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ORIGINAL ARTICLE

Quantifying Residual Soil Moisture through Empirical Orthogonal Functions Analysis to Support Legume-Based Cropping Systems

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Abstract

This study investigates spatiotemporal variability of residual soil moisture during the OND (October-November-December) season in Ethiopia and its implications for crop productivity. Employing advanced statistical techniques, we analyze spatial and temporal distribution of soil moisture across Ethiopia from 1981 to 2020, focusing on selected crops including legumes: chickpea, field peas, common bean, soybean and alfalfa, to assess the potential of residual moisture to support post-rainy season cropping. Results indicate pronounced east-west moisture gradients, with eastern regions of Ethiopia exhibiting lower moisture levels (< 60 kg.m^{-2}) compared to western regions (> 150 kg.m^{-2}). The central highlands, which are pivotal for agricultural activities, demonstrate significant variability in moisture (standard deviations > 25 kg.m^{-2}), with implications on agricultural sustainability. The northern and southeastern tips of the country are particularly vulnerable to prolonged drought, where climate change and frequent dry spells exacerbate moisture deficits, consequently impacting crop productivity. Despite these challenges, promising opportunities for future crop production emerge in the southeastern region, which is characterized by increasing moisture trend over time ($\tau = 0.59$). Findings further indicate that residual moisture adequately meets and supports crop water requirements in the western, central, and southwestern Ethiopia. In these regions, residual moisture supports more than 90% of cropland water requirements of various crops during the initial and late-season growth stages, whereas water requirement coverage drops to less than 20% during the mid-season growth stage. Therefore, by utilizing residual soil moisture alongside supplemental irrigation, Ethiopian farmers can meet crop water needs for double cropping and enhance resilience to climate variability.

Keywords Agricultural sustainability · Climate resilience · EOFs · Legumes · Post-harvest cropping · Residual moisture

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1 Introduction

Understanding the dynamics of soil water availability is central to implementing sustainable agricultural practices, especially in regions prone to seasonal variations in precipitation. Soil water availability refers to the amount of water present in the soil that is accessible to crops for their growth and development (Bhattacharya 2021). It is influenced by a range of factors that include soil type, soil texture, soil structure, and organic matter content. Adequate soil water availability is crucial for crop growth, as water is essential for key physiological processes, including nutrient uptake, photosynthesis, and transpiration (Blum and Blum 2011; Waraich et al. 2011).

Soil moisture (which is correlated with soil water availability) is a fundamental variable crucial for crop productivity worldwide (Gaona et al. 2023). Regardless of the hydrological regime of a particular area, soil moisture is a pivotal component determining crop productivity. However, the process of climate change poses significant challenges to soil moisture regimes, with potential for knock-on effects on crop productivity (Demem 2023; Gornall et al. 2010; Kotir 2011). Agricultural water management technologies and practices are crucial for boosting agricultural output, increasing crop yields, and reducing reliance on unpredictable rainfall systems (Nguru et al. 2023; Srivastav et al. 2021). The dynamics and availability of soil moisture not only influence what crop to grow, but also dictate the timing of cropping patterns, ultimately shaping agricultural strategies and productivity outcomes. Understanding the relationship between climate change and soil moisture dynamics is imperative for devising effective adaptation measures in agriculture (Hatfield et al. 2011). Without comprehensive spatially explicit studies on soil moisture regimes and trends, agricultural transformation efforts such as introduction of a second or third crop in a calendar year remain very limited or constrained by anecdotal evidence.

Across many countries in Africa, including Ethiopia, farmers utilize post-harvest moisture (also known as residual moisture) to cultivate additional crops following the main growing season, thereby increasing agricultural productivity per unit area (Goff et al. 2010; Minta et al. 2014; Mwila et al. 2021). Even in areas characterized by a monomodal climate regime, farmers can harness any residual moisture from the main season to cultivate short-period crops (Kar and Kumar 2009). For example, in Ethiopia, it is common practice to cultivate legumes such as, chickpea during the OND season (Getachew 2019; Kebede 2020; Korbu et al. 2022; Loon et al. 2018). Many legume crops have low water requirements and short growing periods, making them well-suited for cultivation with residual moisture. Beyond their role in crop production, leguminous crops can contribute to soil fertility (Bationo et al. 2011; Mapfumo 2011; Mwila et al. 2021). Nitrogen-fixing legume species introduced during the post-harvest season can enhance soil nitrogen availability, consequently improving productivity for the subsequent main seasons.

Although post-rainy season agricultural practices such as growing second and third crops are crucial for ensuring food security (Howden et al. 2007; Mapfumo 2011), enhancing soil fertility (Bodner et al. 2015; Mwila et al. 2021), and providing fodder for livestock (Brychkova et al. 2022; Minta et al. 2014), their adoption is declining and not universally applicable for several reasons as discussed by Kar and Kumar (2009). This decline in adoption of such practices may arise due to (a) a lack of knowledge regarding suitable crops for residual moisture utilization, (b) uncertainty regarding whether post-harvest moisture levels are adequate to support crop growth, and (c) insufficient awareness among farmers about the efficacy of such practices. In this study, we employed Empirical Orthogonal Functions (EOFs) to classify a large domain into smaller, homogeneous regions and assess the potential of residual soil moisture to meet the water demands of legume crops. This approach allowed us to identify areas with similar moisture variability and evaluate their potential to support secondary cropping. Unlike point-location-based studies, this method enables us to cover larger areas with consistent moisture variability, providing a broader assessment of regional potential.

Climate change can be characterized by heightened variability in precipitation patterns and an increase in the intensity and frequency of extreme weather events (Brown et al. 2017; Cattani et al. 2018; IPCC 2014). As a climate change adaptation approach, post-rainy season cropping could provide a climate resilient option to boost agricultural yields. Given the high variability of post-rainy season moisture availability, improved water management practices are essential (Danga et al. 2009). Efficient water management practices, informed by analysis of soil moisture content and crop water demand, are essential for optimizing post rainy season legume-based cropping systems.

In Ethiopia, optimizing post-rainy season cropping practices is critical, due to the country's distinct climate and variable rainfall patterns. In this study empirical analysis conducted in Ethiopia is leveraged to investigate the optimization of post-rainy season cropping through detailed residual soil moisture analysis. To date, few studies have attempted to investigate post-rainy season moisture availability for the second cropping. For instance, Korbu et al. (2022), have demonstrated a response of chickpea cultivars to varying moisture-stress. In addition, Yang et al. (2021) have illustrated improved cereal crop yields associated with soil moisture conditions in the Upper Blue Nile Basin

(UBNB) by integrating a process-based crop and hydrologic models. These studies have been conducted at both the field level and on a basin-wide scale.

There remains a need to conduct a residual soil water availability assessment for cropping after the main rainy season on a country-wide scale to optimize the utilization of arable lands for double cropping. This study places a specific emphasis on post-rainy season residual soil moisture analysis for informed decision-making. The study has two objectives: (i) to investigate residual soil moisture levels, along with their temporal and spatial fluctuations, following the main rainy season, spanning from October to December (OND) across Ethiopia; (ii) to investigate the viability of cultivating selected legume crops during the post-rainy season, while accounting for the presence of residual soil moisture within identified climatic zones.

2 Materials and Methods

2.1 Study Area and Agroecologies

The study was conducted for Ethiopia, which is positioned in the eastern part of the African continent, and characterized by an extensive complex of mountain ranges and deep valleys, covering much of the central and northern regions (Abera et al. 2019). The country's climate reveals substantial variations due to altitude differences and its proximity to the equator (Fazzini et al. 2015; Jury 2010). Ethiopia experiences distinct wet and dry seasons, with the main rainy season, locally known as kiremt, typically occurring from June to September (JJAS), and a shorter rainy season, called belg, from March to May (MAM) (Segele and Lamb 2005). Figure 1 depicts the study area map and the agroecologies of Ethiopia as defined by the Ethiopian Ministry of Agriculture (MoA).

Agriculture has vast significance for Ethiopia, providing livelihoods for a large portion of the population and making a substantial contribution to the national economy (Evangelista et al. 2013; Yigezu Wendimu 2021). Ethiopia's agroecologies cover a wide spectrum of agricultural

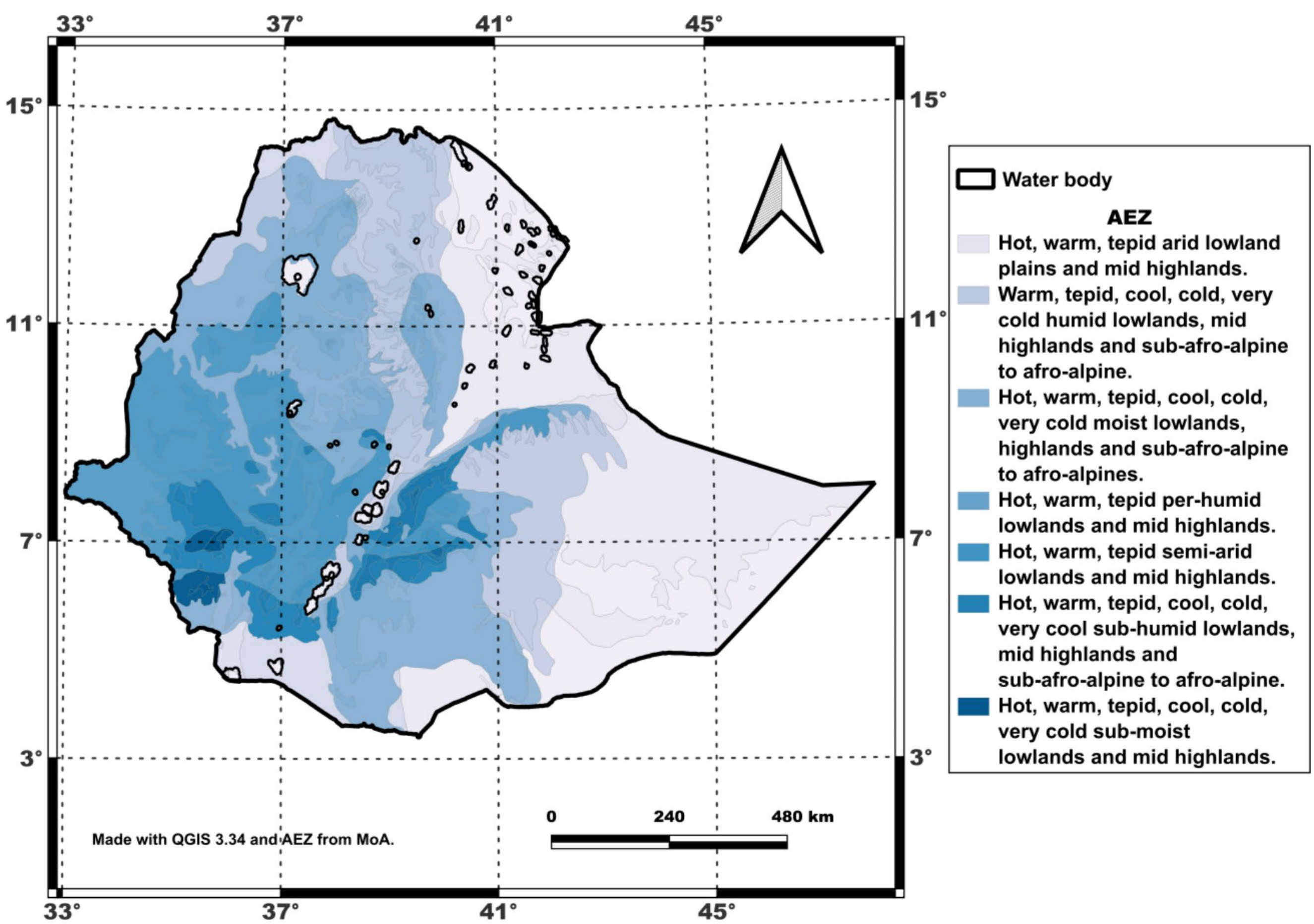

Fig. 1 Study area map showing the distribution of agroecologies in Ethiopia

systems, from highland cropping to pastoralism in lowland areas (Asefa et al. 2020; Demem 2023). Highland agriculture includes the cultivation of crops such as teff, wheat, barley, maize, and pulses. Lowland areas, particularly in the eastern and southeastern parts of the country, have arid to semi-arid climates (Abera et al. 2019). Pastoralism is prevalent in these regions, with communities raising livestock such as cattle, goats, sheep, and camels (Alemayehu et al. 2020). Agro-pastoralism, combining crop cultivation with livestock rearing, is practiced in some lowland areas with access to water sources.

2.2 Climate and Elevation Datasets

This study employs the Global Land Data Assimilation System (GLDAS) dataset, a comprehensive global offline land surface modeling system utilizing the Noah Land surface model, focusing on around 36 land surface fields. The model is driven by observed and reanalysis meteorological fields, facilitating the generation of a diverse array of surface and subsurface soil moisture data across varying depths: the top 10 cm, 10–40 cm, 40–100 cm, and 100–200 cm layers. GLDAS provides multiple versions of the soil moisture dataset, containing v2.0, v2.1, and v2.2 (Beaudoing and Rodell 2019; Rodell et al. 2004). For this study, we specifically utilize v2.0 and v2.1. In v2.0, the Noah land surface model is simulated through enforcing of Princeton meteorological input data for the period spanning 1948 to 2014. On the other hand, v2.1 is generated by combining both model and observational data, covering the time frame from 2000 to the present. The datasets selected for this study have a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$ and are temporally resolved on a daily basis. Considering cultivation of crops with shallow root depth during the post-rainy season, we utilized soil moisture data from the top 40 cm depth for this study.

The GLDAS Elevation dataset, derived from GTOPO30 (EROS 2017; Guth et al. 2021), a global digital elevation model with a horizontal grid spacing of 30 arc seconds, has been sourced from the GLDAS data repository (https://ldas.gsfc.nasa.gov/gldas/elevation). This dataset is utilized in the Penman-Monteith reference evapotranspiration (ET_o) equation to calculate crop water requirements.

Agroclimatology datasets sourced from the National Aeronautics and Space Administration (NASA) via the Prediction Of Worldwide Energy Resources (POWER) platform (https://power.larc.nasa.gov/) and AgERA5 through Copernicus Data Store (CDS) (Boogaard et al. 2020), were utilized for point location and spatial crop water requirements analysis, respectively. These datasets offer a comprehensive range of solar and meteorological data, including rainfall, temperature, wind speed, humidity, and solar radiation, to support research in renewable energy and agricultural applications. Specifically, our study has incorporated temperature variables (minimum, maximum, and mean), relative humidity, solar radiation, wind speed, and dew point temperature from these datasets at $0.25^{\circ} \times 0.25^{\circ}$ spatial resolution.

2.3 Crop Coefficients and Masks Datasets

This study utilizes the crop information database resource (developed by the Food and Agriculture Organization (FAO) of the United Nations) to access crop coefficients for calculating the water requirements of individual crop species (FAO 2023). The FAO database offers extensive information on crop water needs, irrigation techniques, and water management practices for a wide range of crops cultivated globally. It encompasses detailed data on crop-specific parameters, including evapotranspiration rates, irrigation scheduling recommendations, and water use efficiency metrics. In addition, we employed cropland masks version v03 sourced from the Anomaly Hotspots of Agricultural Production (ASAP) data catalog (https://data.jrc.ec.europa.eu/) to quantify cropland fractions across the country (Pérez-Hoyos et al. 2017).

3 Soil Moisture and Crop Water Requirement Analysis Methods

3.1 Spatiotemporal Analysis of OND Residual Soil Moisture

Long-term averages, variabilities, and monotonic shifts in residual soil moisture, were calculated using sample mean, standard deviations, and Kendall-Tau trend statistics, respectively.

To identify and categorize the overall distribution of moisture levels (for assessing the adequacy of moisture to sustain crop water requirements across Ethiopia), we set threshold values denoting dry, normal, and wet conditions. The thresholds for moisture values used to differentiate between wet, normal, and dry days were determined by averaging the respective 10th and 90th percentiles (Heino et al. 2023; Knapp et al. 2015) of moisture levels in each homogeneous climate region over time (Huijgevoort et al. 2012). Considering the extreme soil moisture values below the 10th percentile (86.69 $kg.m^{-2}$) are insufficient to meet the water demands of most crops, and values above the 90th percentile (116.24 $kg.m^{-2}$) represent surplus, we utilized these threshold values to categorize moisture levels into dry (< 86.69 $kg.m^{-2}$), normal (86.69 $kg.m^{-2}$ – 116.24 $kg.m^{-2}$), and wet (> 116.24 $kg.m^{-2}$) conditions. In addition, we defined a dry spell as ten or more consecutive dry days with less than 86.69 kg.m^{-2} (below the 10th percentile) of soil moisture value and assessed the occurrences of dry spells during the season.

The non-parametric Kernel Density Estimation (KDE) technique is employed both temporally and spatially to estimate the probability density distribution of residual soil moisture values. KDE is utilized to identify clusters or areas of heightened density within the dataset, enabling the exploration of its underlying structure (Gramacki 2018; Wang and Scott 2019). This method provides a smoothed approximation of the Probability Density Function (PDF), facilitating a visual representation of the data distribution. To reduce noise in the data, Scott's Rule of Thumb bandwidth selection criterion as discussed by Bashtannyk and Hyndman (2001) is applied. Threshold values of 1.5 for spatial and 1.0 for temporal density distributions analysis are established.

3.2 Homogeneous Climate Regions Classification

To decompose the covariance structure of spatial soil moisture data into dominant modes of variability, EOF analysis Dawson (2016) has been applied to identify major patterns of moisture variability within the dataset. Thus, unsupervised K-means clustering algorithm Li and Wu (2012) is utilized to partition the soil moisture dataset into clusters, minimizing the sum of squared distances between data points and their corresponding cluster centroids. To address drawbacks associated with the traditional K-means algorithm, such as sensitivity to initial centroids and slow convergence issues, we adopted the efficient K-means^{++} initializer and executed the algorithm multiple times with different initializations (Fränti and Sieranoja 2019; Bahmani et al. 2012).

To standardize the data and remove seasonal patterns, a time-mean was calculated at each grid point, and anomalies were then derived. To address changes in grid size particularly at higher latitudes, an area-weighting technique based on the square root of the cosine of latitude was applied (Baldwin et al. 2009; Dawson 2016; Hannachi et al. 2009; Rieger et al. 2021).

Empirical Orthogonal Functions (EOF) analysis was performed on the anomaly data for the OND season, spanning a 40-year period (1981–2020). This analysis identified four dominant modes explaining the highest variability during this season (these EOF modes are provided in supplementary materials Figure S1). Subsequently, KMeans clustering was applied to these EOF modes, resulting in the identification of five centroids representing clusters.

The determination of the number of centroids follows to the Elbow criterion as mentioned by Nainggolan et al. (2019) and was substantiated by domain experts judgment. This approach effectively classified the country into five distinct and non-overlapping homogeneous climate regions. The classification was based on the close association of each data point with the minimum squared distances within its respective region relative to data points in other regions.

3.3 Crop Selection and Crop Water Requirements Analysis

To inform agricultural productivity and climate adaptation among smallholder farmers, we explore the potential of integrating available post-rainy season soil moisture levels with selected drought tolerant legume crop water requirements. One approach involves assessing the water needs of different crop species based on their physiological traits, growth stages, and prevailing environmental conditions. Drawing on both scientific knowledge and traditional farming practices observed across Ethiopia, particularly the cultivation of second crops after the main season (JJAS), we chose legume food and feed crops such as chickpea (*Cicer arietinum*), field peas (*Pisum sativum*), common bean (*Phaseolus vulgaris*), soybean (*Glycine max*) and alfalfa (*Medicago sativa*) for evaluation in leveraging residual soil moisture to support double cropping (Minta et al. 2014).

Crop water requirements (ET_c) are analyzed employing the Penman-Monteith method that is a widely used approach for estimating reference evapotranspiration (ET_o), which represents the rate of evapotranspiration from a well-watered reference surface under standard weather conditions (Abraham and Muluneh 2022; Allen 1998). The formula for calculating ET_o using the Penman-Monteith method is as follows:

$$ET_o = \frac{0.408 \times \Delta \ (R_n - G) + \gamma \ \times \ \frac{900}{T+273} \times \ u \times \ (e_s - e_a)}{\Delta \ + \gamma \ \times \ (1 + 0.34 \times \ u)}$$

Where:

- ET_o = Reference evapotranspiration (mm/day)
- R_n = Net radiation at the crop surface (MJ/m^2/day).
- G = Soil heat flux density (MJ/m^2/day).
- T = Mean daily air temperature at 2 m height (°C)
- u = Wind speed at 2 m height (m/s)
- e_s = Saturation vapor pressure (kPa)
- e_a = Actual vapor pressure (kPa)
- Δ = Slope of the saturation vapor pressure curve (kPa/°C)
- γ = Psychrometric constant (kPa/°C)

The psychrometric constant (γ) is a parameter used to quantify the relationship between air temperature and the vapor pressure gradient in the atmosphere, and it is defined as the ratio of the specific heat of moist air at constant pressure to the latent heat of vaporization of water. The formula to calculate the psychrometric constant is:

$$\gamma = \frac{c_p \cdot P}{\epsilon \cdot \lambda}$$

Where:

- γ = Psychrometric constant (kPa/°C)
- c_p = Specific heat of moist air at constant pressure (kJ/kg/°C)
- P = Atmospheric pressure (kPa)
- ϵ = Ratio of the molecular weight of water vapor to the gas constant for dry air (dimensionless)
- λ = Latent heat of vaporization of water (kJ/kg)

To calculate the psychrometric constant, several parameters are typically employed, including the specific heat of moist air, atmospheric pressure, the ratio of molecular weights between water vapor and dry air, and the latent heat of vaporization of water (Tabari 2010). The following typical values for these parameters are utilized in the calculation process.

- $c_p \approx$ 1.013 kJ/kg/°C
- $P \approx$ Standard atmospheric pressure (calculated based on altitude)
- $\epsilon \approx$ 0.622
- $\lambda \approx$ 2.45 kJ/kg at 0 °C (this value varies slightly with temperature)

The individual components of the Penman-Monteith equation represent different factors influencing evapotranspiration, including radiation, temperature, wind speed, humidity, and soil properties. These components are combined to estimate the overall rate of evapotranspiration from the reference surface. Thus, the crop water requirement is calculated using:

$$ET_c = ET_o \times Kc$$

Where:

- Kc is the crop coefficient

By integrating the selected crops and assuming a uniform planting date of October 1st for all crops, coupled with careful assessments of their water requirements utilizing the FAO-recommended Penman-Monteith method (Allen et al. 2005; Pereira et al. 2021), we present our research findings based on homogeneous climate regions for the OND season.

To better quantify the extent by which post-rainy residual soil moisture supports each crop's water requirements, we used pixel-based spatial analysis. We selected specific pixel locations representing normal (i.e., average), driest (i.e., < 10th percentile), and wettest (i.e., > 90th percentile) conditions and conducted pixel-based assessments of crop water requirements. Furthermore, to refine the analysis solely on croplands, we utilized a cropland mask to exclude non-cropland areas and conducted spatial analysis covering the entire country to assess crop water requirements for the mentioned crops.

The harvest period for all legume crops is considered to be at the end of December, coinciding with the residual soil moisture duration assessed in this study. However, it should be noted that not all crops may reach complete late-stage development or full maturity by this time. In addition, regions exhibiting high soil moisture variability often experience a delayed harvest period compared to areas with lower soil moisture variability (Nepal et al. 2021; Usowicz et al. 2019).

4 Results

4.1 Seasonal and Monthly Post-rainy Soil Moisture Variability

Figure 2 illustrates the long-term soil moisture climatology, standard deviations, and trends in Ethiopia (1981–2020). The wet regions are predominantly located in the central and western parts of the country, with soil moisture exceeding 150 kg.m^{-2} across central-western Ethiopia. A gradient is evident moving from west to east, reaching as low as 60 kg.m^{2} in the southeastern tips of the country (Fig. 2(a)).

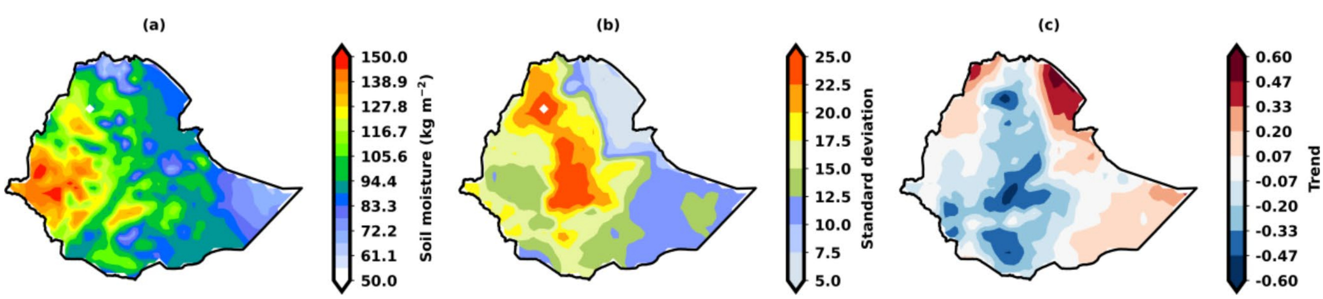

Fig. 2 Seasonal soil moisture (**a**) Climatology, (**b**) Standard deviation, (**c**) Trend in the OND season for 1981–2020 period

Soil moisture exhibits high variability along the central and western highlands, particularly extending from the central highlands to the northwestern tips of the country (standard deviations > 25 $kg.m^{-2}$). In contrast, the eastern low land regions demonstrate relatively low variability, with the northeastern region exhibiting the lowest (standard deviations < 7.5 $kg.m^{-2}$) (Fig. 2(b)). The northeastern and northwestern regions exhibit strong increasing soil moisture trends, while the southeastern region also displays a moderate increase in trends. Overall, there is a decreasing soil moisture trend along the central south-north direction and increasing soil moisture trends in the northwest and eastern regions (Fig. 2(c)).

Figure 3 displays the soil moisture average, variability, and trends during the months of the OND season. The highest soil moisture levels are observed in October, followed by a decrease in November and December (Fig. 3(a-c)). Soil moisture variability follows a similar pattern, as depicted in Fig. 2(b), and this variability also declines from October to December (Fig. 3(d-f)). This decrease in variability may be linked to a reduction in moisture during these months of the season. In contrast, the soil moisture trends are relatively consistent across all months of the season, with slight variations in the magnitude of the trend observed at the central and northeastern tips of the country (Fig. 3(g-i)).

4.2 Long Term Residual Moisture Characteristics Across Ethiopia

Considering the threshold values established (dry days < 86.69 $kg.m^{-2}$ and wet days > 116.24 $kg.m^{-2}$) based on the 10th and 90th percentiles of moisture level values, Fig. 4 illustrates the percentages of wet, normal, and dry days during the season. The majority of wet days are concentrated in the western region (Fig. 4(a)), while normal days are distributed throughout the country, excluding the western and easternmost tips (Fig. 4(b)). A high percentage of dry days is observed primarily at the northern and southeastern tips of the country (Fig. 4(c)).

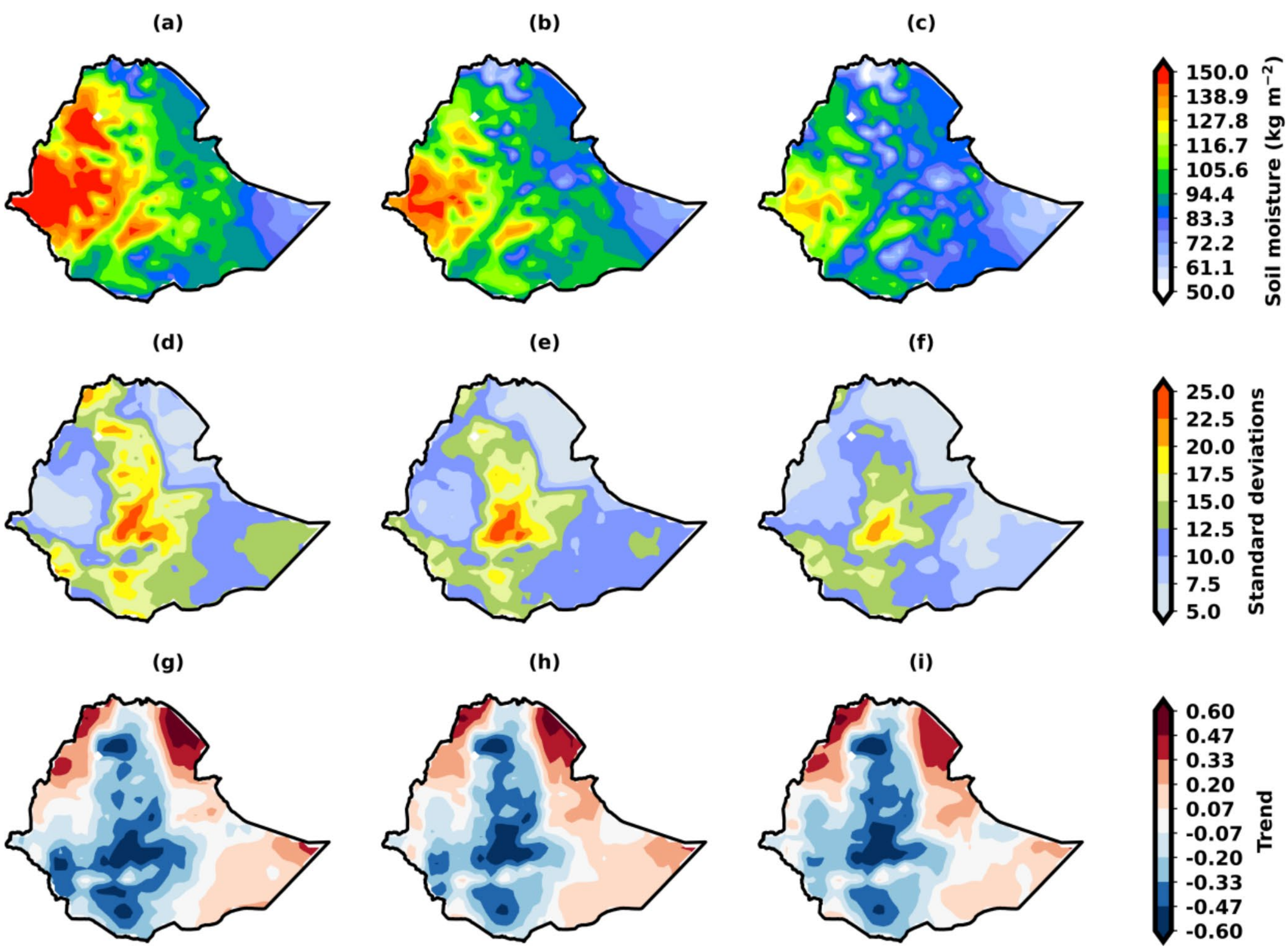

Fig. 3 Soil moisture climatology (first row(a-c)), Standard deviations (second row(d-f)), and Trends (third row(g-i)) are presented for October (first column), November (second column), and December (third column) over the period 1981–2020

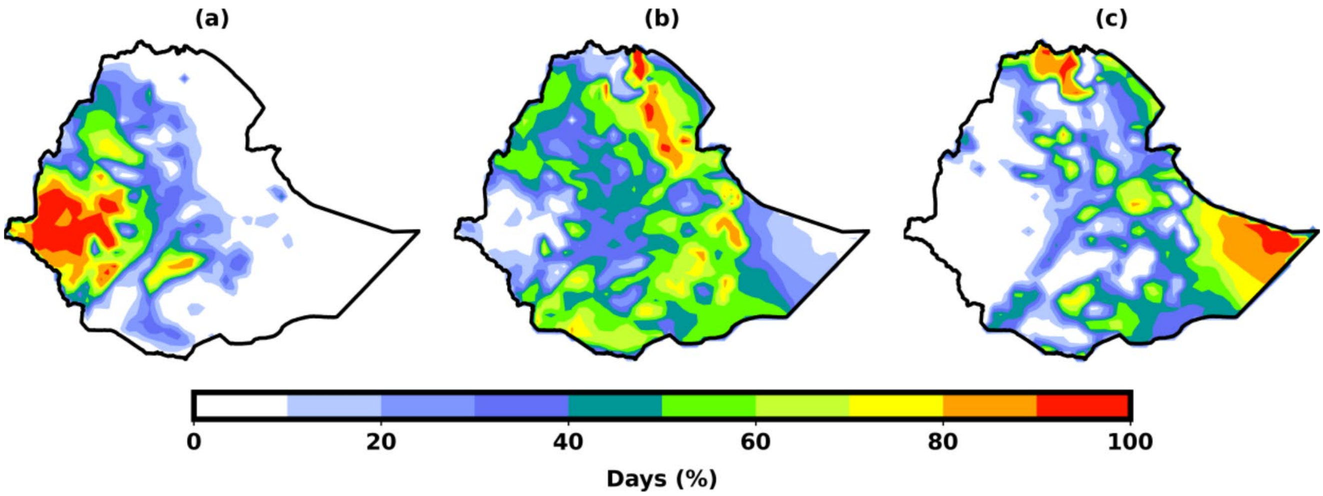

Fig. 4 Seasonal percentages of (**a**) wet days, (**b**) normal days, and (**c**) dry days during the OND season for the period 1981–2020

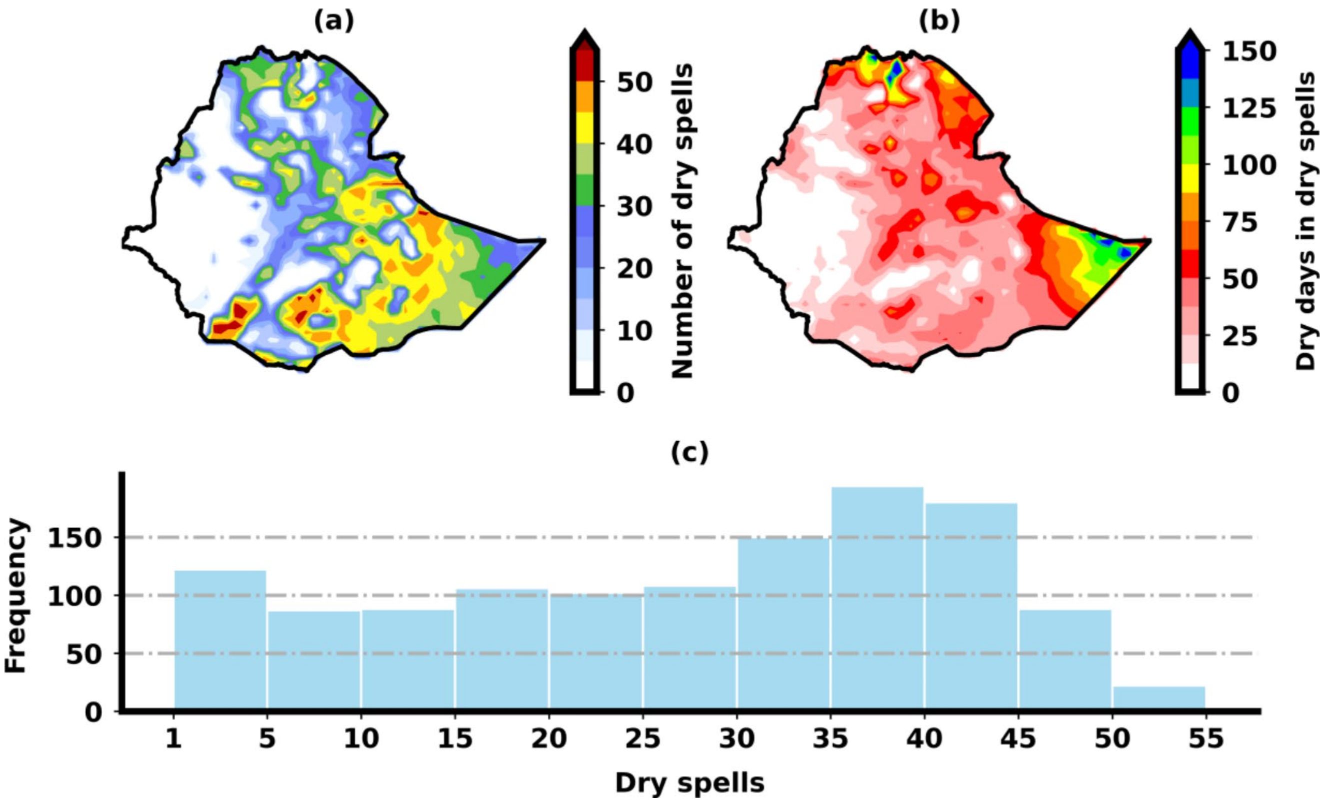

Fig. 5 Seasonal number of (**a**) dry spells and (**b**) number of dry days within dry spells, and (**c**) the frequency of dry spells across Ethiopia for the period 1981–2020

Figure 5 depicts the number of dry spells, count of dry days within those spells, and frequency of dry spell occurrences across the country. A larger number of dry spells occur in the eastern parts of the country, particularly in most areas of southeastern, certain pocket areas in the southwestern tips, and in northern regions of Ethiopia (Fig. 5(a)). In these areas, the number of dry spells is high, with the count of dry days in these spells exceeding 150 days in the northern and southeastern tips of the country (Fig. 5(b)). This suggests the possibility of these regions staying dry (below the minimum threshold) for consecutive seasons. Additionally, a significant number of dry days within dry spells is observed in most parts of the eastern regions, particularly in the central-eastern and northern regions of Ethiopia. Moreover, the frequency of dry spell occurrences ranges from 1 to 55, with the highest frequencies observed between 30 and 45

(Fig. 5(c)). These areas are dispersed throughout the eastern part of Ethiopia, with the southeastern and northern regions revealing a high frequency of dry spells.

4.3 Homogeneous Regions and Their Attributes of Residual Soil Moisture

The regionalization process (see Sect. 3.2) clustered Ethiopia into five homogeneous climate regions: northwest, central, northeast, southwestern-central, and southeast. Figure 6(a) illustrates the five homogeneous climate regions in Ethiopia, determined by post-rainy season (OND) soil moisture levels.

The seasonal cycles of the five homogeneous post-rainy season soil moisture climate regions are depicted in Fig. 6(b), which indicates that the moisture levels in Reg-1, Reg-2, and Reg-3 undergo a gradual decline throughout the months of the season. In contrast, the soil moisture in Reg-4 and Reg-5 increases until the end of October and then starts declining towards the end of the season. Moreover, the initial moisture level of Reg-1 at the start of the season is higher than that of all other regions, and its lowest value at the end of the season is higher than the seasonal maximum moisture of some regions (e.g., Reg-3 and Reg-5). Generally, the moisture level amplitude significantly differs among the homogeneous regions throughout the season Fig. 6(b).

The interannual variabilities of homogeneous moisture regions significantly differ from one another, as demonstrated by the varying amplitudes of moisture anomalies shown in Fig. 7. Notably, there are significant consecutive dry years, i.e., below the long-term average, across homogeneous regions. Examples include the periods of consecutive dry years such as 2007–2012 in Reg-1, 1983–1988 in Reg-3, 2012–2018 in Reg-4, and 1991–1996 in Reg-5. The longest consecutive dry period is observed in Reg-2, spanning from 2001 to 2020, with the exception of two normal years (i.e., 2006 and 2013). In Reg-2, it is notable that the moisture level remains above the long-term mean from 1981 to 2000, except for small negative amplitude anomalies in 1984 and 1987. This region exhibits significant moisture variability and a pronounced decreasing trend in moisture levels, as depicted in Fig. 2(b, c). Moreover, significant wet years, such as 1997–2000, are observed in all regions except Reg-5.

Figure 8 presents the long-term time series smoothed by a 7-year moving average for homogeneous climate regions, showcasing the decadal soil moisture trends in these regions using Kendall-Tau trend test (Hussain and Mahmud 2019). The figure illustrates increasing moisture trends across all regions until 1997. However, after that point, Reg-2 (trend magnitude, $\tau = -0.60$) and Reg-4 ($\tau = -0.67$) reveals decreasing trends, with Reg-2 experiencing a particularly sharp decline. Reg-1's trend continues to increase until 2003, followed by a moderate decline and subsequent increase ($\tau = 0.30$). In contrast, Reg-3 ($\tau = 0.26$) and Reg-5 ($\tau = 0.59$) consistently show increasing moisture levels. It is evident that the magnitude of seasonal decreasing trends in Reg-2 and Reg-4 is substantially high, aligning with the observations in Fig. 8. The increase in soil moisture trends in Reg-1 and Reg-3 is moderate in both seasonal and decadal time scales, while the decadal increase in trend in Reg-5 is considerably larger. On the other hand, the annual trend (as shown in supplementary materials Figure S2) is low in Reg-1, Reg-3, and Reg-5.

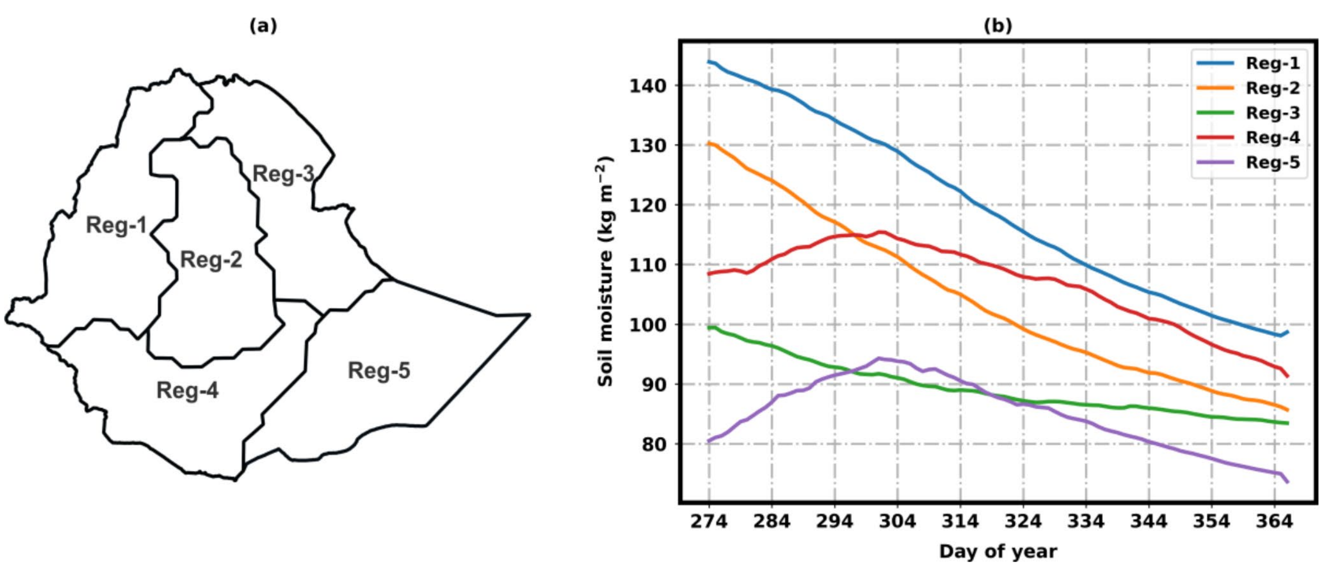

Fig. 6 (**a**) The five homogeneous soil moisture regions in Ethiopia: Northwest (Reg-1), Central (Reg-2), Northeast (Reg-3), Southwestern-central (Reg-4), and Southeast (Reg-5); (**b**) Seasonal cycles of average soil moisture in homogeneous regions for 1981-2020 period

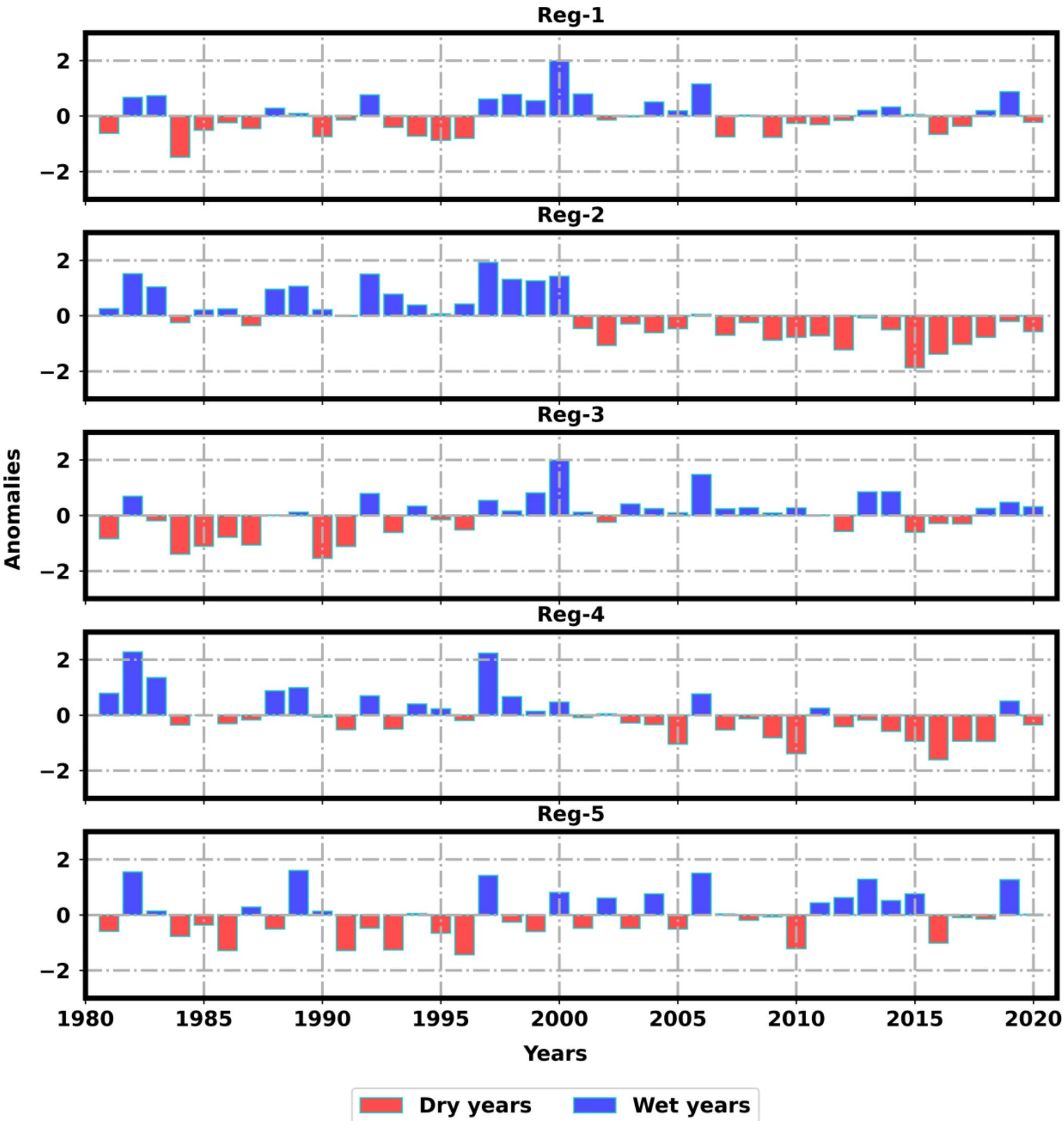

Fig. 7 Interannual variabilities in soil moisture within homogeneous soil moisture regions of Ethiopia

Figure 9 presents the spatial and temporal densities of soil moisture levels. The spatial and temporal coverage of the range of soil moisture values are comparable in their respective homogeneous climate regions. For instance, Reg-1, Reg-2, and Reg-4 reveal a wider range of moisture levels coverage, whereas Reg-3 and Reg-5 exhibit moisture levels concentrated in a narrow band of values. Spatially, Reg-1 and Reg-2 show a moderately left-skewed distribution, while Reg-4 is a bit right-skewed, and Reg-3 and Reg-5 indicate a normal distribution. This suggests that high moisture levels are prevalent in Reg-1 and Reg-2, while the areas in Reg-4 are characterized by relatively lower moisture levels. Temporally, all regions resemble close to a normal distribution.

As indicated in Tables 1 and 79% of the time, post-rainy season moisture values fall between the 10th and

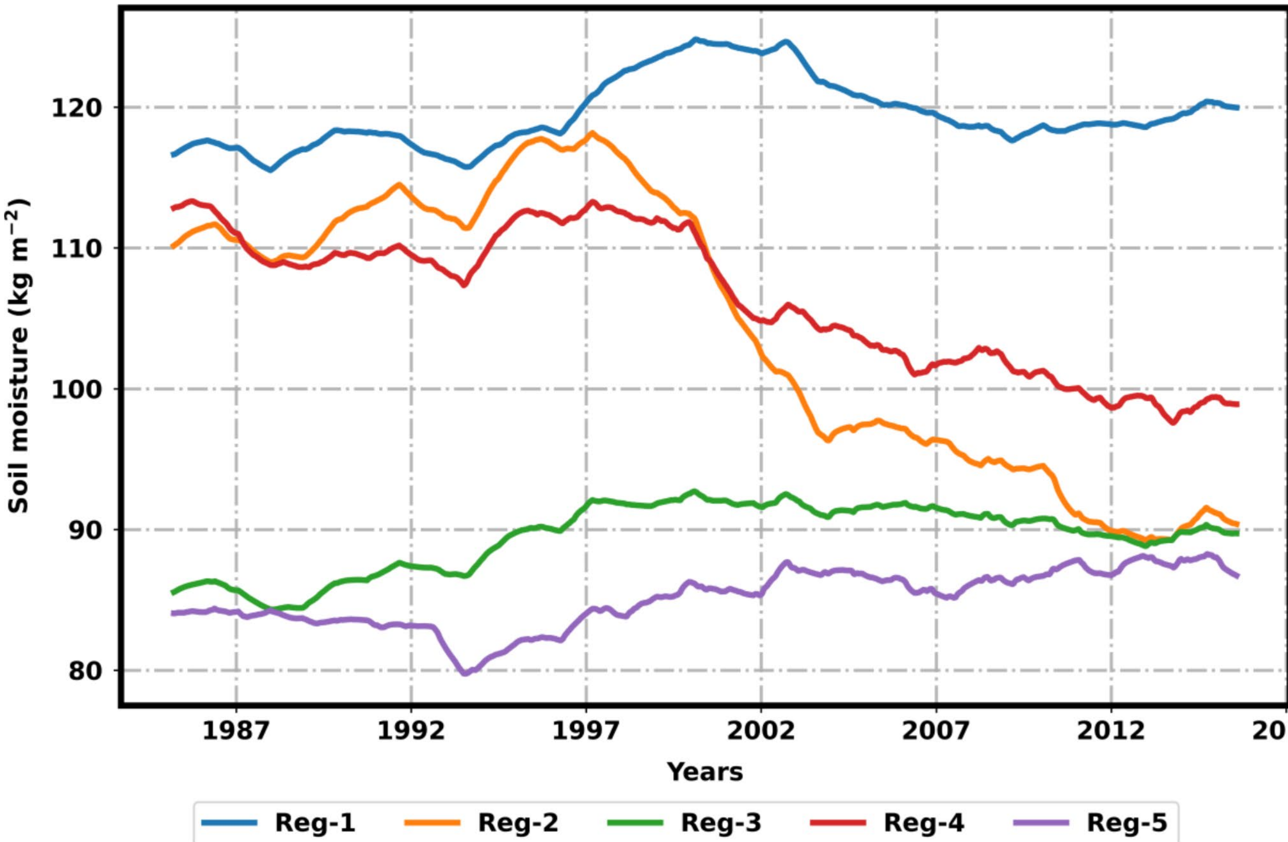

Fig. 8 Long-term temporal trends of residual soil moisture in homogeneous regions of Ethiopia. The long-term time series data is smoothed on a decadal time scale (7 years) to reduce high-frequency variability

90th percentiles in their respective homogeneous climate regions. It is not surprising that temporally every region's 10th to 90th percentiles of moisture values fall within the same percentages, considering that the homogeneous regions were classified based on the temporal variability of the seasonal (OND) soil moisture. However, the spatial coverage of these ranges of values differs from region to region. It is also important to note that the spatial distribution of the highest moisture values in Reg-1, Reg-2, and Reg-4 covers 65.9%, 90.7%, and 48.9% of the regions' areas, respectively. Although Reg-3 and Reg-5 also exhibit a wider area coverage of moisture levels in their respective regions, the range of these values is narrower and smaller in magnitude, as depicted in Fig. 9(c, e).

4.4 Cropping assessment based on crop water requirements

Cropping strategies that can prioritize (a) utilization of residual soil moisture, (b) incorporation of drought-tolerant crops, (c) maintain a short growing season (maximum 120 days), and (d) align with crop water requirements are critical for promoting sustainable agricultural systems in water-scarce regions.

To address this need, we conducted tests on five legume crops known for their ability to withstand low water stress and which are characterized by short growing periods. Table 2 outlines the legume crops, their respective lengths of growing periods across three stages (initial, mid-season, and late), and their corresponding crop coefficients.

Figure 10 indicates the daily water requirements for the five legume crops across different homogeneous regions of Ethiopia characterized by normal, extreme dry, and wet soil moisture conditions. Under wet conditions, soil moisture levels in Reg-1, Reg-2, and Reg-4 in Ethiopia are adequate to meet the daily water needs of these crops. Conversely, Reg-3 and Reg-5 of Ethiopia exhibit sufficient moisture levels to support crop growth until late October, yet these regions experience water stress during the mid-season and late stage, with a water deficit of approximately 5 mm/day in the latter stage. In drier locations, all regions lack adequate moisture to sustain crop growth, even during the initial stage. However, at normal moisture levels, the Reg-1, Reg-2, and Reg-4 regions indicate the potential to support legume crop water requirements if supplemented with

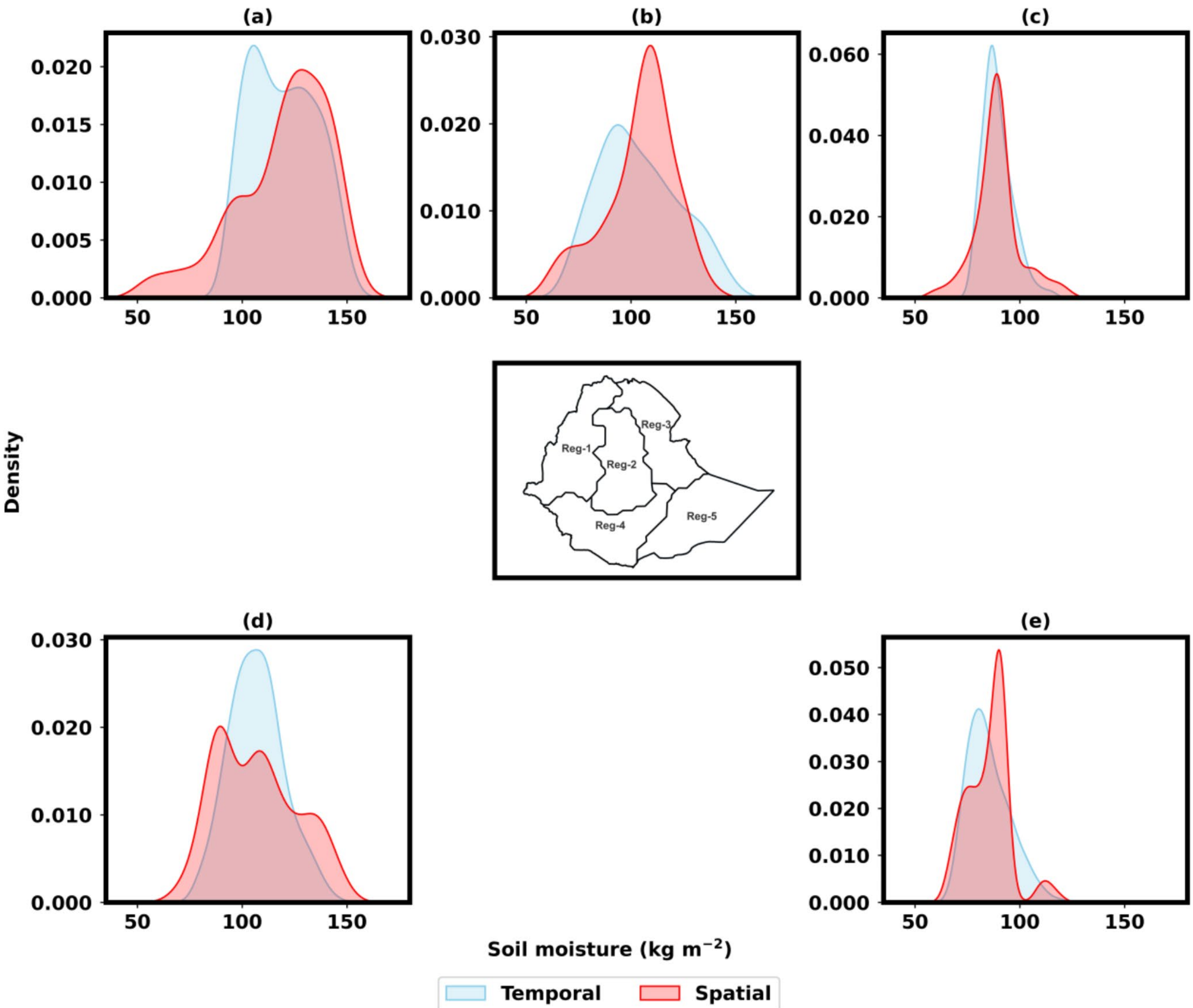

Fig. 9 Spatial and temporal density of soil moisture in homogeneous regions of Ethiopia (1981–2020). The top three panels in the row presents (**a**) Reg-1, (**b**) Reg-2, and (**c**) Reg-3; the central panel displays a map of homogeneous regions, and the last two panels in the row correspond to (**d**) Reg-4 and (**e**) Reg-5

Table 1 Lower (10th) and Upper (90th) percentiles of soil moisture values in homogeneous regions of Ethiopia, along with the percentages of corresponding temporal and spatial soil moisture values coverage within the lower and upper percentiles

Regions	Percentiles [10th — 90th] ($kg.m^{-2}$)	Percentages [Temporal/Spatial]
Reg-1	[99.13–141.31]	[79.74% / 65.58%]
Reg-2	[79.96–132.94]	[79.38% / 90.65%]
Reg-3	[80.78–99.210]	[79.44% / 69.85%]
Reg-4	[90.54–124.49]	[79.67% / 48.89%]
Reg-5	[73.49–99.510]	[79.25% / 80.09%]

Table 2 Crop types, their corresponding crop coefficients (Kc), and growth stages employed to assess crops development during the OND season, utilizing residual soil moisture

Legume Crops	Crop coefficients K_c(days)	Refs.
Chickpea	0.26(25), 1.08(40), 0.52(> 65)	(FAO 2023)
Fieldpeas	0.50(50), 1.15(35), 0.30(> 85)	(FAO 2023)
Common bean	0.40(40), 1.15(35), 0.54(> 75)	(FAO 2023)
Soybean	0.50(30), 1.15(40), 0.50(> 75)	(FAO 2023)
Alfalfa	0.40(30), 0.95(30), 0.40(> 60)	(FAO 2023)

irrigation (maximum of 4.5 mm/day) during the mid-season and late growing stages.

Figure 11 illustrates the spatial distribution of the difference between residual soil moisture and crop water requirements for the five legume crops across cropland areas in Ethiopia. Cropland covers approximately 30.1% of the total country area. At the initial growth stage, a high percentage of cropland areas (99.6% for chickpea, 94.7% for field peas, 99.4% for alfalfa, 99.4% for common bean,

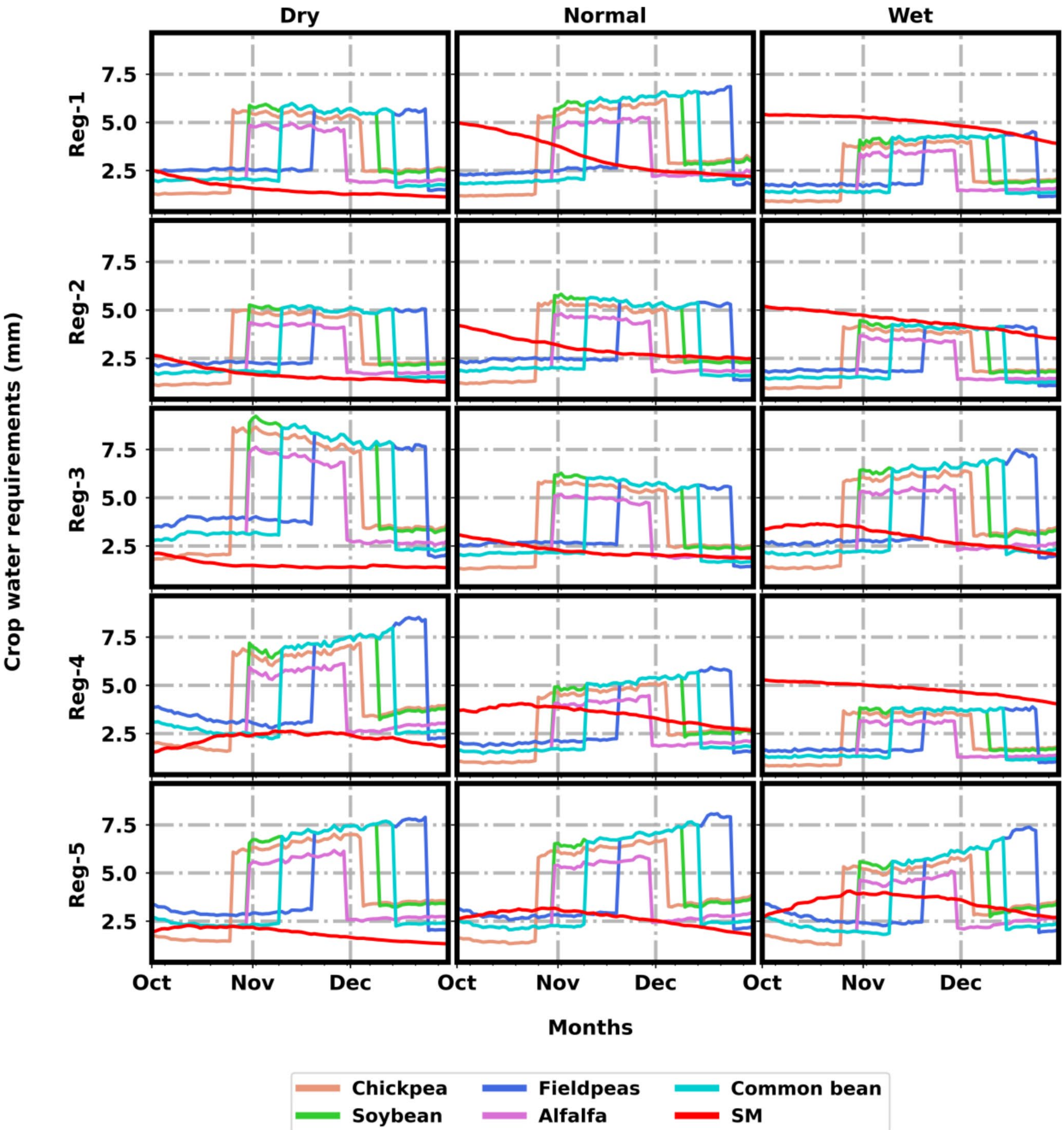

Fig. 10 Daily crop water requirements for chickpea, field peas, common bean, soybean, and alfalfa, alongside available residual soil moisture (SM) during the OND season across regions of Ethiopia. Columns represent soil moisture conditions (dry, normal, and wet) in respective regions, while rows indicate homogeneous regions from Reg-1 to Reg-5

and 97.2% for soybean) support crop water requirements for these crops. These areas are primarily concentrated in the central and western regions of Ethiopia.

During the mid-season growth stage, the spatial coverage significantly reduces to 18.9% for chickpea, 3.6% for field peas, 29.5% for alfalfa, 7.4% for common bean, and 10.4% for soybean. Residual soil moisture in the central and eastern highlands of Ethiopia becomes insufficient to meet mid-season crop water requirements for all crops. In addition, moisture deficits exceeding −4.5 mm/day are observed in the central rift valley, eastern, and northern regions of the country. However, in most parts of the central and western

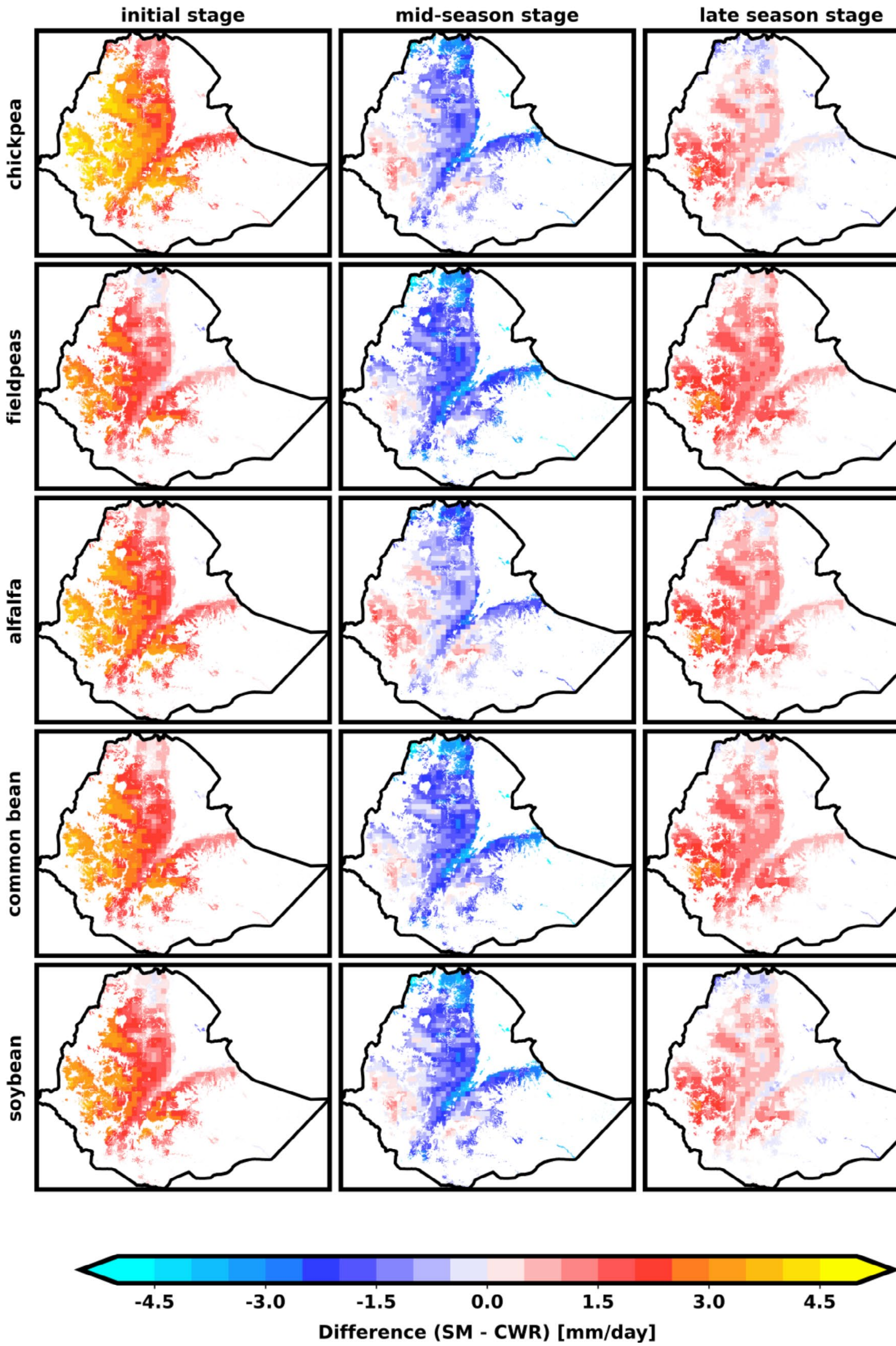

Fig. 11 Spatial distributions across Ethiopia of the difference between residual soil moisture (SM) and crop water requirements (CWR) for chickpea, field peas, alfalfa, common bean, and soybean at their initial, mid-season, and late-season growth stages

highlands of Ethiopia, moisture deficits are less than 1 mm/day, which may be tolerated by legume crops' low moisture resistance capabilities or supplemented by minimal irrigation to sustain crop growth all along this growth stage. During the late-season growth stage, crop water requirements for most of the legume crops investigated are adequately supported by residual moisture across cropland areas, with the exception of chickpea and soybean in the northernmost regions of the country.

5 Discussion

Our study investigates the spatiotemporal variability of soil moisture during the OND season in Ethiopia and its potential contribution to supporting legume-based improvements in agricultural productivity. Through empirical analysis employing advanced statistical techniques, we unraveled the spatial and temporal distribution and trends of soil moisture across Ethiopia over the four decadal period from 1981 to 2020. Our primary focus was to investigate the potential of residual moisture to support post-rainy season cropping of legumes, particularly in light of adverse climate impacts on crop yield and the need for agricultural transformation to meet escalating food demand driven by population growth in the face of a changing climate.

Ethiopia's diverse topography, agroecologies, and climate variability play pivotal roles in shaping the heterogeneous distribution of soil moisture across the country. Our findings demonstrate pronounced soil moisture gradients between the eastern and western regions of Ethiopia, with the former characterized by comparatively lower moisture levels. The eastern regions of Ethiopia predominantly consist of lowlands, comprising a significant portion of the country's landscape. Characterized by arid and semi-arid agroecology, these lowland areas typically receive annual rainfall of less than 200 mm, accompanied by high temperatures reaching up to 50°C (Berihun et al. 2023; Jimma et al. 2024). This combination of climatic factors, including elevated temperatures and limited rainfall, contributes to reduced soil moisture availability in the eastern region, rendering it less conducive to post-rainy season cropping activities as already observed in other studies (Agutu et al. 2021; Temam et al. 2019).

Notably, the central region of Ethiopia, encompassing the highlands renowned for intensive agricultural practices, exhibits substantial moisture variability, imposing challenges regarding the sustainability of future agricultural activities in this crucial agricultural hub. The spatial heterogeneity of soil moisture underscores the need for tailored agricultural strategies that account for local moisture conditions, enabling farmers to spatially and temporally optimize their selection of crop species, crop varieties and management practices based on their specific agroecological context. This is becoming more important because of the protracted impacts of droughts in the horn of Africa and in Ethiopia particularly as mentioned by Degefie et al. (2019), with climate projections indicating that the frequency and intensity of such droughts is likely to increase (Haile et al. 2020).

A key finding is that the eastern regions, particularly the northern and southeastern parts, are identified as particularly vulnerable to unreliable post-rainy season cropping, due to the prevalence of consecutive dry days and frequent dry spells. This finding helps to explain why agriculture is already constrained in these regions for the main season, and exhibits even more serious constraints for the post cropping period. Abera et al. (2019) indicate that the effects of climate change further compound the challenges, impacting surface water availability and exacerbating moisture deficits in these regions of Ethiopia. Conversely, the southeastern region of Ethiopia shows a promising trend with a substantial increase in moisture trends, suggesting potential opportunities for future post-harvest cropping of legume crops. The exponential decline in soil moisture in the Reg-1, Reg-2, and Reg-3 throughout the months of the season is likely explained by the withdrawal of Ethiopian summer rainfall (main rainy season) from northeast to southwest, following the trajectory of the Inter-Tropical Convergence Zone (ITCZ), as described in several studies (Gleixner et al. 2017; Segele and Lamb 2005; Segele et al. 2009) and the soil moisture's correlation with rainfall. The longest consecutive dry period, spanning from 2001 to 2020, is observed in Reg-2, consistent with the findings of Jimma et al. (2023), who utilized annual soil moisture data to assess trends in soil moisture across the country. These year-to-year variabilities within homogeneous climate regions are likely attributed to topographic effects, as well as local and global moisture drivers.

Our study further highlights the capacity of residual soil moisture to fulfill the water demands of selected legume crops, thereby rendering specific areas conducive to post-rainy season cropping, particularly the western, central, and southwestern regions. However, it is noteworthy that supplemental irrigation may be necessary for some crops during the late growing stages in certain areas to mitigate moisture deficits and ensure optimal crop growth and yield. Furthermore, in regions that possess higher soil moisture values, such as wetter pocket areas in the southeastern region, implementation of supplementary irrigation could augment existing moisture levels, thereby enhance the potential for post-harvest cropping in the region.

Our findings have significant implications for sustainable intensification of agriculture in Ethiopia. Firstly, it underscores the potential for cultivating legume crops in non-overlapping growing seasons across different regions of Ethiopia, thereby enabling double harvesting and strengthening food security (Renard and Tilman 2021). Secondly, the availability of residual moisture presents an opportunity to incorporate legumes as secondary crops, potentially enhancing nutritional security because of their high protein content (Kebede 2020; Neda 2020; Semba et al. 2021). Thirdly, the residual moisture during the OND period can contribute to soil fertility replenishment, particularly through its use for the cultivation of legumes for nitrogen fixation. Moreover, our findings bear significance for informing strategic planning initiatives aimed at agricultural transformation in Ethiopia to effectively address food security concerns in the face of a changing climate.

6 Conclusion

Our study provides insights into the spatiotemporal variability of soil moisture in Ethiopia and its potential for enhancing agricultural productivity. By rigorous empirical analysis and employing Empirical Orthogonal Functions, we have identified significant gradients in soil moisture levels across Ethiopia, shaped by its diverse topography, agroecology, and climate variability. These findings emphasize the importance of understanding soil moisture dynamics in optimizing post-rainy season cropping strategies.

Our research findings highlight the vulnerability of certain regions, particularly the eastern areas, to unreliable post-rainy season cropping due to moisture deficits, potentially exacerbated by climate change. However, there are promising opportunities for future legume crop production, especially in the southeastern region, where moisture levels show a notable increasing trend. Furthermore, we emphasize the crucial role of residual soil moisture in sustaining agricultural productivity, particularly in regions characterized by wetter moisture levels. By leveraging this resource and implementing supplemental irrigation where necessary, farmers can enhance their crop yields and resilience to climate variability.

Our study contributes to the broader discourse on agricultural sustainability and resilience to climate change, providing a foundation for future research and informing strategies to enhance food security and livelihoods in Ethiopia. The implications of our findings offer actionable insights for agricultural stakeholders and policymakers. By incorporating our research into decision-making processes, policymakers can formulate evidence-based policies aimed at promoting sustainable agricultural practices and ensuring food security in Ethiopia.

While our findings offer valuable insights for farmers, agricultural stakeholders and policymakers to optimize post-rainy season cropping strategies, we acknowledge the limitations of our study and emphasize the need for further research to deepen our understanding of the predicted crop viability in localized regions. Further research efforts employing process-based crop modeling, and incorporating soil properties and crop management strategies, combined with crop field trials across the different regions, would enhance understanding. Moreover, refining climate datasets through regional modeling approaches can provide more detailed insights by capturing fine-grained spatial variations overlooked in coarse-resolution analyses, thus improving the robustness and accuracy of our findings, and guiding more targeted interventions for sustainable agricultural development in Ethiopia.

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Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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