Machine Learning Techniques for Improving Prediction of Winter Weather Precipitation Types

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*NCAR **M**achine **I**ntegration and **L**earning of the **E**arth **S**ystem*

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Introduction and Motivation

Motivation

Winter precipitation type greatly affects the types of impacts from a winter storm.

Timing of precipitation type transitions affect choices of road treatments and whether or not there are major work, school, and transportation disruptions.

Current p-type algorithms do not incorporate uncertainty into their processes except through ensembles of NWP models.

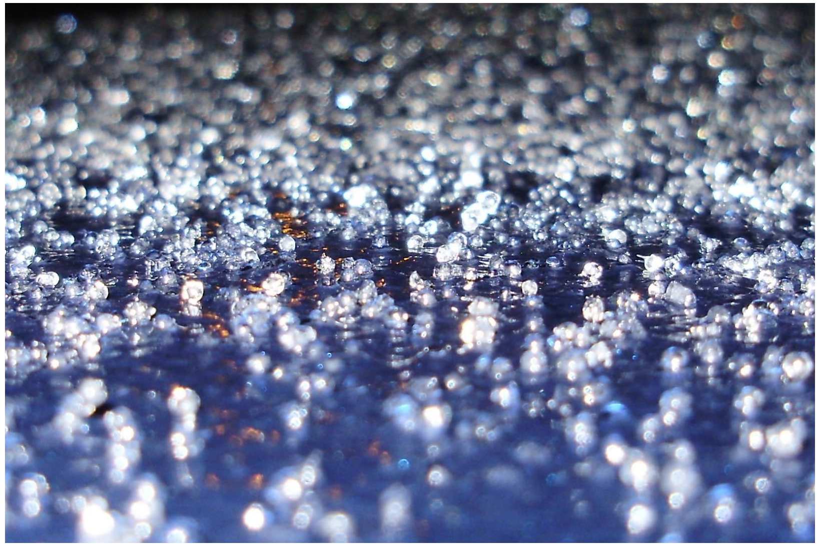
Task

Predict winter weather **precipitation type (p-type)** using **deep learning** with high spatiotemporal accuracy and consistency.

Secondary Objective

Investigate sensitivities and biases within data features.

Develop a ML p-type algorithm that incorporates robust predictive uncertainty estimates.



Benchmark Case - Classifying Precipitation Type

<u>Data</u>

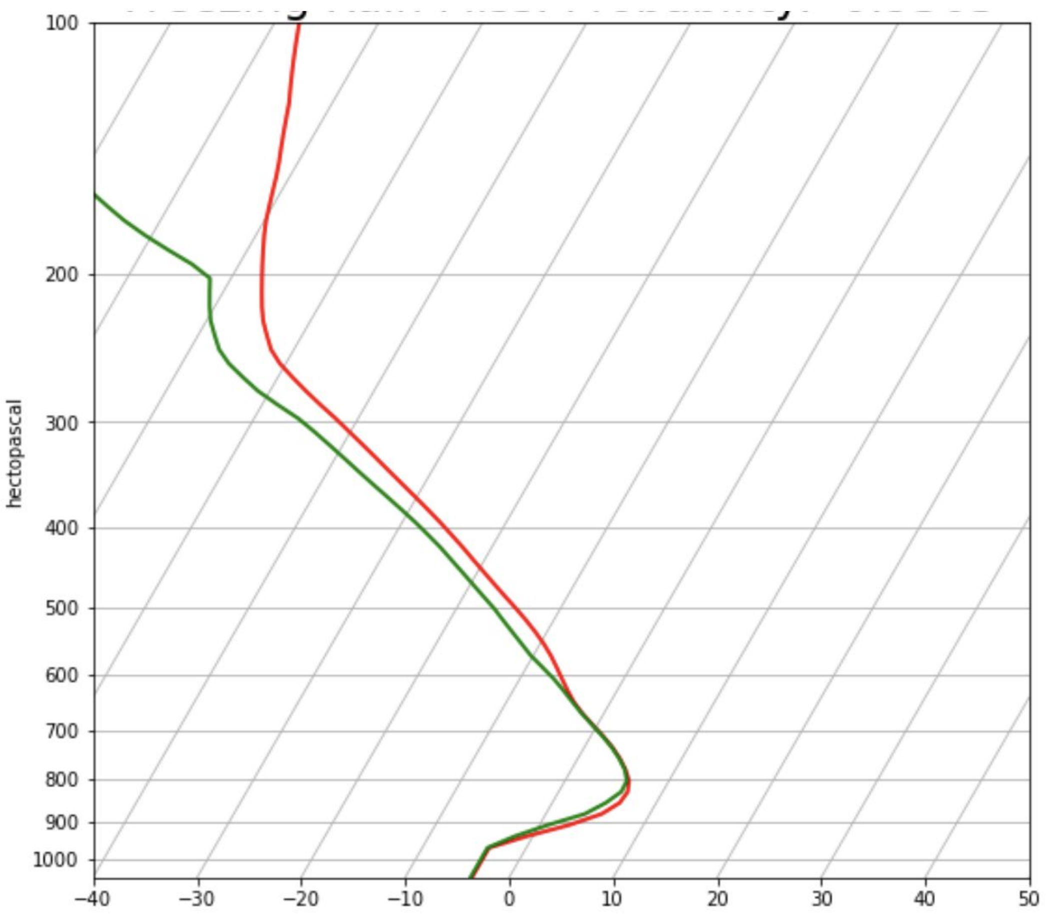
- ➢ **NOAA Rapid Refresh** Vertical Profile
- ➢ Interpolate from pressure to height coords

<u>Input</u> (0 - 5000m above surface, every 250 meters)

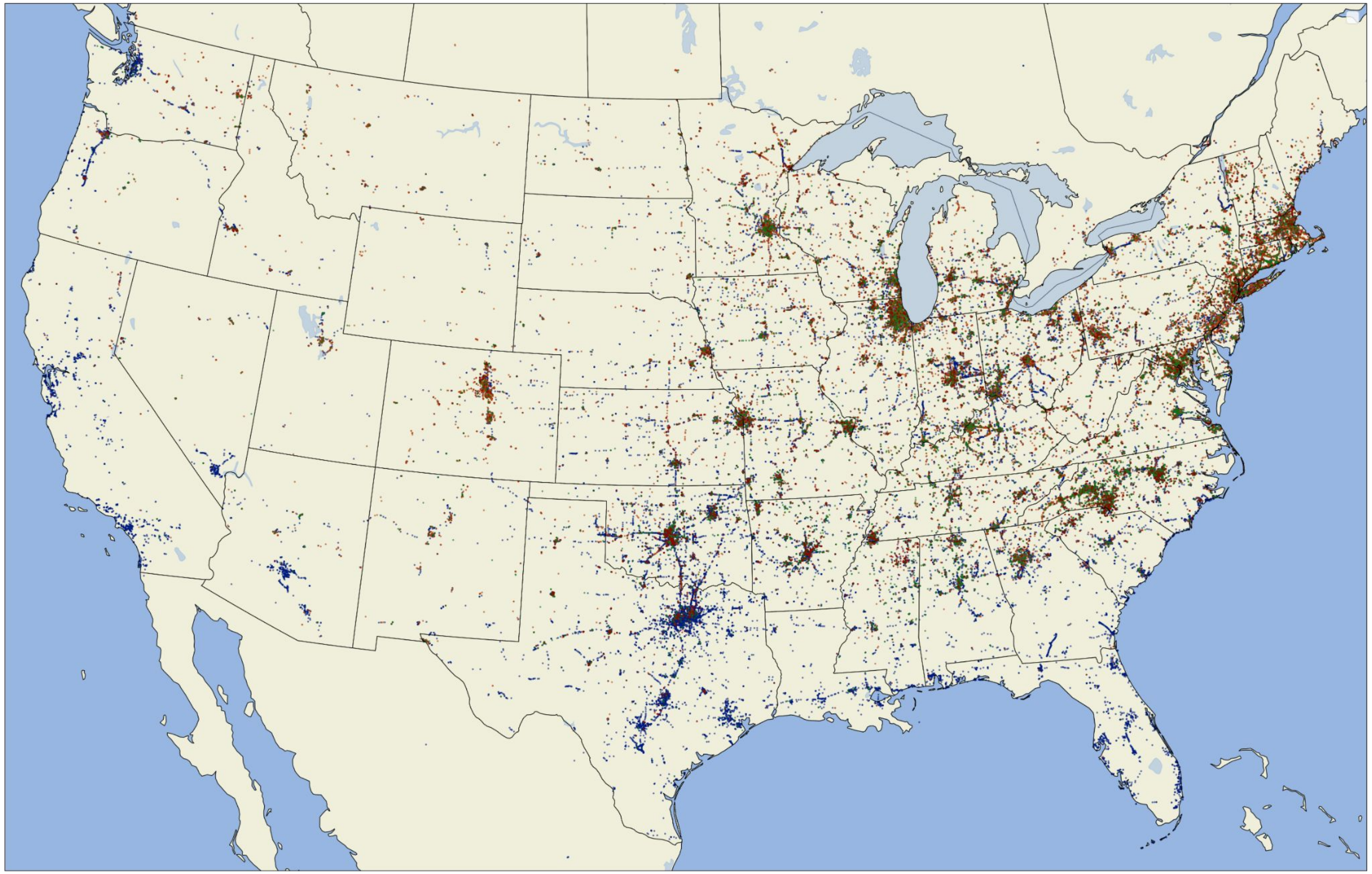
- ➢ Temperature, Dewpoint, U-Wind, V-Wind

<u>Target</u>

- ➢ **mPING** Observations of precipitation types
  - ➢ *Rain, Snow, Sleet, Freezing Rain*



Imbalanced Data mPING



Rain - 59.8%

Snow - 29.0%

Ice Pellets - 8.3%

Freezing Rain - 2.8%

Options for dealing with imbalanced data:

- Under-sample / over-sample
  - Requires lots of data
- Custom loss functions
- **Class weights (with standard loss functions)**

Potential Data Biases

mPING:

- Some users may not be accurately reporting freezing rain and / or ice pellets (sleet)
- Users may be more likely to to report events when they first start rather than uniformly throughout the event
- Not spatially uniform (more observations in highly populated areas)
- Multiple types of observations can coexist at the same time
- Multiple precipitation types can exist within the temporal resolution of the input data (1 hour)

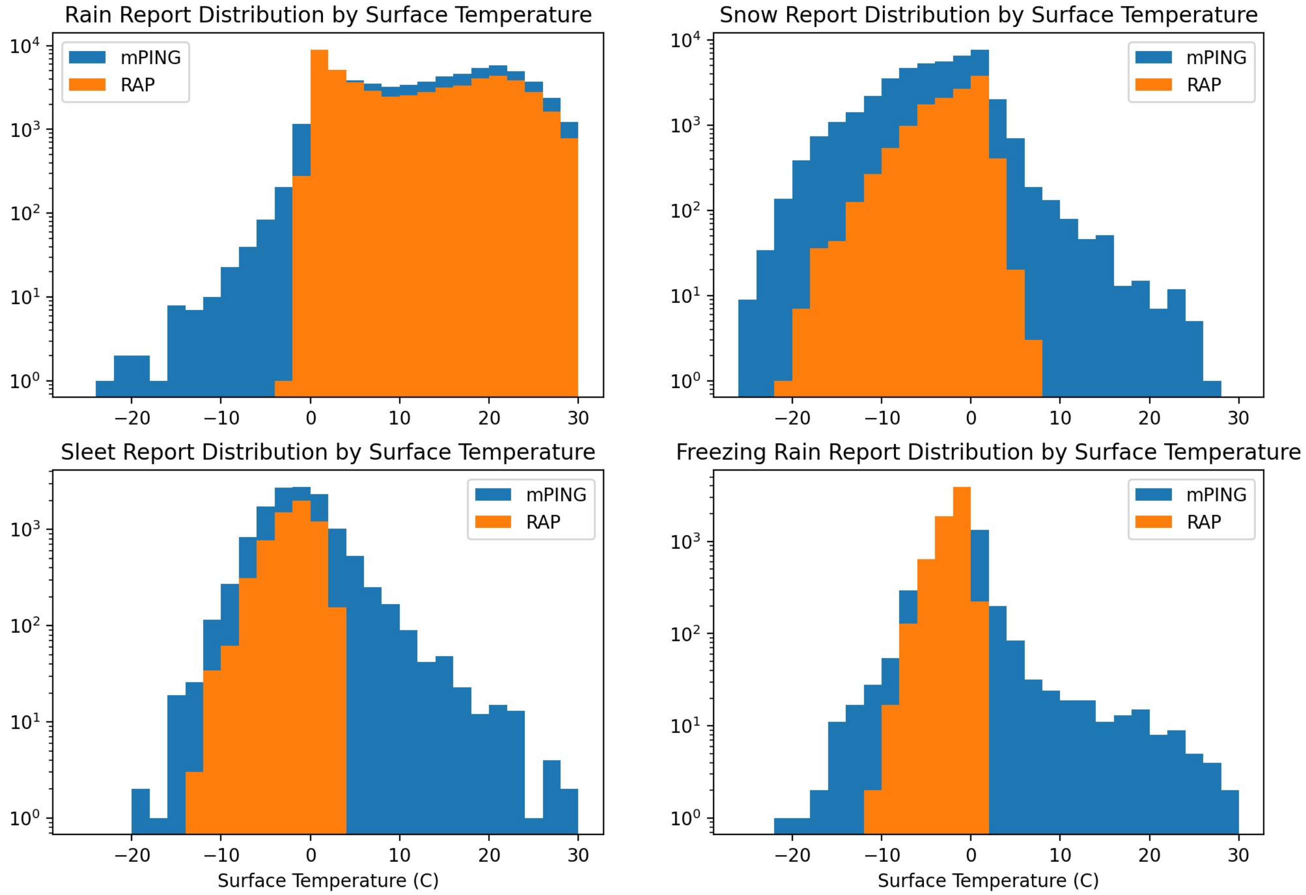
RAP:

- Overly smooth sounding
- Sampled at top of hour rather than when report occurs
- Boundary/surface layer parameterizations affect boundary layer profile

Potential Data Biases

mPING:

- ***Some users may not be accurately reporting freezing rain and / or ice pellets (sleet)***
    - ***Evidence of adversarial data points***
    - ***Evidence Ice pellets (sleet) being confused for hail***



Data Quality Control

mPING:

- ***Some users may not be accurately reporting freezing rain and / or ice pellets (sleet)***
  - ***Evidence of adversarial data points***
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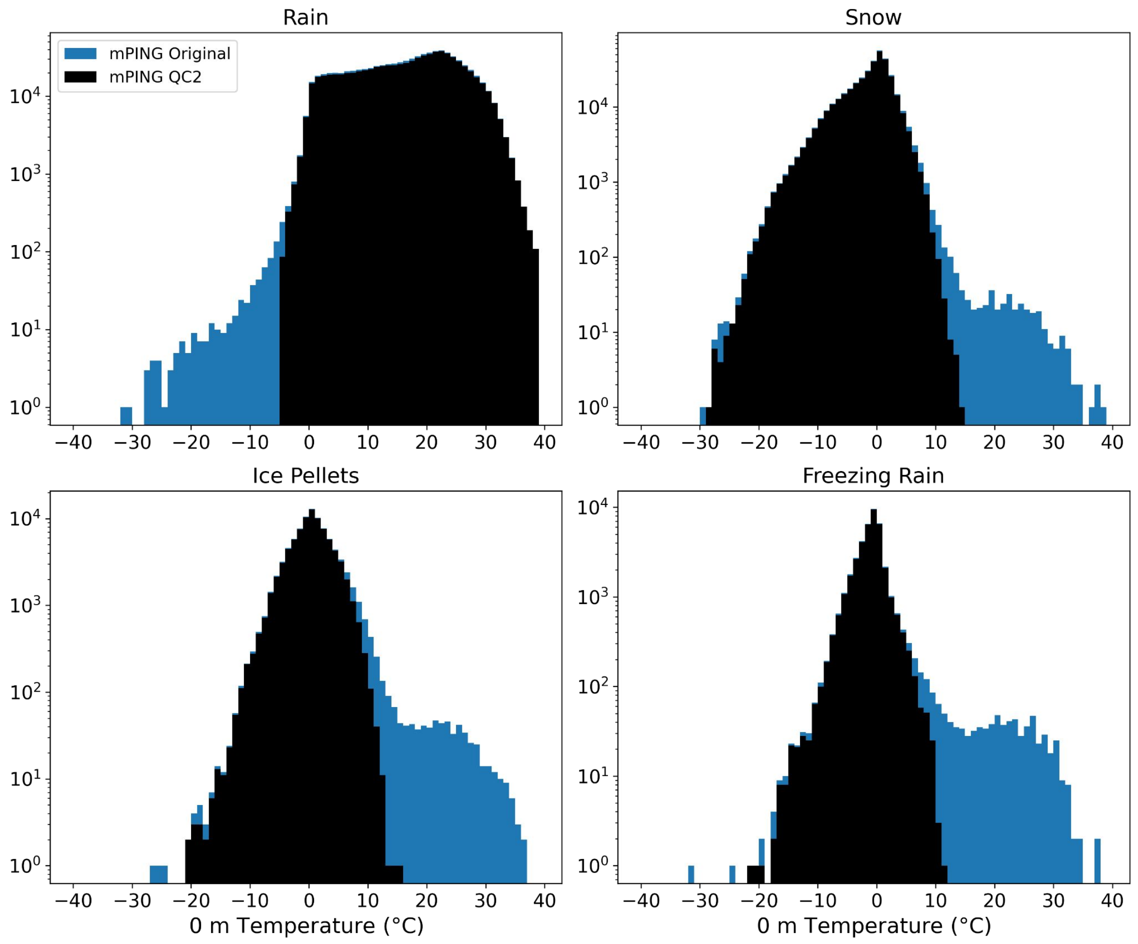
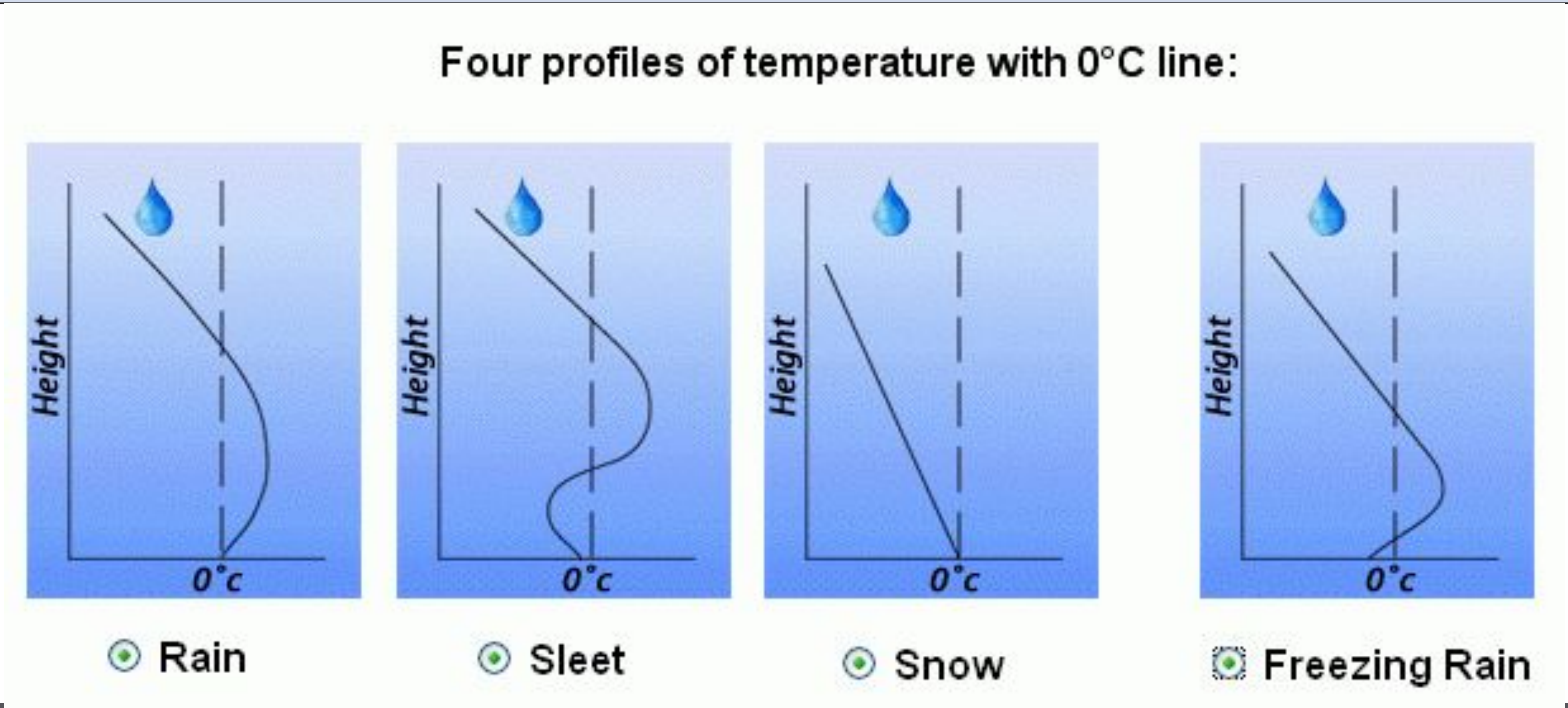


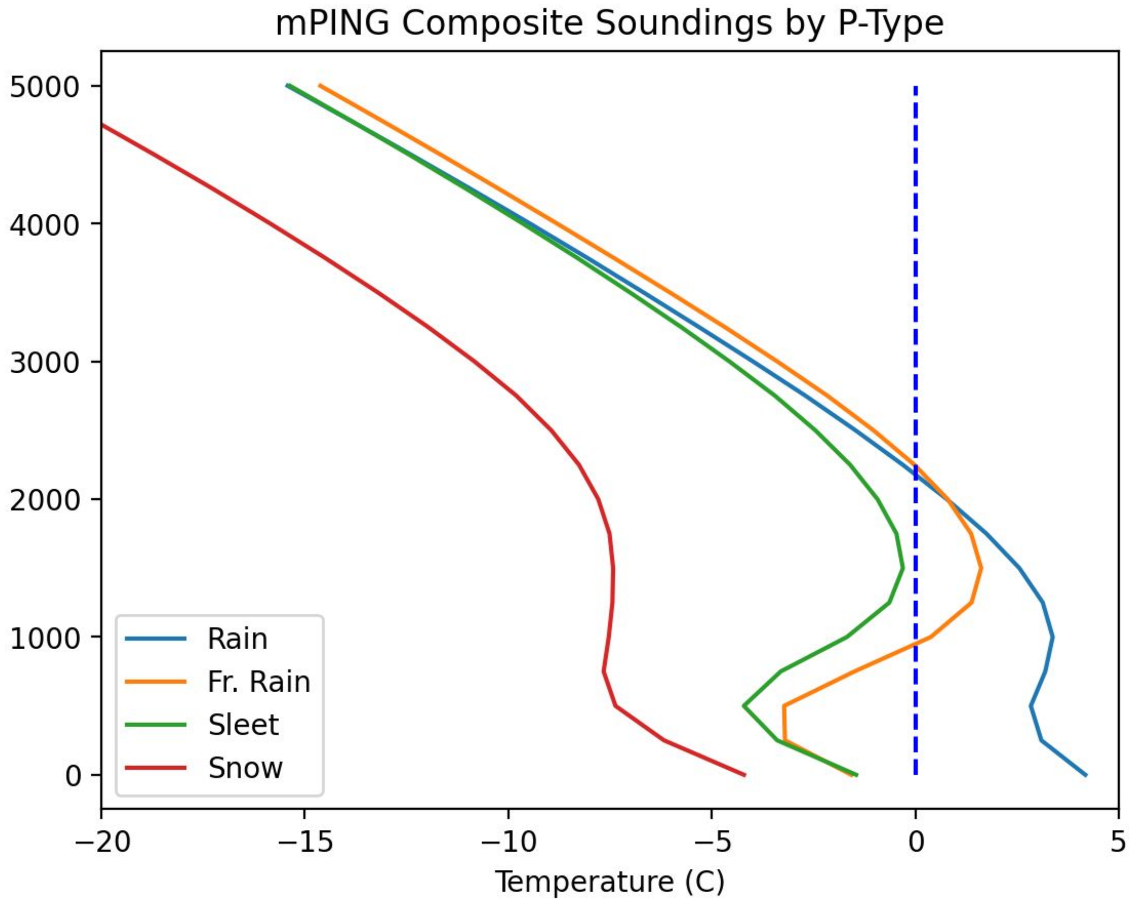
Data Quality Control

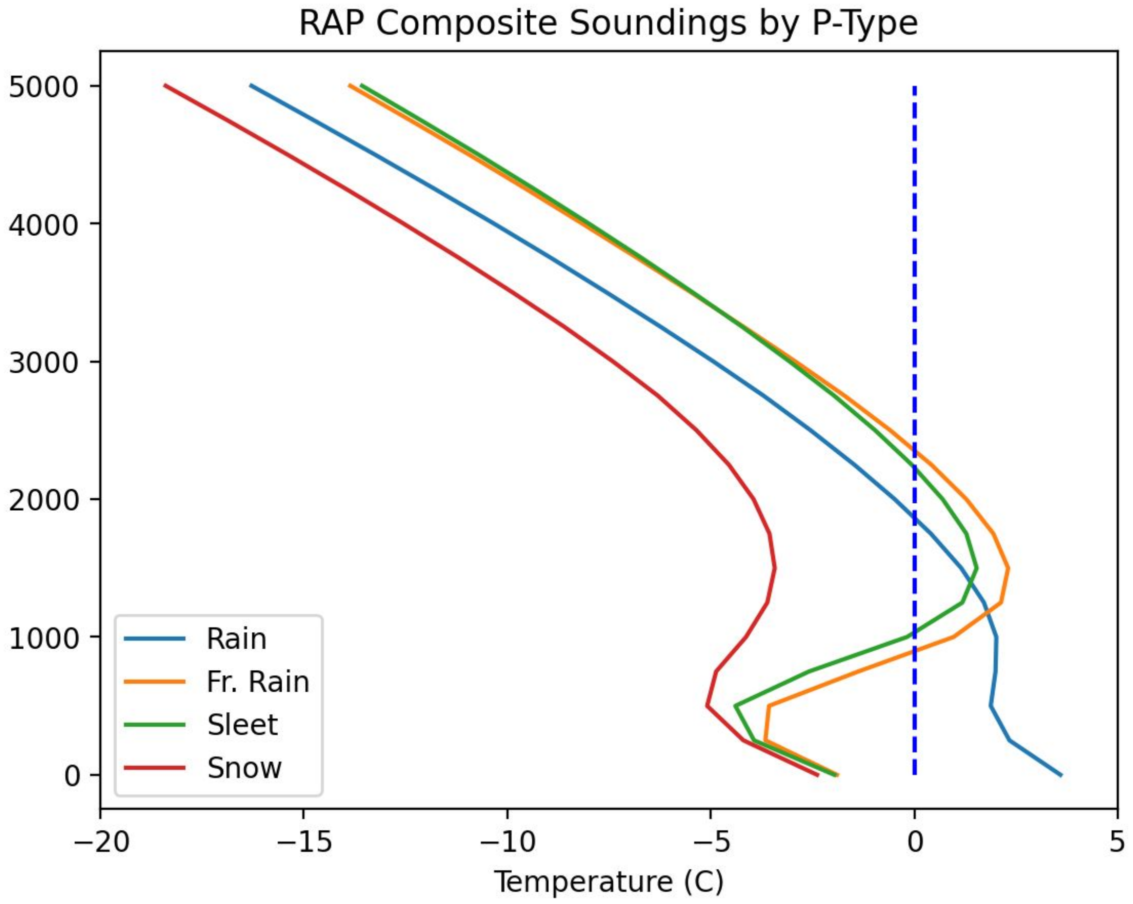
Filter by temperature range and observed or predicted label for each p-type.

Ideally should see average soundings that correspond to classic profile for each p-type.



Composite Soundings

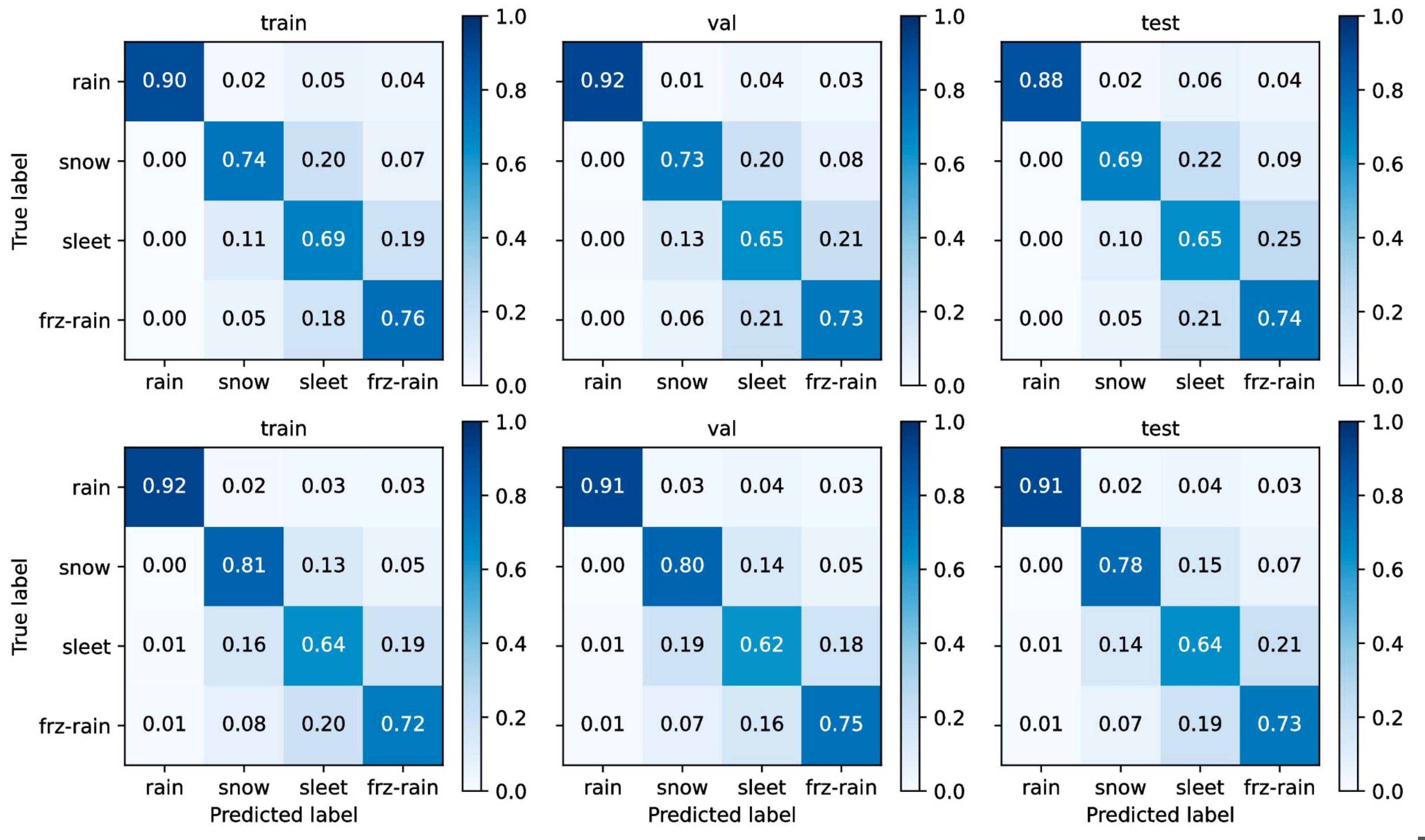




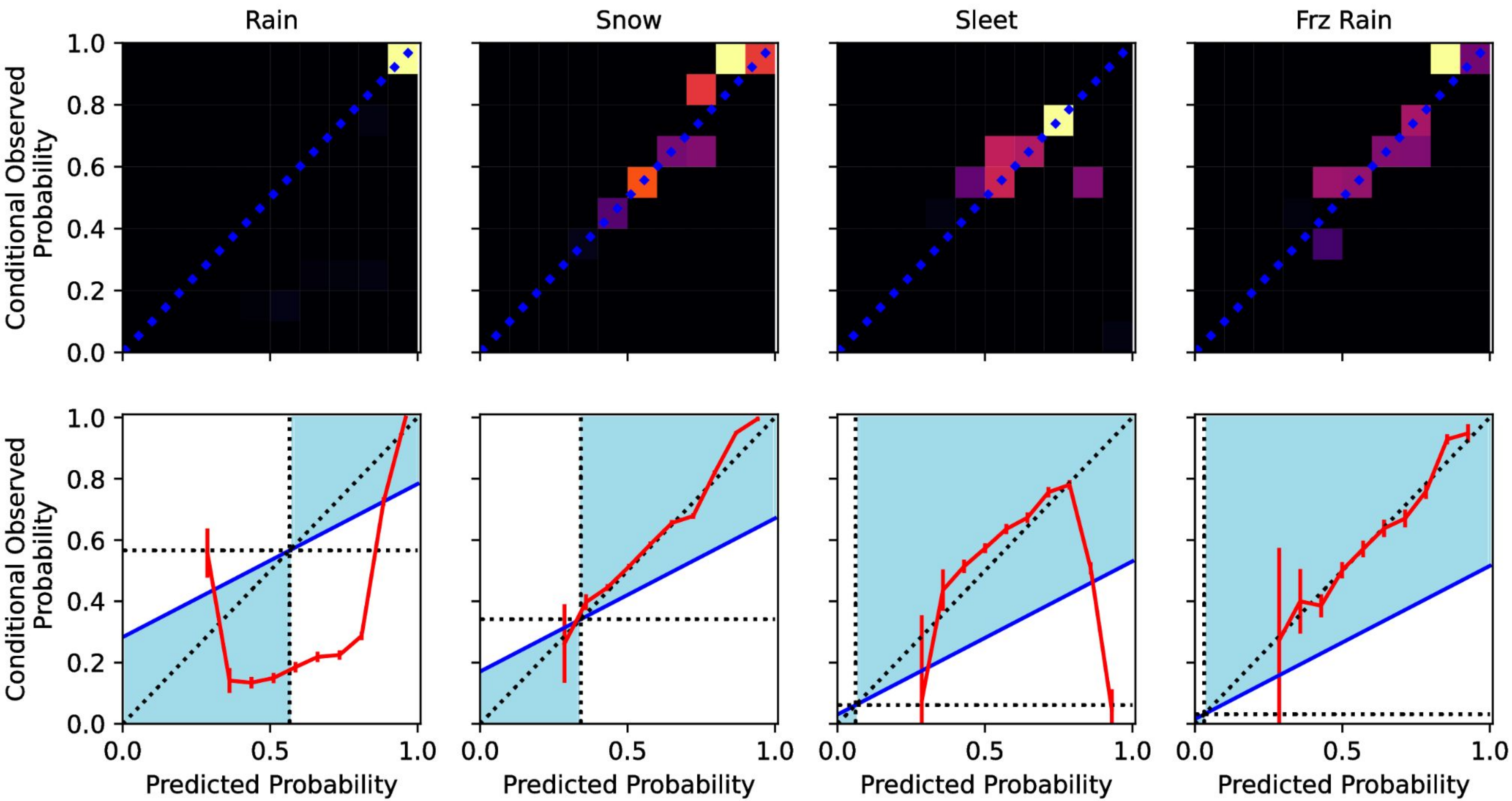
QC Data + weighted / upsampled

Cross-entropy loss

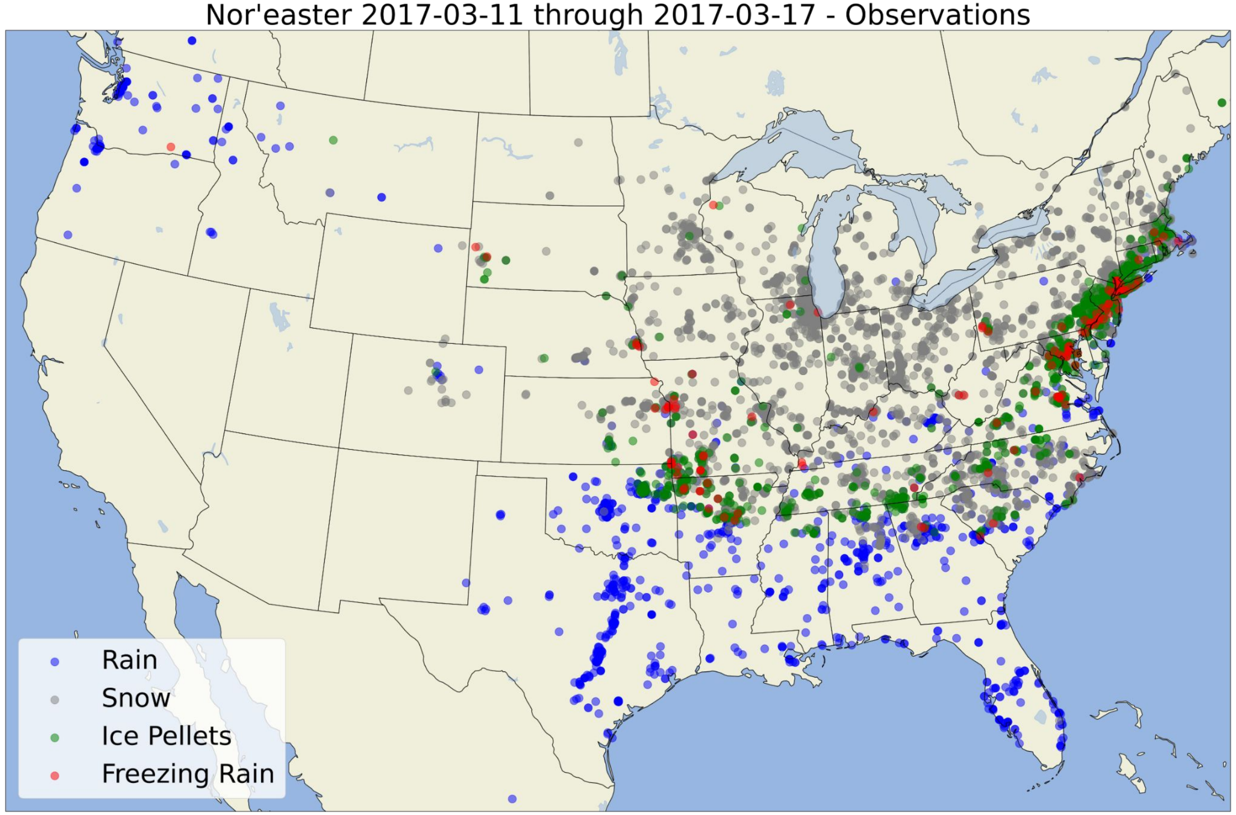
Evidential

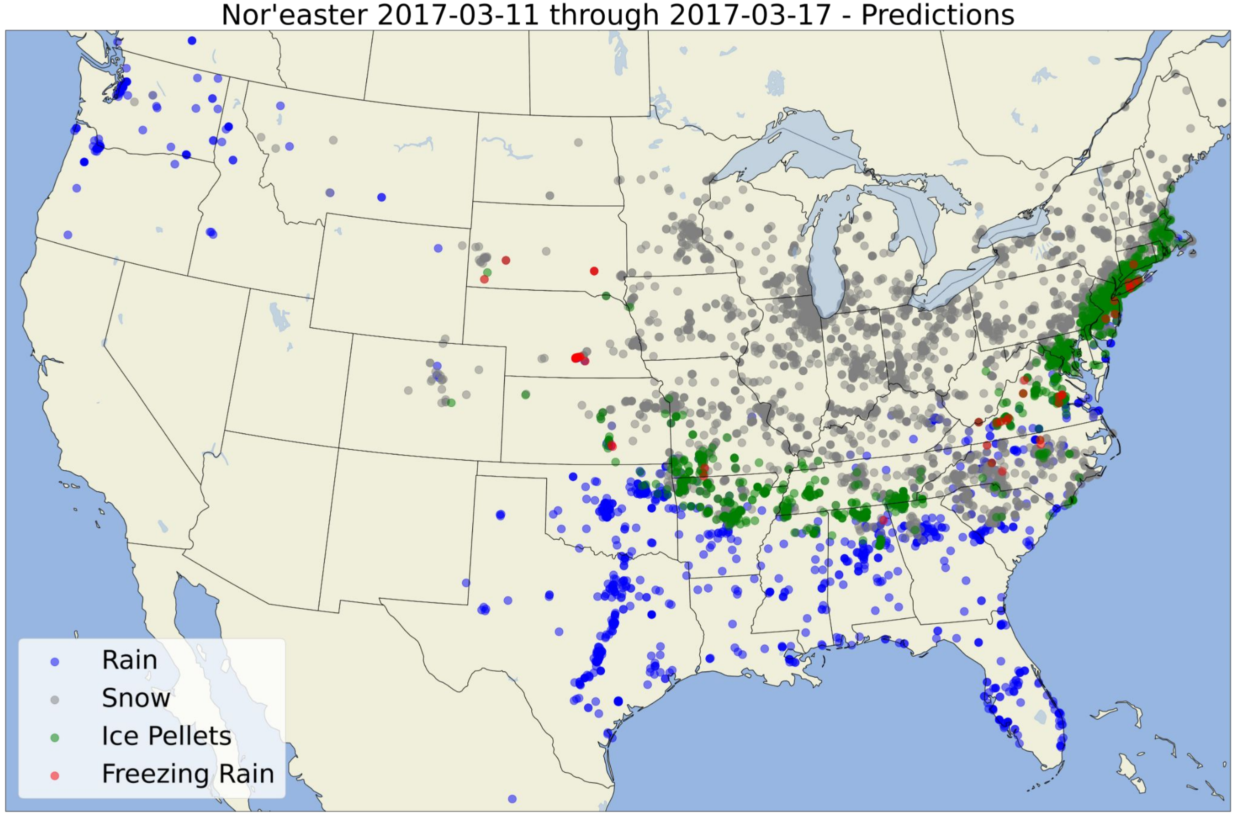


Calibration



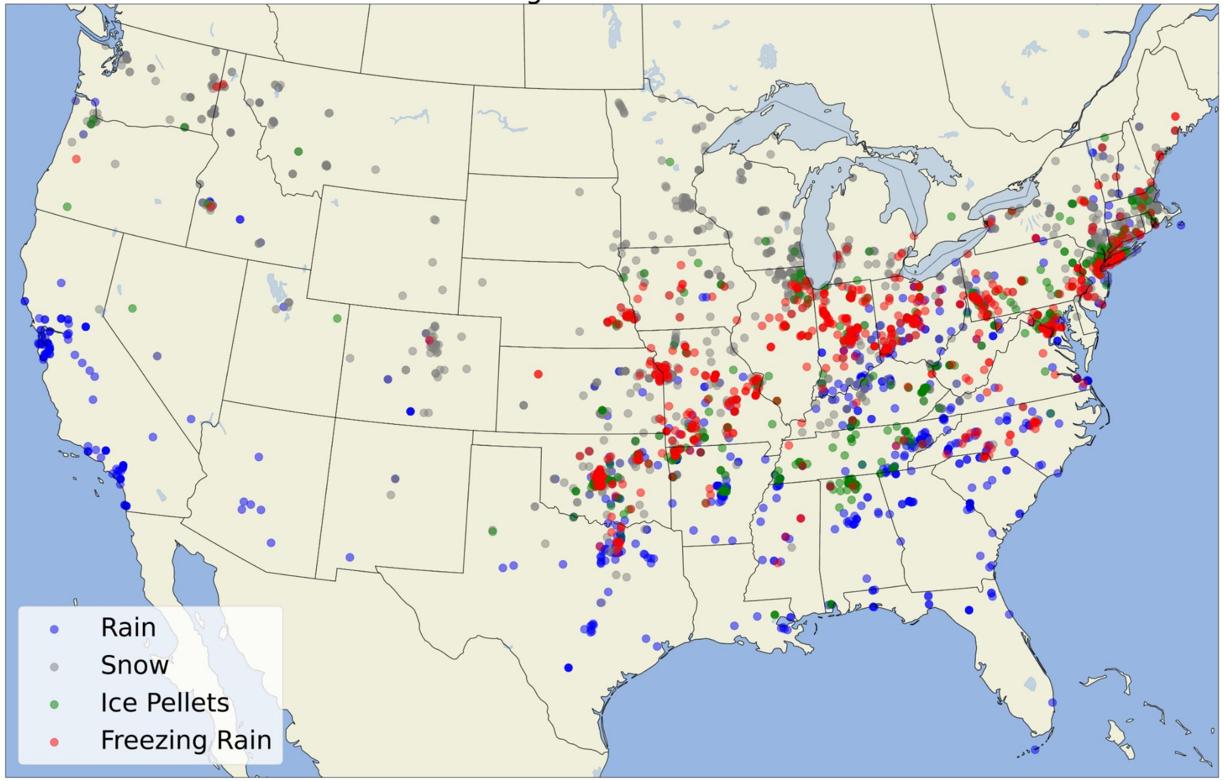
Case Study: Nor’Easter March 2017



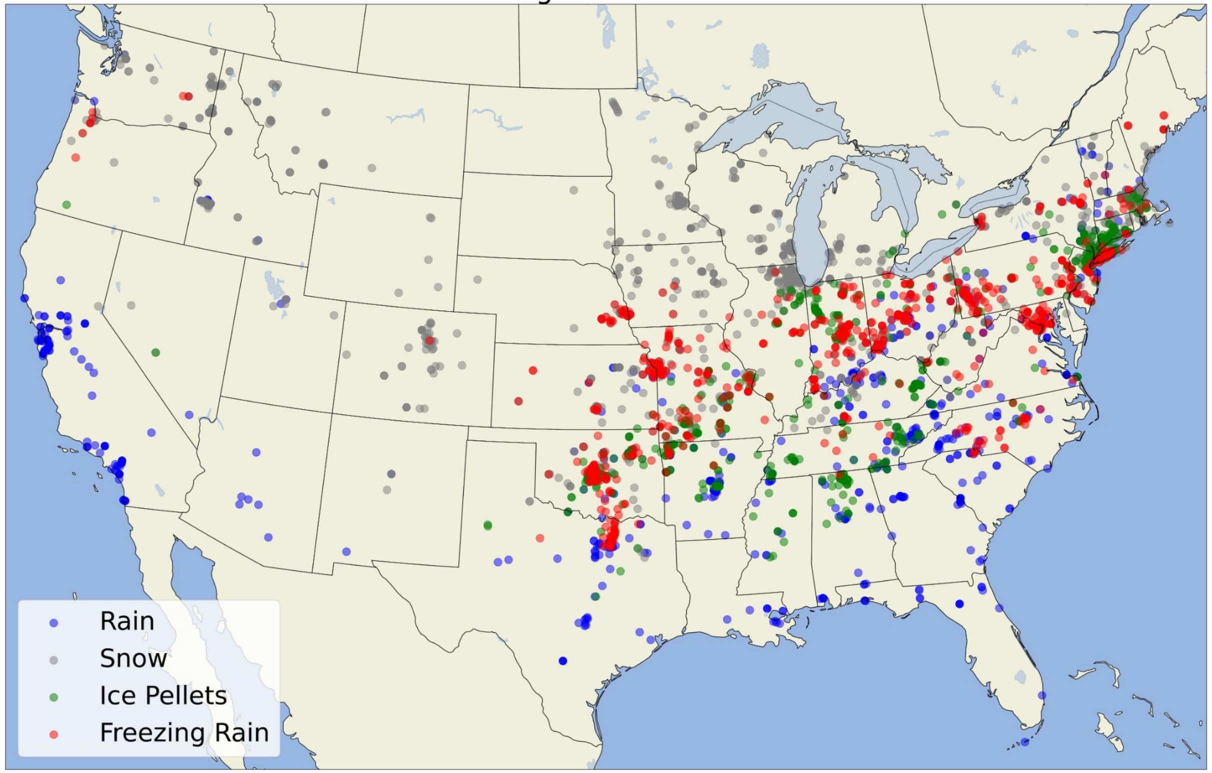


Case Study: Freezing Rain Event: December 2017

2016-12-15 through 2016-12-20 - Observations



2016-12-15 through 2016-12-20 - Predictions



Uncertainty in Machine Learning

Users want to know **when** and **why** machine learning predictions are uncertain.

Goals

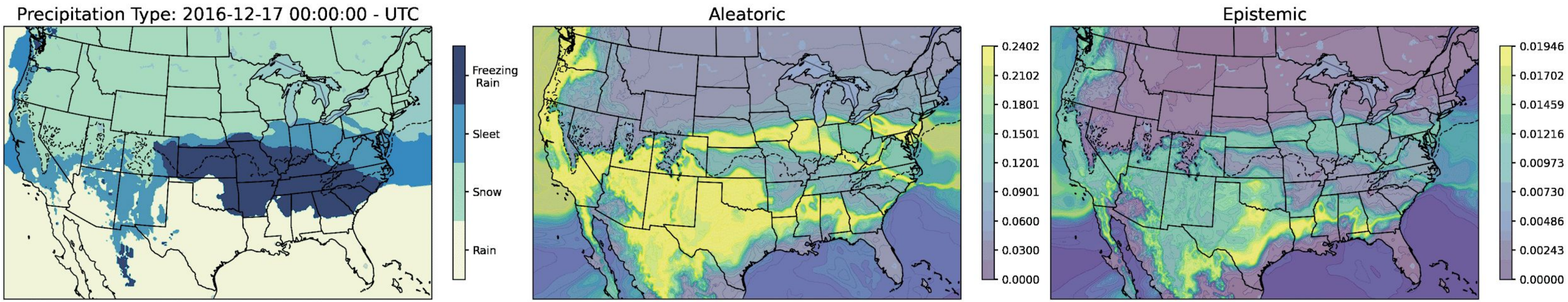
1. Develop a ML p-type algorithm that incorporates robust predictive uncertainty estimates
2. Experiment with forecasters and other decision makers to understand what form of p-type and uncertainty information helps with trustworthiness and decision making

Ways to characterize uncertainty

1. Predict the parameters of parametric distributions
2. Generate samples from a stochastic model or ensembles (Monte Carlo Dropout, Deep Ensembles)
3. Bayesian approaches such as Bayesian Neural Networks, **Evidential Networks**

Image: iStock image edited by MIT News

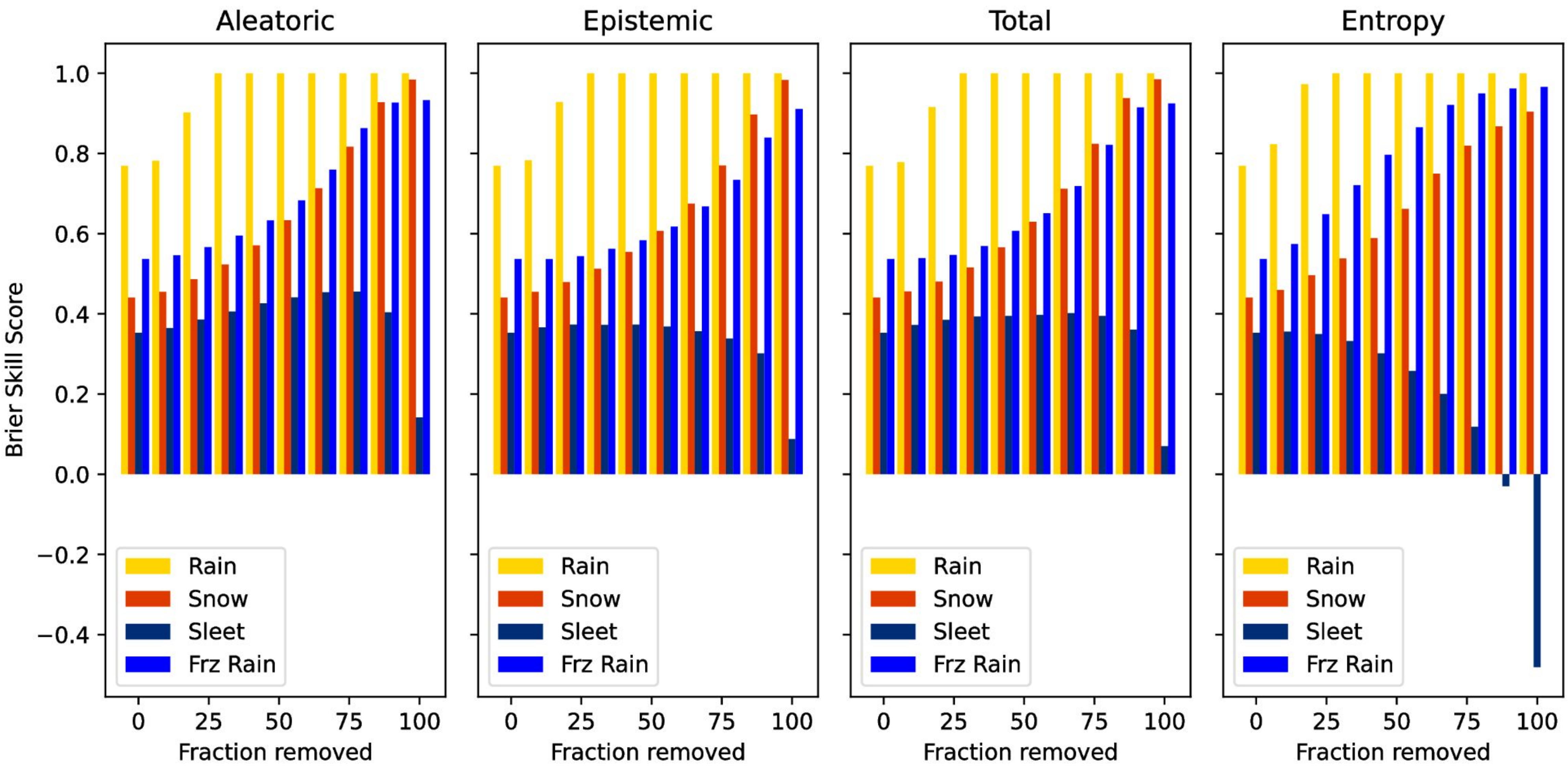
Case Study: Freezing Rain Event December 2016



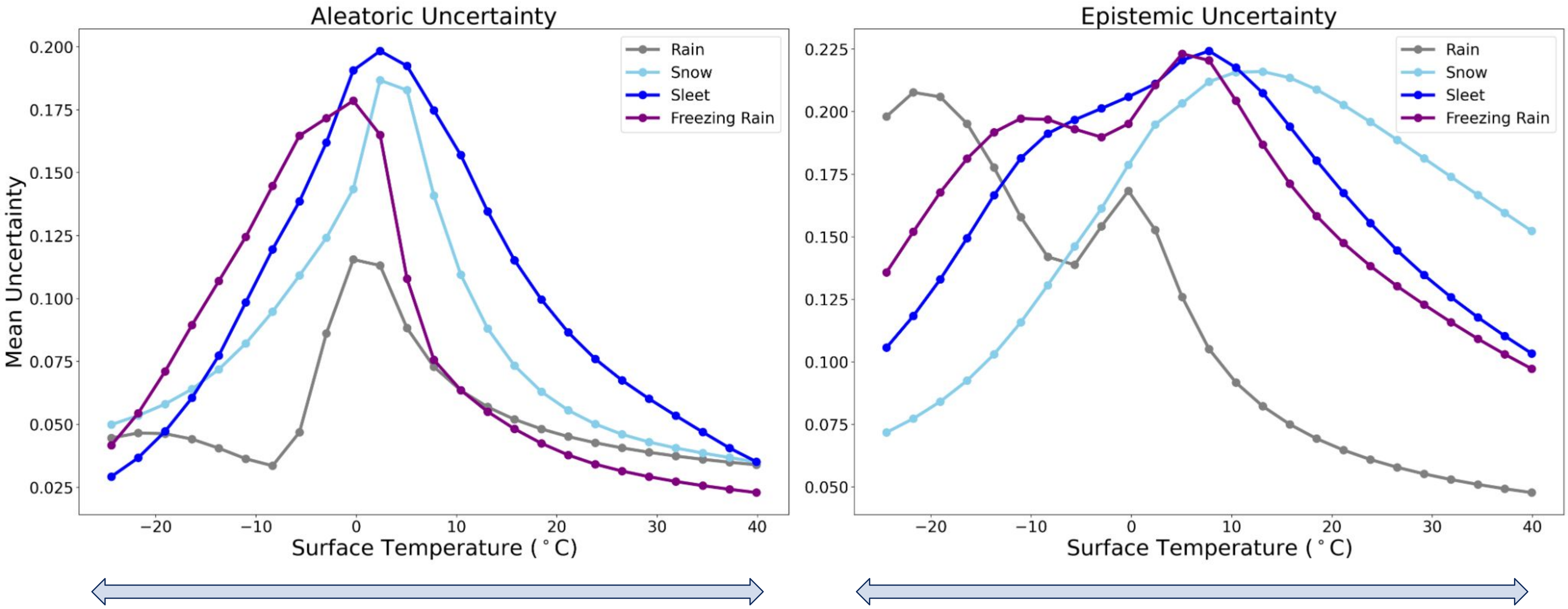
Aleatoric uncertainty high over broad precipitation transition region.

Epistemic uncertainty highest along strong temperature gradients.

Discard Test



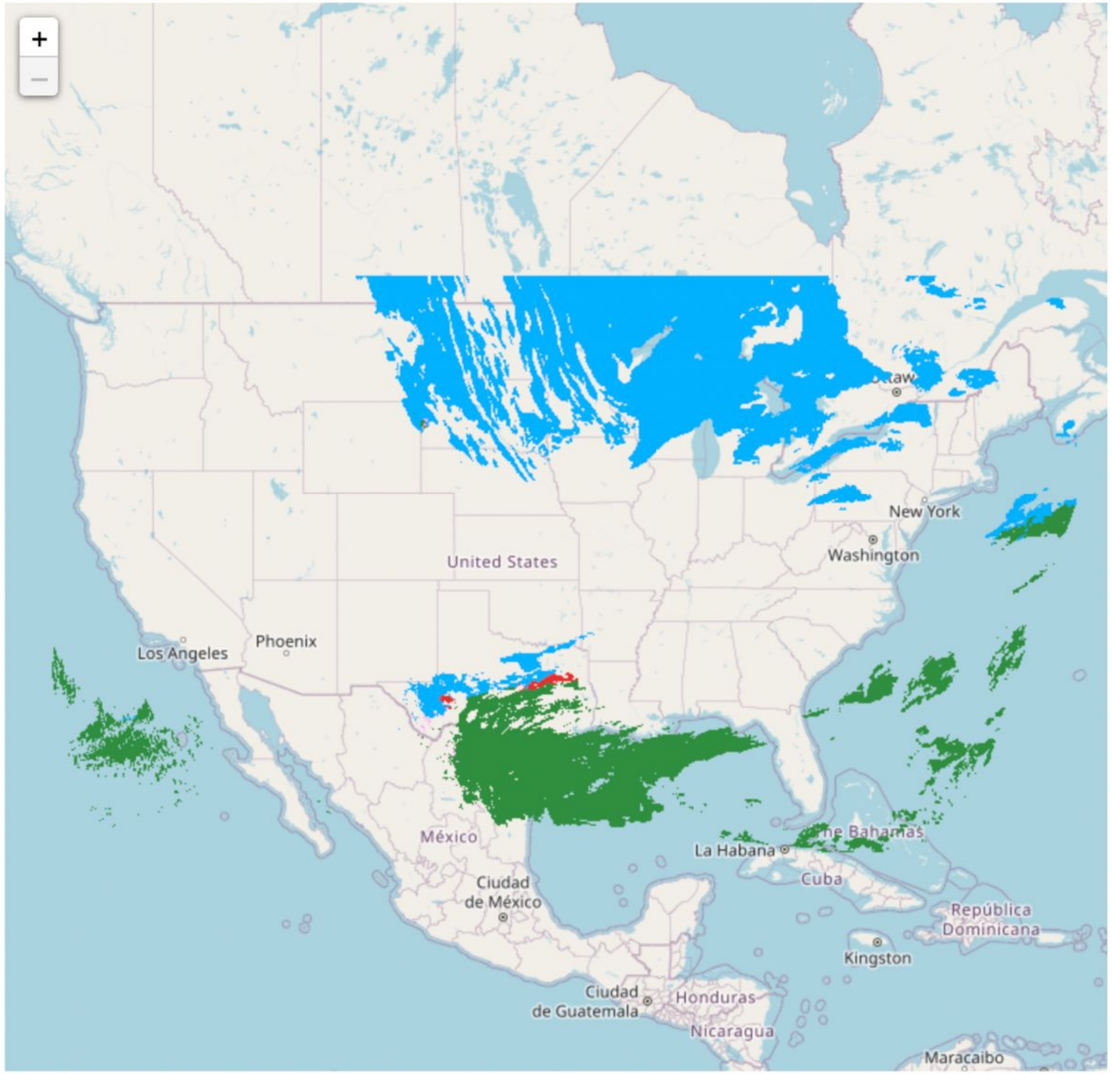
Classification XAI: Partial Dependence of Uncertainties

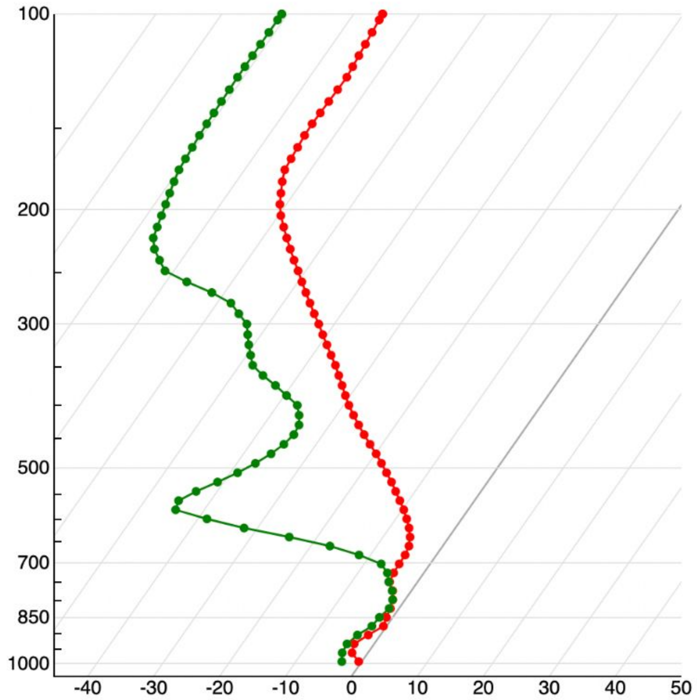


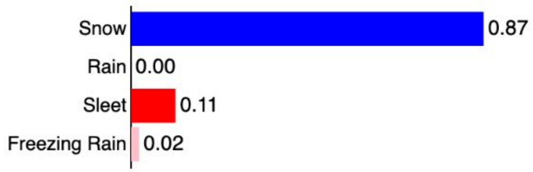
All five levels perturbed from their ***respective*** minimums / maximums to make a more realistic vertical profile.

Interactive Visualization

CNN P-type RAP P-type







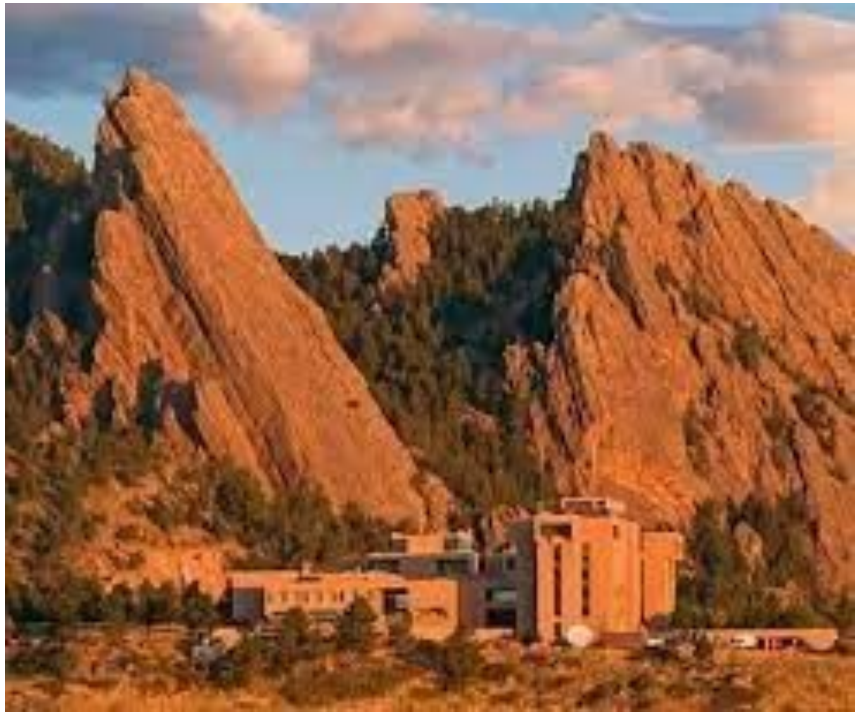
Summary and Future Work

- Uncommon precipitation types such as freezing rain and sleet are challenging to get right!
- The upper limit of model performance is unknown due to many sources of biases.
- XAI and further sensitivity analysis are needed to better understand model performance, confidence and types of uncertainty.
- We are collaborating with Vaisala this summer to do analysis with our models to see if it can improve their road condition algorithms.

Thank you!

How can the community at large help?

More Observations!



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