

Peeking Inside the Black Box: Explainable AI Methods for a Precipitation-type Model



Belen Saavedra^{1,2}, David John Gagne II¹, John Schreck¹, Charlie Becker¹, Gabrielle Gantos¹

¹National Center for Atmospheric Research (NCAR), Boulder, CO, USA, ²Department of Computer Science at Berea College, Berea, KY, USA



1. MOTIVATION

Background Significance

Although machine learning is playing an increasingly important role in decision-making, understanding how ML models make their predictions is often a challenge for the model developers, forecasters and other end users [1]

XAI Pipeline:

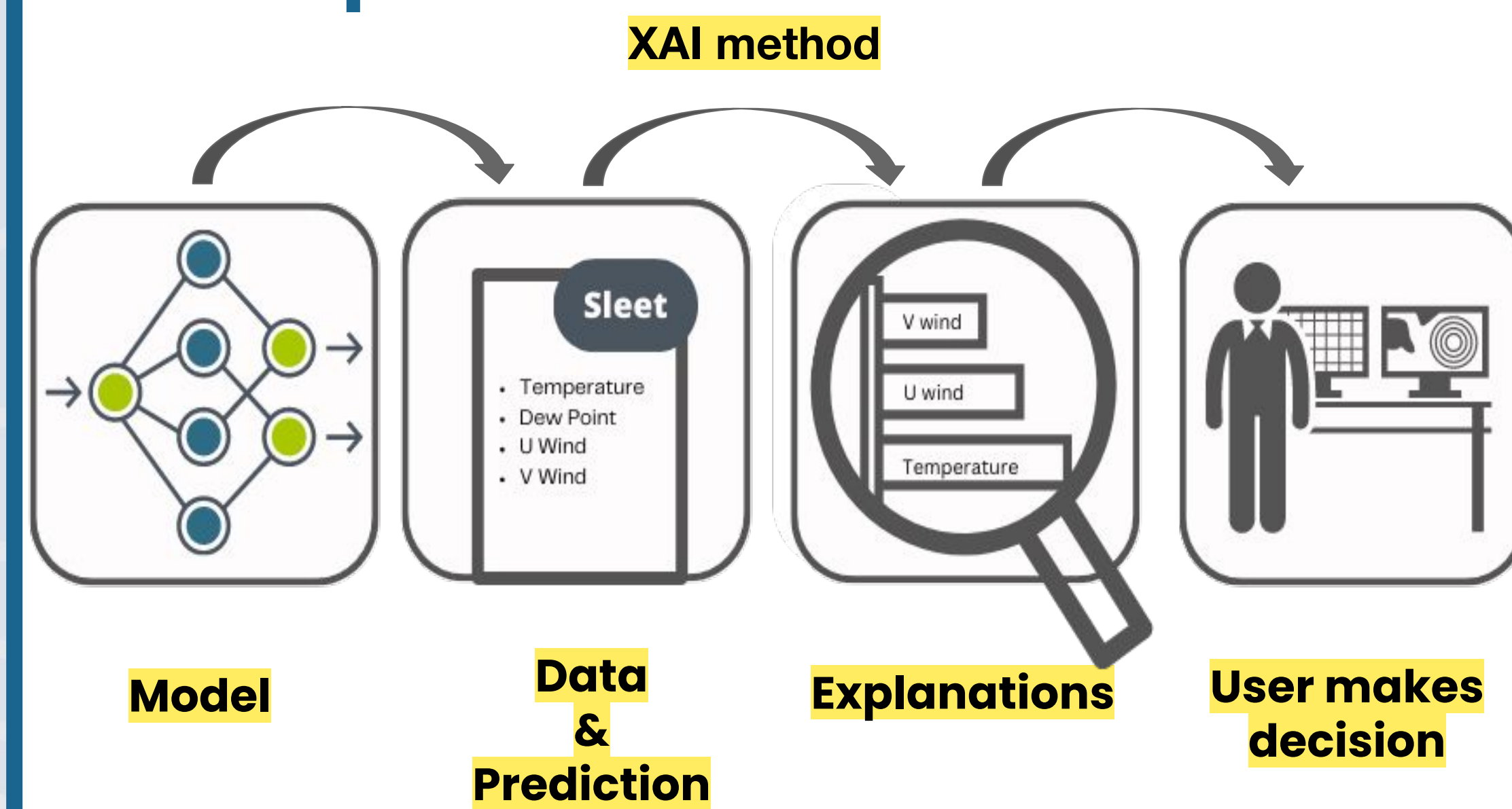


Fig 1. XAI pipeline

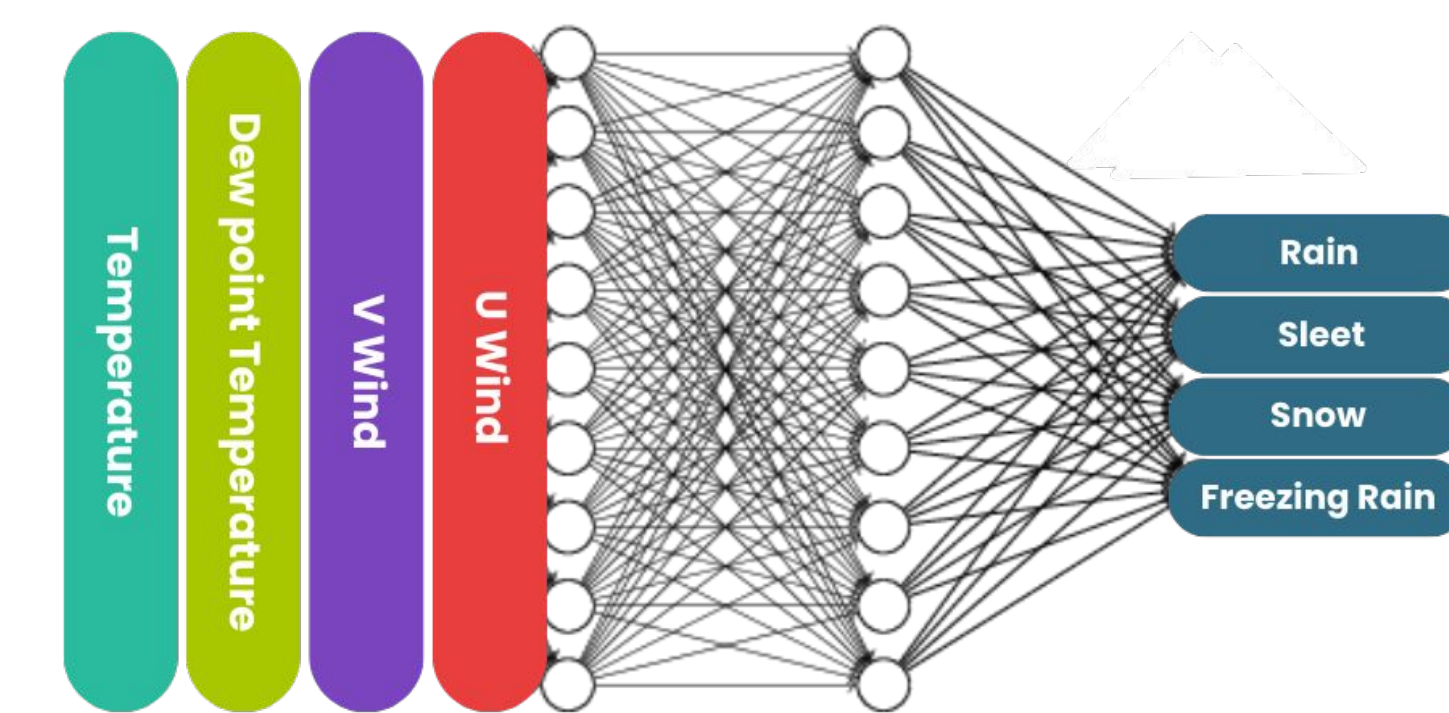
2. OBJECTIVES

- ❖ Evaluate the ML model performance against existing numerical weather models
- ❖ Use different post-modelling XAI methods to **verify that the model is focusing on the most physically relevant features**

3. DATA

- ❖ Input data: The Rapid Refresh (RAP)
- ❖ True Labels: mPING (underreports freezing rain)

4. PRECIPITATION MODEL



Performance:

- ❖ Overprediction of rain
- ❖ Low accuracy predicting sleet and freezing rain

		Normalized by Truth				Unnormalized			
		rain	snow	sleet	frz-rain	rain	snow	sleet	frz-rain
rain	Predicted Label	0.87	0.02	0.07	0.05	194253	3703	16165	10403
snow	Predicted Label	0.00	0.69	0.21	0.10	24	93719	28099	13646
sleet	Predicted Label	0.00	0.09	0.60	0.30	25	2303	14581	7354
frz-rain	Predicted Label	0.00	0.06	0.17	0.77	19	699	2149	9554

5. EXPLAINABLE AI (XAI)

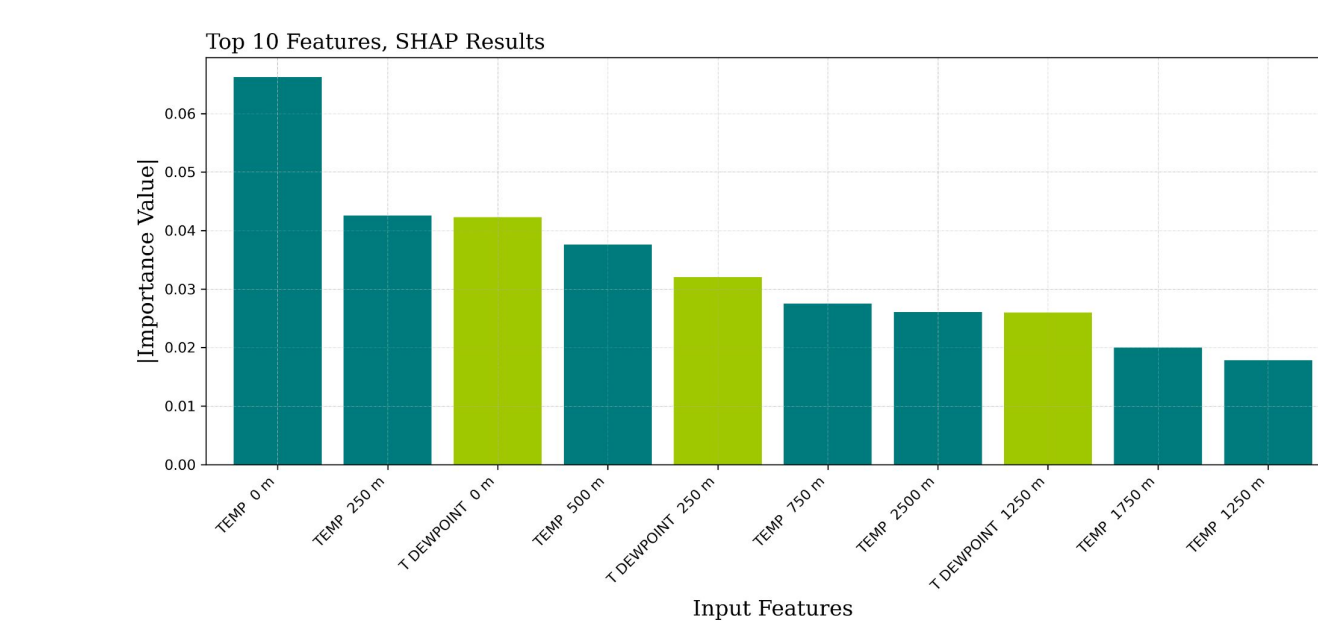


Fig 2. SHAP results

→ Shapley Additive Explanations

- SHAP calculates the average contribution of each feature, representing how much each feature influences the model's prediction

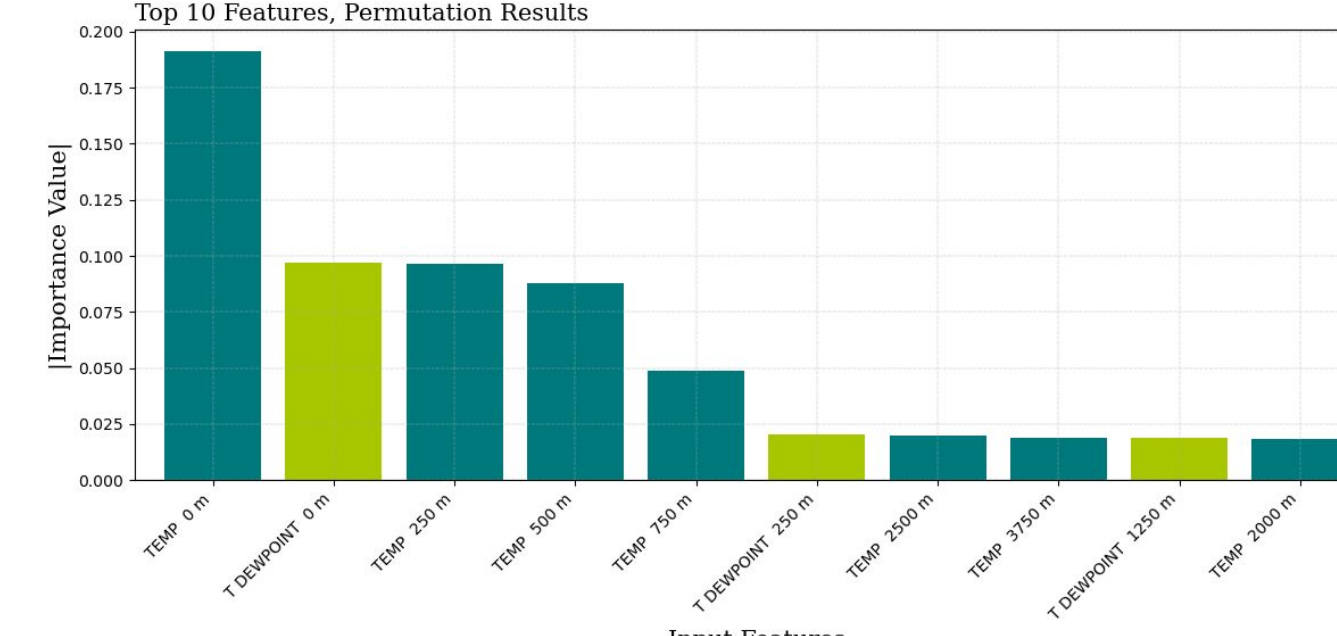


Fig 3. Permutation results

→ Permutation Feature Importance

- Permutation feature importance works by randomly shuffling the values of a single feature and measuring the resulting change in the model's performance

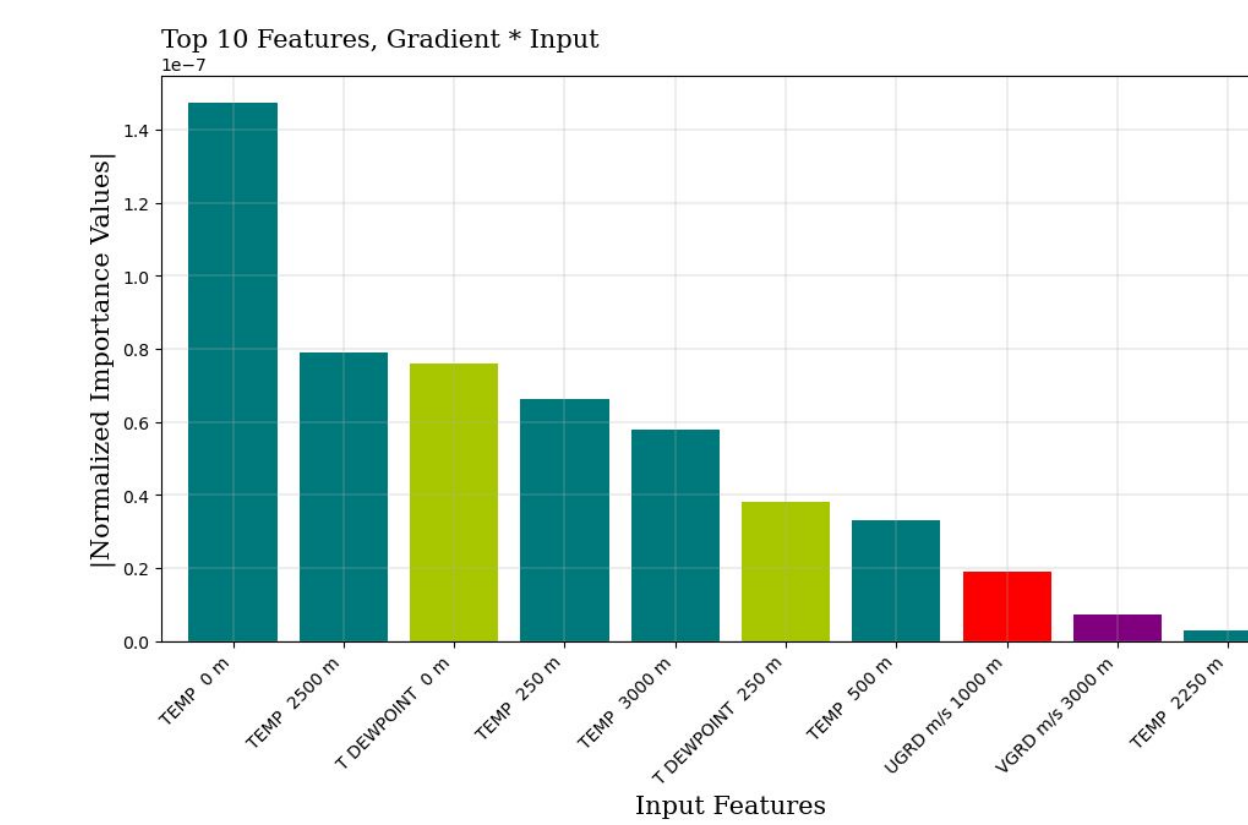


Fig 4. Gradient * Input results

→ Gradient * Input

- This XAI method works by multiplying the gradient of the model's output with the input features

6. CONCLUSIONS

- ❖ Features that have a higher height are more important near the freezing line and fronts
- ❖ Each XAI method provides slightly different results
- ❖ Temperature at 0m is the top feature for each of the methods
- ❖ The Input features that are near the surface tend to be the most important

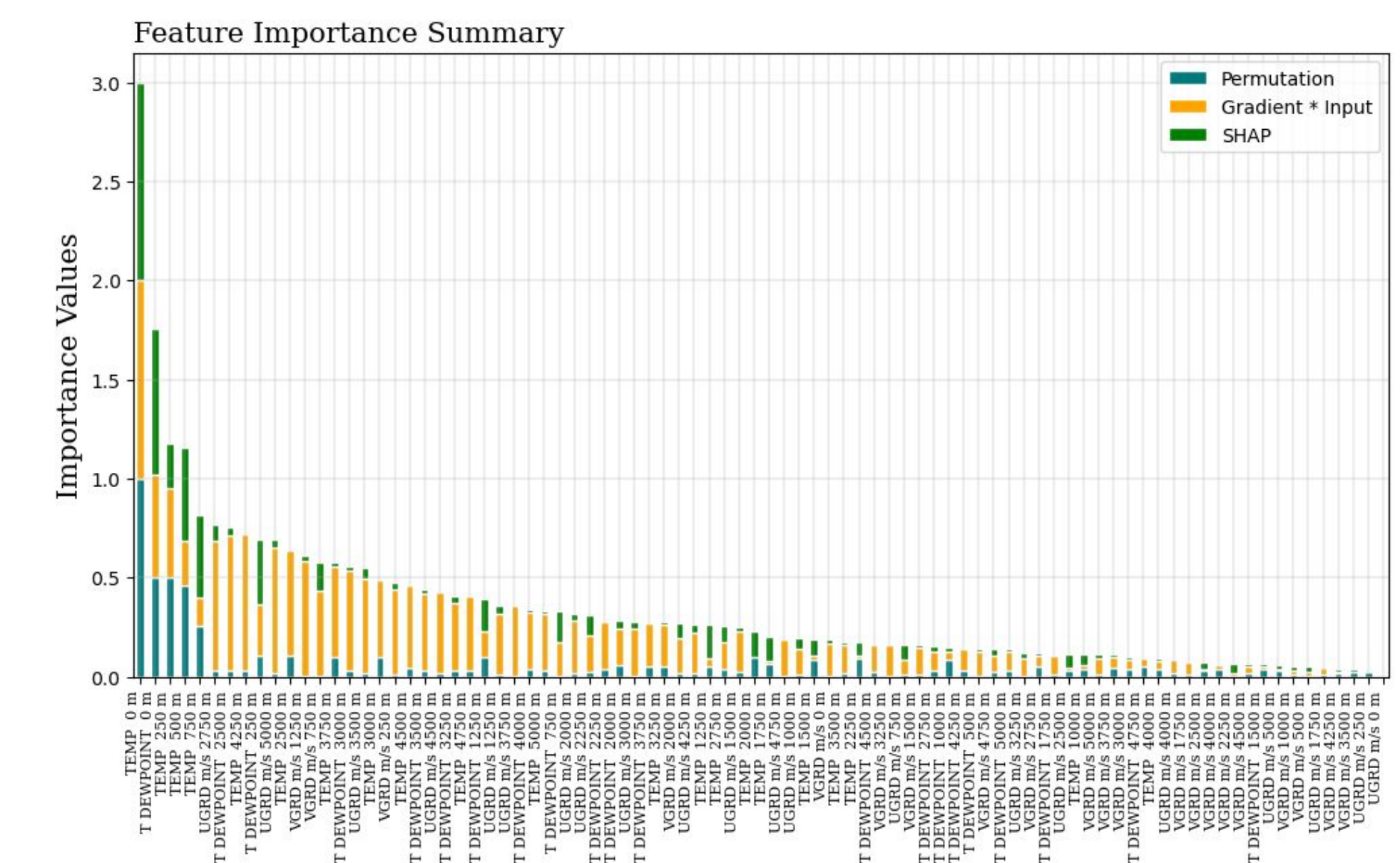


Fig 7. XAI methods summary

7. REFERENCES

[1] McGovern, A., Lagerquist, R., Gagne, D. J., Jergensen, G. E., Elmore, K. L., Homeyer, C. R., & Smith, T. (2019). Making the black box more transparent: Understanding the physical implications of machine learning

Fig 1. Marco Tullio Ribeiro, Sameer Singh, and Carlos Guestrin. "why should i trust you?": Explaining the predictions of any classifier. arXiv preprint arXiv:1602.04938, 2016

8. ACKNOWLEDGMENTS

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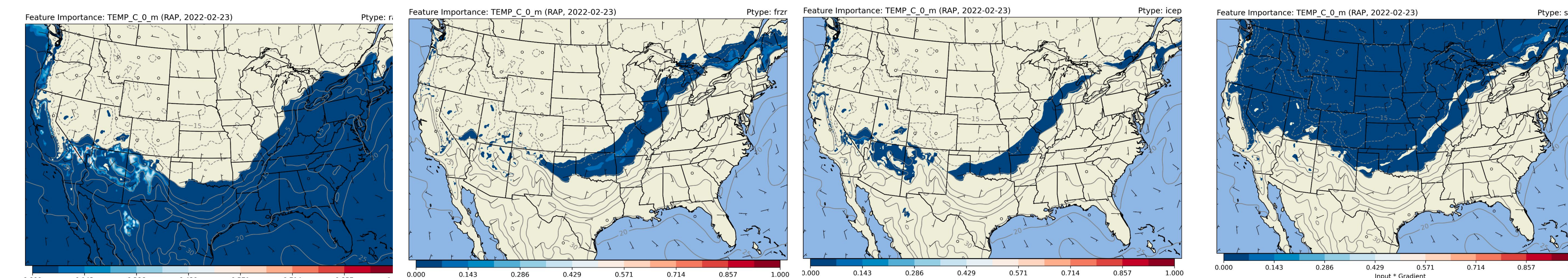


Fig 5. Absolute Gradient * Input values

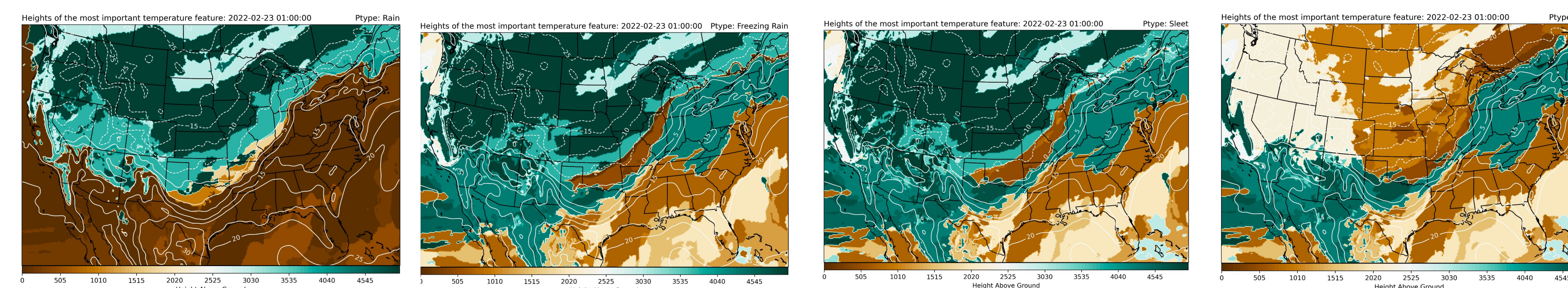


Fig 6. Gradient * Input by height per precipitation type