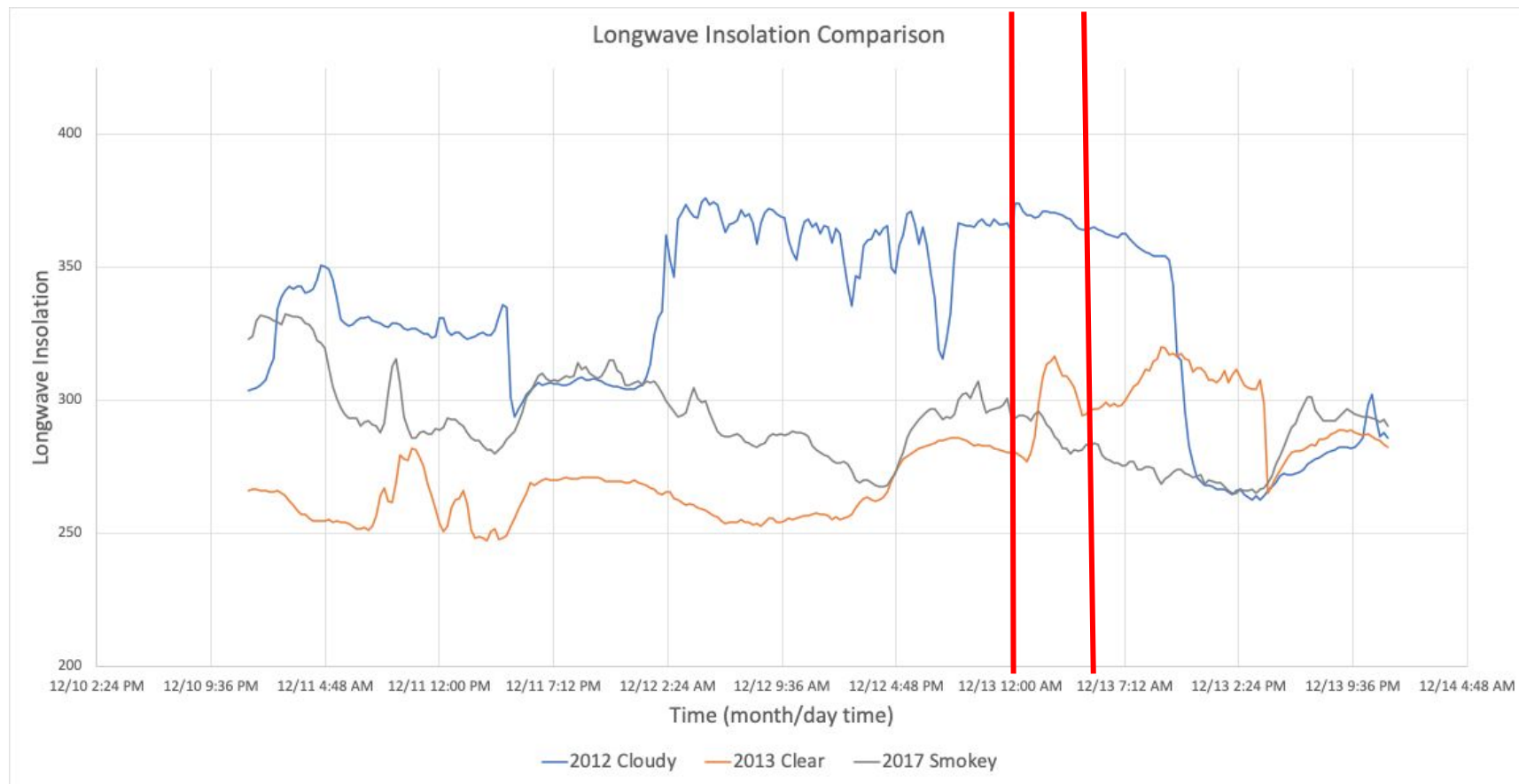
Results: December



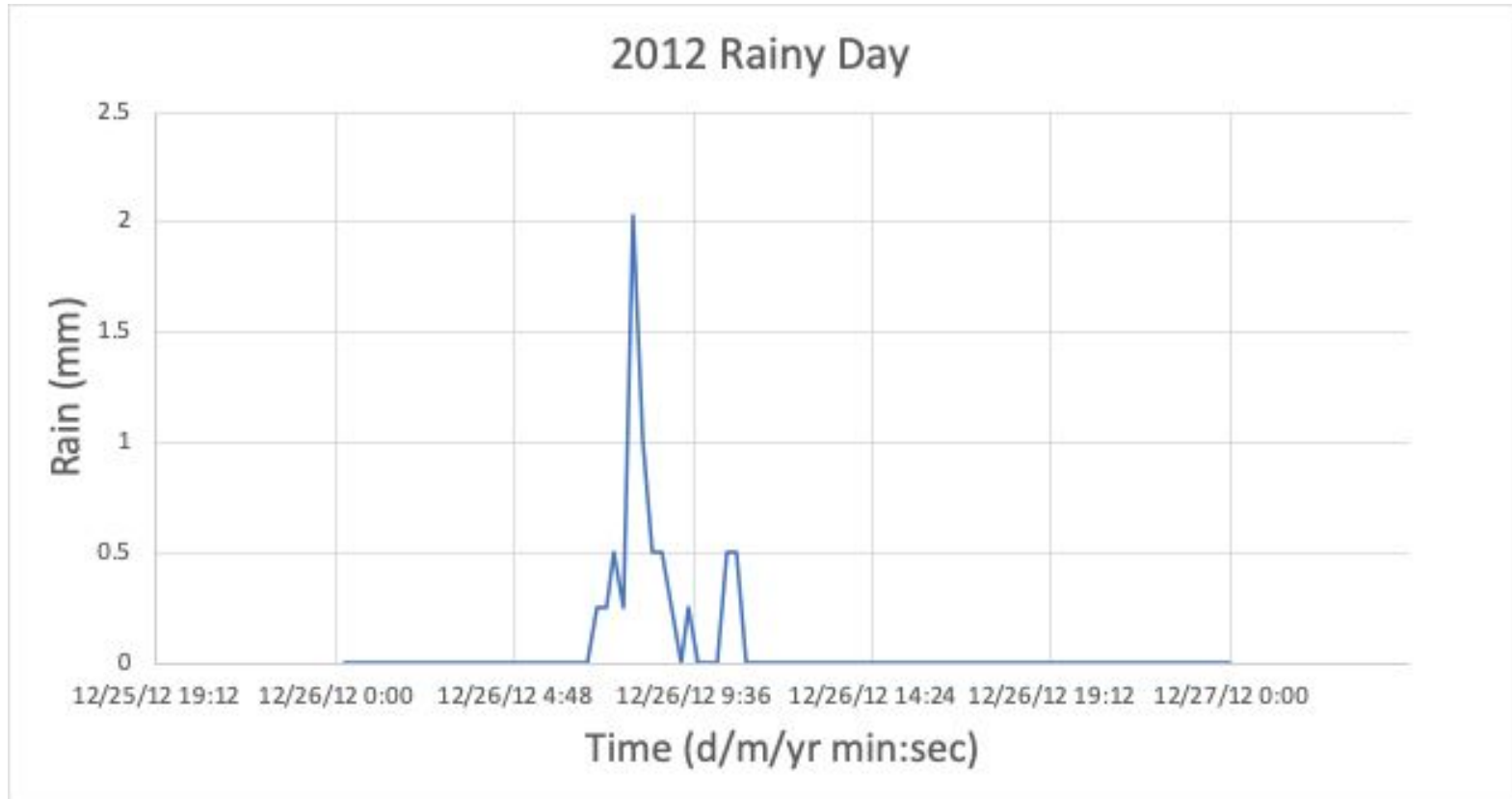
Results: December



Results: December

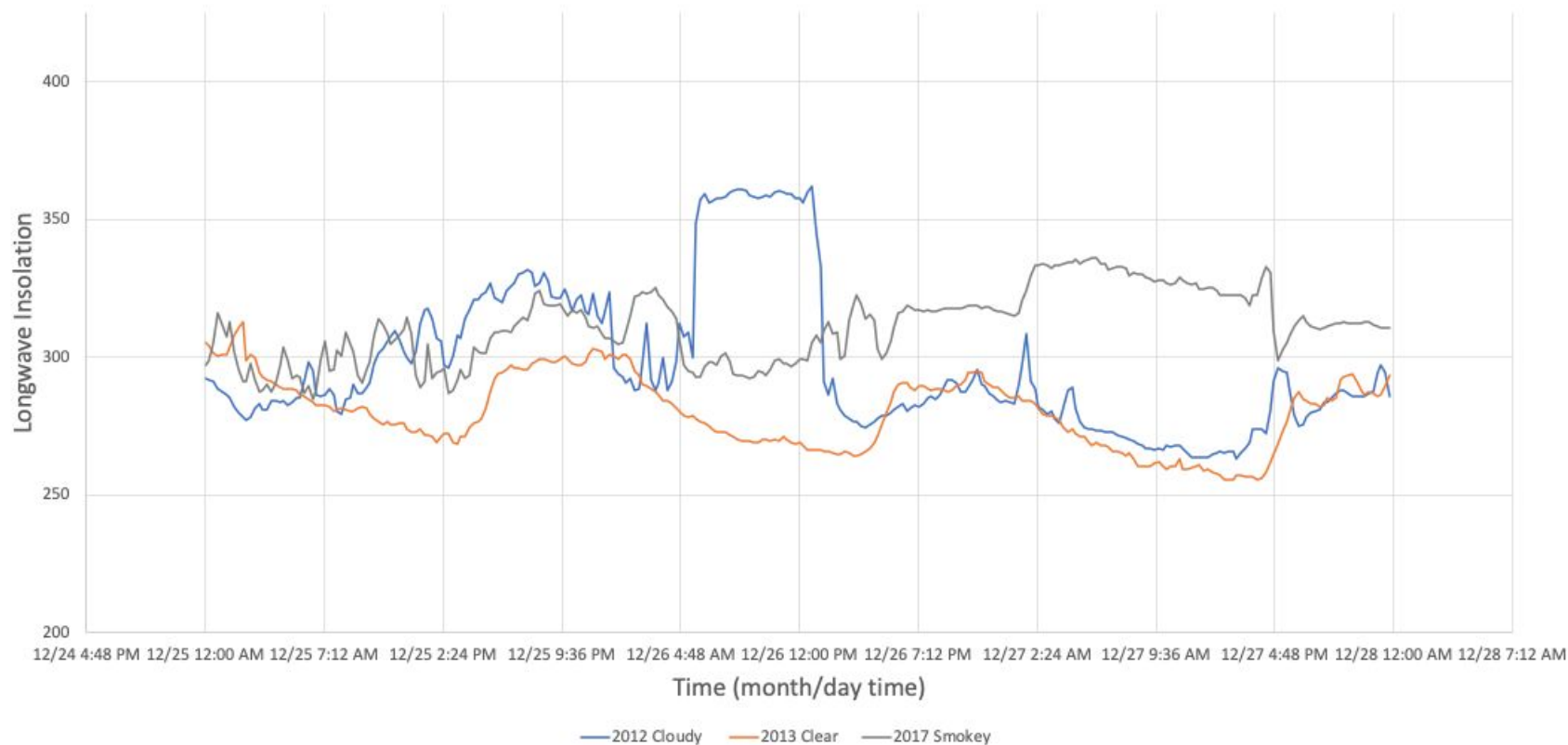


Results: December

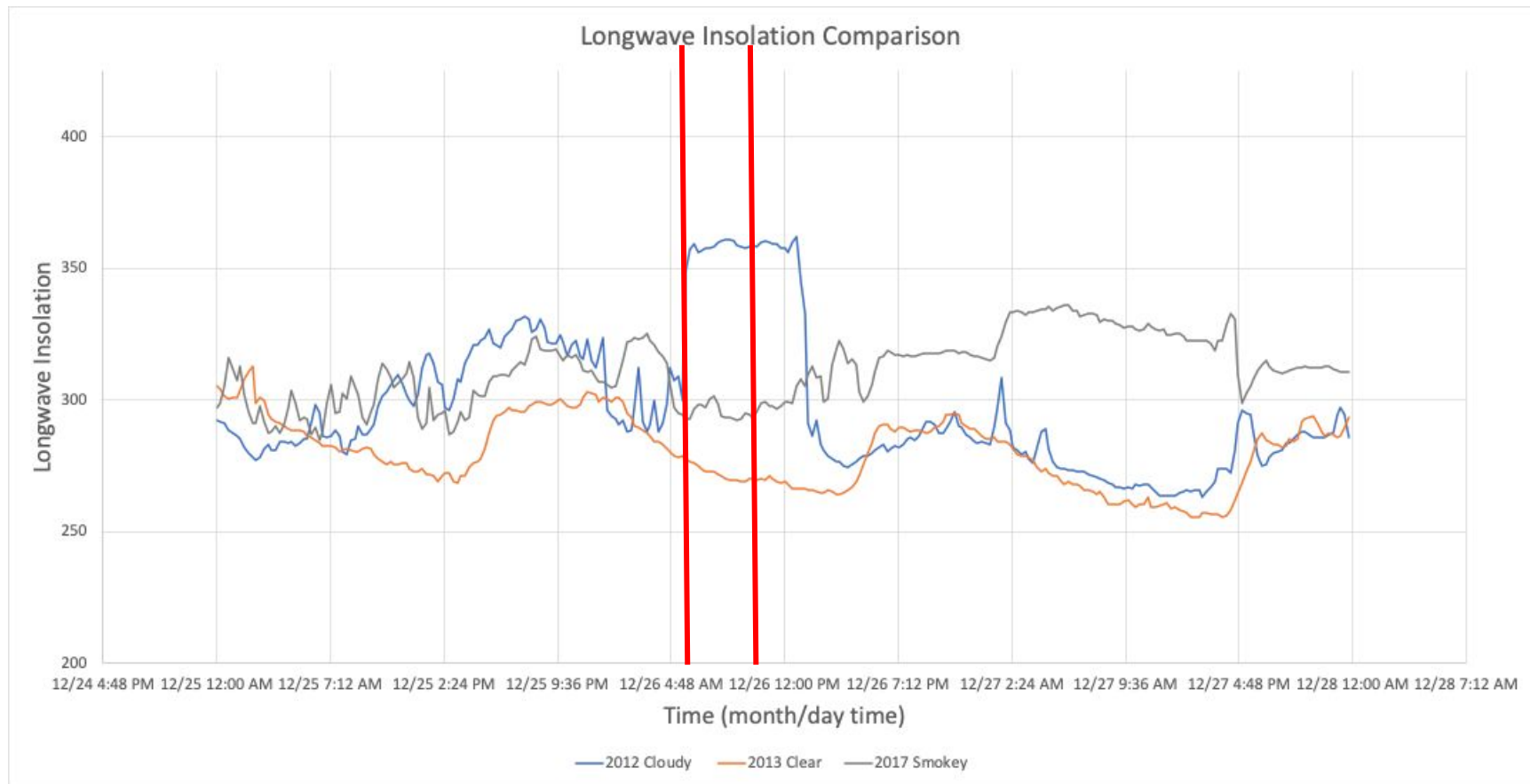


Results: December

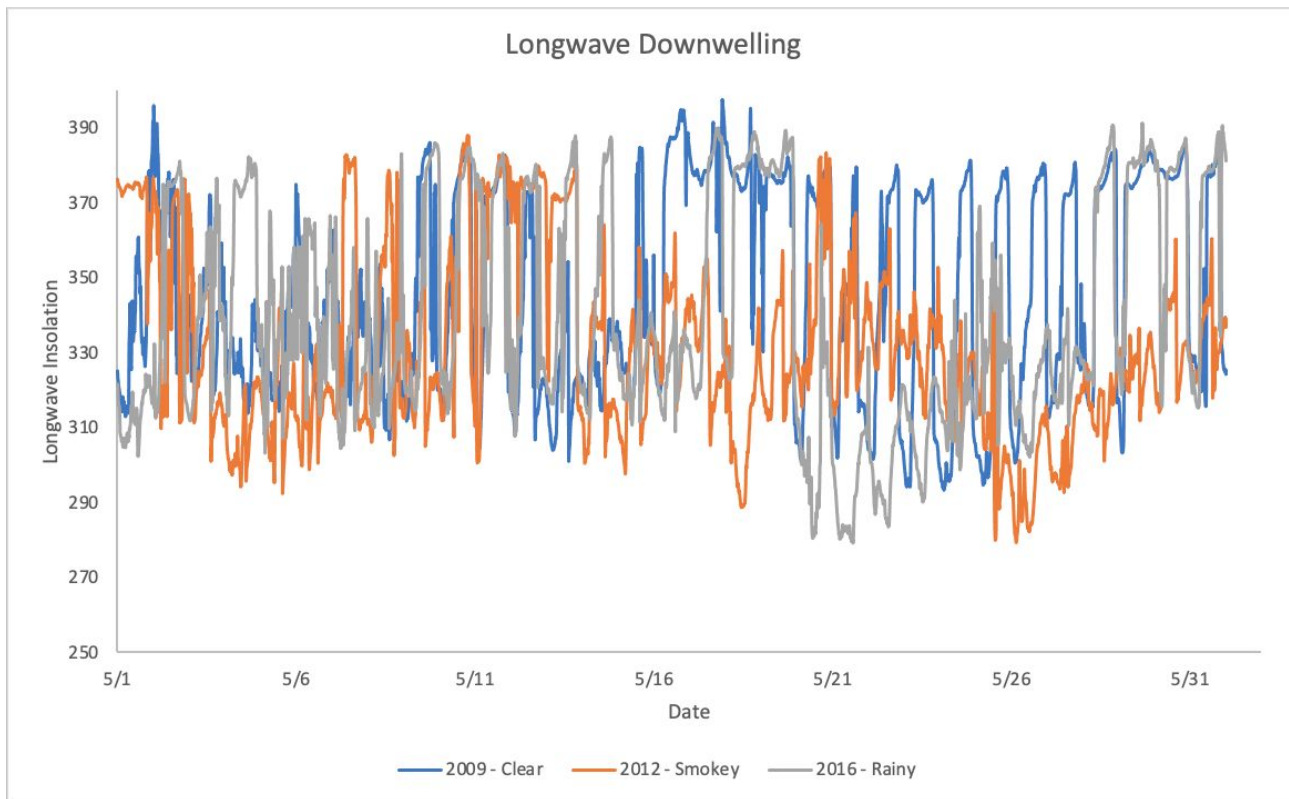
Longwave Insolation Comparison



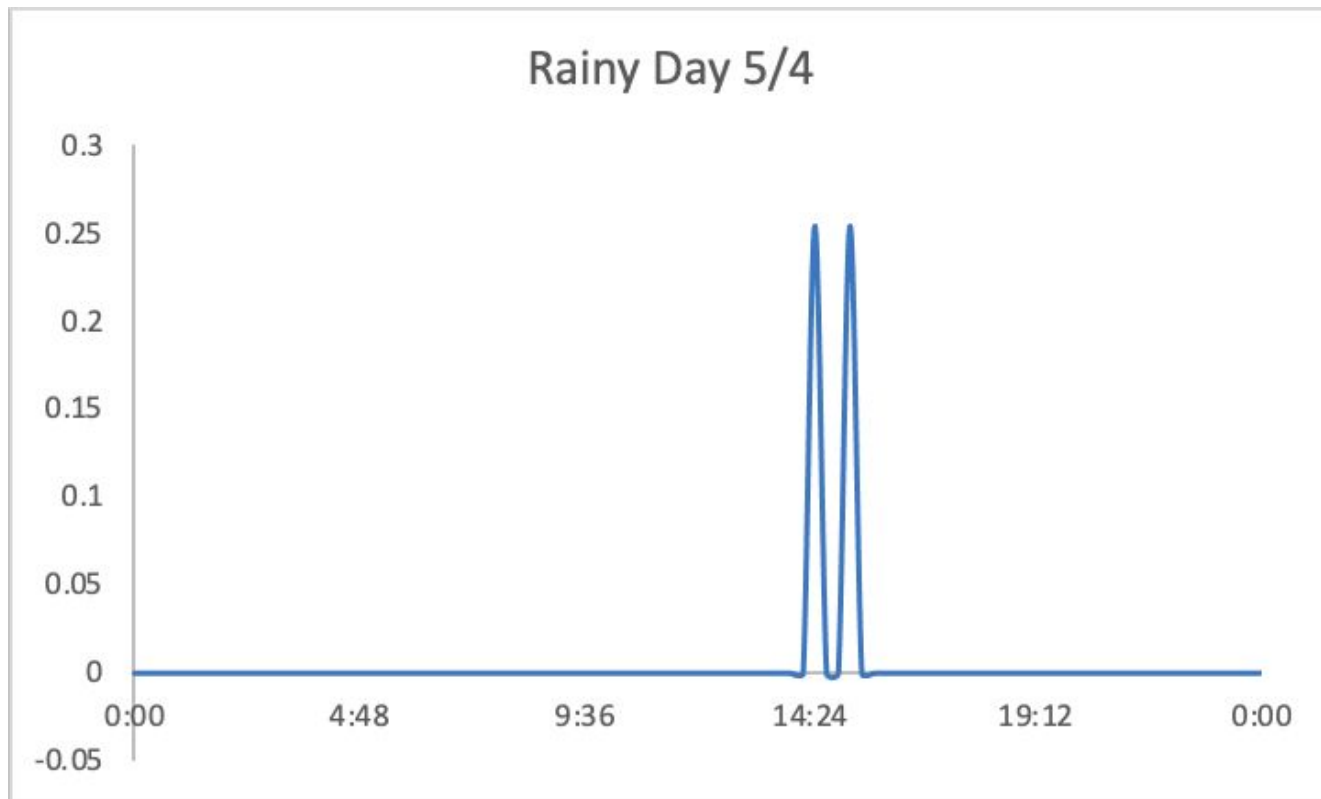
Results: December



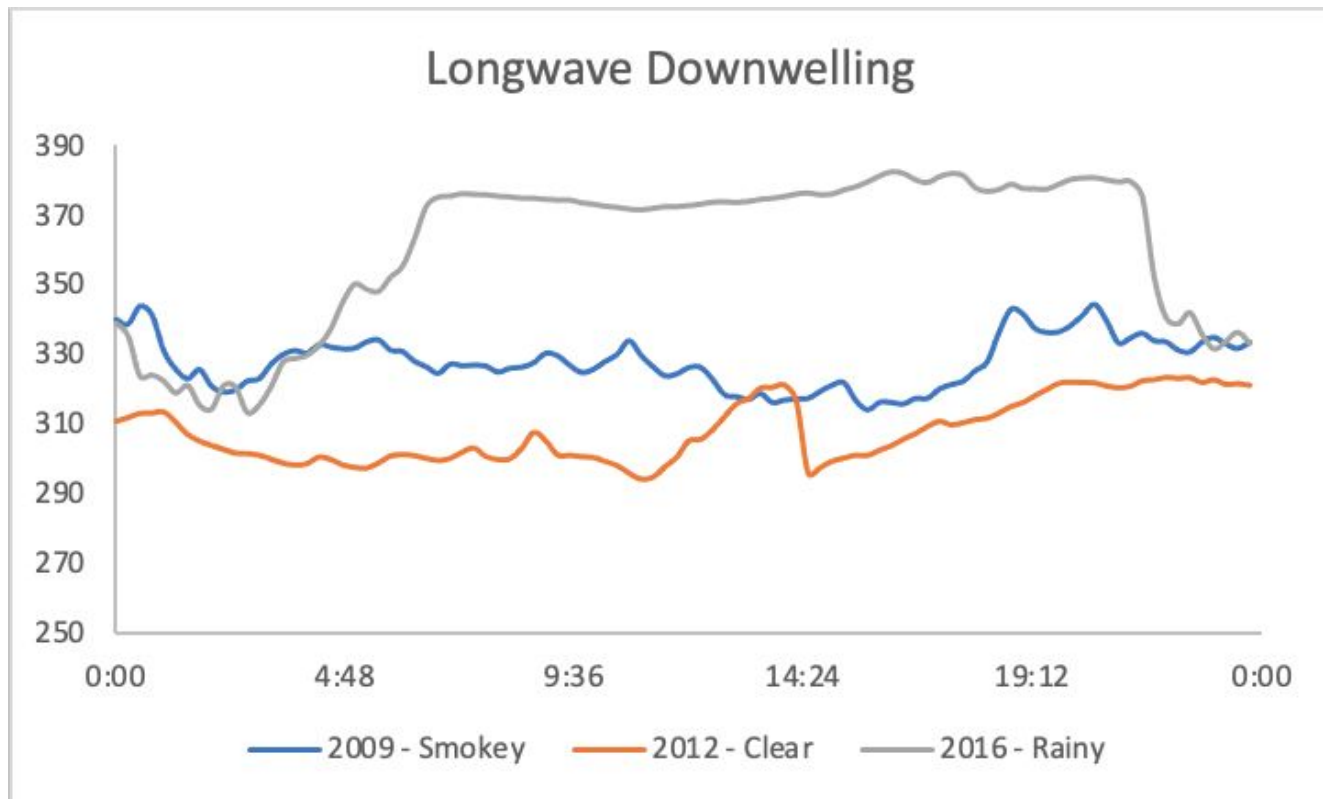
Results: May



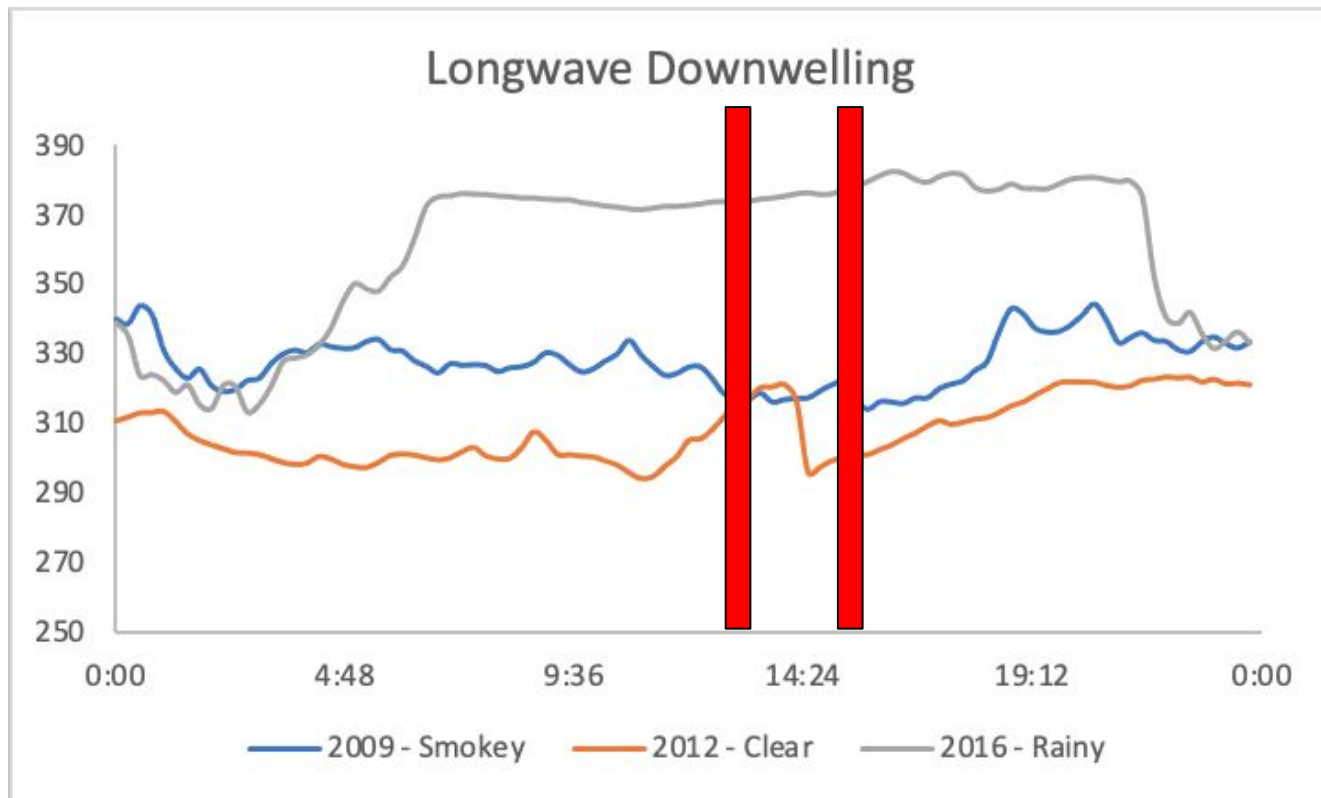
Results: May



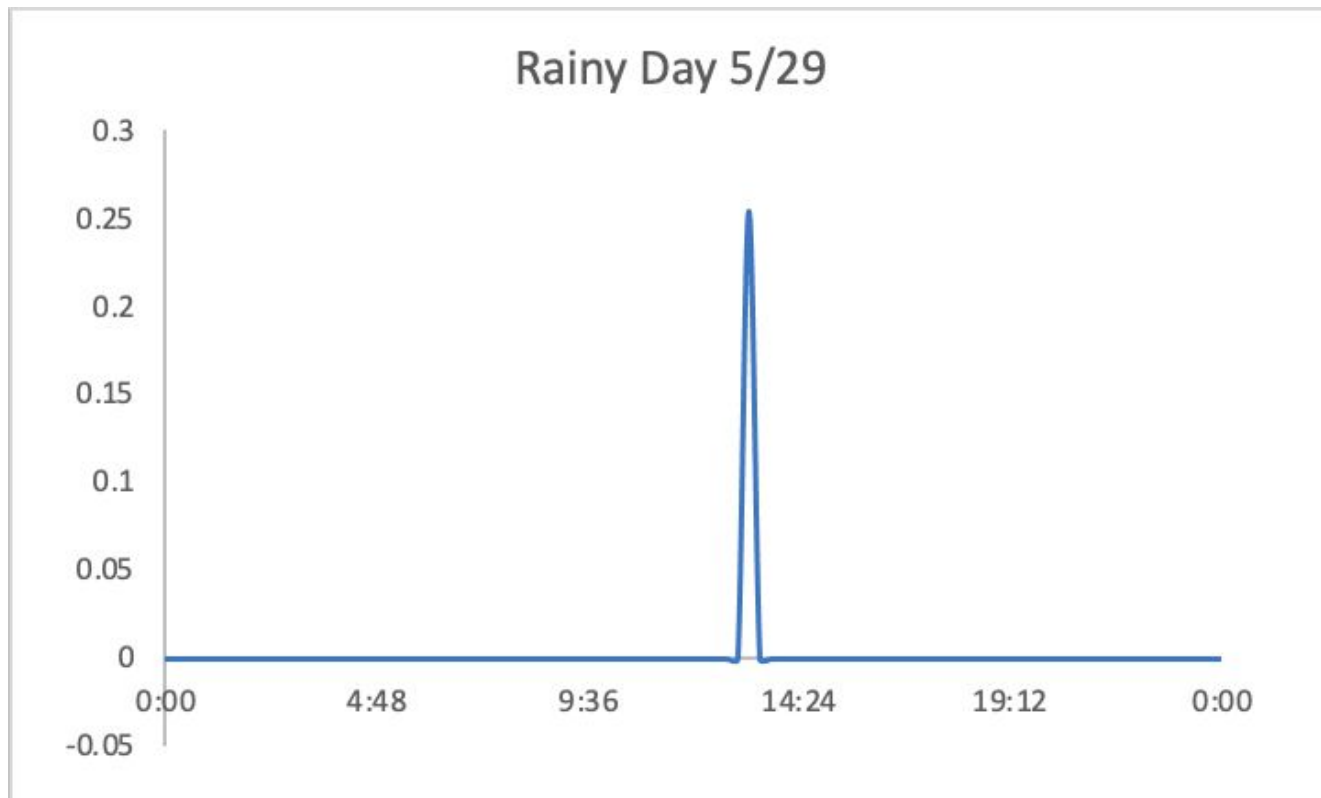
Results: May



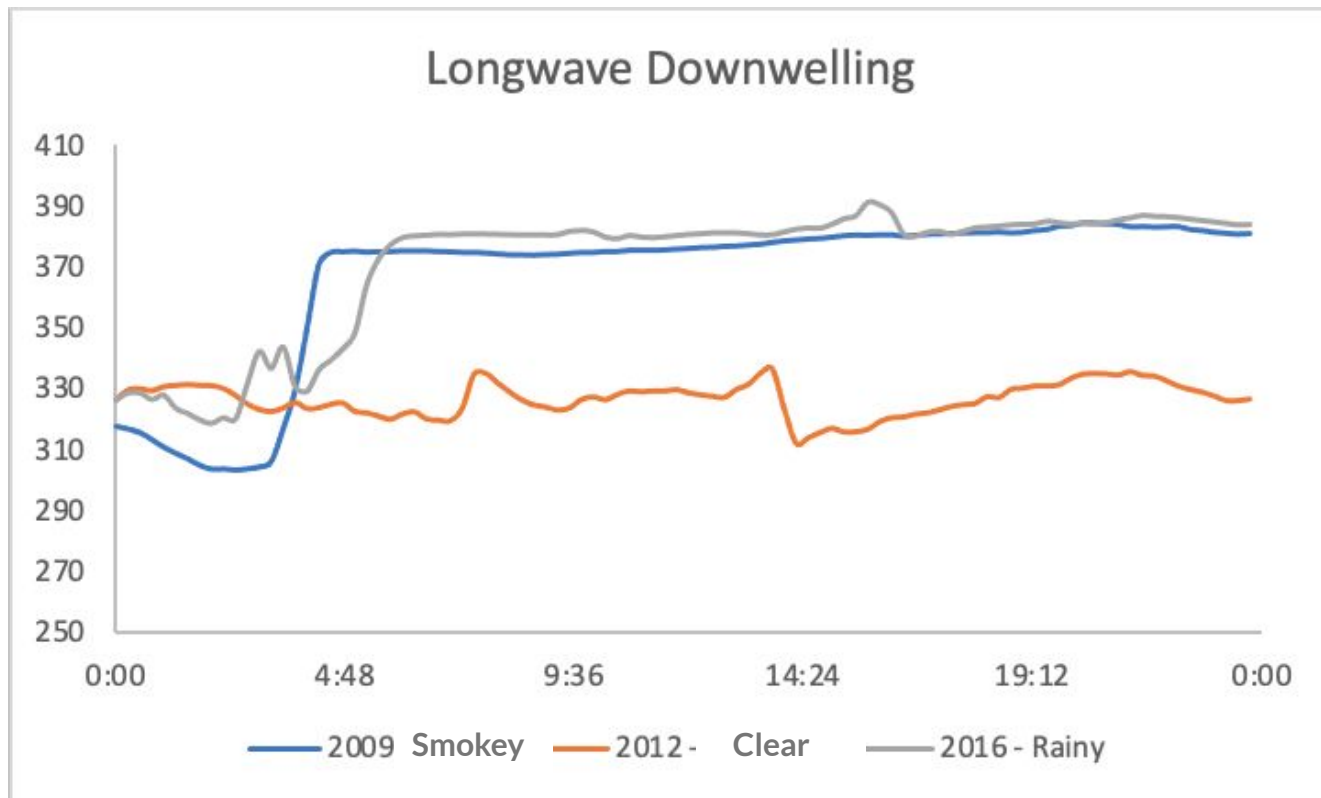
Results: May



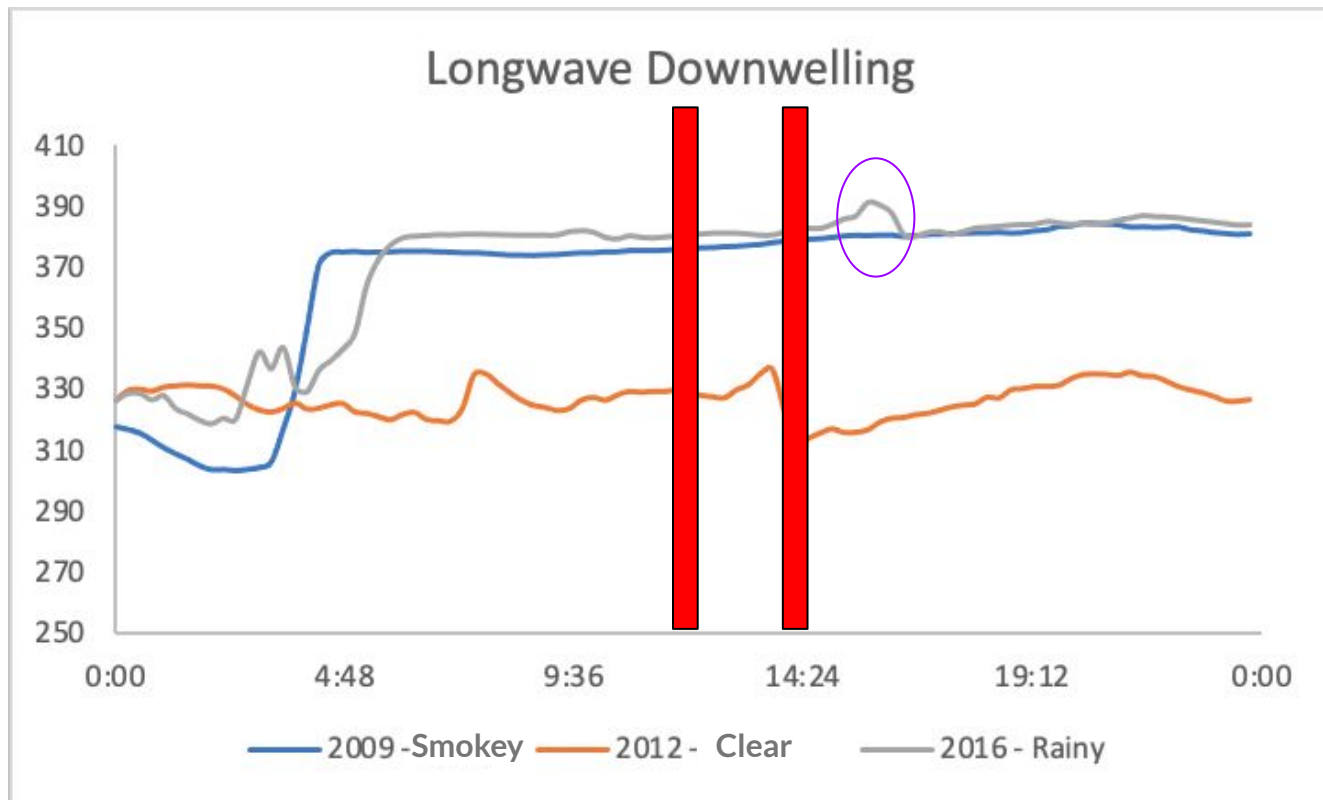
Results: May



Results: May



Results: May



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Experiment 2:

Statistical Analysis of
Smoke, Clear Sky, and
Clouds

Experimental Design

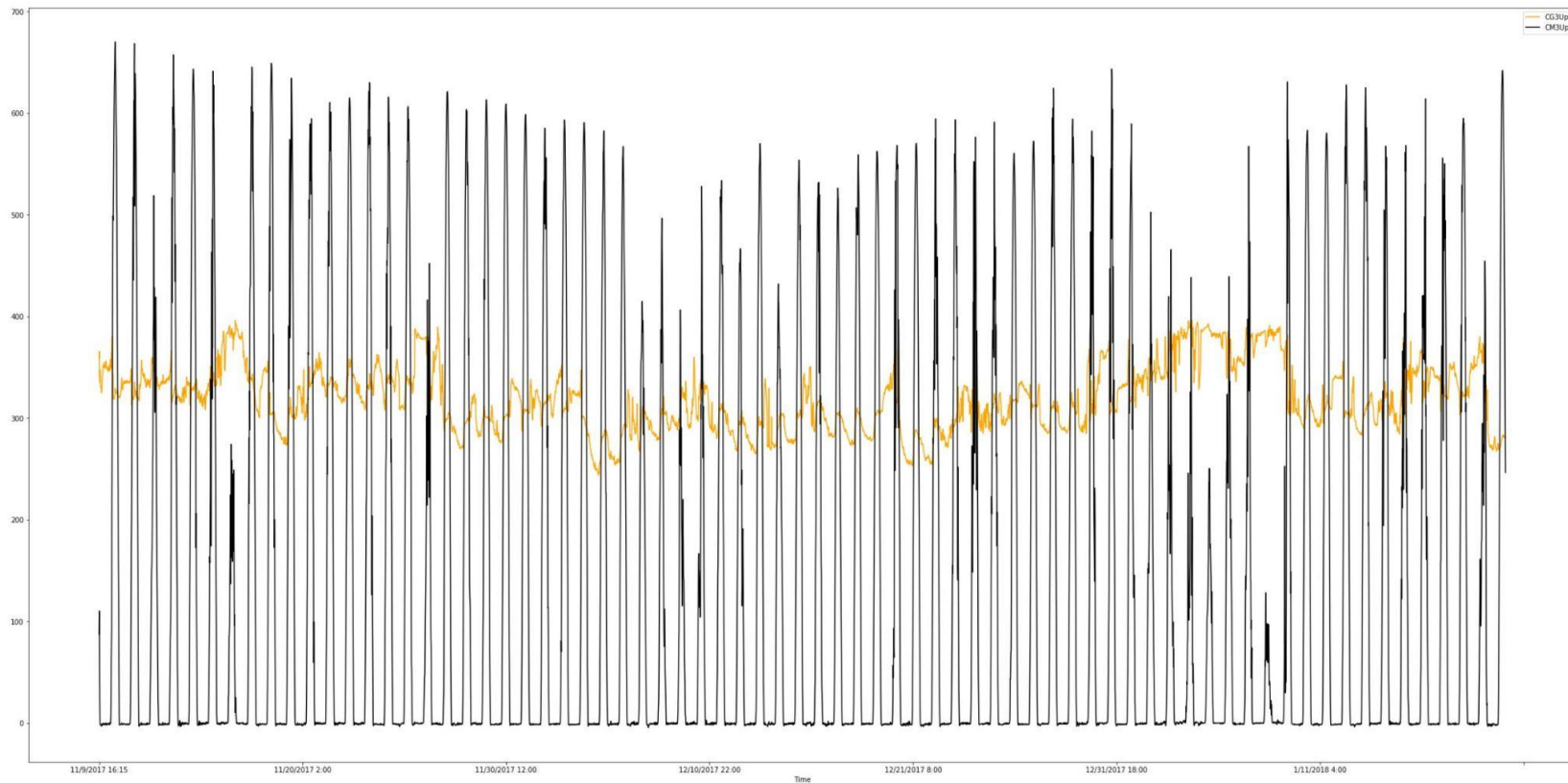
- Dates: Nov 10th, 2017- Jan 20th, 2018
 - Datasets Used:
 - COPR
 - Longwave and Shortwave Downwelling
 - Air Pollution Control District ([APCD](#)) Santa Barbara County
 - Historical AQI Data (entered as smokey if above 50)
 - Historical Weather Data for Goleta
 - [Timeanddate.com](#)
 - Statistical Methods
 - Toeplitz Inverse Covariance-Based Clustering of ([TICC](#)) of Multivariate Time Series Data
 - Logistic Regression Classification
 - KNN Classification
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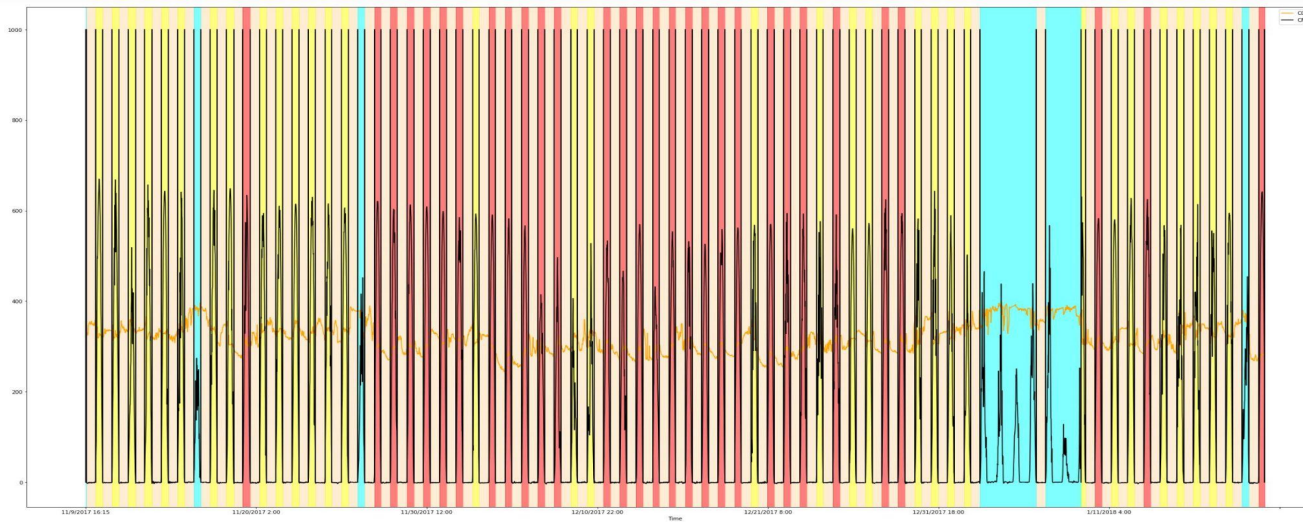
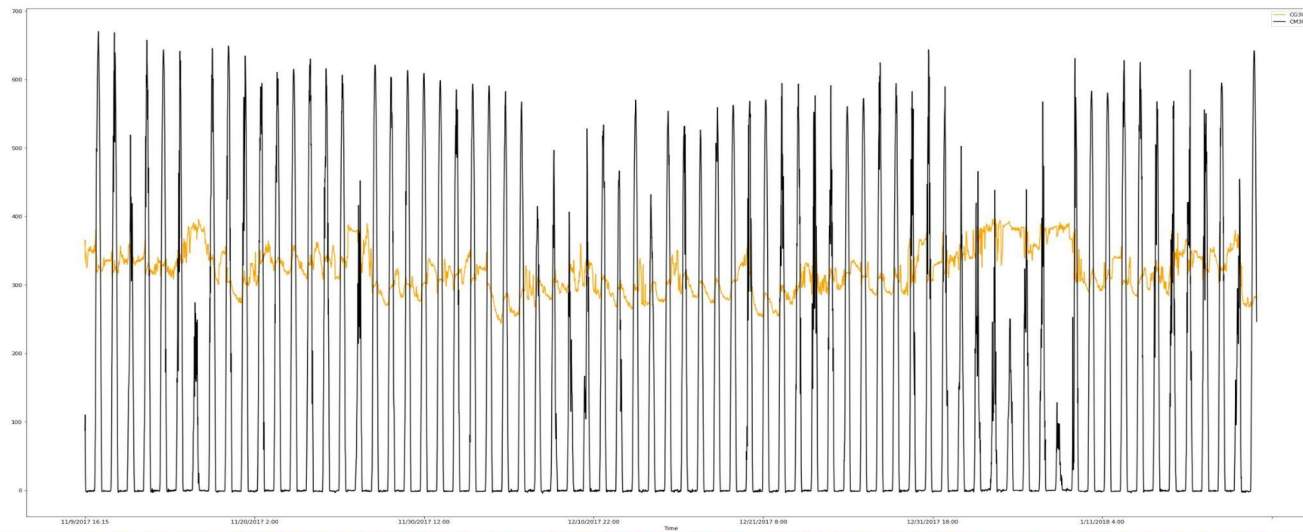
TICC Method

- Takes into account temporal aspect of data
- Simultaneously segment and cluster the time series
- Unsupervised clustering method
- Use cases- clustering a stream of time series data
 - Ie. Driving (knowing when turning), Smart Watch Sensors

$$\underset{\Theta \in \mathcal{T}, \mathbf{P}}{\operatorname{argmin}} \sum_{i=1}^K \left[\overbrace{\|\lambda \circ \Theta_i\|_1}^{\text{sparsity}} + \sum_{X_t \in P_i} \left(\overbrace{-\ell \ell(X_t, \Theta_i)}^{\text{log likelihood}} + \overbrace{\beta \mathbb{1}\{X_{t-1} \notin P_i\}}^{\text{temporal consistency}} \right) \right] \quad (1)$$

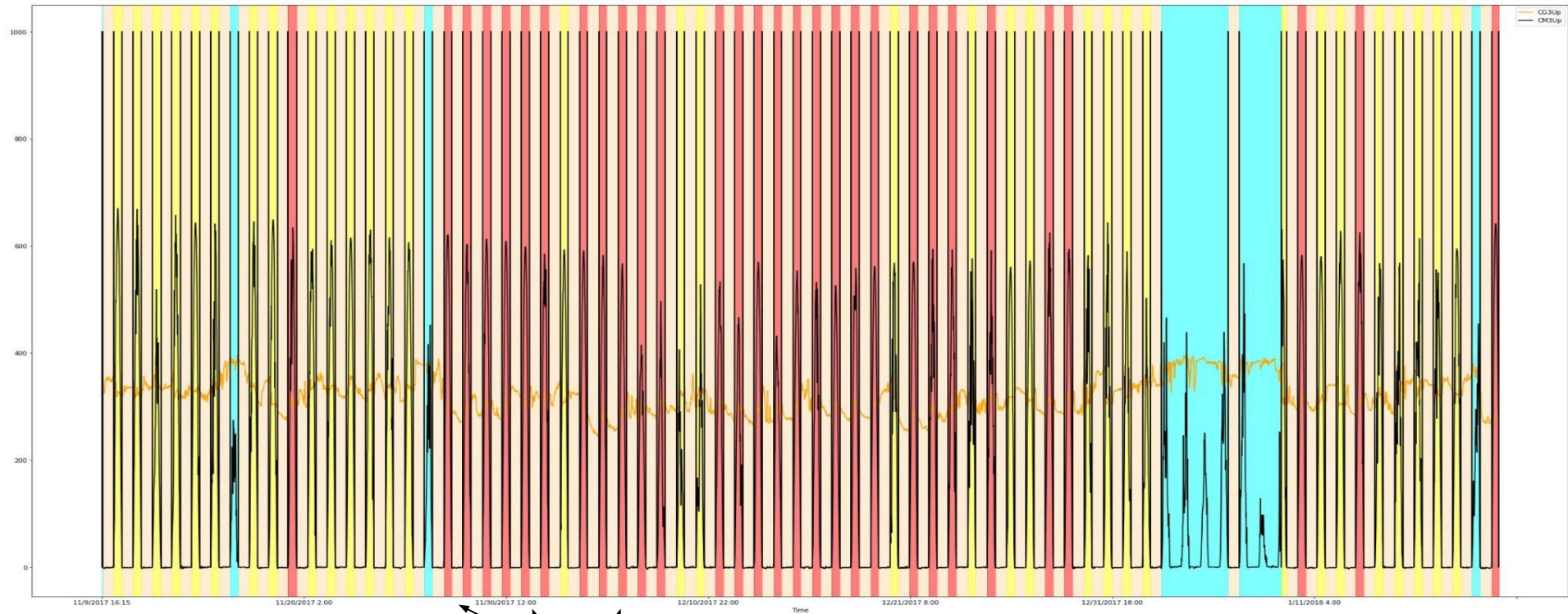
Exploratory Analysis





- Cloud - Cyan
- Fire- Red
- Sunny- Yellow
- Noise- Tan

Rain



Smoke

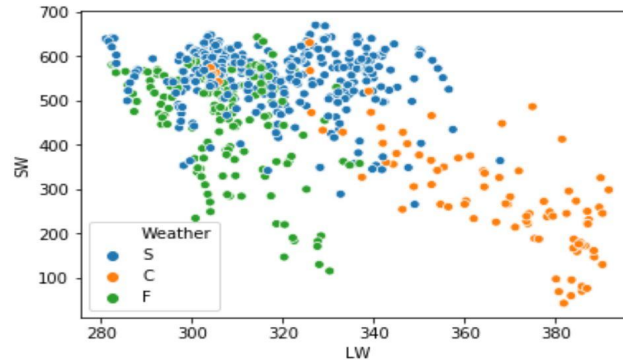


TICC Results

- Clustered the data!
 - Clearly divided into groups of sunny, cloudy, smoky
 - Metric- Sensitivity
 - Clouds: 81%
 - Smoke: 71%
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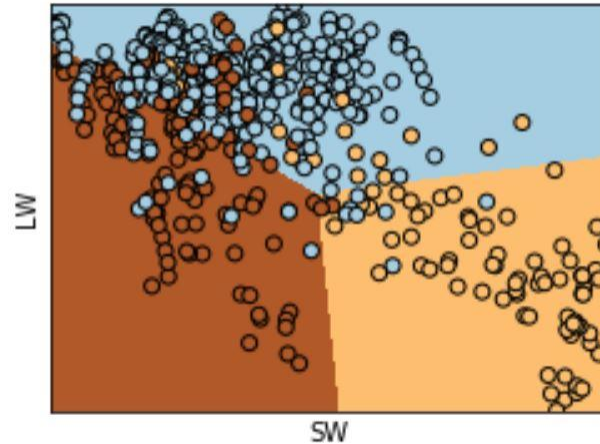
Exploratory Analysis- Supervised Methods

- Taking out temporal aspect, we minimize variability by filtering for readings between 12pm-1pm
- Scraped Historic AQI and Weather data to classify into 3 groups: sunny (S), cloudy(C), smokey (F)



Logistic Regression Classification

- Multiclass Logistic Regression Classification
- Accuracy: 81%



K Nearest Neighbors

- A distance based clustering method
- Split training vs testing data 70:30
- Fitting a $k=3$
 - Accuracy: 75.69%

Discussion:

Experiment 1:

- December
 - Chose two rainy days to compare
 - Limitations
 - Limited rainy time periods
- May
 - There were limitations to the data; hard to find rainy days
 - Clear difference on first day
 - Little to no difference on second day

Experiment 2:

- TICC
 - Chose Nov 10- Jan 20
 - Limitations
 - Hard to find misclassification error
 - Data scraped by hand
 - Small Sample
 - LogReg
 - Limitations
 - Did not use polynomial
 - Based on accuracy of data scraping
 - Would look deeper into relationships with more time
 - KNN
 - Limitations
 - Based on accuracy of data scraping
 - Didn't optimize by iterating over many k's
 - No graph
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Conclusion:

By combining the results of the two experiments, we are able to conclude that:

- The data comparison experiment (1) is able to determine the difference between cloudy and clear days, but not differentiate smokey days
 - Cloudy days have consistently the highest levels of longwave insolation
 - Experiment (2) with TICC shows that in a temporal lens we can differentiate between cloudy, sunny, and smoky days; moreover with our other methods we saw a the effect smoke and clouds had on SW and LW radiation
 - Low SW and High LW: Clouds
 - Low SW and Low LW: Smoke
 - High SW and High LW: Sunny
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References:

Roberts, Dar. IDEAS,
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Accessed 25 April 2021.

“Just Five Questions: Aerosols.” NASA,
<https://climate.nasa.gov/news/215/just-5-questions-aerosols/#:~:text=It%20turns%20out%20that%20most,greenhouse%20gases%20in%20the%20atmosphere.>
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