TEXAS TECH UNIVERSITY™

Extracting Ensemble Information in Real Time to Improve Forecasts of Severe Convection

Brian Ancell

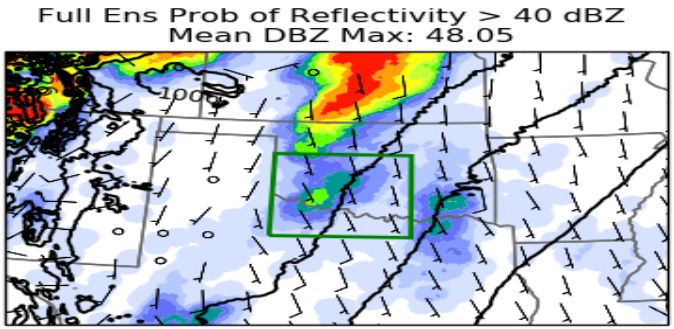
Texas Tech University

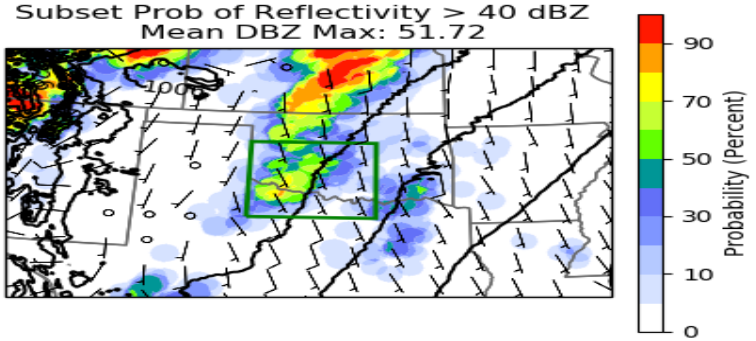
Contributors

Austin Coleman, Chris Weiss, Billy Faletti, Abby Hutson

NOAA Vlab Forum

June 26, 2024





Motivation

1) **Convection-permitting ensembles represent HUGE datasets with vast amounts of information about the predictability of high-impact weather**

Motivation

1) **Convection-permitting ensembles represent HUGE datasets with vast amounts of information about the predictability of high-impact weather**

   - **Different forecast aspects depend on different things earlier in time**

Motivation

1) **Convection-permitting ensembles represent HUGE datasets with vast amounts of information about the predictability of high-impact weather**

- **Different forecast aspects depend on different things earlier in time**
- **Different hazards of the same storms can depend on different things earlier in time**

Motivation

1) Convection-permitting ensembles represent HUGE datasets with vast amounts of information about the predictability of high-impact weather

- **Different forecast aspects depend on different things earlier in time**
- **Different hazards of the same storms can depend on different things earlier in time**

→ The dynamical story grows in complexity further back in time…

Motivation

1) **Convection-permitting ensembles represent HUGE datasets with vast amounts of information about the predictability of high-impact weather**

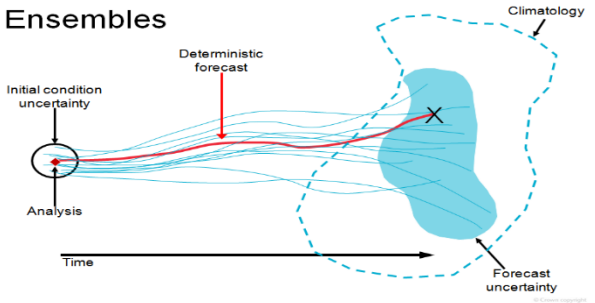
   - **Different forecast aspects depend on different things earlier in time**
   - **Different hazards of the same storms can depend on different things earlier in time**

   → **The dynamical story grows in complexity further back in time…**

2) **One way to extract ensemble information specific to relevant high-impact forecast features is to apply ensemble sensitivity analysis (ESA)**

Ensemble Sensitivity

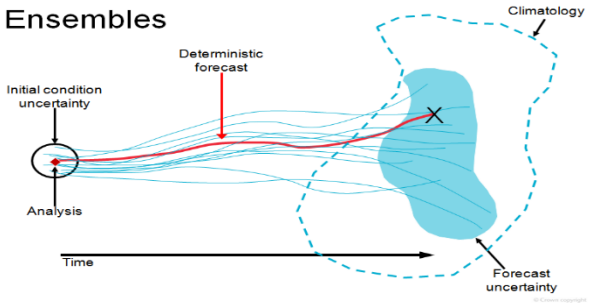
The Basic Recipe:



1) An ensemble of forecasts

2) The choice of a response function (R) at a forecast time

Ensemble Sensitivity

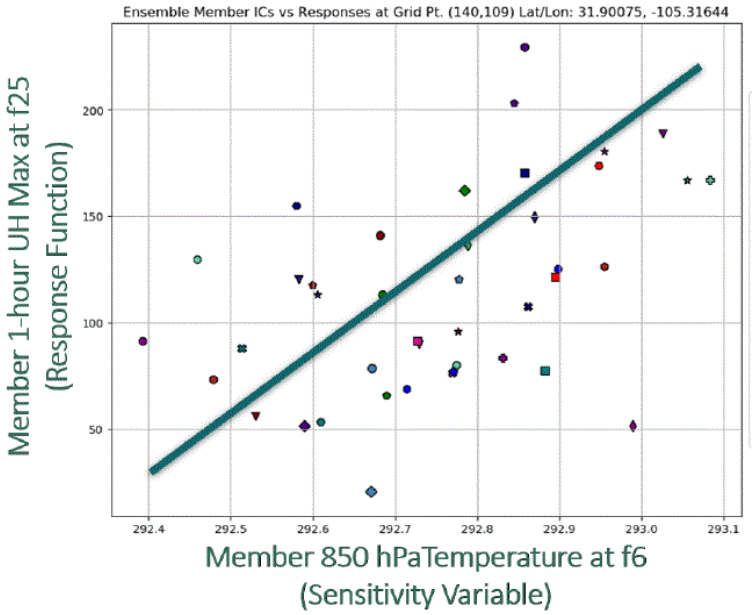


The Basic Recipe:

1) An ensemble of forecasts

2) The choice of a response function (R) at a forecast time

Linear Regression



$$\text{Slope} = \frac{\partial R}{\partial X_o} = \text{Ensemble Sensitivity}$$

$$= \underbrace{\frac{\text{Covariance}(R, X_o)}{\text{Variance}(X_o)}}_{\text{Deep Fundamental Basis}}$$

Other Response Function Examples

1) Wind speed at a point at 24-hr forecast time
2) Coverage of heavy precipitation over an area of interest at 36-hr forecast time

Why Ensemble Sensitivity?

Ensemble sensitivity quickly extracts the important early forecast features (and how they are important) to the evolution and predictability of a specific forecast aspect from large ensemble datasets

Why Ensemble Sensitivity?

Ensemble sensitivity quickly extracts the important early forecast features (and how they are important) to the evolution and predictability of a specific forecast aspect from large ensemble datasets

Operational Usefulness

1) Dynamical understanding – what are the important early forecast features over many cases?

2) Subjective forecast adjustment – can more confidence be placed in members that are better in sensitive regions early in a forecast?

3) **Objective forecast adjustment – can an automated process be developed to adjust ensemble probabilities based on the early forecast skill of members in sensitive regions?**

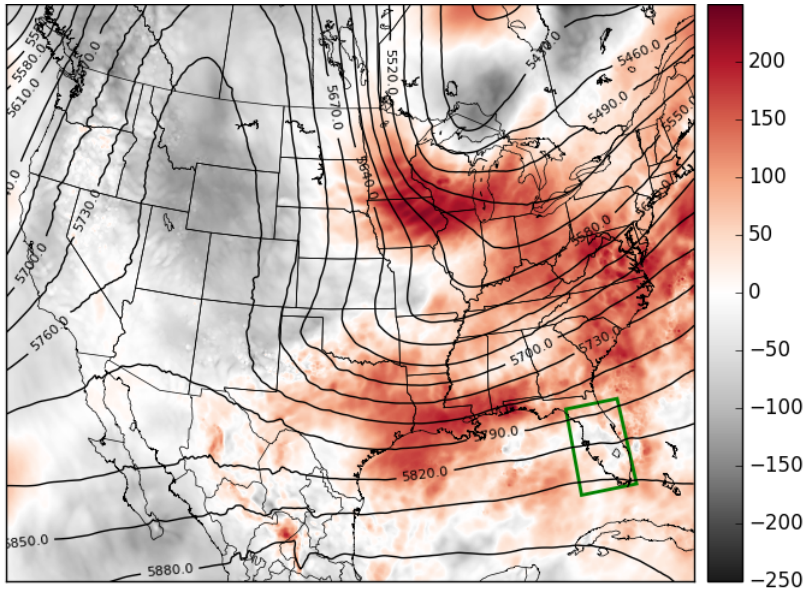
Why Ensemble Sensitivity?

ESA → Can be applied across multiple scales

Forecast Time → 1-2 days

Watch-Outlook Timescales

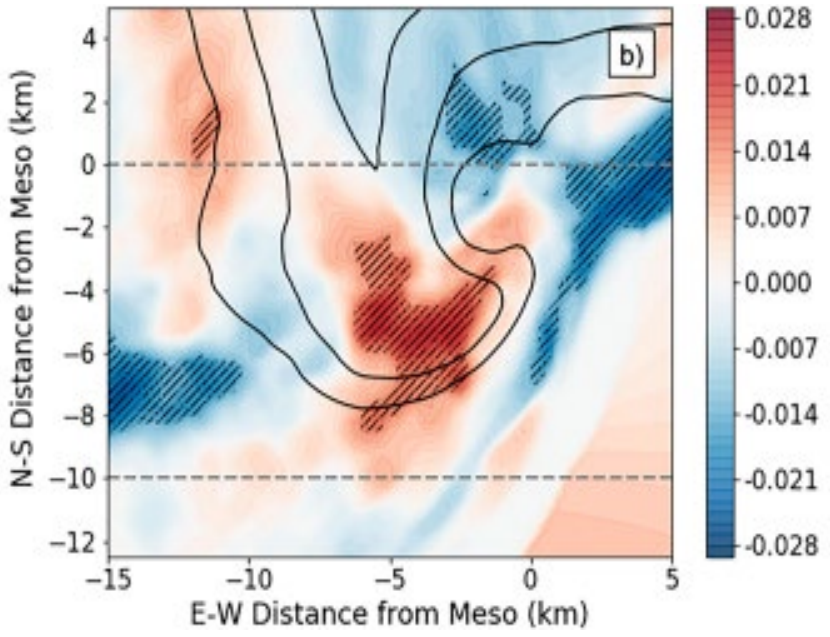
Synoptic-scale Processes



Forecast Time → 1-2 hours

Warning Timescales (WoFs application)

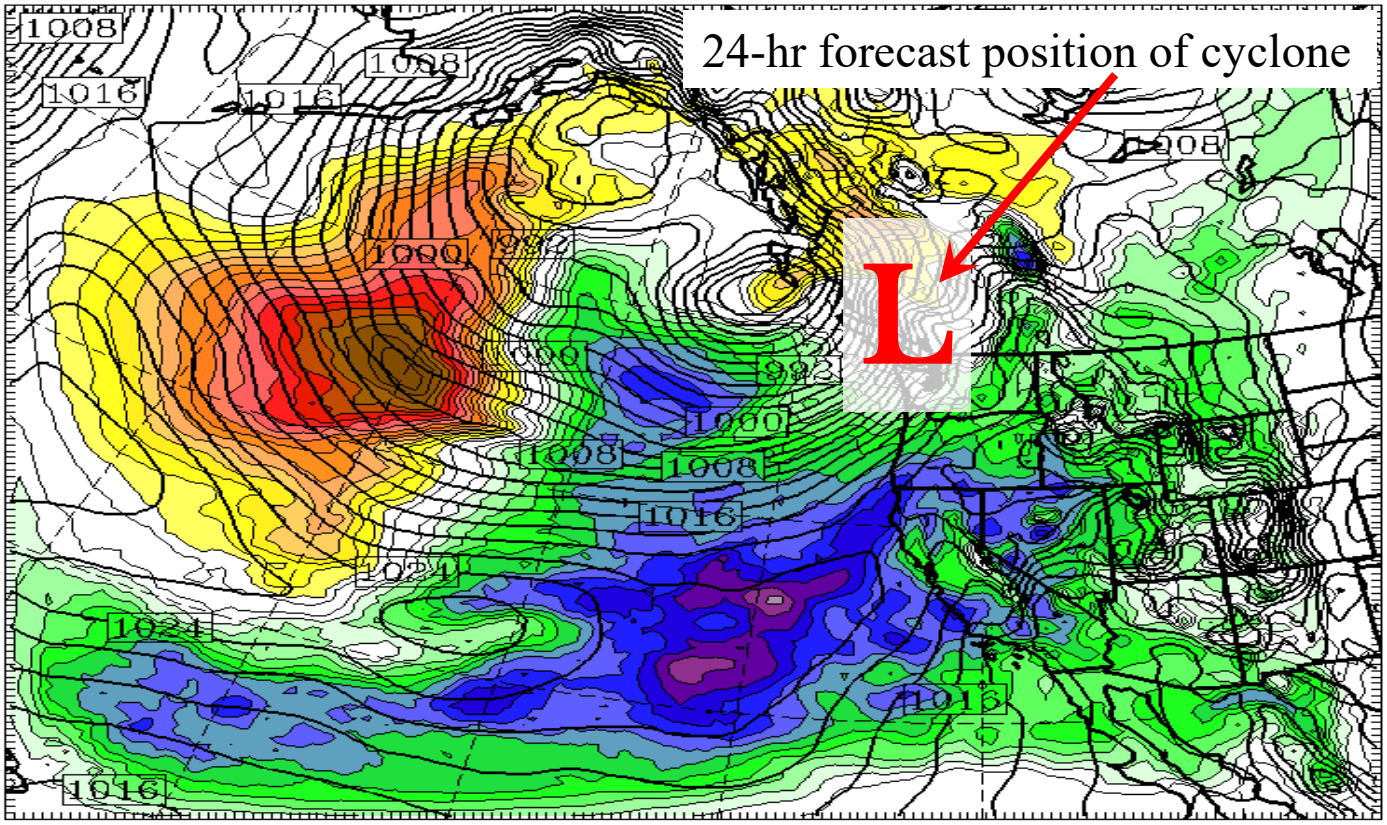
Storm-scale Processes



Ensemble Sensitivity

$$\Delta R \approx \partial R/\partial Xo * \Delta Xo$$

Change in R Sensitivity IC Perturbation

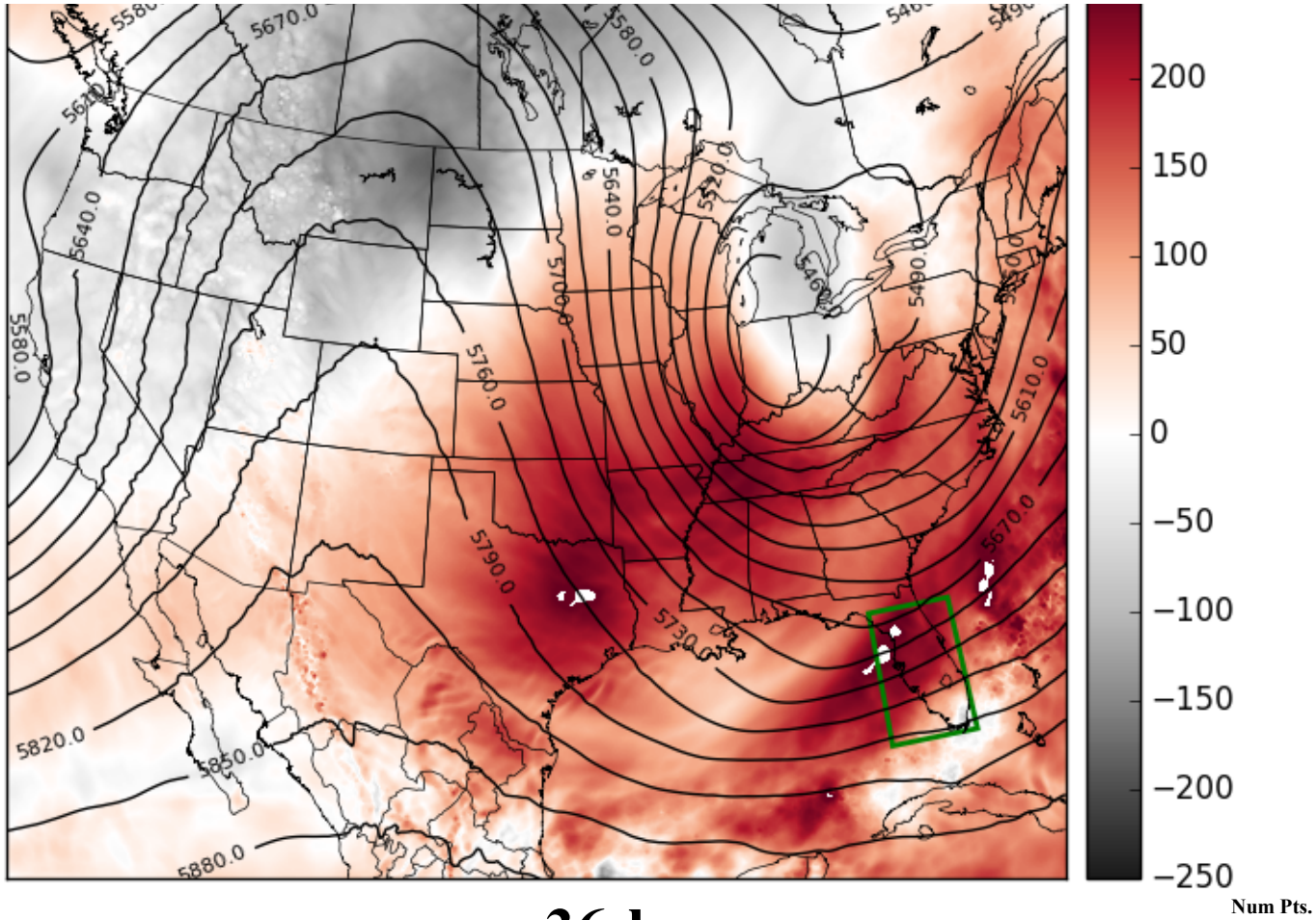


Sensitivity of 24-hr cyclone central pressure to 00-hr SLP

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH

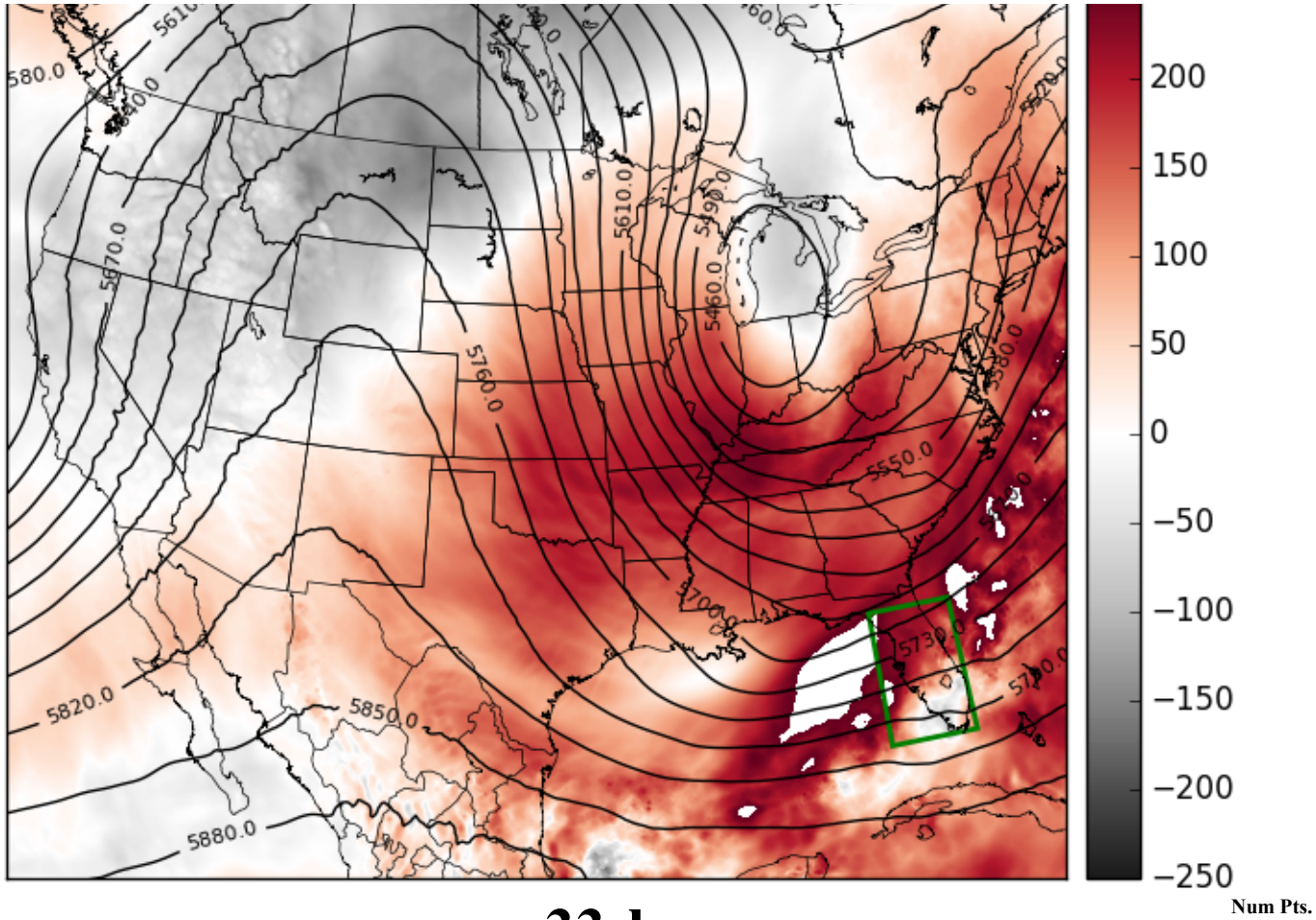


36-hr

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH

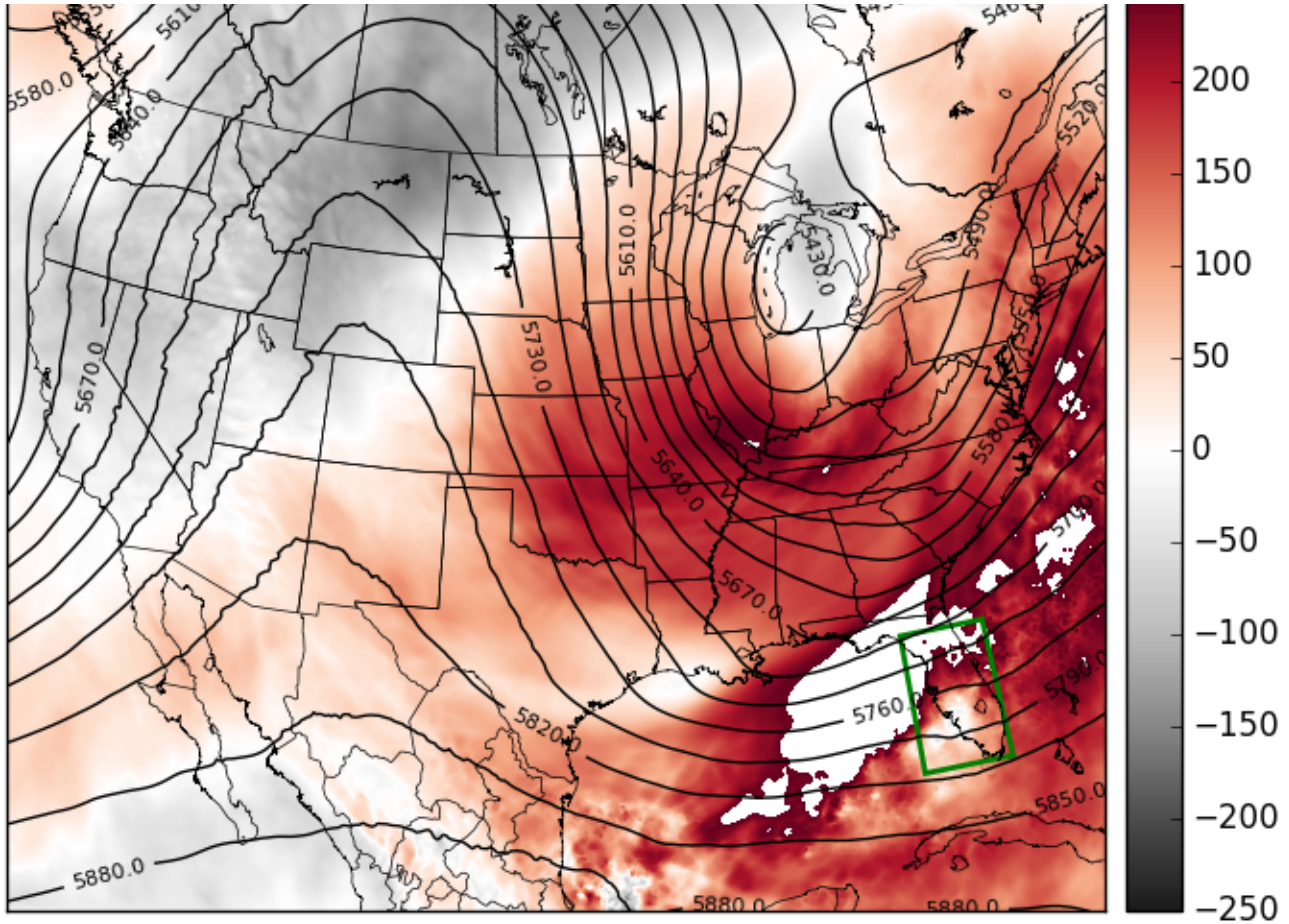


33-hr

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH

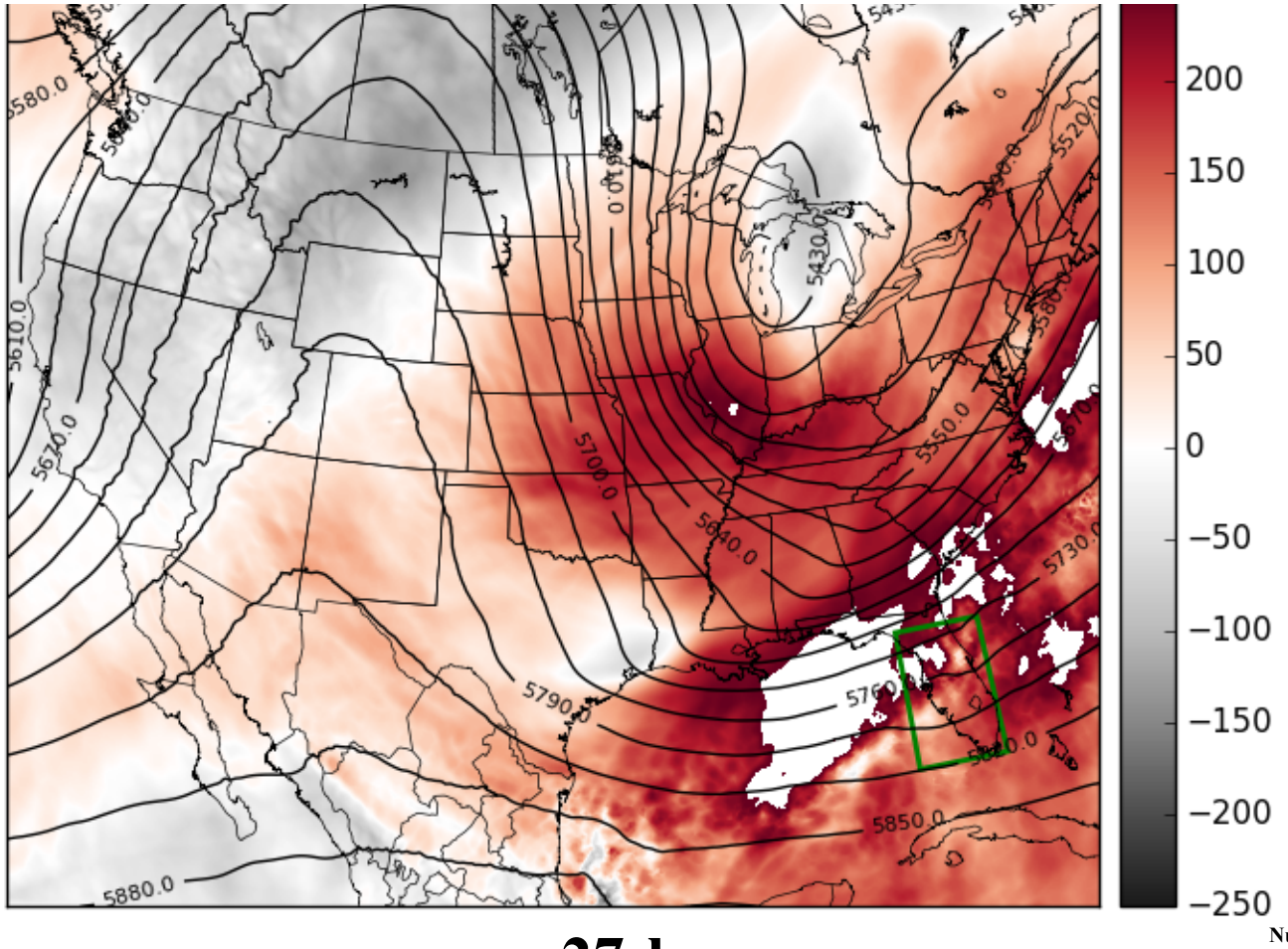


30-hr

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH

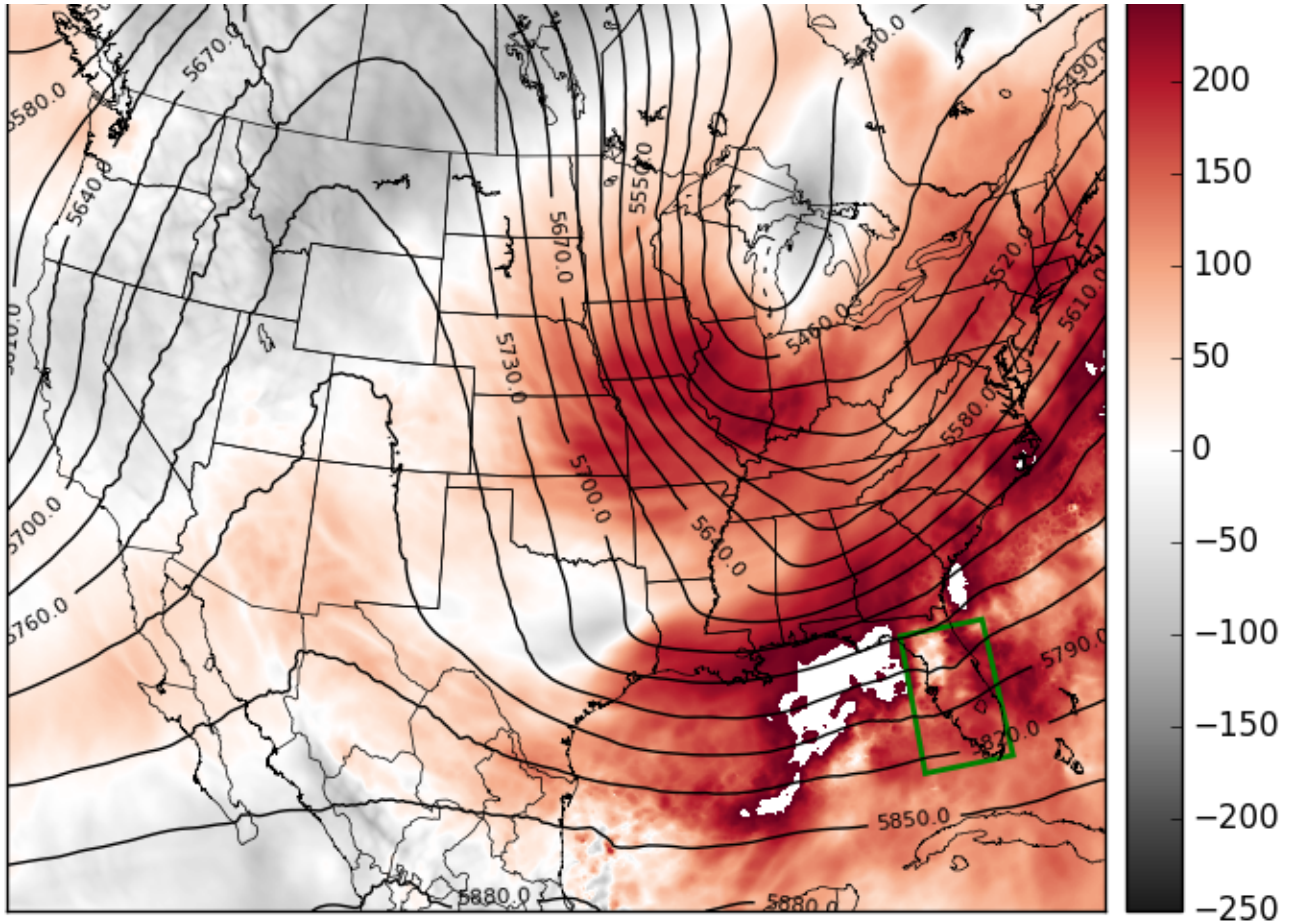


27-hr

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH

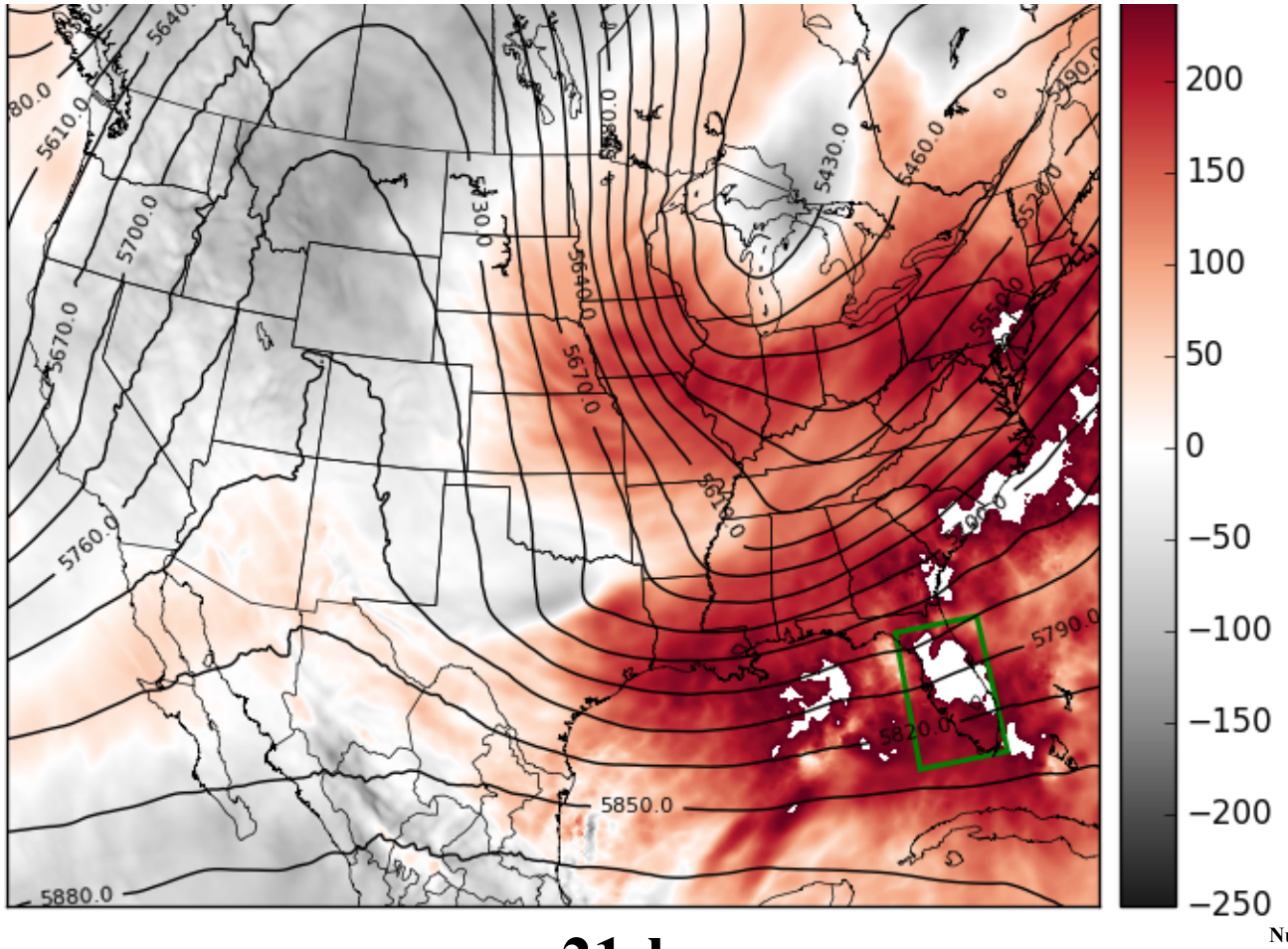


24-hr

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH

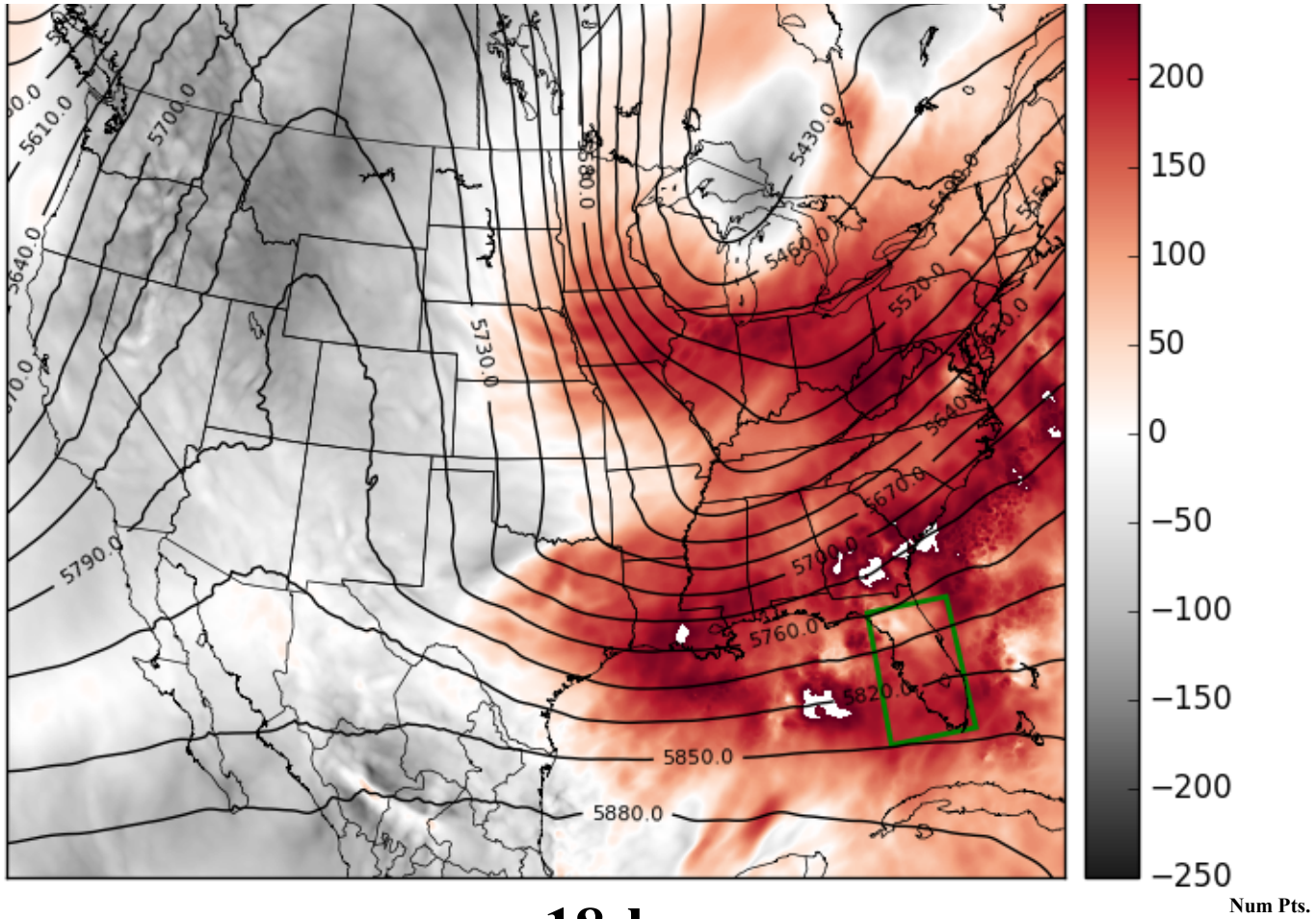


21-hr

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH

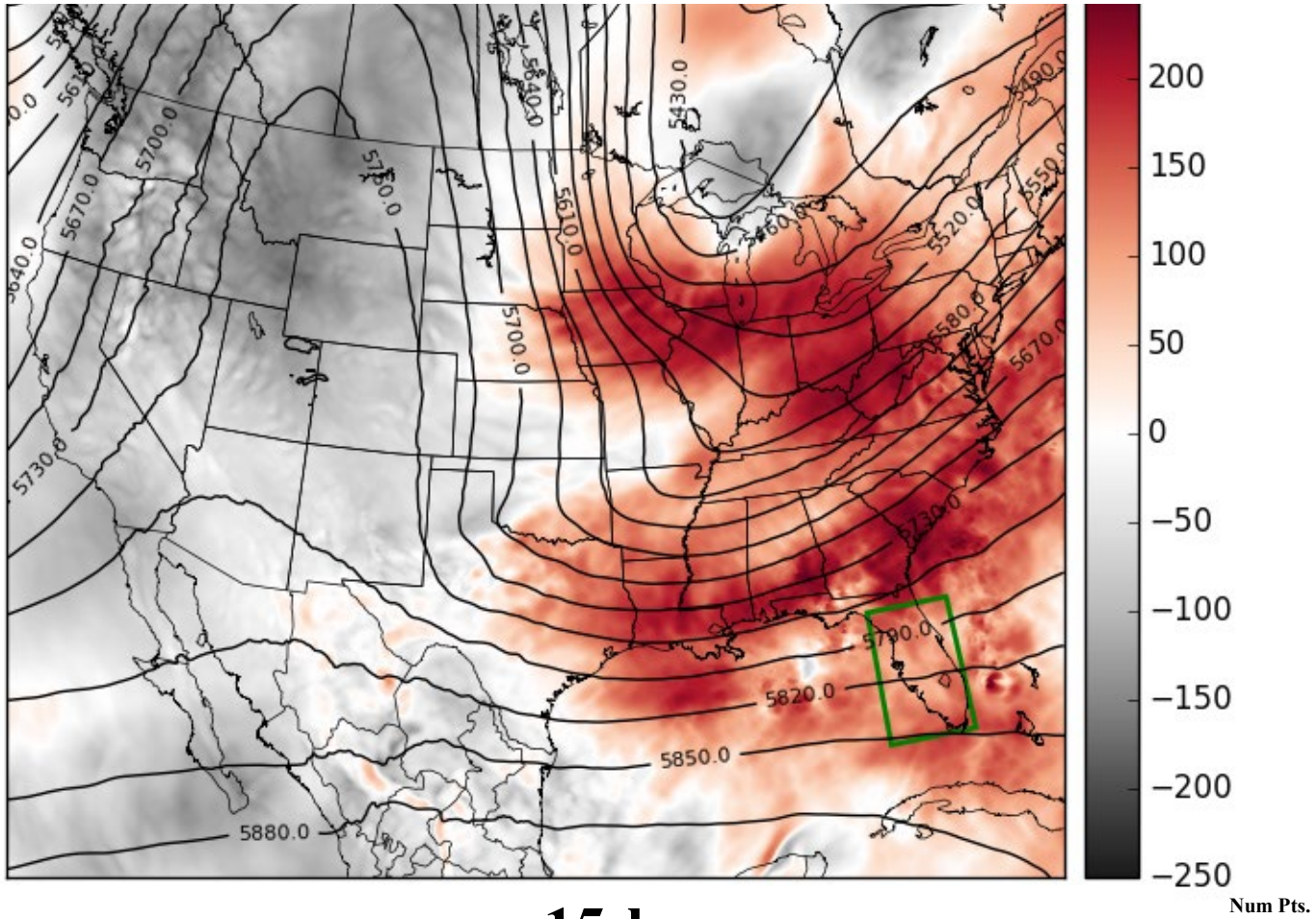


18-hr

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH

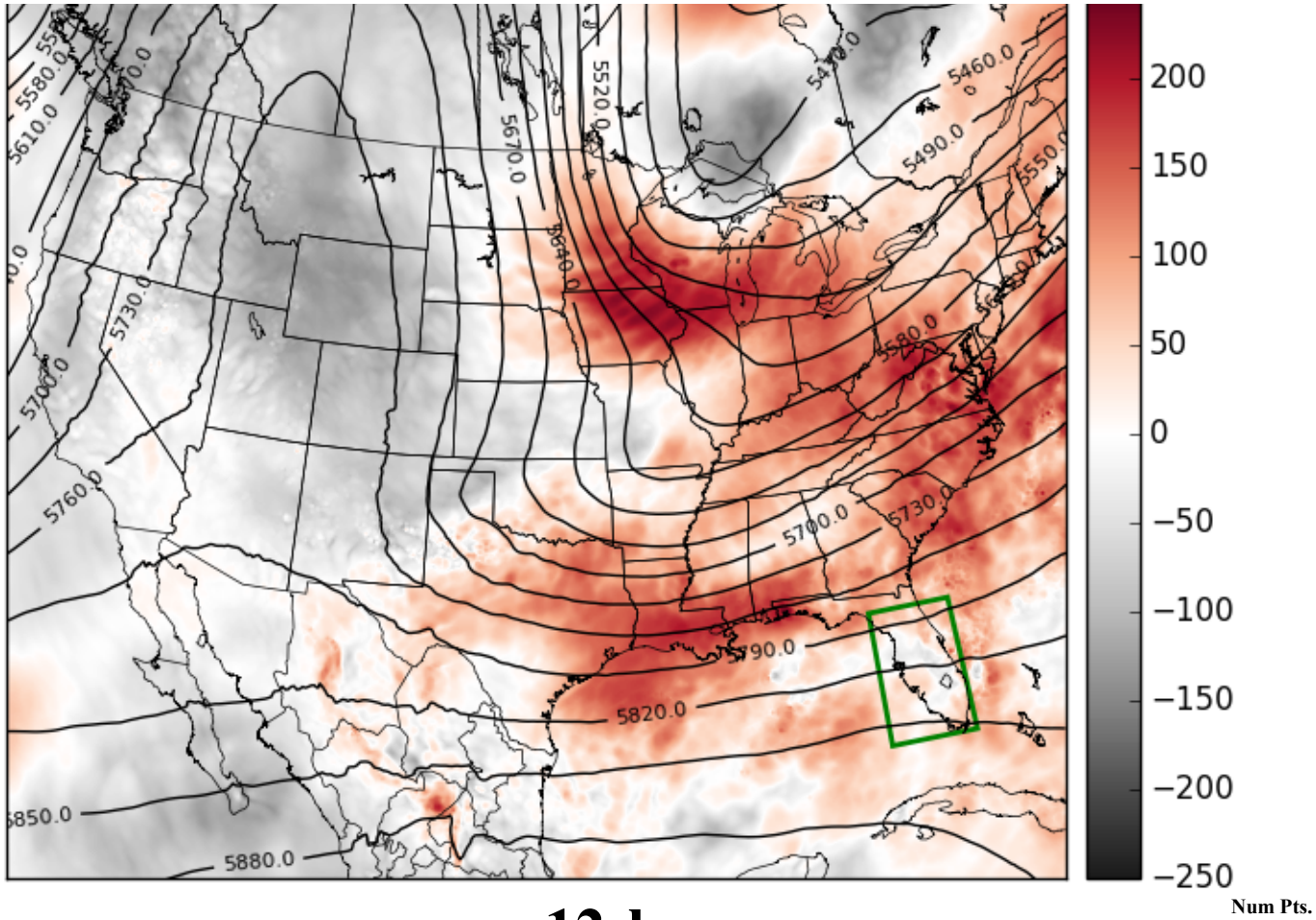


15-hr

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH

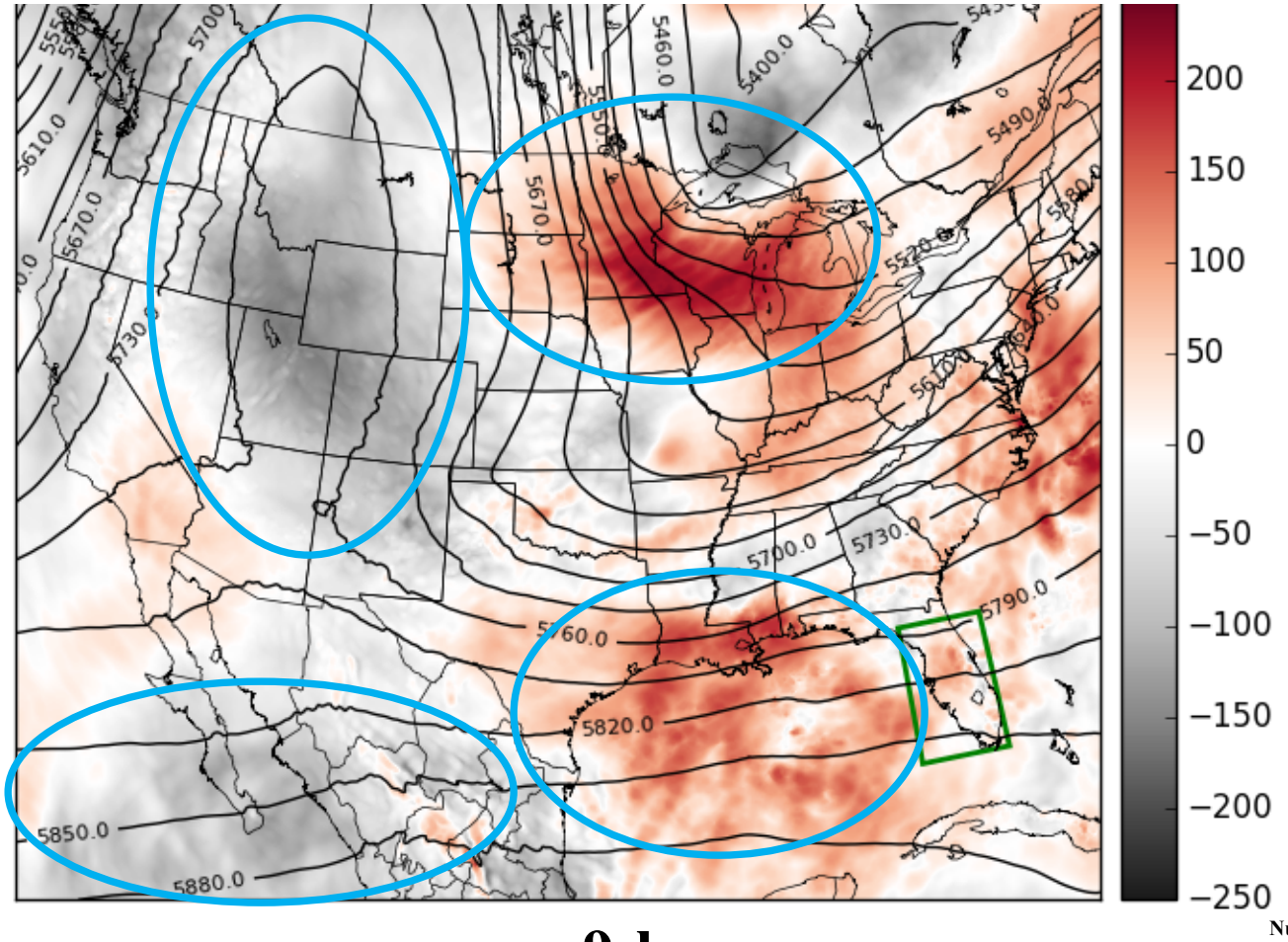


12-hr

Time Evolution of Ensemble Sensitivity Fields

Response → 36-hr storm coverage (green box)

Sensitivity → 500hPa GPH



9-hr

Ensemble Sensitivity-Based Subsetting

A technique that adjusts ensemble probabilities by choosing an ensemble subset with the smallest errors in sensitive regions

Ensemble Sensitivity-Based Subsetting

A technique that adjusts ensemble probabilities by choosing an ensemble subset with the smallest errors in sensitive regions

→ Produces "dead-end forecasts" to specifically improve high-impact forecasts of a chosen response function R

Sensitivity-Based Subsetting: What We've Learned

- **Nonlinearity is not really a problem**

Sensitivity-Based Subsetting: What We've Learned

- **Nonlinearity is not really a problem**
- **Model physics ensembles add difficulty**

Ensemble Sensitivity-Based Subsetting

Sensitivity-Based Subsetting: What We've Learned

- **Nonlinearity is not really a problem**
- **Model physics ensembles add difficulty**
- **Technique provides both success and failure**

Ensemble Sensitivity-Based Subsetting

Sensitivity-Based Subsetting: What We've Learned

- **Nonlinearity is not really a problem**
- **Model physics ensembles add difficulty**
- **Technique provides both success and failure**

common characteristics (flow, distribution, spread…)?

Ensemble Sensitivity-Based Subsetting

Sensitivity-Based Subsetting: What We've Learned

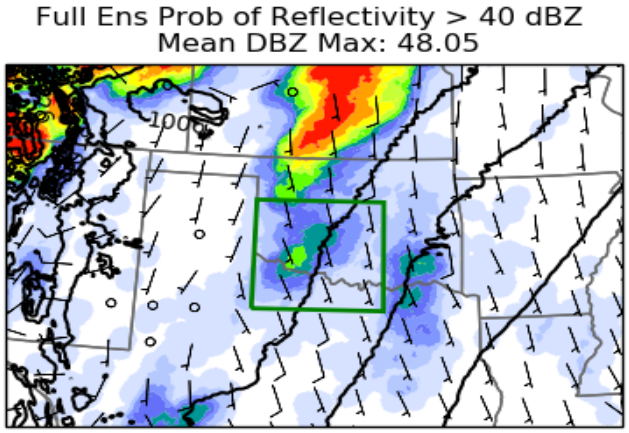
- **Nonlinearity is not really a problem**
- **Model physics ensembles add difficulty**
- **Technique provides both success and failure**

common characteristics (flow, distribution, spread…)?

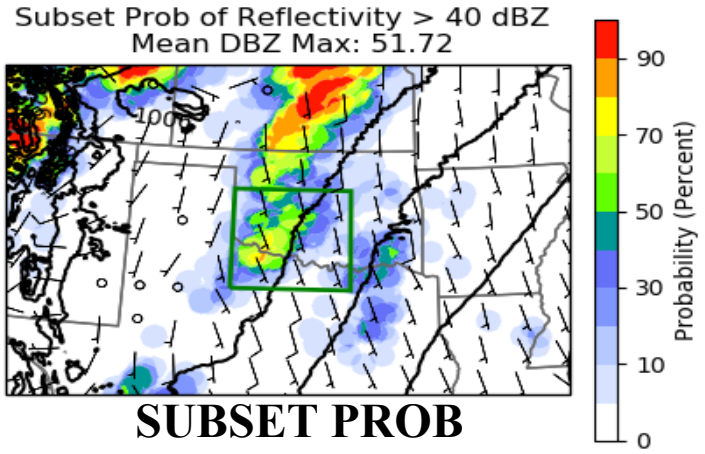
Current Work → Can we predict when the technique will work and when it won't???

Ensemble Sensitivity-Based Subsetting

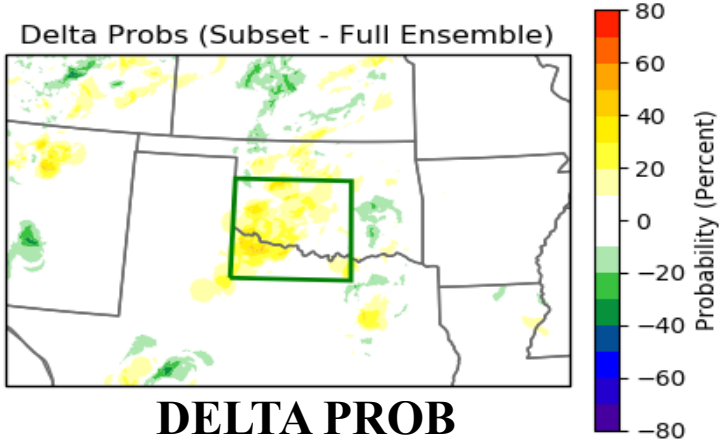
R = Simulated Reflectivity Coverage > 40dBZ (F21-F27)



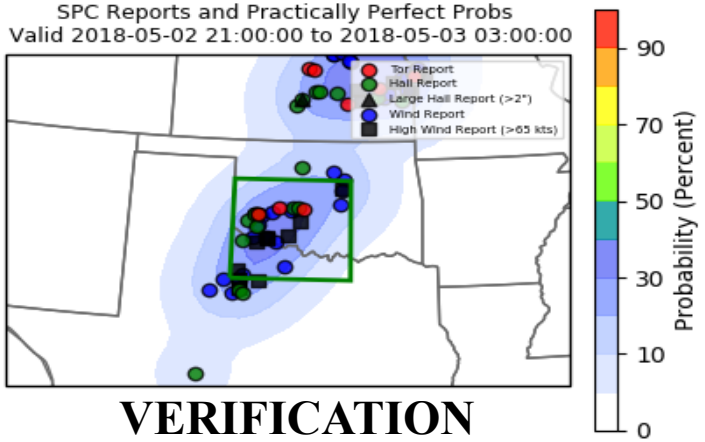
FULL ENSEMBLE PROB



SUBSET PROB

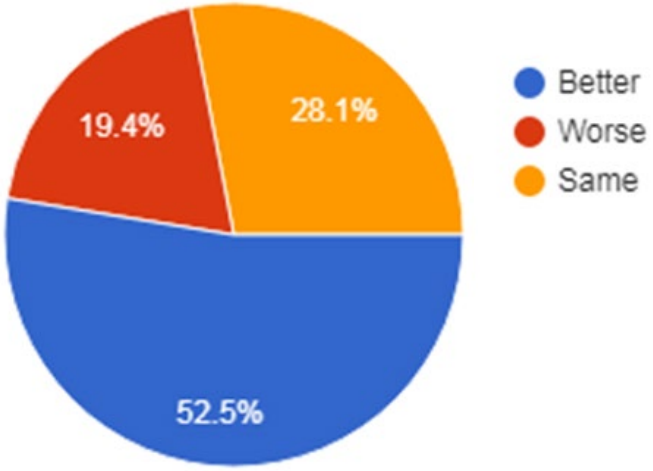


DELTA PROB



VERIFICATION

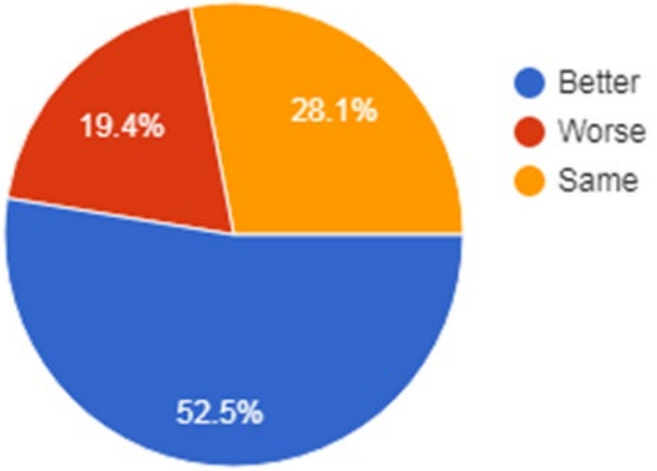
Ensemble Sensitivity-Based Subsetting



Relative to the full ensemble, the forecast skill of the subset **inside** the response function box is...

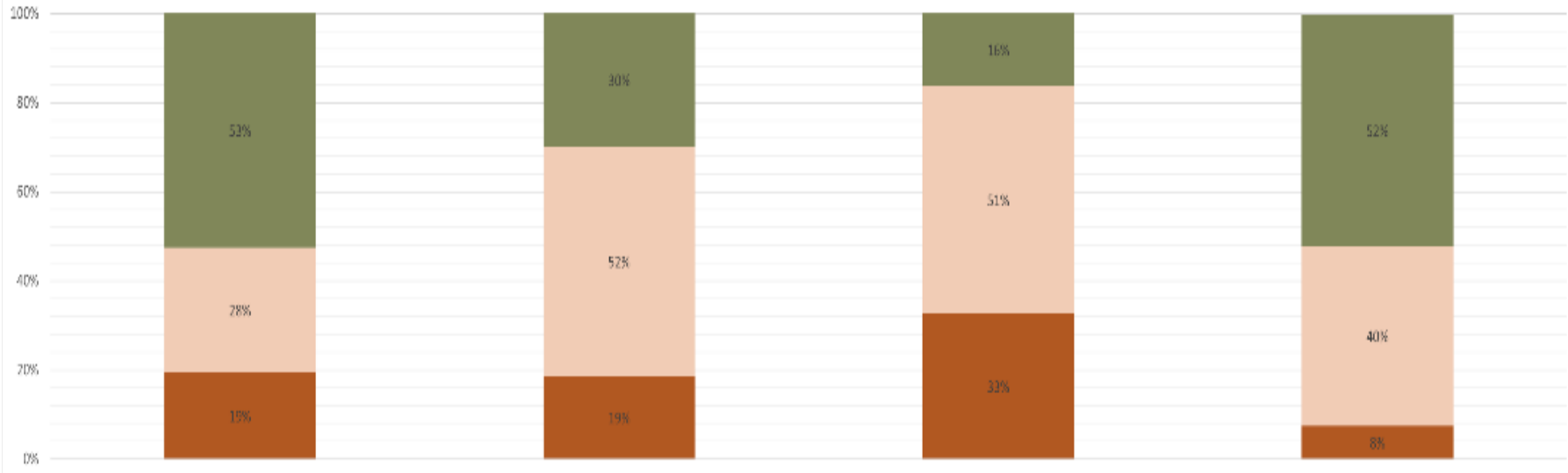
a) Better
b) Worse
c) Same

Ensemble Sensitivity-Based Subsetting



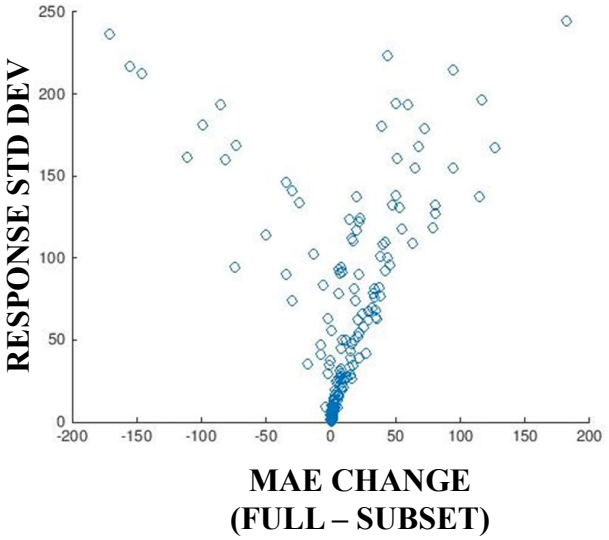
Relative to the full ensemble, the forecast skill of the subset **inside** the response function box is...

a) Better
b) Worse
c) Same

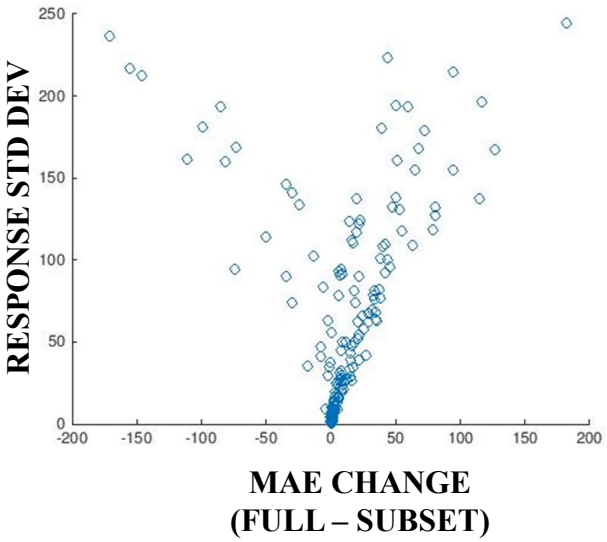


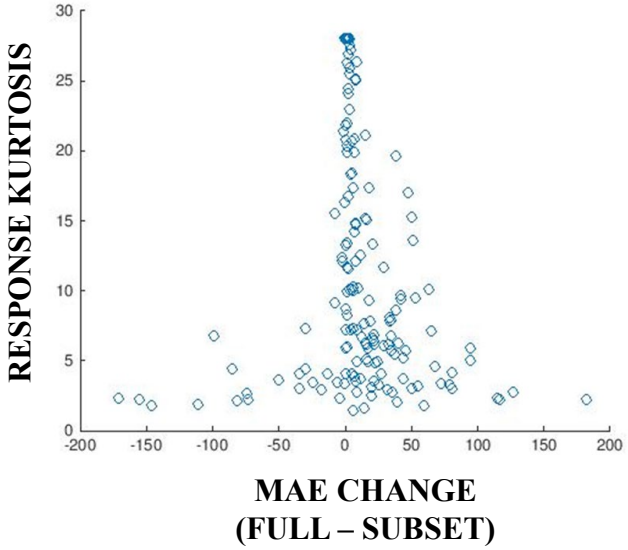
HWT Summary Stats (4 years)

Ensemble Sensitivity-Based Subsetting

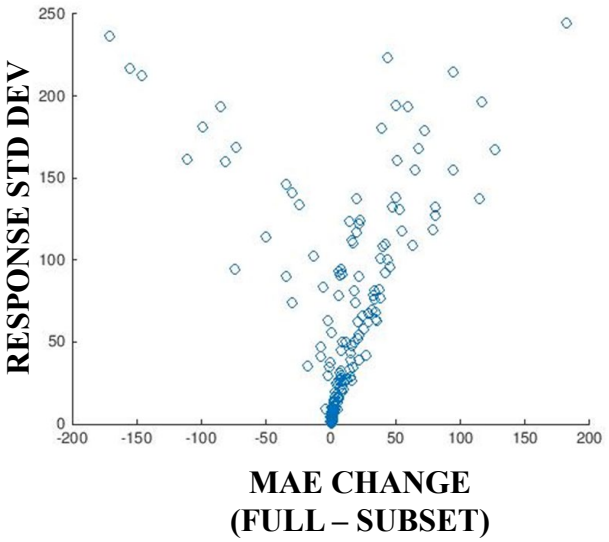


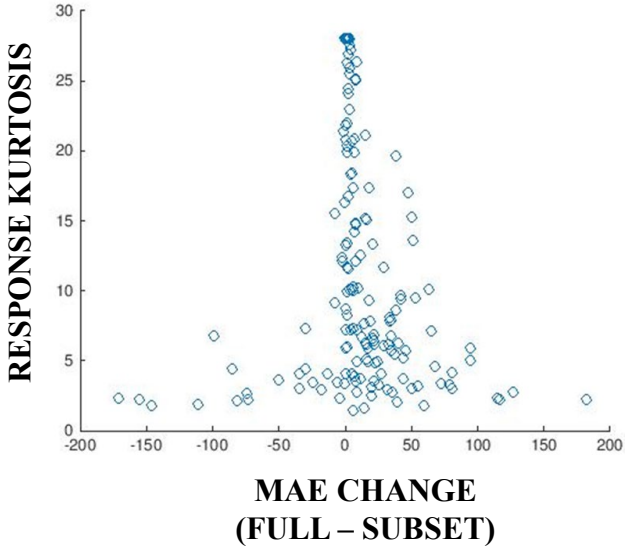
Ensemble Sensitivity-Based Subsetting

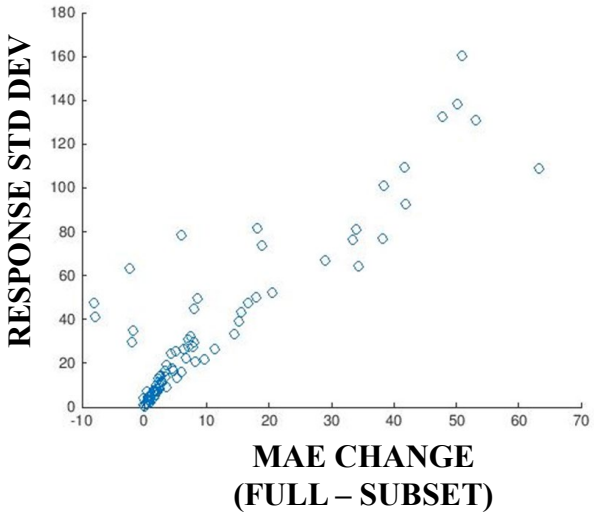




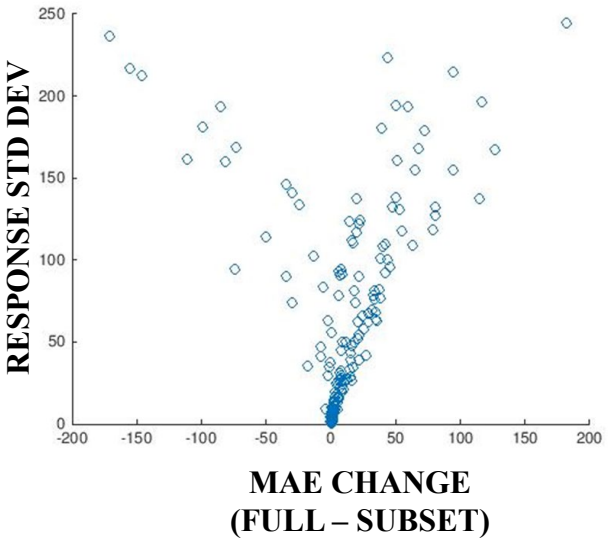
Ensemble Sensitivity-Based Subsetting

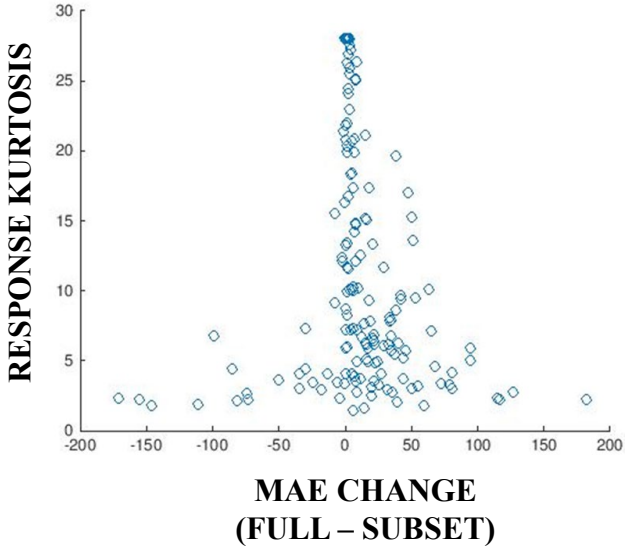


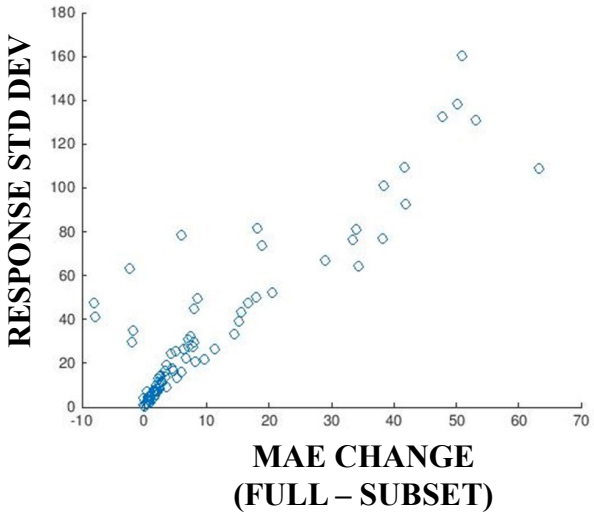




Ensemble Sensitivity-Based Subsetting







Preliminary Insights

→ Response std. dev. does not correlate well to success

→ Response kurtosis associated with success for large values

→ Large kurtosis recovers successful mode of std. dev.

Summary

- **Ensemble sensitivity is a quick, flexible, statistical tool that reveals features linked to the predictability of a specific forecast aspect of interest later in time**
  - **Deep dynamical basis**
  - **Used for dynamical understanding and beneficial forecast adjustment**

Summary

- **Ensemble sensitivity is a quick, flexible, statistical tool that reveals features linked to the predictability of a specific forecast aspect of interest later in time**
  - **Deep dynamical basis**
  - **Used for dynamical understanding and beneficial forecast adjustment**
- **Substantial research on ensemble sensitivity-based subsetting shows it has fundamental potential to improve forecasts in an operational environment at multiple scales**

Summary

- **Ensemble sensitivity is a quick, flexible, statistical tool that reveals features linked to the predictability of a specific forecast aspect of interest later in time**
  - **Deep dynamical basis**
  - **Used for dynamical understanding and beneficial forecast adjustment**
- **Substantial research on ensemble sensitivity-based subsetting shows it has fundamental potential to improve forecasts in an operational environment at multiple scales**
- **How sensitivity-based subsetting can perform in a realistic framework is a key question toward operational use**