



22 Years of Near-zero Cloud Cover Variability across Varying Geographical Landscapes of Southern Africa: A Surprising Anomaly

Mutinta Nkolola^{1*}

¹Kwame Nkrumah University, 80404 Kabwe, Zambia.

Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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ABSTRACT

In physical geography, clouds are known to dictate global energy budgets and to have crucial ripple effects on other climatic variables such as diurnal range of temperature (DTR), a key indicator of climate change. Here, a 115-year state-of-the-art station based gridded dataset from the Climatic Research Unit (CRU) is interrogated to understand the evolution of cloud cover across southern Africa for the period 1901 - 2016. Results show near-constant variability from 1901 – 1922. It was therefore hypothesised that the observed near-constant variability would result in a similar pattern for some climatic variables such as DTR as the opposite would bring into question our current knowledge of geographical mechanisms underlying DTR control across the region. Further analyses showed little to no association between cloud cover and other climatological variables (including DTR) for the period 1901 – 1922 but strong and significant association from 1923 – 2016. This is the first observational evidence of near-constant cloud cover variability; it is surprising, and counterintuitive. This constant variation can be attributed to limited ground-based observations that went into the construction of the CRU gridded dataset during the 1901 – 1922 period and therefore, caution needs to be exercised by studies that need to use the data for the said period. This is a crucial area of scientific enquiry, and a lack of caution can lead to misleading conclusions on cloud cover evolution and how that relates to climate change.

Keywords: Cloud cover; climate change; global change; Southern Africa.

1. INTRODUCTION

70% of the earth is covered by clouds which are known to cut energy losses from the earth by being less emitters of thermal infrared [1], at the same time, their reflective ability of shortwave radiation back to space exerts a net cooling effect on the earth's system [2]. This makes clouds crucial components of energy budgets and thus, the climate system. Although there are considerable studies on clouds-climate system interactions, our knowledge of how to account for them in climate modelling and predictions is limited especially when aerosol-cloud interactions come into play [3].

From a physical geography perspective, it is well established that the energy exchanges associated with evapotranspiration, cloud development, and precipitation are central to the global water cycle thereby making clouds critical components of the water budget [4].

Given their importance, clouds have been studied since time in memorial. In fact, the evolution of cloud observations dates to the pre-satellite era and they have been studied in terms of their formation, development, dispersion, and physics. In general, clouds are observed and classified by their base height, precipitation that falls from them, and morphology. For example, stratified clouds are generally associated with stable air while cumuliform clouds are characterised by turbulent air [5]. These cloud types also differ in optical depth and cloud top pressure [6]. In the International Cloud Atlas Manual on the Observation of Clouds and Other Meteors (WMO-No. 407), the World Meteorological Organization defines standards to be followed by human observers to determine cloud cover. Across southern Africa, cloud cover detection is usually done once every hour apart from at Aviation Meteorological stations which detect clouds even at unscheduled times to issue special aerodrome reports (SPECI) whenever significant weather conditions occur.

While the data collected is indispensable for advancing climate science [7], cloud cover observations are not short of errors especially if less experienced Observers are left without close supervision [8]. Errors are also introduced by reduced visibility due to haze or darkness at night. Given the sparse distribution of meteorological stations across southern Africa [9,10], the spatial resolution of cloud cover

observations is usually coarse thus, introducing another challenge. Because of these reasons, recent studies have focussed on inventing automated cloud detection instruments [11, 7]. Unconventional to ground observations, satellites can now detect cloud cover from above with high temporal and spatial resolution. Perhaps one of the most used satellite cloud products is the International Satellite Cloud Climatology Project (ISCCP) which analyses cloud properties at fine timescales to capture their dynamical processes. Cloud observations have also been done by: lidar e.g. CALIPSO-ST which uses Lidar VIS backscatter and horizontal averaging for cloud detection [12], multi-spectral imagers e.g. MODIS-ST which uses multi-spectral IR/NIR/VIS and time-space variances for cloud detection [13, 14], and IR sounders e.g. HIRS-NOAA a high resolution infrared radiation sounder onboard the NOAA-19 satellite [15].

All these efforts into ensuring that our ability to observe cloud cover and its properties improve are driven by the understanding that cloud cover is vitally important for advancing climate science as well as for other fields such as solar power production which has been found to have large variability via cloud cover modulation [16, 17]. While clouds are observed in each country across southern Africa, little is known about regional cloud cover. This is because the study of regional cloud cover over southern Africa has largely been ignored. A dearth of literature on long-term cloud cover changes across the region is especially apparent. Here, cloud cover across the region for the period 1901 – 2016 is examined. Findings will provide vital insights into how clouds and their relationships with other climatic variables have evolved.

1.1 Data Sources

A high-resolution 115-year state-of-the-art station based gridded dataset - CRU TS4.01 (Climatic Research Unit gridded Time Series version 4.01; Harris et al., [18]) was used to assess cloud cover across southern Africa. CRU TS4.01 is a reliable dataset that has been widely used (e.g. Grotjahn and Huynh, [19]; Nashwan et al., [20]; Mahmood et al., [21]; Libanda et al., [22]; Shiru et al., [23]) to advance climate science across the globe. The Climatic Research Unit of the University of East Anglia leverages monthly climate anomalies from a dense network of meteorological stations across the globe to develop CRU TS4.01 using angular-distance

weighting [18]. A summary of the datasets used in this study is given in Table 1.

2. METHODS

To avoid the methodological weakness of the widely used non-parametric Mann-Kendall statistical test [24, 25] in eliminating the effect of autocorrelation on timeseries data, cloud cover trend changes across southern Africa were quantified using the modified version (m-MK; [26]. To do this, the *modifiedmk* Package in R Programming Language [27] was used. The hypothesis followed in this study is:

H_0 - No monotonic trend found in cloud cover

H_a - Monotonic trend is present in cloud cover

The computation of the m-MK test is mathematically given as:

$$Z_i = \phi^{-1} \left(\frac{R_i}{n+1} \right) \text{ for } i = 1:n, \quad [1]$$

Where R_i refers to the rank of the detrended series, n denotes the time series' length, and ϕ^{-1} is the inverse standard normal distribution function with a mean of 0 and a standard deviation of 1.

The Sen's slope estimator was then employed to compute the magnitude of the observed trends in cloud cover. The Sen's slope calculates both the linear rate of change and associated confidence levels [28]. It is mathematically given as follows:

$$Q = \frac{Y_{i'} - Y_i}{i' - i} \quad [2]$$

Where, $Y_{i'}$ and Y_i are the values at times i' and i , where i' is greater than i , N' is all data pairs for which i' is greater than i . Q is a slope estimate.

Further a Taylor diagram after Taylor [29] was employed to examine how closely $Tmax$, $Tmean$, $Tmin$, DTR, and precipitation are associated with cloud cover. The Taylor diagram is an efficient way of comparing and summarising multiple variables using root mean square error which gives prediction errors or differences between values, correlation coefficient (R) which is a numerical measure of the statistical relation between variables, and standard deviation which measures the dispersion of a dataset relative to its mean.

3. RESULTS AND DISCUSSION

3.1 Near-constant Variability: The Evolution of Cloud Cover

First, interannual mean cloud cover variability (Fig. 1) observed from 1901 – 2016 was interrogated. What stood out from these results is a near-constant variability from 1901 – 1922. At mean cover of 56.3%, a variance of 0.0 and a slope of 0.0 (Table 2), cloud amount remained essentially monotonic for the whole 22-year period across the region. Clouds are known to be easily perturbed even by small anomalies in horizontal or vertical wind vectors [30], temperature [31], or atmospheric pressure [32], thus, the physics behind cloud formation, development, and dispersion suggests that they tend to change rapidly [1]. To this end, a near-zero variability of 22 years is surprising. Results for the period 1923 – 2016 matched expectations with variance generally ranging between 0.3 – 1.39. The lowest cloud amount was 53.7% reported in 2005 while the highest was 58.7% observed in 1967. Mean cloud amount for the whole period (1901 – 2016) was 56%. Overall, there is a decrease (slope: -0.002) in cloud cover over the region with the risk of rejecting the null hypothesis H_0 when true being lower than 5%.

Table 1. Summary of datasets the used in this study. DTR, diurnal temperature range

Dataset	Source	Resolution	Period used
Cloud cover	Harris et al. (2014)	0.5 ⁰ × 0.5 ⁰	1901 – 2016
DTR	Harris et al. (2014)	0.5 ⁰ × 0.5 ⁰	1901 – 2016
Maximum temperature ($Tmax$)	Harris et al. (2014)	0.5 ⁰ × 0.5 ⁰	1901 – 2016
Mean temperature ($Tmean$)	Harris et al. (2014)	0.5 ⁰ × 0.5 ⁰	1901 – 2016
Minimum temperature ($Tmin$)	Harris et al. (2014)	0.5 ⁰ × 0.5 ⁰	1901 – 2016
Precipitation	Harris et al. (2014)	0.5 ⁰ × 0.5 ⁰	1901 – 2016

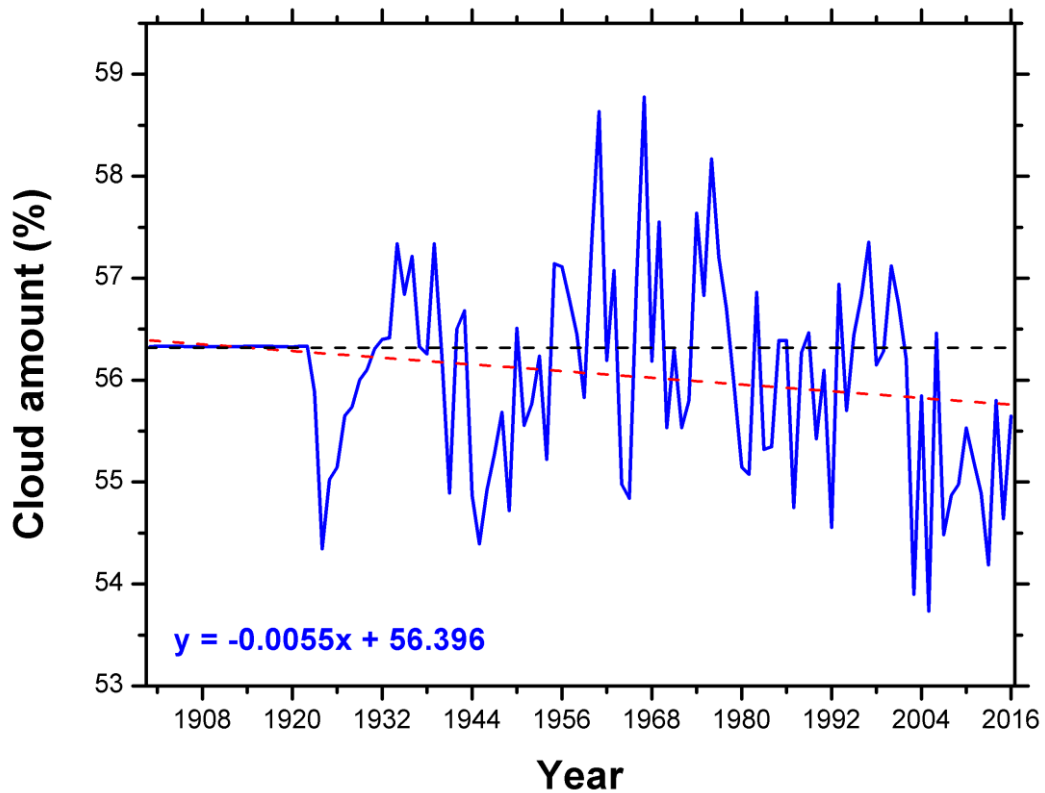


Fig. 1. Internannual variations of cloud cover for the period 1901-2016 across southern Africa averaged over longitudes 10° E - 51° E and latitudes 39° S to the Equator. Black dotted line shows long-term average while the red dotted line signifies trend

Table 2. Cloud cover (%) summary statistics for each of the 22-year segments covering the period 1901-2016 across southern Africa averaged over longitudes 10° E - 51° E and latitudes 39° S to the Equator. For the 2014 – 2016 period, we recognize the limitations of regression analysis on short-term data samples

Metric	1901 - 1922	1923 - 1944	1945 - 1967	1968 - 1990	1991 - 2013	2014 - 2016	1901 - 2016
<i>n</i>	22	22	22	22	22	2	115
σ	0.00	0.67	1.39	0.8	0.8	0.3	0.8
μ (%)	56.3	56.1	56.1	56.2	56.2	55.3	56
α	0.05	0.05	0.05	0.05	0.05	0.05	0.05
<i>Sen's Slope</i>	0.00	0.06	0.11	-0.04	-0.04	-0.07	-0.002

Fig. 2 presents results of the spatial trend analyses. These results indicate that while each of the 22-year segments from 1923 – 2016 was characterised by polarized cloud cover, there is a general spatial uniformity from 1901 – 1922. Specifically, all regions experienced a dampening trend although it was not vastly different from zero (Fig. 2a). A small portion, between latitudes 6° S – 0° and longitudes 9° E - 10° E experienced a positive trend. It is worthy pointing out that during the entire study period, the northern parts of the region exhibited a

positive trend while the southern parts are generally characterised by a decreasing trend. Latitudinal differences in cloud cover have previously been reported by Mao et al., (2019) who found that at the global scale, cloud cover is generally higher between latitudes 36°S and 68°S compared to other regions. These latitudinal differences suggest the effect of local physical geography forcing mechanisms in the formation, development, and dispersion of clouds.

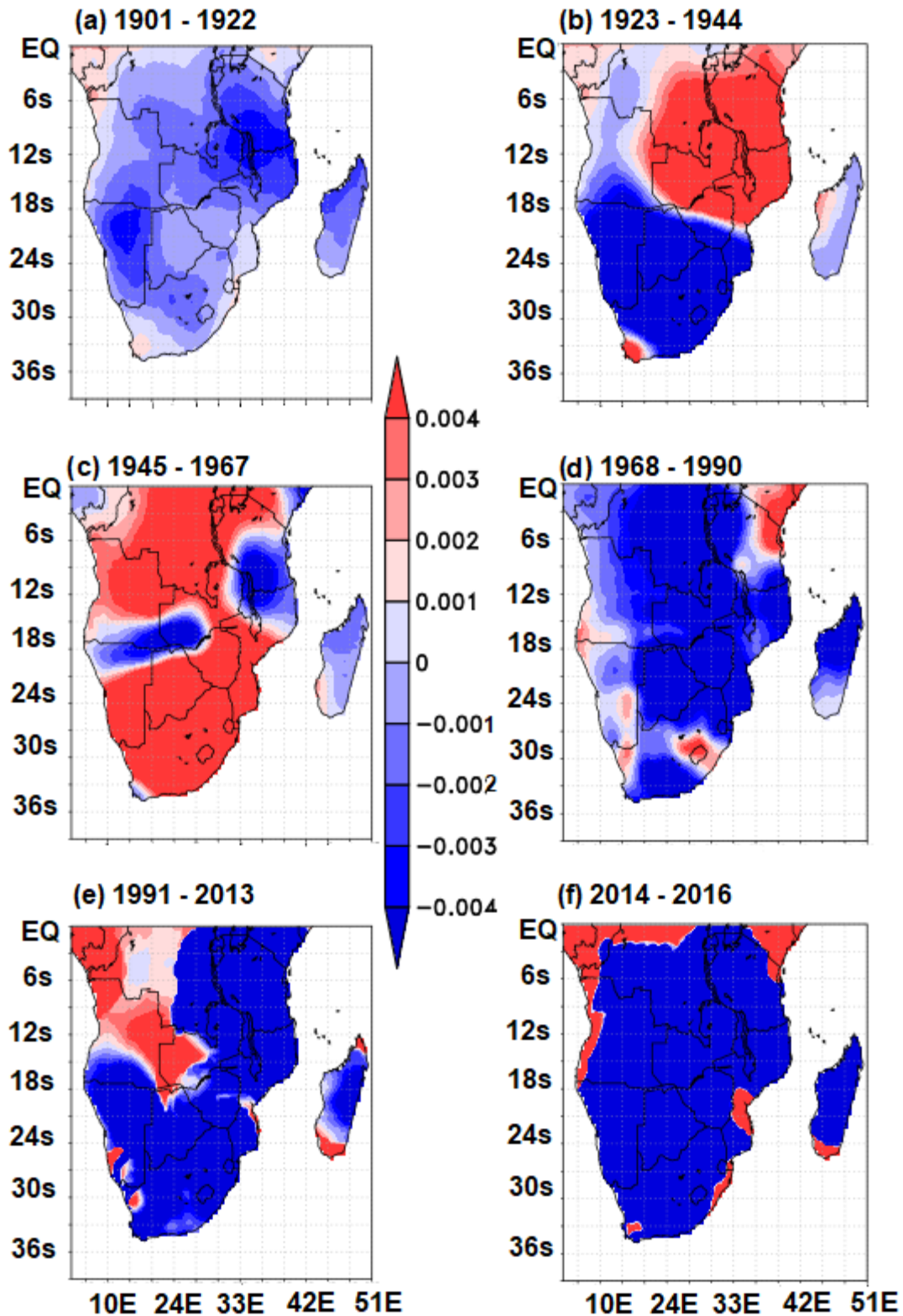


Fig. 2. Spatial distribution of trends in cloud cover for each of the 22-year segments covering the period 1901-2016 across southern Africa averaged over longitudes 10° E - 51° E and latitudes 39° S to the Equator. For the 2014 – 2016 period, we recognize the limitations of regression analysis on short-term data samples

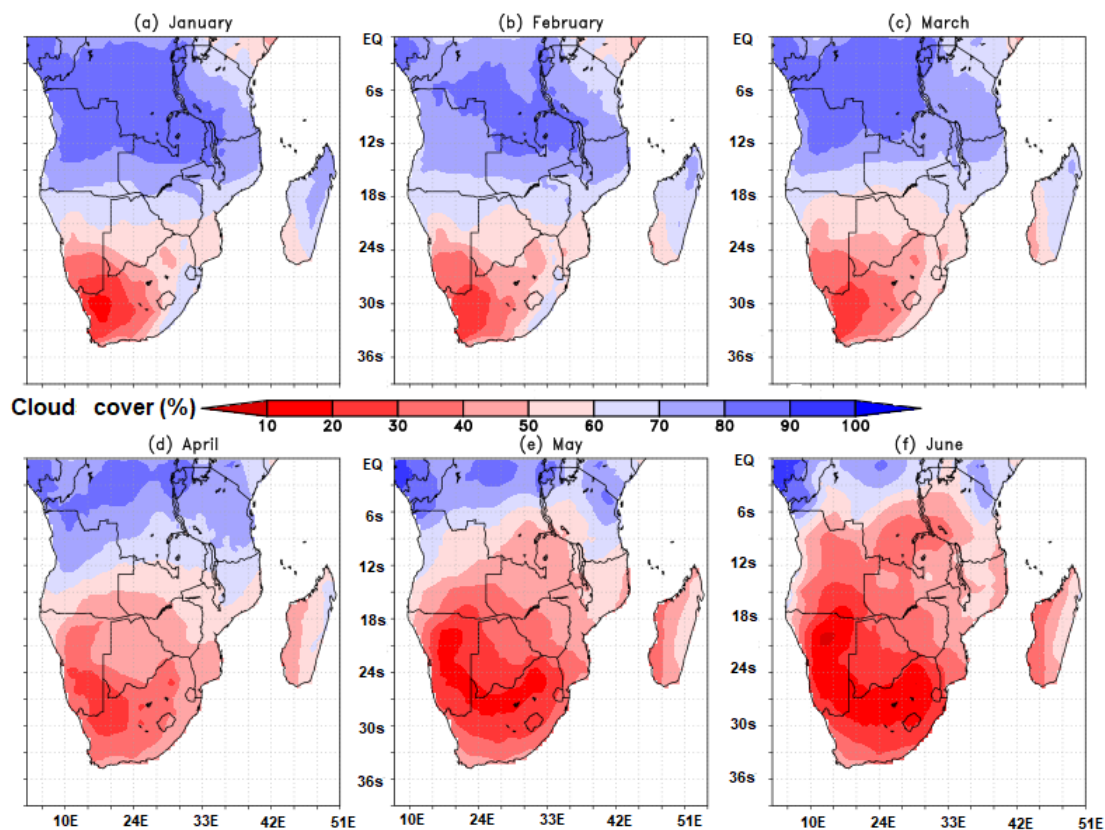
When the spatial patterns of monthly cloud amount during the period 1901-1922 were investigated, no discernible difference from those of 1923 - 2016 were found thus, Fig. 3 displays monthly cloud climatology for the entire study period (i.e. 1901 – 2016). While there are clear differences in coverage from month to month, there is an evident dipole pattern in each month with more clouds in the northern half of the region. Coverage in the southern half especially over the southern part of South Africa is generally less than 50% in all the months while the northern part experiences > 60% especially as one draws closer to the equator. Evidently, there is an upward gradient of cloud cover from the south to the north of the region. This is not surprising as equatorial regions are known to receive more solar irradiance as compared to areas away from the equator [33]. This increases the capacity of equatorial air to hold humidity. When air masses originating from high-pressure zones near the equator blow towards the region, they lead to a surge of humidity which acts as a trigger action for cloud formation.

The observed low cloud cover over much of South Africa is consistent with the findings of Reason [34] who argued that the combination of low cloud cover and equally low minimum

temperature especially in the winter suggest that DTR is 3 - 5^o C more than at comparable latitudinal locations in either South America or Australia at the same time of the year.

In this study, peak cloud amount (68.2%) was observed in January, a month generally characterised by overcasts and precipitation activities across the region, while the lowest (42.5%) was in July, a month that generally exhibits clear skies especially in-land where wind-driven upwelling has little to no effect on temperature and cloud formation.

At the seasonal scale, the dipole pattern of cloud cover observed in Fig. 3 remains evident. Highest cloud amounts occur during the December – February (DJF; Fig. 3a) season while the lowest are during the June – August (JJA; Fig. 3c) period. High amounts of clouds in the DJF season coincide with the occurrence of enhanced convergence zones such as the Intertropical Convergence Zone [35] and the South Indian Convergence Zone (Cook, 2000) which form aggregates of tropical cloud bands and troughs. These convergence zones are also known to encourage the transportation and distribution of moisture – a key requirement for cloud formation.



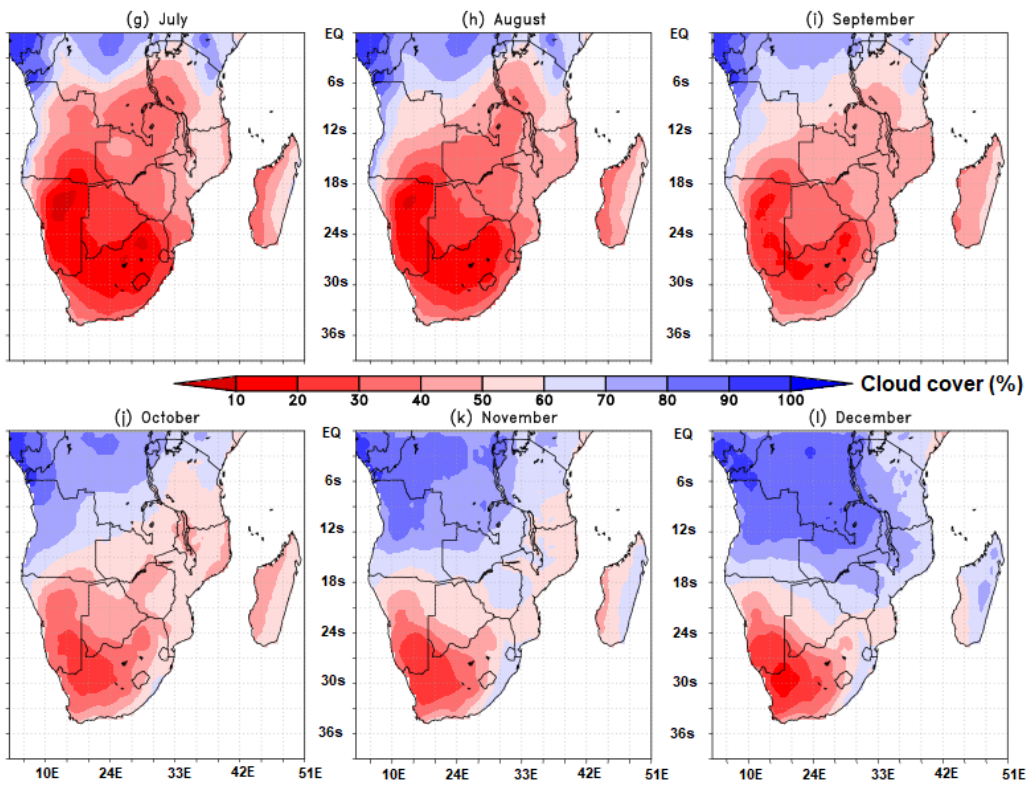


Fig. 3. Monthly climatology of cloud cover for the period 1901 – 1922 across southern Africa averaged over longitudes 10° E - 51° E and latitudes 39° S to the Equator

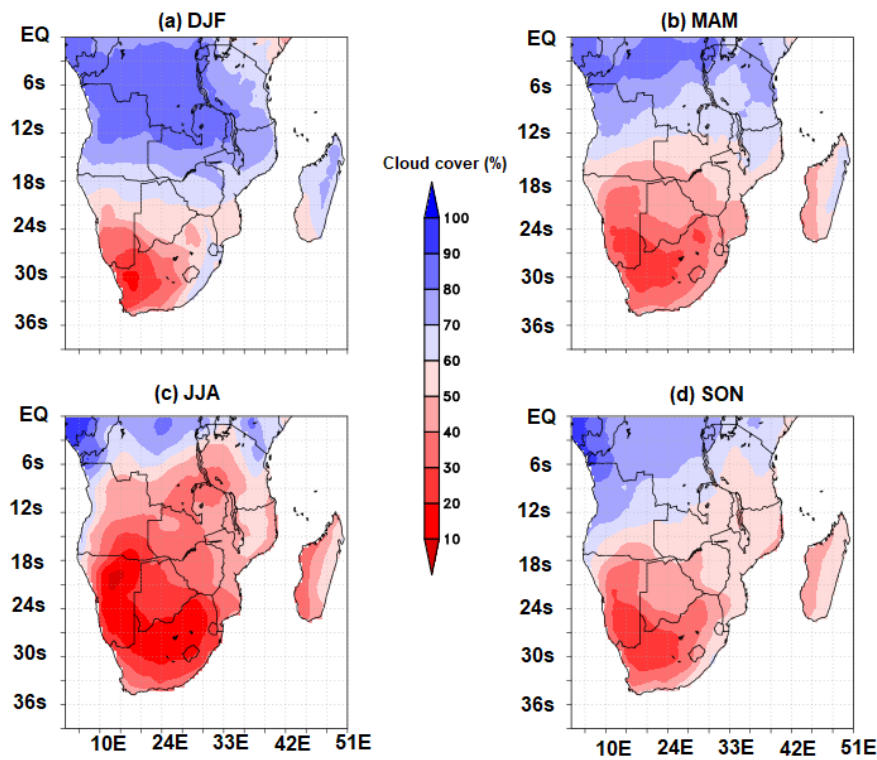


Fig. 4. Seasonal climatology of cloud cover for the period 1901 – 1922 across southern Africa averaged over longitudes 10° E - 51° E and latitudes 39° S to the Equator

3.2 Sensitivity of Precipitation, Temperature, and DTR to Near-Constant Cloud Cover Variability

Precipitation, temperature, and DTR are some of the many meteorological variables closely linked to cloud cover variability. While these variables are widely studied across southern Africa, little is known about regional cloud cover and its feedbacks on these variables is poorly resolved. Therefore, the near-constant variability of cloud cover from 1901 - 1922, an important find with implications on our understanding of how clouds relate to climate change, has remained undocumented until now. Based on data availability, the association of precipitation, temperature, and DTR with cloud cover over the region was interrogated. Fig. 5 indicates that none of the variables mimicked a near-zero variability as observed with cloud cover from 1902 – 1922.

Clouds are known to boost downwelling longwave radiation which leads to spikes in *Tmin*. On the other hand, the reflecting of sunlight dampens *Tmax* (Dai et al., 1999) which leads to DTR plummeting. Based on these

interlinkages, DTR was expected to have an equally near-constant variation during the period 1901 – 1922 especially that clouds are widely documented to be among the primary drivers of DTR [36, 37]. Based on this same understanding, A strong positive relationship between clouds and *Tmin* and a strong but negative relationship between clouds and *Tmax* was expected. Further, our knowledge of the relationship between clouds and precipitation suggests that an increase in clouds would potentially lead to an increase in super-cooled water droplets which would eventually become too heavy to be supported by the atmosphere and thus, succumb to the gravitational pull and fall as precipitation. As such, a strong positive relationship between clouds and precipitation was expected. Results (Fig. 6) of these correlations (*R*) during the 1901 – 1922 period are surprising and counterintuitive. First, the *R* of clouds and precipitation is negative (-0.09). Although not significantly different from 0, it implies that during the period 1901 – 1922, clouds reduced with an increase in precipitation and their relationship was almost 0 – which indicates that precipitation had no dependence on cloud cover change. At 0.48, the *R* of clouds

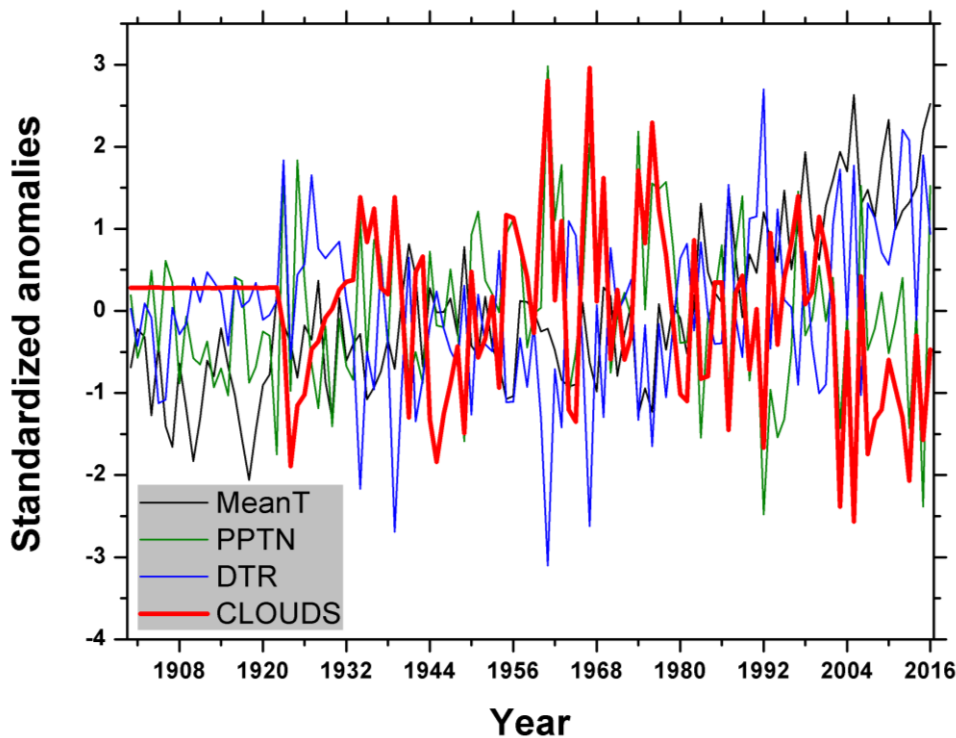


Fig. 5. Variations of normalized anomalies for mean air temperature (MeanT; black curve); precipitation (PPTN; green curve); diurnal range of temperature (DTR; blue curve); and clouds (CLOUDS; thick red curve) for the period 1901 – 1922 across southern Africa averaged over longitudes 10° E - 51° E and latitudes 39° S to the Equator

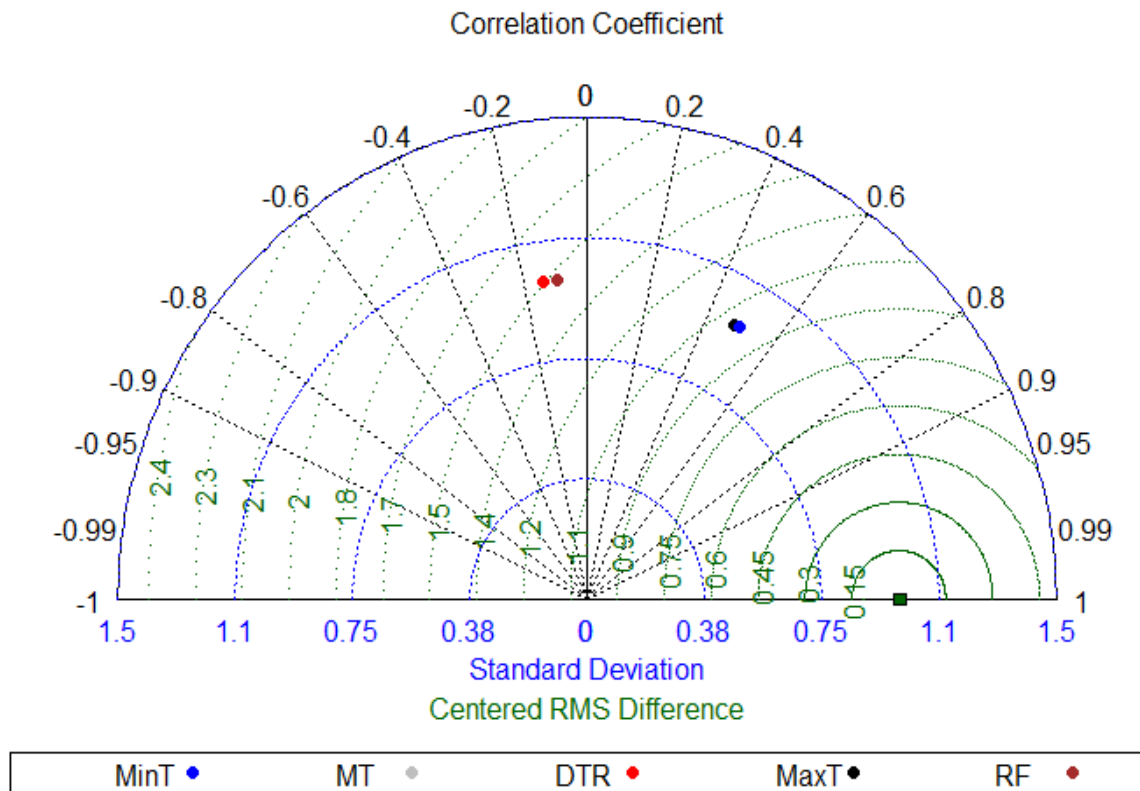


Fig. 6. Taylor diagram of clouds versus: minimum temperature (MinT; blue point); mean temperature (MT; grey point); diurnal range of temperature (DTR; red point); maximum temperature (MaxT; black point); precipitation (RF; brown point) for the period 1901 – 1922 across southern Africa averaged over longitudes 10° E - 51° E and latitudes 39° S to the Equator. For interpretation: the Taylor diagram has three axes: (i) Correlation coefficient is the azimuthal position shown by black dotted lines, (ii) standard deviation is the radial distance from the origin and shown by blue dotted lines, (iii) Centred root mean square (RMS) difference is the distance from the reference point (green square) and represented by green dotted line

and T_{max} was also in an unexpected direction. It showed that T_{max} increased with an increase in cloud cover and this relationship was stronger than that of clouds and precipitation. The R (0.5) of clouds and T_{min} was the strongest and went in the expected direction while that of its relationship with T_{mean} was 0.49. Although weak, the direction of the relationship ($R = -0.13$) between clouds and DTR was as expected.

Considering that some results (Fig. 6) of area averaged correlations e.g. clouds versus precipitation defied logic and current scientific reasoning, spatial correlations on pixel by pixel basis to ascertain how widespread these abnormal relations are were investigated. Results (Fig. 7a) indicate that apart from narrow

coastal and equatorial areas, most pixels have a positive clouds-versus-precipitation relationship. Similar results were observed between clouds versus mean and minimum temperatures (Fig. 7b and c). Fig. 7d displays the relationship between clouds and DTR; the entire sub-continent exhibited, as expected, a negative R . This suggests that although other factors (e.g. vegetation metrics like leaf area index) can influence DTR variation [38], the interannual variability of DTR over southern Africa is to a large extent induced via cloud cover modulation. Perhaps the distribution of the relationship between clouds and T_{max} (Fig. 7e) was the most polarised with areas close to the equator exhibiting negative R values while those further south showing a positive relationship.

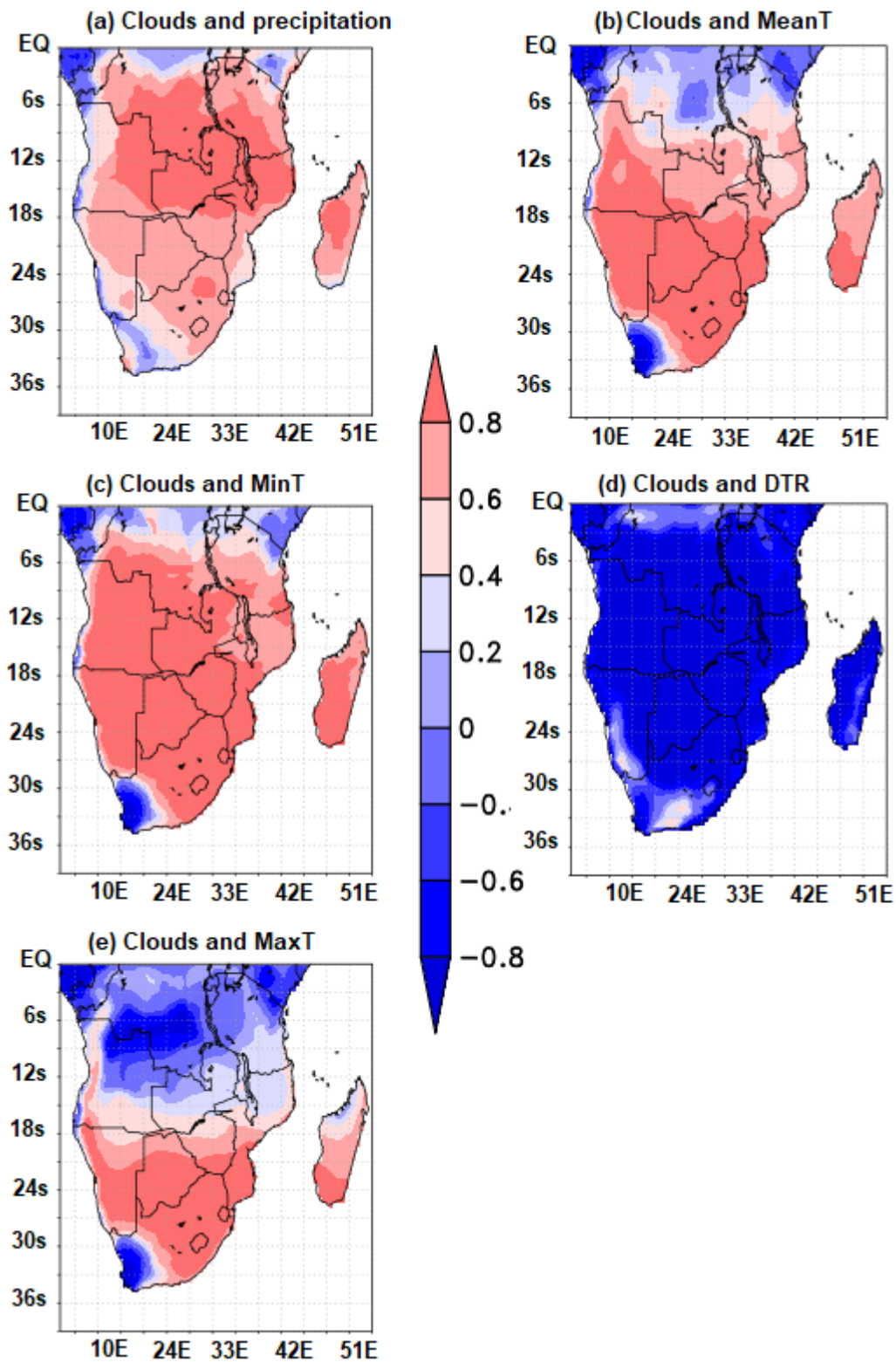


Fig. 7. Spatial correlations of clouds versus: (a) precipitation (b) air temperature (c) minimum temperature (d) diurnal range of temperature (e) maximum for the period 1901 – 1922 across southern Africa averaged over longitudes 10° E - 51° E and latitudes 39° S to the Equator

When correlations for the whole study period were considered, results (Fig. 8) were as expected i.e. a strong and negative relationship between clouds and DTR ($R = -0.77$), a strong and negative relationship between clouds and T_{max} ($R = -0.52$), and a strong positive relationship between clouds and precipitation ($R = 0.56$). However, the relationship between clouds and: T_{mean} was negative ($R = -0.42$), T_{min} was equally negative ($R = -0.29$).

Latitudinal differences in correlations observed in this work have also been reported in previous literature e.g. Tang and Leng, [39] who studied changes in cloud cover, precipitation, and summer temperature across North America and found negative correlations between cloud cover and daily maximum temperature at middle but not at high latitudes. These latitudinal differences indicate that cloud cover can be the most important local factor influencing changes in other climatological variables (e.g. temperature and DTR) in some places but not in others.

While these correlations provide important insights into how (in)sensitive other variables were to near-zero cloud cover variability, they do not sufficiently explain causality which requires more long-term data of other variables such as wind fields in order to disentangle synoptic scale atmospheric circulation mechanisms that may have led to a near-zero cloud cover variability during the period 1901 – 1922. This is the first observational evidence of near-constant cloud cover variability and highlights the need for long-term datasets for other climatic variables. A fuller understanding of the mechanisms that halted cloud cover variability is a crucial area of scientific enquiry as it can potentially add knowledge to how clouds relate or respond to climate change. However, for now, the observed constant variability in cloud cover from 1901 – 1922 can be attributed to limited ground-based observations that went into the construction of the CRU gridded dataset during the 1901 – 1922 period and therefore, caution needs to be exercised by studies that need to use the data for the said period.

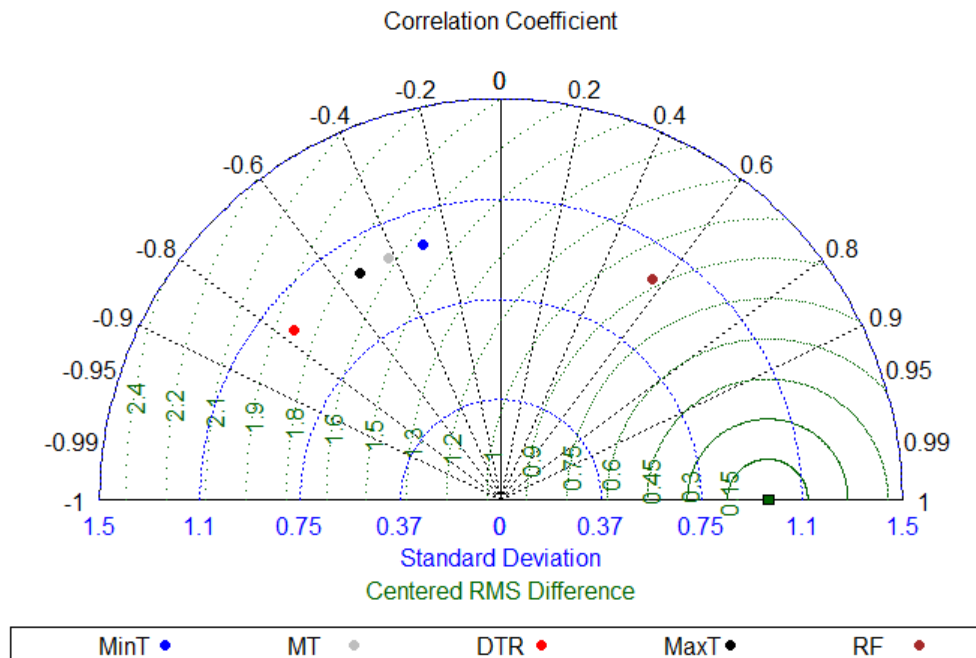


Fig. 8. Taylor diagram of clouds versus: minimum temperature (MinT; blue point); mean temperature (MT; grey point); diurnal range of temperature (DTR; red point); maximum temperature (MaxT; black point); precipitation (RF; brown point) for the period 1901 – 2016 across southern Africa averaged over longitudes 10° E - 51° E and latitudes 39° S to the Equator. For interpretation: the Taylor diagram has three axes: (i) Correlation coefficient is the azimuthal position shown by black dotted lines, (ii) standard deviation is the radial distance from the origin and shown by blue dotted lines, (iii) Centred root mean square (RMS) difference is the distance from the reference point (green square) and represented by green dotted line

4. CONCLUSION

This study provides the first assessment of regional cloud cover across southern Africa. Before this study, evidence of trends in regional cloud cover variability was purely anecdotal. The findings reported here shed new light on long-term (1901 – 2016) variability. The most striking result to emerge from this study is a near-constant cloud cover variability from 1901 – 1922. The observed constant variability in cloud cover from 1901 – 1922 can be attributed to limited ground-based observations that went into the construction of the CRU gridded dataset during the 1901 – 1922 period and therefore, caution needs to be exercised by studies that need to use the data for the said period. The principal limitation of this study was the lack of other long-term meteorological variables such as wind vectors and atmospheric pressure. These could have potentially aided in decoding the circulation mechanisms that led to near-zero cloud cover variability if not the scarcity of ground-based observations. Notwithstanding these limitations, the study found a general decrease (slope: -0.002) in cloud cover with a mean of 56%. Little to no relationship between cloud cover and other climate variables (i.e. *Tmax*, *Tmean*, *Tmin*, DTR, precipitation) for the period 1901 – 1922 but strong and significant association from 1923 – 2016 was found. Apart from the apparent several contributions the findings from this study make to current literature, they highlight the need for long-term climate data across southern Africa – a region infamous for climate data scarcity.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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