

# Sensitivity and Uncertainty Analysis of Physical Parameterization and Initial Conditions on Meteorological Variables and CO<sub>2</sub> Mole Fractions



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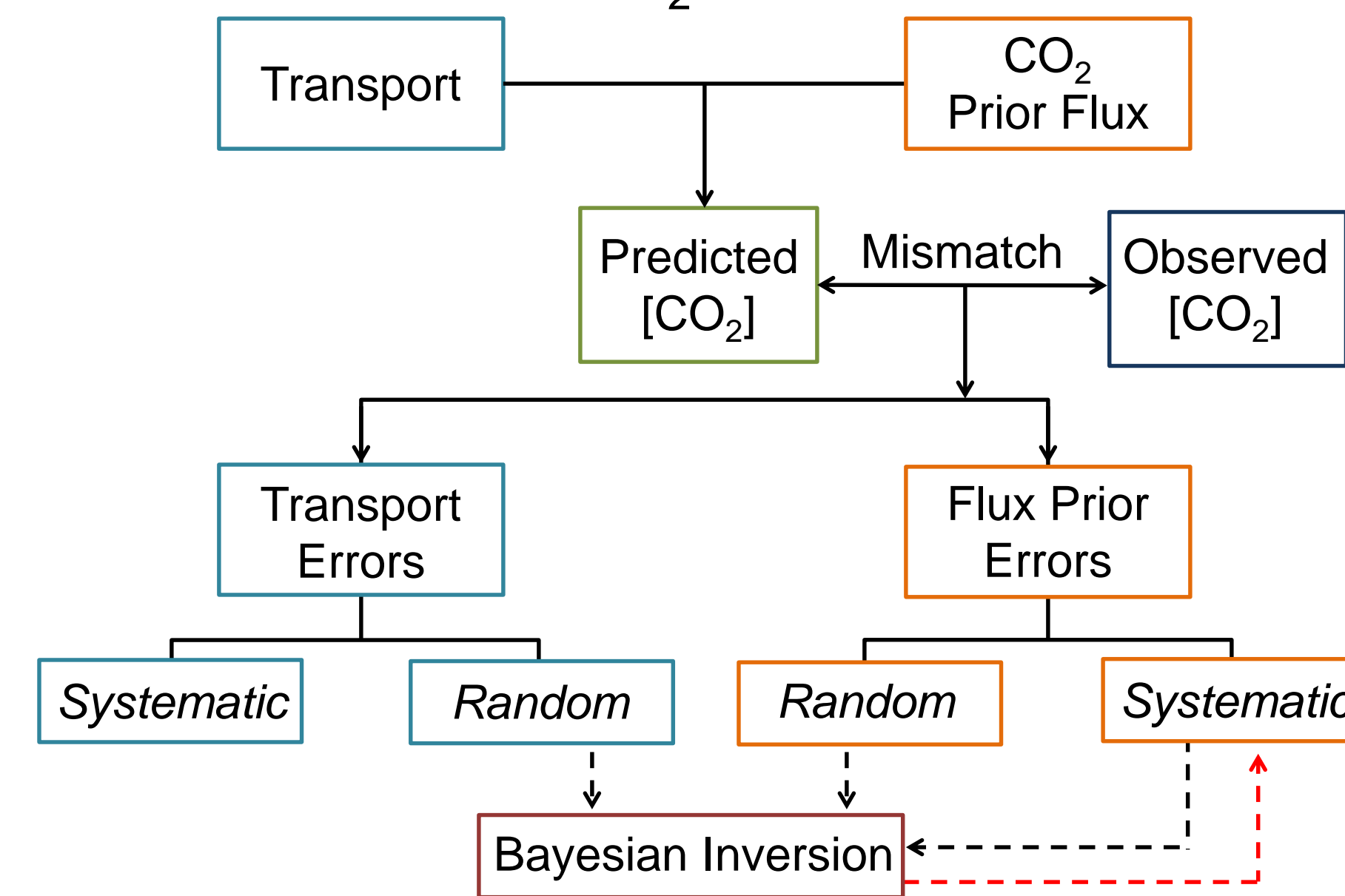
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## Motivation

- Atmospheric inversions uses atmospheric transport models to estimate carbon fluxes by adjusting these fluxes to be optimally consistent with observed CO<sub>2</sub> concentrations.

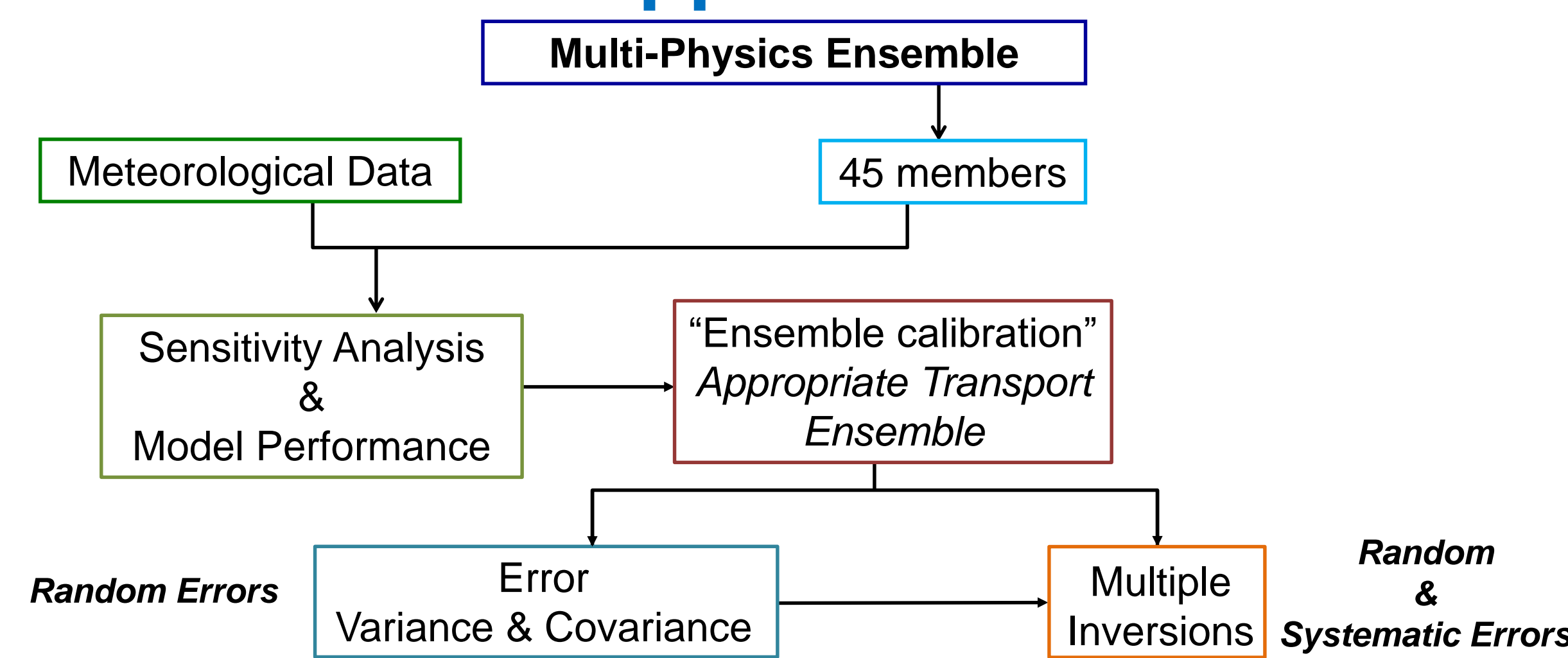


- The inverse system assumes that transport models are only affected by random errors and that systematic errors are unique to prior fluxes.
- This method assumes that the atmospheric transport model uncertainties are known. This leads to model errors that propagate to inverse (or posterior) fluxes, limiting the quality of the optimization.
- The atmospheric inverse system will be more reliable if the atmospheric transport errors are quantified rigorously and if the transport model is unbiased.

## Objectives

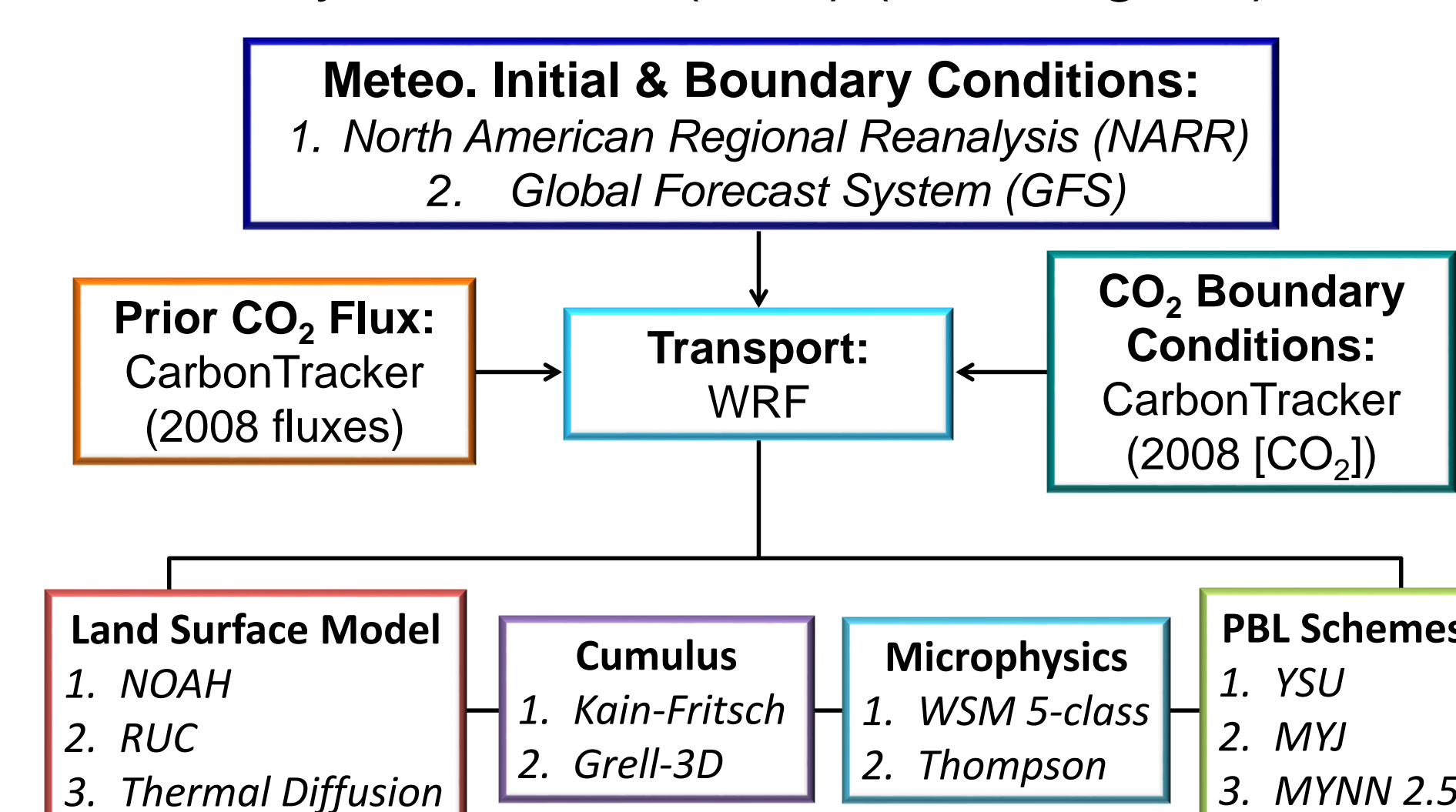
- Quantify the impact of both physics parameterizations and meteorological reanalyses on CO<sub>2</sub> mole fractions.
- Quantify transport errors and explore how sensitive they are to the physics parameterization and reanalysis product.
- Generate a calibrated atmospheric transport ensemble with accuracy and spread that represent systematic and random transport errors.

## Approach



## Multi-Physics Ensemble

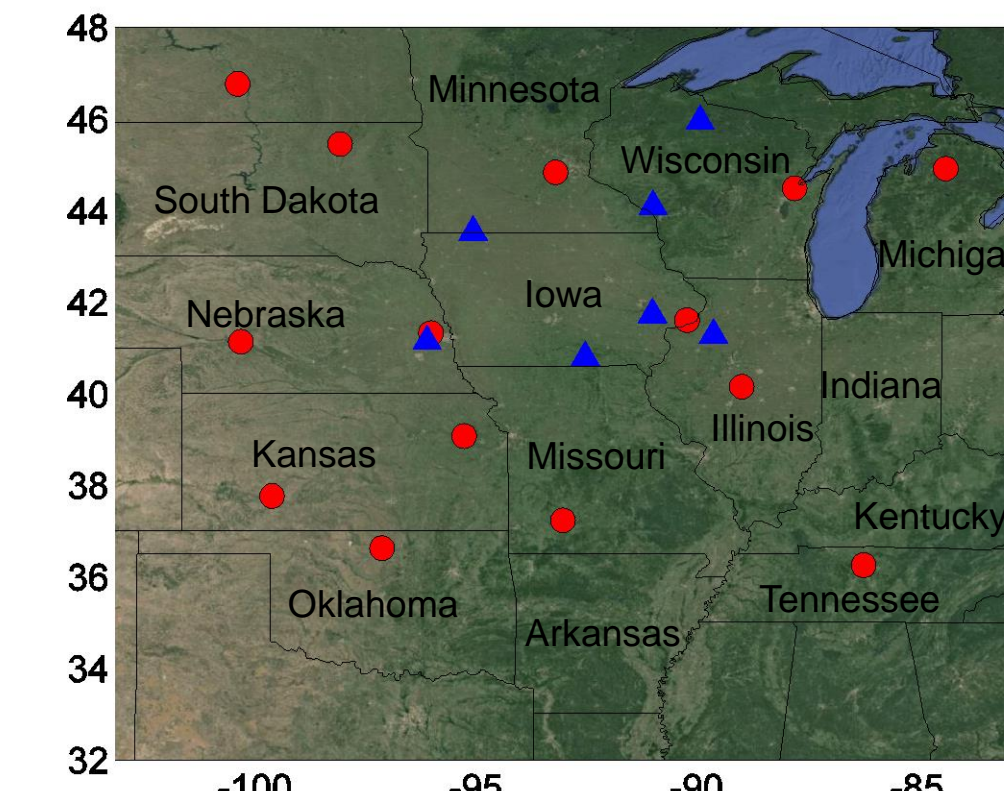
- Our 45-member ensemble is created with the Weather Research and Forecasting (WRF) model that includes the chemistry module (WRF-Chem).
- This ensemble was built using different physical parameterizations and meteorological initial conditions (IC) and lateral boundary conditions (LBC) (see diagram).



**Domain:** Centered in Iowa, covering 1600 km × 1600 km, with 10 km grid resolution  
**CO<sub>2</sub> Flux and LBC:** CarbonTracker (CT) data assimilation system developed at NOAA (Peters et al., 2007)  
**Period:** June 17 to July 21 of 2008

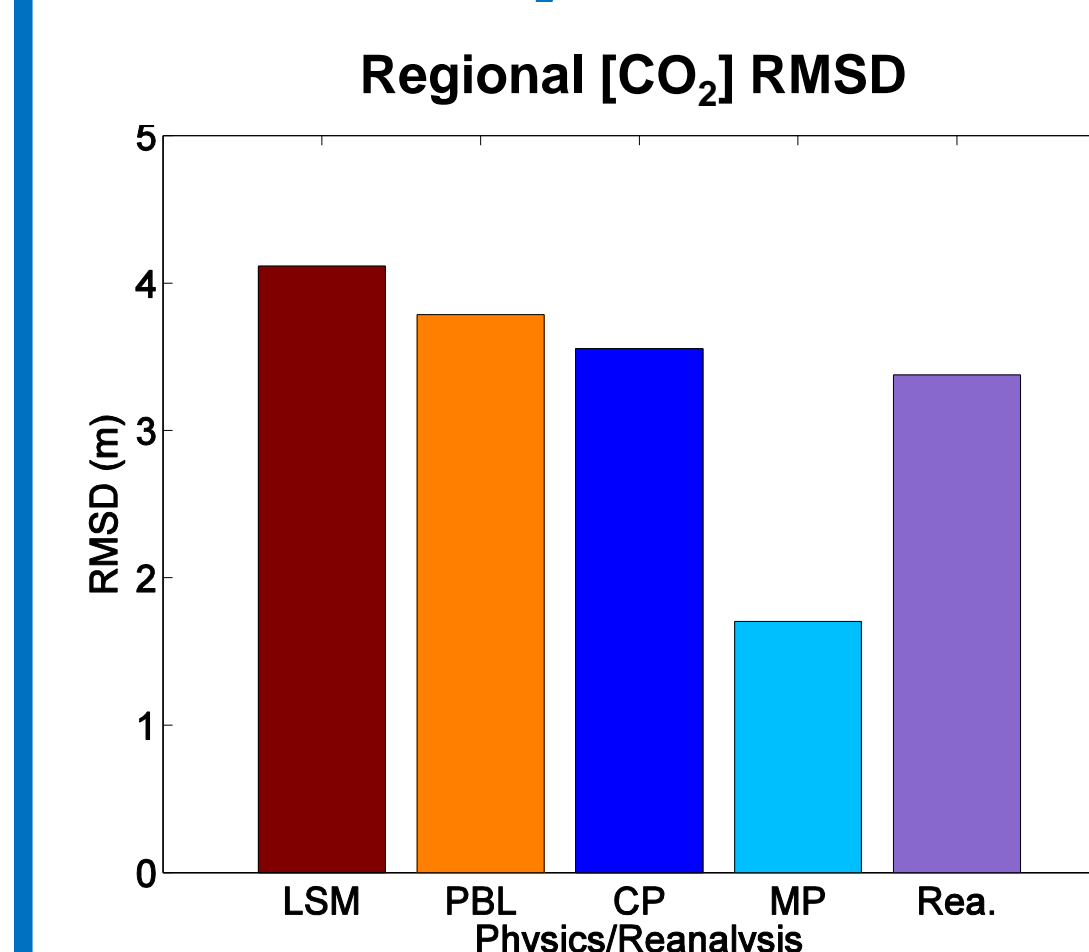
## Data

- To evaluate and calibrate the ensemble we use observations from 14 rawinsonde sites (red circles in the map).
- Wind speed, wind direction and planetary boundary layer height (PBLH) data was evaluated at 0000 UTC.
- PBL depth was estimated using the virtual potential temperature gradient ( $\nabla\theta_v \geq 0.2$  K/m).

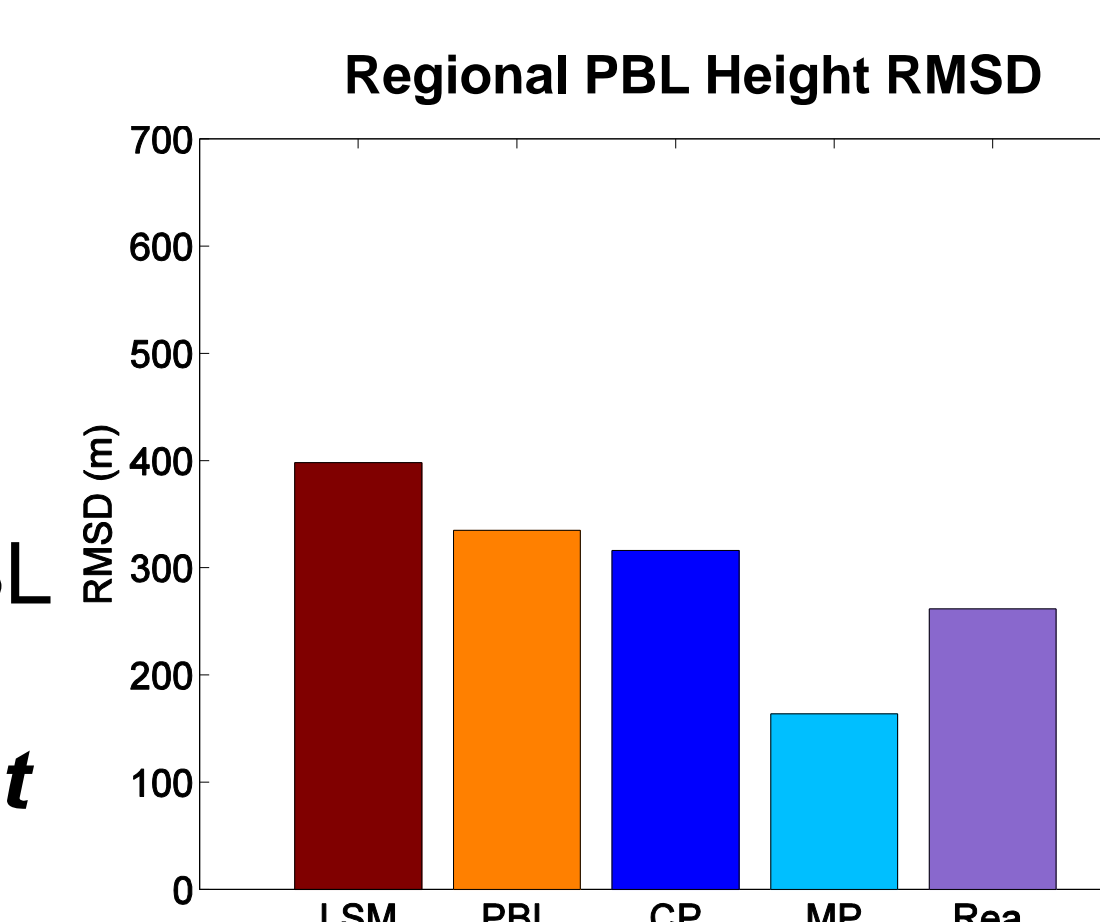


## Sensitivity Analysis & Model Performance

### Impact of Transport Errors on [CO<sub>2</sub>]



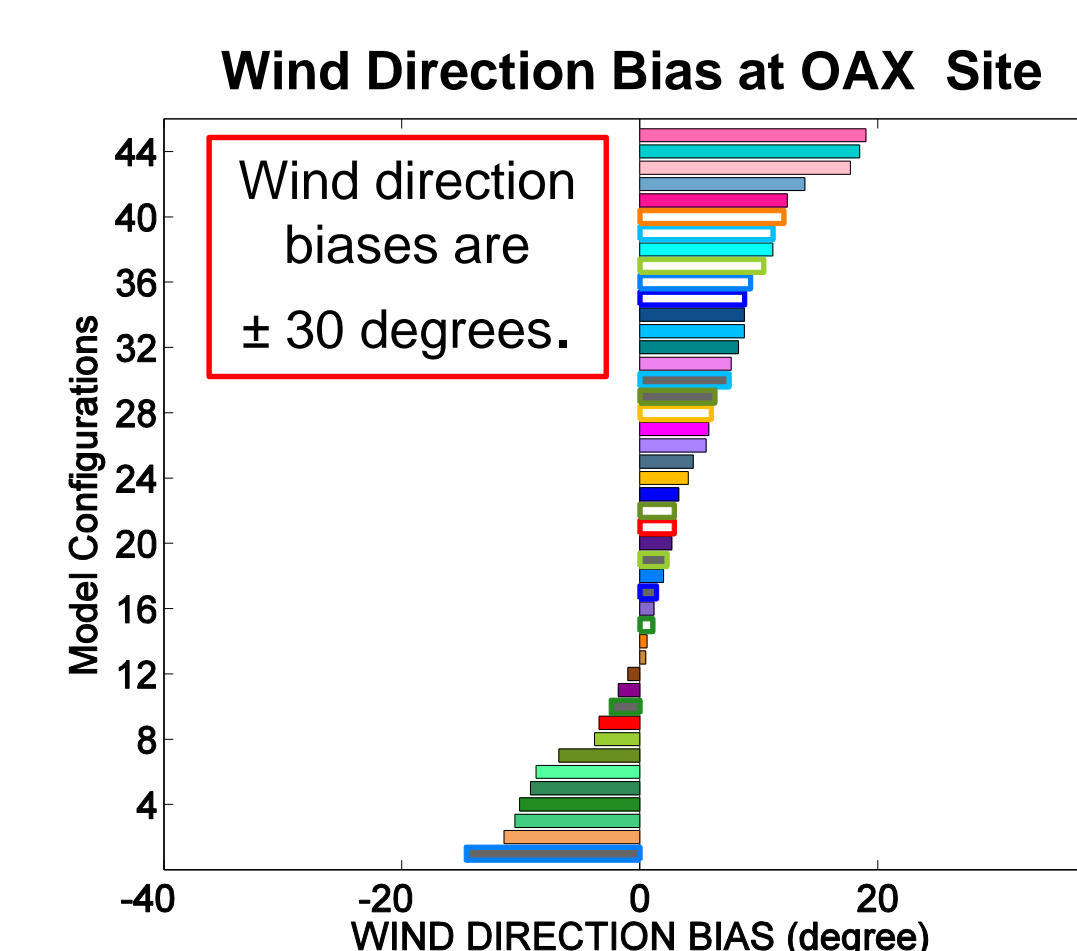
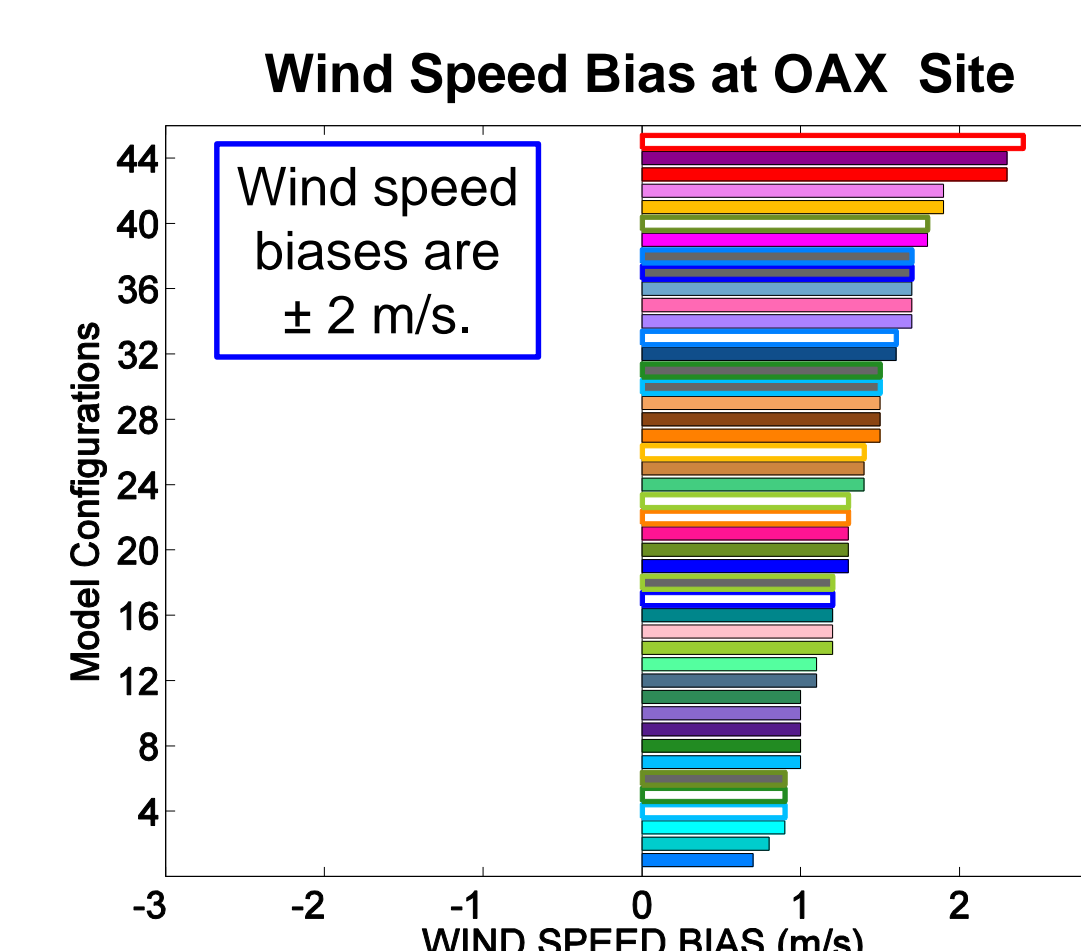
- Model-Ensemble mean comparison used to isolate transport errors.
- PBL physics is not the only physics parameterization that matters.



- LSMs, PBL schemes, Cumulus parameterizations (CP) and Reanalysis all have a big impact on wind speed, wind directions and PBL height errors.
- The order of impact in PBL height errors is similar to the CO<sub>2</sub> mole fraction errors.

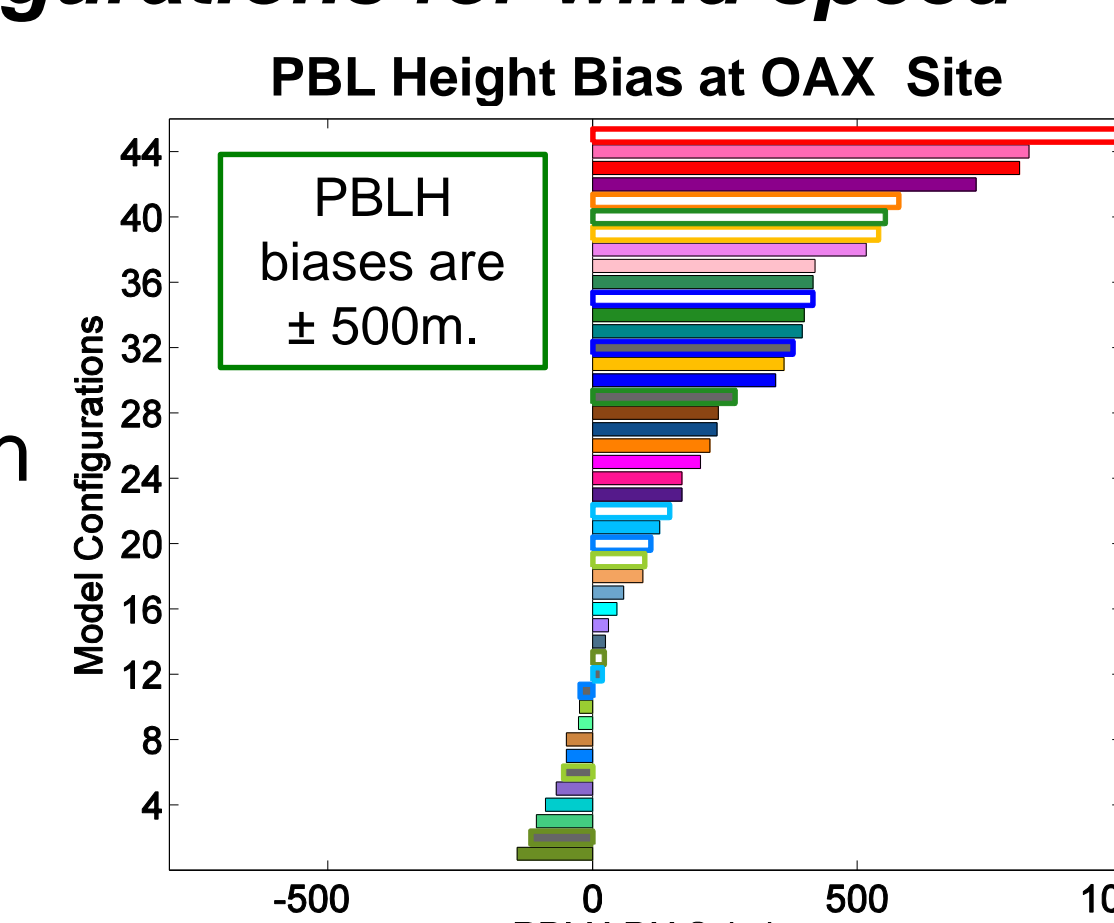
### Unbiased Model

- We estimated the bias over a month for each member of the ensemble (represented by the different color bars).



- For wind speed most of the sites shows a positive bias, whereas for wind direction most of the sites show both positive and negative bias.
- It is hard to define the best configurations for wind speed and wind direction.

- For PBLH most of the sites shows both positive and negative bias.
- PBL height bias is controlled by both the LSMs and PBL schemes.
- PBL height biases can be sorted by model configuration.



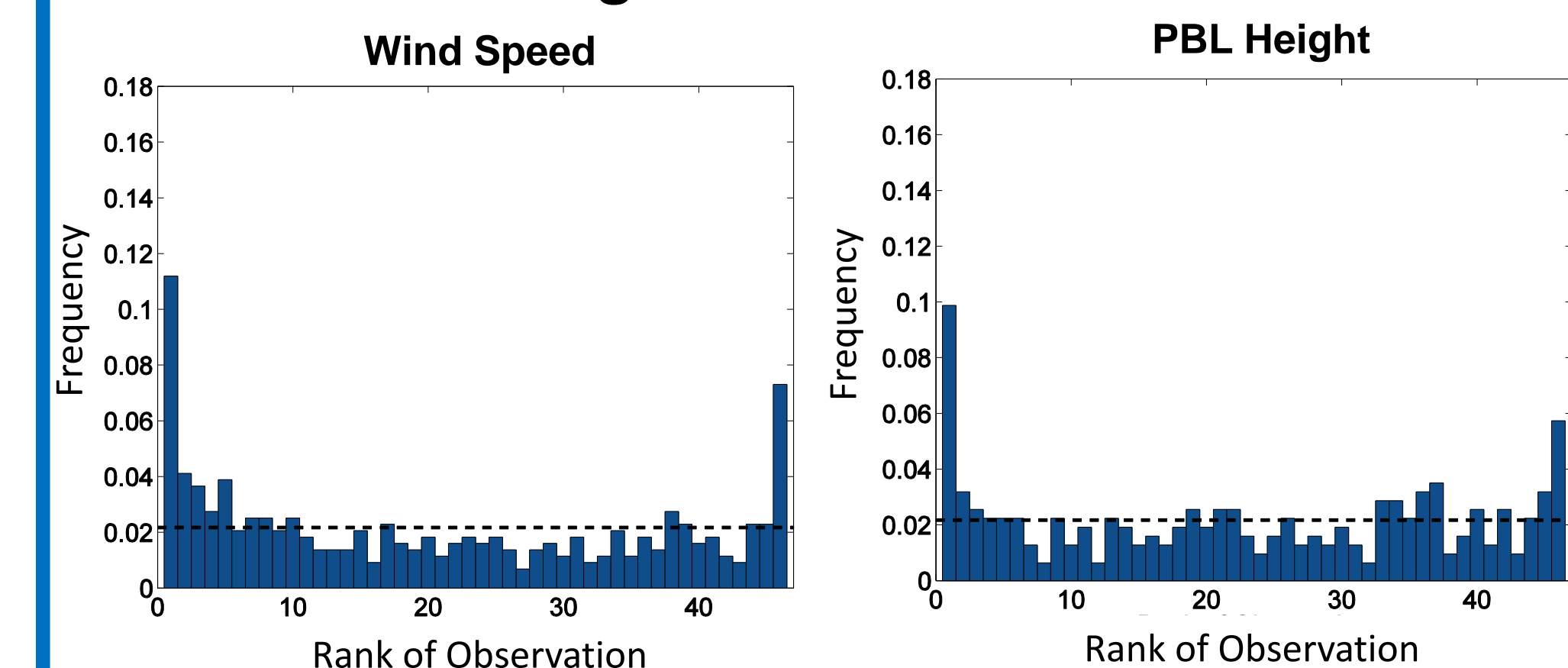
## Synthesis

- Not only the PBL schemes have a significant impact in CO<sub>2</sub> mole fractions, other physics schemes such as LSM and Cumulus parameterizations contribute to CO<sub>2</sub> variability.
- The configuration performance varies over the domain, therefore making it hard to select the best configuration.
- PBL depth bias can be reduced, therefore a best configuration (less bias) exists for this factor alone.
- From a 45-members ensemble, we were able to create a sub-ensemble of 10-members that shows an appropriate spread and smaller bias.

## Ensemble Calibration

### Rank Histogram Score & Bias

- Rank Histogram:** This tool is used to diagnose the bias and the dispersion of the ensemble. An ensemble that is not biased and neither underdispersive nor overdispersive will have a flat rank histogram.



- U-shape rank histogram implies that our ensemble spread is too small.
- Flat rank histogram is needed to estimate transport errors.

- Rank Histogram Score (RHS):** This metric is used to measure the flatness of the rank histogram and should be close to 1.
- Bias:** The bias of the residuals (model-data difference) is used as an additional criteria to choose a sub-ensemble that has an equal or lower bias than the full ensemble.

Variable	RHS	Bias
Wind Speed	6.1	0.66 m
Wind Direction	7.2	-0.41 deg.
PBL Height	3.2	98 m

- The RHS of the full ensemble is higher than one for all the variables.
- PBL height shows the lowest RHS.
- Wind speed and PBL height have positive bias and wind direction shows a negative bias.

### Ensemble Calibration Technique

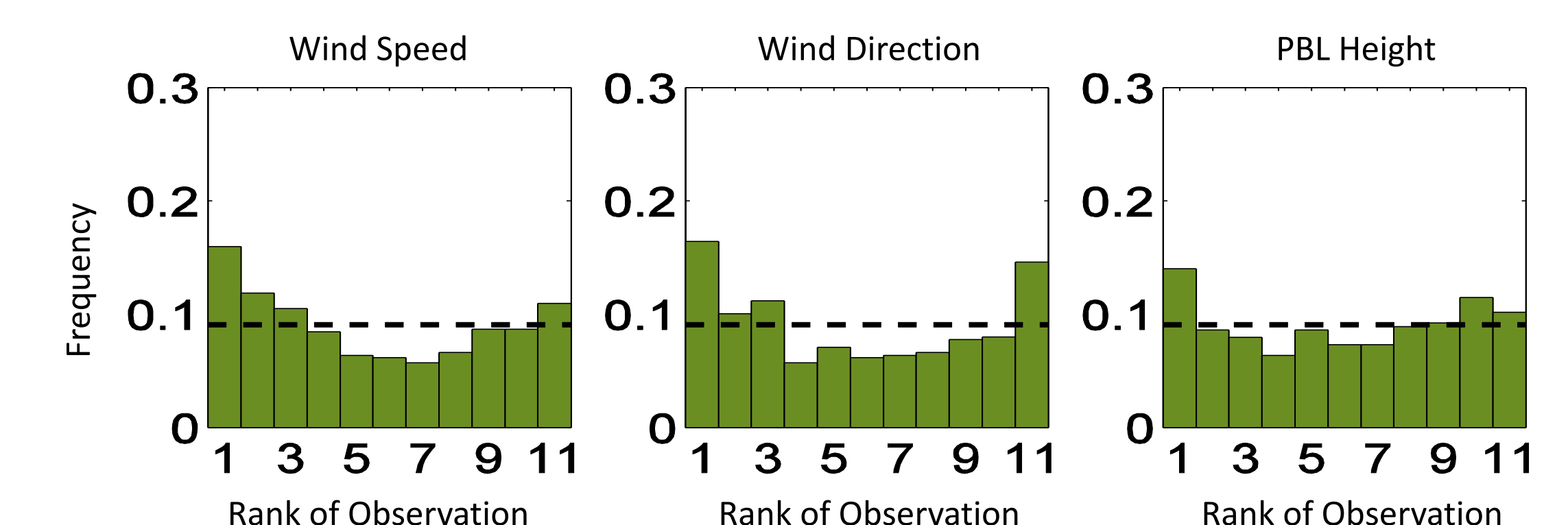
#### Simulated Annealing (SA):

- General probabilistic local search algorithm proposed by Kirkpatrick et al., (1983).
- This optimization method uses a cost function to find the global minimum or optimal solution, in our case a sub-ensemble with a rank histogram score close to one.

### Calibrated Ensemble

- SA technique was applied to calibrate our ensemble for 10, 8 and 5-member sub-ensembles (Garaud and Mallet, 2011).
- The selected sub-ensemble, should have a RHS and bias smaller than the full ensemble.

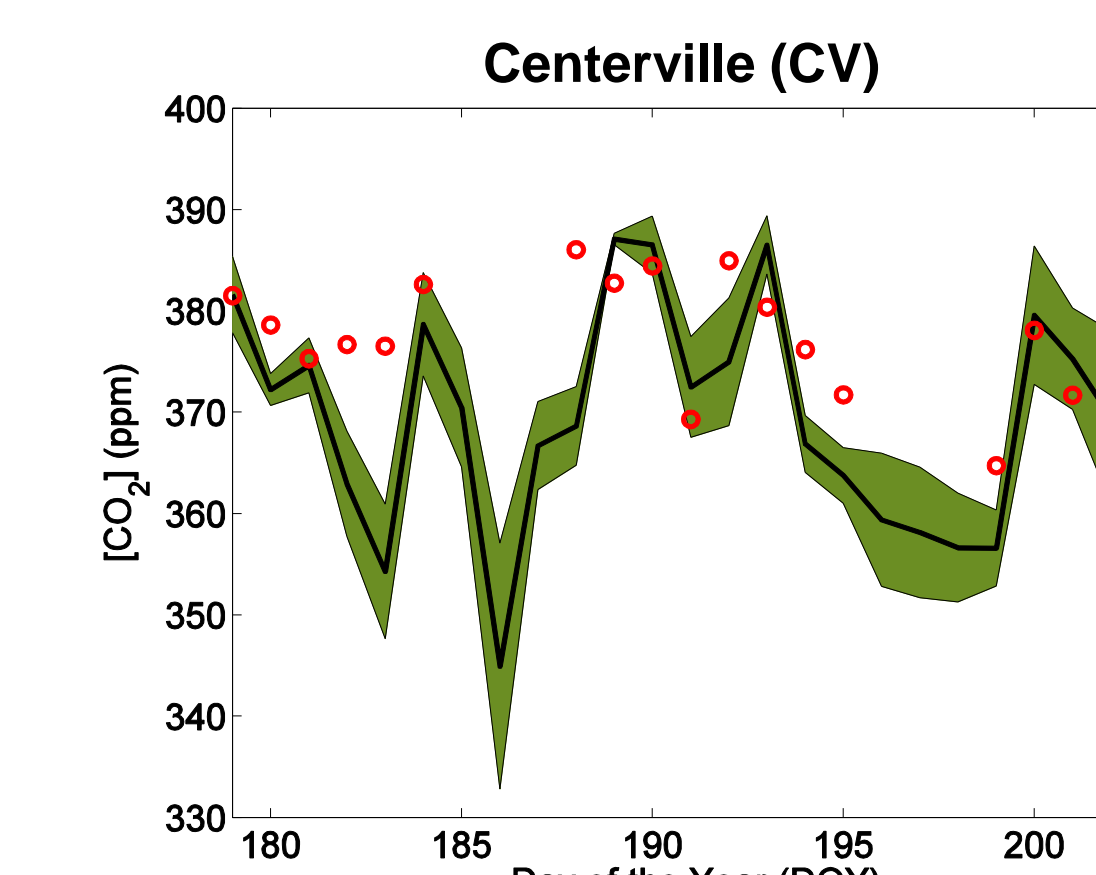
#### Calibrated Ensemble 10-members:



- Wind speed and wind direction still generate a U-shape rank histogram with this calibrated ensemble.
- PBL height has a flat rank histogram and the smallest RHS compare to the rest of the variables.
- Simulated Annealing (green) allows us to find a sub-ensemble that has a smaller bias than the full ensemble (blue – above).

Variable	RHS	Bias
WSPD	4.6	0.53 m/s
WDIR	6.3	-0.21 deg.
PBLH	1.6	78 m

### Future Work: Evaluate Calibrated Ensemble



- Transport errors show large temporal variability
- Interpretation of hourly ensemble-based error variances:
  - Model-data differences larger than transport errors: flux signals still present
  - Observations within transport error bounds: no flux signal left