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Regional responses to oceanic variability constrain global drought synchrony

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Abstract

Synchronized droughts threaten global food security, with concerns about increased frequency and duration under climate change. However, their long-term evolution and physical limits remain unknown. We analyze 61 drought networks over 120 years (1901–2020) of Self-Calibrating Palmer Drought Severity Index (sc-PDSI) data, employing a suite of network synchronization measures and empirical orthogonal functions to unravel the physical drivers and limiters of drought synchrony. Our results show that, contrary to claims that synchronized droughts could affect up to one sixth of the global land mass, the maximum synchronized area fluctuates between 1.84% and 6.5% of the total land mass. Although we observe a strong dependence between drought onset and local crop failures, global drought synchrony is shaped by a dichotomy: temperature trends exacerbate it, while precipitation variability, modulated by sea surface temperature oscillations, limits it. This suggests that although drought hubs are increasing, large-scale synchronization across multiple agricultural regions is less widespread than expected, affecting global food security strategies.

Teaser

Temperature exacerbates drought synchrony, while rainfall variability mediates and limits its global extent.

Introduction

Droughts have severe impacts on water resources, agriculture, energy production, and various socioeconomic activities, making them among the most devastating natural disasters [1, 2].

Droughts manifest through diverse onset and progression rates ranging from slowly intensifying droughts that persist over several seasons to years to rapid-onset flash droughts that can develop within weeks. Both forms cause severe and widespread agricultural, hydrological, and ecological impacts in recent years, underscoring the growing complexity of drought dynamics in a warming climate. [3–6]

The synchronous occurrence of droughts across multiple regions, particularly in global breadbaskets, poses a significant threat to food security and economic stability on a global scale [7, 8]. As global temperatures are expected to rise, the frequency of droughts and associated risks of staple crop failure are also projected to increase [8, 9]. For example, conditional probabilities of crop failure for wheat, rice, maize, and soybeans under moderate drought conditions ($sc\text{-PDSI} \leq -2$) range from 25–51% across continents (Supplementary Table 1, Fig. 1). These probabilities underline the vulnerability of global food systems to simultaneous drought occurrences in major agricultural regions.

Addressing food security risks associated with synchronized droughts is critical for achieving Sustainable Development Goal (SDG) 2 (Zero Hunger) and SDG 13 (Climate Action). Although global temperatures are projected to increase, trends in precipitation and soil moisture exhibit significant regional variability, leading to diverse and region-specific drought impacts [7, 10–13]. This variability underscores the necessity to investigate the historical evolution of synchronized droughts and identify their regional and global drivers and constraints.

Recent advances in complex network analysis and causal discovery have significantly improved our understanding of synchronous extreme weather events [14]. These techniques have elucidated the synchronization patterns of extreme rainfall events and heatwaves globally [15–19]. Similarly, recent drought studies using complex networks have identified influential drought hubs in regions like southern Europe, northeast Brazil, Australia, and northwest USA [20]. However, most studies, such as Chauhan et al. (2024)[21], rely primarily on indices like the Standardized Precipitation Index (SPI), which consider only precipitation, neglecting critical factors such as temperature, evaporation, and soil moisture essential for comprehensive drought assessment[1].

Furthermore, previous analyses often focus on single or limited time periods, leaving the temporal evolution of synchronized droughts largely unexplored. Linear methods, including Empirical Orthogonal Functions (EOFs) and Maximum Covariance Analysis (MCA), have effectively identified climate variability patterns linked to

large-scale oscillations like El Niño-Southern Oscillation (ENSO) [22–25]. Nevertheless, relying solely on linear methods might overlook complex and evolving regional drought connections.

Prior research has also noted uncertainties in drought trend detection due to variations in drought indices and methodological choices. For example, Sheffield et al.[26] questioned the robustness of traditional PDSI formulations, reporting minimal global drought changes over recent decades. Conversely, Dai[27] found increasing global drought trends associated explicitly with global warming. Such differences highlight the sensitivity of drought assessments to the choice of methods and indices, underscoring the need for analyses that complement these approaches.

To address these critical gaps, our study adopts a complementary yet distinct perspective by analyzing the synchronized evolution of drought conditions across regions. We employ both linear and non-linear methods, including Maximum Covariance Analysis (MCA) and event synchronization-based complex network analysis, to comprehensively explore the spatiotemporal dynamics of meteorological droughts and their climatic drivers from 1901 to 2020. Specifically, our study addresses three key research questions: (a) How have globally synchronous drought patterns evolved over the past century in response to large-scale climatic variability? (b) How does regional connectivity contribute to global drought synchronization? and (c) How do temperature and precipitation interactions shape synchronous global drought development?

Using the self-calibrated Palmer Drought Severity Index (sc-PDSI)[28], which integrates multiple climate variables and provides a more comprehensive representation of drought conditions, our analysis reveals how global drought connectivity has evolved under changing climatic conditions. Our findings highlight increased connectivity among drought-prone regions, suggesting higher risks of synchronous droughts in a warming world, moderated by regional rainfall variability driven by sea surface temperature (SST) patterns. Ultimately, our study advances the understanding of drought synchrony by providing insights into the large-scale propagation and intensification mechanisms of drought, supporting targeted resilience strategies for global food security and climate adaptation.

Results

Global Patterns of Crop Yield Failures Under Moderate Drought Conditions

We conducted a conditional probability analysis between crop yield anomalies and moderate drought conditions ($\text{sc-PDSI} \leq -2$) using a global dataset that integrates observed and satellite-based historical yield data (V1.2 and V1.3) [29] at a 0.5-degree resolution for four staple crops: wheat, rice, maize, and soybeans. The analysis was carried out at each grid point where food production data is available. For the 36-year period, We calculated the number of events where both crop yield fell below the long-term mean minus 0.5 times the standard deviation, and the average sc-PDSI during the growing season was less than -2. Our results reveal that conditional probabilities of crop failure exceed 50% at several key food-producing regions (Figure 1). For maize, high probabilities ($\geq 35\%$) are observed across multiple continents, including regions

such as the United States Corn Belt, Southern China, and parts of Southeast Asia (Fig. 1C). Similarly, soybean shows failure probabilities over 40% in South America, particularly Brazil and Argentina, as well as in parts of the North America (Fig. 1D). Wheat exhibits failure probabilities ranging from 27 to 40% (Supplementary Table 1) in regions such as the northern plains of the United States, Canada, Eastern Europe, and Central Asia (Fig. 1A). Rice, predominantly grown in South Asia, Southeast Asia, and sub-Saharan Africa, faces failure probabilities ranging from 25 to 36%, with monsoonal rainfall disruptions posing significant risks to production, particularly in countries like India and Indonesia (Fig. 1B). Similar insights were obtained from the analysis of crop yields falling below a threshold (mean - 1 standard deviation) and sc-PDSI averaged over entire nations using copula methods (see Methods and Supplementary Fig. S1).

Global patterns demonstrate the significant impact of droughts on agricultural production, with at least one major crop in each of the world's key food-producing regions in the world shown to be at a risk of failure during moderate droughts. While these results highlight the connection between drought conditions and crop failures at both local and national scales, they do not offer conclusive insights into whether these regions are likely to experience synchronized droughts on a global scale. Although the joint dependence between sc-PDSI and crop failure is evident, the broader question of whether drought events (and their impact) could align globally, potentially threatening food security, remains unresolved, which is discussed next.

Temporal Evolution of Drought Networks

To understand the evolution and structure of global synchronous droughts, we analyzed the spatio-temporal connectivity of drought events over the full period from 1901 to 2020 using complex network analysis. We constructed a network of moderate drought-onset events ($\text{sc-PDSI} \leq -2$) using the event synchronization technique described in [30]. Fig. 2A shows the degree centrality (DC) corrected for projection distortions. Polar regions inherently have a higher node density per unit area than equatorial regions, which can lead to overestimation of network measures. To correct this, each grid cell DC was weighted by the cosine of its latitude. As shown in Supplementary Fig. S2, applying this correction reduces the apparent degree values at higher latitudes, providing a more physically consistent spatial representation of drought synchrony. [21]

The network reveals a heterogeneous connectivity structure, with prominent drought hubs in regions such as South Africa, western North America, Australia, the Middle East, and South America, consistent with key climatic features such as the Botswana High, Bolivian High, Bilybara High, and North Pacific High [20, 31]. Singh et al.(2022) [32] have shown that increased ENSO variability in a warming climate heightens the risk of concurrent regional droughts. However, the implications of this variability on the synchronization of droughts on a global scale remain unclear.

To examine the impact of oceanic variability on drought synchronization, we segregated El Niño and La Niña years using historical ENSO classifications based on the Extended Multivariate ENSO Index (Supplementary Table 2) and constructed two

separate synchronization networks. The analysis shows that South America and Australia consistently act as drought hubs, but the prominence of these hubs fluctuates significantly between El Niño and La Niña years (Fig. 3(A) and 3(B), Table 1). During El Niño, Australia exhibits a much higher drought degree (732) compared to La Niña (127), reflecting its heightened sensitivity to El Niño-induced moisture deficits and the weakening of the Walker circulation [33]. Conversely, Africa and South America display increased drought degree during La Niña years, with South America showing a marked rise from 201 in El Niño to 301 in La Niña years [34, 35]. This shift in the geographic distribution of droughts during La Niña supports the observation that La Niña tends to drive more dispersed and fragmented drought patterns, whereas El Niño induces more concentrated but intense droughts. Furthermore, the spatial extent of drought onset, measured through the ALL between drought events (Fig. 3(C),(D) and Table 1), is generally greater during La Niña years, particularly in Africa and Asia. This suggests that La Niña disperses the geographic impacts of drought, altering drought synchrony. Our network diagnostics show that El Niño years are characterized by high node degree and low Average Link Length, indicating strong local clustering and spatially coherent drought conditions. In contrast, La Niña years exhibit higher Average Link Length and reduced local clustering, consistent with more spatially heterogeneous and regionally dispersed drought occurrence. This interpretation is in line with previous findings that stronger El Niño events produce more spatially coherent drought anomalies, while La Niña impacts are typically more heterogeneous. [36] In contrast For Europe, ENSO-related drought signals are generally weak because the teleconnections is indirect and strongly modulated by the North Atlantic circulation. Studies show that the ENSO influence varies by season and is often inconsistent across events, resulting in only modest and weak response to ENSO [37] with only small changes in ALL during La Niña periods. During El Niño, much of the southern and southwestern United States tends to experience reduced drought risk because of enhanced winter storm activity, while parts of the Pacific Northwest can become drier. In contrast, La Niña generally increases drought likelihood over the southern U.S. and northern Mexico due to suppressed winter precipitation, while the Pacific Northwest and parts of Canada often become wetter. [38, 39] Taken together, these ENSO-stratified network results align well with established teleconnection behaviour. The increased drought degree over Australia during El Niño and the higher degree across Africa and South America during La Niña match the phase-asymmetric hydroclimatic responses reported in earlier studies. Likewise, the weak and inconsistent ENSO signals seen over Europe are consistent with findings that ENSO influence in mid-latitudes is indirect and strongly seasonal. By quantifying ENSO-phase-specific changes in DC, and spatial propagation (ALL), we reveal how ENSO reorganizes the coherence of drought events rather than only where droughts occur. Supplementary Fig. S3 presents our robustness check of the ENSO–drought relationship. We first performed a regression analysis between standardized Niño-3.4(DJF) anomalies and the leading global drought mode (PC1 of sc-PDSI) to quantify the amplitude-dependent ENSO influence. We then repeated the analysis after removing the strong ENSO years (1982–83, 1997–98, 2015–16). The results show only minor changes in both the correlation and the regression slope, confirming that the ENSO–drought coupling is not

driven by a handful of extreme events. These results indicate that oceanic variability, particularly ENSO phases, introduces asynchronous regional responses, ultimately limiting the global extent of drought synchronization.

To understand regional connectivity within the network, we evaluated the local clustering coefficient, an indicator of how connected neighbors are to each other, providing insight into the degree of local interconnectedness (Supplementary Fig. S4(A)). Regions exhibiting high clustering coefficients (CC) generally indicate locally coherent or spatially continuous drought behavior, consistent with the findings of Mondal et al. (2023), who reported high CC values (≥ 0.3) over Australia and South Africa corresponding to spatially contiguous droughts with limited large-scale synchronization. [20]

In contrast, South America exhibits high degree centrality but low clustering, indicating sparse local networks with greater reliance on large-scale teleconnections. We also quantified the spatial extent of drought synchronization using the average link length (ALL) (Supplementary Fig. S4(B)). The ALL represents the mean geographical distance among significantly synchronized nodes in the drought network. Lower ALL values correspond to regionally confined drought linkages, while higher values reflect teleconnections extending across continents and ocean basins. In our analysis, ALL values range from several hundred to nearly 20,000 km, indicating spatial connections spanning regional to global scales. Similar spatial ranges were reported by Mondal et al. (2023). Coastal regions like western North America and eastern South America exhibit higher ALL, suggesting stronger teleconnections influenced by oceanic and atmospheric processes. In contrast, the interior regions of South America, constrained by topographic barriers such as the Andes, show lower ALL, indicating more localized synchronization.

To assess changes in network structure over time, we employed the methodology outlined in [18], constructing 61 network instances using a 60-year sliding window starting from 1901. Fig. 2B shows the degree centrality distribution across different periods, revealing a heavy-tailed distribution indicative of hubs. To formally evaluate whether the degree distributions differ across historical periods, we quantified distributional divergence using Jeffrey's Divergence and assessed significance using the two-sample Kolmogorov–Smirnov (KS) test. [18] (Supplementary Fig. S5) Both metrics consistently indicate significant differences between periods ($p < 0.001$), demonstrating that the generative processes underlying drought synchrony have shifted over time. These results support our finding that drought synchrony has intensified in recent decades under a warming climate. As the frequency of drought increases (Supplementary Fig. S6), the distribution shifts to the right (Supplementary Table 3), with high degree nodes becoming more common, indicating increased connectivity among drought-affected regions and a reduction in zero-degree nodes (Supplementary Fig. S7), signifying more nodes (or drought-affected areas) actively participating in the network over time. For example, the mean degree centrality increased from 96 during the 1901–1960 period to 147 during 1961–2020, reflecting a significant increase in network connectivity. Fig. 2C shows that a Mann-Kendall trend test indicates 54% of the nodes exhibit increasing degree trends, while 23.5% show decreasing trends. Furthermore, the probability of observing a degree centrality greater than the 90th quantile

($\Pr(\text{Deg} \geq 357)$) increased 1.36 times, increasing from 0.0347 in 1901–1960 to 0.0474 in 1961–2020. This shift underscores the growing inter connectivity of drought-affected regions, with more than half of the regions becoming increasingly interconnected, potentially leading to more widespread and synchronized drought events.

Further analysis of regional variations in degree trends on the continental scale (Supplementary Table 4) reveals that Australia exhibits the most significant increase in positive degree trends (88% of nodes), compared to 52% in South America. Fig. 2D presents box plots of degree centrality across three periods, highlighting increases in mean degree, particularly in earlier periods. Although mean degree increased between 1901–1960 and 1961–2020, the relatively modest rise during the latter period suggests that enhanced oceanic and regional variability, expressed through out of phase SST oscillations and associated precipitation anomalies, acts to constrain further growth in global drought synchronization. The maximum degree centrality observed in our analysis was 3,871 (6.5% of all grid cells) during the 1942–2001 window. This value represents an isolated upper bound, with all other periods showing substantially lower connectivity. This contrasts with earlier studies that reported DC approaching 15,000, which appear considerably higher than what we obtain using the same data source and network construction procedure. [20] The extent to which oceanic variability permits such extensive connectivity remains a question we explore further.

SST Drivers of Drought Variability

Building on the network analysis of global synchronous droughts, we examine the role of sea surface temperature anomalies (SST) in shaping drought patterns using Maximum Covariance Analysis (MCA)[22, 40]. This approach identifies the dominant modes of variability that link SST anomalies with global sc-PDSI patterns. The first mode, shown in Fig. 3A), is strongly associated with the El Niño-Southern Oscillation (ENSO), which explains around 37.6% of squared covariance and their principal components (PCs) are strongly correlated exhibiting a significant correlation ($r = 0.85$, $p < 0.05$) [41].

ENSO phases exert a well-established influence on global weather, with contrasting impacts across regions. For instance, during El Niño events, Peru and Ecuador experience increased rainfall, while northeastern South America faces drought conditions[42]. In India, ENSO weakens monsoon rainfall, and warming of the tropical Indian Ocean exacerbates this effect [22, 43]. Similarly, Australia experiences drought as El Niño disrupts convective rainfall. In Europe, variability driven by the North Atlantic Oscillation (NAO) and Tropical North Atlantic (TNA) modes leading to warmer and wetter conditions in the north, while the south Europe experiences cooler and drier conditions [44, 45].

The second mode, shown in Supplementary Fig. S8, also exhibits ENSO-driven characteristics and The Principal Components (PCs) of SST anomalies and sc-PDSI anomalies shows a correlation of 0.79 ($p < 0.05$) explaining 15.2% of the squared covariance. This mode emphasizes the region-specific nature of SST-drought linkages. For example, in Australia, cooler central Pacific SSTs and negative Indian ocean dipole (IOD) [46] phases reduce drought severity, while in the Indian subcontinent, SST pattern correlates with dipolar drought structure with with wet conditions over the

Indo-Gangetic plains and drought like condition over the southern part of India. In Africa, contrasting responses are observed, with positive correlations in the southern regions of Africa and negative correlations in the Sahel, reflecting localized influences.

These modes highlight the spatial variability of SST influences, with the first mode showing positive correlations in North America, Europe, and South America, and negative correlations in Africa, Australia, and Asia (Fig. 3A). The second mode reveals distinct impacts in Australia and Asia (Supplementary Fig.S8). The contrasting correlations across regions indicate a duality that reflects broken synchrony in global drought patterns, where warming in one oceanic region can simultaneously drive drought in one area while mitigating it in another.

Changing Role of Large-Scale Climate Variability in Drought Patterns

As noted previously (Fig. 2), the latter half of the twentieth century shows a significant increase in drought synchrony, reflected in both degree centrality and link length. To further explore the relationship between sea surface temperature (SST) anomalies and sc-PDSI, we performed a singular value decomposition (SVD) analysis for two periods: 1901–1960 and 1961–2020. During the first period, strong correlations were observed between the SST departure field and sc-PDSI in the central Pacific and Indian Oceans (Fig. 4), consistent with an El Niño–Southern Oscillation (ENSO) pattern. This mode remains dominant in the second period (Fig. 4B), exhibiting an increased influence, as the Squared Covariance Factor (SCF) for this leading mode rose from 32% to 38.8%, highlighting the strengthening of the ENSO and sc-PDSI relationship. Comparing these two periods suggests distinct shifts in the correlation patterns within the Indian and Atlantic Oceans, indicating a growing impact of oceanic variability on global drought synchronization. Beyond the Atlantic and Indian Oceans, we note enhanced correlations in the Central Pacific alongside a higher squared covariance fraction (SCF) of the leading SST–scPDSI mode. This co-occurrence indicates that a larger portion of the joint variability is being organized by Central-Pacific (CP) El Niño dynamics, wherein SST anomalies peak near the dateline and convection shifts westward. Observational analyses show increasing CP El Niño intensity and greater prevalence in recent decades[47], while process-based studies tie future CP frequency to background-state features such as cold-tongue strength[48, 49]. These results suggest that ENSO diversity has evolved, with CP events increasingly modulating global teleconnections[50] and, by extension, the spatial structure of drought synchrony in our network analysis

The second mode, shown in Supplementary Fig. S9, also exhibits increased influence, with the SCF rising from 16.1% to 17.6%. Changes are particularly evident in the Tropical North Atlantic, highlighting the evolving role of SST variability in shaping global drought patterns.

Temperature Exacerbates, Rainfall Variability Modulates Global Drought Synchronization

Given that sc-PDSI as a drought indicator is derived from precipitation and temperature anomalies, together with modulation by land surface properties [28], it is crucial to understand how these driving variables interact with sea surface temperature (SST) to influence global drought patterns. To investigate these interactions, we performed maximum covariance analysis (MCA) on the SST departure field with precipitation (P) and air temperature (T) from 1901 to 2020.

The first leading mode of variability between global precipitation and SST anomalies (Fig. 6A) exhibits varying signs on all continents, reflecting regional differences in response to SST variability. In contrast, the temperature-SST correlations (Fig. 6B) consistently display the same sign globally, underscoring the dominant influence of increasing global temperatures. The first mode for P-SST explains 65.6% of the squared covariance, with the principal components strongly correlated ($r = 0.92$, $p < 0.05$), and captures the characteristic pattern of the El Niño-Southern Oscillation (ENSO). SST anomalies in the equatorial Pacific show opposite signs compared to precipitation anomalies in regions such as Australia, Southeast Asia, and Africa. This pattern is consistent with previous findings [22, 42], underscoring the central role of ocean variability in modulating global precipitation patterns.

In the second mode (Supplementary Fig. S10), which accounts for 8.94% ($r = 0.85$) of the SCF for precipitation and 18.8% ($r = 0.67$) for temperature, the P-SST correlations continue to display contrasting signs across continents, underscoring the regional variability that influences drought patterns. In contrast, the T-SST correlations remain consistent between regions, further emphasizing the widespread impact of rising temperatures globally. The corresponding normalized expansion coefficients of SST-T are presented in Supplementary Fig. S11, confirming the temporal coherence of the leading T-SST mode. Critically, however, the inference of regional consistency is grounded in the spatial loading pattern, whose globally uniform sign indicates a continent-wide and directionally consistent temperature response to SST variability. These findings indicate that while SST variability drives the increasing spatial extent of synchronous droughts, regional differences in precipitation correlations serve as a key modulating factor, limiting the overall degree of synchronization.

Thus, while temperature exacerbates the consistency of drought patterns, precipitation variability modulates their spatial distribution, reducing overall synchrony. The evolving regional climate interactions underscore the importance of further investigating the processes behind these shifts, particularly as global temperatures continue to rise.

Relative Roles of Precipitation and Temperature in Driving Drought Trends

Drought synchrony can increase either due to precipitation deficits becoming more spatially coherent or through rising temperatures uniformly enhancing evaporative demand. To quantify the relative roles of these two mechanisms, we partitioned observed drought severity trends—quantified by the self-calibrating Palmer Drought

Severity Index (scPDSI)—into precipitation-driven and temperature-driven components. For this analysis, we used monthly global precipitation and temperature data from the CRU TS v4.07 dataset spanning 1901–2021. Potential evapotranspiration (PET) was calculated using the Thornthwaite method (see Methods, “Trend-partition experiments”). We chose this method specifically because it relies solely on temperature, thus isolating the influence of temperature-driven evaporative demand from other meteorological variables such as wind speed, humidity, and radiation included in alternative PET methods. Linear trends in scPDSI were estimated using the non-parametric Sen’s slope estimator (see Methods).

Globally, precipitation accounted for approximately two-thirds of the multi-decadal drought severity trends, with contributions remaining consistent at around 66% for 1961–1990 and 67% for 1991–2020 (Fig. 7E). Temperature-driven evaporative demand explained the remaining one-third. At regional scales, precipitation remained the predominant driver, notably in Australia and South America, consistently accounting for more than 75% of the observed trends across both periods (Fig. 7B,D). However, the contribution from temperature-driven evaporation notably increased post-1990 in mid-latitude regions. For instance, in Asia, the temperature contribution rose from 31% (1961–1990) to 36% (1991–2020), and similarly, in Europe from 28% to 38% (Fig. 7A,C,E). In contrast, North America and Africa showed relatively stable contributions throughout, dominated primarily by precipitation variability.

These results collectively indicate that while precipitation variability remains the dominant global driver of drought severity trends, the role of temperature-driven evaporative demand has strengthened significantly in recent decades, particularly in regions experiencing rapid warming. This growing temperature influence contributes meaningfully to observed increases in global drought synchrony, even without a corresponding increase in the spatial coherence of precipitation deficits.

Discussion

Concurrent and synchronized droughts pose significant risks to global food security, as simultaneous failures in key agricultural regions can severely disrupt food supply chains. Given the high probability of staple crop failure during moderate droughts, the potential for concurrent droughts could push global food systems to critical thresholds. We note that teleconnections and synchrony are related but distinct concepts. Teleconnections describe the physical and directional linkages between distant regions mediated through atmospheric and oceanic circulation anomalies such as those associated with ENSO. Synchrony, in contrast, is a statistical measure of the temporal co-occurrence of drought onsets across locations, regardless of whether the underlying mechanisms are shared or independent. While teleconnections can therefore generate synchrony, they are not its sole driver, as coincident regional anomalies or compensating ocean–atmosphere interactions can also align drought timing. This distinction motivates our use of percentage variance explained plots with SST anomalies (Figs. 4–6), which demonstrate that although ENSO accounts for a substantial portion of coupled SST–drought variability, spatial heterogeneity in these relationships indicates

that regional oceanic and atmospheric variability constrains the overall degree of global drought synchronization.

Our findings indicate that although rising temperatures consistently amplify drought severity by increasing evaporative demand globally, regional variability in precipitation continues to constrain the extent of drought synchronization. Despite increasingly strong global teleconnections, the likelihood of large-scale simultaneous droughts on multiple continents remains lower than previously suggested [20]. Understanding this interplay between global climatic drivers and regional precipitation constraints is essential for informing effective resilience strategies in global food security, water resource management, and climate adaptation.

Our analysis explicitly quantifies the relative contributions of temperature and precipitation to drought severity trends. Approximately two-thirds of global drought severity changes are driven by precipitation variability, modulated substantially by sea surface temperature oscillations. Temperature-induced drying contributes the remaining one-third, with its influence notably increasing in mid-latitude regions experiencing rapid warming, such as Europe and Asia [51, 52]. This interplay between intensified evaporative demand from rising temperatures and persistent regional precipitation variability explains the observed increase in drought synchrony in recent decades, highlighting that while global drought synchrony is exacerbated by warming, its overall spatial extent remains constrained by precipitation dynamics.

The constrained global-scale synchronization implies that, despite significant localized drought risks, simultaneous crop failures across multiple major agricultural zones remain unlikely at present. However, the scenario in which regional droughts become increasingly synchronized and extensive, driven by intensified warming or altered precipitation patterns, could destabilize global food systems profoundly. Leveraging spatial variability in drought conditions—through strategic resource allocation and flexible trade policies—can thus provide critical buffers against global-scale disruptions.

Our findings open several important avenues for future investigation. Although the sc-PDSI can exhibit a lag of several months before fully capturing drought onset [53], its integrative treatment of soil moisture deficits makes it well suited for the large-scale and persistent drought behavior examined here. Because our synchrony and network analyses rely on spatial patterns of sustained drought rather than precise onset timing, this lag does not materially affect our conclusions. Moreover, the sc-PDSI provides spatially comparable drought metrics and is widely employed in global drought studies [54], including previous network-based analyses [20], thereby ensuring methodological consistency and facilitating comparison across studies. While the self-calibrating Palmer Drought Severity Index (scPDSI) provided a consistent framework for evaluating drought dynamics at broad spatial and temporal scales, integrating alternative drought indices such as the Standardized Precipitation-Evapotranspiration Index (SPEI) could provide complementary insights into localized and short-term drought processes. Future work could also incorporate multiple observational datasets to test the sensitivity and generalizability of our conclusions, including alternative temperature (e.g., GISS, BEST), precipitation (e.g., GPCC), and sea surface temperature (SST) datasets (e.g., HadISST, Kaplan, COBE). Furthermore, incorporating

direct soil moisture measurements and more detailed representations of vegetation and hydrological processes could further refine predictive models, enhancing the overall understanding of drought dynamics and synchronization under changing climate conditions.

Nevertheless, our findings significantly enhance understanding of global drought synchrony, explicitly clarifying the roles of temperature and precipitation. By identifying how large-scale climatic forcings interact with regional variability, we offer a clearer foundation for predictive modeling and strategic resilience planning. As climate change amplifies drought frequency and severity, strategically leveraging these insights will be critical for safeguarding agricultural stability, ensuring resilient food supply chains, and strengthening adaptive capacities globally.

Methods

Drought Onset and Drought Event

In this study, we define the onset of moderate drought using a threshold approach [17, 20, 21, 55], with a threshold of -2 based on the self-calibrating Palmer Drought Severity Index (sc-PDSI). We use the sc-PDSI due to its popularity as a drought indicator, given its use of the Penman–Monteith method for calculating potential evapotranspiration, which accounts for multiple climate variables and provides a more physically accurate representation of drought conditions. The sc-PDSI is widely recognized for global-scale drought analysis, particularly in the context of global warming, and has been extensively used in studies examining the impact of drought on ecosystems [54, 56, 57].

A drought onset is defined as the first month when the sc-PDSI value falls below this threshold, indicating the start of a moderate drought. Termination is defined as the time when the sc-PDSI value rises above the threshold. The duration of the drought is the period between its onset and termination. Each pair of drought onset and termination is counted as one drought event. We focus on moderate droughts to ensure that a sufficient number of events are captured at each location, providing a robust dataset for analysis.

Event Synchronization (ES)

Event Synchronization (ES) is a non-parametric method used to identify temporal dependencies between events, such as drought onsets. It captures the timing and delays between events without assuming linear relationships. In this study, ES is used to analyze drought onset synchronization across different regions, following the method described in [58–60].

The steps involved in the Event Synchronization approach are as follows:

- For two grid points, i and j , where drought events occur at times t_l^i and t_m^j , calculate the dynamic temporal delay, τ_{lm}^{ij} :

$$\tau_{lm}^{ij} = \min \left\{ \frac{t_{l+1}^i - t_l^i, t_l^i - t_{l-1}^i, t_{m+1}^j - t_m^j, t_m^j - t_{m-1}^j}{2} \right\} \quad (1)$$

where s_i and s_j are the total number of drought events at grid points i and j , respectively. Two events are considered synchronized if the time gap between them does not exceed 3 months.

- Calculate the number of times an event at location i follows an event at location j , denoted $c(i|j)$:

$$c(i|j) = \sum_{l=1}^{s_i} \sum_{m=1}^{s_j} J_{ij} \quad (2)$$

where:

$$J_{ij} = \begin{cases} 1 & \text{if } 0 < t_l^i - t_m^j < \tau_{lm}^{ij} \\ 0.50 & \text{if } t_l^i = t_m^j \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

- The synchronization strength between grid points i and j is then calculated as:

$$Q_{ij} = \frac{c(i|j) + c(j|i)}{\sqrt{s_i s_j}} \quad (4)$$

- Once the ES computation is completed, a synchronization matrix is obtained with dimensions $59,721 \times 59,721$, representing the synchronization strength of drought onsets between all grid points globally.

Complex Network Analysis

Using the adjacency matrix obtained from the Event Synchronization (ES) analysis, we perform Complex Network (CN) analysis to study the synchronization of drought onsets across different regions. The steps involved in the CN analysis are as follows:

- Construct an undirected synchronization network where nodes represent grid locations and edges represent synchronization between two locations. Each edge indicates synchronization but does not imply direction.
- The adjacency matrix, A_{ij}^Q , is symmetric and contains synchronization values for all grid location pairs. We include only statistically significant connections by applying a threshold to the synchronization values. We set this threshold at the top 0.5% (99.5th quantile) of all non-zero synchronization values, denoted as θ .
- Convert the synchronization matrix into a binary adjacency matrix:

$$A_{ij}^Q = \begin{cases} 1 & \text{if } Q_{ij} > \theta \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Network Measures

To quantify the properties of the network, we use the following measures:

- **Degree Centrality (DC):** For a network with N nodes, the degree centrality of a node j measures the number of connections (edges) it has:

$$DC_j = \frac{\sum_{i=1}^{N-1} A_{ij}}{N-1} \quad (6)$$

A high degree centrality indicates that the drought onset at grid point j is synchronized with many other locations.

- **Clustering Coefficient (CC):** The clustering coefficient CC_j of a node j measures how many of its neighbors are also connected to each other. It is calculated as:

$$CC_j = \frac{2\beta}{k_j(k_j - 1)} \quad (7)$$

where β is the number of actual connections between the neighbors of node j , and k_j is the number of neighbors of node j .

- **Average Link Length (ALL):** The average link length measures the average physical distance between connected nodes. It is computed as:

$$ALL = \frac{\sum_{i=1}^{N-1} A_{ij} d_{ij}}{\sum_{i=1}^{N-1} A_{ij}} \quad (8)$$

where d_{ij} is the physical distance between grid points i and j .

Maximum Covariance Analysis

We use maximum covariance analysis (MCA) [40] to identify the coupled patterns of variability of sc-PDSI with sea surface temperature (SST) departure fields, obtained as the departure of each year's SST anomaly at each grid point from that year's global mean SST anomaly. Let X be $N_1 \times T$ (location \times time), and Y be $N_2 \times T$ (location \times time), representing the SST and sc-PDSI anomalies, respectively.

$$\begin{aligned} \frac{1}{T}XY^T &= U\Sigma V^T \\ C &= \frac{1}{T}XY^T \end{aligned} \quad (9)$$

where C is the cross-correlation matrix. The orthonormal matrices U and V contain the spatial modes corresponding to the data fields X and Y respectively, and Σ is the diagonal matrix containing the singular values. The leading modes represent the main pattern of covariance between the two fields.

Time expansion coefficients, which represent how strongly each mode loads on each year, are given as:

$$T_{kU} = U_k^T X$$

$$T_{kV} = V_k^T Y$$

The squared covariance factor SCF_i is:

$$SCF_i = \frac{\sigma_i^2}{\sum_j \sigma_j^2}$$

where σ_i is the i -th singular value and the denominator is the sum of the squares of all singular values.

Impact on Crop Yield

To assess the impact of droughts on crop yields, we used nationally averaged sc-PDSI values, where $\text{sc-PDSI} \leq -2$ 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 [61–63]:

$$\Delta\text{Yield} = \text{Yield}_i - \text{Yield}_{i-1} \quad (10)$$

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.

Conditional Crop Failure Probability Estimation Based on Historical Data

To calculate the conditional probabilities of crop yield failure under drought conditions, we used empirical approach. For each grid point, we first identified all years where the sc-PDSI value during the growing season fell below -2 (indicating moderate drought). We then calculated the proportion of these years in which the crop yield fell below 0.5 times the standard deviation from the long-term mean yield. This proportion represents the conditional probability of crop failure, given the occurrence of a moderate drought. The calculation was performed for each crop across all available grid points. The conditional probability of crop yield failure under moderate drought conditions can be expressed as:

$$P(\text{Crop Failure} \mid \text{Drought}) = \frac{\sum_{i=1}^n I(\text{sc-PDSI}_i < -2 \wedge Y_i < \mu_Y - 0.5\sigma_Y)}{\sum_{i=1}^n I(\text{sc-PDSI}_i < -2)}$$

where:

- n is the number of years,
- $I(\cdot)$ is the indicator function, which equals 1 if the condition inside is true and 0 otherwise,
- sc-PDSI_i is the sc-PDSI value for year i ,
- Y_i is the crop yield for year i ,
- μ_Y is the long-term mean crop yield,
- σ_Y is the standard deviation of crop yield.

	Degree El Niño	ALL El Niño	Degree La Niña	ALL La Niña
Africa	119	6177	144	7112
Asia	119	3776	100	4310
Australia	732	6393	127	5120
North America	79	3507	98	4308
South America	201	5274	301	7096
Europe	111	4157	103	4377

Table 1: El Niño and La Niña Degrees and Average Link Length (ALL) by Continent.

Trend-partitioning experiments

To isolate and quantify the relative contributions of precipitation and temperature to drought severity trends, we employed the self-calibrating Palmer Drought Severity Index (scPDSI). Potential evapotranspiration (PET) was calculated using the Thornthwaite method [64], emphasizing temperature alone, with a fixed Available Water Capacity (AWC) of 100 mm assumed uniformly across all grid cells.

We generated three distinct scPDSI scenarios to explicitly partition precipitation and temperature influences:

1. **Observed run (OBS):**

$$\text{scPDSI}_{\text{OBS}} = f(P_{\text{obs}}, \text{PET}_{\text{obs}}) \quad (11)$$

2. **Fixed-Precipitation run (P-CLIM):**

$$\text{scPDSI}_{\text{P-CLIM}} = f(\bar{P}_{\text{clim}}, \text{PET}_{\text{obs}}) \quad (12)$$

3. **Fixed-PET run (PET-CLIM):**

$$\text{scPDSI}_{\text{PET-CLIM}} = f(P_{\text{obs}}, \bar{\text{PET}}_{\text{clim}}) \quad (13)$$

Here, P_{obs} and PET_{obs} represent observed monthly precipitation and potential evapotranspiration, respectively, from CRU TS v4.07 (1901–2021). \bar{P}_{clim} and $\bar{\text{PET}}_{\text{clim}}$ indicate monthly climatological averages computed over the entire analysis period (1901–2021).

Linear trends were calculated using the non-parametric Sen’s slope estimator [65] applied separately to monthly scPDSI values for two distinct 31-year periods: 1961–1990 and 1991–2020. Monthly trend values were converted to annual trends by scaling with a factor of 12:

$$\text{Annual trend} = 12 \times (\text{monthly Sen's slope}) \quad (14)$$

The fractional contributions of precipitation (F_P) and temperature-driven evapotranspiration (F_T) to the observed drought severity trends were quantified using the differences between the observed trends and those from the sensitivity experiments:

$$F_P = \frac{|\text{Trend}_{\text{OBS}} - \text{Trend}_{\text{P-CLIM}}|}{|\text{Trend}_{\text{OBS}}|} \times 100\% \quad (15)$$

$$F_T = \frac{|\text{Trend}_{\text{OBS}} - \text{Trend}_{\text{PET-CLIM}}|}{|\text{Trend}_{\text{OBS}}|} \times 100\% \quad (16)$$

Spatial patterns and regional summaries of these fractional contributions are presented in the main text (Fig. 7).

Data Availability

This study utilizes gridded monthly sc-PDSI data for the period 1901–2020 at a spatial resolution of $0.5^\circ \times 0.5^\circ$, along with temperature and precipitation fields at the

same resolution, sourced from the Climate Research Unit (CRU) [54, 66]. The scPDSI dataset is available at <https://crudata.uea.ac.uk/cru/data/drought/>, while the temperature and precipitation datasets can be accessed at <https://crudata.uea.ac.uk/cru/data/hrg/>.

Sea surface temperature data are sourced from NOAA's Extended Reconstructed SST V5 (ERSSTv5) dataset [67], provided by NOAA PSL (Boulder, Colorado, USA). The dataset is available on a $2.0^\circ \times 2.0^\circ$ global grid at monthly frequency can be downloaded from: <https://psl.noaa.gov/data/gridded/data.noaa.ersst.v5.html>.

Crop-yield information is obtained from the Global Dataset of Historical Yield (GDHY v1.2+v1.3) [29], which provides annual 0.5° grid-cell yield estimates for maize, rice, wheat, and soybean for the period 1981–2016 can be accessed here: <https://doi.pangaea.de/10.1594/PANGAEA.909132>

Country-level annual crop-yield statistics (tons per hectare) for 1961–2020 are sourced sourced from the Food and Agriculture Organization of the United Nations (FAO) <https://www.fao.org/faostat/en/#data>.

Crop-area estimates for each crop are derived from the MIRCA2000 high-resolution global cropping-area dataset [68].

All datasets used in this study are publicly available from the respective providers as indicated in their citations.

Code availability

Python scripts for the analysis and figures are publicly available on GitHub (<https://github.com/Drought-JohnDoe/Drought-JohnDoe>). We use the `climate.indices` [69] package in python to calculate PET using Thornthwaite method and scPDSI.

Author contributions

Conceptualization: UB, DM, RK

Design of Experiments: UB, DM,HP

Analysis: HP, DM

Writing – Original Draft: HP, UB

Writing – Review & Editing: VM, RK

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Competing interests

The authors declare no competing interests.

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Fig. 1: Conditional probability of crop yield failure and moderate drought across key global regions. Conditional probability of crop yield failure and moderate drought conditions for (A) Wheat, (B) Rice, (C) Maize, and (D) Soybean. Each panel shows the probability of yield falling below 0.5 standard deviation of long term mean (indicative of yield failure) and sc-PDSI values below -2, indicating moderate drought. Maize and Soybean exhibit the highest failure probability across the North and South America. Grey color indicate zero probabilities and white color represents no data available (non cropland). Most nations show at least one crop with a significant probability of failure when moderate droughts occur.(see Methods).

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Fig. 2: Spatial connectivity structure of global droughts. (A) Degree centrality of the global drought network, illustrating areas of high spatial clustering. (B) Degree distribution across different time periods, showing a heavy tail indicative of drought hubs. (C) Temporal trends in degree centrality (1901–2020), identified via the Mann-Kendall test ($p < 0.05$). (D) Box plot of degree centrality for continents across three periods, showing Australia with the highest degree.

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Fig. 3: Spatial connectivity structure and spread of global droughts during ENSO positive and Negative Periods. (A) and (C) Degree Centrality and Average Link Length of the complex network formed using El Niño years (B) and (D) La Niña years respectively.

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Fig. 4: Coupled pattern analysis of sc-PDSI and SST anomalies. (A) Heterogeneous correlation coefficients between sc-PDSI expansion coefficients and SST anomalies (1901–2020) for the first and second leading modes. All correlations are significant at $p < 0.05$.

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Fig. 5: Comparison of MCA analysis of sc-PDSI and SST anomalies between two periods (1901–1960 and 1961–2020). (A) Leading mode during 1901–1960, showing heterogeneous correlation coefficients between SST PC1 and sc-PDSI over land, and sc-PDSI PC1 and SST anomalies over oceans. (B) Same as (A), but for 1961–2020. (C) Difference in leading modes between the two periods (1961–2020 minus 1901–1960).

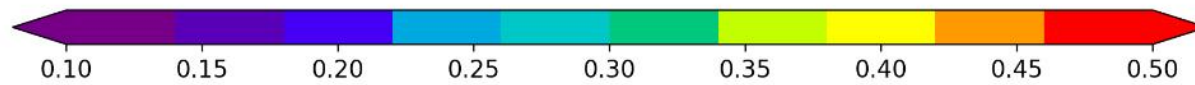
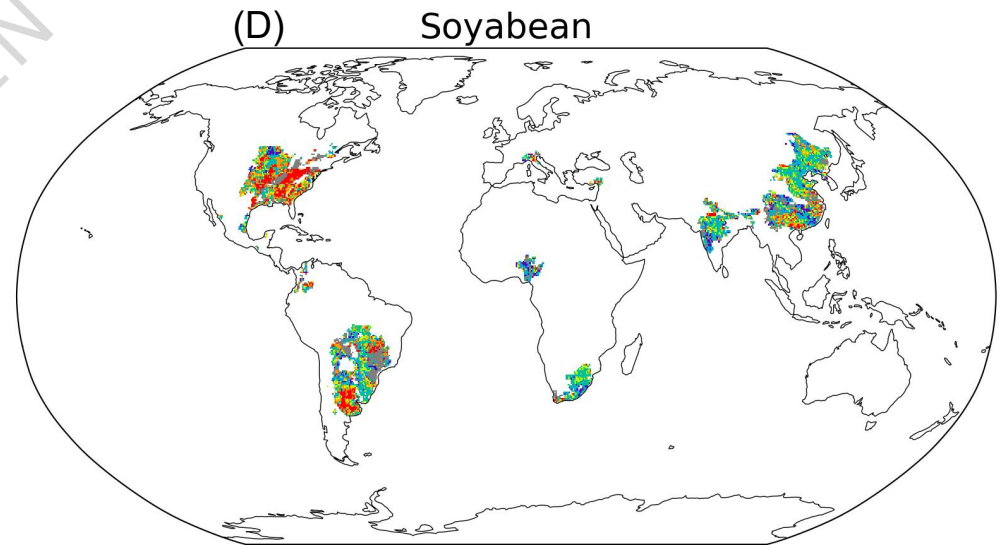
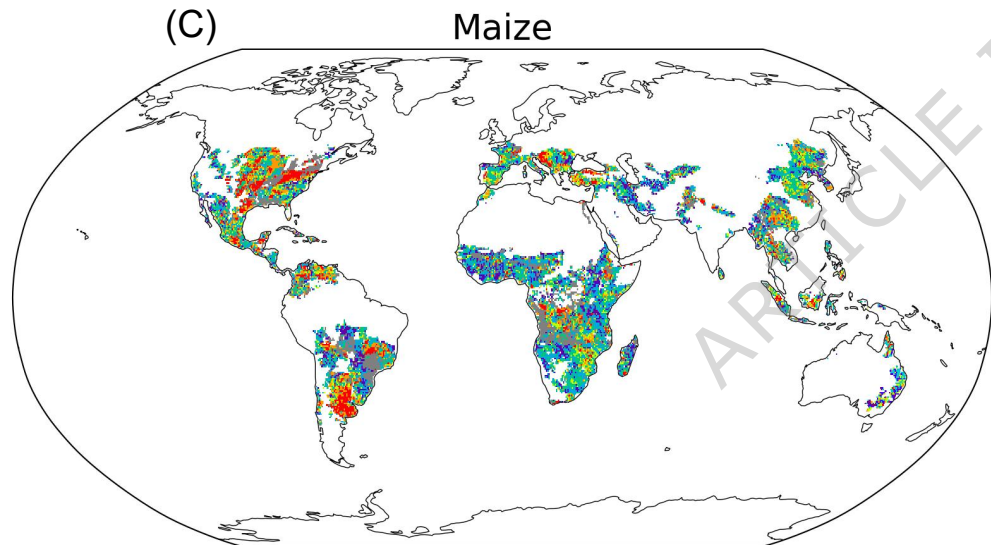
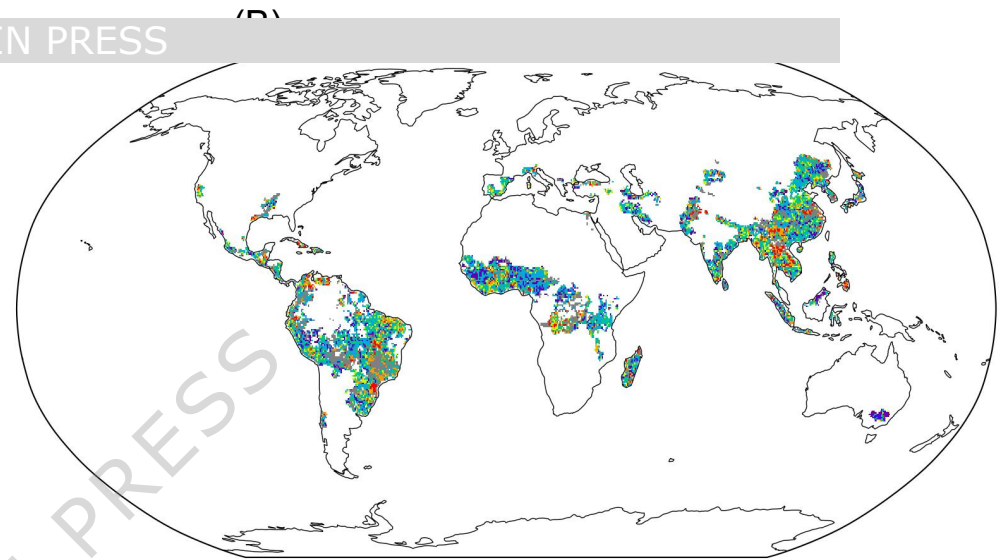
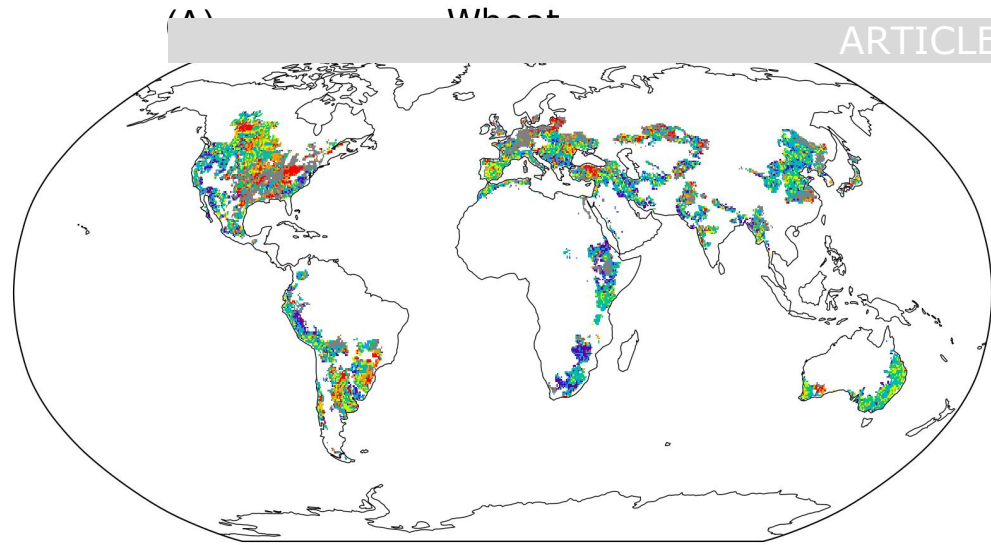
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Fig. 6: First leading modes of variability of precipitation (P) and temperature (T) with anomalies in sea surface temperature (SST). (A) The first mode of P-SST variability explains 65.6% of the squared covariance fraction (SCF) and resembles the ENSO pattern, with SST anomalies in the equatorial Pacific showing opposite signs to precipitation anomalies in Australia, Southeast Asia, and Africa ($r = 0.92$, $p < 0.05$). (B) The first mode of T-SST variability explains 42.4% of the squared covariance fraction ($r = 0.69$, $p < 0.05$), with the dominant influence of global warming removed from global temperature fields.

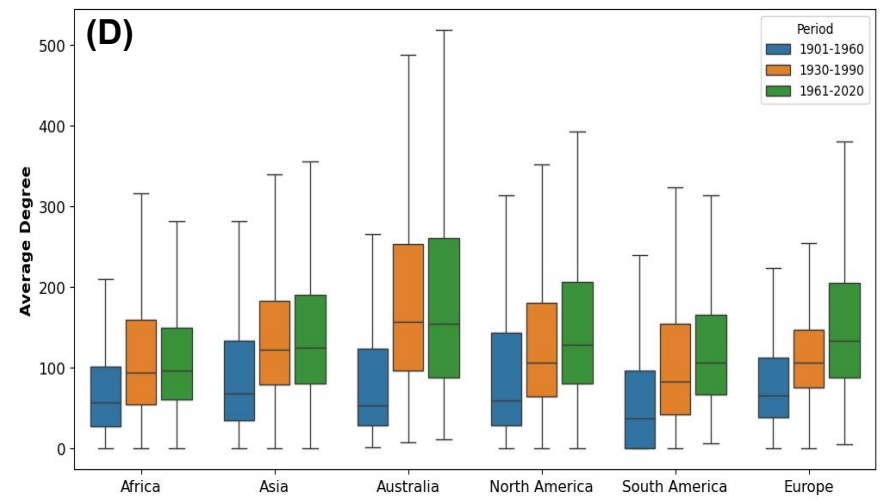
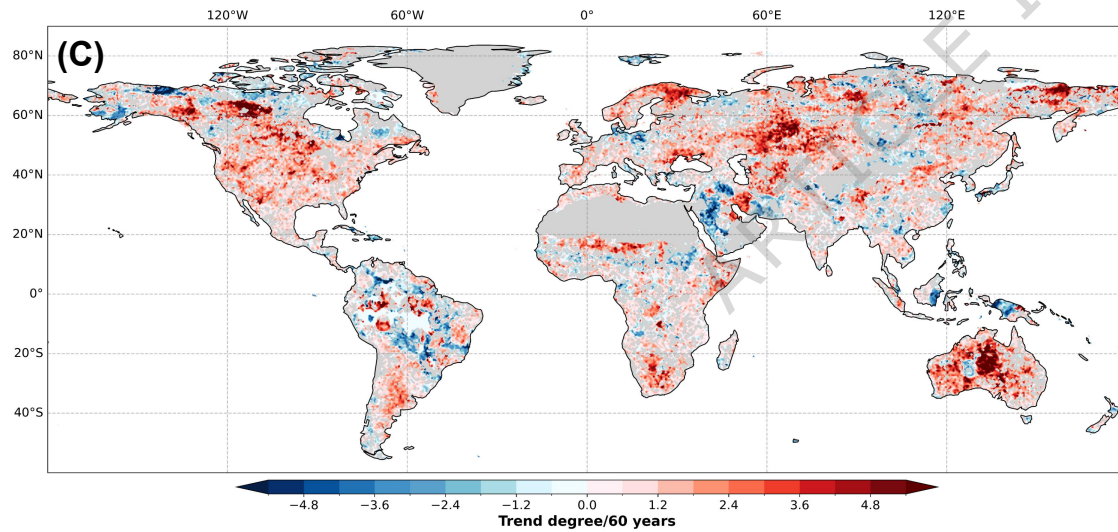
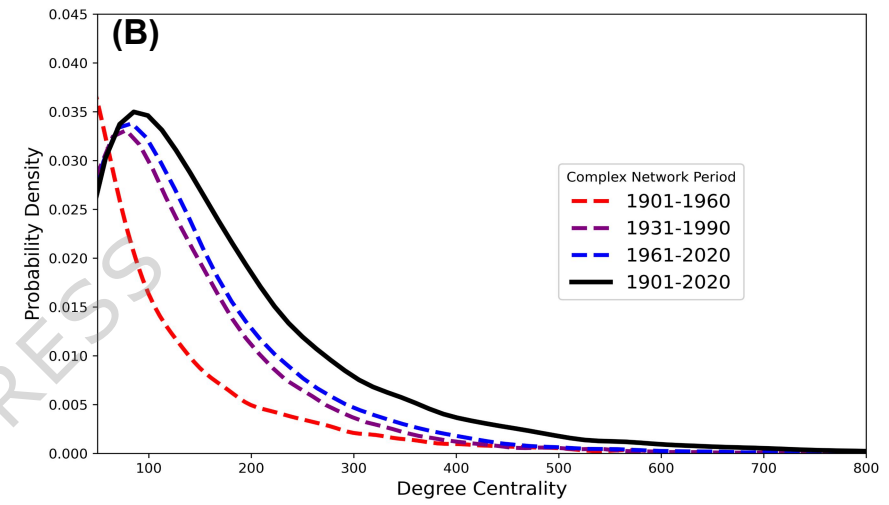
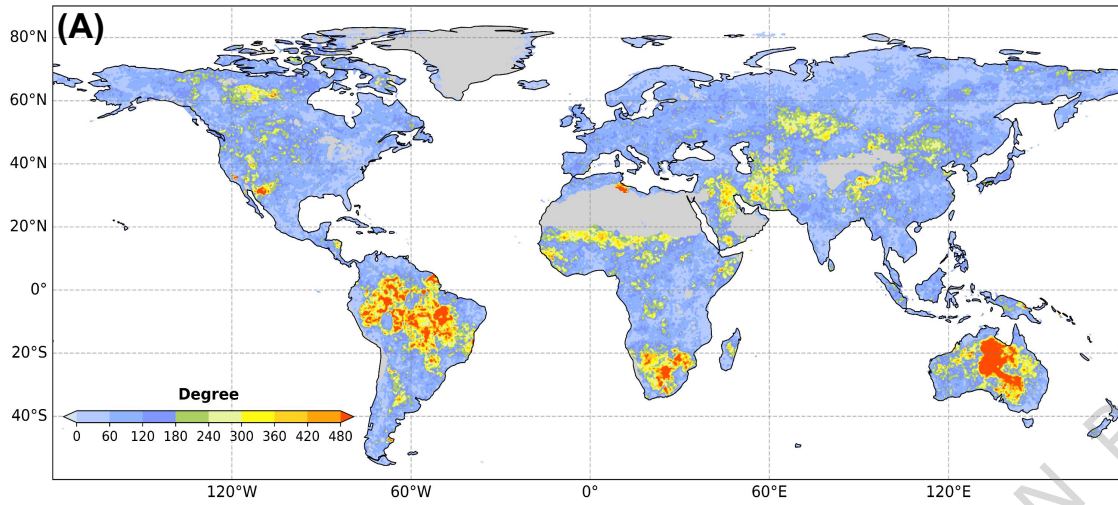
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Fig. 7: Spatial and regional contributions of temperature-driven PET and precipitation to observed scPDSI trends. Panels **A-D** show the percentage contribution of temperature and precipitation to observed changes in monthly self-calibrating PDSI (scPDSI) over two periods: 1961–1990 (A–B) and 1991–2020 (C–D). PET was computed using the Thornthwaite method to isolate the role of temperature alone. Contributions are calculated by comparing scPDSI trends from the observed simulation to two sensitivity experiments: one where precipitation is held fixed at its 1961–1990 climatology (P-CLIM) and another where PET is held fixed (PET-CLIM). Panel E summarizes the regional and global average contributions of temperature and precipitation across continents for both time periods. These trends are influenced by the evolving balance between temperature-driven evaporative demand and precipitation variability, with the role of temperature increasing after 1990, especially in the mid-latitudes, but precipitation remains the dominant driver globally.

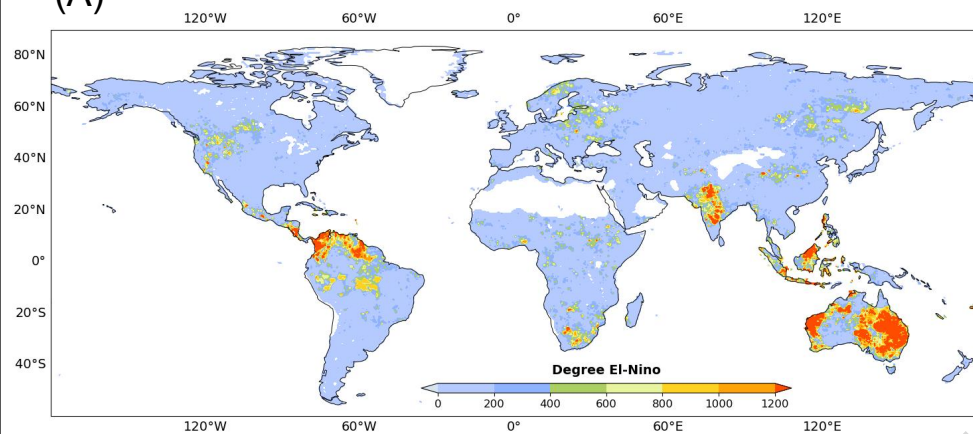
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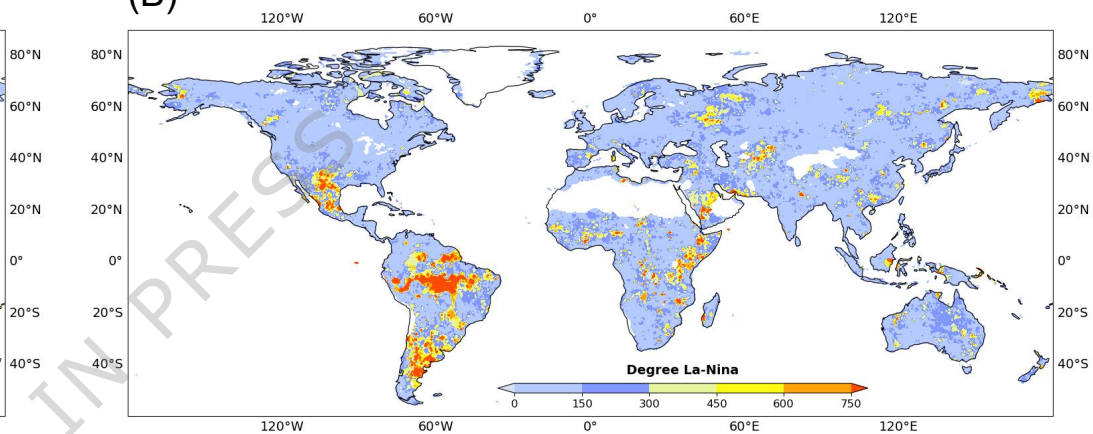
Conditional probability of crop failure



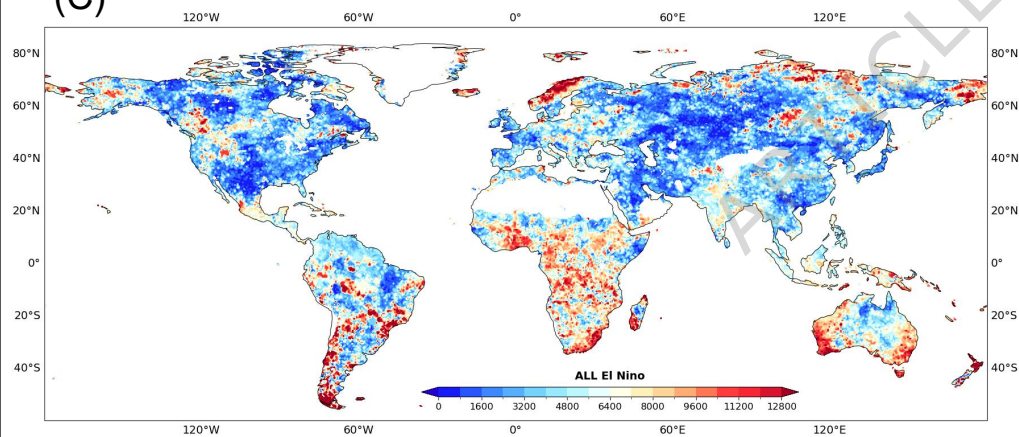
(A)



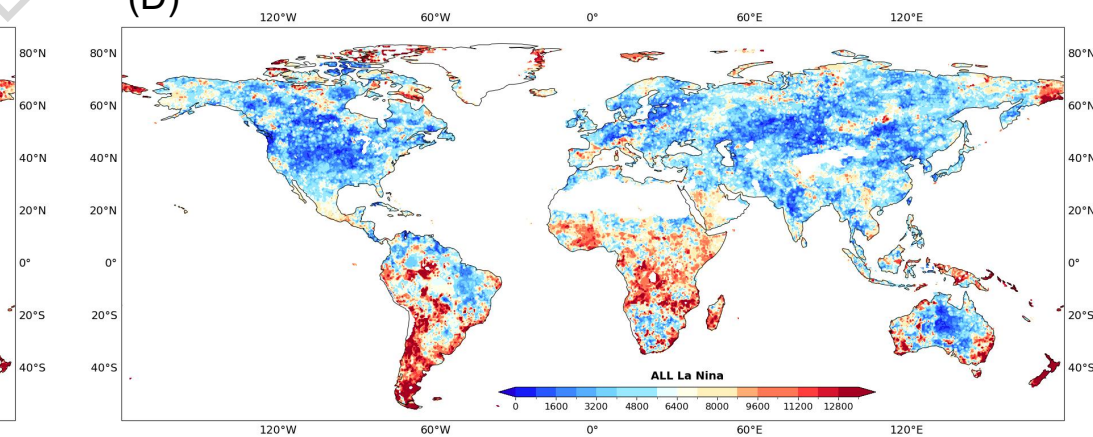
(B)

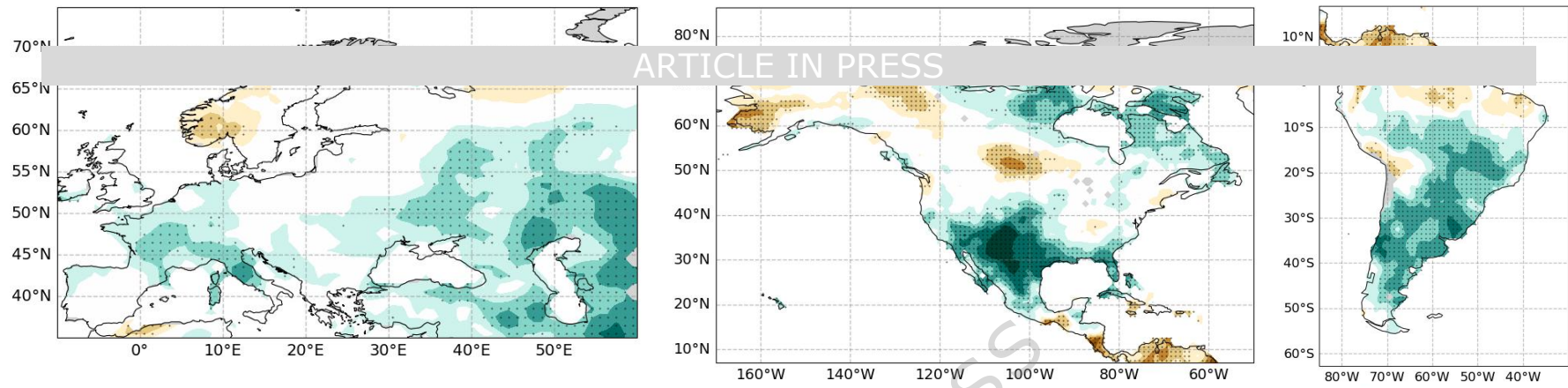


(C)

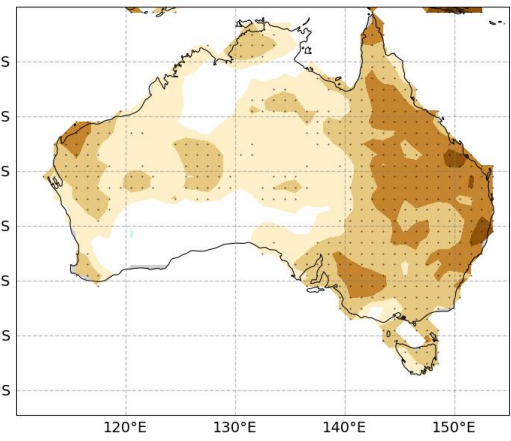
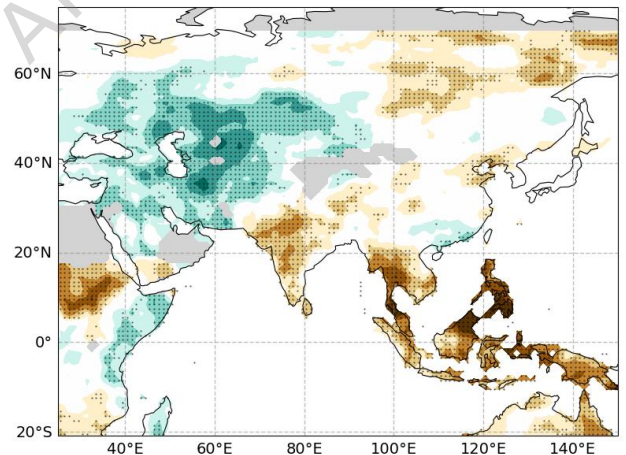
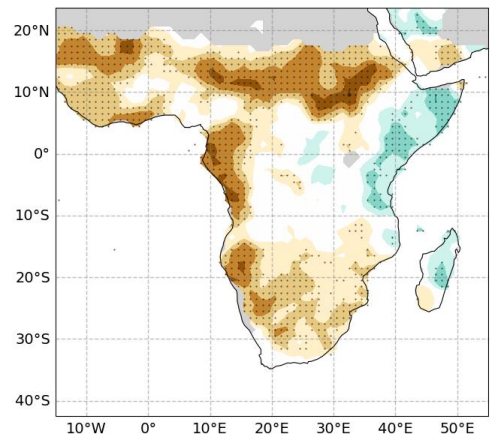
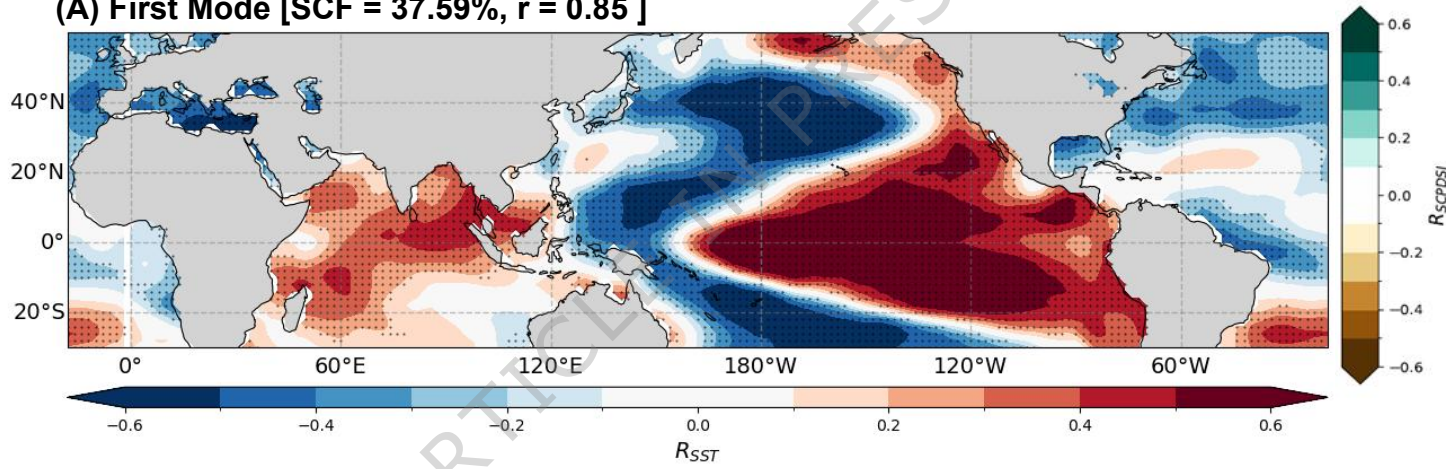


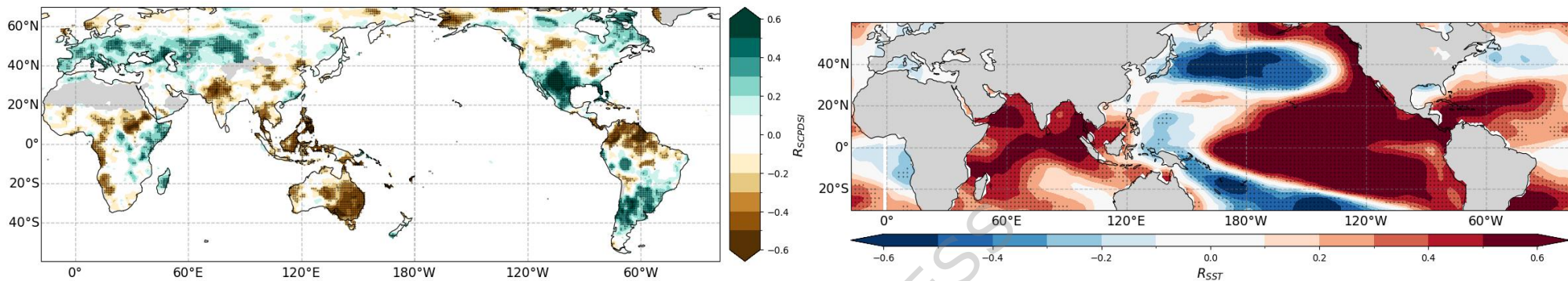
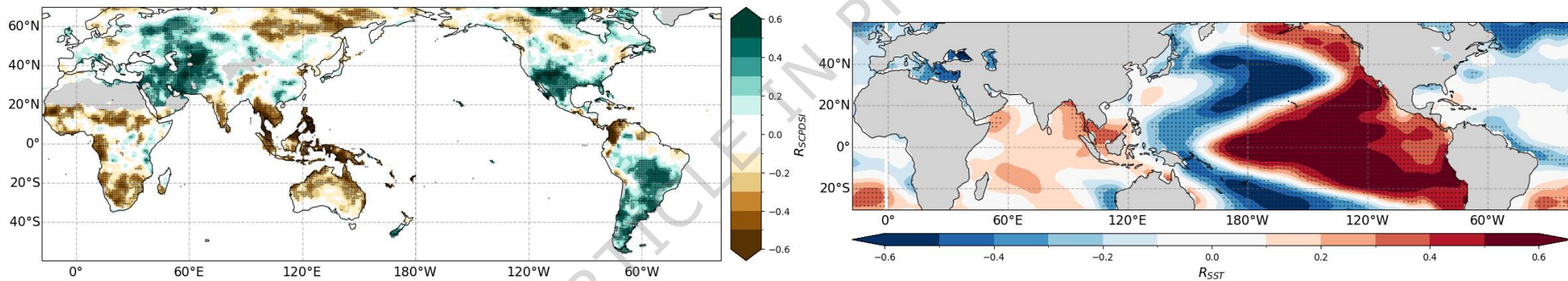
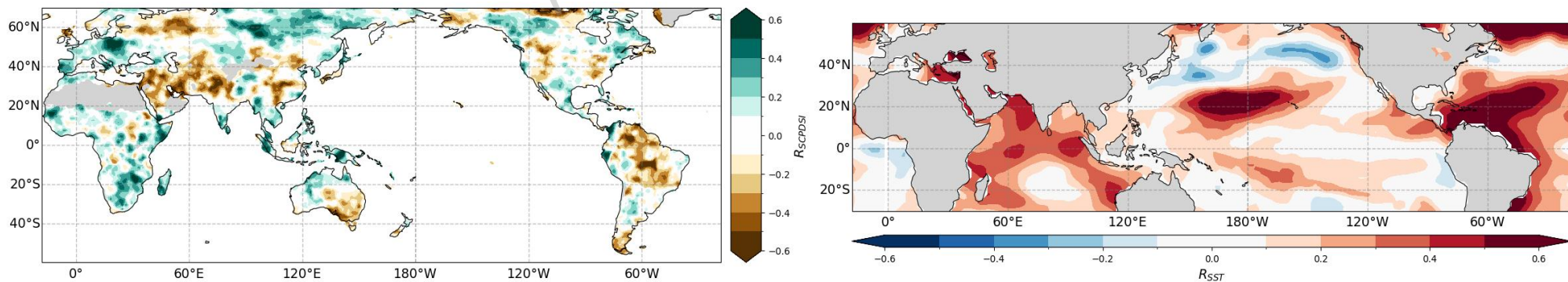
(D)



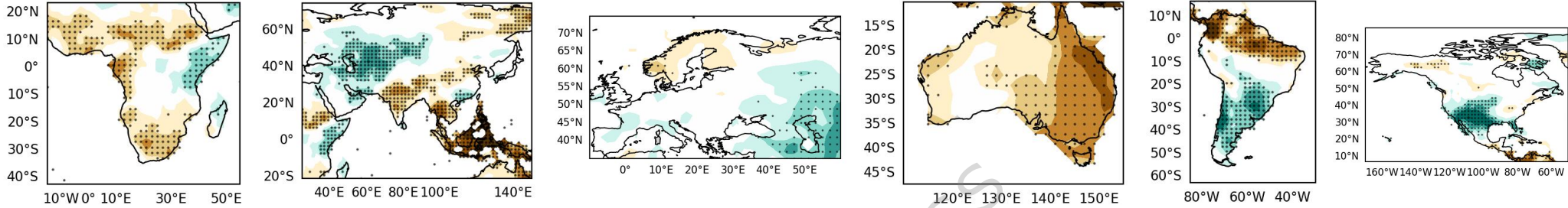
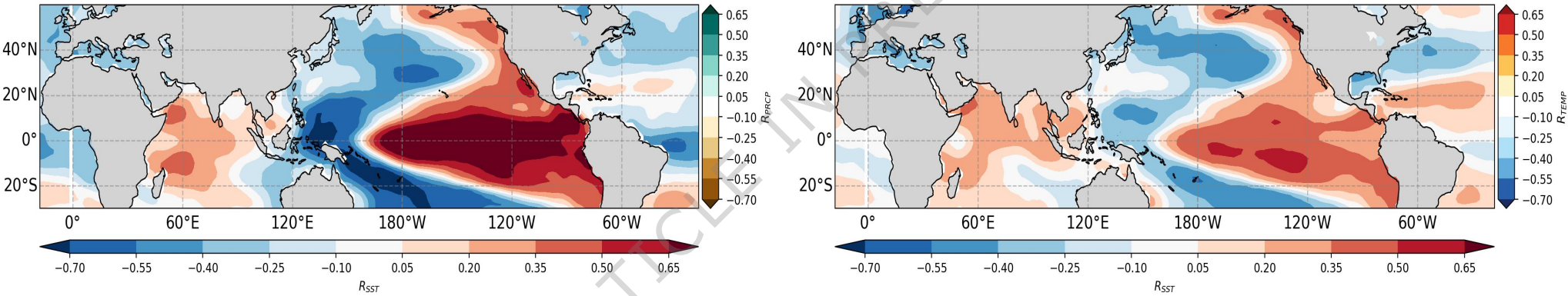


(A) First Mode [SCF = 37.59%, $r = 0.85$]



(A) First**(B) First Mode (1961-2020) [SCF = 38.8 %, $r = 0.86$]****(C) Difference**

P -SST

(A) First Mode P-SST (1901-2020)[SCF = 65.58%, $r = 0.92$](B) First Mode T-SST (1901-2020)[SCF = 42.4%, $r = 0.69$]

T-SST

