



STATISTICAL QUANTIFICATION OF HYDROLOGICAL DROUGHT VARIABILITY AND ITS CLIMATIC-ENVIRONMENTAL DETERMINANTS

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Abstract

Hydrological drought represents a complex water-resource challenge shaped by interactions among climatic variability, catchment characteristics, and environmental conditions. This study statistically quantified the temporal and spatial variability of hydrological drought and evaluated its climatic and environmental determinants across multiple river basins. Hydrological drought was characterized by using the Standardized Streamflow Index and a Q25 low-flow threshold, while climatic and environmental controls were examined using descriptive statistics, temporal and basin-level comparisons, Spearman correlation, and multivariable regression with year fixed effects and catchment-clustered standard errors. The analysis included 6,999 catchment-year observations from 241 catchments. Mean drought intensity was 1.137, with an average of 1.57 drought months and 64.49 low-flow drought days annually. Drought intensity exhibited a significant positive temporal trend and substantial variation among river basins. Annual precipitation was negatively associated with drought intensity, whereas potential evapotranspiration showed a significant positive association. Reservoir influence was negatively associated with drought intensity, while tree cover showed a positive adjusted relationship. The multivariable model explained approximately 21.6% of drought-intensity variability. Overall, the findings demonstrate that hydrological drought cannot be attributed to precipitation variability alone and emphasize the combined roles of climatic forcing, land-surface characteristics, catchment conditions, and human regulation in explaining drought variability.

Keywords: Hydrological drought; Standardized Streamflow Index; Climatic variability; Environmental determinants; Statistical modeling

1. Introduction

Hydrological drought is a reduction in the streamflow, groundwater or other water-storage component that persists, relative to the expected hydrological conditions. Hydrological drought is a different type of drought to meteorological drought, which is based on the lack of precipitation, and captures the cumulative impact of catchment response to climatic forcing, storage processes, land surface properties, and human regulation. Therefore, its development is often delayed, stretched and unevenly distributed. The key components of hydrological drought assessment discussed by Tallaksen and Van Lanen (2023) are streamflow deficits, the duration of the drought, its severity, and the physical processes that influence water availability.

Climate variability and longer-term environmental change have led to an increasing focus on drought occurrence; this is because the timing, duration and severity of droughts can change. Regional differences in historical drought trends and future drought exposure are also large, as evidenced by global assessments, which clearly point towards the need to rely on regionally resolved analyses and not make generalized assumptions (Vicente-Serrano et al., 2022). This spatial heterogeneity is of particular importance in large river-basin systems where the hydroclimatic regimes and catchment properties are highly variable.

Meteorological anomalies can be strongly modified by catchment properties in their conversion to streamflow deficit. Konapala and Mishra (2020) showed that the hydrological drought is jointly determined by climatic conditions and catchment properties, so that there is a need to incorporate atmospheric and landscape variables into the statistical drought model. Streamflow-based indices are especially useful since they directly capture hydrological water availability. The non-stationary standardized streamflow (SSF) framework developed by Wang et al. (2020a) shows the sensitivity of hydrological drought characterization to the changing external drivers, which also include climatic and anthropogenic processes.

Multiple climatic and anthropogenic predictors are also supported by advances in construction of non-stationary drought-indices. Zhang et al. (2021) demonstrated that drought indices accounting for climatic and anthropogenic influences could enhance drought characterization by permitting the drought distributions to vary with the evolution of the environment. Abdelkader and Yerdelen (2022) showed that climatic teleconnections can also help explain temporal drought variability, with large-scale climate indices shown to be related to hydrological drought fluctuations.

In addition to climate, catchment morphology may also have an impact on the duration and intensity of low flow conditions. Veettil (2020) recognized the importance of multiscale climatic, catchment and morphological controls in hydrological drought assessment. However, these physical effects must coexist with other environmental effects, as the effects of long-term water drought on water quality, aquatic environments and water resource reliability also exist (Qiu et al., 2023).

Another important feature is drought propagation. Even though there is a meteorological drought, it does not necessarily result in a hydrological drought because of the time lag associated with catchment storage and runoff processes. Ho et al. (2021) presented a framework to quantify the propagation time from meteorological to hydrological drought and highlighted the dynamic process of drought transformation. Recent studies have also suggested that spatiotemporal drought behavior is affected by interaction among climatic variability, land use/land cover change and by human regulation (Li et al., 2024). In the same way, Wang et al. (2024) found spatial variation in the propagation of meteorological-to-hydrological drought and multiple environmental controls.

In this context, the objective of this study was to quantify the hydrological drought variability statistically and to identify the most significant climatic and environment parameters associated with this drought. The spatial extent included temporal variation, spatial variation within river basins, characteristics of low-flow droughts, drought intensity based on SSI, climatic conditions, land-cover attributes, soil properties, topography, and reservoir influence. The aims were to quantify the intensity, frequency, and duration of droughts; quantify temporal and spatial variability; explore bivariate climatic–environmental associations; estimate the adjusted climatic and environmental associations with hydrological droughts intensity using multivariable statistical modeling.

2. Methodology

2.1 Study Design and Data Preparation

The design utilized was a retrospective secondary-data analysis approach to quantify temporal and spatial variability in hydrological drought and investigate climatic and environmental determinants. Catchment level integration of daily streamflow, meteorological variables and static catchment characteristics. All analyses were completed for 1980–2020, unless valid streamflow observations were not available for a specific catchment. The number of years for each catchment for which there were at least 300 weathered daily observed streamflow data was retained to ensure greater reliability in annual drought estimate comparisons. As per this quality-control criterion, the main analytical panel was 6,999 catchments year observations from 241 catchments. The 15 river basins included in the catchments allowed temporal and basin comparisons (Mangukiya et al., 2025).

Daily meteorological observations were aggregated to annual measures. The daily data were used to derive mean temperatures and annual precipitation by summing the daily values. Annual totals of potential evapotranspiration (PET) and actual evapotranspiration (AET) were estimated. The annual means for relative humidity, wind speed and soil-moisture variables were summarized. Days with precipitation less than 1 mm/day were considered "dry" days, and the longest continuous period of 1 mm/day or less of those dry days were categorized as "maximum dry spell" for each catchment-year. Topography, land cover, soil properties, geological conditions and anthropogenic influence were among the static environmental characteristics.

2.2 Quantification of Hydrological Drought

Hydrological drought was calculated using two complementary methods, the Standardized Streamflow Index (SSI) and a low-flow threshold approach, from observed streamflow. The monthly streamflow values were converted into empirical standardized SSI values where negative values indicated below normal streamflow conditions. Annual hydrological drought intensity was determined as SSImin, minimum monthly SSI for a catchment for a year. A larger positive value thus indicated greater hydrological drought conditions. The annual number of months in which SSI was below -1.0 was defined as drought months, while months with SSI below -1.5 were considered as severe drought months.

The 25th percentile of the observed daily streamflow or catchment-specific 25th percentile of the daily streamflow (Q25) was also used to define low-flow drought characteristics. A drought day was defined as when the measured streamflow fell below Q25. Drought days, number of drought events, mean duration of drought events, and maximum drought events were the drought measures that were taken annually. The annual streamflow variations were represented by

$$CV = [SD(Q)/\text{mean}(Q)] \times 100,$$

where $SD(Q)$ and $\text{mean}(Q)$ denote the standard deviation and mean of daily streamflow within the catchment-year.

2.3 Climatic and Environmental Determinants

Annual precipitation, mean temperature, annual PET, annual AET, surface layer soil moisture, number of dry days and duration of the longest dry spell were the main climatic parameters. Annual precipitation, mean temperature, annual PET, surface soil moisture (Layer 1), maximum dry-spell duration, tree-cover fraction, crop-cover fraction, built-up-area fraction, soil depth, mean catchment slope, and reservoir index were included in the final multivariable analysis. Descriptive and bivariate analyses were performed for other variables such as annual AET that were not included in the final regression. The spatial comparison for the 15 river basins represented was made using the concept of basin membership.

2.4 Descriptive, Temporal, Spatial, and Bivariate Statistical Analysis

Continuous variables were presented as N, mean, standard deviation, minimum, first quartile, median, third quartile, and maximum. The temporal drought variability was assessed on the basis of the mean annual hydrological drought intensity within the available catchments, and the linear temporal trend was estimated to be in the calendar year as an explanatory variable. Basin-level aggregation was used to look at spatial variability. Several hydroclimatic and catchment variables were not normally distributed and associations between drought intensities and individual climatic–environmental determinants were examined with Spearman's rank-order correlation coefficient (ρ). Two-sided $p < .05$ were considered statistically significant. Data for complete observations ($N = 6,999$) were available for correlation analyses; data for reservoir indexes ($N = 6,192$) were available.

2.5 Multivariable Regression and Missing-Data Treatment

A multivariable linear regression model was built with hydrological drought intensity as the dependent variable and standardized the values of the variables. Standardization of continuous predictors was done prior to estimation. Annual precipitation, mean temperature, annual PET, surface soil moisture, maximum dry-spell duration, tree-cover fraction, crop-cover fraction, built-up-area fraction, soil depth, mean slope, and reservoir index were included in the model along with year fixed-effects. The standard errors were clustered at the catchment level, to reflect repeated observations across time within catchments. Model performance was summarized using the R^2 and adjusted R^2 , regression results were reported as standardized beta coefficient (β), cluster-robust standard errors, test statistics, two-sided p -values and 95% confidence intervals.

With the variables needed for the multivariable model, complete-case analysis was used. These missing observations, which were not included in the regression analysis due to the lack of one or more of the variables in the regression model, were not imputed. The number of catchment-year observations in the final regression was 6,192, which represented 208 catchments, while the descriptive panel had 6,999 observations from 241 catchments. Coefficients were understood as modified statistical associations, not cause-and-effect.

2.6 Ethical Considerations

The study relied solely on the second-hand information about hydrological, climatic, geographical and environmental data that were available and were publicly accessible scientific resources. There was no collection of or analysis of human subjects, clinical records, personally identifiable information, biological specimens or personally identifiable information. Hence, informed consent was not possible and formal human-subjects ethical approval was not necessary. For scientific analysis, data were analysed and original measurements preserved, except for those operations specifically described in the aggregation, standardization, construction of drought indices, and quality-control procedures. There was no falsification of observations or any manipulation of observations to achieve statistical significance and there were no missing values handled other than using the predetermined eligibility and complete-case methods.

3. Results

3.1 Hydrological Drought Characteristics and Overall Variability

Table 1 shows that there is significant spatial and temporal variation in hydrological drought conditions. The mean drought intensity (mean SSI) was calculated as 1.137 ± 0.609 and the average catchments had 1.57 months per year with $SSI < -1$ and 0.57 severe drought months with $SSI < -1.5$. The average number of hydrological drought days in the Q25 threshold was 64.49 days/year and the highest recorded was 347 days. The maximum drought was 41.05 days and a single catchment-year experienced 280 days of drought.

Table 1. Descriptive statistics of hydrological drought and climatic variables

Variable	N	Mean	SD	Minimum	Q1	Median	Q3	Maximum
Drought intensity (–SSI Min)	6,999	1.137	0.609	–0.999	0.694	1.120	1.576	2.198
Drought months, SSI < –1	6,999	1.570	2.032	0	0	1	2	12
Severe drought months, SSI < –1.5	6,999	0.567	1.157	0	0	0	1	10
Drought days, Q25	6,999	64.486	65.898	0	0	53	108	347
Maximum drought duration, days	6,999	41.051	48.637	0	0	23	66.5	280
Annual precipitation, mm	6,999	1,251.025	714.410	139.580	825.690	1,081.280	1,415.875	7,571.360
Mean temperature, °C	6,999	26.015	1.062	22.614	25.338	26.115	26.706	29.316
Annual PET, mm	6,999	1,082.146	108.265	907.740	1,018.685	1,052.180	1,096.065	1,606.210
Annual AET, mm	6,999	706.398	228.155	330.840	560.230	635.320	769.445	1,529.390
Surface soil moisture, kg/m ²	6,999	15.010	6.025	4.365	11.011	13.582	16.489	35.908
Dry days, precipitation < 1 mm	6,999	246.420	33.167	137	224.5	250	270	335
Maximum dry spell, days	6,999	73.587	29.883	15	53	68	89	174

Temporal variation is illustrated in Figure 1. Pronounced drought-intensity peaks occurred during the late 1980s, 2002–2004, 2009, 2012, and particularly 2015–2018. The annual mean drought-intensity series showed a modest positive linear trend of approximately 0.0088 intensity units per year, which was statistically significant ($p = .0166$).

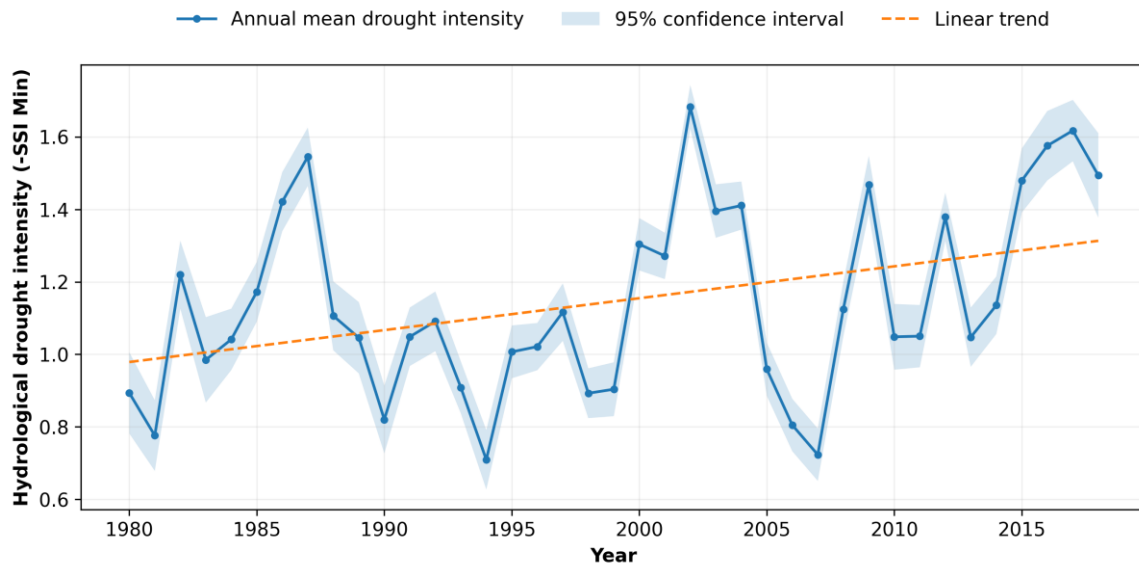


Figure 1. Temporal variability in mean hydrological drought intensity with 95% confidence interval and linear trend

3.2 Spatial Variability Across River Basins

There were clear differences between river basins, with 15 river basins represented. A comparison of the mean drought intensities of the different river basins as reported in Table 2 shows that Subernarekha had the highest mean drought intensity (1.341), followed by Brahmani–Baitarani (1.305), WFRS (1.236), Narmada (1.210), and EFRN (1.208). In contrast, Sabarmati and Pennar had lower mean values of intensities 0.855 and 0.872, respectively, based on SSI. Precipitation alone was not a direct measure of the differences in SSI-based drought intensity, which suggested multiple interacting controls to hydrological drought.

Table 2. Basin-wise variation in hydrological drought and climatic characteristics

River basin	Catchments	Catchment-years	Mean drought intensity	Mean drought months	Mean drought days	Mean precipitation (mm)	Mean max. dry spell (days)
Subernarekha	4	140	1.341	1.886	91.971	1,397.185	57.971
Brahmani-Baitarani	8	263	1.305	1.863	91.939	1,384.733	59.677
WFRS	25	774	1.236	1.571	74.730	2,324.479	51.384
Narmada	18	565	1.210	1.747	81.984	1,120.035	84.179
EFRN	5	134	1.208	1.791	92.679	1,283.010	55.694
Mahanadi	19	682	1.195	1.723	78.336	1,239.816	70.384
Tapi	10	221	1.179	1.602	70.864	860.551	97.796
WFRN	10	214	1.158	1.374	48.364	2,559.134	118.561
Godavari	50	1,323	1.137	1.617	67.569	1,130.354	72.686
Mahi	7	219	1.109	1.826	58.781	846.419	119.479
Cauvery	21	602	1.105	1.661	69.150	1,094.093	60.146
Krishna	41	1,226	1.051	1.433	49.273	945.207	80.631
EFRS	12	368	0.991	1.120	18.848	876.723	58.168
Pennar	6	184	0.872	0.967	30.891	683.983	68.060
Sabarmati	5	84	0.855	1.000	15.952	738.954	120.464

The basin contrast presented in Figure 2 further demonstrates this spatial heterogeneity. The difference between the highest

and lowest basin means approached 0.49 standardized intensity units, supporting basin-sensitive interpretation of drought conditions.

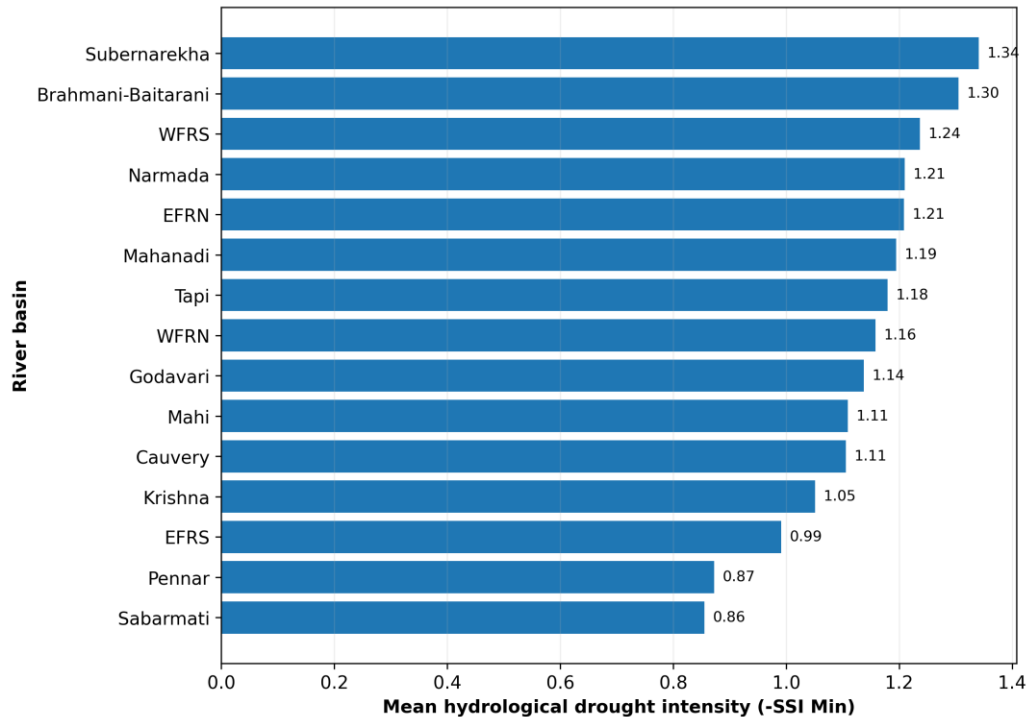


Figure 2. Mean hydrological drought intensity across river basins

3.3 Climatic and Environmental Associations with Drought Intensity

Several climatic and environmental variables were skewed and had large cross catchment ranges and so Spearman correlations were calculated. The inverse statistical relationship between annual precipitation and drought intensity ($\rho = -0.067$, $p < .001$) is shown in Table 3, while the positive relationship between annual PET and drought intensity ($\rho = 0.066$, $p < .001$) is also displayed in Table 3. Tree-cover fraction had the strongest positive bivariate relationship ($\rho = 0.128$, $p < .001$) while the associations of crop cover ($\rho = -0.094$, $p < .001$) and reservoir index ($\rho = -0.096$, $p < .001$) with drought intensity were negative.

Table 3. Spearman associations between drought intensity and climatic–environmental determinants

Predictor	N	Spearman ρ	p-value
Annual precipitation	6,999	−0.067	<.001
Mean temperature	6,999	0.030	.011
Annual PET	6,999	0.066	<.001
Annual AET	6,999	0.046	<.001
Soil moisture L1	6,999	0.029	.016
Maximum dry spell	6,999	−0.052	<.001
Tree-cover fraction	6,999	0.128	<.001
Crop-cover fraction	6,999	−0.094	<.001
Built-up fraction	6,999	−0.034	.005
Soil depth	6,999	0.027	.024
Mean slope	6,999	0.061	<.001
Reservoir index	6,192	−0.096	<.001

The precipitation–drought relationship is displayed in Figure 3. Even though there was a considerable spread between the catchment-years, the fitted association decreased with an increase in annual precipitation as was indicated by the negative Spearman coefficient in Table 3.

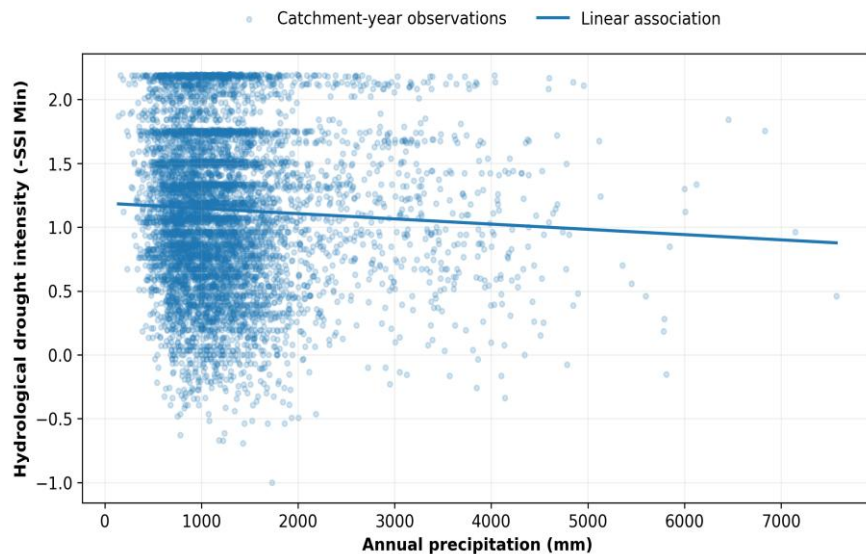


Figure 3. Relationship between annual precipitation and hydrological drought intensity

3.4 Multivariate Climatic–Environmental Determinants

Analyses of adjusted relationships were conducted using a standardized multivariable regression with fixed effects for year and catchment-clustered standard errors. It included drought observations for 208 catchments over 6,192 complete catchment years and accounted for approximately 21.6% of the observed variation in drought intensity ($R^2 = 0.216$; adjusted $R^2 = 0.210$). As shown in Table 4, the coefficient of precipitation was also negatively significant and negatively correlated with the drought intensity ($\beta = -0.140$, $p < .001$) while the annual PET had a positive coefficient ($\beta = 0.075$, $p = .013$). There was a positive adjusted association for tree cover ($\beta = 0.221$, $p < .001$), and a negative association for reservoir index ($\beta = -0.089$, $p < .001$).

Table 4. Standardized regression estimates for hydrological drought intensity

Predictor	Standardized β	Clustered SE	Test statistic	p-value	95% CI
Annual precipitation	-0.140	0.027	-5.135	<.001	-0.193 to -0.086
Mean temperature	0.008	0.022	0.372	.710	-0.035 to 0.052
Annual PET	0.075	0.030	2.493	.013	0.016 to 0.135
Soil moisture L1	-0.092	0.049	-1.889	.059	-0.187 to 0.003
Maximum dry spell	-0.038	0.018	-2.042	.041	-0.074 to -0.002
Tree-cover fraction	0.221	0.065	3.370	<.001	0.092 to 0.349
Crop-cover fraction	-0.023	0.050	-0.471	.637	-0.121 to 0.074
Built-up fraction	-0.044	0.027	-1.658	.097	-0.097 to 0.008
Soil depth	0.020	0.016	1.289	.197	-0.010 to 0.051
Mean slope	-0.056	0.035	-1.609	.108	-0.125 to 0.012
Reservoir index	-0.089	0.017	-5.288	<.001	-0.122 to -0.056

Note: Dependent variable = standardized hydrological drought intensity ($-SSI_{min}$). The model incorporates year fixed effects and standard errors clustered by catchment.

To visualize the standardized estimates, along with their 95% confidence intervals, Figure 4 is provided. The figure shows that the tree cover had the highest positive adjusted coefficient and the annual precipitation had the highest negative climatic coefficient. A similarly strong (although less consistent) negative relationship was found in Reservoir index.

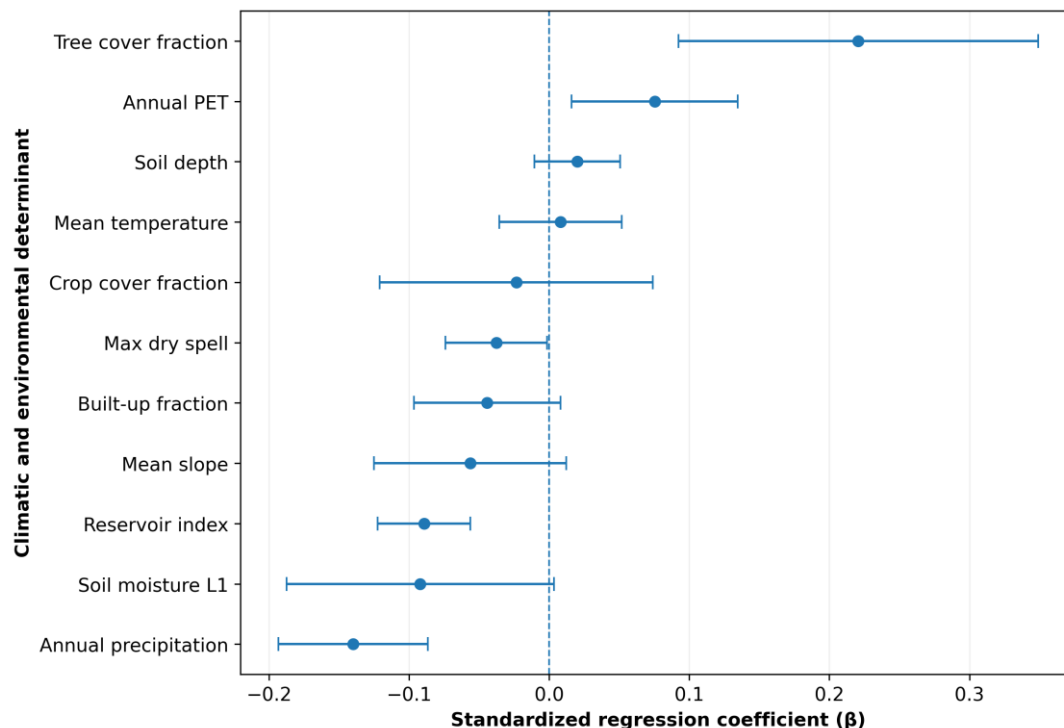


Figure 4. Standardized climatic and environmental coefficients predicting hydrological drought intensity; error bars represent 95% confidence intervals

4. Discussion

The analysis showed that hydrological drought was significantly variable with space and time and had an average of 64.49 hydrological drought days per year, 1.57 SSI defined drought months per year and a mean drought intensity of 1.137. There was a strong positive temporal trend of approximately 0.0088 intensity units per year, indicating that the mean drought intensity during the study period is trending upwards, although there was considerable interannual variability. This pattern is similar to the general concept that hydrological drought is influenced by both climate change and anthropogenic modification, instead of a single stationary forcing process (Jehan zaib et al., 2020).

Spatial heterogeneity is also seen in many respects between river basins. In comparison, Subernarekha and Brahmani–Baitarani had comparatively high mean values of the drought intensity in terms of SSI, while Sabarmati and Pennar had low values of SSI drought intensity. Similar spatial differences have been reported in which meteorological drought propagation into low-flow drought differs based on the hydroclimatic characteristics of the catchment (Houmma et al., 2025). This heterogeneity allows the basin-level characterization instead of the region-wide one.

It also revealed that reliance upon annual precipitation is inadequate for representing hydrological drought. Streamflow has become a more commonly used indicator of water availability in ecological and hydrological droughts due to its ability to include responses from upstream storage and climate, as well as from upstream water bodies. (Jiang et al., 2022). Thus, the weak but statistically significant negative bivariate correlation between annual precipitation and drought intensity is just one aspect of a more complex hydrological response.

Annual precipitation was also significantly negatively associated with drought intensity in standardized regression, while PET was positively associated with drought intensity. The results are consistent with the evidence of climate change altering water supply and air evaporative demand (Du et al., 2024), which can impact drought propagation. Estimated changes in evaporative demand may also drive interactions with vegetation processes and soil-water availability, so intensifying terrestrial water stress even in the context of moderate precipitation changes (Ma & Yuan, 2024).

The negative relationship of surface soil moisture was directionally similar to the hypothesized response of wet antecedent conditions (streamflow deficits) but was not statistically significant at the conventional level. This finding reinforces the concept of hydrological drought as a component of the environmental drought spectrum that encompasses processes in the atmosphere, soil, vegetation, and runoff.

The precipitation–drought association observed was statistically significant but small, reflecting the complicated transformation of meteorological drought to hydrological drought. The authors of Torelló-Sentelles and Franzke (2022) showed that drought effects are not consistently captured by all drought indicators, suggesting that hydrological drought

effects are a function of drought characteristics and regional processes, respectively.

Variability was also attributed to environmental attributes. The association of tree-cover fraction was positive with an adjusted coefficient and reservoir index was highly negative. Vegetation effects on drought conditions can be varied due to vegetation's impacts on evapotranspiration, interception, rooting depth and soil-water extraction, which is not a uniform protective factor (Li et al., 2020). The inverse relationship between reservoir index and streamflow suggests a possible mitigation of some yearly deficits by storage infrastructure, but this association is not causal. Human regulation has the potential to significantly impact drought termination, low-flow persistence, and apparent hydrological response based on observed streamflow records (Wang et al., 2020b).

Climatic and environmental predictors can only account for about 21.6% of drought-intensity variation when combined in the model. This is in line with the findings of Wan et al. (2023) that drought characteristics are not just driven by one climatic driver in all locations but rather emerge as a result of interacting drivers. These natural relationships can also be impacted by anthropogenic intervention, such as reservoir regulation, land-use change and water abstraction (Omer et al., 2020). Lastly, there may be some non-explicit large scale climate oscillations that contribute to the unexplained temporal variability. Other basin systems have been linked to the occurrence and persistence of regional droughts by other lagged atmospheric-oceanic influences like ENSO (Xing et al., 2022). The results confirm a multivariate approach to hydrological drought in which the hydrological drought variability is a function of all the factors mentioned above: precipitation deficiency, evaporative demand, soil-water conditions, land cover, catchment properties and human regulation.

5. Conclusion

This study quantitatively quantified the hydrological drought variability using statistical methods and explored the climatic and environmental drivers of hydrological drought occurrence in various river basins. The results showed that droughts varied significantly in intensity, duration and frequency at both temporal and spatial scales. The mean hydrological drought intensity was 1.137, with an average of 1.57 months and an average of ~64.49 drought days with low flow experienced per year across the catchments. There was a significant positive temporal trend suggesting that drought intensity was generally increasing over the study period but was highly variable from year to year. Basin level comparisons also revealed that the drought hydrological drought conditions were not uniformly distributed, indicating catchment specific characteristics. Both annual precipitation and potential evapotranspiration had a negative and positive correlation with drought intensity, respectively, highlighting the coordinated effect of water supply and its demand in the atmosphere. Reservoir influence had a strong negative association and tree cover a strong positive adjusted association with drought variability. Results of the multivariable model showed that the drought intensity could be explained by about 21.6% of the total variation, suggesting that hydrological drought can be attributed to the interaction between climatic, catchment, land-surface and anthropogenic factors. Results are generally consistent with a multivariate and basin-specific approach to the assessment of hydrological drought. A targeted approach can lead to enhanced drought monitoring, water-resource planning, and the identification of catchments which could be more susceptible to future climatic and environmental stress.

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