Hybrid Variational/Ensemble Data Assimilation

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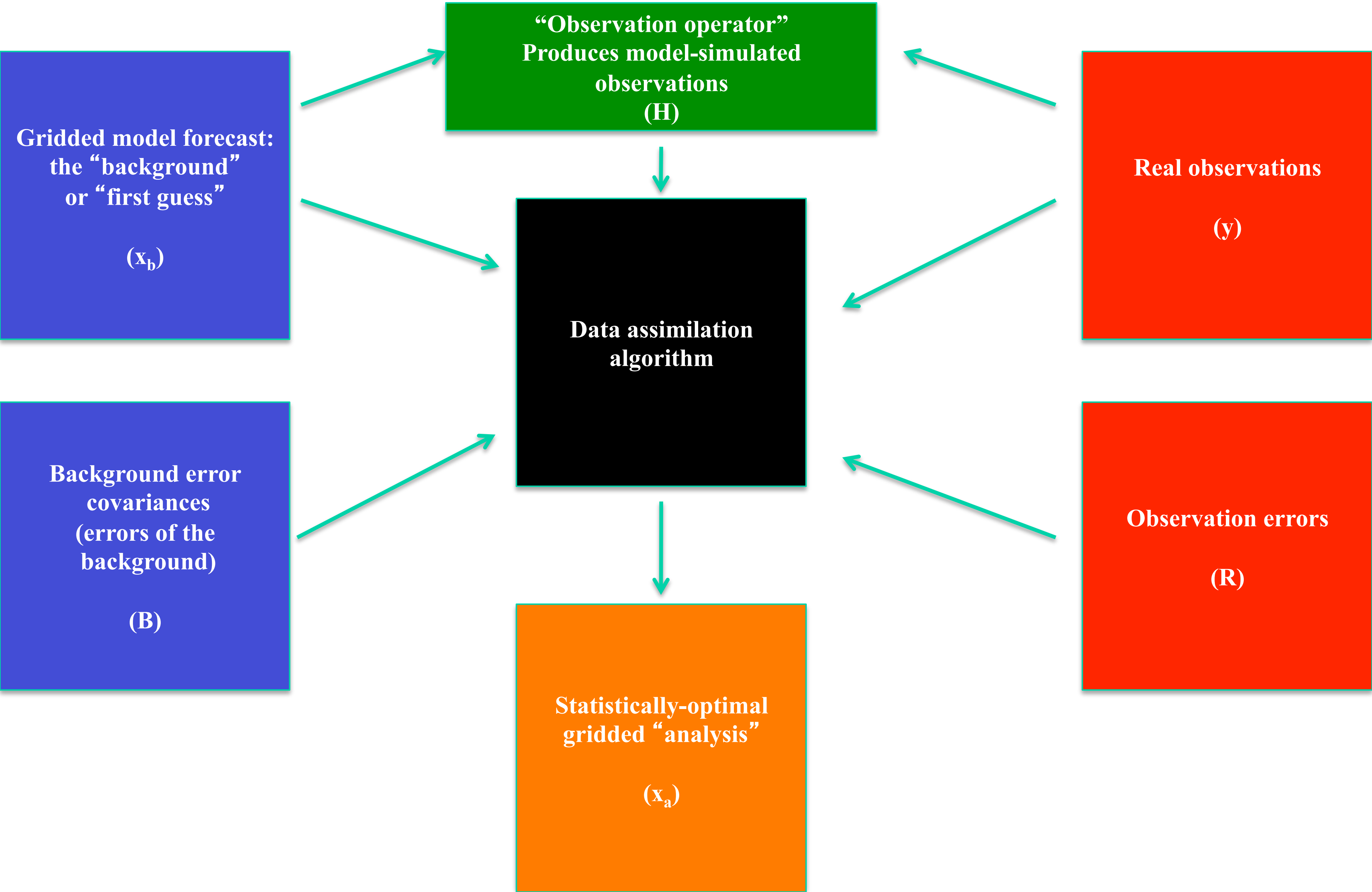
Outline

- Background
- Some results
- Introduction to hybrid practice

What is data assimilation?



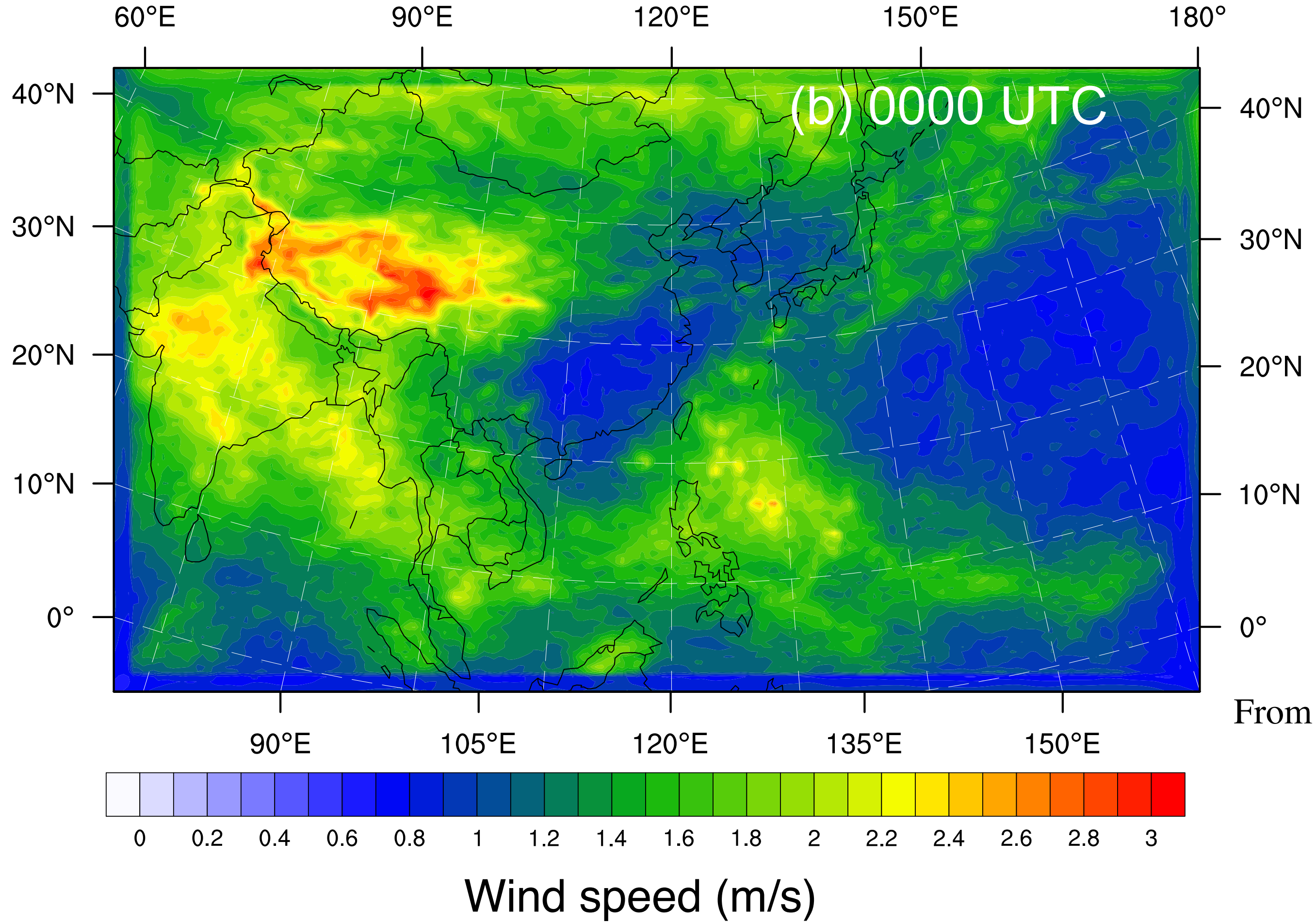
Some data assimilation methods

- Three-dimensional variational (3DVAR)
  – Background error covariances (BECs) typically fixed/ time-invariant
  – May yield poor results when actual flow differs from that encapsulated within the fixed “climatology”

- Ensemble Kalman filter (EnKF)
  – Time-evolving, “flow-dependent” BECs estimated from a short-term ensemble forecast
  – Many different flavors (e.g., ETKF, EAKF)

Ensemble BECs (i.e., spread)

- Average ensemble spread of wind speed over ~3 weeks at 0000 UTC



From Schwartz et al. (2013)

Ensemble BECs (i.e., spread)

•General definition of covariance:

$$\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})$$

•In vector matrix form (here, assume *n* is ensemble size):

$$=\frac{1}{n-1}\sum_{i=1}^{n}(\mathbf{x}_i-\overline{\mathbf{x}})(\mathbf{x}_i-\overline{\mathbf{x}})^{\mathbf{T}}$$

$$=\frac{1}{n-1}\sum_{i=1}^{n}(\delta\mathbf{x}_i)(\delta\mathbf{x}_i)^{\mathbf{T}}$$

“Hybrid” variational/ensemble DA

- “Hybrid” variational/ensemble
  - Incorporates ensemble background errors within a variational (e.g., 3DVAR) framework
  - Combination of fixed and time-evolving background errors
  - Main additional expense compared to 3DVAR is running an ensemble of forecasts

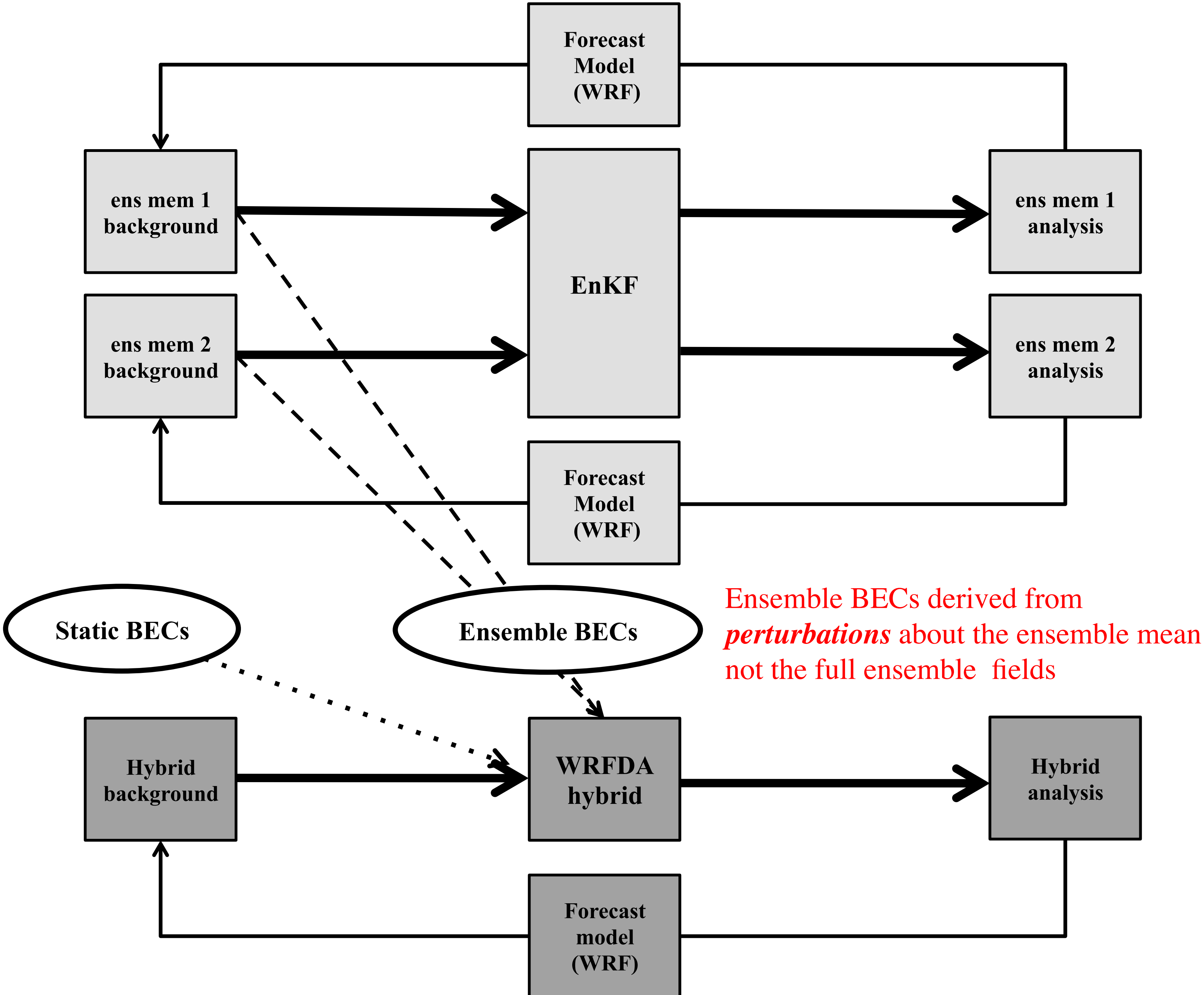
What is Hybrid DA?

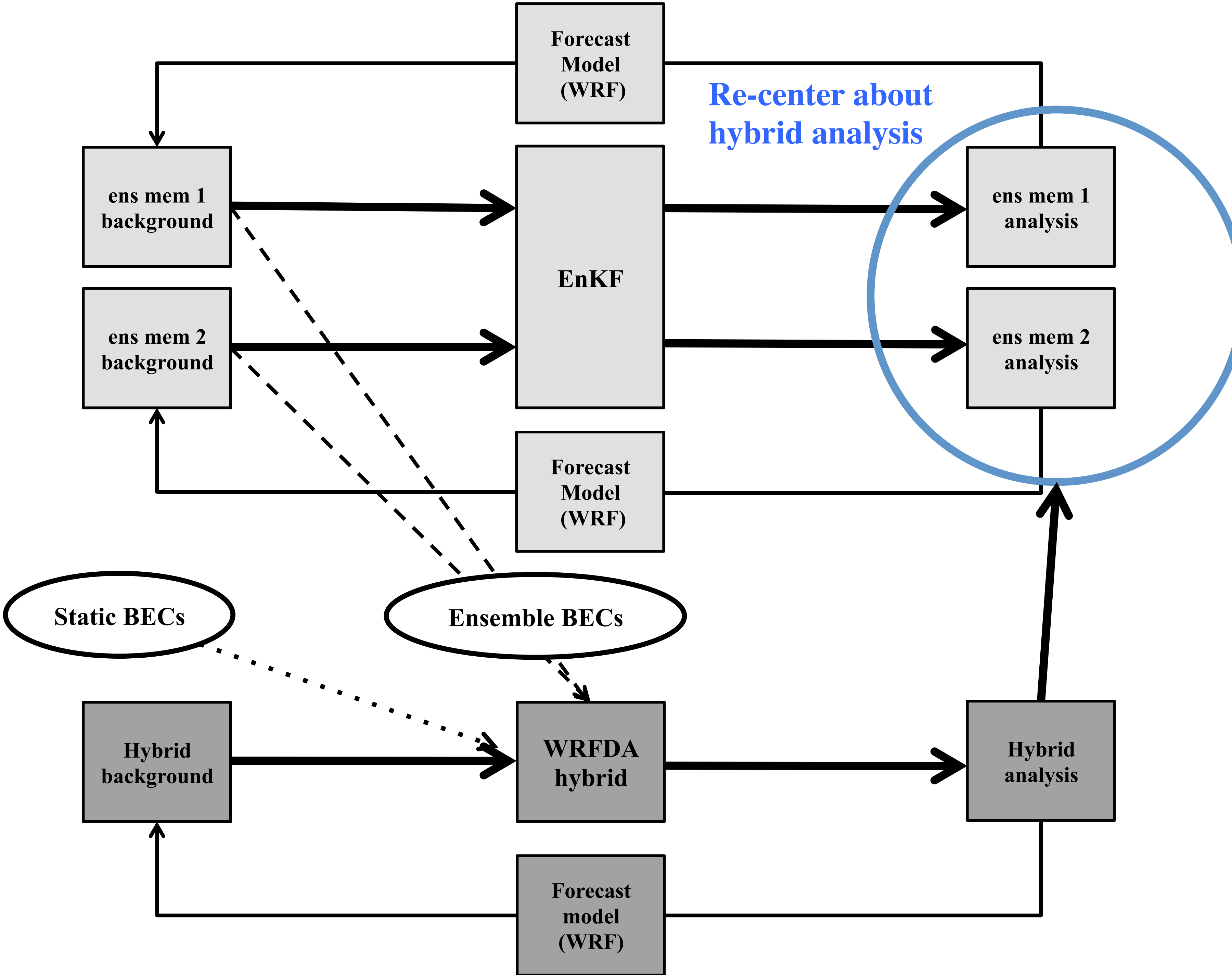
- Deterministic background is analyzed by a variational algorithm (i.e., minimize a cost function)
  - It combines the 3DVAR "climatological" BECs and "errors of the day" from ensemble perturbations

- Traditionally generates a deterministic analysis (like 3DVAR)

- Need a separate system to update ensemble
  - Could be ensemble forecasts already available from operational centers
  - Could be an EnKF-based DA system
  - Could be a multiple model/physics ensemble

- Ensemble needs to be good to well-represent "errors of the day"


Forecast Model (WRF)
ens mem 1 background
EnKF
ens mem 1 analysis
ens mem 2 background
ens mem 2 analysis
Forecast Model (WRF)
Static BECs
Ensemble BECs
Ensemble BECs derived from *perturbations* about the ensemble mean, not the full ensemble fields
Hybrid background
WRFDA hybrid
Hybrid analysis
Forecast model (WRF)



Forecast Model (WRF)
Re-center about hybrid analysis
ens mem 1 background
EnKF
ens mem 1 analysis
ens mem 2 background
ens mem 2 analysis
Forecast Model (WRF)
Static BECs
Ensemble BECs
Hybrid background
WRFDA hybrid
Hybrid analysis
Forecast model (WRF)

Hybrid formulation

(Hamill and Snyder, 2000)

- 3DVAR cost function

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^{\mathrm{T}}\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + \frac{1}{2}[H(\mathbf{x})-\mathbf{y}]^{\mathrm{T}}\mathbf{R}^{-1}[H(\mathbf{x})-\mathbf{y}]$$

- Idea: replace **B** by a weighted sum of static $\mathbf{B}_{\mathrm{s}}$ and the ensemble $\mathbf{B}_{\mathrm{e}}$

$$\mathbf{B} = a_s\mathbf{B}_{\mathrm{s}} + a_e\mathbf{B}_{\mathrm{e}} \circ \mathbf{C}, \qquad a_s = 1 - a_{\mathrm{e}}$$

  - Term **C** is localization for the ensemble
  - Terms a_s and a_e can be tuned to determine how much $\mathbf{B}_{\mathrm{s}}$ and $\mathbf{B}_{\mathrm{e}}$ are weighted

- This form is difficult to implement for a large NWP model
  - Most systems use “extended control variables”

Hybrid formulation used in WRFDA

(Lorenc, 2003)

- Ensemble covariance is included in the 3DVAR cost function through augmentation of control variables

$$J(\mathbf{x},\alpha) = \beta_s \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^{\mathbf{T}}\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + \overbrace{\beta_e \frac{1}{2}\sum_{i=1}^{\mathrm{N}} \alpha_i^{\mathbf{T}}\mathbf{C}^{-1}\alpha_i}^{\text{ensemble control variable } \alpha_i \ (M \times 1)}$$

$$+ \frac{1}{2}[\mathbf{y} - H(\mathbf{x}+\mathbf{x}_e^{'})]^{\mathbf{T}}\mathbf{R}^{-1}[\mathbf{y} - H(\mathbf{x}+\mathbf{x}_e^{'})]$$

$\mathbf{x}_e^{'} = \sum_{\mathrm{i=1}}^{\mathrm{N}} \alpha_i \circ \mathbf{x}_i^{'}$, where $\mathbf{x}_i^{'}$ is the ensemble perturbation for the ensemble member i.

$\circ$ denote element - wise product. α_{i} is in effect the ensemble weight.

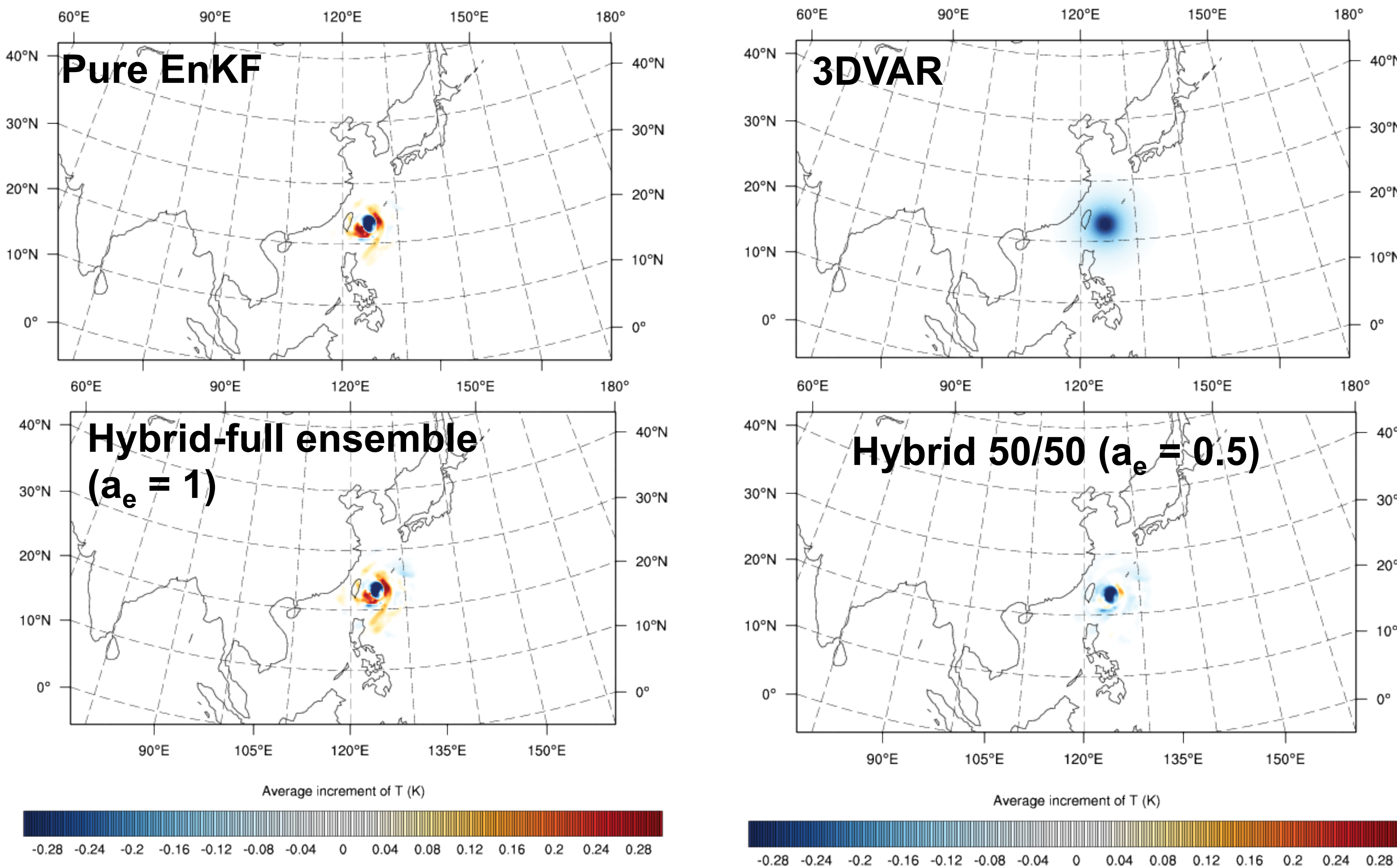
$\mathbf{C}$: correlation matrix (effectively loclization of ensemble perturbations)

- More simply: $J(\mathbf{x},\alpha) = J_b + J_e + J_o$

- β_s and β_e ($1/\beta_s + 1/\beta_e = 1$) can be tuned to have different weight between static and ensemble part

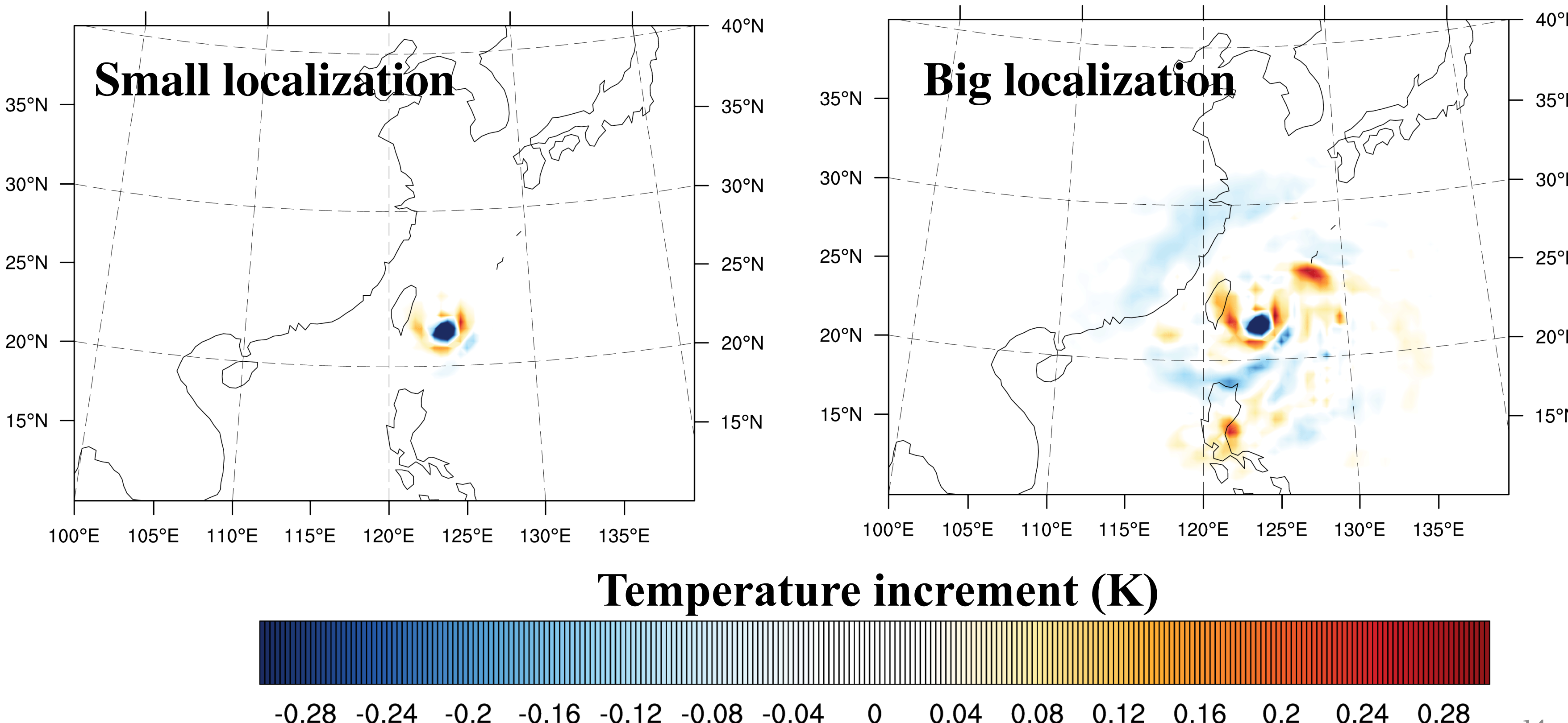
Single observation tests

- **Potential temperature increment, 21st model level**



Meaning of localization

- Localization defines the extent to which an observation can produce an analysis increment
- In this example, 100% of the BECs are from ensemble



Advantages of Hybrid DA

- Hybrid localization is in model space while EnKF localization is usually in observation space

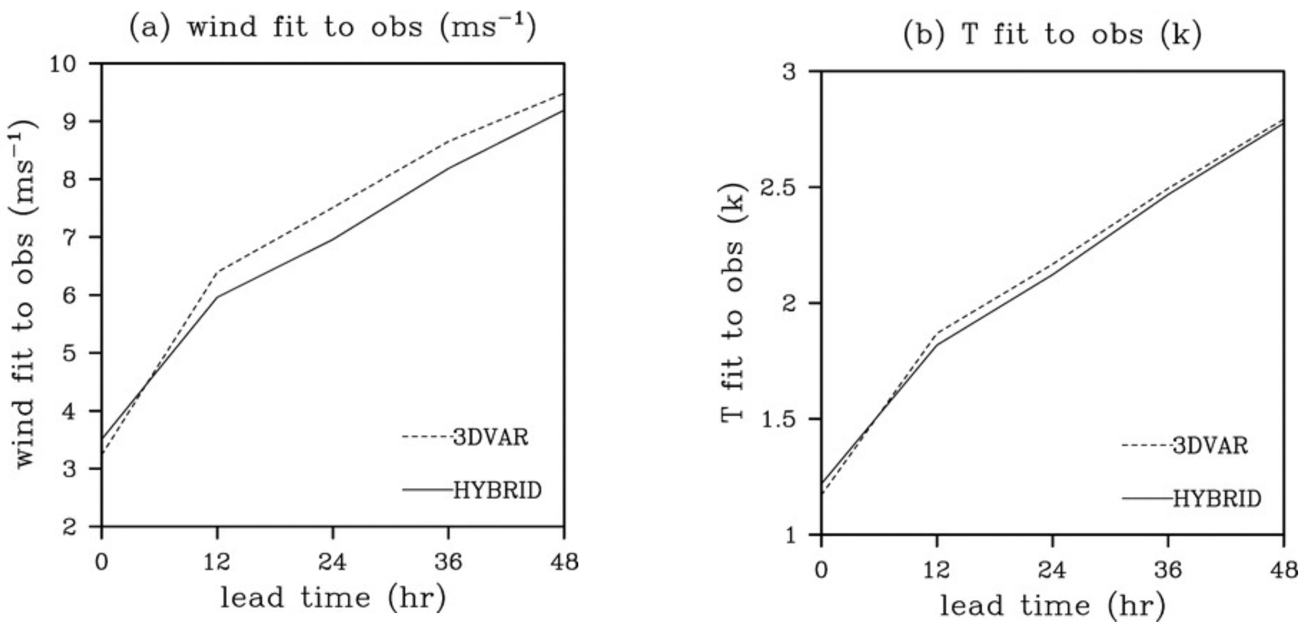
- For some observation types (e.g., radiances), localization is not well defined in observation space

- Easier to make use of existing radiance VarBC in hybrid

- For small ensembles, use of static **B** could be beneficial to have a higher-rank covariance.

Sample results

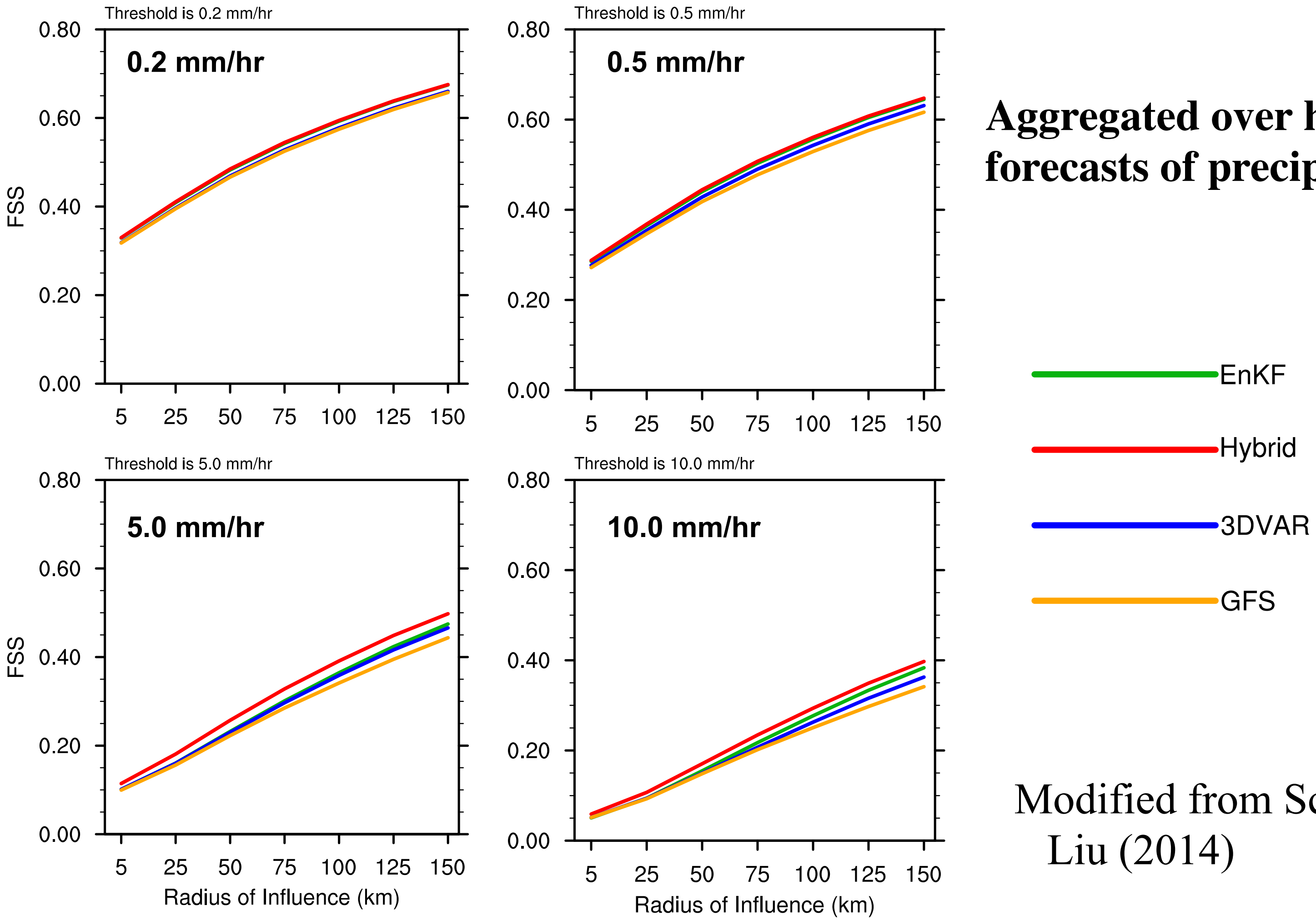
- Example over North America at coarse grid spacing
- Similar results have been obtained by many studies



From Wang et al. (2008)

Hybrid vs. 3DVAR and EnKF

- Fractions skill scores for rainfall (higher is better)

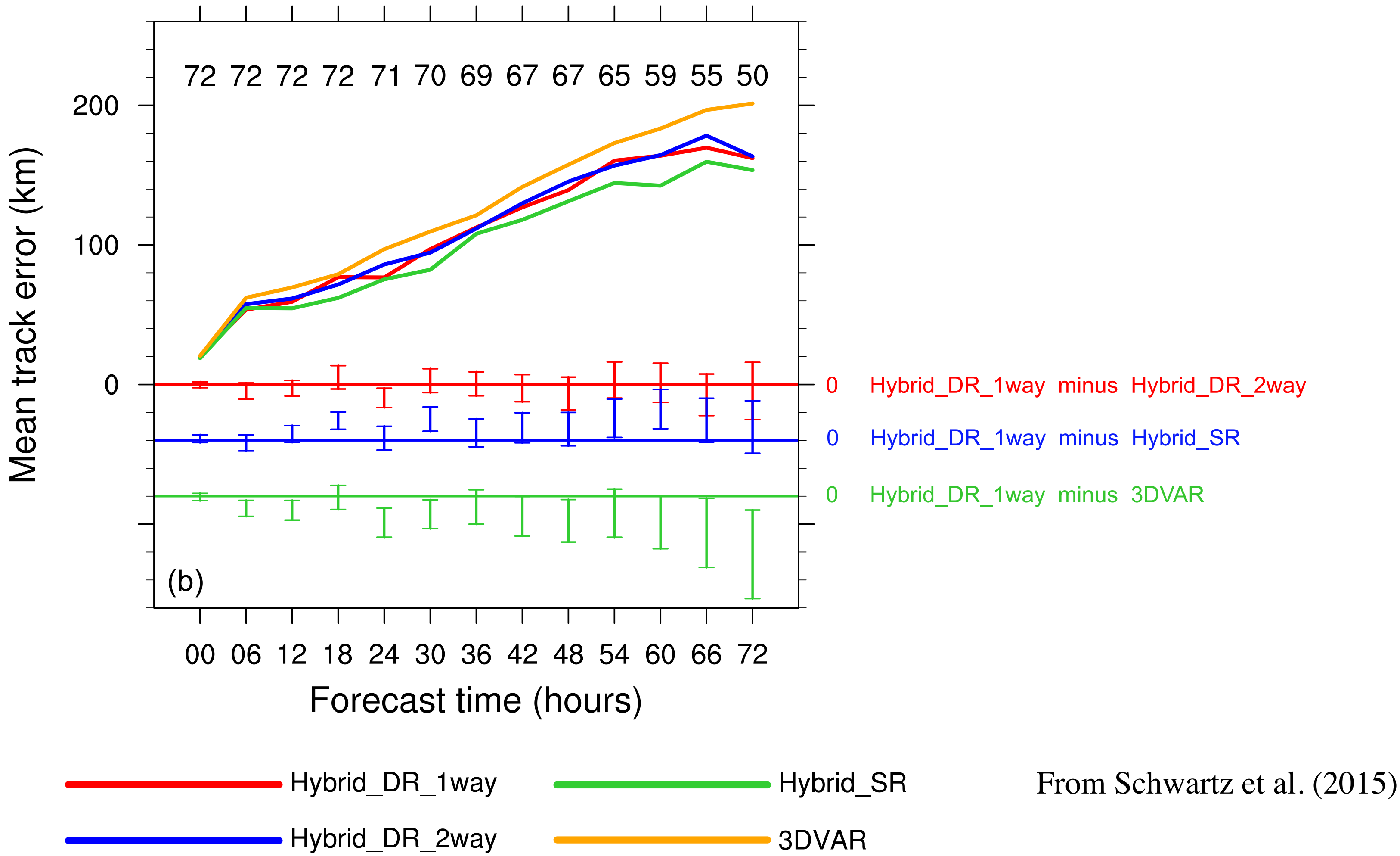


Aggregated over hourly 18-36-hr forecasts of precipitation

Modified from Schwartz and Liu (2014)

Typhoon example

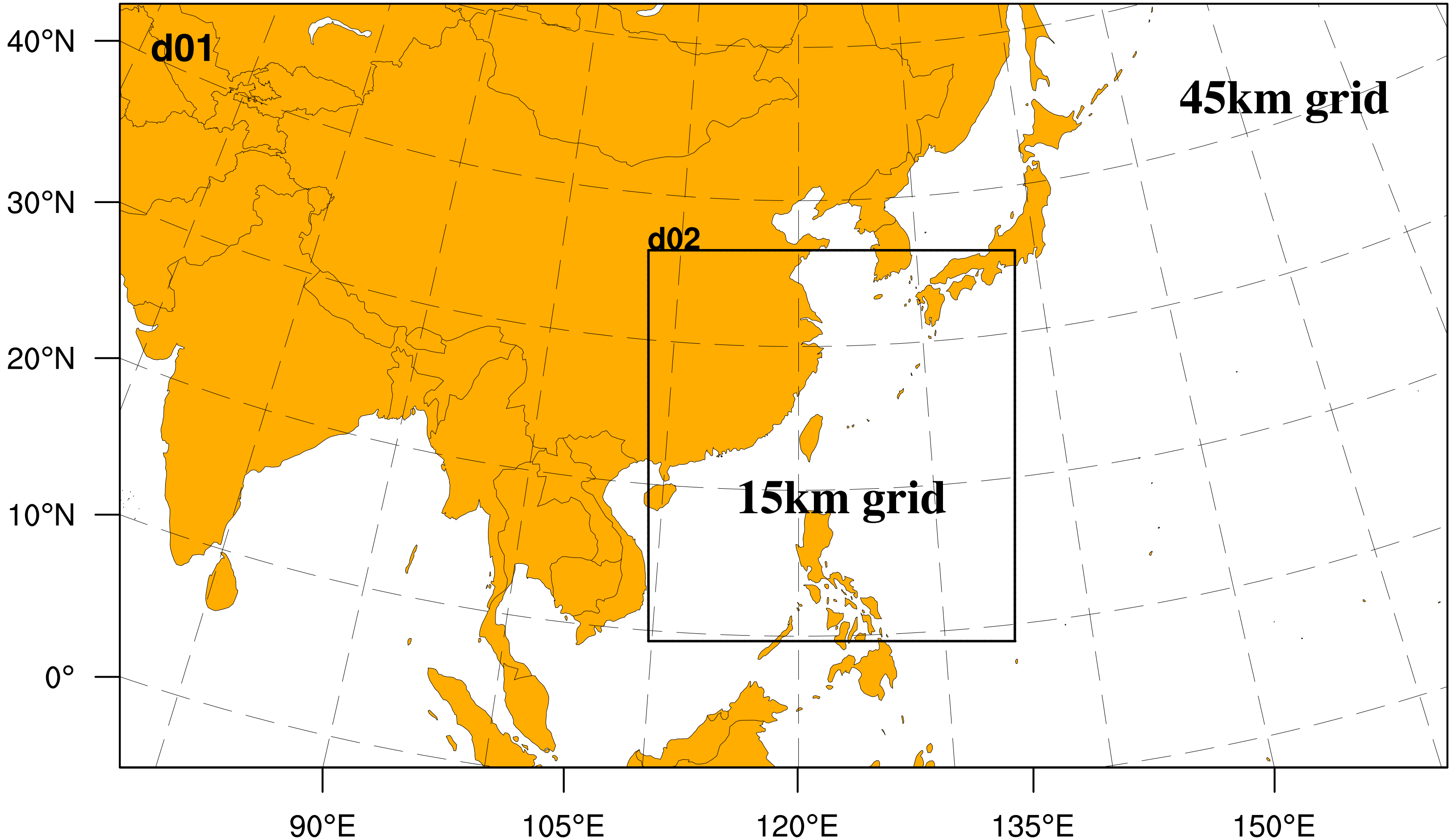
- Mean tropical cyclone track errors



From Schwartz et al. (2015)

Dual-Resolution hybrid (V3.6)

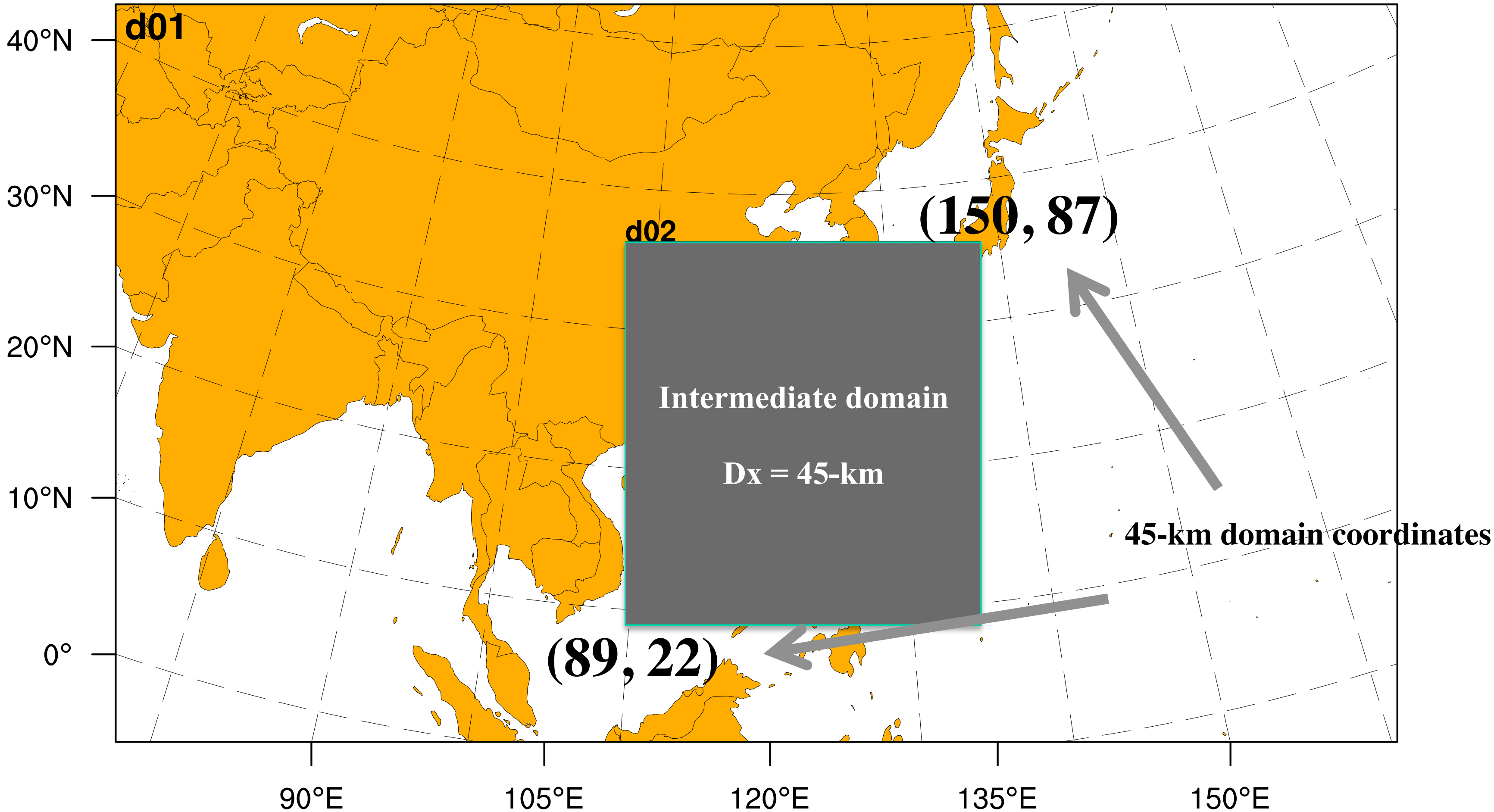
Schwartz et al. (2015; MWR)



Hybrid analysis on 15-km grid but with ensemble perturbation input from 45-km grid

Intermediate domain

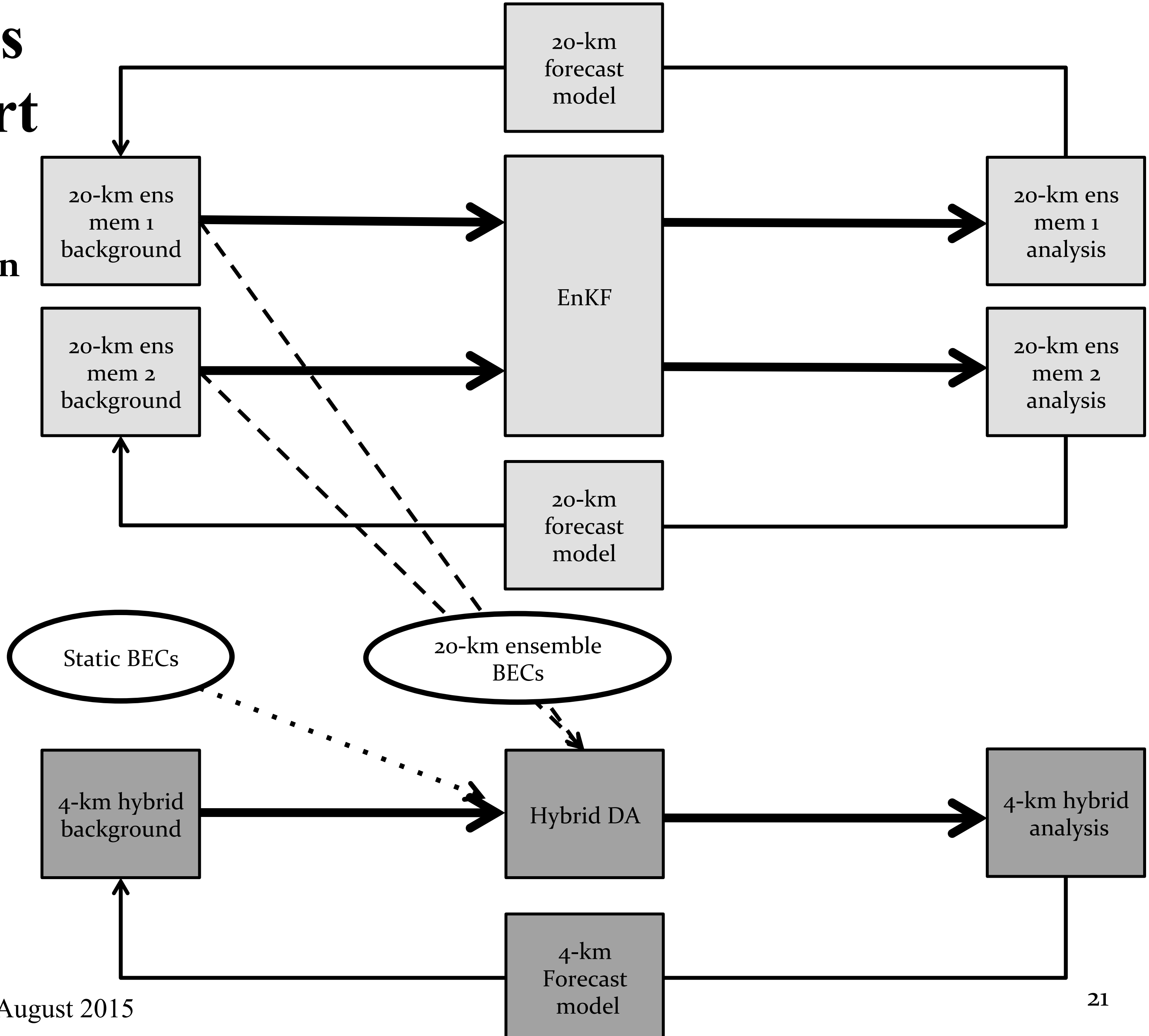
- WRFDA directly reads in d01 ensembles, then cuts to d02 size (making use of WRF model nest namelist setting)



Dual-res flowchart

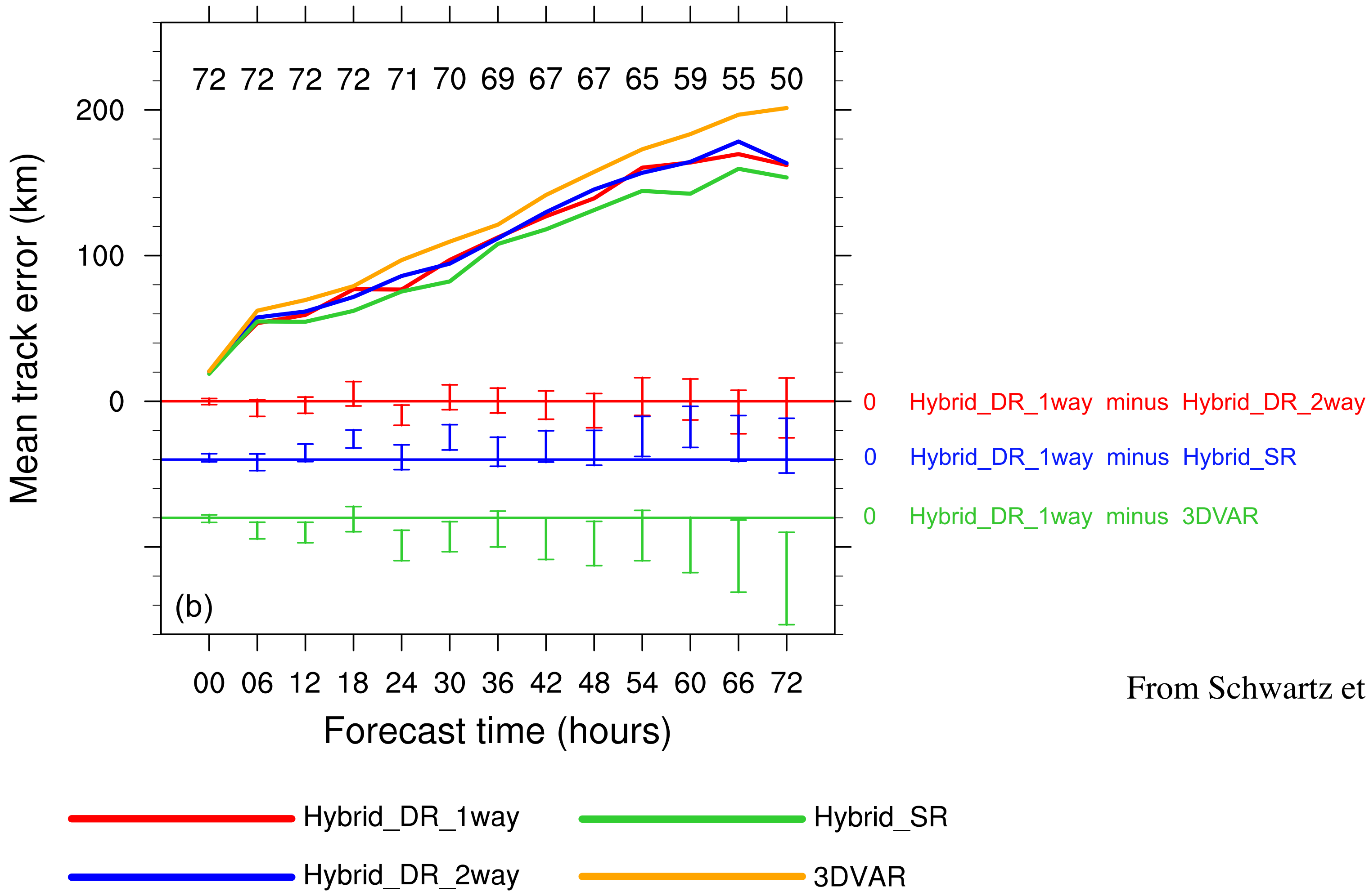
Low-resolution (20-km)

High-res (4-km)



Impact of dual-resolution

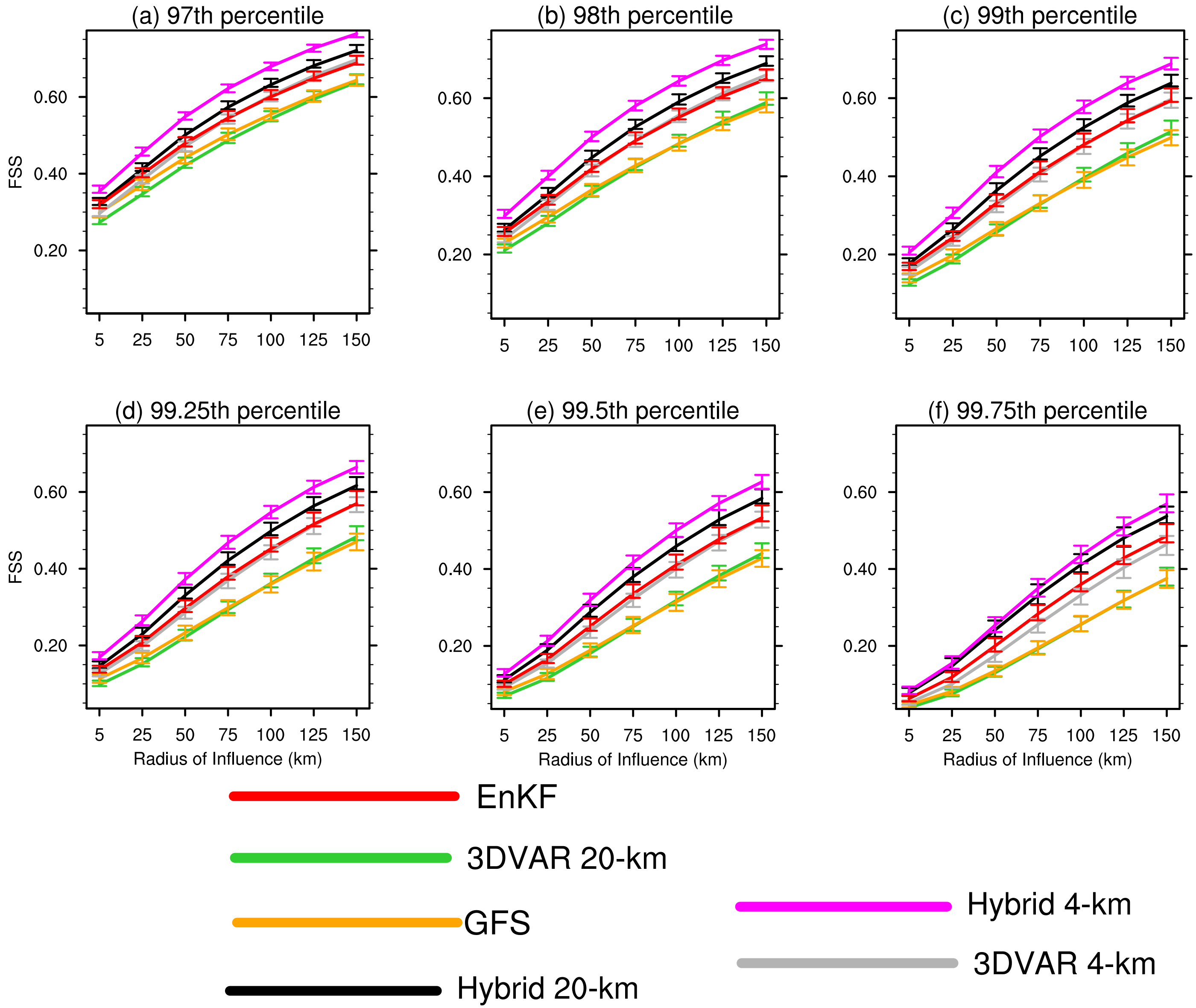
- Mean tropical cyclone track errors



From Schwartz et al. (2015)

Impact of dual-resolution

- Fractions skill score (FSS) aggregated over the first 12 forecast hours and 55 4-km forecasts



Hybrid practice

- **Computation steps:**
  - Compute ensemble mean (**gen_be_ensmean.exe**)
  - Extract ensemble perturbations (**gen_be_ep2.exe**)
  - Run WRFDA in “hybrid” mode (**da_wrfvar.exe**)
  - Display results for: ens_mean, std_dev, ensemble perturbations, hybrid increments, cost function
  - If time permits, play with different namelist settings: “je_factor” and “alpha_corr_scale”
- **Scripts to use:**
  - Some NCL scripts to display results

- **Ensemble generation part not included in current practice**

Namelist for WRFDA in hybrid mode

&wrfvar7
je_factor=2,   # half/half for ensemble and static B weightings (tunable parameter)

&wrfvar16
alphacv_method=2,   # ensemble part is in model space (u,v,t,q,ps)

ensdim_alpha=10,   # ensemble size

alpha_corr_type=3,   # 1=Exponential; 2=SOAR; 3=Gaussian

alpha_corr_scale=750.,   # correlation scale in km (tunable parameter)

alpha_std_dev=1.,

alpha_vertloc=true, (use program "**gen_be_vertloc.exe 42**" **to generate file**)

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