Forward modeling with NoahMP within a data assimilation framework

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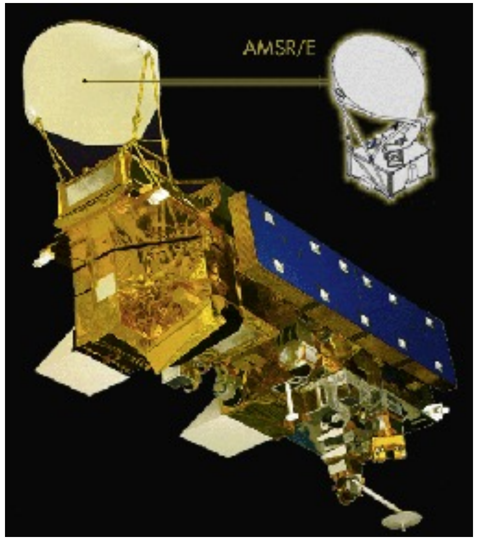
Data Assimilation

Observation



(Image: © NASA)

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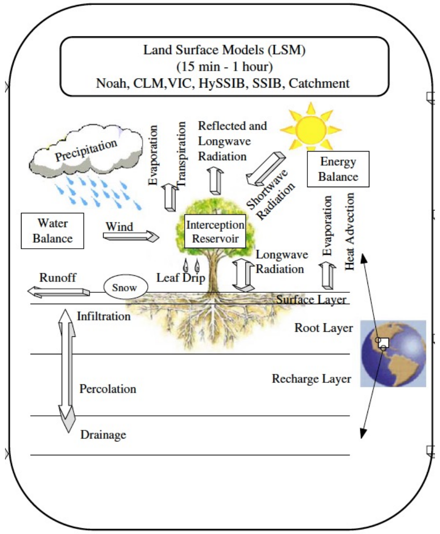
Model



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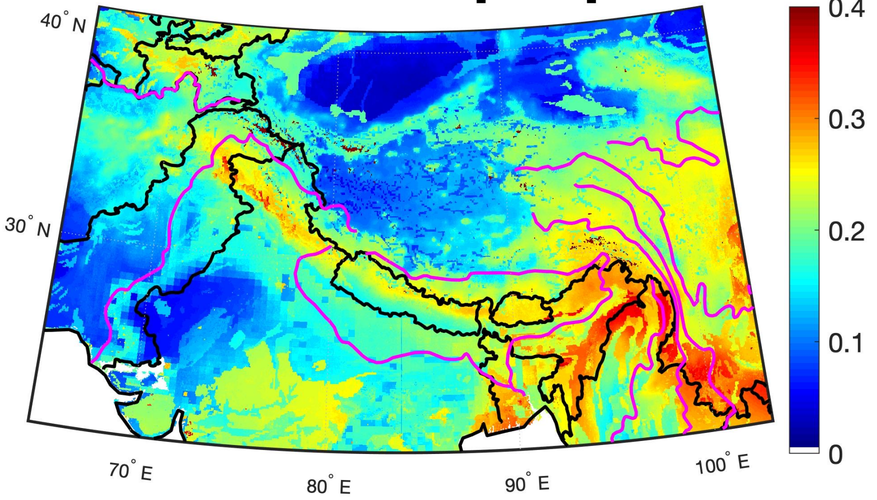
DA Soil Moisture [m^3/m^3]



Optimal estimates
(error ↓ ; accuracy ↑)

NASA Land Information System (LIS)

Software framework for high performance land surface modeling and data assimilation developed by NASA

→

Ensemble Kalman Filter (EnKF)

Data Assimilation

EnKF

ΔT_b assimilation

Results

Soil Moisture assimilation

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Conclusions

Future work

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May 2023

Data Assimilation- Ensemble Kalman Filter (EnKF)

Requirements: forward model, observation operator, and error characteristics of the modeled and observed states

Two main steps:
1) State propagation (using the forward model)
2) State update

$$\underbrace{y_{i,t}^{+}}_{\text{a-posteriori state}} = \underbrace{y_{i,t}^{-}}_{\text{a-priori state}} + \underbrace{K_t}_{\text{Kalman gain}} \underbrace{\left[\underbrace{z_{\Delta Tb} + v_{\Delta Tb}}_{\text{observation + error}} - \underbrace{\mathcal{H}\left(y_{i,t}^{-}\right)}_{\text{predicted observation}} \right]}_{\text{innovation}}$$

Error Covariance

Uncertainty and error is represented via error covariance matrices for both modeled estimates and observations

Assumptions of EnKF

1) unbiased, linear forward model
2) unbiased, linear observation operator
3) jointly Gaussian and mutually independent observation and model errors
4) spatiotemporally uncorrelated errors

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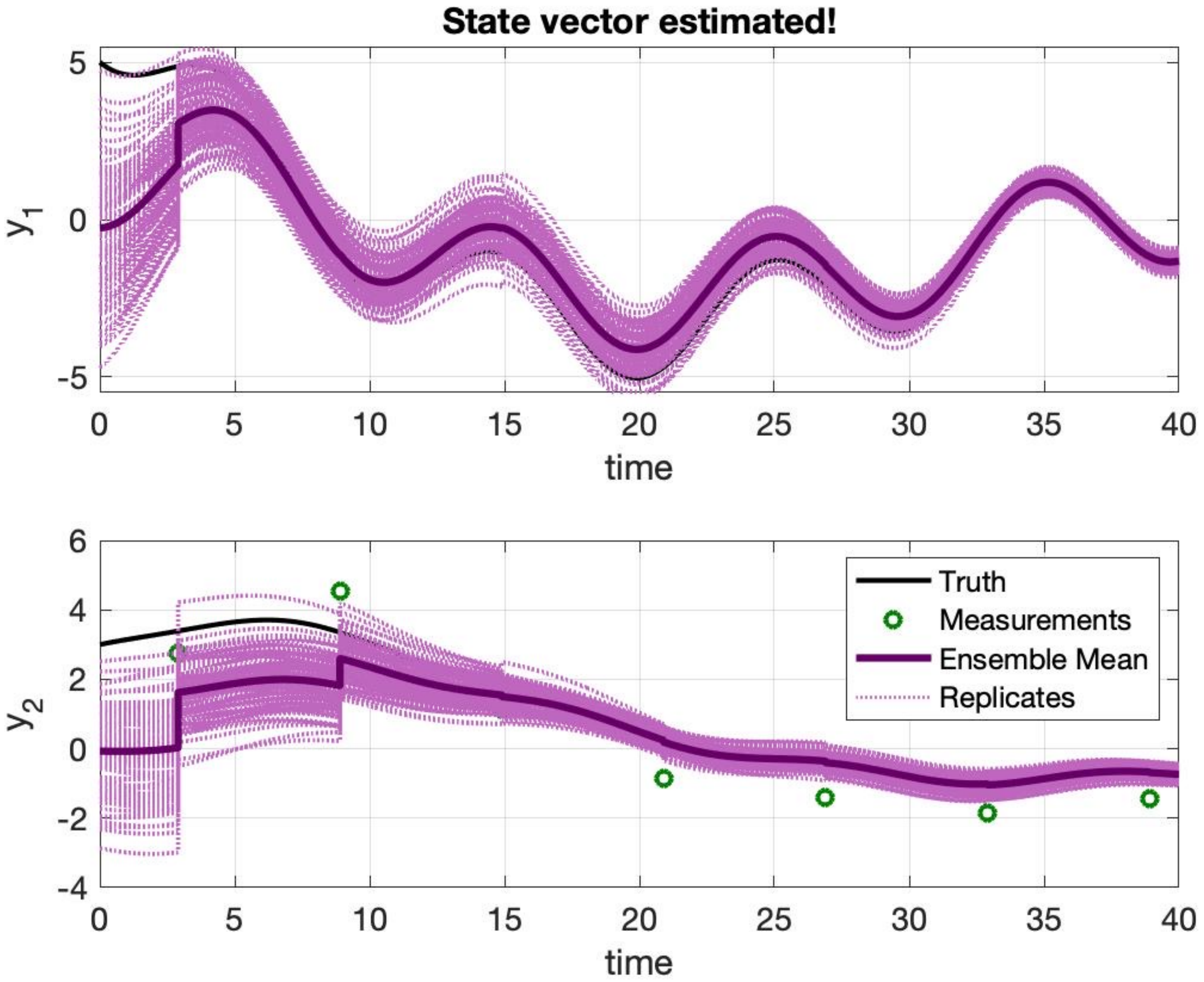
Data Assimilation- Ensemble Kalman Filter (EnKF)

- State vector = y_1 and y_2
- y_1 and y_2 are two correlated random variables
- Error covariance is non-zero
- Initializing y_1 and $y_2 = 0$
- Generate ensembles for y_1 and y_2
- Propagate ensembles using forward model



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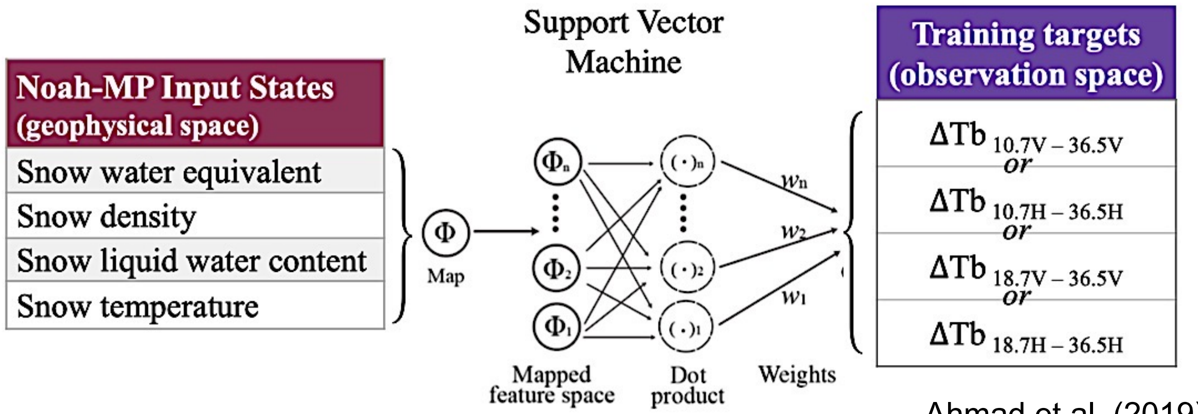
Snow mass (SWE) estimation via assimilation of PMW ΔTb

Assimilation framework

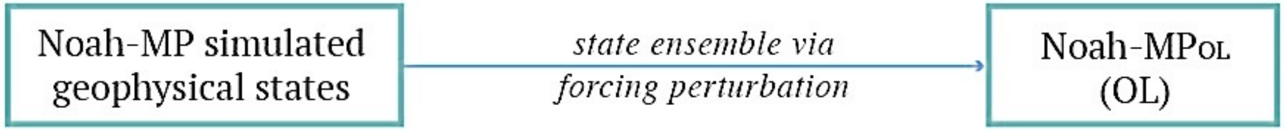
1-D assimilation	20 replicate ensemble
Land surface model	Noah-MP (ver. 3.6)
Boundary conditions	MERRA2
Observations	Advanced Microwave Scanning Radiometer-2 ΔTb
Non-linear observation operator	Support Vector Machine regression
Open Loop (OL)	model-only simulation run
Data assimilation (DA) runs	standard, data-thinning, seasonal
Grid size	0.25° x 0.25° (~25km x 25.5km)

Step-1: Support Vector Machine Regression (Training & Prediction)

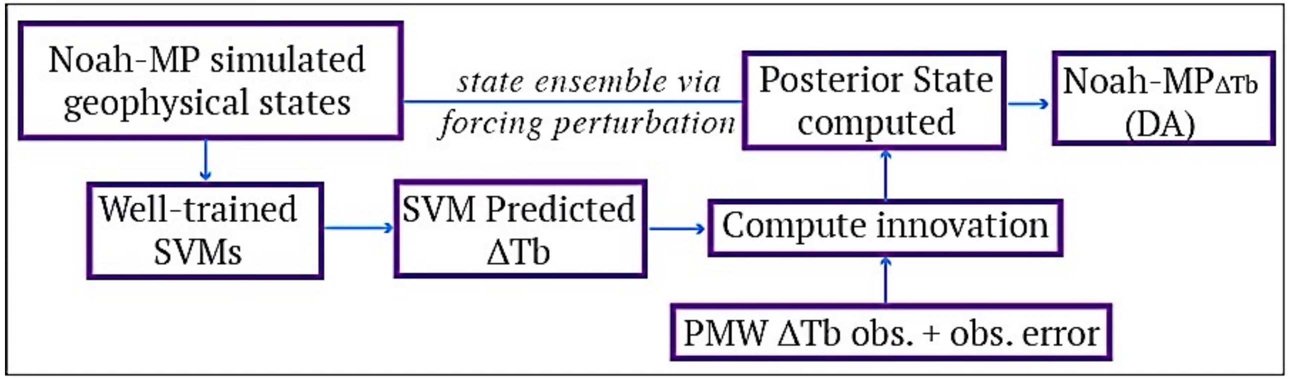


Ahmad et al. (2019)

Step-2 : Noah-MP Open Loop (OL)



Step-3 : Noah-MP Data Assimilation (ΔT_b assimilation)



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Snow mass (SWE) estimation via assimilation of PMW ΔTb

Salient findings:

- ΔTb assimilation improved:

  Bias at 71% and RMSE at 66% of locations with in-situ measurements
- Assimilation performance generally degraded during wet snow conditions
- Increased uncertainty in state ensemble after assimilation
- Ensemble mean after assimilation more consistent with evaluation dataset

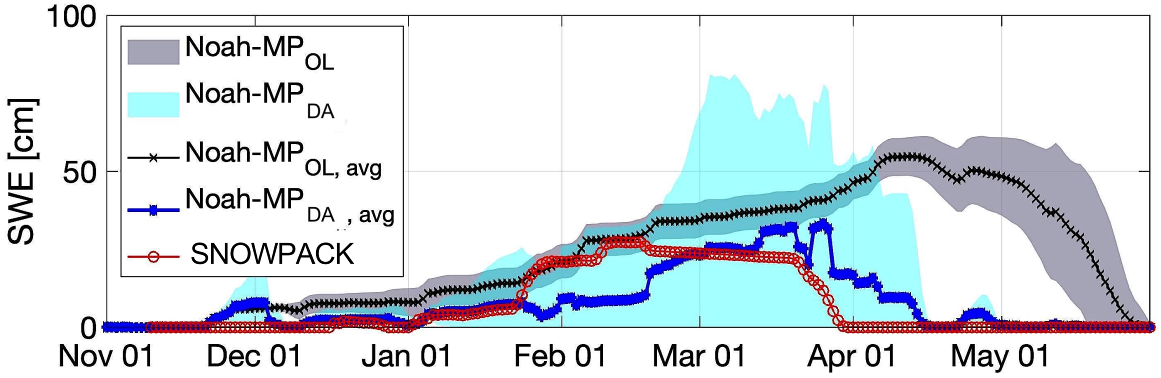


*Figure: Timeseries of Noah-MP$_{OL}$ and Noah-MP$_{DA}$ SWE estimates (standard assimilation) vs. SNOWPACK (AKAH snow depth-based) SWE for the 2016-2017 snow season. Shaded regions represent ensemble mean ±2*std (rejection probability= 95%).*

Limitation:

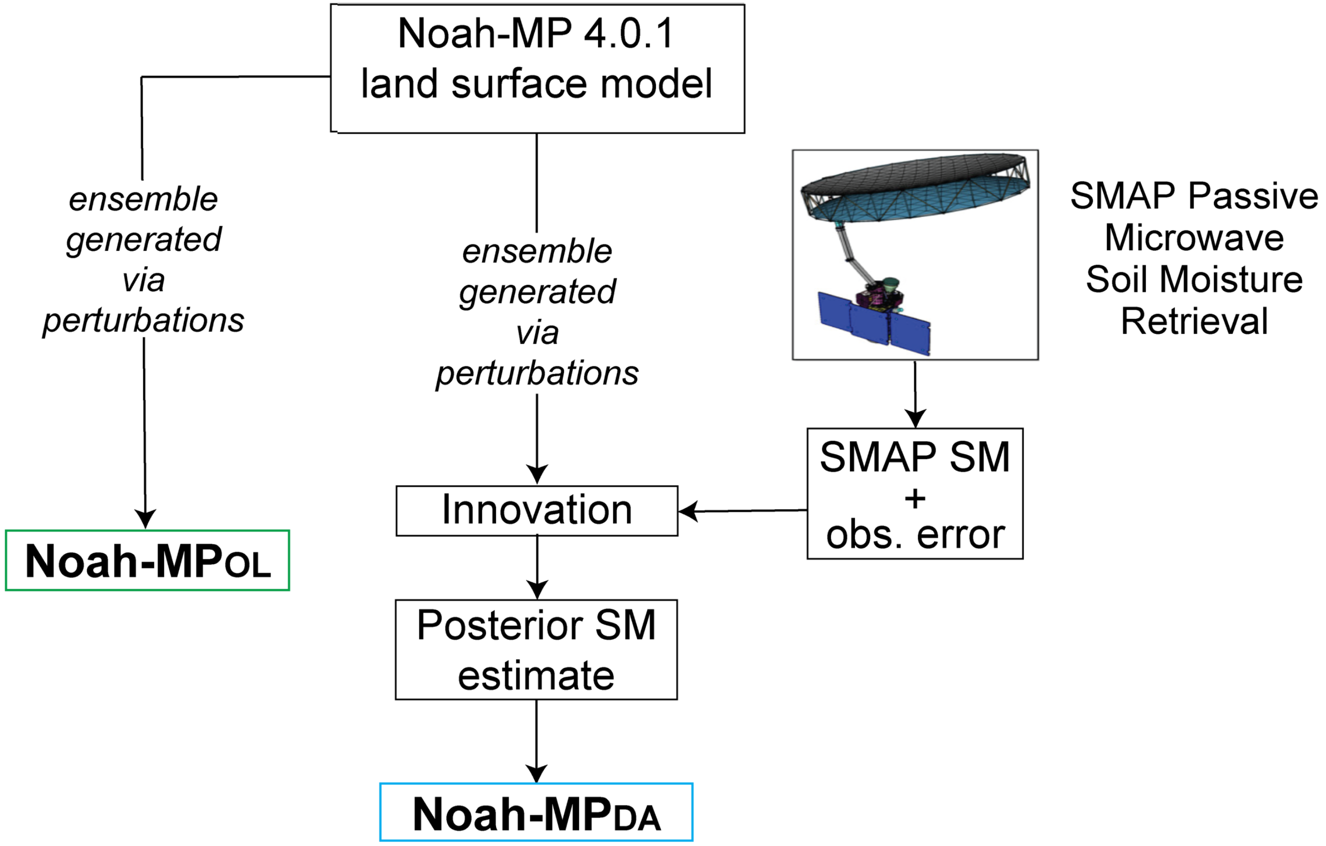
During snow ablation season, PMW brightness temperature signal contained relatively higher information not related to snow mass

Ahmad, J.A., Forman, B.A., Bair, E., and Kumar, S.V., 2021. Passive microwave brightness temperature assimilation to improve snow mass estimation across complex terrain in Pakistan, Afghanistan, and Tajikistan. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, pp.8849-8863, doi: 10.1109/JSTARS.2021.3102965.

Soil moisture (SM) estimation via assimilation of SM retrievals

Assimilation framework

1-D assimilation	20 replicate ensemble
Land surface model	Noah-MP (ver. 4.0.1)
Boundary conditions	MERRA2 / IMERG
Observations	Soil Moisture Active Passive (SMAP) SM retrieval
Open Loop (OL)	model-only simulation
Data assimilation (DA) run	CDF matching No CDF matching
Grid size	0.05^o x 0.05^o (~5km x 5.1km)
Study period	2015-2020



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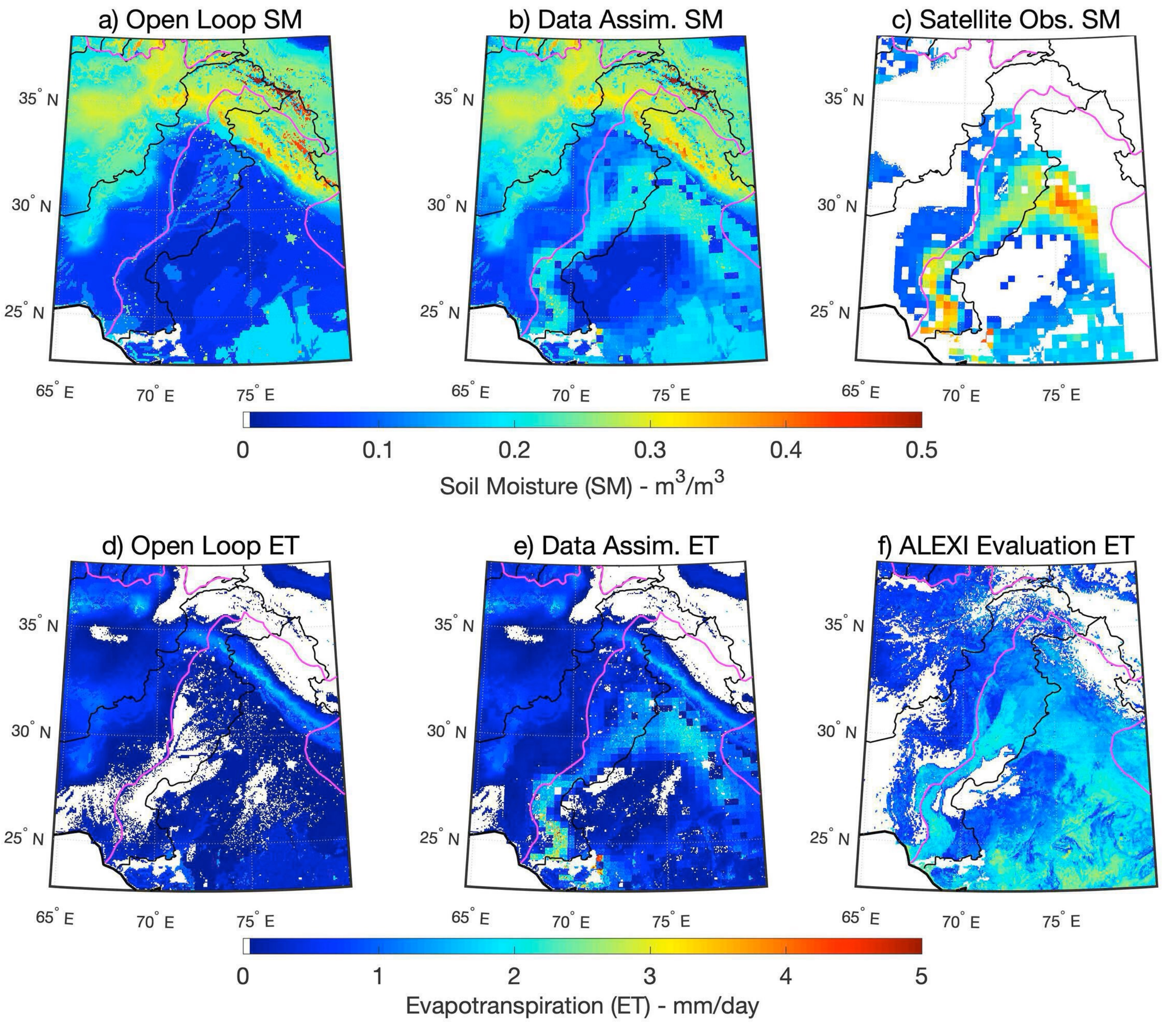
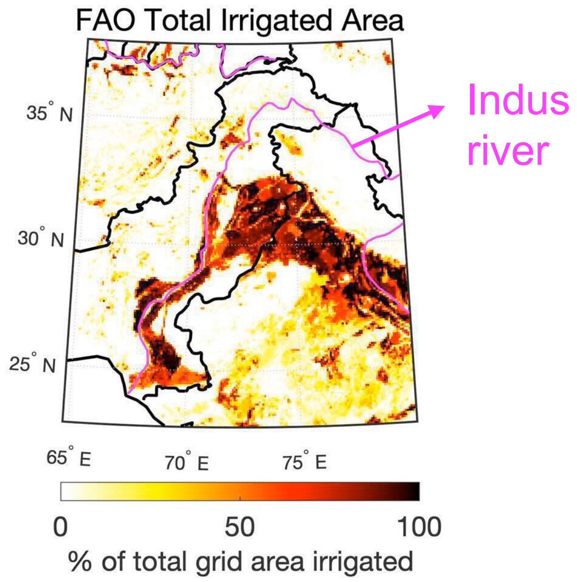
Soil moisture (SM) estimation via assimilation of SM retrievals



01-Jan-2016

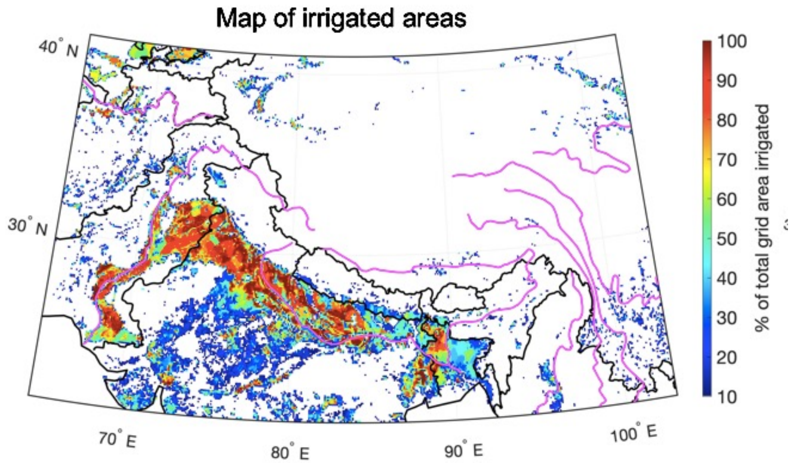
- major rivers
- country borders

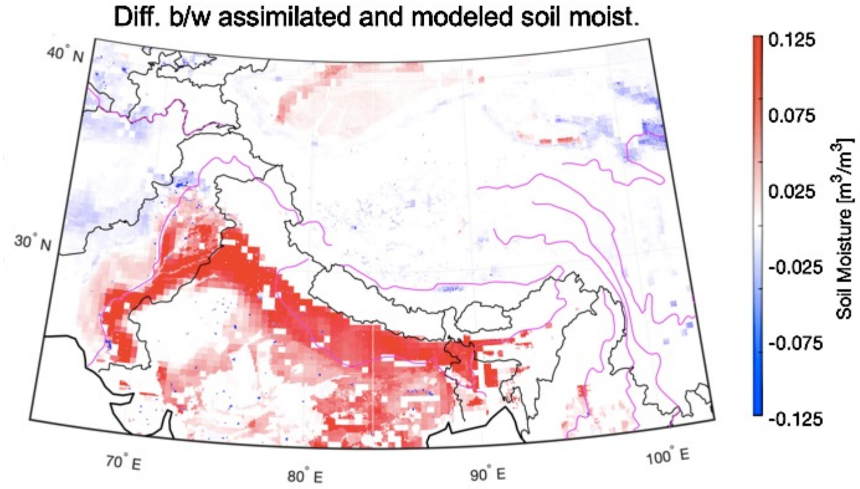


Soil moisture (SM) estimation via assimilation of SM retrievals

Salient findings:

- Evaluation with in-situ meas. across Tibetan Plateau
  Mean bias reduced by 8.4%
  RMSE reduced by 9.4%
  Assimilation occurred during <10% of the total period
- Biases due to unmodeled hydrologic phenomenon (i.e., irrigation) were corrected through assimilation
- Evapotranspiration visibly improved across irrigated areas





Limitation:

Improvements in water cycle did not translate into significantly improved vegetation estimation (carbon cycle)

Ahmad, J.A., Forman, B.A. and Kumar, S.V., 2022. Soil moisture estimation in South Asia via assimilation of SMAP retrievals. Hydrology and Earth System Sciences, 26(8), pp.2221-2243, doi: 10.5194/hess-26-2221-2022.

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Snow mass:

- passive microwave radiation exhibited potential in improving snow mass estimation across complex terrain during snow accumulation season
- difficult to extract snow mass-relevant information during ablation season

Soil moisture:

- assimilation improved soil moisture estimation across croplands by correcting biases due to irrigation
- snow/ice-covered and frozen areas unaffected by soil moisture assimilation

Limitations

- Useful for state specific applications only
- Water budget issues

Funded by the NASA High Mountain Asia Team 2016 and 2018

Future directions

- State specific approach for balancing the water cycle
- Spatial distribution of water across irrigated areas
- Quantification of irrigation using an inverse method?
- Flood mapping using an assimilation framework
- Improvements in land surface model physics