

Predicting GLM Flash Rate Class: Deep Neural Network Approach

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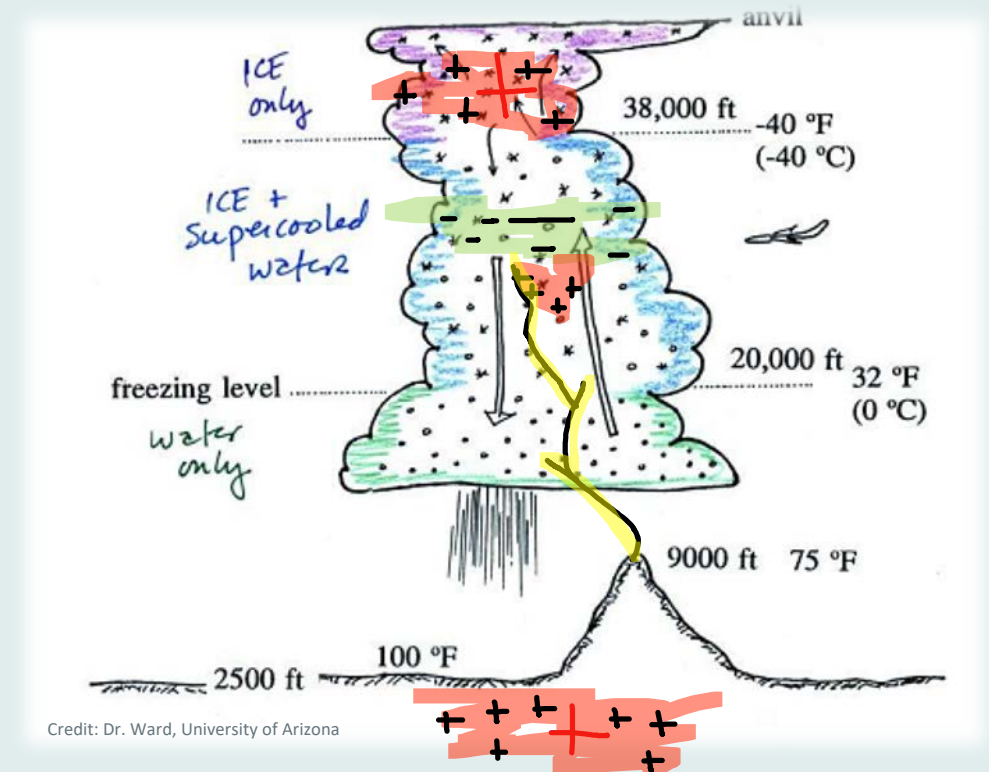
Ting-Chi Wu and Milija Zupanski



Objectives

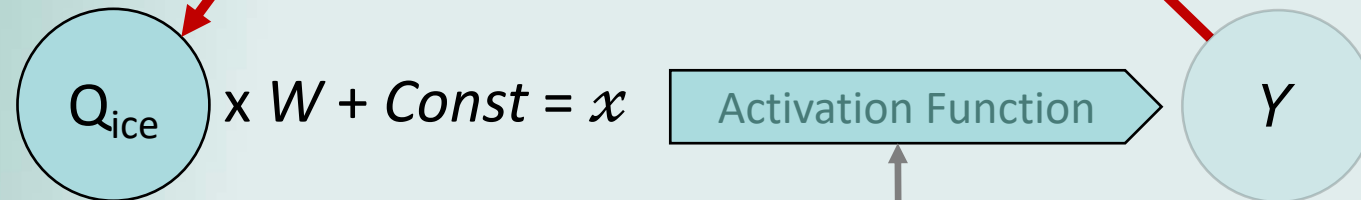
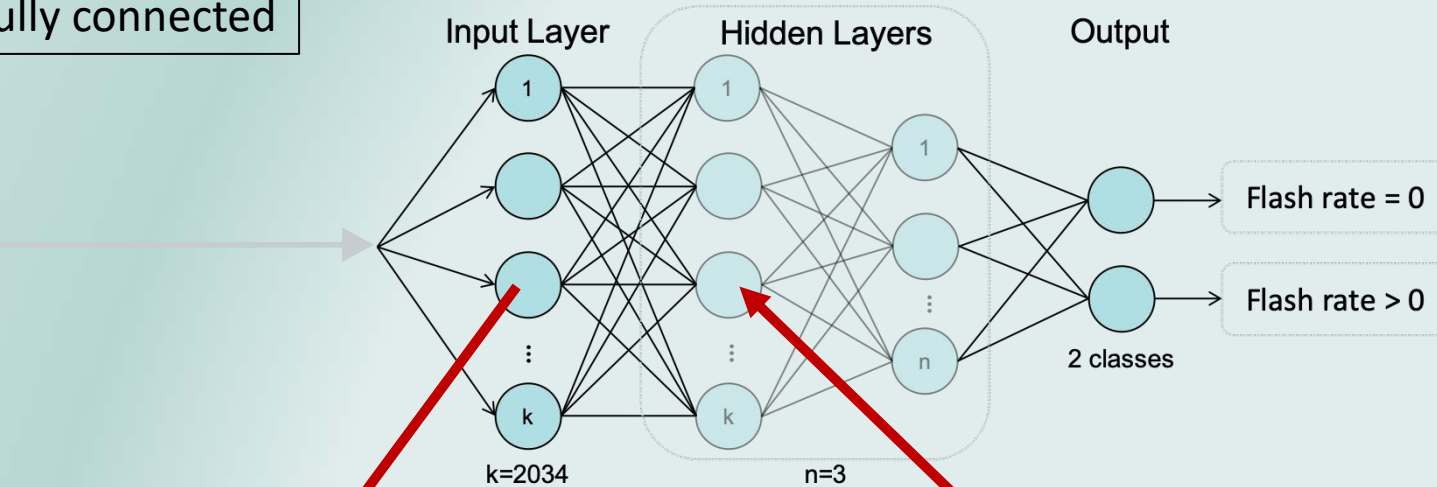
- The overall objective
 - Goal: Improve hurricane forecast by assimilating GLM observations
 - Challenge: GLM observed features (e.g. flash rate) are not common model parameters
 - Solution: Use a *link* between existing model parameters and GLM observations
- Project objective
 - Build a representation of the link between model parameters and GLM observations

Predict GLM flash rate using h-WRF output



Deep Neural Network Model

Fully connected

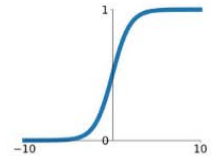


Allows for non-linear links !

Activation Function

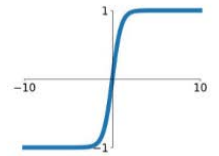
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



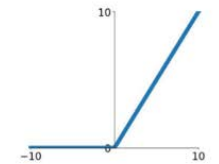
tanh

$$\tanh(x)$$



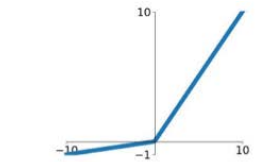
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

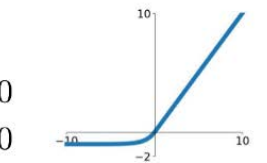


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Data

- Predictors (features) – HWRF output

3-D features

- Total condensate
- Total ice content
- Rime factor
- Specific humidity
- Cloud water mix ratio
- Ice mix ratio
- Snow mix ratio
- Water vapor mix ratio
- Vertical velocity
- Super-cooled liquid water flag

2-D features

- Accumulated precip
- Instantaneous convective precip
- Accumulated convective precip
- Top of conv. levels
- Richardson number
- updraft fractions
- Max vert wind @ 400 mb
- potential t
- 10m wind

- Predictands (labels) – GLM observations

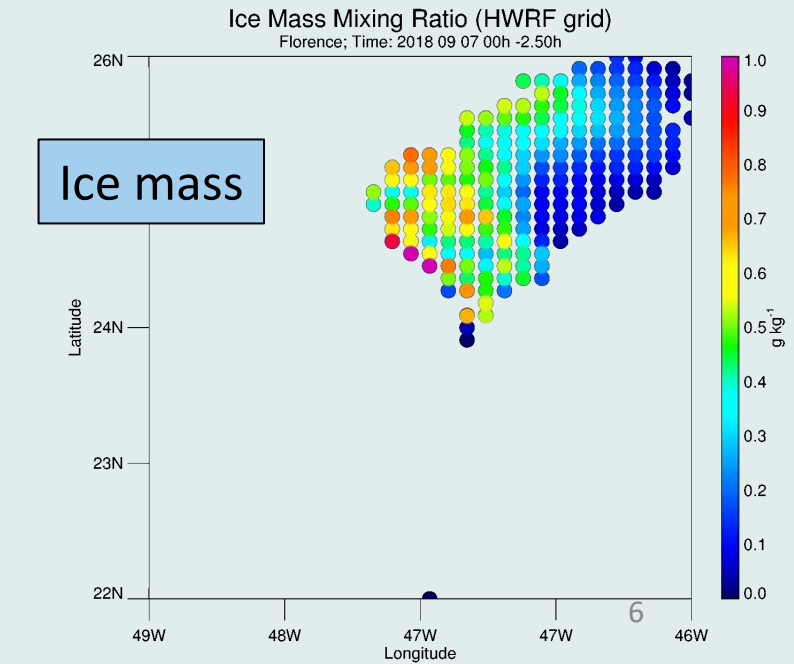
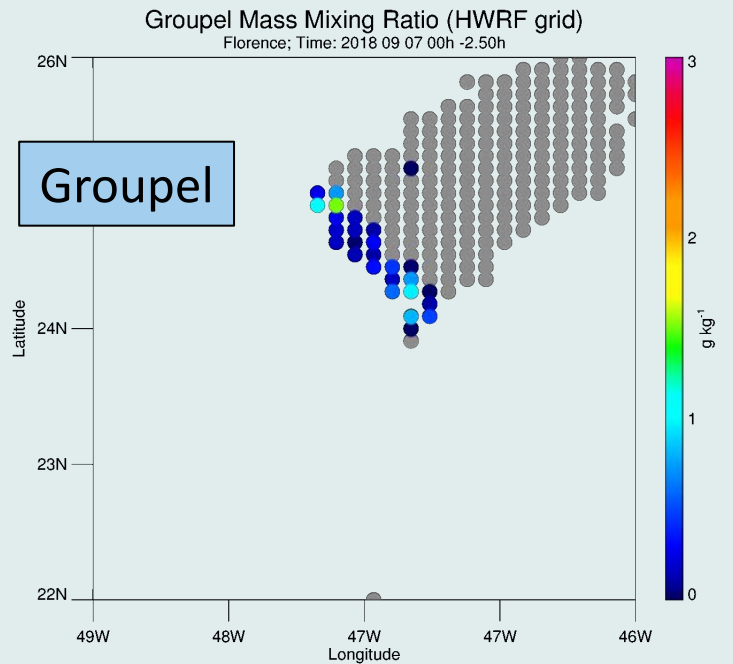
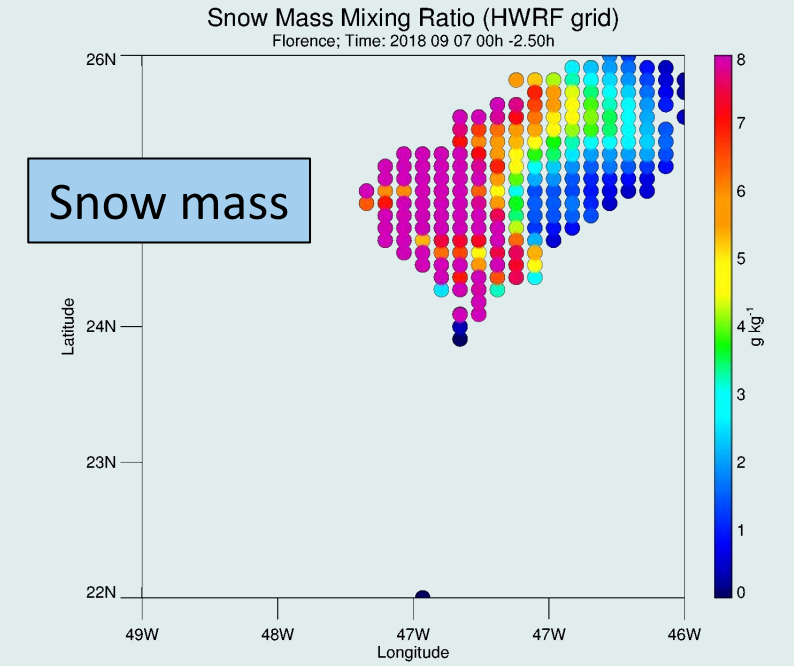
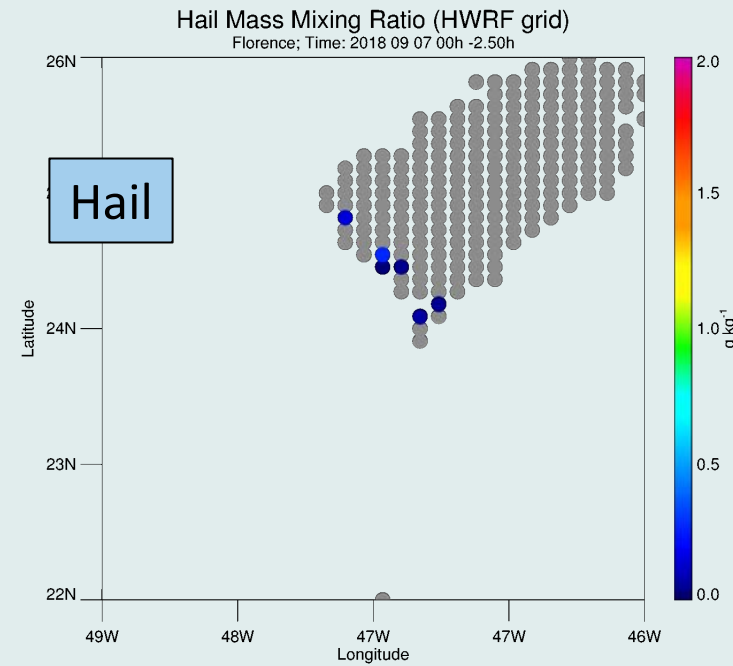
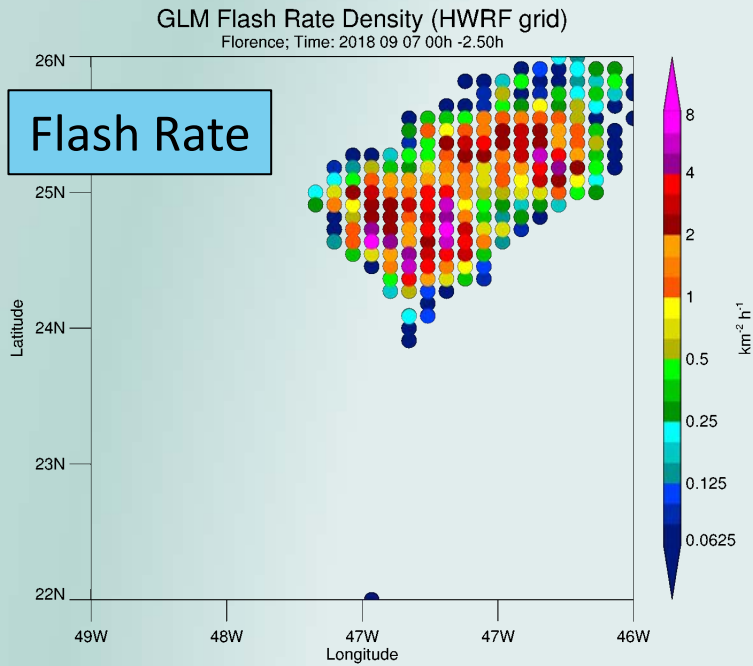
Flash Classes

- 2 classes: yes/no lightning
- 3 classes: no-, low-, high-flash rate
- 4 classes: no-, low-, moderate-, high-flash rate

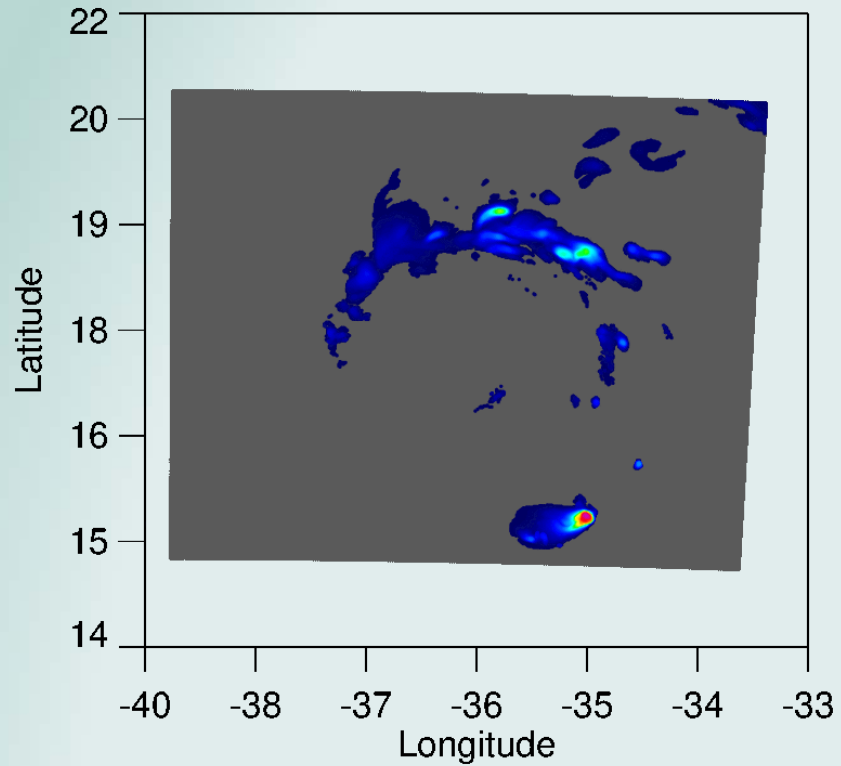
Flash Rate

- Flash rate

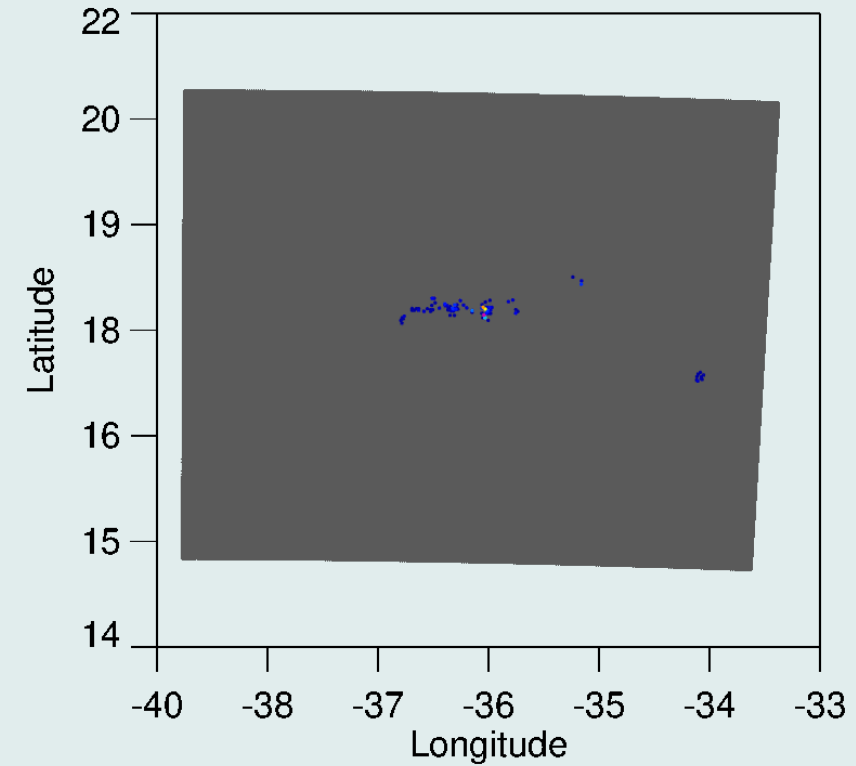
- Note: All mixing ratios here are totaled accounting for delta-pressure but not weighted for geopotential
- Hail is often completely missing
- Graupel is slightly better but still questionable in sense how much it correlates with the FR value



Normalized HWRF Total Column Ice
Florence 20180903 0600 UTC



Normalized GLM Observed Flash Rate
Florence 20180903 0600 UTC

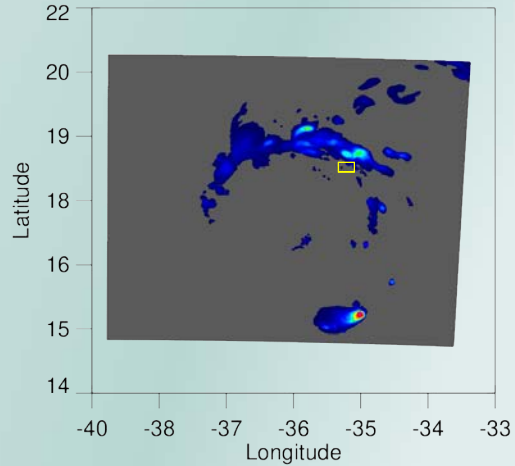


Training dataset

– Relating HWRF output and GLM observations –

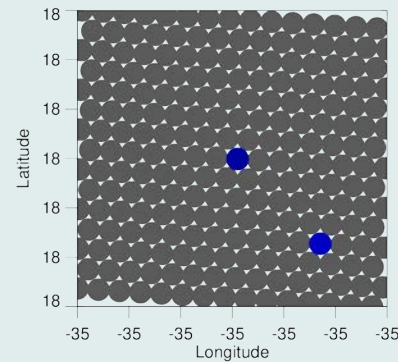
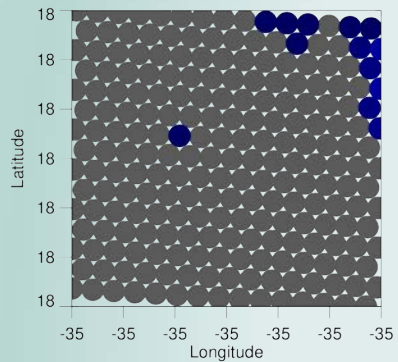
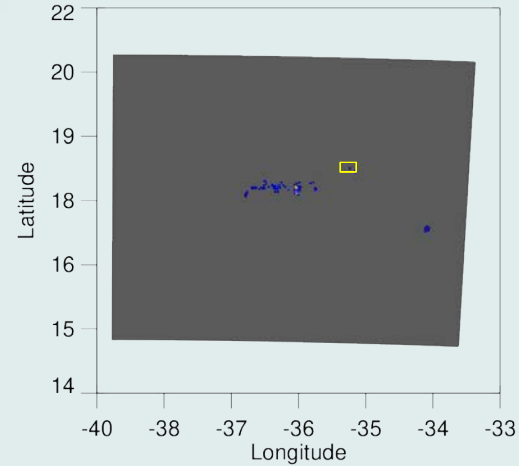
Hwrf Output

Normalized HWRF Total Column Ice
Florence 20180903 0600 UTC



GLM obs

Normalized GLM Observed Flash Rate
Florence 20180903 0600 UTC

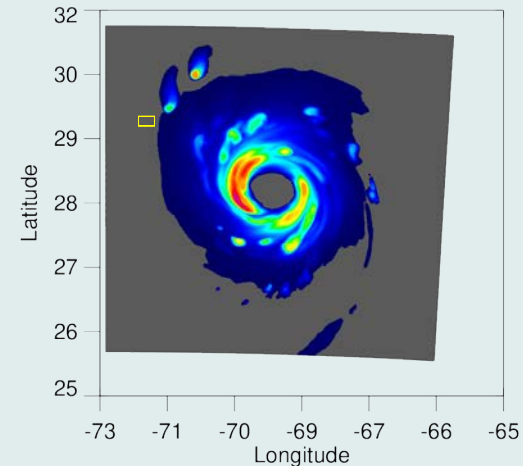


Lon: -35.61
Lat: 18.67



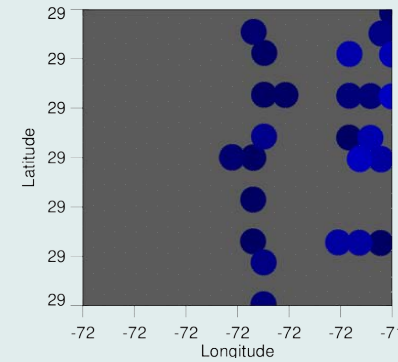
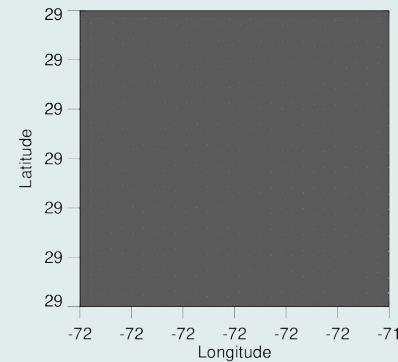
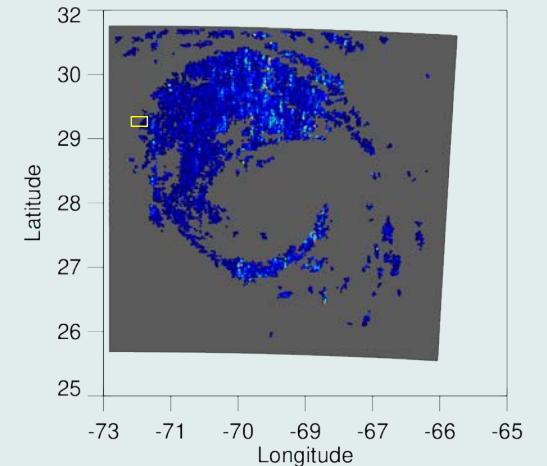
Hwrf Output

Normalized HWRF Total Column Ice
Florence 20180912 0600 UTC



GLM obs

Normalized GLM Observed Flash Rate
Florence 20180912 0600 UTC

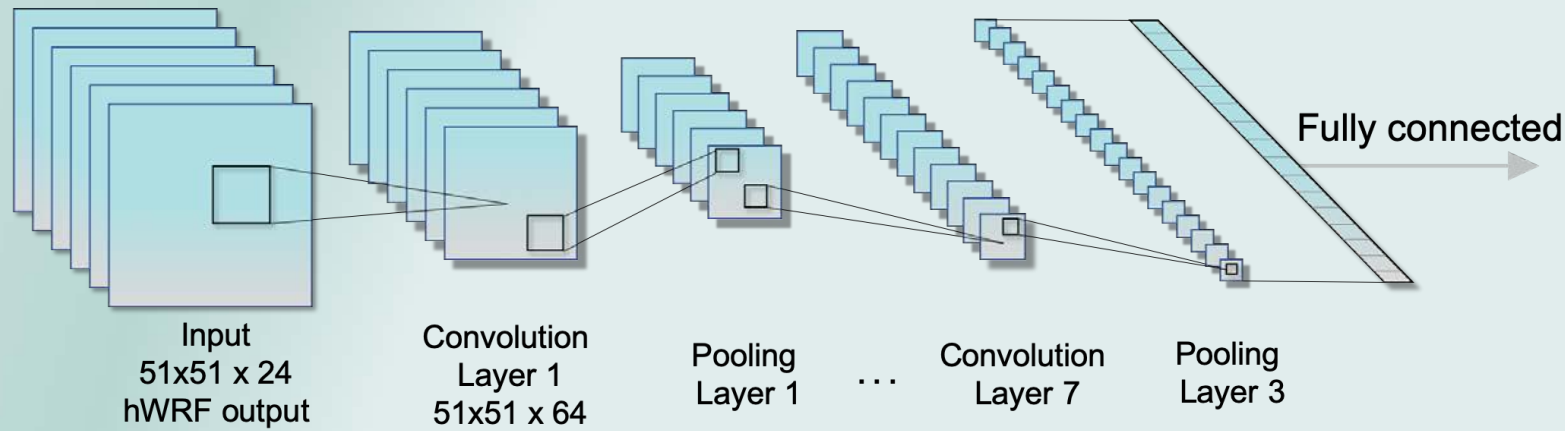


Lon: -72.16
Lat: 29.34



Deep Neural Network Model

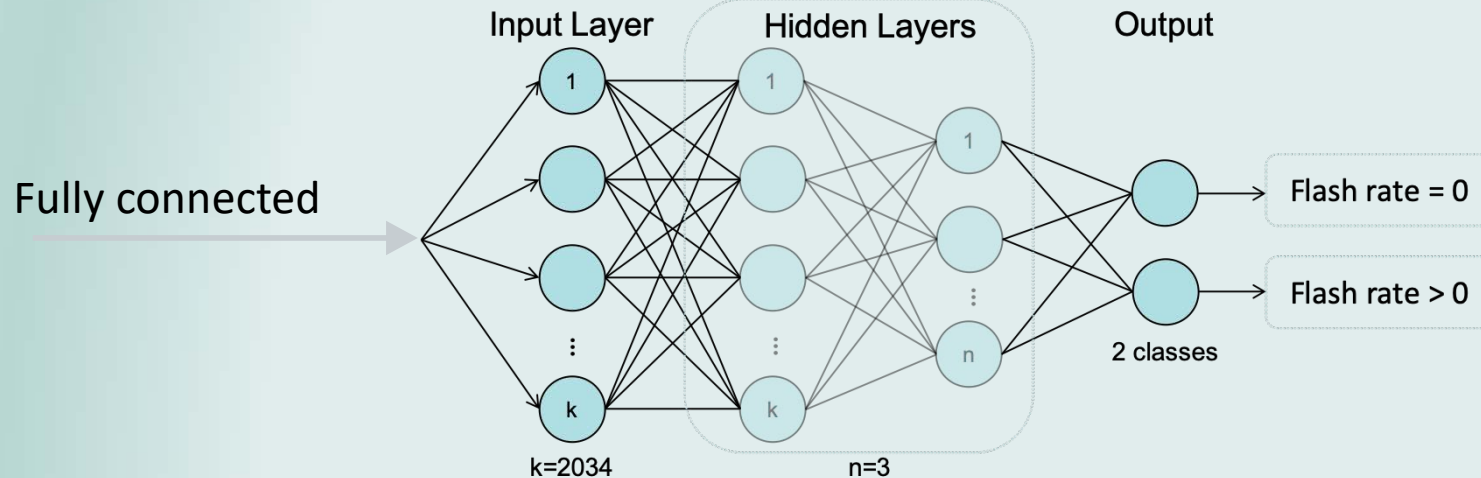
2D Convolutional Neural Network model



CNN Architecture: (51, 51, 24)

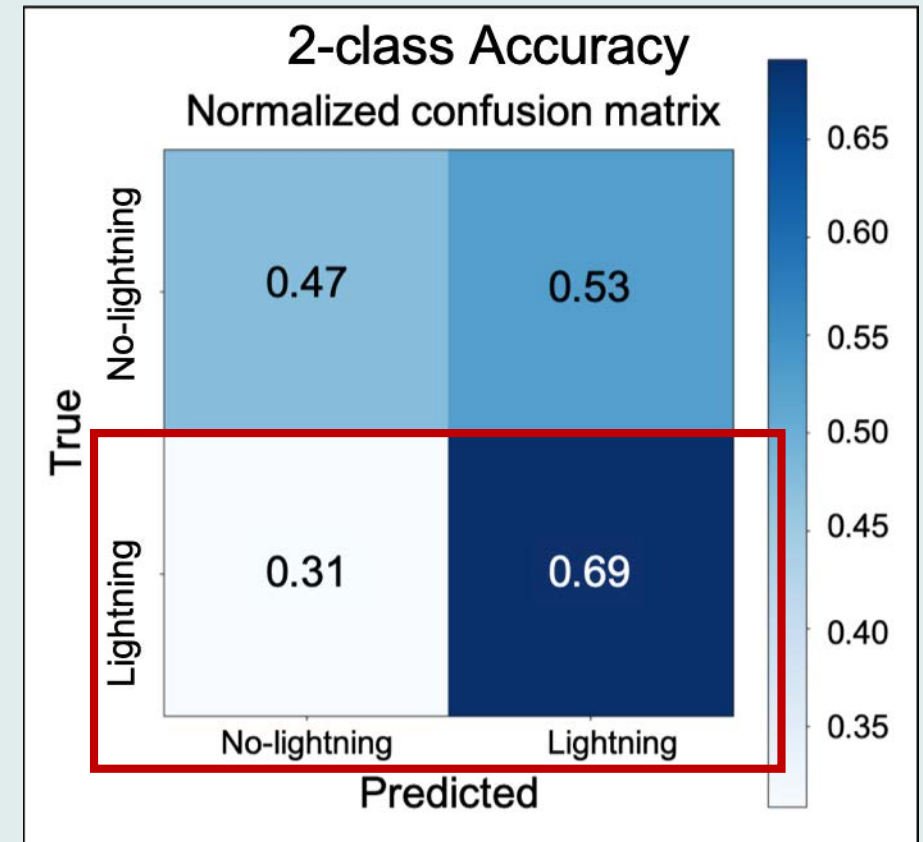
=====
Total params: 402,178

Trainable params: 400,898



Results and Summary

- Focus was on construction of a flexible DNN system. Developed are:
 - Input pipeline (flexibility to ingest any number of input features of multiple dimensions)
 - Model architectures: Fully Connected and CNN
 - Inference models (for testing the results on independent datasets)
- Initial result for the 2-class experiment (yes/no lightning) stands at overall accuracy of 60% with probability of 70% to correctly detect lightning when occurred.
- Currently performed tests on multiple class tasks suggest that models are generally biased towards no-lightning or low-lightning class.



3-class Accuracy [%]

| | | Predicted | | |
|------|------|-----------|-----|------|
| | | Low | Mod | High |
| True | Low | 74 | 11 | 15 |
| | Mod | 64 | 15 | 21 |
| | High | 52 | 11 | 37 |