Data assimilation of image data into a spatialized water and pesticide fluxes model
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The Morcille study site

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 :
  \[ S_p \frac{\partial h}{\partial t} + \frac{\partial S_w}{\partial t} + \nabla [K_s(p_h + i_o)] + q_w \]
- 1D diffusive wave equation at surface:
  \[ \frac{\partial Q}{\partial t} + D \frac{\partial^2 Q}{\partial z^2} + C_o q(h, \psi) \]
- Advection – dispersion equation:
  \[ \frac{\partial C}{\partial t} = \nabla (D \nabla C) - \nabla \psi + R \]
- Linear adsorption and first order decay
  \[ K_d = \frac{C}{C_p} \frac{\partial C}{\partial t} = - \lambda C \]

First results with reactive solute transport

<table>
<thead>
<tr>
<th>Param 1</th>
<th>K_s (m/s)</th>
<th>K_d (m/s)</th>
<th>DT (50 day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vert</td>
<td>2.6e-5</td>
<td>2.32</td>
<td>5.9</td>
</tr>
<tr>
<td>HAV</td>
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<td>2.32</td>
<td>3.6</td>
</tr>
<tr>
<td>Iso Chlo</td>
<td>12</td>
<td>3.8</td>
<td>1.7</td>
</tr>
<tr>
<td>Iso Chlo</td>
<td></td>
<td></td>
<td></td>
</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

\[ x_k = M(x_{k-1}, w_k, t_k, \lambda) \rightarrow \text{CATHY} \]
\[ y_k = H(x_k, w_k, t_k) \rightarrow \text{OBS.} \]

state \[ x_{k-1} \rightarrow x_k \rightarrow x_{k+1} \rightarrow \ldots \]
obs. \[ y_k \leftrightarrow y_k^{\text{alt}} \rightarrow \ldots \]

- Monte Carlo-based approximation of the Kalman filter for the forecast step \((x_k^{(i)})\) and the analysis step \((x_k^{(i)})\)
- 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

\[ \mathcal{J}(x) = \frac{1}{2} \| \mathbf{y} - H(M(x_0, x_t, \ldots)) \|^2_0 + \frac{1}{2} \| (M_{x_0, x_t, \ldots})(x) - y_0 \|^2_0 \]
\[ x^* = \text{argmin}_x \mathcal{J}(x) \rightarrow \text{find} \nabla \mathcal{J}(x^*) = 0 \]
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 assimilation 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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