

Spatial filtering of assimilation ensemble statistics: increase of sample size by local spatial averaging

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Introduction and Plan

Importance of sample size:

- amplitude of sampling noise in the estimated covariances.
- the ensemble size influences the ensemble cost.

1 - Increase of sample size by local spatial averaging

2 - Spatial filtering of standard deviations

3 - Spatial filtering of correlations



1 - Increase of sample size by local spatial averaging

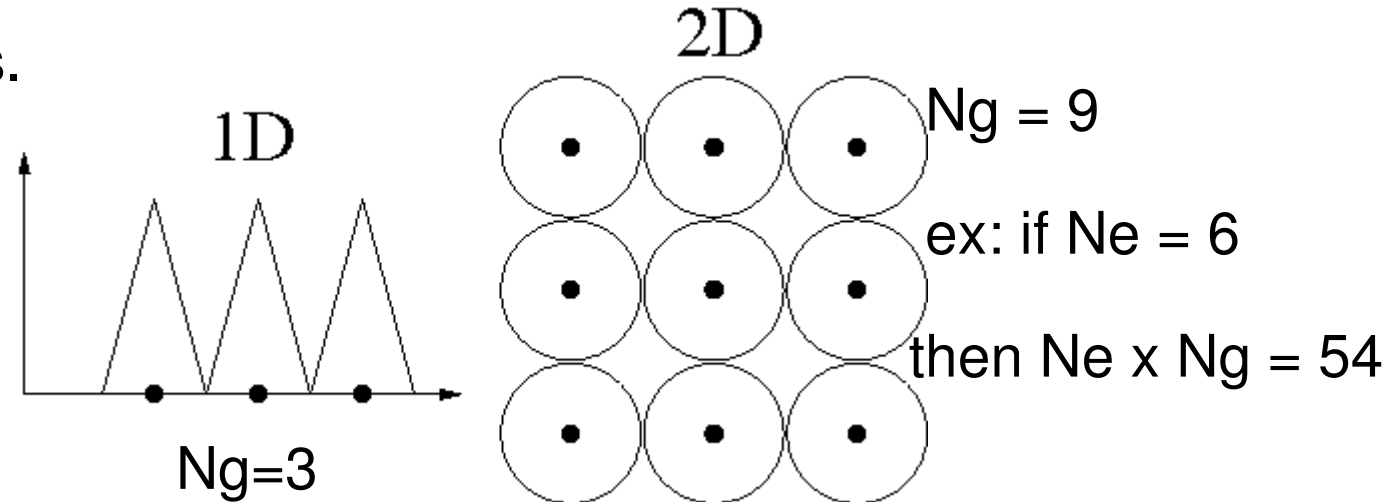


Strategies for ensemble size and cost reduction (assimilation ensemble at Météo France)

- Experiments: a small number of members (e.g. 3 to 10) already provides a lot of information !
- Use ergodic properties: increase sample size by spatial averaging.
- The full assimilation system may be approximated in the error simulation (e.g. resolution or/and 4D-Var vs 3D-Fgat).
- Six global members T359 L46 with 3D-Fgat are running in nearly real time (Arpège).

Increase of statistical sample size through spatial sampling/averaging

Basic idea: MULTIPLY(!) the statistical sample size by a number N_g of gridpoint samples.

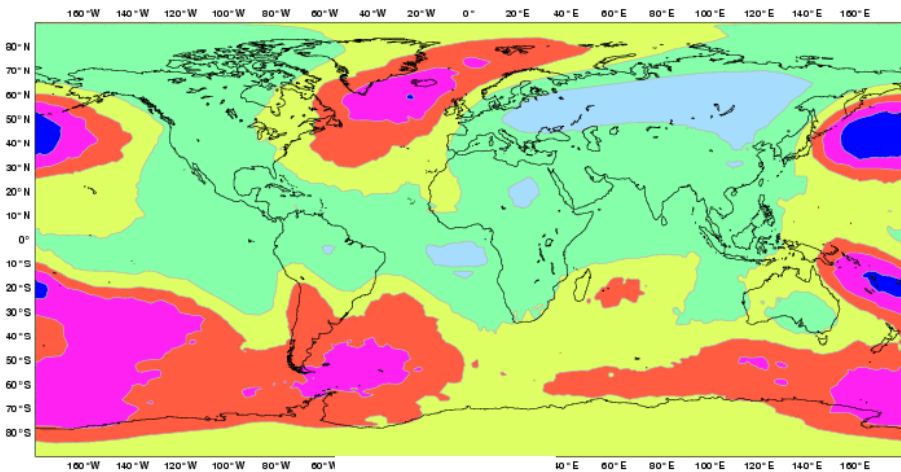


- An "ideal" case: local homogeneity of covariances and (relatively) short correlation length-scales.
- Another way to justify spatial filtering: sampling noise \sim small scale.

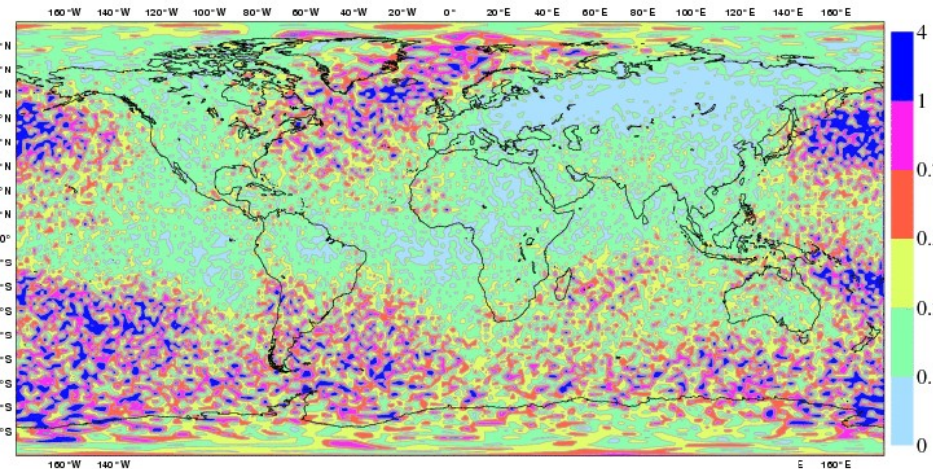
2 - Spatial filtering of standard deviations



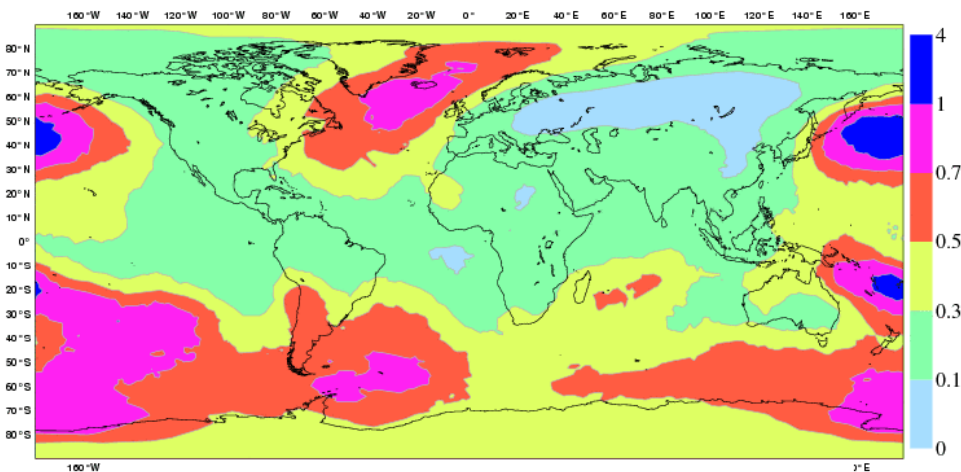
Illustration in a simulated framework



True σ



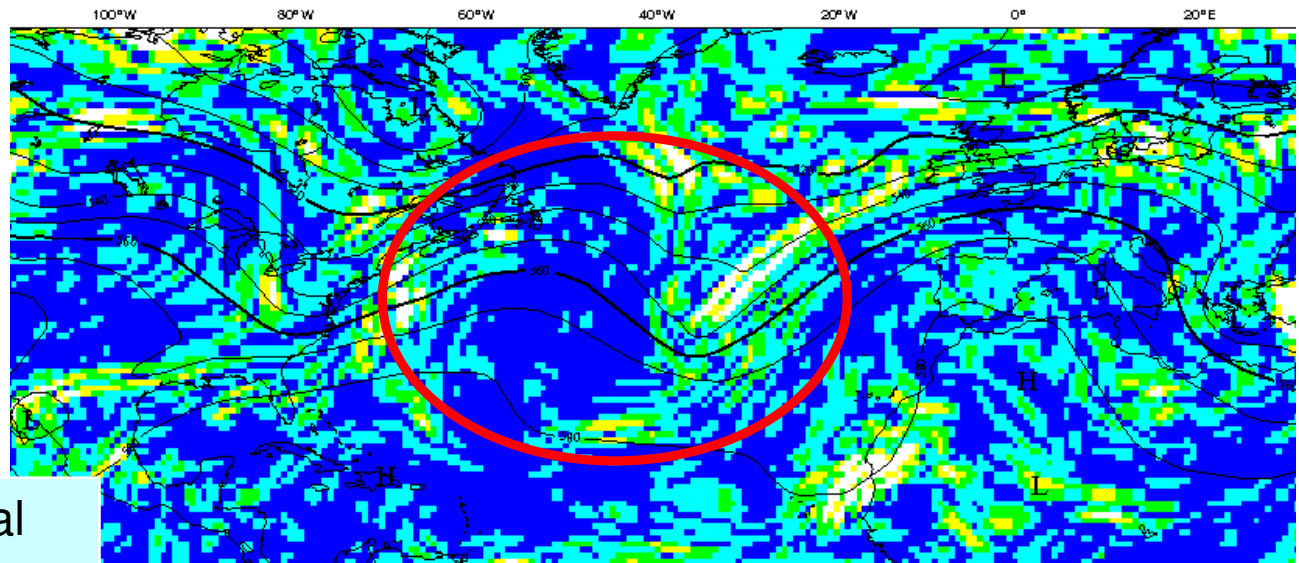
RAW 6-member estimated σ



FILTERED 6-member estimated σ

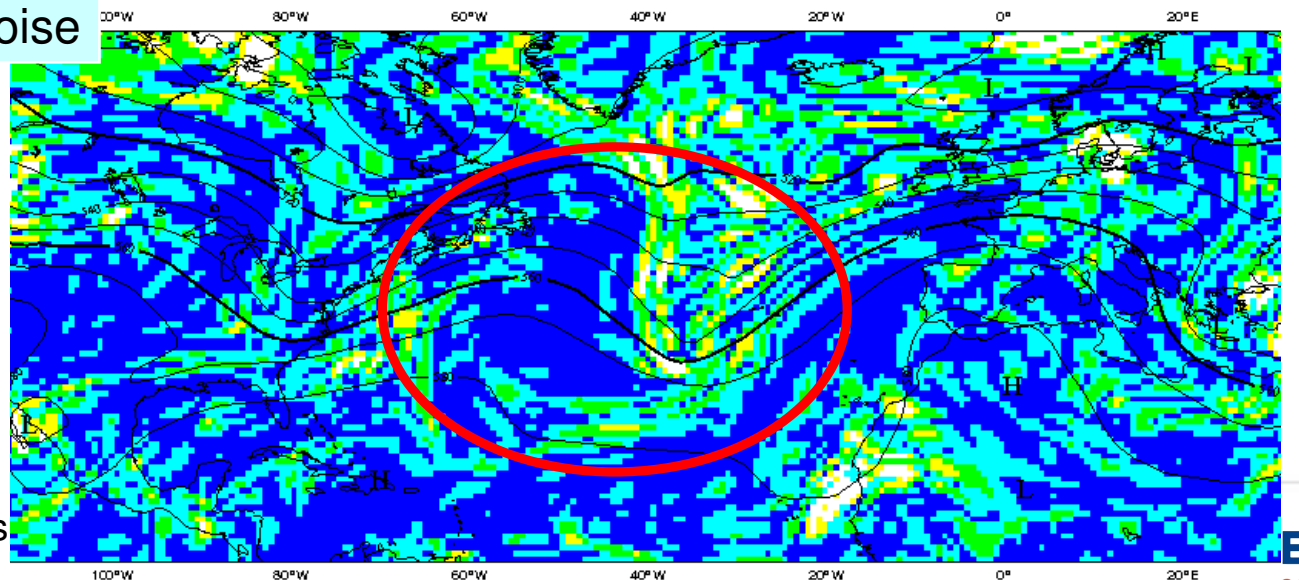
The spatial structure of signal and noise from two independent 3-member ensembles

"RAW" σ_b ENS 1



Common features ~ signal
Differences ~ sampling noise

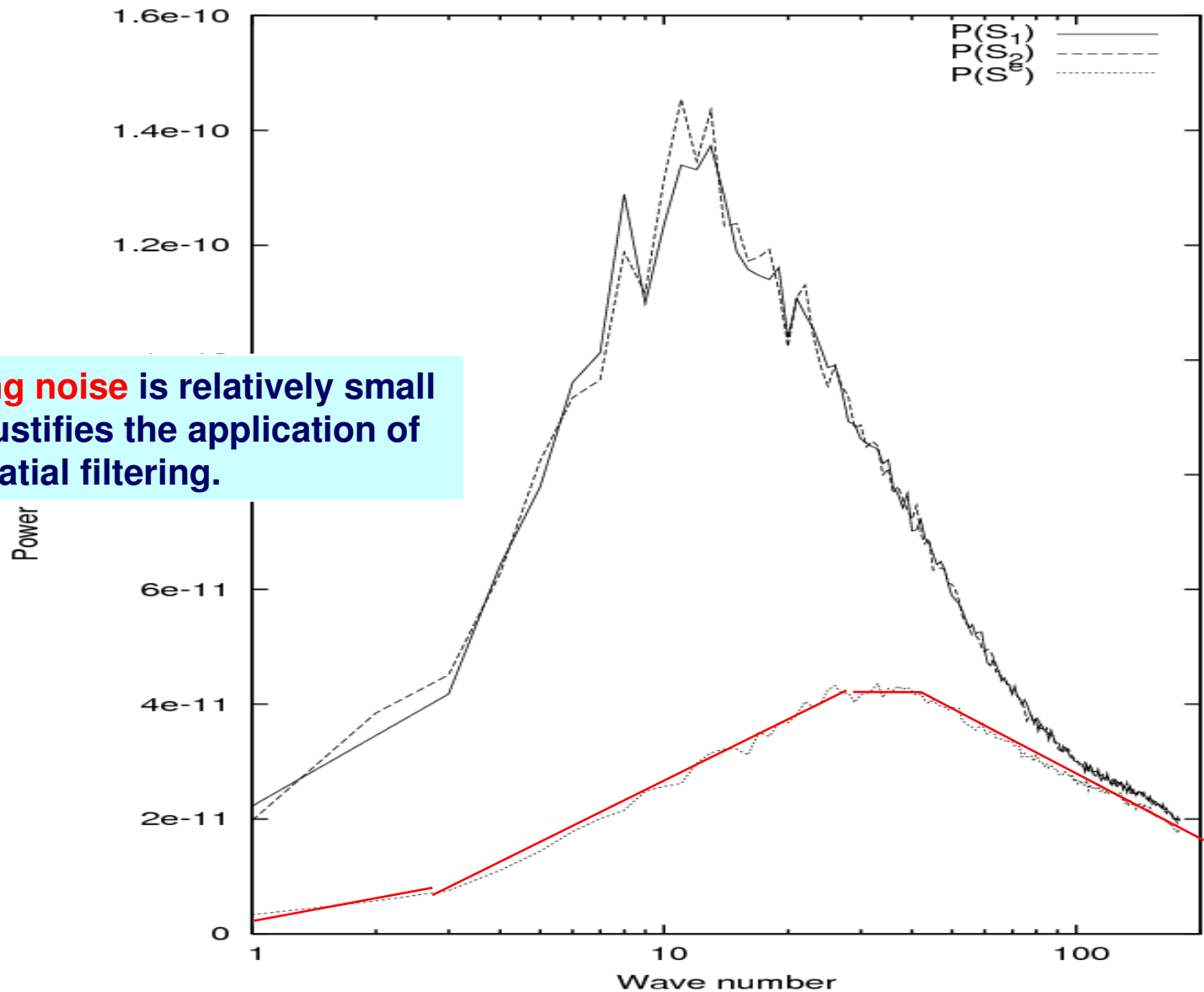
"RAW" σ_b ENS 2



Workshop on Flow-dependent as

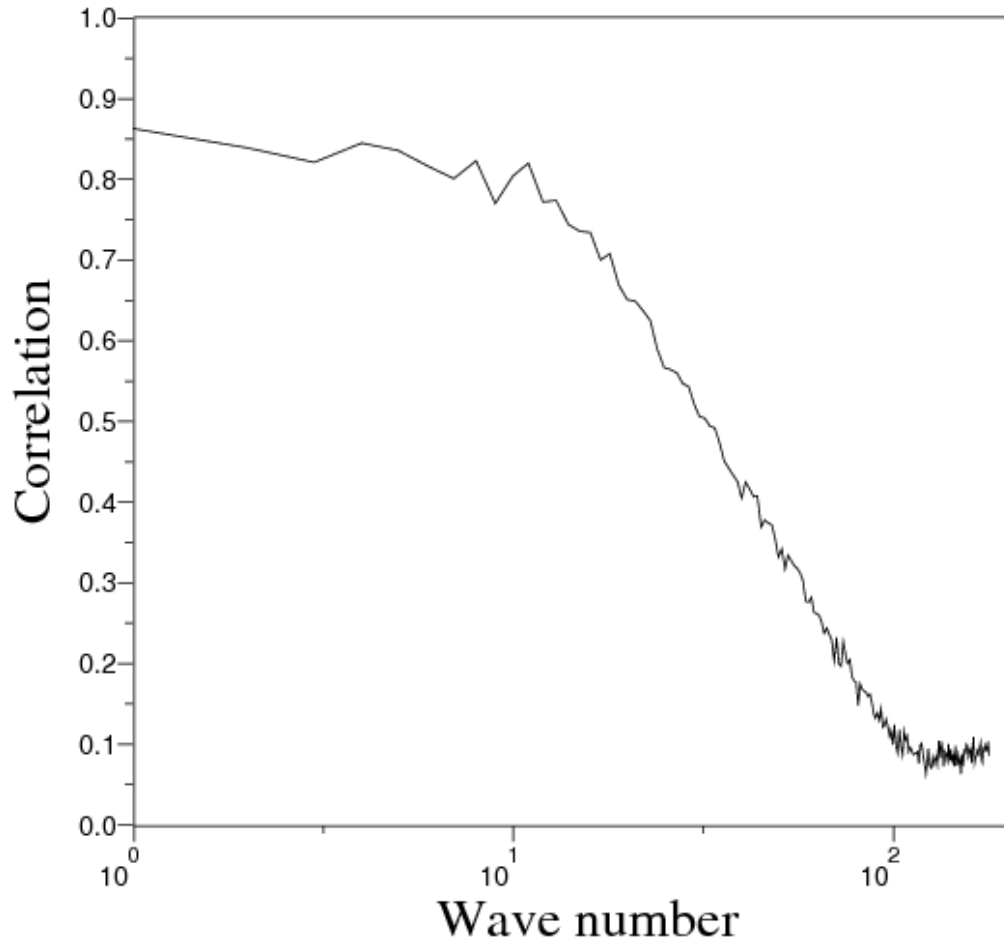
Spectra of sigmab maps and of sampling noise

=> The **sampling noise** is relatively small scale, which justifies the application of spatial filtering.



Can we design an objective and optimal filter ?

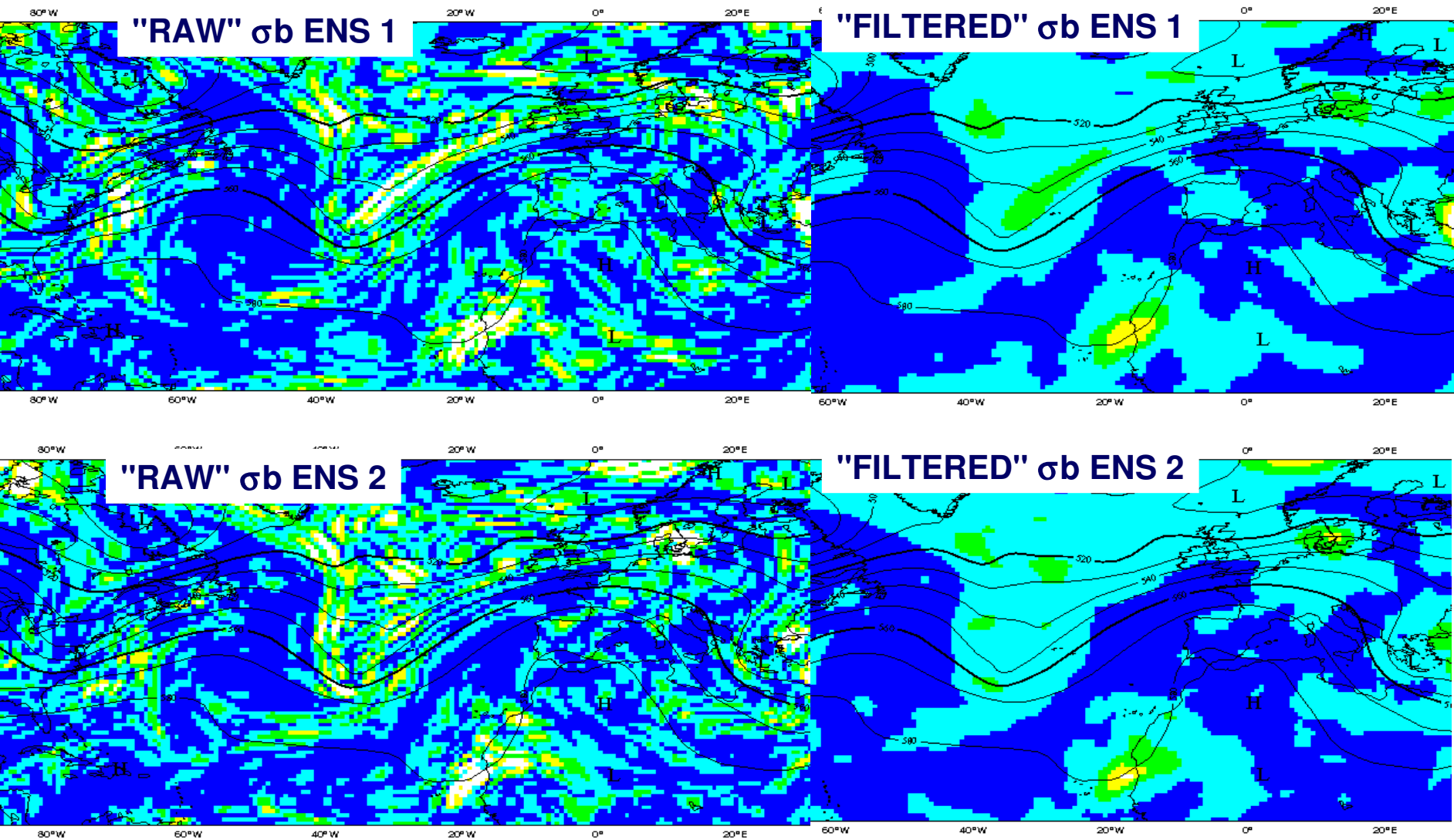
$$\rho = \text{cor}(S_1, S_2)$$



⇒ The two σ_b fields are more coherent in the large scales than in the small scales.

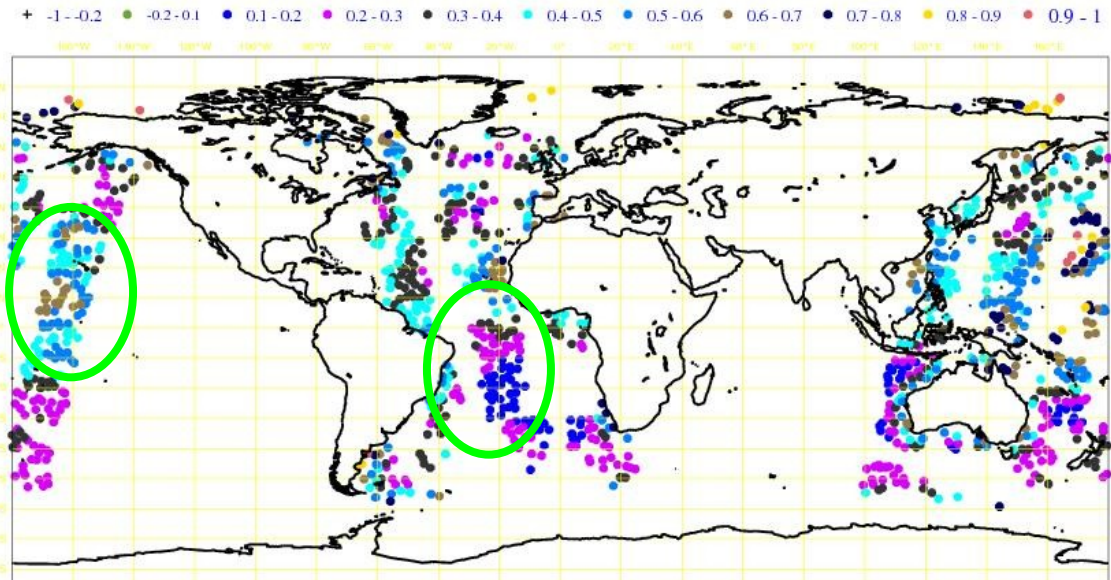
⇒ It can be shown that this spectral correlation can be used as an objective and optimal filtering coefficient !

Spatial filtering of standard deviations



Validation with innovation diagnostics (for one specific day and for HIRS-7)

Ensemble
sigmab's

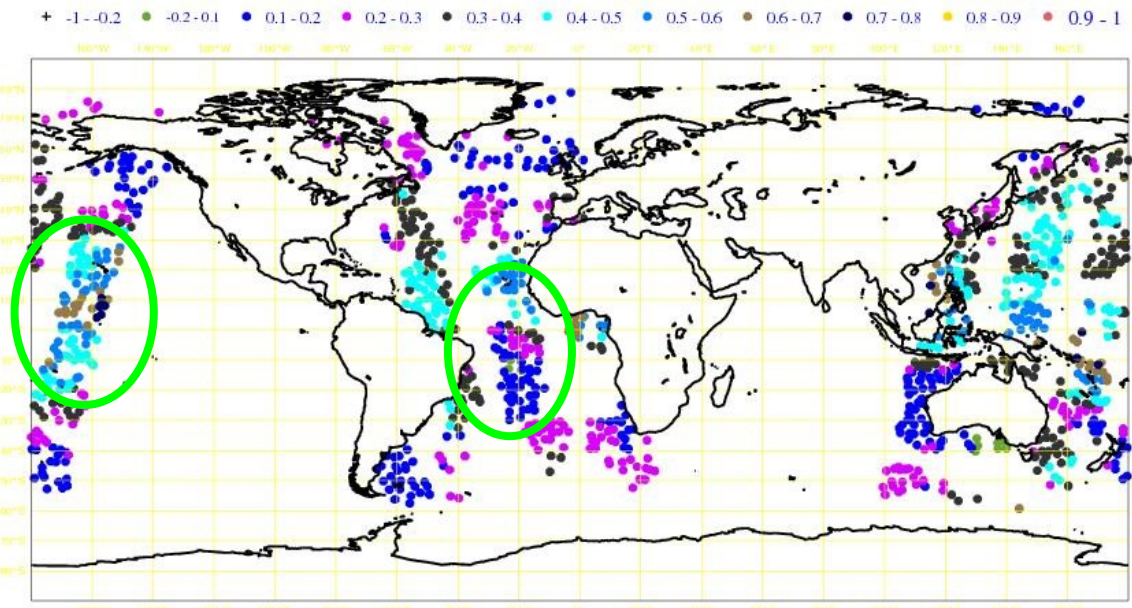


"Observed"
sigmab's

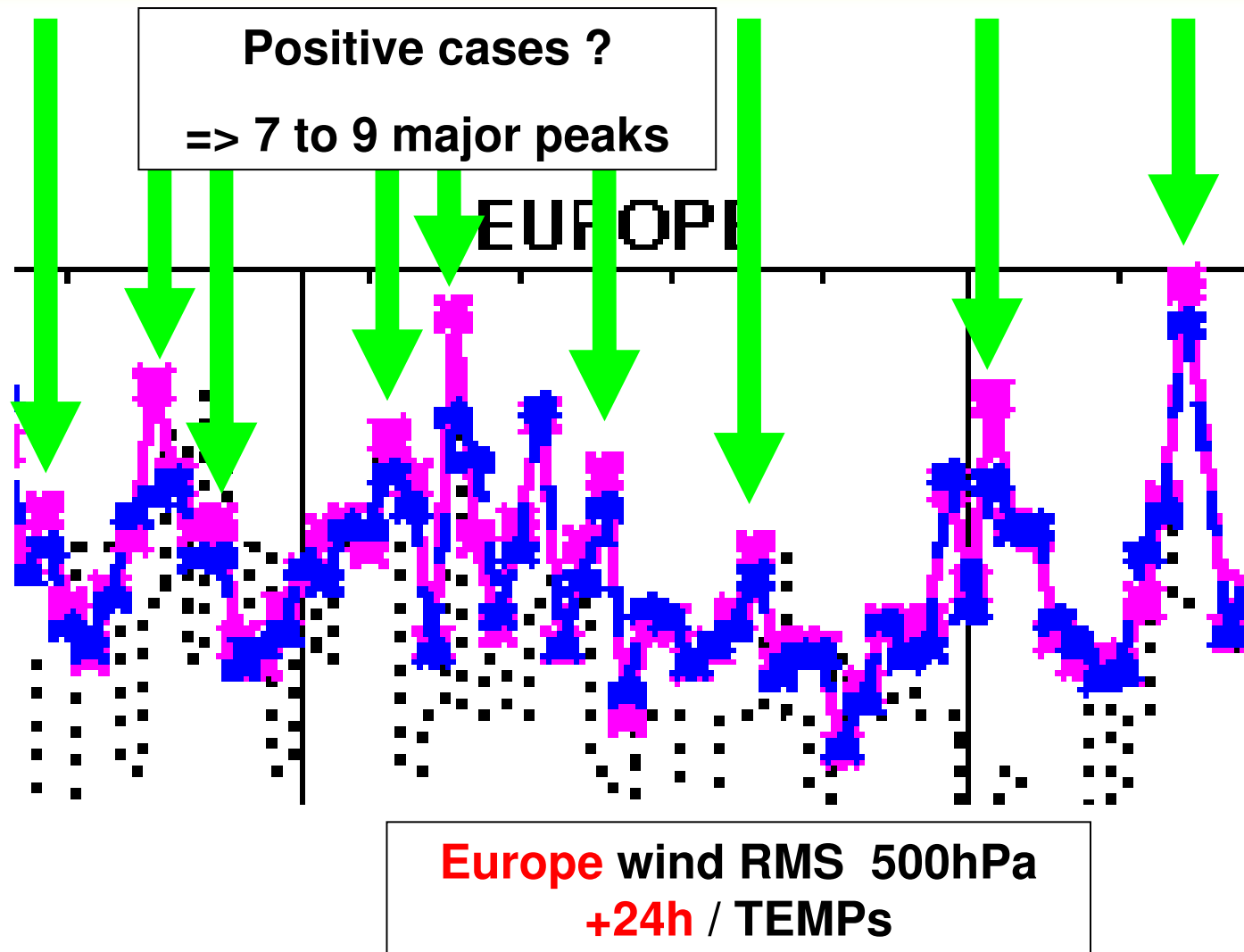
$$\text{cov}(H dx, dy) \sim H B H^T$$

(Desroziers et al 2005)

Workshop on Flow-dependent



Impact of sigmab's of the day in the Arpège 4D-Var (~over two months ; versus “climatological” sigmab's)



3 - Spatial filtering of correlations



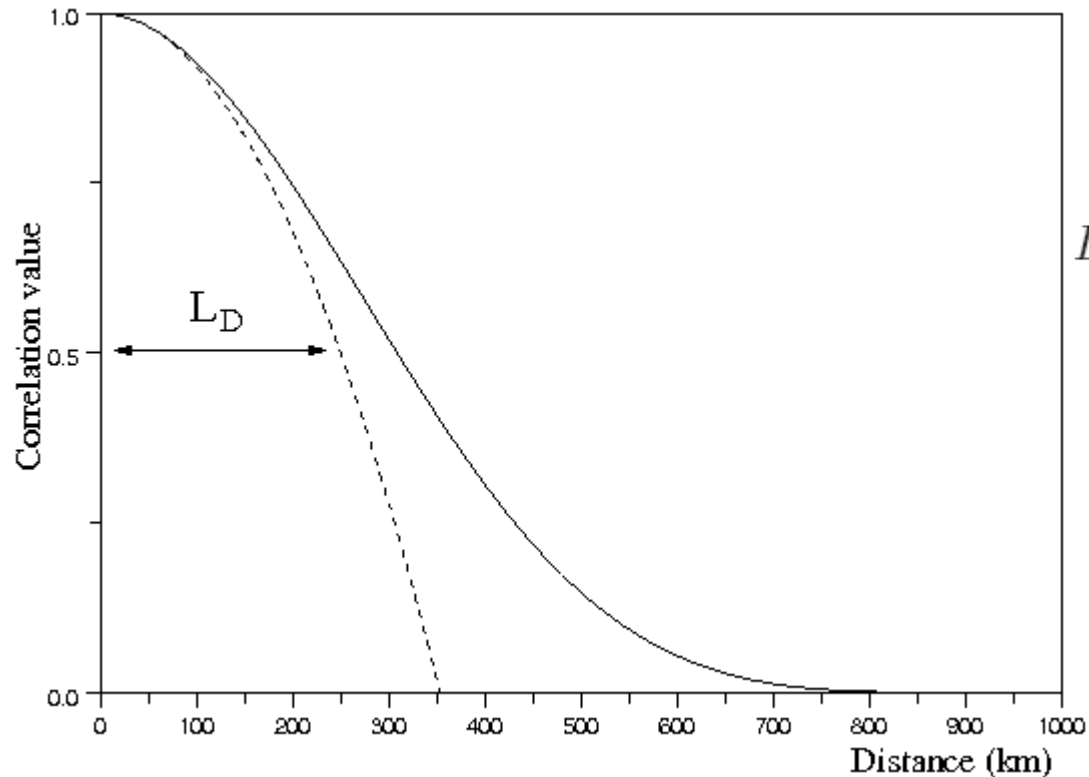
Local averaging of correlations via wavelets

Two extreme approaches in correlation modeling:

- Ens KF: **local** correlation functions are calculated for each gridpoint. => heterogeneity, but it needs a large ensemble.
- Var: a **global average** of correlation functions, via a spectral diagonal approach. => large (spatial) sample, but homogeneity.

=> An attractive compromise is to use wavelets, to calculate a **local average** of correlations.

Diagnosis of length-scale



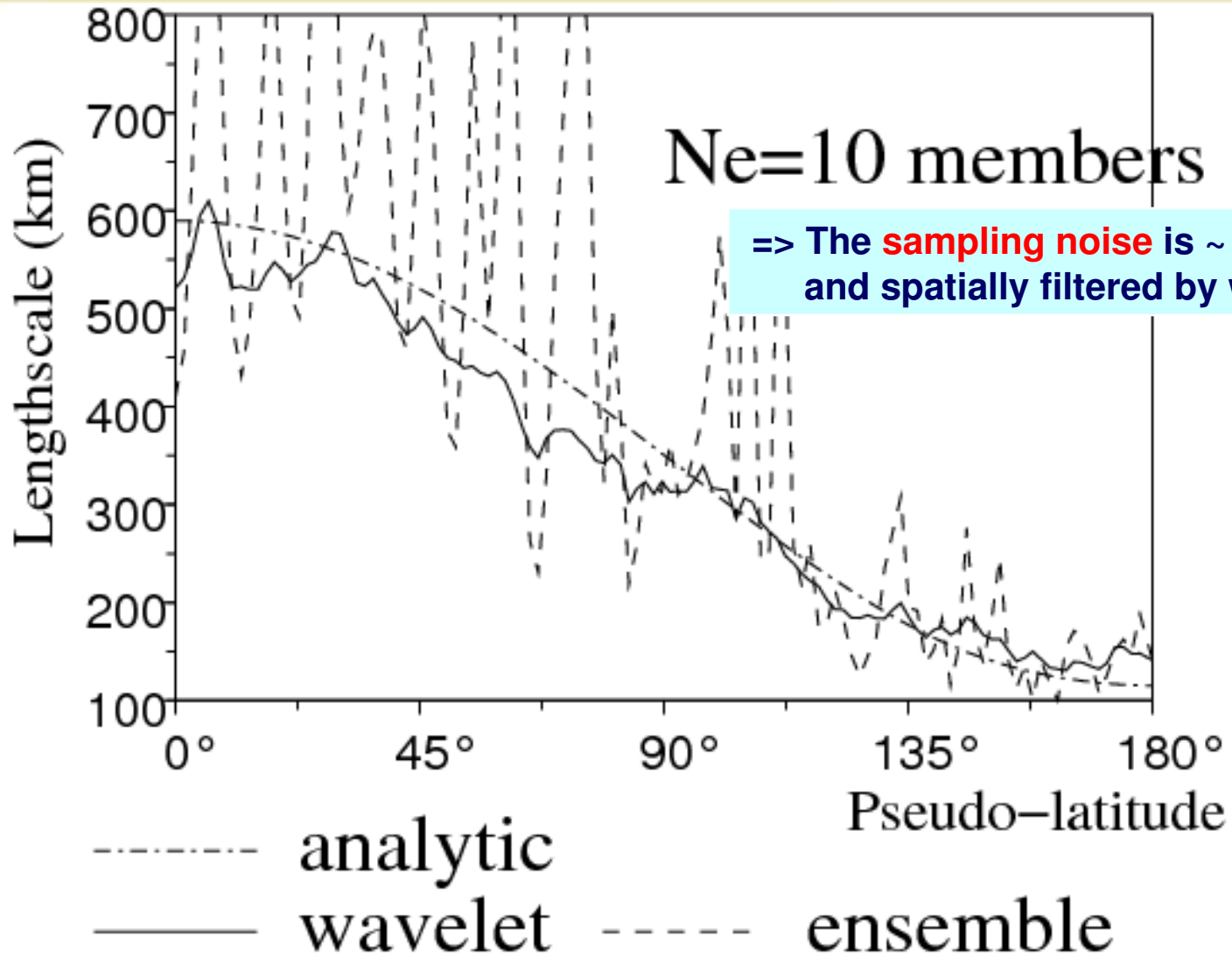
$$L_D = \sqrt{-\frac{1}{\Delta\rho(0)}}$$

$$L_{B\&B} = \sqrt{\frac{\sigma(\varepsilon_b(x))^2}{\sigma(\partial_x \varepsilon_b(x))^2 - (\partial_x \sigma(\varepsilon_b(x)))^2}}$$

$$L_{Pb} = \frac{|\delta x|}{\sqrt{2(1 - \rho(\delta x))}}$$

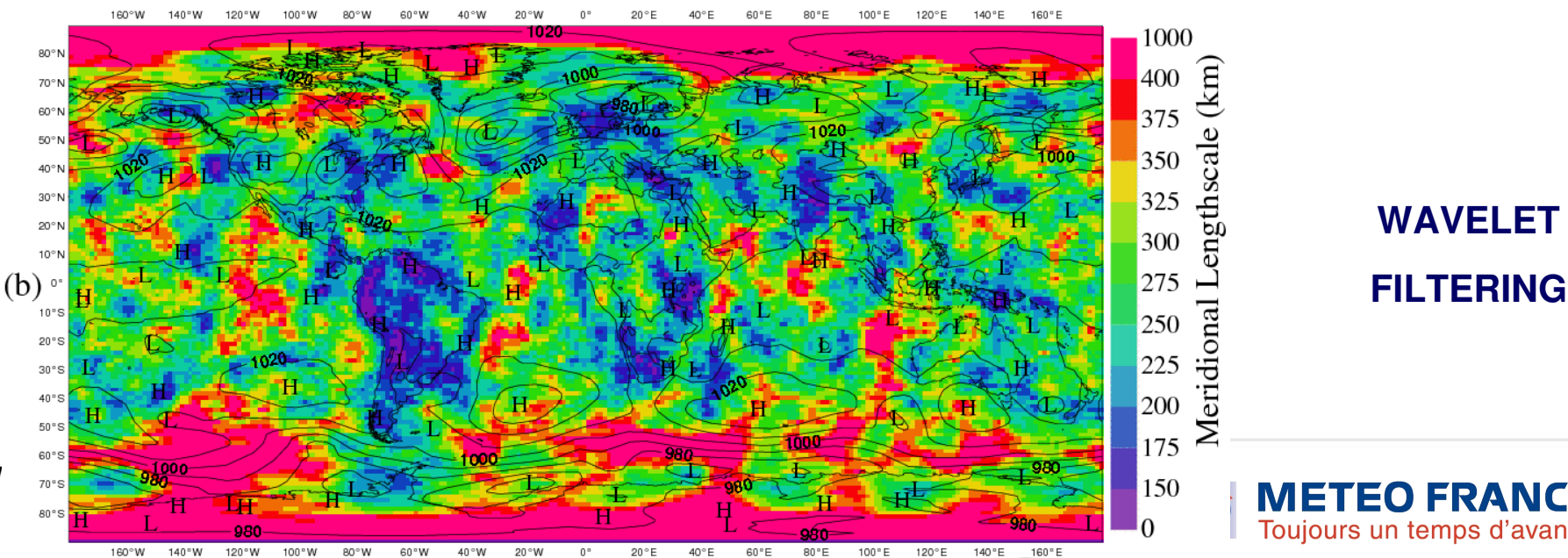
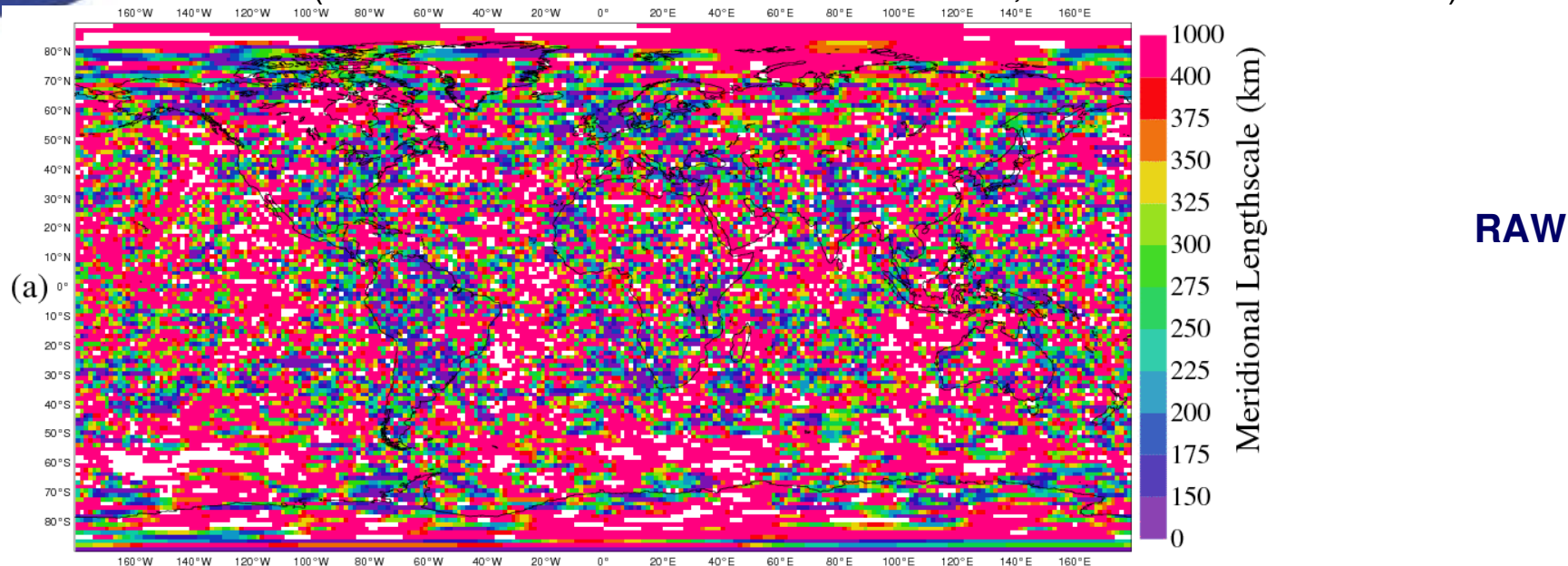
$$L_{Gb} = \frac{|\delta x|}{\sqrt{-2 \ln \rho(\delta x)}}$$

Sampling noise reduction

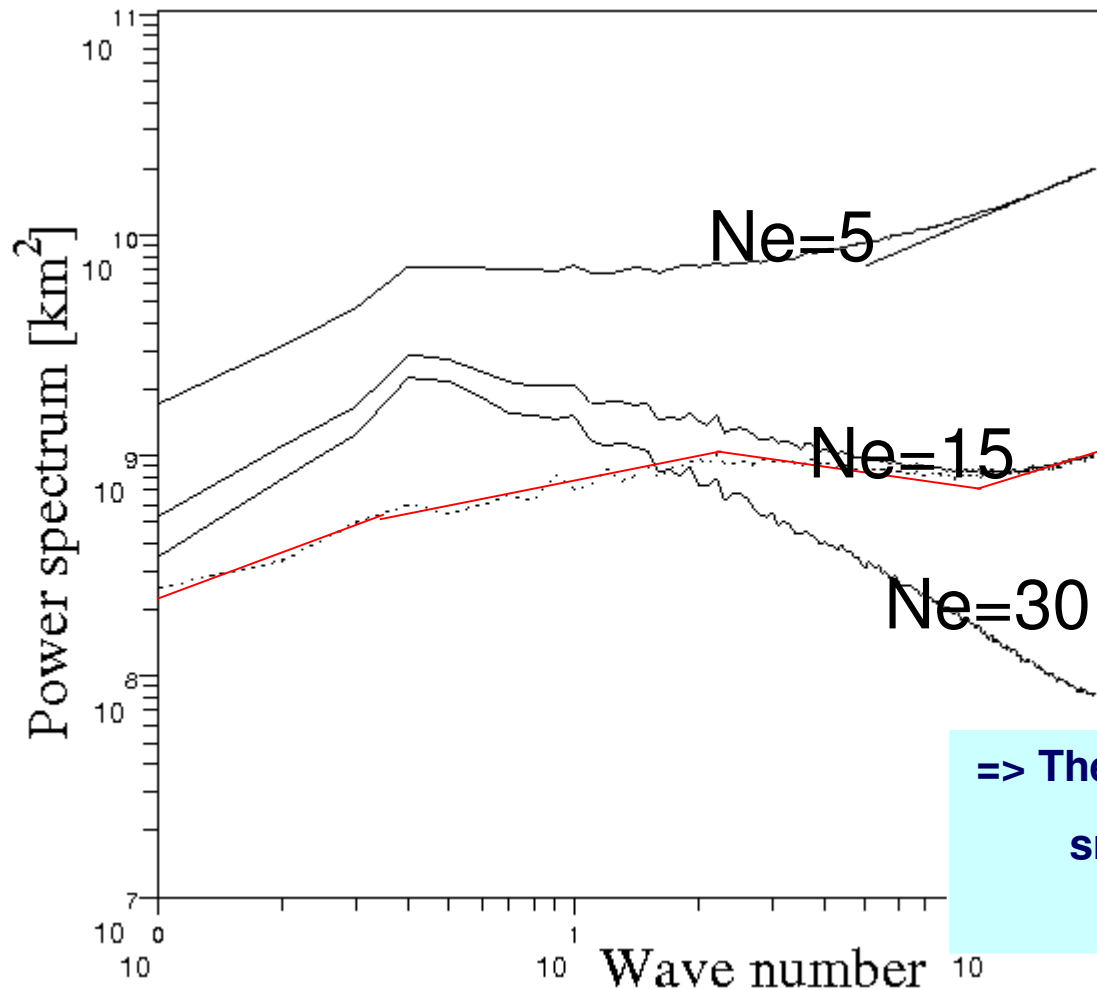


Correlation length-scales of the day

(from a 6-member assimilation ensemble; Pannekoucke et al 2007)

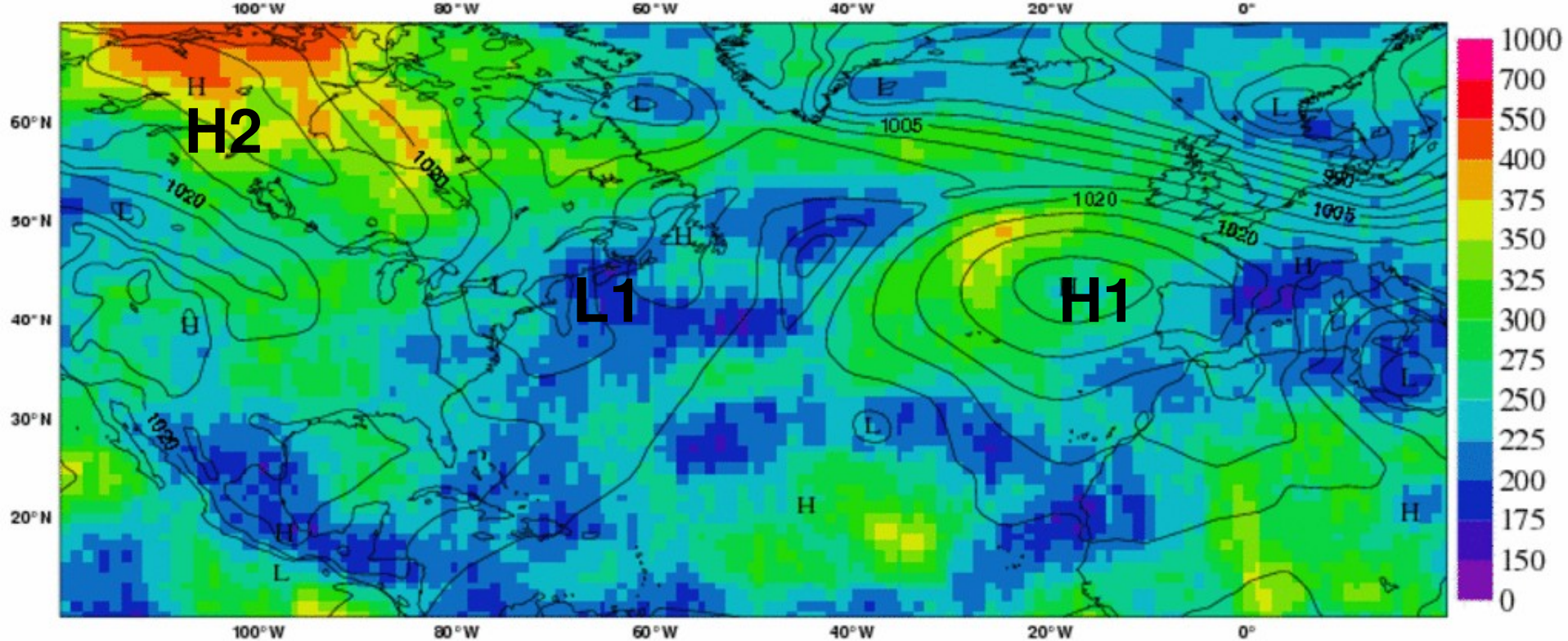


Spectrum of unfiltered length-scale map versus ensemble size



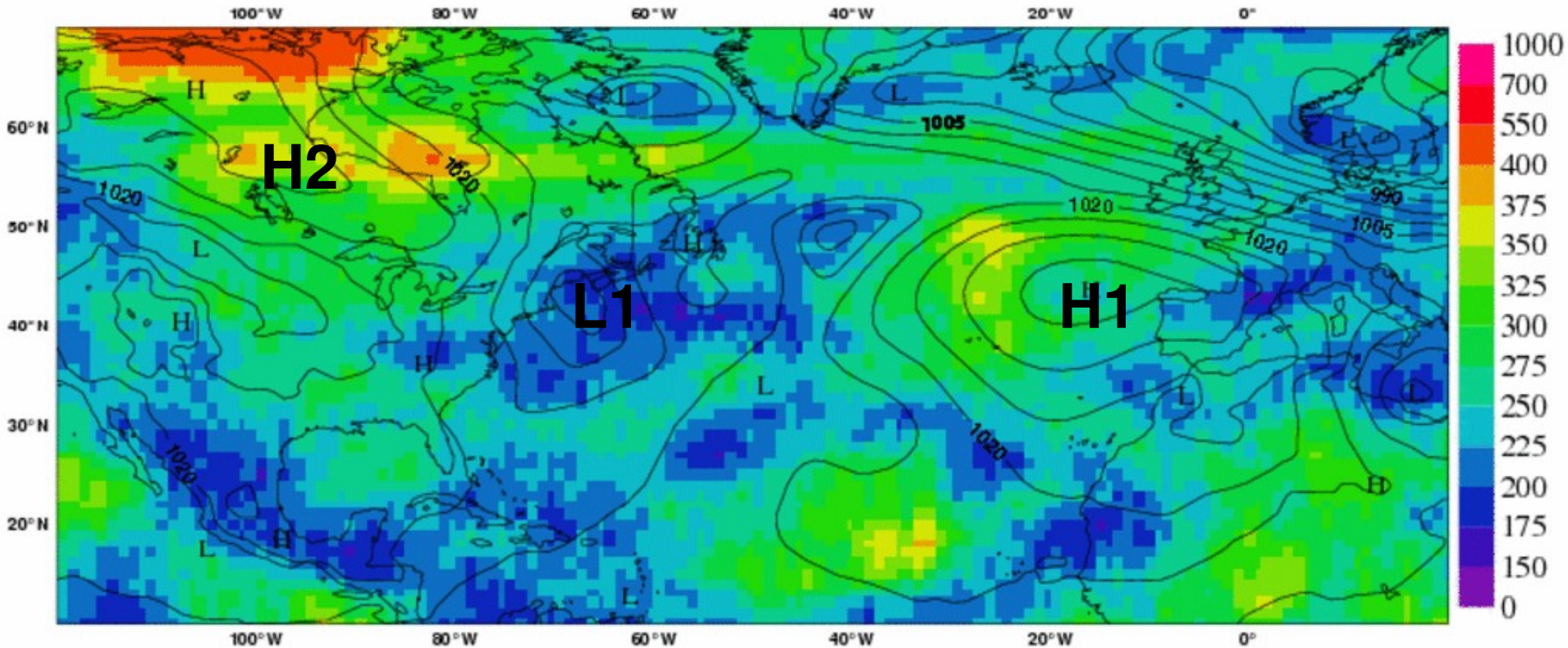
=> The **noise contribution** is relatively small in the large scales, and large in the small scales.

Length-scales of the day



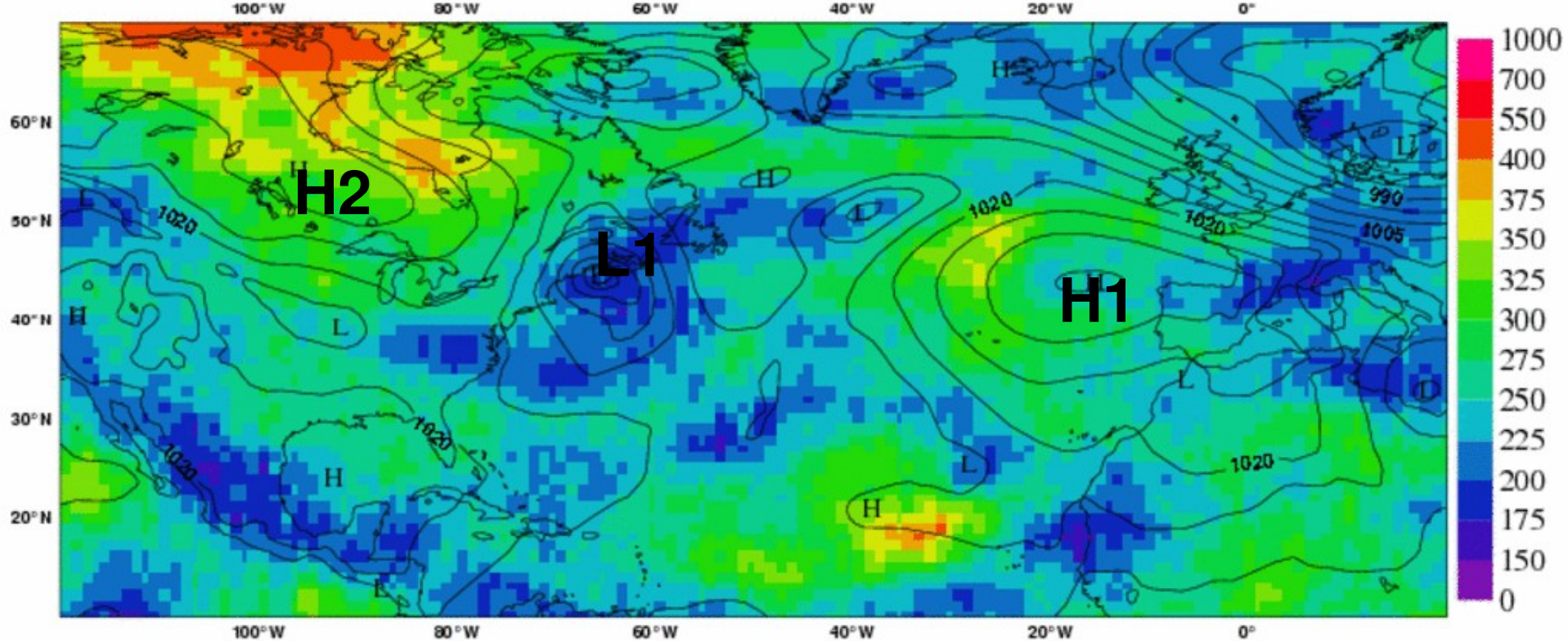
20/01/2005 06UTC (1/12)

Length-scales of the day



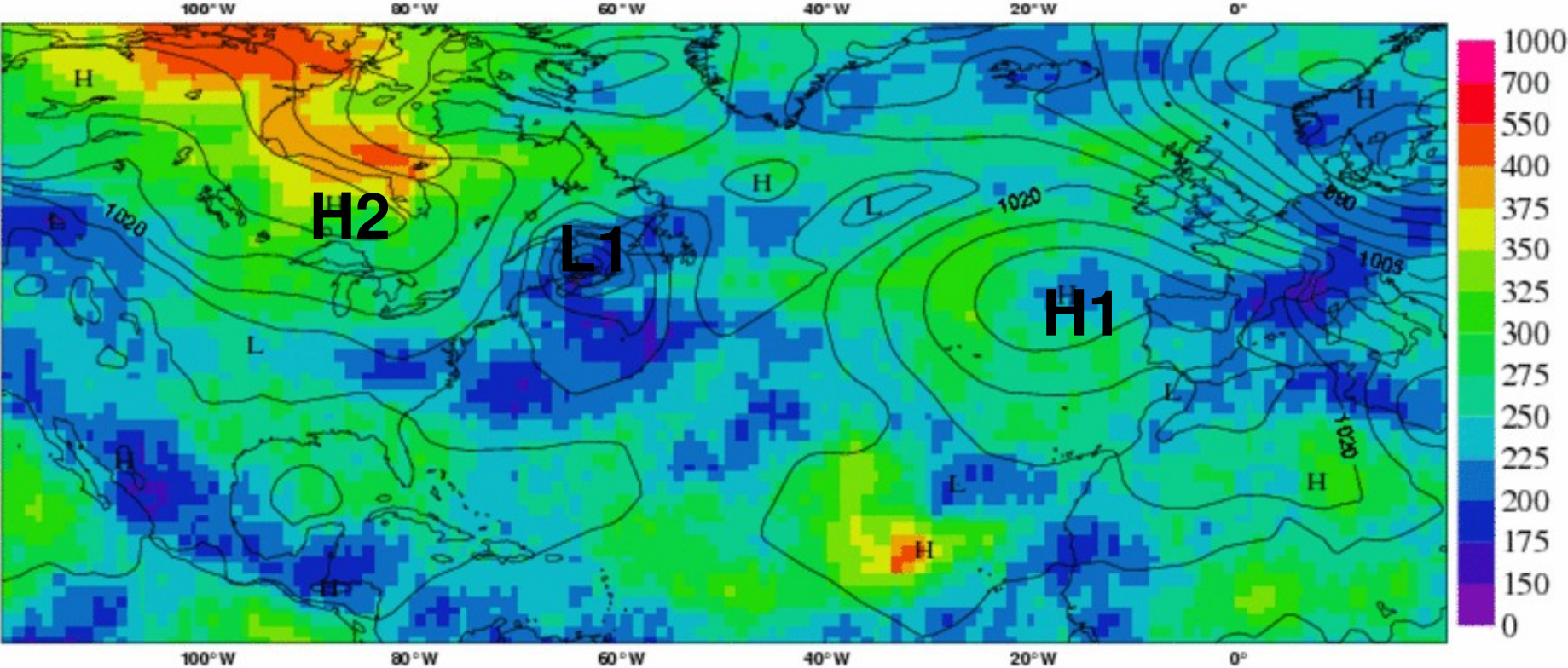
20/01/2005 12UTC (2/12)

Length-scales of the day



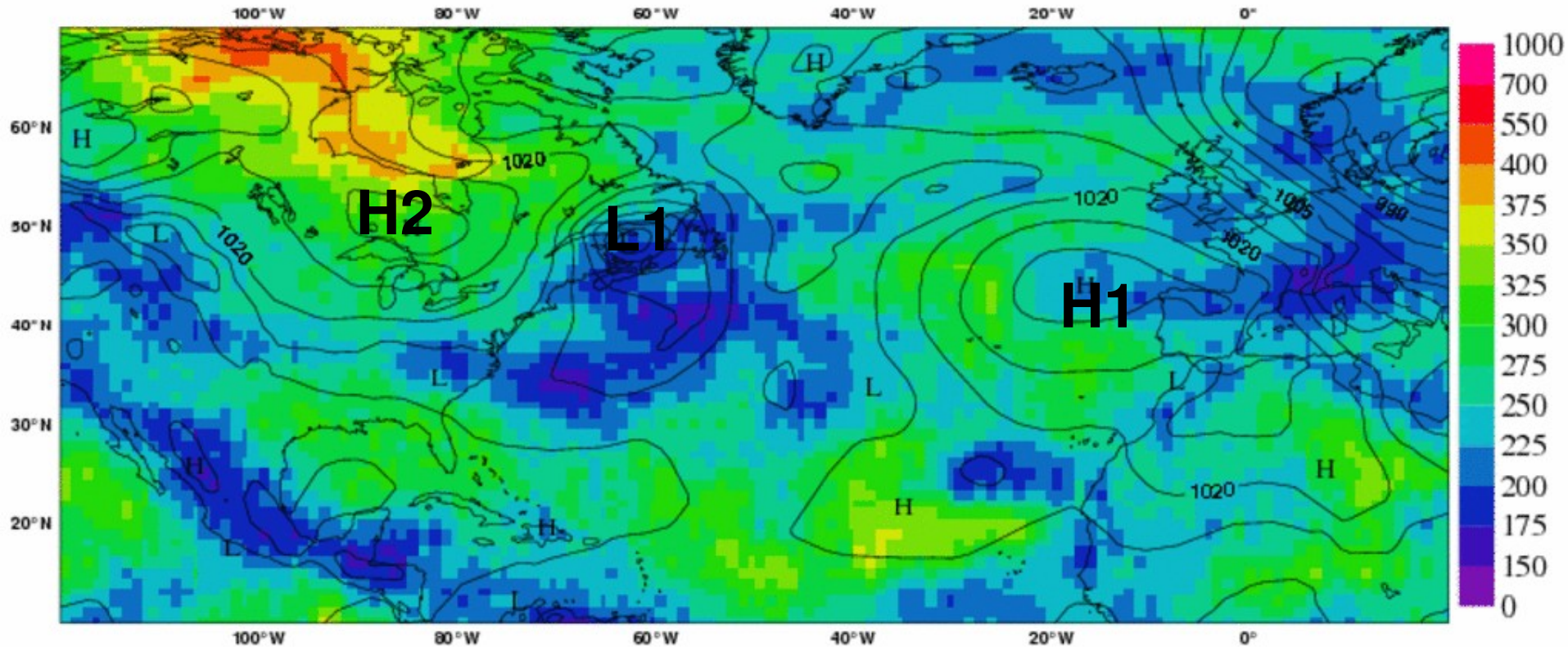
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Length-scales of the day



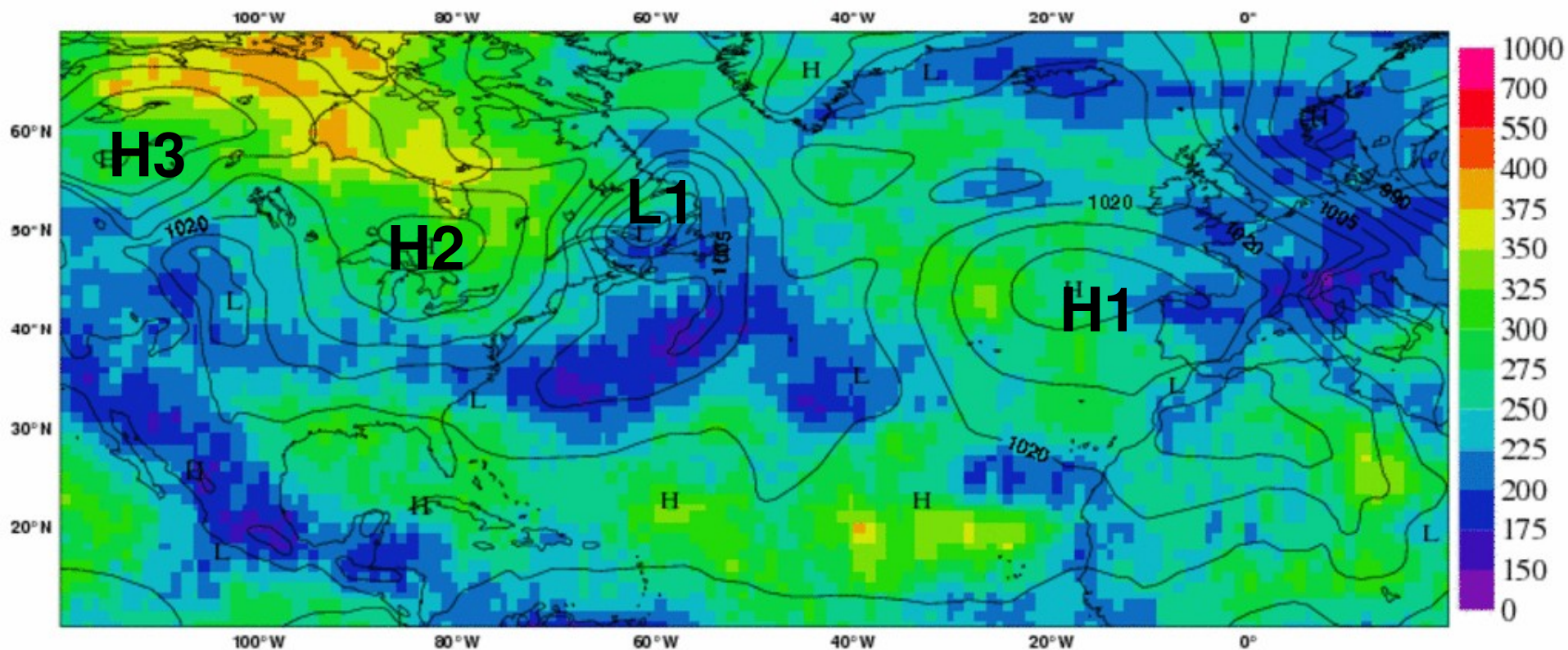
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Length-scales of the day



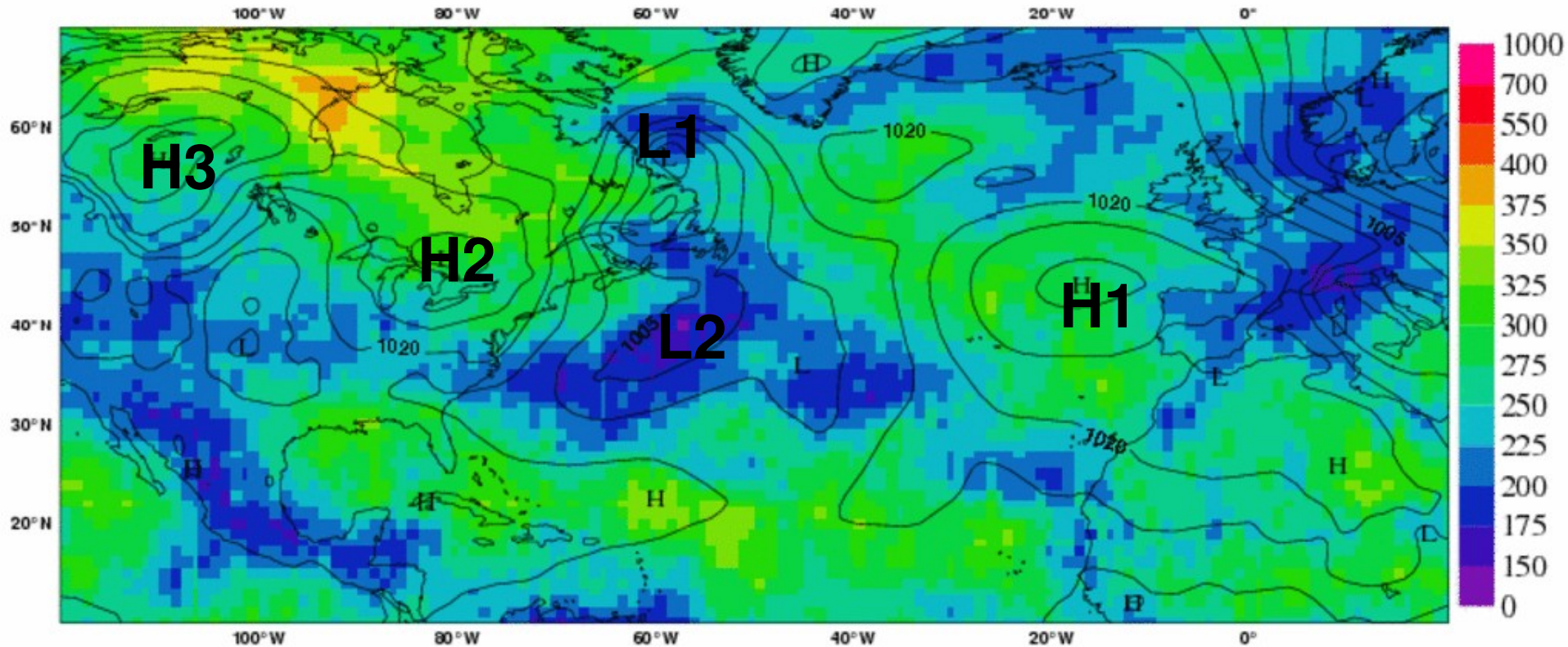
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Length-scales of the day



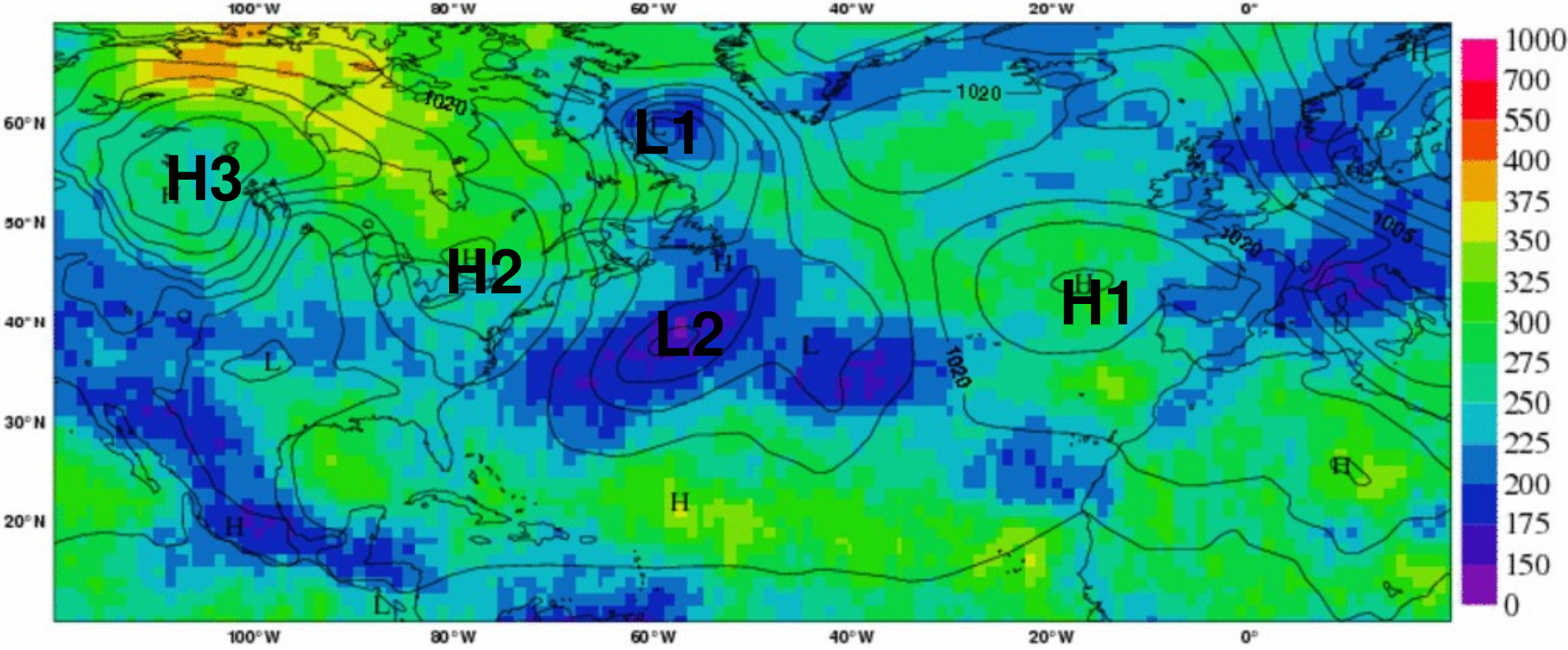
21/01/2005 12UTC (6/12)

Length-scales of the day



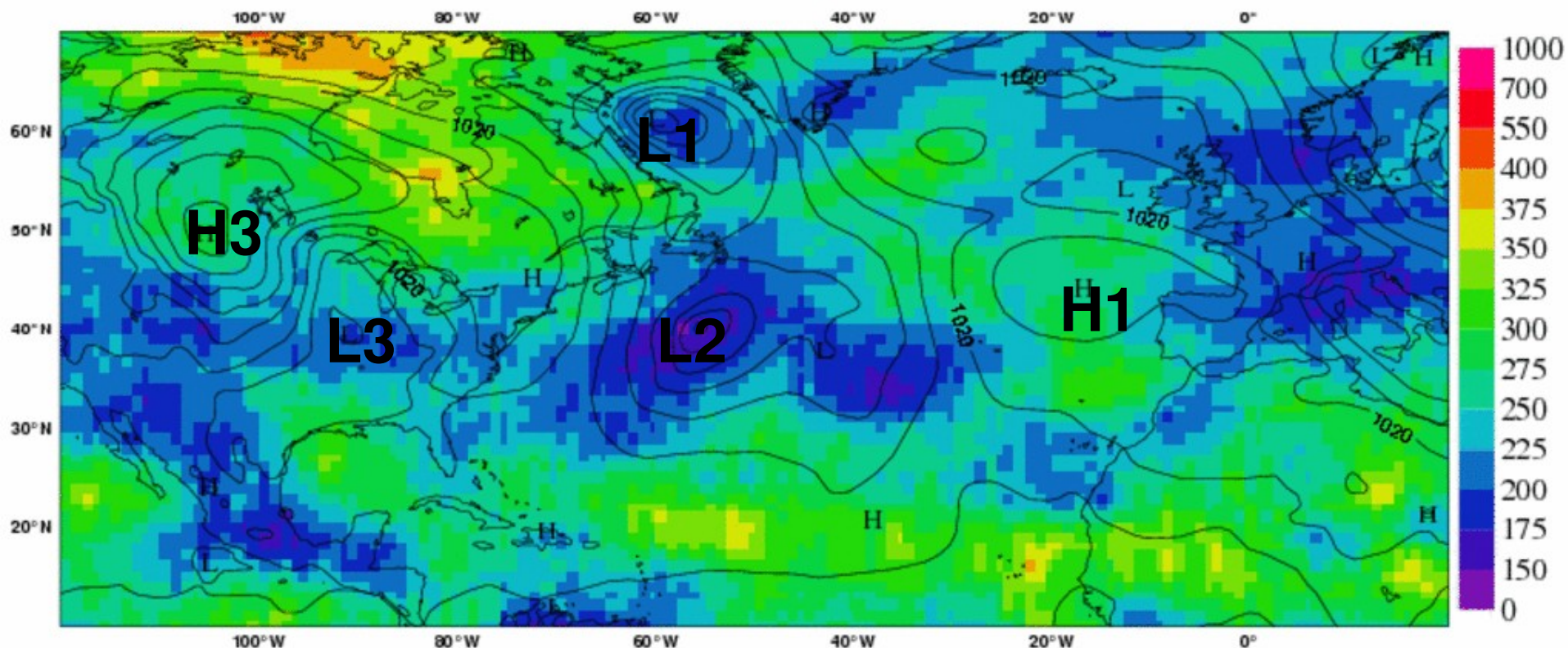
21/01/2005 18UTC (7/12)

Length-scales of the day



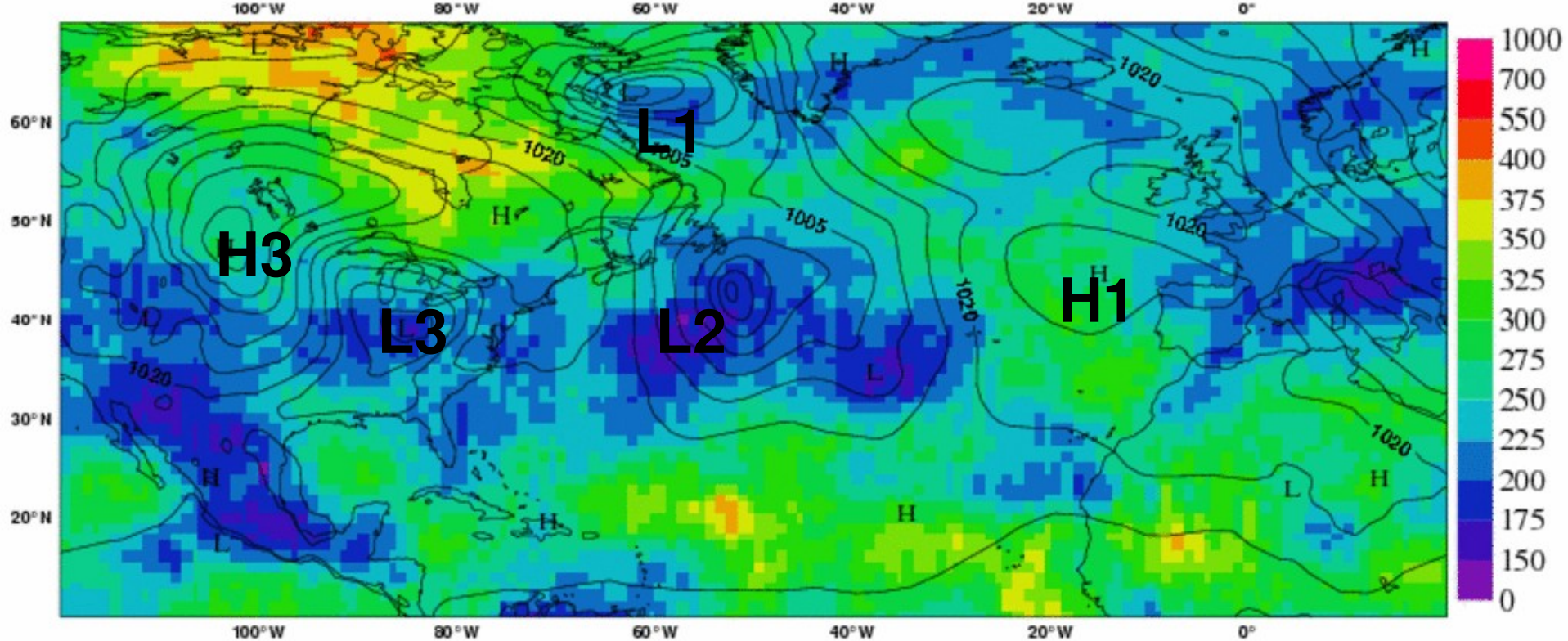
22/01/2005 00UTC (8/12)

Length-scales of the day



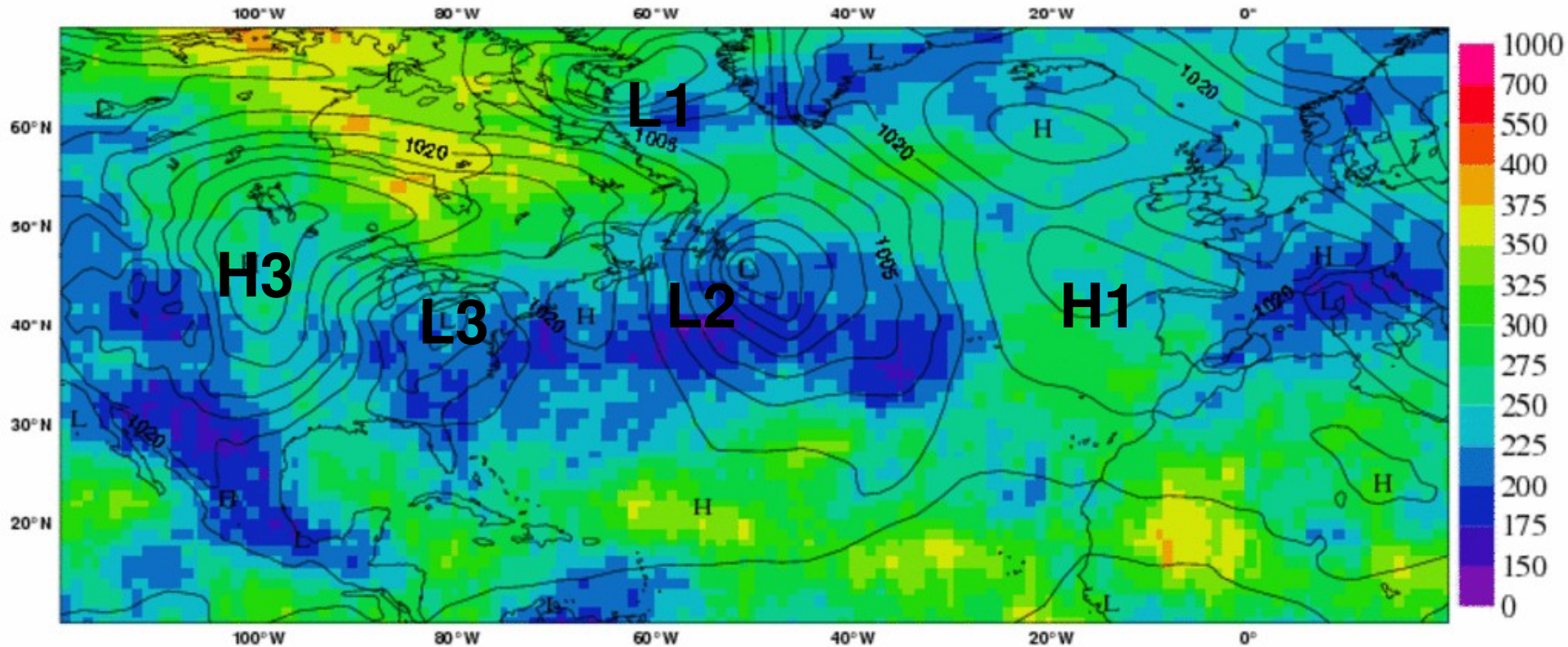
22/01/2005 06UTC (9/12)

Length-scales of the day



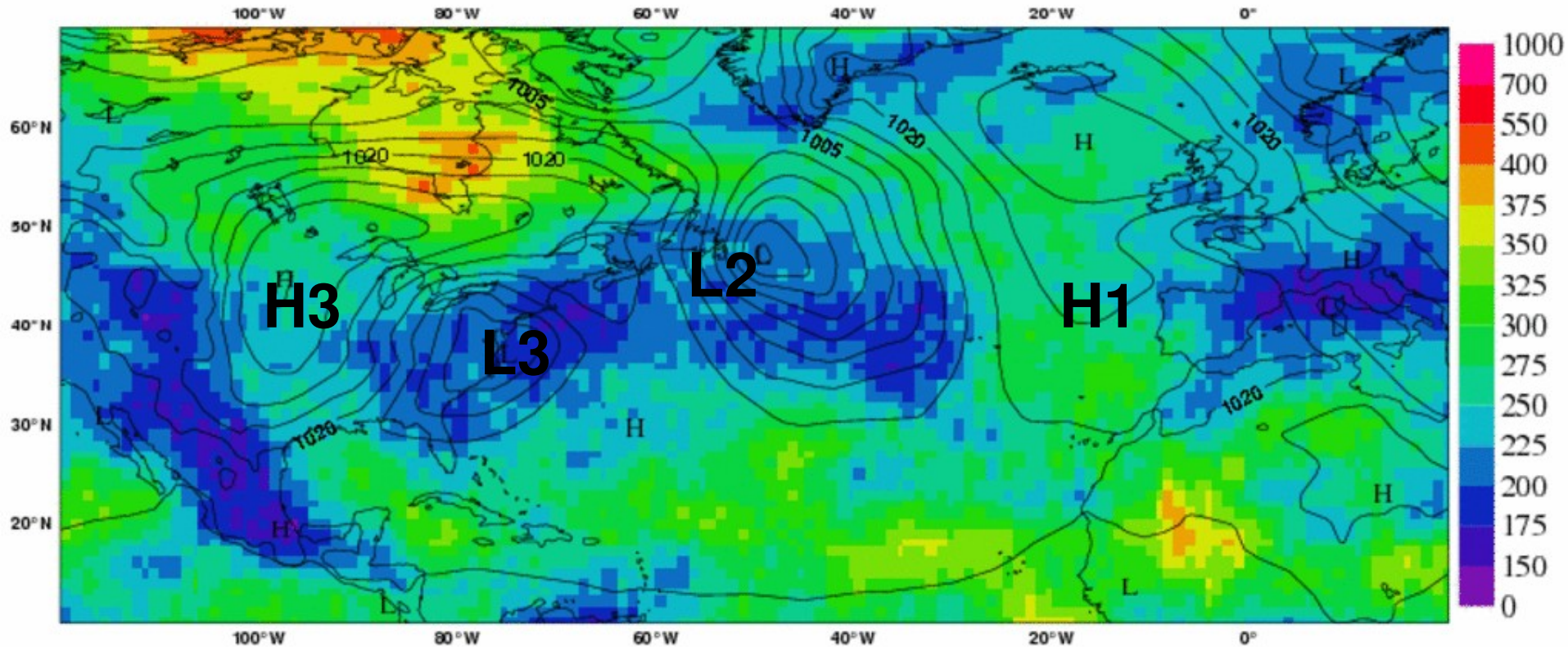
22/01/2005 12UTC (10/12)

Length-scales of the day



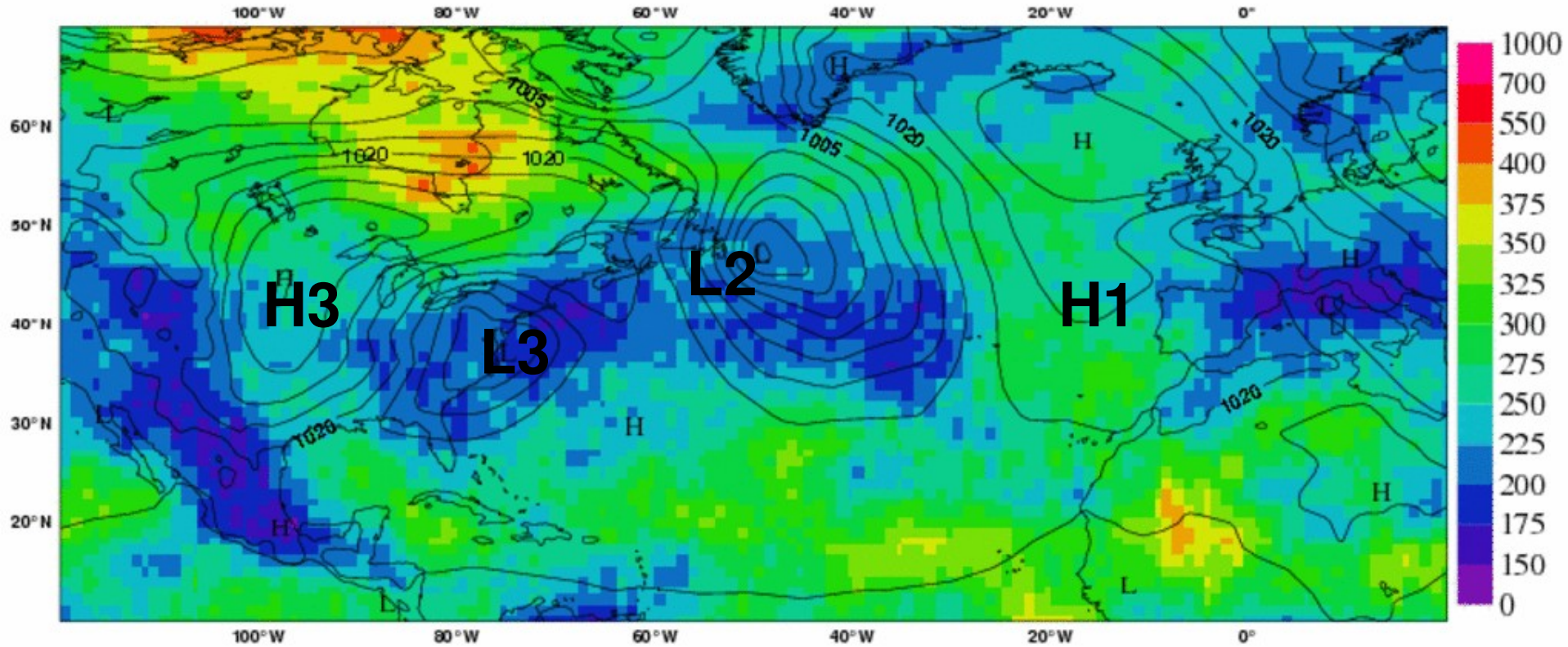
22/01/2005 18UTC (11/12)

Length-scales of the day



23/01/2005 00UTC (12/12)

Discussion



Conclusions and perspectives

- Using an assimilation ensemble and spatial filtering is a promising way to obtain flow-dependent covariances (+ balances) (in a more realistic way than with a simplified background state dependence)
- The spatial filtering is justified by the small scale structure of sampling noise, and it can be optimized objectively.
- The local spatial averaging allows the sample size to be much increased, the ensemble size being MULTIPLIED by a 2D spatial sample size.



Conclusions and perspectives

- The spatial filtering is costless: it may help to make the ensemble size and cost reasonable.
- First impact experiments and comparisons with innovation diagnostics are encouraging. => operational in 2007-2008 ?
- Applications for assimilation diagnostics and ensemble prediction too.

