In the midst of Chaos, good predictions: How Meteorology manages to beat the odds

Eugenia Kalnay

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and the Weather-Chaos Group

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Chaos in Numerical Weather Prediction and how we fight it

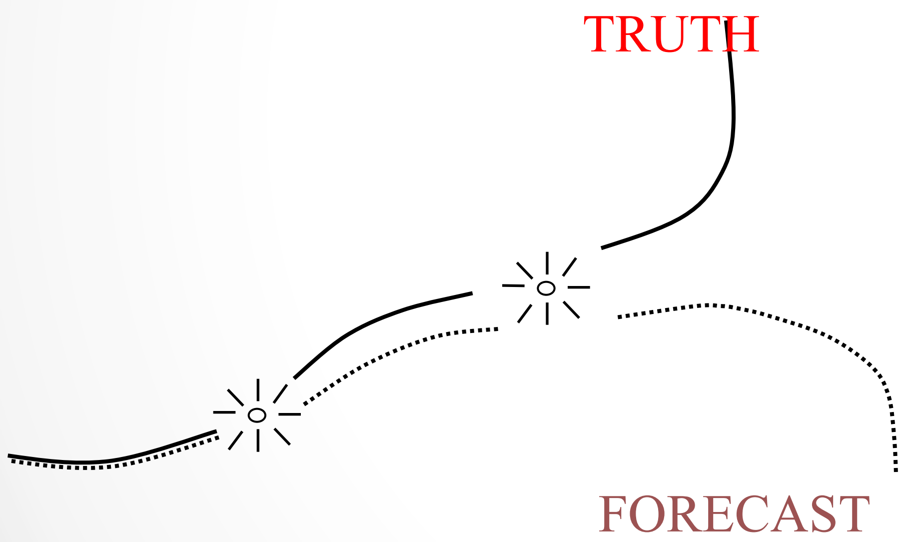
- Lorenz (1963) introduced the concept of "chaos" in meteorology. (Yorke, 1975, coined the name chaos)
  - Even with a perfect model and perfect initial conditions we cannot forecast beyond two weeks: butterfly effect
  - In 1963 this was only of academic interest: forecasts were useless beyond a day or two anyway!
  - Now we exploit "chaos" with ensemble forecasts and routinely produce skillful forecasts beyond a week.
  - The El Niño coupled ocean-atmosphere instabilities are allowing one-year forecasts of climate anomalies
- "Breeding" is a simple method to explore and fight chaos
  - Undergraduate interns found that with breeding they could easily predict Lorenz regime changes and their duration.
  - It will be used to predict solar wind storms.
- Weather-Chaos research led to the UMD Local Ensemble Transform Kalman Filter (LETKF, Hunt et al., 2007)

Central theorem of chaos (Lorenz, 1960s):

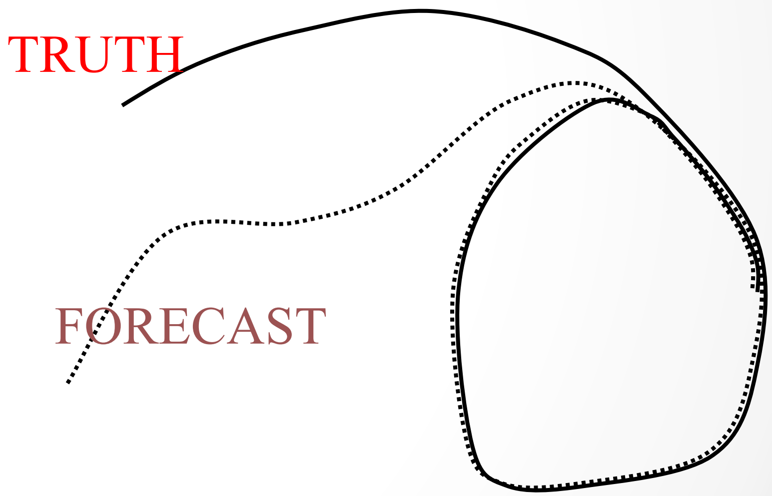
a) Unstable systems have finite predictability (chaos)

b) Stable systems are infinitely predictable

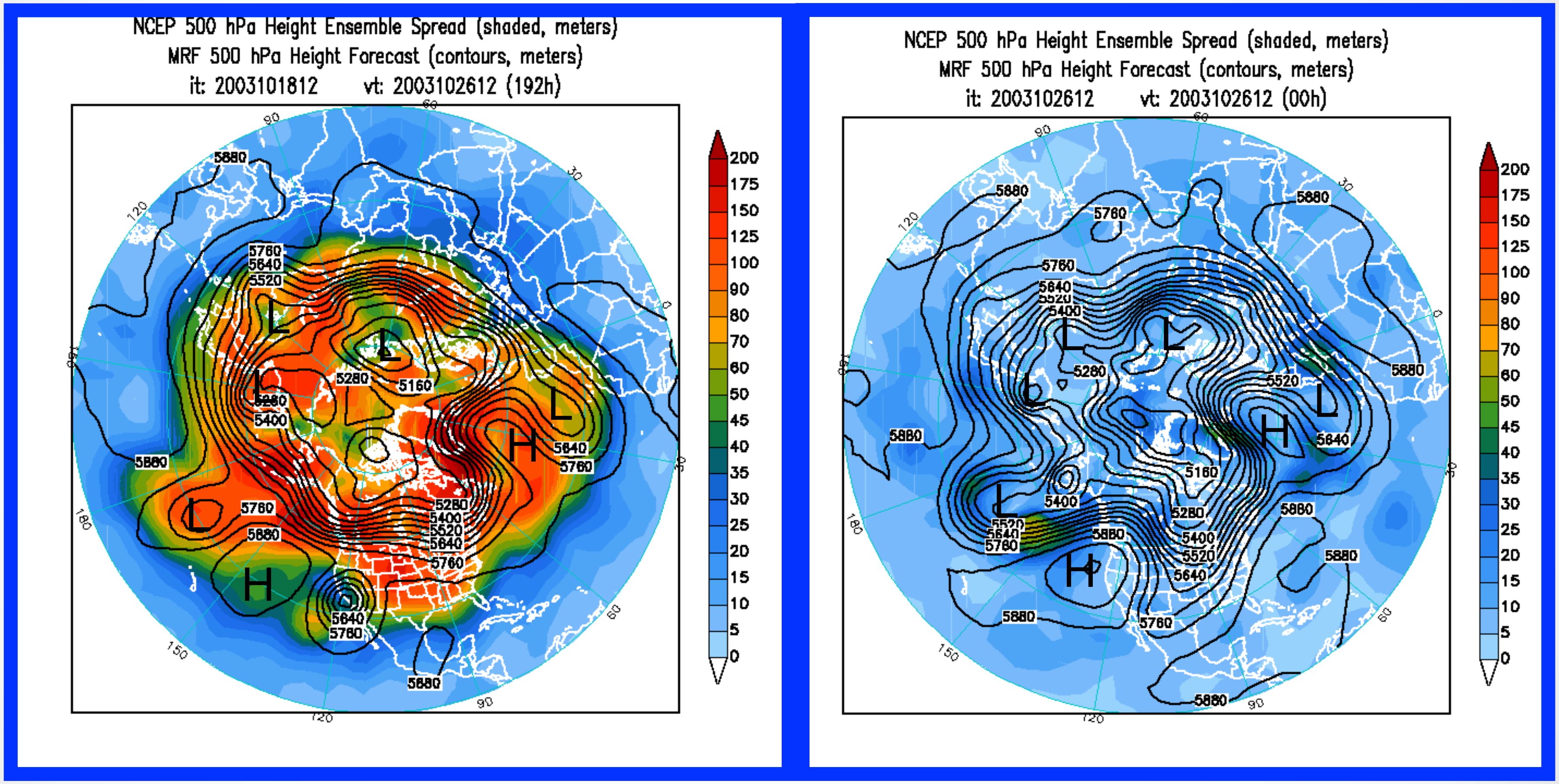
a) Unstable dynamical system



b) Stable dynamical system



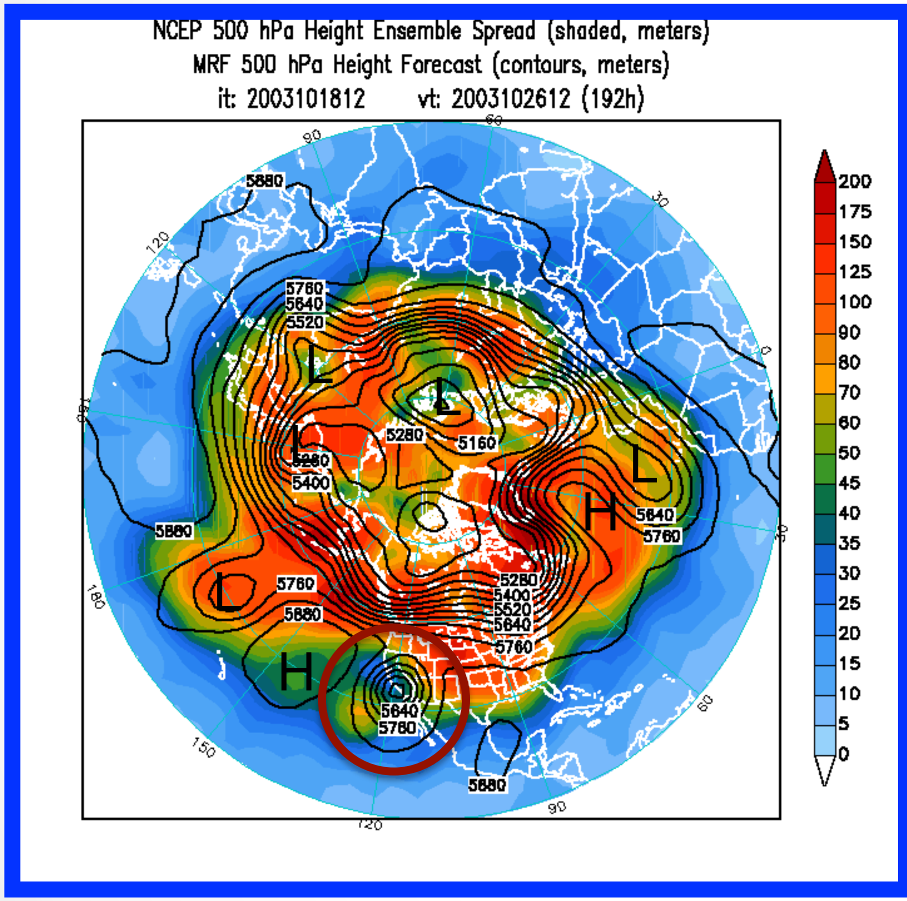
8-day forecast and verification

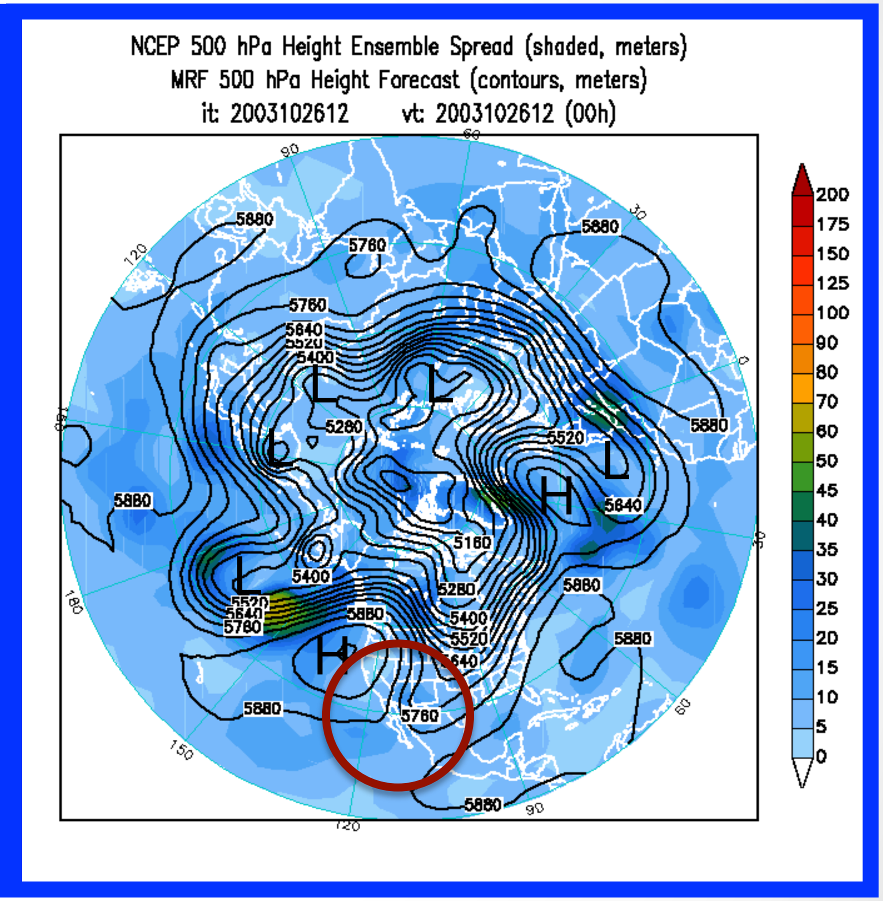


Almost all the centers of low and high pressure are very well predicted after 8 days!

Need good models, good observations, good data assimilation

8-day forecast and verification

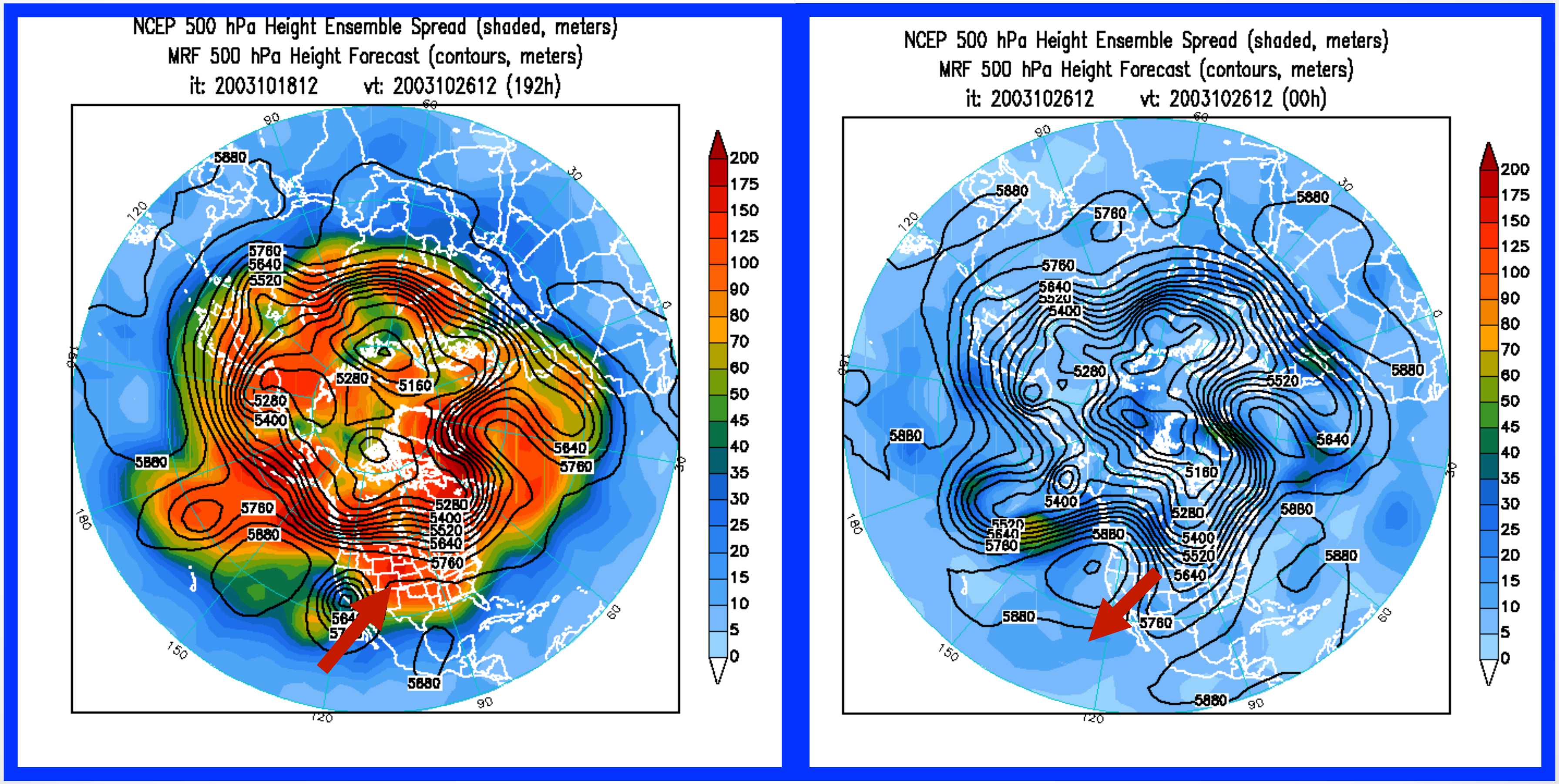




Almost all the centers of low and high pressure are very well predicted after 8 days!

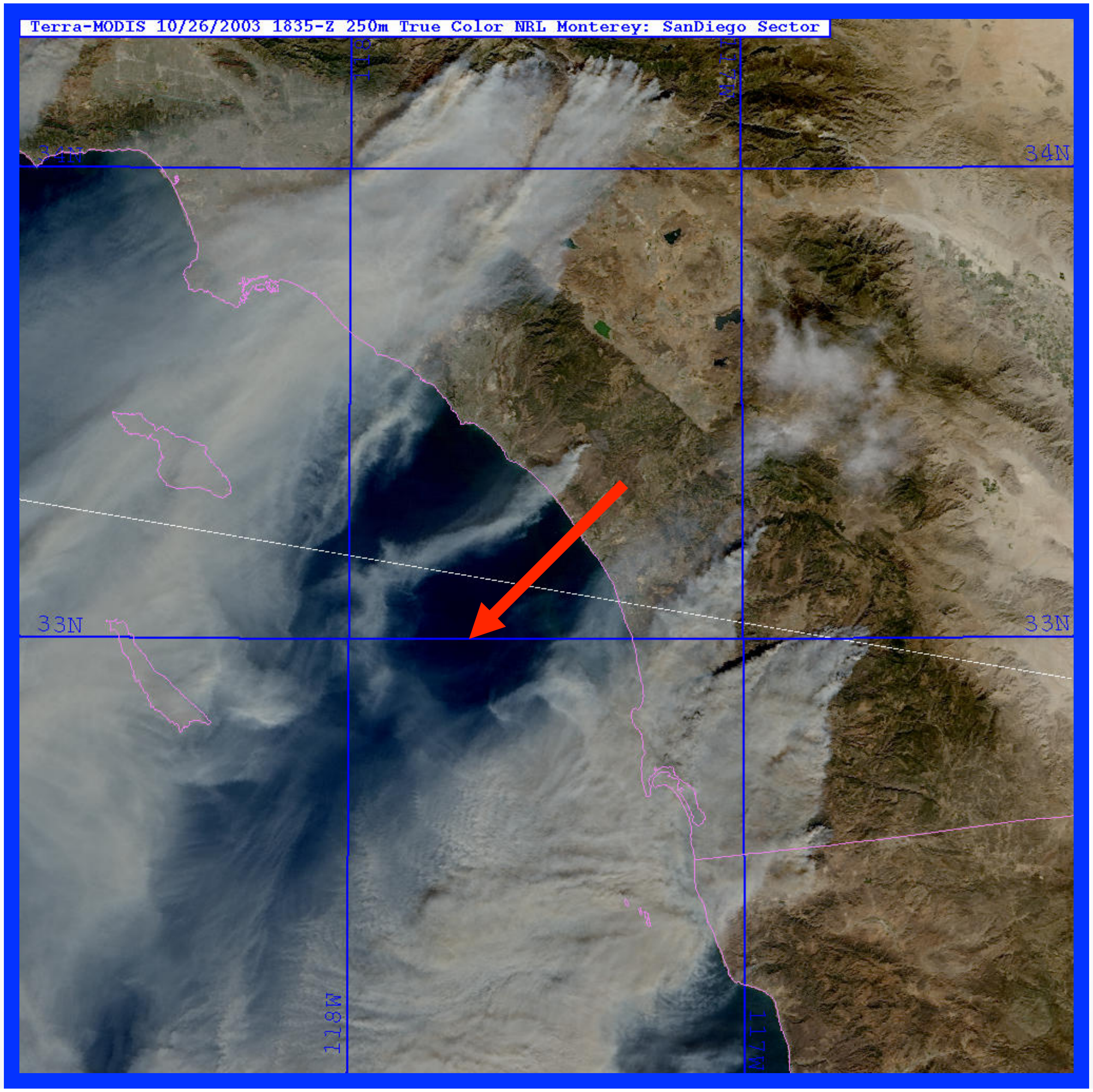
Over Southern California forecast has a cut-off low, not a trough

8-day forecast and verification



Southern California: winds are from the wrong direction!

Fires in California (2003)



Santa Ana winds: locally wrong prediction (8 days in advance!)

A simple chaotic model:
Lorenz (1963) 3-variable model

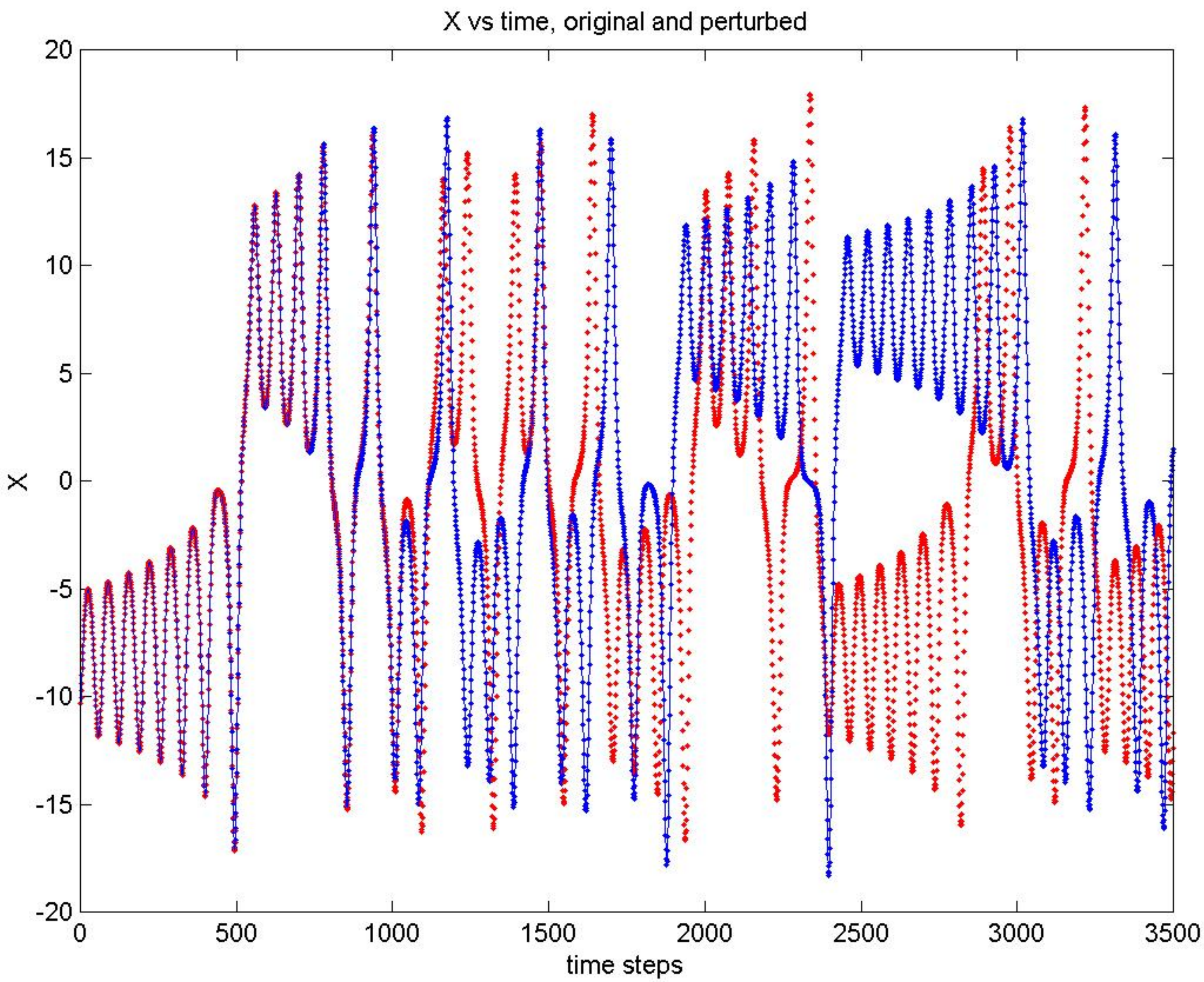
$$\frac{dx}{dt} = \sigma(y - x)$$

$$\frac{dy}{dt} = rx - y - xz$$

$$\frac{dz}{dt} = xy - bz$$

Has two regimes and the transition between them is chaotic

If we introduce an infinitesimal perturbation in the initial conditions, the forecast soon loses all skill



Definition of Chaos
(Lorenz, March 2006, 89 years old)

WHEN THE PRESENT DETERMINES

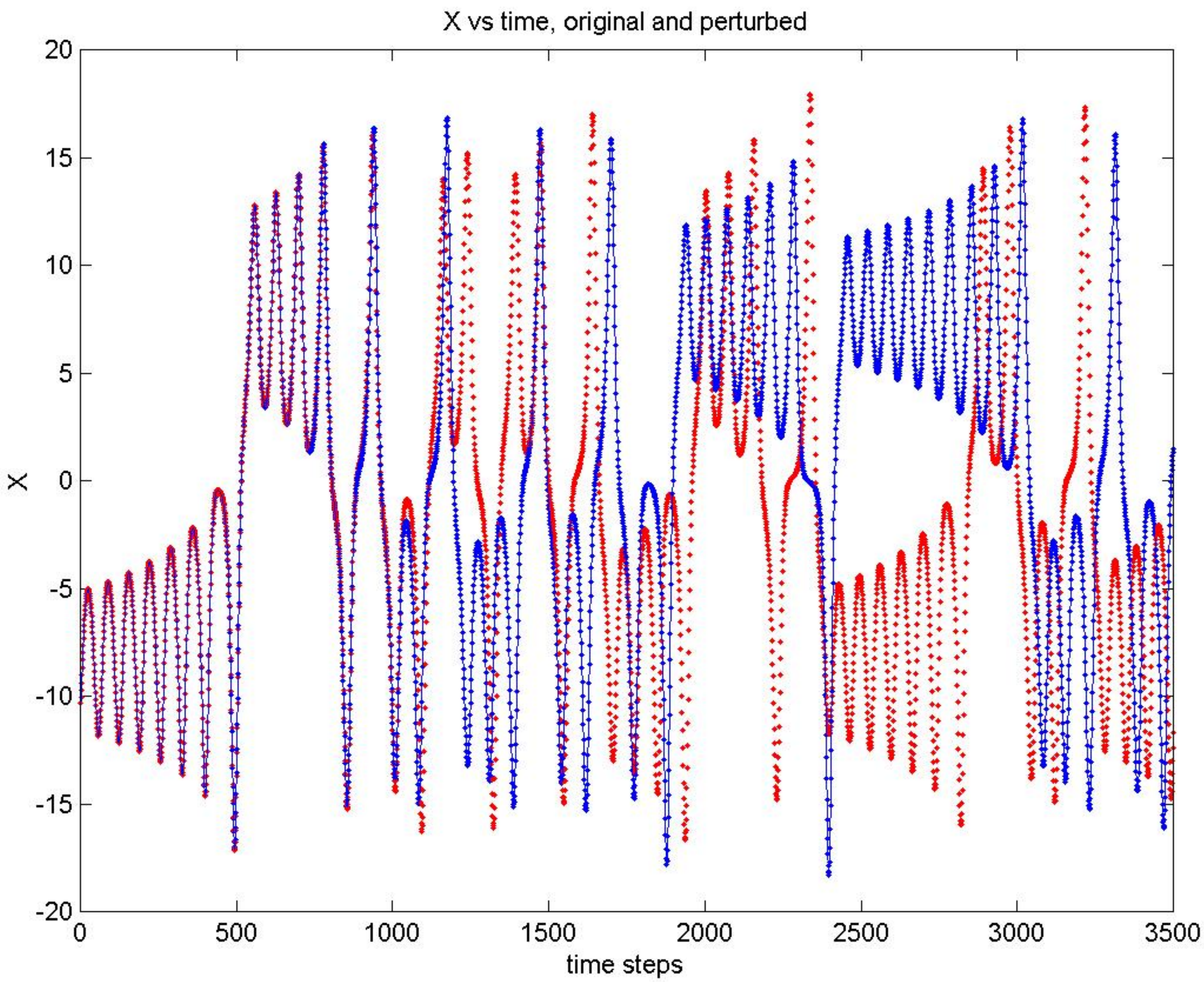
THE FUTURE

BUT

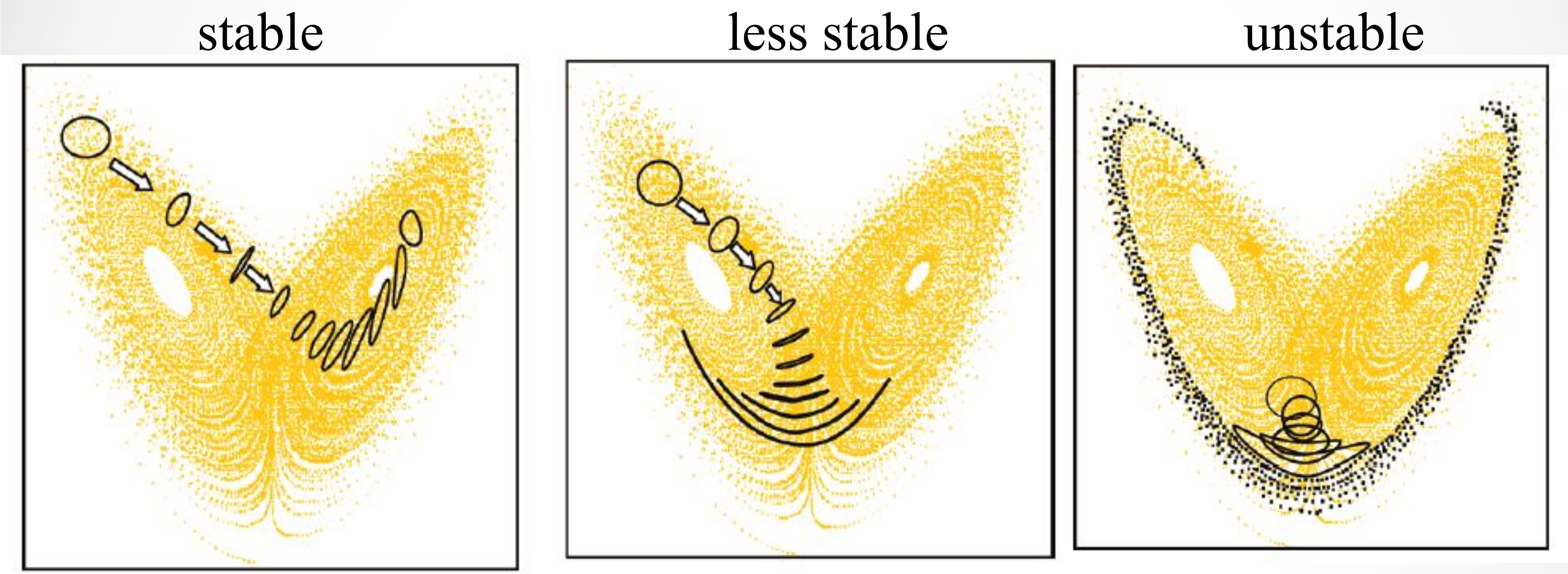
THE APPROXIMATE PRESENT DOES NOT

APPROXIMATELY DETERMINE THE FUTURE

The approximate present does not approximately determine the future!



Predictability depends on the initial conditions (Palmer, 2002):



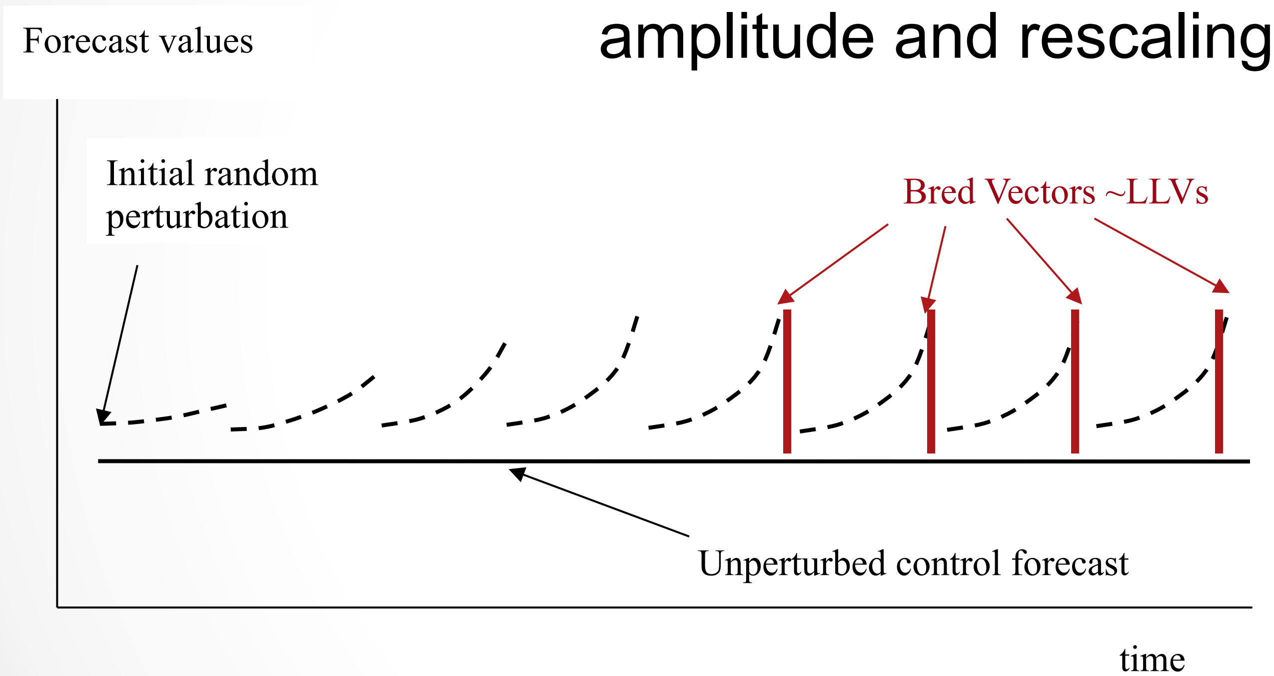
Errors with unstable initial conditions
(with "growing errors of the day")
grow much faster

An 8 week RISE project for undergraduate women (2002)

- We gave a team of 4 RISE intern undergraduates a problem: Play with the famous Lorenz (1963) model, and explore its predictability using "breeding" (Toth and Kalnay 1993), a very simple method to study the growth of errors.
- We told them: "Imagine that you are forecasters that live in the Lorenz 'attractor'. Everybody living in the attractor knows that there are two weather regimes, the 'Warm' and 'Cold' regimes. But what the public needs to know is when will the change of regimes take place, and how long are they going to last!!".
- "Can you find a forecasting rule to alert the public that there is an imminent change of regime?"

Breeding: simply running the nonlinear model a second time, from perturbed initial conditions.

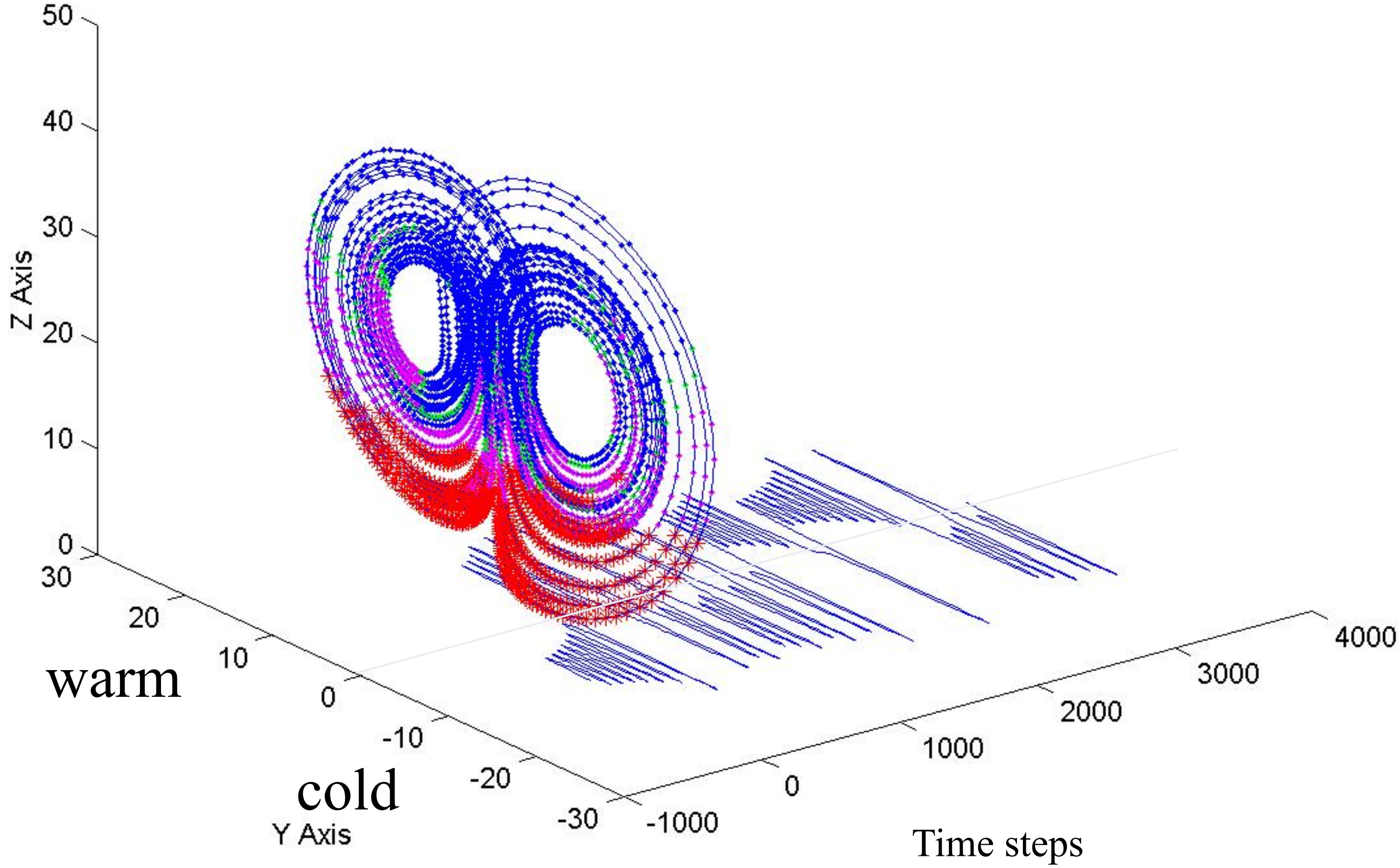
Only two tuning parameters: rescaling amplitude and rescaling interval



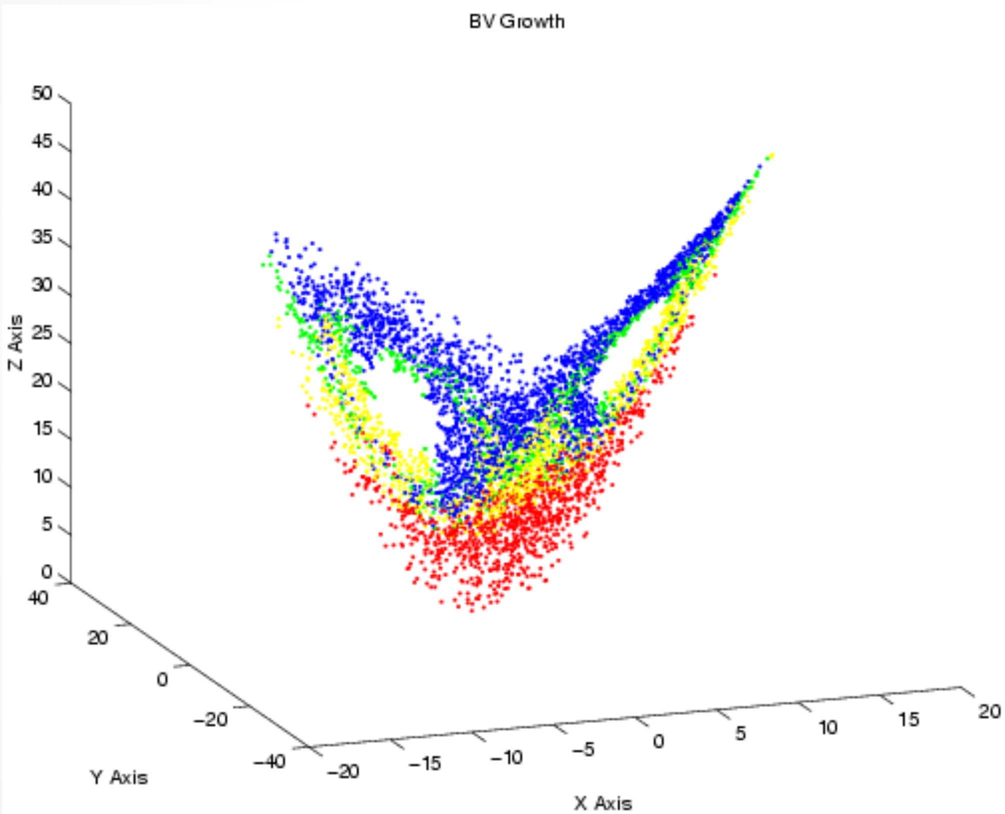
Local breeding growth rate:

$$g(t) = \frac{1}{n\Delta t} \ln\left(|\delta \mathbf{x}| / |\delta \mathbf{x}_0| \right)$$

4 summer interns computed the Lorenz Bred Vector growth rate: red means large BV growth, blue means perturbations decay



In the 3-variable Lorenz (1963) model we used breeding to estimate the local growth of perturbations:

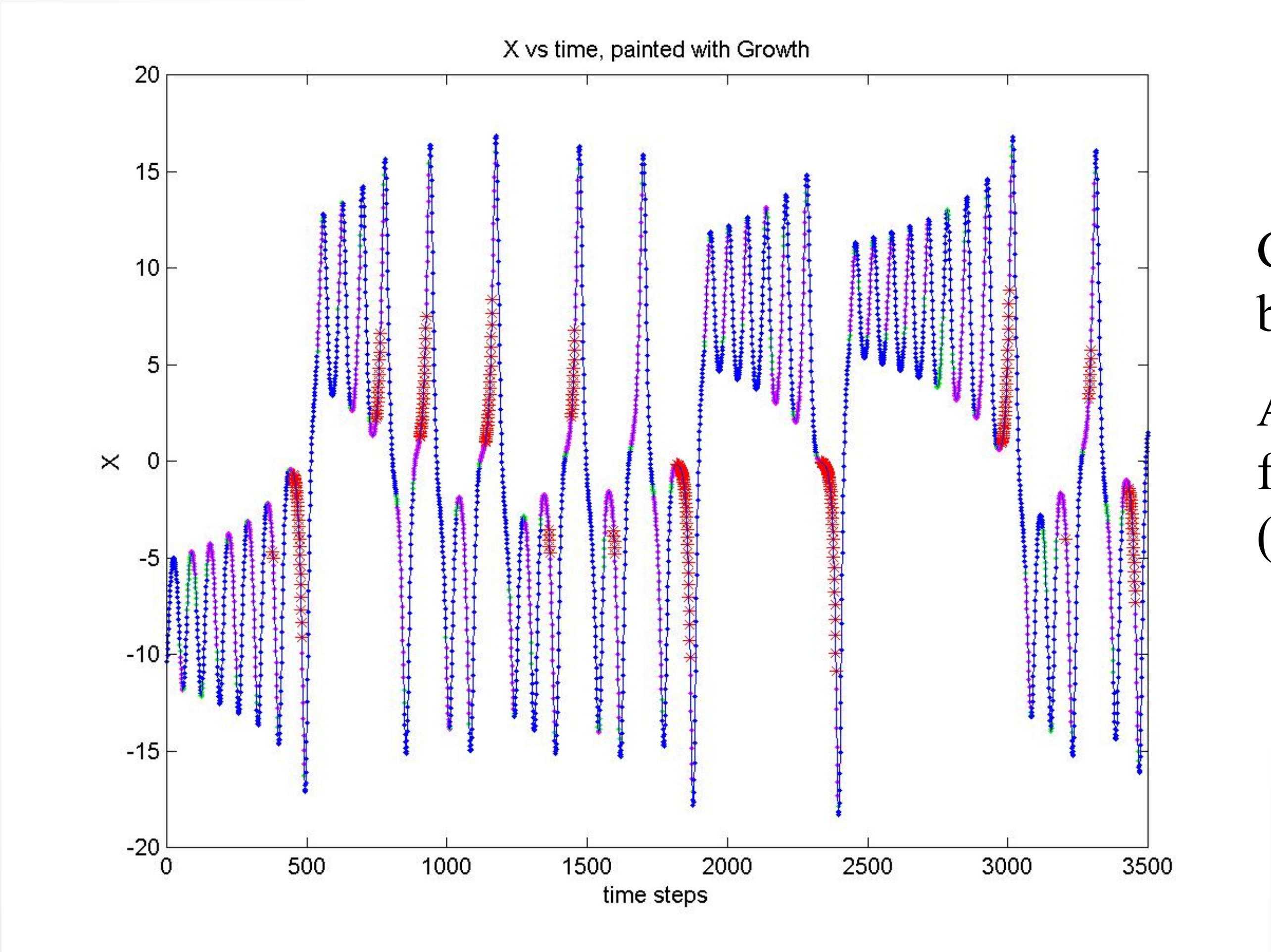


Bred Vector Growth:
red, high growth;
yellow, medium;
green, low growth;
blue, decay

With just a single breeding cycle, we can estimate the stability of the whole attractor (Evans et al, 2004).

This looked promising, so we asked the interns to "paint" x(t) with the bred vector growth, and the result almost made me faint:

This looked promising, so we asked the interns to "paint" x(t) with the bred vector growth, and the result almost made me faint:



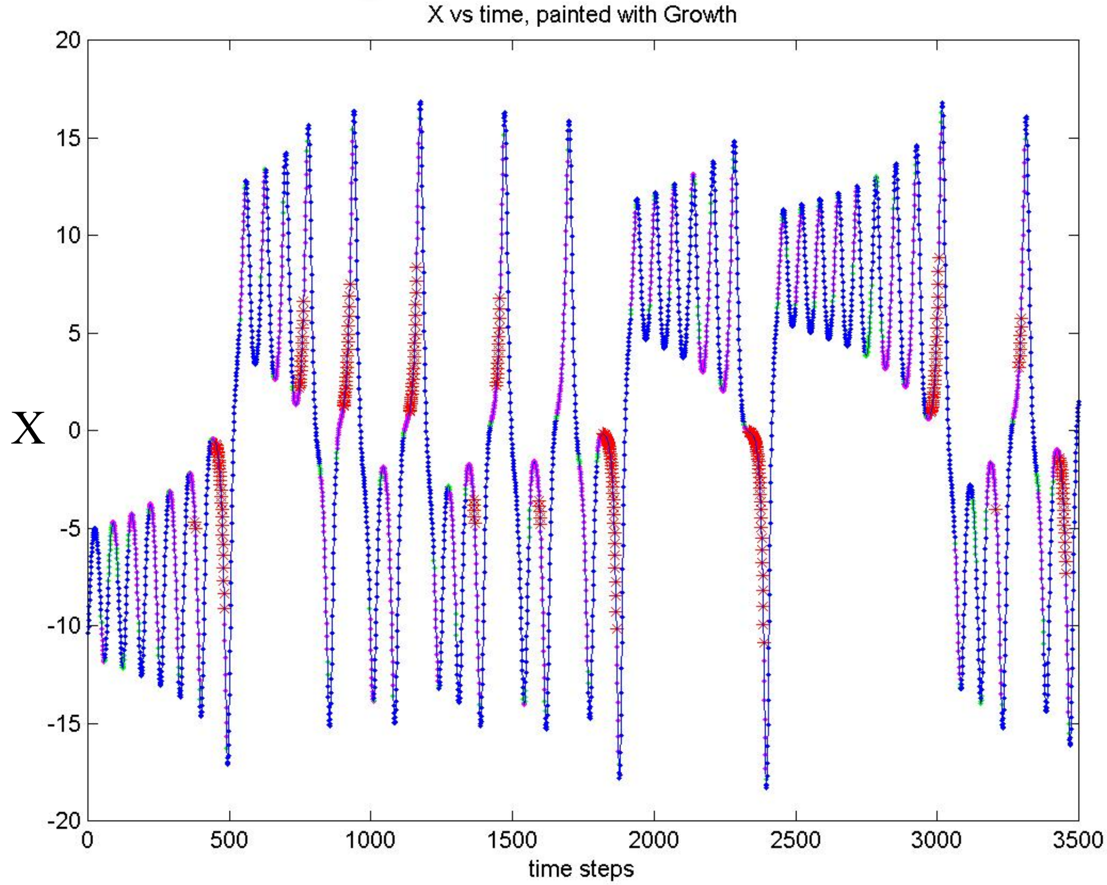
Growth rate of bred vectors:

A * indicates fast growth (>1.8 in 8 steps)

Forecasting rules for the Lorenz model:

“warm”

“cold”



Growth rate of bred vectors:

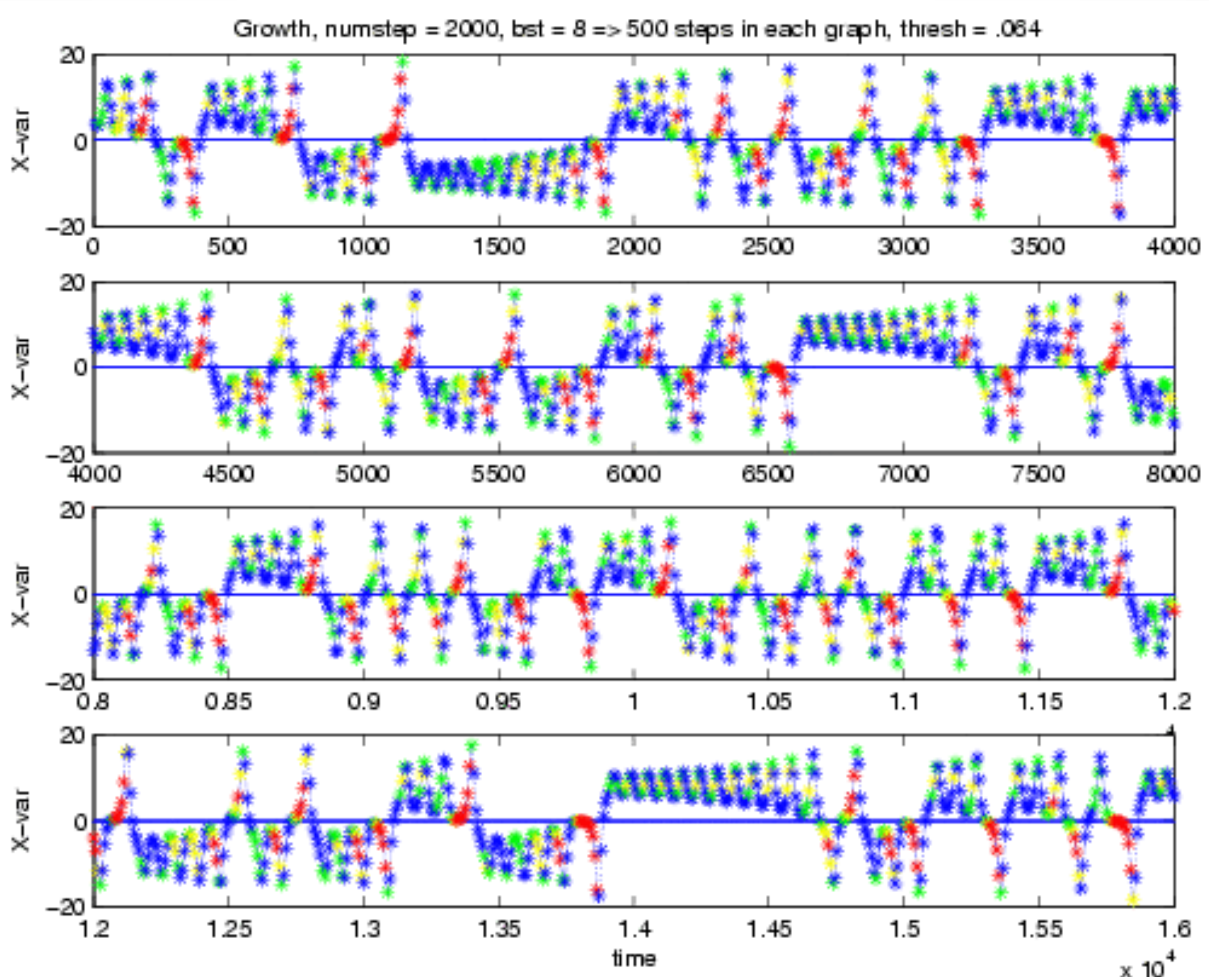
A * indicates fast growth (>1.8 in 8 steps)

Regime change:The presence of red stars (fast BV growth) indicates that the next orbit will be the last one in the present regime.

Regime duration: One or two red stars, next regime will be short. Several red stars: the next regime will be long lasting.

These rules surprised Lorenz himself!

These are very robust rules, with skill scores > 95%



Can we apply these ideas to a physical system for which we don't know the model? Yes we can!

Breeding Vectors in the Phase Space Reconstructed from Time Series Data

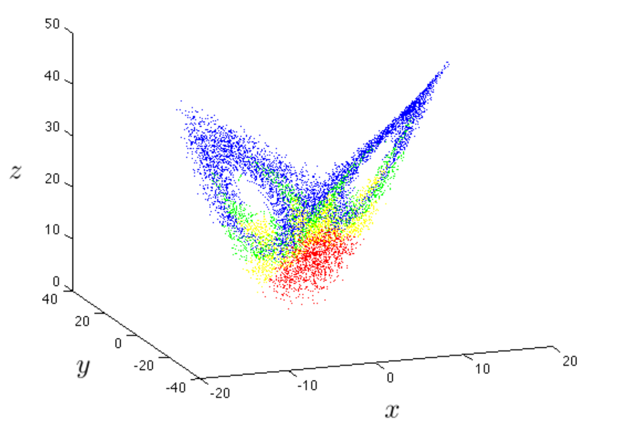
Erin Lynch, D. Kaufman, S. Sharma, E. Kalnay and K. Ide (2013)

For many systems we only know time series of a few variables. We can predict regime changes in the Lorenz model without knowing the dynamical model.

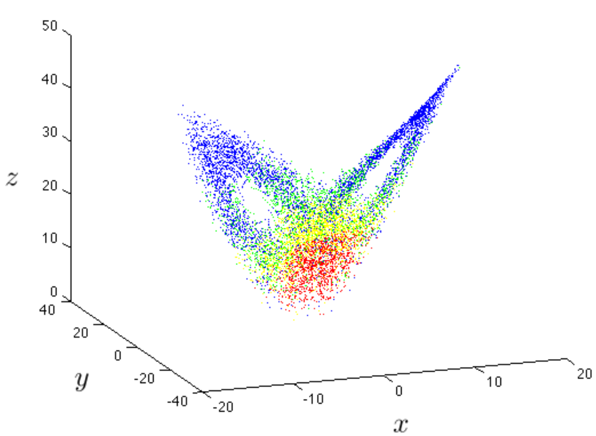
We use:

- Time-delay embedding method to reconstruct the phase space. We only know the time series of x (not y or z) in the Lorenz model (every 8 time steps).
- "Nearest-neighbor" breeding: after rescaling, choose the closest neighbor in the same direction.

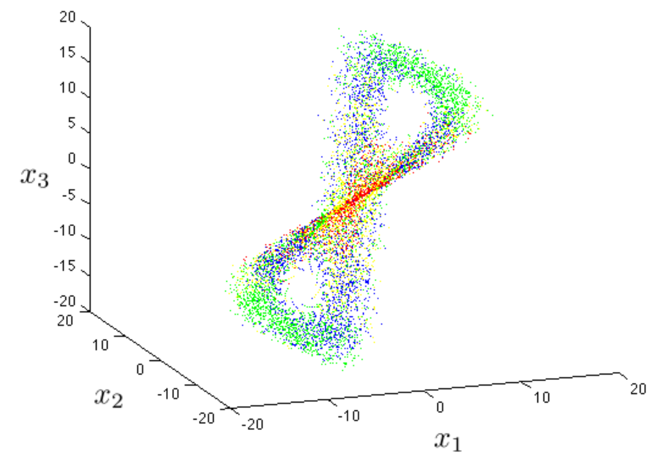
We reconstructed the Lorenz model with time-delay embedding where $\mathbf{x}_i(t_i) = \{x_1(t_i), x_2(t_i), \ldots x_m(t_i)\}$ and $x_k(t_i) = x(t_i - \tau(k-1)\Delta t), m = 3, \tau = 7$



Standard breeding in Lorenz model



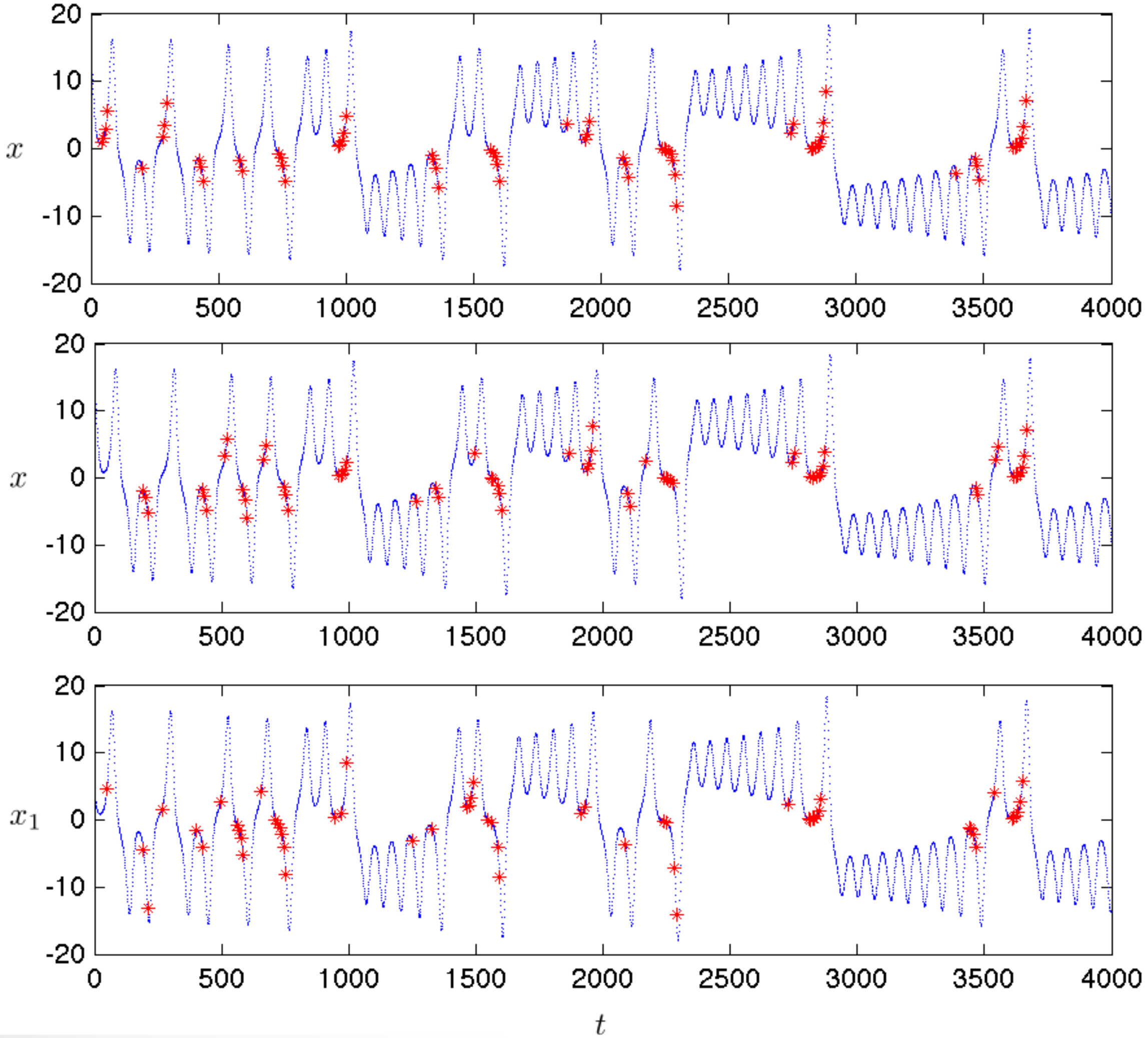
"Nearest-neighbor" breeding in Lorenz model



"Nearest-neighbor" breeding in the embedded space using only x(t)

"Nearest-neighbor" breeding gives results similar to regular breeding, with 0.98 correlation in the rescaled growth. In the embedded case, we do "nearest-neighbor" breeding **without any knowledge of the model**.

The results are very encouraging! The skill in detecting regime change are similar in the original Lorenz model and in the embedded model!



Standard breeding high growth rate in Lorenz model

"Nearest-neighbor" breeding high growth rate in Lorenz model

"Nearest-neighbor" breeding high growth rate in the embedded space using only x(t)

Preliminary results using the LETKF and data assimilation are even more encouraging. We plan to apply this methodology to solar wind data assimilation (Chen and Sharma, 2006)

Summary so far and rest of the talk

- Breeding is a simple generalization of Lyapunov vectors, for finite time, finite amplitude: simply run the model twice, take the difference and rescale…
- Breeding in the Lorenz (1963) model gives accurate forecasting rules for the “chaotic” change of regime and duration of the next regime that surprised Lorenz himself!
- Can be applied to real time series without knowing the model

Rest of the talk:

- The same ideas can be applied to fight chaos in the full forecast models that have dimension 10-100 million rather than just 3!
- In the atmosphere, in the ocean, in Mars, and in coupled systems
- We can also use breeding to understand the **physical mechanisms** of the instabilities that create chaos.

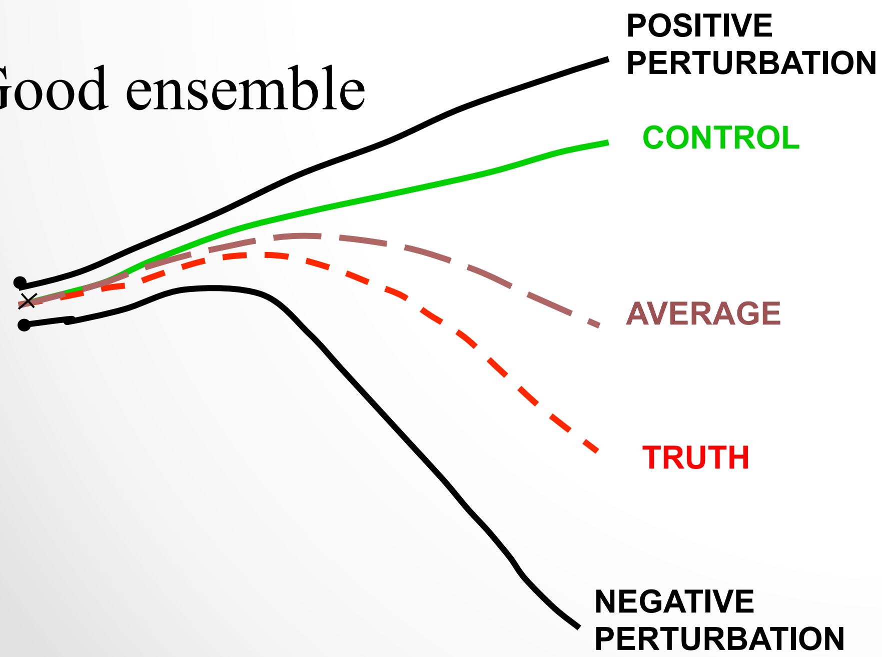
A major tool to "fight chaos" is ensemble forecasting

An ensemble forecast starts from initial perturbations to the analysis…

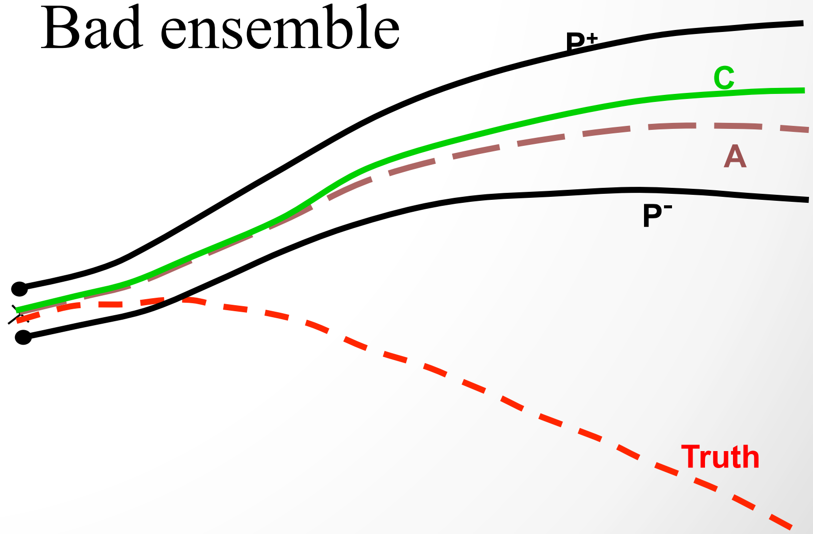
In a good ensemble "truth" looks like a member of the ensemble

The initial perturbations should reflect the analysis "errors of the day".

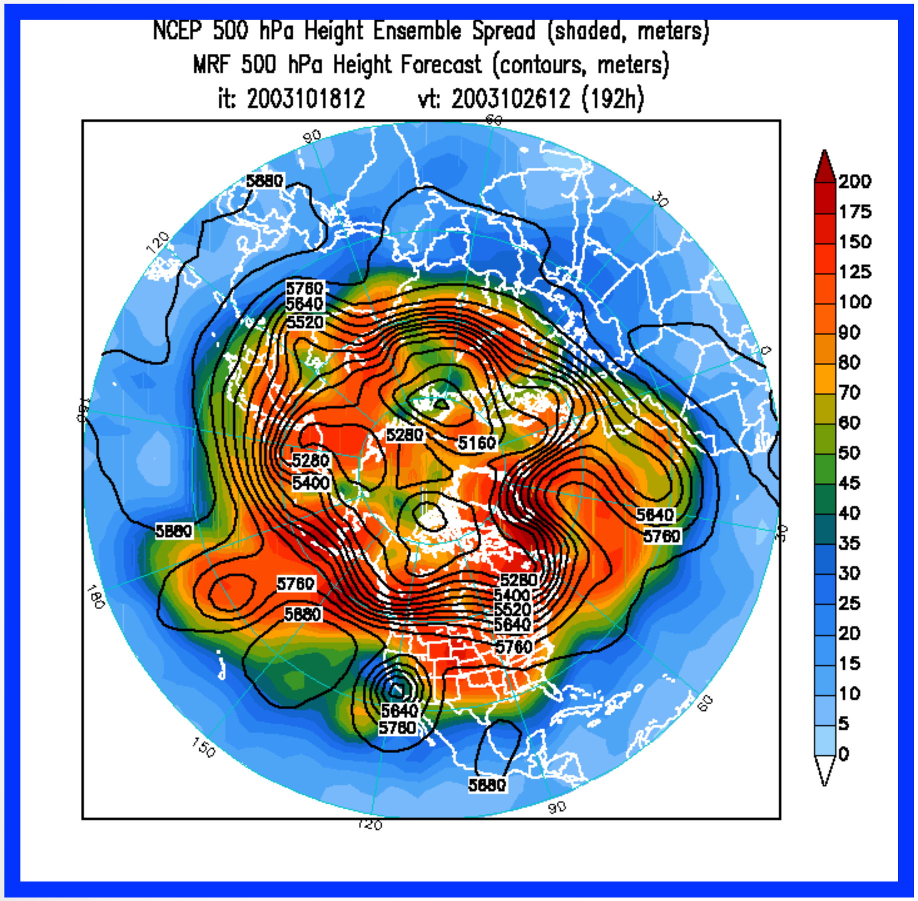
Good ensemble

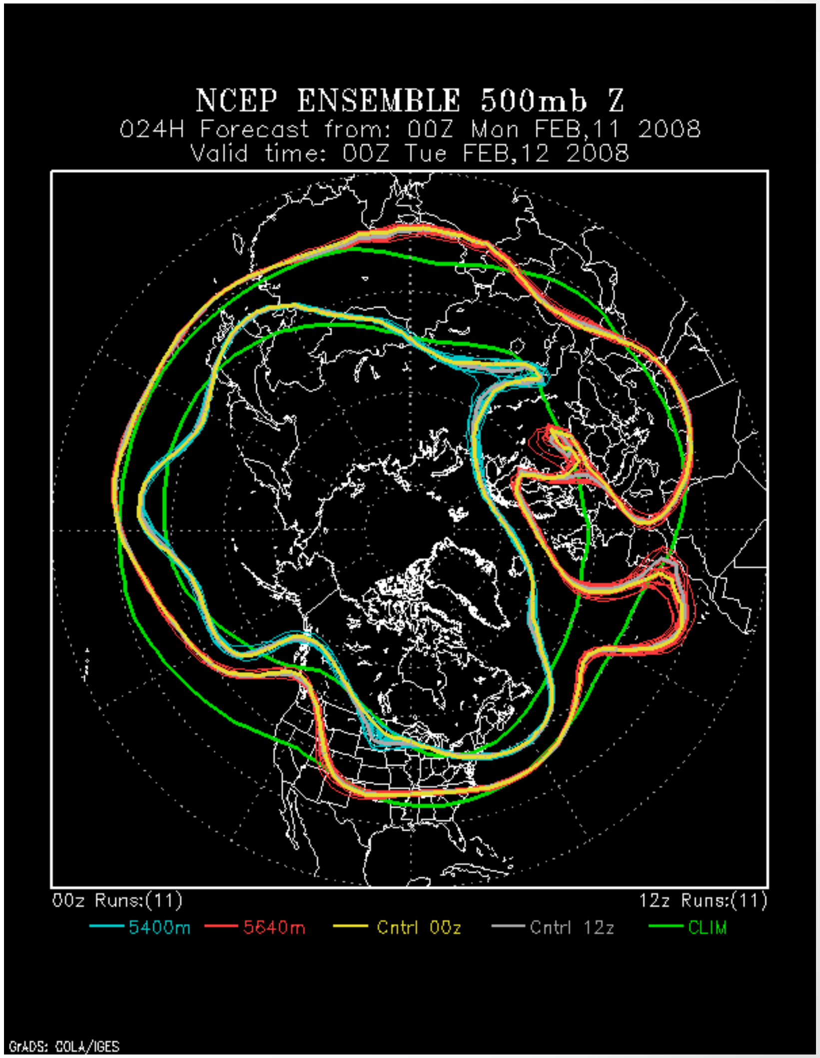


Bad ensemble



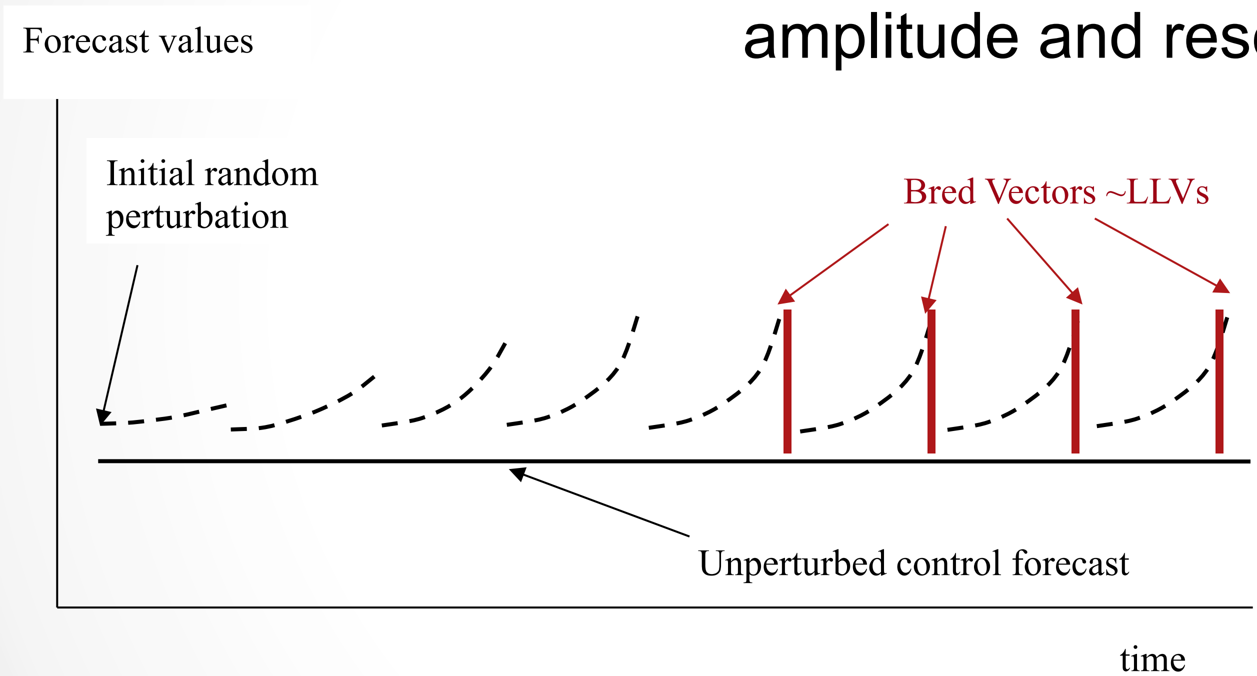
In ensemble forecasting we need to represent the uncertainty: spread or "spaghetti plots"





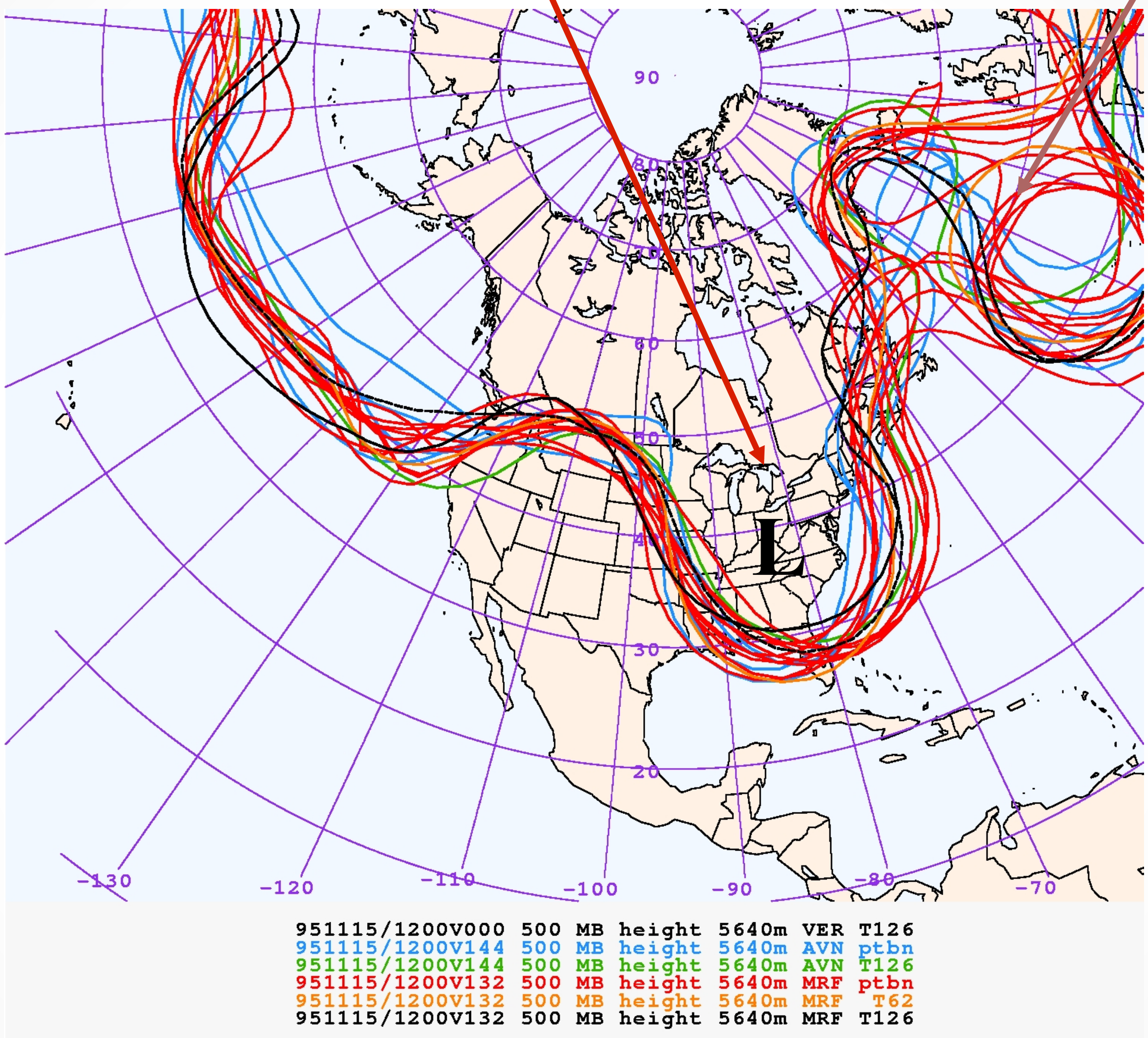
Breeding: running the nonlinear model a second time, from perturbed initial conditions: introduced by Toth and Kalnay (1993) to create initial ensemble perturbations

Only two tuning parameters: rescaling amplitude and rescaling interval



Local breeding growth rate: $$g(t) = \frac{1}{n\Delta t} \ln\left(\left|\delta \mathbf{x}\right| / \left|\delta \mathbf{x}_0\right| \right)$$

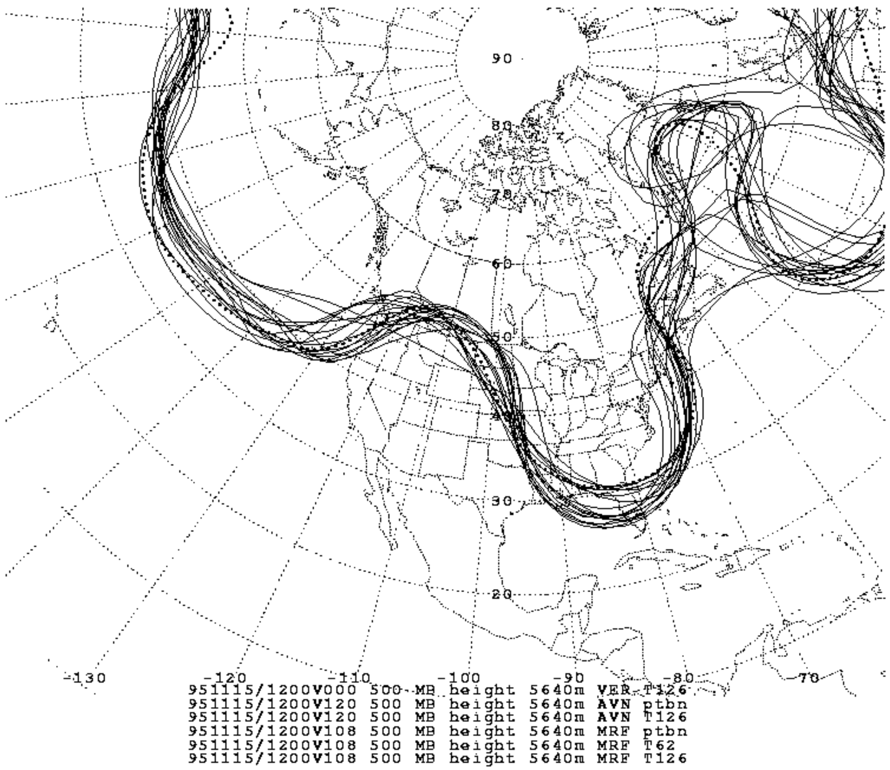
Example of a very predictable 6-day forecast, with "errors of the day"

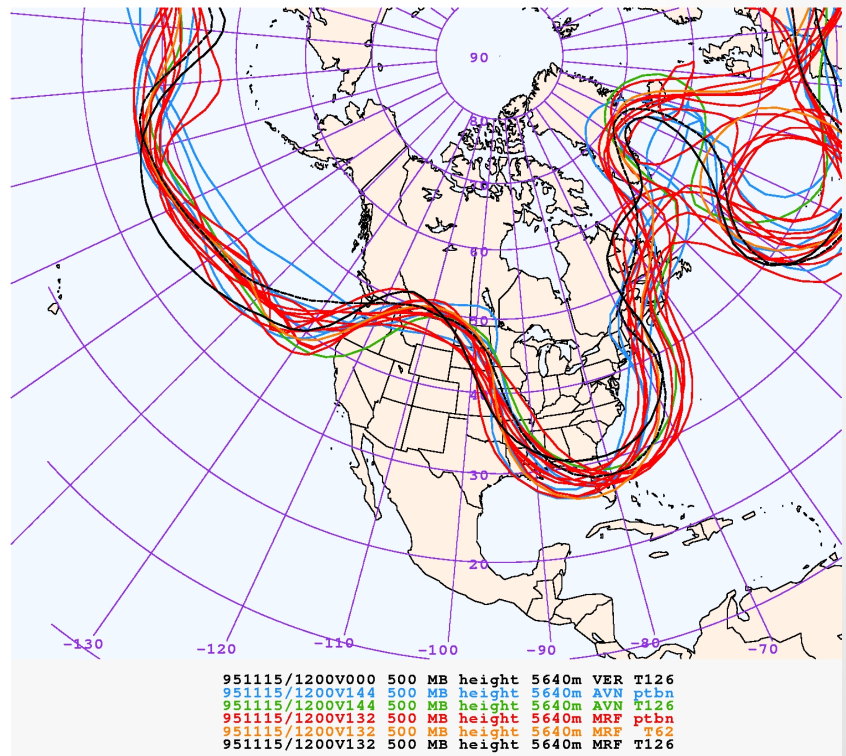


The bred vectors are the growing atmospheric perturbations: "errors of the day"

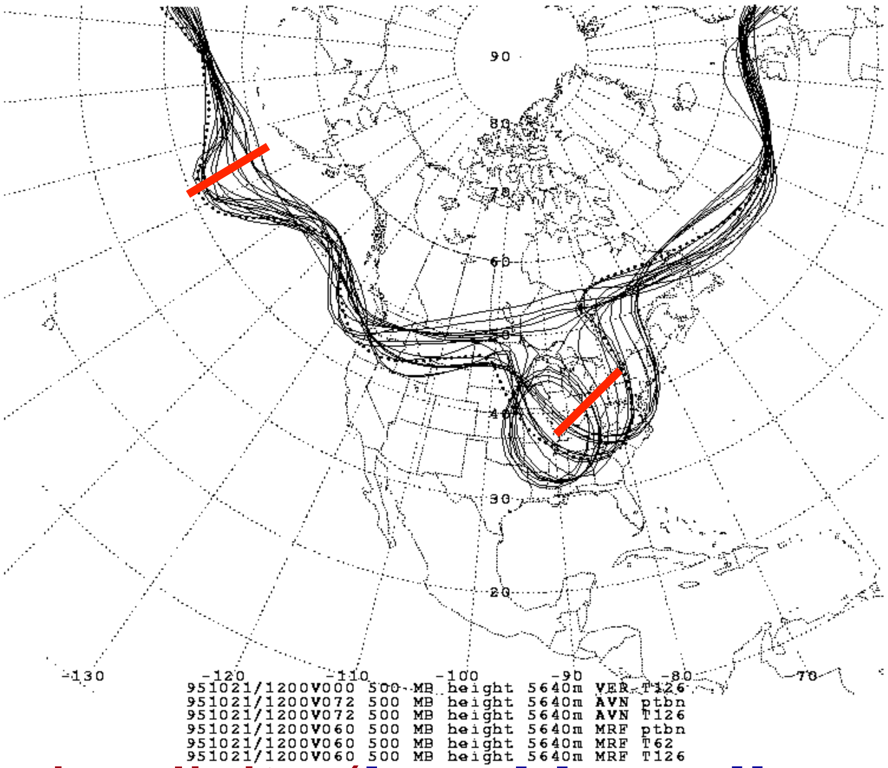
The errors of the day are instabilities of the background flow. At the same verification time, the forecast uncertainties have *the same shape*

4 days and 6 days ensemble forecasts verifying on 15 Nov 1995





Strong instabilities of the background tend to have simple shapes: perturbations lie in a low-dimensional subspace of bred vectors



2.5 day forecast verifying on 95/10/21.

Note that the bred vectors (difference between the forecasts) lie on a 1-D space

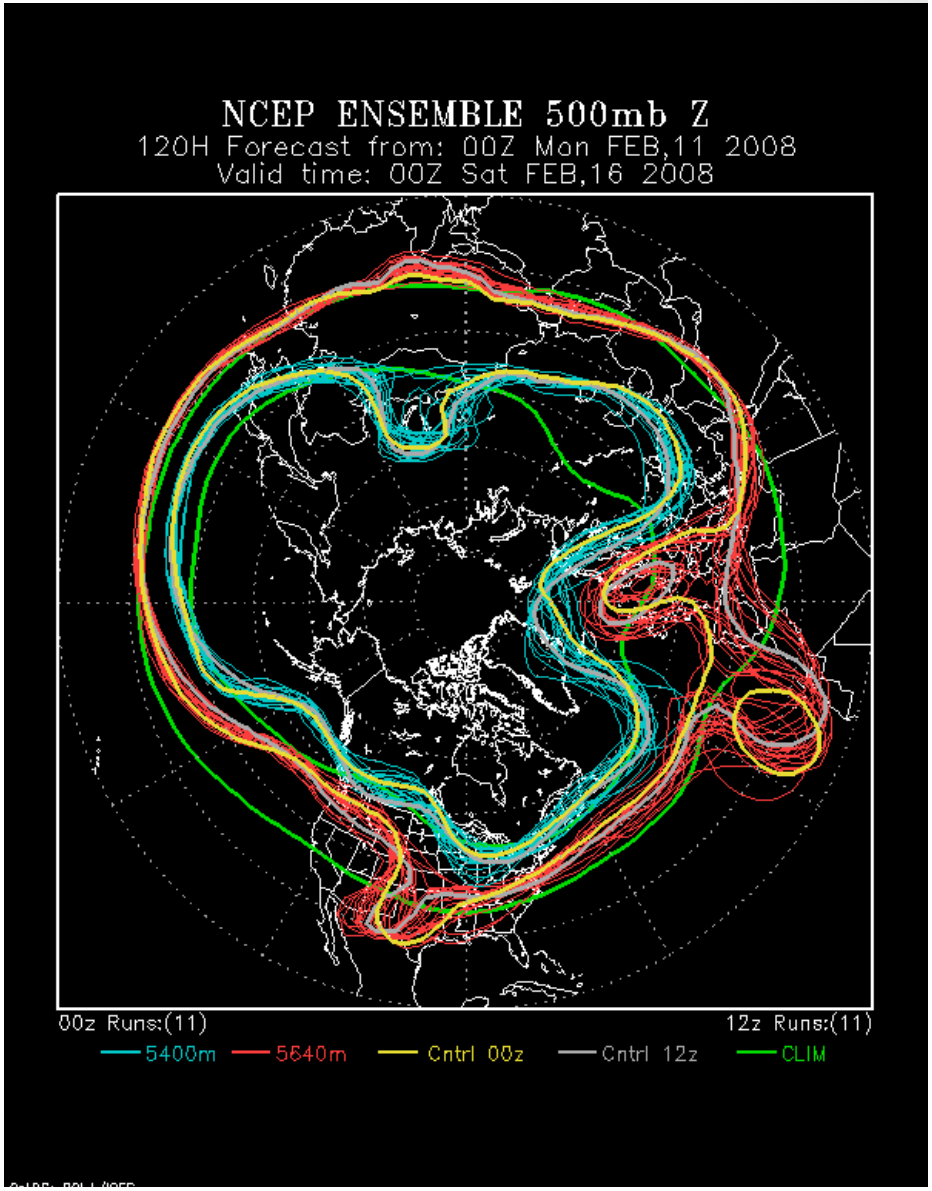
This simplicity (**local low-dimensionality**, Patil et al. 2000) inspired the Local Ensemble Transform Kalman Filter (Ott et al. 2004, Hunt et al., 2007)

5-day forecast "spaghetti" plot

•The ensemble is able to separate the areas that are predictable from the ones that are chaotic.

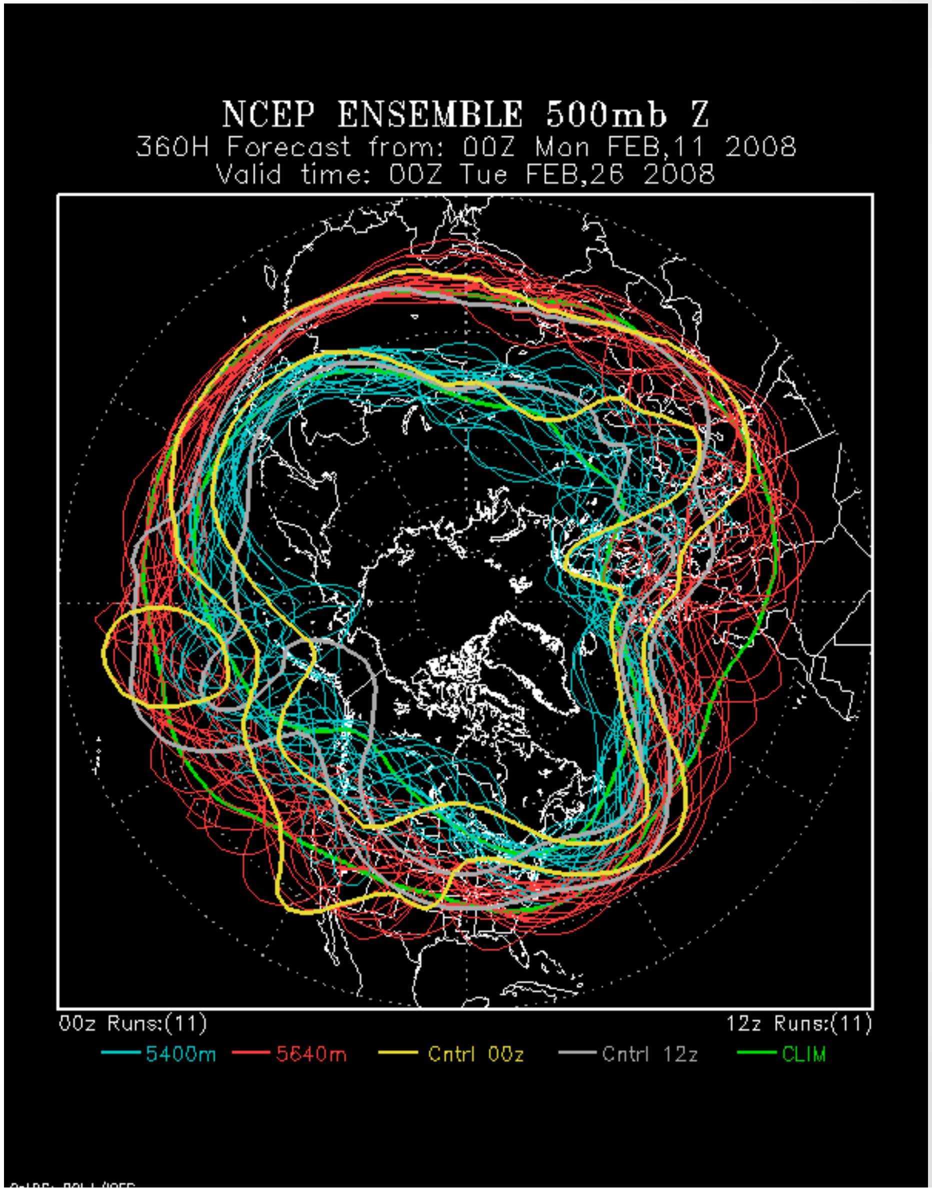
• Even the chaotic ones have local low-dimensionality

• This is what makes possible to do Ensemble Kalman Filter with 50 ensemble members (not a million!) with good results



15-day forecast “spaghetti” plot: Chaos!

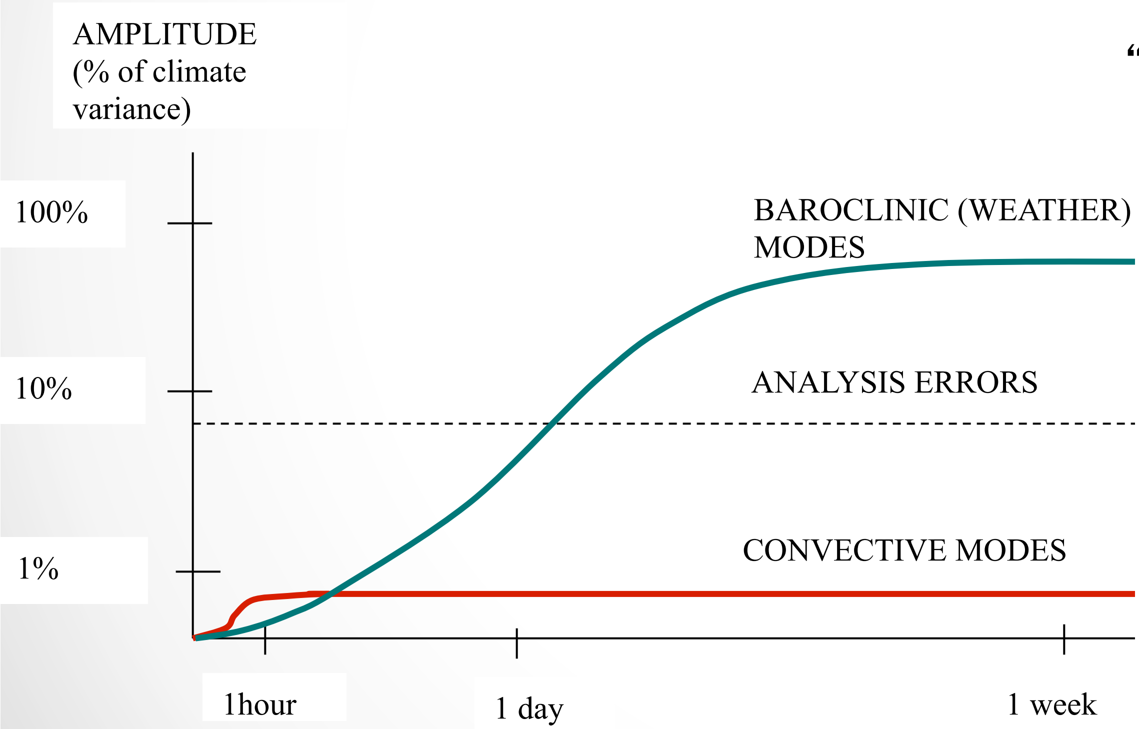
After 15 days, Lorenz’ chaos has won!
No predictability left in the 15-day forecast



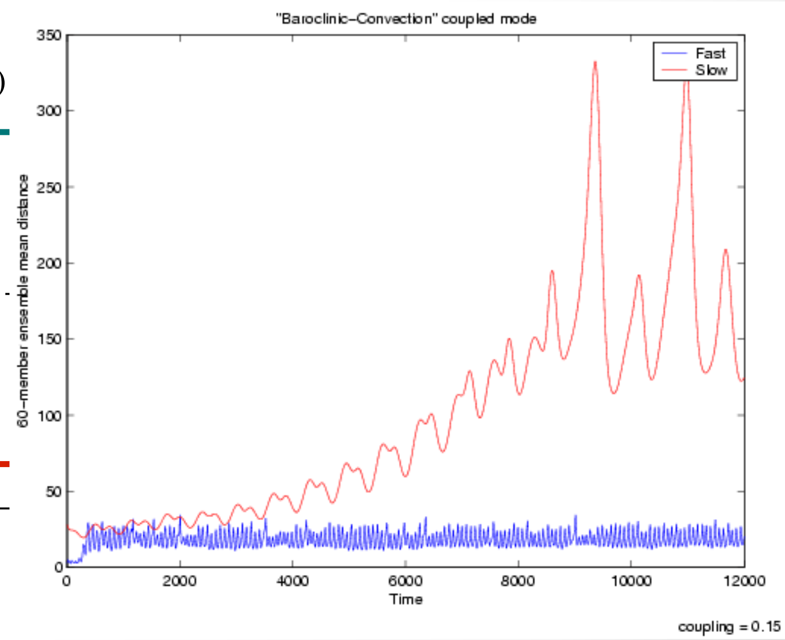
In the rest of this talk, we will look at chaos in coupled fast-slow systems

- The atmosphere has fast (e.g., convective clouds, 20 min) and slow instabilities (e.g., baroclinic or weather instabilities 3-7 days)
- The coupled ocean-atmosphere system has even slower instabilities (El Niño-Southern Oscillation, 3-7 years)
- In order to predict these phenomena, we need to isolate fast and slow instabilities
- If we can predict ENSO, we can predict climate anomalies a year or more in advance

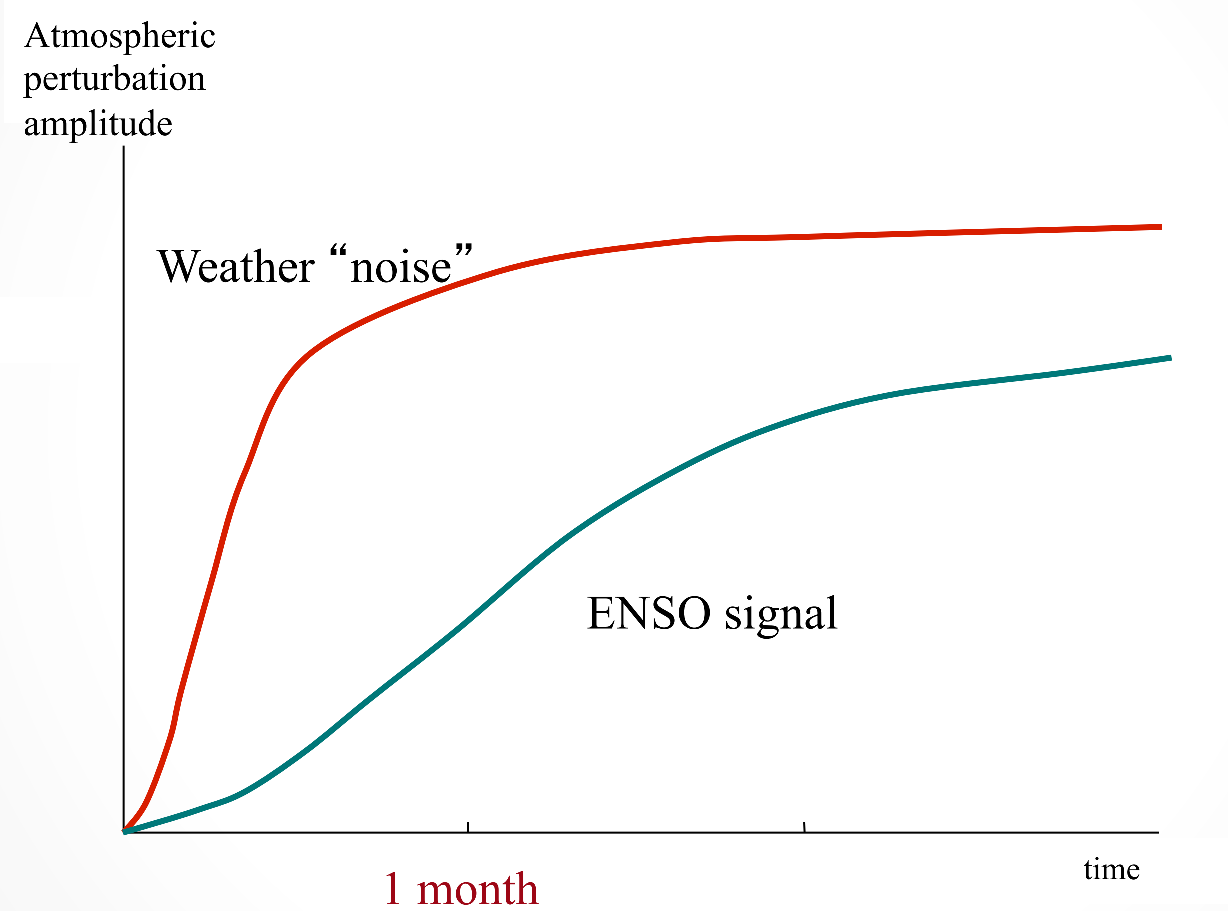
In the atmosphere there are many instabilities, e.g., fast (convective clouds) and slow (baroclinic)
Nonlinear breeding saturates convective noise



"weather + convection" coupled model



Coupled ocean-atmosphere modes (El Niño-Southern Oscillation)
The “weather noise” has large amplitude! Must use the fact that the coupled ocean modes are slower…



Need a long rescaling interval, like 2 weeks or one month

Breeding in a coupled system

- Breeding: finite-amplitude, finite-time instabilities of the system (~Lyapunov vectors)
- In a coupled system there are fast and slow modes,
- A **linear** approach (like Singular or Lyapunov Vectors) will only capture **fast** modes.
- Can we do breeding of the **slow** modes?

We coupled slow and a fast Lorenz (1963) 3-variable models (Peña and Kalnay, 2004)

Fast equations

$$\frac{dx_1}{dt} = \sigma(y_1 - x_1) - C_1(Sx_2 + O)$$

$$\frac{dy_1}{dt} = rx_1 - y_1 - x_1 z_1 + C_1(Sy_2 + O)$$

$$\frac{dz_1}{dt} = x_1 y_1 - bz_1 + C_1(Sz_2)$$

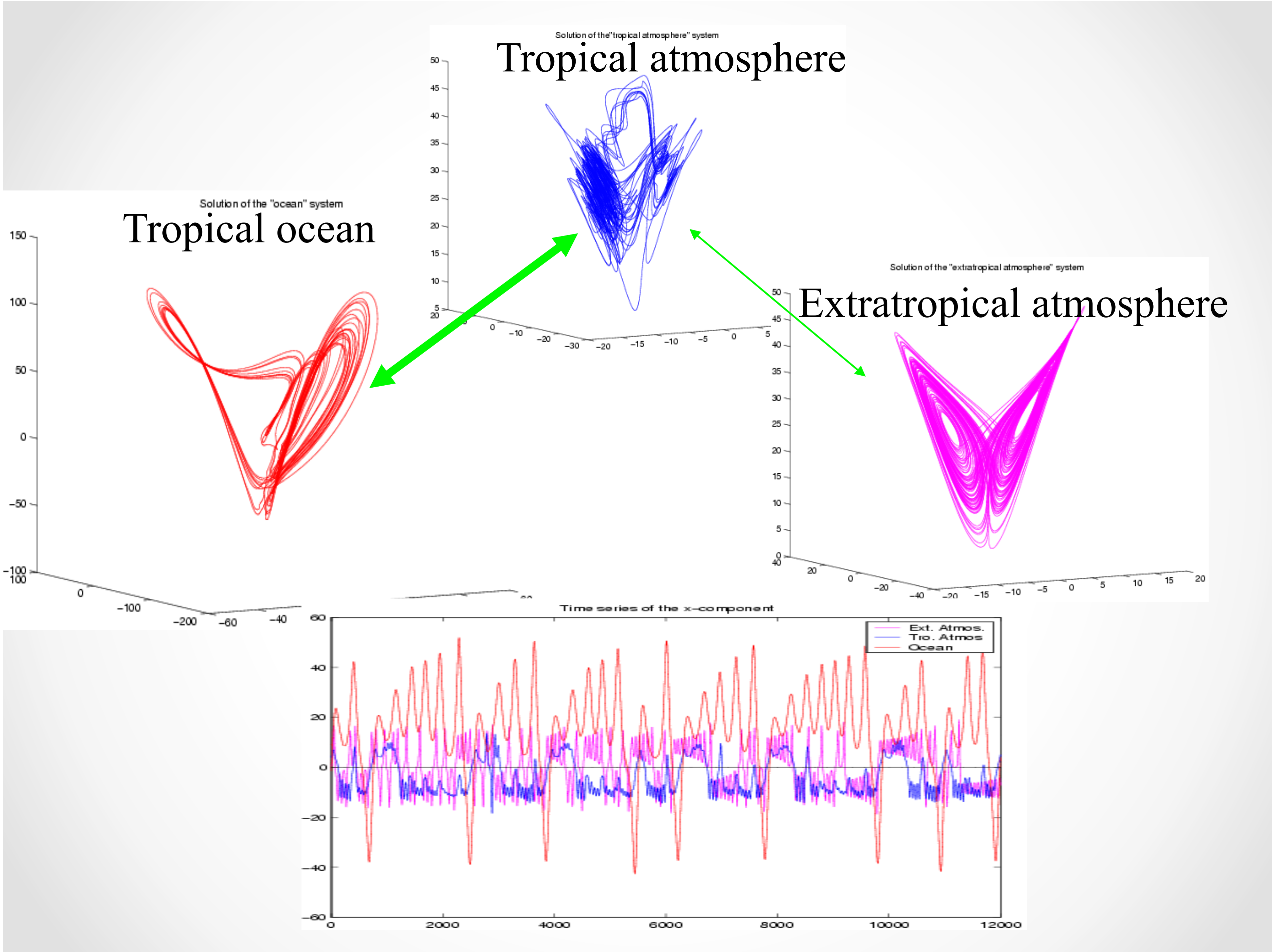
Slow equations

$$\frac{1}{\tau}\frac{dx_2}{dt} = \sigma(y_2 - x_2) - C_2(x_1 + O)$$

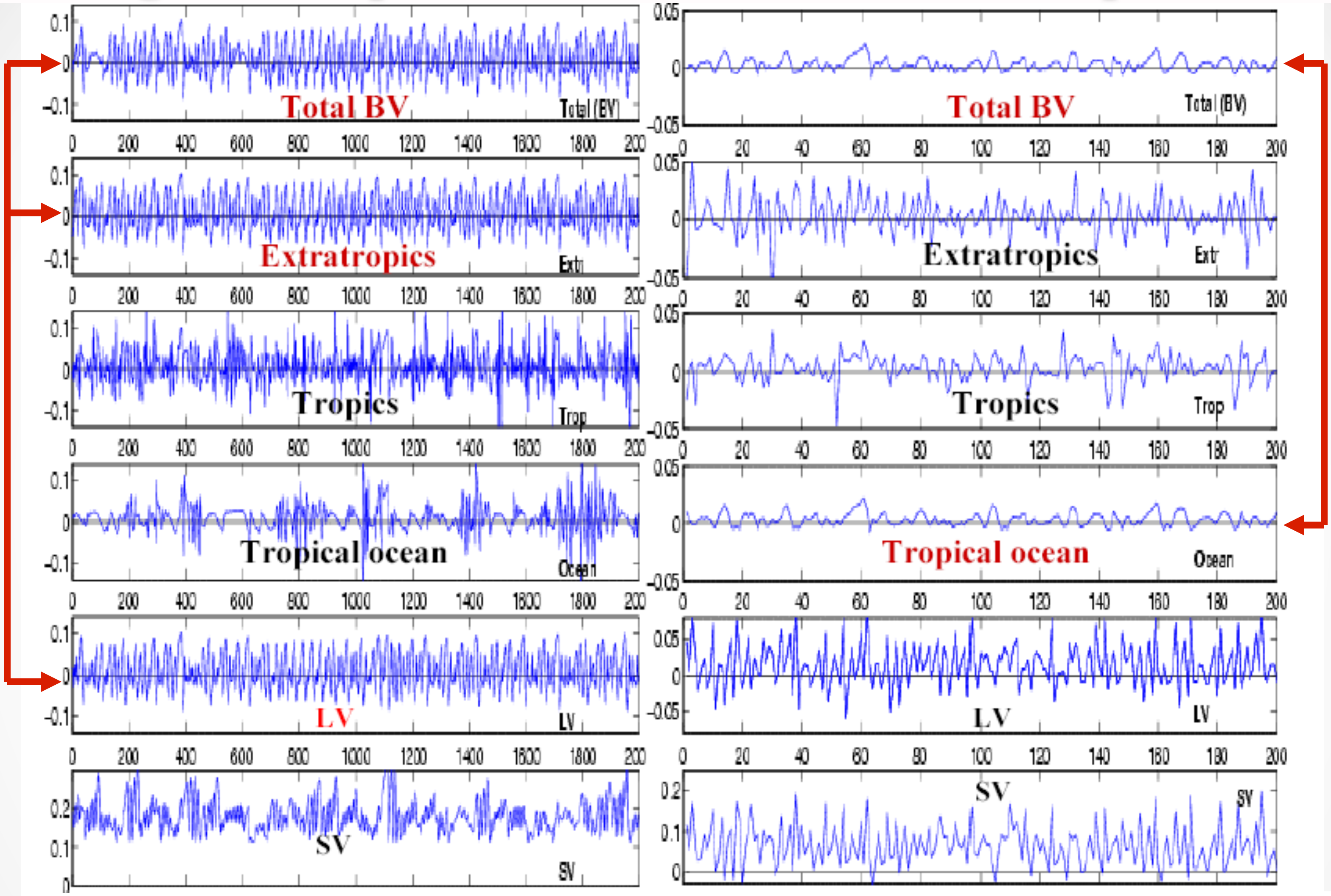
$$\frac{1}{\tau}\frac{dy_2}{dt} = rx_2 - y_2 - Sx_2 z_2 + C_2(y_1 + O)$$

$$\frac{1}{\tau}\frac{dz_2}{dt} = Sx_2 y_2 - bz_2 + C_2(z_1)$$

"Tropical-extratropical" (triply-coupled) system: the ENSO tropical atmosphere is weakly coupled to a fast "extratropical atmosphere" with weather noise


Solution of the"tropical atmosphere" system
Tropical atmosphere
Solution of the "ocean" system
Tropical ocean
Solution of the "extratropical atmosphere" system
Extratropical atmosphere
Time series of the x-component
Ext. Atmos.
Tro. Atmos
Ocean

Breeding in a coupled Lorenz model: "Weather plus ENSO"



Short rescaling interval (5 steps) and small amplitude: fast modes

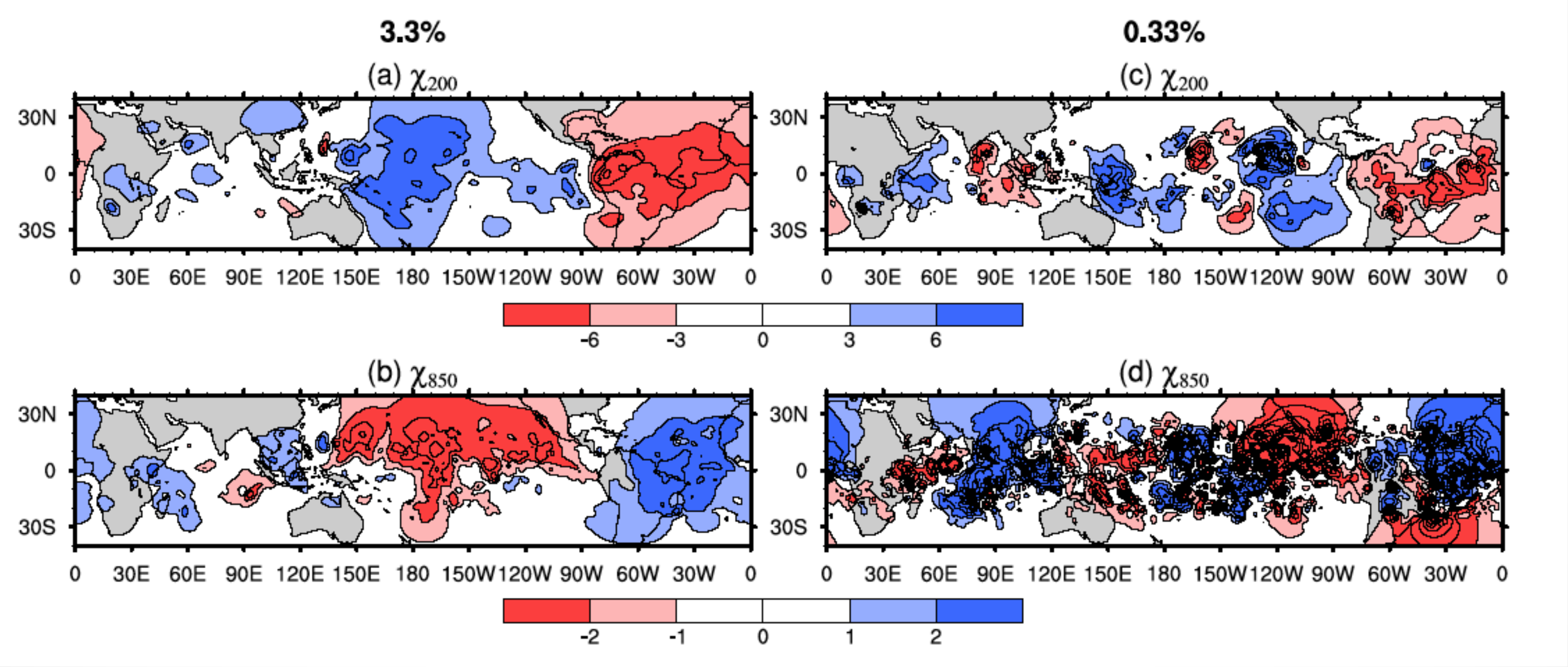
Long rescaling interval (50 steps) and large amplitude: ENSO modes

The linear approaches (LV, SV) cannot capture the slow ENSO signal

Examples of breeding in a coupled ocean-atmosphere system with coupled instabilities

- In coupled fast/slow models, we can do breeding to isolate either the fast or the slow modes
- For slow modes we have to choose a slow variable and a long interval for the rescaling.
- This identifies **coupled instabilities**.
- Examples
  - Madden-Julian Bred Vectors (Chikamoto et al., 2008)
  - NASA operational system with real observations (Yang et al., 2007, MWR)
  - Ocean instabilities and their physical mechanisms (Hoffman et al, 2008)
  - Mars!

Chikamoto et al (2007, GRL): They found the Madden-Julian instabilities BV by choosing an appropriate rescaling amplitude (only within the tropics)



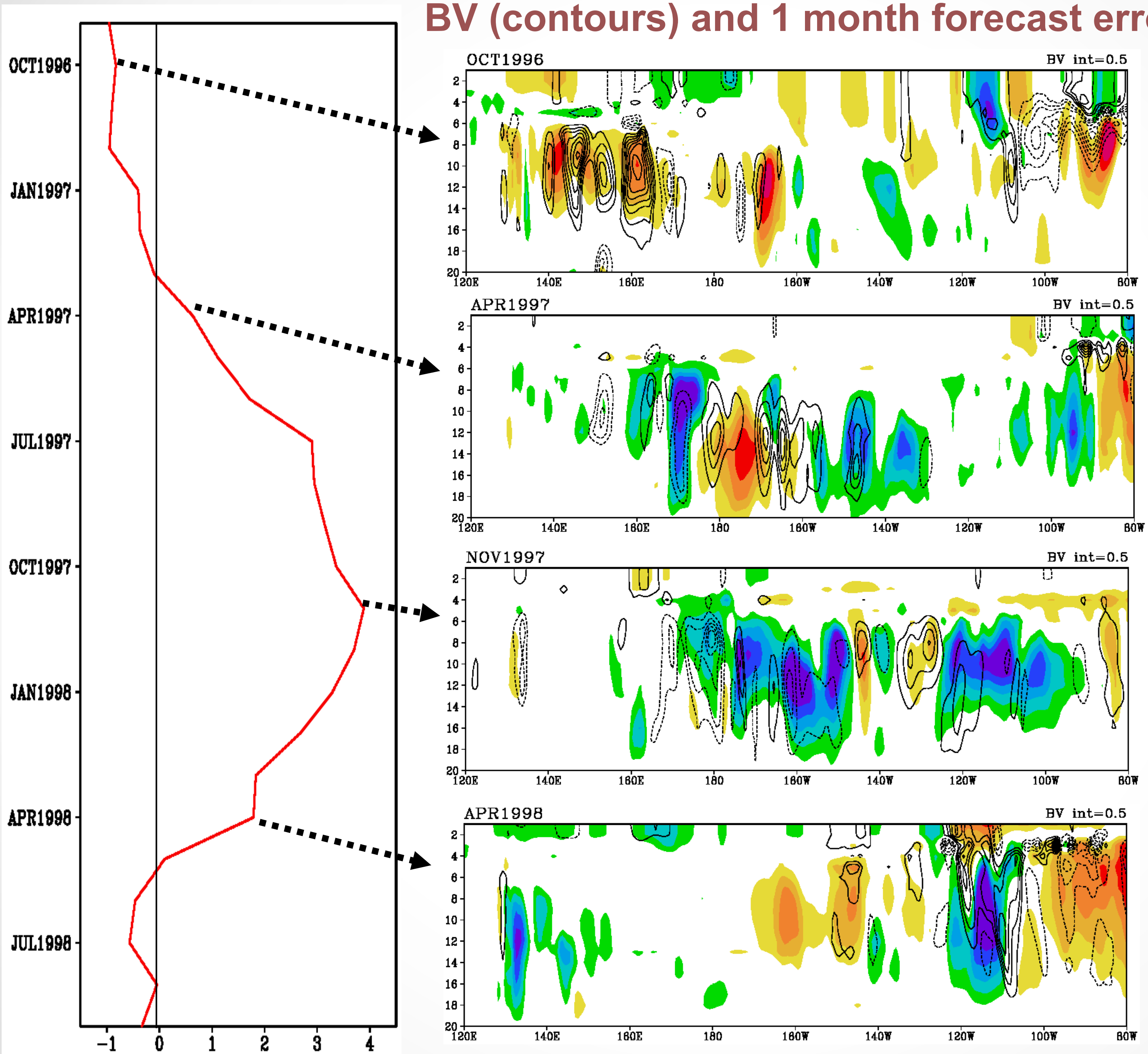
Finding the shape of the errors in El Niño forecasts to improve data assimilation

- **Bred vectors**:
  - Differences between the control forecast and perturbed runs:
  - **Should BVs show the shape of growing errors? Yes!**

- **Advantages**
  - Low computational cost (only two runs)
  - Capture coupled instabilities
  - Improve data assimilation (related to Ensemble Kalman Filter)

Niño3 index

Yang (2005): Vertical cross-section at Equator for BV (contours) and 1 month forecast error (color)



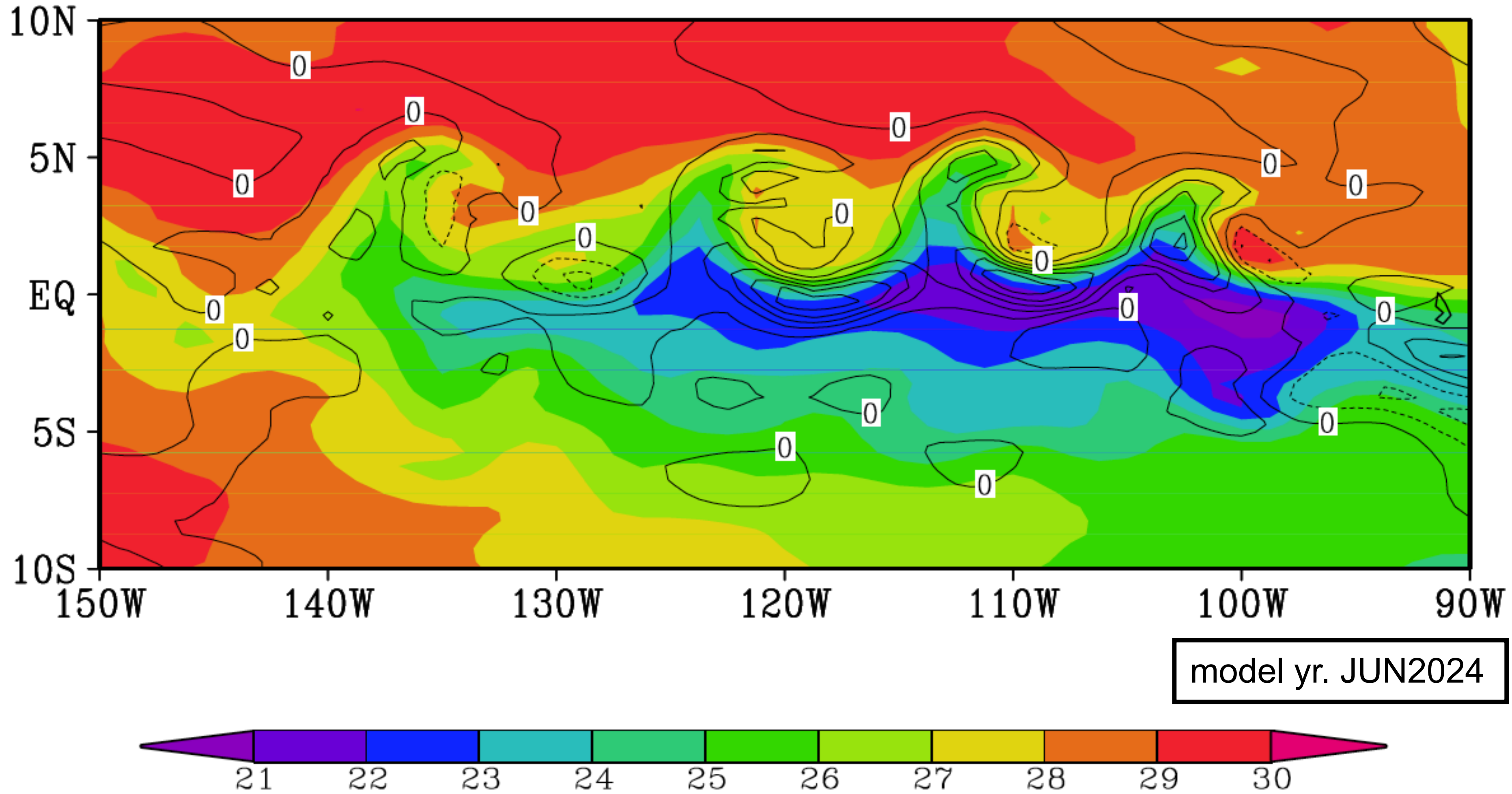
Before 97' El Niño, error is located in W. Pacific and near coast region

During development, error shifts to lower levels of C. Pacific.

At mature stage, error shifts further east and it is smallest near the coast.

After the event, error is located mostly in E. Pacific.

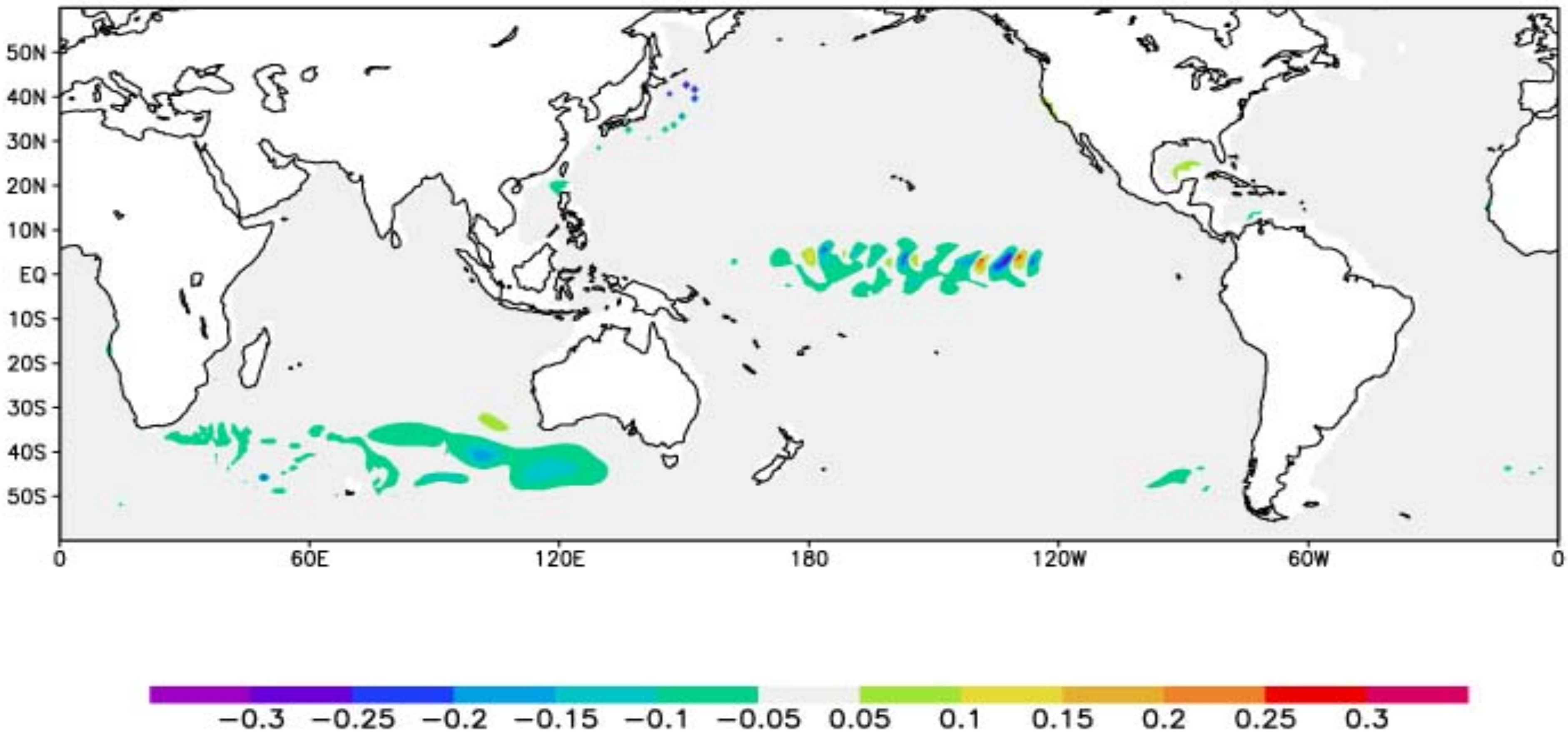
Yang et al., 2006: Bred Vectors (contours) overlay Tropical Instability waves (SST, shades): make them grow and break!



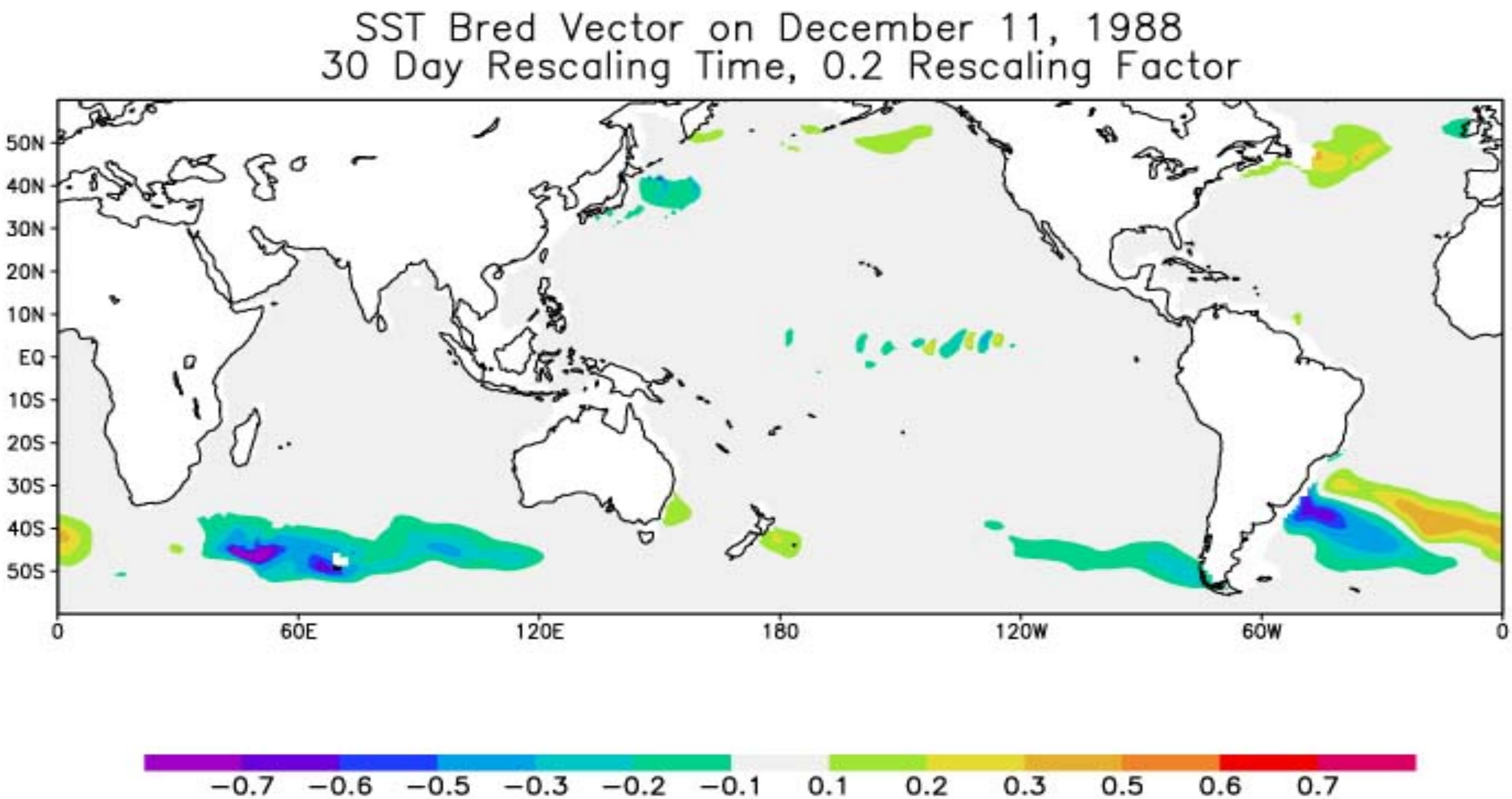
Hoffman et al (2008): finding ocean instabilities with breeding time-scale 10-days captures tropical instabilities

Breeding time scale: 10 days

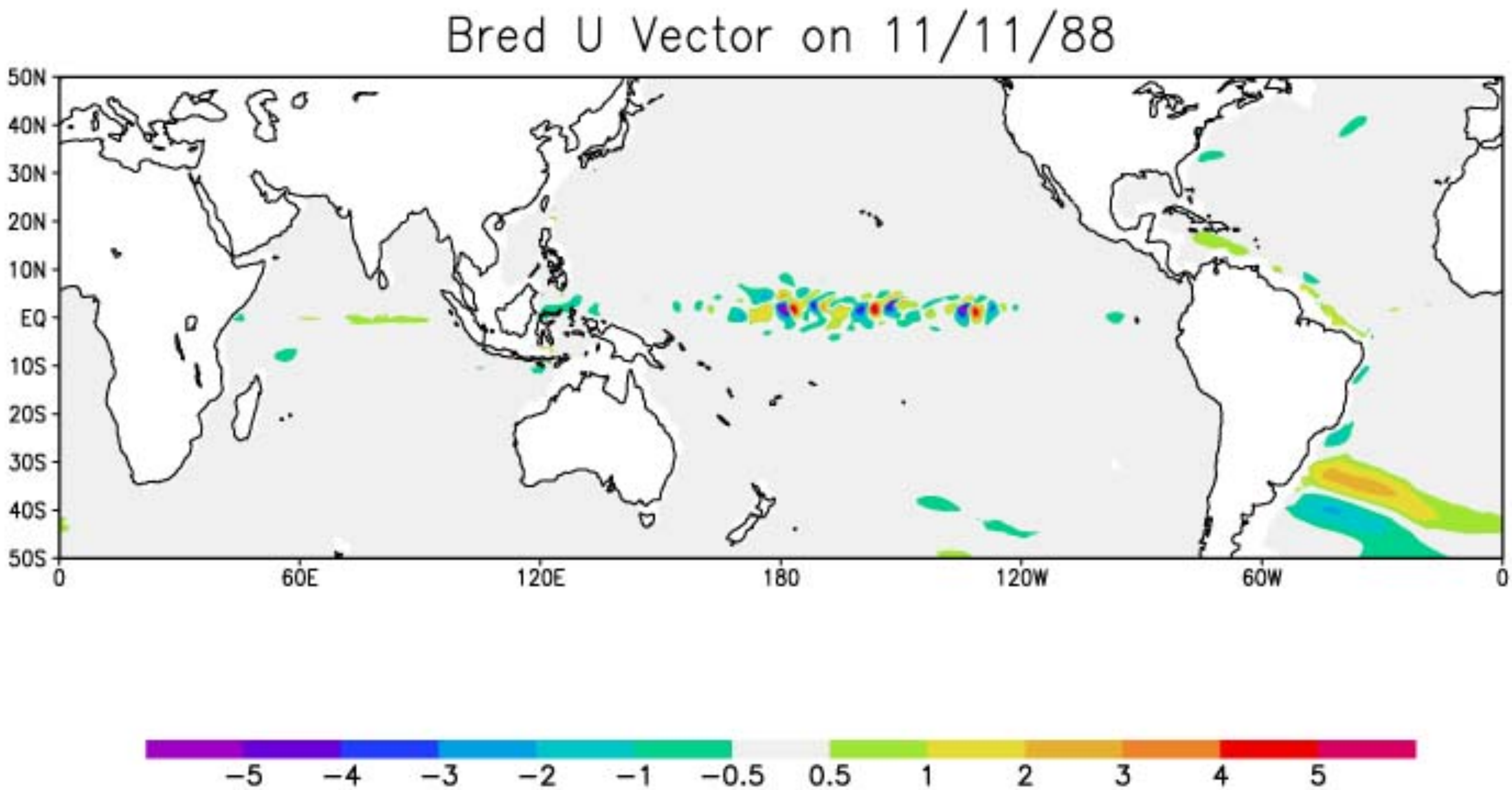
SST Bred Vector on December 1, 1988



When the rescaling time scale is 30 days, extratropical instabilities dominate



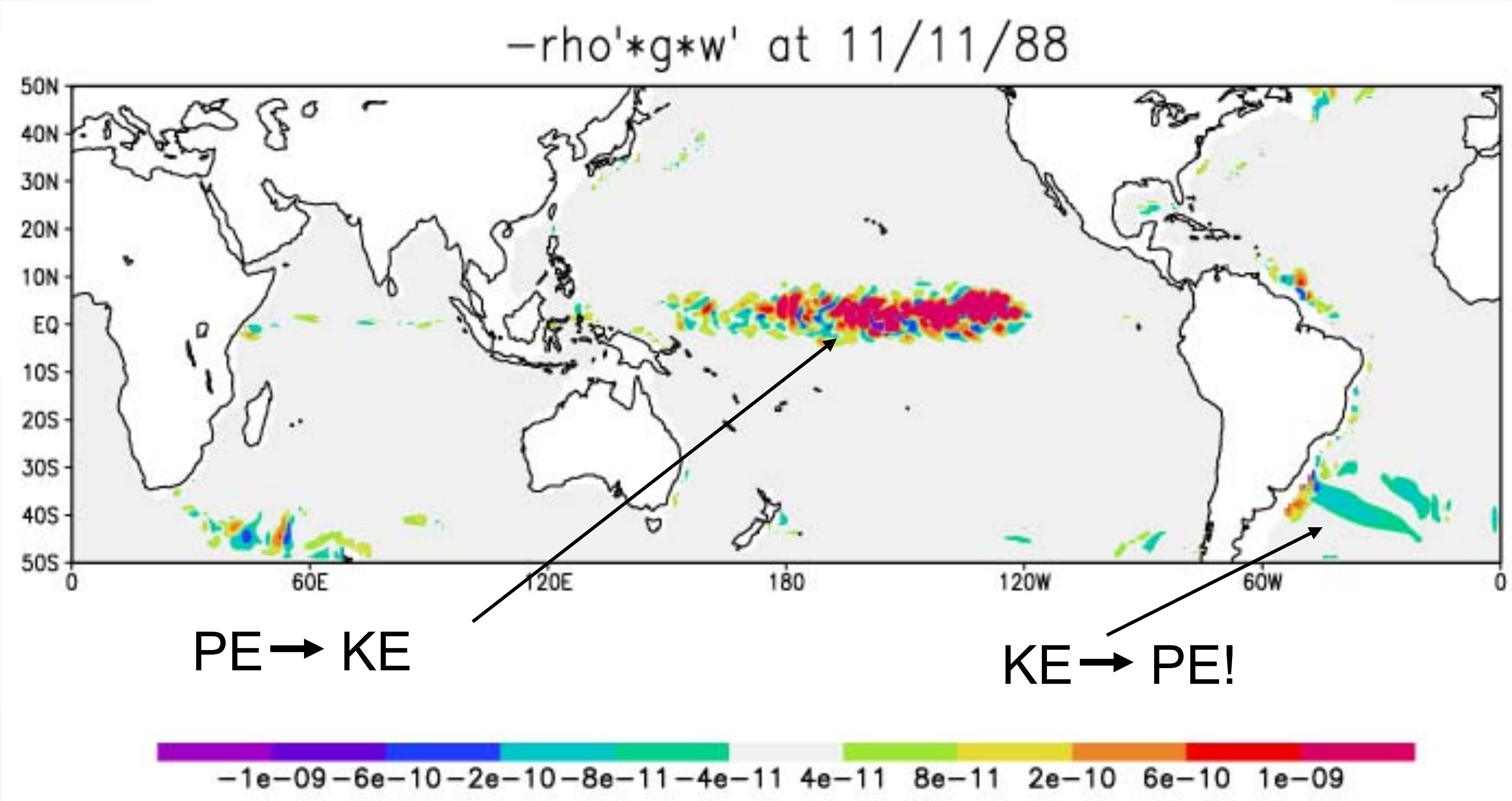
Here we have both Tropical and "South Atlantic Convergence Zone" instabilities. Can we determine the dynamic origin of these instabilities? Yes!



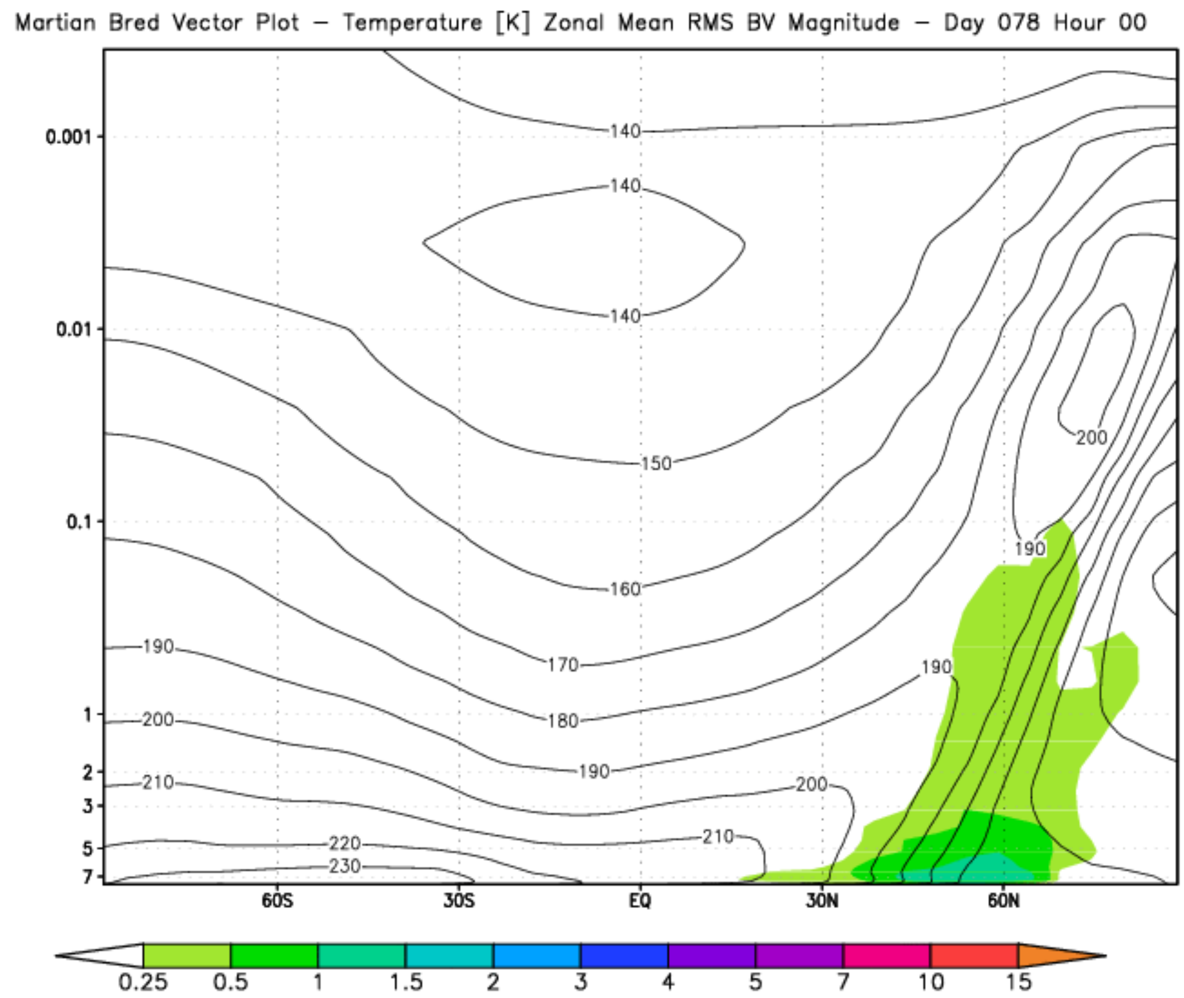
The Bred Vector Kinetic Energy equation can be computed <u>exactly</u> because both control and perturbed solutions satisfy the model equations!

$$\frac{\partial KE_{bv}}{\partial t} = horizontal\ fluxes - \rho_b g w_b + \ldots$$

Conversion from potential to kinetic energy



MGCM-LETKF-TES Martian Atmosphere Reanalysis Project



Day 078 (Ls= 302, Boreal Winter): BV activity near surface temperature front begins to flare up.

Greybush et al., 2011

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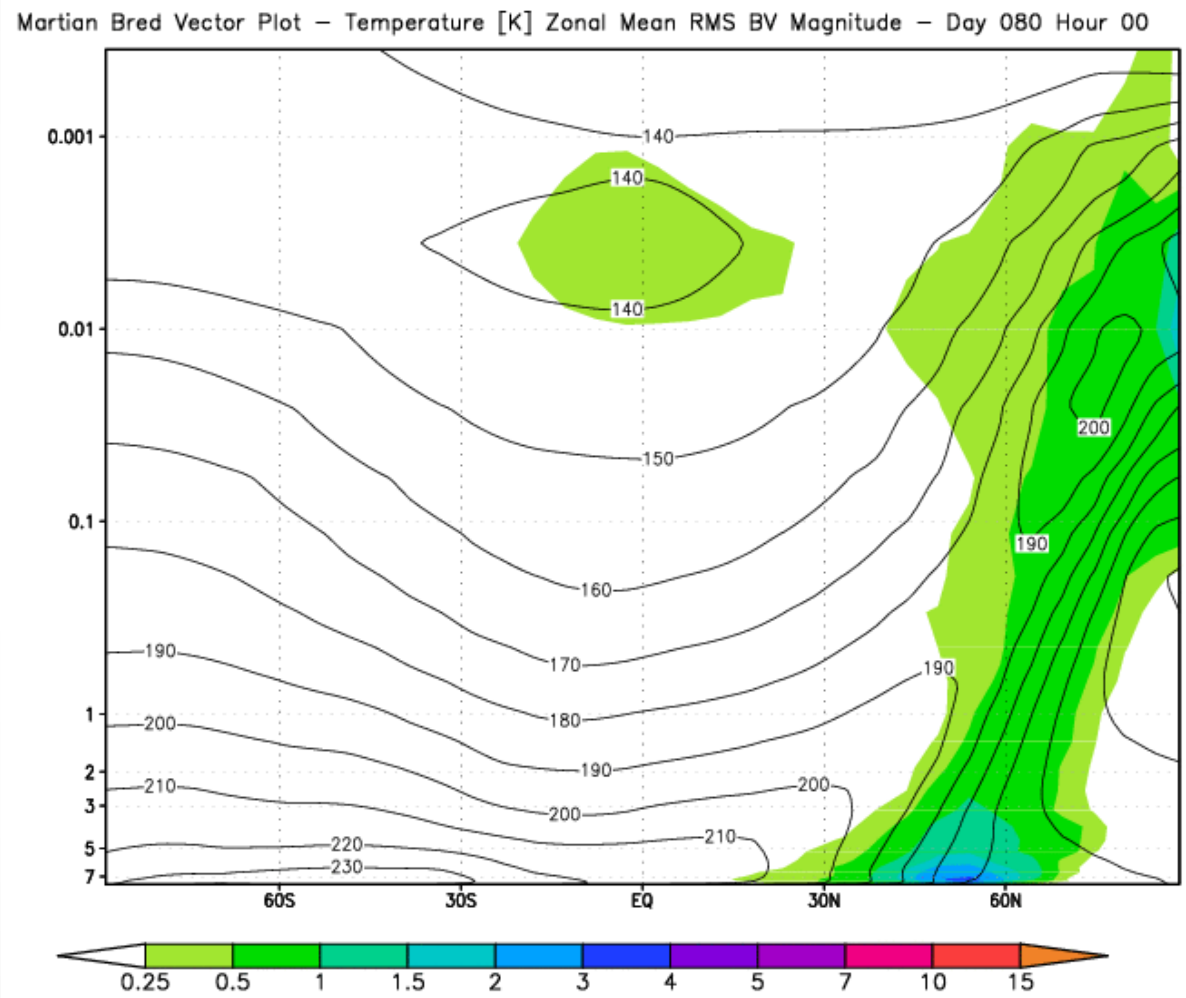

Day 080 (Ls= 304, Boreal Winter): Just two days later, BV now extends vertically along the length of the front. Connection to the upper level tropics begins.

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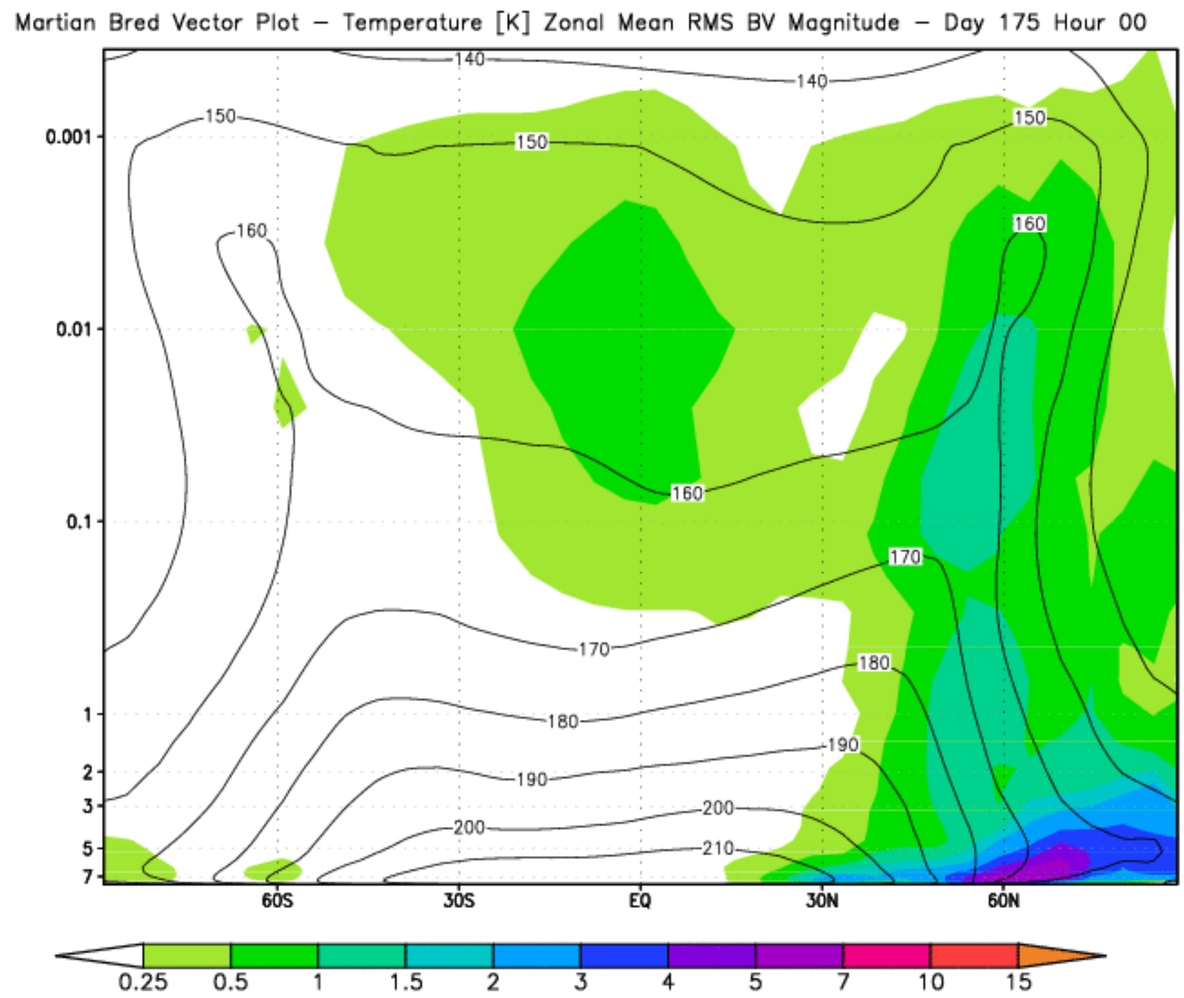

Day 175 (Ls= 358, near boreal vernal equinox): Typical winter BV activity along temperature front with upper level tropical connection. First hint of southern hemisphere activity.

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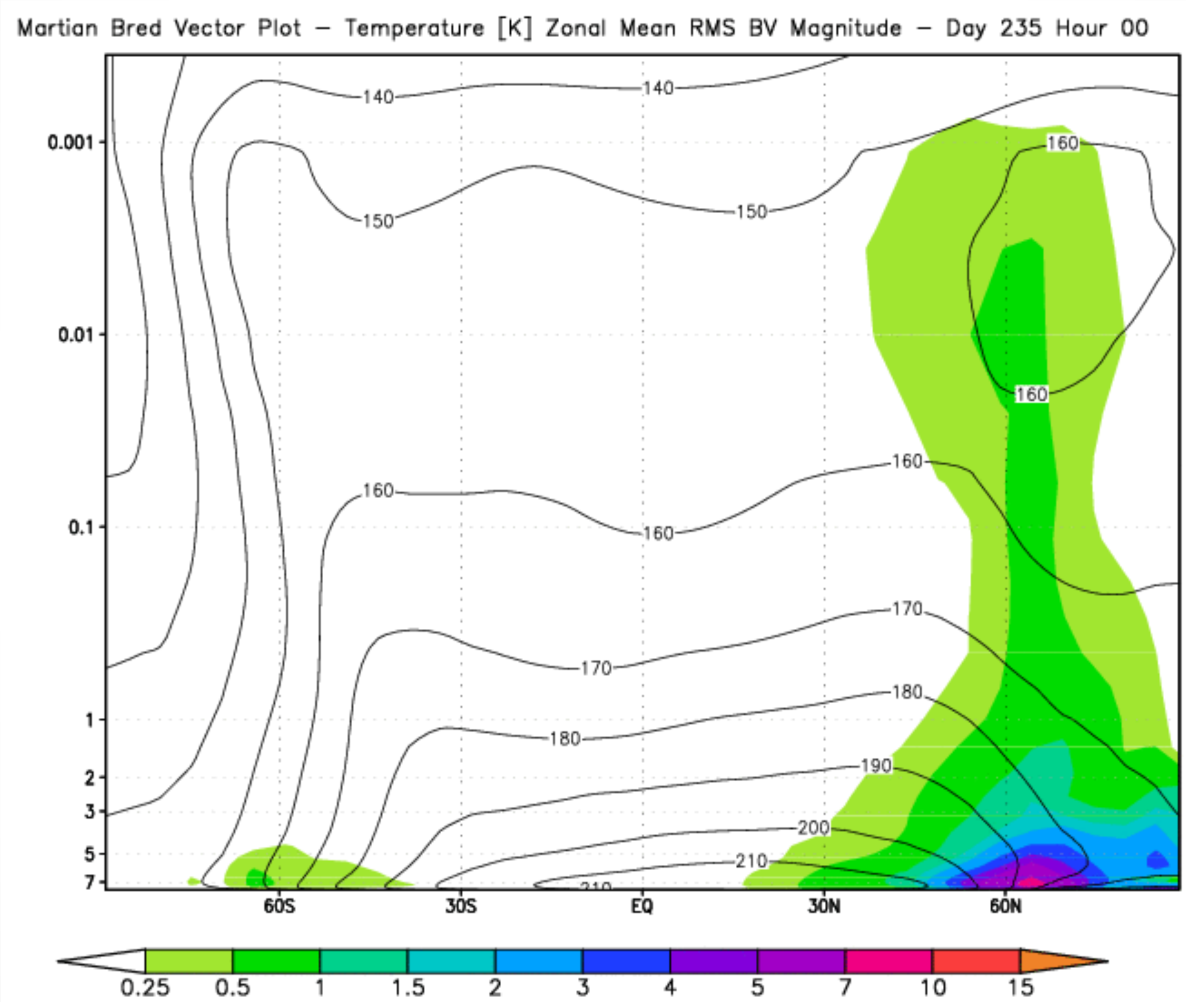

Day 235 (Ls= 22, early boreal spring): Winter BV activity has begun to weaken, as the tropical connection has disappeared.

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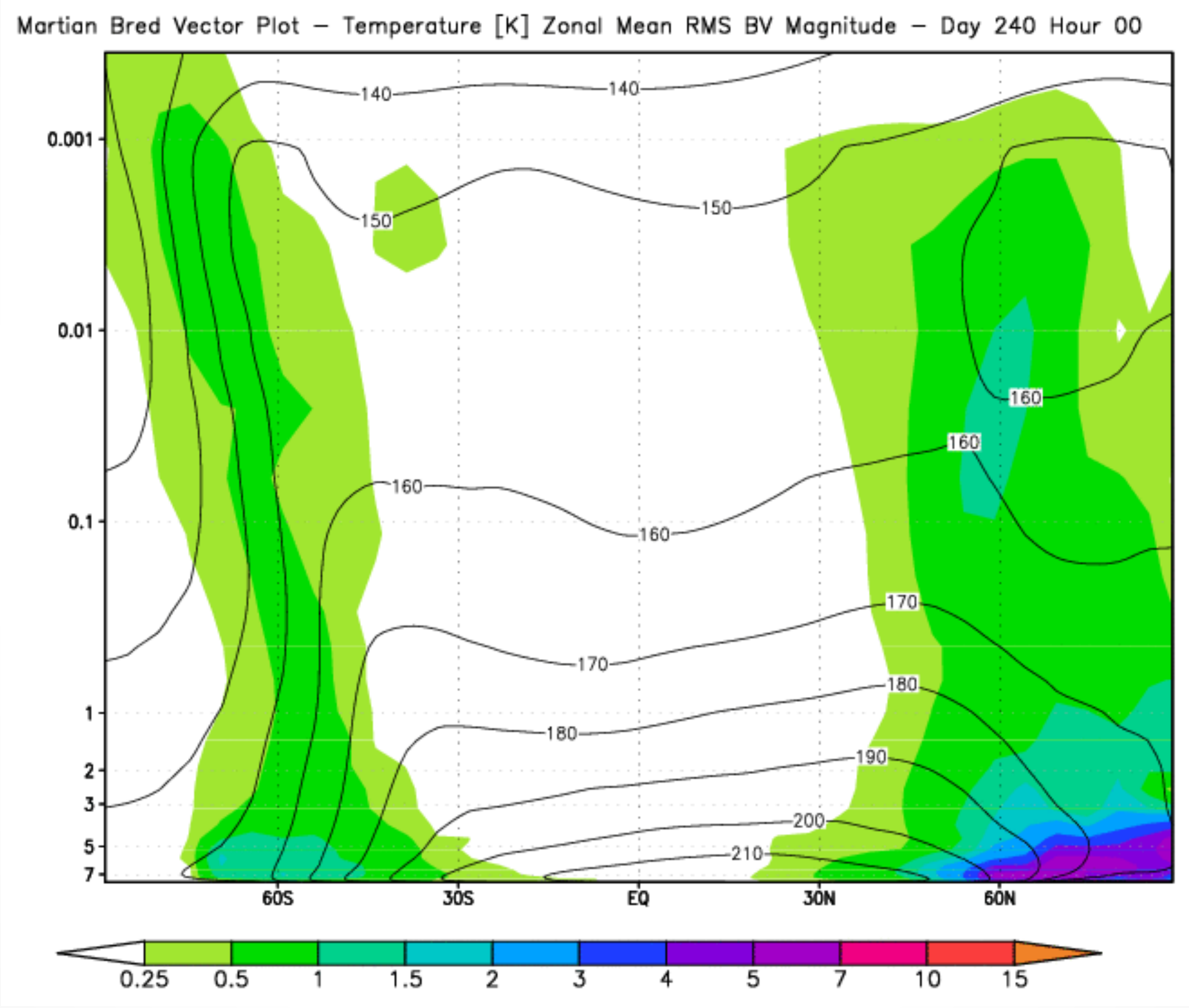
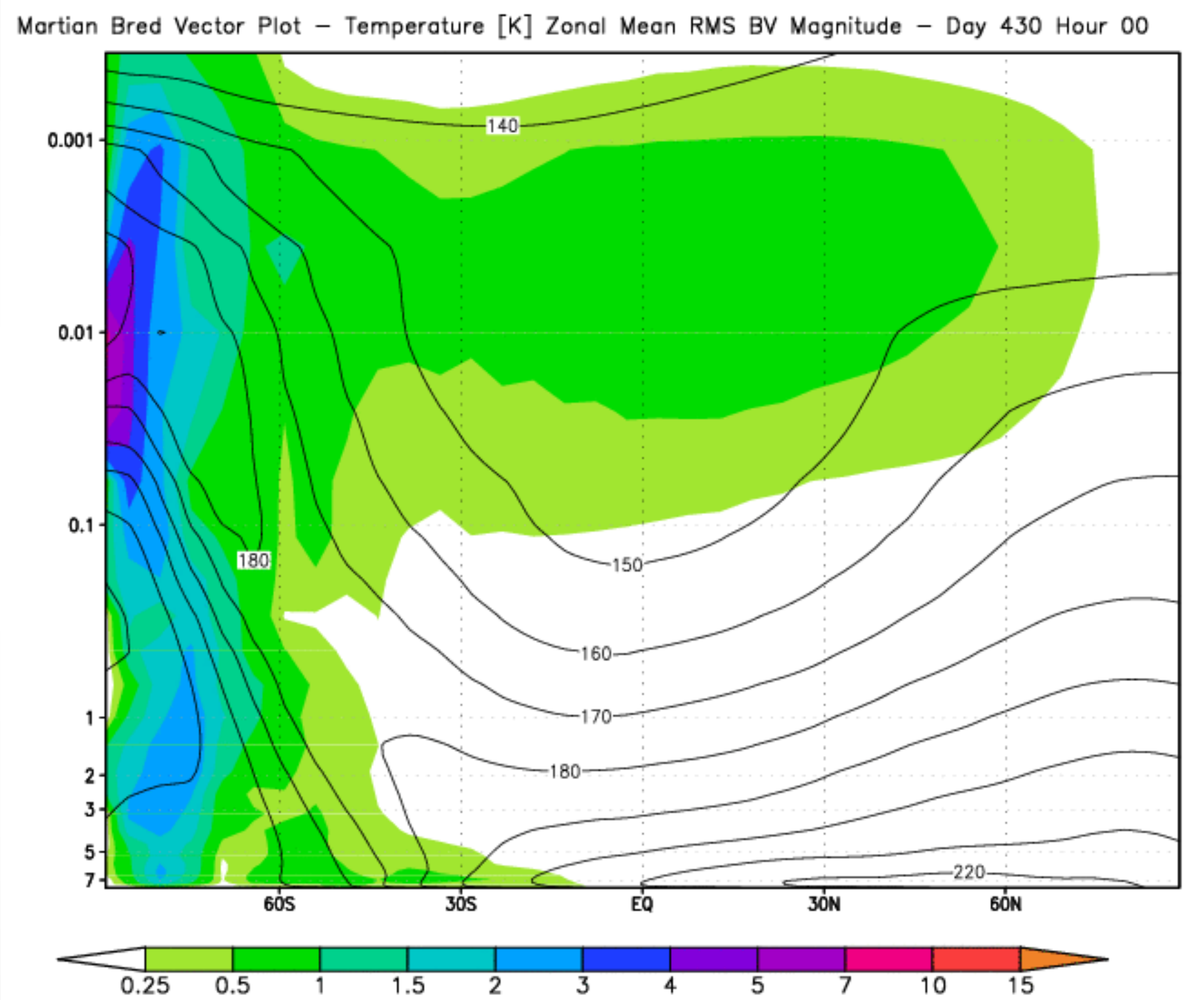


Day 240 (Ls= 230, early boreal spring): Southern hemisphere activity has now grown rapidly along austral front.

MGCM-LETKF-TES Martian Atmosphere Reanalysis Project



Day 430 (Ls= 116. austral mid-winter): Southern hemisphere BV activity now assumes full spatial extent.

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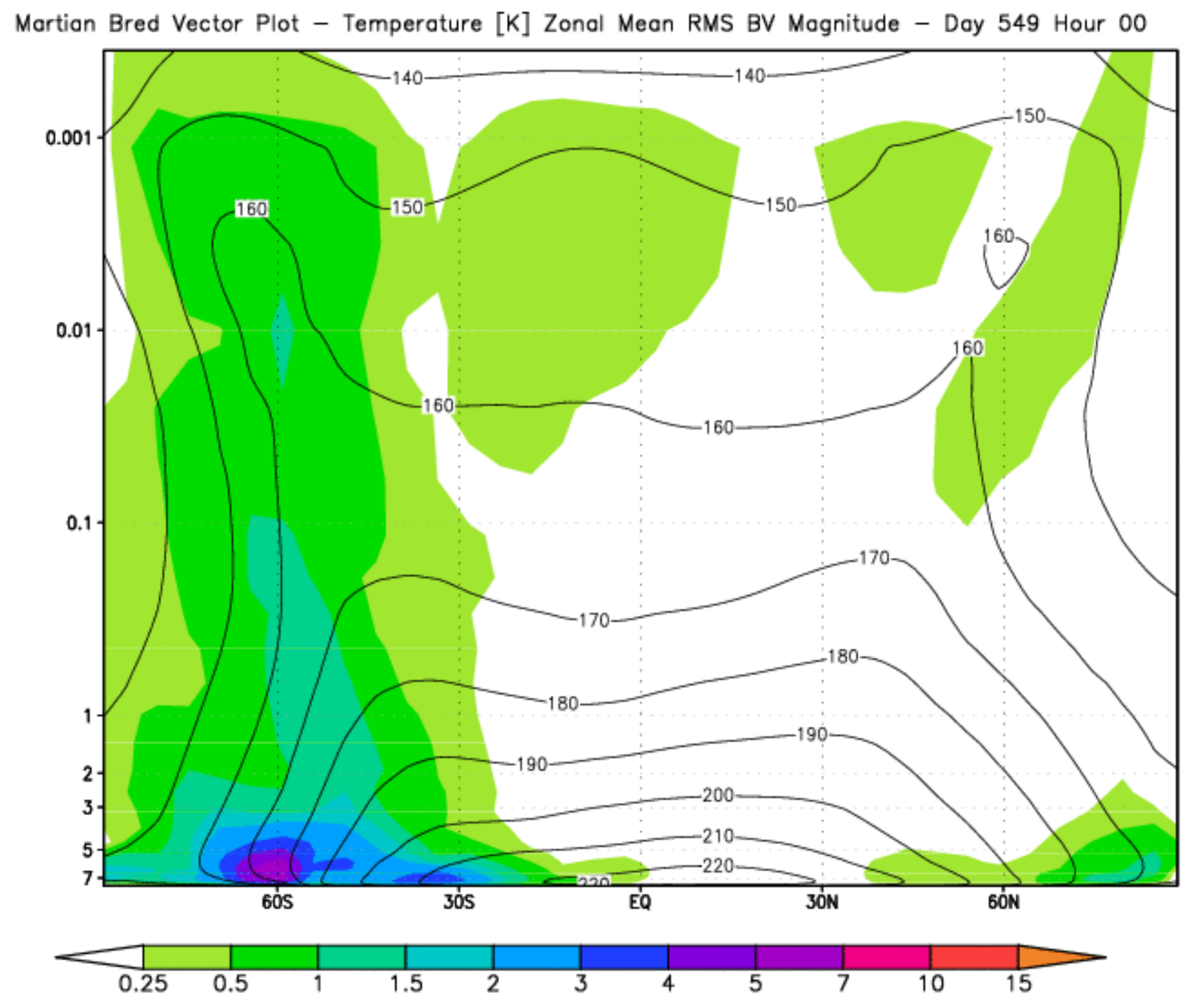

Day 549 (near boreal autumn equinox): Signs BV of activity in the northern hemisphere have resumed.

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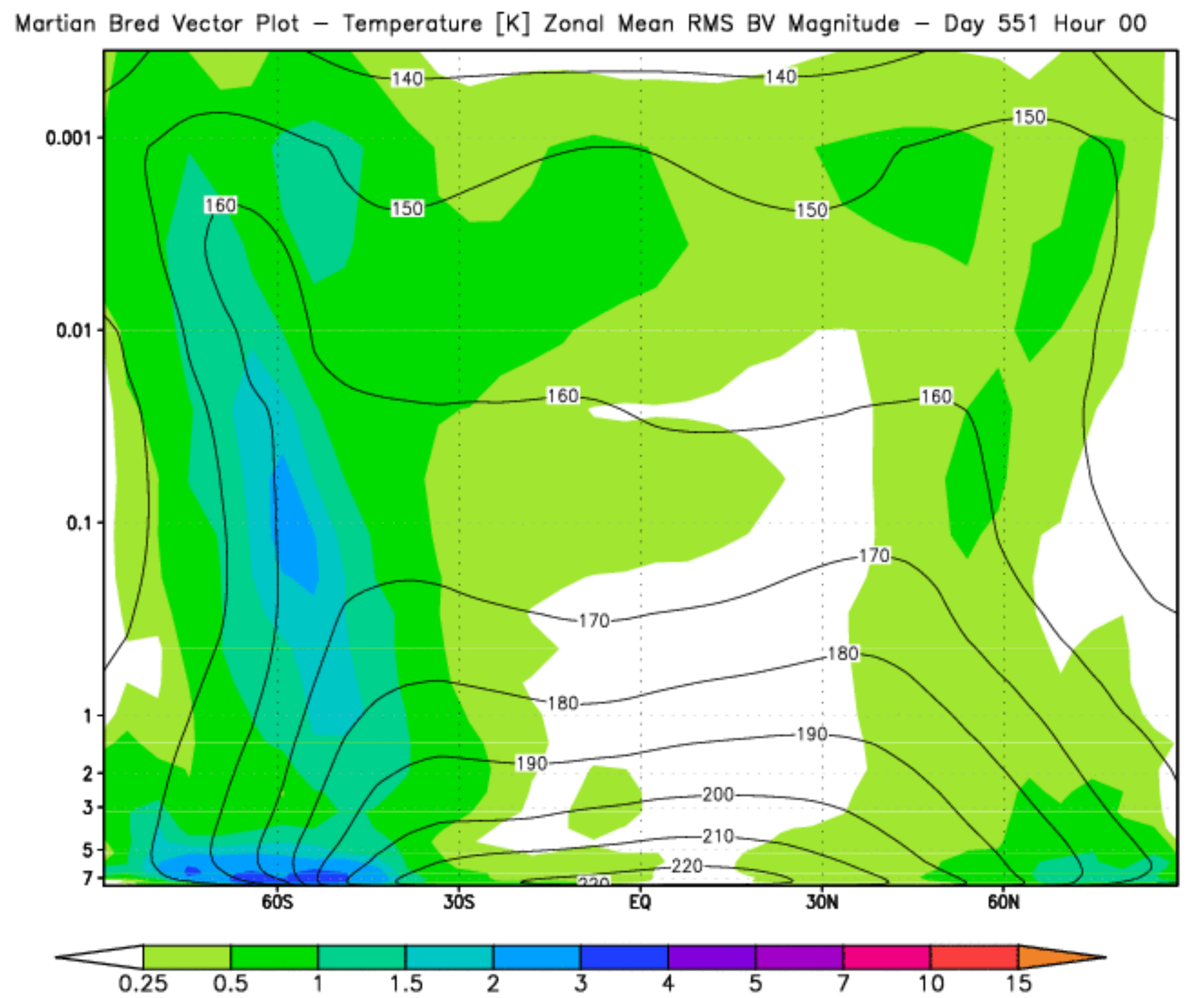

Day 551 (Ls= 180, boreal autumn equinox): Activity in northern hemisphere has extended vertically.

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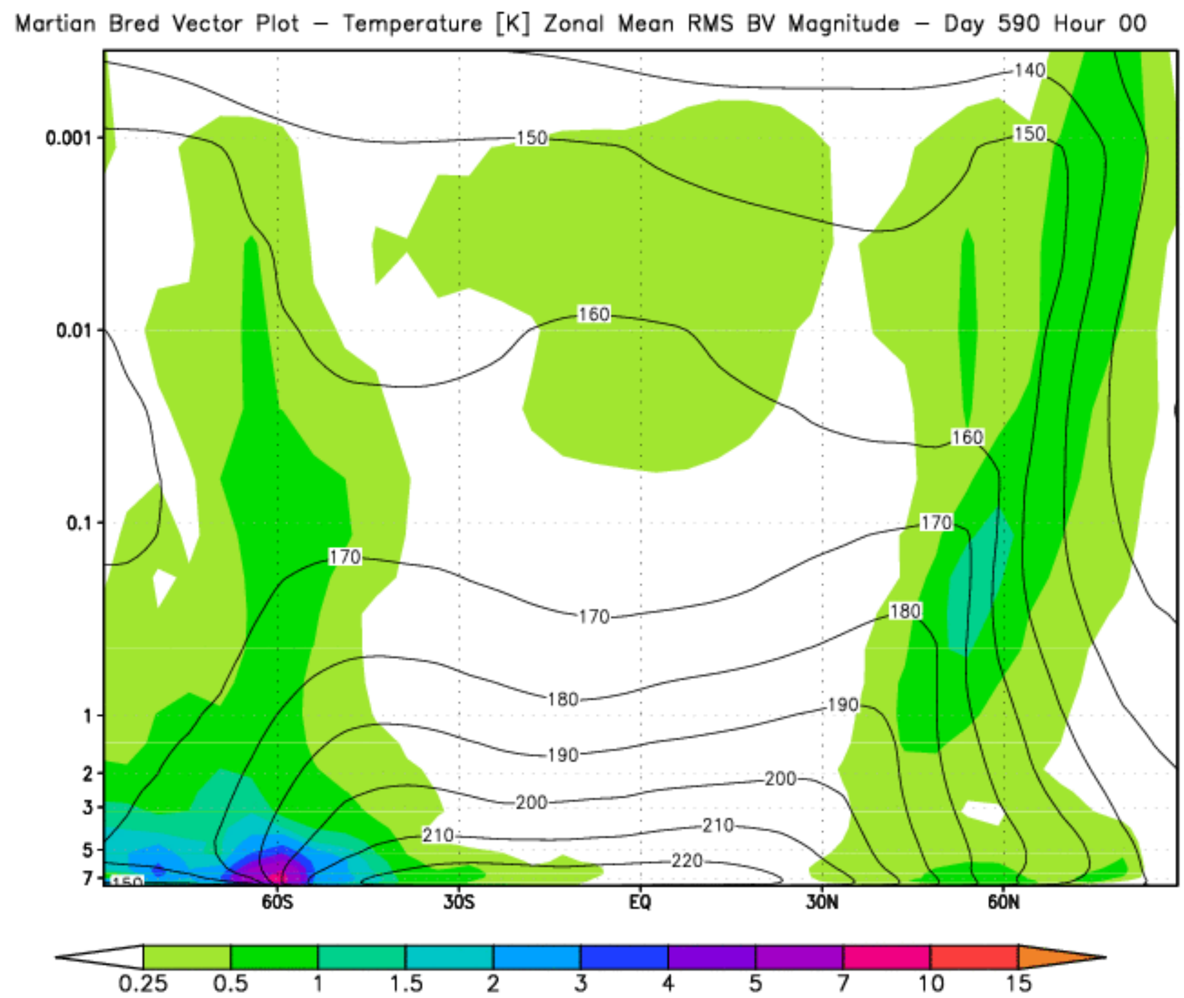

Day 590 (mid boreal autumn): Activity in both hemispheres, but most intense along southern polar front.

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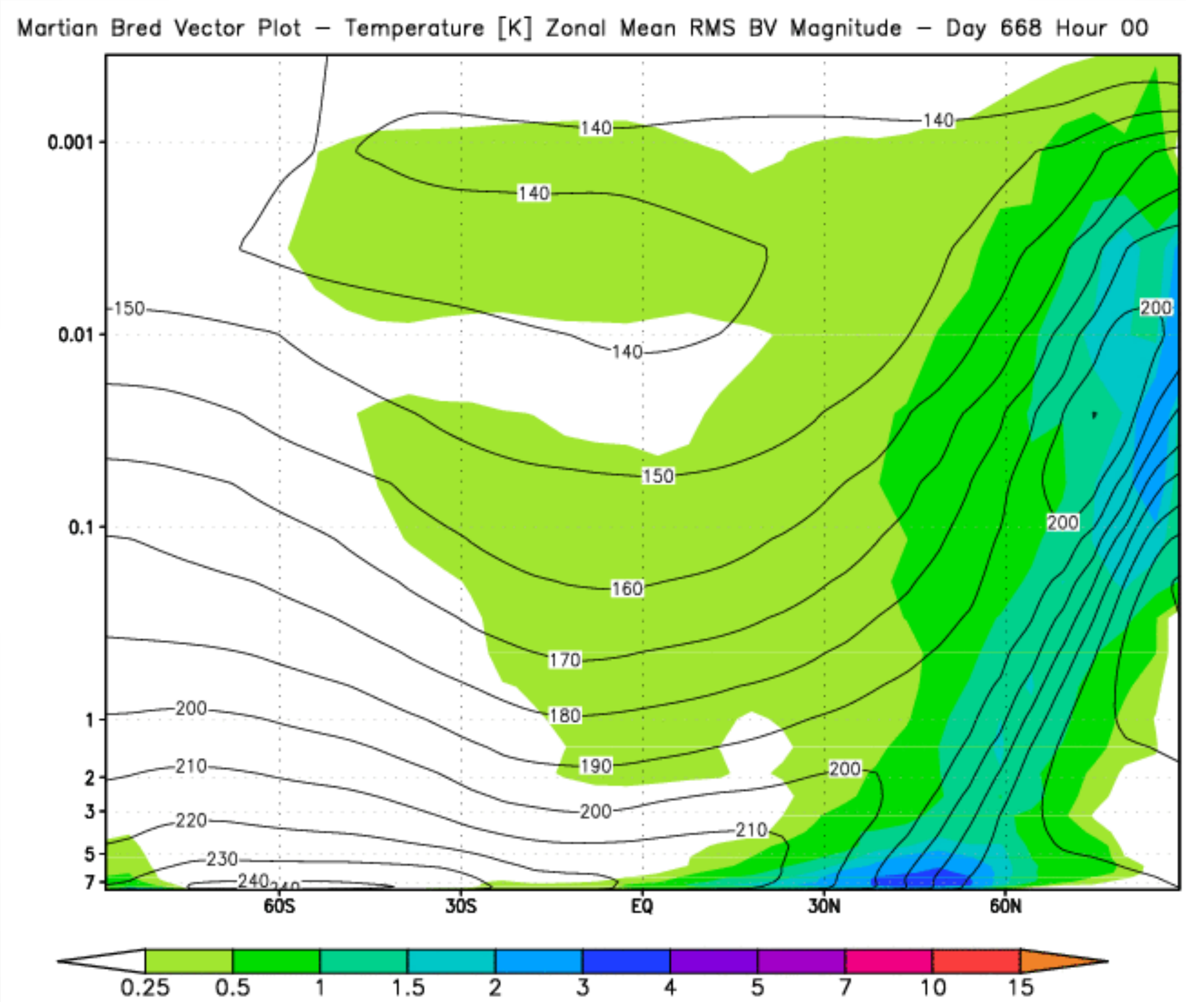

Day 668 (Ls= 252, prior to boreal winter solstice): The seasons have returned full circle, with southern hemisphere activity fading and northern winter dominant.

Summary: We can fight chaos and extend predictability by understanding error growth

- Chaos is not random: it is generated by physical instabilities
- Breeding is a simple and powerful method to find the growth and shape of the instabilities.
- These instabilities also dominate the forecast errors: we can use their shape to improve data assimilation.
- Ensemble Kalman Filter is the ultimate method to explore and "beat chaos" through data assimilation.
- In the "chaotic" Lorenz model the growth of bred vectors predicts regime changes and how long they will last.
- Breeding can be applied to a time series even without knowing the model.
- Nonlinear methods, like Breeding and EnKF, can take advantage of the saturation of fast weather noise and isolate slower instabilities.
- Bred Vectors predict well the evolution of coupled forecast errors
- Bred Vectors help explain the physical origin of ocean instabilities
- Ensembles of BV improve the seasonal and interannual forecast skill, especially during the "spring barrier"