

# “Fighting chaos” in weather and climate prediction

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University of Maryland

**The vision of IMO/WMO: 60 years later**

Presented at the 62-WMO Executive Council meeting  
Geneva, 17 June 2010

ca. 1974



ca. 1974

Charney

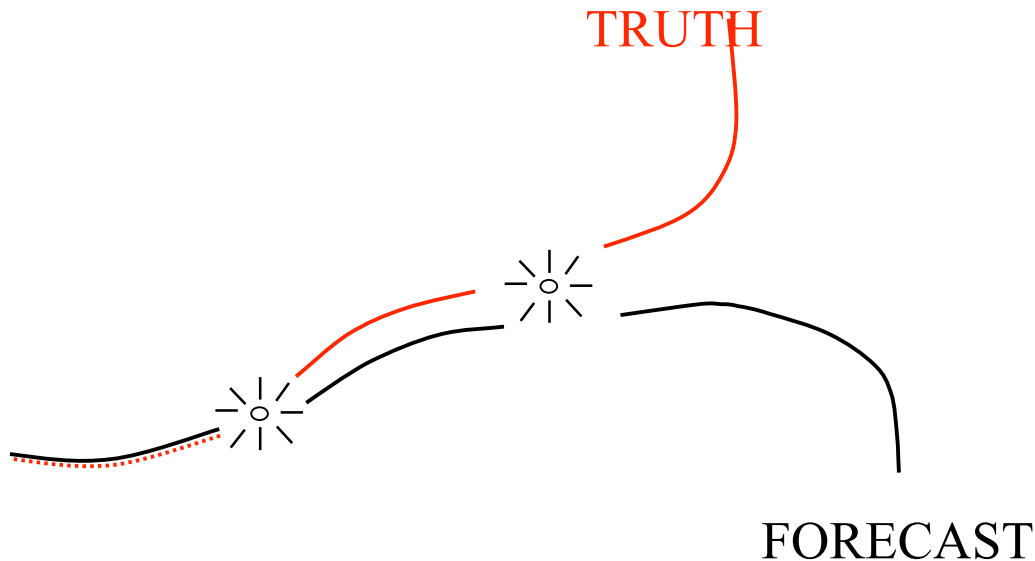
Lorenz





# Numerical Weather Prediction

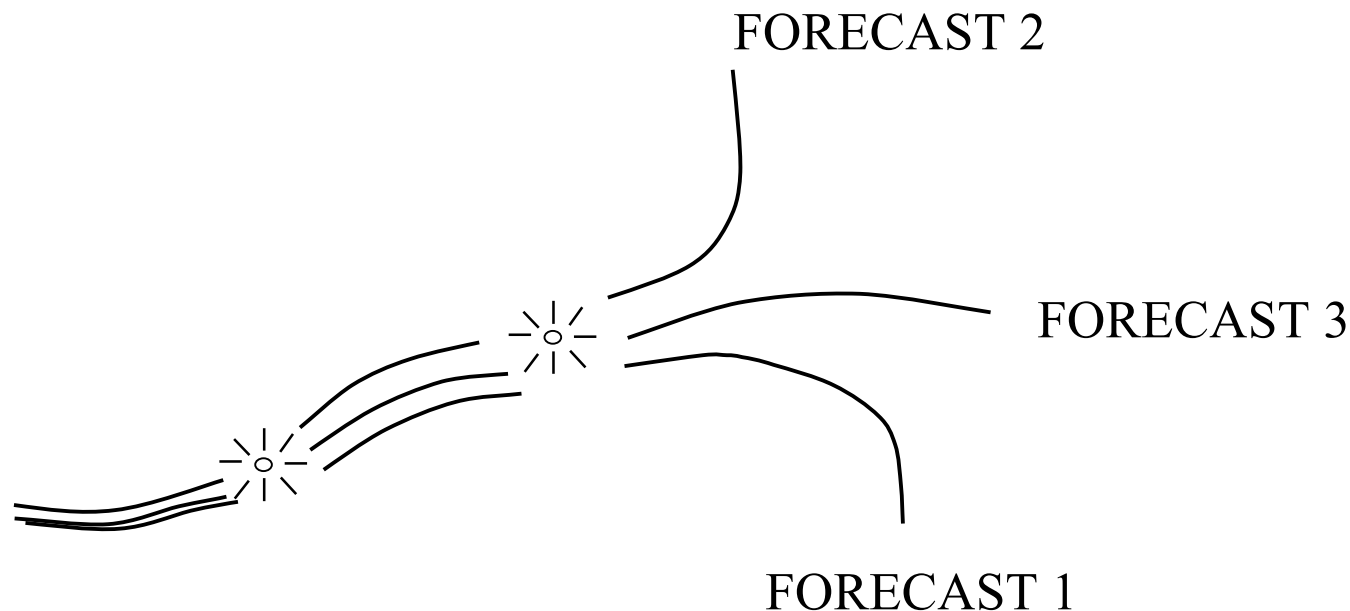
- We create models to simulate the atmosphere
- Instabilities increase forecast errors
- The models need initial conditions (today's analysis)
- Initial conditions have errors
- Errors grow because of instabilities and model error





# Ensemble forecasts

- We create ensembles of forecasts to simulate the uncertainty of the forecasts. **We need to include:**
- Uncertainties in the **initial conditions** (today's analysis errors)
- Uncertainties **in the models** (model errors or deficiencies)



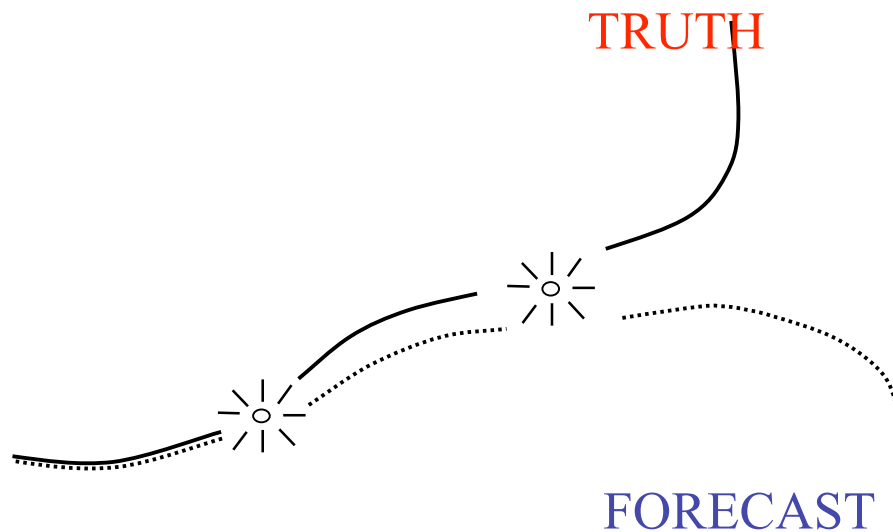
# Chaos in Numerical Weather Prediction and how we fight it with ensembles

- Lorenz (1963) introduced the concept of “chaos” in meteorology:
  - 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!**
  - At that time, statistical prediction was more skillful than with dynamical models.
  - Now we **exploit “chaos” with ensemble forecasts** and routinely produce skillful forecasts beyond a week
  - The El Niño coupled ocean-atmosphere instabilities are allowing **6-12 month** forecasts of ENSO **climate anomalies**

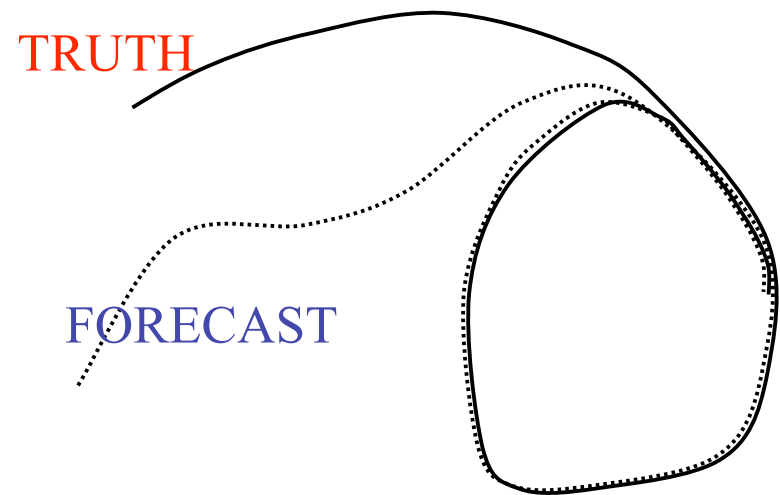
## Central theorem of chaos (Lorenz, 1960s):

- a) **Unstable** systems have **finite predictability** (chaos)
- b) **Stable** systems are **infinitely predictable**

a) Unstable dynamical system



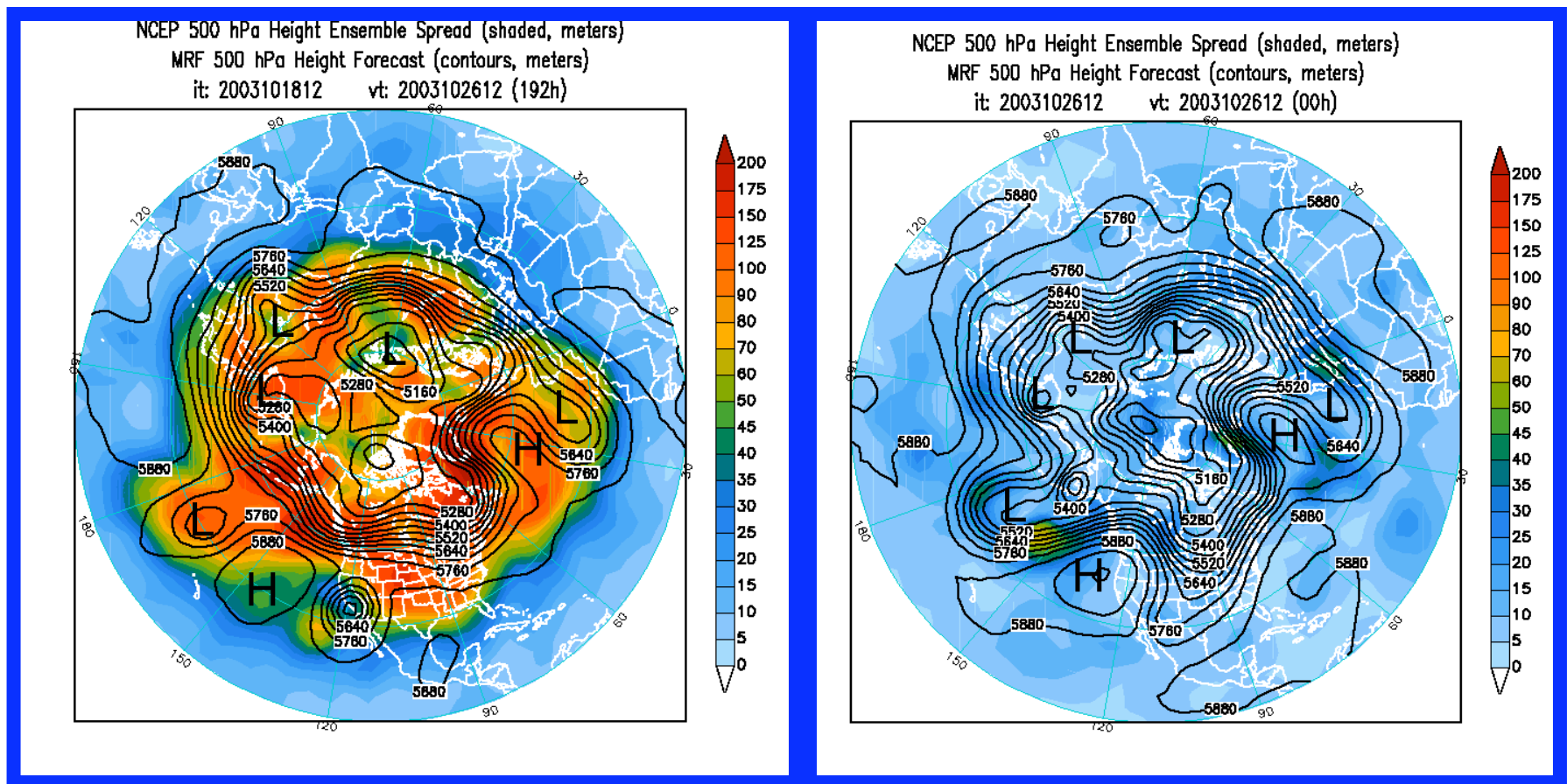
b) Stable dynamical system





# We have come a long way!

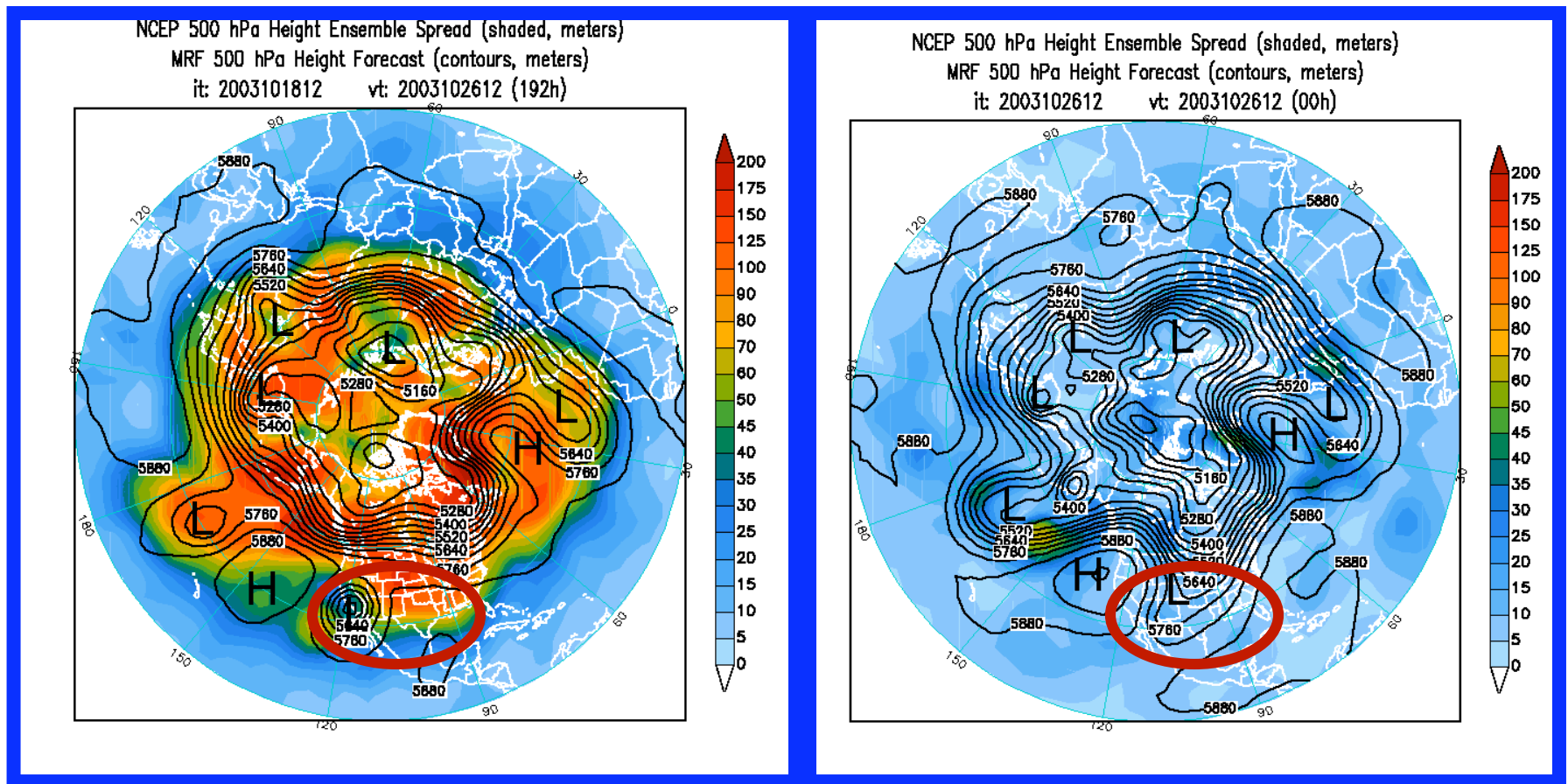
## 8-day forecast and verification



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

Need **good models**, **good observations**, **good data assimilation**

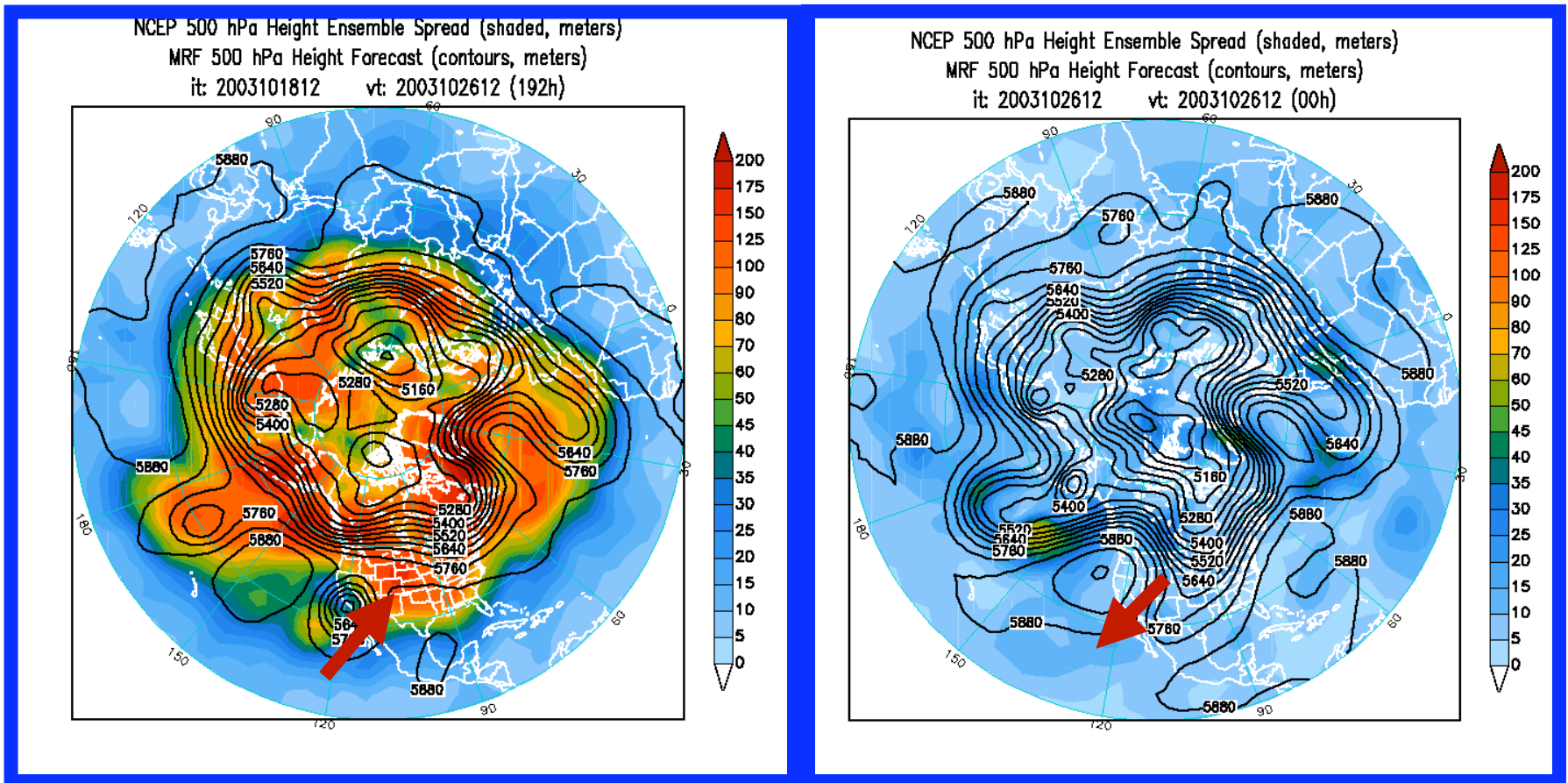
# 8-day forecast and verification



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

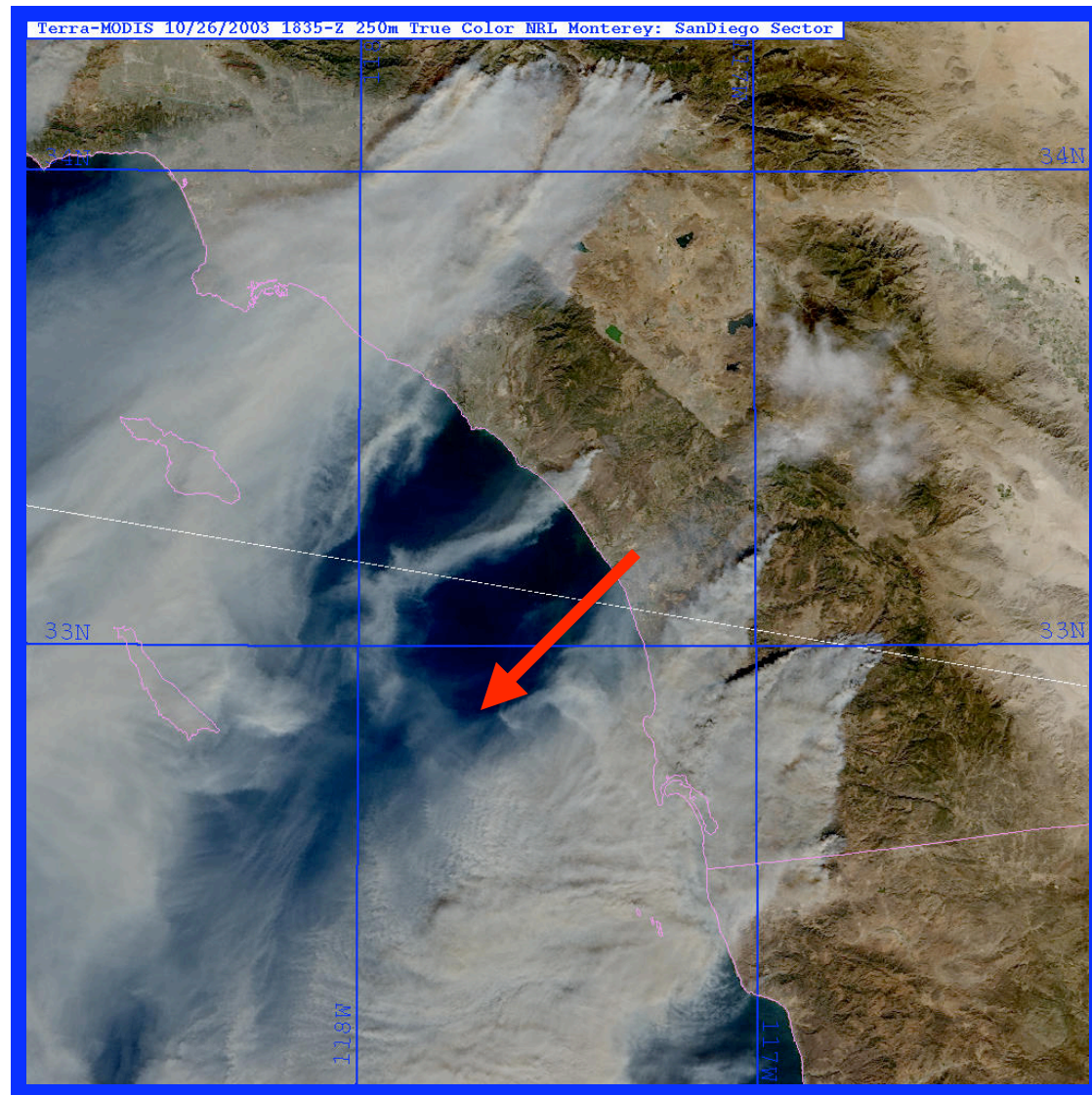
# 8-day forecast and verification



Southern California: **winds** are from the wrong direction!

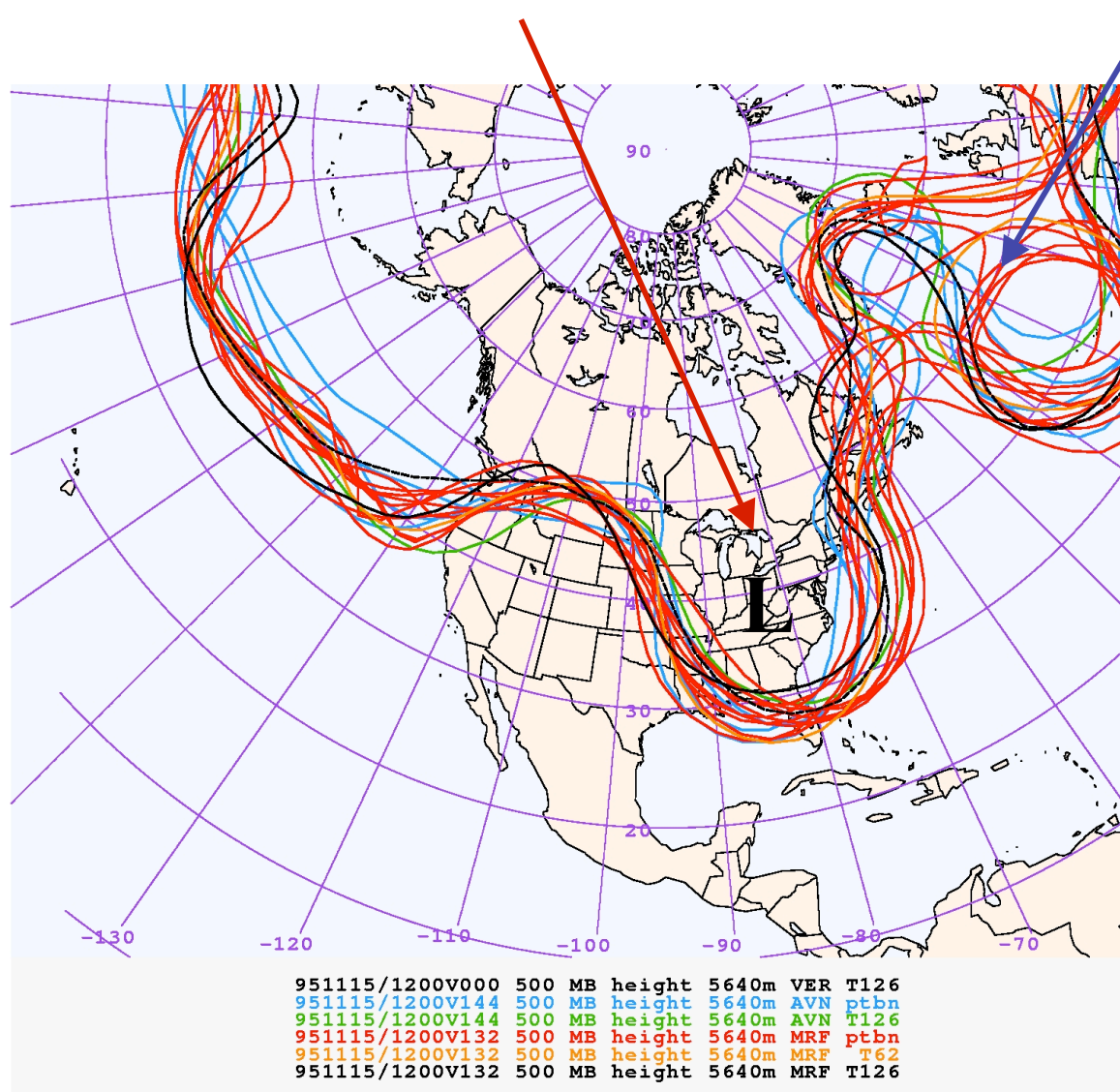


# Fires in California (2003)



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

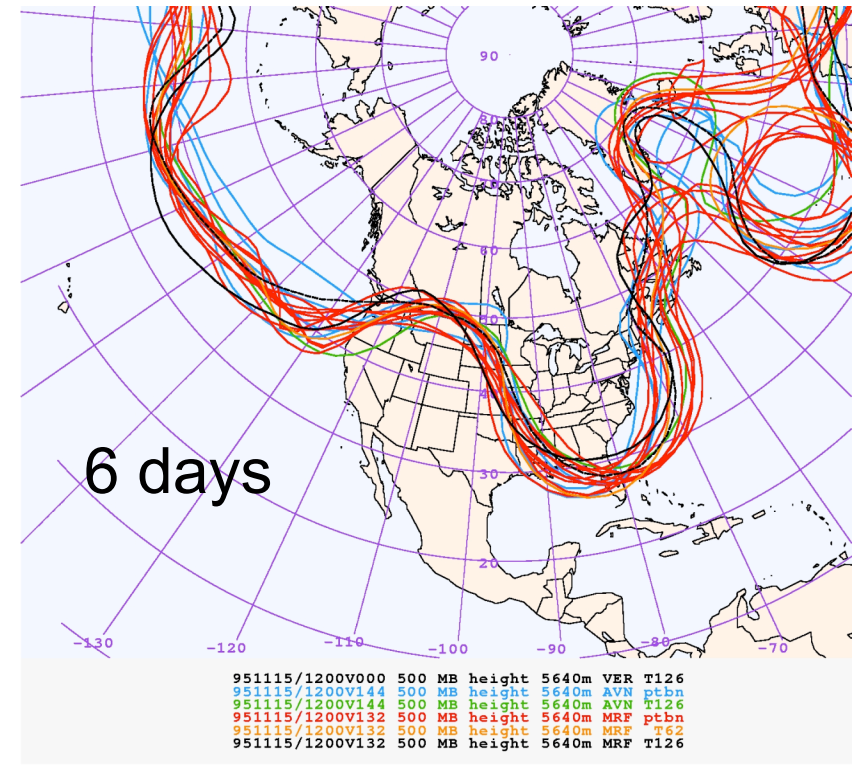
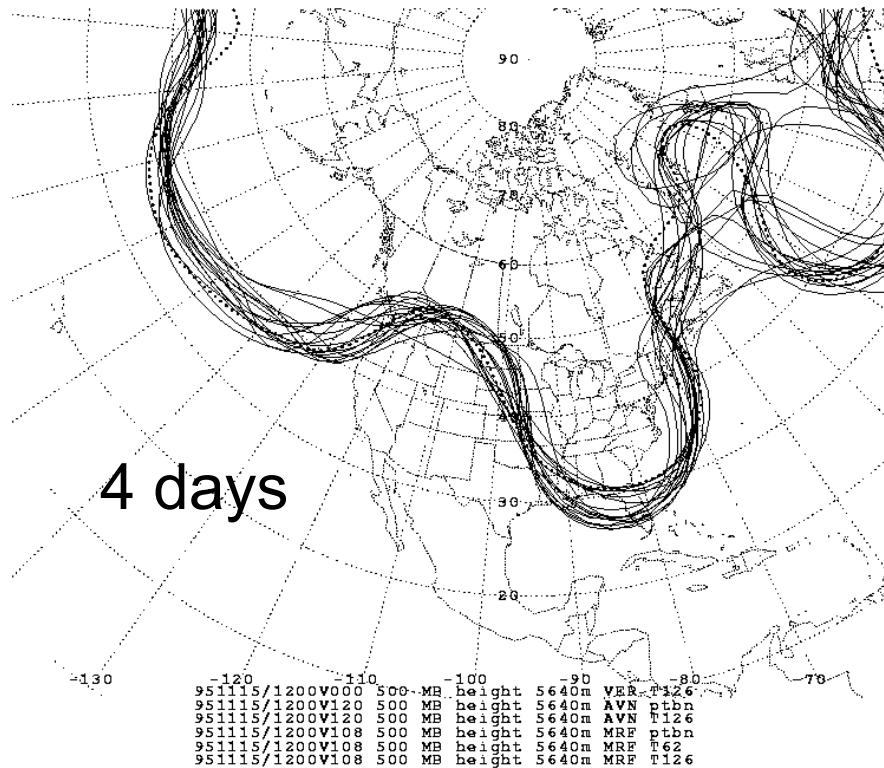
Example of a **very predictable 6-day** forecast, with “errors of the day”



**It shows the growing atmospheric perturbations: the instabilities of the atmospheric flow are the “errors of the day” or bred vectors**

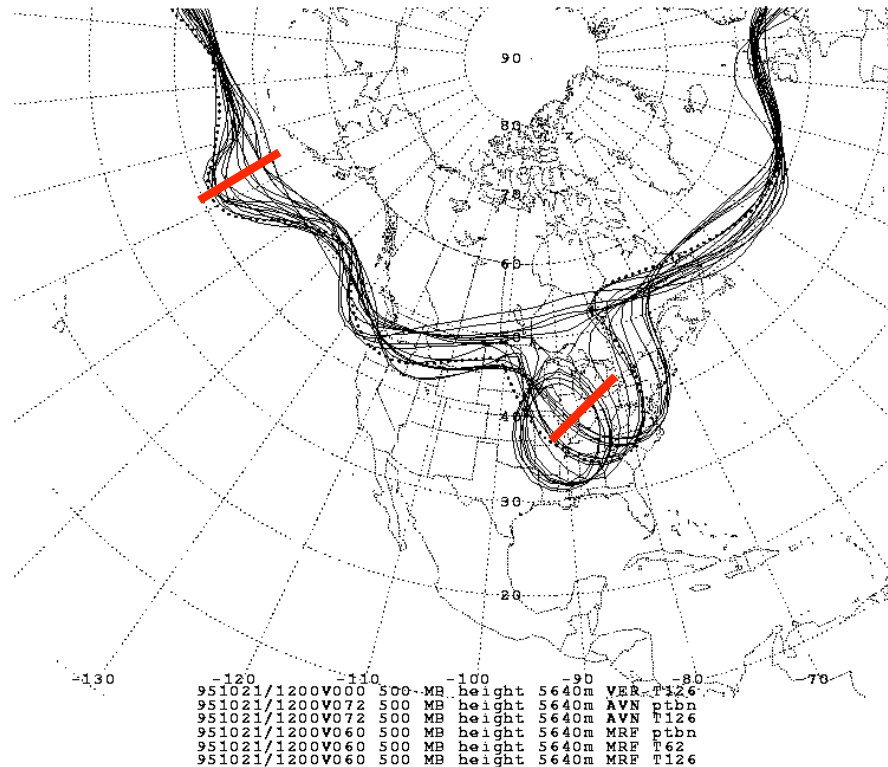


The errors of the day are instabilities of the background flow. At the same verification time, the forecast uncertainties have *the same shape* 4 days and 6 days ensemble forecasts verifying on 15 Nov 1995





Strong instabilities of the background have simple shapes (perturbations lie in a low-dim 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)

# Deterministic Chaos...

In 1951 Charney indicated that NWP forecast skill would break down after a few days, but he attributed this to model errors and errors in the initial conditions...

In the 1950's and 60's the forecasts were skillful for only one or two days.

Statistical prediction skill was equal or better than dynamical predictions.

Until recently this has been also true for El Niño (ENSO) predictions!

Lorenz (1950's) wanted to show that statistical prediction could not match prediction with a nonlinear model for the Tokyo (1960) NWP conference

So, he tried to find a model with non-periodic solutions (otherwise statistics would win!)

He programmed in machine language on a 4K memory, 60 ops/sec Royal McBee computer

He developed a low-order model (12 d.o.f) and changed the parameters and eventually found a nonperiodic solution

Printed results with 3 significant digits (plenty!)

Tried to reproduce results, went for a coffee and

He discovered Chaos!

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

Has two regimes and the transition between them is  
chaotic

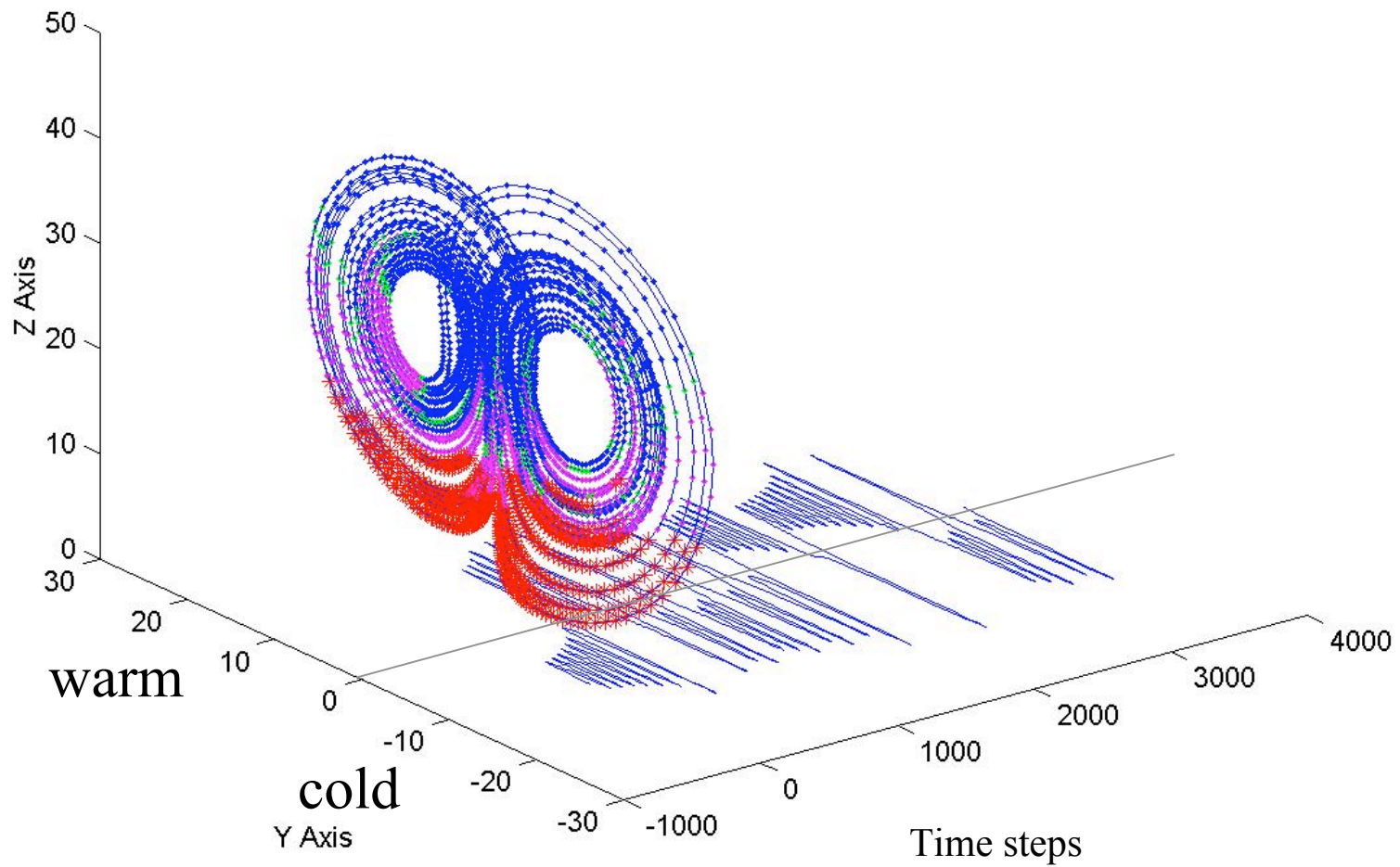
$$\frac{dx}{dt} = \sigma(y - x)$$

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

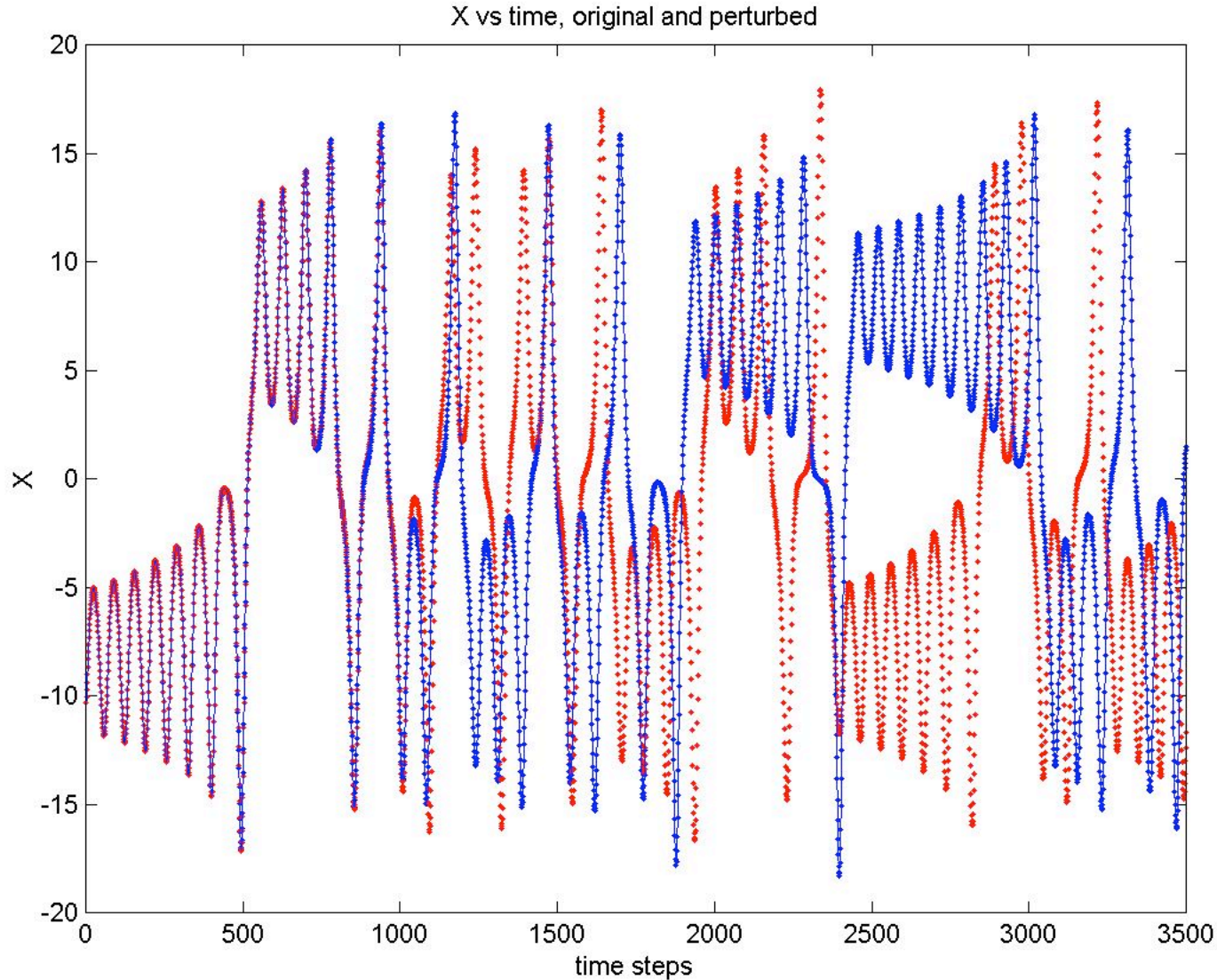
$$\frac{dz}{dt} = xy - bz$$



# Example: Lorenz (1963) model, $y(t)$



Lorenz introduced an infinitesimal perturbation in the initial conditions, and the two solutions diverged



Lorenz (1963) discovered that even with a **perfect model** and **essentially perfect initial conditions** the forecast loses all skill in a **finite time interval**: “A butterfly in Brazil can change the forecast in Texas after one or two weeks”.

**In the 1960's this was only of academic interest: forecasts were useless in two days**

Now, we are getting closer to the **2 week limit of predictability**, and we have to extract the maximum information from a chaotic forecast

# Definition of Deterministic Chaos

(Lorenz, March 2006, 89 yrs)

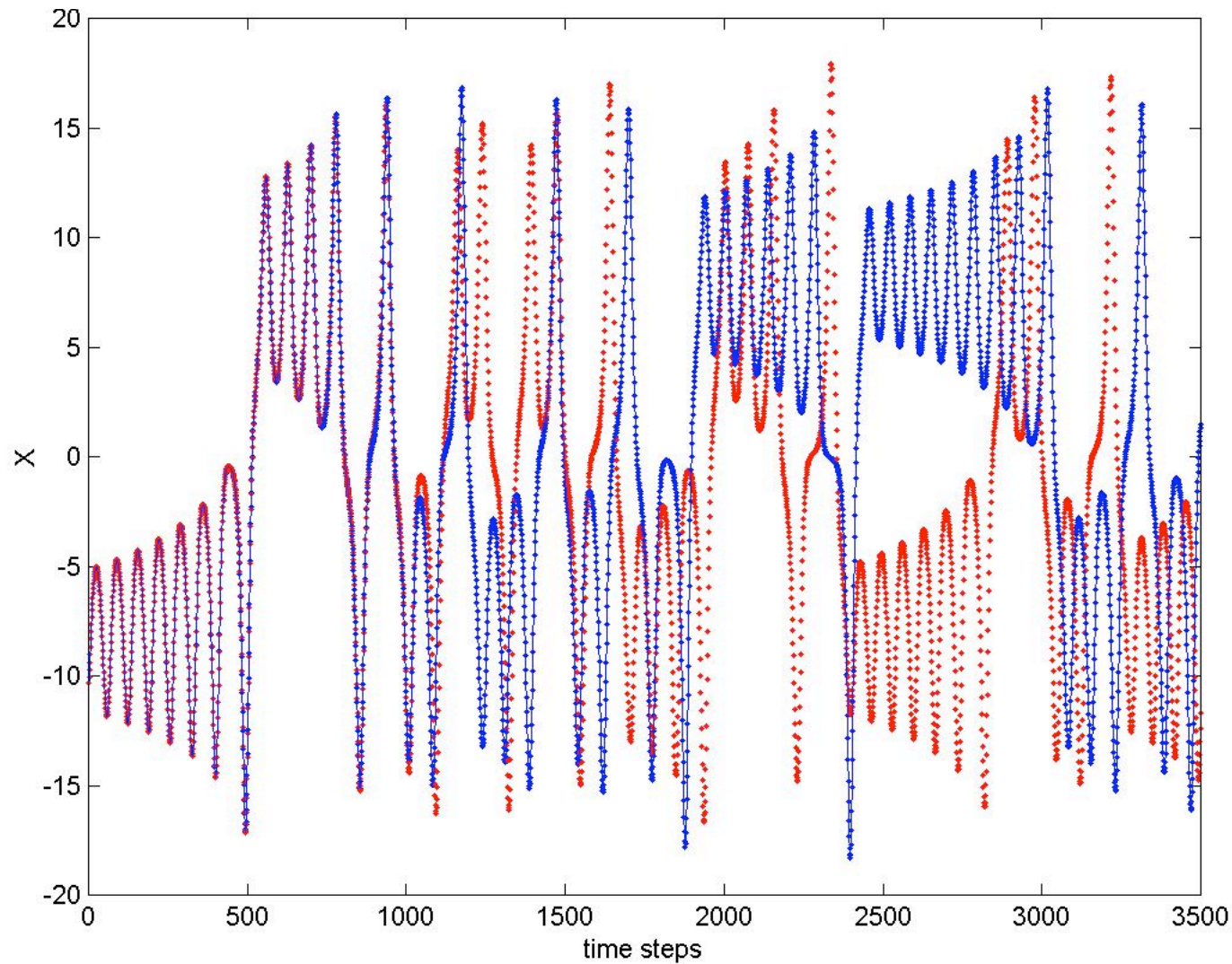
**WHEN THE PRESENT DETERMINES  
THE FUTURE**

**BUT**

**THE APPROXIMATE PRESENT DOES NOT  
APPROXIMATELY DETERMINE THE FUTURE**



We introduce an infinitesimal perturbation  
in the initial conditions and soon the  
forecast **loses all skill**



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

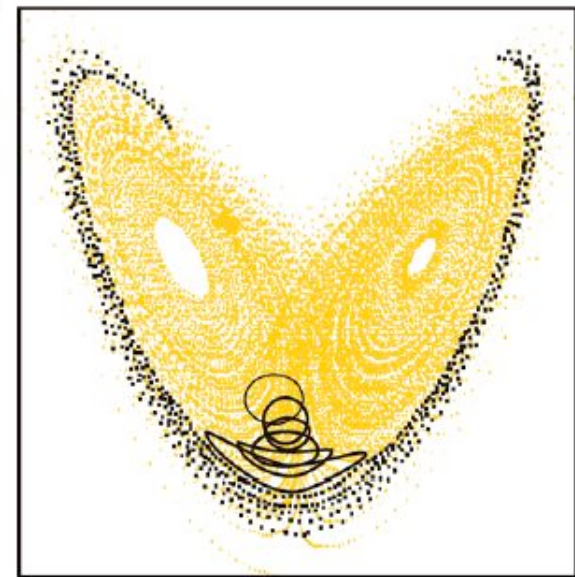
stable



less stable



unstable



A “ball” of perturbed initial conditions is followed with time. Errors in the initial conditions that are unstable (with “errors of the day”) grow much faster than if they are stable

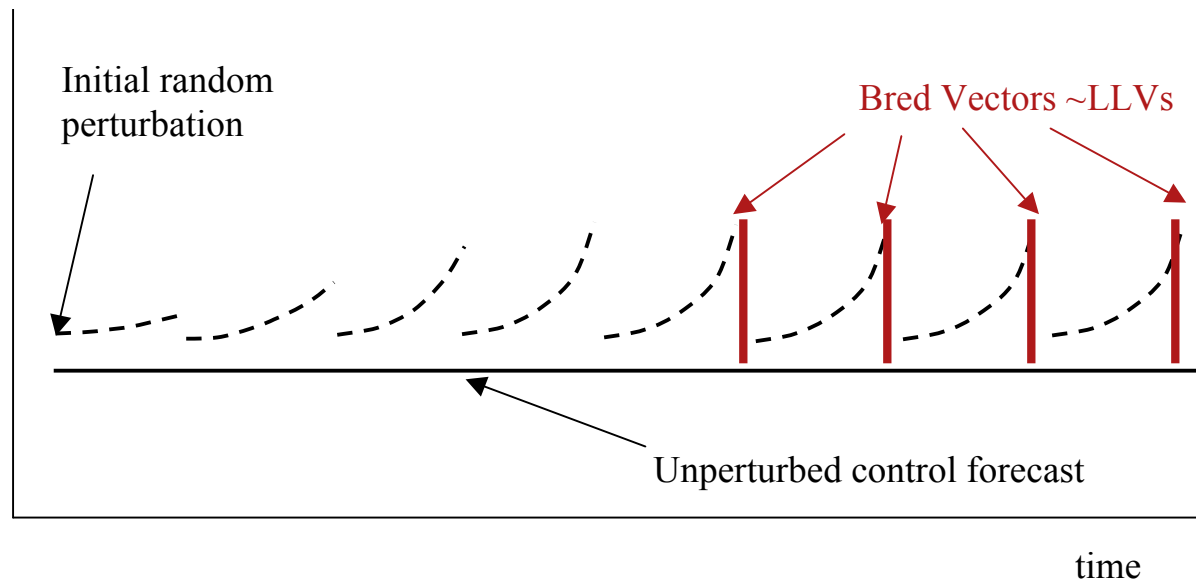
## An 8 week RISE project for undergraduate women (2002)

- 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

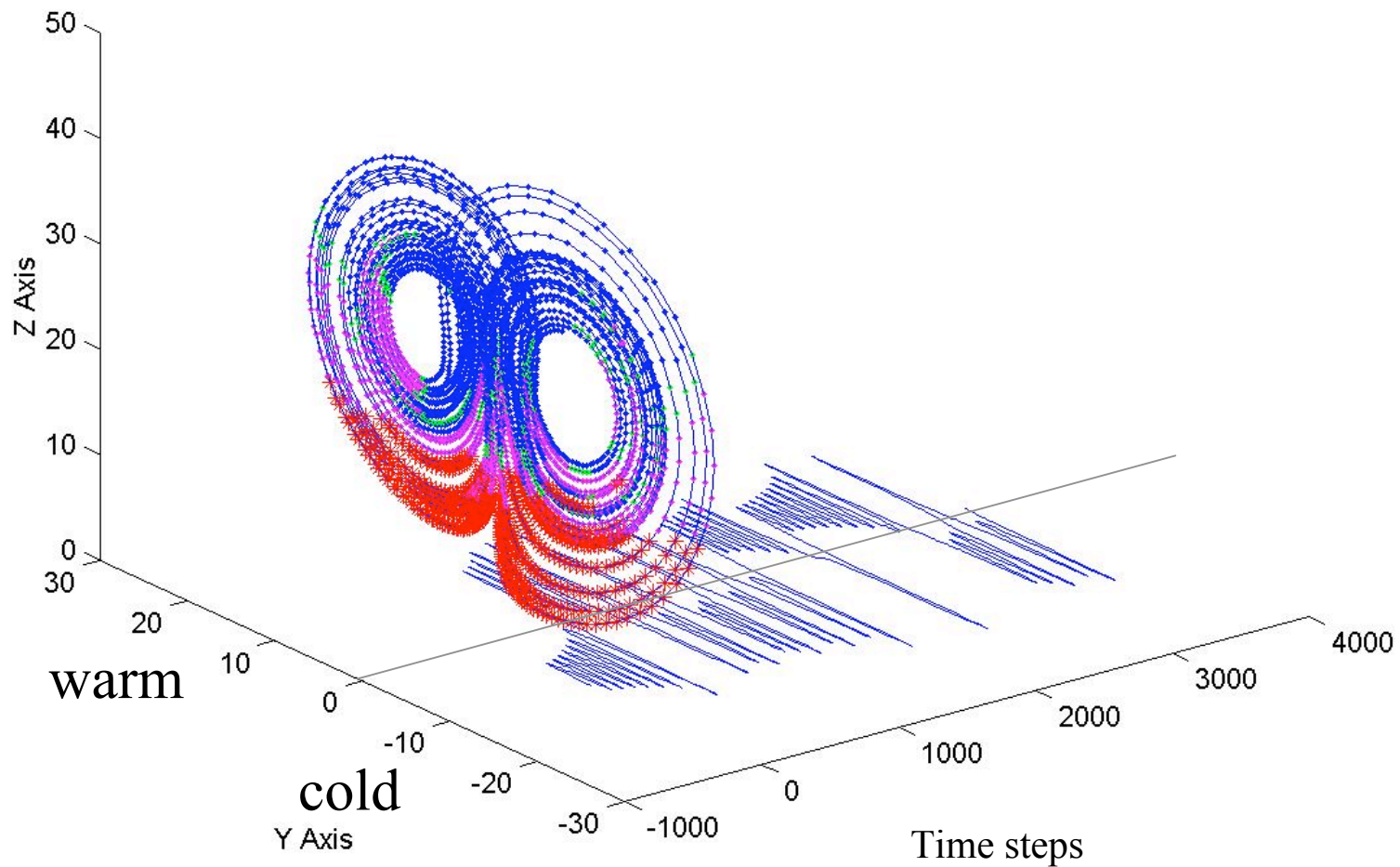
Forecast values



Local breeding growth rate:

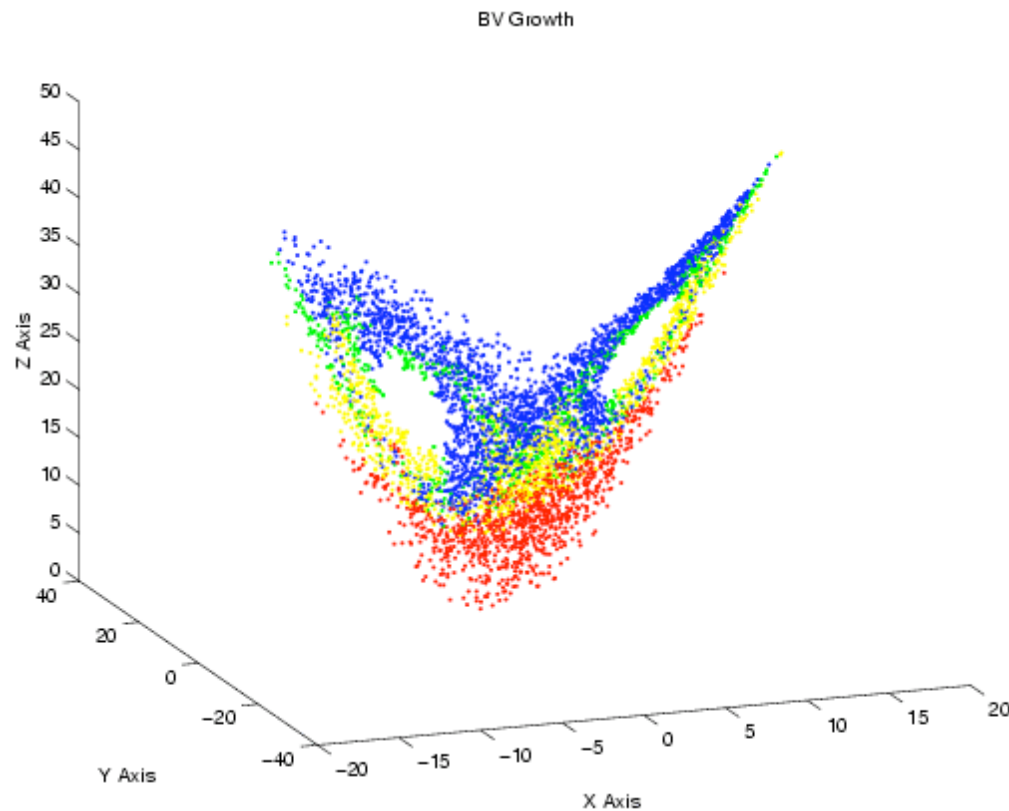
$$g(t) = \frac{1}{n\Delta t} \ln \left( \frac{|\delta \mathbf{x}|}{|\delta \mathbf{x}_0|} \right)$$

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:

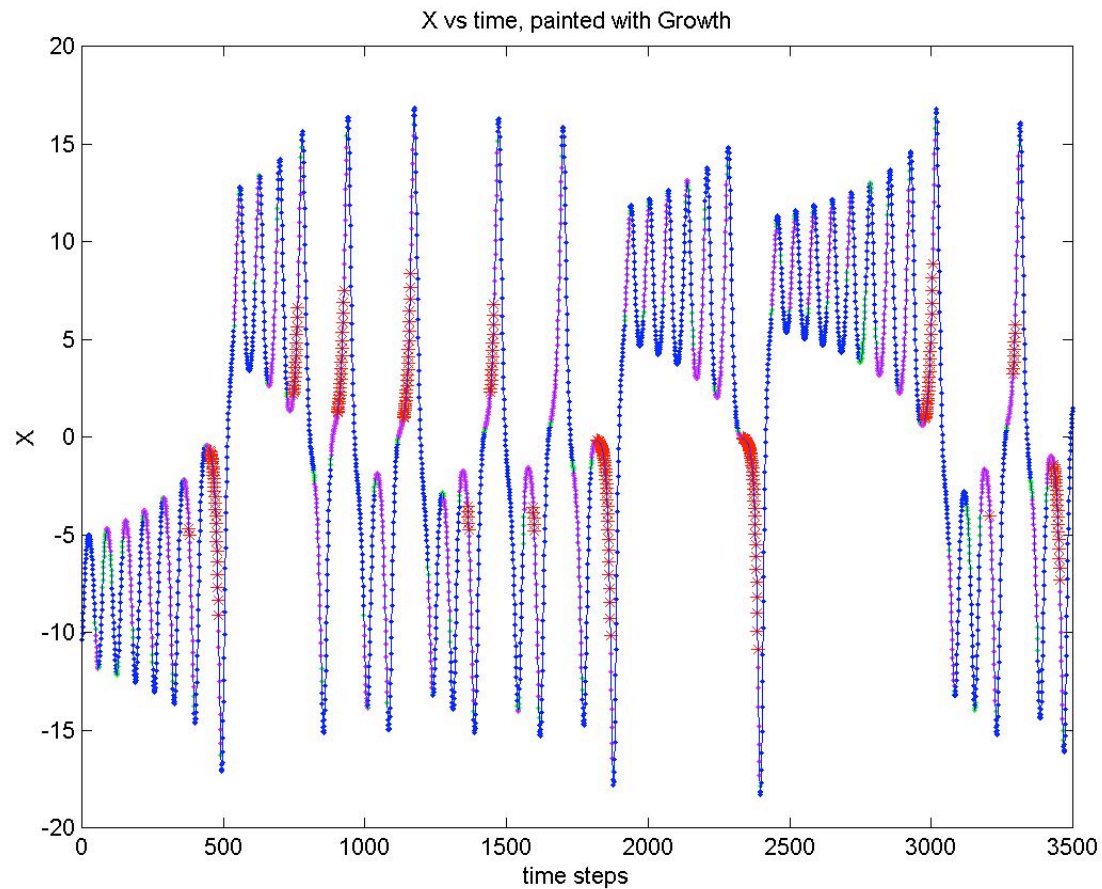


Bred Vector Growth:  
red, high growth;  
yellow, medium;  
green, low growth;  
blue, decay

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:

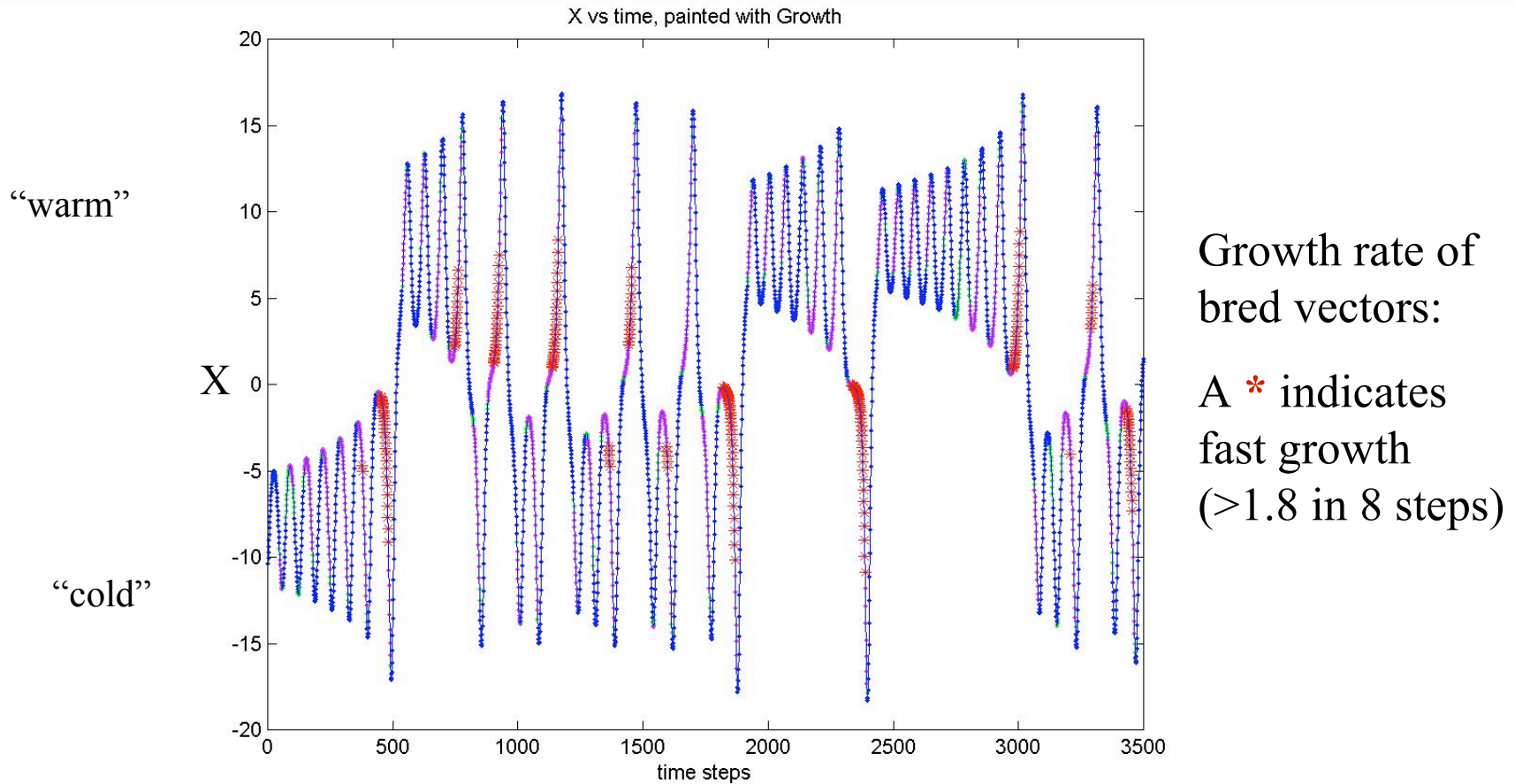
This looked promising, so we asked the interns to “paint”  $x(t)$  with the bred vector growth, and the result almost made me faint:



Growth rate of bred vectors:

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

# Forecasting rules for the Lorenz model:

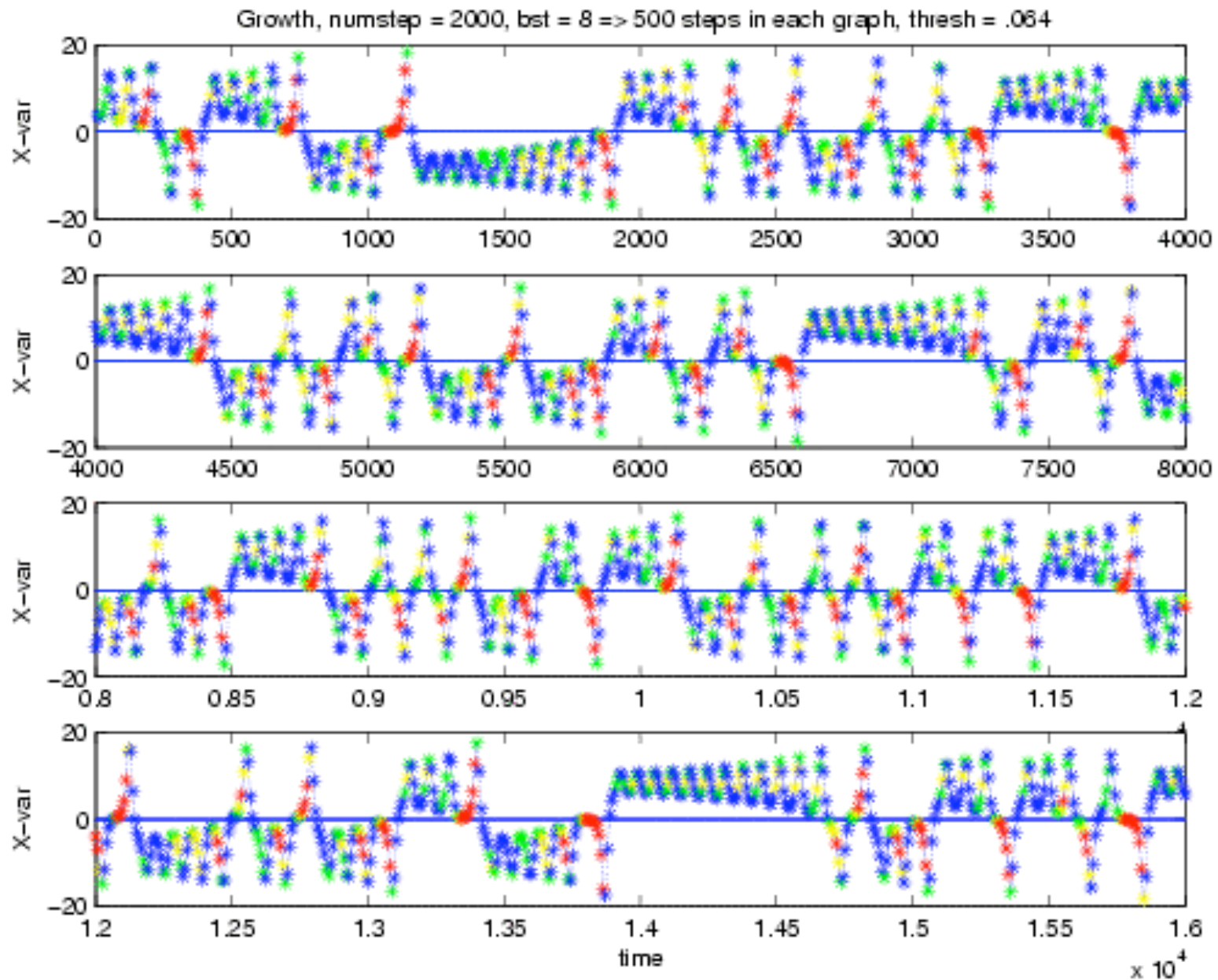


Regime change: The presence of red stars (fast BV growth) indicates that the next orbit will be the last one in the present regime.

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%

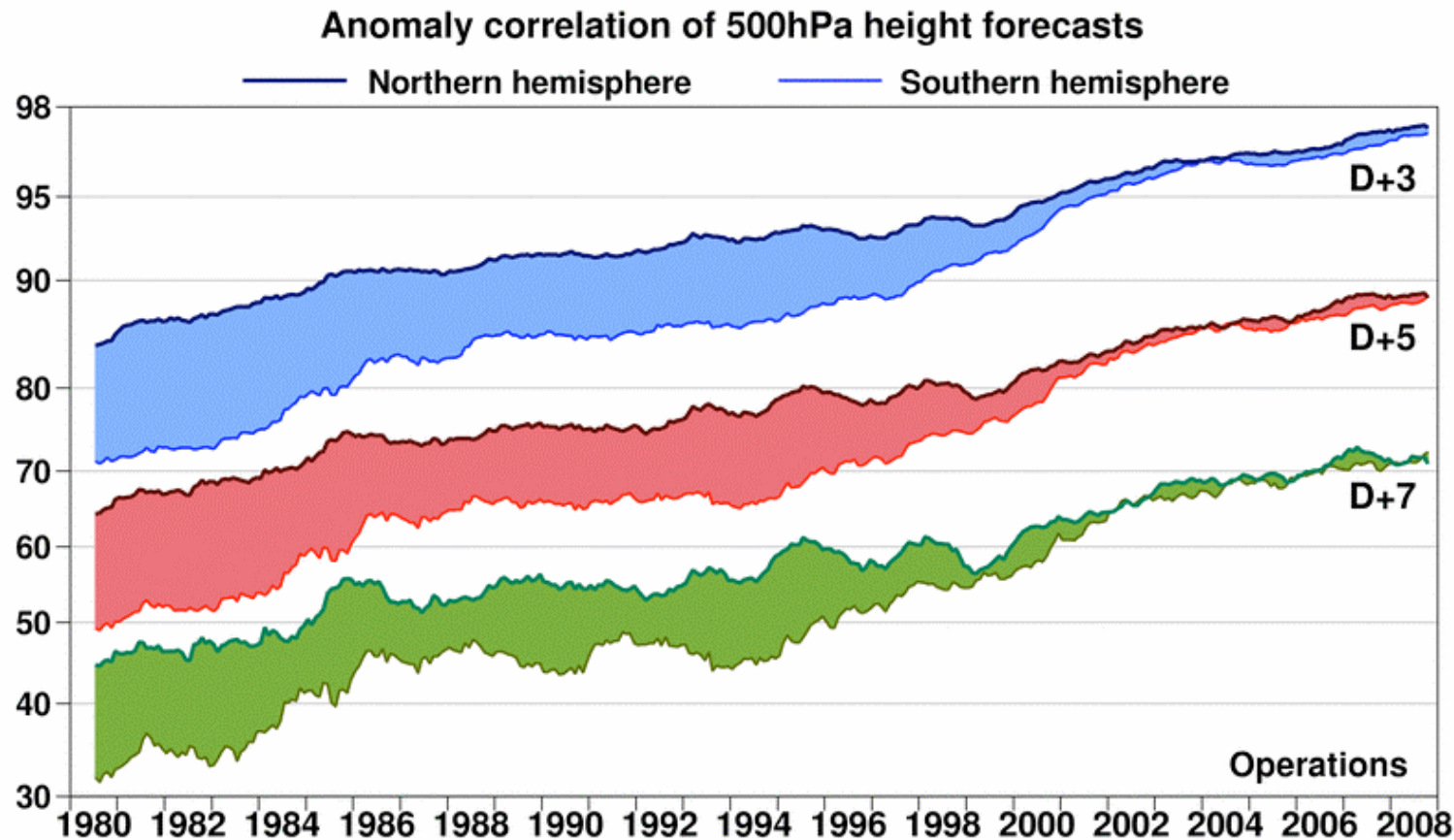




# Summary

- Charney made the first successful NWP, Lorenz discovered “chaos” at about the time IMO => WMO:
- Instabilities (“errors of the day”) make the atmosphere unpredictable beyond two weeks.
- All perturbations evolve to the most unstable shape (Lyapunov Vectors ~ Bred Vectors).
- Breeding in the Lorenz (1963) model gives accurate forecasting rules for the “chaotic” regime change and duration that surprised Lorenz himself!
- With ensemble forecasting, we “fight chaos”, and we can estimate predictability in space and time.
- Can be applied to fast convective storms and to slower ocean-atmosphere instabilities (ENSO).
- Ensemble Kalman Filter also “fights chaos” and is now competitive with 4D-Var.

# Example of NWP success: operational forecasts from ECMWF



Updated from  
Simmons and  
Hollingsworth,  
2002

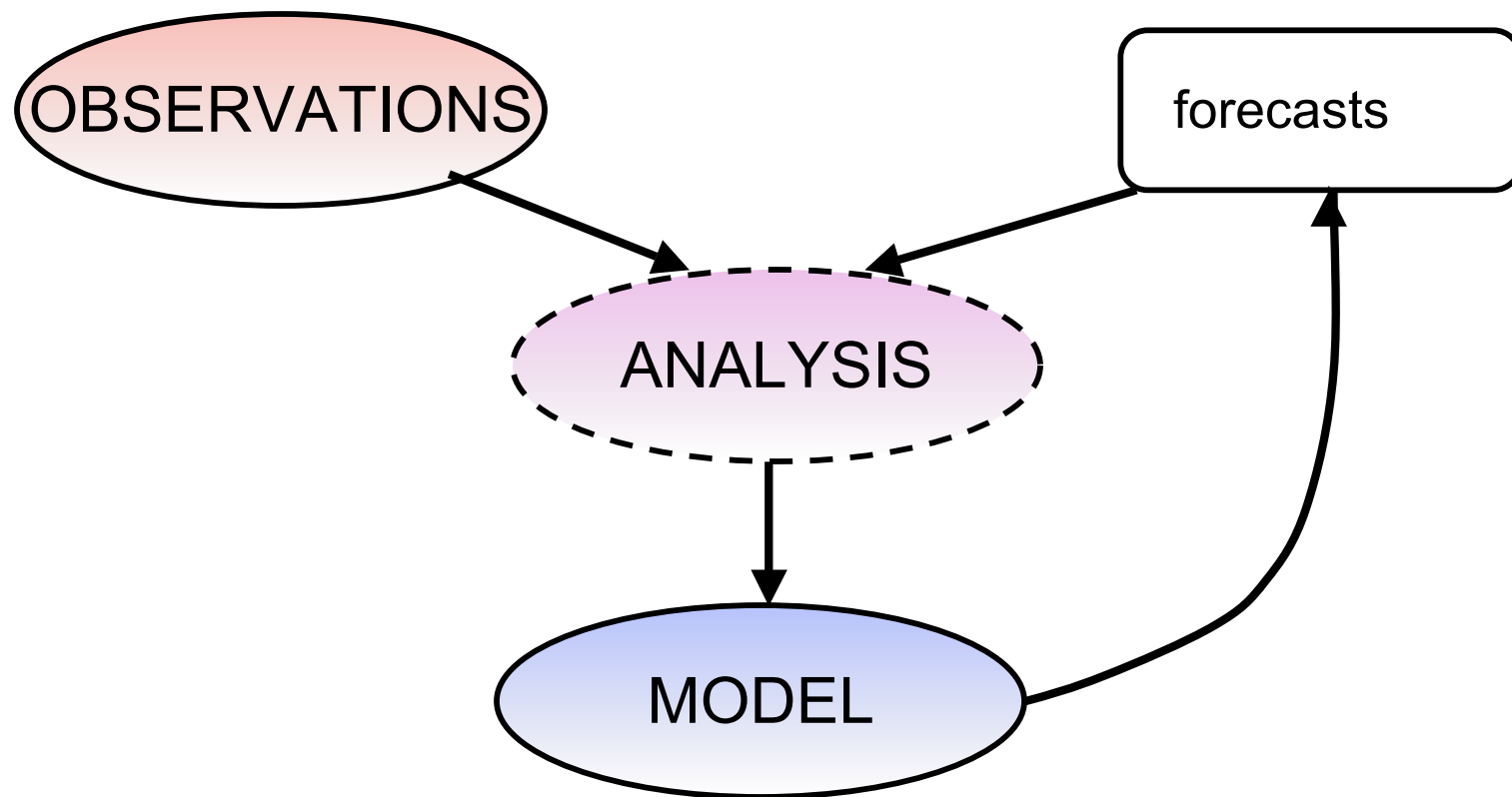
Improvements over time are due to:

- Model improvements
- Data improvements
- Assimilation method improvements (**4D-Var**)

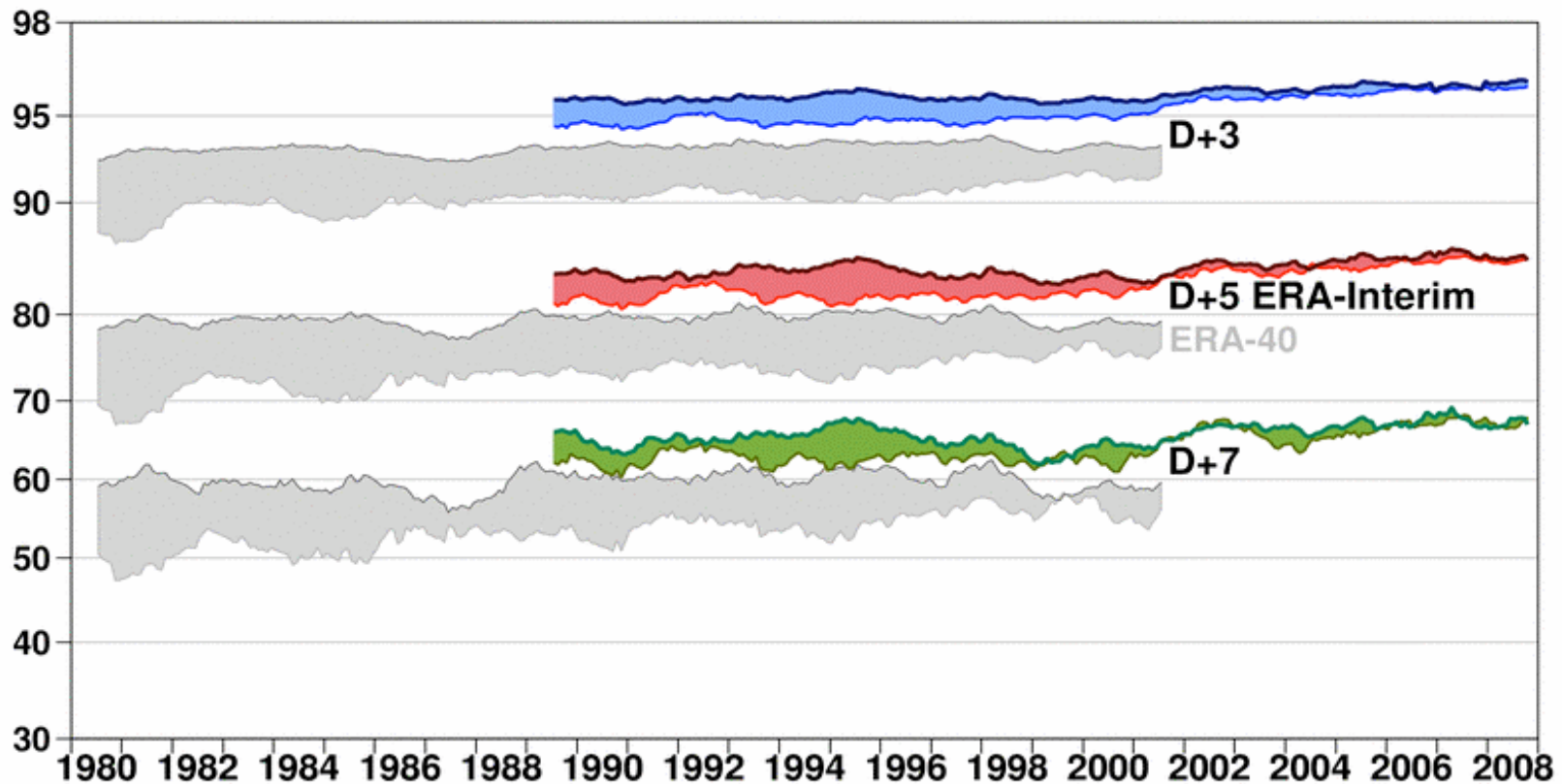
Note how SH caught up with NH in forecast skill!

Data assimilation: We need to continue improving  
observations, analysis and models

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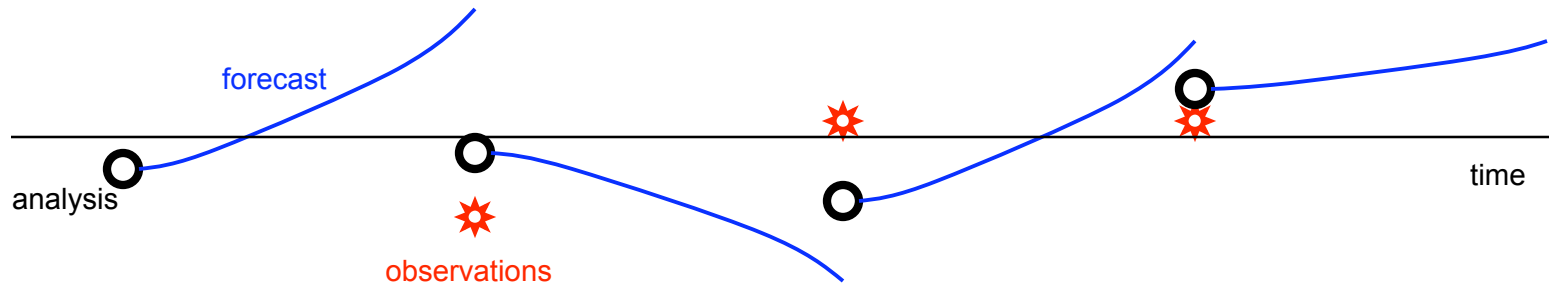


## ERA-Interim (4D-Var) vs. ERA-40 (3D-Var) (Dee, 2009)



ERA-Interim and ERA-40 used exactly the same observations, so the improvement reflects 5 years of development in modeling and data assimilation

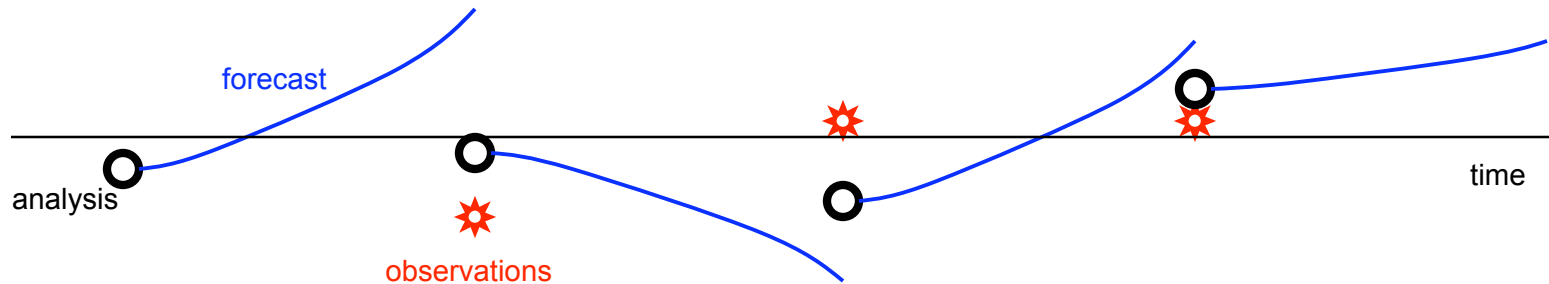
# DATA ASSIMILATION



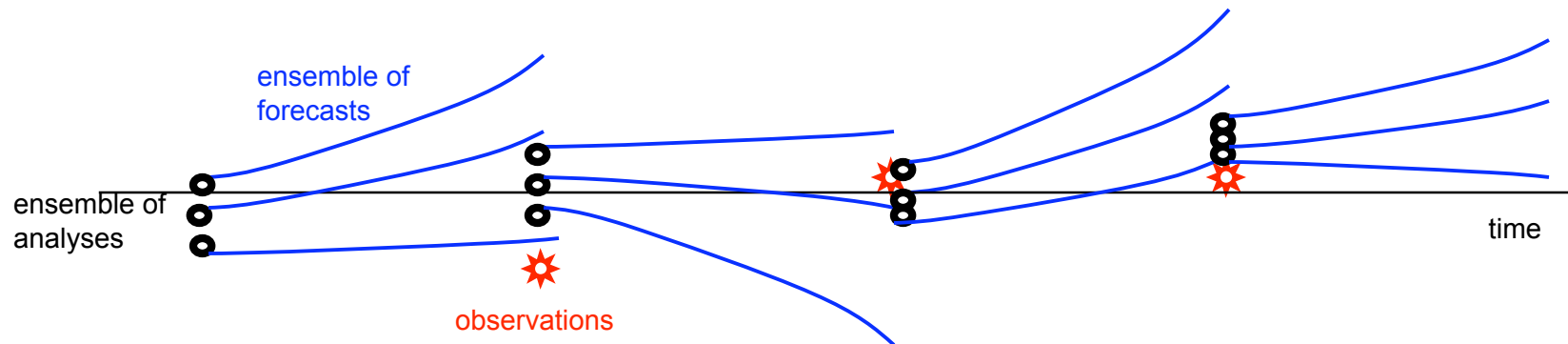
The analysis combines the model **forecast** with **observations**.



# DATA ASSIMILATION: EnKF



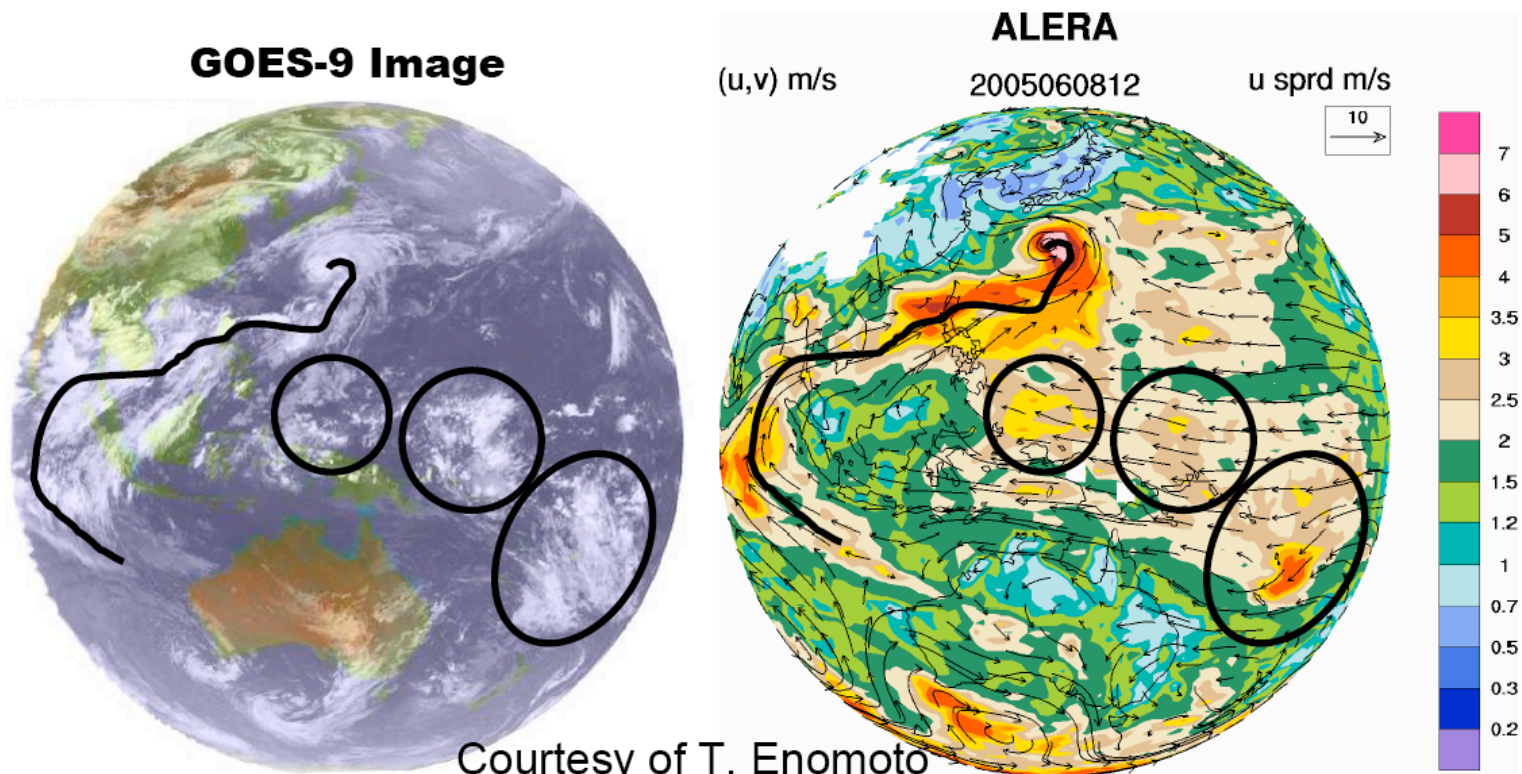
## Ensemble Kalman Filter



The analysis combines the model **forecast** with **observations**.  
The ensembles give the **uncertainty** of the forecast and analysis:  
they provide the **error covariance matrix** between all variables.

# The EnKF gives the uncertainty in the analysis!

(ALERA: AFES-LETKF Experimental Reanalysis)



Courtesy of T. Enomoto  
and Takemasa Miyoshi

## Status of “4D-Var and/or EnKF?”

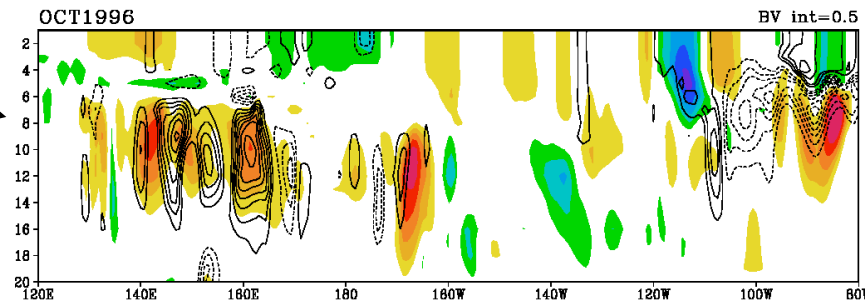
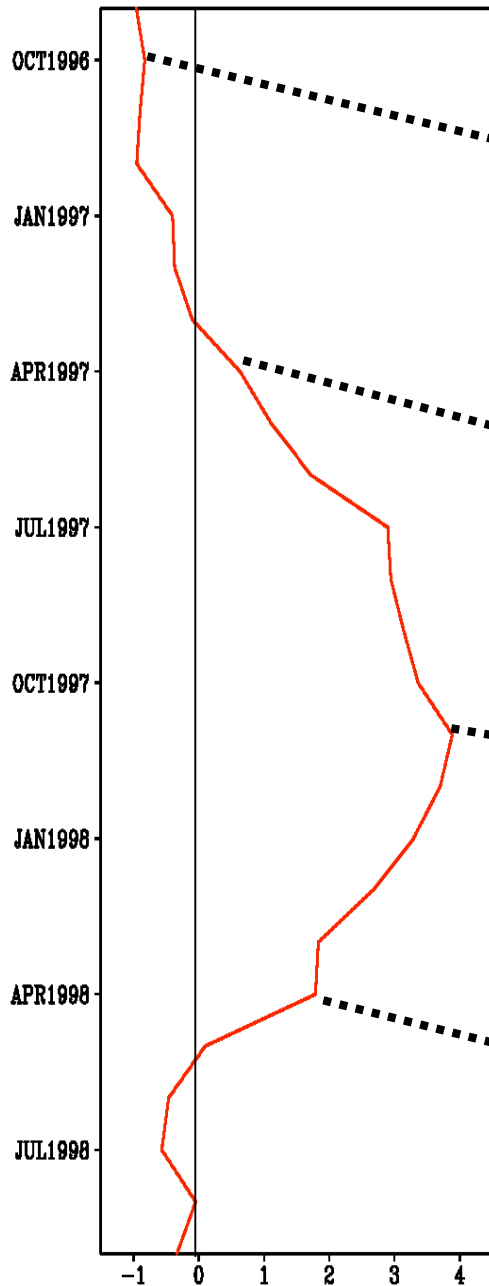
- 4D-Var and EnKF have similar skill (Workshop in Buenos Aires, November 7-10, 2008, Buehner et al., 2009a, b). Canada implemented both 4D-Var and EnKF!
- EnKF has several diagnostic advantages.
- Currently several operational weather centers are also exploring EnKF:
  - JMA
  - Brazil
  - United States
  - Italy
  - Germany
  - ECMWF (for diagnostic studies only)
- **Hybrids** (Var-EnKF) may be optimal.

# ENSO Prediction

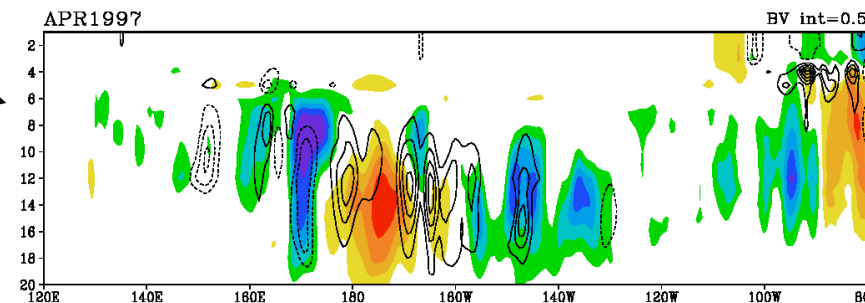
- ENSO is an instability of the coupled ocean-atmosphere
- The same ideas apply but with the longer seasonal and interannual time scales of El Niño
- As in the beginning of NWP, statistical models had more skill than dynamical models for ENSO.
- This is because statistical models are not affected by model errors.
- Now, as in NWP, dynamical coupled ocean-atmosphere models have improved enough to be better than statistical models.

## Niño3 index

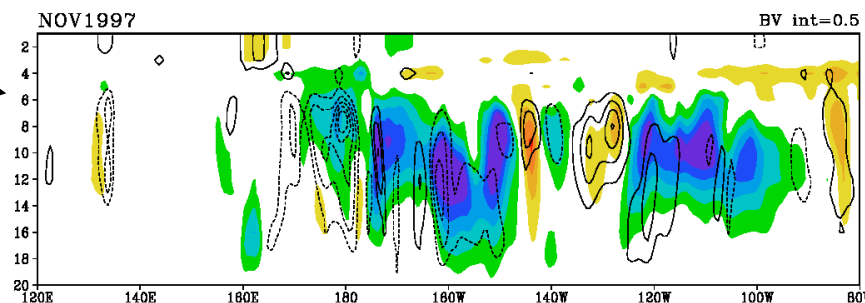
## Yang (2005): Vertical cross-section at Equator for BV (contours) and 1 month forecast error (color)



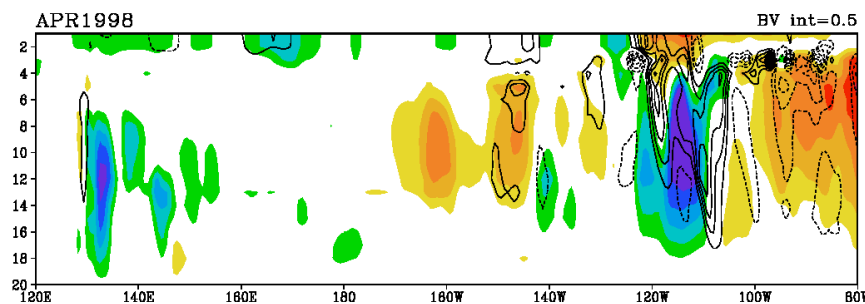
Before 97' El Niño, error is located in W. Pacific and near coast region



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



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

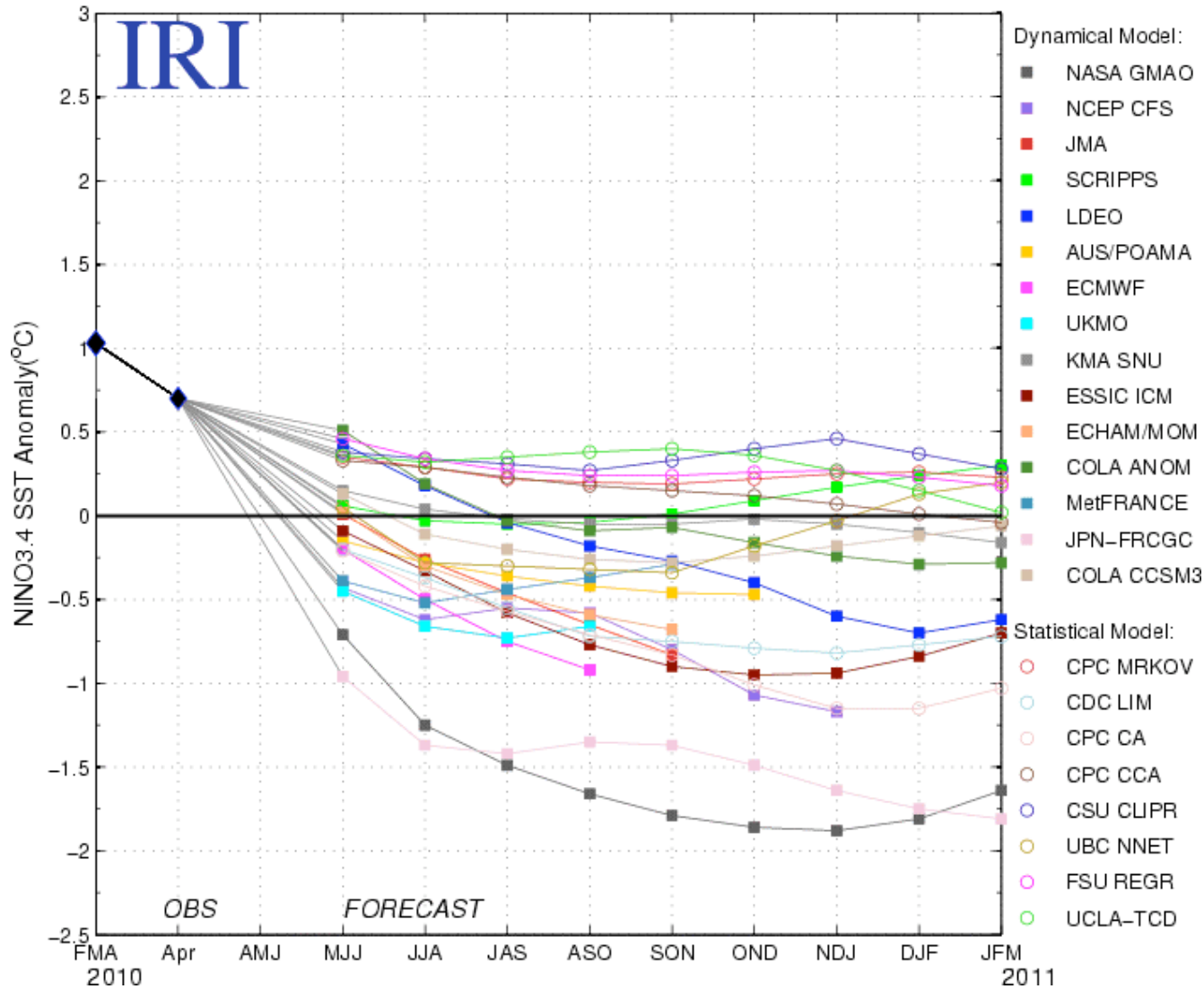


After the event, error is located mostly in E. Pacific.



# ENSO current prediction

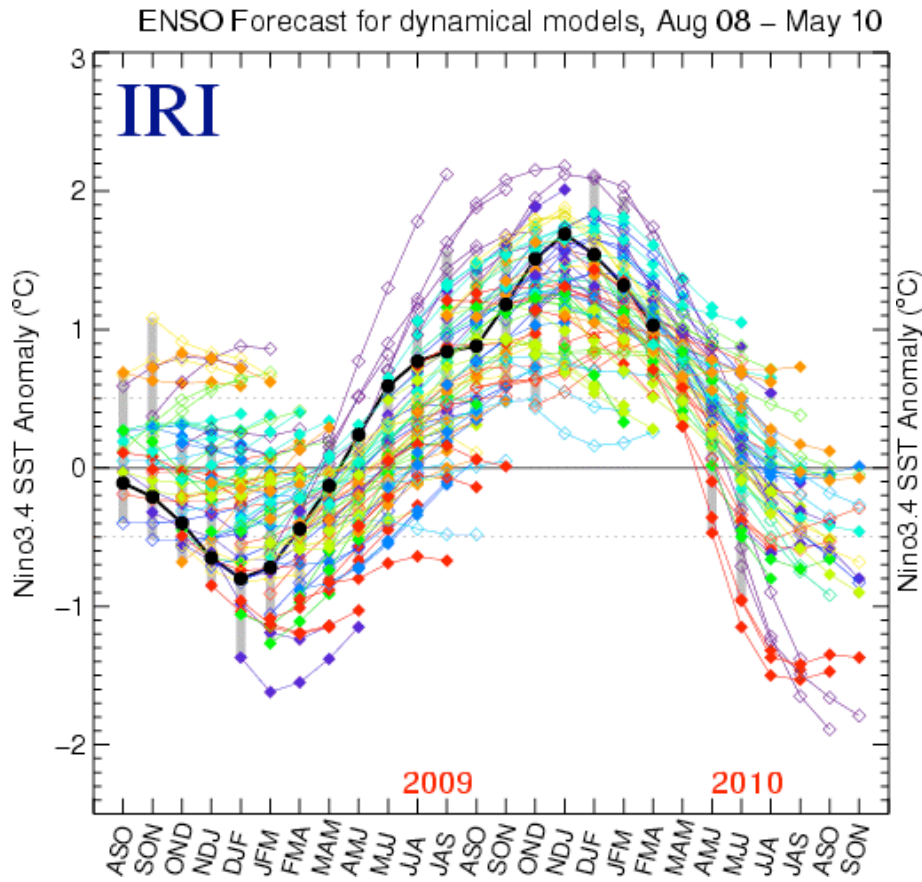
Model Forecasts of ENSO from *May 2010*



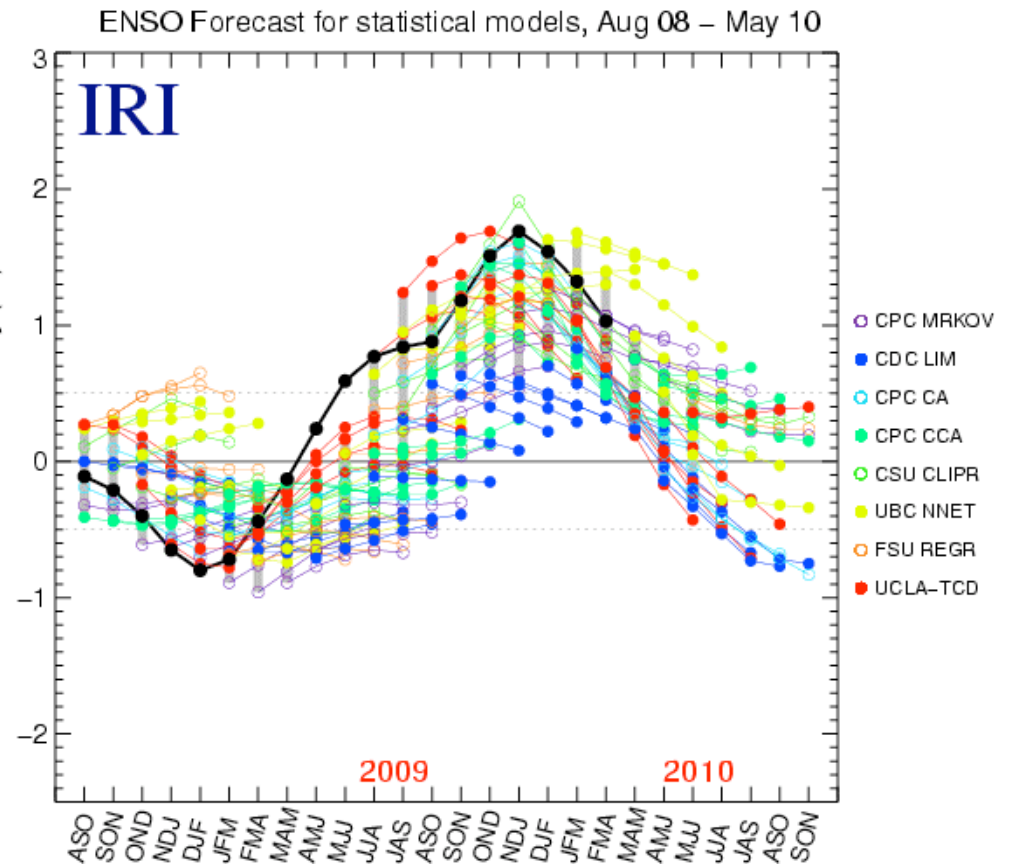
Dynamical  
model  
forecasts

Statistical  
model  
forecasts

# ENSO Predictions (6 months)

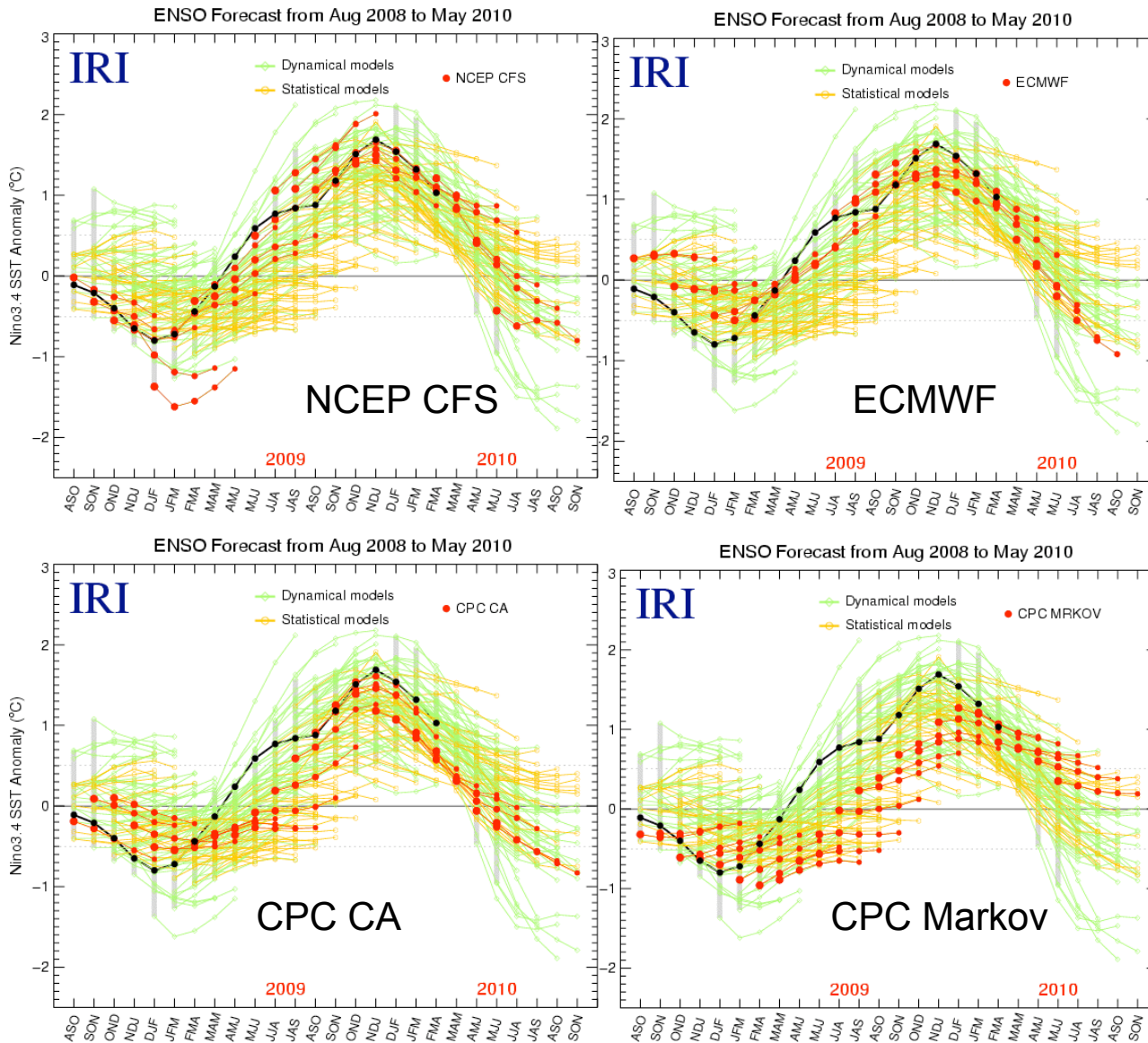


Dynamical forecasts:  
have more courage!



Statistical forecasts:  
go to zero with time

# How do the ENSO predictions compare?



Two very good dynamical coupled models: NCEP and ECMWF

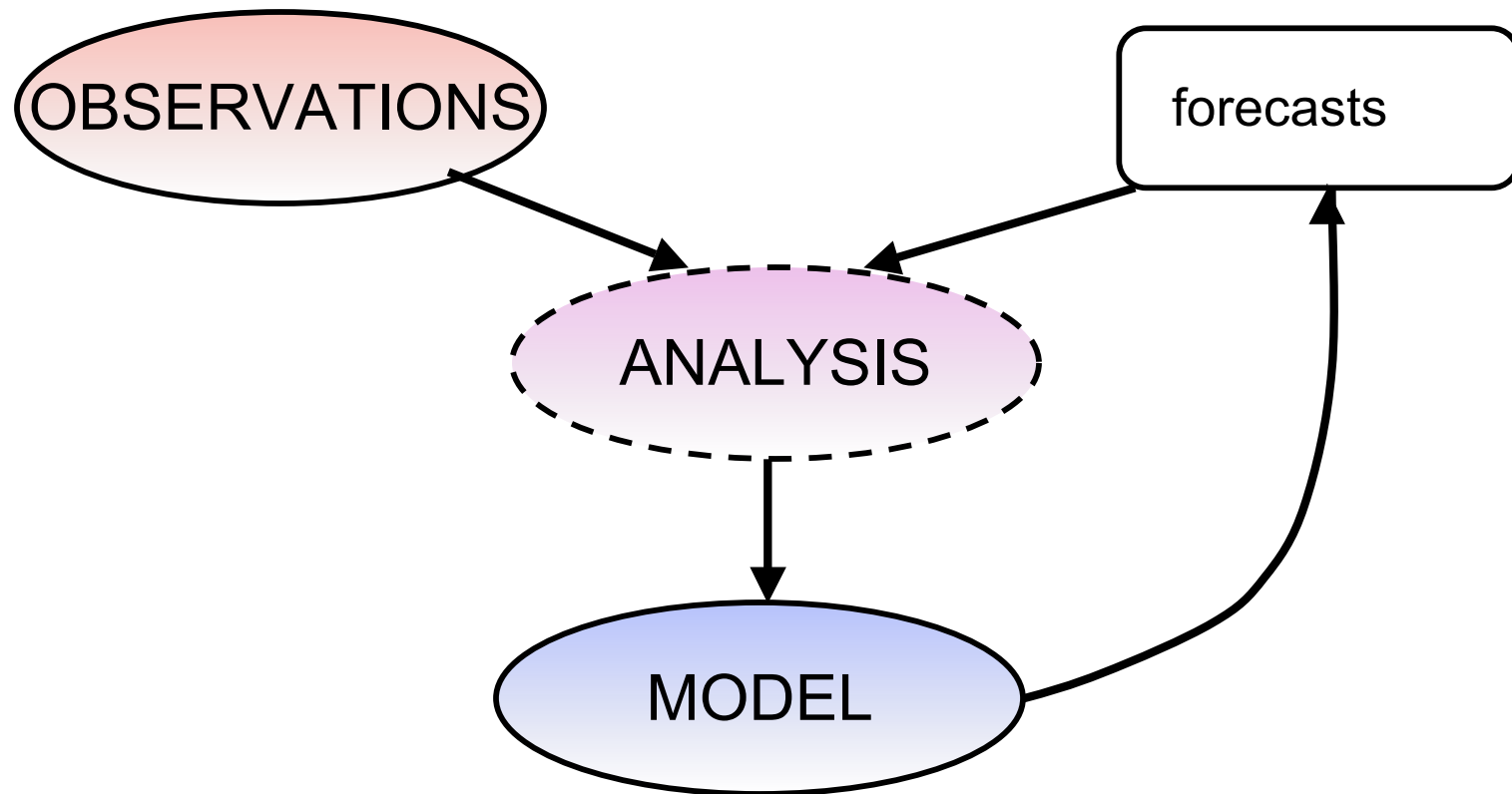
Two very good statistical models: CPC Constructed Analog and Markov

# Summary

- IMO=> WMO on 23 March 1950... this was at the time of the beginning of NWP (Charney et al. 1950) and Chaos theory (Lorenz, 1960, Tokyo).
- Forecast errors grow through instabilities and model errors.
- We can predict changes of regime and their duration for the Lorenz “unpredictable” model.
- We have learned to “fight chaos” with ensembles.
- Similar ideas can be applied to the ENSO coupled instabilities
- Initially statistical methods were better than dynamical models, but models are now better.
- Ensemble Kalman Filter data assimilation also “fights chaos”, and is now competitive with 4D-Var.

There is still a lot to do: We need to continue improving **observations**, **analysis** and coupled **models**

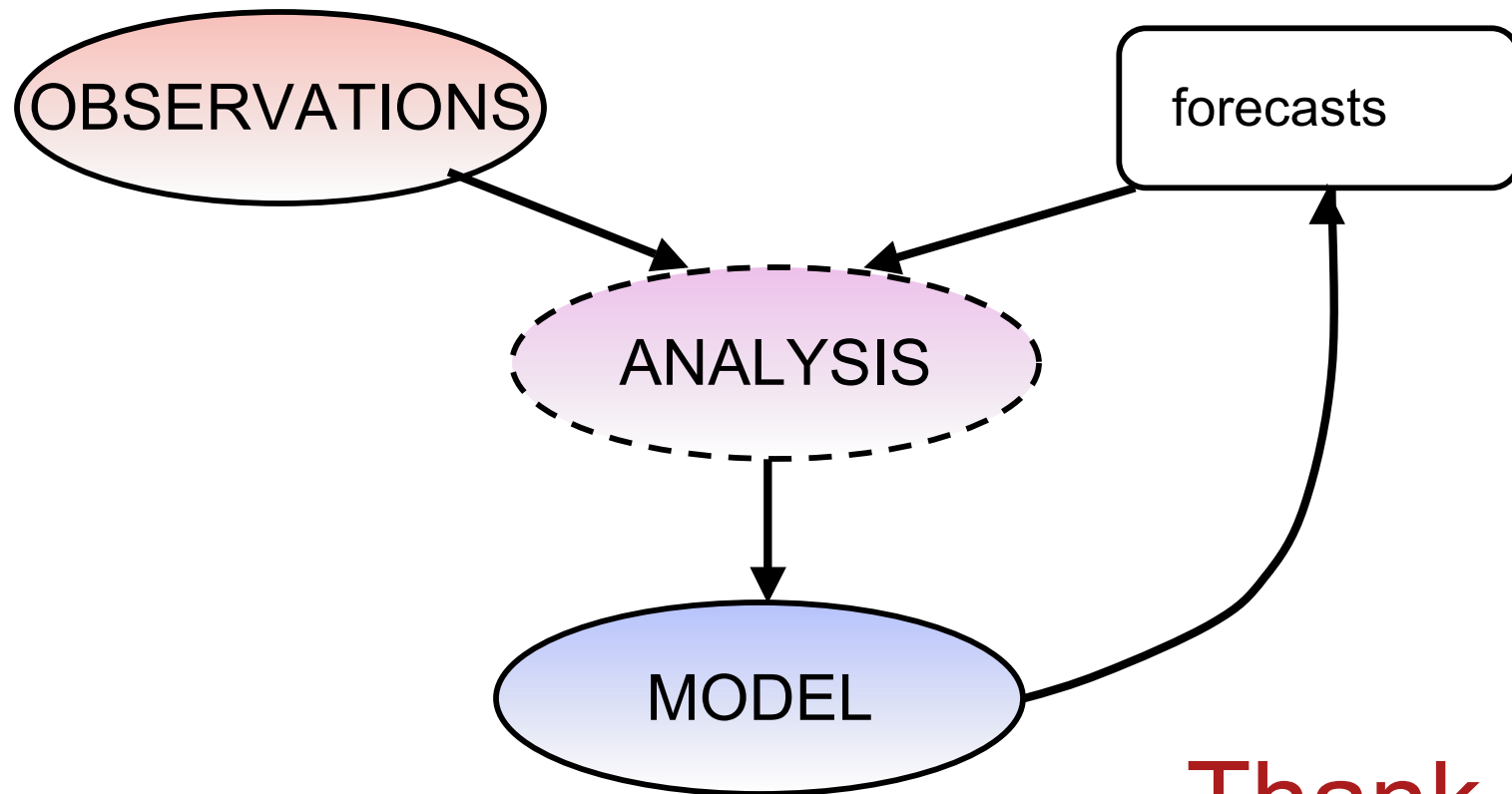
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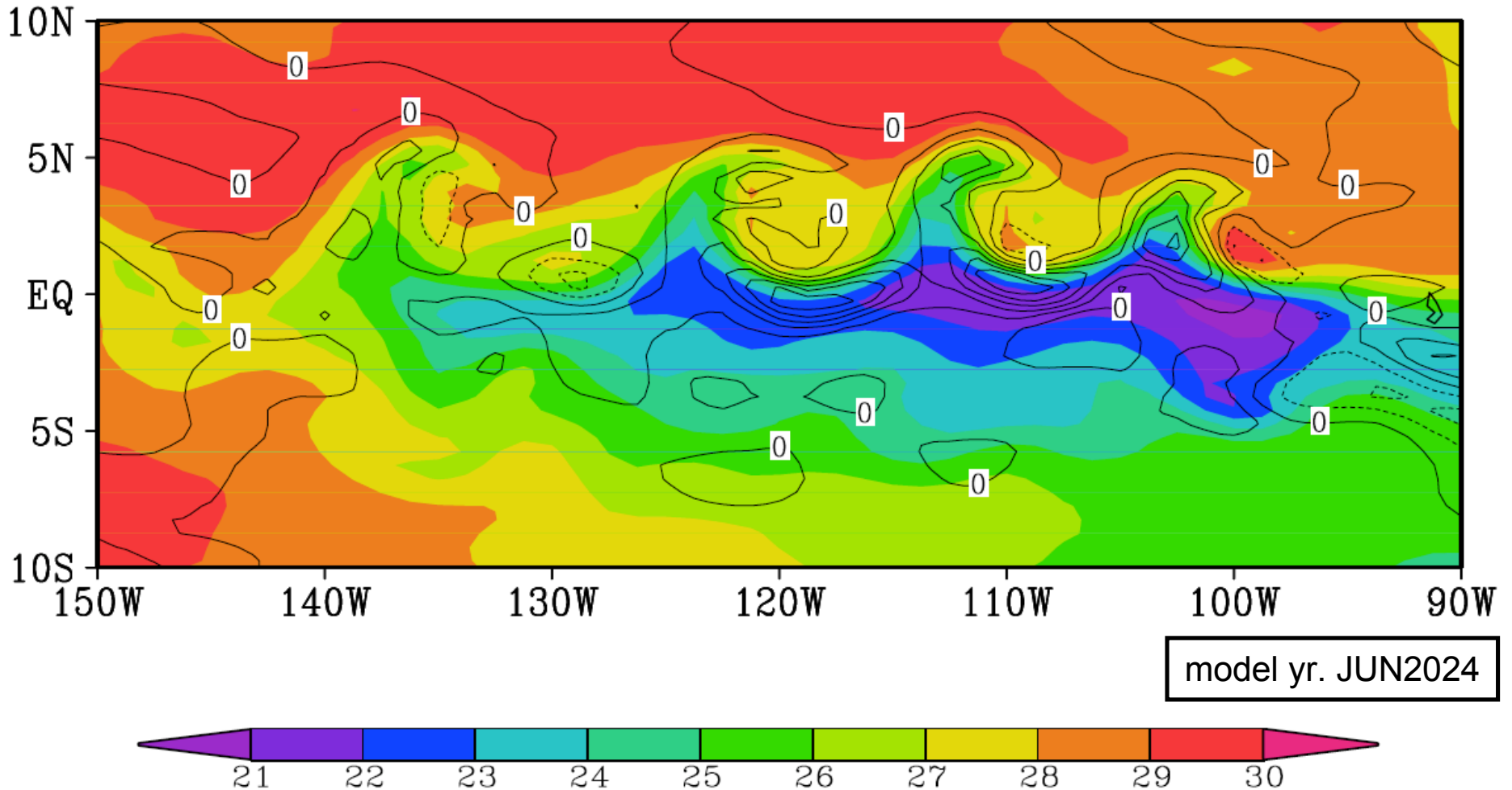
There is still a lot to do: We need to continue improving **observations**, **analysis** and coupled **models**

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**Thank you!**

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



# Example of a good and a bad ensemble

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”

The “bad” ensemble is still useful: it shows there is a model or a system error

