



# Carnegie Mellon University

Study of Cloud Microphysics using Data  
Aggregation & tuning of standard  
atmospheric parametrizations

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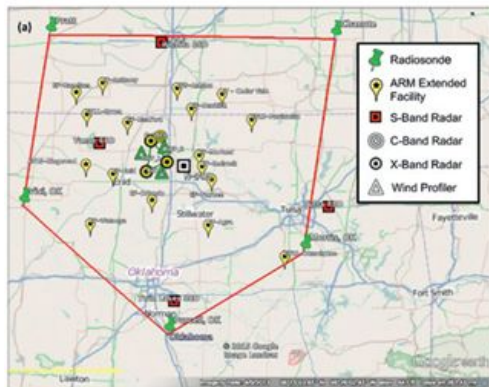
12.14.2020

# Motivation

- Minute changes in extent or location of clouds leads to significant changes in atmosphere
- Uncertainties in the numerical weather models are required to be incorporated into these models for accurate estimations
- Potential reasons for uncertainties
  - Gaps in empirical or theoretical description of cloud processes
  - Inherent variability in spatial-temporal structures in clouds
  - High nonlinearity and complexity of cloud processes
- Practical approach to solve this is to depend on parameterizations which only on bulk chemical properties of aerosols and cloud particles

# Objectives

- Test the efficacy of standard parameterizations in literature for CDNC, LWC and LWP
- Develop an automated script to detect cloud base in convective clouds and a spatial-temporal clustering methodology to output time series data
- Analyze the source of uncertainties in standard parameterizations



Data source: ARM's SGP (Southern Great Plains) observatory  
Campaign: MC3E Field Campaign

# Parameterizations under consideration

$$N_d = \frac{2e^{3\sigma_x^2} \rho^2 \sigma^3}{9\pi q^2}$$

Yang parameterization: LWC, Extinction coefficient

$$N_d = C_3^{\frac{2k}{2+k}} N_0^{\frac{2}{2+k}} w^{\frac{3k}{4+2k}}$$

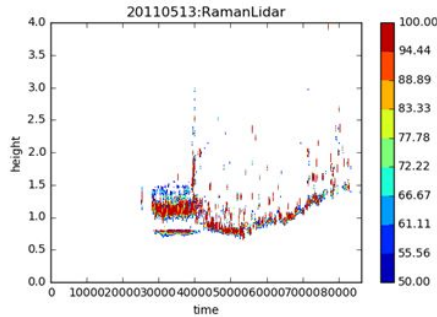
Pinsky parameterization: Temp, CCN, Updraft velocity

$$N_d = \sqrt{\frac{8\alpha^3 \langle r^6 \rangle}{Z_* \pi^3 \langle r^2 \rangle^3}} \left( \frac{K}{K_w} \right)^2$$

Lidar parameterization: Backscatter coefficient, Reflectivity factor, Droplet radius distribution

# Task I- Detection of Cloudbase in liquid clouds

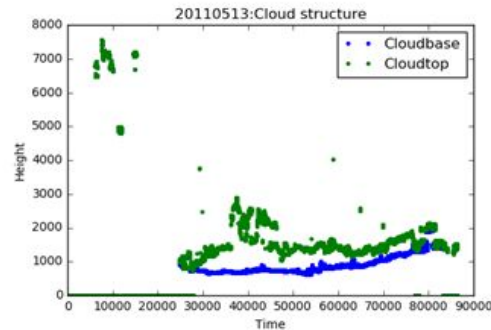
Input



Searching Algorithm

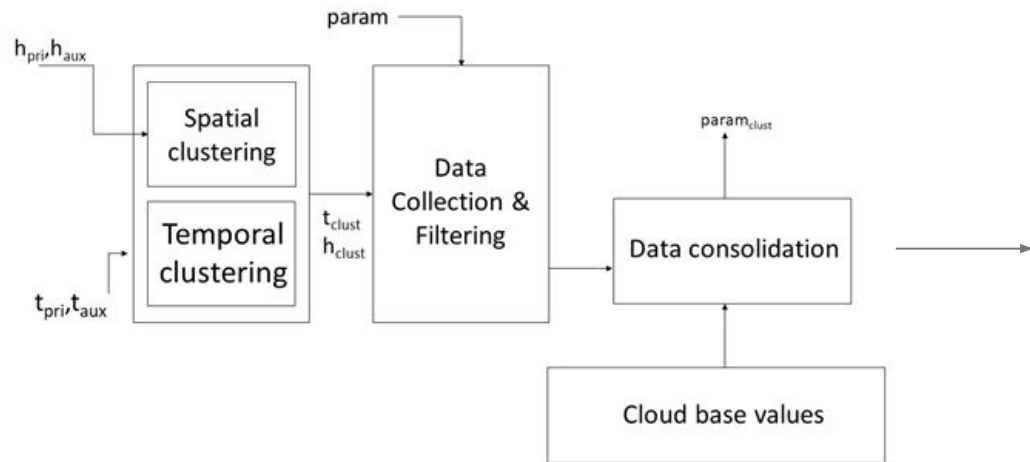
```
t = [t0, t1, t2, ..., tN]; h = [h0, h1, h2, ..., hN], e(ti, hi): Extinction at a point  
for ti in t:  
    for hi in h:  
        if eminimum ≤ e(ti, hi) ≤ emaximum :  
            if 1000 ≤ hi :  
                if e(hi-1, ti) ≤ e(hi, ti) ≤ e(hi+1, ti) :  
                    break
```

Output



1D Time Series of the  
Cloud Base and Cloud  
Top

# Task II: Automated Code for Spatial-Temporal Clustering



```

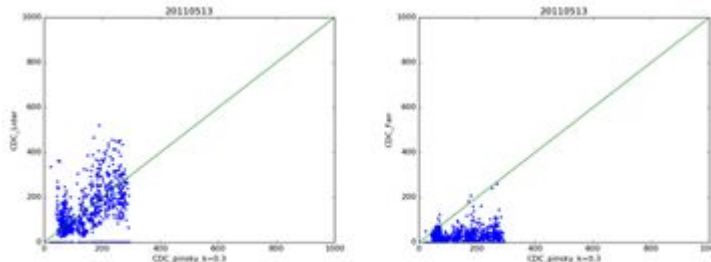
Generating indices for extinction
-----Start of clustering cycle-----
Changing time resolution from 21600->2880
Changing height resolution from 596->667
You are decreasing time resolution
You are increasing height resolution
-----End of clustering cycle-----
Clustering of Retrieved Liquid Water Concentration took 5.26 s
Filtering of Retrieved Liquid Water Concentration took 145.87 s
Total time: 152.22083568572998s
Clustering of Mean Doppler velocity took 4.65 s
Filtering of Mean Doppler velocity took 163.41 s
Total time: 169.7653408050537s
Clustering of Spectral width took 6.52 s
Filtering of Spectral width took 155.09 s
Total time: 162.78985214233398s
Clustering of Reflectivity took 4.76 s
Filtering of Reflectivity took 142.07 s
Total time: 147.98419713974s
Processing temperature
-----Start of clustering cycle-----
Changing time resolution from 144->2880
Changing height resolution from 198->667
You are increasing time resolution
You are increasing height resolution
-----End of clustering cycle-----
    
```

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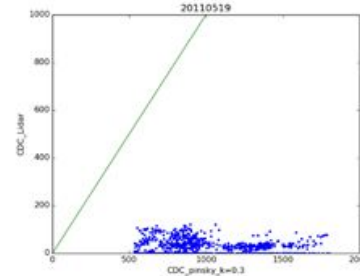
Processing CCN
-----Start of clustering cycle-----
Changing time resolution from 1440->2880
Changing height resolution from 1800->596
You are increasing time resolution
You are decreasing height resolution
-----End of clustering cycle-----
Generating Output file
Date 2880
Time 2880
Height 2880
LWC 2880
LWC_SD 2880
Velocity 2880
Velocity_SD 2880
Spectral_width_SD 2880
Reflectivity 2880
Reflectivity_SD 2880
Temperature 2880
Extinction_low 2880
Extinction 2880
Extinction_high 2880
CCN 2880
Time taken so far 674.44
    
```

Results

Good day

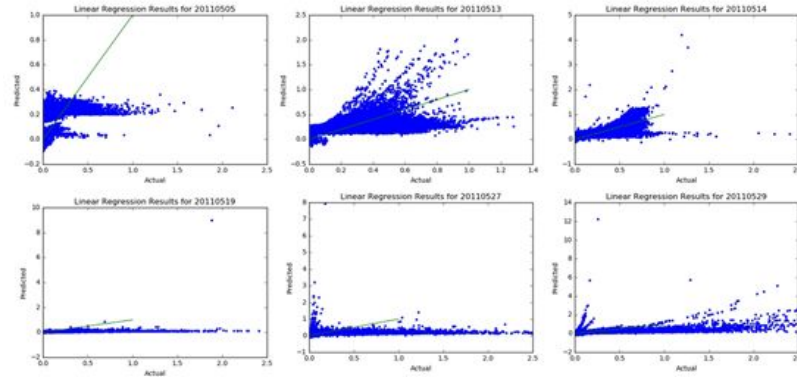


Bad day

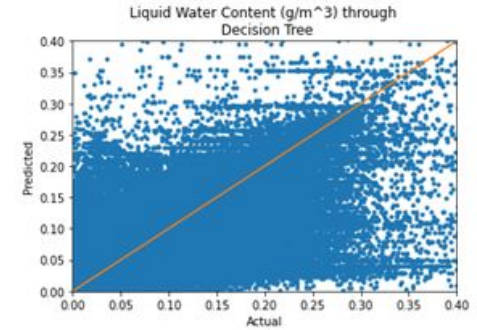
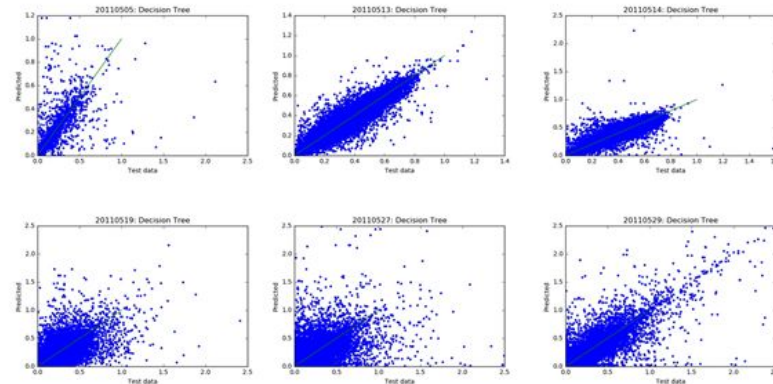


# Task IV: Predictive Models for LWC

Inaccurate models

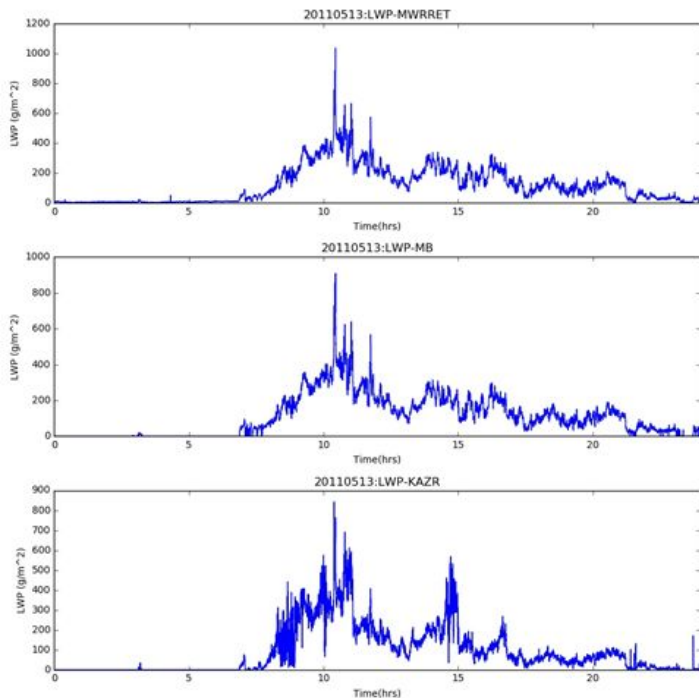


Fair models



# Task V: Analyzing sources of Uncertainties in LWP

$$LWC = \left[ \frac{N_d * Z_{liquid}}{3.6} \right]^{\frac{1}{1.8}} + LWP_t = \int_{h_l=c_{base}}^{h_f=c_{top}} LWC_t(h) * dh \longrightarrow LWP_t = \int_{h_l=c_{base}}^{h_f=c_{top}} \left[ \frac{N_d * Z_{liquid}(h)}{3.6} \right]^{\frac{1}{1.8}} * dh$$



Sources of uncertainty:

1. Clustering of data
2. Cloud base detection
3. Empirical relation
4. Numerical integration



# Accomplishments & Future Work

## Accomplishments

- Development of an automated clustering methodology from scratch
- Detection of sources of uncertainty in standard parametrizations
- Baseline predictive models for LWC

## Future Work

- Tuning the developed clustering methodology for better time-series estimations
- Higher order prediction models using neural networks

# Acknowledgements

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- Department of Chemical Engineering, Carnegie Mellon University

Allowing me to work on the project and develop strong research aptitude

- Aditya Biyani, Hanyu Liu

Peers and research group members

# References

Go to References section of the complete report:

[https://github.com/yashgokhale/CMU-MS-Research/blob/main/Reports/ysg\\_MastersReport.pdf](https://github.com/yashgokhale/CMU-MS-Research/blob/main/Reports/ysg_MastersReport.pdf)