

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

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14th HMT Winter Weather Experiment
January 23, 2024

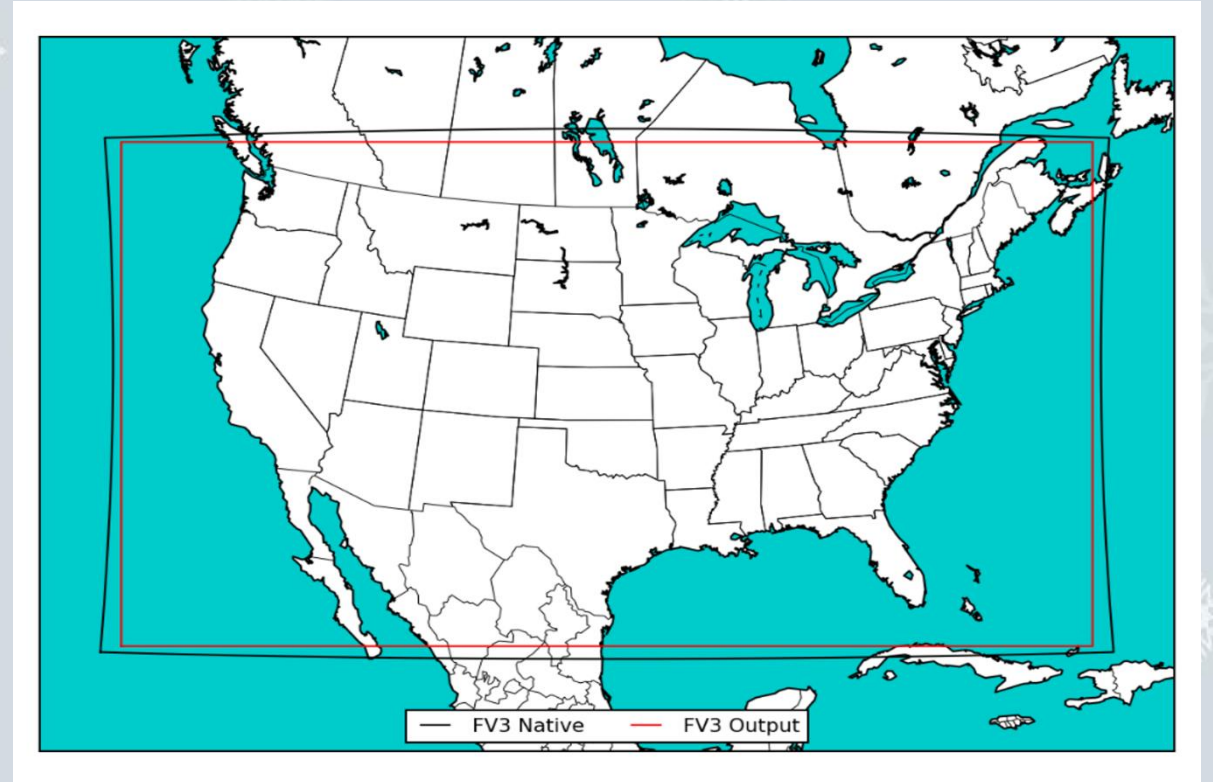
CAPS Ensemble Experiment Goals

- 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

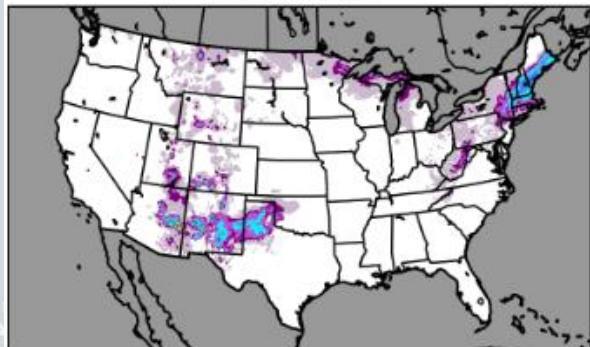
| Experiment | Microphysics | PBL | Surface | LSM | IC/LBC (like system) | AI member |
|------------------------------------|--------------|-----------|---------|--------|-------------------------|--------------|
| GFS IC for Baseline Configuration | | | | | | |
| M0B0L0_PG | Thompson | MYNN | MYNN | 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 | |



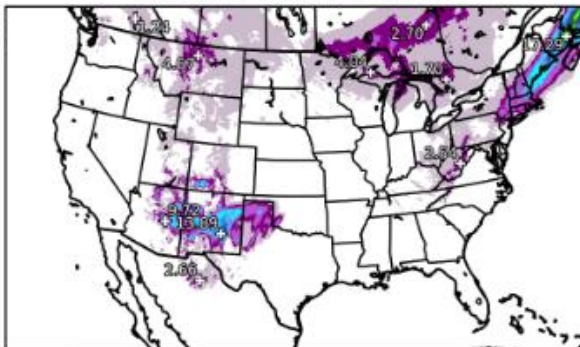
24-25 January 2023 Case

Ensemble 24-hr Snowfall Postage Stamps Valid 1200 UTC 24 Jan 2023 (F36)

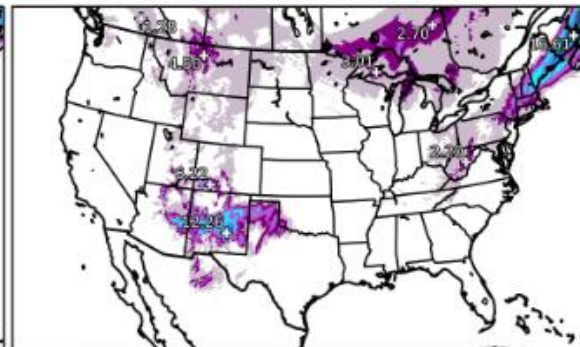
NOHRSCv2



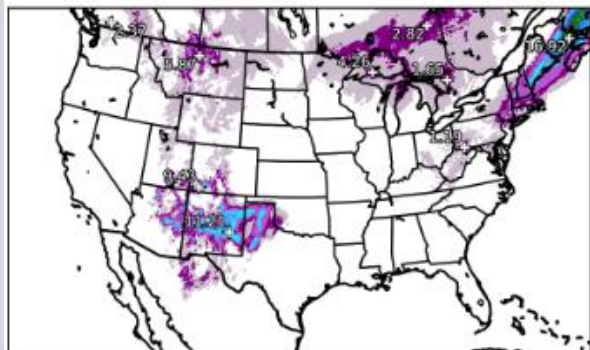
Thompson/MYNN/RUC



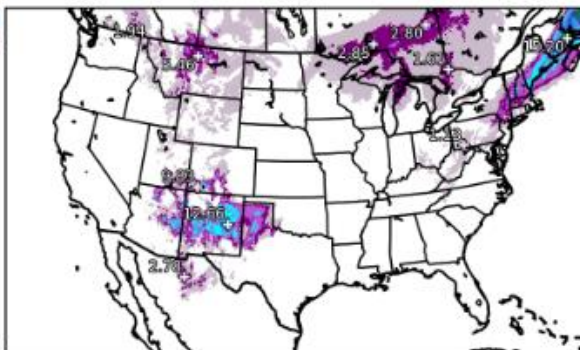
Thompson/TKE-EDMF/NoahMP



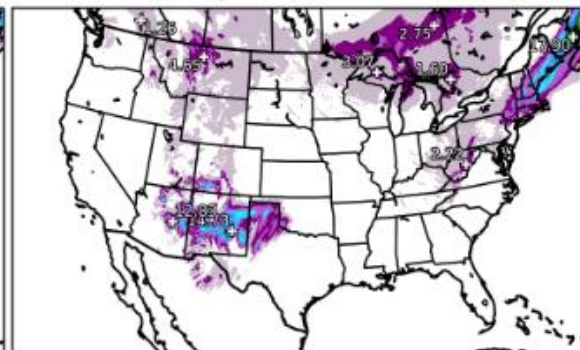
NSSL/MYNN/Noah



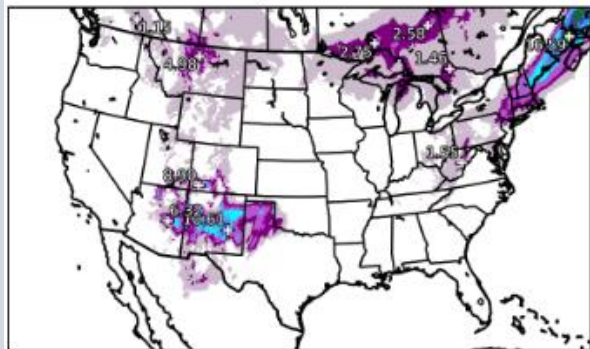
NSSL/TKE-EDMF/RUC



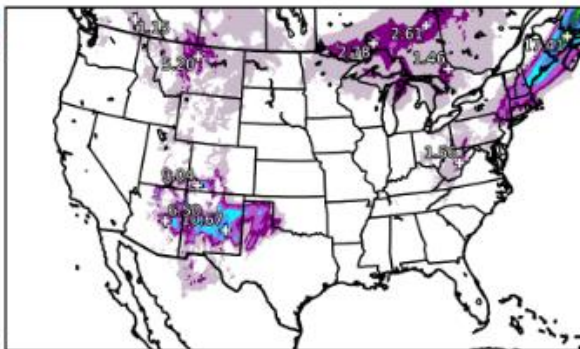
Thompson/MYNN/Noah



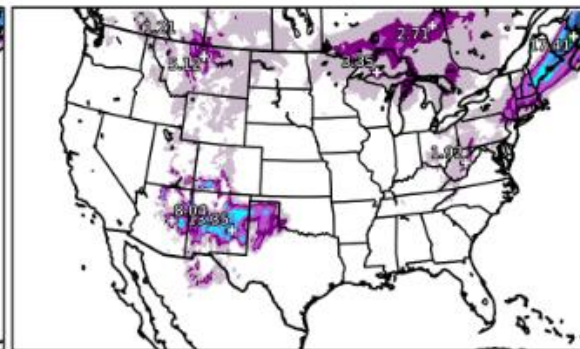
Simple Mean



PM Mean



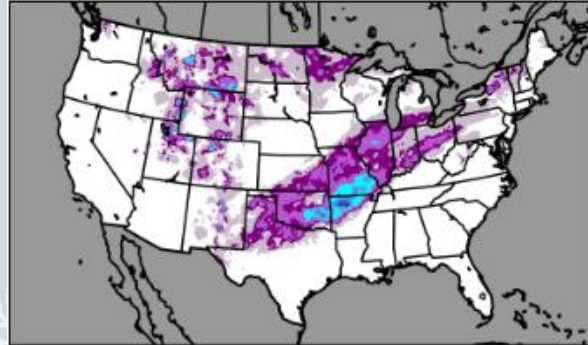
LPM Mean



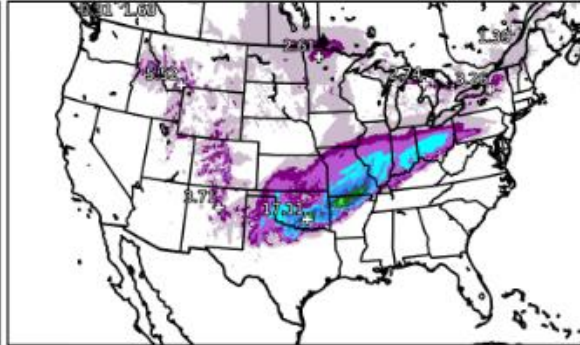
24-25 January 2023 Case

Ensemble 24-hr Snowfall Postage Stamps Valid 1200 UTC 25 Jan 2023 (F60)

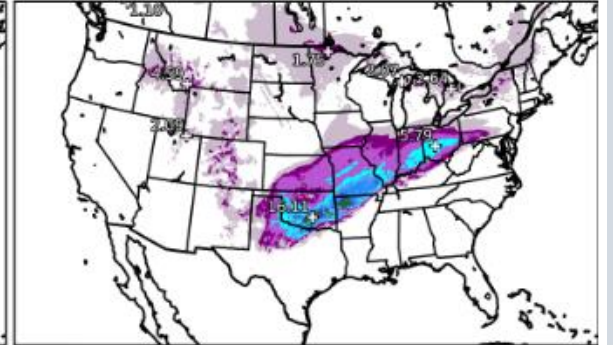
NOHRSCv2



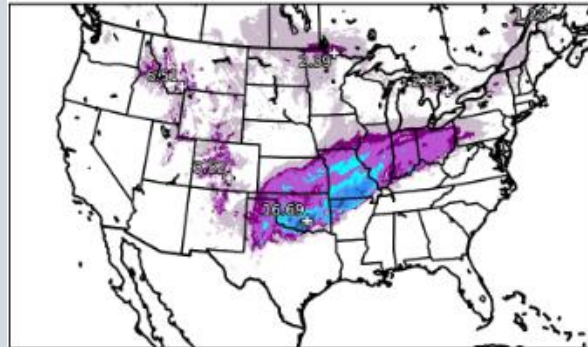
Thompson/MYNN/RUC



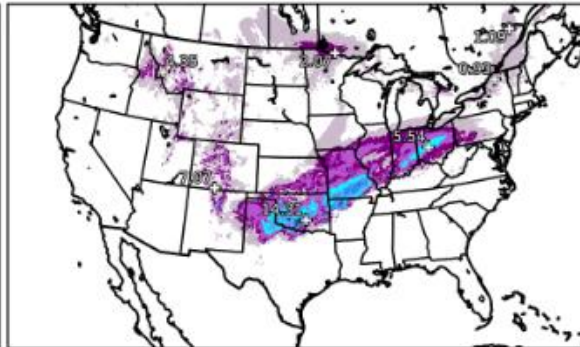
Thompson/TKE-EDMF/NoahMP



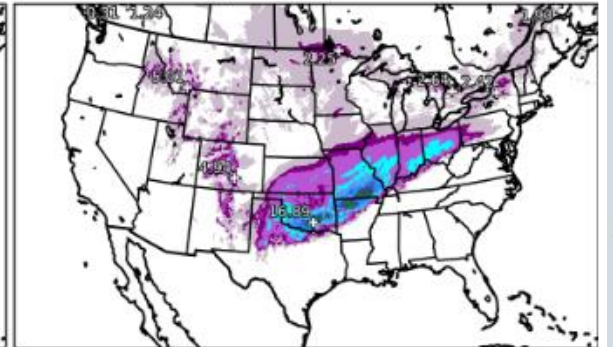
NSSL/MYNN/Noah



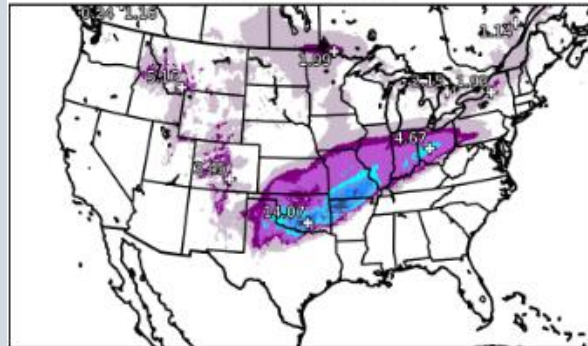
NSSL/TKE-EDMF/RUC



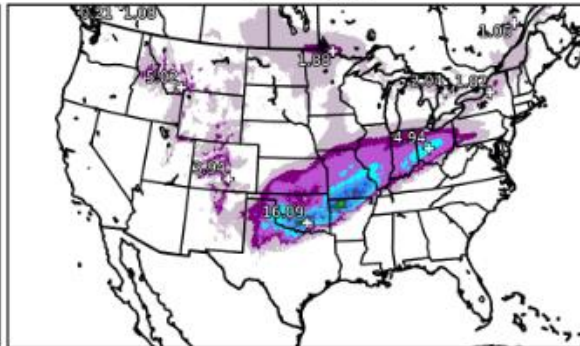
Thompson/MYNN/Noah



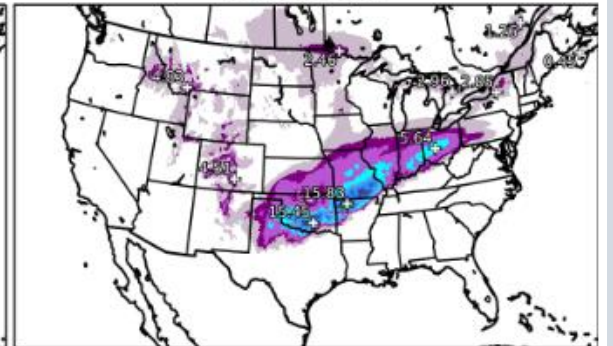
Simple Mean



PM Mean



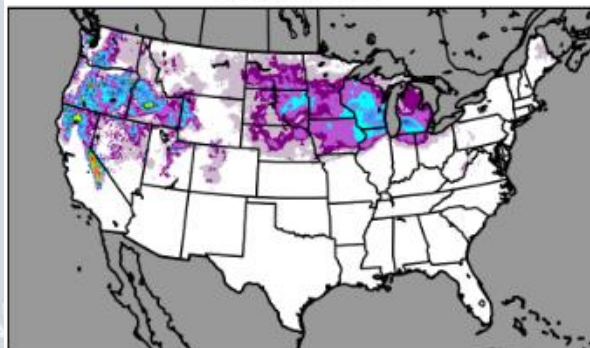
LPM Mean



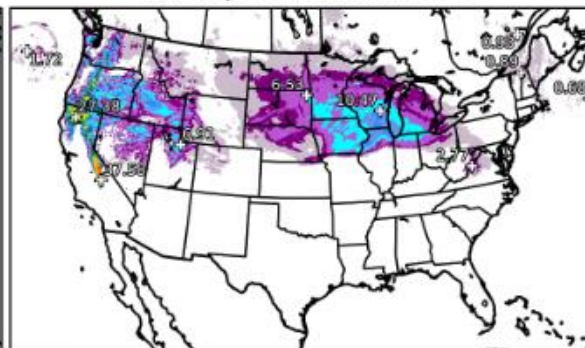
10-11 March 2023 Case

Ensemble 24-hr Snowfall Postage Stamps Valid 1200 UTC 10 Mar 2023 (F36)

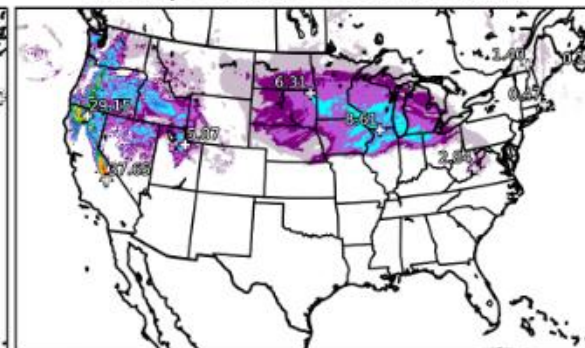
NOHRSCv2



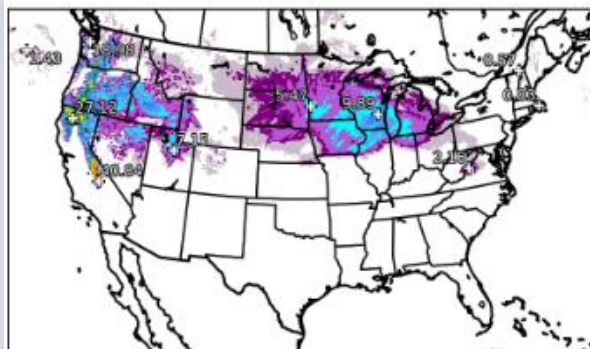
Thompson/MYNN/RUC



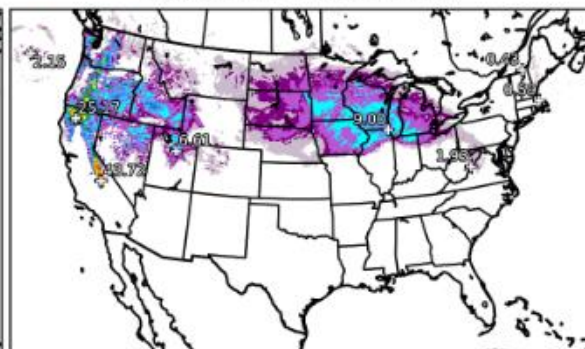
Thompson/TKE-EDMF/NoahMP



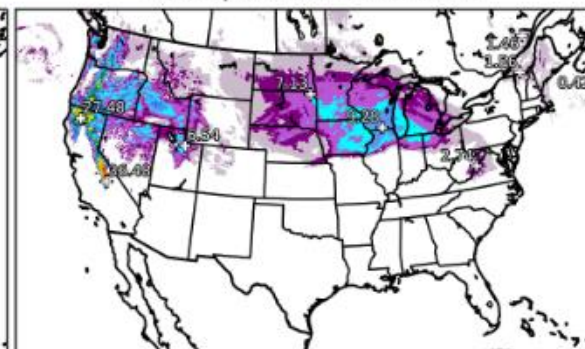
NSSL/MYNN/Noah



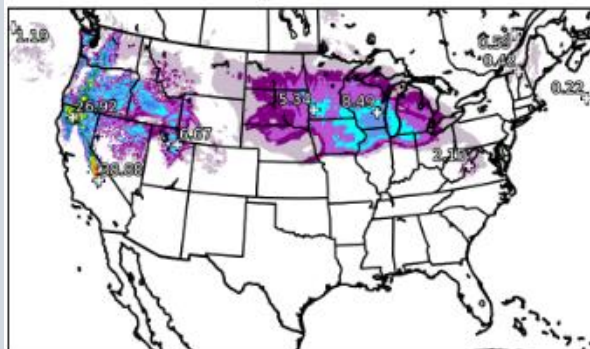
NSSL/TKE-EDMF/RUC



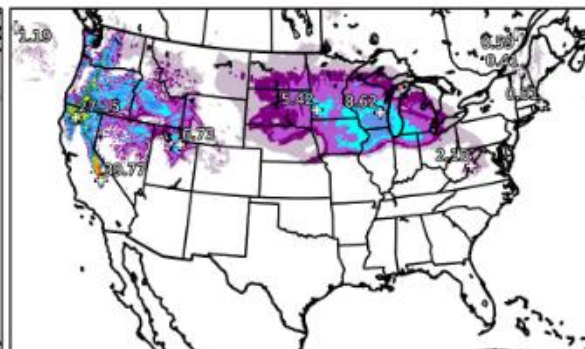
Thompson/MYNN/Noah



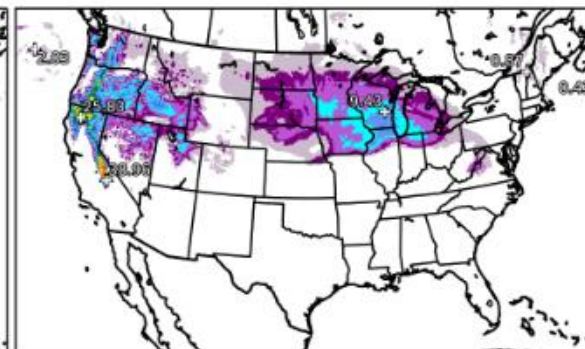
Simple Mean



PM Mean



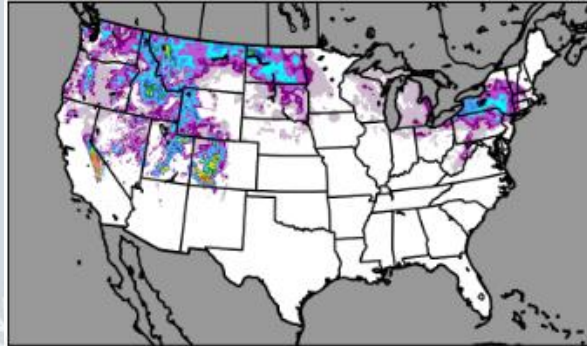
LPM Mean



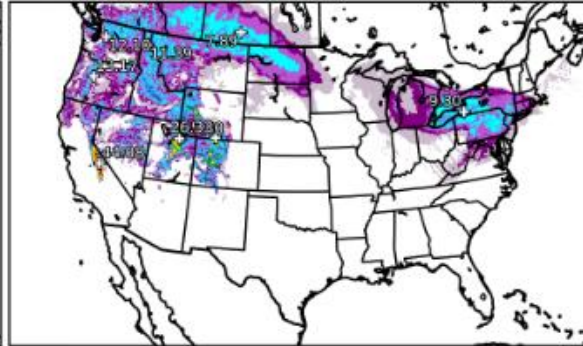
10-11 March 2023 Case

Ensemble 24-hr Snowfall Postage Stamps Valid 1200 UTC 11 Mar 2023 (F60)

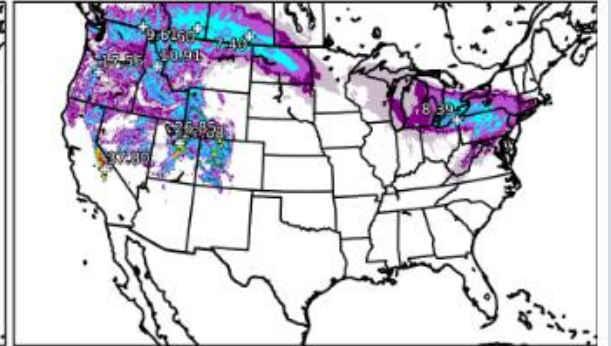
NOHRSCv2



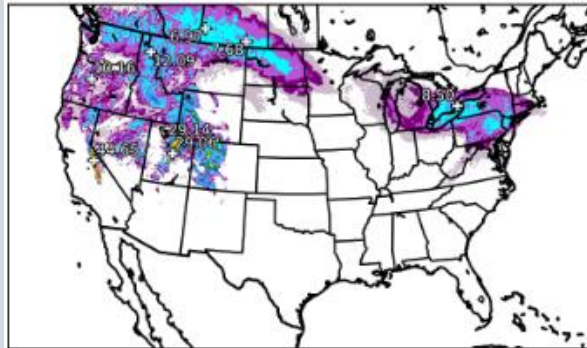
Thompson/MYNN/RUC



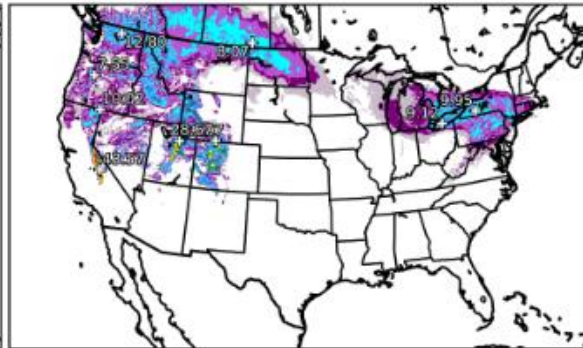
Thompson/TKE-EDMF/NoahMP



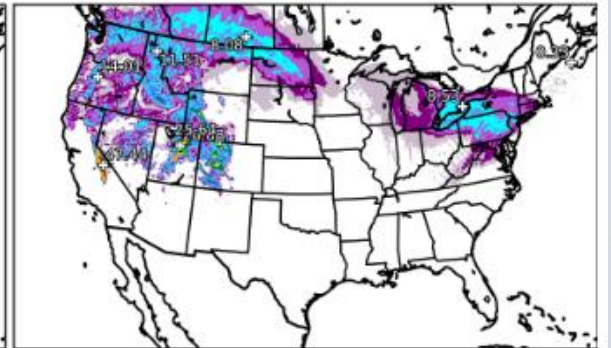
NSSL/MYNN/Noah



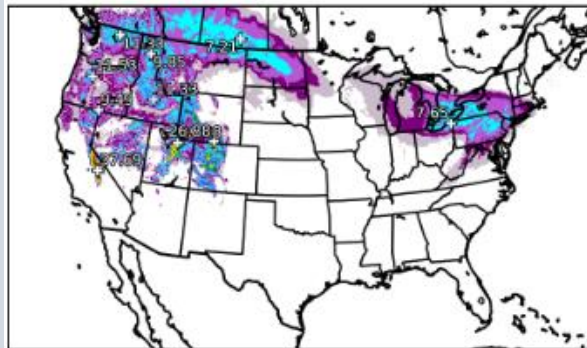
NSSL/TKE-EDMF/RUC



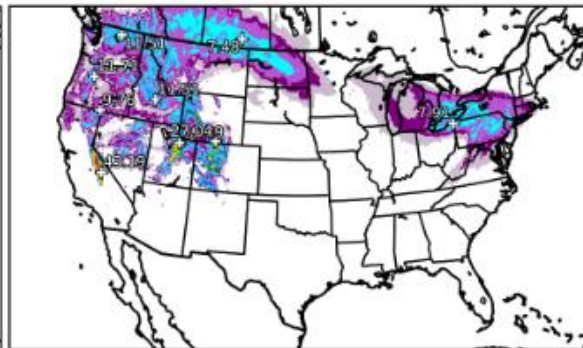
Thompson/MYNN/Noah



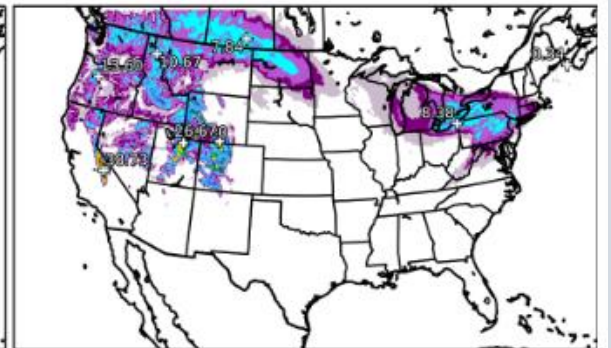
Simple Mean



PM Mean



LPM Mean

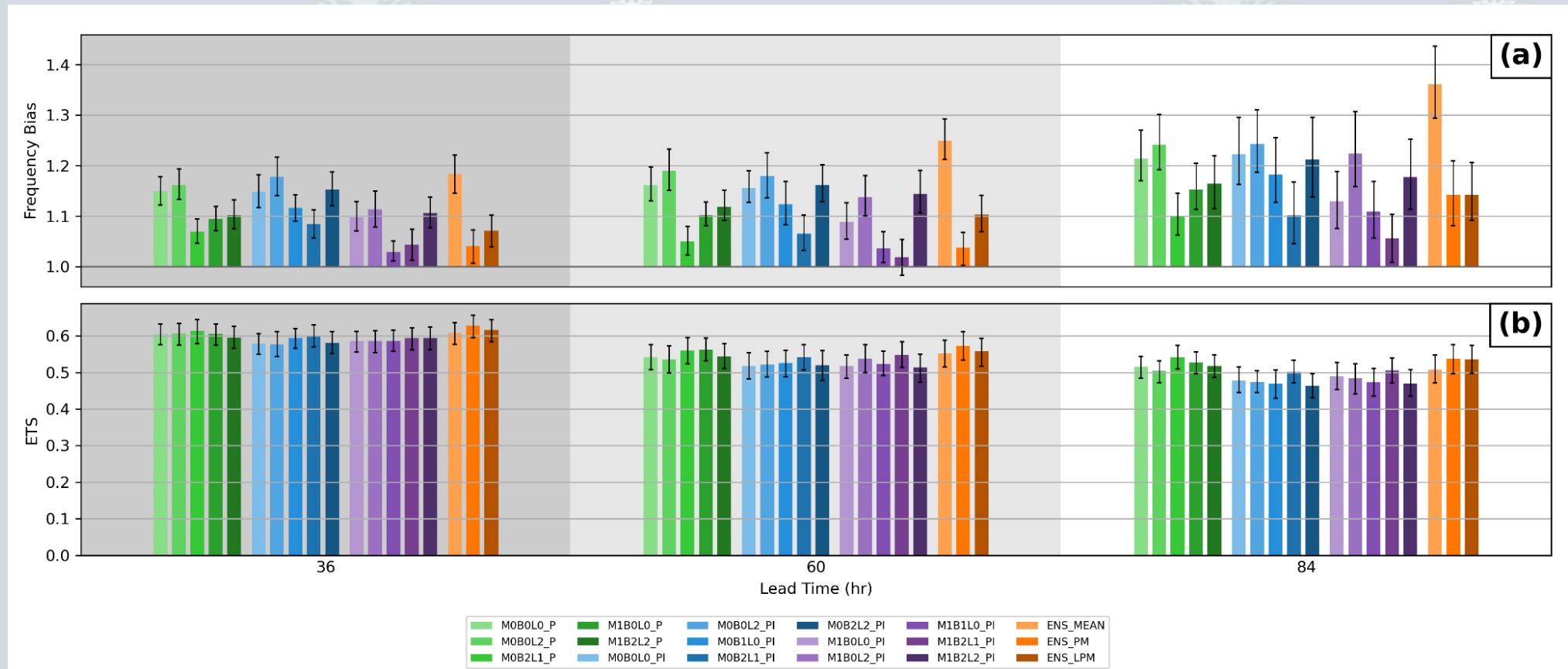


Verification

- 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

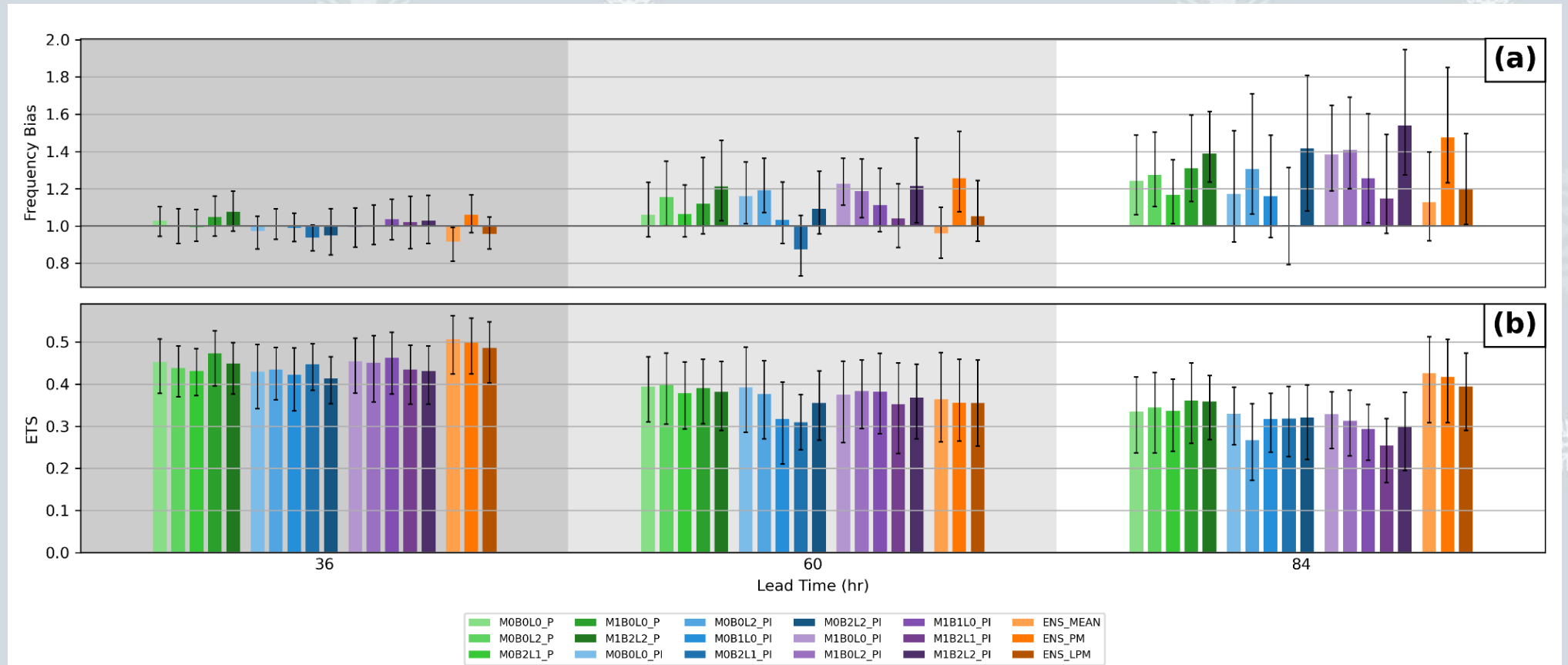


Verification 24-h Precipitation > 1 mm



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

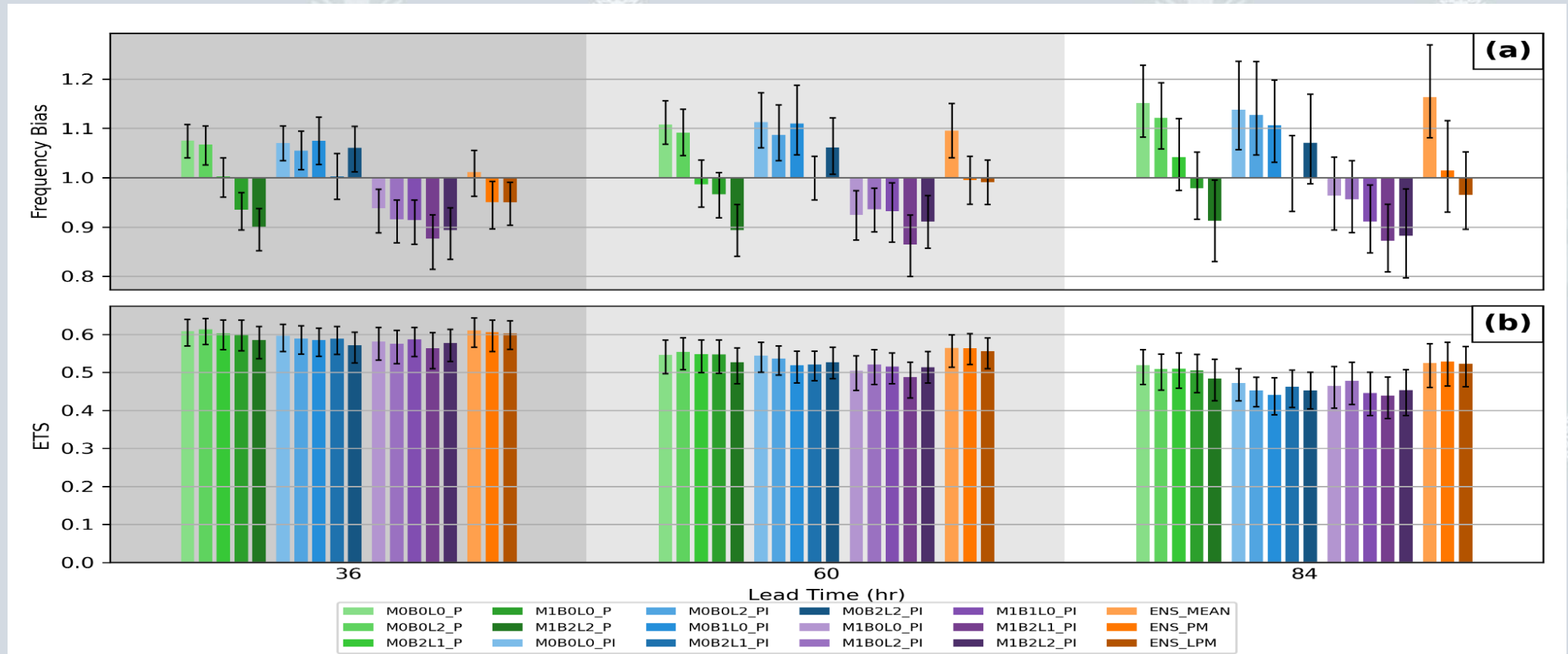
Verification 24-h Precipitation > 25 mm (1-inch)



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

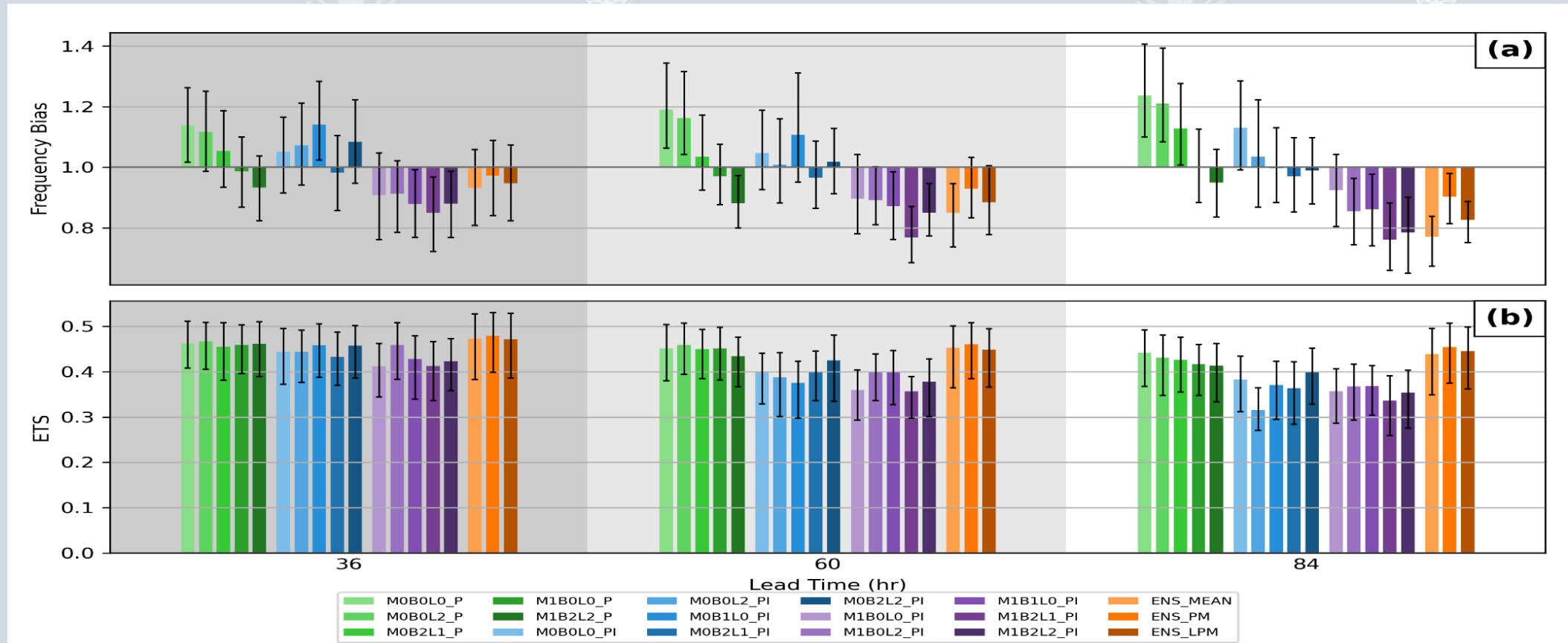


Verification 24-h Snowfall > 1 mm



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

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_P | Thompson | MYNN | MYNN | NOAH | GFS /GFS | AI-1 |
| M1B0L0_P | NSSL | MYNN | MYNN | NOAH | GFS/GFS (WoF) | AI-2 |
| 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 | NOAHM P | GFS/GFS (GFSv16) | AI-3 |
| Physics + IC Perturbation Ensemble | | | | | | |
| M0B1L0_P I | Thompson | Shin-Hong | GFS | NOAH | GEFS_m1 | |
| M0B2L1_P I | Thompson | TKE-EDMF | GFS | NOAHM P | GEFS_m2 | |
| M0B2L2_P I | Thompson | TKE-EDMF | GFS | RUC | GEFS_m3 | AI-4 |
| M1B1L0_P I | NSSL | Shin-Hong | GFS | NOAH | GEFS_m4 | |





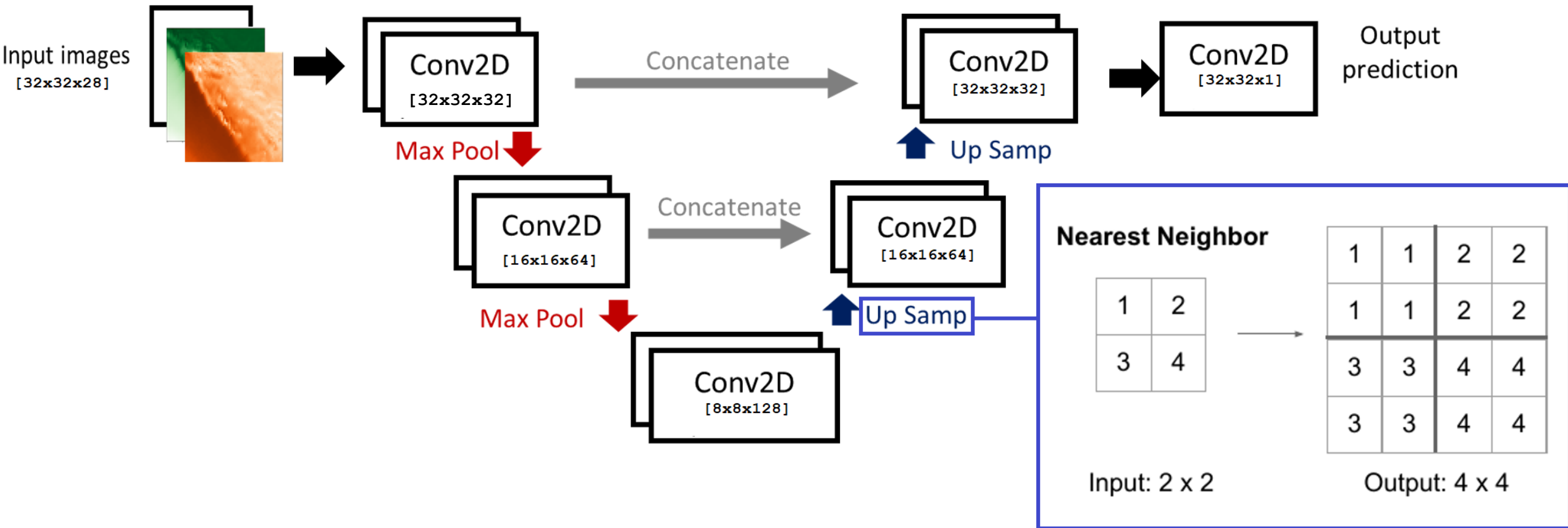
Machine Learning Component

- 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

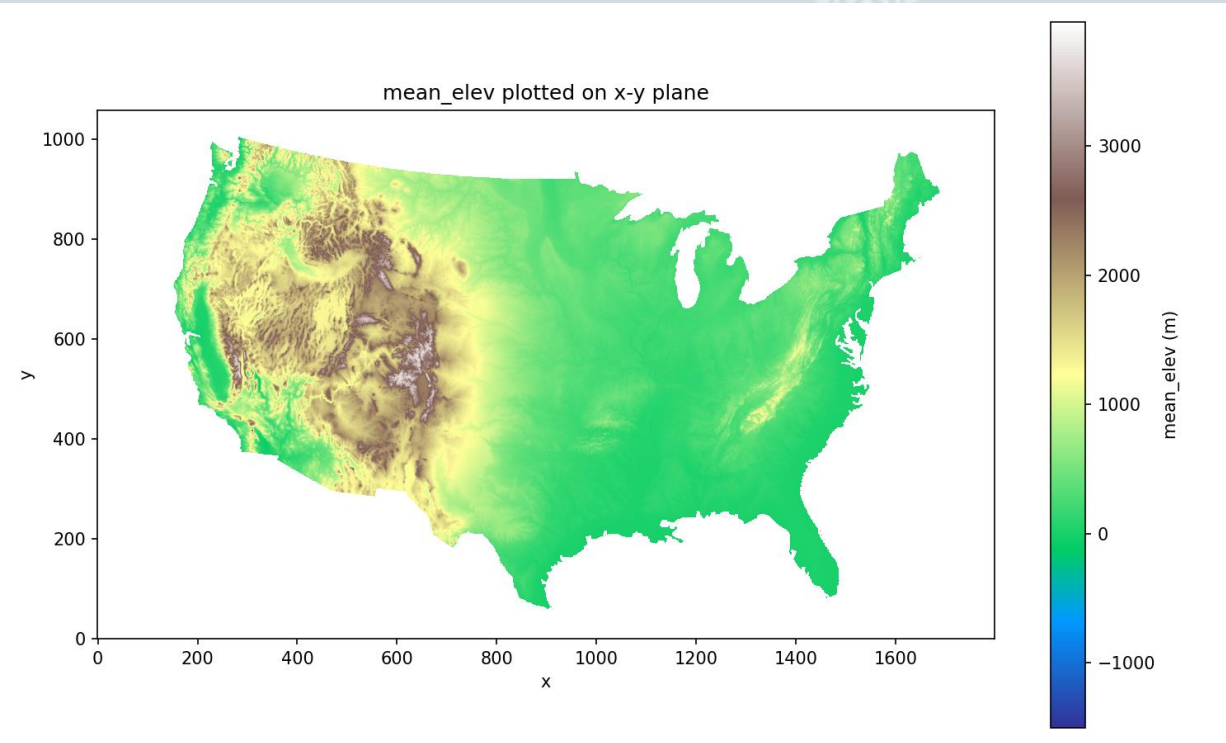
New Variables Added to Snowfall U-Net for 2023-24

| 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 |

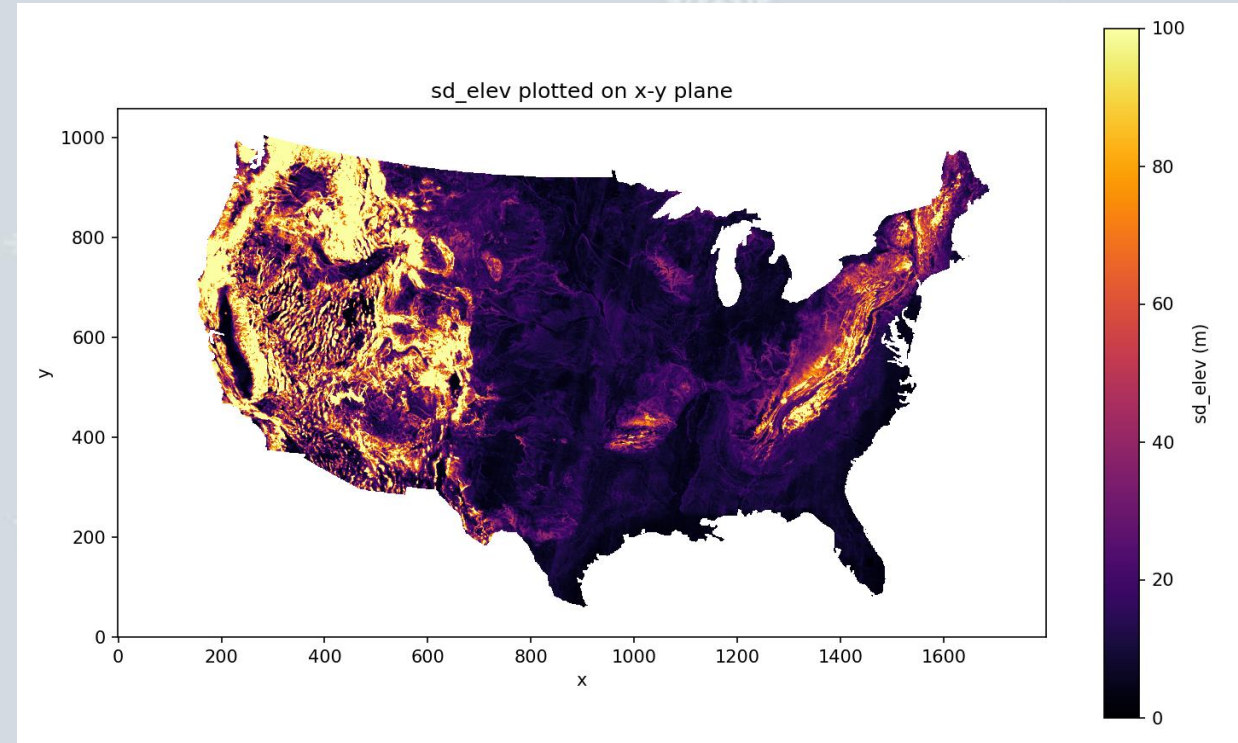


New Variables, Examples

Terrain

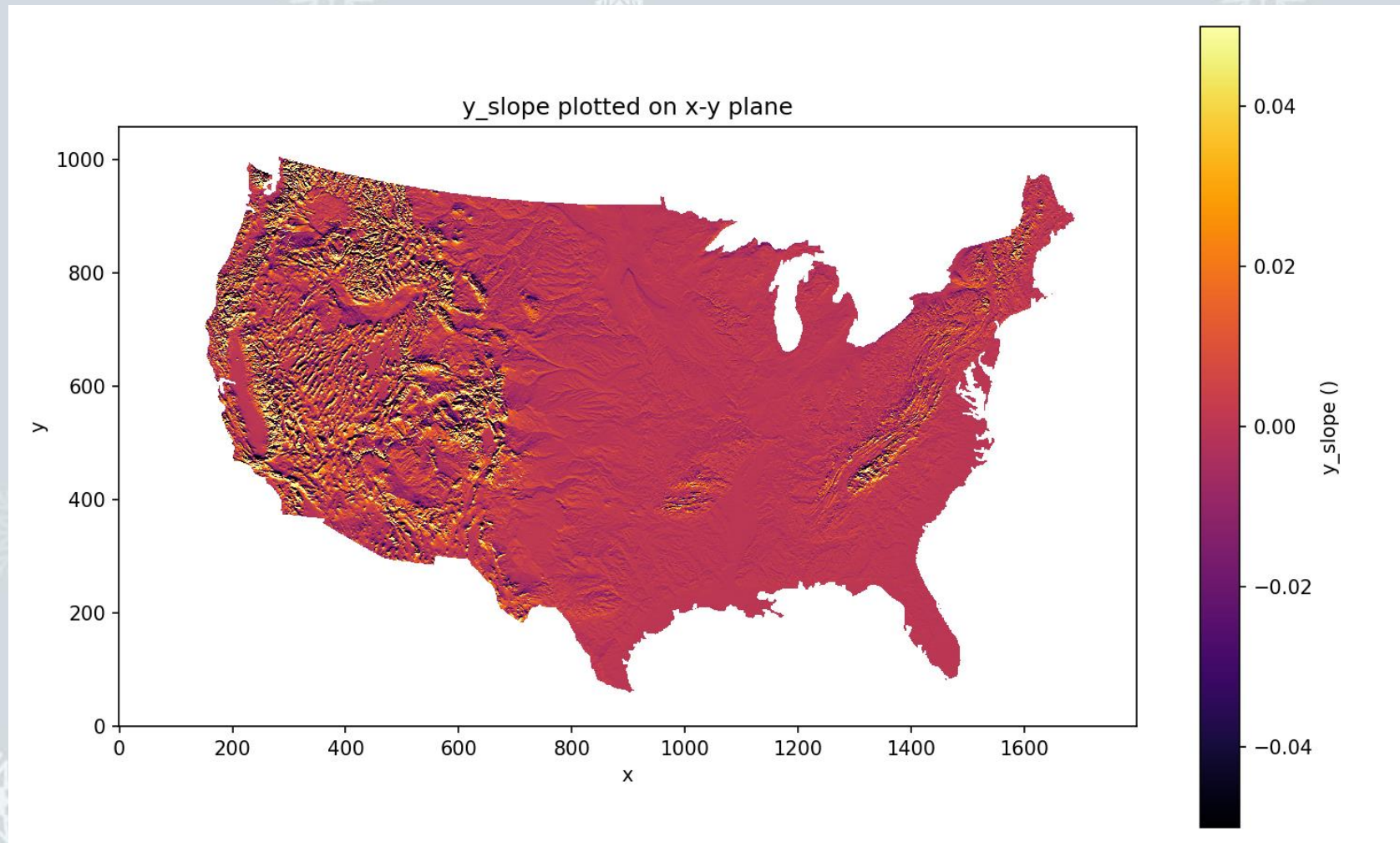


Terrain Standard Deviation



New Variables, Examples

Terrain Slopes



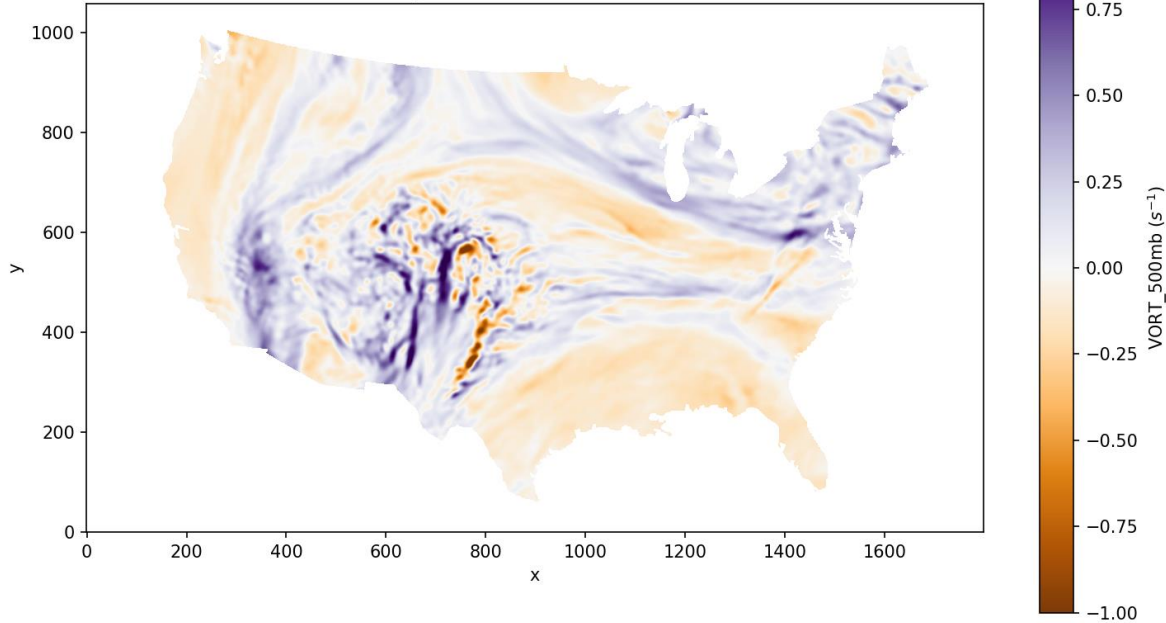
New Variables, Examples

Dynamics – Derived Fields

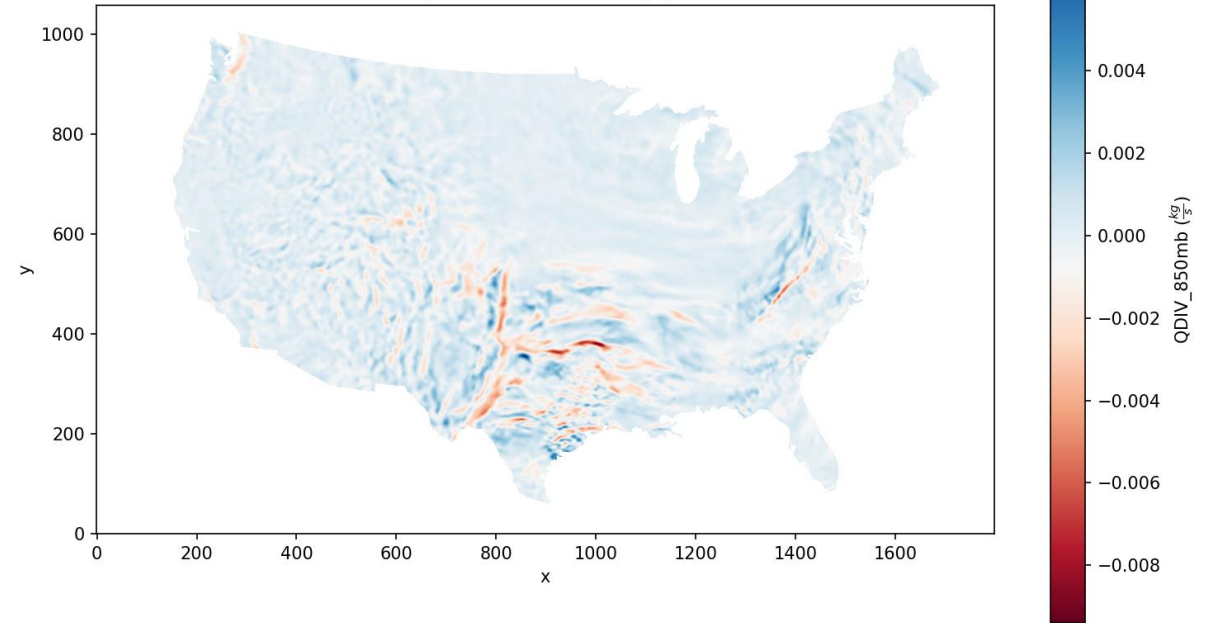
500 hPa Vorticity

850 hPa Moisture Divergence

VORT_500mb plotted on x-y plane



QDIV_850mb plotted on x-y plane



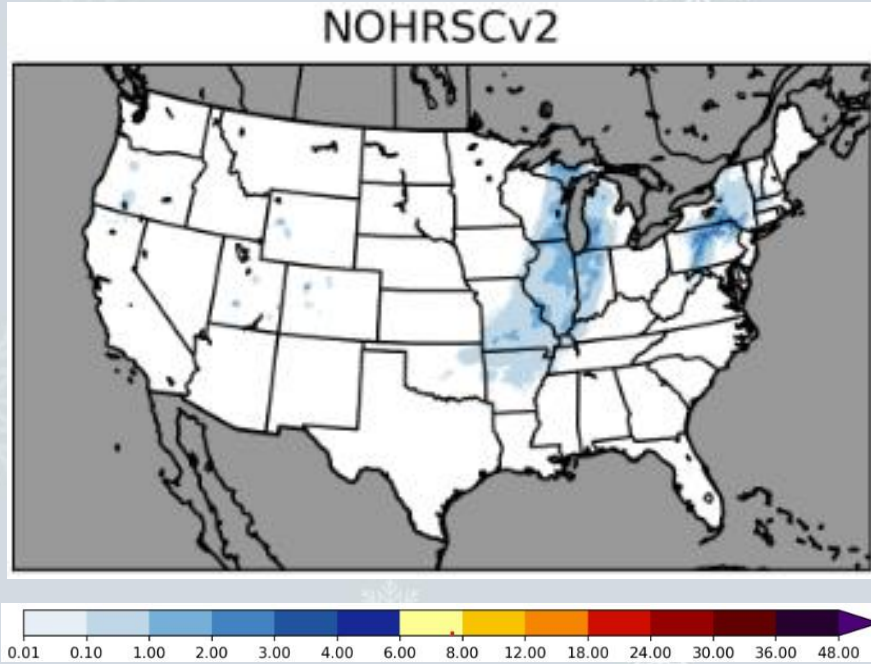
Data/Methods

- 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.

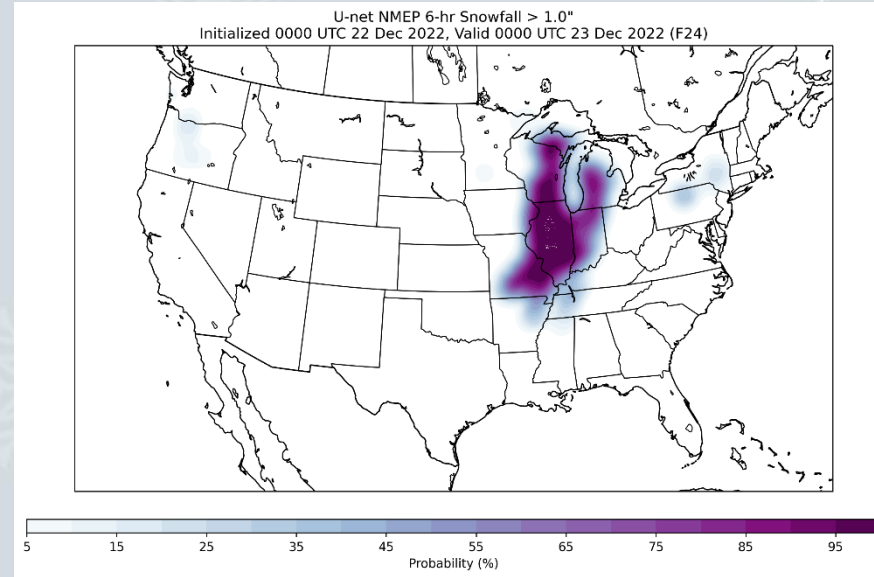


Example Case: 00 UTC 23 Dec 2022 24 h Fcst

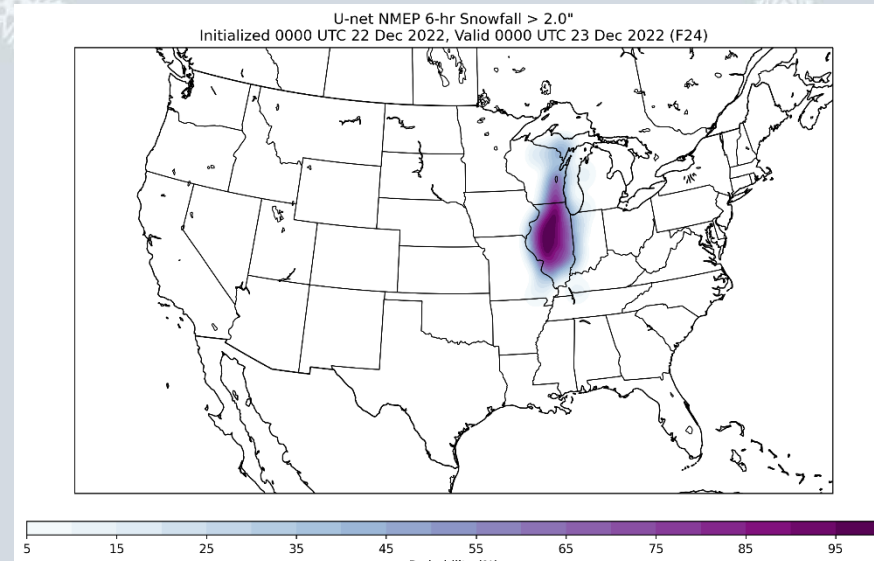
NOHRSC 6-h Snowfall Verification



NMEP U-net 6-h Snowfall > 1.0 in

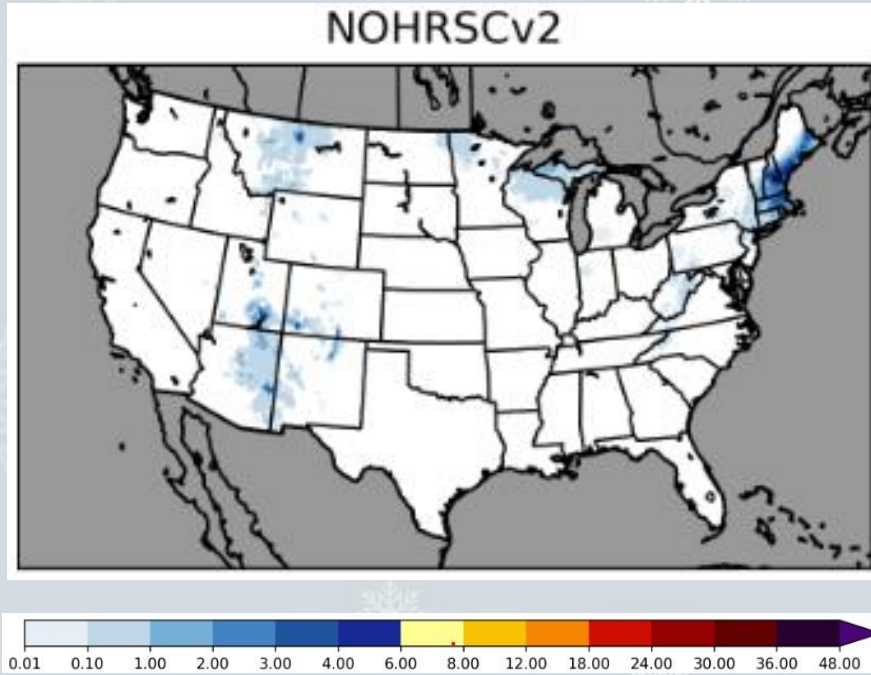


NMEP U-net 6-h Snowfall > 2.0 in

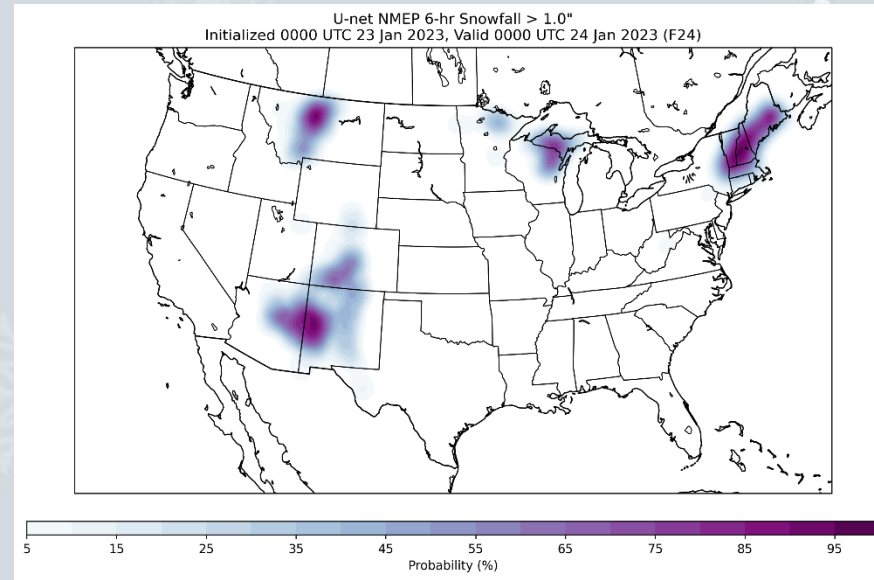


Case: 00 UTC 24 January 2023 24h Fcst

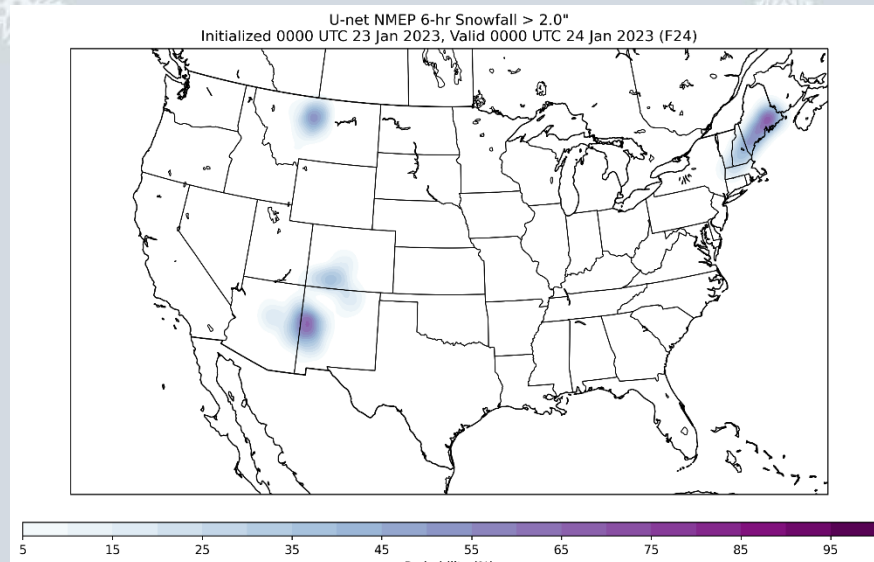
NOHRSC 6-h Snowfall Verification



NMEP U-net 6-h Snowfall > 1.0 in

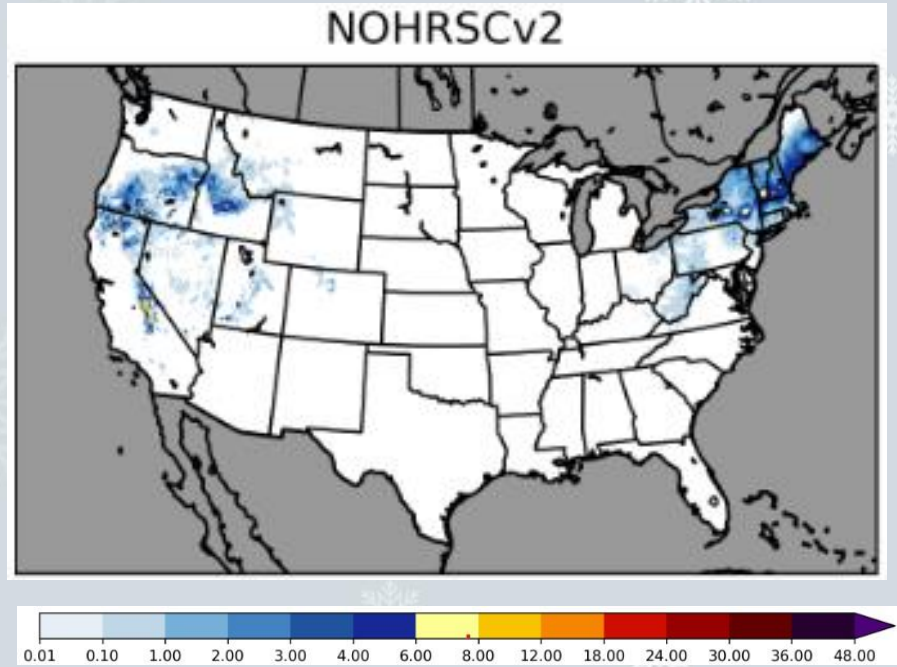


NMEP U-net 6-h Snowfall > 2.0 in

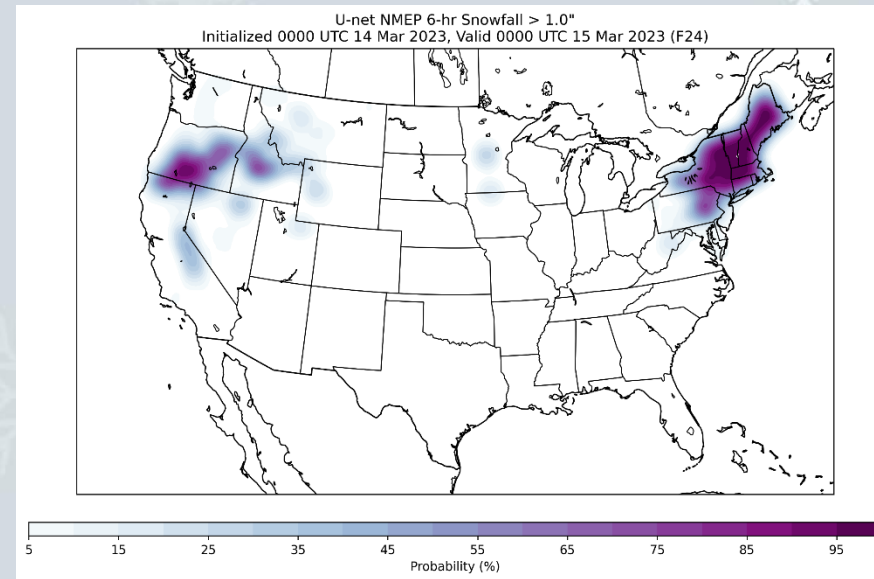


Case: 00 UTC 15 March 2023 24h Fcst

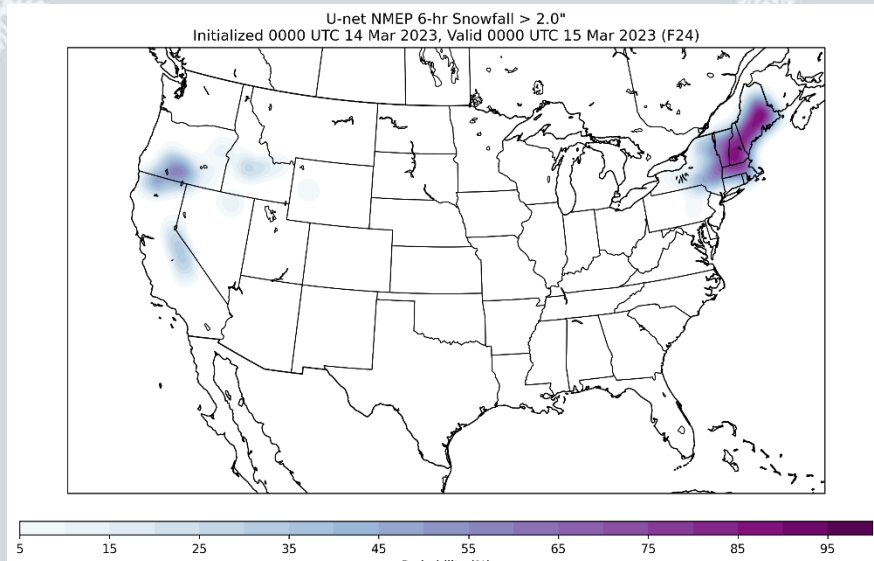
NOHRSC 6-h Snowfall Verification



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/>



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