# MPAS-JEDI 3D/4DEnVar

#### Presented by Jake Liu Based on the materials prepared by I-Han Chen





### **1. Variational Cost Function**

- 2. Ensemble Error Covariance Matrix
- 3. Overview of 3DEnVar
- 4. Setting up a .yaml file for 3DEnVar
- 5. Overview of 4DEnVar
- 6. Setting up a .yaml file for 4DEnVar

## **The Problem**

We want to find the **analysis state** (*x*) that minimizing a cost function with an optimal fit to the background and observations.

$$\boldsymbol{J}(\boldsymbol{x}) = \frac{1}{2} (\boldsymbol{x} - \boldsymbol{x}_b)^T \boldsymbol{B}^{-1} (\boldsymbol{x} - \boldsymbol{x}_b) + \frac{1}{2} (h(\boldsymbol{x}) - \boldsymbol{y})^T \boldsymbol{R}^{-1} (h(\boldsymbol{x}) - \boldsymbol{y})$$

**Distance to background** 

**Distance to observations** 

### **Incremental Cost Function in JEDI**

Liu et al. (2022)

Full-form

Incremental-form

$$J(x) = \frac{1}{2} (x - x_b)^T B^{-1} (x - x_b) + \frac{1}{2} (h(x) - y)^T R^{-1} (h(x) - y)$$
$$\downarrow$$
$$J(\delta x) = \frac{1}{2} (\delta x - \delta x_g)^T B^{-1} (\delta x - \delta x_g) + \frac{1}{2} (H \delta x - d)^T R^{-1} (H \delta x - d)$$
$$\delta x = x - x_g \qquad \delta x_g = x_b - x_g \qquad d = y - h(x_g)$$

#### The minimization deals with increments to a known reference state

- Cost function minimizes  $\delta x = x x_g$  instead of the full state (x)
- Start from  $x_g = x_b$  and  $\delta x_g = 0$
- After minimization->  $x_a = x_g + \delta x$

# Appropriately assign B and R is critical

We want to find the analysis state (x) that minimizing a cost function with **an optimal fit** to the background and observations.

**Distance to background Distance to observations**  $J(\delta x) = \left[\frac{1}{2}(\delta x - \delta x_g)^T B^{-1}(\delta x - \delta x_g)\right] + \left[\frac{1}{2}(H\delta x - d)^T R^{-1}(H\delta x - d)\right]$ 

> The weighting between the two components is determined by B (background error) and R (observation error).

- A larger **B** means background is less accurate -> x will get closer to observation
- A larger **R** means observation is less accurate -> **x** will get closer to background

### Two types of background error covariance (B)

$$J(\delta x) = \frac{1}{2} \left( \delta x - \delta x_g \right)^T \mathbf{B}^{-1} \left( \delta x - \delta x_g \right) + \frac{1}{2} (H \delta x - d)^T \mathbf{R}^{-1} (H \delta x - d)$$

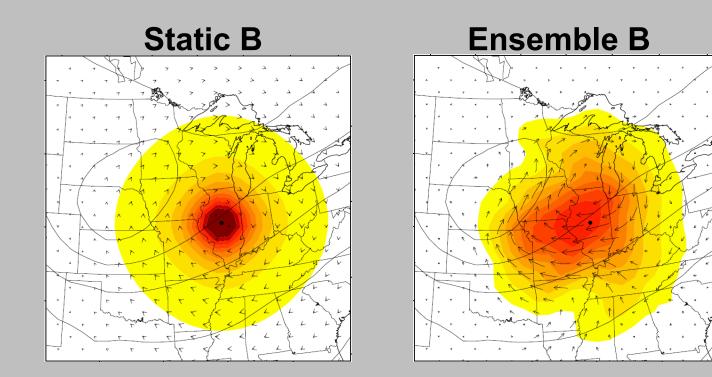
#### 1. Static B

-> from statistic, does not vary with time

### 2. Ensemble B

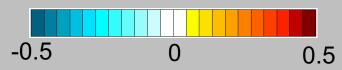
-> flow-dependent, reflect the background error in different time

### Example to show the B effect (Single observation tests)



#### Ensemble **B**:

- Errors of the day are sampled
- flow-dependent update



Increments of temperature (shaded) and horizontal winds (vector)

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### **Derive B matrix from an ensemble of forecasts**

ensemble size

$$B_e = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \overline{x})(x_i - \overline{x})^T$$
State variable of ensemble mean  
State variable of each ensemble member

$$B_e = \frac{1}{n-1} \sum_{i=1}^{n} (\frac{\delta x_i}{\delta x_i}) (\delta x_i)^T$$
  
ensemble perturbation

- The ensemble mean provides an estimation of the truth
- The perturbations from the mean estimate the uncertainty, which is used to model backgrounderror covariance matrix.

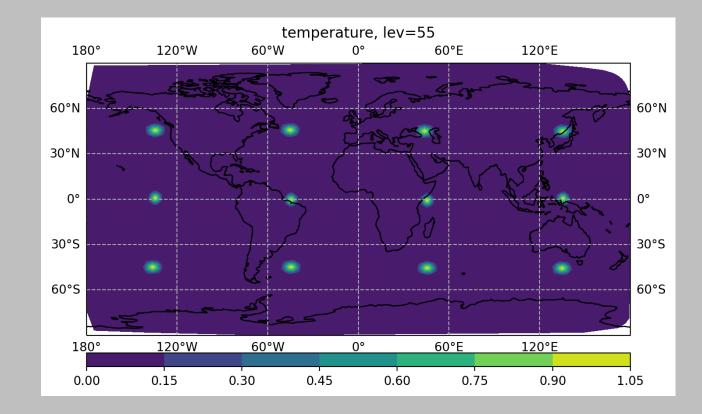
### Localization of the B matix

Because we do not have a complete estimate of **B** (e.g., limited ensemble size) we need to use localization

Basic idea: observations should only influence an area nearby the observation

$$B = L \circ B_e$$

#### Small localization



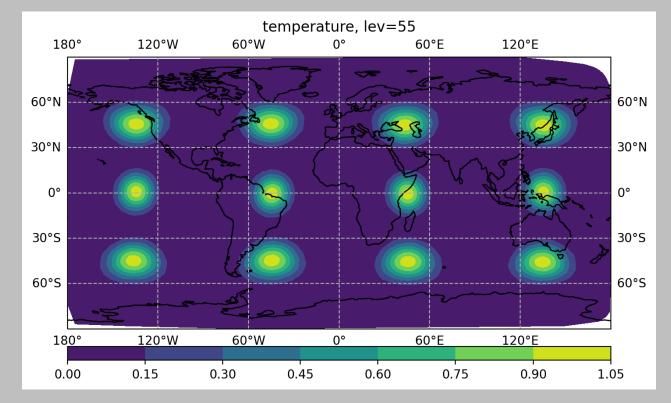
### Localization of the *B* matix

Because we do not have a complete estimate of *B* (e.g., limited ensemble size) we need to use localization

Basic idea: observations should only influence an area nearby the observation

$$B = L \circ B_e$$

#### large localization



### Benefits of using an ensemble to estimate B

- Simple to implement
- Provides a flow-dependent estimate of the errors and uncertainties
   Depends on the quality of the ensemble
- Incorporates ensemble estimate of background errors within the variational update
   Still updates a deterministic forecast

#### EnVar uses a pure ensemble B to updates a deterministic forecast

In hybrid methods, B can be a weighting sum between static B  $(B_s)$  and ensemble B  $(B_e)$ .

$$\boldsymbol{B} = \beta_s \boldsymbol{B}_s + \beta_e \boldsymbol{B}_e$$
$$\beta_s + \beta_e = 1$$

=1

pure ensemble B

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- 2. Ensemble Error Covariance Matrix

### 3. Overview of 3DEnVar

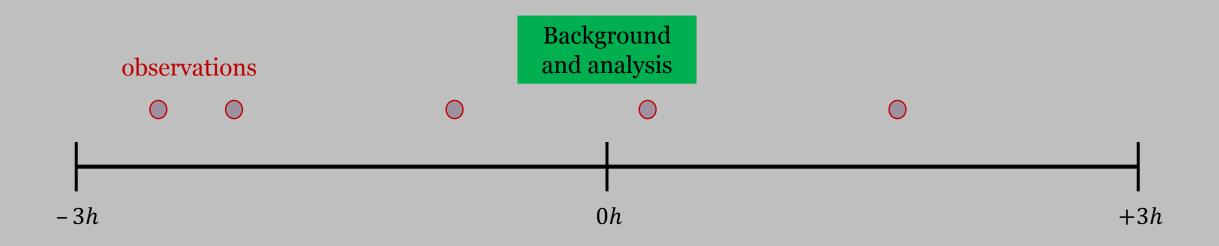
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# **3DEnVar**

$$J(x) = \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b) + \frac{1}{2}(h(x) - y)^T R^{-1}(h(x) - y)$$

- We assume that all observations *y*<sub>o</sub> are valid at the same time.
- Usually valid at the center of the window (i.e. at the same time as x and  $x_b$ )

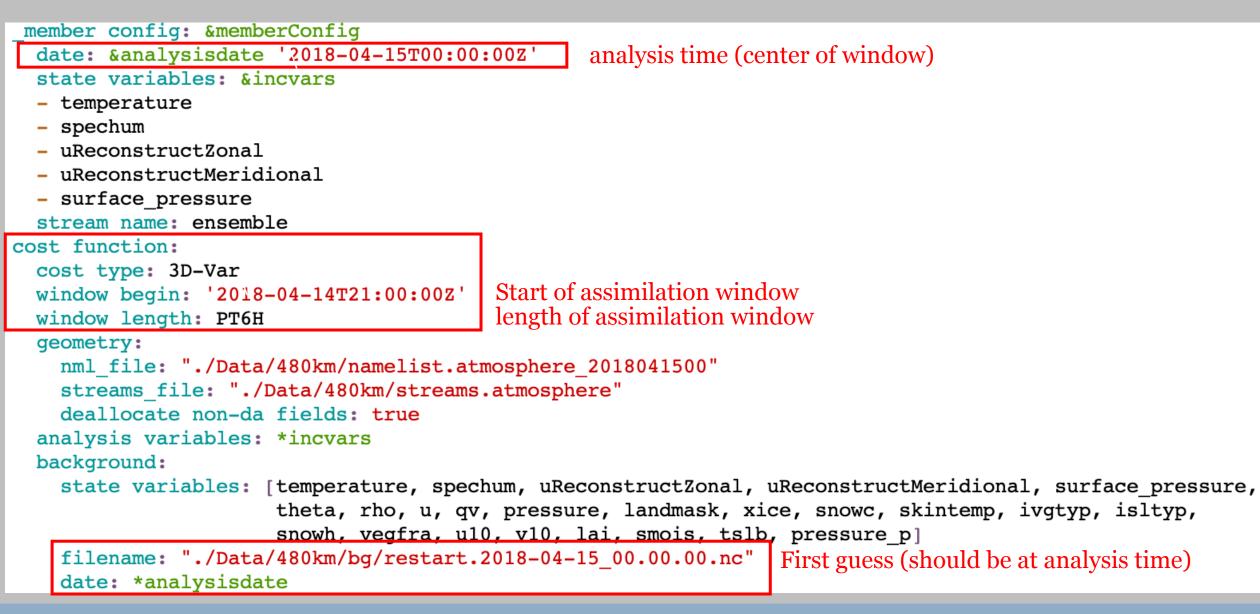
# **3DEnVar using a 6h assimilation window**



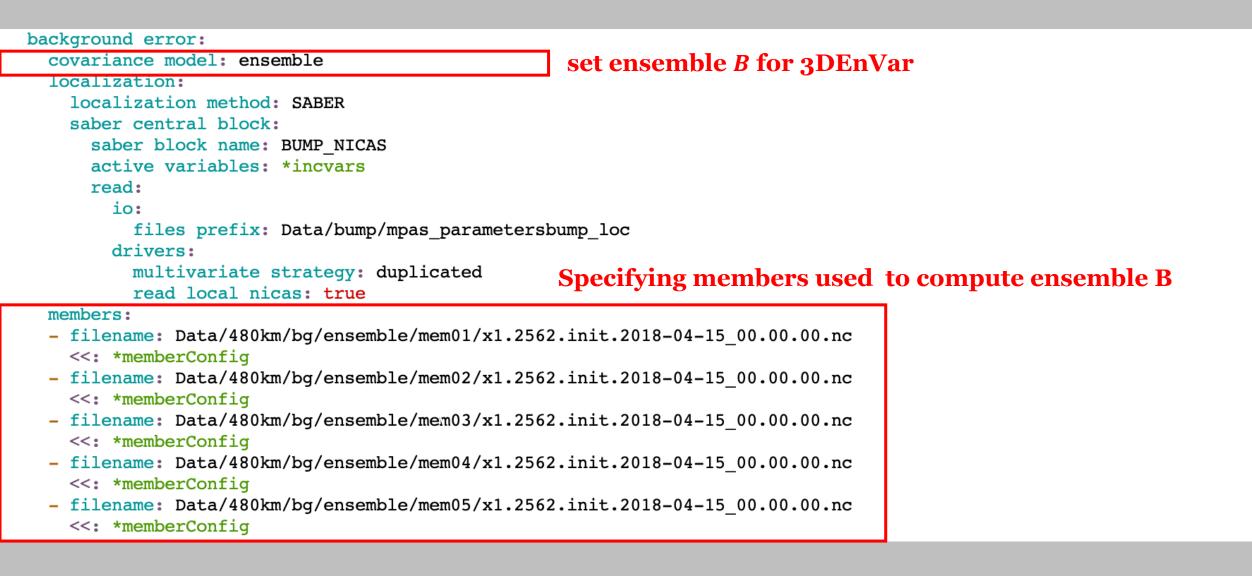
• All observations in 3DEnVar are assumed to be valid at the same time as the background

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### **Configure the analysis time for 3DEnvar**



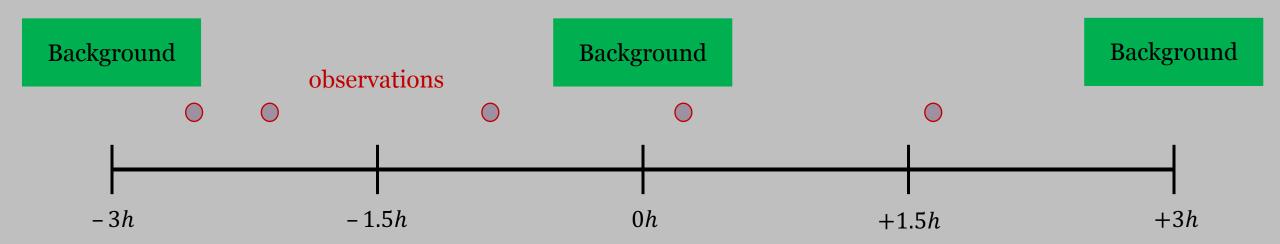
## **Configure the ensemble B**



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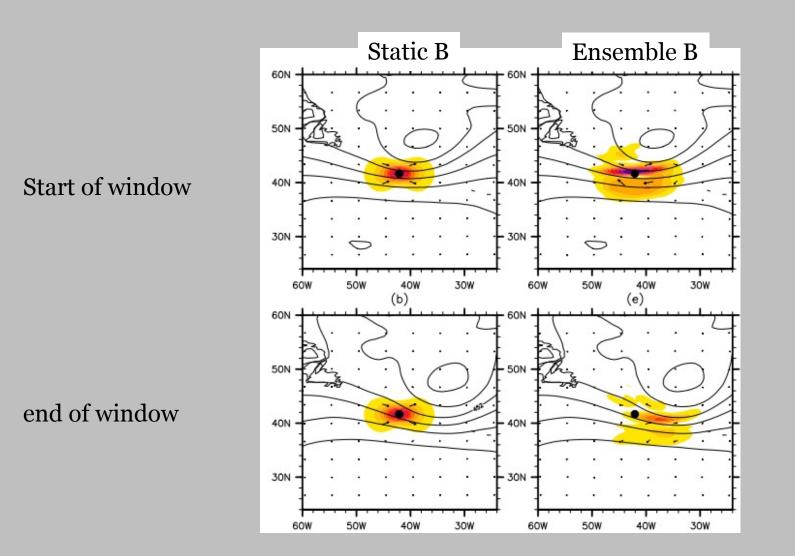
## 4DEnVar

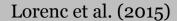
$$J(x) = \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b) + \frac{1}{2} \sum_{k=1}^{K} (Hx_k - y_k)^T R_k^{-1} (Hx_k - y_k)$$



- All observations in 4DEnVar are binned within a smaller subwindow and innovations  $(Hx y_o)$  are calculated relative to background valid at that time.
- Ensemble needed at the center of each subwindow (*K* ensemble required).

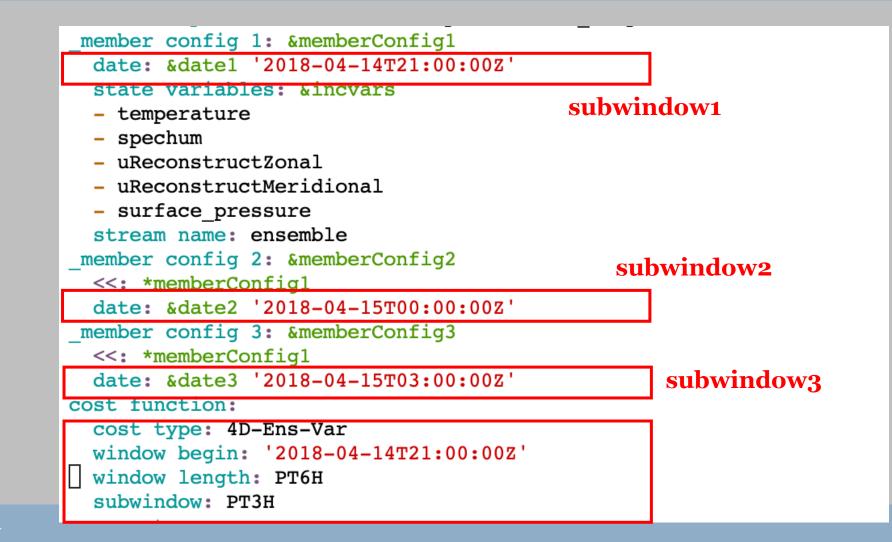
#### The 4D ensemble *B* is used to propagate the innovation





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# **Configure the analysis times for 4DEnvar**



# **Background needed for each subwindow**

```
cost function:
  cost type: 4D-Ens-Var
  window begin: '2018-04-14T21:00:00Z'
  window length: PT6H
  subwindow: PT3H
  geometry:
   nml file: "./Data/480km/namelist.atmosphere 2018041500"
    streams file: "./Data/480km/streams.atmosphere"
  analysis variables: *incvars
  background:
    states:
    - state variables: &stvars
                      [temperature, spechum, uReconstructZonal, uReconstructMeridional, surface pressure,
                     theta, rho, u, qv, pressure, landmask, xice, snowc, skintemp, ivqtyp, isltyp,
                     snowh. vegfra, u10, v10, lai, smois, tslb, pressure p]
                                                                  bg (subwindow 1)
     filename: "./Data/480km/bg/restart.2018-04-14 21.00.00.nc"
      date: *date1
     state variables: *stvars
                                                                  bg (subwindow 2)
     filename: "./Data/480km/bg/restart.2018-04-15 00.00.00.nc"
      date: *datez
     State variables. "Stvars
                                                                  bg (subwindow 3)
     filename: "./Data/480km/bg/restart.2018-04-15 03.00.00.nc"
     date: *date3
```

### **Configure the ensemble B**

background error:	
covariance model: ensemble	set ensemble <i>B</i> for 4DEnVar
localization:	
localization method: SABER	
saber central block:	
saber block name: BUMP NICAS	
active variables: *incvars	
read:	
io:	
files prefix: Data/bump/mpas_parametersbump_loc	
drivers:	
multivariate strategy: duplicated	
read local nicas: true	

#### Member file needed for each subwindow

members:

- states:

  - filename: Data/480km/bg/ensemble/mem01/x1.2562.init.2018-04-15\_03.00.00.nc
    <<: \*memberConfig3</pre>
- states:

  - filename: Data/480km/bg/ensemble/mem02/x1.2562.init.2018-04-15\_03.00.00.nc
    <<: \*memberConfig3</pre>
- states:
  - filename: Data/480km/bg/ensemble/mem03/x1.2562.init.2018-04-14\_21.00.00.nc
    <<: \*memberConfig1</pre>
- states:
- states:

  - filename: Data/480km/bg/ensemble/mem05/x1.2562.init.2018-04-15\_03.00.00.nc
    <<: \*memberConfig3</pre>

# References

- Liu, Z., and Coauthors, 2022: Data assimilation for the Model for Prediction Across Scales -Atmosphere with the Joint Effort for Data assimilation Integration (JEDI-MPAS 1.0.0): EnVar implementation and evaluation. *Geosci. Model Dev.*, 15, 7859–7878, <u>https://doi.org/10.5194/gmd-15-7859-2022</u>.
- Lorenc, A. C., N. E. Bowler, A. M. Clayton, S. R. Pring, and D. Fairbairn, 2015: Comparison of hybrid-4DEnVar and hybrid-4DVar data assimilation methods for global NWP. *Mon. Weather Rev.*, 143, 212–229, <u>https://doi.org/10.1175/MWR-D-14-00195.1</u>.