Terrestrial water storage reconstruction: A Causal Inference approach

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Abstract

This presentation participates in OSPP — Outstanding Student & PhD candidate Presentation contest

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1. What is Terrestrial water storage?

$$R + ET + \Delta S = P \quad (1)$$

- Monitoring TWS allows understanding the changes in Earth's Terrestrial water cycle.
- These changes are driven by
  a) Natural climate variability,
  b) Climate change,
  c) Local human activities such as groundwater pumping for irrigation.

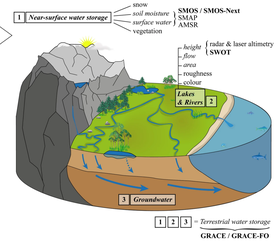


Fig 1: Water storage compartments, Lopez et al., 2020

2. Why Reconstruct?

- Consider inter-annual TWS anomalies in Indus in Death Valley catchment. A similar negative trend is seen in the observation (GRACE) period.
- However with historical record, it is clear that trend in Death Valley is natural variability.
- Such analysis is only possible with longer time series of TWS. Hence a reconstruction of TWS in past is necessary.

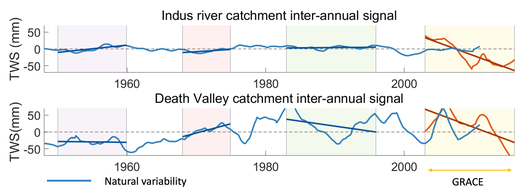
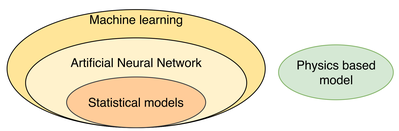


Fig 2: Inter-annual TWS anomalies, Vishwakarma et al., 2020

3. Existing reconstructions



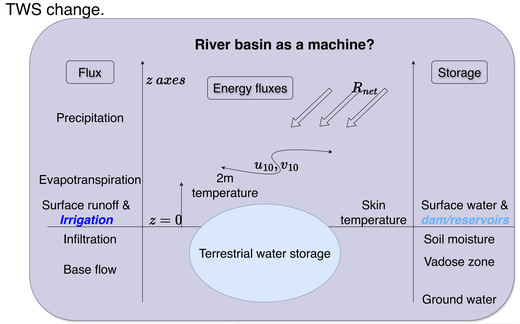
Authors	Predictors	Target	Algorithm
Becker et al., 2011	In situ river discharge	$TWSA$	EOF
Long et al., 2014.	P, T, SM	$TWSA$	MLP
Senviratne et al., 2017	-	$TWSA$	GCM
Humphrey et al., 2017 & Humphrey et al., 2019	P, T	Interannual $TWSA$	MVR
Sun et al., 2019	$P, T, SM, TWSA$	$TWSA$	CNN
Ahmed et al., 2019	$P, T, ET, NDVI$	$TWSA$	ARX
Li et al., 2020	P, T, SST, Climate indices	Trend, interannual & residual $TWSA$	MVR, MLP, ARX
Sun et al., 2020	P, T, model-$TWSA$	$TWSA$	ANN, SARIMAX, MLR
Forootan et al., 2020	Swarm satellite data	$TWSA$	ICA, MVR
Jing et al., 2020	$CLSM, TWSA$	$TWSA$	RF, XGBoost
T Feng et al., 2023	$P, T, LULC, GDP$, Population	$TWSA$	Hyd model+ANN
Yin et al., 2023	$P, T, LAI, R, LULC$	$TWSA$	ANN, MARS, RF, GLM, GAM

4. Limitations of existing approaches

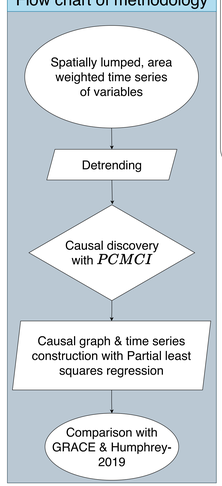
- Machine learning methods are sensitive to training data, this is extremely pertinent to TWS due to its short time series (230+ data points).
- ML methods lack explainability.
- ML methods exploiting correlation based methods fail to identify causal drivers of TWS change.
- Physics based and emprical model have bias, underestimate TWS due to uncertainty in forcing and approximate process representation.

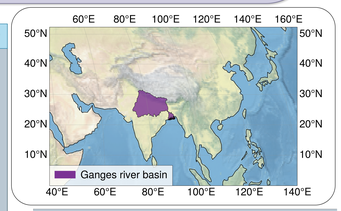
5. Our approach

- We use a causal framework to identify cause-effect relationship in the Ganges basin.
- We assume the basin to behave as machine which allows us to consider the elements of water budget (1) as possible drivers of TWS change.



Flow chart of methodology





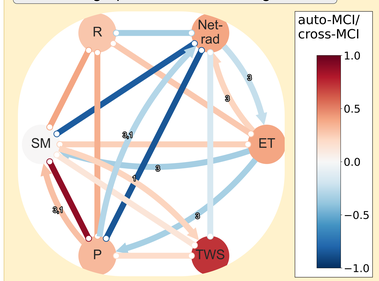
Datasets used

	Variable	Product
Hydrometeorological variables	Precipitation	MSWEP
	Net downward radiation	ERA5-reanalysis
	Soil moisture	ESA-CCI
	Evapotranspiration	GLEAM
	Runoff	Colorado flood observatory
	Terrestrial water storage	CSR-MASCONS
Climate indices	Nino34	NOAA Physical Sciences Laboratory
	NAO	
	IOD	
	PDO	

6. Results

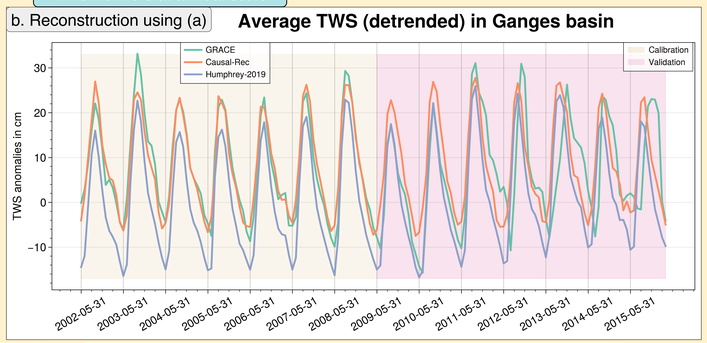
at 95% confidence level; all links identified using Partial correlation as conditional test.

a. Causal graph for TWSA in Ganges basin



TWSA drivers at annual scale

b. Reconstruction using (a)



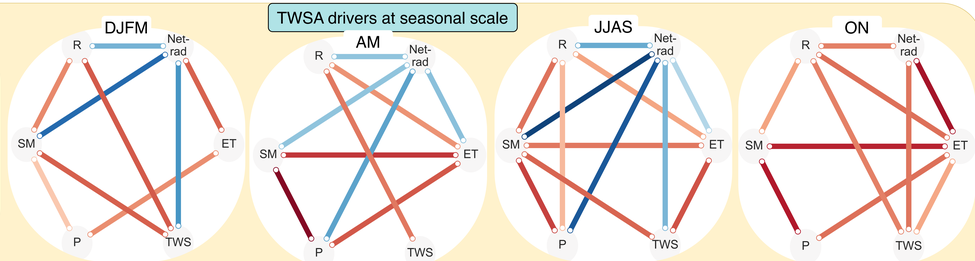
$$TWSA_t = f(P_t, Netrad_t, SM_t, SM_{t-1})$$

$f(.)$ is a linear model estimated using partial least squares regression.

RMSE	NRMSE	NSE	KGE	R^2
10.51	0.91	0.16	-1.67	0.46
9.32	0.81	0.34	0.61	0.43

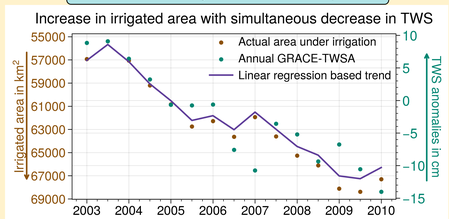
TWSA drivers at seasonal scale

- High contrast in network of seasons compared to (a).
- Interestingly there is no link between TWS and P

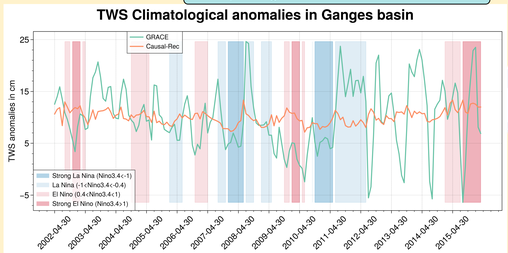


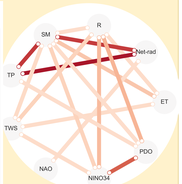
7. Challenges & future work

a. Non-stationarity in data: TWS depletion



b. Exploring inter-annual drivers of TWS





Above network discovered using GPDC as conditional test at 95% confidence level

8. Conclusion

- TWS estimation: Causal drivers are crucial for accuracy.
- Dominant driver: Soil moisture (inter-annual and detrend time scales).
- Underrepresented area: Human influences (e.g., irrigation & ground water extraction) on TWS depletion.
- Inter-annual TWS drivers: Further analysis is requried.

9. Acknowledgements & References

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