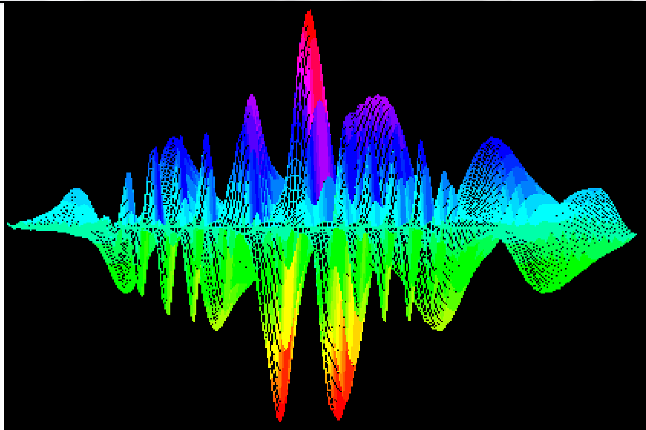
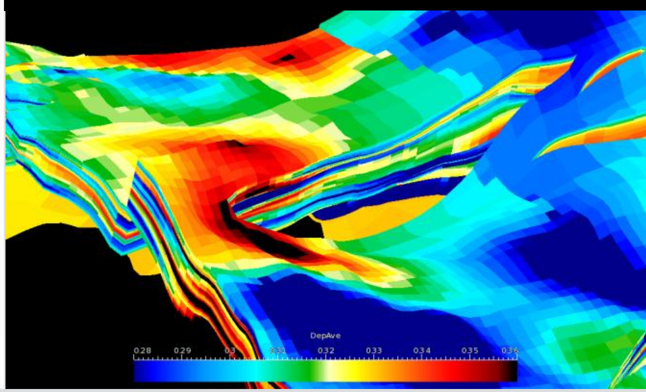
Adaptive multi-scale ensemble-based history matching using wavelets





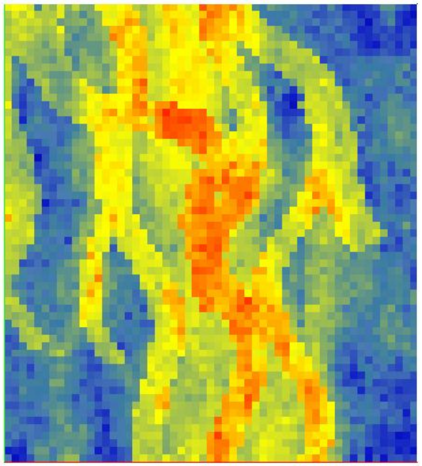
“EnKF workshop “
Bergen May 2013

Théophile Gentilhomme, Dean Oliver, Trond Mannesth, Remi Moyen, Guillaume Caumon

6/4/2013

Motivations

- Match the data and preserve the prior models



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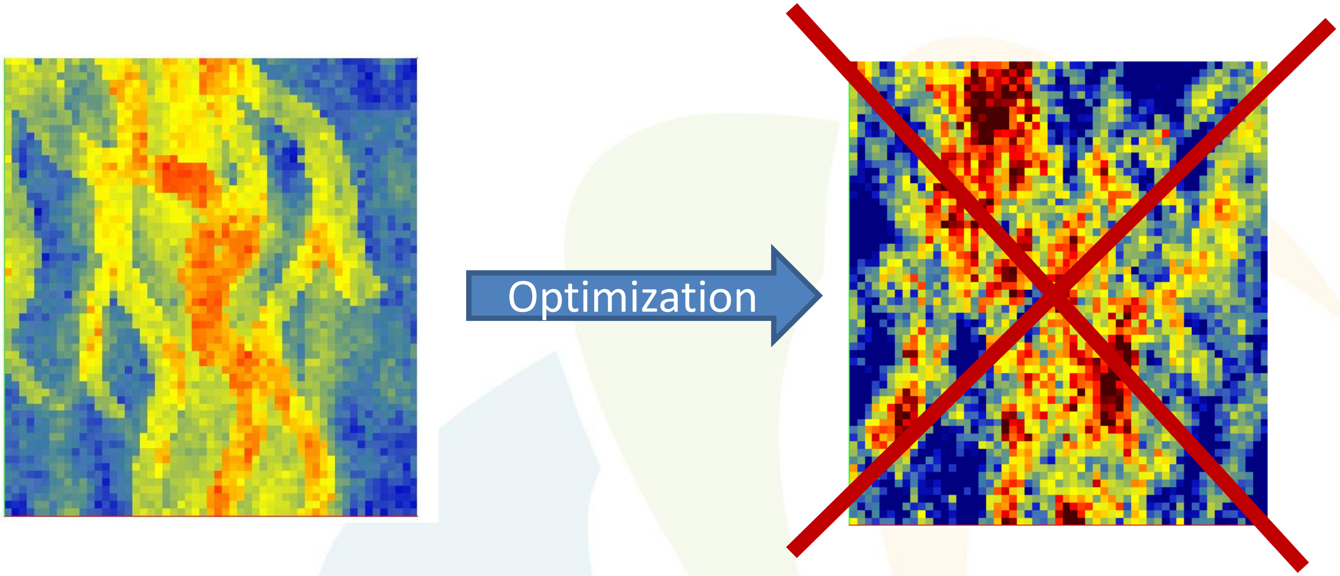

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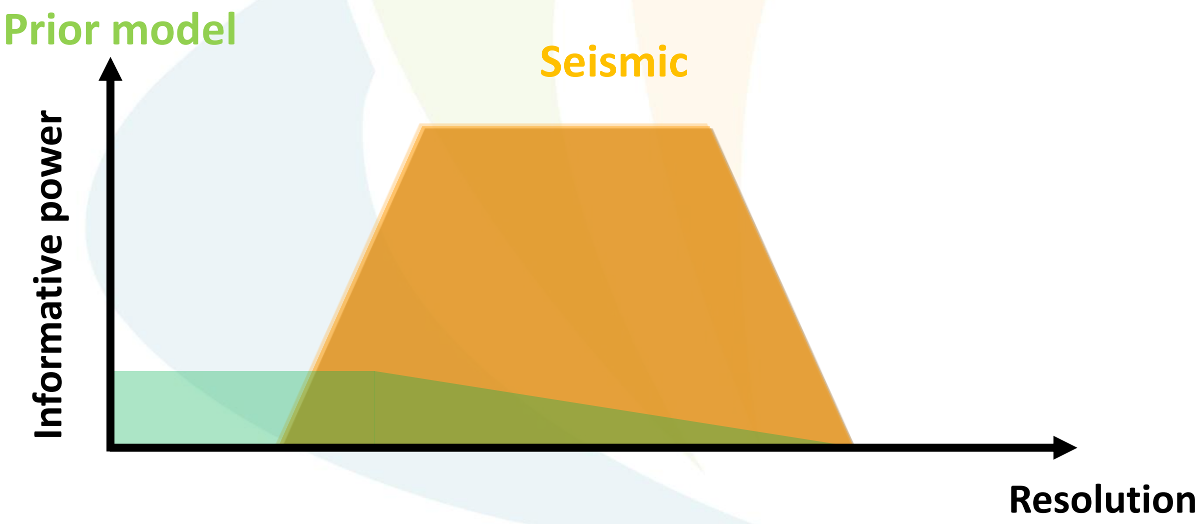

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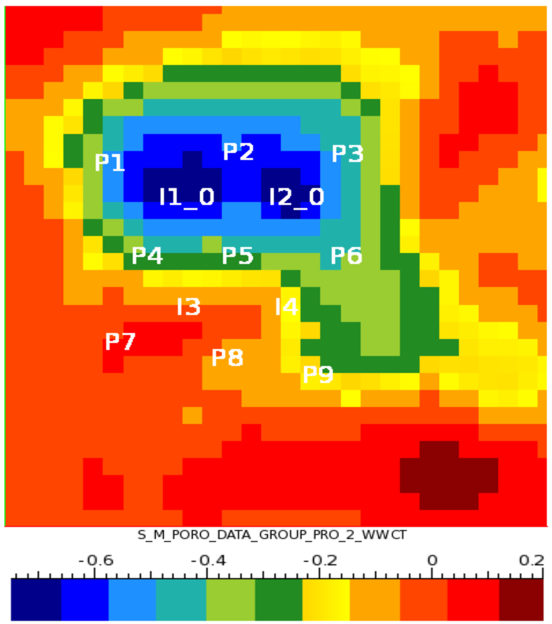

CGGVERITAS

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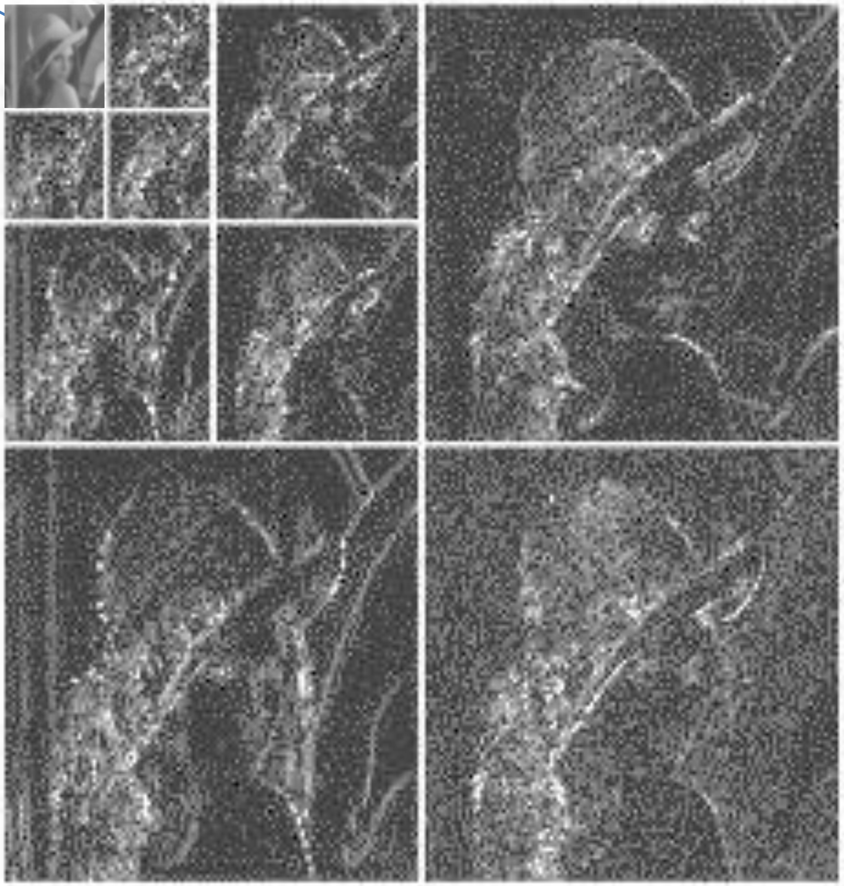
- Ensemble based method:
  - Use of any parameterization

Multi-scale parameterization: wavelets

- Parameterization localized both in space and frequency

Original signal

From [Xiang-Yang, 2008]



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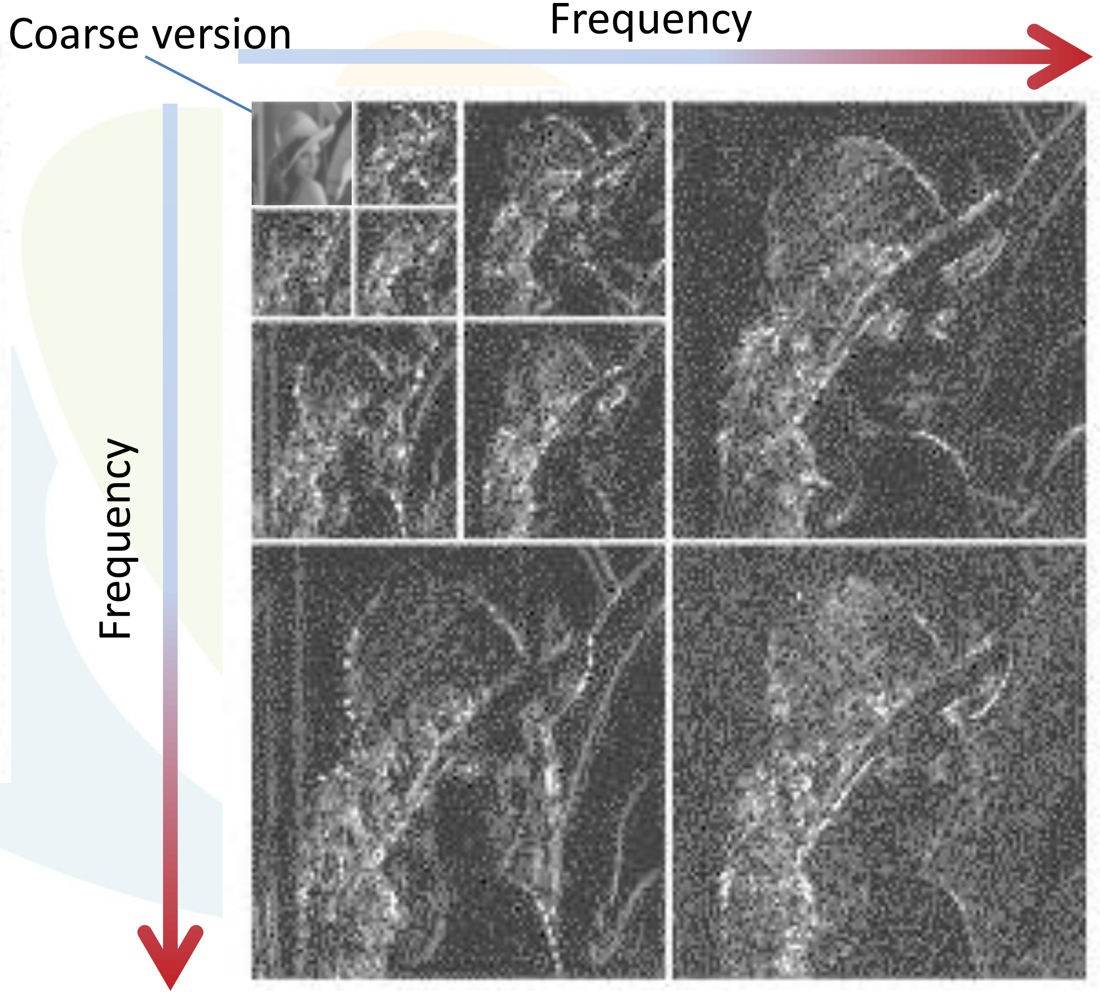

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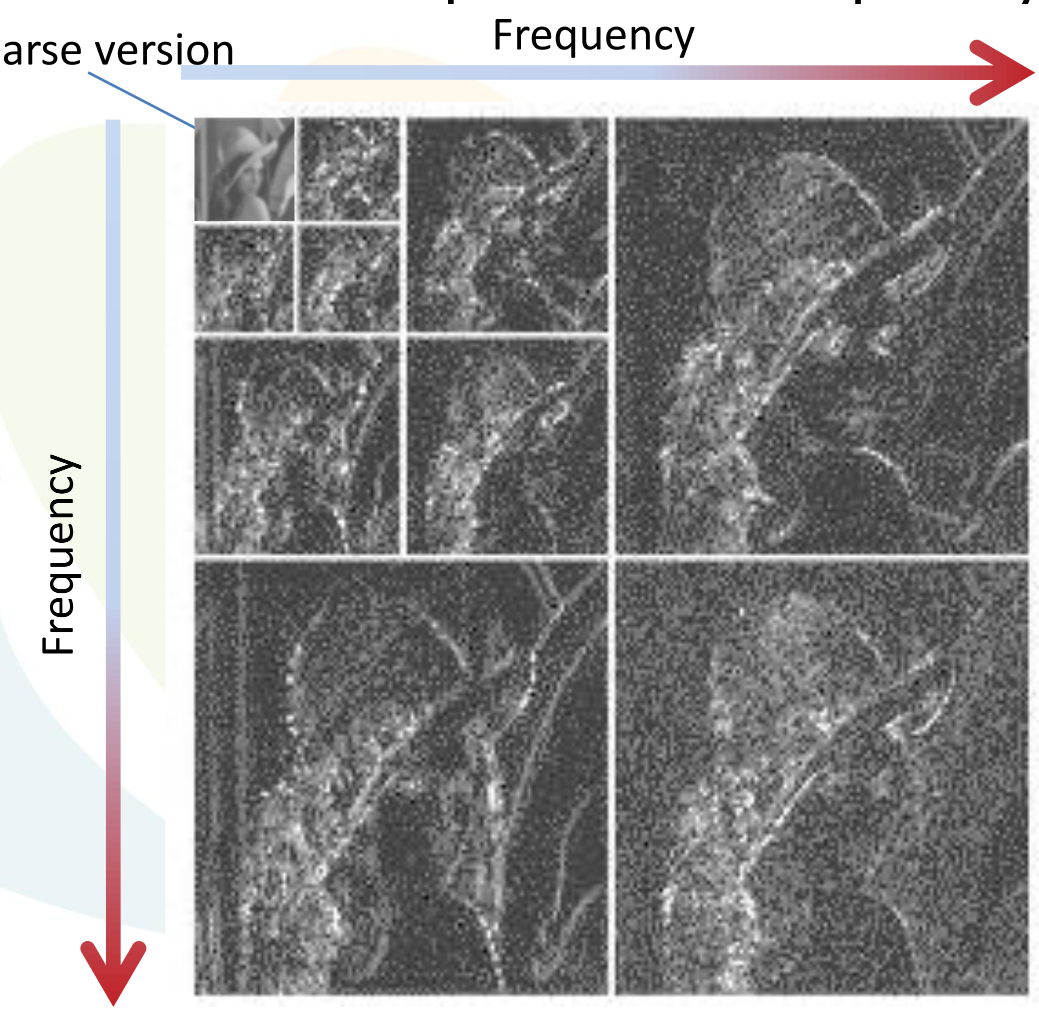

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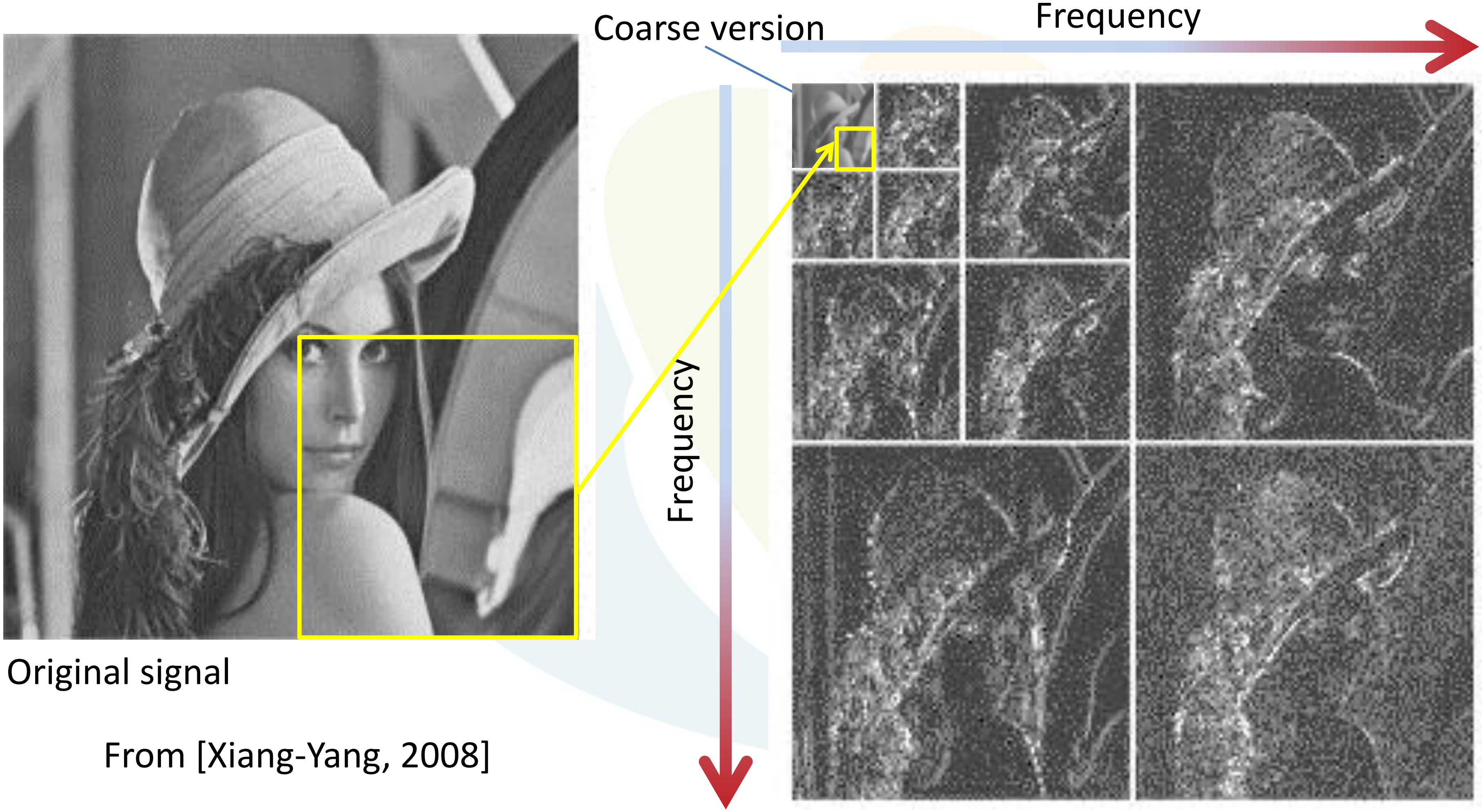

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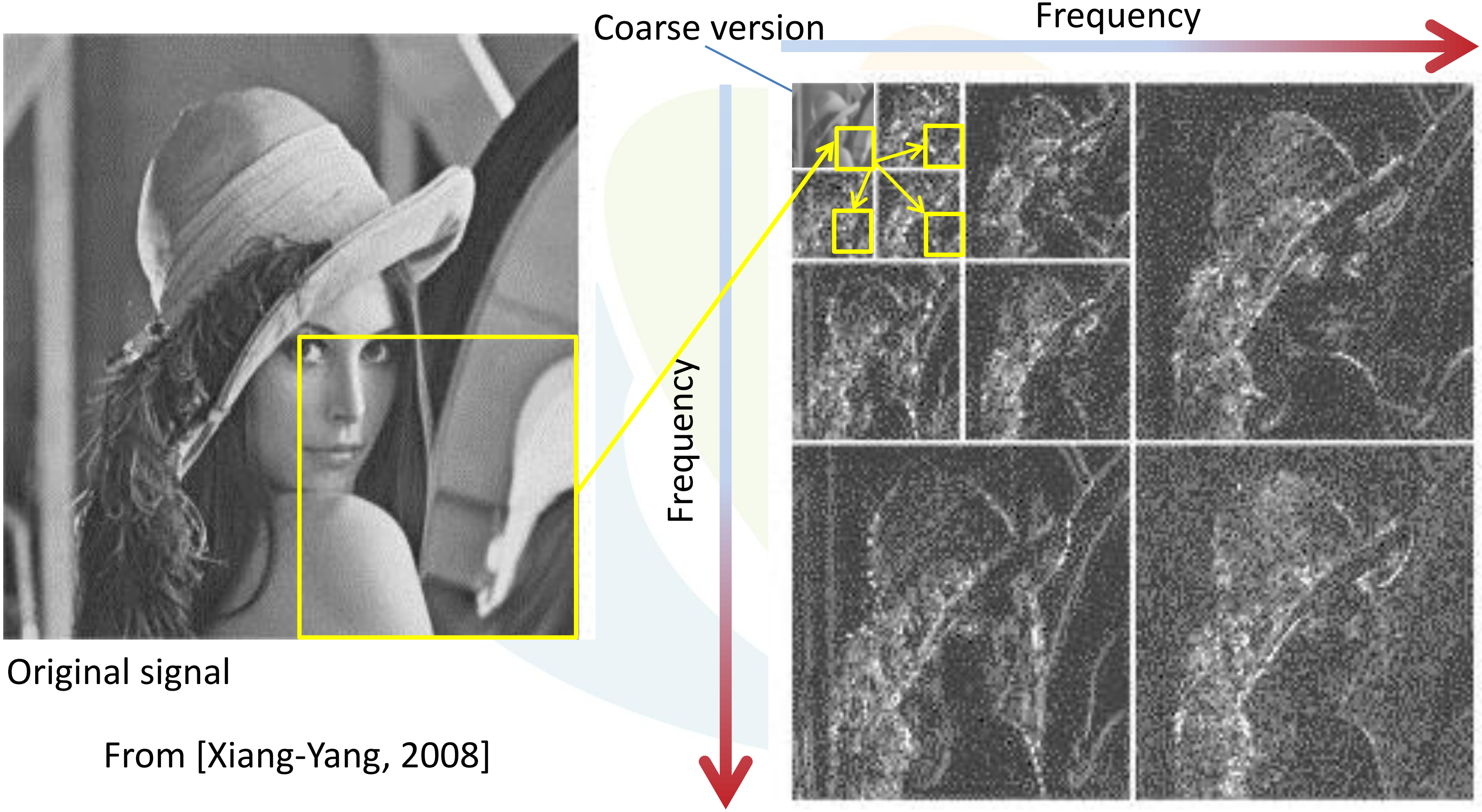

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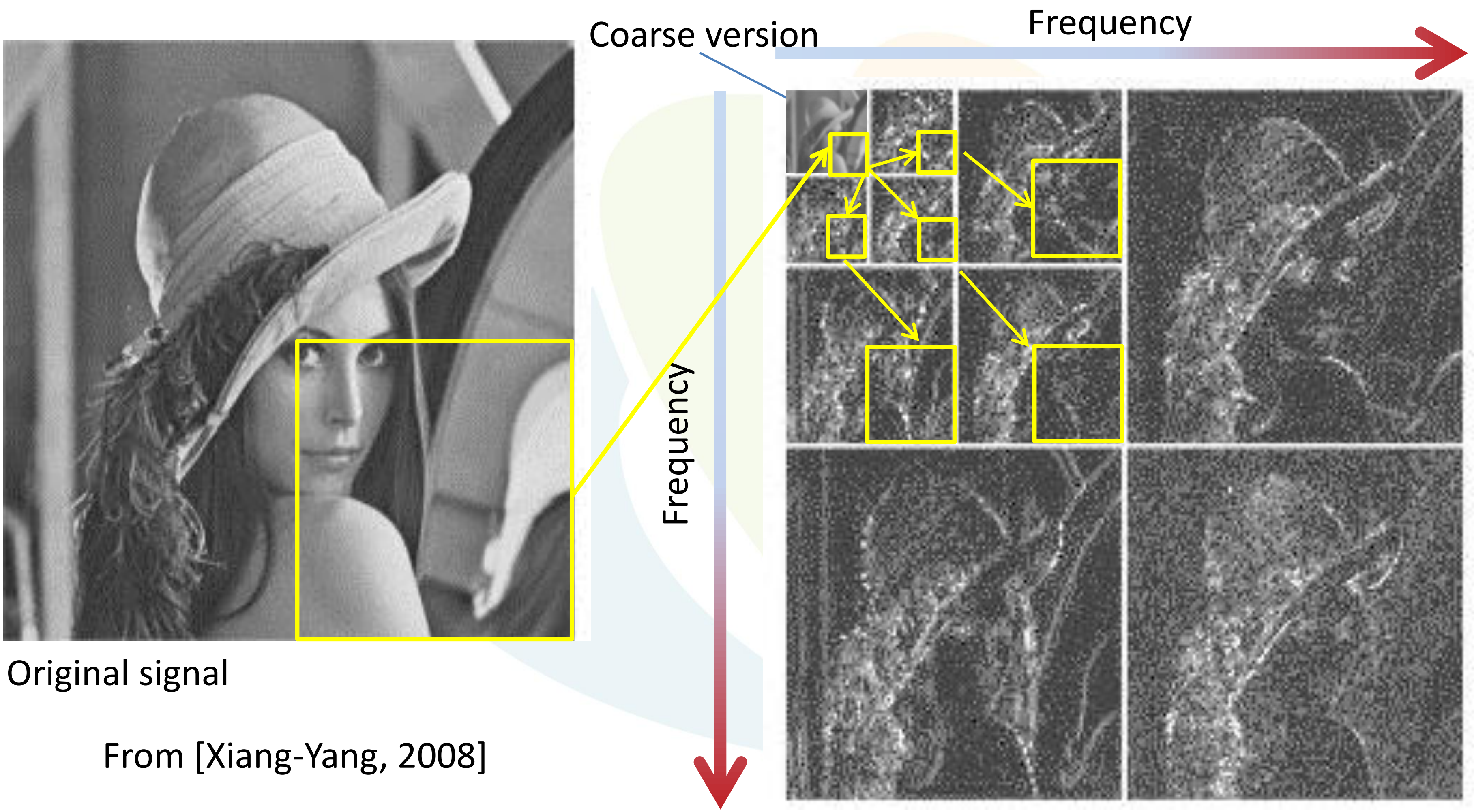

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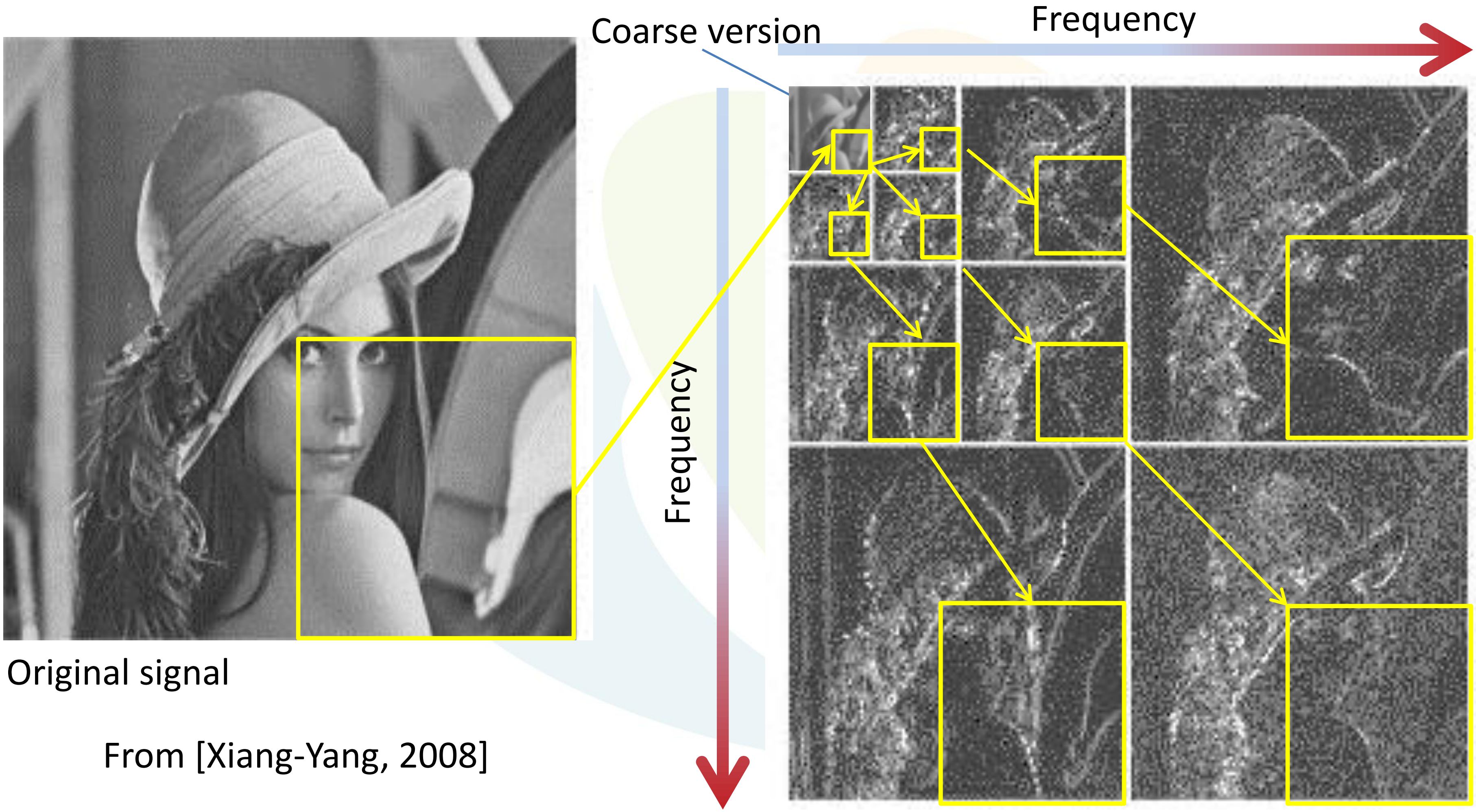

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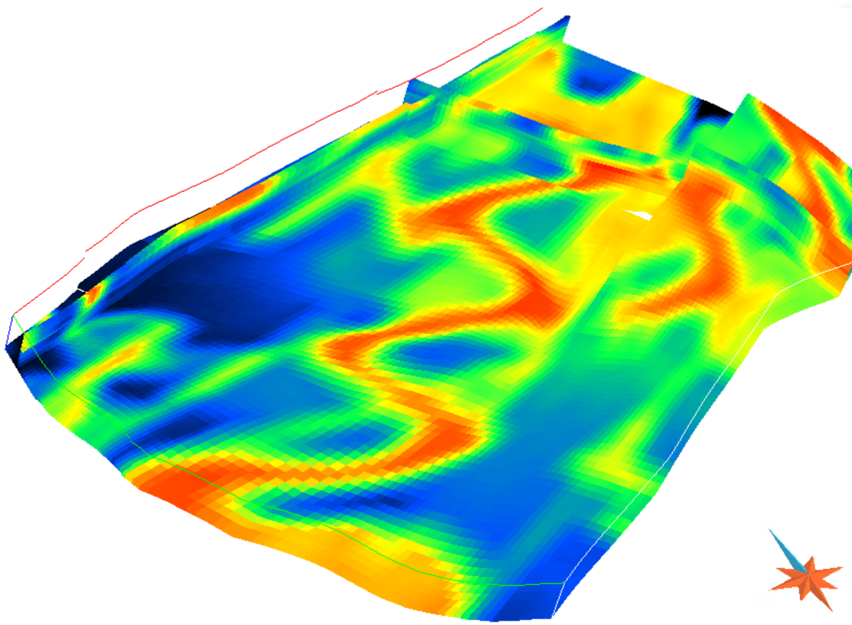
Multi-scale parameterization: wavelets

- Sparse basis: only few coefficients are needed to characterize most significant features:



Initial 3D property

- Second generation wavelets
  - Much more flexible: can be used on stratigraphical grids

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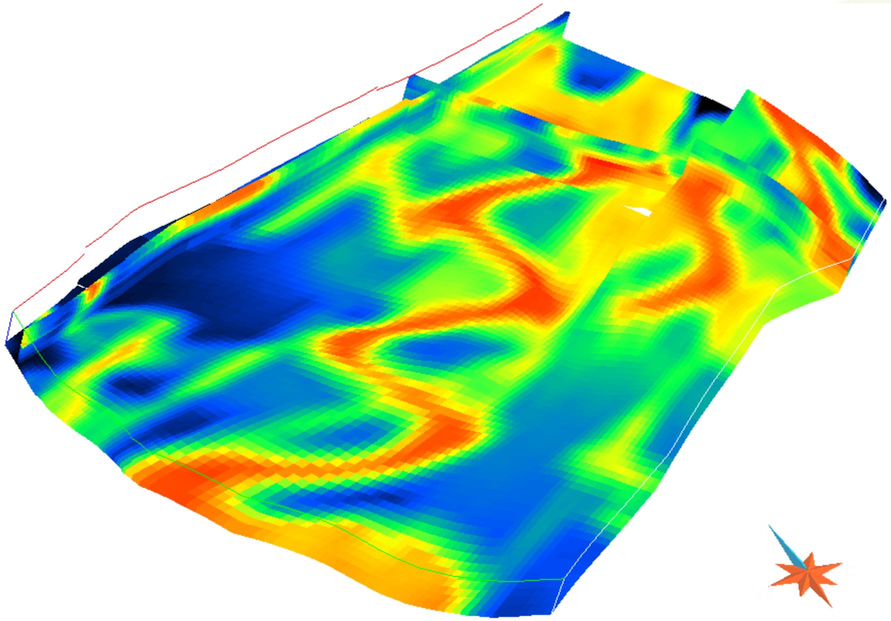

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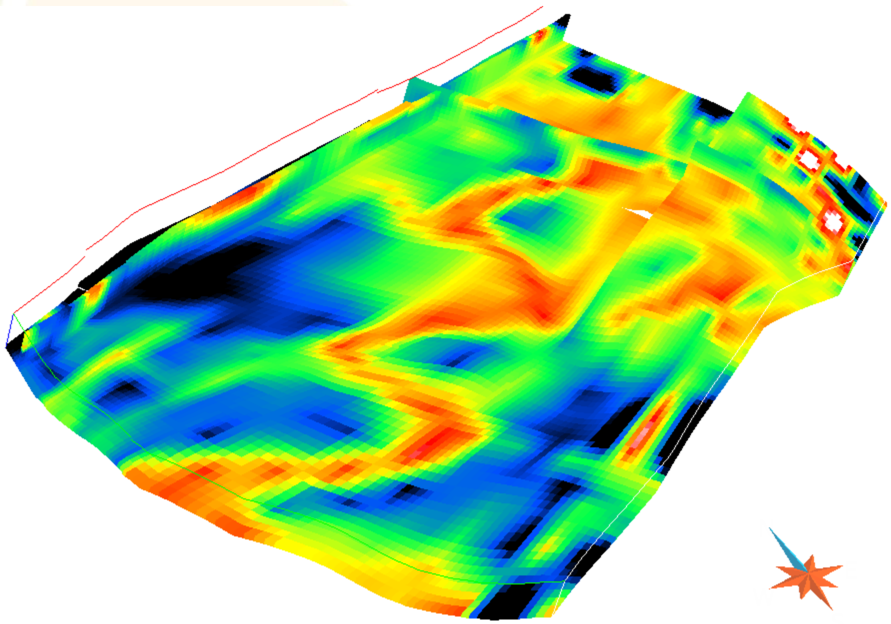
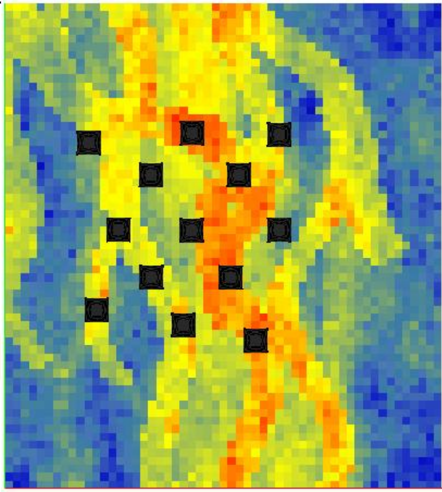


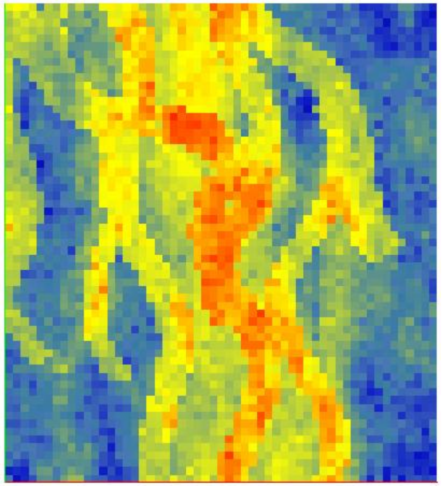
Property reconstructed using 1% of the wavelets coefficients

- Second generation wavelets
  - Much more flexible: can be used on stratigraphical grids

Adaptive multi-scale ensemble based inversion



First parameters to optimize



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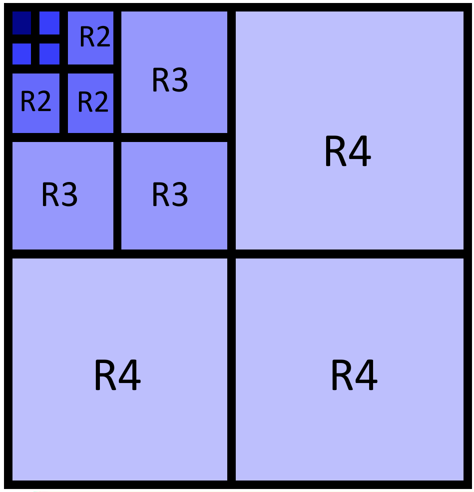
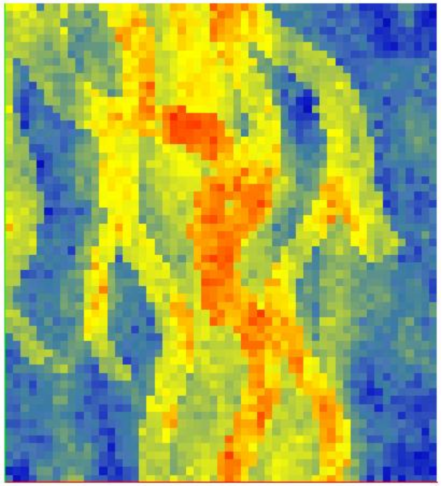


Wavelet decomposition



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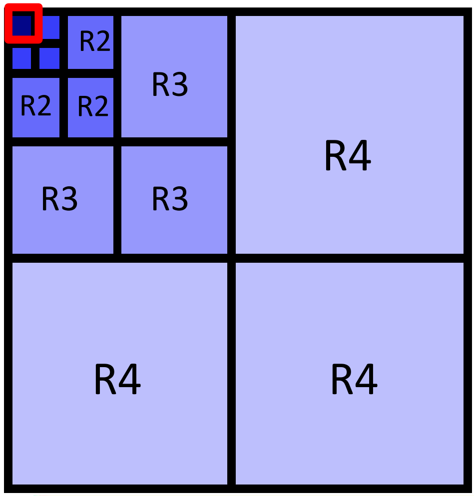

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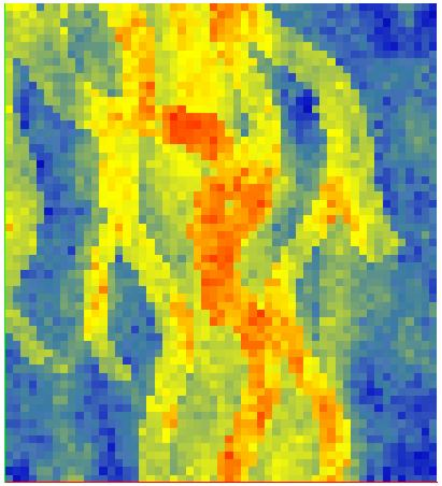

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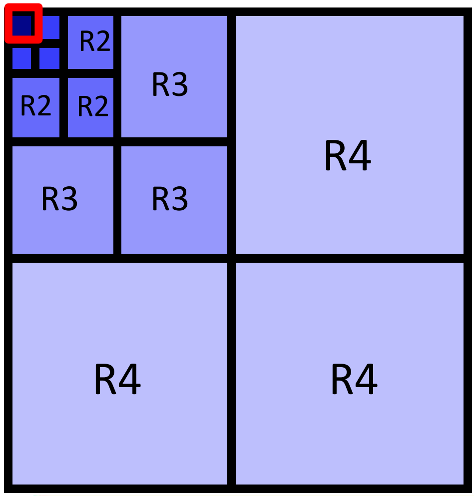

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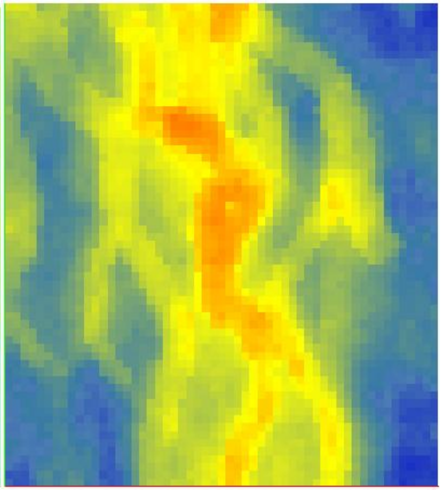
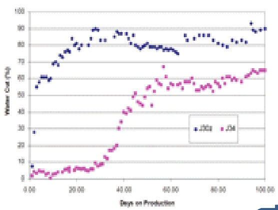
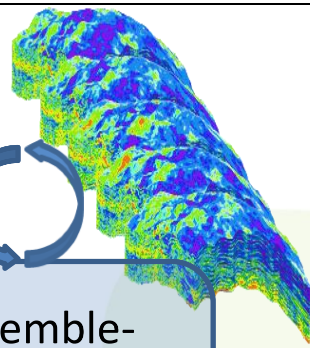


Reversible smoothing assists first optimizatio

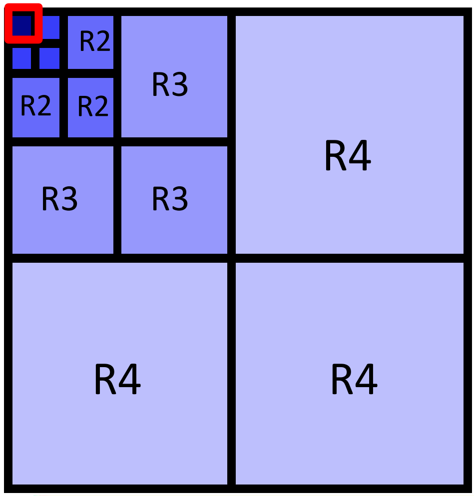
Adaptive multi-scale ensemble based inversion





Ensemble-based Optimization

First parameters to optimize



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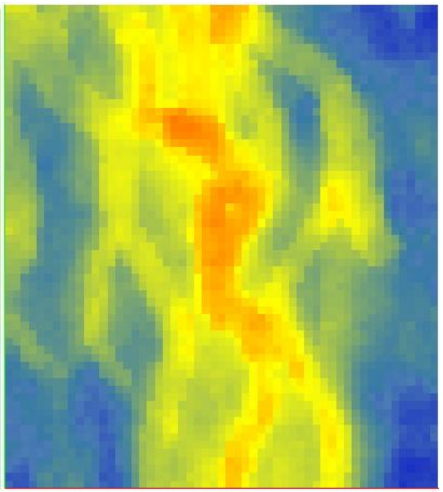

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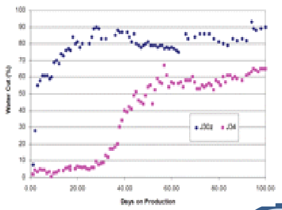
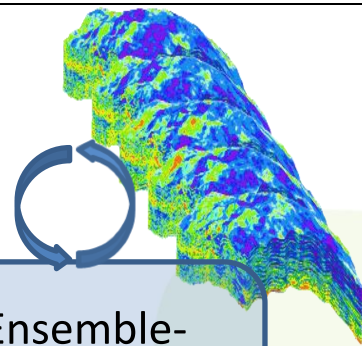
Adaptive multi-scale ensemble based inversion





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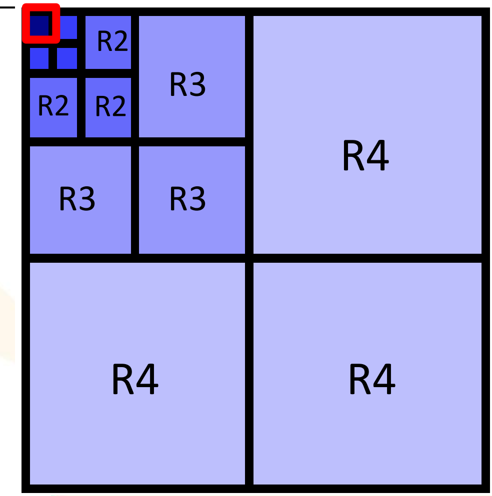
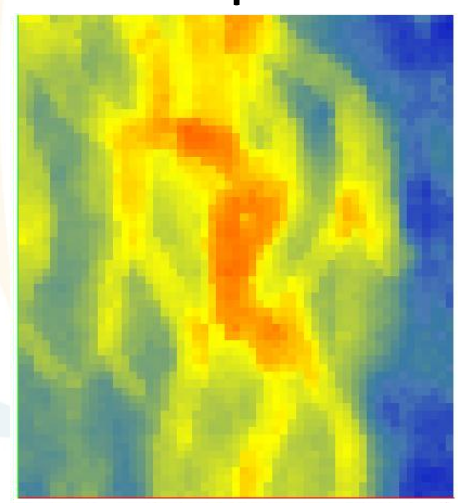


Wavelet decomposition

Coarse update



CGGVERITAS

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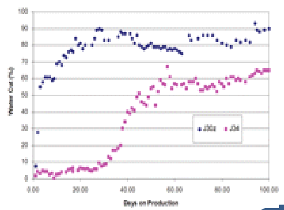

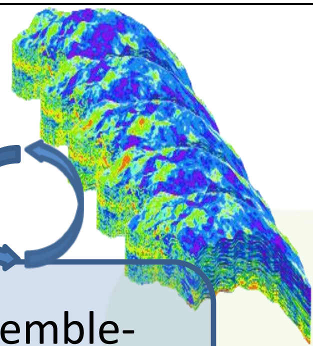

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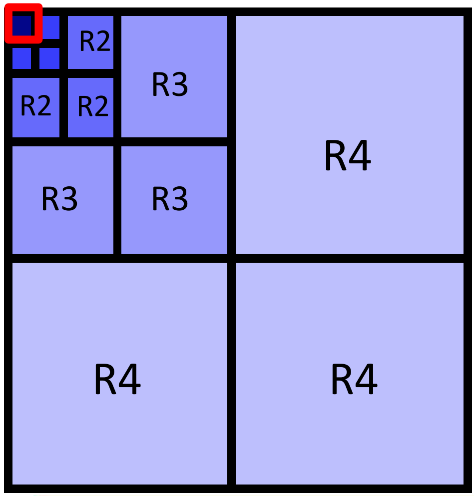


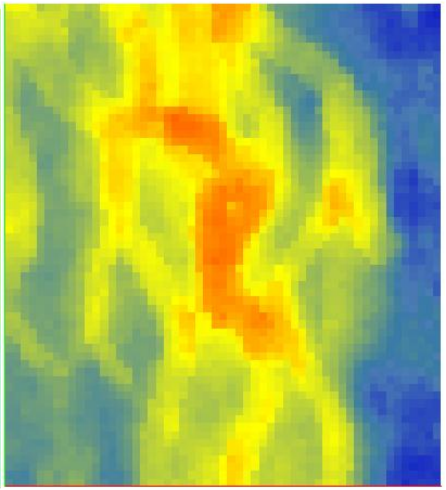
Wavelet decomposition

Sensitivity analysis

Resolution 0

Adaptive localization and refinement

Re-introduction of smoothed frequencies



CGGVeritas

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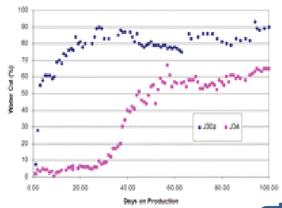

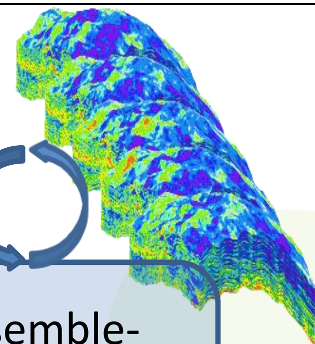

Ensemble-based Optimization

Resolution 1

Adaptive localization and refinement

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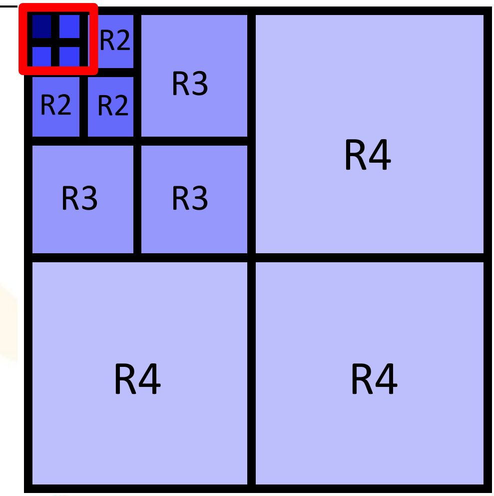

Wavelet decomposition

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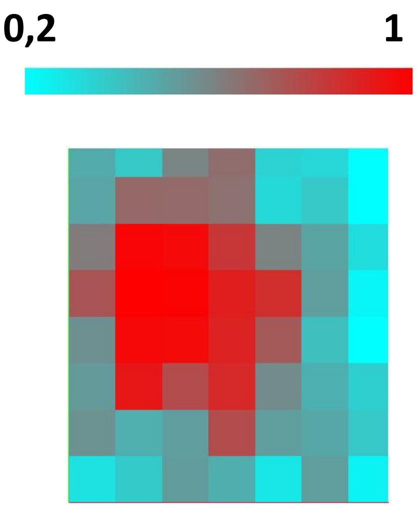
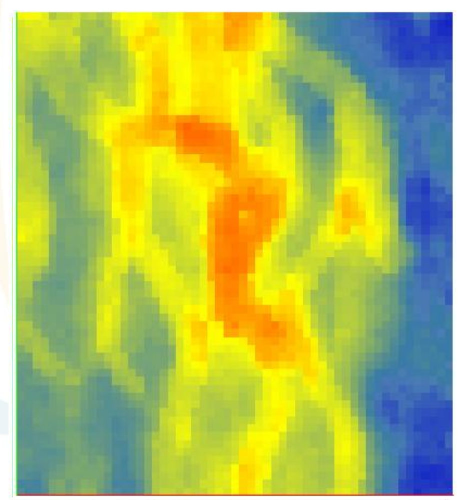
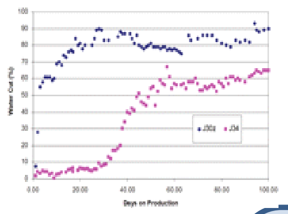
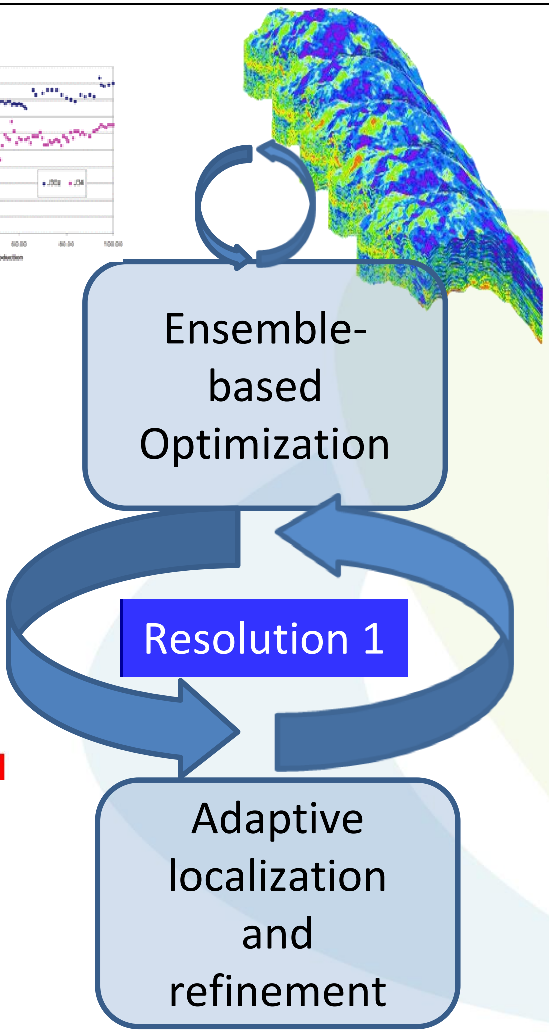




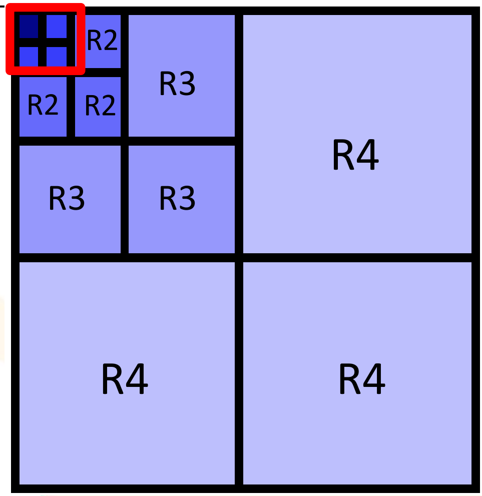
CGGVeritas

Adaptive multi-scale ensemble based inversion



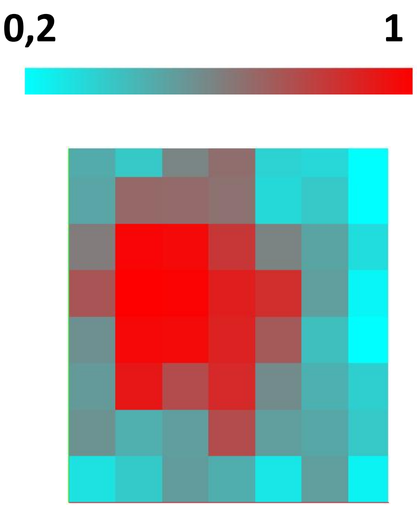


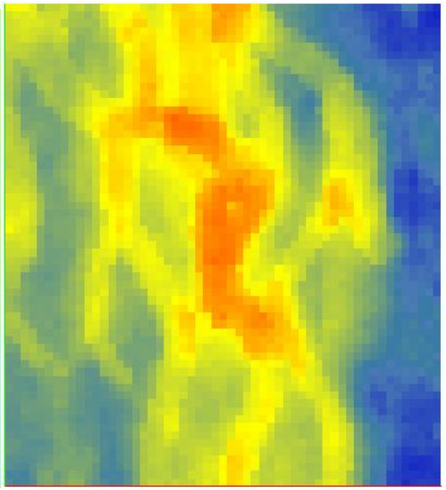
Re-introduction of smoothed frequencies



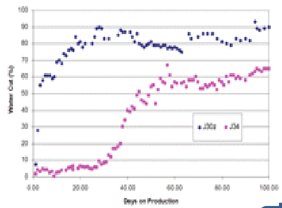
Wavelet decomposition

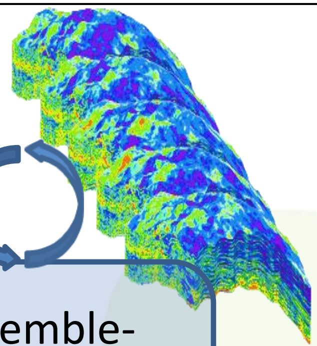
Sensitivity analysis

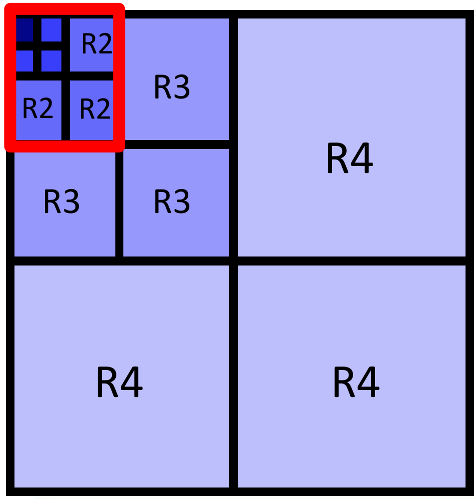




Adaptive multi-scale ensemble based inversion







Wavelet decomposition

Ensemble-based Optimization

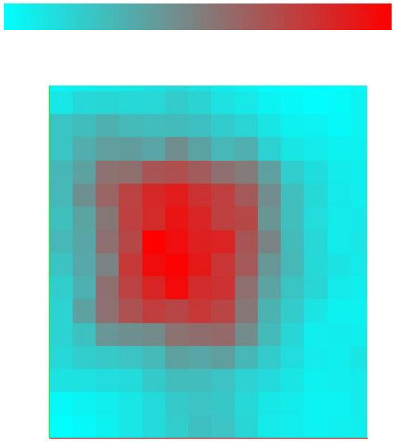
Resolution 2

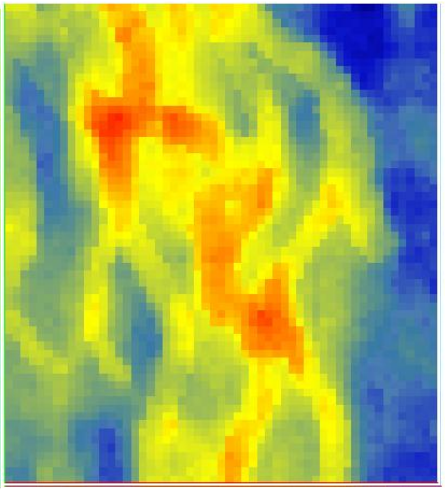
Adaptive localization and refinement

Re-introduction of smoothed frequencies

Sensitivity analysis

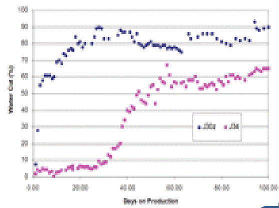
0,2 1

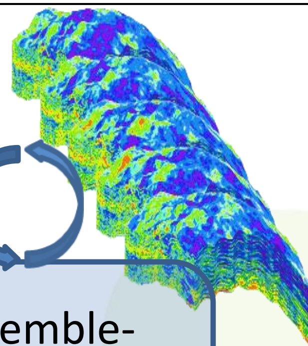




CGGVeritas

Adaptive multi-scale ensemble based inversion



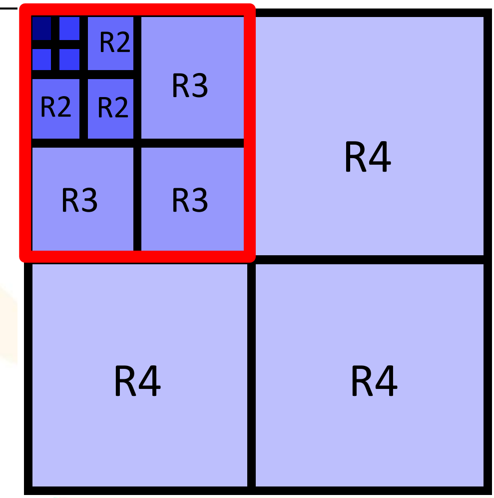


Ensemble-based Optimization

Resolution 3

Adaptive localization and refinement

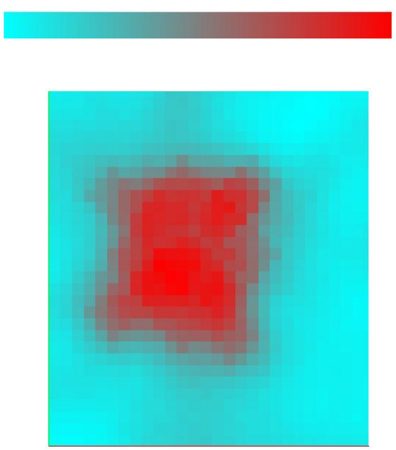
Re-introduction of smoothed frequencies

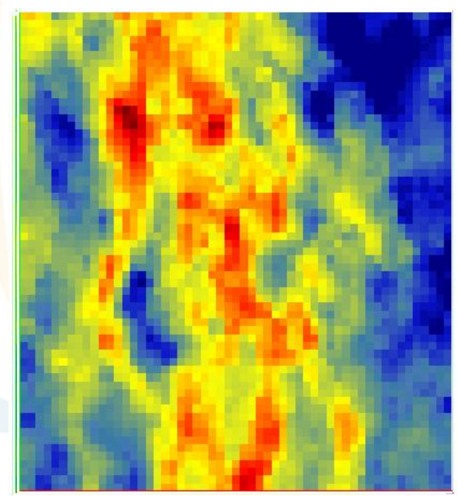


Wavelet decomposition

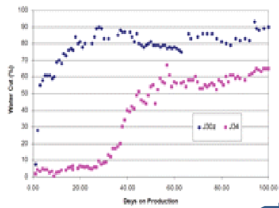
Sensitivity analysis

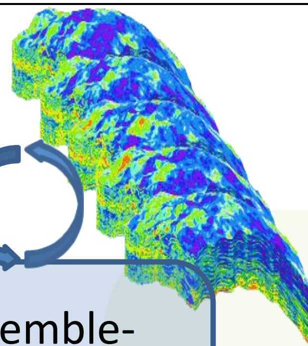
0,2 **1**





Adaptive multi-scale ensemble based inversion



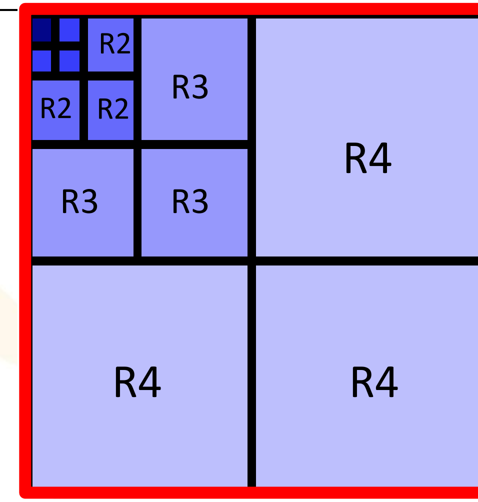


Ensemble-based Optimization

Resolution 4

Adaptive localization and refinement

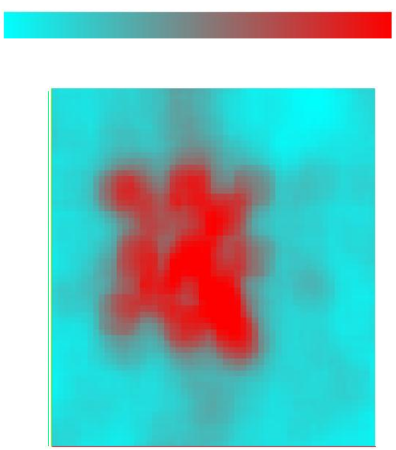
Re-introduction of smoothed frequencies

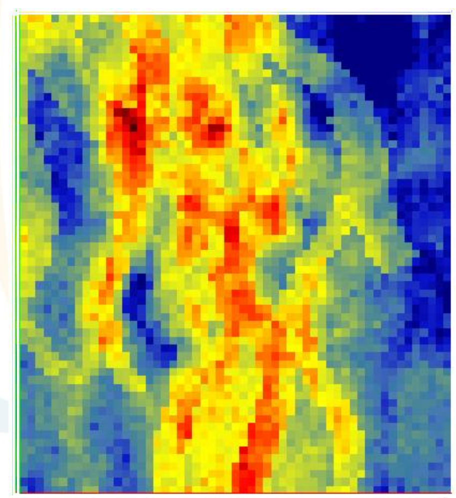


Wavelet decomposition

Sensitivity analysis

0,2 **1**





CGGVeritas

Iterative LM-enRML using wavelet parameterization

- Levenberg-Marquadt optimization:

$$\delta\boldsymbol{\gamma}_{\text{opt}} = \underbrace{-\frac{1}{\lambda+1}(\delta\boldsymbol{\gamma}_{pr} + \boldsymbol{K}(\lambda).\boldsymbol{G}.\delta\boldsymbol{\gamma}_{pr}}_{\textbf{Prior constraint term}} - \underbrace{\boldsymbol{K}(\lambda).\delta\boldsymbol{d}}_{\textbf{Data mismatch term}}$$

where $\boldsymbol{\gamma}$:{vector of wavelet coefficients}, λ:{LM damping factor}, $\boldsymbol{K}$:{similar to Kalman gain}, $\boldsymbol{G}$:{Sensitivity matrix}, $\delta\boldsymbol{d}$:{data mismatch}

- Prior constraint term dominates in insensitive areas
- Data mismatch term dominates in sensitive areas
- Global sensitivity matrix G computed from an ensemble
- Sensitivity matrix is used to automatically compute the localization vector

Key points of the method

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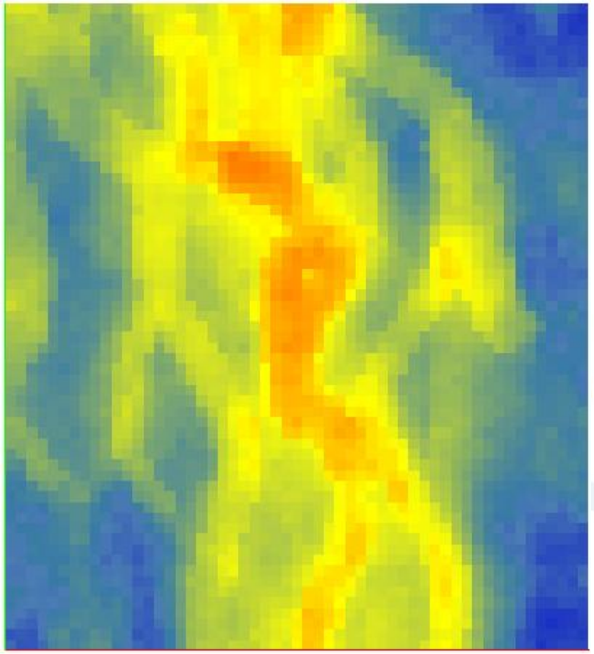
- Initial smoothing:
  - Automatically done by dividing wavelets coefficients
  - Easily reversible
  - Minimize the effects of high frequencies on flow response
  - Preserve the initial main features



Key points of the method

- Initial smoothing:
  - Automatically done by dividing wavelets coefficients
  - Easily reversible
  - Minimize the effects of high frequencies on flow response
  - Preserve the initial main features
- Multi-scale approach
  - The optimization of the low frequencies does not destroying main features
  - The mismatch is significantly decreased when starting the optimization of the high frequencies

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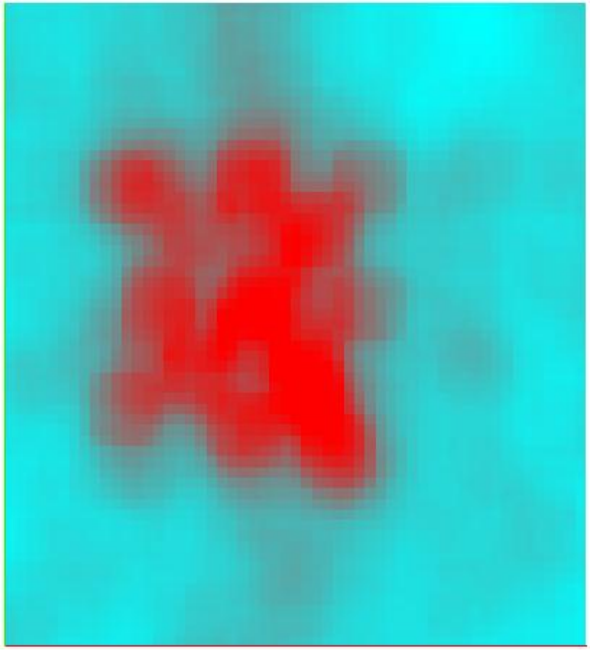
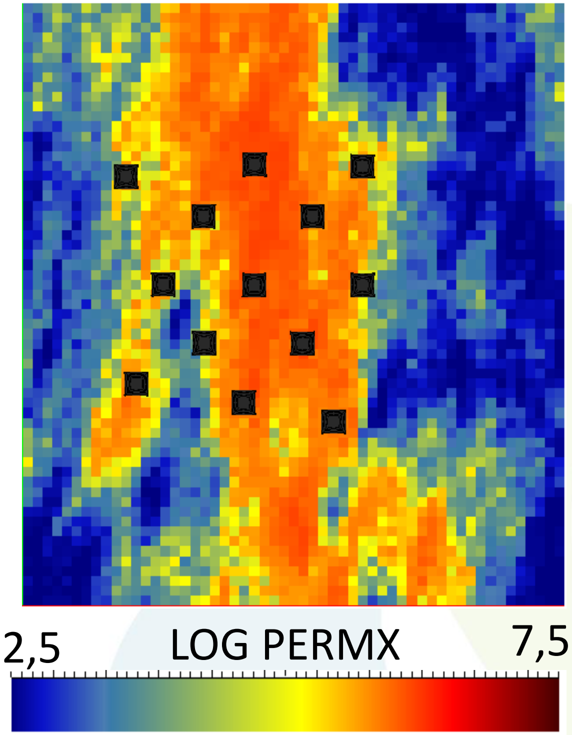
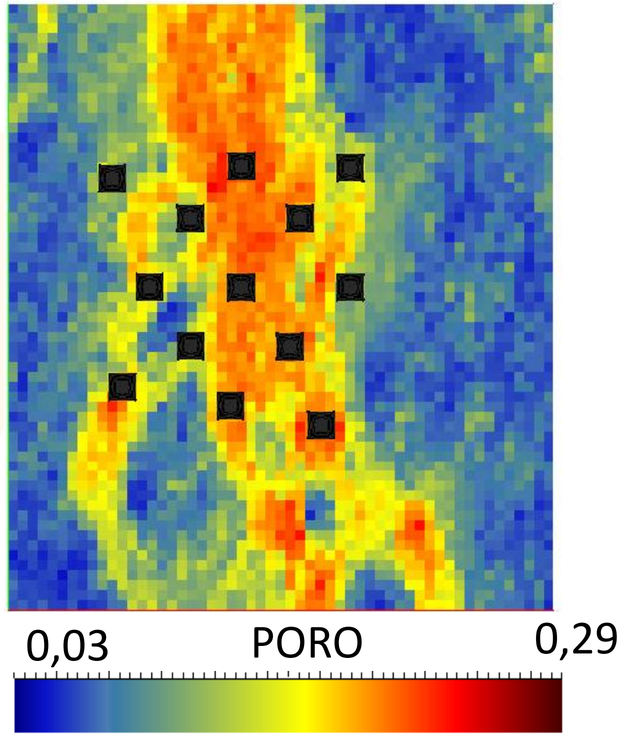
Key points of the method



- Initial smoothing:
  - Automatically done by dividing wavelets coeffi
  - Easily reversible
  - Minimize the effects of high frequencies on flo
  - Preserve the initial main features
- Multi-scale approach
  - The optimization of the low frequencies does r features
  - The mismatch is significantly decreased when optimization of the high frequencies
- Multi-scale Adaptive localization
  - Automatic and dynamic: compute from the current sensitivity matrix
  - Allows large scale updates
  - Good preservation of the prior in insensitive areas

Synthetic 2D case





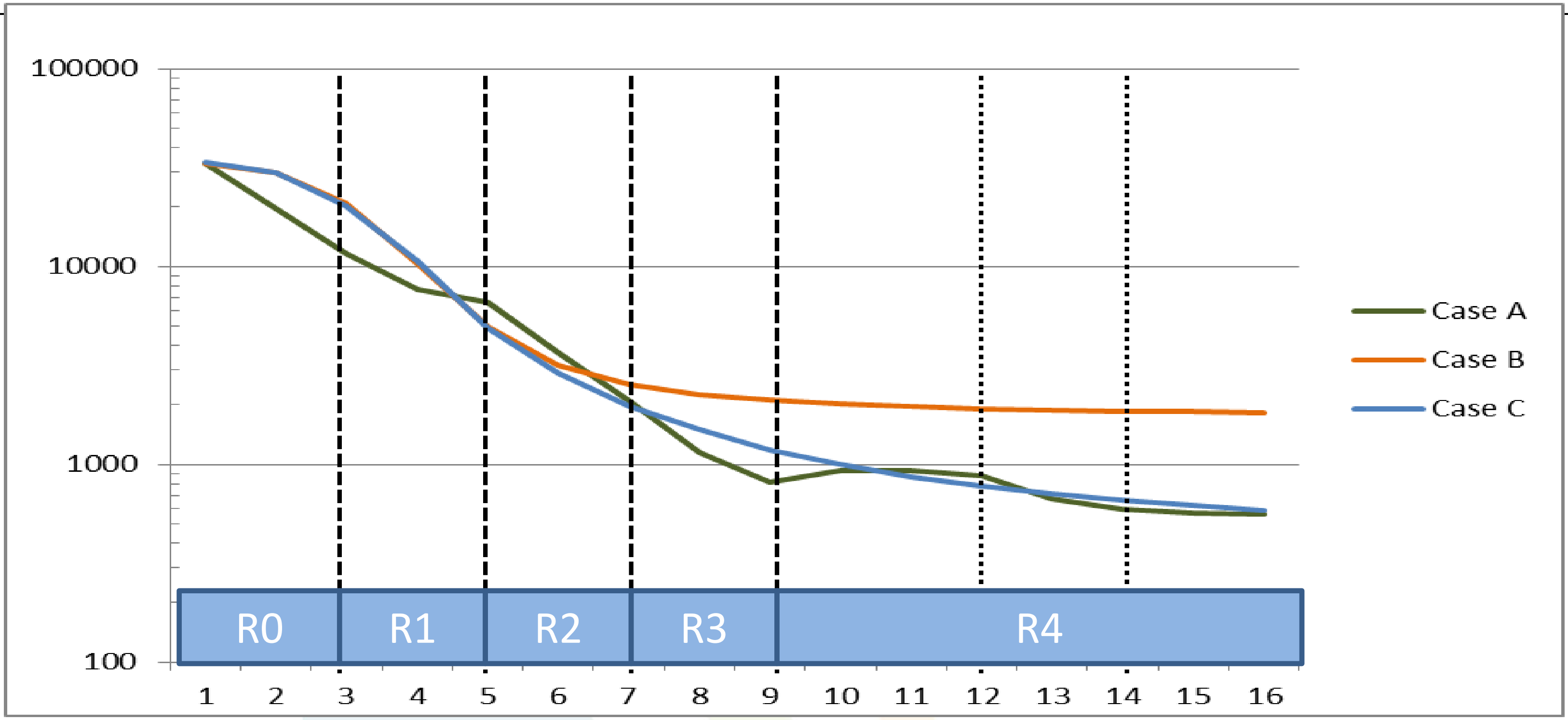
- Grid with 3400 active cells
- 4 injectors (injection rate constraint) and 9 producers (Oil recovery constraint)
- 7,5 years of history: Gas-Oil-Ratio (GOR), water cut (WWCT), pressure (WBHP)

Optimizations

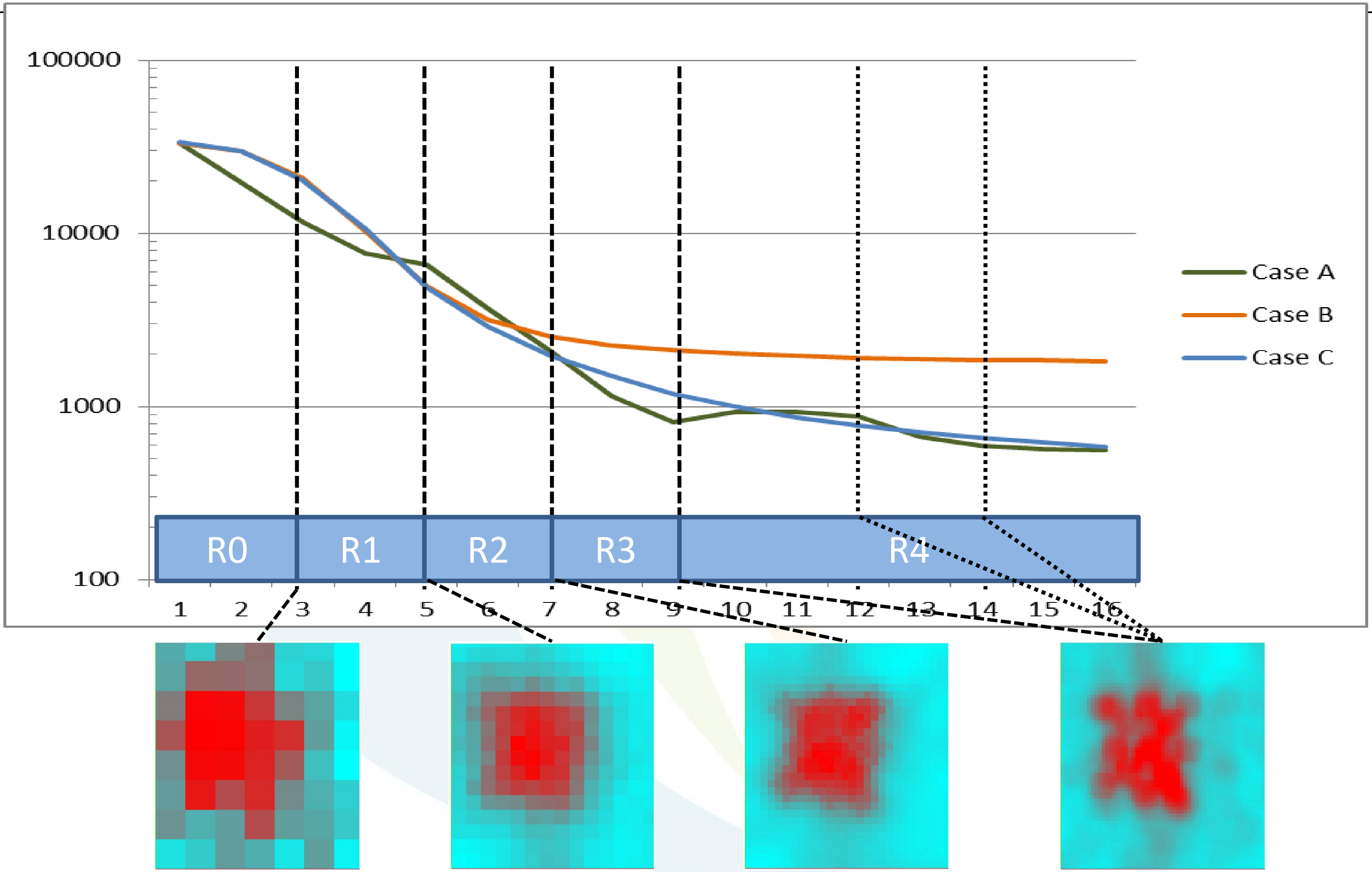
- Case A: Adaptive multi-scale LM-enRML
- Case B: LM-enRML with prior term
- Case C: LM-enRML without prior term

- No a prior localization
- About 350 data points
- Ensemble of 60 realizations generated using object-based modeling
- 15 LM-enRML iterations
- Use the same LM-enRML control parameter λ

Average data mismatches



Average data mismatches



Adaptive localization

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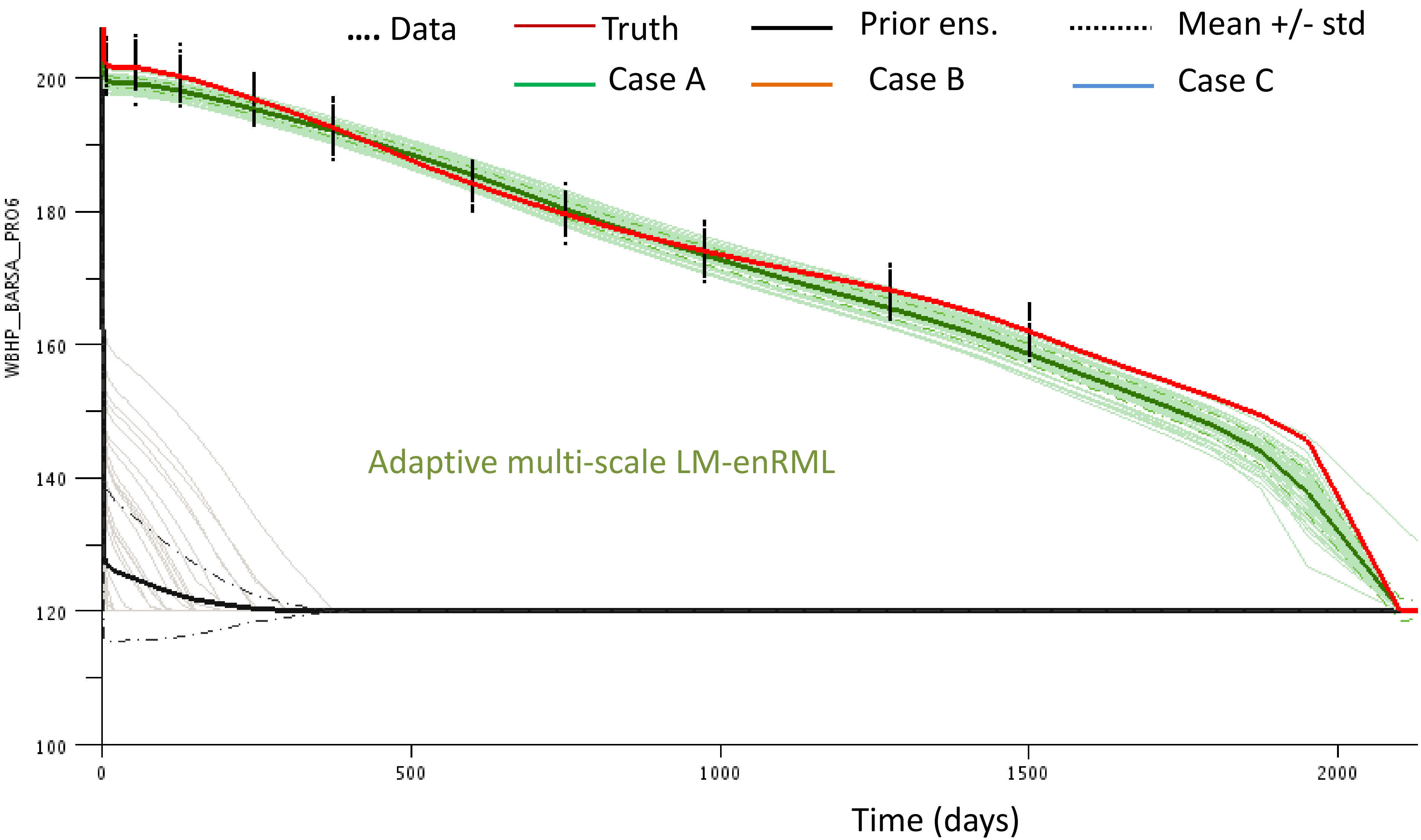
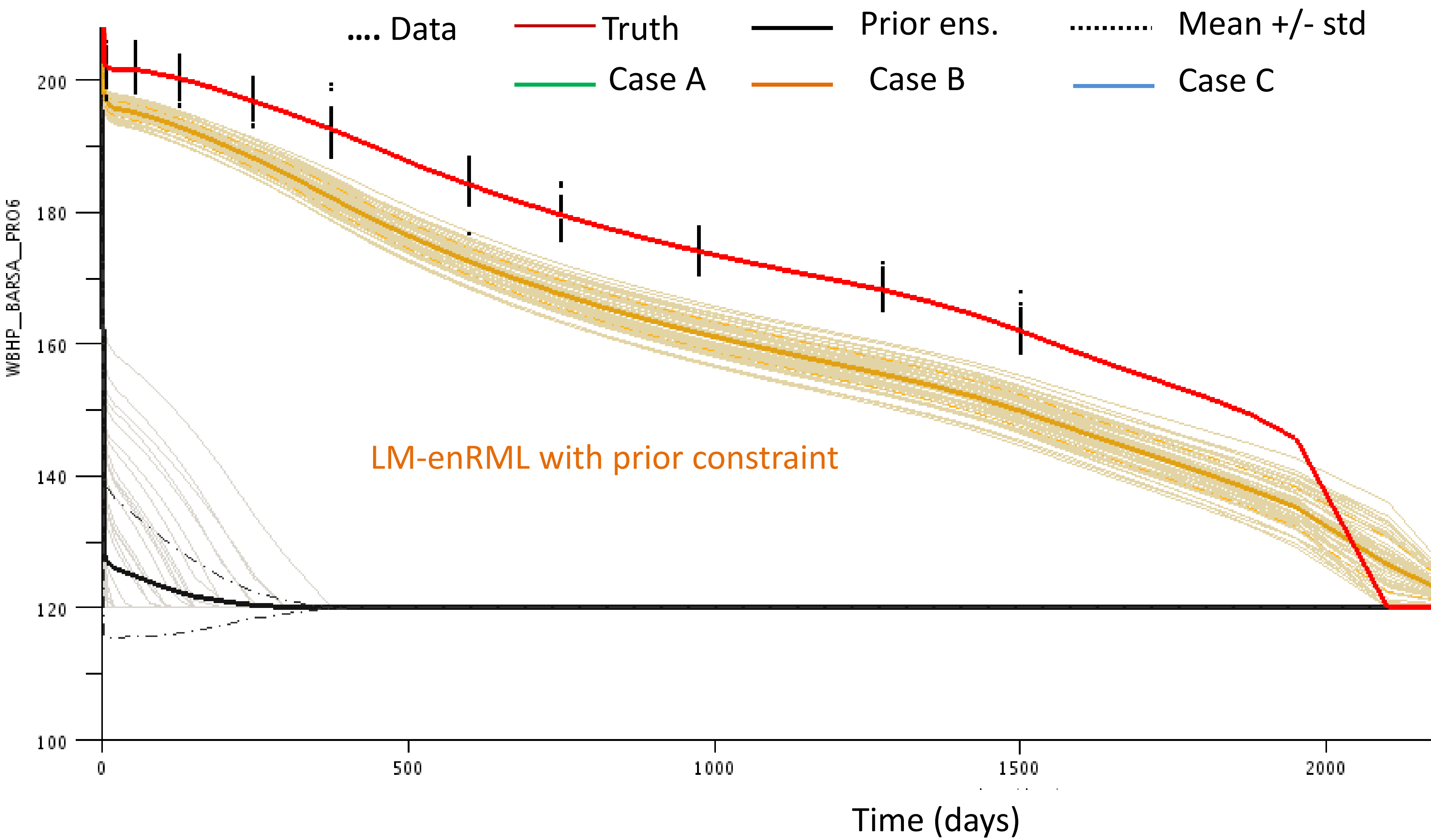
WBHP PRO 6



.... Data
Truth
Prior ens.
Mean +/- std
Case A
Case B
Case C
Adaptive multi-scale LM-enRML
WBHP__BARSA__PRO6
200
180
160
140
120
100
0
500
1000
1500
2000
Time (days)

WBHP PRO 6


.... Data
Truth
Prior ens.
Mean +/- std
Case A
Case B
Case C
LM-enRML with prior constraint
WBHP__BARSA__PRO6
200
180
160
140
120
100
0
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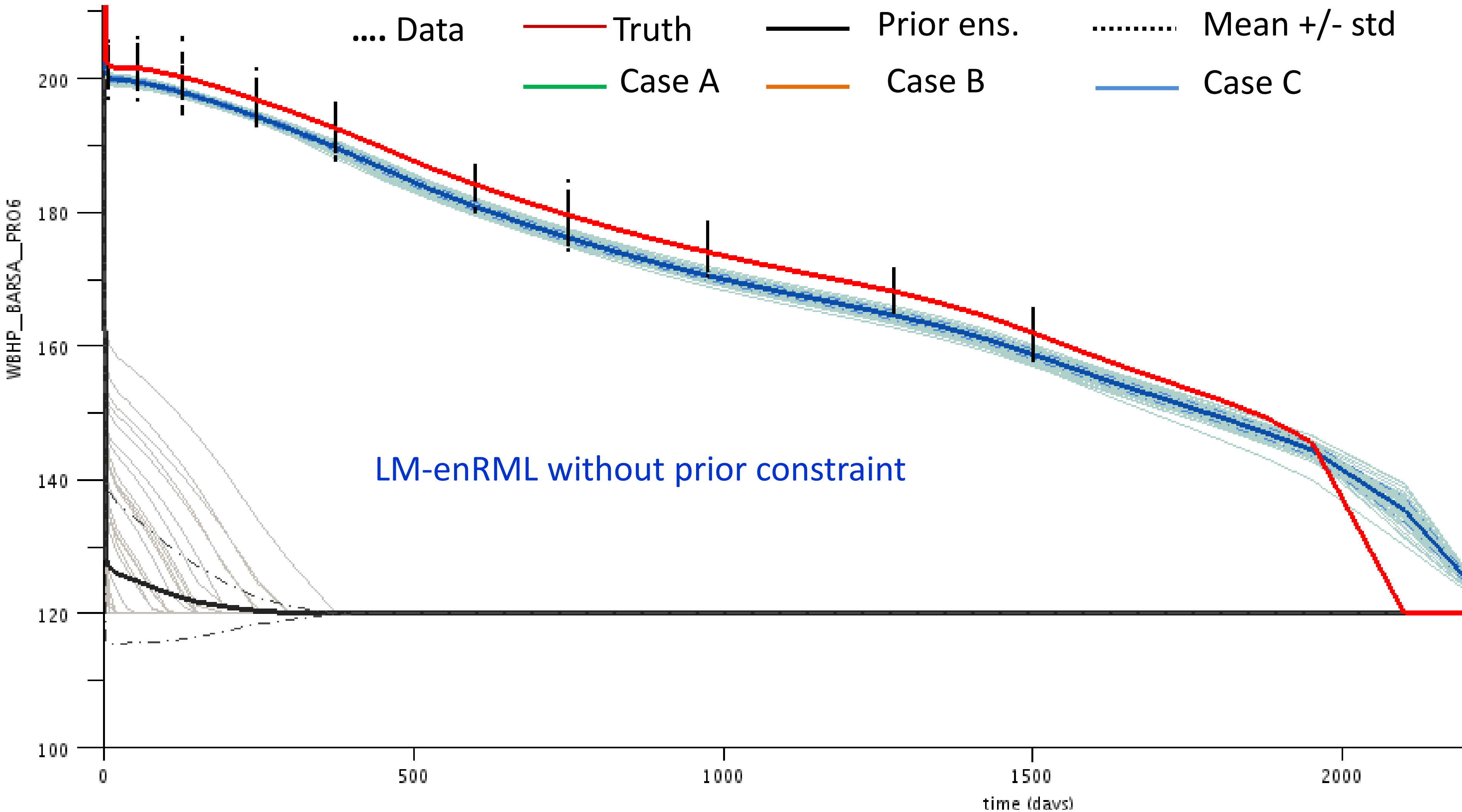
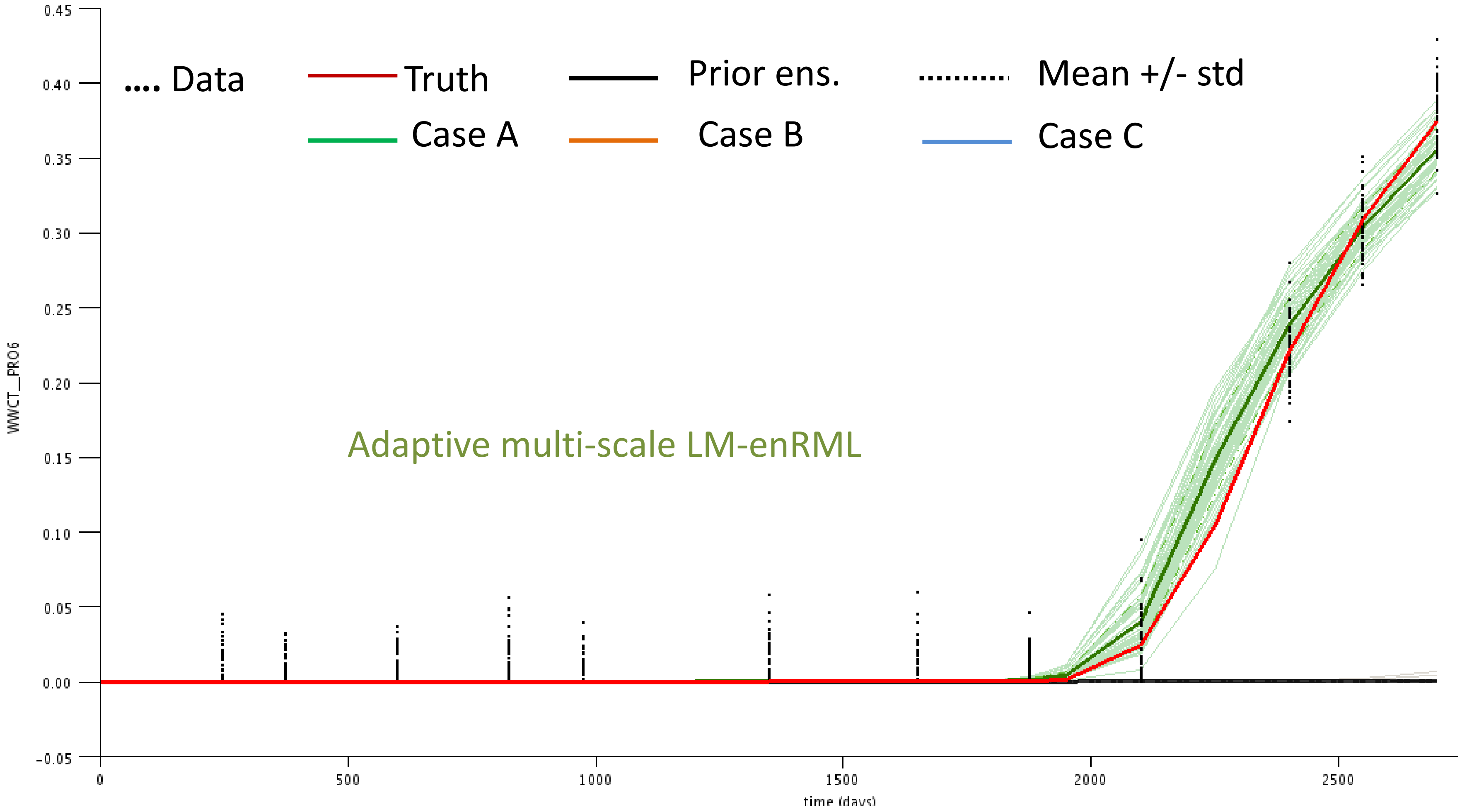
Time (days)

WBHP PRO 6



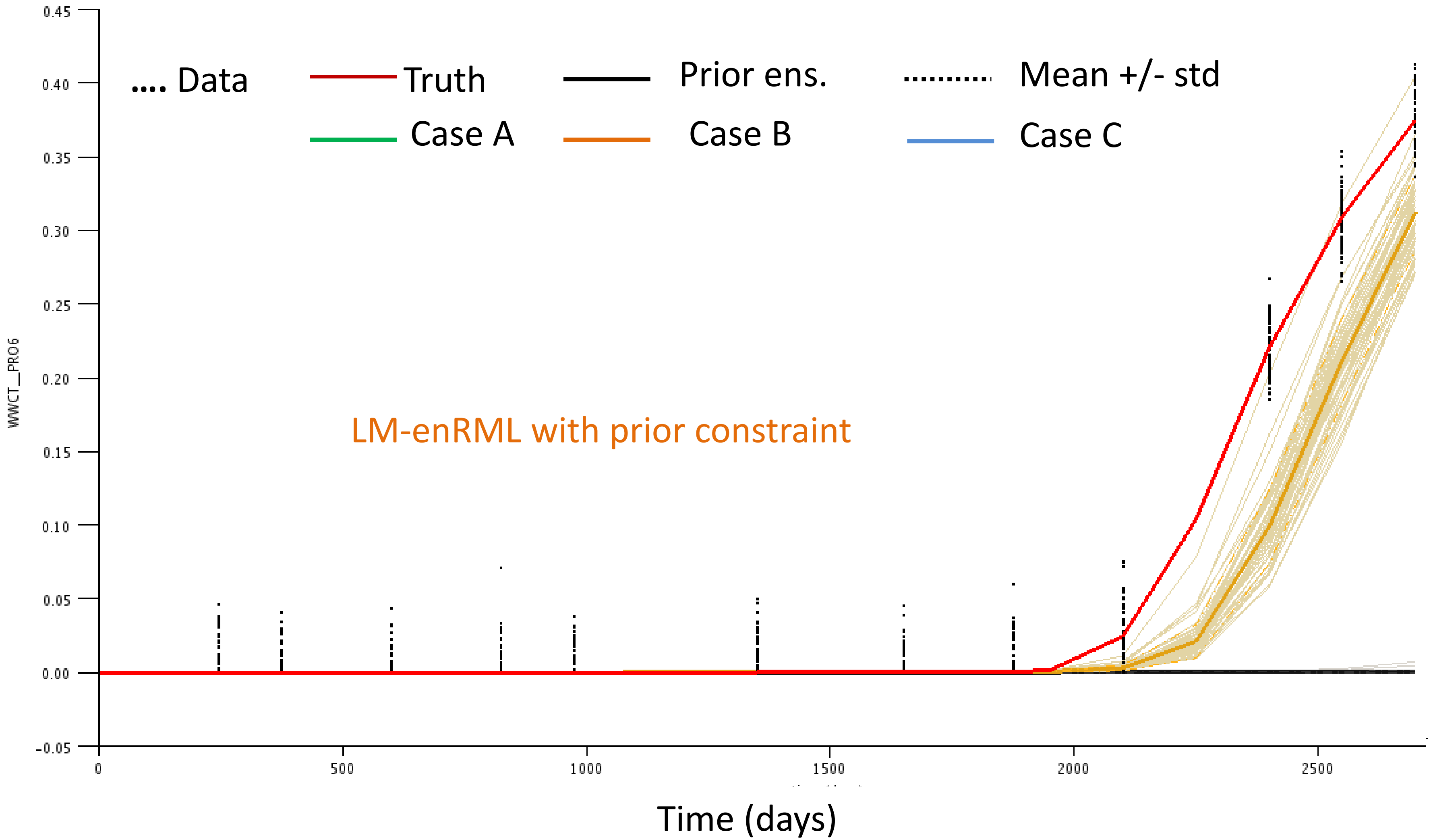
Time (days)

WWCT PRO 6



Time (days)

WWCT PRO 6



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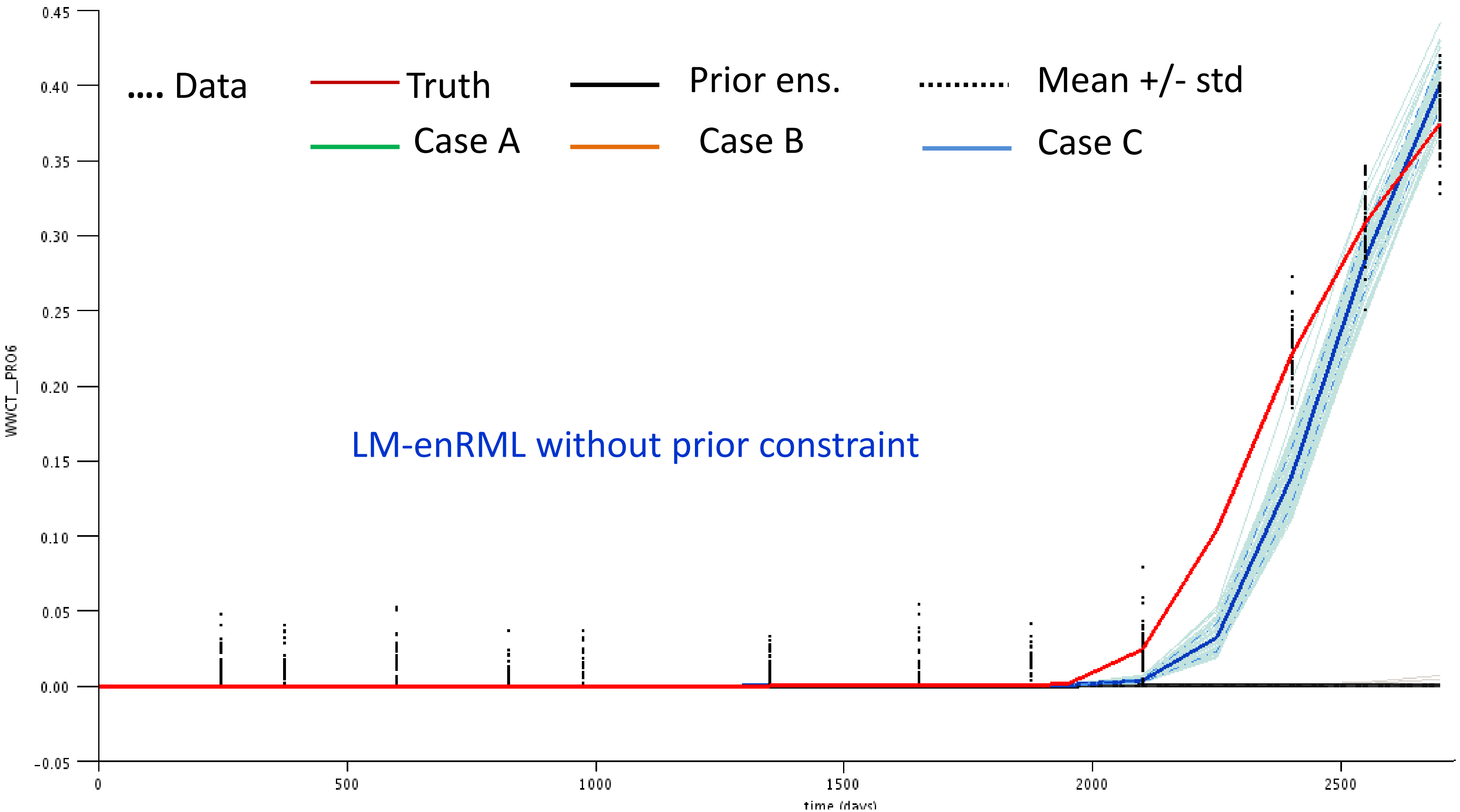
WWCT PRO 6



Time (days)

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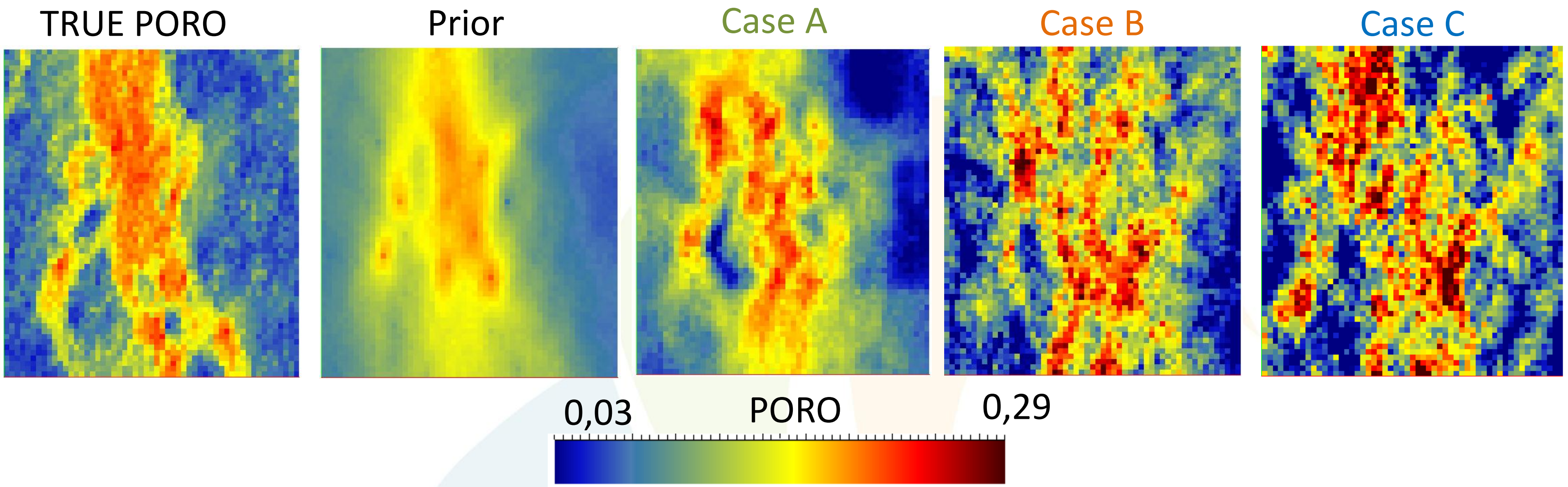
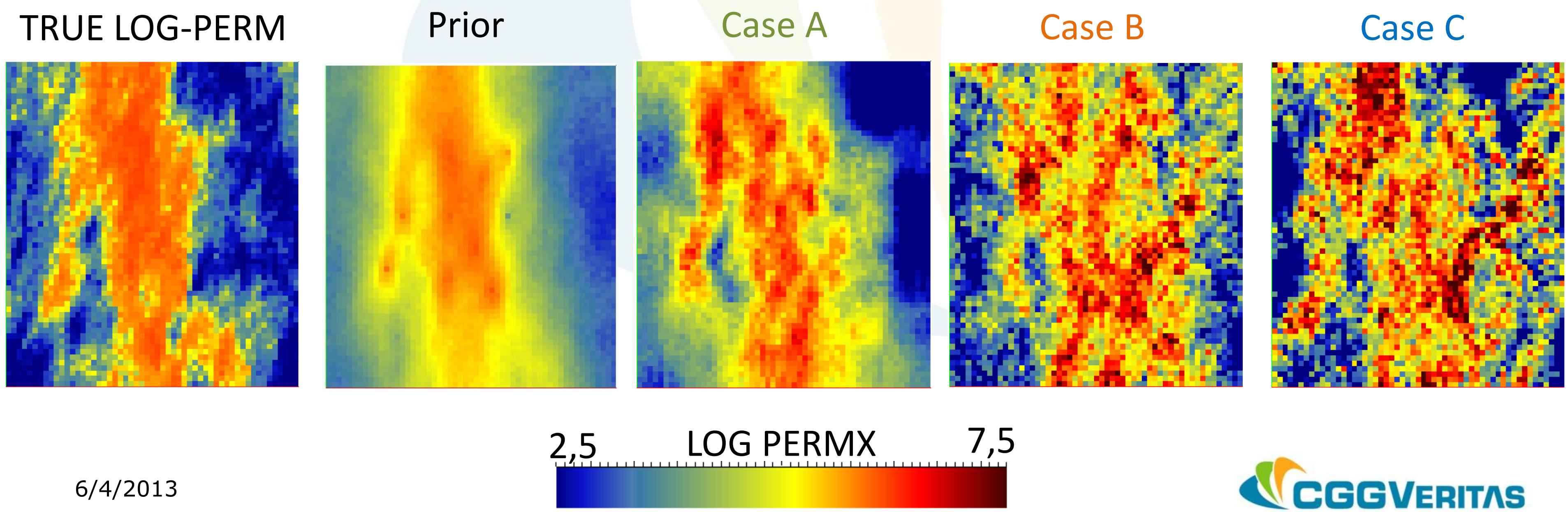
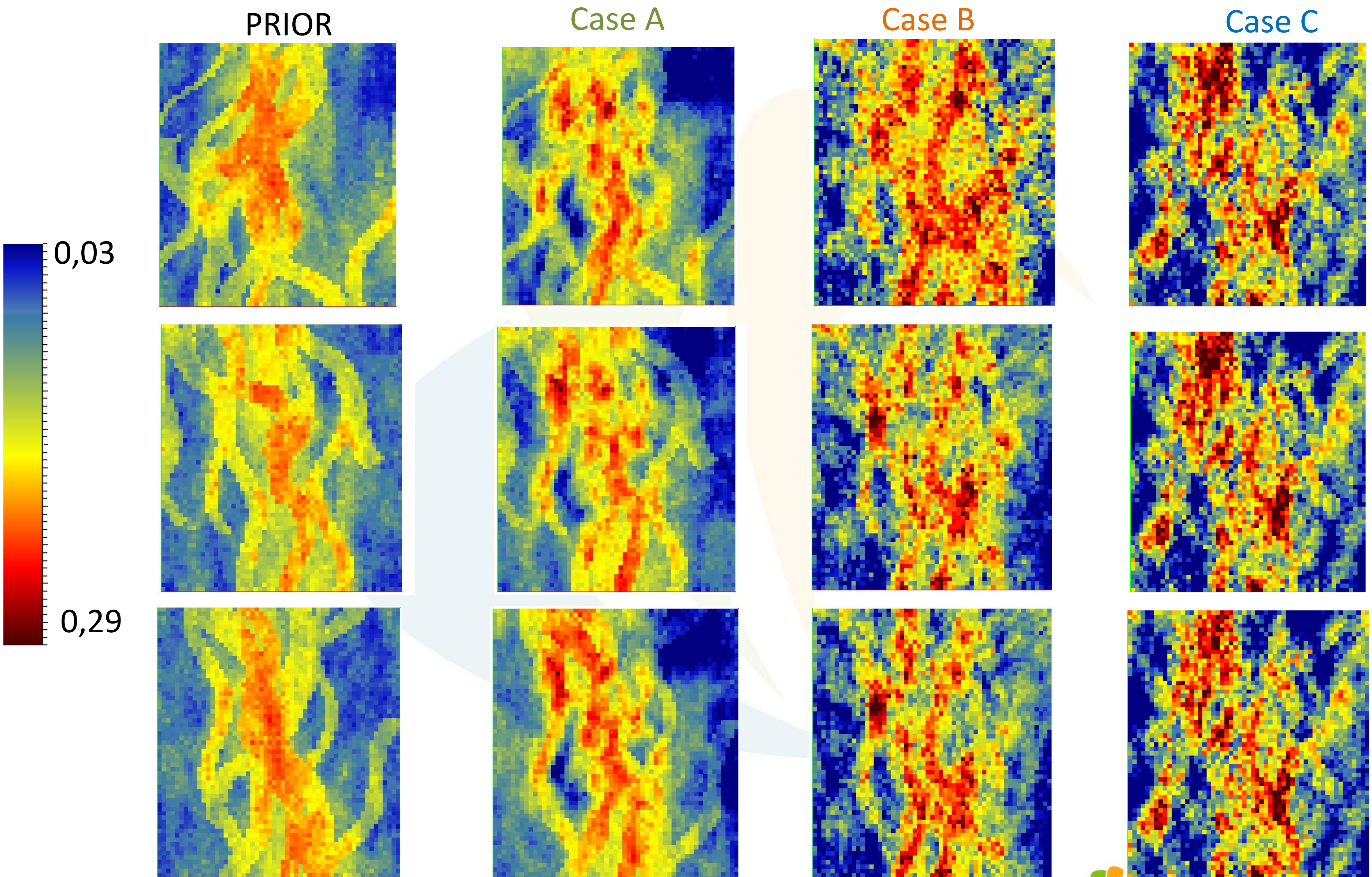
Ensemble averages





PORO realizations



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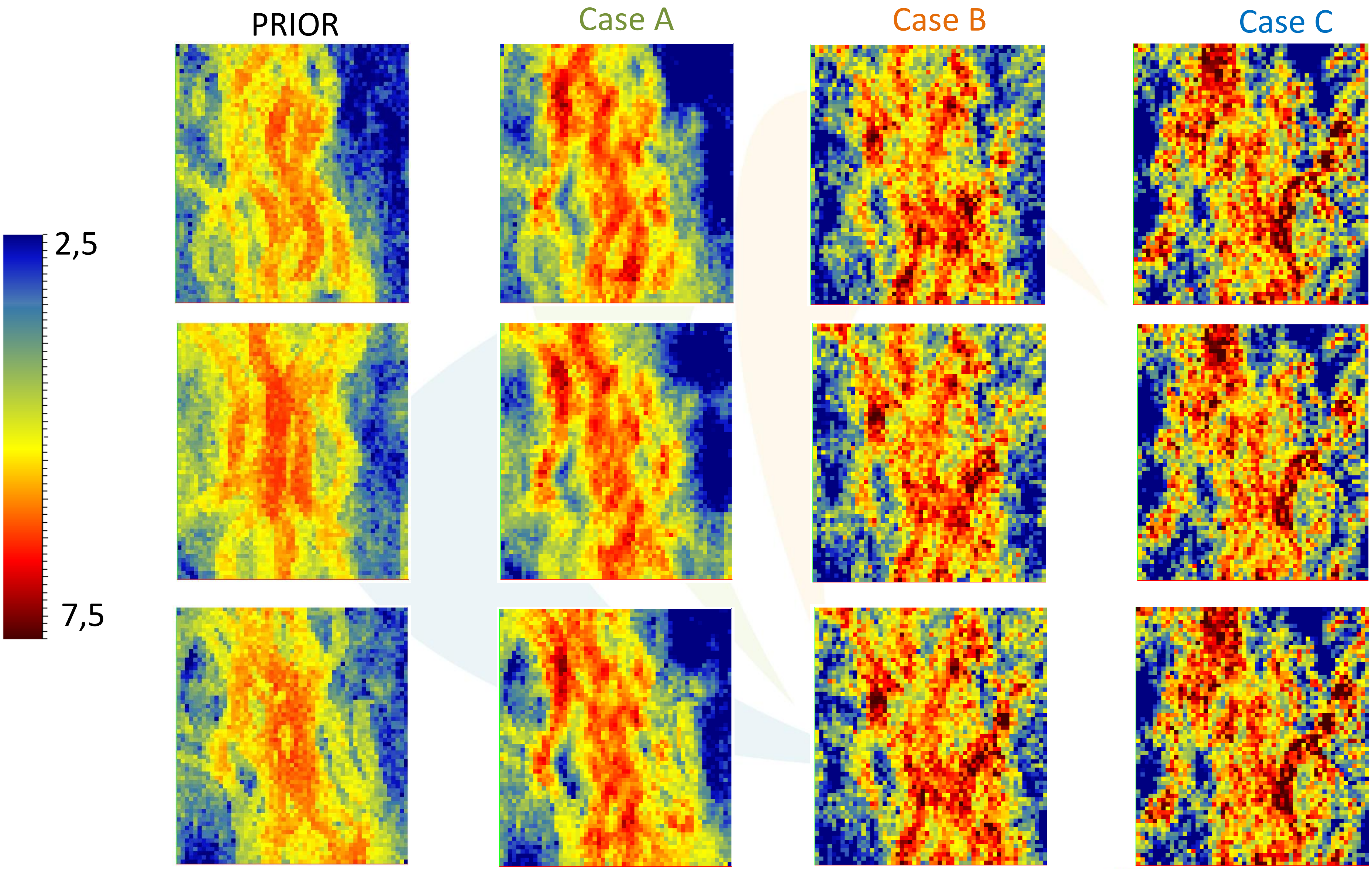
LOG-PERM realizations



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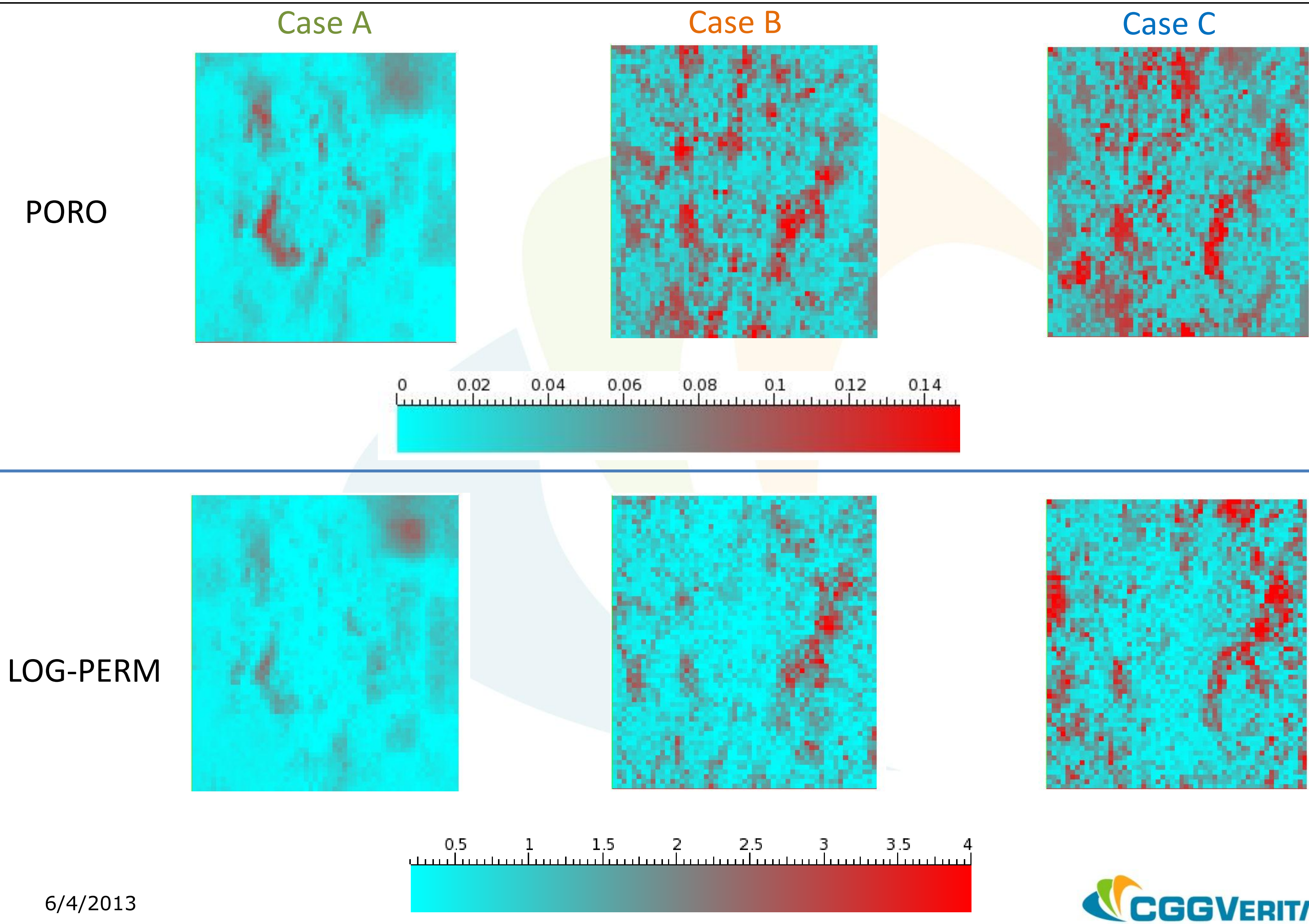
Average deviation from prior



Conclusions

- The wavelet parameterization permits to work both in space and frequency
- The adaptive multi-scale method stabilizes the inversion:
  - Manage to get a good match while minimizing the changes
  - Avoid addition of noise, better preserve the prior and avoid ensemble collapse

- Three keys points of the method:
  - Simplification of the problem (initial smoothing) helps to improve the estimation of G for the large scale coefficients
  - Multi-scale approach: allows a significant reduction of the mismatch by only modifying large scale parameters
  - Adaptive localization: is dynamic, automatic and allows global updates of the field

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Thank you for your attention