

Supporting Information for

Regional response to oceanic variability constrain global drought synchrony

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Methods

Copula Method For joint probability Of crop Failure assessment

To assess the impact of droughts on crop yields, we used nationally averaged sc-PDSI values, where sc-PDSI ≤ -2 indicates moderate drought. Additionally, detrended crop yield data was employed to isolate the impact of climate-induced droughts on agricultural production. The crop yield data was detrended using the first difference (FD) method:

$$\Delta \text{Yield} = \text{Yield}_i - \text{Yield}_{i-1}$$

where ΔYield represents the detrended yield, Yield_i is the crop yield in year i , and Yield_{i-1} is the crop yield in the previous year. This detrending process removes long-term trends from the data associated with technological advancements and other influences, allowing us to focus on climate variability. The analysis spans the period from 1962 to 2020 using the yield data provided by FAO.

To model the dependence between nationally averaged sc-PDSI values (X) and detrended crop yields (Y), we employed a copula-based approach, which allows the separation of marginal distributions from the dependence structure.

The joint cumulative distribution function (CDF) of sc-PDSI and crop yield, $F_{X,Y}(\mathbf{x}, \mathbf{y})$, can be decomposed using Sklar's Theorem into the marginal CDFs, $F_X(\mathbf{x})$ and $F_Y(\mathbf{y})$, and a copula C , which captures the dependency structure:

$$F_{X,Y}(\mathbf{x}, \mathbf{y}) = C(F_X(\mathbf{x}), F_Y(\mathbf{y}))$$

where $C(u, v)$ is the copula function, with $u = F_X(x)$ and $v = F_Y(y)$ representing the marginal CDFs of sc-PDSI and crop yield, respectively. The copula function C provides the joint distribution of these variables independent of their marginals.

We used a parametric bootstrapping goodness-of-fit test to select the best-fitting copula for each country, determining the optimal copula by minimizing the test statistic (Genest et al., 2008; Sadegh et al., 2017).

Calculating Probability of Crop Failure

After selecting the best-fitting copula, we computed the conditional probability of crop yield failure, given moderate drought conditions ($X \leq -2$). Crop failure is defined as the yield falling below a critical threshold, Y_{thr} , which is one standard deviation below the long-term mean yield.

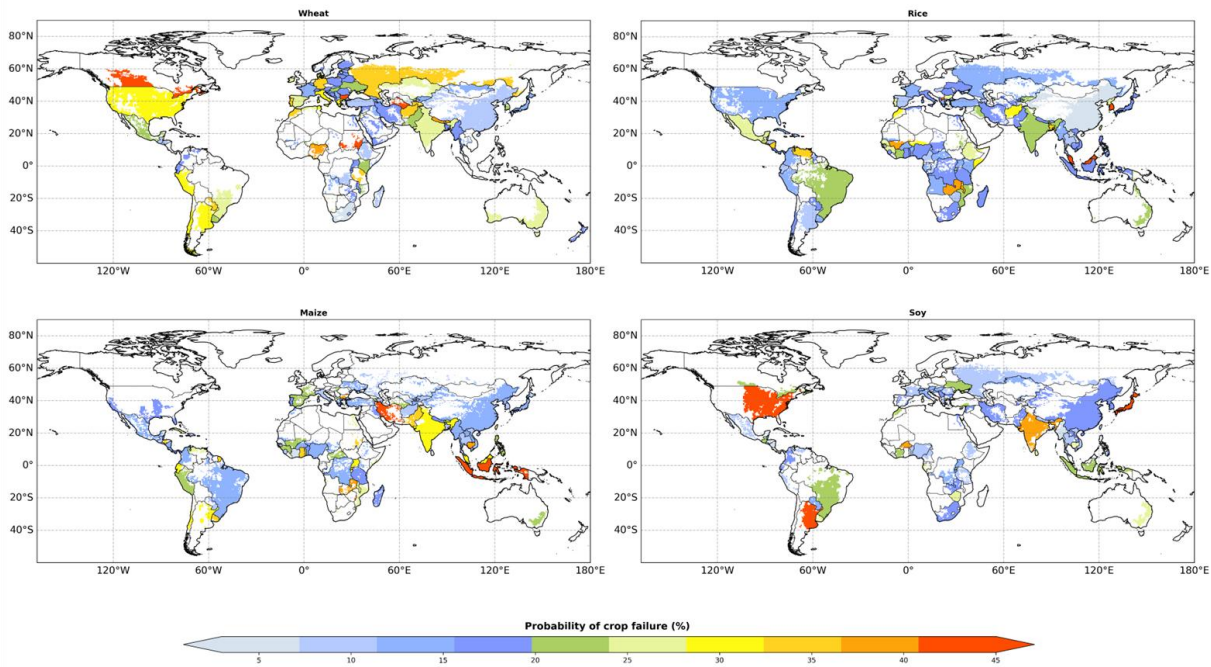
$$P(y \leq Y_{thr} \mid x \leq -2) = C[F_X(-2), F_Y(Y_{thr})] / F_X(-2)$$

This equation provides the conditional probability that the crop yield falls below the threshold Y_{thr} , given that sc-PDSI (X) is less than or equal to -2 (moderate drought).

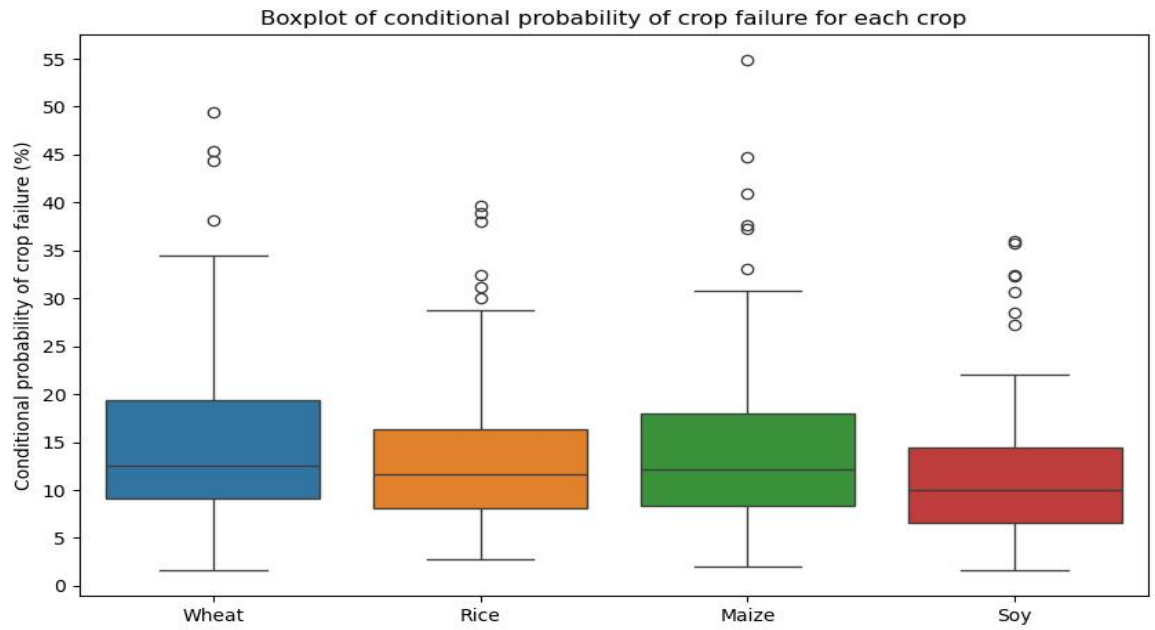
List of Copulas with their expressions and parameter ranges.

Copula Name	Expression	Parameter Range
Gaussian	$\Phi_\rho(u, v)$	$-1 \leq \rho \leq 1$
t	$t_{\nu, \rho}(u, v)$	$\nu > 0, -1 \leq \rho \leq 1$
Clayton	$(u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}$	$\theta > 0$
Gumbel	$\exp(-[(\log u)^\theta + (\log v)^\theta]^{1/\theta})$	$\theta \geq 1$
Frank	$-\frac{1}{\theta} \log \left(1 + \frac{(\exp(-\theta u) - 1)(\exp(-\theta v) - 1)}{\exp(-\theta) - 1} \right)$	$\theta \in \mathbb{R}$
Joe	$1 - [(1 - u)^\theta + (1 - v)^\theta - (1 - u)^\theta (1 - v)^\theta]^{1/\theta}$	$\theta \geq 1$

(A)

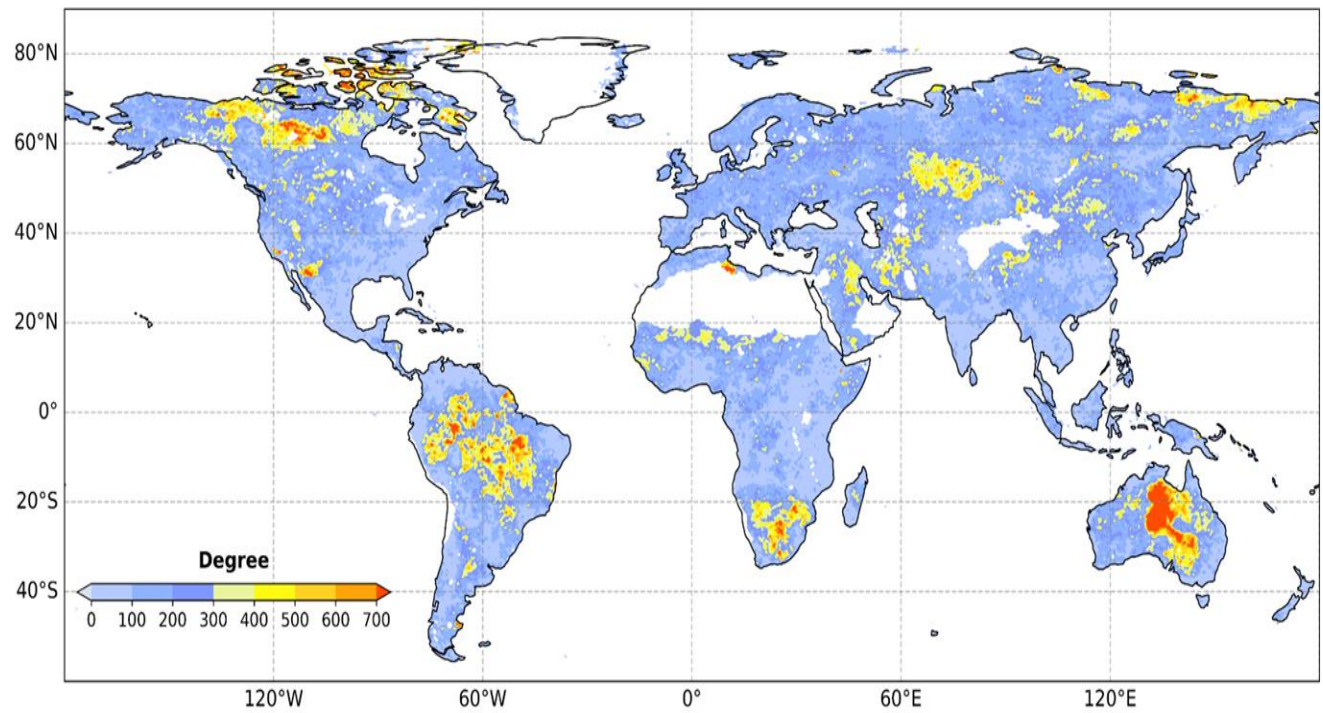


(B)



Supplementary Figure S1

- A.** Conditional probability of crop failure (yield below mean- 1*std). Given that the sc-PDSI is below a certain threshold of -2 indicative of moderate drought conditions calculated using the best fit bivariate copula.
- B.** Box plot for conditional probability of crop failure for staple cereal crops across different countries.



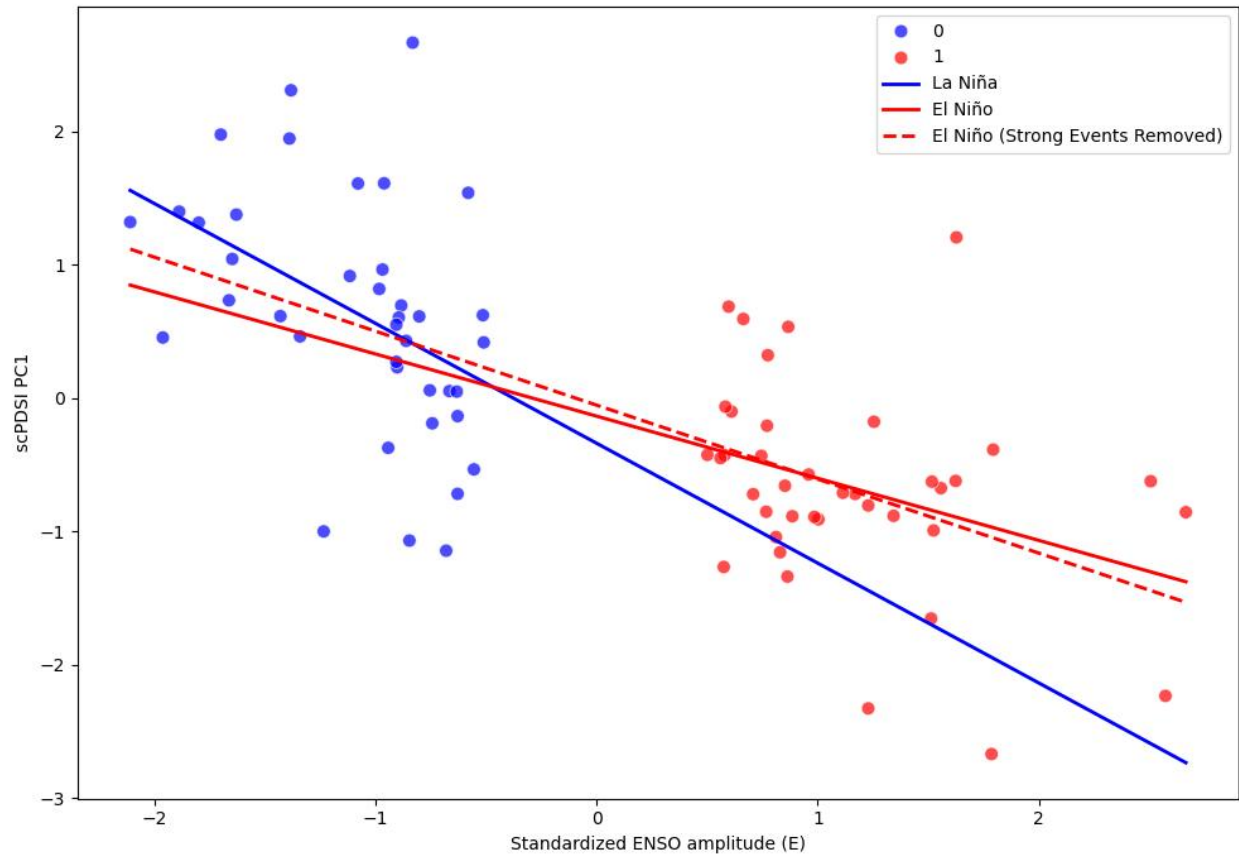
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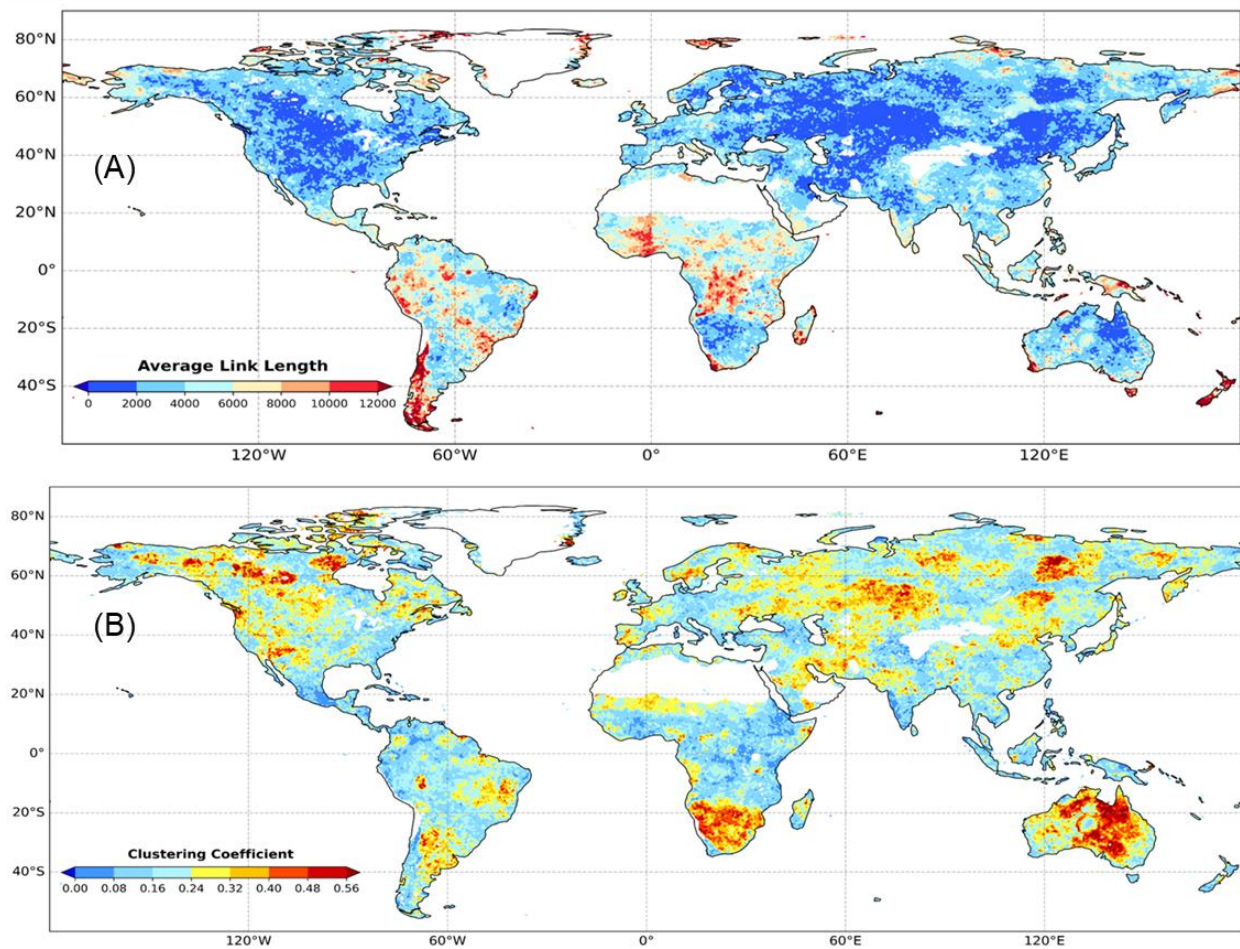
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Supplementary Figure S2 Degree Centrality of complex network formed by ES on drought onset (1901-2020) without correction against projection system (original).



Supplementary Fig S3: Relationship between ENSO amplitude and the leading global drought mode. Scatterplots show scPDSI PC1 regressed onto standardized Niño-3.4 amplitudes for La Niña (blue) and El Niño (red) events. Solid lines indicate ordinary-least-squares fits for all events, while the dashed red line shows the regression after excluding the major strong El Niño years (1982–83, 1997–98, 2015–16). The near-overlap of the two El Niño regression lines demonstrates that the ENSO–drought relationship is robust and not dominated by a small number of extreme events.

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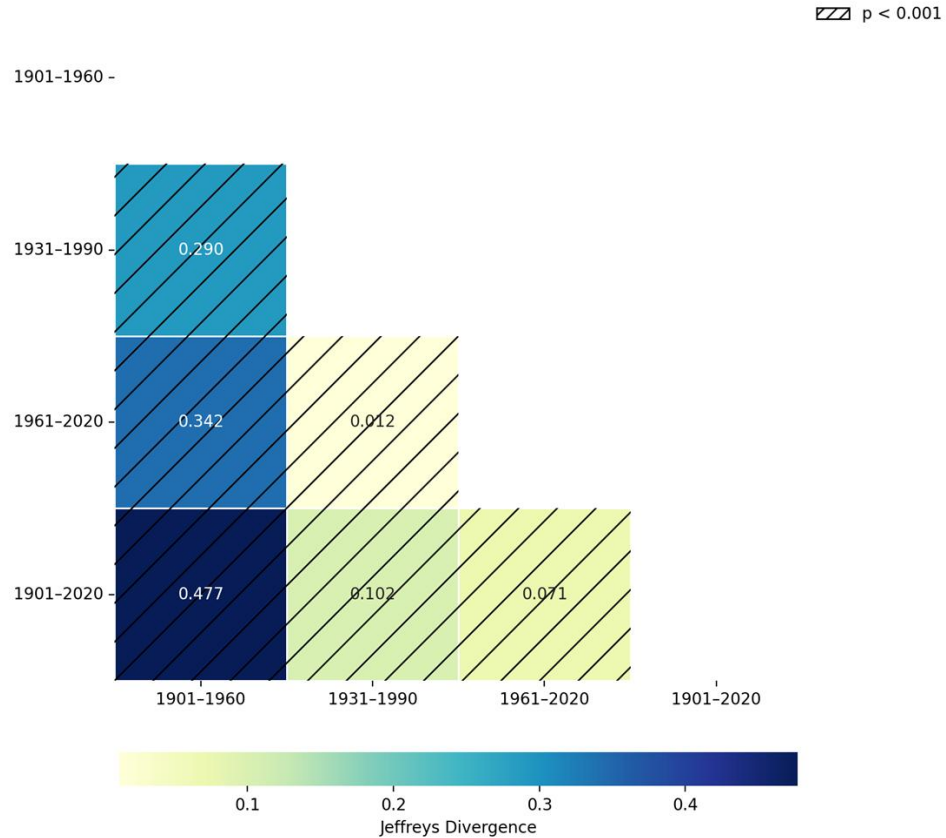


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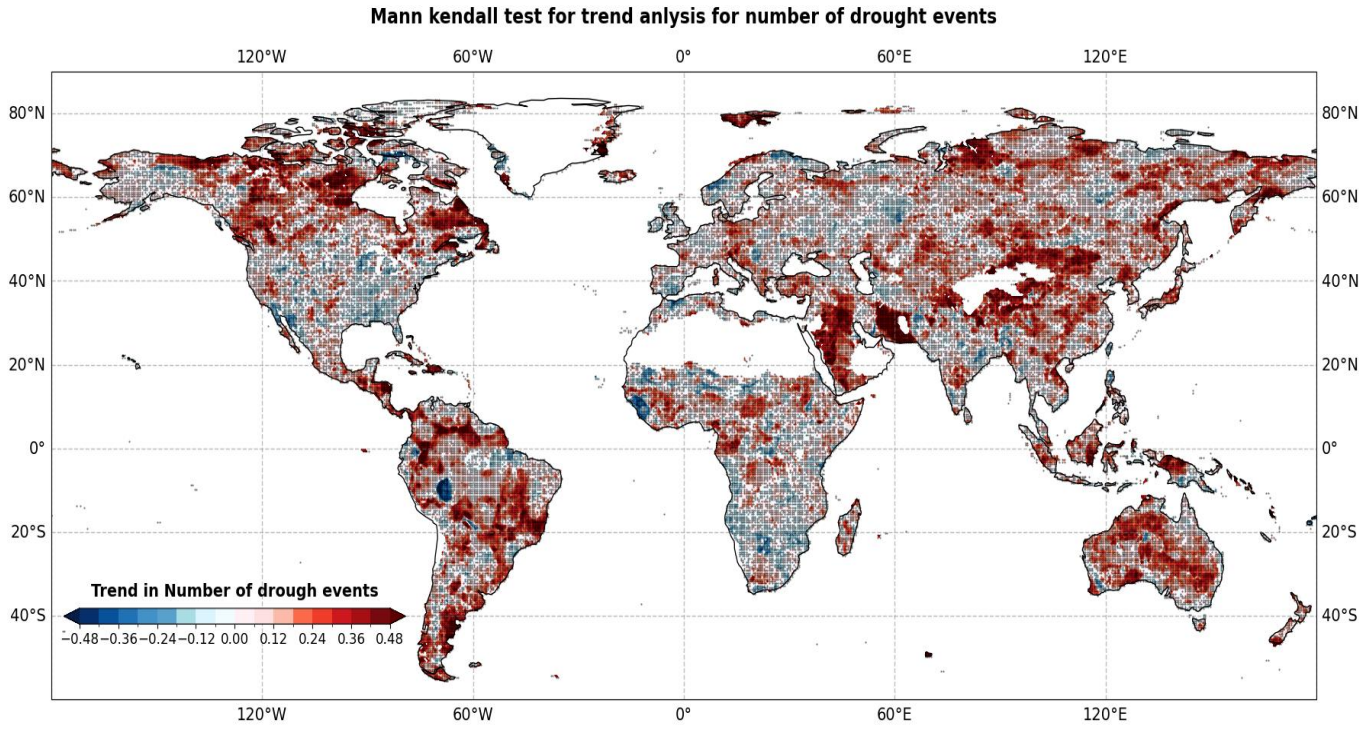
Supplementary Figure S4 Regional and Spatial extent of network connections.

(A) Average Link length for the drought network in the period 1901-2020 with South America having the farthest connections.

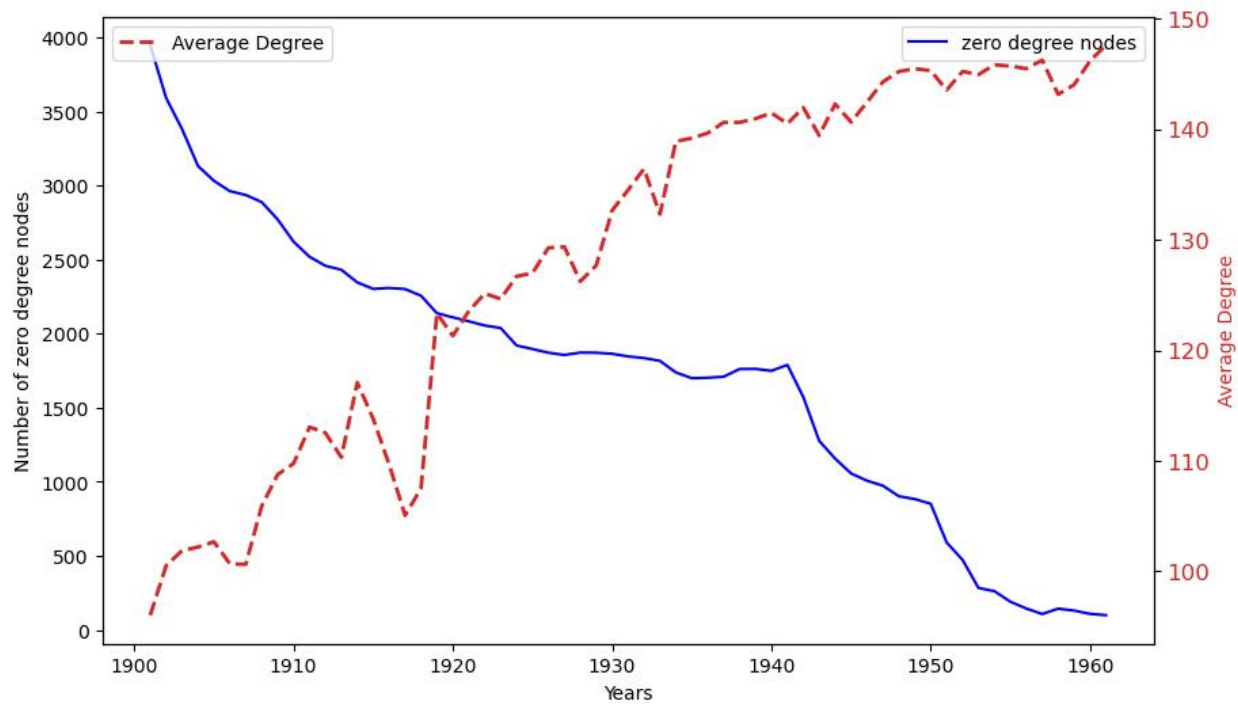
(B) The Local Clustering Coefficient (LCC) for the period 1901-2020 shows the regional interconnectivity between a grid's neighbors. Australia and Africa have very dense interconnectivity between neighbors.



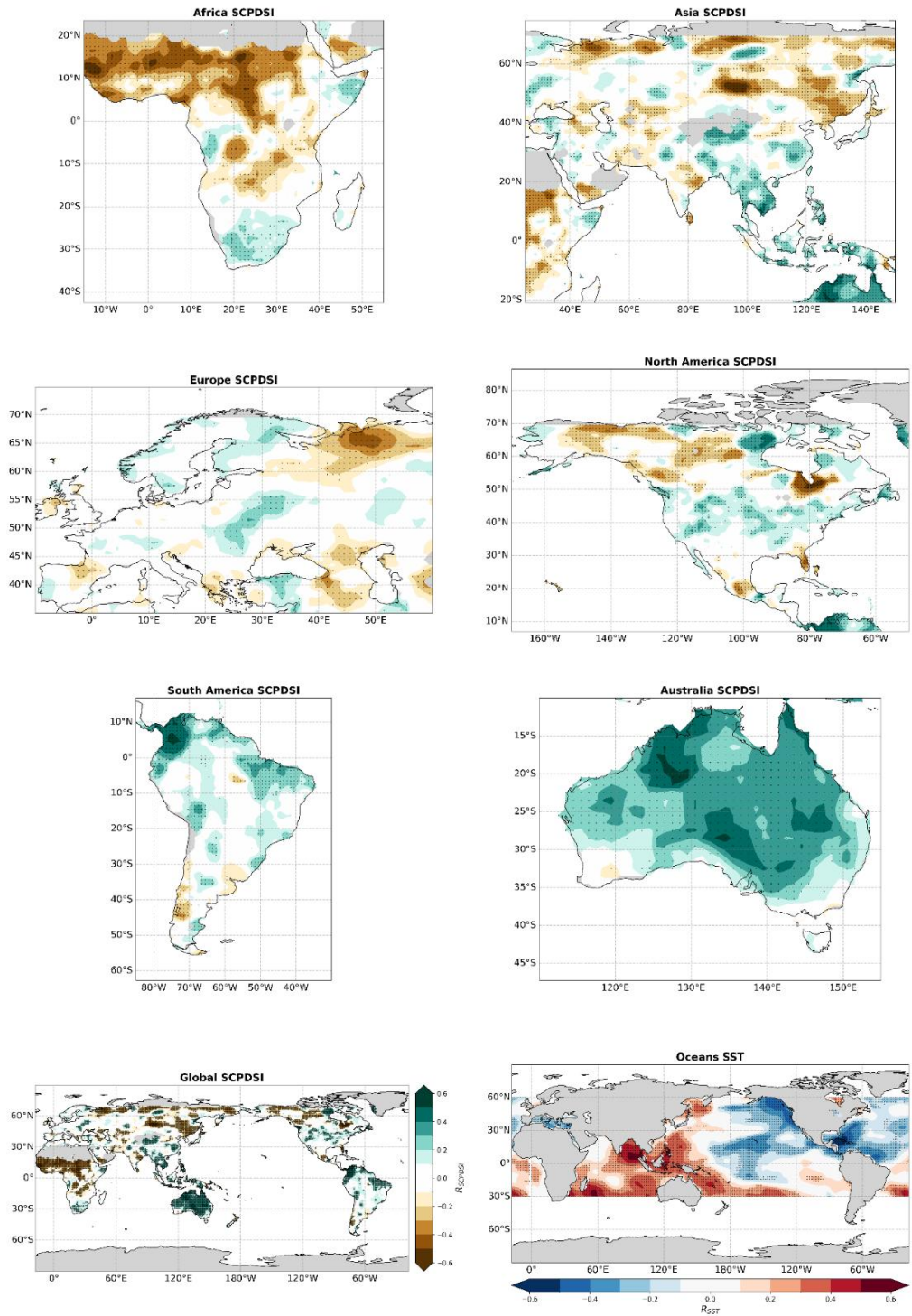
Supplementary Figure S5. Jeffrey's Divergence between degree distributions across the different analysis periods. Hatched boxes indicate pairwise comparisons that are statistically significant at the 0.001 level based on the two-sample KS test, confirming that the underlying generational processes of the distributions differ. Numerical values denote the magnitude of the divergence metric, with larger values reflecting stronger distributional separation.



Supplementary Figure S6 Trends in the frequency of drought events in different periods using Mann Kendall test significant at $p < 0.05$.

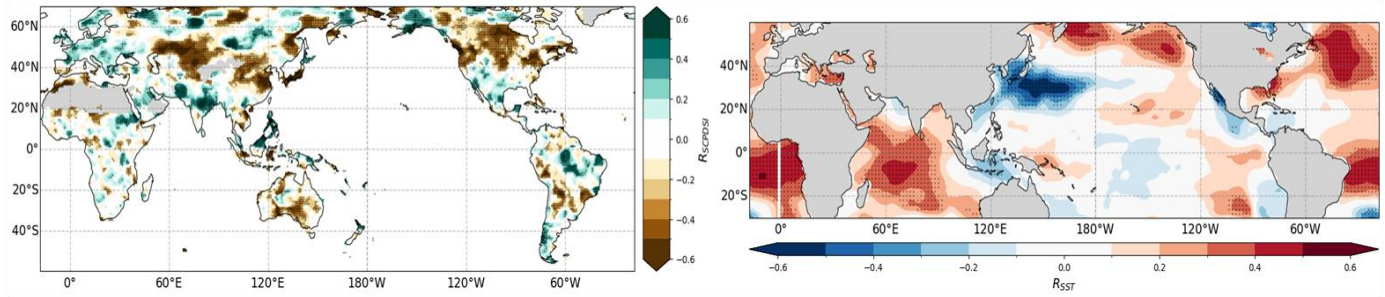


Supplementary Figure S7 Evolution of Number of zero degree nodes and average degree for the 61 instances of Complex network formed using sliding window approach.

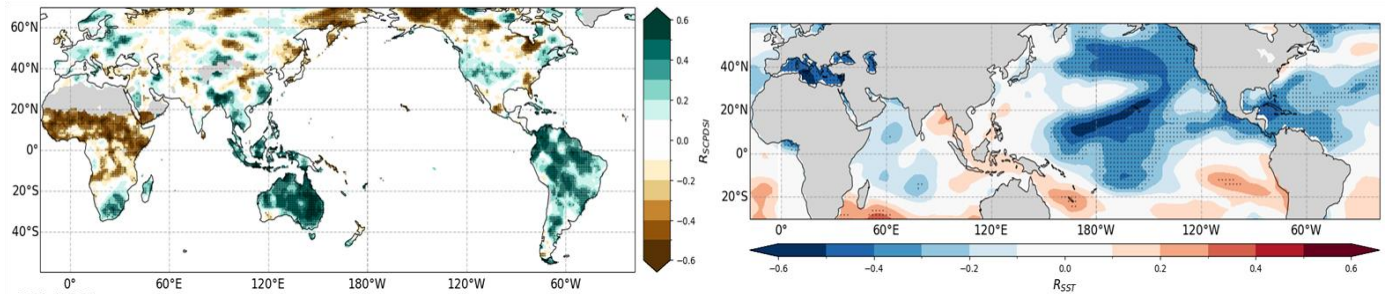


Supplementary Figure S8 Second modes of variability between scPDSI with sea surface temperature (SST) anomalies. The second mode of scPDSI-SST variability explains 15.17% of the squared covariance ($r = 0.79, p < 0.05$).

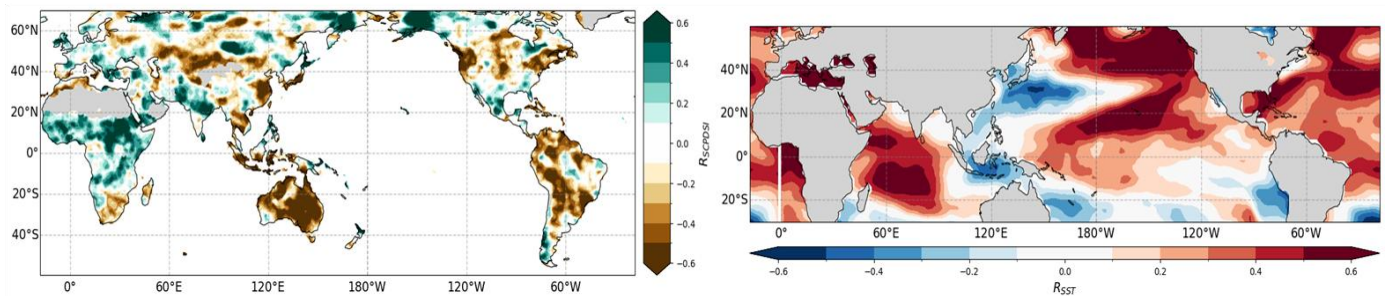
(A) Second Mode (1901-1960) [SCF = 16.1 %, $r = 0.89$]



(B) Second Mode (1961-2020) [SCF = 17.6 %, $r = 0.84$]

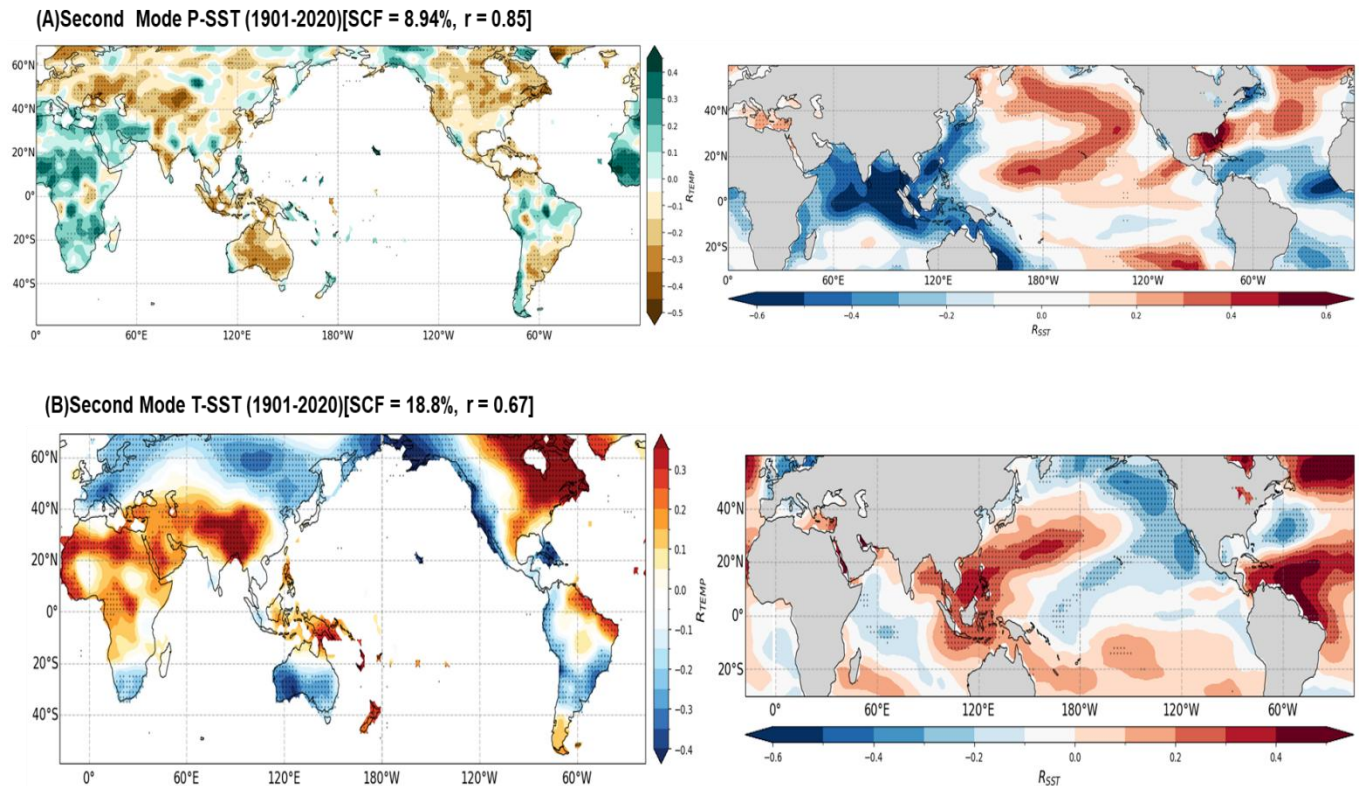


(C) Difference

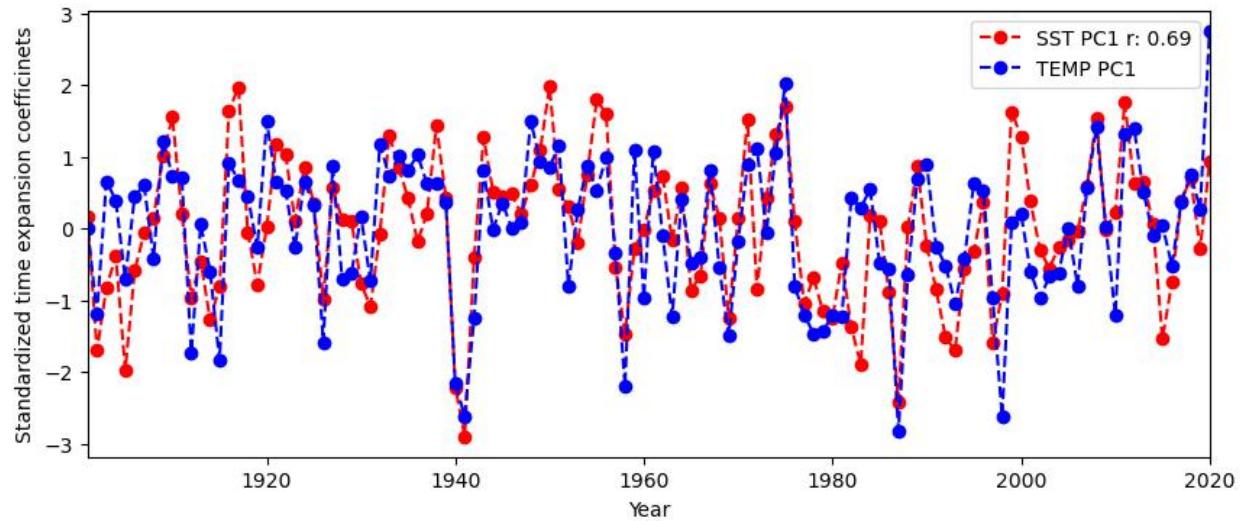


Supplementary Figure S9 Comparison of the MCA Analysis of sc-PDSI and SST Anomalies Between Two Periods (1901-1960 and 1961-2020)

(A) The Second mode obtained during the period of 1901-1960, the colored patterns are heterogeneous correlation coefficient between SST PC1 and sc-PDSI on land and sc-PDSI PC1 and SST departure field over ocean. (B) Same as (A) but for period of 1961-2020 (C) Difference between (1961-2020) and (1901-1960)



Supplementary Figure S10 Second modes of variability between precipitation (P) and temperature (T) with sea surface temperature (SST) anomalies. (A) The second mode of P-SST variability explains 8.94% of the squared covariance($r = 0.85$, $p < 0.05$). (B) The Second mode of T-SST explains around about 18.8% of squared covariance ($r = 0.67$, $p < 0.05$). The dominant influence of global warming has been removed from Global Temperature fields.



Supplementary Fig. S11. Standardized time series of the leading Maximum Covariance Analysis (MCA) modes derived from global land surface temperature and sea surface temperature (SST) fields. The red curve shows the expansion coefficients of the SST leading mode, while the blue curve shows those of the temperature leading mode. Both series are standardized to allow direct comparison of their temporal variability. The two leading modes exhibit a correlation of $r = 0.69$, indicating a strong and coherent co-evolution between global SST anomalies and land surface temperature anomalies over the past century. This shared variability reflects large-scale coupled ocean–atmosphere processes: warm or cool SST patterns tend to be accompanied by corresponding warming or cooling of continental regions. Thus, the leading MCA mode captures the dominant pattern of joint SST–temperature variability, highlighting the tight coupling between oceanic forcing and land climate response.

Supplementary Table 1 : Mean Conditional Probabilities of crop failure ($\text{Yield} < Y_{\text{mean}} - 0.5 \cdot Y_{\text{std}}$) given sc-PDSI < -2 across various continents based on the 1981-2016 global gridded crop data.

	Africa Above Equator	Africa Below Equator	Asia	Europe	North America	South America	Australia
Rice	0.2824	0.3472	0.3367	0.3349	0.3602	0.3313	0.2559
Maize	0.2930	0.3335	0.3376	0.3861	0.4335	0.4018	0.2520
Soybean	0.2708	0.3444	0.3540	0.3995	0.5182	0.4198	nan
Wheat	0.2704	0.2677	0.3413	0.4031	0.4015	0.3747	0.3686

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152 **Supplementary Table 2** Past ENSO Years based on Extended Multivariate ENSO153 Index ([ENSO YEARS LIST](#))

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El Niño	1900,1903,1906,1915,1919,1926,1931,1941,1942,1958, 1966,1973,1978,1980,1983,1987,1988,1992,1995,1998 2003,2007,2010,2016
Neutral	1901-1902,1905,1907-1908,1912-1914,1916,1920-1924 1927-1930,1932-1933,1935-1938,1940,1944-1949,1952-1954, 1957,1959-1961,1963-1965,1967-1970,1972,1975,1977,1979, 1981-1982, 1984-1986,1990-1991,1993-1994,1996-1997, 2001-2002,2004-2006,2009,2013-2015,2017-2020
La Niña	1904,1909,1910,1911,1917,1918,1925,1934,1939,1943,1950, 1951,1955,1956,1962,1971,1974,1976,1989,1999,2000,2008, 2011,2012

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Period	Mean DC	Std	Skewness	Kurtosis	Pr(Deg>X)
1901-1960	96	106	2.43	8.45	0.0347
1931-1990	134.5	111	6.55	143.7	0.0352
1961-2020	147	115	5.34	90.79	0.0474
1901-2020	182	152	3.09	19.15	0.099

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**Supplementary Table 3 :Degree Centrality StatisticsX = 90th quantile of
Degree Centrality from period 1901-2020
X = 357**

Supplementary Table 4 : Trends in Degree and Average Link Length(ALL)

Continent	Increasing ALL(%)	Decreasing ALL(%)	Increasing Degree(%)	Decreasing Degree(%)
Africa	57.54	41.83	71.43	28.22
Asia	30.91	67.15	66.41	32.49
Australia	58.91	31.25	88.51	11.49
North America	41.55	47.93	70.61	26.19
South America	35.53	51.66	52.48	34.85
Europe	41.56	50.10	75.47	23.83

Supplementary References

1. Genest, C., & Rémillard, B. (2008). *Validity of the parametric bootstrap for goodness-of-fit testing in semiparametric models*. Annales de l'I.H.P. Probabilités et Statistiques, 44(6), 1096–1127. <https://doi.org/10.1214/07-AIHP148>
2. Sadegh, M., Ragno, E., & AghaKouchak, A. (2017). *Multivariate Copula Analysis Toolbox (MvCAT): Describing Dependence and Underlying Uncertainty Using a Bayesian Framework*. Water Resources Research, 53(6), 5166–5183. <https://doi.org/10.1002/2016WR020242>