Evidential Deep Learning for Enhanced Winter Precipitation Prediction and Decision-Making

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Motivation

Winter precipitation hazards, such as rain, snow, freezing rain, and sleet, significantly impact human safety and transportation.

Objectives

- Enhance model accuracy and reliability through hyperparameter optimization and quality control of training data.
- Analyze model performance against Numerical Weather Prediction models and investigate failure modes
- Develop visual representations of model results to ensure transparency and reliability for forecasters.

Model Framework

The Precipitation Type (P-Type) Model is similar to a simple dense neural network with a custom evidential loss function.

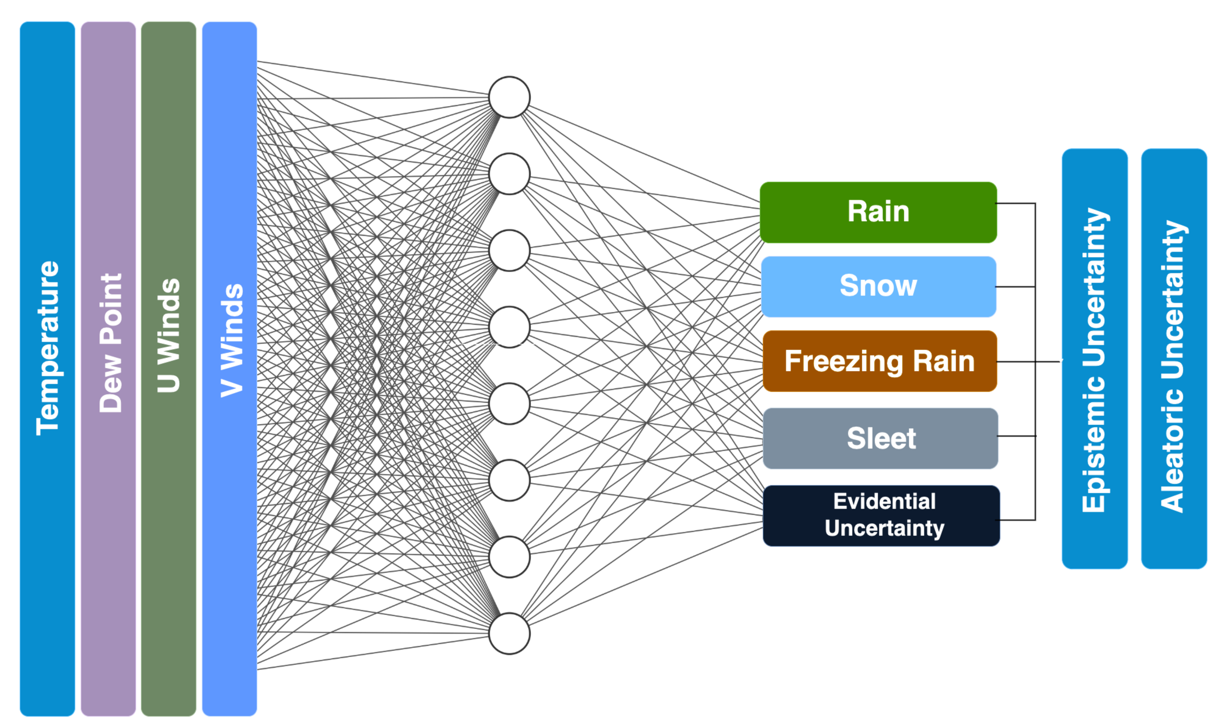

Figure 1: Architecture of P-type Model

Model inputs: Rapid Refresh (RAP) temperature, dew point, u and v wind at 21 heights levels from 0 to 5km
Model outputs: Probabilities of rain, snow, sleet, and freezing rain, including an uncertainty class, which represents epistemic (evidential) uncertainty. Epistemic and aleatoric uncertainties are computed from the probability outputs.
Target: mPING crowd-sourced weather reports

Acknowledgement

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Quality Control

- Locate closest grid cell to mPING coordinate
- **Snow**: surface wet-bulb temp < 3°C
- **Rain**: surface wet-bulb temp > -1°C
- **Freezing Rain & Sleet**: wet-bulb temp < 0°C and at least 1 temperature crossing from -2 to 1°C

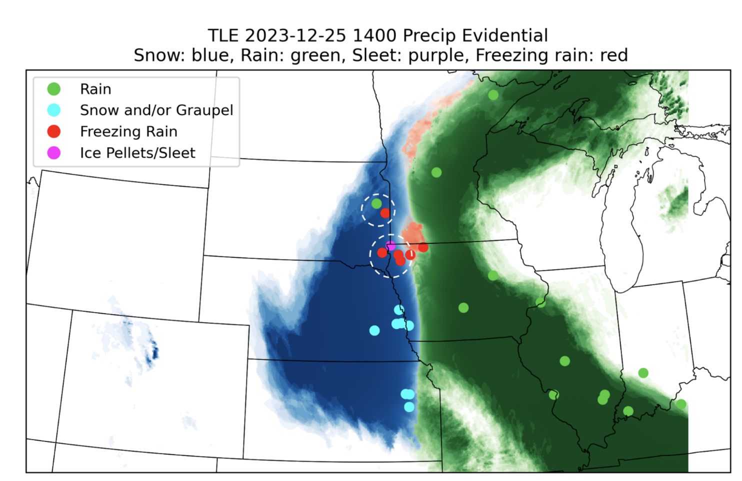

Figure 2: mPING before QC

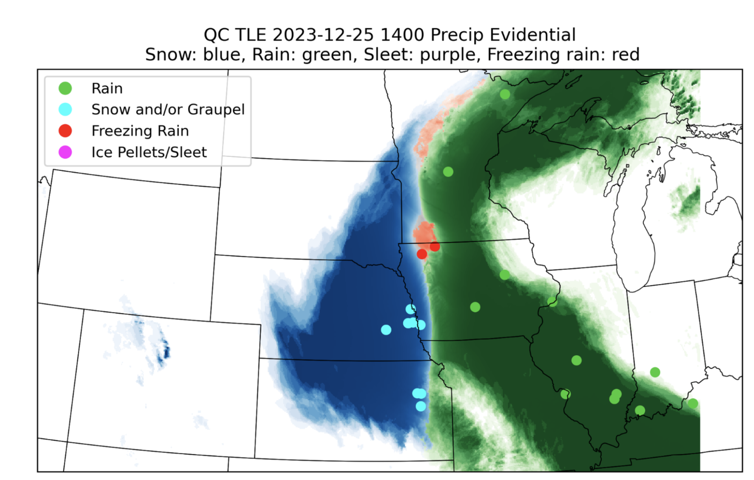

Figure 3: mPING after QC

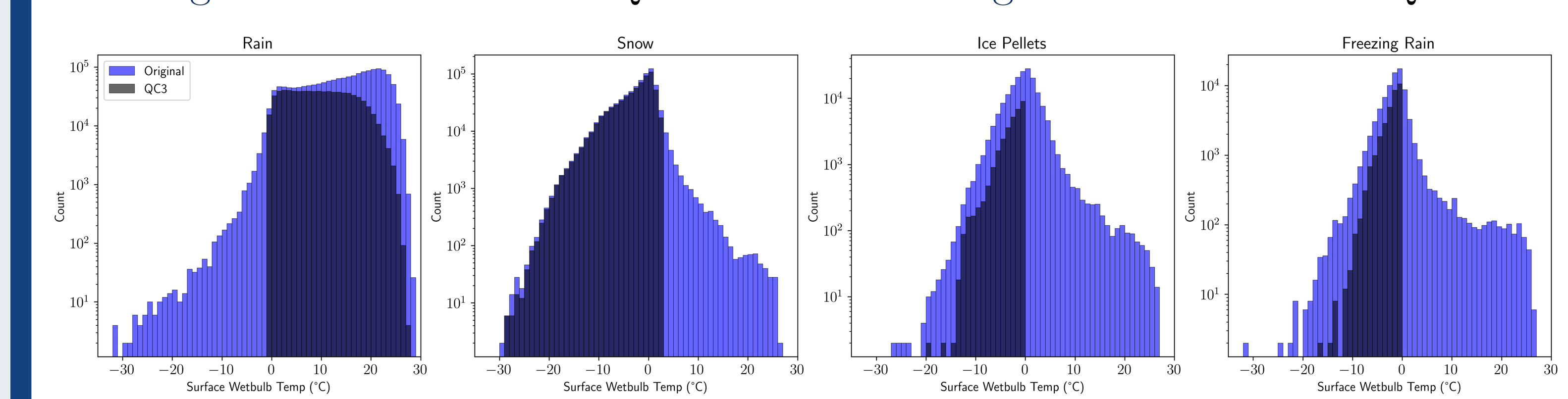

Figure 4: Wetbulb temp distribution pre and post qc

Hyperparameter Optimization

Earth Computing Hyperparameter Optimization **(ECHO)** aims to algorithmically fine-tune model parameters.

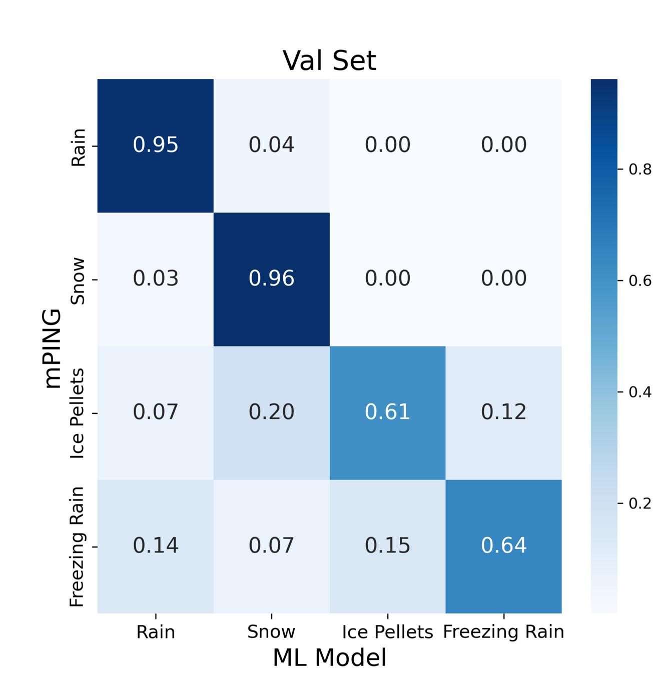

Figure 5: Confusion Matrix Norm=true

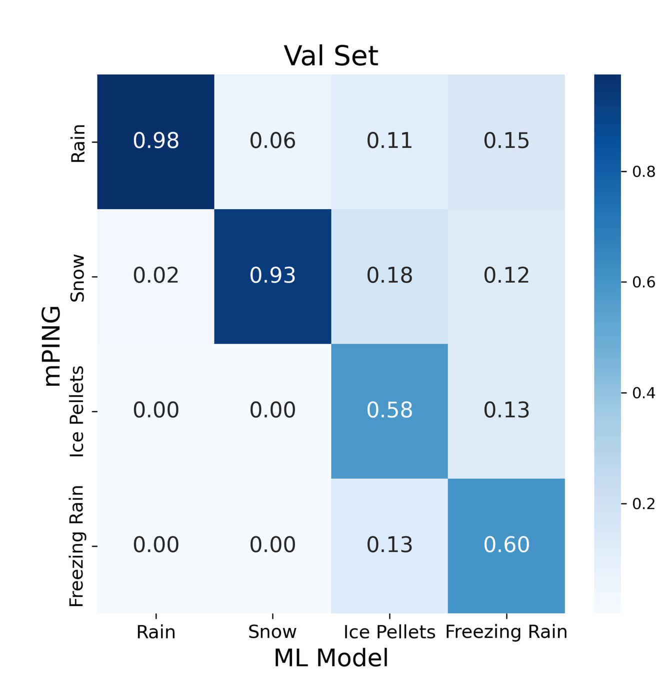

Figure 6: Confusion Matrix Norm=pred

- **Normalize by truth**: Represents the probability of detection for each class. **Normalize by prediction**: Represents the success ratio for each class.
- **Metric**: Average Validation Accuracy

Analysis

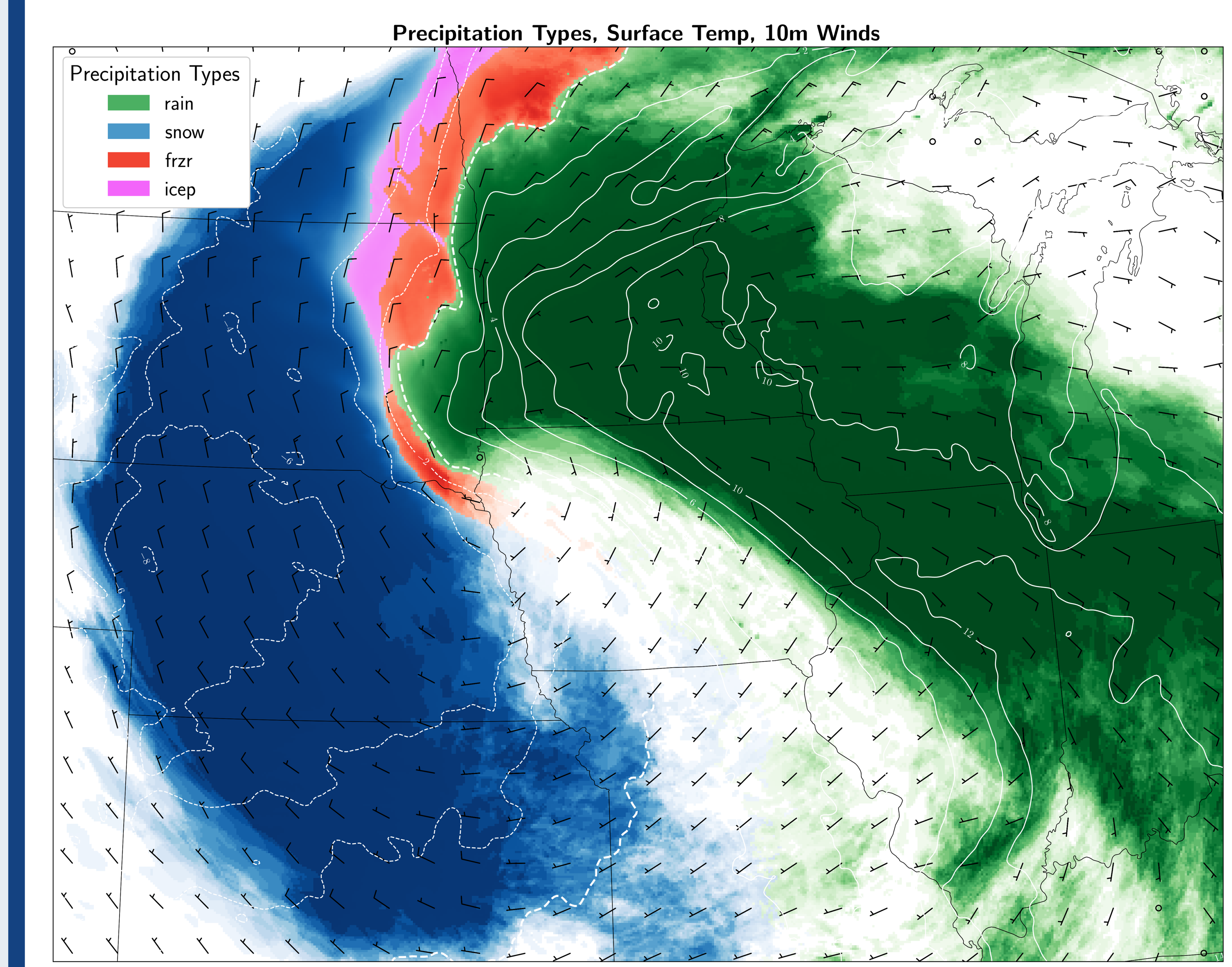

Figure 7: P-Type model output with overlayed HRRR features

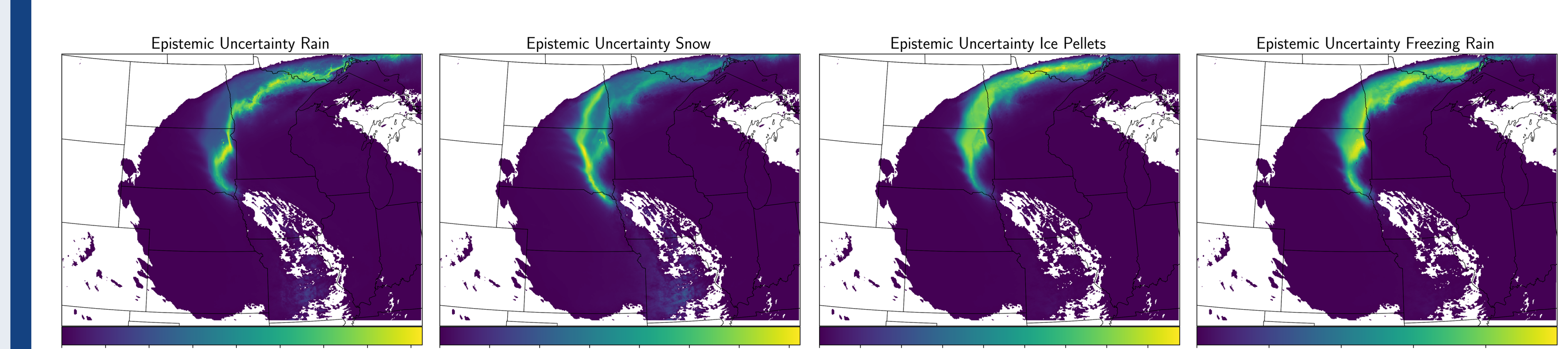

Figure 8: Epistemic uncertainty outputs

Figure 6 shows a case study with categorical precipitation types scaled by probability, including High Resolution Rapid Refresh (HRRR) inputs such as winds and surface temp. Both plots show how the P-Type model uses inputs in its prediction and builds trust by providing insights into the confidence and reliability of the model's predictions.

Conclusion

- Quality control procedures combined with ECHO optimization improves model performance
- P-Type model performs well with rain and snow and under-performs with sleet and freezing rain
- Case studies show evidence of model performance and help forecasters understand the basis for its predictions.