Effective assimilation of SMAP observations using statistical techniques

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1. Introduction

Data assimilation (DA) can be used to merge high-quality SMAP observations with information from a dynamic land surface model. This generates higher resolution estimates of the full soil moisture (SM) profile with complete spatio-temporal coverage and often with a higher skill than that of the model or observations alone.

One key assumption of most DA systems is that the observations are unbiased with respect to the model, which is typically addressed through ***a localized bias correction*** (e.g. CDF-matching).

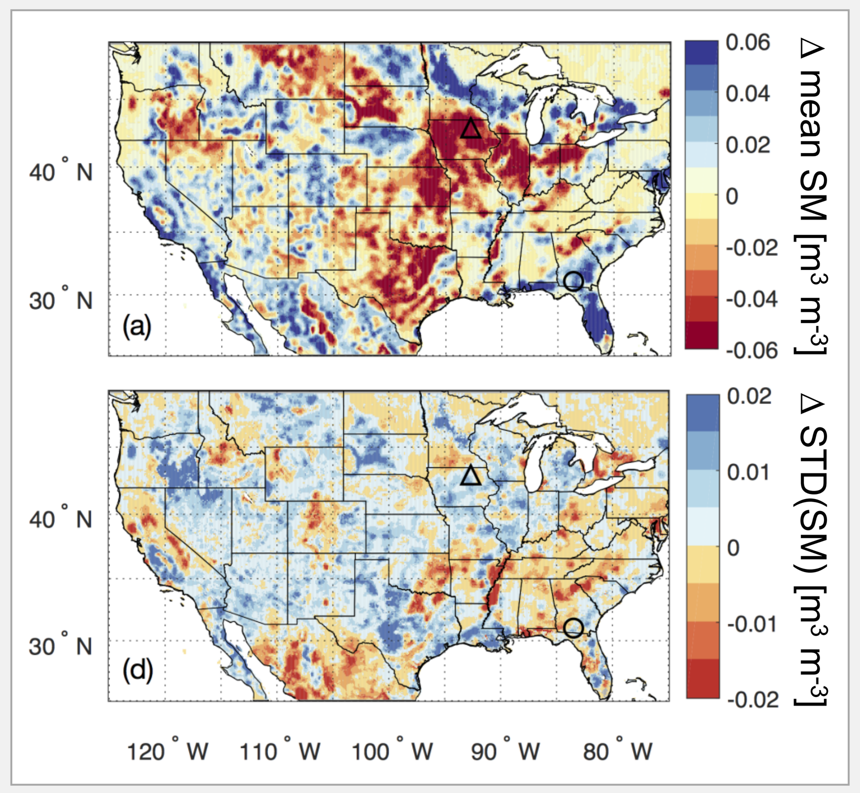

Figure 1: Effect of localized bias correction on soil moisture retrievals.

While this satisfies the DA system requirements, it ***alters the spatial and temporal patterns of the observation mean and variability*** (Figure 1), thereby removing some of the independent information provided by the SMAP observations.

This means that the SMAP observations are not used effectively to inform the model

Here we compare different bias correction methods to determine how the independent SMAP information can be used more effectively.

2. Methodology

Four assimilation experiments with a different bias correction approach were performed:

DA-NN : A Neural Network is used to retrieve SMAP based soil moisture estimates that match the global climatology of the Catchment land surface model [1]. These retrievals are assimilated without further bias correction.

DA-NN-CDF : The SMAP NN soil moisture retrievals are assimilated after applying a 'standard' localized bias correction (local CDF-matching).

DA-L2P-gCDF : The SMAP Level-2 Passive (L2P) soil moisture retrievals are assimilated after applying a global bias correction (global CDF-matching).

DA-L4 : The SMAP Level-4 (L4) soil moisture estimates [2] are generated by assimilating locally rescaled brightness temperatures (Tbs).

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3. Results

3.1 Impact on Soil Moisture Statistics

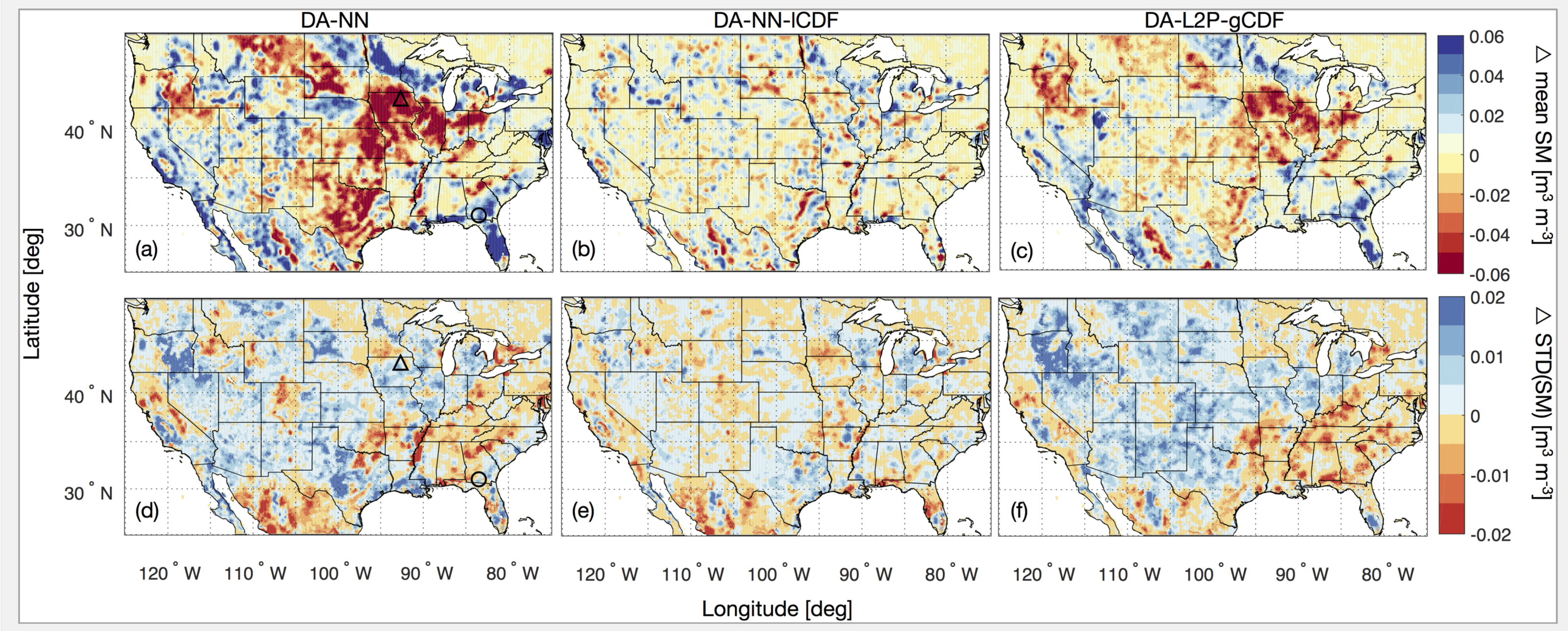

Figure 2: Difference in modeled soil moisture mean and standard deviation between assimilation estimates and model-only simulation. Red colors indicate a drying and decreased variability resulting from the SMAP assimilation.

- Global bias correction introduces SMAP mean spatial and temporal patterns; local bias correction does not.
- Patterns agree across different retrieval products.
- Largest changes occur in predominantly agricultural areas.

3.2 Skill against Ground Observations

Figure 3: Change in correlation, absolute bias and ubRMSE against in situ measurements from the core validation sites for the surface and root zone layer.

- Global bias correction yields larger model skill improvements where SMAP observations are reliable (e.g., SJ site)[3].
- Also leads to larger adverse effects where observations are unreliable (e.g., bias at SF1 site).
- Both global bias correction approaches yield similar skill improvements.
- Soil moisture and Tb assimilation yield similar average skill, but with local differences.

3.3 Impact on Evaporation and Runoff

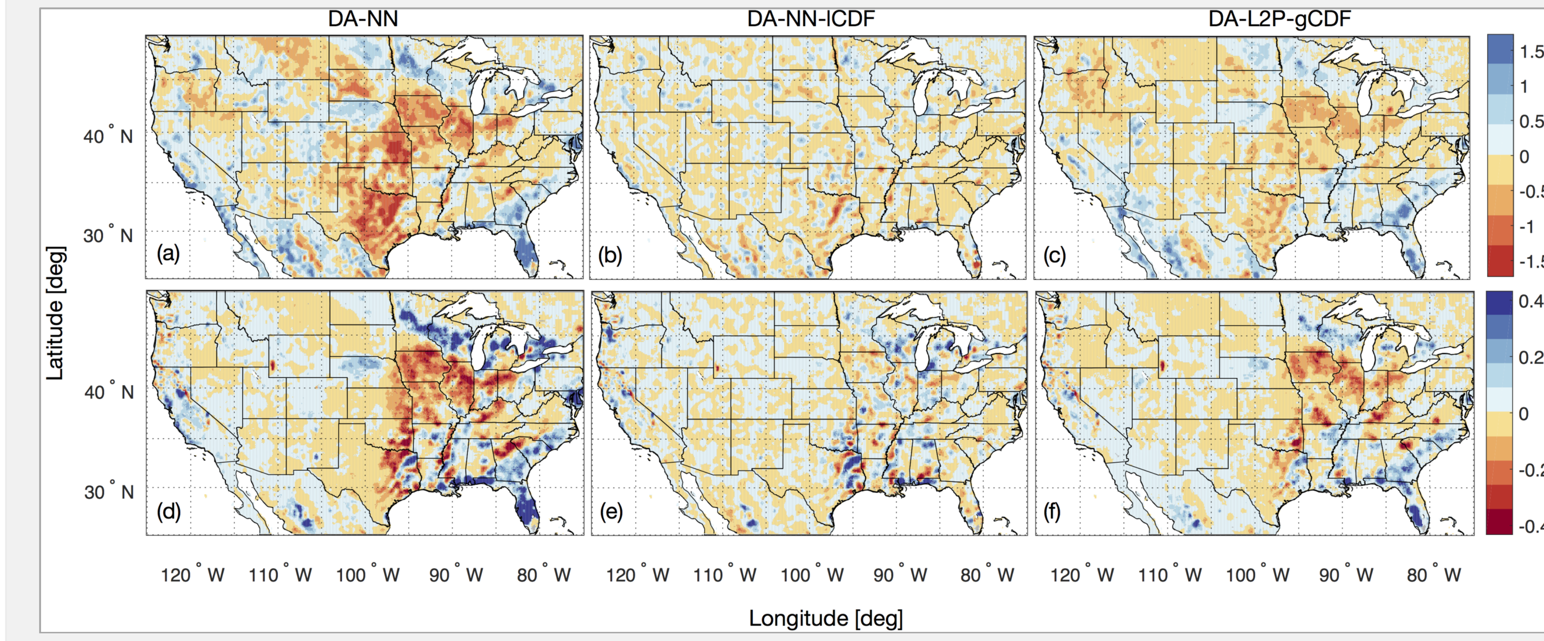

Figure 4: Difference in modeled evaporation and runoff between assimilation estimates and model-only simulation. Red colors indicate a reduction in evaporation and runoff.

- Spatial patterns of changes primarily driven by changes in mean soil moisture.
- Magnitude of changes may be unrealistic.
- Global bias correction should be used in combination with re-evaluation soil moisture – evaporation/runoff connection.

4. Conclusions

- Global bias correction retains more independent satellite information
  (1) Larger SM skill improvements where retrievals are good
  (2) More vulnerable to uncertain SM information
- To successfully use global bias correction method, reliable satellite information needs to be better isolated
  (1) Strict quality control
  (2) More accurate observation error estimates
  (3)Component-wise SM assimilation [4]
- SM and Tb assimilation yield similar average skill, but with local differences
- SM skill improvements with global bias correction do not readily translate to improvements in other land surface variables

References

[1] Kolassa, J., Reichle, R.H., Liu, Q., Alemohammad, S.H., Gentine, P. , et al. (2017a), Estimating surface soil moisture from SMAP observations using a Neural Network technique, *Remote Sensing of Environment* (in press)
[2] Reichle, R., G. De Lannoy, Q. Liu, J.V. Ardizzone, A. Colliander et al. (2017). Assessment of the SMAP Level-4 Surface and Root-Zone Soil Moisture Product using in situ measurements. *Journal of Hydrometeorology*. 18, pp.2621-2645.
[3] Kolassa, J., Reichle, R.H., Liu, Q., et al. (2017b), Data assimilation to extract soil moisture information from SMAP observations, *Remote Sensing* 9 (11), 1179
[4] Draper, C. and Reichle, R.H., (2015).The impact of near-surface soil moisture assimilation at subseasonal, seasonal, and inter-annual timescales. *Hydrology and Earth System Sciences*, 19(12), p.4831.

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