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The Drought Regime in Southern Africa and Recent Climate Change: Long-Term Trends in Climate Elements, Drought Indices and Descriptors

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Abstract

The impacts of climate change are globally evident and cause significant damage to ecosystems and human activities. These impacts intensify social and economic inequality in Southern Africa (SA), where agriculture is vital for livelihoods and economic development. This study aimed to assess long-term trends in climate elements and parameters relevant to drought regimes in SA to identify drought hotspots and relate them to socioeconomic indicators. The methods include the Theil–Sen slope estimator and the Mann–Kendall statistical significance test. The study analysed ERA5 data for the 1971–2020 to compute the Standardised Precipitation Index (SPI) and Standardised Precipitation Evapotranspiration Index (SPEI) drought indices and descriptors. Results of the trend analysis reveal (i) the existence in almost the entire SA of statistically significant trends of increasing temperature and potential evapotranspiration and decreasing precipitation; (ii) increasing drought risk hotspots in the SPI and SPEI across all timescales, in the north central rainforest region, south and southeast of SA, while decreasing in the northwest coast, central west region, and in the northeast more recently; and (iii) hotspots in the drought descriptors within the same regions, but of a smaller size. Our findings pinpoint drought hotspots in regions with moderate-to-high population density and agricultural systems that involve species vital for food security and of considerable socioeconomic and commercial importance, emphasising the significance of our results for managers and decision-makers.

Keywords: trend analysis; climate elements; drought hotspot; climate change; Southern Africa

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1. Introduction

The impacts of anthropogenic climate change are globally evident and alarming [1]. Climate change causes significant and, in many cases, irreversible damage to terrestrial, freshwater, coastal, and open-ocean marine ecosystems [2]. These adverse effects are projected to become more widespread, frequent, and severe, particularly in Africa, where they will intensify social and economic inequality, compromise agricultural productivity, and impact human and animal health, industry, and water resources [2,3]. In Southern Africa (SA), where agriculture is a vital part of rural livelihoods and economic development [4,5], these challenges are further worsened by population growth, limited financial resources,

and inadequate management practices [6], which will adversely affect vulnerable and poor farmer groups with little capacity to adapt [7].

According to the World Meteorological Organisation, extreme climatic and hydrological events, especially droughts, caused significant loss of life and substantial economic damage across Africa between 1970 and 2019 [8]. For example, about 15% of the total population in the Southern African Development Community (SADC) region (two-thirds of SA countries) experienced food insecurity in 2022 [9]. These impacts are likely to intensify, driven by rising trends in surface air temperatures in SA [10,11], changes in precipitation patterns, and increasing frequency and severity of extreme weather events such as droughts, floods and heat waves [12]. Furthermore, the substantial seasonal variability in precipitation [13,14] influenced by sea surface temperature (SST) anomalies and El Niño-Southern Oscillation (ENSO) events [13,15] has significant climatological implications in the SA region [16]. Recent studies on drought in SA from 1971 to 2020 revealed pronounced spatiotemporal variability in drought frequency, duration, severity and intensity. For example, droughts assessed with the Standardised Precipitation Index (SPI) occurred on average once every 2.2 years at the 3-month scale, 3.5 years at the 6-month scale, 5.3 years at the 9-month scale, and 7.9 years at the 12-month scale [17]. Multi-year droughts have also become more frequent [2]. Additionally, the area affected by drought increased by an average of 9.1% per decade when assessed using the Standardised Precipitation Evapotranspiration Index (SPEI), and with slightly lower estimates when using the SPI [17].

The recognised influence of climate variability on natural ecosystems and human activities has generated growing scientific interest in verifying and analysing trends in climate elements as a way to anticipate and mitigate potential future impacts [10,11]. Examining long-term temperature trends is crucial as it provides key insights into the region's climate variability [18]. The existence of statistically significant long-term trends in climate elements (e.g., precipitation and air temperatures) serves as an indicator of climate change and can play a crucial role in changing the spatiotemporal distribution of drought descriptors [17]. In this context, studying potential evapotranspiration (PET) trends is fundamental to understanding the effect of air temperature on drought, which is associated with the processes of evaporation and evapotranspiration, and therefore also essential to support effective water resource management. The interest in determining trends in climate elements extends not only to human activities' demands but also to the needs of natural ecosystems and biodiversity [19]. Consequently, studies highlight that quantifying drought trends is essential to improve our understanding of uncertainties in water demand in diverse natural systems [20].

The literature has revealed an increasing number of studies examining trends in climate variables globally and, more specifically, in SA. For example, Sian et al. [19] assessed trends in precipitation, air temperature, and PET across Africa over the climate normal period of 30 years (1991–2020). Archer et al. [13] analysed the evolution of summer rainfall from 2014 to 2016 in SA, emphasising lessons from drought early warning in SADC and the importance of raising awareness and enhancing people's capacity to adapt to droughts. Sian et al. [14] explored multi-decadal variability and projected changes in precipitation over SA. Nooni et al. [4] provided a spatiotemporal characterisation of evapotranspiration trends related to the self-calibrating Palmer Drought Severity Index (scPDSI) in Sub-Saharan Africa. Um et al. [20] examined drought trends on a broader scale, evaluating the role of PET in drought events in East Asia, Europe, the United States, and West Africa in the Northern Hemisphere. Other researchers investigate trends in climatic elements and parameters, but only in the short or long term and within specific subregions of Africa [21–23]. Despite these valuable contributions, we found no record of any study that has evaluated trends across a wide range of conditions—namely various climatic elements and parameters—over a

recent and extensive period of 50 years, encompassing several subperiods and covering the entire SA [24].

Furthermore, a recent study examined the drought regime in SA, specifically the long-term spatiotemporal distribution, including inter-annual and intra-annual variability of primary drought descriptors across various timescales and drought categories. The study also identified significant trends in precipitation throughout much of SA. This finding prompts the following research questions: Are there statistically significant long-term trends in other climate variables in SA? If so, are these trends consistent over the 50 years? Do the trends occur throughout the year, or are they confined to specific months or seasons? Do long-term trends in climate variables indicate corresponding trends in drought indices? And do these trends in drought indices manifest as changes in drought descriptors?

Therefore, this study aims to address these research questions through a trend analysis that identifies the trend and its statistical significance. This analysis employs the most recent and suitable methodology to evaluate long-term trends of various elements and climate parameters related to drought in SA. Specifically, the trend analysis concentrates on surface air temperature, precipitation, PET, SPI, SPEI, and drought metrics such as drought number (DN), duration (DD), severity (DS), and intensity (DI), as well as the number of drought months (DM). To enhance understanding of these changes, we will examine trends over multiple sub-periods and explore the relationship and influence of climatic variable trends on drought indicators.

This research aims to significantly contribute to filling identified gaps in scientific knowledge and tackling the ongoing challenges posed by droughts and climate change in the Southern Africa (SA) region. Despite the crucial importance of understanding these phenomena, there is a notable lack of comprehensive assessments and detailed knowledge regarding the impacts of droughts and climate change in the Southern Hemisphere, particularly in SA. Existing regional studies are limited in number and scope, often focusing mainly on localised areas rather than offering a broader, continental overview. This fragmented approach leaves considerable gaps in understanding the regional and transboundary dynamics of climate change and droughts, essential for effective planning and mitigation strategies.

The lack of a unified and comprehensive evaluation of these issues creates a significant challenge for decision-makers, as they do not have the necessary data and insights to develop informed policies and strategies. This study fills this critical gap by providing a thorough and region-wide analysis of climate trends and drought regimes over an extended period. By using advanced methodologies and high-resolution data, this research delivers vital information to support local, regional, and national managers and policymakers in reducing the impacts of climate change and droughts. This aligns with the recommendations of the SADC, which has stressed the urgent need for reliable and actionable data to guide sustainable development and resilience-building efforts across the region [9]. The results and conclusions of this study aim to support the mitigation of drought impacts, the development of more effective adaptation and management strategies for water resources and agriculture, the promotion of ecosystem conservation, and the enhancement of adaptation strategies to current and future climate conditions [18].

2. Materials and Methods

2.1. Study Area

SA is situated in the southern hemisphere and is bordered by the Atlantic Ocean to the west and the Indian Ocean to the east (Figure 1a). The region includes 10 countries: Angola, Botswana, Eswatini (Swaziland), Lesotho, Malawi, Mozambique, Namibia, South Africa, Zambia, and Zimbabwe. According to the Köppen–Geiger climate classification (Figure 1b),

SA has three primary climate types: tropical, arid, and temperate [25]. The SA climate is characterised by two seasons: a cool and dry winter, from April to October, and a hot and rainy summer, from November to March [11]. SA has six main terrestrial biomes or ecoregions (Figure 1a): deserts and xeric shrublands; flooded grasslands and savannas; Mediterranean forests, montane grasslands and shrublands; tropical and subtropical grasslands, savannas, and shrublands; and tropical and subtropical moist broadleaf forests [26].

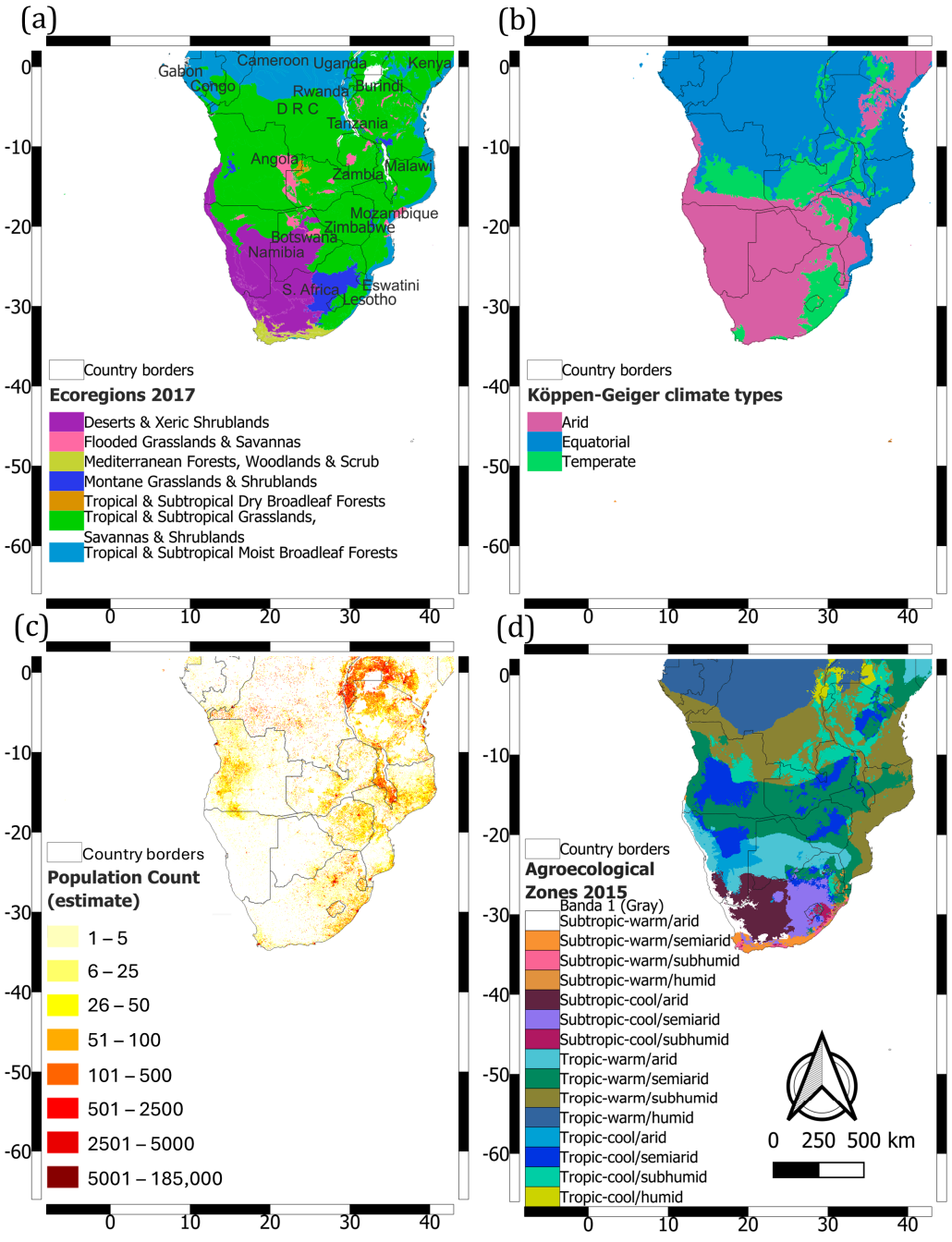


Figure 1. Political map: (**a**) ecoregions, (**b**) Köppen–Geiger climate types of Southern Africa, (**c**) Population Count, (**d**) Agroecological Zones. Adapted from Dinerstein et al. [26], Beck et al. [25], Rose et al. [27] and HarvestChoice and IFPRI [28].

The SA population (Figure 1c) is approximately 204 million people, unevenly distributed (e.g., 31% South African, 18% Angolan, and 16% Mozambican), with high levels of poverty and significant health and food challenges [29]. SADC reports that approximately 40% of SA's total population lives at or below the poverty line. In comparison,

more than 15% of the population faced food insecurity, partly influenced by the impacts of the 2014–2016 El Niño-induced drought. The effects of these climate-socioeconomic relationships tend to grow [9]. Rainfed agriculture is the primary source of subsistence, so agricultural activity is vulnerable to recurring droughts and climate variability in this region [30].

Africa's diverse agroecological zones (AEZs) fundamentally influence the distribution of cropping systems by defining specific environmental conditions such as elevation and climate, which determine the crops that can be successfully cultivated in each region (Figure 1d). The arrangement of various cropping systems across the continent directly correlates with these distinct zones [31,32]. According to Nitin et al. [33], the distribution patterns of AEZs and their associated crops are as follows: the Humid Zone supports cash and perennial crops thriving in high moisture environments, including cacao, rubber, oil palm, and Robusta coffee; cropping systems in the Highland Zone are determined by elevation and generally involve commercial-scale crops that prefer cooler temperatures, such as Arabica coffee (commercial scale), wheat, and tea; cropping systems in arid regions are limited but can support specific crops, often requiring supplementary water, such as maize, cotton, sorghum, and soybean (with irrigation); the Semi-arid and Sub-humid Zones share similar cropping system distributions, focusing on staple food crops and legumes, including maize, beans, peanuts, and soybeans. The desert is classified as an AEZ but lacks a cropping system.

2.2. Data

We used the fifth-generation reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF), known as ERA5, which the Copernicus Climate Change Service provides [34]. This state-of-the-art dataset combines historical, continuous, and homogeneous observational data from 1950 to the present with advanced numerical weather prediction models. ERA5 provides a high spatial resolution of roughly 31 km ($0.25^\circ \times 0.25^\circ$) and hourly and monthly temporal resolution, ensuring a consistent and detailed representation of the Earth's atmosphere, land surface, and ocean conditions. This consistency makes ERA5 especially suitable for long-term studies, such as climate research, trend analysis, and extended monitoring.

Moreover, ERA5's multivariable nature enables integrated analyses by providing a wide range of atmospheric, oceanic, and land variables, such as temperature, wind, humidity, precipitation, and radiation. Additionally, ERA5 employs advanced data assimilation techniques, which integrate observations from multiple sources, including remote sensing data, ground-based measurements, and radiosondes, into a unified, coherent dataset. These techniques effectively address data gaps and correct biases, resulting in a more accurate and reliable representation of the Earth's atmospheric conditions [35].

While satellite remote sensing data is invaluable for a wide range of applications, it has some limitations: (i) certain satellites, such as geostationary satellites, have very low spatial resolution, whereas polar-orbiting satellites typically exhibit low temporal resolution, resulting in long revisit times and potential data gaps [36]; (ii) observations from optical and infrared radiometers onboard satellites are frequently affected by cloud cover, which can obstruct surface observations and reduce data quality in specific regions [37]; (iii) differences in calibration standards between satellite missions can introduce inconsistencies in long-term datasets, complicating cross-mission comparisons and trend analysis [38]; and (iv) inherent limitations, such as temporal gaps in historical data, spatial and temporal resolution constraints, and potential data quality issues, must be carefully considered, particularly in studies that aim to analyse periods predating the advent of satellite technology.

Given these limitations of satellite remote sensing, ERA5 was chosen as the primary dataset for this study because it offers consistent, high-resolution, and long-term data. We obtained ERA5 data covering the period from 1971 to 2020, covering the South African (SA) region, bounded by latitudes 0° and 35° South and longitudes 7.5° West to 42.5° East, with a horizontal resolution of 0.25° × 0.25° (latitude by longitude). Specifically, the meteorological variables extracted included the following: monthly averages of total precipitation (TP); total cloud cover (CC); monthly averages of 10 m wind speed (W10m); daily maximum and minimum temperatures at 2-metre height (TMAX2m and TMIN2m), from which daily and monthly maximum (Tmax) and minimum (Tmin) air temperatures were calculated. Geopotential data were also downloaded to compute Geopotential height (Z). The drought assessment and trend analysis were carried out on the monthly scale.

2.3. Methods

2.3.1. Drought Indicators

The drought was assessed with SPI and SPEI. These indices were calculated for each point of the ERA5 spatial domain and at 3-, 6-, 9- and 12-month timescales. SPI was computed with MATLAB Standardised Drought Analysis Toolbox (SDAT) function (version 1.0.0.0) using monthly TP as input [39,40]. The SPEI was calculated using the Vicente-Serrano R SPEI function based on the water balance [41]. The water balance is the difference between TP and PET. Among all the methods available to estimate PET, the FAO Penman–Monteith equation 56 was selected as the most adequate in the literature [17,42]. PET was computed with Vicente-Serrano R SPEI function using W2m, Tmax, Tmin, Z, CC, and Latitude as input data. Using Allen et al.'s equation, W2m was estimated based on W10m and the Geopotential height [42].

Drought was defined cumulatively as a consecutive series of months during which the drought index remains negative, less than or equal to −1 in at least one month of the drought period, and with drought intensity not exceeding −0.5. The drought descriptors (DM, DN, DD, DS and DI) were calculated using the SPI and SPEI and are specified for a given location and period as follows: DM is the number of drought months, i.e., months when the drought index is negative; DN is the total number of drought events; DD is the drought duration, i.e., the number of months between the start and end of a drought event; DS is the drought severity, i.e., the sum of the drought index values over the drought duration; and DI is the average drought severity, i.e., DS divided by DD [17,43].

2.3.2. Trend Analysis

Linear regression analysis is a statistical technique commonly used to estimate trend components in climate and other areas' time series [44,45]. Simple linear regression is an empirical statistical method that analyses the relationship between two variables—one dependent (in this study, a climate element or drought parameter) and the other independent (in this study, time)—by fitting a straight line to the data that best represents this relationship [45]. Therefore, linear regression models have two key parameters, the intercept and the slope [46]. Negative slope values indicate decreasing trends, while positive values indicate increasing trends [19,47]. However, robust linear regression, such as the Theil–Sen regression, is particularly valuable when data are affected by noise and outliers, as it provides more reliable trend estimates by effectively attenuating the influence of outliers and variability [48].

Therefore, in this study, the trend was assessed using regression analyses to estimate the slope of the regression line with two methodologies: linear regression and the Theil–Sen (TS) slope estimator. Linear regression was performed using a fitting function, which estimates the coefficients of an n-degree polynomial (n = 1, in this case) that best fits (in the

least squares sense) the data time series and also estimates the error, i.e., an estimate of a 95% prediction interval. The TS slope estimator is recognised as a method for robust linear regression, as the median of all possible pairwise slopes between data points [48]. Theil initially developed this regression method [49] and Sen later refined [50]. This is a robust and widely used method in non-parametric regression analyses in climate research.

The statistical significance of the linear regression trend was assessed using the Mann–Kendall (MK) test, a widely employed non-parametric method to evaluate the statistical significance of monotonic trends in climatological, hydrological, and environmental time series [47]. In this test, the null hypothesis (H_0) of no trend is tested against the alternative hypothesis (H_1) of a trend, either increasing or decreasing, in the series [47]. H_0 is rejected if the p-value is less than a predefined significance level, typically 0.05, i.e., the MK test will be evaluated at a 95% confidence level, indicating the presence of a significant trend [47,51,52]. We used a TS slope estimator that determines the trend and statistical significance.

We employed two methods to evaluate trends: (i) comparing the similarities and differences between spatial patterns and values obtained with different approaches, (ii) enhancing confidence in the results, and (iii) validating the findings with outcomes from alternative methods. All trend calculations were conducted for the entire SA region using built-in functions available in MATLAB R2024a, specifically: the polyfit [53], Sen_Slope [54] and Mann_Kendal [55] functions. The Sen_Slope function estimates the slope and the statistical significance (Theil–Sen test). Additionally, since the trend values per month or even year are small, the trend values per decade have been calculated and will be displayed. The trend analysis of the climate element fields and drought indices was conducted using the methodology described above for different periods, namely monthly series for: (i) the entire study period (50 years, 600 months), (ii) subperiods of 30, 25, and 10 years in duration (360, 300, and 120 months), and (iii) each month of the year across the entire study period (50-month series). However, the trending of drought descriptors was performed differently due to the nature of these data.

Drought is an extreme climate event that is relatively rare by definition. The probabilities of moderate (9.2%), severe (4.4%), or extreme (2.3%) drought conditions occurring total 15.9% [17]. Therefore, whether information on drought occurrence or characteristics is attributed to the initial month or distributed throughout the drought, the drought descriptor data are matrices with many more zeros than non-zero values. A large number of zeros in a dataset can significantly influence trend analysis, potentially leading to inaccurate assessments and conclusions. This is because many statistical models, especially those used for count data, assume a specific distribution of values, and a high proportion of zeros can deviate from this assumption, causing issues such as overdispersion or zero-inflation. Careful consideration of the origin and nature of these zeros, along with selecting appropriate statistical models, is crucial for reliable trend analysis [46]. Consequently, trend analysis of drought descriptors was carried out on a 12-element series covering consecutive 50-month periods. The series length was selected to satisfy four criteria: (i) be longer than 10, which is necessary for applying the linear regression and TS slope estimator function; (ii) be as short as possible to minimise or eliminate the number of zeros in the series; (iii) include an integer number of months; and (iv) avoid overlap between periods. Each series element contains the sum (DM and DN) or the average (DD, DS, and DI) of the drought descriptors calculated for the respective 50-month period.

2.3.3. Drought Hotspots

From a drought perspective, a hotspot refers to a geographic area prone to drought conditions due to low and variable rainfall, high temperatures, water scarcity, and socio-economic challenges. These areas are characterised by frequent and intense drought events,

which can cause significant environmental, agricultural, and socio-economic impacts, including reduced water availability, crop failures, food insecurity, and increased vulnerability of local populations. Drought hotspots are often regions where climate change exacerbates existing vulnerabilities, making them critical for monitoring, research, and implementing mitigation and adaptation strategies. Therefore, this study defines a drought hotspot as a region where the trends in drought-related climate variables and parameters are statistically significant and exhibit higher absolute values (i.e., where the strongest increasing and decreasing trends are observed). Drought hotspots will be analysed in relation to population density, ecoregions, AEZs, and farming systems (Figure 1).

3. Results

This section presents the trend analysis results using the TS slope estimator for climate elements (TP, Tmax, Tmin, PET) over the entire study period of 50 years, two consecutive subperiods of 25 years, and each month. These are described to verify seasonality and better understand the observed trends for all months (Section 3.1). It also covers the SPI and SPEI drought indices across four timescales, the complete 50-year period, and the two 25-year subperiods (Section 3.2). Additionally, drought descriptors (DN, DS, DI, DM, and DD) derived from SPI and SPEI are discussed (Section 3.3), along with the relationship between drought hotspots, population density, AEZs, and farming systems (Section 3.4). We do not present figures with all the results obtained, so we focus on the main results and emphasise brevity to avoid redundancy and ensure accuracy and rigour. Only results obtained using the TS slope estimator for trend magnitude and statistical significance testing are presented, as the linear regression and MK test results are similar. The 30-year trends were calculated because this is the period recommended by the World Meteorological Organisation, but are not shown because the results are identical to those obtained for 25 non-overlapping periods. Ten-year trends were calculated to understand the temporal evolution of trends and the trends estimated for the 50, 30, and 25-year periods. These results are not shown because the area with statistically significant trends is much smaller due to the short analysis period. Tables 1–3 present the minimum, maximum and 10th and 90th percentile values of the trends identified in each climate element and parameters analysed to facilitate the interpretation of the Figures.

Table 1. Minimum (Min), maximum (Max), and the 10th and 90th percentiles (P10 and P90) of climate trends (unit/decade) in Southern Africa were estimated using the Theil–Sen Slope method. These include Total Precipitation (TP), Maximum air temperature (Tmax), Minimum air temperature (Tmin), and Potential Evapotranspiration (PET).

	Periods	Min	P10	P90	Max
TP (mm)	1971–2020	−29	−9.3	0.00	7.11
	1971–1995	−28	−4.8	0.39	26.7
	1996–2020	−28	−8.2	0.44	34.1
	1971–2000	−32	−5.1	0.29	14.5
	1991–2020	−35	−9.9	0.14	27.1
Tmax (°C)	1971–2020	−0.13	0.14	0.39	0.59
	1971–1995	−0.25	0.16	0.69	1.05
	1996–2020	−0.50	0.06	0.67	1.25
	1971–2000	−0.22	0.10	0.46	0.83
	1991–2020	−0.37	0.02	0.50	0.90

Table 1. *Cont.*

	Periods	Min	P10	P90	Max
Tmin (°C)	1971–2020	−0.05	0.13	0.26	0.50
	1971–1995	−0.10	0.06	0.39	0.64
	1996–2020	−0.25	0.13	0.34	0.67
	1971–2000	−0.12	0.07	0.30	0.58
	1991–2020	−0.21	0.10	0.29	0.62
PET (mm)	1971–2020	−2.50	0.51	2.49	3.66
	1971–1995	−2.05	0.84	4.66	7.14
	1996–2020	−3.54	−0.20	4.31	6.81
	1971–2000	−1.79	0.55	3.26	6.44
	1991–2020	−3.26	−0.40	3.36	5.62

Table 2. Minimum (Min), maximum (Max), and the 10th and 90th percentiles (P10 and P90) of drought indices' trends (unit/decade) in Southern Africa were estimated using the Theil–Sen Slope method. These include the Standardised Precipitation Index (SPI) and the Standardised Precipitation Evapotranspiration Index (SPEI).

	Trend Analysis for the Period 1971–2020				
	Timescale	**Min**	**P10**	**P90**	**Max**
SPI	3 months	−0.58	−0.42	−0.06	0.39
	6 months	−0.62	−0.50	0.00	0.42
	9 months	−0.65	−0.53	0.06	0.47
	12 months	−0.67	−0.56	0.08	0.50
SPEI	3 months	−0.53	−0.36	0.01	0.38
	6 months	−0.58	−0.43	0.07	0.39
	9 months	−0.60	−0.46	0.13	0.44
	12 months	−0.62	−0.49	0.15	0.47

Table 3. Minimum (Min), Maximum (Max), and the 10th and 90th percentiles (P10 and P90) of drought descriptors' trends (unit/decade) in Southern Africa are estimated using the Theil–Sen Slope method. These include the Drought Number (DN), Drought Months (DM), Drought Duration (DD), Drought Severity (DS), and Drought Intensity (DI), computed with the Standardised Precipitation Index (SPI) and the Standardised Precipitation Evapotranspiration Index (SPEI).

	Trend Analysis for the Period 1971–2020								
		SPI				**SPEI**			
	Timescale	**Min**	**P10**	**P90**	**Max**	**Min**	**P10**	**P90**	**Max**
DN	3 months	−0.93	0.0	0.6	1.3	−0.9	0.0	0.6	1.3
	6 months	−0.8	0.0	0.4	0.8	−0.7	0.0	0.5	0.8
	9 months	−0.67	0.0	0.3	0.6	−0.5	0.0	0.3	0.6
	12 months	−0.46	0.0	0.0	0.5	−0.4	0.0	0.0	0.5
DM	3 months	−9.1	−0.6	8.4	13	−10	1.3	9.6	13
	6 months	−9.6	−1.1	10	13	−11	0.4	11	14
	9 months	−11.3	−2.1	11	13	−13	−0.5	12	14
	12 months	−12.4	−2.7	12	13	−13	−1.2	12	14
DD	3 months	−4.8	−0.4	2.1	11	−5.1	−0.2	2.3	11
	6 months	−6.7	−0.9	2.9	12	−8.1	−0.5	3.3	9.9
	9 months	−7.2	−1.4	3.6	12	−9.6	−0.9	4.2	15
	12 months	−9.8	−2.2	3.9	12	−9.7	−1.2	4.5	13

Table 3. *Cont.*

		Trend Analysis for the Period 1971–2020							
		SPI				SPEI			
	Timescale	**Min**	**P10**	**P90**	**Max**	**Min**	**P10**	**P90**	**Max**
DS	3 months	−11.9	−2.1	0.4	3.9	−14	−7.1	−1	9.5
	6 months	−11.9	−2.7	0.9	5.8	−11	−6.4	0.0	10
	9 months	−12.2	−3.5	1.7	6.4	−13	−6.1	1.1	10
	12 months	−11.9	−4.0	2.3	8.8	−13	−5.2	1.2	12
DI	3 months	−0.34	−0.09	0.03	0.23	−0.33	−0.11	0.01	0.25
	6 months	−0.35	−0.16	0.05	0.26	−0.34	−0.16	0.03	0.28
	9 months	−0.38	−0.17	0.07	0.36	−0.38	−0.18	0.04	0.33
	12 months	−0.38	−0.16	0.09	0.30	−0.36	−0.18	0.03	0.33

3.1. Trends in Climate Variables

TP trend analysis based on the TS slope estimator over the 50-year study period (Figure 2a) revealed widespread decreasing trends across most of the SA region. The most pronounced and statistically significant declines were observed in the Democratic Republic of the Congo (DRC), particularly in the rainforest zone, as well as in Burundi, northern Angola, Mozambique and South Africa. Conversely, statistically significant increasing trends in TP (Figure 2a) were identified in much smaller areas, mainly in the northwestern coast of SA, including the west coast of Angola and Gabon, and small spots in South Africa.

Trend patterns for the 25-year sub-periods (Figure 2b,c) are broadly consistent with those observed over the whole 50-year period, particularly during (i) the first 25-year interval (Figure 2b), where significant decreasing trends were detected in parts of northern SA, South Africa, Lesotho, and southern Mozambique; and, (ii) the second half of the study period for the statistical significance (Figure 2c). Results for these shorter 25-year periods also exhibited high magnitudes in decreasing TP trends (Figure 2b,c). Increasing TP trends for the 25-year periods are much higher than for the 50-year periods. The patterns of TP trends for the 30-year periods are very similar to those obtained for the 25-year periods. However, the Min and P10 values of the decreasing trends are slightly lower.

Trend analysis results for TP for each month of the year and the entire 50-year study period (Figure 3) corroborate the results obtained for all months (Figure 2a) and disclose a seasonal variability in the sign, value and area with statistically significant decreasing and increasing trends. Trends' spatial patterns for all and each month are relatively similar, especially during the core rainy season (from November to April). Min and P10 values of the decreasing trends are smaller this season. Decreasing trends in the dry season are much higher, except in October, when the TP trend Min and P10 are similar to the rainy season. The lowest trends are observed in the DRC, northern Angola, Mozambique and relatively small/localised areas of southern South Africa. Total area with statistically significant trends is approximately constant during the rainy season, but is smaller from June to August and higher in September and November.

During the 50 years, Tmax exhibits a high increasing trend throughout SA, statistically significant in almost the entire territory (Figure 2d). The only exception is a narrow region in a SW-NE direction extending from the northern coast of South Africa toward central SA to southern Zambia. The estimates of Tmax trends for the two consecutive 25-year periods (Figure 2e,f) exhibit spatial patterns compatible with those observed for the entire study period (Figure 2d) and also allow us to verify how Tmax trends have evolved. In the first period (Figure 2e), a region of statistically significant trends extends from the extreme north to 25° S and from the west coast to approximately 35° E. In the second period (Figure 2f), the region of statistically significant trends is smaller and concentrated in the tropical forest

region, the SE region (NE South Africa, Eswatini, and southern Mozambique), and the central-western region (northern Namibia and southern Angola). It is worth noting that statistically significant increasing trends in Tmax are evident across much of SA during both halves of the study period**,** as well as a notable decreasing trend observed, respectively, during the first and second subperiods in the Angolan coast (Figure 2e,f).

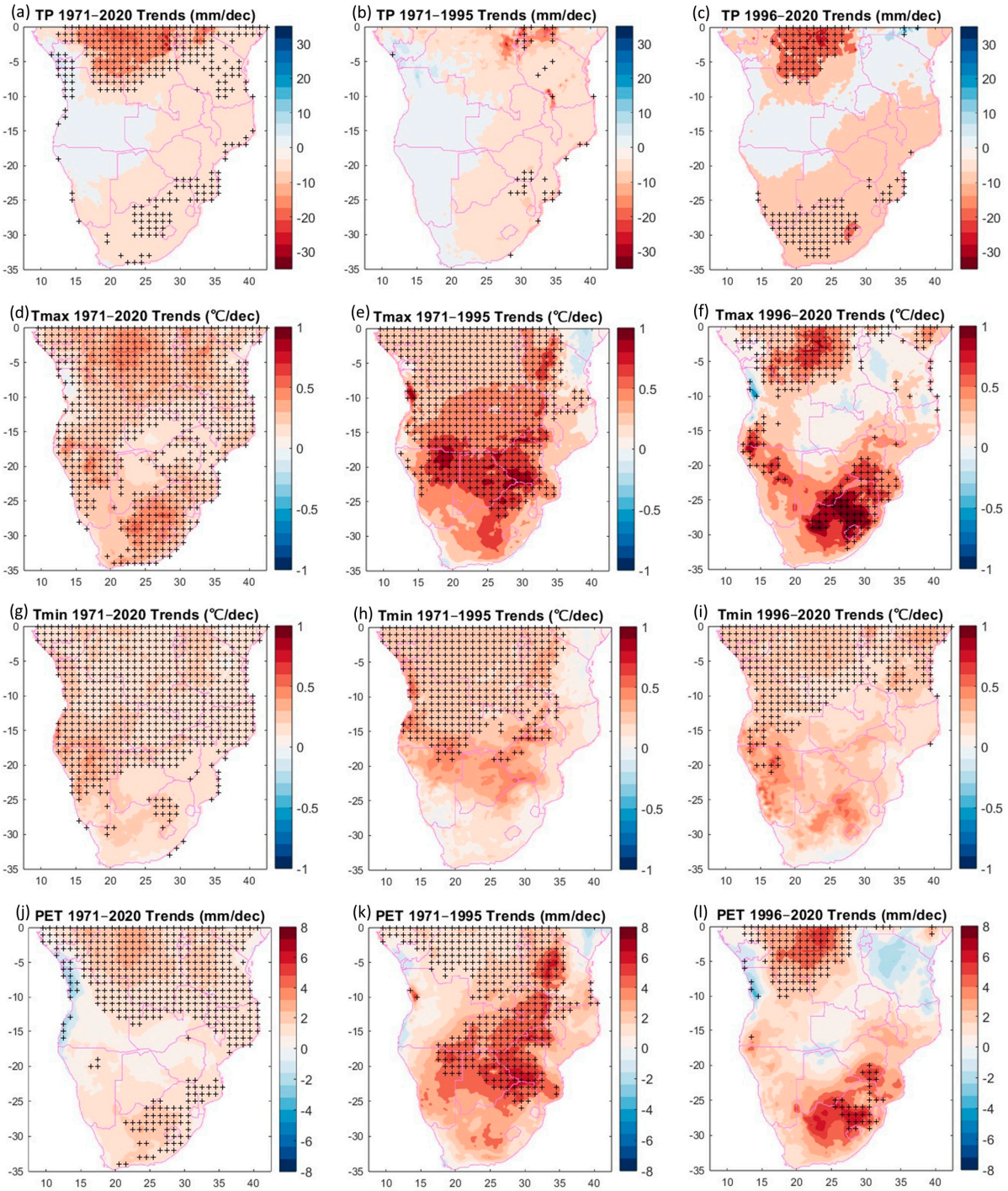


Figure 2. Theil–Sen estimates of trends and statistical significance (+) of Total Precipitation, (TP, panels (**a**–**c**)), Maximum Temperature (Tmax, panels (**d**–**f**)), Minimum Temperature (Tmin, panels (**g**–**i**)) and Potential Evapotranspiration (PET, panels (**j**–**l**)), in the 1971–2020 (**left panels**), 1971–1995 (**central panels**) and 1996–2020 (**right panels**) periods.

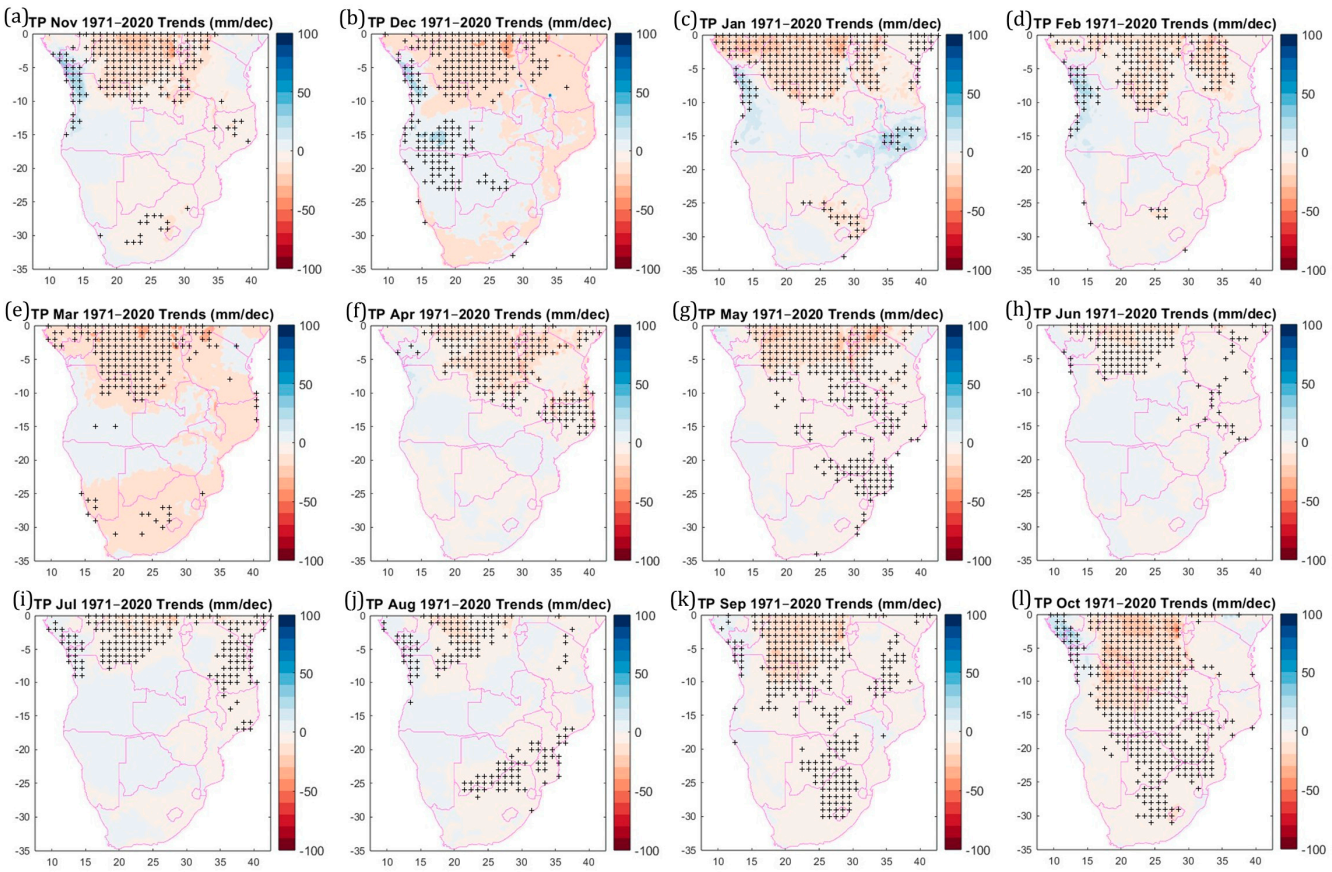


Figure 3. Theil–Sen estimates of trends and statistical significance (+) of Total Precipitation (TP), for each month of the year (November to October), in the 1971–2020 period.

Tmax trend analysis for each month of the year (Figure 4) reveals spatially coherent patterns during most of the rainy season (from December to March), with statistically significant increasing trends in the northern and southern parts of the SA, with relatively high Max and P90 values. During these months, Tmax trends are not statistically significant in the central region of the SA, between −10 and −28° S latitude. The area of significantly increasing trends is the smallest in April, when it is almost confined to the tropical forest region; it increases and spreads southward during the region's dry season (May to October), until it nearly covers the entire SA area in September and October.

The results reveal that Tmin over the 50 years presents increasing trends across much of SA (Figure 2g). Trends in the two 25-year subperiods (Figure 2h,i) also show increasing Tmin, with spatial patterns very similar to those for the entire period. Additionally, the area of statistically significant increasing trends decreases when the analysis evolves from the 50-year (1971–2020) to each subperiod (1971–1995 and 1996–2020). In the first subperiod, the region of statistically significant trends is roughly defined between 0° and 18° S and between the west coast and 35° E (Figure 2h). In the second, the region extends across the entire range of longitudes from 0° to 10° S, with some small areas in northern Namibia and southern Angola (Figure 2i).

Tmin in each month of the year (Figure 5) exhibits statistically significant increasing trends over most of the territory with relatively low seasonality. However, the region with statistically significant increasing trends in Tmin is larger during the rainy season (October to March). A very notable reduction in the area with statistically significant increasing trends is observed in the region between latitudes (- 10° S and - 35° S), especially in April (Figure 5f), in South Africa, Botswana, Zambia, Zimbabwe, Mozambique, Malawi, Lesotho, and Eswatini and in May (Figure 5g) in Botswana, Zambia, Zimbabwe, Mozambique,

and Malawi. During these months, Tmin even shows decreasing trends (although not statistically significant) in smaller areas within these regions.

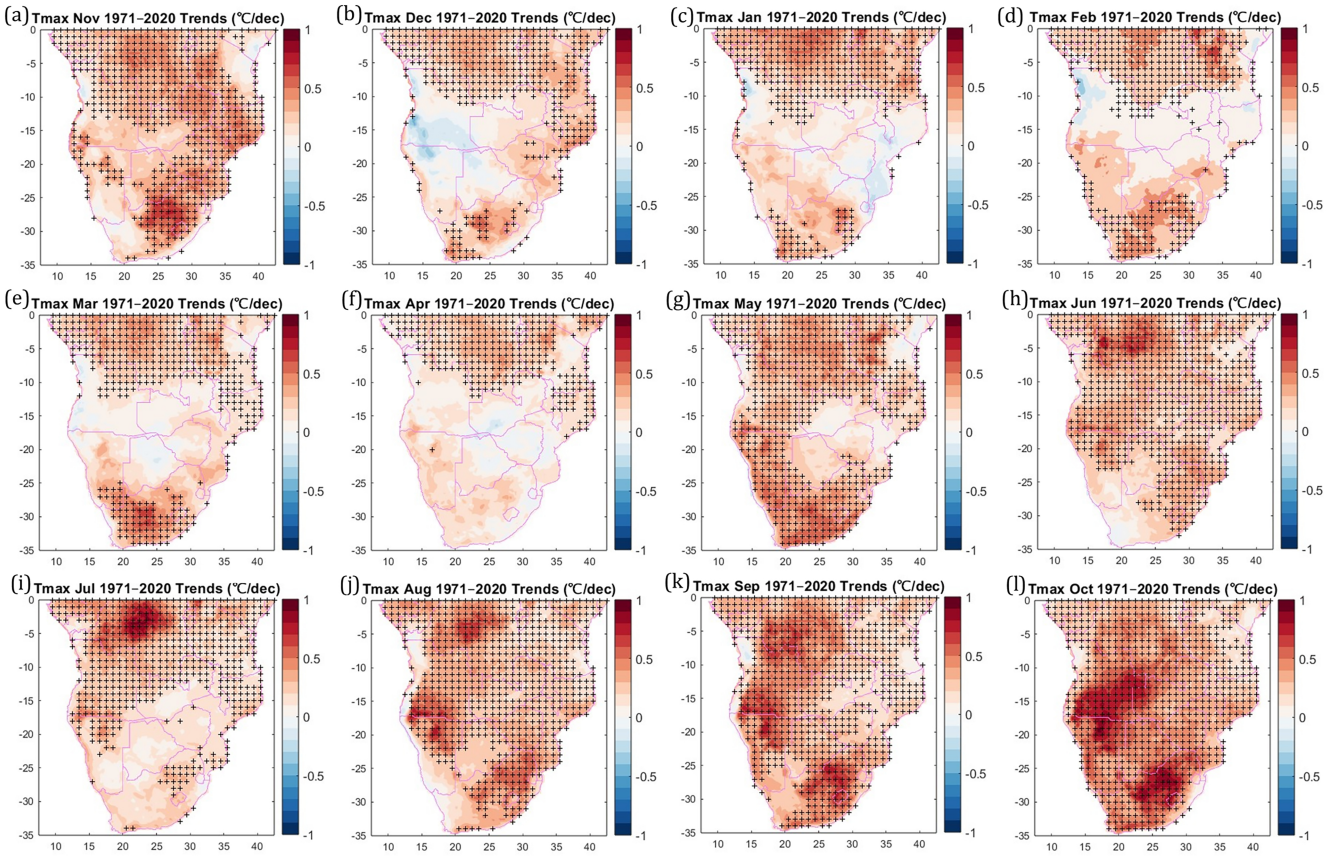


Figure 4. Theil–Sen estimates of trends and statistical significance (+) of maximum temperature (Tmax), for each month of the year (November to October), in the 1971–2020 period.

The PET trend analysis for the entire period (Figure 2j) and the two subperiods (Figure 2k,l) also reveals statistically significant increasing and decreasing trends in SA. The patterns of these trends are similar and appear to result from the patterns of the dependent climatic elements. The PET trend pattern for the entire period is very similar to the corresponding TP pattern, with positive and significant trends in the tropical forest region that decrease as they extend to South Africa, along the east coast. A region of negative trends on the coast of Angola also characterises this pattern. The trend patterns observed in the two subperiods resemble those obtained for Tmax. In the first period (1971–1995), the region of statistically significant trends is the north, from the west coast to 35° E, and the central region. In the second (1996–2020), the region of statistically significant trends is smaller, and includes the tropical forest and the SE region (NE South Africa, Eswatini, and southern Mozambique). Still, the maximum PET trends are similar to those of the first subperiod. Results reveal that PET exhibits increasing trends over the 50 years across the entire SA region, which doubled in the two 25-year subperiods.

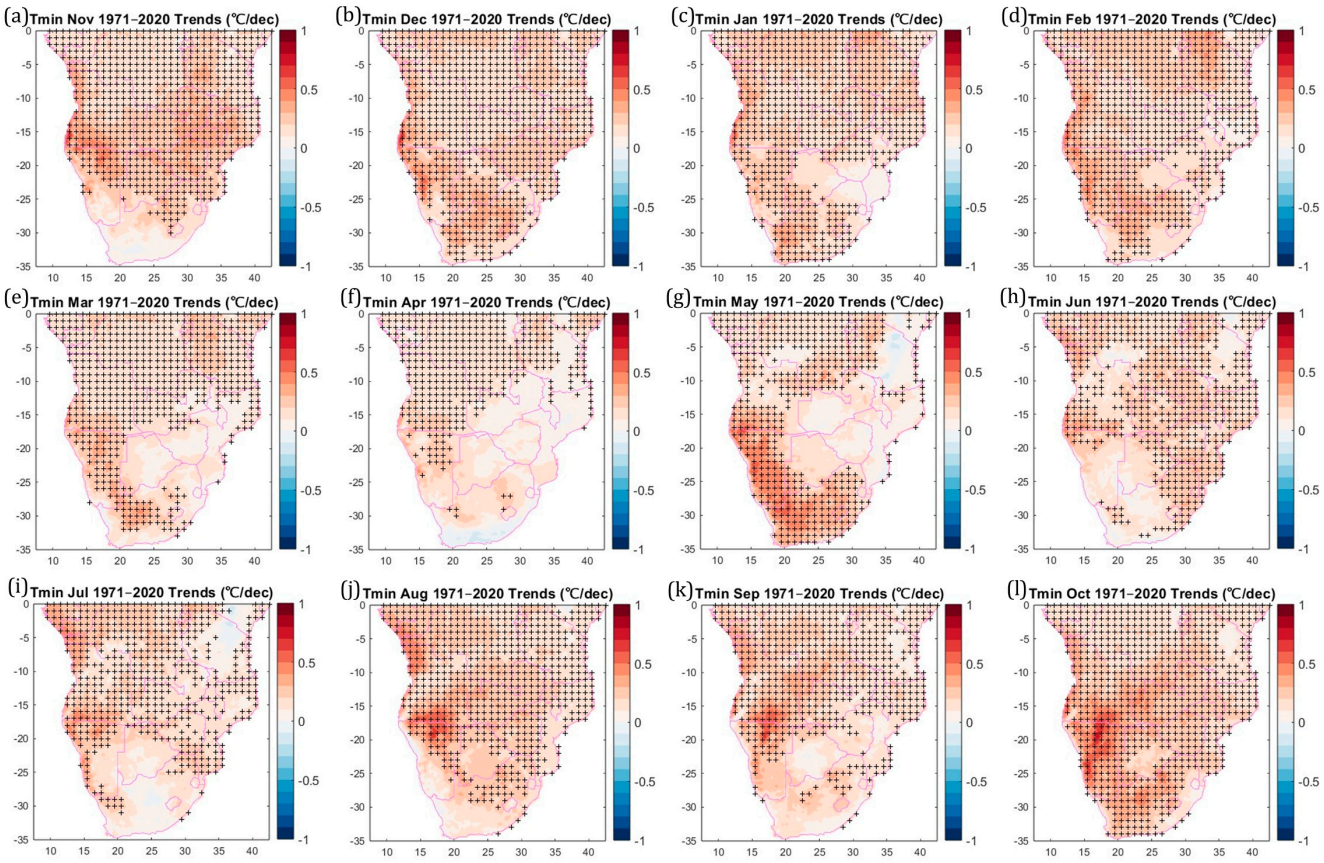


Figure 5. Theil–Sen estimates of trends and statistical significance (+) of minimum temperature (Tmin), for each month of the year (November to October), in the 1971–2020 period.

PET trends in each month of the year (Figure 6) exhibit high seasonality, with very different results for the dry and rainy seasons. Briefly and simply, in the dry season, trends are essentially increasing throughout SA, except for the small coastal region of Angola, similar to what is observed in the TP pattern (Figure 2a). In the rainy season, trends are also increasing in SA, except for a central region that varies in size and shape. Statistically significant trends are observed where the trends assume greater magnitudes. On the other hand, PET exhibits decreasing trends throughout almost the entire annual cycle, reaching minimum values in December. The PET lowest decreasing trends are particularly evident in Angola, Namibia, western Zambia, northern South Africa, and Botswana.

3.2. Trends in Drought Indices

Results of the trend analysis for the drought indices can be summarised as follows. The spatial patterns of the trends obtained for the two indices (Figures 7 and 8 and Table 2) are very similar. In addition, the trend patterns obtained for the entire period are relatively identical to those obtained for the first subperiod, but significantly different from the second ones. Nevertheless, the trend patterns for the whole period appear to result from the patterns obtained for each subperiod. The trends in the 50 years increase with the timescale, but the spatial pattern remains very similar. The maximum absolute trend values and area of statistically significant trends are higher for SPEI than for SPI. For the 1971–1995 period, the SPEI decreases from −0.7 on the 3-month time scale to −1.12 on the 12-month time scale. The area of statistically significant decreasing trends (decreased precipitation; increased drought) is much higher than for the increasing trends (increased precipitation; decreased drought), especially for the 50-year and first 25-year subperiod (1971–1995). The area of statistically significant increasing trends increases with the timescale, especially

during the most recent subperiod (1996–2020), when the SPEI trends reach their maximum value at the 12-month scale.

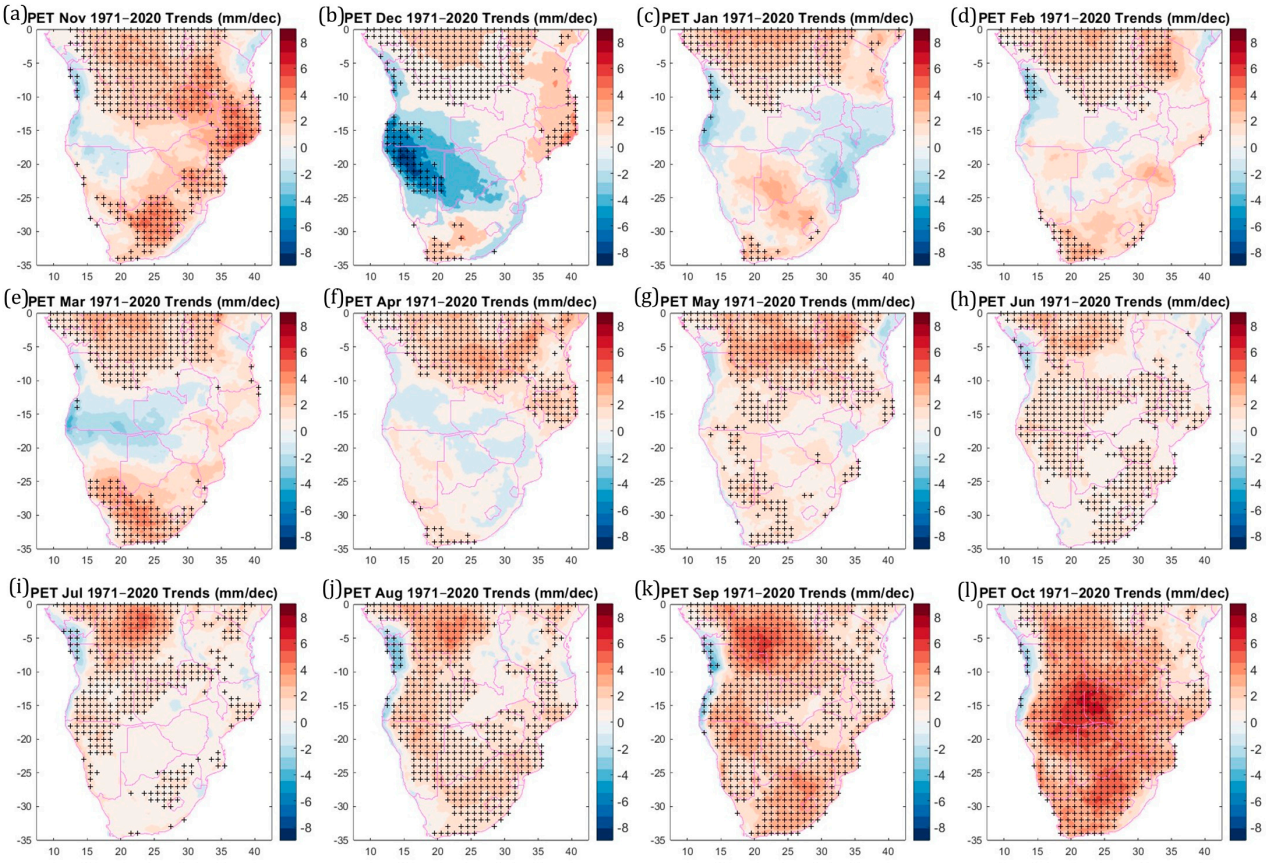


Figure 6. Theil–Sen estimates of trends and statistical significance (+) of Potential Evapotranspiration (PET), for each month of the year (November to October), in the 1971–2020 period.

In more detail, the patterns of the drought indices trends during the 50-year study period (Figures 7 and 8) are characterised by statistically significant negative trends in almost the entire SA, especially in the northern region of the tropical forests (DRC and north Angola), with decreasing intensity towards the central east and south region. Statistically significant increasing trends occur along the west coast and in southern Angola, northern Namibia, southern Zambia, and extend in the central region to north of Zimbabwe as the timescale increases (Figure 7a–d). Trends for the first 25-year sub-period (Figure 7e–h) present a meridional pattern with negative values in the longitudinal range between 20° W and 40° E, affecting most countries in the Central-East region, and increasing trends in a narrower West region, mostly over much of Angola, northern Namibia, and southern South Africa. In the second subperiod (1996–2020) (Figure 7i–l), statistically significant negative trends are observed in the tropical forest region, NE of Angola, DRC, Gabon and in southern SA (20 to 35° S), while increasing trends are evident in the NE of SA at the 3-month timescale but expands to the central and west coast as the timescale increases.

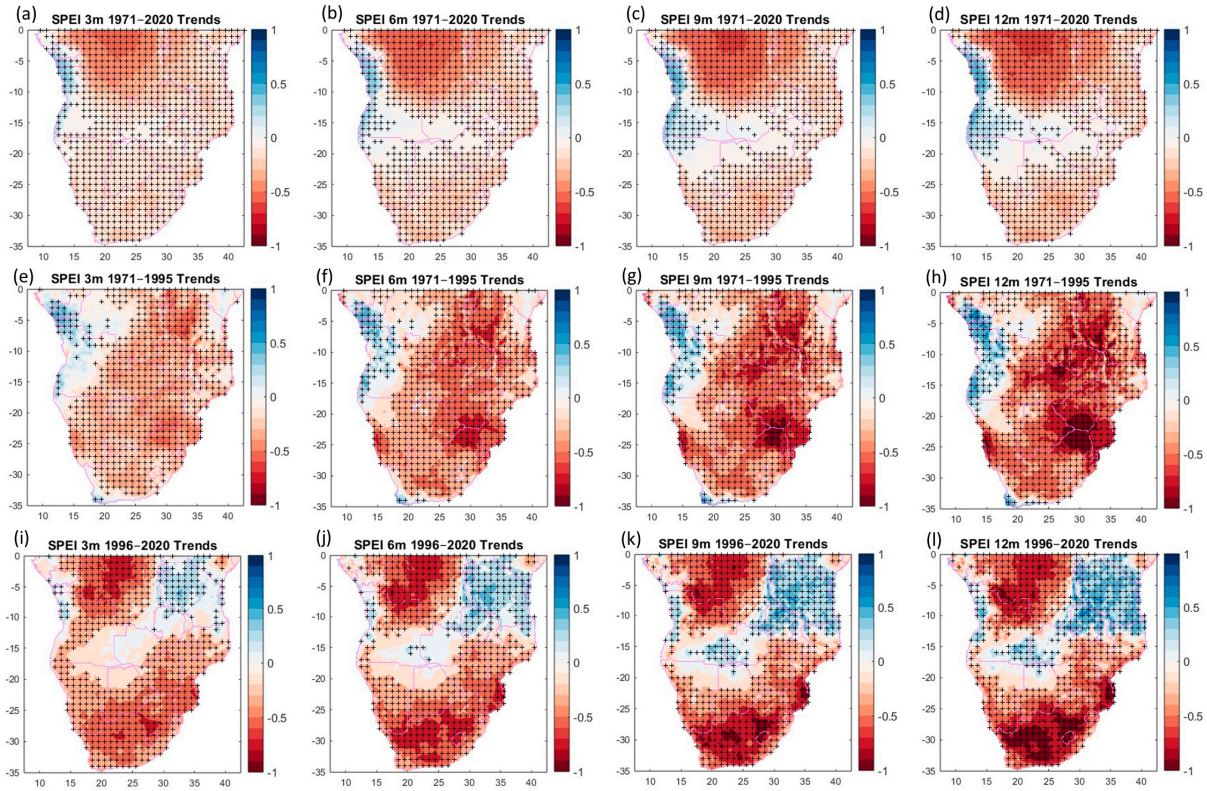


Figure 7. Theil–Sen estimates of trends and statistical significance (+) of the Standardised Precipitation Evapotranspiration Index (SPEI) at the 3-, 6-, 9- and 12-month timescales (from left to right) in the 1971–2020 (**upper panel**), 1971–1995 (**middle panel**) and 1996–2020 (**lower panel**) periods.

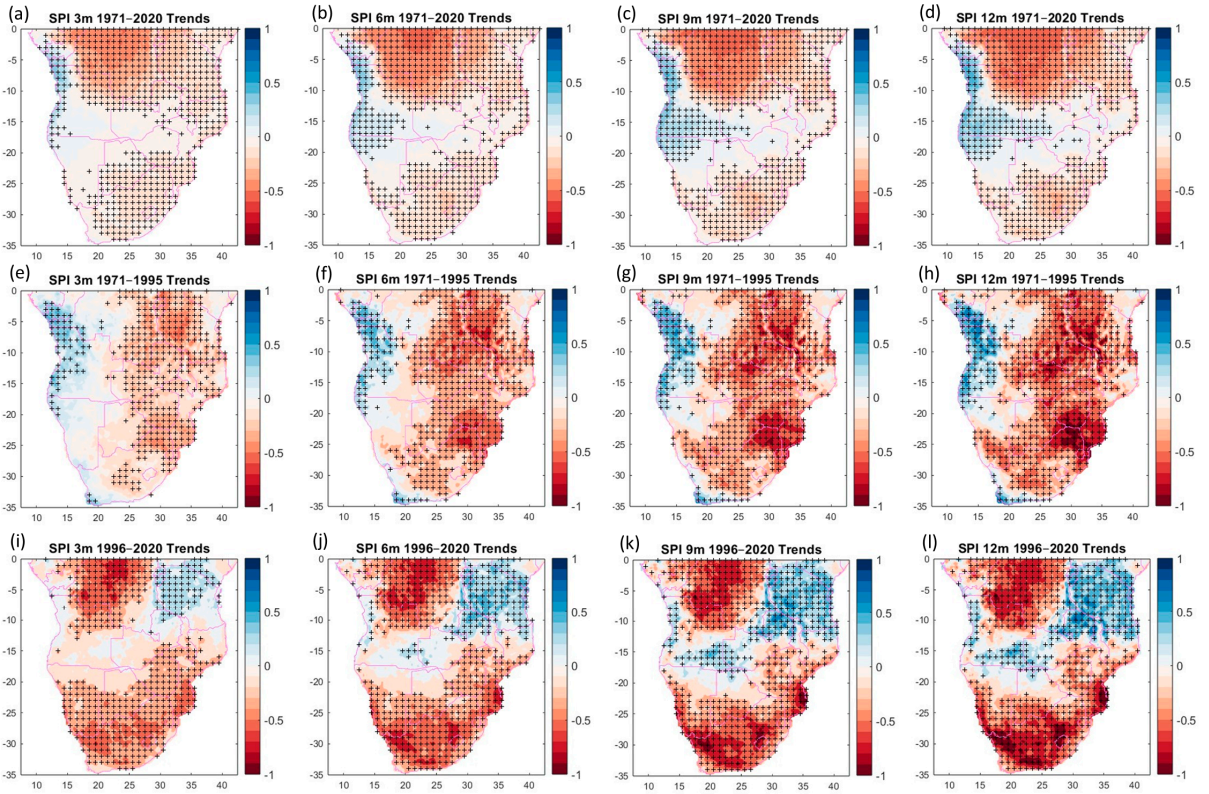


Figure 8. Trends and statistical significance (+) estimated with the Theil–Sen of SPI; at the 3-, 6-, 9- and 12 months timescales (from left to right) in the 1971–2020 (**upper panels**), 1970–1995 (**middle panels**) and 1996–2020 (**bottom panels**) periods.

3.3. Trends in Drought Descriptors

The spatial patterns and trend values derived from the SPEI (Figure 9 and Table 3) over the 1971–2020 period are generally consistent with those obtained from the SPI (Figure 10 and Table 3). Four significant results are observed in general. First, the trend pattern for all drought descriptors is very similar, in the sense that it is characterised by increasing trends across almost the entire SA territory except for a narrow region of the Angolan coast, which, in some cases (DM, DD and, to a lesser extent, DS and DI), extends inland, in a latitudinal band around 15° S, almost to the eastern (at the 6-, 9- and 12-month timescales). Second, the trend values may vary, but the trend patterns for each descriptor do not change significantly as the timescale increases. One of the exceptions is the DM, for which an increase in the area of decreasing trend and a decrease in the area of statistically significant trend are observed, in the same latitudinal band around 15° S. The other is observed in the central region of SA for DD, DS and DI. While for the 3-month timescale, the pattern is relatively smooth in the central and south SA (at south of 10° S), two regions of positive (south of Angola/Angola Coast and Zimbabwe/north Limpopo and south Zambezi) and negative (Orange and southern Congo/northern Zambezi basins) statistically significant trends become evident, as the timescale increases. Third, the area with statistically significant trends decreases as the timescale increases. Fourth, the trend maximum absolute value for DM, DS and DI calculated with the SPEI on all time scales is higher than that calculated with the SPI. The opposite is true for DN at the 3-month scale and DD at the 9- and 12-month scales.

The main difference in the trend patterns of drought descriptors occurs in the tropical forest region as the time scale increases. For DN, high increasing trends are observed at the region's boundaries at the 3-month timescale, but trends rapidly vanish as the timescale increases. For DM, the highest decreasing trends are observed in the tropical forest region, and the area of high increasing trends increases from the 3- to the 6-month timescale. Still, the area of statistically significant trends decreases with the timescale. For DD, DS, and DI, high increasing trends are only observed in the tropical region for the 3-month scale, but cease to exist as the time scale increases. Statistically significant trends are primarily located in the tropical forest region's borders at the 3-month scale, but rapidly decrease with the timescale.

In addition to the similarities and slight differences in the spatial patterns of trends in drought descriptors, it is essential to mention the regions where their higher and lower values are observed. The DN (Figure 9a–d) exhibits statistically significant, primarily increasing, trends in a small number of gridpoints within the data network, decreasing with timescale. The biggest DN decreasing trends are observed when computed with SPEI in the northeast SA, decreasing with the timescale. Conversely, decreasing DN trends are more evident along the coasts of Angola and Gabon, at the 3-month timescale (Figure 9a). DM trends (Figure 9e–h) reach the highest values in the northern tropical forest region and the lowest on the Angolan coast, at the most extended timescales. The highest DD increasing trends were also detected at the longest and decreased at the shorter time scales. DD decreasing trends do not change significantly with the timescale and are concentrated along the western Angolan coast and the central region around the 10° S (Figure 9i–l). The DS trends (Figure 9m–p) increase with the timescales and are characterised by significant decreasing trends in the southern SA, inside (at the 3-month timescale) and around the tropical forest region (other timescales), and increasing trends in the Angolan coast extending to Gabon, and northwest Namibia. In general, the DI's decreasing trends (Figure 9q–t) decrease with the time scale in the northern and southern regions, while the increasing trends generally increase with the time scale in the NW coast.

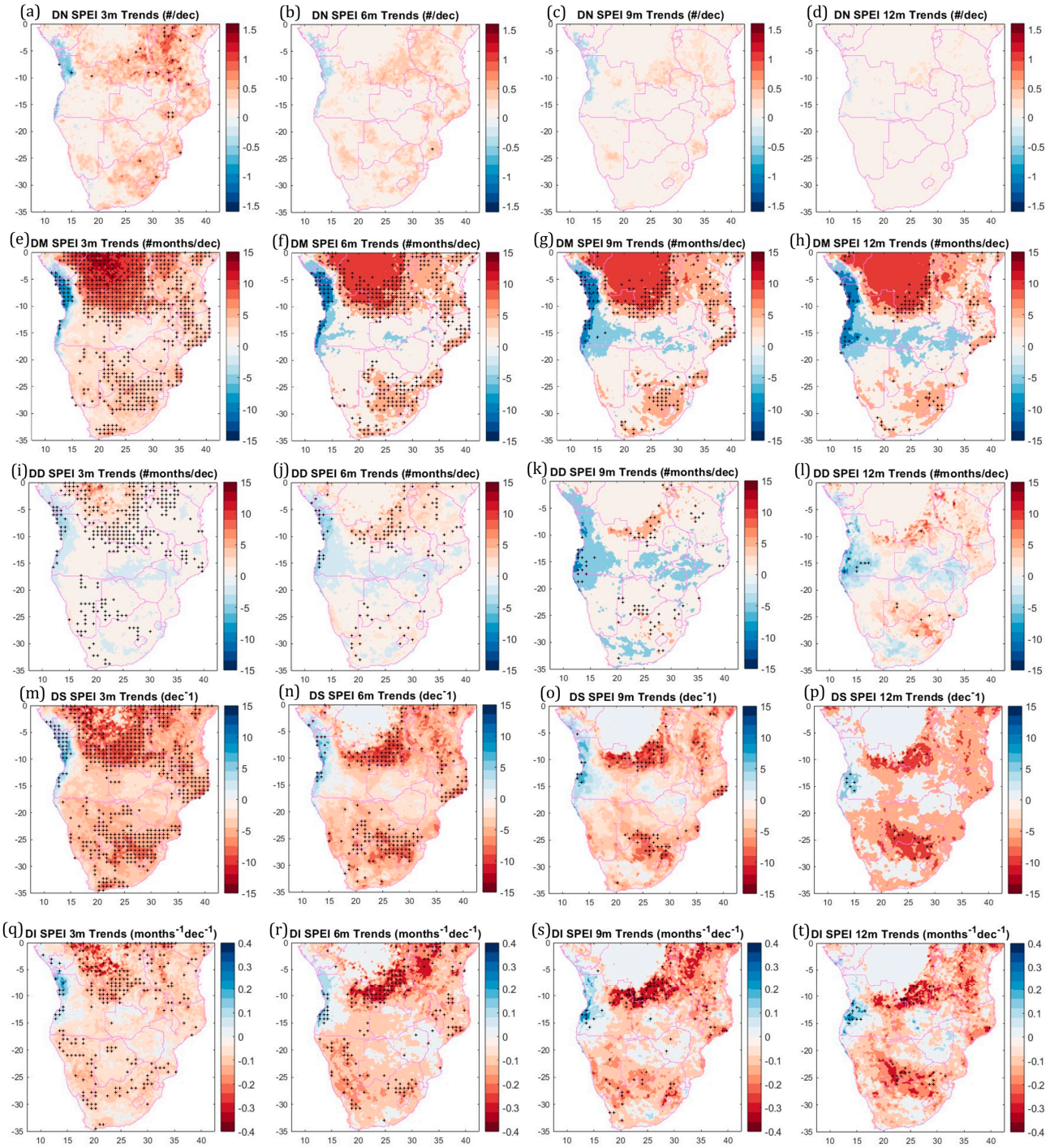


Figure 9. Theil–Sen estimates of trends and statistical significance (+) of drought descriptors computed with the Standardised Precipitation Evapotranspiration Index (SPEI), at the 3-, 6-, 9- and 12-month timescales, namely: Drought Number (DN, panels (**a**–**d**)); Drought Months (DM, panels (**e**–**h**)), Drought Duration (DD, panels (**i**–**l**)), Drought Severity (DS, panels (**m**–**p**)), Drought Intensity (DI, panels (**q**–**t**)), in the 1971–2020 period.

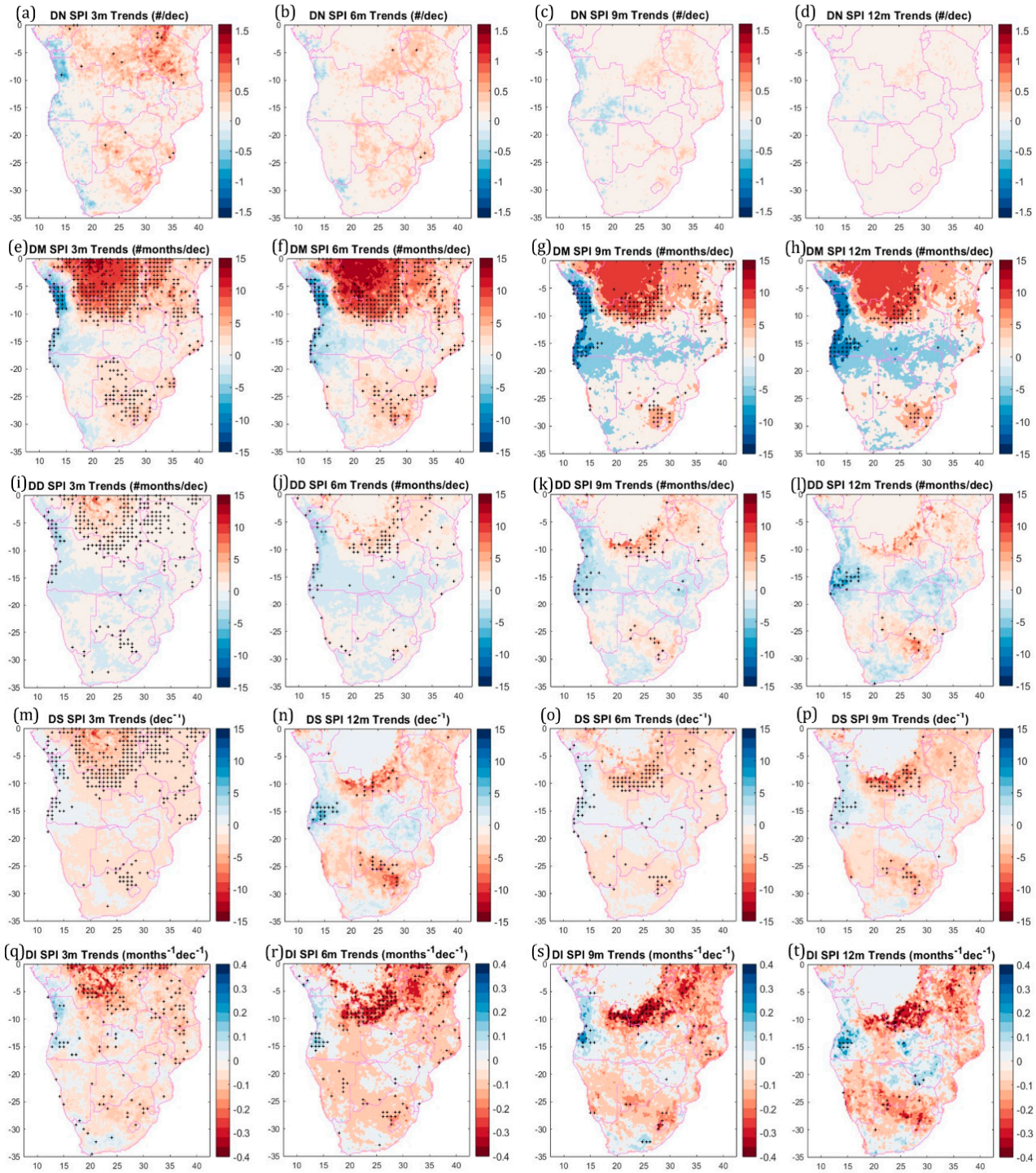


Figure 10. Trends and statistical significance (+) estimated with the Theil–Sen of SPI: Drought Number (DN, panel (**a**–**d**)); Drought Months (DM, panel (**e**–**h**)), Drought Duration (DD, panel, (**i**–**l**)), Drought Severity (DS, panel (**m**–**p**)), Drought Intensity (DI, panel (**q**–**t**)) for the 3-, 6-, 9- and 12-month timescales in the period 1971–2020.

3.4. Drought Hotspots, Population, Ecoregions, Agroecological and Farming Systems

The previous results allow us to identify drought hotspots, which indicate significant, consistent, coherent and persistent trends. One of the most critical hotspots, with the highest absolute trend values, occurs in the north-central tropical forest region, in the Hot and Humid Tropic AEZ, mainly with the forest-based farming system (Figure 1). This is a very consistent hotspot, as it is observed in TP, Tmax, PET, and SPI and SPEI indices

at all time scales (3 to 12 months), and very coherent, as it corresponds to an increase in Tmax and PET and a decrease in TP and drought indices. It is a persistent (observed in the long-term trend and throughout the year) and worrying hotspot, as it has become more evident in the most recent climatological period, especially in TP, Tmax, and PET. It is a compound drought–heat event rather than drought alone, indicating worsening drought conditions. This hotspot may affect many people (moderate population density) and the production of cocoa, rubber, palm oil, and Robusta coffee.

Another hotspot of worsening drought risk is observed in the southern region, especially in the southeast region, in the drought indices, Tmax, and PET, and in the most recent climatological period. This hotspot coincides with specific ecoregions (Deserts and xeric shrublands, Montane grasslands and shrublands) or those extending from the south and southeast of SA (Tropical and subtropical grasslands, savannas and shrublands, Mediterranean forests, woodlands and scrub, and Tropical and subtropical moist broadleaf forests). This hotspot affects the most densely populated area of SA, and agricultural systems (Agropastoral; Maize, Perennial, and Highland mixed farming systems) of the AEZ (tropical and subtropical cool sub-humid and semiarid) of this region, including the Highlands, where Arabica coffee, tea, and wheat are produced.

A hotspot of decreasing long-term drought trends is observed in the western coastal region of Gabon and Angola, in the TP (and throughout the year), PET (and throughout the rainy season), and three-month drought indices increase southward and inland, along the Angola-Namibia border, over the timescales. This hotspot is observed in the long-term trend analysis (1971–2020), but mainly and to a greater extent in the first climatological period (1987–1995). Therefore, this hotspot of decreasing drought conditions likely benefited a region with moderate population density, the Deserts and xeric shrublands and Tropical and subtropical grasslands, savannas, and shrublands ecoregions, tropical warm/semiarid AEZs, and agropastoral and Highland mixed farming systems.

Another hotspot of decreasing drought trend is observed only in the trend analysis performed on drought indices and in the second climatological period (1996–2020), in the NE region, with increasing dimension with the timescale. This hotspot is likely a consequence of growing trends in TP and decreasing trends in Tmax in the same area and period, although not statistically significant. This hotspot of decreasing drought conditions has benefited a highly populated region of the Tropical and subtropical grasslands, savannas, and shrublands ecoregion, AEZs, primarily in the sub-humid and semiarid tropical areas, with mainly mixed maize, agropastoral, and highland perennial farming systems.

4. Discussion

This study aimed to verify the existence of changes in the drought regime in SA in the recent past. Data and methods were selected using strict criteria to ensure the robustness and reliability of the results. The trend analysis was conducted on meteorological fields with a very long temporal span and high spatial resolution to guarantee reliability and detect detailed patterns for the size of the study area, respectively, extracted from a latest-generation database, considered the best or among the best globally for the study of weather and climate [34,48,54]. A suitable, reliable, and widely used methodology in recent climate research was employed to evaluate trends and their statistical significance [4,48,56]. Furthermore, trends were evaluated over different periods, including a very long-term span (50 years), several subperiods (30, 25, and 10 years), and each month of the year, to better understand the overall trends throughout the study. This approach was used to identify seasonality, assess the consistency of trends over time, and explore the potential impacts of (multi)decadal variability on these trends.

The trends in climate elements provide evidence of climate change and suggest their potential influence on the drought regime in SA during the study period, since drought indices are calculated based on these climate elements [2]. Nevertheless, the results obtained from the SPI and SPEI trend analysis (Figures 7 and 8) are noteworthy for several reasons. Firstly, statistically significant trends were observed at all temporal scales across most of SA, especially for the SPEI, an outcome inconsistent with other climatic elements and parameters. The larger area of statistically significant trends in the SPEI compared to the SPI can be explained by the fact that the former index more effectively captures the influence of multiple climatic elements on drought occurrence in SA [57]. These findings may strengthen the understanding that rising air temperatures can enhance the impacts of falling precipitation and potentially worsen drought conditions in the SA region [17]. Therefore, when assessing drought characteristics within the context of climate change, the role of PET and the utilisation of SPEI are crucial [58]. Secondly, SPI and SPEI exhibit decreasing trends in most of the SA, which are explained by underlying climatic factors. For instance, a negative TP trend indicates a higher number of months with below-average TP, implying more months with negative SPI and SPEI values, and thus, more frequent drought conditions towards the end of the study period. Beyond their significance and value, the trends in drought indices are relatively unexpected results, as the analysed drought indices are standardised indices whose values typically fluctuate within a narrow range (−3 to +3), following a normal distribution. This means that trends in drought indices are strongly limited by these characteristics, which may also affect their statistical significance [57]. Furthermore, drought index trends closely align with climatic variables, with SPI showing a strong correlation with TP (Figure 2a–c) and SPEI correlating with PET. This high level of agreement appears in both long-term and climatological patterns and can be attributed to SPI being derived solely from TP. At the same time, SPEI is calculated from the water balance, making it more responsive to combined changes in TP and PET [57]. Nevertheless, the results of the SPI (Figure 8) and SPEI trend analyses are very similar and align with the findings of studies conducted in other regions, where these indices also display a similar trend [58].

The trends observed in the drought indices align with the findings of earlier studies, especially those documenting the effects of climate change in sub-Saharan Africa, including shifts in mean temperature, rainfall, and the severity of other extreme weather events [5]. The predominantly decreasing trends observed in both SPI and SPEI across all timescales (Figures 7 and 8), indicating worsening drought conditions over much of SA—particularly in the north-central tropical rainforest and xeric shrubland desert regions of southern South Africa (Figure 1)—are driven by consistent climate factors, namely rising temperatures and declining precipitation [56,59]. The widespread declining trends in SPI and SPEI across most of SA strongly align with Chivangulula et al.'s findings [17] who reported that, on average, the drought-affected area, as assessed by these indices, has increased over time. In contrast, the positive SPI and SPEI trends identified in localised regions of Angola, northwestern Namibia and Zambia, Burundi, Kenya, and northern Mozambique (Figures 7 and 8) are consistent with previous studies from 2015 to 2016, which showed positive trends in western South Africa, along the Namibian coast, in northern Mozambique, and in central Madagascar [14]. Moreover, SPI and SPEI trends strengthen with longer timescales, indicating that below-average rainfall (i.e., drought, shown by negative index values) and above-average or excessive rainfall (positive trends) tend to become more intense over time in the affected regions.

Identifying statistically significant increasing and decreasing trends in drought indices across all scales and most of SA is a finding of considerable importance. These indices offer objective measures of below-average (dry) or above-average precipitation conditions

and are widely employed in local, regional, and global drought monitoring systems. The observed trends in the drought descriptors (Figures 9 and 10) are simple to interpret. They can be understood by examining the trends in the drought indices from which they are derived and the previously discussed climatic elements. For instance, the larger absolute values and broader spatial extent of statistically significant trends in the drought descriptors calculated with SPEI are linked to the higher trends in this drought index than SPI, as previously mentioned. The spatial patterns of the drought descriptors mirror those of the drought indices (Figures 9 and 10), TP and PET (Figure 2). The widespread increasing trends in the descriptors across SA—especially in north-central and southern SA—are heavily connected to notable decreases in TP (Figure 2a) and increases in the drought indices, Tmax (Figure 2d,f,g), and PET (Figure 2j–l). Conversely, the significant negative trends in drought descriptors observed in the NW coastal region of SA reflect opposite trends in drought indices and climatic factors.

The similarity between the trend patterns of drought descriptors and drought indices is obvious for DM, DD, and DS. This can be explained by trends in the drought indices and how these descriptors are defined. For example, a decreasing trend in the drought index (indicating worsening drought conditions) directly corresponds to increasing trends in DM, and vice versa. An upward trend in DM increases the chances of a rising DD (number of drought months) and, consequently, a higher DS (total of the index over the drought duration). However, it is much less likely to cause a statistically significant increase in DN and DI (average DS over the drought period). An increase in DI requires consistent decreases in drought index values throughout the drought period. Nonetheless, the increasing DI across much of SA observed in this study aligns with the findings of Chivangulula et al. [17] for the northern and central regions of SA. The notable rise in drought descriptor trends aligns with recent studies for the same region and period, which reported significant increasing trends in the annual average extent of drought-affected area [17].

The relatively small area of statistically significant trends, both positive and negative, in drought descriptors—particularly in DN—stands in contrast to the extensive area of significant trends in drought indices. Although these findings may seem unexpected, they are primarily due to the inherent characteristics of the drought indices and how drought is defined. As mentioned, the drought indices used in this study are standardised and follow a normal distribution, with a mean of zero and a standard deviation of one. This means that the positive and negative values are roughly equal, accounting for about half of the months over the study period. These proportions are largely unaffected by the presence of trends. Additionally, the criteria used to define drought (see Section 2.3.1) further limit the number of months that can contribute to drought events. This restriction on the number of drought-contributing months has at least two implications. First, it introduces a limitation in assessing drought using these indices. Therefore, drought indices' trends are more significant for cautious management and policy-making purposes and should be regarded as more critical than drought descriptors' trends. Secondly, there is a close relationship between the number and duration of droughts. DD may need to decrease for DN to increase, and vice versa. This explains the observed patterns of rising DN alongside falling DD, for example, in SA's central and southern regions. Furthermore, while a decrease in DD would typically lead to a reduction in DS, it does not necessarily impact DI, providing insight into the relationships among the drought descriptor patterns. Nevertheless, the observed increase in DI across much of SA in this study aligns with the finding of Chivangulula et al. [17] for the northern and central regions of SA. In summary, the limited number of months that can contribute to drought explains why the other descriptors do not show significant increases, making it difficult to identify statistically significant trends.

The most notable feature of the drought descriptor trend patterns is the presence of very high values (e.g., in the DM) alongside very low, statistically insignificant values in the other descriptors, especially for timescales longer than three months, in the tropical forest region. This outcome stems from a few droughts—only one, although very long—across many of the data points in that region. Furthermore, the value and statistical significance of drought descriptor trends tend to decline with increasing timescales, particularly for the rising trends observed in central and northeastern SA. These findings are probably linked to the reduced spatial extent of statistically significant trends in the indices at longer timescales and the trends in climatic elements, namely increasing TP and decreasing Tmax and PET during the second climatological period in the same region.

Trends in climatic elements, drought indices, and drought descriptors worsening drought conditions are closely linked to climate type and vegetation cover (Figure 1). The most notable and statistically significant trends tend to occur at the boundaries between climate types, indicating possible transitions in climate type and vegetation cover over time. For instance, the intensification of drought conditions observed in the central and northeastern regions, around 10° S, suggests a possible shift from climate type A to C, while in the southeast region of SA, a transition from climate type C to B is indicated. Conversely, alleviating drought conditions along the northwest coast, particularly in Angola and extending inland to roughly 15° S, points to potential transitions from climate type B to C and C to A. These potential shifts align with studies documenting changes in climate types during the mid- and late 20th century [60]. The identified trends might be connected to recent alterations in the Hadley circulation reported in various studies [61,62], including its poleward expansion (both widening and displacement) and uncertain changes in intensity. These shifts have variable impacts across Africa, altering precipitation patterns, including the tropical precipitation belt. This results in more intense and intermittent rainfall and reduced precipitation in SA, with consequential effects on agricultural systems and water resources.

It is essential to discuss why the drought hotspots indicate significant, consistent, coherent, and persistent trends. One factor is that climate type (Figure 1) directly and indirectly influences the global spatial distribution of natural ecosystems, agroforestry and agricultural species and production, and other sectors of human activity in each region [63]. Koo & Pardey [64] characterise the African agrarian landscape as highly location-sensitive. On the one hand, the geography of global agricultural production depends on other natural spatial factors that affect its biological basis, such as altitude, soil type, and the occurrence of pests and diseases. On the other hand, it depends on spatially sensitive economic factors, including access and proximity to markets, input and output prices, and the political environment within which agricultural markets operate. Furthermore, African agriculture is poorly mechanised (only 5.9% of farms surveyed in eight countries use tractors), reliant on animal traction (25% of farms), and, consequently, heavily dependent on manual labour (75% of farms). Thus, these authors state that, with some exceptions, the locations of people and agricultural production are reasonably close to each other at a country's geographical scale in Africa. In short, high-population-density regions in southern Africa tend to have smaller farm sizes and more intensive farming systems, such as maize-mixed and highland perennial systems. In contrast, low-population-density areas are dominated by extensive farming systems, such as pastoral and arid pastoral systems, which rely on grazing and have limited access to agricultural services [65]. These characteristics and relationships explain the strong spatial congruence and correlation between the distribution of climate types, ecoregions/biomes, AEZs, and population density (Figure 1). Naturally, this congruence extends to other sectors of human activity in the sub-Saharan region, such as cattle and small ruminant livestock [66].

Another factor is that, in southern Africa, population density varies across regions and relates to the farming systems in place [65]. Density is higher in the Highland Perennial Farming System of eastern South Africa and Zimbabwe, which features high access to agricultural services, sub-humid to humid conditions, and intensive farming practices. Moderate density occurs in Western and eastern central Southern Africa within the Maize Mixed Farming System, characterised by medium access to agricultural services, sub-humid conditions, smaller farm sizes, and intensive maize cultivation. Similarly, moderate density is present in the western coastal region of Angola, within Agropastoral and Highland Mixed farming systems, and in the Root Tuber Crop farming system spanning from Gabon to central SA, along the Angola-DRC border. Regions with very low population density are found in the Pastoral Farming System of Namibia and Botswana, characterised by arid or semi-arid conditions, extensive grazing, and limited access to agricultural services. Additionally, very low-density regions exist in the Arid Pastoral and Oasis Farming System, located in extremely arid parts of southern Africa, such as areas of Namibia and Botswana, marked by scarce agricultural resources and minimal access to agricultural services.

Despite careful decisions regarding data and methods, this study still has certain limitations. As previously discussed, the characteristics of drought indices are not limitations per se but require careful interpretation of the results. On the other hand, standardised indices offer advantages, such as the ability to compare results across different regions, climate types, and precipitation regimes. Using observed data rather than estimated and reanalysed data would also have been preferable. However, to our knowledge, no sufficiently large PET databases exist that cover all of SA with adequate spatial density. In any case, PET was estimated using the FAO Penman–Monteith equation 56, which is widely considered the most reliable method [17,42]. The ERA5 dataset improved over previous versions and can effectively describe the spatial and temporal patterns of climate elements and hydrological variables. Nevertheless, several authors [67] emphasised some limitations, including underestimating precipitation in mountainous, arid, or high-altitude areas and overestimating minimum temperatures. These issues are more relevant in local and short-term studies. Nevertheless, results with different datasets may lead to slightly different results.

The results highlight avenues for future research. To complement this study, the potential presence of trends in factors and variability in precipitation across SA, associated with large-scale climate variability modes, reported by several authors, could be further investigated. For example, interannual and decadal variability in rainfall and temperature is consistent with global patterns influenced by large-scale climate drivers, particularly the ENSO, as well as the regional Hadley and Walker circulations systems [61]. The high seasonal variability of TP in sub-Saharan Africa, particularly within the latitudinal band between 10° S and 22° S, is often influenced by ENSO and other SST anomalies [15,16]. Strong to moderate El Niño years can increase the probability of below-average precipitation in SA by more than 50% [13]. On the other hand, a detailed assessment of the drought regime in SA, incorporating multi-index, multi-scale, and multi-metric approaches for different periods and future climate scenarios, would be a natural extension of this study.

Overall, these study results enhance our understanding of past drought regime evolution and offer insights into their potential development in the near future. We believe these findings are highly relevant, providing valuable guidance for the academic community, civil society, and policymakers in developing more effective strategies, regulations, and policies for managing and adapting to extreme weather events such as droughts and water shortages. Understanding changes in drought-related variables and regimes is essential to legislate and manage water resources availability, drought risk and agricultural production [68].

5. Conclusions

This study aimed to evaluate whether recent climate change has affected the drought regime in southern Africa. It examined long-term trends in drought-related climate variables, indices, and descriptors across multiple timescales, using robust regression methods to ensure accurate results. The key findings include the following: (i) statistically significant trends across all variables and periods; (ii) consistent long-term trend patterns of climatic elements and drought parameters, aligning well with previous studies, which aids interpretation and validation; (iii) widespread increasing trends in Tmax and Tmin throughout the region; (iv) increasing trends in PET across nearly the entire region, especially in the SE and north–central and eastern tropical forest zones, with decreasing trends along the NW coast; (v) a contrasting trend pattern observed in TP; (vi) the trend patterns of drought indices and descriptors generally mirror these patterns, although the area of decreasing trends extends from the NW coast inland, around 10 °s, as the timescale lengthens; (vii) the spatial extent of statistically significant trends is much broader in the drought indices, covering almost the entire region for the SPEI, particularly at the 3-month timescale, than in the drought descriptors, reflecting the inherent characteristics of the indices used; (viii) the long-term trend patterns of climate variables are clearly interpretable based on trends observed in the subperiods, specifically (ix) for the climatological (25- and 30-year) and decadal periods, with more recent periods (1991–2020 and 1996–2020) showing patterns more closely resembling these trends; and (x) for each month, indicating pronounced seasonality in the magnitude, statistical significance, and even the direction of trends, notably between dry and rainy seasons. Finally, drought hotspots were identified, categorising regions into increasing or decreasing drought risk levels and then relating them to population or agricultural zone metrics. These hotspots allow us to evaluate combined drought-heat events rather than those based solely on precipitation and pinpoint regions where rising or falling drought trends will challenge water and drought management. The results indicate that the main and most recent hotspots occur in areas with moderate-to-high population density, within ecoregions highly sensitive to precipitation variability, affecting agroecological zones and farming systems where some of the most essential crops for food security and high economic value are produced. These findings are highly relevant and valuable to drought and water resource managers and policymakers across southern African countries, especially when viewed alongside existing projections of future drought regimes.

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Abbreviations

ECMWF	European Centre for Medium-Range Weather Forecasts
SPEI	Standardised Precipitation Evapotranspiration
SPI	Standardised Precipitation Index
PET	Potential evapotranspiration
SA	Southern Africa
SADC	Southern African Development Community
SST	Sea Surface Temperature
ENSO	El Niño-Southern Oscillation
scPDSI	self-calibrating Palmer Drought Severity Index
DN	Drought Number
DD	Drought Duration
DS	Drought severity
DI	Drought intensity
DM	Number of Drought Months
TP	Total Precipitation
CC	total Cloud Cover
W10m	Wind speed and directions at 10m
W2m	Wind speed and directions at 10m
TMAX2m	Maximum air Temperature at 2m
TMIN2m	Minimum air Temperature at 2m
Tmax	Maximum monthly air Temperature
Tmin	Minimum monthly air temperature
Z	Altitude (Geopotential height)
SDAT	Standardised Drought Analysis Toolbox
TS	Theil–Sen
MK	Mann–Kendall
DRC	Democratic Republic of the Congo
P10	10th percentile
P90	90th percentile
IPCC	Intergovernmental Panel on Climate Change

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