

## Wavelet-based analysis of hydro-climatic and vegetation dynamics in heterogeneous agro-climatic zones of East Africa

Pacifique Batungwanayo <sup>a,b,\*</sup>, Marnik Vanclooster<sup>b</sup>, Alice Alonso<sup>b</sup> and Alan Frendy Koropitan<sup>c</sup>

<sup>a</sup> University of Burundi Doctoral School, Bujumbura, Burundi

<sup>b</sup> Earth and Life Institute, Université Catholique de Louvain, Louvain-la-Neuve, Belgium

<sup>c</sup> Faculty of Fisheries and Marine Sciences, IPB University, Bogor, Indonesia

\*Corresponding author. E-mail: pacifique.batungwanayo@ub.edu.bi

 PB, 0000-0003-1748-7604

### ABSTRACT

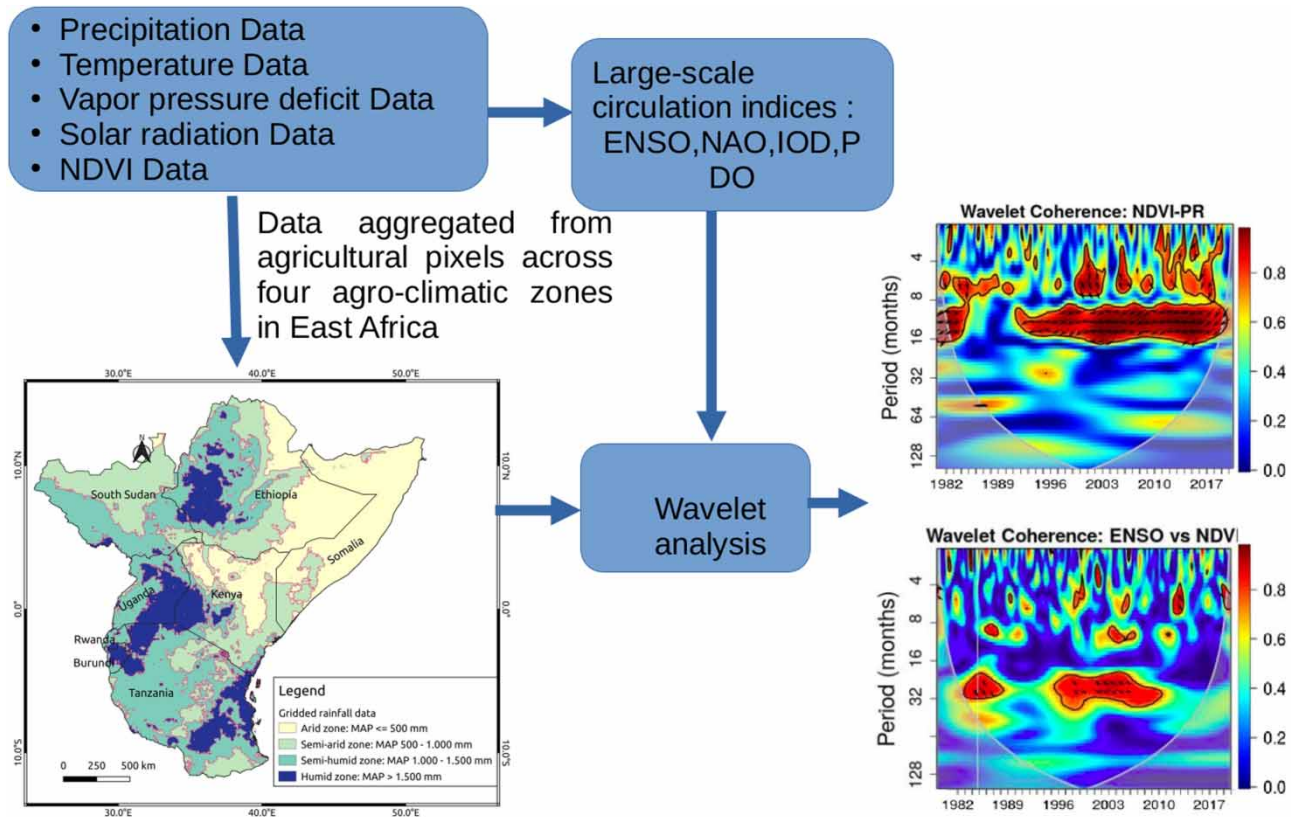
Natural and human-induced factors profoundly affect agricultural crop production in East Africa, sparking ongoing debates about their relative significance. This study investigates the impact of localized hydro-climatic variables like precipitation, temperature, vapor pressure deficit, and water deficit on crop production. Additionally, it examines climate oscillations such as El Niño-Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), North Atlantic Oscillation (NAO), and Pacific Decadal Oscillation (PDO). Employing the Normalized Difference Vegetation Index (NDVI) metric, analysis focuses on four climatic zones, ranging from arid to humid. Results suggest that the dominant periodicities for NDVI and hydro-climatic factors are annual (8-16 months) and intra-annual (4-8 months), while circulation indices exhibit inter-annual and inter-decadal periodicity. The study reveals that vegetation dynamics are more sensitive to annual and intra-annual fluctuations in hydro-climatic factors compared to inter-annual and inter-decadal oscillations in circulation indices. The bi-variate wavelet coherence (WTC) analysis reveals that precipitation and ENSO are the most significant factors explaining vegetation variability, while multiple wavelet coherence (MWC) analysis demonstrates that all variables contribute significantly to NDVI variability. This research underscores the importance of wavelet techniques in deciphering complex relationships between hydro-climatic factors and crop production, with implications for agricultural management and policy in East Africa.

**Key words:** climatic zones, climate oscillations, East Africa, hydro-climatic variables, vegetation dynamics, wavelet analysis

### HIGHLIGHTS

- Advanced wavelet analysis probes hydro-climatic factors' intricate ties with vegetation dynamics.
- Localized variables' impacts, broader circulation indices' influence, and dominant periodicities are revealed.
- The study offers a comprehensive understanding of East African vegetation variability.

## GRAPHICAL ABSTRACT



## 1. INTRODUCTION

The Earth's vegetation plays a crucial role in keeping the carbon cycle balanced and facilitating essential energy exchanges between the atmosphere and Earth's surface. Its importance goes beyond just ecology, influencing terrestrial ecosystems globally (Funk & Brown 2006; Yvon-Durocher *et al.* 2010; Bégué *et al.* 2011; Xu *et al.* 2020). As humans emit carbon dioxide, terrestrial and marine ecosystems absorb a significant portion of these emissions, helping regulate climate and preserve soil, water, and air quality (Bardgett *et al.* 2008; Smith *et al.* 2013). The looming threat of climate change emphasizes the need to protect ecosystems from its impacts (Zommers *et al.* 2016; Pandit *et al.* 2021).

To understand the intricate relationship between climate change and terrestrial ecosystems, researchers widely employ the NDVI as a metric for vegetation dynamics and their correlation with climatic factors. Studies cover various scales – from the global stage (Krich *et al.* 2020) to regional scenes, like the Sahel, Africa, East Africa, China, the Horn of Africa, Ethiopia, and even local specifics in certain regions (Anyamba *et al.* 2002; Herrmann *et al.* 2005; Batungwanayo *et al.* 2020; Measho *et al.* 2021; Muir *et al.* 2021; Nzabarinda *et al.* 2021; Yonaba *et al.* 2021; Lian *et al.* 2022). Changes in precipitation significantly affect vegetation cover, while in some areas, temperature proves a more reliable factor influencing NDVI variability (Cao *et al.* 2014; Sun *et al.* 2015a; Sun *et al.* 2015b). Ongoing research aims to predict changes in NDVI during different periods for a comprehensive understanding of the link between climate change and vegetation dynamics (Funk & Brown 2006; Zambrano *et al.* 2018).

The growth patterns of vegetation and the regional climate variability that shapes them result from larger-scale mechanisms governing the redistribution of heat and motion across Earth's atmospheric, oceanic, and hydrologic systems (Bothale & Katpatal 2014; Yang *et al.* 2016). Ocean-atmosphere oscillations – ENSO, IOD, NAO, and PDO – emerge as influential factors in seasonal climate variability and ecosystems (Yang *et al.* 2018). ENSO and IOD, in particular, play a crucial role in explaining vegetation dynamics in southern and eastern Africa, impacting terrestrial ecosystems (Anyamba *et al.* 2002; Stige *et al.* 2006; Williams & Hanan 2011; Hao *et al.* 2020). The effects of ENSO events on southern Africa's terrestrial

ecosystems are closely tied to drought and heat extremes (Vashisht & Zaitchik 2018). Similarly, IOD significantly contributes to regional climate variability, influencing climate patterns in the Indian Ocean basin (Birkett *et al.* 1999; Saji *et al.* 1999; Williams & Hanan 2011). Despite recognizing the role of ocean–atmosphere oscillations like ENSO and IOD in vegetation dynamics and regional climate variability, the precise mechanisms behind these effects remain elusive. Further investigation is needed to comprehend the potential impacts of changes in local hydro-meteorological factors or teleconnection regional climatic factors on vegetation dynamics in East Africa.

Over the years, researchers have employed various methods to understand how vegetation responds to local hydro-climatic variables and regional teleconnections. Traditional approaches, such as correlation tests, are common in multivariate time series analysis to examine relationships between hydro-climatic variables like precipitation and temperature (Zhang *et al.* 1997, 2018; Shi *et al.* 2019; Kim *et al.* 2023). However, these methods often fall short of revealing suitable time series relationships across different time scales, especially when dealing with the non-linear and non-stationary nature of ecological data (Torrence & Compo 1998; Han *et al.* 2024). Ecological processes, such as vegetation dynamics and their hydro-climatic drivers, typically violate the stationarity assumption inherent in many traditional analytical methods. Despite this, existing studies often rely on linear trend analysis and coherence assessments between vegetation proxies and hydro-climatic variables (Martínez & Gilbert 2009; Wu *et al.* 2024). These conventional methods fail to address the inherent non-linear and non-stationary characteristics of ecological data. Linear approaches are limited in their ability to capture transient relationships between vegetation dynamics and their drivers, account for gradual changes enforced by environmental and anthropogenic variables, and properly assess the dynamic and complex interactions within heterogeneous agro-climatic regions (Wang *et al.* 2024).

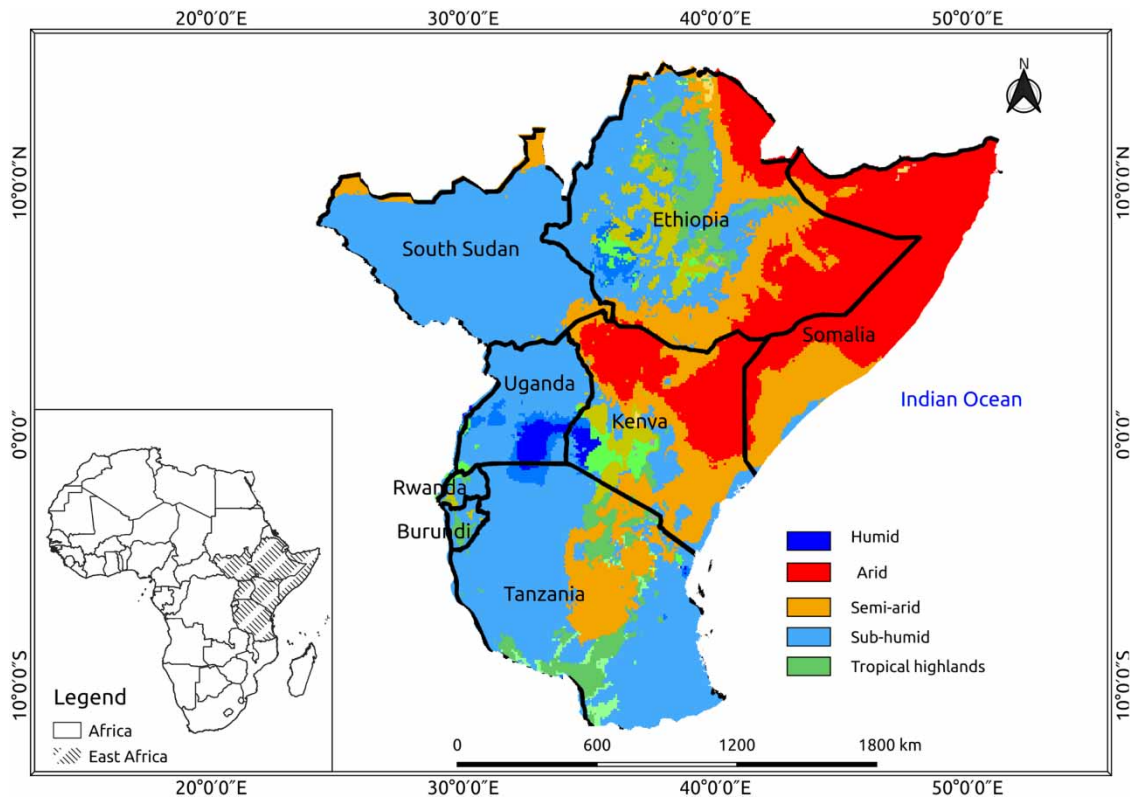
Therefore, time-scale decomposition approaches, particularly wavelet analysis, are more suitable for understanding vegetation changes over time and their response to climate change. The variability of local and regional climatic indicators differs significantly, resulting in several quasi-periodic frequencies in the frequency and time domains. Wavelet transforms simultaneously analyze signals in both domains, utilizing continuous wavelet transform (CWT), wavelet coherence (WTC) and multiple wavelet coherence (MWC) techniques (Torrence & Compo 1998; Grinsted *et al.* 2004). These methods are effective for non-stationary systems as they detect localized multivariate relationships and estimate scale-specific multivariate relationships. Compared to other methods, wavelet analysis is better suited for capturing the variability of time series data across multiple scales, which is crucial for understanding the impact of climate change on vegetation dynamics (Hu & Si 2016).

Within the East African region, no comprehensive investigations have been conducted regarding the influence of large-scale circulation indices and various local hydro-climatic factors controlling vegetation dynamics at diverse time–frequency scales. Therefore, this study aims to fill this gap, using CWT, WTC, and MWC (i) to explore the fluctuations in vegetation and hydro-climatic factors, (ii) to discern the distinct and combined connections between climate modes of variability and local hydro-climatic factors in relation to vegetation dynamics, and (iii) to investigate the impact of individual and combined monthly meteorological factors and large-scale circulation indices on vegetation variability across different climatic zones in East Africa. The study contributes to understanding the mechanisms linking vegetation dynamics to climate variability. If the identified relationships between large-scale circulation indices and vegetation productivity are predictive, they could be valuable tools for early warning systems and decision-making support in addressing climate-related disasters and food insecurity.

## 2. STUDY AREA, DATA, AND METHODS

### 2.1. Study area

This study is focused on the East African region, which includes Burundi, Kenya, Rwanda, Somalia, South Sudan, Uganda, Ethiopia, and Tanzania (as shown in Figure 1), with a total area of about 4.2 million square kilometers. Due to the movement of the Inter-tropical Convergence Zone (ITCZ), East Africa's climate is diverse, and this is linked to its two rainy seasons (Sachs *et al.* 2009), the longer one lasting from March to May (MAM) and the shorter one from October to December (OND) (Kalisa *et al.* 2019). The mean annual precipitation (MAP) can vary from less than 500 mm to over 1,500 mm, depending on the region's latitude and altitude, with mountainous areas experiencing exceptionally high precipitation. The vegetation in East Africa relies heavily on rainfall, and agriculture is a crucial driver of the region's economy. About 80% of East Africa's population lives from agriculture. East African mountains such as Kilimanjaro, Rwenzori, Virunga, Kenya, and Elgon, play an essential role in regulating the climate, with elevations ranging from sea level to 5,895 m (EAC 2016; Kalisa *et al.* 2019). The Indian Ocean is an important trade route and a significant source of moisture for the region, connecting the East African nations with the Middle East and Asia.



**Figure 1** | Geographical location of the study area (East Africa) within the African continent, and its climatic zones based on the Köppen classification system.

Eastern Africa is characterized by diverse agro-climatic zones, ranging from arid and semi-arid regions to humid and semi-humid areas. The primary land uses in these regions include subsistence farming, commercial agriculture, pastoralism, and agroforestry (Few *et al.* 2015; Sinore & Wang 2024). Subsistence farming remains predominant, with smallholder farmers relying heavily on rainfall for crop production, making them vulnerable to climatic variability and extreme weather events. The socio-economic context of eastern Africa's agricultural lands is shaped by a high dependence on agriculture for livelihoods, with significant portions of the population engaged in farming activities. This dependence on agriculture makes food security a critical issue, especially given the frequent occurrences of droughts and floods in the region (Mubenga-Tshitaka *et al.* 2023; Omotoso *et al.* 2023). Additionally, political stability and governance play crucial roles in agricultural productivity and resilience. Policies related to land tenure, agricultural subsidies, and market access significantly impact farmers' ability to adapt to climatic changes (Desalegn *et al.* 2024; Karume 2024).

The main productive constraints in eastern Africa's agricultural lands include significant climatic variability, soil degradation, economic limitations, political and institutional challenges, and technological gaps. The region experiences substantial climatic variability, posing challenges for consistent agricultural production due to variations in rainfall patterns and frequent droughts and floods. Soil fertility issues, such as erosion, nutrient depletion, and salinity, limit crop growth, and productivity. Economic constraints, including limited access to financial resources and agricultural inputs, are exacerbated by inadequate infrastructure, affecting market access and post-harvest management. Governance issues, such as land tenure insecurity and inadequate agricultural policies, hinder farmers' ability to invest in and improve their practices. Lastly, the slow adoption of modern agricultural technologies due to a lack of awareness, training, and resources limits the efficiency and resilience of agricultural practices (Ahmed & Ahmed 2023; Ndayisaba *et al.* 2023; Waaswa *et al.* 2024).

## 2.2. Data sets

Monthly precipitation data spanning from 1982 to 2020 were acquired from the 'Climate Hazard Group InfraRed Precipitation with Station' (CHIRPS) satellite product, developed by the 'Climate Hazards Group' at the University of California,

Santa Barbara. CHIRPS combines satellite imagery and ground station data to deliver precise precipitation estimates at a spatial resolution of  $0.05^\circ$  (approximately 5.3 km) and a temporal resolution of 1 day (Funk *et al.* 2015). Renowned for its advantages over alternative precipitation datasets, CHIRPS has found applications in climate and drought monitoring, crop yield prediction, and disaster risk reduction (Cattani *et al.* 2018; Dinku *et al.* 2018; Belay *et al.* 2019; Muthoni *et al.* 2019; Nkunzimana *et al.* 2019; Batungwanayo *et al.* 2020). The daily data have been aggregated into monthly averages.

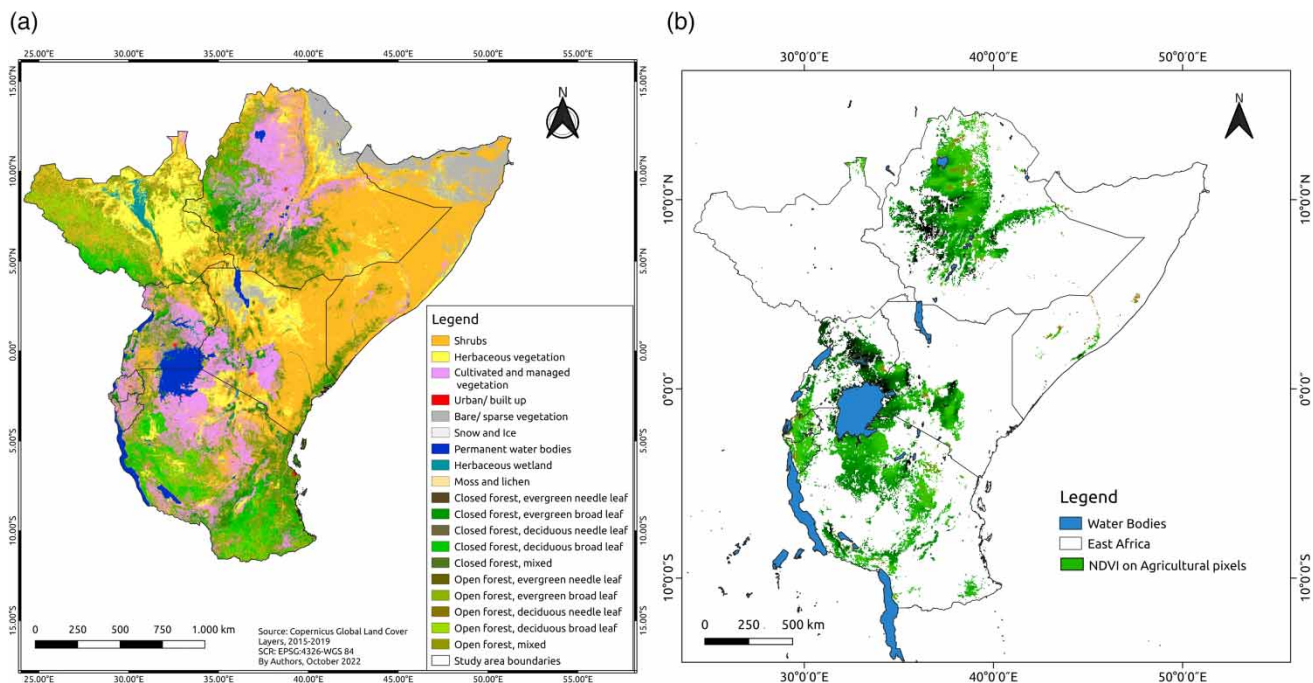
Land use data used in this study were extracted from the Copernicus Global Land Service (CGLS) product, specifically the International Geosphere-Biosphere Program land cover classification for 2015–2019 (Buchhorn *et al.* 2020). The study focused on cultivated and managed vegetation/agriculture (see Figure 2) to examine agricultural dynamics in response to climatic constraints, excluding perennial woody plants because of their greater resilience to seasonal weather fluctuations.

The study utilized the longest available NDVI dataset (1982–2020), obtained from the Climate Data Record (CDR) of the ‘Advanced Very High-Resolution Radiometer’ (AVHRR) aboard NOAA satellites. This dataset, with a spatial resolution of 5,566 m and a temporal resolution of 1 day, was accessed through the Google Earth Engine (GEE) platform (Vermote *et al.* 2019; Alonso *et al.* 2016; Gorelick *et al.* 2017). The analysis considered pixels masked to agricultural land, with monthly averages calculated. Local climate factors – vapor pressure deficit (VPD), water deficit (Wdef), temperature (T), and downward surface solar radiation (RD) – were retrieved from the TerraClimate dataset on GEE (Abatzoglou *et al.* 2018), crucial for understanding vegetation dynamics and climate change impacts (Deryng *et al.* 2014; Villarreal *et al.* 2016; Yuan *et al.* 2021). To assess global climatological patterns’ impact on East African vegetation dynamics, four teleconnection indices were employed. The Oceanic Niño Index (ONI), defining ENSO (Huang *et al.* 2017), the Indian Ocean Dipole Mode Index (DMI), and the NAO index, along with the PDO, were analyzed. Data were obtained from the National Centre for Environmental Information (<http://www.ngdc.noaa.gov>).

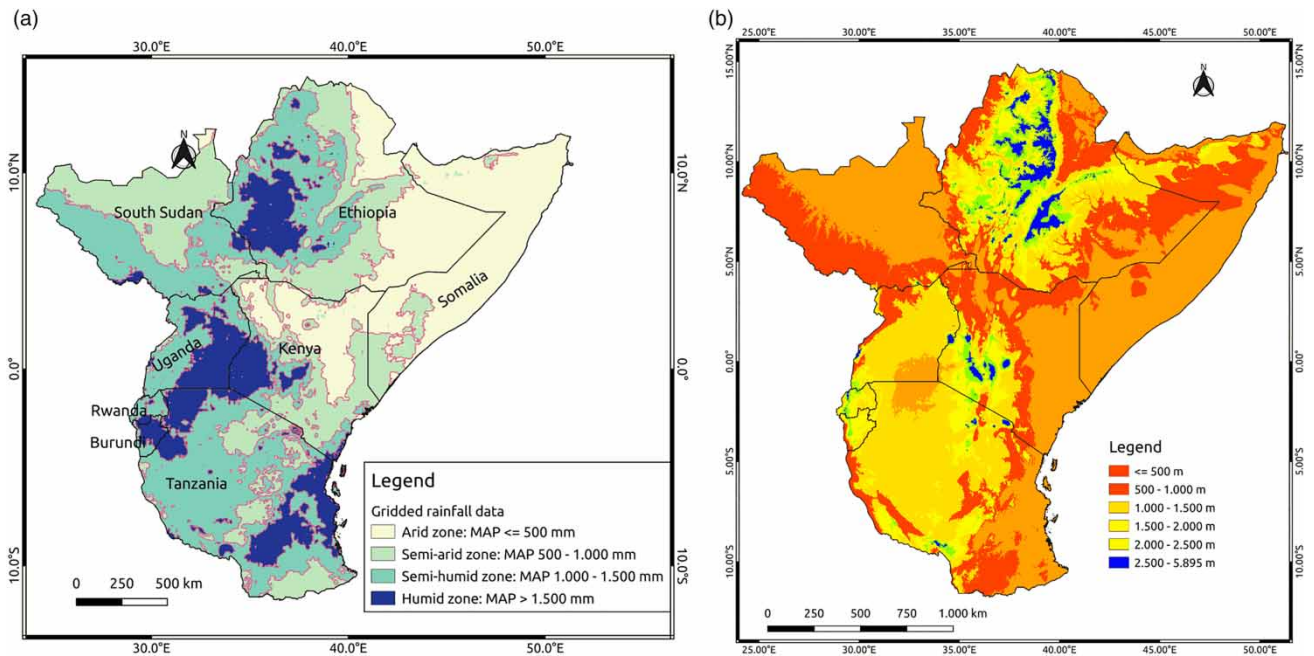
## 2.3. Methods

### 2.3.1. Zonation

The study area exhibits significant heterogeneity in terms of climatic and topographical conditions. A clustering approach was employed to assess the impact of meteorological factors on vegetation. In this study, the study area was divided into four zones based on MAP: MAP < 500 mm, 500 mm < MAP < 1,000 mm; 1,000 mm < MAP < 1,500 mm, and MAP > 1,500 mm. These zones were designated as arid, semi-arid, semi-humid, and humid, as shown in Figure 3(a). While



**Figure 2** | LULC for the study area (a) and agricultural pixels considered (b).



**Figure 3** | Study area zonation based on MAP (a) and elevation (b).

precipitation alone may not be sufficient for climate classification, a comparison with the widely used Köppen classification system (Figure 1) revealed similarities, indicating the reliability of our approach despite precipitation's limitations as a sole determinant. The alignment between our partition and the established Köppen–Geiger maps further substantiates its validity. Furthermore, studies by Vuille *et al.* (2003) and Pepin *et al.* (2022) highlight the significant influence of elevation on climate patterns, validating our incorporation of the elevation map into our classification (Figure 3(b)). All hydro-climatic variables considered, as well as NDVI were aggregated to each of the defined zones.

### 2.3.2. Wavelet analysis

The Fourier transform is a commonly used mathematical method for analyzing signals and extracting information from data. Still, it is limited for non-stationary signals, as it cannot consider both spectral components and time of occurrence. The wavelet transform overcomes this limitation by preserving the temporal localization of frequencies, making it popular in signal processing and hydroclimatology (Turki *et al.* 2016; Xu *et al.* 2019; Das *et al.* 2020). The CWT, introduced by Morlet *et al.* (1982), is a fast-decaying oscillation wavelet with zero means and localized in frequency and time. It decomposes time series into different time scales using a family of functions formed by translations and dilations of a single function  $\psi(t)$  called the mother wavelet. It is defined as follows:

$$W(s, \tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \psi^* \left( \frac{t - \tau}{s} \right) dt \quad (1)$$

$$\psi_{(t, \tau)} = \frac{1}{\sqrt{s}} \left( \frac{t - \tau}{s} \right) \quad (2)$$

The wavelet transform is represented by  $W(s, \tau)$ , where  $x(t)$  is the analyzed time series that is recorded in a discrete-time sequence ( $t$ ) with a uniform interval of  $\delta t$ ,  $\tau$ , and  $s$  define the time shift and the scale, respectively, and  $\psi$  and  $\psi^*$  stand for the wavelet function and the complex conjugate, respectively.

The wavelet transform is a flexible mathematical method for analyzing signals requiring spectral components and time considerations. It is achieved by decomposing the time series into different time scales using the mother wavelet function. The Morlet wavelet is a commonly used complex wavelet function in hydroclimatology due to its admissibility condition of being zero-mean and localized in both time and frequency space (Farge 1992). The dimensionless frequency controls the time and

scale resolution of the wavelet function, where higher (lower) frequency increases (decreases) scale resolution and decreases (increases) time resolution (Araghi *et al.* 2017). More details of the methods are found in Torrence & Compo (1998).

We determine the intensity of covariance between NDVI data and local hydro-climatic factors or large-scale circulation indices using WTC and MWC. Nalley *et al.* (2016) employed these methods to evaluate the coherence of CWT time–frequency space and determine the strength of the relationship between two or more time series. WTC and MWC are prevalent in geophysics (Wang *et al.* 2019) and meteorology (Torrence & Compo 1998).

The WTC is defined as follows:

$$R_{xy}^2 = \frac{|S(W_{xy}(s, \tau))|^2}{S(|W_x(s, \tau)|^2)S(|W_y(s, \tau)|^2)} \quad (3)$$

where  $S$  is the smoothing operator;  $W_x(s, \tau)$  is CWT of time series  $x(t)$ ;  $W_y(s, \tau)$  is CWT of time series  $y(t)$ ;  $W_{xy}(s, \tau)$  is the cross-wavelet power of two time series  $x(t)$  and  $y(t)$ .  $R_{xy}^2$  lies within the range of 0–1, with 0 indicating the absence of any correlation between the two time series and 1 indicating a perfect correlation between them. The cross-wavelet power  $W_{xy}$  between two time series ( $x(t), y(t)$ ) is defined as follows:

$$W_{xy}(s, \tau) = W_x(s, \tau)W_y^*(s, \tau) \quad (4)$$

where  $W_x(s, \tau)$  is the CWT of time series  $x(t)$ ;  $W_y^*(s, \tau)$  is the complex conjugate of the CWT of time series  $y(t)$ . The wavelet coherence statistical significance level is estimated using Monte Carlo methods and considered a 95% significance level (Grinsted *et al.* 2004). Further, an extension of bivariate coherence, MWC, was used to understand the correlation localized in the scale-location domain. The MWC between a response variable  $Y$  and a set of multiple predictors  $X(X = X_1, X_2, \dots, X_q)$ , at scale  $s$  and location  $\tau$  can be expressed as:

$$\rho_m^2(s, \tau) = \frac{W^{X,Y}(s, \tau)W^{X,X}(s, \tau)^{-1}W^{Y,X}(s, \tau)^*}{W^{Y,Y}(s, \tau)} \quad (5)$$

where  $W^{Y,X}(s, \tau)$  is a matrix representing the smoothed cross-wavelet power spectra between the response variable  $Y$  and predictor variables  $X$ ,  $W^{X,X}(s, \tau)$  is a matrix representing the smoothed auto- and cross-wavelet power spectra among multiple predictor variables  $X$ ;  $W^{Y,Y}(s, \tau)$  is the smoothed wavelet power spectrum of the response variable  $Y$ ; and  $W^{Y,X}(s, \tau)^*$  represents the complex conjugate of the matrix  $W^{Y,X}(s, \tau)$ . Details on MWC formulation can be found in Hu & Si (2016).

To evaluate the factors that affect vegetation growth, we employed the average power of wavelet coherence (APWC) and the percent area of significant coherence (PASC) (Hu & Si 2016). The PASC and APWC indicate the degree to which a given control factor can explain vegetation variation. We analyzed 38 years of NDVI data to identify the controlling factors for vegetation growth. Afterward, we examined the average values for all time scales to identify the most crucial factors. Three scenarios (i.e., single, pairwise, and factor combinations) were used to identify the controlling factors for vegetation growth based on the number of factors involved. If the additional factor in a pairwise or factor combination scenario increases the success probability by at least 5%, it is considered significant (Hu *et al.* 2017). Finally, we selected the best factor combinations based on the wavelet coherence analysis results. However, it is worth noting that while using multiple control factors might result in a higher APWC, it does not always lead to a higher PASC (Hu & Si 2016; Zhao *et al.* 2018). The analysis was performed with python software.

The presence of fluctuations in a time series can introduce a wide range of variations in the wavelet spectrum, posing challenges in detecting changes or discontinuities within the data. To address this issue, the scale-averaged spectrum is computed, which involves the weighted summation of the wavelet power spectrum across a specific range of scales. This approach allows for a more comprehensive understanding of any abrupt changes present in the data. Consequently, the lower panels of Figures 5(a)–5(d) illustrate the average spectrum within the 8- to 16-month band for the precipitation time series, indicating the averaged power over time with a 95% significance level.

### 3. RESULTS

#### 3.1. The variability of factors at each climatic zone

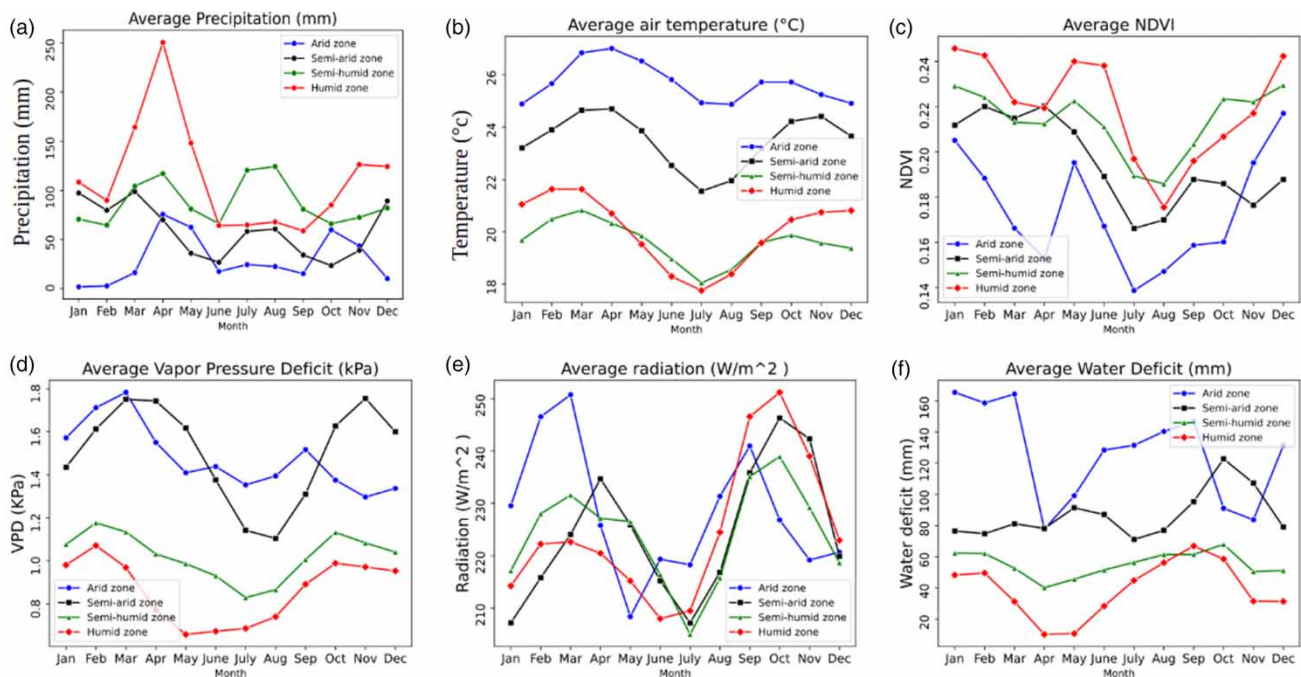
Monthly averages for hydro-climatic factors and vegetation follow the same pattern for the study areas (Figure 4). Considering the relatively colder climate of the humid zone (with more than 1,500 mm of annual precipitation), a lower temperature range (compared to other zones) is expected ((Figure 3(a)), while the amount of precipitation is higher than in other zones (Figure 3(b)). The classification of the areas according to the annual rainfall distribution is consistent with the climatic zones and altitudes in East Africa. Low rainfall (<500 mm) is observed in arid regions, while high rainfall (>1,500 mm) is observed in humid and semi-humid areas whose topography consists mainly of highlands (Kalisa *et al.* 2019). Two distinct wet and dry seasons are observed in arid and humid areas, while no apparent seasonality is observed in the semi-arid and semi-humid areas.

Looking at the vegetation characteristics of the studied area, we note a distribution consistent with precipitation, with a peak in May and a decline in July and August (Figure 4(c)). The water deficit, radiation, and vapor pressure deficit are similarly distributed in the different zones and follow precipitation dynamics (Figures 4(d), 4(e), 4(f)). Their higher range occurs in the zone whose MAP is less than 500 mm, mainly in January and February.

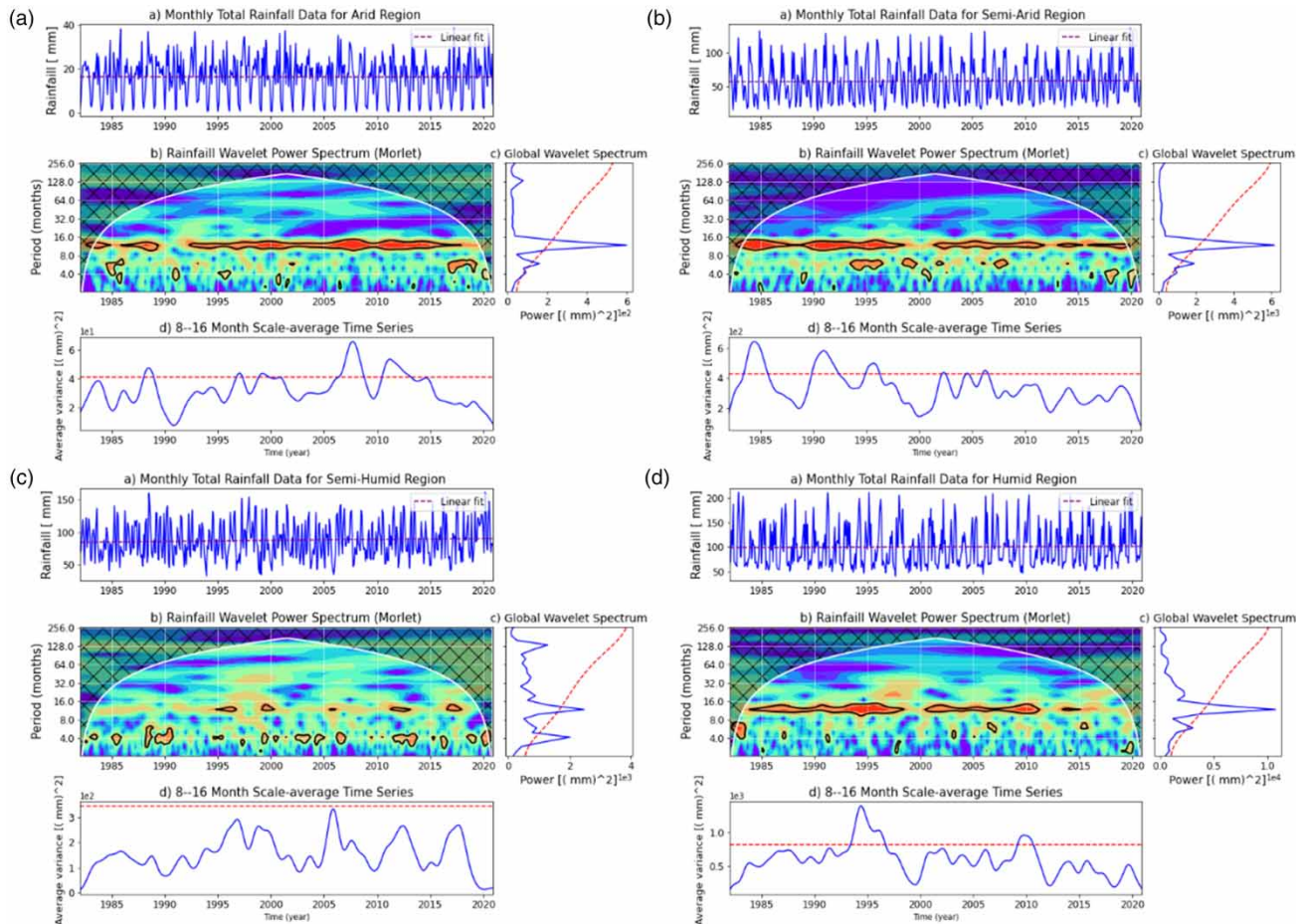
Our research reveals noteworthy declines in RD across all climatic zones. This observation is consistent with the findings of prior studies by Gilgen *et al.* (2009) and Yuan *et al.* (2021), both of which noted adverse decadal trends in solar radiation within specific African regions. Although precipitation exhibited no significant trends over our study period, the arid zone experienced a modest decline, while the other zones displayed an increase, albeit statistically non-significant (see Table 1). Temperature and vapor pressure deficit demonstrated increasing trends in all climatic zones, with significant trends observed throughout the study period. Specifically, the semi-arid, semi-humid, and humid zones displayed increasing trends, with the humid zone exhibiting significant results, whereas the arid zone displayed an insignificant negative trend.

#### 3.2. Periodic features of the monthly hydro-climatic series and vegetation

The analysis of monthly hydro-climate and vegetation series across four distinct climatic zones employs the wavelet transform to evaluate their variability. Figure 5 presents the monthly rainfall time series, accompanied by its respective wavelet power spectra, encompassing a 39-year data span (see Supplementary Material for other hydro-climatic factors). This spectral



**Figure 4** | The average monthly time series for various variables in the four studied areas: (a) air temperature, (b) precipitation, (c) NDVI, (d) VPD (vapor pressure deficit), (e) RD, and (f) water deficit.



**Figure 5** | Wavelet analysis of monthly rainfall data for different climatic regions (a) arid, (b) semi-arid, (c) semi-humid, and (d) humid. Top: monthly rainfall series. Middle and bottom: wavelet and scaled-average wavelet power spectrum (8–16 months' band). Right: global wavelet power spectrum. Colors indicate decreasing wavelet power: red, orange, yellow, and blue.

representation visually illustrates the power distribution in the waveform, utilizing a color scale that transitions from red (indicating high power) to blue (indicating low power). The cone of influence (COI), highlighted in white, demarcates the region where wavelet power might be deemed unreliable due to potential edge-effect artifacts. Bounded by lines on the wavelet power spectrum and the axes in the middle panels, the COI is a critical consideration. The right and bottom panels of Figure 5 showcase the global wavelet spectrum (GWS) and the scale-averaged wavelet spectrum (SAW). The red dashed curves delineate the 95% confidence levels, providing a statistical context for the findings.

The middle panels of Figure 5(a)–5(d) show how well the wavelet transform can identify patterns in rainfall time series in different climate zones. The monthly rainfall time series follows a slight downward trend in the arid region. In contrast, a slight increase is observed in the other climate regions, as shown by the dashed red lines in the upper panels (Figure 5(a)–5(d)) and supported by the trend test results in Table 1. At a 95% significance level, the power spectra show more power concentrations (thick black contours) between 8- and 16-month bands for rainfall, meaning there is an annual signal in the climate zones. However, two weak signals are observed in the semi-humid zone for the 8–16-month band. The integration of power over time reveals a strong and statistically significant peak above the 95% confidence level in the global wavelet spectra, assuming a red noise background as indicated by the presence of dashed red lines. This confirms the annual frequency (12-month periodicity) and seasonal frequency (6-month periodicity) of rainfall time series (right panels of Figure 5(a)–5(d)). The GWS accurately measures a time series's power spectrum, making it an excellent way to describe the data variability (Adeputan & Falayi 2019). The GWS has two peak periods for rainfall data depending on the location. For example, there are two peak periods for rainfall data in the semi-humid region for the 4–8-month band and the 8–16-month band. Generally, the significance for the 4–8-month bands is lower (right panels of Figure 5(a)–5(d)).

**Table 1** | Mann–Kendall test for hydro-climatic factors and NDVI at monthly scales over the study period

| Region     | PR<br>Z-value | T<br>Z-value | VPD<br>Z-value | Wdef<br>Z-value | RD<br>Z-value | NDVI<br>Z-value |
|------------|---------------|--------------|----------------|-----------------|---------------|-----------------|
| Arid       | −0.07         | 3.98**       | 2.09*          | 1.32            | −4.18**       | −0.039          |
| Semi-arid  | 0.63          | 2.74**       | 3.64**         | 3.00**          | −4.72**       | 0.762           |
| Semi-humid | 1.06          | 4.00**       | 4.05**         | 0.52            | −4.52**       | 0.253           |
| Humid      | 0.84          | 3.23**       | 2.73**         | 1.45            | −4.86**       | 5.654**         |

Note: PR, precipitation; T, temperature; VPD, vapor pressure deficit; Wdef, water deficit; RD, solar radiation; NDVI, normalized difference vegetation index.

\*Significance level set at 95% level.

\*\*Significance level set at 99% level.

In the arid region, notable wet periods occurred in 2007 and 2011, while the years between 1989 and 1992 and after 2015 experienced dry conditions, based on the scale-average power spectrum (lower panels of [Figure 5\(a\)–5\(d\)](#)). The semi-arid region exhibited wet intervals between 1983 and 1986, as well as from 1989 to 1993. In comparison, the humid region displayed heightened wetness in 1995 and 2010 when compared to other time periods.

The wavelet analysis of monthly temperature time series in four regions reveals distinct patterns. In the arid region, significant power concentrations with a periodicity of 8–16 months are observed during 1983–1987 and 1990–2010. Additionally, a strong wavelet power spectrum with a periodicity of 4–8 months is noted from 1982 to 2019. Similar patterns with varying periodicities are observed in the semi-arid, semi-humid, and humid zones (see [Figure 7](#)). NDVI time series patterns are also assessed (Appendix 2). Arid and semi-humid zones exhibit a 6-month periodicity, while other zones show a 1-year periodicity. The arid and semi-humid zones also display periodicities of 32–64 months. Strong 4–8-month periodicities are observed in the global wavelet spectrum for arid, semi-humid, and humid zones. Wavelet analysis of VPD, water deficit, and solar radiation time series (Appendix 3–5) reveals distinctive patterns across climatic zones. VPD exhibits a consistent 1-year periodicity across all regions, with an additional 6-month periodicity in arid and semi-arid regions. Solar radiation patterns align with seasonal variations, and the humid region also exhibits an annual periodicity. The comprehensive wavelet analysis, as conducted in this study, provides valuable insights into the patterns and variations of temperature, NDVI, VPD, water deficit, and solar radiation across diverse climatic zones.

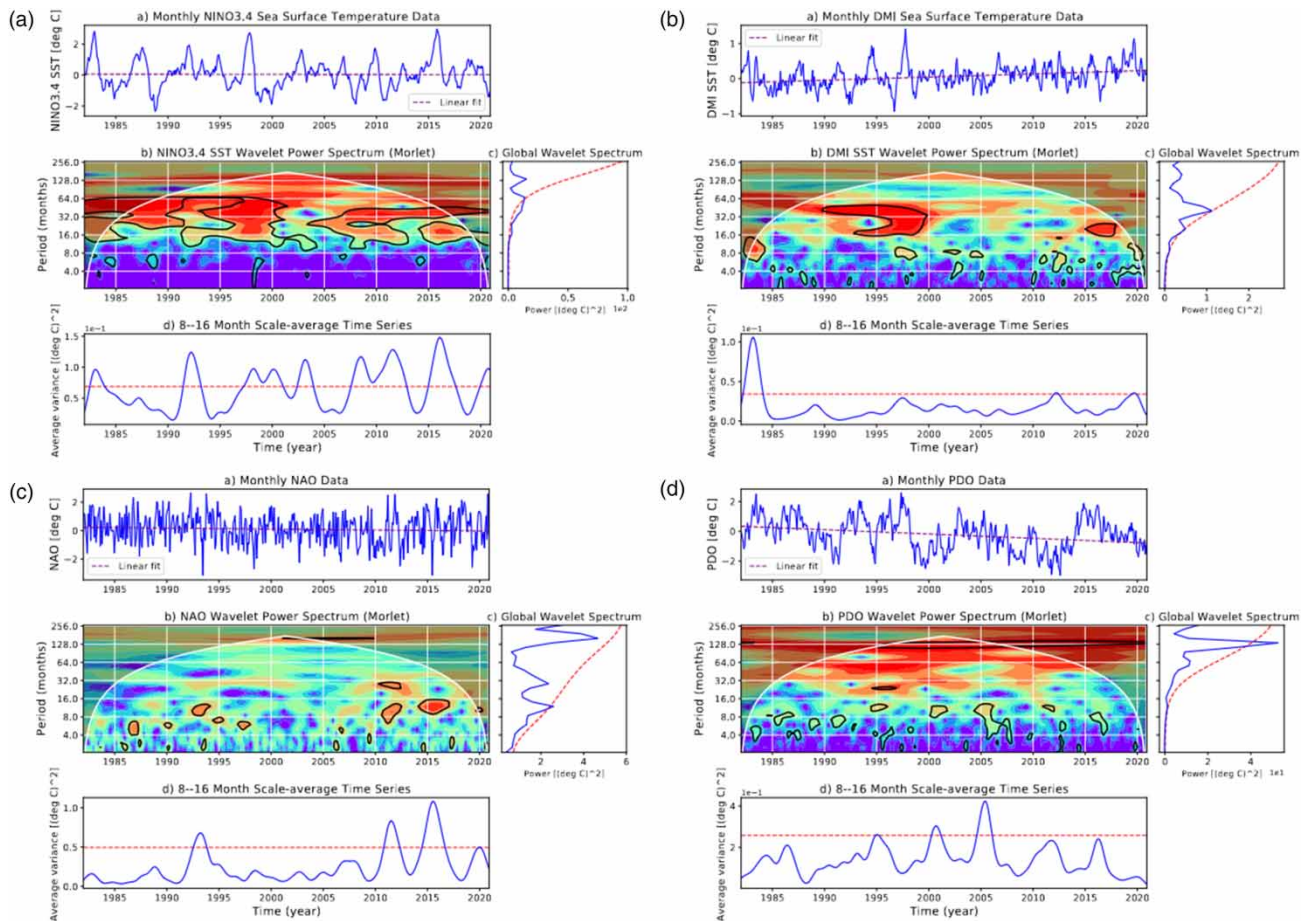
### 3.3. Periodic features of the monthly climate oscillations

[Figure 6](#) illustrates the dynamic fluctuations in climate oscillations across various temporal scales, employing an advanced wavelet transform methodology. The prominently outlined regions in bold black contours indicate substantial wavelet power exceeding the 95% significance threshold, suggesting potential influences from recurring patterns against white noise. Furthermore, these distinct black contours highlight noteworthy instances of significant wavelet power within the dataset, also at the 95% significance level, potentially attributed to the impact of a white noise process. Significantly, the visualization unveils identifiable recurring patterns characterized by periodicities spanning 1–5.3 years, evident within specific time intervals discerned within the ENSO time series.

Specifically, periodicities of 16–64 months are identified during the years 1982–1985, 24–64 months during 1985–1991, 12–64 months during 1995–2000, and 12–48 months during 2007–2013. For DMI, peaks of periodicities of 16–32 and 32–64 months are present, although they do not exhibit global significance at the 95% significance level. Furthermore, a periodicity around 1982–1983 is noted for the 8–16-month band, with breaks observed in other years.

Significant wavelet power contours are detected for NAO and PDO with periodicities of 4–8 months and 8–16 months, as well as a periodicity of 128 months (approximately 10 years) that exhibits peaks in the GWS. The study emphasizes the pre-eminence of ENSO and IOD as key contributors to inter-annual climate variability in East Africa, as also indicated by [Kebachio \(2022\)](#). Furthermore, it recognizes the impact of PDO and NAO on the inter-decadal scale. While acknowledging the study's data limitations, particularly regarding potential multidecadal variability in PDO, the research underscores its focus on inter-annual variability.

In [Figure 6](#), the wavelet spectra portrayed in the middle panels exhibit a notable alignment with the global power spectra featured in the right panels. These global power spectra represent the amalgamation of all local wavelet power spectra for



**Figure 6** | Wavelet analysis of large-scale circulation indices series, (a) ENSO, (b) DMI, (c) NAO, and (d) PDO, with the top panel: the indices series, middle panel: wavelet power spectrum, bottom panel: scaled-average wavelet power spectrum over the 8–16-months' band, right panel: global wavelet power spectrum.

each scale, offering insights into dominant scales free from temporal fluctuations. The GWS unveils significant oscillations, encompassing periodicities of 12–64 months for ENSO, 128 months for PDO, and notable oscillation periods of 8–16 and 128 months for NAO. Additionally, the GWS indicates trending significant oscillation periods of 16–32 and 32–64 months for DMI. This comprehensive analysis contributes to a nuanced understanding of climate variability at different scales, shedding light on the influential factors in the region.

### 3.4. Links between vegetation and its controlling factors

#### 3.4.1. Through APWC and PASC perspectives

Tables 2 and 3 provide an overview of the relationship between NDVI and individual or combined meteorological and climate oscillations within the four climatic zones. The analysis utilizes the metrics of APWC and PASC. The tables highlight the highest APWC values for both single and combined meteorological factors and climate oscillations, which are indicated by underlining. Conversely, the highest PASC values are represented by areas enclosed by thick contours and are denoted in bold for the respective climatic zones. It is noteworthy that the APWC and PASC values exhibit variations across the different climatic zones and individual cases, providing valuable insights into the diverse associations between NDVI and meteorological or climate factors within each zone.

Based on the APWC values, the analysis reveals that ENSO holds the greatest significance as a large-scale atmospheric circulation index in the arid zone, while DMI plays a key role in the semi-arid zone. In contrast, PDO emerges as the primary

**Table 2** | Quantification of the APWC and the PASC concerning the relationship between vegetation and specific large-scale circulation indices

| Large-scale circulation indices | Arid zone    |               | Semi-arid zone |               | Semi-humid zone |               | Humid zone   |               |
|---------------------------------|--------------|---------------|----------------|---------------|-----------------|---------------|--------------|---------------|
|                                 | APWC         | PASC (%)      | APWC           | PASC (%)      | APWC            | PASC (%)      | APWC         | PASC (%)      |
| One factor                      |              |               |                |               |                 |               |              |               |
| ENSO                            | <u>0.376</u> | <b>10.120</b> | 0.294          | 3.085         | 0.326           | 4.925         | 0.318        | 4.195         |
| IOD                             | 0.337        | 7.647         | <u>0.360</u>   | 5.455         | 0.357           | 6.035         | 0.354        | 4.270         |
| PDO                             | 0.366        | 4.401         | 0.357          | 2.780         | <u>0.375</u>    | 3.350         | <u>0.355</u> | 3.227         |
| NAO                             | 0.361        | 6.390         | 0.293          | <b>8.591</b>  | 0.300           | <b>8.349</b>  | 0.309        | <b>9.512</b>  |
| Two factors                     |              |               |                |               |                 |               |              |               |
| ENSO-IOD                        | 0.523        | 20.820        | 0.486          | 14.041        | 0.498           | 13.955        | 0.488        | 12.654        |
| ENSO-PDO                        | 0.529        | <b>21.800</b> | 0.475          | 11.122        | 0.489           | 15.082        | 0.463        | 11.541        |
| ENSO-NAO                        | <u>0.531</u> | 21.295        | 0.499          | <b>19.444</b> | 0.530           | <b>20.607</b> | 0.497        | 19.003        |
| IOD-PDO                         | 0.527        | 22.599        | 0.496          | 13.650        | 0.505           | 13.994        | 0.495        | 12.298        |
| IOD-NAO                         | 0.525        | 20.662        | <u>0.546</u>   | 18.989        | <u>0.536</u>    | 20.038        | <u>0.528</u> | <b>19.227</b> |
| PDO-NAO                         | 0.519        | 17.363        | 0.497          | 17.615        | 0.502           | 17.682        | 0.493        | 16.211        |
| Three factors                   |              |               |                |               |                 |               |              |               |
| ENSO-IOD-PDO                    | <u>0.685</u> | 38.772        | 0.625          | 33.028        | 0.625           | 31.676        | 0.622        | 29.220        |
| ENSO-IOD-NAO                    | 0.647        | 37.837        | 0.651          | <b>37.029</b> | <u>0.658</u>    | <b>40.889</b> | <u>0.632</u> | <b>36.260</b> |
| ENSO-PDO-NAO                    | 0.655        | 38.913        | <u>0.669</u>   | 36.322        | 0.656           | 39.504        | 0.619        | 33.369        |
| IOD-PDO-NAO                     | 0.658        | <b>42.893</b> | 0.653          | 36.555        | 0.634           | 35.103        | 0.624        | 32.514        |
| Four factors                    |              |               |                |               |                 |               |              |               |
| ENSO-IOD- PDO-NAO               | 0.749        | 58.769        | 0.858          | 59.462        | 0.758           | 56.671        | 0.739        | 54.72         |

driver of NDVI in the remaining climatic zones. On the other hand, the PASC analysis demonstrates that ENSO primarily influences NDVI in the arid zone, while NAO assumes a central role in the other climatic zones.

Examining the prevailing meteorological factors, the APWC values indicate that precipitation exhibits higher values in the semi-arid and humid zones, while temperature demonstrates significance in the arid and semi-humid zones. This highlights the variability of vegetation within the study area in relation to large-scale and meteorological variables. Furthermore, the PASC values presented in [Tables 2 and 3](#) illustrate that local meteorological parameters exert a stronger influence on vegetation fluctuations across all climatic zones compared to climate oscillations. Precipitation emerges as the meteorological factor with the highest PASC, with values of 25.89% in the semi-arid zone and 20.67% in the humid zone, thereby serving as an optimal individual factor for explaining variations in vegetation. Temperature follows suit, with the semi-humid zone displaying the highest PASC at 19.21%. NAO proves to be the most influential index driving vegetation dynamics in the semi-humid zone, while ENSO assumes this role in the arid zone. Conversely, PDO demonstrates a relatively weaker association with vegetation variations among the considered climate oscillations.

[Tables 2 and 3](#) further delve into potential combinations of climate oscillations and meteorological factors that provide enhanced explanations for variations in vegetation. Particularly noteworthy are the combined indices of ENSO-NAO, IOD-NAO, PDO-NAO, and PDO-NAO, which exhibit higher APWC values in the arid, semi-arid, semi-humid, and humid zones, respectively. When three factors are combined, IOD-PDO-NAO yields a higher APWC for the semi-humid and humid zones, IOD-PDO-NAO for the arid zone, and ENSO-PDO-NAO for the semi-arid zone. The combination of multiple factors amplifies the PASC, as demonstrated in [Table 2](#). Specifically, the combination of four factors results in the highest PASC (greater than 5%, considered significant), along with an elevated APWC. [Table 3](#) also presents combinations of two, three, and four meteorological factors. Similar to the climate oscillations, an increase in the number of combined factors corresponds to an increased APWC. Among the two-factor combinations, PR-T explains vegetation variability in all studied zones except the humid zone, where PR-VPD exhibits the highest APWC.

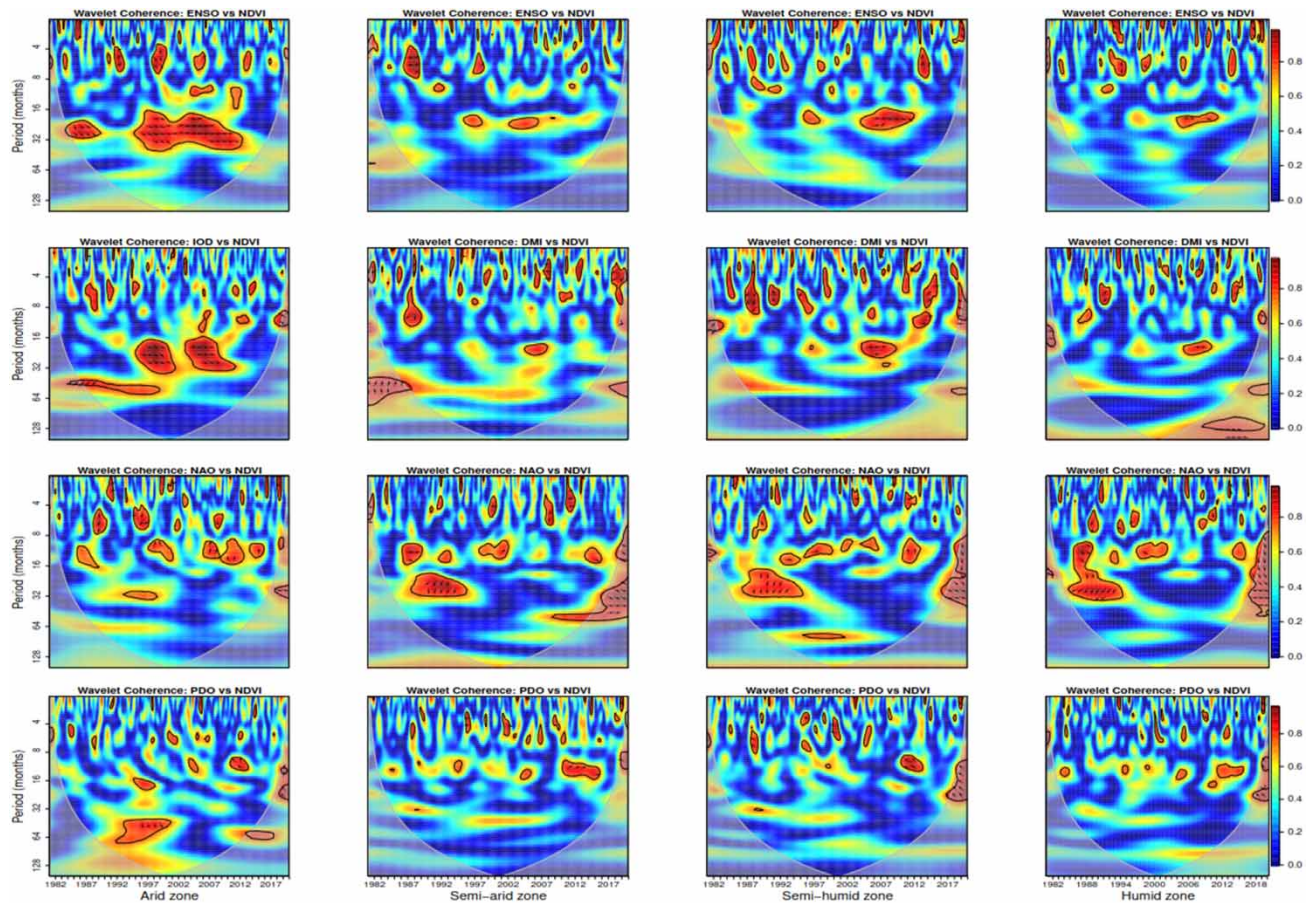
**Table 3** | Quantification of the APWC and the PASC concerning the relationship between vegetation and individual and combined meteorological factors

| Climate factor  | Arid zone    |              | Semi-arid zone |              | Semi-humid zone |              | Humid zone   |              |
|-----------------|--------------|--------------|----------------|--------------|-----------------|--------------|--------------|--------------|
|                 | APWC         | PASC (%)     | APWC           | PASC (%)     | APWC            | PASC (%)     | APWC         | PASC (%)     |
| One factor      |              |              |                |              |                 |              |              |              |
| PR              | 0.422        | 16.39        | <u>0.519</u>   | <b>25.89</b> | 0.446           | 18.02        | <u>0.472</u> | <b>20.67</b> |
| T               | <u>0.467</u> | <b>16.51</b> | 0.480          | 18.66        | <u>0.482</u>    | <b>19.21</b> | 0.441        | 19.11        |
| VPD             | 0.456        | 19.81        | 0.439          | 19.89        | 0.451           | 16.57        | 0.435        | 16.39        |
| Wdef            | 0.417        | 11.754       | 0.418          | 8.977        | 0.371           | 6.715        | 0.407        | 12.518       |
| RD              | 0.374        | 13.85        | 0.397          | 14.72        | 0.397           | 14.91        | 0.394        | 14.75        |
| Two factors     |              |              |                |              |                 |              |              |              |
| PR-T            | <u>0.605</u> | <b>30.18</b> | <u>0.657</u>   | <b>43.31</b> | <u>0.628</u>    | <b>36.64</b> | 0.608        | 32.07        |
| PR-RD           | 0.551        | 27.52        | 0.605          | 34.36        | 0.582           | 33.11        | 0.607        | <b>35.75</b> |
| PR-VPD          | 0.575        | 30.04        | 0.631          | 40.76        | 0.609           | 32.85        | <u>0.614</u> | 34.44        |
| T-VPD           | 0.596        | 29.70        | 0.620          | 34.27        | 0.606           | 31.61        | 0.550        | 28.06        |
| T-RD            | 0.586        | 28.05        | 0.590          | 30.50        | 0.610           | 34.96        | 0.575        | 27.91        |
| RD-VPD          | 0.572        | 28.05        | 0.556          | 30.50        | 0.584           | 34.96        | 0.559        | 27.91        |
| Three factors   |              |              |                |              |                 |              |              |              |
| PR-T-RD         | <u>0.720</u> | 44.13        | 0.745          | 58.83        | 0.710           | 45.45        | <u>0.736</u> | 54.40        |
| PR-T-VPD        | 0.701        | <b>46.45</b> | <u>0.757</u>   | <b>60.64</b> | 0.707           | 44.72        | 0.701        | 49.72        |
| PR-RD-VPD       | 0.659        | 39.97        | 0.725          | 51.80        | <u>0.716</u>    | <b>48.89</b> | 0.727        | <b>55.05</b> |
| T-RD-VPD        | 0.657        | 41.62        | 0.715          | 50.31        | 0.678           | 44.47        | 0.669        | 44.13        |
| All factors     |              |              |                |              |                 |              |              |              |
| PR-T-Rad-VPD-RD | 0.835        | 60.02        | 0.762          | 54.41        | 0.831           | 63.91        | 0.801        | 71.27        |

### 3.4.2. Time-frequency domain coherence

The wavelet coherence analysis establishes significant links between the evaluated hydro-climatic factors and climate indices and NDVI across different times and scales. In this section, we unveil the outcomes of the wavelet coherence analysis, shedding light on diverse hydro-climatic factors and large-scale climate oscillations, as depicted in [Figures 7 and 8](#). These visual representations showcase periodic attributes within a comprehensive study span of up to 128 months. The contours delineating red regions indicate heightened significance at a 95% confidence level. Crucially, the presence of the white line, emblematic of the cone of influence, serves to differentiate non-significant periodic features resulting from edge effects from those deemed significant within the cone of influence, as established by prior research ([Beyene et al. 2022](#)). It is noteworthy that discernible annual periodic characteristics permeate all study areas, manifesting as intermittent interruptions, sustained annual periodicity, or exhibiting intra-annual to decadal periodic patterns.

The results unveil that coherence between the climate indices and NDVI manifests for brief durations, showcasing an intermittent connection ([Figure 7](#)). Specifically, the wavelet coherence between ENSO and NDVI displays intermittent relationships at seasonal (4–8 months) and annual (12 and 18 months) scales. Notably, significant coherence between ENSO and NDVI is discerned during specific periods in diverse climatic zones, such as 1984–1987 and 1994–2010 in the arid zone, 2000–2010 in the semi-humid zone, and 2006–2013 in the humid zone, at inter-annual scales. Similar coherence is identified during other periods in various zones at seasonal scales. These findings align with prior research ([Camberlin et al. 2001](#); [Su et al. 2001](#); [Vashisht & Zaitchik 2018](#)), indicating that fluctuations in the central and eastern equatorial Pacific ocean temperature, coupled with atmospheric changes, have exerted influence on climate variability across East Africa. This impact is particularly pronounced during intense El Niño phases and moderate El Niño phases, leading to droughts in the tropics, including eastern tropical Africa, thereby affecting vegetation production ([Rojas et al. 2014](#); [Detsch et al. 2016](#)). Moreover, noteworthy associations are observed around 1998/1999, coinciding with an intense La Niña event, further affirming the established link between vegetation dynamics and ENSO events in the study region.

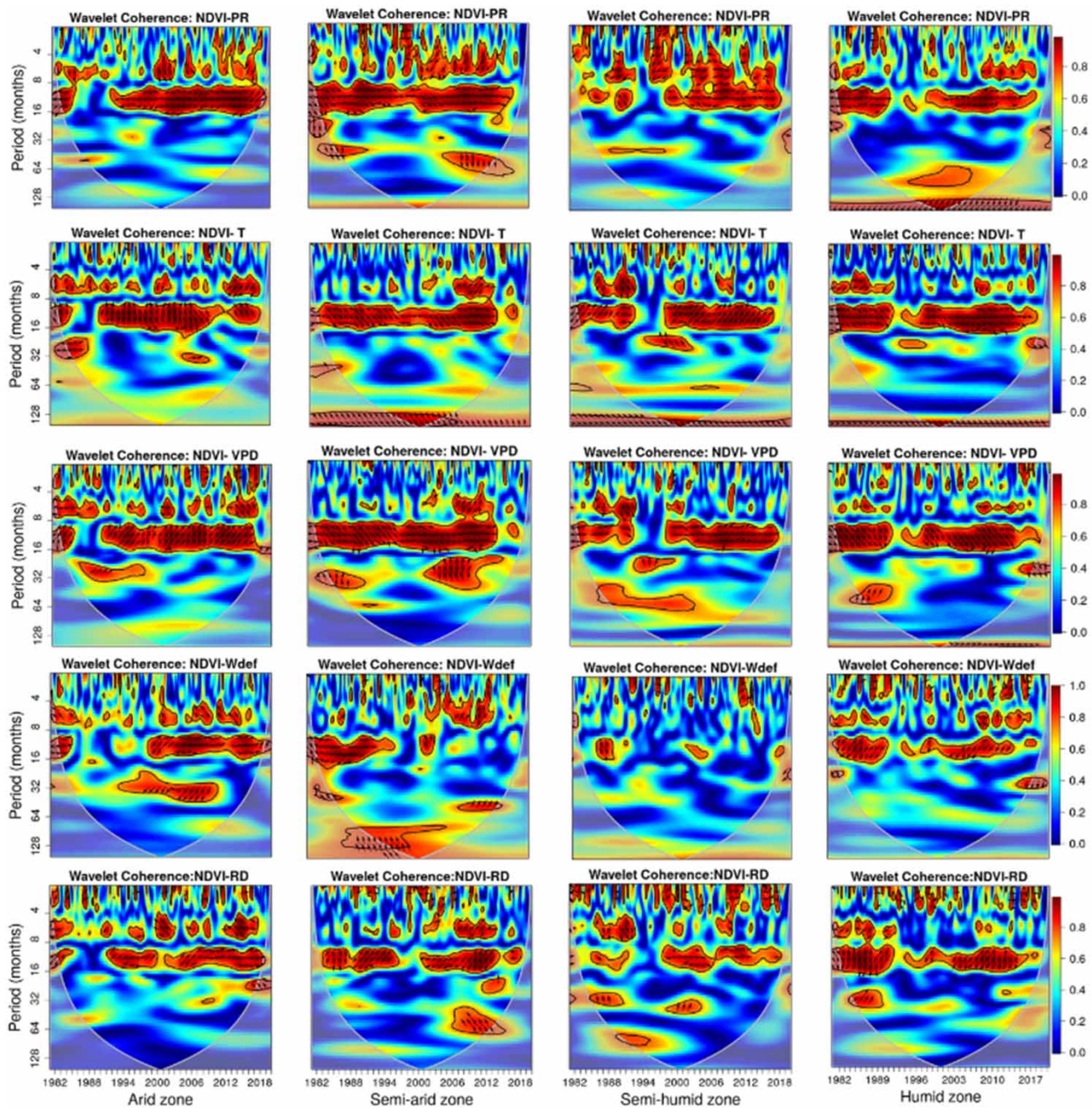


**Figure 7** | Wavelet coherence between monthly NDVI and ENSO, DMI, NAO, and PDO in four climatic zones. The significant level is presented as a thick contour.

In addition to ENSO, the IOD exacerbates drought conditions during El Niño events in Sub-Saharan Africa, with corresponding impacts from La Niña events. The wavelet coherence analysis reveals intermittent coherence between IOD and NDVI at inter-annual scales (16–32 months) from 1997 to 2010 in the arid zone, featuring sporadic occurrences at seasonal and annual scales in other climatic zones. A notable short-term correlation with a seasonal periodicity (less than 8 months) is observed, where IOD leads NDVI (Grinsted *et al.* 2004).

Moreover, the findings indicate significant coherence between NAO and NDVI at seasonal (4–8 months), annual (8–16 months), and bi-annual (16–32 months) scales. Strong coherence is evident from 1986 to 1996 in semi-arid and semi-humid zones, and from 1985 to 1990 and from 2017 to 2020 in the humid zone on a bi-annual scale. NAO emerges as a prominent influencer of terrestrial biosphere variability, particularly in the Northern Hemisphere (Dahlin & Ault 2018; Wu *et al.* 2021). Notably, the results suggest some coherence between PDO and NDVI for shorter durations at seasonal and annual scales.

The variability of hydro-climatic parameters also plays a role in influencing vegetation dynamics. Figure 8 depicts resonance periods between climatic parameters and NDVI, typically ranging from 4 to 16 months over an extended period. Water deficit sporadically associates with NDVI. The coherence analysis illustrates the influence of precipitation on monthly NDVI in all regions, particularly within the 8–16 month time scale. Additional coherence is observed at various scales in different years and zones. For instance, the semi-arid zone exhibits coherence on a time scale of 31–64 months, while the humid zone displays solid inter-annual to decadal coherence during 2000–2003 (64–128 months or 5.3–10.6 years). Intermittent intra-annual and inter-decadal variations across all zones are observed for other factors, including temperature, water deficit, vapor pressure deficit, and solar radiation. The semi-humid zone exhibits multi-scaled and varied coherence influenced by radiation. Notably, significant inter-annual scale coherence is observed in different climatic zones on time scales of 24–32 months, 16–34 months, 16–64 months, and 32–64 months for vapor pressure deficit, covering most of the time



**Figure 8** | Wavelet coherence between monthly NDVI and PR, T, VPD, Wdef, and RD in four climatic zones. The significant level is presented as a thick contour.

between 1982 and 2020. Additionally, a significant coherence is noted between water deficit and vegetation on the decadal scale (64–128 months) in the semi-arid zone from 1986 to 2005 ([Chen et al. 2020](#)).

These findings affirm the pivotal role of precipitation in vegetation production, underscoring the intricate interplay between spatial and temporal conditions, vegetation types, and precipitation anomalies within dynamic hydrological systems. Consistent with prior research emphasizing the profound impact of rainfall variability on vegetation production in East Africa ([Kalisa et al. 2019](#)), the wavelet coherence analysis establishes a robust coherence between monthly NDVI and temperature across all zones at an annual scale (8–16 months). Moreover, notable coherence is identified on time scales of 4–8 months, especially in the arid zone during various years, the semi-arid zone around 2005–2010, and the semi-humid zone from 1995 to 1990.

The comprehensive wavelet coherence analysis unveils significant associations among various hydro-climatic factors, large-scale climate indices, and NDVI. These insights shed light on the intricate relationships and influences among these variables, emphasizing the necessity of considering ENSO, IOD, NAO, PDO, precipitation, temperature, and other climatic parameters for a comprehensive understanding of vegetation dynamics and hydro-climatic interactions in East Africa.

#### 4. DISCUSSION

The response of vegetation to climate variability is a fundamental inquiry within ecological research (Anyamba & Tucker 2005; Batungwanayo *et al.* 2020). Numerous studies have investigated the teleconnections between vegetation dynamics and both local- and global-scale climatic variables, focusing on factors like rainfall, temperature, soil moisture, and global climatic oscillations (Anyamba *et al.* 2002; Anyamba & Tucker 2005; Kalisa *et al.* 2019). However, these studies often rely on simple correlation analyses and overlook the time–frequency perspective. Our study addresses this gap by examining the teleconnections between NDVI and hydro-meteorological factors along with large-scale atmospheric circulation indices across four agro-climatic zones in East Africa using wavelet coherence. Moreover, we have used two wavelet coherence measures of APWC and PNPS in order to quantitatively decipher the vegetation-climate relationships.

The obtained results provide significant insights into the degradation and management of agricultural lands in East Africa. The variability of vegetation, as indicated by NDVI, is closely linked to both meteorological factors and large-scale atmospheric circulation indices across different climatic zones. This information is crucial for understanding and mitigating land degradation in the region. In the arid zone, ENSO is identified as the most influential large-scale atmospheric circulation index. The APWC values highlight that ENSO significantly impacts NDVI, particularly during intense and moderate El Niño phases (1984–1987, 1994–2010), which are known to cause droughts and reduce vegetation productivity. These findings align with previous studies (Rojas *et al.* 2014; Detsch *et al.* 2016). Effective management strategies should focus on adaptive measures to mitigate ENSO-related droughts, such as introducing drought-resistant crops and improving irrigation practices.

The IOD is a significant driver of vegetation variability in the semi-arid zone. The APWC values indicate intermittent influence at inter-annual scales (1997–2010). The combined effects of ENSO and IOD amplify drought conditions, exacerbating land degradation. Integrated land management practices that consider the combined impact of these indices are essential. These might include soil conservation techniques, agroforestry, and the implementation of water-saving technologies. The semi-humid and humid zones exhibit a complex interplay of multiple climatic drivers, with the NAO and the PDO playing significant roles. The APWC and PNPS values demonstrate that NAO has a strong influence on vegetation dynamics at various scales, from seasonal to bi-annual. These findings suggest that large-scale climatic patterns originating from the Northern Hemisphere have far-reaching impacts on East African agriculture. Adaptive measures could include diversifying crop species and promoting sustainable agricultural practices that enhance soil health and productivity.

Precipitation emerges as the most critical local meteorological factor influencing vegetation across all zones, with the highest PNPS values in the semi-arid (25.89%) and humid (20.67%) zones. This underscores the importance of water availability in sustaining agricultural productivity. Management strategies should prioritize water conservation and efficient water use, such as rainwater harvesting, improved irrigation systems, and the restoration of degraded watersheds. Temperature also plays a significant role, particularly in the arid and semi-humid zones. High coherence between temperature and NDVI at annual scales indicates that rising temperatures, likely due to global climate change, could further exacerbate land degradation by increasing evapotranspiration rates and reducing soil moisture availability. To counteract these effects, land management practices should focus on enhancing soil organic matter through composting and cover cropping, which can improve soil moisture retention and reduce temperature stress on crops.

The study highlights the benefits of combining multiple climatic factors and meteorological parameters to better explain vegetation variability. Combinations of ENSO-NAO, IOD-NAO, and PDO-NAO, as well as combinations of precipitation and temperature, yield higher APWC values, indicating a more comprehensive understanding of the drivers of vegetation dynamics. This integrative approach should be mirrored in land management strategies, promoting practices that simultaneously address multiple climatic and environmental factors.

The results of this study provide a detailed understanding of the climatic drivers of vegetation variability in East Africa, which is essential for developing effective land management strategies. By considering both large-scale atmospheric circulation indices and local meteorological factors, adaptive measures can be tailored to the specific needs of each climatic zone. Such strategies will not only mitigate land degradation but also enhance the resilience and sustainability of agricultural lands

in East Africa. These findings highlight the critical need for integrated, multi-faceted approaches to land management that are informed by continuous monitoring and a deep understanding of climatic influences.

The MWC methodology, as used in this study, demonstrates its superiority in capturing multiscale connections and incorporating various explanatory factors, particularly for non-stationary data. Previous research has shown that large-scale climatic signals only occasionally provide the most accurate indicators of vegetation dynamics (Carilla *et al.* 2023; Jing *et al.* 2023). Instead, meteorological factors such as temperature and rainfall, either individually or in combination, prove to be more valuable due to their direct influence on vegetation dynamics (Kalisa *et al.* 2019). The influence of large-scale atmospheric circulation indices on hydrological and meteorological processes leads to alterations in vegetation cover and related processes within humid and dry tropical regions (Adepitan & Falayi 2019; Adepoju *et al.* 2019). The correlation between meteorological factors and large-scale circulation indices in East Africa has been established in numerous studies employing Pearson's or Spearman's correlation analysis, as well as wavelet analysis (Nicholson 2015; Fer *et al.* 2017; Kalisa *et al.* 2019). This relationship also impacts agricultural production.

Although extreme climatic indices are influenced by multiple factors simultaneously, research examining these connections has primarily focused on two variables. Furthermore, the MWC results demonstrate, as expected, that increasing the number of independent variables enhances the APWC and PNPS values across all climatic zones. For meteorological factors and large-scale circulation indices, high coherence is observed in the arid zone, followed by the semi-arid, semi-humid, and humid zones. This suggests that the addition of just one extra factor can significantly contribute to vegetation changes. A higher significance of APWC and PNPS indicates that a specific explanatory factor can effectively account for variations in vegetation. However, even when considering all combinations of large-scale circulation indices and meteorological factors to explain vegetation changes, the PNPS values may not reach their maximum potential. This indirectly suggests that changes in vegetation indices are exceedingly complex. Given that changes in meteorological factors are influenced by numerous factors, discerning the effects of localized anomalies in large-scale circulation indices from more general changes becomes challenging (Song *et al.* 2020). The analysis results also imply that vegetation dynamics and agricultural production are influenced by meteorological factors, anomalies in large-scale circulation indices, and other factors, such as the impact of human activity. Consequently, these limitations warrant further detailed investigation in future studies.

## 5. CONCLUSIONS

This study aimed to investigate the impact of meteorological factors and large-scale oscillation patterns on vegetation dynamics in four distinct climatic zones in East Africa, based on annual rainfall distribution. Wavelet analysis was employed to analyze vegetation variations, utilizing the CWT, and WTC approaches. The findings revealed significant variations in climatic characteristics across regions, influenced by teleconnections from different parts of the world. Individual meteorological factors or combinations thereof were found to be better predictors of vegetation changes compared to climate oscillations. The PASC demonstrated the strongest relationship with climatic elements and circulation indices in describing vegetation alterations. WTC analyses highlighted that meteorological factors outperformed climate oscillations in explaining vegetation changes in East Africa. However, considering other factors and developing regional agro-meteorological models that account for climate change impacts and hydrological processes are essential to comprehensively address agro-climatic constraints. Wavelet analysis has proven valuable in understanding vegetation dynamics in East Africa, particularly through the wavelet coherence technique, which elucidates the relationship between two time series and their frequency variations over time. The frequency-time domain analysis provided by wavelet analysis enables the exploration of time-varying frequency relationships in vegetation studies. The findings have potential implications for agricultural management and policy in the region.

A comprehensive comparison of the results from the WTC and MWC analyses revealed that vegetation dynamics in East Africa are most effectively explained by a combination of one to three hydro-climate factors or large-scale oscillation indices. Specifically, the combination of precipitation and temperature emerged as the best predictor of vegetation variation in the arid, semi-arid, and semi-humid zones. In contrast, for the humid zone, the combination of precipitation and relative humidity was identified as the most effective predictor.

Our analysis demonstrated the significant impact of adding an additional factor, as evidenced by an increase of at least 5% in the PASC across all regions and cases. This finding underscores the importance of considering multiple hydro-climate factors to accurately capture vegetation dynamics. Among the hydro-climate predictors, precipitation and temperature were

consistently found to be the most influential. Furthermore, the study highlighted the role of large-scale oscillations, with the ENSO and the IOD, in combination with the NAO, emerging as dominant predictors across all climatic zones. These large-scale oscillations play a crucial role in shaping the regional climate patterns, thereby influencing vegetation dynamics. The use of both WTC and MWC analyses provided a robust framework for understanding the complex interactions between vegetation and climatic variables. By identifying the most effective combinations of predictors, our study offers valuable insights for developing targeted strategies for managing agricultural lands in East Africa, considering the significant impact of both local hydro-climate factors and large-scale oscillations on vegetation.

Our findings offer valuable insights into the complex interactions between hydro-climatic variables and vegetation dynamics. These insights have practical implications for early warning systems and decision-making in managing climate-related risks and food security. While our methodology shows promise, further research is needed to refine its predictive capabilities and translate our results into actionable recommendations for stakeholders. By integrating our findings with broader ecological and socio-political frameworks, we can develop more robust strategies for sustainable land management in East Africa. In future research, wavelet analysis could be extended to address other critical water resource issues in the East Africa region, including the prediction of groundwater levels, streamflow variations, and drought forecasting.

## ACKNOWLEDGEMENTS

This research constitutes a component of the doctoral study undertaken by P. Batungwanayo at the Doctoral School of the University of Burundi. We express our sincere gratitude for the financial support provided by the Académie de recherche et d'enseignement supérieur (ARES). The authors extend their appreciation to the creators of various open-source datasets employed in this study. Additionally, we extend our thanks to all anonymous contributors whose insightful comments have significantly contributed to the enhancement of this paper.

## DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

## CONFLICT OF INTEREST

The authors declare there is no conflict.

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First received 19 March 2024; accepted in revised form 15 June 2024. Available online 1 July 2024