

# Snow-to-liquid ratio prediction over the northeast United States using machine learning

November 13, 2024 NROW Presentation

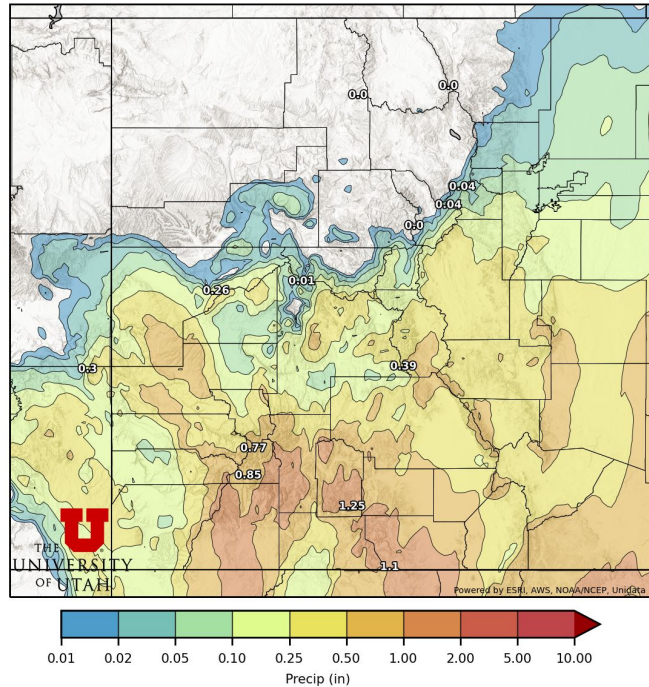
Michael Pletcher, Peter Veals, Randy Chase, Steve Hilberg, Noah Newman, Andrew Rosenow, and Jim Steenburgh



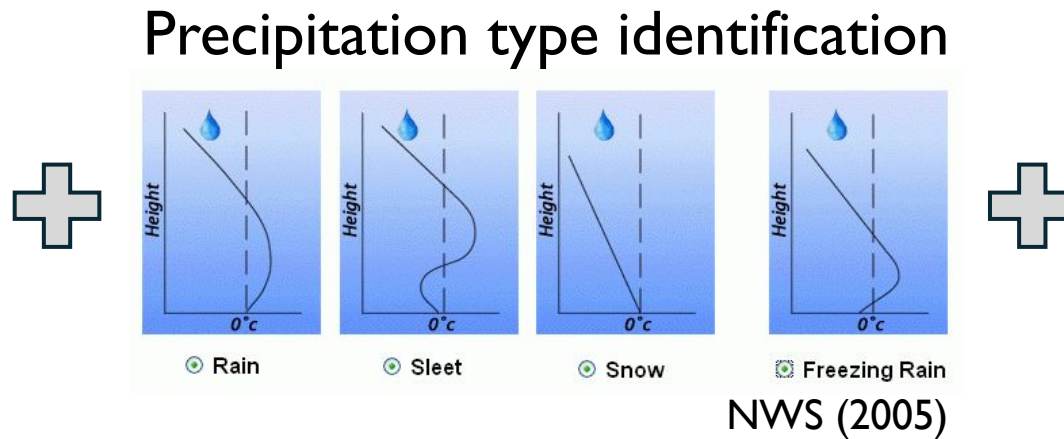


# What is needed to produce a snowfall forecast?

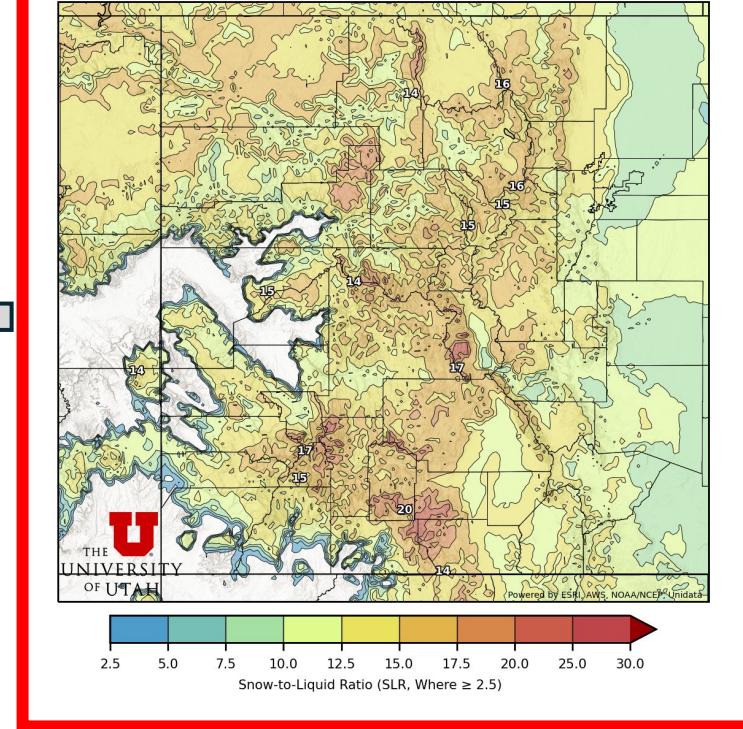
Quantitative precipitation forecast (QPF)



Precipitation type identification



Snow-to-liquid ratio (SLR)



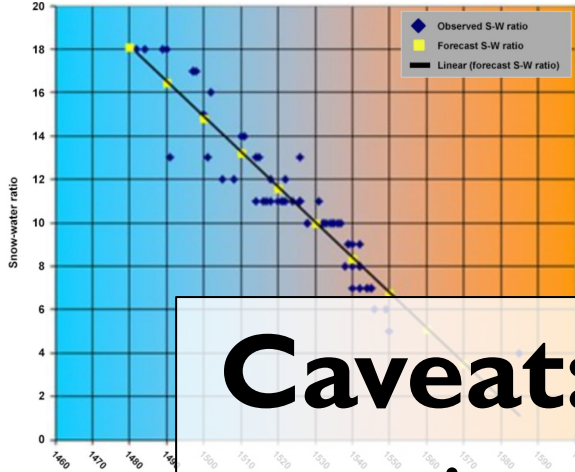
## Issues

- QPF biases exist and vary among models; precipitation type depends on many physical processes; no widely accepted SLR methodology
- CONUS-wide validation of snowfall and SLR forecasts has yet to be implemented

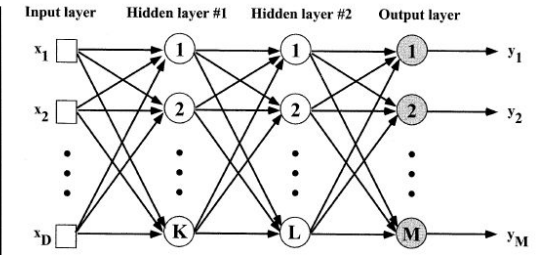
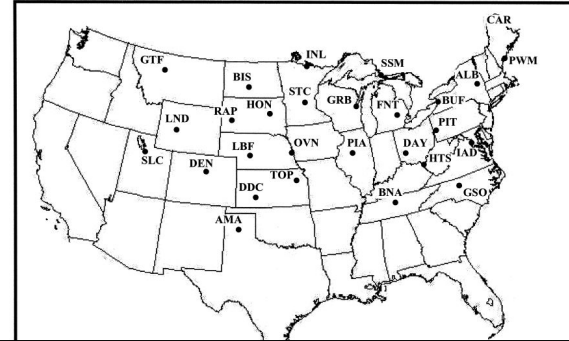
# Operational SLR forecast methods

Roebber et al. (2003)

850 – 700 mb thickness

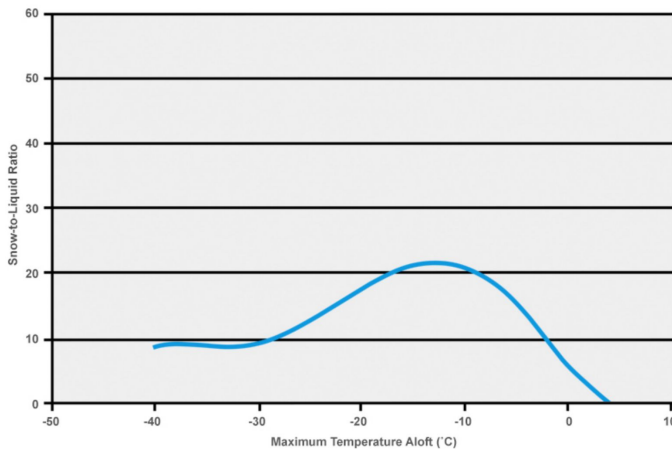


- Relationship between 850 - 700 mb thickness to predict

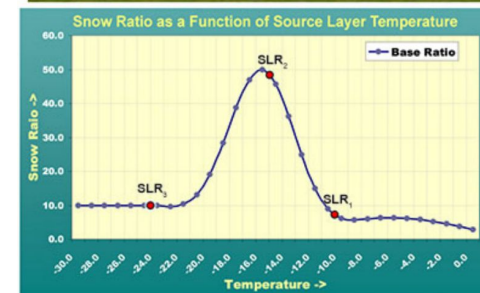
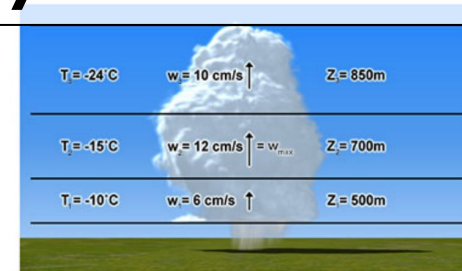


- Uses a neural network

**Caveat:** Some methods were developed for certain regions and may yield skewed results



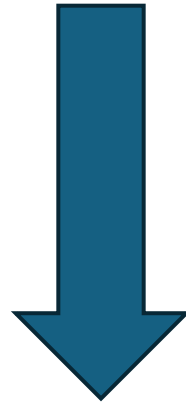
- Maximum temperature between 2000 ft AGL and 400 hPa



- Uses vertical velocity and temperature in “cloudy” regions to predict SLR

## **Goal:**

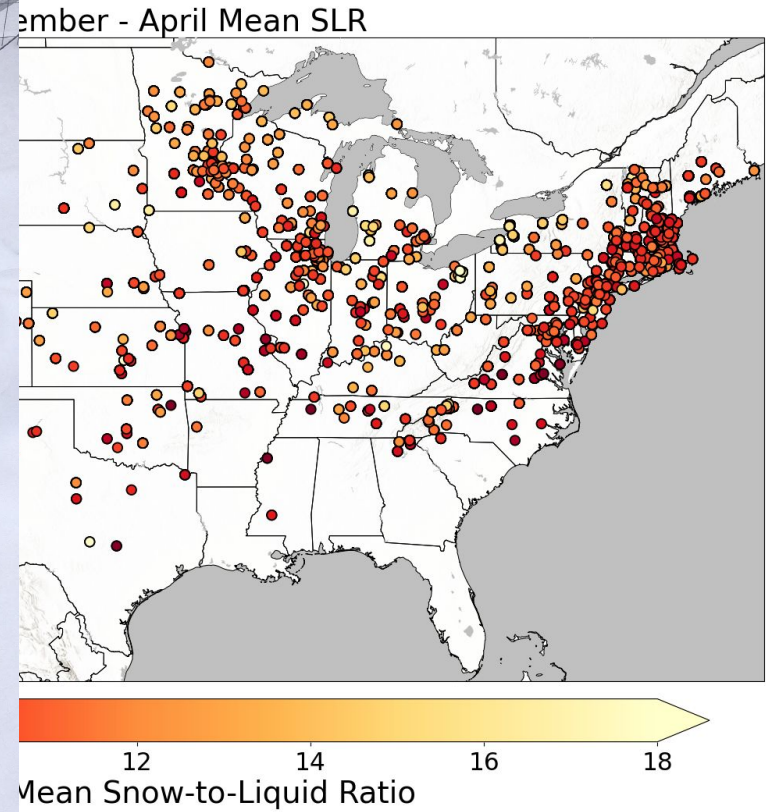
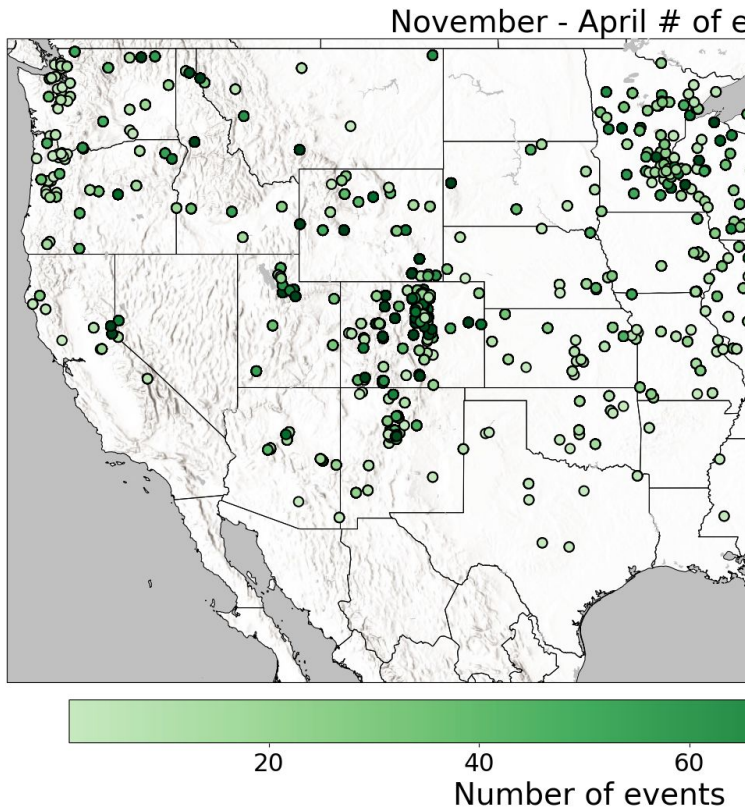
Develop and verify a new SLR prediction method using machine learning methods and a CONUS-wide snowfall observation network



Train a random forest algorithm to predict SLR and compare results with existing SLR methods



# CoCoRAHS Observing Network



- 921 unique sites across
- Only included sites with snow gauges or tipping buckets)

periods  
snowfall (no weighing

# Random forest algorithm development

## Input features

Variable	Levels
Temperature	300, 600, 900, 1200, 1500, 1800, 2100, 2400 m above ground level
Wind speed	300, 600, 900, 1200, 1500, 1800, 2100, 2400 m above ground level
Relative humidity	300, 600, 900, 1200, 1500, 1800, 2100, 2400 m above ground level
Latitude	N/A
Longitude	N/A
Elevation	N/A

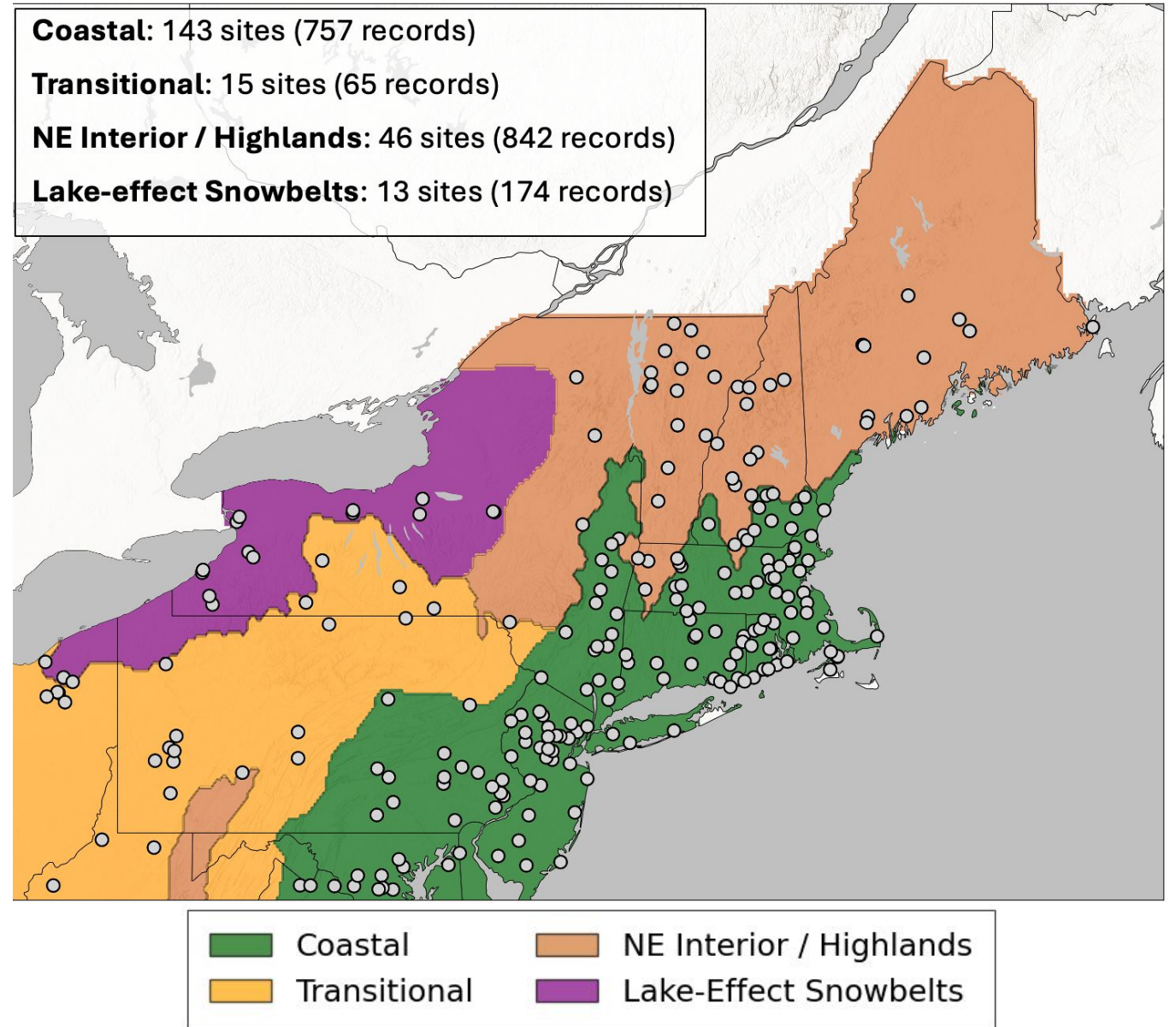
Most predictors were chosen based on results from previous studies [Roebber et al. (2003); Cobb and Waldstreicher (2005); Alcott and Steenburgh (2010)]

- **Random forest (RF):** Aggregates predictions from an ensemble of decision trees to make a deterministic prediction
- Trained with ERA5 0.25° Reanalysis and CoCoRAHS site 24-h SLR observations; 60/40 train/validate split
- Training period: December 2000 to April 2022
- Testing period: November 2022 to April 2024 (testing performed on the HRRR)

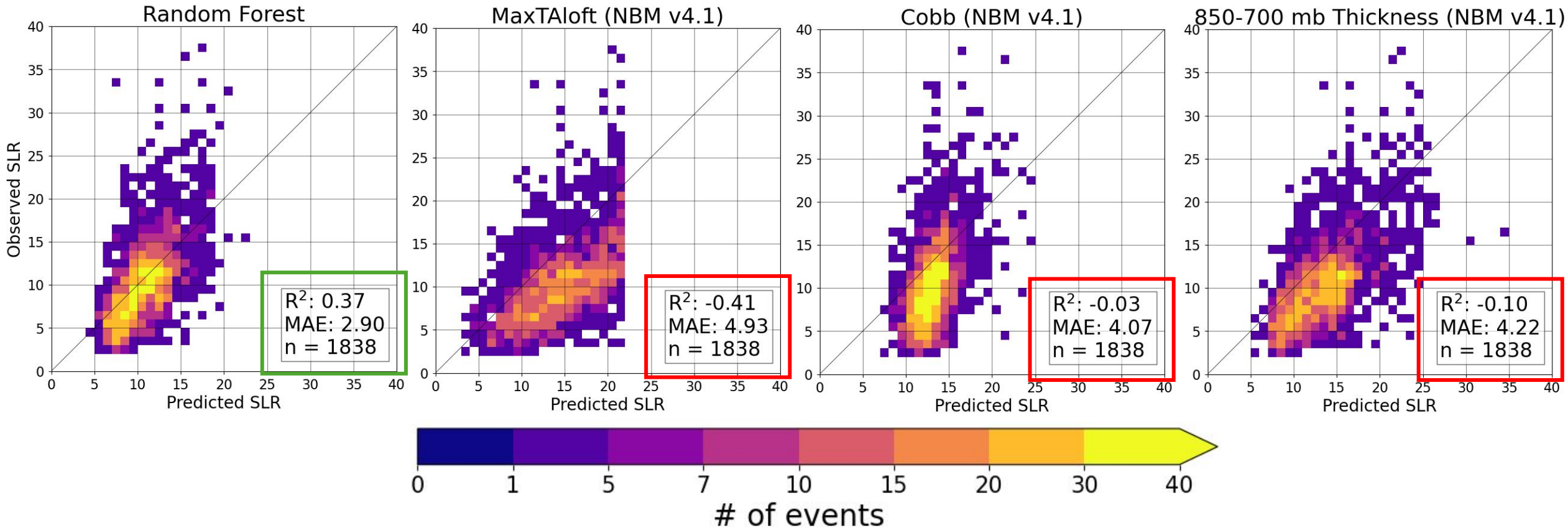


# Northeast CONUS Snow Climates

- Eight CONUS snow climates defined using
  - National Operational Hydrologic Remote Sensing Center (NOHRSC) Snow Analysis
  - Baxter et al. (2005) SLR Climatology
- Initially used k-means clustering
- Test SLR method performance within each snow climate



# Northeast CONUS SLR method performance

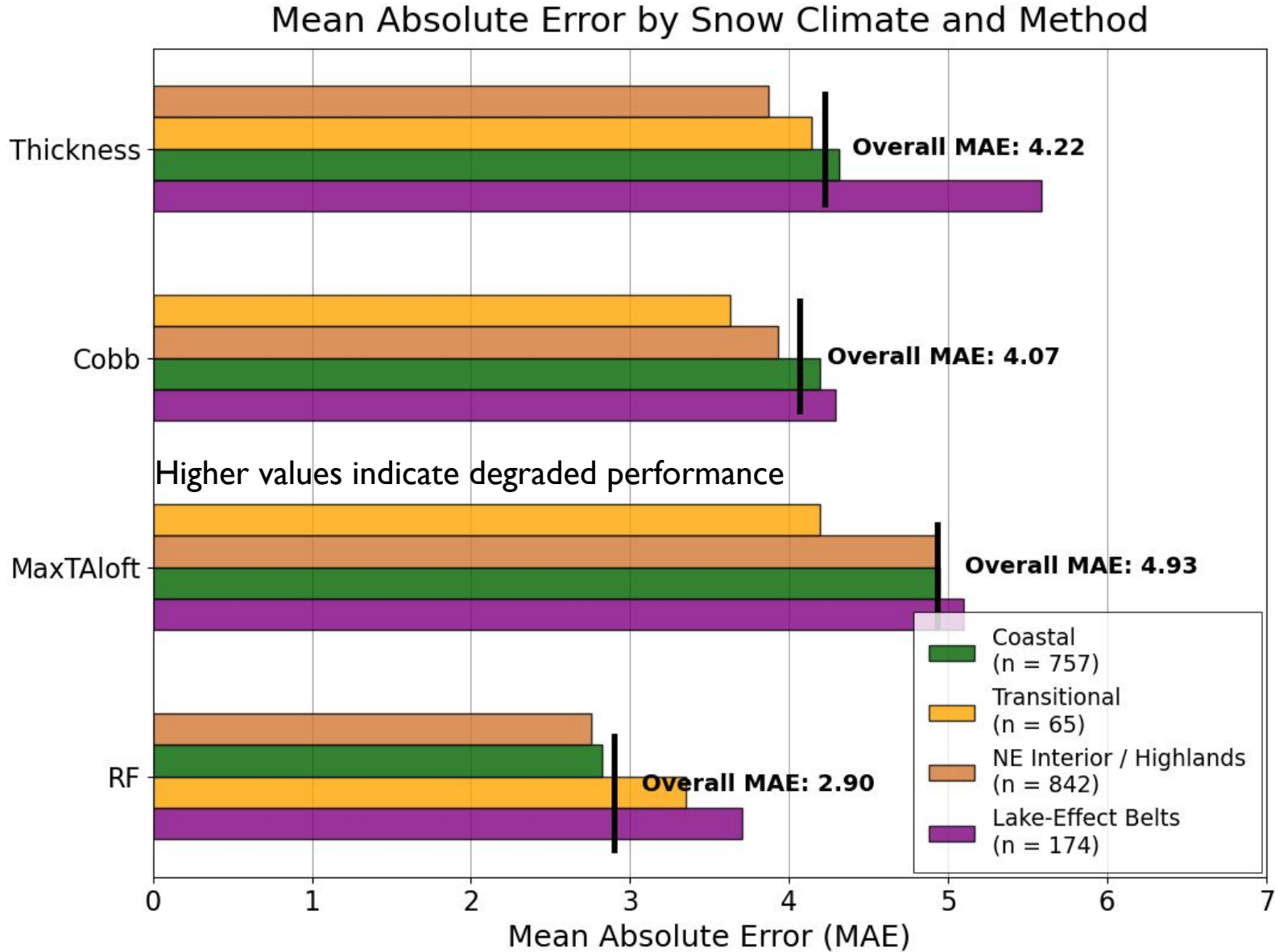


- ERA5, CONUS-wide trained model applied to the HRRR from November 2022 to April 2024
- RF performs best across the northeast CONUS

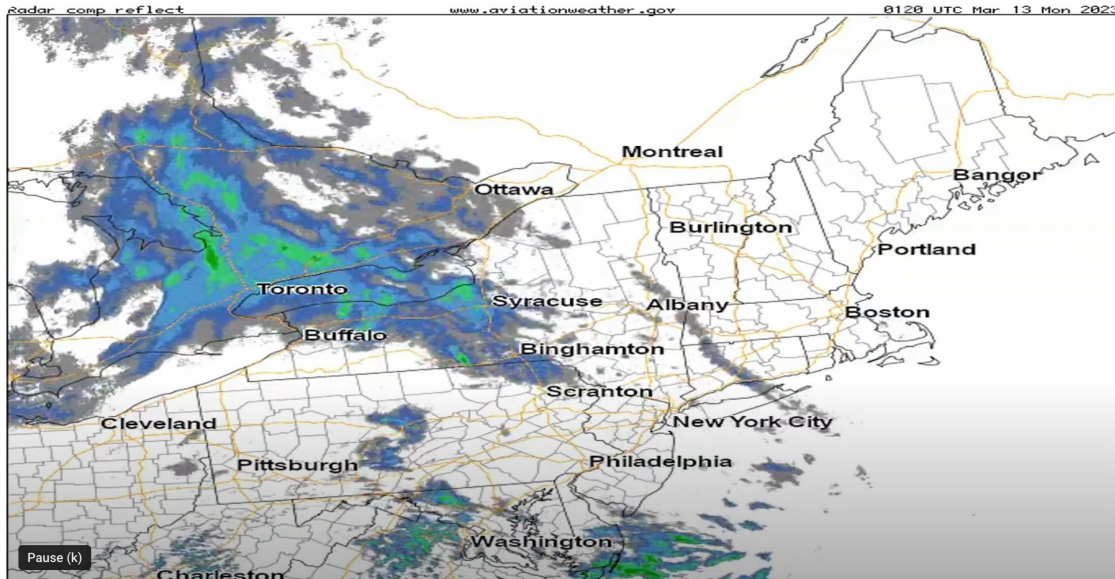


# Northeast CONUS Snow Climate Performance

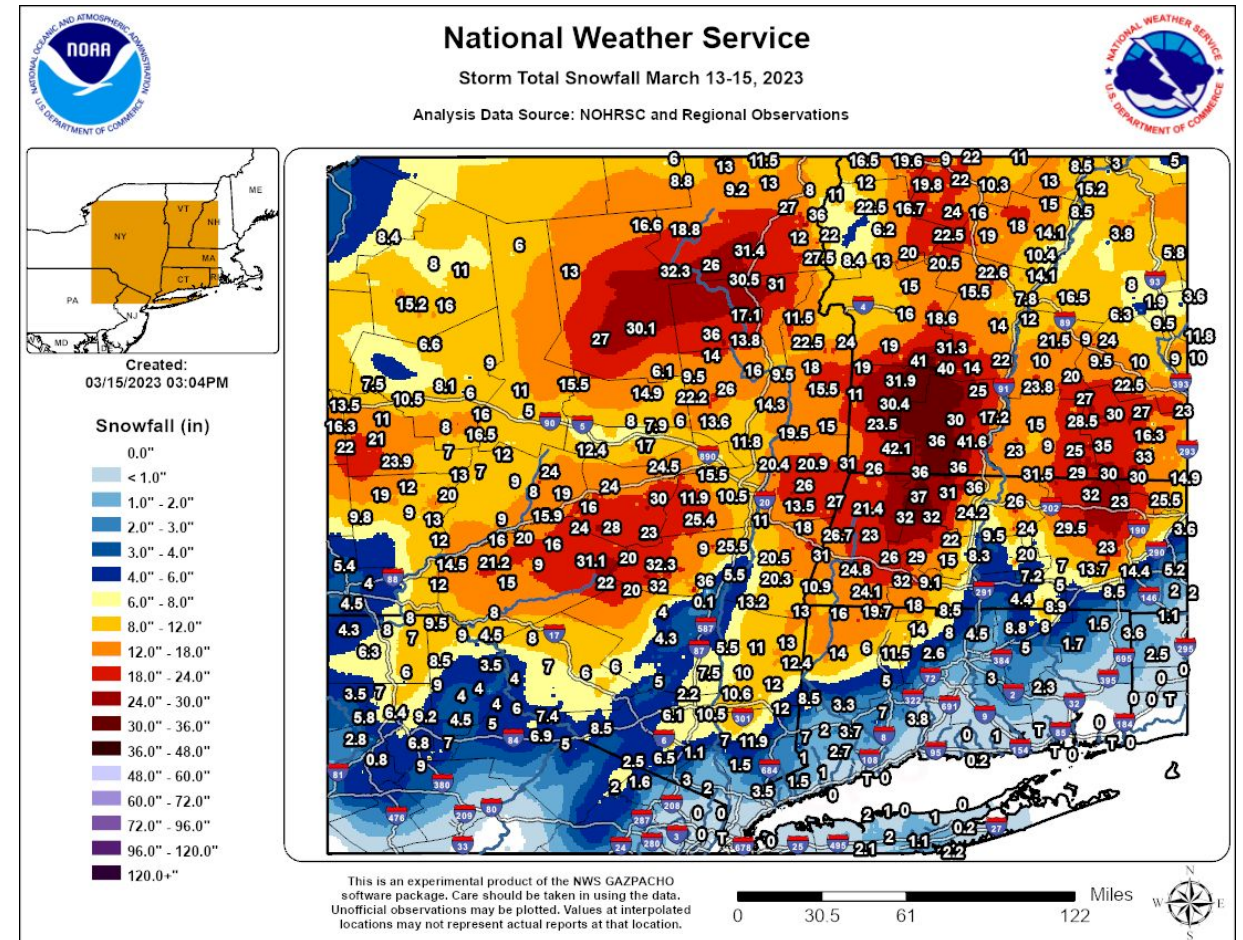
- RF exhibits lowest MAE for all snow climates; MaxTAloft highest
- All methods are least accurate for lake-effect events
- Modest spread in predictability for each climate



# March 13 – 15, 2023 Nor'easter Case Study



NWS (2023)

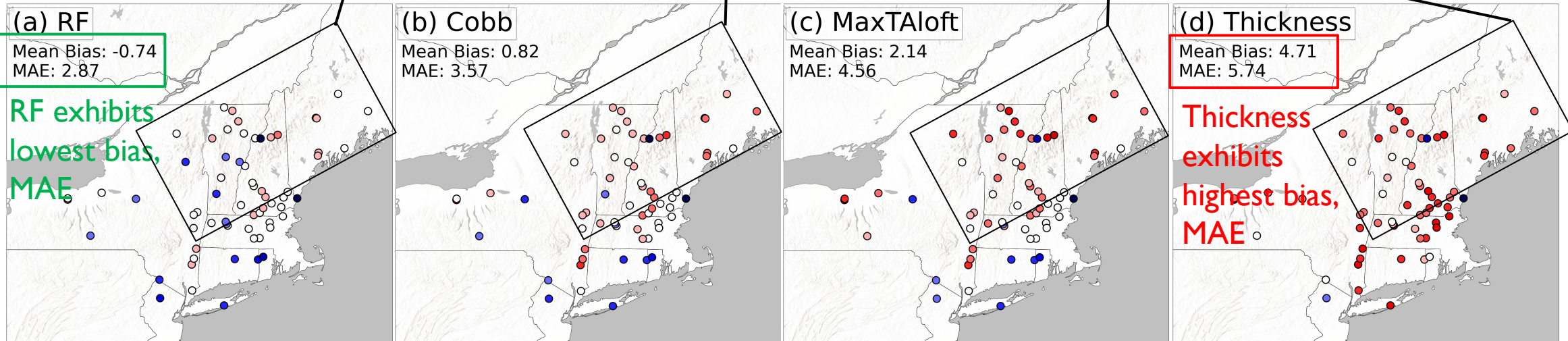
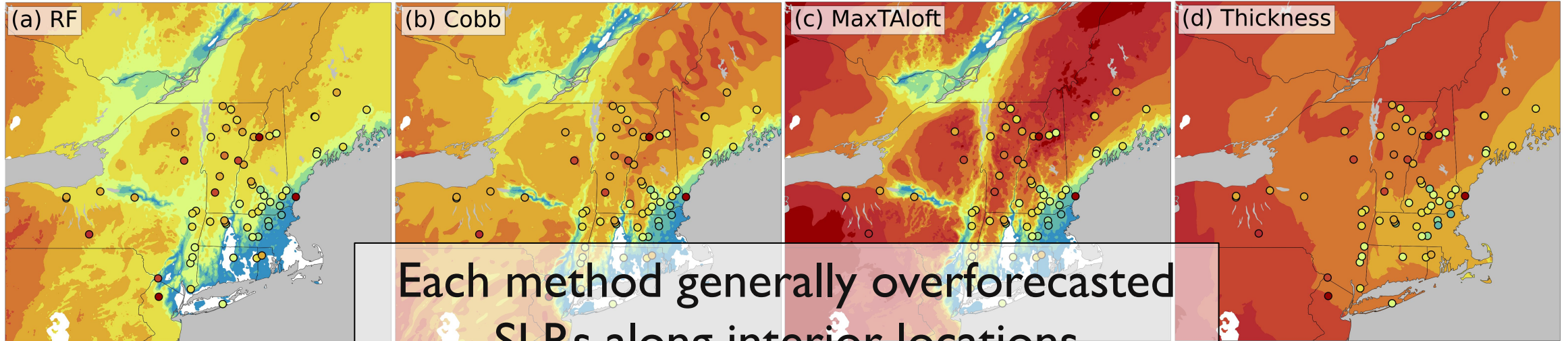


NWS (2023)

- Widespread snowfall totals  $> 12$  inches, locally 30+ inches
- Began as rain/wintry mix in valleys/mountains, transitioned to a heavy, wet snow by midday March 14
- Orographic enhancement over Greens, Berkshires, Adirondacks, Catskills

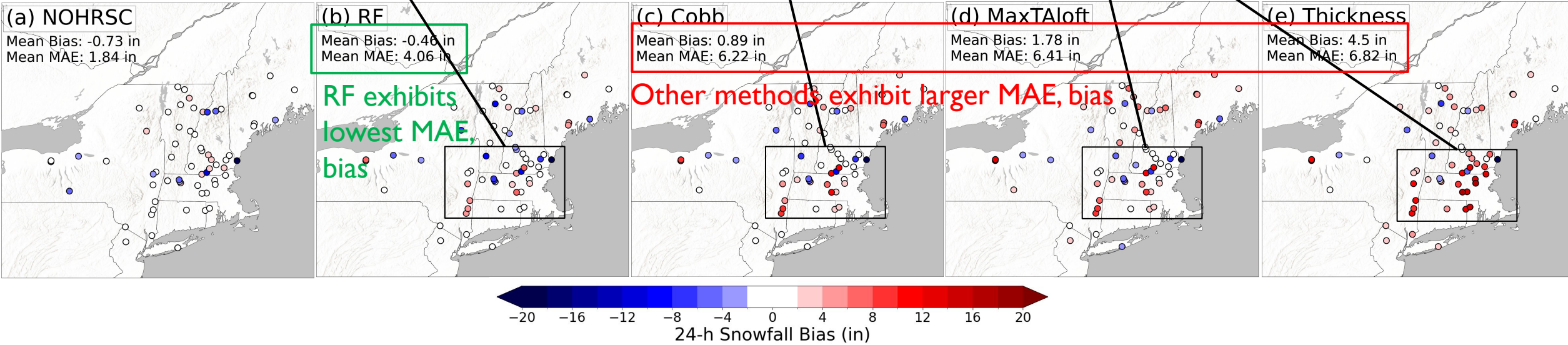
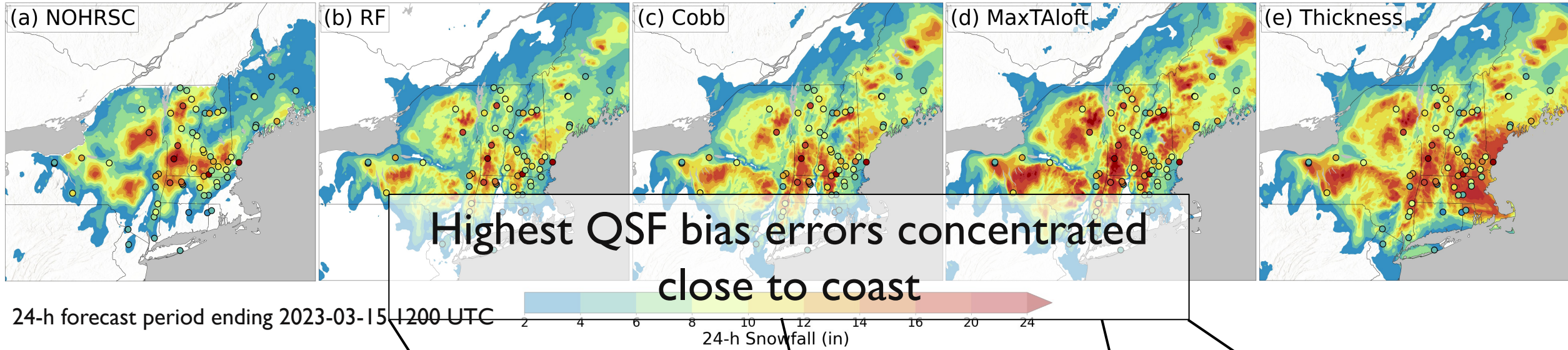


# Case Study Verification: 24-h SLRs





# Case Study Verification: 24-h QSF





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# Conclusions

- A random forest SLR algorithm trained on CONUS-wide snowfall observations was developed and tested against operational SLR methods in different snow climates
- The RF outperforms operational SLR methods across the northeastern U.S., especially along coastal and interior northeast CONUS areas
- The RF performs reasonably for a high snow / SWE event, highlighting its accuracy during high-impact winter storms

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# Future work

- Understand which environments (i.e., marginal temperature environments, high or low QPF, etc.) lead to accurate or poor SLR forecasts
- Further verify snowfall amounts across longer time scales
- Add in results from the Roebber et al. (2003) SLR prediction method