



Ensemble forecast verification

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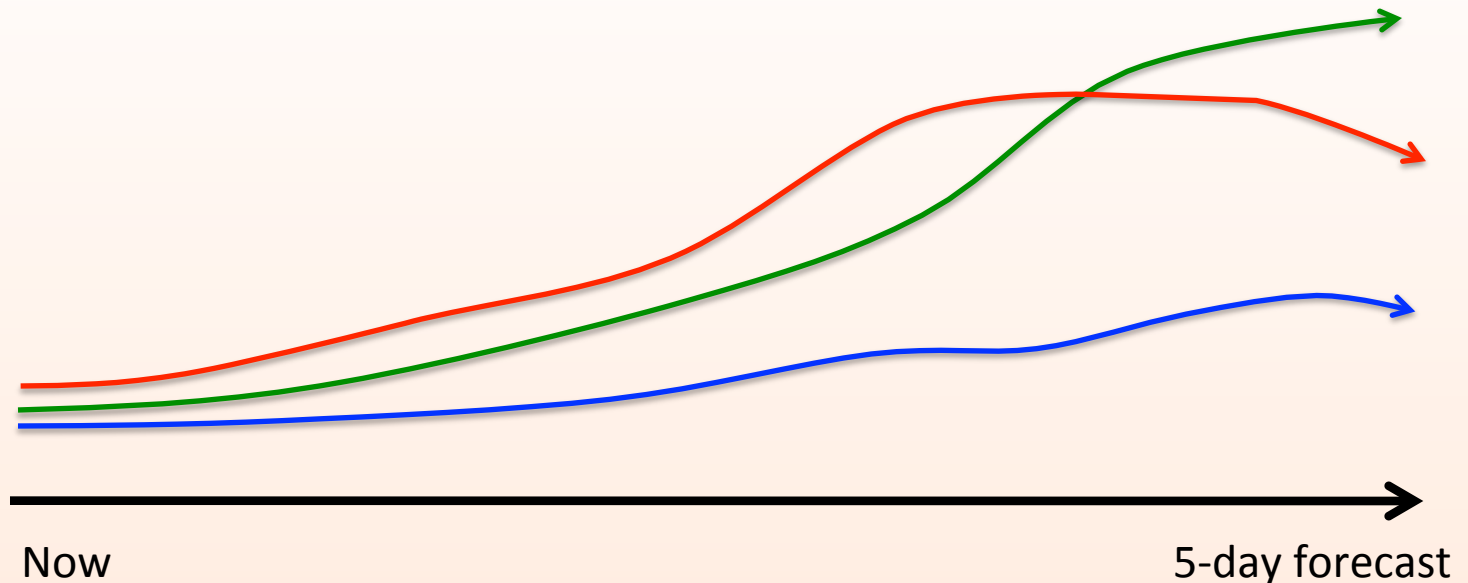
NCAR is sponsored by the National Science Foundation

Ensemble verification

- Many concepts are important for ensemble verification
- The literature is rich with ideas and metrics
 - Can only scratch the surface in a 30 minute talk
- I'll discuss some aspects of ensemble verification that can be confusing

Ensemble predictions

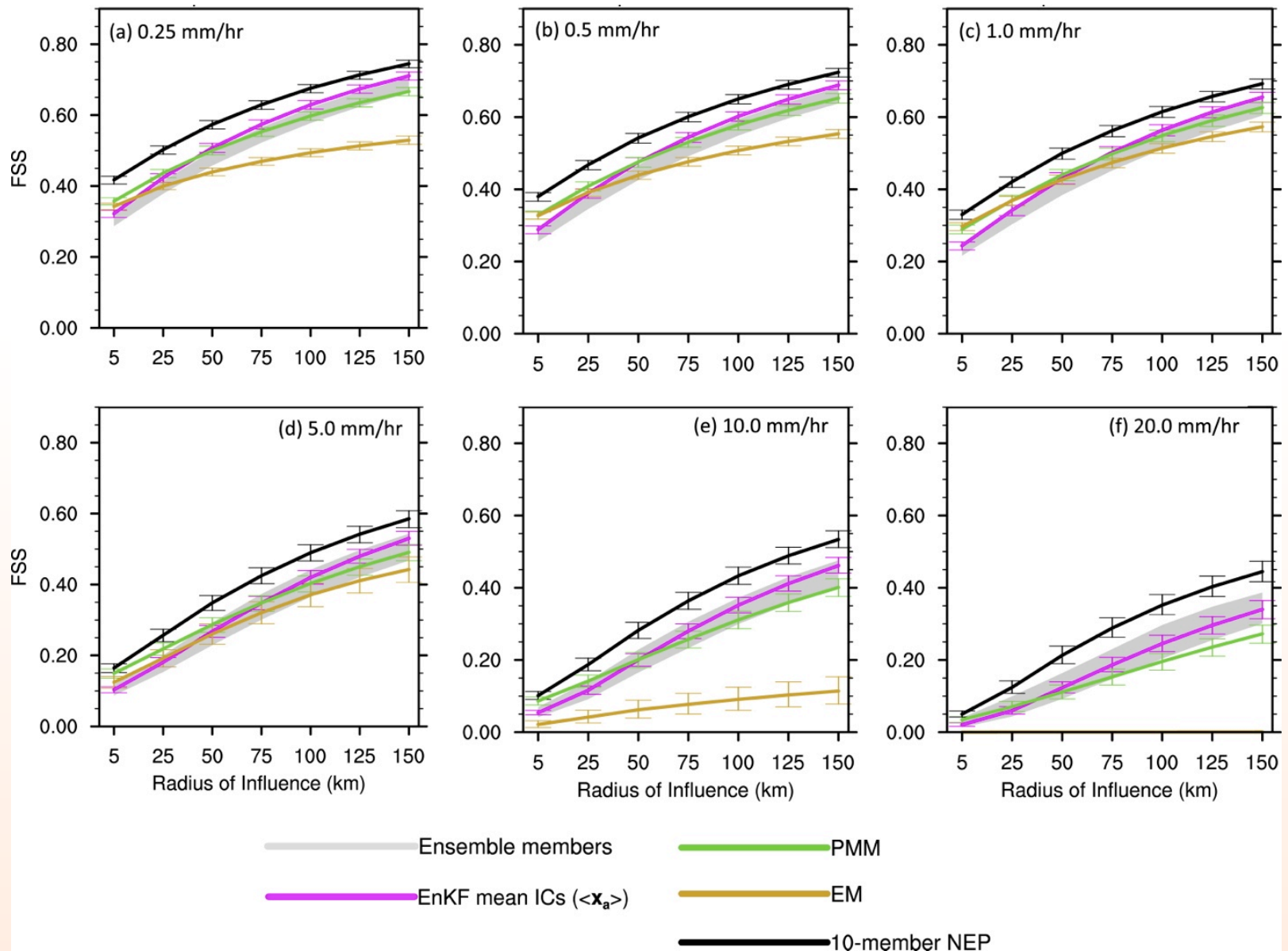
- Each individual member of an ensemble forecast is a deterministic forecast
- Tempting to verify each member individually with deterministic approaches



Value of ensembles

- Ensemble value comes primarily from probabilities
 - Ensembles should be verified probabilistically
- Trying to find the “best” deterministic forecast from an ensemble is not a great idea
 - Ignores probabilistic value from ensembles
- Ensemble mean and probability matched mean are sometimes useful

Probabilistic forecasts are best



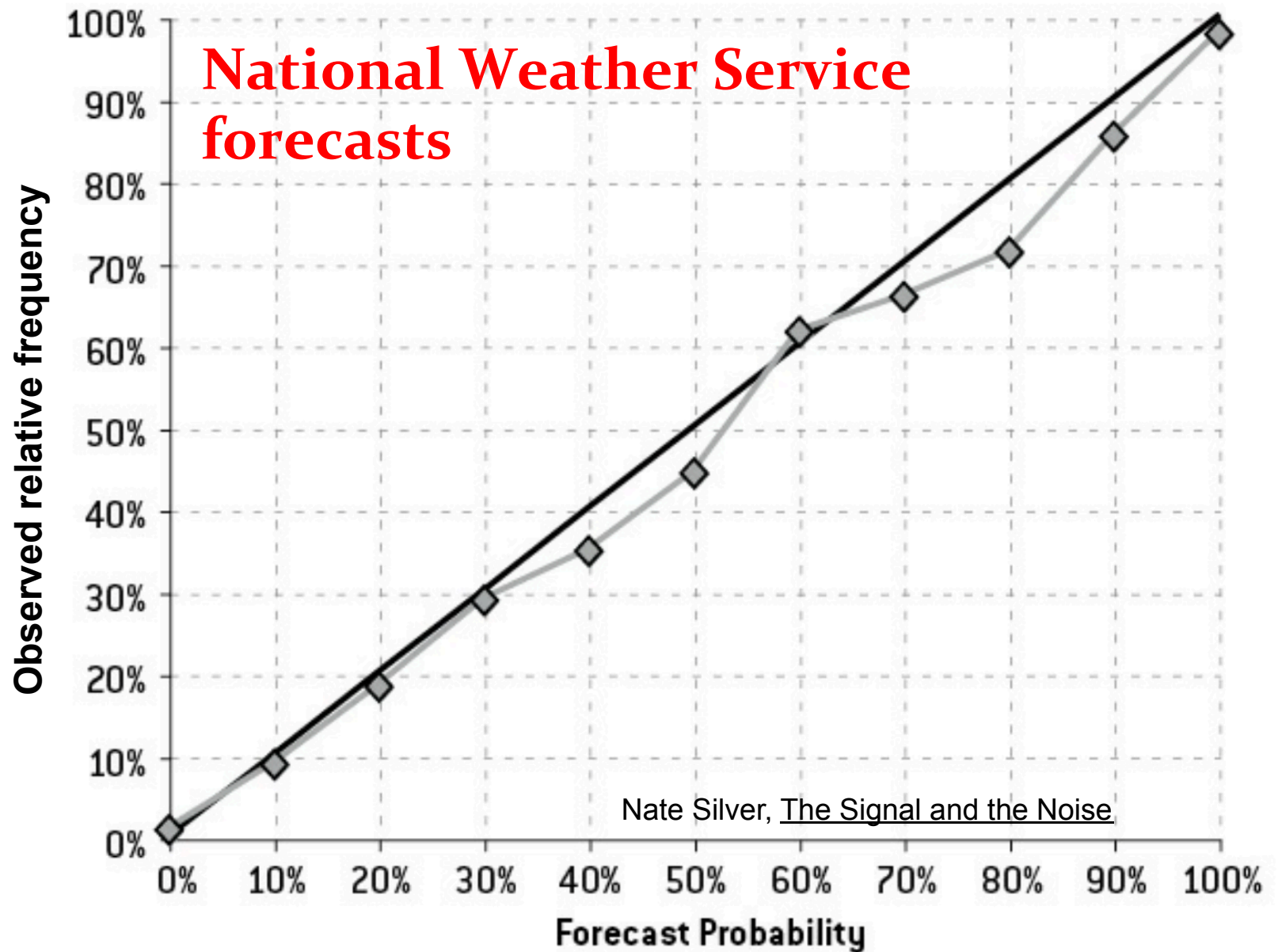
Deterministic vs. probabilistic forecasts

- Deterministic forecasts:
 - Only 0% or 100% probabilities
- Probabilistic forecasts:
 - Convey uncertainty on a *continuum* between 0% and 100%
- Probabilistic forecast quality cannot be verified with a single event

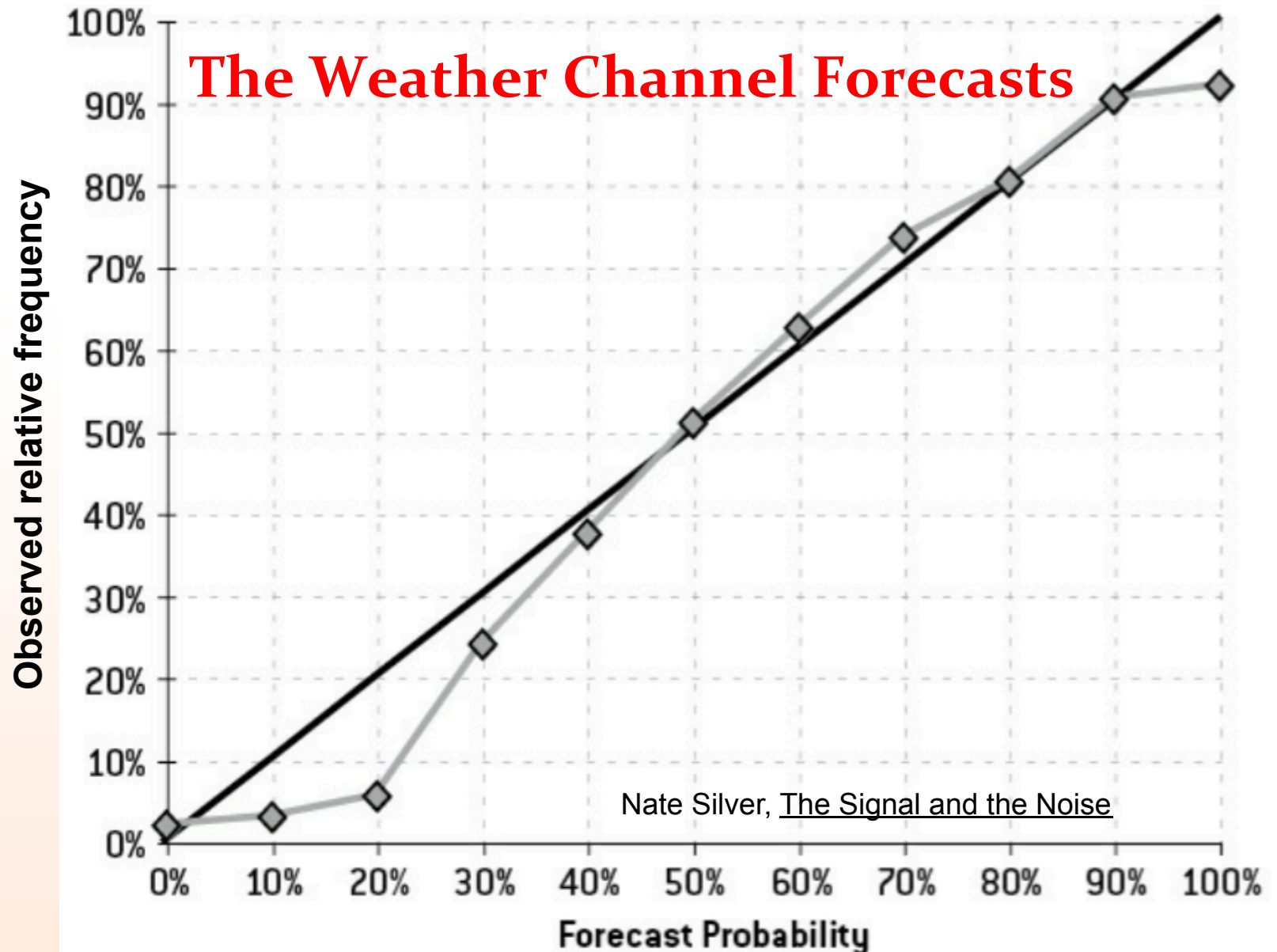
Reliability

- Reliability
 - Given a probabilistic forecast of an event, how often does the event actually occur?
- An important part of an ensemble system
 - Post-processing can improve ensembles that have poor reliability

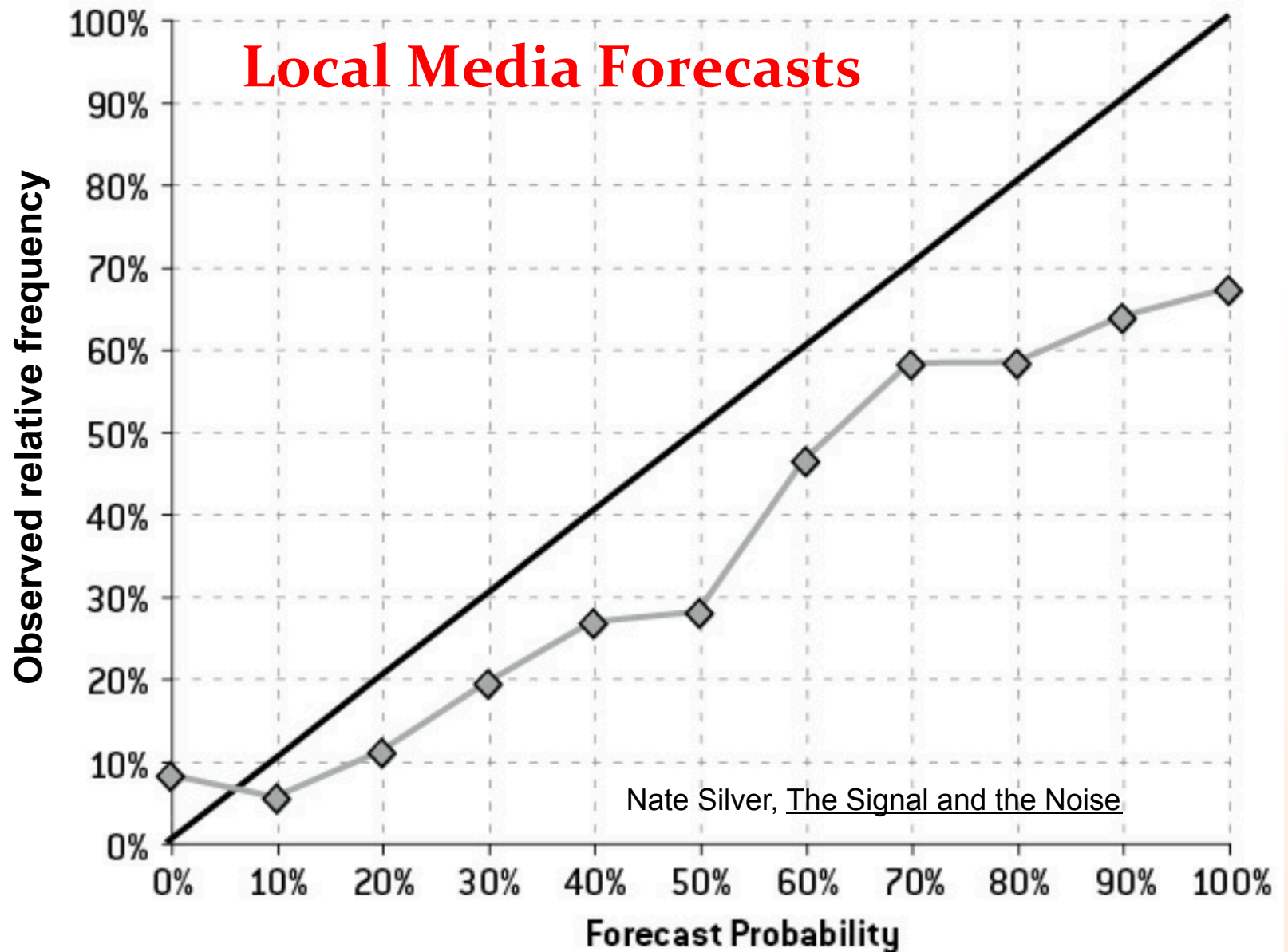
Reliability



Reliability



Reliability



Brier score (BS)

- The Brier score (BS) is commonly used to verify probabilistic forecasts:

$$BS = \frac{1}{N} \sum_{i=1}^N (p_i - o_i)^2$$

- p_i : Probabilistic forecast at point i
- o_i : Observations at i . $o_i = 1$ if the event occurred at i and $o_i = 0$ otherwise

Brier score decomposition (Murphy 1973)

- Brier score can be decomposed into 3 terms:

$$BS = \underbrace{\frac{1}{N} \sum_{k=1}^K n_k (p_k - \bar{o}_k)^2}_{\text{reliability}} - \underbrace{\frac{1}{N} \sum_{k=1}^K n_k (\bar{o}_k - \bar{o})^2}_{\text{resolution}} + \underbrace{\bar{o}(1 - \bar{o})}_{\text{uncertainty}}$$

- Uncertainty term depends only on *observations*
 - Therefore, BS should not be used to compare forecasts from different samples
 - Use a Brier skill score (BSS) to circumvent this issue
 - BSS compares a BS to a reference BS

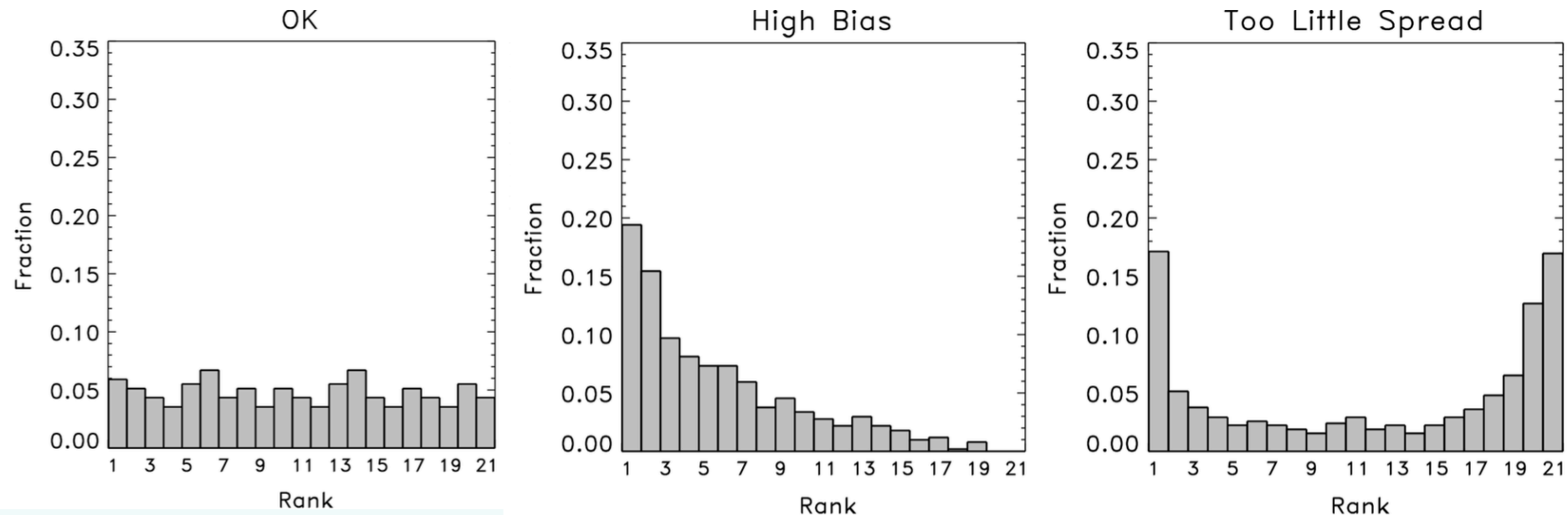
Rank histogram

- Examines ensemble spread
 - Do observations fall within range of the ensemble?
- Sort ensemble members in increasing order and determine where the observation lies with respect to the ensemble members



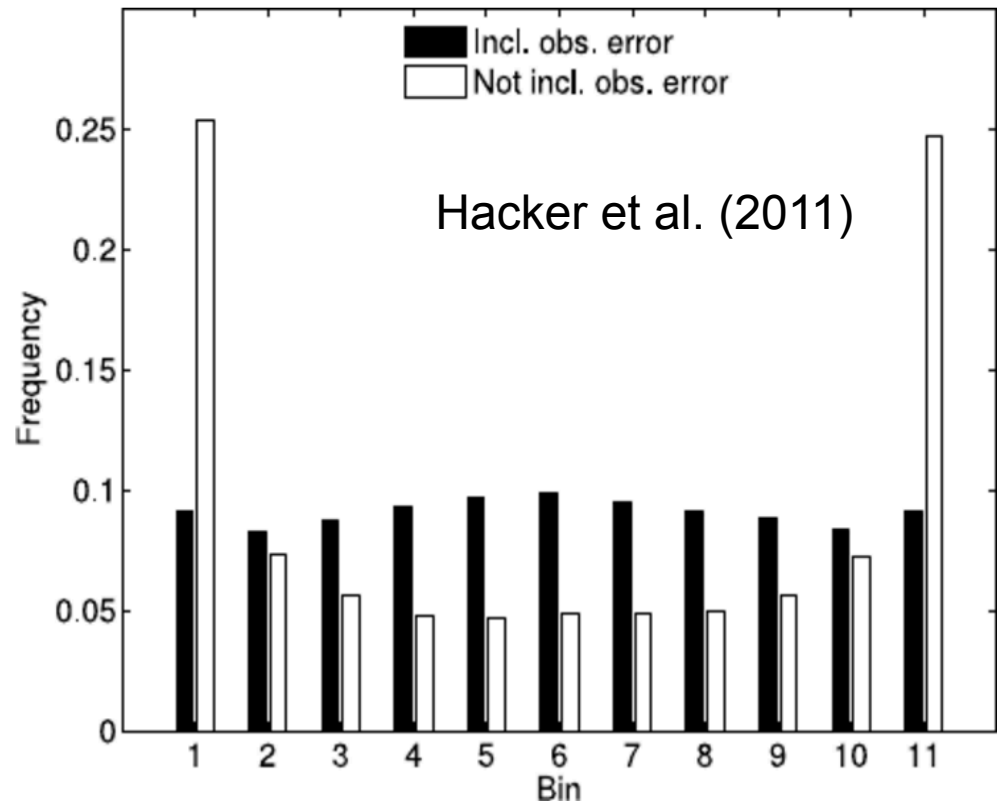
Rank histogram

- Examines ensemble spread
 - Do observations fall within range of the ensemble?



Rank histogram

- Should consider observation errors when producing rank histograms
 - Observation error = measurement error + representativeness error
 - Add noise to each ensemble member
- Hamill (2001) also discusses issues with rank histogram interpretation



“It’s a beautiful day in the neighborhood”

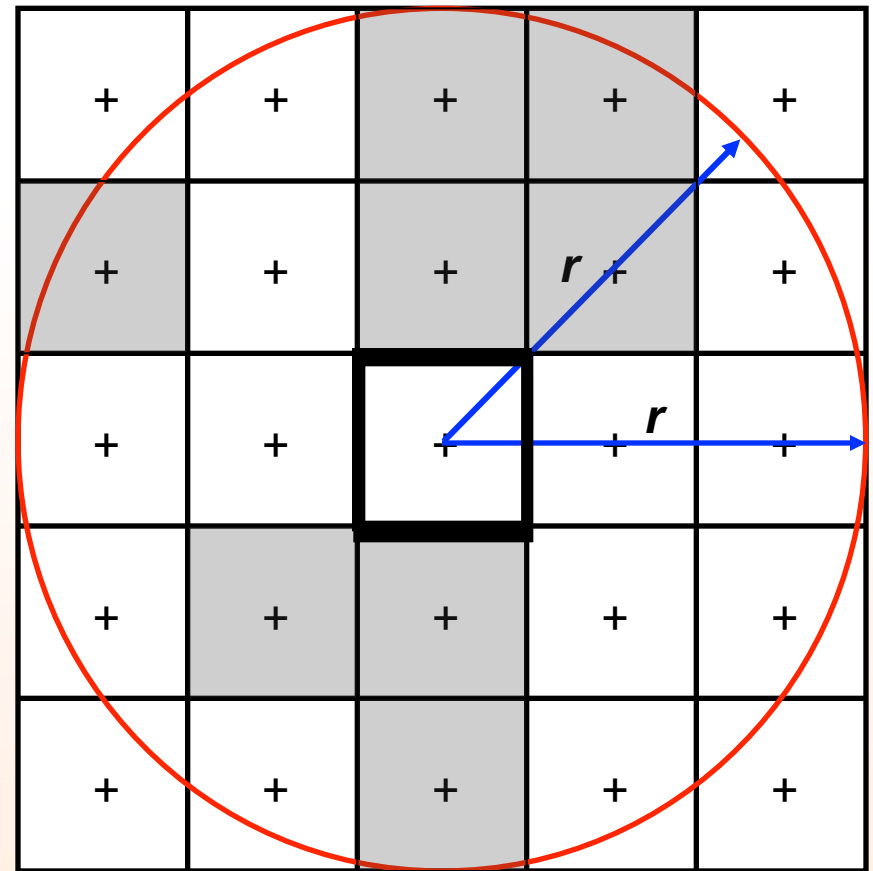


- High-res models are inaccurate at the grid scale
 - Verification methods requiring forecast and observed events match at the grid scale are inappropriate
- Instead, use a “neighborhood approach”
 - Specify a “neighborhood length scale” that defines the tolerance for error
 - Can use either square or circular geometry

Neighborhood approach option 1

- Pick a threshold
- The threshold has been met or exceeded in the shaded boxes
- Can be viewed as a spatial average (i.e., a *smoother*)

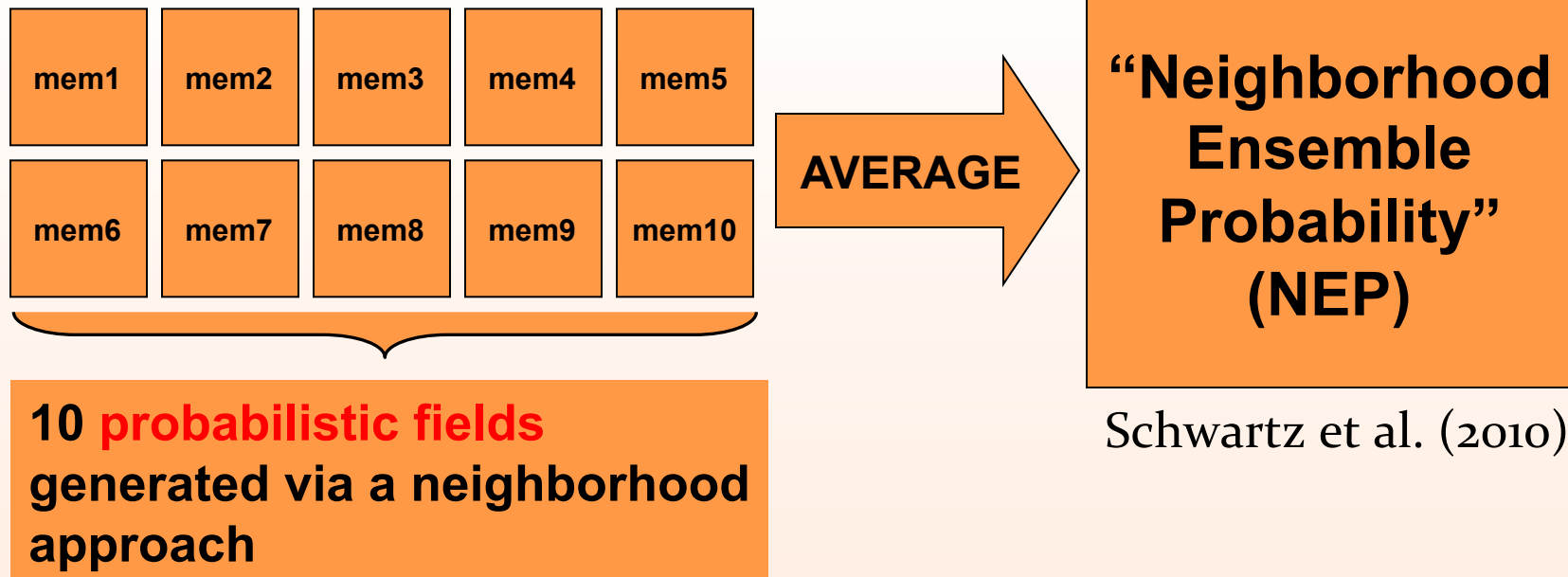
Hypothetical model output



$$P = 8/21 = 38\%$$

Neighborhood approach applied to ensembles option 1

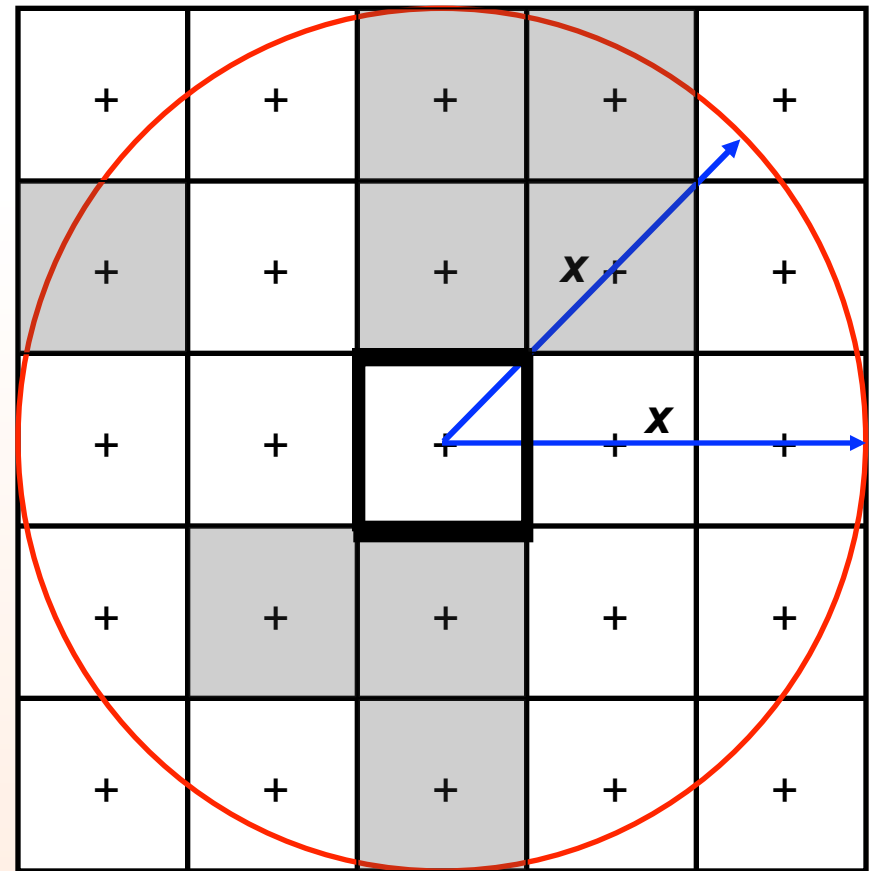
- Apply neighborhood approach as described on previous slide to each ensemble member separately
 - For each member, get a value **between 0 and 1**
 - Average all probabilistic fields



Neighborhood approach option 2

- Pick a threshold
- The threshold has been met or exceeded in the shaded boxes
- If the threshold is met or exceeded *anywhere* within the neighborhood, give the point a value of 1

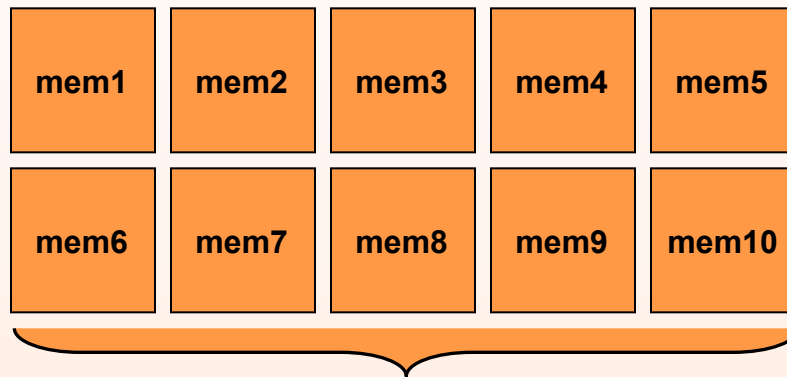
Hypothetical model output



P = 100%

Neighborhood approach applied to ensembles option 2

- If, at a point, an **event occurs anywhere within the neighborhood**, give the point a value of 1, otherwise 0
 - Do this for all ensemble members individually
 - Average across the ensemble to get a probability **between 0 and 1**



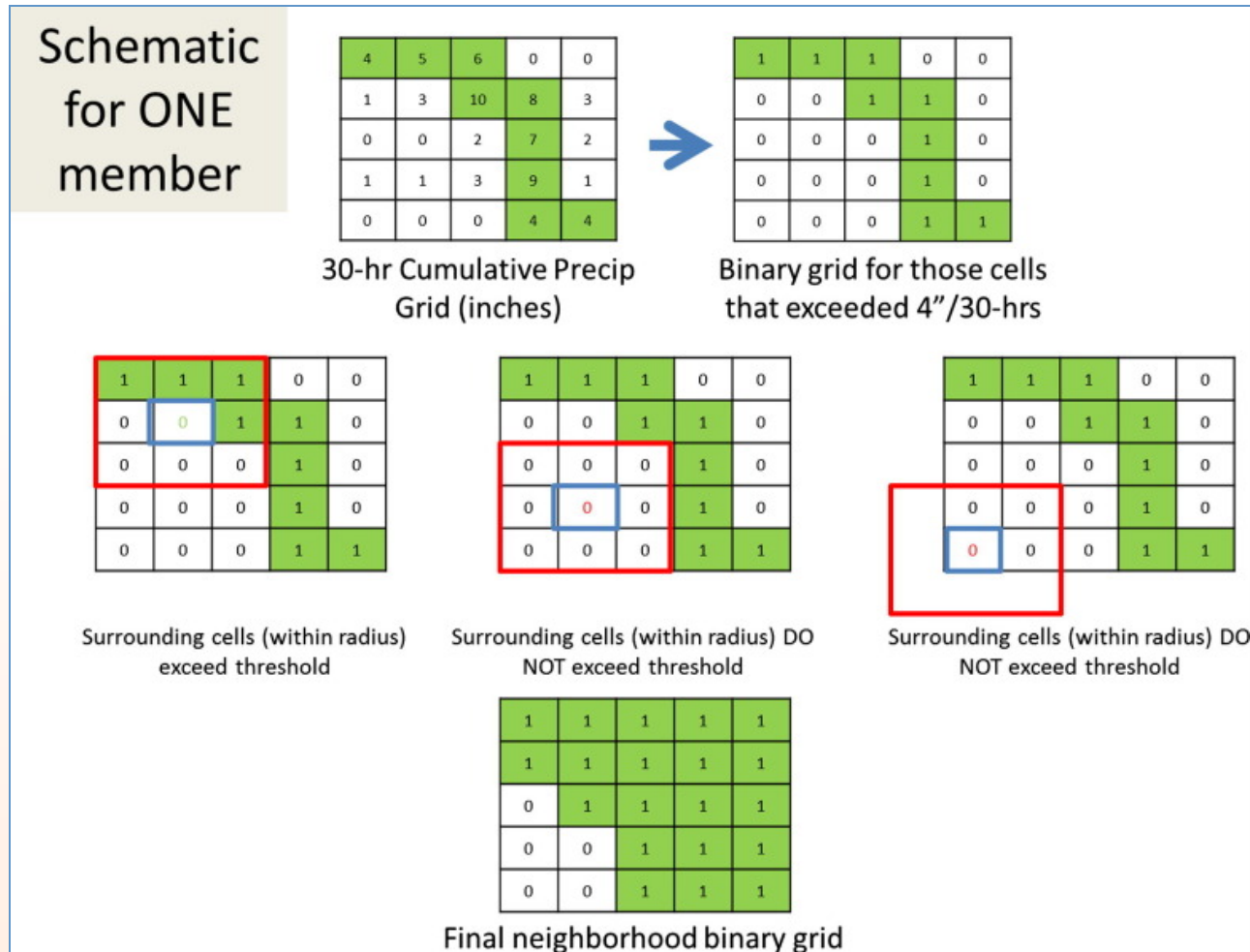
10 binary fields generated via a neighborhood approach

AVERAGE

**“Neighborhood
Maximum
Ensemble
Probability”
(NMEP)**

Schematic of NMEP

- From Hardy et al. (2016)



- Do this for N members, then average the fields

Interpretations

- NEP
 - “Probability of an event occurring *at grid point i* ”
(considering the neighborhood length scale)
 - Grid-scale probability
 - Spatial scale of event: the grid-scale
- NMEP
 - “Probability of an event occurring *within x km of i* ”
 - Non-grid-scale probability
 - Spatial scale of event: larger than grid-scale (x km)

Further interpretations

- NEP

- Neighborhood length scale is a *smoothing* scale (r)
- Smooths probabilities
- Discretized in intervals of $1/N^*N_b$ (effectively continuous)

N : ensemble size

N_b : number of points in the neighborhood

- NMEP

- Neighborhood length scale is a *searching* scale (x)
- Discretized in intervals of $1/N$

See Schwartz and Sobash (2017) for more on NEPs and NMEPs

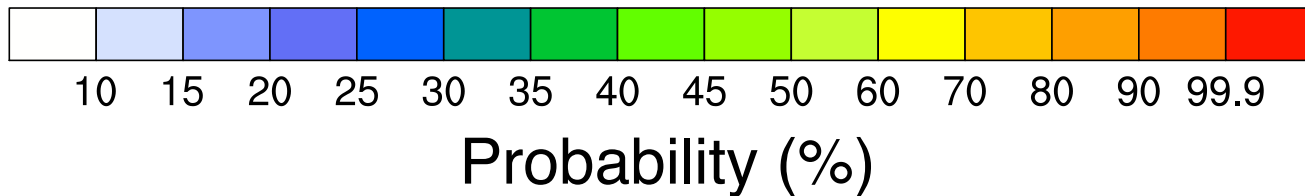
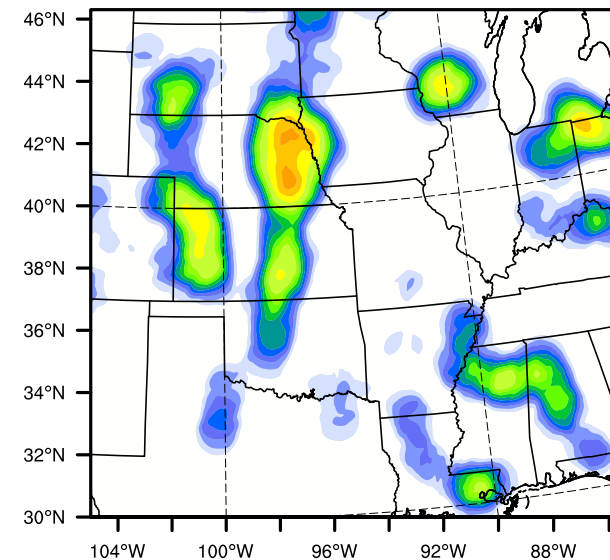
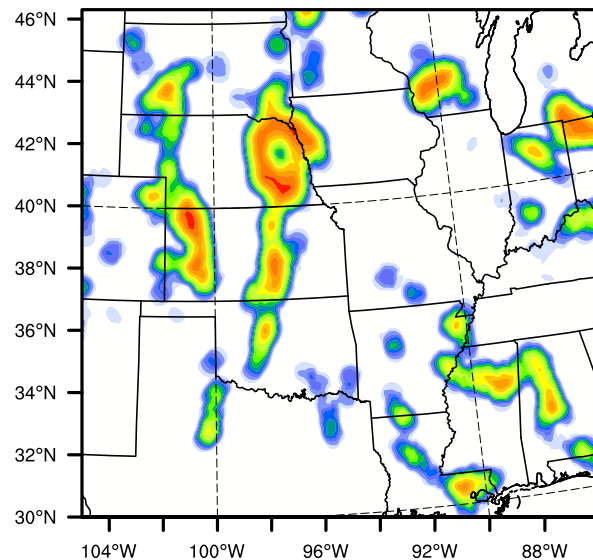
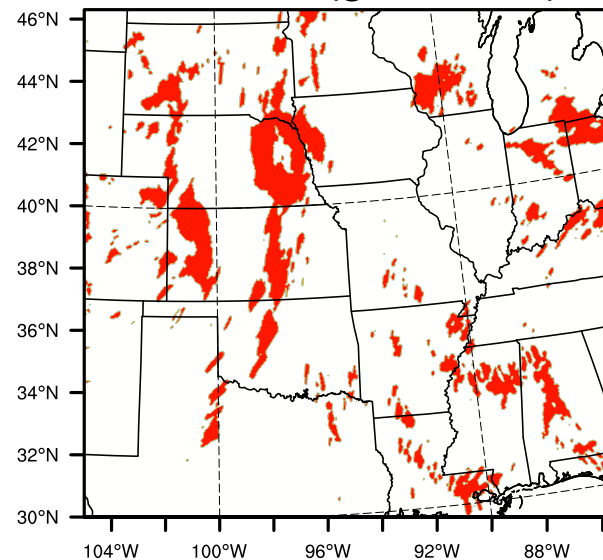
NEPs for a single member

- NEPs of 1-h precipitation ≥ 1.0 mm/h

$r = 0$ km (grid scale)

$r = 50$ km

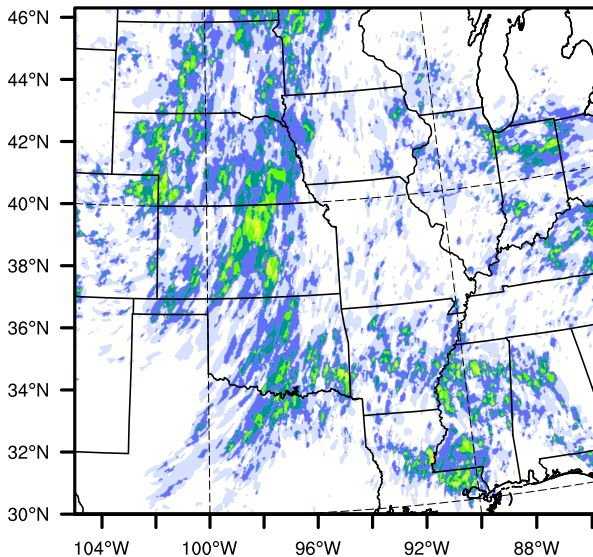
$r = 100$ km



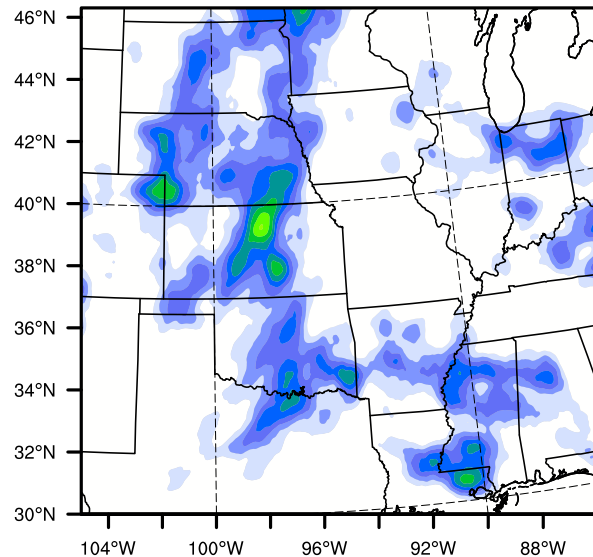
NEPs for a 10-member ensemble

- NEPs of 1-h precipitation ≥ 1.0 mm/h

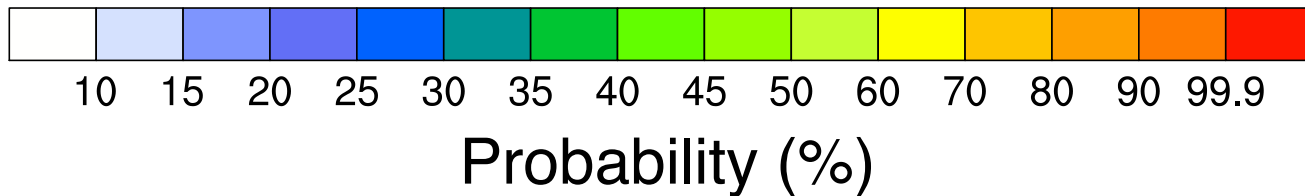
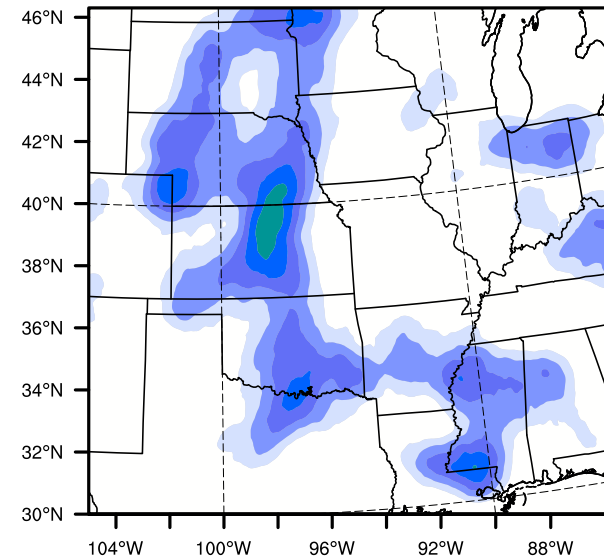
$r = 0$ km (grid scale)



$r = 50$ km



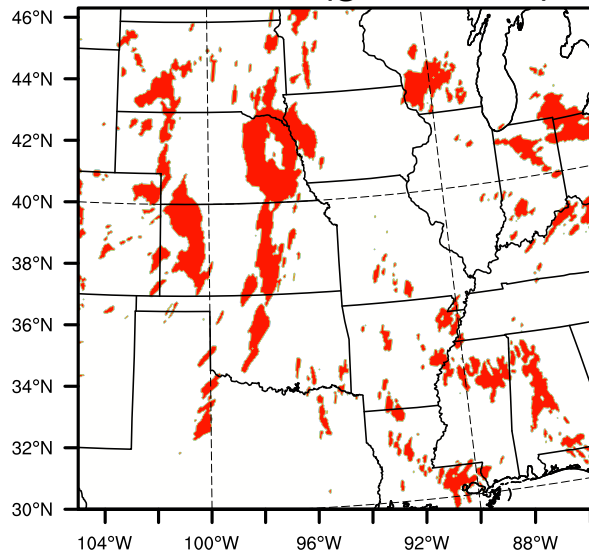
$r = 100$ km



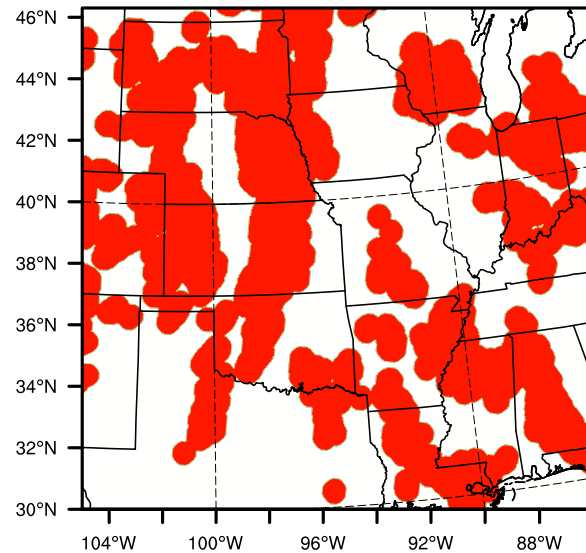
NMEPs for a single member

- NMEPs of 1-h precipitation ≥ 1.0 mm/h

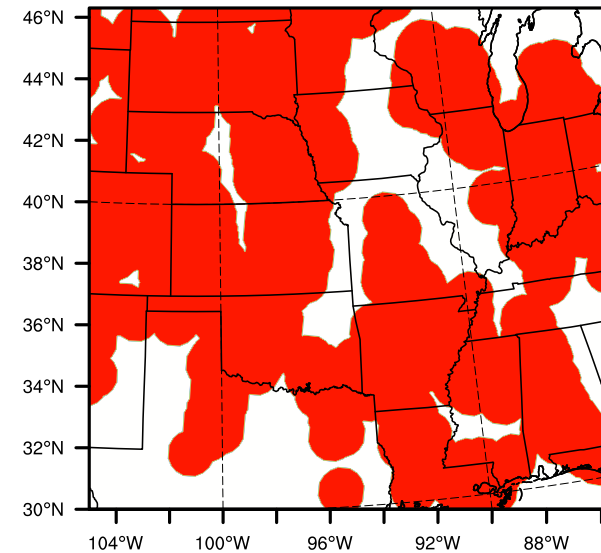
$x = 0$ km (grid scale)



$x = 50$ km



$x = 100$ km

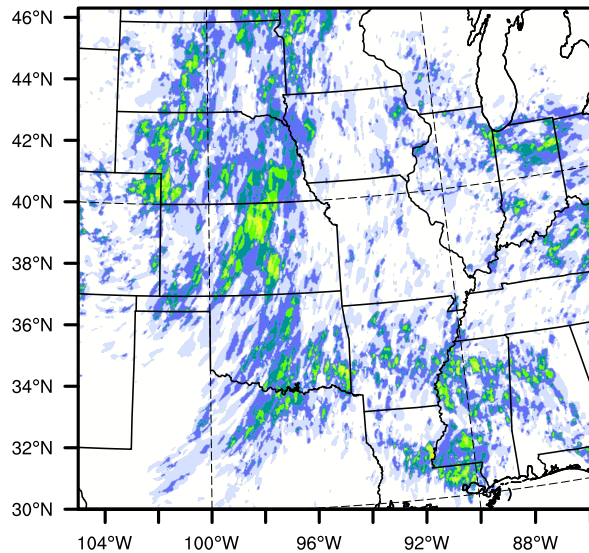


Probability (%)

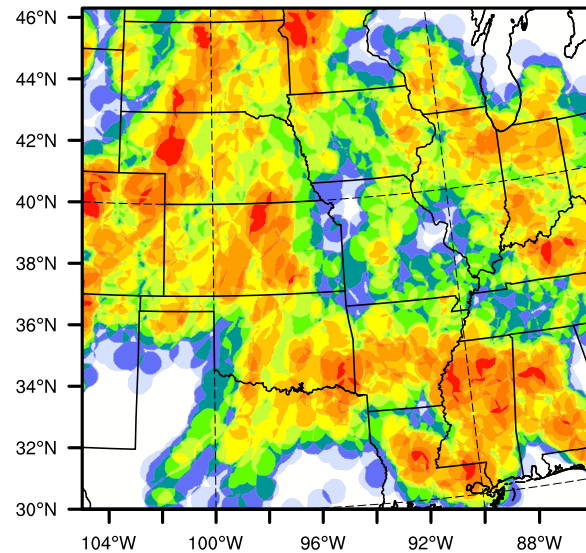
NMEPs for a 10-member ensemble

- NMEPs of 1-h precipitation ≥ 1.0 mm/h

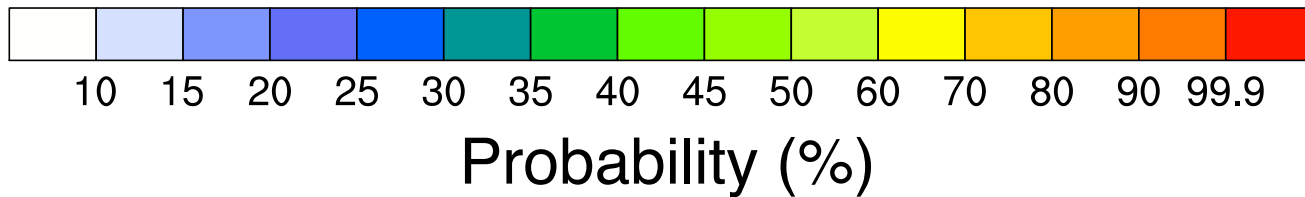
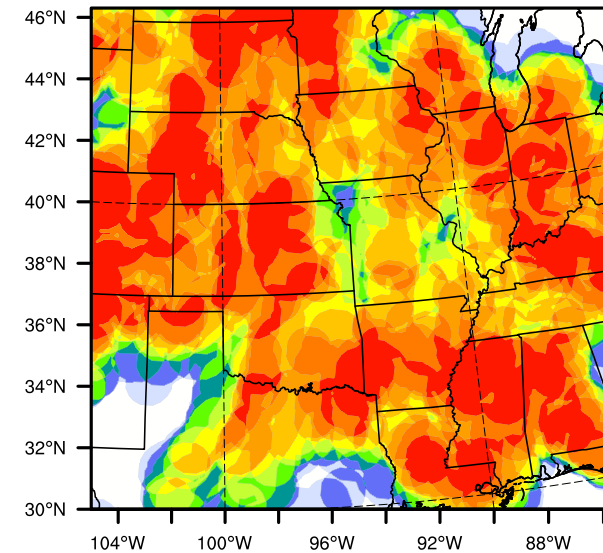
$x = 0$ km (grid scale)



$x = 50$ km

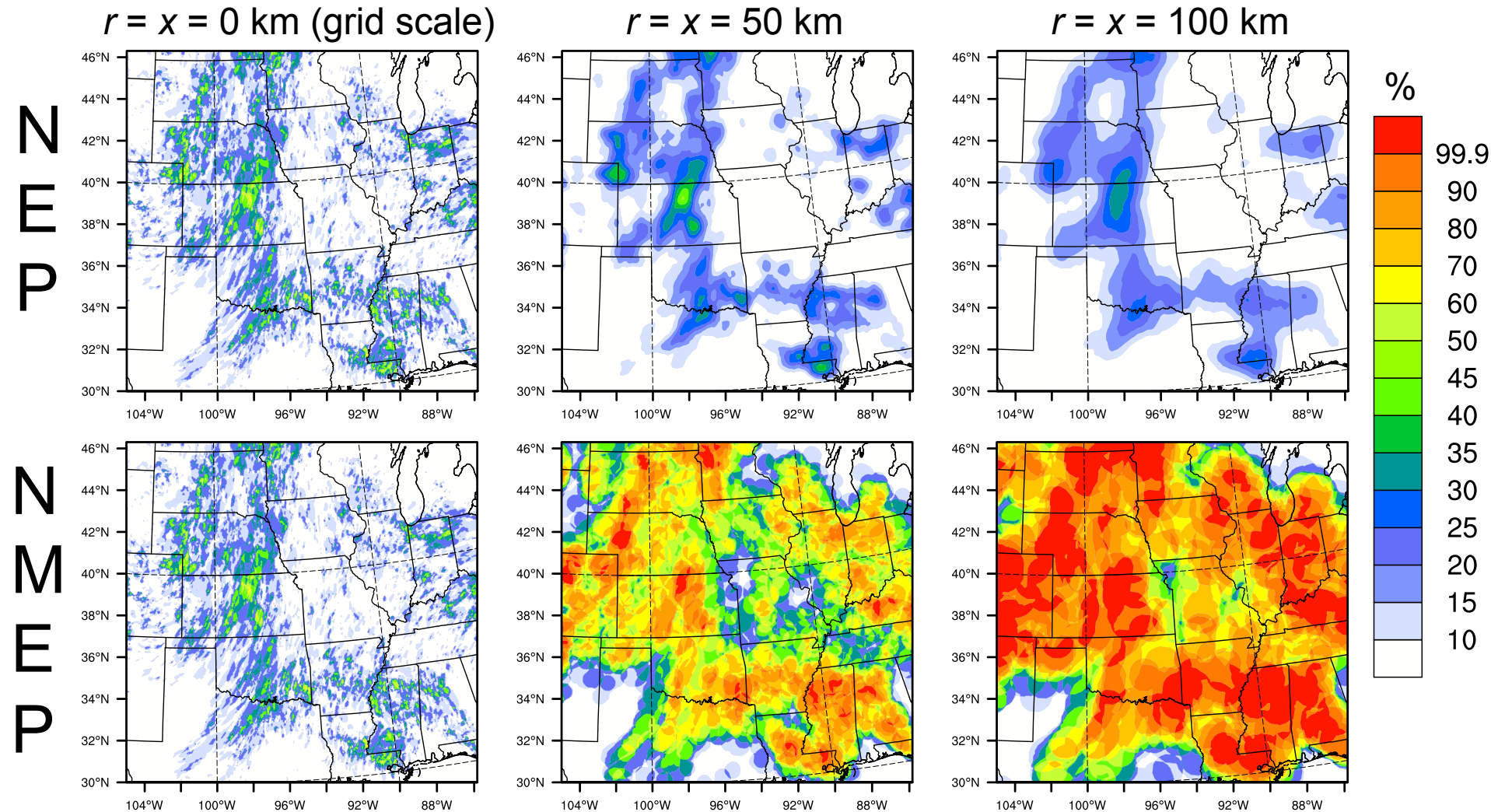


$x = 100$ km



10-member ensemble NEPs and NMEPs

- NEPs/NMEPs of 1-h precipitation ≥ 1.0 mm/h



Some references

- Hacker, J., and Coauthors, 2011: The U.S. Air Force Weather Agency's mesoscale ensemble: Scientific description and performance results. *Tellus*, **63A**, 625–641, doi:10.1111/j.1600-0870.2010.00497.x.
- Hamill, T. M., 2001: Interpretation of rank histograms for verifying ensemble forecasts. *Mon. Wea. Rev.*, **129**, 550–560, doi:10.1175/1520-0493(2001)129<0550:IORHFV>2.0.CO;2.
- Hardy, J., J. J. Gourley, P.-E. Kirstetter, Y. Hong, F. Kong, and Z. L. Flamig, 2016: A method for probabilistic flash flood forecasting. *Journal of Hydrology*, **541**, 480–494, doi:10.1016/j.jhydrol.2016.04.007.
- Murphy, A. H., 1973: A new vector partition of the probability score. *J. Appl. Meteor.*, **12**, 595–600, doi:10.1175/1520-0450(1973)012<0595:ANVPOT>2.0.CO;2.
- Murphy, A. H., 1993: What is a good forecast? An essay on the nature of goodness in weather forecasting. *Wea. Forecasting*, **8**, 281–293, doi:10.1175/1520-0434(1993)008<0281:WIAGFA>2.0.CO;2.
- Schwartz, C. S., and Coauthors, 2010: Toward improved convection-allowing ensembles: Model physics sensitivities and optimizing probabilistic guidance with small ensemble membership. *Wea. Forecasting*, **25**, 263–280, doi:10.1175/2009WAF2222267.1.
- Schwartz, C. S., G. S. Romine, K. R. Smith, and M. L. Weisman, 2014: Characterizing and optimizing precipitation forecasts from a convection-permitting ensemble initialized by a mesoscale ensemble Kalman filter. *Wea. Forecasting*, **29**, 1295–1318, doi:10.1175/WAF-D-13-00145.1.

References

Schwartz, C. S., and R. A. Sobash, 2017: Generating probabilistic forecasts from convection-allowing ensembles using neighborhood approaches: A review and recommendations. *Mon. Wea. Rev.*, In press, doi: 10.1175/MWR-D-16-0400.1.

Wilks, D., 1995: Statistical Methods in the Atmospheric Sciences. Academic Press, 464pp.

A useful powerpoint: <http://www.atmos.umd.edu/~ekalnay/syllabi/AOSC630/ensemble101.pdf>

Take-home messages

- Verify ensembles probabilistically
 - Do not treat ensembles as a collection of deterministic forecasts!
- Be careful dealing with observations in the Brier score and rank histogram
- If using a neighborhood approach, explicitly state your methods and interpretations of resulting probabilistic fields

Why ensemble forecasts are desirable

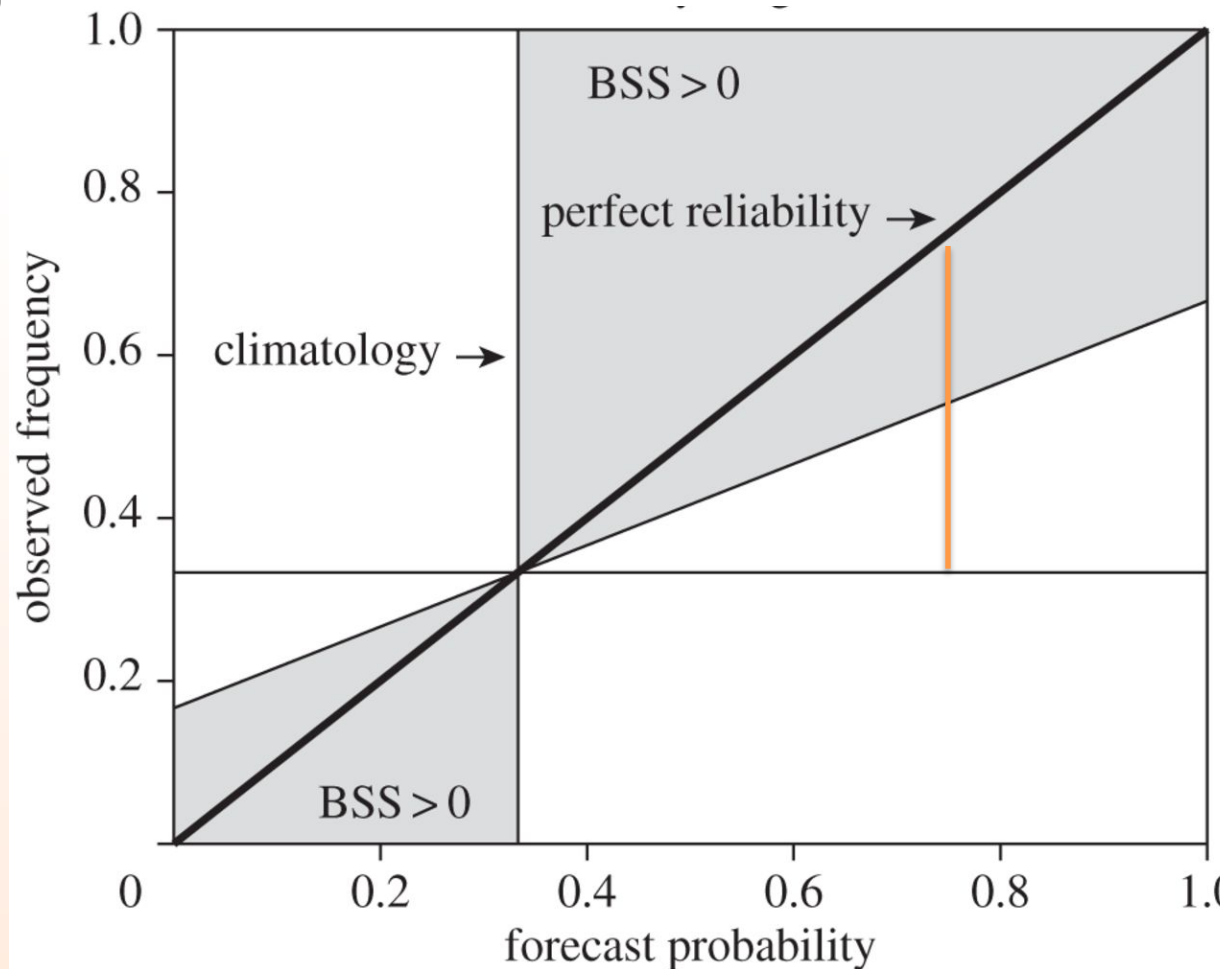
- Quantification of uncertainty
 - Naturally produces probabilities!
 - Allows forecasters to forecast their “true beliefs”
 - Allows users to make decisions based on expected value and cost-loss scenarios
- Errors of different members cancel when combining forecasts across members
 - Forecasts combining information across all members are better than single deterministic forecasts

Resolution

- Resolution refers to the ability of the ensemble to distinguish between various events
- Unlike reliability, resolution cannot be easily fixed!
 - Accordingly, some people believe resolution is the most important aspect of an ensemble

Attributes diagram

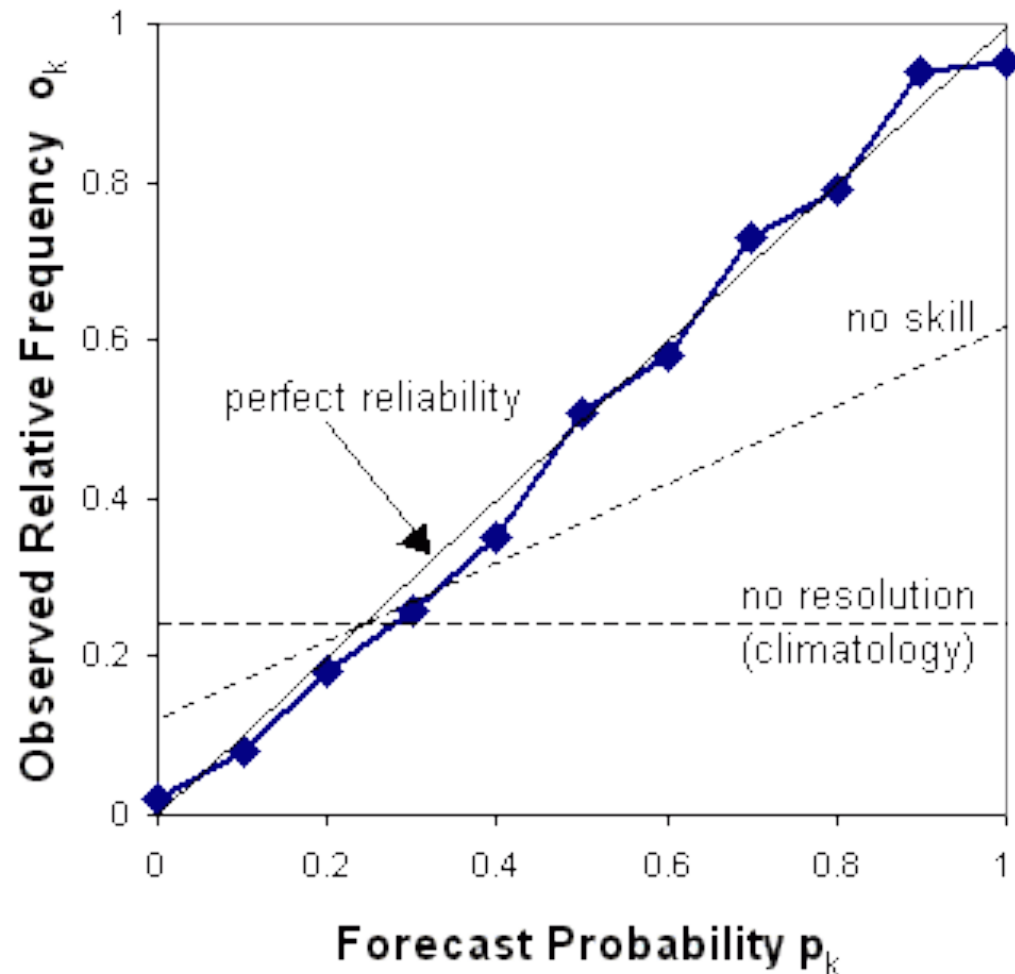
- Synthesize information about reliability, resolution, and Brier skill score
 - See Wilks (1995)



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Attributes diagram

- Synthesize information about reliability, resolution, and Brier skill score
 - See Wilks (1995)



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