FV3-LAM-Based CAM Ensemble & Machine Learning Products for the HMT Winter Weather Experiments

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14th HMT Winter Weather Experiment
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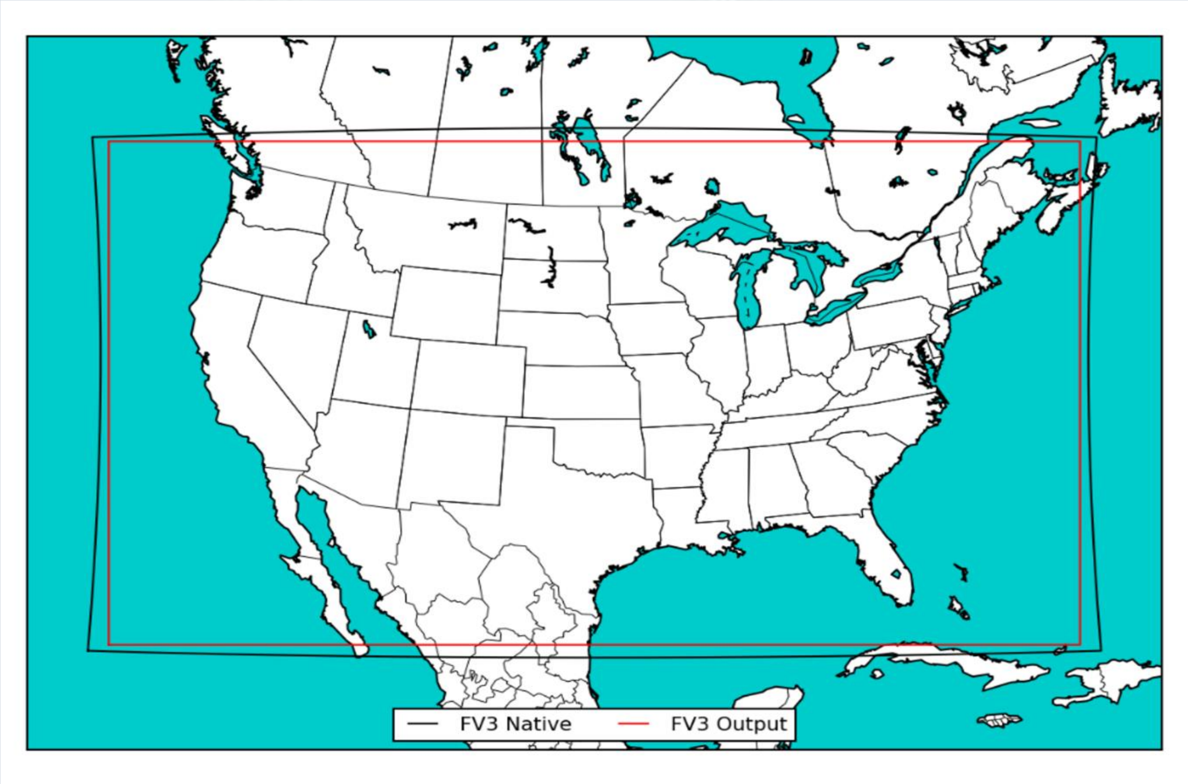
CAPS Ensemble Experiment Goals

- Test FV3 CAM ensemble in quasi-operational winter setting: HMT Winter Weather Experiments
- Generate 15-member CAM ensemble forecast
- Test various physics combinations for possible operational use
  such as nascent Rapid Refresh Forecast System
- Test and evaluate ensemble consensus methods including Local Probability Matched Mean and Spatial-Aligned Mean
- Develop machine learning (ML) algorithms to create probabilistic rainfall and snowfall forecasts

Real-time 13th WWE (2022-2023) FV3-LAM CAM Ensemble Configuration

- 15 FV3-LAM members
- 3 km grid spacing (GFDL grid)
- 64 vertical levels
- 84-hr forecasts initialized at 00 UTC
- Run at Texas Advanced Computing Center – Frontera
- Total of 30 days run for objective verification and ML training
- Results posted to web: https://caps.ou.edu/forecast/realtime/

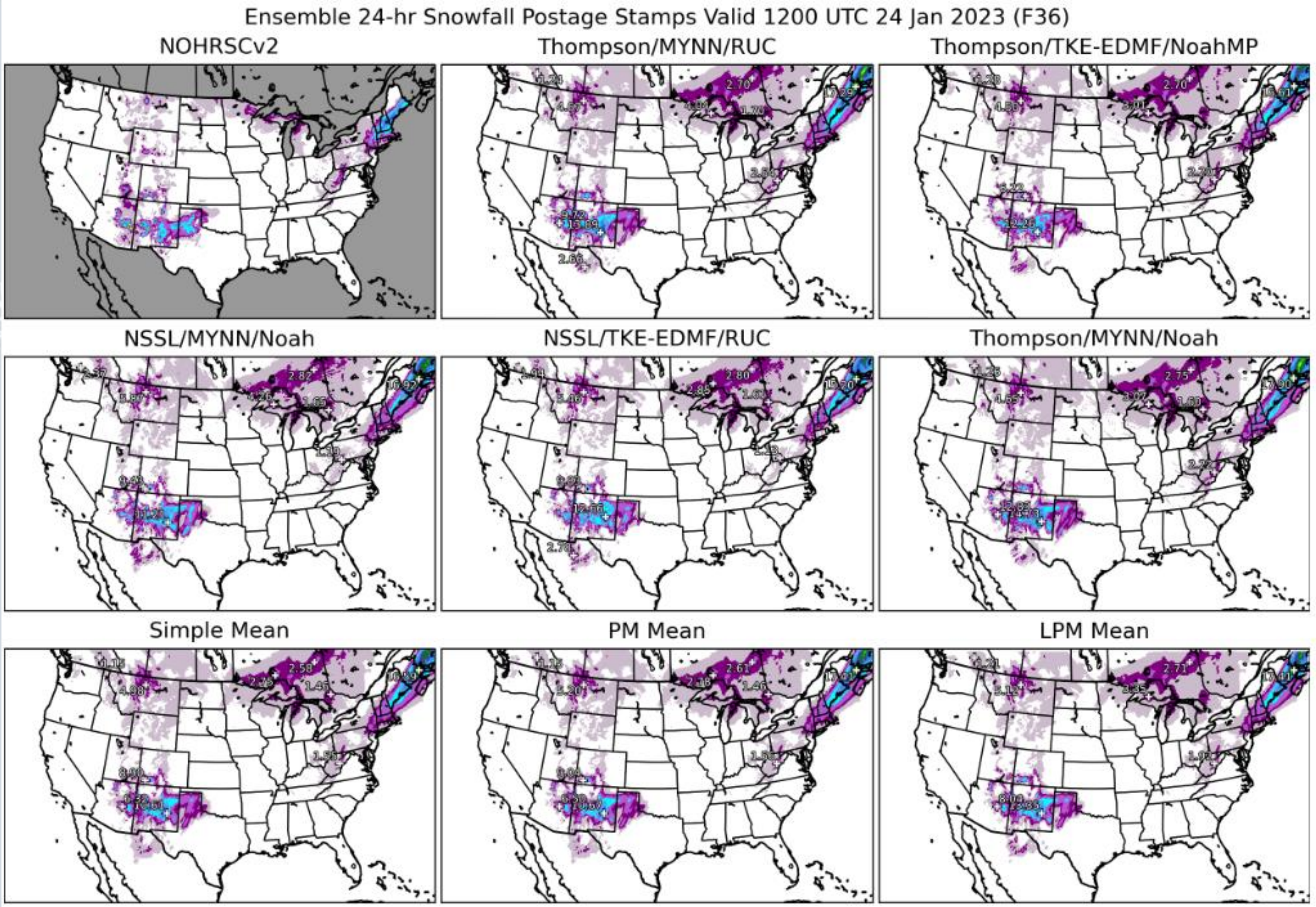


13th WWE 2022-23 15 Members

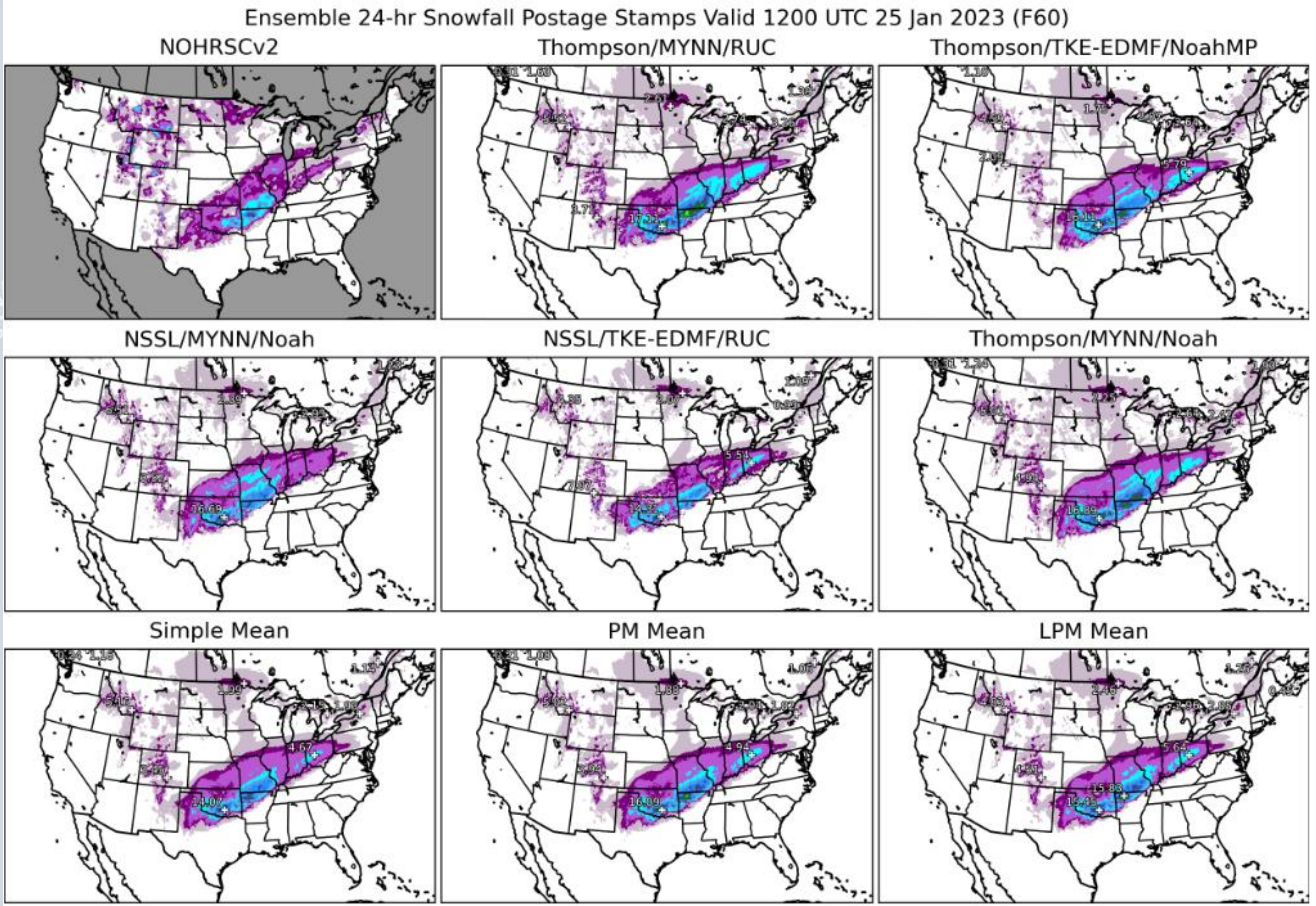
Naming
M: Microphysics
B: Boundary Layer
L: Land Sfc Model
PG: GFS Initial/Bndy Cdx
PI: Initial perturbations

Experiment	Microphysics	PBL	Surface	LSM	IC/LBC (like system)	AI member
GFS IC for Baseline Configuration						
M0B0L0_PG	Thompson	MYNN	MYNN	NOAH	GFS /GFS (RRFSv0)	AI-1
M1B0L0_PG	NSSL	MYNN	MYNN	NOAH	GFS/GFS (WoF)	AI-2
M0B0L2_PG	Thompson	MYNN	MYNN	RUC	GFS/GFS (RRFS)	AI-3
M1B2L2_PG	NSSL	TKE-EDMF	GFS	RUC	GFS/GFS (Mixed)	
M0B2L1_PG	Thompson	TKE-EDMF	GFS	NOAHMP	GFS/GFS (GFSv16)	AI-4
Physics + IC Perturbation Ensemble						
M0B0L0_PI	Thompson	MYNN	MYNN	NOAH	GEFS_m1	
M0B1L0_PI	Thompson	Shin-Hong	GFS	NOAH	GEFS_m2	
M0B2L1_PI	Thompson	TKE-EDMF	GFS	NOAHMP	GEFS_m3	
M0B0L1_PI	Thompson	MYNN	MYNN	NOAHMP	GEFS_m4	
M0B2L2_PI	Thompson	TKE-EDMF	GFS	RUC	GEFS_m5	
M1B0L0_PI	NSSL	MYNN	MYNN	NOAH	GEFS_m6	
M1B1L0_PI	NSSL	Shin-Hong	GFS	NOAH	GEFS_m7	
M1B2L1_PI	NSSL	TKE-EDMF	GFS	NOAHMP	GEFS_m8	
M1B0L1_PI	NSSL	MYNN	MYNN	NOAHMP	GEFS_m9	
M1B2L2_PI	NSSL	TKE-EDMF	GFS	RUC	GEFS_m10	

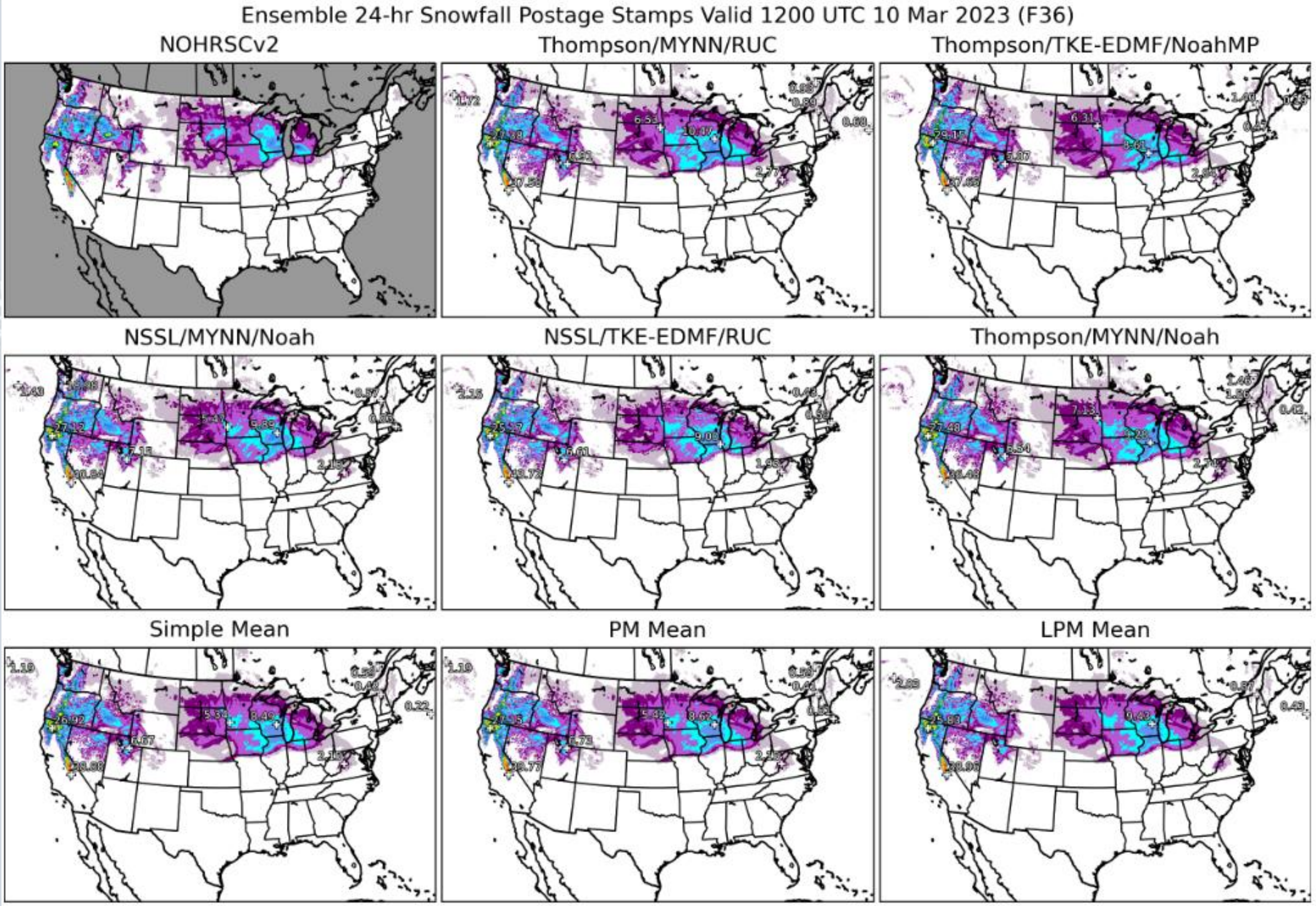
24-25 January 2023 Case



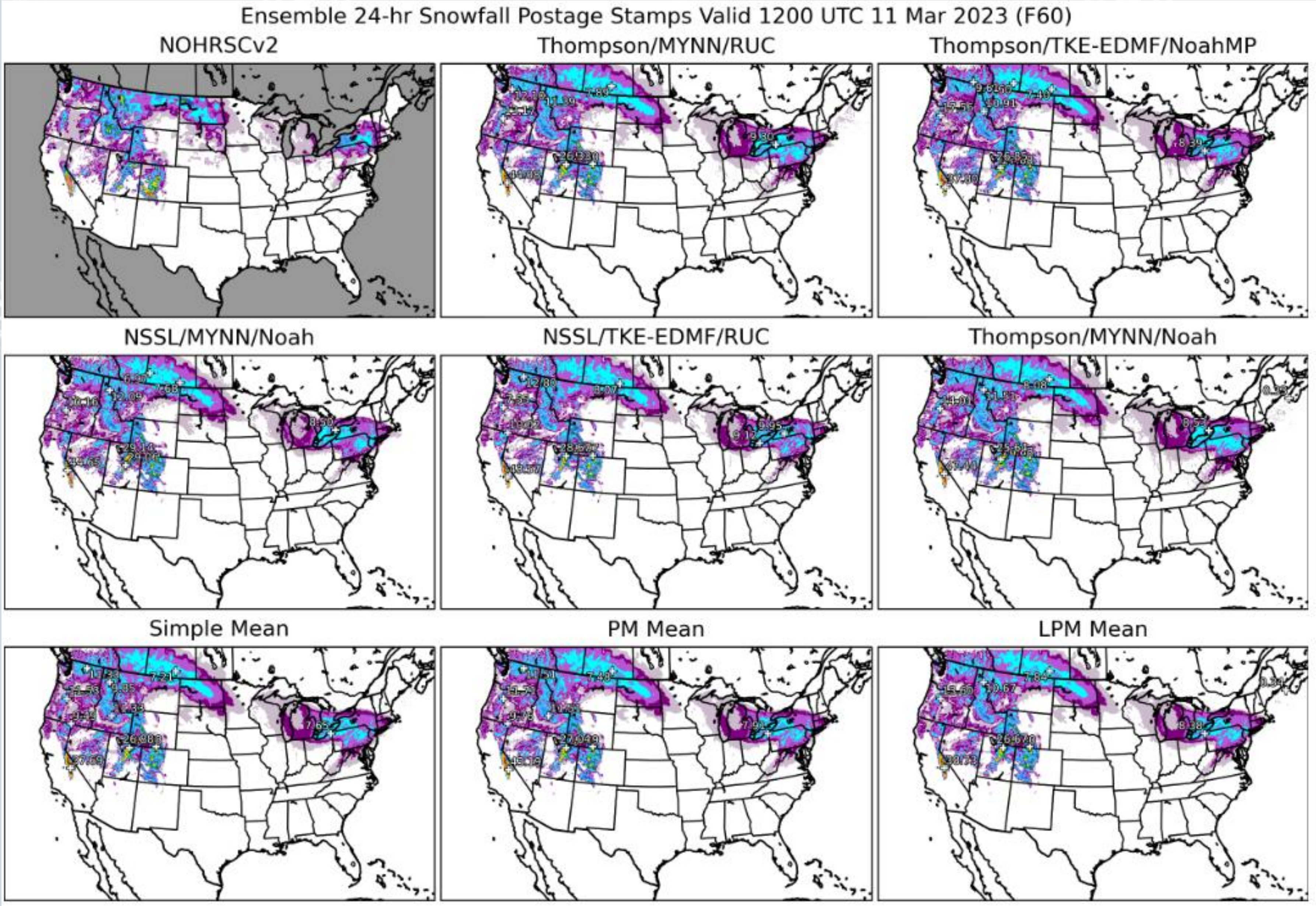
24-25 January 2023 Case



10-11 March 2023 Case



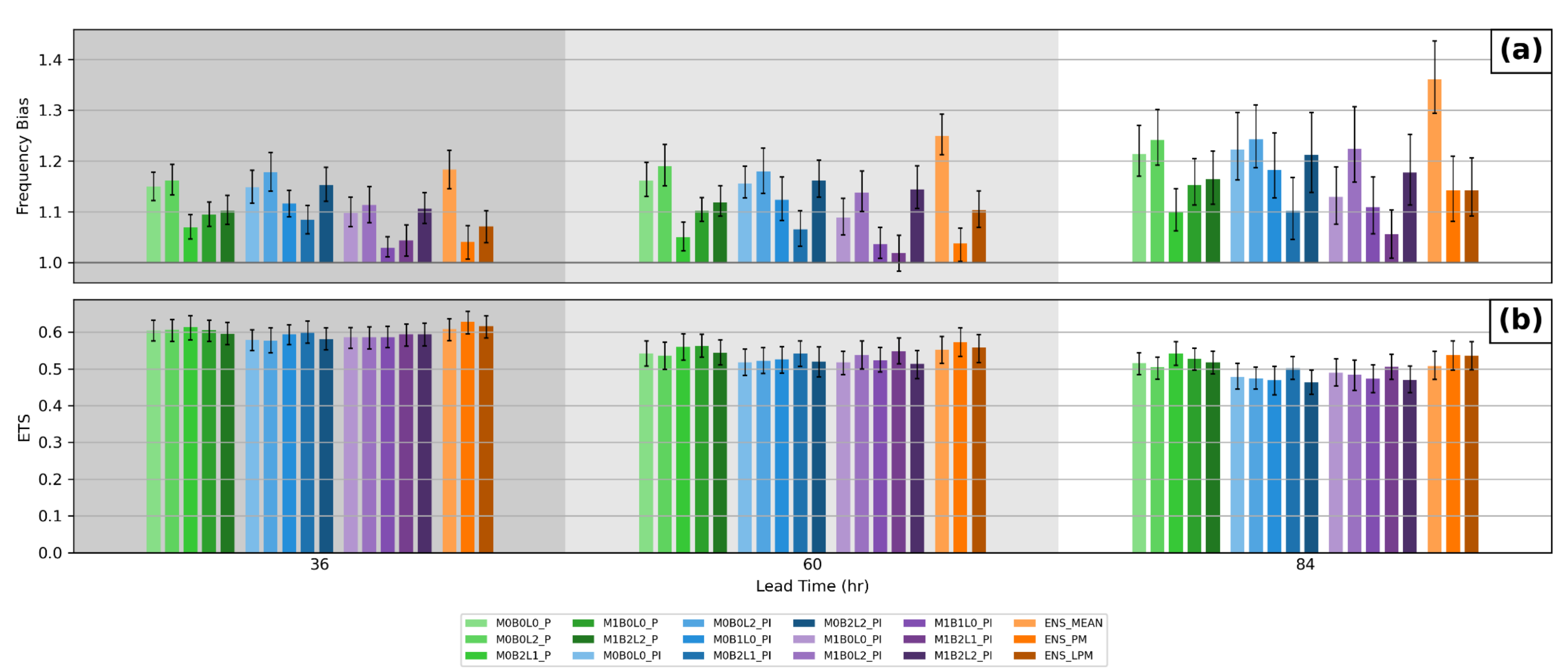
10-11 March 2023 Case



Verification

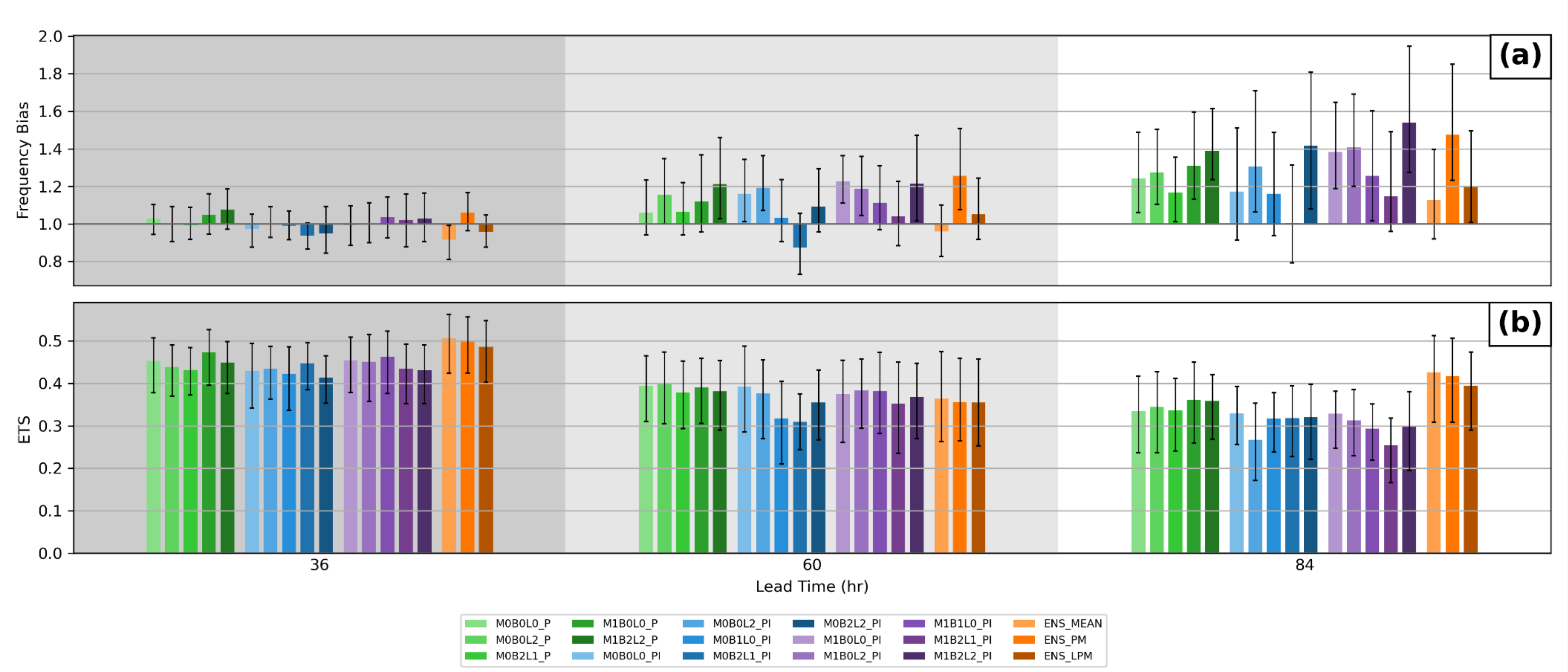
- Precipitation: Stage-4 Precipitation
- Snowfall: NOHRSC Snowfall Analysis
- MET-Plus from DTC is used
  - Areal Coverage Bias
  - Equitable Threat Score
  - Various Thresholds at 30 km neighborhood radius

Verification 24-h Precipitation > 1 mm



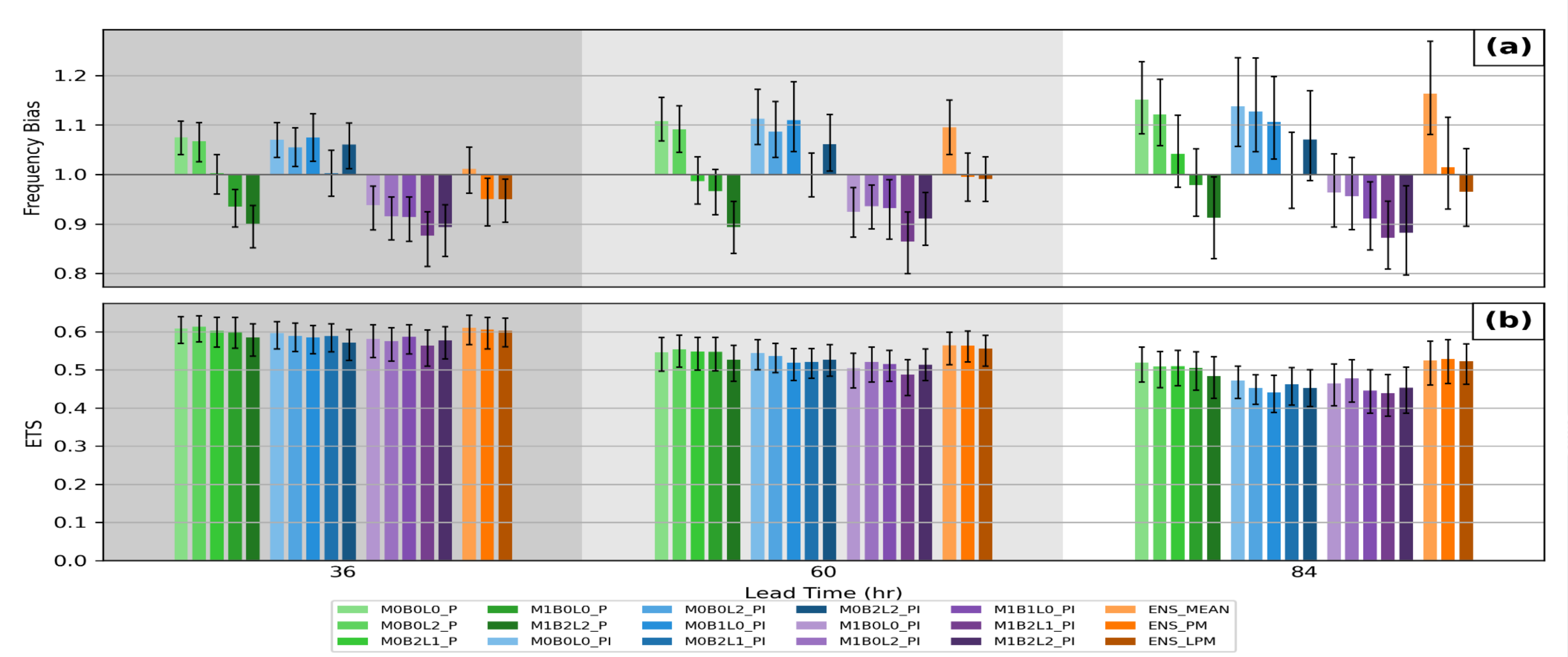
Overforecast of precipitation area, varies by member, NSSL generally less biased.
ETS scores similar despite differences in bias, ensemble means outperform.

Verification 24-h Precipitation > 25 mm (1-inch)



Less overforecasting at higher threshold, though some bias at 84 h
Ensemble means outperform at near-term (36) and especially longer term (84h)..

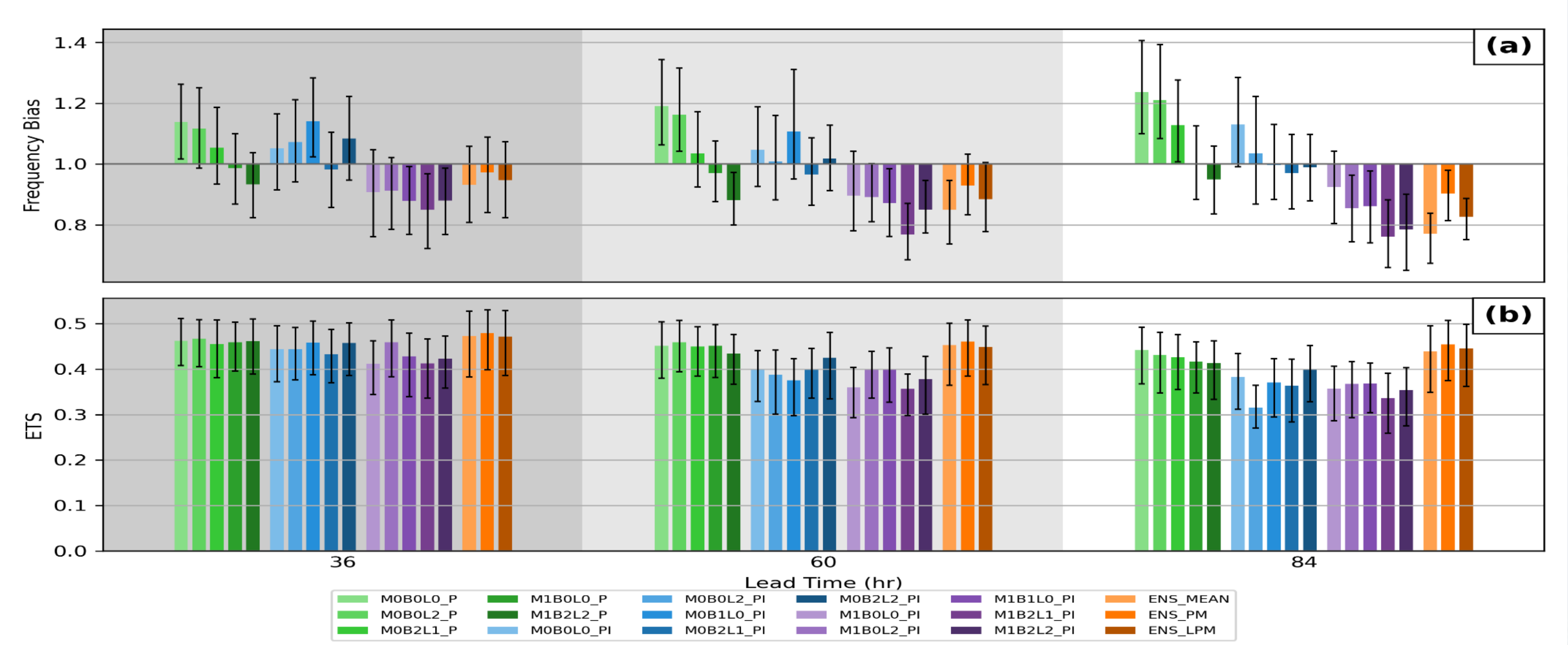
Verification 24-h Snowfall > 1 mm



Mixed biases, with low bias in NSSL Microphysics members

Less difference among ETS scores, ensembles outperform, esp at 86 h

Verification 24-h Precipitation > 75 mm (3-inch)



3-inch biases similar to 1 mm with NSSL microphysics slightly low biased
ETS scores similar among members with NSSL having slightly lower due to bias and means outperforming, especially at 84 h

14th WWE 2023-24 11 Members

Naming
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PI: Initial perturbations

Experiment	Microphysics	PBL	Surface	LSM	IC/LBC (like system)	AI member
GFS IC for Baseline Configuration						
M0B0L0_P	Thompson	MYNN	MYNN	NOAH	GFS /GFS	AI-1
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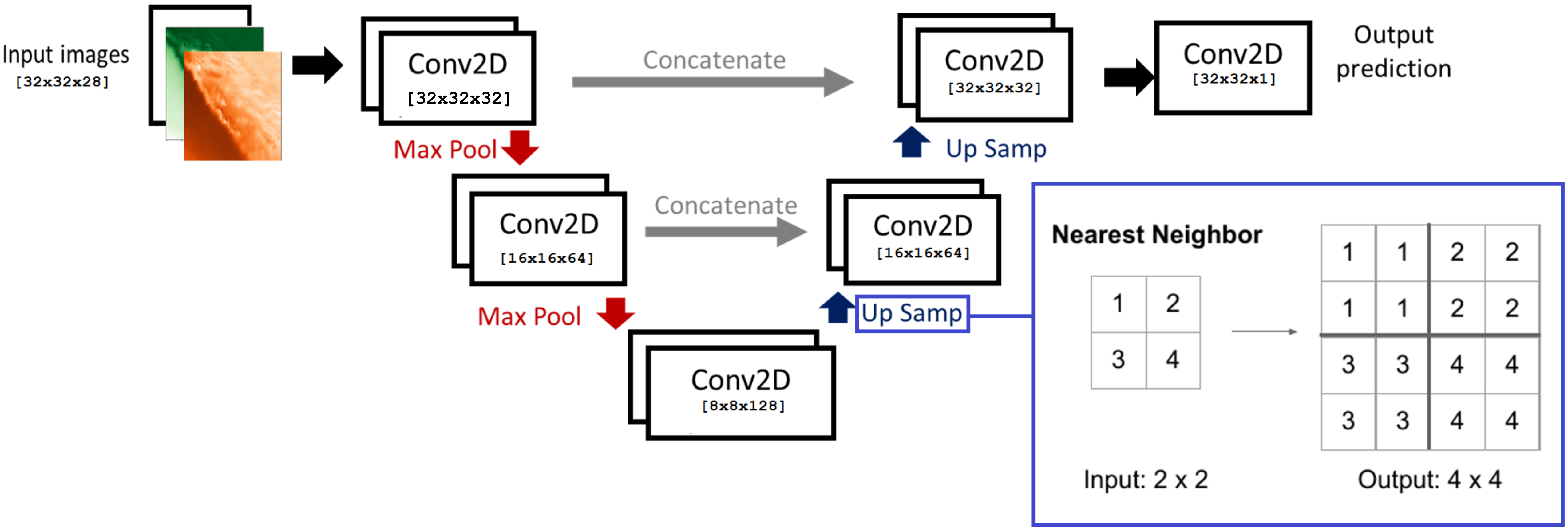
M0B0L2_P	Thompson	MYNN	MYNN	RUC	GFS/GFS (RRFSm1)	
M1B2L2_P	NSSL	TKE-EDMF	GFS	RUC	GFS/GFS (RRFSmphys8)	
M0B2L1_P	Thompson	TKE-EDMF	GFS	NOAHMP	GFS/GFS (GFSv16)	AI-3
Physics + IC Perturbation Ensemble						
M0B1L0_PI	Thompson	Shin-Hong	GFS	NOAH	GEFS_m1	
M0B2L1_PI	Thompson	TKE-EDMF	GFS	NOAHMP	GEFS_m2	
M0B2L2_PI	Thompson	TKE-EDMF	GFS	RUC	GEFS_m3	AI-4
M1B1L0_PI	NSSL	Shin-Hong	GFS	NOAH	GEFS_m4	

Machine Learning Component

- Collaboration with NSF AI2ES Institute hosted at OU
- U-Net Convolutional Neural Network (Deep Learning)
- Builds upon ML hail prediction work in HWT (2017-2021) and ML rainfall prediction in HMT FFaIR
- Uses HREF plus 4 CAPS Ensemble Members

U-Net Data/Methods

- Structure for CAPS FV3 Precipitation & Snowfall U-Net:
  - Patch size, number of connections, and number of layers are being evaluated as hyper-parameters (architecture shown below may change in later iterations)



U-Net Data/Methods

CAPS U-Net for **Rainfall** uses **23** 2D NWP **forecast variables** relevant to rainfall prediction

Variable	Level(s) Used
Geopotential height	500 hPa
Temperature	500, 700, 850 hPa; 2 m AGL
Dewpoint	500, 700, 850 hPa; 2 m AGL
u- and v- wind components	500, 850 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	
Echo-top height	
CAPE	
Mean Sea Level Pressure	
Terrain height	

U-Net Data/Methods

CAPS U-Net for **Snowfall** uses **28** 2D NWP **forecast variables** relevant to snowfall prediction

Variable	Level(s) 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	
Echo-top height	
Mean Sea Level Pressure	
Categorical SNOW, ICEP, FRZR, and RAIN	binary yes/no based on PTYPE at surface

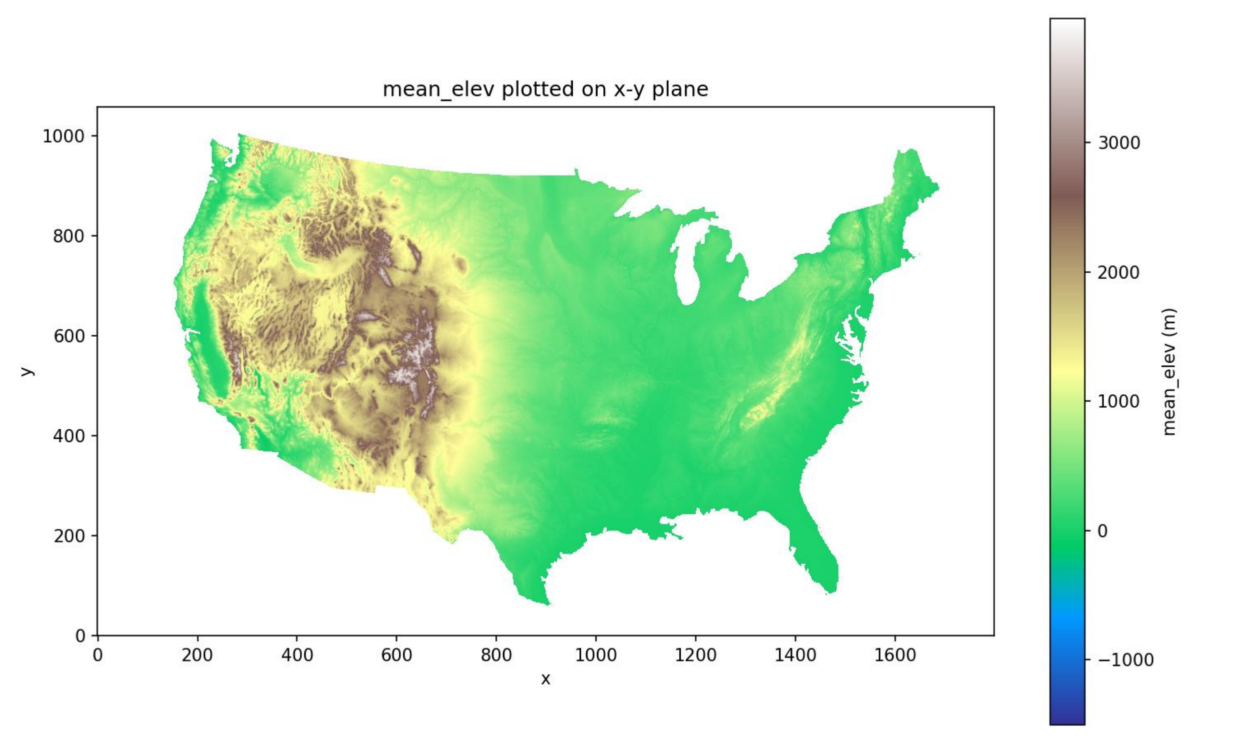
U-Net Data/Methods

New Variables Added to Snowfall U-Net for 2023-24

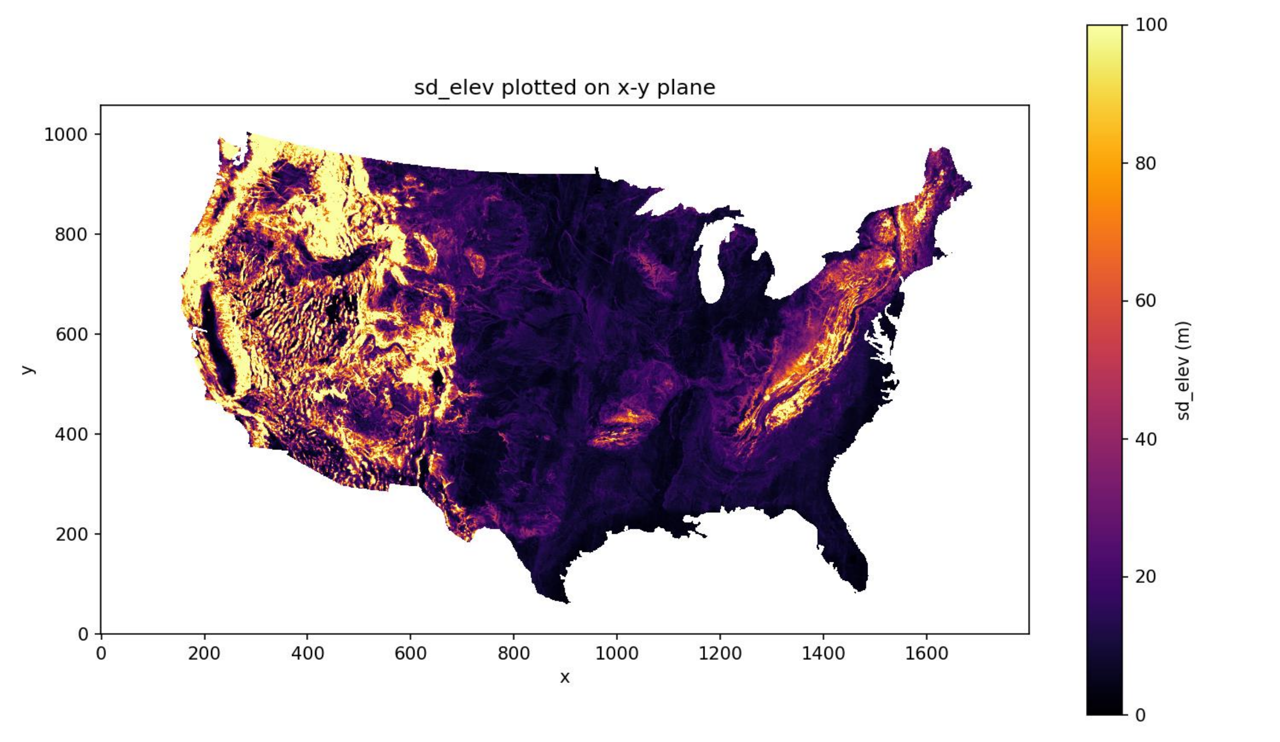
Variable	Notes/Level(s) Used
Terrain Mean, Standard Deviation, Slope	Source: ASTER Global Digital Elevation Model
Vorticity	850 hPa and 500 hPa
Divergence	850 hPa and 500 hPa
Moisture Convergence	850 hPa and 10 m AGL
Land Use Classification	Classifications: WSSI Land Use Factor

New Variables, Examples

Terrain

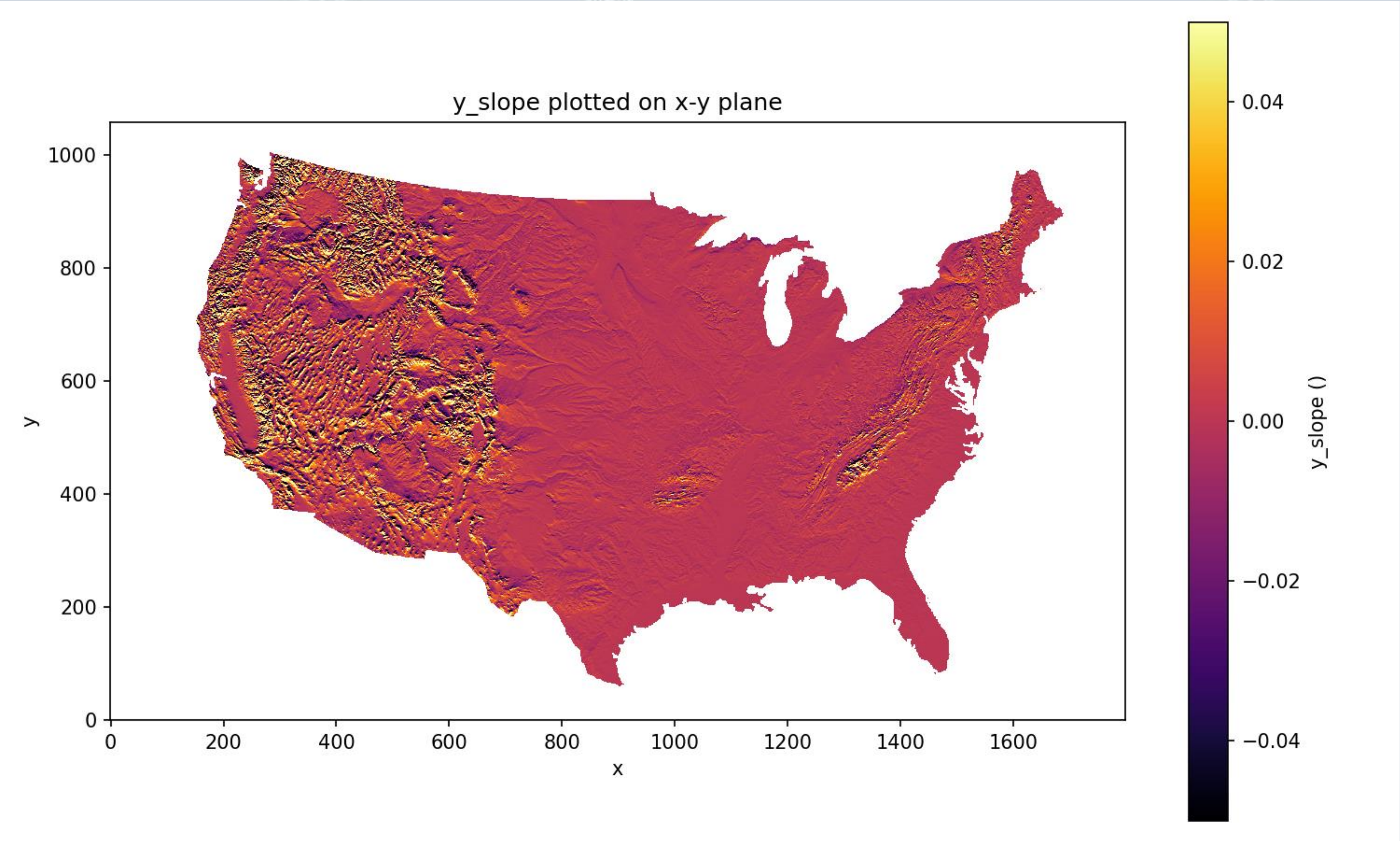


Terrain Standard Deviation



New Variables, Examples

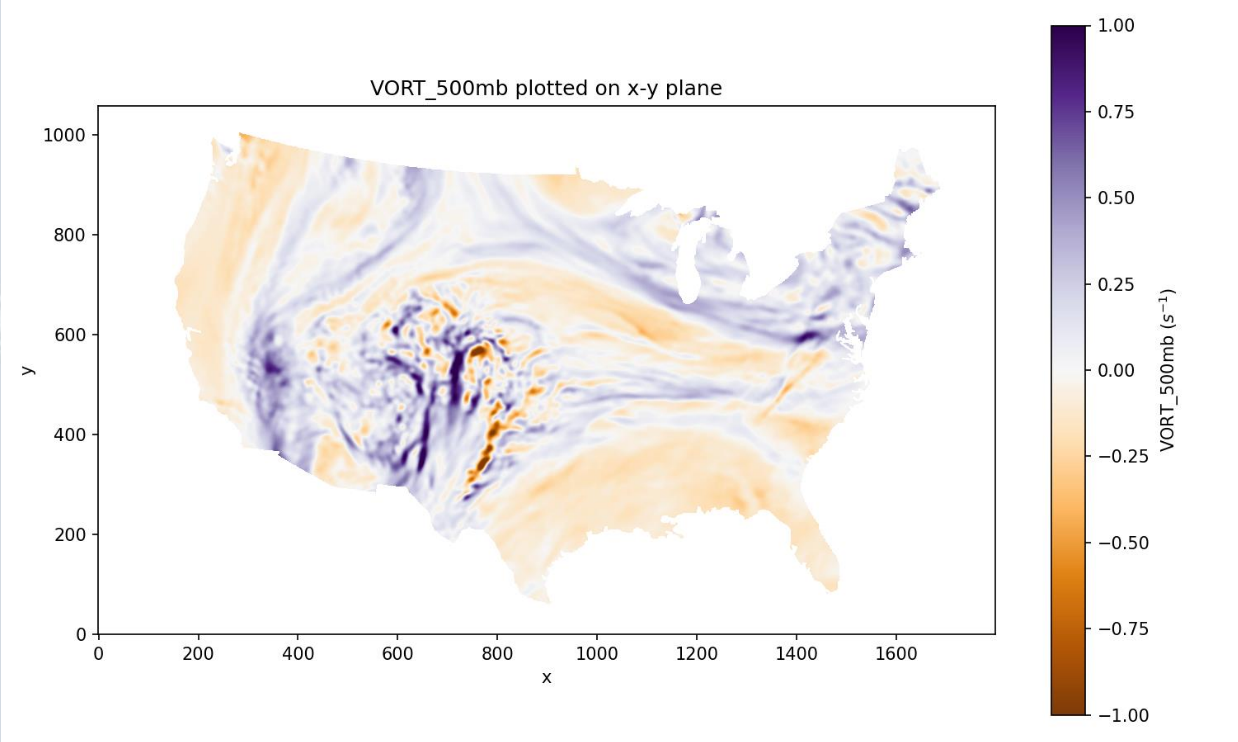
Terrain Slopes



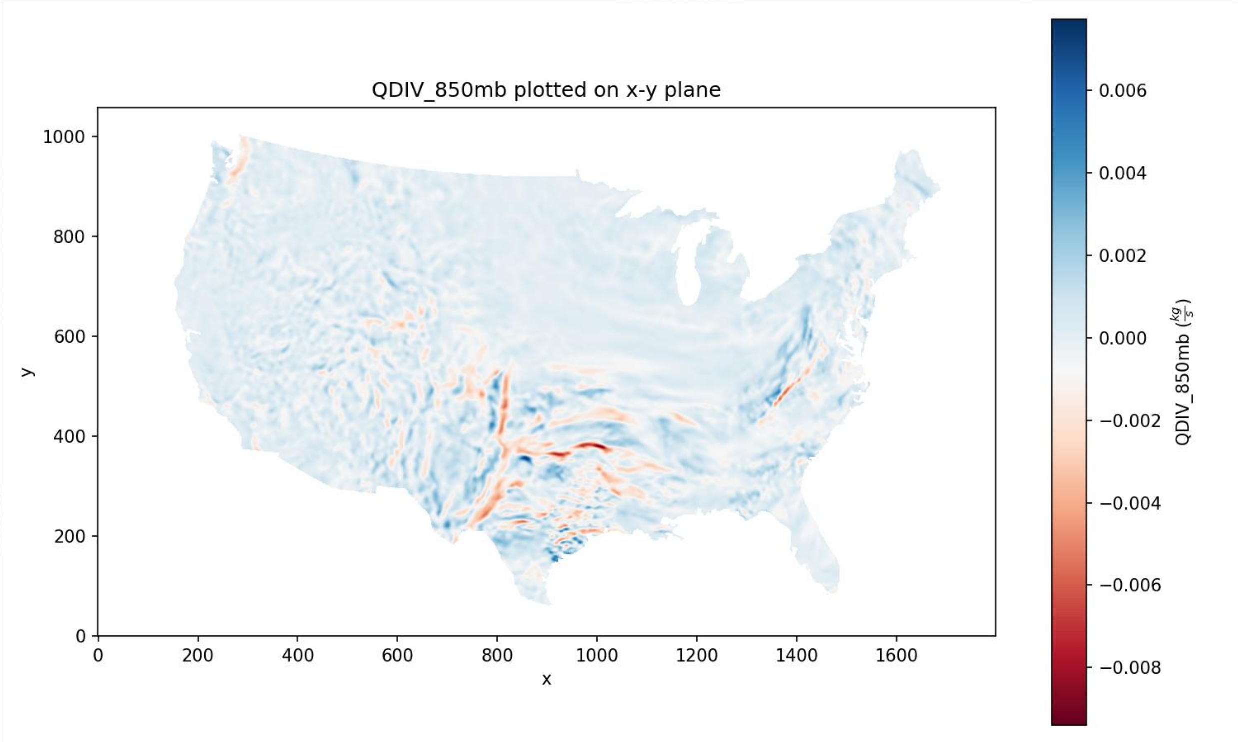
New Variables, Examples

Dynamics – Derived Fields

500 hPa Vorticity



850 hPa Moisture Divergence

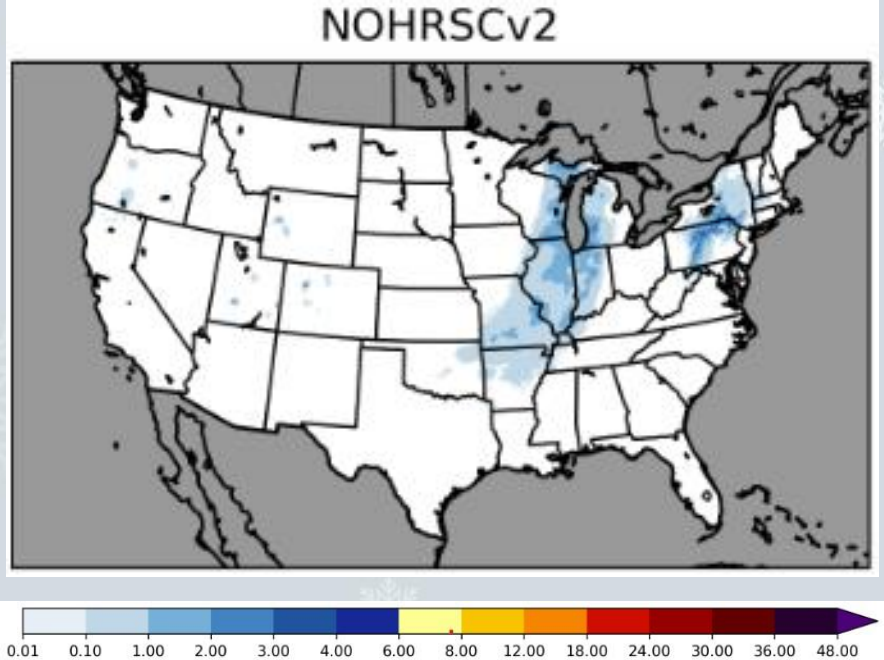


Data/Methods

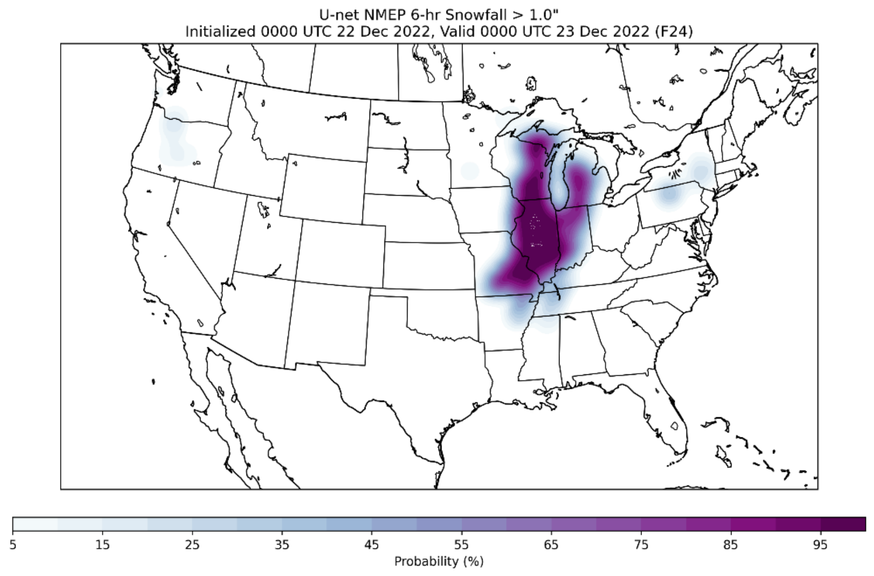
- Predict: Probability of 6-h snowfall > 1, 2, and 3 inches.
  Look at snowfall amount internally (experimental for 2023-24)
- Truth for training: NOHRSC snowfall analyses
- Patchwise U-Net predictions on 64 x 64 overlapping grid square patches.
  - Patches are stitched together to form the full CONUS prediction
  - Patch overlap & light smoothing reduces discontinuity at patch boundaries
- Ensemble HREF+ probability is calculated from individual member probabilities using NEP (Neighborhood Ensemble Probability) and NMEP (Neighborhood Max Ensemble Probability) methods.

Example Case: 00 UTC 23 Dec 2022 24 h Fcst

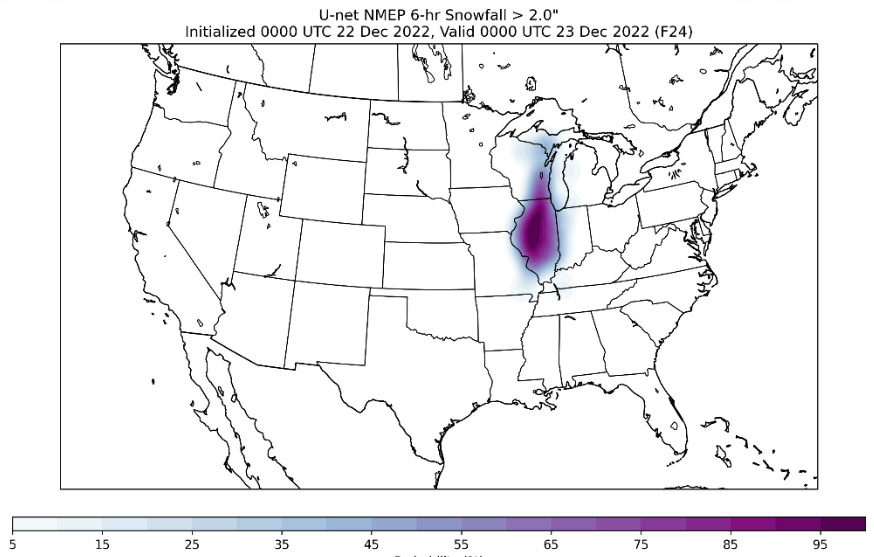
NOHRSC 6-h Snowfall Verification



NMEP U-net 6-h Snowfall > 1.0 in

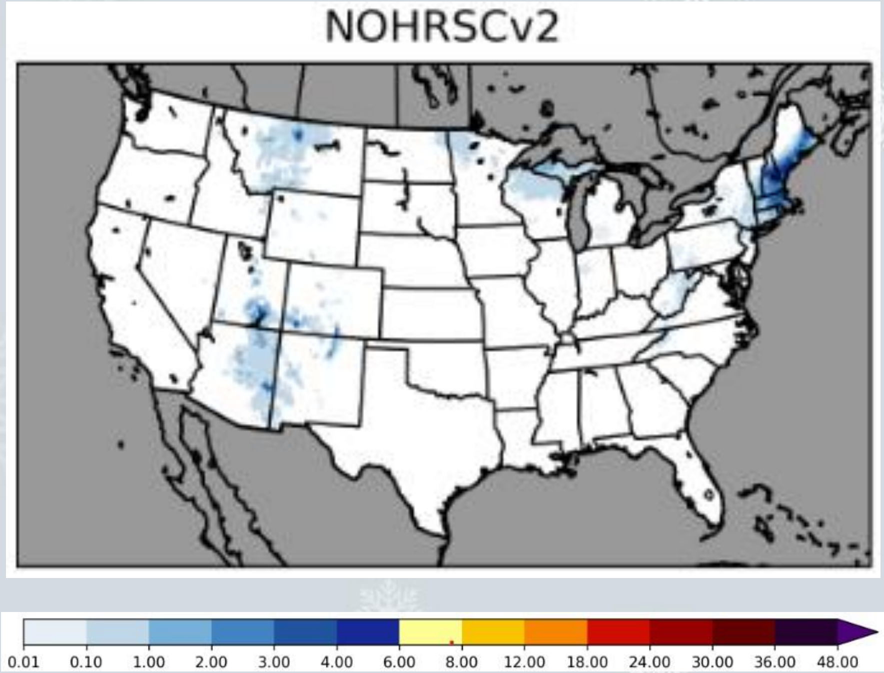


NMEP U-net 6-h Snowfall > 2.0 in

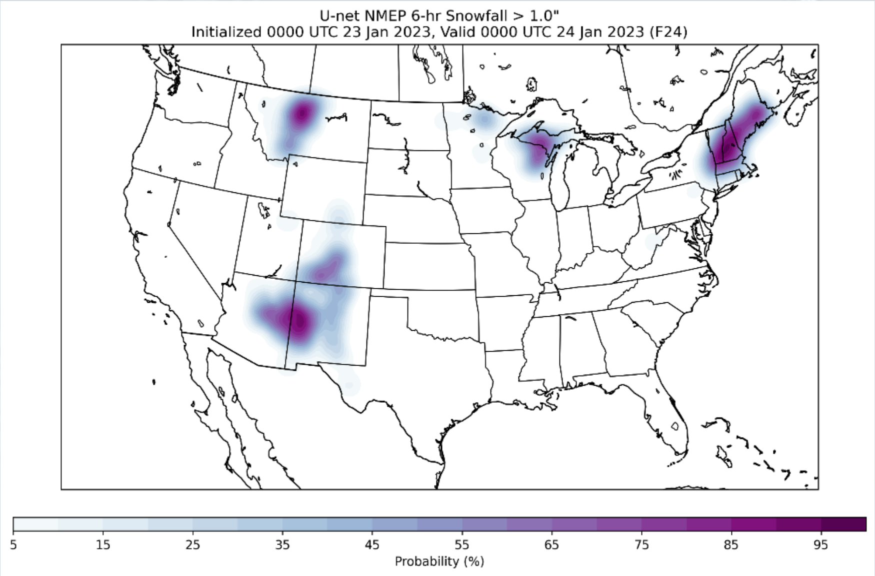


Case: 00 UTC 24 January 2023 24h Fcst

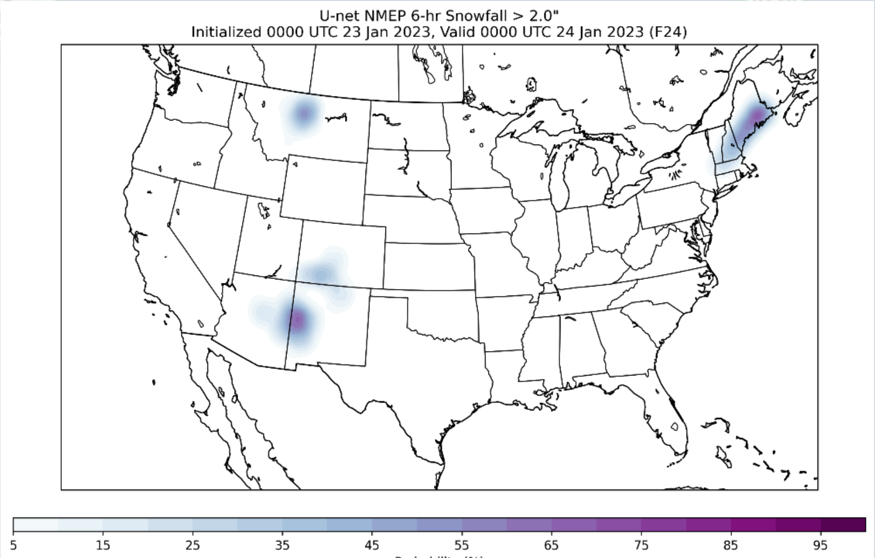
NOHRSC 6-h Snowfall Verification



NMEP U-net 6-h Snowfall > 1.0 in

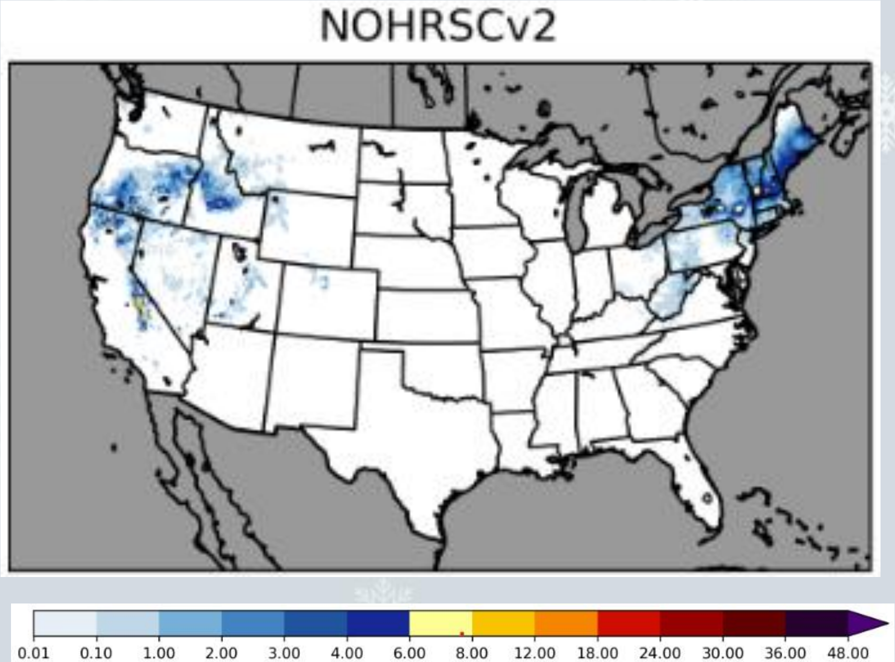


NMEP U-net 6-h Snowfall > 2.0 in

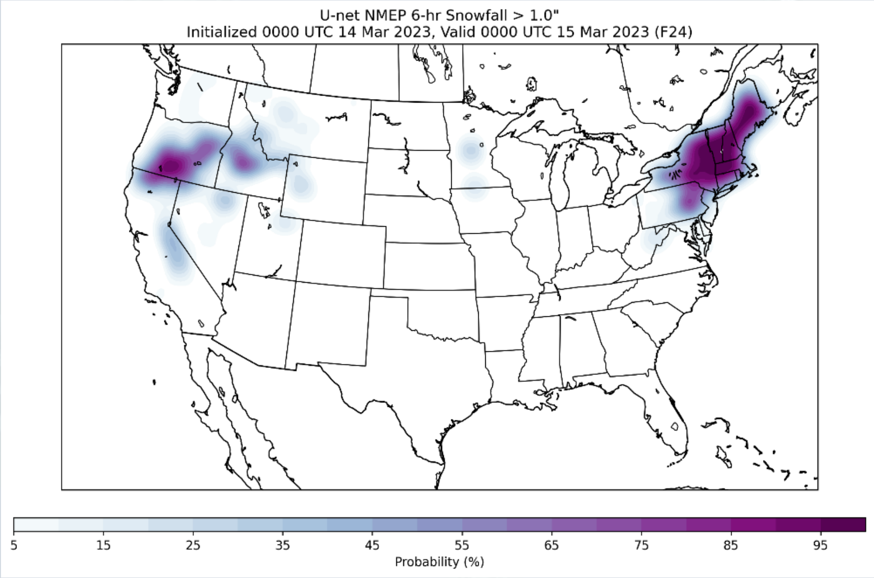


Case: 00 UTC 15 March 2023 24h Fcst

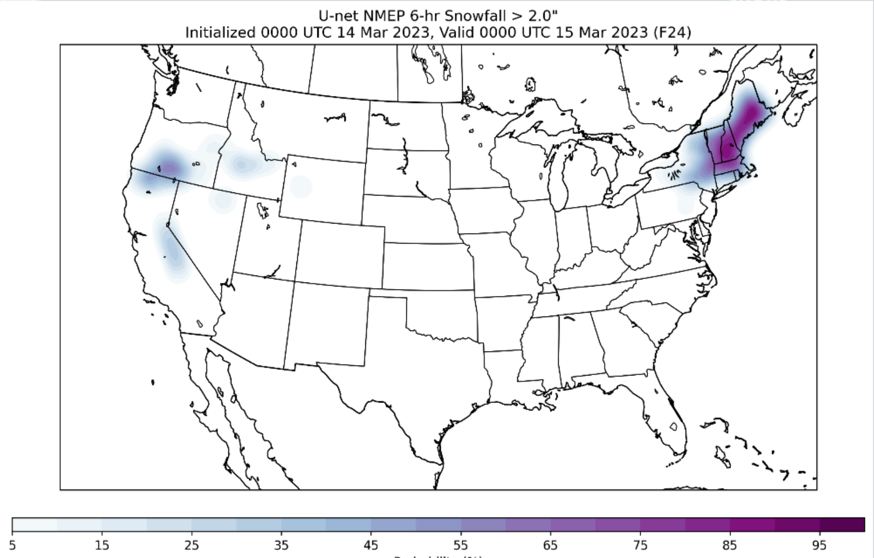
NOHRSC 6-h Snowfall Verification



NMEP U-net 6-h Snowfall > 1.0 in



NMEP U-net 6-h Snowfall > 2.0 in



CAPS ML Status

- First iteration CAPS HREF+ U-Net for Snowfall prediction performs reasonably, although much room remains for further improvement and refinement.
- The neighborhood maximum ensemble probability (NMEP) configuration appears to be most suitable compared to NEP.
- We will be evaluating the impact of new derived variables and will be refining the ML algorithm
- After the fact we will look at ML for winter 10-m wind speed forecasts in prep for creating impacts guidance (WSSI).
- More details on ML at AI Conference, AMS 2024 (Baldwin et al.)

Conclusions

- All 15 ensemble members appear to capture the spatial patterns of the precipitation rather well.
- For rain/no-rain threshold (≥ 1 mm), all members tend to overforecast for all three lead times.
- For a higher rain threshold (≥ 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/

Acknowledgments

Computing:

- NSF Texas Advanced Supercomputing Center (TACC) *Frontera*

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