



# FV3-LAM Convection-Allowing Model Forecasts and Ensemble Consensus Products for the 13<sup>th</sup> HMT Winter Weather Experiment

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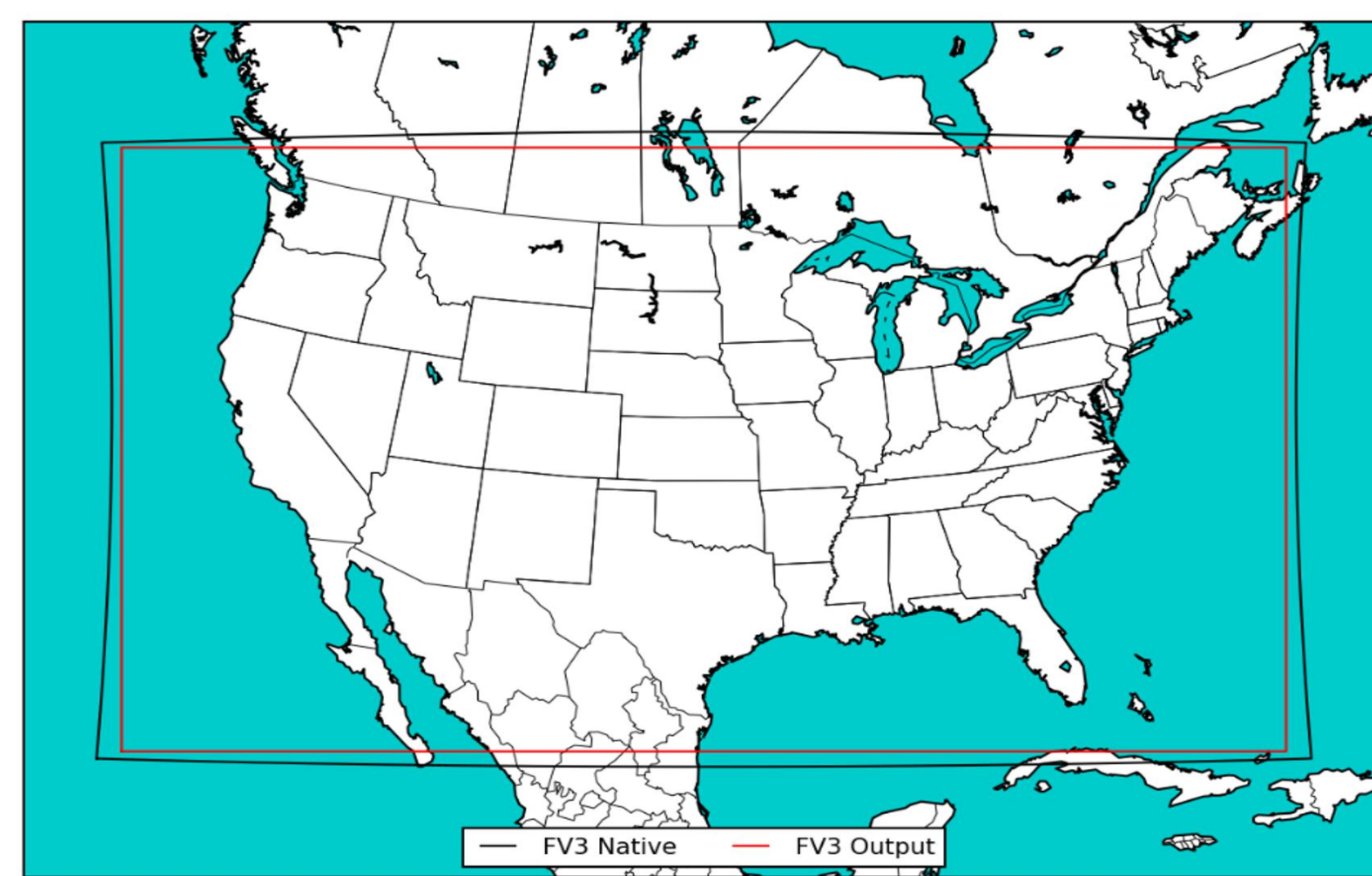


## Experiment Goals

- Test FV3 CAM ensemble in quasi-operational winter setting 13<sup>th</sup> HMT Winter Weather Experiment
- Generate 15-member CAM ensemble forecast
- Test various physics combinations for possible operational use
- Test and evaluate ensemble consensus methods including Local Probability Matched Mean and Spatial-Aligned Mean
- Use a machine learning (ML) algorithm to create probabilistic rainfall and snowfall forecasts

## FV3-LAM CAM Ensemble Configuration

- Unified Forecast System SRW App v2.1.0
- 15 FV3-LAM ensemble members
- 3 km grid spacing (“RRFS\_CONUS\_3km” grid)
- 64 vertical levels
- 84-h forecasts initialized at 00 UTC from GFS
- Run at Texas Advanced Computing Center (TACC) on Frontera
- A total of 30 selected dates from 17 November 2022 through 14 March 2023



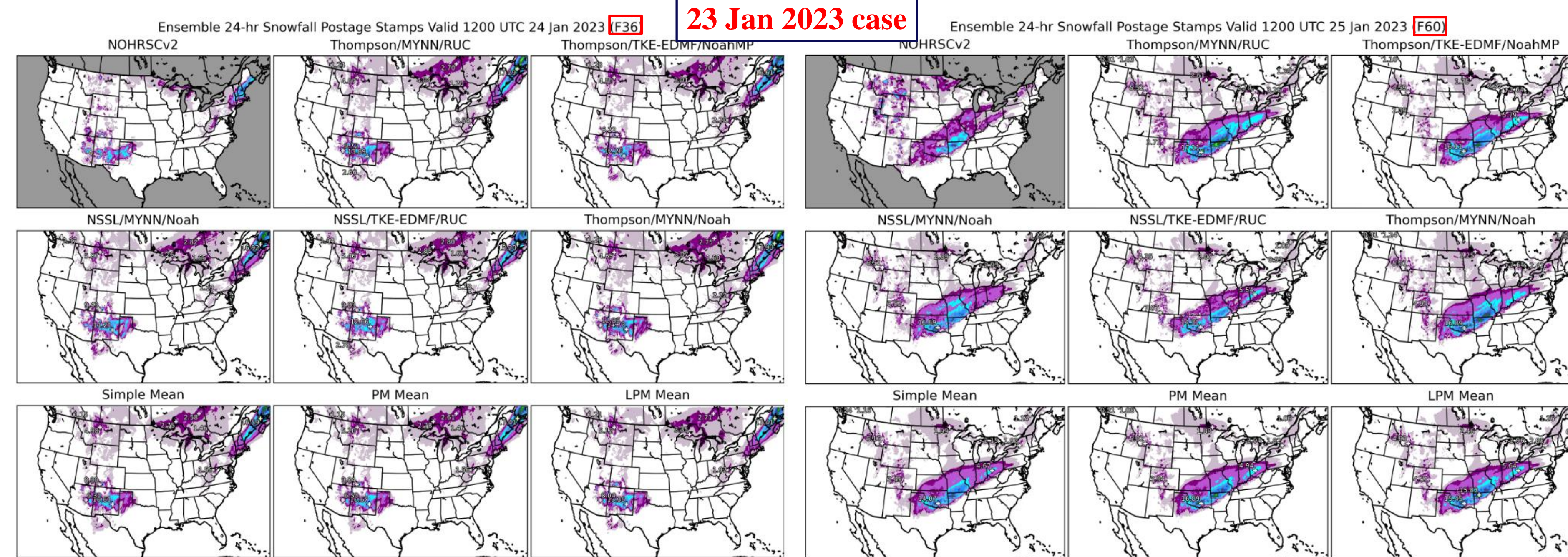
Experiment ID	ICs/LBCs	Microphysics	PBL	Surface Layer	LSM
M0B0L0_P	GFS	Thompson (0)	MYNN (0)	MYNN	NOAH (0)
M0B0L2_P	GFS	Thompson (0)	MYNN (0)	MYNN	RUC (2)
M0B2L1_P	GFS	Thompson (0)	TKE-EDMF (2)	GFS	NOAHMP (1)
M1B0L0_P	GFS	NSSL (1)	MYNN (0)	MYNN	NOAH (0)
M1B2L2_P	GFS	NSSL (1)	TKE-EDMF (2)	GFS	RUC (2)
M0B0L0_PI	GEFS m1	Thompson (0)	MYNN (0)	MYNN	NOAH (0)
M0B0L2_PI	GEFS m4	Thompson (0)	MYNN (0)	MYNN	RUC (2)
M0B1L0_PI	GEFS m2	Thompson (0)	Shin-Hong (1)	GFS	NOAH (0)
M0B2L1_PI	GEFS m3	Thompson (0)	TKE-EDMF (2)	GFS	NOAHMP (1)
M0B2L2_PI	GEFS m5	Thompson (0)	TKE-EDMF (2)	GFS	RUC (2)
M1B0L0_PI	GEFS m6	NSSL (1)	MYNN (0)	MYNN	NOAH (0)
M1B0L2_PI	GEFS m9	NSSL (1)	MYNN (0)	MYNN	RUC (2)
M1B1L0_PI	GEFS m7	NSSL (1)	Shin-Hong (1)	GFS	NOAH (0)
M1B2L1_PI	GEFS m8	NSSL (1)	TKE-EDMF (2)	GFS	NOAHMP (1)
M1B2L2_PI	GEFS m10	NSSL (1)	TKE-EDMF (2)	GFS	RUC (2)

M: Microphysics  
B: PBL/Surface scheme  
L: Land Surface Model  
P: Physics perturbation only  
PI: Physics + IC/LBC perturbations

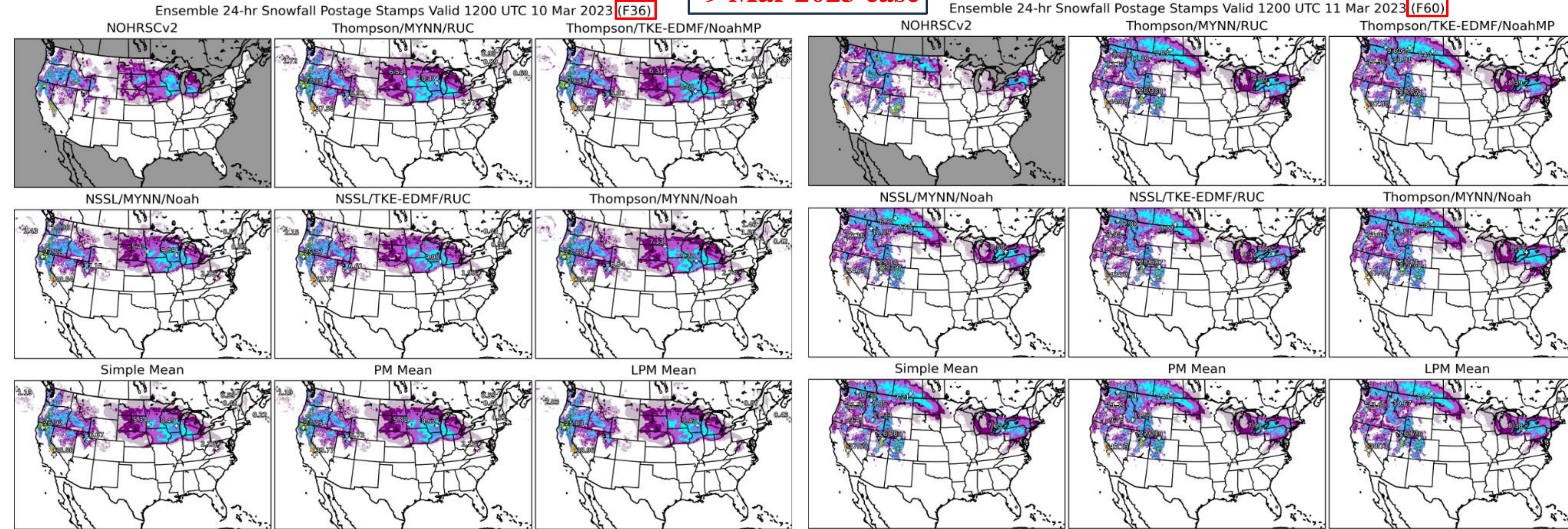
## NOHRSCv2: Snowfall analysis

PM Mean: Probability Matched ensemble mean

LPM Mean: Localized Probability Matched ensemble mean

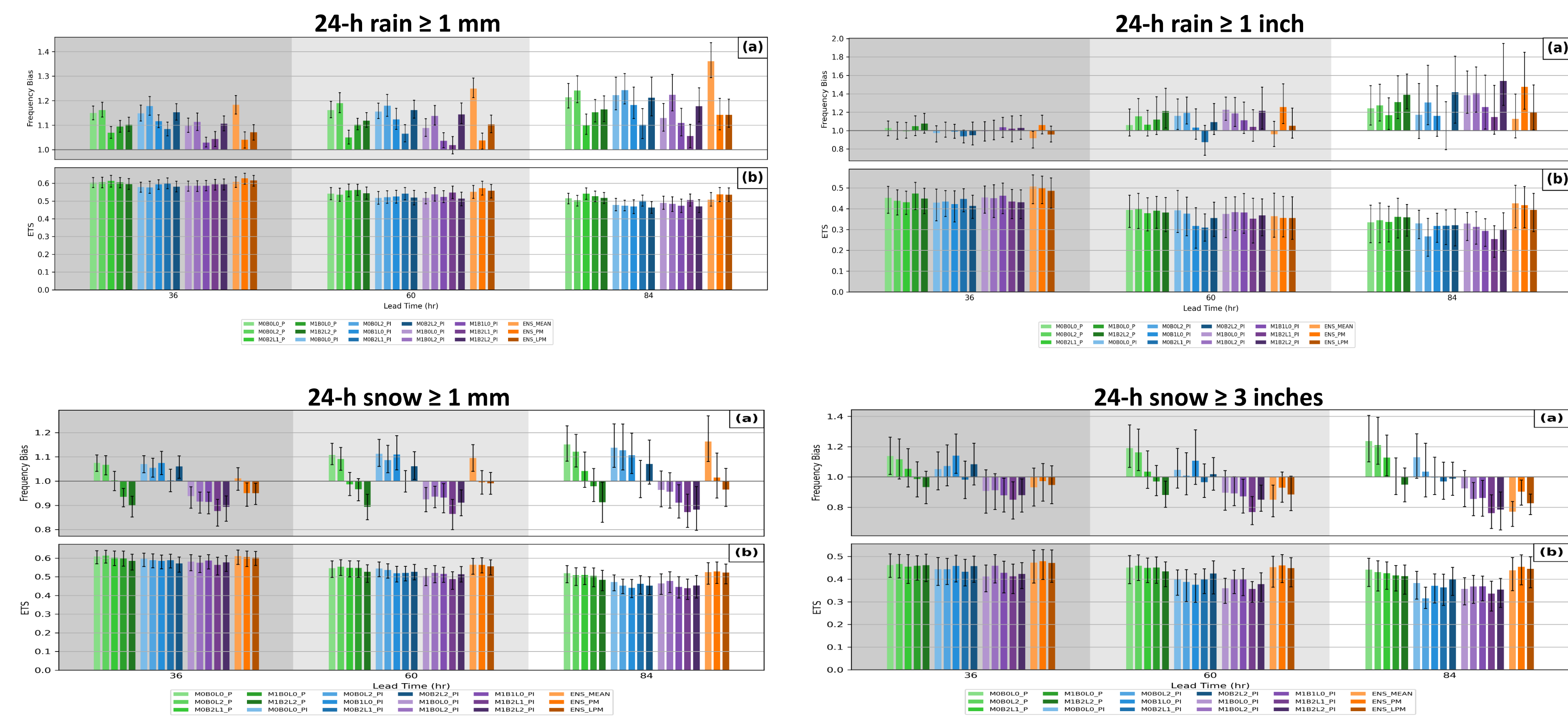


## 9 Mar 2023 case



## Selected Bulk Verification Statistics

- Statistics for the 15 ensemble members are colored shades of green, blue, and purple. Three different lead times are shown.
- Statistics for three versions of the ensemble mean are colored shades of brown.
- Frequency bias: < 1.0 → an under-forecast ; > 1.0 → an over-forecast
- ETS: Equitable Threat Score ; larger values → a better forecast
- Top two figures → statistics for 24-h rain accumulation ; bottom two figures → statistics for 24-h snow accumulation
- A 30 km neighborhood radius is used in the verification.

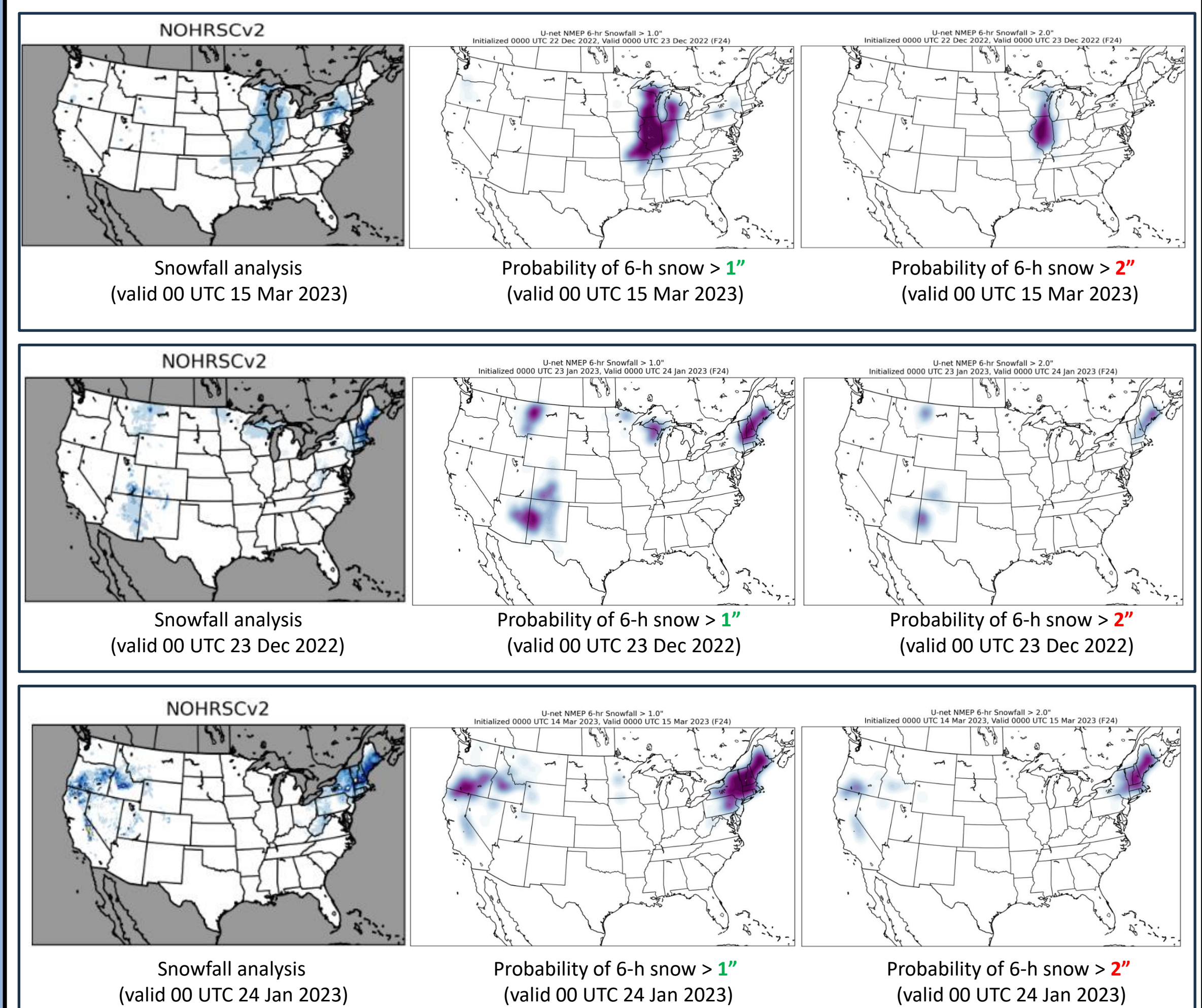


## Machine Learning: Probabilistic Forecasts of Snowfall

- Trained on a 4 CAPS FV3-LAM members and 8 High Resolution Ensemble Forecast (HREF) members.
- 0-36 hour probabilistic forecasts of rainfall and snowfall exceeding specified thresholds (1”, 2”, and 3” accumulation over 6 hours for snowfall).
- For snowfall, 25+ two-dimensional input variables are used for training. See table below.
- A neighborhood ensemble probability (NEP; not shown in figures) and a neighborhood maximum ensemble probability (NMEP) are generated. [neighborhood radius = 45 km ; Gaussian smoother applied]

Variable	Levels Used
Geopotential Height	500 hPa
Temperature	500, 700, 850, 925, 1000 hPa; 2 m AGL
Dewpoint	500, 700, 850, 925, 1000 hPa; 2 m AGL
u- and v- wind components	500 hPa; 10 m AGL
6-h maximum reflectivity	1 km AGL
Precipitable water	column-integrated
Hourly maximum updraft velocity	column maximum
6-h accumulated precipitation	
6-h accumulated snowfall	
Categorical precipitation type	
Echo-top height	
Mean sea level pressure	

- Input variables were selected to provide information important for snowfall.
- All variables listed are used for snowfall predictions, whereas rainfall predictions use all variables, excluding those colored blue.



## Conclusions

- All 15 ensemble members appear to capture the spatial patterns of the precipitation rather well.
- For rain/no-rain threshold ( $\geq 1$  mm), all members tend to overforecast for all three lead times.
- For a higher rain threshold ( $\geq 1$  inch), the overforecast appears at longer lead times.
- For both the lower and higher snow thresholds, the NSSL microphysics members (M1\*) tend to underforecast, whereas the other members slightly overforecast.
- The ensemble means generally outperform any single ensemble member for both rain and snow (as measured by the ETS).
- Although further work remains, machine learning (ML) provides a viable companion product for producing probabilistic precipitation forecast guidance.
- CAPS forecast ensemble output (including ML ensemble forecasts): <https://caps.ou.edu/forecast/realtime/>

We acknowledge the UFS Development Team (2022, Nov. 17). Unified Forecast System (UFS) Short-Range Weather (SRW) Application (Version 2.1.0). Zenodo. <https://doi.org/10.5281/zenodo.7277602>. Testbed work is done in collaboration with the NOAA WPC HMT Testbed group. The numerical modelling experiments were performed using resources at the Texas Advanced Computing Center (TACC) at the University of Texas at Austin. Verification provided by NOAA NOHRSC snow analysis and NOAA RFC Stage-4 precipitation. This work is supported by NOAA grants NA19OAR4590141 and NA22OAR4590522.