ASSIMILATING SATELLITE SOIL MOISTURE AND FLOOD EXTENT MAPS INTO A FLOOD PREDICTION MODEL.

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A powerful tool for flood management and prediction: hydrological modelling

Need for observations to set up, calibrate and evaluate these models. Issues:

- Traditional observations are punctual (pb of representativeness).
- Observations are scarcely distributed and observation networks tend to be further reduced (e.g. stream gauges).
- Ground observations not always reliable during flood events.

=> Need for new observation techniques: good candidates: satellite SAR flood images, and satellite derived soil moisture products.
MORE AND MORE READILY AVAILABLE (RADAR) OBSERVATIONS

Day–Night–All weather acquisitions
Synoptic view of large areas
MORE AND MORE READILY AVAILABLE (RADAR) OBSERVATIONS

Day–Night–All weather acquisitions

Synoptic view of large areas

Flood extent Maps
→ e.g. Sentinel-1 (every 2-3 days over Europe, 6-12 days globally)

Soil Moisture Maps
→ e.g. SMOS (every ~3 days)

Research question: Are these EO datasets sufficient for calibrating a distributed conceptual hydrological model?
THE CONCEPTUAL HYDROLOGICAL MODEL
**THE MODEL STRUCTURE**

\[ \text{ET}(x,t) = f(PET_{\text{Pen-Mon}}) \]

\[ P(x,t) \]

\[ \text{Smax}_{UR1}(x) \]

\[ \text{Smax}_{UR2}(x) \]

\[ \text{S}_{UR1}(x,t) \]

\[ \text{S}_{UR2}(x,t) \]

\[ \text{S}_{FR}(x,t) \]

\[ \text{S}_{SR}(x,t) \]

\[ \text{S}_{Rout}(x,t) \]

\[ \text{Q}(x-1,t) \]

\[ \text{Q}(x,t) \]

**Soil moisture soil layer URi (m}^3\cdot\text{m}^{-3})**

\[ SM_{uri} = EFC_{uri} \cdot S_{uri}/S_{max_{uri}} \]
THE MODEL STRUCTURE

We distribute Surface water volume over topography to obtain flood extent maps and flooded area

Topography information

Simulated flood extent map
ASSIMILATION DESIGN
ASSIMILATION DESIGN: THE OBSERVATION

Data Assimilation

Satellite soil moisture maps

Satellite flood extent maps
The assimilation design parameter updating strategy involves the following components:

- \( ET(x,t) = f(PET_{Pen-Mon}) \)
- \( P(x,t) \)

**Soil Moisture Observation**

- \( S_{max_{UR1}}(x) \)
- \( ET_{ur1}(x,t) \)
- \( S_{UR1}(x,t) \)
- \( S_{UR2}(x,t) \)
- \( S_{max_{UR2}}(x) \)
- \( ET_{ur2}(x,t) \)

**Upper UR soil layer**

**Deeper UR soil layer**

**Flood Extent Observation**

- \( S_{FR}(x,t) \)
- \( S_{SR}(x,t) \)
- \( S_{Rout}(x,t) \)
- \( Q(x-1,t) \)
- \( Q(x,t) \)

\( ERA-5 \)

\( Q(x,t) \)

\( S_{FR}(x,t) \)

\( S_{SR}(x,t) \)

\( S_{Rout}(x,t) \)

Surface Water Reservoir

**Fast Reservoir**

**Slow Reservoir**

\( ET(x,t) = f(PET_{Pen-Mon}) \)

\( ERA-5 \)

\( P(x,t) \)
THE ASSIMILATION DESIGN: A TEMPERED PARTICLE FILTER

Bayes Theorem:

\[ p(\theta|o) = \frac{p(o|\theta)}{p(o)} p(\theta) = \prod_{n=1}^{K} \frac{p(o|\theta)\varphi_{n-\varphi_{n-1}}}{p(o)} p(\theta) \]

0 = \varphi_0 < \varphi_1 < \varphi_2 < \cdots < \varphi_K = 1

First Guess (32 random parameter sets)

Particle weight computation using \( \varphi_1 - \varphi_0 \) (\( \varphi_1 \) so that Neff = N/2)

Particle Resampling

Particle mutation using a Random Walk Metropolis Hasting algorithm

After Herbst et al., 2019
THE ASSIMILATION DESIGN: A TEMPERED PARTICLE FILTER

Bayes Theorem: \[ p(\theta|o) = \frac{p(o|\theta)}{p(o)}p(\theta) = \prod_{n=1}^{K} \frac{p(o|\theta)\phi_n^{-\phi_{n-1}}}{p(o)}p(\theta) \]

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After Herbst et al., 2019
SYNTHETIC TWIN EXPERIMENTS
SYNTHETIC TWIN EXPERIMENTS: SYNTHETIC TRUTH AND OBSERVATION

Model forward run (9 years, hourly)

Soil moisture (SM): One Obs. every 3 days

\[ \varepsilon_{SM} = \mathcal{N}(0, 0.04) \]

Flooded Area (FA)
One Obs. every 3 days

\[ \varepsilon_{FA} = \mathcal{N}(0, 0.05 \times FA(t)) \]
SYNTHETIC TWIN EXPERIMENTS: MODEL CALIBRATION USING SM+FA

Final Perf:
RMSE(SM)=0.004

Final Perf:
RMSE(FA)=0.35km²

Final Perf:
NSE(Q)=0.99
SYNTHETIC TWIN EXPERIMENTS: MODEL CALIBRATION USING FA ONLY

Final Perf:
RMSE(FE)=0.17km²

Final Perf:
NSE(Q)=0.99
SYNTHETIC TWIN EXPERIMENTS: CALIBRATED MODEL EVALUATION

SM+FA

Perf:
RMSE(FA)=0.16km²

FA only

Perf:
RMSE(FA)=0.49km²

Perf:
NSE(Q)=0.99

Perf:
NSE(Q)=0.98
CONCLUSION & NEXT STEPS

• We carried out a synthetic experiment using a TPF of the joint assimilation of satellite flooded area and soil moisture observation.
• The results are really promising as the calibrated model is predicting surface runoff accurately both during the calibration and the validation periods.
• This opens the floor for applications at large scale over poorly gauged areas.

Next steps:
• To further investigate the added value of soil moisture data.
• To carry out real test case experiments.
Thank you for your attention

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Questions?

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