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Prediction of Hydrological Drought Patterns in Data Scarce Regions using Catchments' Physio-Climatic Attributes

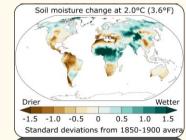
Theme: Climate Change | TS-F1 Parallel Session - F1.6 21st December 2023, 11:30 AM to 01:30 PM (Venue: SH-6)

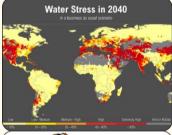


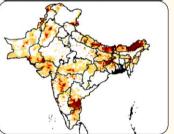
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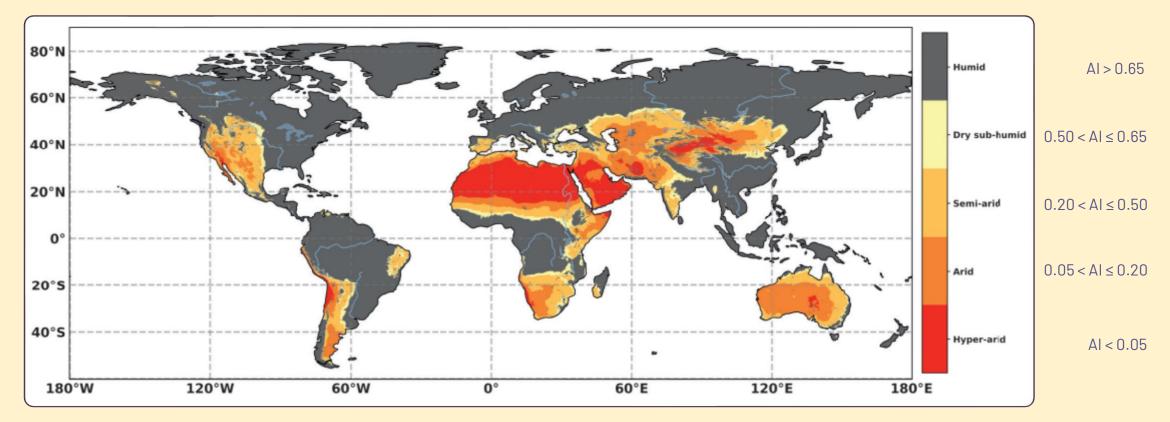








Drought: drier than normal conditions¹



Geographical distribution of drylands, delimited based on the aridity index (AI) 2 .

Past droughts (western United States, southeast Australia and northeast China, Russia, and the central United States), hint that climate change may be a forcing factor, and this is only likely to get worse with time.

Reliable projections of streamflow are challenging due to climate change

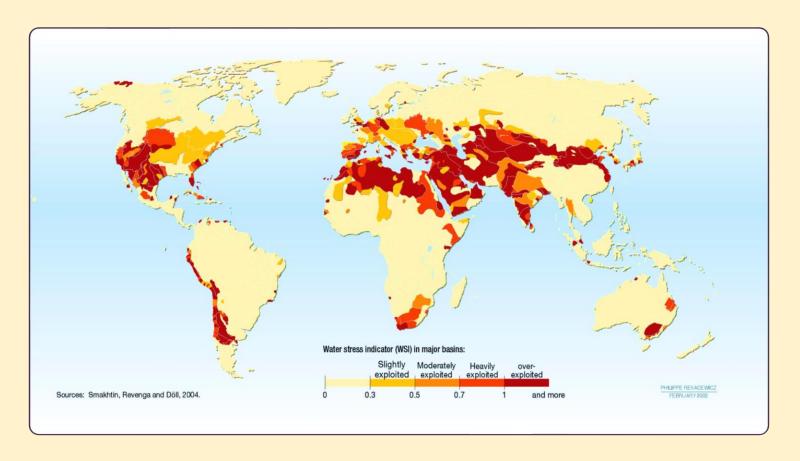


Figure: Water stressed region of the world shown in the orange and red. Water stress is the condition where total water withdrawals approach the difference between precipitation and evaporation¹.

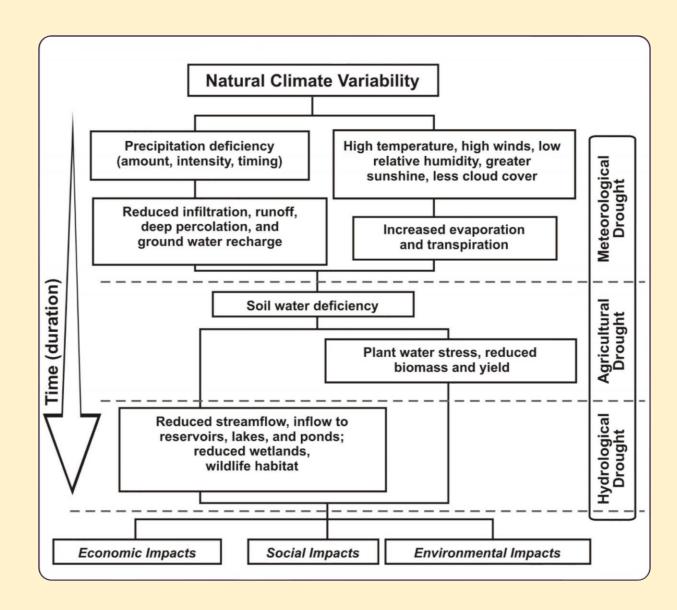
Obtaining future streamflow projection crucial for water resource management and hydrological drought projection.

Measure drought as a physical phenomenon

All droughts originate from a deficiency of precipitation or abnormality in temperature ranges.¹

Deficiency is soil moisture leads to agriculture drought and low inflow to stream characterize as hydrological drought.

Drought have variability of impacts such as Social, economic etc.



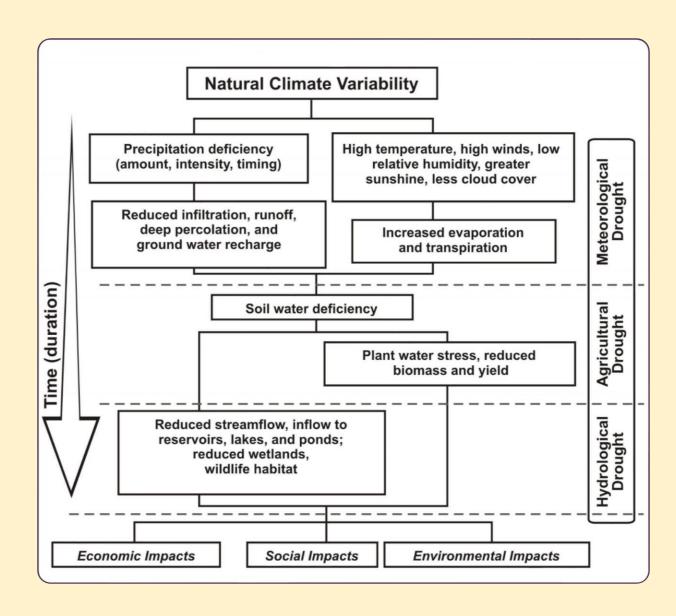
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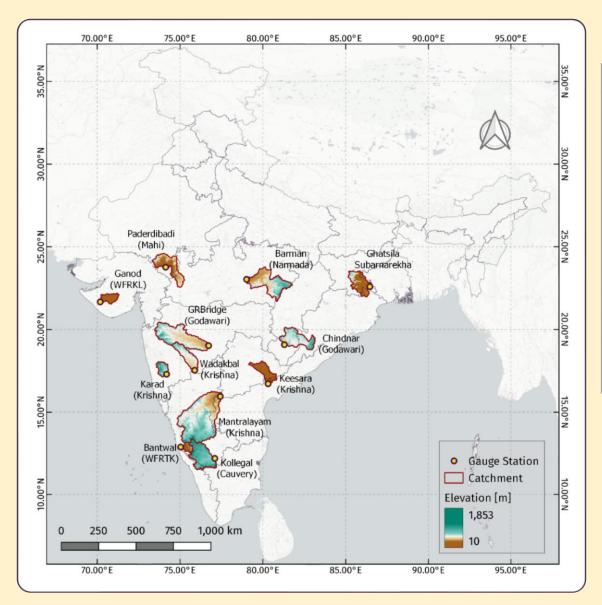
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Drought have variability of impacts such as Social, economic etc.

Understanding hydrological drought with the help of meteorological drought



Study area and data



ID	Catchment	Basin	Latitude	Longitude	Area [km²]
C01	Bantwal	WFRTK	12.88	75.04	3273.78
C02	Barman	Narmada	23.03	79.02	26250.96
C03	Chindnar	Godawari	19.08	81.30	17887.55
C04	G.R. Bridge	Godawari	19.02	76.73	33331.76
C05	Ganod	WFRKL	21.67	70.18	5491.60
C06	Ghatsila	Subarnarekha	22.59	86.46	14151.04
C07	Karad	Krishna	17.29	74.19	5441.53
C08	Keesara	Krishna	16.72	80.32	10226.00
C09	Kollegal	Cauvery	12.19	77.10	21757.82
C10	Mantralayam	Krishna	15.95	77.43	64576.91
C11	Paderdibadi	Mahi	23.76	74.13	16355.93
C12	Wadakbal	Krishna	17.53	75.89	12030.70

- Discharge data is collected from the India-WRIS site (<u>https://indiawris.gov.in/wris/</u>) for the 12 catchments.
- We use catchments with continuous 30 years (1 Jan 1980 to 31 Dec 2009) of daily streamflow data.

Methodology

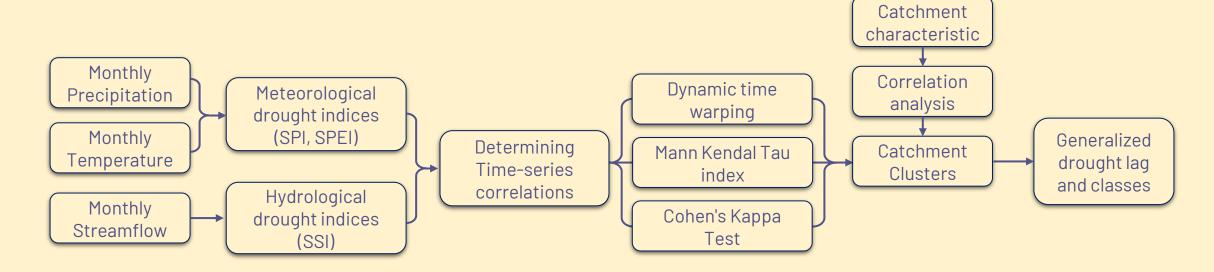
- We converted the precipitation, temperature, and discharge time series to monthly using the monthly mean of daily values.
- Drought indices are computed for:

Meteorological drought:

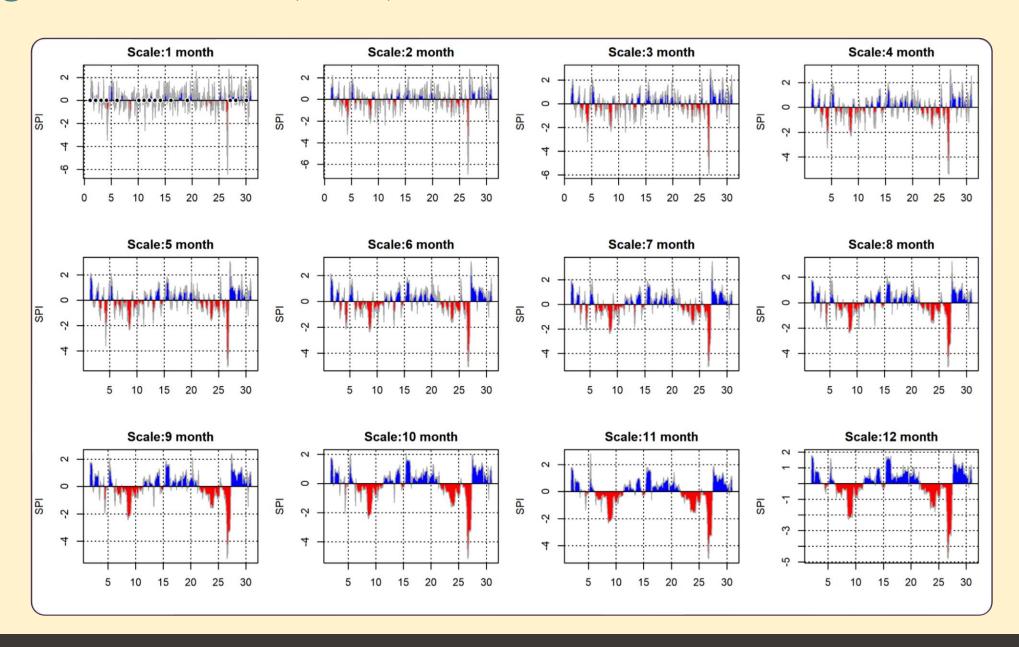
- 1. Standardized Precipitation Index (SPI)
- 2. Standardized Precipitation and Evaporative Index (SPEI)

Hydrological drought: Standardize streamflow index (SSI)

 Normalized cumulative distances are computed to identify the correlation relationship between the Metrological and Hydrological drought time series.



Drought Indicators: SPI, SPEI, and SSI



MD (SPI and SPEI) correlation with HD (SSI) for a catchment

Catchment: Bantwal (C01)

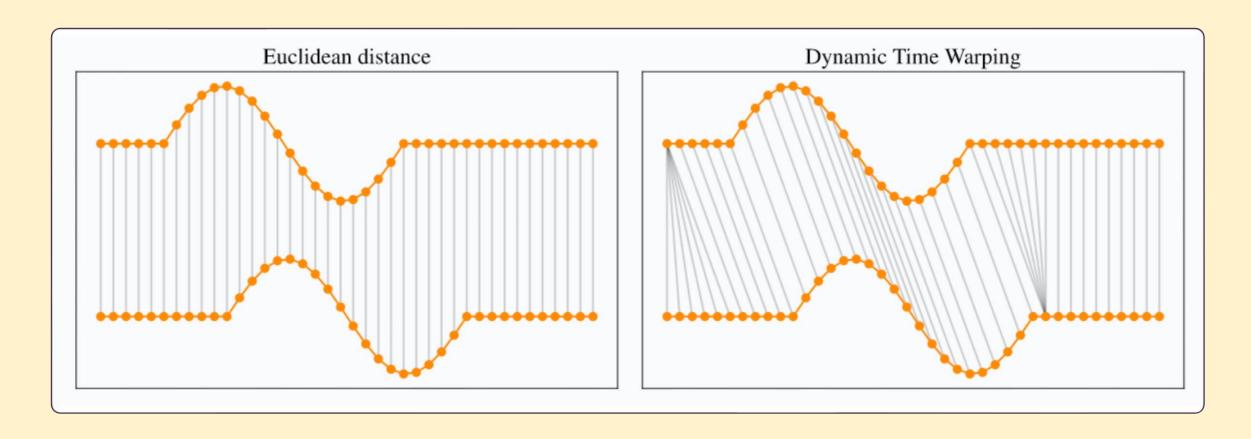
		Standardized Streamflow Index (SSI)													
		01	02	03	04	05	06	07	80	09	10	11	12		
	1	0.48	0.30	0.26	0.26	0.23	0.23	0.22	0.21	0.16	0.14	0.15	0.15		
<u>-</u>	2	0.41	0.46	0.34	0.32	0.31	0.30	0.29	0.28	0.24	0.21	0.21	0.21		
(SPI)	3	0.37	0.44	0.47	0.38	0.36	0.36	0.36	0.35	0.31	0.27	0.26	0.26		
Precipitation Index	4	0.36	0.43	0.48	0.51	0.43	0.42	0.43	0.43	0.39	0.35	0.33	0.33		
ion I	5	0.35	0.41	0.46	0.51	0.54	0.48	0.49	0.49	0.46	0.42	0.40	0.39		
pitat	6	0.36	0.42	0.45	0.50	0.55	0.60	0.55	0.54	0.52	0.48	0.46	0.45		
reci	7	0.38	0.43	0.46	0.48	0.52	0.58	0.64	0.60	0.57	0.53	0.51	0.50		
	8	0.39	0.44	0.48	0.50	0.51	0.55	0.61	0.66	0.61	0.57	0.55	0.54		
Standardized	9	0.35	0.41	0.46	0.49	0.51	0.53	0.58	0.64	0.67	0.62	0.59	0.58		
tand	10	0.30	0.36	0.41	0.45	0.49	0.52	0.56	0.60	0.65	0.67	0.63	0.62		
Ś	11	0.27	0.33	0.38	0.42	0.46	0.50	0.54	0.58	0.62	0.65	0.67	0.65		
	12	0.26	0.31	0.35	0.39	0.43	0.48	0.52	0.56	0.60	0.63	0.66	0.68		

									•	-		
J	01	02	03	04	05	06	07	80	09	10	11	12
Index	0.56	0.37	0.30	0.31	0.26	0.24	0.23	0.23	0.18	0.16	0.17	0.16
	0.52	0.57	0.43	0.40	0.36	0.34	0.33	0.33	0.28	0.24	0.24	0.24
pirat	0.48	0.56	0.60	0.49	0.44	0.43	0.42	0.42	0.38	0.33	0.31	0.31
Evapotranspiration	0.46	0.54	0.60	0.63	0.53	0.50	0.50	0.51	0.46	0.41	0.39	0.38
apoti	0.45	0.51	0.57	0.62	0.66	0.58	0.57	0.58	0.54	0.49	0.46	0.45
	0.45	0.51	0.55	0.61	0.66	0.71	0.65	0.64	0.61	0.56	0.54	0.52
atior	0.46	0.53	0.57	0.59	0.63	0.70	0.76	0.71	0.67	0.62	0.60	0.58
Precipitation	0.46	0.53	0.58	0.61	0.62	0.67	0.74	0.79	0.73	0.68	0.65	0.63
	0.42	0.50	0.56	0.60	0.62	0.65	0.71	0.77	0.80	0.73	0.70	0.68
dizec	0.37	0.45	0.51	0.56	0.60	0.64	0.68	0.74	0.78	0.80	0.76	0.74
Standardized	0.34	0.41	0.47	0.52	0.57	0.62	0.67	0.71	0.75	0.78	0.80	0.77
Star	0.33	0.39	0.44	0.49	0.54	0.59	0.64	0.68	0.73	0.76	0.78	0.80

Standardized Streamflow Index (SSI)

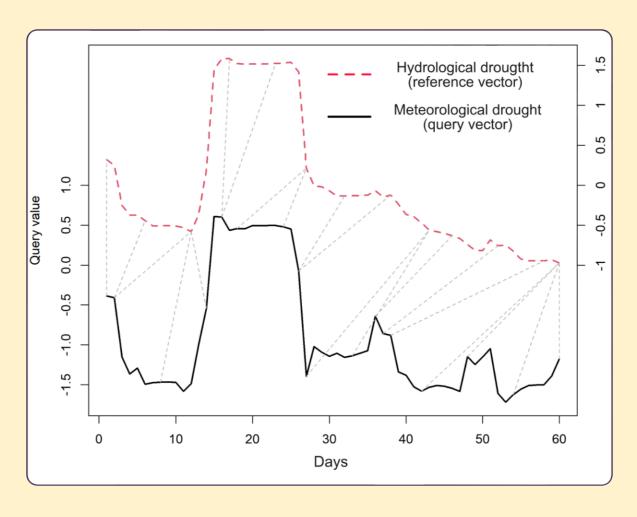
Finding lag relationship with Dynamic Time Warping (DTW)

Dynamic Time Warping (DTW) to measuring the similarity between two temporal time series (drought timeseries).



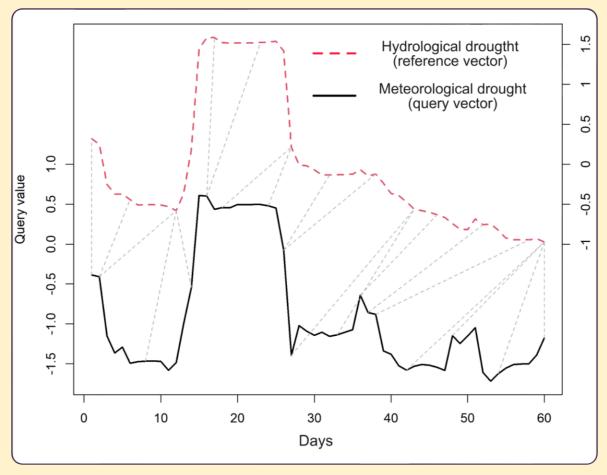
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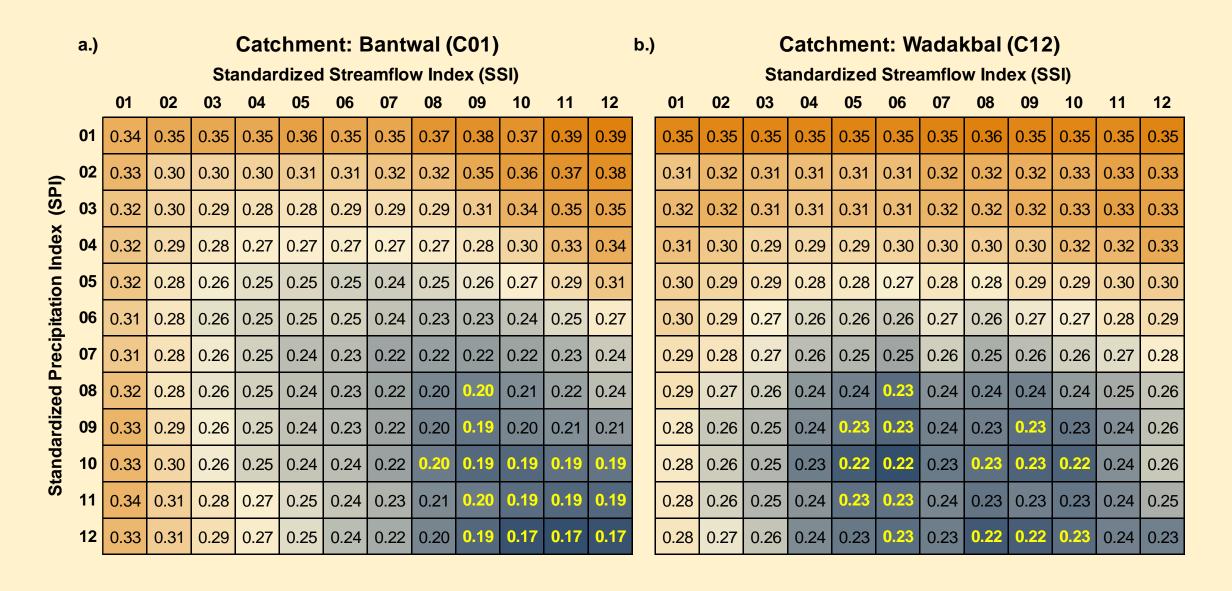
Finding lag relationship with Dynamic Time Warping (DTW)

Dynamic Time Warping (DTW) to measuring the similarity between two temporal time series (drought timeseries).



We use dynamic time warping (DTW) (Giorgino, 2009) to find the lag between each time series.

Normalized distance for DTW lag correlation in normalized distance



Normalized distance with Dynamic Time Warping

Computed mean normalized distance value between MD (SPI, SPEI) HD(SSI) with Dynamic Time Warping.
Lower normalized distance represents HD and MD time-series have a higher

• DTW considers variations in timing sequences that may have different speeds or timing patterns.

similarity.

- DTW finds patterns in time-related data where precise matching is essential.
- DTW calculates a distance measure, showing how similar two sequences are after accounting for timing variations.

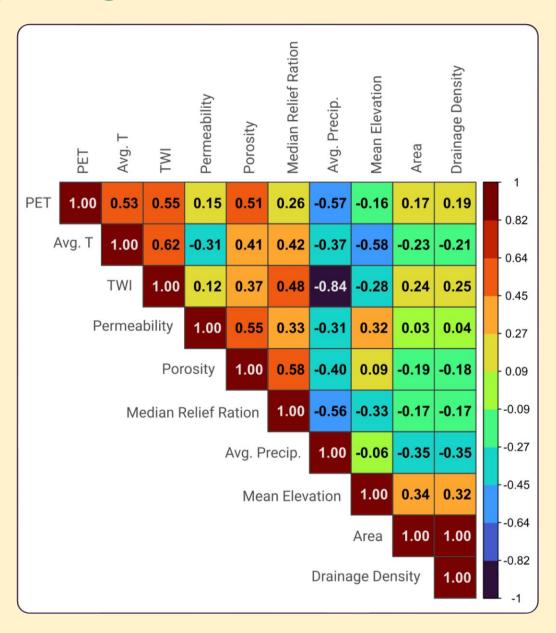
3 Month SSI - SPI SSI - SPEI			6 M	onth SSI - SPEI		12 Month SSI - SPI SSI - SPEI		
Bantwal	0.31	0.29	0.25	0.23	0.17	0.15		0.35
Barman	0.33	0.32	0.28	0.27	0.20	0.22		
Chindnar	0.31	0.28	0.24	0.23	0.16	0.16		- 0.30
G.R. Bridge	0.34	0.33	0.28	0.27	0.25	0.23		
Ganod	0.25	0.30	0.26	0.26	0.20	0.18		- 0.25
Ghatsila	0.30	0.29	0.24	0.25	0.18	0.19		
Karad	0.31	0.32	0.25	0.26	0.16	0.18		
Keesara	0.29	0.30	0.23	0.22	0.19	0.18		- 0.20
Kollegal	0.28	0.28	0.22	0.23	0.18	0.18		
Mantralayam	0.32	0.33	0.25	0.27	0.22	0.21		- 0.15
Paderdibadi	0.31	0.30	0.26	0.24	0.19	0.19		
Wadakbal	0.31	0.32	0.26	0.27	0.23	0.22		0.10
								0.10

Catchment characteristics and clustering for regionalization

Gauge Station	Area [km²]	•••
Bantwal	3274	•••
Barman	26251	•••
Chindnar	17888	•••
GRBridge	33332	•••
Ganod	5492	•••
Ghatsila	14151	•••
Karad	5442	•••
Keesara	10226	•••
Kollegal	21758	•••
Mantralayam	64577	•••
Paderdibadi	16356	•••
Wadakbal	12031	•••

Correlation analysis plot of catchment characteristics for cluster analysis.

Color represents the correlation value between ±1(1 is positive, -1 is a negative correlation)



Clustering to identify the similar catchments

Clusters	#2	#3	#4	#5	#6	#7	#8
Bantwal	2	3	3	3	3	3	3
Barman	1	1	4	4	4	4	4
Chindnar	1	1	4	4	4	7	7
G.R. Bridge	1	1	1	5	5	5	5
Ganod	1	2	2	2	2	2	8
Ghatsila	1	1	4	4	4	4	4
Karad	1	1	4	4	4	7	7
Keesara	1	2	2	2	2	2	2
Kollegal	1	1	4	1	6	6	6
Mantralayam	1	1	1	5	1	1	1
Paderdibadi	1	1	1	5	1	1	1
Wadakbal	1	1	1	5	5	5	5

- K-means clustering is shown in the table below.
- Twelve catchments are grouped based on eight catchment characteristics.
- Each column shows the number of clusters used to group catchments.
- We highlighted two catchments, "Ganod" and "Keesara," that show similar clustering when classifying all the catchments with 2 to 8 clusters.

Clustering to identify the similar catchments

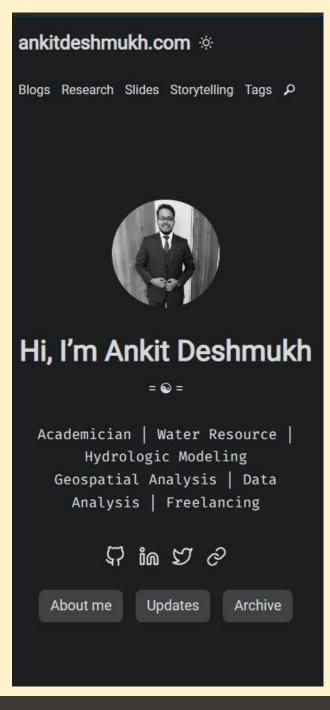
Clusters	#2	#3	#4	#5	#6	#7	#8
Bantwal	2	3	3	3	3	3	3
Barman	1	1	4	4	4	4	4
Chindnar	1	1	4	4	4	7	7
G.R. Bridge	1	1	1	5	5	5	5
Ganod	1	2	2	2	2	2	8
Ghatsila	1	1	4	4	4	4	4
Karad	1	1	4	4	4	7	7
Keesara	1	2	2	2	2	2	2
Kollegal	1	1	4	1	6	6	6
Mantralayam	1	1	1	5	1	1	1
Paderdibadi	1	1	1	5	1	1	1
Wadakbal	1	1	1	5	5	5	5

Lag is identify with DTW and similarly of catchment with physic climatic property based corrections.

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Conclusion

- We compute the relation between Hydrological and meteorological drought.
- Proposed the way to compute the lag between hydrological and meteorological drought.
- Framework to utilize the catchment characteristics for drought generalization of ungauged catchment.



Thank you! Questions?

Reach out to me:

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