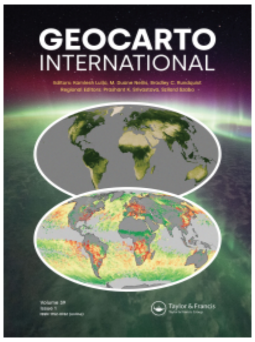

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Assessing environmental drivers of vegetation health using enhanced vegetation index and principal component analysis: a case study of the Cradle Nature Reserve, Gauteng province, South Africa

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ABSTRACT

Protected environments, such as the Cradle Nature Reserve, are susceptible to environmental factors, including rainfall, temperature, and soil moisture, which affect vegetation health and productivity. This study explores vegetation growth dynamics using Enhanced Vegetation Index (EVI) time series derived from Sentinel-2 imagery from 2019 to 2023. Principal Component Analysis (PCA) was applied to reduce data dimensionality and extract the most influential environmental variables. The analysis identified two dominant components: Factor 1 (F1), strongly associated with rainfall and soil moisture, which explained 72.12% of the variance, and Factor 2 (F2), linked to temperature, accounting for an additional 17.96%. Water availability emerged as the primary determinant of vegetation vigor, while temperature played a secondary but critical role by increasing evapotranspiration rates and intensifying vegetation stress during dry seasons. Seasonal stress responses were captured by examining EVI variations across wet and dry periods, revealing vegetation's sensitivity to both moisture presence and thermal extremes.

HIGHLIGHTS

- The Enhanced Vegetative Index (EVI) significantly correlates with rainfall, soil moisture, and temperature, indicating its impact on vegetation health.
- PCA's primary components (F1 and F2) account for 90.080% of data variability.
- F1 examines the impact of environmental factors on overall plant well-being, while F2 investigates individual effects of temperature and moisture on plant health.
- Eigenvector analysis clarifies the intricate connections between environmental factors and vegetation health.

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1. Introduction

Monitoring vegetation growth dynamics plays a pivotal role in understanding and managing ecosystem health, particularly in grassland ecosystems that are highly sensitive to climatic fluctuations. Vegetation indices, such as the EVI, have become essential for assessing vegetation greenness, productivity, and density, with applications across diverse ecological zones (Matsushita et al. 2007; Ogungbuyi et al. 2023). Remote sensing techniques, especially those leveraging high-resolution satellite imagery from platforms like Sentinel-2, have been widely used to evaluate vegetation changes over time and to support sustainable land management practices (Schwieder et al. 2020; Fernández-Habas et al. 2021). By detecting subtle variations in chlorophyll content and canopy structure, these indices serve as sensitive indicators of vegetation health under changing climatic conditions (Matsushita et al. 2007; Chowdhury et al. 2024; Whig et al. 2024). However, understanding the drivers behind these changes remains challenging due to the complex and interrelated nature of climatic variables. In this context, structured analytical approaches, such as Principal Component Analysis and multilinear regression are crucial for disentangling the combined effects of temperature, rainfall, and soil moisture on vegetation dynamics.

Despite advancements, several challenges and gaps persist in effectively capturing the nuances of vegetation responses to environmental variability. Research by Cui et al. (2022) and Santiago et al. (2022) demonstrated the strong influence of rainfall, temperature, and soil moisture on vegetation health, showing that these factors are pivotal in driving seasonal biomass accumulation. However, most studies fall short in clearly separating the compounded effects of these variables, which is a critical gap this study addresses using Principal Component Analysis (PCA) and multilinear regression to overcome multicollinearity and clarify the relative importance of each factor. While NASA documentation highlights the importance of specific MERRA-2 metrics, such as T2M_MAX (maximum temperature), PRECTOTCORR (corrected total precipitation), and GWETROOT (root zone soil moisture), in assessing key environmental variables like rainfall, temperature, and soil moisture that influence vegetation health (NASA Global Modeling and Assimilation Office (GMAO)), 2020), many studies report challenges in disentangling the individual and combined effects of these variables across different seasonal phases (Walter 2018). Similarly, Shen et al. (2022) highlighted the advantages of incorporating high-resolution climate datasets, such as MERRA-2, for more accurate environmental monitoring but indicated that further research is needed to fully integrate these data with vegetation indices for comprehensive ecological analysis. Schwieder et al. (2020) underscored the potential of Sentinel-2 data in assessing grassland conditions but emphasised the need for additional research to improve accuracy across different grassland types, seasons, and management practices. Further challenges related to data dimensionality and multicollinearity are commonly encountered in remote sensing applications, as noted by Li et al. (2011) and Mountrakis et al. (2011), who highlighted how these issues complicate accurate predictions. Addressing these complexities, Li et al. (2011) proposed machine learning approaches that help reduce dimensionality, while Mountrakis et al. (2011) reviewed the effectiveness of Support Vector Machines (SVM) in managing multicollinear variables, ultimately aiming to improve ecological and vegetation health assessments. Collectively, these studies emphasise the ongoing need for sophisticated methods and high-resolution datasets to support precise and actionable insights in vegetation monitoring. To address the challenge of multicollinearity among environmental variables such as rainfall, soil moisture, and temperature, this study proposes the use of Principal

Component Analysis (PCA) to reduce dimensionality and multilinear regression to assess the relative influence of the key climatic factors on vegetation dynamics

Recent studies emphasise that climatic and anthropogenic factors influencing vegetation dynamics are often complex and interdependent. For instance, research by Bao et al. (2023) found that shifts in temperature and precipitation patterns significantly affect soil moisture, net primary productivity, and carbon storage, all of which impact vegetation resilience, particularly in agroecosystems vulnerable to climate change. Similarly, Sultan et al. (2024) demonstrated how climate variability, combined with human activities such as land use change, drives significant alterations in vegetation cover and productivity, underscoring the compounded effects of natural and anthropogenic stressors on ecosystem stability. However, gaps remain in understanding how these interactions vary spatially and temporally in different ecosystems, such as grasslands. Similarly, Xu et al. (2024) examined climate and human influences on vegetation in East Africa, revealing the intricate dynamics of vegetation responses to both natural and anthropogenic pressures, yet recommending further research on how these patterns differ within protected ecological reserves like the Cradle Nature Reserve. As a protected area that has transitioned from farming to wildlife conservation, the site offers a valuable context for examining how both natural climatic variables and anthropogenic factors influence vegetation dynamics. Its unique combination of climatic extremes, biodiversity importance, and historical land use makes the Cradle Nature Reserve an ideal case study. Moreover, its status as a grassland ecosystem in a transitional climate, with seasonal rainfall variability and periodic droughts contributing to semi-arid conditions, provides critical insight into vegetation–climate interactions in water-limited environments.

To investigate these dynamics, our study applies advanced statistical approaches, specifically, multilinear regression and Principal Component Analysis (PCA), to examine the impact of key climatic drivers on vegetation dynamics in the Cradle Nature Reserve. These methods allow for detailed analysis of factor interactions while mitigating issues related to multicollinearity, thus providing clearer insights into the primary drivers of vegetation changes (Li et al. 2011; Mountrakis et al. 2011). The objectives of this study are to (i) determine the influence of critical environmental factors on vegetation health, (ii) assess spatio-temporal variability in vegetation responses, and (iii) establish an integrative methodology that combines remote sensing and climate data to identify dominant environmental drivers. By filling these gaps, our research seeks to inform data-driven management and conservation practices for protected ecological reserves, providing a replicable approach for similar areas where maintaining ecological balance is paramount.

2. Materials and method

2.1. Study area

The Cradle Nature Reserve, referred to as Figure 1, covers an area of almost 8000 hectares within the COHWHS. It is renowned for its diverse plant life, with a particular emphasis on blooming plants. The reserve also boasts a broad range of animal species, including over 200 different types of birds (SA-Venues.com 2022; Matyukira and Mhangara 2023). Meteorological variables such as temperature and rainfall, essential for plant growth and development, impact the vegetation in the reserve. The region receives an annual rainfall of 650 to 750 mm, with summer temperatures reaching a maximum of 39 °C and winter temperatures dropping as low as −12 °C. This climatic variability creates a dynamic environment conducive to the growth of plants (SA-Venues.com 2022). The reserve is located in a climatic region characterized by Rocky Highveld Grassland, which is well-suited to

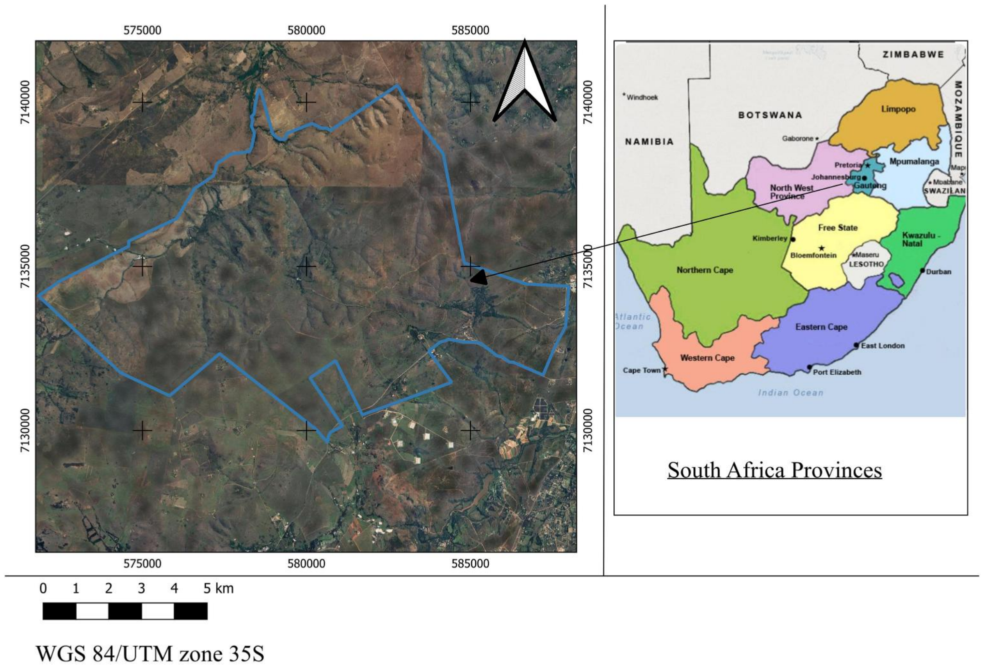

Figure 1. Study area: Cradle Nature Reserve, Gauteng province, South Africa.

fire and has a major influence on the vegetation structure (FLOW Communications 2022). Natural springs, watercourses, streams, and tributaries to the Magalies and Crocodile Rivers provide vital moisture that sustains the diverse plant life (FLOW Communications 2022). Furthermore, the reserve's historical utilisation of land, which includes both subsistence and commercial farming, has resulted in alterations to the distribution of flora. The reintroduction of wild animal species, which have distinct grazing tendencies compared to domesticated cattle, has further impacted these changes (Matyukira and Mhangara 2023). The unusual vegetation dynamics observed in the area are a result of the climatic circumstances and the reserve's geological features, including dolomitic sinkholes that protect tree species from natural forest fires (FLOW Communications 2022). These circumstances, combined with the importance of the reserve as a tourist attraction and its value for biodiversity in protected heritage areas, highlight the necessity of comprehending and conserving the original plant cover. This flora serves as an indicator of historical habitats and diets (Matyukira and Mhangara 2023). The preservation of rangelands is critical for wildlife grazing within the nature reserve, highlighting the intricate relationship between climate and vegetation. Relevant studies by Xiang et al. (2024) and Xu et al. (2024) provide insights into climate and human impacts on vegetation dynamics, shedding light on how factors like temperature, precipitation, and land use influence vegetation phenology and growth patterns, which are pertinent in managing a protected ecological site such as the Cradle Nature Reserve.

2.2. Methods of data acquisition, processing, and analysis

Cloud-contaminated scenes were removed using Sentinel-2 quality assurance (QA) bands to maintain the integrity of the time series analysis. Rather than applying gap-filling algorithms, images with significant cloud cover were excluded entirely. The study used

Sentinel-2 multispectral imagery from January 2019 to December 2024, accessed *via* the Copernicus Open Access Hub. To facilitate data download, we automated the retrieval process using the Sentinel Application Platform (SNAP) toolkit (European Space Agency (ESA) 2022), which enabled batch processing based on cloud cover, the area of interest, and the specified time range. Subsequent image processing and analysis were conducted in QGIS 3.36.0, an open-source geographic information system. For each image, the Enhanced Vegetation Index (EVI) was calculated using the following formula (QGIS Documentation 2024):

$$EVI = 2.5 \times \frac{NIR - RED}{NIR + 6X\ \ RED - 7.5\ \ X\ \ BLUE + 1} \tag{1}$$

where *NIR, RED,* and *BLUE* represent the reflectance values of the respective bands (QGIS Development Team 2020; MapScaping 2023). These values were derived from Sentinel-2 Level-2A surface reflectance products, which are atmospherically corrected and radiometrically calibrated, ensuring the suitability of inputs for vegetation index computation. The use of EVI enhances sensitivity to vegetation signals in areas of dense biomass and minimises soil background and atmospheric influences.

To generate monthly averages, individual EVI images were stacked, and the mean pixel value was calculated across each stack, resulting in a composite image for each month. These monthly composites were exported as TIFF files for further analysis, providing a consistent basis for tracking vegetation dynamics over time (QGIS Documentation 2024). The surface maps were generated at a 10-meter spatial resolution, aligning with Sentinel-2's spatial detail, which enables fine-scale detection of vegetation responses and supports the study's objective of assessing localised environmental impacts.

For spatial analysis, surface maps were produced using ArcGIS 10.8.2 software. Data from 14 meteorological stations were integrated to ensure comprehensive spatial coverage (Esri (Environmental Systems Research Institute) 2022). This process yielded a total of 180 surface maps, 60 per environmental variable across the study period. The monthly data extracted from these maps were subsequently used to examine the relationships between environmental variables and vegetation health through the application of multilinear regression and Pearson correlation analysis, as described below:

$$EVI = \beta 0 + \beta 1(\text{Rainfall}) + \beta 2(\text{Temperature}) + \beta 3(\text{Soil Moisture}) + \epsilon \tag{2}$$

where $\beta 0$ is the intercept, $\beta 1$, $\beta 2$, and $\beta 3$ represent the change in EVI per unit change in rainfall, temperature, and soil moisture, respectively, and ϵ is the error term (Jobson 1991; Bevans 2023).

The Pearson correlation coefficient was calculated as follows:

$$r = \frac{\sum(Xi - X^{-})(Yi - Y^{-})}{\sqrt{\sum(Xi - X^{-})^2 \sum(Yi - Y^{-})^2}} \tag{3}$$

Values were classified as follows: $r > 0.5$ (strong positive), $0.3\ \le r \le 0.50.3$ (moderate positive), $0 \le r < 0.30$ (weak positive), $-0.3 \le r < 0\text{-}0.3$ (weak negative), $-0.5 \le r\ < -0.3$ (moderate negative), and $r\ < -0.5$ (strong negative) (Turney 2024).

We also applied principal component analysis (PCA) (Marukatat 2023) to examine the influence of climatic variables on vegetation growth, providing a comprehensive view of meteorological impacts in the study area. The entire data processing workflow, from data collection and EVI computation to surface map generation, statistical extraction, correlation analysis, PCA, and result analyses, is summarised in Figure 2.

We chose to focus on the winter and summer seasons due to their distinct climatic characteristics, which are particularly impactful on vegetation health and environmental variables in the study area. Summer coincides with peak rainfall, supporting vigorous plant growth, whereas winter is typically marked by low temperatures, potential frost, and limited soil moisture—factors that constrain vegetation activity and increase environmental stress. These two seasons represent climatic extremes that offer valuable insight into vegetation responses under contrasting temperature, precipitation, and moisture regimes (Weltzin et al. 2020). Analysing these seasons allows for a comprehensive understanding of the seasonal dynamics affecting EVI and other environmental factors, helping us better capture the range of influences on vegetation health within the study period.

This rigorous methodology enabled detailed analysis of factor interactions and ensured replicability for future research.

3. Results and analysis

3.1. A spatio-temporal analysis of EVI and other environmental factors

The spatial distributions of the Enhanced Vegetation Index (EVI), Rainfall (RF), Temperature (Temp), and Soil Moisture (Soil) in the Cradle Nature Reserve during the winter and summer seasons from 2019 to 2023 are illustrated in Figures 3 and 4, respectively. These results align with ecosystems where seasonal variations play a pivotal role in vegetation dynamics, particularly in regions with pronounced climatic seasonality (Stahl and McColl 2022). Figure 3 shows relatively low EVI values during winter, ranging from −0.04 to 0.52, reflecting reduced vegetation health due to limited rainfall and soil moisture. Minimal rainfall values, particularly in areas with lower EVI, emphasize the impact of water scarcity on vegetation. Winter temperatures are stable yet cooler (9.84 °C to 13.95 °C), limiting photosynthesis, as seen in similar studies on winter vegetation responses in protected areas (Gui et al. 2019). Soil moisture is consistently low (0.39 to 0.47), further restricting water availability, which is essential for winter vegetation survival (Rasheed et al. 2022). In contrast, Figure 4 reveals higher EVI values in summer, ranging from −0.10 to 0.80, indicative of enhanced vegetation health driven by increased rainfall and favourable temperatures. Rainfall peaks at 391.79 mm in 2021, directly supporting vegetation growth, a pattern commonly observed in regions where seasonal rainfall variations significantly influence vegetation productivity (Weltzin et al. 2020). Temperatures rise to between 14.15 °C and 22.06 °C, fostering a conducive environment for vegetation productivity. Soil moisture levels increase as well (0.38 to 0.45), reflecting better water availability in summer, consistent with seasonal cycles of surface soil moisture that enhance vegetation vigor across ecosystems (Stahl and McColl 2022).

A comparison between Figures 3 and 4 highlights the seasonal variability in vegetation health and environmental drivers. EVI values consistently increase in summer, underlining the role of rainfall and temperature as primary factors in supporting vegetation during warmer months. Enhanced rainfall distribution in summer correlates with higher EVI regions, while elevated soil moisture contributes to robust vegetation. These findings are consistent with studies on vegetation response to seasonal rainfall and temperature changes across similar ecosystems (Seneviratne et al. 2010; Walter 2018).

The results underscore the critical influence of rainfall, temperature, and soil moisture on vegetation dynamics within the Cradle Nature Reserve, highlighting the importance of these factors in seasonal ecosystem management. This aligns with broader research conducted by Guo et al. (2021), which emphasizes the reliance of vegetation growth on

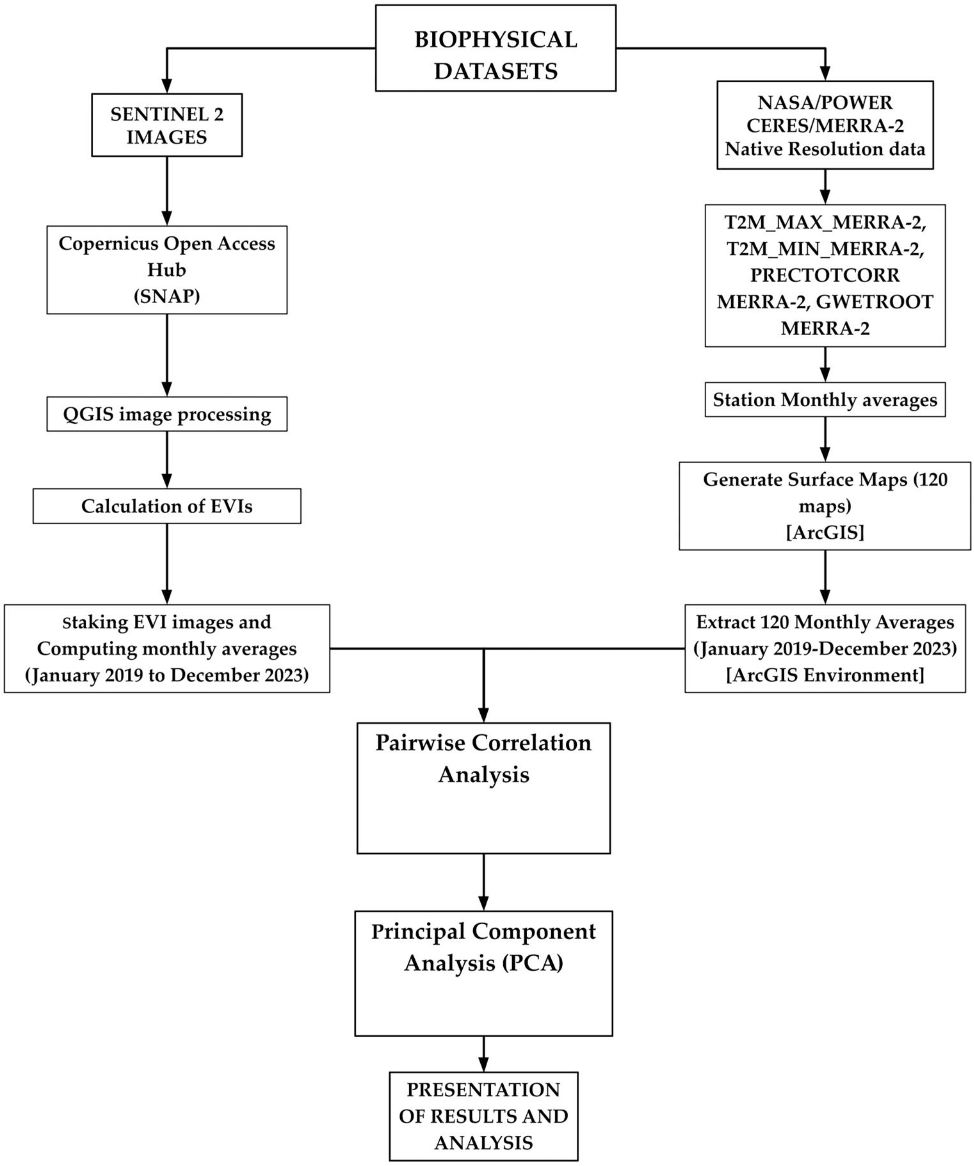

Figure 2. Schematic of workflow for data collection, processing, EVI computation, surface map generation, extraction of data statistics, pairwise correlation analysis, PCA, and results analyses.

seasonal water availability in subtropical regions, where variations in temperature and precipitation play key roles in ecosystem productivity. Continuous monitoring of these climatic factors is essential for adaptive management strategies in protected ecosystems.

3.2. Trend analysis of climatic variables and vegetation health indicators in the Cradle Nature Reserve (2019–2023)

Figure 5 illustrates the monthly trends for rainfall and EVI from January 2019 to December 2023, along with linear regression lines, while Figure 6 presents the monthly

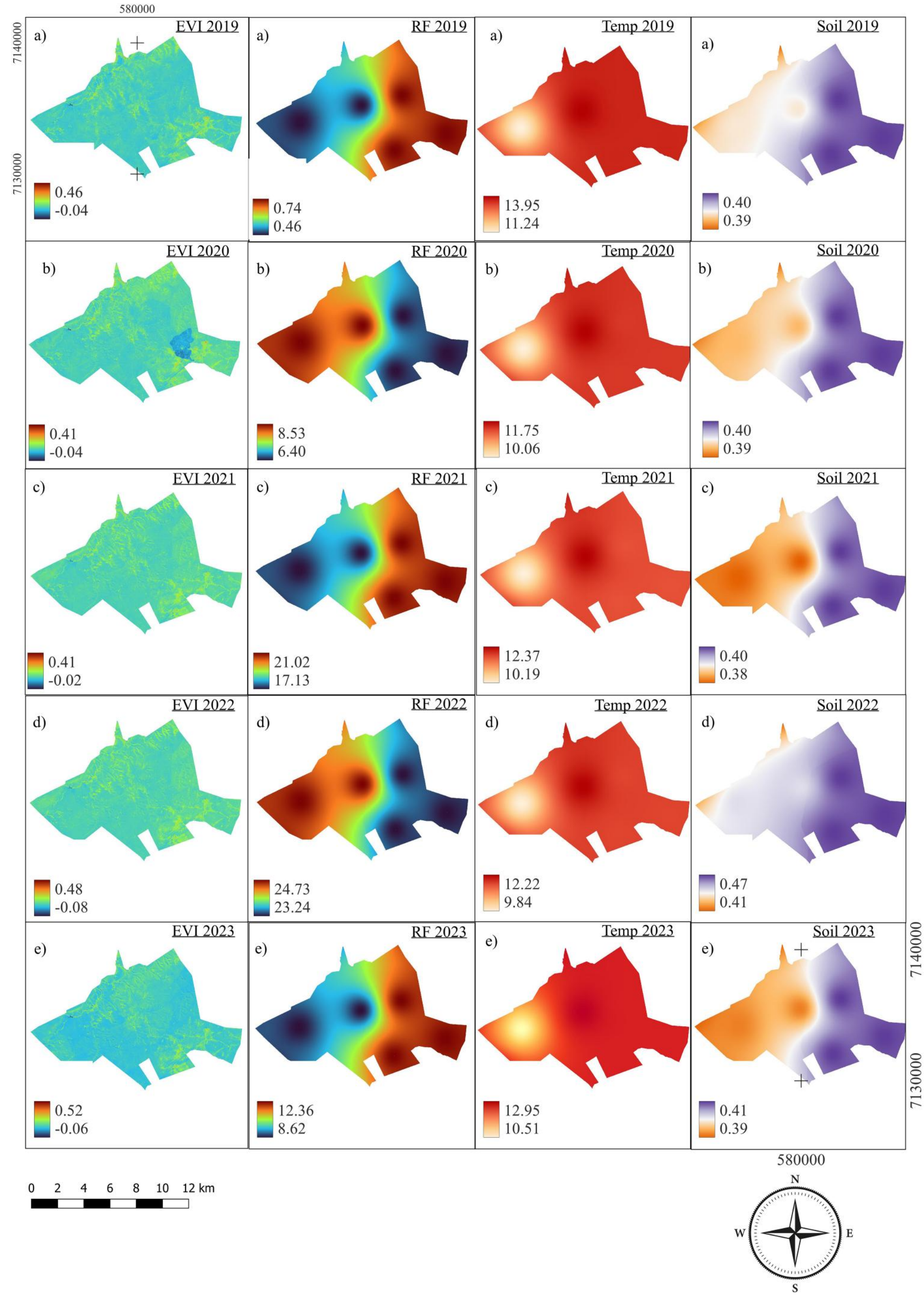

Figure 3. Winter spatial distribution of EVI, rainfall (RF), temperature (temp), and soil moisture (soil) in the Cradle Nature Reserve (2019–2023).

trends for temperature, EVI, and soil moisture over the same period. The rainfall trendline in Figure 5, represented by the equation $y = -0.0606x + 56.581$, indicates a gradual decrease in rainfall over time, as suggested by the negative coefficient (-0.0606).

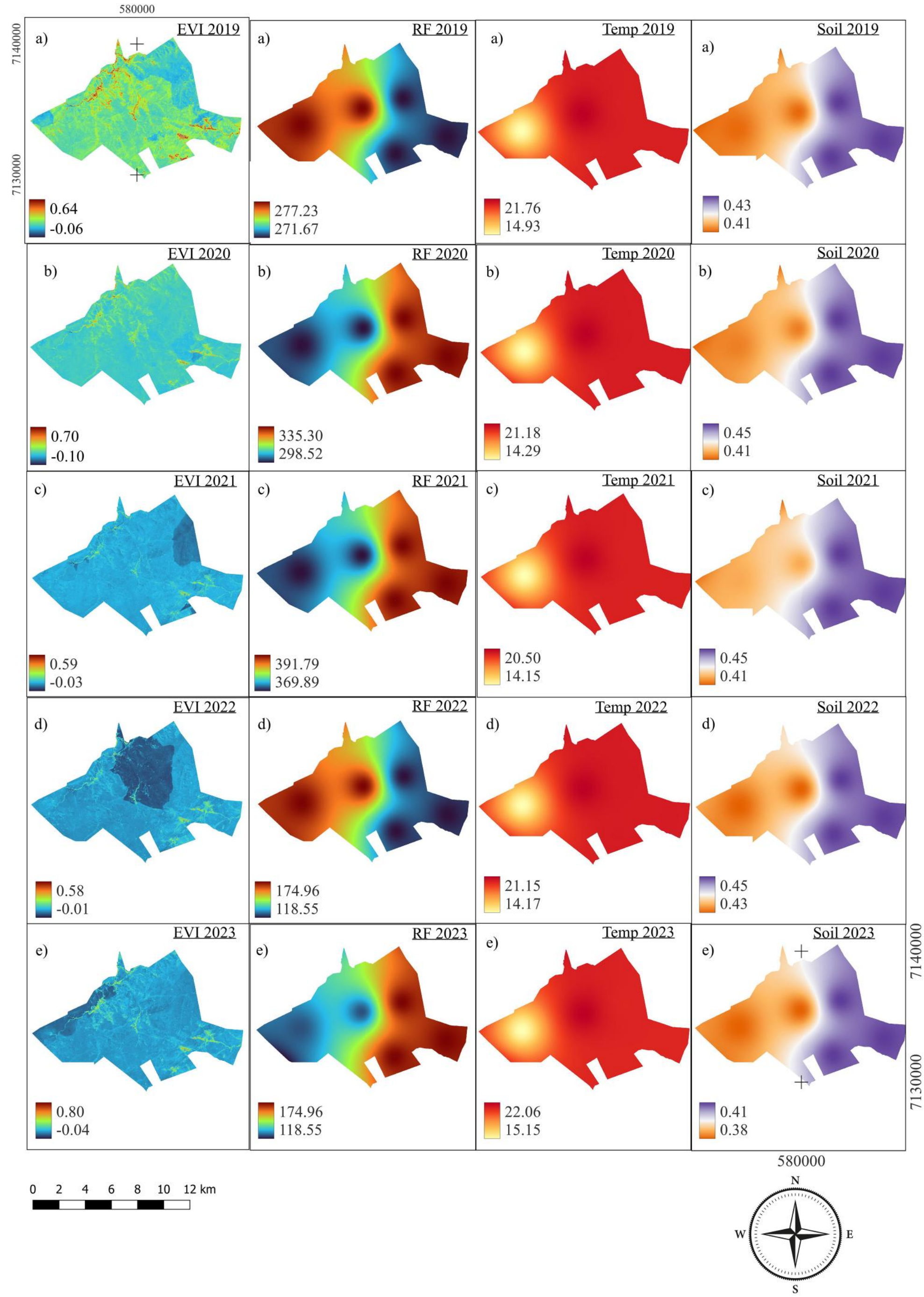

Figure 4. Summer spatial distribution of EVI, rainfall (RF), temperature (temp), and soil moisture (soil) in the Cradle Nature Reserve (2019–2023).

The y-intercept (56.581) represents the baseline rainfall level at the start of the study period. This trend suggests that rainfall in the study area is gradually declining, potentially affecting vegetation health and ecosystem resilience. Similar patterns are observed in studies of hydrological responses to climate change, such as in the Hanjiang River Basin,

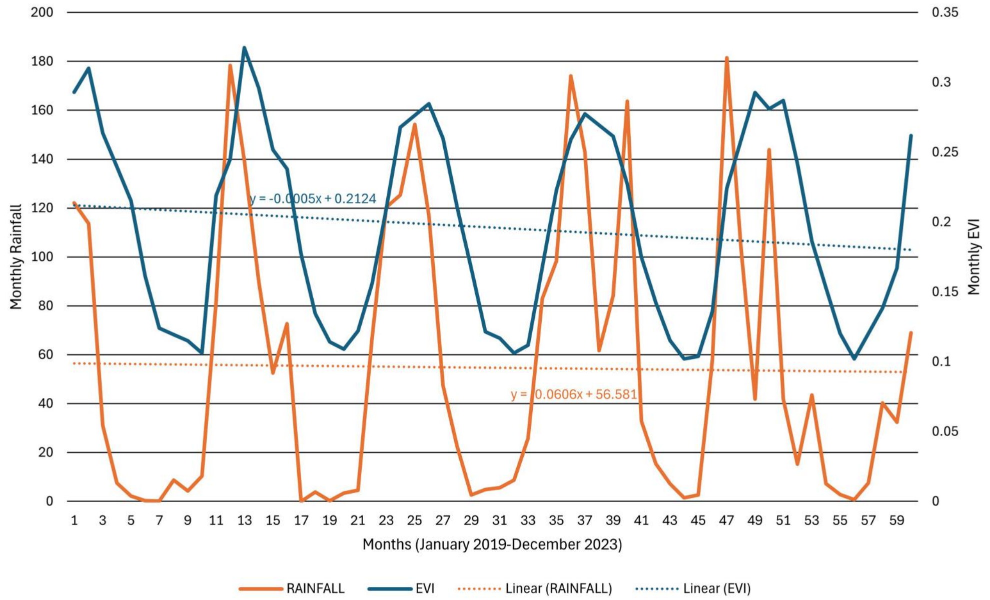

Figure 5. Monthly rainfall and enhanced vegetation index (EVI) trends with linear regression (January 2019–December 2023).

where projections indicate that climate and land use changes may lead to variable impacts on water availability and hydrological cycles, with outcomes highly dependent on carbon emission levels (Yang et al. 2025). The EVI trendline in Figure 5, given by $y = -0.0005x + 0.212424$, also has a slightly negative coefficient (-0.0005), suggesting a marginal decrease in EVI over time. The initial EVI value of 0.2124 at the start of the period serves as a baseline. This minor downward trend in the EVI could imply a reduction in vegetation vigor or photosynthetic activity, potentially influenced by the observed decline in rainfall and shifts in other climatic factors. Research from the semi-arid Northern Cape region of South Africa underscores the importance of rainfall in determining vegetation productivity, where EVI values have been found to closely track rainfall patterns, while factors like fire and herbivory exert minimal effects (Tokura et al. 2016).

In Figure 6, the temperature trendline $y = -0.0048x + 17$ also shows a slight negative slope (-0.0048), indicating a gradual decrease in monthly temperature over the study period. The y-intercept of 17.3 represents the initial temperature value. This cooling trend may impact plant growth and productivity, as temperature is crucial to these processes. Research from urban ecosystems like Wuhan, China, shows that temperature fluctuations can alter ecosystem services, affecting vegetation health, biodiversity, and functions like air purification (Gui et al. 2019). Similarly, the soil moisture trendline in Figure 6, represented by $y = -0.0001x + 0.441$, shows a minimal negative slope (-0.0001), suggesting a very slight decrease in soil moisture content over time. The y-intercept (0.441) reflects the initial soil moisture level at the start of the period. Although the decrease is subtle, it may still impact vegetation, especially during dry seasons. Research on natural vegetation restoration in tropical karst areas of southwestern China shows that soil moisture plays a key role in supporting plant growth and ecosystem stability (B. Zhang et al. 2024).

The combined downward trends in rainfall, EVI, temperature, and soil moisture observed in Figures 5 and 6 suggest that the Cradle Nature Reserve may be experiencing subtle environmental changes with potential implications for vegetation health and

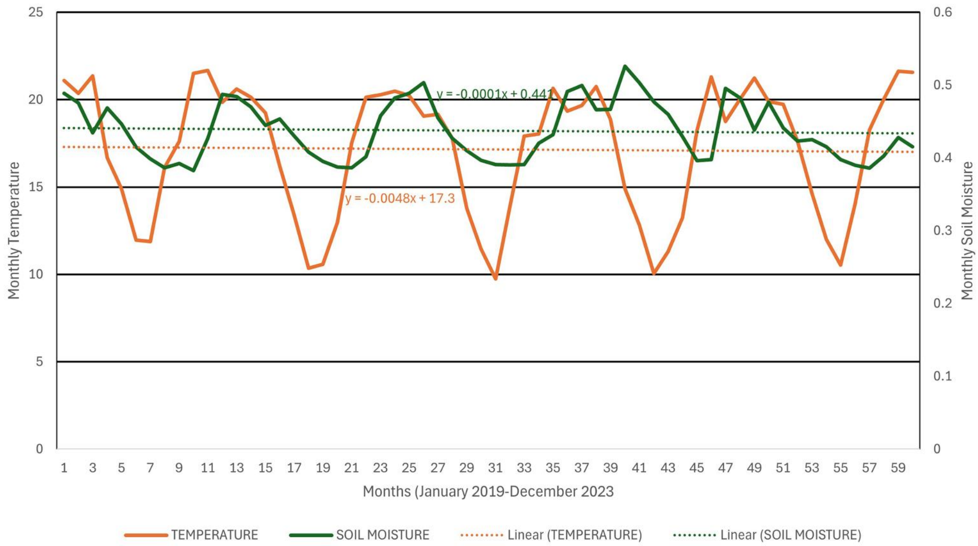

Figure 6. Monthly temperature and soil moisture trends with linear regression (January 2019–December 2023).

ecosystem dynamics. These findings underscore the importance of continuous monitoring and management of environmental parameters to support ecosystem resilience in the face of gradual climate changes. The trends observed here align with broader research on climate change impacts, such as the effects of climate variability on crop yields in China and ecosystem responses in other regions, underscoring the interconnectedness of climate factors and vegetation health (Aslam et al. 2022; Gui et al. 2019; Tokura et al. 2016; B. Zhang et al. 2024).

3.3. Statistical analysis of vegetation and climatic factors

Table 1(a) presents Pearson Correlation coefficients and their significance levels, indicating the strength and direction of the linear relationships among EVI, Rainfall, Temperature, and Soil Moisture. The EVI exhibits significant positive relationships with rainfall ($r = 0.70$), temperature ($r = 0.62$), and soil moisture ($r = 0.76$). This indicates that the EVI also tends to increase as these independent variables increase. The correlation coefficient between rainfall and soil moisture is 0.767, suggesting a strong positive relationship. Similarly, the correlation coefficient between rainfall and temperature is 0.576, showing a moderately positive relationship. This implies a connection between higher rainfall, higher soil moisture, and slightly higher temperatures. The correlation coefficient of 0.296 indicates a modest link between temperature and soil moisture. The significance levels (Sig. 1-tailed) show that all correlations are statistically significant ($p < 0.001$), except for the link between temperature and soil moisture, which is significant at the $p < 0.011$ level. This indicates that the correlations are highly unlikely to be the result of random chance. There is a probability of less than 1% (or 1.1%, specifically for temperature and soil moisture) that such significant correlations would happen without an actual relationship.

Table 1(b) presents a concise overview of a regression model where EVI is the dependent variable. The R (0.866) indicates a significant and positive correlation between the independent variables (rainfall, temperature, and soil moisture) and the dependent variable (EVI). The coefficient of determination (R^2) value of 0.75 indicates that the

Table 1. a.b: Correlation and regression analysis of EVI with climatic and soil variables (*n* = 60).

			EVI	Rainfall	Temperature	Soil Moisture
		Mean	0.20	54.73	17.15	0.44
		Std. Deviation	0.07	56.19	3.72	0.04
(a)	**Pearson Correlation**	EVI	1.00	0.71	0.62	0.76
		Rainfall	0.71	1.00	0.58	0.77
		Temperature	0.62	0.58	1.00	0.30
		Soil Moisture	0.76	0.77	0.30	1.00
	Sig. (1-tailed)	EVI	.	<0.001*	<0.001*	<0.001*
		Rainfall	0.00	.	0.00	0.00
		Temperature	0.00	0.00	.	0.01
		Soil Moisture	0.00	0.00	0.01	.
(b)	**R**	R^2	**Std. Error of the Estimate**		**Change Statistics**	
				R^2 Change	F Change	df1
	0.87	0.75	0.04	0.75	55.98	3.00
					Sig. F Change	df2
					<0.001*	56
					PRESS	Durbin-Watson
					0.084	0.76

*Statistically significant at 1%.
PRESS is a measure of a model's predictive accuracy, df denotes the number of values free to vary, F is a statistic for comparing model fits, and Sig. indicates the probability of the result occurring by chance.

independent variables used in the model can account for 75% of the variability seen in EVI. The adjusted coefficient of determination (R^2) (0.737) is a measure that considers the number of predictors in the model. It indicates significant explanatory power. The estimate's standard error (0.0356) is the average deviation of the observed values from the regression line. A lower score implies a more optimal fit of the model to the data. The F change (55.976) and Sig. F change (<0.001) values indicate that the regression model as a whole is statistically significant, with the independent variables demonstrating a good ability to predict EVI. PRESS (Predictive Residual Sum of Squares) quantifies the model's ability to make accurate predictions. A lower score (0.084) indicates a higher level of forecasting accuracy. The Durbin-Watson statistic of 0.76 suggests the presence of positive autocorrelation in the residuals. This is a concern because it can impact the dependability of the regression results. Overall, the model shows a strong and significant relationship between the independent variables and EVI, but the Durbin-Watson value suggests that the residuals are not independent, which could be a concern for the model's assumptions.

The ANOVA Table 2(a) indicates that the regression model is statistically significant in its whole, with an F-value of 55.976 and a p-value of less than 0.001. This shows that the model offers a significant explanation for the differences in the dependent variable. Upon scrutinising the coefficients in Table 2(b), we notice a mixture of favourable and unfavourable results: The coefficient for RAINFALL is 0.0, indicating that rainfall has no significant effect on the model. This is supported by a p-value of 0.444. The variable TEMPERATURE has a coefficient of 0.009 and a p-value of less than 0.001, suggesting a significant and positive impact on the dependent variable. The soil moisture coefficient is 1.2300, and its p-value is less than 0.001, indicating a significant and positive correlation with the dependent variable. The results may not be very useful in explaining the relationship between the variables because the minuscule amount of rainfall can have a pivotal impact in real-life scenarios. The Durbin-Watson statistic of 0.76, as shown in the table, suggests the existence of positive autocorrelation. This means that the residuals, or errors, are not independent. This statement challenges a basic assumption of regression analysis

Table 2. Statistical analysis of environmental factors influencing EVI.

(a)	ANOVA				
	Sum of Squares	df	Mean Square	F	Sig.
Regression	0.21	3.00	0.07	55.98	<0.001
Residual	0.07	56.00	0.00		
Total	0.28	59.00			

(b)	**Coefficients**				
	Unstandardised Coefficients		**Standardised Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta		
(Constant)	−0.49	0.09		−5.51	<0.001
RAINFALL	0.00	0.00	−0.10	−0.77	0.44
TEMPERATURE	0.01	0.00	0.47	5.50	<0.001
SOIL MOISTURE	1.23	0.19	0.70	6.42	<0.001

(c)	**95.0% Confidence Interval for B**		**Collinearity Statistics**	
	LB	UB	T	VIF
(Constant)	−0.66	−0.31		
RAINFALL	0.00	0.00	0.28	3.60
TEMPERATURE	0.01	0.01	0.62	1.62
SOIL MOISTURE	0.85	1.61	0.38	2.64

(d)	**Residuals Statistics**			
	Min	**Max**	**Mean**	**Stdev.**
Predicted Value	0.08	0.29	0.20	0.06
Residual	−0.07	0.06	0.00	0.03
Std. Predicted Value	−1.93	1.51	0.00	1.00
Std. Residual	−1.89	1.75	0.00	0.97

Note: The dependent variable of this study was EVI.

and could lead to inaccurate estimations. Although statistically significant, the temperature coefficient may not have a major practical impact. In conclusion, while the model demonstrates statistical significance, the practical significance and reliability of the findings are unknown due to the lack of significance in rainfall and potential issues with autocorrelation. It is critical to address these challenges before relying on the model for further interpretation or decision-making. These findings highlight the interconnectedness of climatic conditions and their collective influence on plants, underscoring the importance of comprehensive environmental research for ecological comprehension. Moreover, the existence of robust relationships necessitates further investigation of the environmental components by principal component analysis (PCA). The results of the multilinear regression analysis for Table 2(c) and (d) show that the constant term hurts the dependent variable EVI, as shown by the negative confidence interval. The rainfall coefficients are zero within the confidence range, indicating that they do not significantly predict EVI. Additionally, rainfall has a high variance inflation factor (VIF) of 3.6, suggesting multicollinearity issues.

The relationship between temperature and EVI is positive and statistically significant. A decent VIF value suggests that there is less concern about multicollinearity. The soil moisture variable is a strong EVI predictor. However, its variance inflation factor (VIF) of 2.6370 indicates the possibility of multicollinearity. The residual statistics show that the model's predictions are consistent, with a mean of zero and standard deviations within an acceptable range. However, Principal Component Analysis (PCA) might be better in this case because it reduces the number of dimensions, making the model simpler by turning correlated predictors into a smaller group of uncorrelated components. PCA components reduce multicollinearity by being orthogonal, preventing the new predictors in the regression model from being affected by multicollinearity. Principal Component Analysis (PCA) enhances model interpretation by identifying the most significant variance components, thereby facilitating comprehension of the fundamental structure of the data. In summary, PCA could provide a more robust and interpretable model, especially when multicollinearity is a concern, as indicated by the VIF values in the regression analysis. The use of PCA in analysing the Enhanced Vegetative Index (EVI) and its environmental factors is important due to the strong correlations and multicollinearity identified in the multilinear regression analysis. PCA's capacity to condense intricate and interconnected variables into major components simplifies the data, improving comprehensibility and uncovering the main elements that impact vegetation health. This approach not only simplifies the interrelationships between several variables but also helps to visually represent the data, promoting a more profound comprehension of how climatic factors such as rainfall, temperature, and soil wetness collectively influence vegetation. Therefore, principal component analysis (PCA) is essential for obtaining a deeper ecological understanding and guiding strategic decision-making in environmental research conducted at the Cradle Nature Reserve.

3.4. Principal component analysis (PCA)

Before conducting the PCA, all variables (EVI, rainfall, temperature, and soil moisture) were standardised to have a mean of zero and a standard deviation of one. This ensured that the differences in measurement scales did not bias the results, and that each variable contributed equally to the component extraction.

3.4.1. PCA suitability tests

To assess the appropriateness of applying Principal Component Analysis (PCA) to the dataset, we conducted Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, see Table 3. Bartlett's test yielded a chi-square value of 156.78 with 6 degrees of freedom and a p-value < 0.0001, indicating statistically significant correlations among variables. This confirms that the variables are sufficiently interrelated to justify the use of PCA. The overall KMO value was 0.581, which is slightly below the commonly accepted threshold of 0.60, suggesting mediocre sampling adequacy. However, individual KMO values for EVI (0.65) and rainfall (0.67) were acceptable, while soil moisture (0.52) and temperature (0.46) were marginal. Despite the low overall score, the KMO values support cautious application of PCA, particularly given the exploratory nature of the study and the acceptable Bartlett's test results.

3.4.2. Descriptive statistics of environmental variables

Table 4 provides descriptive statistics for Enhanced Vegetation Index (EVI), rainfall, temperature, and soil moisture, along with their respective means, ranges, and standard deviations. The EVI ranges from 0.10 to 0.32, with a mean of 0.20 and a standard deviation of

Table 3. Bartlett's Test of sphericity and Kaiser-Meyer-Olkin (KMO) sampling adequacy results for PCA suitability.

Test	Value	Interpretation
Bartlett's Chi-square (df = 6)	156.78	Significant correlation between variables ($p < 0.0001$)
Kaiser-Meyer-Olkin (Overall KMO)	0.581	Marginal sampling adequacy
Individual KMO – EVI	0.65	Acceptable
Individual KMO – Rainfall	0.672	Acceptable
Individual KMO – Temperature	0.464	Poor
Individual KMO – Soil Moisture	0.522	Marginal

Table 4. Descriptive statistics of environmental variables affecting EVI ($n = 60$).

Variable	Min	Max	Mean	Std. deviation
EVI	0.10	0.32	0.20	0.07
Rainfall	0.02	181.45	54.73	56.19
Temperature	9.75	21.66	17.15	3.72
Soil Moisture	0.38	0.53	0.44	0.04

Table 5. Eigenvalues, explained variance, and cumulative variability from PCA.

Eigenvalues	F1	F2	F3	F4
Eigenvalue	2.88	0.72	0.29	0.10
Variability (%)	72.12	17.96	7.30	2.62
Cumulative (%)	72.12	90.08	97.38	100.00

0.07, indicating moderate vegetation density and relatively consistent conditions across the study area. Rainfall exhibits substantial variability, ranging from 0.02 to 181.45 mm with a standard deviation of 56.19 mm, reflecting the intermittent precipitation patterns typical of the region. Temperature and soil moisture show moderate variability as well, with temperature ranging from 9.75 °C to 21.66 °C (mean = 17.15 °C) and soil moisture between 0.38 and 0.53 (mean = 0.44).

3.4.3. Component retention, Eigenvalues, and scree plot analysis

To further assess the structure and underlying patterns among these environmental variables, a Principal Component Analysis (PCA) was performed. The PCA extracted four principal components (F1 to F4), with eigenvalues and explained variability presented in Table 5. The scree plot in Figure 7 illustrates the magnitude of each component's eigenvalue and the cumulative variance explained.

Component retention was guided by a combination of the Kaiser criterion (eigenvalues > 1), cumulative variance threshold (≥80%), and scree plot analysis. According to the Kaiser criterion, only F1 was retained. However, given that F1 and F2 together account for over 90% of the total variance, and the scree plot (Figure 7) shows a sharp decline after the second component, F1 and F2 were considered the dominant explanatory factors. For completeness and exploratory interpretation, F3 and F4 were retained as they contributed to capturing minor yet potentially meaningful residual variation, bringing the cumulative variance explained to 100%.

3.4.4. Interpretation of principal components

Given the presence of strong correlations among environmental variables—particularly between rainfall, soil moisture, and temperature, Principal Component Analysis (PCA) was employed to address potential multicollinearity and reduce data dimensionality. Multicollinearity can distort the reliability of statistical models and obscure the interpretation of individual variable effects. By transforming the correlated variables into a set of orthogonal (uncorrelated) principal components, PCA ensures that each component captures a distinct source of variance. This transformation improves the statistical robustness, interpretability, and predictive utility of subsequent analyses, such as regression modeling.

The PCA results reveal that F1 and F2 are the most influential components, together accounting for 90.08% of the total variance in the dataset. F1, with an eigenvalue of 2.885, explains 72.12% of the variability and is strongly associated with rainfall and soil moisture, highlighting water availability as the dominant environmental factor influencing vegetation health. F2, with an eigenvalue of 0.718, explains an additional 17.96% and is

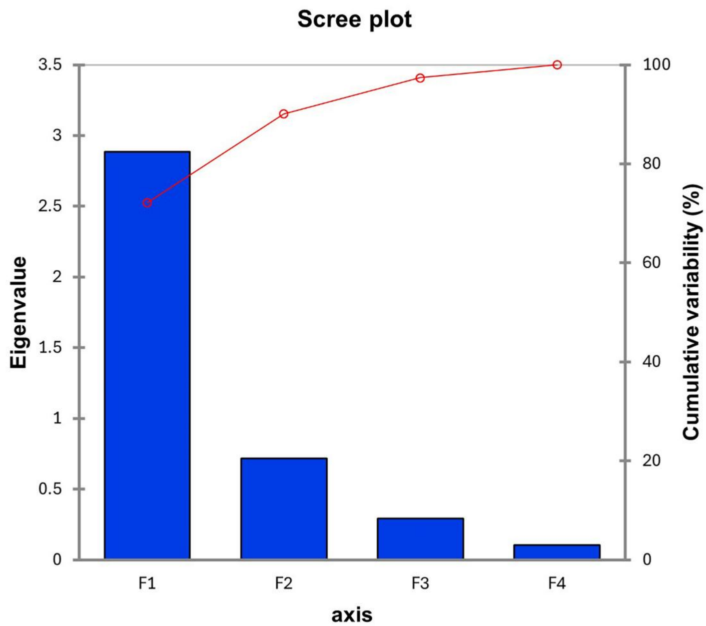

Figure 7. Scree plot of principal component eigenvalues.

primarily aligned with temperature, emphasizing its role in driving evapotranspiration and seasonal vegetation stress. The clarity offered by this orthogonal structure strengthens ecological interpretation and enhances the applicability of the framework in future vegetation-climate interaction studies.

Components F3 and F4, although explaining smaller portions of variance (7.30% and 2.62%, respectively), were retained to evaluate potential latent patterns and finer-scale variability. F3 exhibited notable associations with rainfall and EVI, capturing residual variability not explained by the dominant components F1 and F2, while F4 was mainly aligned with soil moisture, possibly reflecting localised moisture retention effects. Although their eigenvalues were considerably lower (0.29 for F3 and 0.10 for F4), these components contribute additional insight into interactions between EVI, soil moisture, and temperature under specific conditions. This interpretation aligns with findings by Bradford et al. (2019), who emphasised the importance of rainfall and soil moisture in sustaining vegetation productivity in water-limited ecosystems, and Finger-Higgens et al. (2022), who demonstrated how temperature variability significantly influences vegetation health through its effects on evapotranspiration and stress during extreme conditions.

Table 6 provides insights into the relationships between factors (F1, F2, F3, F4) and environmental variables (EVI, Rainfall, Temperature, and Soil Moisture), breaking down the strength of associations between each factor and the original environmental variables. Factor 1 (F1) shows strong positive loadings with Rainfall (0.53) and Soil Moisture (0.5), indicating that F1 primarily represents the combined influence of water availability on vegetation health. This finding is consistent with previous studies, including the work of Matsushita et al. (2007), which emphasised that water availability is one of the most critical factors influencing vegetation productivity. Matsushita et al. (2007) demonstrated that in regions where water is a limiting resource, variations in water supply have a direct impact on vegetation growth and overall ecosystem dynamics, making it a key determinant of vegetation productivity. Similarly, the strong loadings of F1 on rainfall and soil

Table 6. Factor loadings and variable correlations in environmental data analysis.

Eigenvectors				
Factors	F1	F2	F3	F4
EVI	0.54	−0.01	−0.69	−0.49
Rainfall	0.53	−0.10	0.72	−0.43
Temperature	0.42	0.82	0.04	0.40
Soil Moisture	0.50	−0.57	−0.06	0.65
Correlations between variables				
EVI	0.92	−0.01	−0.37	−0.16
Rainfall	0.91	−0.08	0.39	−0.14
Temperature	0.71	0.69	0.02	0.13
Soil Moisture	0.85	−0.48	−0.03	0.21

moisture in this study underscore the same principle, showing that these factors directly impact vegetation health, as reflected by high correlations with EVI (0.92 for F1 and 0.91 for Rainfall, and 0.85 for Soil Moisture). On the other hand, Factor 2 (F2) has a high loading on Temperature (0.82), suggesting that temperature fluctuations have a distinct yet significant role in influencing vegetation.

Building on insights from studies in arid and semi-arid regions, temperature plays a significant role in influencing soil moisture retention and photosynthetic rates, thereby indirectly affecting vegetation productivity and overall ecosystem health (Zhou et al. 2022). The biplot of variables (Figure 8) visually reinforces this understanding, showing the relationships between environmental factors (Temperature, Rainfall, EVI, and Soil Moisture) along the primary axes, F1 and F2, which together explain 90.08% of the total variance. Figure 8 provides a biplot illustrating how environmental variables cluster along the first two principal components. Rainfall, soil moisture, and EVI group closely along the F1 axis, highlighting their strong interrelationships and collective contribution to water availability. In contrast, temperature aligns with the F2 axis, confirming its distinct role as a separate driver of vegetation dynamics. This spatial clustering supports the interpretation of F1 as representing water availability and F2 as thermal stress

With F1 accounting for 72.12% and F2 for 17.96% of the total variance, the biplot clearly shows that temperature is most strongly associated with F2, indicating its independent influence on vegetation through physiological mechanisms such as photosynthesis regulation and moisture retention. Meanwhile, the strong loading of rainfall, EVI, and soil moisture on F1 underscores the dominant role of water availability in supporting vegetation productivity. The correlation patterns further reinforce these relationships, with temperature showing a strong correlation (0.69) with F2, highlighting its unique contribution to vegetation health under varying climatic conditions (Zhou et al. 2022). Together, these findings present a comprehensive understanding of how water availability and temperature interact as primary determinants of vegetation dynamics within the study ecosystem.

Table 7 provides the contributions and squared cosines of environmental variables (EVI, rainfall, temperature, and soil moisture) across four principal components (F1, F2, F3, F4), highlighting the extent to which each factor accurately represents the variables. The squared cosine values close to 1 indicate strong representation by a factor, while values near 0 suggest weak representation. F1 strongly represents EVI (0.84) and rainfall (0.82), confirming the dominant role of water availability in vegetation health, as noted by Bradford et al. (2019), which emphasises rainfall and soil moisture as primary factors in sustaining vegetation productivity. Soil moisture also has a strong representation in F1 (0.72), further underscoring the importance of water-related factors in vegetation health.

F2 primarily captures the influence of temperature, as shown by its high squared cosine value (0.67), indicating that temperature is a key driver in vegetation dynamics

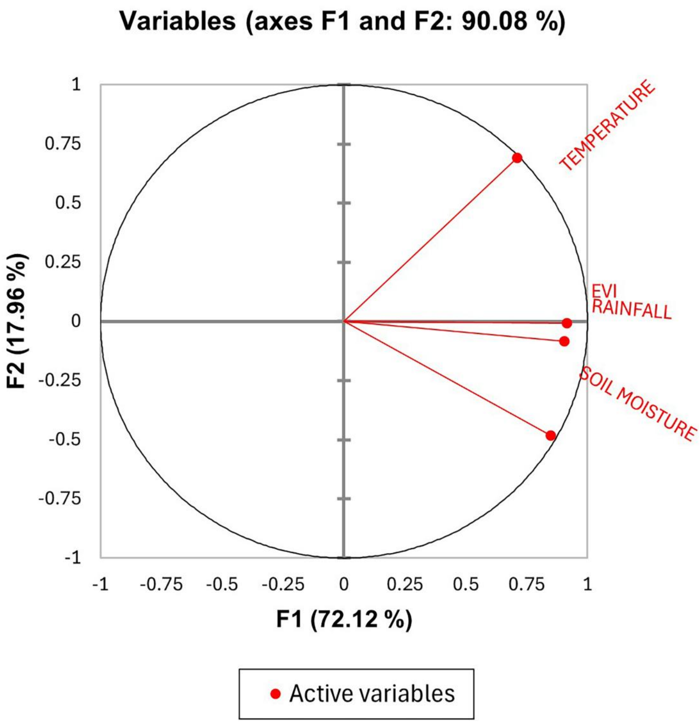

Figure 8. Biplot of variables and the most influential factors F1 and F2.

Table 7. Variable contributions and squared cosines in principal component analysis.

Contributions of the variables (%)				
Factors	F1	F2	F3	F4
EVI	29.03	0.01	46.99	23.97
Rainfall	28.45	0.96	52.48	18.11
Temperature	17.48	66.65	0.13	15.74
Soil Moisture	25.03	32.38	0.41	42.18
Squared cosines of the variables				
EVI	0.84	0.00	0.14	0.03
Rainfall	0.82	0.01	0.15	0.02
Temperature	0.50	0.48	0.00	0.02
Soil Moisture	0.72	0.23	0.00	0.04

through its impact on evapotranspiration and plant stress, particularly in extreme conditions, as supported by Finger-Higgens et al. (2022). F2 also moderately represents soil moisture (0.23), suggesting that temperature and moisture interact to influence vegetation health, especially during seasonal extremes. F3 contributes to the variability of rainfall (52.48%) and EVI (46.99%), showing that high rainfall positively influences vegetation indices, even when other environmental factors are less prominent. This pattern aligns with research findings by B. Zhang et al. (2021), which demonstrate the positive effects of abundant rainfall on vegetation health. In contrast, F4 has moderate contributions from soil moisture (42.18%) and EVI (23.97%), reflecting the supportive role of soil moisture in maintaining vegetation health, particularly when other conditions, like temperature, are less extreme.

In summary, F1 and F2 emerge as the primary components influencing vegetation dynamics, with F1 capturing water availability factors (rainfall and soil moisture) and F2

Table 8. Bootstrapped PCA loadings summary.

Variable	F1 Mean	F1 CI	F2 Mean	F2 CI	F3 Mean	F3 CI	F4 Mean	F4 CI
EVI	0.91	(0.88, 0.93)	−0.01	(−0.05, 0.03)	−0.37	(−0.42, −0.32)	−0.16	(−0.20, −0.11)
Rainfall	0.91	(0.87, 0.93)	−0.08	(−0.12, −0.03)	0.39	(0.34, 0.45)	−0.14	(−0.18, −0.09)
Temperature	0.7	(0.66, 0.73)	0.69	(0.65, 0.72)	0.02	(−0.03, 0.06)	0.13	(0.08, 0.18)
Soil Moisture	0.85	(0.81, 0.88)	−0.48	(−0.53, −0.44)	−0.03	(−0.08, 0.02)	0.21	(0.17, 0.25)

representing temperature. This analysis aligns with existing literature on the importance of rainfall, soil moisture, and temperature in regulating vegetation health, highlighting these as the dominant drivers in this study area.

3.4.4.1. Bootstrapped sensitivity analysis. To assess the robustness of the PCA results, a bootstrapped sensitivity analysis was conducted using 1,000 resamples (see Table 8). This analysis evaluated the stability of factor loadings for the key environmental variables across the four principal components. The results confirmed that loadings for the dominant component F1 remained consistently strong for EVI (mean = 0.91, 95% CI: 0.88–0.93), rainfall (mean = 0.91, CI: 0.87–0.93), and soil moisture (mean = 0.85, CI: 0.81–0.88), reinforcing the interpretation that water-related variables are the primary drivers of vegetation dynamics in the Cradle Nature Reserve. Similarly, temperature consistently aligned with F2 (mean = 0.69, CI: 0.65–0.72), affirming its role as an independent driver of thermal stress and evapotranspiration. Although F3 and F4 exhibited more variability, they retained coherent loadings and contributed to capturing finer-scale residual interactions among the variables.

These findings indicate that the PCA structure is statistically robust across sampling variations, and that the associations between environmental variables and their respective principal components are stable, interpretable, and meaningful. While spatial autocorrelation was not explicitly incorporated within the PCA framework, we addressed spatial heterogeneity through the generation and analysis of high-resolution surface maps for EVI and climatic variables (Sections 3.1 and 3.2). These spatial analyses provided contextual support for interpreting the PCA results, revealing localised ecological dynamics and spatial patterns in vegetation responses. For future work, we recommend the integration of spatially explicit PCA methods, such as geographically weighted PCA, to directly capture spatial dependencies and improve the spatial interpretability of component-based analyses in ecological studies.

4. Discussion

Within the Cradle Nature Reserve, a protected grassland ecosystem focused on managing game species, our analysis provides insights into the impact of key environmental drivers on vegetation health. The EVI demonstrates substantial positive associations with rainfall and soil moisture and a moderate correlation with temperature, indicating that these climatic factors play a critical role in maintaining vegetation health. This finding underscores the sensitivity of grassland ecosystems to variations in water availability and thermal conditions, which directly influence vegetation resilience and the food resources available for the reserve's wildlife (Zhong et al. 2010). The choice of rainfall, temperature, and soil moisture as the primary impact factors is based on their well-documented influence on vegetation dynamics in grassland ecosystems. Rainfall and soil moisture directly affect water availability for plants, which is a limiting factor in many ecosystems (Van den Hoof et al. 2018; Warter et al. 2021). Temperature impacts physiological processes like photosynthesis and evapotranspiration, particularly during extreme seasonal conditions (Derardja et al. 2024). Other environmental variables were considered but found to be less impactful in this context due to the specific climate and ecological characteristics of the Cradle Nature Reserve.

The statistical methods employed, including multilinear regression and Principal Component Analysis (PCA), were selected to provide a robust analysis of these interactions. PCA, in particular, was chosen over other dimensionality-reduction techniques because of its effectiveness in revealing underlying patterns in multivariate data by reducing data complexity while retaining significant information. By identifying the principal components (F1 and F2) that explain 90.08% of the variance, PCA enables us to highlight the primary environmental drivers influencing vegetation health while mitigating multicollinearity issues that can complicate other statistical methods (Chen et al. 2022; Greenacre et al. 2022). The PCA analysis reveals that F1, which likely represents the combined influence of rainfall and soil moisture, is the dominant factor impacting vegetation health. High correlations between F1 and EVI, rainfall, and soil moisture indicate that water availability is crucial for sustaining vegetative growth, which in turn supports the reserve's game species. F3, with its elevated EVI and rainfall levels, exemplifies how water availability drives strong vegetation health, while F2's low EVI and high temperatures indicate vegetation stress, likely caused by extreme heat. This highlights the susceptibility of vegetation to temperature fluctuations, especially during periods of limited moisture (Hopke 1992; Walter 2018).

The trend analysis of climatic variables over the study period (2019-2023) further supports these findings. As illustrated in Figures 5 and 6, both rainfall and soil moisture exhibit slight downward trends, indicating a potential reduction in water availability over time. The decline in rainfall (slope = −0.0606) and EVI (slope = −0.0005) underscores a gradual decrease in vegetation health, possibly influenced by the declining availability of water. This is consistent with other studies, such as in the Hanjiang River Basin, which have demonstrated that reductions in rainfall and other hydrological shifts due to climate change can adversely impact vegetation resilience and ecosystem health (Yang et al. 2025). Additionally, the slight decrease in temperature observed over the period may also contribute to reduced growth, as (Derardja et al. 2024). These combined trends highlight the importance of continuous monitoring to manage ecosystem resilience in the face of gradual climate changes.

The F2 component captures the independent effects of temperature and soil moisture, which are critical for understanding vegetation resilience in response to environmental stressors. The biplot visualization and eigenvector analysis further clarify these relationships, with F2 distinguishing the distinct roles of temperature and soil moisture in plant adaptation. The inverse relationship between soil moisture and both components is particularly noteworthy, suggesting that water scarcity poses a significant challenge for vegetation and can impact the entire trophic hierarchy within the reserve (Abonyi et al. 2022; Finger-Higgens et al. 2022).

The substantial squared cosine values in factor analysis confirm the importance of rainfall and EVI within Factor 1, reinforcing their critical impact on vegetation health. F4, which demonstrates high soil moisture levels conducive to plant growth, and F3, where vegetation thrives despite lower moisture, illustrate the resilience of the ecosystem. These findings indicate that while rainfall and soil moisture are primary drivers, the ability of vegetation to adapt under varying conditions is crucial for the stability of the ecosystem (Li et al. 2020; Teague and Kreuter 2020; Zaiontz 2024). The insights gained from the correlation analysis also emphasise the strong relationships among rainfall, soil moisture, and EVI. The correlation coefficients indicate significant positive relationships between EVI and all three environmental factors, with soil moisture showing the strongest correlation ($r = 0.76$), followed closely by rainfall ($r = 0.70$) and temperature ($r = 0.62$). The high coefficient of determination ($R^2 = 0.75$) from the regression model further confirms that these factors collectively account for a substantial portion of the variability in EVI, underscoring their importance as primary drivers of vegetation health.

The combined trend analysis, PCA, and correlation findings underscore the interconnectedness of climatic factors, particularly rainfall, temperature, and soil moisture, in influencing vegetation health within the Cradle Nature Reserve. These results highlight the need for continuous environmental monitoring to support adaptive management practices, ensuring the resilience of the ecosystem in response to gradual changes in climatic conditions. This study provides a foundation for similar assessments in other grassland ecosystems, offering insights that can inform sustainable land management and conservation strategies (Milazzo et al. 2023; Park et al. 2021; Wang et al. 2021; S. Zhang et al. 2022).

5. Conclusion

This study investigated the environmental drivers of vegetation health in the Cradle Nature Reserve using Enhanced Vegetation Index (EVI) time series and Principal Component Analysis (PCA) from 2019 to 2023. Aligned with the study's objectives, the findings revealed that rainfall and soil moisture, captured in PCA's Factor 1 (F1), are the dominant drivers of vegetation growth, explaining over 72% of the variance. Temperature, represented in Factor 2 (F2), emerged as a secondary yet influential factor, primarily through its role in intensifying evapotranspiration and inducing thermal stress during dry seasons. These results highlight the utility of PCA in simplifying complex ecological datasets and clarifying the independent roles of closely interrelated climatic variables.

The practical implications of these findings are significant for land managers. Monitoring the spatio-temporal variability of rainfall and soil moisture can inform adaptive practices such as rotational grazing, controlled burning, and strategic reforestation. Likewise, temperature trends may serve as early warning indicators for drought stress, enabling proactive interventions to maintain ecosystem stability. To further enhance climate resilience, this study recommends the adoption of soil moisture retention techniques such as mulching and cover cropping, the restoration of riparian buffers, and the use of native drought-tolerant species in revegetation programs.

Despite its strengths, this study acknowledges several limitations that warrant consideration. The application of PCA assumes linear relationships among variables and depends on data standardisation, which may obscure important non-linear ecological interactions. Additionally, the spatial and temporal resolution of some input variables, particularly soil moisture, may limit the granularity and precision of the analysis. To enhance future vegetation-climate assessments, we recommend the use of higher-resolution datasets and the inclusion of additional environmental drivers, such as solar radiation, wind patterns, and land cover dynamics, which may offer deeper ecological insights. Moreover, to address spatial dependencies more explicitly, future studies should consider integrating spatially informed techniques, such as Geographically Weighted PCA, to improve the interpretability of component structures across heterogeneous landscapes. These enhancements would contribute to a more comprehensive and spatially robust understanding of vegetation responses to environmental change.

The adaptability of the proposed analytical framework extends its utility beyond the Cradle Nature Reserve. With appropriate local calibration, it can be applied to other protected or semi-arid landscapes to support biodiversity monitoring, ecosystem service evaluations, and land degradation mitigation under increasing climatic variability. Incorporating machine learning approaches and socio-economic variables in future studies will also strengthen the predictive capacity and relevance of vegetation monitoring for sustainable land-use planning.

A key contribution of this research is the development of a replicable analytical framework that integrates remote sensing data with multivariate statistical approaches to assess vegetation dynamics in protected grassland ecosystems. While many existing studies struggle with multicollinearity among climatic variables, this study demonstrates how PCA effectively disentangles these relationships, thereby offering methodological improvements for future ecological monitoring and decision-making.

Authors contributions

Conceptualisation: C.M and P.M, Methodology: C.M and P.M, Validation: C.M., pm, E.G., Formal analysis: C.M., pm, E.G., Investigation: C.M., pm, E.G., Writing-Original Draft: C.M., pm, E.G., Writing-Review & Editing: C.M., pm, E.G., J.H.

Disclosure statement

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Data availability statement

The corresponding author can provide the datasets used in the current study upon reasonable request.

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