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Development and analysis of a long-term soil moisture data set in three different agroclimatic zones of South Africa

Understanding the potential impacts of climate variability/change on soil moisture is essential for the development of informed adaptation strategies. However, long-term in-situ soil moisture measurements are sparse in most countries. The objectives of this study were to develop and analyse the temporal variability of a long-term soil moisture data set in South Africa. In this study, a water balance model was used to reconstruct long-term soil moisture data sets from 1980 through 2018, in three sites that represent the diverse agroclimatic conditions of South Africa. Additionally, long-term changes and variability of soil moisture were examined to investigate the potential impacts of climate variability on soil moisture. The results of the Mann–Kendall test showed a non-significant decreasing trend of soil moisture for inland stations at a rate between -0.001 and -0.02 mm per annum. In contrast, a statistically significant (at 5% level of significance) increasing trend of soil moisture for a coastal station at a rate of 0.1131 mm per annum was observed. The findings suggest that the Bainsvlei and Bronkhorstspruit stations located in the inland region are gradually becoming drier as a result of decreasing rainfall and increasing air temperature. In contrast, the Mandeni station located in the coastal region is becoming wetter as a result of increasing rainfall, despite the increase in air temperature. The findings indicate that climate variability is likely to change the soil moisture content, although the influence will vary with region and climatic conditions. Therefore, understanding the factors that affect soil moisture variability at the local scale is critical for the development of informed and effective adaptation strategies.

Significance:

- Long-term modelled estimates were used to investigate the potential impacts of climate variability on soil moisture in three different agroclimatic conditions of South Africa.
- Results show that inland regions are gradually becoming drier as a result of decreasing trends of rainfall and increasing air temperatures while coastal regions are becoming wetter as a result of increasing trends of rainfall.
- This study indicates that climate variability is likely to change soil moisture, although various regions will be affected differently.
- The development of informed adaptation strategies at the local scale is critical to cope effectively with climate variability.

Introduction

Soil moisture plays a critical role in the partitioning of energy fluxes between the land and the atmosphere through its influence on soil reflectivity, emissivity and thermal capacity.[1-3] Soil moisture also plays a critical role in the partitioning of rainfall into different components of the water balance, such as runoff, drainage and soil evaporation through its influence on infiltration rate.[2] Therefore, soil moisture is a key parameter controlling the exchange of carbon, water and energy fluxes between the land and the atmosphere ecosystems.[3-5] Moreover, soil moisture is a key variable that regulates local, regional and global climates through its influence on near-surface air temperatures and feedbacks of rainfall.[5-8] Consequently, soil moisture was identified by the Global Climate Observing System initiative as an essential climate variable.[9]

Soil moisture is a critical parameter in the forecasting and assessment of weather-induced extreme events such as heatwaves, droughts and floods, which are likely to increase in both frequency and intensity as a consequence of the projected climate change in southern Africa.[10-12] Analysis of the trends and variability of the long-term soil moisture data set could be used to detect changes in the water cycle associated with climate change and thus could support climate change modelling and forecasting.[3,4,13-18] Therefore, the long-term soil moisture data set is critical for sustainable agricultural productivity, and efficient management and sustainable use of natural resources within the context of climate change adaptation.[1,16,19,20]

Despite the critical role of soil moisture in weather and climate systems, long-term and representative in-situ soil moisture measurements are sparse in most countries.[3,15,21,22] The scarcity of long-term records of in-situ soil moisture data sets could be attributed to financial constraints that limit the establishment and maintenance of expensive monitoring networks.[13,23] Mittelbach et al.[24] argued that the scarcity of long-term in-situ soil moisture measurements is due to the delayed recognition of the critical role of soil moisture in weather forecasting and climate modelling. In recent years, huge efforts have been undertaken to establish specific soil moisture monitoring networks in some countries to investigate long-term variability in soil moisture and to validate remotely sensed as well as hydrologically modelled soil moisture estimates.[13,15,23-25]

Remotely sensed and hydrologically modelled soil moisture estimates are often used to provide comprehensive soil moisture data sets for weather and climate research studies as a result of the lack of long-term and representative soil moisture measurements.[3,13-18,22,26] Despite the high spatial resolution at a lower cost of remote sensing products, most of the available satellites can only sense very shallow soil depth (2–7 cm) and they have a very poor quality under dense vegetation and mountainous environments.[2,15,20,26,27] On the other hand, long records of weather data of parameters such as air temperature and rainfall are often readily available at good quality in some countries.[13,15,17] Therefore, the use of historical weather data to estimate soil moisture is an alternative and appropriate approach for obtaining long-term soil moisture information.[6,13,17,19,28]

Models have been successfully used to extend and analyse long-term soil moisture data sets within the context of climate change in various countries.[13,15,17,28] However, very few, if any, studies have been conducted to develop and analyse long-term soil moisture data sets under the climatic conditions of South Africa, which was described by Davis and Vincent[11] as the hotspot for climate change. Given the variability of the climatological, biogeographical, pedological and lithological characteristics across South Africa, an understanding of long-term trends and variability of soil moisture is expected to reveal potential impacts of climate change on soil moisture in this region.

Myeni[29] developed and validated a simplified soil moisture model with minimal data input requirements in Bainsvlei, Bronkhorstspruit and Mandeni sites, representing different agroclimatic conditions of South Africa. The findings of Myeni[29] showed that daily soil moisture content can be estimated well from climate data and minimal soil physical properties using a multi-layered soil moisture model, with root mean square error values less than 7.3 mm. These findings gave confidence that this developed model could be reliably used for reconstructing long-term soil moisture data sets with daily temporal resolution under different agroclimatic conditions of South Africa.

In South Africa, most of the in-situ soil moisture measurements have been collected only since 2014, while co-located weather stations have been reporting standard meteorological data since the beginning of the millennium, and in some cases, for some decades prior.[30] We aimed to reconstruct long-term soil moisture data sets from 1980 to 2018 (39 years) using a soil moisture model developed by Myeni[29], at three selected sites that represent different agroclimatic conditions in South Africa. Furthermore, we aimed to address the following pertinent questions: Has the soil moisture changed significantly during the recent last 39 years (1980–2018) in three sites under contrasting agroclimatic conditions of South Africa? And could climate variability and change explain the observed changes in soil moisture at these sites?

Study site description

The study was conducted at three well-calibrated automatic weather stations, situated at Bainsvlei, Bronkhorstspruit and Mandeni, which represent three different agroclimatic zones found in South Africa (Figure 1, Table 1). Distributions of mean monthly rainfall and air temperature (T_{air}) at the three locations are presented in Figure 2. Detailed information about these stations and the measurement descriptions have been reported by Myeni[29].

Methods and materials

Model description

The multi-layered soil moisture model of Myeni[29] was used in this study. In this model, the user divides the profile into layers based on the observed vertical variability in soil physical properties. The daily water balance for the upper layer (i) is calculated as:

$$\theta_{(t)i} = \theta_{(t-1),i} + P_{(t)} - ET_{(t),i} - R_{(t)} - D_{(t),i} \qquad \text{Equation 1}$$

where $\theta_{(t),i}$ is the volumetric soil moisture content of the upper layer (mm), $\theta_{(t-1),i}$ is the volumetric soil moisture content of the upper layer on the previous day (mm), P(t) is the precipitation (mm), ET(t_i is the actual evapotranspiration from the upper layer (mm),R(t) is the total surface runoff (mm) and D(t),$_i$ is the deep drainage from the topsoil layer (mm).

Daily water balance for the bottom layer ($i+1$) is calculated as:

$$\theta_{(t)\,i+1} = \theta_{(t-1),\,i+1} + D_{(t),i} - ET_{(t),\,i+1} - D_{(t),\,i+1} \qquad \text{Equation 2}$$

where $\theta_{(t),i}$ is the volumetric soil moisture content of the layer $i+1$ (mm), $\theta_{(t-1),i+1}$ is the volumetric soil moisture content at layer $i + 1$ on the previous day (mm) and $D_{(t),i+1}$ is the volume of water exceeding the field capacity of soil layer $i + 1$.

The model assumes no bare surface evaporation or interception losses as the land cover should always be short grass at standard weather station sites.[3,15,21,22] Furthermore, the model assumes that runoff occurs only when precipitation exceeds the infiltration capacity of the topsoil layer and water in excess of the field capacity storage of the top layer will drain to the bottom layer. The model requires soil water retentivity properties such as wilting point, field capacity and saturation of each soil layer. The model also requires measurements or estimates of reference evapotranspiration (ET_0) in addition to rainfall as climate inputs to estimate daily soil moisture storage at point scale. The detailed model description is given in Myeni[29].

Data collection and processing

Climate data

The daily measurements of solar irradiance (R_S in MJ/m^2), minimum air temperature ($T_{air\ min}$ in °C), maximum air temperature ($T_{air\ max}$ in °C), minimum relative humidity (RH_{min} in %), maximum relative humidity (RH_{max} in %) and wind speed (U in m/s) for the period between 1979 and 2018 for each station were extracted from the databank of the Agricultural Research Council of South Africa. The choice of this data set was based on the availability of the complete data set which is of sufficient duration to track trends as a result of climate variability as recommended by Burn and Elnur[33]. Retrieved data underwent a data quality control process to identify erroneous, suspicious and implausible data, for example, daily rainfall values greater than 200 mm or less than zero, T_{min} greater than T_{max}; R_s values less than zero or greater than 35 MJ/m^2; relative humidity values less than zero or RH_{min} greater than RH_{max}; and U values less than zero or greater than 10 m/s^{-1}. Furthermore, erroneous, suspicious and impossible values were patched using good quality data from nearby weather stations (within a radius of 100 km) to obtain complete long-term data sets of good quality. An inverse distance weighting method was used to estimate missing or erroneous daily rainfall and RH from neighbouring station data based on the recommendations of Moeletsi et al.[30] The multiple regression method was used to estimate missing or erroneous $T_{air\ min}$, $T_{air\ max}$ and U values from neighbouring station data based on the recommendations of Shabalala et al.[34] The Hargreaves–Samani equation was used to estimate missing or erroneous daily R_s from measurements of $T_{air\ min}$ and $T_{air\ max}$ based on the recommendations of Abraha and Savage[35].

Soil characteristics

The number of layers per profile and thickness of each layer were defined based on soil physical properties (Table 2).[29]

Reconstruction of long-term soil moisture data sets

To initialise a soil moisture model, a rainy day between October and December of the year 1979, with a daily rainfall above 25 mm and a total rainfall of three preceding days exceeding 30 mm was identified for each station, assuming soil moisture at field capacity. This is a reasonable assumption as soils are generally wet during this rainy season in these stations. To reconstruct long-term soil moisture data sets, the model was run starting on the identified date using historical climate data and soil properties of each station, with initial soil moisture at field capacity. The estimates of the year 1979 were then discarded, only the remaining 39 years' (1980–2018) estimates were used for analysis purposes. A similar approach was used by DeLiberty and Legates[36] to reconstruct soil moisture data sets from the historical climate data sets using the water balance approach. Estimates of soil moisture storage of each layer were summed into total soil moisture content stored in a profile of 60 cm at each station. Daily soil moisture estimates were then averaged to produce monthly estimates, which were used for analysis purposes.

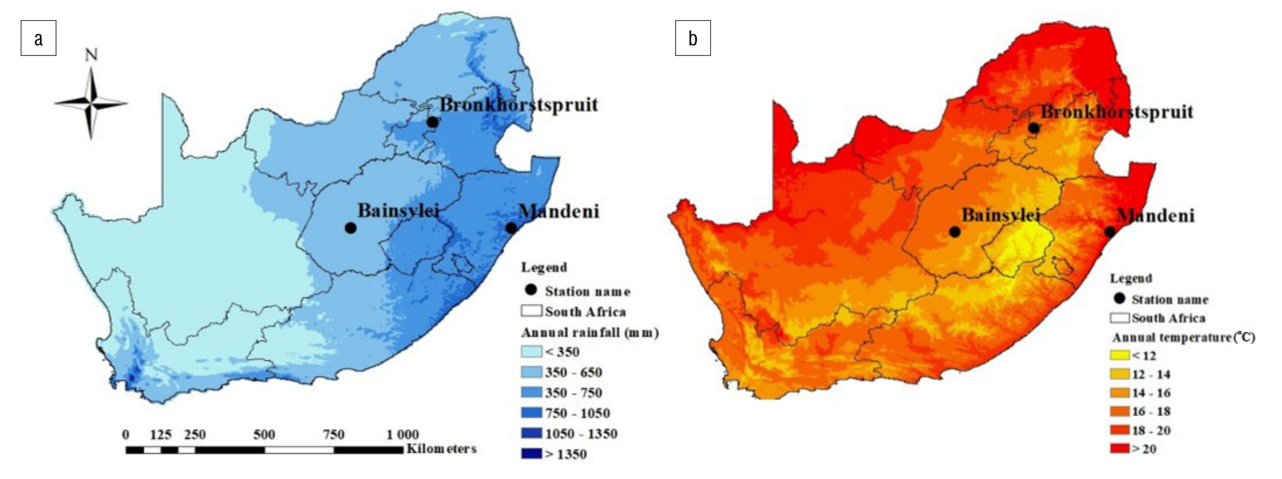

Figure 1: Long-term (a) mean annual rainfall and (b) mean annual air temperature at the soil moisture measurement stations used for model evaluation within South Africa.[31]

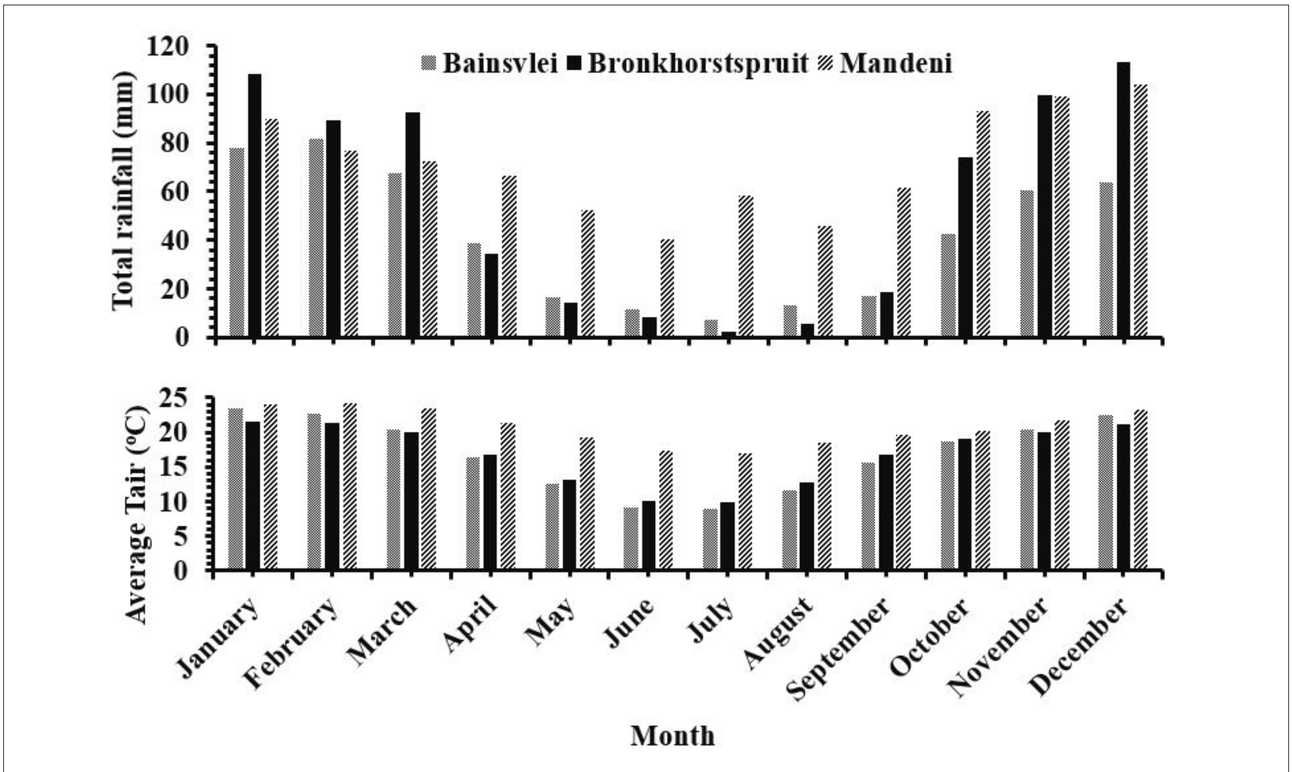

Figure 2: Distribution of monthly rainfall and air temperature (T_{air}) at three weather stations.

Table 1: Characteristics of the three sites in this study

Station name	Latitude (S)	Longitude (E)	Elevation (m)	MAP (mm)	T_{air}(°C)	Climate conditions
Bainsvlei	-29.146	26.146	1290	550	17	Arid, steppe and cold arid
Bronkhorstspruit	-25.702	28.799	1500	677	16	Warm temperate, dry winter and warm summer
Mandeni	-29.156	31.344	107	910	25	Warm temperate, fully humid and hot summer

MAP, mean annual precipitation; T_{air}, mean annual air temperature

Note: The description of climatic conditions was based on the Köppen–Geiger climate classification of Conradie[32].

Table 2: Characteristics of soil layers at all stations

Station	Soil layer	Thickness (cm)	Textural class	θ_{wp}(m³ m⁻³)	θ_{fc}(m³ m⁻³)	θ_{sat}(m³ m³)
Bainsvlei	1	0-40	Sand	0.05	0.14	0.23
	2	40-60	Sandy loam	0.10	0.24	0.30
Bronkhorstspruit	1	0-15	Sand	0.04	0.14	0.24
	2	15-40	Loamy sand	0.07	0.19	0.28
	3	40-60	Sandy loam	0.09	0.22	0.34
Mandeni	1	0-60	Sand	0.02	0.08	0.11

θ_{wp}, θ_{fc} and θ_{sat} are soil moisture content at the wilting point, field capacity and saturation points, respectively.

Data analyses

The Mann–Kendall and Theil–Sen slope non-parametric statistical methods were used to detect the direction and extent of temporal trends in the long-term soil moisture data set.

These statistical methods have been successfully used in detecting trends and changes in long-term soil moisture time series.[14,23] The main advantages of the non-parametric statistical methods are that missing values are allowed and these tests do not make any assumptions about the distribution of the data.[37,38] Furthermore, these methods have low sensitivity to outliers and heterogeneous time series.[39] These statistical tests were run in XLSTAT software (https://www.xlstat.com/en/).

Mann–Kendall test

The Mann–Kendall test statistic S of Kendall[40] was used in this study to assess the monotonic trends in the soil moisture over time. The test statistic S is calculated based on Mann[41], Kendall[40] and Yue et al.[37] as:

$$S = \Sigma_{i=1}^{n-1} \Sigma_{j=i+1}^{n} sgn(x_j - x_i), \qquad \text{Equation 3}$$

where n is the number of data points, x_j and x_i are data values in time series at time j and i ($j > i$), respectively. Furthermore, $sgn(x_j - x_i)$ is the sign function given by:

$$sgn(x_j - x_i) = \begin{cases} -1 \text{ if } (x_j - x_i) < 0 \\ 0 \text{ if } (x_j - x_i) = 0 \\ +1 \text{ if } (x_j - x_i) > 0 \end{cases} \qquad \text{Equation 4}$$

For a sample size $n > 10$, a normal approximation to the Mann–Kendall test may be used.[40] The variance statistic is then computed as:

$$Var(S) = \frac{n(n-1)(2n+5) - \Sigma_{t=1}^{m} t_i(t_i-1)(2t_i+5)}{n} \qquad \text{Equation 5}$$

where n is the number of observations and t_i are the ties of the sample time series. The standard normal variable (Z_s) was used to identify the direction of the trend and its significance:

$$Z_s = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, \text{ if } S>0 \\ 0, \text{ if } S=0 \\ \frac{S+1}{\sqrt{Var(S)}}, \text{ if } S<0 \end{cases} \qquad \text{Equation 6}$$

where positive Z_s values indicate an increasing trend while negative values indicate a decreasing trend. The significance of the trends was tested at the significance levels of 95% and 99%.

The Theil–Sen slope estimator

The Theil–Sen slope estimator of Sen was used to give an indication of the magnitude of the linear trends in the soil moisture over time. According to Da Silva et al.[38], a linear model $f(t)$ can be described as:

$$f(t) = Q_i + B, \qquad \text{Equation 7}$$

where Q_i is Sen's slope and B is the constant. To derive an estimate of Q_i, the slopes of all data pairs are calculated:

$$Q_i = \frac{x_j - x_k}{j - k}, \; i=1, 2...N, \qquad \text{Equation 8}$$

where X_j and X_k are data values at time j and k ($j>k$), respectively. The median of Sen's slope is calculated as:

$$Z_s = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, \text{ if } S>0 \\ 0, \text{ if } S=0 \\ \frac{S+1}{\sqrt{Var(S)}}, \text{ if } S<0 \end{cases} \qquad \text{Equation 9}$$

The sign of Q_{med} reflects the data trend direction, whereas its value gives the magnitude of the slope of the trend. A positive Q_{med} value indicates an increasing trend while a negative value indicates a decreasing trend over time.

Results and discussion

Variability of the long-term soil moisture data set

The results of the statistical tests on the monthly averages of soil moisture for 39 years at all stations are presented in Table 3. The monthly mean soil moisture values ranged between 68.51 mm and 92.64 mm at Bainsvlei station in September and February, respectively. The monthly mean soil moisture values ranged between 100.26 mm and 114.63 mm at Bronkhorstspruit station in August and January, respectively. The monthly mean soil moisture values ranged between 33.68 mm and 37.10 mm at Mandeni station in January and October, respectively. Despite the highest annual rainfall received at Mandeni station, Bronkhorstspruit station had the highest soil moisture (108.55 mm) while Mandeni station had the lowest (35.13 mm). The highest soil moisture content at Bronkhorstspruit station could be attributed to higher water-holding capacity as a result of relatively high clay and organic carbon contents as also reported by Myeni[29]. The lowest soil moisture content at Mandeni station could be attributed to the low water-holding capacity of sandy soils, which dominated this site.[29] The results further showed the seasonal soil moisture pattern, with wet conditions in summer and dry conditions in winter months. The findings of our study agree with the findings of Pan et al.[18], who reported that soil moisture peaked in February and was minimal in July in the summer regions of South Africa.

Table 3: Basic statistics and Mann–Kendall trend analysis of soil moisture for 39 years (1980–2018) at all stations

Station	Month	Minimum (mm)	Maximum (mm)	Mean (mm)	Standard deviation	Mann–Kendall test	Sen's slope
Bainsvlei	January	59.95	124.61	85.27	17.39	0.136	0.291
	February	61.61	130.56	92.64	19.07	0.028	0.053
	March	62.45	131.56	91.32	14.62	-0.109	-0.223
	April	67.25	141.29	90.82	18.38	0.028	0.071
	May	61.64	116.31	79.64	14.49	0.128	0.200
	June	59.49	120.60	74.14	13.80	0.142	0.187
	July	59.07	88.70	69.15	8.77	0.042	0.043
	August	58.82	93.40	68.68	8.91	-0.023	-0.021
	September	58.72	122.03	68.51	12.30	-0.220	-0.157
	October	58.75	126.67	74.57	14.69	-0.117	-0.145
	November	61.18	119.12	82.21	14.73	-0.090	-0.217
	December	61.71	115.90	82.13	14.82	0.069	0.125
	Annual	66.34	94.25	79.84	6.21	-0.009	-0.004
Bronkhorstspruit	January	103.21	131.19	114.63	6.43	0.001	0.000
	February	102.94	143.06	113.88	9.34	-0.042	-0.049
	March	100.09	134.51	114.16	8.77	-0.163	-0.176
	April	98.69	140.43	109.52	8.61	0.055	0.053
	May	96.95	125.55	105.32	6.71	0.152	0.106
	June	96.76	125.07	102.79	5.44	0.009	0.002
	July	96.74	106.99	100.46	2.32	-0.112	-0.021
	August	96.74	108.52	100.26	2.22	-0.171	-0.021
	September	98.00	119.43	102.19	4.18	-0.260	-0.067
	October	100.09	124.33	109.44	5.71	0.015	0.013
	November	102.06	131.95	114.71	7.57	0.001	0.004
	December	106.61	133.29	115.52	6.37	0.015	0.016
	Annual	104.21	113.26	108.55	2.24	-0.015	-0.005
Mandeni	January	19.50	49.30	33.68	10.04	0.409*	0.553
	February	19.75	47.94	34.53	8.84	0.371*	0.444
	March	19.38	52.66	34.43	8.15	0.328*	0.362
	April	21.99	47.83	36.72	6.57	0.182	0.146
	May	20.61	49.21	34.99	7.56	-0.155	-0.146
	June	20.41	49.83	34.42	8.95	-0.444	-0.480
	July	20.26	50.93	35.41	10.05	-0.409	-0.547
	August	19.66	47.21	34.31	7.85	-0.341	-0.363
	September	24.06	45.84	35.15	5.72	-0.136	-0.106
	October	21.82	49.31	37.10	7.83	0.385*	0.420
	November	20.53	49.19	35.80	8.73	0.466**	0.526
	December	19.65	51.14	35.07	9.91	0.393*	0.585
	Annual	30.33	43.09	35.13	3.17	0.317*	0.129

*$p<0.05$, **$p<0.001$

The Mann–Kendall test and Sen's slope statistical tests were applied to the time series of soil moisture estimates from 1980 to 2018 at the three stations, and the trend analysis for all months and the whole year are also presented in Table 3. The results of the Mann–Kendall test at the Bainsvlei station show a marginal increasing trend of soil moisture in January, February, April, May, June, July and December, while the remaining months show a non-significant decreasing trend. For the Bronkhorstspruit station, the results show a marginal decreasing trend of soil moisture in February, March, July, August and September, while the remaining months show a marginal increasing trend. The results further show that soil moisture increased significantly from October to March, while the remaining months show a marginal decreasing trend at the Mandeni station. These findings suggest that wet seasons have become wetter while dry seasons have become drier at the eastern coastal regions in recent years.

In South Africa, an increase in air temperature and the variability of rainfall is expected as a result of predicted climate change.[10] Therefore, understanding the effects of air temperature and rainfall on soil moisture is critical in the determination of the impacts of climate variability on soil moisture status in this region. The regression graph of the mean annual air temperature and mean annual soil moisture indicate that air temperature explains about 2% of the variation in soil moisture at Bainsvlei and Bronkhorstspruit stations, but only 1% at Mandeni station (Figure 3). Results also indicate the negative linear relationship between air temperature and soil moisture as expected. The regression graph of the mean annual rainfall and mean annual soil moisture indicate that more than 70% of the variation in soil moisture can be explained by air temperatures across all stations (Figure 4). The results also indicated a positive and significant effect of rainfall on soil moisture status as expected.

To investigate the potential impacts of climate variability on soil moisture changes, long-term trends in soil moisture were compared with rainfall and air temperature trends (Figure 5). The mean annual soil moisture results indicate a marginal decrease in soil moisture from 1980 to 2018 at the Bainsvlei and Bronkhorstspruit stations, at a rate of -0.02 and -0.001 mm per annum, respectively. Furthermore, the trends indicate that Bainsvlei and Bronkhorstspruit stations are becoming warmer, with increases of 0.04 and 0.02 °C per annum, while mean annual rainfall shows decreasing trends at a rate of -0.97 and -1.05 mm per annum, respectively. An increase in temperatures at the Bainsvlei and Bronkhorstspruit stations could have enhanced the rate of ET(*t*) which removes moisture from the soil and decreases soil moisture content. However, T_{air} is not the only climatic factor controlling the rate of ET(*t*), because *U* and *RH* also play a critical role. Furthermore, the rate of ET(*t*) is also limited by the amount of soil moisture available in the soil, such that ET(*t*) will be limited if the soil moisture content is below the wilting point, even though T_{air} could be increasing.[42] Therefore, the relationship between T_{air} and soil moisture is not explicit, as also noted by Cheng et al.[14] These findings are in agreement with Wang et al.[43] who noted that the effect of temperature on soil moisture is relatively low as the result of low soil moisture available for evapotranspiration in semi-arid regions. The findings of this study suggest that Bainsvlei and Bronkhorstspruit stations are gradually becoming drier as a result of decreasing trends of rainfall with possibly a small influence of increasing air temperature.

In contrast, there was a significant increase in mean annual soil moisture at the Mandeni station, at a rate of 0.11 mm per annum. The increase in soil moisture at the Mandeni station could be attributed to the observed significant increasing trend of rainfall at a rate of 15.89 mm per annum. The findings of this study suggest a strong correlation between rainfall and soil moisture and agree with previous studies that have reported that soil moisture closely follows trends of rainfall, whether drying or wetting.[14,17,43] Furthermore, the findings suggest that Mandeni station is gradually becoming wetter as a result of the increasing trend of rainfall, even though air temperatures are also increasing.

Overall discussion

Long-term temporal variation in soil moisture revealed that 1983, 1992, 1998 and 2015 were the driest years while 1987 and 2000 were the wettest years. These findings confirm the extreme droughts and floods that were experienced in this region in these years.[11] The occurrence of floods in South Africa is often associated with tropical cyclones while the occurrence of droughts is often associated with the El Niño-Southern Oscillation phenomenon.[11] The findings of this study confirm the suitability of the model estimates to capture variation in soil moisture very well. Therefore, the model estimates could be reliably used to provide long-term soil moisture data sets for climatic research.

The findings of this study indicate that Bainsvlei and Bronkhorstspruit stations located inland are experiencing drier conditions while the Mandeni station located in the coastal region is experiencing wetter conditions, especially in the summer months. The findings are consistent with those of previous studies which predicted that eastern coastal parts of South Africa are expected to become wetter while the inland parts are expected to be drier as a result of predicted climate change.[11,12,44,45] The expected drying of inland parts is likely to pose water scarcity challenges while the wetting of eastern coastal parts is likely to induce erosion and flood risks. Furthermore, changes in soil moisture attributed to climate variability are likely to affect various sectors – such as agriculture and water supply – that are primarily dependent on soil moisture availability.

The findings of this study suggest that air temperatures have been increasing across South Africa, at an average of 0.36 °C per decade over the past recent 39 years. These findings are consistent with the observed increase in air temperatures at a rate of 0.4 °C per decade over the past 54 years (1961–2014) in the southern African region, as reported by Davis and Vincent[11]. Furthermore, these findings are also consistent with the observed increase in global average temperature at a rate of 0.6 °C per decade estimated by IPCC[10].

The findings of this study confirm that climate variability and change are likely to change soil moisture content in South Africa, as also noted by Cheng et al.[14] However, the findings also suggest that the influences of climate change on soil moisture will vary with region and climatic conditions. Therefore, understanding the factors that affect soil moisture variability at the local scale is critical for the development of informed adaptation strategies to support efficient management and sustainable use of natural resources.

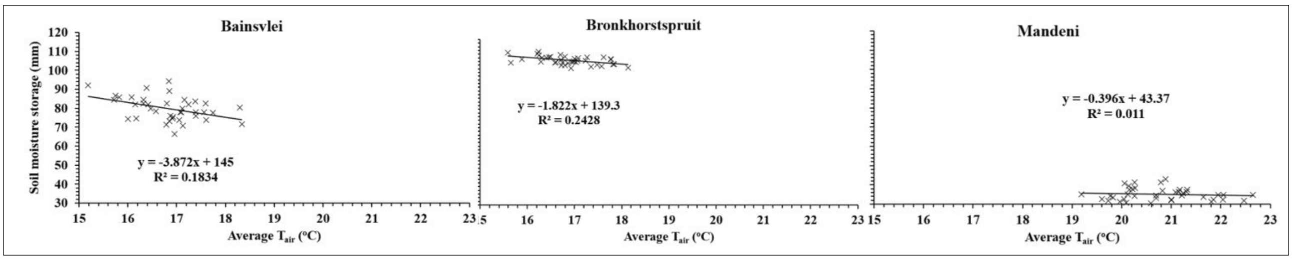

Figure 3: Regression plots of average annual air temperature (T_{air}) and average annual soil moisture over 39 years at three different locations.

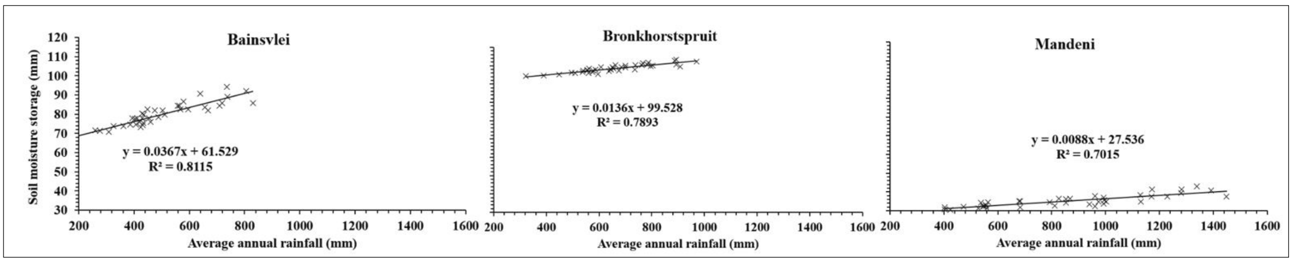

Figure 4: Regression plots of average annual rainfall and average annual soil moisture over 39 years at three different locations.

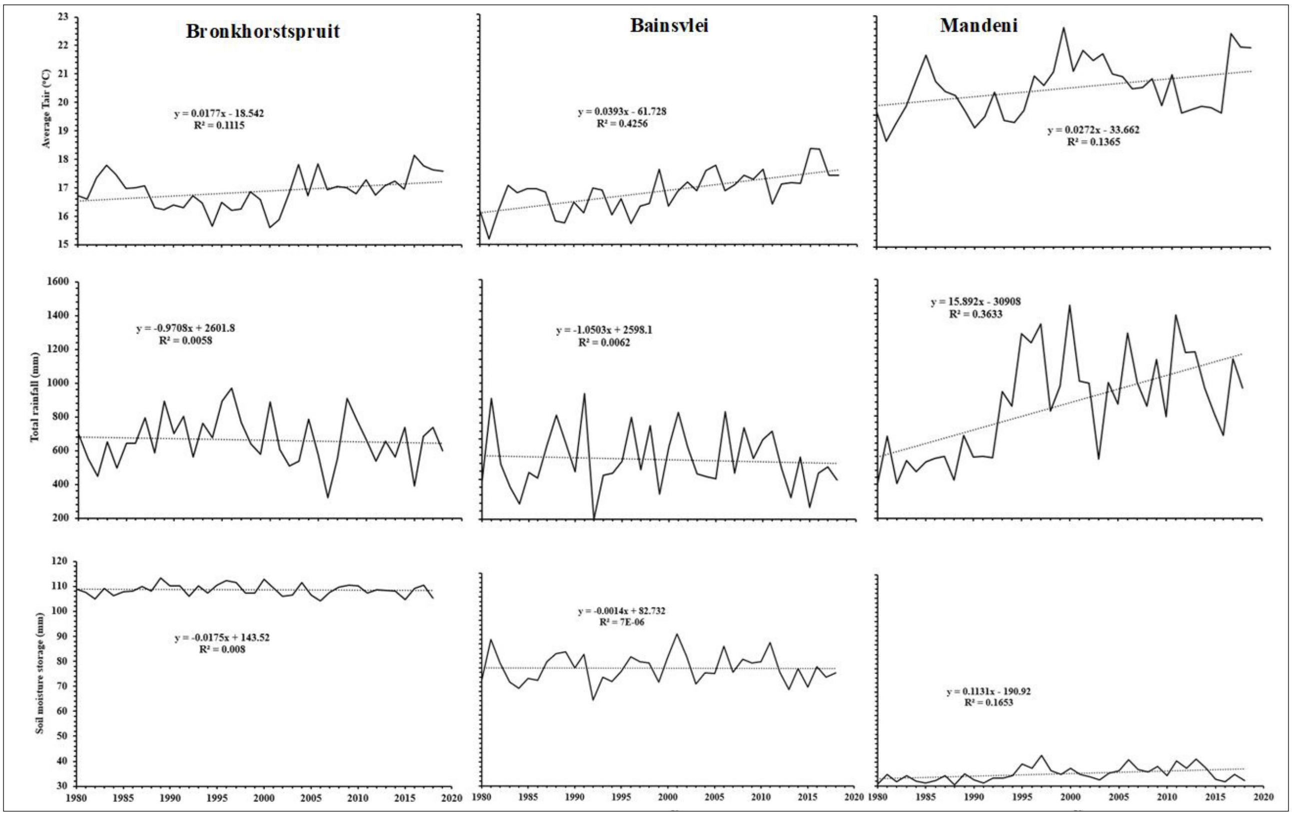

Figure 5: Temporal variations and linear trends of average air temperature (T_{air}), annual rainfall and soil moisture over the last 39 recent years at different stations.

Conclusions

Soil moisture is a critical parameter in the forecasting and assessment of weather-induced extreme events, which are likely to increase as a consequence of the expected climate change in this region. In this study, a water balance model was used to reconstruct long-term soil moisture data sets from 1980 to 2018 (39 years) in three stations that represent the different agroclimatic conditions of South Africa. Additionally, long-term changes and variability of moisture were examined to investigate the potential impacts of climate variability on soil moisture.

The results of the study show a marginal decreasing trend of annual soil moisture at the Bainsvlei and Bronkhorstspruit stations located inland. In contrast, the Mandeni station located in the coastal region is gradually becoming wetter as a result of the increasing trend of rainfall, despite the increase in air temperatures. These findings suggest that inland regions are becoming drier while coastal regions are becoming wetter, especially in the summer months in this country.

Our study confirms that increasing climate variability and climate change are likely to alter the soil moisture content status in this country, although their effects will vary with agroclimatic conditions. Therefore, there is a vital need for the understanding of factors that affect soil moisture variability at the local scale for the development of informed adaptation and mitigation strategies. Our study also demonstrates the suitability of the model estimates to provide comprehensive soil moisture data sets for weather and climate research studies, given that long-term and representative in-situ soil moisture measurements are often lacking in many countries, especially in developing countries.

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Competing interests

We declare that there are no competing interests.

Authors' contributions

L.M.: Conceptualisation, methodology, data collection and analysis, writing – original. M.E.M. and A.D.C.: Methodology, review and editing, supervision.

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