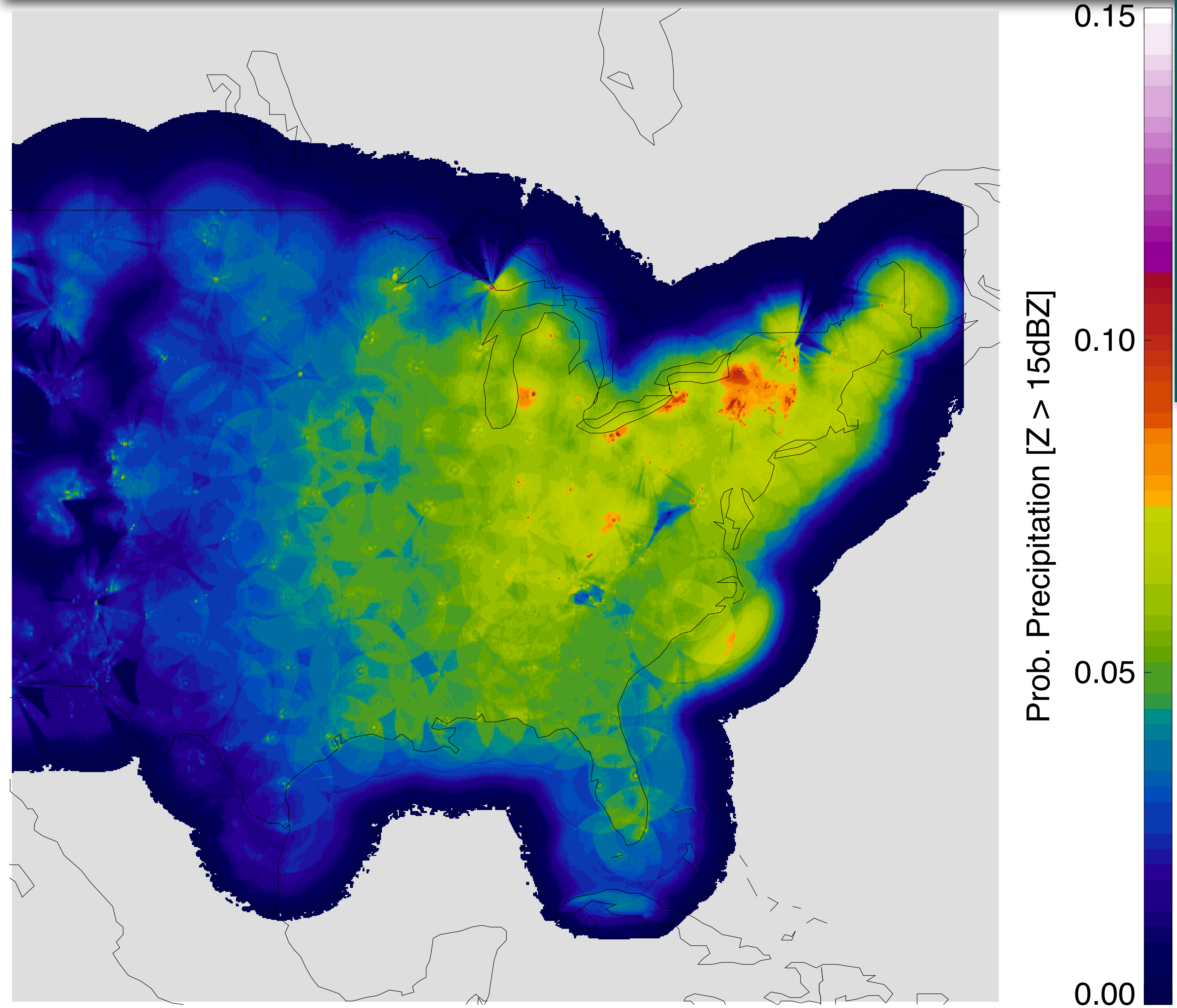
Why do we seek help from “big data” in nowcasting of precipitation?

Data description,
Introduction,
Motivation
Research presentation

Radar Data

Used here: 17 years of quasi-continuous records.

Reflectivity at a resolution 4x4 km², every 15min.



PLUS

NSEP Reanalysis

Data every 3h

The NWP model data

Ming Xue

Description of the CAPS SSEF ensembles. All ensemble members, except one, assimilate radar data.

Year	Forecast length	IC/LBC/PHYS	MP only	PBL only	Miscellaneous
2008	30h	8 members; MP : Thompson, Ferrier, WSM6; SW : Dudhia, Goddard; PBL : MYJ, YSU.	-	-	WRF-ARW V2.2; CN :MP : Thompson, SW -Goddard, PBL -MYJ; all : LW -RRTM; LSM -Noah.
2009	30h	8 members; MP : Thompson, Ferrier, WSM6; SW : Dudhia, Goddard; PBL : MYJ, YSU; LSM : Noah, RUC.	-	-	WRF-ARW V3.0.1.1; CN :MP: Thompson, SW -Goddard, PBL -MYJ, LSM -Noah; all : LW -RRTM.
2010	30h	9 members; MP : Thompson, WDM6, Ferrier, WSM6, Morrison; PBL : MYJ, YSU, QNSE, MYNN; LSM : Noah, RUC.	3 members; MP : WDM6, Ferrier, WSM6, Morrison; PBL : MYJ; LSM : Noah.	2 members; MP : Thompson; PBL : MYNN, QNSE; LSM : Noah.	WRF-ARW V3.1.1; CN :MP: Thompson, PBL -MYJ, LSM -Noah; all : LW -RRTM, SW -Goddard; 2 IC-only members.
2011	36h	17 members; MP : Thompson, WDM6, Ferrier (+), WSM6, Morrison, M-Y; PBL : MYJ, YSU, QNSE, MYNN, ACM2; LSM : Noah, RUC.	10 members, MP : Thompson-v31, Ferrier (2), WSM6 (5), Morrison, M-Y, WDM6; PBL : MYJ; LSM : Noah.	10 members; MP : Thompson, PBL : MYJ (4), YSU QNSE, MYNN, ACM2 (3), YSU-Thompson; LSM : Noah.	WRF-ARW V3.2.1; CN :MP -Thompson, PBL -MYJ, LSM -Noah; all : LW -RRTM, SW -Goddard; Radar-DA cycled member(CC).
2012	36h	-	3 members, MP : Morrison, M-Y, WDM6; PBL : MYJ; LSM : Noah.	4 members; PBL : ACM2, YSU, QNSE, MYNN; MP : Thompson; LSM : Noah.	WRF-ARW V3.3.1; CN :MP -Thompson, PBL -MYJ, LSM -Noah; all : LW -RRTM, SW -Goddard; 1 SKEB member.
2013	48h	13 members; MP : Thompson, WDM6, Morrison, M-Y; PBL : MYJ, YSU, QNSE, MYNN, ACM2; LSM : Noah, RUC.	6 members, MP : WDM6, NSSL, Morrison, M-Y, WSM6; PBL : MYJ; LSM : Noah.	10 members; PBL : YSU, ACM2, QNSE, MYNN; MP : Thompson; LSM : Noah.	WRF-ARW V3.4.1; CN :MP -Thompson, PBL -MYJ, LSM -Noah; all : LW -RRTMG, SW -RRTMG; 1 member MP coupled to radiation.

Physics options used in the ensemble: MP-Thompson (Thompson et al.,2008), Ferrier (Ferrier et al.,2002),WSM6 (Hong and Lim,2006), WDM6 (Lim and Hong, 2010), Morrison (Morrison et al.,2009), M-Y (Milbrandt and Yau,2005); PBL-MYJ (Janji 1994),YSU (Hong et al.,2006),QNSE (Sukoriansky et al.,2005), MYNN (Nakanishi and Niino, 2006), ACM2 (Pleim, 2007);LSM-Noah (Tewari et al.,2004), RUC (Benjamin et al.,2004); SW -Dudhia(Dudhia,1989), RRTMG (Iacono et al.,2008), Goddard (Chou and Suarez,1999); Isls LW-RRTM (Mlawer et al.,1997),RRTMG (Iacono et al.,2008).

Mesoscale nowcasting in the past

(1 to 500 km) (forecasting for 0 to 6h)

In the beginning there were analogues:

“BIG DATA” was in a forecaster’s memory (accumulated experience for situations analogous to the present) and the processing algorithms were conceptual models.

Conceptual models:

a complex problem reduced to a system with few proxy variables.

Best example in my memory:

Hector Grandoso forecasting occurrence of hailstorms in Mendoza

Then computers became more and more powerful:

NWP became the future.

Models became better, numerical methods improved, more and more physics was added...

Then, deterministic chaos cast a shadow, model errors became an issue, physical parameterizations are always poor approximations to reality, nature is constantly perturbed at the smaller scales and runs away from model predictions....

Ensemble forecast accounted for uncertainties, dada assimilation would correct the drift the NWP shortcomings.

Forecast improved continuously over time (at least at 500mb)!

AND ALL THE WHILE, MESOSCALE PRECIPITATION STUBBORNLY REFUSED TO BE WELL PREDICTED QUANTITATIVELY

WHAT IS THE PRESENT SITUATION?

Madalina Surcel

Surcel, M , et al, 2015: A study on the scale-dependence of the predictability of precipitation patterns, J. Atmos. Sci., 72, 216–235.

Methodology in a nutshel:

1- take 1-h accumulations of precipitation patterns, form radar and model forecasts

2- decompose by scale, λ

3- compare these patterns scale by scale (band-pass)

4- from this comparison determine λ_0, the scale at which predicability is totally lost as a function of lead time:

That is, at λ_0 forecast and verification are totally decorrelated.

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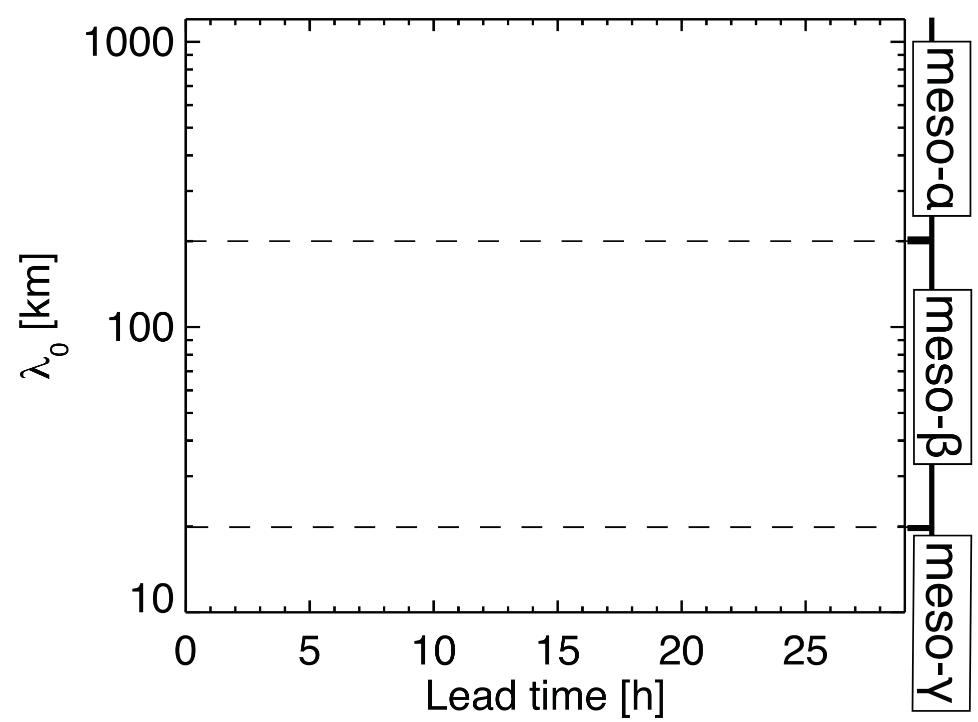

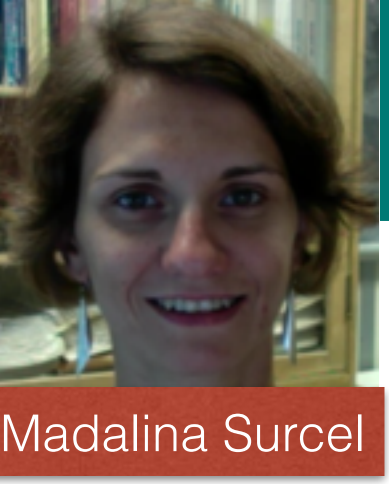

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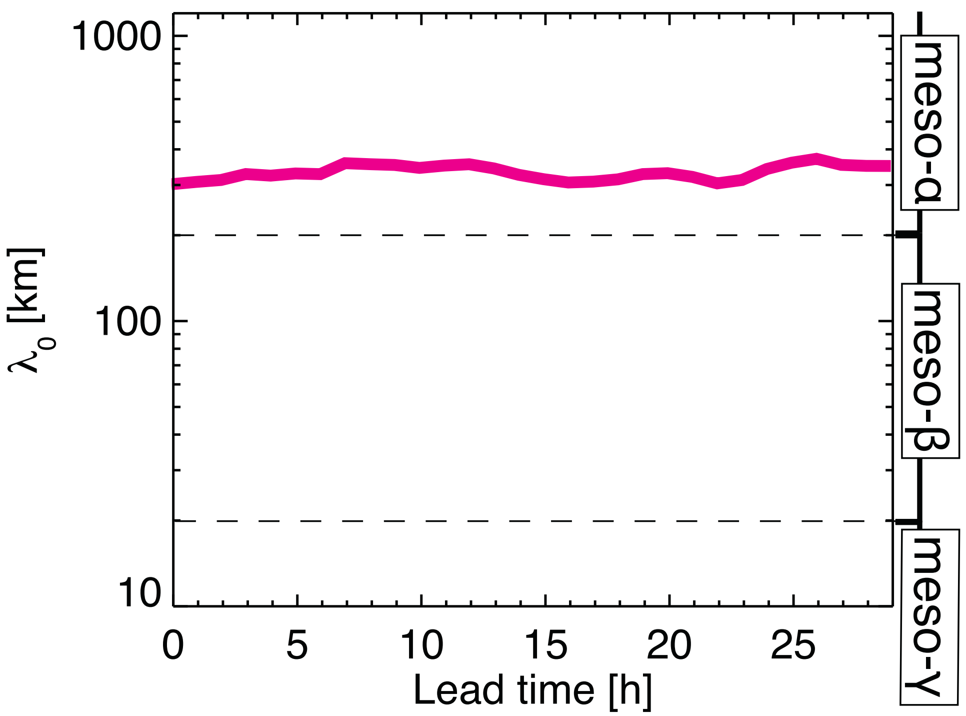

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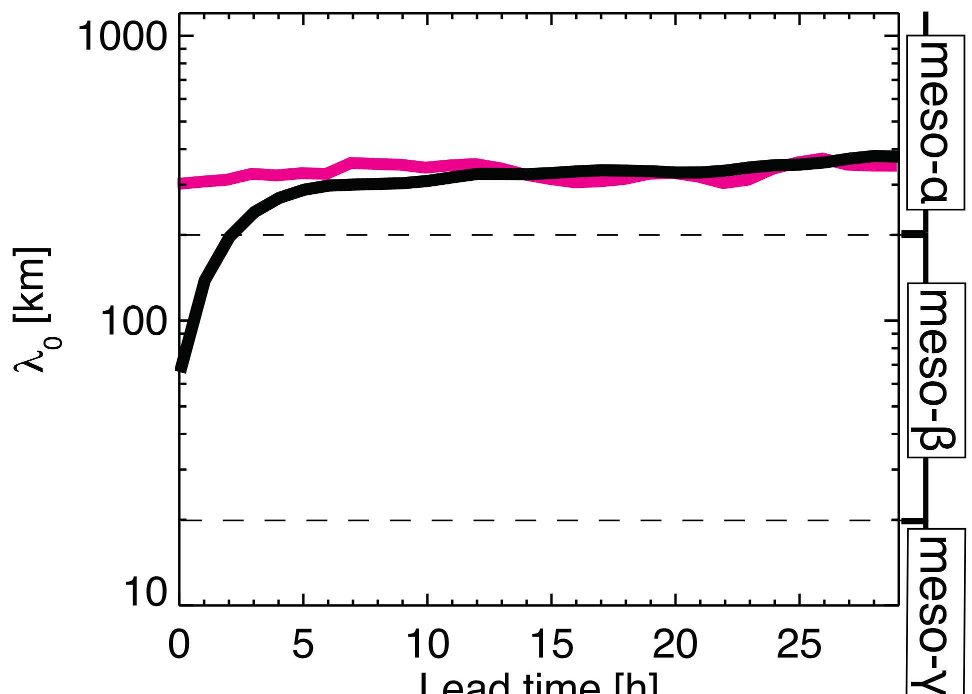

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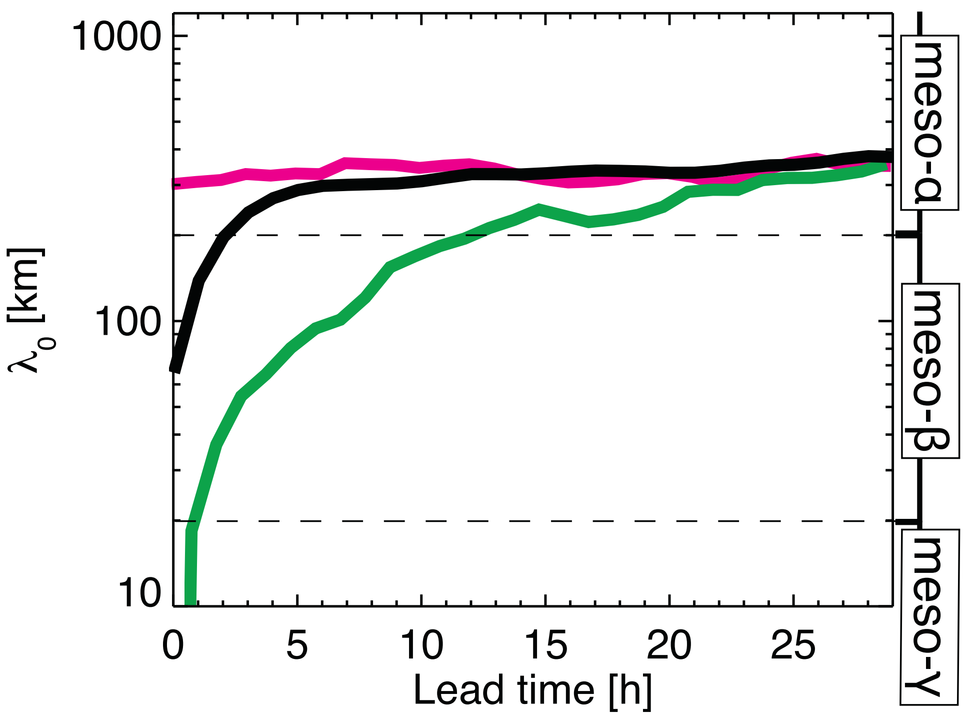

NWP with Radar Data Assim. veryfied by observations

NWP with Radar Data Assim. veryfied by NWP (intrinsic)

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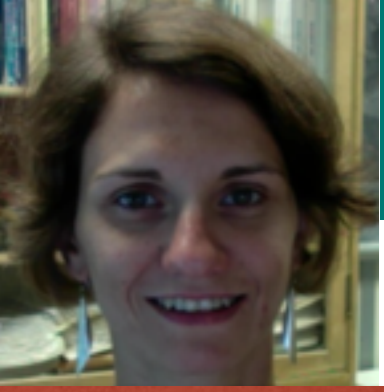
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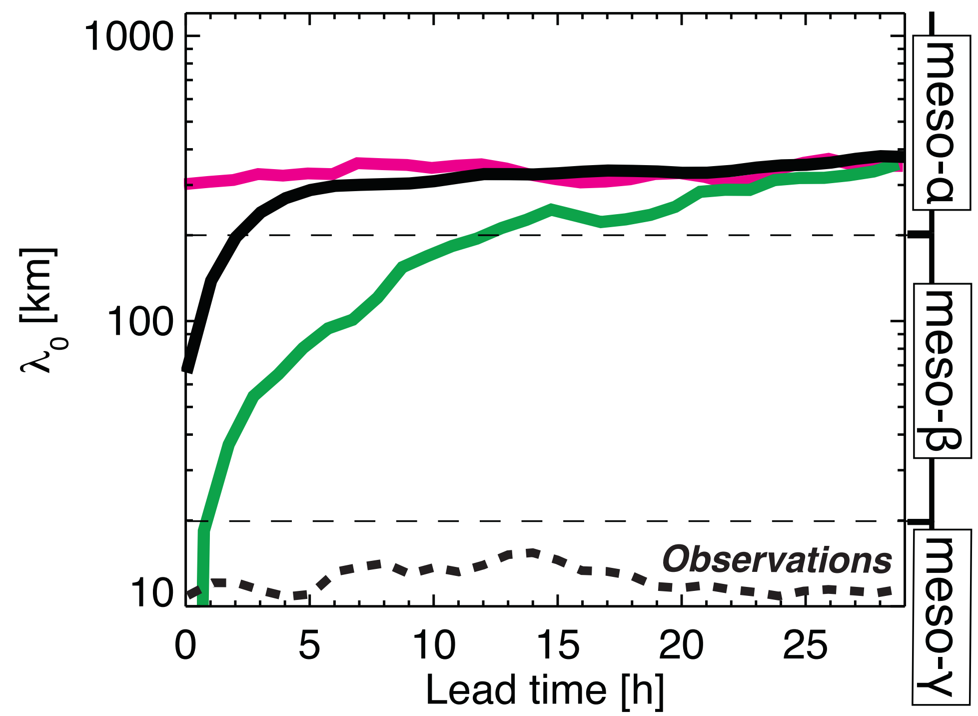

contribution from errors in observations

NWP with Radar Data Assim. veryfied by observations

NWP with Radar Data Assim. veryfied by NWP (intrinsic)

Limits to Mesoscale Predictability

Madalina Surcel

Summary of model validation with radar data:

With no radar data assimilation scales smaller than ~300km are not predictable

Effect of Radar Data Assimilation lasts forever, but the improvement in skill (small) lasts up to ~4h lead time (roughly as the spin-up time)

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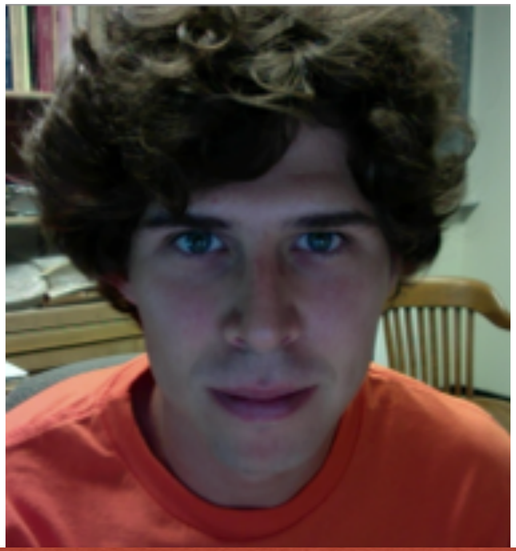
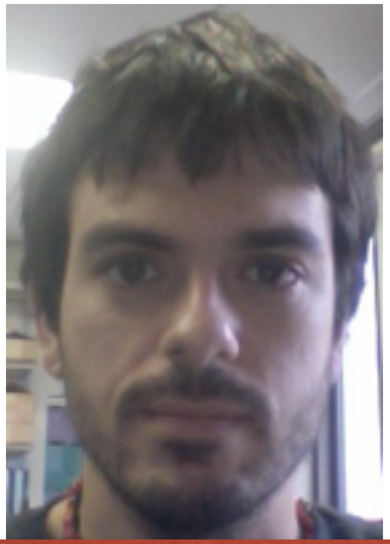
FOR PRECIPITATION, BEYOND THESE SHORT LIMITS AND SMALLER SCALES THERE CAN ONLY BE PROBABILISTIC FORECASTING / NOWCASTING.

Can we improve short term forecasting of precipitation with the available long term radar records and model outputs?

Isztar Zawadzki, McGill University, Presenting work of:



Aitor Atencia Ruiz de Gopegui



Bernat Puigdomènech Treserras

And many thanks to M.K. Yau and F. Fabry for comments and support

BACK TO ANALOGUES

(but now with data instead of subjective experience)

Probabilistic Nowcasting of Precipitation Using "Analogues" (Similar Patterns);

Preliminary Comparison with NWP.

Analogue selection criteria

For every radar map similar patterns were searched in 17 years of radar archives. Similarity is defined by a decision-tree comprising the following criteria:

1. Spatial cross-correlation between Rainfall patterns
2. Location to account for Geographical factors
3. Temporal correlation to select for similarity of Motion & Evolution of patterns
4. Time of the day and year to account for the Diurnal and Annual cycles

Analogue selection criteria

5- Synoptic situation to account for influence of Large scale forcing

There are three main factors needed for rainfall occurrence: instability, moisture and forcing.

The variables more appropriate were found to be:

temperature, T at 50 kPa,
specific humidity at 70 kPa and
pressure vertical velocity, ω at 85 kPa.

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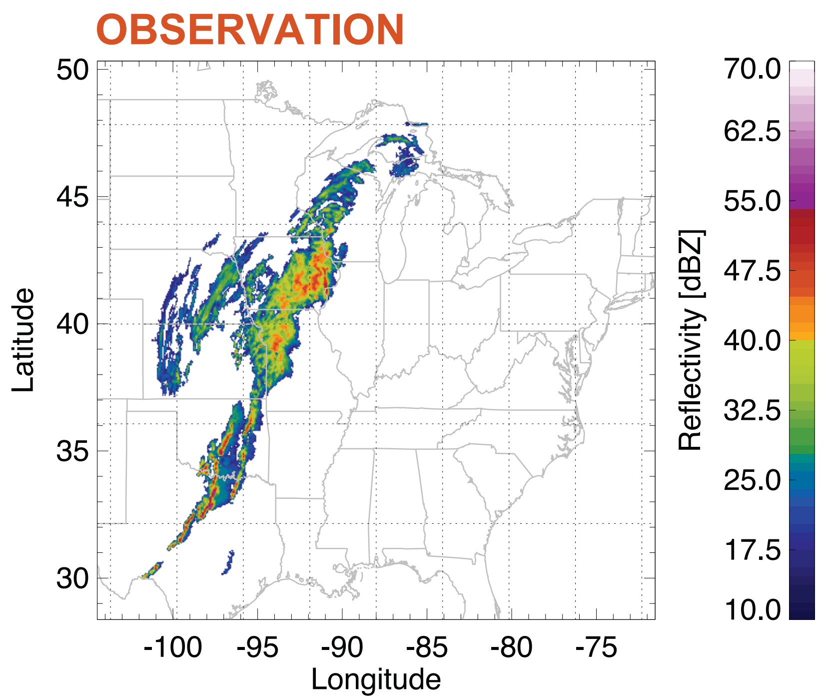
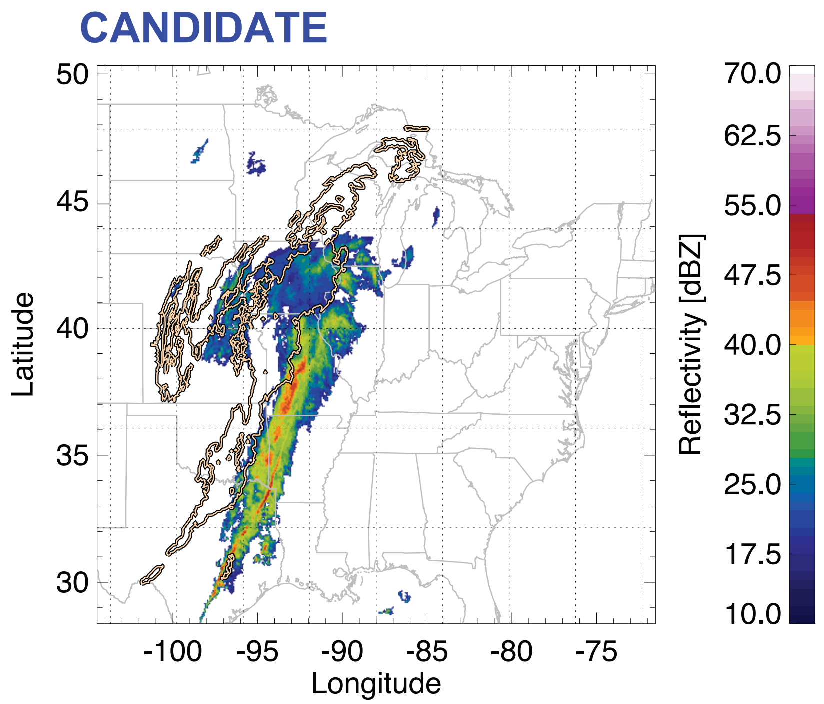
Why these 7 parameters? Because this is the conceptual model framework to which we are used and we understand, and black-box approach like SOM did not work for precipitation patters. Surely it can be refined.

Analogue selection criteria



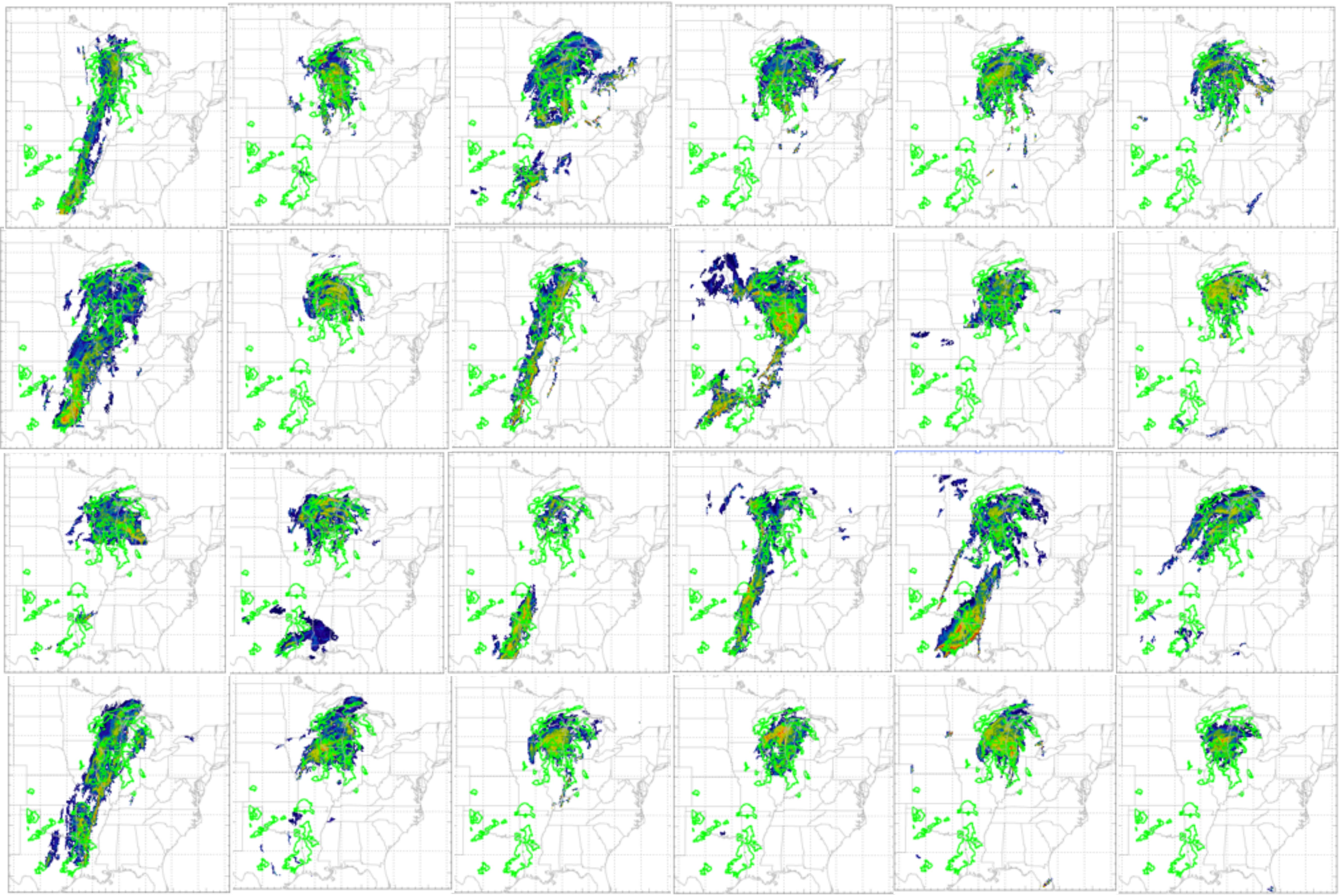


For all criteria the degree of similarity between the observation and the analogue candidate is determined by the desired ensemble number of "analogues" available in the records.

The number of "analogues" can be adjusted so that the ensemble is not over nor under-dispersive. The latter can be evaluated by the nowcast of the previous time.

Thus, the procedure can be made adaptable to the situation.

Example of Analogues



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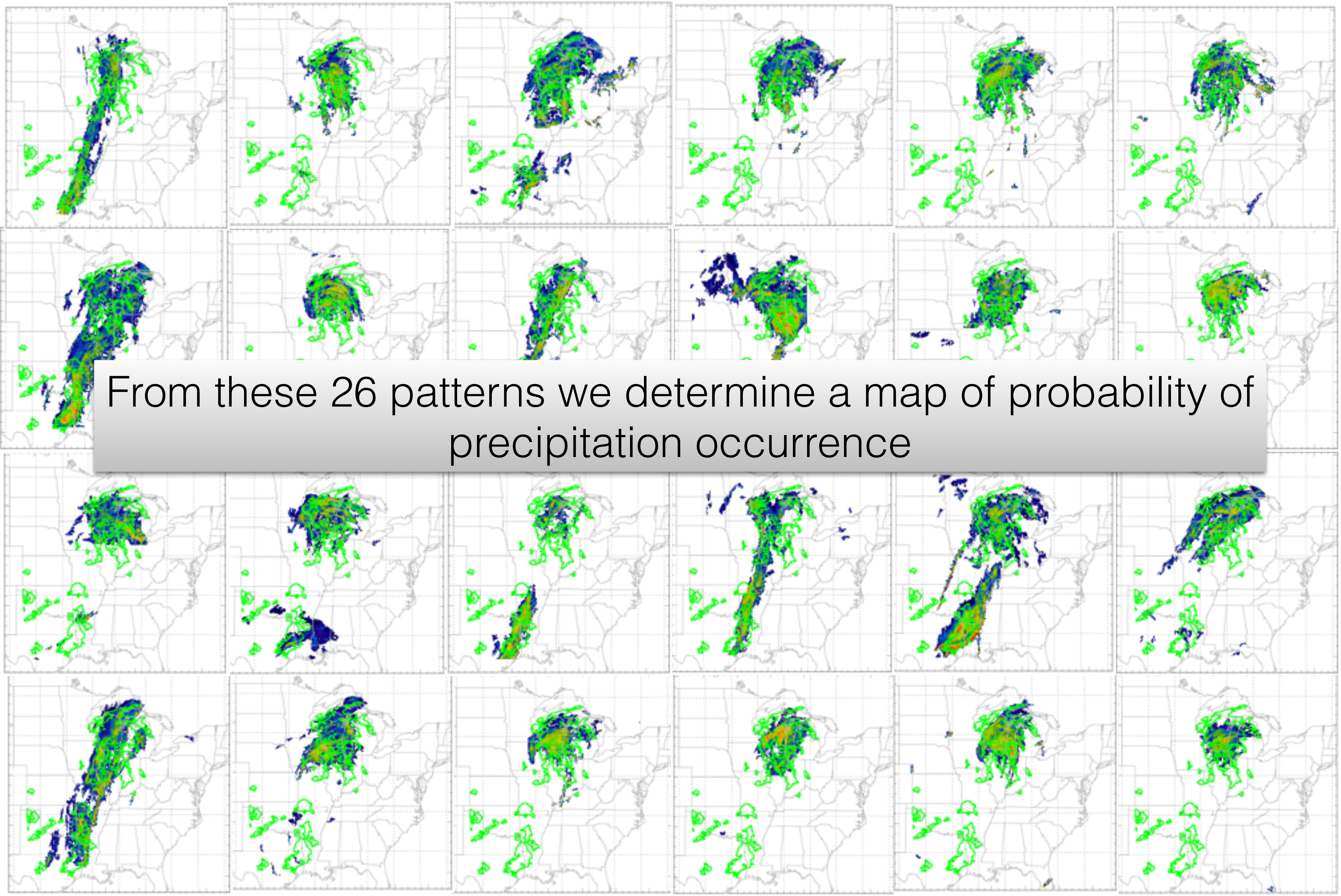
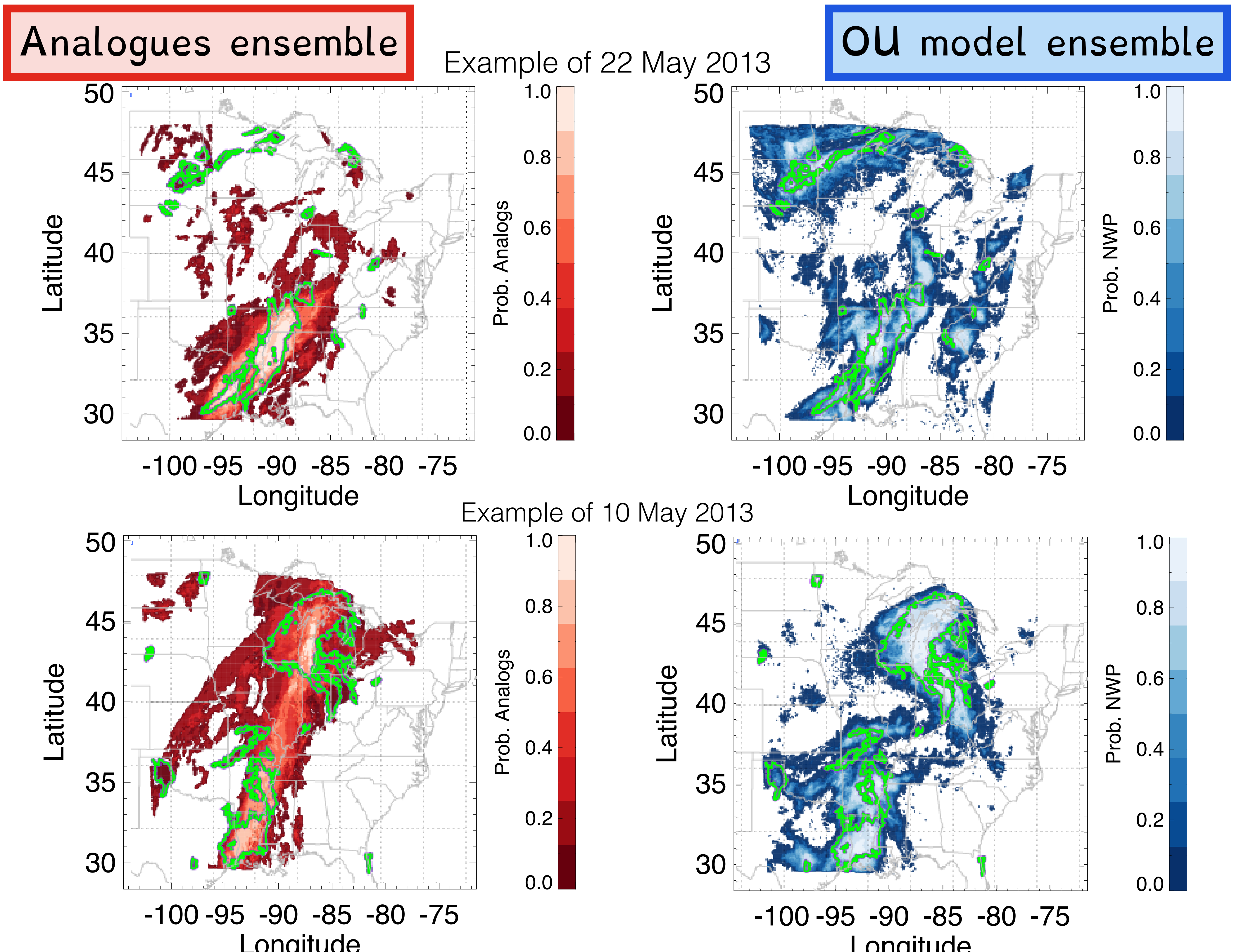


From these 26 patterns we determine a map of probability of precipitation occurrence

Comparison of Probability of Precipitation

Maps of probability of precipitation derived from 26 members ensembles.

Green contours are radar verification



Skill Comparison (probability)

(For 26 events from 31st April to 12th June and 26 members ensembles)

Relative Operating Characteristic, ROC:

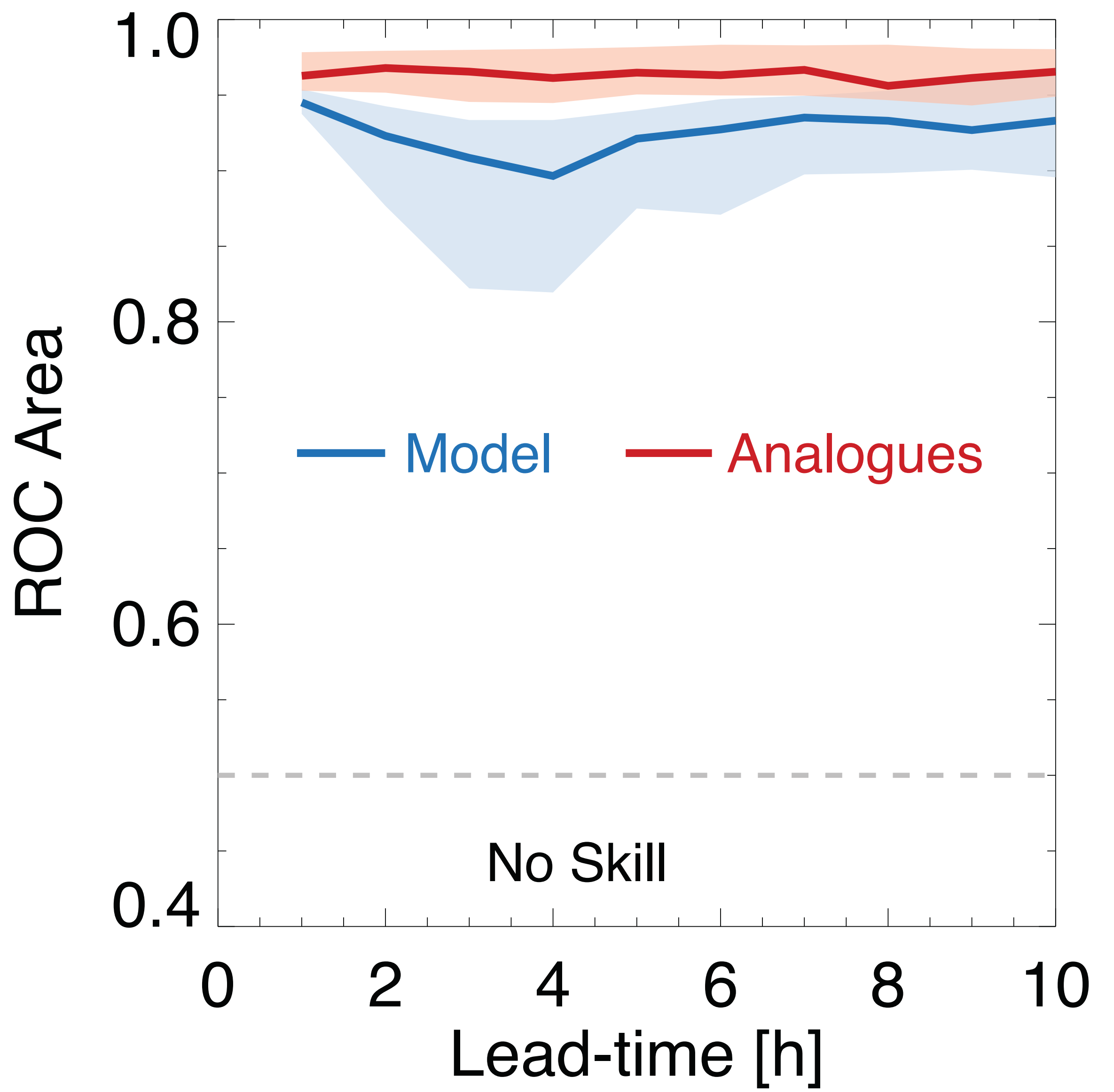
$$ROC\ Area = \int POD\ d(FAR)$$

$$POD = \frac{hit}{hit + miss}$$

$$FAR = \frac{false\ alarm}{false\ alarm + correct\ negatives}$$

Answers the question: What is the ability of the forecast to discriminate between precipitation events and non-events?

Range: 0 to 1. 0.5 = no skill. **Perfect score:** 1



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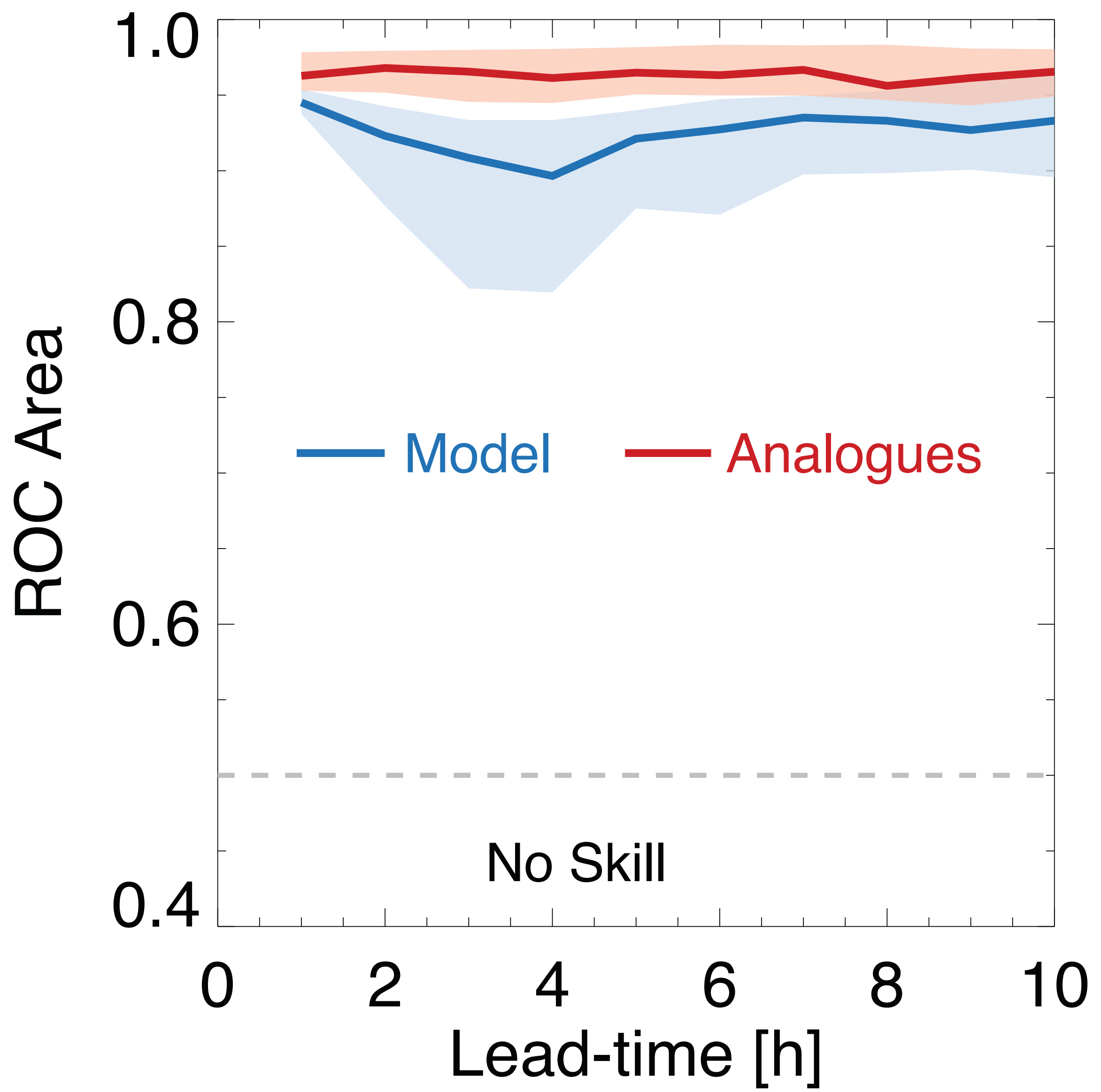

Even though the patterns were different, the probability map have a reasonable performance with both techniques.

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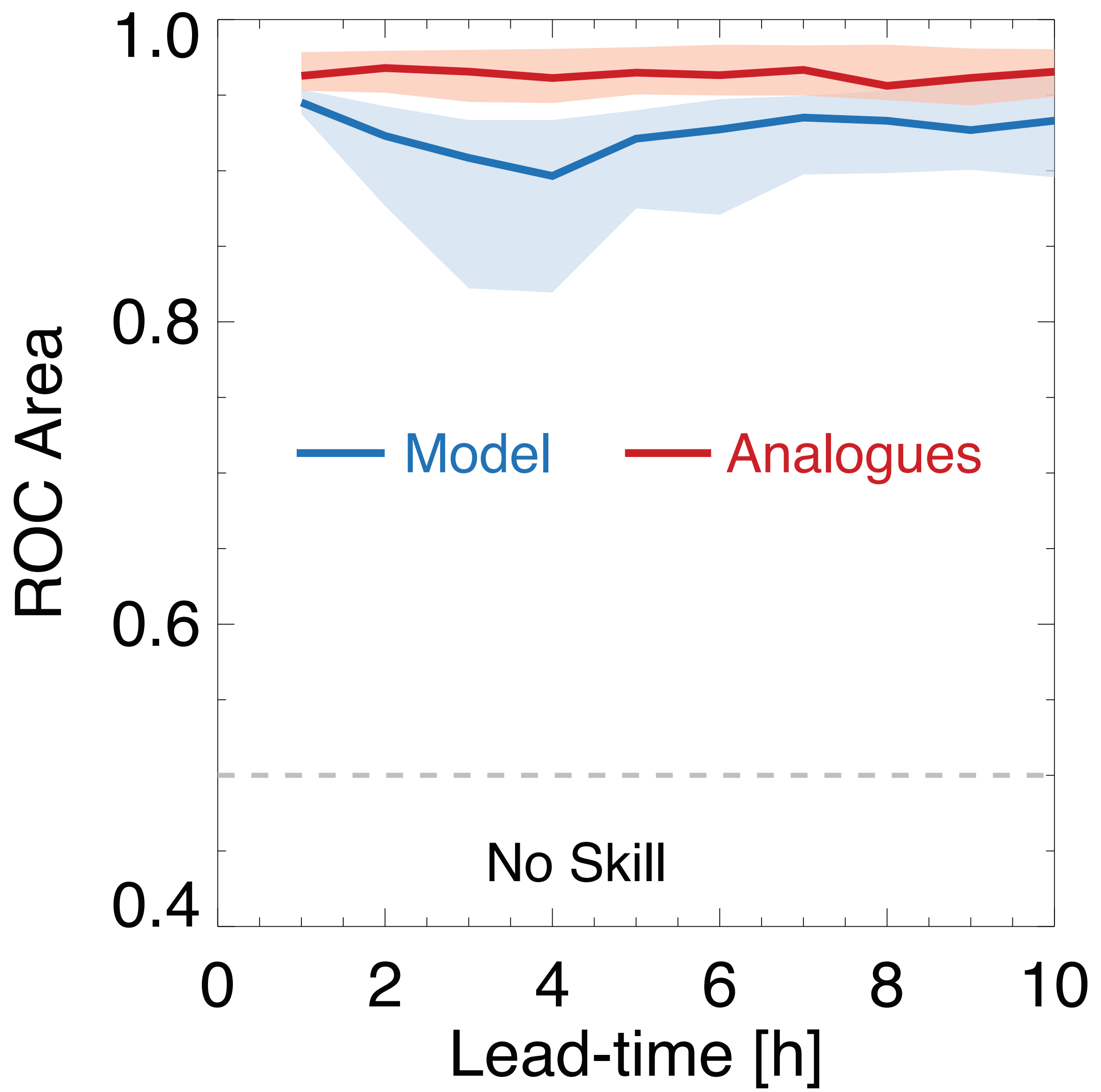


Even though the patterns were different, the probability map have a reasonable performance with both techniques.

The differences are statistically significative.

Skill Comparison (probability)

(For 26 events from 31st April to 12th June and 26 members ensembles)

$$Brier\,Score = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\frac{1}{N_m}\sum_{j=1}^{N_m} f_j\right) - o_i\right]^2$$

i indicates points in space (N);

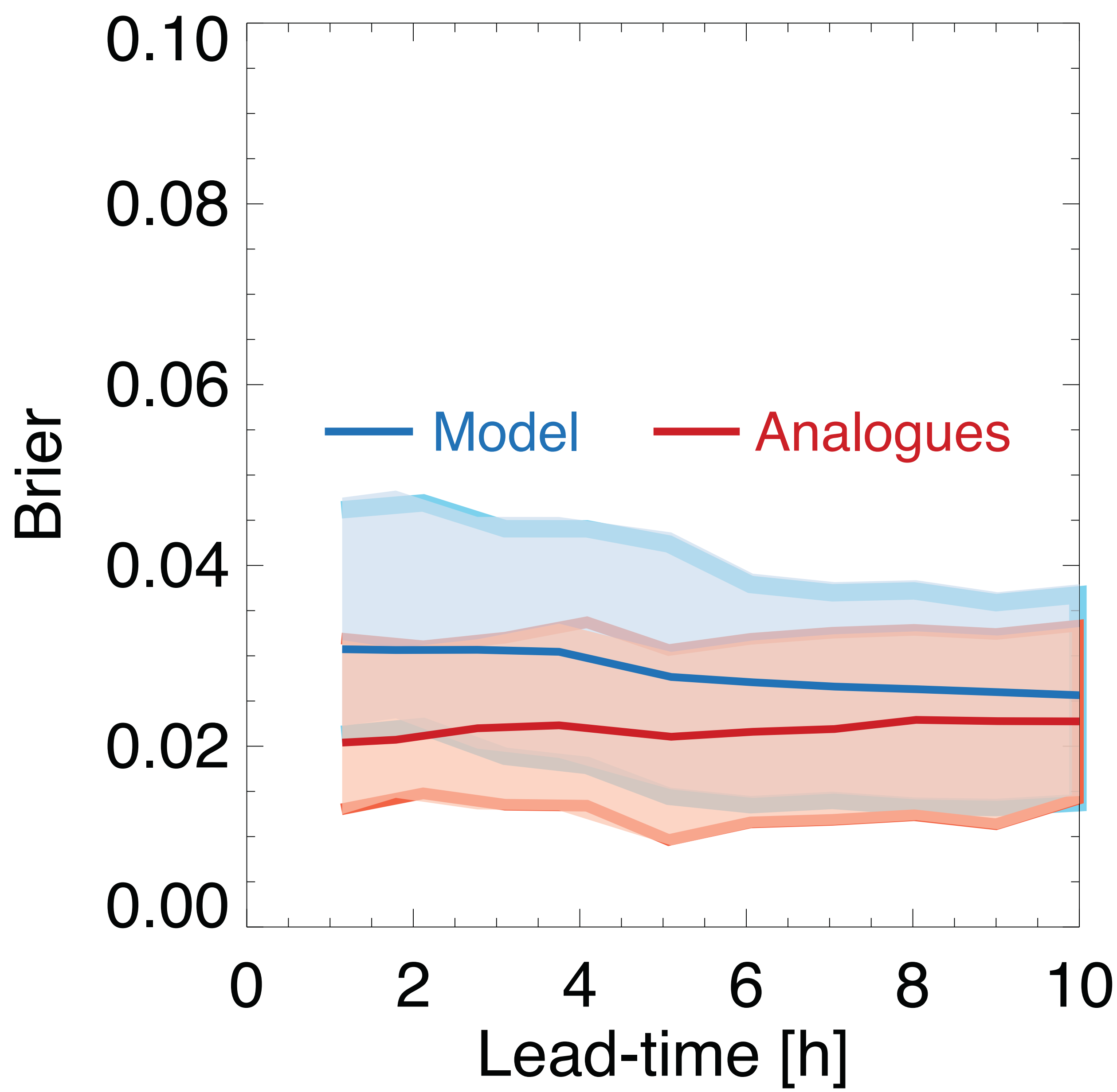
j indicates members (N_m)

f is forecast value: 0, miss; 1, hit

o_i is observation: 0, miss; 1, hit

Answers the question: What is the magnitude of the probability forecast errors?

Range: 0 to 1 **Perfect score:** 0



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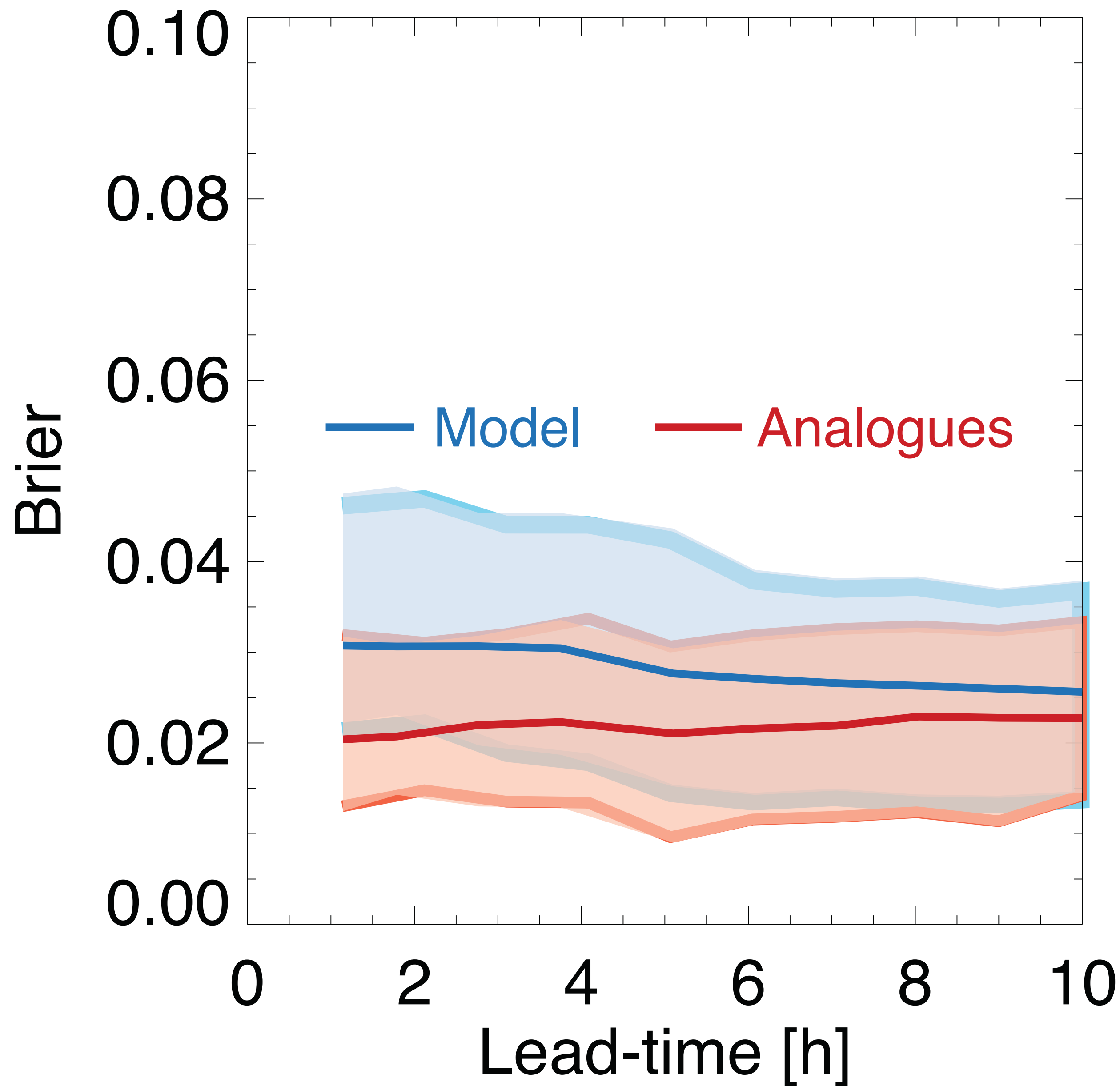

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Skill Comparison (RMS)

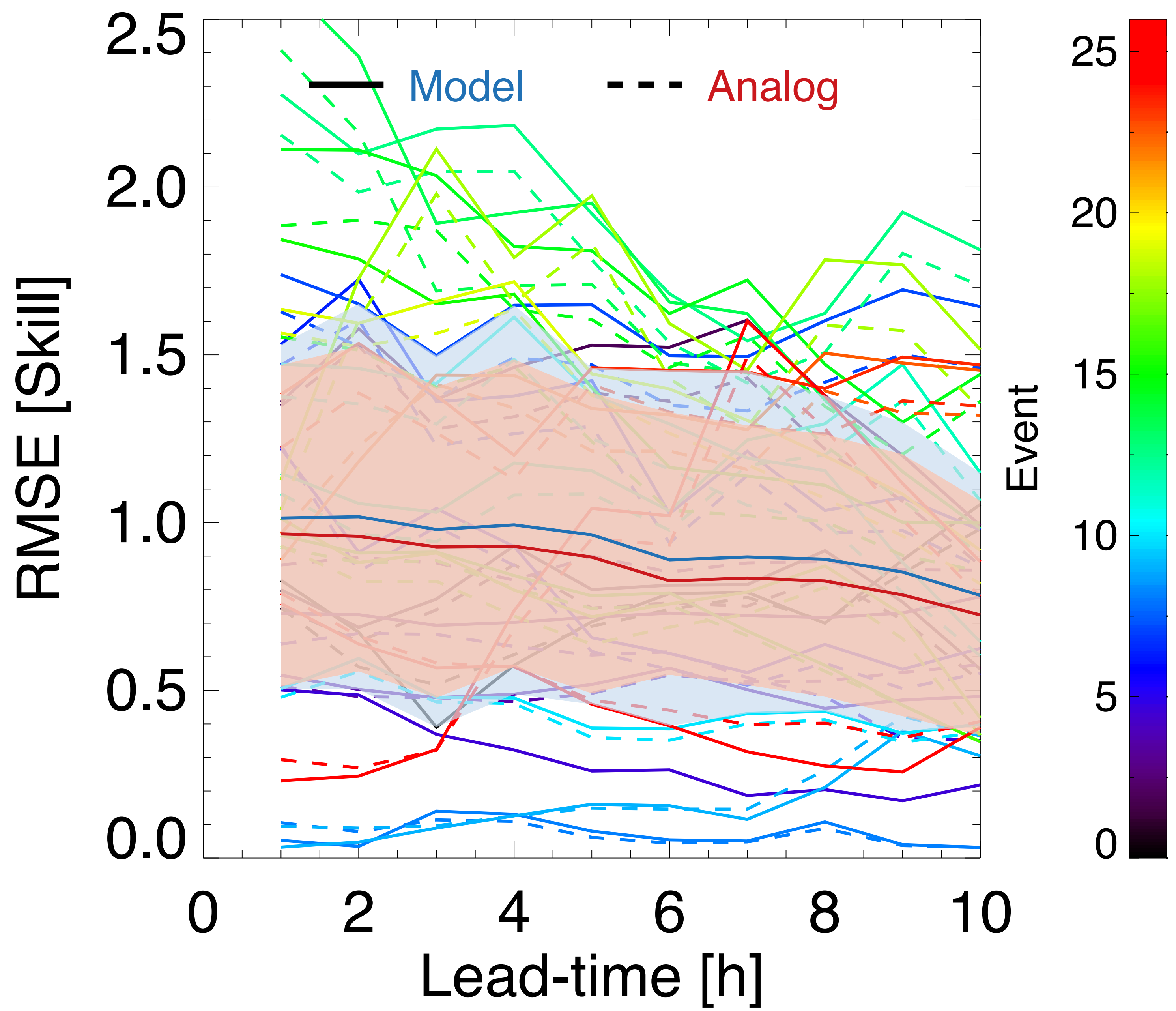
(For 26 events from 31st April to 12th June and 26 members ensembles)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_o - \overline{f})^2}$$

i indicates point (N);

R_0 is observation

$\overline{f}$ is average of members



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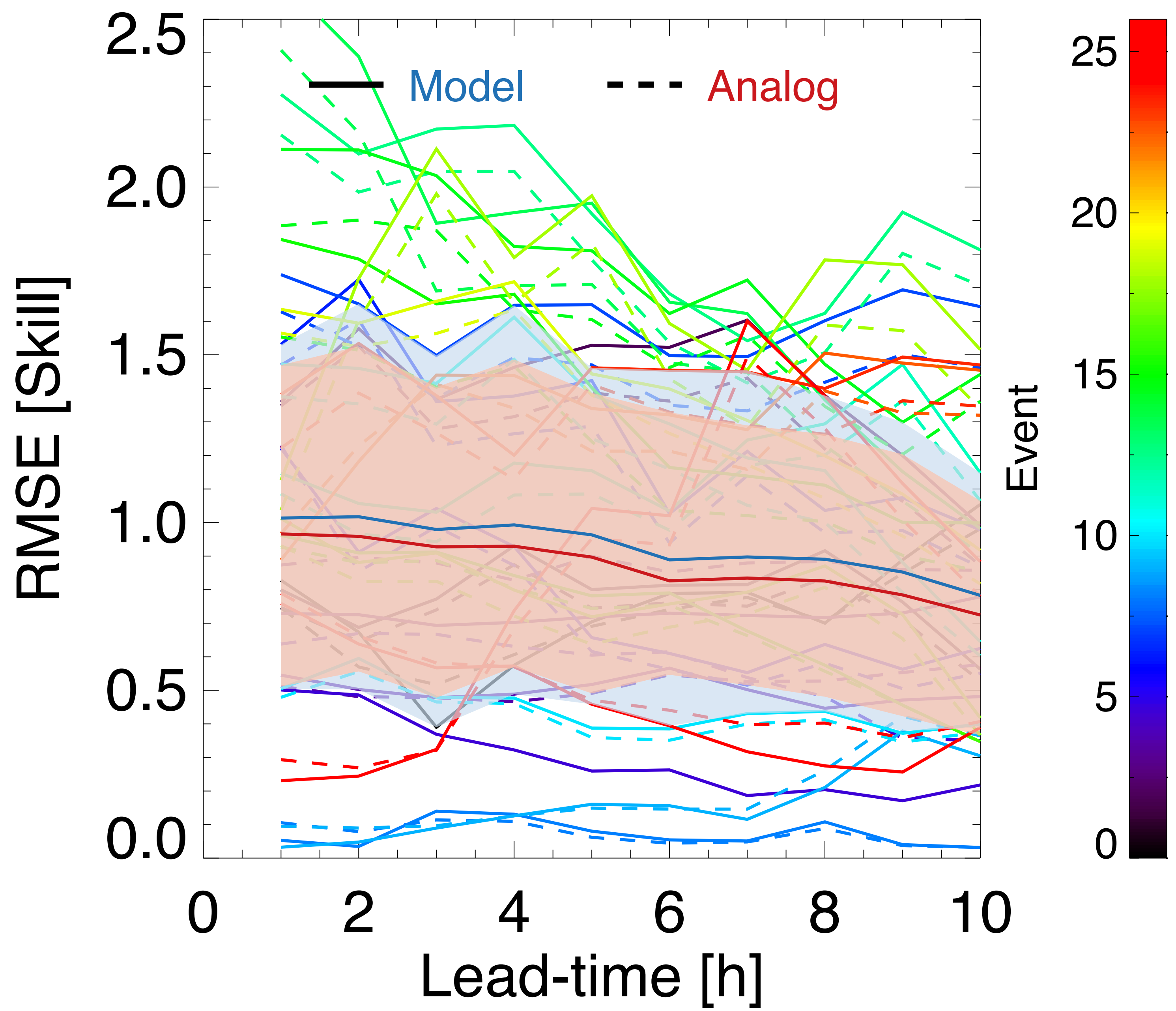

The differences are statistically significative.

Analogues have more information on the probability and intensity of precipitation.

Do analogues ensembles forecasts cover observations? Skill-Spread Ratio

(For 26 events from 31st April to 12th June and 26 members ensembles)

$$Spread = \sqrt{\frac{1}{N(N_m - 1)}\sum_{i=1}^{N}\sum_{j=1}^{N_m}(f_j - \bar{f})^2}$$

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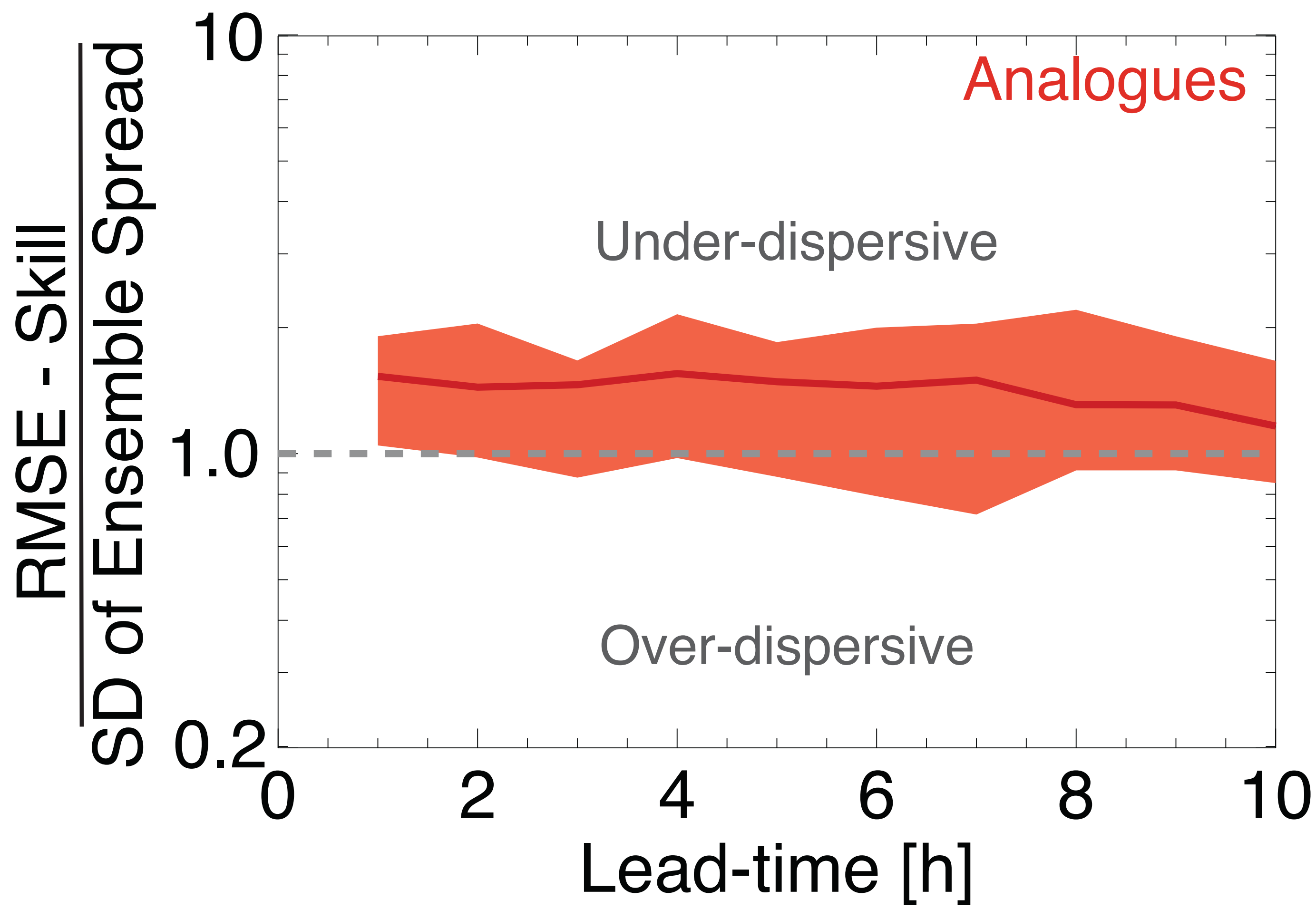

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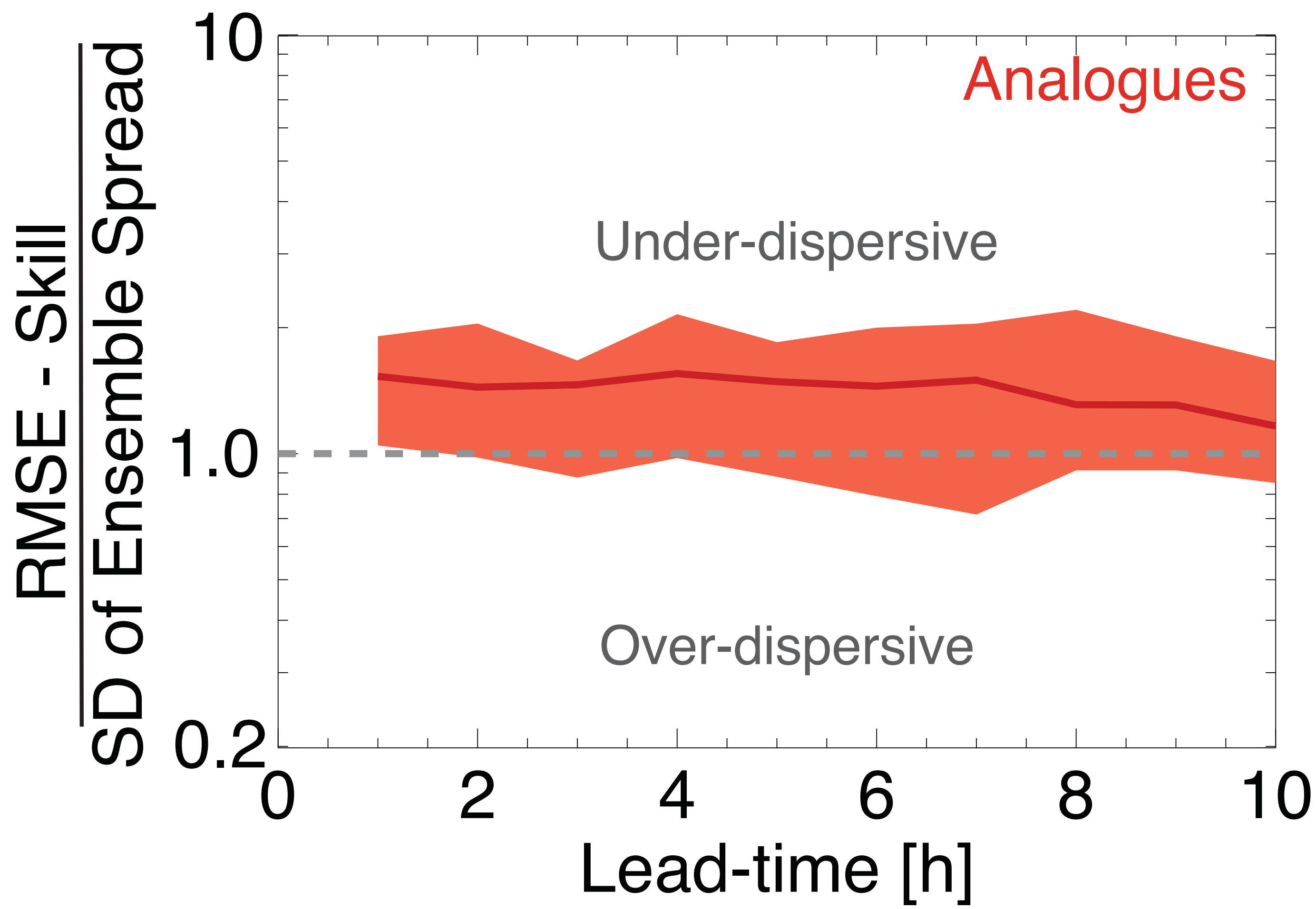

The small under-dispersivity is perhaps due to the limited number of ensemble members

Do model ensembles forecasts cover observations? Skill-Spread Ratio

(For 26 events from 31st April to 12th June. For 26 members ensembles, and for 15 most dispersive members)

$$Spread = \sqrt{\frac{1}{N(N_m - 1)} \sum_{i=1}^{N} \sum_{j=1}^{N_m} (f_j - \overline{f})^2}$$

i indicates point (N);

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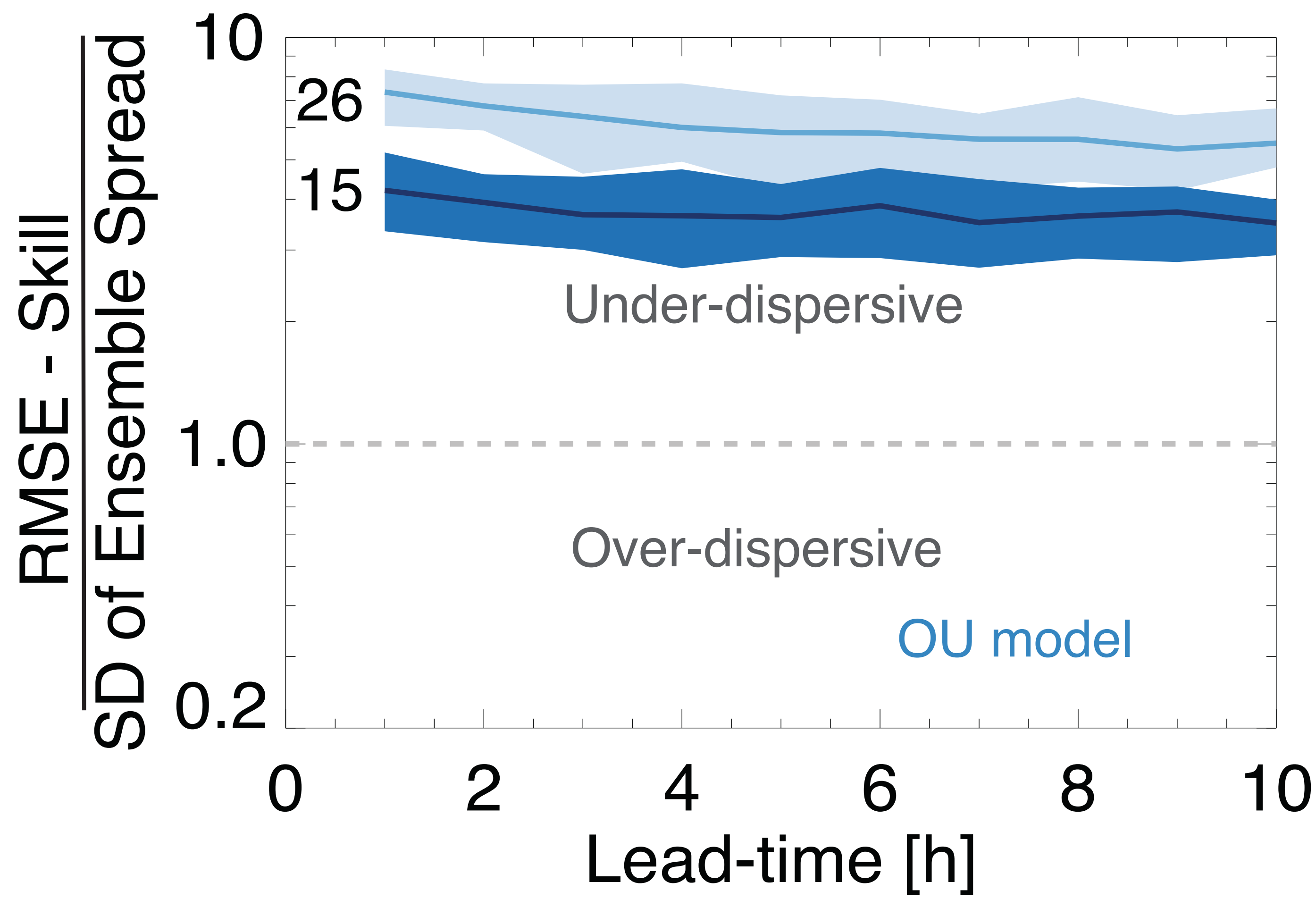

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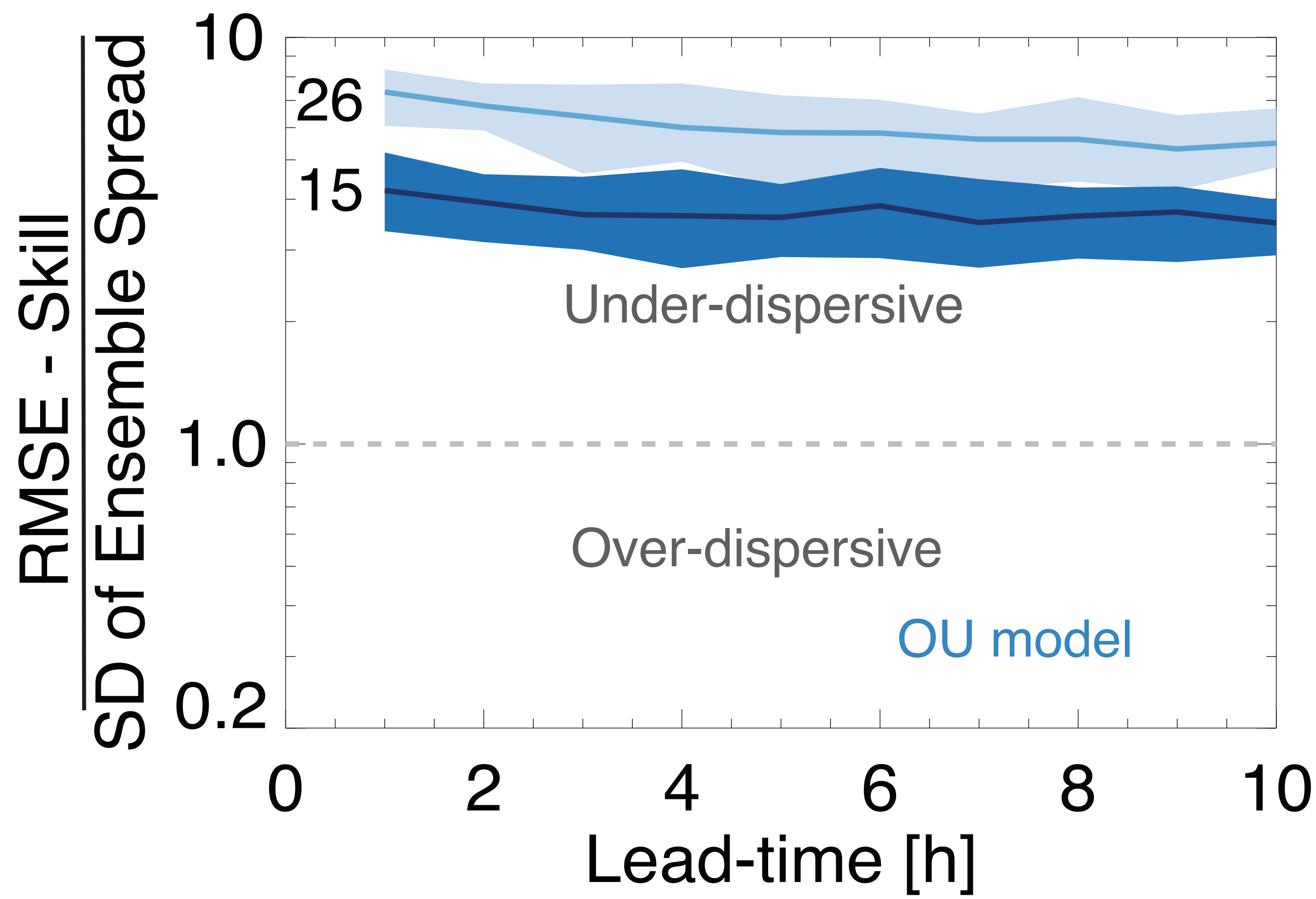


And it is not bias. It is hard to get model ensembles sufficiently dispersive.

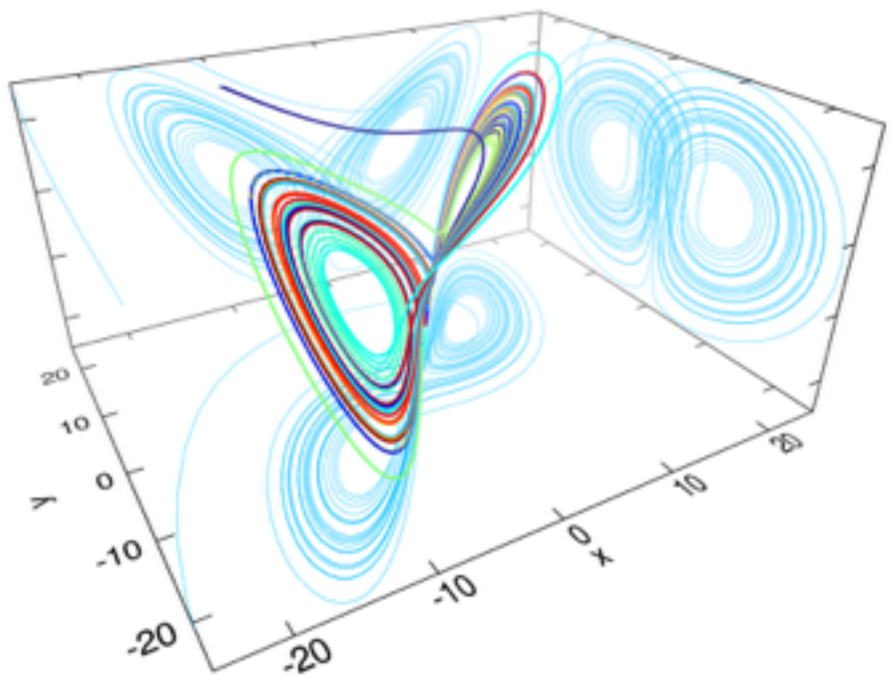
NEXT

True analogues: close states on an attractor.

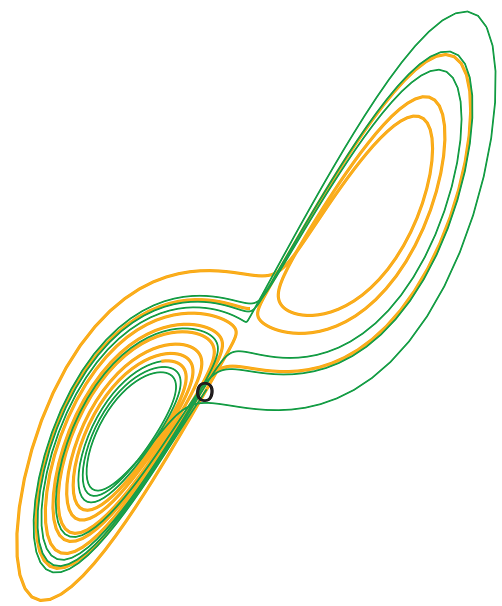
The Lorenz attractor

$$\frac{dx}{dt}=\sigma(y-x); \quad \frac{dy}{dt}=x(\rho-z)-y; \quad \frac{dz}{dt}=xy-\beta z \quad \sigma=10;\rho=28;\beta=8/3$$

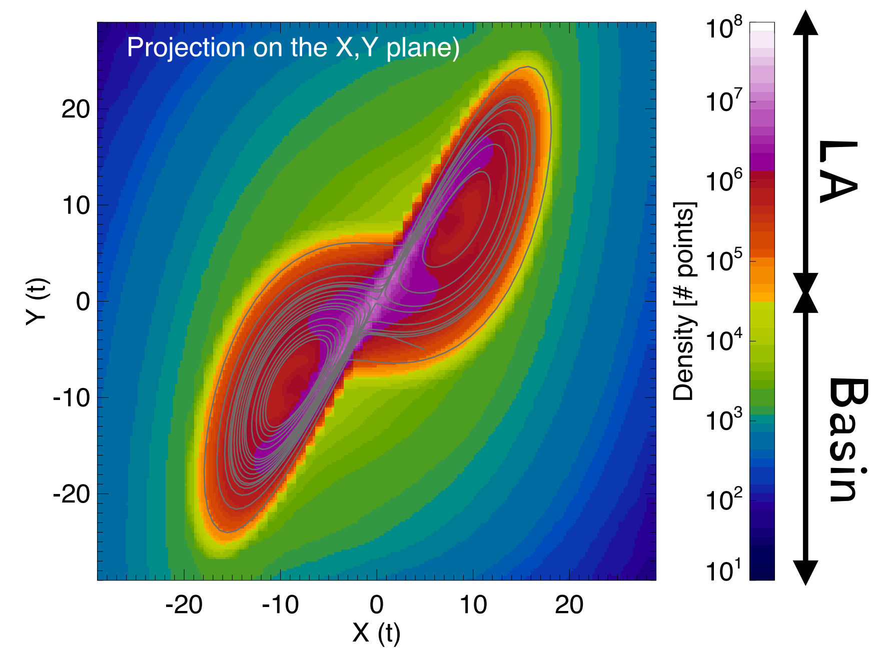
As a 3-D trajectory with 2-D projections

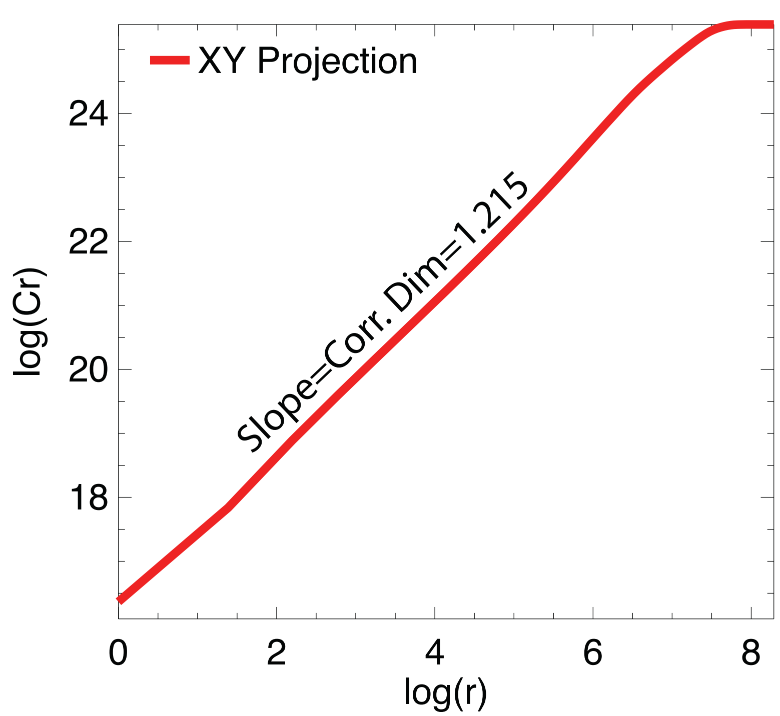


The X-Y projection of a sparse attractor



The X-Y projection of the full attractor: high density of trajectories (points)





Dimension (fraction of phase space occupied by the attractor)

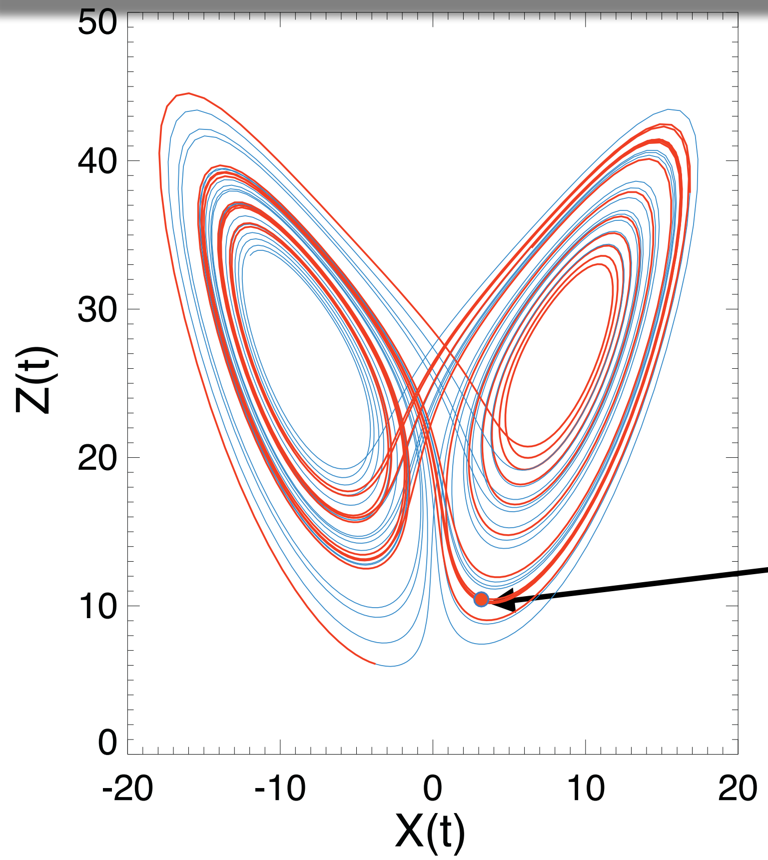
Correlation Dimension:

1-take a circle of radius **r** and count the total n◦ of points within the circle for all positions in the domain, **Cr**

2- Repeat for all **r** and plot **log Cr** vs **log r**

The slope is the CD

Forecasting with the attractor

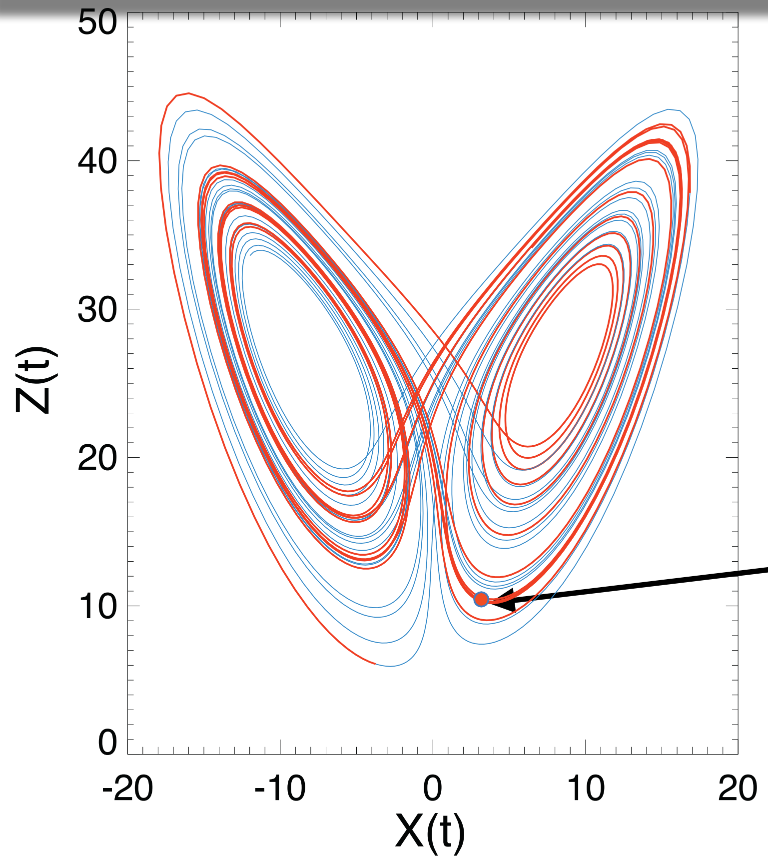


The trajectory of the LA attractor is obtained by solving three differential equations.

If the time of each point of the trajectory is recorded the equations are no longer needed. The attractor is “DATA”

Starting from the red point we can obtain the future trajectories (red) of all the analogues within the point. This is the analogues ensemble forecast.

Forecasting with the attractor



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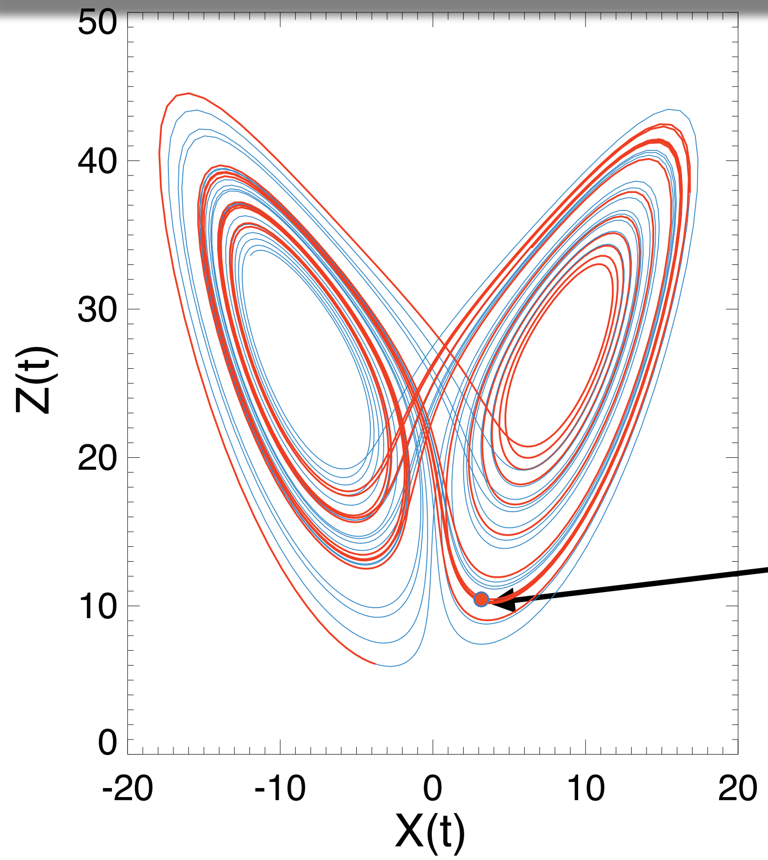
An ensemble forecast of x at time t_f is made by choosing a set of close values on the attractor around $x(t_0)$, $y(t_0)$, $z(t_0)$, the **ANALOGUES**, and then following the evolution of the ensemble average of x as well as their spread in time until the forecast time t_f.

Forecasting with the attractor



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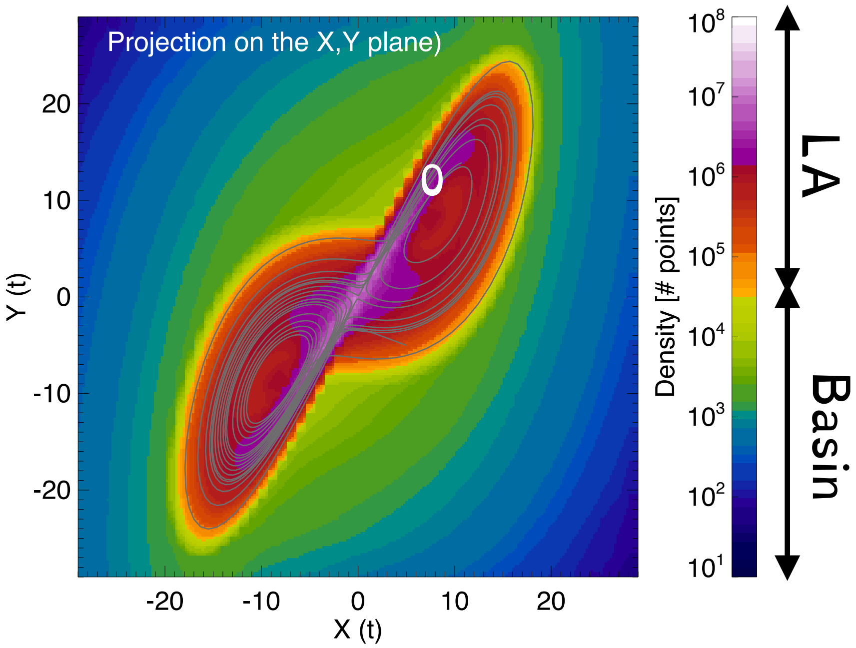
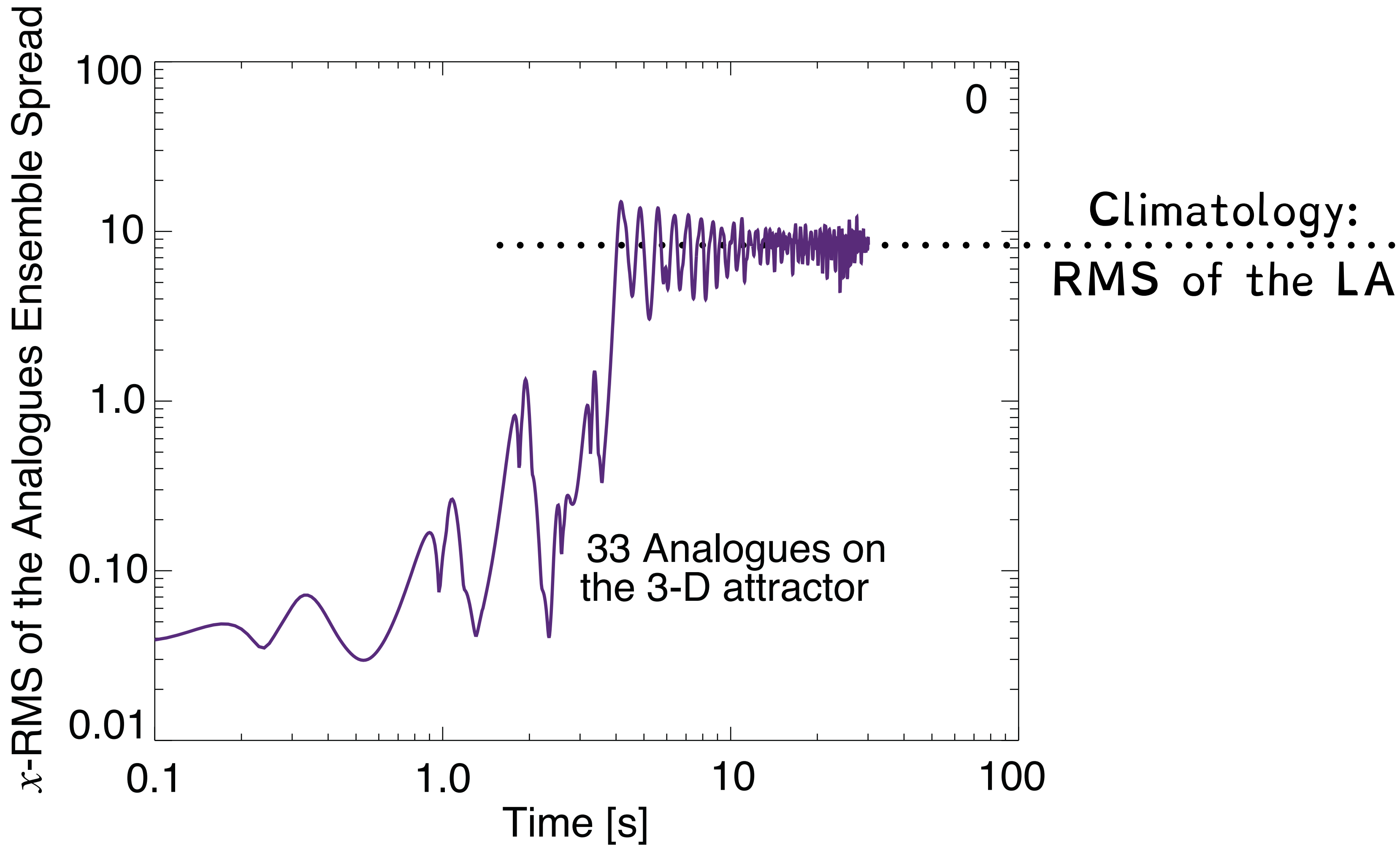
If the equations for a system are known it may be more practical to get a solution every time a forecast is needed than have the huge table for all the solutions.

But, for the atmosphere we ignore the exact equations. Moreover, we cannot compute all the solutions from the equations we have.

What happens if we only have a reduced dimension?





The value of the forecast by analogues-ensemble is measured by the distance of the curve to the RMS of climatology.

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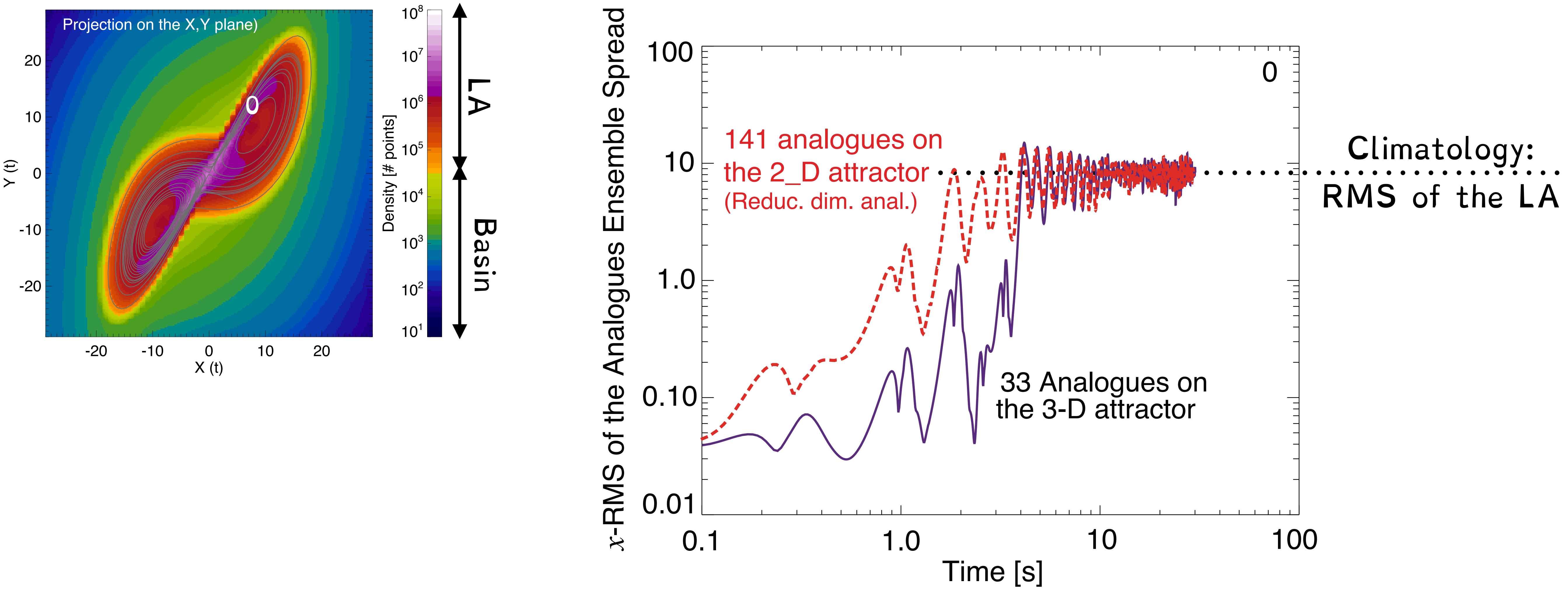

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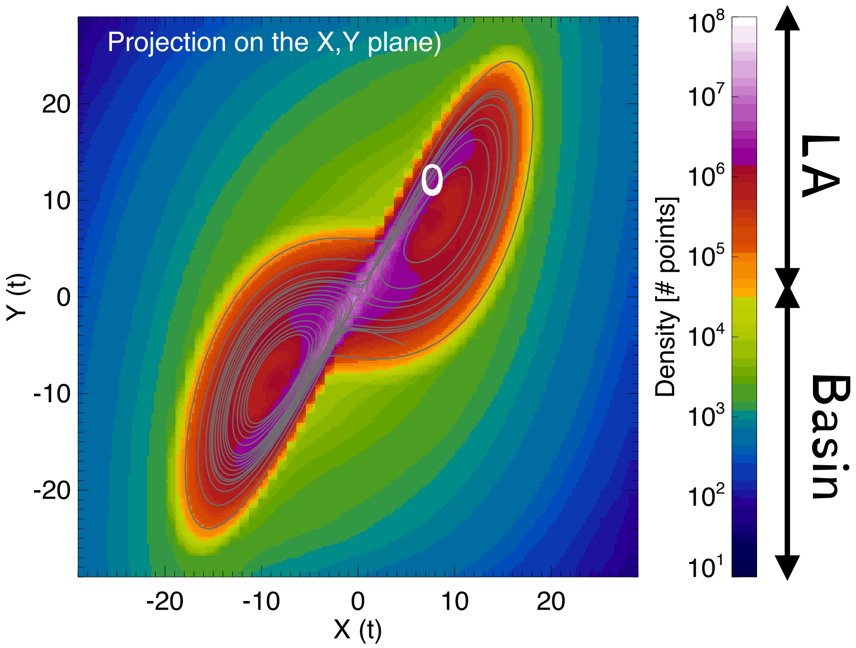

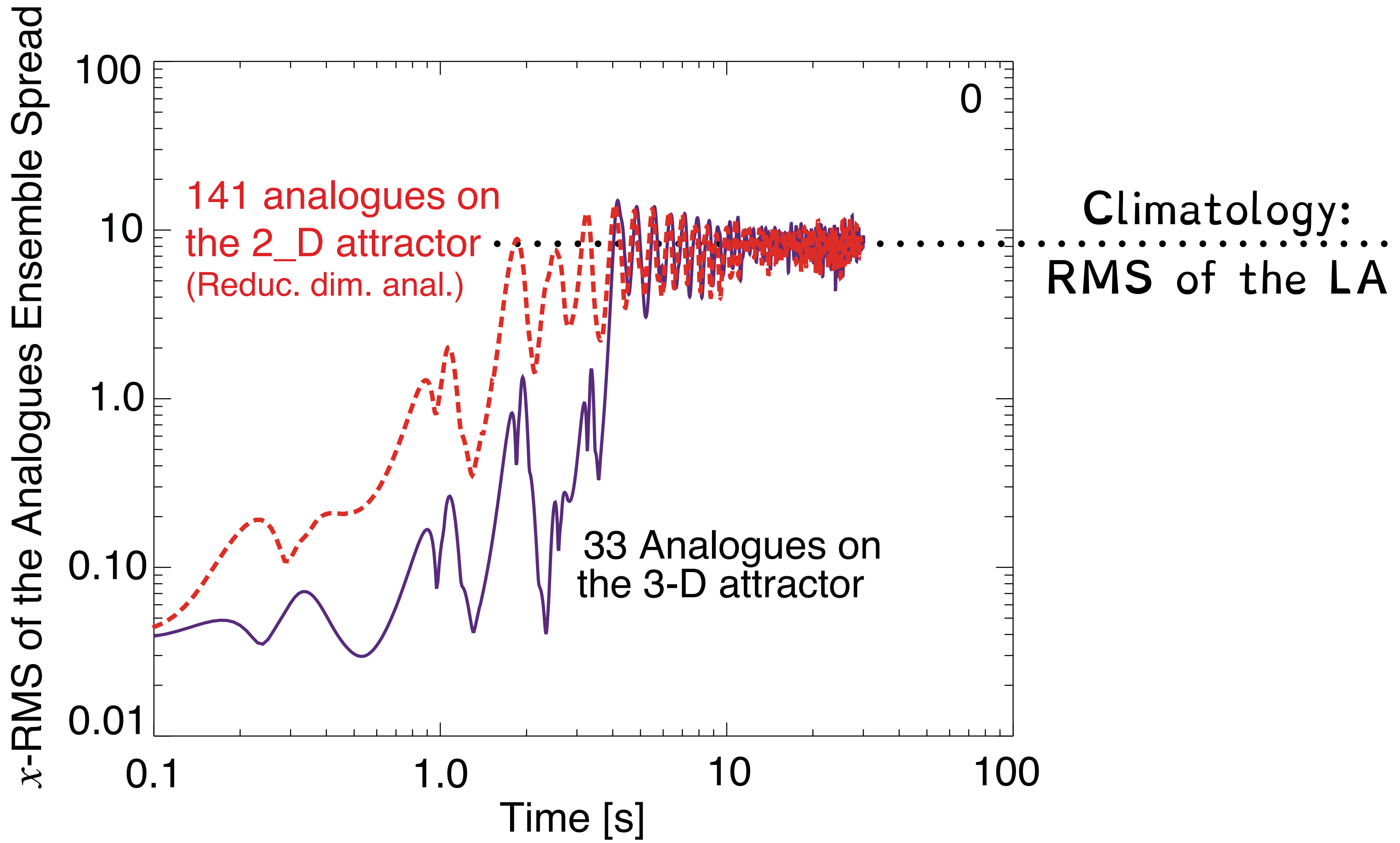

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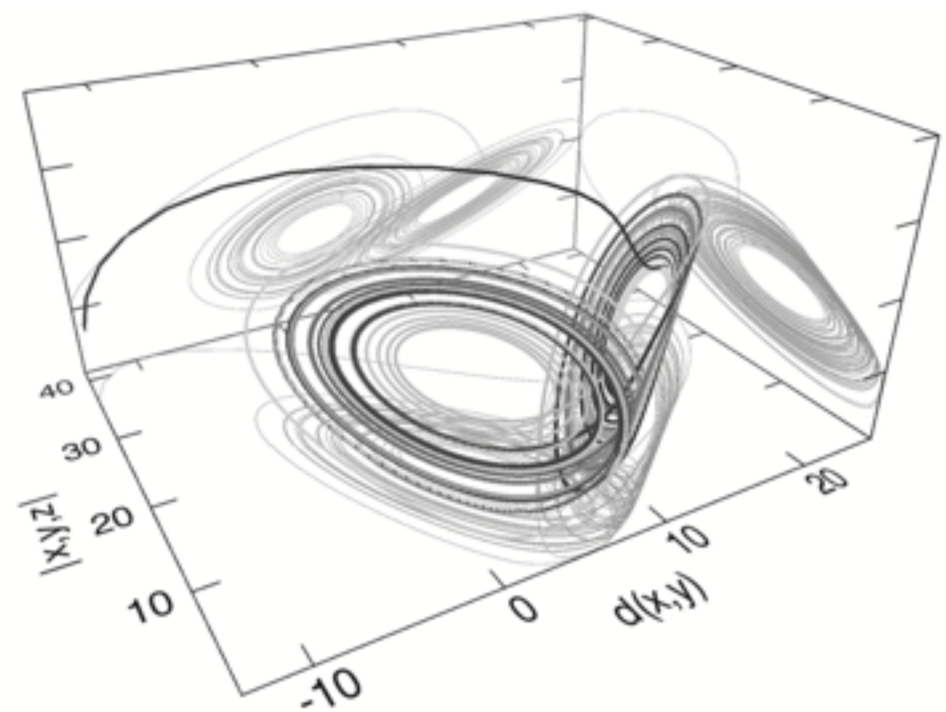
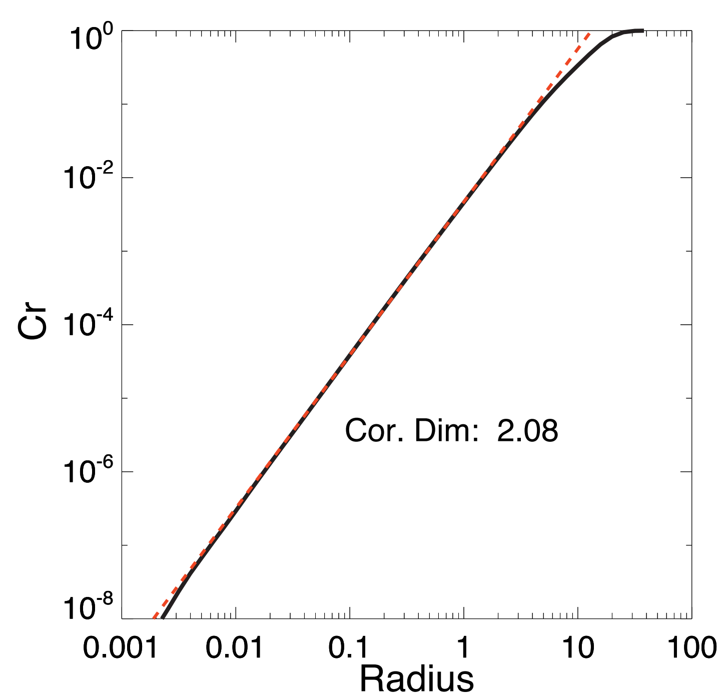
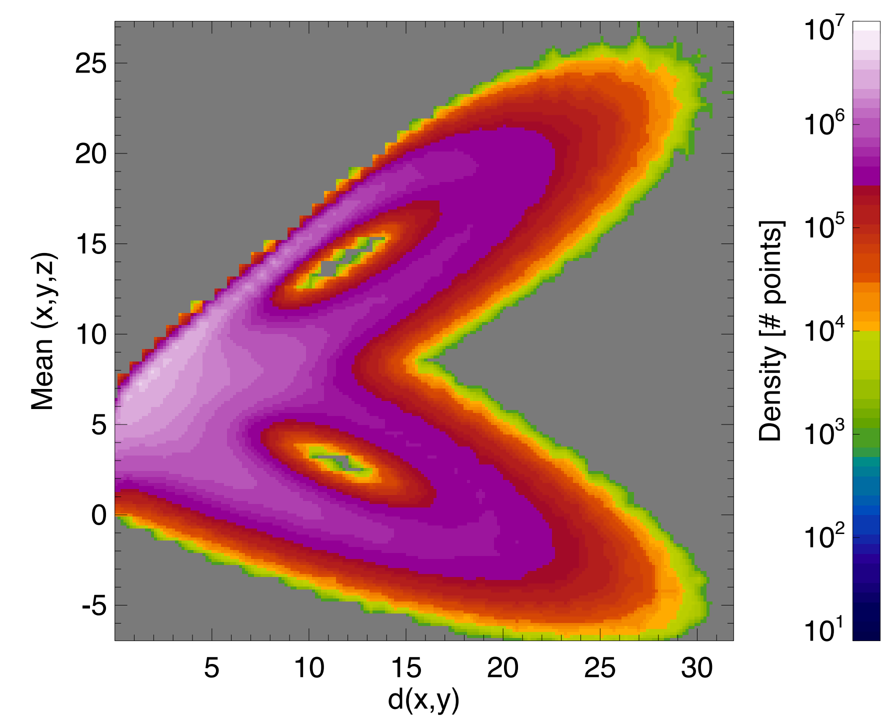
The analogues ensemble forecast from the reduced dimension attractor contains a greater amount of information than climatology.

Must we know the exact variables of the phase space?

We can taylor the attractor to fit our needs. Say, we want to forecast the mean of x,y,z, the eccentricity of x,z, $[z^2/(x^2+z^2)]^{1/2}$, and the euclidian distance between x and y. From the original attractor we can construct an attractor in these coordinates:



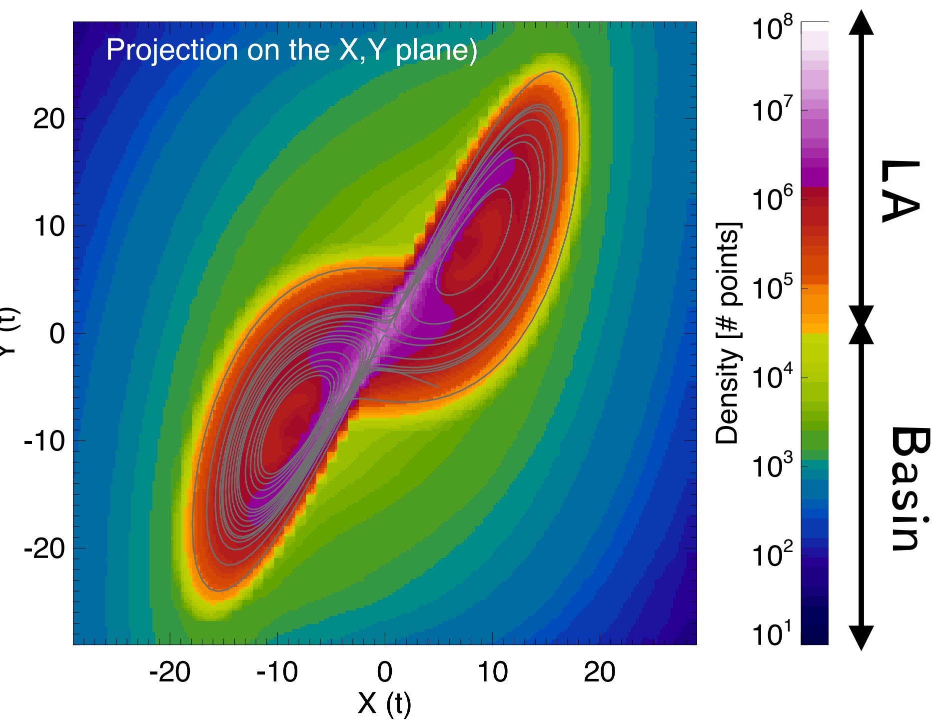




The attractor conserves all its characteristic.

WE CAN USE PROXY VARIABLES TO DEFINE THE PHASE SPACE

Is this low order system relevant for Nowcasting of such a high order system as precipitation?



Consider the attractor as the climatology of the system represented as the **joint probability of the phase-space variables**, $p(x|y|(z)$. The number of variables can be reduced, or use proxy variables, and still the ensemble of analogues will have predictive value.

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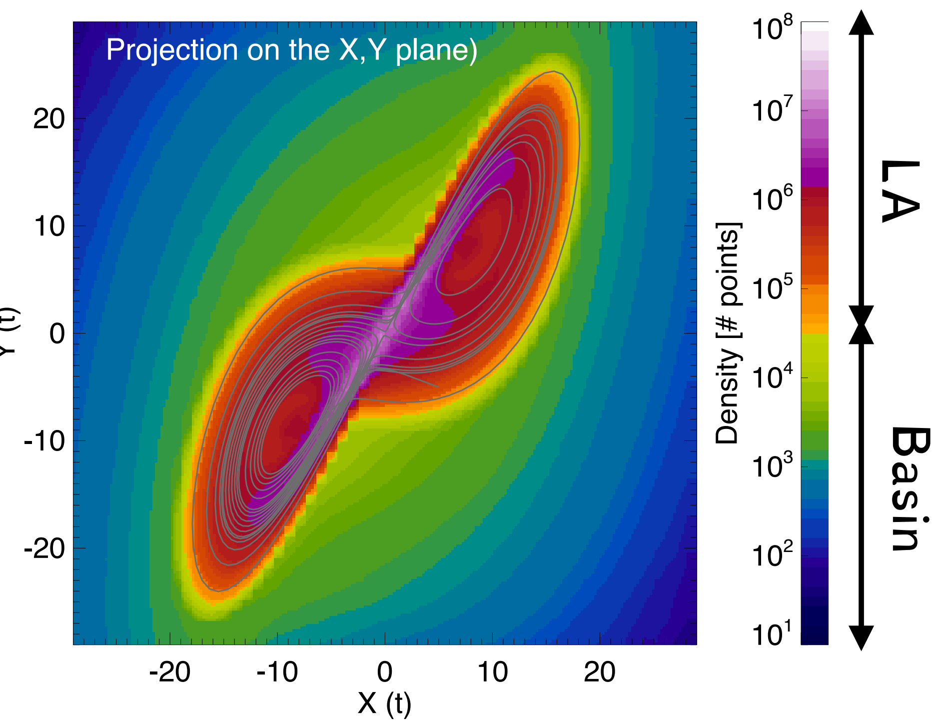

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OUR GOAL IS TO EXPLORE THE USE OF RADAR DATA, TOGETHER WIH OTHER DATA, TO CONSTRUCT A CLIMATOLOGY OF THE JOINT PROBABILITY OF RELEVANT VARIABLES, WHICH WE WILL CALL "RAIN ATTRACTOR" AND STUDY ITS NOWCASTING POTENTIAL

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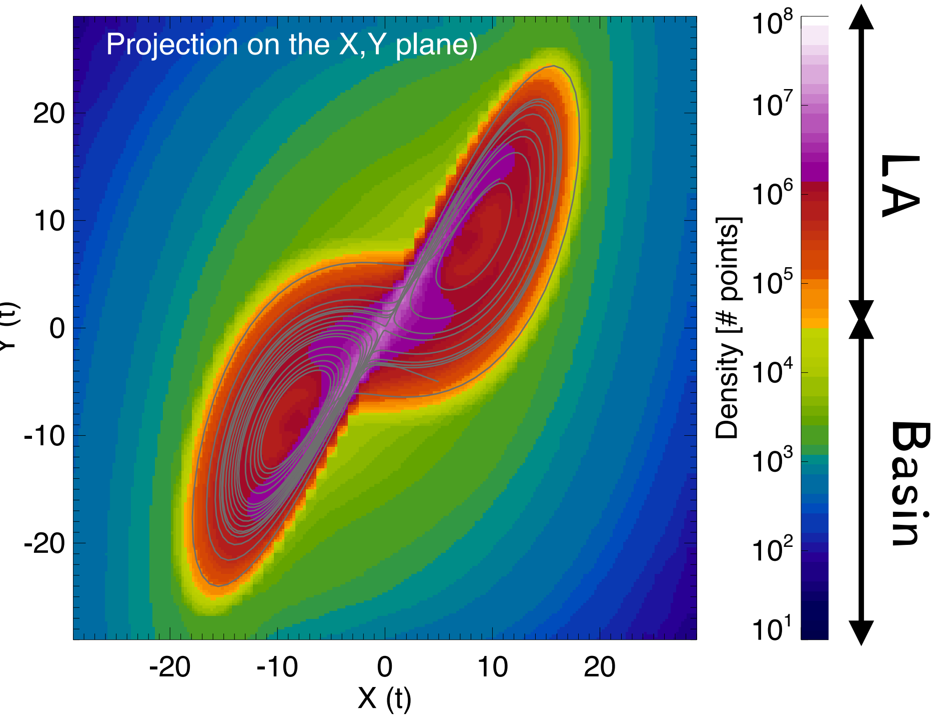

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What are "RELEVANT VARIABLES"?

Here we go back to conceptual models and Hector Grandoso.

A first attempt at a “Rain Attractor”

From 17 years of continental composites of precipitation patterns we can construct a 5-D (sparce) RAIN ATTRACTOR. The phase space we use is comprised of one thermodynamic variable and 4 statistical properties of the pattern:

70-50 kPa thickness (every 3h, from reanalysis),

Area of precipitation,

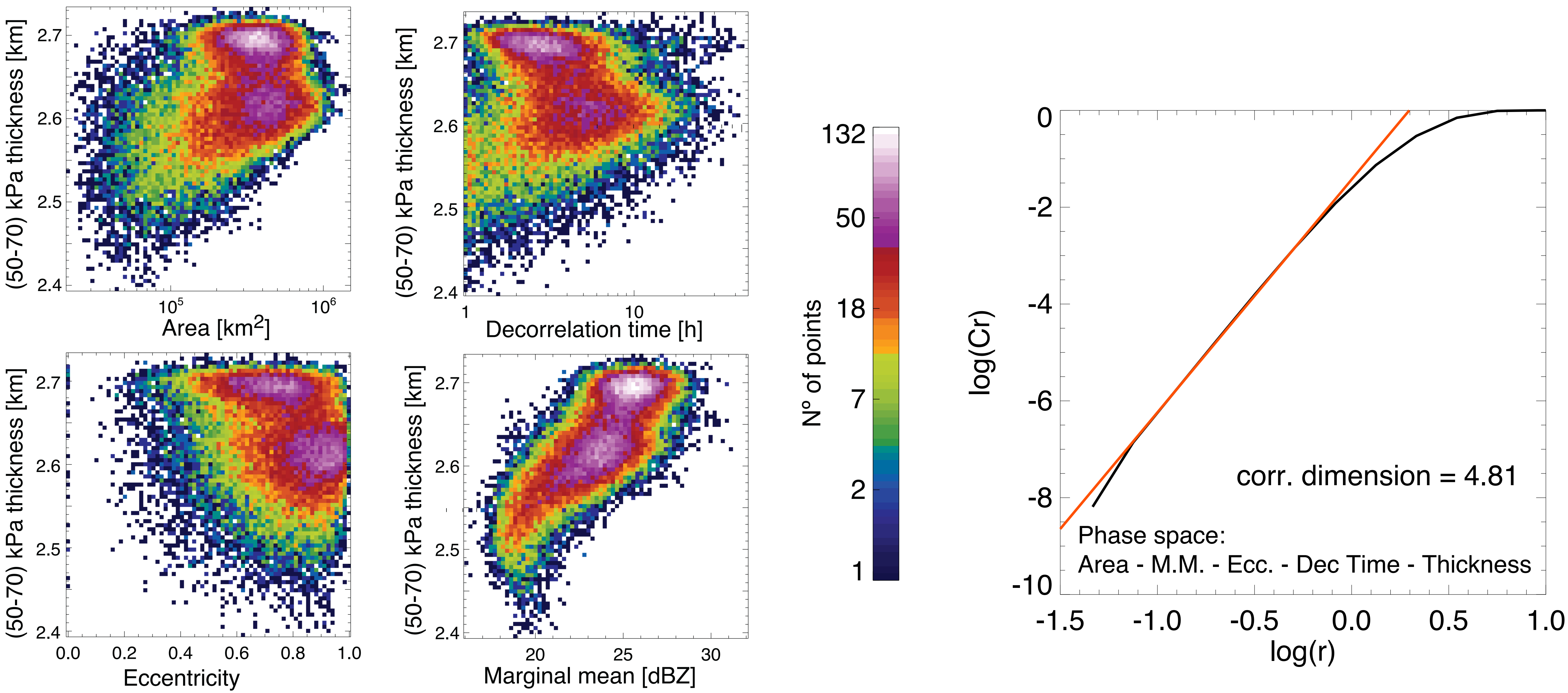
its Eccentricity,

Marginal Mean reflectivity,

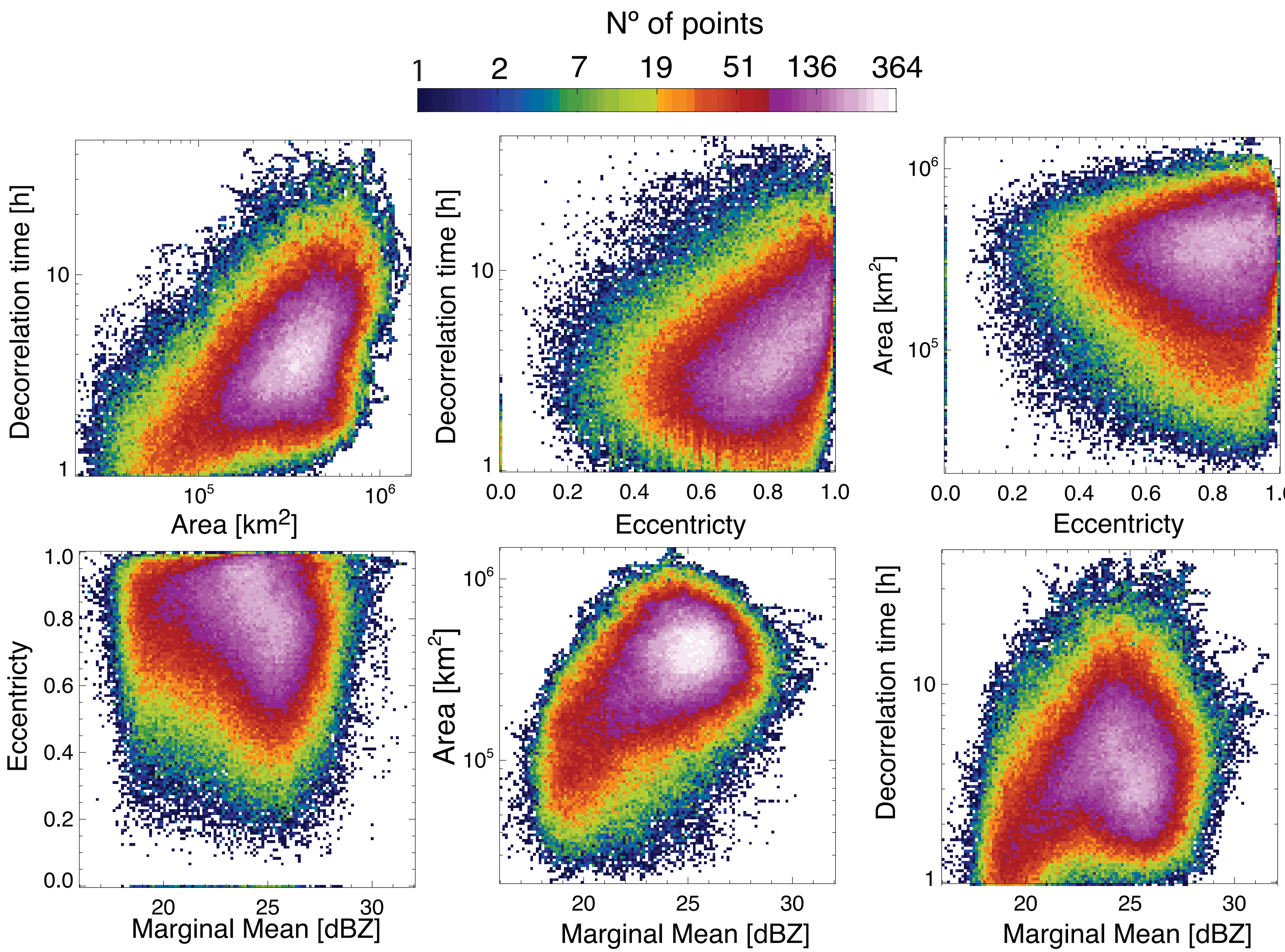
Decorrelation time.

Here we will use all variables or a smaller dimension subset of them.

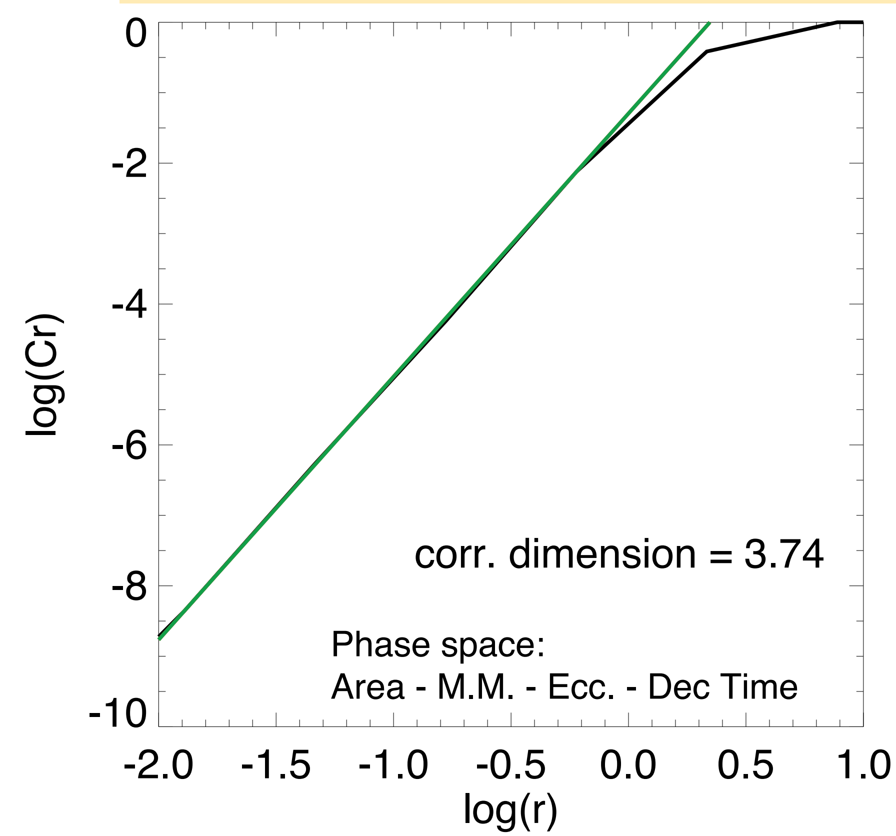
Density Projections of a 5-D Rain Attractor



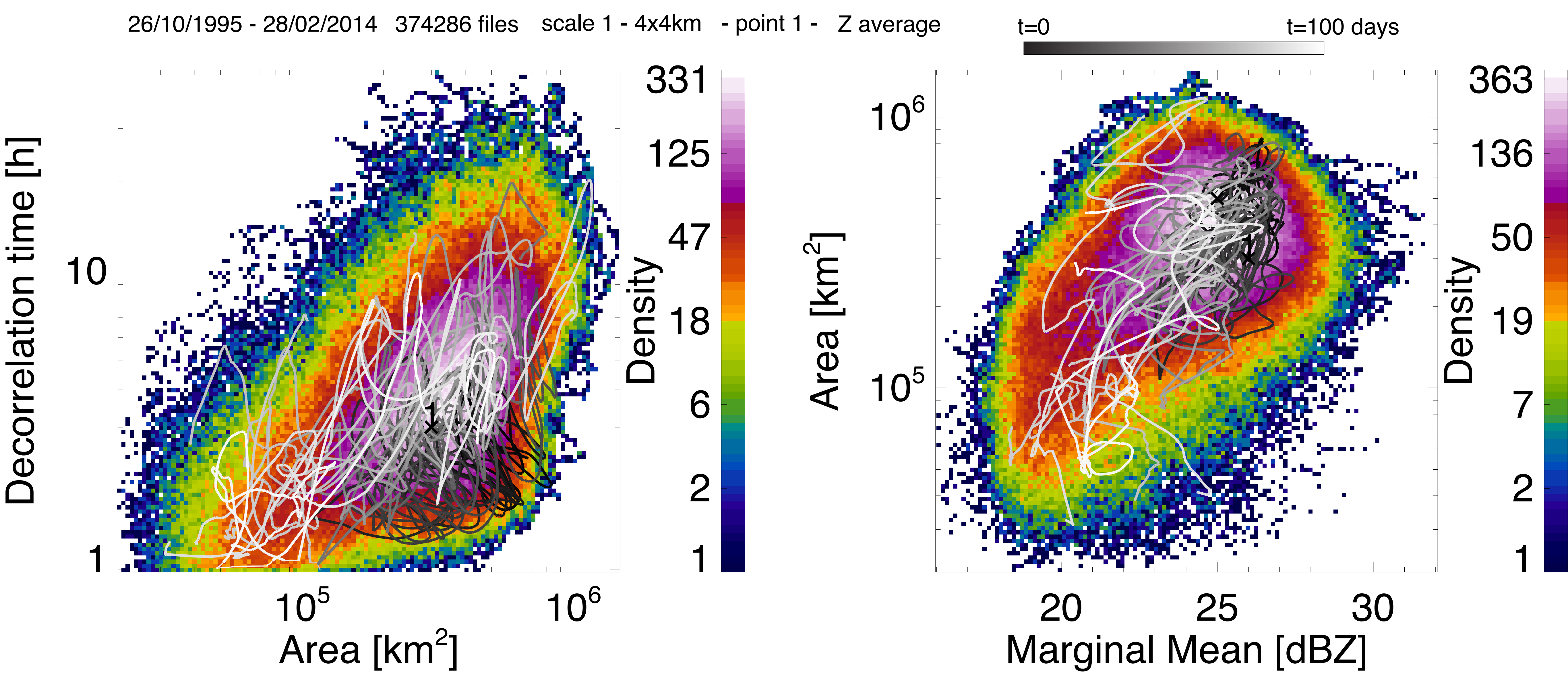
The other Projections of the Rain Attractor



For this 4-D attractor:



Trajectories on the Rain Attractor



Forecast and Ensemble Spread on the Rain Attractor

How does it work? Say, at the present time we have only marginal mean (MM).

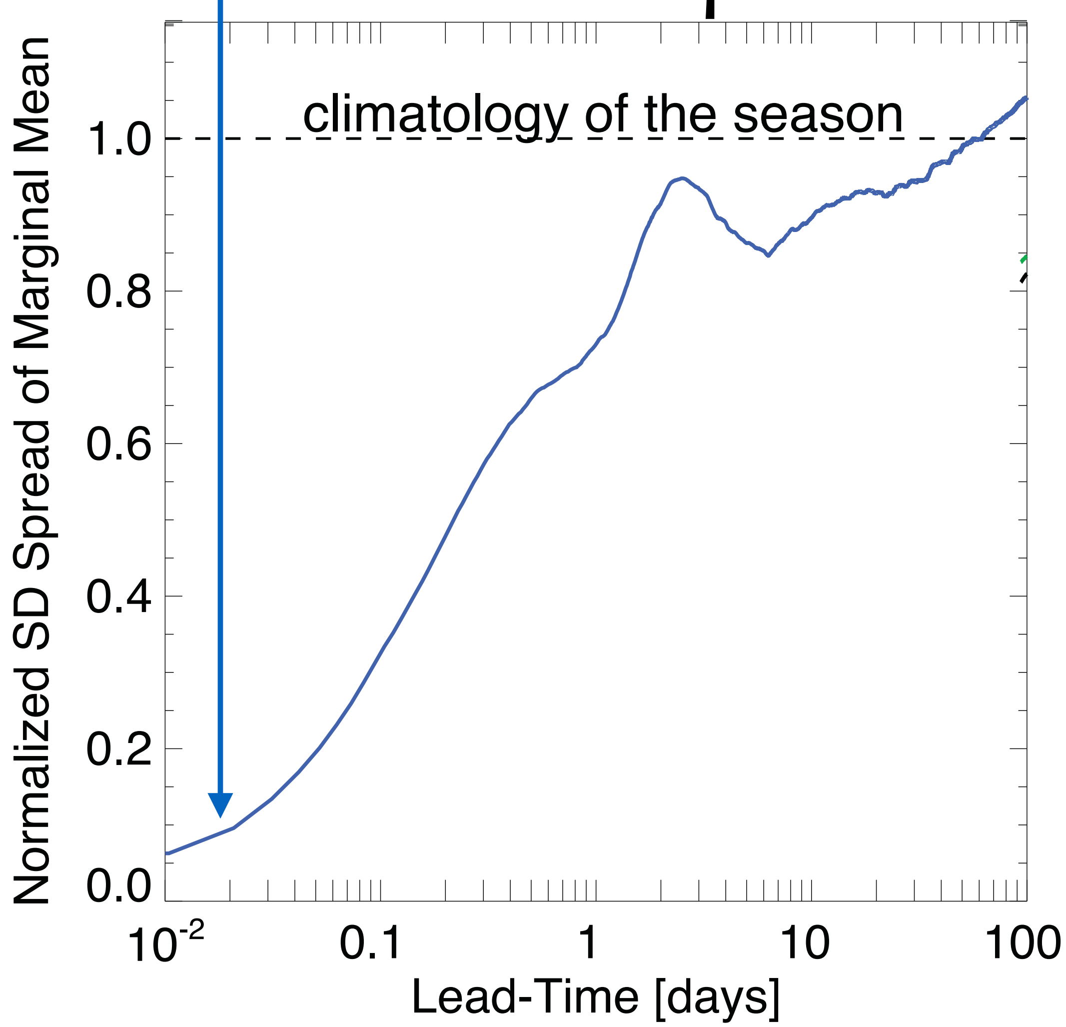
1-Select in the 1-D attractor 250 cases with the closest MM

2-Make the ensemble forecast

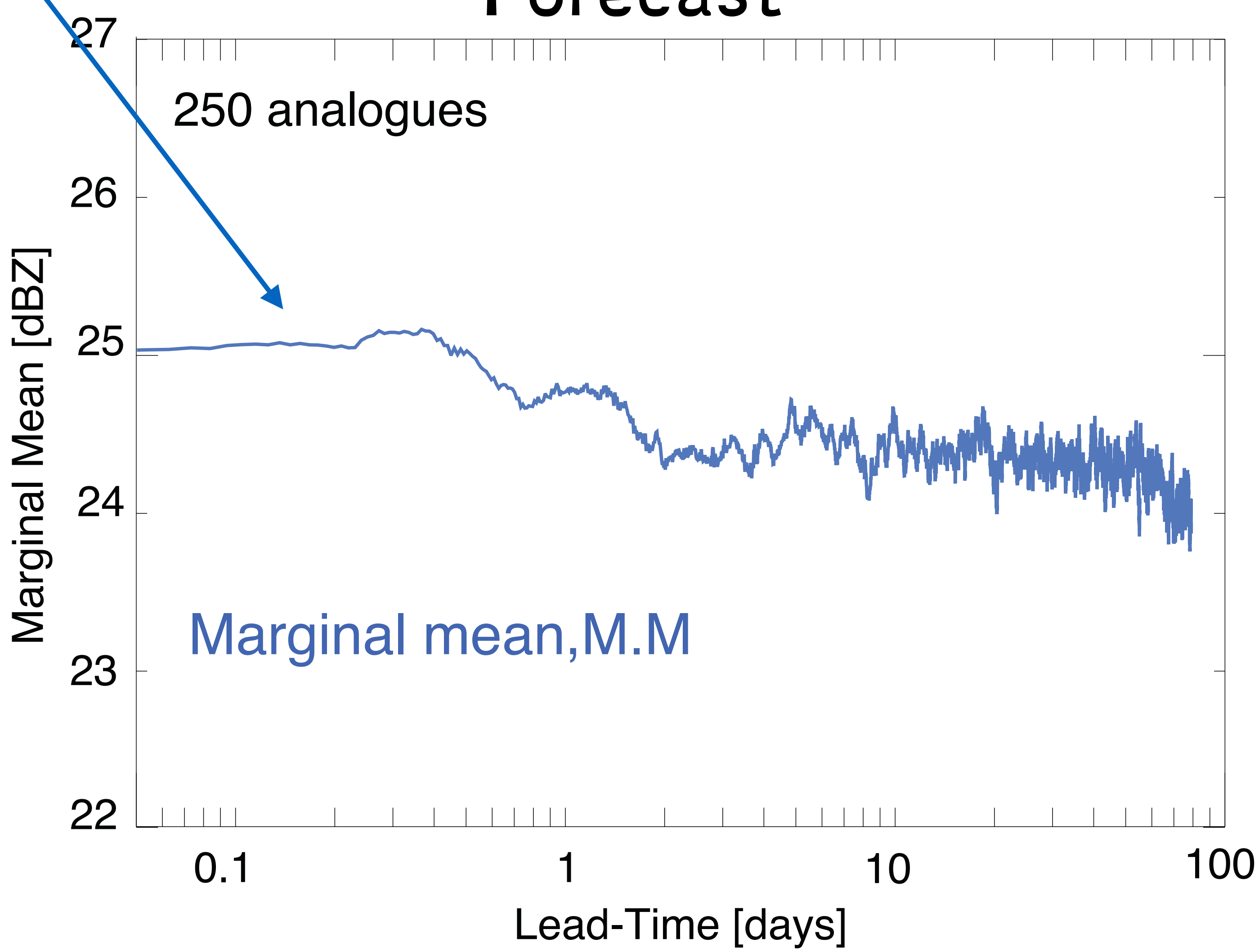
3-Measure the ensemble spread

We see that there is a skill better than climatology for ~2 days.

Ensemble spread



Forecast

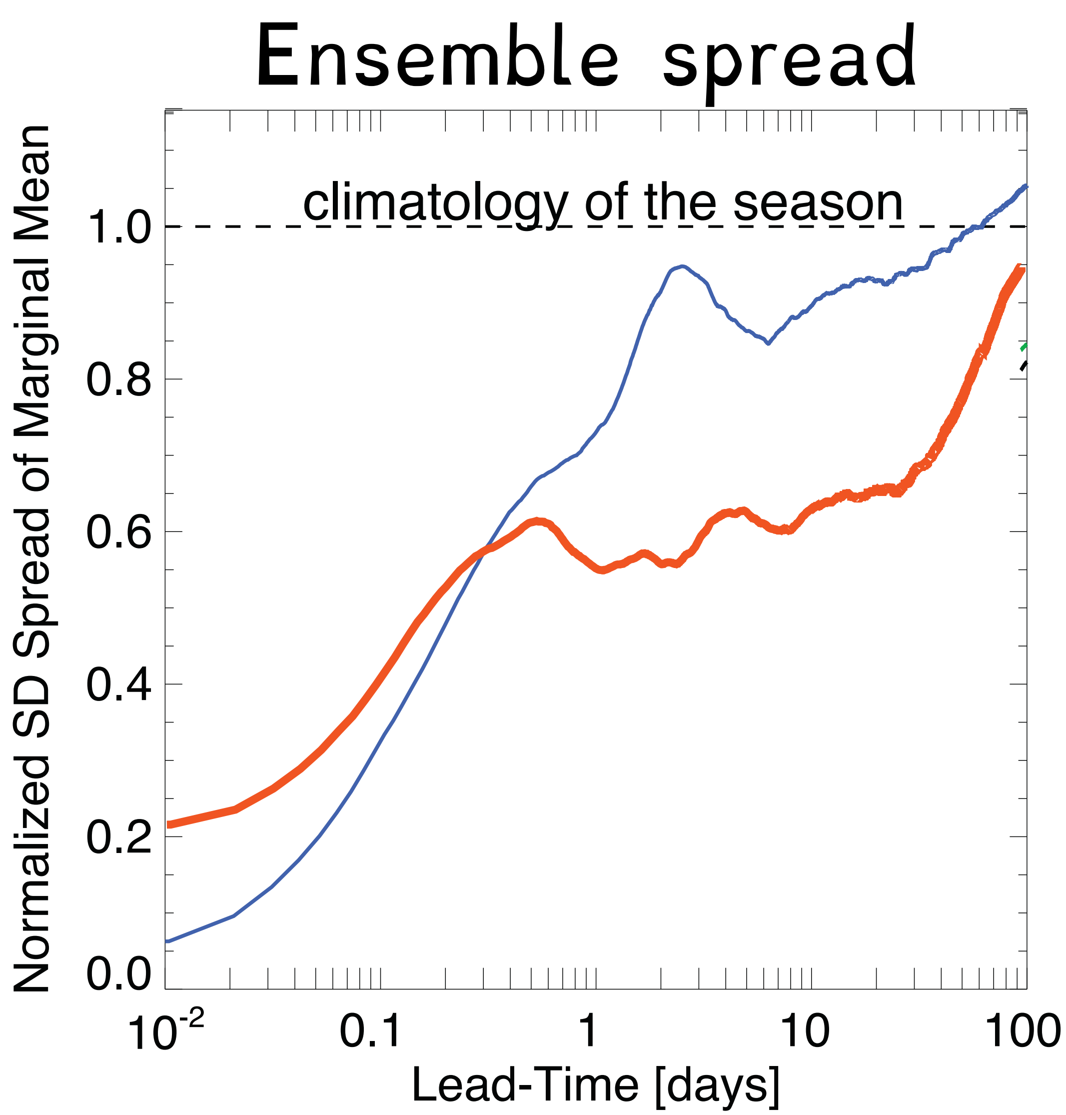


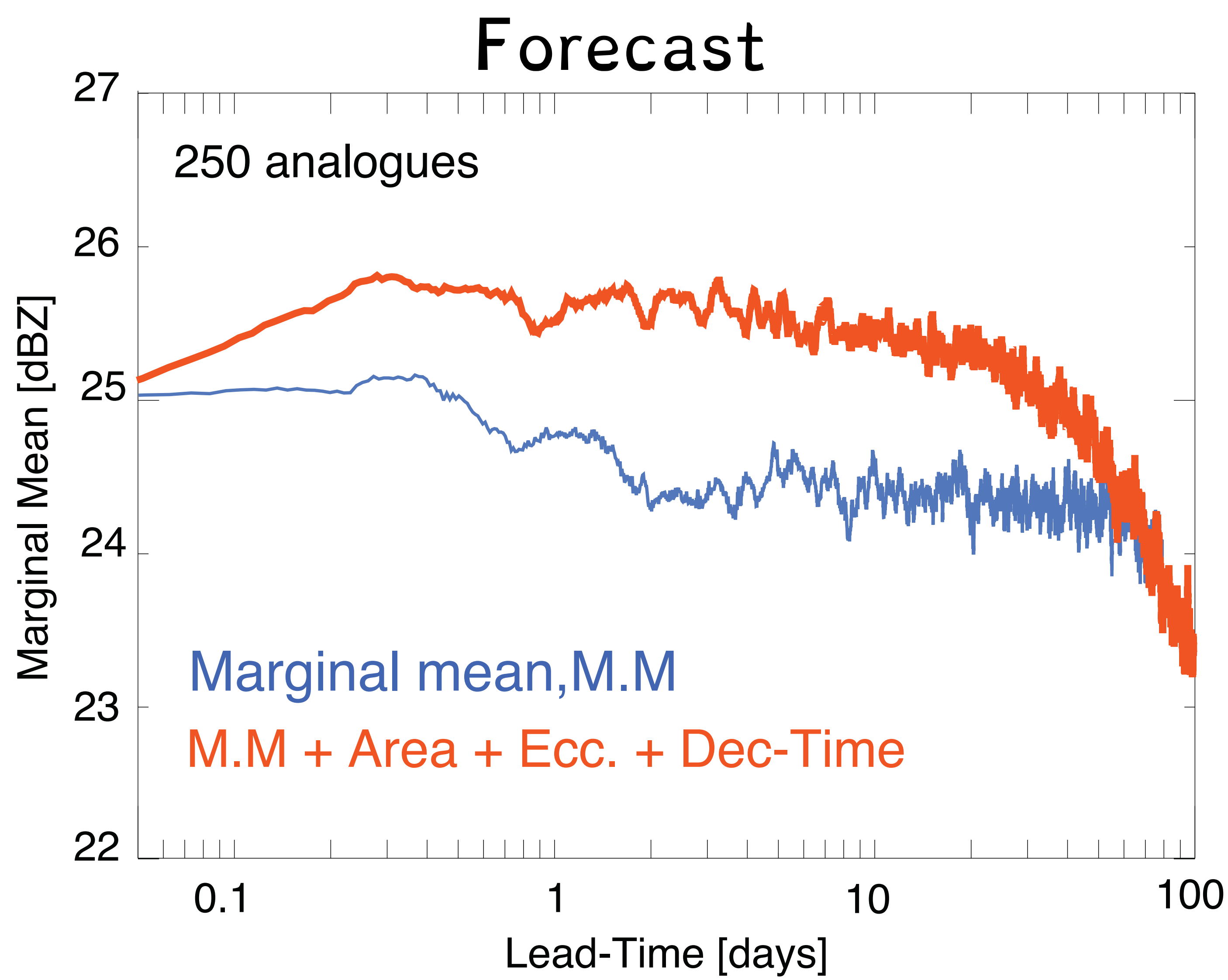
Forecast and Ensemble Spread on the Rain Attractor

Now add to MM the Area, Eccentricity and Decorrelation Time of the pattern.

1-Select in this 4-D attractor 250 cases with the closest values of these 4 parameters
2-Make the average ensemble forecast
3-Measure the ensemble spread

We see that the skill is much better than climatology for ~10 days.





Forecast and Ensemble Spread on the Rain Attractor

Now we take the 50-70 kPa Thickness, MM, and Decorrelation Time.

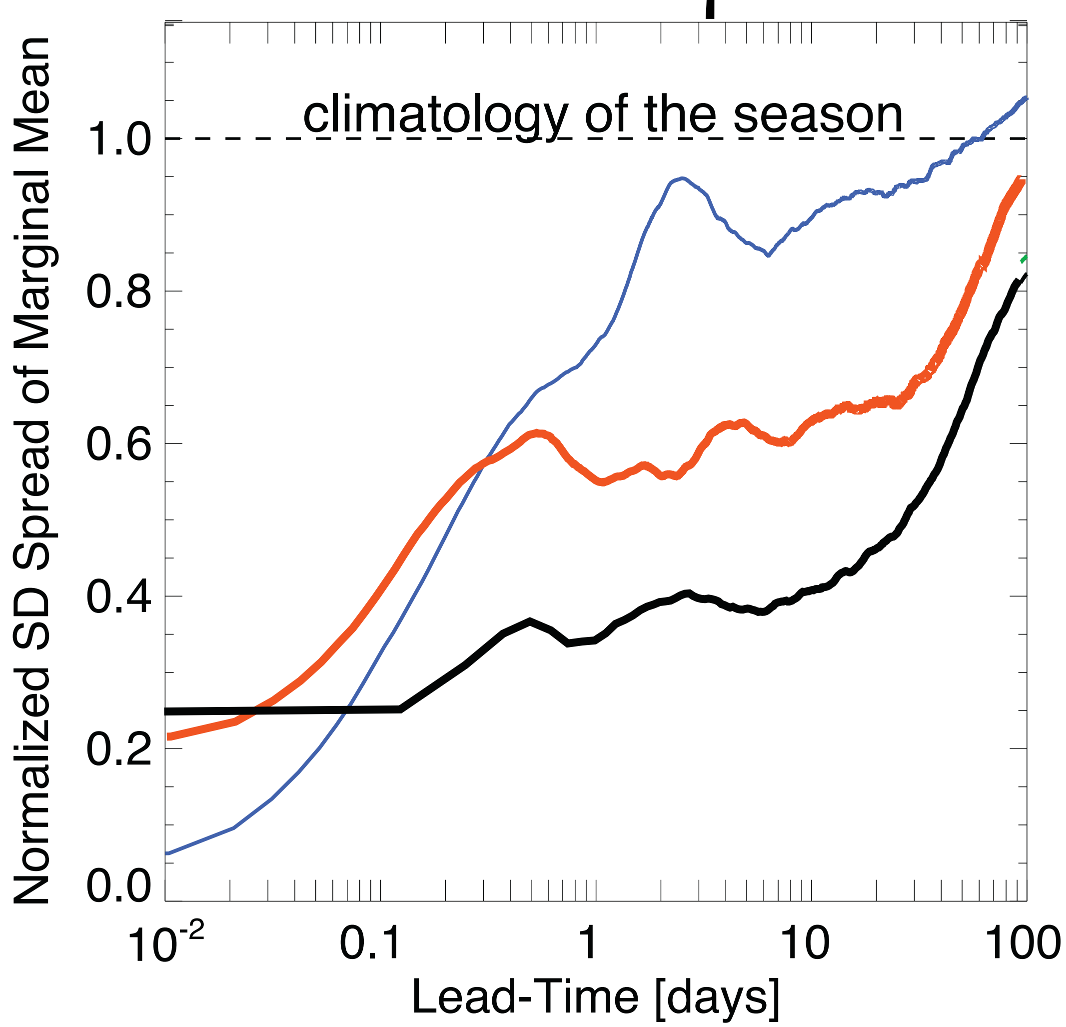
1-Select in this 3-D attractor 250 cases with the closest values of the 3 parameters

2-Make the average ensemble forecast

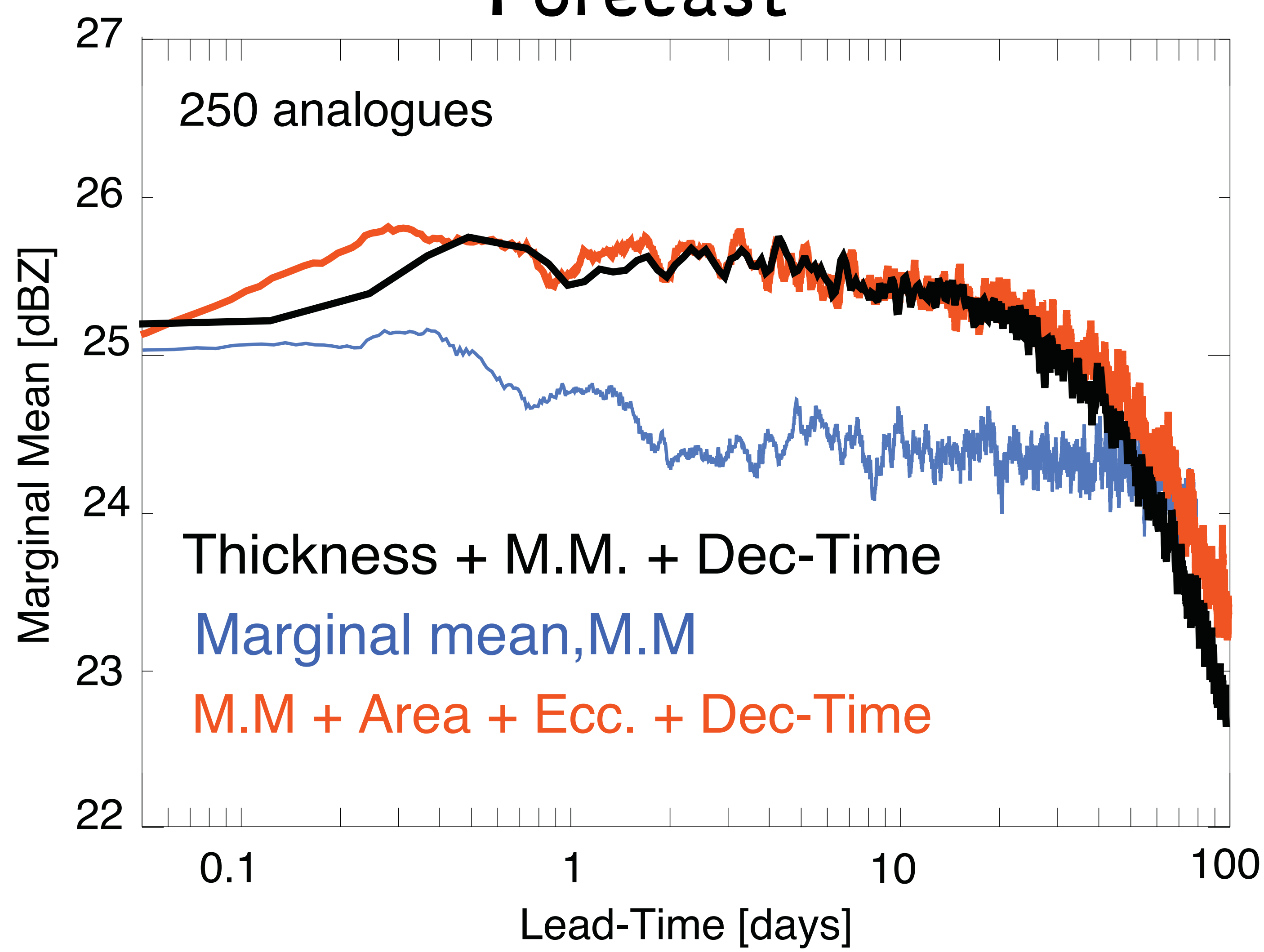
3-Measure the ensemble spread

We see that the skill is much better than climatology for ~30 days and longer.

Ensemble spread

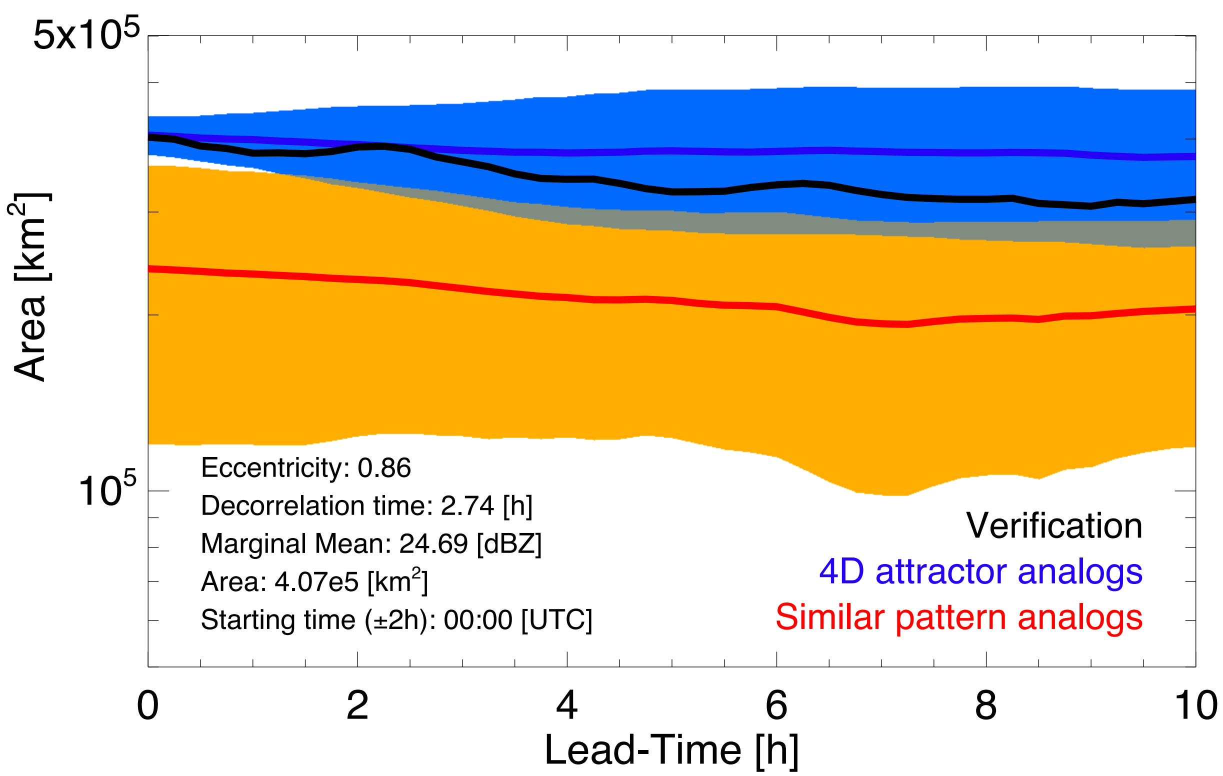


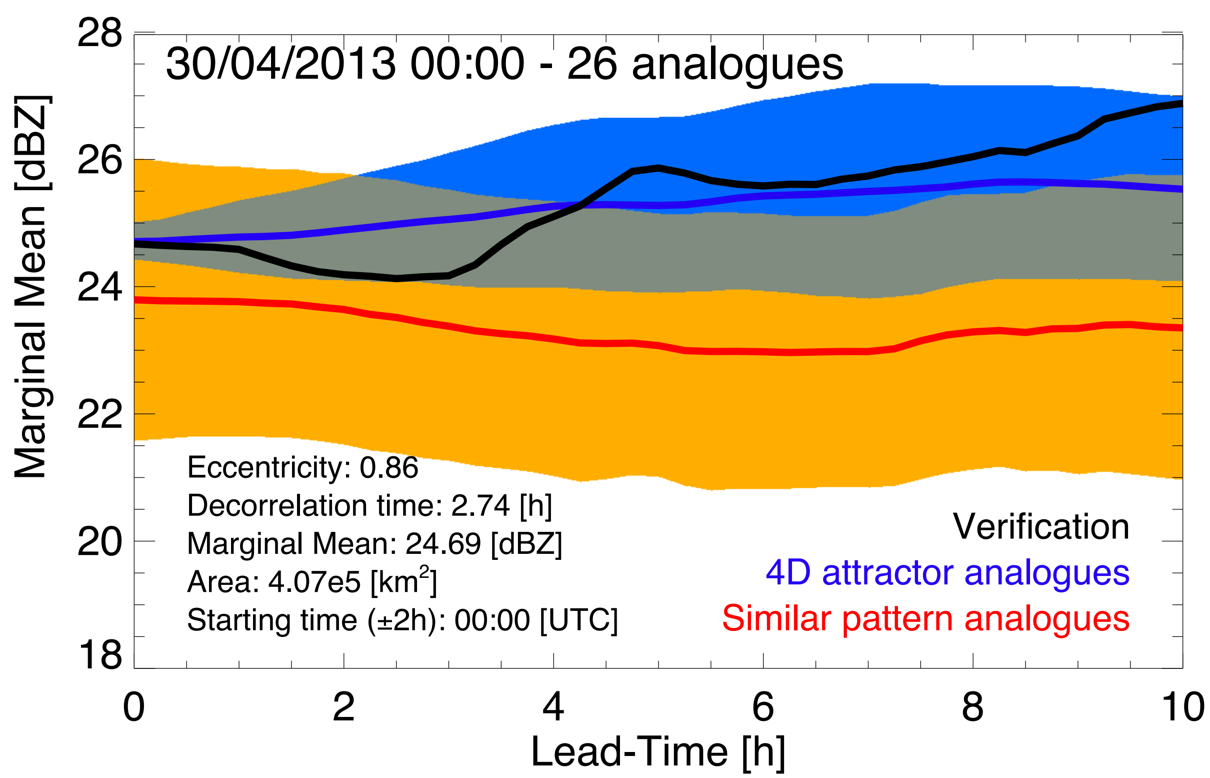
Forecast



Comparison of Performance

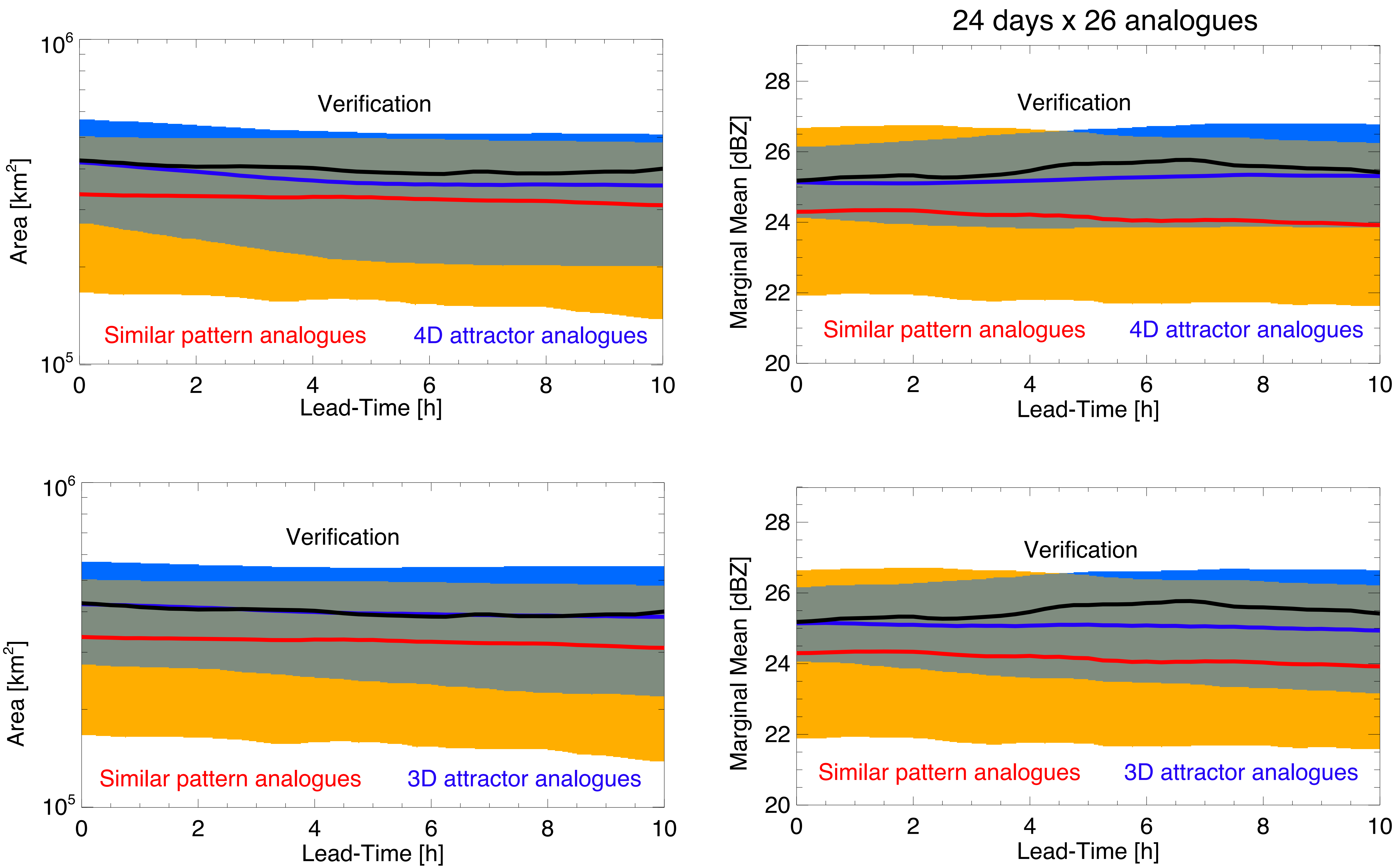
Not surprisingly, attractor analogues are better at predicting Area and Marginal Mean that similar patterns. They were tailored for this purpose!





Comparison of Performance

And the average of 24 days:



This was a first exploration of the “Rain Attractor”. It looks promising.

NEXT:

This attractor approach is now moving to Switzerland where it became part of an **SNSF AMBIZIONE** project (Urs German, Loris Foresti).

Combination with satellite data, surface data, orography;

Search for the smallest most effective phase space (principal components?)

State dependence

.....

A PhD position available

THANK YOU