WRF/DART – Application examples

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Outline:

WRF/DART has been applied to a variety of problems, some Examples of past applications are provided here:

- Ensemble forecast initialization:
    - Hurricane prediction
    - Convective storm prediction
- Diagnosing model error
- Parameter estimation
- Severe storm analysis
- Atmospheric chemistry
- Observation impact
- Ensemble-based sensitivity analysis

More on DART at: Anderson, J., and Coauthors, 2009: The Data Assimilation Research Testbed: A Community Facility. *Bull. Amer. Meteor. Soc.*, **90**, 1283–1296.

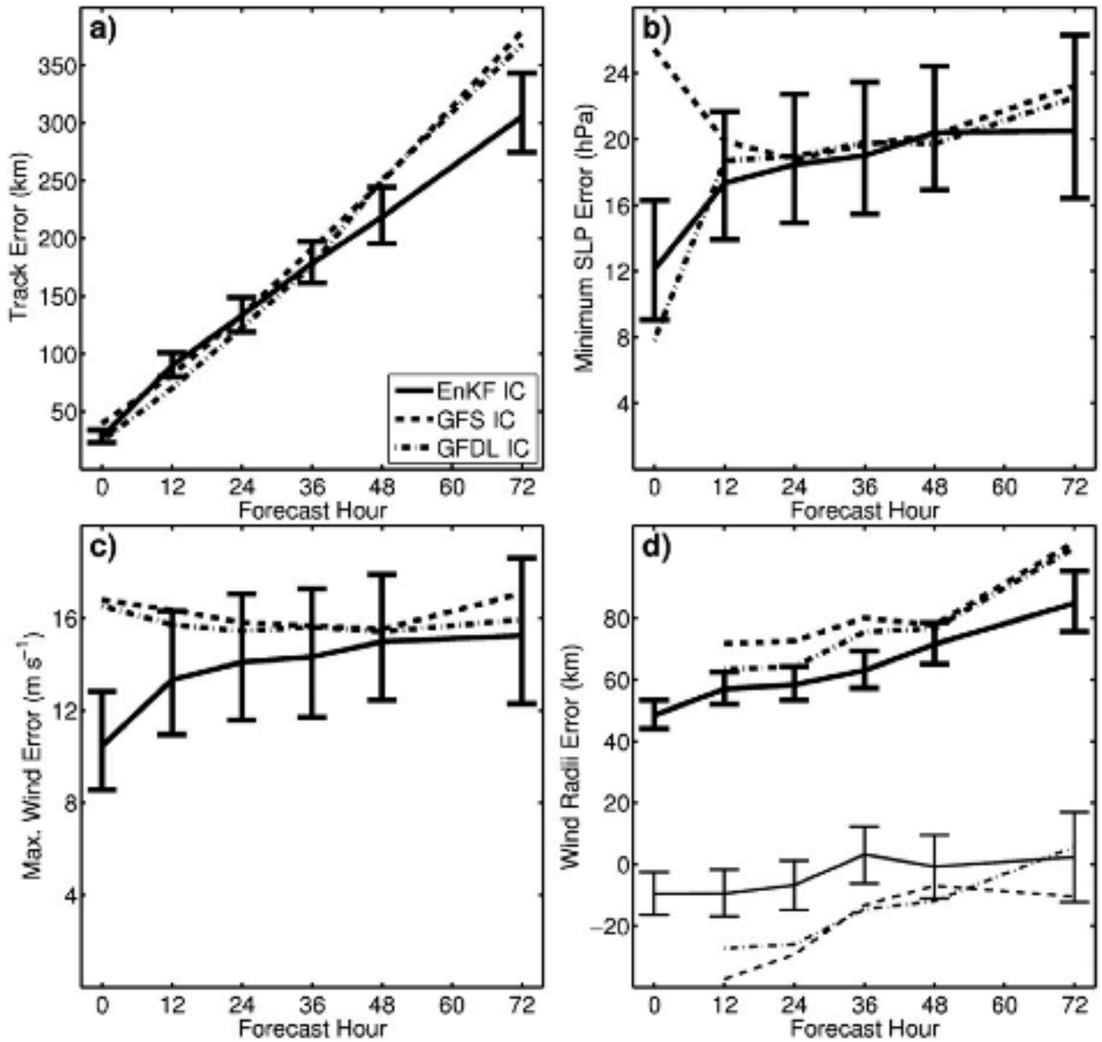
Ensemble initial conditions (ICs) for forecasts

Benefits of a WRF/DART approach for ensemble IC:

- analysis uncertainty based on current state and available observations
- model first guess on same attractor as forecast model
- known systematic analysis and model error
- equally likely forecasts (assuming identical forecast model)

Can also use a random member or the ensemble mean analysis (different evolution – but can be more skillful) for deterministic forecasts

Hurricane prediction:

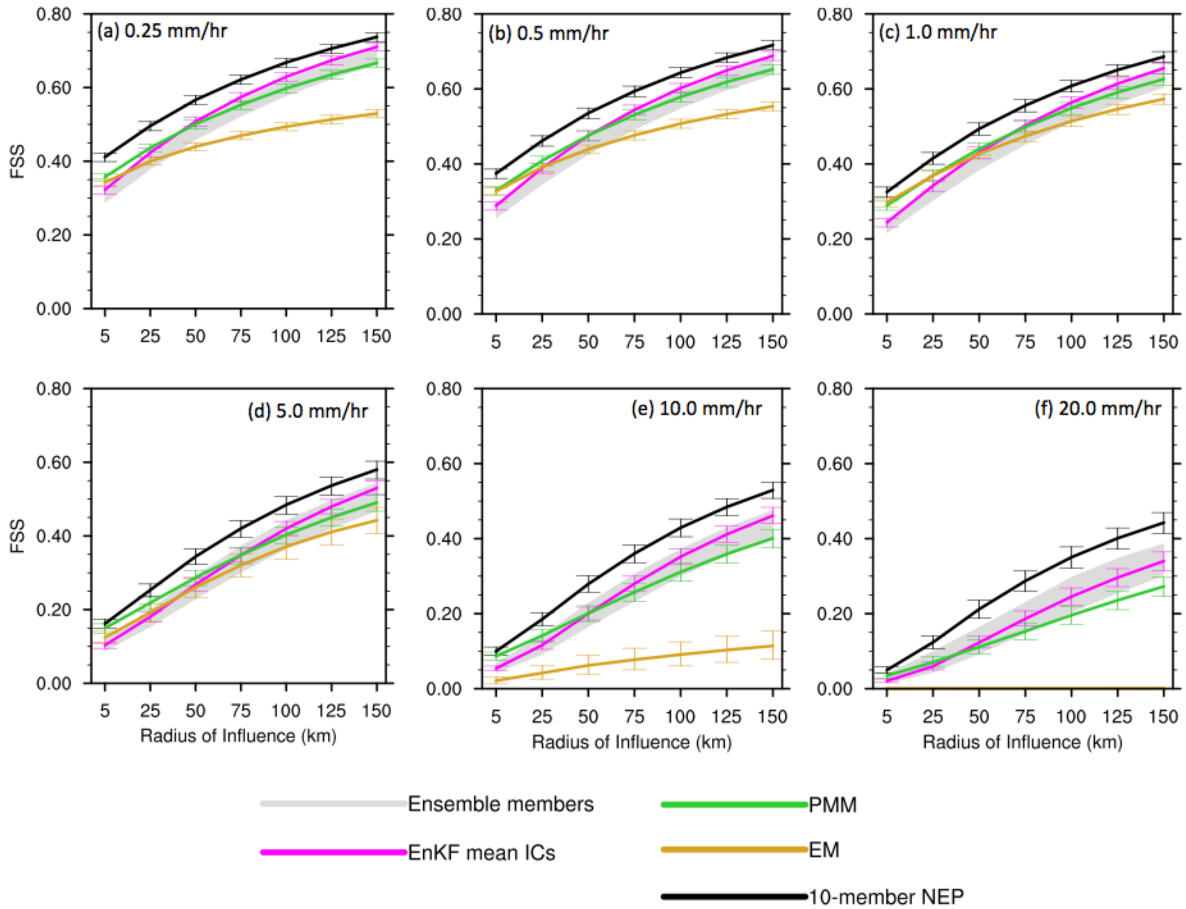


Torn 2010, MWR: Fig. 12

Ensemble forecasts from WRF/DART based ICs

Ensemble forecast hurricane track errors similar to errors from other operational analysis systems but here includes forecast uncertainty information owing to IC uncertainty

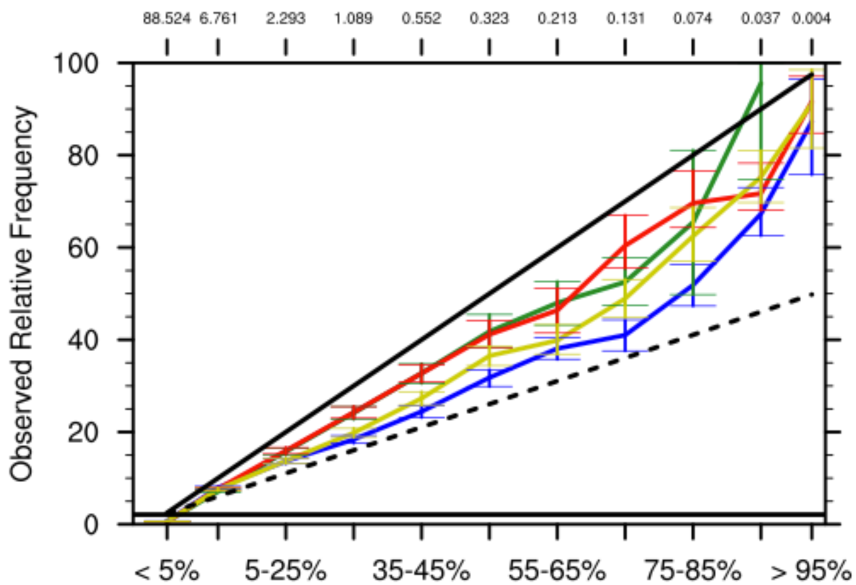
Convective storm prediction:



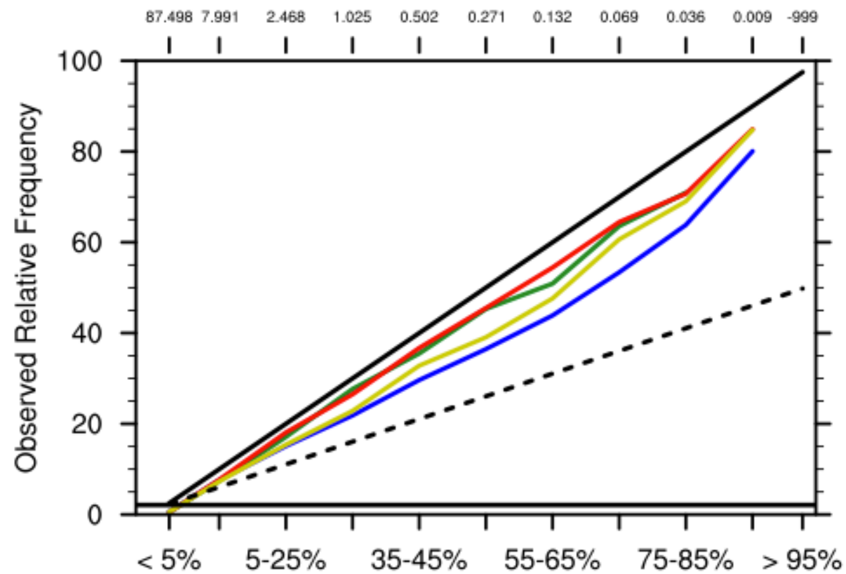
Improved precipitation forecast skill when ensemble forecast is used for probabilistic guidance, deterministic forecasts from ensemble mean analysis outperforms forecasts from individual members, ensemble mean   Schwartz et al., Submitted to WAF

Convective storm prediction:

50 km neighborhood



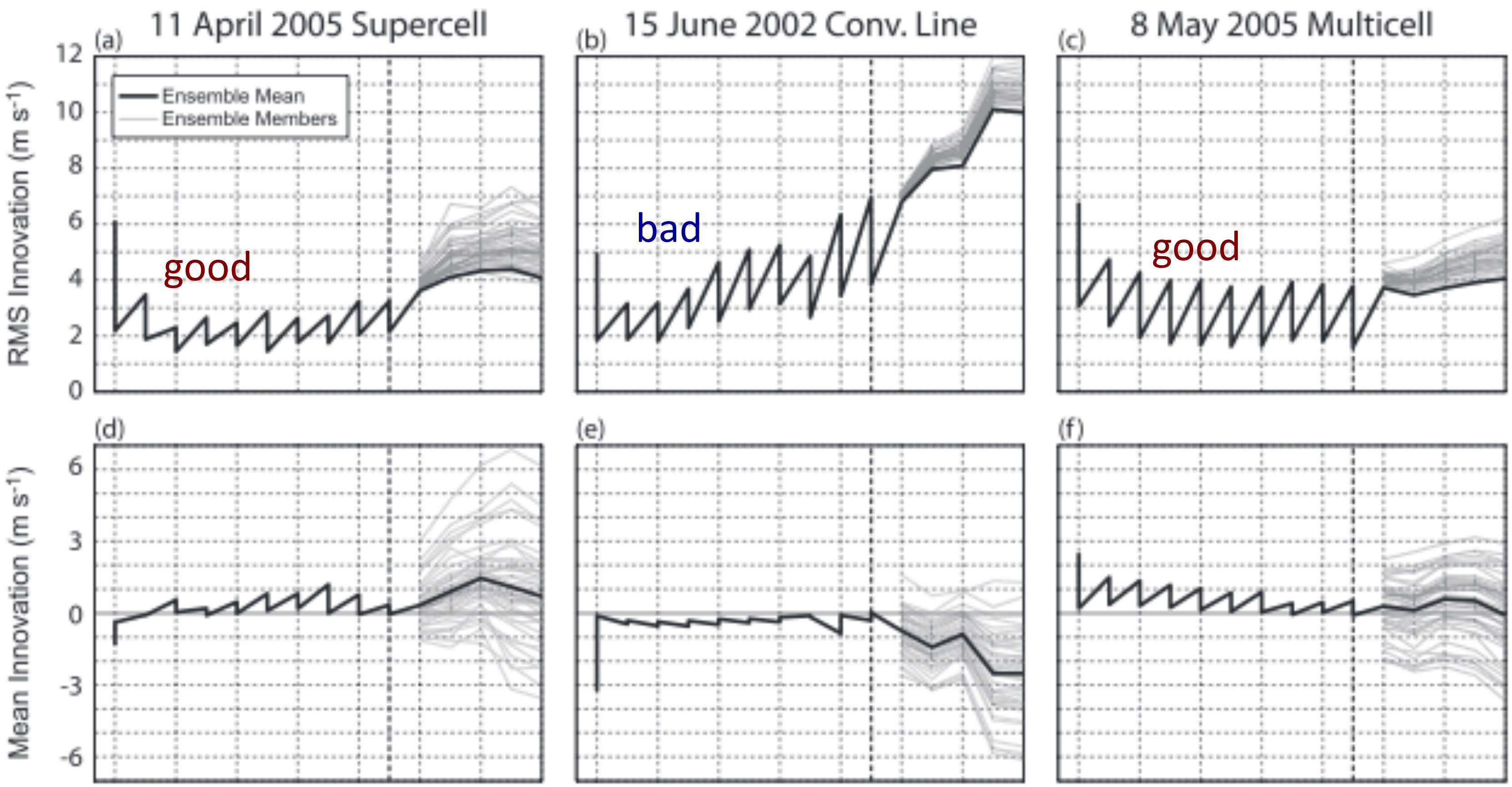
100 km neighborhood



Perfect reliability would be along diagonal.
WRF/DART IC only is blue curve

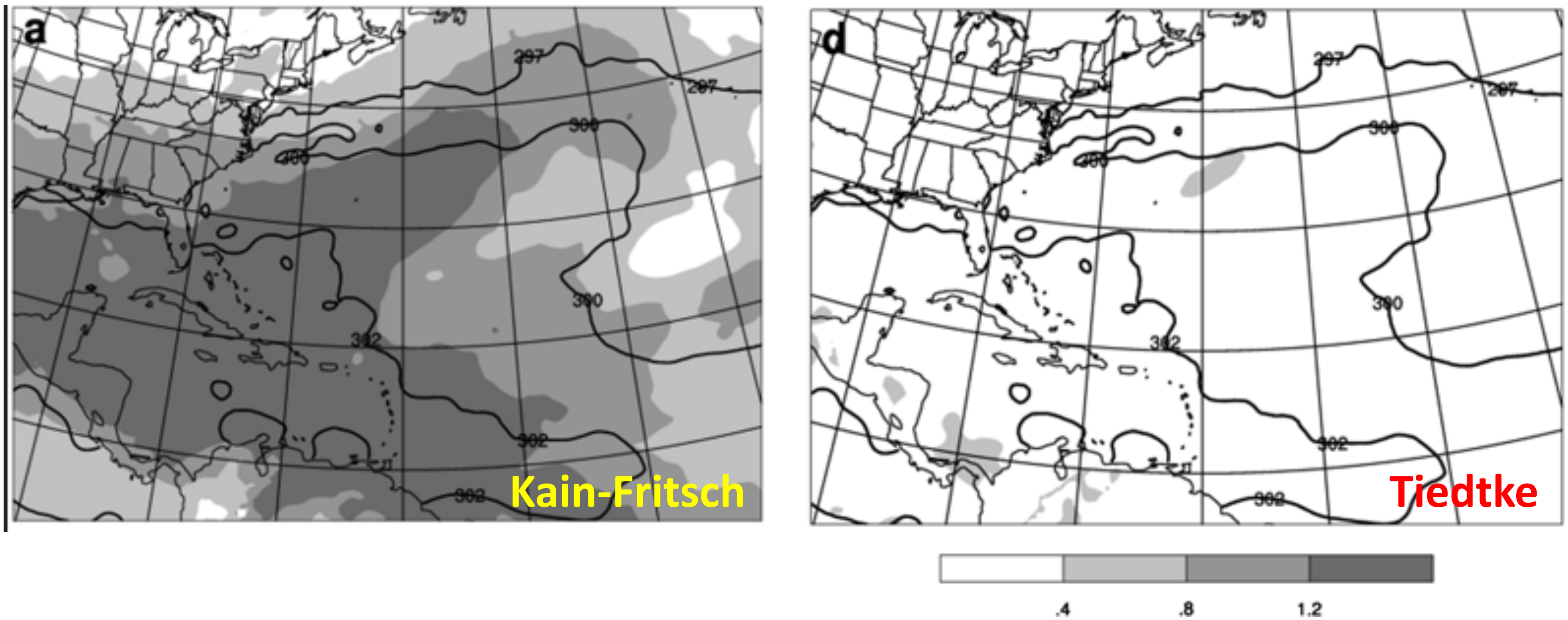
Forecast reliability with WRF/DART initial uncertainty remains under-dispersive, so still may need to add additional complexity such as representing model error and lateral boundary uncertainty

Convective storm prediction:



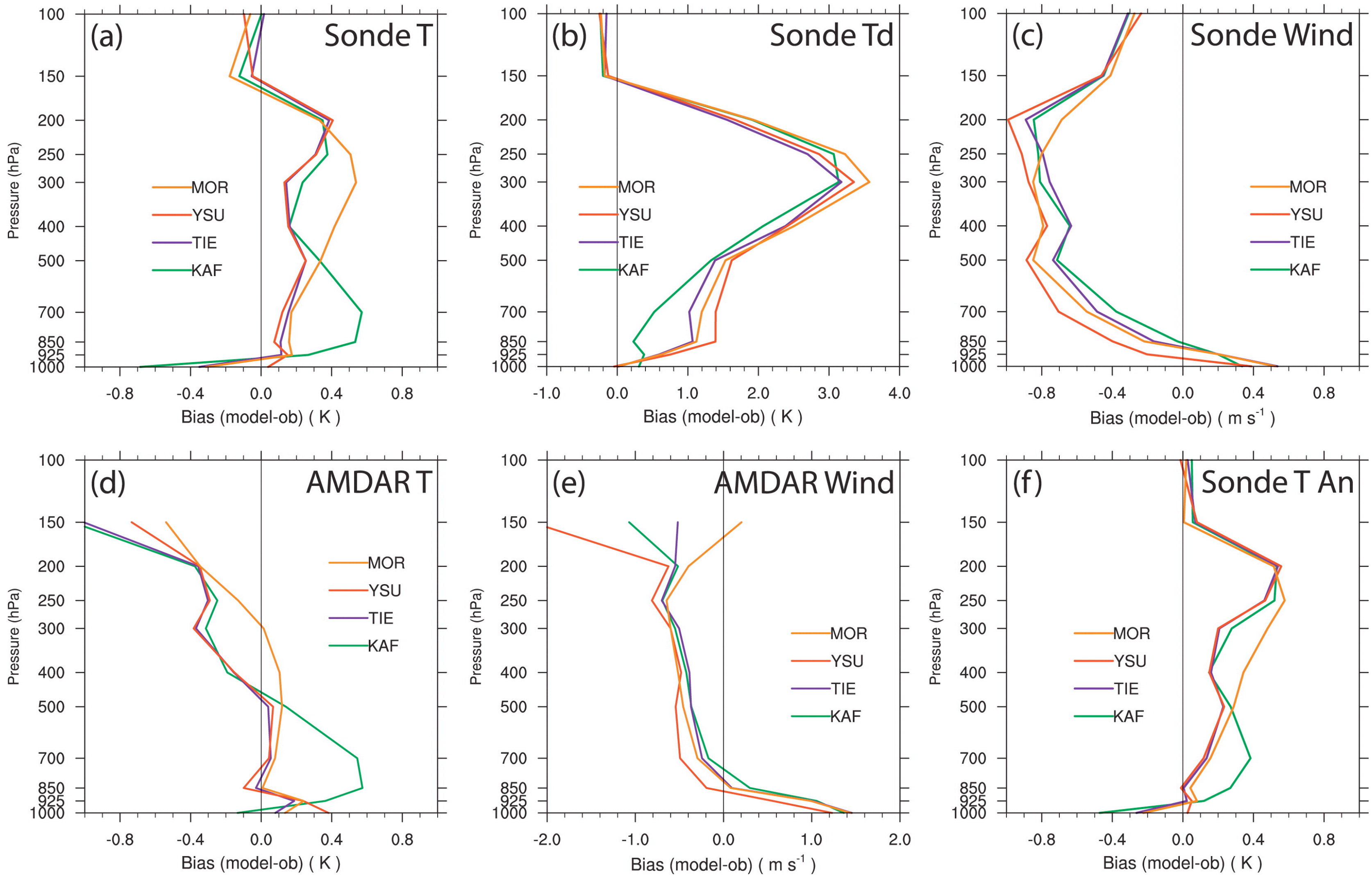
Analysis performance and predictability can vary by convective organization. Shown RMS innovation and bias for radial velocity observations   Aksoy et al., 2010, MWR

Diagnosing model error – fit to analysis



Time averaged differences in 700 mb temperature between cycled EnKF analysis and GFS analysis – larger errors at left tied to shallow cumulus scheme of Kain-Fritsch cumulus parameterization
Torn and Davis, 2012

Diagnosing model error – fit to observations



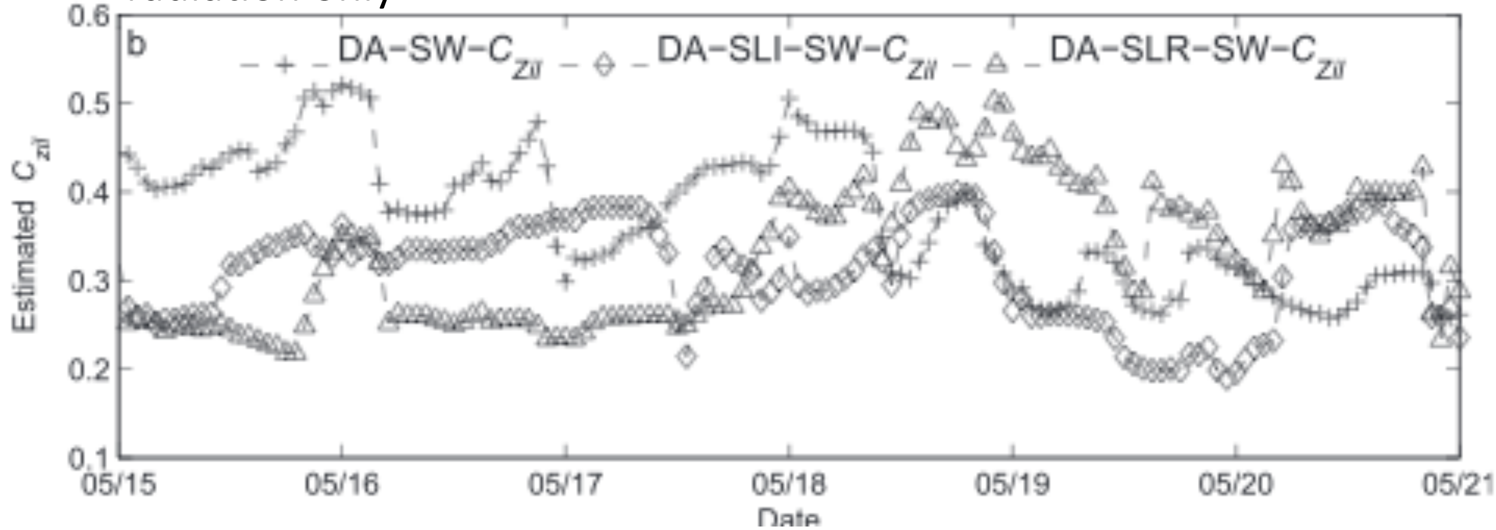
Can also consider the long term model fit to observations. Differences in observation platform climatology are also evident. Romine et al. 2013, MWR

Parameter estimation

Assimilate shortwave radiation only

Assimilated shortwave and soil obs

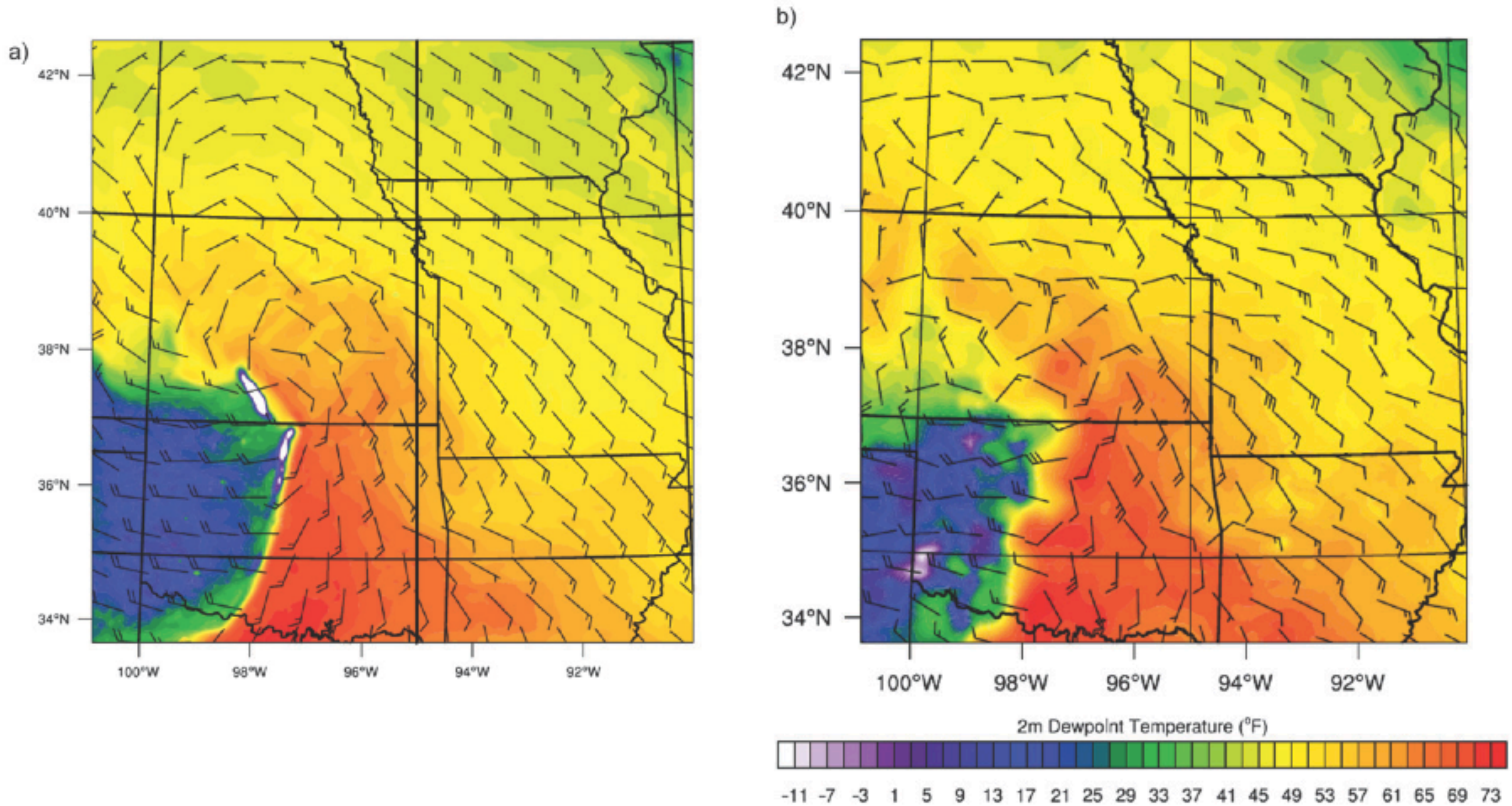
'Perfect' soil state



Can also use filter for parameter estimation problems, here to improve estimation of the Zilitinkivich constant (default 0.1), which regulates the coupling between the model state and the land surface state – Hacker and Angevine, 2013, MWR

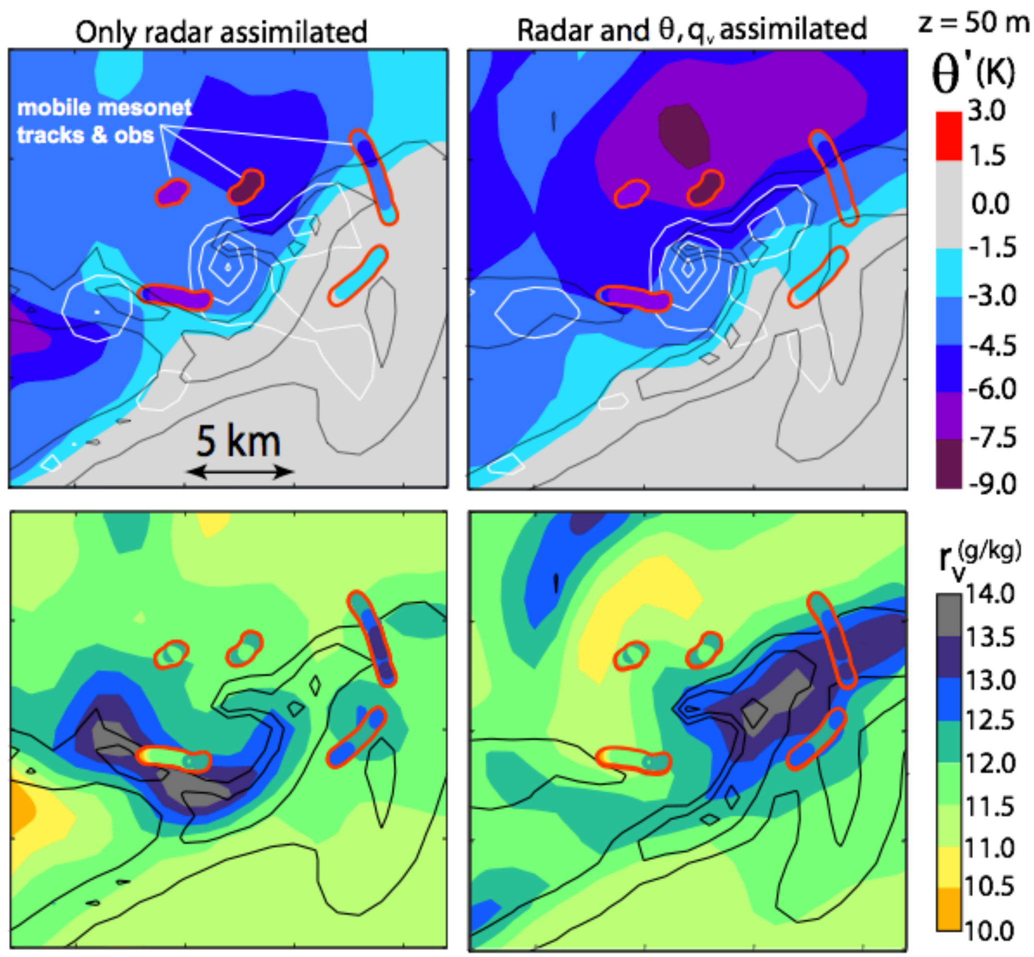
This study used WRF single column model

Mesoscale analysis



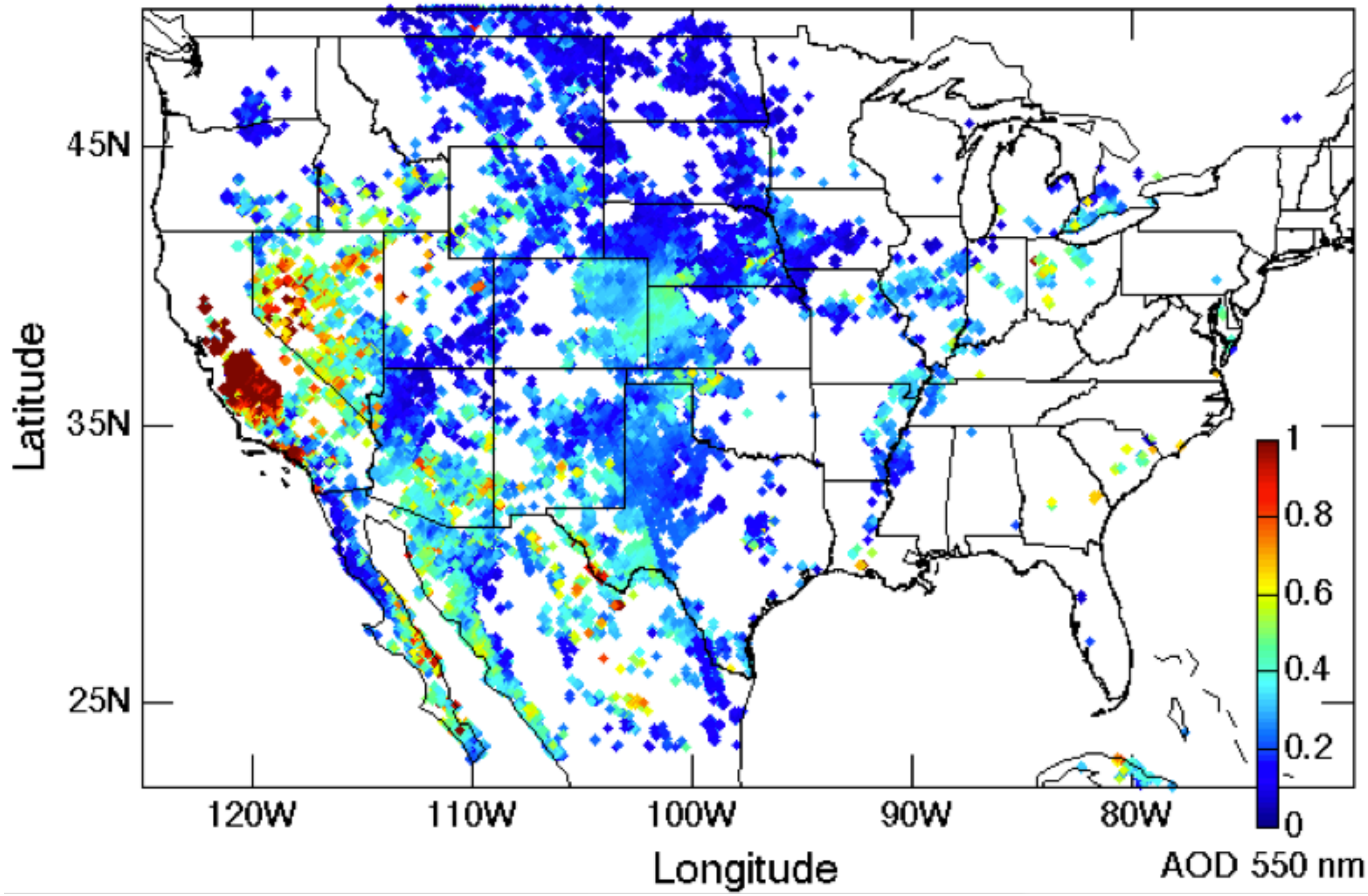
Comparison of DART EnKF analysis to Real-Time Mesoscale Analysis (RTMA), former has far more realistic structure than 2dvar analysis Knopfmeier and Stensrud, 2013

Severe storm analysis



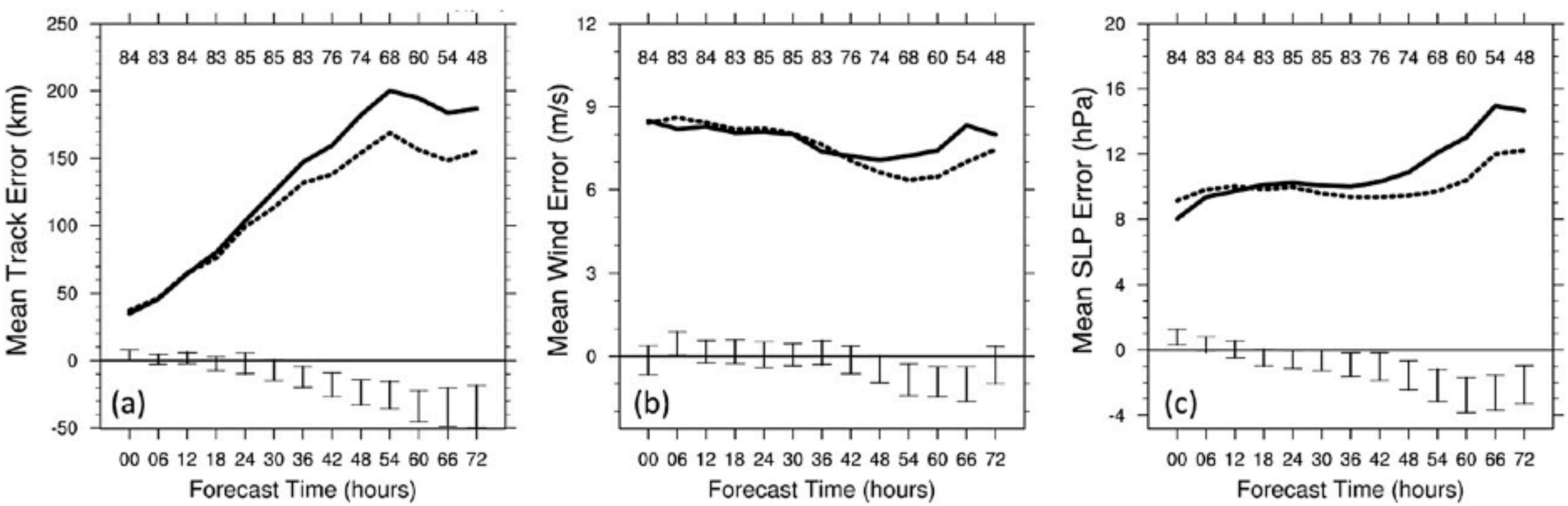
More consistent storm analysis of cold pool characteristics when both radar observations and surface weather observations are assimilated
Marquis et al, 2014, MWR in press

Atmospheric chemistry using WRF-CHEM



Seek to improve chemistry analysis from meteorology observations, and also improving meteorology from chemistry observations. Shown, Aerosol Optical Depth (AOD) from a satellite based product (IASI)

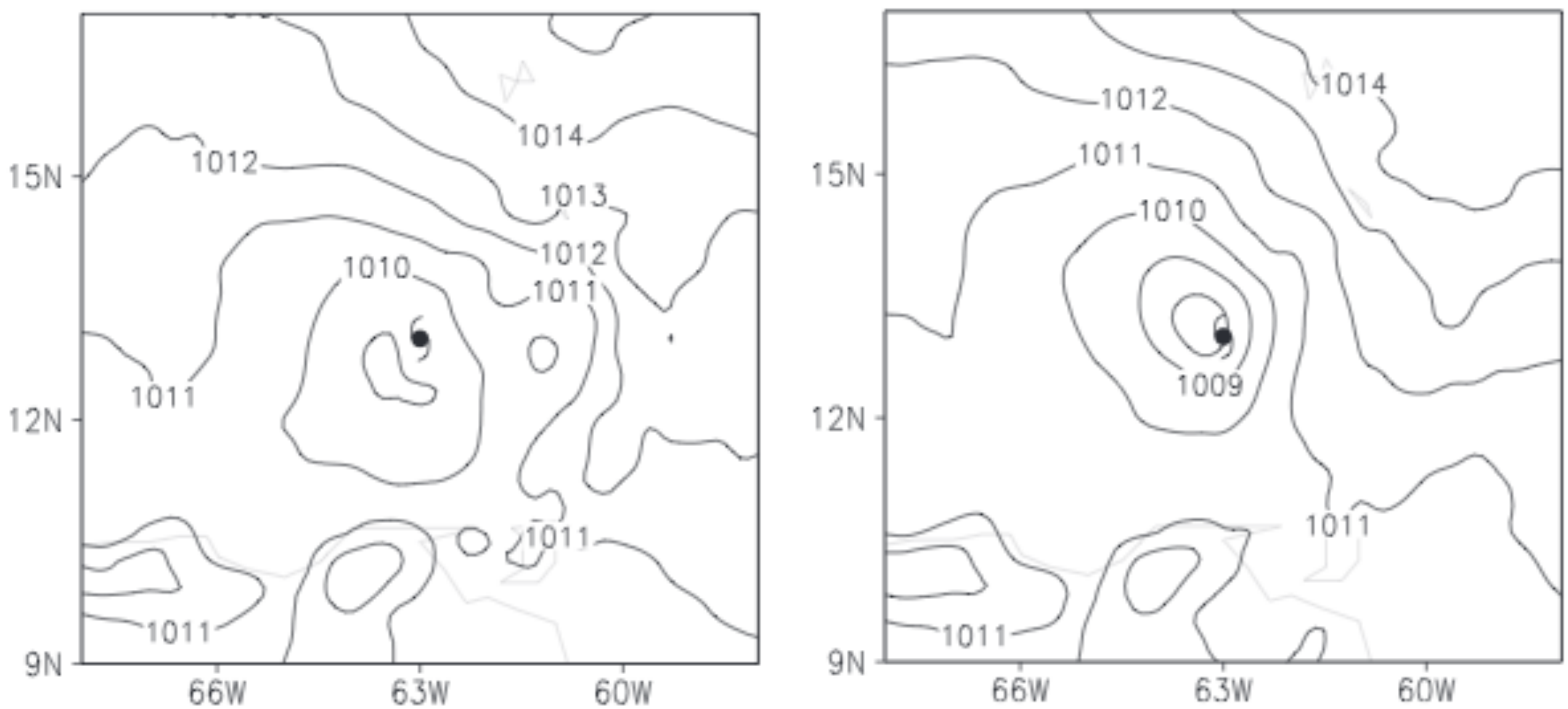
Observation impact studies



Reduction in 2008 season Atlantic basin hurricane track and intensity forecast errors from assimilation of AMSU-A radiance observations

Liu, Z., et al. 2013, MWR

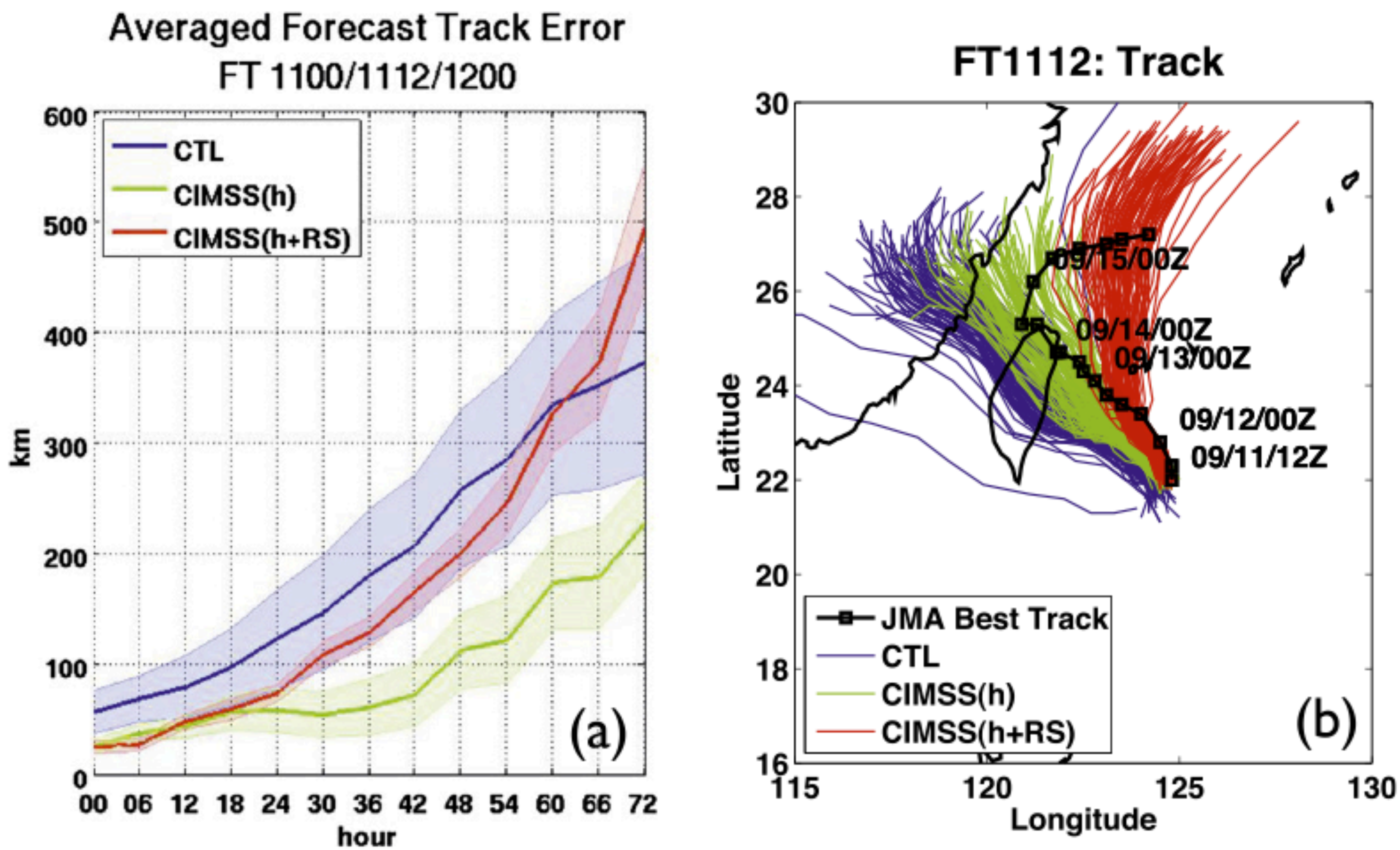
Observation impact studies



Impact of GPS radio occultation observations – improved representation of tropical storm environment – led to better forecasts of storm intensity

Liu, H., et al., 2012, MWR

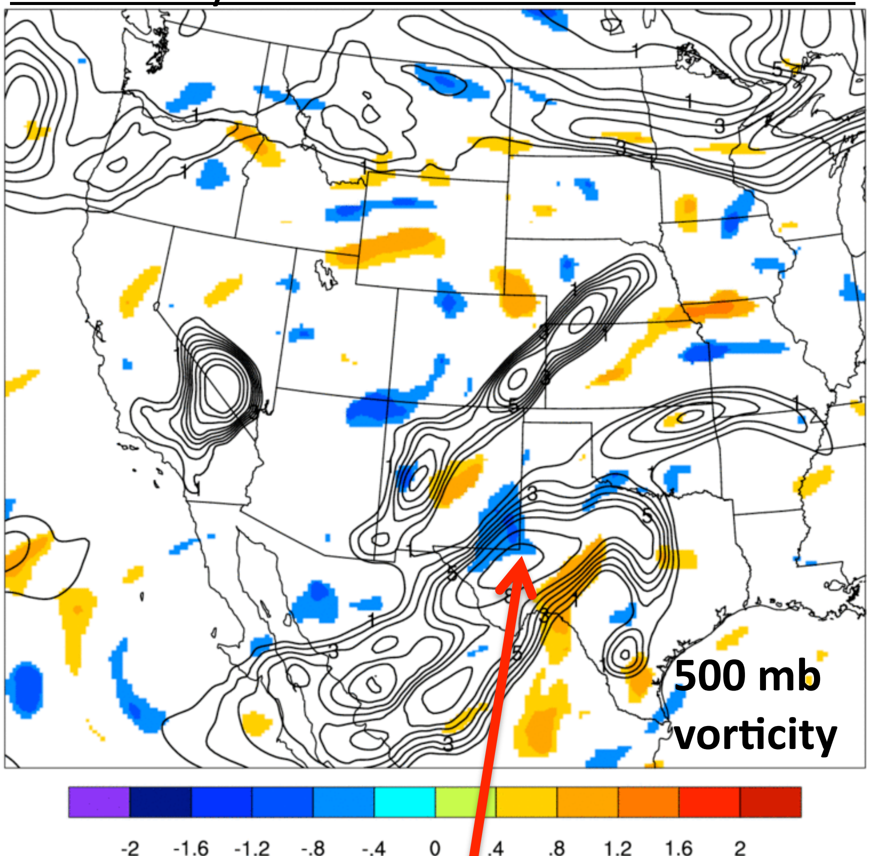
Observation impact studies



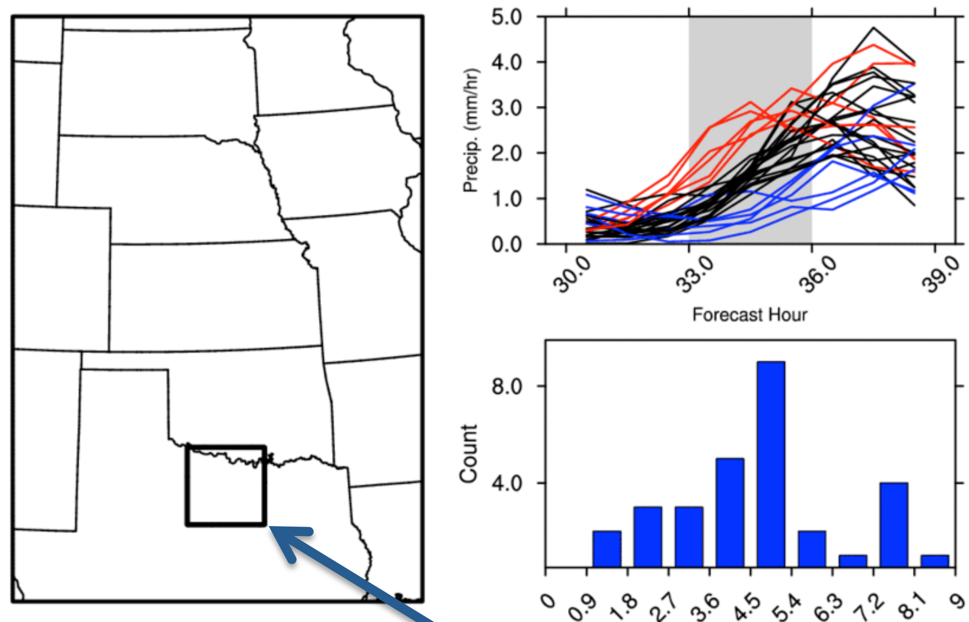
Impact of special atmospheric motion vector data sets on analysis and forecasts for TC Sinlaku. Initial analyses look similar, but large differences in forecasts after day 1 Wu et al., 2014, MWR

Ensemble sensitivity analysis

Sensitivity of earlier forecast to metrics



Forecast metrics from 2013-05-14 12UTC



Shifting disturbance in SW Texas further ESE is associated with more precipitation in box

Ensemble based method for computing forecast sensitivity to initial conditions, warm (cool) colors – increase (decrease) in field at 12 UTC associated with more precipitation in area at right from Fhr 33-36

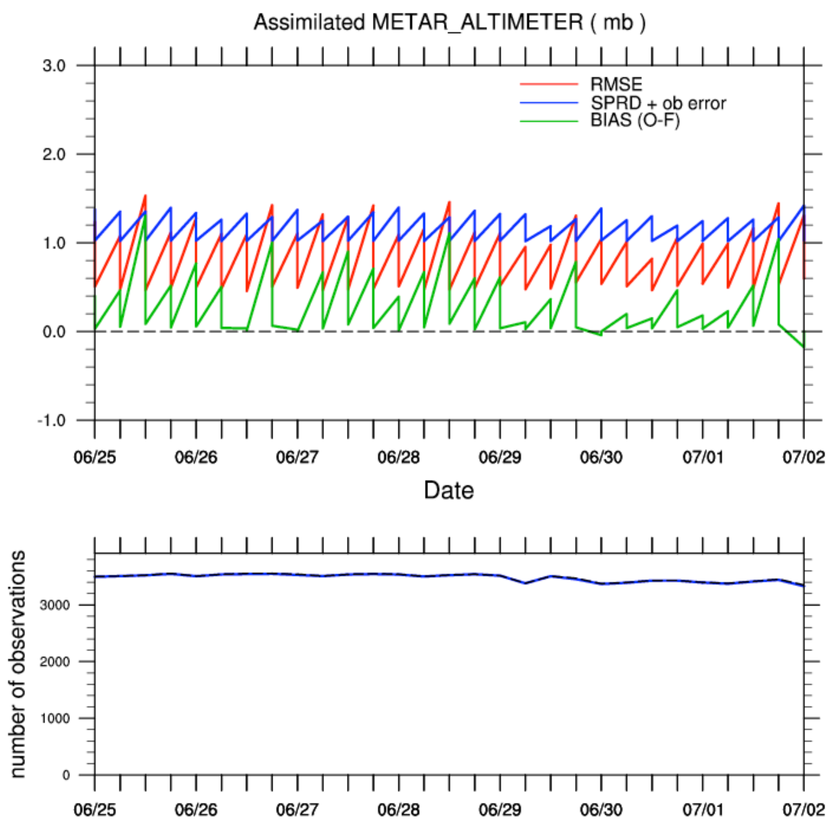
Realtime ensemble analysis and forecast demonstrations using WRF/DART

Realtime WRF/DART systems:

- at NCAR for hurricane prediction since 2009
- NCAR Springtime convective forecasts since 2011
  - supported DC3, MPEX field campaign operations
- at SPC/NSSL Spring Experiment since 2013

Tuning WRF/DART

After a successful cycled assimilation period, additional tuning is potentially need to achieve better performance



<u>Observation diagnostics</u>:

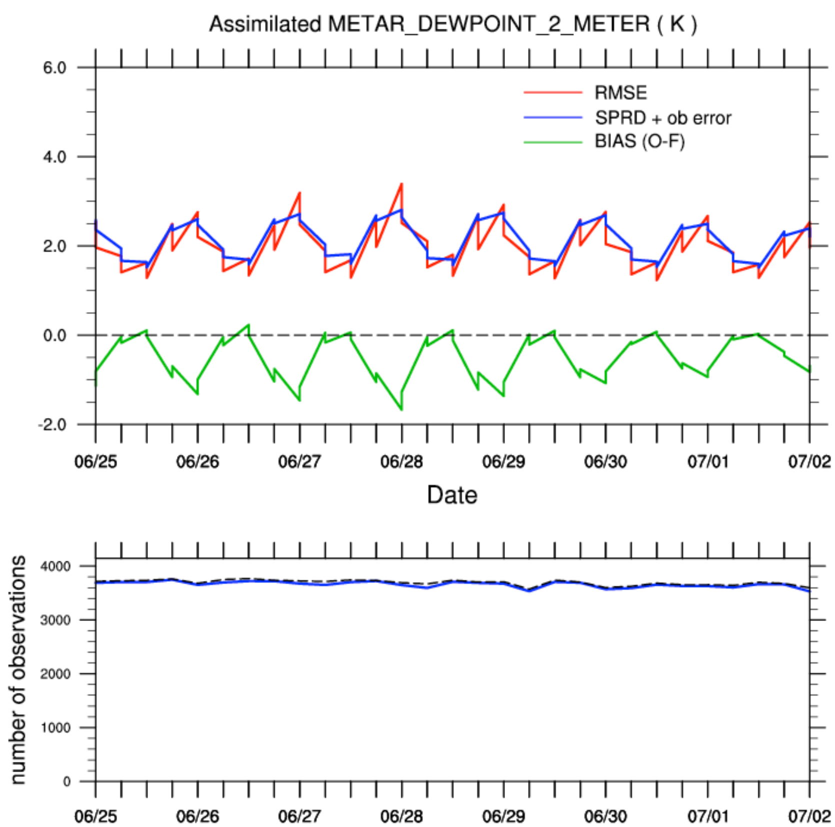
'Sawtooth' diagram – both prior and posterior fit plotted

Here, surface altimeter observations reliably Fit prior state. Shows bias in prior, and total spread is often larger than RMS error – thus, performance could be improved by reducing the assigned observation error

Reducing bias more complex.... Implied error in mean temperature of model state

Tuning WRF/DART

Some observations have more complex behavior, e.g. surface Moisture which has a significant diurnal cycle



<u>Observation diagnostics</u>:

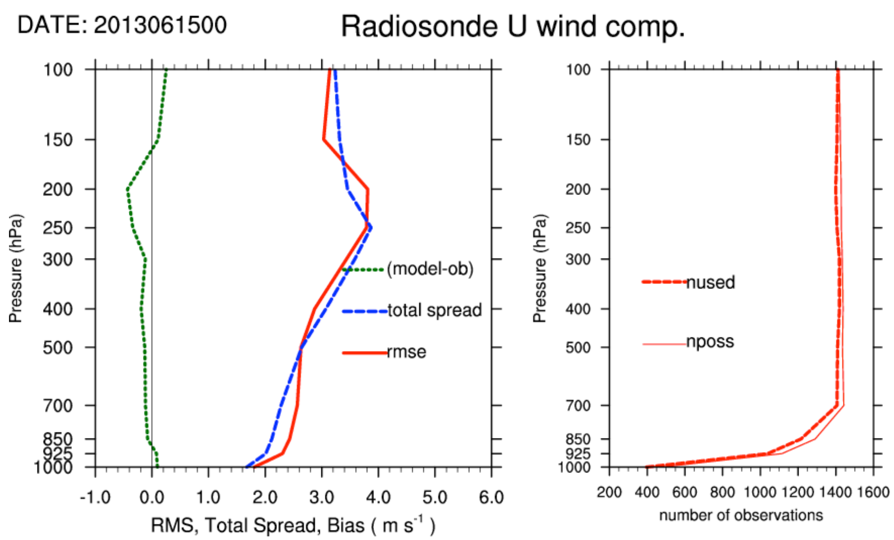
'Sawtooth' diagram – both prior and posterior fit plotted

Here, surface dewpoint, which has observation error assignment based on the relative humidity.

Well tuned errors, but there is a wet bias in during the daytime

Tuning WRF/DART

Some observations make sense to view as vertical profiles, such as radisonde observations



<u>Observation diagnostics</u>:

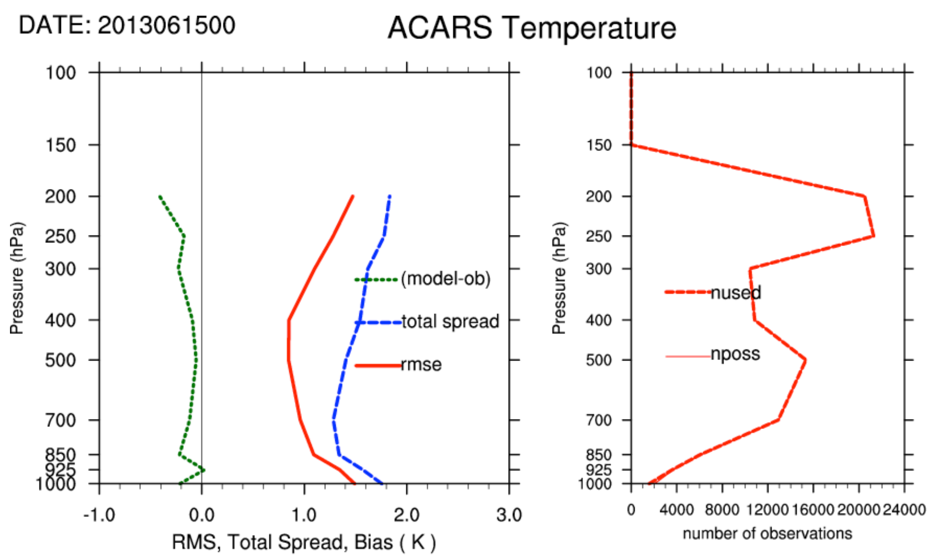
Prior fit only shown here

Here, well tuned fit (can be misfit with NCEP statistics for wind errors, which has a wintertime tuning for the jet level)

Model winds are a bit slow at the jet level (200-250 mb)

Tuning WRF/DART

Sometimes you may want to have poorer fit to a particular observation type



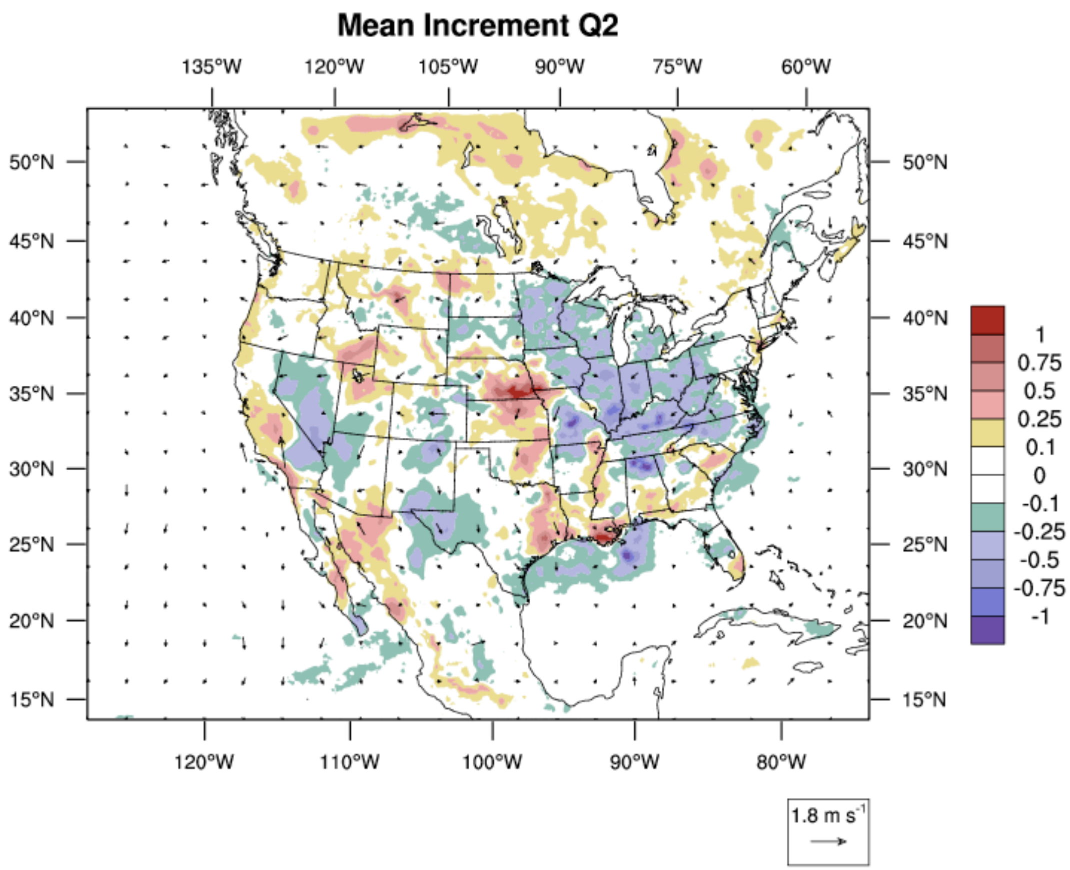
Observation diagnostics:

Prior fit only shown here

Here, well RMS errors are smaller than total spread, but we have lots of these observations, and they have a known temperature bias. Reducing the weight of the ACARS observations improves the fit to the more trusted radiosonde temperatures. This is demonstration Of the 'art' of WRF/DART

Tuning WRF/DART

May want to look at the spatial distribution of mean fit to observations



State space

Time averaged (1 week) analysis increments of the WRF state variable 2 m water vapor

Analysis is removing moisture on average where blue, adding moisture where red

Next: exercises to explore some tools for diagnosing the system

Questions?

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