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 distances definition in the DA scheme and 2011. 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 :
  \[ S_p \frac{\partial h}{\partial t} + \frac{\partial S_w}{\partial t} + \nabla \cdot [K_s \nabla (\psi + i_h)] + q_{aw} = \frac{\partial Q}{\partial t} = D_i \frac{\partial^2 Q}{\partial t^2} + C_q (h, \psi) \]
- Advection – dispersion equation
  \[ \frac{\partial C}{\partial t} = \nabla \cdot (D \nabla C) – \nabla (\nabla C) + R \]
- Linear adsorption and first order decay
  \[ K_D = \frac{C_i}{\partial \chi} = -\lambda C \]

First results with reactive solute transport

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( K_s ) (m/s)</th>
<th>( K_D ) (m/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vert.</td>
<td>5.6e-6</td>
<td>12</td>
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<tr>
<td>HAV</td>
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<tr>
<td>param2</td>
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</tr>
</tbody>
</table>

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, …)
- 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

\[ \begin{align*}
    x_k &= M(x_{k-1}, w_k, t_k, \lambda) \\
    y_k &= H(x_k, \beta_k, t_k) \\
    \text{state} \ldots x_{k-1} \rightarrow x'_{k-1} \rightarrow x'_{k-1} \\
    \text{obs.} \ldots y'_k \leftrightarrow y^k \\
\end{align*} \]

- Monte Carlo-based approximation of the Kalman filter for the forecast step \( (x_{k-1}^W) \) and the analysis step \( (x_{k}^W) \)
- 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

\[ J(x) = \frac{1}{2} \| H(M_{x_{x-1}}(y) - y_{x_{x-1}x}) \|^2 + \sum_i \| \nabla_j \|_{\hat{\beta}} \| \nabla_j \|
\]

- 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 assimilation method*, very simple to implement but can be very efficient (Paniconi et al., 2003)
- The weighting functions can incorporate prior information about the spatial and temporal variability

References:

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