Probabilistic comparison of the information in the rainfall field from NWP and analogue-based forecasts.

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Outline

- Motivation and working hypothesis
- Dataset and NWP ensemble forecast
- Analogue selection technique
- Deterministic and probabilistic comparison
- Spatial merging of the two forecasts
- Conclusions

Motivation

Atmospheric system

Precipitation is a complex processes which depends on several factors.
(Rainfall fields is used as an indicator)

It is a chaotic - stochastic system.
Predictability limits.

How can we predict the evolution of the rainfall field?

Motivation

Atmospheric system

Precipitation is a complex processes which depends on several factors.
(Rainfall fields is used as an indicator)

It is a chaotic - stochastic system.
stability limits.

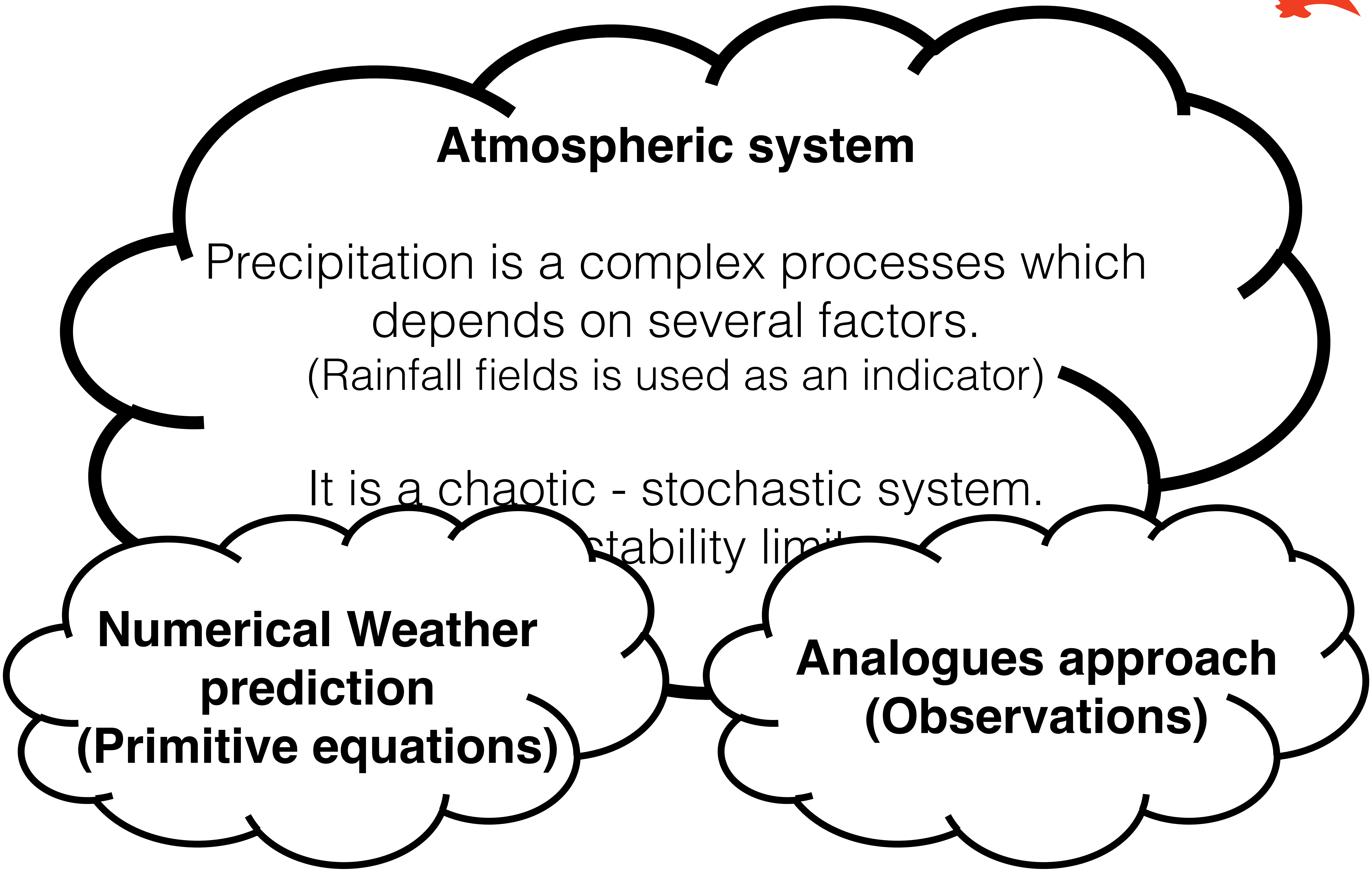
Numerical Weather prediction (Primitive equations)

Motivation

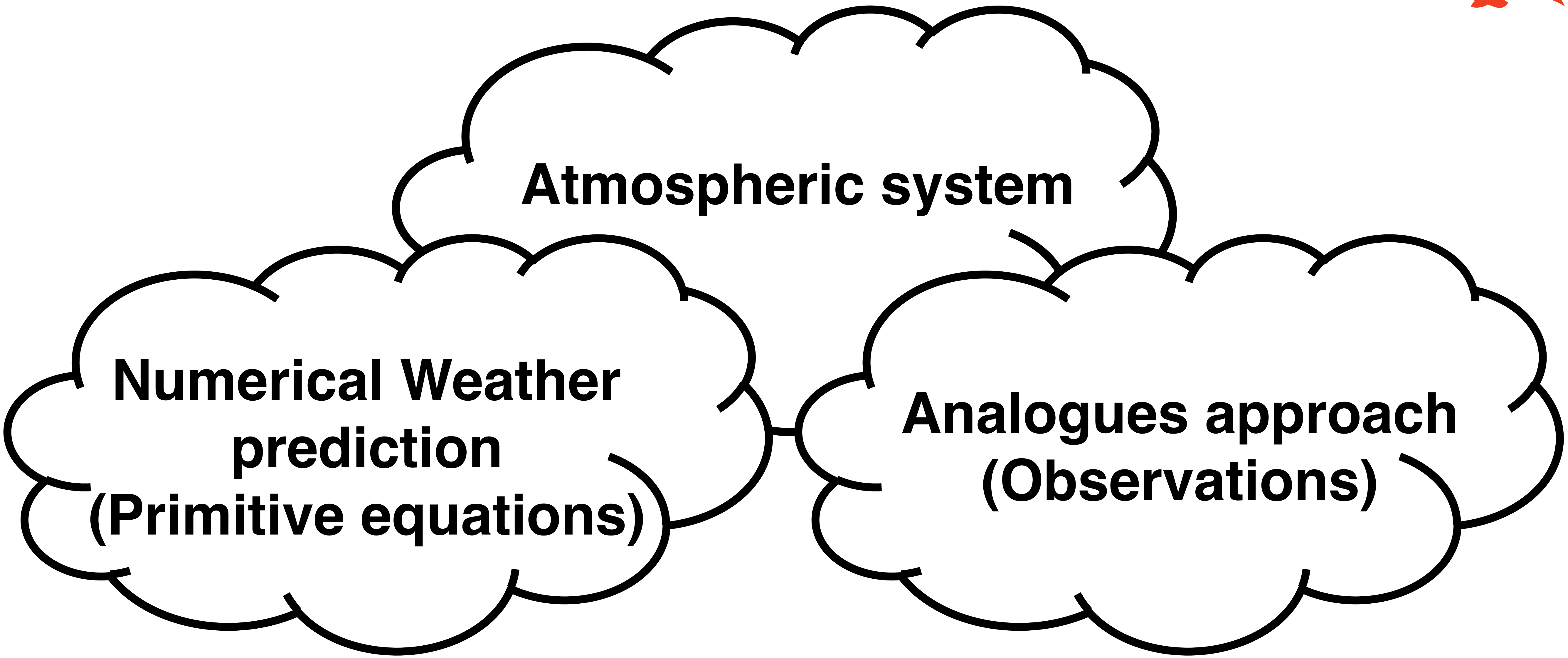
Analogs idea

Lorenz (1969, 1973) proposed an ingenious method of studying classical atmospheric predictability using naturally occurring analogs from past records of atmospheric observations. He proposed that if it ***were possible to find*** *two rather closely resembling atmospheric states, the rate which the differences between the two states growth would give a measure of the classical predictability* error growth.

Motivation


Atmospheric system
Precipitation is a complex processes which depends on several factors.
(Rainfall fields is used as an indicator)
It is a chaotic - stochastic system.
Numerical Weather prediction (Primitive equations)
Analogues approach (Observations)

Motivation



Is it possible to realize a forecast in a high dimensional system?

Do we have a long enough dataset for searching analogues?

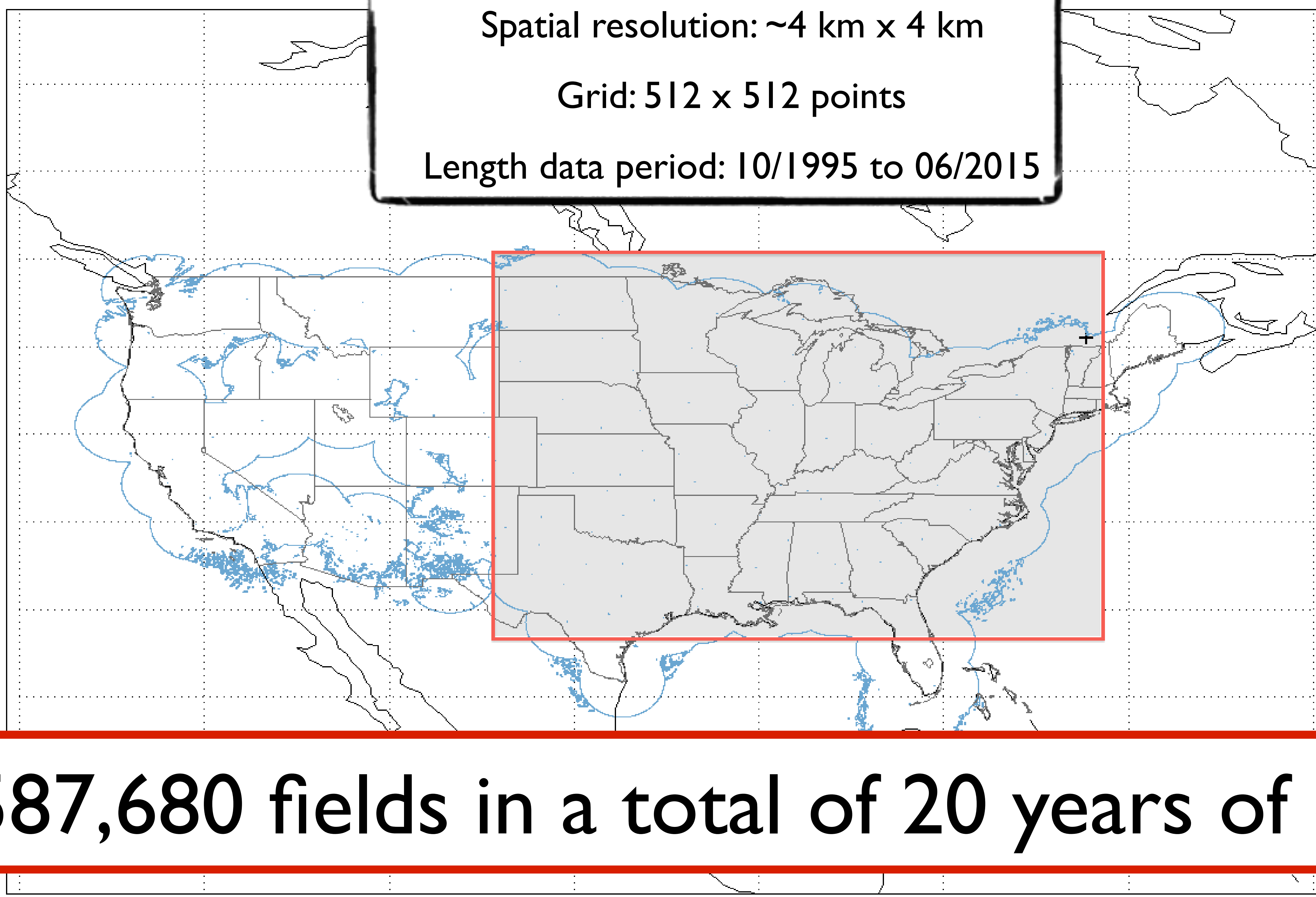
Dataset

Temporal resolution : 15 minutes

Spatial resolution: ~4 km x 4 km

Grid: 512 x 512 points

Length data period: 10/1995 to 06/2015



587,680 fields in a total of 20 years of data

Dataset

The domains has 512 x 512 pixels but only 212’394 of them are rainfall data because of the radar coverage.

Phase space is a space in which all possible states of a system are represented.

There are $\sim 4.5 \bullet 10^{10}$ possible combinations (states) of rainfall fields. (We have only 587,680 rainfall images ~ 0.001%)

There is no enough data to obtain close enough states

Van den Dool (1994) concluded that it is needed **10^{30} years** to obtain analogues that match to within current **observational errors**

Working hypothesis

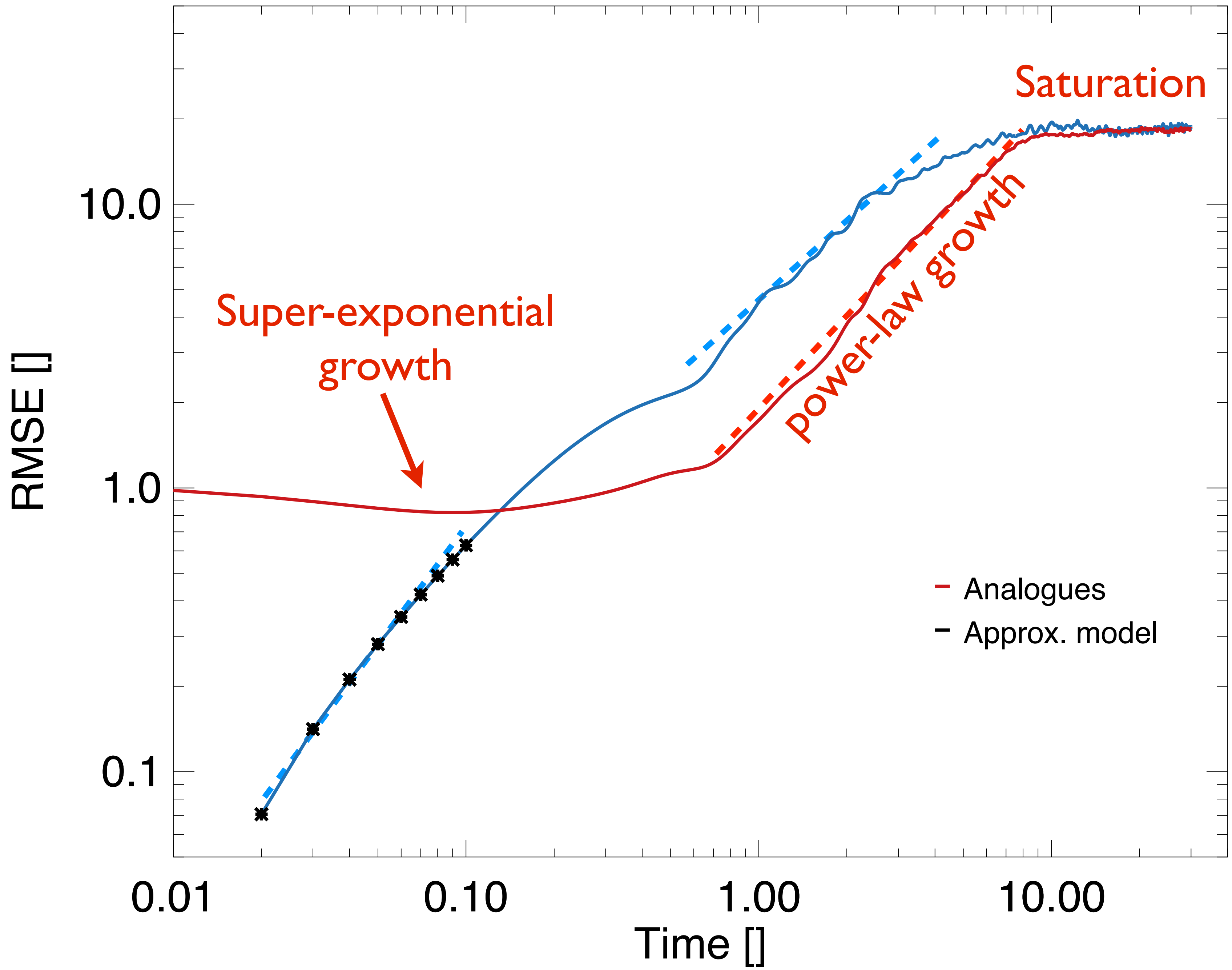
Do we need that the obtained analogues match within current observational errors?

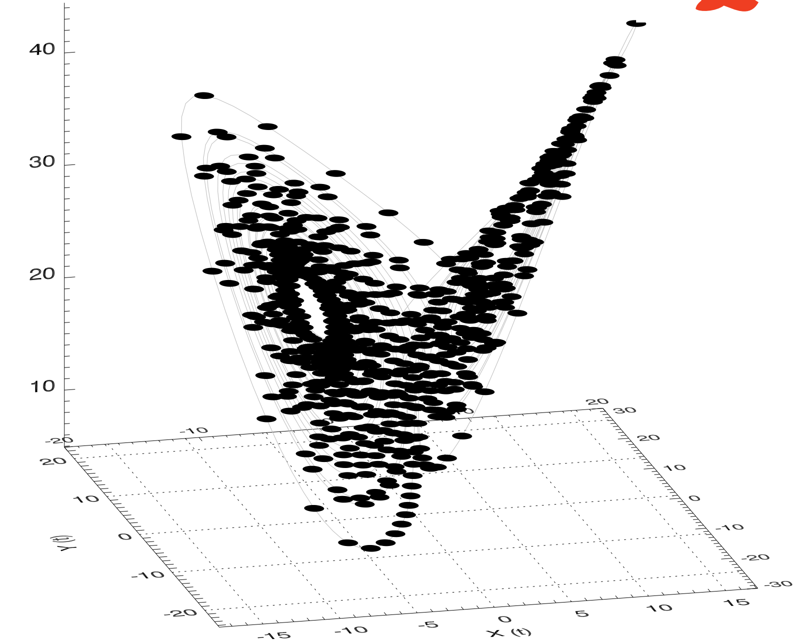
The NWP equations are approximations of the system, so the model **could** have also errors in the forecast due to these approximations in the equations.

-Experiment: Lorenz 63 model (three coupled differential equations)

- **Approximated model:** The same model with **different model parameters** but EXACTLY the same initial conditions.
- **Analogues:** The same model with EXACT model parameters but **different initial conditions**. These results reflect the DEPENDENCE ON INITIAL CONDITIONS.

Working hypothesis



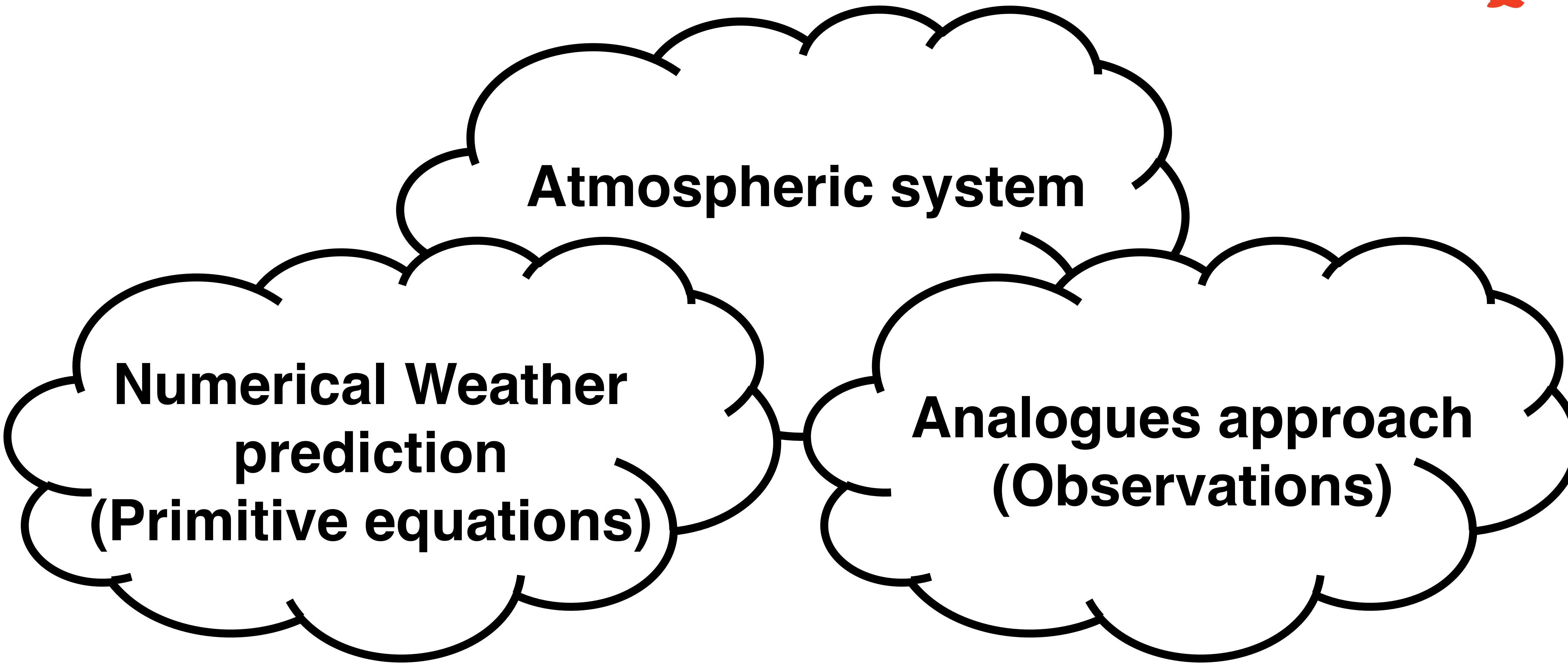


Model parameters:

Param	Model 1	Model 2
σ	10	9.995
ρ	28	27.5
β	8/3	8.02/3

We have tried to reduce the error in the parameters to obtain a similar behaviour than the other predictability. The slope has not a exponential behaviour yet. **Different chaotic dynamics**.

Motivation



Is this hypothesis still valid for high dimensional systems?

Is it any predictability skill in the past observations?

NWP ensemble forecast

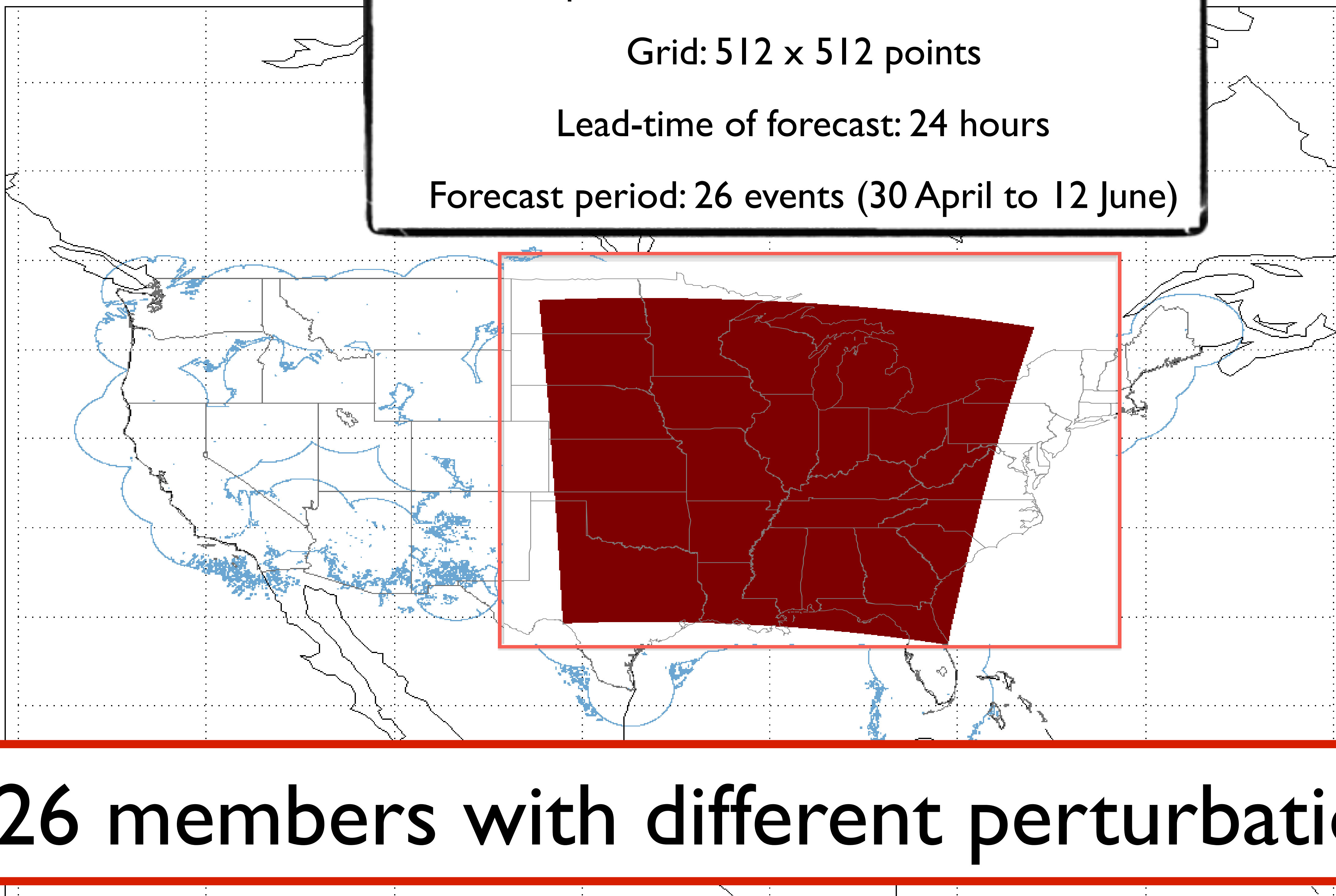
Temporal resolution : 1 hour

Spatial resolution: ~4 km x 4 km

Grid: 512 x 512 points

Lead-time of forecast: 24 hours

Forecast period: 26 events (30 April to 12 June)



26 members with different perturbations

NWP ensemble forecast

Model outputs: available from CAPS using the WRF, Advanced Research WRF core (ARW)

Ensemble code	Radar data assimilation	IC/LCB perturbations	Physics perturbations
c0	NO	NO	NO
cn	YES	NO	NO
m3-m15	YES	YES	YES
m16-26	YES	NO	YES

Full resolution radar data from the nationwide WSR88D radar network (both reflectivity and radial wind) were analyzed into the ICs using the **ARPS 3DVAR** and Complex Cloud Analysis package (Hu et al. 2006).

Analog searching technique

Selection of analogues:

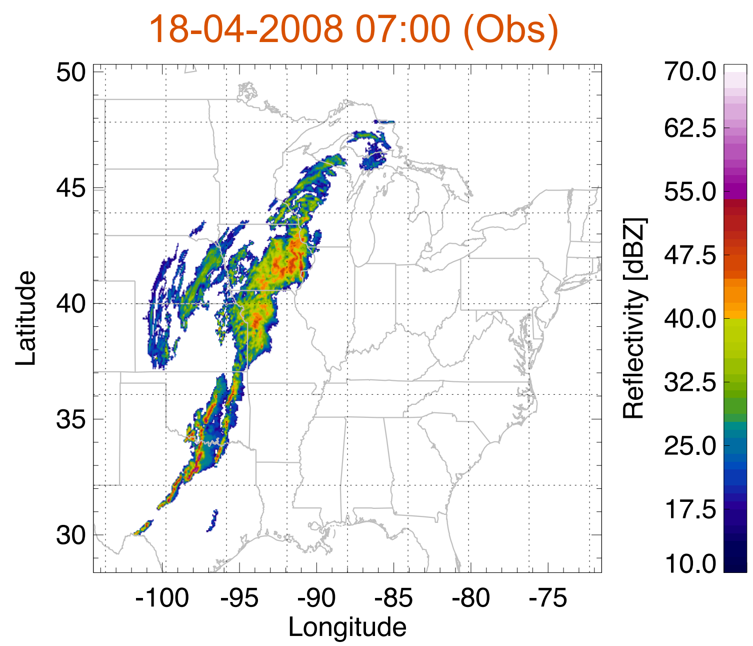
1. Spatial correlation → Rainfall patterns
2. Location → Geographical factors
3. Temporal correlation → Motion & evolution
4. Time of the day and of the year → Diurnal/ Annual cycle
5. Synoptic situation → Large scale forcing

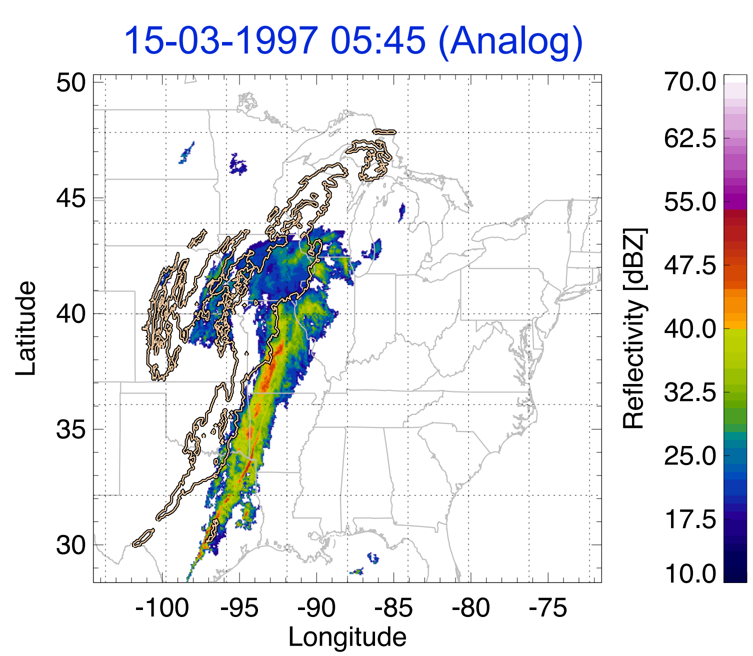
local dynamic analogs (Li and Ding, 2012)

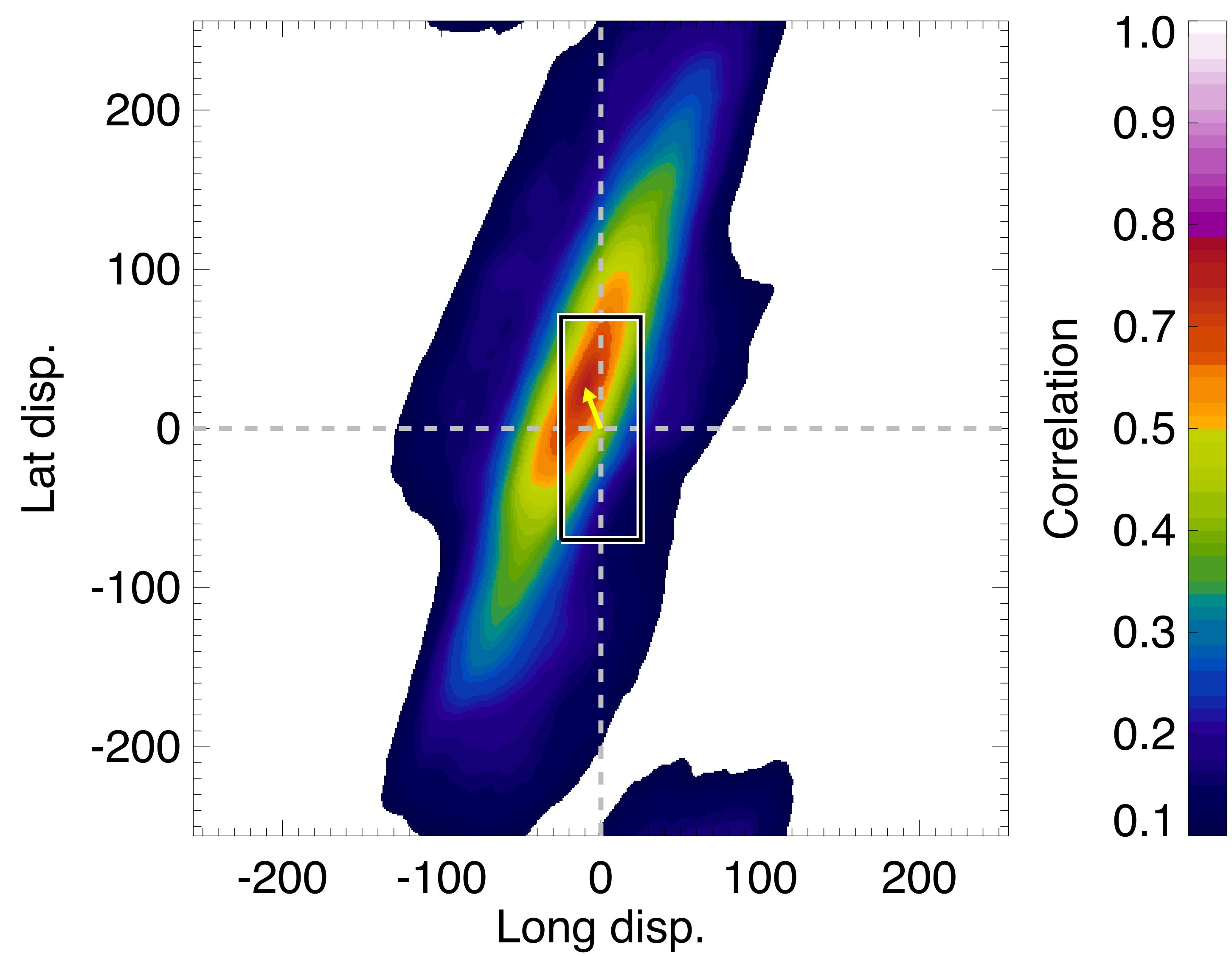
Distance   Dynamics   Large-scale forcing

Analog searching technique

1. Spatial cross-correlation → Rainfall pattern

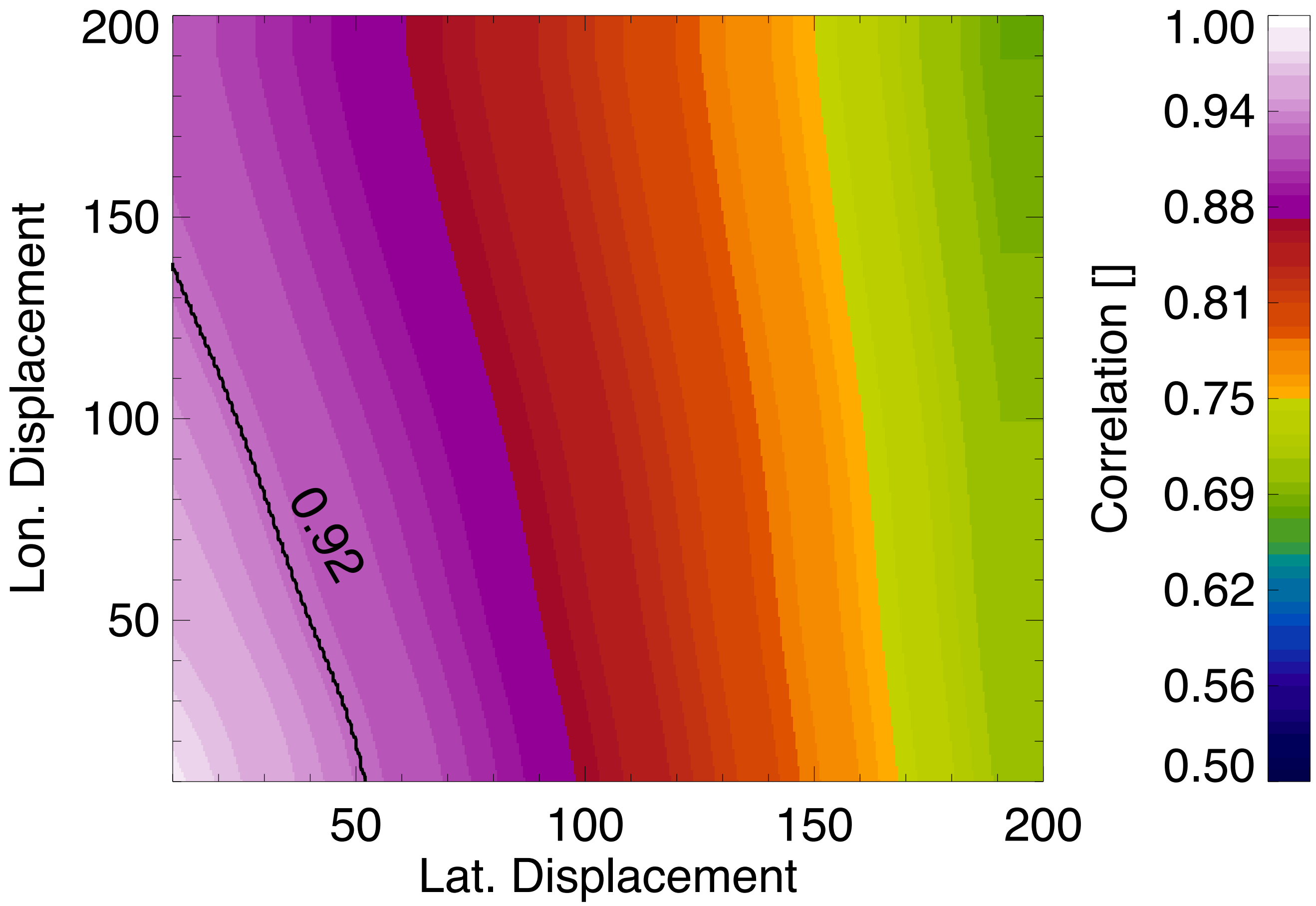


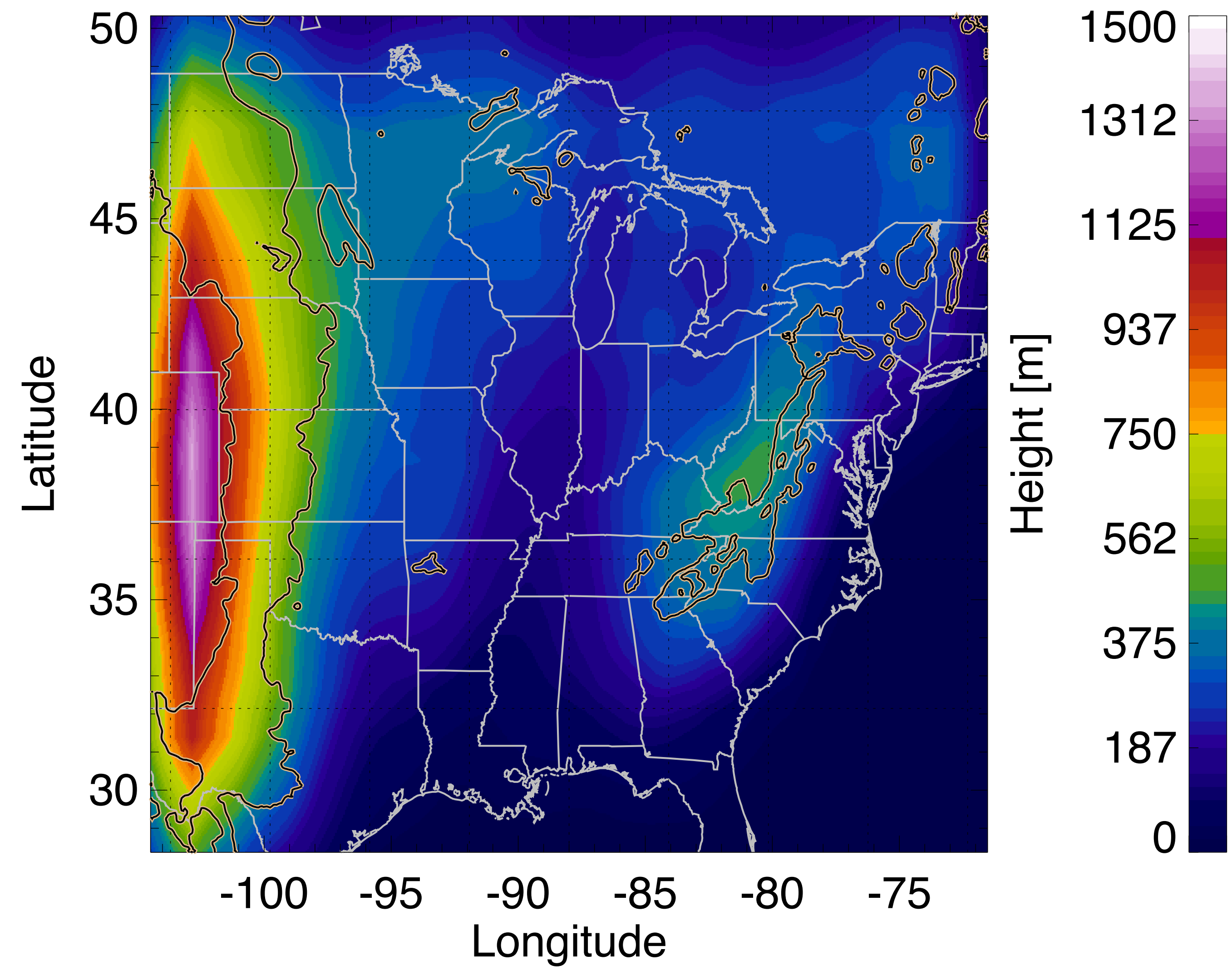




Analog searching technique

2. Location → Geographical factors

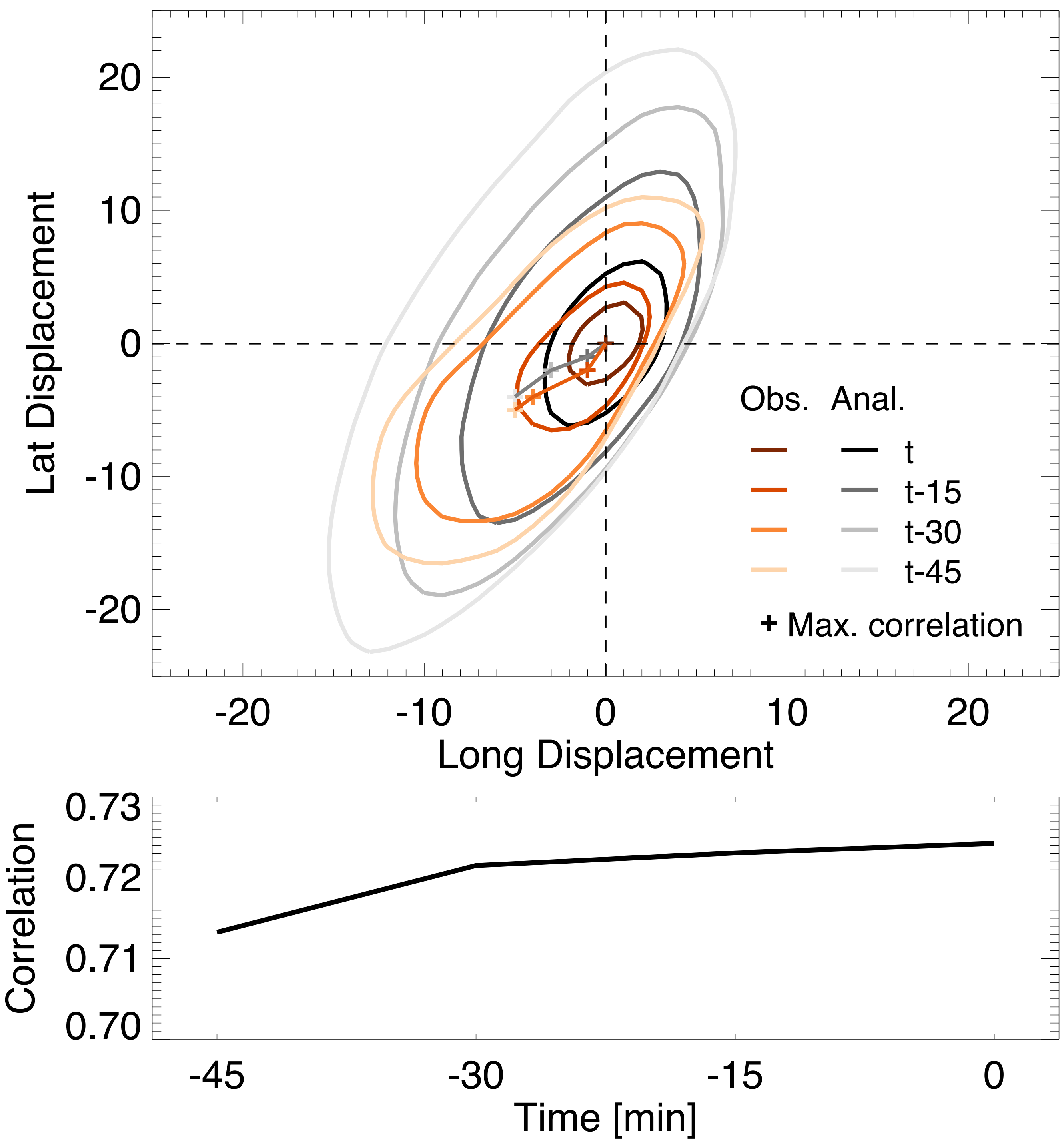


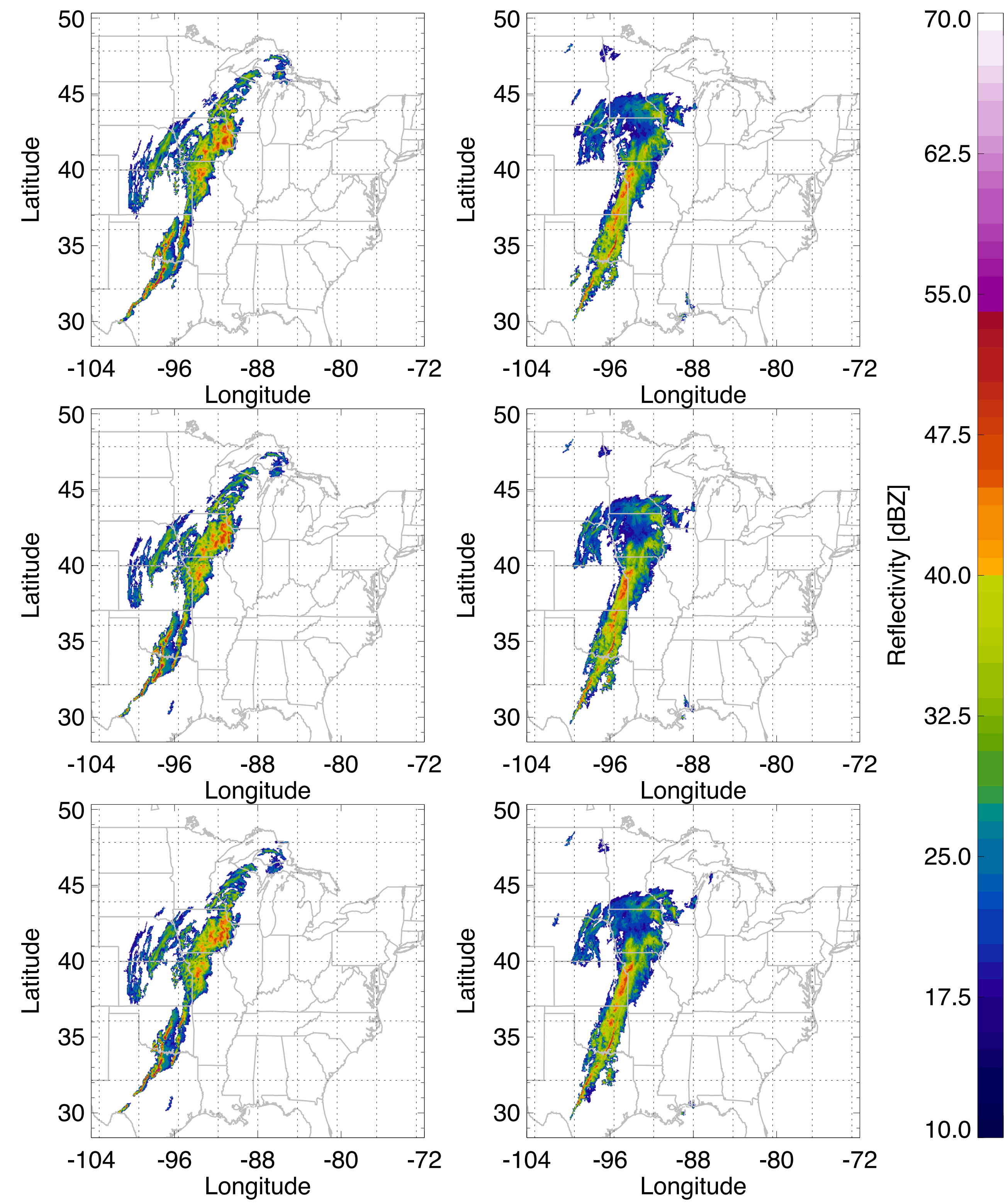


The 50 pixels area of search was selected initially. The 140 was obtain to maintain the correlation of the smooth DEM with the actual DEM.

Analog searching technique

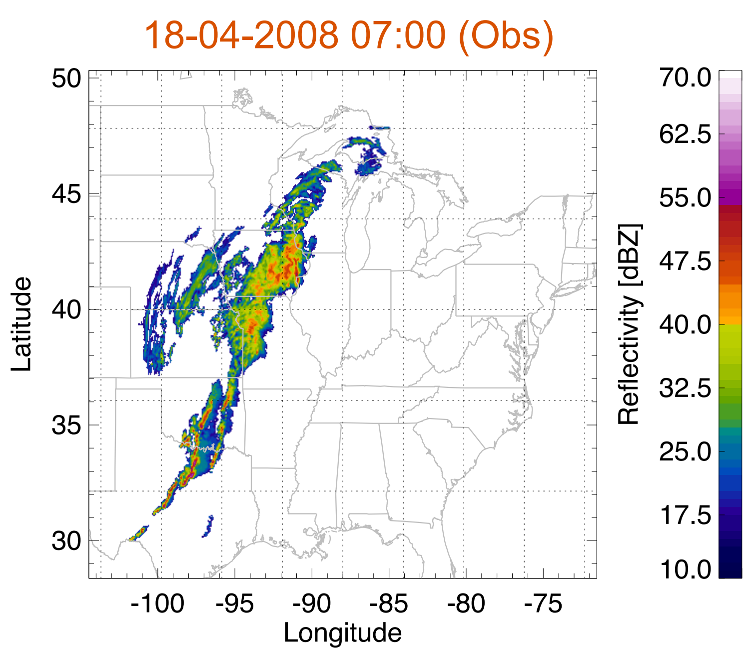
3. Temporal correlation → Motion & evolution

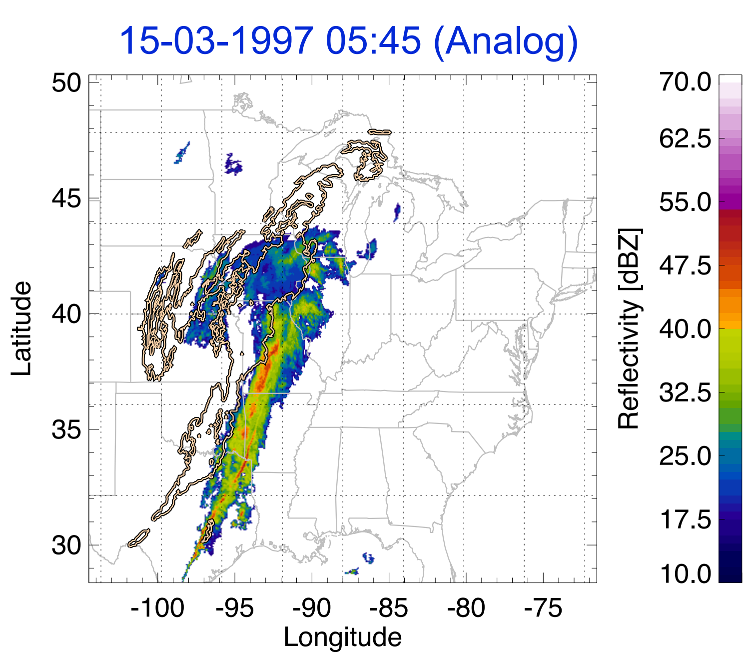


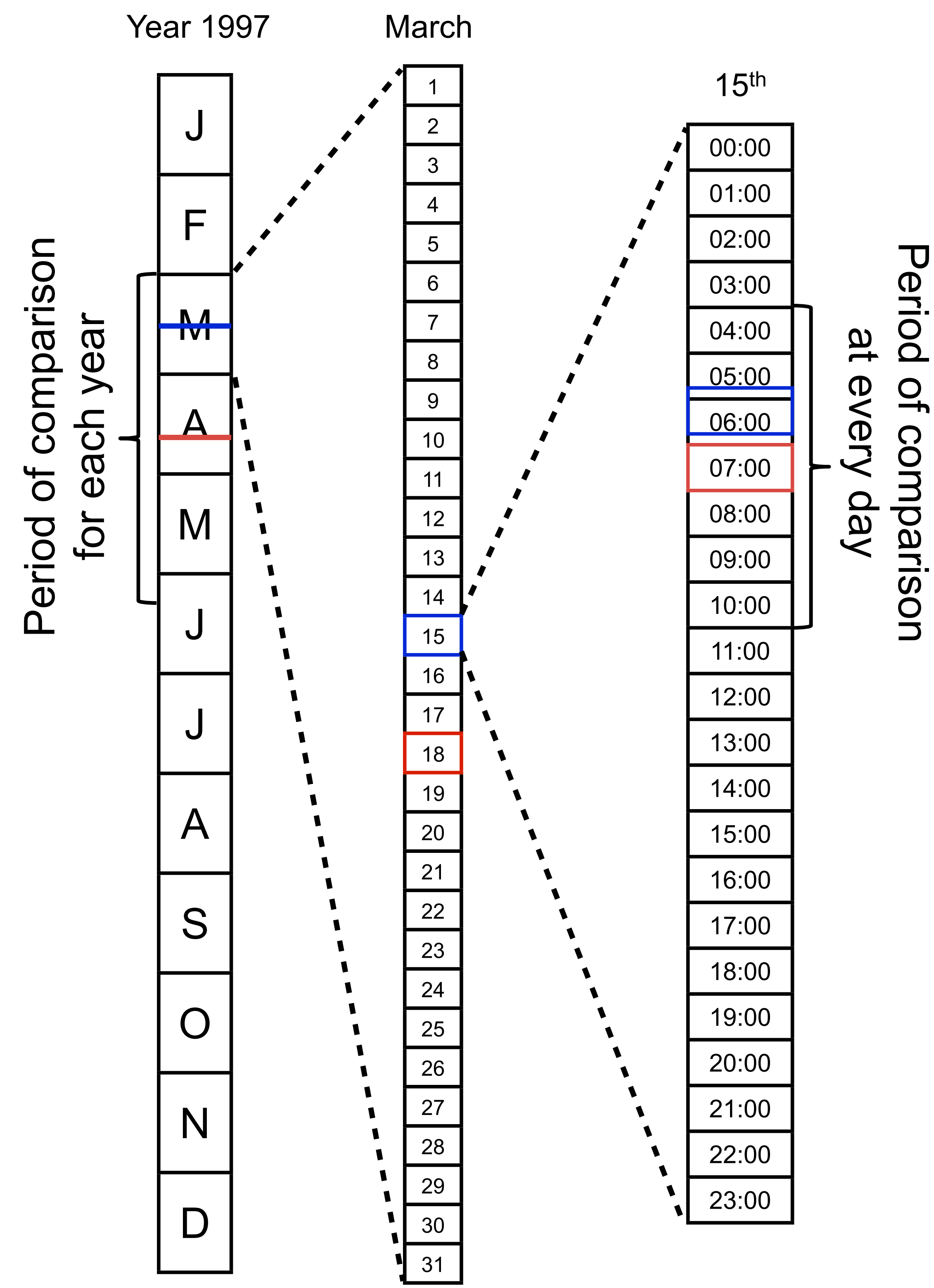


Analog searching technique

4. Time of the day and of the year → Diurnal/Annual cycle

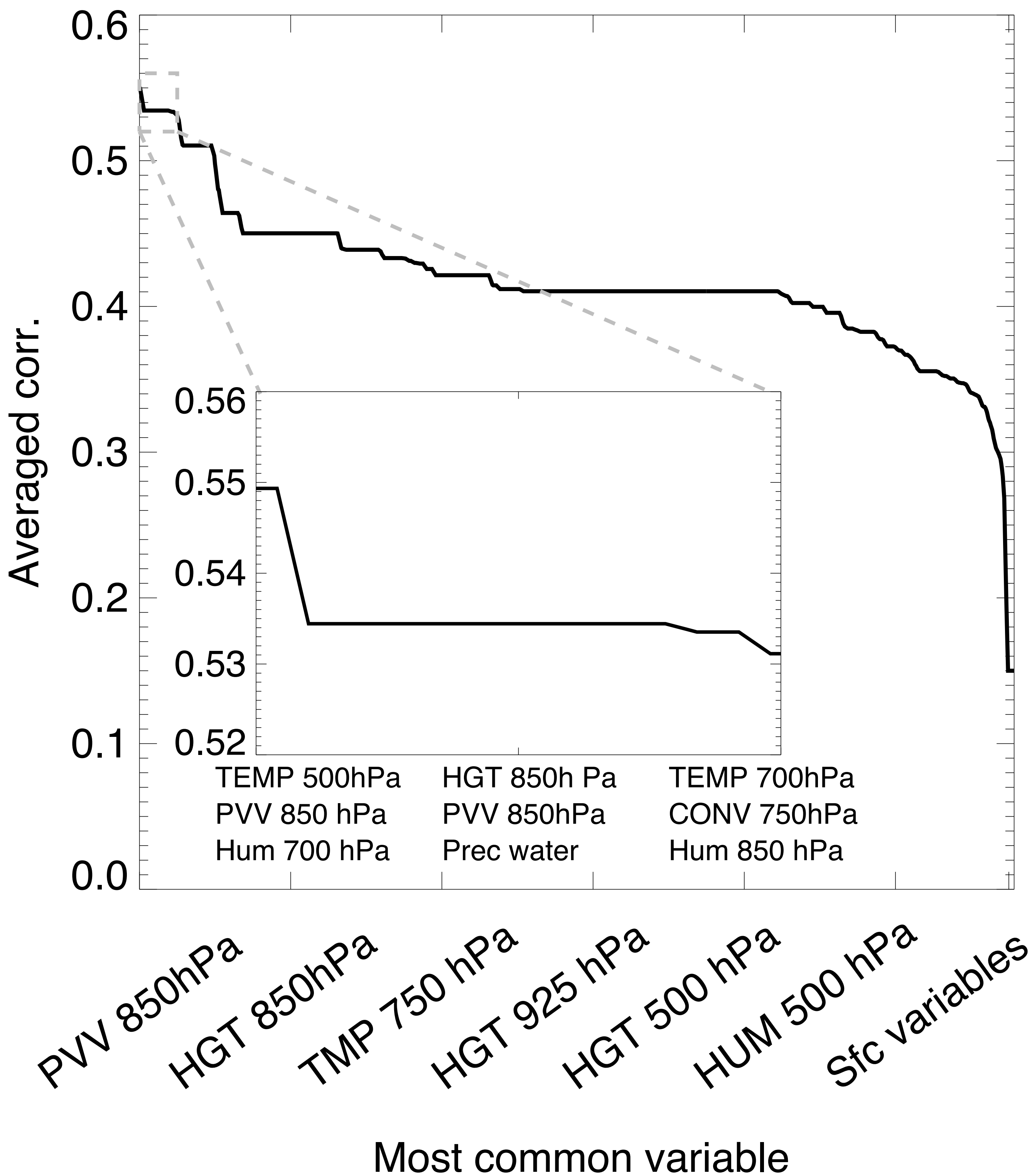






Analog searching technique

5. Synoptic situation → Large scale forcing

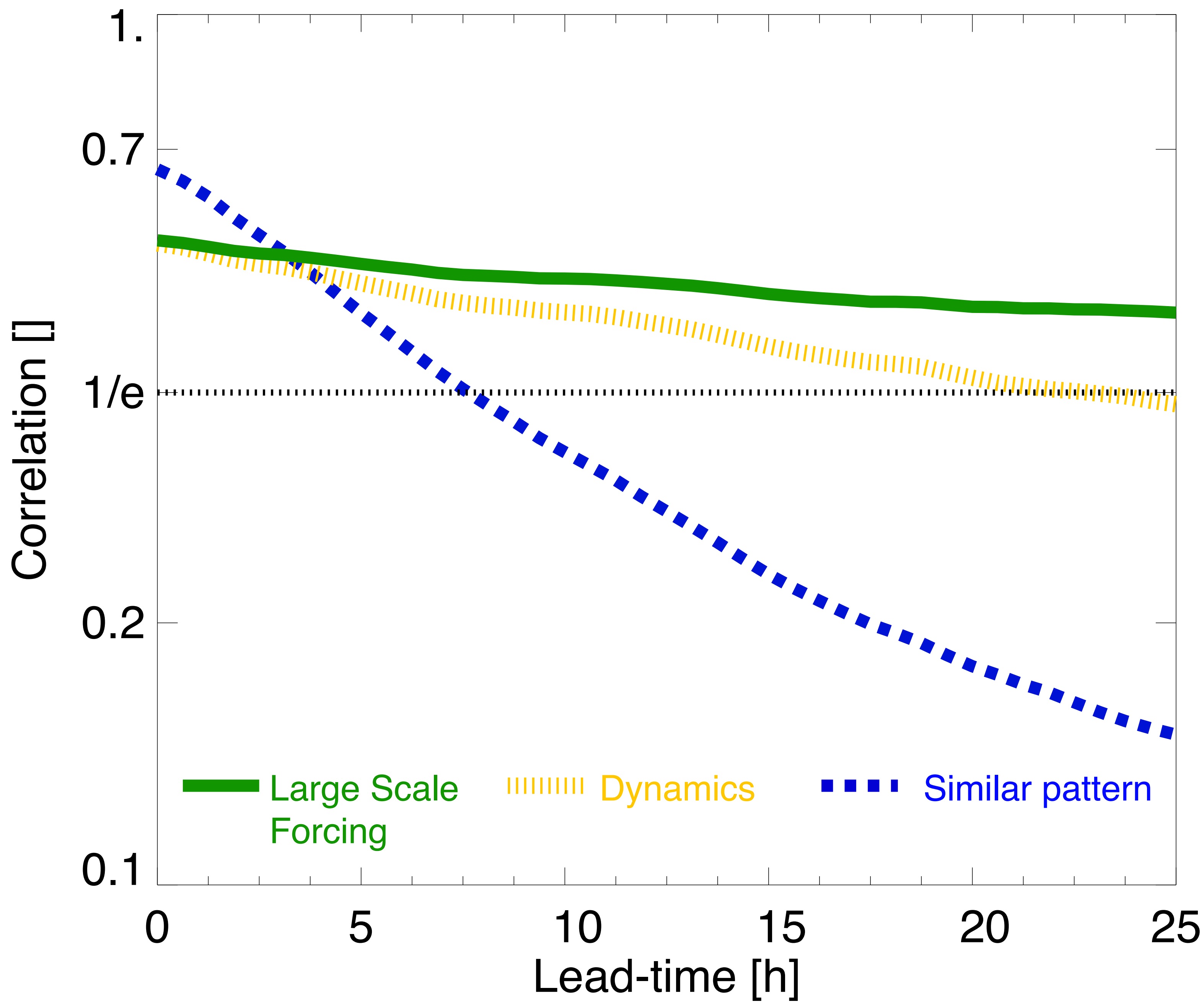


There are three main factors needed in rainfall occurrence: **instability**, **moisture** and **forcing**.

In order to select these variables, a study of many different variables has been carried out. While this study indicated some sensitivity to the choice of variables, **temperature at 500hPa**, **pressure vertical velocity at 850 hPa** and **humidity at 700 hPa** were found most appropriate to characterize the spatial distribution of rainfall.

In this step these three variables are compared by computing the **root mean square error** to check if the external large scale forcing is similar for the analogues selected.

Analog searching technique



Distance Dynamics Large-scale forcing

Comparison of both forecasts

A. Deterministic indexes:

   A. Correlation — Similarity of patterns

   B. Skill and Spread — Errors and reliability

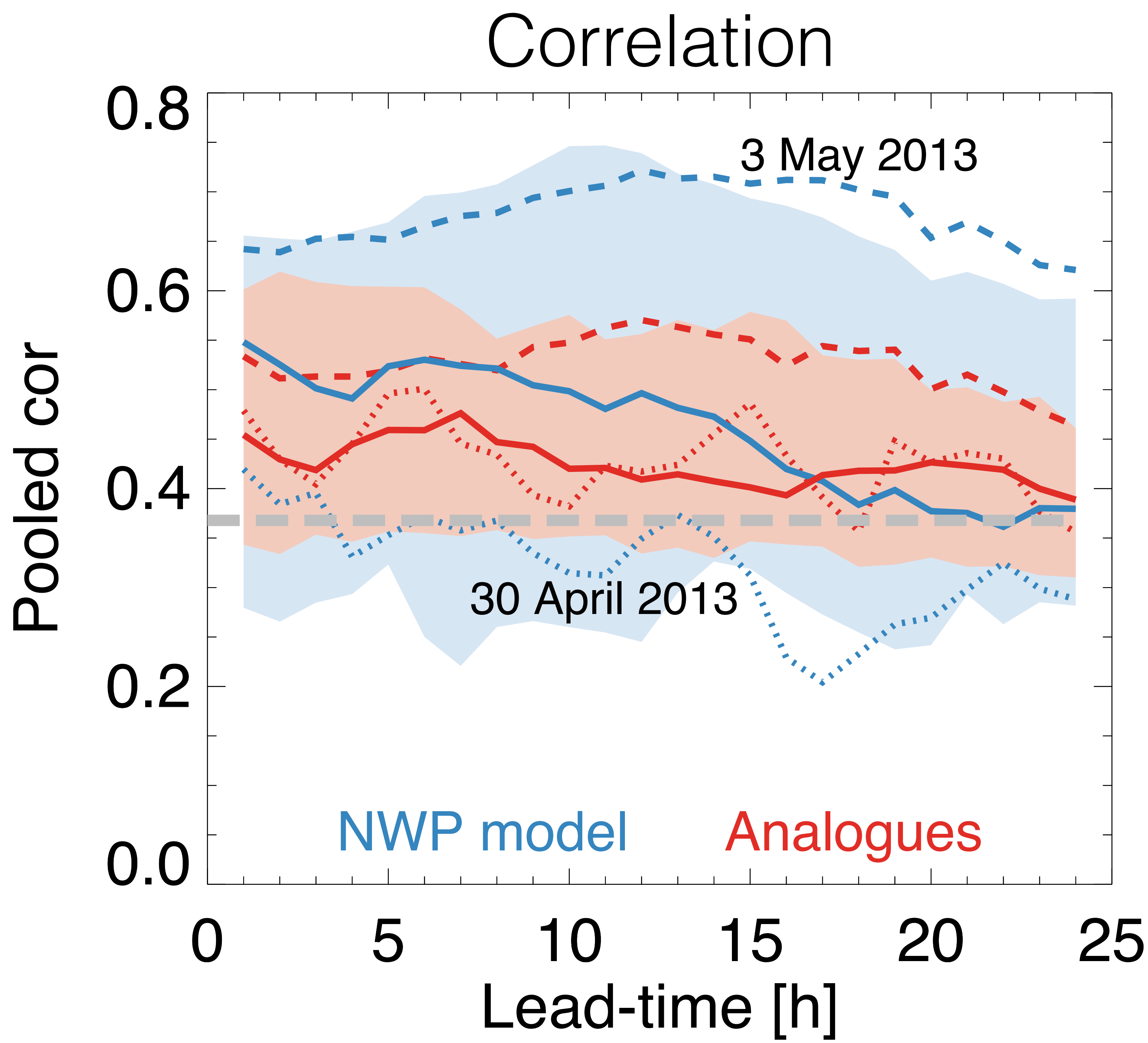
   C. Scales in the mean — Decorrelation

B. Probabilistic indexes:

   A. Brier Score — Skill of probability

   B. ROC Area under the curve — Discrimination

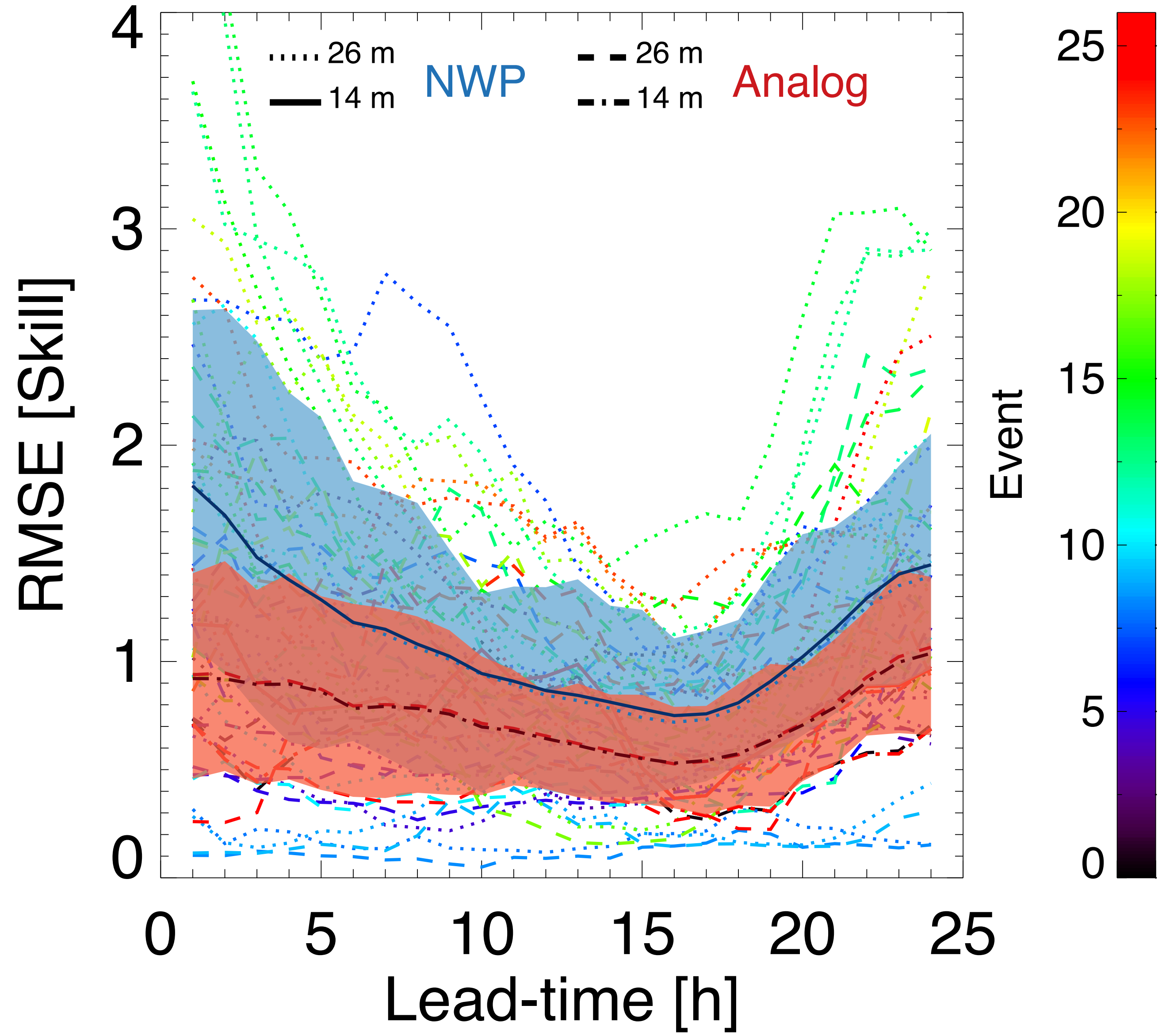
Deterministic comparison



The NWP model reproduces better the pattern of precipitation

Deterministic comparison

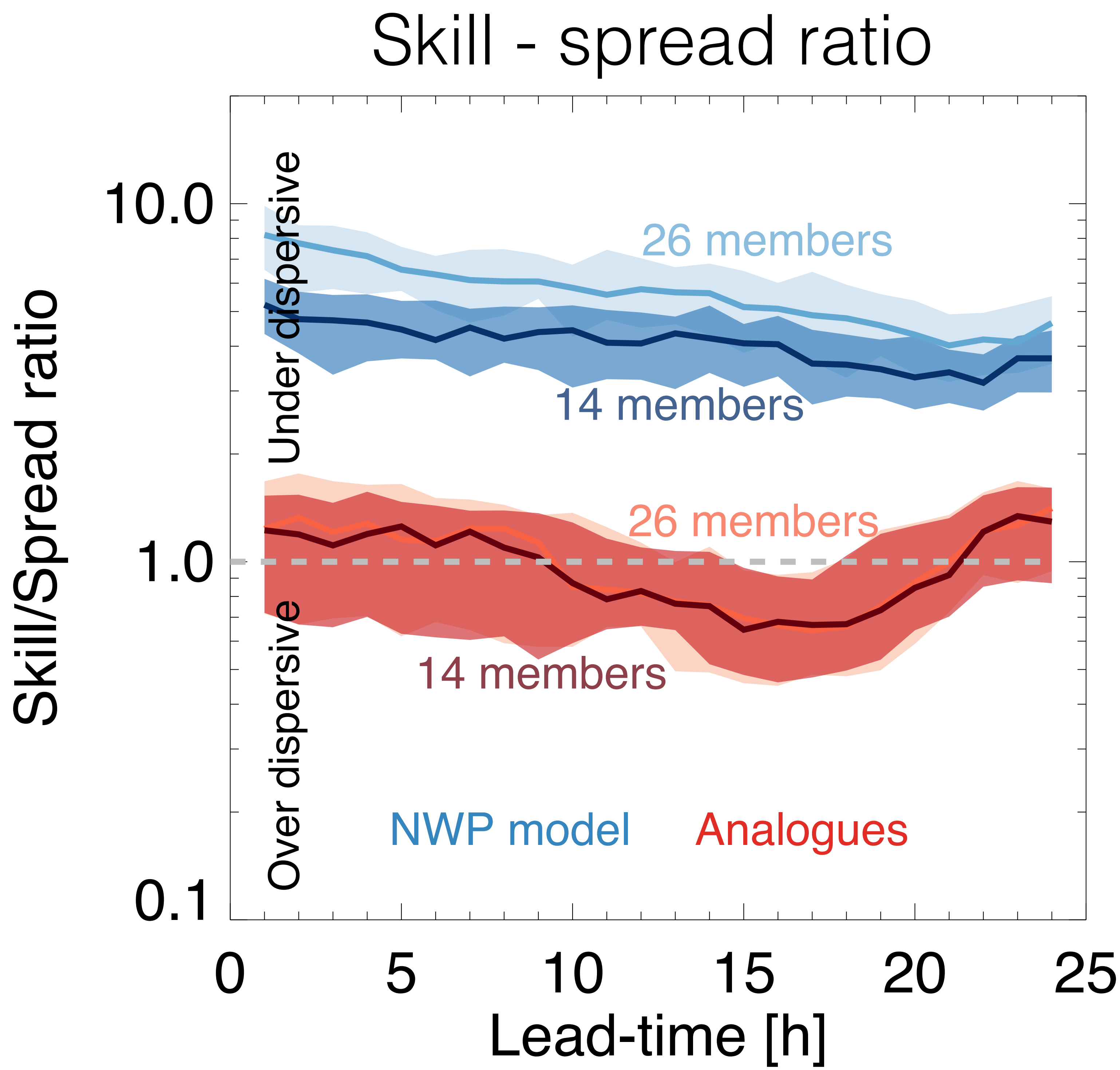
Skill of ensemble mean



a) RMSE averaged over the different events.

The ensemble mean skill is better for the Analogues forecast

Deterministic comparison



$$RMSE = \sqrt{\frac{1}{N_p} \cdot \sum_{i=1}^{N_p} (z_i - \hat{f}_i)^2}$$

$$Spread = \sqrt{\frac{1}{N_p(N_m - 1)} \cdot \sum_{i=1}^{N_p} \sum_{j=1}^{N_m} (f_{ij} - \hat{f}_i)^2}$$

According to Whitaker and Loughe (1998), the ensemble spread should be similar to the skill of the ensemble mean measured by the root mean square error (RMSE) to ensure a correct representation of the forecast uncertainty. This equality relation comes from the idea that in a perfect ensemble, any of the members should be indistinguishable from the truth and the truth could be one of the members.

The ensemble of analogues is well calibrated whereas the NWP is under dispersive

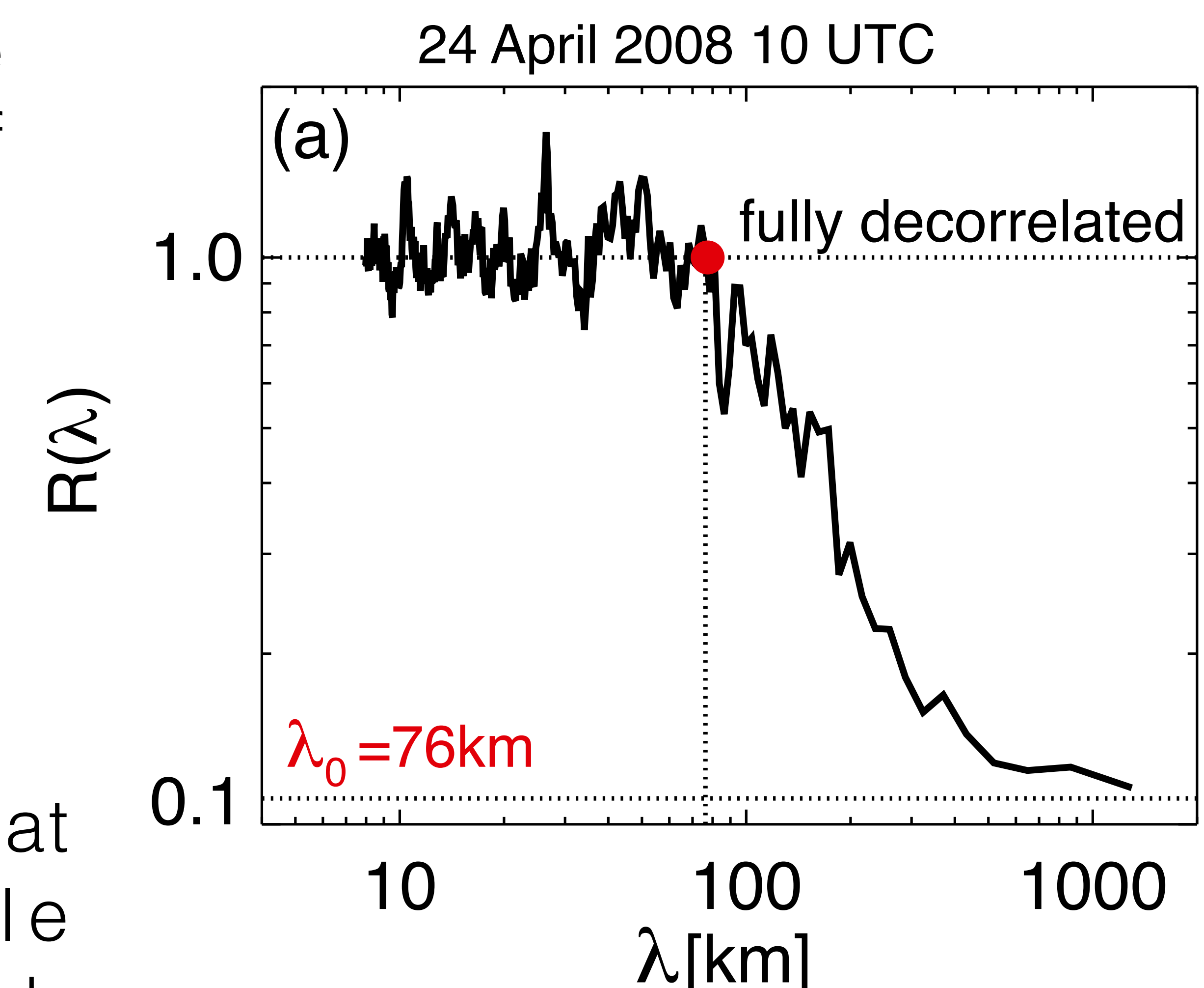
Comparison of scales

$$\mathrm{Var}\left(\sum_{i=1}^{N} X_i\right) = \sum_{i=1}^{N} \mathrm{Var}(X_i) + \sum_{i \neq j} \mathrm{Cov}(X_i, X_j) \xrightarrow{\mathrm{Cov}(X_i,\, X_j) = 0} \frac{\sum_{i=1}^{N} \mathrm{Var}(X_i)}{\mathrm{Var}\left(\sum_{i=1}^{N} X_i\right)} = 1$$

The variance can be analyzed as a function of the scale by using Fourier decomposition and then define:

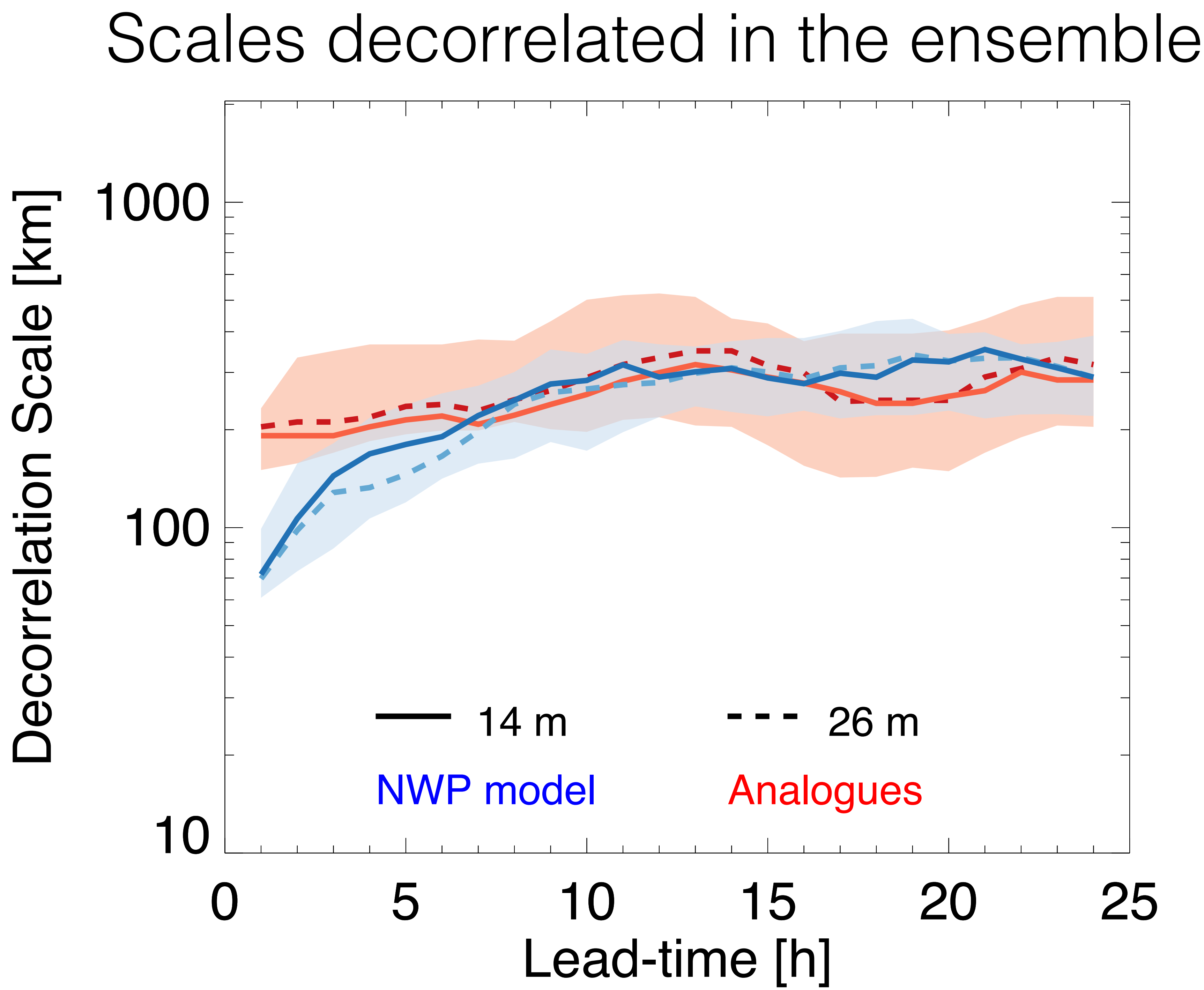
$$R(\lambda) = \frac{\sum_{i=1}^{N} P_{X_i}(\lambda)}{P_{X_T}(\lambda)}$$

obtaining the scales at which the ensemble members are decorrelated.



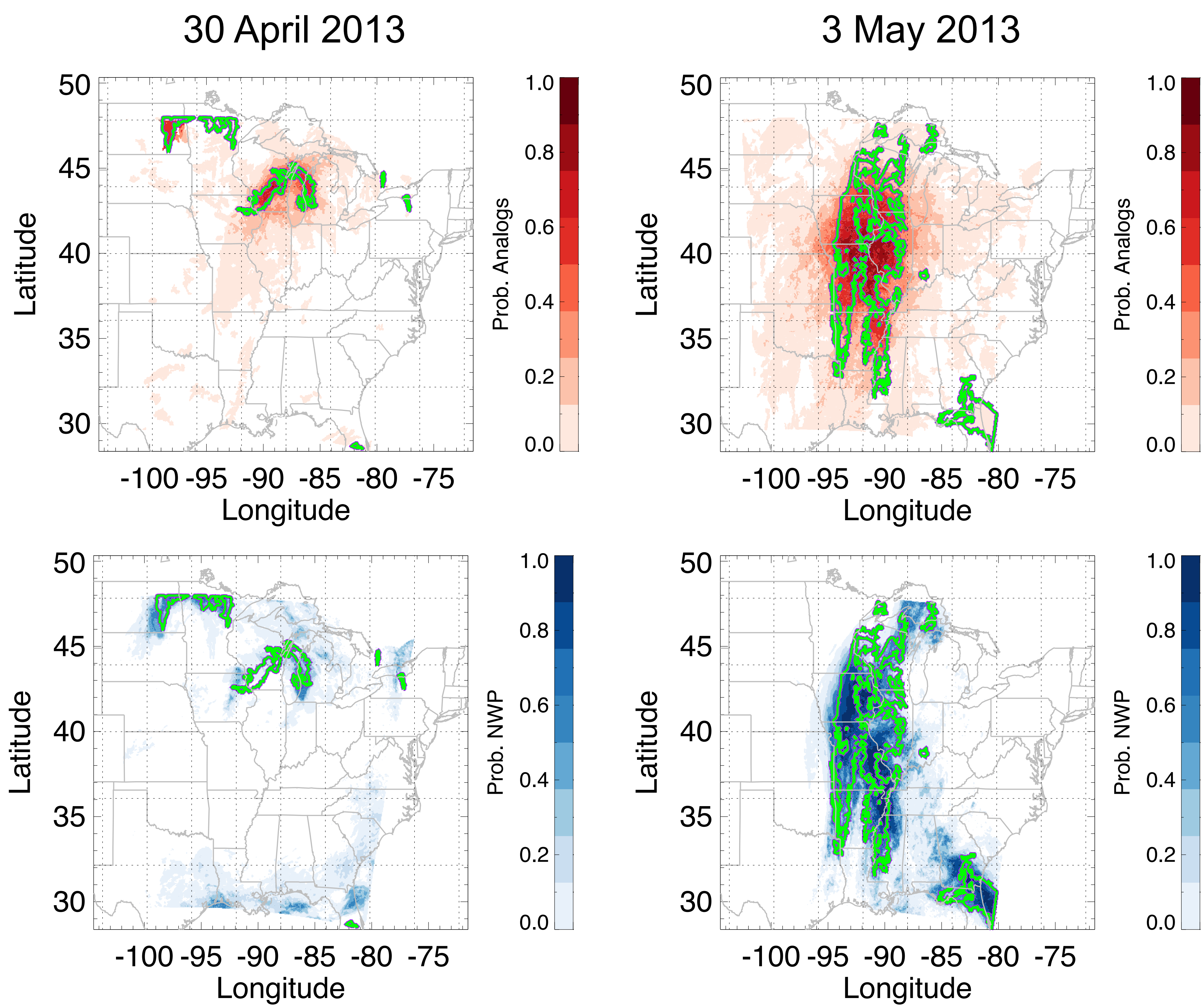
From Surcel et al (2015)

Comparison of scales



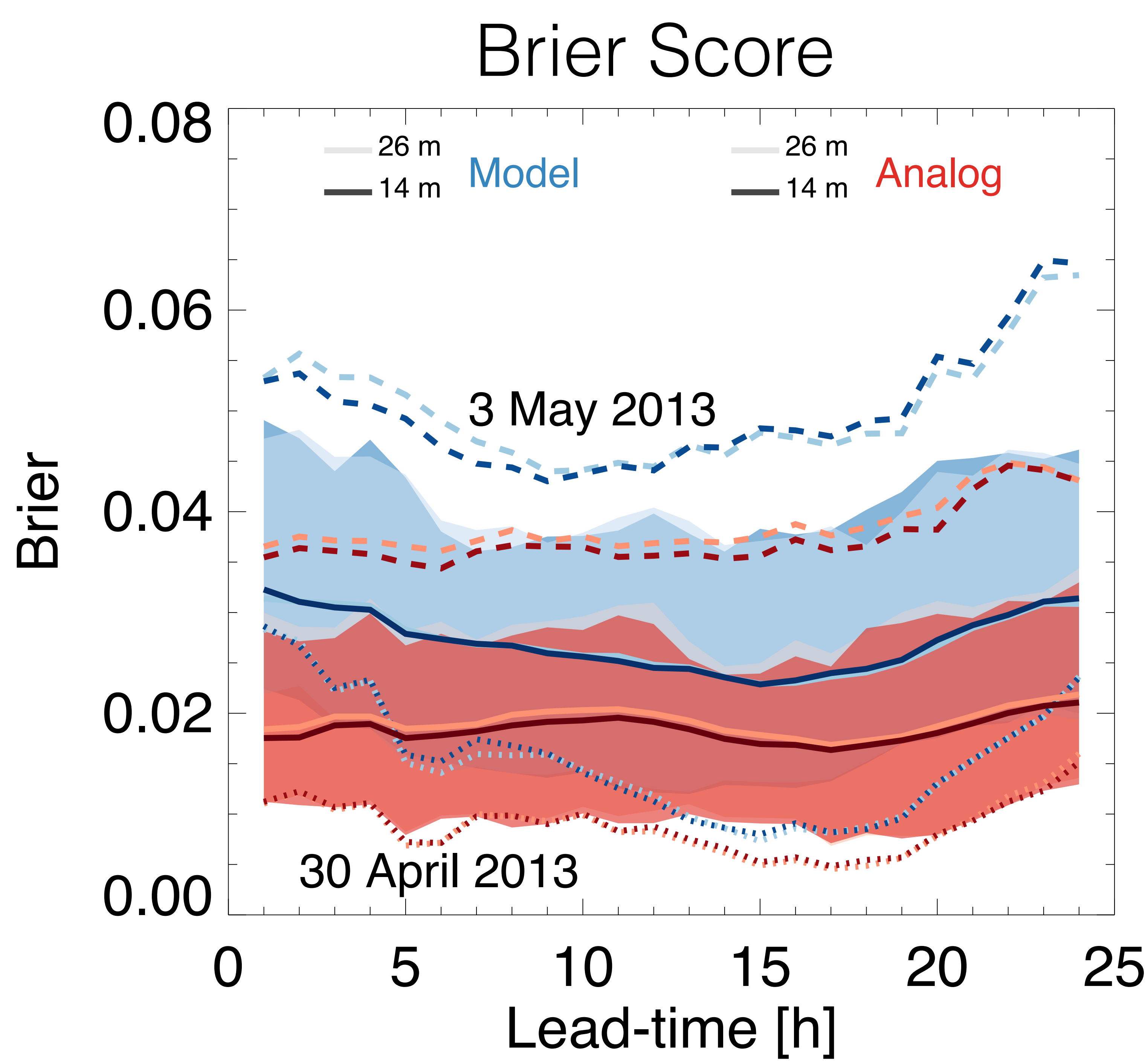
The scales represented in both forecast are similar after 6 hours (spin-up period).

Probabilistic comparison



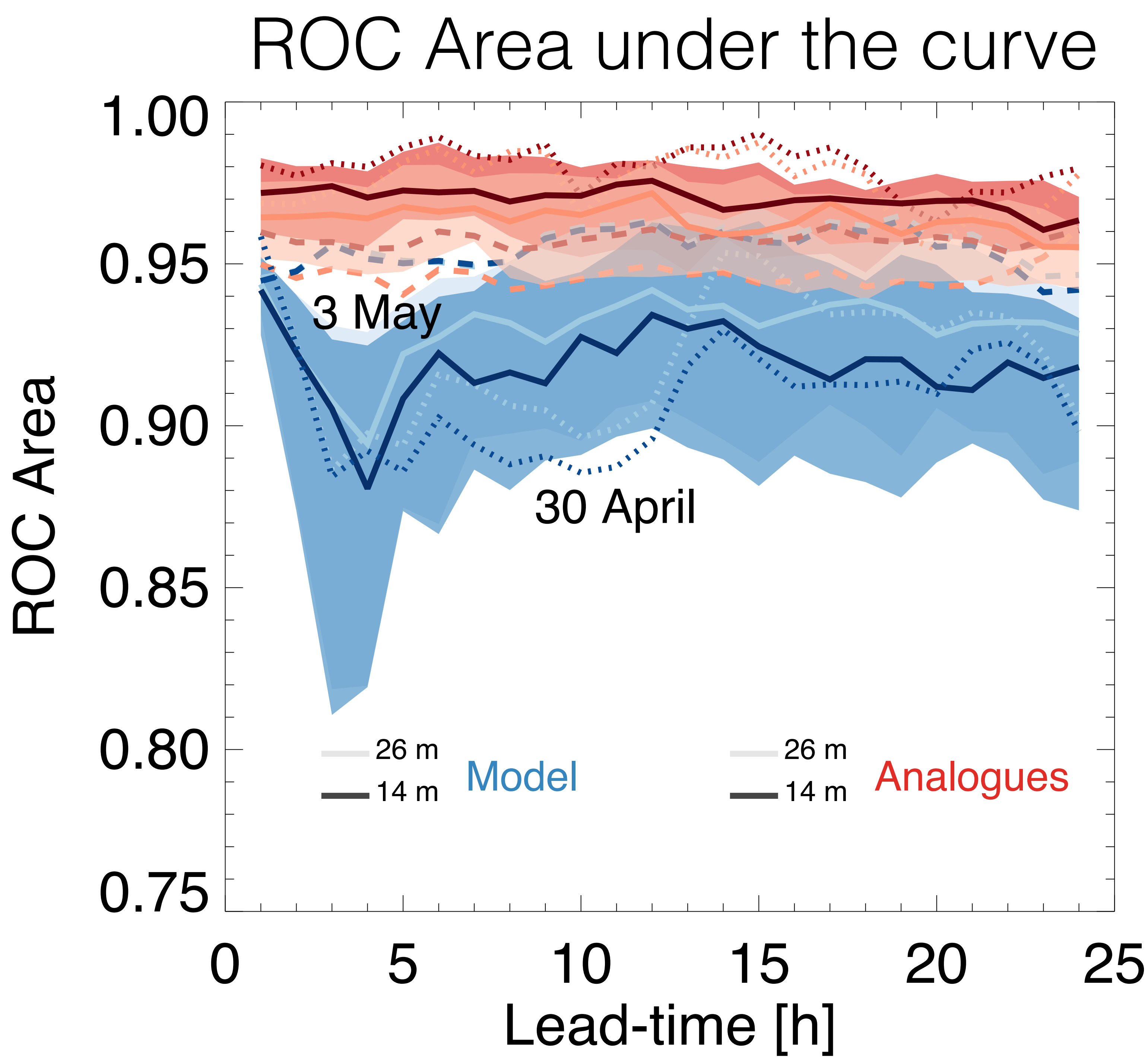
15 dBZ
0.3 mm/h

Probabilistic comparison



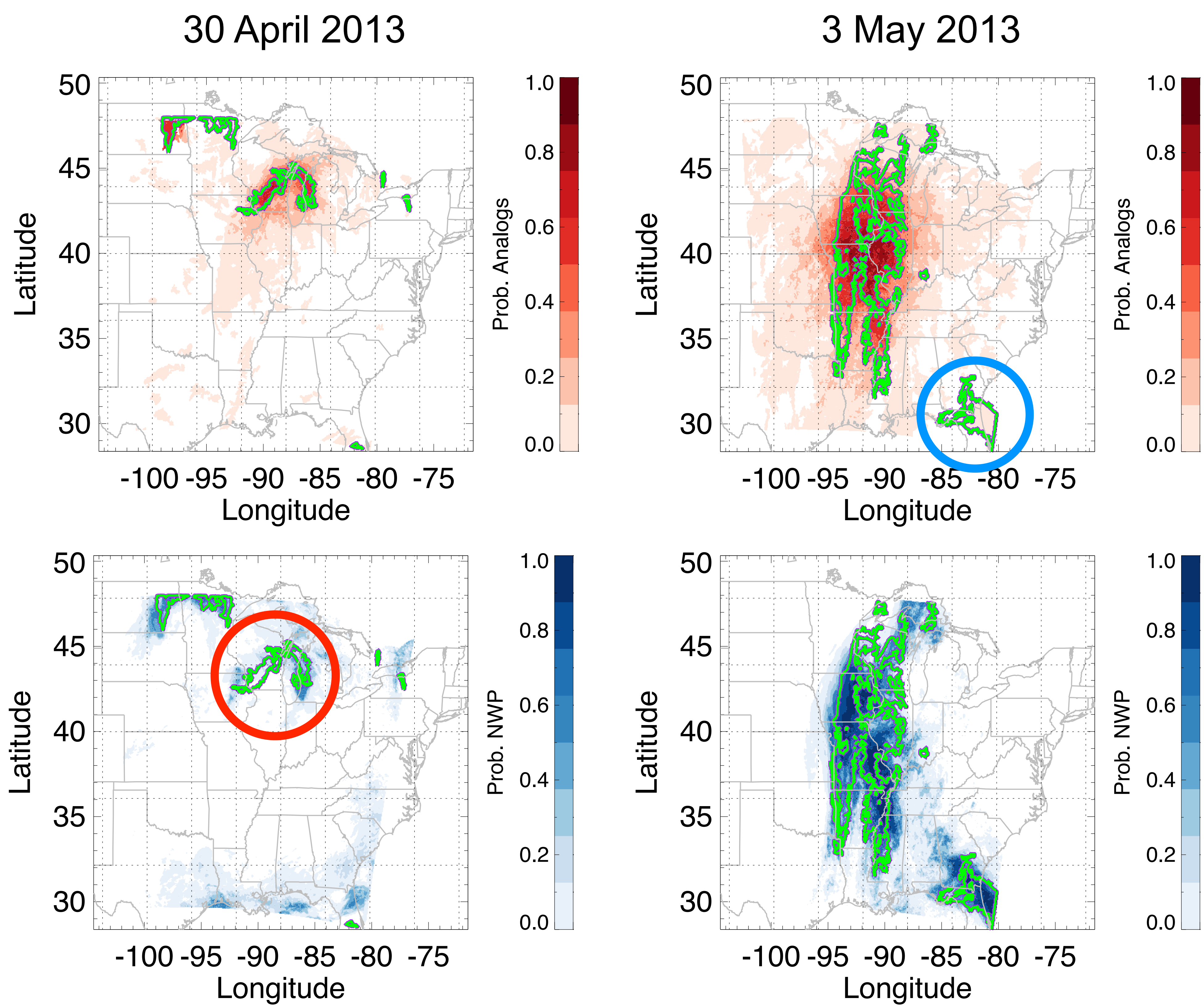
The brier score is significantly better for the analogue-based probability map.

Probabilistic comparison



The probability of detection/false alarm ratio is higher for the analogues

Complimentary information



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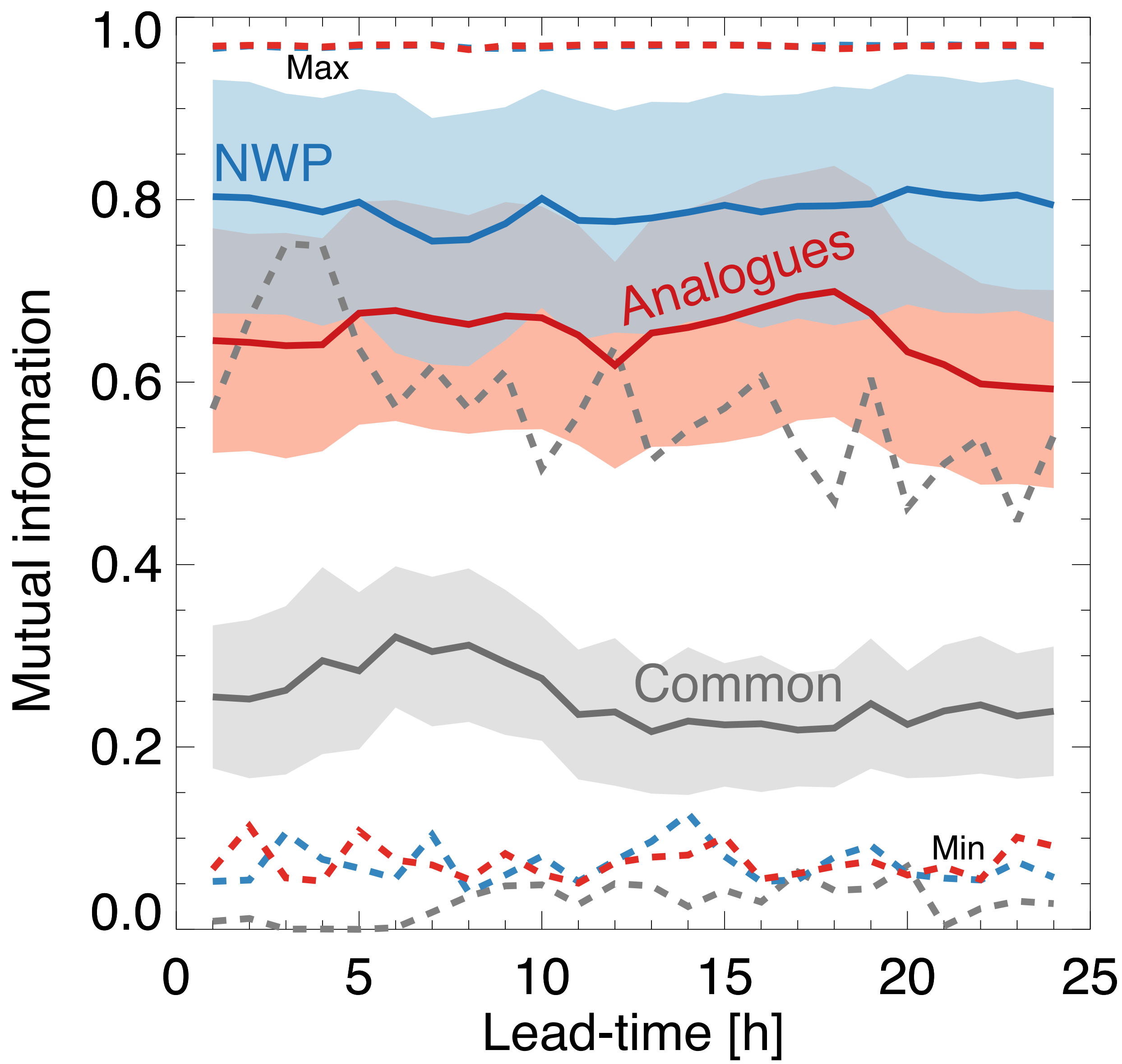
Complimentary information



The correlation between the ensemble ECM and the actual error field covariance is computed for the NWP and the analogues.

The correlation between the ensemble ECM of both the NWP and analogues is also computed to account for the common information in these two ensemble forecast.

Having a larger correlation between any of the forecasts and the actual error field than between the two of them means that there is complementary information.

The value of this information is similar during the 24 hour forecasting period.

Spatial merging of two forecast ensembles

(Merging people talent)

Aitor Atencia and Pierre Tandeo

Ideas from: Pierre Ailliot
William Kleiber
Isztar Zawadzki

State of the art

- The recent literature only approach the problem by using a **global weight** to the ensembles members. Two studies deal differently with the weights:

  - Probabilistic blending (Kober et al.,2014):

$$P_{blend,i} = w_R(\tau) \cdot P_R(\tau) + w_C(\tau) \cdot P_{C,i}$$

  - Bayesian weighting (Raynaud et al.,2015):

$$p(\mathbf{y}_q | \mathbf{x}_q^k) = \left(1 + \frac{||\mathbf{y}_q - H(\mathbf{x}_q^k)^2||}{\sigma^2} \right)^{-1}$$

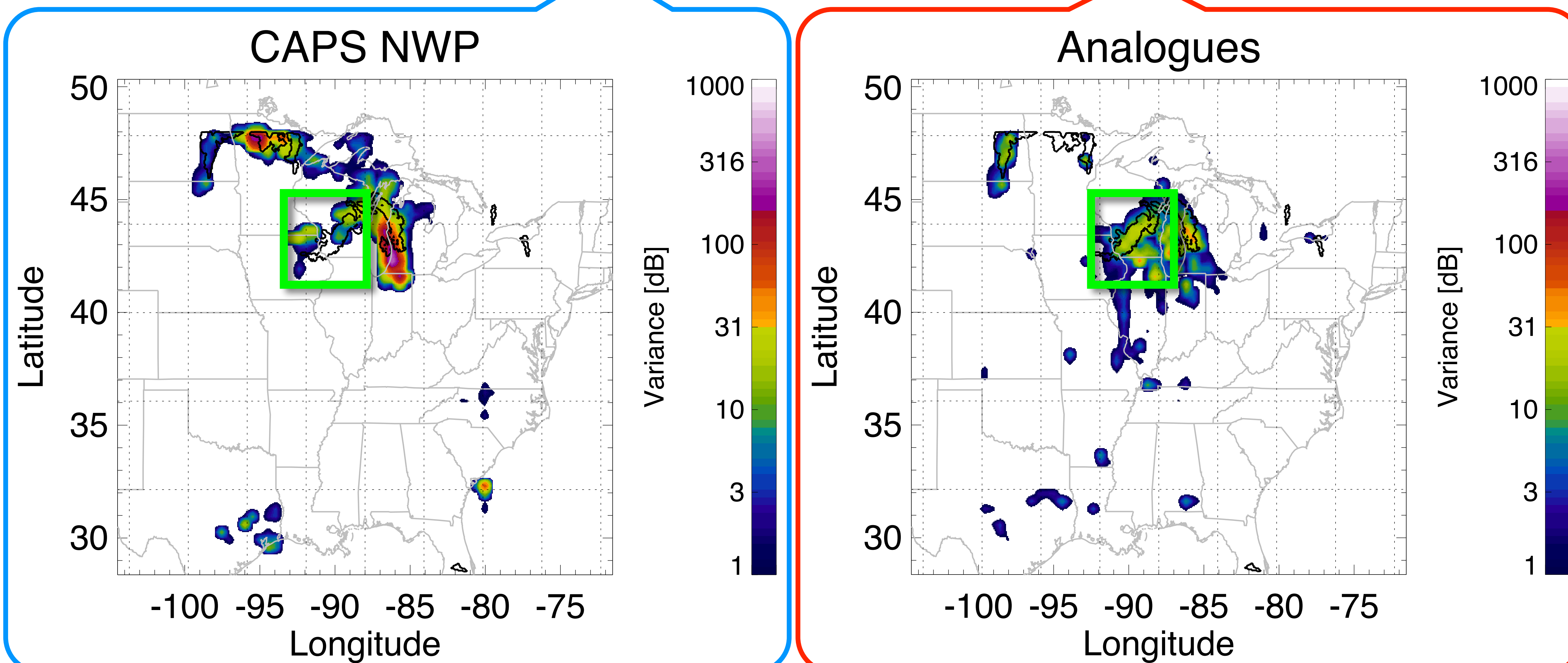
- **Kober et al.**: Aspects of short-term probabilistic blending in different weather regimes, 2014.
- **Raynaud et al.**: Application of a Bayesian weighting for short-range lagged ensemble forecasting at the convective scale, 2015.

Spatial merging

The optimal merging is obtained by minimization of the cost function:

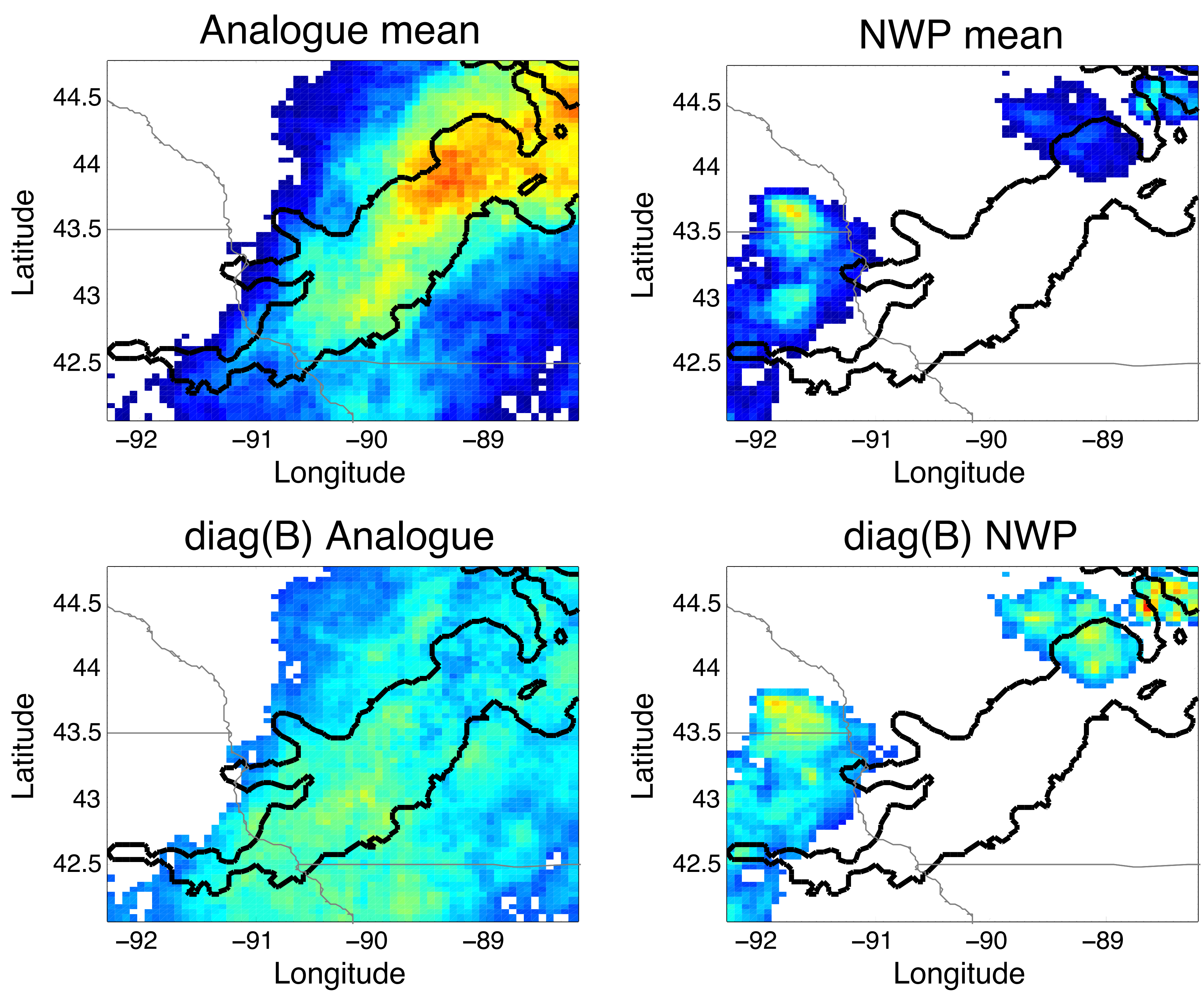
analysis NWP Analogues

$$J = [x - x_m]^T B_m^{-1} [x - x_m] + [x - x_a]^T B_a^{-1} [x - x_a]$$



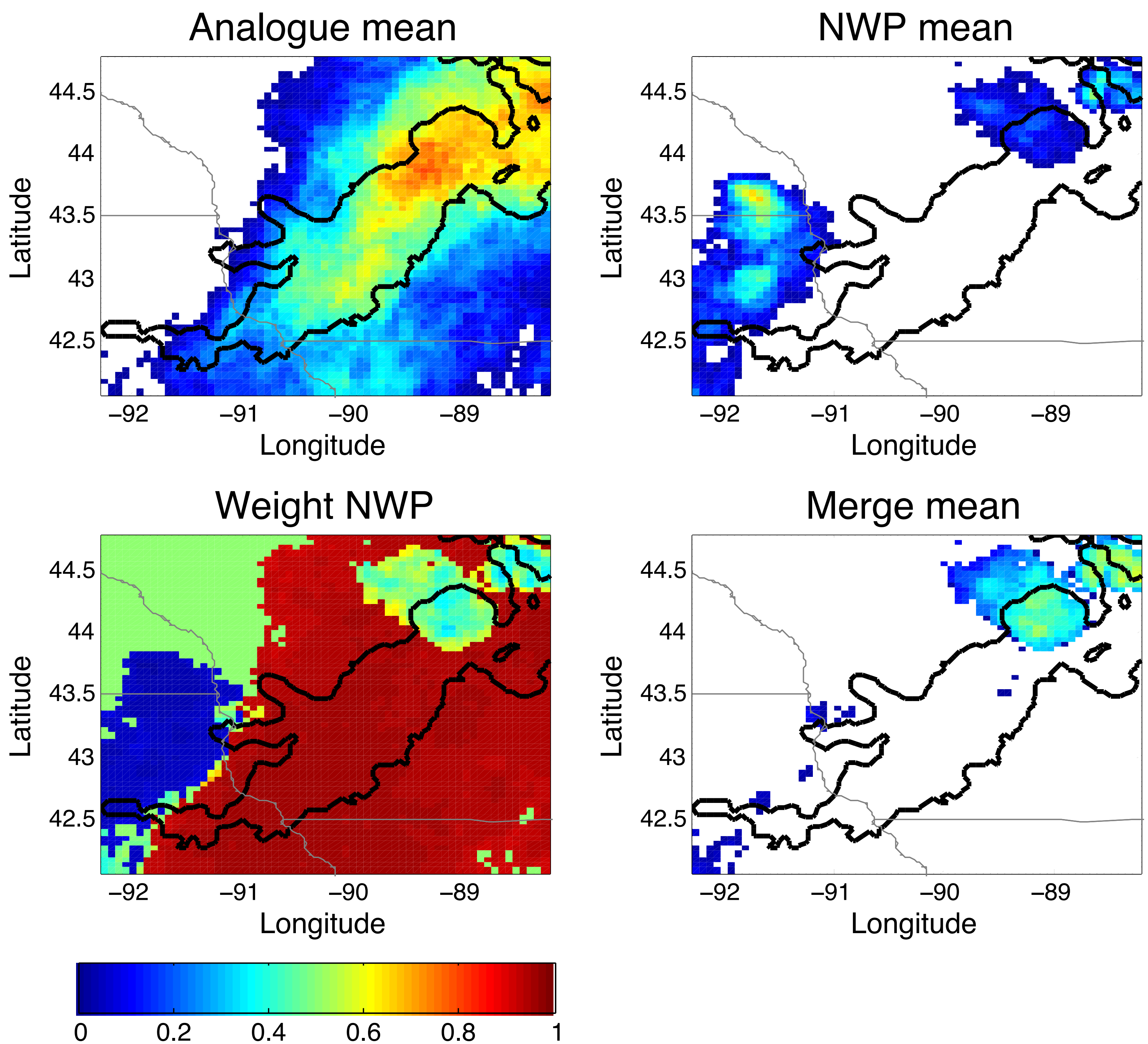
Spatial merging

The test is centered in an small area (64 x 64 pixels) where one of the ensemble forecast has a low variance but large error (due to bias).



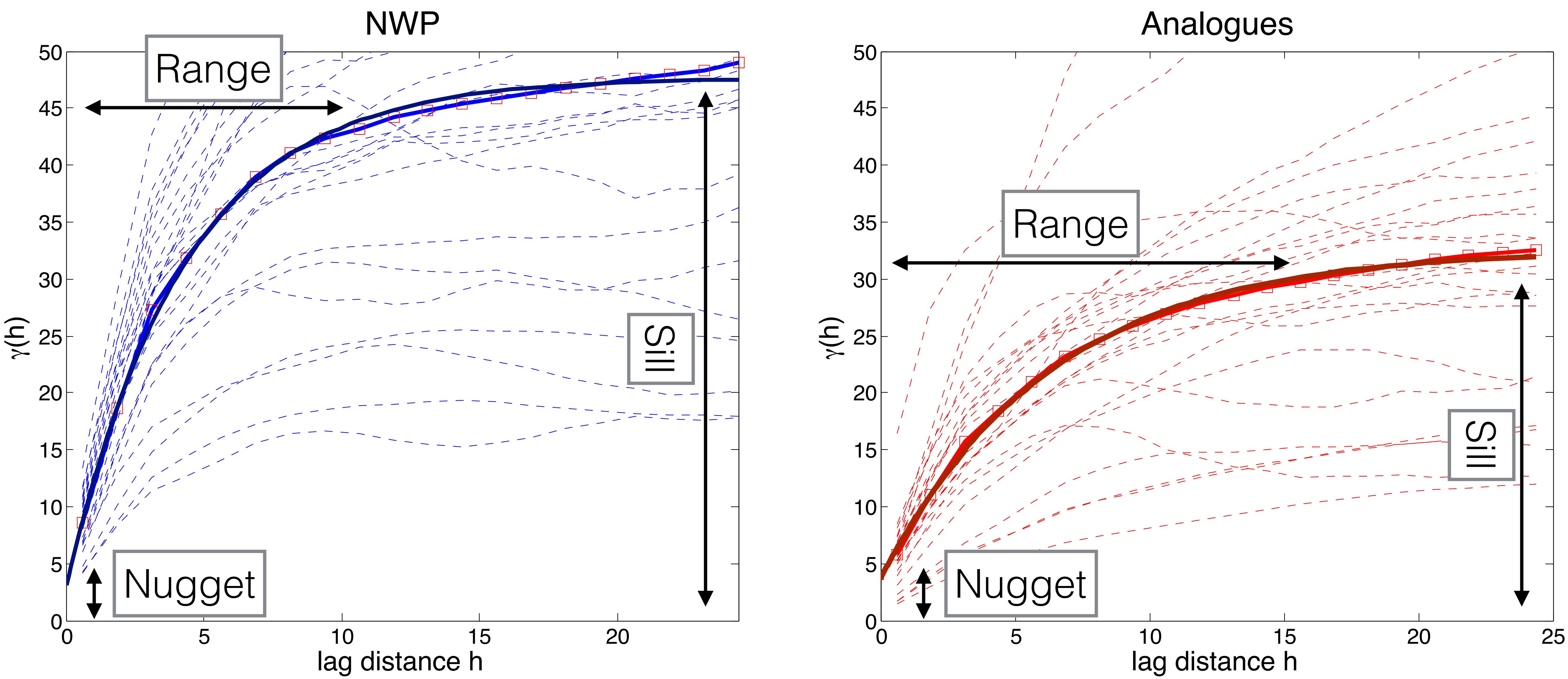
Spatial merging

The problem with the optimal interpolation is the area with no rain is highly weighted because no bias is assumed.



Spatial merging

In order to correct this problem, the variogram of both dataset is study. The nugget is used to avoid the areas with 0 variance.

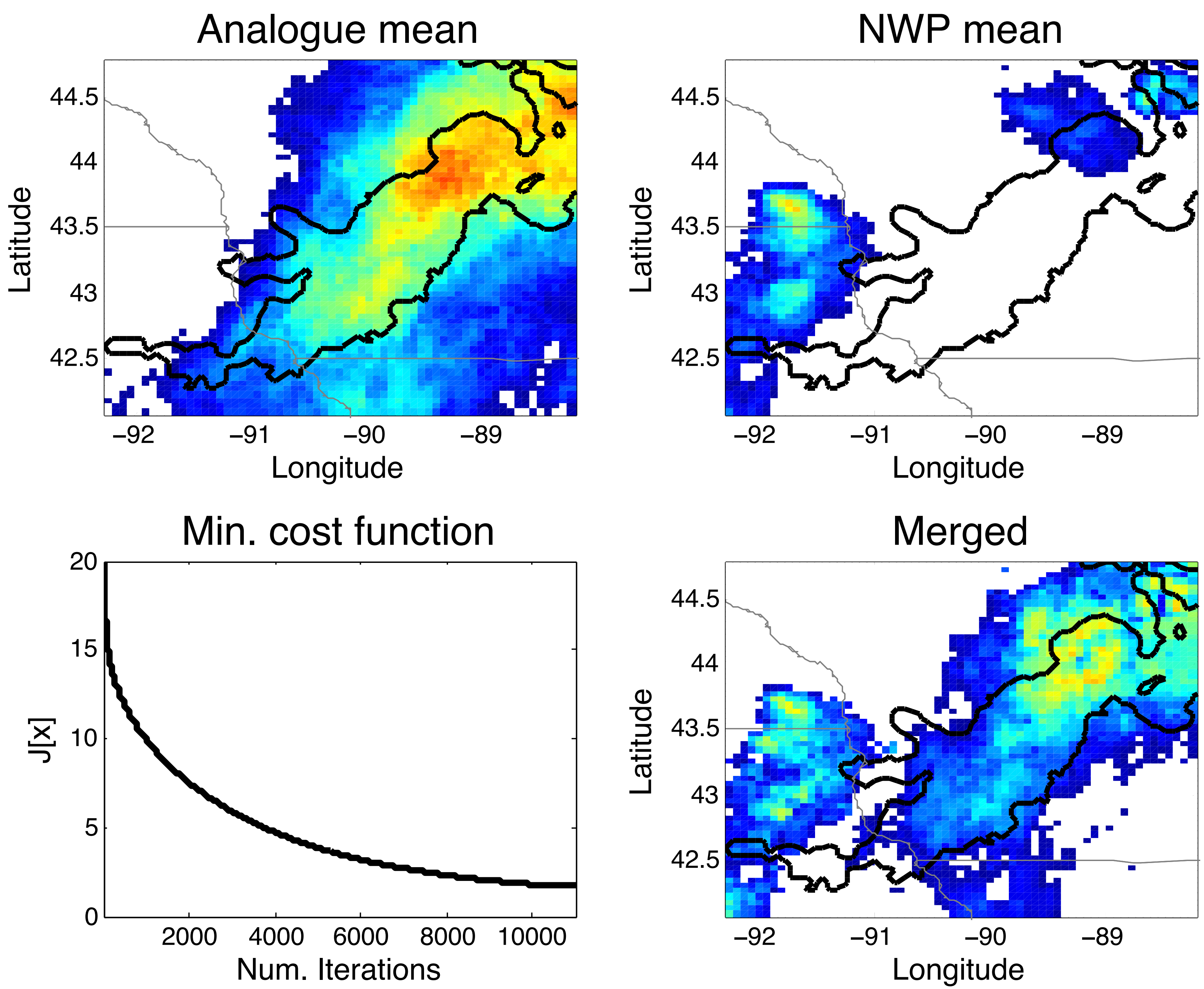


The nugget is added to the B matrix cancelling all the 0 values.

The effect in the optimal interpolation is observed by a change of weights.

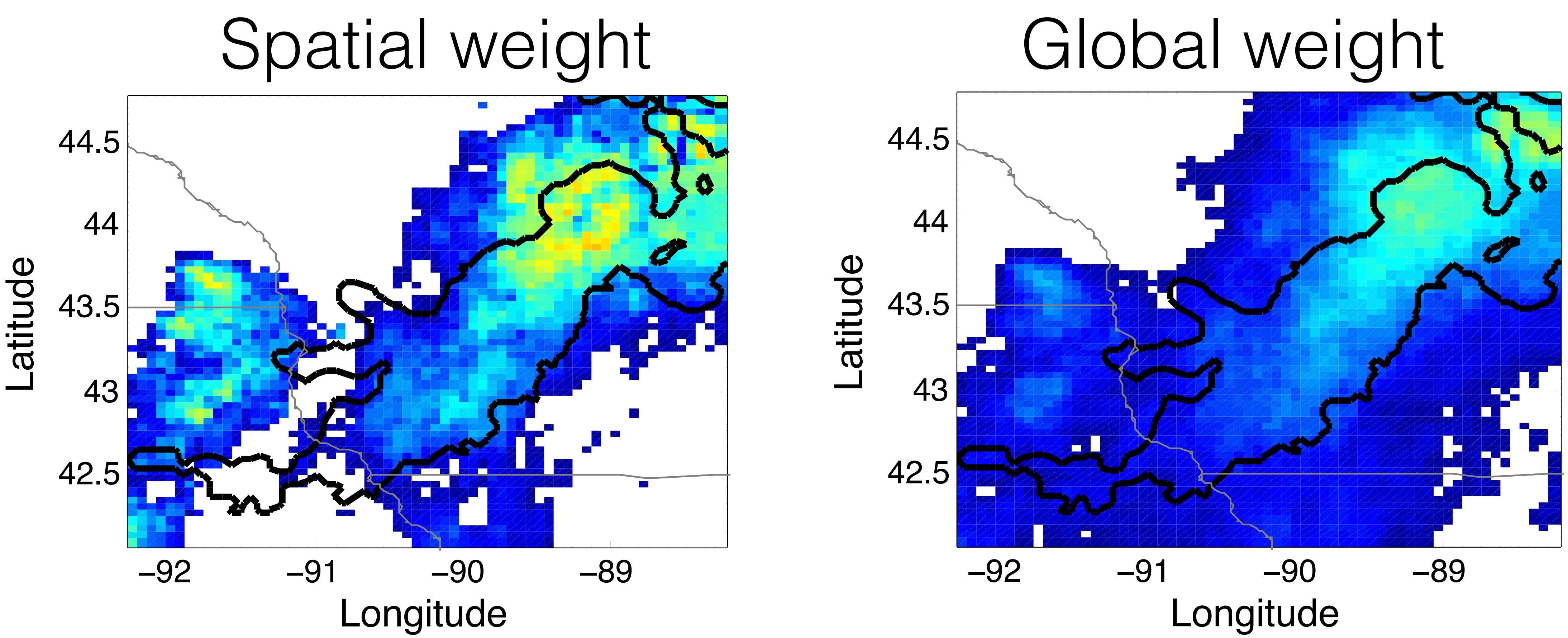
Spatial merging

Using an empirical covariance matrix from the ensemble, part of the smoothness is avoided constructing a more realistic mean.



Spatial merging

The first eyeball comparison with the global weight blending shows some improvement in the shape of the rainfall and, most important, in the scales represented in the rainfall merged field.



Conclusions

- **Analogues** are possible in our datasets if **dynamic** and forcing conditions are imposed.
- The **information** in the analogues forecast is mostly in the **ensemble** of them than in the single members.
- This **information is complementary** (poorly correlated) between analogue-based forecast and NWP prediction systems.
- The **spatial weight** shows **promising results** in merging the two forecast systems.

Thank you for
your attention

Merci beaucoup pour
votre attention

WORK SHOP
STOCHASTIC WEATHER GENERATORS
VANNES 17>20 MAY 2016