
Observing Network Design for Improved Prediction of Geophysical Fluid Flows

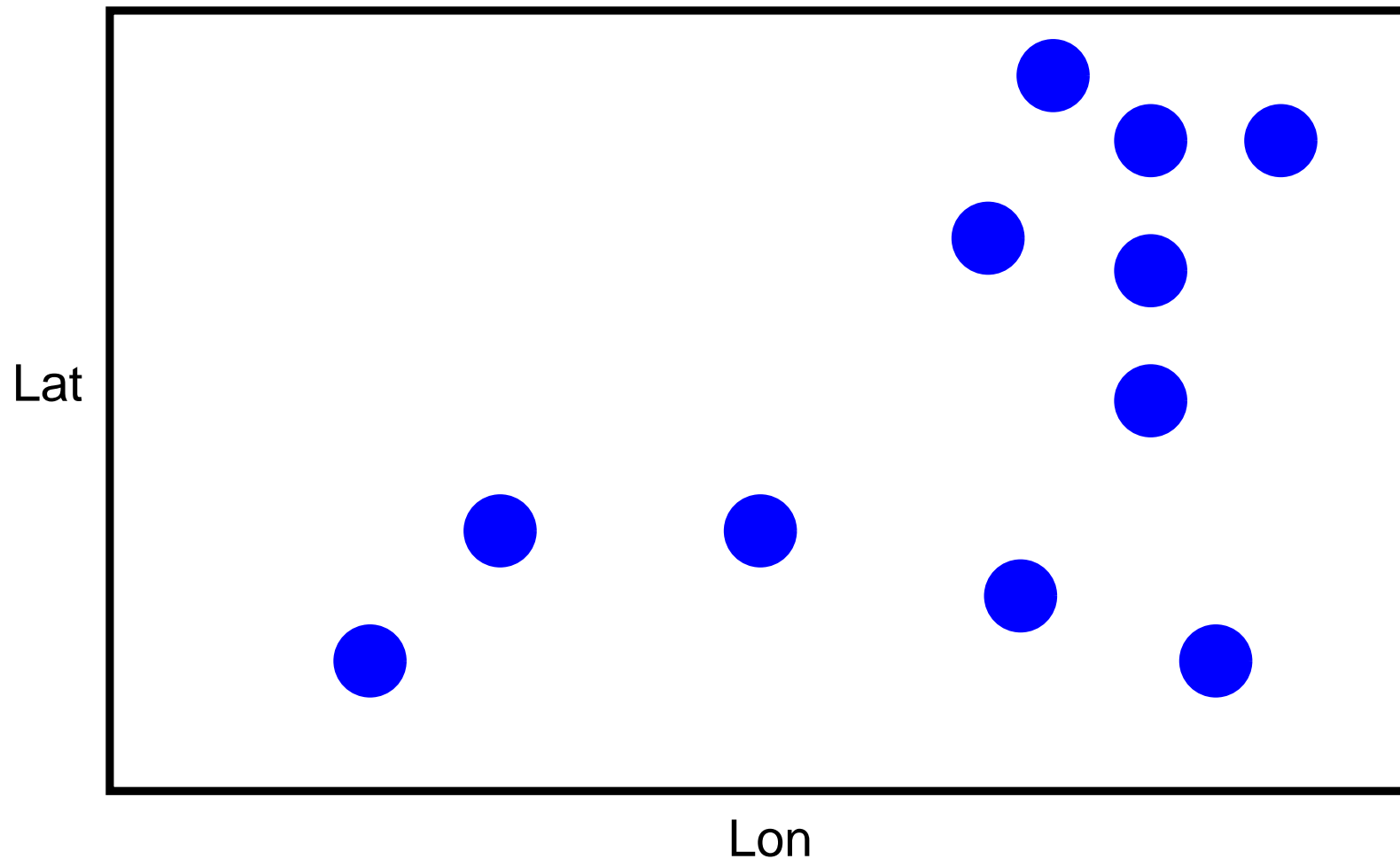
Analysis of Ensemble Methods

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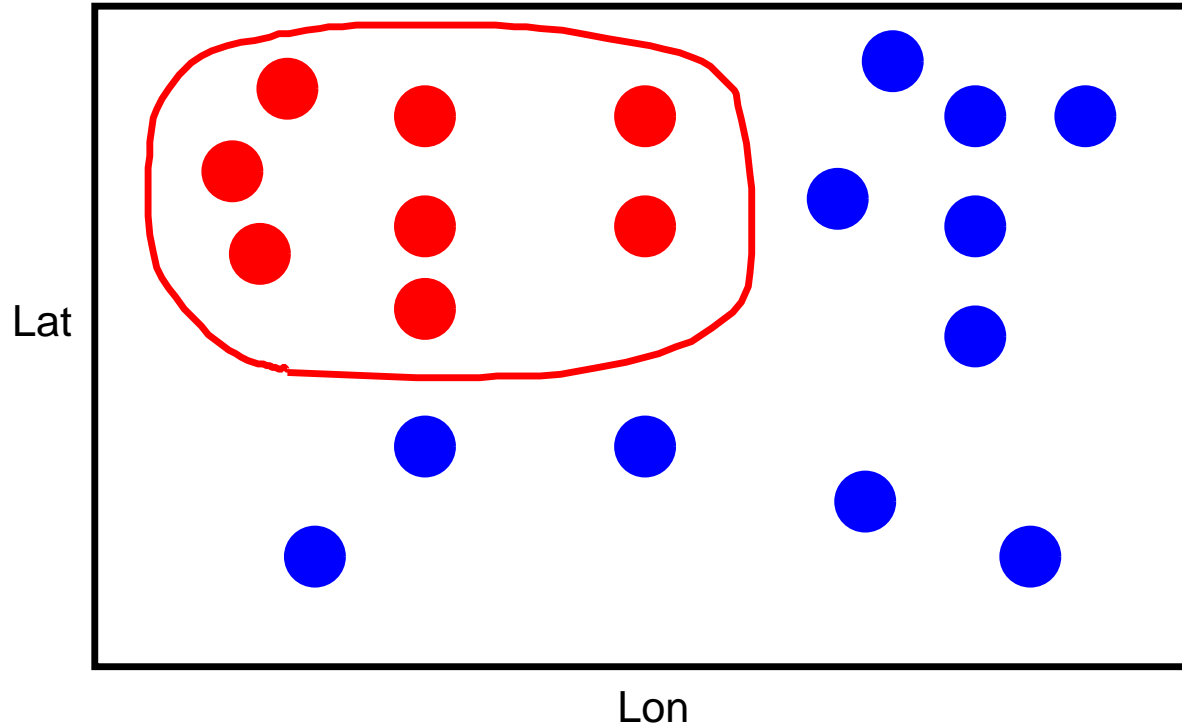
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- Thanks to the DAI for supporting visits to NCAR

The Background Observing Network



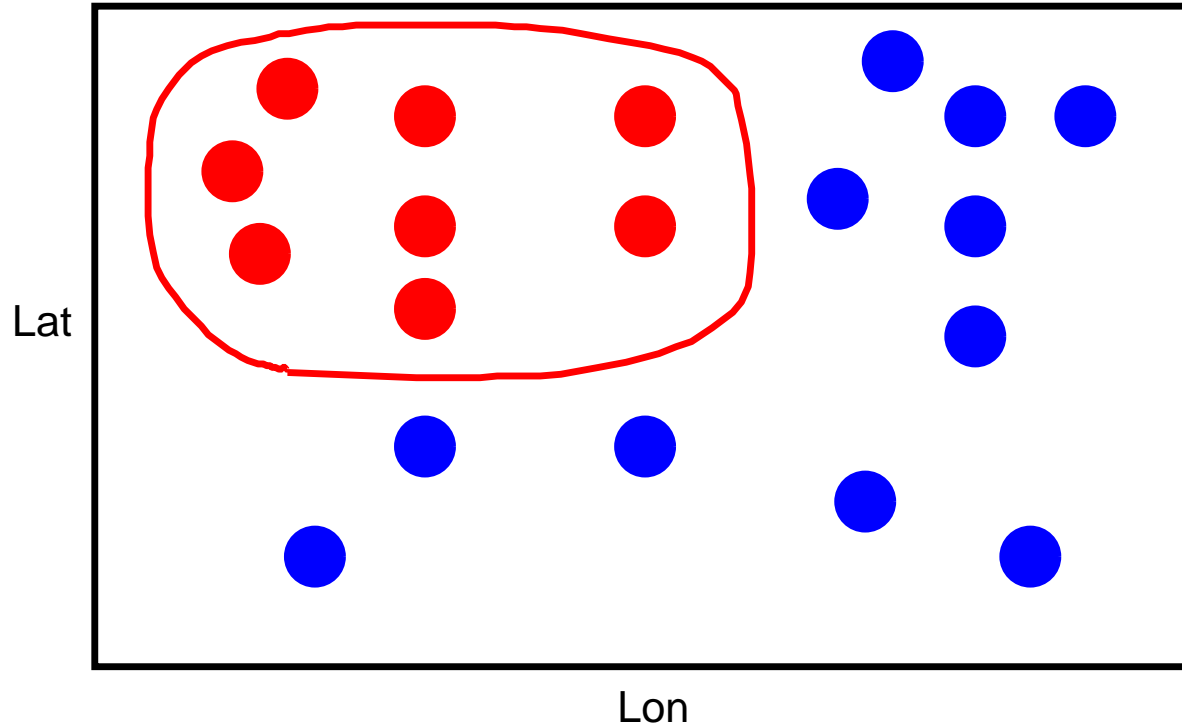
What type of problem is of interest?

The Problem



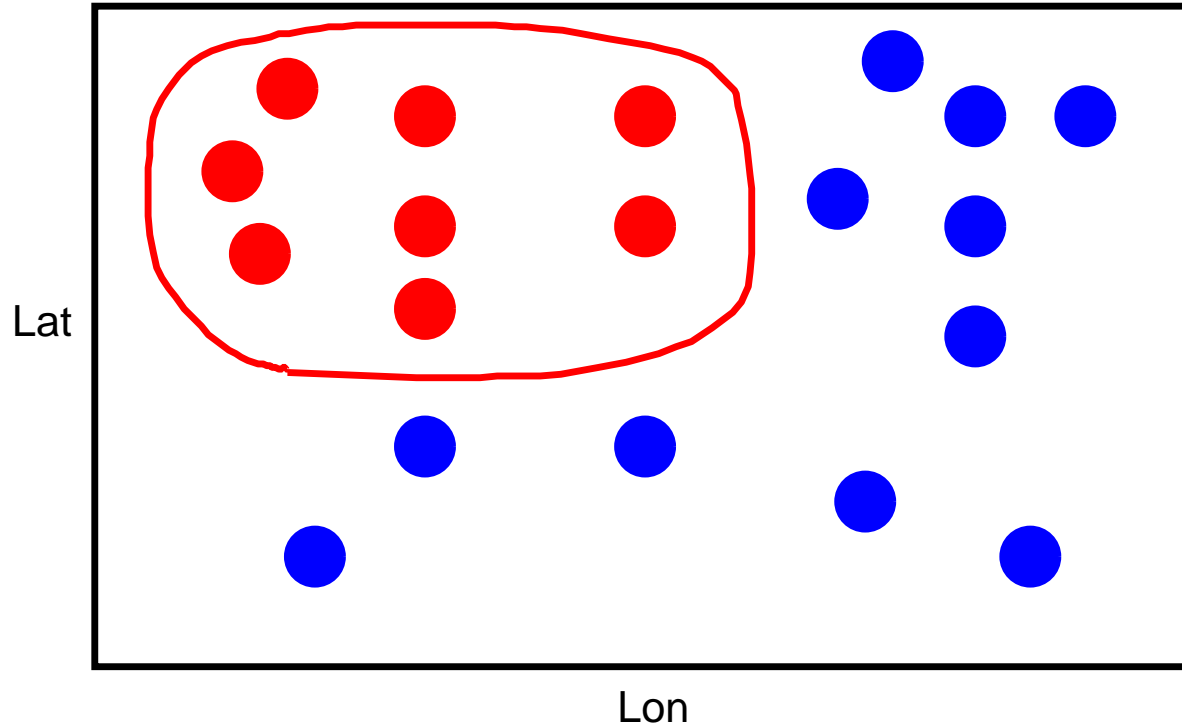
- For X dollars - can purchase 8 new **RED TYPE** instruments

The Problem



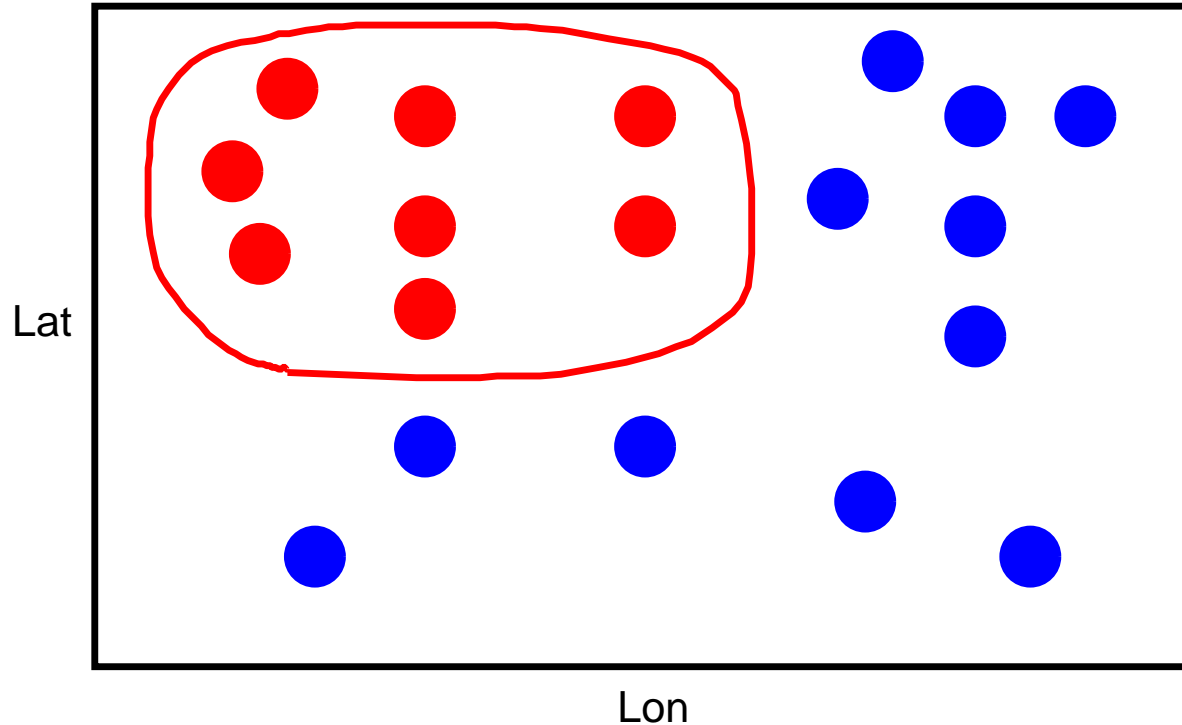
- To assess the value - must find the optimal locations of the **MOVABLE** observations given the **BACKGROUND** network

The Problem



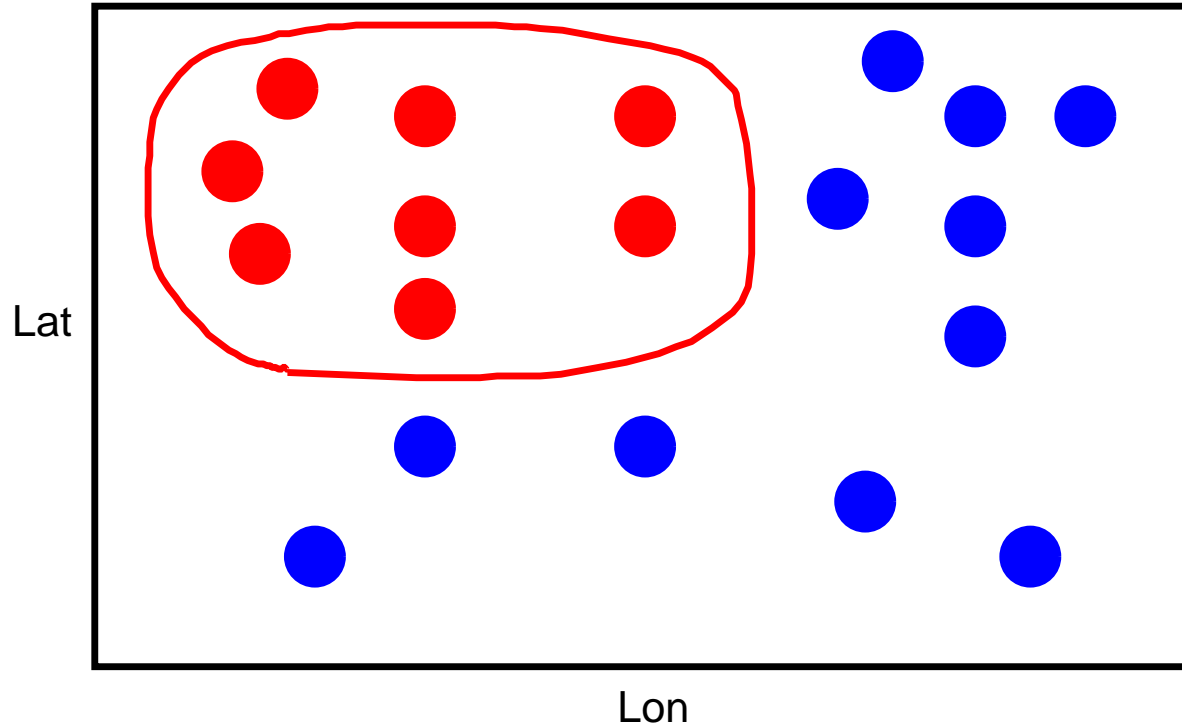
- Field experiments are often impractical, expensive and time consuming

The Problem



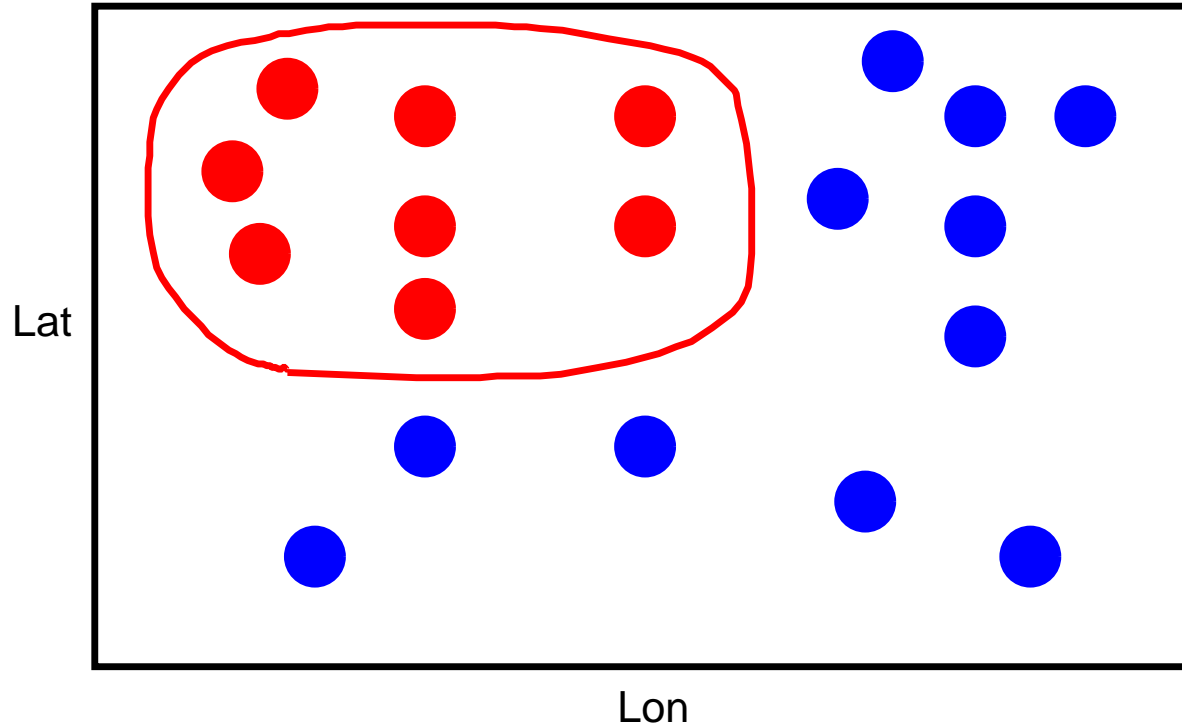
- Use simulations of the forecasting/assimilation cycle (can include economic benefit models)

The Problem



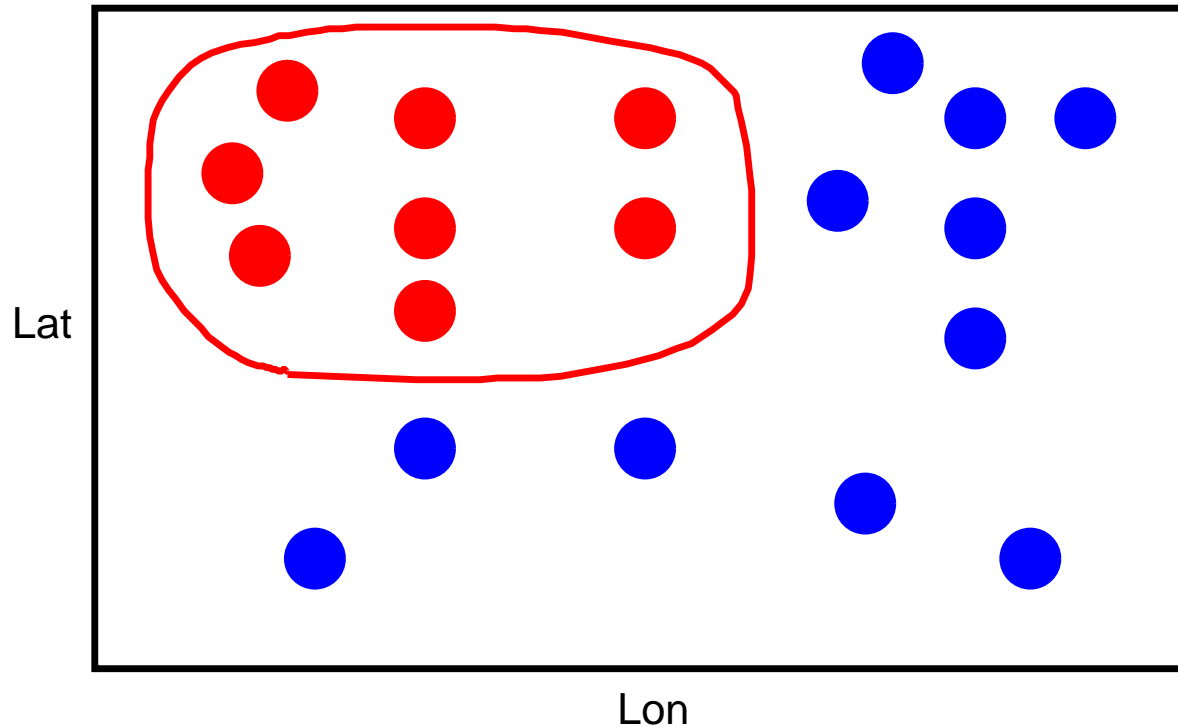
- The goal is to use the simulations as a guide in designing real networks of observations

The Problem



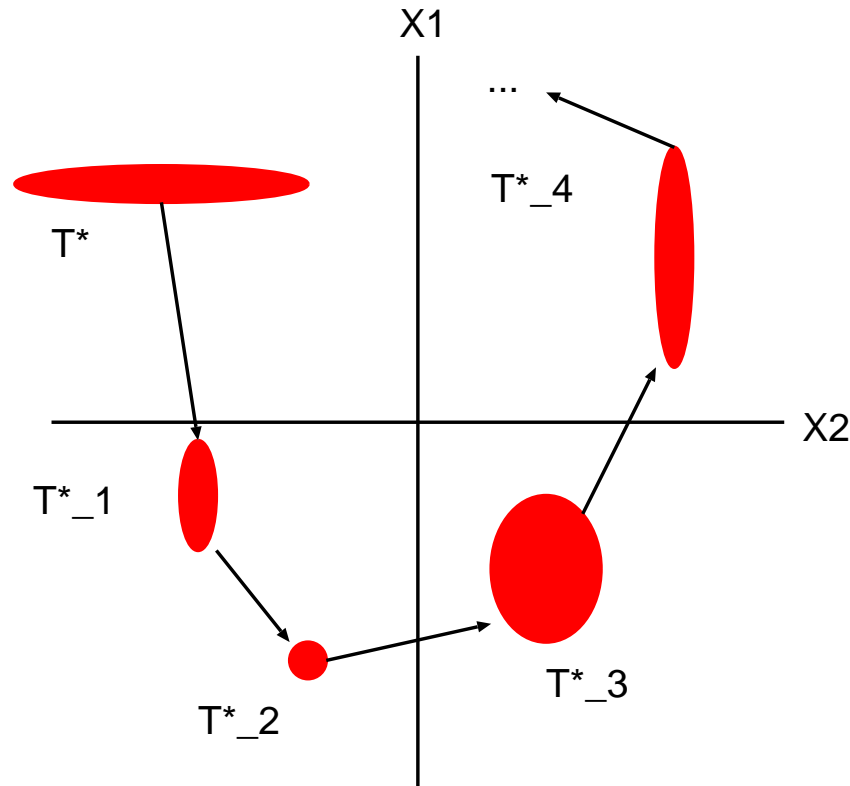
- To assess value - we must have a suitable framework for optimizing networks

The Problem



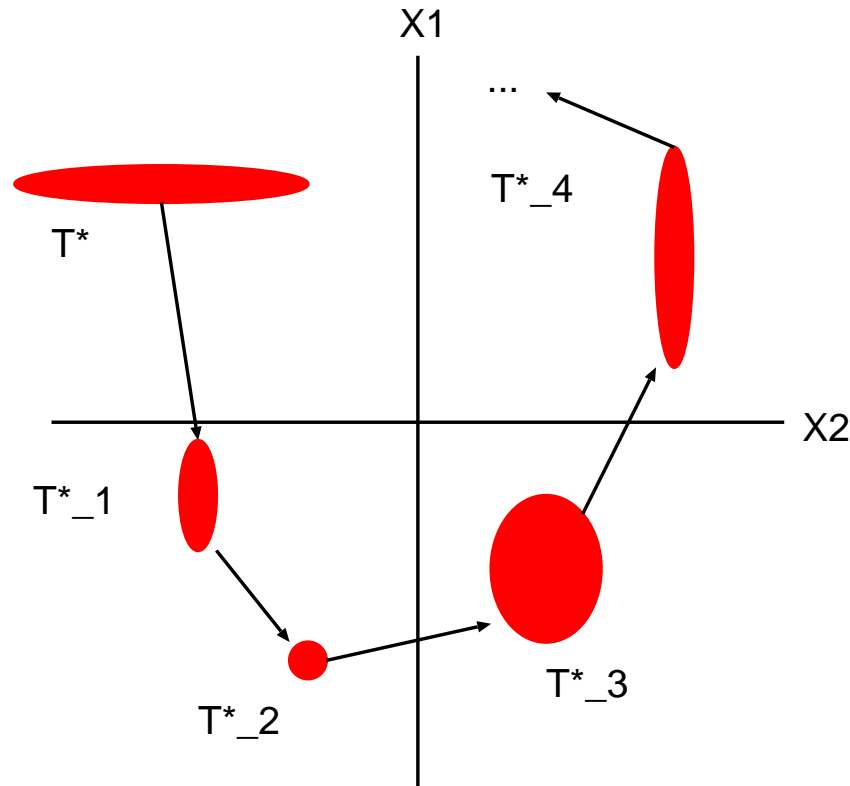
- This type of problem is central to THORPEX (a current 10 year international predictability experiment)

Evaluating the Value of H_1 Using OSSEs



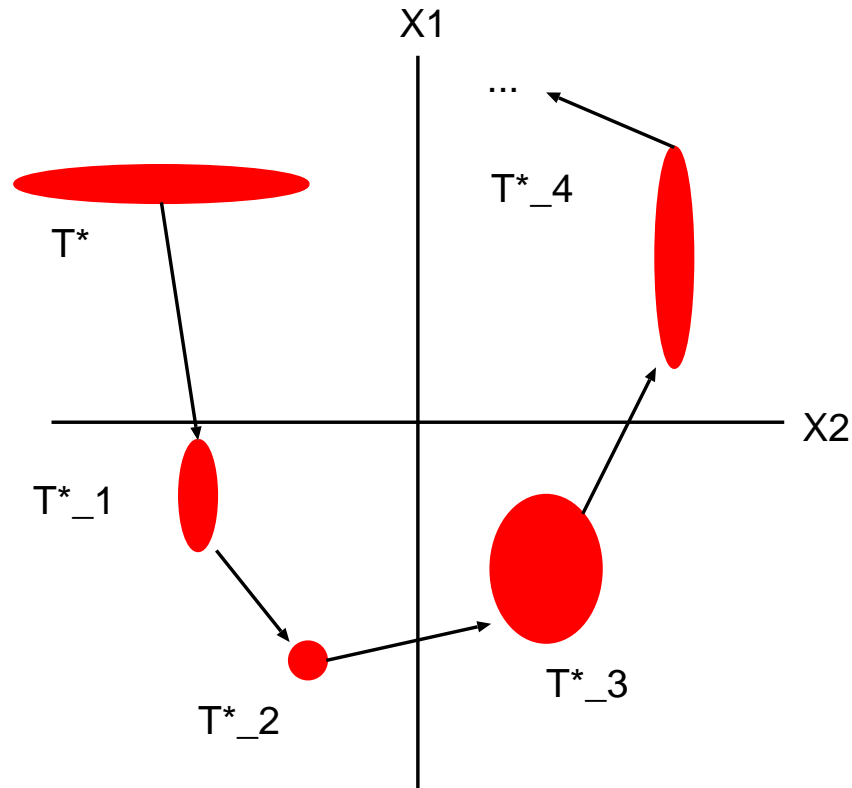
- H_1 includes both **MOVABLE** and **BACKGROUND** observations

Evaluating the Value of H_1 Using OSSEs



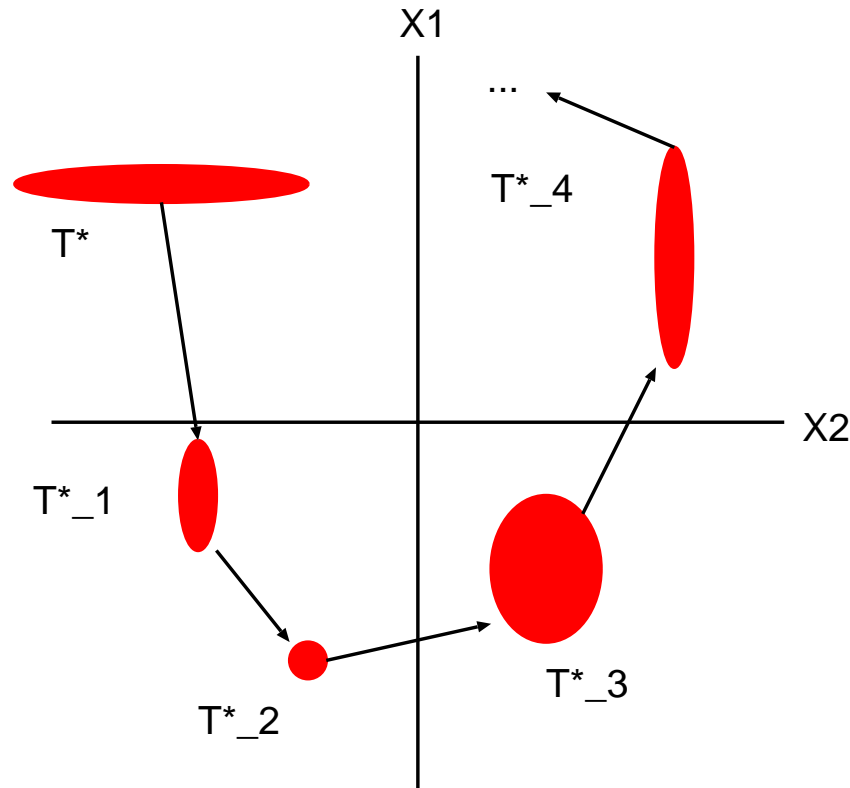
- Averaging independent error estimates amounts to an evaluation of an objective function $\Phi(H_1)$

Evaluating the Value of H_1 Using OSSEs



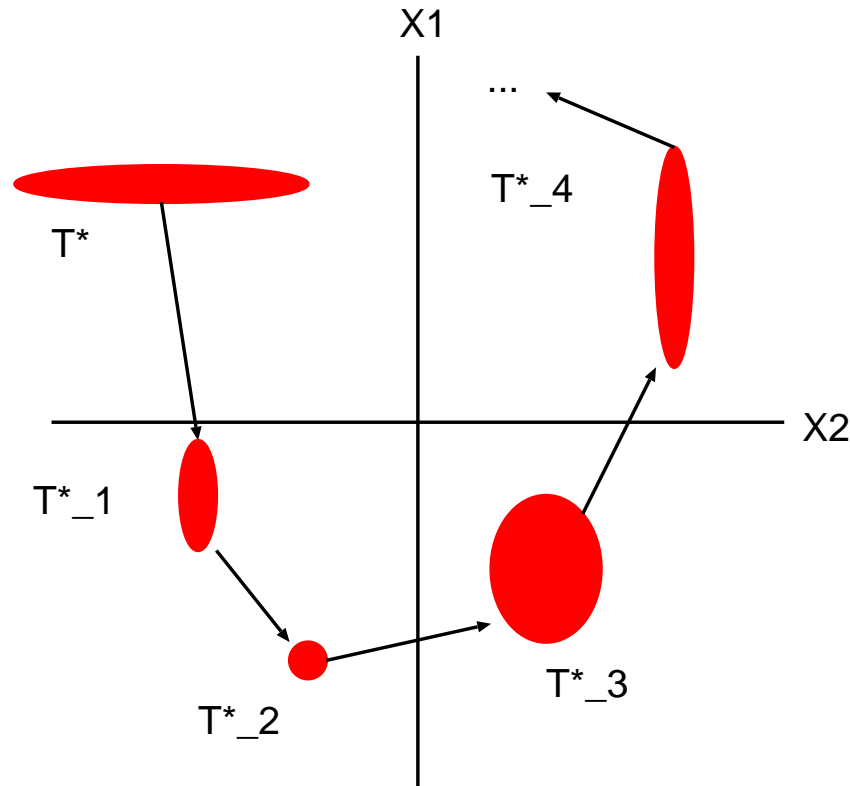
- Our objective - minimize Φ

Evaluating the Value of H_1 Using OSSEs



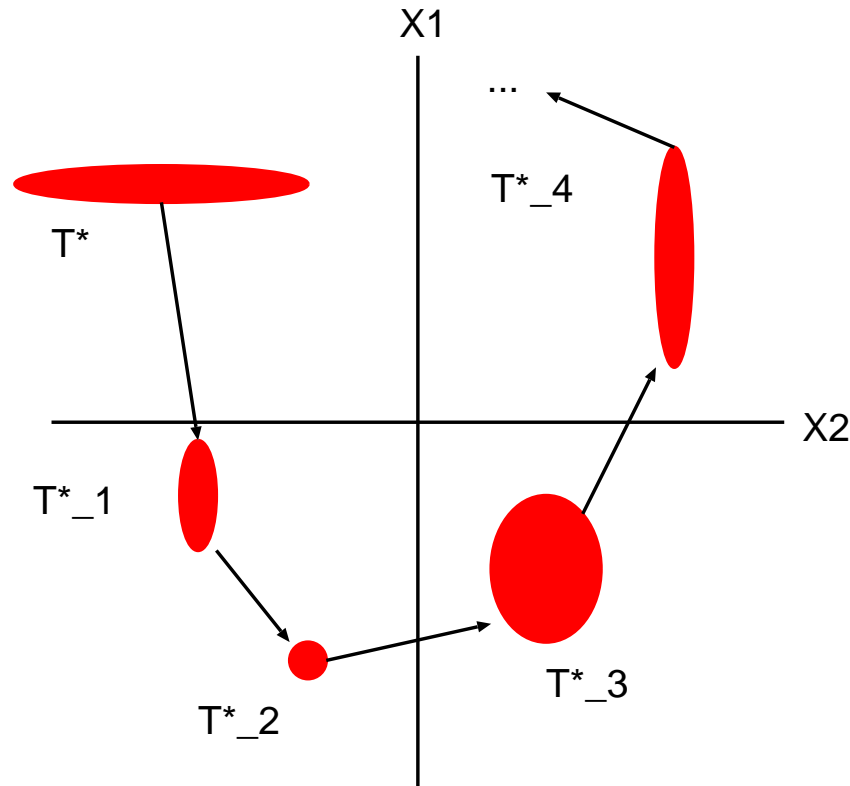
- Simple optimization method - try all conceivable configurations of H_1 and pick the minimum

Evaluating the Value of H_1 Using OSSEs



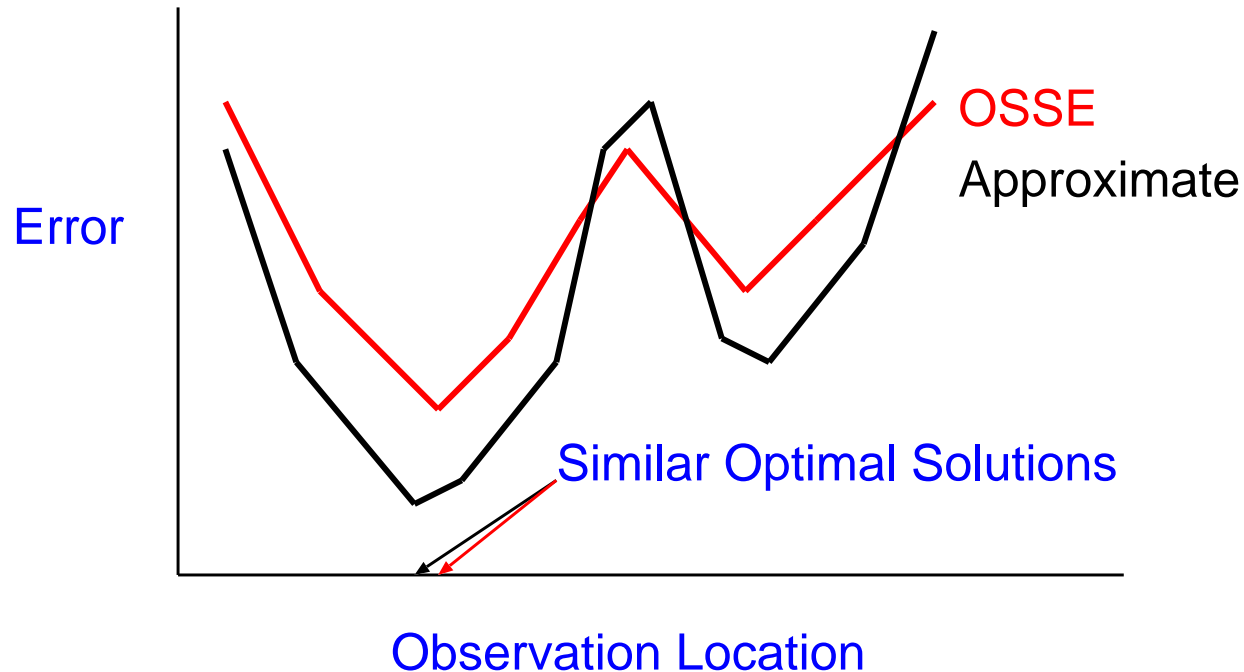
- For more advanced optimization techniques - still need to evaluate Φ many times and it should be smooth

Evaluating the Value of H_1 Using OSSEs



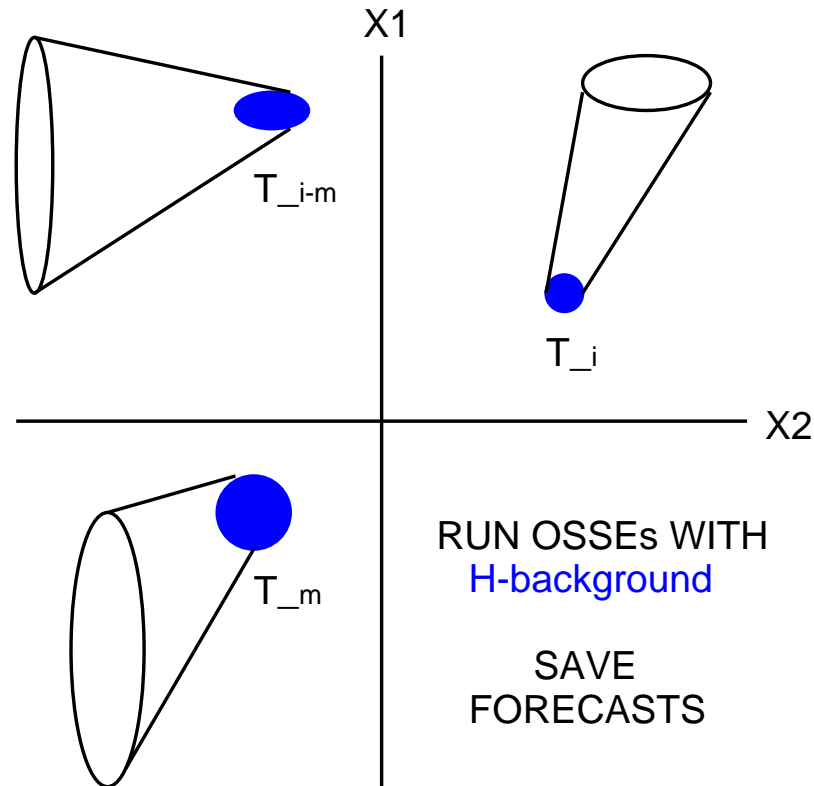
- For realistic GCMs - using OSSEs to evaluate Φ is expensive

Approximating Information Derived from OSSEs



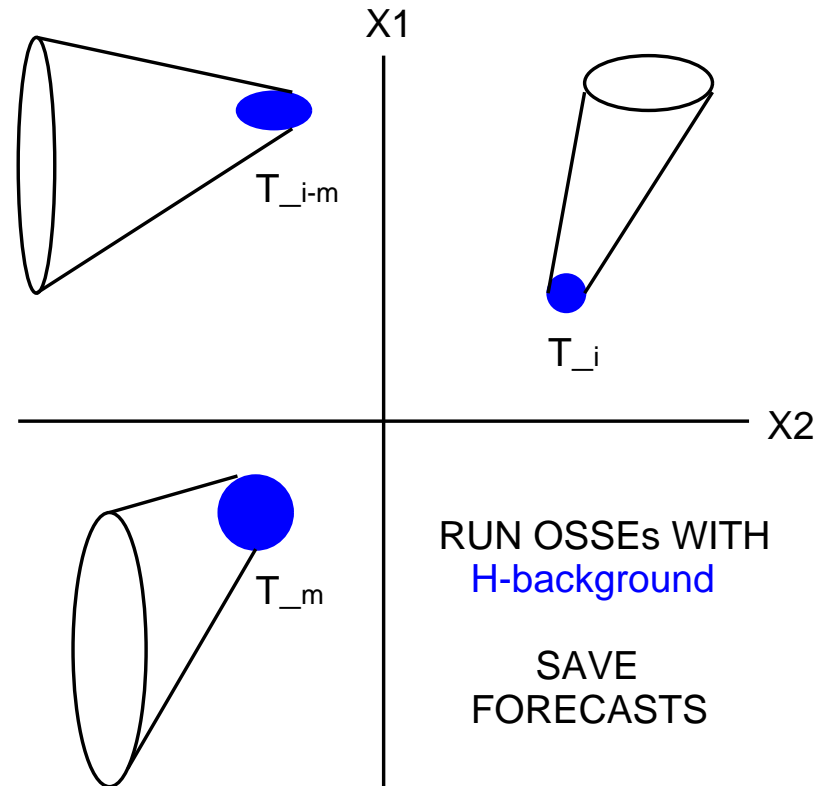
- How can we obtain a statistically and dynamically significant approximation of information derived from OSSEs?

A Solution - Retrospective Design Algorithm



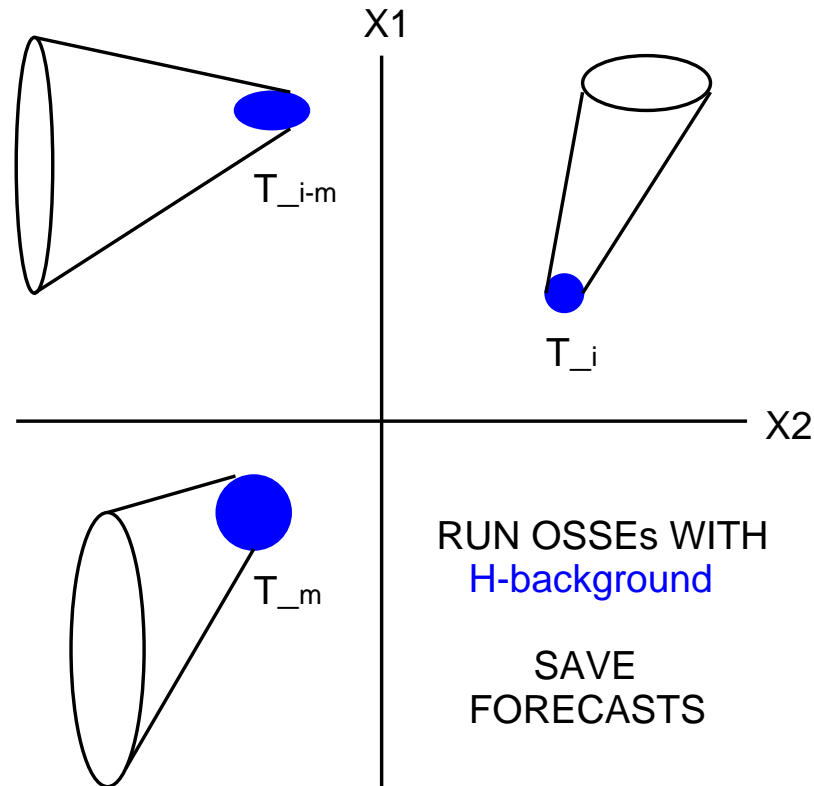
- Trial network H_1 made up of $H_{background}$ and $H_{movable}$

A Solution - Retrospective Design Algorithm



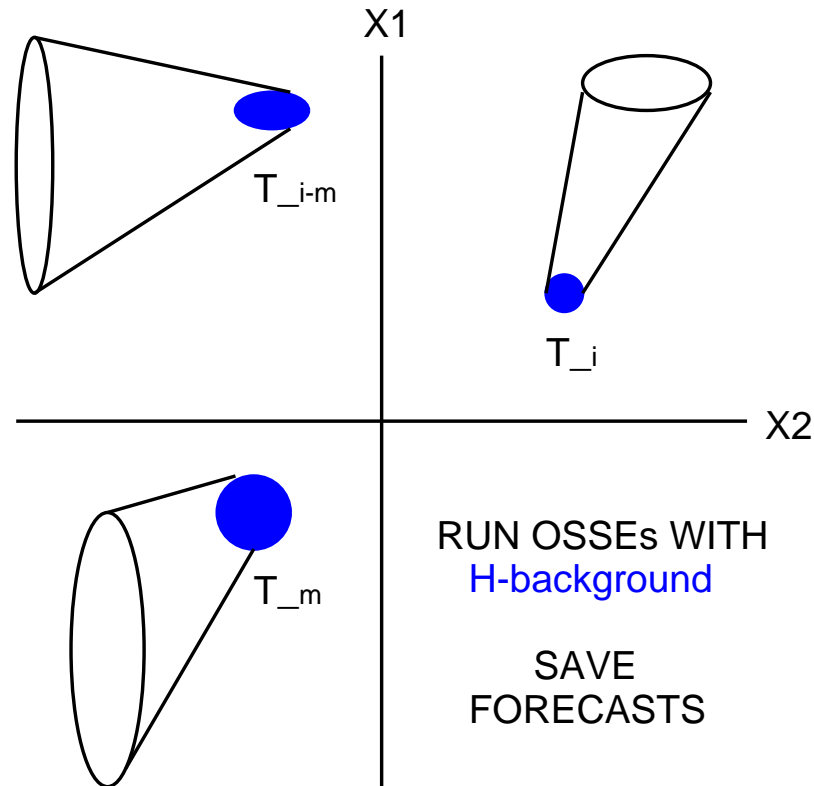
- Begin by running OSSEs with $H_{background}$ and store ensemble forecasts

A Solution - Retrospective Design Algorithm



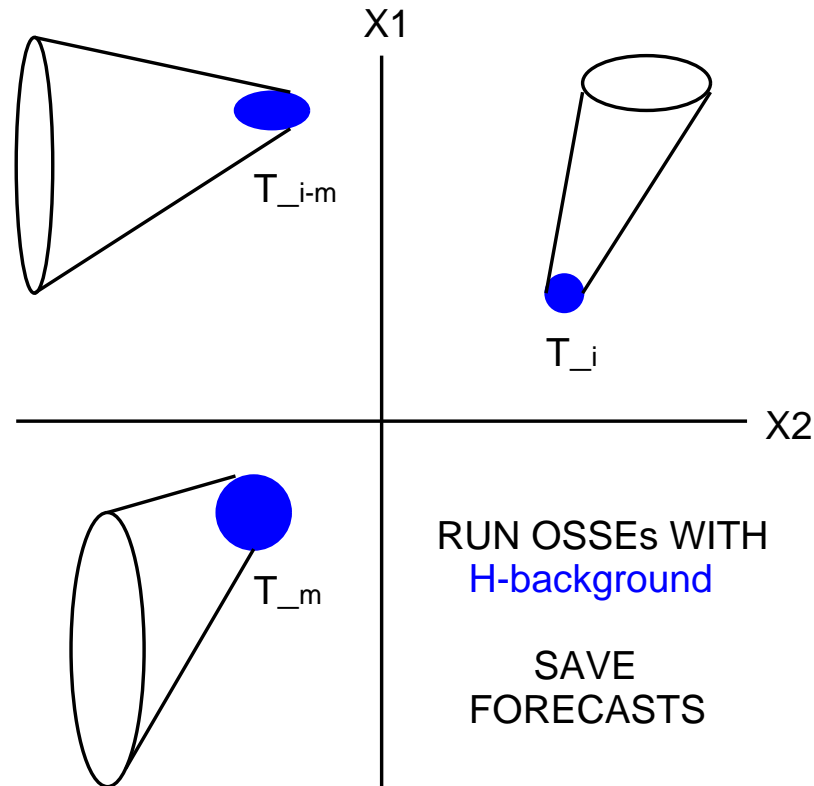
- Need to assess added information if network is switched to H_1

A Solution - Retrospective Design Algorithm



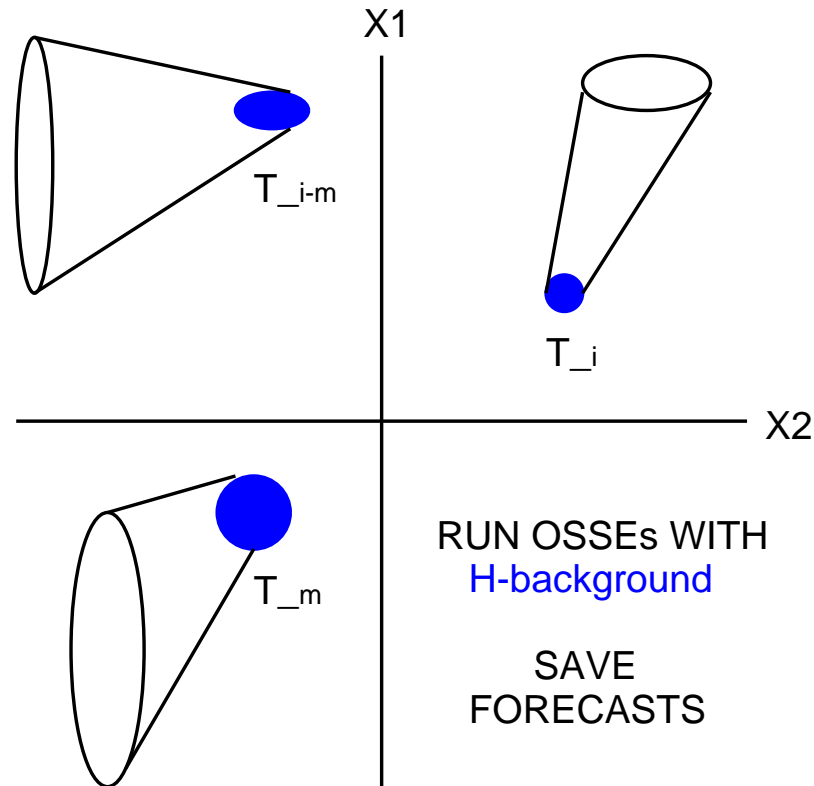
- For each initial time - could begin an OSSE under the influence of H_1 - still expensive

A Solution - Retrospective Design Algorithm



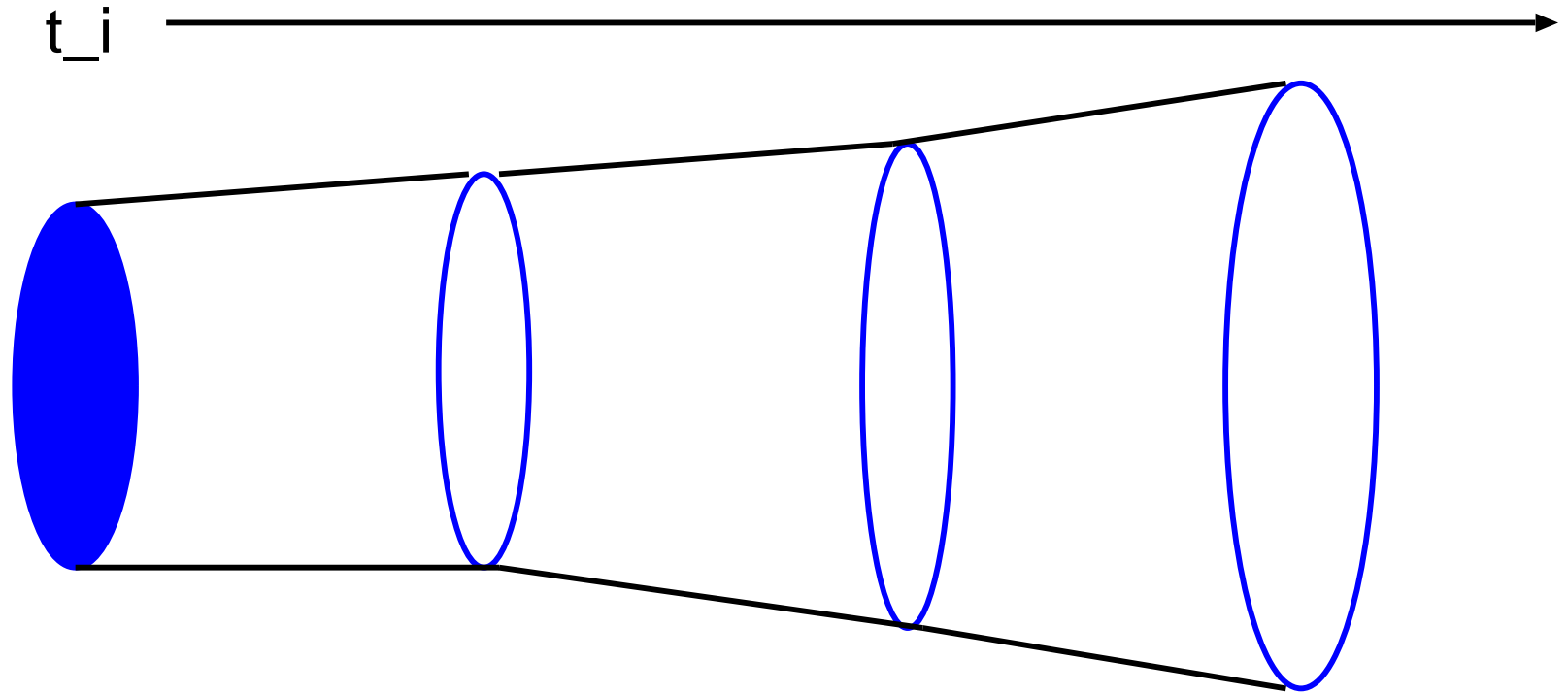
- Some approximation needs to be introduced

A Solution - Retrospective Design Algorithm



- Technique makes use of ensembles generated from the OSSE with $H_{background}$

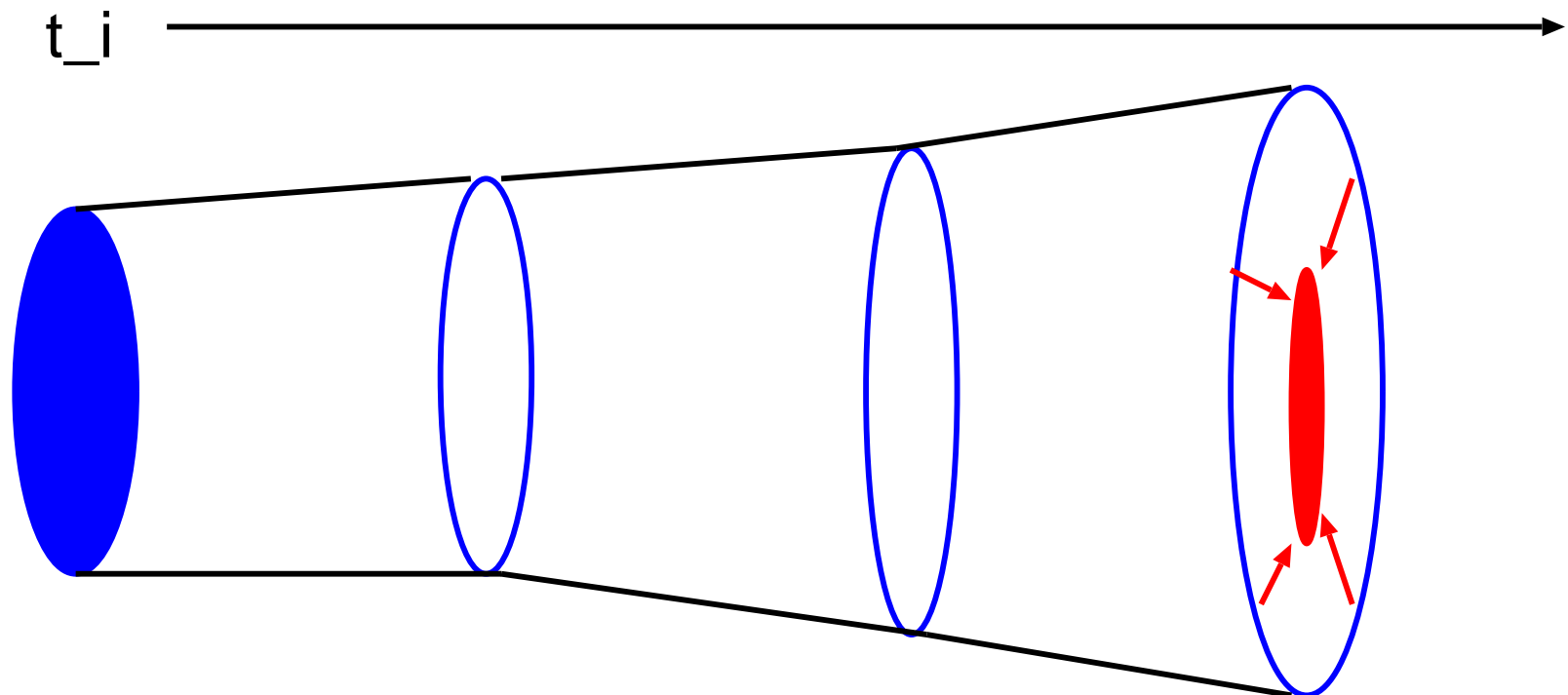
Retrospective Design Algorithm II



$H_{\text{background}}$

An ensemble forecast generated at t_i during
the OSSE with $H_{\text{background}}$

Retrospective Design Algorithm II

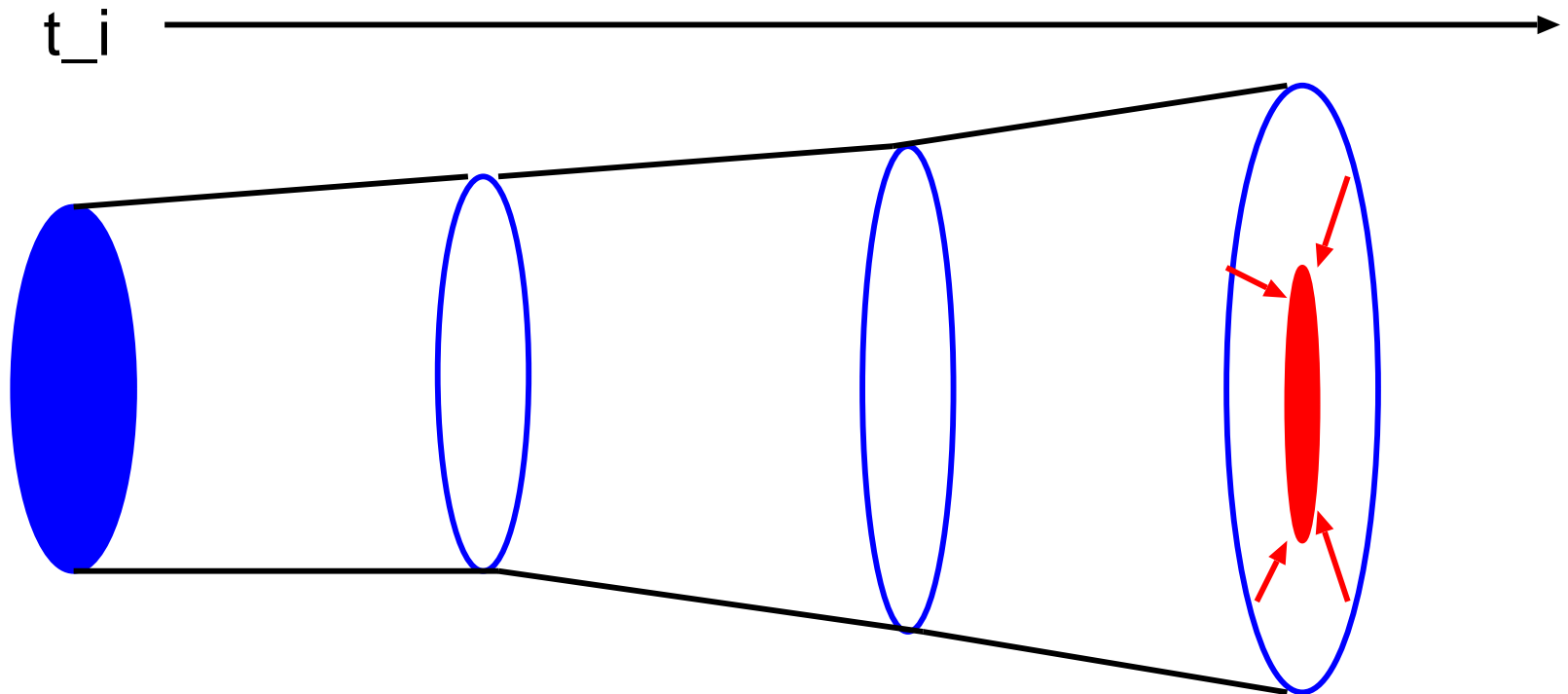


$H_{\text{background}}$ $H_1 = H_{\text{background}} + H_{\text{movable}}$

From t_{i+1} onward, assume the observing network is H_1 - the trial network

Want to compute the covariance of the atmosphere given H_1 for some time $t > t_i$

Retrospective Design Algorithm II

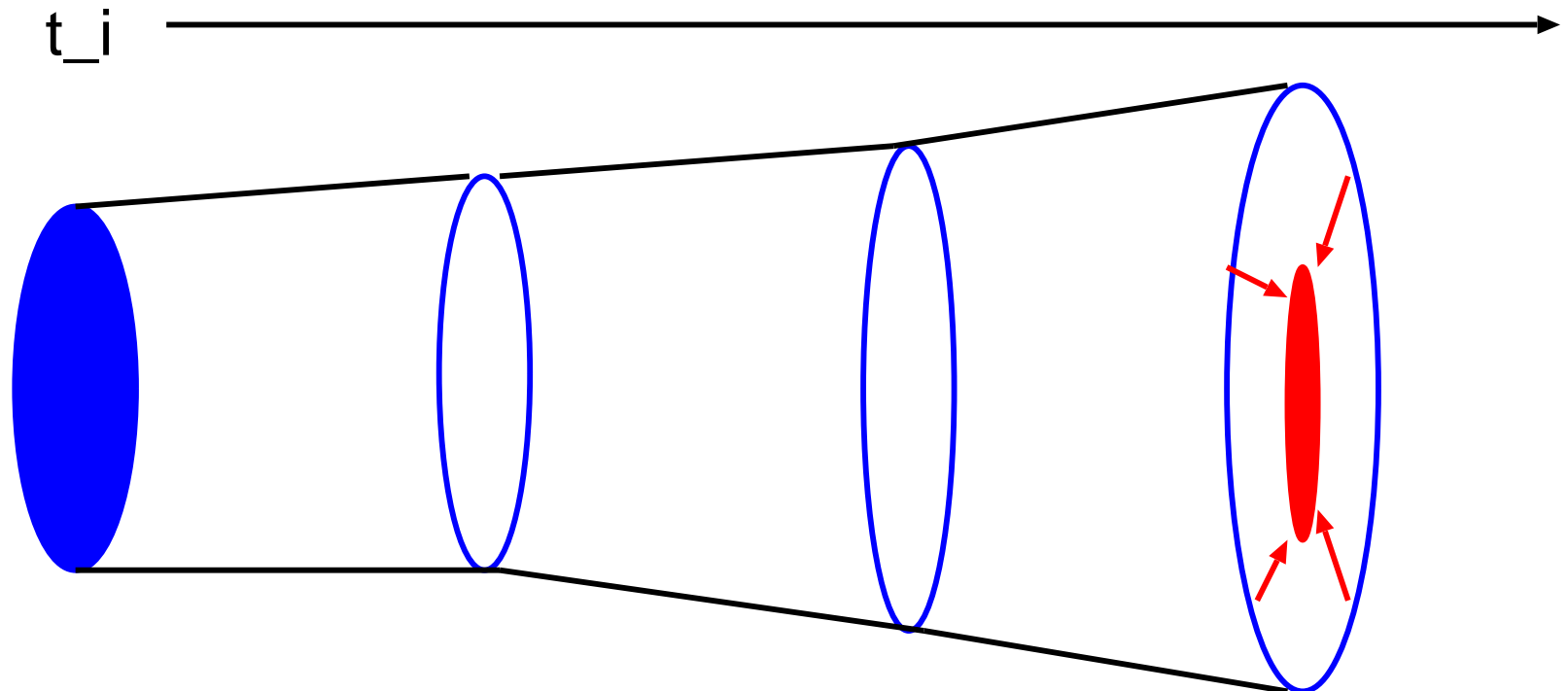


$$H_{\text{background}} \quad H_1 = H_{\text{background}} + H_{\text{movable}}$$

Without re-running the forecast model - an EnKF based algorithm exists for computing the atmosphere's covariance at $t > t_i$ given trial network

$$H_1 = H_{\text{background}} + H_{\text{movable}} - \text{KEY POINT}$$

Retrospective Design Algorithm II



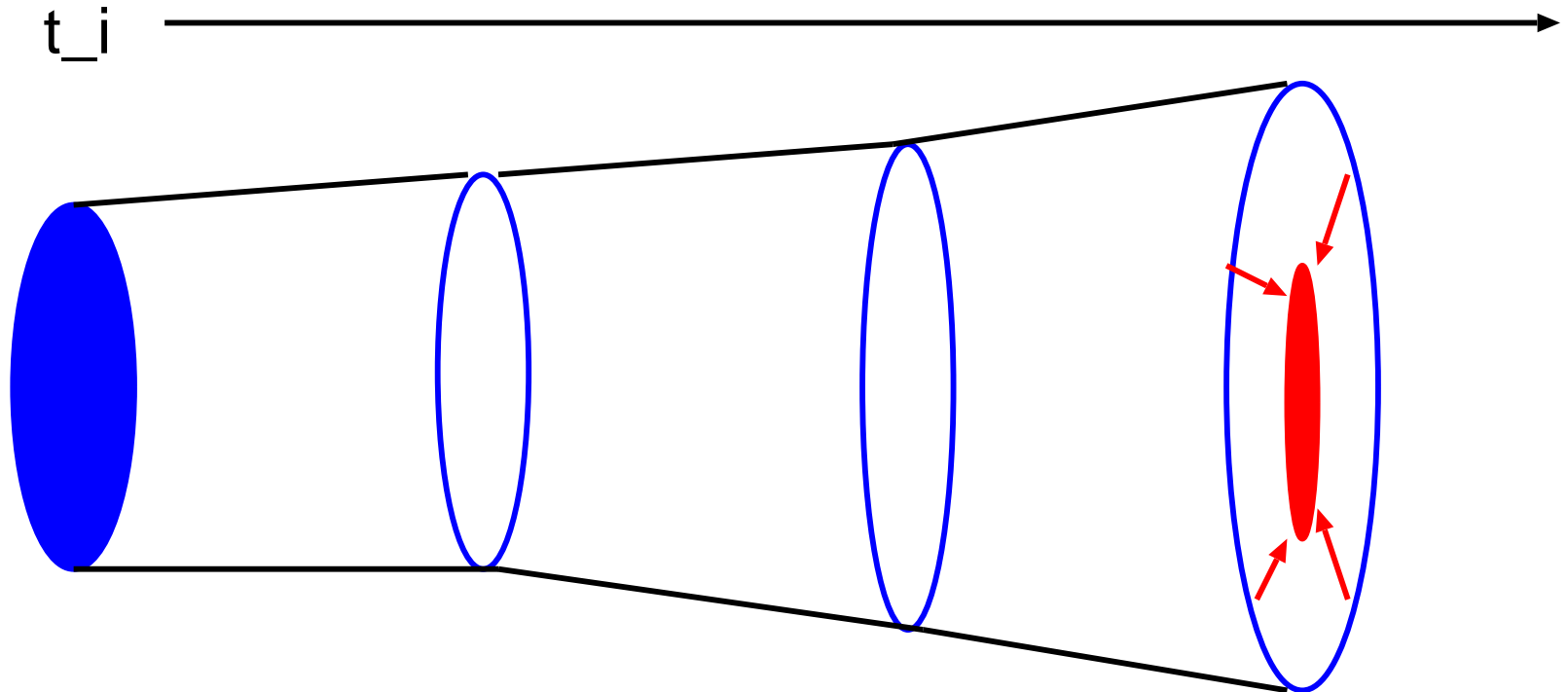
$$H_{\text{background}} \quad H_1 = H_{\text{background}} + H_{\text{movable}}$$

Theory says that:

Covariance at $t > t_i$ equivalent to what would be obtained via a sequential in time filtering procedure for linear dynamics

Useful information for weakly nonlinear evolution

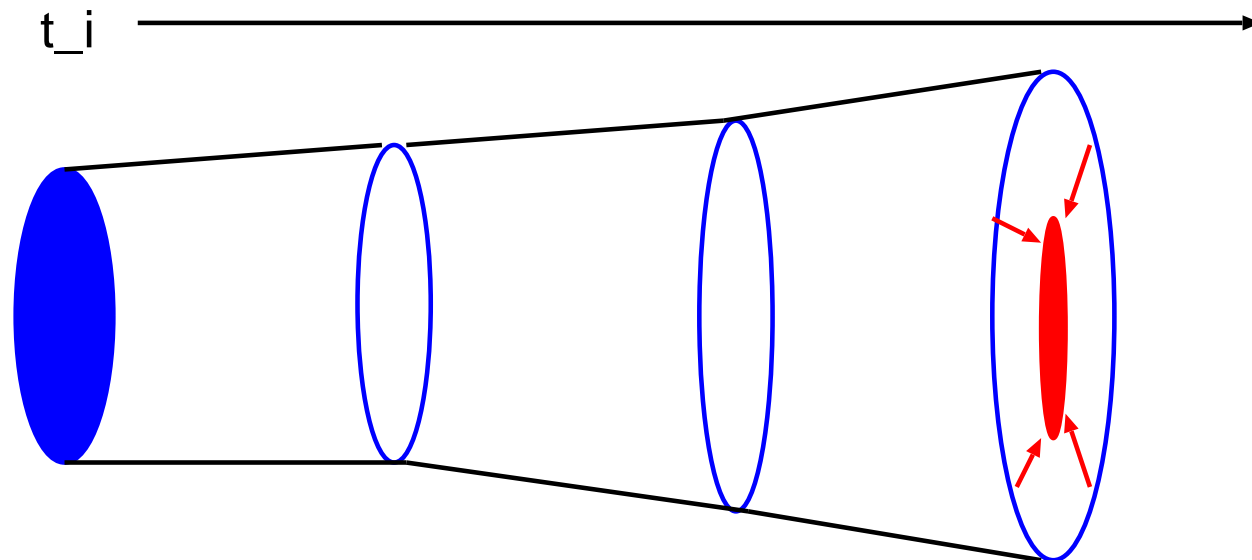
Retrospective Design Algorithm II



$$H_{\text{background}} \quad H_1 = H_{\text{background}} + H_{\text{movable}}$$

- Must consider linear dynamical time scale!
- Sampling errors must be handled properly!
- Method expected to work well for systems that adjust quickly to observations - evidence in CAM results

Retrospective Design Algorithm II



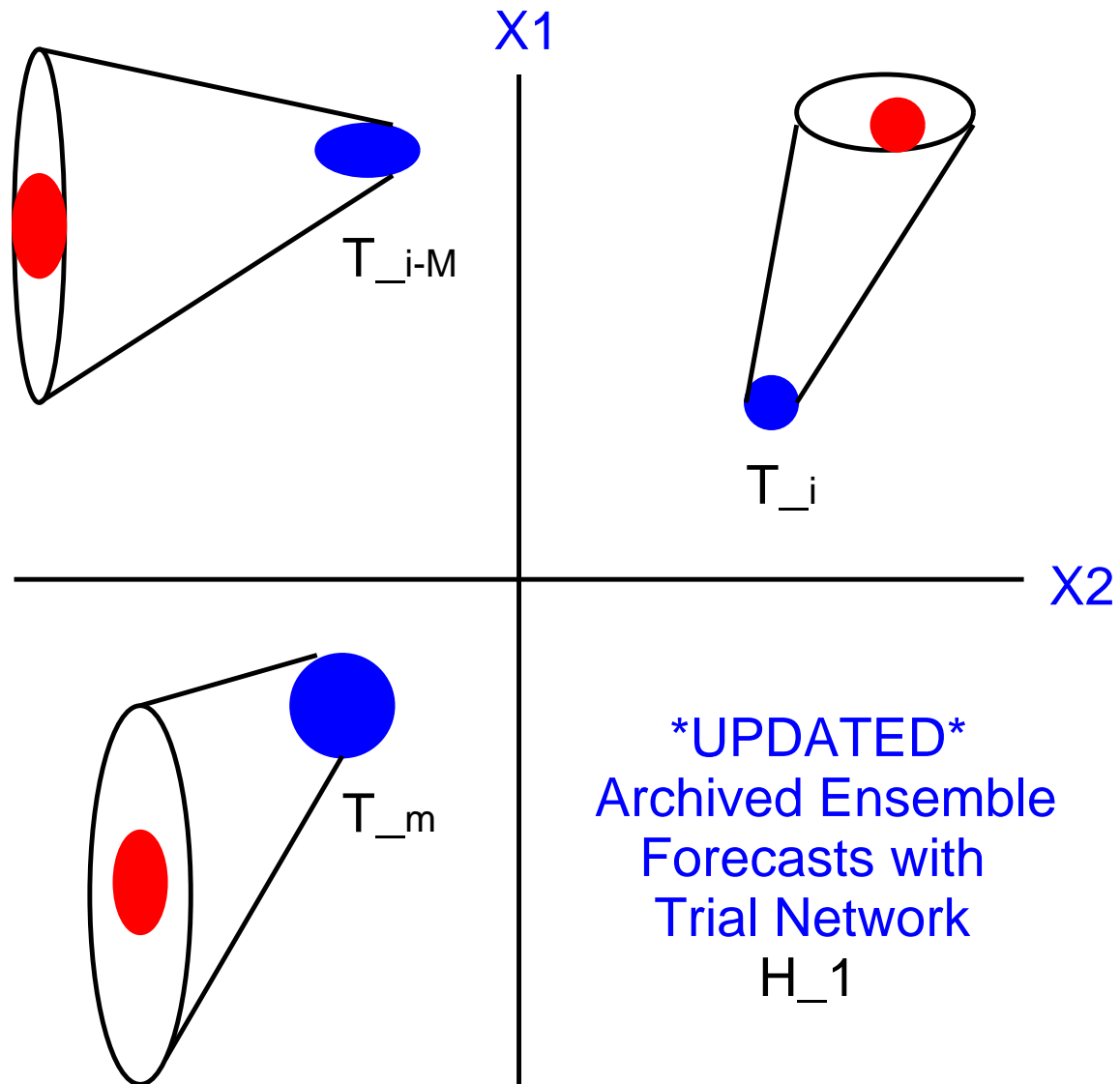
$$H_{\text{background}} \quad H_1 = H_{\text{background}} + H_{\text{movable}}$$

Computational cost

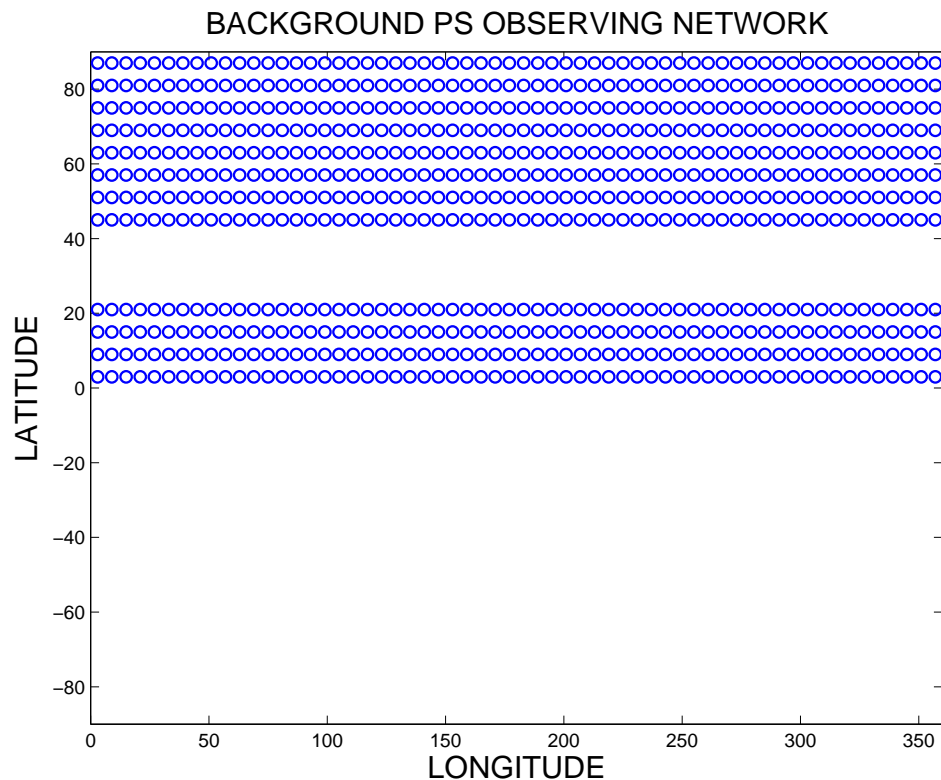
~ Cost of assimilating number of MOVABLE obs

Again, no repeated integrations of model equations required

Evaluate the Objective Function using the RDA

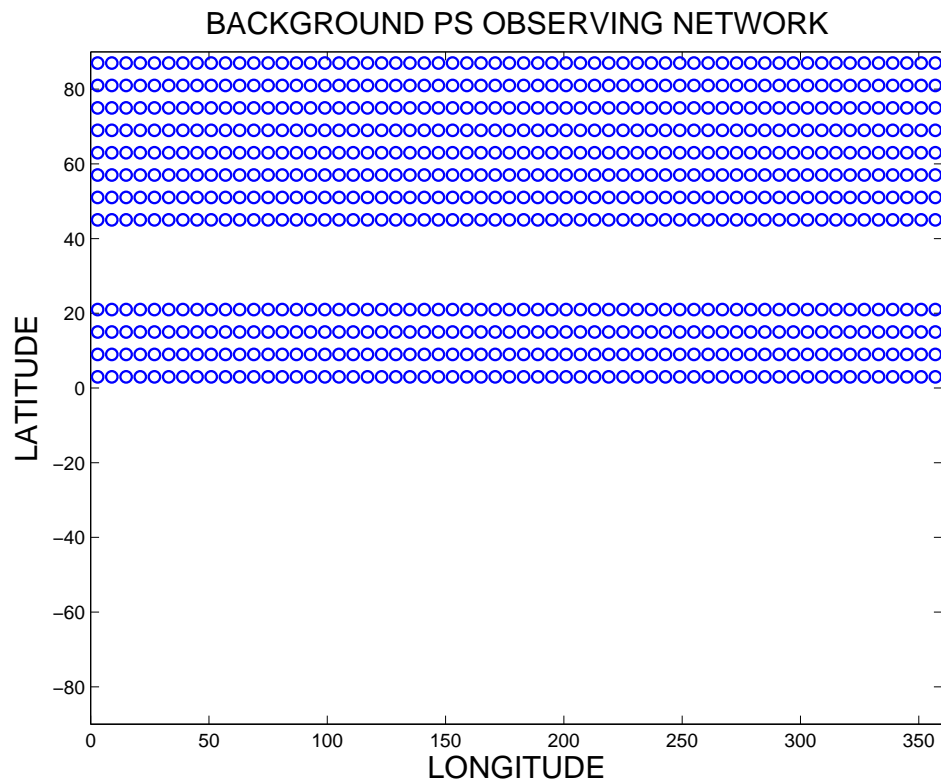


Surface Pressure Network Design in a GCM



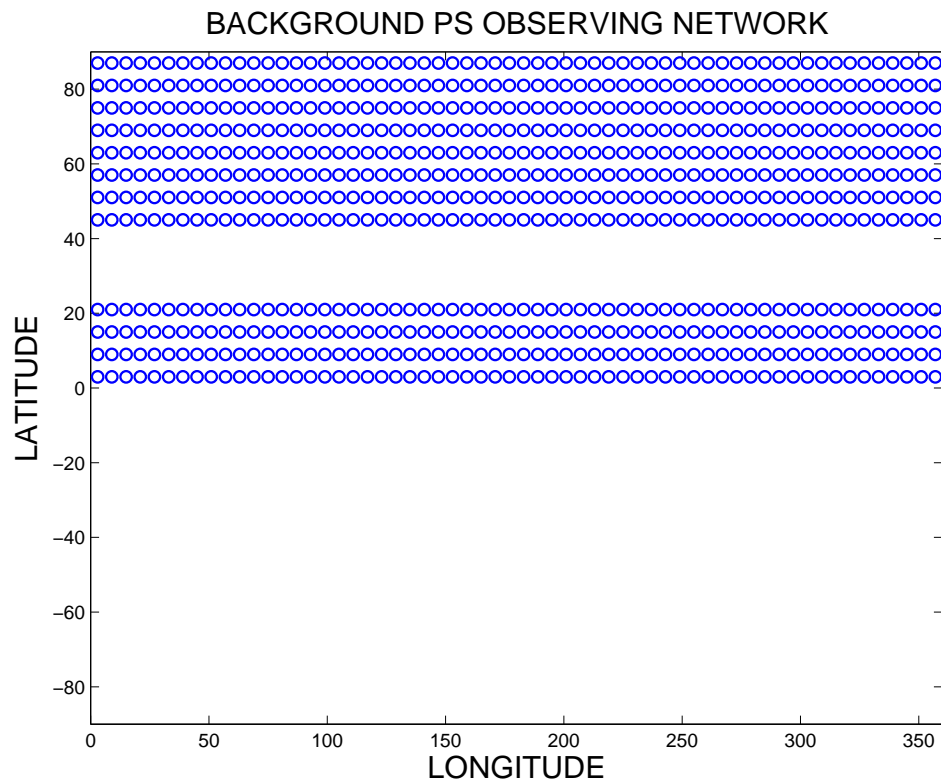
- BACKGROUND network of surface pressure observations - 7 mb observational standard deviation - assimilate every 12 hours

Surface Pressure Network Design in a GCM



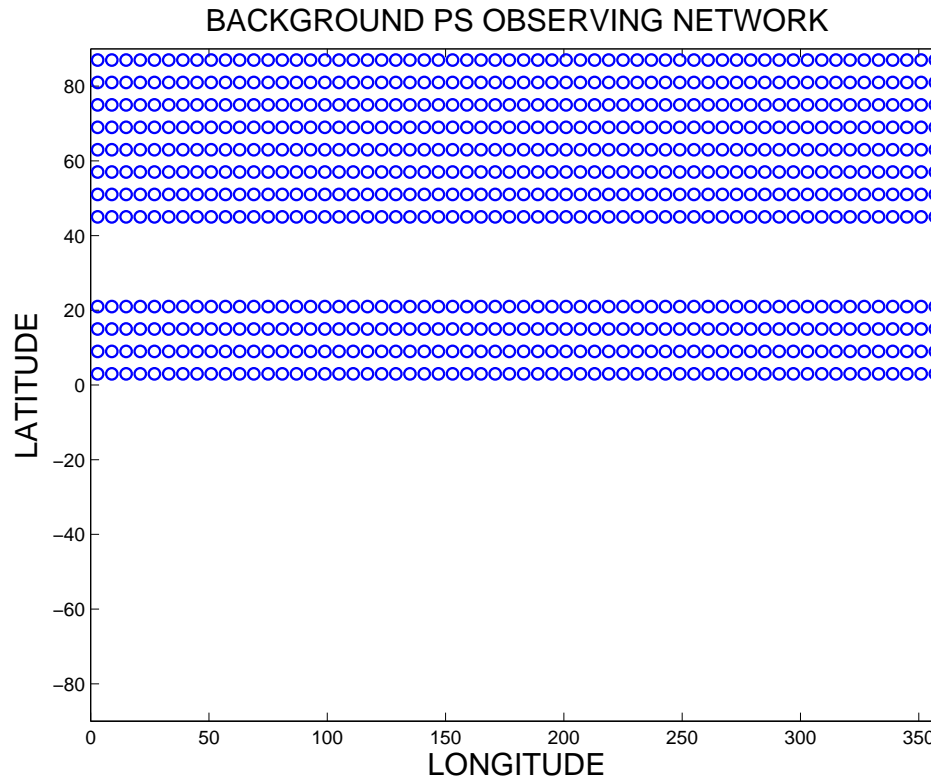
- Run an EAKF with $N = 20$ ensemble members (with localization and no inflation) in a Held-Suarez configuration of an AGCM

Surface Pressure Network Design in a GCM



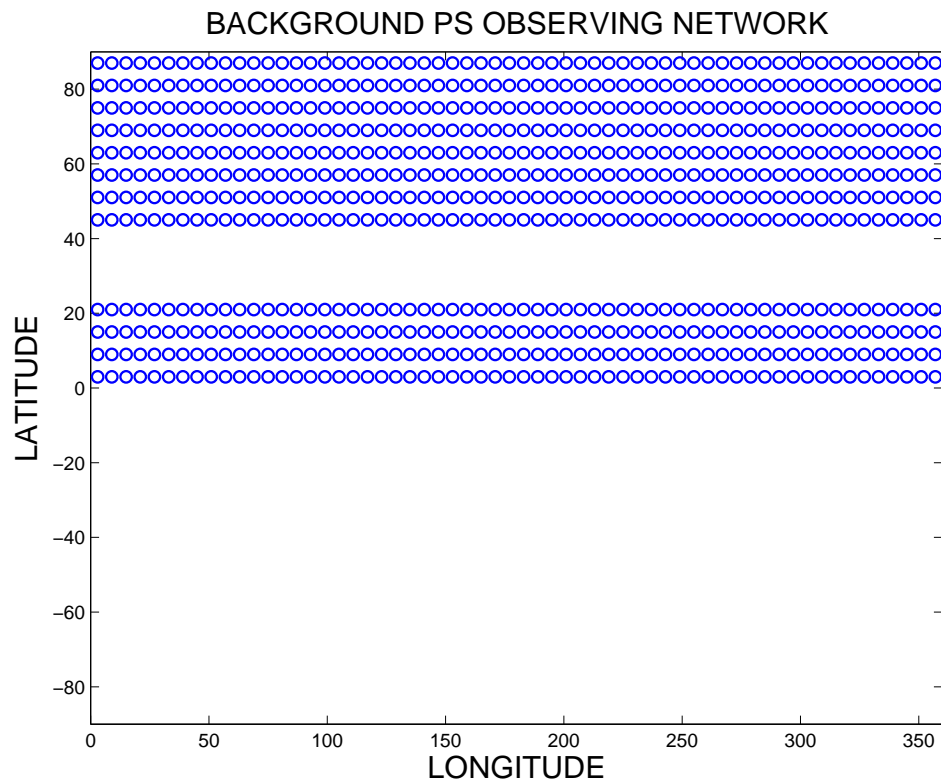
- Model is forced with a zonally symmetric pole to equator temperature gradient, with boundary layer friction

Surface Pressure Network Design in a GCM



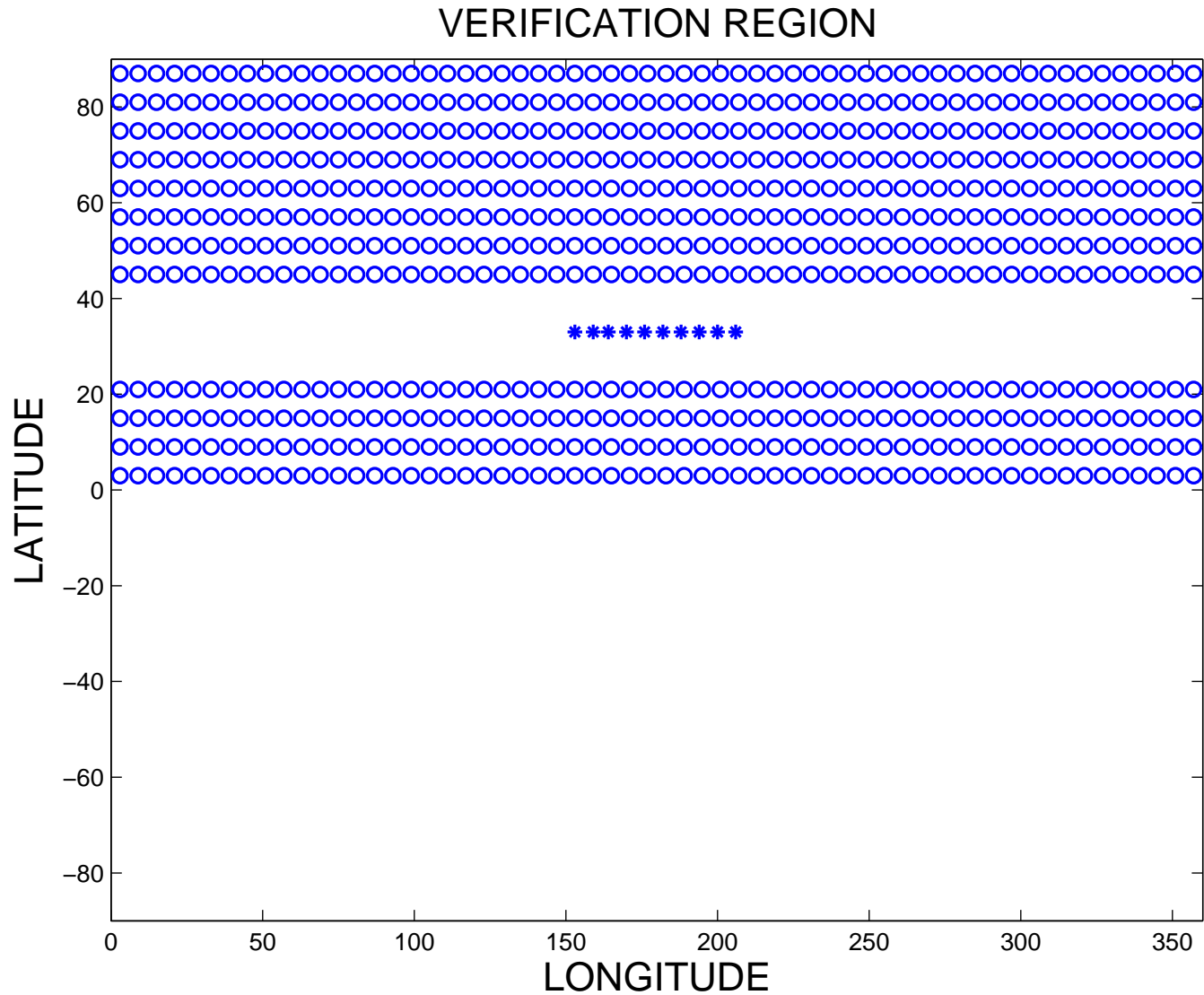
- Low resolution - 5 vertical levels and 60×30 horizontally

Surface Pressure Network Design in a GCM

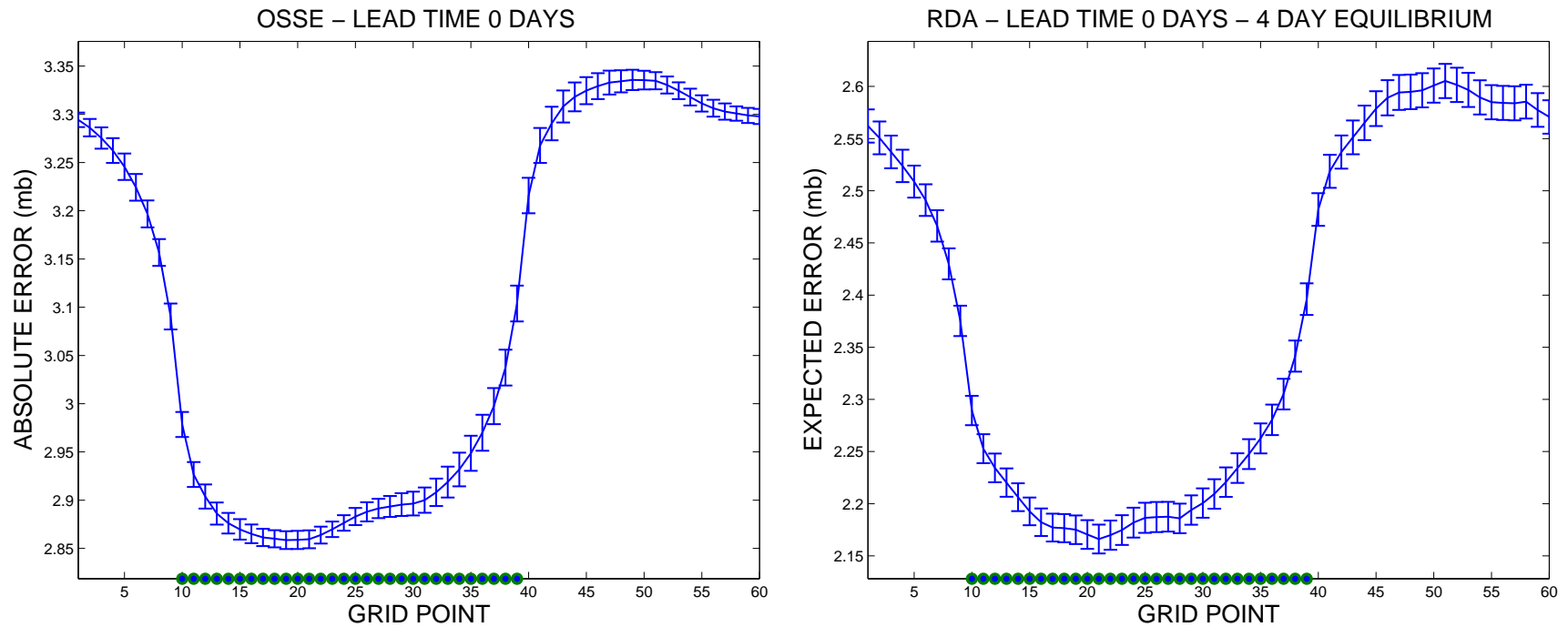


- Temperature gradient drives a baroclinically unstable flow in the mid-latitudes

The Experiment

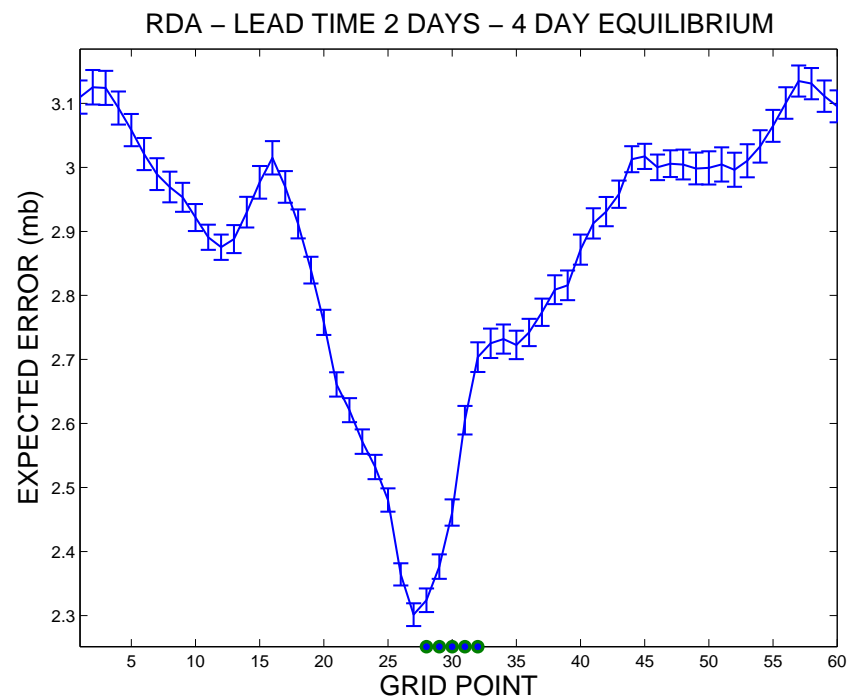
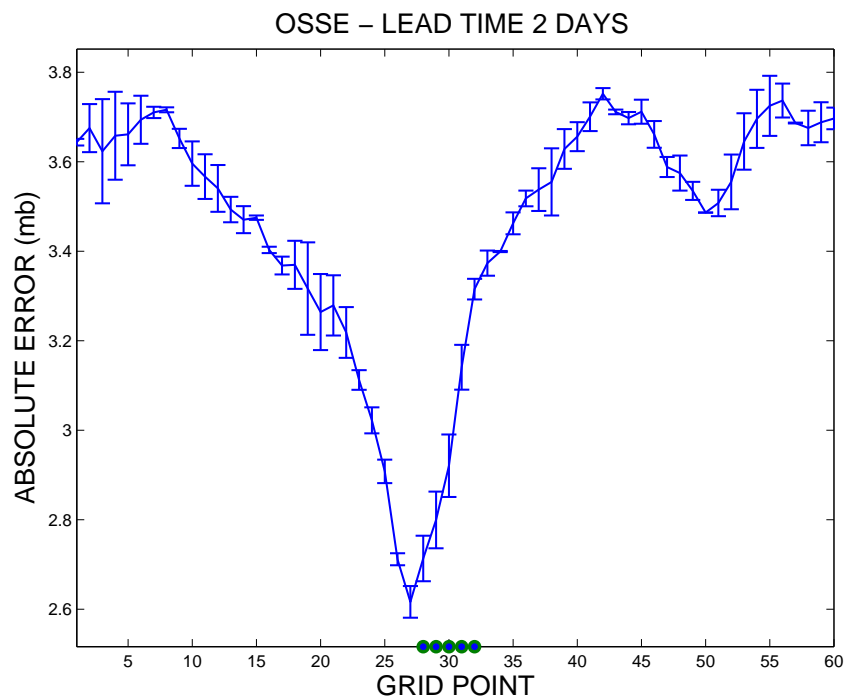


Comparison of Cost Functions I



- Verification region - half the latitude band
- Forecast lead time - 0 days

Comparison of Cost Functions II



- Verification region - 5 consecutive grid points
- Forecast lead time - 2 days

Conclusions

- The ability of the Retrospective Design Algorithm to mimic information derived by running OSSEs has been demonstrated for non-trivial design problems in a GCM

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- Can envision using the RDA for network design in realistic prediction systems - key is efficiency in computing Φ allows for use of optimization

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- The motivation for using the Retrospective Design Algorithm is computational efficiency
- Can envision using the RDA for network design in realistic prediction systems - key is efficiency in computing Φ allows for use of optimization
- The RDA is not system specific
- Working actively on Adaptive Observations (Targeting)

Interactions with DART

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