Journal of Geoscience and Earth Observation
http://dx.doi.org/10.62762/JGEO.2026.291236

RESEARCH ARTICLE

Climate-Driven Vegetation Dynamics and Future Projection over Ethiopia Using NDVI and Google Earth Engine

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Abstract

Climate change increasingly affects vegetation dynamics and ecosystem health worldwide. This study investigates historical and projected vegetation dynamics in Ethiopia using the Normalized Difference Vegetation Index (NDVI) to assess spatial and temporal patterns of vegetation change and their relationship with climate variability. Seasonal NDVI climatology, anomalies, trends, and future projections were analyzed using AVHRR and MODIS satellite datasets combined with CMIP6 climate projections. Google Earth Engine (GEE) JavaScript workflows were employed to examine vegetation dynamics during the October–January (ONDJ), February–May (FMAM), and June–September (JJAS) seasons from 1991 to 2024 and to project NDVI changes for 2015–2100 under SSP2-4.5 and SSP5-8.5 scenarios. Regression analysis evaluated climate–NDVI relationships, while the Mann–Kendall test and Sen's slope estimator determined the significance and magnitude of vegetation trends. Results reveal substantial spatial variability in vegetation dynamics. Significant NDVI increases occurred in many highland regions, whereas declines were observed in drought-prone areas, particularly in eastern Ethiopia and the Afar region. Decadal analyses (1991–2000, 2001–2010, 2011–2024) showed enhanced vegetation across northern, western, central, and southern Ethiopia, reflecting the combined influence of rainfall variability, climatic extremes, topography, and land cover. Future projections indicate moderate NDVI changes under SSP2-4.5 and greater spatial variability under SSP5-8.5, with potential greening in northern, western, central, and southwestern Ethiopia, and persistent vegetation stress in eastern and Afar areas. The study demonstrates the effectiveness of GEE for large-scale vegetation monitoring and provides valuable information for drought early-warning systems, climate-resilient agricultural planning, and ecosystem management in Ethiopia.

Keywords: NDVI, vegetation trend, climate change, Ethiopia, google earth engine.

Submitted: 24 May 2026
Revised: 24 June 2026
Accepted: 29 June 2026
Published: 19 August 2026

Vol. 1, **No.** 2, 2026.
10.62762/JGEO.2026.291236

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Citation
Tullu, G. M. (2026). Climate-Driven Vegetation Dynamics and Future Projection over Ethiopia Using NDVI and Google Earth Engine. *Journal of Geoscience and Earth Observation*, 1(2), 85–100.

1 Introduction

Climate change is a major global challenge that affects vegetation dynamics and ecosystem stability. Changes in temperature, rainfall patterns, and the frequency of extreme events have altered vegetation growth, distribution, and productivity across many regions [1]. In Ethiopia specifically, pronounced temporal and spatial variability in rainfall has been documented across different agro-ecological zones, with significant implications for vegetation cover and ecosystem health [2]. These changes demonstrate the high sensitivity of terrestrial ecosystems to climate variability and long-term environmental transformation. As climate variability intensifies, understanding vegetation responses has become essential for sustainable environmental management.

The seasonal and interannual variability of the Normalized Difference Vegetation Index (NDVI) across East Africa highlights the close relationship between vegetation and climate drivers [3]. NDVI is derived from satellite observations and is widely used to monitor live green vegetation. It provides a quantitative measure of vegetation health, greenness, and productivity [4]. Because of its sensitivity to climate variability, NDVI has become a key tool for assessing ecosystem responses to environmental change.

Temporal fluctuations in NDVI are strongly linked to rainfall and temperature variability [5, 6]. In many parts of East Africa, rainfall is the primary factor controlling vegetation productivity. Variations in rainfall magnitude and distribution regulate soil moisture availability and directly influence plant growth [7, 8]. Areas with adequate and consistent rainfall generally show higher NDVI values, while rainfall deficits are associated with reduced vegetation vigor.

Temperature also influences NDVI variability. In arid and semi-arid environments, high temperatures often have a negative relationship with vegetation growth. Increased heat enhances evapotranspiration and moisture stress, which limits plant development [1, 9]. Therefore, NDVI variability reflects the combined effects of rainfall and temperature. Understanding these interactions improves drought monitoring, climate-vegetation modeling, and ecosystem management under increasing climatic uncertainty.

Ethiopia is highly vulnerable to climate variability due to its diverse agro-ecological zones and heterogeneous vegetation types [10]. Variations in rainfall regimes, temperature patterns, and extreme events significantly affect ecosystem productivity and agricultural sustainability. Monitoring vegetation dynamics in Ethiopia is therefore essential. The NDVI, first introduced by Tucker [11], remains one of the most reliable indicators of vegetation condition. Derived from satellite imagery, NDVI provides consistent spatial and temporal assessments of vegetation productivity. Its capacity to detect seasonal and long-term changes makes it particularly suitable for climate-vegetation studies. Identifying spatial and temporal vegetation patterns supports informed decision-making in land use planning, drought preparedness, and climate adaptation [12]. Improved understanding of NDVI trends enhances environmental resilience and promotes sustainable resource management in Ethiopia.

Advances in geospatial technologies have improved large-scale environmental monitoring. Google Earth Engine is a cloud-based platform that enables planetary-scale geospatial analysis using Google's computational infrastructure [13–15]. It provides access to extensive satellite archives and allows efficient processing of large environmental datasets. This capability supports long-term vegetation monitoring and climate-ecosystem analysis without the need for local high-performance computing systems.

NDVI can be calculated using satellite sensors such as the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) within Google Earth Engine [16–18]. Previous studies in Ethiopia have demonstrated the effectiveness of such satellite-derived NDVI datasets for capturing spatiotemporal vegetation trends and their responses to climate variability [19, 20]. Integrating multi-sensor datasets enhances the continuity and reliability of long-term vegetation analysis. Cloud-based processing enables consistent NDVI computation across large spatial domains and extended time periods. This approach strengthens the application of remote sensing for seasonal monitoring and climate-ecosystem research.

This study investigates climate-driven vegetation dynamics in Ethiopia using NDVI and cloud-based geospatial analysis. Seasonal vegetation variability was examined for Bega (October–January), Belg (February–May), and Kiremt (June–September) during 1991–2024. In addition, future NDVI

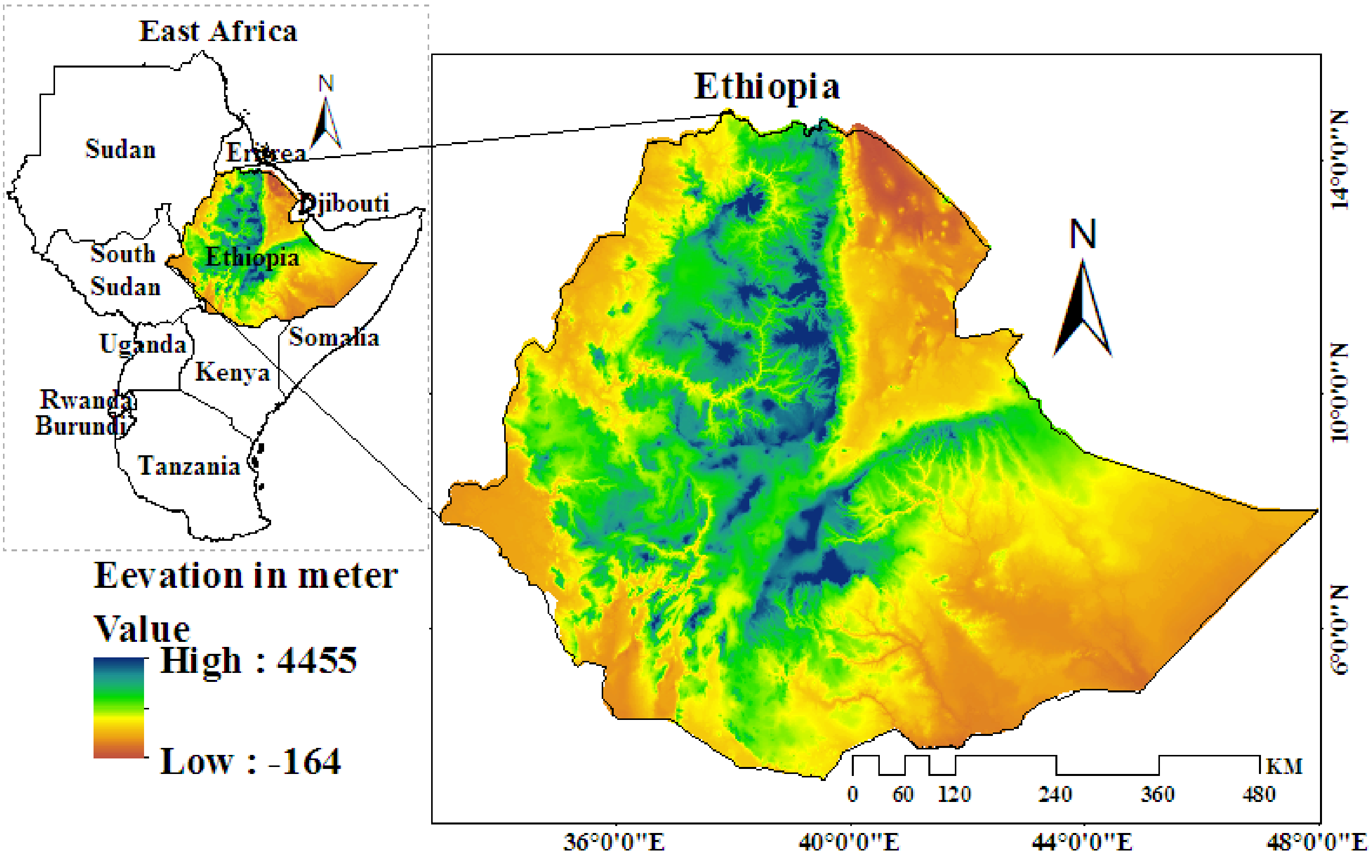

Figure 1. Study area and elevation in meter.

projections were analyzed for 2015–2100 to assess potential long-term ecosystem responses under changing climatic conditions. The findings contribute to a deeper understanding of vegetation-climate interactions in Ethiopia. Such knowledge is essential for strengthening ecosystem resilience, improving sustainable land management, and supporting climate adaptation and conservation strategies at national and regional levels.

2 Study Area

Ethiopia is located in East Africa between 3°N–15°N latitude and 33°E–48°E longitude, occupying a geographically and ecologically diverse region of the Horn of Africa. The country is bordered by Eritrea to the north, Sudan and South Sudan to the west, Kenya to the south, Somalia to the southeast, and Djibouti to the east. This strategic location contributes to the country's climatic complexity and environmental variability. Ethiopia exhibits remarkable topographic heterogeneity, with elevations ranging from lowland desert areas below sea level in the Afar Depression to high mountain peaks exceeding 4,400 meters above sea level in the Ethiopian Highlands (Figure 1).

3 Data and Methodology

3.1 Datasets

This study utilized satellite-derived Normalized Difference Vegetation Index (NDVI) data obtained from the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS), both of which provide long-term and consistent records of global vegetation conditions [21, 22]. These datasets are widely recognized for their reliability in monitoring vegetation health, productivity, and temporal dynamics across regional and global scales.

The NDVI dataset covered the period from 1991 to 2024 and was processed and analyzed using Google Earth Engine, a cloud-based geospatial analysis platform that enables efficient handling of large satellite datasets [14].

To ensure continuous temporal coverage, AVHRR NDVI data from the Global Inventory Modeling and Mapping Studies (GIMMS) were used for the early period (1991–2000) [17, 21], while MODIS NDVI data were used for the more recent period (2001–2024) [18]. These datasets were harmonized and merged within Google Earth Engine using

JavaScript-based processing workflows to produce a consistent long-term NDVI time series.

Specifically, the AVHRR NDVI data were accessed from the Image Collection ('NOAA/CDR/AVHRR/NDVI/V5'), while MODIS NDVI data were obtained from the Image Collection ('MODIS/061/MOD13Q1'). The two datasets were combined using a merging approach to maintain temporal continuity and improve the reliability of vegetation monitoring across the entire study period. Similarly, ERA5 monthly reanalysis climate data were accessed from (`ECMWF/ERA5/MONTHLY`), historical climate data were obtained from the TerraClimate dataset (`IDAHO_EPSCOR/TERRACLIMATE`), and future climate CMIP6 data were accessed from (`NASA/GDDP-CMIP6`) (MIROC6, MPI-ESM1-2-HR, MPI-ESM1-2-LR, MRI-ESM2-0, and NorESM2-MM used as multi-model ensemble (MME)), all available through the Google Earth Engine data catalog [14]. In addition, future NDVI projections for the period 2015–2100 were generated using Climate-NDVI regression models integrated with CMIP6 climate projections, enabling assessment of potential long-term vegetation responses under changing climate conditions.

Two Shared Socioeconomic Pathways (SSPs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) were used in this study: SSP2-4.5 and SSP5-8.5 [23]. SSP2-4.5, the "Middle-of-the-Road" scenario, assumes that societal and technological trends follow historical patterns, leading to intermediate greenhouse gas emissions and a radiative forcing of approximately 4.5 W m^{-2} by 2100. SSP5-8.5, the "High Emissions" or "Fossil-fueled Development" scenario, is characterized by rapid economic growth and continued high dependence on fossil fuels, resulting in high greenhouse gas emissions and a radiative forcing of 8.5 W m^{-2} by the end of the century. Under this high-emission pathway, greenhouse gas concentrations are projected to rise continuously, driving pronounced increases in global temperature, significant alterations in precipitation patterns, and a higher frequency of climate extremes.

To complement the vegetation analysis, rainfall data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) were incorporated to examine seasonal and annual rainfall climatology for the period 1991–2024 [24]. The analysis involved calculating mean NDVI values for the main seasonal periods: October–January (ONDJ), February–May (FMAM), and June–September (JJAS). Seasonal and long-term NDVI trends were evaluated to identify spatial and temporal vegetation patterns.

Furthermore, the study investigated the relationships between NDVI and key climatic variables, particularly precipitation and temperature, to better understand the influence of climate variability on vegetation dynamics. This integrated approach provides a comprehensive assessment of historical vegetation variability and future projections, supporting improved understanding of climate-vegetation interactions and sustainable environmental management in Ethiopia.

3.2 Data analysis Methods

3.2.1 NDVI Processing and Trend Analysis

The NDVI data were processed and analyzed using JavaScript-based workflows implemented within Google Earth Engine, enabling efficient large-scale geospatial computation and long-term vegetation monitoring. Seasonal NDVI climatology was calculated by averaging NDVI values for the three principal seasons: October–January (ONDJ), February–May (FMAM), and June–September (JJAS). These seasonal averages provided a baseline for evaluating vegetation dynamics and identifying spatial and temporal patterns across Ethiopia. Additional tools used GeoCLIM for rainfall climatology, ArcGIS for spatial analysis of NDVI climatology and NDVI anomaly, and Python for temporal analysis of NDVI-climatology, NDVI-historical and projection across SSP2-4.5 and SSP5-8.5 scenarios.

To assess deviations from normal vegetation conditions, NDVI anomalies were computed by subtracting the long-term seasonal mean NDVI from the corresponding seasonal NDVI values. This approach allowed for the identification of periods of above-normal (positive anomaly) and below-normal (negative anomaly) vegetation conditions, which are often associated with favorable or unfavorable climatic conditions, respectively.

Trend analysis was conducted using Sen's slope estimator and the Mann–Kendall statistical test. Sen's slope was applied to quantify the magnitude and direction of NDVI trends over time, while the Mann–Kendall test was used to evaluate the statistical significance of these trends. These non-parametric methods are widely used in environmental studies due to their robustness in detecting monotonic trends in long-term time series data. Statistical significance of

NDVI trends was evaluated at the 95% confidence level ($\alpha = 0.05$), and trends with $p < 0.05$ were classified as statistically significant.

Future NDVI projections were estimated using climate-driven regression models that incorporate climate variables derived from Global Climate Models (GCMs). Specifically, the projections were based on the ensemble mean NDVI derived from multiple GCM simulations, ensuring improved reliability and reduced uncertainty in predicting future vegetation responses under changing climatic conditions. The climate–NDVI regression models were constructed using ordinary least squares (OLS) multiple linear regression, with seasonal precipitation and mean temperature as independent variables and seasonal NDVI as the dependent variable. Model performance was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE), and only models with statistically significant predictors ($p < 0.05$) were retained for future NDVI projection.

3.2.2 *NDVI Calculation and Interpretation*

The Normalized Difference Vegetation Index (NDVI), originally developed by Tucker [11], is calculated based on the proportional difference between near-infrared (NIR) and red (R) reflectance values. The mathematical expression for NDVI is given as:

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \tag{1}$$

This index exploits the distinct spectral characteristics of vegetation, where healthy plants strongly reflect near-infrared radiation while absorbing red light for photosynthesis. For example, in MODIS imagery, the near-infrared reflectance is represented by Band 2 (841–876 nm), while the red reflectance is represented by Band 1 (620–670 nm). These spectral bands enable accurate quantification of vegetation health and density.

NDVI values range from -1 to $+1$, providing a continuous quantitative measure of vegetation condition. Values approaching $+1$ indicate dense, healthy, and actively growing vegetation, while values near zero typically represent bare soil or sparse vegetation. Negative values generally correspond to non-vegetated surfaces such as water bodies, clouds, or barren land. Lower positive values may indicate vegetation under environmental stress, particularly due to moisture deficits or elevated temperatures [20].

4 Results and Discussion

The results of the regression analysis reveal the strength and nature of the relationships between climate variables and vegetation dynamics across Ethiopia. The climate-NDVI regression models demonstrate that variations in precipitation and temperature significantly influence vegetation productivity, although the magnitude and direction of these relationships vary spatially. Areas characterized by strong rainfall dependence show positive correlations between NDVI and precipitation, whereas regions experiencing higher temperature stress often exhibit weaker or negative associations.

Trend detection analysis using the Mann-Kendall test confirms the statistical significance of observed NDVI trends over the study period. This non-parametric test identifies whether vegetation changes are systematic and persistent rather than random fluctuations. Complementarily, Sen's slope estimator quantifies the magnitude and direction of change, indicating whether vegetation greenness has increased or decreased and at what rate over time. Together, these methods provide a robust assessment of long-term vegetation dynamics.

Future NDVI projections based on climate-driven regression models and ensemble climate simulations indicate notable spatial variability in vegetation response under different climate scenarios. Some regions are projected to experience potential greening associated with favorable rainfall conditions, while others may face vegetation decline due to increased temperature stress and moisture deficits. These spatial differences underscore the heterogeneous nature of Ethiopia's ecosystems and their varied sensitivity to climate change.

4.1 Seasonal and Annual Rainfall Climatology

The Bega season (ONDJ), occurring from October to January, is predominantly dry across most regions, contributing less than 10% of annual rainfall [25]. Precipitation during Bega is highly unreliable and erratic, offering limited support to vegetation growth or agricultural activity. The short rains, locally referred to as the Belg (FMAM) season, occur from February to May and are characterized by considerable regional variability and erratic spatial distribution compared to the main Kiremt rains. Most regions of Ethiopia, with the exception of the southern and southeastern lowlands, experience the short rainy season locally known as Belg, which occurs from February to May (FMAM). During this period, rainfall is highly variable both spatially and temporally, reflecting significant regional differences in precipitation distribution. High maximum temperatures are also commonly observed throughout the season [26]. This erratic nature makes the Belg rains less predictable and more localized, contributing to complex patterns of soil moisture availability, vegetation growth, and agricultural productivity across the affected regions. Belg rainfall contributes only a modest portion of Ethiopia's annual precipitation, approximately 15% [26], and exhibits pronounced spatial heterogeneity. Moderate rainfall is typically observed over southwestern and central Ethiopia, whereas eastern regions often receive minimal precipitation during this season.

In contrast, the Kiremt season (JJAS) represents the primary rainy period, accounting for roughly 50–76% of the country's annual rainfall [25]. Kiremt rainfall is generally more spatially coherent, with the highest totals recorded over western and northwestern Ethiopia and the lowest in the eastern lowlands. This season dominates national precipitation patterns and plays a critical role in sustaining agricultural production and hydrological resources.

The spatial distribution of seasonal and annual rainfall across Ethiopia is presented in Figure 2. Annual rainfall climatology reflects the overarching dominance of Kiremt precipitation, with the highest annual totals concentrated in western Ethiopia and the lowest totals occurring in eastern and southeastern areas. These seasonal rainfall patterns underscore the strong spatial and temporal variability of precipitation in Ethiopia, which is largely shaped by topography, atmospheric circulation patterns, and regional climate systems.

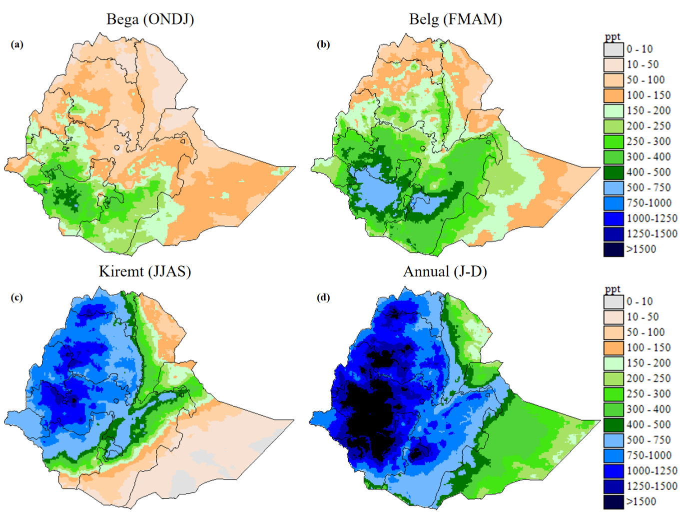

Figure 2. Seasonal (Bega, Belg, and Kiremt) and annual rainfall climatology over Ethiopia during 1991–2024.

4.2 Spatial Analysis of Seasonal NDVI Sen's Slope

The spatial analysis of seasonal NDVI using Sen's slope involves evaluating the magnitude and direction of trends in Normalized Difference Vegetation Index (NDVI) values over time across different locations in Ethiopia. This approach combines temporal trend analysis with spatial mapping to identify areas experiencing significant changes in vegetation health. By calculating NDVI for each season-Bega (ONDJ), Belg (FMAM), and Kiremt (JJAS)-and assessing its temporal trends, the analysis reveals both the intensity and spatial distribution of vegetation changes across the country.

NDVI serves as a quantitative indicator of vegetation condition and greenness, and examining its seasonal trends provides insights into environmental changes such as deforestation, land degradation, or climate-related impacts. The magnitude of seasonal NDVI trends, as indicated by Sen's slope, reflects areas with improved vegetation greenness (values ≥ 0.01), particularly in northern, western, central, and most southern regions of Ethiopia during Bega (western, south, southwestern and some parts of central, north and eastern), Belg (enhanced across western, south, southwestern, most parts of central, eastern, some parts of south eastern and northern of the regions), and Kiremt seasons (similarly improved vegetation greenness across northern, northwest, western, some parts of south, southwest, and central of Ethiopia), the rest of northeast, most parts of eastern and south eastern of Ethiopia indicated vegetation greenness decreased with Sen's slope magnitude less than or equal to -0.01 values (Figure 3).

Regression analyses further highlight the strength of climate-vegetation relationships, demonstrating how variations in precipitation and temperature influence vegetation dynamics. Mann-Kendall tests confirm the statistical significance of observed NDVI trends, while Sen's slope quantifies their magnitude, offering a clear measure of vegetation change over time.

Seasonal NDVI climatology was calculated for Ethiopia's three major rainfall seasons: Bega (ONDJ), Belg (FMAM), and Kiremt (JJAS). Decadal climatology was generated for 1991–2000, 2001–2010, and 2011–2024 and compared with the overall 1991–2024 climatology to assess long-term vegetation dynamics and responses to climatic variability.

Across all seasons, NDVI exhibited strong spatial variability, with consistently higher vegetation greenness in western, southwestern, central, and

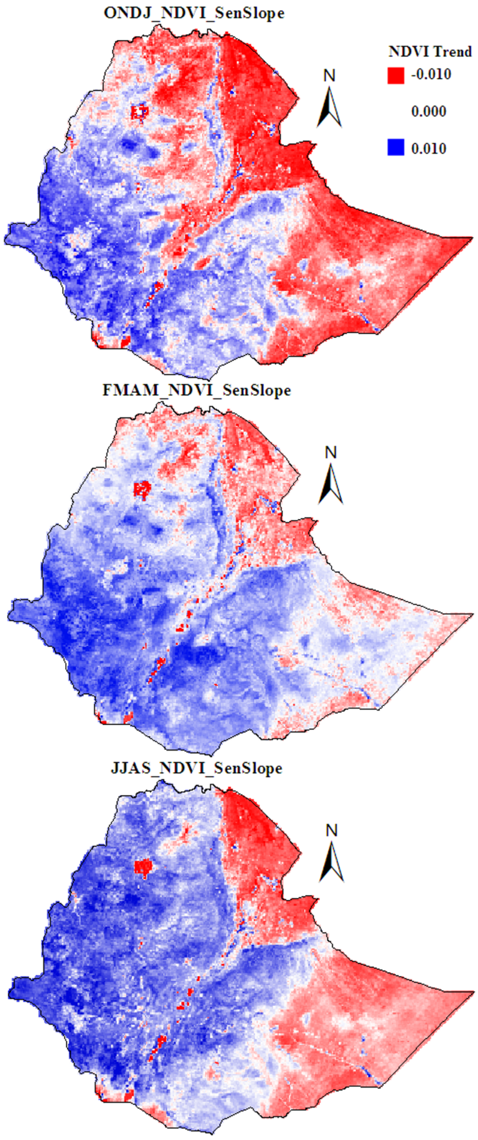

Figure 3. Seasonal (Bega, Belg, and Kiremt) Normalized Difference Vegetation Index (NDVI) Sen's slope trend magnitude during 1991–2024.

highland regions, and lower values in the eastern, southeastern, and northeastern lowlands. These patterns reflect the influence of rainfall distribution, topography, land cover, and moisture availability. Decadal comparisons indicate generally stable vegetation conditions with localized increases in greenness in western and central Ethiopia and persistent low vegetation cover in arid and semi-arid regions.

Seasonal NDVI anomalies were calculated relative to the long-term seasonal mean to assess vegetation responses to climatic variability across Ethiopia. Positive anomalies indicate above-average vegetation greenness associated with favorable moisture conditions, whereas negative anomalies represent vegetation stress and potential drought impacts. The anomaly analysis for the periods 1991–2000, 2001–2010, 2011–2024, and the overall 1991–2024 climatology reveals considerable spatial and temporal variability in vegetation dynamics across the country.

Seasonal NDVI anomalies for ONDJ, FMAM, and JJAS were computed relative to the 1991–2020 climatological baseline. Anomalies were calculated as the difference between seasonal NDVI and the long-term seasonal mean. Decadal anomaly maps were generated for 1991–2000, 2001–2010, and 2011–2024, consistent with the climatological periods used throughout this study. Spatial extent of positive and negative anomalies was quantified using pixel-area statistics and expressed both in square kilometers and percentage of the total study area.

Across all seasons, positive NDVI anomalies were generally concentrated in northern, western, central, southwestern, and southern Ethiopia, reflecting favorable rainfall conditions and enhanced vegetation productivity. In contrast, negative anomalies were more common in eastern, southeastern, and northeastern lowlands, where recurrent moisture deficits and rainfall variability limit vegetation growth. These patterns highlight the strong influence of climate variability on ecosystem productivity and vegetation health.

The Bega season climatology showed the lowest NDVI values due to dry-season conditions. Nevertheless, western, southwestern, and southern Ethiopia maintained relatively higher greenness because of forest cover and residual soil moisture. Decadal analyses reveal minor increases in vegetation greenness in central and western highlands, while eastern and northeastern lowlands consistently exhibited sparse vegetation throughout the study period (Figure 4(a–d)).

During the Bega season, positive anomalies were observed in parts of northern, northeastern, eastern, southeastern, western, and southern Ethiopia during different decades, indicating localized improvements in dry-season vegetation conditions associated with residual soil moisture and favorable rainfall. Areas of negative anomalies were primarily confined to arid and semi-arid lowlands, reflecting persistent vegetation stress during the dry season (Figure 5(m–p)).

The Belg season climatology exhibited moderate vegetation greenness and greater spatial variability, reflecting the irregular nature of short-season rainfall.

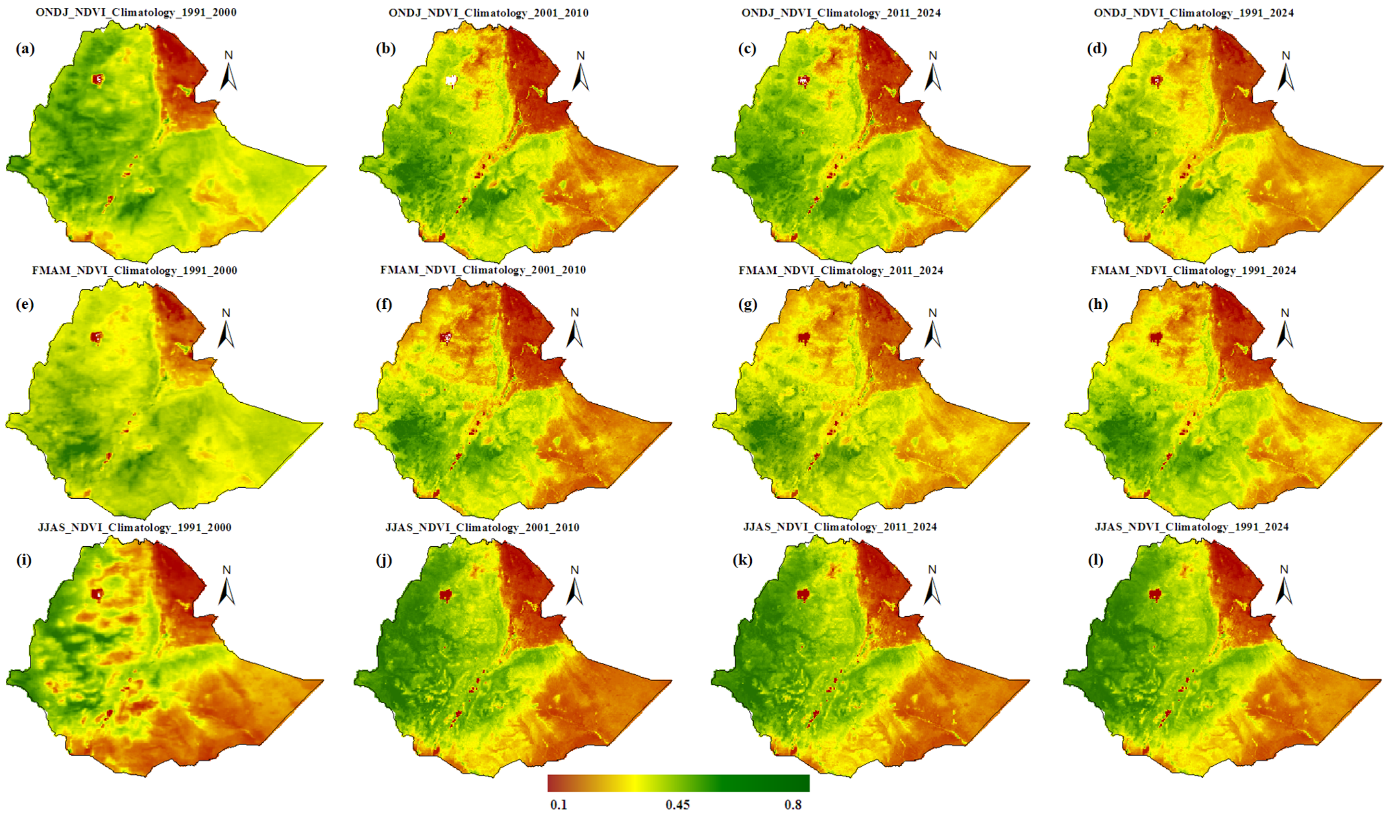

Figure 4. Decadal (ten years) analysis of Bega (a, b, c, and d), Belg (e, f, g, and h), and Kiremt (i, j, k, and l) seasons for Normalized Difference Vegetation Index (NDVI) Climatology.

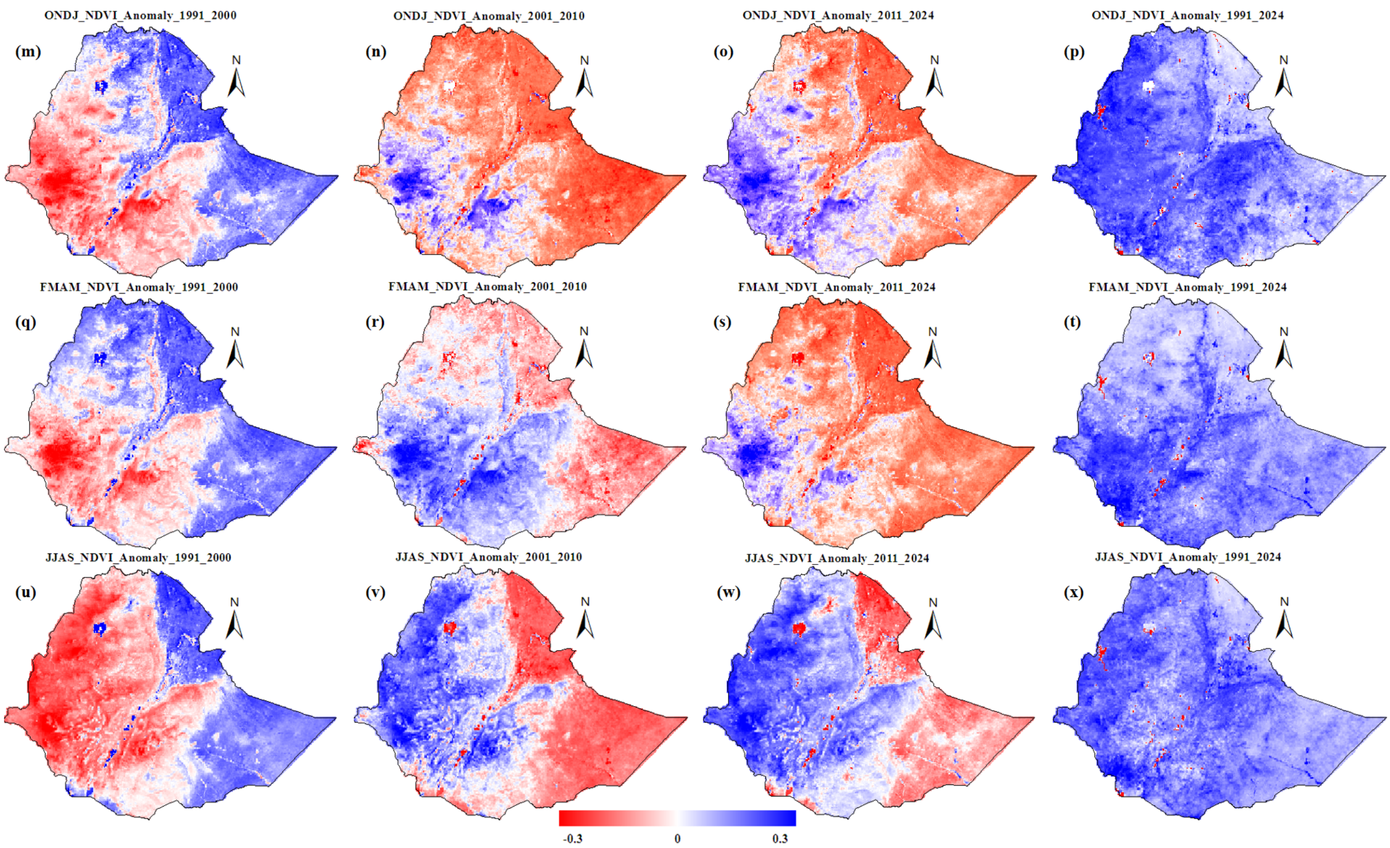

Figure 5. Decadal analysis of Bega (m, n, o, and p), Belg (q, r, s, and t), and Kiremt (u, v, w, and x) seasons for NDVI anomalies during 1991–2024. Anomalies represent deviations from the 1991–2020 climatological baseline for each grid cell, with positive values indicating above-average and negative values indicating below-average vegetation conditions.

Enhanced greenness was observed across northern, western, central, southwestern, and southern Ethiopia, particularly during 1991–2000 and 2001–2010. Although vegetation conditions remained generally stable during 2011–2024, localized variations were evident, especially in northern and northeastern regions, highlighting the sensitivity of Belg vegetation growth to rainfall fluctuations (Figure 4(e–h)).

Belg season anomalies exhibited the greatest spatial variability, reflecting the irregular nature of Ethiopia's short rains. Positive anomalies were observed across northern, western, central, southern, and southwestern highlands during different decades, while negative anomalies persisted in parts of the eastern and northeastern lowlands. The observed patterns demonstrate the strong sensitivity of vegetation growth to fluctuations in Belg rainfall (Figure 5(q–t)).

The Kiremt season climatology recorded the highest NDVI values and the most extensive vegetation cover, corresponding to Ethiopia's principal rainy season. Strong vegetation productivity was consistently observed across northern, western, central, and southwestern Ethiopia throughout all decades. While localized variability occurred in northeastern and southeastern regions, the long-term climatology confirms the dominant role of Kiremt rainfall in sustaining vegetation growth, ecosystem productivity, and agricultural activities across the country (Figure 4(i–l)).

Kiremt season anomalies generally showed widespread positive greenness across northern, western, central, and southwestern Ethiopia, reflecting the influence of the main rainy season on vegetation productivity. Although localized negative anomalies occurred in eastern and northeastern regions, the overall pattern indicates that Kiremt rainfall plays a dominant role in sustaining vegetation growth and ecosystem productivity throughout the country (Figure 5(u–x)).

Overall, the seasonal anomaly analysis demonstrates significant spatial heterogeneity in vegetation responses to climatic variability. The results provide valuable information for identifying drought-prone areas, evaluating ecosystem resilience, and supporting sustainable land management, agricultural planning, and climate adaptation strategies in Ethiopia.

4.3 Temporal Analysis of Seasonal Normalized Difference Vegetation Index

Seasonal Normalized Difference Vegetation Index (NDVI) time series demonstrated higher greenness (positive values) during 1991–2024. During the seasons, the NDVI time series increases gradually due to rainfall enhancement during the Bega and Kiremt seasons, and slightly decreases during the Belg season when comparing magnitudes across seasons. Trend analysis shows increased NDVI trends during 2001–2010 and 2011–2024, whereas a decreasing trend was observed during the first decade of 1991–2000 (Figure 6).

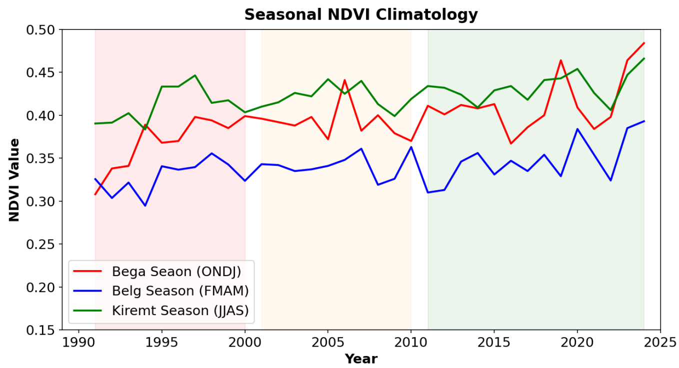

Figure 6. Seasonal Bega, Belg, and Kiremt Normalized Difference Vegetation Index (NDVI) time series climatology during 1991–2000, 2001–2010, and 2011–2024.

The analysis of seasonal Normalized Difference Vegetation Index (NDVI) time series for Ethiopia over the period 1991–2024 reveals overall positive vegetation responses, indicating periods of above-average greenness and favorable moisture conditions. Across the three major rainfall seasons-Bega (ONDJ), Belg (FMAM), and Kiremt (JJAS), the NDVI time series exhibits seasonal variation linked to rainfall patterns.

During the Bega and Kiremt seasons, NDVI values show a gradual increase, reflecting enhanced vegetation growth driven by sufficient rainfall and improved soil moisture. In contrast, the Belg season exhibits a slight decrease in NDVI, which corresponds to the short and highly variable nature of the Belg rains. Comparison of NDVI magnitude across the seasons indicates that Kiremt consistently supports the highest vegetation greenness, followed by Bega, while Belg maintains relatively lower values due to its erratic precipitation.

Overall, the seasonal NDVI time series and trend analysis provide valuable insights into temporal

Table 1. Region-wise NDVI trend statistics (Sen's slope and Mann-Kendall significance) for selected administrative regions of Ethiopia during 1991–2024.

Region	Sen's Slope	Kendall's τ	Trend	Significance
Oromia	0.0021	0.31	Increasing	Significant
Amhara	0.0012	0.15	Increasing	Not Significant
Afar	-0.0035	-0.42	Decreasing	Significant
Somali	-0.0028	-0.35	Decreasing	Significant
Gambela	0.0041	0.52	Increasing	Significant

Table 2. Summary of NDVI trend statistics by region for Ethiopia (1991–2024).

Region	NDVI Trend	Significance	Interpretation
Oromia	Increasing	Significant ($p < 0.05$)	Vegetation improving due to rainfall recovery and land management
Amhara	Slight Increase	Not significant	Stable vegetation with minor improvement
Tigray	Increasing	Significant ($p < 0.01$)	Strong greening trend, possible restoration programs
Somali	Decreasing	Significant ($p < 0.05$)	Vegetation decline linked to drought frequency
Afar	Decreasing	Significant ($p < 0.01$)	Severe drought and arid conditions impact vegetation
SNNPR	Increasing	Significant ($p < 0.05$)	Agricultural expansion and favorable rainfall
Benishangul-Gumuz	Strong Increase	Significant ($p < 0.01$)	Forest and vegetation expansion
Gambella	Strong Increase	Significant ($p < 0.01$)	Dense vegetation growth
Harari	Stable	Not significant	Minimal vegetation change
Addis Ababa	Decreasing	Significant ($p < 0.05$)	Urban expansion reduces vegetation
Dire Dawa	Decreasing	Significant ($p < 0.05$)	Urbanization and dry climate effects

vegetation dynamics, the influence of seasonal rainfall, and spatial variability in ecosystem productivity. These findings are critical for understanding regional vegetation responses to climate variability, identifying areas vulnerable to drought, and supporting sustainable land management and climate adaptation strategies.

A summary of regional NDVI trend statistics, including Sen's slope and Mann-Kendall significance, is presented for selected administrative regions of Ethiopia (Table 1). Regression results indicate the strength of climate-vegetation relationships. Mann-Kendall results show statistical significance of trends, while Sen's slope quantifies magnitude. Future projections indicate spatial variation in vegetation response under different climate scenarios.

At the catchment scale, climate variability has also been shown to exert significant control on NDVI dynamics in Ethiopian river basins, with rainfall anomalies explaining a substantial proportion of interannual vegetation variability [27]. Overall, NDVI trends across Ethiopia show significant spatial variability. Western and central regions, including Benishangul-Gumuz, Gambella, Oromia, and SNNPR, exhibit statistically significant increasing trends, indicating vegetation recovery and favorable climatic conditions. In contrast, eastern, northeastern and southeastern regions such as Afar and Somali show significant decreasing trends, reflecting persistent drought stress. Urban areas, including Addis Ababa and Dire Dawa, demonstrate declining NDVI trends associated with rapid urban expansion. These results confirm strong regional differences in vegetation response to climate variability and land use change (Table 2).

4.4 Historical and Future NDVI Projections and Vegetation Response under SSP2–4.5 and SSP5–8.5 scenarios over Ethiopia

The historical baseline (1991–2014) indicates moderate spatial variability in NDVI across the region. It should be noted that the near-term projection period (2015–2040) partially overlaps with the observational record (1991–2024); the period 2015–2024 was therefore used for model validation, while the full projection period extends from 2015 to 2100 following CMIP6 scenario conventions. Vegetation responses have remained relatively stable, with localized increases and decreases reflecting regional climate dynamics. The historical record shows minor NDVI fluctuations, primarily reflecting gradual climate adjustments rather than abrupt ecosystem shifts. The map reveals moderate greening in the highlands and western parts of Ethiopia, while eastern lowlands exhibit slight declines in vegetation vigor, providing a historical context for understanding annual NDVI changes (Figure 7(d)).

Historical and future projections of the Normalized Difference Vegetation Index (NDVI) were evaluated under two CMIP6 shared socioeconomic pathways: SSP2–4.5 (intermediate stabilization scenario) and SSP5–8.5 (high-emission scenario) for three future periods: near-term (2015–2040), mid-term (2041–2070), and end-term (2071–2100). The spatial patterns reveal contrasting magnitudes and variability of vegetation response across Ethiopia. Temporal projections of NDVI under SSP2-4.5 and SSP5-8.5 scenarios indicate an overall increase across near-term, mid-term, and end-term periods (Figure 7(e-j)).

Under SSP2–4.5, projected NDVI changes indicate generally moderate spatial variability across all time horizons. Vegetation responses remain relatively stable compared to the historical baseline, with localized increases and decreases depending on regional climate dynamics. The near-term projections suggest minor NDVI fluctuations, primarily reflecting gradual climate adjustments rather than abrupt ecosystem shifts. In the mid- and end-term periods, moderate greening is projected in the highlands and western parts of Ethiopia, while eastern lowlands exhibit slight declines in vegetation vigor (Figure 7(e-g)).

In contrast, SSP5–8.5 demonstrates substantially larger spatial variability and stronger vegetation responses. Under this high-emission pathway, NDVI projections indicate intensified drying signals

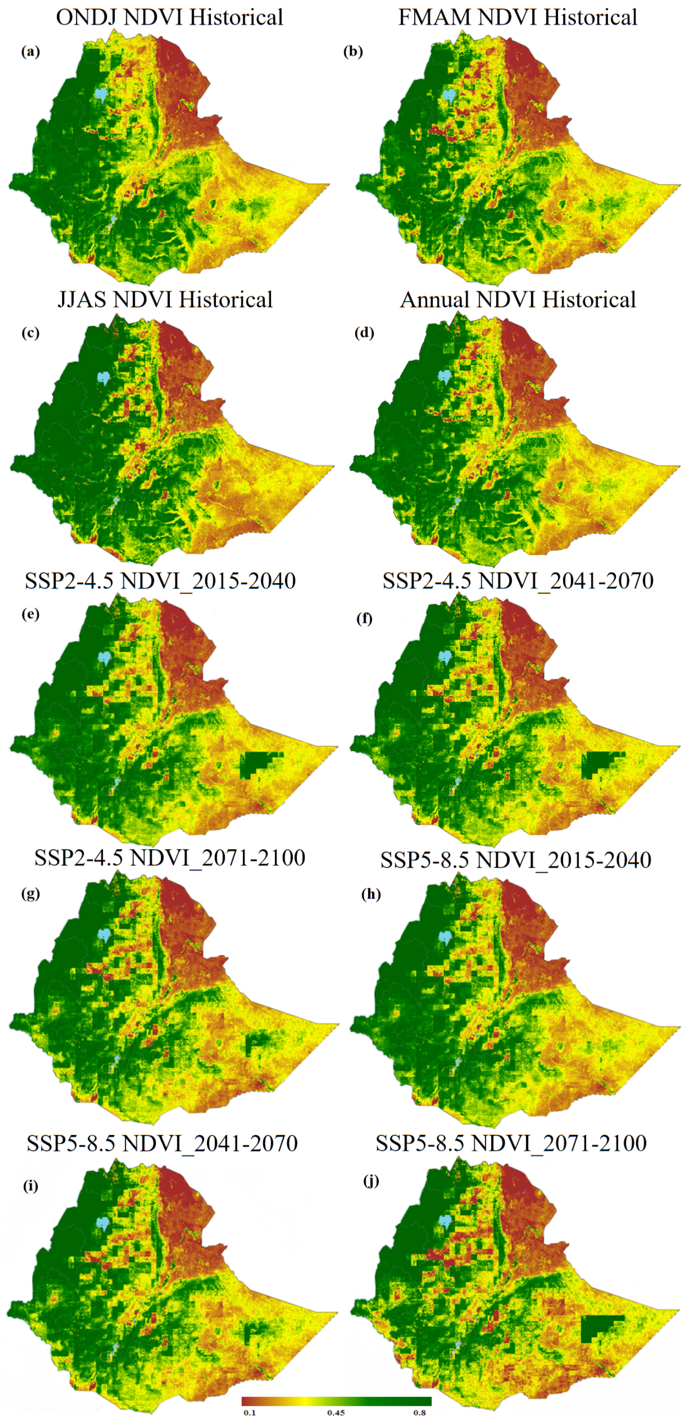

Figure 7. Spatial distribution of NDVI for the historical baseline (d) and projected changes under SSP2–4.5 (e, f, g) and SSP5–8.5 (h, i, j) scenarios across near-term (2015–2040), mid-term (2041–2070), and end-term (2071–2100) periods.

in arid and semi-arid zones, coupled with more pronounced greening in moisture-favored regions. The magnitude of change increases progressively from near-term to end-term periods, suggesting heightened ecosystem sensitivity to warming and precipitation shifts (Figure 7(h-j)).

The projections indicate strong drying signals across eastern Ethiopia, particularly in Afar and surrounding lowland regions. These areas show declining NDVI due to increased evapotranspiration and reduced moisture availability. In contrast, northern, western, central, and southwestern Ethiopia exhibit potential greening trends associated with projected rainfall increases and favorable moisture conditions. These trends are more consistent under SSP2–4.5 and more variable under SSP5–8.5.

In the near-term period (2015–2040), NDVI changes remain moderate across most regions. In the mid-term (2041–2070), spatial divergence increases, with greening in highland regions and drying in eastern Ethiopia. In the end-term period (2071–2100), SSP5–8.5 shows strong spatial heterogeneity, suggesting increasing ecosystem vulnerability and regional contrasts in vegetation productivity.

Seasonal NDVI change indicated normal to positive value across northwestern, some parts of northern, few parts of central, and some parts of southeastern; in other case, northeastern, eastern, few parts of southwestern, and southeastern Ethiopia obtained moderate NDVI change (near to zero). The remains of NDVI change across some parts of central, western, southern indicated below zero (negative value) (Figure 8).

Temporal projections of NDVI under SSP2-4.5 and SSP5-8.5 for the near-term, mid-term, and end-term periods showed an increasing trend over time across all seasons and on an annual basis (Figure 9). Near-term (2015–2040): NDVI changes are relatively moderate under SSP2–4.5 and slightly more variable under SSP5–8.5. Most regions show limited deviation from baseline conditions, though early signs of drying emerge in eastern Ethiopia. Mid-term (2041–2070): Spatial divergence becomes more pronounced. Greening intensifies in western and central highlands, while eastern and northeastern regions show stronger NDVI declines under SSP5–8.5. End-term (2071–2100): Under SSP2–4.5, vegetation changes remain moderate and spatially structured. Under SSP5–8.5, however, NDVI variability becomes substantial, with pronounced drying in arid regions and amplified greening in rainfall-favored zones. This suggests increasing spatial heterogeneity of ecosystem responses under high-emission futures.

The contrasting responses between SSP2–4.5 and SSP5–8.5 emphasize the sensitivity of Ethiopian ecosystems to greenhouse gas emission trajectories.

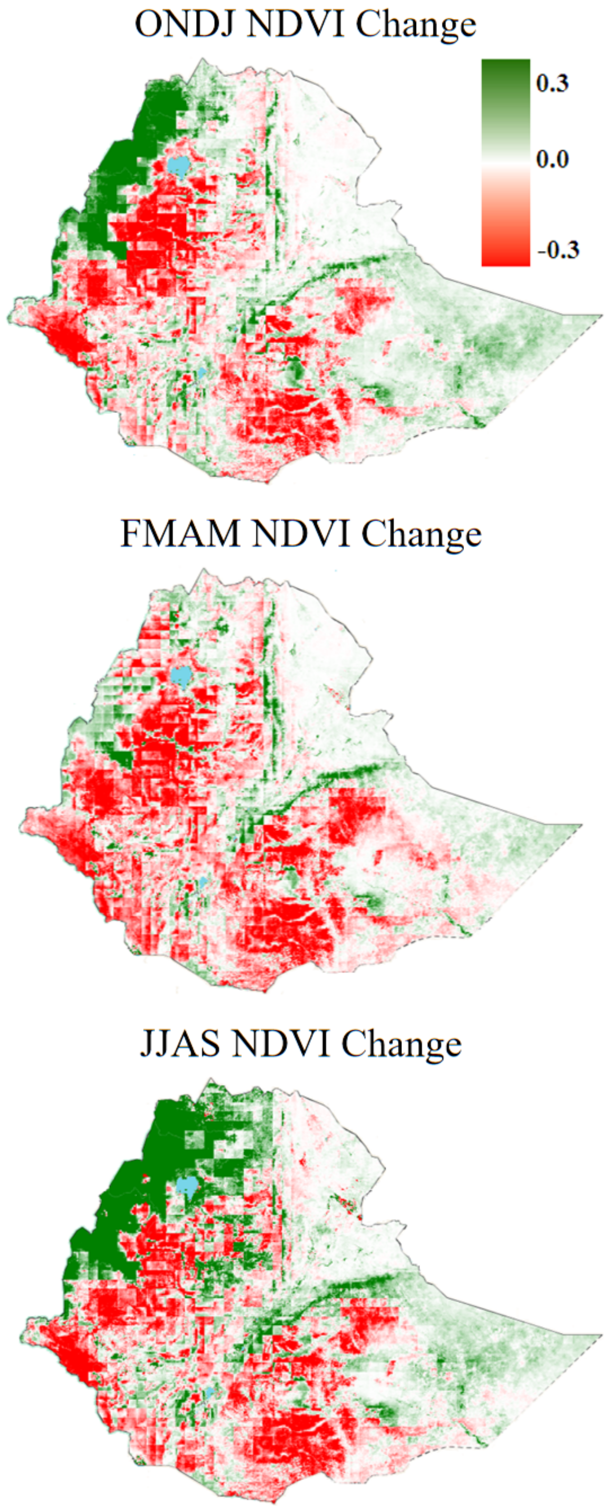

Figure 8. Spatial distribution of projected NDVI change across ONDJ, FMAM, and JJAS seasons during 2015–2100.

While intermediate stabilization leads to moderate vegetation shifts, high-emission conditions generate stronger spatial contrasts and potential ecosystem stress, particularly in already vulnerable eastern and northeastern regions.

Key implications include:

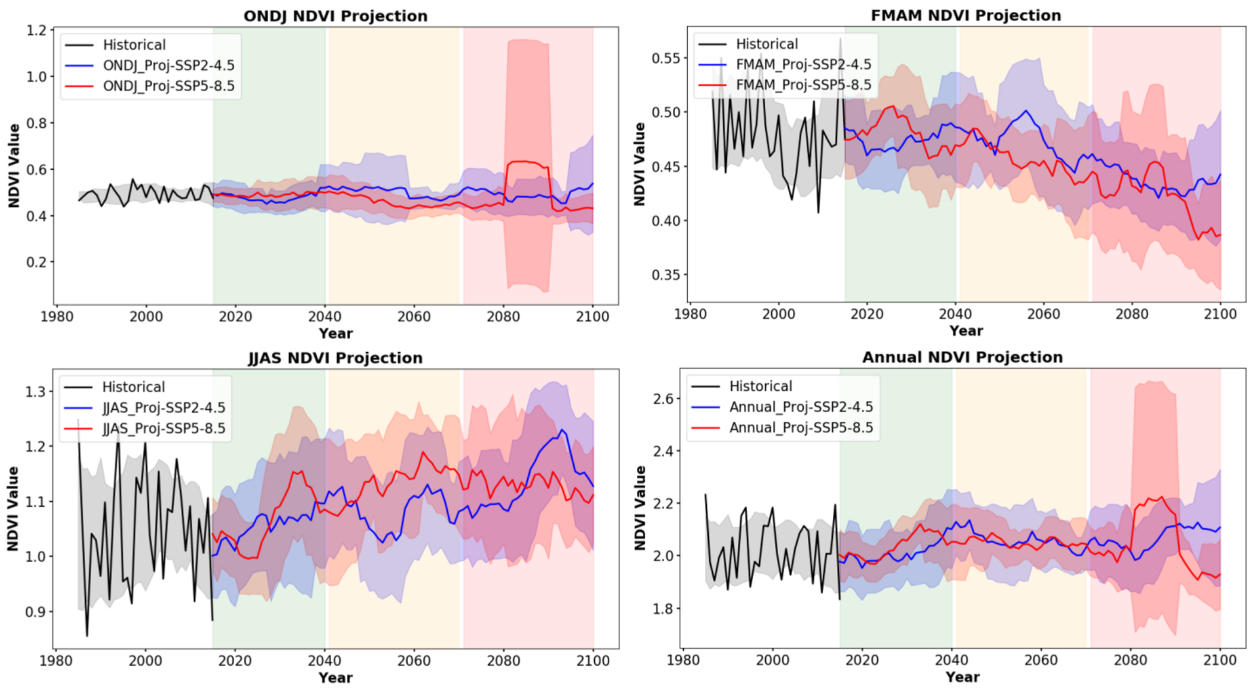

Figure 9. Temporal historical and projected NDVI for seasonal (a) Bega, (b) Belg, (c) Kiremt, and (d) Annual across SSP2–4.5 and SSP5–8.5 scenarios for near-term, mid-term, and end-term periods during 2015–2100.

- Increased soil moisture deficiency risk and vegetation degradation in eastern lowlands and Afar.
- Potential agricultural productivity gains in highland and western regions under moderate rainfall enhancement.
- Greater spatial heterogeneity of vegetation patterns under high-emission scenarios.
- Increased uncertainty and climate-driven ecological instability toward the end of the century.

Future NDVI projections indicate that vegetation dynamics across Ethiopia will likely become increasingly spatially differentiated. Under SSP2–4.5, NDVI changes remain moderate and regionally structured. Under SSP5–8.5, however, substantial variability emerges, characterized by intensified drying in eastern regions and potential greening in highland and western areas. These findings highlight the importance of emission mitigation strategies in moderating ecosystem impacts and underscore the role of regional climate variability in shaping future vegetation patterns across Ethiopia.

The observed NDVI trends across Ethiopia are closely aligned with patterns of rainfall variability and broader climate change impacts. Seasonal and decadal analyses demonstrate that vegetation greenness responds dynamically to fluctuations in precipitation, with increases in NDVI generally corresponding to periods of higher rainfall, while decreases align with dry spells or drought-prone conditions.

Future NDVI projections indicate potential shifts in vegetation distribution and productivity across Ethiopia, with important implications for agricultural systems, ecosystem stability, and natural resource management. Consistent with earlier studies, vegetation dynamics in the Horn of Africa are strongly modulated by rainfall variability, particularly the timing and intensity of seasonal precipitation (e.g., March–May "Belg" and June–September "Kiremt" seasons) [25]. Regions currently exhibiting strong greening trends may experience changes in vegetation vigor under future climate scenarios, while already climate-sensitive areas in eastern and northeastern Ethiopia are projected to face further declines in vegetation cover due to increased aridity and rainfall variability.

These findings are broadly consistent with satellite-based and modeling studies showing that NDVI in East Africa is highly sensitive to interannual rainfall fluctuations and drought frequency [16, 29]. Consistent with this, Liou and Mulualem [28] document strong spatiotemporal associations between drought episodes and vegetation greenness decline over Ethiopia, reinforcing the dominant role of hydroclimatic variability in regulating ecosystem productivity. However, unlike some global-scale studies that emphasize CO_2 fertilization effects in semi-arid regions, the present results suggest that moisture limitation remains the primary control on vegetation response in much of Ethiopia, particularly outside irrigated or high-altitude zones.

Overall, the results demonstrate that vegetation changes across Ethiopia are jointly controlled by seasonal rainfall variability and longer-term climatic trends. The dominant influence of precipitation is consistent with prior regional studies emphasizing rainfall as the primary limiting factor for ecosystem productivity in semi-arid Africa [30, 31]. However, the strength of NDVI–rainfall coupling may vary spatially due to land degradation, irrigation expansion, and anthropogenic land-use change, which can either amplify or weaken climate-driven vegetation responses.

It is important to acknowledge several sources of uncertainty in these projections. First, NDVI-based analyses are subject to sensor-related uncertainties, atmospheric effects, and saturation in densely vegetated areas, which may limit sensitivity in high biomass regions. Second, CMIP6-based climate inputs carry structural uncertainty related to differences in model physics, parameterizations, and emission scenarios. Third, internal climate variability introduces additional uncertainty at interannual and decadal scales, particularly for rainfall-dependent vegetation dynamics in East Africa. Finally, the absence of explicit representation of land-use change, irrigation expansion, and CO_2 fertilization feedbacks in simplified NDVI–climate relationships may lead to biases in long-term vegetation projections.

Despite these limitations, the consistency of NDVI–precipitation relationships across multiple studies increases confidence in the robustness of the observed patterns. Future work should incorporate multi-model ensembles, improved land-surface parameterizations, and socio-economic scenarios to better constrain uncertainty and enhance the reliability of vegetation projections.

These findings are consistent with the drought impact assessments reported by Liou and Mulualem [28], who demonstrate that vegetation cover responses in Ethiopia are closely coupled with the occurrence and intensity of rainfall deficits. The results highlight the sensitivity of Ethiopia's ecosystems to climate variability and reinforce the critical role of precipitation in driving vegetation dynamics.

Overall, the study demonstrates significant vegetation changes across the country, which are largely influenced by both seasonal and interannual rainfall variability and longer-term climate trends. Understanding these dynamics is essential for informing sustainable land management, agricultural planning, and ecosystem conservation under current and future climate conditions.

5 Conclusion

This study provides important insights into climate-driven vegetation dynamics in Ethiopia and offers valuable guidance for land managers, policy makers, and other stakeholders. By analyzing seasonal trends and patterns in NDVI over multiple decades, the research enhances our understanding of how climate variability and change impact vegetation health, ecosystem productivity, and spatial distribution across different ecological zones.

The findings have broad relevance across fields such as ecology, conservation biology, environmental science, and natural resource management. By identifying areas of increasing or declining vegetation greenness, the study supports evidence-based decision-making for sustainable land use, ecosystem conservation, and climate adaptation strategies.

The research also highlights the effectiveness of Google Earth Engine as a tool for large-scale vegetation monitoring and climate impact assessment. NDVI analysis using this cloud-based platform enables the processing of vast satellite datasets, calculation of vegetation indices, and generation of ready-to-analyze outputs with minimal computational overhead.

Overall, this study demonstrates the power of cloud-based Earth observation workflows, showing that even complex analyses of terabytes of satellite imagery can be executed efficiently through streamlined cloud-based scripting workflows. Such approaches provide a scalable and practical framework for monitoring vegetation dynamics, projecting future ecosystem changes, and supporting sustainable environmental management across Ethiopia and similar regions.

While this study provides valuable insights into the seasonal and annual responses of NDVI to climatic factors, several limitations are acknowledged. Notably, the exclusive focus on seasonal and annual responses overlooks the potential importance of monthly variations, as well as the role of soil moisture and composite analysis of oceanic drivers. To provide a more comprehensive understanding of NDVI variations in the region, future research should prioritize the incorporation of these dimensions.

In light of the challenges posed by vegetation changes, this study underscores the need for continuous monitoring programmes and the development of predictive models for NDVI and associated climatic factors. The implementation of such initiatives would significantly enhance our capability to anticipate vegetation shifts and inform the development of adaptive strategies to mitigate the negative impacts of climate change. By adopting a proactive and predictive approach, policymakers and stakeholders can better prepare for the potential consequences of vegetation changes, ultimately minimizing the risks associated with climate-related disturbances. Individuals and stakeholders should consider the findings of this study as a reference when making decisions about land use management, conservation, and climate change mitigation in Ethiopia. Further research should be conducted to explore the relationships between seasonal and annual NDVI and climate variables, and to examine the potential impacts of climate change on vegetation health and dynamics in Ethiopia.

The study's findings should be used to inform the development of early warning systems for drought and other climate-related hazards, and to support the implementation of climate-resilient agriculture, ecosystem response and conservation practices in Ethiopia.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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