Assimilating surface moisture satellite images into a coupled and spatialized water quality model: strategies and challenges

Emilie Rouzies, Claire Lauvernet, Arthur Vidard

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Emilie Rouzies (INRAE, France)

PhD supervised by Arthur Vidard (LJK/Inria, France) and Claire Lauvernet (Inrae, France)

Introduction

Context

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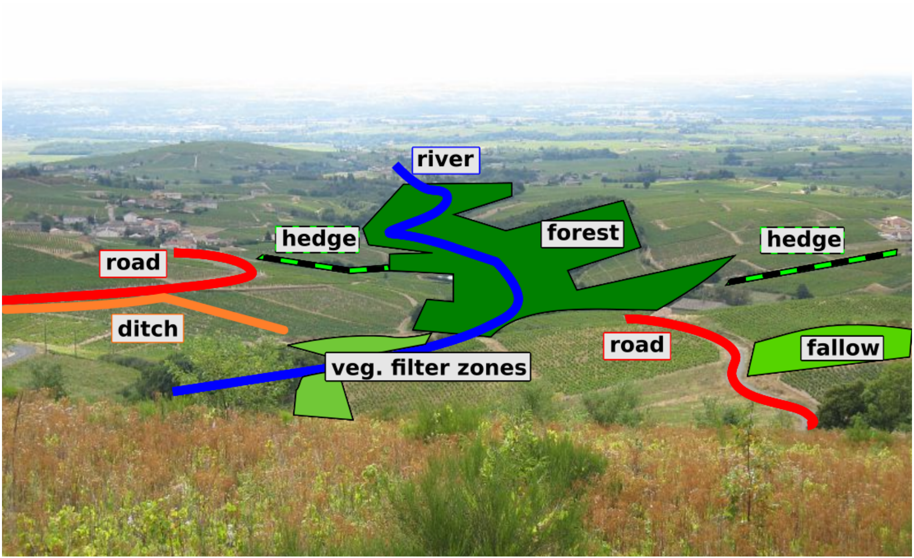
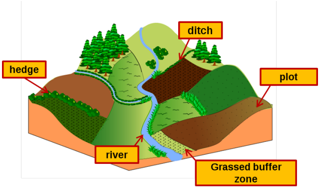
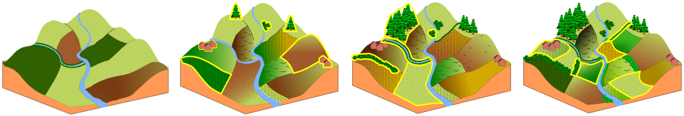


Development of the **PESHMELBA** model (Rouzies et al. 2019) to simulate pesticide transfers and fate on small agricultural catchments

- ✓ Simulations of heterogenous landscapes composed of plots, vegetative filter zones, hedges, ditches and rivers

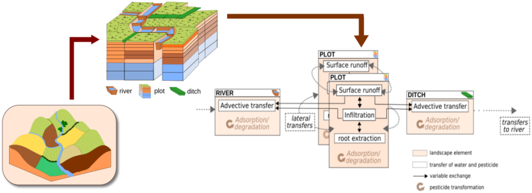


- ✓ Modular structure to explore landscape management scenarios



Introduction
The PESHMELBA model

- ✓ Process-oriented, fully spatialized model
- ✓ Water transfers on surface and subsurface + pesticide advection, adsorption and degradation



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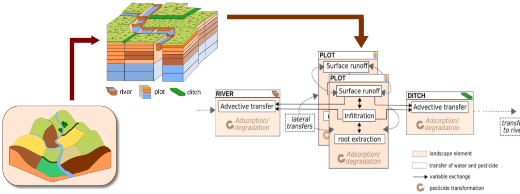
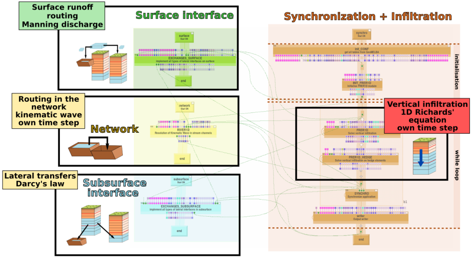


- ✓ One module ≡ one process or ensemble of processes on a landscape element
- ✓ Coupling of modules within the OpenPALM coupler (Buis, Piacentini, and Déclat 2006) turning the structure flexible



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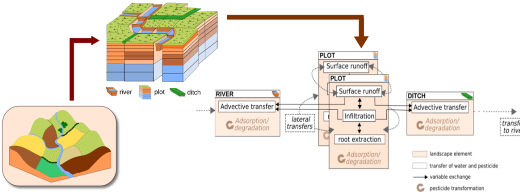

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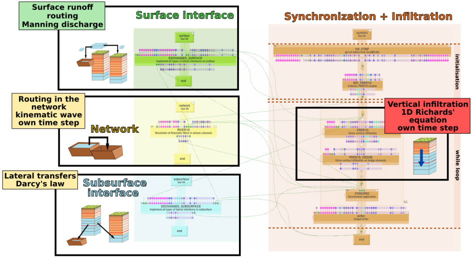

⇒ **Complex structure may lead to additionnal difficulties to diagnose model behavior!**

PhD Objectives

We have a dream that one day PESHMELBA will be used as a decision-making tool to set up management scenarios and to identify an optimal landscape configuration for pesticide transfer mitigation.

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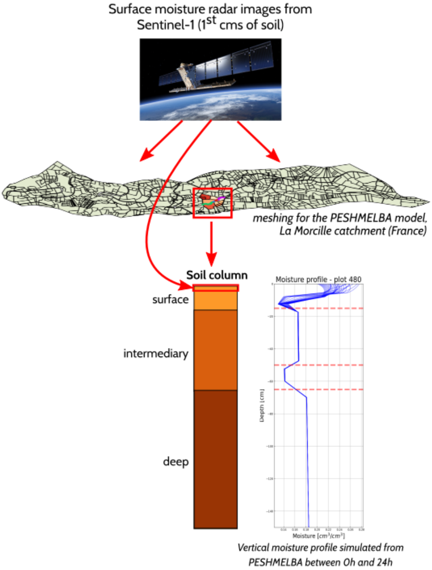
PhD objectives

1. Quantify: performing an uncertainty analysis and a sensitivity analysis of the model
2. Reduce: performing data assimilation to integrate different sources of data: soil moisture images, ERT measurements and in-situ data of pesticide concentration

1. Assimilate surface moisture images to improve moisture dynamics modelling **both in surface and subsurface**
2. Estimate input parameters that would be set for the landscape management scenarios exploration

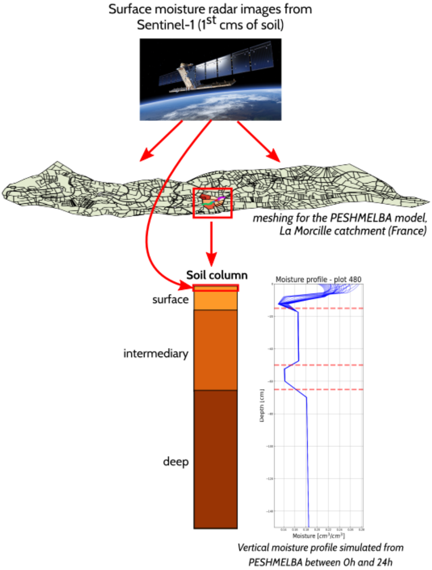


Vertical moisture profile simulated from PESHMELBA between 0h and 24h

1. Assimilate surface moisture images to improve moisture dynamics modelling **both in surface and subsurface**

2. Estimate input parameters that would be set for the landscape management scenarios exploration

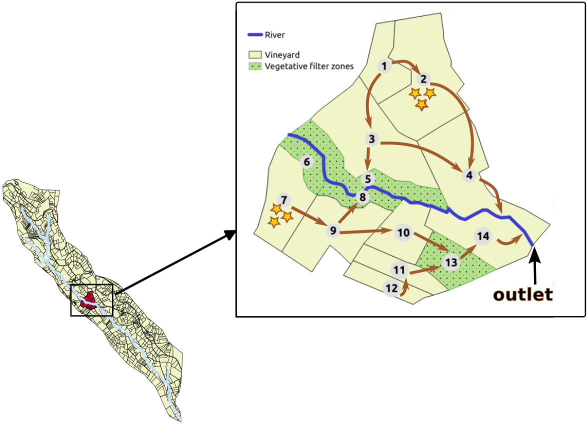
⇒ Joint-estimation abilities are investigated



Material and method

Study case

First attempt of GSA and DA in the PESHMELBA model: let's keep it simple...but realistic! (types of landscape elements, number of parameters, climate conditions...)



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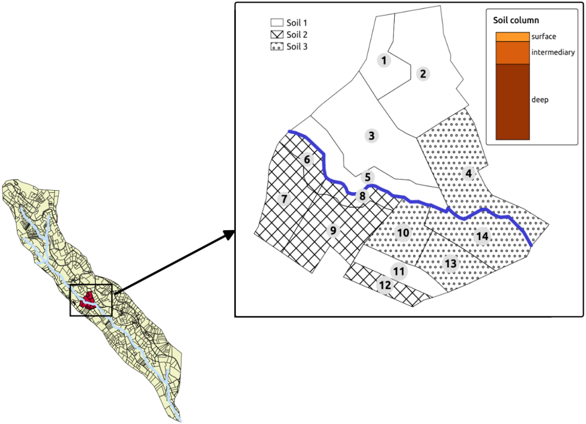

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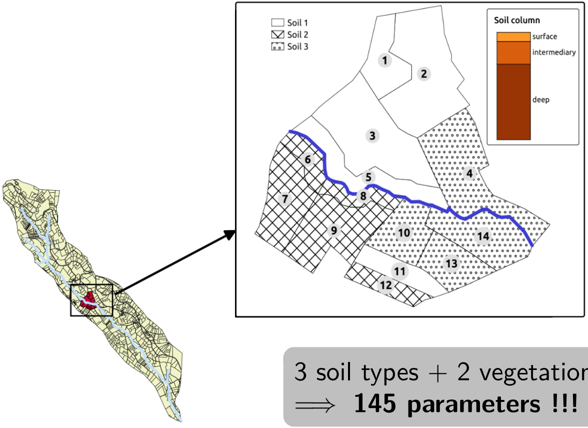
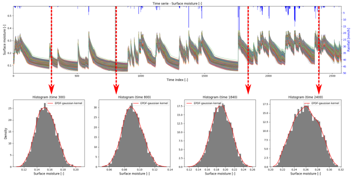
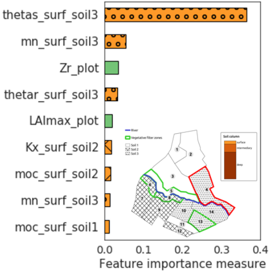


3 soil types + 2 vegetation types + ...
$\Longrightarrow$ **145 parameters !!!**

Main findings from UA/GSA on moisture temporal serie:



✓ Surface moisture is mostly gaussian.

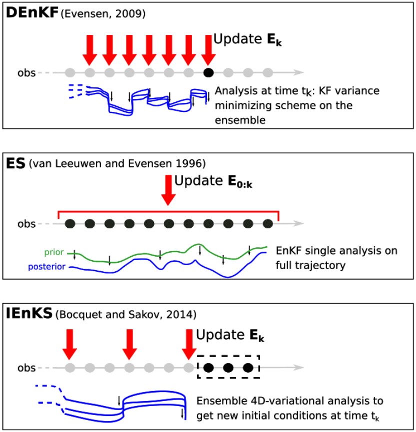


✓ High dependency on surface water content at saturation θ_{sat}.
$\Rightarrow$ Joint-estimation will focus on estimating such parameters

Material and method

DA method

Chosen method should be suited to heterogeneous structure of the model, highly nonlinear processes and landscape discontinuities **but** also suited to PESHMELBA high computational cost.



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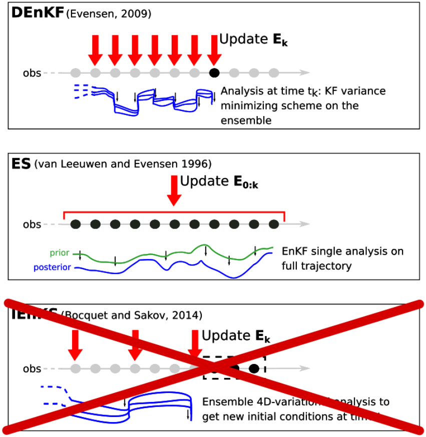
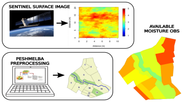


Computational cost for iterative method cannot be afforded ...

Observation

- ✓ Twin experiments
- ✓ Freq. of observation: 24h (⚠ overestimated)
- ✓ Obs. error : $\sim$ 5% of observed surface moisture
- ✓ Assumption: one surface moisture observation per landscape element



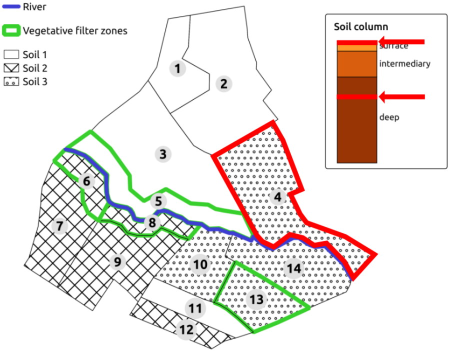
Ensemble

- ✓ 50 members
- ✓ Ensemble spread by perturbing the 145 input parameters

DEnKF set-up

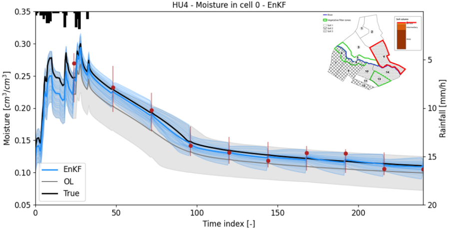
- ✓ State vector dimension : 316 (will increase ++ for real case application)
- ✓ No inflation

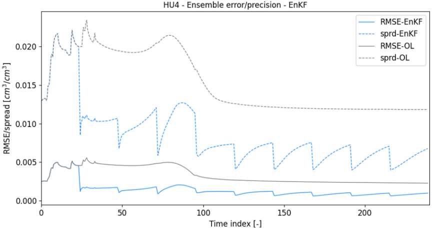
Results
EnKF vs ES



Results
EnKF vs ES

Surface moisture time serie





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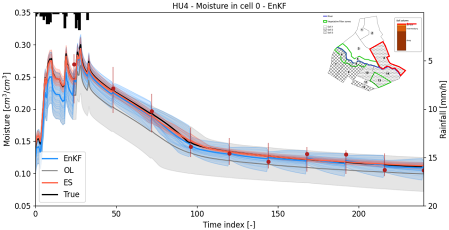

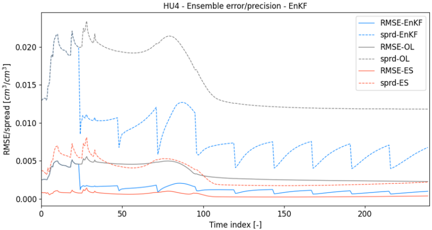

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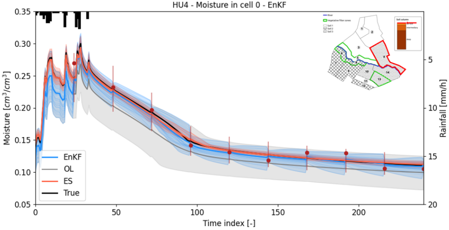
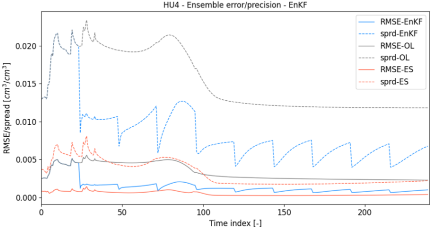
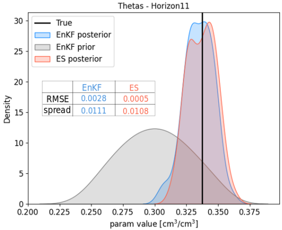
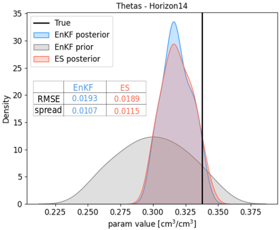
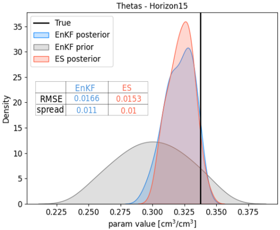




Surface parameters



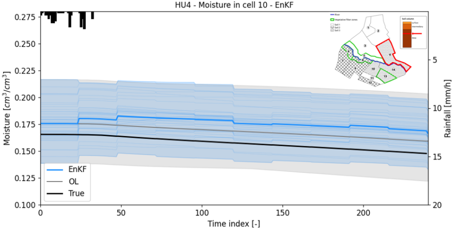


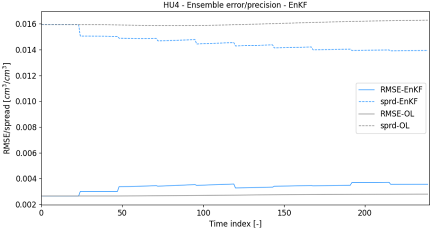


Results

EnKF-subsurface

Subsurface moisture time serie





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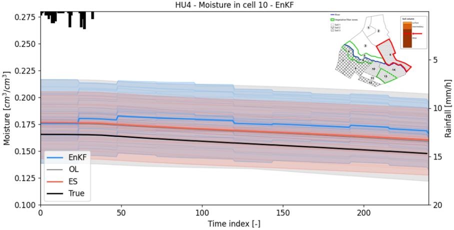

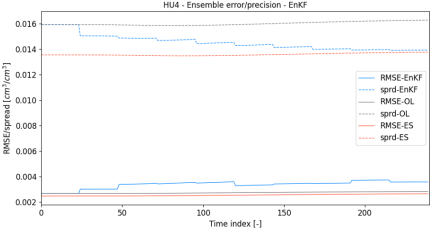

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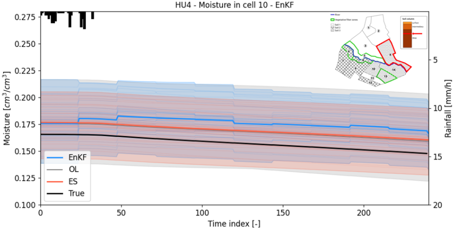
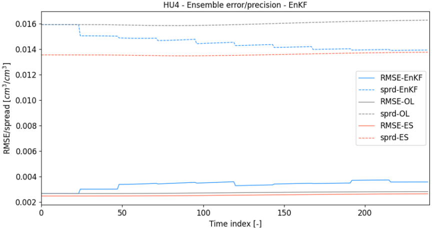
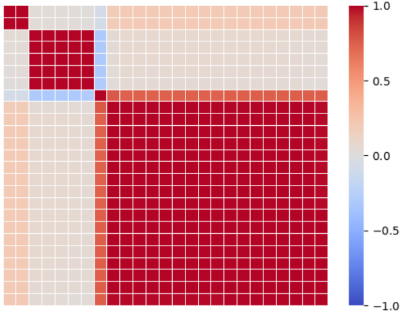




⇒ No strong effect of DA to correct moisture in subsurface compartment

Results

Correlation matrix - extract



Extract of the ensemble correlation matrix for numerical cells from plot 14 at time 24h

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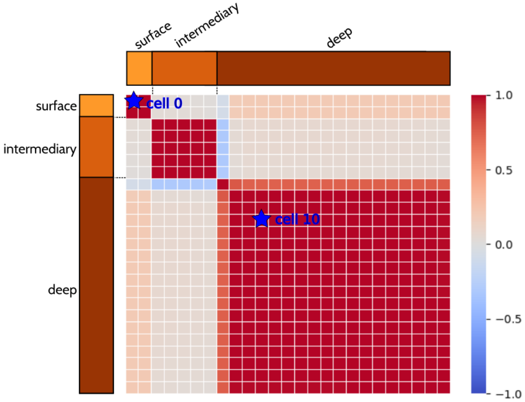

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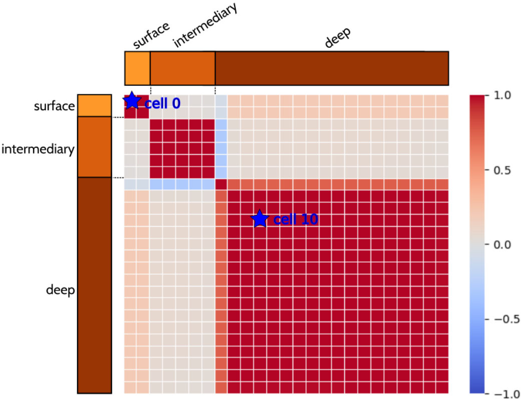
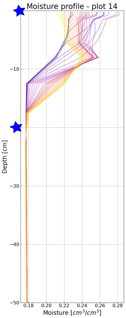


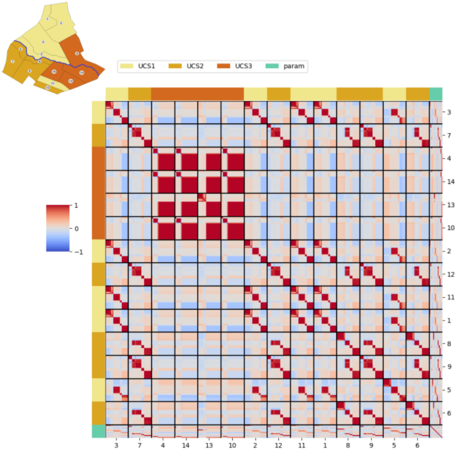
Extract of the ensemble correlation matrix for numerical cells from plot 14 at time 24h

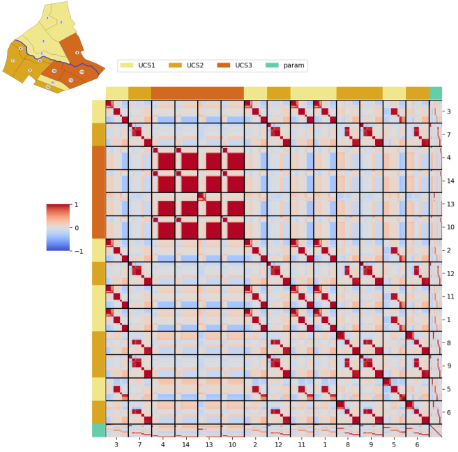
No correlation can be established between surface and subsurface. Dynamics strongly differs between the model compartments.



Results

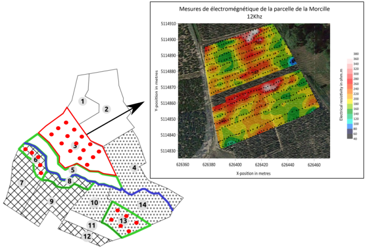
Full correlation matrix





Ponctual moisture observations in subsurface may improve DA performances.

Next step: try and integrate field measurements from Electrical Resistivity Tomography (ERT)



Accounting for observation error correlation

Strategy

Available data sources: satellite surface moisture images + ponctual ERT measurements: both affected by spatial correlations of error

⚠ Spatial correlations are often ignored (**R** treated as diagonal matrix): may lead to unsatisfactory DA performances (Stewart, Dance, and Nichols 2013; Chabot et al. 2015)

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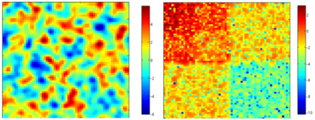
⇒ Chabot et al. 2015; Chabot, Nodet, and Vidard 2020: use of **multiscale transformations** (Fourrier, wavelet,...)

Allows for parcimonious representation of the signal + description of noise influence on structures instead of pixels



Left: correlated white noise. Right: decomposition of the noise in a wavelet space with three scales. From Chabot et al. (2020)

Accounting for observation error correlations

Technical implementation

- ✓ Obs is described by its coefficients in the wavelet basis by wavelet operator $\mathbf{W}$: $\mathbf{y_w} = \mathbf{W}\mathbf{y}$
- ✓ Error covariance matrix can be approximated by a diagonal matrix $\mathbf{D}_w$ in this new basis. A change of variable is performed :

$$\mathbf{D}_w = \mathbf{W}^\mathbf{T}\mathbf{R}\mathbf{W}$$

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DEnKF Analysis scheme is re-written:

$$\mathbf{x}^a = \overline{\mathbf{x}}^f + \mathbf{X}^f \mathbf{w}^a$$

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⇒ Should lead to affordable additional computational cost (Chabot, Nodet, and Vidard 2020)

Conclusion

- ✓ On-going development of a DA framework based on ensemble methods in the PESHMELBA coupled model.
- ✓ Assimilating surface moisture images allows for satisfying correction of surface moisture variable and surface parameters estimation
- ✓ Correction does not propagate towards subsurface component
- ✓ **Next step (1)**: integration of ERT measurements may improve DA performances for the subsurface
- ✓ **Next step (2)**: wavelet transformation to account for observation error spatial correlations (satellite images and ERT measurement)