Improved ensemble representation of soil moisture in SWAT for data assimilation applications

Amol Patil and RAAJ Ramsankaran
Hydro-Remote Sensing Applications (H-RSA) Group,
Department of Civil Engineering
Indian Institute of Technology, Bombay
Mumbai, India

SWAT 2018
IIT Madras, Chennai, India
Why soil moisture?

Why Soil Moisture is so Important in Hydrological Modelling?

Controls partitioning of rainfall into runoff, infiltration, and evapotranspiration.

However, it possesses a lot of uncertainties ….

The accurate measurements of soil moisture is a tedious task over large spatial extents.
Satellite observations

Other sources of soil moisture information over large spatial scales includes satellite observations.

- SMAP
- ASCAT
- SMOS

Spatial Resolution ??
Accuracy ??
Depth ??
Data gaps ??

http://hsaf.meteoam.it/description-sm-ascat-ab-nrt.php
Data Assimilation

Combines information from imperfect models and uncertain data in optimal way (BLUE) to achieve uncertainty reduction.
**Data assimilation: overview**

Where, \( K = \Sigma_t^{xz} [\Sigma_t^{zz} + \Sigma_t^z]^{-1} \) and for scalar case \( \Sigma_t^a = \frac{\Sigma_t^x}{[\Sigma_t^x + \Sigma_t^z]} \).
Current problems

Extrapolating the observed information from surface layer to soil profile during ensemble model simulations is the one of major hurdle being experienced by past studies (e.g. Chen et al. 2011) and hence some of them have adopted slightly sub-optimal algorithms (e.g. use of nudging method by Lievens et al. 2015).

Therefore improved methodologies for ensemble forecasting of soil moisture at multiple soil layers is required.
Objective of this study

To provide better surface to sub-surface soil moisture error correlation without altering model physics during ensemble simulations.
The present study has been carried out in Munneru river basin which is one of the left tributaries of Krishna River, India.

Area – 10156 Km²
Lat –16° 41’ N to 18° 7’ N
Long – 79° 7’ E to 80° 50’ E

Figure: Geographical location of the study area along with the land use information, river network and stream gauge locations.
## Study Area, Data and Model

### Table: List of datasets used in the present study

<table>
<thead>
<tr>
<th>Data type</th>
<th>Dataset</th>
<th>Source</th>
<th>Scale/Resolution</th>
<th>Period</th>
<th>Remarks</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Forcing Variable</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rainfall</td>
<td>IMD Gridded</td>
<td>0.25° x 0.25°</td>
<td>2003 – 2013</td>
<td>Interpolated gauge data</td>
<td>Pai et al., (2014)</td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>IMD Gridded</td>
<td>1° x 1°</td>
<td>2003 – 2013</td>
<td>Interpolated gauge data</td>
<td>Srivastava et al., (2009)</td>
<td></td>
</tr>
<tr>
<td>Humidity</td>
<td>NCEP – CFSR</td>
<td>0.25° x 0.25°</td>
<td>2003 – 2013</td>
<td>Reanalysis</td>
<td>Saha et al., (2010)</td>
<td></td>
</tr>
<tr>
<td>Wind Speed</td>
<td>NCEP – CFSR</td>
<td>0.25° x 0.25°</td>
<td>2003 – 2013</td>
<td>Reanalysis</td>
<td>Saha et al., (2010)</td>
<td></td>
</tr>
<tr>
<td>Solar Radiation</td>
<td>NCEP – CFSR</td>
<td>0.25° x 0.25°</td>
<td>2003 – 2013</td>
<td>Reanalysis</td>
<td>Saha et al., (2010)</td>
<td></td>
</tr>
<tr>
<td><strong>State Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Soil moisture</td>
<td>SMOS L3</td>
<td>0.25° x 0.25°</td>
<td>2010 – 2013</td>
<td>Passive microwave retrievals</td>
<td>Kerr et al., (2001)</td>
<td></td>
</tr>
<tr>
<td><strong>Outflow</strong></td>
<td>Discharge</td>
<td>CWC Gauge</td>
<td>-</td>
<td>2006 - 2013</td>
<td>Observed gauge data</td>
<td>CWC, (2012)</td>
</tr>
<tr>
<td><strong>Thematic Data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land Use</td>
<td>NRSC</td>
<td>1:250,000</td>
<td>2007</td>
<td>Derived from AWiFS optical data</td>
<td>NRSC, (2008)</td>
<td></td>
</tr>
<tr>
<td>Soil</td>
<td>FAO HWSD V1.2</td>
<td>1:5,000,000</td>
<td>2009</td>
<td>Prepared from soil survey datasets</td>
<td>FAO/IIASA/ISRIC/ISS CAS/JRC, (2012)</td>
<td></td>
</tr>
<tr>
<td>Topography</td>
<td>SRTM GDEM</td>
<td>90 m</td>
<td>2002</td>
<td>Interferometric SAR product</td>
<td>Jarvis, (2008)</td>
<td></td>
</tr>
</tbody>
</table>
Study Area, Data and Model

SWAT Hydrology Model

\[ Q_{surf} = \left( Q_{surf} + Q_{surf-1} \right) \left( 1 - \exp \left( \frac{-s_{surf}}{t_{conc}} \right) \right) \]

Surface Runoff Lag Time

Transmission Losses (Lane's method (1982))

Lateral Flow Lag time

\[ Q_{lat} = \left( Q_{lat} + Q_{lat-1} \right) \left( 1 - \exp \left( \frac{-1}{T_{lat}} \right) \right) \]

Lateral Flow (Kinematic Storage Model, Sloan et al. (1983))

Sub-basin outlet

Base flow (Hoogdout (1940))

\[ Q_{gw} = \frac{8000 \cdot K_{sat} \cdot h_{wbl}}{L_{gw}} \]

Shallow Aquifer

One per sub basin

Percolation to Deep Aquifer

Deep Aquifer

Canopy Storage

Evapotranspiration

Precipitation

Excess Rainfall (SCS-CN/GA)

HRU (i)

Soil Layer 1

Soil Layer n

Percolation to Shallow Aquifer (Sangrey, et al. (1964)).

Revap

Tributary Channel
Methods

Figure: Flowchart of the ensemble model simulation and data assimilation methodology
Methods

Model Calibration: 2006-2009

Model Validation: 2010-2012

Forecast Error

Sampling method used: Latin Hypercube

Number of Ensemble: 100

Rainfall error std. dev.: 0.15*Rainfall magnitude

Direct perturbation to soil layers:
- layer 1 (0-50mm) - 0.1 mm/mm
- layer 2 (0-50mm) - 0.07 mm/mm
- layer 3 (0-50mm) - 0.01 mm/mm
  (Vertical error correlation of one)

Perturbation to soil storages: 0.1 mm/mm
  (Error correlation of one with ensemble inflow to soil layer)

Observation Error

Observation error is defined using data quality flags varying from 0.01 to 0.25 mm/mm standard deviation
Methods

Scenario 1 (EnKF1)

Perturbed (stochastically represented) only model forcing and state variables

Scenario 2 (EnKF2)

Perturbed (stochastically represented) only model forcing and state variables as well as key model parameters representing soil water routing.
**Results: error correlation**

Error correlation between surface and sub-surface soil moisture

Scatter plot of error correlation of the first layer to each subsurface layer with respect to the mean ensemble inflow to soil profile for
(a) EnKF1 run with unperturbed soil water storage capacity, and
(b) EnKF2 run with perturbed soil water storage capacity

**Key outcomes**

- The error correlation of forecasted soil moisture increased along with profile soil water inflow.
- Improvement in correlation shows that better coupling between top soil layer and second soil layer than top layer to third layer which is more realistic.
## Results: error correlation

<table>
<thead>
<tr>
<th></th>
<th>EnKF1</th>
<th>EnKF2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corr_{lyr,12}</td>
<td>0.10</td>
<td>0.29</td>
</tr>
<tr>
<td>Corr_{lyr,13}</td>
<td>0.09</td>
<td>0.16</td>
</tr>
</tbody>
</table>

### Key outcomes

- The error correlation structure is improved most of the times during entire simulation period.
- The overall improvement in error correlation is again better for second layer than top layers than bottom ones.

### Table: Average error correlation of the first layer to each subsurface layer over entire basin (mean ensemble inflow >5mm)

(a) EnKF1 run with unperturbed soil water storage capacity, and
(b) EnKF2 run with perturbed soil water storage capacity
Results Soil Moisture assimilation

Figure: Comparison of observed and simulated soil moisture for all model runs
(Patil and Ramsankaran, 2017)
Results: stream flow evaluation

NSE\_OL = 0.573  \hspace{1cm} NSE\_EnKF1 = 0.667  \hspace{1cm} NSE\_EnKF2 = 0.703

Key outcomes

- Model simulations for rising limb and recession limb flood hydrograph have shown significant improvements
- Overall EnKF2 run gives best assimilation performance

Figure: Comparison of observed and simulated streamflow for all model runs

(Patil and Ramsankaran, 2017)
Conclusions and Future Directions

• Randomizing the key parameters in soil water routing facilitates ensemble soil water storages which further improves the error correlation structure required for data assimilation applications

• The SMOS soil moisture can be used for improving the streamflow estimates by assimilating into large-scale distributed hydrological models operating at a daily time step

• Further studies are needed to understand the requirements of model structures that could handle stochastic or ensemble model simulations to help related applications.
Publication

Based on this concept, a recent article is available at https://www.sciencedirect.com/science/article/pii/S0022169417307357