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Claire Lauvernet, Laure-An Gatel, Claudio Paniconi, Matteo Camporese, Anna Botto, Arthur Vidard, Maëlle Nodet

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

C. Lauvenet 1, L. Gatel 2, C. Paniconi 2, M. Camporese 3, Anna Botto 3, A. Vidard 4, M. Nodet 4

1 INRS-ETE, Université du Québec, Canada – 2 INRA, UMR: Modèles et Systèmes Agricoles, Versailles, France – 3 LERMA, CNRS/ENSTA ParisTech, Paris, France – 4 LIRIS, Université de Lyon, Lyon, France

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:
  \[ \nabla \cdot \nabla \phi + \nabla \cdot \left( K_r \nabla \psi \right) + q_{sw} \]
• 1D diffusive wave equation at surface:
  \[ \frac{\partial Q}{\partial t} + c_s \frac{\partial Q}{\partial x} = D_s \frac{\partial^2 Q}{\partial x^2} + c_s q_s(h, \psi) \]
• Advection – dispersion equation:
  \[ \frac{\partial C}{\partial t} = \nabla (D_c \nabla c) - \nabla \left( \psi \frac{\partial c}{\partial x} \right) + R \]
• Linear adsorption and first order decay
  \[ K_d = c_v \frac{\partial c}{\partial t} = -\lambda C \]

The Morcille study site (Beaujolais)

• small watershed (8.8 km²)
• 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.

Model setup on a simplified hillslope

Parameter unit Zone 1 Zone 2
\[ K_r \] m/s 0.81 (1.056) 0.735 (1.162)
\[ c_s \] (cm/s) 0.032 0.036
\[ D_s \] m²/s 2.51 (1.81) 2.51 (1.81)
\[ K_d \] m³/m² 45.1 45.1
\[ \text{Pesticide} \] unknown

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

Which DA method?

Twin experiments

Simulation of virtual temporal series of surface water images with CATHY

Deterministic Ensemble Kalman filter

\[ \begin{align*}
\mathbf{x}_k &= 
\mathcal{M}(\mathbf{x}_{k-1}, \mathbf{w}_k, \mathbf{z}_k, \lambda) \quad \rightarrow \quad \text{CATHY} \\
\mathbf{y}_k &= 
\mathcal{H}(\mathbf{x}_k, \mathbf{z}_k) \quad \rightarrow \quad \text{OBS.}
\end{align*} \]

\[ \mathbf{x}_k \rightarrow \mathbf{y}_k \quad \text{obs. . . . } \quad \mathbf{y}_k \rightarrow \mathbf{y}_k \quad \text{OBS. . . . } \]

• Monte Carlo-based approximation of the Kalman filter for the forecast step \((\mathbf{x}_k^{(m)})\)
• and the analysis step \((\mathbf{x}_k^{(A)}))
• State augmentation to update the model
• 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 spatialized \(K_s\)
• perturbation of observations? Ens.TKF

4DVar

\[ J(s) = \frac{1}{2} \| x - s \|^2 + \frac{1}{2} \| \mathcal{H}(\mathcal{M}_{w+m}(s)) - y^\text{obs} \|^2 \]

\[ s = \text{argmin}_s J(s) \quad \rightarrow \quad \text{find \nabla J(s)} = 0 \]

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, long as the adjoint model coded.