

Precipitation governs structural uncertainty and physical attribution of drought trends

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Supplementary Text 1. PET algorithms.

The Penman-Monteith equation (PM method) for reference crop (PET_{PM} , $mm \cdot day^{-1}$) is given by:

$$PET_{PM} = \frac{0.408\Delta_a(R_n - G) + \gamma_s \frac{900}{T_a + 273} u_2 (e_s - e_a)}{\Delta_a + \gamma_s (1 + 0.34u_2)} \quad (1)$$

where R_n is net radiation ($MJ \cdot m^{-2} \cdot day^{-1}$), G is the surface heat flux ($MJ \cdot m^{-2} \cdot day^{-1}$), u_2 is the wind speed at 2 meters height ($m \cdot s^{-1}$), γ_s is the psychrometric constant ($kPa \cdot ^\circ C^{-1}$), Δ_a is the slope of the saturated vapor pressure as a function of air temperature ($kPa \cdot ^\circ C^{-1}$), T_a is the air temperature at 2 meters height ($^\circ C$), e_s is the saturation vapor pressure at T_a (kPa) and e_a is the actual vapor pressure at dew point temperature (T_d) (kPa).

The slope of the saturated vapor pressure curve (Δ_a) ($kPa \cdot ^\circ C^{-1}$) as a function of T_a is given by:

$$\Delta_a = \frac{4098 \cdot e_s}{(T_a + 237.3)^2} \quad (2)$$

The psychrometric constant γ_s ($kPa \cdot ^\circ C^{-1}$) is calculated as:

$$\gamma_s = \frac{c_p \cdot P_s}{\lambda_s \cdot \varepsilon} \quad (3)$$

where c_p is the specific heat of the air at constant pressure ($1.01 kJ \cdot kg^{-1} \cdot ^\circ C^{-1}$), P_s is the surface pressure (kPa), ε is the molecular weight ratio of water vapor to dry air (typically 0.622), λ_s is the latent heat of vaporization ($KJ \cdot kg^{-1}$), evaluated at surface temperature (T_s) and expressed as a function of T_s , such that the psychrometric constant γ_s is consistently evaluated at T_s , in line with the energy-balance perspective adopted in the energy-based PET formulations.

$$\lambda_s = 2501 - 2.361 \times T_s \quad (4)$$

The saturation vapor pressure (e_s) (kPa) based on air temperature (T_a) ($^\circ C$) is calculated as:

$$e_s = 0.6108 \cdot e^{\frac{17.27 \cdot T_a}{T_a + 237.3}} \quad (5)$$

The actual vapor pressure (e_a) (kPa) based on dew point temperature (T_d) ($^\circ C$) is derived as:

$$e_a = 0.6108 \cdot e^{\frac{17.27 \cdot T_d}{T_d + 237.3}} \quad (6)$$

Penman PET for open water (PET_{PE-OW}) (PE-OW method) ($mm \cdot day^{-1}$) is calculated as:

$$PET_{PE-OW} = \frac{\Delta_a(R_n - G) + 6.43(1 + 0.536u_2)\gamma_s(e_s - e_a)}{\lambda_s(\Delta_a + \gamma_s)} \quad (7)$$

All variables in Eq. 7 are defined as above.

This energy-based PET approach assumes that all available energy is transformed to latent heat (LE), with no sensible heat (H) under wet conditions. However, this assumption is apparently invalid in actual ecosystems. Therefore, a variety of empirical formulations of energy-based PET has been developed to improve the estimation of non-water-stressed ET. The most recent energy-based PET (PET_e) builds on the estimation of Bowen ratio in wet conditions (β_w):

$$PET_e = \frac{1}{1 + \beta_w} \frac{R_n}{\lambda_s} \quad (8)$$

where β_w denotes the actual Bowen ratio when the surface is wet. Yang et al. (2019) proposed a wet surface β_{w_Yang} (Eq. 9) and optimized for saturated surfaces such as oceans, which captures the subtle variations in energy partitioning under wet conditions. Similarly, Zhou & Yu (2024)

revised β_w and showed that the PET_e based on β_{w_Zhou} (Eq. 10) estimated under dry conditions can approximate actual ET accurately when the surface becomes saturated.

The wet surface Bowen ratios β_{w_Yang} (YA method) and β_{w_Zhou} (ZY method) can be estimated by the following equations:

$$\beta_{w_Yang} = 0.24 \frac{\gamma_s}{\Delta_s} \quad (9)$$

$$\beta_{w_Zhou} = \frac{\gamma_s(T_s - T_a)}{(e_s^* - e_a)} \quad (10)$$

To avoid unrealistic values, β_{w_Zhou} calculated using Eq. 10 was constrained within physically reasonable bounds following Zhou and Yu. Specifically, for each month, if $\beta_{w_Zhou} < \beta_{w_Yang}$, β_{w_Zhou} was set to β_{w_Yang} ; if $\beta_{w_Zhou} > \beta$, β_{w_Zhou} was set to the actual Bowen ratio (β , the ratio of sensible over latent heat). γ_s is the psychrometric constant ($kPa \cdot ^\circ C^{-1}$), calculated as Eq. 3. The slope of the saturated vapor pressure curve (Δ_s) ($kPa \cdot ^\circ C^{-1}$) as a function of T_s is given by:

$$\Delta_s = \frac{4098 \cdot e_s^*}{(T_s + 237.3)^2} \quad (11)$$

The saturation vapor pressure (e_s^*) based on surface temperature (kPa) is calculated as:

$$e_s^* = 0.6108 \cdot e^{\frac{17.27 \cdot T_s}{T_s + 237.3}} \quad (12)$$

The energy-only PET from Milly & Dunne (2016) (MD method) is calculated as:

$$PET = 0.8 * \frac{R_n - G}{\lambda_s} \quad (13)$$

All variables in Eq. 13 are defined as above. At the monthly timescale considered here, ground heat flux (G) is generally small relative to net radiation term and is thus neglected ($G = 0$) in all PET formulations presented above.

The PET formulation by Kim et al (2023) (KIM method) is formulated within the specific humidity system:

$$\lambda_s PET_{Kim} = \frac{2RH_a s + \gamma_{sh}}{2RH_a s + 2\gamma_{sh}} (R_n - G) \quad (14)$$

where PET_{Kim} represents the evapotranspiration rate ($mm \cdot day^{-1}$); RH_a represents the relative humidity of the atmospheric state near the land surface (dimensionless fraction); s is the slope of the saturation specific humidity curve ($kg \cdot kg^{-1} \cdot ^\circ C^{-1}$); and γ_{sh} is the psychrometric constant in the specific humidity system ($kg \cdot kg^{-1} \cdot ^\circ C^{-1}$). The slope s is defined as the derivative of saturation specific humidity (q^*) with respect to temperature (T):

$$s = \frac{dq^*}{dT_a} \quad (15)$$

$$\gamma_{sh} = \gamma_a \frac{dq^*}{de_s^*} \quad (16)$$

where dq^* is derived from the saturation vapor pressure and atmospheric pressure (P_s). Crucially, the latent heat of vaporization (λ_s) and the psychrometric constant (γ_{sh}) are parameterized using the surface skin temperature (T_s) to reflect the energy state at the evaporating surface. Crucially, the latent heat of vaporization (λ_s) and the psychrometric constant (γ_{sh}) are calculated based on the surface skin temperature (T_s), while the slope s is determined by the air temperature (T_a).

Supplementary Text 2. Robustness test using Type I, Type II, and Type III ANOVA.

To examine whether the dominance of precipitation uncertainty was an artifact of the sequential nature of Type I ANOVA, we conducted an additional robustness test using Type I, Type II, and Type III sums of squares under a crossed three-factor additive model. This test was performed using the same quasi-global SPEI trend summaries as those used in the main nested ANOVA analysis. Specifically, for each spatial configuration, the input data consisted of the Sen's slope estimates of SPEI trends derived from the full historical 240-member ensemble. Each ensemble member represents one unique factorial combination of 10 precipitation datasets, 4 meteorological datasets used to calculate PET, and 6 PET methods, yielding $10 \times 4 \times 6 = 240$ SPEI trend estimates.

The dependent variable in the ANOVA model was the long-term Sen's slope of the spatially averaged SPEI time series for each ensemble member. We repeated the analysis across six spatial sensitivity cases: three annual precipitation masks, 100 mm, 180 mm, and 250 mm, each applied to two spatial domains, the full global land domain and the quasi-global 50°S–50°N domain. These six cases correspond to the trend summary files generated for 100 mm global, 180 mm global, 250 mm global, 100 mm 50°S–50°N, 180 mm 50°S–50°N, and 250 mm 50°S–50°N domains, respectively.

For each case, three independent categorical predictors were extracted from the ensemble metadata: precipitation dataset, PET meteorological data source, and PET method. The precipitation factor included 10 datasets: ERA5_Land, MSWX100, JRA-3Q, MERRA-2, MSWEP, CHIRPSV2, CRU, CPC, GPCC, and PRECL. The PET meteorological data source factor included four datasets: ERA5_Land, MSWX100, JRA-3Q, and MERRA-2. The PET method factor included six formulations: PE-OW, PM, and four energy-constrained or energy-based PET formulations. Thus, the robustness test used the following crossed additive model:

$$\text{Trend} * ijk = \mu + P_i + D_j + M_k + \varepsilon * ijk \quad (17)$$

where $\text{Trend} * ijk$ is the Sen's slope of the SPEI time series for the ensemble member constructed using precipitation dataset (P_i), PET meteorological data source (D_j), and PET method (M_k). The residual term ($\varepsilon * ijk$) represents the unexplained variance not attributable to these three main effects.

Unlike the hierarchical nested ANOVA used in the main analysis, this crossed model excludes derived grouping variables such as precipitation type and PET method class. This avoids rank deficiency and aliasing among nested terms, because precipitation type is fully determined by the individual precipitation dataset and PET method class is fully determined by the individual PET method. The crossed model therefore provides a cleaner test of whether the overall dominance of precipitation datasets is sensitive to the choice of ANOVA sum-of-squares definition.

Because the historical ensemble was constructed as a fully balanced factorial design, with each of the 10 precipitation datasets combined with all 4 PET data sources and all 6 PET methods, the three main effects are orthogonal in the additive model. Consequently, Type I, Type II, and Type III sums of squares yielded identical variance fractions across all tested spatial domains and precipitation masks. This result indicates that the estimated dominance of precipitation datasets is not a consequence of the order in which factors enter the Type I ANOVA model.

Across the six spatial sensitivity cases, precipitation datasets consistently explained the largest fraction of SPEI trend variance, ranging from 58.4% to 73.6%. In contrast, PET meteorological data sources explained 10.6%–16.5%, and PET methods explained 11.2%–19.0%. For the core 180 mm, 50°S–50°N domain, precipitation explained 71.5% of the total variance under Type I, Type II, and Type III ANOVA alike, whereas PET data sources and PET methods explained only 10.7% and 12.7%, respectively. These additional tests confirm that the conclusion of precipitation-

dominated structural uncertainty is robust to the choice of sum-of-squares definition and is not an artifact of sequential factor ordering in Type I ANOVA.

Supplementary Text 3. Sensitivity analysis across spatial domains, precipitation masks, and temporal scales.

As detailed in our spatial sensitivity analysis (Supplementary Figs. 6, 8), modifying the annual precipitation mask (testing 100 mm, 180 mm, and 250 mm thresholds) and expanding the spatial domain (comparing the 50°S–50°N band to a fully global extent) consistently yield precipitation as the primary source of variance, accounting for 58.4% to 73.9% of the total uncertainty in SPEI trend. Furthermore, we evaluated the sensitivity of these SPEI trends across different accumulation time scales from 1 to 24 months—ranging from short-term meteorological (SPEI-1, 3) to long-term hydrological droughts (SPEI-12, 24) (Supplementary Fig. 8). To ensure a rigorous, strictly consistent temporal comparison that accounts for the 24-month antecedent data requirement of SPEI-24, this multi-scale assessment was standardized over the 1983–2024 period. The multi-scale analysis reveals a scale-dependent pattern. While the ensemble mean signals consistently capture a quasi-global drying trend (ranging from -0.0021 to -0.0027 yr⁻¹), the structural spread (standard deviation) among the 240 ensemble members increases substantially at longer accumulation time scales. This widening spread is consistent with the accumulation of water-balance anomalies at longer SPEI time scales, which can increase sensitivity to persistent differences among forcing products. Crucially, however, when decomposing this expanding uncertainty using our ANOVA framework, the underlying variance attribution remains consistent. Across all accumulation time scales from 1 to 24 months, precipitation consistently accounts for the largest fraction of variance (ranging from 68.2% to 74.5%) in SPEI trends (Supplementary Fig. 8). Although additional algorithmic choices in SPEI calculation, such as baseline reference periods and distribution functions, may also introduce uncertainty into drought assessments (Um et al., 2017; Stagge et al., 2015), these factors were not explicitly varied in our ensemble design. The large ensemble experiments analyzed here show that the choice of precipitation forcing alone produces a substantial structural spread across the tested accumulation time scales. Together, these results establish that, within the uncertainty dimensions examined in this study, uncertainties in historical global drought trends calculated with SPEI are primarily associated with discrepancies among precipitation products, a dominant structural uncertainty that persists across the spatial domains, accumulation time scales, and PET methods tested here.

Supplementary Text 4. Robustness and scaling behavior of ANOVA-based uncertainty decomposition.

Two additional scaling effects further clarify the uncertainty hierarchy. First, variance attribution depends on whether ANOVA is applied before or after spatial aggregation. Second, the relative importance of precipitation increases with SPEI accumulation timescale. We first observed a critical spatial scaling effect that sheds light on the inherent limitations of traditional observational networks. The aforementioned dominance of precipitation (e.g., 64.8% for the gauge-only ensemble) emerges when computing grid-wise ANOVA first, which preserves local spatial noise. However, when we reverse the order—calculating the regional mean time series prior to ANOVA partitioning (Supplementary Fig. 15)—the variance attribution fundamentally shifts. Spatial averaging reduces spatially heterogeneous precipitation-product differences, thereby lowering their contribution to regional-mean trend variance. Within the gauge-only ensemble over the 50°S–50°N domain, aggregating the time series first causes precipitation’s variance contribution to decrease from 64.8% to 30.9%, and further to 12.6% when the domain is expanded globally, allowing PET uncertainties to surge to nearly 77.4%. This collapse of precipitation-attributable variance likely reflects a combination of spatial cancellation during aggregation and structural limitations of gauge-based products in data-sparse regions (e.g., across Africa, the Amazon, and high latitudes) within gauge-only products, which may partly reflect the dependence of gauge-based gridded

products on interpolation and climatological constraints in data-sparse regions upon large-scale spatial averaging.

Furthermore, in the domain-expansion sensitivity test, where high-latitude regions are included, PET-related uncertainty increases substantially (Supplementary Fig. 15), indicating that PET formulation choices become more influential outside the core 50°S–50°N analysis domain. While previous literature has conceptually warned that standard PET algorithms struggle in high-latitude environments due to complex snow/ice thermodynamics, low sun angles, and energy-limited atmospheric boundary layers (Walston et al., 2023), our nested ANOVA quantifies the increased sensitivity of drought-trend estimates to PET formulation choices when high-latitude regions are included. As the domain expands poleward, the systemic structural divergence between different PET methodologies becomes more pronounced. This critical distinction yields a fundamental insight: while precipitation robustly dictates the spatial heterogeneity of local drought, the systemic baseline of globally averaged drought trajectories is acutely sensitive to PET parameterizations. This is particularly true when the underlying precipitation data suffers from severe observational sparsity and when the spatial domain incorporates high-latitude regions where standard PET formulations are more sensitive to assumptions about radiation, aerodynamic conductance, snow/ice surfaces, and energy limitation in cold regions.

In stark contrast to the spatial low-pass filtering, expanding the drought memory across the temporal continuum (from SPEI-1 to SPEI-24) yields a distinctly opposite, yet equally profound, scaling effect (Supplementary Fig. 16–19). It is intuitively tempting to assume that as the integration timescale lengthens from short-term meteorological droughts to long-term hydrological droughts, the cumulative thermodynamic forcing of PET would increasingly dominate the uncertainty profile. The multi-scale spatial ANOVA data explicitly rejects this hypothesis. One plausible explanation is that temporal integration smooths part of the seasonal divergence among PET formulations, whereas persistent differences among precipitation products accumulate over longer SPEI windows. Conversely, observational biases and systemic errors inherent in precipitation products act as a compounding integral. As the drought memory lengthens, persistent precipitation differences accumulate over longer SPEI integration windows. Consequently, across the 50°S–50°N domain, the grid-wise variance contribution of precipitation systematically intensifies at longer timescales—rising from 68.4% for SPEI-1 to 81.2% and 80.7% for SPEI-12 and SPEI-24, respectively, while PET uncertainties concurrently shrink. This demonstrates that the structural uncertainty of longer-term moisture deficits relevant to hydrological drought impacts is even more heavily tethered to precipitation observational limits than that of short-term meteorological anomalies.

Finally, we tested whether the ANOVA-based dominance of precipitation uncertainty is driven by any single precipitation product. To this end, we conducted a leave-one-precipitation-product-out analysis, in which one precipitation dataset was removed at a time from the original factorial ensemble before recalculating the variance decomposition (Supplementary Fig. 37). Across the 50°S–50°N domain and all major continental regions, precipitation remained the largest contributor to SPEI trend uncertainty regardless of which precipitation product was excluded. This robustness is particularly evident over the quasi-global domain, Asia, North America, and South America, where precipitation consistently accounts for the majority of variance across all exclusion experiments. Although the relative contributions of PET methods, PET datasets, and interaction terms become more visible in regions such as Australia and Europe, they do not overturn the dominant role of precipitation-related uncertainty. These results indicate that the precipitation dominance identified in the main ANOVA analysis is not an artifact of one influential precipitation product, but rather reflects a structurally persistent uncertainty hierarchy across the multi-source SPEI ensemble.

Supplementary Tables

Supplementary Table 1. Overview of the meteorological datasets used in this study.

Meteorological datasets	Version/Access Date	Spatial resolution	Temporal Resolution used	Data type	Reference	Access URL
MSWX100	V100	0.1°×0.1°	Monthly	Multi source	(Beck et al., 2022)	https://www.gloh2o.org/mswx/
ERA5_Land	2025.06	0.1°×0.1°	Monthly	Reanalysis products	(Muñoz-Sabater et al., 2021)	https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=overview
JRA-3Q	2026.05	0.375°×0.375°	Monthly	Reanalysis products	(Kosaka et al., 2024)	https://www.data.jma.go.jp/jra/html/JRA-3Q/index_en.html
MERRA-2	Version 2	0.5°×0.625°	Monthly	Reanalysis products	(Gelaro et al., 2017)	https://gmao.gsfc.nasa.gov/gmao-products/merra-2/
MSWEP	V2.8	0.1°×0.1°	Monthly	Satellite-related products	(Beck et al., 2019)	https://www.gloh2o.org/mswep/
CRU	TS_V4.09	0.5°×0.5°	Monthly	Gauge-based products	(Harris et al., 2020)	https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.09/
CHIRPS	V2	0.05°×0.05°	Monthly	Multi source	(Funk et al., 2015)	https://www.chc.ucsb.edu/data/chirps
CPC	2026.05	0.5°×0.5°	Monthly	Gauge-based products	(Xie et al., 2010)	https://www.psl.noaa.gov/data/gridded/data.cpc.globalprecip.html
GPCC	Version 2025	0.5°×0.5°	Monthly	Gauge-based products	(Schneider et al., 2008)	https://psl.noaa.gov/data/gridded/data.gpcc.html
PRECL	2026.04	0.5°×0.5°	Monthly	Gauge-based products	(Chen et al., 2002)	https://www.psl.noaa.gov/data/gridded/data.precl.html

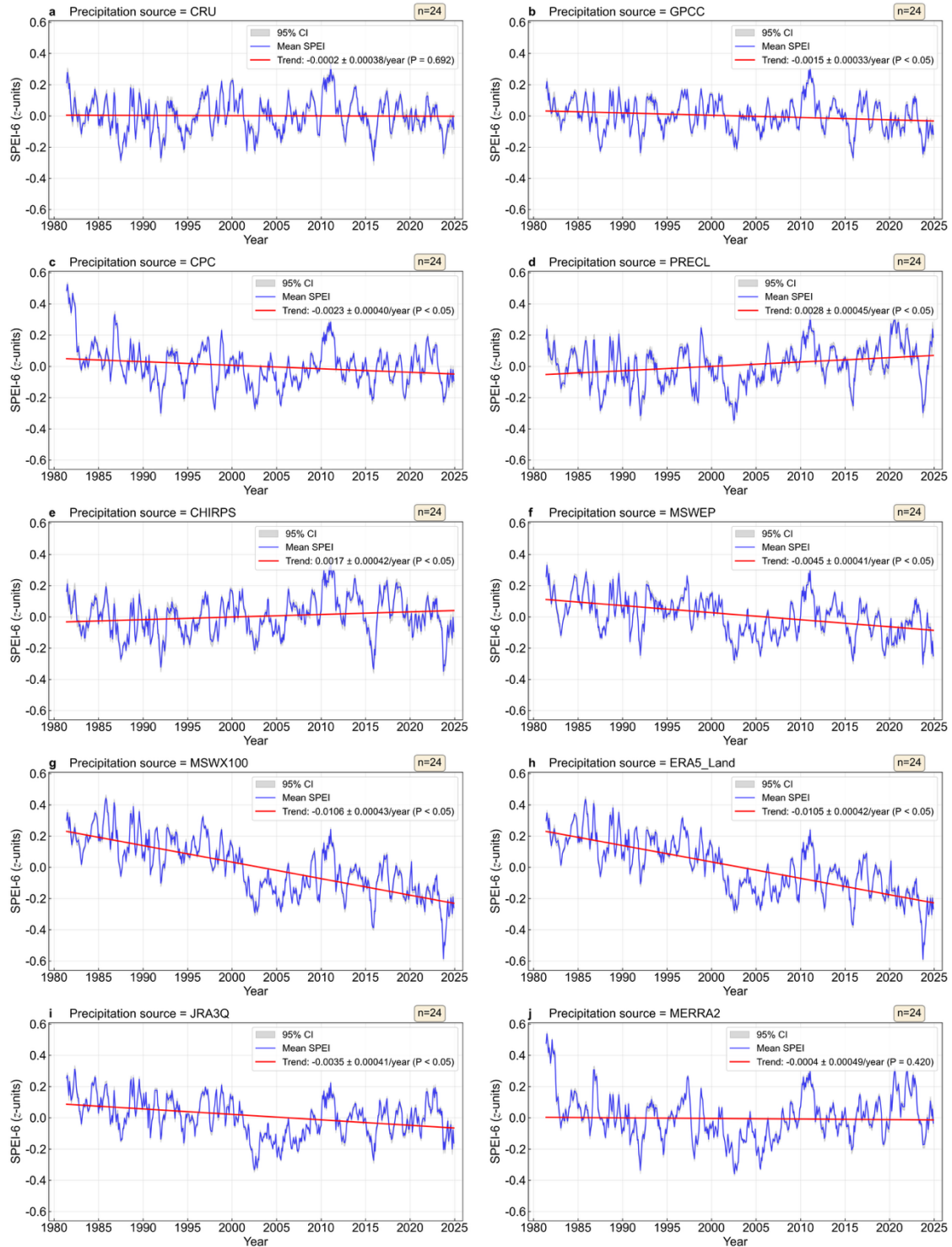
Supplementary Table 2. Quasi-global (50° S to 50° N) average 6-month SPEI trend (z-units yr⁻¹) and associated uncertainty analysis.

Category	Sources	N	Mean ± Std	Range
Precipitation sources	MSWX100	24	-0.0106 ± 0.0022	[-0.0146, -0.0067]
	ERA5_Land	24	-0.0105 ± 0.0021	[-0.0142, -0.0069]
	MSWEP	24	-0.0045 ± 0.0026	[-0.0099, -0.0008]
	JRA3Q	24	-0.0035 ± 0.0024	[-0.0087, -0.0001]
	CPC	24	-0.0022 ± 0.0025	[-0.0077, 0.0014]
	GPCC	24	-0.0014 ± 0.0027	[-0.0073, 0.0023]
	MERRA2	24	-0.0004 ± 0.0025	[-0.0059, 0.0032]
	CRU	24	-0.0001 ± 0.0034	[-0.0075, 0.0045]
	CHIRPS	24	0.0017 ± 0.0036	[-0.0061, 0.0065]
	PRECL	24	0.0028 ± 0.0037	[-0.0052, 0.0080]
PET Methods	PM	40	-0.0053 ± 0.0044	[-0.0144, 0.0021]
	PE-OW	40	-0.0056 ± 0.0047	[-0.0146, 0.0031]
	ZY	40	-0.0020 ± 0.0050	[-0.0113, 0.0071]
	YA	40	-0.0019 ± 0.0050	[-0.0111, 0.0071]
	MD	40	-0.0010 ± 0.0051	[-0.0103, 0.0080]
PET Dataset	ERA5_Land	60	-0.0041 ± 0.0050	[-0.0142, 0.0046]
	MSWX100	60	-0.0045 ± 0.0052	[-0.0146, 0.0043]
	JRA3Q	60	-0.0027 ± 0.0050	[-0.0119, 0.0055]
	MERRA2	60	-0.0002 ± 0.0045	[-0.0085, 0.0080]

Supplementary Table 3. Robustness of variance decomposition to ANOVA sum-of-squares type.

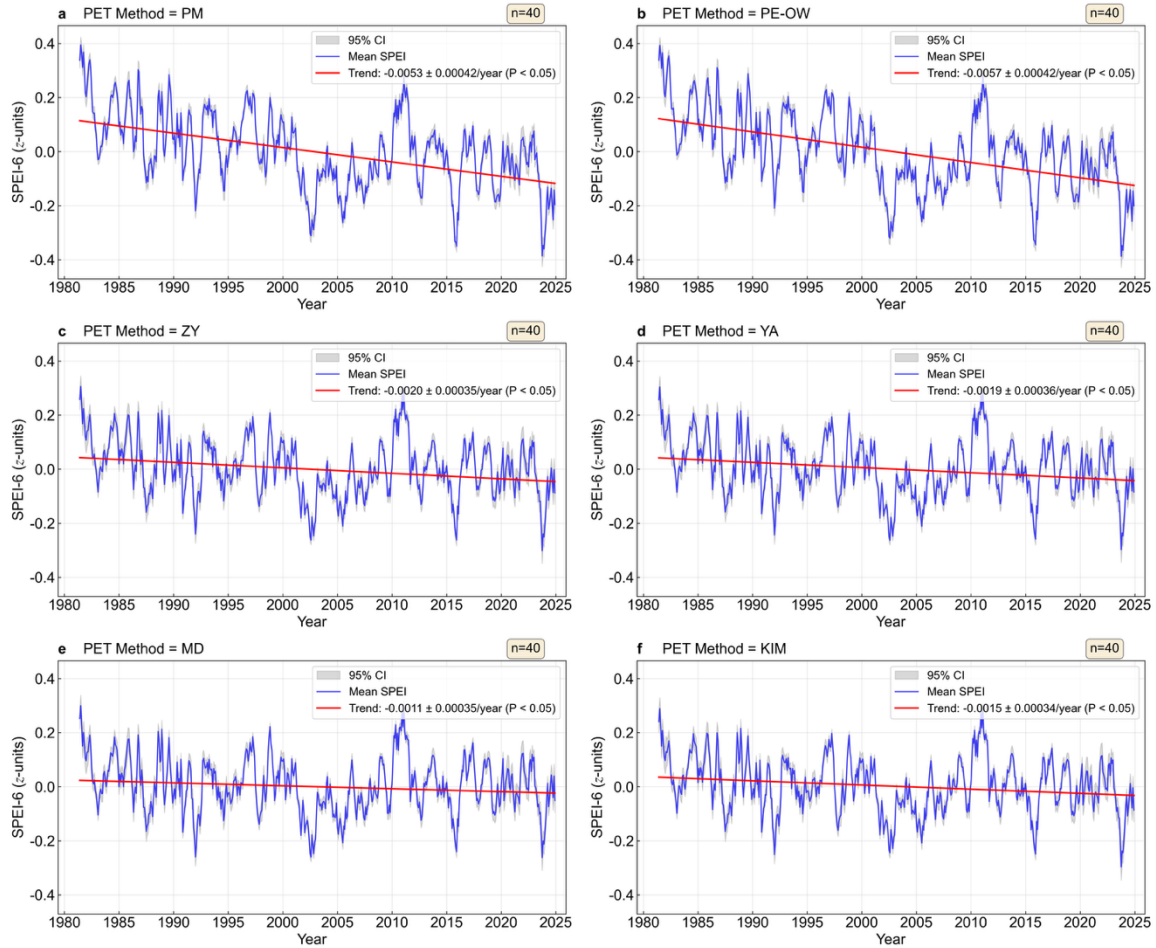
Spatial case	ANOVA type	Precipitation source (%)	PET data source (%)	PET method (%)	Residual (%)
100 mm, Global	Type I = Type II = Type III	58.4	15.1	19	7.5
180 mm, Global	Type I = Type II = Type III	62.6	15.9	15.7	5.7
250 mm, Global	Type I = Type II = Type III	64.5	16.5	14.2	4.8
100 mm, 50°S–50°N	Type I = Type II = Type III	66.6	10.6	16	6.8
180 mm, 50°S–50°N	Type I = Type II = Type III	71.5	10.7	12.7	5.1
250 mm, 50°S–50°N	Type I = Type II = Type III	73.6	11.1	11.2	4.2

Supplementary Figures

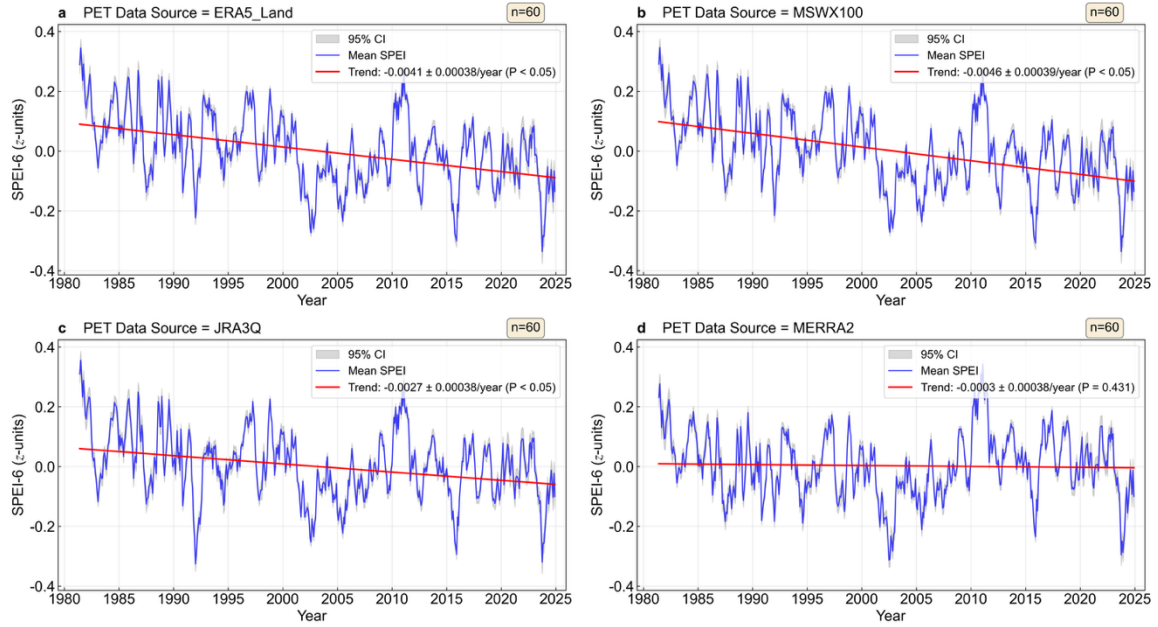


Supplementary Fig. 1 Time series and linear trends of the quasi-global average 6-month SPEI across 10 precipitation sources. (a–j) SPEI time series and their corresponding linear trends (z-units yr^{-1}) derived from precipitation data provided by (a) CRU, (b) GPCC, (c) CPC, (d) PRECL, (e) CHIRPSV2, (f) MSWEP, (g) MSWX100, (h) ERA5_Land, (i) JRA3Q, and (j) MERRA2. The

quasi-global average is calculated over the quasi-global land areas (50°S to 50°N), excluding regions with an average annual precipitation below 180 mm. For each precipitation source, the SPEI is computed as the ensemble mean of 24 members, representing all possible combinations of the six PET methods and four PET data sources.

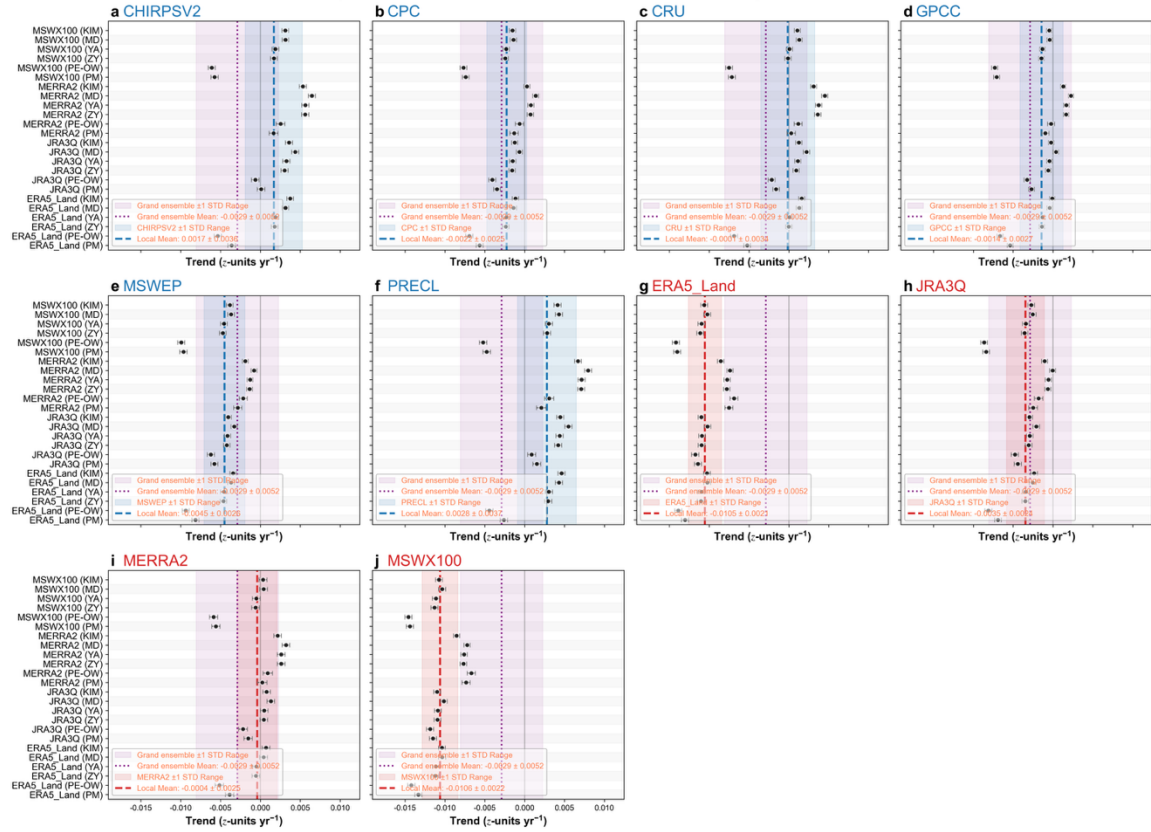


Supplementary Fig. 2 Time series and linear trends of the quasi-global average 6-month SPEI across six PET methods. (a–f) SPEI time series and their corresponding linear trends (z-units yr⁻¹) calculated using the (a) PM, (b) PE-OW, (c) ZY, (d) YA, (e) MD, and (f) KIM methods. The quasi-global average is calculated over the quasi-global land areas (50°S to 50°N), excluding regions with an average annual precipitation below 180 mm. For each PET method, the SPEI is computed as the ensemble mean of 40 members, representing all possible combinations of the 10 precipitation sources and four PET data sources.

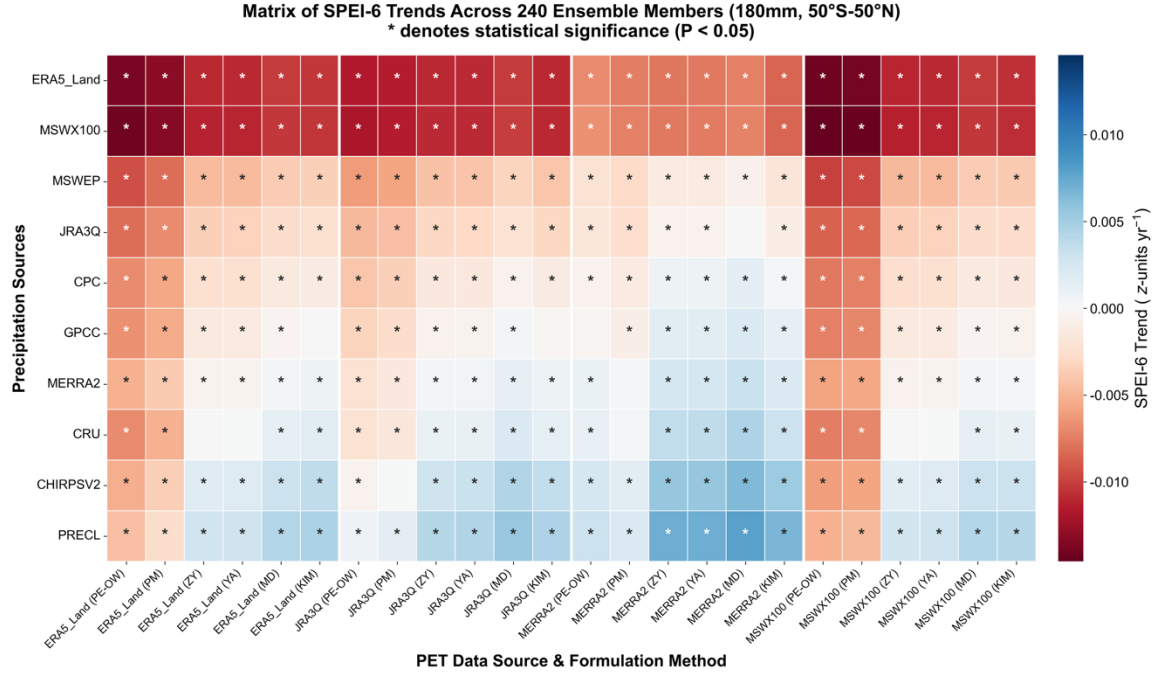


Supplementary Fig. 3 Time series and linear trends of the quasi-global average 6-month SPEI across four PET data sources. (a–d) SPEI time series and their corresponding linear trends (z-units yr⁻¹) derived using PET data from (a) ERA5_Land, (b) MSWX100, (c) JRA3Q, and (d) MERRA2. The quasi-global average is calculated over the quasi-global land areas (50°S to 50°N), excluding regions with an average annual precipitation below 180 mm. For each PET data source, the SPEI is computed as the ensemble mean of 60 members, representing all possible combinations of the 10 precipitation sources and six PET methods.

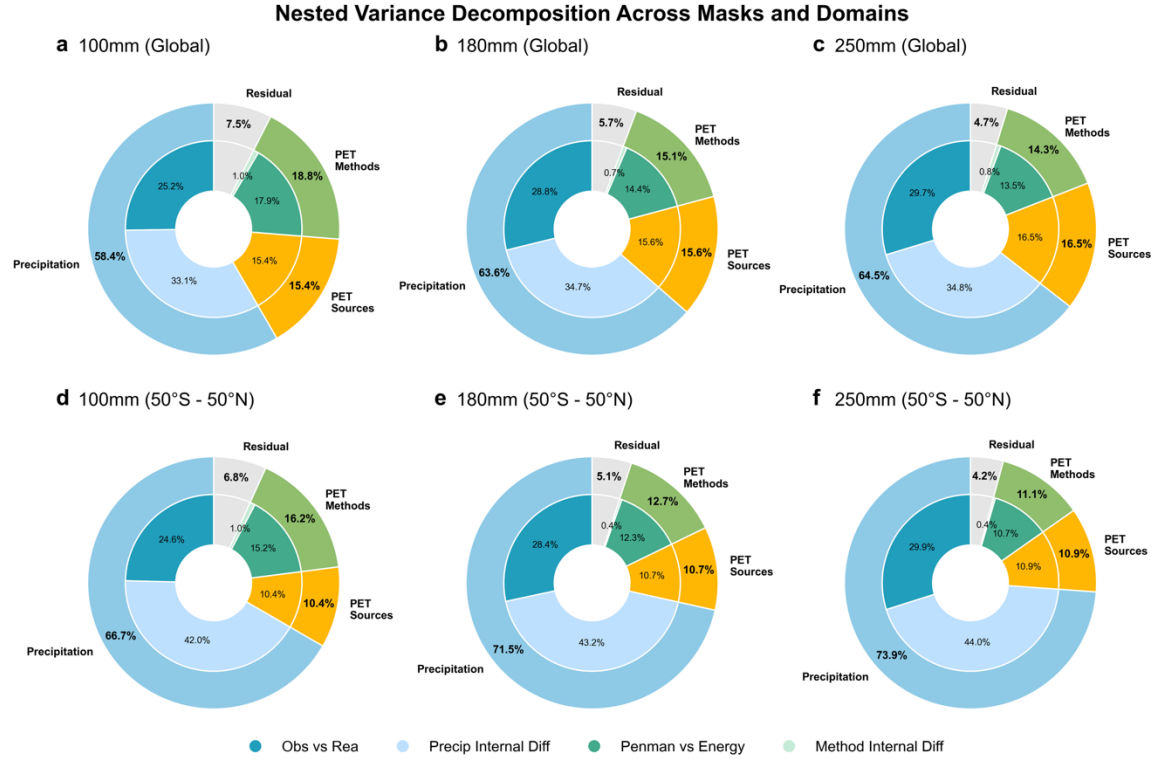
Spread of 24 PET Combinations Across 10 Precipitation Sources



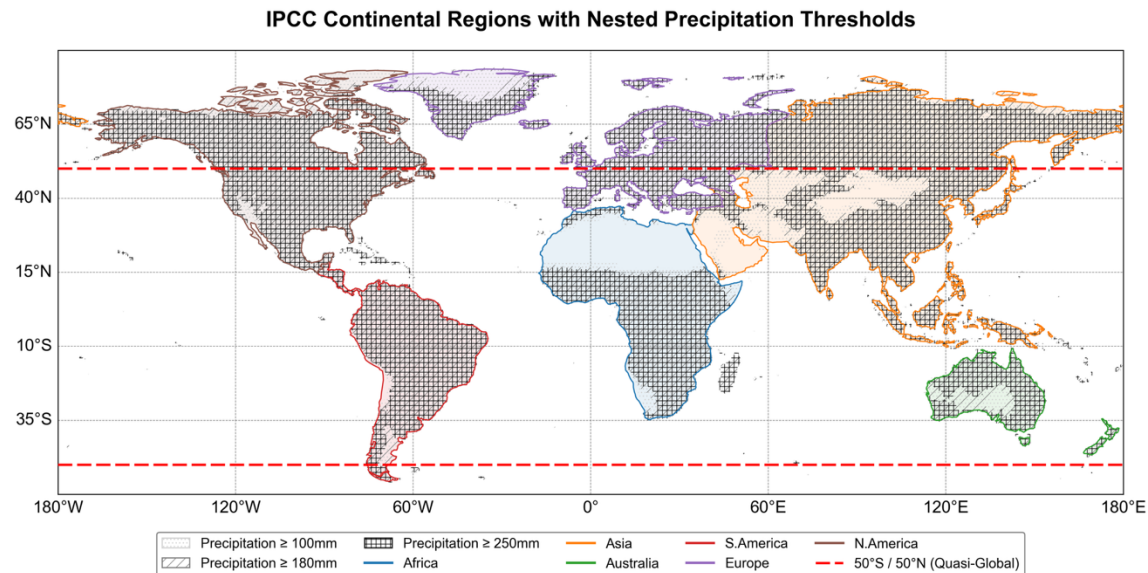
Supplementary Fig. 4 Forest plot of quasi-global average 6-month SPEI trends across 10 precipitation sources. The trends (z-units yr⁻¹) are derived from 240 SPEI time series, (a-j) grouped by precipitation source in alphabetical order: CHIRPSV2, CPC, CRU, GPCC, MSWEP, PRECL, ERA5_Land, JRA3Q, MERRA2, and MSWX100. Each precipitation source category includes the ensemble of trends calculated from all possible combinations of six PET methods and four PET data sources. The quasi-global average is calculated over the quasi-global land areas (50°S to 50°N), excluding regions with an average annual precipitation below 180 mm.



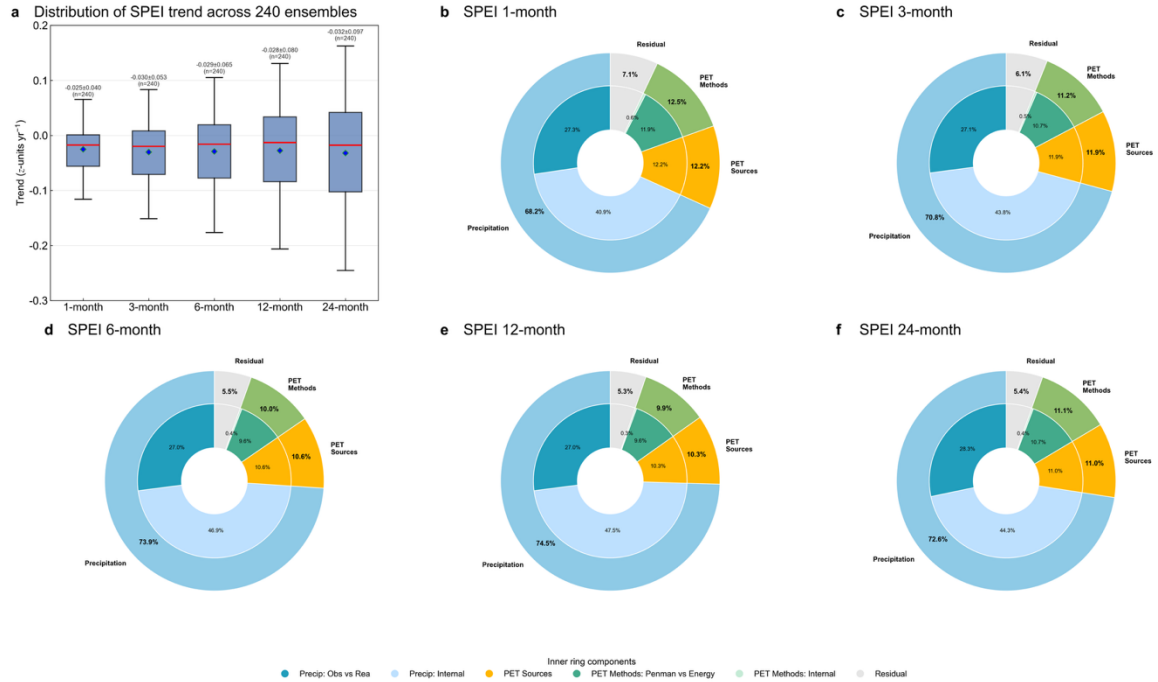
Supplementary Fig. 5 Heatmap of quasi-global average 6-month SPEI trends across precipitation sources and PET method–data source combinations. The heatmap illustrates the SPEI trends (z-units yr⁻¹) for the 240 individual SPEI time series. The vertical axis represents the 10 precipitation sources (sorted by the magnitude of the trends), and the horizontal axis displays the 24 possible combinations of the six PET methods and four PET data sources. The quasi-global average is calculated over the quasi-global land areas (50°S to 50°N), excluding regions with an average annual precipitation below 180 mm. Asterisks (*) denote statistically significant trends ($P < 0.05$).



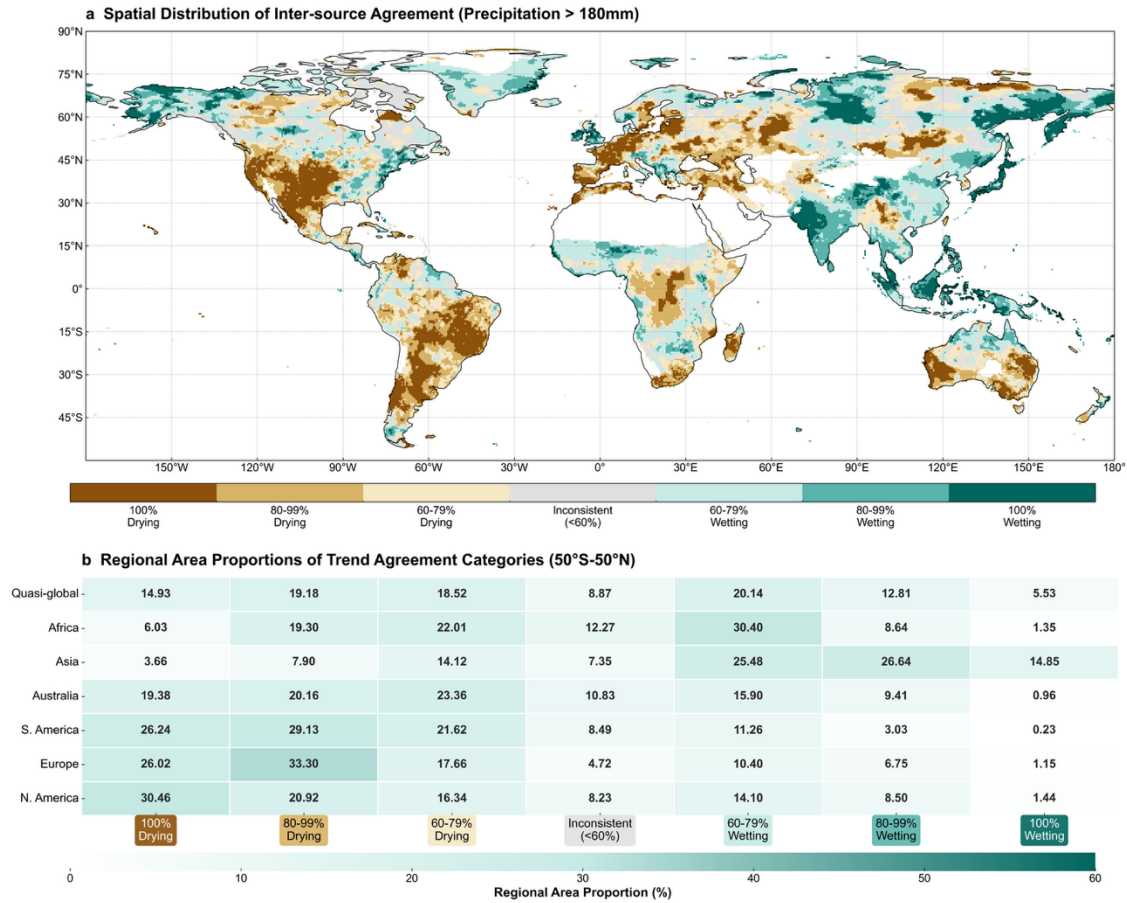
Supplementary Fig. 6 Relative contributions of different uncertainty sources to quasi-global and global 6-month SPEI trends under varying precipitation mask thresholds. The format of all panels is identical to Fig. 1f. Panels (a–c) show the relative contributions for global land areas, while panels (d–f) display the results for the quasi-global land areas (50°S–50°N). The columns correspond to different average annual rainfall exclusion thresholds: 100 mm (a, d), 180 mm (b, e), and 250 mm (c, f). The classification of uncertainty sources is consistent with Fig. 1: “Obs” includes precipitation sources from CRU, GPCC, CPC, PRECL, CHIRPS, and MSWEP, whereas “Rea” represents the remaining four reanalysis precipitation sources. Penman-based PET methods include PE-OW and PM, while energy-based PET methods include ZY, YA, MD, and KIM.



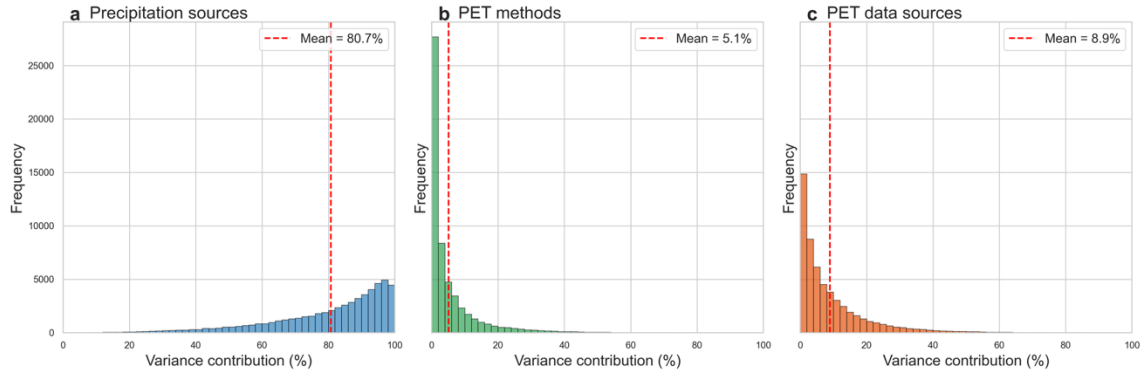
Supplementary Fig. 7 Spatial domains for analysis and precipitation exclusion masks. The map illustrates the continental boundaries used to define regions for extracting zonal trend means. The two red dashed lines demarcate the quasi-global latitudinal band from 50°S to 50°N. Nested precipitation masks are applied to exclude extremely dry regions, defined by multi-year average annual precipitation thresholds. Areas exceeding these thresholds are indicated by different hatch patterns: ≥ 100 mm (stippling), ≥ 180 mm (forward slashes, //), and ≥ 250 mm (crosses, ++).



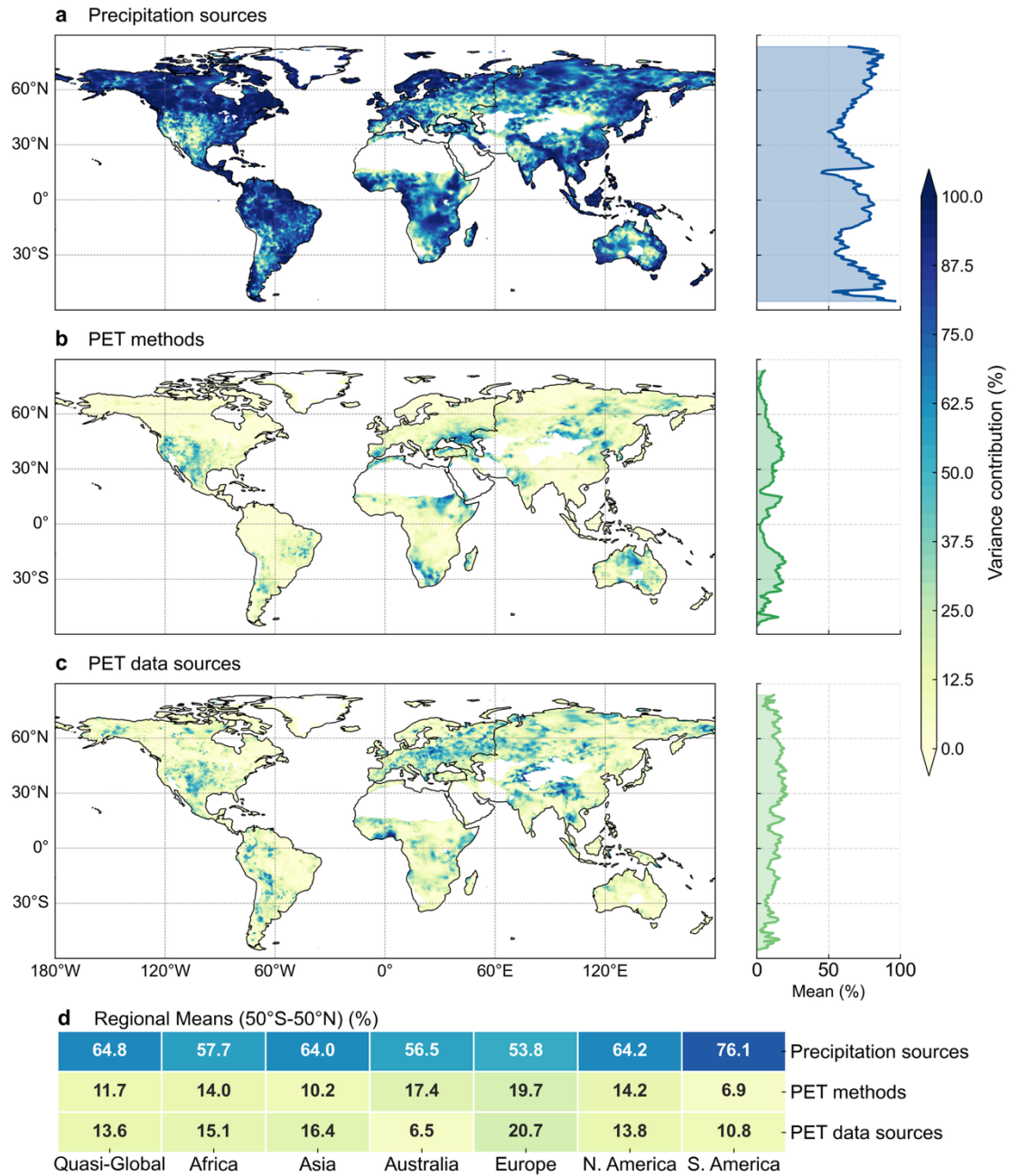
Supplementary Fig. 8 Sensitivity of SPEI trend uncertainties to different time scales (1983–2024). **(a)** Box plots illustrating the distribution of SPEI trends across the 240 datasets for five distinct time scales (scale = 1, 3, 6, 12, and 24 months). **(b–f)** Relative contributions of different uncertainty sources to the SPEI trend uncertainty for the 1-month **(b)**, 3-month **(c)**, 6-month **(d)**, 12-month **(e)**, and 24-month **(f)** scales, respectively. The format of panels **(b–f)** is identical to main **Fig. 1f**. To ensure a consistent temporal length across all scales, all time series are truncated to the period 1983–2024. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with an average annual rainfall below 180 mm. The classification of uncertainty sources (Obs, Rea, Penman-based, and energy-based PET methods) is identical to main **Fig. 1f**.



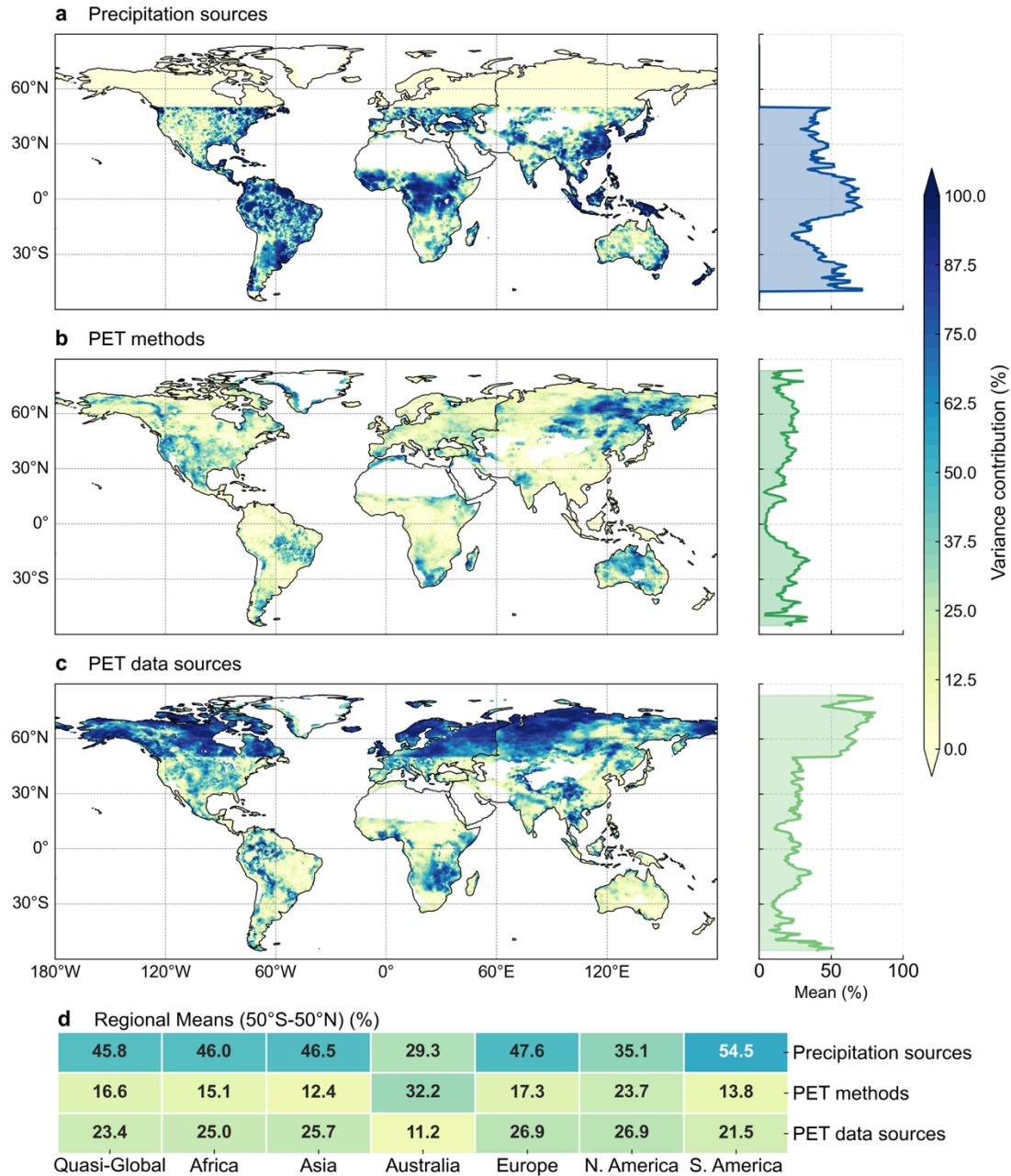
Supplementary Fig. 9 Spatial consistency of the 6-month SPEI trends across 10 precipitation sources. **(a)** Spatial distribution of the consistency among the 10 precipitation datasets regarding the SPEI trend. **(b)** Regional statistics illustrating the percentage of the land area exhibiting different levels of consistency. The regional statistics in (b) are calculated exclusively for the quasi-global land areas (50°S–50°N), excluding regions with an average annual rainfall below 180 mm. The consistency is defined as the percentage of precipitation sources that agree on the sign of the SPEI trend.



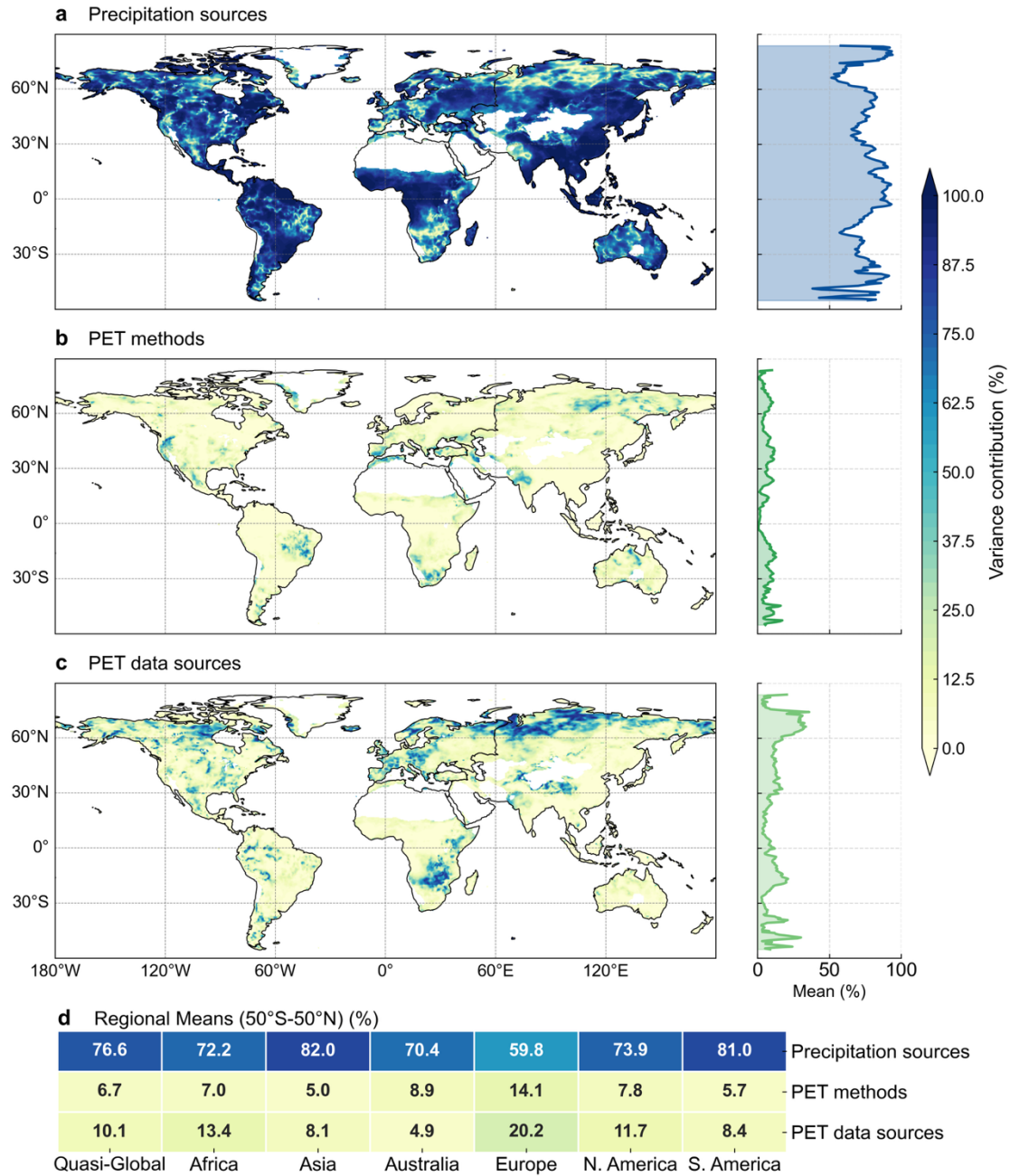
Supplementary Fig. 10 Frequency distribution of the variance contributions derived from the ANOVA grid-point analysis. (a–c) Frequency statistics (histograms) of the fractional variance contributions across all valid grid points shown in Figure 4. The panels correspond to the variance explained by (a) precipitation sources, (b) potential evapotranspiration (PET) methods, and (c) PET data sources. The analysis is restricted to grid points within regions with an average annual rainfall beyond 180 mm.



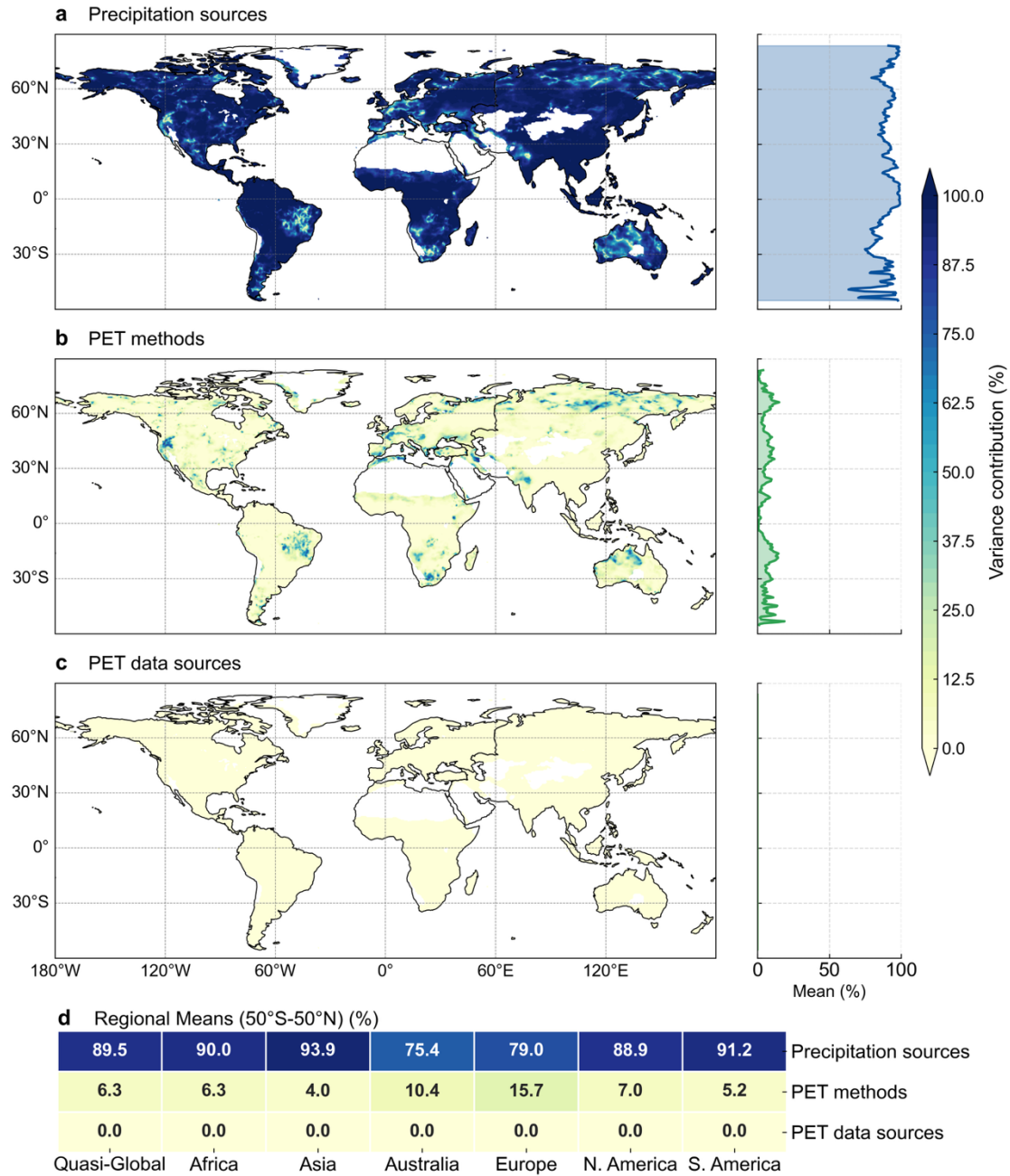
Supplementary Fig. 11 Spatial distribution and regional statistics of uncertainty sources in the 6-month SPEI trends, based exclusively on gauge-based precipitation sources. The format of all panels is identical to Fig. 4. The ANOVA decomposition is performed using a subset of datasets restricted to four gauge-based precipitation sources (CRU, GPCC, CPC, and PRECL), combined with the full set of six PET methods and four PET data sources. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The spatial distribution of residuals in the ANOVA analysis is not shown.



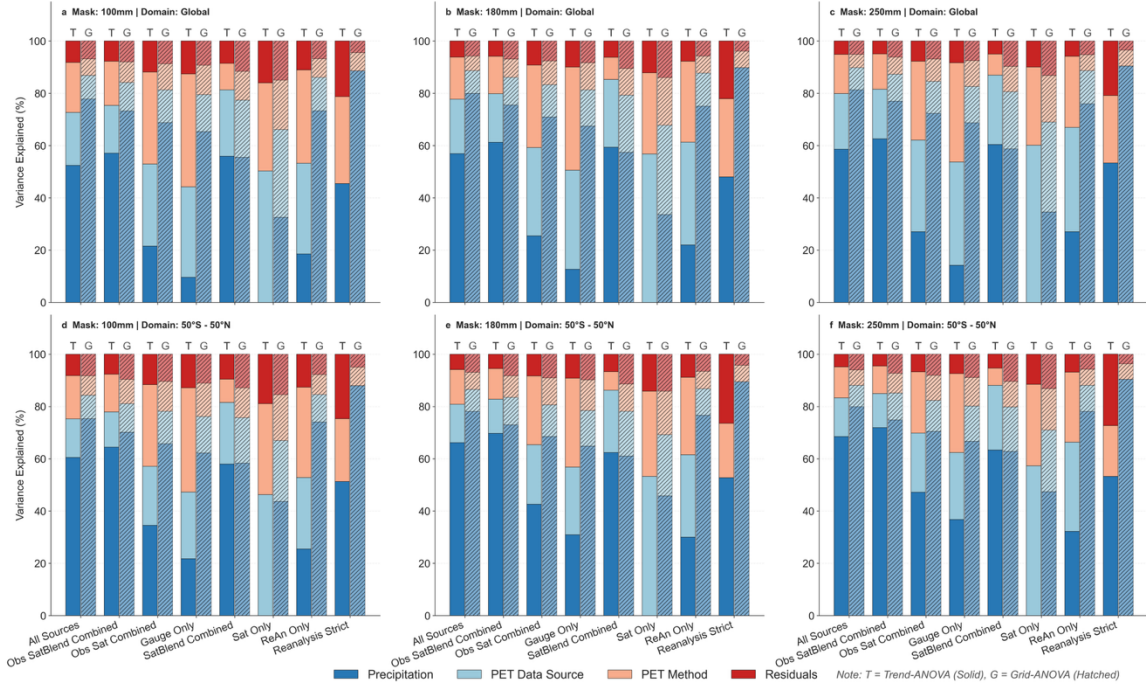
Supplementary Fig. 12 Spatial distribution and regional statistics of uncertainty sources in the 6-month SPEI trends, based exclusively on satellite-based precipitation sources. The format of all panels is identical to Fig. 4. The ANOVA decomposition is performed using a subset of datasets restricted to two satellite-based precipitation sources (CHIRPSV2 and MSWEP), combined with the full set of six PET methods and four PET data sources. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The spatial distribution of residuals in the ANOVA analysis is not shown.



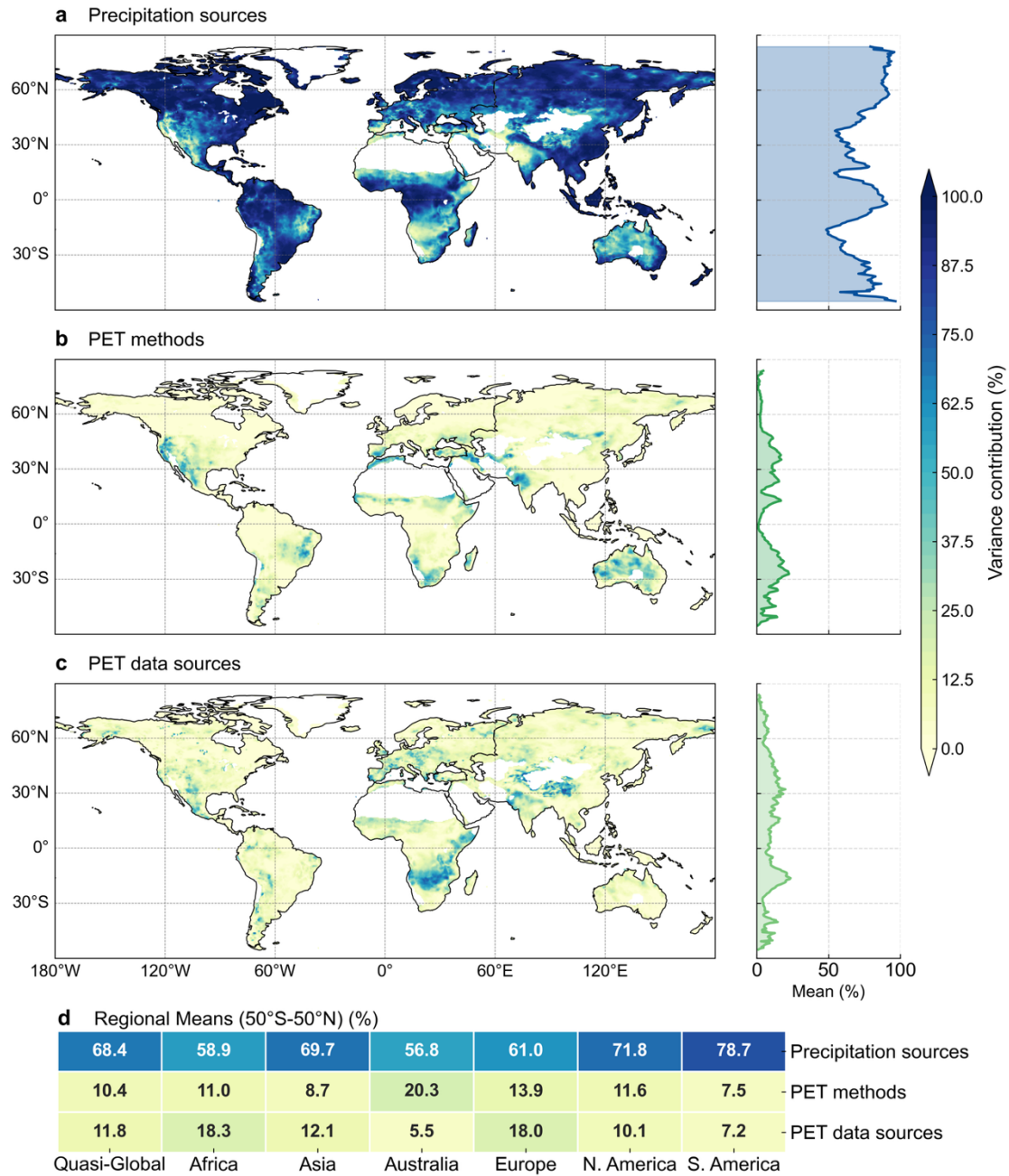
Supplementary Fig. 13 Spatial distribution and regional statistics of uncertainty sources in the 6-month SPEI trends, based exclusively on reanalysis precipitation sources. The format of all panels is identical to Fig. 4. The ANOVA decomposition is performed using a subset of datasets where the precipitation inputs are restricted to three reanalysis sources (ERA5_Land, JRA3Q, and MERRA2), combined with the full set of six PET methods and four PET data sources. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The spatial distribution of residuals in the ANOVA analysis is not shown.



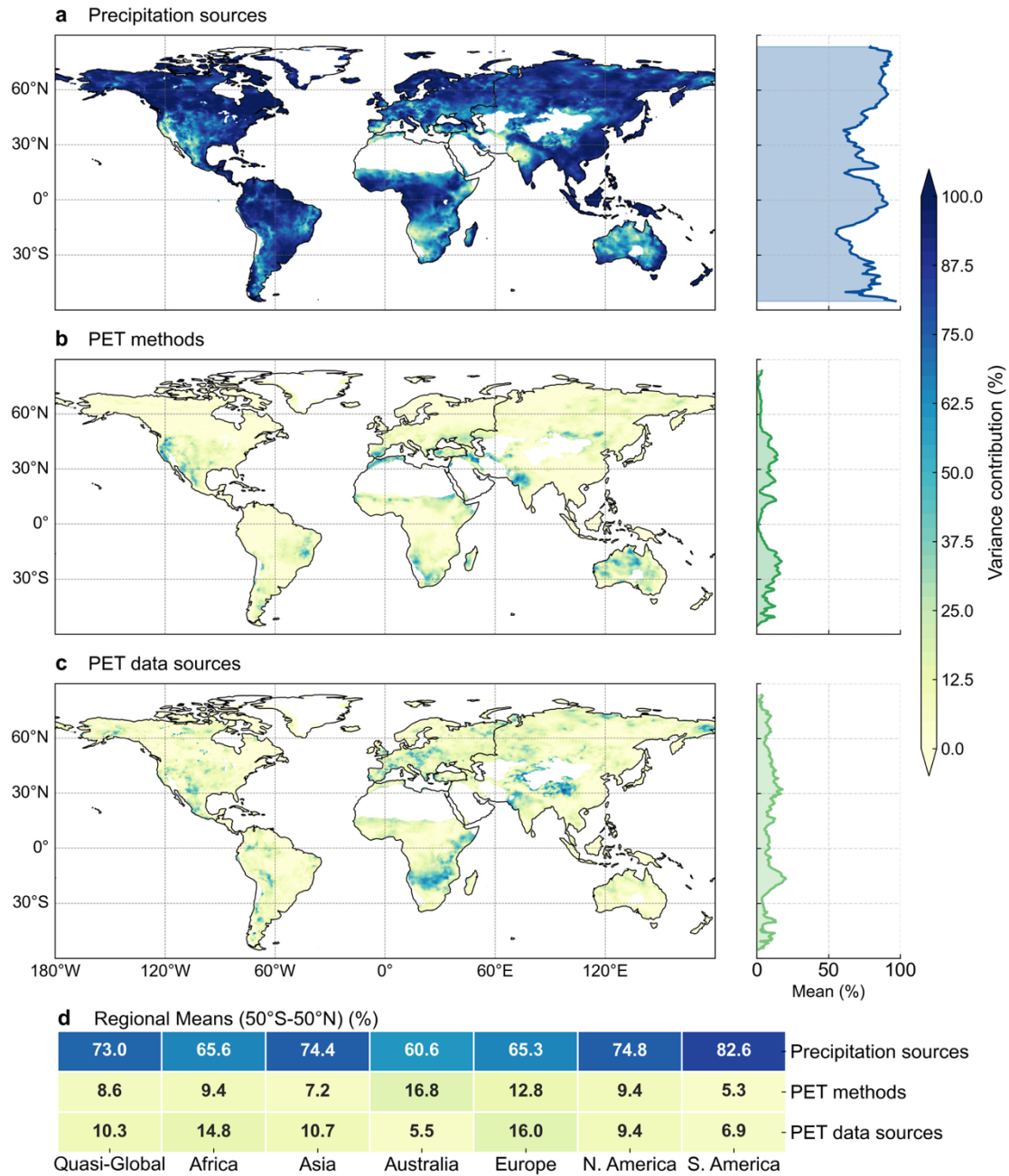
Supplementary Fig. 14 Spatial distribution and regional statistics of uncertainty sources in the 6-month SPEI trends under a strictly coupled reanalysis datasets. The spatial mapping and regional statistics follow the layout of Fig. 4. In this strictly coupled experimental design, precipitation and PET data are sourced simultaneously from the same underlying reanalysis models (ERA5_Land, JRA3Q, and MERRA2) to preserve physical consistency; consequently, the variance contribution from independent PET data sources is zero by design. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The spatial distribution of residuals in the ANOVA analysis is not shown.



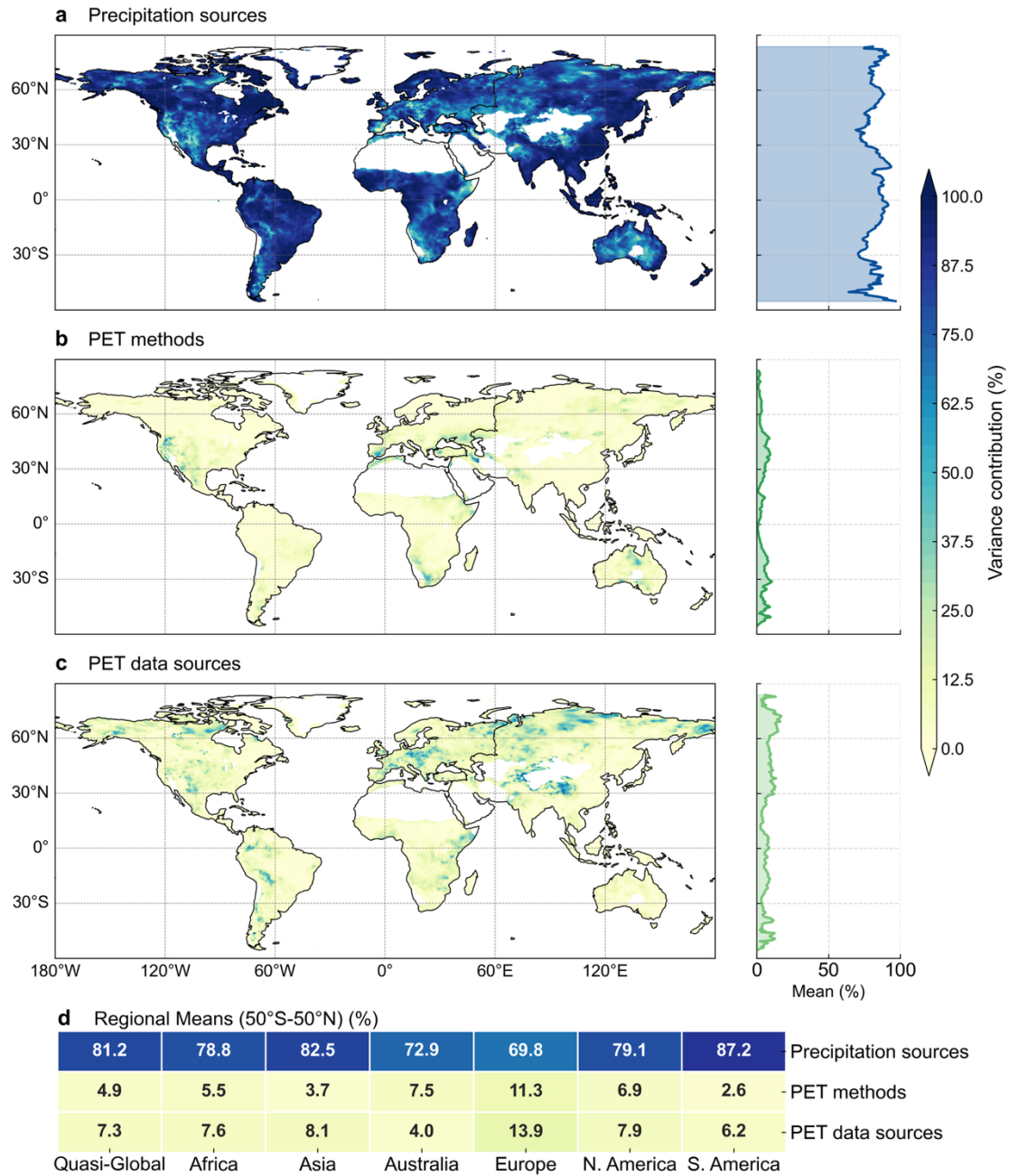
Supplementary Fig. 15 Comparison of variance contributions to SPEI trends derived from two distinct ANOVA statistical frameworks (“Trend-ANOVA” vs. “Grid-ANOVA”). (a–f) Relative variance explained by precipitation sources, PET data sources, PET methods, and residuals across eight experimental combinations of precipitation datasets. The solid bars denoted by “T” represent the Trend-ANOVA approach, where the spatial mean SPEI time series is aggregated first, followed by trend extraction and ANOVA decomposition. The hatched bars denoted by “G” represent the Grid-ANOVA approach, where trend extraction and ANOVA decomposition are performed at individual grid points first, and the resulting variance fractions are subsequently spatially averaged. The top row panels (a–c) display results for the global land area, while the bottom row panels (d–f) show results for the quasi-global land areas (50°S–50°N). The columns correspond to different average annual precipitation exclusion masks: 100 mm (a, d), 180 mm (b, e), and 250 mm (c, f). The eight experimental groups on the x-axis correspond to the following precipitation subset combinations: (1) All Sources (all 10 products); (2) Obs_SatBlend_Combined (4 gauge-based, 2 satellite-based, and MSWX100); (3) Obs_Sat_Combined (4 gauge-based and 2 satellite-based); (4) Gauge_Only (CRU, GPCC, CPC, PRECL); (5) SatBlend_Combined (CHIRPSV2, MSWEP, and MSWX100); (6) Sat_Only (CHIRPSV2, MSWEP); (7) ReAn_Only (3 reanalysis products: ERA5_Land, JRA3Q, MERRA2); and (8) Reanalysis_Strict (the same 3 reanalysis products, but strictly coupled with their own internal PET data). Except for the “Reanalysis_Strict” group, all experimental setups are fully crossed with the six PET methods and four independent PET data sources.



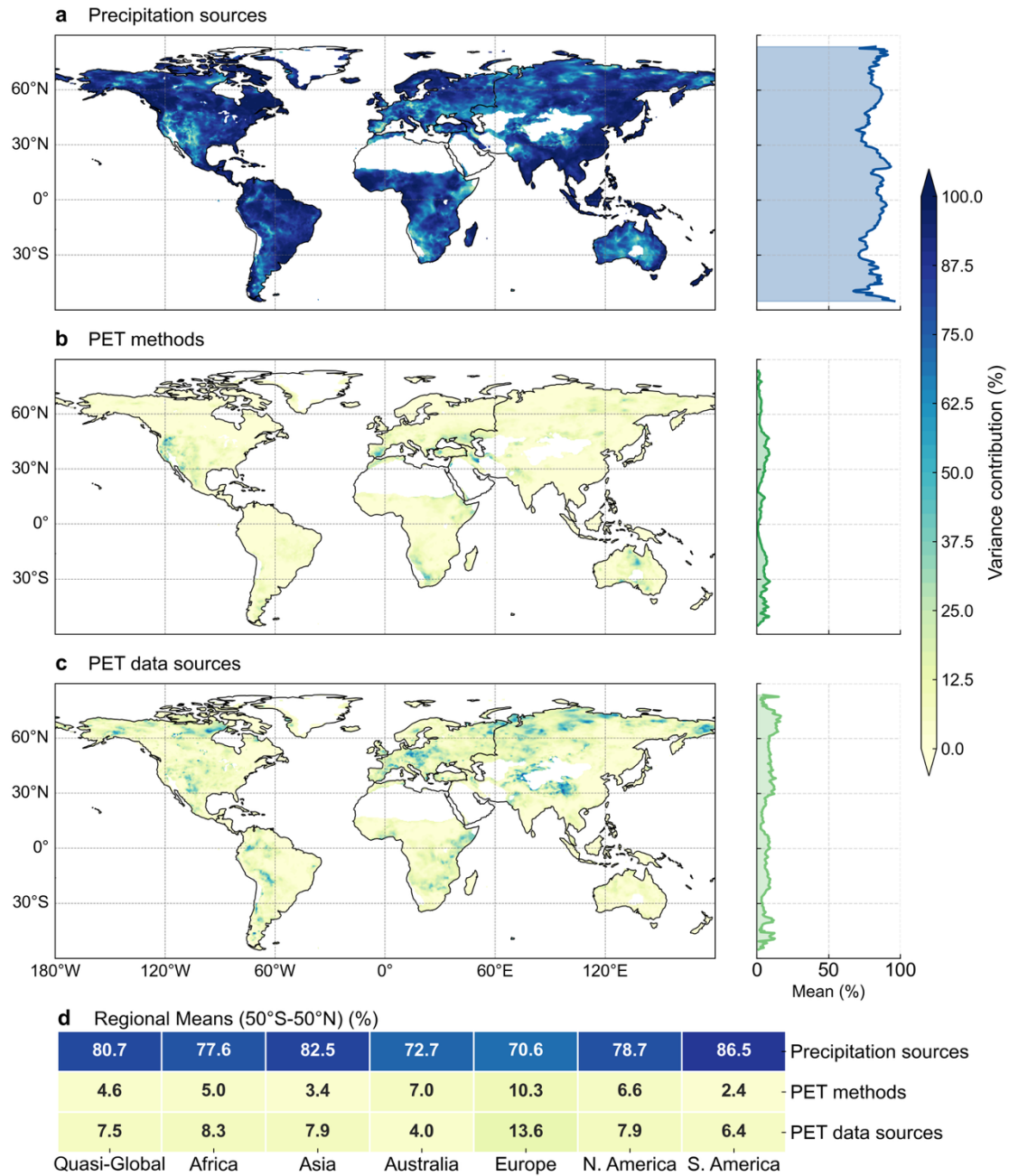
Supplementary Fig. 16 Spatial distribution and regional statistics of uncertainty sources in the 1-month SPEI trends. The format of all panels is identical to Fig. 4. The ANOVA decomposition is performed on the 1-month SPEI time series. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The spatial distribution of residuals in the ANOVA analysis is not shown.



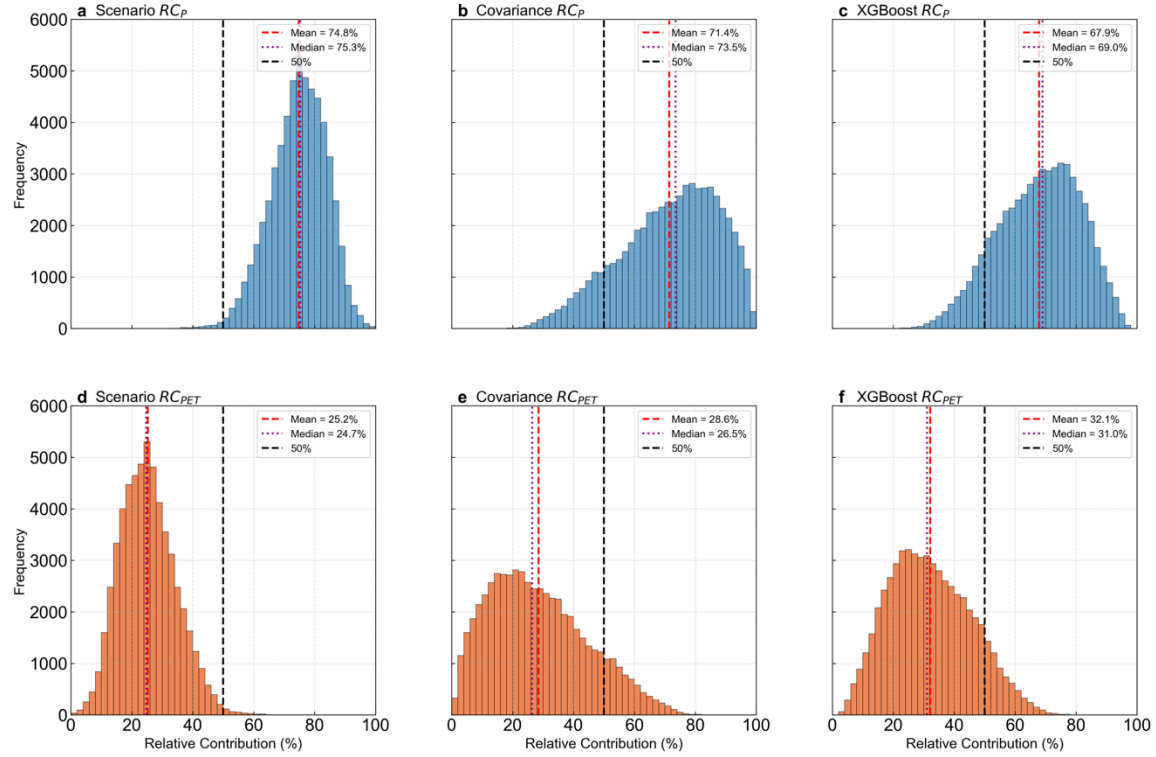
Supplementary Fig. 17 Spatial distribution and regional statistics of uncertainty sources in the 3-month SPEI trends. The format of all panels is identical to Fig. 4. The ANOVA decomposition is performed on the 1-month SPEI time series. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The spatial distribution of residuals in the ANOVA analysis is not shown.



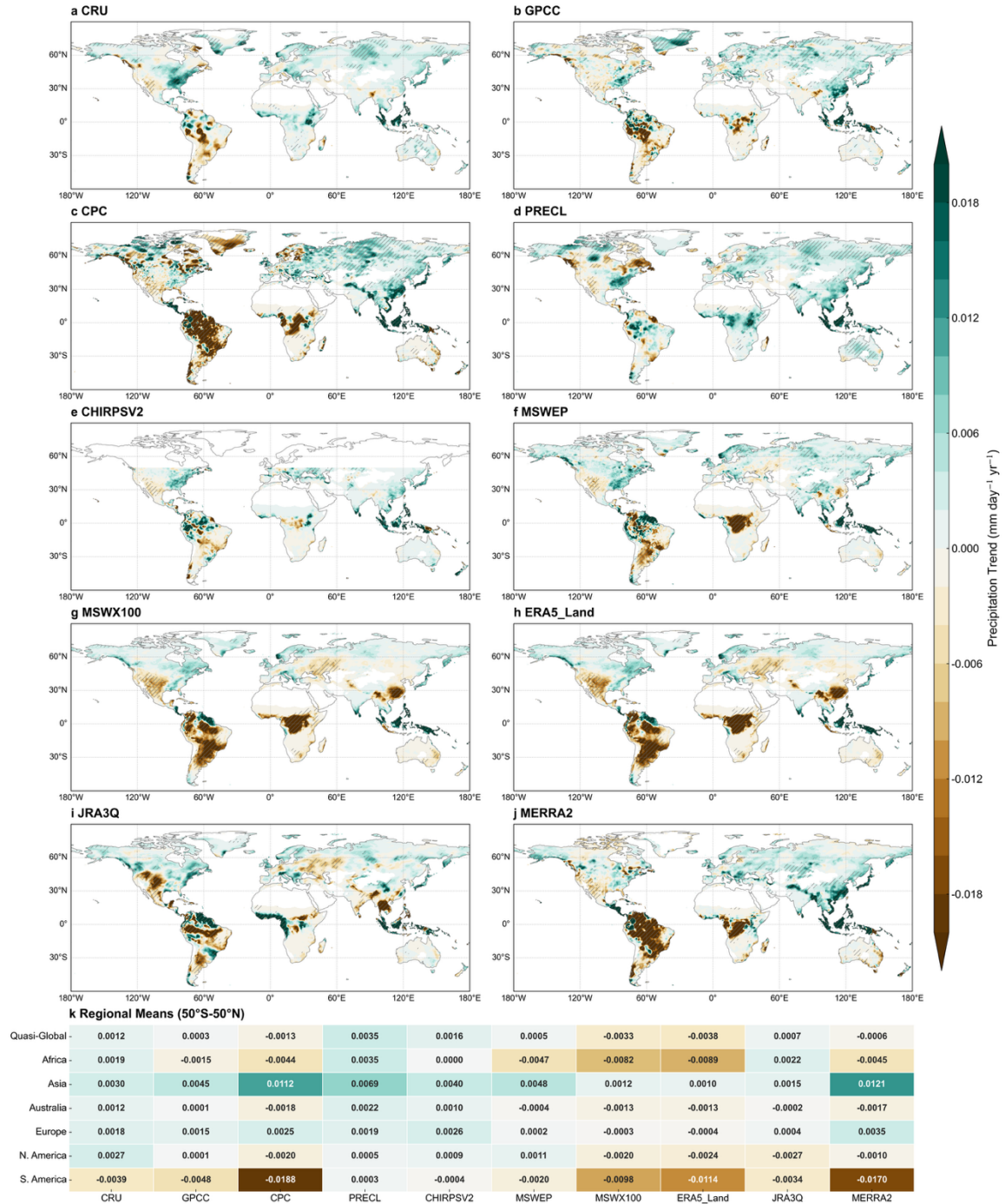
Supplementary Fig. 18 Spatial distribution and regional statistics of uncertainty sources in the 12-month SPEI trends. The format of all panels is identical to Fig. 4. The ANOVA decomposition is performed on the 1-month SPEI time series. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The spatial distribution of residuals in the ANOVA analysis is not shown.



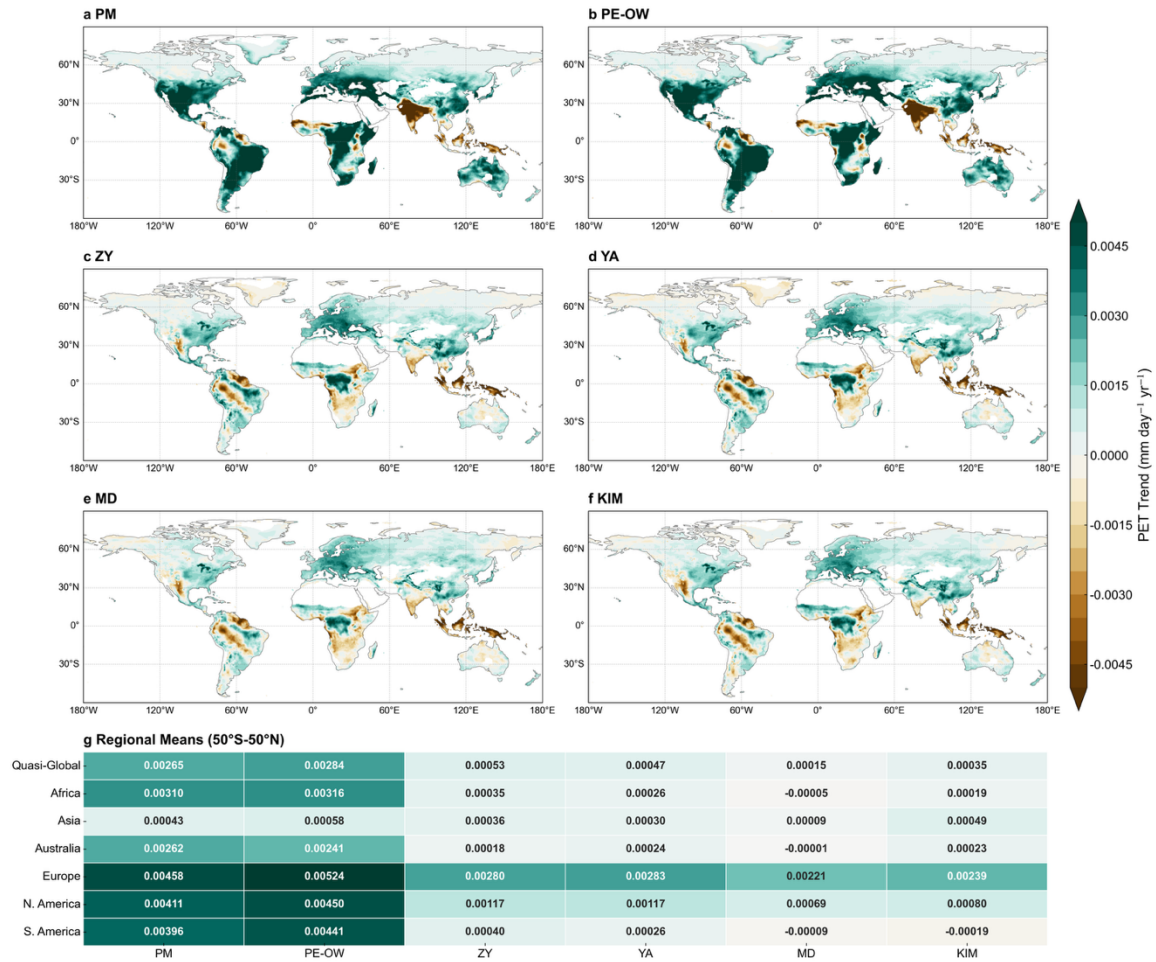
Supplementary Fig. 19 Spatial distribution and regional statistics of uncertainty sources in the 24-month SPEI trends. The format of all panels is identical to Fig. 4. The ANOVA decomposition is performed on the 1-month SPEI time series. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The spatial distribution of residuals in the ANOVA analysis is not shown.



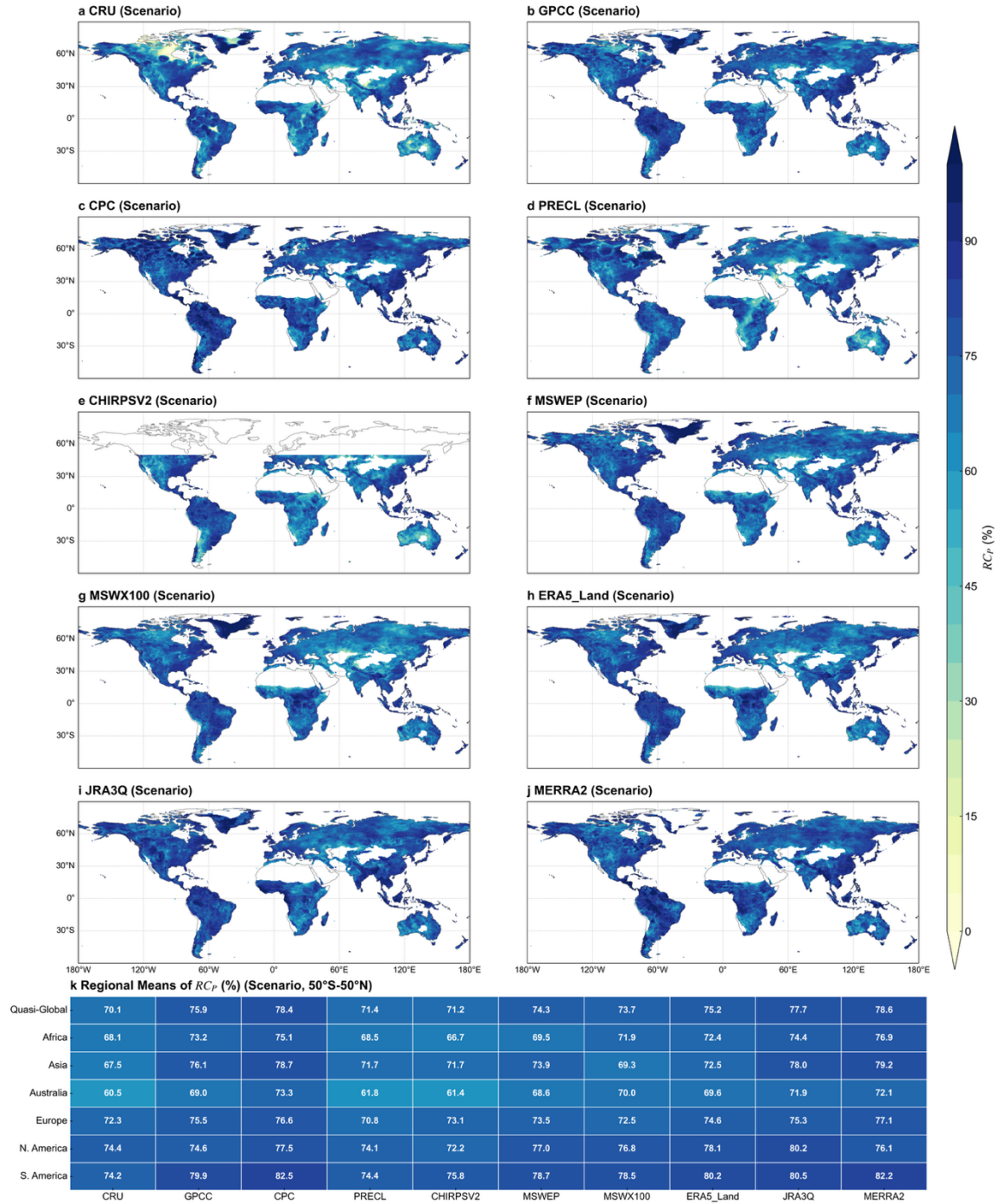
Supplementary Fig. 20 Frequency distribution of precipitation (RC_P) and potential evapotranspiration (RC_{PET}) contributions to SPEI changes across global grid points. (a-c) Frequency statistics (histograms) of the PR contributions derived from the spatial fields calculated using the Scenario, Covariance, and XGBoost methods, corresponding to Fig. 5a, 5c, and 5e, respectively. (d-f) Frequency statistics of the PET contributions derived from the spatial fields for the Scenario, Covariance, and XGBoost methods, corresponding to Fig. 5b, 5d, and 5f, respectively. The data are extracted from all global land grid points, excluding extremely dry regions with an average annual rainfall below 180 mm.



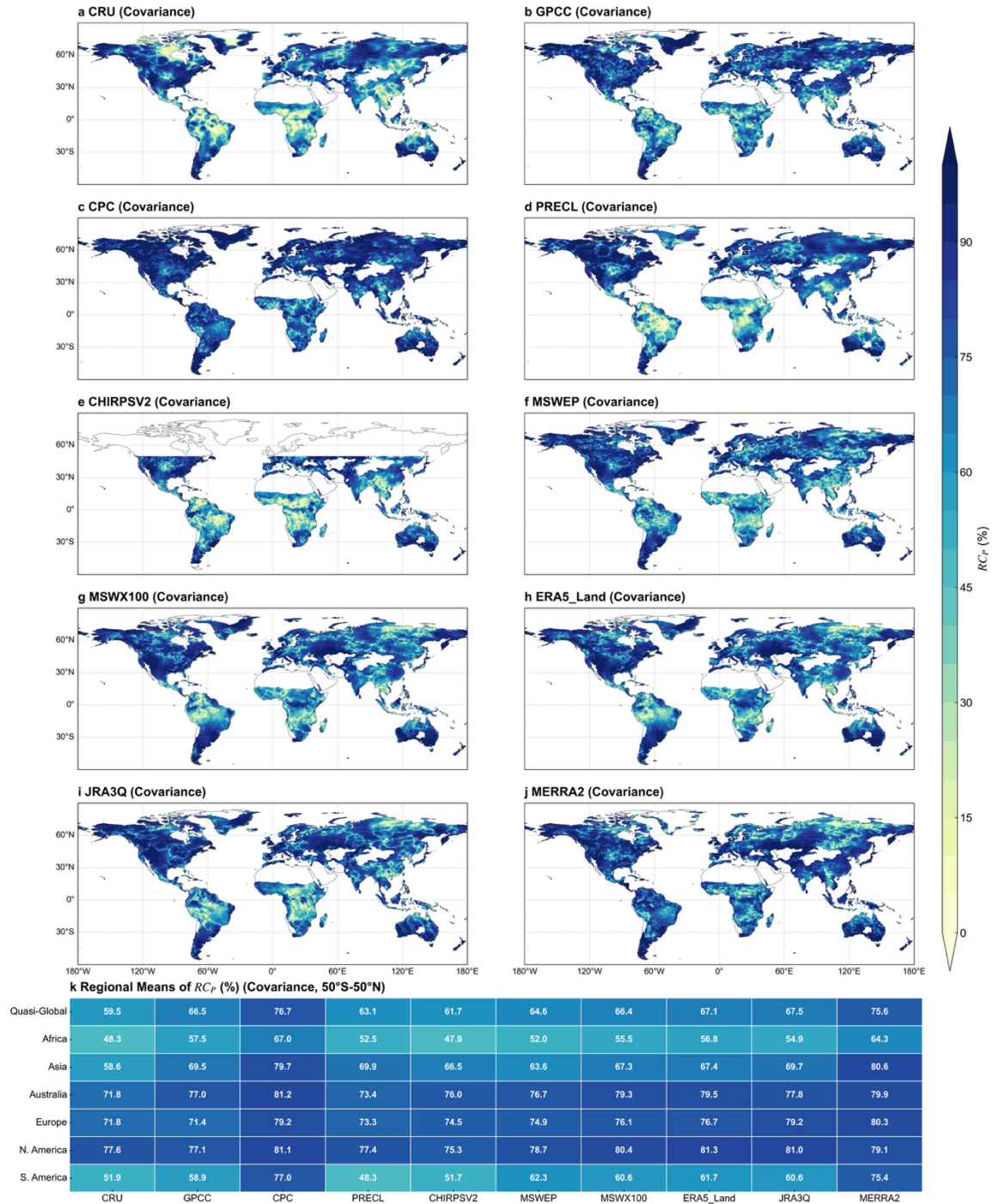
Supplementary Fig. 21 Spatial patterns and regional means of the precipitation trends for 1981–2024. (a–j) Spatial distribution of the precipitation trends (mm day⁻¹ yr⁻¹) calculated from each of the 10 precipitation datasets. The 10 precipitation sources are: (a) CRU, (b) GPCC, (c) CPC, (d) PRECL, (e) CHIRPSV2, (f) MSWEP, (g) MSWX100, (h) ERA5_Land, (i) JRA3Q, and (j) MERRA2. (k) Regional means extracted from the spatial fields shown in (a–j). Stippling indicates statistical significance ($P < 0.05$) where applicable. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The regional boundaries used for calculating regional means can be found in Supplementary Fig. 7.



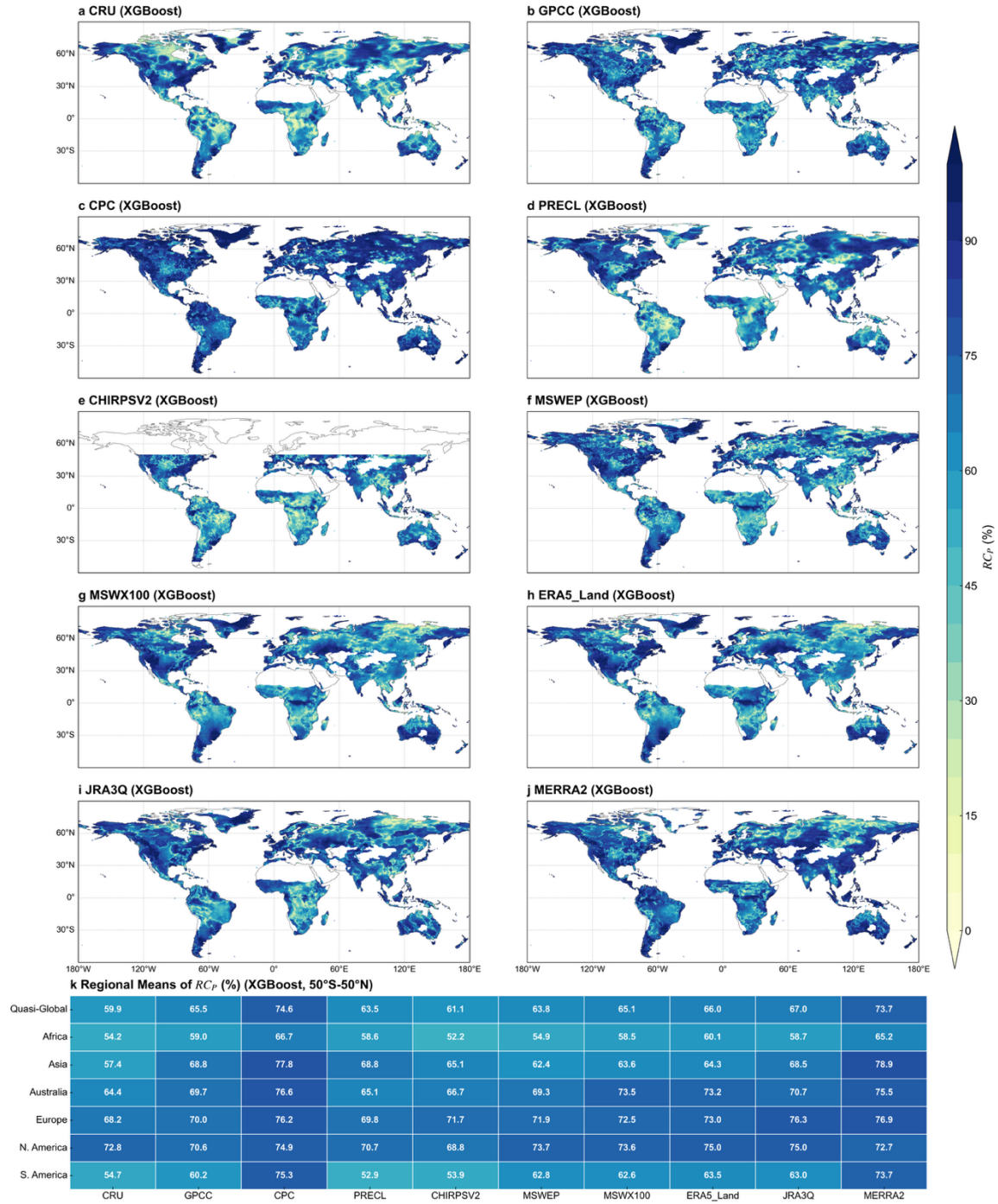
Supplementary Fig. 22 Spatial patterns and regional means of the potential evapotranspiration (PET) trends for 1981–2024. (a–f) Spatial distribution of the PET trends ($\text{mm day}^{-1} \text{yr}^{-1}$) calculated as the ensemble mean for each of the six PET methods (see Supplementary Text 1). The six PET methods are: (a) PE-OW, (b) PM, (c) ZY, (d) YA, (e) MD, and (f) KIM. (g) Regional means extracted from the spatial fields shown in (a–f). Stippling indicates statistical significance ($P < 0.05$) where applicable. Regional averaging is performed over the quasi-global land areas (50°S – 50°N), excluding regions with average annual rainfall below 180 mm. The regional boundaries used for calculating regional means can be found in Supplementary Fig. 7.



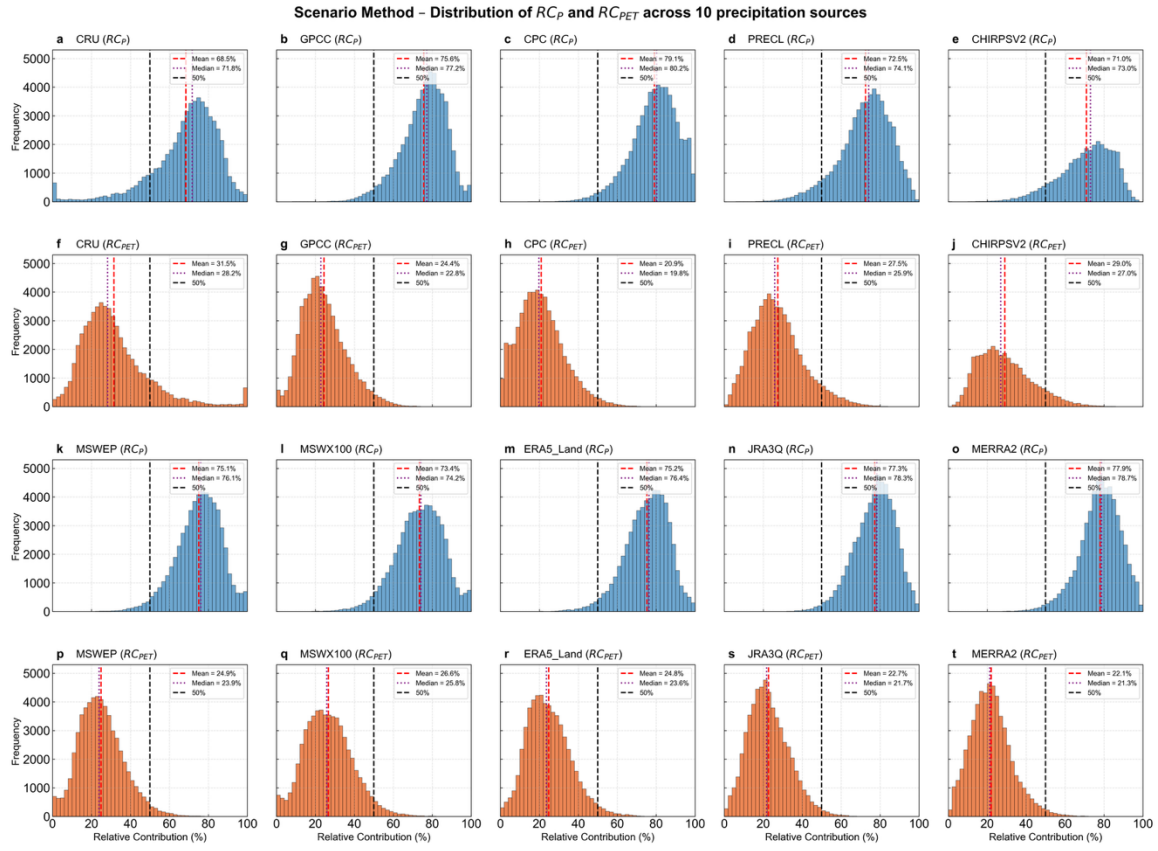
Supplementary Fig. 23 Spatial patterns and regional means of precipitation contributions (RC_p) to SPEI changes calculated using the Scenario method. (a–j) Average RC_p for each of the 10 precipitation datasets, derived by averaging the corresponding members classified by precipitation source. The 10 precipitation sources are: (a) CRU, (b) GPCC, (c) CPC, (d) PRECL, (e) CHIRPSV2, (f) MSWEP, (g) MSWX100, (h) ERA5_Land, (i) JRA3Q, and (j) MERRA2. (k) Regional means extracted from the spatial fields shown in (a–j). Stippling indicates statistical significance ($P < 0.05$) where applicable. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The regional boundaries used for calculating regional means can be found in Supplementary Fig. 7.



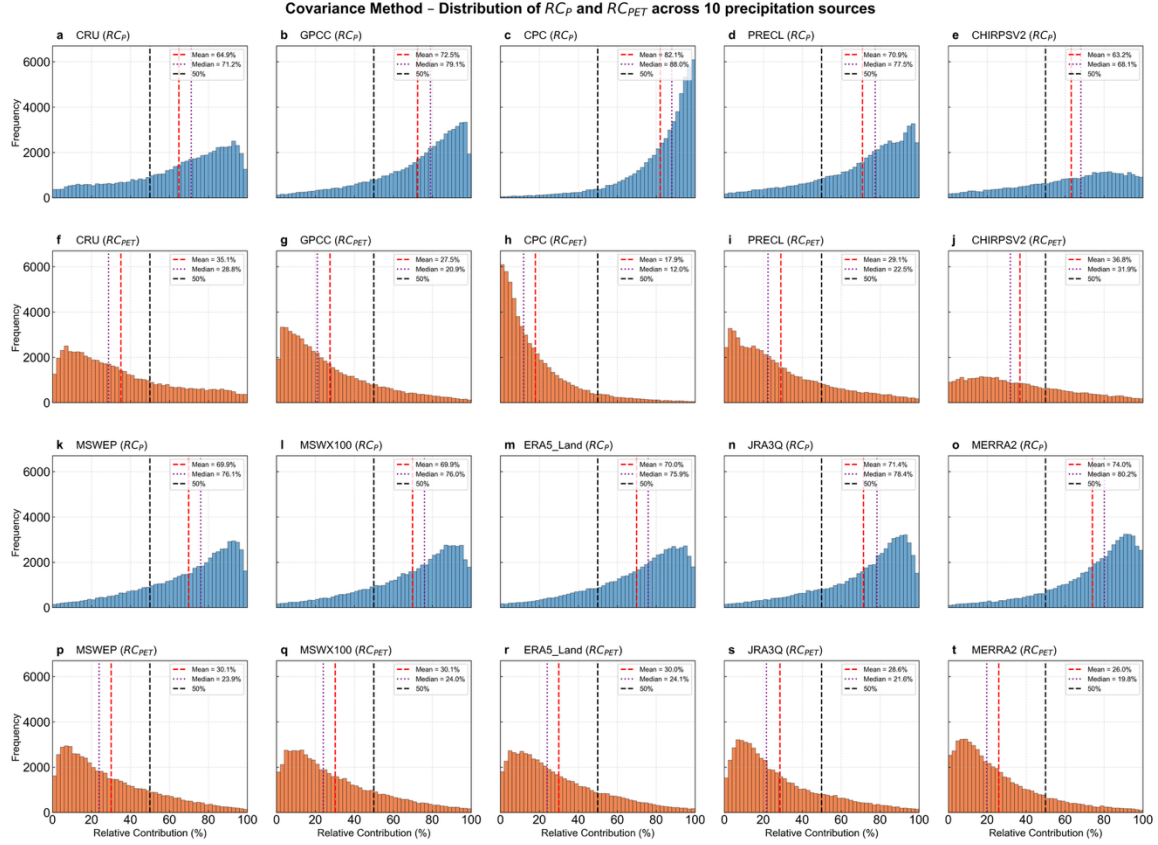
Supplementary Fig. 24 Spatial patterns and regional means of precipitation contributions (RC_p) to SPEI changes calculated using the Covariance method. (a–j) Average RC_p for each of the 10 precipitation datasets, derived by averaging the corresponding members classified by precipitation source. The 10 precipitation sources are: (a) CRU, (b) GPCC, (c) CPC, (d) PRECL, (e) CHIRPSV2, (f) MSWEP, (g) MSWX100, (h) ERA5_Land, (i) JRA3Q, and (j) MERRA2. (k) Regional means extracted from the spatial fields shown in (a–j). Stippling indicates statistical significance ($P < 0.05$) where applicable. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The regional boundaries used for calculating regional means can be found in Supplementary Fig. 7.



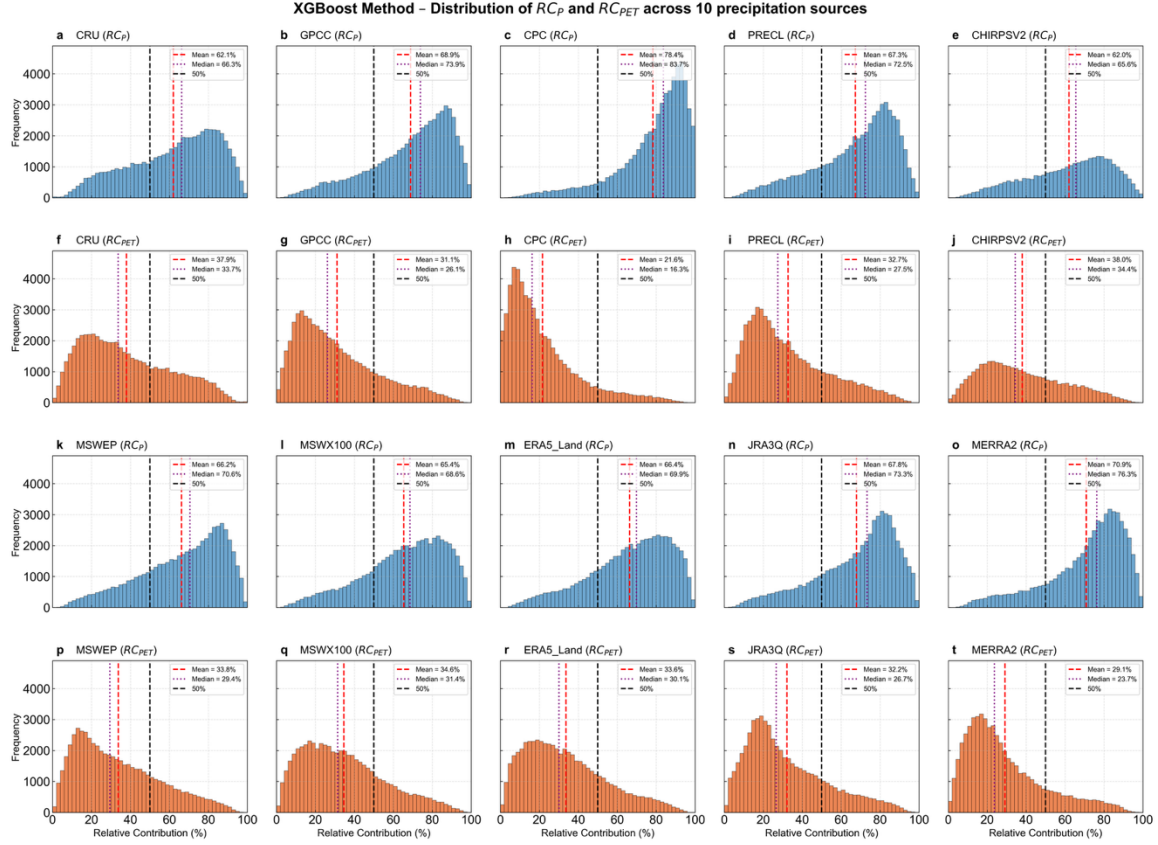
Supplementary Fig. 25 Spatial patterns and regional means of precipitation contributions (RC_P) to SPEI changes calculated using the XGBoost method. (a–j) Average RC_P for each of the 10 precipitation datasets, derived by averaging the corresponding members classified by precipitation source. The 10 precipitation sources are: (a) CRU, (b) GPCC, (c) CPC, (d) PRECL, (e) CHIRPSV2, (f) MSWEP, (g) MSWX100, (h) ERA5_Land, (i) JRA3Q, and (j) MERRA2. (k) Regional means extracted from the spatial fields shown in (a–j). Stippling indicates statistical significance ($P < 0.05$) where applicable. Regional averaging is performed over the quasi-global land areas (50°S–50°N), excluding regions with average annual rainfall below 180 mm. The regional boundaries used for calculating regional means can be found in Supplementary Fig. 7.



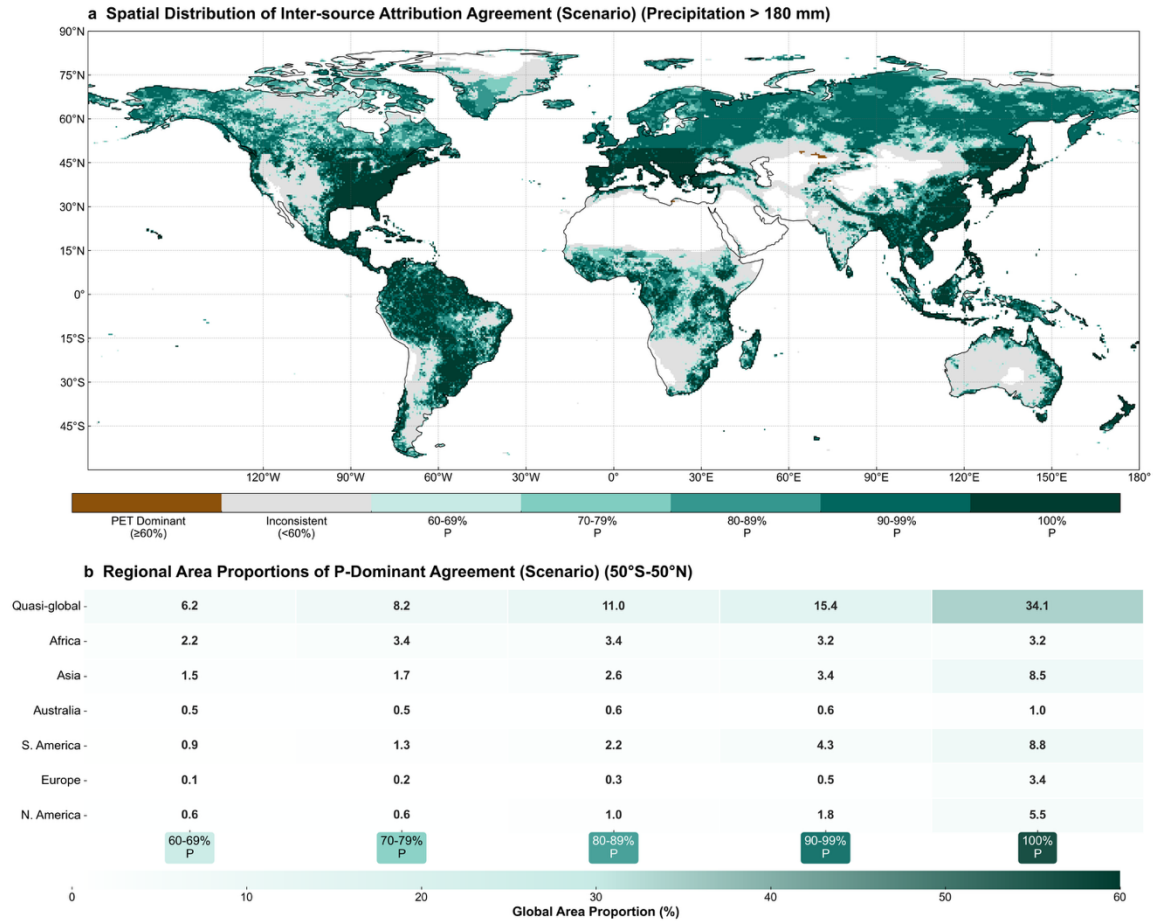
Supplementary Fig. 26 Frequency distribution of precipitation (RC_P) and potential evapotranspiration (RC_{PET}) contributions to SPEI changes calculated using the Scenario method. The figure displays frequency statistics (histograms) extracted from global grid points, arranged in 20 panels (four rows and five columns). Panels (a–e) and (f–j) represent the PR and PET contributions, respectively, for the first five precipitation sources: (a, f) CRU, (b, g) GPCC, (c, h) CPC, (d, i) PRECL, and (e, j) CHIRPSV2. Panels (k–o) and (p–t) represent the PR and PET contributions, respectively, for the remaining five sources: (k, p) MSWEP, (l, q) MSWX100, (m, r) ERA5_Land, (n, s) JRA3Q, and (o, t) MERRA2. The data are extracted from all global land grid points, excluding extremely dry regions with an average annual rainfall below 180 mm.



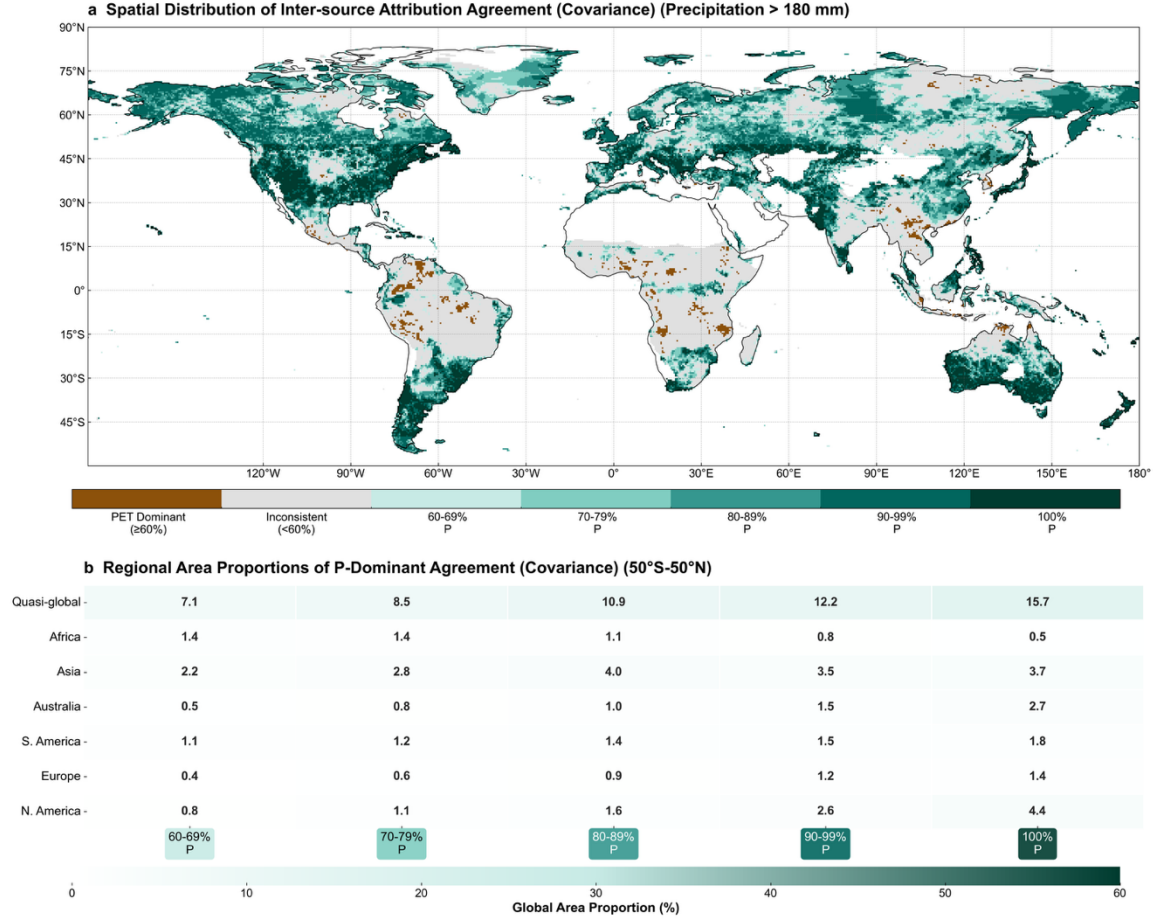
Supplementary Fig. 27 Frequency distribution of precipitation (RC_P) and potential evapotranspiration (RC_{PET}) contributions to SPEI changes calculated using the Covariance method. The figure displays frequency statistics (histograms) extracted from global grid points, arranged in 20 panels (four rows and five columns). Panels (a–e) and (f–j) represent the PR and PET contributions, respectively, for the first five precipitation sources: (a, f) CRU, (b, g) GPCC, (c, h) CPC, (d, i) PRECL, and (e, j) CHIRPSV2. Panels (k–o) and (p–t) represent the PR and PET contributions, respectively, for the remaining five sources: (k, p) MSWEP, (l, q) MSWX100, (m, r) ERA5_Land, (n, s) JRA3Q, and (o, t) MERRA2. The data are extracted from all global land grid points, excluding extremely dry regions with an average annual rainfall below 180 mm.



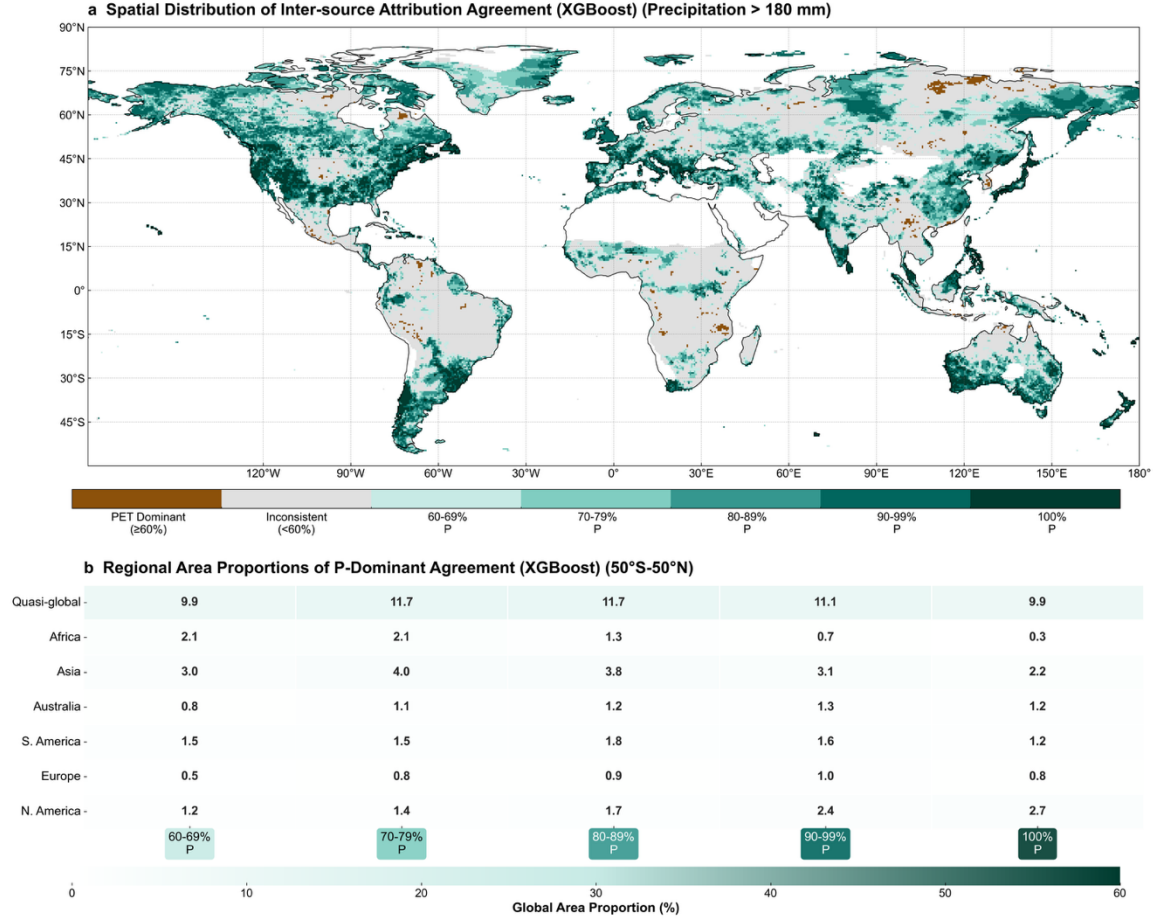
Supplementary Fig. 28 Frequency distribution of precipitation (RC_P) and potential evapotranspiration (RC_{PET}) contributions to SPEI changes calculated using the XGBoost method. The figure displays frequency statistics (histograms) extracted from global grid points, arranged in 20 panels (four rows and five columns). Panels (a–e) and (f–j) represent the PR and PET contributions, respectively, for the first five precipitation sources: (a, f) CRU, (b, g) GPCC, (c, h) CPC, (d, i) PRECL, and (e, j) CHIRPSV2. Panels (k–o) and (p–t) represent the PR and PET contributions, respectively, for the remaining five sources: (k, p) MSWEP, (l, q) MSWX100, (m, r) ERA5_Land, (n, s) JRA3Q, and (o, t) MERRA2. The data are extracted from all global land grid points, excluding extremely dry regions with an average annual rainfall below 180 mm.



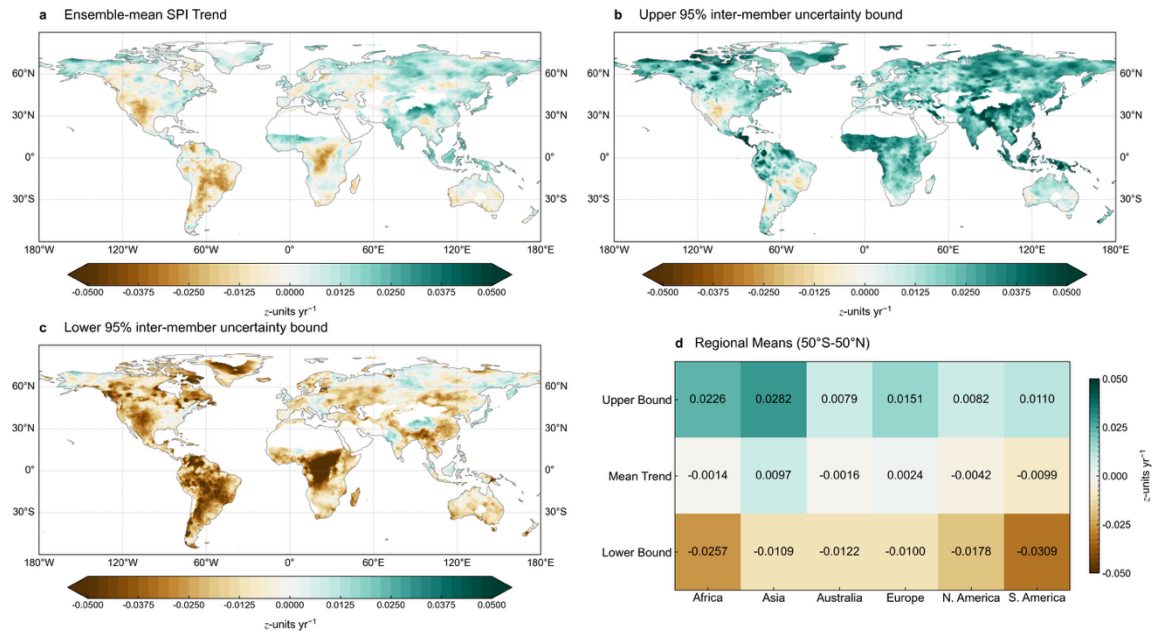
Supplementary Fig. 29 Spatial consistency of precipitation dominance in driving SPEI changes across 10 precipitation sources, calculated using the Scenario method. (a) Spatial distribution of the consistency among the 10 precipitation datasets regarding precipitation as the dominant driver of the SPEI trend. (b) Regional statistics illustrating the percentage of the total quasi-global land area exhibiting different levels of consistency. The regional statistics in (b) are calculated relative to the total valid area within the quasi-global band (50°S–50°N), excluding regions with an average annual rainfall below 180 mm. For each precipitation source, a grid cell is classified as precipitation-dominated only when at least 80% of the valid PET-combination members indicate $RC_P > RC_{PET}$; otherwise, it is not counted as a robust precipitation-dominated grid cell for that source. Consistency is then defined as the percentage of the 10 precipitation sources that agree on precipitation being the dominant contributing factor.



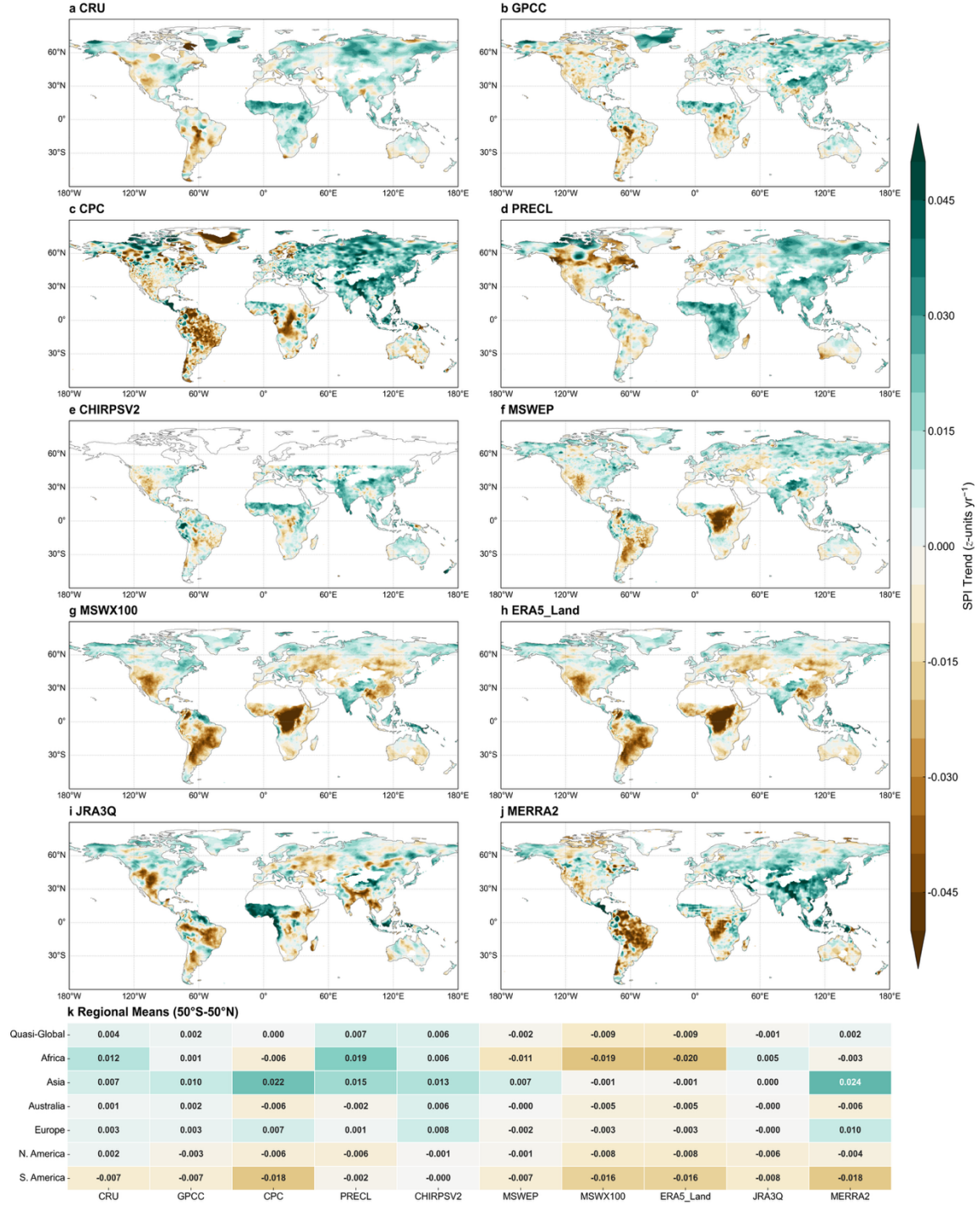
Supplementary Fig. 30 Spatial consistency of precipitation dominance in driving SPEI changes across 10 precipitation sources, calculated using the Covariance method. (a) Spatial distribution of the consistency among the 10 precipitation datasets regarding precipitation as the dominant driver of the SPEI trend. (b) Regional statistics illustrating the percentage of the total quasi-global land area exhibiting different levels of consistency. The regional statistics in (b) are calculated relative to the total valid area within the quasi-global band (50°S–50°N), excluding regions with an average annual rainfall below 180 mm. For each precipitation source, a grid cell is classified as precipitation-dominated only when at least 80% of the valid PET-combination members indicate $RC_P > RC_{PET}$; otherwise, it is not counted as a robust precipitation-dominated grid cell for that source. Consistency is then defined as the percentage of the 10 precipitation sources that agree on precipitation being the dominant contributing factor.



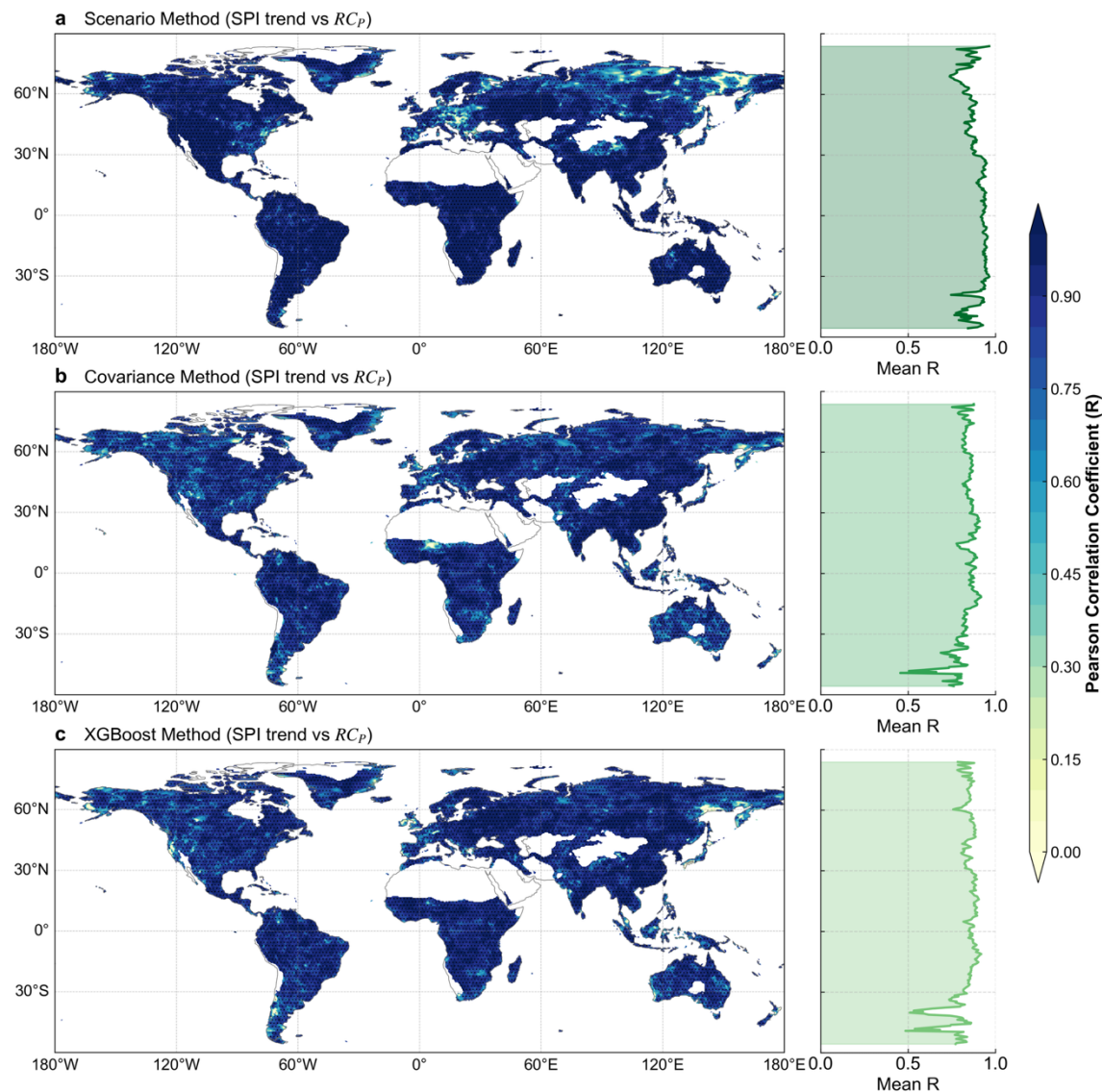
Supplementary Fig. 31 Spatial consistency of precipitation dominance in driving SPEI changes across 10 precipitation sources, calculated using the XGBoost method. (a) Spatial distribution of the consistency among the 10 precipitation datasets regarding precipitation as the dominant driver of the SPEI trend. (b) Regional statistics illustrating the percentage of the total quasi-global land area exhibiting different levels of consistency. The regional statistics in (b) are calculated relative to the total valid area within the quasi-global band (50°S–50°N), excluding regions with an average annual rainfall below 180 mm. For each precipitation source, a grid cell is classified as precipitation-dominated only when at least 80% of the valid PET-combination members indicate $RC_P > RC_{PET}$; otherwise, it is not counted as a robust precipitation-dominated grid cell for that source. Consistency is then defined as the percentage of the 10 precipitation sources that agree on precipitation being the dominant contributing factor.



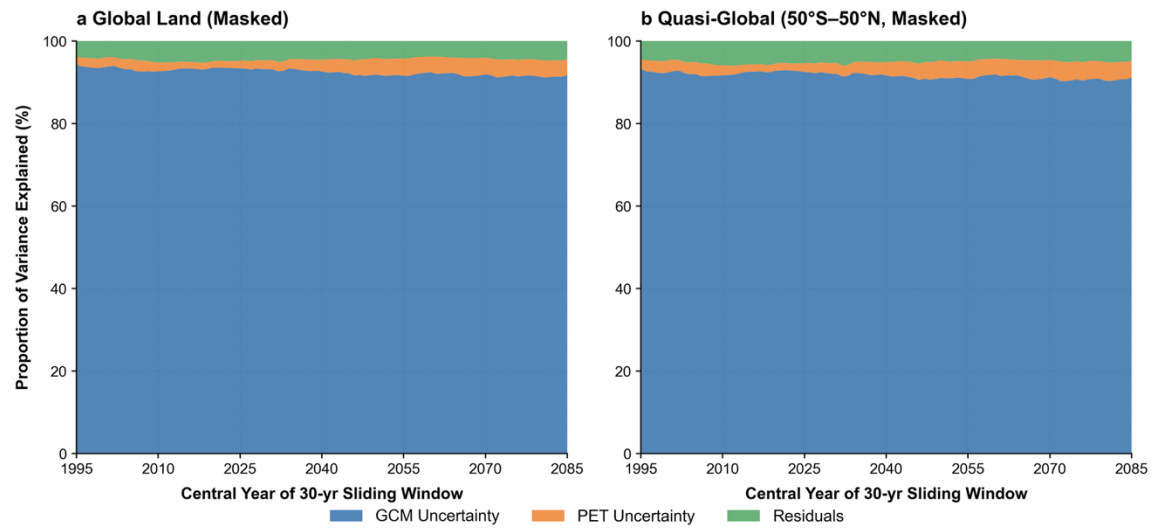
Supplementary Fig. 32 Spatial patterns and regional means of the 6-month SPI trend (z-units yr^{-1}) for 1981–2024. (a) Ensemble-mean SPI trend derived from 10 SPI series. (b) Upper limit of the 95% inter-member uncertainty bound of the SPI trend. (c) Lower limit of the 95% inter-member uncertainty bound of the SPI trend. Stippling indicates grid cells where the ensemble-mean SPI trend is statistically significant ($P < 0.05$). The significance test was applied to the aggregated ensemble SPI time series rather than to the inter-member uncertainty bounds shown in (b) and (c). (d) Regional means of the three fields shown in (a)–(c). Regional mean trends were extracted over the quasi-global land areas (50°S–50°N), excluding regions with an average annual rainfall below 180 mm. The regional boundaries used for calculating regional means are shown in Supplementary Fig. 7.



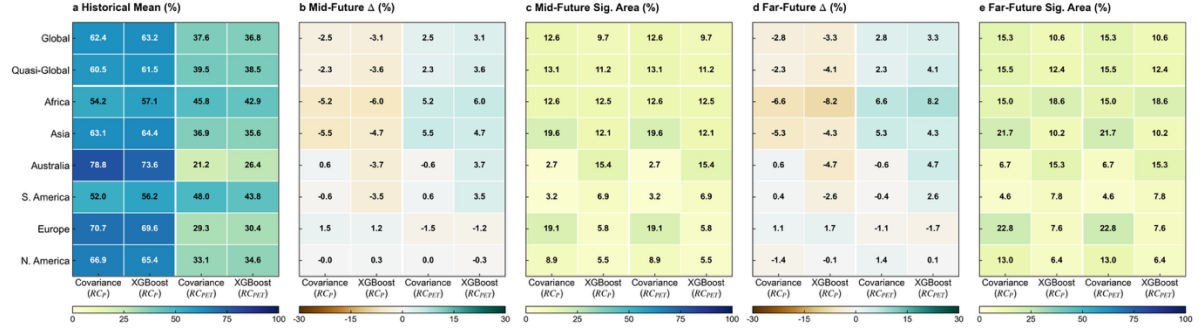
Supplementary Fig. 33 Spatial patterns and regional means of the 6-month SPI trend (z-units yr^{-1}) for 1981–2024. (a–j) SPI trend for each of the 10 precipitation datasets, derived. The 10 precipitation sources are: CRU (a), GPCC (b), CPC (c), PRECL (d), CHIRPSV2 (e), MSWEP (f), MSWX100 (g), ERA5_Land (h), JRA3Q (i), and MERRA2 (j). (k) Regional means extracted from the spatial fields shown in (a–j). Stippling indicates statistical significance ($P < 0.05$) where applicable. Regional averaging is performed over the quasi-global land areas (50°S – 50°N), excluding regions with average annual rainfall below 180 mm. The regional boundaries used for calculating regional means can be found in Supplementary Fig. 7.



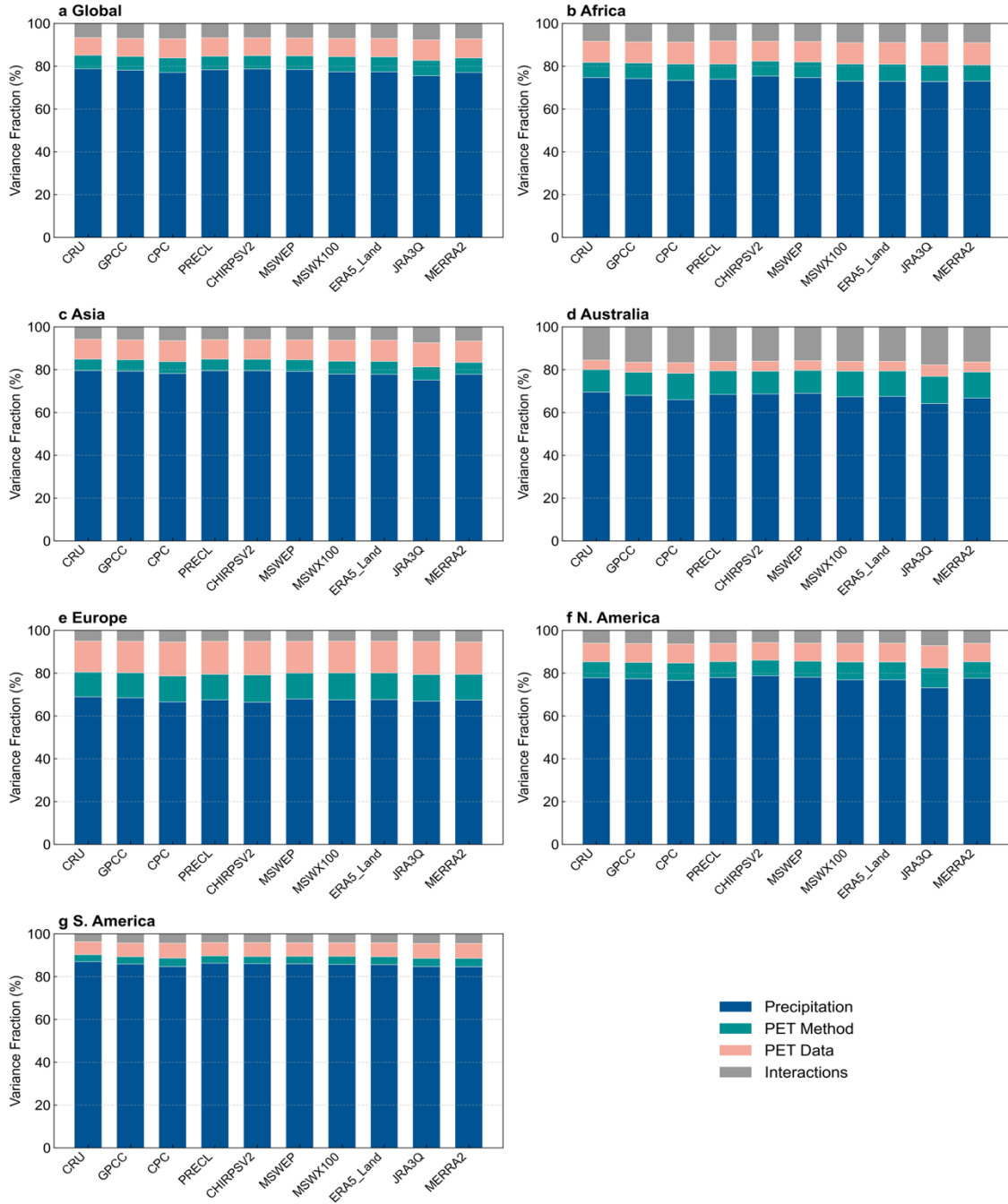
Supplementary Fig. 34 Correlation between SPI trends and the signed precipitation contribution to SPEI trends across three attribution methods. (a–c) Spatial gridded maps of the Pearson correlation between Standardized Precipitation Index (SPI) trends and the signed precipitation contribution isolated from SPEI trend attribution. The signed precipitation contribution is derived from the (a) Scenario, (b) Covariance, and (c) XGBoost methods. Here, the signed contribution is used instead of the unsigned relative contribution RC_P because it preserves the wetting or drying direction of precipitation-driven SPEI changes, making it directly comparable with SPI trends. In contrast, the unsigned RC_P only quantifies the relative magnitude of precipitation influence and removes directional information. The right-hand panels show the corresponding zonal mean correlations. The correlation analysis is performed using valid grid points after excluding regions with mean annual precipitation below 180 mm.



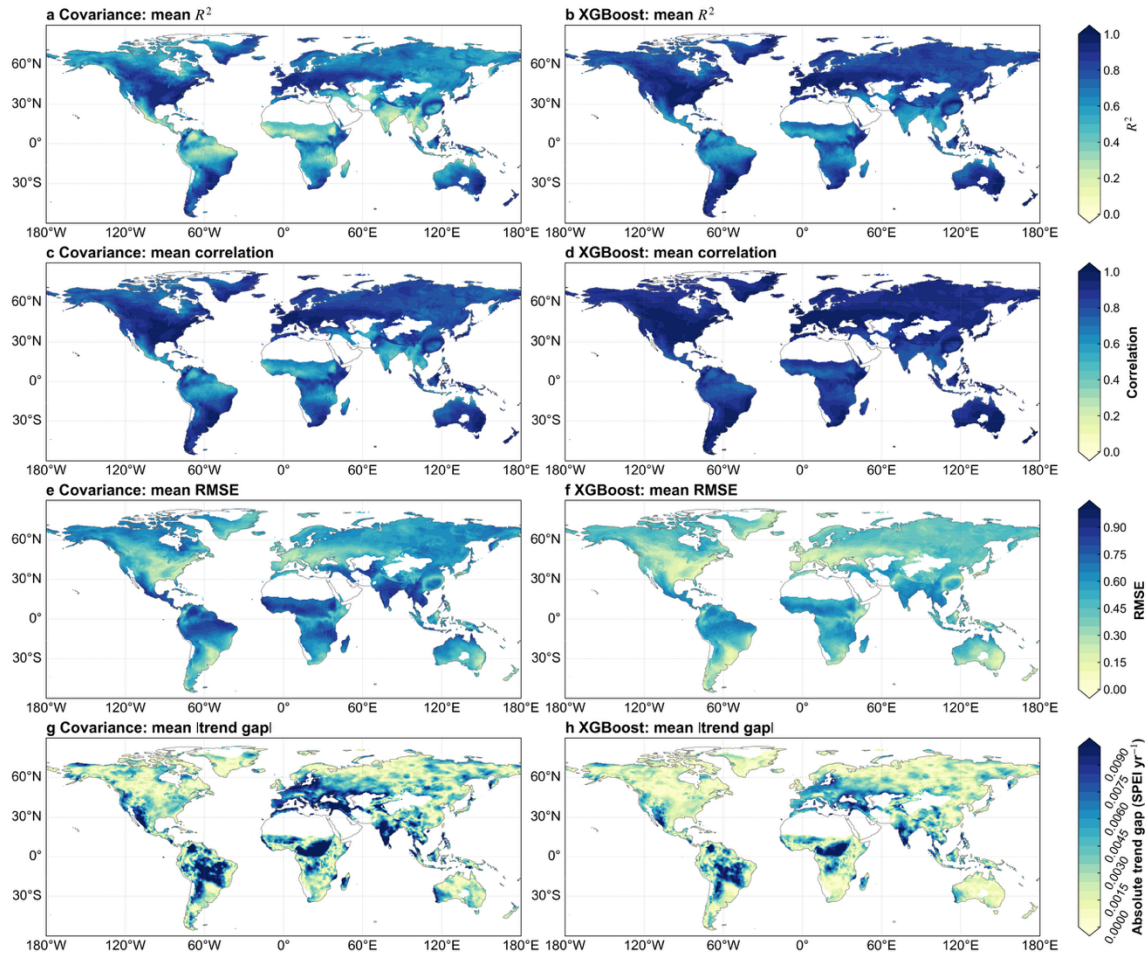
Supplementary Fig. 35 Temporal evolution of the variance contributions derived from the ANOVA decomposition using CMIP6 data. (a) Temporal variations of the relative contributions of different uncertainty sources over global land areas. (b) Temporal variations of the relative contributions over quasi-global land areas (50°S–50°N). The spatial averaging for both panels is performed by excluding regions with an average annual rainfall below 180 mm.



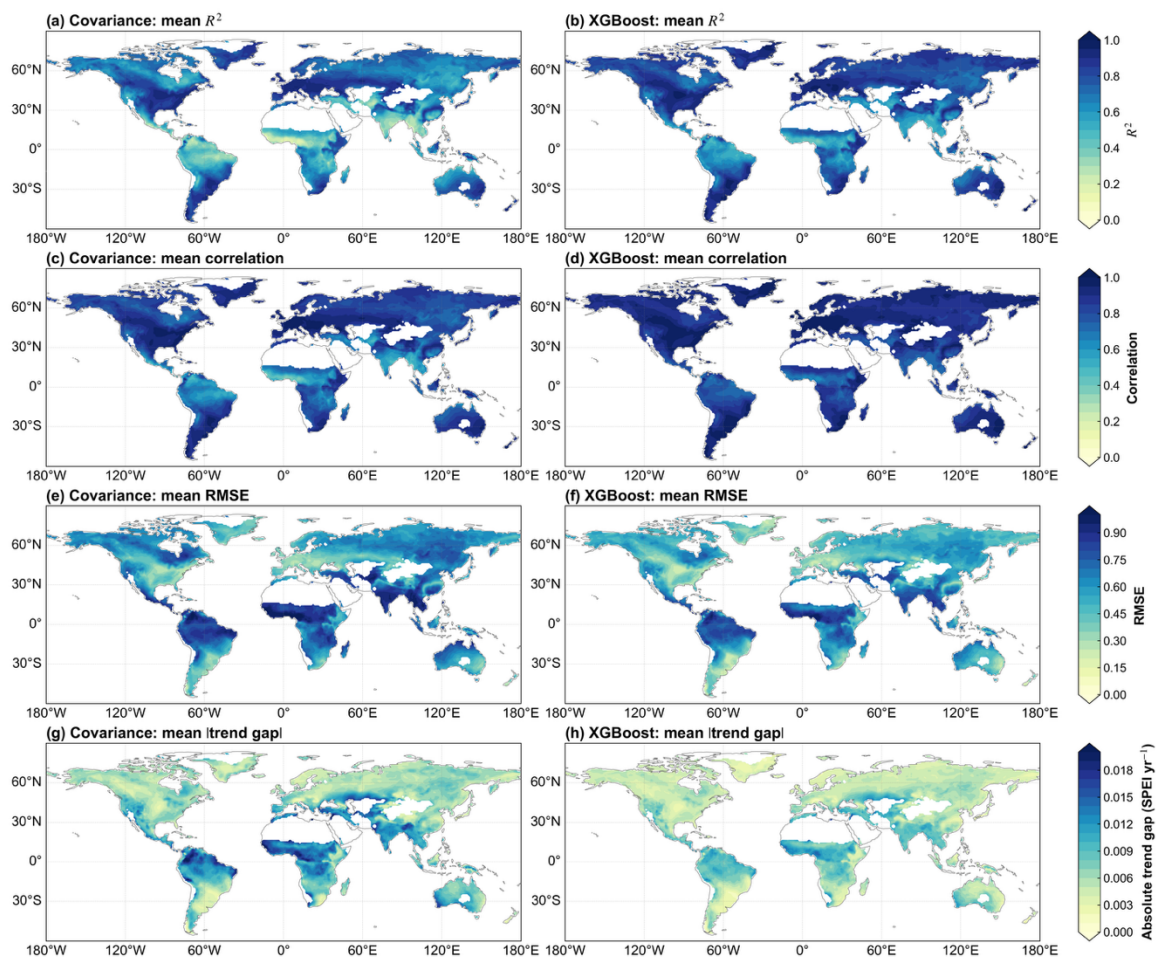
Supplementary Fig. 36 Heatmap of regional mean precipitation (RC_p) and potential evapotranspiration (RC_{PET}) contributions to SPEI trends across historical and future periods. Regional statistics are extracted from the gridded multi-model ensemble fields shown in Fig. 7, computed via Covariance and XGBoost methodologies. The panels illustrate: (a) the historical baseline (1996–2015) mean contributions; (b, d) the absolute projected changes (Δ) for the mid-future (2036–2055) and far-future (2066–2085) periods, respectively; and (c, e) the corresponding Significant Area (Sig. Area) percentages. Here, the Sig. Area refers to the spatial extent—expressed as a percentage of the valid regional landmass—where the projected thermodynamic shifts exhibit high confidence. Specifically, it represents the area where over 75% of the climate models strictly agree on the direction of the projected trend, thereby quantifying multi-model consensus rather than a standard p-value. Regional averaging (excluding Global and Quasi-global rows) is strictly confined to land areas within 50°S–50°N, with hyper-arid regions (annual rainfall < 180 mm) consistently masked out.



Supplementary Fig. 37 Robustness of ANOVA-based uncertainty decomposition to individual precipitation dataset exclusion. Stacked bars show the fractional variance contributions of precipitation datasets, PET methods, PET datasets, and their interactions to SPEI trend uncertainty after excluding one precipitation dataset at a time from the original 240-member SPEI ensemble. The x-axis indicates the precipitation dataset removed from the ensemble before conducting the ANOVA analysis. Results are shown for the 50°S–50°N domain and major continental regions after applying the 180 mm precipitation mask. The analysis evaluates whether the dominance of precipitation-related uncertainty remains robust to the exclusion of any single precipitation product. Subpanels represent different spatial domains: (a) Quasi-global (50°S–50°N), (b) Africa, (c) Asia, (d) Australia, (e) Europe, (f) North America, and (g) South America.



Supplementary Fig. 38 Historical reconstruction skill of the Covariance-based and XGBoost-SHAP attribution frameworks. Subpanels compare four evaluation metrics between the two attribution models: (a, b) mean coefficient of determination (R^2), (c, d) mean Pearson correlation, (e, f) mean root mean square error (RMSE), and (g, h) mean absolute trend gap. The left column shows results from the Covariance-based regression framework, while the right column shows results from the XGBoost-SHAP framework. The absolute trend gap is calculated as the absolute difference between the reconstructed and observed SPEI trends. Results are based on the historical 240-member SPEI ensemble after applying the 180 mm precipitation mask. This evaluation demonstrates the spatial performance of the two attribution frameworks in reconstructing historical SPEI variability and trend, thereby supporting their use for attribution analysis.



Supplementary Fig. 39 Evaluation of reconstruction skill for CMIP6 future attribution using the Covariance and XGBoost-SHAP frameworks. Subpanels compare four evaluation metrics between the two attribution models: (a, b) mean coefficient of determination (R^2), (c, d) mean Pearson correlation, (e, f) mean root mean square error (RMSE), and (g, h) mean absolute trend gap. The left column shows results from the Regression/Covariance framework, while the right column shows results from the XGBoost-SHAP framework. The absolute trend gap is calculated as the absolute difference between the reconstructed and target SPEI trends. Results are derived from the CMIP6 projection ensemble after applying the 180 mm precipitation mask. This evaluation assesses the spatial reliability of the two attribution frameworks for reconstructing future SPEI variations and trends, supporting their use in moving-window attribution analyses under non-stationary climate projections.

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