NCAR
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NSF

Toward 1-km ensemble forecasts over large domains

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Mesoscale & Microscale Meteorology
MMM
LABORATORY

Motivation

- Several studies have examined high-resolution model sensitivity to horizontal grid spacing
  - Always in deterministic frameworks
  - What about probabilistic forecast sensitivity to grid spacing?

- Little work comparing a coarse-resolution (but still convection-allowing) ensemble to an even higher-resolution deterministic forecast

- A 27-member 3-km ensemble costs similarly as a single 1-km deterministic forecast

Experimental design

- Three forecast sets:
  - 30-member 3-km ensemble forecasts (3KM_ENS30)
  - 10-member 3-km ensemble
    - Just a subset of the 30-member 3-km ensemble (3KM_ENS10)
  - 10-member 1-km ensemble (1KM_ENS10)

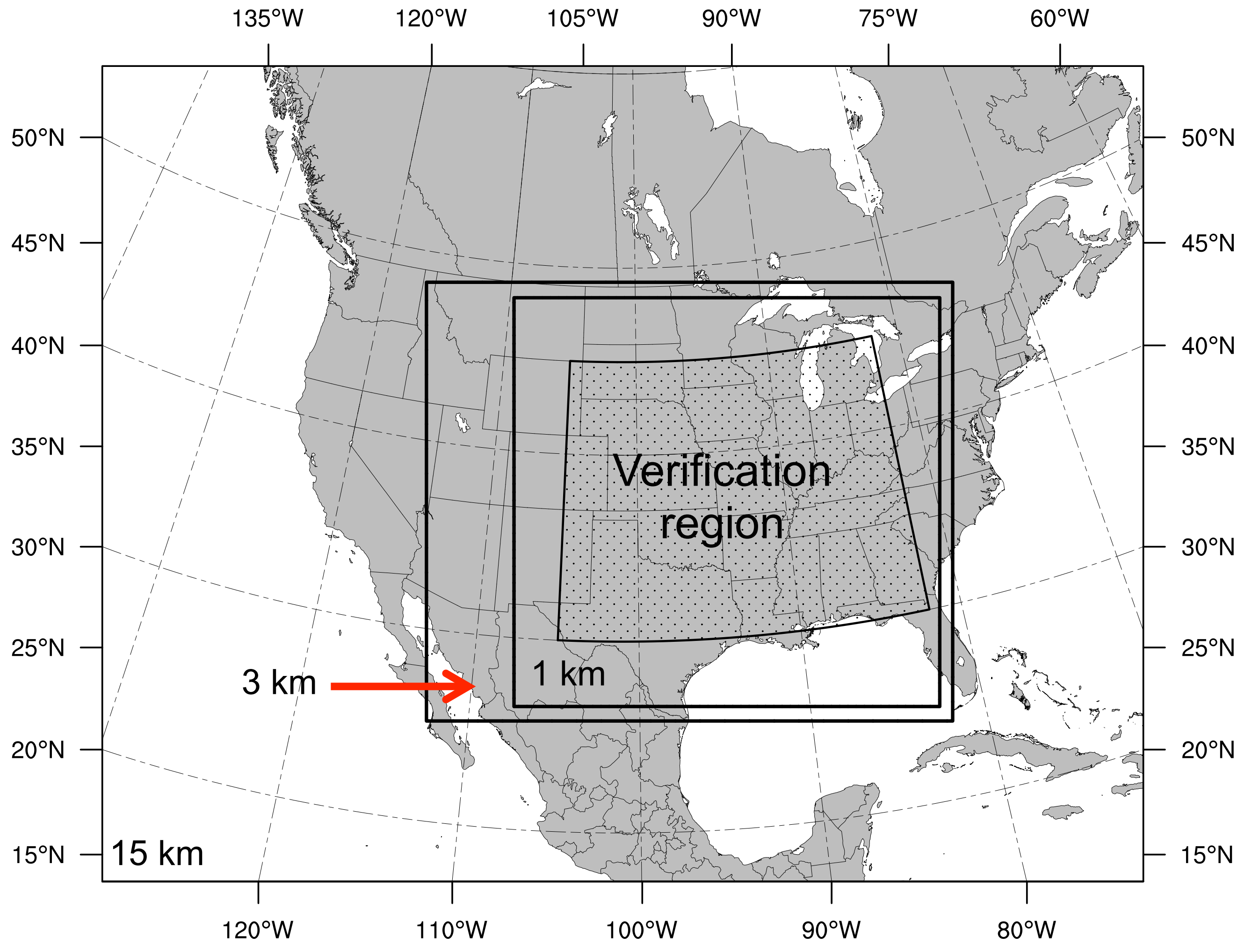
- Verified individual ensemble members and probabilistic forecasts

- Examined 32 forecasts initialized at 0000 UTC
  - Ensemble Kalman filter (EnKF) data assimilation initialization
  - Between 15 May and 15 June 2013
  - 48-hr forecast length

Computational domains

- EnKF data assimilation only on 15-km domain

• 1- and 3-km forecasts have identical 15-km initial conditions



WRF settings and physics

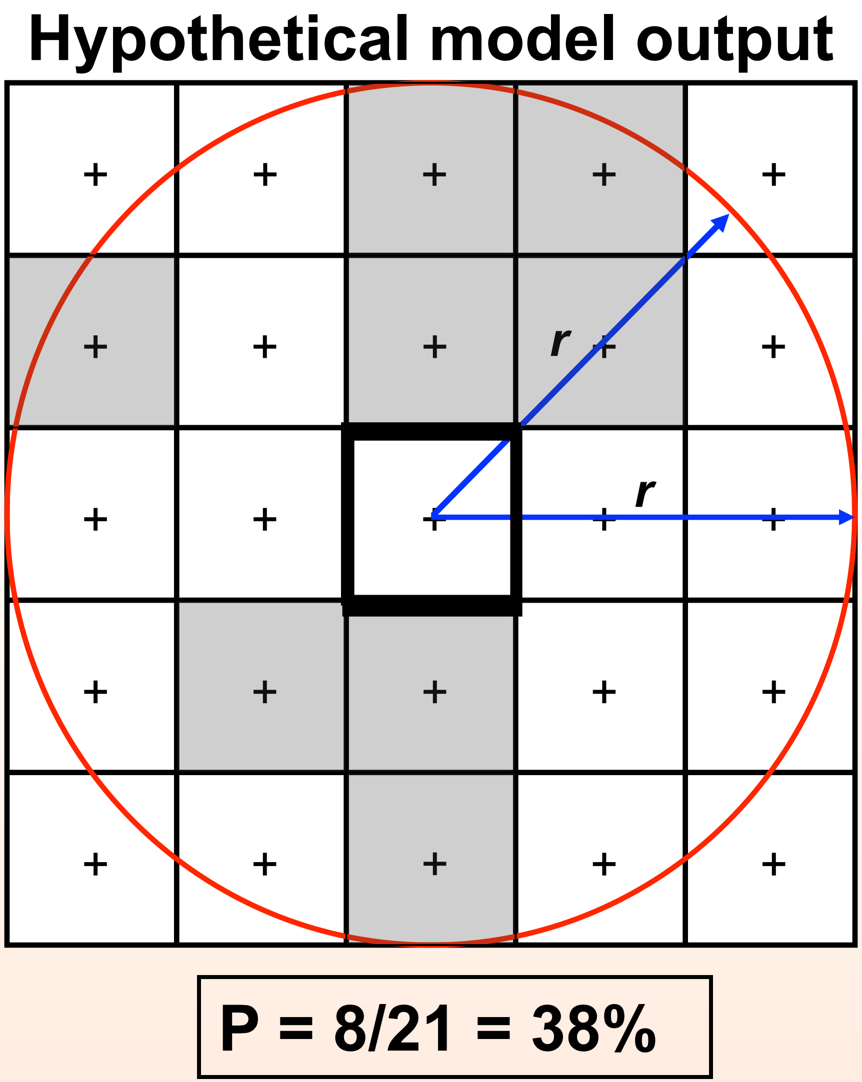
- WRF-ARW (version 3.3.1)
- 40 vertical levels, 50-hPa top
- Physics (*"CONUS suite" introduced in WRF v3.9*)
  - Thompson microphysics
  - RRTMG longwave and shortwave radiation with aerosol and ozone climatologies
  - MYJ PBL
  - Tiedtke cumulus parameterization on 15-km domain
  - NOAH land surface model
- Same physics for all ensemble members and forecasts

Precipitation verification

- NCEP Stage IV observations as "truth"
  - 4.7-km horizontal grid spacing
- Model forecasts interpolated to Stage IV grid
  - This did not introduce meaningful errors
- Precipitation forecasts bias-corrected to focus on displacement errors
- All statistics aggregated over 32 forecasts

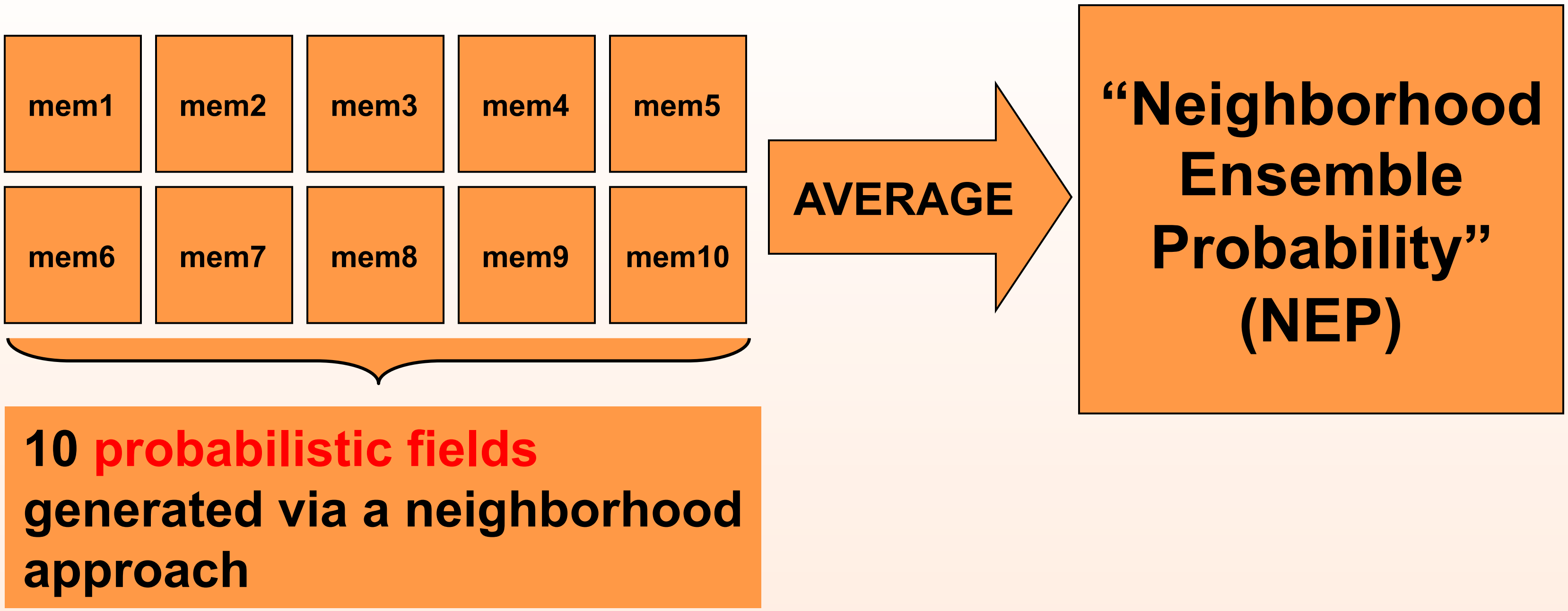
How to create probabilities from deterministic guidance?

- Use a “neighborhood approach”
- r = 2.5 times the grid spacing
- The event has occurred in the shaded boxes
- This method was used to verify individual ensemble members



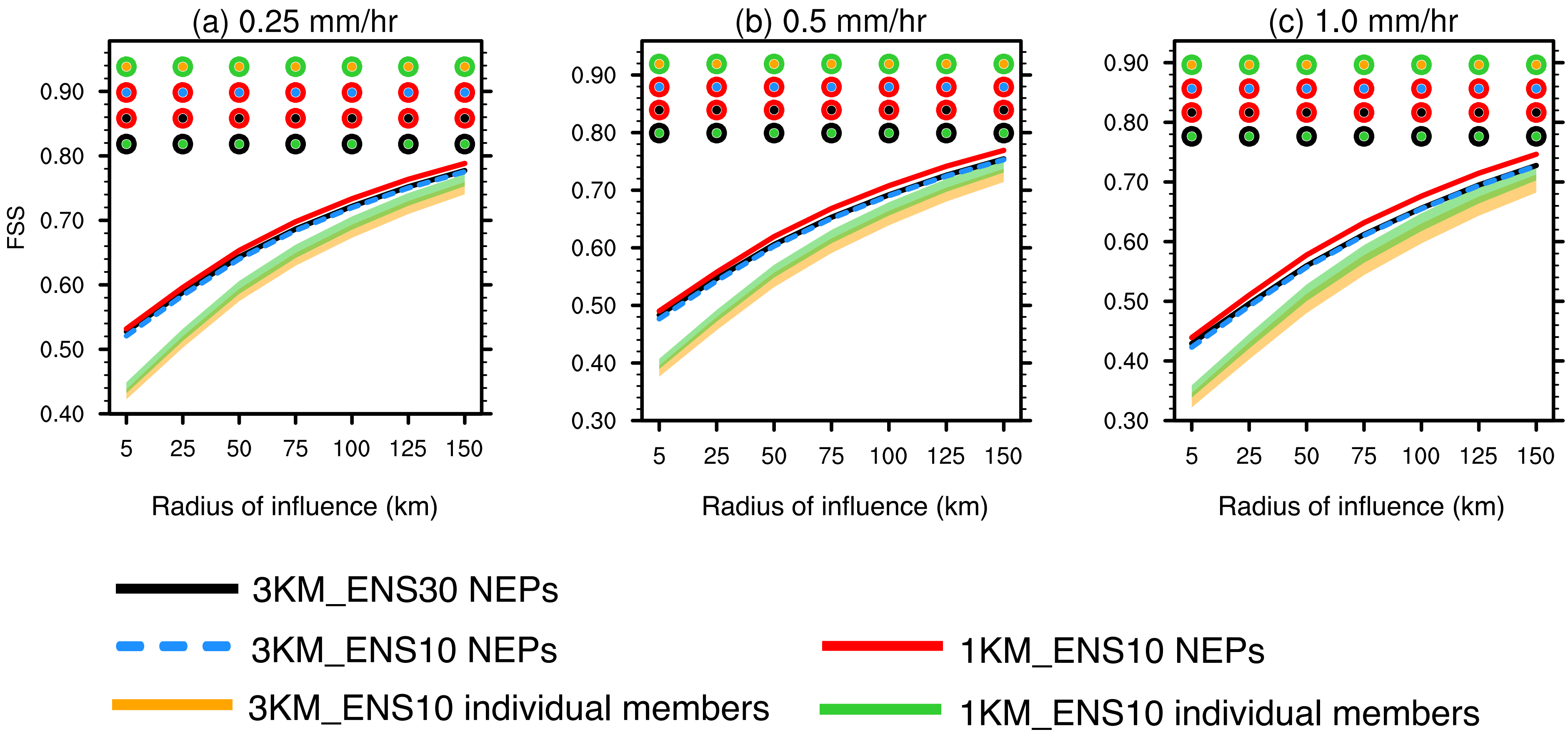
Neighborhood approach applied to probabilistic forecasts

- Apply neighborhood approach as described on previous slide to each ensemble member separately
  - For each member, get a value between 0 and 1
  - Average all probabilistic fields



Fractions skill score (FSS)

- Aggregated over 32 1-12-hr forecasts



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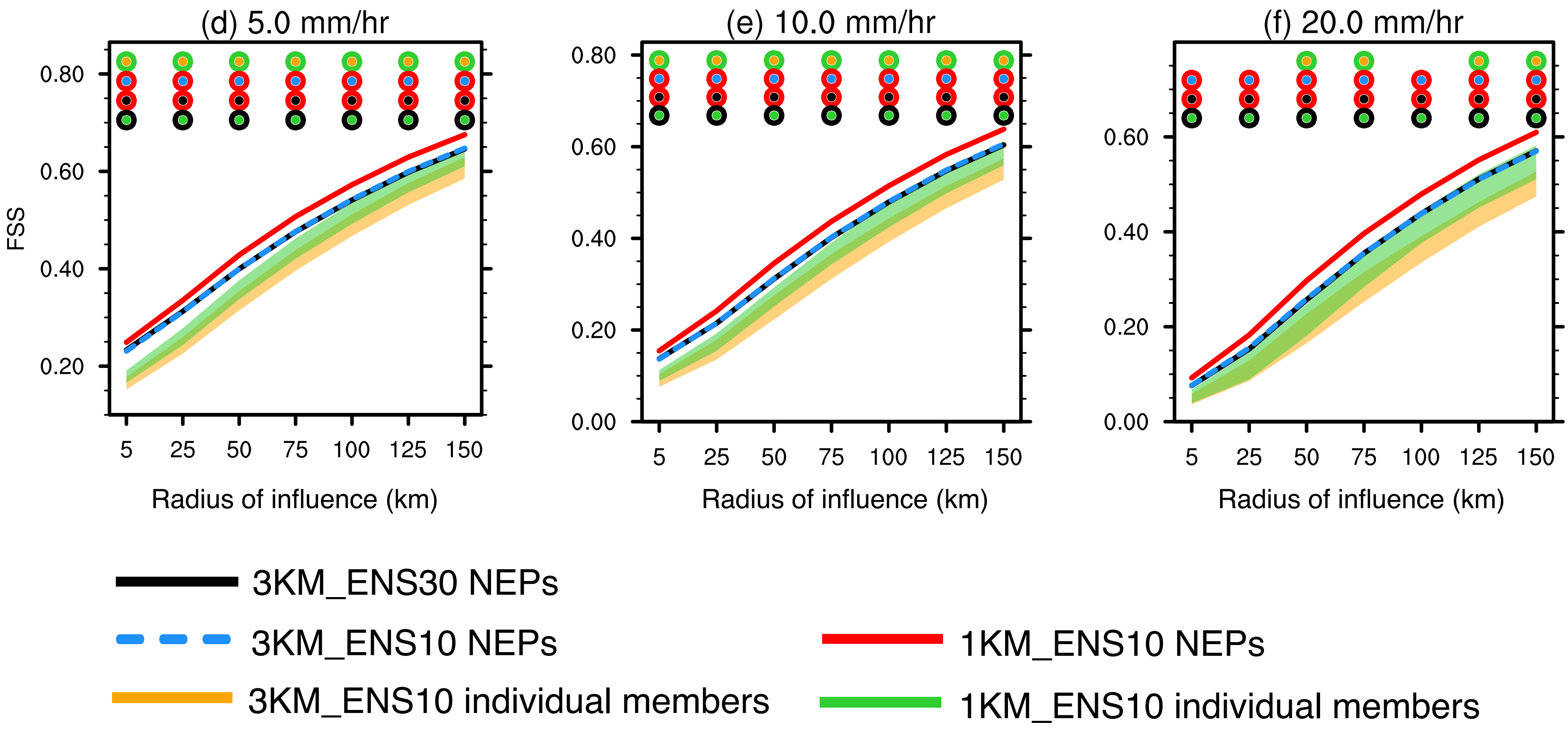
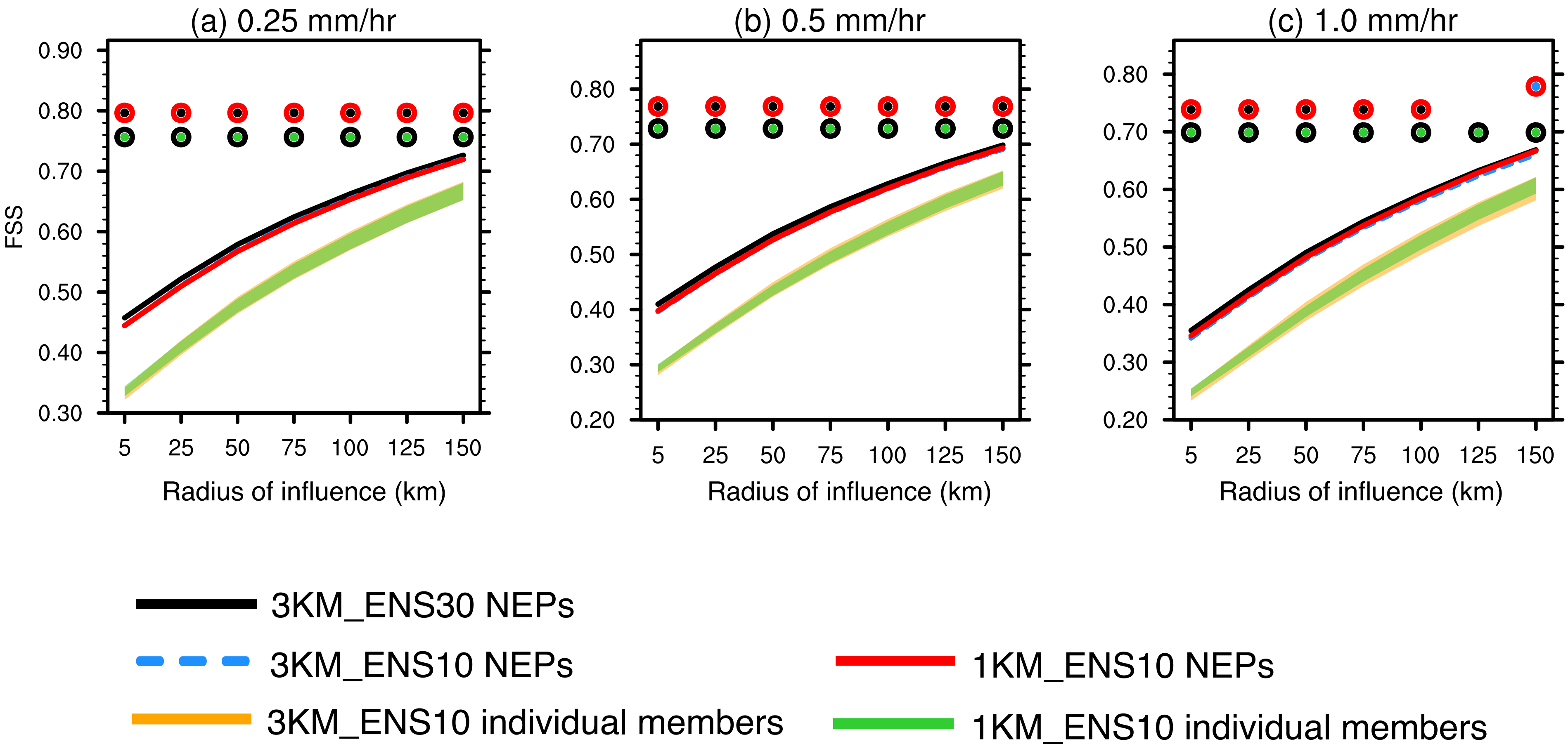


Fractions skill score (FSS)

- Aggregated over 32 18-36-hr forecasts



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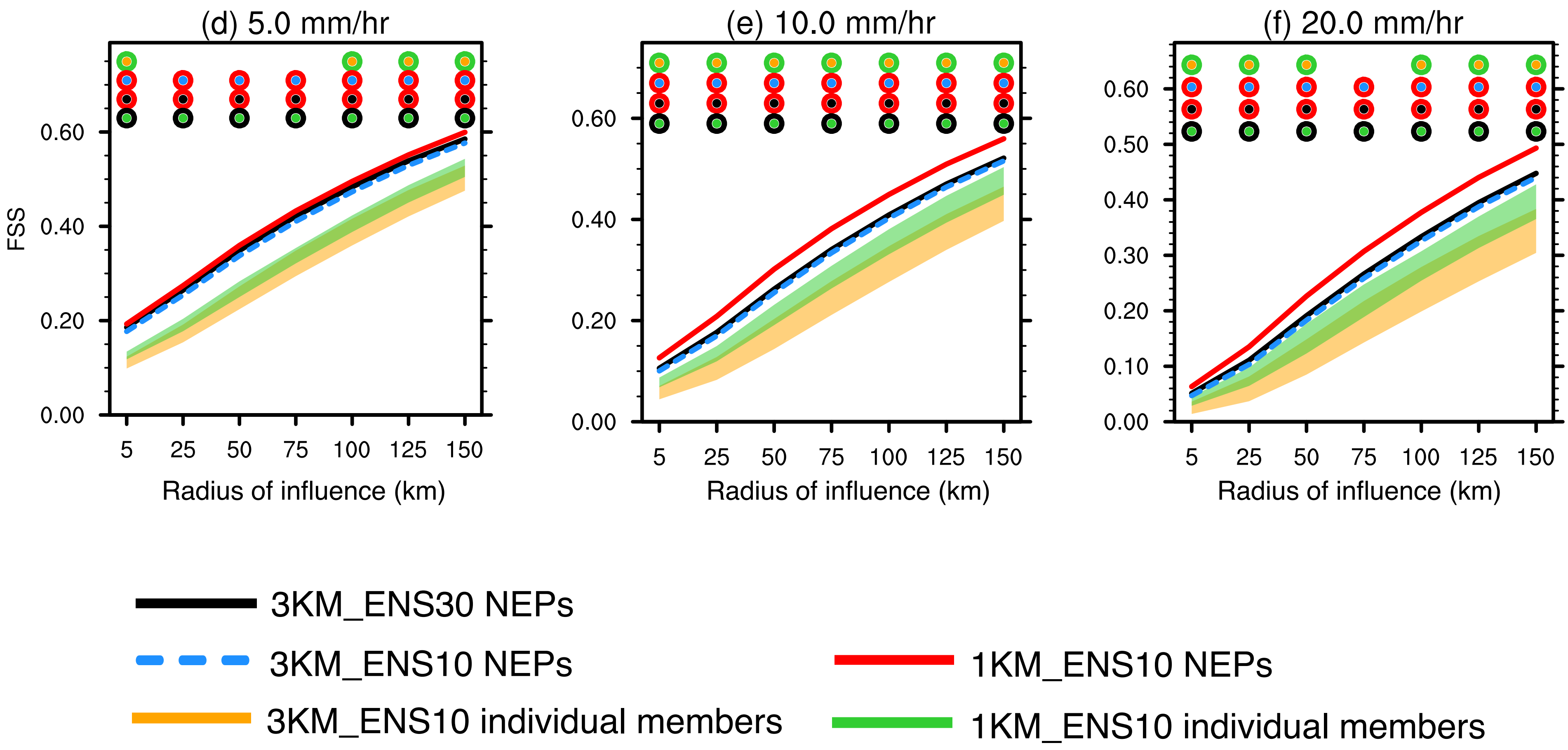


Questions

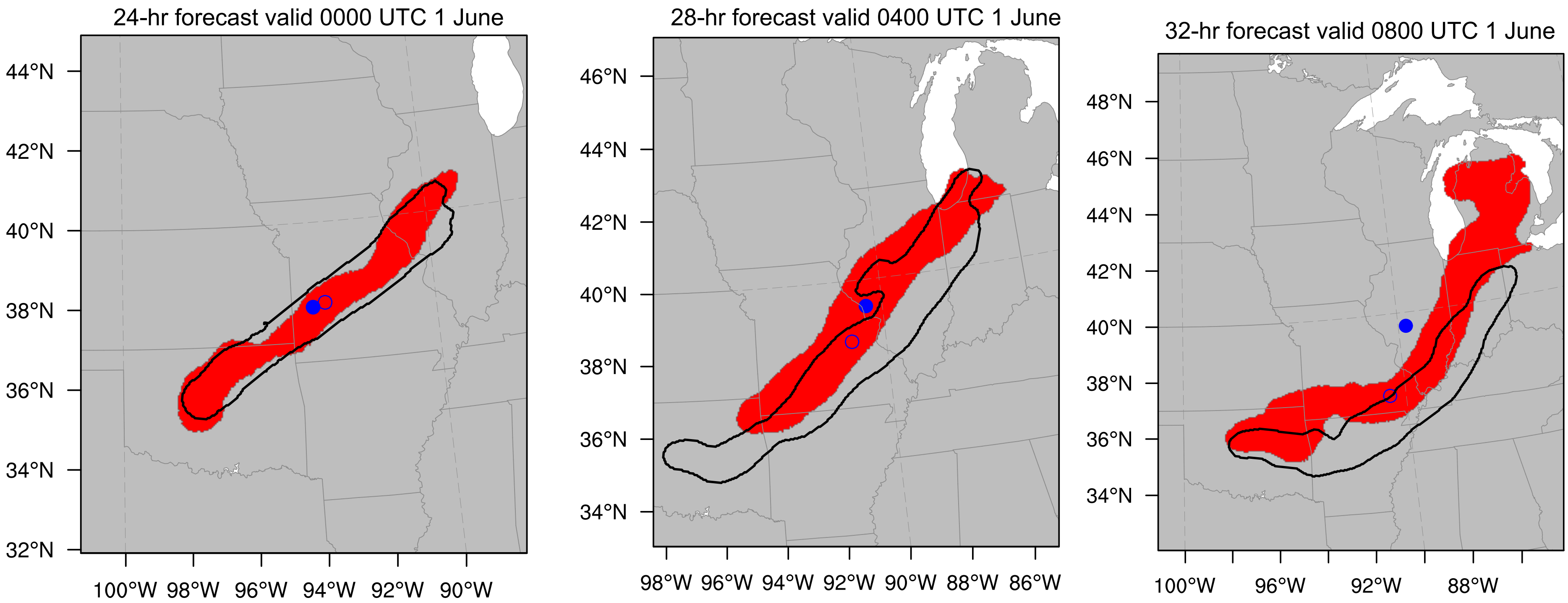
- Why were 1-km forecasts better at higher rainfall rates?
- Subjectively, it appeared that 1-km MCSs moved more quickly than 3-km MCSs
- We performed object-based verification to try to quantify MCS propagation speed and cold pool strength
- Used MODE from the MET software

MODE methods

- Defined *probabilistic objects* from 10-member 3- and 1-km ensembles
  - Object: contiguous region where smoothed probabilities of 1-hr precip > 5.0 mm/hr exceeded 10% (50-km smoother)
  - Imposed minimum area thresholds (α) to focus on large MCSs
- Also defined objects for individual members and Stage IV observations
- Matched 1- and 3-km objects using centroid distance
  - Statistics only produced for matched 1- and 3-km objects

Case study: 31 May 2013

- 3-km (shaded) and 1-km objects (contours)

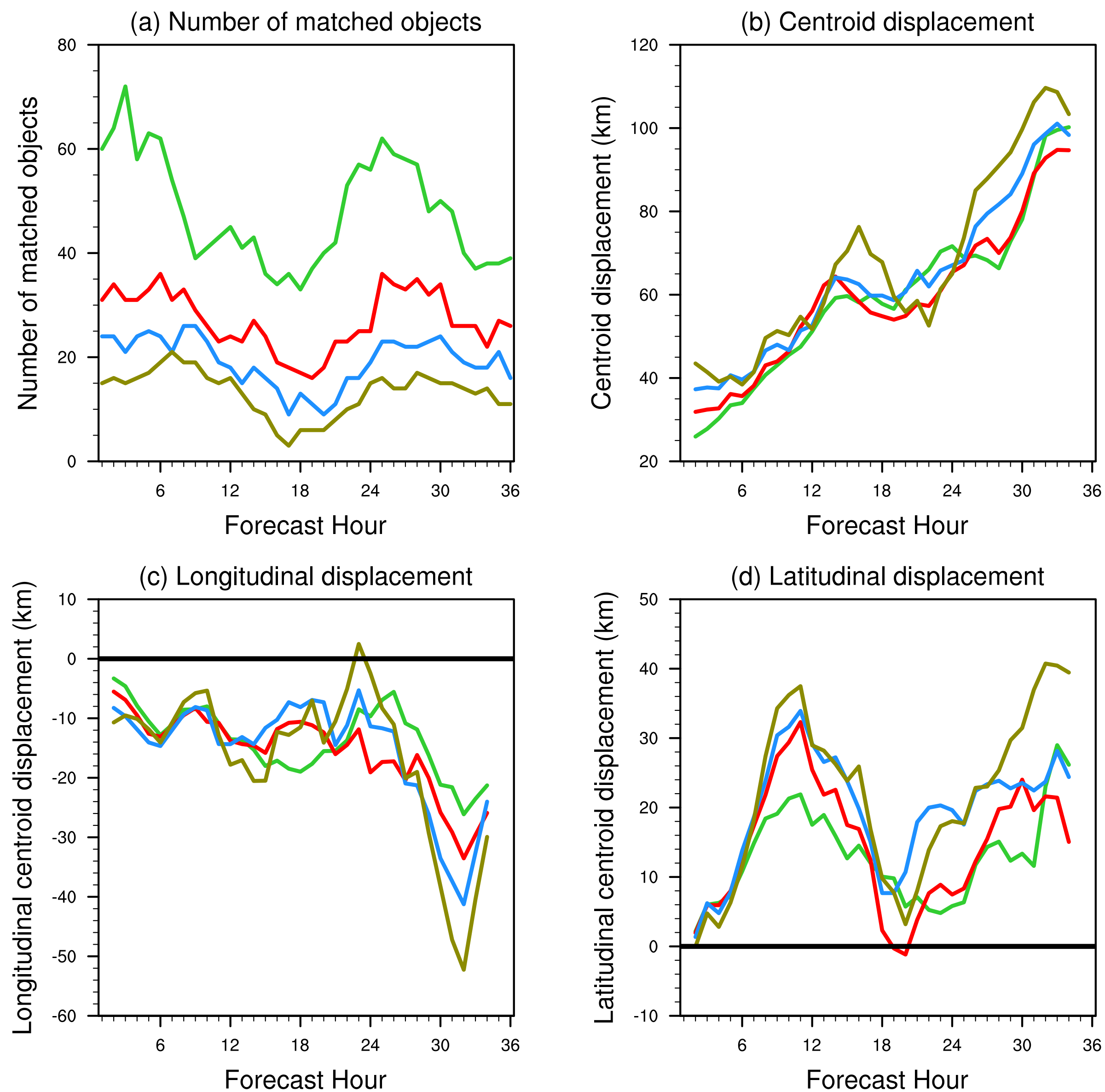


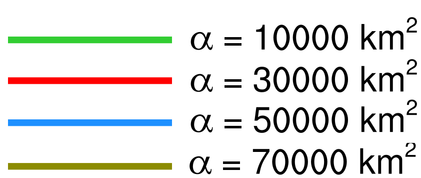
- Object: contiguous region where smoothed probabilities of 1-hr precip > 5.0 mm/hr exceeded 10% (50-km smoother)

Differences between 3- and 1-km objects

- Bulk statistics over all 32 days

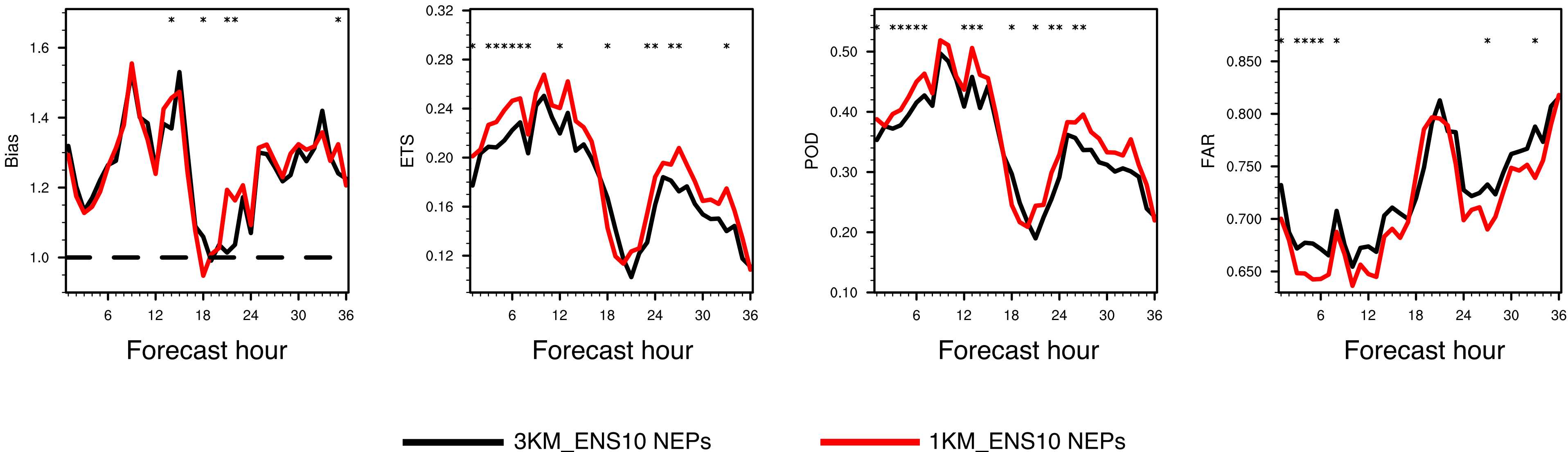
Convention for differences: 3-km minus 1-km





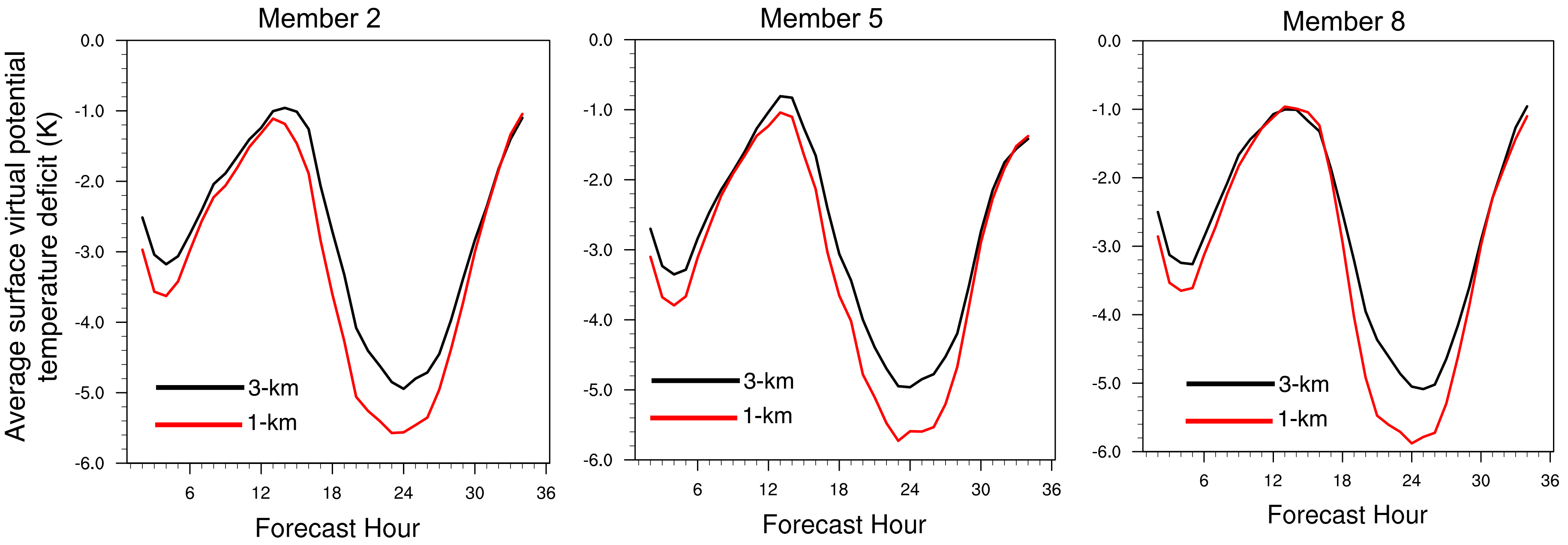
Comparison with Stage IV objects

- Verification metrics comparing 1- and 3-km objects with probabilistic Stage IV objects
  - Minimum object areas: 30000 km²



Cold pool strengths

- Mean cold pool strengths as a function of forecast hour



- Also a shift in the 1-km distributions toward stronger (colder) cold pools

Summary

- For precipitation, 3-km ensembles appear better than 1-km deterministic forecasts, on average

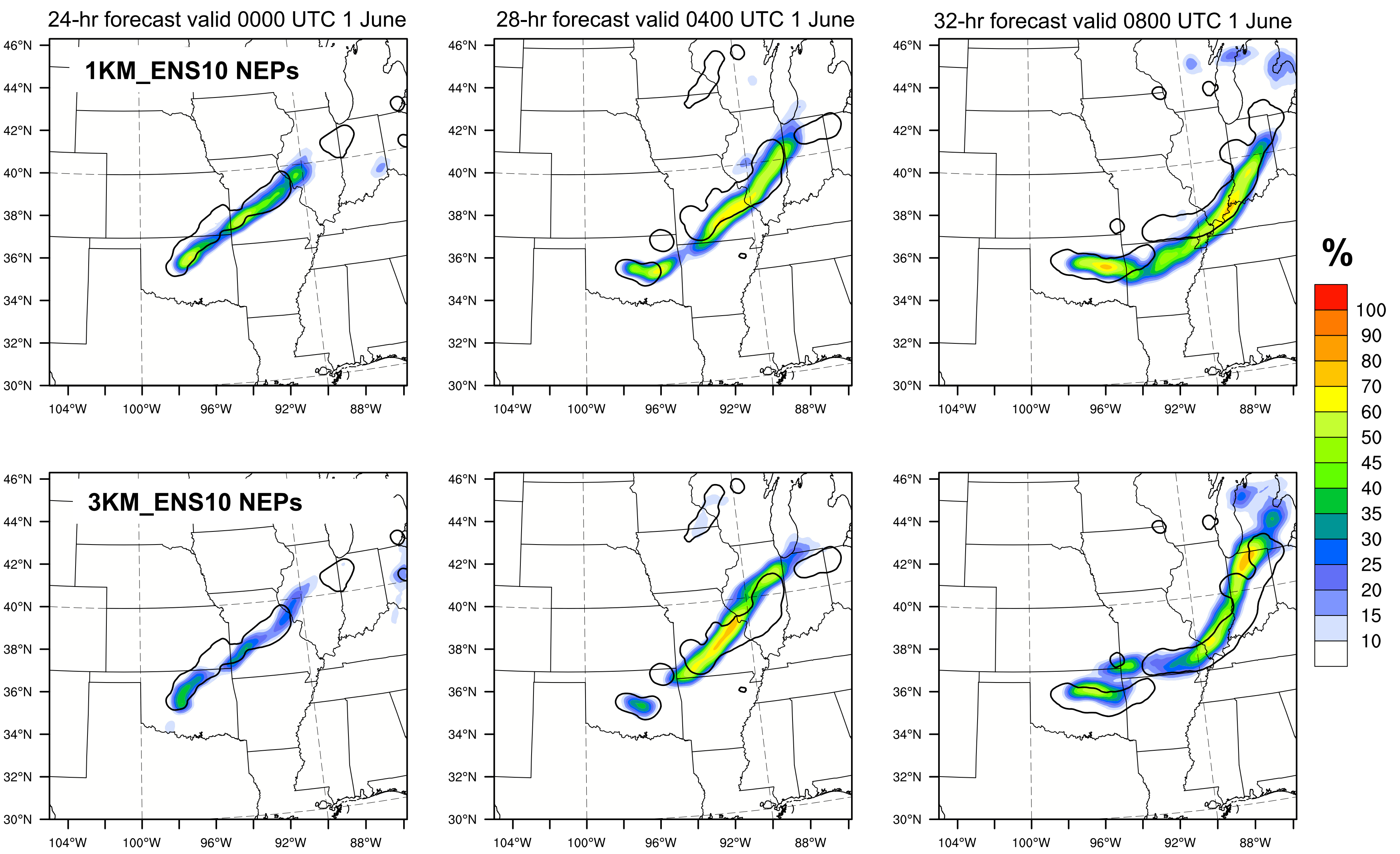
- 1-km ensembles appear best, especially at heavier rainfall rates

- Improved 1-km forecasts associated with stronger 1-km cold pools and better MCS placement

- All the gory details here:
  - Schwartz et al. (2017); MWR; doi:10.1175/MWR-D-16-0410.1

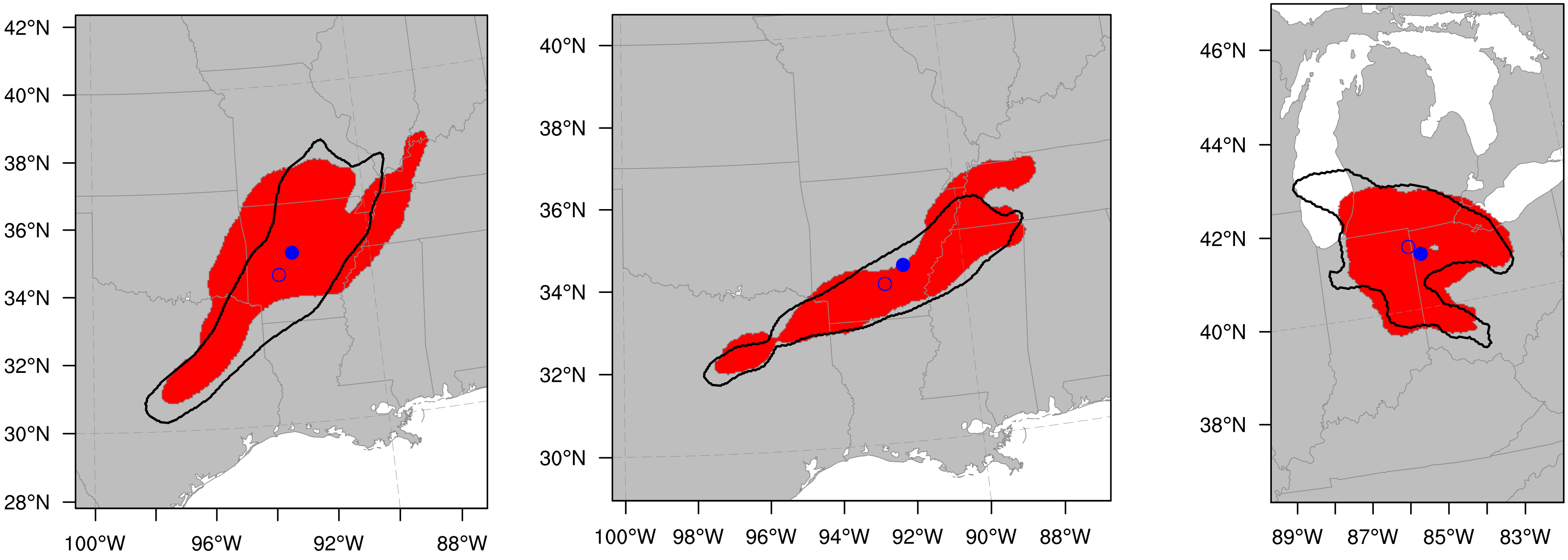
Case study: 31 May 2013

- Probability of precipitation exceeding 5.0 mm/hr



Forecast objects

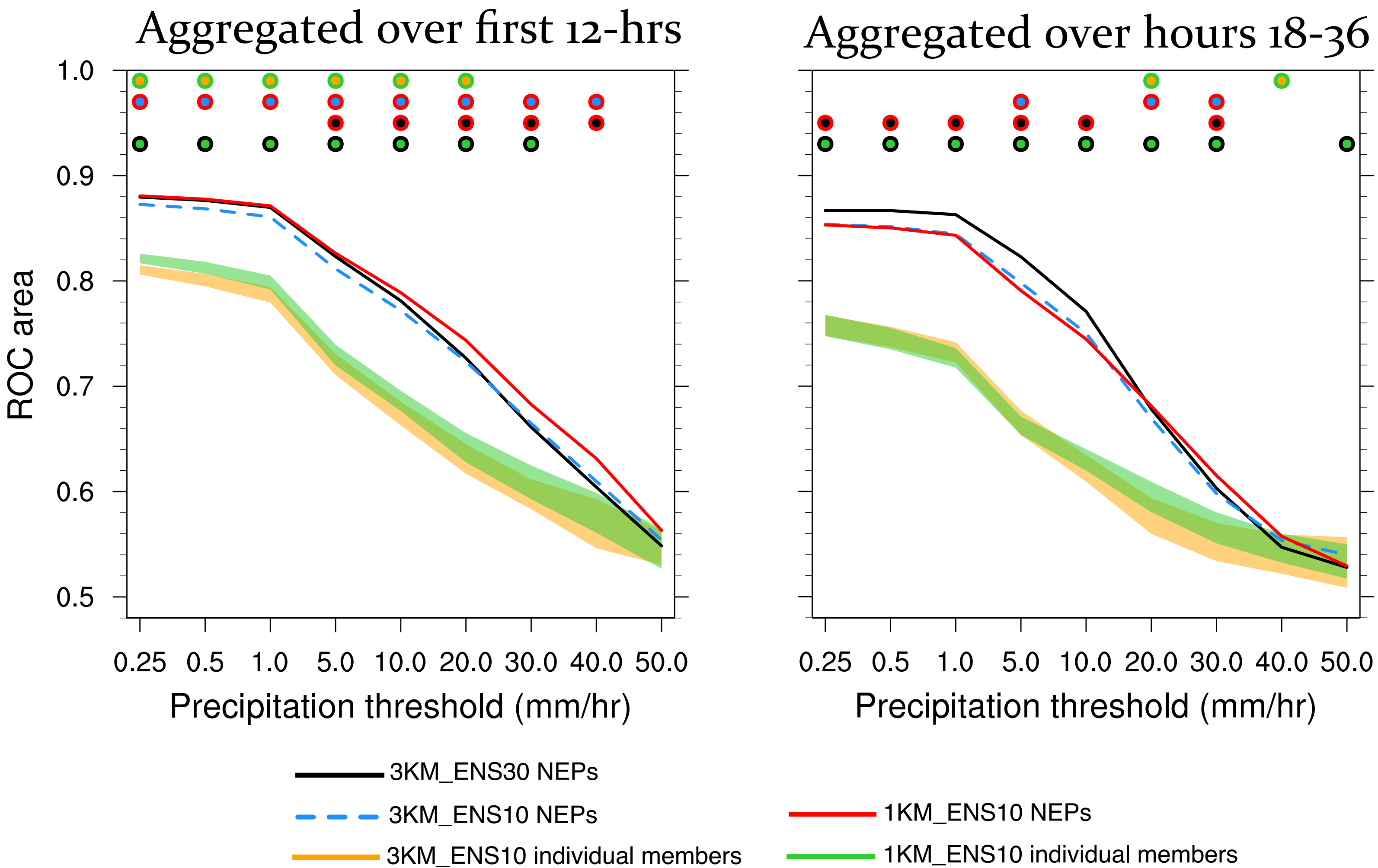
- Snapshots of forecast objects
  - 3-km (shaded) and 1-km objects (contours)



- Object: contiguous region where smoothed probabilities of 1-hr precip > 5.0 mm/hr exceeded 10% (50-km smoother)

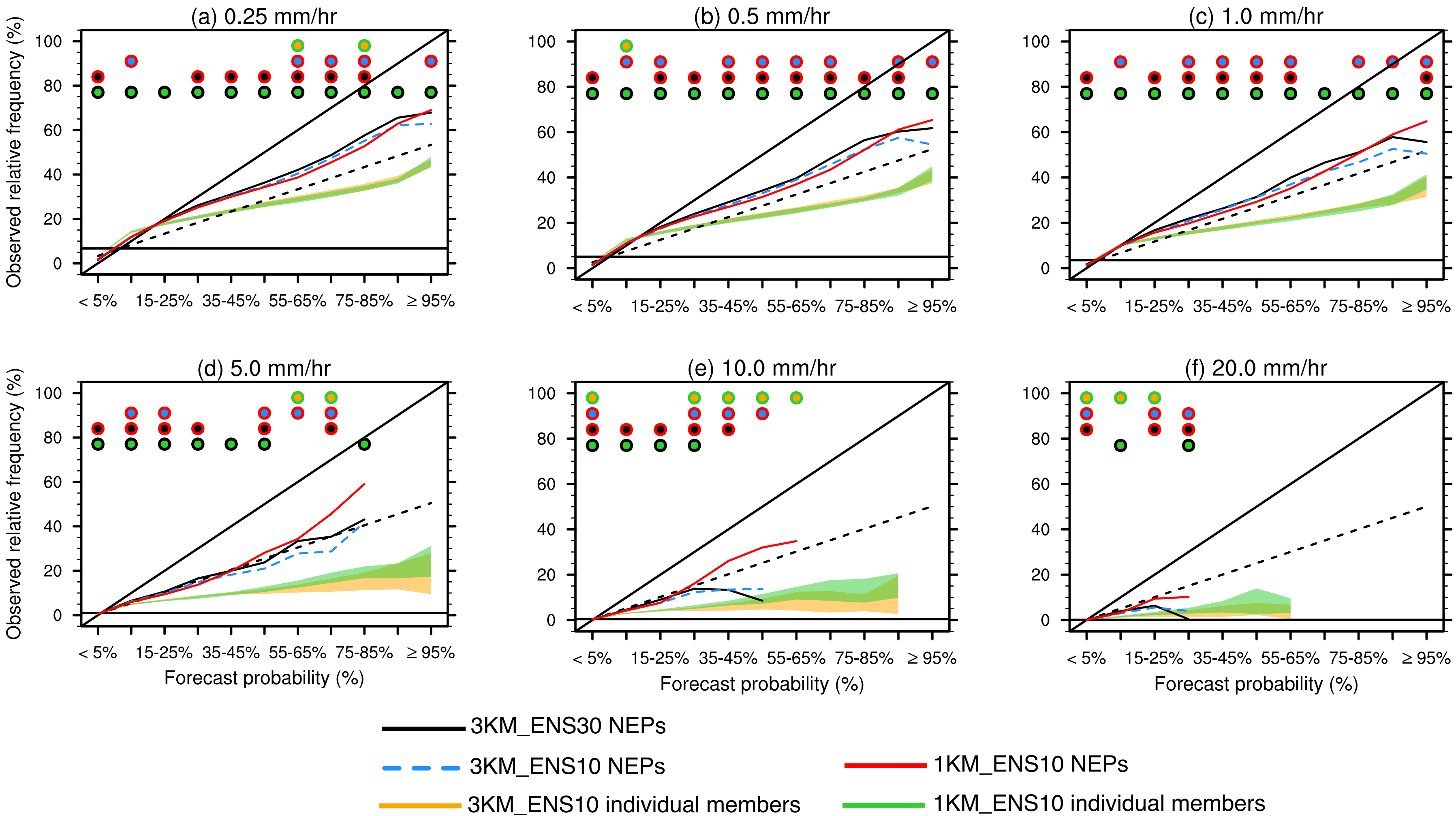
ROC areas

- Aggregated over 32 forecasts
  - 50-km radius of influence (similar findings with other radii)



Reliability diagrams

- Aggregated over 32 forecasts between 18-36 hours
  - 50-km radius of influence (similar findings with other radii)



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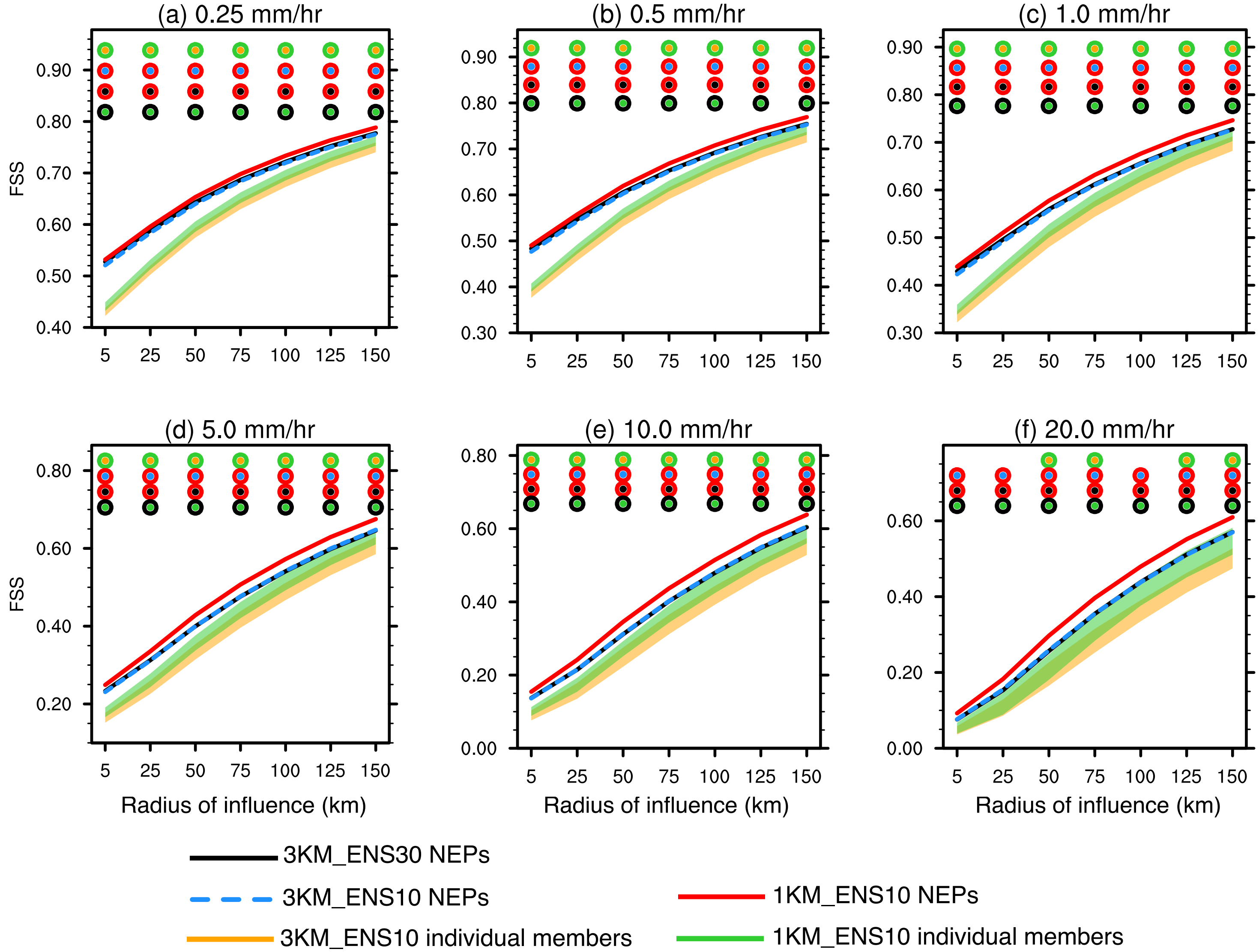

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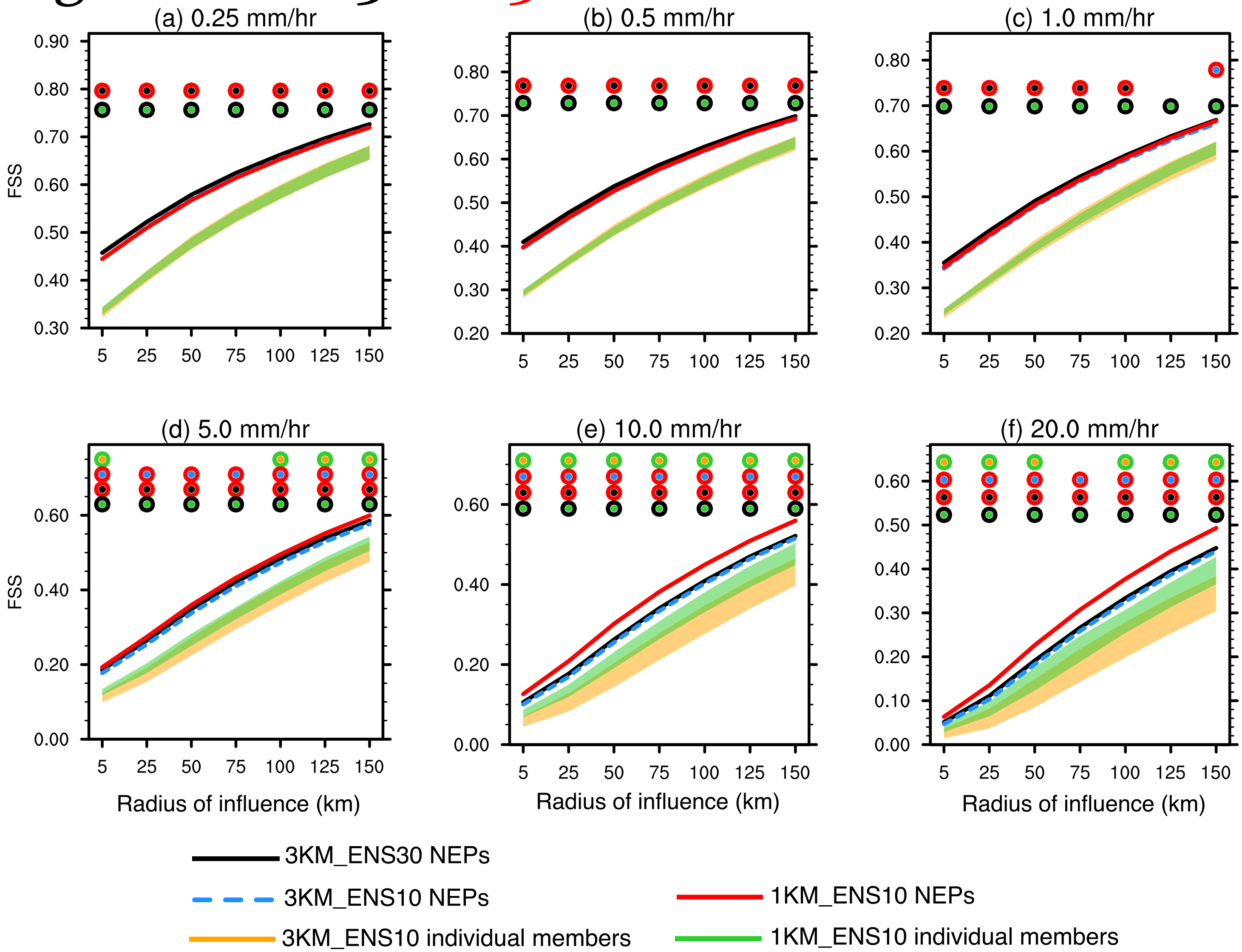
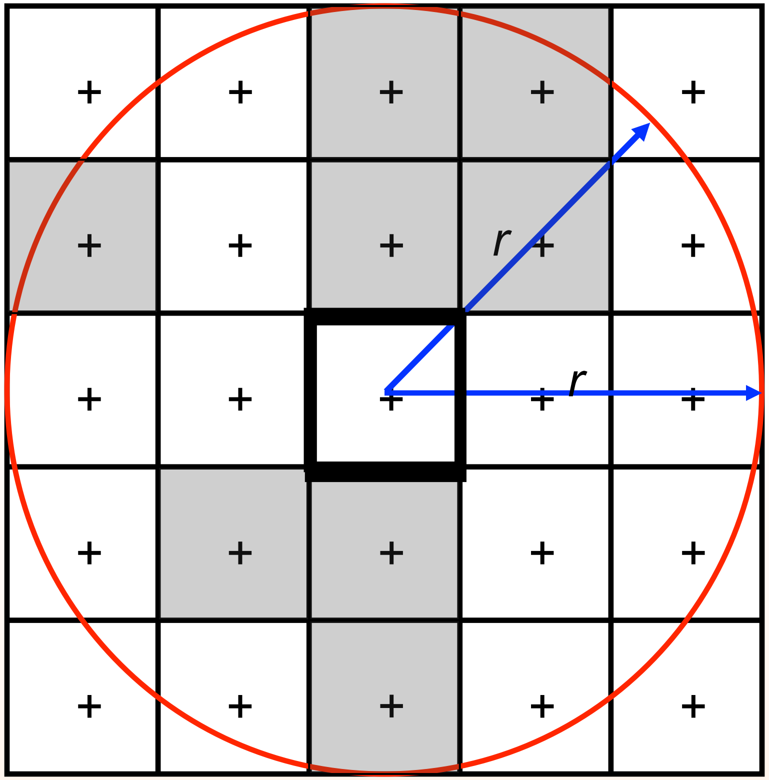
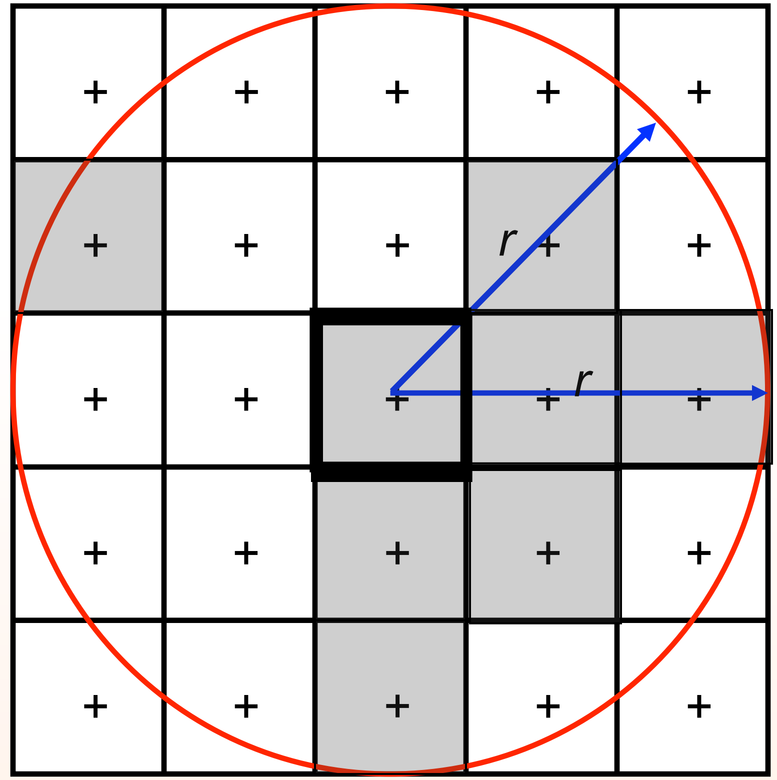


Example Applied to Model and Observations

Model output



Observations



P = 8/21 = 38%

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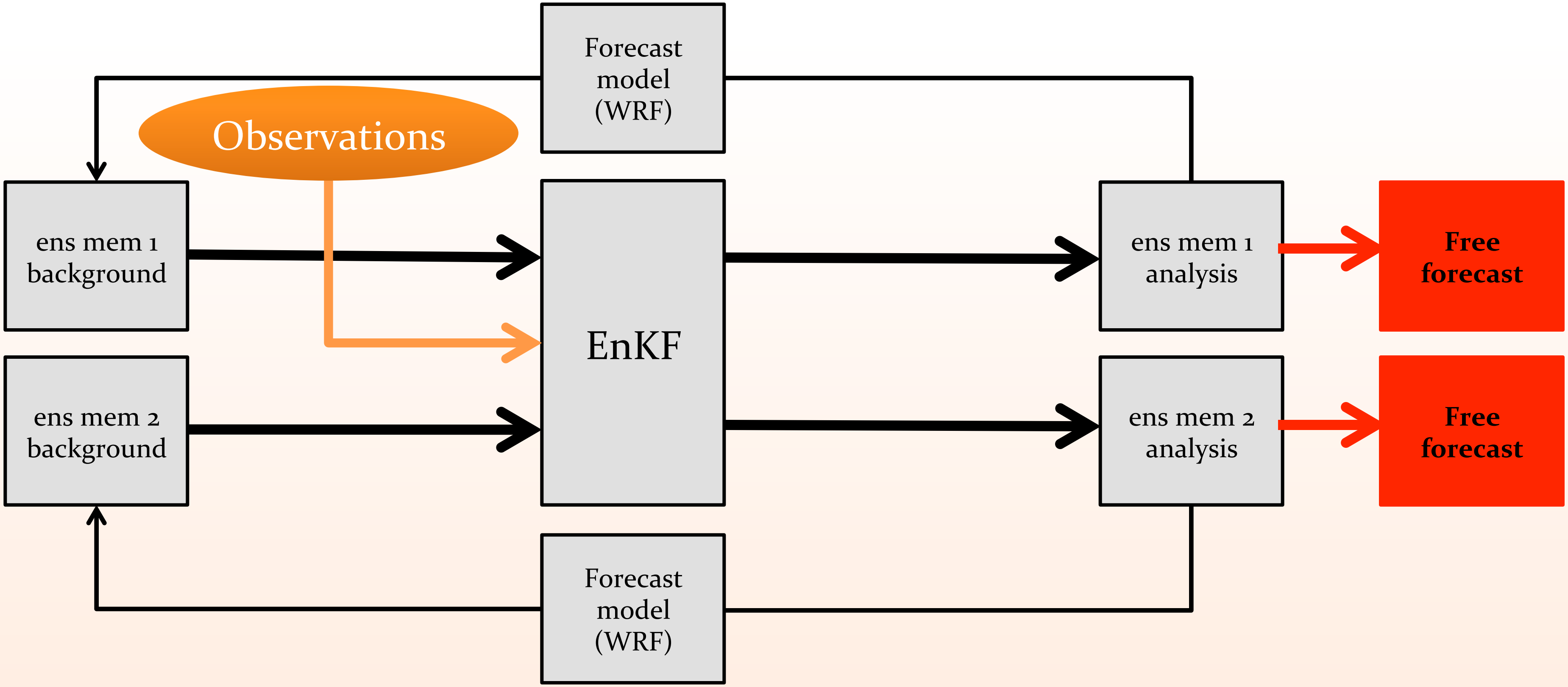
A perfect forecast using this neighborhood approach

Ensemble Kalman filter initialization

- Initial conditions for all ensemble members are dynamically consistent
  - No ad hoc assumptions or use of external models



What is data assimilation?