Assimilation of image data into a spatialized water and pesticide flux model

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Abstract : 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 well describe data in space, but only water related, and at limited time frequency.

The ADIMAP project 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 fluxes simulation and estimates of hydrological parameters. This poster discusses the proposed methodology as well as the available study site data and modeling components.

CATHY-Pesticide 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

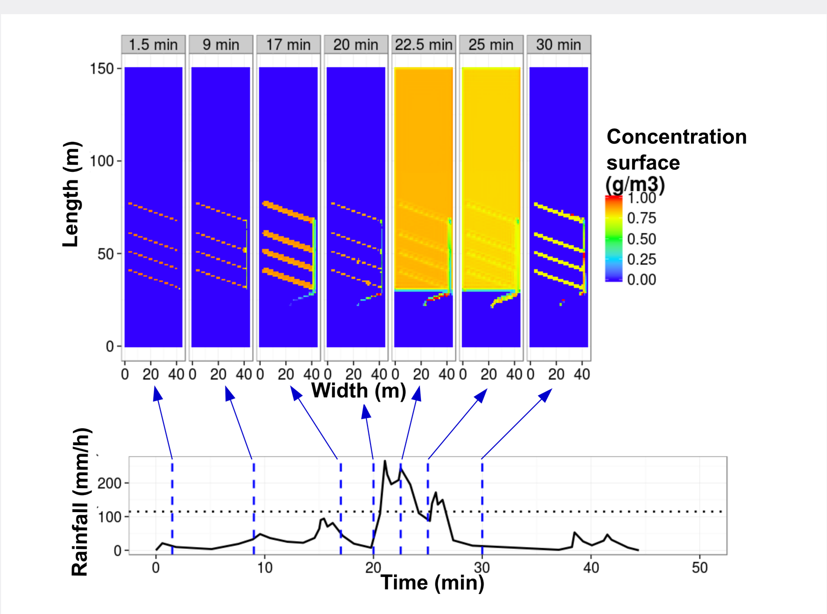
$K_d = \frac{C_s}{C_w}\ \frac{\partial C}{\partial t} = -\lambda C$

The Morcille study site (Beaujolais)

[L. Liger - Irstea]

- small watershed ($8.8 km^2$)
- 70% of vineyard
- high risk of pesticide contamination
- steep slopes > 25%
- permeable sandy soils
- continental climate with Mediterranean influence
- Research on pesticides since 1985
- River quality and flow monitored between 2006 and 2011.

Reactive solute transport on a short event



- Dynamics are reproduced, but significant delay
- Sensitivity Analysis showed high influence of hydrodynamic characteristics on solute transfer outputs

[see Gatel pres. on wednesday Session 43!]

⇒ Need to reduce uncertainty

⇒ Need to better parametrize CATHY spatialized hydrodynamic characteristics

DA for pesticide transfer modeling

Modeling pesticide transfer in a watershed is particularly complex :

- very high heterogeneity 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

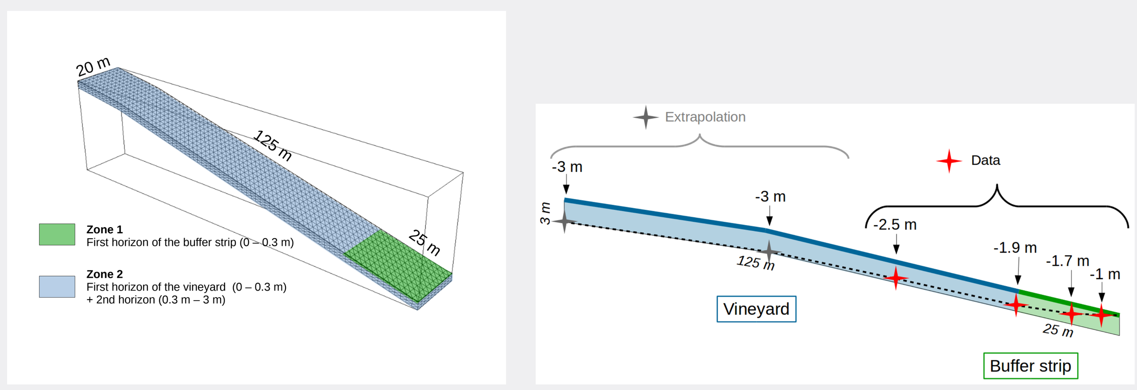
→ DA would improve input parameters characterisation and pesticide transfer understanding.

Hypothesis:

Assimilating *hydrological* variables will improve the *pesticide* fluxes simulations and the input parameters estimates.

⇒ **Coupled Data Assimilation**

Model setup on a simplified hillslope



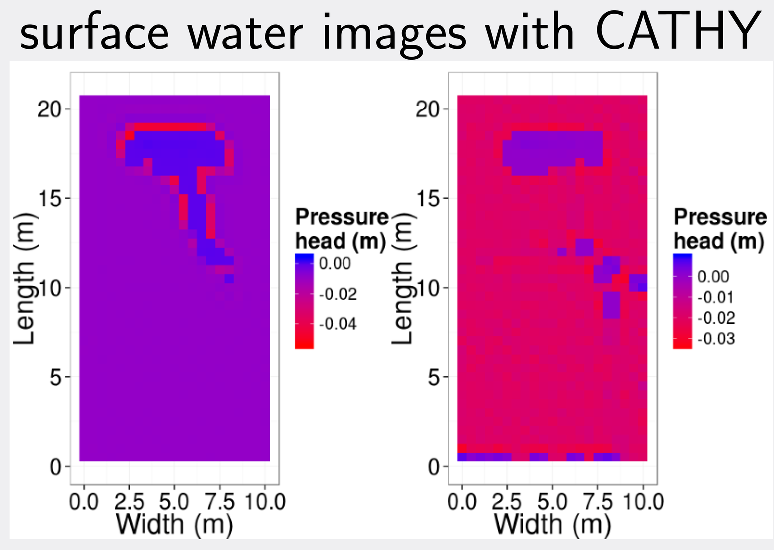
Parameter	unit	Zone 1 (mean,sd)	Zone 2 (mean,sd)
K_s	$m.s^{-1}$	(-8.817,0.69)	(-10.652,0.69)
θ_s	-	(0.54,0.054)	(0.42,0.042)
θ_r	-	(0.15,0.0375)	
n	-	(1.46,0.146)	(1.52,0.152)
α	cm^{-1}	(0.032,0.0096)	(0.1,0.03)
K_d Diuron	$m^3.g^{-1}$	(27.5 , 3.1)	(5.1 , 1.2)
K_d Teb	$m^3.g^{-1}$	(45.1, 30)	(1.98,1.43)
$K_{strickler}$	$m^{1/3}.s^{-1}$	(30,10)	
$Pond_{min}$	m	(0.0025,0.0075)	

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, diagonal error covariance matrices
- 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

Twin experiments

Simulation of virtual temporal series of surface water images with CATHY



Which DA method?

Deterministic Ensemble Kalman filter

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

state $\dots\ \mathbf{x}^a_{k-1} \rightarrow \mathbf{x}^f_k \quad \mathbf{x}^a_k \rightarrow \mathbf{x}^f_{k+1} \dots$

obs. $\dots\ \mathbf{y}^f_k \leftrightarrow \mathbf{y}^{obs}_k \dots$

- Monte Carlo-based approximation of the Kalman filter for the forecast step $(\mathbf{x}^{(i),f}_k)$ and the analysis step $(\mathbf{x}^{(i),a}_k)$
- 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
- perturbation of observations ? Ens.TKF

4DVar

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

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

with B and R background and observation error covariance matrices

- would allow testing 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 MC estimation, as long as the adjoint model coded.

References : [1] Camporese et al., 2010. Surface-subsurface flow modeling with path-based runoff routing, boundary condition-based coupling, and assimilation of observation data. WRR. 46.,2. [2] Chabot, V. et al., 2015. Accounting for observation errors in image data assimilation. Tellus A; Vol 67 (2015). [3] Gatel,L. et al. 2016. Effect of surface and subsurface heterogeneity on the hydrological response of a grassed buffer zone, accepted to JoH . [4] Gatel,L. et al. 2016. Implementation and testing of reactive transport processes for a coupled physically based model Comp. Methods in Water Res., June 2016, Toronto. [5] Paniconi, C. et al., 2003. Newtonian nudging for a Richards equation-based distributed hydrological model. AWR 26, 161–178. [6] Pasetto, D. et al., 2015. Impact of sensor failure on the observability of flow dynamics at the Biosphere 2 LEO hillslopes. AWR, 86 B, 327–339. [7] Weill, S. et al., 2011. Coupling water flow and solute transport into a physically-based surface–subsurface hydrological model. AWR 34, 128–136.

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