Adaptive SM bias-correction

UKMO-ECMWF meeting, 5th June 2023

David Fairbairn, Patricia de Rosnay, Pete Weston

david.fairbairn@ecmwf.int

European Centre for Medium-Range Weather Forecasts

Background

ASCAT and SMOS bias-correction

- ASCAT and SMOS level 2 surface soil moisture (SM) observations assimilated in ECMWF SM analysis
- ASCAT level 2 SSM bias-correction (BC) based on seasonal CDF matching (Scipal et. al. 2008, De Rosnay et. al. 2013) - local (pointwise) BC
- SMOS neural network product trained on ECMWF soil moisture analysis (Rodriguez-Fernandez et. al. 2019) - implicit global BC
- Adaptive SM BC allows for spatial and temporal variability e.g. satellite changes, model upgrades

SEKF SM analysis

De Rosnay et. al. 2013

State update:

$$\mathbf{x}^a(t_i) = \mathbf{x}^b(t_i) + \mathbf{K}_i[\mathbf{y}^o(t_i) - H_i(\mathbf{x}^b)], \tag{1}$$

Bias-free Kalman gain:

$$\mathbf{K}_i = [\mathbf{B}^{-1} + \mathbf{H}_i^T\mathbf{R}^{-1}\mathbf{H}_i]^{-1}\mathbf{H}_i^T\mathbf{R}^{-1}, \tag{2}$$

The Jacobian linking the k^{th} observation to analysed soil moisture layer j:

$$\mathbf{H}_{k,j} = \frac{cov(H_k(\mathbf{x}^{eda}), \mathbf{x}_j^{eda})}{var(\mathbf{x}_j^{eda})}.c_j, \tag{3}$$

where $c_j = 1/(1 + (j-1).\alpha_{sekf})$ are empirical tapering coefficients ($\alpha_{sekf} = 0.6$)

Two-stage bias filter

Adapted from De Lannoy et. al. 2007 and Draper et. al. 2013

Biased observations ($\tilde{\mathbf{y}}^o$) partitioned into the analysed bias ($\mathbf{z}^a(t_i)$) and the non-biased term ($\mathbf{y}^o(t_i)$):

$$\tilde{\mathbf{y}}^o(t_i) = \mathbf{z}^a(t_i) + \mathbf{y}^o(t_i). \tag{4}$$

State update:

$$\mathbf{x}^a(t_i) = \mathbf{x}^b(t_i) + \mathbf{K}_i[\tilde{\mathbf{y}}^o(t_i) - \mathbf{z}^a(t_i) - H_i(\mathbf{x}^b)]. \tag{5}$$

The bias update is calculated as follows:

$$\mathbf{z}^a_l(t_i) = \mathbf{z}^b_l(t_i) + \mathbf{L}_{i,l}[\tilde{\mathbf{y}}^o_l(t_i) - \mathbf{z}^b_l - H_{i,l}(\mathbf{x}^b)], \tag{6}$$

where l is the observation type (ASCAT or SMOS NN)

Two-stage bias filter

Adapted from De Lannoy et. al. 2007 and Draper et. al. 2013

Bias state Kalman gain (in observation space):

$$\mathbf{L}_{i,l} = [\mathbf{B}^{\mathbf{z}}_l][\mathbf{R}_l + \mathbf{B}^{\mathbf{z}}_l + \mathbf{H}_{i,l}\mathbf{B}\mathbf{H}^T_{i,l}]^{-1}, \tag{7}$$

Bias covariance matrix $\mathbf{B}^{\mathbf{z}}_l$ assumed to be proportional to $\mathbf{B}$:

$$\mathbf{B}^{\mathbf{z}}_l = \frac{\gamma}{1-\gamma}\mathbf{H}_{i,l}\mathbf{B}\mathbf{H}^T_{i,l}, \tag{8}$$

with $\gamma = 0.25$ chosen for these experiments. Persistence model for bias forecast:

$$\mathbf{z}^b_l(t_{i+1}) = \mathbf{z}^a_l(t_i). \tag{9}$$

Experimental setup

Adaptive SM bias-correction

- Experiments performed with stand-alone surface analysis (SSA, Fairbairn et. al. 2019)

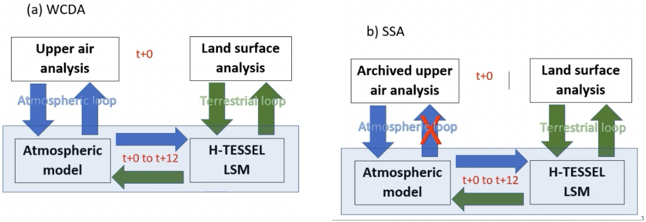


Figure: Weakly coupled (WCDA) setup (left) and SSA setup (right)

- Resolution Tco399 (25 km), period 2019-2022
- Experiment with adaptive BC for ASCAT and SMOS

Experimental results

Global mean ASCAT SM departures

- ASCAT-C introduced (green vertical), ASCAT-A retired (red vertical)

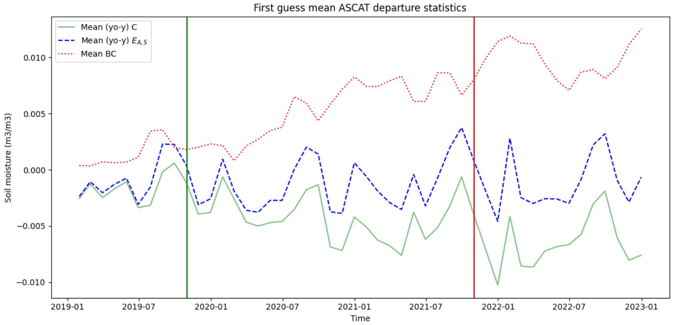


Figure: ASCAT SM departures with/without adaptive BC

Experimental results

Global ASCAT obs count

- ASCAT-C introduced (green vertical), ASCAT-A retired (red vertical)

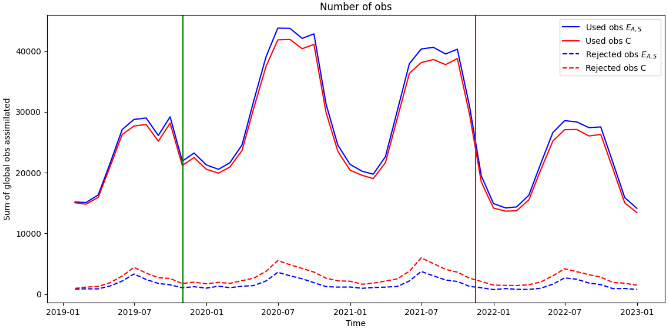
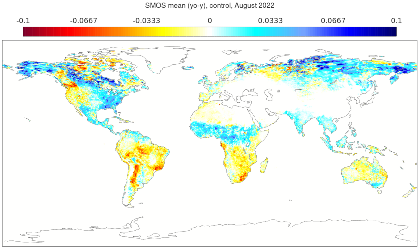


Figure: ASCAT SM obs count with/without adaptive BC

Experimental results

SMOS SM departures, global, August 2022



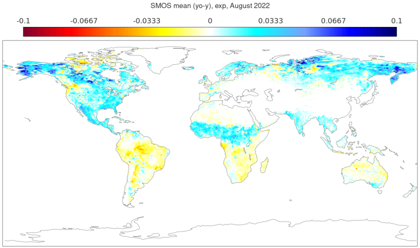


Figure: SMOS SM departures without (left) and with (right) adaptive BC

Experimental results

SMOS SM departures, lat/lon=25°S/140°E (Eastern Australia)

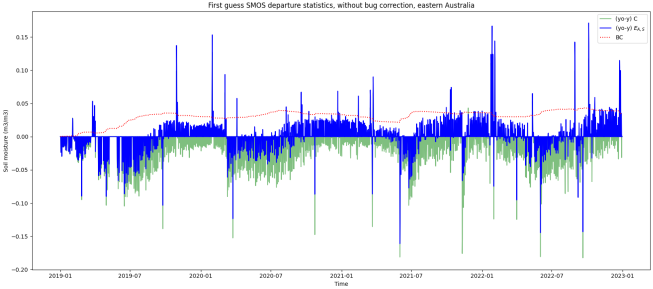


Figure: SMOS SM departures: control (green), experiment (blue) and bias correction (red dotted)

Summary

- Separate ASCAT and SMOS NN BC developed using two-stage bias filter
- Adaptive BC corrects biases introduced by Metop-ASCAT satellite changes
- Adaptive BC corrects some local biases in SMOS NN
- Adaptive BC leads to small forecast improvements in RH2m RMSE in the Tropics (see extra slides)

References

Dee, D., and R. Todling, 2000: Data assimilation in the presence of forecast bias: The geos moisture analysis. MWR, 128, 3268–3282, https://doi.org/10.1175/1520-0493(2000)128⟨3268: 452 DAITPO⟩2.0.CO;2.

De Rosnay, P., Drusch, M., Vasiljevic, D., Balsamo, G., Albergel, C. and Isaksen, L., 2013. A simplified Extended Kalman Filter for the global operational soil moisture analysis at ECMWF. Quarterly Journal of the Royal Meteorological Society, 139(674), pp.1199-1213.

Fairbairn, D. P. de Ronsay, and P. Browne, “The new stand-alone surface analysis at ECMWF: Implications for land-atmosphere DA coupling,” J. Hydrometeor, 2019. https://doi.org/10.1175/JHM-D-19-0074.1

De Lannoy, G., R. Reichle, P. Houser, V. Pauwels, and N. Verhoest, 2007: Correcting for forecast 443 bias in soil moisture assimilation with the ensemble kalman filter. Water Resour. Res., 43, W09 410, https://doi.org/10.1029/2006WR005449.

Draper, C., R. Reichle, G. D. Lannoy, and B. Scarino, 2015: A dynamic approach to addressing observation-minus-forecast bias in a land surface skin temperature data assimilation system. J. Hydrometeor., 16.

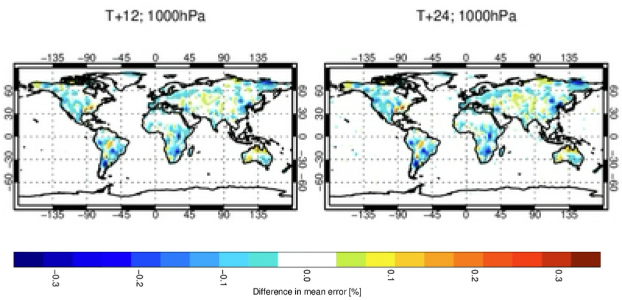
Rodrıguez-Fernandez, N., P. De Rosnay, C. Albergel, P. Richaume, F. Aires, C. Prigent, and Y.Kerr, 2019: SMOS Neural Network Soil Moisture Data Assimilation in a Land Surface Model and Atmospheric Impact. Remote Sensing, 11(11), 1334, https://doi.org/10.3390/rs11111334.

Scipal, K., M. Drusch, and W. Wagner, 2008: Assimilation of a ers scatterometer derived soil moisture index in the ecmwf numerical weather prediction system. Advances in water resources, 31(8), 1101–1112, https://doi.org/https://doi.org/10.1016/j.advwatres.2008.04.013.

Validation

Global mean RH forecast error

- Mean 1000 hPa RH forecast error in experiment vs control (validated against ECMWF operational analysis over 2022):



Validation

RMSE, Tropics

- RMSE averaged over the Tropics (validated against ECMWF operational analysis over 2022):

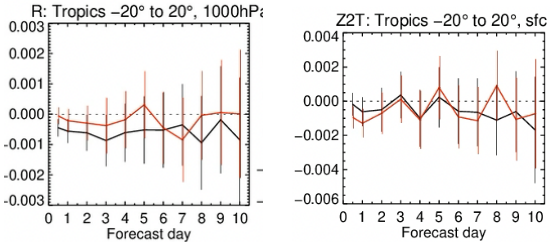


Figure: Relative RMSE (vs control) days 1-10, Black line=adaptive BC, left RH 1000hPa, right T2m.