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An Open-Data Point-Location Drought Benchmark for Australia: SPI–SPEI Variability, Persistence, and Warming-Amplification Analysis Using SILO Data

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Abstract: Australia’s drought risk is shaped by both precipitation deficits and atmospheric water demand, but long-term comparisons are sensitive to drought-index formulation, PET choice, and hotspot-weighting assumptions. This study develops an open-data point-location drought benchmark for Australia using daily SILO DataDrill records from nine selected locations for 1900–2025. Monthly hydroclimatic variables were derived from rainfall, temperature, SILO FAO56 short-crop reference PET, and Morton PET for sensitivity analysis. SPI-12 was calculated from 12-month precipitation accumulation using gamma distribution fitting, while SPEI-12 was calculated from 12-month climatic water balance using generalized logistic distribution fitting. Drought-event metrics, persistence indicators, Hamed–Rao modified Mann–Kendall and Sen’s slope tests, SPI–SPEI divergence metrics, and a sensitivity-tested composite hotspot score were used to compare drought behaviour among locations. Results showed strong cross-location differences in drought frequency, duration, severity, persistence, and warming-amplified drought stress. FAO56 PET improved the physical consistency of water-balance drought assessment relative to temperature-only PET formulations. SPI–SPEI divergence was most pronounced at Alice Springs, whereas Perth and Adelaide showed the most robust high hotspot ranks due to combined severity, persistence, and recent drought-month concentration. Random-weight sensitivity analysis confirmed Perth and Adelaide as the most stable top-ranked locations. The study provides a transparent benchmark for point-location drought comparison and a foundation for future gridded drought-risk assessment in Australia.

Keywords: drought; SPI; SPEI; SILO DataDrill; FAO56 potential evapotranspiration; drought hotspot screening

1. Introduction

Drought is one of the most complex hydroclimatic hazards because it develops slowly, persists across multiple temporal scales, and propagates from meteorological deficits to agricultural, hydrological, ecological, and socio-economic impacts. Unlike flood or storm hazards, drought does not have a single point of onset or termination; it is defined by accumulated water deficits relative to local climatic conditions, the sensitivity of land–water systems, and the exposure of human and ecological systems to prolonged dryness. This makes drought assessment intrinsically multidimensional, requiring not only rainfall-based indicators but also metrics that account for atmospheric water demand, drought persistence, event severity, and hydroclimatic context [1–11].

Australia provides a particularly important setting for drought research. It is widely recognized as one of the driest inhabited continents and is characterized by strong rainfall variability, marked hydroclimatic contrasts, and



high sensitivity of water resources, agriculture, ecosystems, and urban water supplies to multi-year rainfall deficits [5,12–14]. Its climate includes tropical monsoonal rainfall in the north, humid and sub-humid conditions along parts of the eastern coast, temperate climates in the southeast, Mediterranean-type rainfall regimes in the southwest and south, semi-arid transition zones, and extensive arid interior landscapes. As a result, drought in Australia cannot be interpreted as a spatially uniform phenomenon. A rainfall anomaly that constitutes a major drought in one location may have different hydrological or ecological implications elsewhere depending on rainfall seasonality, antecedent soil moisture, evaporative demand, reservoir dependence, groundwater buffering, and land-use characteristics [15–19].

The scientific and institutional understanding of drought in Australia has developed over more than a century. Early work was largely descriptive and climatological, focusing on rainfall deficiencies, agricultural losses, river-flow reductions, and historical drought chronology rather than standardized drought indices. Major droughts such as the Federation Drought of the late nineteenth and early twentieth centuries, the World War II drought of approximately 1937–1945, and later post-war drought episodes shaped both public memory and water-management practice [5,16,20–22]. These earlier studies and official records established drought as a recurrent feature of the Australian hydroclimate, but they also reflected the limitations of the period: sparse observing networks, limited computational capacity, and the absence of nationally consistent gridded datasets or standardized drought metrics.

Modern Australian drought research has increasingly emphasized the diversity of drought-generating mechanisms and the limitations of single-index interpretation. Verdon-Kidd and Kiem [16] showed that the Federation, World War II, and Big Dry/Millennium droughts differed in severity, spatial footprint, seasonality, and climate-driver context. Ummenhofer et al. [23] linked severe southeast Australian droughts to Indo-Pacific climate variability, while Cai et al. [24] and King et al. [25] demonstrated that Australian rainfall variability is influenced by interacting large-scale modes such as ENSO, the Indian Ocean Dipole, and extratropical circulation patterns. Later work further clarified that drought development and termination in southeast Australia are closely related to moisture-transport pathways and synoptic-scale circulation anomalies rather than rainfall deficits alone [26–30].

The Millennium Drought substantially intensified scientific interest in Australian drought processes, impacts, and water-resource vulnerability. Van Dijk et al. [31] described the 2001–2009 Millennium Drought in southeast Australia as an exceptional event with major implications for water resources, ecosystems, agriculture, economy, and society. The event highlighted the amplification of rainfall deficits through runoff, soil moisture, streamflow, groundwater, and water-allocation systems. Subsequent work showed that multi-year drought can alter rainfall–runoff relationships, particularly in drier catchments, and that hydrological recovery after prolonged drought may not be immediate even when rainfall returns to near-normal conditions [32]. These findings are central for Australian water management because meteorological drought does not necessarily translate linearly into hydrological drought, water-supply stress, agricultural losses, or public-health outcomes [14,33].

A further challenge is that Australian drought is occurring in a warming climate. Rainfall trends across Australia are spatially heterogeneous, but multiple studies have identified substantial changes in southern and southwestern rainfall regimes, especially in cool-season rainfall [12,34–37]. In southwest Western Australia, rainfall decline has been accompanied by disproportionate reductions in streamflow and water availability, demonstrating the non-linear sensitivity of water resources to climatic shifts. In the southeast, rainfall decline, increasing temperatures, and changes in atmospheric circulation have affected drought risk, fire weather, and hydroclimatic extremes [37–40]. In northern Australia, monsoon variability and long-term rainfall changes introduce a different drought context, where wet-season failure, monsoonal variability, and interannual circulation anomalies may dominate drought behaviour [41]. Consequently, drought assessment based only on precipitation may underrepresent the role of rising atmospheric water demand and location-specific drought-generation mechanisms.

This is why the joint use of the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) is particularly relevant for Australian drought assessment. SPI provides a precipitation-based measure of meteorological drought and remains widely used because of its simplicity, multi-timescale structure, and relatively low data requirement [2,42,43]. SPEI extends the SPI concept by incorporating the climatic water balance, commonly represented as precipitation minus potential evapotranspiration, making it sensitive to warming-related increases in atmospheric water demand [4,44]. The difference between SPI and SPEI is therefore useful for identifying locations where drought stress is not merely rainfall-driven but is amplified by atmospheric demand. However, index selection and implementation also introduce uncertainty, because SPI, SPEI, PDSI, soil-moisture indices, and other drought metrics can differ in their representation of drought timing, severity, persistence, ecological relevance, and hydrological impact [7,19,45,46].

Recent climate-projection studies have further reinforced the need for transparent and reproducible drought assessments. Mpelasoka et al. [47] compared drought indices for climate-change impact assessment over Australia,

while Kirono and Kent [48] evaluated rainfall and potential evaporation from global climate models for regional drought projections. Feng et al. [49] assessed projected drought changes across the wheat belt of southeastern Australia, and Kirono et al. [50] updated Australian drought projections using standardized precipitation and soil-moisture indices. More recently, Eccles et al. [51] used high-resolution downscaled CMIP6 simulations to assess changes in SPI- and SPEI-based drought characteristics, while Cheung et al. [52] evaluated projected drought frequency, intensity, and duration across Australia. At broader scales, global drought studies also indicate that warming can reshape drought occurrence, persistence, and intensity, although the magnitude and regional expression of these changes depend strongly on index selection, model uncertainty, reference period, and the treatment of evaporative demand [8–11,53].

Despite this rich literature, there remains a need for compact, reproducible, and open-data-based drought benchmarks that enable transparent comparison of long-term drought behaviour across selected Australian locations. Existing studies have often focused on specific drought events, selected basins, particular climate drivers, operational monitoring products, agricultural systems, health impacts, compound hazards, or future projections [13,18,30,32,33,54,55]. Fully gridded national drought monitoring and projection products are essential for spatially complete assessment, but they may not always provide a simple, reproducible, point-location benchmark that jointly evaluates SPI and SPEI behaviour, drought frequency, duration, severity, persistence, trend behaviour, SPI–SPEI divergence, and the sensitivity of composite hotspot rankings. Such a benchmark is useful as a transparent screening and comparison tool, provided that its point-location scope is clearly distinguished from a spatial drought atlas or regionalized national mapping product.

This study addresses this need by developing an open-data point-location drought benchmark for Australia using long-term SILO DataDrill climate data. The analysis is based on nine selected Australian point locations that capture a range of broad climate settings, including tropical northern, humid eastern, temperate southeastern, southern dry-temperate, southwestern Mediterranean-type, cool-temperate, and arid inland settings. These locations are not intended to represent full hydroclimatic regions or to provide a spatial drought atlas of Australia. Rather, they are used as transparent benchmark points for comparing long-term drought-index behaviour, persistence, trend signals, and atmospheric-demand-related divergence under a consistent open-data workflow.

The study makes four main contributions. First, it recalculates long-term SPI-12 and SPEI-12 using probabilistic distribution fitting, with SPI-12 derived from 12-month accumulated precipitation and SPEI-12 derived from 12-month climatic water balance. Second, it replaces temperature-only Thornthwaite potential evapotranspiration with SILO FAO56 short-crop reference potential evapotranspiration as the primary PET input, while retaining Morton potential evapotranspiration for sensitivity analysis. Third, it evaluates drought-event characteristics, drought persistence, and trend behaviour using a serial-correlation-aware Hamed–Rao modified Mann–Kendall test together with Sen’s slope. Fourth, it develops a transparent composite hotspot screening score and evaluates its robustness using leave-one-component-out and random-weight sensitivity analyses.

The main contribution of this study is therefore not the development of a new drought index or a fully spatial national drought atlas, but the construction of a reproducible and sensitivity-aware benchmark for interpreting long-term drought behaviour across selected Australian point locations. By combining open climate data, probabilistic SPI/SPEI calculation, event-based metrics, persistence analysis, serial-correlation-adjusted trend testing, SPI–SPEI divergence, and hotspot-weighting sensitivity, the study provides a practical baseline for future drought research. The framework can be extended in future work using gridded analyses, soil moisture, streamflow, groundwater levels, reservoir storage, vegetation stress, or climate-model projections, but its present value lies in its transparency, reproducibility, and explicit treatment of key methodological sensitivities.

2. Materials and Methods

2.1. General Methodological Framework

This study develops an open-data point-location drought benchmark to assess long-term drought variability, persistence, trend behaviour, and warming-amplified drought stress across selected Australian locations. The workflow was designed as a reproducible benchmark rather than a site-specific hydrological model or a fully gridded national drought atlas. Therefore, all locations were analysed using the same climate-data source, temporal coverage, monthly aggregation procedure, drought-index calculation method, drought-event threshold, trend-analysis approach, and hotspot-screening structure. This standardized workflow is consistent with drought-index and drought-monitoring studies emphasizing the need to combine precipitation, water-balance, event-based, persistence-based, and trend-based information when characterizing drought risk [3,5–7,19].

The methodological framework consists of six main stages: (i) selection of nine Australian point locations; (ii) retrieval and preprocessing of long-term daily SILO climate data; (iii) aggregation of daily climate records to

monthly hydroclimatic variables; (iv) calculation of SPI-12 and SPEI-12 using probabilistic distribution fitting; (v) extraction of drought-event, persistence, trend, and SPI–SPEI divergence metrics; and (vi) synthesis of point-location drought behaviour through a transparent composite hotspot-screening score. The study locations and methodological workflow are summarized in Figure 1. Panel A shows the selected Australian point locations, while Panel B summarizes the analytical workflow, including open climate-data retrieval, monthly hydroclimatic processing, probabilistic SPI-12 and SPEI-12 calculation, drought-event and persistence analysis, serial-correlation-adjusted trend testing, SPI–SPEI divergence assessment, and composite hotspot-sensitivity analysis.

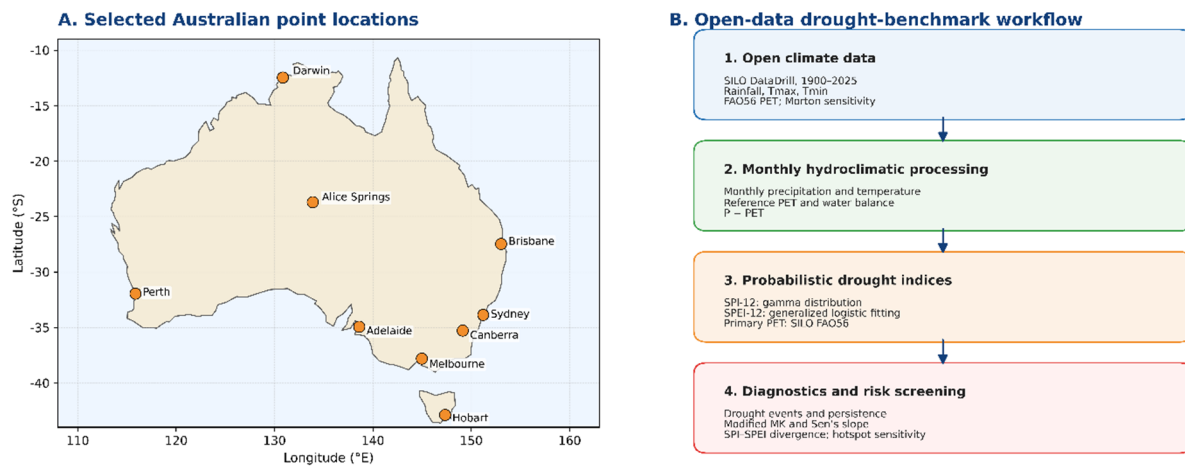


Figure 1. Selected Australian point locations and the open-data drought-benchmark workflow used in this study. (A) Nine point locations used for the analysis across Australia. (B) Analytical workflow showing the use of SILO DataDrill climate data, monthly hydroclimatic processing, probabilistic drought-index construction, and diagnostics/risk-screening steps.

2.2. Selected Australian Point Locations

Nine Australian point locations were selected to provide a compact comparison across contrasting broad climate settings: Darwin, Brisbane, Sydney, Canberra, Melbourne, Adelaide, Perth, Hobart, and Alice Springs. These locations span tropical northern, humid eastern, temperate southeastern, inland southeastern, southern dry-temperate, southwestern Mediterranean-type, cool-temperate island/coastal, and arid inland settings. The selection was intended to provide a transparent point-location benchmark across major climatic contrasts rather than to define statistically representative hydroclimatic regions.

The selected locations should therefore not be interpreted as spatially representative of all local-scale catchment, ecological, groundwater, agricultural, or urban water-supply conditions in Australia. Each location corresponds to a SILO grid point and is used as a benchmark for comparing drought-index behaviour under a consistent open-data workflow. This distinction is important because the present study does not perform spatial interpolation, gridded drought mapping, regionalization, or catchment-scale hydrological modelling.

The coordinates of the selected locations were rounded to the nearest SILO DataDrill grid cell. The original coordinates, rounded SILO grid coordinates, and broad descriptive climate settings are listed in Table 1.

Table 1. Selected Australian point locations used in the point-based drought-benchmark assessment.

Location	Latitude (°S)	Longitude (°E)	SILO Grid		Broad Climate Setting
			Latitude	Longitude	
Darwin	−12.4634	130.8456	−12.45	130.85	Tropical northern coastal point
Brisbane	−27.4698	153.0251	−27.45	153.05	Humid subtropical eastern coastal point
Sydney	−33.8688	151.2093	−33.85	151.20	Temperate eastern coastal point
Canberra	−35.2809	149.1300	−35.30	149.15	Inland temperate southeastern point
Melbourne	−37.8136	144.9631	−37.80	144.95	Temperate southeastern coastal point
Adelaide	−34.9285	138.6007	−34.95	138.60	Southern dry-temperate/Mediterranean-type point
Perth	−31.9505	115.8605	−31.95	115.85	Southwestern Mediterranean-type point
Hobart	−42.8821	147.3272	−42.90	147.35	Cool-temperate island/coastal point
Alice Springs	−23.6980	133.8807	−23.70	133.90	Arid inland point

2.3. Climate Data Source and Preprocessing

Daily climate data were obtained from the Scientific Information for Land Owners (SILO) climate database using the DataDrill API. SILO provides long-term spatially interpolated Australian climate records and has been widely used in agricultural, hydrological, environmental, and climate-impact studies. The construction of the SILO climate archive and its interpolation framework have been described by Jeffrey et al. [56].

For each selected location, daily data were retrieved for 1900–2025. The primary variables used in the analysis were daily rainfall, maximum temperature, minimum temperature, and SILO FAO56 short-crop reference potential evapotranspiration. SILO Morton potential evapotranspiration was also retrieved and retained for sensitivity analysis. Daily rainfall, maximum temperature, and minimum temperature were used to derive monthly precipitation and mean temperature, while SILO FAO56 short-crop reference PET was used as the primary atmospheric-demand input for SPEI-12 calculation.

2.4. Data Completeness and Early-Period Uncertainty

Daily record completeness was evaluated before monthly aggregation. For each location, the expected daily calendar sequence for 1900–2025 was compared with the downloaded SILO records, and the number of unique daily observations, duplicate records, and missing calendar days was checked. Source-code metadata columns provided by SILO were also inspected where available to document the provenance of interpolated daily variables.

Although the downloaded daily time series were complete for the selected locations, early twentieth-century Australian climate data may still be affected by lower station density and greater interpolation uncertainty in some areas. To account for this limitation, the full-period analysis for 1900–2025 was supplemented with a 1950–2025 sensitivity analysis. The sensitivity analysis was used to evaluate whether the main drought-event, persistence, and SPI–SPEI divergence results were strongly dependent on the earliest part of the record. These checks are reported in Supplementary Tables S2–S4.

2.5. Monthly Aggregation and Hydroclimatic Variables

Daily records were aggregated to the monthly time scale before drought-index calculation. Monthly precipitation was calculated as the sum of daily rainfall values within each month:

$$P_m = \sum_{d=1}^{n_m} P_{daily,d} \quad (1)$$

where P_m is monthly precipitation, $P_{daily,d}$ is daily rainfall on day d , and n_m is the number of days in month m .

Daily mean temperature was calculated from daily maximum and minimum temperature:

$$T_{mean,d} = \frac{T_{max,d} + T_{min,d}}{2} \quad (2)$$

where $T_{mean,d}$ is daily mean temperature, $T_{max,d}$ is daily maximum temperature, and $T_{min,d}$ is daily minimum temperature.

Monthly mean temperature was then calculated as the arithmetic mean of daily mean temperature values within each month:

$$T_{mean,m} = \frac{1}{n_m} \sum_{d=1}^{n_m} T_{mean,d} \quad (3)$$

where $T_{mean,m}$ is monthly mean temperature.

Monthly FAO56 PET was calculated as the sum of daily SILO FAO56 short-crop reference PET values:

$$PET_m^{FAO56} = \sum_{d=1}^{n_m} PET_{daily,d}^{FAO56} \quad (4)$$

where PET_m^{FAO56} is monthly FAO56 reference potential evapotranspiration.

The monthly climatic water balance used for the primary SPEI-12 calculation was then calculated as:

$$D_m^{FAO56} = P_m - PET_m^{FAO56} \quad (5)$$

where D_m^{FAO56} is the monthly climatic water balance. Positive values indicate moisture surplus relative to atmospheric demand, whereas negative values indicate moisture deficit.

For sensitivity analysis, the same water-balance calculation was repeated using SILO Morton potential evapotranspiration:

$$D_m^{Morton} = P_m - PET_m^{Morton} \quad (6)$$

where D_m^{Morton} is the Morton-based monthly climatic water balance. Thornthwaite PET was not retained as the primary PET input in the analysis because the main water-balance assessment was based on the physically more complete SILO FAO56 reference PET product.

2.6. Calculation of SPI-12 and SPEI-12

Two standardized drought indicators were used: the 12-month Standardized Precipitation Index (SPI-12) and the 12-month Standardized Precipitation Evapotranspiration Index (SPEI-12). SPI was introduced by McKee et al. [2] to quantify precipitation anomalies across different accumulation periods and remains widely used because of its simplicity and multi-timescale structure [42]. SPEI extends the SPI concept by incorporating the climatic water balance and is therefore sensitive to atmospheric water demand [4,44]. The joint use of SPI and SPEI allows precipitation-driven drought behaviour to be compared with water-balance-based drought stress.

SPI-12 was calculated from 12-month accumulated precipitation:

$$P_{12,m} = \sum_{i=0}^{11} P_{m-i} \quad (7)$$

where $P_{12,m}$ is the 12-month accumulated precipitation ending in month m .

SPEI-12 was calculated from 12-month accumulated FAO56 climatic water balance:

$$D_{12,m}^{FAO56} = \sum_{i=0}^{11} D_{m-i}^{FAO56} \quad (8)$$

where $D_{12,m}^{FAO56}$ is the 12-month accumulated climatic water balance ending in month m . The first 11 months of each time series were therefore treated as undefined for the 12-month accumulation scale.

To preserve seasonality, distribution fitting was performed separately for each calendar month. Distribution-fitting diagnostics are reported in Supplementary Table S7. SPI-12 was calculated by fitting a gamma distribution to the 12-month accumulated precipitation series for each calendar month and transforming the cumulative probability to the standard normal variate:

$$SPI_{12,m} = \Phi^{-1}[F_{\gamma,j}(P_{12,m})] \quad (9)$$

where $F_{\gamma,j}$ is the fitted gamma cumulative distribution function for calendar month j , and Φ^{-1} is the inverse standard normal distribution function.

SPEI-12 was calculated by fitting a generalized logistic distribution to the 12-month accumulated FAO56 climatic water-balance series for each calendar month:

$$SPEI_{12,m} = \Phi^{-1}[F_{GLO,j}(D_{12,m}^{FAO56})] \quad (10)$$

where $F_{GLO,j}$ is the fitted generalized logistic cumulative distribution function for calendar month j . This distribution was selected because SPEI water-balance values can be negative and because generalized logistic fitting is commonly used in SPEI implementations [4,44].

A Morton-based SPEI-12 series was also calculated using $D_{12,m}^{Morton}$ for PET-sensitivity analysis. However, unless otherwise stated, SPEI-12 in the main text refers to the FAO56-based primary SPEI-12.

Negative SPI-12 and SPEI-12 values indicate drier-than-normal conditions, whereas positive values indicate wetter-than-normal conditions. The main drought threshold used in this study was -1.0 , representing moderate-or-worse drought conditions, consistent with common drought-index classification practice [2,42].

2.7. Drought-Event Identification and Event Metrics

Drought events were extracted separately from the SPI-12 and SPEI-12 time series. A drought event was defined as a continuous sequence of months in which the drought index was less than or equal to -1.0 . An event began when the index first fell to or below -1.0 and ended when the index rose above -1.0 . Event-based drought analysis is useful because it provides information on drought duration, severity, and intensity that cannot be represented by a single monthly index value [3,6,7].

For drought event e , duration was calculated as:

$$L_e = n_e \quad (11)$$

where L_e is event duration in months and n_e is the number of consecutive drought months in event e .

Drought-event severity was calculated as the absolute cumulative drought-index deficit during the event:

$$S_e = |\sum_{k=1}^{n_e} Z_k| \quad (12)$$

where S_e is event severity and Z_k is the drought-index value during drought month k . Because all months included in the event have $Z_k \leq -1.0$, larger values of S_e indicate more severe cumulative drought conditions.

Drought-event intensity was calculated as:

$$I_e = \frac{S_e}{L_e} \quad (13)$$

where I_e is mean drought intensity.

The minimum index value during each event was also recorded:

$$Z_{\min,e} = \min(Z_1, Z_2, \dots, Z_{n_e}) \quad (14)$$

Drought-event frequency was expressed as the number of events per 100 years to account for record length:

$$F_{100} = \left(\frac{N_e}{Y_v} \right) \times 100 \quad (15)$$

where F_{100} is drought-event frequency per 100 years, N_e is the total number of drought events, and Y_v is the number of valid years in the analysed record.

2.8. Drought Persistence and Drought-Month Ratio

Drought persistence was assessed using event duration and drought-month ratio metrics. Long-duration droughts can have different hydrological and socio-economic implications from frequent short droughts, particularly for reservoir systems, groundwater recovery, agricultural stress, ecosystem response, and water-supply planning [5,31,32].

The drought-month ratio was calculated as:

$$DMR = \left(\frac{N_d}{N_v} \right) \times 100 \quad (16)$$

where DMR is the drought-month ratio in percent, N_d is the number of drought months, and N_v is the number of valid months in the selected period.

A moving 5-year drought-month ratio was calculated to identify multi-year drought recurrence and persistence:

$$DMR_{5y,t} = \left(\frac{N_{d,5y,t}}{N_{v,5y,t}} \right) \times 100 \quad (17)$$

where $DMR_{5y,t}$ is the 5-year moving drought-month ratio at time t , $N_{d,5y,t}$ is the number of drought months in the 5-year moving window, and $N_{v,5y,t}$ is the number of valid months in the same window.

Three persistence indicators were used in the main drought-event assessment: longest drought duration, maximum 5-year drought-month ratio, and drought-month ratio for the recent period 2000–2025. These metrics were calculated separately for SPI-12 and SPEI-12.

2.9. Trend Analysis

Trend behaviour was assessed using the Hamed–Rao modified Mann–Kendall test and Sen’s slope estimator. The Mann–Kendall test is widely used in hydroclimatic studies because it is non-parametric, does not require normally distributed data, and is relatively robust to outliers [57,58]. However, hydroclimatic time series often exhibit serial correlation, which can inflate the significance of the classical Mann–Kendall test. Therefore, the Hamed–Rao modified Mann–Kendall test was used as the primary significance test because it adjusts the variance of the Mann–Kendall statistic for autocorrelation [59]. Sen’s slope was used to estimate monotonic trend magnitude [60]. Classical Mann–Kendall results were retained only as a supplementary comparison.

For a time series $x_1, x_2, \dots, x_n$, the Mann–Kendall statistic was calculated as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (18)$$

where:

$$\text{sgn}(x_j - x_i) = \begin{cases} 1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases} \quad (19)$$

The variance of S was calculated with tie correction and then adjusted for serial correlation following the Hamed–Rao modification. The adjusted variance can be expressed as:

$$Var^*(S) = Var(S) \times CF \quad (20)$$

where CF is the correction factor derived from the significant autocorrelation structure of the ranked time series. The standardized test statistic was then calculated using the adjusted variance:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var^*(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{Var^*(S)}}, & S < 0 \end{cases} \quad (21)$$

Sen's slope was used to estimate monotonic trend magnitude:

$$\beta = median\left(\frac{x_j - x_i}{t_j - t_i}\right), j > i \quad (22)$$

where β is Sen's slope. Positive values indicate increasing trends, while negative values indicate decreasing trends.

Trend analysis was applied to four annual or multi-year drought metrics: annual mean SPI-12, annual mean SPEI-12, 10-year moving SPI-12 drought-month ratio, and 10-year moving SPEI-12 drought-month ratio. The 10-year moving drought-month ratio was calculated as:

$$DMR_{10y,t} = \left(\frac{N_{d,10y,t}}{N_{v,10y,t}}\right) \times 100 \quad (23)$$

where $DMR_{10y,t}$ is the 10-year moving drought-month ratio at time t . Trend significance was evaluated using the Hamed–Rao modified Mann–Kendall p -value, and trend magnitude was reported using Sen's slope.

2.10. SPI–SPEI Divergence and Warming-Amplification Assessment

To evaluate the influence of atmospheric water demand on drought conditions, SPI–SPEI divergence was calculated as:

$$WAI_m = SPI_{12,m} - SPEI_{12,m} \quad (24)$$

where WAI_m is the warming-amplification index for month m . Positive WAI_m values indicate that SPEI-12 is lower than SPI-12, meaning that the water-balance-based drought signal is drier than the precipitation-only signal. This condition was interpreted as evidence that atmospheric water demand contributes to drought intensification. The use of SPI–SPEI comparison for identifying temperature- or evaporative-demand-related drought intensification is consistent with the conceptual basis of SPEI and with drought-index comparison studies [4,7,19,44].

Four SPI–SPEI divergence metrics were calculated. First, mean absolute SPI–SPEI divergence across all valid months was calculated as:

$$|WAI|_{all} = \frac{1}{N} \sum_{m=1}^N |WAI_m| \quad (25)$$

This metric describes the average magnitude of divergence between SPI-12 and SPEI-12 without cancellation between positive and negative values.

Second, mean WAI during drought months was calculated as:

$$WAI_{dry} = \frac{1}{N_{dry}} \sum_{m \in dry} WAI_m \quad (26)$$

where dry months were months in which $SPI_{12} \leq -1.0$ or $SPEI_{12} \leq -1.0$.

Third, the percentage of SPEI-only drought months was calculated as:

$$SPEI_{only} = \left[\frac{N(SPEI_{12} \leq -1.0 \cap SPI_{12} > -1.0)}{N_v} \right] \times 100 \quad (27)$$

where N_v is the number of valid months.

Fourth, the difference between SPEI-based and SPI-based cumulative drought severity was calculated as:

$$SA = S_{SPEI} - S_{SPI} \quad (28)$$

where SA is severity amplification, S_{SPEI} is cumulative severity based on SPEI-12, and S_{SPI} is cumulative severity based on SPI-12. Positive SA values indicate stronger cumulative drought severity when atmospheric water demand is included through FAO56 PET.

2.11. Composite Drought Hotspot Screening and Sensitivity Analysis

A composite drought hotspot score was developed to synthesize drought frequency, duration, severity, persistence, and warming amplification into a single point-location screening metric. The score was designed as a transparent comparative index rather than an optimized drought-risk prediction model. Its purpose was to summarize multiple drought dimensions consistently across the selected locations while making the normalization and weighting assumptions explicit. SPEI-12 was used as the primary index for the composite score because it includes both precipitation and atmospheric water demand.

Five normalized components were used: drought-event frequency, mean drought duration, cumulative drought severity, maximum 5-year drought-month ratio, and warming-amplification component. Each component was normalized to a 0–1 scale using min–max normalization:

$$X'_r = \frac{X_r - X_{min}}{X_{max} - X_{min}} \quad (29)$$

where X'_r is the normalized value for location r , X_r is the original component value for location r , X_{min} is the minimum value among all selected locations, and X_{max} is the maximum value among all selected locations.

The warming-amplification component was calculated from three normalized indicators: positive WAI during drought months, percentage of SPEI-only drought months, and positive severity amplification. Negative amplification values were set to zero because they do not represent stronger SPEI-based drought stress:

$$A'_r = \frac{WAI'_{dry,r} + SPEI'_{only,r} + SA'_{+,r}}{3} \quad (30)$$

where A'_r is the normalized warming-amplification component for location r .

The equal-weight composite hotspot score was then calculated as:

$$DHS_r = \frac{F'_r + Du'_r + S'_r + P'_r + A'_r}{5} \quad (31)$$

where DHS_r is the drought hotspot score for location r , F'_r is normalized drought-event frequency, Du'_r is normalized mean drought duration, S'_r is normalized cumulative severity, P'_r is normalized persistence, and A'_r is normalized warming amplification. Higher DHS_r values indicate stronger combined drought hotspot characteristics within the limits of the point-location benchmark.

Because equal weighting is a methodological assumption, hotspot-score robustness was evaluated using two sensitivity analyses. First, a leave-one-component-out analysis recalculated the hotspot score after removing each component in turn. Second, a random-weight Monte Carlo sensitivity analysis was performed using 10,000 random non-negative weight combinations normalized to sum to one. Ranking stability was summarized using top-three ranking probability and rank-correlation diagnostics. These sensitivity analyses were used to identify robust high-ranking locations and to distinguish stable hotspot signals from rankings that were sensitive to weighting assumptions. The leave-one-component-out and random-weight sensitivity results are reported in Supplementary Tables S5 and S6.

3. Results

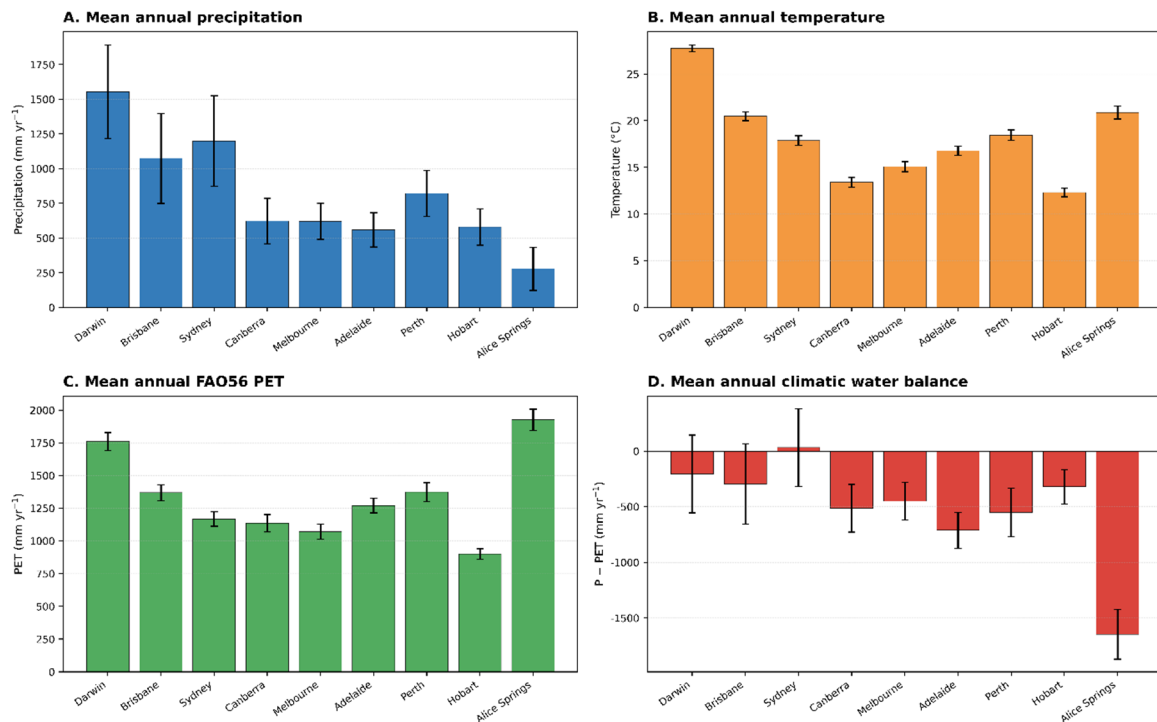
3.1. Hydroclimatic Baseline of the Selected Point Locations

The long-term hydroclimatic baseline showed clear contrasts among the nine selected Australian point locations (Table 2; Figure 2). Mean annual precipitation was highest in Darwin, at 1554.7 mm yr⁻¹, followed by Sydney with 1199.7 mm yr⁻¹ and Brisbane with 1073.8 mm yr⁻¹. Perth also had relatively high mean annual precipitation compared with the southern inland and arid locations, reaching 821.9 mm yr⁻¹. In contrast, Alice Springs recorded the lowest mean annual precipitation, with 279.5 mm yr⁻¹, confirming the strong aridity of the inland benchmark point. Canberra, Melbourne, Adelaide, and Hobart formed an intermediate-to-dry group, with mean annual precipitation ranging from 558.8 to 623.0 mm yr⁻¹.

Temperature patterns also differed clearly among locations. Darwin had the highest mean annual temperature, at 27.7 °C, while Alice Springs also showed a relatively high mean annual temperature of 20.9 °C despite its inland setting. Brisbane and Perth followed, with mean annual temperatures of 20.5 °C and 18.4 °C, respectively. Hobart was the coolest location, with a mean annual temperature of 12.3 °C, followed by Canberra at 13.4 °C.

Table 2. Long-term hydroclimatic baseline statistics for the selected Australian point locations during 1900–2025.

Location	Mean Annual Precipitation (mm)	SD Precipitation (mm)	Mean Annual Temperature (°C)	SD Temperature (°C)	Mean Annual FAO56 PET (mm)	SD FAO56 PET (mm)	Mean Annual P–PET (mm)	SD P–PET (mm)
Darwin	1554.7	336.6	27.7	0.4	1759.7	68.9	−204.9	349.9
Brisbane	1073.8	324.4	20.5	0.5	1368.9	60.3	−295.1	359.2
Sydney	1199.7	325.4	17.9	0.5	1167.5	55.4	32.30	349.5
Canberra	623.0	164.0	13.4	0.5	1136.2	66.3	−513.2	215.1
Melbourne	621.3	129.7	15.1	0.5	1070.7	58.1	−449.4	170.3
Adelaide	558.8	123.3	16.8	0.5	1270.5	56.1	−711.7	161.4
Perth	821.9	165.7	18.4	0.6	1373.3	73.3	−551.4	216.5
Hobart	580.0	130.2	12.3	0.5	900.1	41.1	−320.1	154.4
Alice Springs	279.5	155.5	20.9	0.7	1926.0	81.0	−1646.5	223.9

**Figure 2.** Long-term hydroclimatic baseline of the selected Australian point locations for 1900–2025. (A) Mean annual precipitation. (B) Mean annual temperature. (C) Mean annual FAO56 reference potential evapotranspiration. (D) Mean annual climatic water balance, calculated as precipitation minus FAO56 PET. Error bars indicate interannual standard deviation.

The FAO56 PET baseline highlighted the importance of atmospheric water demand in the point-location comparison. Mean annual FAO56 PET was highest at Alice Springs, reaching $1926.0 \text{ mm yr}^{-1}$, followed by Darwin at $1759.7 \text{ mm yr}^{-1}$. Perth and Brisbane also had high mean annual FAO56 PET, at 1373.3 and $1368.9 \text{ mm yr}^{-1}$, respectively. Hobart had the lowest mean annual FAO56 PET, at 900.1 mm yr^{-1} . These results show that PET gradients do not simply follow precipitation gradients; for example, Alice Springs had the lowest precipitation but the highest FAO56 PET.

The climatic water balance, calculated as precipitation minus FAO56 PET, provided the clearest distinction between moisture-surplus and moisture-deficit locations. Sydney was the only location with a positive long-term mean annual water balance, at 32.3 mm yr^{-1} . All other locations had negative mean annual water-balance values. The strongest deficit occurred at Alice Springs, with $-1646.5 \text{ mm yr}^{-1}$, followed by Adelaide with $-711.7 \text{ mm yr}^{-1}$, Perth with $-551.4 \text{ mm yr}^{-1}$, Canberra with $-513.2 \text{ mm yr}^{-1}$, Melbourne with $-449.4 \text{ mm yr}^{-1}$, Hobart with $-320.1 \text{ mm yr}^{-1}$, Brisbane with $-295.1 \text{ mm yr}^{-1}$, and Darwin with $-204.9 \text{ mm yr}^{-1}$. Although Darwin had the highest precipitation, its high evaporative demand produced a negative long-term climatic water balance.

This confirms that rainfall amount alone is insufficient for interpreting drought-relevant hydroclimatic stress across the selected locations. These contrasts also provide a physical basis for interpreting the later drought-index results. Locations such as Alice Springs and Adelaide are influenced by strong atmospheric water demand relative to precipitation supply, whereas Sydney's comparatively favourable long-term water balance reflects the combined effect of higher precipitation and lower FAO56 PET than the arid and dry-temperate benchmark locations.

Therefore, differences in drought behaviour among the selected locations are expected to arise not only from precipitation variability but also from the local balance between moisture supply and evaporative demand.

3.2. Temporal Evolution of SPI-12 and SPEI-12

The temporal evolution of SPI-12 and SPEI-12 revealed substantial interannual and multi-decadal variability across all selected point locations (Figure 3). In most locations, SPI-12 and SPEI-12 followed broadly similar wet and dry phases, indicating that precipitation variability remained an important control on 12-month drought fluctuations. However, the two indices did not always coincide. SPEI-12 frequently indicated stronger or more persistent drought conditions when climatic water-balance deficits were greater than precipitation deficits alone.

All locations showed repeated transitions between positive and negative standardized-index phases over the 1900–2025 period. Several locations experienced multi-year episodes in which SPI-12 or SPEI-12 remained below -1.0 , indicating moderate-or-worse drought conditions. Perth, Adelaide, and Melbourne showed visually persistent negative phases during parts of the late twentieth and early twenty-first centuries, particularly in SPEI-12. Alice Springs showed strong episodic variability, with sharp transitions between wet and dry phases, reflecting the high variability of the arid inland hydroclimatic setting.

The SPI–SPEI comparison also shows that including FAO56 PET can alter the perceived intensity and persistence of drought conditions. This effect is most relevant where evaporative demand is high or where warming-related atmospheric demand intensifies climatic water-balance deficits. Therefore, the temporal comparison of SPI-12 and SPEI-12 provides the basis for the subsequent event, persistence, trend, and SPI–SPEI divergence analyses.

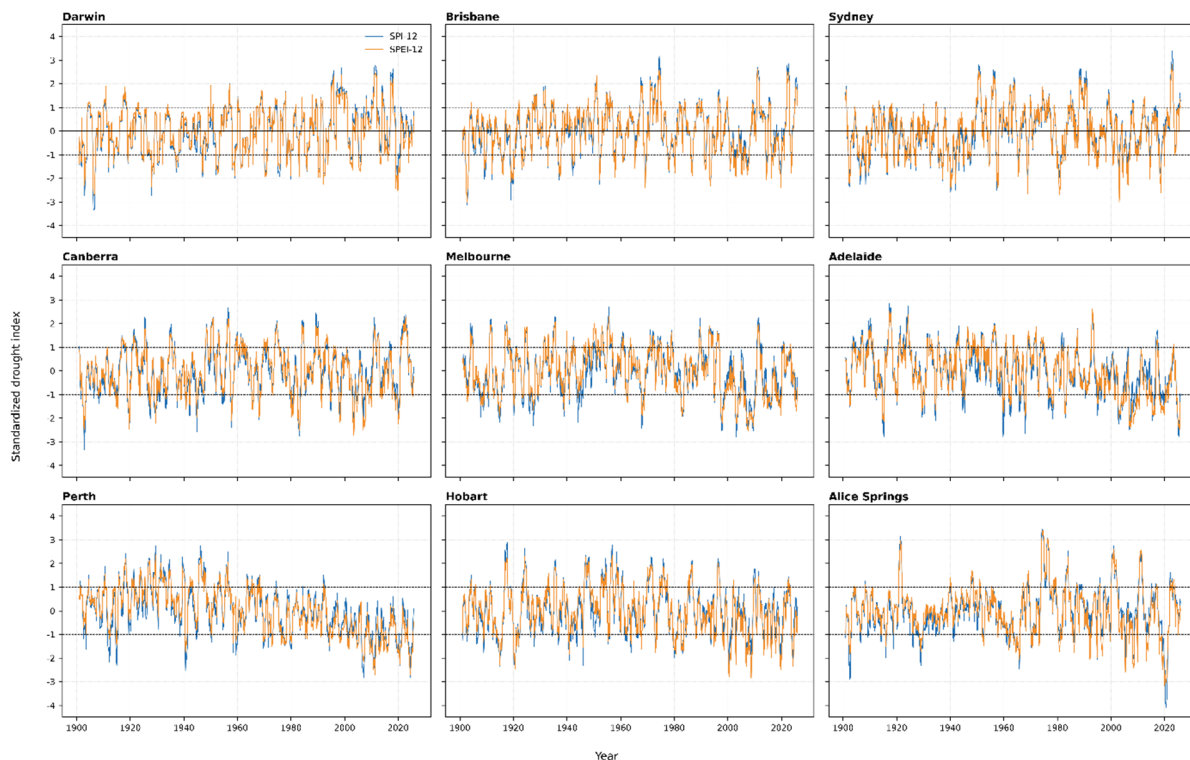


Figure 3. Temporal evolution of probabilistic SPI-12 and SPEI-12 across the selected Australian point locations. Blue lines show SPI-12 calculated from 12-month accumulated precipitation using gamma distribution fitting, while orange lines show SPEI-12 calculated from 12-month accumulated climatic water balance using FAO56 PET and generalized logistic distribution fitting. Dashed horizontal lines indicate the ± 1 standardized drought-index thresholds, and the solid horizontal line indicates zero.

3.3. Drought-Event Frequency, Duration, Severity, and Intensity

Drought-event analysis showed clear differences between precipitation-based and water-balance-based drought behaviour among the selected point locations (Table 3; Figure 4). For SPEI-12, drought-event frequency was highest in Sydney, with 52.8 events per 100 years, followed by Hobart with 43.2 events per 100 years and Canberra with 38.4 events per 100 years. The lowest SPEI-12 drought-event frequency occurred in Alice Springs, with 26.4 events

per 100 years. For SPI-12, drought-event frequency was highest in Hobart, at 48.0 events per 100 years, followed by Sydney and Canberra, both at 41.6 events per 100 years, and Melbourne at 39.2 events per 100 years.

Mean drought duration showed a different pattern from event frequency. SPEI-12 drought events lasted longest in Perth, with a mean duration of 6.9 months, followed by Melbourne and Alice Springs, both at 6.8 months. Brisbane, Darwin, and Adelaide also showed relatively long mean SPEI-12 drought durations, ranging from 6.3 to 6.5 months. Under SPI-12, mean drought duration was highest in Darwin, at 6.3 months, followed by Adelaide at 5.9 months and Brisbane and Perth at 5.7 months. These results indicate that locations with frequent drought events were not necessarily those with the longest events. This difference suggests that drought recurrence and drought persistence are controlled by partly different hydroclimatic mechanisms. Locations with relatively frequent but shorter events, such as Sydney and Hobart, appear to reflect recurrent standardized precipitation or water-balance anomalies around a comparatively wetter baseline. In contrast, longer SPEI-based drought durations in Perth, Melbourne, Adelaide, and Alice Springs indicate that once water-balance deficits develop, high evaporative demand, rainfall seasonality, or multi-year moisture deficits can prolong drought conditions. For example, Sydney and Hobart had relatively high event frequency but shorter mean event duration, whereas Perth and Melbourne showed longer and more persistent SPEI-based drought events.

Table 3. Drought-event characteristics derived from SPI-12 and SPEI-12 for the selected Australian point locations.

Location	Index	Valid Months	Drought Months	Drought-Month Ratio (%)	Number of Events	Event Frequency (Events 100 yr ⁻¹)	Mean Duration (Months)	Longest Duration (Months)	Cumulative Severity	Mean Intensity	Minimum Index
Darwin	SPI-12	1501	247	16.5	39	31.2	6.3	15	368.8	1.41	−3.33
Darwin	SPEI-12	1501	254	16.9	40	32.0	6.4	23	384.0	1.39	−2.71
Brisbane	SPI-12	1501	240	16.0	42	33.6	5.7	14	359.4	1.36	−3.13
Brisbane	SPEI-12	1501	259	17.3	40	32.0	6.5	16	392.8	1.41	−3.03
Sydney	SPI-12	1501	241	16.1	52	41.6	4.6	19	354.4	1.36	−2.79
Sydney	SPEI-12	1501	245	16.3	66	52.8	3.7	19	372.5	1.35	−3.01
Canberra	SPI-12	1501	231	15.4	52	41.6	4.4	15	346.6	1.32	−3.34
Canberra	SPEI-12	1501	237	15.8	48	38.4	4.9	15	363.1	1.33	−2.73
Melbourne	SPI-12	1501	240	16.0	49	39.2	4.9	39	373.2	1.31	−2.78
Melbourne	SPEI-12	1501	266	17.7	39	31.2	6.8	48	392.9	1.27	−2.53
Adelaide	SPI-12	1501	241	16.1	41	32.8	5.9	23	373.8	1.37	−2.81
Adelaide	SPEI-12	1501	266	17.7	42	33.6	6.3	36	394.3	1.27	−2.45
Perth	SPI-12	1501	252	16.8	44	35.2	5.7	23	383.0	1.36	−2.83
Perth	SPEI-12	1501	277	18.5	40	32.0	6.9	31	402.7	1.26	−2.72
Hobart	SPI-12	1501	239	15.9	60	48.0	4.0	21	342.0	1.27	−2.55
Hobart	SPEI-12	1501	240	16.0	54	43.2	4.4	21	366.6	1.30	−2.88
Alice Springs	SPI-12	1501	190	12.7	46	36.8	4.1	27	299.7	1.28	−4.07
Alice Springs	SPEI-12	1501	224	14.9	33	26.4	6.8	39	347.7	1.36	−3.19

Cumulative drought severity further highlighted the importance of water-balance-based drought stress in southern and southwestern locations. For SPEI-12, the highest cumulative severity was observed in Perth, at 402.7, followed by Adelaide at 394.3, Melbourne at 392.9, Brisbane at 392.8, and Darwin at 384.0. For SPI-12, Perth again had the highest cumulative severity, at 383.0, followed by Adelaide at 373.8, Melbourne at 373.2, and Darwin at 368.8. Alice Springs had the lowest cumulative severity for both SPI-12 and SPEI-12, despite its strong climatic water deficit. This apparent contrast reflects the standardized nature of the indices and indicates that arid baseline climate does not automatically translate into the highest standardized drought-event frequency or cumulative severity.

Mean drought intensity varied less strongly than frequency, duration, or cumulative severity. Across most locations, mean intensity values were approximately between 1.26 and 1.41. The minimum index values indicate that severe drought episodes occurred at all selected locations. The most negative SPI-12 value occurred in Alice Springs, at −4.07, followed by Canberra at −3.34 and Darwin at −3.33. The most negative SPEI-12 value occurred in Alice Springs, at −3.19, followed by Brisbane at −3.03 and Sydney at −3.01. These results show that although cumulative event behaviour differed among locations, each point experienced severe standardized drought episodes during the study period.

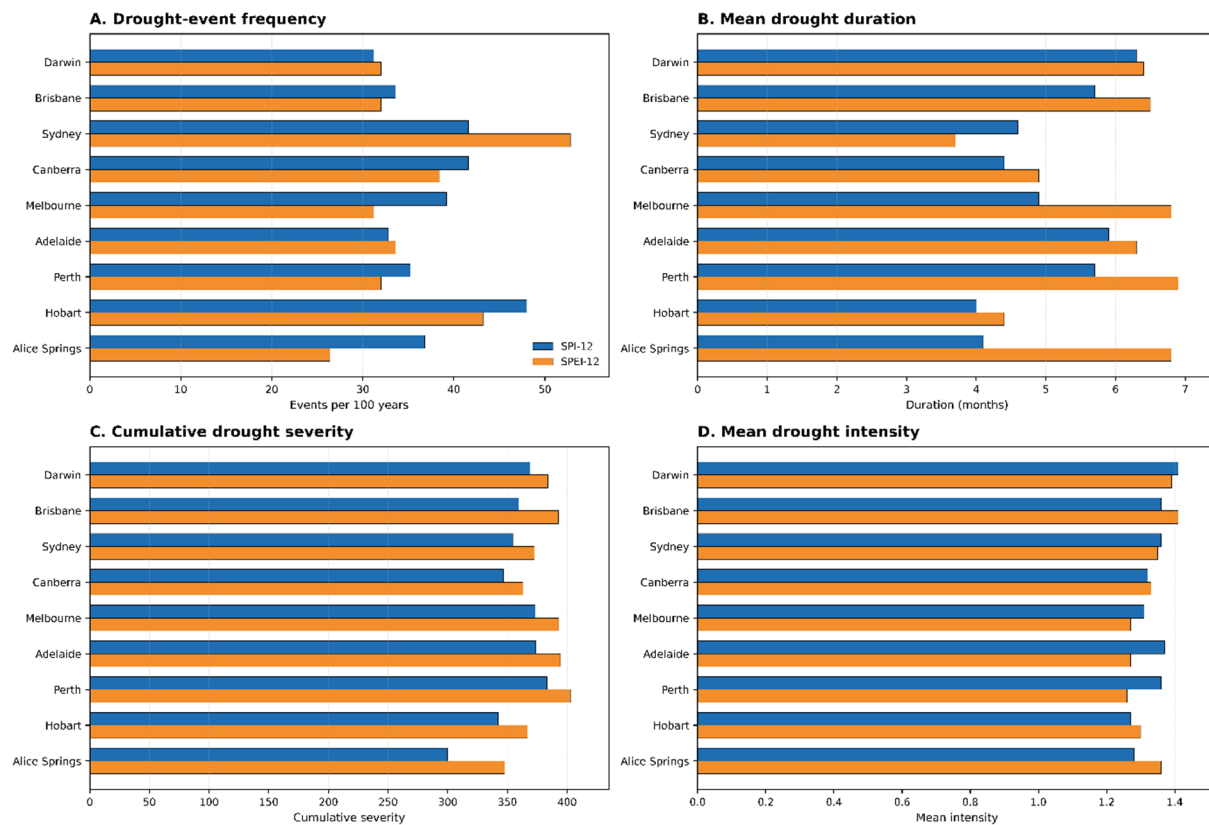


Figure 4. Drought-event characteristics derived from SPI-12 and SPEI-12 for the selected Australian point locations. (A) Drought-event frequency expressed as events per 100 years. (B) Mean drought duration. (C) Cumulative drought severity. (D) Mean drought intensity. Drought events were defined as continuous periods in which SPI-12 or SPEI-12 was less than or equal to -1.0 .

3.4. Drought Persistence and Drought-Month Ratio

The persistence analysis further distinguished locations with frequent drought recurrence from those with longer-lasting drought episodes (Figure 5). The longest SPEI-12 drought duration was observed in Melbourne, where drought conditions persisted for 48 consecutive months. Alice Springs also showed a long maximum SPEI-12 drought duration of 39 months, followed by Adelaide with 36 months and Perth with 31 months. For SPI-12, the longest drought duration was again observed in Melbourne, at 39 months, followed by Alice Springs at 27 months and Adelaide and Perth at 23 months. These results show that the inclusion of FAO56 PET increased the estimated maximum drought persistence at several locations, especially Melbourne, Alice Springs, Adelaide, and Perth.

The maximum 5-year drought-month ratio identified the strongest multi-year concentration of drought months. Melbourne had the highest SPEI-12 maximum 5-year drought-month ratio, at 85.0%, followed by Adelaide at 78.3% and Perth at 75.0%. Alice Springs also showed a high SPEI-12 maximum 5-year drought-month ratio, at 65.0%. Under SPI-12, the highest maximum 5-year drought-month ratios occurred in Melbourne and Perth, both at 65.0%, followed by Alice Springs at 61.7% and Sydney at 60.0%. These values indicate that several locations experienced 5-year periods in which more than half of all months were classified as drought months.

Mean 5-year drought-month ratios were more similar across locations than the maximum values, generally clustering between approximately 15% and 18% for most SPI-12 and SPEI-12 series. However, the recent-period drought-month ratio for 2000–2025 showed stronger differentiation. Perth had the highest recent drought-month ratio, with 44.2% for SPI-12 and 56.1% for SPEI-12. Adelaide also showed a high recent drought-month ratio, increasing from 33.0% for SPI-12 to 51.6% for SPEI-12. Melbourne had a recent SPEI-12 drought-month ratio of 43.6%, compared with 29.2% for SPI-12. Alice Springs also showed a clear increase from 15.4% under SPI-12 to 26.3% under SPEI-12. These results indicate that FAO56 PET substantially increased recent drought classification at Perth, Adelaide, Melbourne, and Alice Springs. The stronger recent SPEI-12 drought-month ratios at these locations are physically consistent with the role of atmospheric water demand in extending water-balance drought conditions. In Perth and Adelaide, this effect coincides with strong persistence and significant drying signals, whereas in Alice Springs it reflects the sensitivity of an arid inland setting to high PET even when standardized event frequency is not the highest among the selected locations.

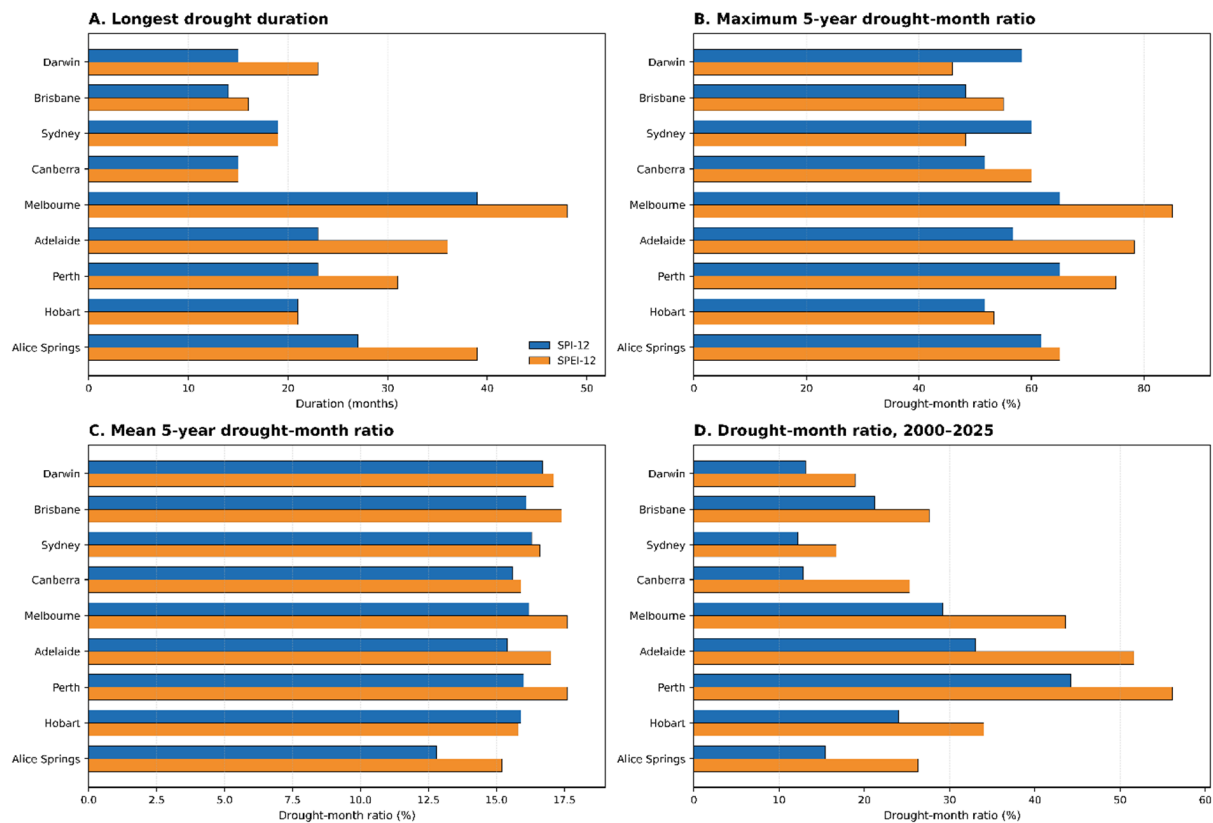


Figure 5. Drought persistence and drought-month ratio metrics derived from SPI-12 and SPEI-12. (A) Longest drought duration. (B) Maximum 5-year drought-month ratio. (C) Mean 5-year drought-month ratio. (D) Drought-month ratio for the recent period 2000–2025. Drought months were defined using the threshold $\text{SPI-12 or SPEI-12} \leq -1.0$.

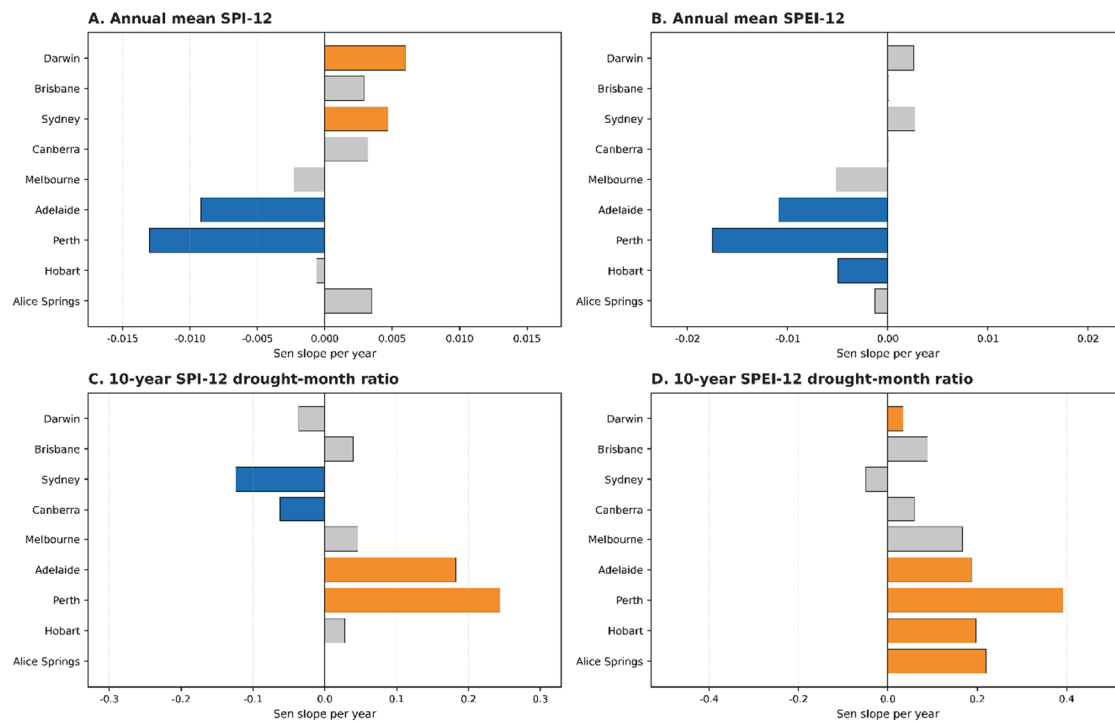
3.5. Trend Behaviour of Drought Indices and Drought-Month Ratios

Trend analysis using the Hamed–Rao modified Mann–Kendall test and Sen’s slope revealed contrasting patterns in annual mean SPI-12, annual mean SPEI-12, and 10-year moving drought-month ratios (Figure 6; Supplementary Table S1). Annual mean SPI-12 showed significant positive trends in Darwin and Sydney, with Sen’s slopes of 0.0060 yr^{-1} and 0.0047 yr^{-1} , respectively. In contrast, Adelaide and Perth showed significant negative SPI-12 trends, with Sen’s slopes of -0.0092 yr^{-1} and -0.0130 yr^{-1} , respectively. Brisbane, Canberra, Melbourne, Hobart, and Alice Springs did not show significant annual mean SPI-12 trends after serial-correlation adjustment.

Annual mean SPEI-12 trends showed a more water-balance-sensitive drying signal. Adelaide and Perth exhibited significant negative SPEI-12 trends, with Sen’s slopes of -0.0109 yr^{-1} and -0.0175 yr^{-1} , respectively. Hobart also showed a significant negative SPEI-12 trend, with a Sen’s slope of -0.0050 yr^{-1} . Perth had the strongest annual mean SPEI-12 drying trend among the selected locations. By contrast, Darwin, Brisbane, Sydney, Canberra, Melbourne, and Alice Springs did not show statistically significant annual mean SPEI-12 trends under the modified Mann–Kendall test.

The 10-year moving drought-month ratio provided additional insight into changes in drought persistence. For SPI-12, significant positive trends were observed in Adelaide and Perth, with Sen’s slopes of 0.1823 and 0.2439 percentage points yr^{-1} , respectively. Significant negative SPI-12 drought-month-ratio trends occurred in Canberra and Sydney, with Sen’s slopes of -0.0625 and -0.1239 percentage points yr^{-1} , respectively. Other locations did not show significant SPI-12 drought-month-ratio trends after serial-correlation adjustment.

For SPEI-12, increasing 10-year drought-month-ratio trends were more evident. Significant positive trends occurred in Adelaide, Alice Springs, Darwin, Hobart, and Perth. Perth showed the strongest increase, with a Sen’s slope of 0.3922 percentage points yr^{-1} , followed by Alice Springs at 0.2193 percentage points yr^{-1} , Hobart at 0.1971 percentage points yr^{-1} , Adelaide at 0.1871 percentage points yr^{-1} , and Darwin at 0.0342 percentage points yr^{-1} . Brisbane, Canberra, Melbourne, and Sydney did not show significant SPEI-12 drought-month-ratio trends under the modified Mann–Kendall test. These results indicate that the strongest and most robust drying and persistence signals were concentrated in Perth and Adelaide, while some locations with high event or persistence metrics, such as Melbourne, did not show statistically significant monotonic trends after autocorrelation adjustment.



Orange bars indicate significant increasing trends, blue bars indicate significant decreasing trends, and grey bars indicate non-significant trends based on the Hamed–Rao modified Mann–Kendall test at $p < 0.05$.

Figure 6. Serial-correlation-adjusted drought trend slopes for the selected Australian point locations. (A) Sen's slope of annual mean SPI-12. (B) Sen's slope of annual mean SPEI-12. (C) Sen's slope of the 10-year moving SPI-12 drought-month ratio. (D) Sen's slope of the 10-year moving SPEI-12 drought-month ratio. Trend significance was assessed using the Hamed–Rao modified Mann–Kendall test, and trend magnitude was quantified using Sen's slope. Orange bars indicate significant increasing trends, blue bars indicate significant decreasing trends, and grey bars indicate non-significant trends at $p < 0.05$.

3.6. SPI–SPEI Divergence and Warming-Amplified Drought Stress

The SPI–SPEI divergence analysis showed that atmospheric water demand altered drought classification and severity to different degrees among the selected point locations (Figure 7). Mean absolute SPI–SPEI divergence across all valid months was highest in Adelaide and Alice Springs, at approximately 0.25, followed by Perth, Melbourne, Hobart, and Canberra. Lower mean absolute divergence values were observed in Darwin, Sydney, and Brisbane. This indicates that the long-term magnitude of SPI–SPEI separation was greatest in locations where the inclusion of FAO56 PET most strongly changed the standardized drought signal. The pattern is physically plausible because SPI responds only to precipitation anomalies, whereas SPEI incorporates the balance between precipitation and atmospheric demand. As a result, the largest SPI–SPEI separation occurred where PET exerted the strongest influence on accumulated water balance, particularly at Alice Springs and Adelaide, and to a lesser extent at Perth and Melbourne.

During drought months, mean WAI was highest in Alice Springs, at 0.10, indicating that SPEI-12 was generally drier than SPI-12 during drought conditions at the arid inland location. Hobart, Brisbane, Sydney, Canberra, Darwin, and Adelaide also showed positive mean drought-month WAI values, though at smaller magnitudes. Perth was close to zero, while Melbourne showed a slightly negative mean drought-month WAI. This indicates that the direction and magnitude of SPI–SPEI divergence were not uniform across locations or drought episodes.

The percentage of SPEI-only drought months further highlighted the role of atmospheric water demand. Alice Springs had the highest SPEI-only drought-month percentage, at 4.86%, followed by Adelaide at 4.20%, Perth at 4.06%, Melbourne at 4.00%, Canberra at 3.93%, and Hobart at 3.46%. Lower values occurred in Brisbane, Sydney, and Darwin. These results show that SPEI-12 identified additional drought months beyond those detected by SPI-12, particularly in the arid inland and several southern or southwestern locations.

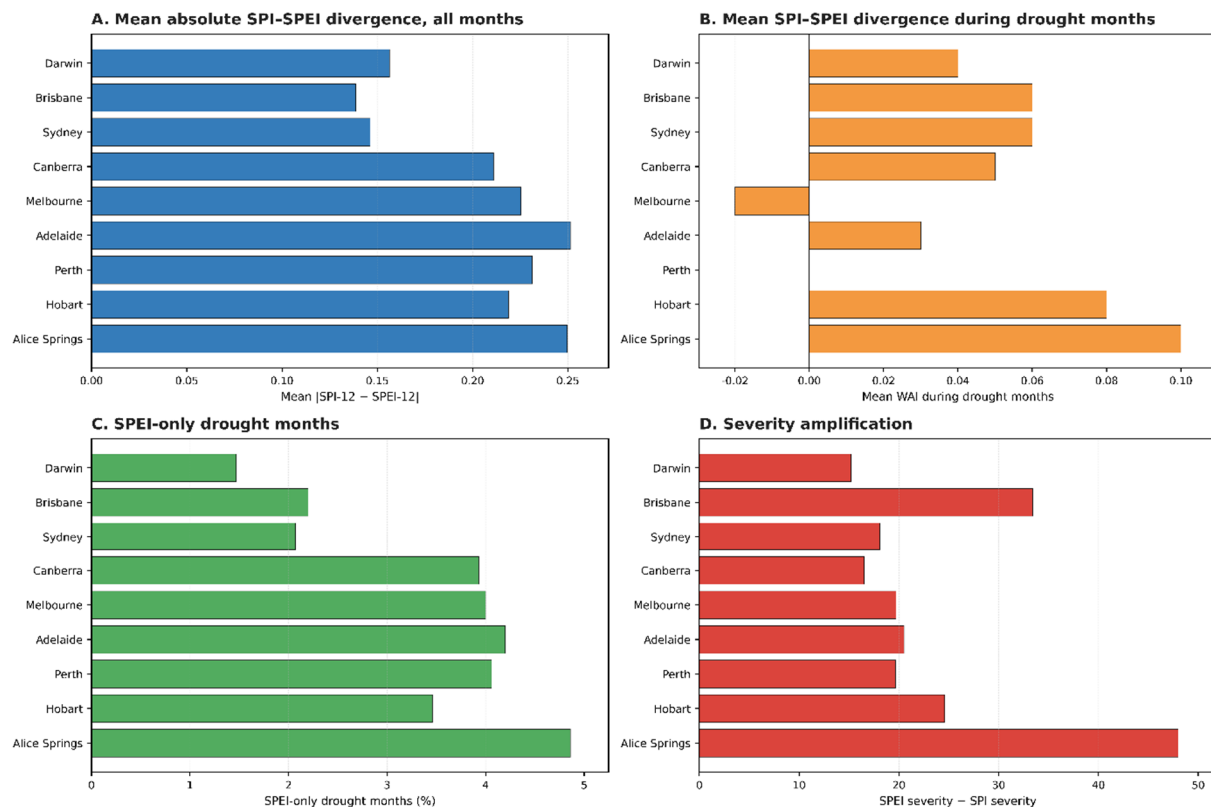


Figure 7. SPI-SPEI divergence and warming-amplified drought stress across the selected Australian point locations. (A) Mean absolute SPI-SPEI divergence across all valid months, calculated as mean $|SPI-12 - SPEI-12|$. (B) Mean SPI-SPEI divergence during drought months, where positive values indicate stronger SPEI-based drought stress relative to SPI. (C) Percentage of months in which SPEI-12 indicated drought while SPI-12 did not. (D) Severity amplification, calculated as SPEI-based cumulative drought severity minus SPI-based cumulative drought severity. Positive values indicate stronger drought stress when atmospheric water demand is included through FAO56 PET.

Severity amplification was strongest in Alice Springs, where SPEI-based cumulative severity exceeded SPI-based cumulative severity by 48.0. Brisbane had the second-highest severity amplification, at 33.4, followed by Hobart at 24.6, Adelaide at 20.5, Melbourne at 19.7, Perth at 19.7, Sydney at 18.1, Canberra at 16.5, and Darwin at 15.2. Overall, the SPI-SPEI divergence results show that warming-amplified drought stress was not spatially uniform across the benchmark locations. Alice Springs stood out as the clearest atmospheric-demand-amplification case, whereas Perth and Adelaide combined substantial SPI-SPEI divergence with stronger persistence, severity, and trend signals.

3.7. Composite Drought Hotspot Ranking and Sensitivity

The composite hotspot analysis synthesized drought frequency, duration, cumulative severity, persistence, and warming-amplification components into a transparent point-location screening score (Table 4; Figure 8). The equal-weight composite score ranked Perth highest among the selected locations, with a hotspot score of 0.702. Perth's leading rank was driven by maximum normalized duration, severity, and persistence components, combined with a moderate warming-amplification component. Adelaide ranked second, with a score of 0.632, reflecting strong duration, severity, persistence, and warming-amplification components. Melbourne ranked third, with a score of 0.614, mainly because of high duration, severity, and persistence components, although its modified Mann-Kendall trend signals were not statistically significant.

Brisbane ranked fourth, with a composite score of 0.508. Its score was supported by relatively high duration, severity, and warming-amplification components, despite weaker persistence. Alice Springs ranked fifth, with a score of 0.442. This location had the maximum warming-amplification component but low frequency and severity components, showing that it is best interpreted as a distinctive atmospheric-demand-amplification hotspot rather than an overall drought-frequency or cumulative-severity hotspot. Hobart ranked sixth, with a score of 0.417, reflecting a relatively high frequency component but lower duration and persistence. Darwin, Sydney, and Canberra ranked seventh, eighth, and ninth, with scores of 0.370, 0.348, and 0.333, respectively.

Table 4. Composite drought-hotspot ranking for the selected Australian point locations.

Location	Frequency Component	Duration Component	Severity Component	Persistence Component	Warming-Amplification Component	Composite Hotspot Score	Rank
Perth	0.21	1.00	1.00	1.00	0.30	0.70	1
Adelaide	0.27	0.81	0.85	0.80	0.42	0.63	2
Melbourne	0.18	0.97	0.82	0.80	0.30	0.61	3
Brisbane	0.21	0.88	0.82	0.17	0.46	0.51	4
Alice Springs	0.00	0.97	0.00	0.24	1.00	0.44	5
Hobart	0.64	0.22	0.34	0.33	0.56	0.42	6
Darwin	0.21	0.84	0.66	0.00	0.13	0.37	7
Sydney	1.00	0.00	0.45	0.00	0.29	0.35	8
Canberra	0.46	0.38	0.28	0.13	0.42	0.33	9

Mechanistically, the leading hotspot scores reflect different combinations of drought processes. Perth and Adelaide ranked highly because severity, duration, persistence, and drying trends coincided, indicating a multi-dimensional drought signal. Melbourne's high ranking was driven mainly by event duration and persistence rather than by a significant monotonic trend. Alice Springs, by contrast, had a lower overall composite score but a distinct amplification-dominated profile, showing that atmospheric-demand sensitivity can represent a different drought mechanism from event recurrence or cumulative standardized severity.

The component structure confirms that no single drought metric controlled all hotspot rankings. Perth and Adelaide emerged as the most robust high-ranking locations because several components were simultaneously high. Melbourne also had a high equal-weight score, but its interpretation requires caution because its trend metrics were not significant after serial-correlation adjustment. Alice Springs had a different hotspot profile, dominated by warming amplification rather than event frequency or cumulative severity. Sydney and Hobart showed relatively high frequency components but lower duration, persistence, or amplification components.

The random-weight Monte Carlo sensitivity analysis (Supplementary Table S6) provided an additional check on the equal-weight ranking. Perth had the highest probability of remaining in the top three, at 90.5%, followed by Adelaide at 86.2% and Melbourne at 66.5%. Alice Springs had a top-three probability of 20.4%, reflecting its sensitivity to weights assigned to warming amplification. Sydney and Hobart had top-three probabilities of 14.5% and 12.2%, respectively, while Brisbane had a lower top-three probability of 8.2% despite its fourth-place equal-weight rank. Canberra and Darwin had very low top-three probabilities. The mean Spearman rank correlation between random-weight rankings and the equal-weight ranking was 0.739, with a 5th–95th percentile range from 0.067 to 0.967. These results indicate that Perth and Adelaide were the most robust composite hotspots among the selected point locations, while mid-ranked locations were more sensitive to weighting assumptions.

4. Discussion

4.1. Hydroclimatic Contrasts and the Importance of Atmospheric Water Demand

The results show that drought-relevant hydroclimatic stress across the selected Australian point locations cannot be interpreted from precipitation alone. Darwin had the highest mean annual precipitation among the benchmark locations, yet its long-term climatic water balance was negative because atmospheric water demand was also high. Conversely, Sydney received less rainfall than Darwin but was the only selected location with a positive long-term mean annual FAO56-based climatic water balance. Alice Springs provided the clearest opposite case: it combined the lowest mean annual precipitation with the highest FAO56 PET and the strongest mean annual water-balance deficit. These contrasts confirm that drought-relevant hydroclimatic stress depends on the interaction between precipitation supply and atmospheric water demand, rather than rainfall totals alone.

This finding is consistent with the broader Australian drought literature, which emphasizes strong spatial diversity in rainfall regimes, evaporative demand, drought-generating mechanisms, and water-resource sensitivity across the continent [5,12,28,41]. It also supports the methodological decision to use FAO56 reference PET as the primary atmospheric-demand input in the SPEI analysis. A temperature-only PET estimate can provide a simple benchmark, but it may not sufficiently represent the spatial structure of evaporative demand in a continent where radiation, humidity, and aridity gradients are central to drought stress. The FAO56-based results therefore provide a more physically consistent basis for interpreting climatic water-balance drought than the earlier temperature-only PET formulation.

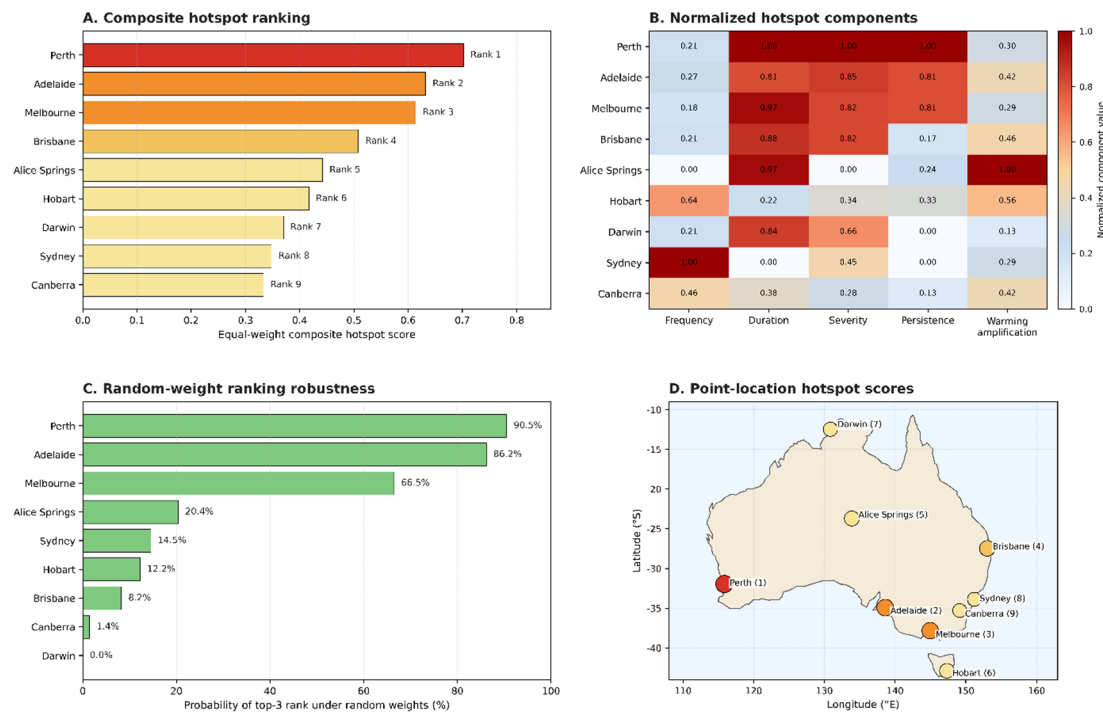


Figure 8. Composite drought-hotspot ranking and weighting-sensitivity diagnostics for the selected Australian point locations. (A) Equal-weight composite hotspot score based on normalized drought frequency, duration, severity, persistence, and warming-amplification components. (B) Normalized component values contributing to the composite score. (C) Random-weight sensitivity analysis showing the probability of each location remaining within the top three hotspot ranks under 10,000 random weighting combinations. (D) Spatial distribution of point-location hotspot scores and ranks.

The SPI–SPEI comparison is particularly relevant in this context. SPI-12 captures precipitation anomalies, whereas SPEI-12 incorporates the climatic water balance and therefore responds to atmospheric water demand [4,44]. In warm, arid, or high-evaporation settings, a precipitation anomaly may underestimate drought stress if evaporative demand is not considered. The results from Alice Springs, Adelaide, Perth, and Melbourne show that FAO56 PET can substantially increase drought classification or persistence relative to precipitation-only SPI. This supports the view that precipitation-only drought indices should be interpreted carefully in drought assessments where atmospheric demand is expected to intensify water-balance deficits [8–11].

4.2. Event-Based Drought Behaviour and Persistence

The drought-event results demonstrate that drought frequency, duration, severity, and intensity describe different aspects of drought behaviour. Sydney and Hobart had relatively high drought-event frequencies, but their mean event durations were not among the longest. In contrast, Perth, Melbourne, Adelaide, Brisbane, Darwin, and Alice Springs showed longer mean SPEI-12 drought durations, indicating that drought risk at these locations is more strongly associated with persistence once drought conditions develop. This distinction is important because drought-management responses differ depending on whether risk is driven primarily by frequent recurrence, long event duration, cumulative severity, or high intensity.

The cumulative severity results emphasized the importance of southern and southwestern drought stress. Perth, Adelaide, Melbourne, Brisbane, and Darwin had the highest SPEI-12 cumulative severity values among the selected locations. The strong severity values for Perth, Adelaide, and Melbourne are consistent with previous evidence of hydroclimatic stress in southern and southwestern Australia, where rainfall decline, catchment drying, and water-resource sensitivity have been widely documented [12,31,32,34–37]. These findings also align with studies showing that prolonged drought can alter rainfall–runoff relationships and that hydrological recovery may lag behind meteorological recovery, particularly in drier catchments [32].

Alice Springs requires a different interpretation. It had the lowest cumulative drought severity for both SPI-12 and SPEI-12, despite having the strongest long-term climatic water-balance deficit. This does not imply low water scarcity or low drought vulnerability. Standardized drought indices measure anomalies relative to local climatology; they do not directly measure chronic aridity or absolute water limitation. Therefore, an arid location can have relatively low standardized drought-event frequency or cumulative severity while still experiencing

severe absolute water stress. The later SPI–SPEI divergence and hotspot-component results confirm that Alice Springs has a distinct drought profile, driven more by atmospheric-demand amplification than by event frequency or cumulative standardized severity.

The persistence metrics further clarify these differences. Melbourne had the longest drought duration under both indices, and FAO56-based SPEI increased maximum drought persistence at several locations, especially Melbourne, Alice Springs, Adelaide, and Perth. The maximum 5-year drought-month ratio showed that Melbourne, Adelaide, Perth, and Alice Springs experienced periods in which drought conditions accounted for more than half of the months in a 5-year window. These results show that drought persistence can be more informative than event counts alone, particularly for water-supply systems, agriculture, groundwater recharge, ecosystem stress, and drought recovery.

The recent-period drought-month ratios for 2000–2025 are especially relevant for water-scarcity assessment. Perth, Adelaide, Melbourne, and Alice Springs all showed higher recent drought-month ratios under SPEI-12 than under SPI-12. This indicates that water-balance drought conditions were more persistent than precipitation-only drought conditions in the recent period. Such a pattern is consistent with the expectation that warming can increase drought stress by raising atmospheric water demand even where rainfall trends are heterogeneous [8–11,51,52]. For drought monitoring and planning, this means that rainfall-based metrics may not fully represent the stress experienced by soils, vegetation, reservoirs, and water balances under warmer conditions.

4.3. Trend Behaviour under Serial-Correlation Adjustment

The trend analysis provides a more cautious interpretation than the original classical Mann–Kendall formulation because the results use the Hamed–Rao modified Mann–Kendall test to account for serial correlation. This is important because hydroclimatic drought series can be autocorrelated, and ignoring serial dependence may overstate statistical significance. After this adjustment, the clearest and most consistent drying signals were concentrated in Perth and Adelaide.

Annual mean SPI-12 showed significant negative trends in Perth and Adelaide, while annual mean SPEI-12 also showed significant negative trends in these two locations, with Perth displaying the strongest SPEI-12 drying slope. Hobart additionally showed a significant negative SPEI-12 trend. These findings are consistent with the broader literature on rainfall decline, drying, and water-resource stress in southern and southwestern Australia [12,34–37]. The stronger SPEI-12 drying signal in Perth relative to SPI-12 indicates that climatic water-balance drying was more pronounced than precipitation-only drying, supporting the interpretation that atmospheric demand contributes to drought intensification in areas already affected by rainfall decline.

The 10-year moving drought-month-ratio trends add a persistence-based perspective. For SPI-12, significant increases were mainly limited to Adelaide and Perth. For SPEI-12, significant increases were detected in Adelaide, Alice Springs, Darwin, Hobart, and Perth, with Perth again showing the strongest increase. This indicates that the inclusion of FAO56 PET makes increasing drought-month persistence more evident at several locations. However, the results also show that drought trends are not uniform. Some locations with high event or persistence metrics, such as Melbourne, did not show statistically significant monotonic trends after serial-correlation adjustment. This distinction is important: a location can experience severe or persistent drought episodes without necessarily having a statistically significant long-term monotonic drying trend.

The positive or non-significant trends in several locations also reinforce the need to avoid a homogeneous national interpretation. Australian drought behaviour is shaped by regionally variable rainfall regimes, climate drivers, and atmospheric circulation patterns [15,23–30,41]. Therefore, the present results should be interpreted as point-location trend diagnostics under a consistent methodology, not as a spatially complete national drought trend map.

4.4. SPI–SPEI Divergence and Atmospheric-Demand Amplification

The SPI–SPEI divergence analysis provides one of the clearest indications that atmospheric water demand can alter drought interpretation. Mean absolute SPI–SPEI divergence was largest at Adelaide and Alice Springs, followed by Perth, Melbourne, Hobart, and Canberra. This shows that the magnitude of separation between precipitation-only drought and water-balance drought was not uniform across the selected benchmark points. The result is consistent with the conceptual basis of SPEI, which is designed to incorporate the effect of atmospheric demand on drought severity [4,44].

Alice Springs was the clearest atmospheric-demand-amplification case. It had the highest drought-month WAI, the highest SPEI-only drought-month percentage, and the strongest severity amplification. This is physically plausible because arid inland environments are highly sensitive to evaporative demand. Even when precipitation anomalies are not extreme relative to local climatology, high PET can intensify climatic water-balance deficits.

This also explains why Alice Springs did not rank highest in standardized event frequency or cumulative severity but still emerged as the strongest warming-amplification location.

Southern and southwestern locations also showed important SPEI-related signals. Adelaide, Perth, and Melbourne had high recent SPEI-12 drought-month ratios and substantial SPEI-only drought-month percentages. This indicates that atmospheric demand contributed to additional drought classification beyond precipitation deficits alone. In locations where rainfall decline, persistent drought episodes, and high evaporative demand interact, the resulting drought stress may be more severe than suggested by SPI alone. This agrees with studies on compound dry-hot conditions and drought intensification under warming, where co-occurring moisture deficits and heat can increase environmental and socio-economic impacts [29,30,38,39].

The divergence results also show why SPI and SPEI should be interpreted together rather than treated as interchangeable. SPI remains valuable because it isolates precipitation anomalies and has low data requirements. SPEI adds information about atmospheric-demand-driven water-balance stress. When the two indices agree, drought interpretation is more robust. When they diverge, the difference is diagnostically useful because it identifies locations or periods where evaporative demand changes the drought signal.

4.5. Composite Hotspot Screening and Robustness of Rankings

The composite hotspot score was designed as a transparent screening index rather than an optimized drought-risk prediction model. This distinction is important because equal-weight composite indicators depend on normalization and weighting assumptions. The value of the score is therefore not that it provides a definitive drought-risk ranking, but that it synthesizes multiple drought dimensions consistently and makes the assumptions explicit.

Under the equal-weight formulation, Perth ranked first among the selected point locations, followed by Adelaide, Melbourne, Brisbane, and Alice Springs. Perth's leading rank was driven by maximum normalized duration, severity, and persistence components, together with a moderate warming-amplification component. Adelaide ranked second because it combined strong duration, severity, persistence, and warming-amplification components. These two locations also had the most robust high-rank behaviour in the random-weight sensitivity analysis, with top-three probabilities of 90.5% for Perth and 86.2% for Adelaide. This supports the interpretation that Perth and Adelaide are the most stable composite drought hotspots among the selected benchmark locations.

Melbourne ranked third in the equal-weight score and had a 66.5% probability of remaining in the top three under random weighting. Its high ranking was driven primarily by duration, severity, and persistence components. However, Melbourne's trend metrics were not statistically significant after serial-correlation adjustment. Therefore, Melbourne should be interpreted as a high event-severity and persistence location in the composite screening framework, not as a location with a robust monotonic drying trend in the modified Mann-Kendall analysis.

Alice Springs had a different hotspot profile. It ranked fifth overall, but it had the maximum warming-amplification component. This shows that a single composite score can hide important mechanistic differences. Alice Springs was not the leading location in terms of event frequency or cumulative standardized severity, but it was the location where SPEI most strongly exceeded SPI in drought characterization. Therefore, the arid inland benchmark point should not be interpreted as low risk simply because its standardized event metrics were lower. Its drought relevance lies in chronic aridity and high sensitivity to atmospheric demand.

Hobart and Sydney had relatively high frequency components but lower duration, persistence, or amplification components. Brisbane ranked fourth in the equal-weight score but had a lower top-three probability under random weighting, indicating that its ranking was more sensitive to the weighting structure. Canberra ranked lowest because it combined relatively low persistence and low amplification despite moderate event-frequency characteristics. These differences confirm that drought hotspot interpretation depends on which drought dimension is emphasized.

4.6. Methodological Implications, Limitations, and Future Extensions

The framework has three main methodological implications. First, PET selection matters. Replacing Thornthwaite PET with SILO FAO56 reference PET changed the hydroclimatic baseline and strengthened the physical basis of the SPEI analysis. This is particularly important in Australia because evaporative demand varies strongly across climatic settings. Second, probabilistic SPI and SPEI calculation is preferable to empirical month-wise standardization for a drought-index study intended to be comparable with established SPI/SPEI practice. Third, serial-correlation-aware trend testing provides a more conservative and defensible interpretation of hydroclimatic trends than the classical Mann-Kendall test alone.

The study also has limitations. The analysis is based on nine selected SILO point locations and should not be interpreted as a spatial drought atlas, a national gridded assessment, or a formal regionalization of Australian

drought risk. The selected locations capture broad climatic contrasts, but they cannot represent all catchment-scale hydrological processes, soil-moisture dynamics, groundwater buffering, reservoir operations, irrigation demand, vegetation stress, or ecological drought responses. Standardized indices also measure anomalies relative to local climate and therefore do not directly represent absolute water scarcity. This limitation is particularly relevant for arid locations such as Alice Springs.

Another limitation is that SILO is an interpolated climate product. Although the downloaded daily records were complete for the selected locations and source-code fields were inspected where available, early twentieth-century uncertainty may still be higher because of lower station density in parts of Australia. The 1950–2025 sensitivity analysis was included to address this issue, but it cannot fully remove uncertainty associated with historical interpolation. In addition, the composite hotspot score is a screening tool based on selected components and weighting assumptions. The random-weight and leave-one-component-out analyses help assess robustness, but they do not make the score an optimized prediction model.

Future work should extend the present point-location benchmark into a fully gridded drought-risk assessment using the same FAO56-based SPI/SPEI workflow. Additional variables such as soil moisture, streamflow, groundwater levels, reservoir storage, vegetation indices, land use, irrigation demand, and population or agricultural exposure would allow drought hazard to be linked more directly with hydrological and socio-economic impacts. Climate-model projections could also be incorporated to evaluate whether the historical SPI–SPEI divergence and hotspot-screening patterns persist or intensify under future warming scenarios. In this sense, the present study should be viewed as a transparent and reproducible benchmark that provides a foundation for broader spatial and impact-based drought assessment.

5. Conclusions

This study developed a transparent and reproducible open-data point-location drought benchmark for Australia using long-term SILO DataDrill climate records for nine selected locations during 1900–2025. The framework combined hydroclimatic baseline assessment, FAO56-based climatic water balance, probabilistic SPI-12 and SPEI-12 calculation, drought-event and persistence metrics, Hamed–Rao modified Mann–Kendall and Sen’s slope trend analysis, SPI–SPEI divergence diagnostics, and sensitivity-tested composite hotspot screening. The study was not intended to provide a gridded national drought atlas or a formal regionalization of Australian drought risk; rather, it provides a consistent benchmark for comparing drought behaviour across selected locations under a common open-data workflow.

The hydroclimatic baseline confirmed that drought-relevant water stress cannot be inferred from precipitation alone. Darwin had the highest mean annual precipitation among the selected locations, but its high atmospheric water demand produced a negative climatic water balance. Alice Springs combined the lowest precipitation with the highest FAO56 PET and the strongest long-term water-balance deficit. Sydney, by contrast, was the only location with a positive long-term mean annual climatic water balance. These contrasts show that atmospheric water demand is essential for interpreting drought stress across climatically diverse Australian settings.

The SPI-12 and SPEI-12 results showed that precipitation variability remains a major control on long-term drought fluctuations, but the inclusion of FAO56 PET changed drought classification, persistence, and severity at several locations. SPEI-12 generally indicated stronger recent drought persistence than SPI-12 in Perth, Adelaide, Melbourne, and Alice Springs. SPI–SPEI divergence was most pronounced in Alice Springs, where SPEI-only drought months and severity amplification showed that atmospheric water demand substantially strengthened the water-balance drought signal relative to precipitation-only SPI.

The trend and hotspot analyses identified Perth and Adelaide as the most robust high-ranking drought locations in the point-location benchmark. Both locations showed significant negative trends in annual mean SPI-12 and SPEI-12 and significant increases in drought-month persistence. The equal-weight composite hotspot score ranked Perth first, Adelaide second, and Melbourne third, while random-weight sensitivity analysis confirmed Perth and Adelaide as the most stable top-ranked locations. Melbourne had strong duration, severity, and persistence components, but its monotonic trend signals were not statistically significant after serial-correlation adjustment. Alice Springs ranked lower in the overall composite score but had the strongest warming-amplification component, indicating a distinct drought profile dominated by atmospheric-demand sensitivity rather than event frequency or cumulative standardized severity.

Overall, the study provides a reproducible and sensitivity-aware benchmark for interpreting long-term drought behaviour across selected Australian point locations. Its main value lies in integrating open climate data, physically improved PET representation, probabilistic SPI/SPEI calculation, event-based drought characterization, persistence analysis, autocorrelation-adjusted trend testing, SPI–SPEI divergence, and hotspot-weighting

sensitivity within a single coherent workflow. Future work should extend this point-location framework to fully gridded analyses and incorporate soil moisture, streamflow, groundwater levels, reservoir storage, vegetation stress, irrigation demand, socio-economic exposure, and climate-model projections to support more spatially complete drought-risk and water-scarcity assessments for Australia.

Supplementary Materials

The additional data and information can be downloaded at: <https://media.sciltp.com/articles/others/2607281503349950/WSD-26060121-SM.xlsx>. Detailed supporting analyses are provided in the Supplementary material. Supplementary Table S1 presents the complete Hamed–Rao modified Mann–Kendall and Sen’s slope statistics for annual mean SPI-12, annual mean SPEI-12, and 10-year moving SPI-12 and SPEI-12 drought-month ratios across all selected point locations. Supplementary Table S2 reports SILO daily data completeness for the 1900–2025 and 1950–2025 periods, while Supplementary Table S3 summarizes SILO source-code availability for the downloaded variables. Supplementary Table S4 presents the sensitivity of drought-event, persistence, and SPI–SPEI divergence metrics to the analysis period. Supplementary Tables S5 and S6 provide the leave-one-component-out and random-weight Monte Carlo sensitivity analyses for the composite hotspot ranking. Supplementary Table S7 reports the drought-index distribution fitting diagnostics used to support the probabilistic SPI-12 and SPEI-12 calculations.

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Data Availability Statement

The climate data used in this study are publicly available from the Australian SILO climate database through the SILO DataDrill service. Daily rainfall, maximum temperature, minimum temperature, SILO FAO56 short-crop reference potential evapotranspiration, and SILO Morton potential evapotranspiration records were retrieved for the selected point locations and processed to generate the monthly hydroclimatic variables, SPI-12, SPEI-12, drought-event metrics, trend statistics, SPI–SPEI divergence metrics, and hotspot-screening outputs used in this study. The processed tables and supplementary analysis outputs are provided with the manuscript as Supplementary material.

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Conflicts of Interest

The author declares no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the author used AI-assisted tools only for language polishing, grammar checking, and improving readability. The author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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