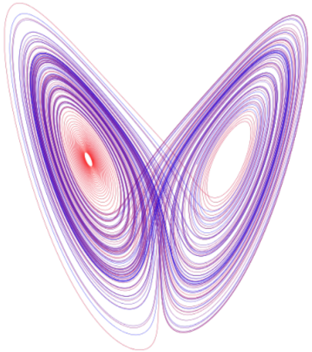
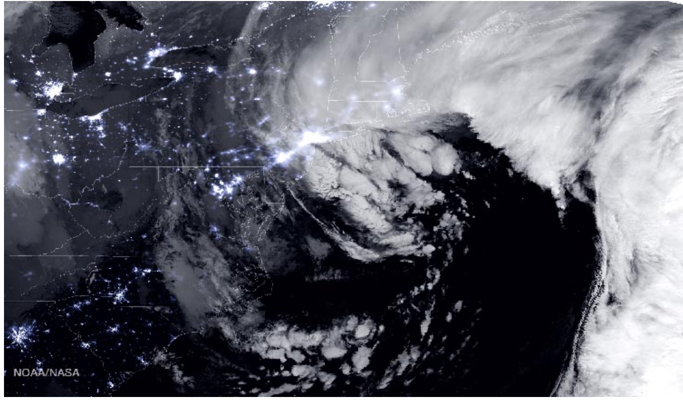




Evaluating Predictability of High-Impact Weather using Convective-Allowing Ensemble Forecasts: Winter Snowstorms and Spring Thunderstorms

Steven J. Greybush

and graduate students Seth Saslo and Glen Hanson

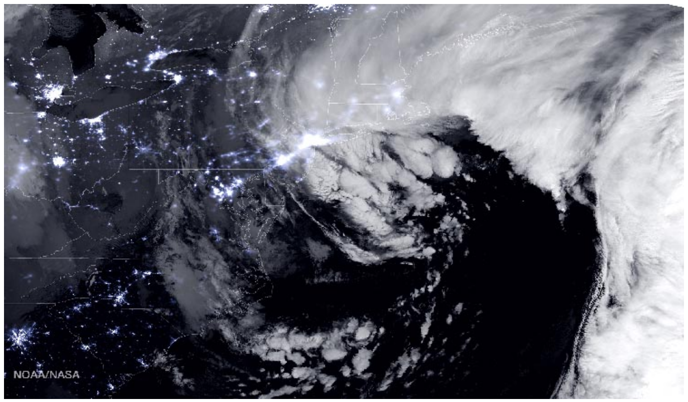
The Pennsylvania State University, USA

UMD / PSU DA Workshop; College Park, MD

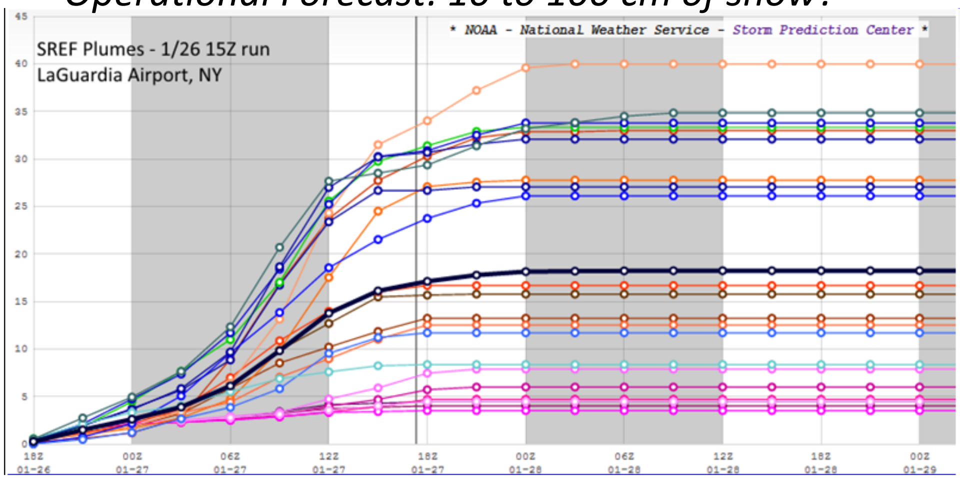
June 26, 2017

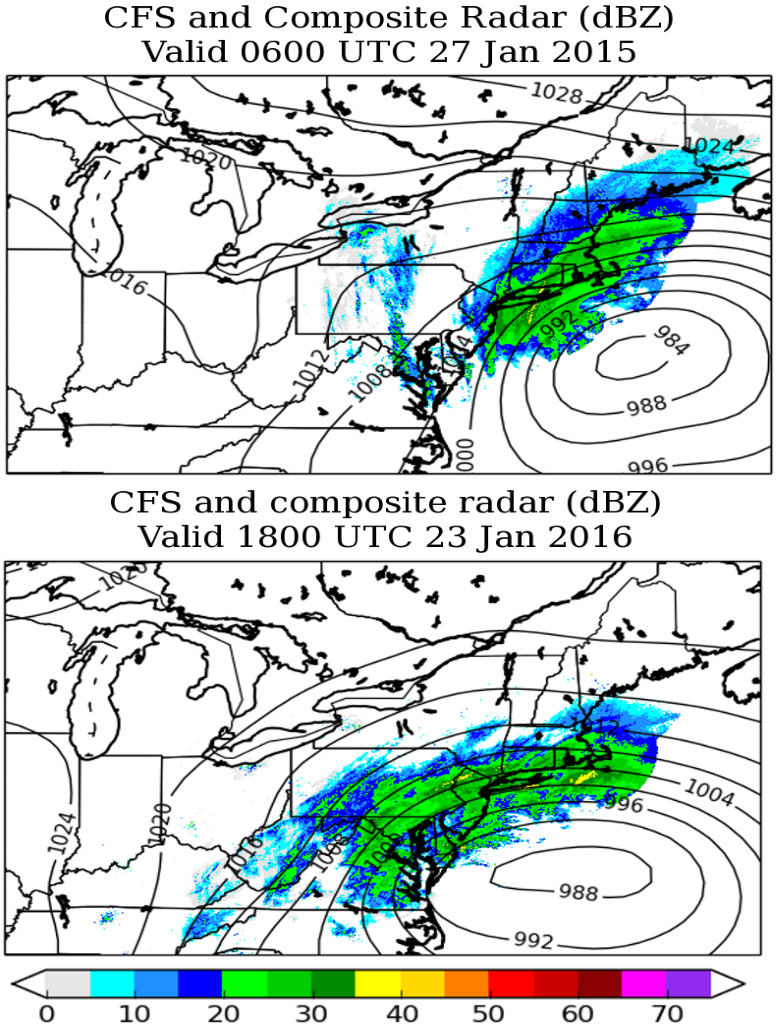
Acknowledgements: Fuqing Zhang, David Stensrud, George Young (PSU) Rich Grumm (NWS)

Assessing the Ensemble Predictability of East Coast Winter Storms



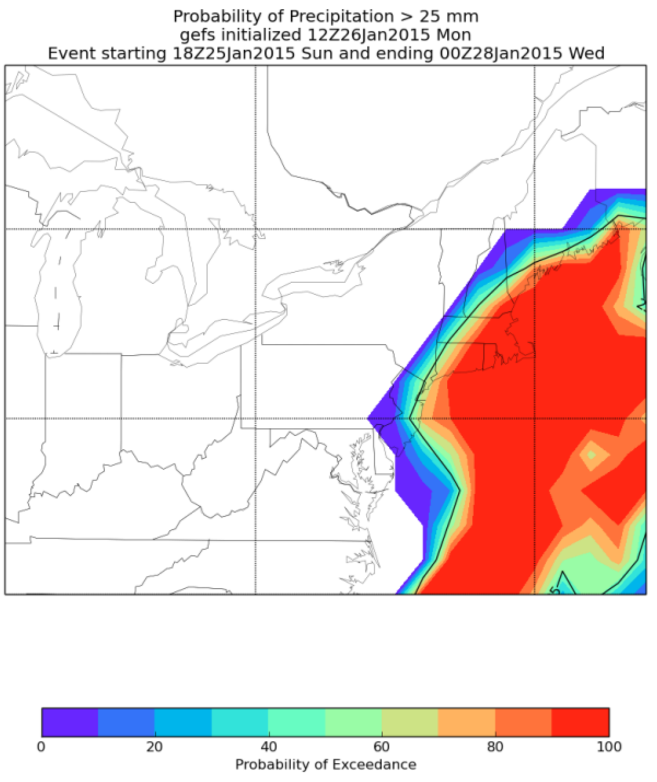
Operational Forecast: 10 to 100 cm of snow?

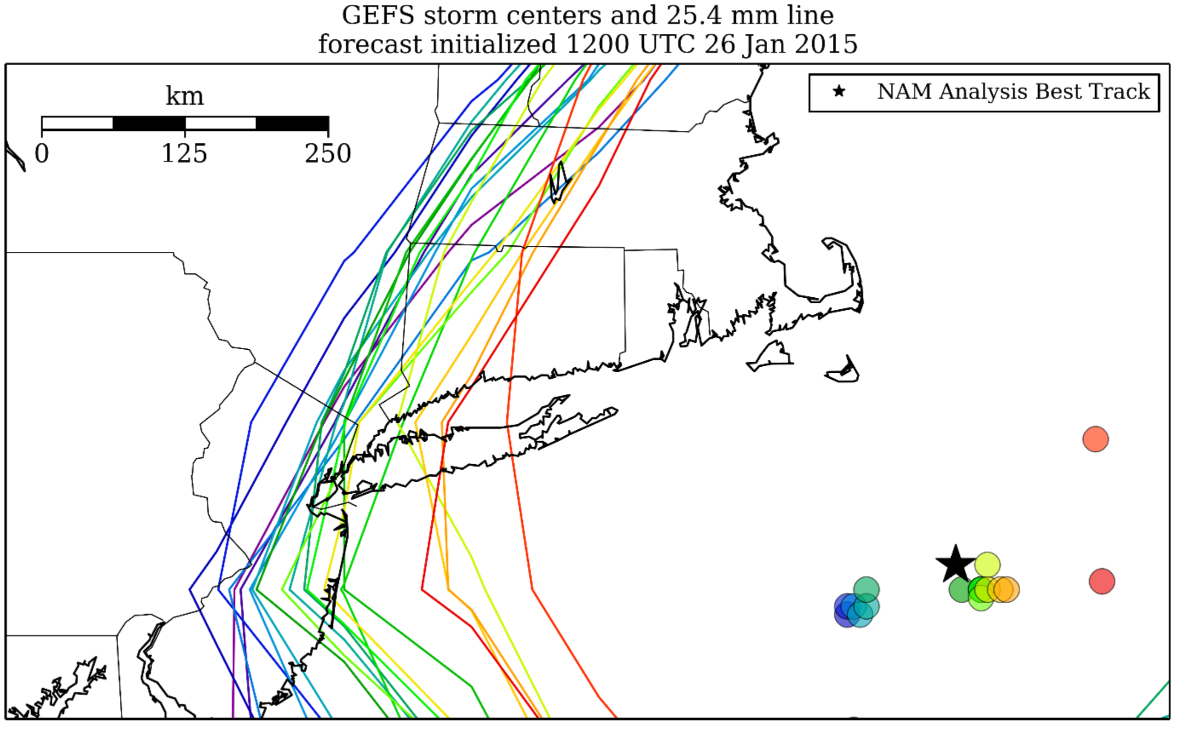




Greybush, Saslo, and Grumm, 2017, WAF

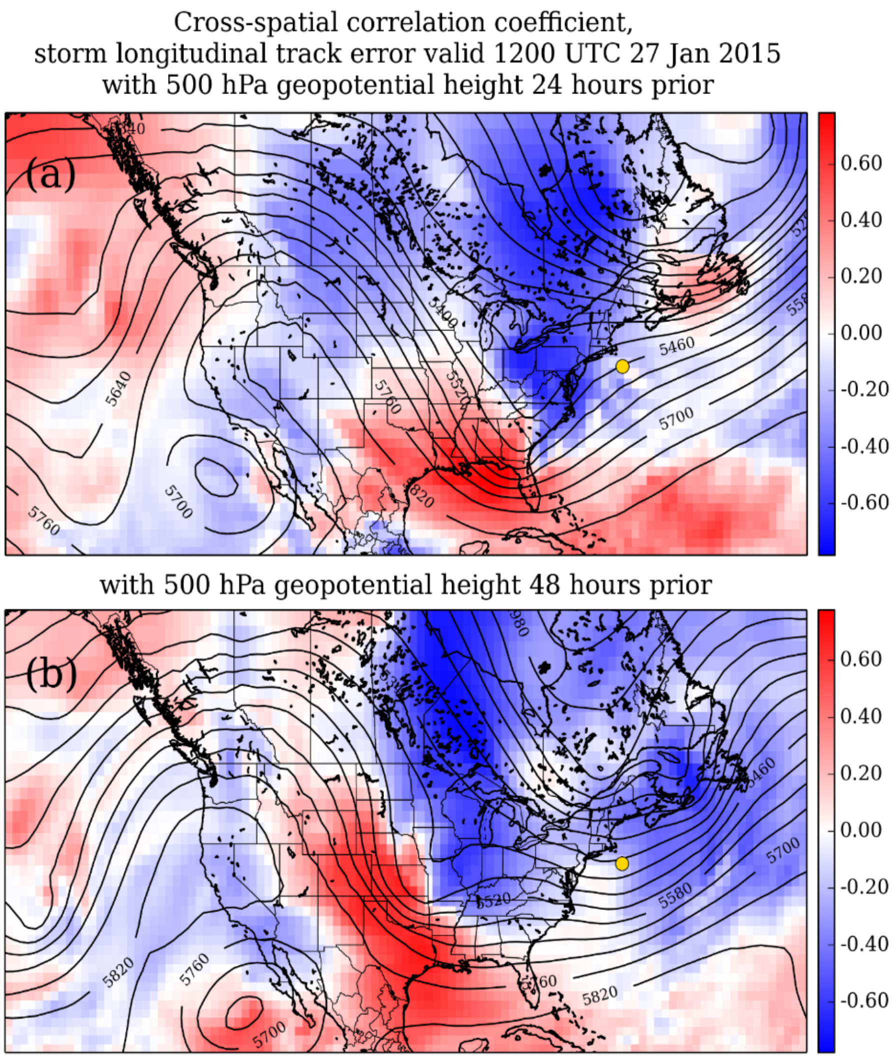
Origins of Ensemble Spread for January 2015 Snowstorm





Tight gradient in probability of precipitation (left) linked to position of coastal low pressure (right).

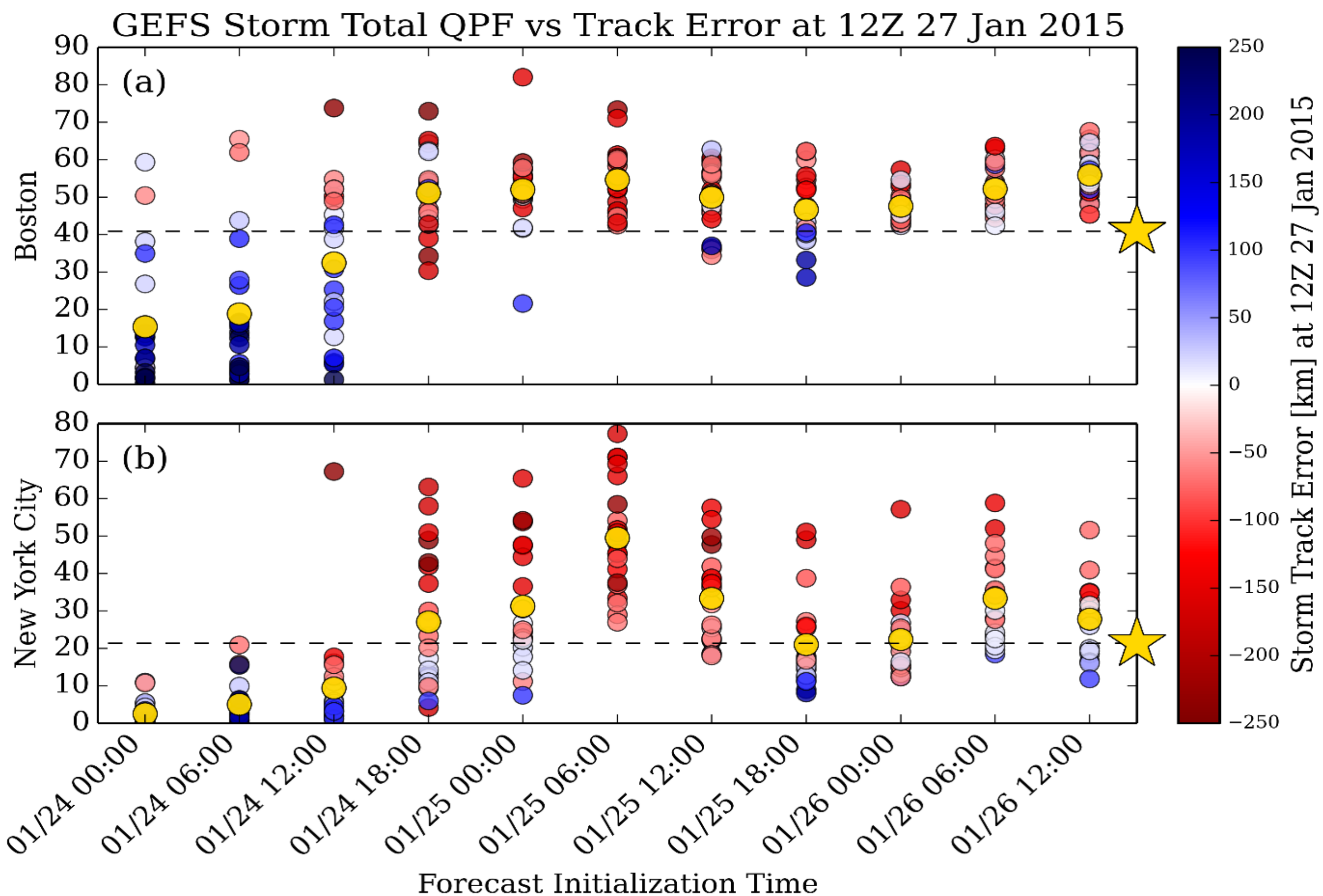
Ensemble Sensitivity



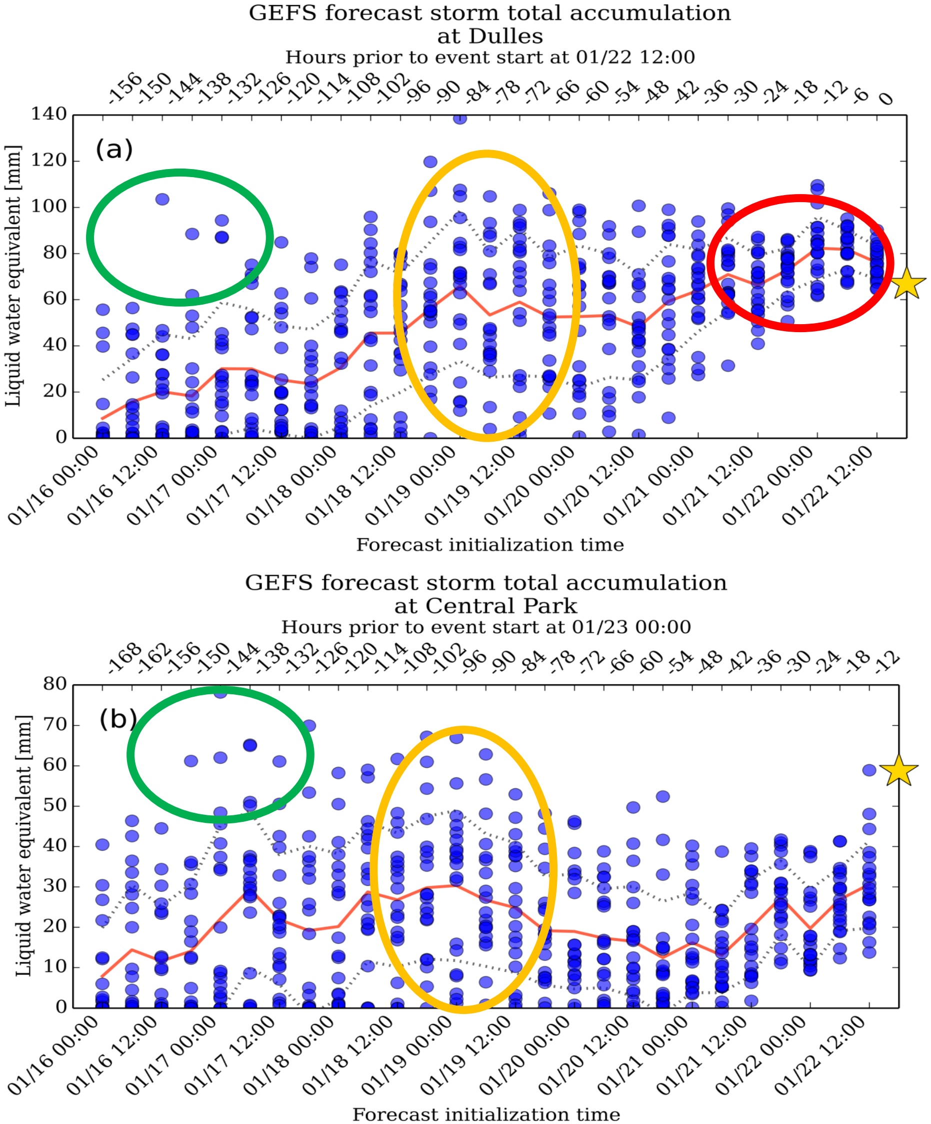
Position error in coastal low traced backwards in time to uncertainties in synoptic scale flow (contours) using ensemble sensitivity (shading).

Red: 500 mb height field is positively correlated with eastward track error.

QPF and Track Error as function of Forecast Lead Time



Predictability Horizons



To answer: How far in advance is a feature predictable?

First, identify an event (location, variable type, etc.).

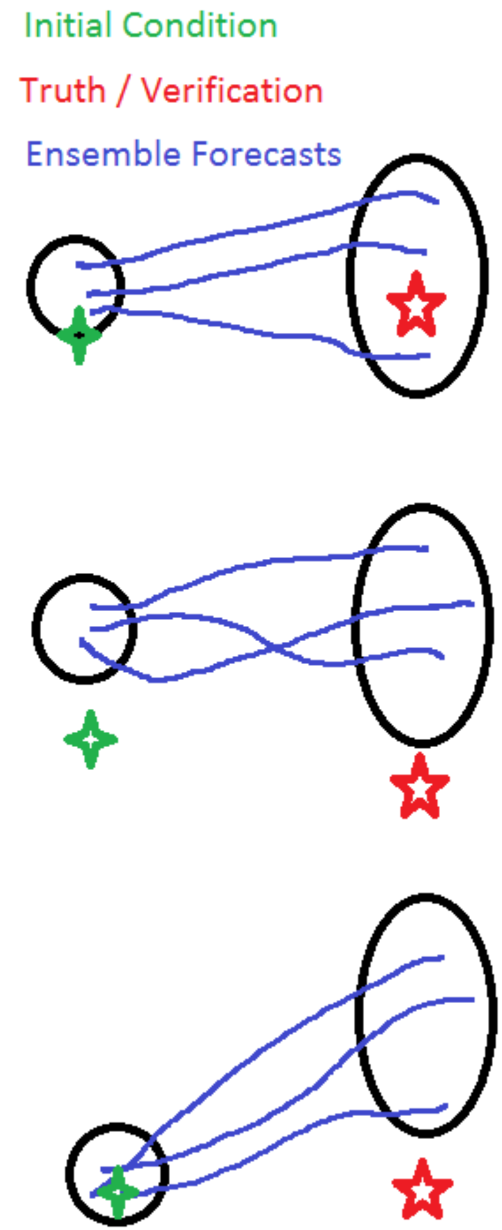
Then characterize, using the ensemble, the:

- initial detection
- emergence of a signal
- convergence of solutions

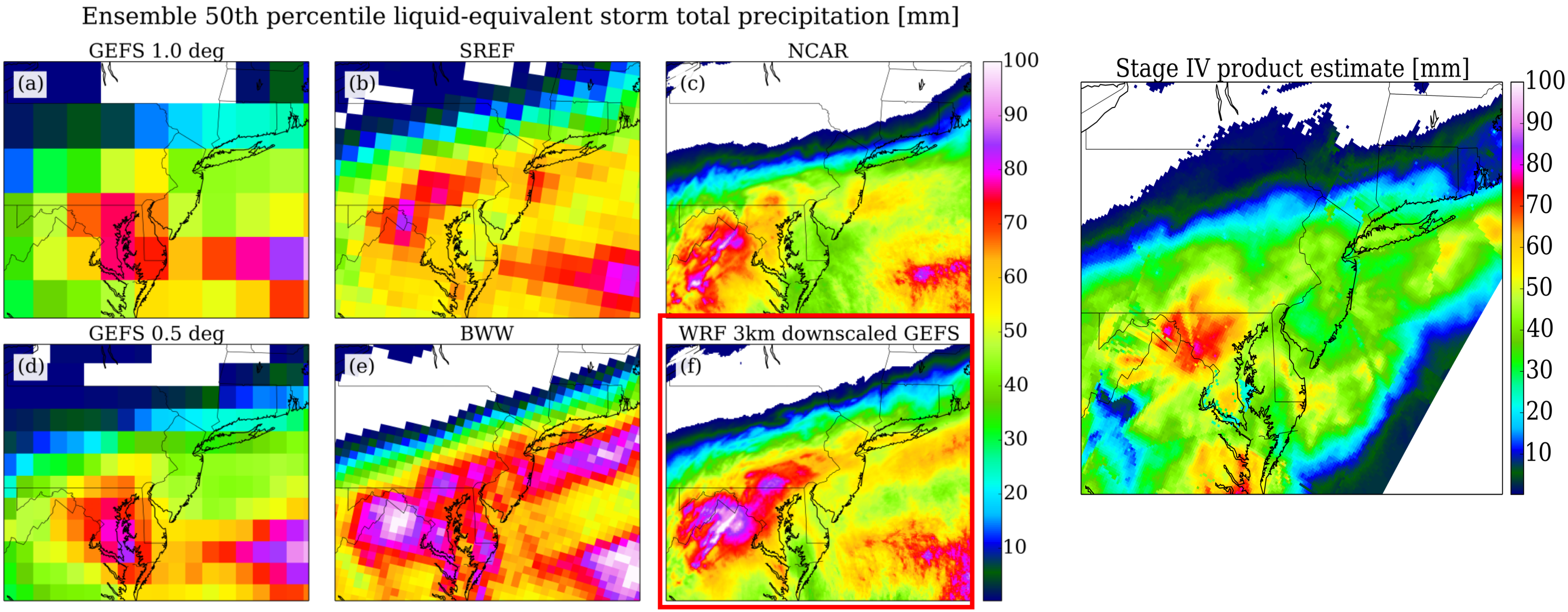
General Goals with Ensemble Prediction

- Compare ensemble spread and error statistics.
- Characterize predictability timescales.
- Understand origins of forecast errors and spread growth.
- Design ensemble DA and perturbation methods to maintain spread / skill relationship and achieve reliable forecasts.

- Challenge: ensemble design and DA in light of instabilities and model error

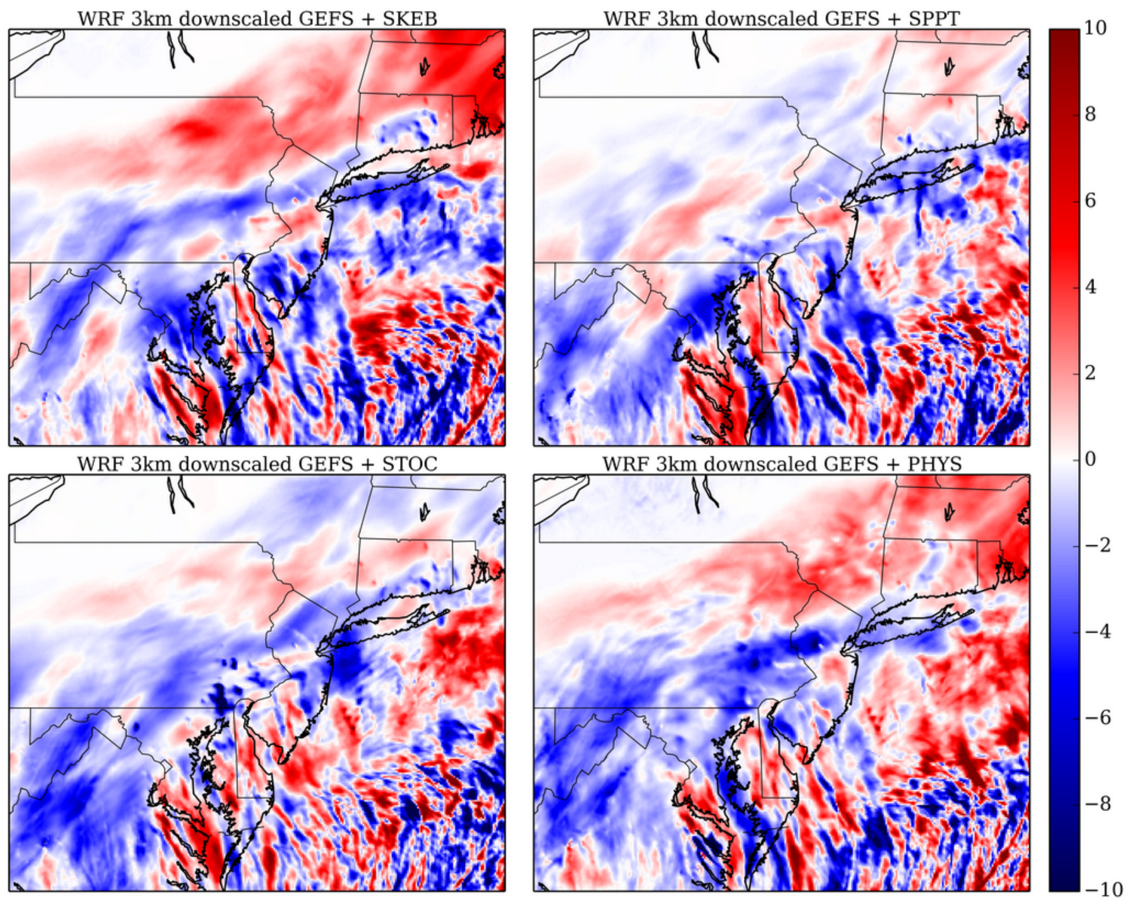


Convective-Allowing Ensembles for Winter Storms



Precipitation from operational and convective-allowing ensembles (left) compared to radar-estimated observations (right).

Which perturbation method is best?



Control (GEFS+ WRF)
CRPS = 6.638

SKEB = Stochastic Kinetic Energy Backscatter
CRPS = 6.483

SPPT = Stochastically Perturbed Parameterization Tendency
CRPS = 6.480

STOC = SKEB + SPPT
CRPS = 6.494

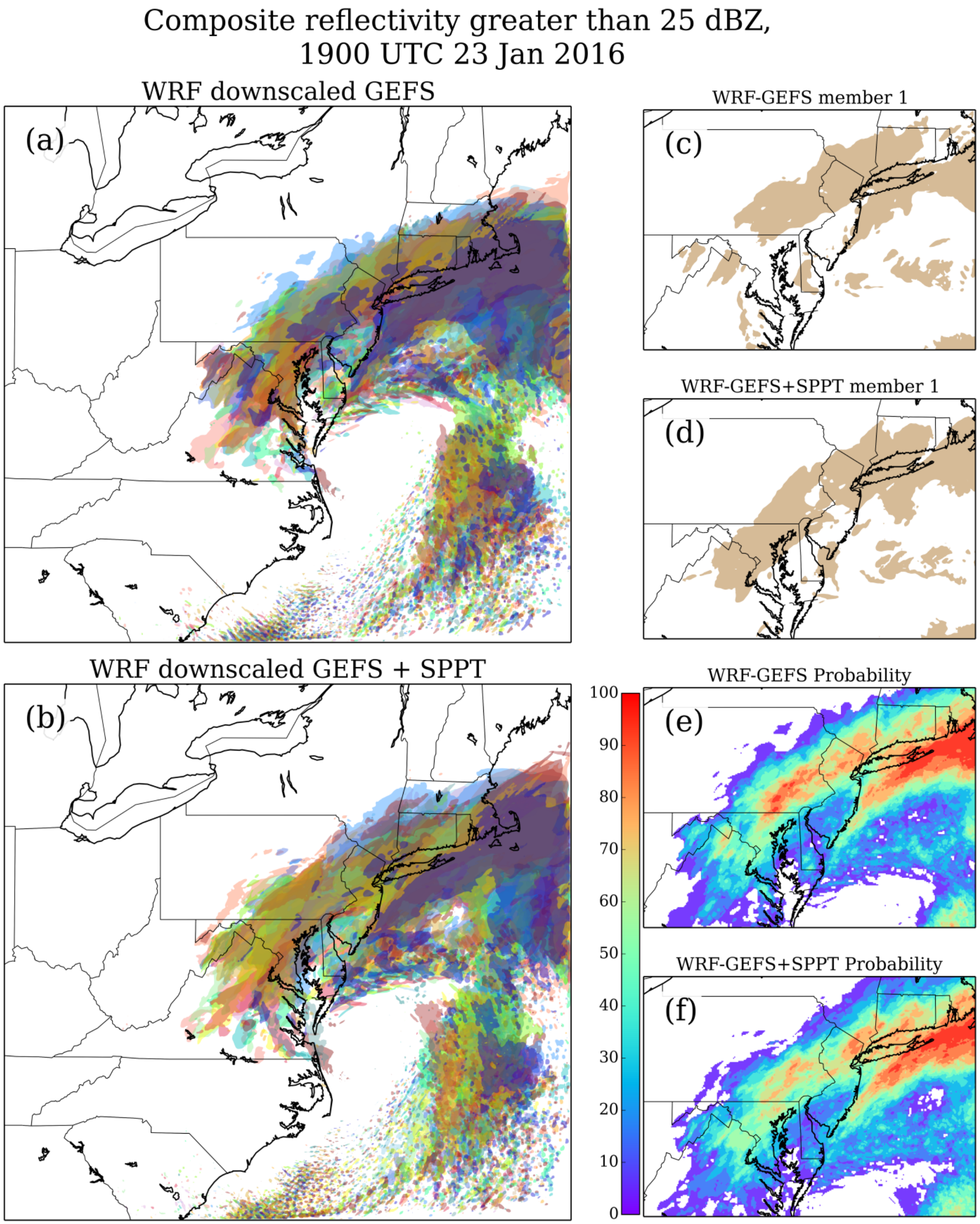
PHYS = multiple model physics schemes
CRPS = 6.088

CRPS = continuous ranked probability skill score; lower is better

Understanding Predictability

Intrinsic Predictability:
Even if we have a perfect model, and nearly perfect initial conditions,
predictability is limited.
Estimate using ensemble spread of perfect model, as initial perturbations become smaller.

Practical Predictability:
Given our current (limited) observing system and (imperfect) models, how far ahead can we skillfully forecast a weather phenomenon.
Need to account for model error; e.g. include perturbations in forecast phase.



Impact Of Assimilating Surface Pressure Observations From Smartphones On A Regional, High Resolution Ensemble Forecast: Observing System Simulation Experiments

Glen Hanson

MS Thesis

Advisor: Dr. Steven Greybush

DEPARTMENT OF
METEOROLOGY
COLLEGE OF EARTH AND
MINERAL SCIENCES

The Economist

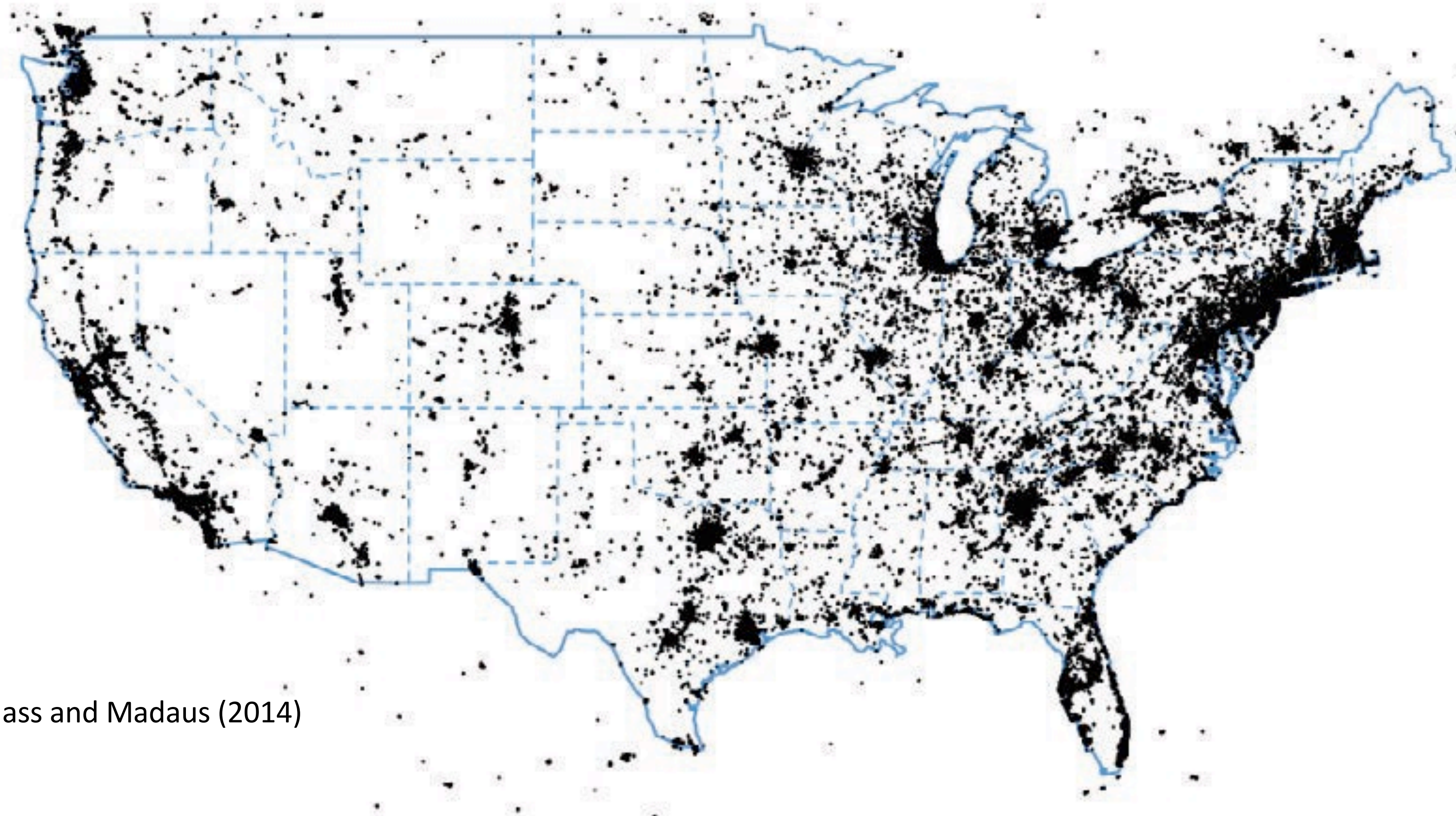
Meteorology

Counting raindrops

How to use mobile-phone networks for weather forecasting

Feb 9th 2013| from the print edition

Potential Density of Smartphone Observations

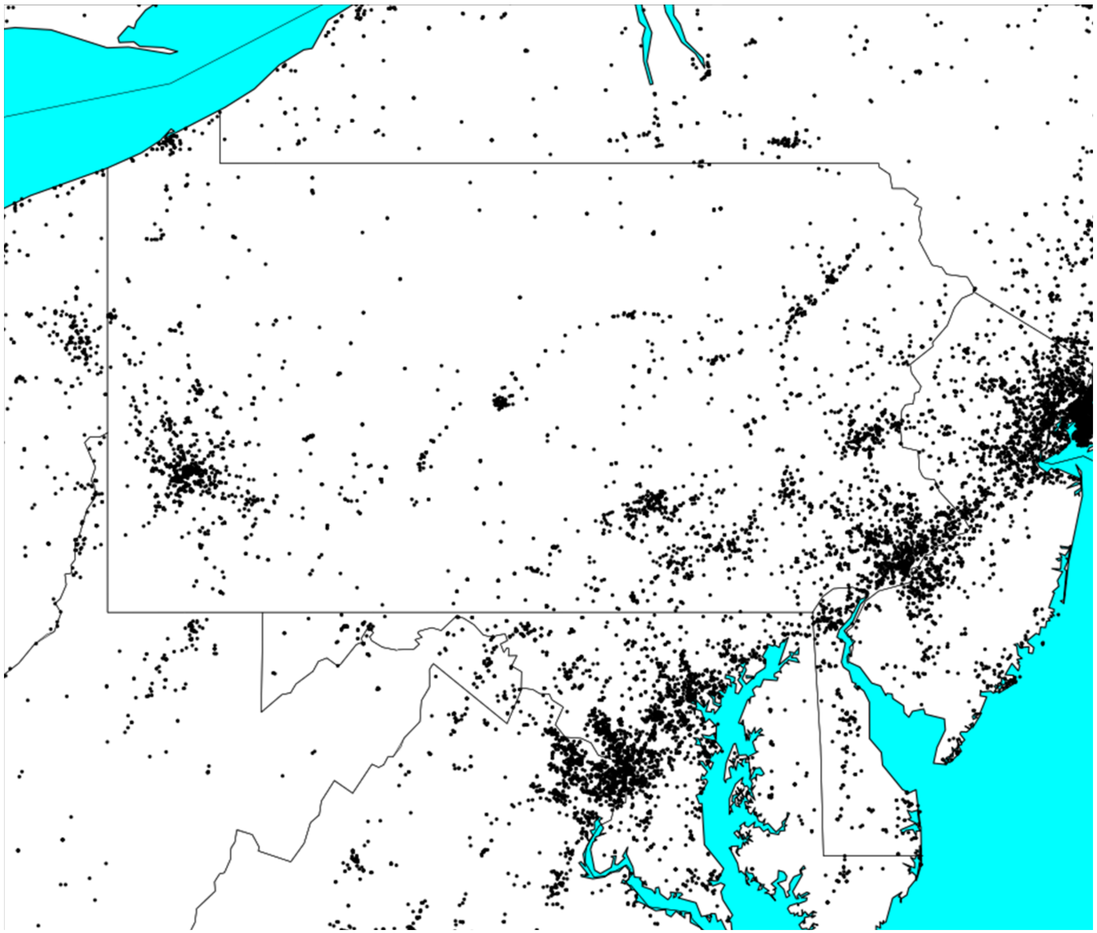


From: Mass and Madaus (2014)

Guiding Research:

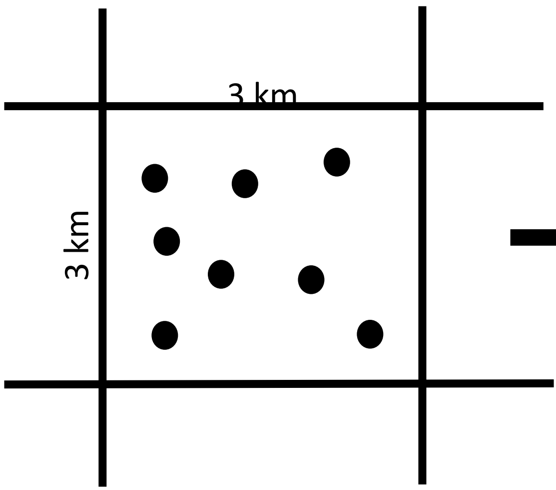
Clifford F. Mass and Luke E. Madaus, 2014: **Surface Pressure Observations from Smartphones: A Potential Revolution for High-Resolution Weather Prediction**?. *Bull. Amer. Meteor. Soc.*, 95,1343–1349.
Wheatley, D., and D. Stensrud, 2010: **The impact of assimilating surface pressure observations on severe weather events in a WRF mesoscale ensemble system**. *Mon. Wea. Rev.,* 138, 1673–1694.
Madaus, L. E., G. J. Hakim, and C. F. Mass, 2014: **Utility of dense pressure observations for improving mesoscale analyses and forecasts**. *Mon. Wea. Rev.,* 142, 2398–2413.

PressureNet Data



- Collected data from 27 February 2015 – 13 May 2015 (75 days)
- Hourly data sets contained an average of 15,000 observations on the domain shown

Determining PressureNet Error



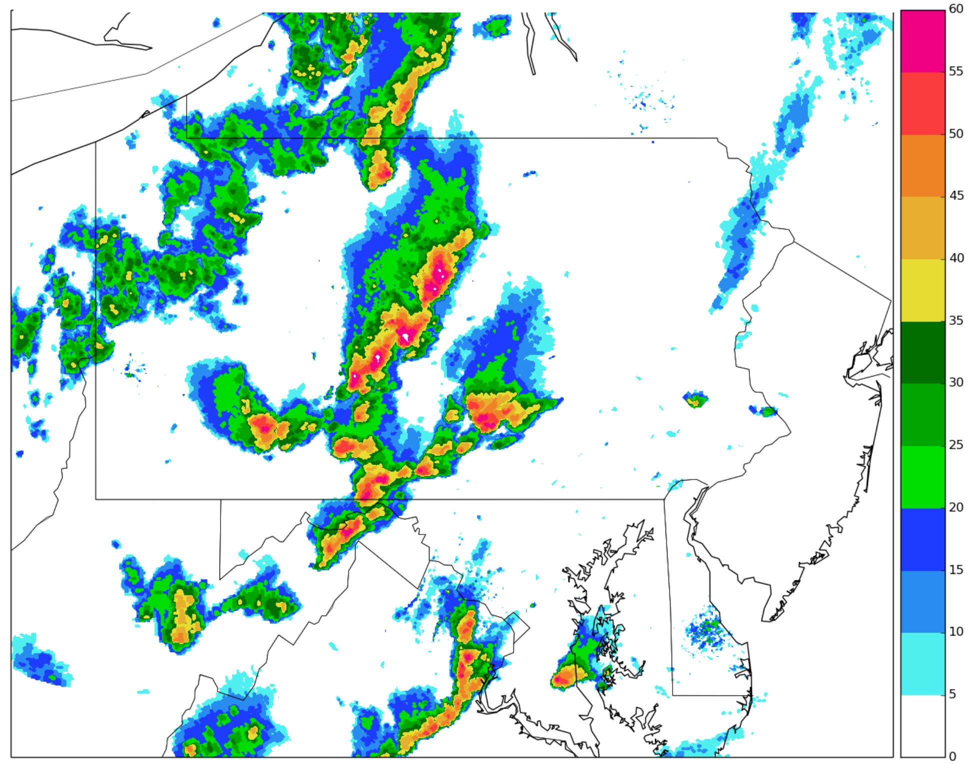
Standard deviation for each spatial grid averaged over entire domain... and then averaged for entire 75 days of data

2.34 hPa

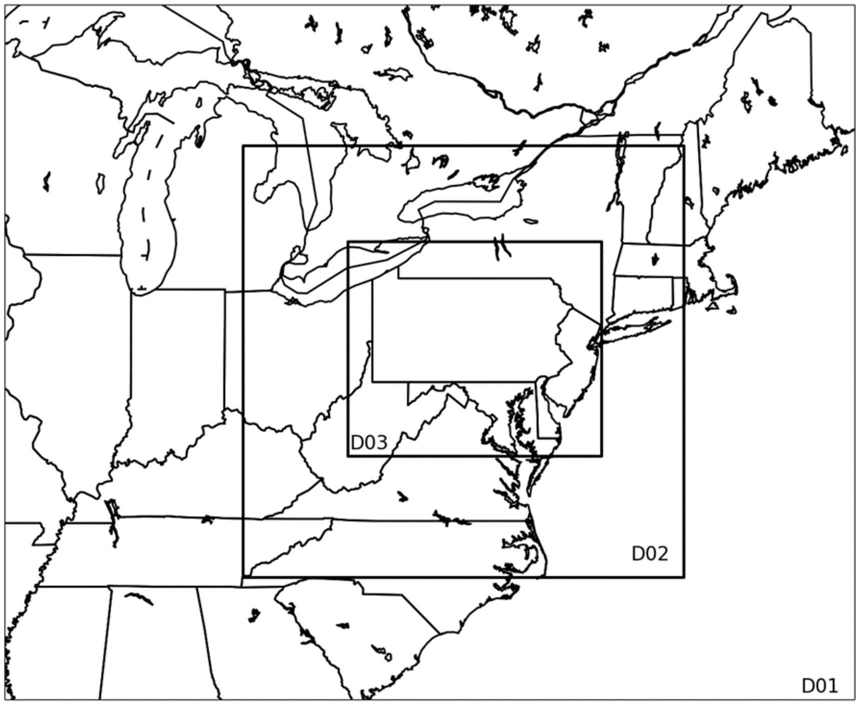
Case Study: Severe Thunderstorms in Pennsylvania

CampusWeatherService @PSUWeather · Apr 20
Use caution on roadways in #statecollege

Observed composite reflectivity: 20 April 2015; 2330 UTC

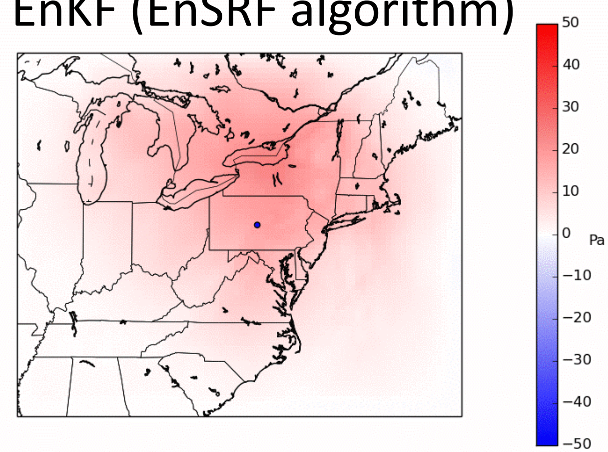


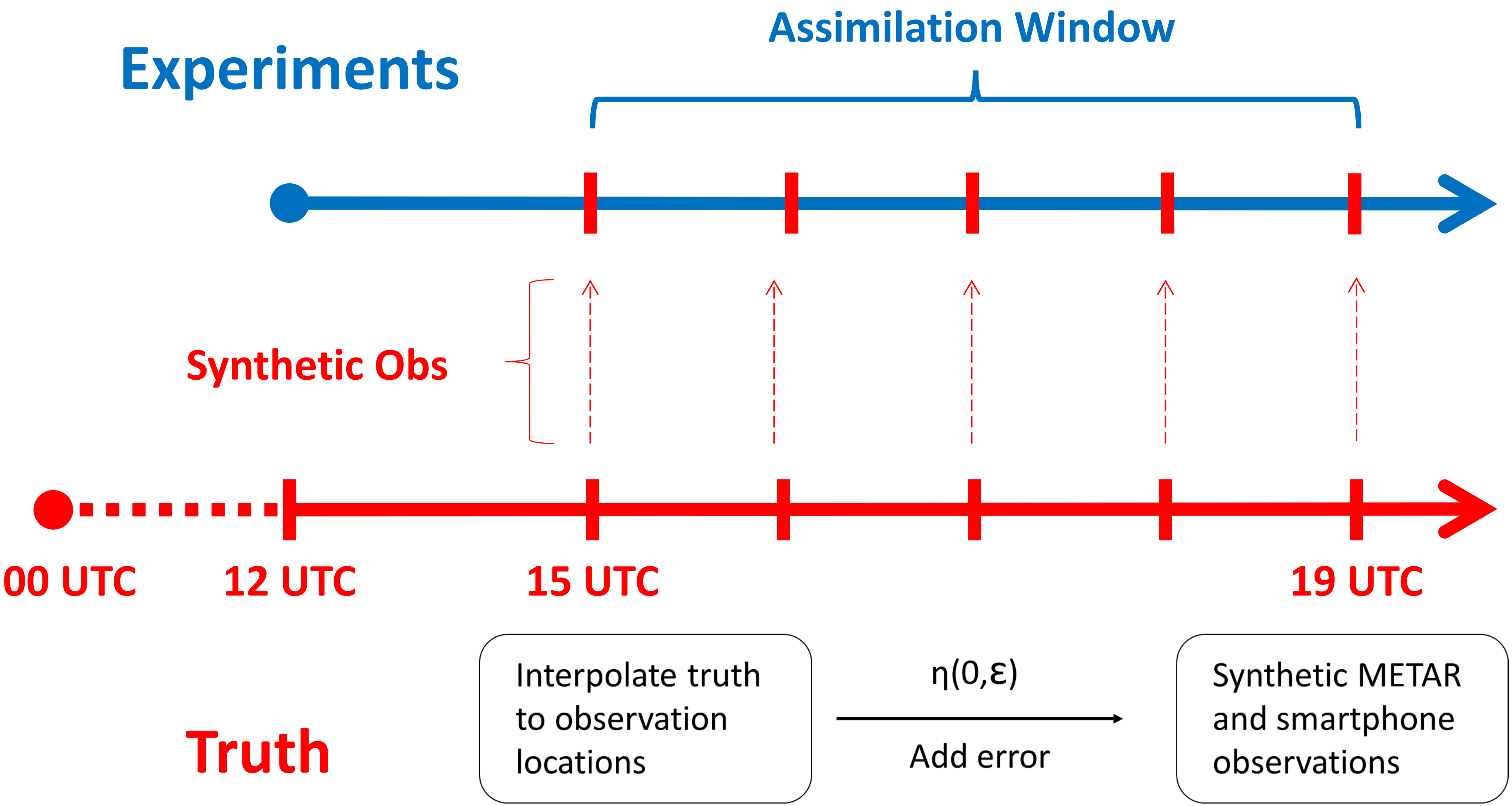
Observing System Simulation Experiment



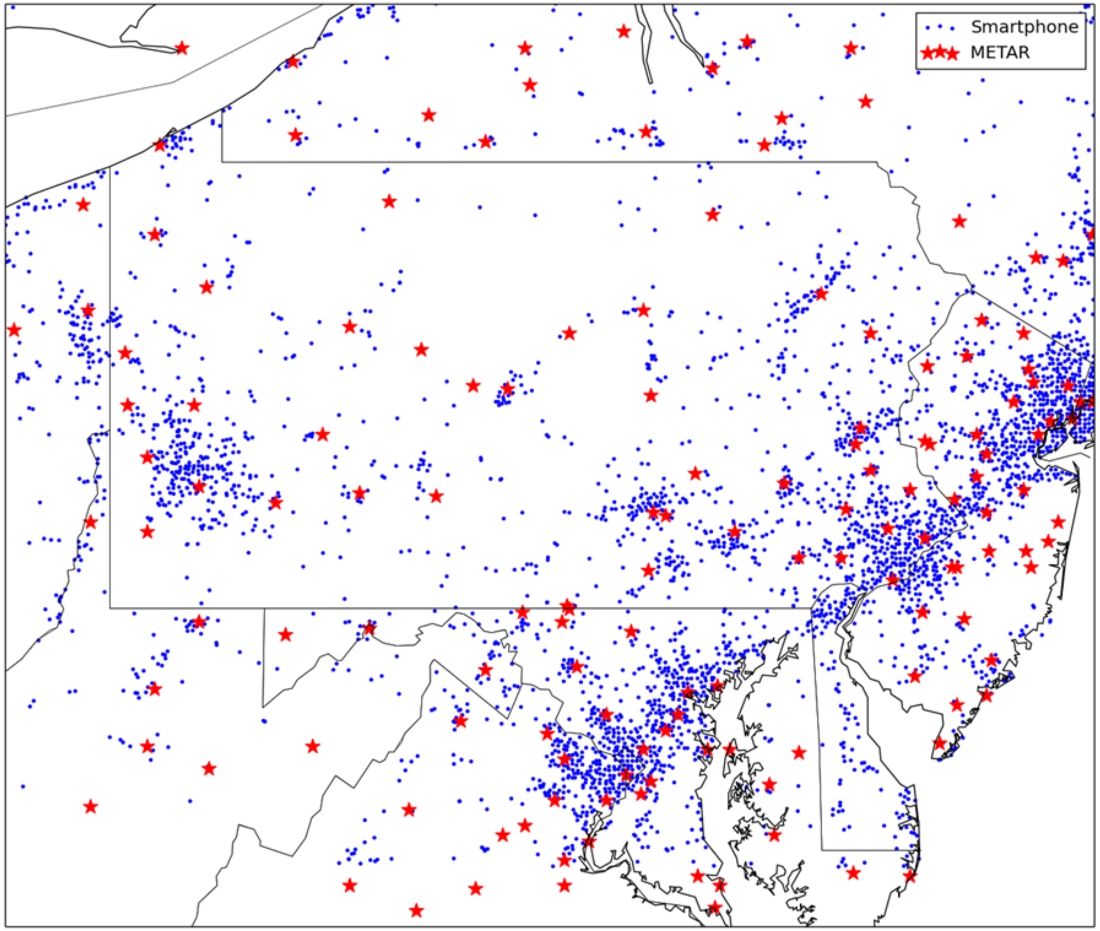
- WRF-ARW Version 3.7 and the PSU WRF-EnKF Data Assimilation System
- 27, 9, and 3 km grid spacing in domains
- No convective parameterization in D03
- Truth created from single deterministic WRF forecast initialized at 00 UTC 20 April 2015

- Use PSU EnKF (EnSRF algorithm)





Assimilation Window
Experiments
Synthetic Obs
00 UTC
12 UTC
15 UTC
19 UTC
Truth
Interpolate truth to observation locations
η(0,ε)
Add error
Synthetic METAR and smartphone observations



“Super-observations” created for smartphone observations

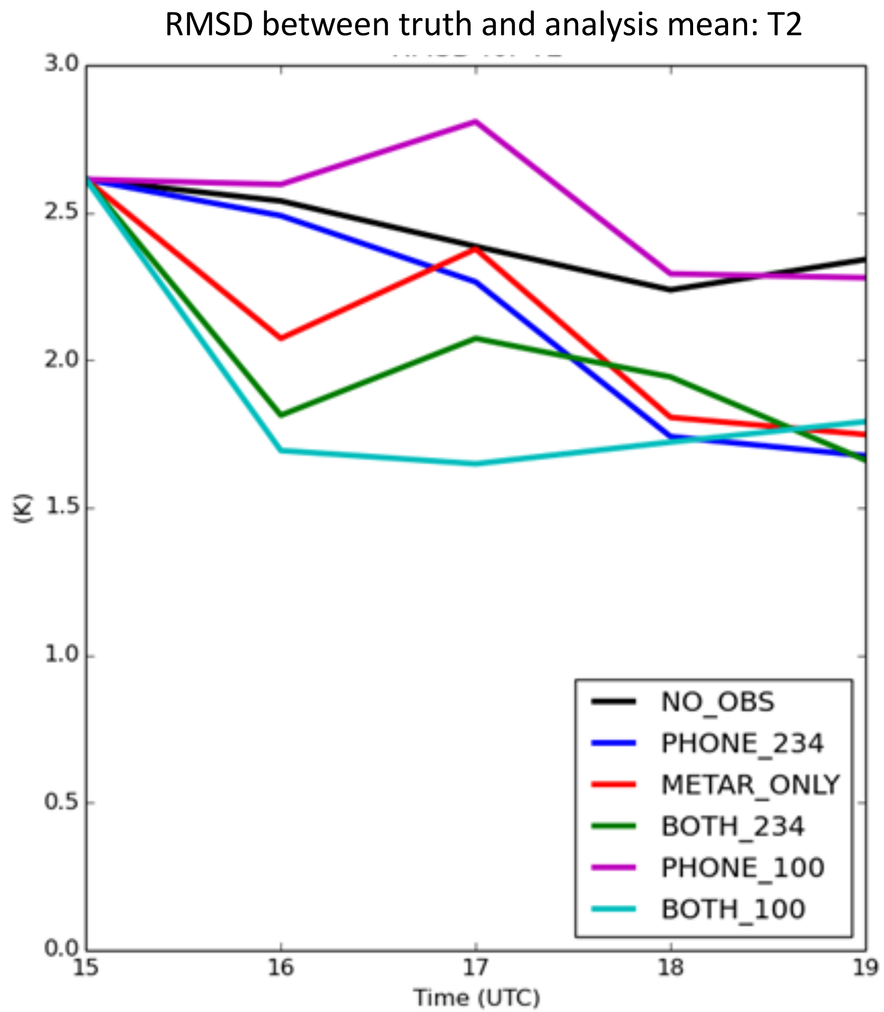
- Observations location identical for every experiment
  - 150 METAR observations
  - 3,508 smartphone observations

Research Goals

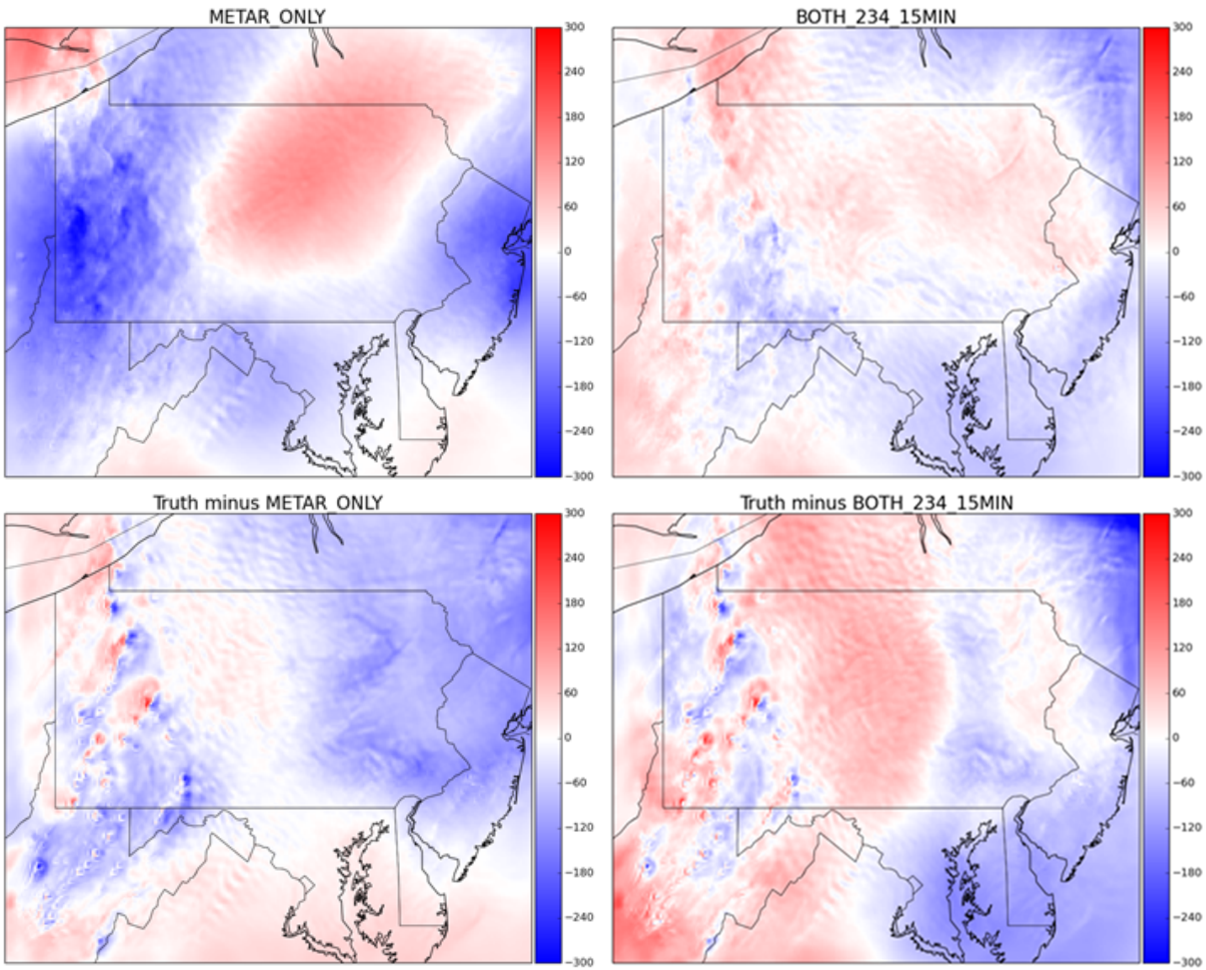
- Determine the impact the assimilation of surface pressure observations from smartphones have on a regional ensemble forecast using an EnKF
  - Use observing system simulation experiments (OSSEs) to robustly analyze simulations
  - Tested sensitivity to:
    - Horizontal localization
    - Observation error
    - Assimilation frequency

- Smartphone observations led to analysis update that better represents the spatial patterns in the truth (previous slide)

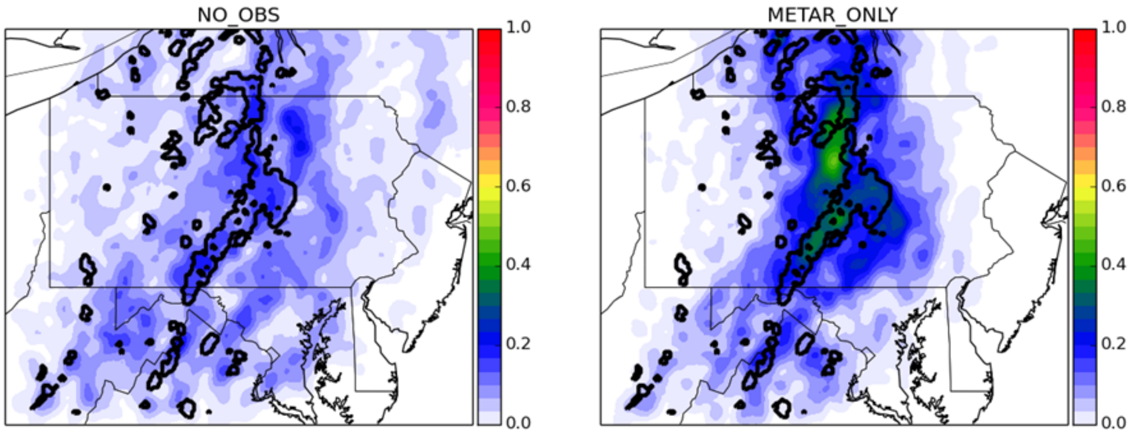
- Meaningful signal from smartphones for variables other than pressure



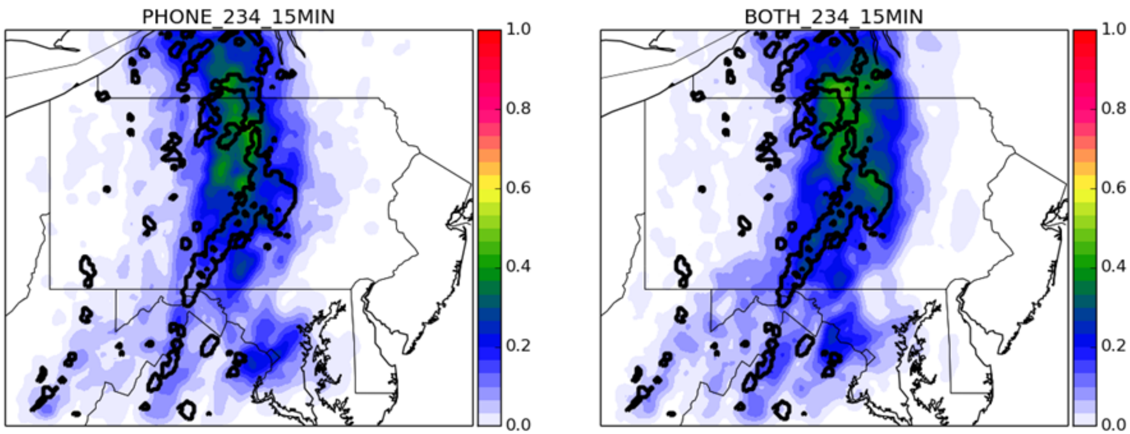
19 UTC Mean Analysis Update: PSFC



Rapid assimilation of smartphone observations appear to capture mesoscale pressure signatures in areas of convection better than the METAR only case

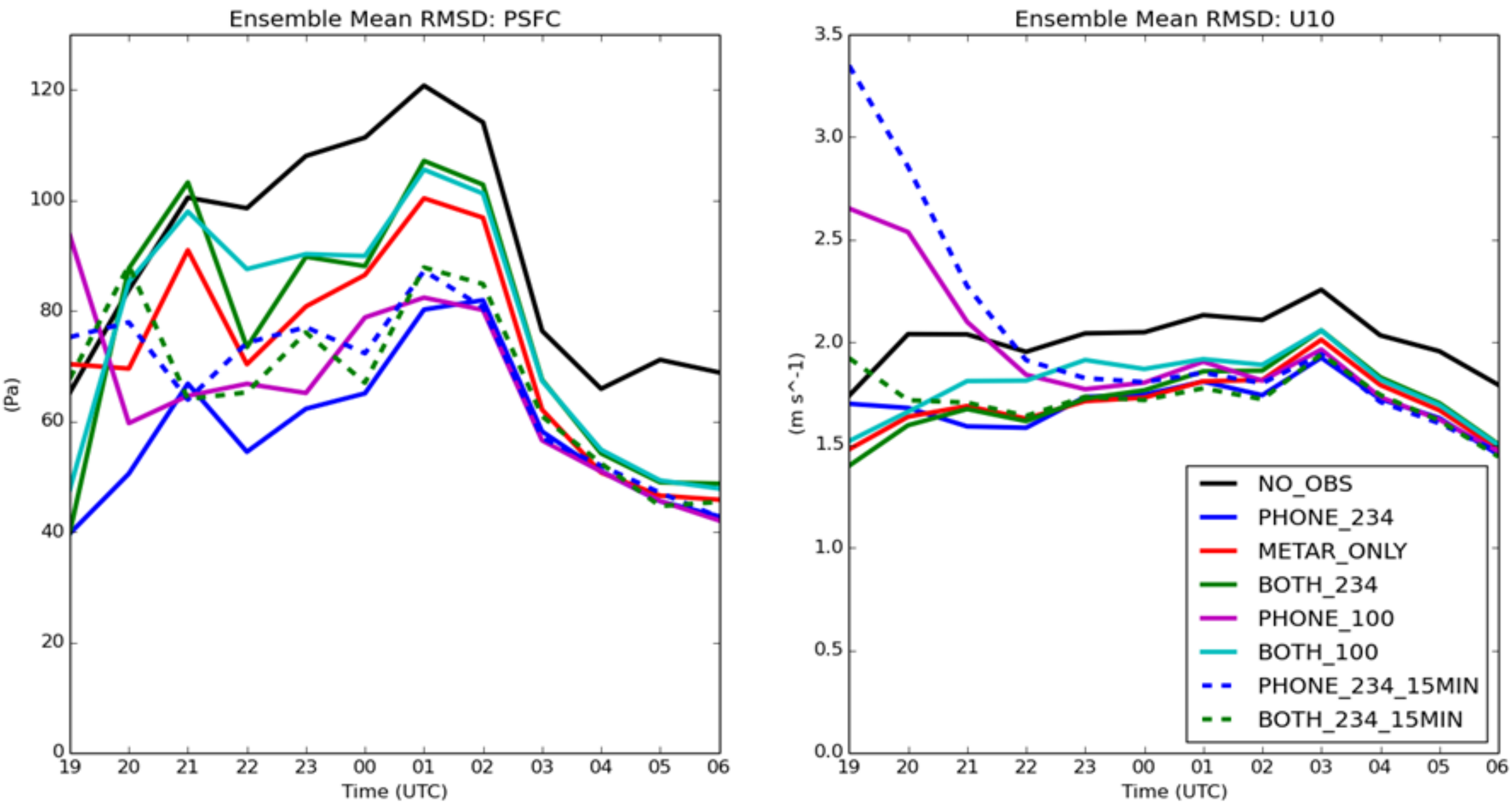


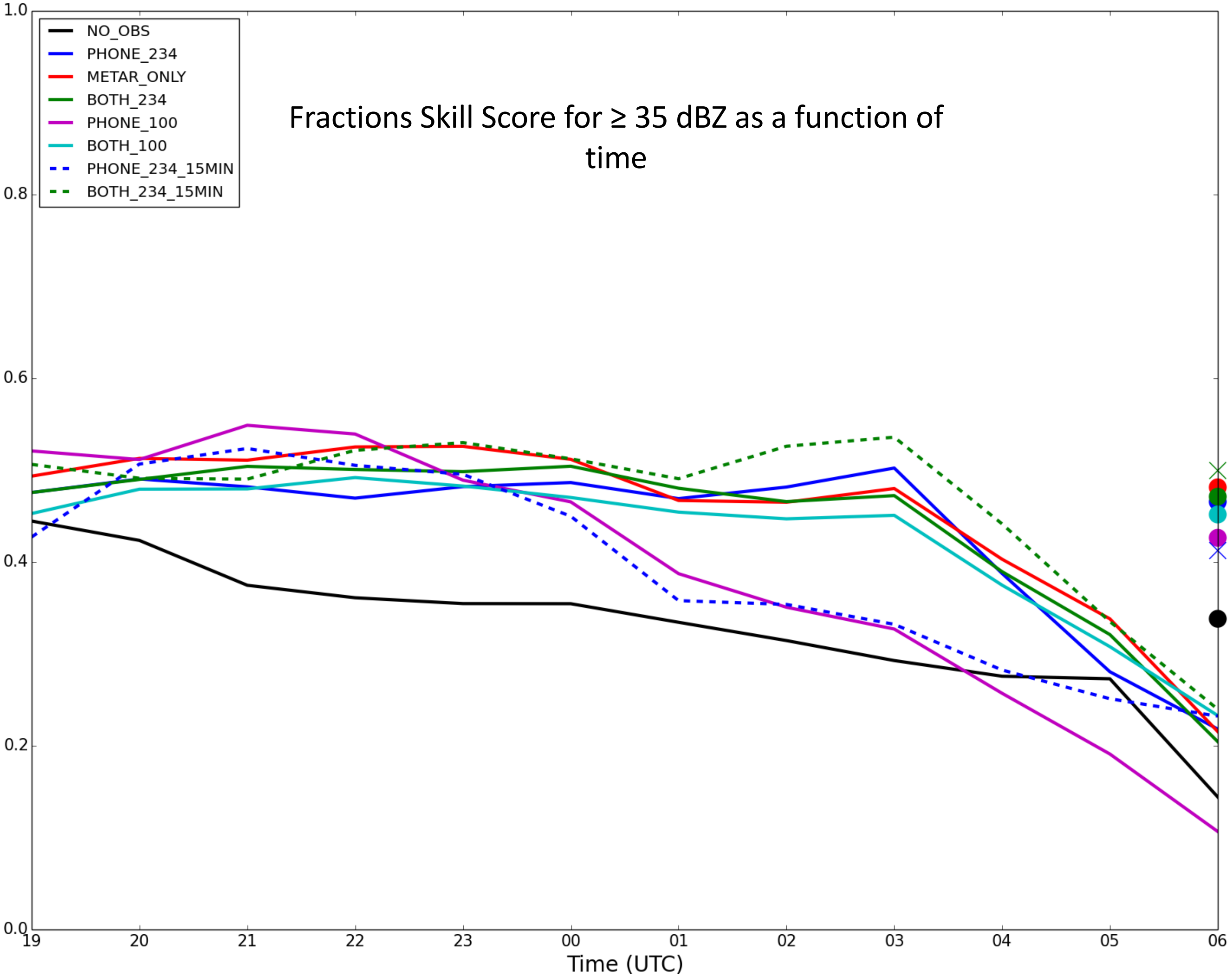
Neighborhood Ensemble Probability for ≥ 35 dBZ: 23 UTC
Truth in black contour



- All observations, regardless of type, led to higher probability regions that better match the truth than the NO_OBS case
- Smartphone observations don't appear to be causing spurious convection
- Difficult to make definitive assessment of ensembles with only quantitative/spatial data

RMSD between truth and ensemble mean





- BOTH_234_15MIN has the best average performance
- PHONE_234 and BOTH_234 are comparable to METAR_ONLY
- For this simulation, lower (1.00 hPa) smartphone observation error did not perform as well as other experiments

Summary of Results

- 500 km HROI used to balance accuracy and computational resources
  - Using 500 km HROI for METAR observations with a 150 km HROI for smartphone observations led to further improvements.
- Rapid assimilation of smartphone data improved analysis results
  - Positive impact for other variables besides pressure
- BOTH_234_15MIN produced simulation with most forecast skill
  - Seen in FSS and AUC
- PHONE_234 has similar skill to METAR_ONLY

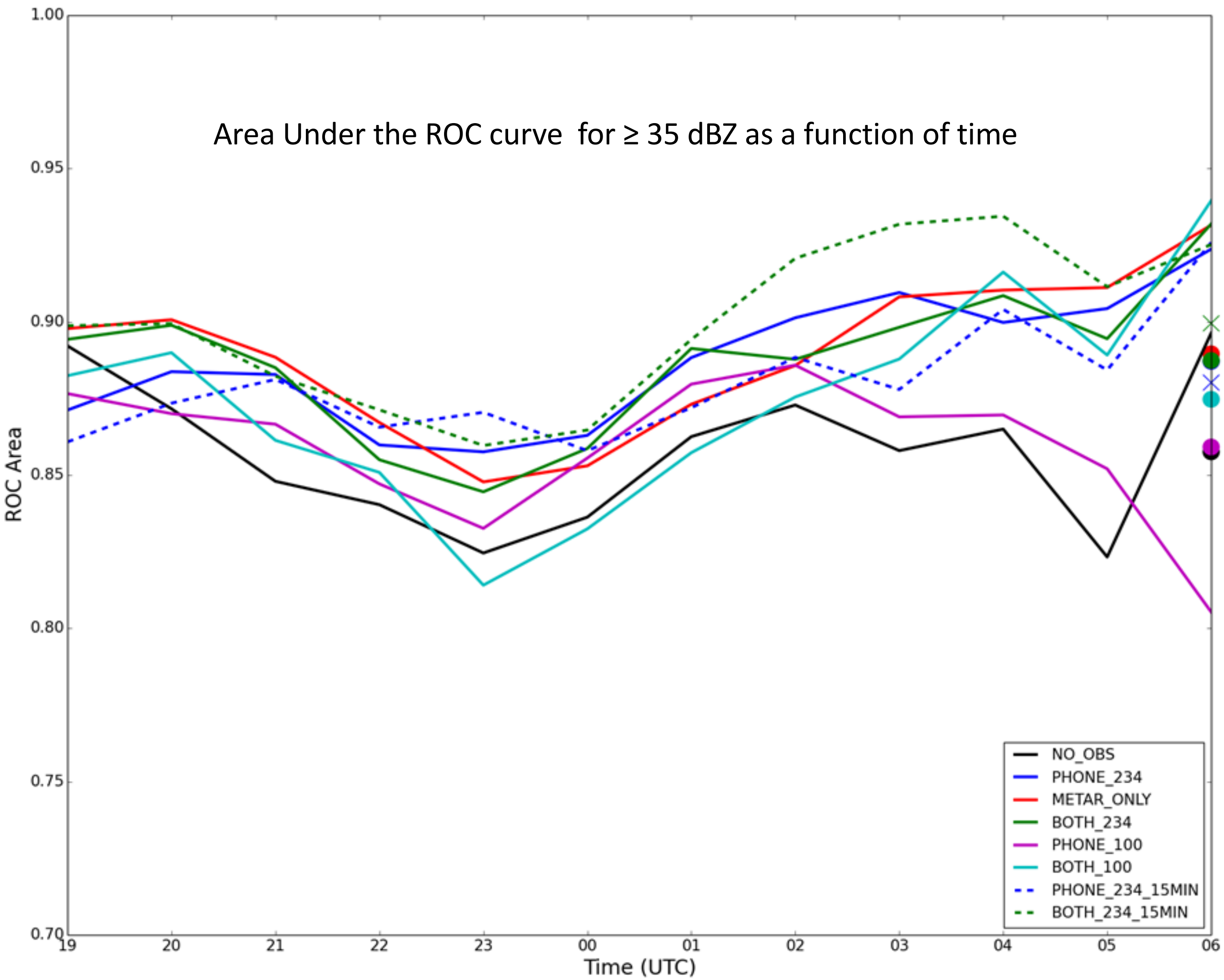
Conclusions

- Smartphone observations can have a positive impact on the ensemble forecast of a convective event in a regional model using EnKF data assimilation
- Assimilating smartphone observation every 15 min had the most impact on the ensemble performance
  - Consistent with Radar data assimilation techniques
- Smartphone observations could be used in conjunction with conventional observations or possibly as the sole source of observations in a data-denied area

Experiment Name	Experiment Description
NO_OBS	No observations assimilated
METAR_ONLY	Only assimilated synthetic METARs
PHONE_234	Assimilated synthetic smartphone obs (2.34 hPa error) 500 km ROI
BOTH_234	Assimilated synthetic smartphone obs (2.34 hPa error) and synthetic METARs
PHONE_100	Assimilated synthetic smartphone obs (1.00 hPa error) 500 km ROI
BOTH_100	Assimilated synthetic smartphone obs (1.00 hPa error) and synthetic METARs
PHONE_234_100KM	Assimilated synthetic smartphone obs (2.34 hPa error) 100 km ROI
PHONE_234_1000KM	Assimilated synthetic smartphone obs (2.34 hPa error) 1,000 km ROI
PHONE_234_15MIN	Assimilated synthetic smartphone obs (2.34 hPa error) every 15 min
BOTH_234_15MIN	Assimilated synthetic smartphone obs (2.34 hPa error) and synthetic METAR obs every 15 min

Quantitative Verification

- Fractions Skill Score (FSS)
  - Computed from fractions Brier Score (FBS)
  - Normalized against worst possible FBS
    - Perfect Forecast = 1
    - No Skill = 0
- Relative Operating Characteristic (ROC) curves
  - Created from a range of neighborhood probability thresholds
  - Area under the curve (AUC) is a measure of forecast skill
    - AUC $\geq$ 0.7 represents useful forecast



- BOTH_234_15MIN has the best average performance
- PHONE_234 and BOTH_234 are comparable to METAR_ONLY
- Rapid assimilation of smartphone observations makes noticeable improvement