MPAS Ensemble Forecasts of Heavy Rainfall: Does Adding Members Add Value?

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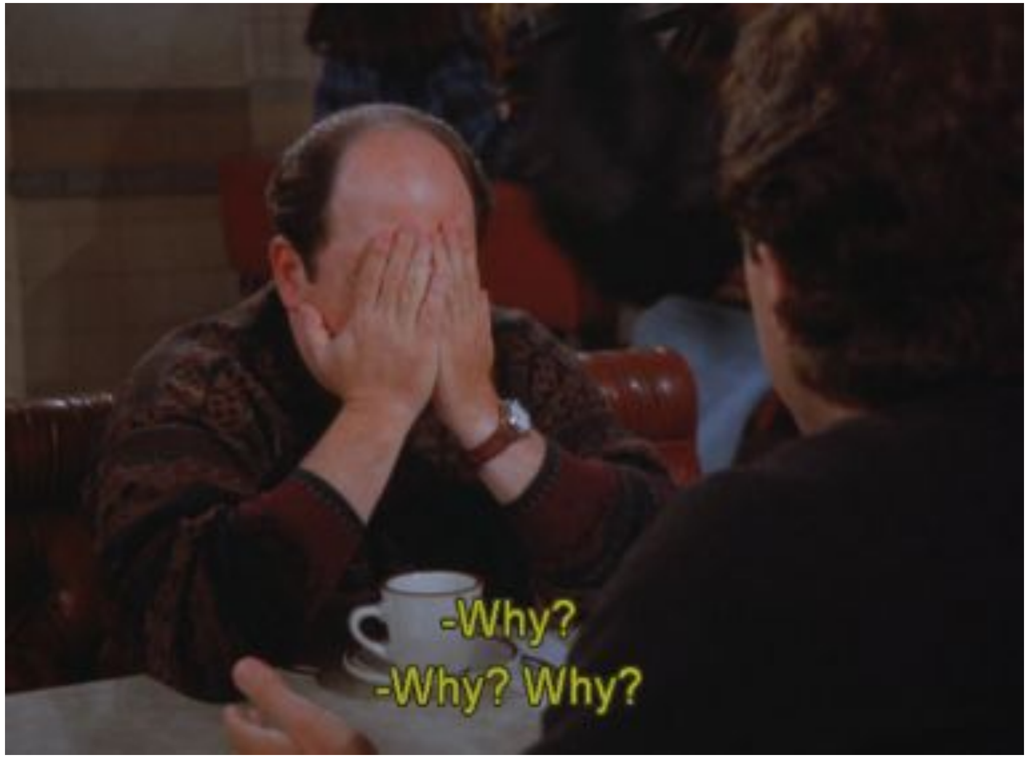
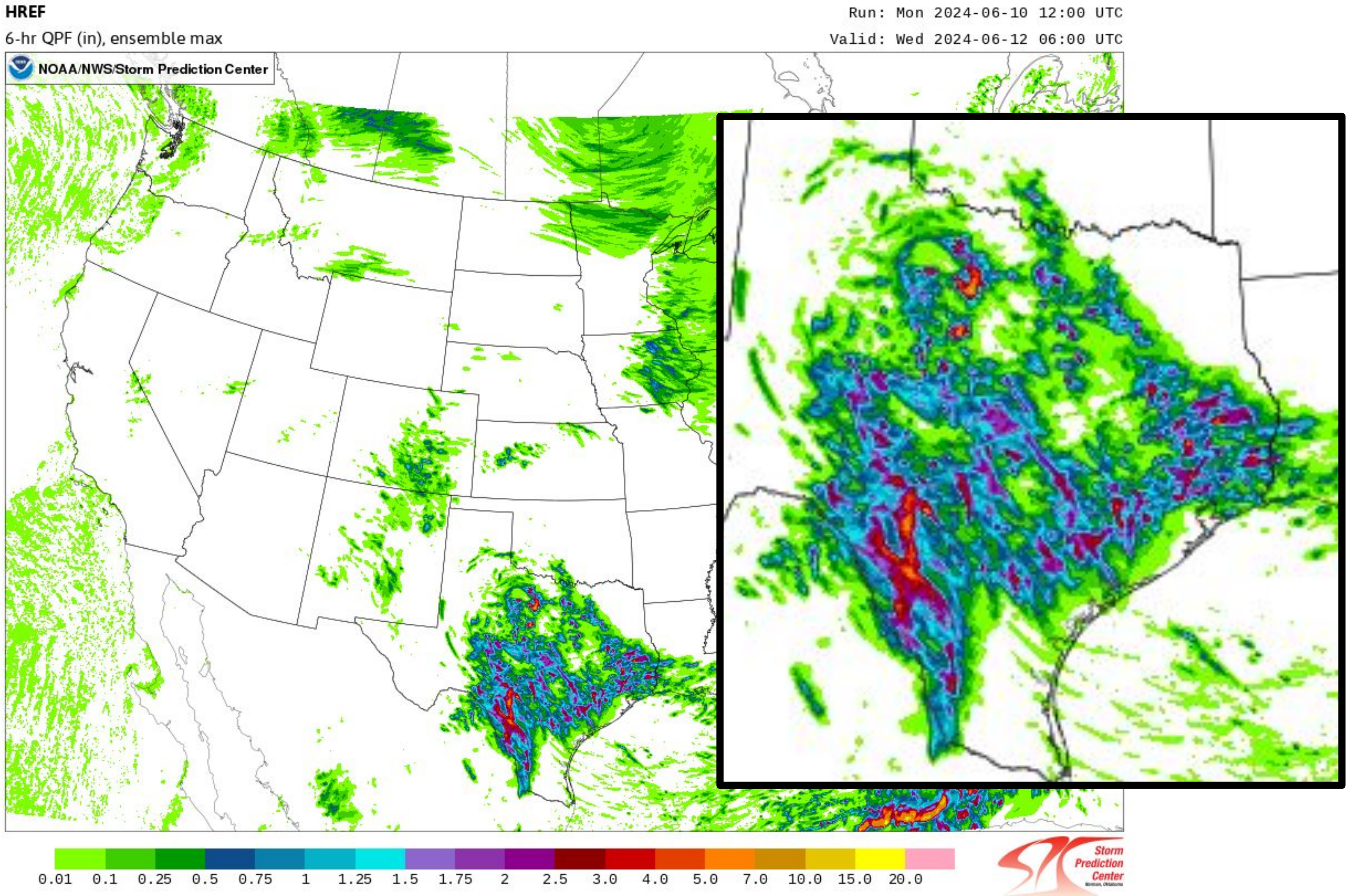
11 Jun 2024

Full Disclosure



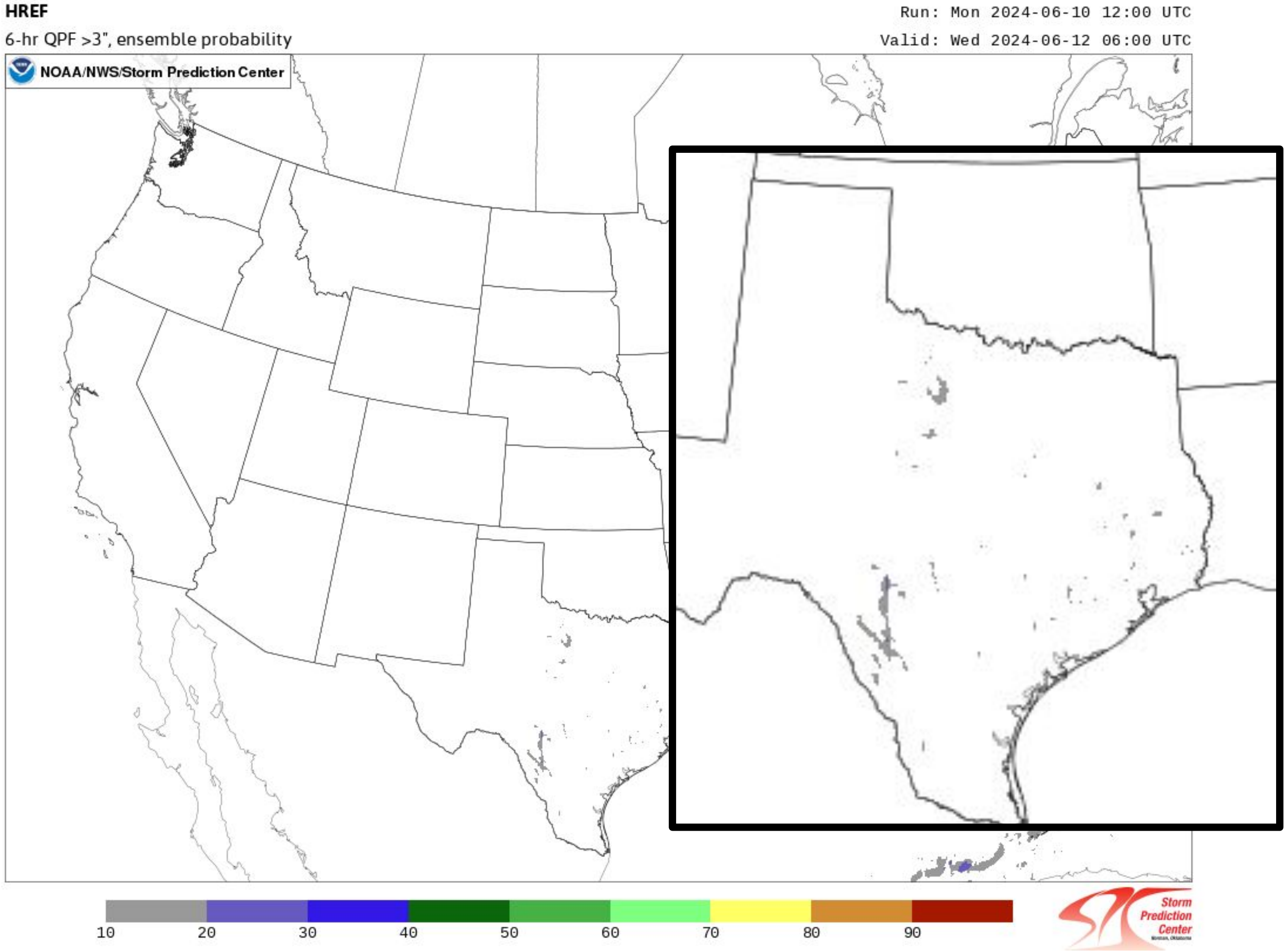
Background: Challenges with ensemble forecasts of extreme precipitation

- When forecasting short-duration convective rainfall, most grid points in most members have zero QPF
- This issue is particularly evident with small (≤ 10-member) ensembles



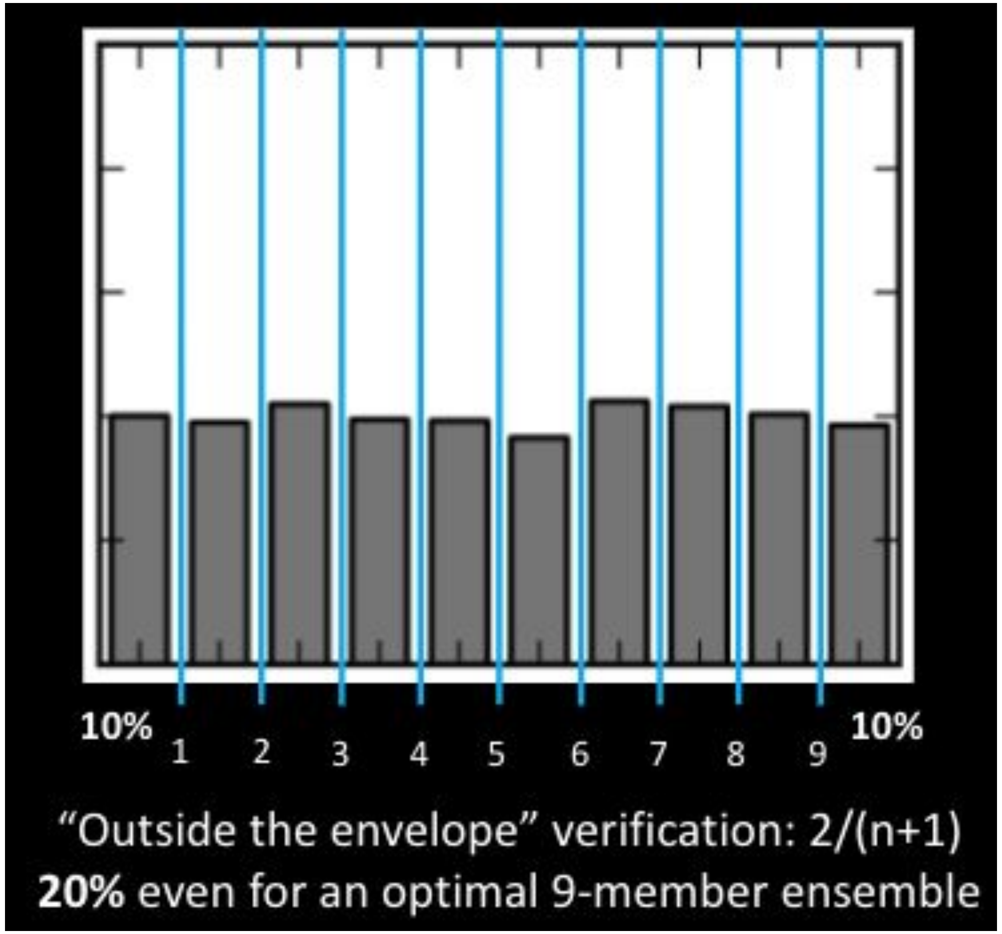
Background: Challenges with ensemble forecasts of extreme precipitation

- Point-based probabilities of high thresholds are mostly zero or 1/n (1 member hits the threshold)
- With commonly used postprocessing techniques like simple smoothing, fractional coverage, neighborhood maximum and EAS, if the local maximum is 5.9”, the probability of 6” will be zero.



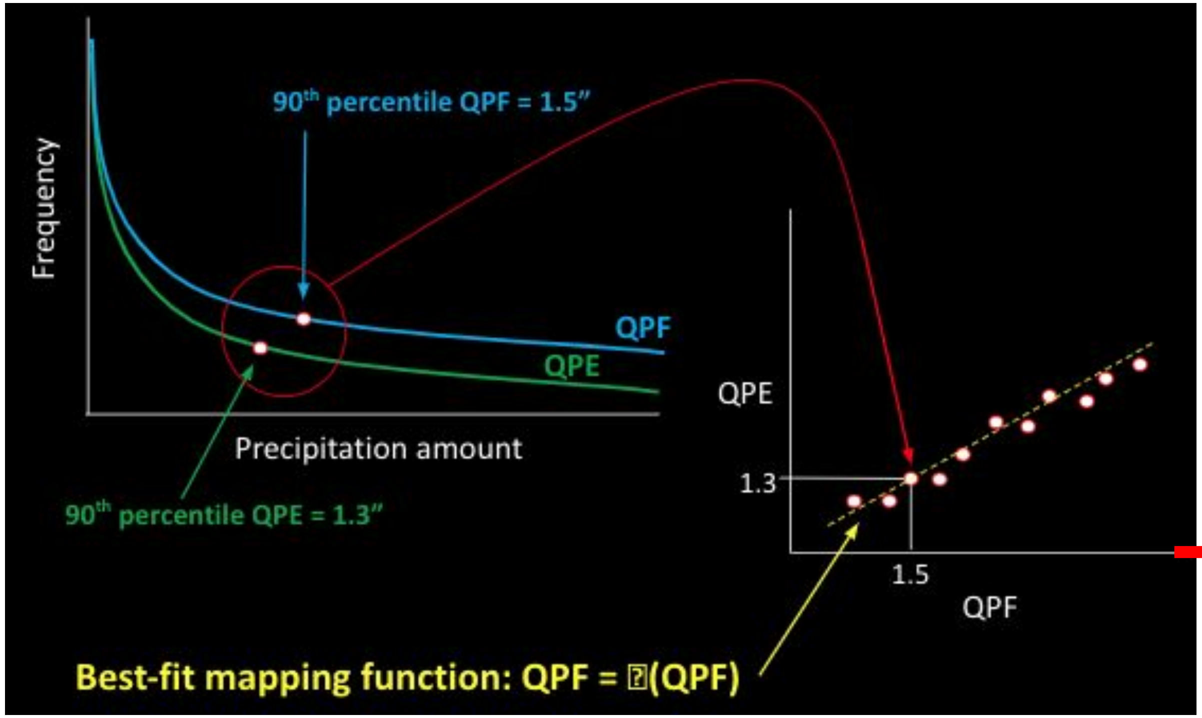
Background: Challenges with ensemble forecasts of extreme precipitation

- Even for a well-calibrated 10-member ensemble, outside-the-envelope verification should be *expected* 18% of the time
- Without advanced postprocessing, this value can only be reduced by adding members, or by making the forecasts worse (e.g., increasing bias of some members to widen the envelope)



Background: Challenges with ensemble forecasts of extreme precipitation

- The sample size of extreme precipitation events is inherently limited, so bias-correction methods are poorly trained on these high-impact events and must extrapolate fitting functions



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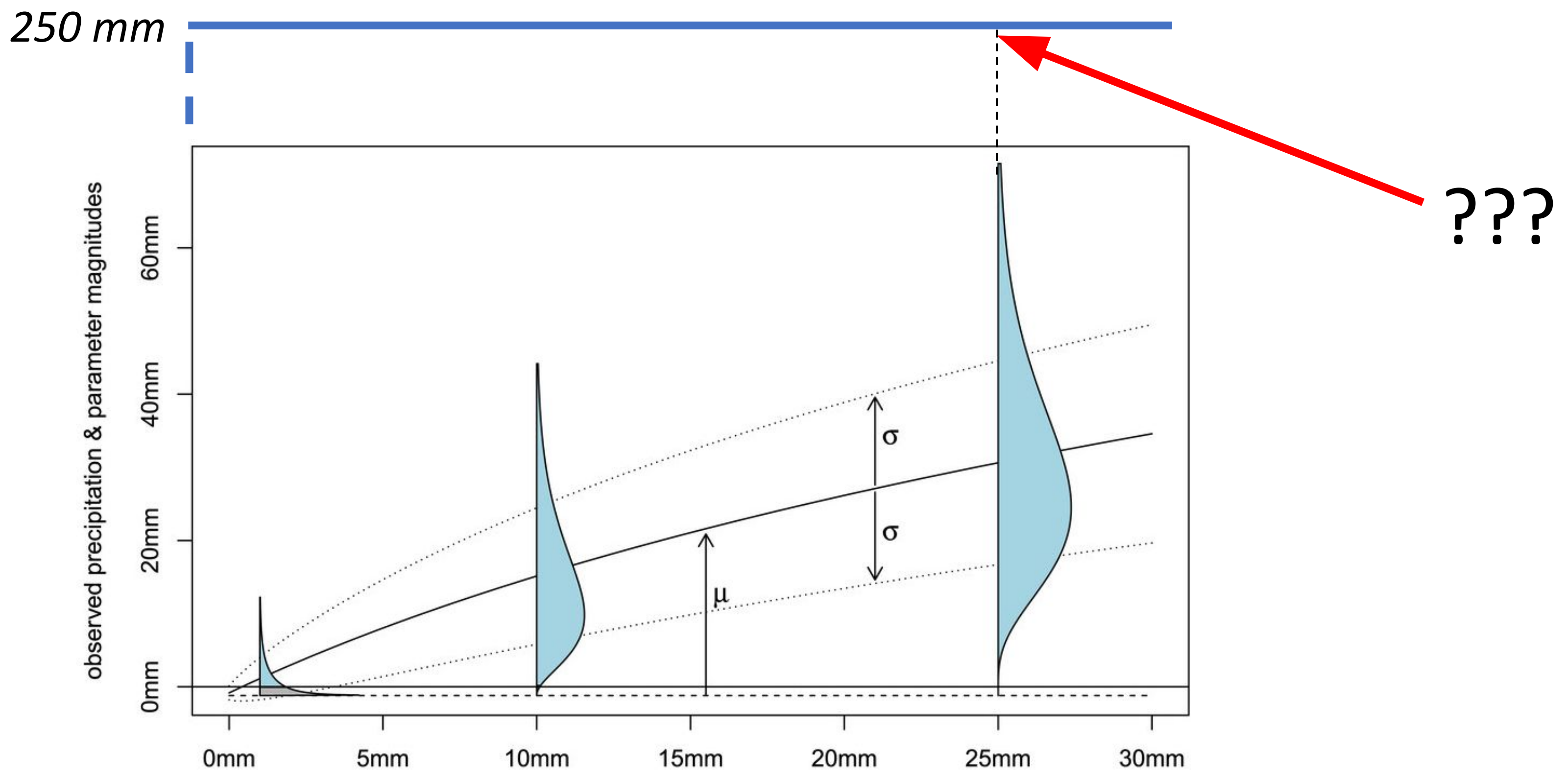
Background: Challenges with ensemble forecasts of extreme precipitation

- Similarly, postprocessing techniques that produce a full calibrated PDF also have limited utility in the far end of the distribution:



Scheuerer and Hamill (2015)

Background: Challenges with ensemble forecasts of extreme precipitation

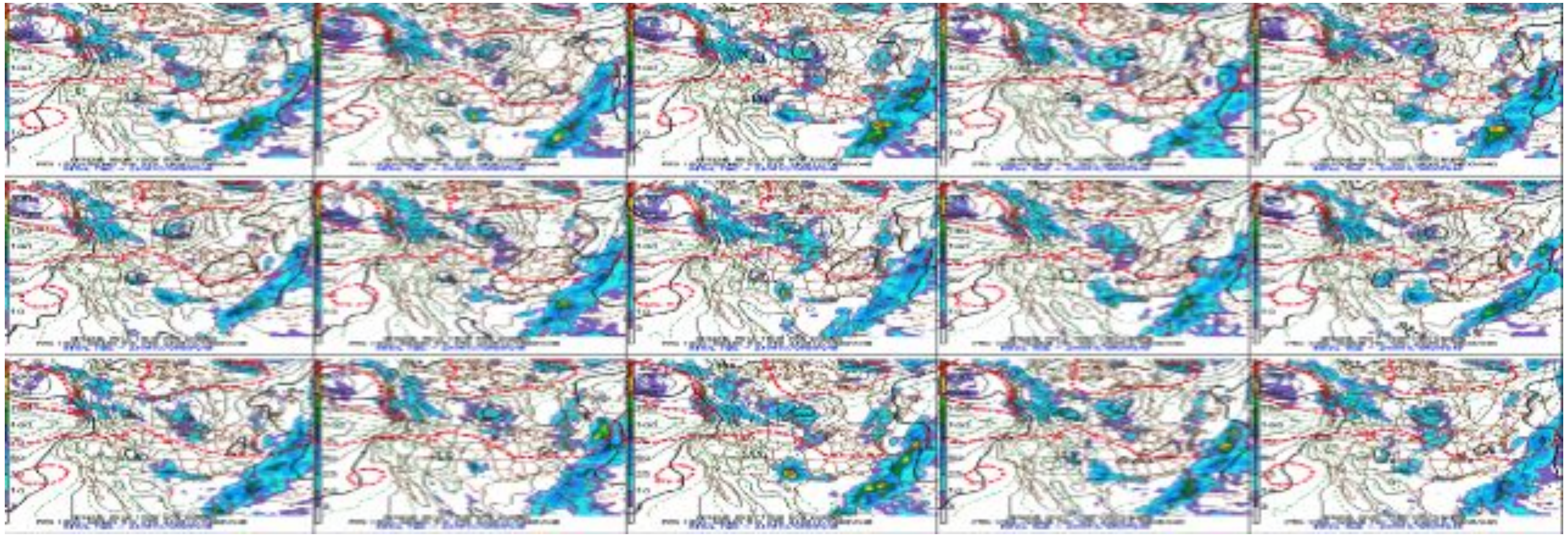
- Machine learning holds potential, but still suffers from lack of training data for truly extreme events. Long retrospective NWP can help, and can be run sparsely (e.g., 1 day per week)
- Ultimately, **larger** ensembles based on **better dynamical models** with **better physics** will position any postprocessing or AI method to achieve better results.

AI

Background: Visualization Challenges

- Low probabilities of extreme QPF can indicate:
  - one member of the ensemble has extreme amounts, but the rest do not

    - OR -
  - all members of the ensemble have extreme amounts but in varying locations and/or times

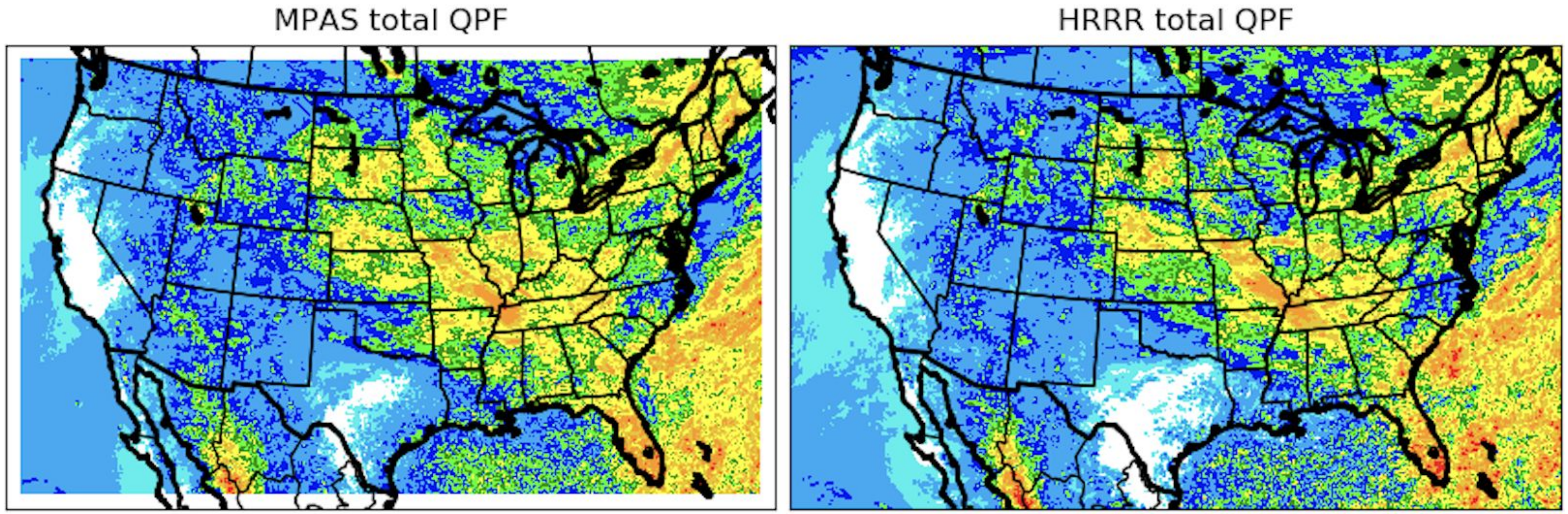


Goal 1: Miss the MPAS training but somehow figure out how to run MPAS

- NSSL was already doing real-time runs on Jet over CONUS, capable of RRFS or HRRR init and use of NSSL or Thompson MP
- NSSL team also found the magic combinations of modules to allow all MPAS components to work under Rocky 8
- No use of Rocoto or namelists. Controlled by shell scripts. Namelists built within shell scripts. Changes require intimate knowledge of driver scripts.
- Great place to start but needed changes to suit our needs and facilitate configuration changes

Deterministic Experiments

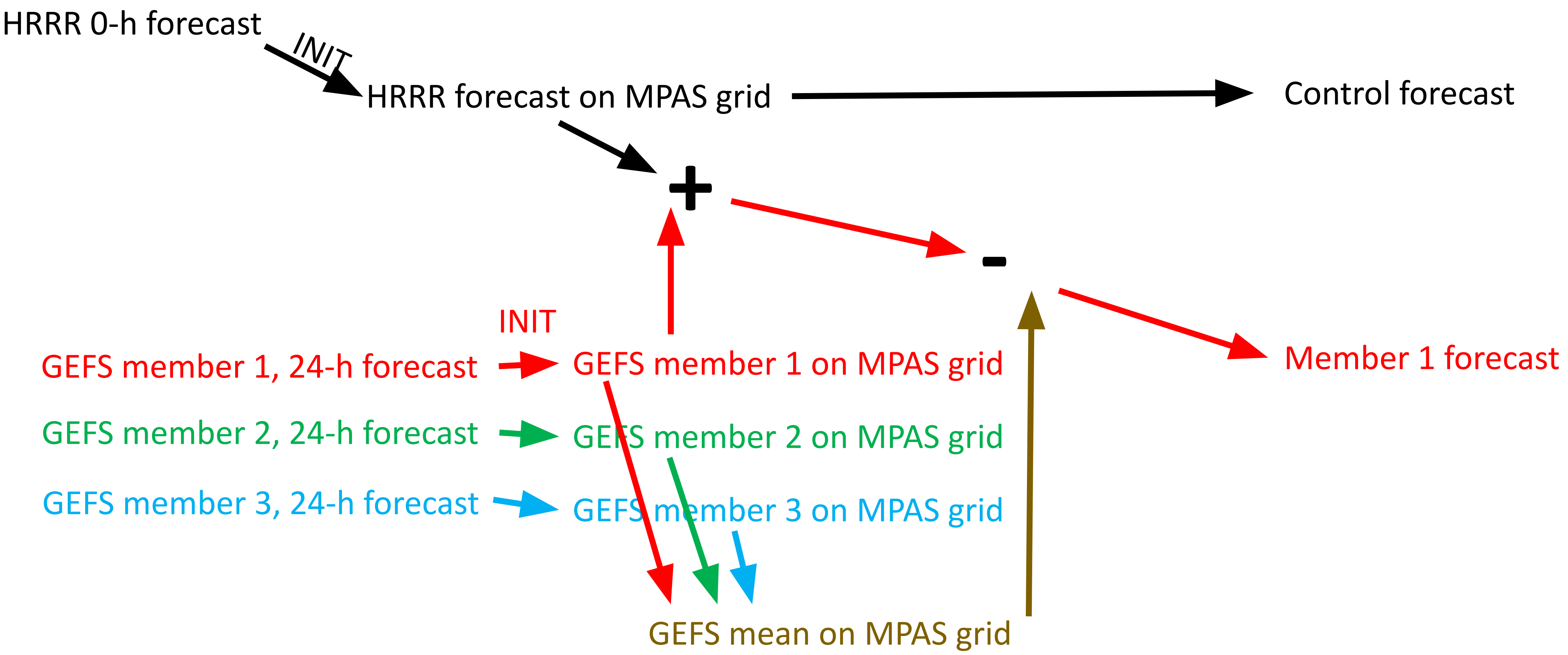
- Initial goals: make it run, assess computing needs, identify common problems with workflow tasks. Then make it run again when the entire OS changes.
- Configuration: ICs and LBCs from HRRR (0-h offset). Thompson MP, RUC LSM. Tested a real-time case using data on /public, but my focus is on retrospective periods
- No DA. Relying on a “warm” start from HRRR 0-h forecast
- Summer retro: 00z, 36-h forecasts from 25 Jul – 9 Aug 2023



Goal 2: Make an Ensemble

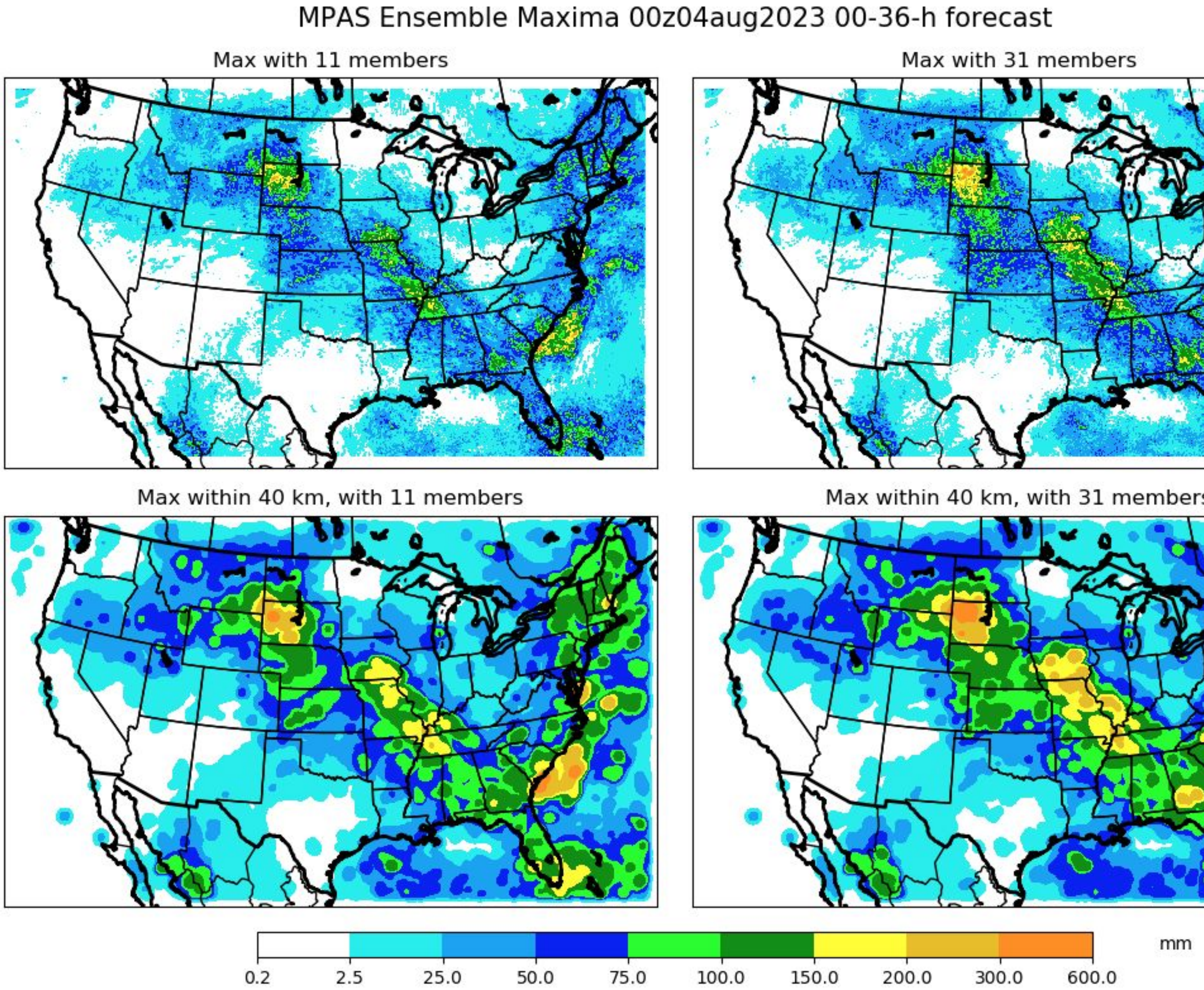
- OK, the model run and the output isn't ridiculous. Now what?
- MPAS physics is miles behind RRFS physics, perhaps even HRRRv4
- Focus on questions that are independent of model version, i.e., MPAS-to-MPAS comparisons, and use a single, non-stochastic physics suite
- Current topics:
    - How much mileage (spread) can we get out of a simple IC-only ensemble?
    - Can we better anticipate high-end/extreme precipitation events with larger ensembles (large = 30 members, small = 5, vs. 10 in HREF)?
    - Which GEFS forecast length achieves optimal spread-skill relationship when used for member IC perturbations (e.g., 0/24/48-h)?
    - How can we better visualize spread in precipitation forecasts for a large ensemble?
    - Can we significantly improve spread-skill relationship with the use of LBC and/or soil-moisture perturbations?

Ensemble Perturbation Flow Chart

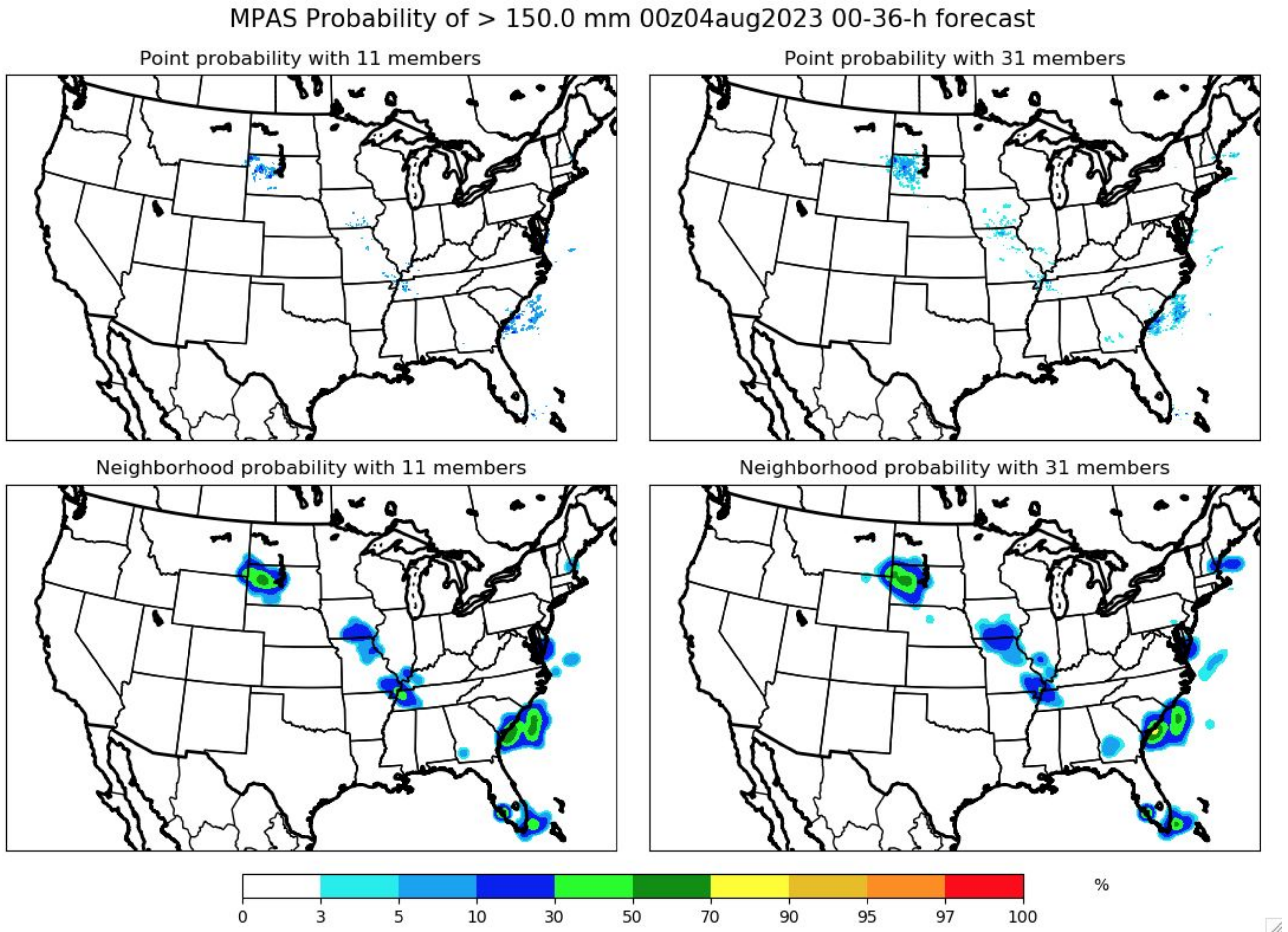


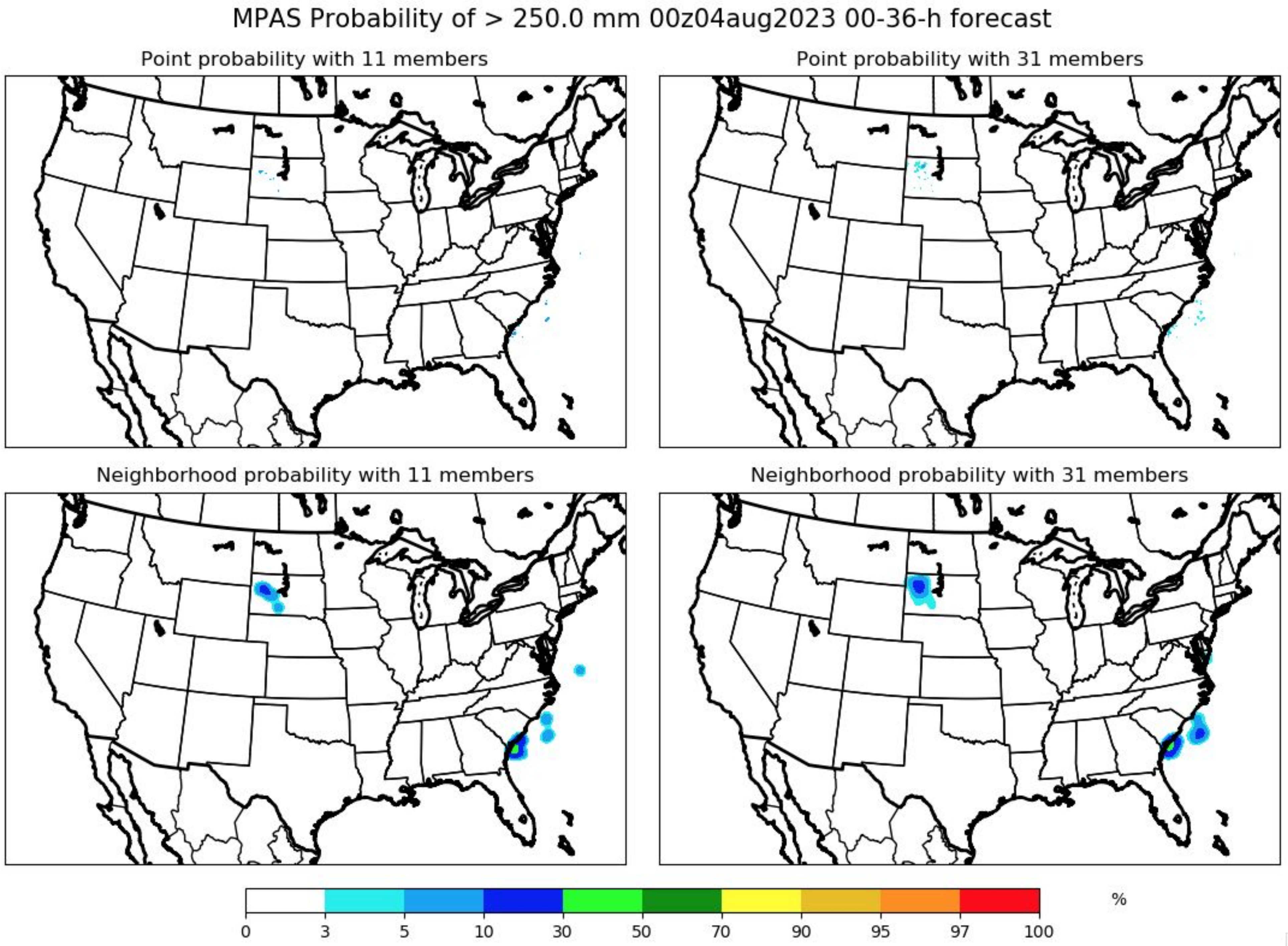
Ensemble Workflow – very HRRR-like!

ungrib	Convert input IC/LBC GRIB-2 files into an intermediate format
init	Interpolate ICs ***and GEFS members*** onto the integration grid
lbc	Interpolate LBCs onto the integration grid
gefsmean	***Compute mean of GEFS members on MPAS grid***
pert	***Add GEFS member values (Θ, u, q_v) to control forecast, subtract ensemble mean***
model	Perform model integration and generate netCDF output
mpassit	Convert MPAS output files to WRF-like netCDF files
upp	Postprocess WRF-like netCDF output to produce HRRR-like GRIB-2 files
img	Use Python to generate png images from GRIB-2 files (optional)
clean	Remove intermediate files, IC/LBCs, MPAS output grids, etc.

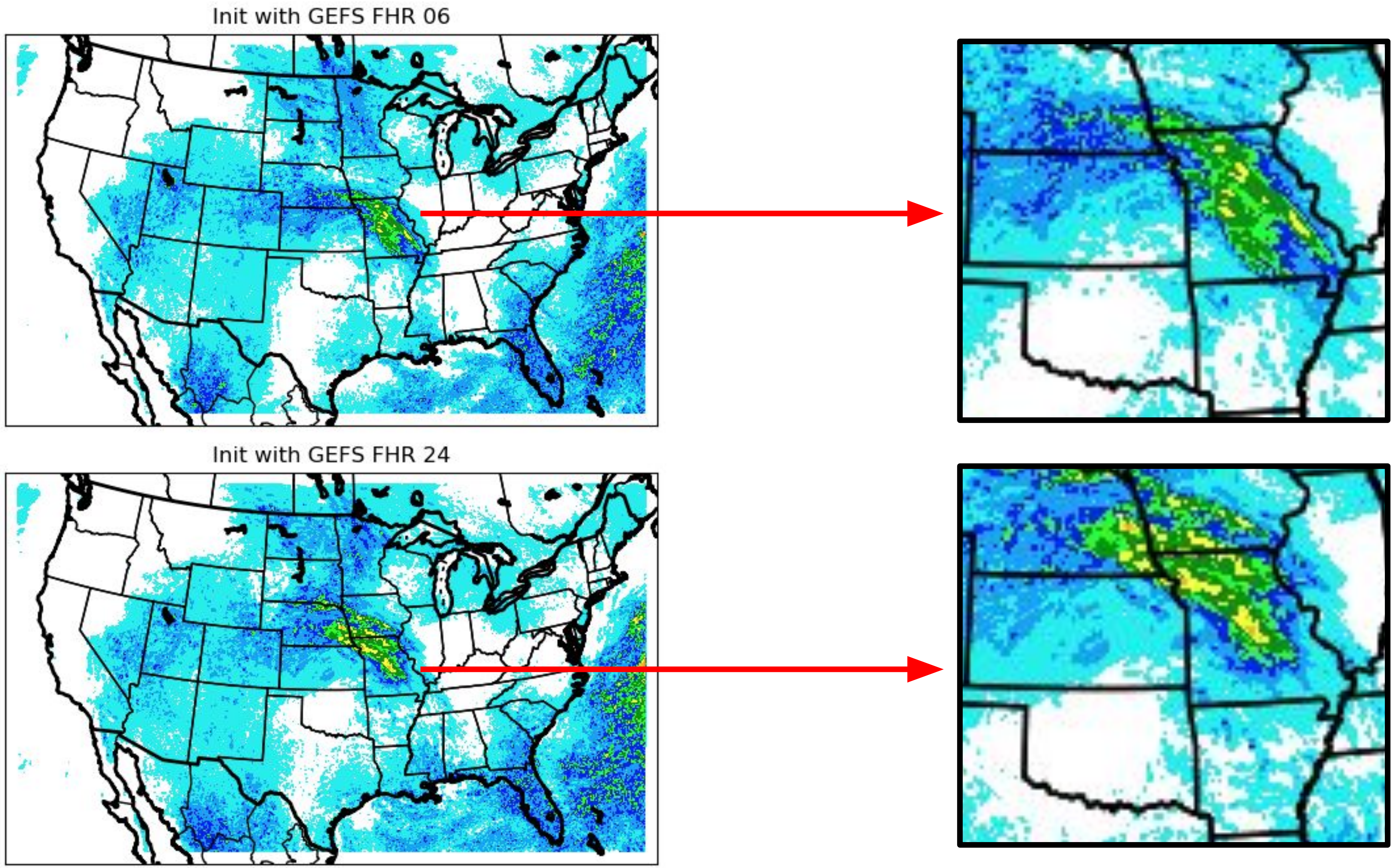


MPAS Ensemble Maxima 00z04aug2023 00-36-h forecast
Max with 11 members
Max with 31 members
Max within 40 km, with 11 members
Max within 40 km, with 31 members
mm
0.2
2.5
25.0
50.0
75.0
100.0
150.0
200.0
300.0
600.0


MPAS Probability of > 150.0 mm 00z04aug2023 00-36-h forecast
Point probability with 11 members
Point probability with 31 members
Neighborhood probability with 11 members
Neighborhood probability with 31 members
%
0
3
5
10
30
50
70
90
95
97
100



MPAS Probability of > 250.0 mm 00z04aug2023 00-36-h forecast
Point probability with 11 members
Point probability with 31 members
Neighborhood probability with 11 members
Neighborhood probability with 31 members
0
3
5
10
30
50
70
90
95
97
100
%


Init with GEFS FHR 06
Init with GEFS FHR 24

Next Steps

- Multiple 31-member case studies of extreme precipitation events
- Perturb additional fields at model initialization (soil moisture/temperature, LBCs, etc)
- 1-2-week retro simulations once ideal configuration established
- Explore visualization techniques for large ensembles
- Provide retrospective ensemble output for machine learning experiments