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Satellite-based spatiotemporal analysis of vegetation and climate controls on wildebeest migration in the Serengeti ecosystem

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Abstract

The Serengeti ecosystem supports one of the world's most iconic large-mammal migrations, yet the relative influence of climate and vegetation dynamics on wildebeest movement remains incompletely quantified. This study used open-source satellite and climate datasets in Google Earth Engine, combined with GIS-based spatial analysis, to examine seasonal relationships among vegetation greenness, precipitation, and temperature across the Serengeti ecosystem and selected migratory zones. Vegetation condition was represented by the Normalized Difference Vegetation Index (NDVI) derived from Sentinel-2 imagery, while temperature and precipitation were obtained from the ERA5-Land monthly dataset. Monthly zonal statistics were computed for the ecosystem and key migration zones corresponding to March, June, and October. Correlation and multiple regression analyses were then applied to assess the combined influence of climate variables on vegetation dynamics. Results showed a clear seasonal pattern in which NDVI closely tracked rainfall variability, with high vegetation greenness during wet months, a marked decline during the dry season, and recovery after the onset of the short rains. Regression analysis indicated that one-month lagged precipitation, and temperature together explained a substantial proportion of NDVI variation ($R^2=0.70$), confirming that vegetation response to rainfall is delayed rather than immediate. The findings reinforce the view that wildebeest migration is shaped primarily by rainfall-driven vegetation dynamics, while temperature acts indirectly through its influence on moisture balance and forage persistence. This study demonstrates the value of integrating remote sensing, GIS, and statistical analysis to understand the environmental drivers of wildebeest movement, while offering broader insight into migration ecology and conservation monitoring.

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INTRODUCTION

The Serengeti ecosystem, spanning northern Tanzania and southwestern Kenya, is internationally renowned for its spectacular annual wildebeest migration. This phenomenon is recognized as one of the seven natural wonders of Africa and as a natural wonder of the world. Covering approximately 30,000 km², the ecosystem includes Serengeti National Park, the Ngorongoro Conservation Area, several adjoining game reserves (Maswa, Ikorongo, Grumeti, and Kijereshi), the Ikona Wildlife Management Area, the Loliondo Game Controlled Area, and Kenya's Maasai Mara National Reserve (Figure 1). Together, these protected areas support one of the largest remaining migratory systems on Earth, sustaining extensive herbivore populations and complex predator–prey dynamics.

The Serengeti's migratory cycle is closely linked to seasonal patterns of rainfall, vegetation productivity, and water availability. From January to March, wildebeest herds concentrate on the short grass plains of the southern Serengeti and the Ngorongoro Conservation Area, where nutrient rich grasses provide optimal forage and calving conditions. As the long rain diminishes and pastures begin to dry, the herds move northwest between April and June toward the central Serengeti and the Grumeti River, typically reaching the western corridor by June. Between July and September, they continue northward into the Maasai Mara, undertaking perilous crossings of the Mara River. From October onward, with the onset of the short rains, the herds gradually return southward through the eastern Serengeti and Ngorongoro, completing the annual migratory loop by December (Figure 2).

Understanding how environmental variability shapes this migration is critical for both ecological insight and conservation planning. While food availability and surface water are widely recognized as key drivers of wildebeest movement, other climatic factors, particularly precipitation and temperature, interact with vegetation dynamics in ways that are not yet fully quantified. This study uses open-source satellite data and a geospatial approach to analyze how vegetation health (NDVI), precipitation, and temperature vary across key migratory zones and seasons, and how these patterns align with the known timing and routes of wildebeest movements.

The remainder of this paper is structured as follows. Section 2 presents the literature review, focusing on animal migration, the environmental drivers of wildebeest movement, and the role of remote sensing and GIS in migration studies. Section 3 describes the data and methods employed, including the derivation of NDVI, temperature, and precipitation variables, as well as the zonal and statistical analyses used in the study. Section 4 presents the results and discussion of the temporal, spatial, and statistical findings. The final section concludes the paper by summarizing the key findings and outlining their implications, limitations, and recommendations for future work.

LITERATURE REVIEW

Animal migration is a complex ecological process occurring across diverse species and spatial scales, from small insects to large mammals such as blue whales (Tucker et al., 2018). Movements range from regular seasonal migration, like the Serengeti wildebeest migration, to single-lifetime events observed in species such as the painted lady butterfly (Vanessa cardui) (Stefanescu et al., 2013; Aikens et al., 2020). Migration is primarily driven by ecological and environmental factors including breeding, food and water availability, predator avoidance, and responses to climatic variability (Abrahms et al., 2021) and thus represents an adaptive strategy that enables species to exploit favorable conditions and sustain population survival.

Within the Serengeti ecosystem, migration is a defining ecological feature involving approximately 1.4 million wildebeests, 200,000 zebras, and 700,000 Thomson's gazelles (Kideghesho, 2006; Kauffman et al., 2021). These herbivore movements are closely linked to seasonal rainfall and vegetation productivity, which jointly determine forage and water availability. During the wet season, wildebeest move northward in search of newly sprouted

pastures and surface water, whereas the southward return migration coincides with the regeneration of nutrient-rich short-grass plains, particularly important for lactating females (Msoffe et al., 2019; Kauffman et al., 2021). Previous studies emphasize that rainfall and green biomass are the primary drivers of these movements (Holdo et al., 2009; Boone et al., 2006; Merkle et al., 2019; Aikens et al., 2020), while temperature exerts a more indirect influence by shaping evapotranspiration rates and vegetation growth. Migration therefore not only secures access to breeding grounds and food resources but also enhances genetic exchange and stabilizes herbivore populations across the ecosystem (Tucker et al., 2018).

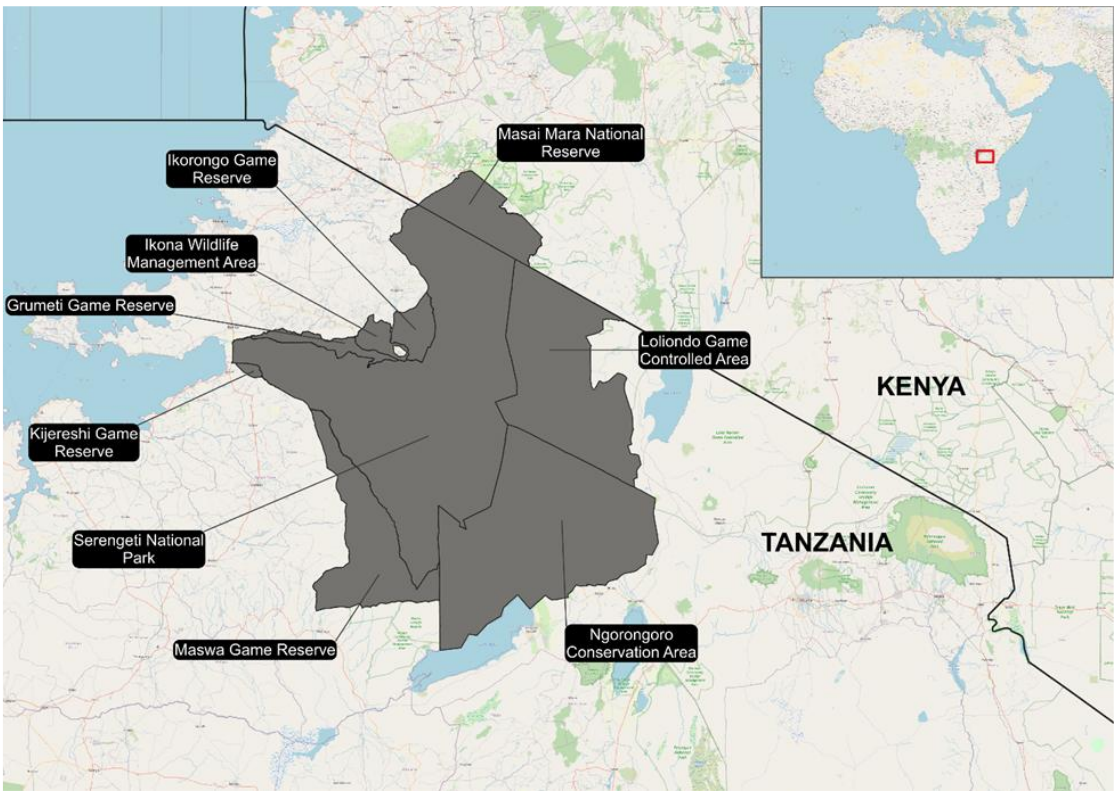


Figure 1. Location of Serengeti ecosystem

Recent advances in remote sensing and GIS provide powerful tools for investigating migration–environment relationships. Satellite observations enable continuous, large-scale monitoring of vegetation dynamics, rainfall patterns, and surface conditions (Pettorelli et al., 2018), and their repetitive coverage supports temporal change detection across migration cycles (Xie et al., 2020). However, issues such as cloud cover, atmospheric interference, and methodological differences in change detection can constrain data quality and comparability. Despite these challenges, the integration of remote sensing and GIS offers an effective framework for quantifying environmental drivers of wildlife movement in complex landscapes such as the Serengeti.

While most research has focused on forage and water availability as the primary determinants of wildebeest migration, temperature and other climatic factors remain comparatively understudied. This study addresses that gap by using open-source satellite data and GIS to analyze how vegetation health (NDVI), precipitation, and temperature jointly influence wildebeest movement within the Serengeti ecosystem.

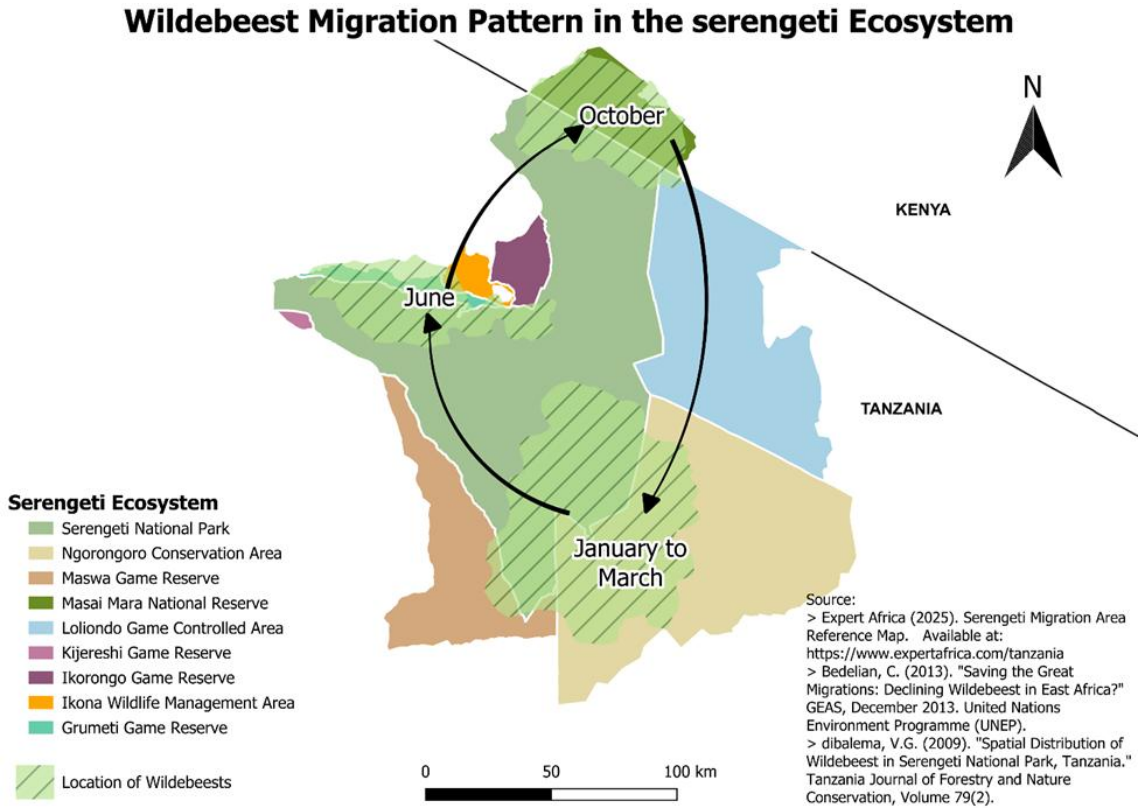


Figure 2. Wildebeest Migration Pattern in the Serengeti Ecosystem

DATA AND METHODS

The study area, comprising the Serengeti ecosystem and its migratory zones, was delineated using shapefiles generated in QGIS from the OpenStreetMap (OSM) Data Model together with additional built-in geoprocessing tools, following established open-source workflows for environmental spatial database development and cartographic analysis (Brovelli et al., 2017). Figure 3 depicts the analytical workflow used to derive and analyze NDVI, temperature, and precipitation across Serengeti migratory zones.

Let the study domain be denoted by $S \subset \mathbb{R}^2$, representing the spatial extent of the Serengeti ecosystem, and let $Z_i \subset S$ denote the i-th migratory zone, where $i \in$ {March,June,October}. These polygon layers were used for spatial clipping, zonal analysis, map layout, and visualization. All spatial data were projected to the WGS 84 / UTM Zone 36S coordinate reference system (EPSG:32736), which preserves metric properties needed for reliable distance- and area-based analysis. In this projected system, Euclidean distance between two points $p_1 = (x_1, y_1)$ and $p_2 = (x_2, y_2)$ is defined as shown in Equation 1, and polygon area A is expressed in square meters, providing a consistent basis for environmental spatial modelling (Wang et al., 2012).

$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (1)$$

Environmental variables, including vegetation condition, land-surface temperature, and precipitation, were derived from open-source satellite and climate datasets in Google Earth Engine (GEE), a cloud-based platform widely used for large-scale geospatial and time-series remote sensing analysis (Gorelick et al., 2017; Tamiminia et al., 2020).

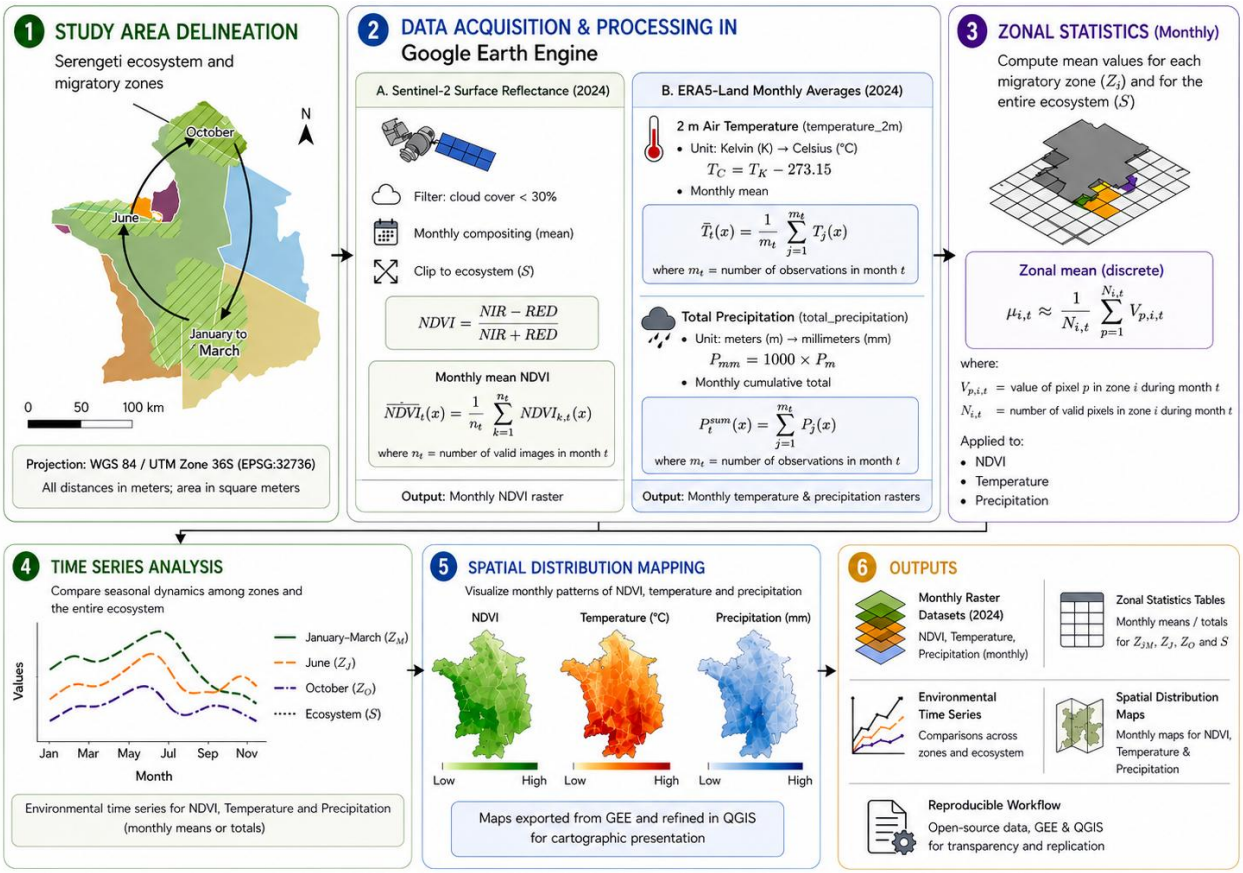


Figure 3. Workflow for analyzing spatiotemporal environmental variability in the Serengeti ecosystem

Vegetation condition was represented using the Normalized Difference Vegetation Index (NDVI), a dimensionless spectral index commonly used as a proxy for photosynthetic activity, vegetation productivity, and forage availability in ecological studies (Pettorelli et al., 2011). NDVI was calculated from Sentinel-2 Surface Reflectance imagery as stipulated in Equation 2:

$$\mathrm{NDVI} = \frac{NIR - RED}{NIR + RED}, \tag{2}$$

where NIR is the reflectance in the near-infrared band (Band 8) and RED is the reflectance in the red band (Band 4). NDVI values theoretically range from -1 to +1, with higher positive values indicating denser and healthier vegetation, values near zero indicating sparse vegetation or bare ground, and negative values often corresponding to bare soil, water, snow, or urban areas. Sentinel-2 images acquired during 2024 with cloud cover below 30% were filtered, composited into monthly mean images, and clipped to the ecosystem boundary S. Formally, if NDVI_(k,t) (x) denotes the NDVI value at pixel x in image k for month t, the monthly mean NDVI was computed as shown in Equation 3:

$$\overline{NDVI}_t(x) = \frac{1}{n_t}\sum_{k=1}^{n_t} NDVI_{k,t}(x) \tag{3}$$

where n_t is the number of valid images available in month t.

Temperature and precipitation data were obtained from the ERA5-Land Monthly Averages dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), which provides gridded land-surface meteorological variables suitable for hydrological and ecological analyses (Muñoz Sabater et al., 2021). The 2 m air temperature variable (temperature_2m) was converted from Kelvin to degrees Celsius using Equation 4:

$$T_C = T_K - 273.15, \tag{4}$$

where T_K is temperature in Kelvin and T_C is temperature in degrees Celsius. Total precipitation (total_precipitation) was converted from meters to millimeters using Equation 5:

$$P_{mm} = 1000 \times P_m. \quad (5)$$

where P_m is precipitation depth in meters and P_{mm} is precipitation depth in millimeters. For each month t, temperature was summarized using the monthly mean, while precipitation was summarized using the monthly cumulative total. If $T_j(x)$ denotes temperature observations and $P_j(x)$ precipitation observations within month t can be computed using Equation 6 and Equation 7 respectively:

$$\overline{T}_t(x) = \frac{1}{m_t} \sum_{j=1}^{m_t} T_j\,(x) \quad (6)$$

$$P_t^{\text{sum}}(x) = \sum_{j=1}^{m_t} P_j\,(x), \quad (7)$$

where m_t is the number of temporal observations in month t.

To characterize environmental variability across migratory habitats, zonal statistics were computed for the three key migratory zones Z_i and for the entire ecosystem S. Zonal statistics summarize raster values over a defined polygon region. For a raster variable $V_t(x)$ at month t, the zonal mean over zone Z_i was calculated as shown in Equation 8.

$$\mu_{i,t} = \frac{1}{|Z_i|} \int_{Z_i} V_t\,(x)\,dx \quad (8)$$

where $|Z_i|$ denotes the area of zone Z_i, and $V_t(x)$ represents the value of the environmental variable at location x. In raster implementation, this is approximated by the arithmetic mean of all pixels within the zone as presented in Equation 9.

$$\mu_{i,t} \approx \frac{1}{N_{i,t}} \sum_{p=1}^{N_{i,t}} V_{p,i,t} \quad (9)$$

where $V_{p,i,t}$ is the value of pixel p in zone i during month t, and $N_{i,t}$ is the number of valid pixels. This procedure was applied to NDVI, temperature, and precipitation to produce monthly time series describing environmental trajectories across space and time (Chen et al., 2015; Conrad et al., 2015).

To compare seasonal dynamics among zones and relative to the broader ecosystem, the results were used to generate time-series charts illustrating temporal variability across zones relative to the entire ecosystem. Spatial distribution maps were exported from GEE and refined in QGIS for cartographic presentation.

RESULTS AND DISCUSSION

Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) was used to assess vegetation dynamics across the Serengeti ecosystem during 2024. The NDVI time-series analysis shows a clear seasonal pattern consistent with rainfall variability as shown in Figure 4. NDVI values peak between January and May (approximately 0.55–0.65), reflecting the wet season when vegetation is most productive. Values decline sharply during the dry months of June to September (around 0.2–0.3), before recovering from October to December with the onset of short rains. Across the three migratory zones (March, June, and October), NDVI trends remain broadly similar to the overall ecosystem average, indicating synchronized vegetation responses across the landscape.

Spatial NDVI maps further support these temporal patterns as indicated in Figure 5. Vegetation cover is widespread and vigorous during the wet season (January–May), becomes sparse and patchy during the dry months (June–September), and regenerates toward the year's end (October–December). However, the spatial distribution of greenness remains relatively uniform within a given month, suggesting that NDVI alone does not fully account for the timing or direction of wildebeest movements.

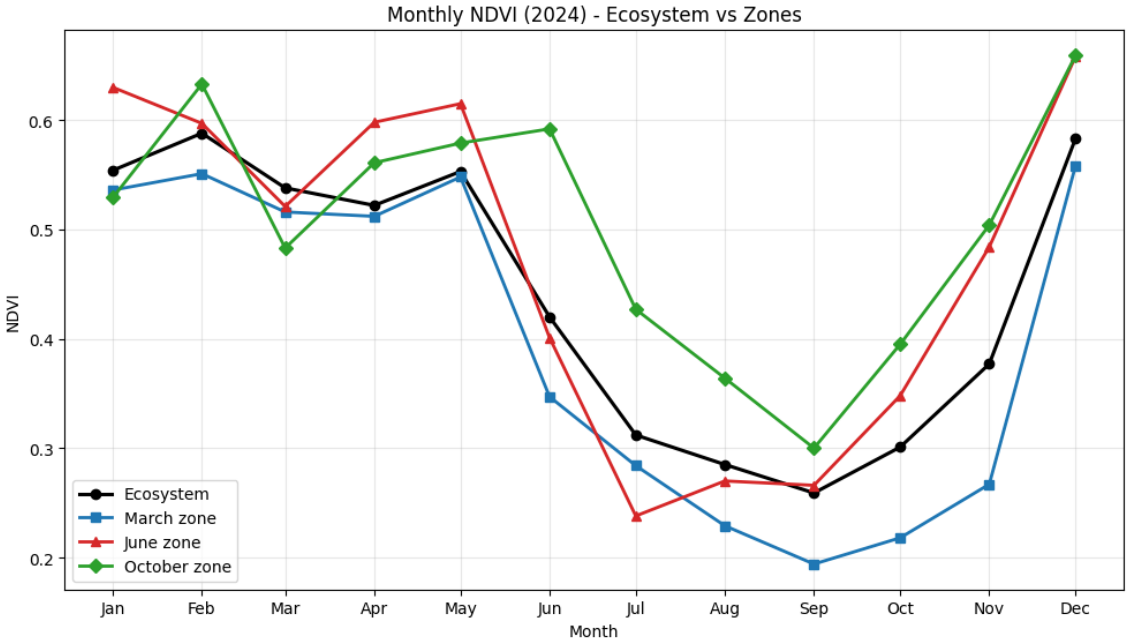


Figure 4. Time-series chart showing monthly NDVI values for the Serengeti ecosystem and selected migration zones in 2024

Temperature

The 2024 temperature analysis reveals clear spatial and temporal variability across the Serengeti ecosystem (Figure 6). Mean monthly temperatures ranged between 19.5°C and 25.5°C, showing relatively stable ecosystem-wide conditions but distinct seasonal differences within the migratory zones. The June zone consistently recorded the highest mean values (reaching ~25.5°C in September), reflecting its generally warmer and more arid conditions. In contrast, the March and October zones exhibited milder temperatures that closely followed the ecosystem trend, with slight increases early in the year for the March zone, possibly influencing the timing of early migratory movements.

Spatial temperature distribution maps for March, June, and October 2024 further confirm these patterns as shown in Figure 7. Warmer areas appear in the central and northwestern parts of the ecosystem during the dry season, while cooler zones dominate during the wet months. Despite these spatial gradients, wildebeest occupy regions with comparable mean temperatures during different times of the year, indicating that temperature alone does not directly determine migration routes.

Precipitation

Precipitation across the Serengeti ecosystem during 2024 exhibits a distinct bimodal rainfall regime, characteristic of East Africa, with long rains from March to May and short rains from October to December (Figure 8). The March zone recorded the highest rainfall, coinciding with elevated NDVI values and dense vegetation cover, conditions that attract large wildebeest concentrations early in the year. In contrast, June represents the driest phase, with precipitation dropping below 500 mm across all migratory zones, corresponding to reduced forage availability and the northward migration of herds. October marks the onset of the short rains, initiating vegetation recovery and signaling the southward return migration.

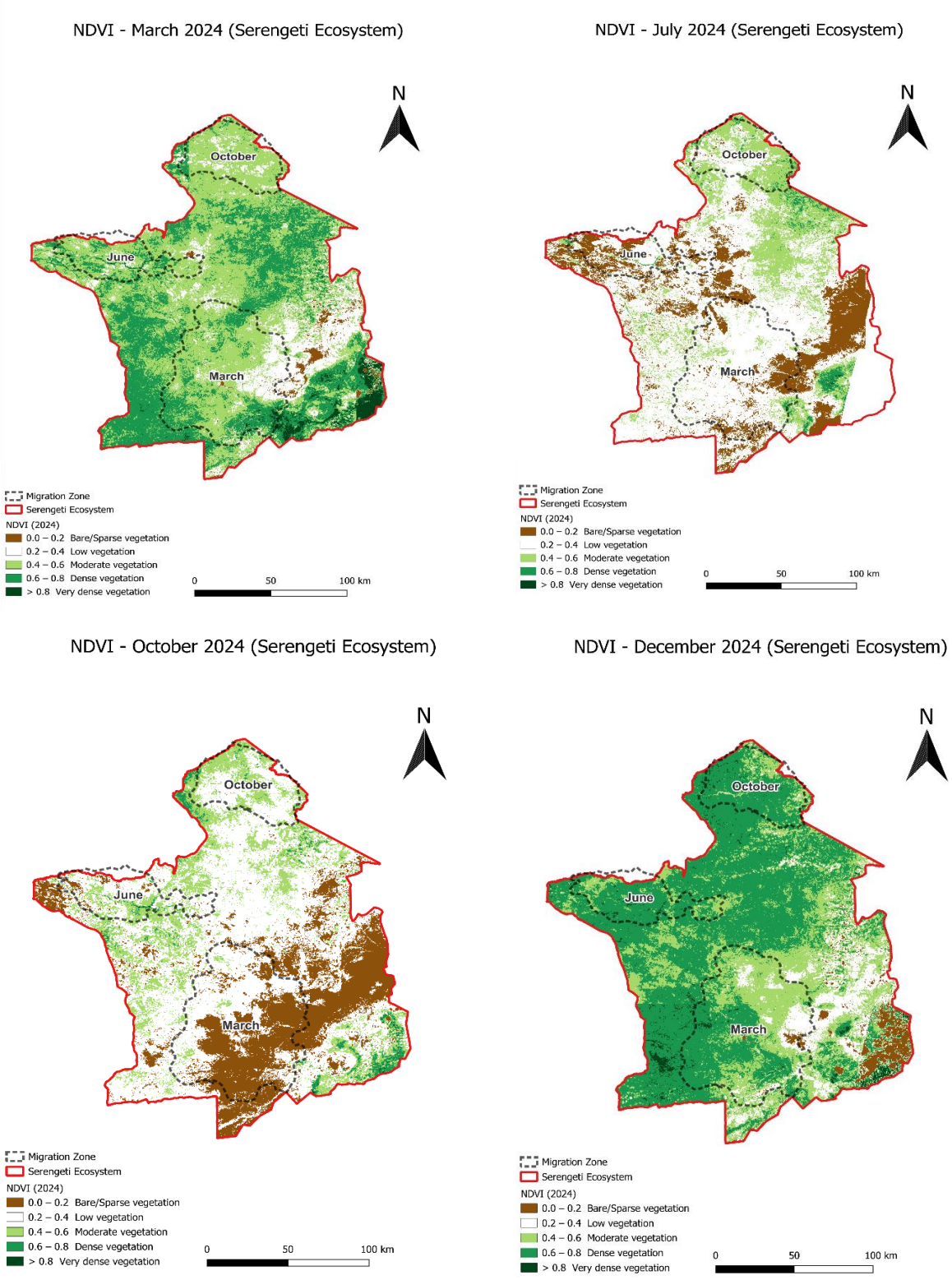


Figure 5. Monthly NDVI maps across the Serengeti ecosystem for March, July, October, and December 2024

The precipitation maps reveal pronounced seasonal contrasts as indicated in Figure 9. In March, widespread high-intensity rainfall dominates much of the ecosystem, reflecting the long-rain peak. By June, the maps are characterized by low rainfall values and extensive dry areas, indicative of the dry season minimum. In October, moderate rainfall reappears across the

southern and central regions, illustrating the transition into the short-rain period. The viridis color scheme ranging from dark purple and blue for low rainfall to green and yellow for high rainfall effectively visualizes these gradients, highlighting zones of hydrological variability that shape ecological productivity.

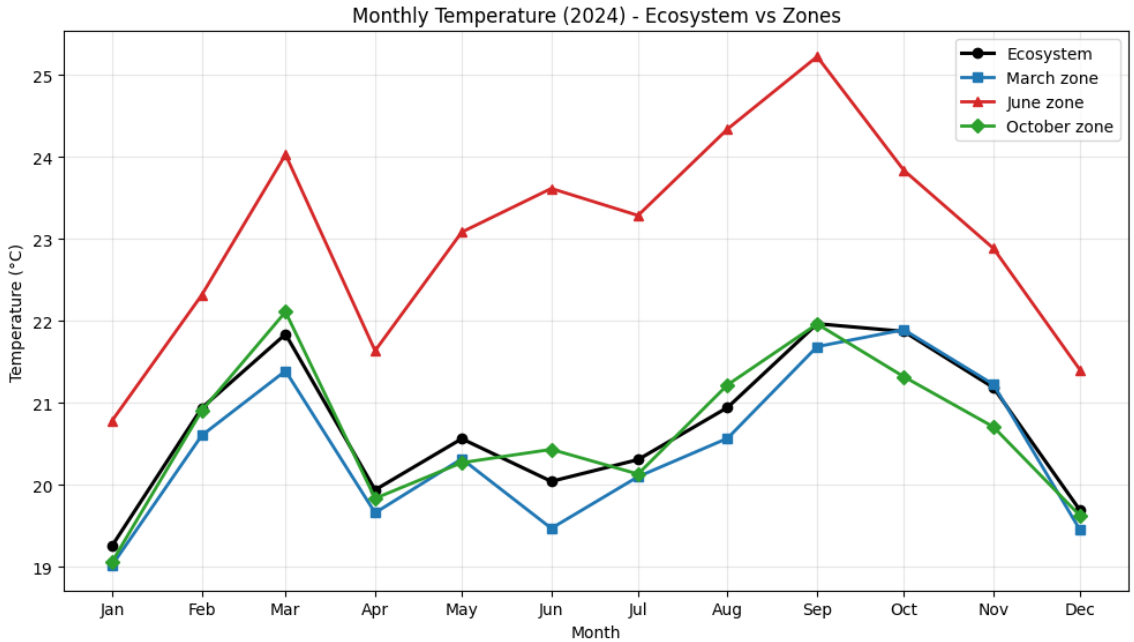


Figure 6. Time-series mean temperature chart for the Serengeti ecosystem and migratory zones (2024)

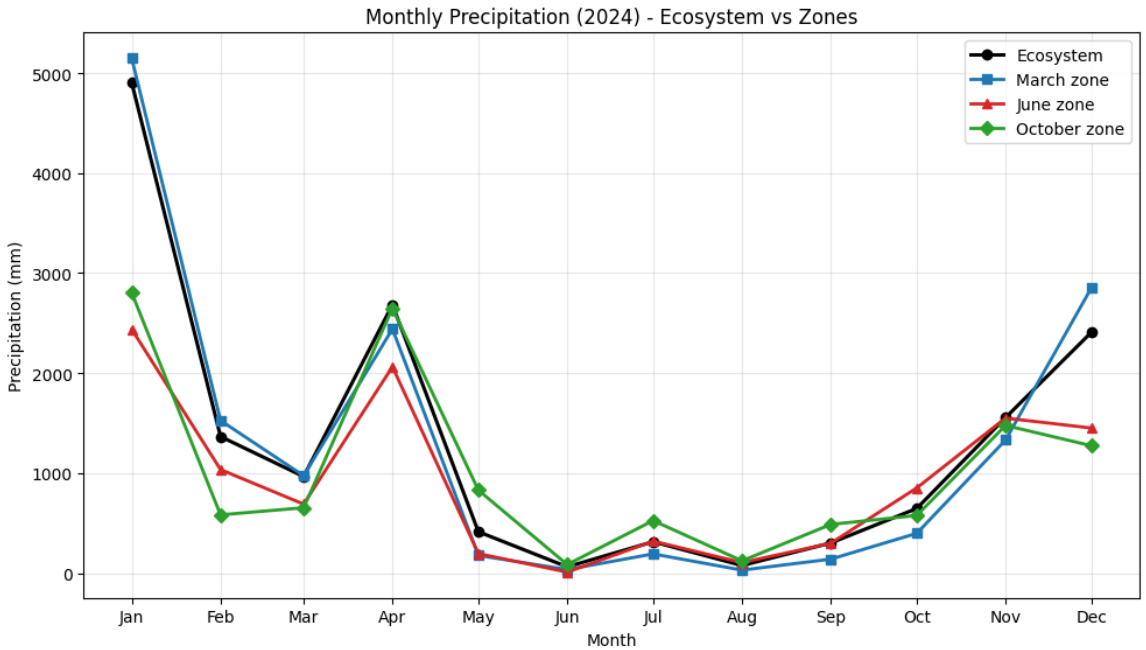


Figure 8. Monthly precipitation trends for the Serengeti ecosystem and migratory zones (2024)

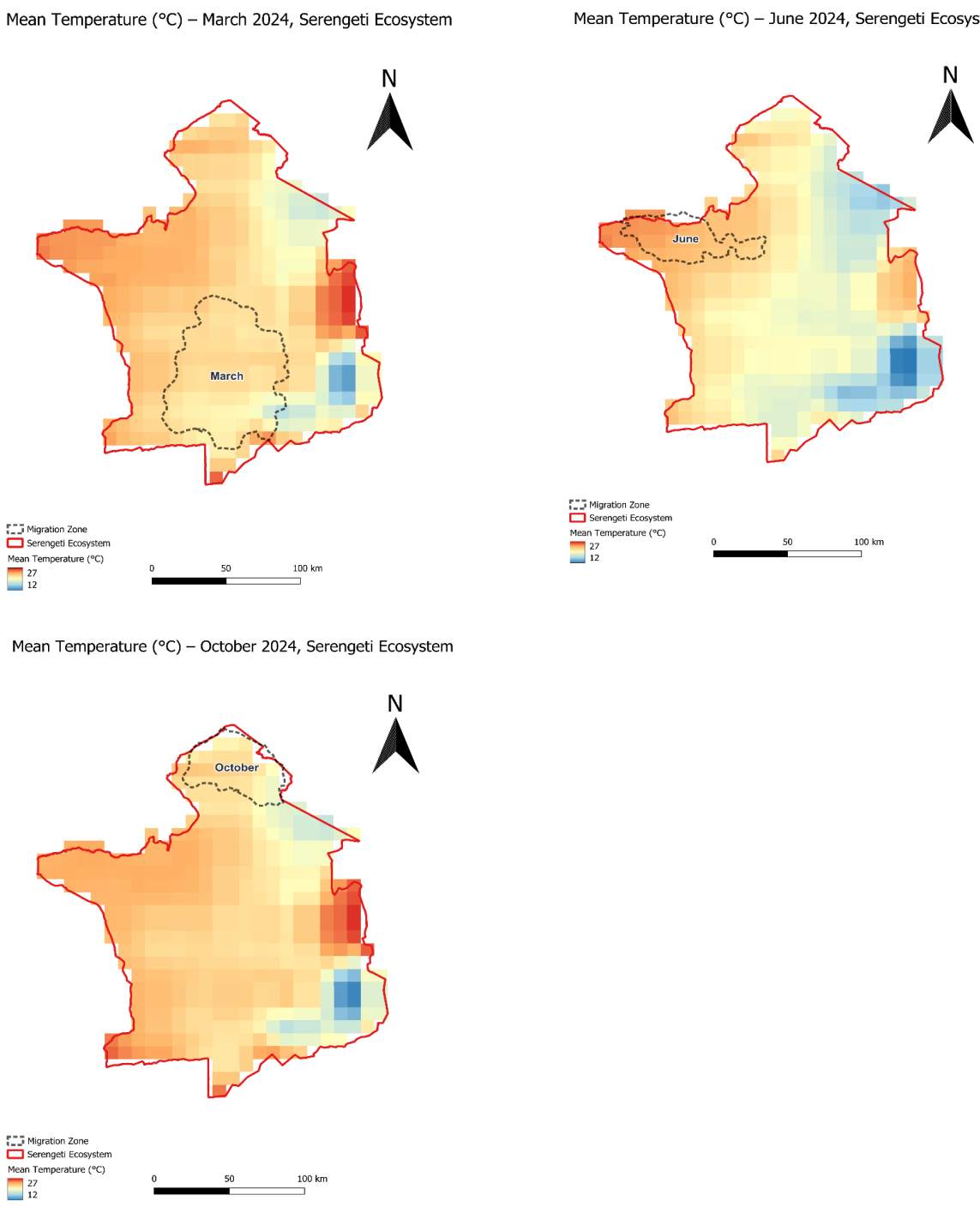


Figure 7. Mean temperature distribution (°C) across the Serengeti ecosystem for March, June, and October 2024

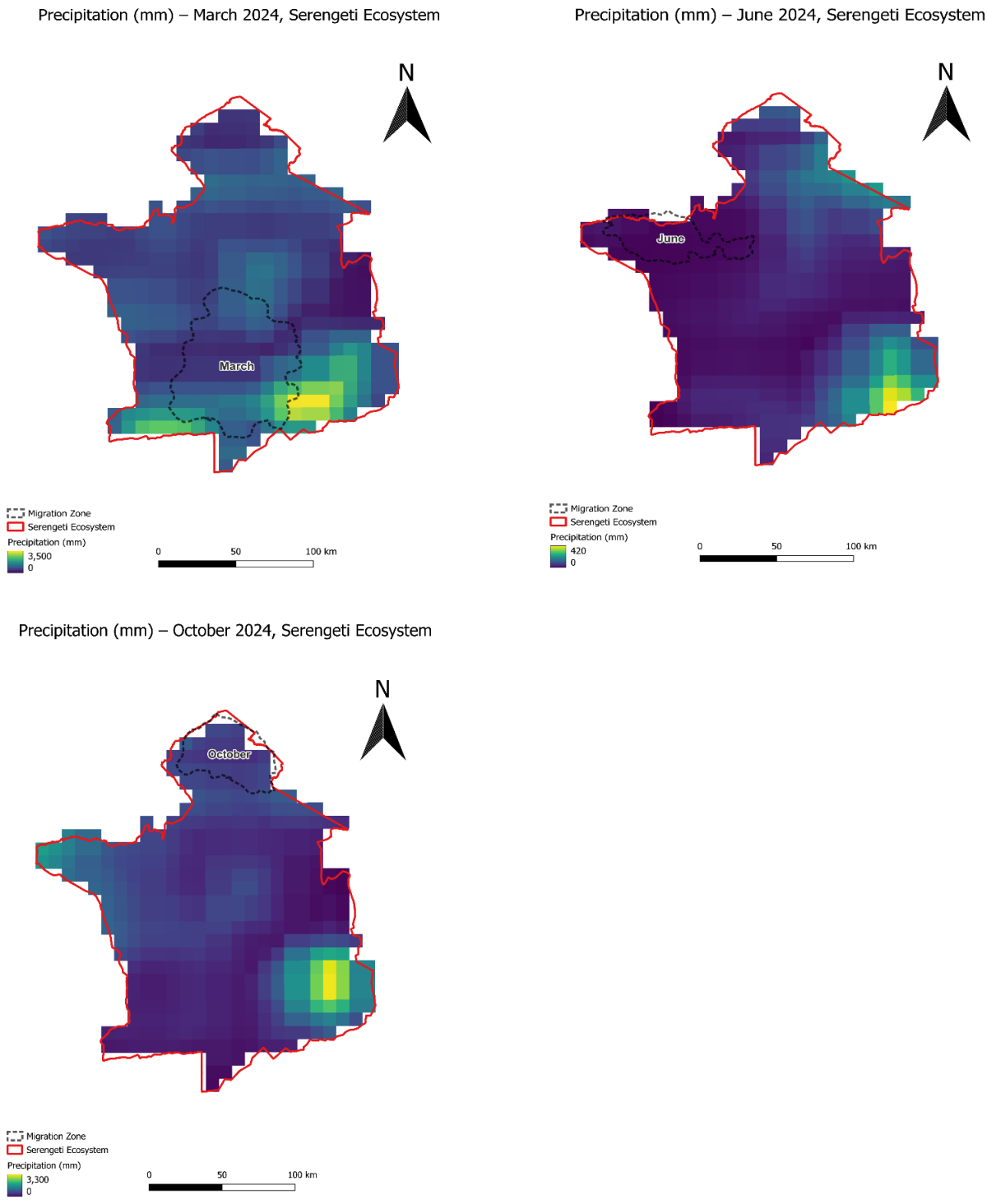


Figure 9. Monthly total precipitation maps for March, June, and October 2024. Color scales are adjusted per month to enhance visibility of spatial patterns

Integrated Statistical Analysis

The statistical analysis of the 2024 data provides further support to the temporal and spatial patterns observed in the preceding sections. As shown in Figure 10, NDVI has a moderate positive relationship with precipitation and a moderate negative relationship with temperature, while precipitation and temperature are inversely related. These results indicate that vegetations greenness generally increases when rainfall increases and tends to decline when temperatures

become higher. In the same way, the negative relationship between precipitation and temperature reflects the seasonal structure already observed across the Serengeti ecosystem, where wetter months are associated with relatively cooler conditions and drier months with warmer surface environments.

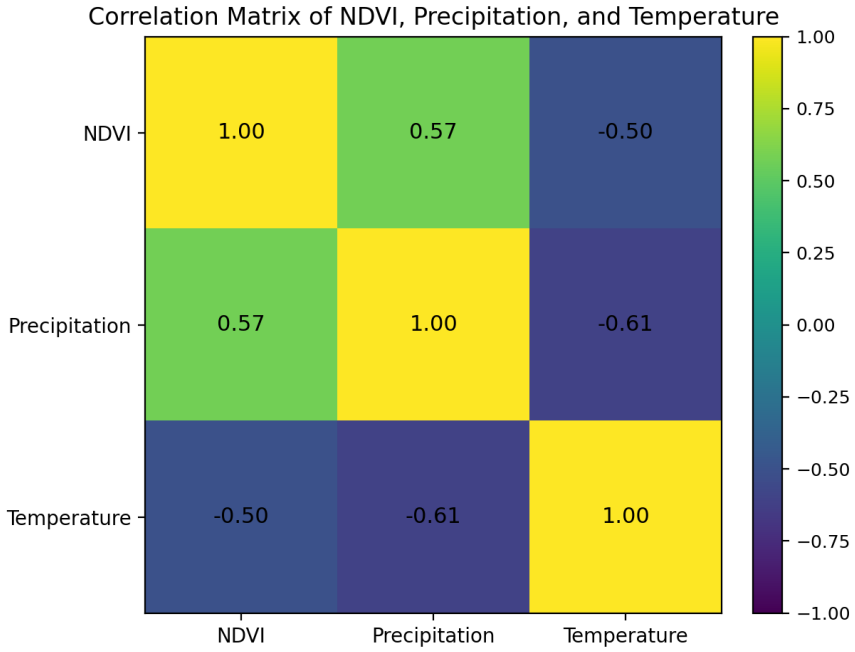


Figure 10. A heatmap showing the correlation coefficients among NDVI, precipitation, and temperature

To further assess the combined influence of climatic conditions on vegetation dynamics, a multiple linear regression analysis was conducted using NDVI as the dependent variable and precipitation together with temperature as explanatory variables. Two models were tested to compare the effect of rainfall timing on vegetation response: one model used precipitation of the same month, while the other used one-month lagged precipitation. The comparison shows that the model with one-month lagged precipitation performed better than the model using same-month precipitation, indicating that vegetation greenness responds more strongly to rainfall received in the preceding month than to rainfall of the current month. The non-lagged model produced a lower explanatory power ($R^2 = 0.37$), whereas the lagged model explained a substantially greater proportion of the variation in NDVI ($R^2 = 0.70$). Based on this comparison, the final regression model was specified using one-month lagged precipitation and temperature as predictors of NDVI, as shown in Equation 10:

$$NDVI = 1.533 + 6.6.37x10^{-5} PrecipationLag - 0.0566 Temperature. \quad (10)$$

The regression results show that the model explains a substantial proportion of the variation in NDVI ($R^2 = 0.70$), indicating that the combined effect of rainfall and temperature accounts for much of the seasonal vegetation behavior observed in the ecosystem. The positive regression coefficient for lagged precipitation confirms that increased rainfall contributes to vegetation recovery and greening, whereas the negative coefficient for temperature indicates that warmer conditions are associated with declining vegetation conditions.

An important finding from the statistical analysis is the lag effect observed between precipitation and NDVI. As illustrated in Figure 11, the relationship between the two variables becomes clearer when precipitation is considered with a one-month delay relative to NDVI, indicating that vegetation does not respond instantly to rainfall events. Rather, the response occurs after some time, likely because the received rainfall must first infiltrate the soil, contribute to moisture availability, and support plant growth before its effect becomes visible in vegetation

greenness. This delayed response is ecologically meaningful because it shows that the connection between rainfall and forage conditions is not immediate but operates through short-term seasonal processes within the ecosystem.

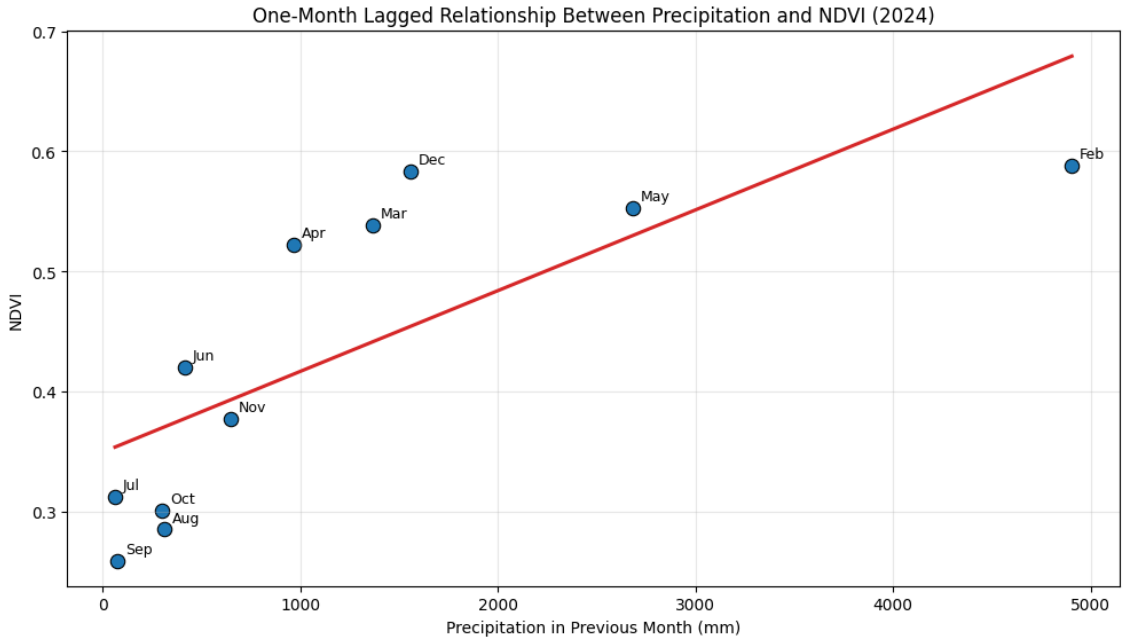


Figure 11. A scatter plot of NDVI against 1-month lagged precipitation, ideally with a fitted trend line

The standardized monthly time-series shown in Figure 12 further highlights the interdependence among the three variables. Peaks in precipitation are followed by increases in NDVI, whereas temperature generally varies in the opposite direction, particularly during the dry season when vegetation greenness declines. Taken together, the regression results, the lag relationship, and the standardized temporal patterns indicate that the Serengeti ecosystem functions as an interconnected climatic and ecological system in which precipitation, temperature, and vegetation are closely linked.

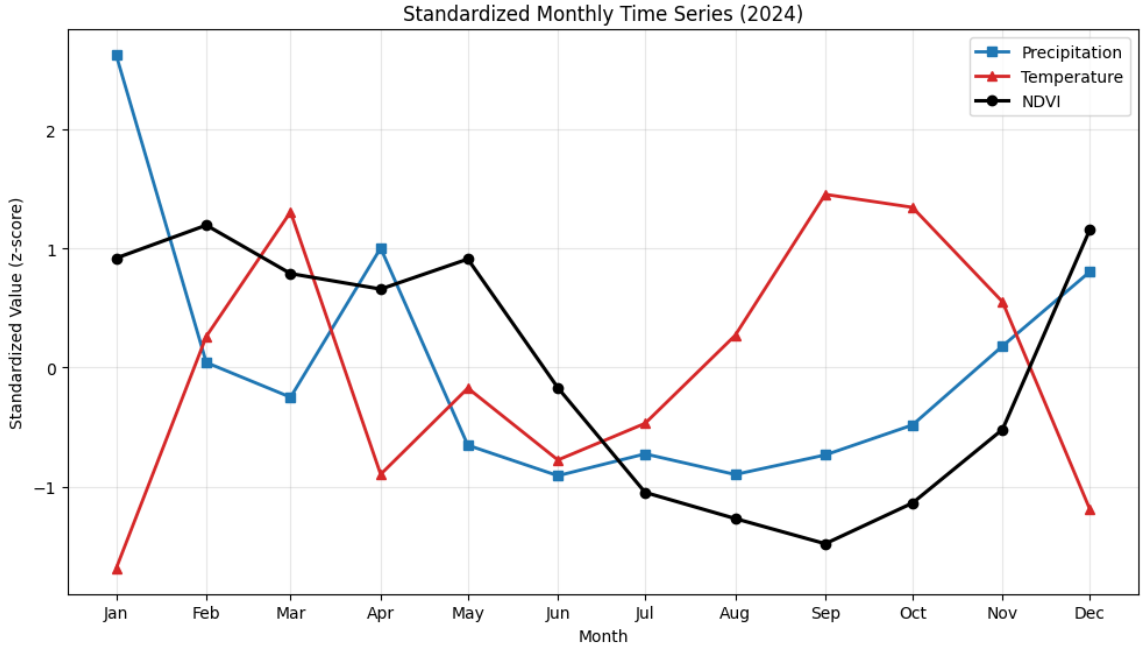


Figure 12. A single plot with standardized (z-score) NDVI, precipitation, and temperature over the 12 months

CONCLUSION

This study has shown that the seasonal variation of precipitation, vegetation greenness, and temperature across the Serengeti ecosystem is closely connected to the environmental conditions that shape wildebeest migration, consistent with recent work linking rainfall extremes to vegetation conditions and migration timing in the Serengeti–Mara ecosystem (Mtewele et al., 2023). The results indicate that rainfall remains the main controlling factor because it determines soil moisture availability, supports vegetation growth, and creates the forage conditions on which migratory herbivores depend (Kalisa et al., 2019; Nzabarinda et al., 2021). NDVI followed this seasonal pattern closely, with high values during the wet months, a strong decline during the dry season, and recovery after the onset of the short rains, mirroring satellite-based descriptions of seasonal vegetation cycles in Serengeti and surrounding savannas. Temperature, although important, played a more indirect role by influencing moisture loss and the persistence of vegetation during periods of limited rainfall.

The statistical analysis has strengthened this interpretation by showing that NDVI is positively related to precipitation and negatively related to temperature, while the regression results further demonstrate that lagged precipitation and temperature together explain a substantial proportion of the variation in vegetation greenness. The lagged relationship between rainfall and NDVI is especially important because it suggests that vegetation does not respond immediately to rainfall, but after a short period during which moisture becomes available for plant growth (Feng et al., 2023). This means that the ecological conditions influencing wildebeest movement are not only determined by present rainfall, but also by rainfall received in the preceding period. In this respect, the study provides further evidence that migration in the Serengeti is linked to shifting patterns of resource availability that develop gradually across time and space rather than responding solely to instantaneous weather conditions.

The findings also have wider ecological and management implications. They show that the Serengeti ecosystem functions as an interconnected climatic and ecological system in which changes in one variable are reflected in the others, in agreement with continental-scale syntheses of coupled rainfall–temperature–vegetation trends (Kalisa et al., 2019; Nzabarinda et al., 2021; Nooni et al., 2024). Because rainfall strongly influences vegetation productivity and temperature affects the persistence and quality of that productivity, even relatively small changes in seasonal climate patterns may alter the timing, quality, and distribution of forage resources across migratory zones. This has implications not only for wildebeest movement, but also for the many other species and ecological processes that depend on the same seasonal resource base, including other migratory herbivores, resident herbivores, and predators. The results therefore suggest that monitoring rainfall and vegetation dynamics using satellite data can provide a useful basis for understanding ecosystem conditions and anticipating periods of ecological stress.

At the same time, the study has some limitations that should be recognized. First, the analysis is based on one year of satellite-derived environmental data and therefore reflects short-term seasonal behaviour rather than long-term climatic variability. While the 2024 patterns are clear, a longer time series would be needed to determine whether the same relationships remain stable across wet years, dry years, and periods of climatic anomaly, because longer records frequently reveal breakpoints and nonlinear vegetation responses to climate forcing (Huang et al., 2021). Second, the study focused on NDVI, precipitation, and temperature as key environmental variables, but wildebeest migration is also influenced by other factors such as surface water availability, soil nutrients, grazing pressure, landscape connectivity, and human disturbance (Bartzke et al., 2018; Li et al., 2025). As a result, the findings should not be interpreted to mean that migration is controlled by climate alone; rather, climate-related variables provide an important environmental framework within which other ecological and behavioral factors operate. In addition, the use of zonal averages may reduce local-level variability within migratory areas, meaning that some finer spatial differences may not be fully captured in the present analysis. Future studies could therefore be improved by incorporating longer time series,

additional ecological variables, and more advanced nonlinear modelling approaches to better capture complex environmental interactions that may not be fully explained by linear relationships alone.

AUTHOR CONTRIBUTIONS

Daniel Morgan Kwayu: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Visualization, Writing Original Draft, Writing, Review and Editing, Project Administration. The author has read and approved the final manuscript.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest regarding the publication of this manuscript.

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