FV3-LAM CAM Ensemble Predictions and Consensus Products for Predicting Heavy Rain in the FFaIR Experiments

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2024 FFaIR Experiment
June 27, 2024

Hydrometeorology Testbed

- **Hydrometeorology Testbed R2O-O2R Experiments**
  - Organized by the NOAA Weather Prediction Center
  - Bring together researchers & operational forecasters
  - FFaIR (June-August)
    - Evaluate new products for flash flood and excessive rainfall forecasts
  - Winter Weather Experiment (November – March)
    - Evaluate new products for snowfall forecasts

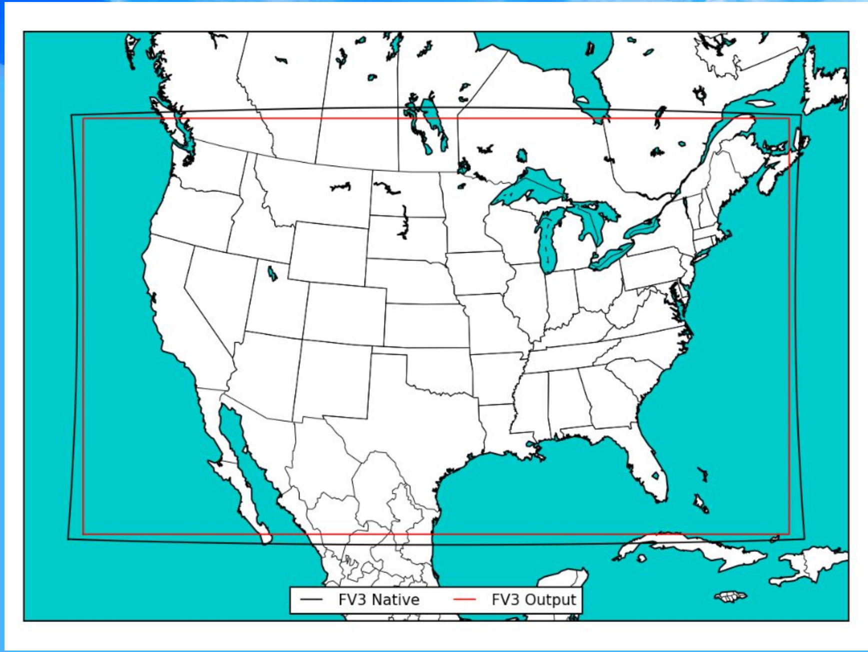
- **CAPS Contribution**
  - HMT participant since 2016 (HWT since 2007)
  - Multi-member 3-km CONUS CAM Ensemble Forecasts
  - Ensemble Consensus Products
  - Participate in Forecasting Exercises (EROs, MRTP, etc)

CAPS FFaIR Real-Time Ensembles

Research Goals

- Test various FV3-LAM Physics Combinations
- 2022-23: Contribute to RRFS design & testing
- 2024: Add JEDI Radar Data Assimilation
- Develop and Evaluate Novel Ensemble Consensus Methods
  - Spatial-Aligned Mean
  - Machine Learning Probabilistic Products

2023 HMT FFaIR Configurations



- 15 FV3-LAM members
- 3 km grid spacing CONUS grid
- 84-hr forecasts initialized at 00Z
- Code: Latest UFS FV3-LAM Short Range Weather App 1.0.1 Base code
- Run on Frontera at the Texas Advanced Computing Center (TACC)

FRONTERA

TACC ACCESS Advancing Innovation

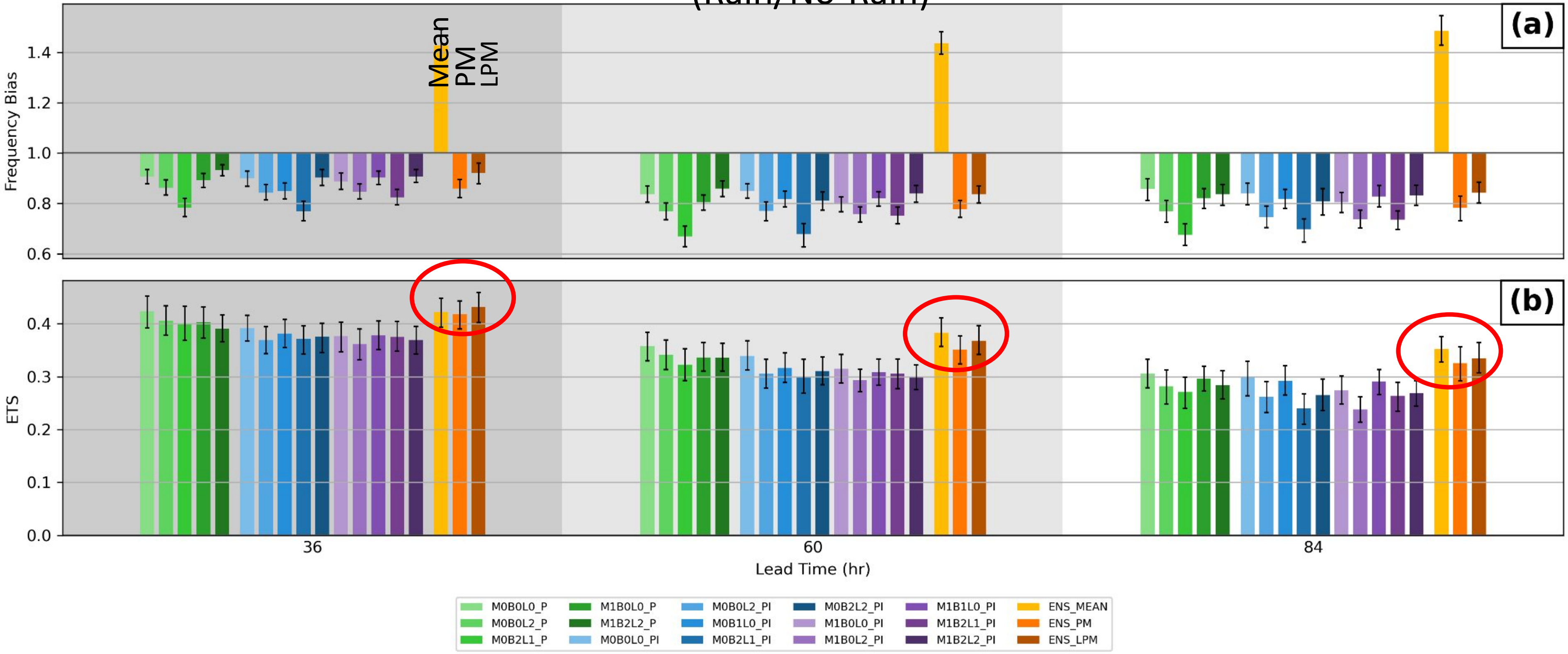
CAPS FV3-LAM 2023 FFaIR 15 Members

Naming
M: Microphysics
B: Boundary Layer
L: Land Sfc Model
P: 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	NOAHMP	GFS/GFS (GFSv16)	AI-3
Physics + IC Perturbation Ensemble						
M0B0L2_PI	Thompson	MYNN	MYNN	RUC	GEFS_m1	
M0B1L0_PI	Thompson	Shin-Hong	GFS	NOAH	GEFS_m2	
M0B2L1_PI	Thompson	TKE-EDMF	GFS	NOAHMP	GEFS_m3	
M0B0L0_PI	Thompson	MYNN	MYNN	NOAH	GEFS_m4	
M0B2L2_PI	Thompson	TKE-EDMF	GFS	RUC	GEFS_m5	AI-4
M1B0L2_PI	NSSL	MYNN	MYNN	RUC	GEFS_m6	
M1B1L0_PI	NSSL	Shin-Hong	GFS	NOAH	GEFS_m7	
M1B2L1_PI	NSSL	TKE-EDMF	GFS	NOAHMP	GEFS_m8	
M1B0L0_PI	NSSL	MYNN	MYNN	NOAH	GEFS_m9	
M1B2L2_PI	NSSL	TKE-EDMF	GFS	RUC	GEFS_m10	

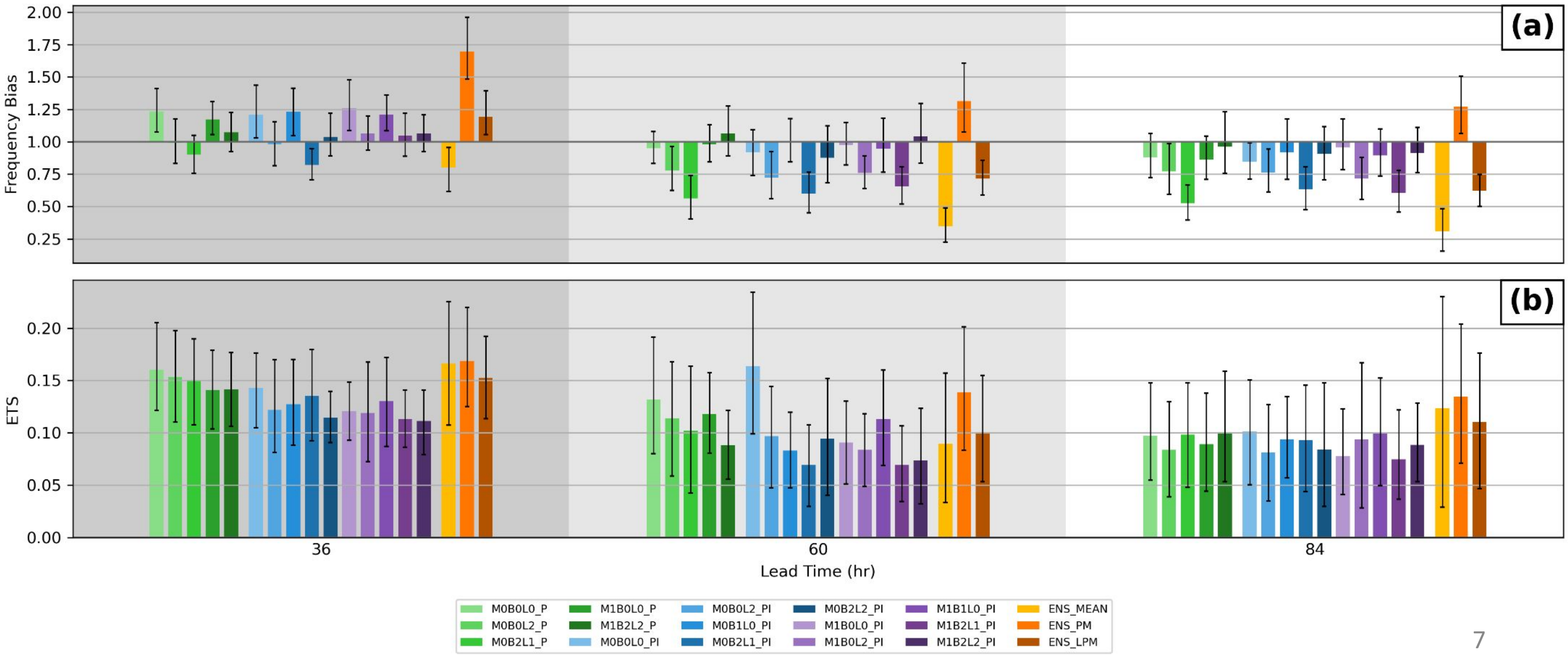
2023 FFaIR Precip Verification 1 mm

24-h Precip 30-km Neighborhood Threshold: 1 mm (Rain/No-Rain)



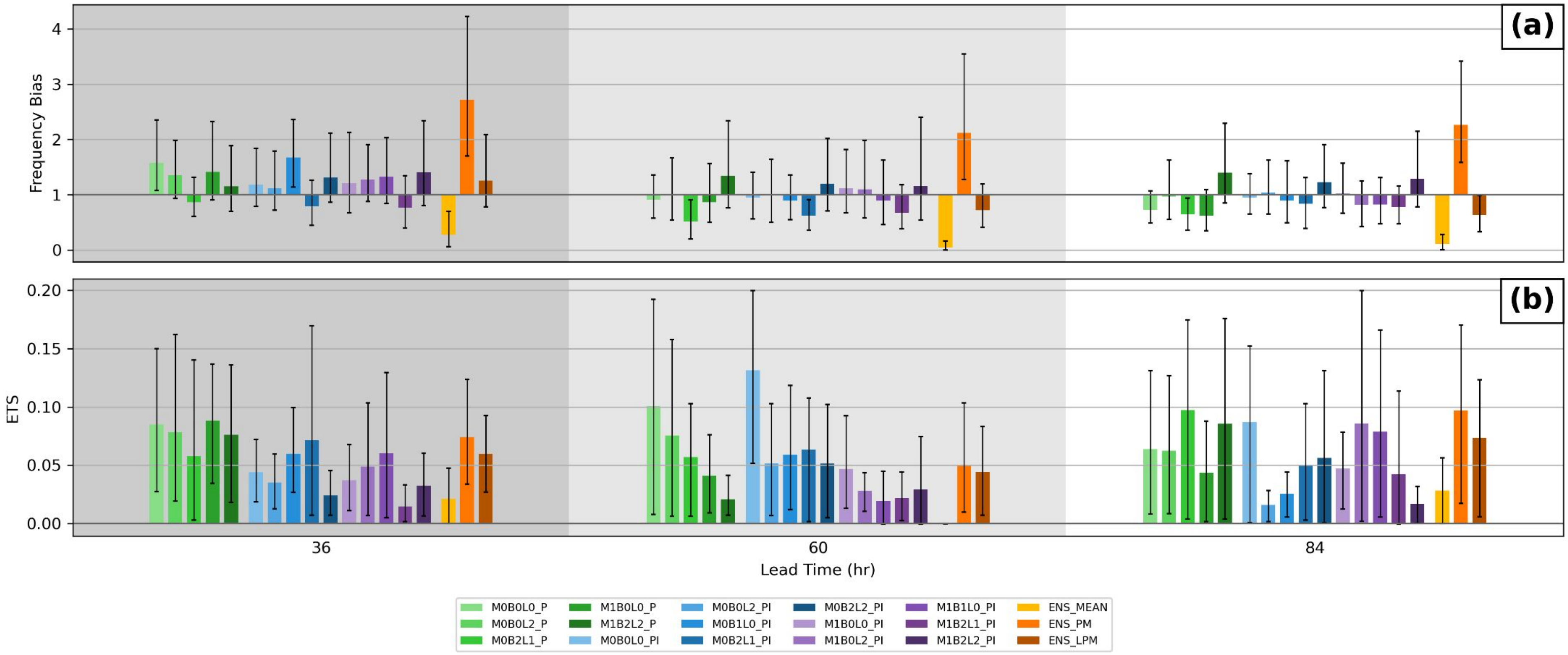
2023 FFaIR Precip Verification 25 mm

24-h Precip 30-km Neighborhood Threshold: 25 mm (1 inch)



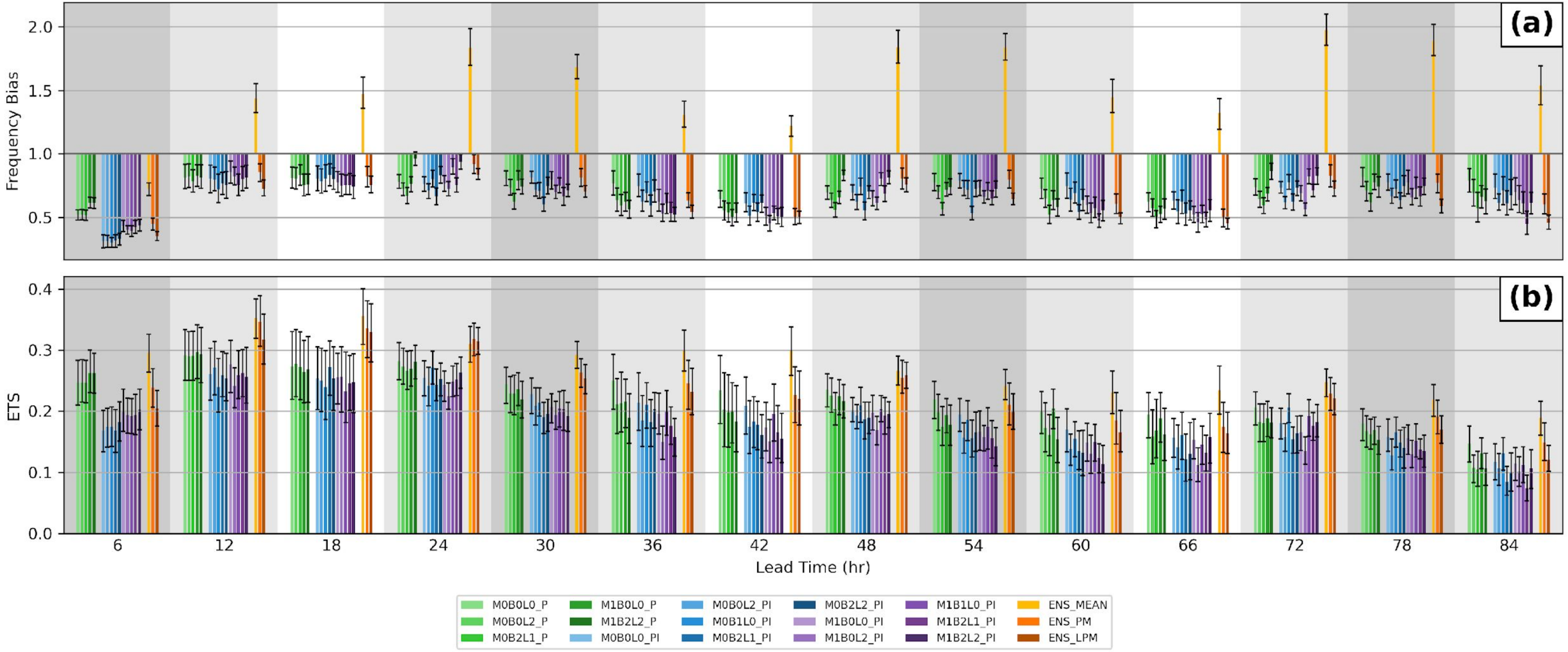
2023 FFaIR Precip Verification 50 mm

24-h Precip 30-km Neighborhood Threshold: 50 mm (2 inch)



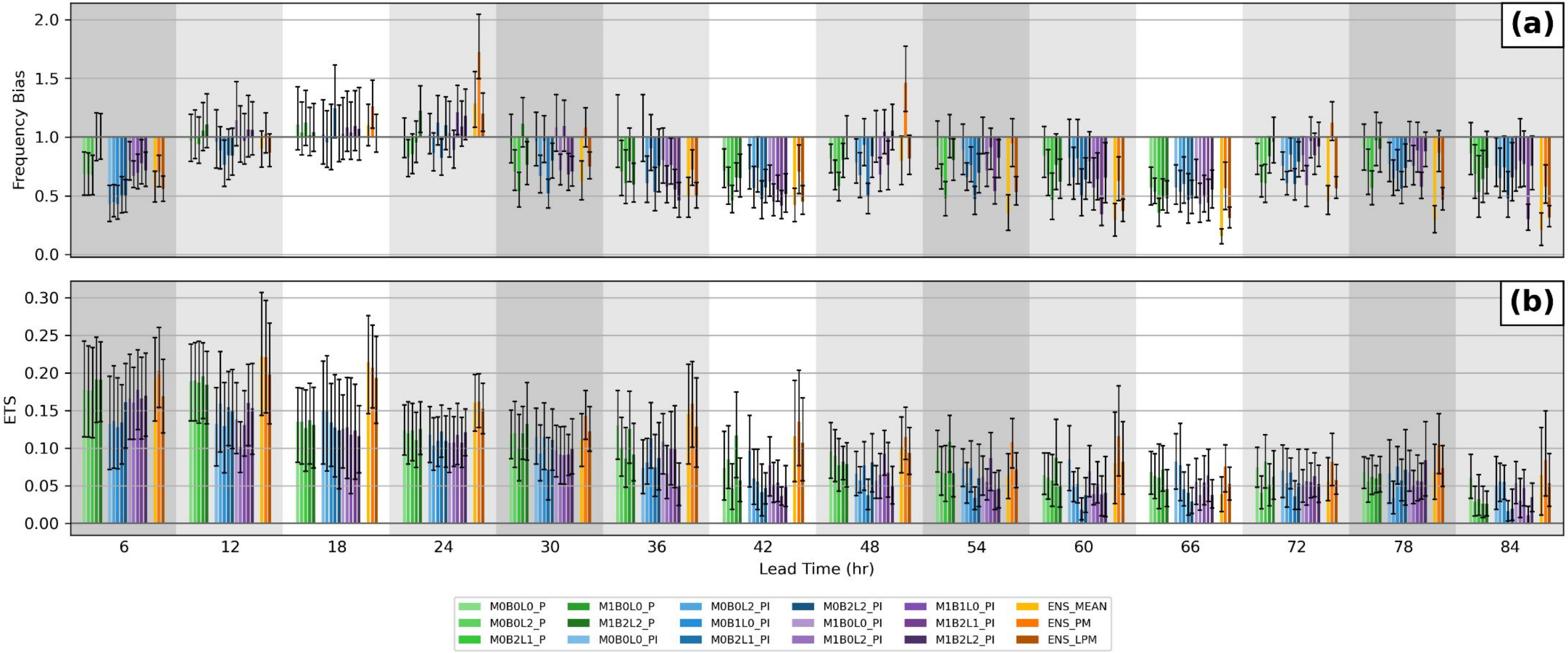
2023 FFaIR Precip Verification 1 mm

6-h Precip 30-km Neighborhood Threshold: 1 mm (Rain/No Rain)



2023 FFaIR Precip Verification 10 mm

6-h Precip 30-km Neighborhood Threshold: 10 mm

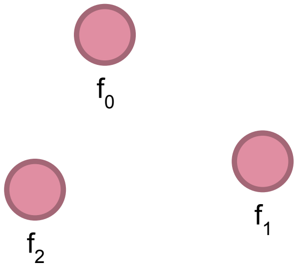


Spatially Aligned Mean

PM and LPM are focused on **the intensity of the fields**

It is common to have Convection Initiation (CI) location and propagation speed differences among models.
To better preserve the spatial structures of the fields: Spatially Aligned Mean

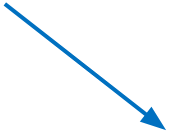
1. Consider three separate forecasts of rain:



2. Determine individual spatial shifts among all members, for example:

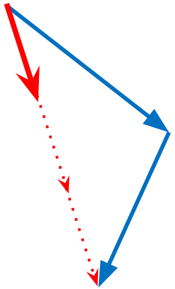
$f_{0,0}$ == f_0 to f_0 = 0

$f_{0,1}$ == f_0 to f_1

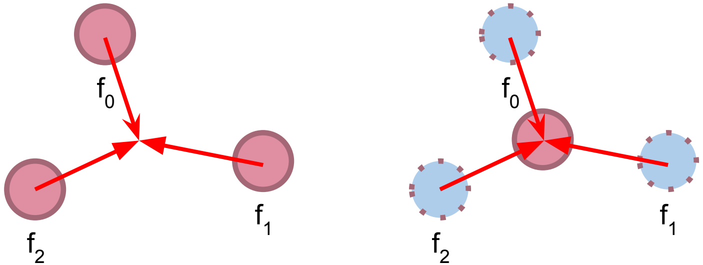


$f_{0,2}$ == f_0 to f_2

Correction of f_0 f_{0c}= ($f_{0,0}$ + $f_{0,1}$ + $f_{0,2}$) / 3

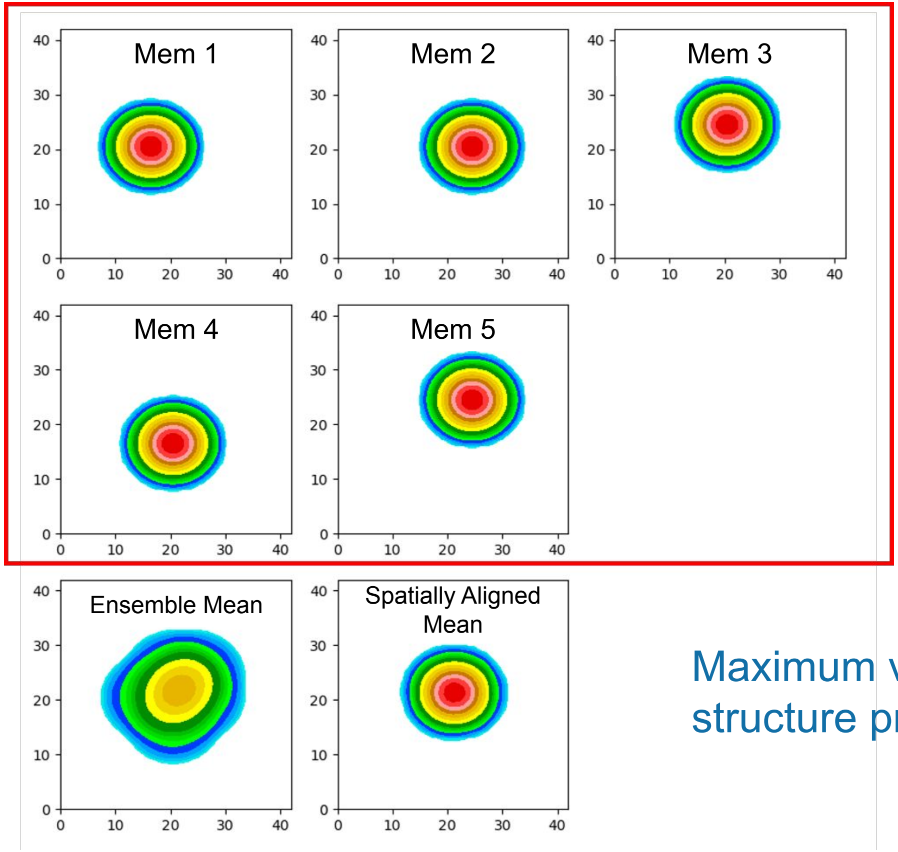


3. Calculate point-wise mean after spatial alignment completed:



Spatially Aligned Mean – The Algorithm

Analytic case example



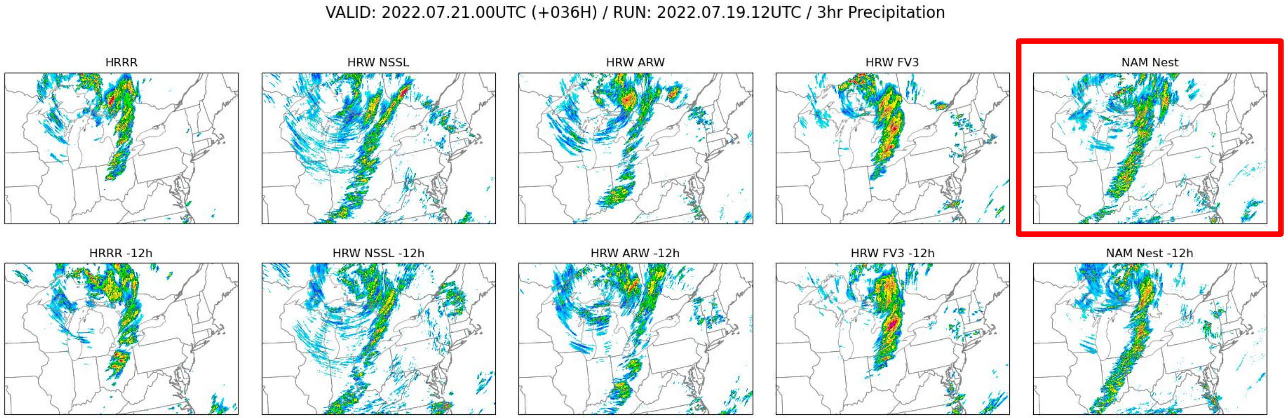
Maximum value *and* structure preserved

Spatially Aligned Mean – the Algorithm

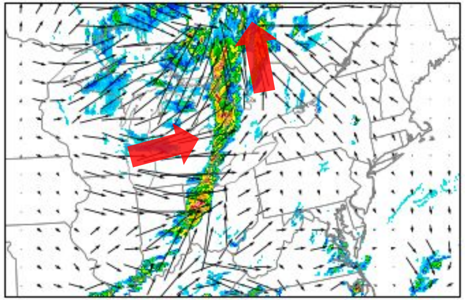
Each patch moves one direction, but they overlap with nearby patches and can be applied again with decreasing patch size

- Therefore features can be stretched, **rotated**, and contracted

Rotation example:



Individual HREF Members

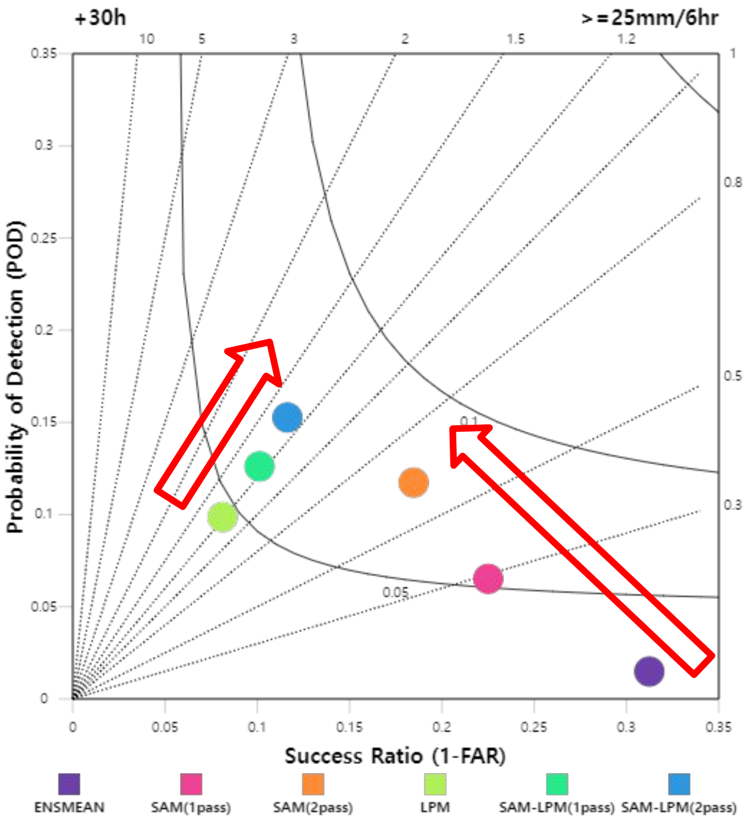


Re-aligned NAM Nest Member

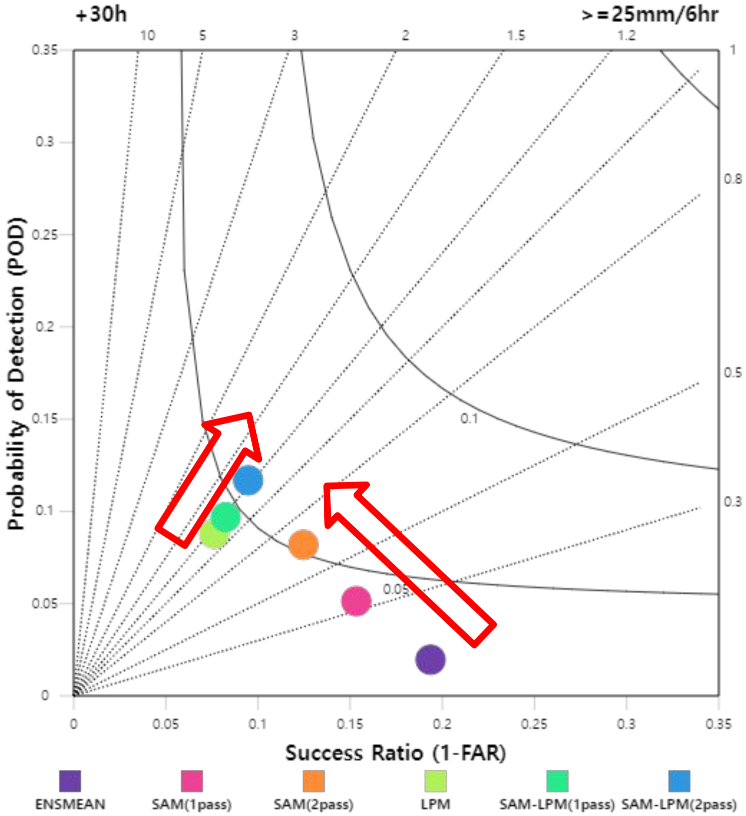
Spatially Aligned Mean Research with HREF in 2023 FFaIR Period

Verification results of 6 weeks of 2023 FFaIR period

HREF



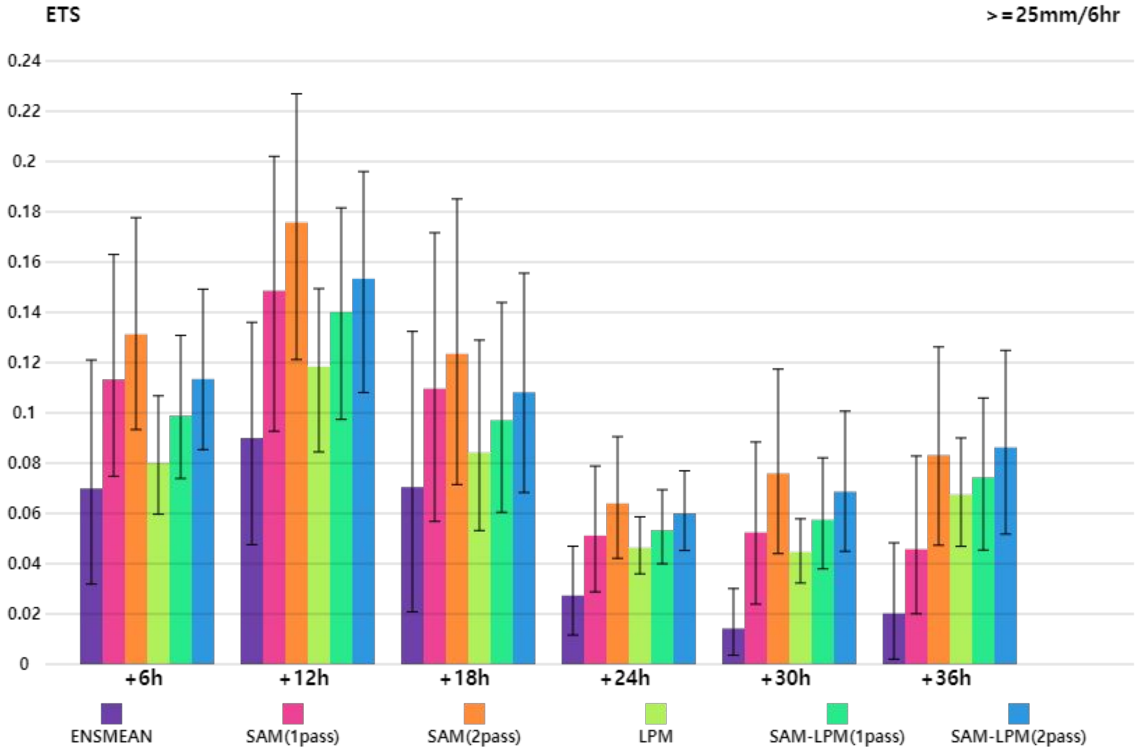
CAPS FV3-LAM



Spatially Aligned Mean: HREF in 2023 FFaIR Period

Verification results of 6 weeks of 2023 FFaIR period

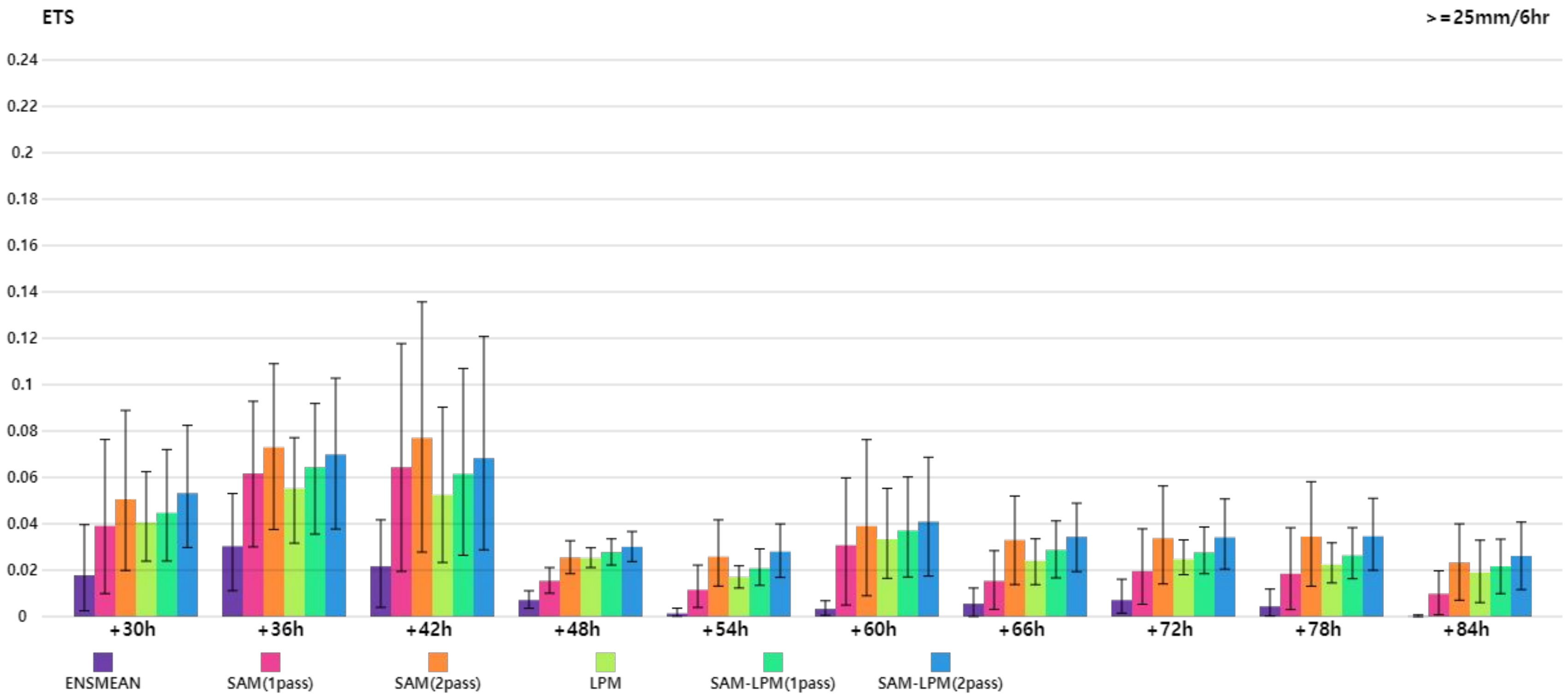
HREF



Spatially Aligned Mean: FV3-LAM in 2023 FFaIR Period

Verification results of 6 weeks of 2023 FFaIR period

CAPS FV3-LAM

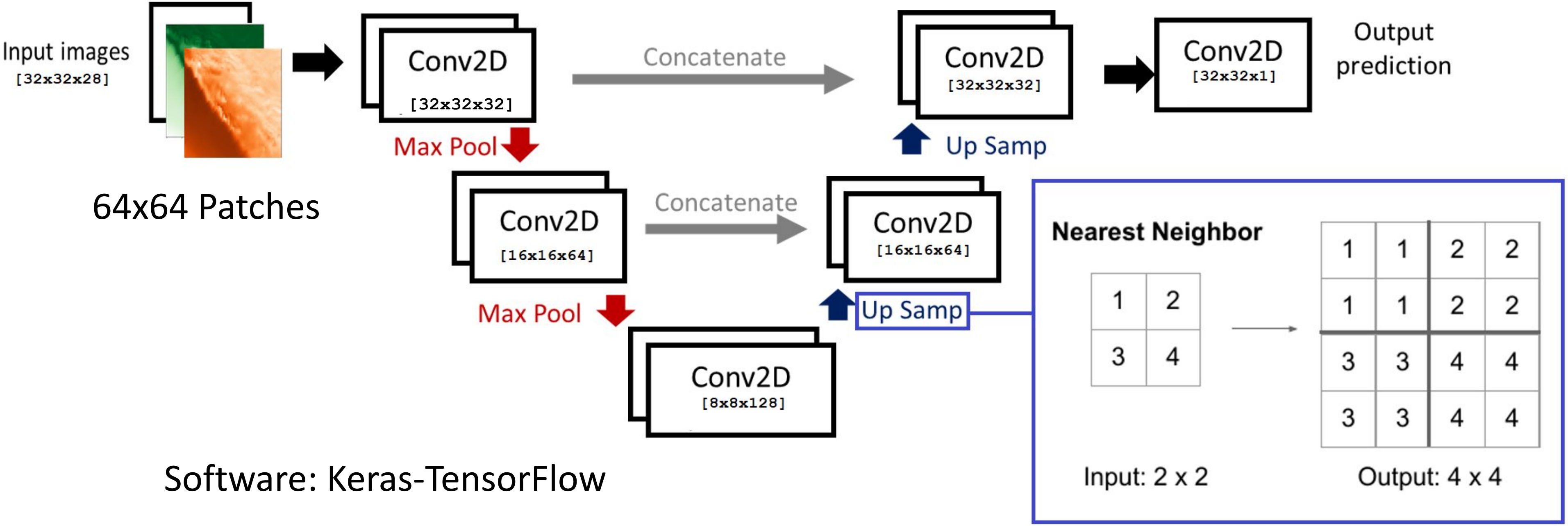


Machine Learning Development

- Collaboration with AI2ES Center
- U-Net Convolutional Neural Network (Deep Learning)
- Real-time probabilistic rainfall forecasts during FFaIR
- Builds upon ML hail prediction work in HWT (2017-2021)
- Trained using HREF plus 4 members of
  prior years' CAPS FV3-LAM Ensemble (HREF+)

Machine Learning U-Net

- Structure for CAPS FV3 Precipitation 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)



64x64 Patches

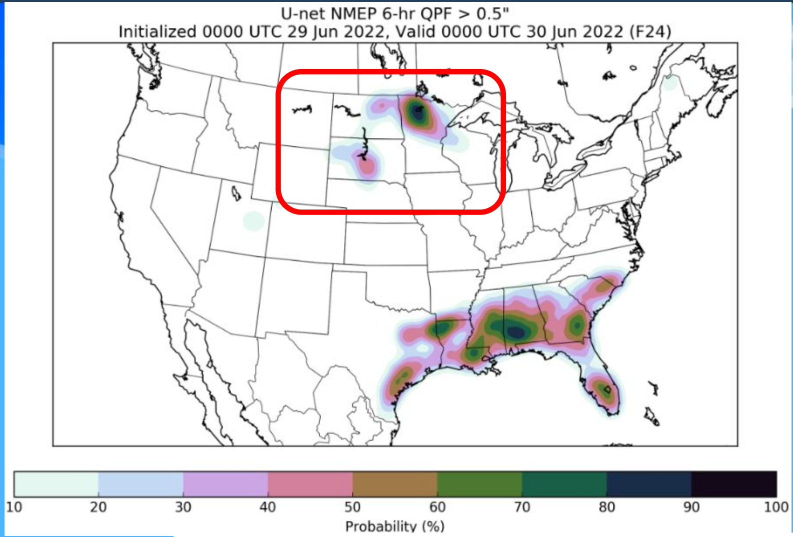
Software: Keras-TensorFlow

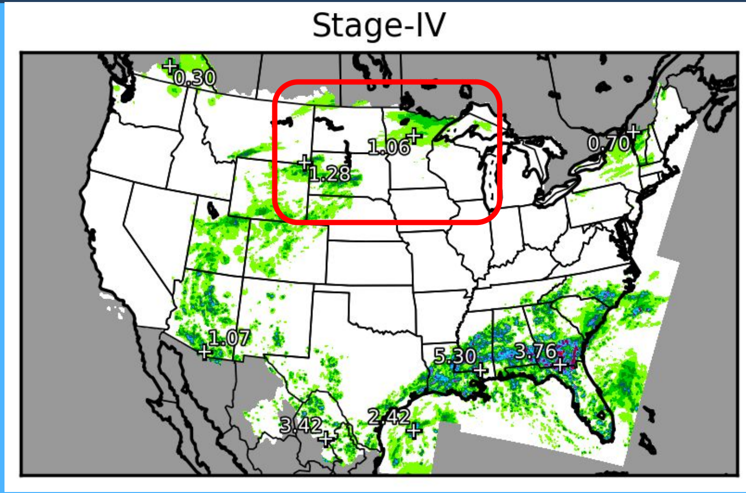
2023 U-Net Data/Methods

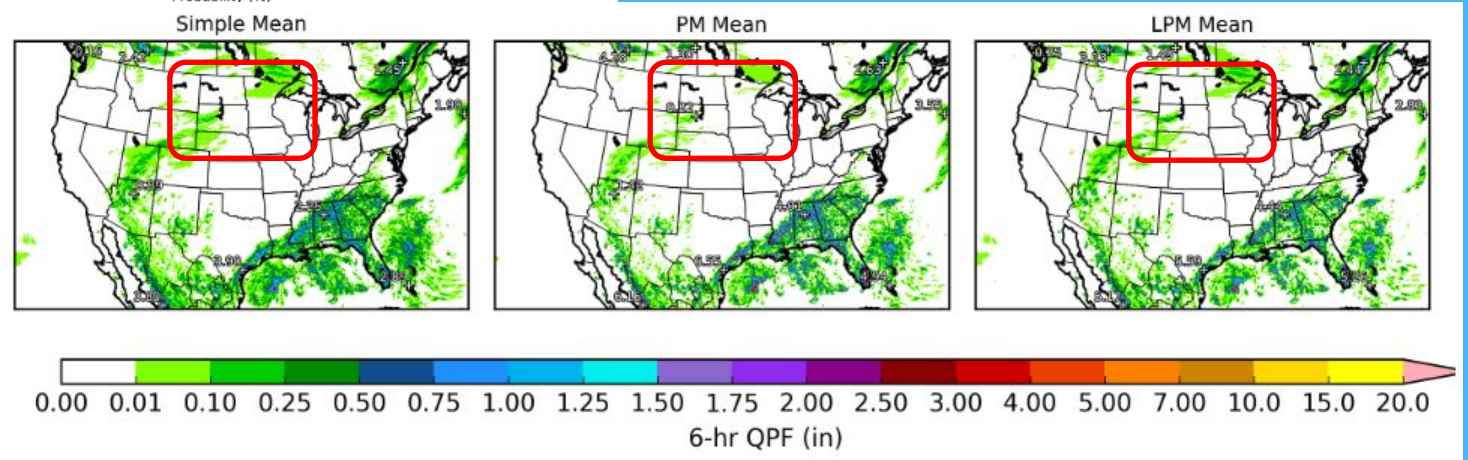
CAPS U-Net for Rainfall Prediction uses **23** 2D NWP **forecast variables** relevant to rainfall prediction :

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	

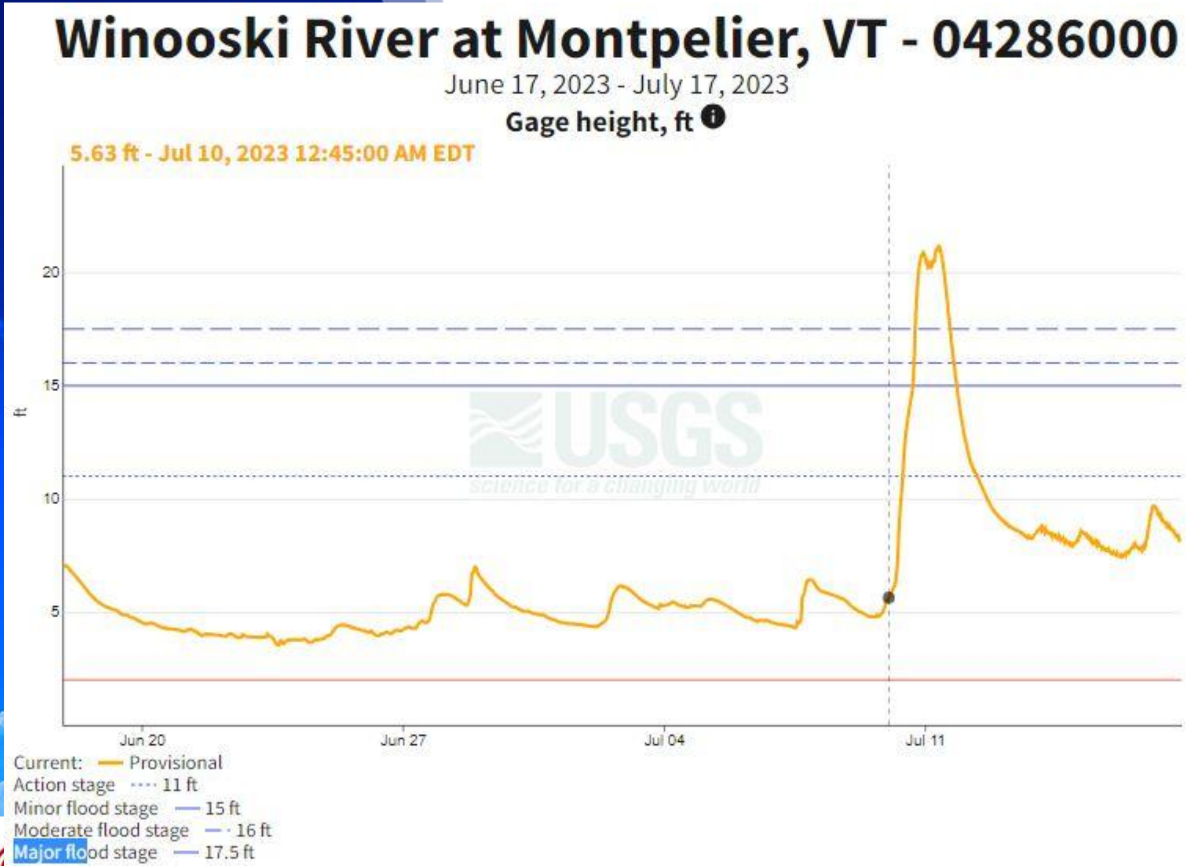
ML Forecasts – Example from 2022 FFaIR

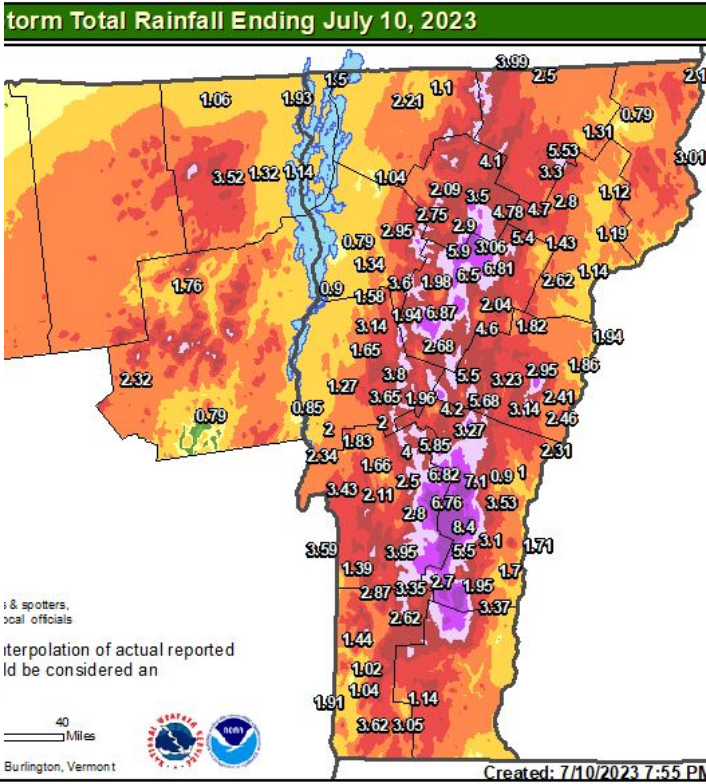




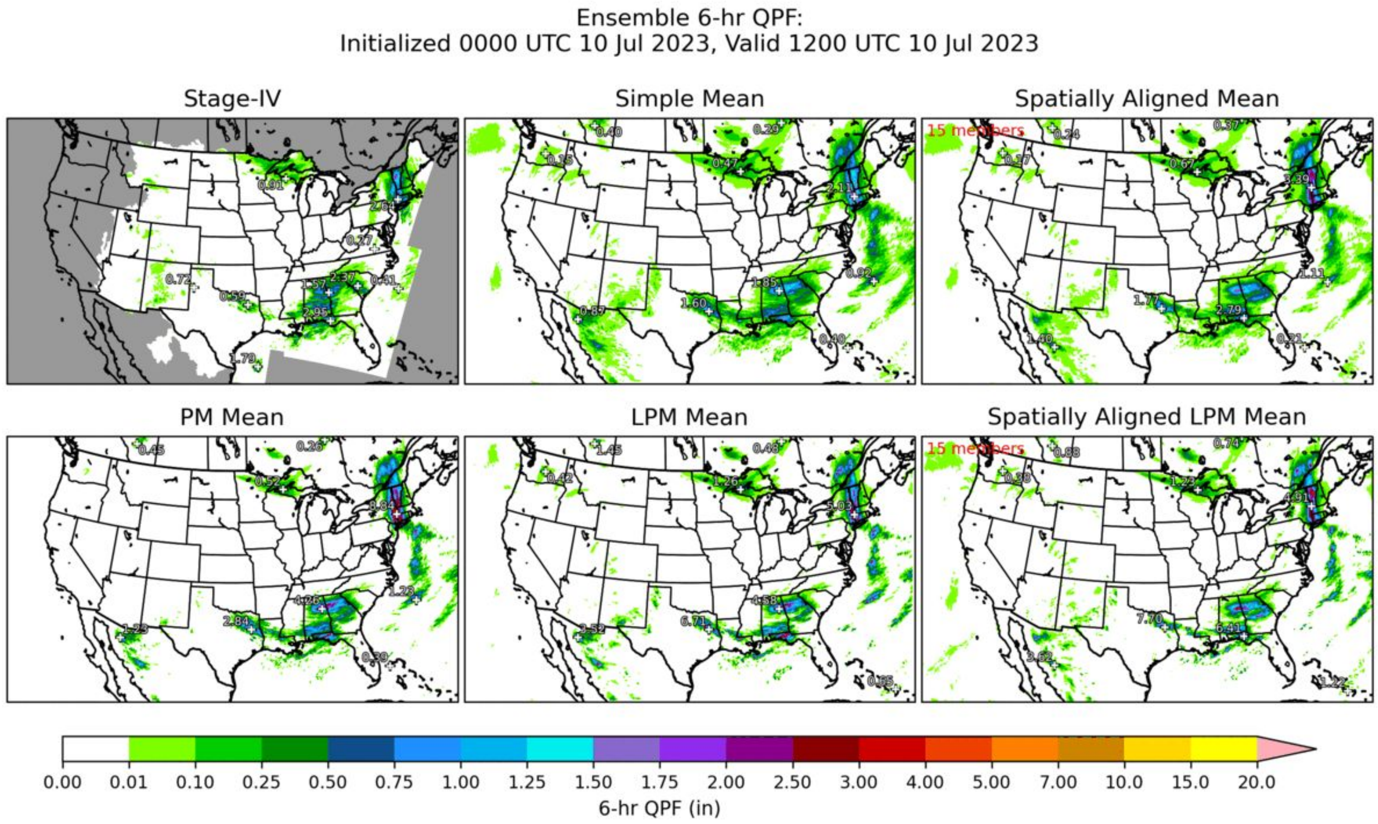


July 10-11, 2023 Vermont Flash Flooding

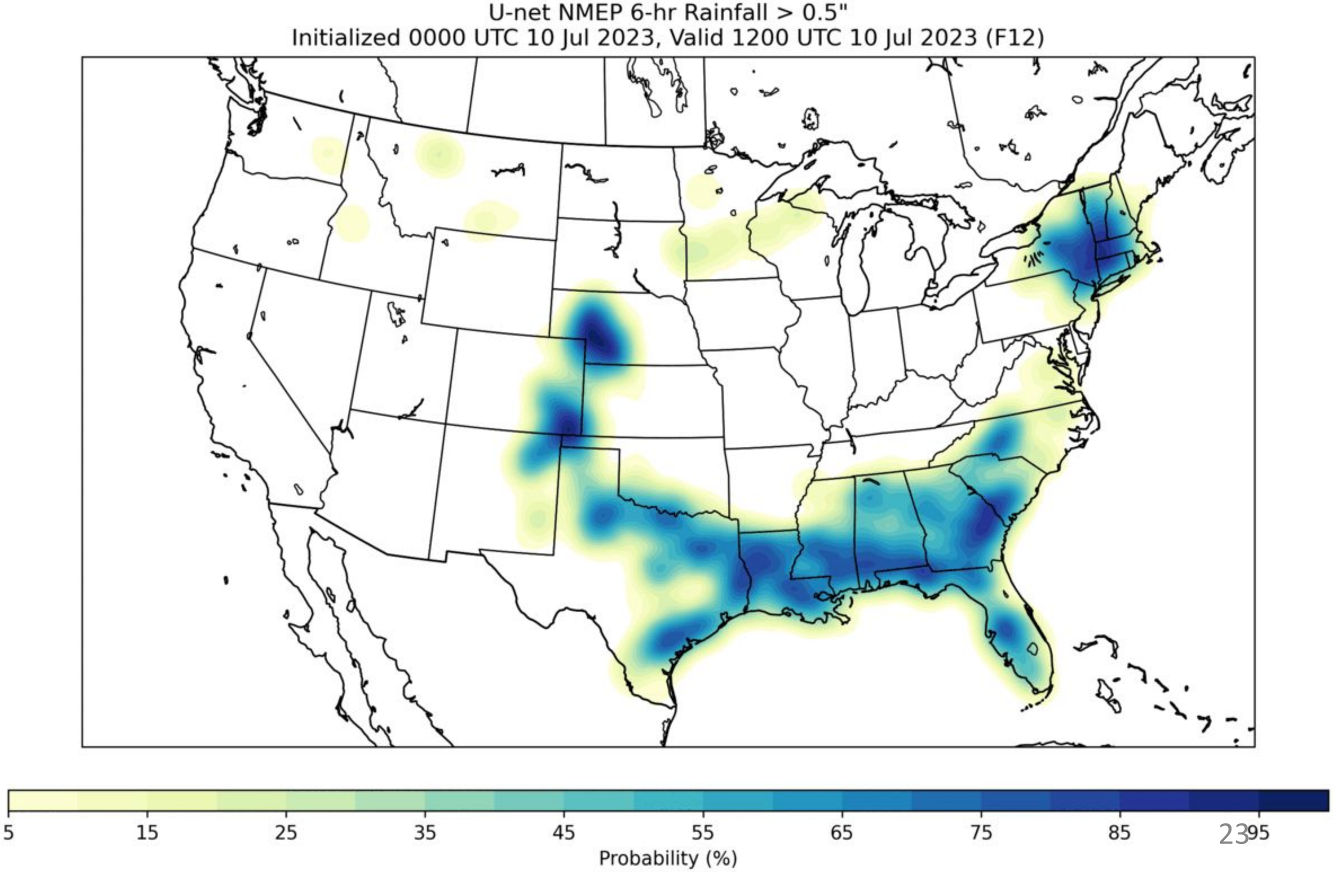




July 10-11, 2023 Forecast Ensemble Consensus Products



ML NMEP Probabilities



Preliminary ML Conclusions - 2023

- First iteration CAPS HREF+ U-Net for rainfall prediction performs reasonably, although much room remains for further improvement and refinement.
- The Neighborhood Maximum Ensemble Probability (NMEP) configuration appears to be much better calibrated than the NEP version—NMEP will be used going forward.
- Further improvement and tuning is under way including use of derived fields in addition to the base model output
- Additional rainfall forecast probabilities are planned (e.g., exceedance of return intervals).

CAPS Ensemble 2024 FFaIR

real-time mode

	MP	PBL	SFC	LSM	CU	IC/LBC	Notes
M0B0L2C0_Z	Thompson	MYNN	MYNN	RUC	G-F deep	ensmean/GFS	**ZDA CNTL**
M0B2L2C0	Thompson*	TKE-EDMF	GFS	RUC*	G-F dp*+sh	m01/GEFS m01	ZDA m001
M0B0L2C1	Thompson*	MYNN*	MYNN*	RUC*	saSAS deep	m02/GEFS m02	ZDA m002
M0B0L1C0	Thompson*	MYNN*	MYNN*	Noah MP	G-F deep*	m03/GEFS m03	ZDA m003
M0B2L1C0	Thompson*	TKE-EDMF	GFS	Noah MP	G-F dp*+sh	m04/GEFS m04	ZDA m004
M0B0L1C1	Thompson*	MYNN*	MYNN*	Noah MP	saSAS deep	m05/GEFS m05	ZDA m005
M1B2L2C0	NSSL#	TKE-EDMF	GFS	RUC*	G-F dp*+sh	m06/GEFS m06	ZDA m006
M1B0L2C1	NSSL#	MYNN*	MYNN*	RUC*	saSAS deep	m07/GEFS m07	ZDA m007
M1B0L1C0	NSSL#	MYNN*	MYNN*	Noah MP	G-F deep*	m08/GEFS m08	ZDA m008
M1B2L1C0	NSSL#	TKE-EDMF	GFS	Noah MP	G-F dp*+sh	m09/GEFS m09	ZDA m009
M1B0L1C1	NSSL#	MYNN*	MYNN*	Noah MP	saSAS deep	m10/GEFS m10	ZDA m010
M0B0L0	Thompson	MYNN	MYNN	Noah	-	GFS/GFS	AI-1
M1B0L0	NSSL	MYNN	MYNN	Noah	-	GFS/GFS	AI-2
M0B2L1	Thompson	TKE-EDMF	GFS	Noah MP	-	GFS/GFS	AI-3
M0B2L2	Thompson	TKE-EDMF	GFS	RUC	-	GFS/GFS	AI-4
M17 (MPAS)	Thompson	MYNN	MYNN	Noah	-	GFS/GFS	**MPAS member**
M0B0L2C0_L	Thompson	MYNN	MYNN	RUC	G-F deep	ensmean/GFS	**Lightning DA CNTL**
M0B0L2C0_N	Thompson	MYNN	MYNN	RUC	G-F deep	ensmean/GFS	**NoDA CNTL**

Naming Convention
FV3-LAM Options
M0: Thompson MP
M1: NSSL MP
B0: MYNN PBL
+MYNN SFClayer
B2: TKE-EDMF PBL
+ GFS SFClayer
L0: Noah LSM
L1: Noah MP LSM
L2: RUC LSM
C0 : G-F
C1: saSAS

Timeline (Using GEFS; 3 times DA: 2330/2345/0000)

17 CDT	18 CDT	19 CDT	20 CDT	21 CDT	22 CDT	23 CDT	00 CDT	01 CDT	02 CDT	03 CDT	04 CDT	05 CDT	06 CDT	07 CDT
18 EST	19 EST	20 EST	21 EST	22 EST	23 EST	00 EST	01 EST	02 EST	03 EST	04 EST	05 EST	06 EST	07 EST	08 EST
22 UTC	23 UTC	00 UTC	01 UTC	02 UTC	03 UTC	04 UTC	05 UTC	06 UTC	07 UTC	08 UTC	09 UTC	10 UTC	11 UTC	12 UTC
						GFS/ GEFS at 00 UTC on Frontera								
GEFS At 18 UTC On Frontera	Spin-up FCST	DA 2330 UTC Reflectivity	DA 2345 UTC Reflectivity	DA 0000 UTC Conv	DA 0000 UTC Z									
	23 UTC MRMS	00 UTC MRMS FED												
			00 UTC RAPBUFR											

GEFS has 30 members ; less time for DA

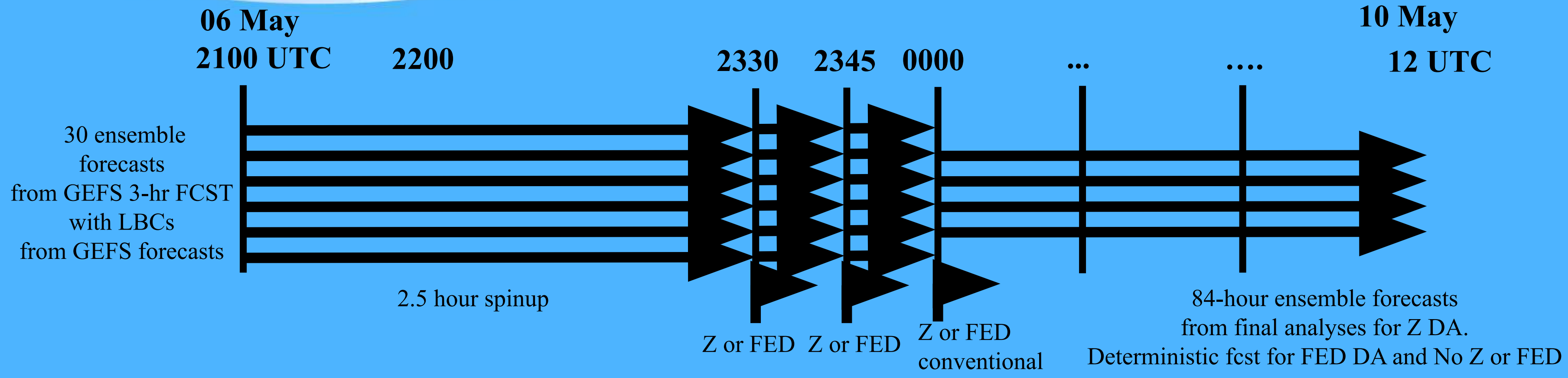
Current DA configuration is expected to prepare ICs before cold-start runs.

4 AI members which are initialized with GFS can be started after 4-5 UTC

Warm-start using DA analysis can be started after 5-6 UTC in that case

FlowChart

Case of 07 May 2024



- Initial BKG Ensemble: 2.5 hr forecasts using GEFS ensemble (30)

EXP		2330	2345	0000
ZDA		Z	Z	Conv + Z
LDA		FED	FED	Conv + FED
NoDA				Conv

Observations Assimilated in JEDI LETKF DA

Observation to be assimilated

conventional

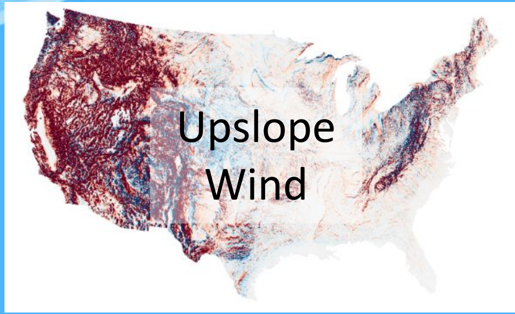
OBS	Source File	Source Loc.	Variable	QC
ADPUPA	RAP PrepBUFR	NCEP HTTPS*	u, v, T and q	Gross, QualityMarker
ADPSFC - METAR,SFCSHP - SYNOP			u, v, T, q and ps	Gross, QualityMarker
PROFILER			u and v	Gross, **Superob in GSI^**
RW	RAP NEXRAD BUFR	NCEP HTTPS*	rw	Gross, **Superob in GSI^**
Radar Reflectivity	MRMS mosaic grib2	AWS S3 MRMS **	Z	-
Lightning	GOES 16 netcdf	NOAA JET (GSL)	GLM FED	-

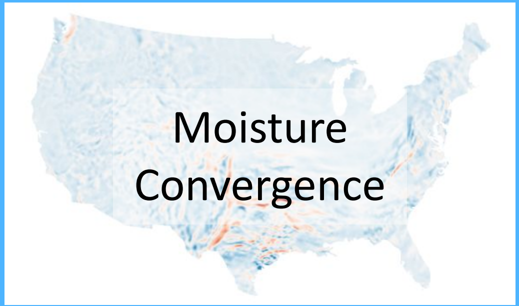
- CONV_Z (Conventional + Z) will operate in real-time mode.
- CONV_F (Conventional + FED) will run in non-real-time mode (afternoon, weekend, off-week, etc.).

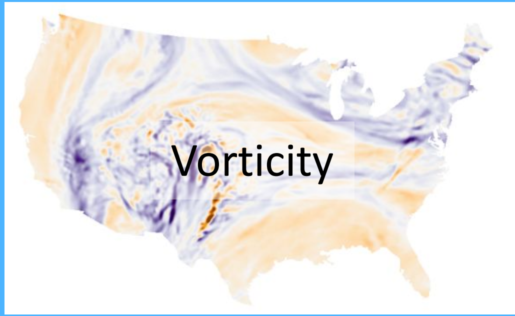
New ML Variables: Derived Fields

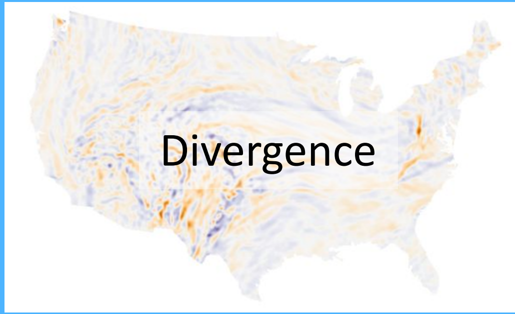
- Leverage domain knowledge of relationships between features

- Gaussian smoothing ($\sigma = 3$) applied to all fields incorporating the gradient of an existing field



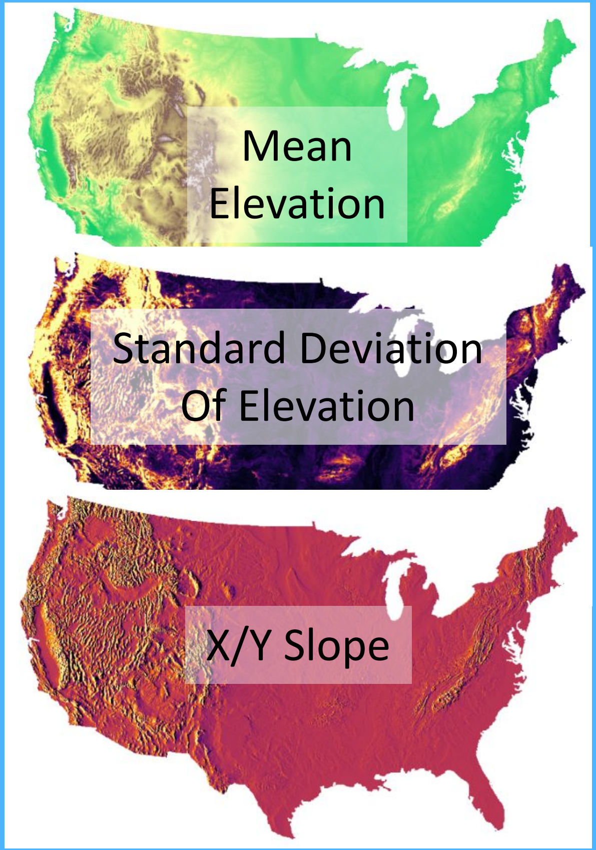






New ML Variables: Elevation

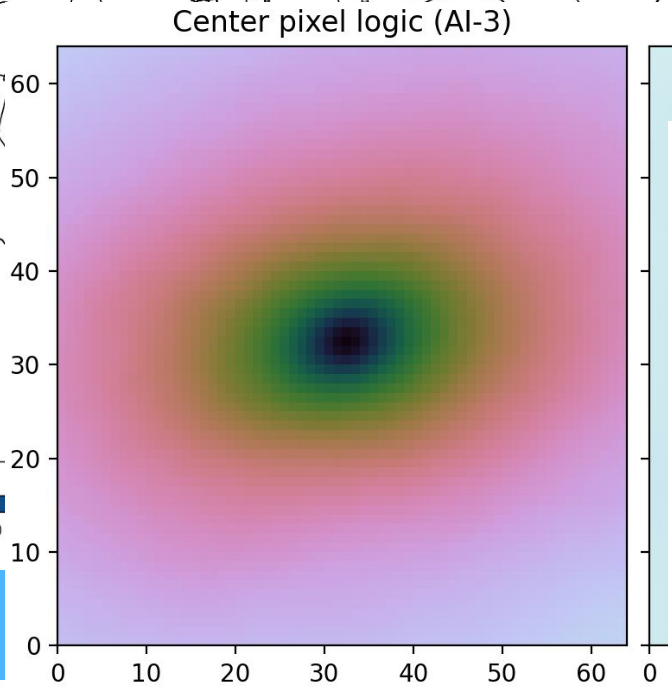
- Elevation data from ASTER GDEM V3
  - 1 arc-second resolution (~30m)
- Computed bulk statistics for each HREF grid cell (mean, std dev)
- Fit least-squares linear regression model across each HREF grid cell to approximate terrain's slope in X-Y directions

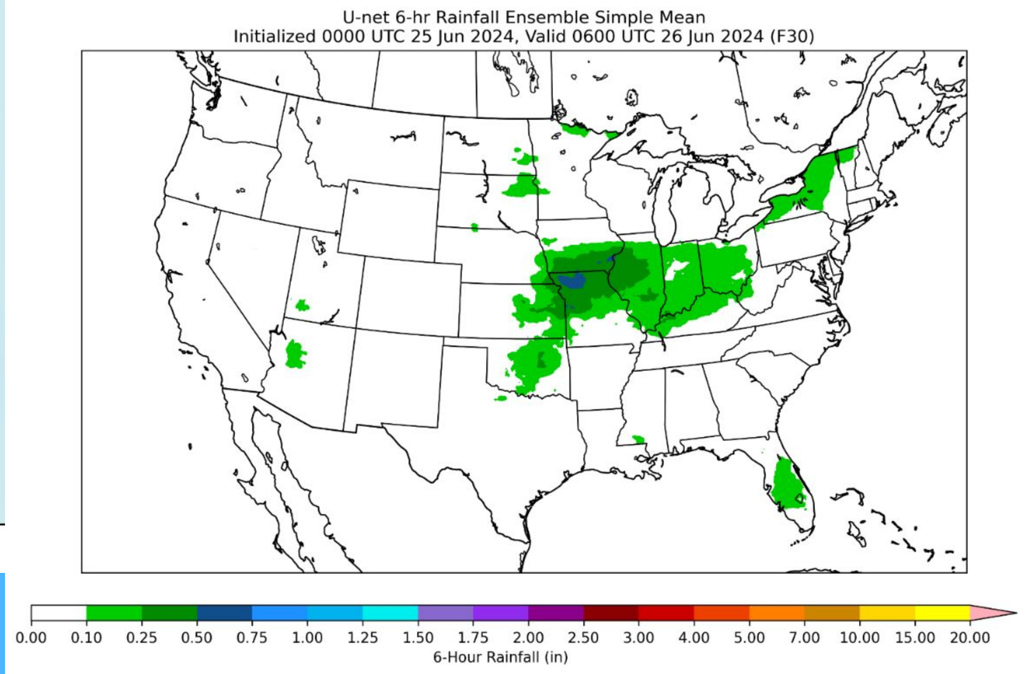


Summer Precip Full Predictor List

Variable	Level(s) Used
Geopotential height	500, 850hPa
Temperature, Dewpoint	500, 700, 850hPa; 2 m AGL
u- and v- wind components	500, 850hPa; 10 m AGL
6-h maximum reflectivity	1 km AGL
Hourly maximum updraft velocity	column maximum
6-h accumulated snowfall	
Terrain Mean, Standard Deviation, Slope	
Echo-top height	
Mean Sea Level Pressure	
Land Use Classification	Classification: WSSI Land Use Factor
Vorticity	500, 850 hPa
Divergence	500, 850 hPa
Precipitable Water	Total Column

Development Status: ML Mean Precipitation





Forthcoming Publications…

Spatial-Aligned Mean:

Lee, C-J, K.A. Brewster, N. Snook, P. Spencer, and J. Park, 2024: **Spatial Aligned Mean: A Method to Improve Consensus Forecasts of Precipitation from Convection Allowing Model Ensembles**, Wea. and Forecasting, Conditionally accepted.

FV3-LAM Ensemble Studies:

Snook, N., J. Park, M. Xue, K.A. Brewster, M. Johnson, T. Supinie, X-M. Hu, J.R. Carley, S. Liu and M. Hu, 2024: **Evaluation of CAPS Convection-Allowing FV3-LAM Ensembles during the 2022 HWT Spring Forecasting Experiment to Inform the Design of the Rapid Refresh Forecast System (RRFS)** , Wea. and Forecasting, Conditionally Accepted.

Johnson, M., N. Snook, J. Park, M. Xue, K.A. Brewster, T. Supinie and X-M. Hua, 2024: **Severe Weather Verification of a FV3-LAM regional ensemble during the 2022 NOAA Hazardous Weather Testbed Spring Forecasting Experiment**, Wea. and Forecasting, Conditionally Accepted.

Acknowledgments/Contact

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    Texas Advanced Supercomputing Center (TACC) Frontera

- Funding: NOAA/OAR/OWAC Testbed Grants:
  NA19OAR4590141 & NA22OAR4590522
  UFS R2O Grant NA16OAR4320115

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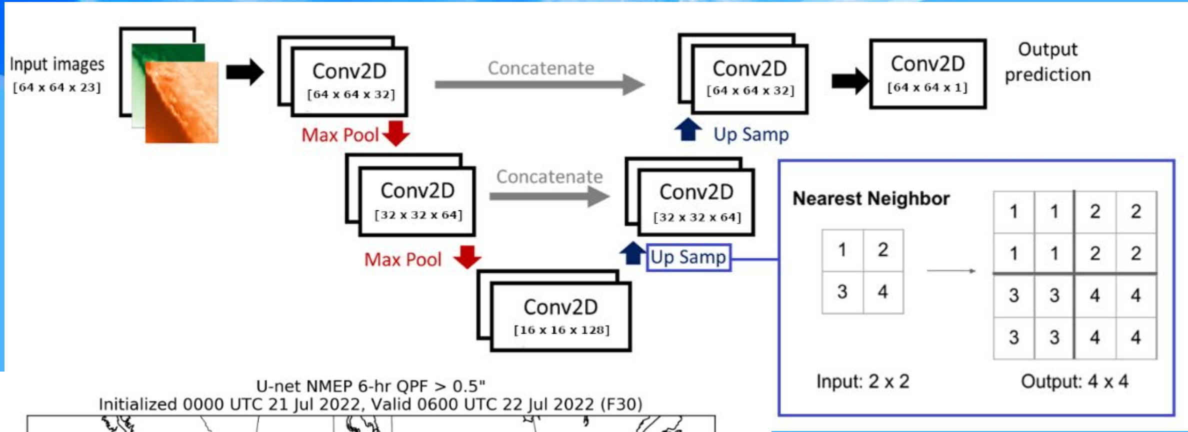
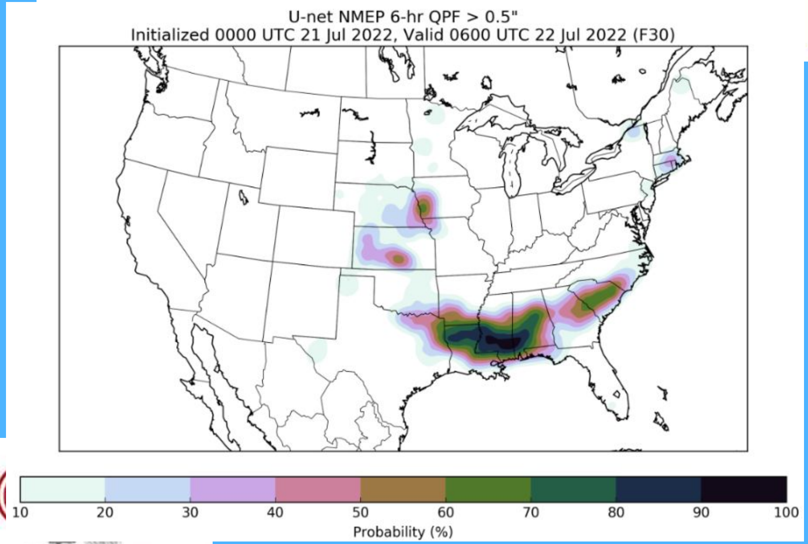
Realtime Ensemble Forecasts Online

https://www.caps.ou.edu/forecast/realtime

Bonus Slides

Methods – U-Net for Rainfall Prediction





- **2D U-Net** implemented using **Keras**, **Tensorflow**, and the Python "**keras_unet_collection**" library in Python 3.
- The architecture (top left) chosen after preliminary testing with different U-net depths, patch sizes, and training hyperparameters.
- A U-Net using this architecture was trained for each ensemble member, and neighborhood ensemble probability (NEP) and neighborhood maximum ensemble probability (NMEP) were generated from the ensemble of U-Net outputs.
  - Neighborhood radius: 45 km (15 grid points)
  - Gaussian smoother with a standard deviation of 90 km

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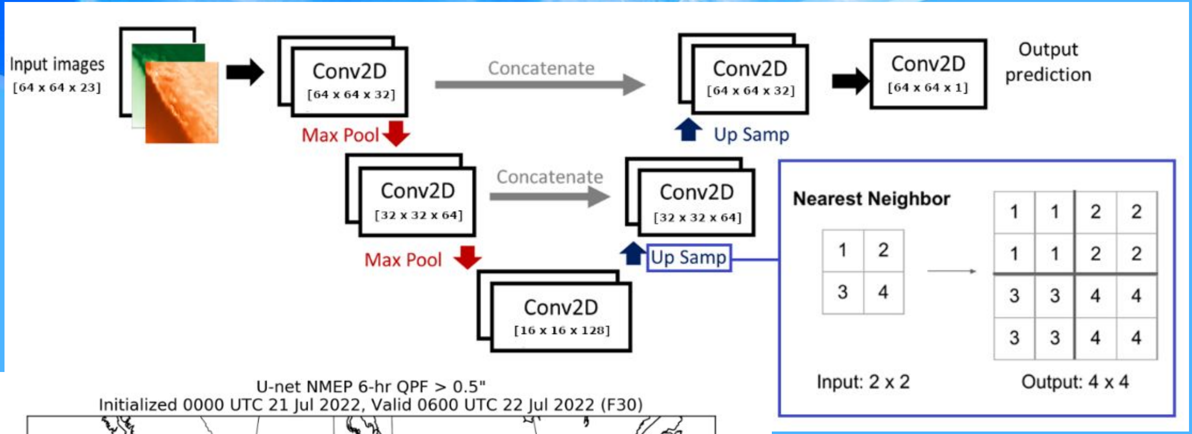

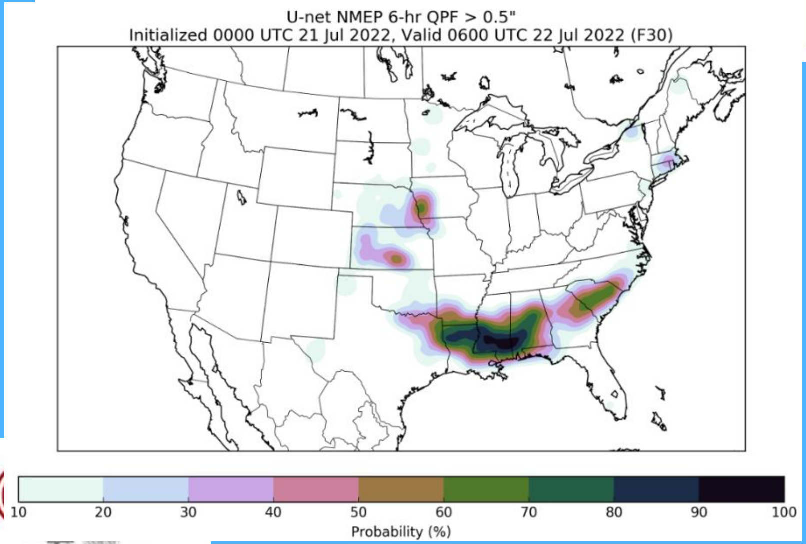

- U-Net output is predicted 6-h accumulated rainfall
  - Predictions are performed on 64 x 64 patches and are stitched together to produce full-conus prediction
  - Patch overlap and light smoothing reduces patch boundary discontinuities.
- Outputs are produced for probability of rainfall/snowfall exceeding given thresholds.
  - 2022: 0.5” in 6 h
  - 2023: 0.5”, 1.0”, and 2.0” in 6 h
- Result: probabilistic forecast product suitable as guidance for areas of moderate- to high-impact rainfall that combines information from the full HREF + 4 CAPS ensemble members (HREF+).