Data assimilation of image data into a spatialized water and pesticide fluxes model

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Physically-based models represent detailed surface/subsurface transfer, but the required spatial information does not allow their operational use. In situ data on pesticides in a catchment are usually rare and not continuous in time and space. Satellite images, on the other hand, well describe data in space, but only water related, and at limited time frequency. This study aims to exploit these 3 types of information (model,in situ data, images) with data assimilation methods adapted to image data, in order to improve pesticide and hydrological parameters and better understand physical processes. This poster discusses the proposed methodology as well as the available study site data and modeling components.

The Morcille study site

[L. Liger- Irstea —]

The Morcille (Beaujolais Region, France) is a small watershed with high risk of pesticide contamination:

- steep slopes ($> 25\%$), 70% of vineyard
- permeable sandy soils
- continental climate with Mediterranean influence
- Research on pesticides since 1985
- River quality and flow monitored between 2006 and 2011.

CATHY Hydrological model

Coupled surface/subsurface flow and transport [1-7]

- Richards eq. for variably saturated porous media :

$$S_w S_s \frac{\partial \psi}{\partial t} + \phi \frac{\partial S_w}{\partial t} = \nabla[K_s K_r(\nabla\psi + \eta_z)] + q_{ss}$$

- 1D diffusive wave equation at surface:

$$\frac{\partial Q}{\partial t} + c_k \frac{\partial Q}{\partial s} = D_h \frac{\partial^2 Q}{\partial s^2} + c_k q_s(h, \psi)$$

- Advection – dispersion equation

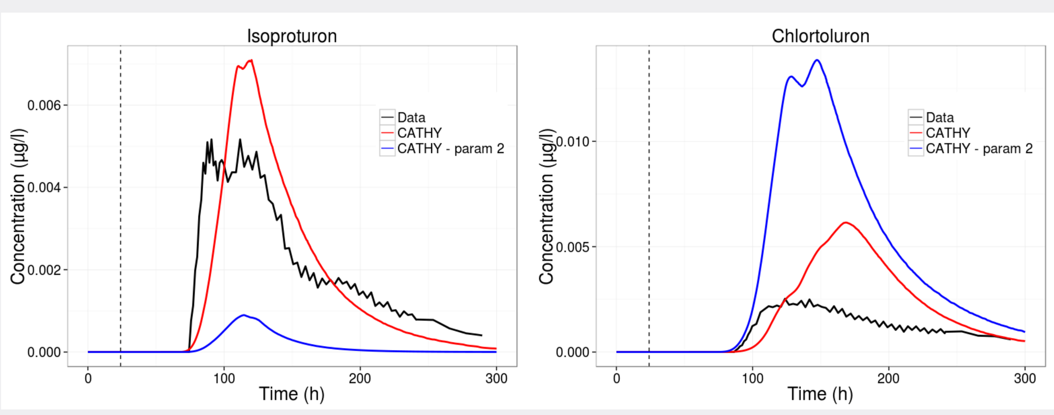
$$\frac{\partial C}{\partial t} = \nabla(D\nabla c) - \nabla(\vec{v} c) + R$$

- Linear adsorption and first order decay

$K_d = \frac{C_S}{C_W}\ \frac{\partial C}{\partial t} = -\lambda C$

First results with reactive solute transport

	K_s (m/s)	K_d Iso	K_d Chlo	DT50 (day) Iso	DT50 (day) Chlo
param1	Hor. = 2.5e-5 Vert. = 5.6e-6	2.32	5.9	12	59.1
param2	H&V = 3.33e-5	2.32	2.4	3.8	1.7



[Gatel et al., 2016]

param1 = CATHY, measured parameters
param2 = CATHY, param. calibrated for HYDRUS

- Timing is reproduced, but significant delay
- Need to better parametrize CATHY spatialized hydrological and solute parameters

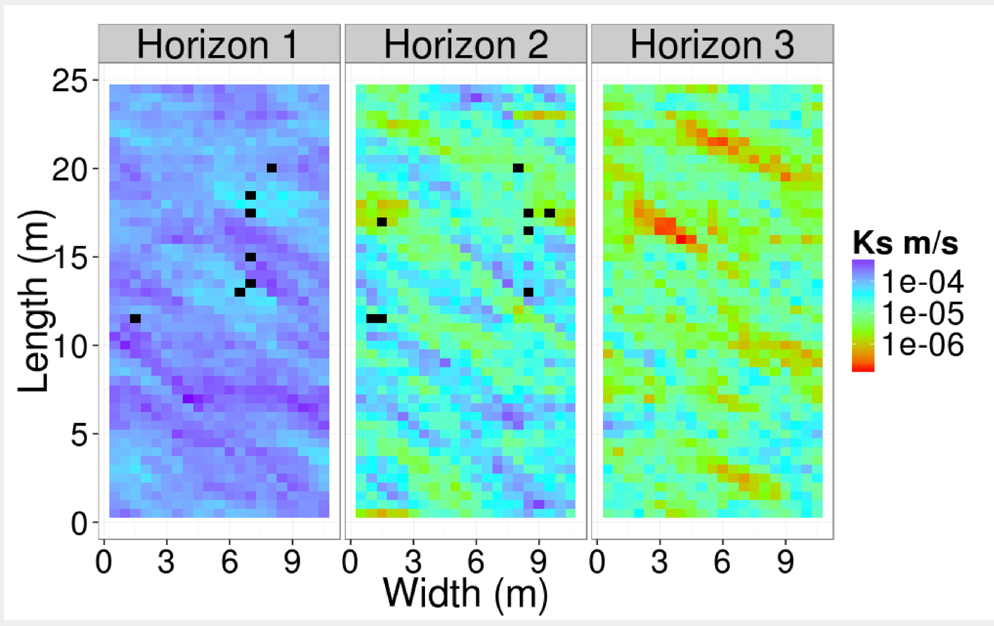
DA for pesticide transfer modeling

Modeling pesticide transfer in a watershed is particularly complex :

- very high heterogenity of the system
- many processes in interaction
- few information on physico-chemical interactions of molecules
- lack of data deep in the soil

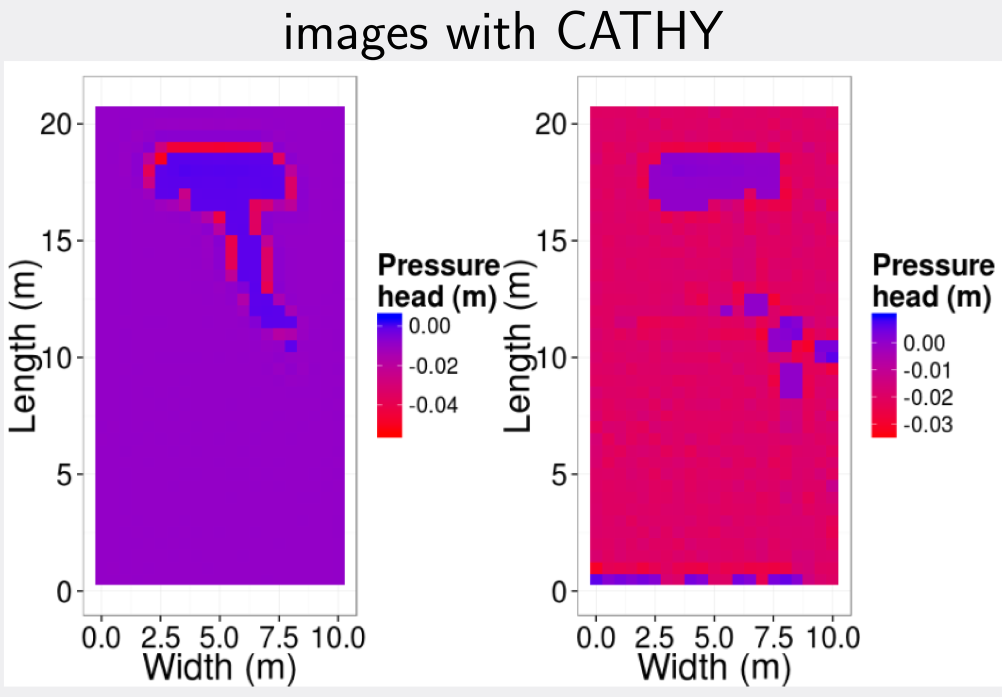
→ research focuses on development of modeling in function of chosen processes to describe
→ DA would improve input parameters characterisation and pesticide transfer understanding.

High spatial heterogeneity



Twin experiments

Simulation of virtual temporal series of surface water images with CATHY



Assimilation of images

- Usually, remote sensing data and sequences are under-used, though their content in information is very high (shapes evolution, correlations, . . .)
- HR Images would also help to identify the landscape elements (grass strips, hedges,. . .)
- In classical approaches : uncorrelated noise, because the proper description and numerical manipulation of non-diagonal error covariance matrices is complex
- How to provide observation error covariance matrices adapted to spatially correlated errors? [2]
- Focusing on the observations operator description, and distances definition in the DA scheme

Which DA method?

Ensemble Kalman filter

$$\begin{cases} \mathbf{x}_k = \mathcal{M}(\mathbf{x}_{k-1}, w_k, t_k, \lambda) & \longrightarrow \text{CATHY} \\ \mathbf{y}_k = \mathcal{H}(\mathbf{x}_k, v_k, t_k) & \longrightarrow \text{OBS.} \end{cases}$$

$$\begin{array}{lccccccc} \text{state} & \ldots & \mathbf{x}^a_{k-1} & \rightarrow & \mathbf{x}^f_k & & \mathbf{x}^a_k & \rightarrow & \mathbf{x}^f_{k+1} & \ldots \\ & & & & \downarrow & & \uparrow & & \downarrow & \\ \text{obs.} & \ldots & & & \mathbf{y}^f_k & \leftrightarrow & \mathbf{y}^{obs}_k & & & \ldots \end{array}$$

- Monte Carlo-based approximation of the Kalman filter for the forecast step ($\mathbf{x}_k^{(i),f}$) and the analysis step ($\mathbf{x}_k^{(i),a}$)
- State augmentation to update the model parameters
- applicable to non-linear large-scale problems
- successfully tested in Cathy :
  Camporese et al. 2009 → assimilation of pressure head and streamflow improves surface and subsurface responses
  Pasetto et al. 2015 → assimilation of water content improved the parameter estimation of spatialised Ks

4DVar

$$J(x) = \frac{1}{2}\|x - x_b\|^2_B + \frac{1}{2}\Sigma_i \|\mathcal{H}(\mathcal{M}_{t_0 \to t_i}(x)) - y_i^{obs}\|^2_R$$

$$x^a = argmin J(x) \longrightarrow find \nabla J(x^a) = 0$$

with B and R background and observation error covariance matrices

- would allow testing many more situations to help estimate the input parameters for the hydrological part of CATHY
- would reduce uncertainty for the pesticides transfer part
- no need for expensive Monte Carlo estimation, as long as the adjoint model coded.

Nudging / BFN : to consider?

- the poor man's data assimation method", very simple to implement but can be very efficient (Paniconi et al., 2003)
- the weighting functions can incorporate prior knowledge about the spatial and temporal variability

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This study is part of LEFE/MANU project ADIMAP -- many thanks to D. Heitz for the Irstea beamer template