

Soil Moisture Week



Webminar 07/11/2019

Soil Moisture data assimilation for flood prediction

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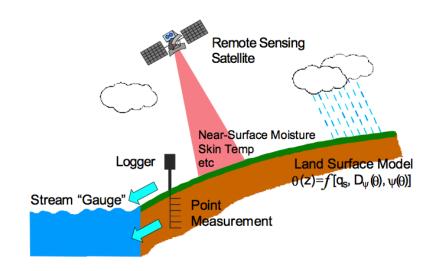


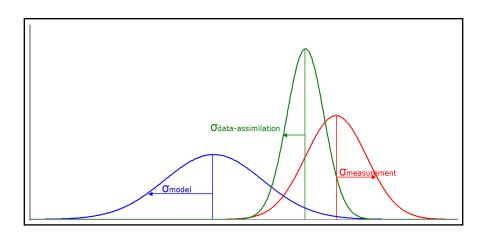
Data Assimilation

Charney et al. [1969] first suggested combining current and past data in an explicit dynamical model, using the model's prognostic equations to provide time continuity and dynamic coupling amongst the fields. This concept has evolved into a family of techniques known as data assimilation.

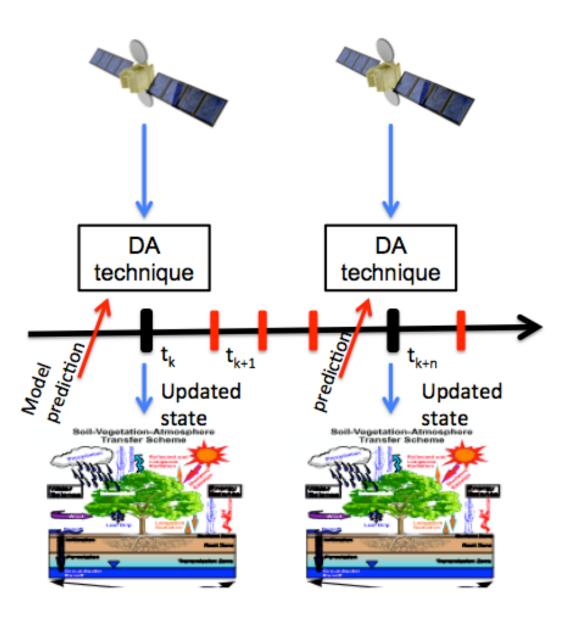
Data assimilation is used operationally in oceanography and meteorology, but in hydrology it is only recently that international research activities have been deployed.

In essence, hydrologic data assimilation aims to utilize both our hydrologic process knowledge as embodied in a hydrologic model, and information that can be gained from observations. Both model predictions and observations are imperfect and we wish to use both synergistically to obtain a more accurate result. Moreover, both contain different kinds of information, that when used together, provide an accuracy level that cannot be obtained when used individually.

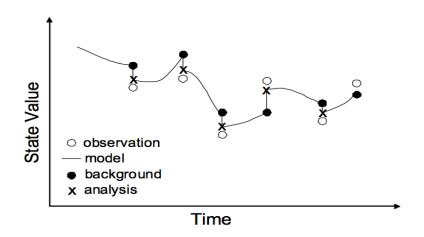




Data Assimilation



<u>Data Assimilation merges observations & model</u> <u>predictions to provide a superior state estimate.</u>



Measurement errors:

Retrieval errors

Model errors:

- Initialization error.
- Errors in atmospheric forcing data.
 Errors in model physics (model not perfect).
- Errors in representation (sub-grid processes).
- Errors in parameters (soil and vegetation)

(some) Open questions in DA

- 1. Which is the best DA techniques?
- 2. How can satellite data be used in a framework for DA in hydrological models?
- 3. Which is the proper model configuration?
- 4. Which is the impact of DA on the hydrological cycle?

Data Assimilation Technique

Direct insertion (Houser et al. 1998; Walker et al. 2001a)

Statistical correction (Houser et al. 1998)

Successive correction Bergthorsson and Döös (1955)

Analysis correction Lorenc et al. (1991)

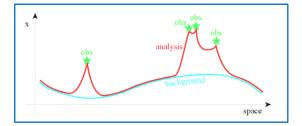
Nudging (Stauffer and Seaman 1990)

Optimal interpolation (Lorenc et al. 1991)

Kalman Filters, simple, extended, ensemble (Evensen)

Particle filter (Kalman, 1960; Evensen 1994, Gordon et al. 1993)

Sequential

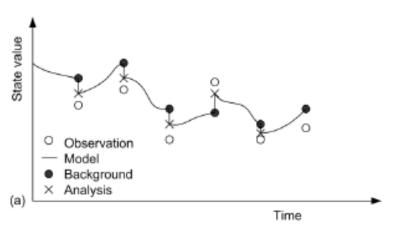


Variational (Reichle et al 2001, Liu and Gupta, McMillan et al 2013, Ercolani and Castelli 2017)

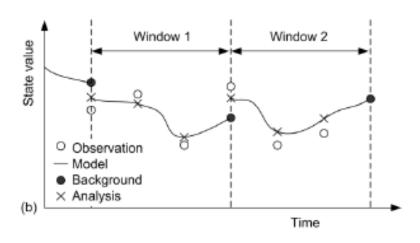
Houser, De Lannoy and Walker (2012). Hydrologic Data Assimilation, Approaches to Managing Disaster - Assessing Hazards, Emergencies and Disaster Impacts, http://www.intechopen.com/books/approaches-to-managing-disaster-assessing-hazards-emergencies-and- disaster-impacts/land-surface-data-assimilation

Data Assimilation Technique

Sequential



Variational



Theoretically given a model integration with finite time interval, and assuming a perfect model, 4D-Var and the Kalman filter yield the same result at the end of the assimilation time interval however:

- can deal with a wide range of model error
- Simple, flexible and more suitable for near real time applications
- Discontinuity in the correction – model shocks

- more optimal in the assimilation window
- more difficulties in including model error and more sensitive to the non linearity of the model
- considerable computational cost

Data Assimilation Technique

The assimilation technique is particularly important in some cases

Samuel, J. et al. 2014 (JoH) "[...] In the streamflow assimilation, soil moisture states were markedly Distorted [...]"

"General filtering approaches in hydrologic data assimilation, such as the ensemble Kalman filter (EnKF), are based on the assumption that uncertainty of the current background prediction can be reduced by correcting errors in the state variables at the same time step. However, this assumption may not be valid when assimilating stream discharge into hydrological models to correct soil moisture storage due to the time lag between the soil moisture and the discharge ..."

Li et al. 2013 (WRR)

The EnKF is designed to update model-forecasted state predictions at the same time an observation is acquired. No attempt is made to reanalyze previous model predictions in response to a particular observation. In contrast, the **Ensemble Kalman Smoother (EnKS)** can be used to update all model states predictions within a fixed lag of past time (Dunne and Entekhabi, 2005). Crow and Ryu, 2009 (HESS)

Nudging

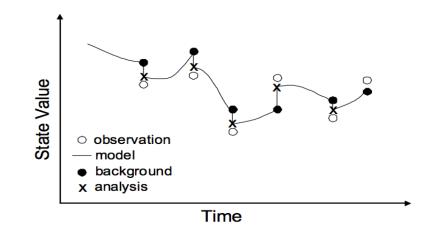
$$SM_{mod}^{+}(t) = SM_{mod}^{-}(t) + K \cdot [SM_{obs}(t) - SM_{mod}^{-}(t)]$$

*SM*_{obs}: observed *SM*

 SM_{mod}^- : background modelled SM

K : gain, takes into account the uncertainties of both the model and the satellite observation

$$K = \frac{\sigma_{mod}}{\sigma_{mod} + \sigma_{obs}}$$

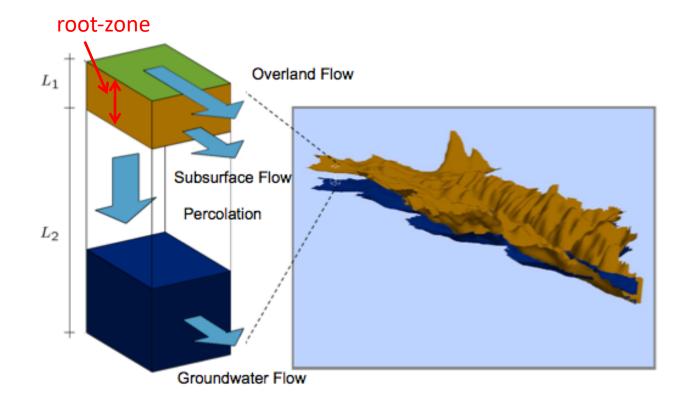


 SM_{mod}^+ : updated modelled SM

One key question in the nudging data assimilation technique is the choice of the gain matrix K. If K is equal to 1 the observations are assumed very reliable and modelled variable is replaced by the observation (direct insertion);

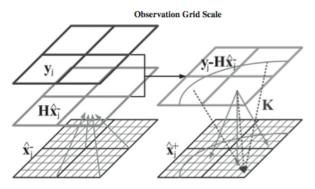
if K is equal zero no update is done.

Satellite data give information of soil moisture for the first centimetres of the soil. This may not match the layer depth simulated by the model (different climatology and considerable bias)



Usually satellite soil
moisture data
CANNOT be directly
used within
hydrological models

- A. "Transform" the sat. SSM in the "same" modelled variable
 - → Filtering
- B. Adjusting the observation to match the climatology of the model
 - → Bias handling



Lumped and distributed model must be considerate in different way

Model Grid Scale

Upscaling (H) of the state forecast to the coarse observation scale Downscaling (K) of the innovation to the fine model scale

Bias Handling: Several potential strategies exist and have been applied in hydrologic data assimilation

Variance matching (VM) (Brocca et al. 2010, 2012, Matgen et al. 2011, Chen et al. 2011)

Linear rescaling

Linear regression techniques (LR)

Cumulative distribution function matching (CDF) (Reichle and Koster 2004)

Anomaly based cumulative distribution (aCDF)

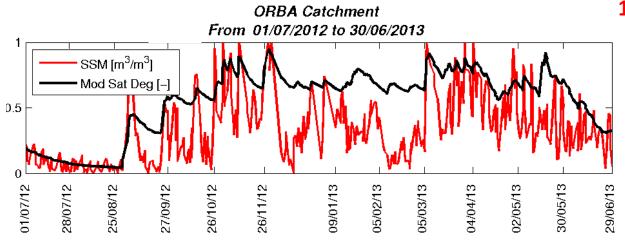
Triple collocation analysis-based approach (TCA) (Stoffelen 1998, Yilamz and Crow 2013)

Simple rescaling techniques may perform equally well to more complex ones
Massari et al. 2015

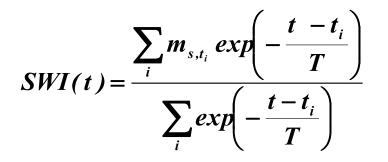
$$SAT^* = \frac{SAT - \mu(SAT)}{\sigma(SAT)} \cdot \sigma(SD_{\text{mod}}) + \mu(SD_{\text{mod}})$$

$$SAT^* = \frac{SAT - \min(SAT)}{\left[\max(SAT) - \min(SAT)\right]}$$

$$\cdot \left[\max(SD_{\text{mod}}) - \min(SD_{\text{mod}})\right] + \min(SD_{\text{mod}})$$



Filtering → SWI

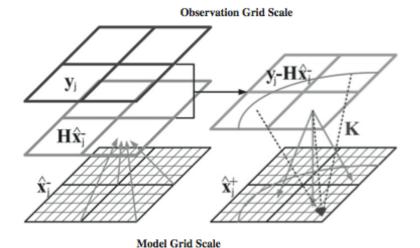


2. Bias handling

$$SAT^* = \frac{SAT - \mu(SAT)}{\sigma(SAT)} \cdot \sigma(SD_{\text{mod}}) + \mu(SD_{\text{mod}})$$

$$SAT^* = \frac{SAT - \min(SAT)}{\left[\max(SAT) - \min(SAT)\right]}$$

$$\cdot \left[\max(SD_{\text{mod}}) - \min(SD_{\text{mod}})\right] + \min(SD_{\text{mod}})$$



Upscaling (H) of the state forecast to the coarse observation scale

Downscaling (K) of the innovation to the fine model scale

Fig. 2. A schematic diagram of the 3-D EnKF approach illustrated for four coarsescale pixels, each containing 4 × 6 fine-scale pixels.

The 1-D EnKF application assimilates a priori partitioned observations at the fine scale model grid cells.

The 3-D EnKF algorithm downscales the coarse observations within the assimilation scheme and uses multiple coarse observation grid cells, as shown in Fig. 2.

Sahoo et al., 2013 -AWR

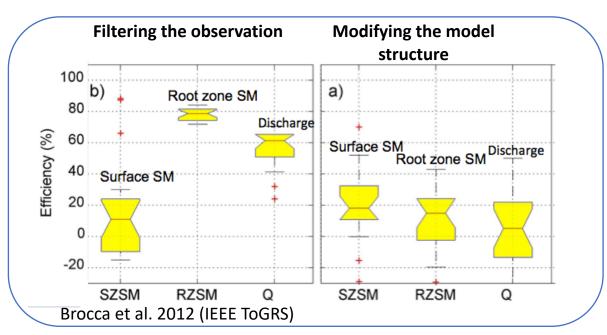
After the assimilation the analysis is bias-corrected to bring the output to the true climatology

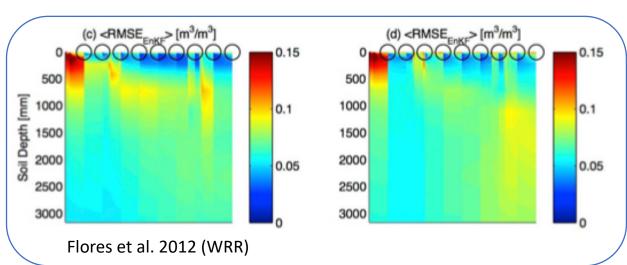
Both the EnKF algorithms produce fine-scale results that are closer to the in situ data than either the model open loop or the satellite observations alone. The 3-D EnKF slightly outperforms the 1-D EnKF and better preserves realistic spatial patterns because of the colored spatial error correlations and the corresponding impact of multiple coarse observation grid cells

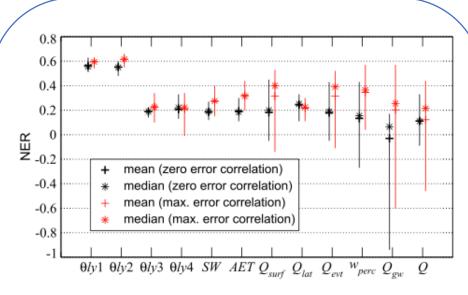
In Situ: Loumagne et al., 2001 (HSJ), Aubert et al., 2003 (JoH), Anctil et al., 2008 (JoH), Matgen et al., 2006 (IAHS), Lee et al. 2011 (AWR), Matgen et al. (2011) (AWR)

Satellite: Houser et al. 1998 (WRR), Pauwels et al., 2001, 2002 (JoH, HP), Crow et al. 2005 (GRL), Matgen et al., 2006 (IAHS), Reichle et al (2008), Crow and Ryu (2009) (HESS), Brocca et al., 2010 (HESS), Chen et al. (2011) (AWR), Montzka et al (2011) (JoH), Matgen et al. (2011) (AWR), Brocca et al. 2012 (IEEE TGRS), Chen et al. 2014 (JoH)

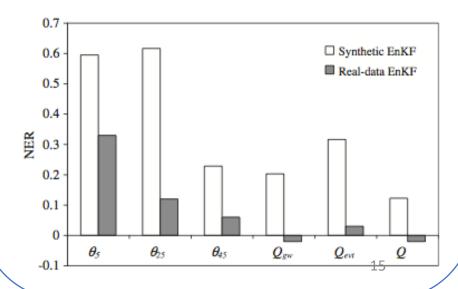
"There is a strong need to estimate soil moisture content through assimilating remotely sensed soil moisture into a long-term, physically based distributed catchment scale hydrologic model. Most of the previous studies that explored DA for runoff simulation used conceptual rainfall-runoff models (Aubert et al. 2003; Weerts and El Serafy, 2006; Crow and Ryu, 2009; van Delft et al. 2009) or lumped models (Jacobs et al 2003) or for short-term period with real measurements (Pauwels et al. 2001)". Han et al. 2012

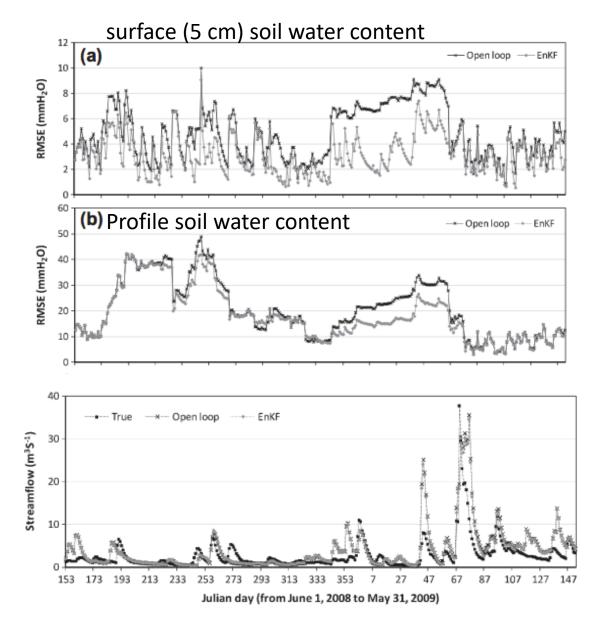






Chen et al. 2011 (AWR)





Han et al., 2012

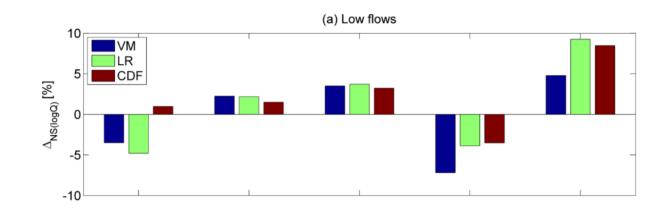
Synthetic experiments using SWAT model Results of assimilation:

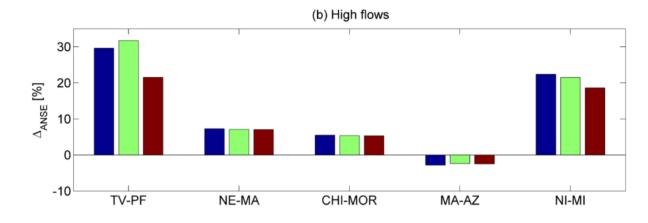
- great impact on soil moisture
- small impact on discharge
- impact on discharge is a function of soil type
- the capability of the SSM assim. for improving streamflow is constrained by the accuracy of precipitation
- Model predicted antecedent soil moisture is less than the true soil moisture (θ_{predicted} < θ_{true} ≈ θ_{EnKF}) and current precipitation is overestimated.
- Model predicted antecedent soil moisture is greater than the true soil moisture (θ_{predicted} > θ_{true} ≈ θ_{EnKF}) and current precipitation is overestimated.
- 3) Model predicted antecedent soil moisture is less than the true soil moisture ($\theta_{predicted} < \theta_{true} \approx \theta_{EnKF}$) and current precipitation is underestimated.
- 4) Model predicted antecedent soil moisture is greater than the true soil moisture ($\theta_{predicted} > \theta_{true} \approx \theta_{EnKF}$) and current precipitation is underestimated.

Massari et al., 2015

How the catchment area, soil type, climatology, rescaling technique, observation and model error selection may affect the results of the assimilation

- (i) DA of SM generally improves discharge predictions (with a mean efficiency of about 30%);
- (ii) unlike catchment area, the soil type and the catchment specific characteristics might have a remarkable influence on the results;
- (iii) simple rescaling techniques may perform equally well to more complex ones





Laiolo et al., 2016 - Cenci et al 2016

Hydrological model: Continuum (phisically based distributed)

Satellite Products
3 SM PRODUCTS DERIVED FROM ASCAT
SMOS SM PRODUCT

Assimilation scheme:

- 1. NUDGING MODEL SCALE
- NUDGING SATELLITE SCALE
- ENSEMBLE KALMAN FILTER

 MODEL SCALE

modelled discharge with DA compared with: Observed discharge and "Open Loop" run (without DA)



Fig. 1. Study areas. Overview of the catchments under investigation: OB (red), CS (light blue), and MG (purple).

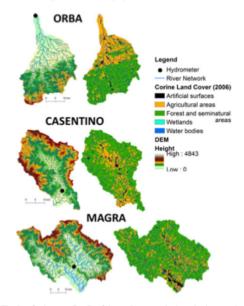
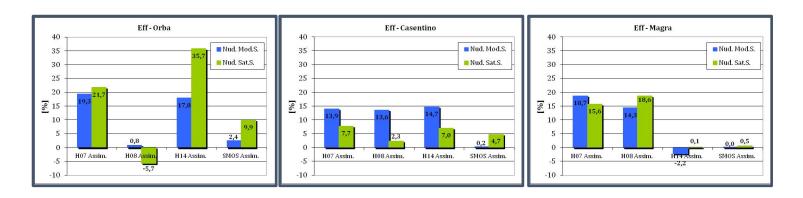
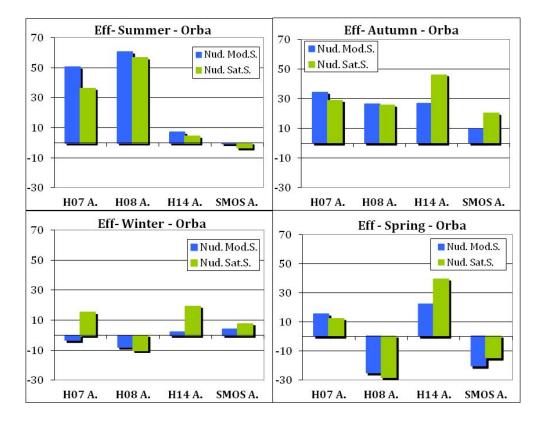


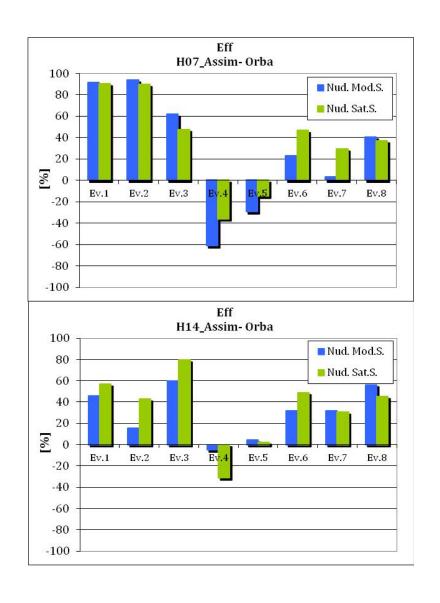
Fig. 2. Study areas: Details of the eatchments under investigation: gauging stations (left column), the topography (left column), the Corine land cover— Level I (right column) and the hydrography (both columns).

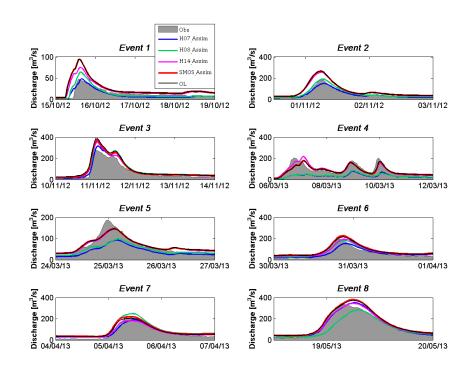




remotely sensed data could be used to update a physically-based, distributed hydrological model applied to a small catchment using a careful data elaboration and a **simple DA technique** which is easy to be applied for Civil Protection purposes in an operative flood forecasting framework.

improvements of SM assimilation were high especially in **summer and autumn** while in winter some problems occurred.





the positive results of the assimilation experiments allow to conclude that, similarly to what found in Wanders et al., 2014, satellite data could be used to improve the model performance for ungauged basins

Conclusions

- Assimilations of Soil moisture products generally improve the performances of an hydrological model, generally improves discharge predictions
- Unlike catchment area, the soil type and the catchment specific characteristics might have a remarkable influence on the results;
- Simple rescaling techniques may perform equally well to more complex ones;
- Reliability differs according to the climatic region and the accuracy of satellite retrievals. Small/no improvements in small improvement of the discharge simulations when SM was assimilated.
- No well-accepted guidelines about how to optimally choose appropriate settings within a DA experiment based on data and basin characteristics, and the "optimal" DA configuration still appears to be a complex task
- DA of SM is not a simple task and one should carefully test the optimality of the assimilation experiment prior to drawing any general conclusions.





