XAI and Active Learning for Predicting Winter Weather Precipitation Type

Eliot Kim

NCAR SIParCS and AIML Intern

University of Wisconsin-Madison

Mentors: John Schreck and David John Gagne II

July 26th, 2022

This material is based upon work supported by the National Center for Atmospheric Research, which is a major facility sponsored by the National Science Foundation under Cooperative Agreement No. 1852977.

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Introduction and Motivation

Task

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

Objective 1

Difficult to interpret “black -box” deep learning models → Explore **Explainable AI (XAI)** to…

- verify physical consistency of predictions
- motivate further research
- facilitate stakeholder communication

Objective 2

Difficult to predict ice and freezing rain due to biased observations and imbalanced data → **Evidential Active Learning** to…

- Increase data efficiency
- Improve performance for difficult labels

Figure 1: Aftermath of Tennessee ice storm, February 2022

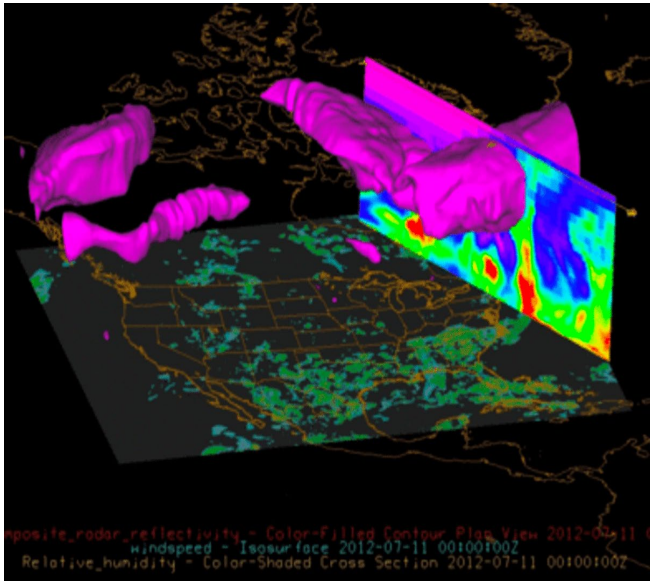


Figure 2: 3D visualization of RAP wind velocity, relative humidity, and reflectivity variables

Data Sources: Outputs

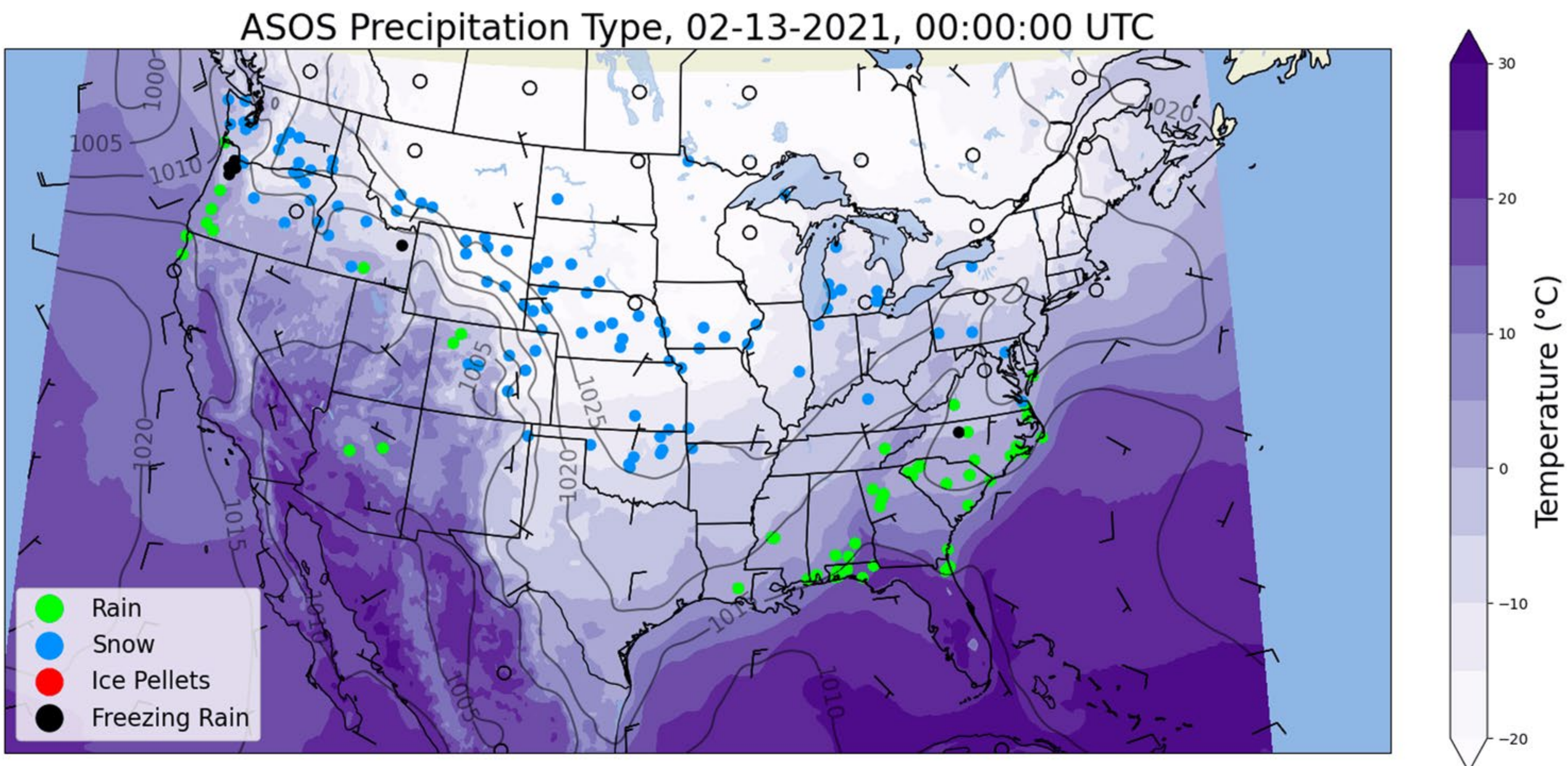


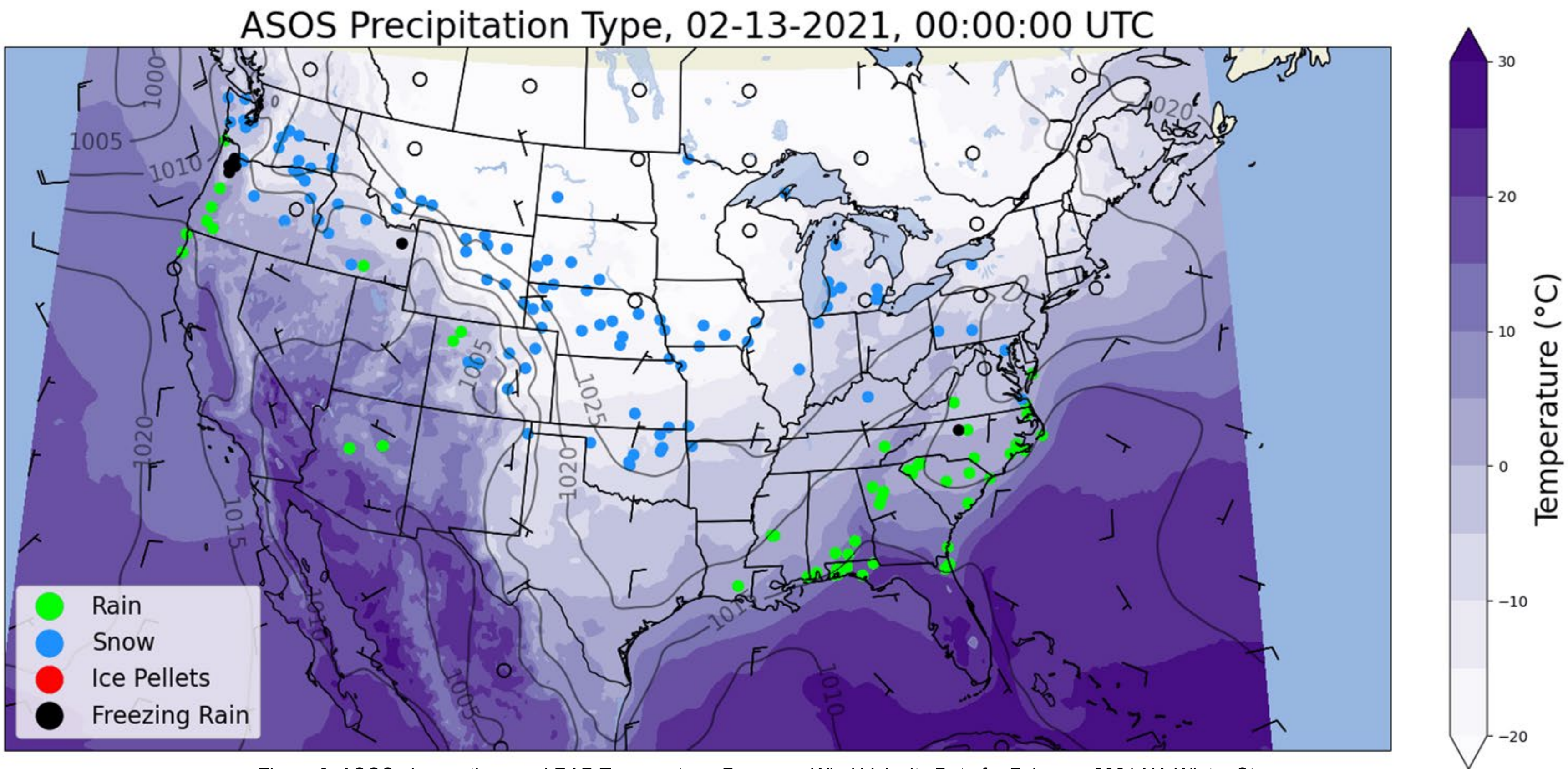
Figure 3: ASOS observations and RAP Temperature, Pressure, Wind Velocity Data for February 2021 NA Winter Storm

OUTPUT DATA

ASOS: 852 fixed automated p-type monitors → **Only 15% report ice**

mPING: Crowd-sourced p-type observation → **Under-reports freezing rain**

Data Sources: Outputs



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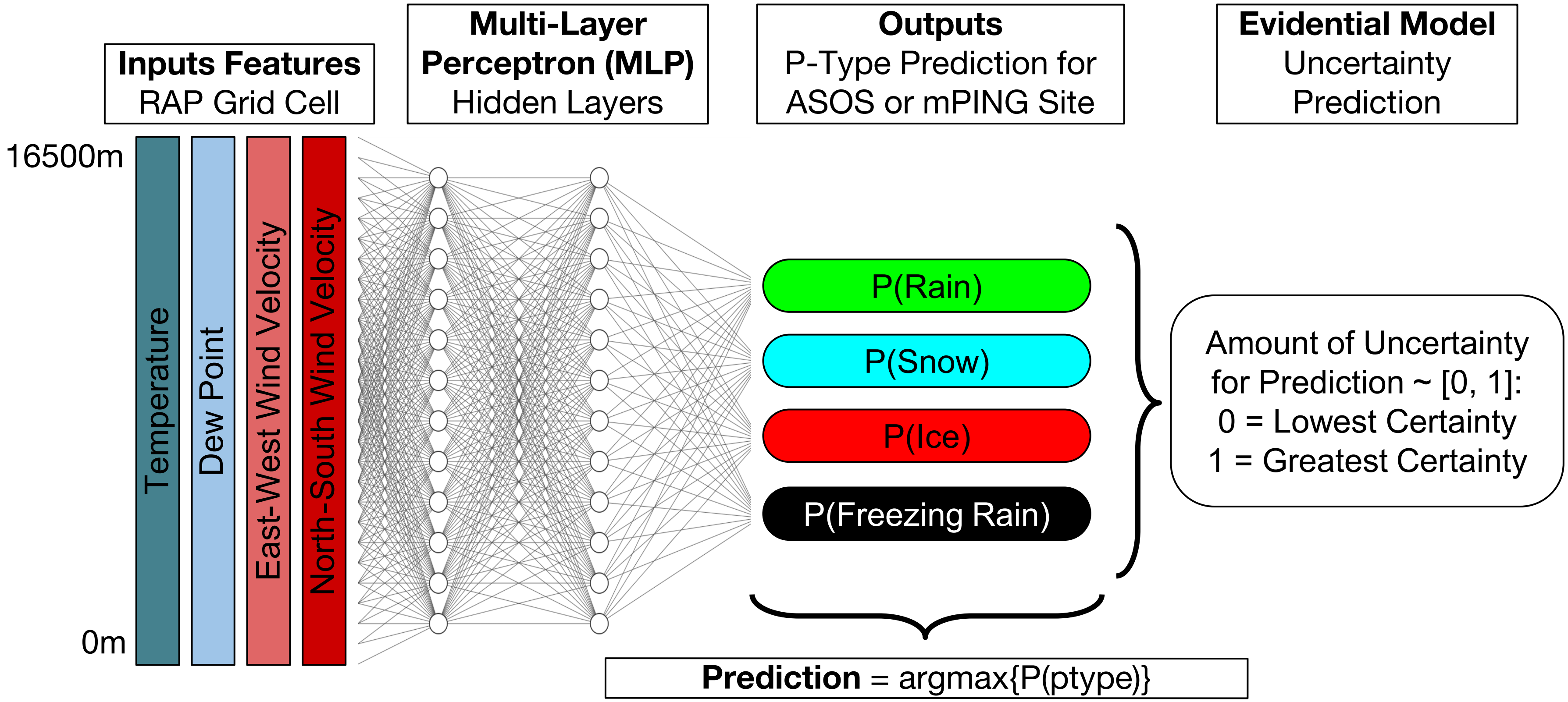
INPUT DATA

RAP (Rapid Refresh): Numerical weather model by NCEP (National Centers for Environmental Prediction) → grid cell over each p-type obs. → Temperature, Dewpoint, Wind Velocity from 0m to 16500m in atmosphere

Neural Networks: Overview



Model	Loss Function	Hidden Layers	Nodes per Layer	mPING Test Accuracies			
				Rain	Snow	Ice	FzRain
Simple MLP	Cross Entropy	1	100	94%	92%	41%	28%
ECHO-Optimized MLP (ECHOMLP)	Cross Entropy	12	105	88%	75%	65%	59%
Simple Evidential MLP (EvidMLP)	Evidential Digamma	1	100	94%	90%	17%	6%

Explainable AI (XAI): Introduction

Which input features are important for accurately predicting p -type?

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→ **Permutation Importance**

- Calculate change in prediction accuracy from original model after randomly shuffling each input feature one-by-one
- Conducted on **mPING Simple MLP**

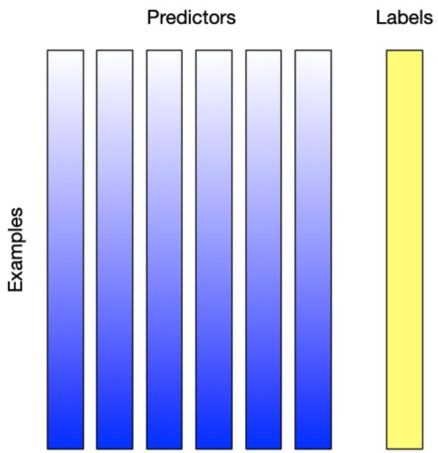

Figure 4: Illustration of Backwards Pass Permutation Importance

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How does the neural network use input features to compute p-type predictions?

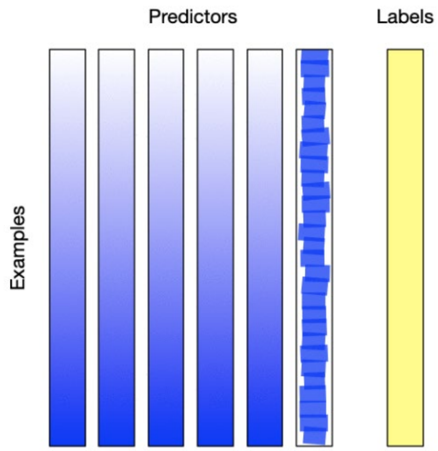

Figure 4: Illustration of Backwards Pass Permutation Importance


Figure 5: SHAP Example for Image Classification. Red = Positive Contribution, Blue = Negative Contribution.

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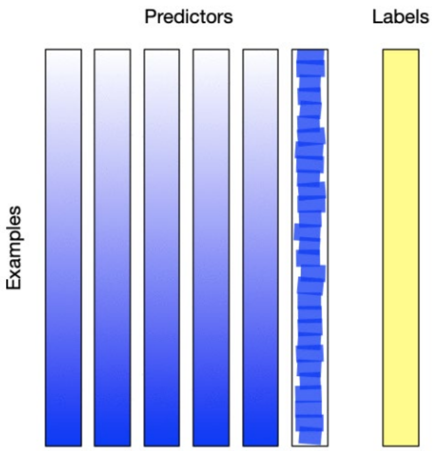


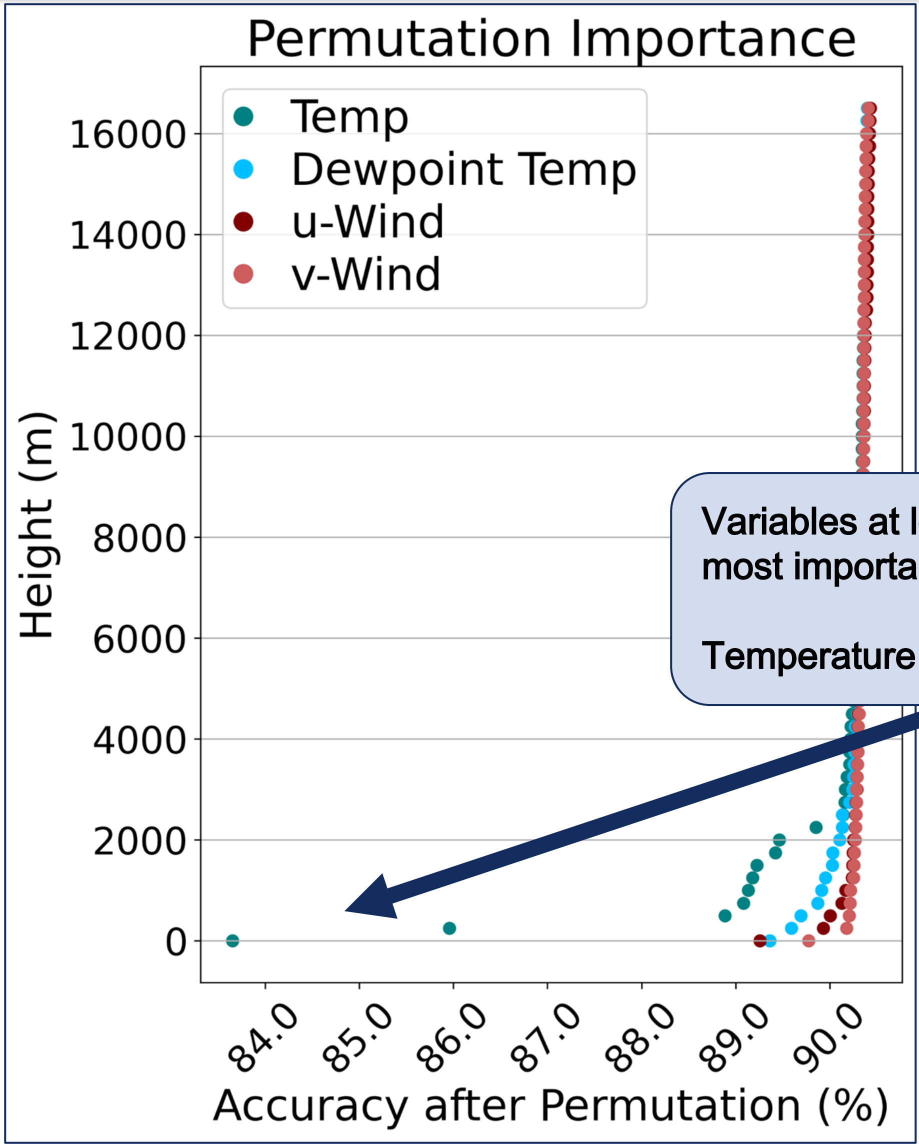
Figure 4: Illustration of Backwards Pass Permutation Importance

How does the neural network use input features to compute p-type predictions?
→ **SHAP (SHapley Additive exPlanations)**

- Computes contribution of each feature towards each model prediction
- More detailed interpretation of model than Permutation Importance
- Conducted on mPING **Simple MLP**, mPING **ECHOMLP**, and ASOS and mPING **Simple EvidMLP**

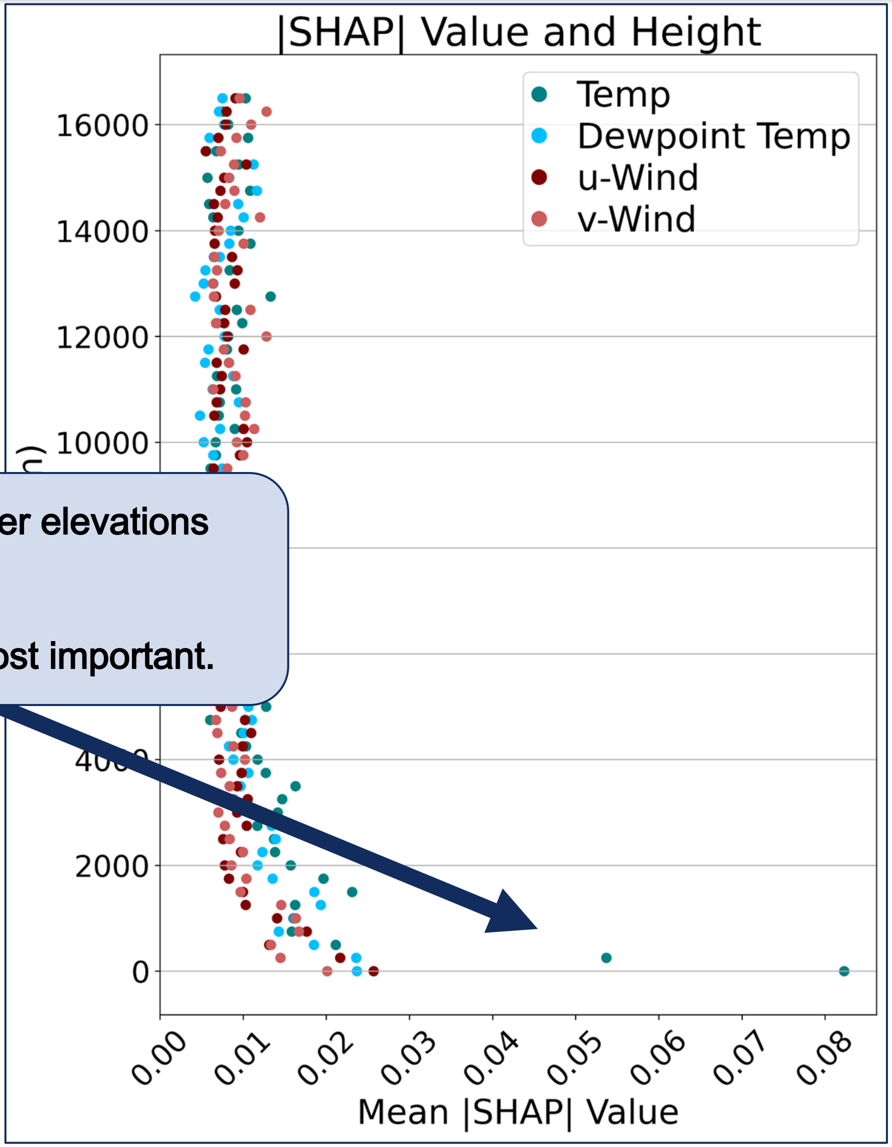
Figure 5: SHAP Example for Image Classification. Red = Positive Contribution, Blue = Negative Contribution.

XAI Results | mPING Simple MLP

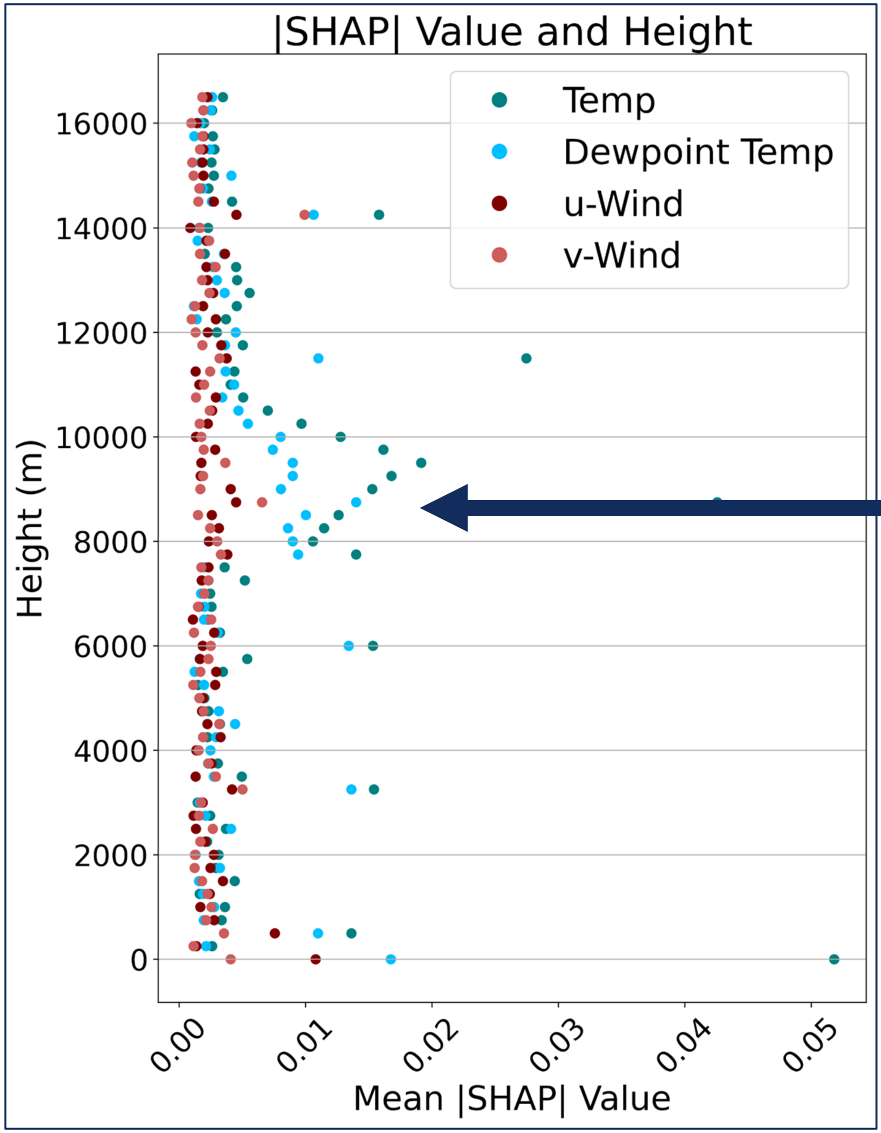


Variables at lower elevations most important.

Temperature most important.

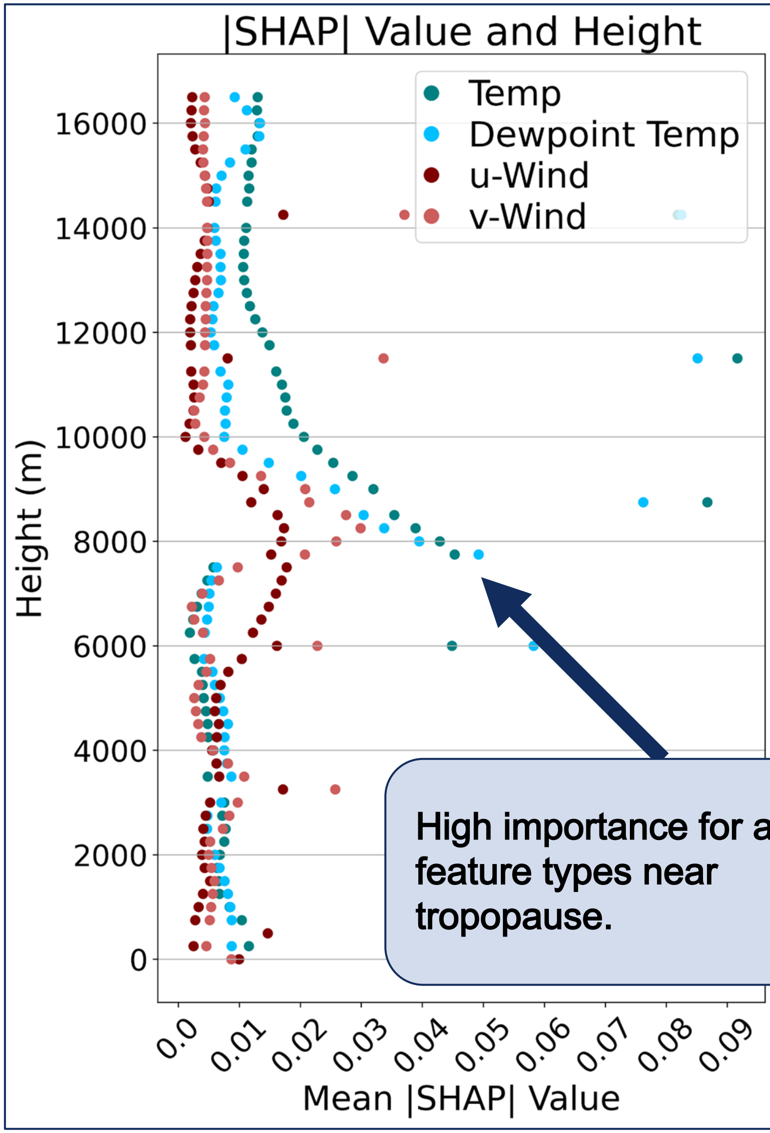


XAI: SHAP Results | mPING ECHO -Optimized MLP

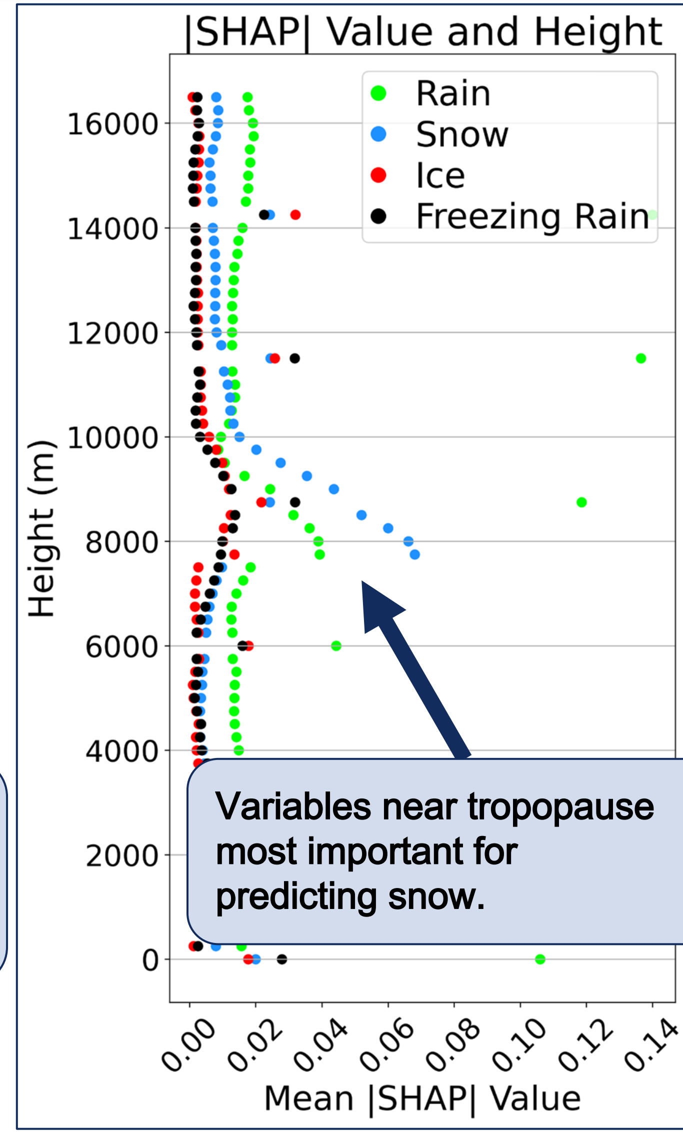


High importance for Temperature and Dewpoint near tropopause.

XAI: SHAP Results | mPING Evidential MLP | P -Type



High importance for all feature types near tropopause.



Variables near tropopause most important for predicting snow.

XAI: Conclusions

Conclusions

- Simple MLP learned high importance near surface
- Complex ECHOMLP and simple EvidMLP learned high importance near surface and near tropopause

Future Work

- Conduct SHAP analysis for ECHO-optimized EvidMLP
- Investigate important variables near tropopause
- XAI methods for clusters of highly correlated variables

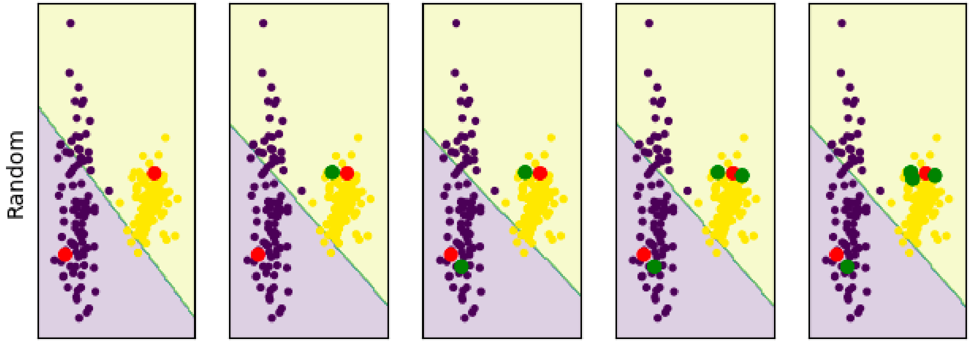
Significance

Neural networks learn physical patterns in atmospheric data
→ Enables intuitive understanding of complex models by stakeholders

Next Section: Active Learning

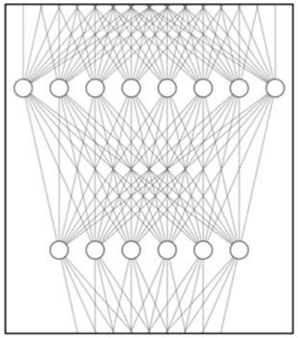
Active Learning: Motivation

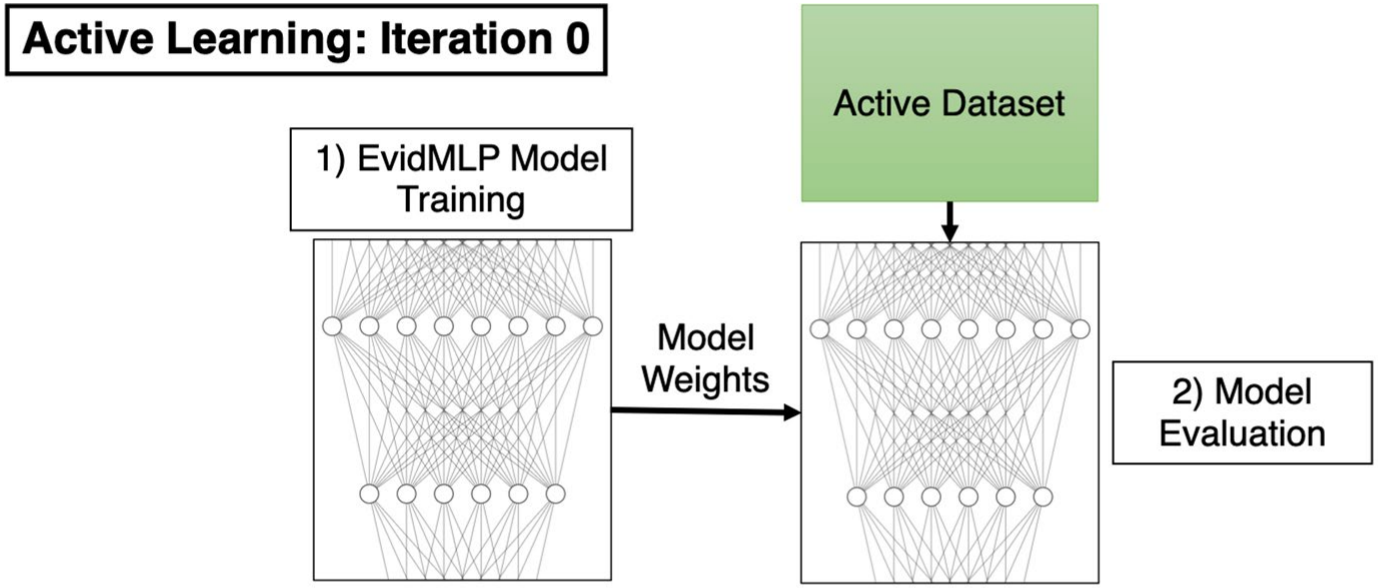
Regular Training: Sample Inefficient



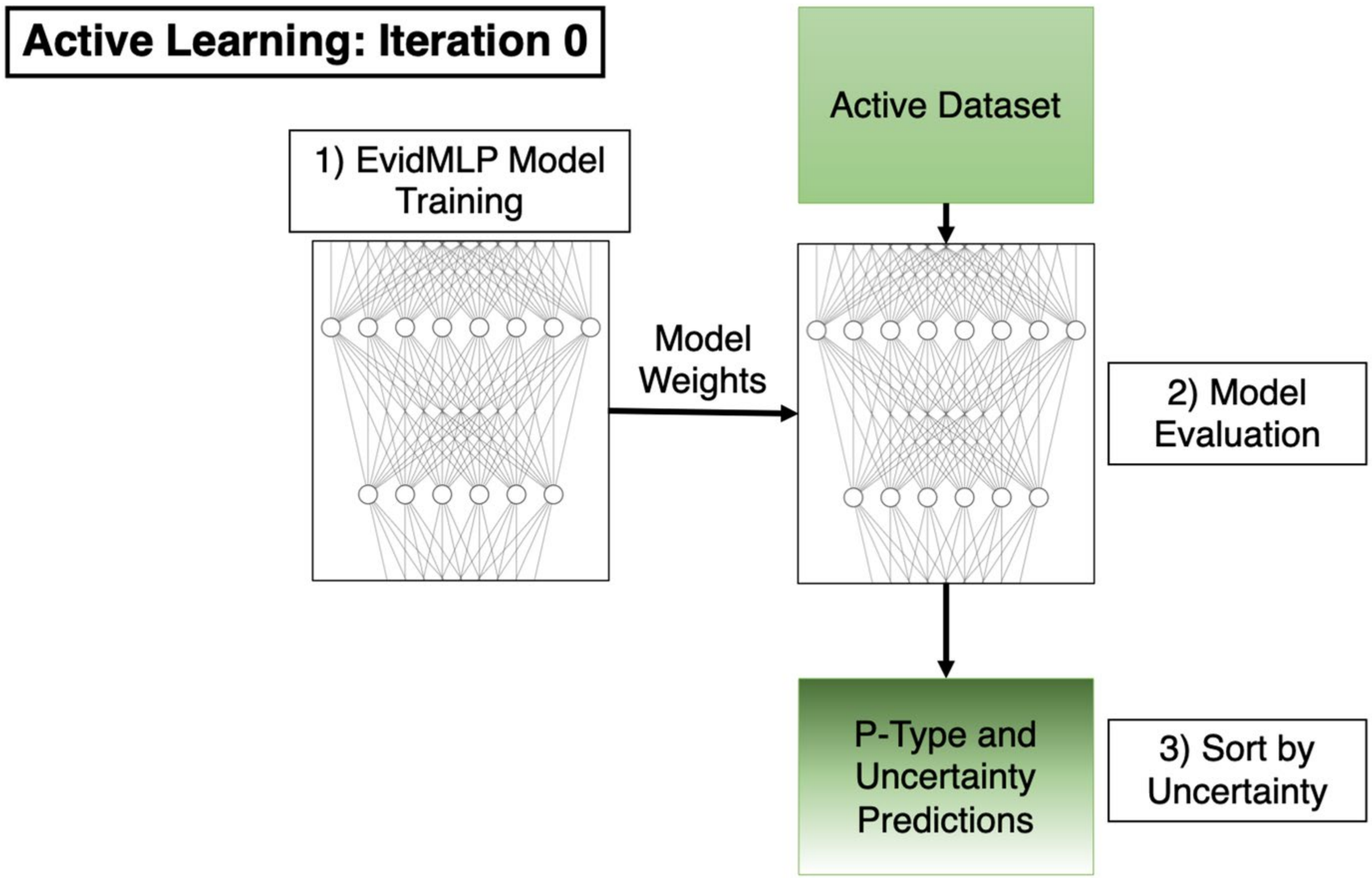
Active Learning: Iteration 0

1) EvidMLP Model Training




Active Learning: Iteration 0
Active Dataset
1) EvidMLP Model Training
Model Weights
2) Model Evaluation

Active Learning: Method



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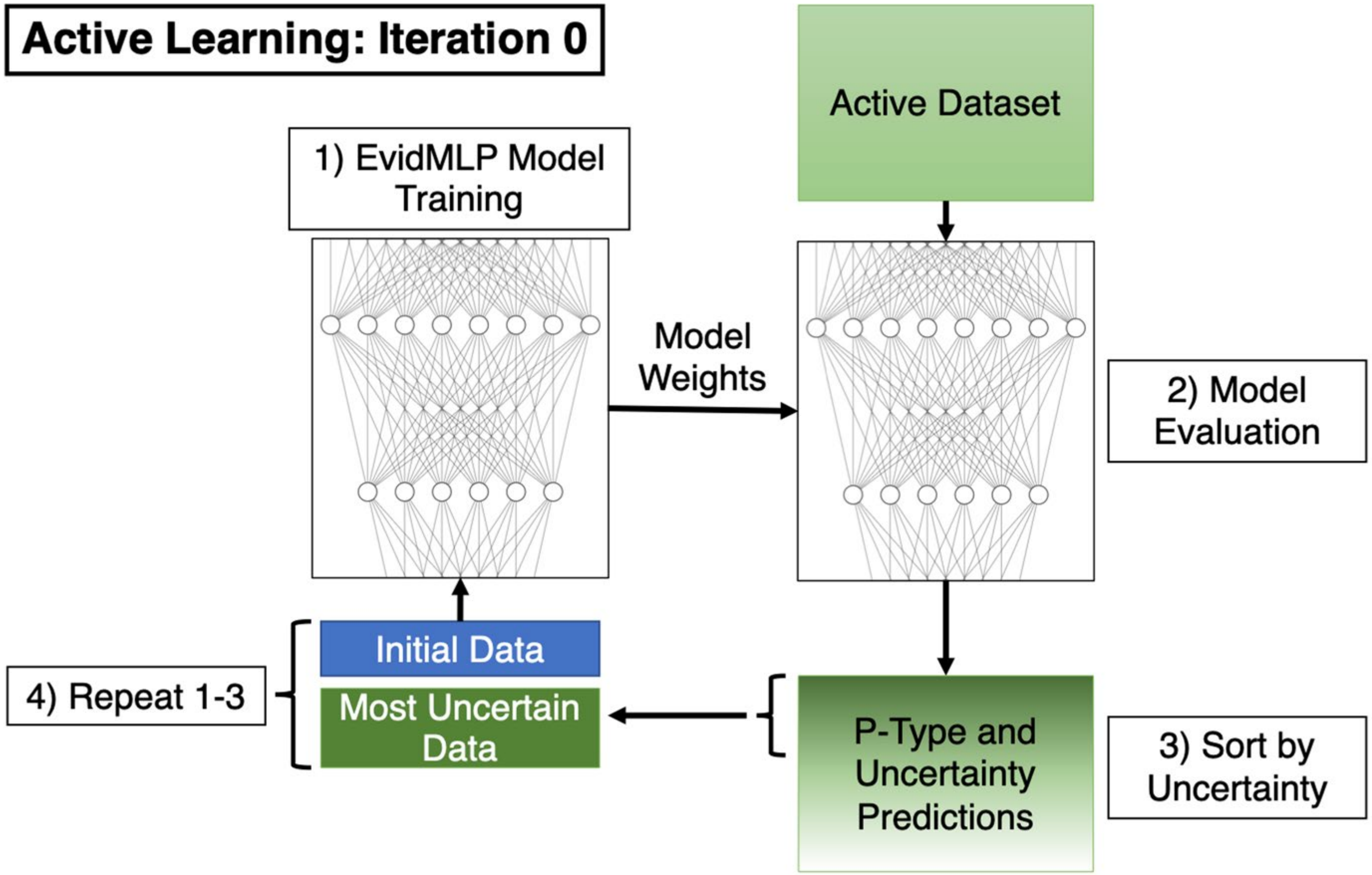

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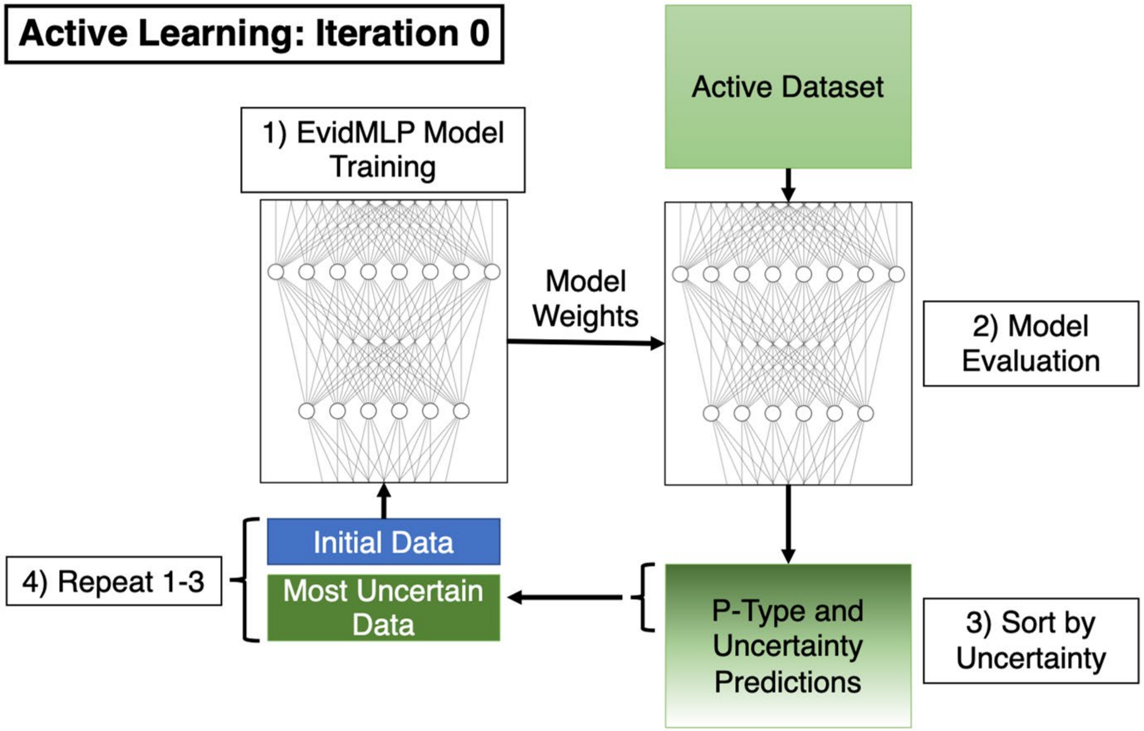
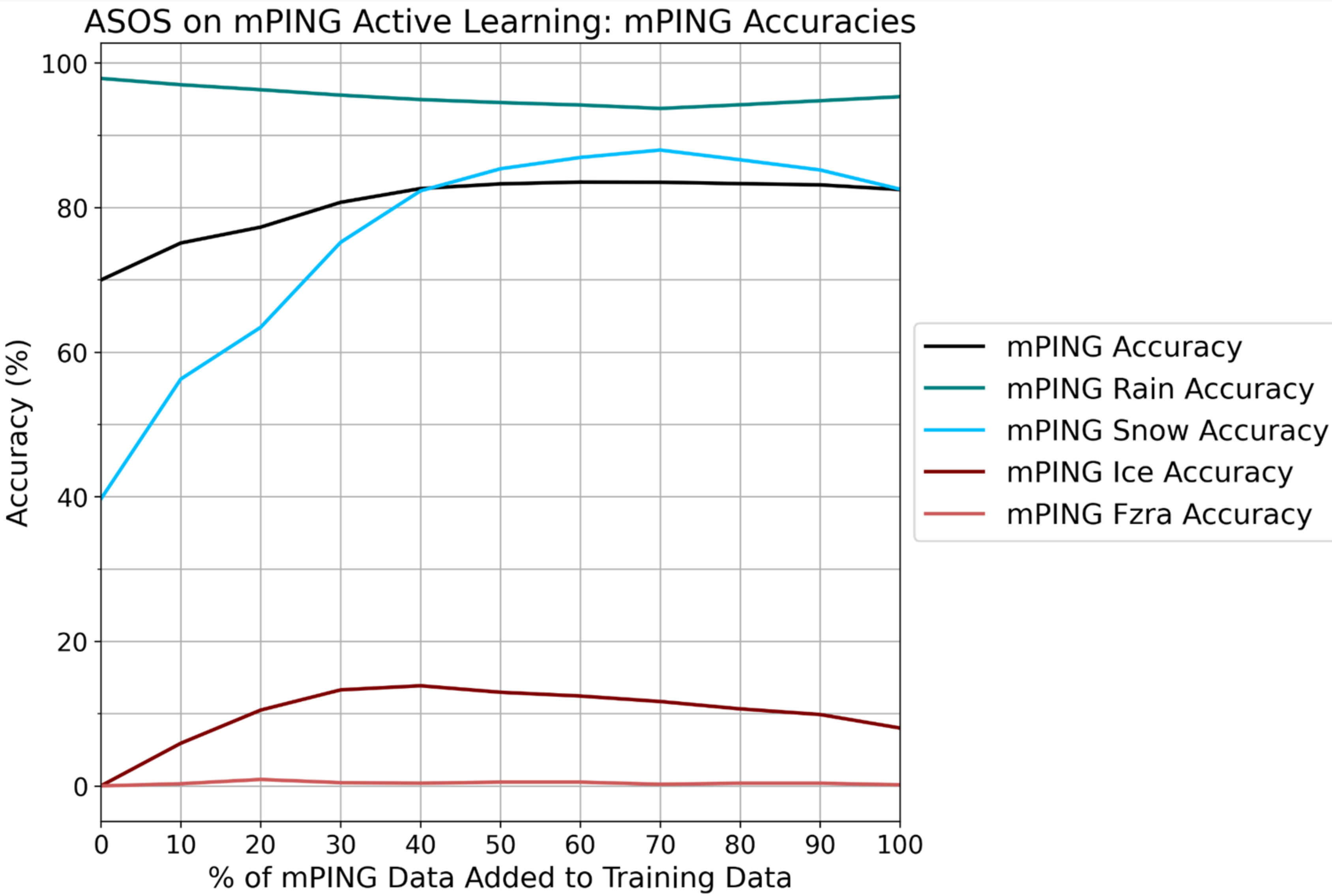
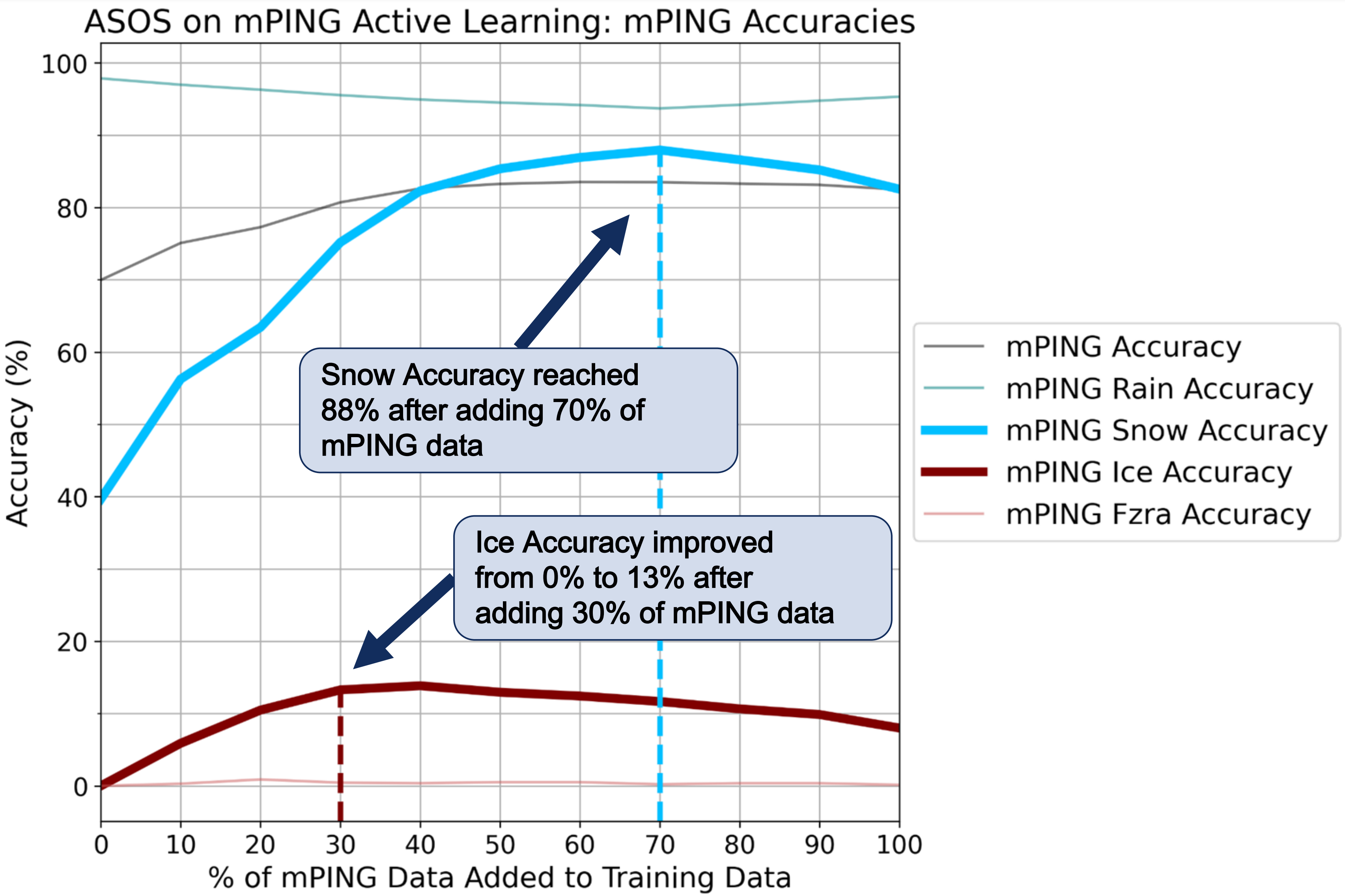


Active Learning Experiments (% of Full)	
Initial Data	**Active Data**
ASOS (10%)	ASOS (90%)
ASOS (100%)	mPING (100%)
mPING (10%)	mPING (90%)

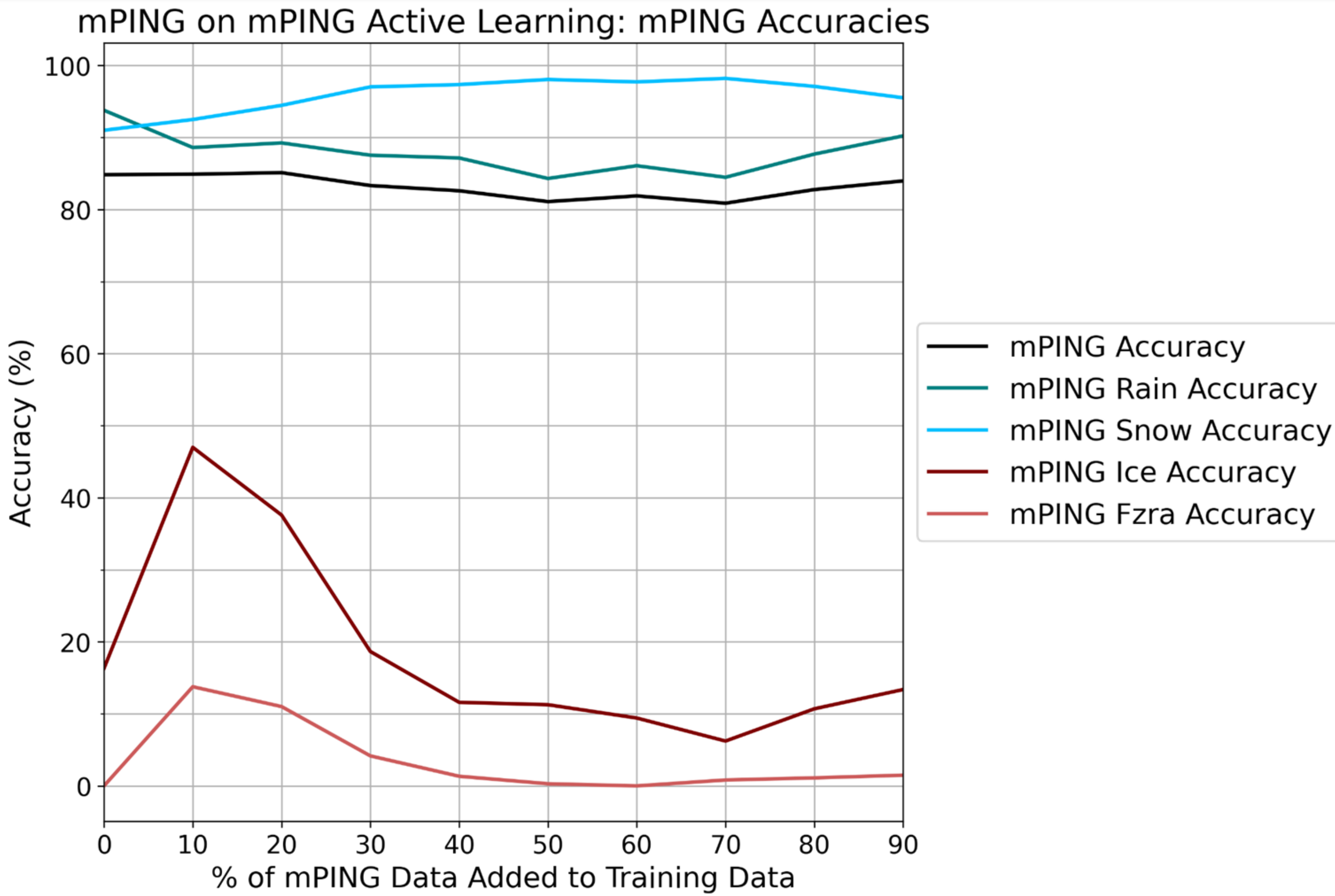
Active Learning: Results | ASOS on mPING



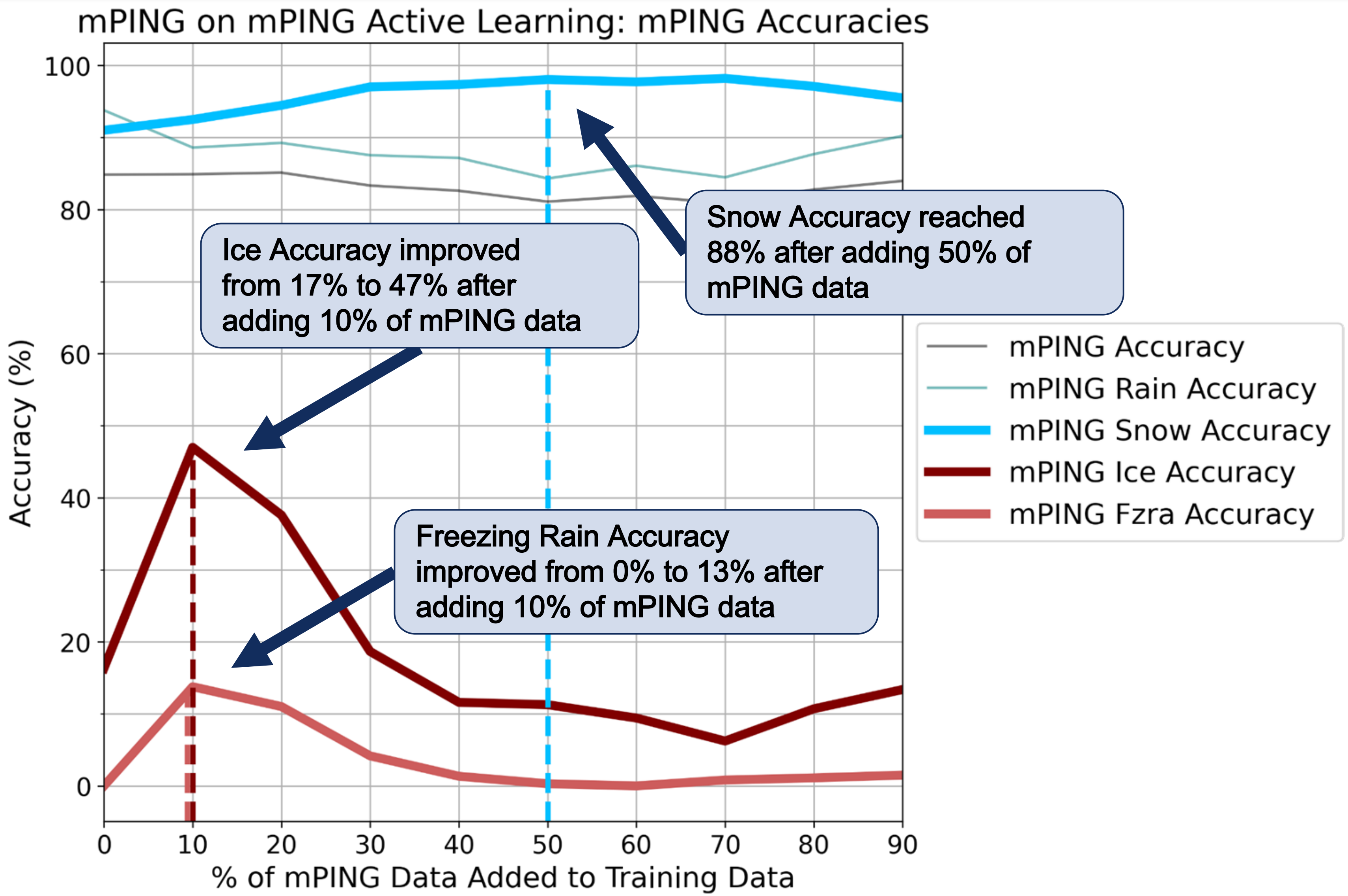
Active Learning: Results | ASOS on mPING



Active Learning: Results | mPING on mPING



Active Learning: Results | mPING on mPING



Active Learning: Conclusions

Conclusions

- Able to improve accuracy for most difficult labels while maintaining performance for other labels
  - Snow, Ice, Freezing Rain accuracy peaks with 20-50% of full dataset
  - Rain performance remains adequate

Future Work

- Conduct ensemble experiments to verify Active Learning results and obtain baseline for comparison
- Incorporate unlabeled data and hand-labeling into Active Learning pipeline
- Conduct XAI at each Active Learning Iteration → Do feature importances change?

Significance

Accurate p-type prediction with simple models and a fraction of full training data

Acknowledgements

Double rainbow while biking down NCAR hill last week!

- Mentors John Schreck and David John Gagne, and AIML scientists (special shoutout to Gabrielle Gantos and Keely Lawrence for invaluable data processing!)

- Virginia Do, Francesgladys Pulido, Jerry Cyccone, and the intern cohort for an unforgettable summer!

Questions and Feedback?

References

Figure 1: https://tennesseelookout.com/2022/02/07/memphis-ice-storm-crystalizes-need-for-resilient-reliant-action/

Figure 2: https://www.ncei.noaa.gov/products/weather-climate-models/rapid-refresh-update

Figure 4: https://permutationimportance.readthedocs.io/en/latest/methods.html

Figure 5: https://github.com/slundberg/shap

Figure 6: https://dsgissin.github.io/DiscriminativeActiveLearning/2018/07/05/AL-Intro.html

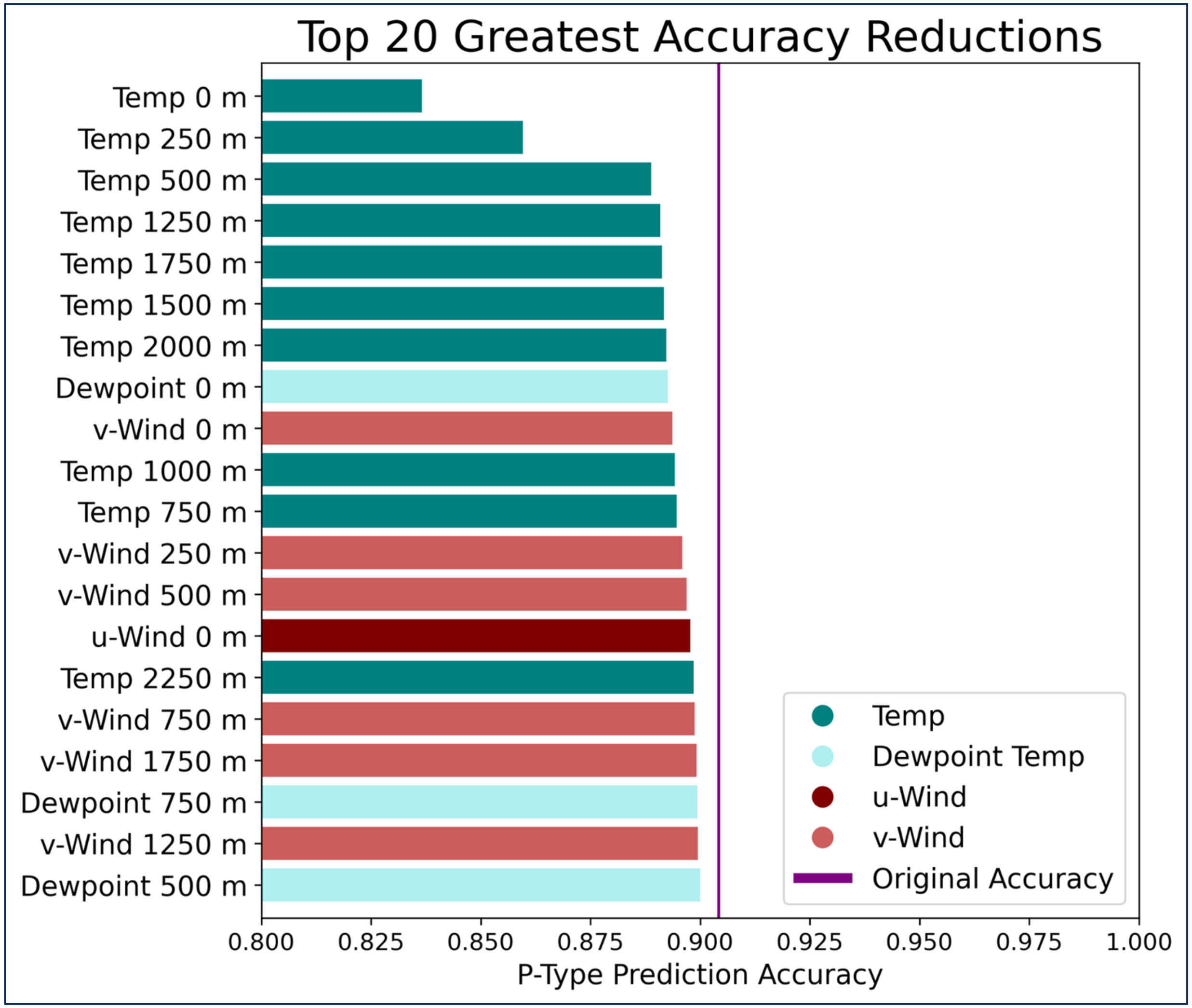
Additional Sources

https://permutationimportance.readthedocs.io/en/latest/

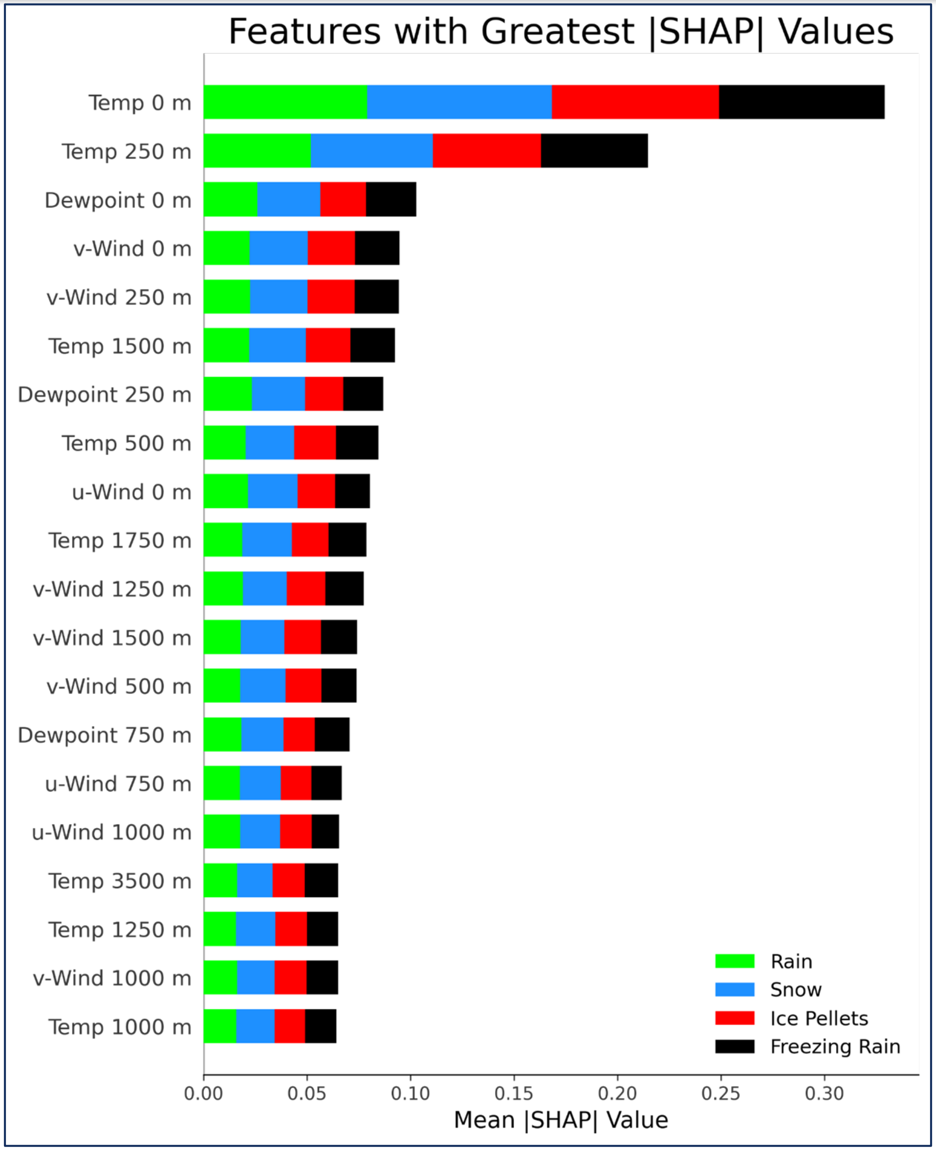
https://journals.ametsoc.org/view/journals/wefo/30/3/waf-d-14-00068_1.xml

https://pubs.acs.org/doi/10.1021/acscentsci.1c00546

Appendix: XAI



Appendix: XAI



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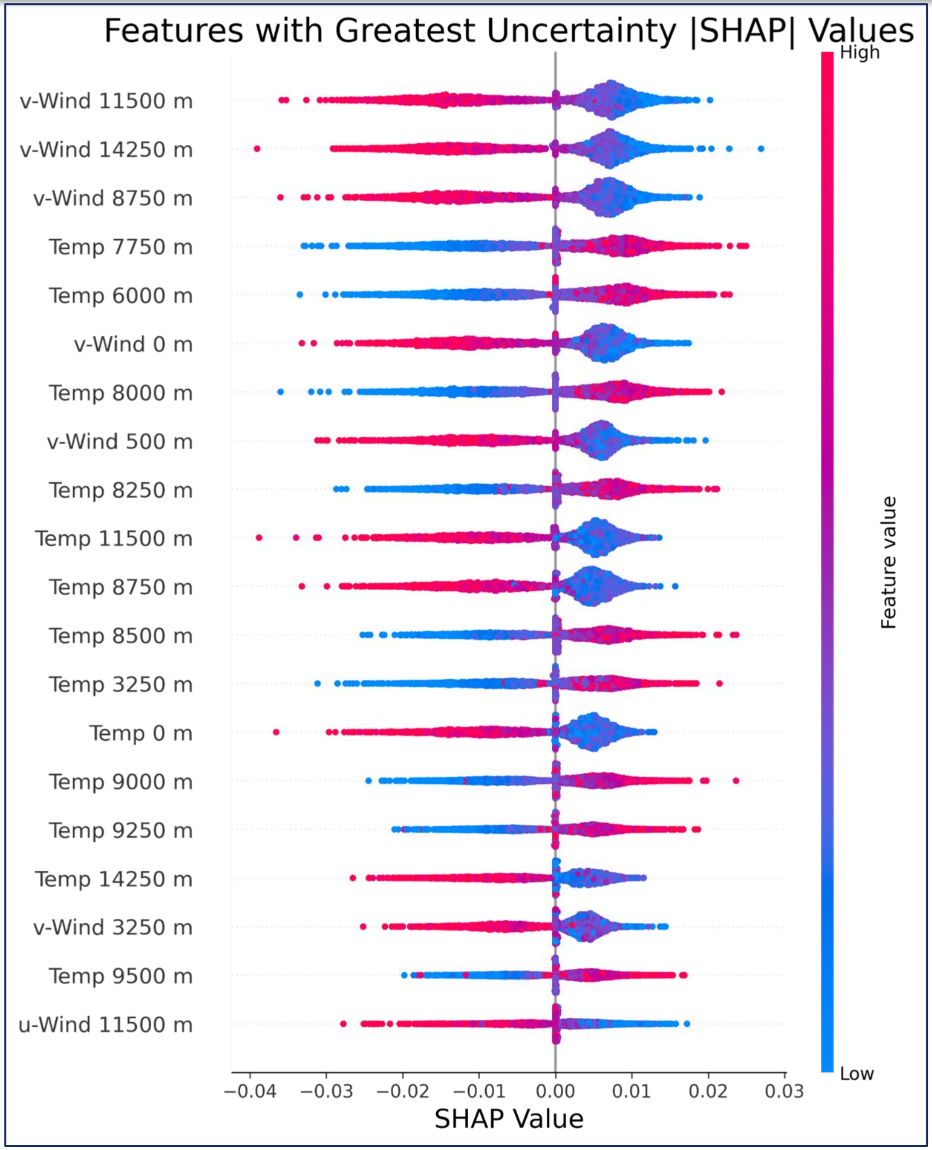
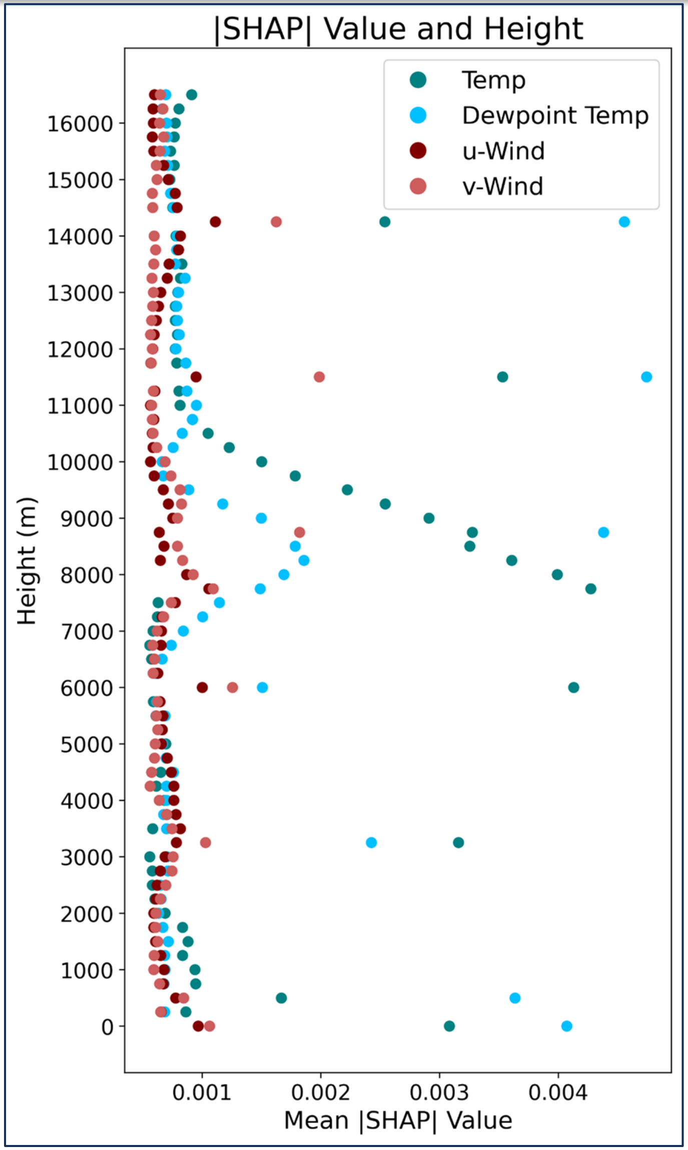
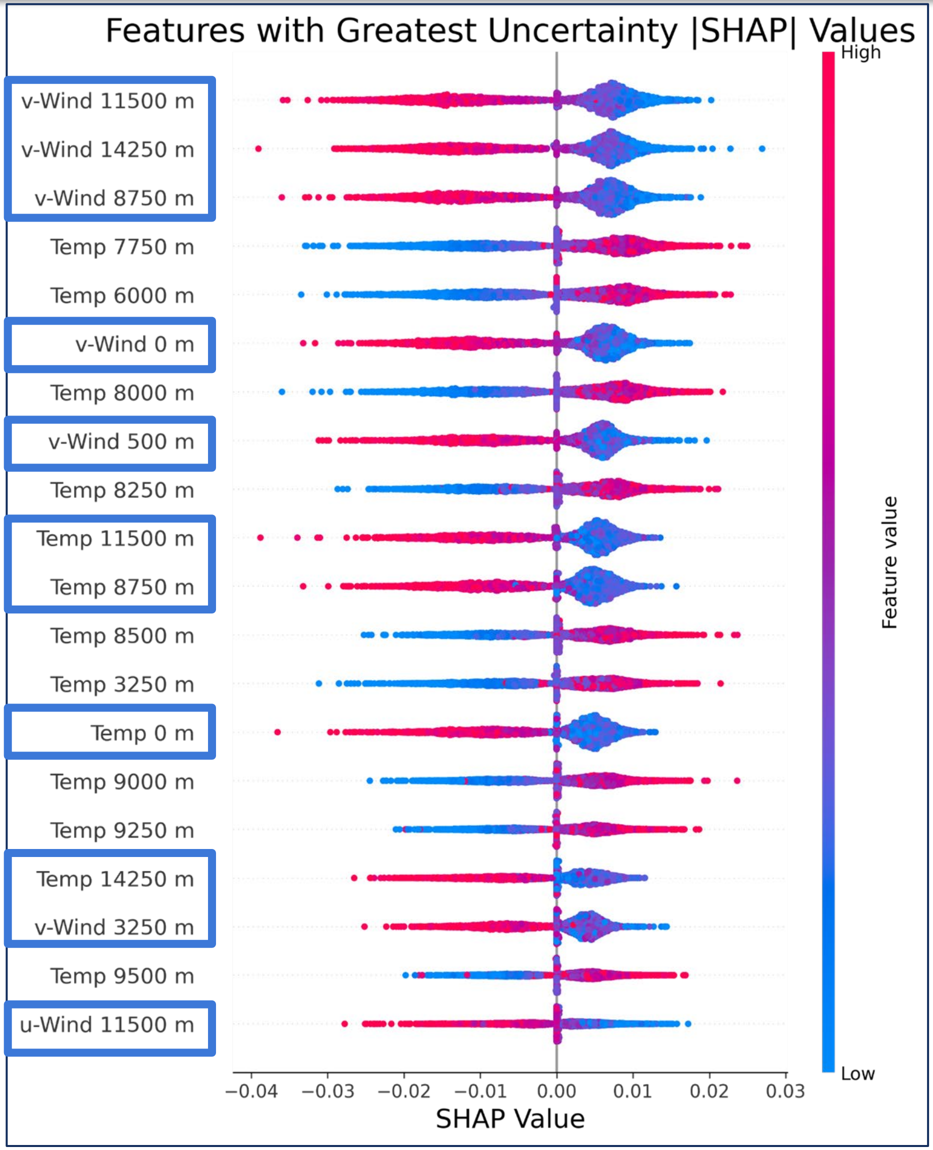
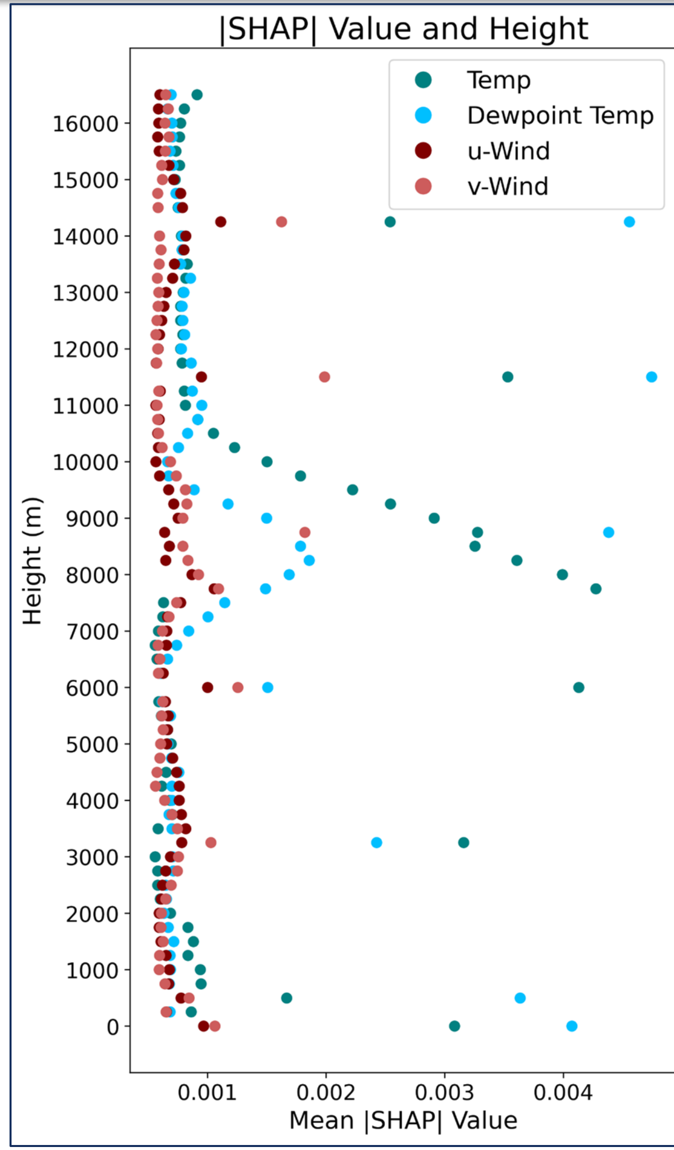




Appendix: XAI

Negative [Feature Value] ~ SHAP Correlation

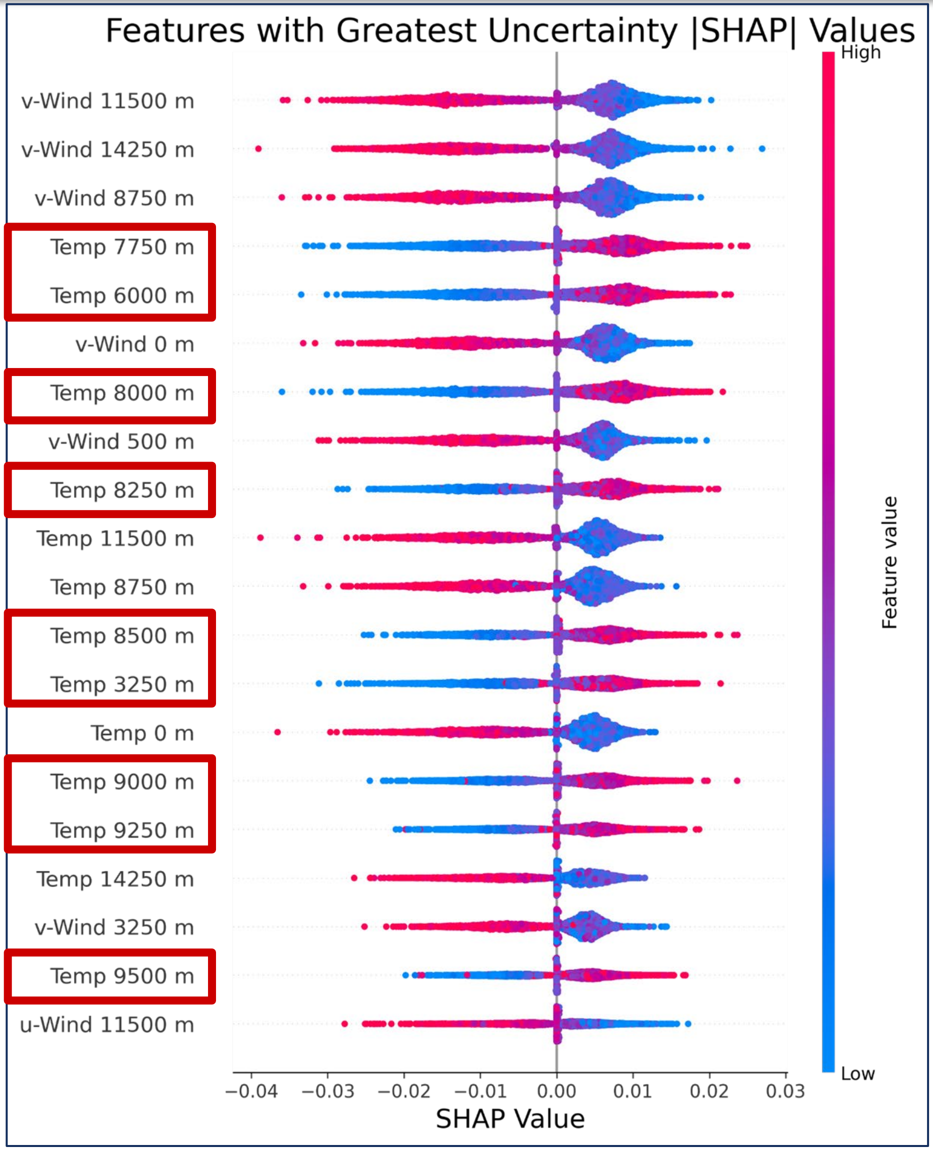


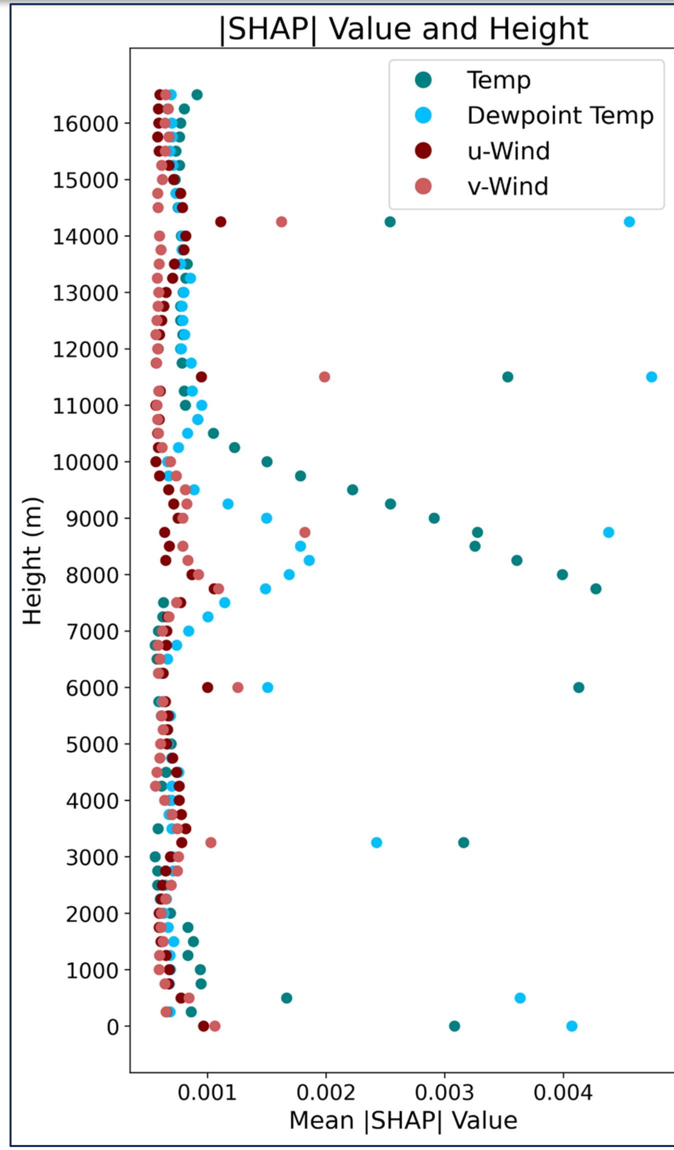


Higher wind velocity associated with lower SHAP values → Greater Certainty of p -type prediction!

Appendix: XAI

Positive [Feature Value] ~ SHAP Correlation





Higher upper troposphere temperature associated with larger SHAP values → Lower Certainty of p -type prediction!

Appendix: Active Learning