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Trends and variability of temperature and evaporation over the African continent:
Relationships with precipitation

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Highlights
- Trends and variability in long-term (1991-2015) temperature, potential evapotranspiration (PET) and precipitation across Africa were assessed.
- Africa experienced warming trends at an average rate of about 0.2°C per decade.
- Over most areas of the African continent, weak and negative correlation (p>0.01) was found between precipitation and temperature (or PET).
- Monthly shifts of locations with significant correlation between precipitation and temperature (or PET) follows the Inter Tropical Convergence Zone migration.

GRAPHICAL ABSTRACT

Abstract:
This study analyzed changes in the long-term (1901–2015) monthly values of Potential Evapotranspiration (PET), precipitation, minimum (Tmin) and maximum (Tmax) temperature across Africa to quantify trends and assess co-variability between the climatic variables. Both warming and drying trends were observed across the continent. The 1979–2015 warming was stronger than that from 1901 to 1940. Some cooling occurred from 1941 to the mid–1970s. The 1901-2015 annual Tmax, Tmin, and PET averaged over Africa exhibited increasing/drying trends across the continent at rates of 0.18 °C, 0.22°C, and 3.5 mm per decade, respectively. The 1961-1990 annual precipitation averaged over the whole continent showed that Africa experienced drying at a rate of about -28 mm per decade. When considering the period 1961-2015 the precipitation decrease was a rate of about -8 mm per decade. From 1901 to 1915, areas around the Lake Victoria in East Africa and along the western coastline south of the Equator experienced wetting at rates up to 36 mm per decade. Significant ($p<0.01$) warming trends occurred in Sudan, Southern and Northern Africa. Positive PET trends were significant ($p<0.01$) in the warm Mediterranean climate, and the western part of South Africa. Long-term temperature increase and precipitation decrease across Northern Africa possibly indicated Sahara desert expansion over time. Except in the warm desert climate, the continent exhibited high precipitation variability. The equatorial climate experienced low temperature and PET variability. The strongest coherence between precipitation and temperature existed at multiple scales (6–8 years). Correlations between precipitation and PET (or temperature) were mostly negative and weak ($p>0.01$). Because sensitivity of Tmin to local influences is higher than that of Tmax, areas with strong negative correlation were larger in coverage for Tmax than those of Tmin. These results call for planned measures to tackle food insecurity in sub-Saharan Africa.

**Keywords**: Trend analysis; Climate variability; Temperature trends; Global warming; Precipitation trends; Potential evapotranspiration trends; Wavelet coherence, Africa
1. Introduction

Due to anthropogenic forcing, the 21st century warming will be large in Africa (Intergovernmental Panel on Climate Change IPCC, 2013). This signals a worrying situation for struggles aimed at tackling the food insecurity challenge especially in the sub-Saharan region where subsistence heavily depends on smallholder farming. Several studies have been conducted on changes in hydro-climatic variables such as temperature, Potential Evapotranspiration (PET), and precipitation (Pcp) in Africa for planning of predictive adaptation to the impacts of climate variability on hydro-meteorology and agro-meteorology. Some of these studies include Bush et al. (2020), Mubialiwo et al. (2020), Onyutha (2020), Ahokpossi (2019), Nashwan and Shahid (2019), Camberlin (2017), Moron et al. (2016), Oloruntade et al. (2016), MacKellar et al. (2014), Mekasha et al. (2014), Nyeko-Ogiramoi et al. (2013), Ozer and Mahamoud (2013), Morishima and Akasaka (2010), Kizza et al. (2009), Kruger and Shongwe (2004), Grist and Nicholson (2001), King’uyu et al. (2000), Nicholson (2000), and Beltrando and Camberlin (1993). However, most of these studies: (i) were conducted over small areas using short-term data selected over different periods, (ii) focused on analyses of trends or variability but not both, (iii) did not consider changes in Pcp, PET, and temperature in a single research work, (iv) made use of series aggregated to seasonal (for instance, March-April-May, June-July-August) blocks, (v) did not consider the effect of seasonality and long-term persistence on trend results, and (vi) did not examine the cross-correlation among temperature, Pcp, and PET.

Detection of trends in Pcp, PET and temperature tends to be affected by the variability in the data. Superimposed cycles of natural cyclical variability could be misinterpreted as a monotonic trend (Jain and Lall, 2001; Onyutha, 2016a; Armal et al., 2018). Such an effect can be amplified by the uncertainty due to finite sample size. Regarding trend analyses, it is known that the longer the data, the better the results. However, "the period referred to as the so-called ‘long-term’ is so subjective that the question of what data record length gives bias-free trend results cannot be clearly answered" (Onyutha et al., 2016). The presence of a significant monotonic trend in long-term data may indicate the impact of some external forcing on the system. Therefore, when the data has a significant trend, detrending should be done and detrended series used for variability analyses. In short, variability should also be quantified alongside trend analyses for planning predictive adaptation. Furthermore, data from some months can have apparent trends while the null hypothesis $H_0$ (no trend) may be rejected based on series aggregated at annual or seasonal time scale. The possible heterogeneity of trends
among monthly data can render conclusions made on trends detected using annual data ambiguous. In the same vein, although the $H_0$ (natural randomness) can be apparently rejected for data of some months, the $H_0$ may not be rejected for the series of a given year or season. Above all, by the time of writing this paper, there were no studies found conducted on a monthly timescale to examine the co-variation of sub-trends in Pcp and those in PET or temperature considering the entire African continent.

The importance of investigating the co-variation of Pcp with PET or temperature can be looked at in two ways. Firstly, analyses of possible large-scale ocean-atmosphere drivers of Pcp across the African continent were already conducted in studies such as Onyutha (2018a), Maidment et al. (2015), and Nicholson and Selato (2000). Therefore, possible influences of the variation in large-scale ocean-atmosphere conditions on the variability of hydro-climatic variables such as temperature and PET can be inferred from the drivers of Pcp. This can be important to predict an upcoming periods of warming and drying in the various regions of the African continent. The second importance of assessing the co-variation of Pcp with PET or temperature is for an insight into the changes in water budget estimates especially for arid and semi-arid regions. In arid regions, annual Pcp is always less than the annual PET. It may be vital to note that semi-arid and humid ecosystems are mainly driven by the changes in Pcp. Environmental changes (such as depletion of groundwater, desertification, soil erosion, and woody plant encroachment) alongside the high variability in Pcp largely affect the ecohydrology of water-limited ecosystems in arid regions. Linkage between Pcp and PET across arid regions can enhance understanding of how water controls influence plant community composition, function, and structure. For the Mediterranean climate, shrubland ecosystems tend to be vulnerable to the increasing temperature and reduced water availability (Usodomenech et al., 1995). Nevertheless, due to the global warming or increasing temperature, the evaporative demand was projected by an IPCC assessment to increase almost everywhere (Bates et al., 2008). The implications of this projection (like for ecosystems) vary across climatic regions. In other words, some regions may be disproportionately affected by the impacts of climate change and variability. Given the wide variety of climatic regions across Africa, predictive adaptation requires comprehension of the directions and magnitudes of observed or historical trends in temperature, PET and Pcp across the entire continent.

Therefore, this study aimed at making use of long-term (1901–2015) monthly Pcp, temperature, and PET on a spatial grid of 0.5°×0.5° resolution covering all the countries of the
African continent (see Figure A1 of the Supplementary Material M1) to: (i) quantify trend
directions and magnitudes at monthly time scale, and (ii) examine the co-variation of Pcp along
with temperature and PET. This was done while taking into account the effects of seasonality
and persistent fluctuations in the series on the results of analyses.

2. Materials and Methods

2.1. Data

Climatic Research Unit (CRU) Time-Series (TS) version 4.0 (CRU TS4.0) (Harris et al.,
2014) over the period 1901–2015 was downloaded in gridded (0.5°×0.5°) form via
https://crudata.uea.ac.uk/cru/ (accessed: 18th June, 2017). The downloaded CRU TS4.0 data
comprised minimum (Tmin, °C) and maximum (Tmax, °C) temperature as well as Pcp and
PET (mm). Each variable was at monthly temporal resolution.

The PET (mm/day) data of the CRU TS4.0 (Harris et al., 2014) was computed using a
variant of the Penman-Monteith method (Allen et al., 1994) based on half degree gridded vapor
pressure (hPa), wind speed (m/s), cloud cover (%), and absolute values of Tmax, Tmin, mean
temperature (°C), and wind speed (m/s). The monthly PET total (mm) used in this study
comprised sum of the daily PET values in each month.

The CRU data sets used in this study were obtained from gauge interpolations. Several
areas across Africa especially in the sub-Saharan Africa lack dense weather stations.
Furthermore, several weather stations are not continuously operations due to poor maintenance
of data recording or observation equipment coupled with interruptions by political turmoil
(Onyutha, 2018). The accuracy of interpolation products depends on the number of gauge
stations in a particular location. Therefore, the accuracy of the results and uncertainties ranges
might vary across the continent.

Obtaining reliable estimates of evaporation (or flow of water from land to the atmosphere)
continues to remain a challenging task. Estimating evaporation using distributed model
requires high resolution spatio-temporal description of land use and land cover types and these
spatial data are always lacking. In some cases, estimates of terrestrial evaporation are made
from satellites. However, the challenge is that the flux of the terrestrial evaporation cannot be
directly sensed from the satellites (Martens et al., 2017). Nevertheless, there are several
advances in improving evaporation estimates over large scales. Examples of such advances
include data-driven estimate of global land evapotranspiration from 1982 to 2008 (Jung et al.,
2010), understanding the response of terrestrial evaporation to teleconnection patterns
(Martens et al., 2018), and the GLEAM (Global Land Evaporation Amsterdam Model) data sets (Martens et al., 2017; Miralles et al., 2011) downloadable via https://www.gleam.eu/ (accessed: 14th June 2020). Despite the above examples of advances, evaporation data sets based on information from satellites are normally of short-term record. Eventually, the CRU TS4.0 data sets were adopted for this study because of their reliability and long-term records gridded at a spatial (0.5°×0.5°) scale covering the entire African continent. Since the number of weather stations influence interpolation products at a given location, spatial similarities of results from analyses based on the CRU TS4.0 data should not be assessed at the level of an individual location but instead over a region or large area (Onyutha, 2018a).

The data at grid points over land were thoroughly checked and confirmed to have no missing values. The long-term mean of the data used in this study can be seen from Figure CS1 to Figure CS4 of the Supplementary Material M1.

2.2. Trend analyses

Taking into account the influence of seasonality (here, a season is taken as a month) on results of trend analyses can be done in two steps. Firstly, the trend statistic values are computed separately for each month. This is done for both trend directions and magnitudes. In the second procedure, the results of trends in the various months are combined into an overall or global trend measure.

2.2.1. Seasonal trend directions

To detect monotonic trends, a method that uses Cumulative Sum of the Difference (CSD) between exceedance and non-exceedance counts of data points (Onyutha, 2016b) was used. The details of this method can be seen in Section A.2 of the Supplementary Material M1.

Analyses of trend directions were done in three steps. Firstly, the seasonal CSD trend test was conducted using data (or Tmax, Tmin, PET, and Pcp) at each grid point. In the second step, CSD trend test was separately conducted to test the \( H_0 \) (no trend) using data of each month. Thirdly, the cumulative effects of temporal variations in the full time series of Tmax, Tmin, PET, and Pcp were graphically assessed using series averaged over all the grid points on land mass across the continent. To do so, the following procedure was taken: (i) at each grid point, data of a particular month was separately extracted from the full time series, (ii) for a particular year (like 1901), the average of data for a given month (such as January) across all
the grid points was computed, and (iii) as step (ii) but separately repeated for each of the months.

2.2.2. Trend magnitudes

The linear trend slope in the data of each month at a given grid point was computed using the method of Sen (1968) and Theil (1950). The details of this method can be found in Section A.2 of the Supplementary Material M1. The trend magnitudes obtained based on the Tmax, from the various months were averaged. The averaging procedure was repeated for Tmin, PET and Pcp.

2.3. Variability analyses

There are two ways variability can be quantified to test the $H_0$ (natural randomness) using the CSD-method namely the use of variability CSD-statistic, and temporal variation of CSD-based sub-trends.

2.3.1 CSD variability statistic

The first step in analyses of variability is quantification of trend in the long-term data. If the $H_0$ (no trend) is rejected at $\alpha$, the series is first detrended. In this case, the CSD-based variability (Onyutha, 2018a) can be quantified in the detrended series. If the $H_0$ (no trend) is not rejected at $\alpha$, there is no need to perform detrending, and variability can be quantified using the original data.

To derive the CSD variability statistic, the differences between exceedance and non-exceedance counts of the data values in the series resulting from the first step are obtained. The number of times the transformed series crosses the reference is obtained as the variability statistic. From this, the standardized CSD statistic $Z^*$ is computed. Based on a two-tailed test and using $Z_{\alpha/2}$ (which denotes the standardized normal variate at the selected $\alpha$), the $H_0$ (natural randomness) can be rejected if $|Z^*| \geq Z_{\alpha/2}$; otherwise, the $H_0$ is not rejected.

In this study, the $H_0$ (natural randomness) was tested using Tmax, Tmin, PET, and Pcp at each grid point. The variability was categorized as very high, high, moderate, low, and very
low for statistic $Z^\ast$ values in the ranges 0–1.63, 1.64–1.95, 1.96–2.57, 2.58–2.80, $\geq$2.81, respectively. The details of the procedure on how to test the $H_0$ (natural randomness) using CSD variability statistic can be found in the Section A.3 of the Supplementary Material M1.

2.3.2 Temporal variation in sub-trends

The $H_0$ (natural randomness) was also tested using values of sub-trend statistic. To compute temporal sub-trends in a given series using the CSD-based method, the $H_0$ (no trend) is tested in the long-term data. If the $H_0$ (no trend) is rejected, detrending of the data is done and the CSD-based method of quantifying variability is applied to detrended data. If the $H_0$ (no trend) is not rejected at $\alpha$, CSD method is applied to the original data.

In the next step, a particular time scale (which has time unit of the series) is chosen such as 5, 10, and 15 years for annual data. The choice of the time scale depends on the purpose of the study. For instance, to assess climate fluctuations, the time scale can be set to about 30 years. However, this study considered 15-year time scale to assess multi-decadal variability in sub-trends. The 15-year data period is relevant as the design life of some water supply systems of an irrigation scheme (Onyutha, 2016c), water supply projects or risk-based water resources applications (Onyutha, 2018a). A window of chosen length (15 years in this case) is passed in an overlapping way from the beginning to the end of the series. Over each time slice, the CSD trend statistic $Z$ is computed. The variability of the sub-trends is obtained in terms of the variation in the values of $Z$ with the corresponding time (for instance, a year) of observation (Onyutha, 2018a). To test the $H_0$ (natural randomness), variability thresholds at selected $\alpha$ can be constructed using $\pm Z_{\alpha/2}$. If all the $Z$ values fall within the thresholds, the $H_0$ is not rejected; otherwise, the $H_0$ is rejected. Further crucial clarification on the CSD method for variability analyses based on temporal changes in sub-trends can be found in Appendix A. These procedures can be found implemented in CSD-VAT (which stands for CSD-Variability Analyses Tool) freely downloadable via https://sites.google.com/site/conyutha/tools-to-download (accessed: 18 August 2019).

2.3.2 Comparison of sub-trends in Pcp with those of Tmax, Tmin, and PET

At each grid point, the CSD sub-trend statistic values were computed using Tmax, Tmin, PET, and Pcp considering the entire period 1901-2015. Co-variability of sub-trends from the
climatic variables (Pcp, Tmax, Tmin, and PET) was quantified by testing the $H_0$ (no correlation) using Pearson correlation.

2.3.3. Wavelet coherence

The association of the variation in Tmax, Tmin and PET with Pcp variability was assessed in terms of wavelet coherence. Pcp, Tmax, Tmin, and PET were converted from monthly to annual series and averaged over the entire continent. Prior to the application of wavelet coherence, each series was standardized (through subtraction of the mean of the mean and division by the standard deviation). Based on bivariate wavelet analysis, the wavelet coherence computes correlation measure between any two given series at all the periodicities through time. Wavelet coherence was computed for six combinations of the climatic variables including Pcp and Tmax, Pcp and Tmin, Pcp and PET, Tmax and Tmin, PET and Tmin, and PET and Tmax. Continuous wavelet transform was applied to each of the combinations to find regions in time frequency space where the two time data sets under consideration co-vary. A total of 1000 Monte Carlo randomizations were used to assess significance of the coherence.

3. Results

3.1. Trends and variability

3.1.1. Trends

Time series plots for Pcp and PET (Figure 1 a-e) were made using data extracted at a number of locations from different climatic conditions of the continent including warm semi-arid climate (WSAC), warm desert climate (WDC), equatorial climate (EC), humid subtropical climate (HSTC), and cold semi-arid climate (CSAC). The average of the Pcp from the various climate types can be seen in Figure 1 f. The location (longitude, latitude) at which the data for WSAC, WDC, EC, HSTC, and CSAC were extracted was (-11.25°, 13.25°), (1.25°, 24.25°), (20.25°, 0.25°), (24.75°, -15.75°), and (25.75°, -27.75°), respectively. What is noticeably common for data of the various climate types is the positive trend in PET (Figure 1 a-e) from around 1985 to 2015 (end of data). Furthermore, the decrease in Pcp (Figure 1 a-d) from around 1960 to the end of the data period is also generally evident across the various climate types. At some locations (for instance, see Figure 1 c and e) the data before 1940
showed minimal deviations from a certain constant value. This could be because of data quality problem. Such locations possibly had few weather stations before 1940. For the desert condition (Figure 1 b), the annual Pcp volume was generally lower than those of other types of climate.

The results of trends in the data of each month can be found from Figure CS5 to Figure CS12 of the Supplementary Material M1. Based on trends results from the various months, Figure 2 was obtained. Generally, the entire African continent (except Madagascar) was characterized by warming trends with respect to both Tmin and Tmax. Large increases in both Tmax and Tmin at rates between 0.08 and 0.25°C per decade were exhibited in Sudan as well as the northwestern and southern parts of Africa (Figure 2 e–f). For these increases of Tmax and Tmin, the $H_0$ (no seasonal trend) was rejected ($p<0.01$ or $|Z|>2.57$) (Figure 2 a-b) in most locations. For the cooling trends in Madagascar (Figure 2 d–e), the $H_0$ (no seasonal trend) was not rejected ($p>0.05$ or $|Z|<1.96$) (Figure 2 a-b). Except over some West African countries, the spatial distributions of Z values for Tmax and Tmin were comparable (Figure 2 a–b).

Most parts of the continent were characterized by monthly PET increase at rates between 0.1 and 0.04 mm per year (Figure 2 g). Large increases in PET at rates between 0.05 and 0.085 mm per year were along the western coastline of South Africa, northwestern areas like Tunisia, as well as some portion around Lake Victoria in the equatorial region of East Africa. For these increases at the specified locations, the $H_0$ (no seasonal trend) was rejected ($p<0.01$ or $|Z|>2.57$) as seen from Figure 2 c. Along the coastline of the Gulf of Guinea, some patches of areas exhibited decreases in PET at rates as low as -0.077 mm/year. However, for these decreases, the $H_0$ (no seasonal trend) was not rejected ($p>0.01$ or $|Z|<2.57$) as seen from Figure 2 c.

Monthly Pcp across the continent was mainly characterized by drying at rates as low as -0.20 mm/year (Figure 2 h). Pcp decreases of at rates between -0.3 and -0.2 mm/year were confined along the coastal areas of Guinea, Sierra Leone, and Gambia (Figure 2 f). However, for the decreases, the $H_0$ (no seasonal trend) was not rejected ($p>0.05$ or $|Z|<1.96$). Furthermore, Pcp increases were mainly of magnitudes between 0 and 0.1 mm/year. These increases were in the Great Lakes region, West of the Southern Africa and Madagascar (except
its southernmost area) (Figure 2 h). However, for both Pcp increase and decrease, the $H_0$ (no trend) was mostly not rejected ($p > 0.05$) (Figure 2 d).

3.1.2. Variability

Figure 3 shows an overall average of the CSD variability $Z^*$ values obtained from data of various months (as can be seen from Figure CS13 to Figure CS16 of the Supplementary Material M1). The values $1.64, 1.96, 2.58,$ and $2.81$ in the legend of Figure 3 are the thresholds for rejecting the $H_0$ at $\alpha = 0.10, 0.05, 0.01,$ and $0.005$, respectively. Areas with low variability ($Z^* > 2.81$) in $T_{\text{max}}$ ($T_{\text{min}}$) were mainly between $10^\circ$ S and $5^\circ$ N ($10^\circ$ N and $10^\circ$ S). High variability ($Z^* < 1.63$) in temperature was mainly in Mozambique, Egypt, Mauritania, Western Sahara and around Lake Victoria (Figure 3 a-c). For Pcp, high variability was exhibited in South Africa, West Africa (especially along the Gulf of Guinea), East Africa, Madagascar, areas with warm Mediterranean climate (Figure 3 d). Pcp variability was low ($Z^* > 2.81$) across the Sahara and Namib–Kalahari deserts. The significance of the variability statistic was found to vary from one region to another (Figure 3 a-d). This (based on Figure CS13 to Figure CS16 of the Supplementary Material M1) was found to depend on the month being considered.

3.3. Co-variability of sub-trends from the selected climatic variables

Results for the correlation between Pcp sub-trends and those of $T_{\text{max}}, T_{\text{min}}$ and PET can be seen in Figure 4, Figure 5, and Figure 6, respectively. In these Figures 4–6, the values $0.25$ and $0.31$ are the thresholds for rejecting the $H_0$ (no correlation) at $\alpha = 0.01$ and $0.001$, respectively. From May to September, strong negative correlation between Pcp and $T_{\text{max}}$ (Figure 4 e-i), PET (Figure 6 e-i) and $T_{\text{min}}$ (Figure 5 e-i) were confined within the region $4^\circ$ N–$21^\circ$ N. In the Southern Africa (or generally South of $8^\circ$ S), strong negative correlation between Pcp and $T_{\text{max}}$ was exhibited from January to March, May, October and December (Figure 4 a-c, e, j, l). Strong negative correlation ($p < 0.001$) between Pcp and $T_{\text{max}}$ or Pcp and PET was obtained in the data of February, March, October, and November and especially along
the coast of the Mediterranean Sea. Strong positive correlation between Pcp and Tmin of March (Figure 5 c) was confined to Mozambique, Zambia and Zimbabwe. However, for October (Figure 5 j) and August (Figure 5 h), the strong positive correlation between Pcp and Tmin was mainly confined to South Africa, and the coastal areas along the Gulf of Guinea, respectively. Positive correlation between Pcp and Tmax (Figure 4 g-h) as well as Pcp and Tmin (Figure 5 g-h) of July and August was exhibited along the Gulf of Guinea (as well as North of Morocco and Algeria). Over East Africa, strong negative correlation ($p<0.001$) was obtained between Pcp and Tmax of April and November (Figure 4 d, k). In general, by January and February, the areas with strong correlation between Pcp and temperature or PET were far South of the Equator. From March through April and May to June, the areas where the $H_0$ (no correlation) was rejected ($p<0.001$) for strong negative correlation become less and less spatially coherent but with more and more shifts northwards as far as close to 14° N. Slightly past the middle of the year (July or August), the band of strong negative correlation exists in the Northern hemisphere as far as close to 20° N. The described shifts in the areas with strong correlation between Pcp and temperature was more clearly evident for Tmax than Tmin.

Generally, it is noticeable that in most areas, coefficients of the correlation between the sub-trends of Pcp and those of Tmax (Figure 4 a-l), Pcp and Tmin (Figure 5 a-l), and Pcp and PET (Figure 6 a-l) were mainly negative. Evidently, these negative correlative relationships were mostly weak ($p>0.01$) or fell in the range of coefficients between 0 and -0.24. However, areas with strong negative correlations were larger for Tmax and PET than that of Tmin. On the other hand, areas with positive correlation were larger for Tmin than those of the Tmax and PET. Furthermore, by comparing maps for corresponding months, the coefficients of the correlation between Pcp and Tmax (Figure 4 a-l) were spatially more comparable with results for PET (Figure 6 a-l) than those of Tmin (Figure 5 a-l).

Figure 7 shows results of wavelet coherence analysis. The reliable data within the "cone of influence" away from the edge effects are indicated by the colored region. Areas with significant coherency are enclosed in bold black lines derived using the Monte Carlo randomizations. The strength of coherence between the time series at each period through time.
can be seen in terms of the colors. The color at the bottom (top) of the legend bar indicates low (high) coherency.

The strength of the co-variation of Pcp with Tmax, Tmin or PET was patchy through time (Figure 7 a-c). The strongest coherence between Pcp and PET occurred at multiple scales (2–5 years, Figure 7 a). Coherence between Pcp and PET was strong over the periods 1905–1925 and 1985–2005 (Figure 7 a). Pcp cycled in anti-phase with PET from 1985 to 2005. The strongest coherence between Pcp and Tmin (or Tmax) existed at multiple scales (6–8 years, Figure 7 b-c). Strong coherence of Pcp with Tmax and Tmin existed over the periods 1901–1935 (Figure 7 b) and 1901–1925 (Figure 7c), respectively. Pcp cycled in anti-phase with Tmax from 1901 to 1935. Coherence between PET and temperature remained strong at multiple scales (from one up to about 30 years) over the entire data period 1901–2015. The arrows show phase relationships between the variables within the areas of strong coherence. In Figure 7 d-f, the arrows point to the right meaning that PET and Tmax, PET and Tmin as well as Tmin and Tmax are in phase. This indicates that PET is strongly influenced in a positive way by temperature. Some arrows in Figure 7 a-c point to the left indicating that Pcp and PET or Pcp and temperature are in anti-phase. From 1901 to 1935, Pcp cycled downwards with Tmin at multiple scales (15–16 years). This means that Tmin led Pcp by $\pi/2$. However, Pcp cycled upwards with Tmin at multiple scales (1–4 years, Figure 7 c). This means that Tmin led Pcp by $\pi/2$.

FIGURE 7 AND ITS CAPTION

4. Discussion

4.1. Trends and variability results

This study's results especially on trends are consistent with the findings from several previous studies. The confidence in the evidence for warming over land regions across the African continent is high (Niang et al., 2014). Throughout the 20th century, the African
continent warmed at a rate of 0.58°C per century (Hulme et al., 2001). Significant warming of the African temperatures occurred between 1979 and 2010 (Collins, 2011).

In the equatorial region (specifically around the Lake Victoria in East Africa), Nyeko-Ogiramoi et al. (2013) and Kizza et al. (2009) found mainly positive trends in the seasonal rainfall. Furthermore, Tmin and Tmax over the period 1970–2010 generally exhibited increasing trends (Nyeko-Ogiramoi et al., 2013). Significant warming and drying was confirmed in the western equatorial Africa (Bush et al., 2020) confirmed. Pcp and Tmin data from the Lopé’s weather in Gabon observed over the period 1984–2018 revealed that warming occurred at a rate of +0.25 °C per decade and this was accompanied by drying rate of −75 mm per decade (Bush et al., 2020).

The West African Sahel was characterized by a general warming trend from 1960 to 2010 (Ly et al., 2013). Even the data from various stations across the Volta basin of West Africa between 1960 and 2002 exhibited significant warming trends (Neumann et al., 2007). Pcp exhibited a decrease especially along the Gulf of Guiniea and in the Congo River basin (Onyutha, 2018a).

For Egypt and Sudan, this study showed that (i) Tmax and Tmin exhibited increasing trends at rates in the range 0.041–0.25°C/decade, (ii) Pcp decreased at rates between -25 and zero mm/decade, (ii) PET yielded positive trends with magnitudes over the range 1.32–4.8 mm/decade. In another study (El Kenawy et al., 2019), the Tmax in Egypt was found to exhibit stronger warming than Tmin over the period 1983–2015. Conversely, Nashwan et al. (2019) showed that the Tmin increased (0.08–0.29 °C/decade) much faster than Tmax (0.07–0.24 °C/decade) across Egypt. Rainfall across Egypt was also demonstrated to be characterized by decreasing trends (Gado et al., 2019).

For South Africa, Karl et al. (1993) also reported positive trends in both Tmax and Tmin over the period 1951–1991. According to MacKellar et al. (2014), the Tmax of South Africa from 1960 to 2010 exhibited a positive trend. However, decreasing trends in both Tmax and Tmin in South Africa between 1940 and 1989 were reported by Muhlenbrunch-Tegen (1992). Furthermore, Hulme et al. (2001) showed a cooling tendency over the coastal areas of South Africa considering the period 1901–1995. In this study, cooling was not evident in the coastal areas of South Africa but instead in Madagascar (near the eastern coastal area of South Africa). Some possible discrepancies in results from this paper with those of previous studies were due
to the difference in data periods used, for instance, 1901–1995 (Hulme et al., 2001), 1940–1989 (Muhlenbrunch-Tegen, 1992), and 1901–2015 for the present study. Trend results depend on the period considered for analyses (Onyutha et al., 2016). Another reason is that the effect of seasonality (which previous researchers did not take into account) was explicitly considered in this study.

4.2. Co-variation of Pcp with Tmax, Tmin and PET

The general negative coefficients of correlation between Pcp and temperature sub-trends indicated that as the temperature was increasing, Pcp totals tended to be characterized by a decline or vice versa. However, as temperature increased, PET also increased. In other words, a direct relationship exists between temperature and PET. High temperature means an increased amount of energy for the conversion of liquid water to water vapor. Besides, an increase in temperature causes widening of stomata from plant leaves to allow more escape of water vapor than under a condition with reduced temperature. The water to meet the evaporation and transpiration demands is supplied by Pcp. Thus, as Pcp increases, PET is also expected to increase. However, PET rates amid Pcp are controlled by several factors such as: (i) humidity (evaporation rates get lowered when an area is too humid), (ii) wind speed (evaporation rates increase so long as air is moving or humidity is being cleared by wind), (iii) soil moisture state (in a dry soil, prior to evaporation, nature permits infiltration and sufficient water uptake by plants or vegetation), and (iv) vegetation or plant type (whereas trees and crops are generous in losing water, some plants like Cacti naturally prefer holding onto their water instead of easily giving it up for transpiration). Importantly, dry conditions especially on land mean more sunshine and less evaporative cooling.

At some locations for which the \( H_0 \) (no correlation) was rejected \((p<0.001)\), it suggests that multi-decadal temporal changes in temperature could be inferred from the variation in Pcp. However, considering the long-term, it is evident that the temperature-Pcp co-variation depends on the period used for analyses something which also holds true for the relationship between PET and Pcp. For instance, as shown in Figure C1 of the Supplementary Material M1, Tmax, PET and Tmin generally exhibited negative trend slopes over the period 1941–1978; however, positive trends were obtained over the periods 1901–1940 and 1979–2015. On the other hand, Pcp was on average characterized by positive and negative trends over the periods 1901–1960 and 1961 to 1990, respectively. Thus, trend slopes in both temperature and Pcp as
well as PET were positive from 1901 to 1940. However from 1979 to 1990, temperature and
PET were increasing while Pcp was declining over time. Actually, rise in temperature increases
the atmospheric evaporative demand, and eventually, Pcp is expected to increase. This is
because high temperature enhances rising of the warm moisture thereby producing convection.

Despite the general warming across Africa, some regions were characterized by drying trends
while in other areas Pcp increased. Besides, the warming trends across the various regions of
the continent follow different influences. For instance, the Tropical North Africa is very warm
due to a number of reasons including the following (Moron et al., 2016): (i) it has low latitude
and receives a large amount of incoming solar radiation, (ii) its elevation is mostly less than
1000m, and (iii) advection of cool oceanic air from the Tropical North Africa towards the
interior (Sahelian and Sudanian belts) is inhibited by the general Easterly trade winds coupled
with the size of the African continent North of the Equator.

Pcp totals differ across the various regions and this can be thought of in terms of the
influence from the shifts in ocean currents and wind patterns. For instance, heat motion is
majorly influenced by ocean dynamics while the cycles of the El Niño Southern Oscillations
(ENSO) responsible for the wet and dry conditions in several areas follow the atmosphere-
ocean interactions. According to Trenberth et al. (2010), during the La Niña phase, there is a
major uptake of heat by the ocean. The absorbed heat is stored in the tropical western Pacific.
The ocean cools as the atmosphere responds with typical El Niño weather patterns forced from
the region (Trenberth et al., 2010) and this tends to be a typical source of influence on Pcp
across various areas of the world.

The monthly spatial transition in the correlation between temperature and Pcp described
in the section of Results is typical of the latitudinal migration of the Inter-Tropical Convergence
Zone (ITCZ). However, the analogy with the ITCZ migration was clearer for Tmax than Tmin.
This is because the sensitivity of temperature extremes to local influences is higher for Tmin
than Tmax. The Pcp patterns and distributions across Africa dominantly rely on the migration
of the ITCZ. A band of Pcp moves with the ITCZ as it migrates from its most southern location
(in January) to the northern extreme (by July). Lack of high spatial coherence in the correlation
from the equatorial region is due to the joint impacts of the Great Lakes and the high mountains
on Pcp and temperature. The joint impact of the lake and upslope breezes has considerable
influence on convection, and subsequently temperature. It is also worth noting that in cool
highland areas, Pcp tends to be associated with above normal temperature; however, in
lowland, hot environments and early parts of the rainy seasons, Pcp occurrence is associated with below normal temperature (Camberlin, 2017).

4.3. General implications of the warming and drying trends

The warming trends found in most parts of the continent have wide-ranging implications. A positive trend in temperature means an increase in the intensity of heat waves thereby leading to many cases of illnesses or even deaths in several regions of the continent given the high vulnerability of the local populations. Continued increase of temperature presents high possibility of severe and/or persistent dry conditions. This is because PET depends on Tmax and Tmin. Thus, positive trends in Tmax and Tmin mean increasing PET totals. An increase in PET leads to a decline in soil moisture especially if Pcp is insufficient, thus, severe lack of water for crops. By inducing water and heat stresses, dry conditions (due to soaring temperatures, high evaporation and subsequent decline in soil moisture) negatively affect crop production. Increasing temperature and declining Pcp totals lead to crop failure thereby exercebating food insecurity which is already a formidable challenge for subsistence of the poor population across Africa (especially in the sub-Saharan region). The dry and wet conditions in a number of locations across the continents tend to be characterized by late onset of Pcp, reduced length of wet season (or longer than normal dry conditions), and soaring temperatures. Such changes tend to greatly affect drylands. Dryland ecosystems are sensitive to changes in temperature and Pcp.

For predictive adaptation in areas or regions with significant positive trends in temperature (Tmax and Tmin) and PET, smallholder farming should be based on drought-tolerant crop varieties. Good farming practices (for instance, using mulching to improve soil moisture and fertility) should be encouraged for smallholder farmers. However, tackling food insecurity challenge amid uncertain climatic conditions especially in the sub-Saharan Africa requires an interplay of science and policy roles (Onyutha, 2019). For instance, the policy makers should ensure speedy variety testing and approval of the new crop varieties being developed. This should be done while addressing factors which hamper the adoption of scientifically improved crop varieties by farmers. Global collaboration in science is crucial in tackling food insecurity in Africa with respect to scientific research to support agriculture. Further measures that could be taken include increasing access to markets for farmers, promotion of non-farm activities, minimizing differences in priorities across various sub-sectors of farming in sub-Saharan...
Africa, and addressing disparity in initiatives of regional and national dynamics (Onyutha, 2018c).

Deviations of Pcp and temperature from their normal conditions increase the risk of conflicts (Hsiang and Meng, 2014; Hendrix and Salehyan, 2012). How local population responds to the impacts of increased warming and drying may lead to various other repercussions. Migration as an adaptive response to local environmental pressures (Tacoli 2009; Warner, 2010) leads to health risks (Serdeczny et al 2016) and tensions between ethnic groups, political and legal restrictions, and competition for (and limitations on) access to land (Tacoli, 2009). According to Burke et al. (2009), the likelihood of civil war is higher for hotter years. In other words, warming increases the risks of civil wars in Africa (Burke et al., 2009). Conversely, Aldhous (2010) remarked that civil war in Africa has no link to global warming. Thus, climate should not be blamed for African civil wars (Buhaug. 2010). Nonetheless, exacerbation of conflicts by the influence of drying and warming trends cannot be disregarded depending on a number of factors considered for analysis such as: what indicators of conflicts are used, which region is considered, and what period (or time frame) is chosen. Besides, how drying and warming trends lead to conflicts can be in an indirect way and thus, difficult to unearth. This could be why there continues to be lack of evidence on the relationship between violent conflict and climate change (Gleditsch, 2012). It remains a fact that local population will always tend to adapt to prolonged local environmental stresses. For instance, due to prolonged condition of extreme heat and severe drought, pastoral communities adapt by moving from one place to another. This migration may be further and wider than when conditions of heat and water stresses are short-lived. Competition for resources (such as water, land, and pasture) by the occupants of an area and the immigrants can heighten conflicts. For the local communities to adapt to the impacts of warming and drying trends on livelihood, there should be poverty alleviation through actionable policies that promote non-farm income generating activities, and creation of job or employment opportunities to the rural population.

Increasing temperature and PET alongside declining Pcp totals imply decrease in rainfall-runoff volumes. Thus, if warming and drying trends continue, future water supply from rivers will be characterized by seasonal shortages. There are several applications which depend on volumes of water in the rivers. Some of these applications include irrigation, reservoir operations, hydropower scheduling, and flow control for ecological purposes. Increasing water demand for irrigation and hydropower production is compounded by the pressure from high
population growth especially in the sub-Saharan region. It is known that groundwater is the
key source of safe drinking water in sub-Saharan Africa (MacDonald et al., 2009). However,
drying and warming trends also pose serious risk of reducing volumes of water to recharge
groundwater. To adapt to the impacts of warming and drying trends, there should be sustainable
use of water resources.

4.4. Implications of changes in PET, temperature and Pcp for arid environments

How changes in temperature, Pcp and other climatic factors affect regional
evapotranspiration and net primary productivity in various arid environments of the world have
been widely studied (Onyutha, 2016c; Bai et al., 2014; McVicar et al., 2011). Variation in Pcp
was found to significantly ($p<0.05$) explain changes in PET across the River Nile riparian
countries (Onyutha, 2016c). In another relevant study for an arid environment (though in the
northwest China), Bai et al. (2014) quantified the contributions of agricultural oasis expansion,
management practices and climate change to net primary production and evapotranspiration.
Furthermore, McVicar et al. (2011) assessed the implication of trends in observed terrestrial
near-surface wind speeds for evaporation.

Results of this study are vital for an insight into the ecohydrology of water-limited
ecosystems. In arid regions, evapotranspiration comprises a significant water budget
component (Glenn et al., 2010). Generally, water (followed by nitrogen) is the most vital
limiting variable for plant growth in arid conditions (Smith et al., 1997). Therefore, in arid
regions, plant community composition, function, and structure tend to be greatly influenced by
possible controls on water movement (Loik et al., 2004). Eventually, the amount of water that
becomes available for root water uptake also is affected (Young et al., 2009). On one hand, it
may be held that water can be efficiently used by vegetation in dryland ecosystems (Huxman
et al., 2004). On the other hand, water use efficiency might be variable based on the
composition of plant species over the landscape (Huxman et al., 2005). As opposed to arid
regions, semi-arid systems tend to be mainly driven by Pcp. Long-term changes in climatic
variables such as PET and Pcp may be linked the impacts of human factors. For instance, rapid
expansion of cropland and intensive agricultural management practices can greatly affect regional carbon and water budgets (Bai et al., 2014). Other relevant human factors which lead to changes in climatic variables include over-grazing, massive deforestation, transition in land-use or cover, and urbanization. An insight into the present and potential future vegetation and water availability in arid environments can be obtained by understanding the regulation of ecosystem evapo-transpiration (Wilske et al., 2009).

Positive trends in PET (and temperature) imply an increase in the demand of crop water requirements. Cropping system in sub-Saharan Africa is almost entirely rainfed. However, addressing the issue water shortage to enhance crop yield implies an increase in irrigation requirements. In irrigated and desert areas, water shortage in turn indirectly affects soil salinity of the root zone (Abderrahman et al., 1991). Especially under elevated water requirements, plants tend to consume some water from the leaching fraction thereby increasing soil salinity and subsequent yield loss (Abderrahman et al., 1991).

Results of long-term trend and decadal changes in evapotranspiration (and Pcp) indicate whether the given region will be wetter or drier than its past climatic conditions. Findings of this study can be useful for a careful planning of water resources management, for instance, to determine how much water can be used to support environmental needs after safely being allocated for human use (Bunting et al., 2014). Long-term increase in PET and a negative trend in Pcp imply that the ratio of PET to Pcp was increasing over time. The ratio of evapo-transpiration to Pcp is important in arid and semi-arid ecosystems (Glenn et al., 2014). This is because water not lost through evapotranspiration can produce runoff and groundwater recharge thereby influencing erosion, aquifer properties and regional stream flows (Milly, 1994). Furthermore, changes in the ecohydrological variables or factors such as the ratio of PET to Pcp can be taken to indicate transition in vegetation communities especially across drylands (Heilman et al., 2014). For instance, the ratio of evapo-transpiration to Pcp varies across woodland, grassland and shrubland ecosystems.
Before 2000, Sahara desert was shown to be changing in size by both expanding and contracting at some points in time (Tucker and Nicholson, 1999; Tucker et al., 1991). Recently, Sahara desert has also been found to be characterized by an amplified warming trend (Zhou, 2016; Cook and Vizy, 2015). However, this study's results indicating an increasing trend in the long-term (1901–2015) temperature and PET accompanied by Pcp decrease across North Africa point toward the Sahara desert expansion. The variation (especially the increase) in the size of the Sahara desert has implications in terms of the influence of Saharan dust on the Sea surface temperatures as well as the occurrences of the Atlantic hurricane (see Evan et al., 2016). If Sahara desert continues to expand in the future it will have significant socio-economic and environmental impacts. For instance, the affected population will have to live under abnormal water-stressed conditions. Furthermore, many people will be displaced by the harsh environmental conditions. The question to answer would be: what steps should be taken? It is worth noting that apart from low rainfall and dry conditions, other factors which enhance desertification and subsequent degradation of soils include dust transport and wind erosion (McLeod, 1976). Therefore, some of the critical steps to be taken in line with desertification include: reinstating degraded soil ecosystems, and scaling-up land-use and/or land management practices which are sustainable.

5. Conclusions

In this study, trends and variability were analyzed in long-term (1901–2015) monthly Tmax, Tmin, PET and Pcp. Each climatic variable was obtained in gridded form with (0.5°×0.5°) spatial resolution over the entire African continent. The variation of sub-trends in Pcp and those of Tmax, Tmin, and PET was compared through correlation analysis.

The African continent was characterized by warming over the periods 1901–1940 and 1979 till 2015 (end of data). However, the continent experienced some cooling from 1941 to the mid–1970s. The warming of the continent from 1979 to 2015 was stronger than that over the period 1901–1940. The increasing/drying trends in the 1979–2015 annual Tmax, Tmin, PET averaged over the entire continent were at rates of 0.18 °C, 0.22°C, and 3.5 mm, respectively. The 1961-1990 annual Pcp averaged over the whole continent showed that Africa experienced drying at a rate of about -28 mm per decade. When considering the period 1961-
2015 the Pcp decrease was a rate of about -8 mm per decade. Areas around the Lake Victoria in East Africa and along the western coastline south of the Equator were characterized by wetting at rates as high as 36 mm per decade. Sudan, Southern and Northern Africa were shown to have experienced significant ($p<0.01$) warming trends. Positive PET trends were significant ($p<0.01$) in the warm Mediterranean climate, and the western part of South Africa. Some regions were characterized by drying trends while in other areas Pcp increased.

Temperature and PET variability was low in the equatorial climate. Areas with high variability in temperature included Mozambique, Egypt, Mauritania, Western Sahara, and Lake Victoria region. Pcp variability was high across the continent. However, Sahara and Namib–Kalahari deserts were characterized by low Pcp variability.

The strength of the co-variation of Pcp with Tmax, Tmin or PET was patchy through time. The strongest coherence between Pcp and PET occurred at multiple scales (2–5 years). Pcp cycled in anti-phase with PET from 1985 to 2005. The strongest coherence between Pcp and Tmax (or Tmin) existed at multiple scales (6–8 years). Strong coherence of Pcp with Tmax and Tmin existed over the periods 1901–1935 and 1901–1925, respectively.

Negative (and weak) correlation was mainly found between Pcp and temperature and/or PET. Thus, as the temperature increases, Pcp totals tend to decrease. However, temperature–Pcp co-variation and the relationships between PET and Pcp depend on the period used for analyses. Monthly spatial variation in locations with strong correlation between temperature and Pcp was found to be analogous to the latitudinal migration of the ITCZ. However, there was generally lack of high spatial coherence in the correlation between Pcp and temperature in the equatorial region. This was because of the joint impact of the breeze from the Great Lakes and that from the high mountains on convection, and subsequently temperature.

Increasing temperature can amplify the intensity of heat waves. This brings about many cases of illnesses or even deaths in affected areas. Increasing PET and decreasing Pcp totals can lead to decline in soil moisture thereby increasing crop water stress. Smallholder farming in affected areas should be based on drought-tolerant crop varieties and good farming practices such as the use of mulching to improve soil moisture and fertility.

Deviations of Pcp and temperature from their normal conditions can lead to migration of some communities (like the nomads) as an adaptation response to local environmental
pressures. This can bring about conflicts between the existing community in a particular location and the immigrants due to competition for access to resources such as agricultural land and pasture or water for livestock. It is important to remark that how drying and warming trends lead to conflicts may be in an indirect way and, thus, difficult to unearth. To avoid such conflicts, government needs to embark on poverty alleviation through actionable policies that promote non-farm income generating activities, and creation of job or employment opportunities to the rural population.

If the warming and drying trends continue, future water supply from rivers will be characterized by seasonal shortages, and volumes of water to recharge groundwater will decrease. In such cases, hydrological applications which rely on the volumes of water in the river or groundwater will be affected. It is vital to plan predictive sustainable use of water resources to cope with possible impacts of warming and drying trends on water resources in affected areas. The possible indication of the Sahara desert expansion presents significant socio-economic and environmental impacts such as abnormal water stress. Some of the adaptive measures for the affected areas include reinstating degraded soil ecosystems, and scaling-up land-use and/or land management practices which are sustainable.

This study showed the co-variability of Pcp with temperature or PET. This indicates that the influences of the changes in large-scale ocean-atmosphere conditions on the variability of temperature and PET can be inferred from the drivers of Pcp. Results for analyses of the co-variation of several climate indices with Pcp across the entire African continent can be found in a number of studies such as Onyutha (2018a) and Nicholson and Selato (2000).

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Appendix A: Clarification on the CSD method for variability analyses

Analyses of the co-variation of Tmax, Tmin, PET and precipitation were based on the sub-trends. The CSD method of quantifying variability is based on the application of an overlapping moving window of length $L$ (which can be in years). If there is a positive sub-trend in the data points within the window at the first location (or $i = 1$), it can be possible that when the window is slid by one step forward ($i = 2$), the resulting sub-trend also becomes positive. The influence from the first sub-trend diminishes as the position of the window being slid approaches $i = L$. This autocorrelation behavior can be enhanced by a long-term trend (if present) in the data. In dealing with this, there are a number of points to consider for the correct application of the CSD-method and interpretation of the variability results.

i) A significant trend in the long-term data should first be removed from the data by detrending procedure such that the CSD-method is applied to detrended data. If the $H_0$ (no trend) is not rejected at the selected $\alpha$, the CSD-method is applied to the original data without detrending.

ii) The choice of the window length must be made with respect to the purpose of the application for which the study is being conducted. For hydro-meteorological applications $L = 5, 10, \text{ and } 15$ years can be used.

iii) In applying CSD method, differences between exceedance and non-exceedance counts of data points are used in places of the actual data values. This avoids the possibility of a large value (or outlier) influencing the sub-trend in a particular sub-series or data points within a time slice.

iv) The variance of CSD-statistic is corrected from the influence of autocorrelation when testing the significance of the sub-trend in data points in every time slice.

v) Two values of CSD-based sub-trend statistic can be considered independent if they are at least $L$ data points apart, where $L$ as mentioned shortly before is the window length.

vi) The sub-trends can be negative for some time slices but positive over others thereby characterizing variability or random temporal variation in the data.

vii) The application of the CSD method for quantifying variability in the data through temporal variation in the sub-trends cannot be considered complete without testing the $H_0$ (natural
randomness). At a selected $\alpha$, the $100\times(1-\alpha)\%$ confidence interval is constructed on the values of the sub-trend statistic plotted against corresponding time of observations. For illustration consider 15-year window was used for applying CSD variability test at $\alpha=0.05$. Furthermore, let us take that the sub-trend statistic at $i=10$ is 1.99. This means that the slope of the linear trend line fitted to the 15 data points covered by the window at $i=10$ is positive and for this the $H_0$ (no trend) can be rejected at $\alpha=0.05$. Over certain consecutive data years, the values of the CSD-based sub-trend statistic can fall outside the $100\times(1-\alpha)\%$ confidence interval and in this case, the $H_0$ (natural randomness) can be rejected.

viii) It is important to check on the validity of the oscillation highs (lows) or periods over which the values of the CSD sub-trend statistic are consecutively positive (negative). To do so, temporal variation in the sub-trends based on climatic data at one weather station should be compared with those from other stations within the same region. Furthermore, if the oscillations in the temporal sub-trends in the data can be explained by the oscillations in particular climatic driver based on large-scale ocean-atmosphere interactions (such as El Nino Southern Oscillation, North Atlantic Oscillation, and Atlantic Multi-Decadal Oscillation), it means that the likelihood of the temporal variability being due to natural randomness is low.
Figure 1: Temporal variation in annual Pcp and PET extracted over the a) WSAC, b) WDC, c) EC, d) HSTC, and e) CSAC as well as the average of the data from a)-e). The legends of all the charts are the same as that in b).
Figure 2: Overall standardized trend statistic $Z$ for monthly (a) $\text{Tmax}$ ($^\circ\text{C}$), (b) $\text{Tmin}$ ($^\circ\text{C}$), (c) $\text{PET}$ (mm), and (c) precipitation (Pcp, mm), and trend slopes for (e) $\text{Tmax}$, (f) $\text{Tmin}$, (g) $\text{PET}$, and Pcp averaged for all the months from January to December.
Figure 3: Overall standardized variability statistic $Z^*$ for (a) Tmax, (b) Tmin, (c) PET, and (d) Pcp based on data for all the months from January to December.
Figure 4: Coefficients of correlation between Pcp and Tmax for the months of (a) January to (l) December.
Figure 5: Coefficients of correlation between Pcp and Tmin for the months of (a) January to (l) December
Figure 6: Coefficients of correlation between Pcp and PET for the months of (a) January to (l) December
Figure 7: Wavelet coherence plots for a) Pcp and PET, b) Pcp and Tmax, and Pcp and Tmin, d) PET and Tmax, e) PET and Tmin, and f) Tmax and Tmin