

# Assimilating GOES-R Latent Heating in FV3 using Machine Learning

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+ Best wishes for your PhD Defense!

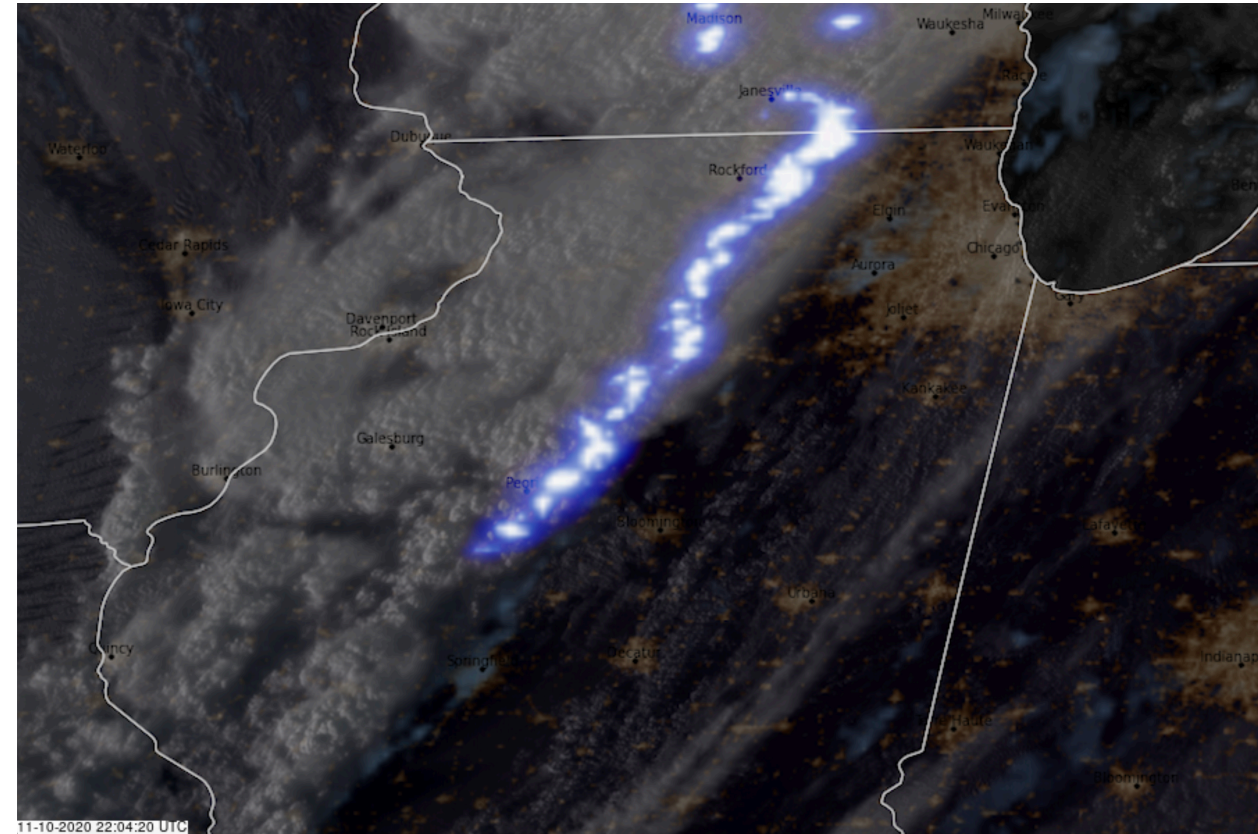
\* Presenting author

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07-December-2020

# Importance and Motivation

- Severe weather has tremendous impacts on human life and the economy:
  - <https://www.ncdc.noaa.gov/billions/>
- Convective-scale numerical weather prediction is an important tool for Preparedness and Response to severe weather hazards
- Good forecasts require data to initialize storms in the models
- Motivation: to bring the benefits of GOES-R Series observations to convective-scale data assimilation



Severe storms sweeping across the Midwest

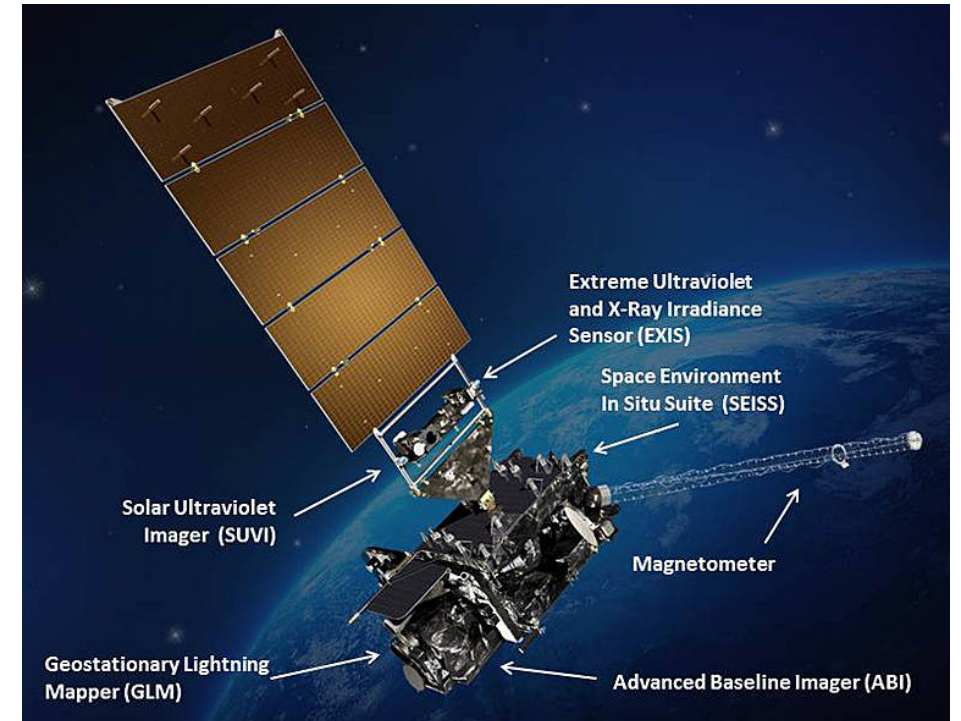
Image credit: Dakota Smith (CIRA)

[http://rammb.cira.colostate.edu/ramsdisk/online/loop\\_of\\_the\\_day/](http://rammb.cira.colostate.edu/ramsdisk/online/loop_of_the_day/)



# Introduction

- Statement of the problem
  - GOES data have long been used by human forecasters for situational awareness
  - Limited usage in numerical weather prediction, especially in cloudy or precipitating pixels
- Statement of the opportunity
  - 3x greater spectral resolution
  - 4x greater spatial resolution
  - 5x greater temporal resolution
  - Lightning mapping



GOES-R Satellite

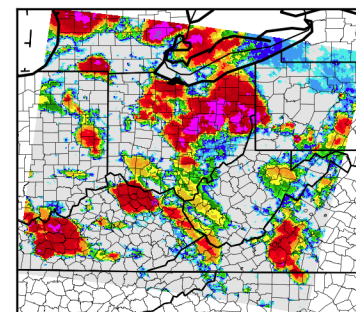
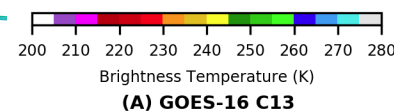
Image credit: NASA

<https://www.nasa.gov/content/goes-r/index.html>

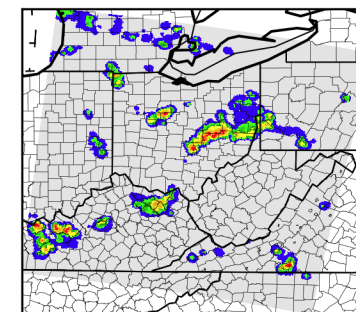
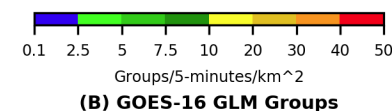
# Why Machine Learning?

- Convolutional approaches use spatial information and spatial context
  - No spatial information: Panel D
  - With spatial information: Panel G
- Truth: Panel C
- Critical for cloudy and precipitating scenes where radiances saturate
- Machine learning (ML) provides convenient framework for fusing radiances and lightning
  - Panel H, Panel I

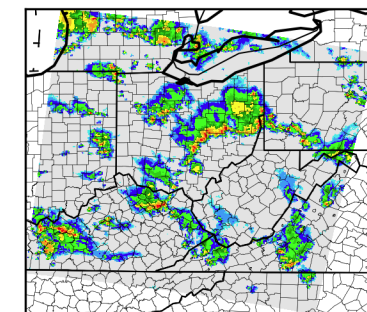
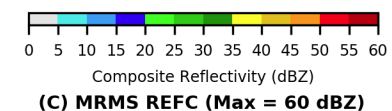
Hilburn, K. A., I. Ebert-Uphoff, and S. D. Miller, 2020: Development and interpretation of a neural network-based synthetic radar reflectivity estimator using GOES-R satellite observations. *J. Appl. Meteor. Climatol.*, <https://doi.org/10.1175/JAMC-D-20-0084.1>.



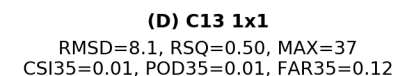
(A) GOES-16 C13



(B) GOES-16 GLM Groups

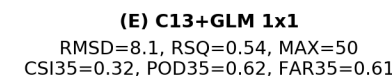


(C) MRMS REFC (Max = 60 dBZ)



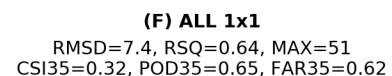
(D) C13 1x1

RMSD=8.1, RSQ=0.50, MAX=37  
CSI35=0.01, POD35=0.01, FAR35=0.12



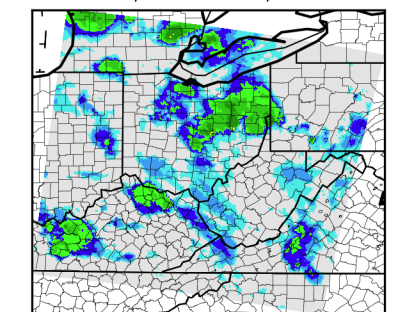
(E) C13+GLM 1x1

RMSD=8.1, RSQ=0.54, MAX=50  
CSI35=0.32, POD35=0.62, FAR35=0.61



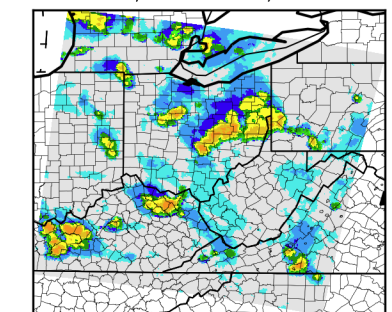
(F) ALL 1x1

RMSD=7.4, RSQ=0.64, MAX=51  
CSI35=0.32, POD35=0.65, FAR35=0.62



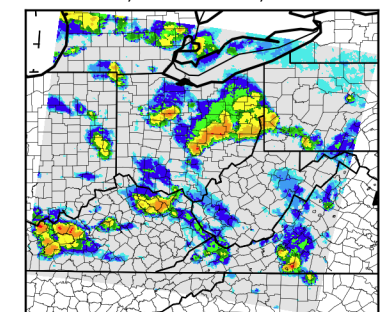
(G) C13 3x3

RMSD=7.8, RSQ=0.54, MAX=52  
CSI35=0.18, POD35=0.24, FAR35=0.56



(H) C13+GLM 3x3

RMSD=7.1, RSQ=0.64, MAX=54  
CSI35=0.34, POD35=0.55, FAR35=0.53



(I) ALL 3x3

RMSD=6.6, RSQ=0.70, MAX=55  
CSI35=0.34, POD35=0.55, FAR35=0.53

# Datasets

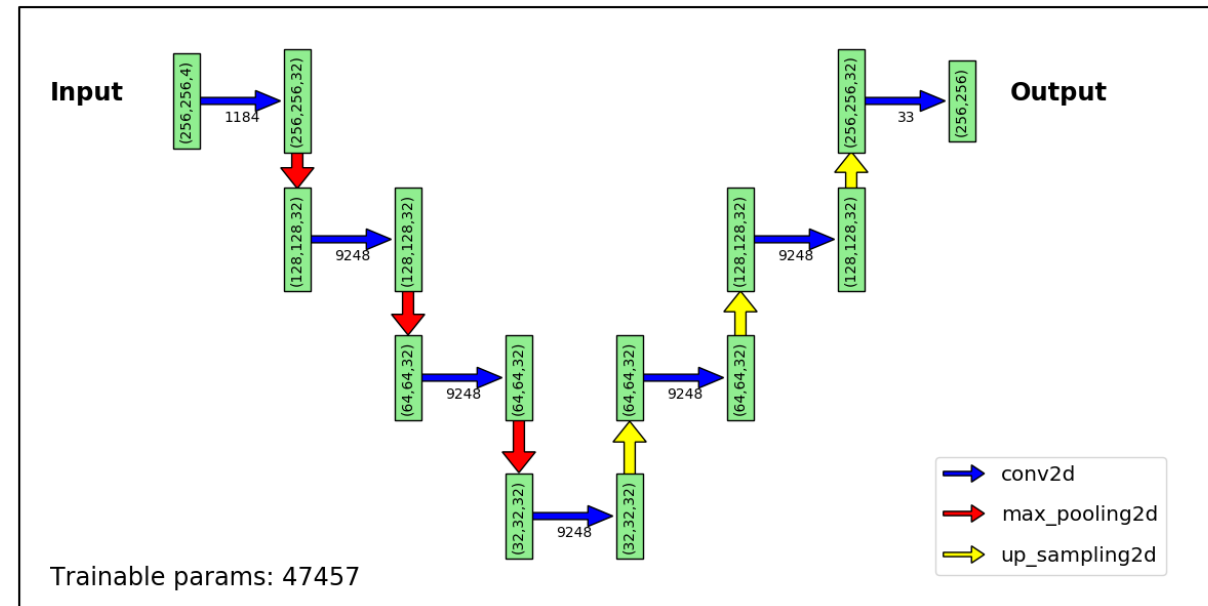
- These datasets combine GOES and MRMS data on the HRRR grid (3x3 km)
- The smallest dataset (CONUS1) gave good results when data augmentation was used
- The medium dataset (CONUS2) gave a good depiction of warm season convective-scale phenomena
- Effective number of samples is based on 50x50 pixel (150x150 km) receptive field for GREMLIN model
- The largest dataset (CONUS3) has been prepared and experiments are underway

Dataset	Number of Images	Image Size	Effective Number Samples	Reference
CONUS1	225	256 x 256	5,850	Hilburn et al. (2019) Joint Satellite Conference
CONUS2	1,800	256 x 256	46,800	Hilburn et al. (2020) J. Appl. Meteor. Climatol.
CONUS3	63,850	1799 x 1059	48,653,700	This presentation



# ML Models

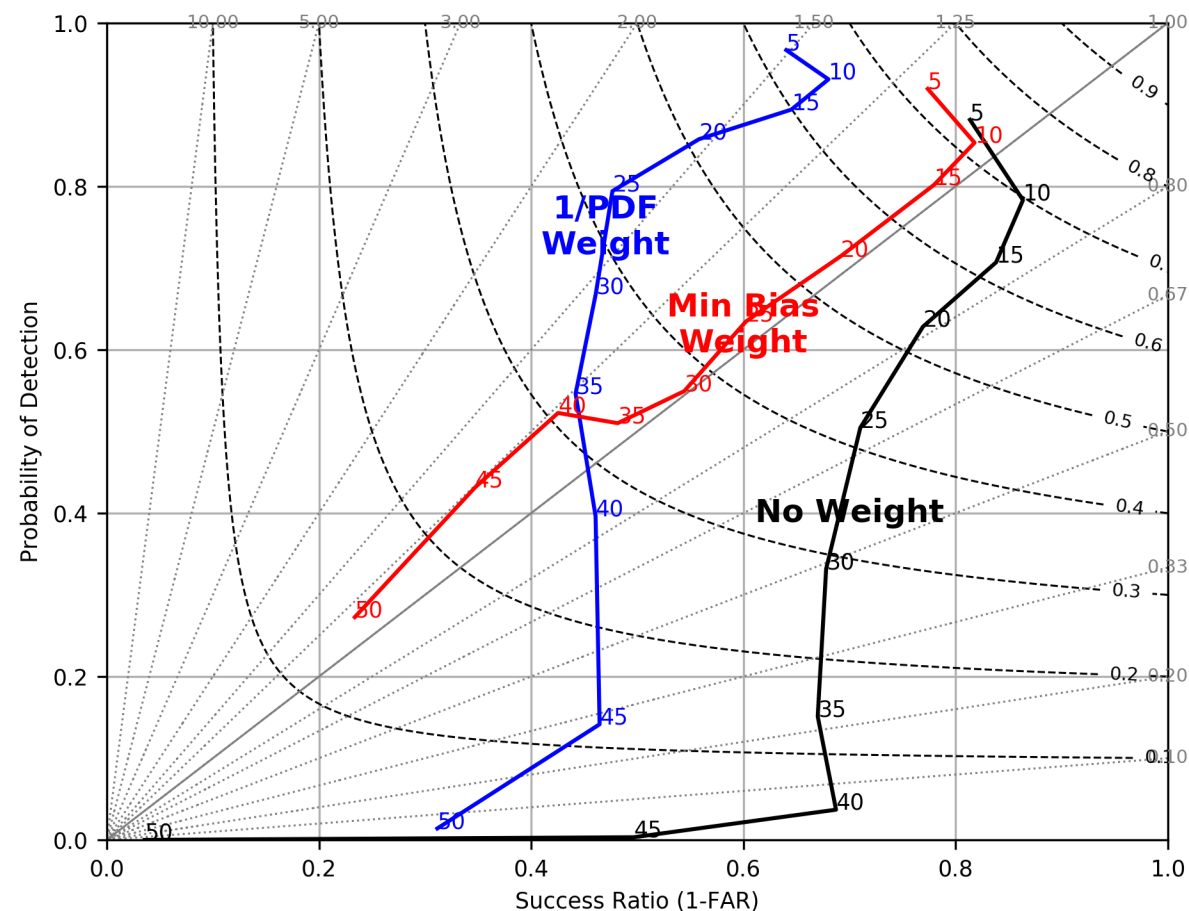
- GREMLIN: GOES Radar Estimation via Machine Learning to Inform NWP
- The theoretical receptive field for this model is 50x50 pixels, which is the neighborhood over which inputs are combined to produce one output pixel
- The new larger dataset will allow experiments with deeper models that have larger receptive fields



# Loss Functions and Metrics

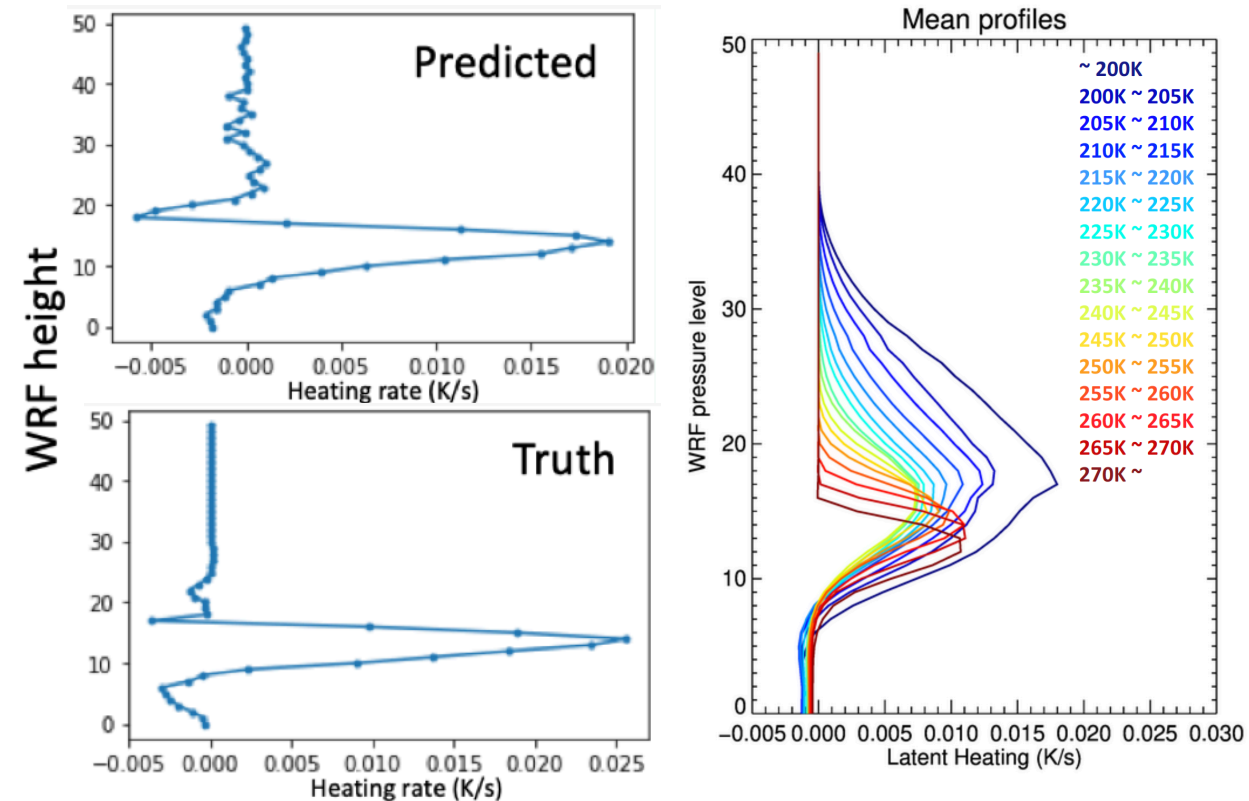
- The GREMLIN model was trained using a weighted loss function to put more emphasis on the relatively infrequent higher reflectivity values
- A performance diagram was used to ensure that GREMLIN provides good estimates across all reflectivity values
- Recent work using neighborhood loss functions, such as Fraction Skill Score, show promise to improve results by avoiding the double-penalty problem with misplaced convective-scale features

Hilburn, K. A., I. Ebert-Uphoff, and S. D. Miller, 2020: Development and interpretation of a neural network-based synthetic radar reflectivity estimator using GOES-R satellite observations. *J. Appl. Meteor. Climatol.*, <https://doi.org/10.1175/JAMC-D-20-0084.1>.



# Ongoing and Future Work

- Extending GREMLIN to all conditions using:
  - Larger dataset
  - Deeper model
  - Solar reflective bands
- Vertical profile model
  - Using a fully-connected (dense) NN shows promise based on WRF OSSEs (left panels)
  - Latent heating profiles show expected physical relationship with cloud top temperature (right panel)
- Uncertainty estimator
  - Estimating observation errors for DA
- DA experiments, OSSEs



Yoonjin Lee, PhD Dissertation: Using GOES-16 ABI Data to Detect Convection, Estimate Latent Heating, and Initiate Convection in a High-Resolution Model.



# Key Results

- The ability of Convolutional Neural Networks to utilize spatial context is essential for this application and offers breakthrough improvement in skill compared to traditional pixel-by-pixel based approaches.
- The usage of Machine Learning in Data Assimilation applications provides new information content from satellite data that is currently going unused, especially for cloudy and precipitating scenes.

# Significance and Broader Impact

- Addresses NOAA goals and NESDIS Strategic Plan
  - Utilization of GOES-R sensors
  - ABI+GLM data fusion
- Supports NWS Commitment to building Weather-Ready Nation
  - Extending the value of satellite imagery and products
  - Improving weather forecast services and numerical predictions
- In addition to data assimilation applications, this work is also relevant to aviation and nowcasting applications
- Contact:
  - Kyle Hilburn ([Kyle.Hilburn@colostate.edu](mailto:Kyle.Hilburn@colostate.edu))
  - Yoonjin Lee ([Yoonjin.Lee@colostate.edu](mailto:Yoonjin.Lee@colostate.edu))

# Acknowledgements

- This work is supported by the NOAA GOES-R Program under grant NA19OAR4320073
- Thank you to NOAA RDHPCS for access to the Fine Grain Architecture System on Hera
- YL and KH thank Imme Ebert-Uphoff (CSU) for asking insightful questions that helped shape this research

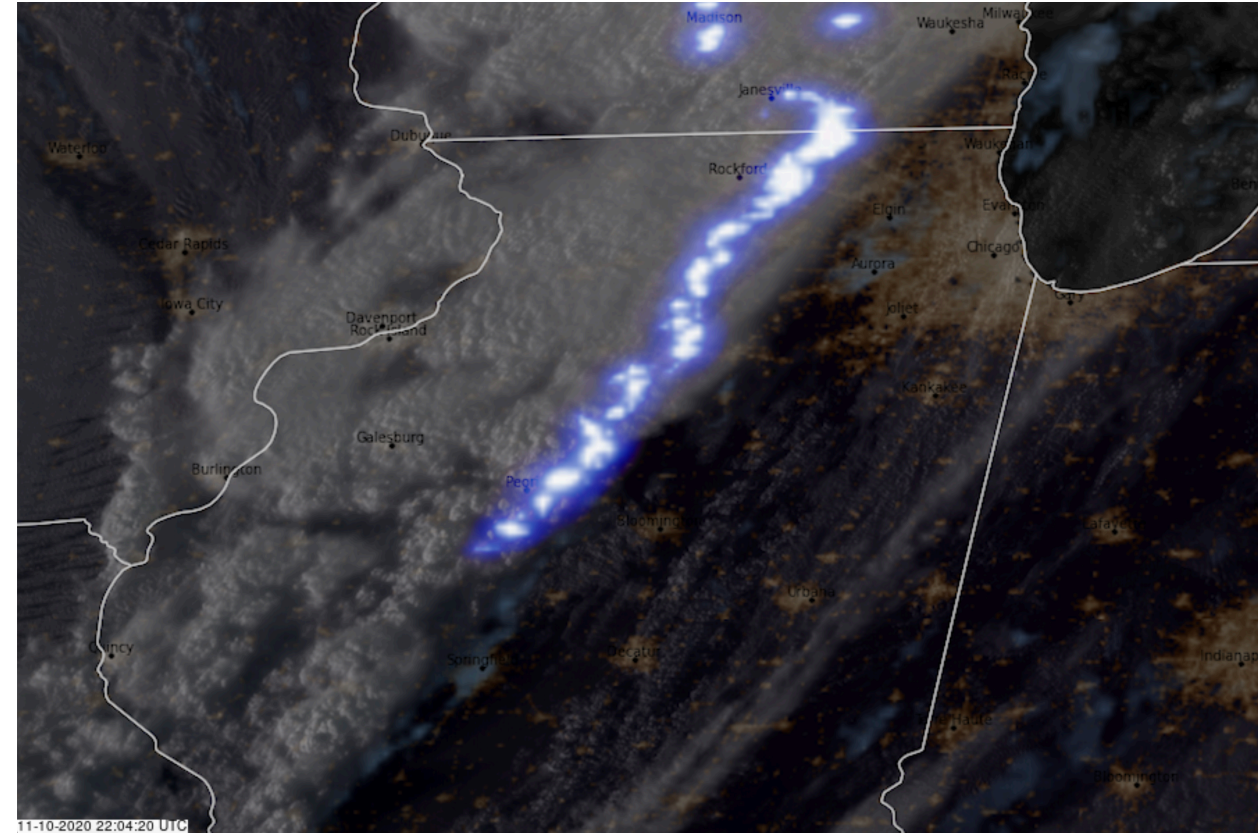




# Overview Slides

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