A machine learning postprocessor to mitigate QPF errors for improved hydrometeorological forecasting

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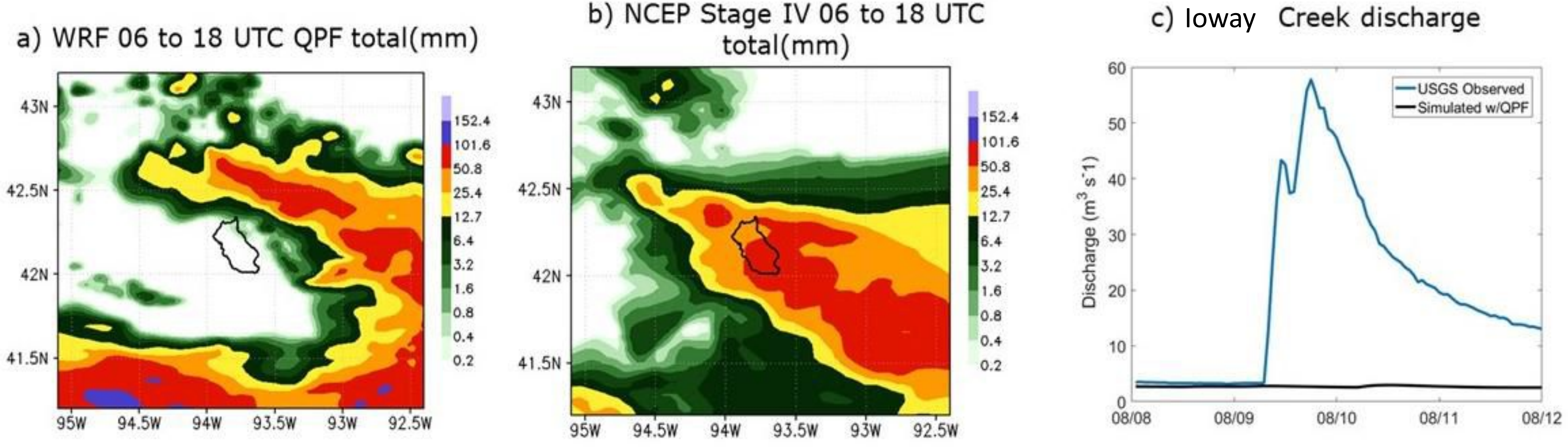
Motivation

- Prior research shows the biggest errors in MCS rainfall forecasts tend to be related to displacement, not so much areal coverage or rainfall intensity over longer periods (6-24 h or more)
- Average displacement errors are 100-200 km, which may not seem bad to a meteorologist, but are problematic for hydrological modeling/streamflow prediction in smaller basins
- Our prior work has found it difficult to determine in advance what type of displacement error will occur (systematic errors are rare) although more complex methods (quadrant of initial hour displacement) suggest it might be possible to do so using machine learning

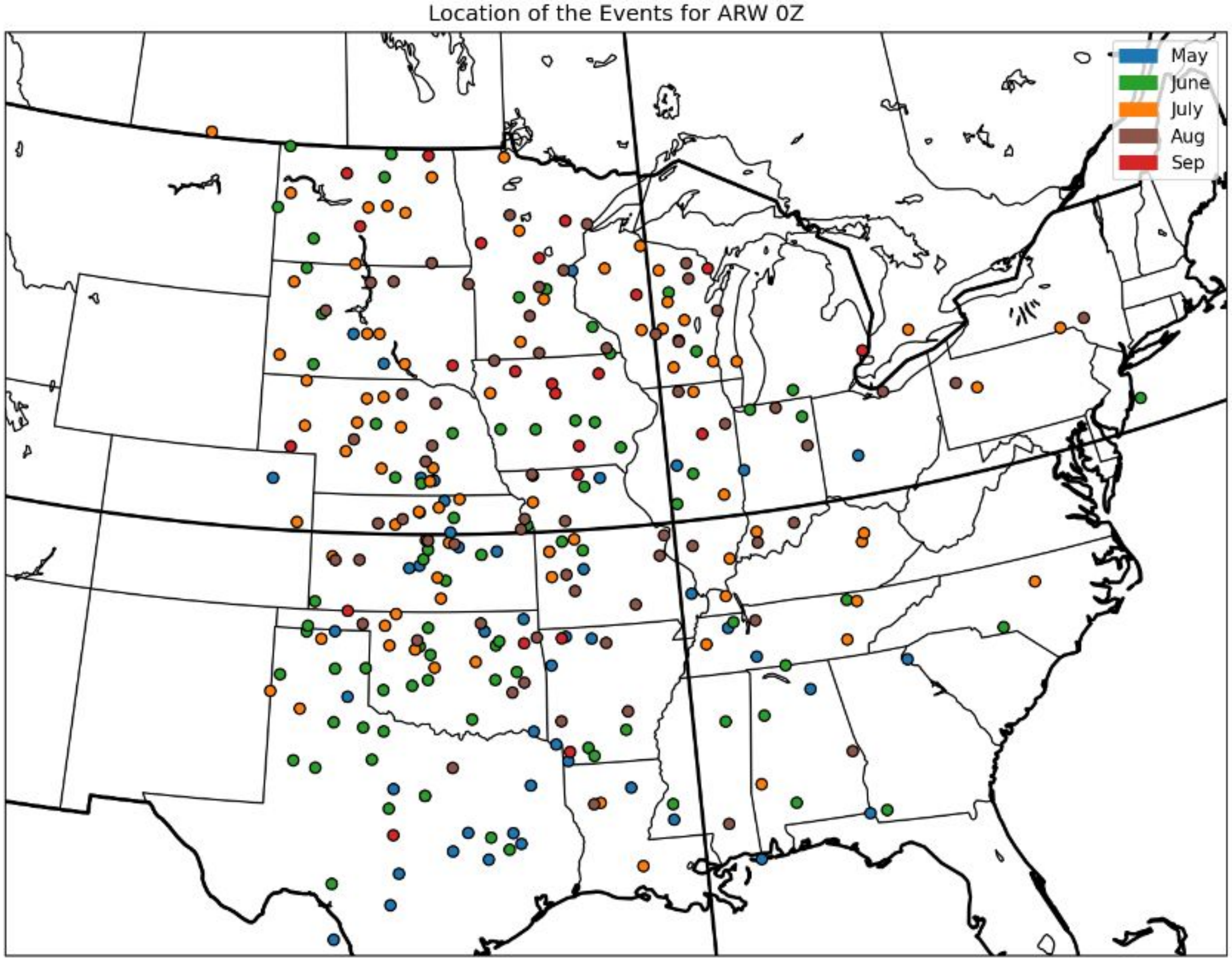


Example of relatively good 12-h rainfall forecast (left) compared to observations (middle) that was completely wrong for the small Ioway Creek basin in Ames, IA. The forecast showed no rain in the basin, but heavy amounts covered it, resulting in some flooding.

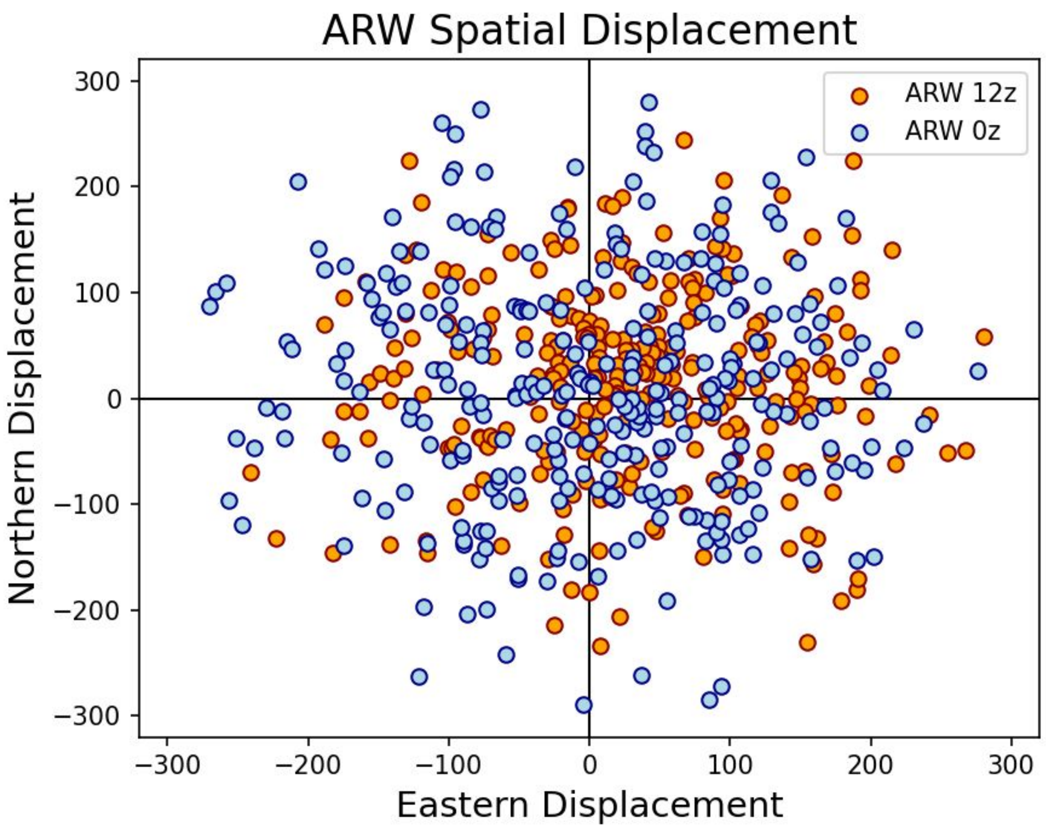
Methodology

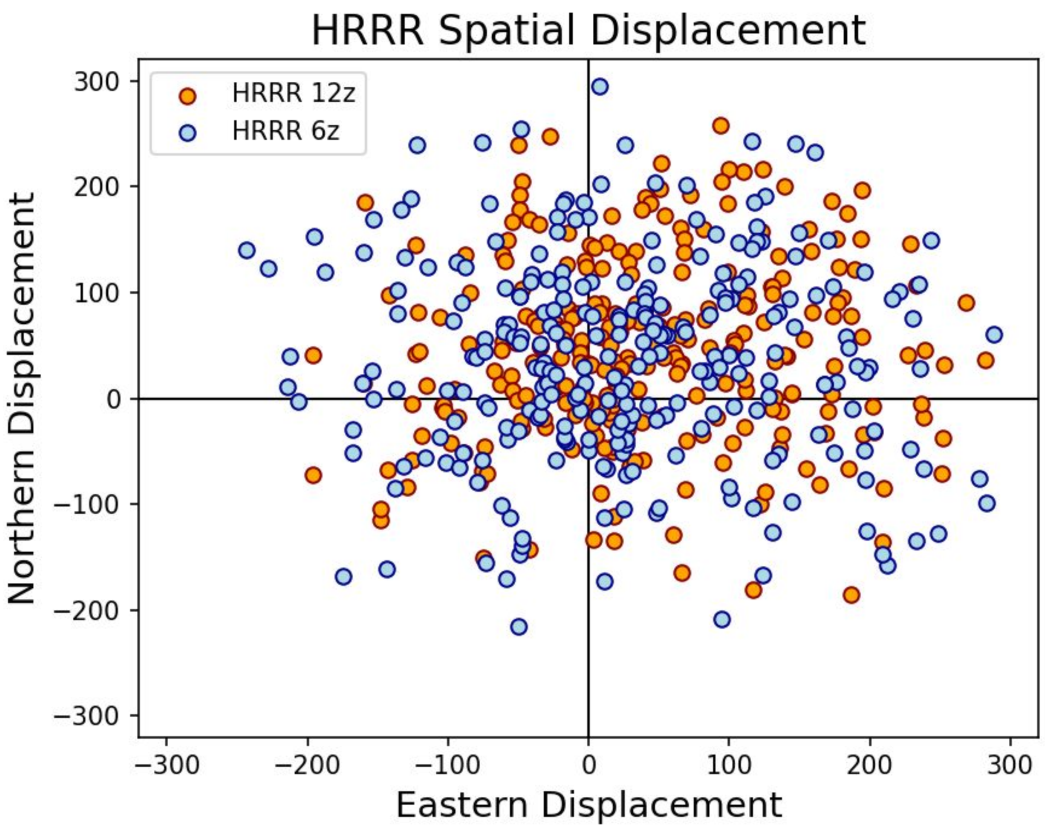
- Approximately 300 MCS cases were found from 8 of the 10 HREF members (FV3 members excluded due to recent implementation – not enough training data) during May-Sept. 2018-2023.
- 24-hr QPF was extracted from each 12z HREF member from before the event (MCSs happened in the first 24-h period).
- Observations came from Multi-Radar/Multi-Sensor System.
- MODE was used to identify individual MCS objects, match forecasted and observed MCSs, and calculate metrics for each object (cases without matches or suspicious matches were excluded)

Geographical Distribution of Cases



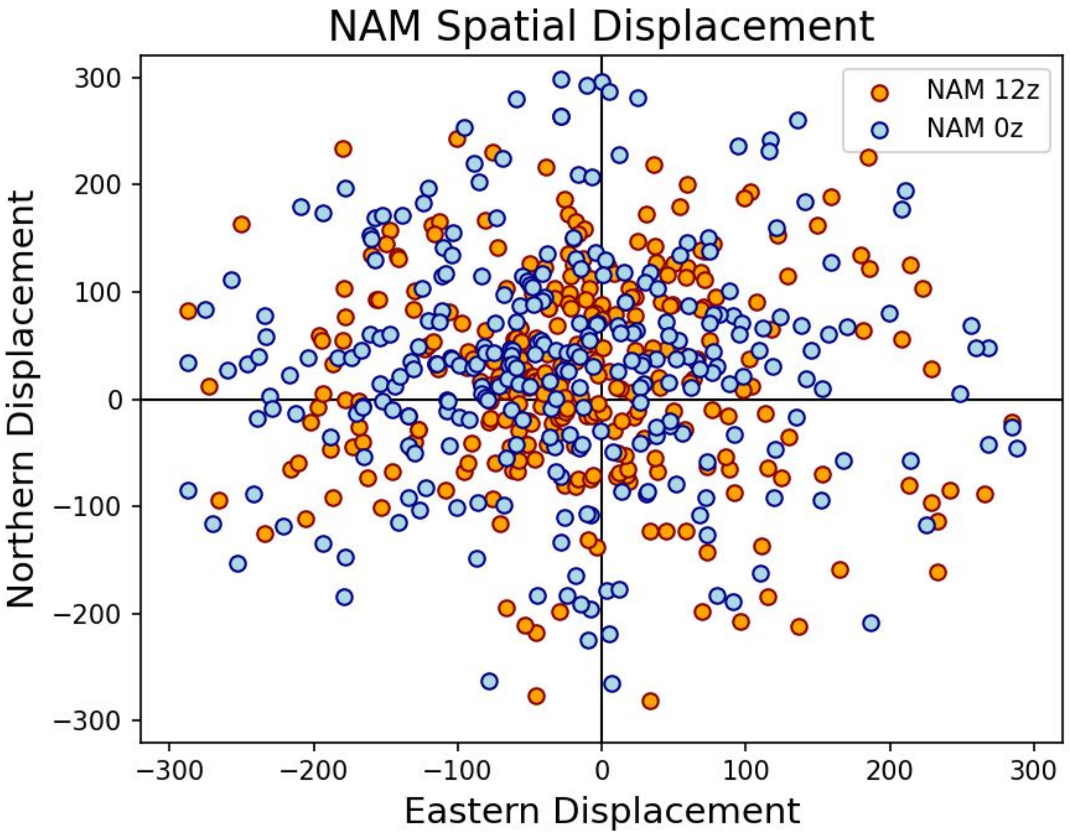
DISPLACEMENT ERRORS FOR 4 MEMBERS

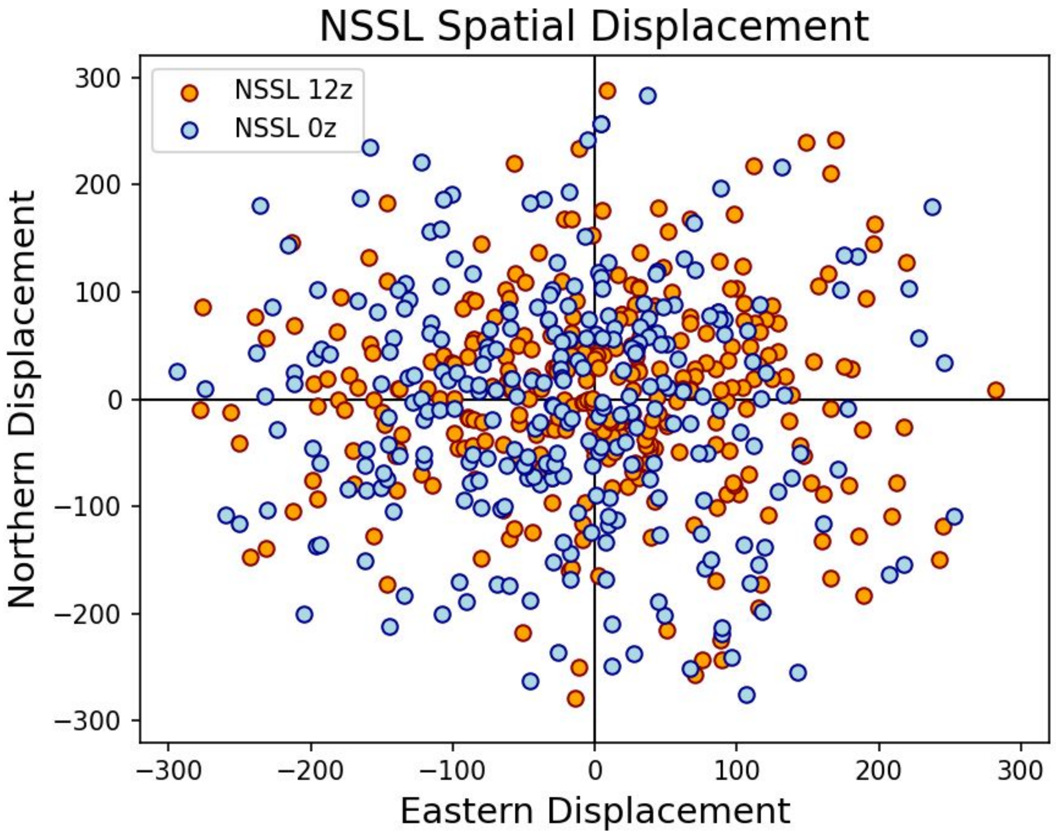


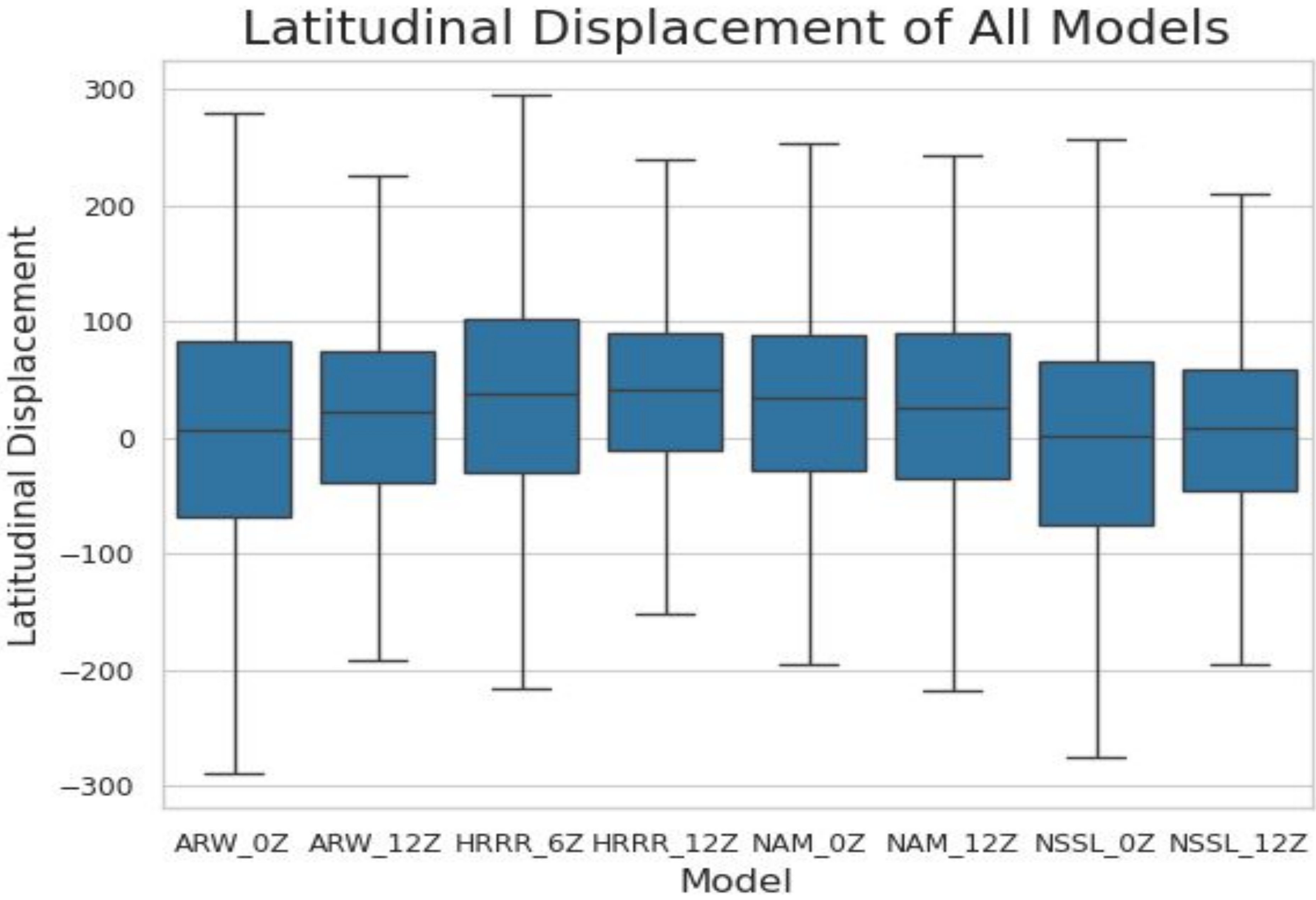


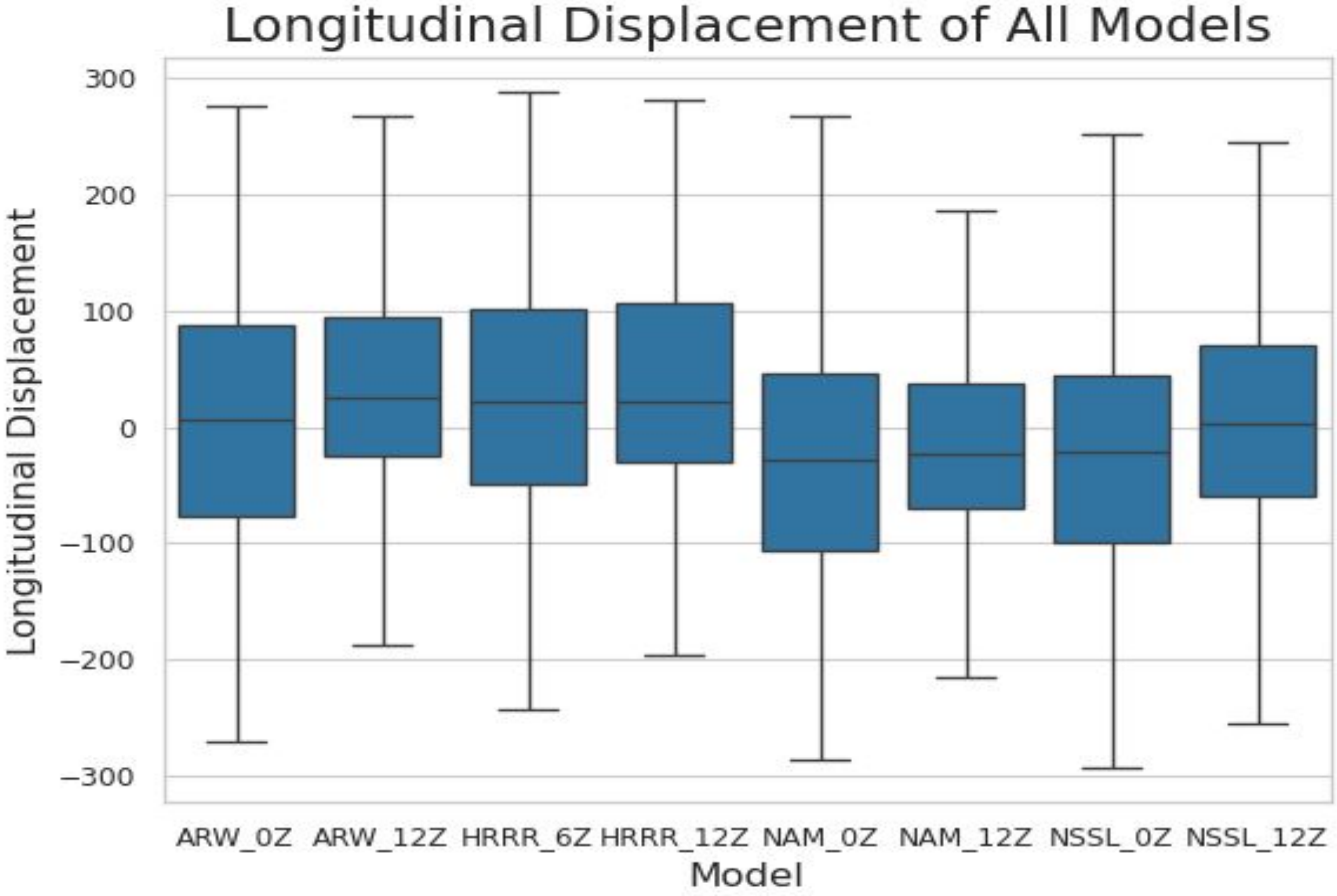
Little or no systematic bias

DISPLACEMENT ERRORS FOR 4 OTHER MEMBERS

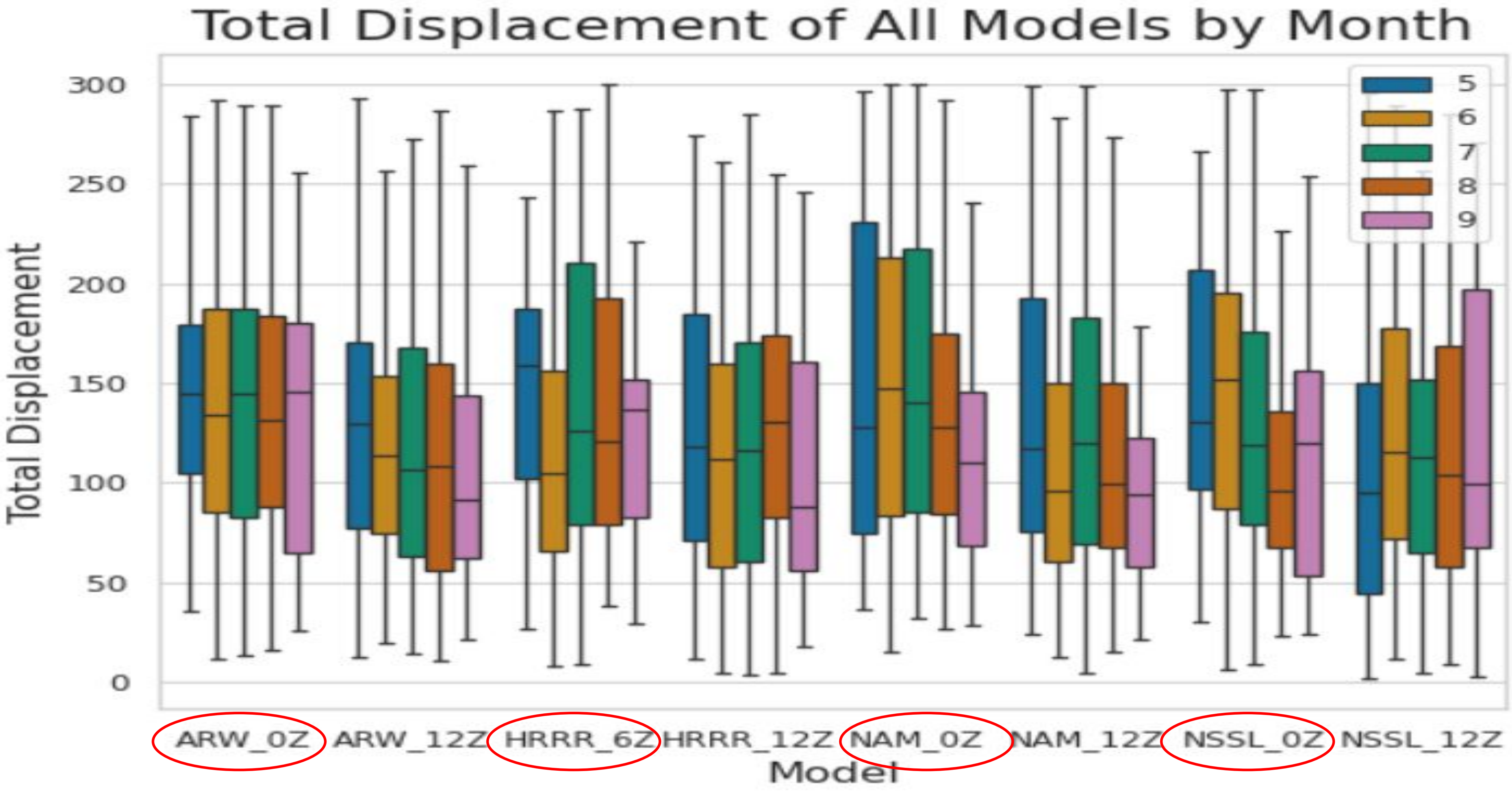




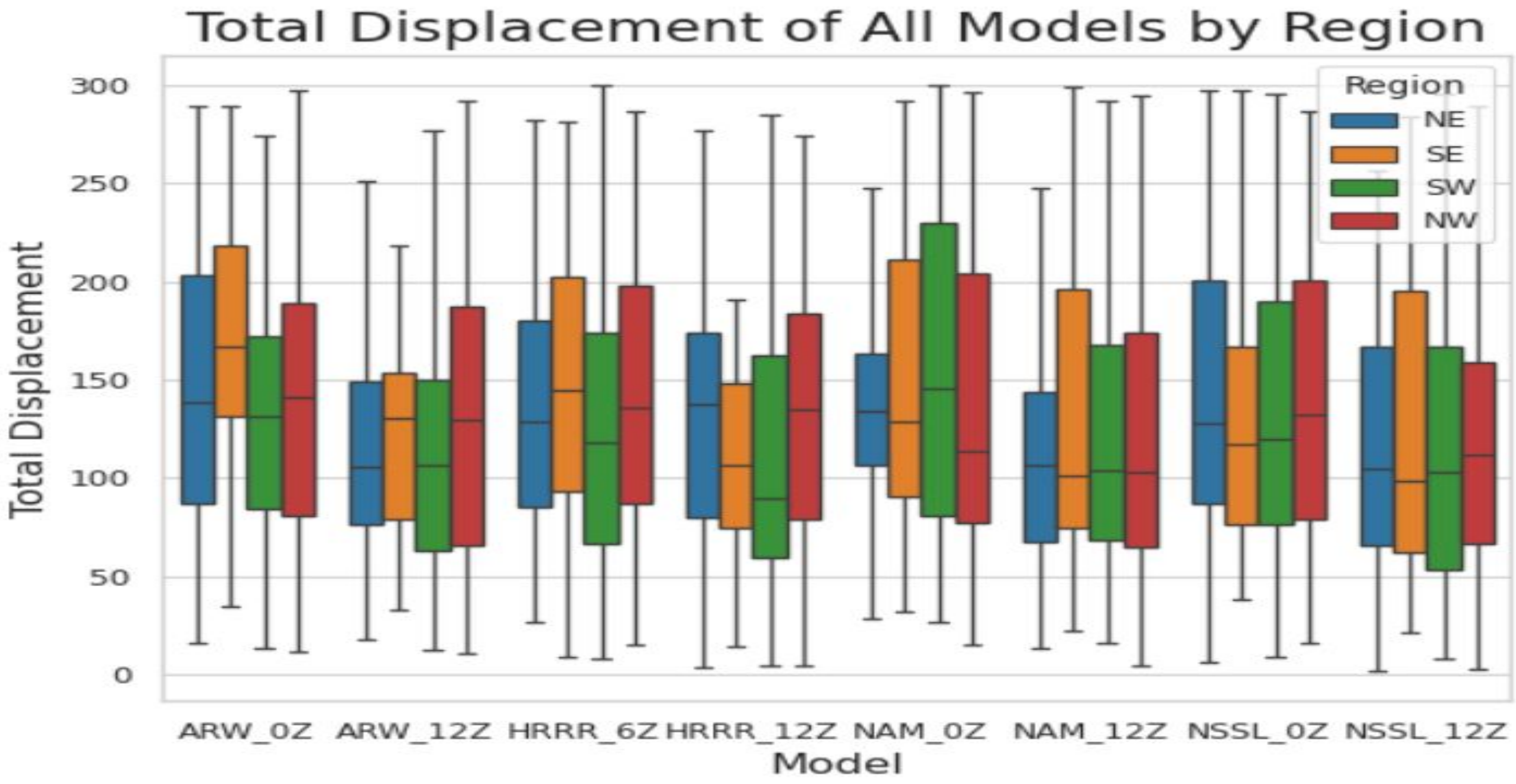

Latitudinal Displacement of All Models
Latitudinal Displacement
300
200
100
0
−100
−200
−300
ARW_0Z
ARW_12Z
HRRR_6Z
HRRR_12Z
NAM_0Z
NAM_12Z
NSSL_0Z
NSSL_12Z
Model


Longitudinal Displacement of All Models
300
200
100
0
−100
−200
−300
Longitudinal Displacement
ARW_0Z
ARW_12Z
HRRR_6Z
HRRR_12Z
NAM_0Z
NAM_12Z
NSSL_0Z
NSSL_12Z
Model

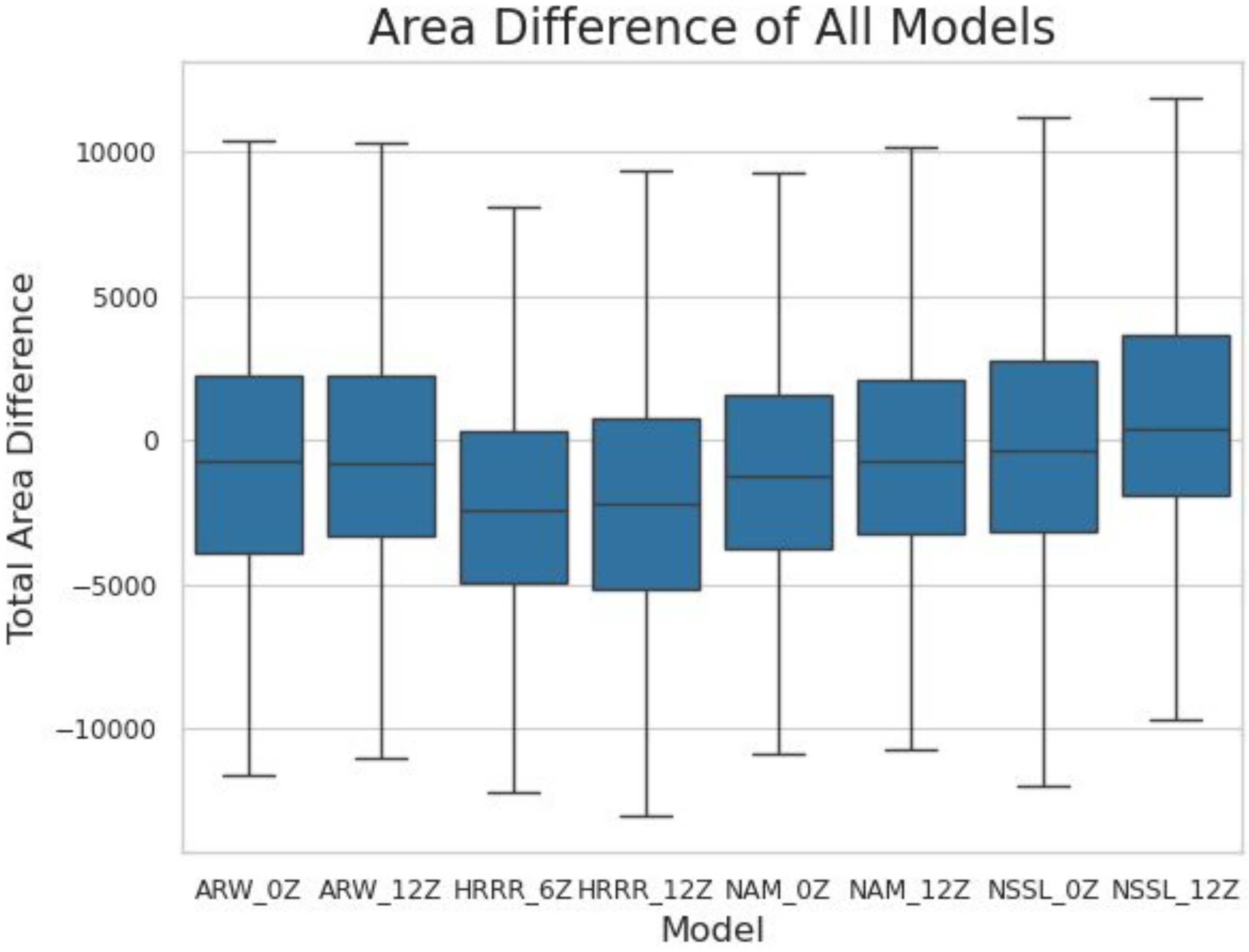
Time Lagged Members tend to have larger displacement errors



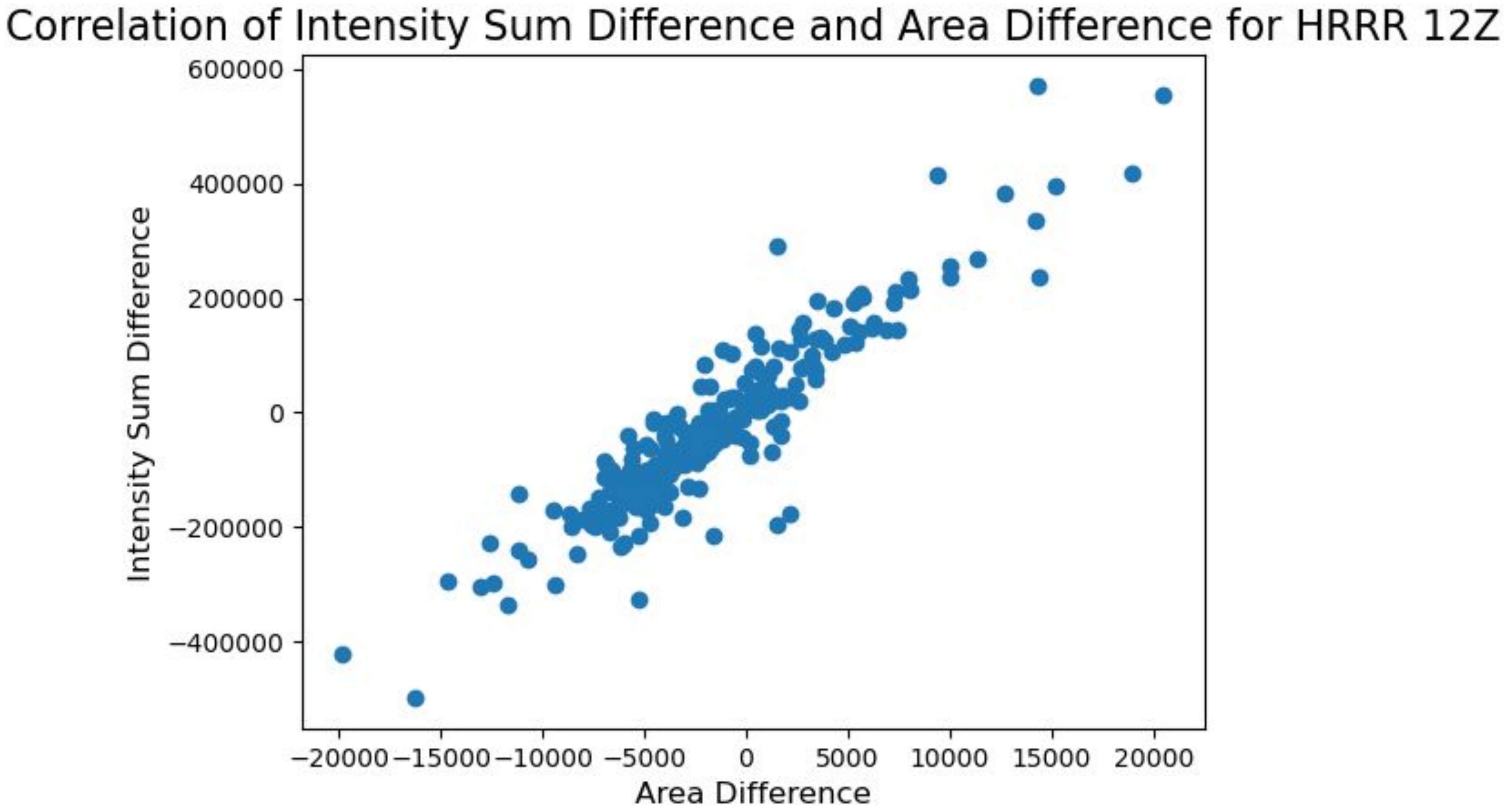
No one has bragging rights as being the hardest place to forecast!



Most models have a small negative area bias (too small a region of rainfall > 0.5")



Area errors correlate well with Intensity Sum Errors (total volume of water) suggesting rate errors overall are not large



Machine Learning Results

Can displacement information be combined with other MODE information or environmental information to predict displacement error in advance?

Previous Approaches

1) Train ML with MODE variables + 5x5 grid of SPC mesoanalysis parameters *with focus on predicting Lat (N/S) and Lon (E/W) Displacement Errors*
   - *Best average displacement error (Lasso): **119.6 km***

2) Same as above, but averages and max/mins calculated for 5x5 grid of mesoanalysis (reduce dimensionality)
   - *Best average displacement error (Lasso): **121.7 km***

3) Train with the error in HREF's forecast of different weather variables relative to SPC mesoanalysis variables, *pivoted to predicting observed centroids due to promising results*
   - *Best average displacement error (Lasso): **107.5 km***

4) Ensemble Approach: Train ML on centroid forecasts of all 8 members of HREF, *no mesoanalysis data provided*
   - *Best average displacement error (Random Forest): **107.9 km***

850 to 500 mb Lapse Rate	C km-1	LR85
Observed 500 mb temperature	C	S5TC
Shear from 300 to 850 mb	kt	SH38
Surface temperature	Deg C	TMPC
Surface Dew point	Deg C	DWPC
Surface U wind component	kt	UWND
Surface V wind component	kt	VWND
Surface relative humidity	%	RELH
Surface wind divergence	s-1	WDIV
Surface relative vorticity	s-1	RVRG
Surface Based CAPE	J kg-1	SBCP
Surface based CIN	J kg-1	SBCN
Most Unstable CAPE	J kg-1	MUCP
Most Unstable CIN	J kg-1	MUCN
Sfc to 3 km U shear component	kt	U3SV
Sfc to 3 km V shear component	kt	V3SV
Sfc to 6 km U shear component	kt	U6SV
Sfc to 6 km V shear component	kt	V6SV
Precipitable water	inches	INPW
Cloud base temperature	C	MLCT
Sfc based LCL height	m	SLCH

**List of 21 SPC Mesoanalysis parameters used for training*

Final Approach

1. Centroid Forecasts from 8 HREF members
2. Impute for Missing Members
3. Calculate Weighted Average Centroid
4. Collect SPC Mesoanalysis Around Weighted Centroid
5. Train ML Models
6. Prediction Using Best ML Model (Lasso)

**Weights estimated from training data by minimizing great circle distance errors*

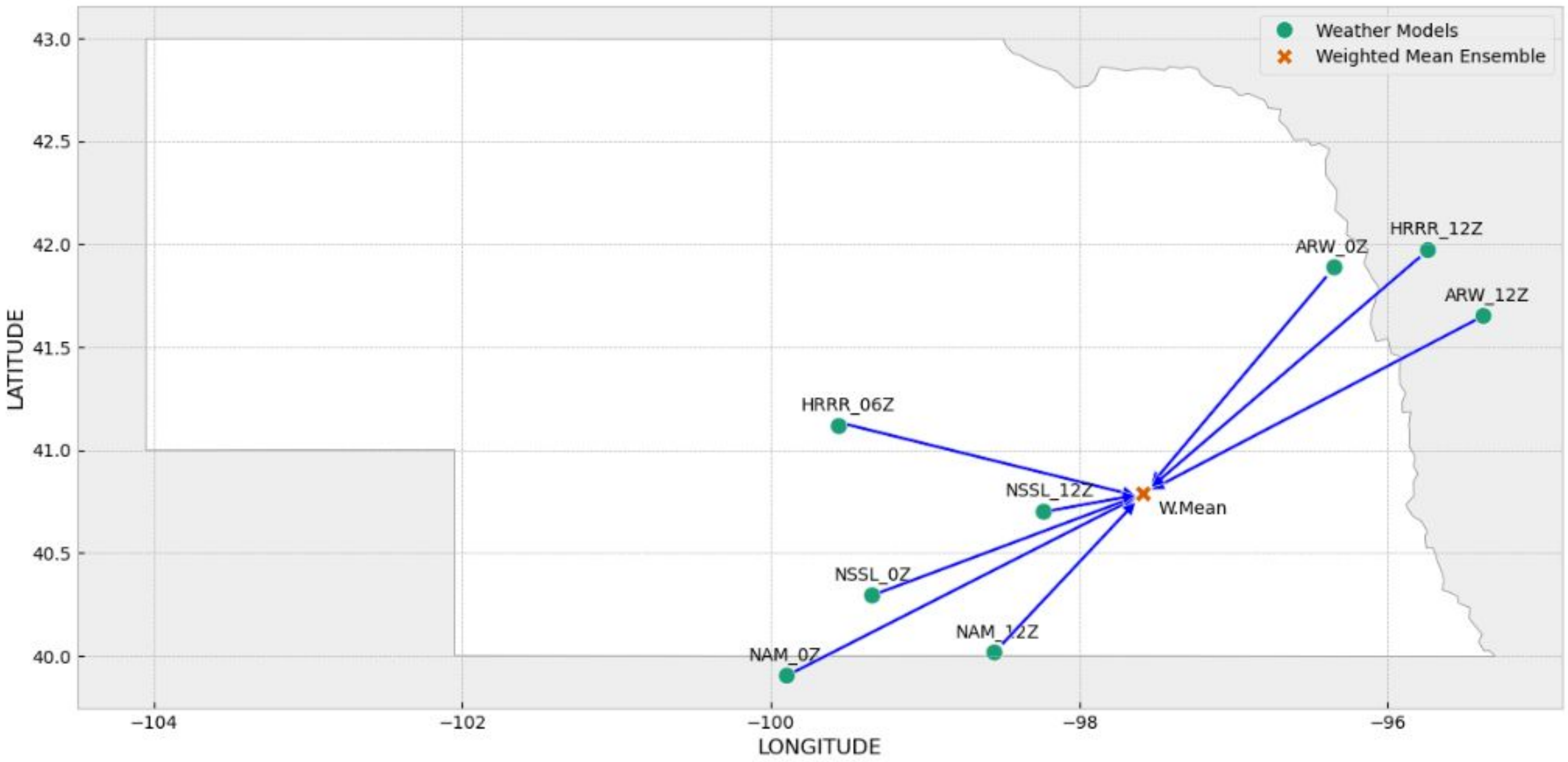
**Compute means of NW and SE quadrants of 5x5 grid*

Comparison of Ensemble Models

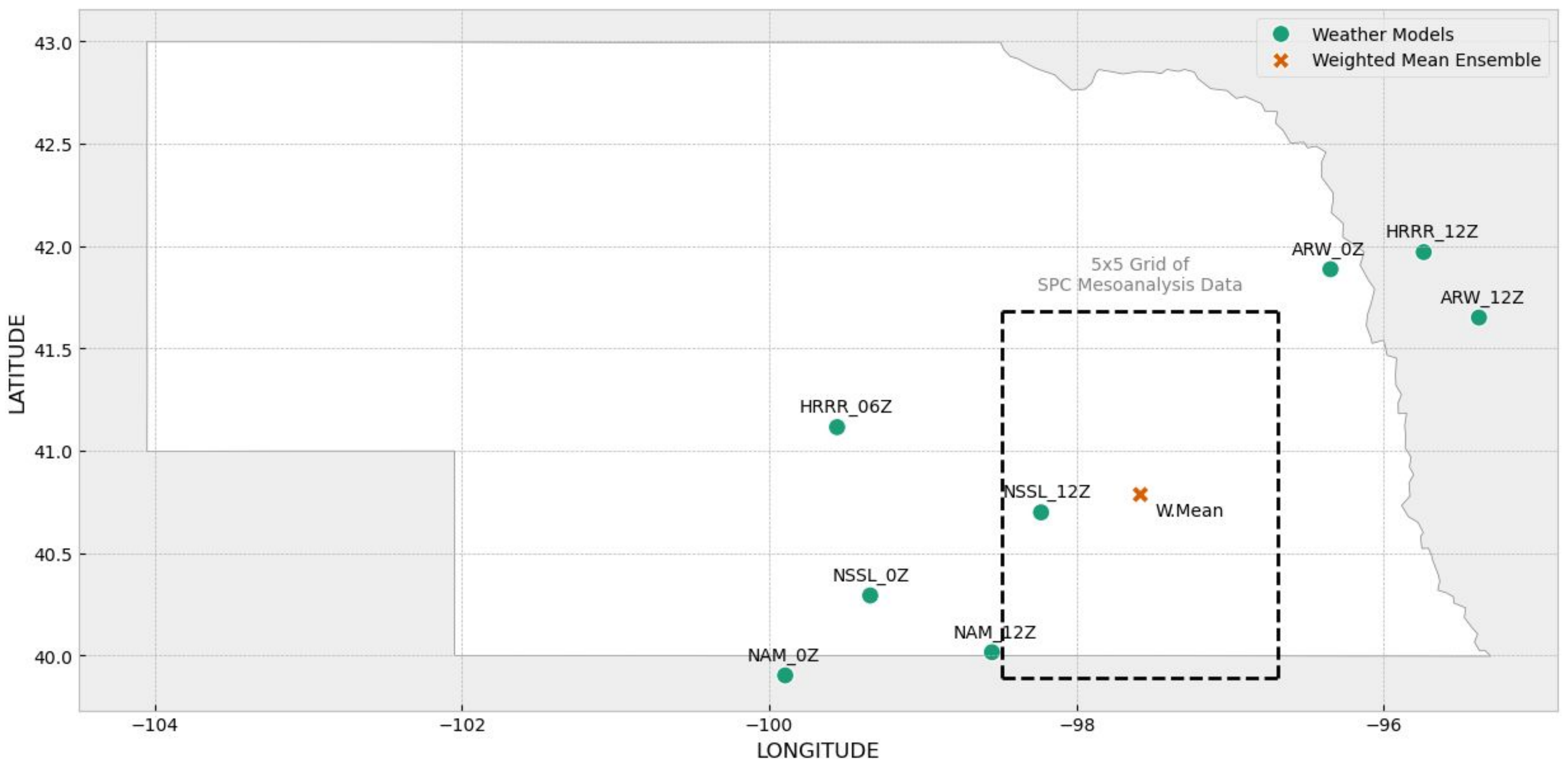
	RMSE_LON
LASSO_Ensemble	1.111910
ElasticNet Ensemble	1.111910
Ridge Ensemble	1.155091
NSSL_12Z	1.230685
HRRR_12Z	1.331884
XGB Ensemble	1.378440
ARW_12Z	1.414029
NAM_12Z	1.429587
RF Ensemble	1.458352
ARW_0Z	1.616313
AdaBoost Ensemble	1.666726
NAM_0Z	1.707398
NSSL_0Z	1.708506
HRRR_06Z	1.741558

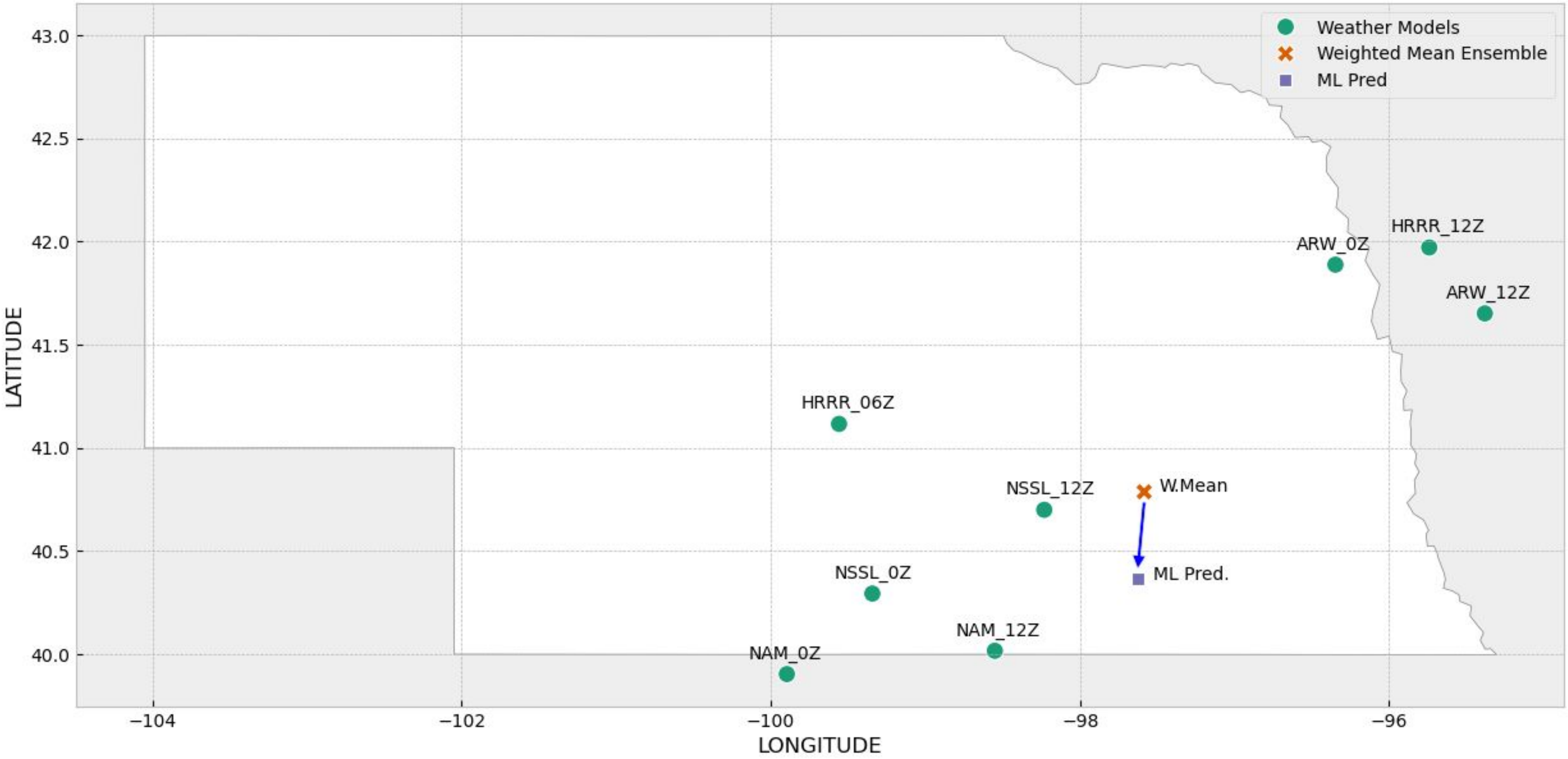
	RMSE_LAT
LASSO_Ensemble	0.693091
ElasticNet Ensemble	0.693091
Ridge Ensemble	0.710001
XGB Ensemble	0.758522
AdaBoost Ensemble	0.802168
RF Ensemble	0.806632
ARW_12Z	0.880204
NSSL_12Z	0.924346
NAM_12Z	0.994644
HRRR_12Z	1.140635
ARW_0Z	1.142007
HRRR_06Z	1.280322
NAM_0Z	1.392643
NSSL_0Z	1.414058

	Distance Error
LASSO_Ensemble	103.225321
Elastic Net_Ensemble	103.225321
Ridge_Ensemble	107.175415
NSSL_12Z	121.568915
XGB_Ensemble	124.808007
RF_Ensemble	128.012010
ARW_12Z	130.380494
NAM_12Z	137.867432
HRRR_12Z	138.751843
AdaBoost_Ensemble	140.522592
HRRR_06Z	162.881492
ARW_0Z	165.463582
NAM_0Z	177.811254
NSSL_0Z	181.285676



Weather Models
Weighted Mean Ensemble
HRRR_12Z
ARW_0Z
ARW_12Z
HRRR_06Z
NSSL_12Z
W.Mean
NSSL_0Z
NAM_12Z
NAM_0Z
43.0
42.5
42.0
41.5
41.0
40.5
40.0
LATITUDE
−104
−102
−100
−98
−96
LONGITUDE


Weather Models
Weighted Mean Ensemble
5x5 Grid of
SPC Mesoanalysis Data
HRRR_12Z
ARW_0Z
ARW_12Z
HRRR_06Z
NSSL_12Z
W.Mean
NSSL_0Z
NAM_12Z
NAM_0Z
LATITUDE
LONGITUDE
43.0
42.5
42.0
41.5
41.0
40.5
40.0
−104
−102
−100
−98
−96



Weather Models
Weighted Mean Ensemble
ML Pred
HRRR_12Z
ARW_0Z
ARW_12Z
HRRR_06Z
NSSL_12Z
W.Mean
ML Pred.
NSSL_0Z
NAM_12Z
NAM_0Z
43.0
42.5
42.0
41.5
41.0
40.5
40.0
LATITUDE
−104
−102
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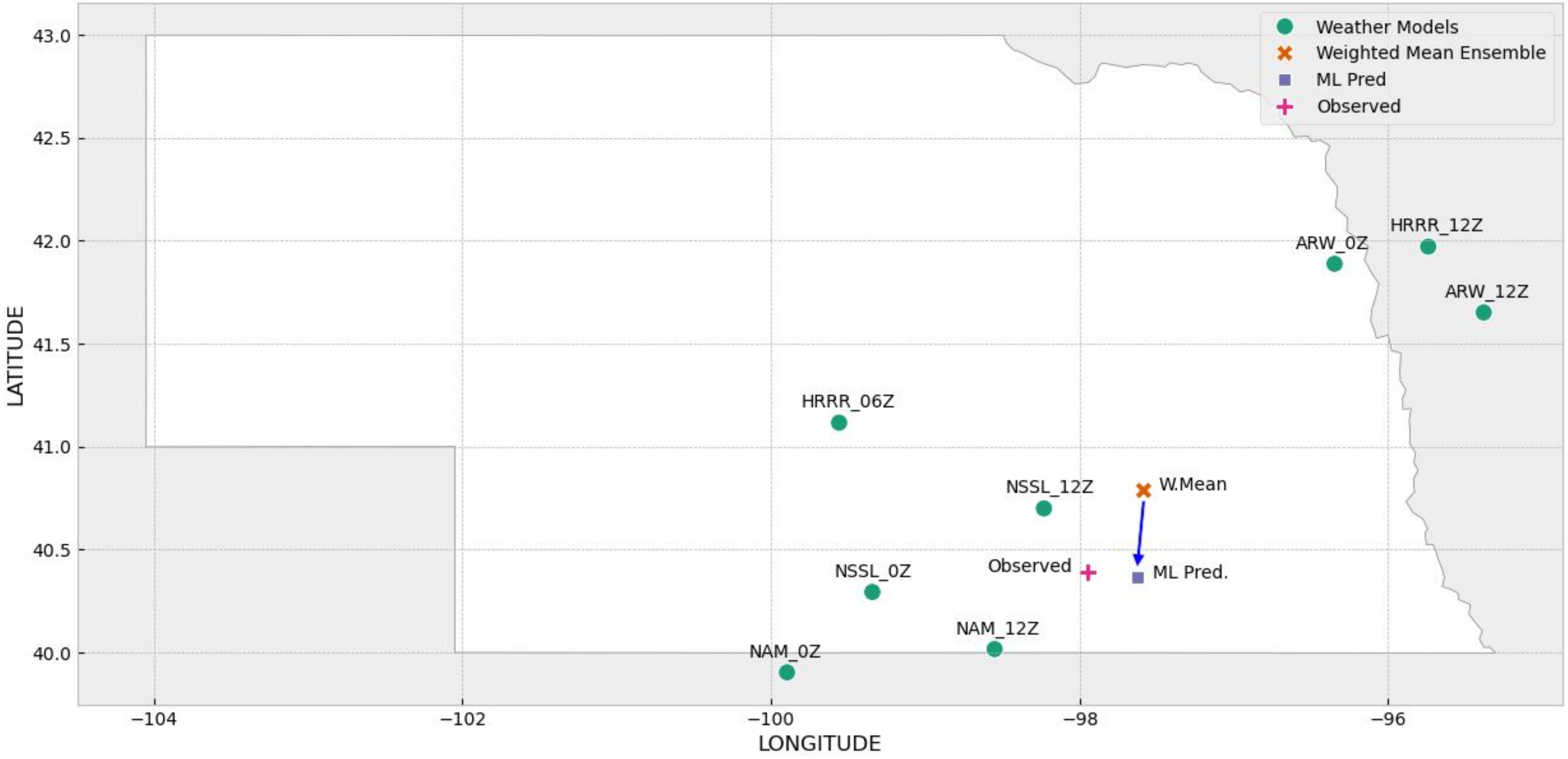
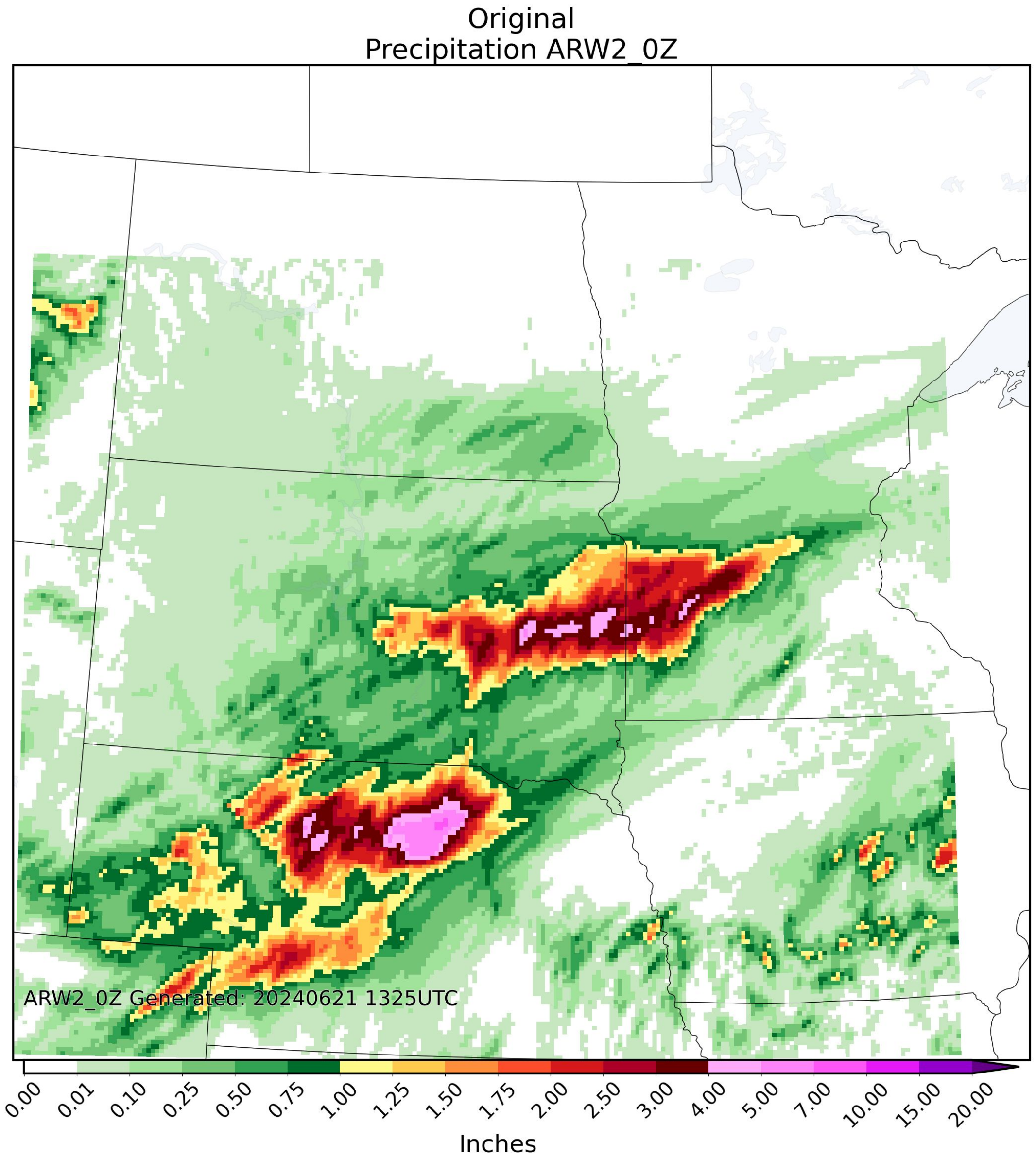
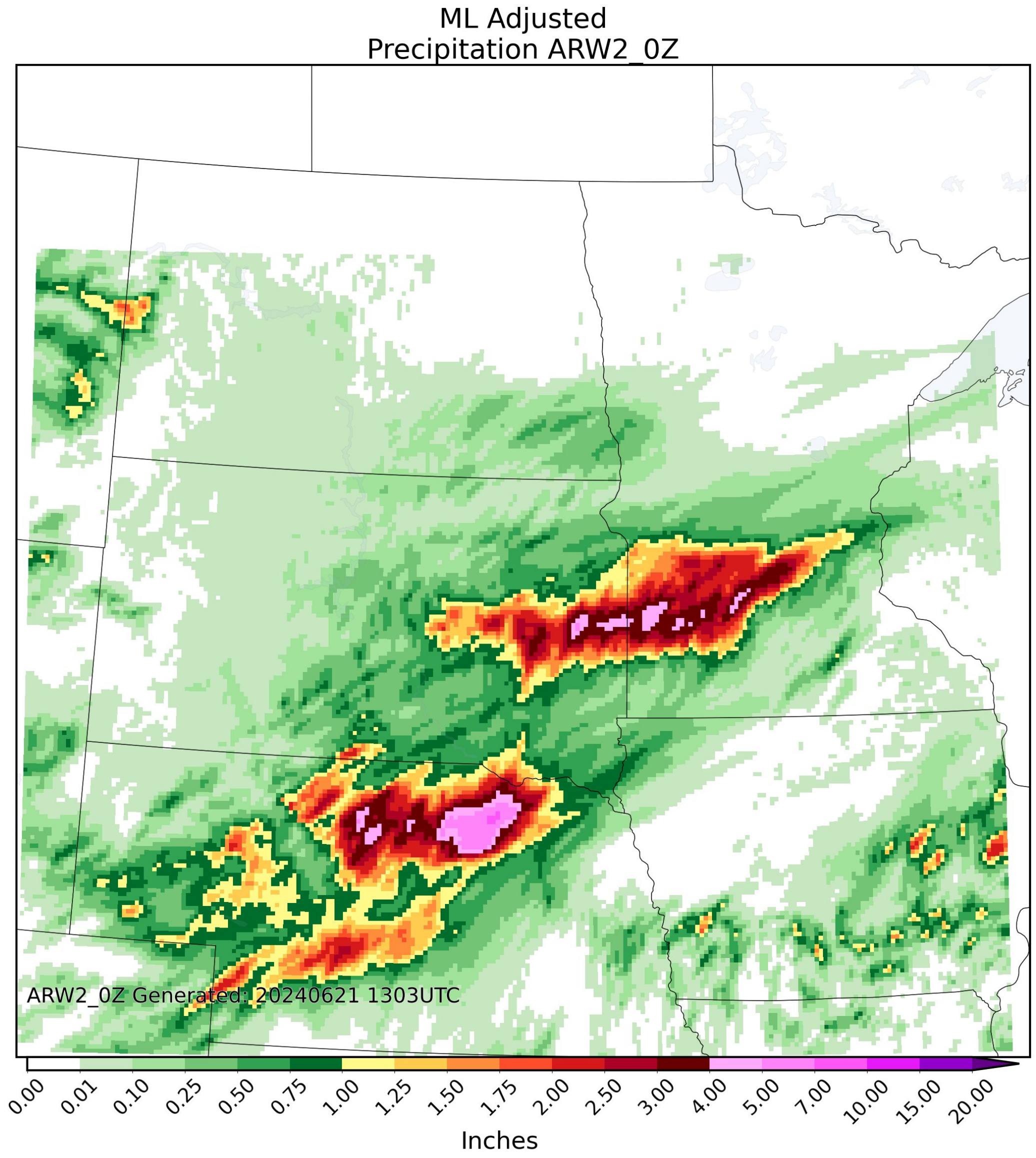
−98
−96
LONGITUDE

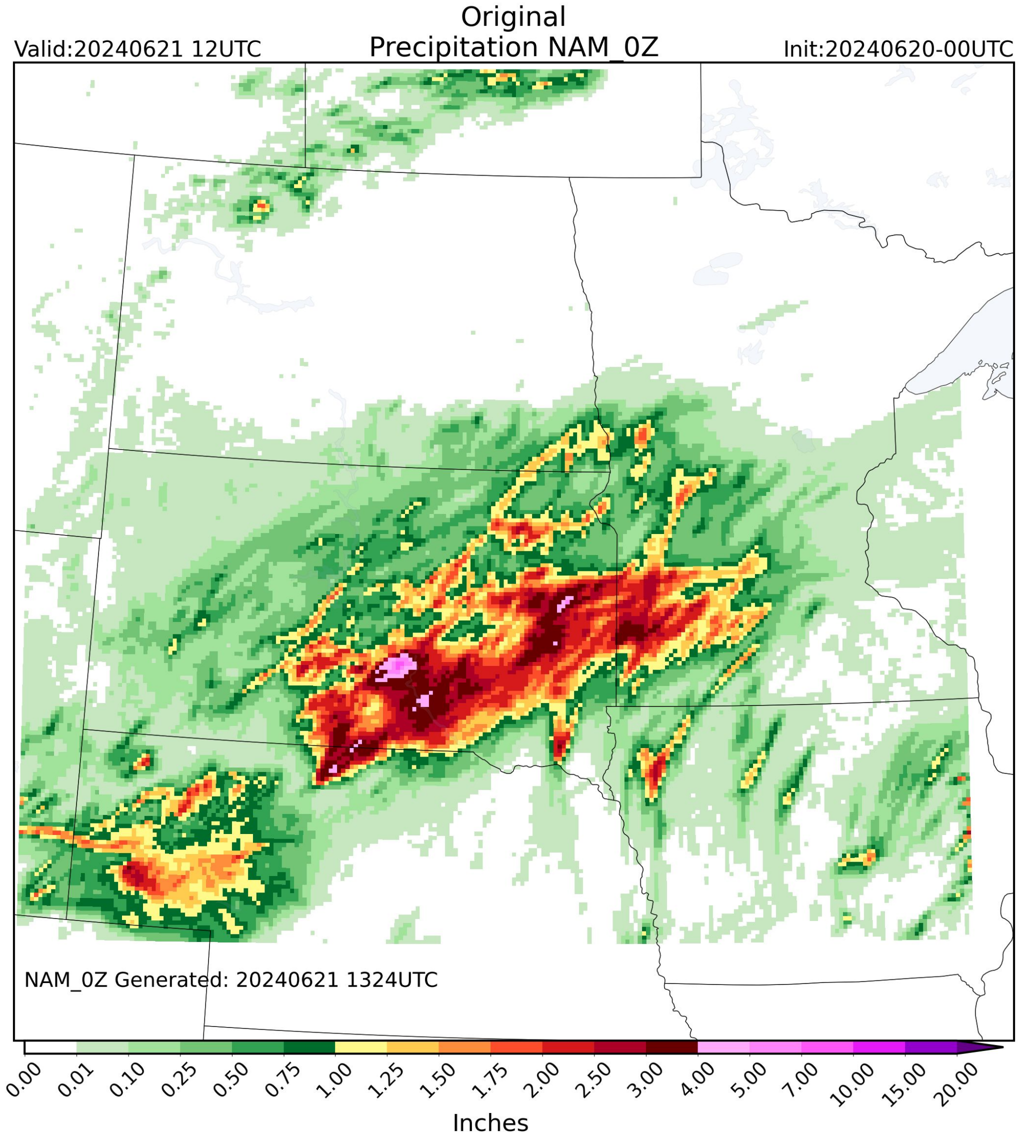


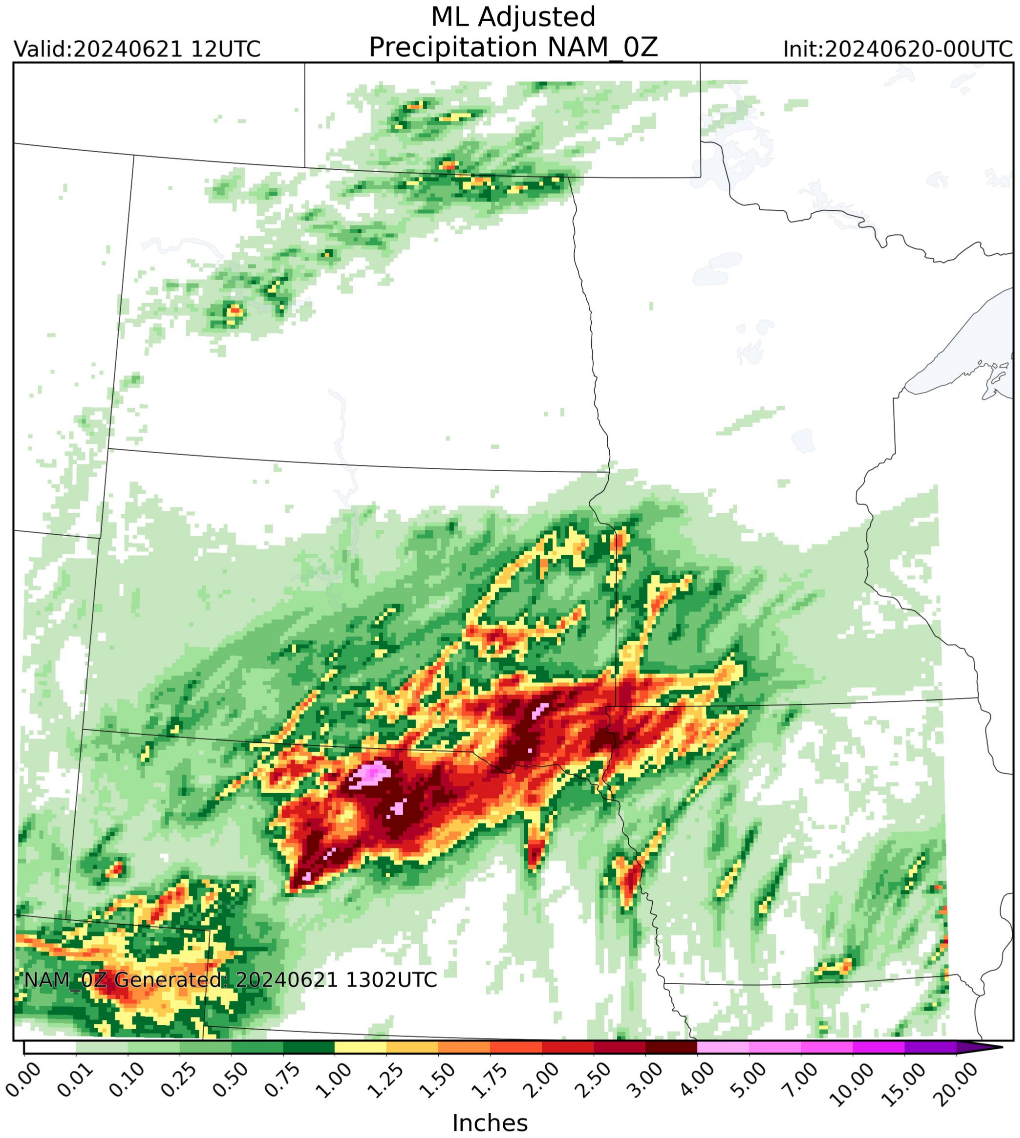
Weather Models
Weighted Mean Ensemble
ML Pred
Observed
HRRR_12Z
ARW_0Z
ARW_12Z
HRRR_06Z
NSSL_12Z
W.Mean
Observed
ML Pred.
NSSL_0Z
NAM_12Z
NAM_0Z
43.0
42.5
42.0
41.5
41.0
40.5
40.0
LATITUDE
−104
−102
−100
−98
−96
LONGITUDE



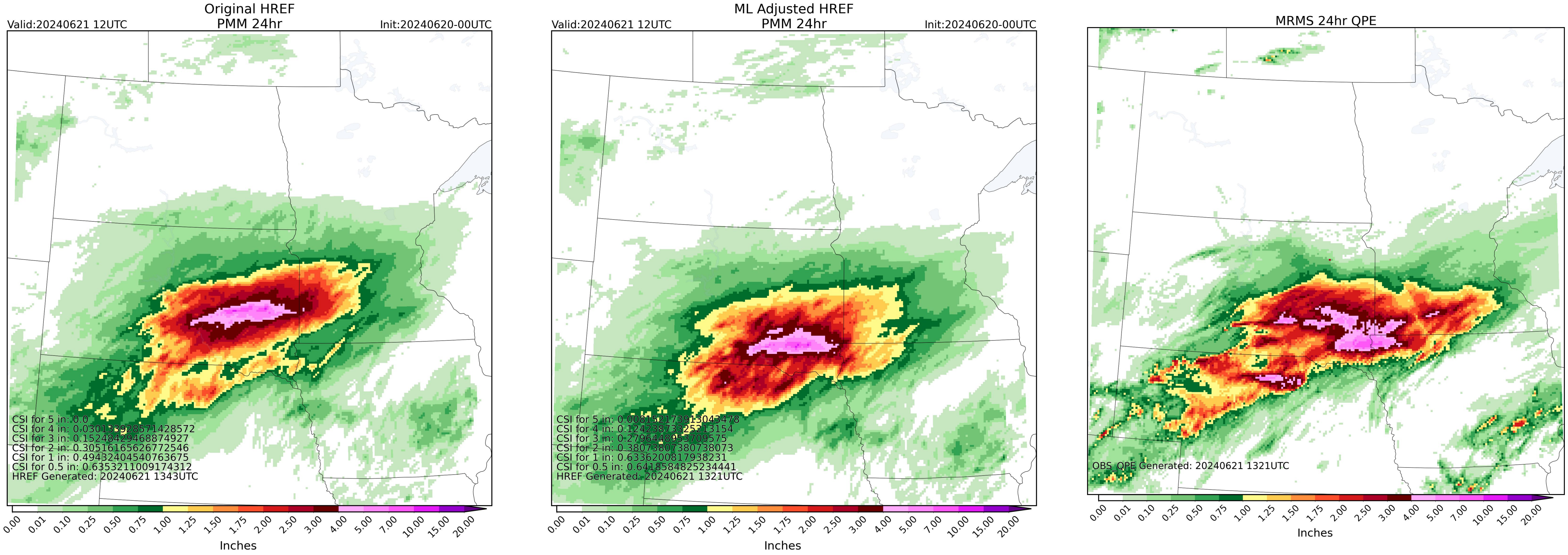


In this example case (from last Thursday, where serious flooding hit far southeastern SD), a small shift mostly eastward is performed on the 0Z ARW2





A much greater shift mostly southward is performed on the 00z NAM

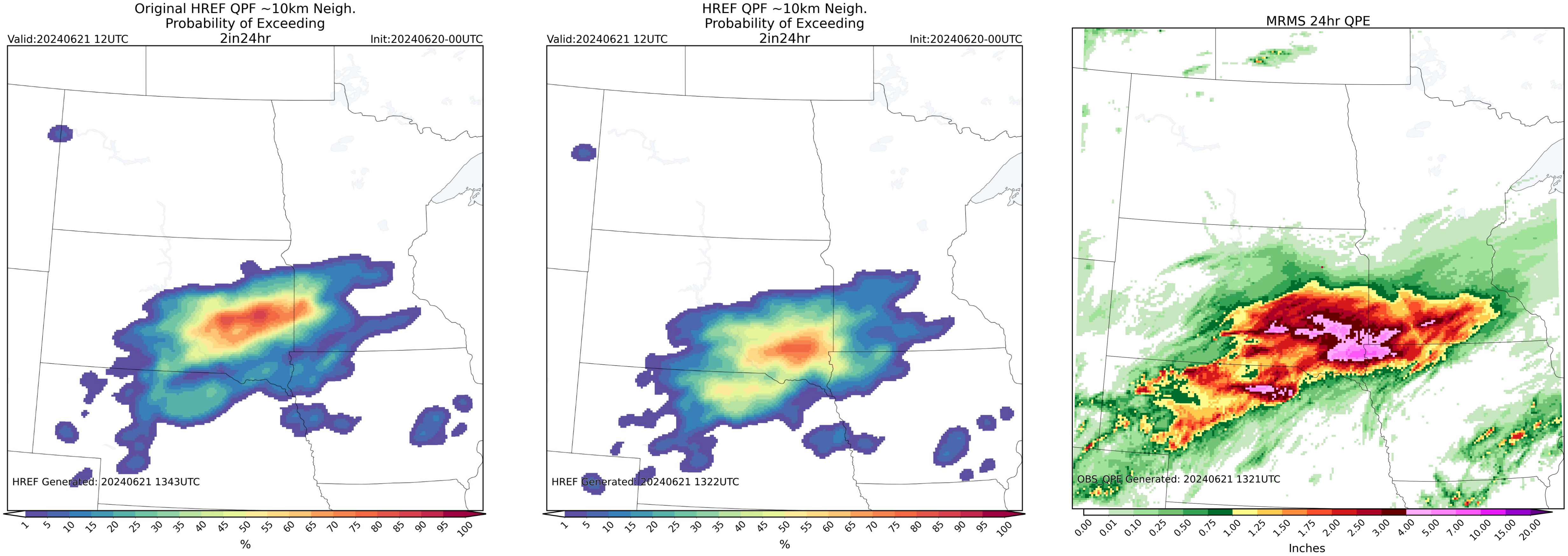


The resulting Probability Matched Mean forecast shows the ML approach shifted the heavy rain band substantially farther south putting it much closer to the observed heaviest rain in far southeastern SD, and better capturing another region of 5-inch rains in north-central NE. CSI values improved dramatically with the ISU technique (1 inch from .49 to .63, 2 inch from .31 to .38, 3 inch from .15 to .28, 4 inch from .006 to .016 and even 5 inches from 0 to 0.08

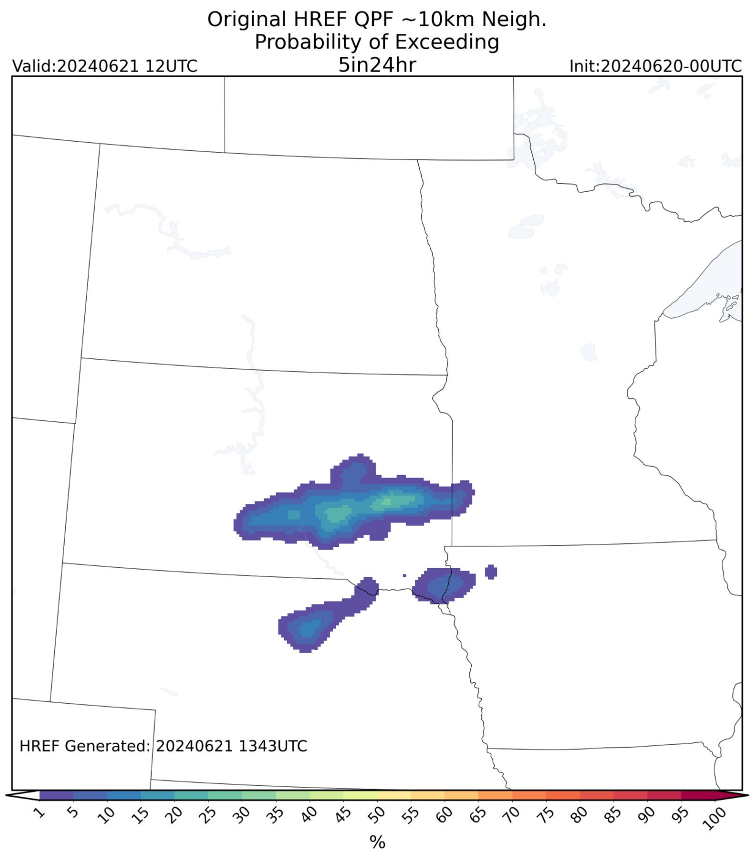
Average CSI values since start of FFAIR (11 days)

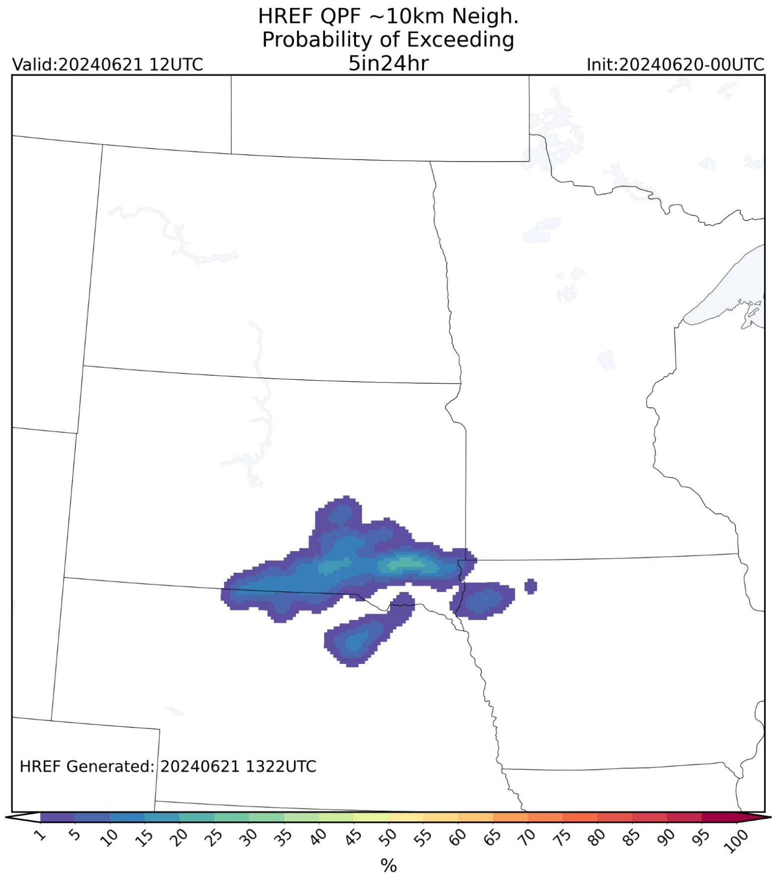
Threshold	HREF orig	ISU-ML
0.5”	0.376	0.363
1”	0.19	0.214
2”	0.047	0.063
3” (2 cases >0)	0.018	0.029
4” (1 case >0)	0.006	0.016
5” (1 case >0)	0.0002	0.013

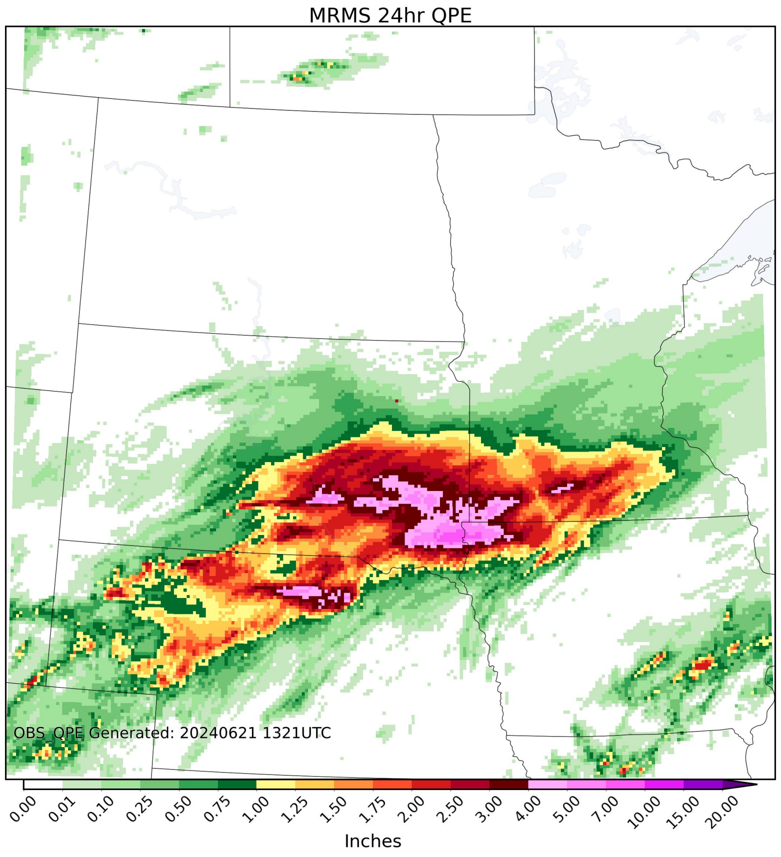
Increasingly large improvements in CSI for thresholds of 1 inch or greater



Probability of Exceedance for 2 inch of rain also shows southward shift and better match with observations







Same for Probability of Exceedance for 5 inch of rain – the shift improves the forecast noticeably in this event

Discussion

Predicting the observed centroids instead of the displacement errors of each HREF member yields a better fit to the data.

Ensemble models are highly effective in making predictions (weighted average of member centroids yields a rather good forecast).

The addition of SPC mesoanalysis data in the ML tool further improves centroid predictions.

Summary

- **Climatology assessment is nearing completion. Displacement errors' lack of biases and correlation to weather parameters has challenged the original ML concept.**

- **Area and intensity errors may be more easily managed.**

- **The use of ML to improve upon a weighted average of HREF ensemble centroid positions has yielded much better results than all prior tests. This tool is being evaluated in FFAIR 2024.**

- **Next steps:**
  - **Verification of QPF and adjusted QPF**
  - **Analysis of FFAIR feedback**
  - **Testing QPF with FLASH**