# Can We Improve Precipitation Phase Partitioning in the National Water Model and NextGen Formulations? (Yes)


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## Objectives

1. *Evaluate* the precipitation phase partitioning method used in National Water Model v3 and other Noah-MP options
2. *Optimize* precipitation phase partitioning performance with methods that can be deployed in NextGen formulations
3. *Determine* best practices for precipitation phase partitioning in National Water Model v4 and beyond.

### *What is precipitation phase partitioning?*

- The model process of splitting incoming precipitation into rain and snow, or rain, snow, and mixed precipitation
- These functions often use near-surface meteorology to determine phase because of a relative lack of observations
- The most common methods are thresholds and ranges, and most of these rely on air temperature only

## Precipitation Phase Partitioning Methods

**National Water Model (Noah-MP)**

- NWM v3 currently uses the Jordan (1991) method:

**Jordan (1991)**

$$SnowFrac = \begin{cases} 1 \text{ when } T_a \leq 0.5°C \\ 1 - (-54.632 + 0.2 * (T_a + 273.15)) \text{ when } 0.5°C < T_a < 2°C \\ 0.6 \text{ when } 2°C < T_a < 2.5°C \\ 0 \text{ when } T_a \geq 2.5°C \end{cases}$$

- Noah-MP can also use $T_a$ thresholds and weather model input

**Thresh.**

$$SnowFrac = \begin{cases} 1 \text{ when } T_a \leq Thresh \\ 0 \text{ when } T_a > Thresh \end{cases}$$

**NextGen Formulations**

- Noah-OWP-Modular: $T_w$, ranges, and binary logistic regression model

**Range**

$$SnowFrac = \begin{cases} 1 \text{ when } T_a \leq Thresh_{snow} \\ \left(\frac{Thresh_{rain} - T_a}{Thresh_{rain} - Thresh_{snow}}\right) \text{ when } Thresh_{snow} < T_a < Thresh_{rain} \\ 0 \text{ when } T_a \geq Thresh_{rain} \end{cases}$$

**Binary Logistic Regr.**

$$SnowProb = \frac{1}{1 + exp(-10.04 + 1.41 \times T_a + 0.09 \times RH)}$$

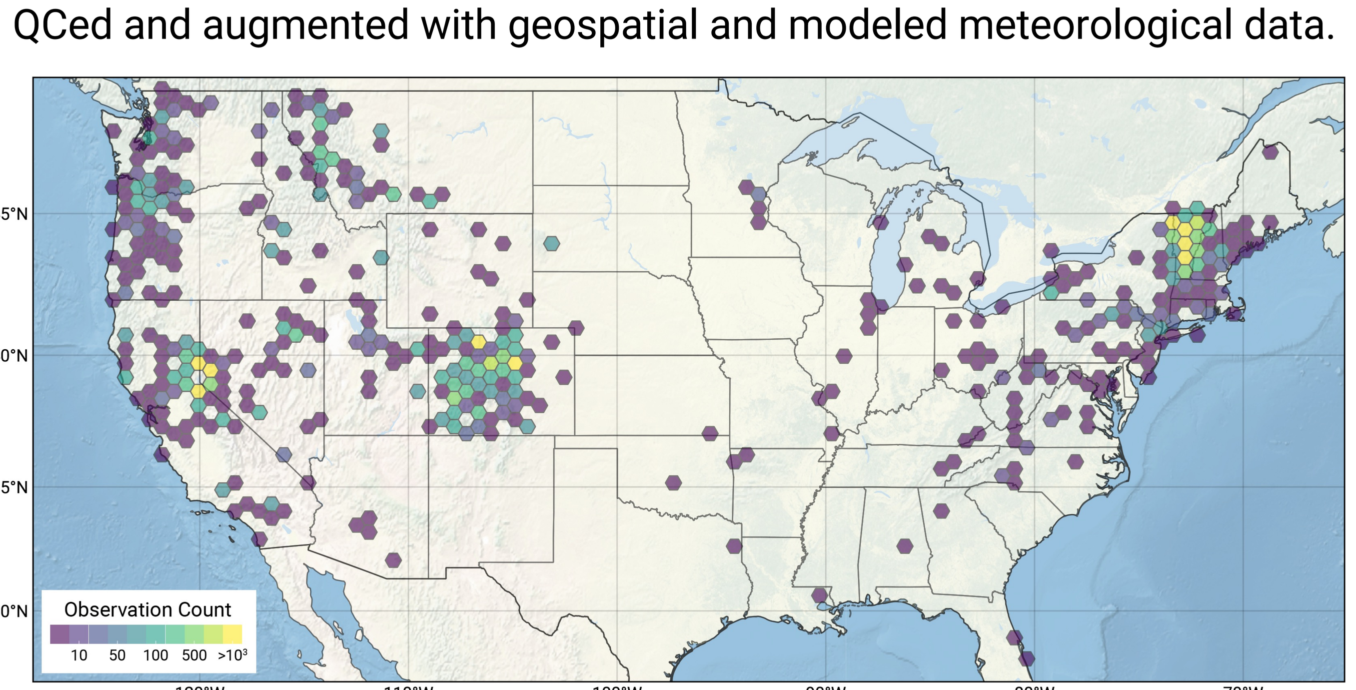
- Snow-17: $T_a$ threshold, snow-line data, and snow fraction forcing

**Machine Learning**

- Random forest (RF), XGBoost (XG), and a Multilayer Perceptron—a type of Artificial Neural Network (ANN)

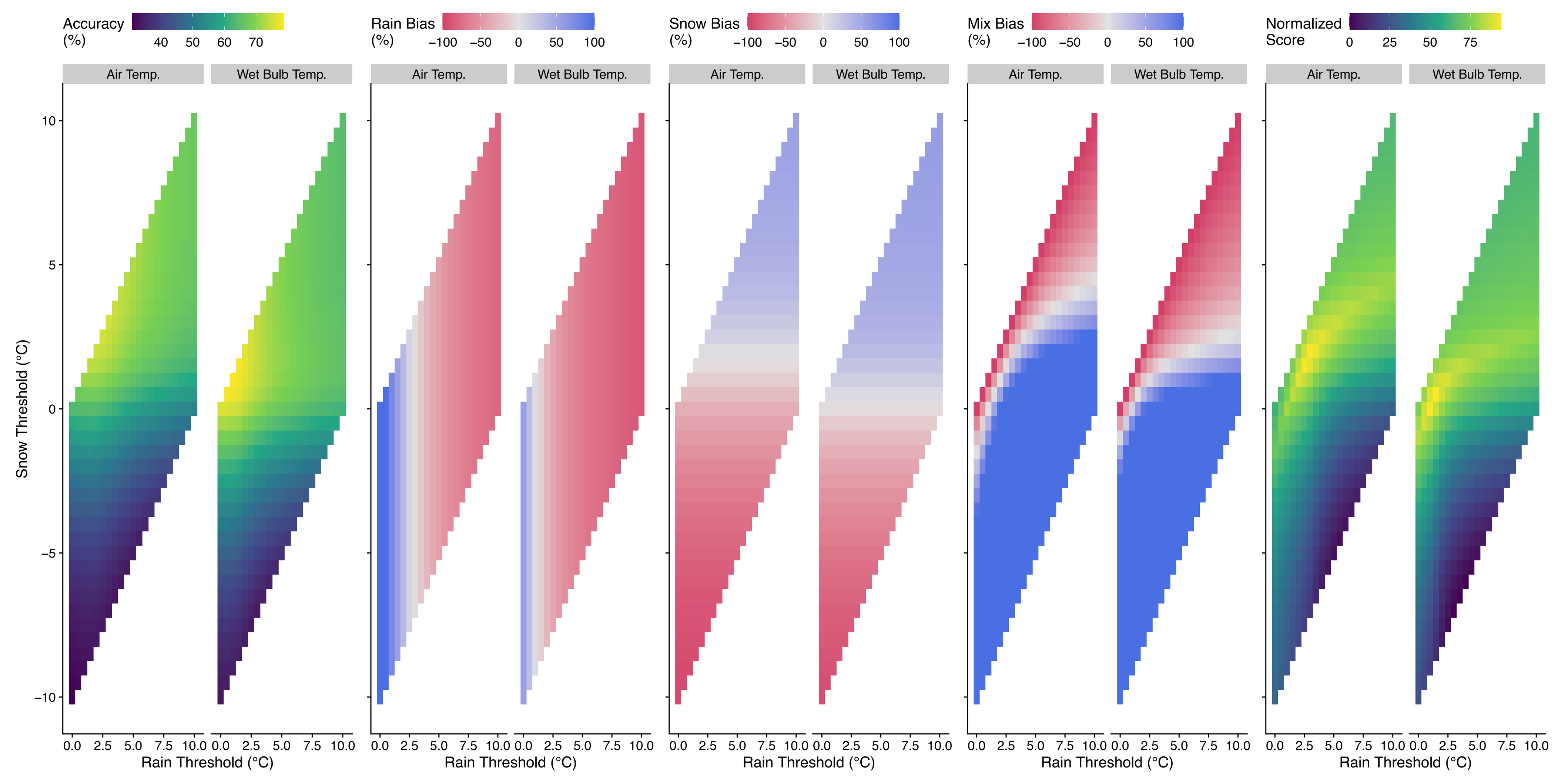
## Mountain Rain or Snow Dataset

38.5 thousand crowdsourced rain, snow, and mixed precipitation observations submitted by volunteer observers via a browser-based app. QCed and augmented with geospatial and modeled meteorological data.

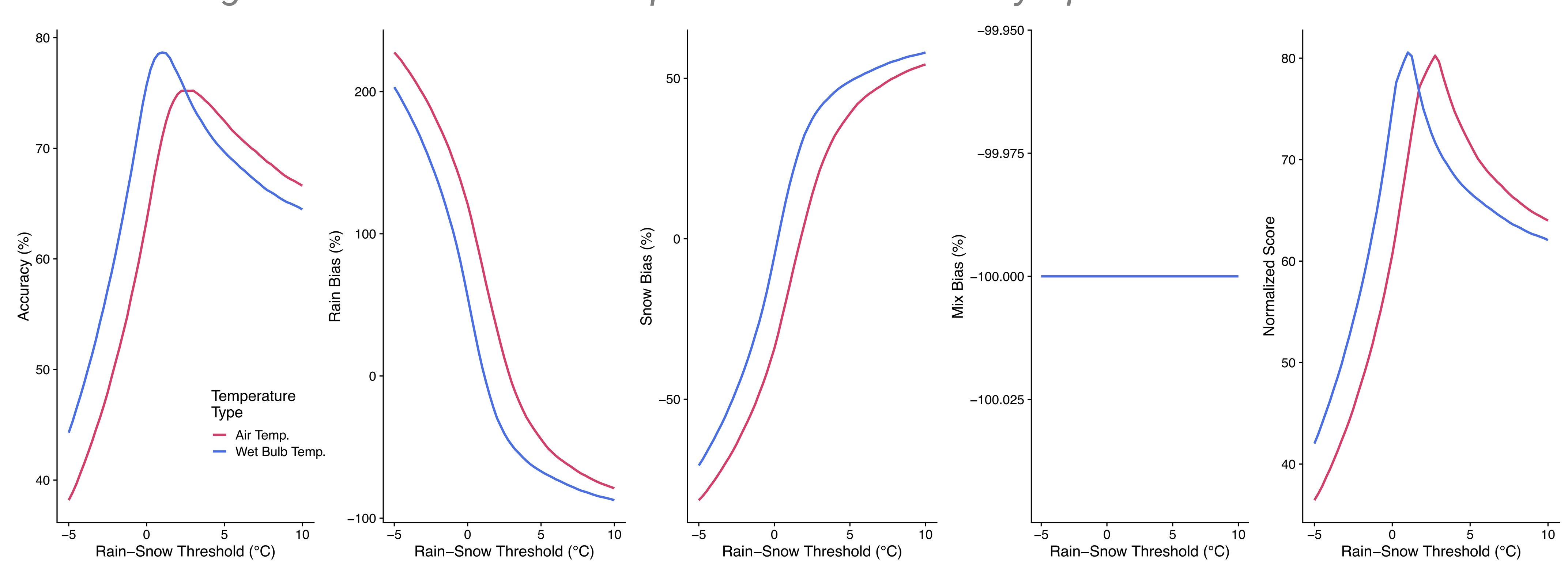



## Optimization Against Observations Improves Performance

*Matrix of Ranges Compared to Obs to Identify Optimum All-Snow and All-Rain Thresholds*




*Vector of Single-Value Thresholds Compared to Obs to Identify Optimum Rain-Snow Thresholds*




- Thresholds and ranges using wet bulb temperature are consistently the most accurate
- Most ranges overpredict mixed precipitation and those using narrower mixed ranges are more accurate
- Interesting differences in rain, snow, and mixed precipitation bias patterns

## Which Is Good Because the NWM Default Struggles

- Jordan (1991) overpredicts rain and mixed at expense of snow, accuracy is poor
- Other Noah-MP and LSM options struggle as well
- Ranges have better scores, while thresholds have better accuracy
- Top 25 methods by accuracy use wet bulb temperature
- Nearly even split of air and wet bulb temperature methods by score

*Table of Top Performing and Selected Methods*

| Method | Normalized Score | Accuracy (%) | Rain Bias (%) | Snow Bias (%) | Mix Bias (%) | Notes |
|---|---|---|---|---|---|---|
| $T_w$ range 0.5°C to 1.5°C | 94.1 | 76.8 | -13.5 | 6.1 | -0.9 | Highest scoring $T_w$ range |
| $T_a$ range 1.5°C to 2.5°C | 93.3 | 72.6 | 12.6 | -4.6 | -5.1 | Highest scoring $T_a$ range |
| $T_a$ range 2.5°C to 3.0°C | 85.9 | 74.4 | -4.6 | 13.8 | -60.6 | Most accurate $T_a$ range |
| $T_w$ range 1.0°C to 1.5°C | 85.4 | 77.9 | -13.5 | 16.7 | -55.6 | Most accurate $T_w$ range |
| $T_w$ threshold 1.0°C | 80.6 | 78.7 | 5.9 | 16.7 | -100 | Most accurate method |
| $T_a$ threshold 2.75°C | 80.3 | 75.2 | 3.8 | 17.7 | -100 | Highest scoring $T_a$ thresh. |
| $T_a$ threshold 2.5°C | 79.6 | 75.2 | 12.6 | 13.8 | -100 | Most accurate $T_a$ thresh |
| $T_a$ threshold 2.2°C | 78.7 | 75.1 | 24.4 | 8.5 | -100 | Noah-MP option |
| Jordan (1991) | 77.2 | 67 | 12.6 | -24.6 | 98.4 | NWM v 3 method |
| Binary logistic regression | 77 | 76.4 | 45.7 | -0.9 | -100 | Noah-OWP-Modular option |
| $T_a$ range -0.5°C to 0.5°C | 74 | 60.2 | 99.3 | -41.8 | -11.5 | VIC method |
| $T_a$ threshold 0.0°C | 60.6 | 63.4 | 120.9 | -34.2 | -100 | Noah-MP option |
| $T_a$ range -1.0°C to 3.0°C | 51.9 | 55.8 | -4.6 | -48.1 | 259.3 | UEB method |

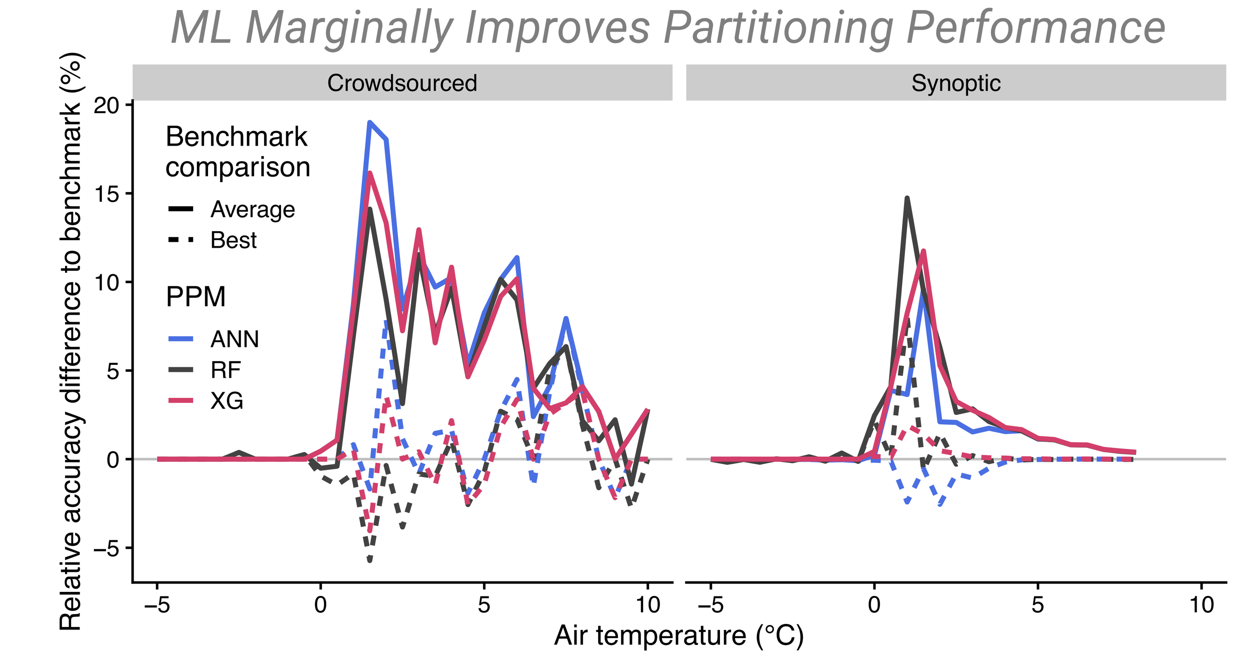
## Best Practices for Now

- Stop using the NWM default Jordan (1991) method
- Use a method that applies wet bulb temperature
- Deploy an optimized threshold if accuracy is paramount
- Choose a range with a small gap between all-snow and all-rain thresholds to minimize biases of all phases

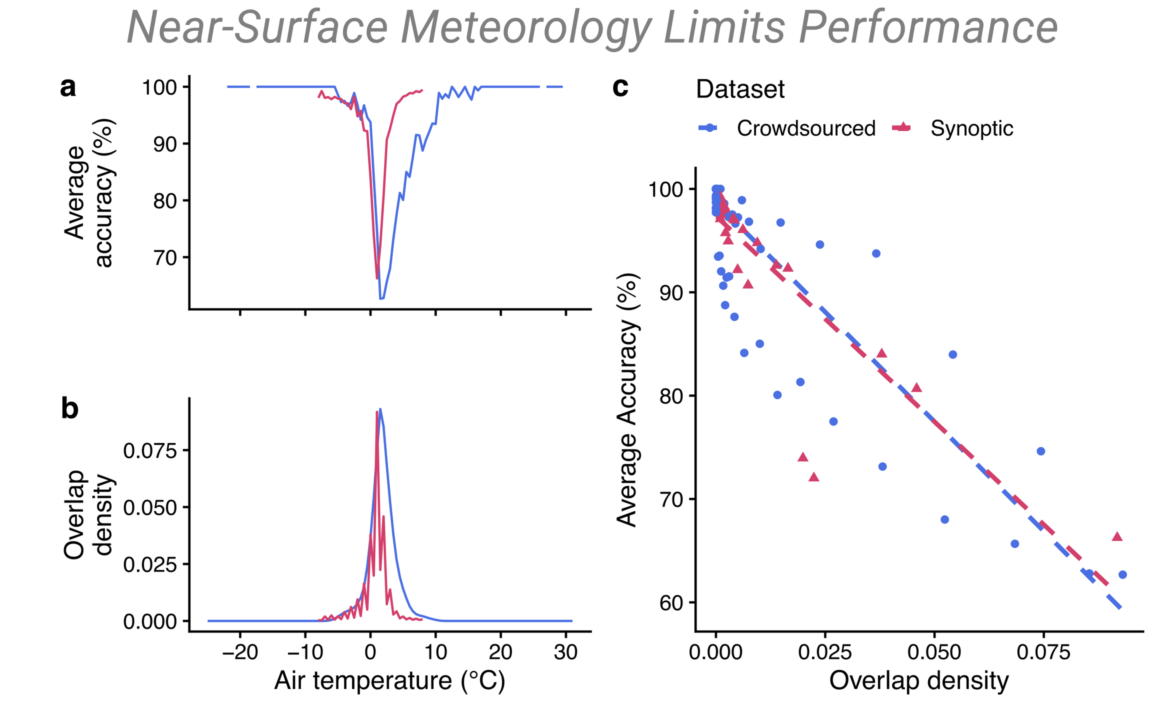
## What about Machine Learning?

- Jennings et al. (2025) applied three ML techniques to the crowdsourced data and a synoptic dataset of 17.8 million obs

*ML Marginally Improves Partitioning Performance*




*Near-Surface Meteorology Limits Performance*





*Jennings, K.S., Collins, M., Hatchett, B.J. et al. Machine learning shows a limit to rain-snow partitioning accuracy when using near-surface meteorology. Nat Commun* ***16****, 2929 (2025).*


## Some Caveats and Limitations

- Study used crowdsourced data from select CONUS mountain regions
- The optimized values *should not be viewed as applicable across the whole NWM forecast domain* without further research
- Mixed precipitation is difficult to predict
- Score metric assigns equal weight to all biases despite mixed comprising a low percentage of total precipitation

## Learn More!

Scan this QR code to learn how to join the Mountain Rain or Snow project in your region.

Scan this QR code to view the code and data from this analysis.


## Acknowledgments

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