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Impact of snow data assimilation on river discharge

Thanks:
Souhail Boussetta, Gabriele Arduini, Gianpaolo Balsamo and Patricia de Rosnay (ECMWF)

NWP in Portugal
IPMA, Lisbon, 26-27 November 2018

Overview

- Analysis using 2D Optimal interpolation (OI)
  - Application to snow depth
- Surface-only simulations with and without sequential assimilation
  - Impact on snow cover & river discharge
- Surface & assimilation related ideas for collaboration:
  - Near-surface & precipitation analysis;
  - Satellite Land-surface temperature ;

2D Optimal interpolation

Generic data assimilation

$$\mathbf{x}^{\mathrm{a}} = \boldsymbol{x}^{b} + \boldsymbol{W}[\boldsymbol{y}^{o} - \boldsymbol{H}(\boldsymbol{x}^{b})]$$

$\mathbf{x}^{\mathrm{a}}$ - analysis; $\mathbf{x}^{\mathrm{b}}$ -first guess; $\boldsymbol{W}$ – weights;
$\boldsymbol{y}^{o}$ - observations; $\boldsymbol{H}$ –observations operator

In the case of OI **W** is determined by minimizing the analysis errors at each grid-point (not a global cost function as 3DVAR).

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The optimal weights (**w**) are given for each point p :$(\boldsymbol{B}+\boldsymbol{R})\boldsymbol{w} = \boldsymbol{b}$

$\boldsymbol{b}$ **-** background error covariance between obs. and model (vector)

$$\sigma_b^2 \times \mu(i,p), \sigma_b \;\; = \boldsymbol{3cm}$$

$\boldsymbol{B}$ – background field errors between obs. (matrix):

$$\sigma_b^2 \times \mu(i,j), \sigma_b \;\; = \boldsymbol{3cm}$$

$\boldsymbol{R}$ – Covariance matrix of the observation errors : $\sigma_o^2 \boldsymbol{I}$, σ_o=**4 cm**

μ contains the horizontal and vertical structure functions (**empirical**)

$$\mu = \left(1 + \frac{\Delta L}{L_x}\right) \exp\left(-\frac{d}{L_x}\right) \exp\left(-\left(\frac{\Delta Z}{L_z}\right)^2\right)$$, L_x=55km , L_z=800 m

As used by ECMWF in the operational snow analysis.

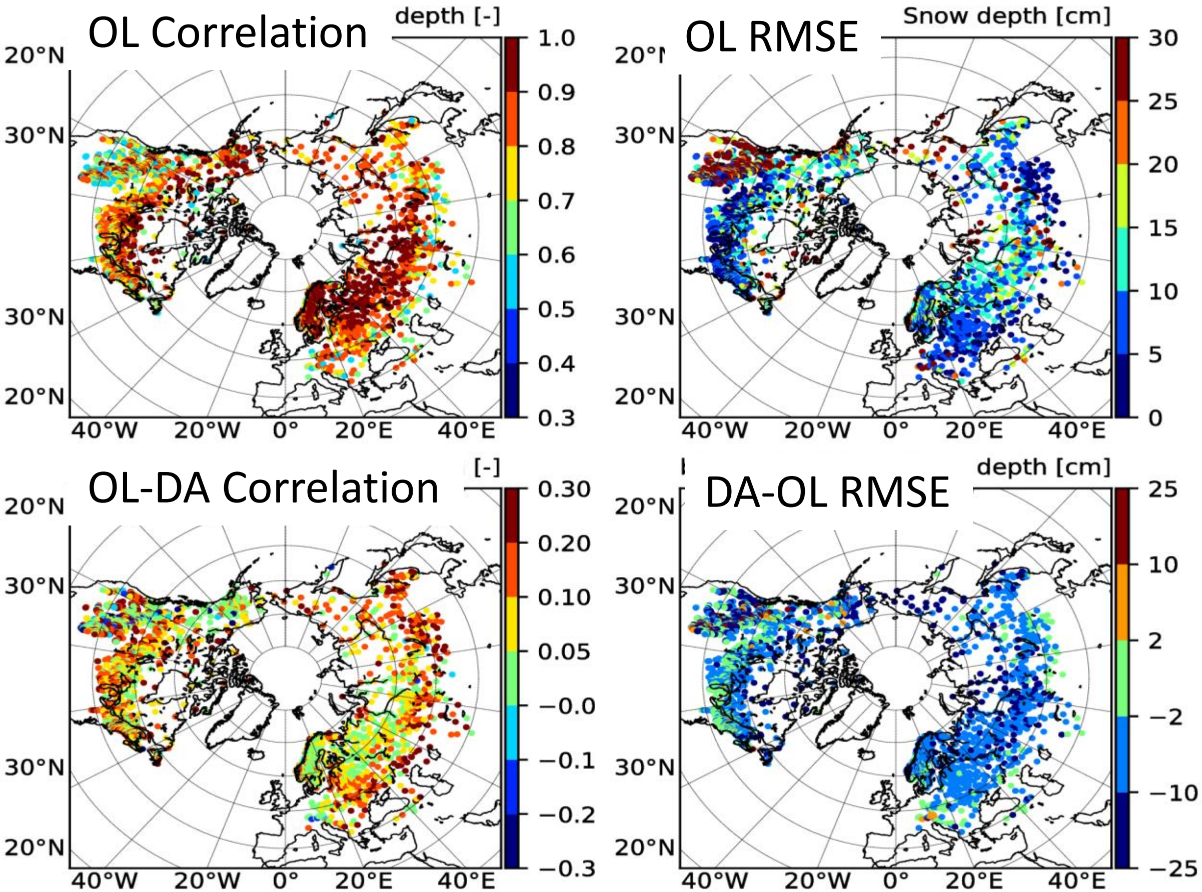
Surface simulations and data

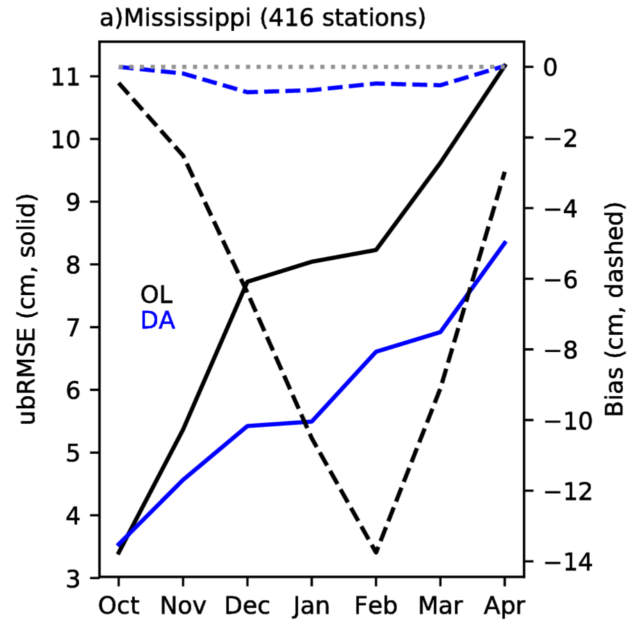
- Surface only (offline) simulations with the ECMWF land surface scheme **HTESSEL** and river routing with **CaMa-Flood**;
  - Driven by ERA-Interim + MSWEP (precipitation) for the period **2000-2013** globally at **0.25x0.25**

- Open loop simulation, i.e. no data assimilation (**OL**)
- Data assimilation (**DA)**
  - Sequential, 24h window, daily observations of **snow depth** from GHCN (no time-stamp), first guess and analysis at 00 UTC;

- Independent validation using satellite **snow cover** (IMS, 4 km) and **river discharge** from GRDC;

Snow depth validation





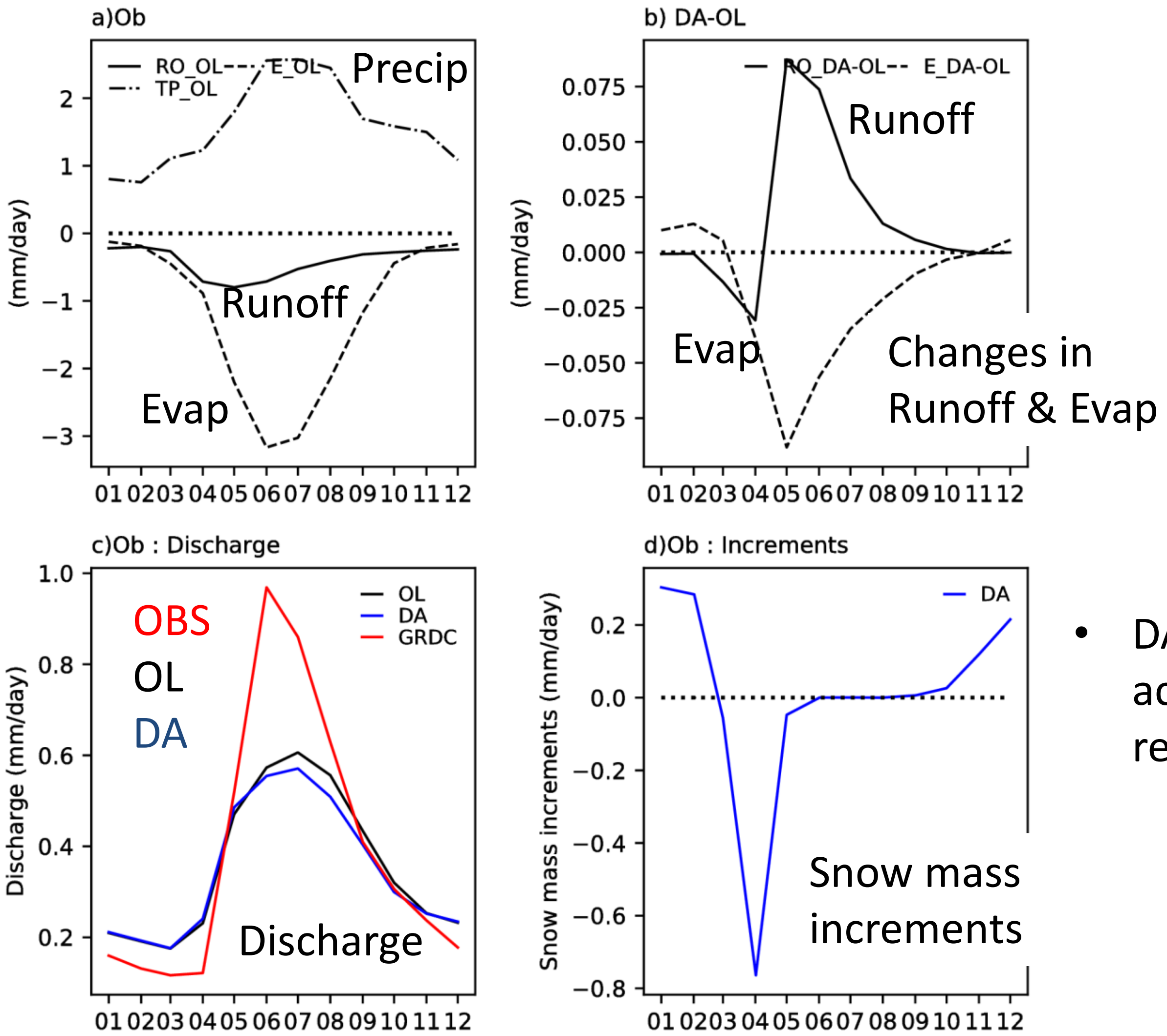
Clear improvement of snow depth with DA (expected !)

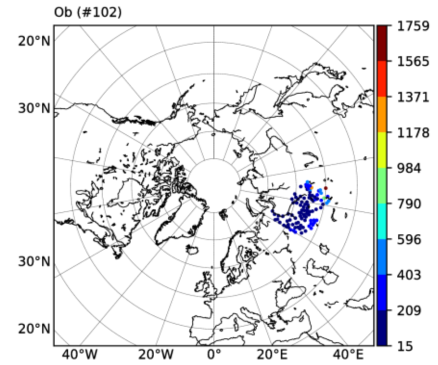
Snow cover & River discharge

	Discharge Correlation		Discharge Percent Bias		Snow cover Correlation	
Basin	OL	DA	OL	DA	OL	DA
Amur	0.85	0.77	-15	-22.6	0.66	0.71
Yenisey	0.87	0.85	-19.3	-26.4	0.57	0.62
Ob	0.92	0.92	-8.3	-10.9	0.65	0.72
Volga	0.67	0.73	-17.8	-13.4	0.57	0.64
Colorado	0.33	0.23	35.1	158.3	0.78	0.86
Columbia	0.8	0.82	20.2	48.8	0.7	0.75
Mackenzie	0.82	0.83	-15.1	-20.2	0.6	0.62
Yukon	0.81	0.78	-1.5	-8.9	0.51	0.6
Mississippi	0.82	0.78	-35.2	-31.8	0.75	0.82
Nelson	0.46	0.29	-44.6	-40.6	0.63	0.71
St Lawrence	0.51	0.53	-25.8	-21.5	0.71	0.76

- Improved snow cover (independent data);
- Mixed impact on river discharge, why ?

Water balance in the Ob basin





- DA adds snow in the accumulation period and removes snow in Spring
    - Late melting ?
    - Density errors?
    - The removed water is “gone” from the system;

Final Remarks

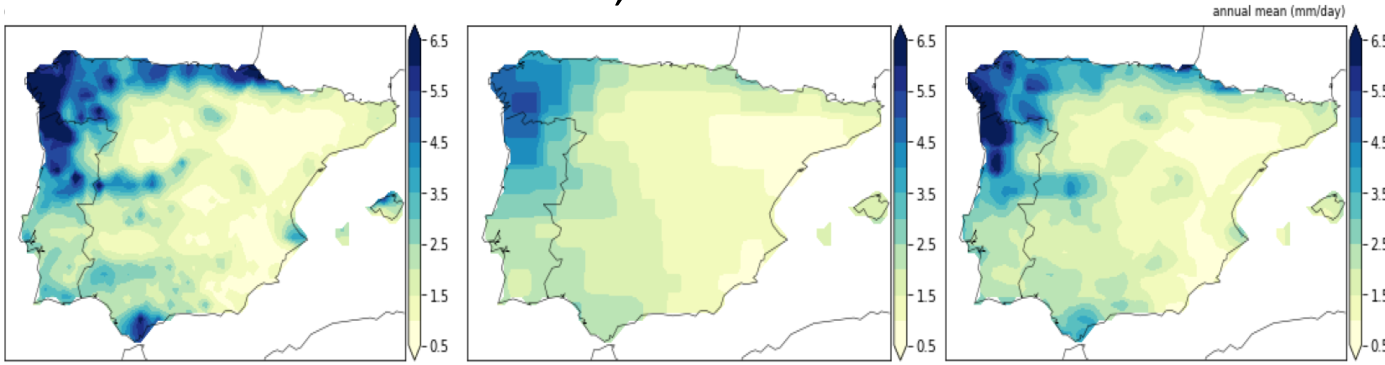
- 2D OI of in-situ snow depth clearly improved snow depth and cover – key variables for NWP;
- Water conservation is key element to guarantee consistence and added value of DA in downstream applications;
- 2D OI provides snow depth analysis : Model update could explore other methodologies, e.g. EKF enhance information propagation (e.g. via snow density and albedo);
- Surface-only land data assimilation is a very powerful tool; fast (2 days to simulate 10 years at 0.25x0.25); flexible integration of observations; development of components in python to quick proof of concept, etc.

- 2D OI is a very good methodology to merge in-situ surface observation with model background.
  - What about Precipitation ?
  - And satellite LST ?

Near-surface & precipitation analysis

Tiago Silva MOG project 2018

Guess which is ERA-Interim, ERA5 and Observations?



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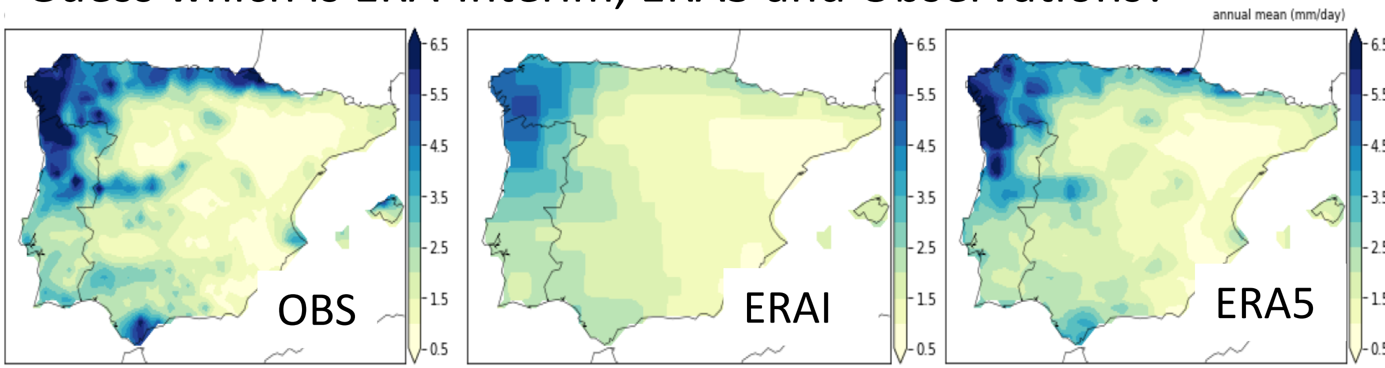

- 2D OI could be applied to merge the in-situ daily precipitation from rain-gauges with ERA5, providing a merged dataset (at any resolution), taking advantage of both model and observations:
  - Also provides an “automatic” quality control to station data
  - Long-term 1950- to real-time monitoring of precipitation
    - From climate studies to NWP LAM land initialization (e.g. as in MERRA2 – NASA reanalysis)
- Could be also applied to T2m and D2m (if there is + data then in synop as it was already included in ERA5).

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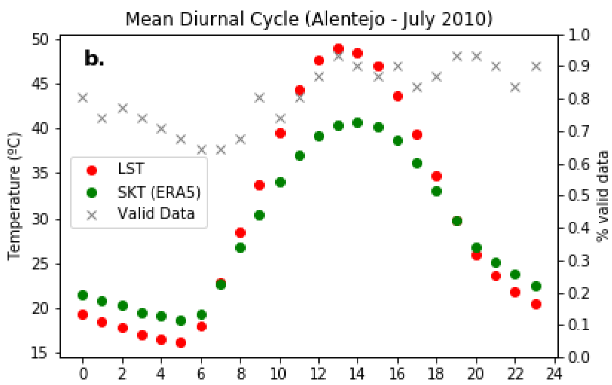
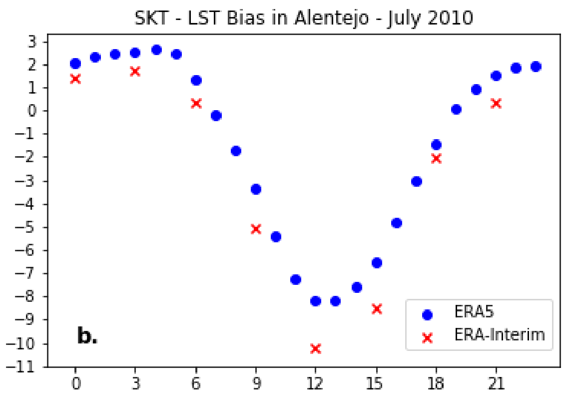
Land Surface Temperature

- LST is a crucial variable linking surface to the atmosphere (via turbulent exchanges & radiative transfer);
- Probably the best observed surface variable from satellite (resolution and temporal frequency);
- But not assimilated !





- Model is too far away from observations:
  - Need to understand why and if it can be improved;
- Instantaneous and local information challenging for data assimilation

Frederico's Poster. FCT funded project 2018-2021, collaboration with IPMA LandSAF (Isabel, João, Sofia)