Land Data Assimilation in China: A review

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1. Data assimilation in China: a quick review
LDAS sisters and developers in China

(1) First LDAS in China
(2) Multi-model and observation operators
(3) Multiple data
(4) Rich application directions

(1) Operational weather forecast
(2) Dual-pass LDAS
(3) Novel assimilation
(4) The Global Microwave Land Data System;

From Prof. Kun Yang
Dual-pass LDAS at ITP: (1) first dual-pass LDAS prototype; (2) model operator: SiB2; (3) microwave Tb data

Minimization scheme

\[ F(T_{b_{\text{obs}}} - T_{b_{\text{sim}}}) \]

\[ T_{bp} = T_g (1 - \Gamma_p) \exp(-\tau_c) + T_c (1 - \omega)[1 - \exp(-\tau_c)][1 + \Gamma_p \exp(-\tau_c)], \]

TMI/AMSR/AMSR-E
(6.9/10.6 and 18.7 GHz)

WSfc

\( R^\uparrow \)

\( R^\downarrow \)

Base flow

Infiltrate and Diffuse

Transpiration

\( \text{Radiation transfer in canopy} \)

\( \text{Interception} \)

\( \text{Surface radiation} \)

\( \text{Vegetation emission} \)

Vegetation layer

Surface

Yang et al., 2007, JMSJ;
Qin et al., 2009, JGR
Yang et al., 2009, J. Hydrometeorology
Yang et al., 2016, J Hydrology
The Global Microwave Land Data System at ITP: (1) dual-pass LDAS; (2) Novel assimilation

- A Dual-pass Assimilation-Calibration strategy (Tian et al., 2009, JGR)
- A POD-based ensemble 4DVar method (Tian et al., 2010, Tellus-A; 2008, JGR)
- A EnCNOP-P parameter calibration method (Tian et al., 2010, WRR)
- A BMA-based observation operator framework (Tian et al., 2011, JGR)
2. Data assimilation method development
Comparisons of nonlinear non-Gaussian filtering algorithms

- UKF is a good choice in nonlinear Gaussian problems;
- The performance of the Kalman filter depends on the accurate estimation of system and observation error;
- For nonlinear non-Gaussian Problem, the best option is particle filter;
- Balance between calculation accuracy, numerical stability and computational efficiency.

Table of the algorithms, the mean of the RMSE and the error standard deviations for experiment A calculated over 100 independent runs with $\Delta t_{obs}=0.1$

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$x$</th>
<th>$y$</th>
<th>$z$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>S.D.</td>
<td>RMSE</td>
</tr>
<tr>
<td>Unscented Kalman filter (UKF)</td>
<td>1.157</td>
<td>1.340</td>
<td>1.872</td>
</tr>
<tr>
<td>Ensemble Kalman filter (EnKF)</td>
<td>1.102</td>
<td>1.421</td>
<td>1.811</td>
</tr>
<tr>
<td>Particle filter (SIR-PF)</td>
<td>1.179</td>
<td>1.298</td>
<td>1.909</td>
</tr>
<tr>
<td>Unscented particle filter (UPF)</td>
<td>1.076</td>
<td>1.270</td>
<td>2.022</td>
</tr>
</tbody>
</table>

Han & Li, 2008. Remote Sensing of Environment
Dual Ensemble Kalman Smoother for simultaneous estimation of soil moisture and soil properties

Soil moisture

Surface (5cm)

<table>
<thead>
<tr>
<th></th>
<th>24h</th>
<th>72h</th>
<th>240h</th>
</tr>
</thead>
<tbody>
<tr>
<td>EnKF</td>
<td>0.059</td>
<td>0.070</td>
<td>0.093</td>
</tr>
<tr>
<td>DEnKF</td>
<td>0.044</td>
<td>0.047</td>
<td>0.054</td>
</tr>
<tr>
<td>EnKF-EnKS</td>
<td>0.039</td>
<td>0.041</td>
<td>0.045</td>
</tr>
<tr>
<td>DEnKS</td>
<td>0.035</td>
<td>0.038</td>
<td>0.040</td>
</tr>
</tbody>
</table>

Root-zone (20cm)

<table>
<thead>
<tr>
<th></th>
<th>24h</th>
<th>72h</th>
<th>240h</th>
</tr>
</thead>
<tbody>
<tr>
<td>EnKF</td>
<td>0.042</td>
<td>0.051</td>
<td>0.072</td>
</tr>
<tr>
<td>DEnKF</td>
<td>0.037</td>
<td>0.036</td>
<td>0.042</td>
</tr>
<tr>
<td>EnKF-EnKS</td>
<td>0.028</td>
<td>0.031</td>
<td>0.037</td>
</tr>
<tr>
<td>DEnKS</td>
<td>0.025</td>
<td>0.028</td>
<td>0.032</td>
</tr>
</tbody>
</table>

Deep (80cm)

<table>
<thead>
<tr>
<th></th>
<th>24h</th>
<th>72h</th>
<th>240h</th>
</tr>
</thead>
<tbody>
<tr>
<td>EnKF</td>
<td>0.019</td>
<td>0.025</td>
<td>0.046</td>
</tr>
<tr>
<td>DEnKF</td>
<td>0.064</td>
<td>0.043</td>
<td>0.015</td>
</tr>
<tr>
<td>EnKF-EnKS</td>
<td>0.054</td>
<td>0.062</td>
<td>0.067</td>
</tr>
<tr>
<td>DEnKS</td>
<td>0.052</td>
<td>0.057</td>
<td>0.060</td>
</tr>
</tbody>
</table>

Chu et al., 2015, SCIENCE CHINA Earth Sciences; Chen et al., 2015, Advances in Water Resources
Assimilating the MODIS LST products at CEOP Mongolian reference (Sep 1-30), the estimation of land surface temperature can increase 2K averagely.

One-dimensional experiment of assimilating AMSR-E data for snow state estimation

- Data: CEOP Siberia reference; Land model: CoLM; Radiative transfer model of snow: MEMLS
A frozen soil model is used as dynamic model

\[ T_{\text{eff}}(t) = T_0(t) + \frac{1}{\kappa_e \sec \theta_t} \left( \frac{\partial T_t(z,t)}{\partial z} \right)_{z=0} \]

Radiative transfer of microwave signal by considering frozen soil scattering darkening

Jin & Li, 2009, Science China Earth Sciences
3. Chinese Land Data Assimilation System

- Observation operator
  - Radiative transfer model

- Data
  - Forcing
  - Parameters
  - Observations

- Model operator
  - Land surface model
  - Distributed hydrological model

- Data Assimilation
  - EnKF
  - 4DVA
  - Particle filter
  - VFSA

Li et al., 2007, Progress in Natural Science; Huang & Li, 2008a, Remote Sensing of Environment
Huang et al., 2012, IEEE Transactions on Geoscience and Remote Sensing
Data sets used in the Chinese Data Assimilation System

- ITPCAS forcing data (0.1degree, 3hour), Chen et al., 2011, JGR
- Soil texture data, Shangguan et al., 2012, Geoderma; Dai et al., 2013, JHM
- Land cover and vegetation data, Ran et al., 2012, IJGIS
- Validation data, different sources
Assimilating MODIS Snow Cover Products into Land Surface Model: A Case Study in Northern Xinjiang, China

Xinjiang, 2012-2013

Observation Simulation Assimilation

Snow Depth Evolution

BIAS

RMSE
Summary on CLDAS

• A multivariate, multi-source, and multi-purpose LDAS of China has been developed by a joint effort of different institutions.
• Various kinds of remote sensing data and data products can be operationally assimilated.
• DA results have been preliminarily validated.
• Results have not been published, data have not been published as well, systematic validation is still required.
4. Catchment Scale Eco-Hydrological Data Assimilation
A catchment scale eco-hydrological data assimilation system

\[ p(x_k | y_k) = \frac{p(y_k | x_k) p(x_k | y_{k-1})}{p(y_k | y_{k-1})} \]

Han et al., 2012, Hydrology and Earth System Sciences
Han et al., 2013, Vadose Zone Journal
Han et al., 2014, Water Resources Research
Han et al., 2015, PloS One; Han et al., 2015, HESS
Han et al., 2015, Geoscientific Model Development Discussions
HiWATER: An eco-hydrological experiment designed from an interdisciplinary perspective addresses problems including **heterogeneity, scaling, uncertainty**, and closing water cycle at the watershed scale.

Data information system: [http://heiheedata.org/hiwater](http://heiheedata.org/hiwater)

More information: [http://hiwater.westgis.ac.cn/](http://hiwater.westgis.ac.cn/)

Li et al., *BAMS*, 2013
High-resolution precipitation data by data assimilation at Heihe river basin

Joint assimilation of cosmic-ray and land surface temperature at Heihe river basin

- Cosmic Ray measures the 12 cm~76 cm soil moisture in a 300 m radius (non-invasive, intermediate scale)

[Image of Cosmic Ray equipment]

Highlight: a Cosmic-ray forward model was used as an observation operator

[Graphs showing correlation between Observed ET and Estimated ET]

Han et al., 2015, Hydrology and Earth System Sciences
An improved observation localization strategy in data assimilation by incorporating Geostatistics

Mean basin scale soil moisture RMSE values

10 cm depth soil moisture RMSE

Han et al., 2012, Hydrology and Earth System Sciences; Han et al., 2015, PLoS One
Ecological data assimilation system at catchment-scale

Bayes’s theorem

\[ p(\theta | D) = \frac{P(D | \theta) p(\theta)}{p(D)} \]

Sampling distribution (Maximum likelihood)

Prior Distribution

Posterior Distribution

Zhu et al., 2010, HESS; Zhu et al., 2011, Tree Physiology; Zhu et al., 2014, Geoscientific Model Development

Crop yield estimation by assimilating LAI into crop growth model

Wang et al., 2013, EMS; Wang et al., 2013, European Journal of Agronomy
Summary on catchment scale DAS

• A high-resolution, multivariate, and multi-source data assimilation system of the Heihe River Basin has been developed.
• Synthetic and true-data experiments have been conducted.
• Observational data and data products are plentiful but many of them have not been used yet.
• The objective is to improve the predictability and observability of watershed ecohydrology as well as operational usability such as irrigation scheduling and groundwater pumping.
5. Ongoing projects
Paleoclimate data assimilation--scheme description

1. Model Operator
   ---- Climate Model
   (1). GCM: CCSM4
   (2). EMIC: LOVELIME

2. Climate model simulations
   Run
   (2). Directly Assimilate
       (1). Indirectly Assimilate

3. Observation Data
   (1). Proxy-based reconstructions
e.g. Temperature reconstruction
   (2). Proxy Data
e.g. Tree-ring width, Ice Core

4. Observation Operator
   (1). Map Matrix
   (2). Forward model

5. Data Assimilation Algorithm
   e.g. Time-averaged EnSRF

6. DA-based Reconstructions of Past Climate

High Performance Computation Platform

Fang & Li, 2016, SCIENCE CHINA Earth Sciences
Temperature reanalysis over high-Asia through assimilating tree-ring widths chronologies

Data assimilation method: Time-averaged EnSRF
Observation: 61 tree-ring widths chronologies
Observation operator: VS-Lite, SLR, BLR
6. Summary

• Large scale and catchment scale DASs that truly assimilate various kinds of remote sensing observations have been developed.

• Integration
  • Multivariate, multi-source data assimilation
  • Eco-hydrology applications
  • Paleoclimate reconstruction
  • Historical LUCC reconstruction

• Next step efforts
  • System refinement and validation
  • Operational application in ecohydrological forecasting and water resource management
陆面数据同化培训与研讨会

第二届中科院陆面数据同化研讨会 2013.4.27, 北京

第三届陆面数据同化培训班

第三届中科院陆面数据同化研讨会 2014.10月，北京
The 7th International Workshop on Catchment Hydrological Modeling and Data Assimilation (CAHMDA-VII)

Aug 20-24, 2017, Xi’an, China

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Thank you!