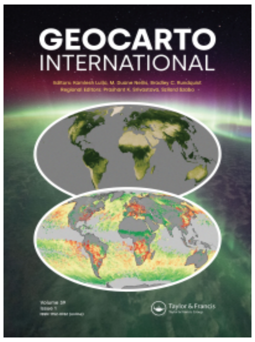

Taylor & Francis
Taylor & Francis Group

Geocarto International

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tgei20

Modelling topographic influences on vegetation vigour in the Cradle Nature Reserve, Gauteng province, South Africa

Charles Matyukira, Paidamwoyo Mhangara & Eskinder Gidey

To cite this article: Charles Matyukira, Paidamwoyo Mhangara & Eskinder Gidey (2024) Modelling topographic influences on vegetation vigour in the Cradle Nature Reserve, Gauteng province, South Africa, Geocarto International, 39:1, 2395313, DOI: 10.1080/10106049.2024.2395313

To link to this article: https://doi.org/10.1080/10106049.2024.2395313

Published online: 28 Aug 2024.

GEOCARTO INTERNATIONAL
2024, VOL. 39, NO. 1, 2395313
https://doi.org/10.1080/10106049.2024.2395313

Modelling topographic influences on vegetation vigour in the Cradle Nature Reserve, Gauteng province, South Africa

Charles Matyukira[a], Paidamwoyo Mhangara[a] and Eskinder Gidey[a,b]

[a]School of Geography, Archaeological & Environmental Studies, Faculty of Science, University of the Witwatersrand, Johannesburg, South Africa; [b]Department of Land Resources Management and Environmental Protection (LaRMEP), College of Dryland Agriculture and Natural Resources, Mekelle University, Mekelle, Tigray, Ethiopia

ABSTRACT

The study explores topography and vegetation changes in the Cradle Nature Reserve's landscape, which is characterised by interconnected water infiltration and drainage patterns with geological features such as sinkholes, using indices such as the Enhanced Vegetation Index (EVI), the Topographic Position Index (TPI), the Topographic Ruggedness Index (TRI), and the Topographic Wetness Index (TWI). The high-resolution satellite images, including Sentinal-2A, the Shuttle Radar Topography Mission Digital Elevation Model, and NASSA Power Rainfall, Temperature, and Ground Wetness in the Root Zone-Modern Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), were analysed using advanced statistical models. The software tools Stata/SE v.13.1, QGIS v.3.36, and ArcGIS desktop v. 10.8.2 were utilised for this analysis. The results emphasise the significance of incorporating topography into ecological research and highlight the necessity of focused conservation initiatives to address habitat suitability and erosion risk in challenging landscapes. Specifically, the results show that the Enhanced Vegetation Index (EVI) has a strong negative correlation with the Topographic Position Index (TPI) ($R^2 = 0.95$), indicating that TPI usually decreases as EVI increases. This relationship is influenced by landscape features such as sinkholes and depressions, which impact plant health. Additionally, the strong positive relationship between EVI and percentage slope gradient ($R^2 = 0.85$) offers valuable insights for environmental studies and land management practices. Additionally, TRI shows a negative correlation with EVI ($R^2 = 0.94$), emphasising the impact of terrain ruggedness on vegetation density. TWI analysis strongly correlates with slope gradients ($R^2 = 0.96$), highlighting topography's role in hydrological dynamics. Despite these insights, we acknowledge limitations such as scale dependency and the inability to capture fine terrain details. Integrating topographic information into ecological assessments and land management strategies is crucial for promoting

ARTICLE HISTORY
Received 13 June 2024
Accepted 16 August 2024

KEYWORDS
EVI; TWI; TPI; TRI; slope gradients; Cradle Nature Reserve; South Africa

CONTACT Paidamwoyo Mhangara paida.mhangara@wits.ac.za

conservation, sustainable practices, landscape ecology understanding, and biodiversity preservation decision-making.

HIGHLIGHTS

- EVI strongly correlates negatively with TPI, suggesting how plant health is impacted by topographic positioning.
- The negative correlation between TRI and EVI emphasises how terrain ruggedness impacts vegetation density.
- The TWI analysis highlights how slope gradients influence moisture distribution and hydrological dynamics.
- Efficient topographic information is necessary for understanding ecosystem conservation and sustainable management.

1. Introduction

The effects of topographic influences on vegetation health are one of the most significant environmental issues that have accelerated the phenomenon of land degradation in Africa (Gidey et al. 2023). For instance, the management and research endeavours in the Cradle Nature Reserve, situated in South Africa, encounter the urgent matter of comprehending and resolving the complex interrelationships among vegetation dynamics, hydrology, and topography within the reserve's distinctive karst environment. The ecological system in question is distinguished by its intricate topography, in which variables including the distribution of moisture, the condition of the vegetation, and the ruggedness of the terrain have significant impacts on ecological processes (Berhanu and Bisrat 2018; Kopecký et al. 2021). The Topographic Wetness Index (TWI) and Enhanced Vegetation Index (EVI) are pivotal metrics that provide essential information regarding the distribution of vegetation and the availability of moisture throughout the terrain (Cantón et al. 2004; Kopecký et al. 2021). Nevertheless, habitat suitability, water runoff, and soil erosion are all impacted by slope gradients, which further complicates the management and conservation of this ecosystem (Wu et al. 2018; Talebi Khiavi and Mostafazadeh 2022). Additionally, the Topographic Position Index (TPI) and the Terrain Ruggedness Index (TRI) provide crucial information regarding the relative elevation and ruggedness of the terrain, thereby facilitating comprehension of hydrological processes and the characteristics of various landscapes (Jones et al. 2000; Różycka et al. 2017; Dilts et al. 2022; Al-Sababhah 2023). To safeguard the distinctive ecosystem services and biodiversity of the Cradle Nature Reserve, it is critical for management strategies to comprehend the synergies and trade-offs that exist among these indicators. Monitoring, evaluation, and management strategies must incorporate these elements to educate conservation efforts and guarantee this fragile karst ecosystem's long-term viability and resilience.

The interaction between wetness and vegetation, as expressed as TWI and the EVI, provides valuable information about the influence of topography on ecosystem dynamics (Cantón et al. 2004; Berhanu and Bisrat 2018; Kopecký et al. 2021). TWI is a metric that quantifies the impact of landform characteristics on the movement and storage of water (Berhanu and Bisrat 2018; Kopecký et al. 2021). Within the Cradle Nature Reserve, TWI plays a vital role in indicating the availability and distribution of moisture across the karst landscape. Interconnected water infiltration and drainage patterns characterise this landscape, which is closely tied to geological features like sinkholes and underground caves (Zhou and Beck 2008). In addition to TWI, EVI offers a quantitative evaluation of vegetation health and density, providing a way to analyse the spatial arrangement of plant communities in relation to topographic characteristics (Berhanu and Bisrat 2018; Kopecký et al. 2021). A thorough assessment of TWI and EVI indices leads to an understanding of how topographic factors influence vegetation dynamics in the karst environment. This includes the impact of wetness and vegetation on species composition, habitat suitability, and ecosystem resilience (Cantón et al. 2004; Kopecký et al. 2021). Within the Cradle Nature Reserve, the integration of TWI and EVI assessments elucidates the complex interactions between topography, hydrology, and vegetation within the karst landscape (Zhou and Beck 2008; Sharma 2010; Berhanu and Bisrat 2018; Allende-Prieto et al. 2024). High TWI values correspond to areas with enhanced moisture retention, often associated with depressions and valley bottoms where vegetation thrives due to increased water availability (Yang et al. 2020; Geremew et al. 2023). Conversely, low TWI values indicate drier upland areas with sparse or patchy vegetation (Cantón et al. 2004; Kopecký et al. 2021; Chipatiso 2023; Minh et al. 2024). EVI data further refine our understanding by quantifying the health and density of vegetation across varying topographic conditions, revealing how vegetation responds to moisture gradients and geological features characteristic of karst environments (Zhou and Beck 2008; Sharma 2010; Berhanu and Bisrat 2018). By harnessing the complementary information provided by TWI and EVI, conservation efforts in the Cradle Nature Reserve can prioritise areas of ecological significance, identify vulnerable ecosystems, and implement targeted management strategies to safeguard the unique biodiversity and ecosystem services supported by the karst landscape (Monz et al. 2021; Heštera et al. 2024; Thannoun and Ismaeel 2024).

The relationship between the TWI and the percentage slope gradients tells us a lot about how the landscape changes over time and how water moves through it (Wu et al. 2018; Talebi Khiavi and Mostafazadeh 2022). We observe a distinct pattern in landscape dynamics, where flat and level areas exhibit higher TWI values than sloping and steep terrain. This suggests that regions with minimal slope gradients can retain moisture more. As the steepness of slopes increases, the values of the TWI progressively decrease, indicating a decrease in water accumulation and an increase in the potential for runoff (Talebi Khiavi and Mostafazadeh 2022). Topography significantly influences the distribution of moisture and the occurrence of hydrological processes in karst landscapes (Zhou and Beck 2008; Sharma 2010; Xiao et al. 2023). Similar patterns in previous studies conducted in similar karst environments suggest that we can universally apply the TWI as a tool to understand landscape heterogeneity and guide land management and conservation strategies in karst regions (Liu et al. 2021; Talebi Khiavi and Mostafazadeh 2022). In addition, slope gradients have a significant impact on ecological processes in natural landscapes, including water runoff, soil erosion, nutrient cycling, microclimate dynamics, and landslide risks (Matsushita et al. 2007; Yang et al. 2020).

Increased inclines frequently enhance water runoff, leading to elevated soil erosion and sediment transportation. These processes have a significant impact on nutrient cycling, soil structure, and the overall health of the ecosystem (Toni Jo Smith et al. 2010; Wubie and Assen 2020; Dani et al. 2023). The movement of water across the terrain, influenced by the steepness of slopes, impacts the flow of streams, the replenishment of groundwater, and the creation of wetlands. Steeper slopes lead to faster runoff, while gentler slopes promote better water retention and infiltration (Wang et al. 2015; Yang et al. 2020; Dani et al. 2023). In addition, slopes impact local microclimates by affecting the amount of sunlight and moisture, affecting the distribution of vegetation, the composition of species, and the suitability of habitats. In addition, slopes have an impact on local microclimates by affecting the amount of sunlight and moisture, which in turn affects the distribution of vegetation, the composition of species, and the suitability of habitats (Cantón et al. 2004; Toni Jo Smith et al. 2010; Wubie and Assen 2020; Yang et al. 2020; Wagari and Tamiru 2021). Specific slope angles support diverse plant communities, which in turn contribute to the formation of vegetation zones, increased biodiversity, and varied habitats along gradients (Toni Jo Smith et al. 2010; Dani et al. 2023). The availability of nutrients is also impacted by the steepness of slopes, which in turn affects the growth patterns of plants and the dynamics of nutrient cycling (Wang et al. 2015). Furthermore, the inclination of a slope directly affects the likelihood of landslides, as steeper slopes are more susceptible to such occurrences. These landslides can have detrimental effects on the stability of vegetation and the structure of the soil (Toni Jo Smith et al. 2010; Wang et al. 2015; Wubie and Assen 2020; Yang et al. 2020; Dani et al. 2023). In addition, a slope's inclination directly affects the likelihood of landslides, as steeper slopes are more susceptible to such occurrences. Landslides, in turn, can disrupt the stability of vegetation and the structure of the soil (Yang et al. 2020).

Nevertheless, vegetation can alleviate this danger by securing the soil and diminishing erosion. Finally, the distribution of plant roots adjusts to the slope's incline, with species with shallow roots flourishing on steep slopes and trees with deep roots providing stability on more gradual slopes. This adaptation affects both the stability of the soil and the absorption of nutrients. References (Wubie and Assen 2020; Yang et al. 2020; Wagari and Tamiru 2021) support this information. The interconnected processes highlight the importance of incorporating topography into ecological studies, as they collectively shape ecosystems and enhance their ability to withstand and maintain stability over time. The interconnections between these processes highlight the importance of incorporating topography into ecological studies, as they collectively mold ecosystems and enhance their ability to withstand and maintain their long-term viability. The comprehensive understanding of erosion control and soil stability guides the efficient administration of these issues, which include a range of strategies that incorporate vegetation cover, water management, ecological restoration, land use planning, conservation priorities, and educational outreach (Raihan 2023; Zhang et al. 2023). An essential aspect of these efforts is acknowledging vegetation cover as a crucial factor in soil stabilisation, utilising its ability to improve water retention, decrease surface runoff, mitigate flood hazards, and establish riparian buffer zones (Wang et al. 2015; Wubie and Assen 2020). Techniques such as slope revegetation and terracing effectively tackle erosion challenges, while knowledge of EVI-slope relationships guides decision-making in land use planning and conservation priorities (Fasona et al. 2018). Educational outreach initiatives also raise community awareness about the critical importance of vegetation cover and promote the adoption of sustainable land use practices, ultimately supporting ecosystem resilience and sustainability (Stephenson 2019).

The Topographic Position Index (TPI) is a crucial tool in landscape analysis that determines the relative elevation of points in relation to their surrounding terrain using elevation data (Jones et al. 2000; Al-Sababhah 2023). TPI is a method that compares the elevation of each cell in a Digital Elevation Model (DEM) with the average elevation of the surrounding area. Positive values in TPI indicate higher positions, such as ridges. Conversely, negative values signify depressions, such as valleys, as indicated by references (Jones et al. 2000; Al-Sababhah 2023; Zhang et al. 2023). TPI is crucial in understanding the complex karst landscapes found in the Cradle Nature Reserve. It helps to unravel the hydrological complexities, including the balance of water, the movement of cold air, the effects of wind, soil erosion and deposition, and the suitability of habitats. Also, the fact that TPI is related to other topographic factors like the EVI, hillshade, aspect, TWI, and slope gradients makes it easier to describe larger areas. It shows how complexly landforms and ecosystem dynamics interact (Jones et al. 2000; Wang et al. 2015; Talebi Khiavi and Mostafazadeh 2022; Al-Sababhah 2023). Many studies, including those by Robinson et al. 2019, Wang et al. 2015, and W. Zhang et al. 2023, show that EVI and TPI are positively related. These studies show how changes in the height of the land affect the health and distribution of plants in a complex way.

However, using TPI has inherent limitations, notably its scale dependency, which introduces nuances in result interpretation (Jones et al. 2000; Al-Sababhah 2023). TPI computations depend on the size of the neighbourhood used to determine mean elevation, and variations in this parameter result in disparate TPI values and potentially skew the identification of specific landforms such as depressions or ridges (Jones et al. 2000; Al-Sababhah 2023). Additionally, while TPI provides a window into the relative positioning of points within their terrain context, it may fall short of capturing the intricacies of landform size and shape (Jones et al. 2000). TPI might not be able to tell the difference between different types of landforms, which could make it less useful for getting more detailed information about where plants are found (Jones et al. 2000; Al-Sababhah 2023), especially in karst environments with sinkholes, caves, and other complicated features. TPI is a key tool for determining how topography affects plant life in karst ecosystems. It works best when combined with other terrain analysis methods and used correctly at the right scales.

As quantified by the Terrain Ruggedness Index (TRI), topographic ruggedness is pivotal in understanding ecological dynamics and landscape characterisation (Różycka et al. 2017). TRI, defined as the mean of the absolute differences in elevation between a focal cell and its surrounding cells, provides valuable insights into the total elevation change across neighbouring cells (Amatulli et al. 2018; Dilts et al. 2022). Dilts et al. 2022 highlight the multifaceted relationship between TRI and ecological variables such as EVI, emphasising the need for researchers to consider various aspects of ruggedness, including elevation variability and aspect diversity in ecological applications. Moreover, Matsushita et al. 2007) demonstrated the feasibility of using TRI alongside vegetation indices like NDVI for mapping rugged terrain suitable for agricultural purposes, showcasing the practical relevance of TRI in land management studies.

Nevertheless, TRI has certain constraints. However, quantifying elevation changes may not accurately represent the intricate features of terrain morphology and microtopography (Różycka et al. 2017; Dilts et al. 2022). In addition, TRI may be susceptible to variations in cell size and resolution, which could impact the accuracy of its measurements, especially in regions with diverse terrain (Amatulli et al. 2018; Dilts et al. 2022). Although TRI has limitations, it is a valuable tool for assessing terrain roughness and understanding its impact on ecological processes and landscape management. Różycka et al. 2017 illustrate the range of TRI values observed in various terrains and landforms, highlighting its usefulness in comprehending changes in the landscape. Bradley et al. 2010 have shown that incorporating TRI into groundwater resource mapping highlights its significance in environmental studies and land management practices.

This study aims to find out how using the TWI, EVI, TRI, TPI, and percentage slope gradient assessments can help us learn more about how the karst landscape of the Cradle Nature Reserve's topography affects how ecosystems work. By analysing these important topographic factors, we aim to clarify how they collectively affect vegetation growth and changes, moisture distribution, terrain roughness, and habitat suitability in the distinct karst environment. Through this thorough analysis, we will gain a valuable understanding of the interaction between topography and ecosystem processes, which will guide the development of land management strategies, conservation efforts, and ecological restoration initiatives tailored to karst landscapes' unique challenges and opportunities.

2. Method and materials

2.1. Study area

The study area is located within the Cradle of Humanity World Heritage Site (COHWHS) in South Africa, specifically between longitudes 27°42'58" (E) and 27°52'57" (E) and latitudes 25°51'13"(S) and 25°51'19" (S). It covers approximately 8000 hectares within a larger area of 47,000 hectares in the Gauteng and North-West provinces (Bradley et al. 2010; Buchanan 2010; Matyukira and Mhangara 2023). The COHWHS, acknowledged by the United Nations Educational, Scientific and Cultural Organization (UNESCO) for its paleoanthropological importance, showcases karst landforms formed by the chemical weathering of rocky material. These landforms create a diverse environment that promotes high densities of plant species. The Cradle Nature Reserve, part of the COHWHS, displays various plant and animal life. Climate factors like temperature, precipitation, and fire patterns affect its diverse vegetation structure, which is home to more than 200 species of birds (Matyukira and Mhangara 2023). The reserve receives an average annual rainfall of 650 to 750 mm. The temperatures in the reserve vary from 39 °C in summer to −12 °C in winter, which contributes to the formation of its Rocky Highveld Grassland environment (SA-Venues.com 2022). Natural springs, watercourses, and streams sustain the vegetation, while historical land use practices and the reintroduction of wildlife influence the evolving vegetation patterns (SA-Venues.com 2022; Matyukira and Mhangara 2023). Dolomitic sinkholes have a significant impact on vegetation dynamics. They protect specific tree species from forest fires, emphasising the importance of conservation efforts to preserve native vegetation and maintain sustainable rangelands for grazing by game animals (FLOW Communications 2022). Researchers (Zhou and Beck 2008; Ghorbani 2015; Zhu et al. 2018; Xiao et al. 2023), have conducted research that provides valuable insights into the intricate relationships between climatic factors and vegetation dynamics, thereby enhancing our understanding of ecological processes within the Cradle Nature Reserve.

2.2. Methods of data acquisition, processing, and analysis

We utilised QGIS version 3.36.0 (Maidenhead) to execute the following approach:

1. Digital Elevation Model (DEM) Acquisition:
   - The DEM was obtained using the STRM Downloader plugin (Daniel O'Donohue, 2023) and a shapefile of the designated study area, 'STUDY_AREA'.
2. DEM Preprocessing:
   - To ensure an accurate representation of the terrain, the Fill Sinks tool (Wang and Liu, 2006) was used on the DEM to address any depressions or sinks.
   - This tool was accessed via the Processing menu: Processing → Toolbox → SAGA → Terrain Analysis → Hydrology → Fill Sinks.
   - The input DEM was specified, and the tool was executed to fill the sinks in the elevation model.
3. Slope Calculation:
   - The slope values were calculated using the 'Slope' tool to understand the terrain's degree of steepness (QGIS Documentation, 2024).

Table 1. Slope gradient classes (Food and Agriculture Organization of the United Nations 2006).

Class	Description	%
1	Flat	0-0.2
2	Level	0.2-0.5
3	Nearly Level	0.5-1.0
4	Very Gentle Sloping	1-2
5	Gently Sloping	2-5
6	Sloping	5-10
7	Strong Sloping	10-15
8	Moderate Sloping	15-30
9	Steep	30-60
10	Very Steep	>60

- The tool was accessed via the Processing menu: Processing → Toolbox → Raster Terrain Analysis → Slope.
- The input DEM was specified, and the tool was executed to generate a new layer containing slope values measured in degrees.

4. Slope Classification:
   - Slope gradients were categorised into groups based on FAO guidelines (Food and Agriculture Organization of the United Nations 2006), referring to Table 1.
   - The reclassify tool in the QGIS GRASS plugin was utilised for this purpose.
   - This tool was accessed via the Processing menu: Processing → Toolbox → SAGA → Terrain Analysis—Morphometry → Reclassify.
   - Slope ranges and their corresponding classes were defined accordingly.
5. Satellite Image Analysis:
   - The study employed Sentinel-2 multispectral images for December 2023.
   - These images were obtained from the Copernicus Open Access Hub, which provides unrestricted access to Sentinel data (European Union, 2024).
   - The Sentinel Application Platform (SNAP) toolkit facilitated the download process, enabling batch retrieval based on parameters such as cloud cover percentage, area of interest (defined by a shapefile), and specified time range (European Union, 2024).
6. Vegetation Index Calculation:
   - Once the images were acquired, they were analysed using QGIS.
   - The Enhanced Vegetation Index (EVI) for each image was calculated using the raster calculator in QGIS, following the equation (Eq. 1).
   - The EVI formula integrates reflectance measurements from the near-infrared (NIR), red (RED), and blue (BLUE) spectral bands. The EVI improves vegetation detection while minimising the influence of soil and atmospheric conditions (MapScaping, 2023).

$$\mathrm{EVI} = 2.5 \times \frac{(NIR - RED)}{(NIR + 6 \times RED - 7.5 \times BLUE + 1)} \tag{Eq. 1}$$

7. EVI Aggregation and Classification:
   - Individual EVI images were aggregated by overlaying them and calculating the average value for each pixel. This process produced a composite image showing the mean EVI for December 2023.
   - The composite was saved as a tiff file for further analysis.

Table 2. Vegetation health and density value interpretation.

Vegetation health and density status	EVI Value
Very poor	−0.10 to 0.12
Poor	0.12 to 0.22
Normal	0.22 to 0.42
Good	0.42 to 0.72
Very good	0.72 to 1.00

- Using NDI threshold values adopted from Gidey et al. 2018, Table 2, the EVI values were categorised into groups
- The classification process was performed using the reclassify tool in the QGIS GRASS plugin.
- Utilising NDVI values as a threshold for EVI ensures accurate evaluation of vegetation, effectively capturing vegetation responses with greater precision under different conditions. This approach was believed to ensure uniformity when transitioning to EVI while enhancing sensitivity, making it optimal for research on plant health and ecosystem dynamics within the designated study area (Matsushita et al. 2007).

8. Slope to Vector Conversion:
   - The 'Raster to Vector (Polygon)' tool was employed to transform the raster slope layers into a vector format, specifically a polygon shapefile, to facilitate subsequent analysis and visualisation (QGIS Server Guide/Manual, 2023).
   - This plugin was accessed via the Processing menu: Processing → Toolbox → GDAL → Raster conversion → Rasterize (vector to raster).
9. Data Streamlining:
   - The 'Dissolve' tool (QGIS Server Guide/Manual, 2023) combined neighbouring polygons with identical slope classifications into larger polygons, effectively streamlining the dataset.
   - This tool was accessed via the Vector menu: Vector → Geoprocessing Tools → Dissolve, specifying the field containing slope class information.
10. Topographic Indices Calculation:
    - The Topographic Wetness Index (TWI), Topographic Position Index (TPI), and Terrain Ruggedness Index (TRI) were calculated from a filled DEM in QGIS.
    - TWI was computed using the plugin SAGA tools integrated within QGIS, employing the equation (Eq. 2), where 'a' represented the upslope contributing area and 'B' denoted the slope gradient in radians (Daniel O'Donohue, 2023; OpenCourseWare for GIS, 2024).

$$TWI = ln\left(\frac{a}{\tan(B)}\right) \quad \text{(Eq. 2).}$$

    - TPI was computed by comparing the elevation of each cell in the DEM to the mean elevation of its surrounding neighbourhood, characterising the terrain as ridges, flat areas, or valleys (QGIS Server Guide/Manual, 2023).
    - TRI was derived using the equation (Eq. 3) to calculate the elevation differences between adjacent cells, where 'z_i' represented the elevation of each cell, 'z_{mean}' denoted the mean elevation of the surrounding cells, and 'n'

represented the number of cells within the analysis window (QGIS Server Guide/ Manual, 2023).

$$\mathrm{TRI} = \frac{\sqrt{\sum_{i=1}^{n} \left(z_i - z_{mean}\right)^2}}{n} \qquad \text{(Eq. 3)}$$

11. Random Points Generation and Raster Value Extraction:
    - Random points were created in QGIS using the Vector → Research Tools → Random Points Inside Polygons function, with the study area shapefile as the input layer and 500 points selected.
    - A minimum distance of 100 meters between points was set, and the points were generated within the region of interest (ROI).
    - Raster values were extracted by accessing the Processing → Toolbox menu, locating the Sample Raster Values tool, choosing the randomly generated point layer as the input, and selecting the raster TIFF as the layer to sample from.
    - The tool was used to retrieve the raster values at the precise locations of each randomly selected point, and a new point layer containing attributes with the extracted raster values was created for further analysis or visualisation.
12. Correlation Matrix Calculation:
    - Raster values were used to calculate the correlation matrix in Stata/SE 13.1 Windows version.
    - A strong positive correlation was deemed to have a Pearson correlation coefficient greater than r = 0.5.
    - Correlation coefficients (r) were categorised as follows: 0.3-0.5 (moderate positive correlation), 0–0.3 (weak positive correlation), 0 (no correlation), −0.3 to −0.5 (moderate negative correlation), and less than −0.5 (strong negative correlation) (Turney, 2024).
13. Environmental Data Acquisition:
    - Environmental data was obtained using NASA/POWER CERES/MERRA-2 Native Resolution data, focusing on four variables: T2M_MAX_MERRA-2, T2M_MIN_MERRA-2, PRECTOTCORR MERRA-2, and GWETROOT MERRA-2 (NASA Global Modeling and Assimilation Office, 2020; National Aeronautics and Space Administration, 2023).
    - Data was collected from 14 strategically positioned meteorological stations, ensuring comprehensive spatial coverage within and around the study area as defined by our study area shapefile.
    - T2M_MAX_MERRA-2 provided insights into the highest temperatures recorded at 2 meters above the Earth's surface, while T2M_MIN_MERRA-2 provided data on the lowest temperatures.
    - Monthly station temperature for December 2023 was determined by averaging these two temperature variables.
    - PRECTOTCORR MERRA-2 indicated water input, while GWETROOT MERRA-2 determined soil wetness (NASA Global Modeling and Assimilation Office, 2020; Shen et al., 2022; National Aeronautics and Space Administration, 2023).
    - Monthly averages of PRECTOTCORR MERRA-2 and GWETROOT MERRA-2 were calculated to generate surface maps.
    - The NASA POWER Data Access Viewer was used to choose the 'CERES/ MERRA-2 Native Resolution' dataset, customise data retrieval parameters, and obtain the dataset in NetCDF format, which was then converted to CSV format

for ArcGIS integration (Shen et al., 2022; National Aeronautics and Space Administration, 2023).
- Rigorous quality control measures were implemented to ensure data reliability, including outlier detection, spatial and temporal consistency checks, and validation against historical records from ground stations (Shen et al., 2022).

14. Further Analysis and Visualisation:
    - Statistical measures for each dissolved classified EVI zone within TWI, TPI, and TRI TIFF maps were calculated to analyse plant health on different slopes.
    - Dissolved and classified percentage gradient zones within the EVI and TWI TIFF maps were analysed to measure vegetation health across different slope gradients.
    - Patterns and trends in vegetation changes in response to slope gradients and soil factors were identified.
    - These insights provided valuable information for understanding ecology, managing land, and planning conservation strategies.

By systematically following this approach, we ensured a comprehensive and coherent terrain and vegetation analysis method in the designated study area.

3. Results and discussion

3.1. Evaluation of environmental factors and vegetation vigour

A nuanced ecological landscape unfolds after careful examination of Figure 1 and Table 3 in tandem with Table 1. The weak positive correlations between the Enhanced Vegetation Index (Figure 1a), precipitation (Figure 1g), and air temperature (Figure 1e), while statistically significant only for temperature, underscore the role of these climatic factors in influencing vegetation health, albeit not as robustly as initially anticipated (Różycka et al. 2017). The weak positive correlation between EVI and the Topographic Ruggedness Index (Figure 1d) piques our interest, suggesting that plants thrive slightly better in rougher terrain. This intriguing finding could be attributed to a more diverse range of habitats in such landscapes, sparking further curiosity and the desire for deeper exploration. (Pinto-Correia et al. 2018; Nainggolan et al. 2024). However, the lack of statistical significance in the weak positive correlation between EVI and the Topographic Wetness Index (Figure 2b) suggests that other factors may influence the relationship between vegetation health and soil moisture. We expect a strong positive correlation between RF and temperature, as warmer temperatures often increase evaporation and, consequently, precipitation. There aren't many strong or statistically significant links between RF and other topographic indices (TPI and TRI) or between Temp and other topographic indices (TPI, TRI, and TWI). This means that temperature and rainfall don't have a lot of direct effects on the landforms (Gidey et al. 2018; Zhu et al. 2018). The moderately negative correlations between TPI and TWI, as well as between TRI and TWI, are highly significant, indicating that the wetness decreases as the topography becomes more rugged or the position more extreme. This could have implications for water runoff, erosion, and the distribution of vegetation types (Różycka et al. 2017). These correlations present a rich and multi-faceted understanding of how various environmental factors interact with each other and the landscape. They underscore the crucial role of considering a multitude of variables, a key aspect of our work, when studying ecological patterns and processes, reinforcing the significance of our research.

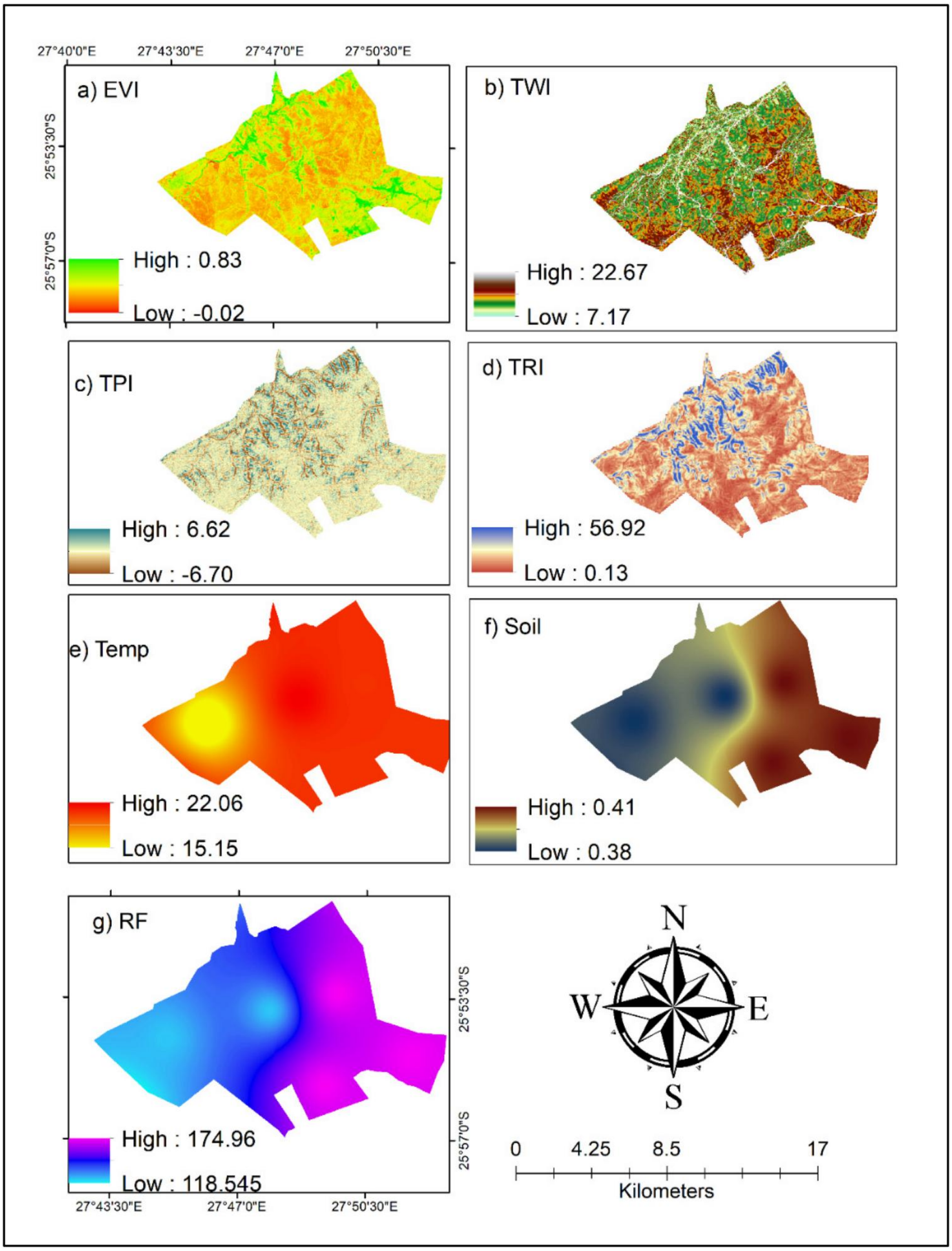

Figure 1. The spatial distribution of (a) Enhanced vegetation index (EVI), (b) topographic wetness index (TWI), (c) topographic position index (TPI), (d) topographic ruggedness index (TRI), (e) air temperature (temp), (f) root zone soil moisture (soil) and (g) total precipitation (RF).

3.2. Determination of vegetation health status along slope gradients

Table 4 reveals that flat areas, which make up only 0.27% of the land, have an average EVI of 0.31, suggesting moderate vegetation health. Flat regions, which make up 0.25% of the land, have an average EVI of 0.27, suggesting slightly lower vegetation health. Nearly level slopes, which make up 0.60% of the land, have an average EVI of 0.26, suggesting

Table 3. Summary of topographic, vegetation, meteorological, and hydrological variables.

Variable	Low	High
Topographic and Vegetation Indices		
EVI	−0.02	0.83
TWI	7.17	22.67
TPI	−6.7	6.62
TRI	0.13	56.92
Meteorological and Hydrological variables		
Air temperature (Temp)	15.15	22.06
Root zone soil moisture (Soil)	0.38	0.41
Total precipitation (RF)	118.55	174.96

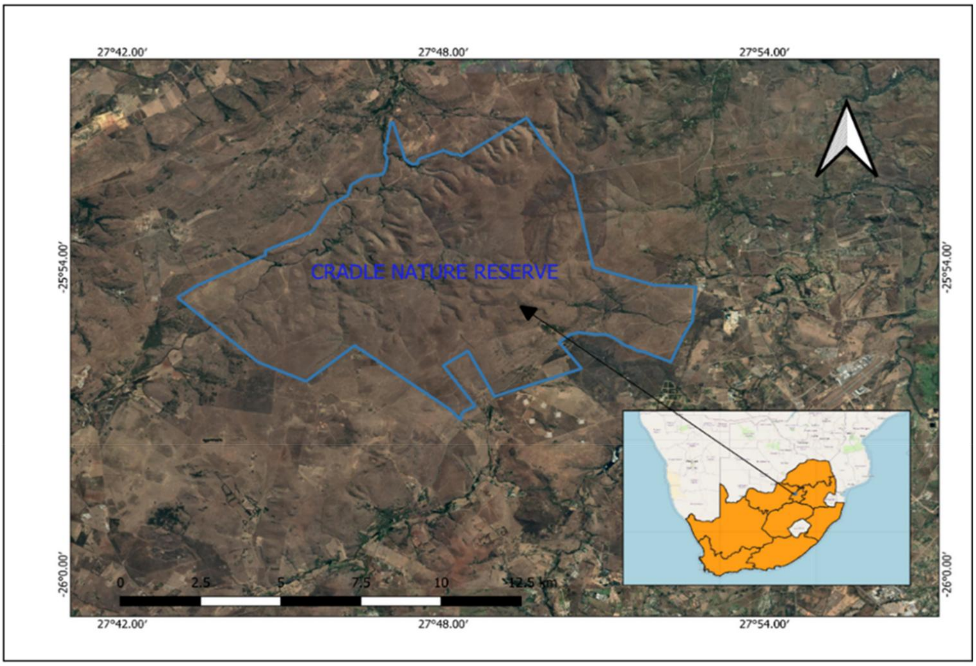

Figure 2. Location of the study (Matyukira and Mhangara 2023).

they are more prevalent and have comparable vegetation health to level areas. Gently sloping areas, which make up 13.87% of the land, have an average EVI of 0.26, suggesting they are common and can sustain moderate vegetation health. The reserve is predominantly characterized by sloping areas, accounting for 31.08% of the land. Steep slopes, which account for 20.39% of the land, have the lowest average EVI value of 0.25, suggesting less dense or less healthy vegetation. Moderate slopes, which account for 24.70% of the total area, contribute to moderate vegetation health. Steep slopes, which make up 6.55% of the total area, have a higher average EVI value of 0.30, indicating improved vegetation health on more inclined gradients. Very steep slopes, which occupy only 0.09% of the land, have the highest average EVI value of 0.38, indicating resilient vegetation.

The study on vegetation health and slope gradients in Cradle Nature Reserve reveals a complex relationship between these variables. The R^2 value of 0.8447 indicates a close relationship between EVI and percentage slope gradients, providing valuable insights for environmental studies and land management (Figure 3). Steep slopes, although rare,

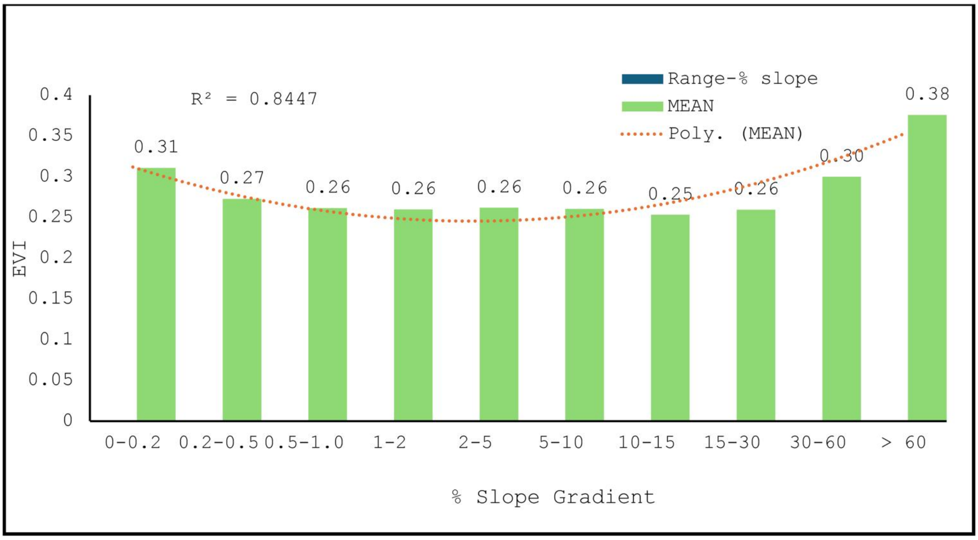

Figure 3. Relationship between the Enhanced vegetation Index (EVI) and slope gradient.

Table 4. Relationship between the Enhanced vegetation Index (EVI) and slope gradient.

	Percentage Slope			EVI			
Slope Gradient Description	Range-% slope	Area in km2	Area%	Min	Max	Mean	STD
Flat	0-0.2	0.23	0.27	0.0	0.68	0.31	0.11
Level	0.2-0.5	0.22	0.25	0.0	0.70	0.27	0.08
Nearly Level	0.5-1.0	0.52	0.60	0.0	0.61	0.26	0.06
Very Gentle Sloping	1-2	1.92	2.21	0.0	0.68	0.26	0.07
Gently Sloping	2-5	12.08	13.87	0.0	0.75	0.26	0.07
Sloping	5-10	27.07	31.08	0.0	0.83	0.26	0.07
Strong Sloping	10-15	17.76	20.39	0.0	0.73	0.25	0.06
Moderate Sloping	15-30	21.52	24.70	0.0	0.74	0.26	0.06
Steep	30-60	5.71	6.55	0.2	0.68	0.30	0.07
Very Steep	> 60	0.08	0.09	0.2	0.77	0.38	0.10

exhibit robust vegetation health, while more common, strong-sloping areas show lower vegetation health. Factors such as soil stability, moisture availability, and microclimate conditions could be responsible for these variations. These findings align with previous research on soil compaction and porosity, which shows significant variations influenced by land cover change and slope gradient. Cultivated land and steeper slopes tend to have a higher bulk density and lower total porosity, whereas forested land and gentler slopes exhibit a lower bulk density and higher porosity. Changes in land cover and slope gradient can negatively affect soil quality, such as soil fertility, stability, and overall ecosystem health. Furthermore, changes in land use, land cover, and slope gradient can affect soil organic carbon (SOC) content, potentially reducing carbon footprints in agri-food systems. Overall, these results emphasize the importance of considering topography when assessing plant health and understanding slope gradients' impact on ecological processes, soil dynamics, and ecosystem functioning in semi-arid areas.

3.3. Statistical relationships among the environmental factors and vegetation vigour

Table 5 displays the correlations between different environmental variables. There is a weak positive correlation between the Enhanced Vegetation Index (EVI) and precipitation

Table 5. Correlation of EVI with climatic and topographic variables ($n = 500$).

	EVI	RF	TEMP	TPI	TRI	TWI
EVI	1.000					
RF	0.112	1.000				
TEMP	0.143	0.576	1.000			
TPI	−0.224	0.073	0.039	1.000		
TRI	0.138	−0.158	0.093	0.022	1.000	
TWI	0.101	0.087	0.044	−0.283	−0.415	1.000

Statistically significant at 5%.
Note: EVI: Enhanced vegetation index; TWI: Topographic wetness index; TPI: Topographic position index; TRI: Topographic ruggedness index; TEMP: Mean air temperature; RF: Total precipitation.

(RF), but this correlation is not statistically significant ($r = 0.1115$, $p = 0.0128$). On the other hand, there is a weak positive correlation between EVI and air temperature (TEMP), which is statistically significant ($r = 0.1432$, $p = 0.0014$). Additionally, there is a moderately negative correlation between EVI and the topographic position index (TPI), which is highly significant ($\mathrm{r} = -0.2238$, $p = 0$). Furthermore, there is a weak positive correlation between EVI and the topographic ruggedness index (TRI), which is statistically significant ($r = 0.1378$, $p = 0.0021$). Lastly, there is a weak positive correlation between EVI and the topographic wetness index (TWI), but this correlation is not statistically significant ($r = 0.101$, $p = 0.0238$). Furthermore, there is a strong and highly significant positive relationship between precipitation (RF) and air temperature (TEMP), with a correlation coefficient (r) of 0.5755 and a p-value of 0. On the other hand, there is a weak positive correlation between RF and TPI with a correlation coefficient of 0.0734, but this correlation is not statistically significant ($p = 0.1017$). Additionally, there is a moderately negative and highly significant correlation between RF and TRI, with a correlation coefficient of −0.1578 and a p-value of 0.0004. Finally, there is a weak positive correlation between RF and TWI with a correlation coefficient of 0.0871, but this correlation is also not statistically significant ($p = 0.052$). Additionally, there are low positive correlations between TEMP and TPI ($r = 0.0386$, $p = 0.3897$), TEMP and TRI ($r = 0.0928$, $p = 0.0385$), and TEMP and TWI ($r = 0.0441$, $p = 0.3261$), all of which are not statistically significant. The Total Performance Index (TPI) and the Total Wellness Index (TWI) display a moderate negative correlation, which is highly significant ($\mathrm{r} = -0.2828$, $p = 0$). Similarly, TRI and TWI also demonstrate a moderate negative correlation, which is highly significant ($\mathrm{r} = -0.4154$, $p = 0$). These findings emphasise the intricate connections between environmental factors, revealing both meaningful and meaningless correlations. This calls for additional research to gain a deeper understanding of the underlying dynamics.

The correlation analysis results provide valuable insights into ecological dynamics and landscape characterisation, consistent with previous studies that have examined the connections between topography, vegetation, and climate variables. The weakly positive relationship between the EVI and the TRI suggests that areas with rough terrain may have less vegetation cover. This aligns with research indicating that regions characterised by more pronounced inclines and poorer soil conditions typically exhibit lower levels of vegetation coverage (Dilts et al. 2022). The inverse correlation between the EVI and the TPI indicates that areas with depressions or sinkholes tend to have more robust vegetation. This finding aligns with previous studies that have demonstrated the impact of topographic characteristics on the spatial arrangement of plant life (Robinson et al. 2019; Yates et al. 2019; Branton and Robinson 2020). The results emphasise the significance of incorporating topography into ecological research and the necessity of focused conservation initiatives to tackle habitat suitability and erosion risk in challenging landscapes. Furthermore, the correlations discovered in the study can provide valuable insights for

Table 6. Multi-linear regression analysis using all the pixels of the remote sensing data.

Model Summary	Total sample units (population) ($n = 101360$)						
R-squared	Adjusted R-squared	Root Mean Squared Error	Mean Absolute Error	F-statistic	Intercept		
Rsq	Rsqadj	RMSE	MAE	F	b0	AIC	BIC
0.08	0.08	55.20	44.60	1467.92	−1239.14	813121.11	813187.80

	Coefficients			
Variables	Coefficient	F-statistic	AIC	BIC
RF	−4.40	829.84	813945.63	813991.26
Soil	8408.68	728.16	813844.72	813890.35
Temp	4.71	959.80	814074.46	814120.09
TPI	10.12	2459.67	815549.58	815595.22
TRI	−1.76	3528.09	816587.42	816633.06
TWI	−3.03	955.43	814070.13	814115.76

EVI: Dependent Variable; AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.

developing field experiments and sampling strategies. Researchers may choose to concentrate their efforts on regions characterised by high TWI values in order to investigate water-related ecological processes or vegetation dynamics. This approach is based on the understanding that the availability of moisture has a significant impact on the health of vegetation (Nainggolan et al. 2024). Similarly, recognising the inverse correlation between TRI and EVI can aid in sampling across various levels of terrain roughness to investigate its impact on vegetation. This knowledge can then improve data comprehension and facilitate ecological process modelling. Ultimately, these discoveries can contribute to conservation and land management strategies by integrating data on the correlation between various factors and vegetation indices, such as EVI (Różycka et al. 2017). This will facilitate habitat restoration, biodiversity conservation, and the implementation of sustainable land use practices.

Additionally, the multiple linear regression analysis of the dependent variable EVI, based on a large sample size of 101,360, provides reliable estimates (Table 6). The model, while statistically significant with a high F-statistic of approximately 1467.918, demonstrates low explanatory power with an R-squared value of around 8%. This indicates that the predictors explain only a small portion of the variance in EVI. The prediction errors are moderate, with an RMSE of approximately 55.201 and an MAE of about 44.597. The large negative intercept value (-1239.137) and the information criteria (AIC and BIC) suggest that the model is reasonably well-fitted, with AIC being slightly better due to less penalization.

Among the predictors, Root Zone Moisture (Soil) stands out as the most influential, boasting the highest positive coefficient and the lowest AIC and BIC values, indicating an excellent model fit. Total Precipitation (RF) and Topographic Wetness Index (TWI) also exhibit good model fits with relatively low AIC and BIC values and significant F-statistics. While TRI and TPI are strong predictors with high F-statistics, they add more complexity to the model, as reflected in their higher AIC and BIC values. Air Temperature (Temp) and TWI maintain a good balance between influence and model fit. The direction of the relationships is such that positive coefficients (Root Zone Moisture, Air Temperature, TPI) indicate direct relationships with EVI, whereas negative coefficients (Total Precipitation, TRI, TWI) indicate inverse relationships. In summary, Root Zone Moisture

Table 7. Relationship between Enhanced vegetation Index (EVI) and topographic wetness Index (TWI).

	EVI			TWI			
Vegetation health and density status	Value	Area in km2	%	Min	Max	Mean	STD
Very poor to poor	– 0.10 to 0.22	22.46	26.15	7.9	21.78	10.85	1.55
Normal	0.22 to 0.42	60.55	70.49	7.2	22.67	11.24	2.05
Good	0.42 to 0.72	2.88	3.35	7.2	22.60	12.13	3.21
Very good	0.72 to 1.00	0.01	0.01	8.5	13.66	10.93	1.90
	Total:	85.89	100.00	–	–	–	–

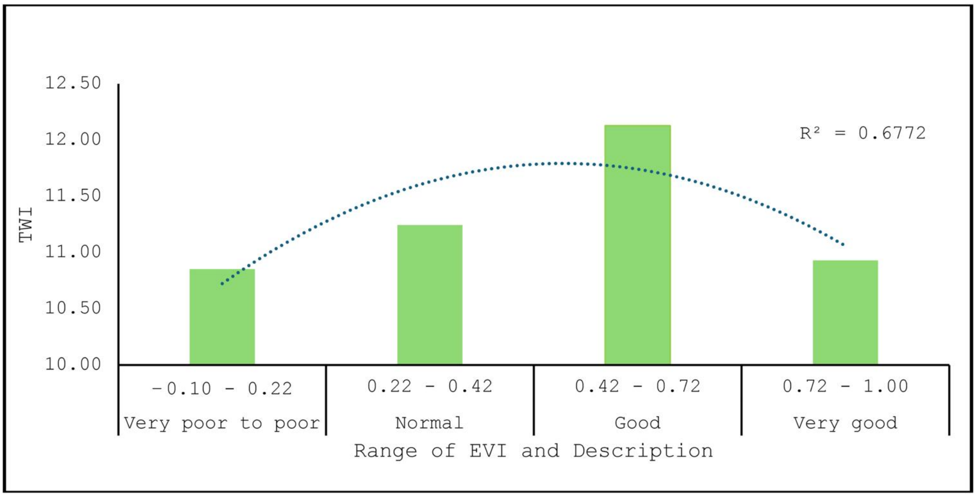

Figure 4. Relationship between the Enhanced vegetation Index (EVI) and topographic wetness Index (TWI).

(Soil) is the most impactful predictor with the best model fit, while other predictors like TRI, TPI, Total Precipitation, TWI, and Air Temperature also significantly influence EVI, each with varying degrees of model fit and complexity.

3.3.1. Determining the statistical relationship between the EVI and TWI

The analysis of vegetation health and density status in relation to the EVI range Table 7, the percentage of the study area (Cradle Nature Reserve), and the mean TWI reveal distinct patterns. The study area is predominantly characterised by the 'Normal' EVI range, which covers the largest portion of the land area (60.55 km2, or 70.49% of the study area). In comparison, a substantial proportion falls within the 'Very Poor to Poor' category (22.46 km2, 26.15% of the study area), indicating lower vegetation health. Conversely, areas classified as 'Good' and 'Very Good' are limited, with 'Good' covering 2.88 km2 (3.35% of the study area) and 'Very Good' encompassing a negligible 0.01 km2 (0.01% of the study area), suggesting that higher vegetation health and density are less prevalent. Mean TWI values generally correspond with vegetation health, with higher values indicating better water content and health, except for the 'Very Good' category, which exhibits a mean TWI (10.93) similar to the 'Very Poor to Poor' class, possibly due to its small area representation. Changes in TWI can explain approximately 67.72% of the variability in EVI, according to the R-squared value of 0.6772 (Figure 4). The analysis results indicate a strong relationship between vegetation health, as indicated by the EVI range, and the mean TWI within the study area of Cradle Nature Reserve. As TWI increases (indicating higher moisture availability), there tends to be an associated increase in EVI (reflecting healthier vegetation). Regions with higher TWI values indicate enhanced moisture retention and will likely foster more vigorous vegetation growth. Drier upland areas with lower TWI values may exhibit sparser vegetation cover. The predominance of the 'Normal' EVI range, covering the largest portion of the study area, suggests that most of the landscape exhibits average to moderate vegetation health. This aligns with previous studies that have found a positive correlation between moderate EVI values and healthy vegetation cover (Li et al. 2010; Martin et al. 2021; Almalki et al. 2022; Mpanyaro et al. 2024). These studies emphasised remote sensing, particularly the Enhanced Vegetation Index (EVI), for monitoring vegetation health and mapping changes in arid environments like the Cradle Nature Reserve. Further, they highlighted the moderate positive correlation between precipitation, streamflow, and vegetation health, suggesting the utility of EVI and TWI in assessing ecosystem dynamics and human impacts within the reserve. Conversely, the substantial proportion of the study area classified as 'Very Poor to Poor' indicates areas with lower vegetation health. This situation is attributed to factors such as land degradation, habitat fragmentation, or human activities, as concluded in our previous study of the same study area (Matyukira and Mhangara 2023).

The low number of areas classified as 'Good' and 'Very Good' suggests that the Cradle Nature Reserve has a lower prevalence of high vegetation health and density. This discovery aligns with research emphasising the difficulties of preserving excellent vegetation cover in protected areas, frequently caused by invasive species, habitat degradation, or insufficient management techniques (Ekka et al. 2022; Pulido-Chadid et al. 2023). Remarkably, average TWI values typically align with vegetation's health, as higher TWI values indicate superior water content and overall health [(Mpanyaro et al. 2024). This discovery aligns with prior studies that have shown the significant role of topographic wetness in shaping vegetation dynamics. Researchers have observed that regions with greater moisture levels sustain more robust vegetation (Almalki et al. 2022). Nevertheless, it is worth mentioning that the 'Very Good' category displays a mean TWI that is comparable to the 'Very Poor to Poor' class despite its relatively small area representation. Local variations in topography, soil composition, or microclimate conditions within the Cadle Nature Reserve may account for the discrepancy. Topography influences climate variations over small distances, resulting in a range of microclimates distinguished by variations in temperature, moisture levels, and exposure to wind and sunlight. Microclimates are important indicators of the distribution of various natural ecosystems (A joint project of NatureServe and The National Park Service National Capital Region 2024). Additional examination of these anomalies could yield valuable insights into the intricate relationships among topography, hydrology, and vegetation health (Ekka et al. 2022; A joint project of NatureServe and The National Park Service National Capital Region 2024). In summary, the findings emphasise the significance of considering the EVI and the TWI when evaluating changes in vegetation and the overall landscape condition. This information is valuable for guiding conservation and management initiatives in the Cradle Nature Reserve and other similar ecosystems.

3.3.2. Analysis of the relationship between TWI and slope gradient

Table 8 shows that a small fraction (0.27%) of the landscape consists of flat areas with a slope ranging from 0.2% to 0.2%. These flat areas have an average TWI of 18.35. Similarly, level areas with a slope between 0.2% and 0.5% comprise another small portion (0.25%) of the landscape, with an average TWI of 15.00. Approximately 0.60% of the land consists of nearly level areas with a slope ranging from 0.5% to 1.0%. These areas have an

Table 8. Relationship between the TWI and slope gradient.

	Percentage Slope			TWI			
Slope Gradient Description	Range-% slope	Area in km2	%	Min	Max	Mean	STD
Flat	0-0.2	0.23	0.27	12.98	22.67	18.35	3.02
Level	0.2-0.5	0.22	0.25	12.08	22.64	15.00	2.64
Nearly Level	0.5-1.0	0.52	0.60	11.35	21.33	13.89	2.44
Very Gentle Sloping	1-2	1.92	2.21	10.66	21.13	12.91	2.27
Gentle Sloping	2-5	12.08	13.87	9.74	21.52	12.25	2.01
Sloping	5-10	27.07	31.08	9.05	20.68	11.61	1.73
Strong Sloping	10-15	17.76	20.39	8.64	20.15	10.94	1.62
Moderate Sloping	15-30	21.52	24.70	7.95	19.80	10.29	1.71
Steep	30-60	5.71	6.55	7.28	19.10	9.78	1.82
Very Steep	> 60	0.08	0.09	7.17	12.59	8.96	1.09
Total: 87.12			100.00				

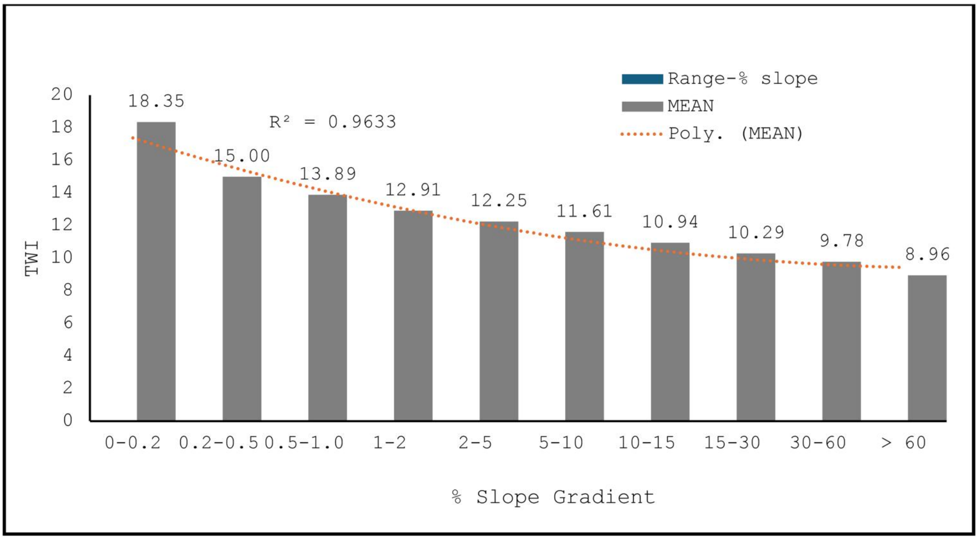

Figure 5. Relationship between topographic Wetness Index and slope gradient.

average TWI of 13.89. On the other hand, gentle slopes with a slope ranging from 1% to 2% cover about 2.21% of the land and have an average TWI of 12.91. Most of the land is sloping, with a slope ranging from 2% to 5%, accounting for 13.87% of the total area. These areas have an average TWI of 12.25. The largest category of slopes is the strong slopes, with a slope ranging from 5% to 10%, covering 31.08% of the total area. These slopes have an average TWI of 11.61. The slopes with a moderate gradient (10–15% slope) have a substantial coverage of 20.39% and an average TWI of 10.94. On the other hand, the steeper slopes (30–60% slope) are smaller but still significant, covering 6.55% of the area and having a mean TWI of 9.78. Steep slopes with a gradient greater than 60% are uncommon, accounting for only 0.09% of the total. These slopes have an average TWI value of 8.96. These findings shed light on the distribution of wetness across various slope gradients, providing crucial insights into the landscape's diversity and the hydrological processes in the study area. Changes in the slope gradient account for around 96.33% of the variation in TWI, as indicated by the high R-squared value (approaching 1) in Figure 5. The TWI decreases as the slope gradients get steeper, indicating reduced moisture availability. Simply put, the TWI decreases when the slope gradient becomes steeper.

The results of this study demonstrate a distinct correlation between the TWI and the steepness of slopes in the Cradle Nature Reserve. These results provide a valuable understanding of the area's landscape diversity and water movement. Steep slopes have reduced moisture retention while increasing water flow and drainage patterns, as low TWI values indicate. This, in turn, affects the distribution of vegetation (Yang et al. 2020; Geremew et al. 2023). Flat and nearly level areas with minimal slope gradients have higher average TWI values than sloping and steep terrain. For example, flat areas with slopes between 0 and 0.2% show the highest average TWI of 18.35, which suggests that these regions have a greater ability to retain moisture. As the steepness of slopes increases, the average TWI values gradually decrease, indicating a decrease in water accumulation and an increase in the potential for runoff. This pattern is especially noticeable in regions with steep inclines (>5% slope), where the average TWI decreases to 11.61, suggesting reduced moisture retention and increased runoff rates. These findings align with prior research investigating the correlation between TWI and slope gradients in different landscapes, offering valuable insights into landscape dynamics and hydrological processes (Winzeler et al. 2022). Previous research in similar settings has found similar patterns, showing that flat or slightly sloped areas tend to have higher TWI values than steep areas (Wu et al. 2018; Winzeler et al. 2022). The study showed a clear pattern: areas that are flat or almost flat have higher TWI values than those that are sloped or steep, meaning that areas with less slope gradients are better at keeping water. Research in various ecosystems, including mountainous areas and coastal plains, has also documented similar trends of declining TWI as slope gradients increase (Winzeler et al. 2022). As slopes' steepness increases, the TWI values decrease gradually, indicating a decrease in water accumulation and an increase in the potential for runoff. This relationship highlights the importance of topography in shaping the distribution of moisture and hydrological processes within Karst landscapes (Bradley et al. 2010; Buchanan 2010; Xiao et al. 2023). Comparable Researchers have found similar patterns in similar Karst environments, showing that TWI is a useful tool for understanding landscape diversity and planning land management and conservation strategies in Karst regions (Cantón et al. 2004; Bradley et al. 2010; Wu et al. 2018; Winzeler et al. 2022). This study enhances our comprehension of landscape heterogeneity by examining moisture distribution across various slope gradients. It provides information for land management and conservation strategies to maintain the Cradle Nature Reserve's hydrological integrity.

3.3.3. Exploration of the statistical relationship between TPI and EVI

Table 9 demonstrates clear correlations between the Enhanced Vegetation Index (EVI) and Topographic Position Index (TPI) for various vegetation categories in the study area. Approximately 26.15% of the area has Very Poor to Poor Vegetation. These areas have a mean TPI of 0.23, which suggests that the terrain is slightly elevated. Most of the landscape, accounting for 70.49%, comprises normal vegetation areas. These areas have a

Table 9. Relationship between the TPI and EVI.

	EVI			TPI			
Vegetation health and density status	Range-EVI	Area in km2	%	Min	Max	Mean	STD
Very poor to poor	– 0.10–0.22	22.46	26.15	−3.78	4.48	0.23	0.7
Normal	0.22–0.42	60.55	70.49	−6.70	6.62	−0.06	0.9
Good	0.42–0.72	2.88	3.35	−6.46	4.73	−0.52	1.2
Very good	0.72–1.00	0.01	0.01	−2.48	0.87	−0.49	0.8
		Total: 85.89	100.00	–	–	–	–

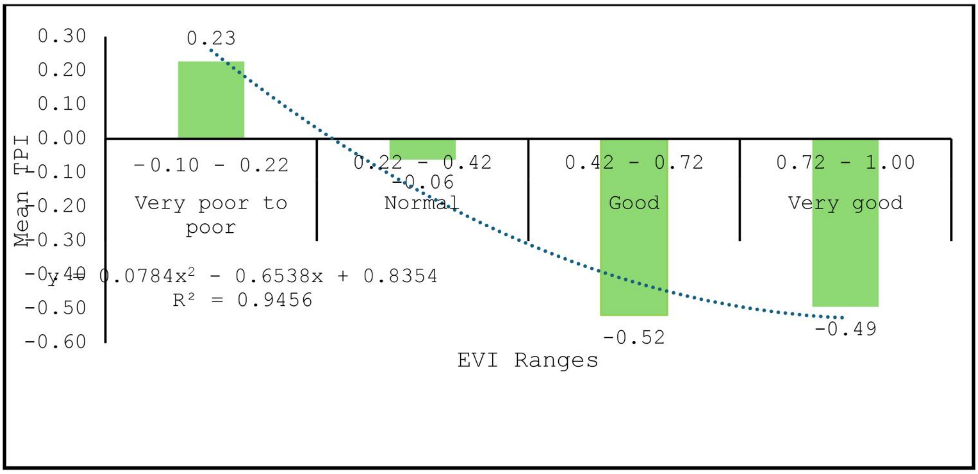

Figure 6. Relationship between the topographic position Index (TPI) and EVI.

mean TPI value of approximately zero (-0.06), indicating relatively flat terrain. On the other hand, the Good and Very Good Vegetation categories, which comprise 3.35% and 0.01% of the total area, respectively, exhibit negative mean TPI values (-0.52 and −0.49), indicating the presence of lower-lying regions or depressions. These findings emphasise the impact of topographic position on the distribution of vegetation. The high R-squared value of 0.9456 (Figure 6) indicates a robust correlation between TPI and EVI, providing strong evidence for the association between topography and vegetation patterns. This highlights the significance of considering both aspects in landscape analysis. The findings from the analysis provide valuable insights into the relationship between TPI and EVI within a karst environment, such as the study area under consideration. Understanding the interplay between topography and vegetation is crucial in karst landscapes, where terrain features such as sinkholes and ridges are prevalent. The results indicate that areas categorised as Very Poor to Poor Vegetation, which may correspond to depressions or sinkholes, exhibit slightly elevated mean TPI values (0.23), suggesting these regions are not as depressed as expected. Conversely, Normal Vegetation areas, typically associated with flat terrain, show a mean TPI close to zero (-0.06), aligning with the expectation of relatively flat landforms. However, the Good and Very Good Vegetation categories, representing lower-lying regions or depressions, display negative mean TPI values (-0.52 and −0.49, respectively), indicating the presence of sinkholes or depressions where vegetation might thrive due to increased moisture availability. These findings are consistent with similar studies conducted in karst environments. For example, (Robinson et al. 2019) observed comparable relationships between TPI and vegetation health in semiarid southwestern Australia regions, highlighting the importance of considering topographic influences on vegetation dynamics. Similarly, (Zhang et al. 2023) and (Wang et al. 2015) found correlations between TPI and EVI in arid basins and river basins, respectively, emphasising the universal applicability of TPI-EVI relationships across diverse landscapes. Overall, the results underscore the significance of topographic position in shaping vegetation distribution and health in karst environments, providing valuable insights for ecological modelling and conservation efforts.

While the findings provide valuable insights into the relationship between the TPI and the EVI, it's essential to acknowledge certain limitations inherent in the use of TPI (Jones et al. 2000; Robinson et al. 2019; Al-Sababhah 2023). One significant limitation is its scale dependency, which can influence the interpretation of results. The neighbourhood size, which determines the mean elevation around each cell in the DEM (Al-Sababhah 2023), influences TPI calculations. As a result, variations in neighbourhood size can lead to different TPI values and may affect the identification of specific landforms, such as depressions or ridges (Jones et al. 2000; Al-Sababhah 2023). Additionally, while TPI provides valuable information about the relative position of a point within its surroundings, it does not account for the size or shape of landforms (Al-Sababhah 2023). Therefore, TPI alone may not fully capture the complexity of terrain features in karst environments, where sinkholes, caves, and other intricate landforms are common (Al-Sababhah 2023; Zhang et al. 2023). Furthermore, TPI may not differentiate between different depressions or ridges, limiting its ability to provide detailed insights into vegetation distribution patterns. Despite these problems, TPI is still useful for studying how topography affects plant life in karst environments (Jones et al. 2000; Al-Sababhah 2023; Zhang et al. 2023) when used with other terrain analysis methods and at the right scales.

3.3.4. TRI and EVI relationship

Table 10 demonstrates the range of the EVI across various land quality categories, spanning from −0.10 to 1.00. The TRI notably impacts this variation. The area categorised as Very Poor to Poor covers 22.46 km^2, which accounts for 26.15% of the total area. The TRI values in this category range from 0.13 to 50.52, with an average of 8.53 and a standard deviation of 4.73. In the normal category, which accounts for 60.55 km^2 (70.49% of the total area), the TRI ranges from 0.13 to 56.92. The average TRI value is 10.08, with a standard deviation of 7.10. The Good category covers 2.88 km^2, which accounts for 3.35% of the total area. The TRI values in this category range from 0.13 to 52.33, with an average of 10.57 and a standard deviation of 8.67. Finally, the Very Good category encompasses an area of 0.01 km^2, which accounts for 0.01% of the total area. The TRI values in this category range from 4.14 to 49.90, with an average of 16.44 and a standard deviation of 17.92. The correlation between TRI and EVI suggests that as TRI values increase, EVI values decrease, indicating a reduction in vegetation in rough terrain. Lower TRI values are typically associated with higher EVI values, indicating a higher vegetation density in smoother terrain. Furthermore, the strong correlation between TRI and EVI, as evidenced by the high R-squared value of 0.942 (Figure 7), provides additional support for the connection between topography and vegetation patterns. This highlights the importance of considering both factors in landscape analysis. The inverse relationship between topography and vegetation distribution emphasises the impact of landforms on plant life's spatial arrangement, providing valuable knowledge for land management and ecological research.

The summary's results strongly link the TRI and the EVI in the Cradle Nature Reserves. These results are typical of larger patterns seen in similar settings. The relationship between TRI and EVI is important for understanding how vegetation changes over

Table 10. TRI and EVI relationship.

	EVI			TRI			
Vegetation health and density status	Range-EVI	Area in km2	%	Min	Max	Mean-TRI	STD
Very poor to poor	− 0.10–0.22	22.46	26.15	0.13	50.52	8.53	4.73
Normal	0.22–0.42	60.55	70.49	0.13	56.92	10.08	7.10
Good	0.42–0.72	2.88	3.35	0.13	52.33	10.57	8.67
Very good	0.72–1.00	0.01	0.01	4.14	49.90	16.44	17.92
Total:		85.89	100	–	–	–	–

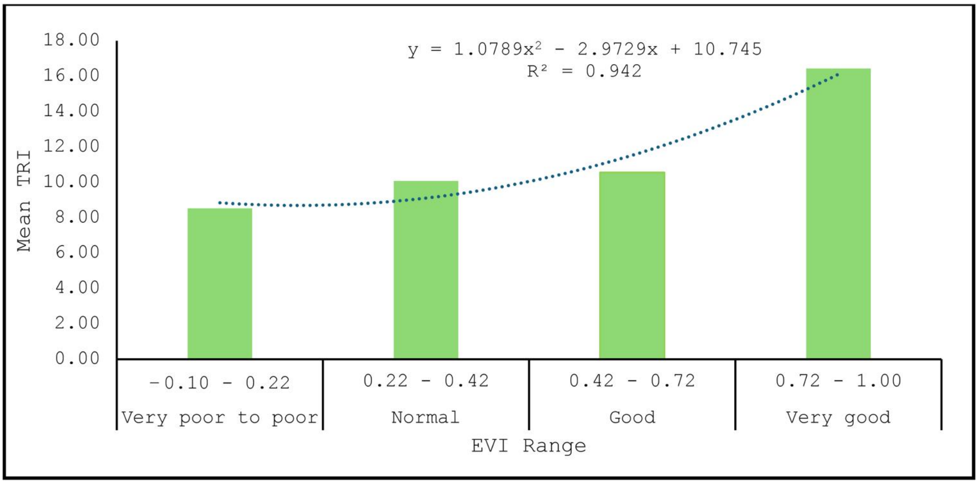

Figure 7. Relationship between the topographic ruggedness Index (TPI) and EVI.

time in karst areas like the Cradle Nature Reserves, where topography changes a lot (Różycka et al. 2017). Research elsewhere confirms a negative correlation between TRI and EVI, highlighting the impact of rugged terrain on vegetation density. These results align with more general ecological ideas and affect how land is managed in karst landscapes. They show how important it is to use targeted conservation efforts and sustainable development methods to protect ecosystem functionality and biodiversity (Riley and Degloria 1999; Zhu et al. 2018). The study by Dilts et al. (2022) says that the connection between the EVI and the TRI is complicated and is affected by different aspects of topographic ruggedness (Dilts et al. 2022). In ecological settings, variations in elevation and diversity in aspect may be important. This means that the relationship between EVI and TRI may be different depending on these factors (Riley and Degloria 1999; Jones et al. 2000; Dilts et al. 2022). This nuanced understanding highlights the intricate relationship between topographic ruggedness and vegetation dynamics, indicating the influence of multiple factors and ecological processes like habitat concealment and escape terrain (Riley and Degloria 1999; Pinto-Correia et al. 2018; Stojilković 2022).

4. Conclusion

Our study examines the complex connection between the physical features of the land and the changes in plant life in karst environments, specifically in the Cradle Nature Reserve. We can gain an extensive understanding of landscape diversity, water flow, and ecosystem health by examining the EVI in conjunction with the TPI, the TRI, and the TWI. The results highlight the importance of topographic characteristics such as sinkholes, depressions, and slope gradients in influencing the distribution and condition of vegetation. A strong correlation between TPI and EVI is evident, with variations among various vegetation categories indicating the impact of moisture availability on vegetation patterns. Also, the fact that TRI goes down as EVI increases shows how rough terrain affects vegetation cover since smoother terrains tend to have more vegetation. Our study of TWI also demonstrates the impact of slope gradients on moisture dispersion, emphasising the significant influence of topography on water movement in karst terrains. These observations enhance our comprehension of how ecosystems function and provide valuable information for managing and conserving the Cradle Nature Reserve and similar habitats. Nevertheless, it is crucial to recognise the inherent limitations of topographic indices like TPI and TRI, including their dependence on scale and inability to represent intricate terrain features accurately. Hence, we advise exercising prudence and performing supplementary analyses when interpreting the findings. In summary, our research emphasises the significance of incorporating topographic data into ecological evaluations and land management plans to advance conservation efforts and promote sustainable ecosystem management practices in karst environments. Our research findings help to enhance our understanding of landscape ecology by explaining the intricate relationships between topography and vegetation dynamics. Additionally, these findings provide valuable insights for decision-making processes aimed at preserving biodiversity and ensuring the functionality of ecosystems.

Authors' contributions

Conceptualization: C.M., pm, E.G., Methodology: C.M., pm, E.G., 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.

Disclosure statement

There is no conflict of interest in this work.

Funding

This project was funded by the University of the Witwatersrand School of Geography, Archaeology, and Environmental Studies in South Africa.

Data availability statement

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

References

A joint project of NatureServe and The National Park Service National Capital Region. 2024. Topography | explore natural communities. [accessed 2024 Apr 20]. https://explorenaturalcommunities.org/ecology-basics/physical-setting/topography.

Allende-Prieto C, Roces-García J, Sañudo-Fontaneda LÁ. 2024. The high-resolution calibration of the topographic wetness index using PAZ satellite radar data to determine the optimal positions for the placement of smart sustainable drainage systems (SuDS) in urban environments. Sustainability (Switzerland). 16(2):598. doi: 10.3390/su16020598.

Almalki R, Khaki M, Saco PM, Rodriguez JF. 2022. Monitoring and mapping vegetation cover changes in arid and semi-arid areas using remote sensing technology: a review. Remote Sens (Basel). 14(20):5143. doi: 10.3390/rs14205143.

Al-Sababhah N. 2023. Topographic position index to landform classification and spatial planning, using GIS, for Wadi Araba, South West Jordan. Environ Ecol Res. 11(1):79–101. doi: 10.13189/eer.2023.110106.

Amatulli G, Domisch S, Tuanmu MN, Parmentier B, Ranipeta A, Malczyk J, Jetz W. 2018. Data descriptor: a suite of global, cross-scale topographic variables for environmental and biodiversity modeling. Sci Data. 5(1):180040. doi: 10.1038/sdata.2018.40.

Berhanu B, Bisrat E. 2018. Identification of surface water storing sites using topographic wetness index (TWI) and normalized difference vegetation index (NDVI). JNRD. 8:91–100. doi: 10.5027/jnrd.v8i0.09.

Bradley C, Cross J, Durand JF, Ellis R, Groenewald J, Grove A, Holland M, Jamison AA, Kenyon P, Krige G, et al. 2010. The karst system of the cradle of humankind world heritage site. Water Res Commis. 410(1):88–101.

Branton C, Robinson DT. 2020. Quantifying topographic characteristics of wetlandscapes. Wetlands. 40(2):433–449. doi: 10.1007/s13157-019-01187-2.

Buchanan M. 2010. The karst system of the cradle of humankind world heritage site: a collection of 13 issue papers by the South African karst working group. Water Res Commis Pretoria. 1:1–427.

Cantón Y, Del Barrio G, Solé-Benet A, Lázaro R. 2004. Topographic controls on the spatial distribution of ground cover in the Tabernas badlands of SE Spain. Catena (Amst). 55(3):341–365. doi: 10.1016/S0341-8162(03)00108-5.

Chipatiso E. 2023. Flood risk mapping: quantifying topographic wetness index to determine flood risk zones for mutoko district in Zimbabwe. https://www.worldweatheronline.com/mutoko-weather-averages/mashonaland-east/zw.aspx.

Dani RS, Divakar PK, Baniya CB. 2023. Diversity and composition of plants species along elevational gradient: research trends. Biodivers Conserv. 32(8-9):2961–2980. doi: 10.1007/s10531-023-02638-3.

Daniel Odonohue. 2023 Apr 10. Topographic wetness index in QGIS. MAPSCAPING. [accessed 2024 Apr 10]. https://mapscaping.com/topographic-wetness-index-in-qgis/.

Dilts TE, Blum ME, Shoemaker KT, Weisberg PJ, Stewart KM. 2022. Topographic ruggedness indices in ecology: past, present and future [Internet]. doi: 10.21203/rs.3.rs-1700794/v1.

Ekka P, Parmar K, Parmar V, Kumar A, Saikia P. 2022. Role of protected area in conservation and sustainable management of biodiversity: an Indian perspective. In: Panwar P, Shukla G, Bhat JA, Chakravarty S, editors. Land degradation neutrality: achieving SDG 15 by forest management. Singapore: Springer Nature Singapore; p. 229–247. doi: 10.1007/978-981-19-5478-8_13.

European Union ESA (ESA). 2024. Copernicus data space ecosystem | Europe's eyes on earth. European Union, European Space Agency (ESA). [accessed 2024 Apr 7]. https://dataspace.copernicus.eu/.

Fasona MI, Soneye ASO, Gregory AJ, Egonmwan RI. 2018. Geo-spatial evaluation of the land-use and landscape metrics of omo-shasha-oluwa forest reserves landscape: the conservation challenge for wildlife. Lagos J Geo-Inform Sci. 5:1–19.

FLOW Communications. 2022. Maropeng and sterkfontein caves. [accessed 2022 May 23]. https://www.maropeng.co.za/content/page/environment-and-climate.

Food and Agriculture Organization of the United Nations. 2006. Soil formation factors. In Guidelines for soil description. Food and Agriculture Organization of the United Nations; p. 12–13.

Geremew B, Tadesse T, Bedadi B, Gollany HT, Tesfaye K, Aschalew A. 2023. Impact of land use/cover change and slope gradient on soil organic carbon stock in Anjeni watershed, Northwest Ethiopia. Environ Monit Assess. 195(8):971. doi: 10.1007/s10661-023-11537-7.

Ghorbani MS. 2015. Karst landscape as a settling factor in Kamyaran area: past and present. Phys Geogr Res Quarter. 47(4):517–531. doi: 10.22059/jphgr.2015.56047.

Gidey E, Dikinya O, Sebego R, Segosebe E, Zenebe A, Mussa S, Mhangara P, Birhane E. 2023. Land use and land cover change determinants in Raya Valley, Tigray, Northern Ethiopian Highlands. Agriculture. 13(2):507. doi: 10.3390/agriculture13020507.

Gidey E, Dikinya O, Sebego R, Segosebe E, Zenebe A. 2018. Using drought indices to model the statistical relationships between meteorological and agricultural drought in raya and its environs, Northern Ethiopia. Earth Syst Environ. 2(2):265–279. doi: 10.1007/s41748-018-0055-9.

Heštera H, Plantak M, Gernhardt D. 2024. Correlations between topographic wetness index and soil moisture in the pannonian region of croatia. GT. 19(1/2024):89–102. doi: 10.21163/GT_2024.191.07.

Jones KB, Heggem DT, Wade TG, Neale AC, Ebert DW, Nash MS, Mehaffey MH, Goodman IA, Hermann KA, Selle AR, et al. 2000. Assessing landscape condition relative to water resources in the Western United States: a strategic approach. In: Sandhu SS, Melzian BD, Long ER, Whitford WG, Walton BT, editors. Monitoring ecological condition in the Western United States: proceedings of the fourth symposium on the environmental monitoring and assessment program (EMAP), San Francisco, CA, April 6–8, 1999. Dordrecht: Springer Netherlands; p. 227–245. doi: 10.1007/978-94-011-4343-1_19.

Kopecký M, Macek M, Wild J. 2021. Topographic wetness index calculation guidelines based on measured soil moisture and plant species composition. Sci Total Environ. 757:143785. doi: 10.1016/j.scitotenv.2020.143785.

Li Z, Li X, Wei D, Xu X, Wang H. 2010. An assessment of correlation on MODIS-NDVI and EVI with natural vegetation coverage in Northern Hebei Province, China. Proc Environ Sci. 2; p:964–969. doi: 10.1016/j.proenv.2010.10.108.

Liu C, Huang Y, Wu F, Liu W, Ning Y, Huang Z, Tang S, Liang Y. 2021. Plant adaptability in karst regions. J Plant Res. 134(5):889–906. doi: 10.1007/s10265-021-01330-3.

MapScaping. 2023. Calculating NDVI using QGIS - April 6, 2024. MapScaping.com. [accessed 2024 Apr 6]. https://mapscaping.com/calculating-ndvi-using-qgis/.
Martin CA, Proulx R, Vellend M, Fahrig L. 2021. How the relationship between vegetation cover and land-cover variance constrains biodiversity in a human dominated world. Landscape Ecol. 36(11): 3097–3104. doi: 10.1007/s10980-021-01312-9.
Matsushita B, Yang W, Chen J, Onda Y, Qiu G. 2007. Sensitivity of the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) to topographic effects: a case study in high-density cypress forest. Sensors (Basel). 7(11):2636–2651. doi: 10.3390/S7112636.
Matyukira C, Mhangara P. 2023. Land cover and landscape structural changes using extreme gradient boosting random forest and fragmentation analysis. Remote Sens (Basel). 15(23):5520. doi: 10.3390/rs15235520.
Minh NQ, Huong NTT, Khanh PQ, Hien LP, Bui DT. 2024. Impacts of resampling and downscaling digital elevation model and its morphometric factors: a comparison of hopfield neural network, bilinear, bicubic, and kriging interpolations. Remote Sens (Basel). 16(5):819. doi: 10.3390/rs16050819.
Monz CA, Gutzwiller KJ, Hausner VH, Brunson MW, Buckley R, Pickering CM. 2021. Understanding and managing the interactions of impacts from nature-based recreation and climate change. Ambio [Internet]. 50(3):631–643. doi: 10.1007/s13280-020-01403-y.
Mpanyaro Z, Kalumba AM, Zhou L, Afuye GA. 2024. Mapping and assessing riparian vegetation response to drought along the buffalo river catchment in the Eastern Cape Province, South Africa. Climate. 12(1):7. doi: 10.3390/cli12010007.
Nainggolan L, Ni CF, Darmawan Y, Lo WC, Lee IH, Lin CP, Hiep NH. 2024. Cost-effective groundwater potential mapping by integrating multiple remote sensing data and the index–overlay method. Remote Sens (Basel). 16(3):502. doi: 10.3390/rs16030502.
NASA Global Modeling and Assimilation Office (GMAO). 2020. MERRA-2. Modern-era retrospective analysis for research and applications, version 2. [accessed 2024 Apr 6]. https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data_access/.
National Aeronautics and Space Administration. 2023. NASA. [accessed 2023 Apr 29]. https://www.nasa.gov/.
Pinto-Correia T, Guiomar N, Ferraz-de-Oliveira MI, Sales-Baptista E, Rabaça J, Godinho C, Ribeiro N, Sá Sousa P, Santos P, Santos-Silva C, et al. 2018. Progress in identifying high nature value montados: impacts of grazing on hardwood rangeland biodiversity. Rangel Ecol Manag. 71(5):612–625. doi: 10.1016/j.rama.2018.01.004.
Pulido-Chadid K, Virtanen E, Geldmann J. 2023. How effective are protected areas for reducing threats to biodiversity? A systematic review protocol. Environ Evid. 12(1):1–10. doi: 10.1186/s13750-023-00311-4.
QGIS Documentation. 2024. QGIS user guide. https://docs.qgis.org/334/en/docs/user_manual/index.html. [accessed 2024 May 21]. https://docs.qgis.org/3.34/en/docs/user_manual/index.html.
QGIS Server Guide/Manual (QGIS 3.36.0). 2023. 8.1. Lesson: raster to vector conversion—QGIS documentation.
Raihan A. 2023. The dynamic nexus between economic growth, renewable energy use, urbanization, industrialization, tourism, agricultural productivity, forest area, and carbon dioxide emissions in the Philippines. Energy Nexus. 9:100180. doi: 10.1016/j.nexus.2023.100180.
Riley SJ, Degloria SD. 1999. A terrain ruggedness index that quantifies topographic heterogeneity. https://www.researchgate.net/publication/259011943.
Robinson TP, Di Virgilio G, Temple-Smith D, Hesford J, Wardell-Johnson GW. 2019. Characterisation of range restriction amongst the rare flora of Banded Ironstone Formation ranges in semiarid south-Western Australia. Aust J Bot. 67(3):234–247. doi: 10.1071/BT18111.
Różycka M, Migoń P, Michniewicz A. 2017. Topographic wetness index and terrain ruggedness index in geomorphic characterisation of landslide terrains, on examples from the sudetes, SW Poland. Zeitschrift für Geomorphol Suppl Issu. 61(2):61–80. doi: 10.1127/zfg_suppl/2016/0328.
SA-Venues.com. 2022. Cradle nature reserve, gauteng. [accessed 2022 May 23]. https://www.sa-venues.com/game-reserves/cradle.php.
Sharma A. 2010. Integrating terrain and vegetation indices for identifying potential soil erosion risk area. Geo-Spatial Inform Sci. 13(3):201–209. doi: 10.1007/s11806-010-0342-6.
Shen S, Gerasimov I, Lei G, Bosilovich GM, Wei Li A, Meyer JD. 2022. What (and how) MERRA-2 reanalysis data are used in applied sciences (4) NASA Global Modeling and Assimilation Office. AGU - iPosterSessions.com (agu-vm-0). [accessed 2024 Apr 7].
Stephenson PJ. 2019. Integrating remote sensing into wildlife monitoring for conservation. Envir Conserv. 46(3):181–183. doi: 10.1017/S0376892919000092.

Stojilković B. 2022. Towards transferable use of terrain ruggedness component in the geodiversity index. Resources. 11(2):22. doi: 10.3390/resources11020022.

Talebi Khiavi H, Mostafazadeh R. 2022. The spatiotemporal dependencies of terrain indices with soil characteristics in a steep hillslope mountainous area. Arab J Geosci. 15(10):937. doi: 10.1007/s12517-022-10220-4.

Thannoun RG, Ismaeel OA. 2024. Flood risk vulnerability detection based on the developing topographic wetness index tool in geographic information system. IOP Conf Ser Earth Environ Sci. 1300(1):012012. doi: 10.1088/1755-1315/1300/1/012012.

Toni Jo Smith B, Jo Smith T, Benner SG, Flores AN, Committee Molly Gribb SM, Committee James McNamara SP. 2010. Using soil moisture trends across topographic gradients to examine controls on semi-arid ecosystem dynamics chair, supervisory committee using soil moisture trends across topographic gradients to examine controls on semi-arid ecosystem dynamics defense committee and final reading approvals of the thesis submitted by thesis title.

Turney S. 2024. Pearson correlation coefficient (r) | guide & examples. Scribbr. [accessed 2024 Apr 9]. https://www.scribbr.com/statistics/pearson-correlation-coefficient/.

Wagari M, Tamiru H. 2021. RUSLE model based annual soil loss quantification for soil erosion protection: a case of fincha catchment, Ethiopia. Air Soil Water Res. 14:117862212110462. doi: 10.1177/11786221211046234.

Wang L, Liu H. 2006. An efficient method for identifying and filling surface depressions in digital elevation models for hydrologic analysis and modelling. Int J Geogr Inf Sci. 20(2):193–213. doi: 10.1080/13658810500433453.

Wang B, Zhang G, Duan J. 2015. Relationship between topography and the distribution of understory vegetation in a Pinus massoniana forest in Southern China. Int Soil Water Conservat Res. 3(4):291–304. doi: 10.1016/j.iswcr.2015.10.002.

Winzeler HE, Owens PR, Read QD, Libohova Z, Ashworth A, Sauer T. 2022. Topographic wetness index as a proxy for soil moisture in a hillslope catena: flow algorithms and map generalization. Land (Basel). 11(11):2018. doi: 10.3390/land11112018.

Wu M, He HS, Zong S, Tan X, Du H, Zhao D, Liu K, Liang Y. 2018. Topographic controls on vegetation changes in alpine tundra of the Changbai Mountains. Forests. 9(12):756. doi: 10.3390/f9120756.

Wubie MA, Assen M. 2020. Effects of land cover changes and slope gradient on soil quality in the Gumara watershed, Lake Tana basin of North–West Ethiopia. Model Earth Syst Environ. 6(1):85–97. doi: 10.1007/s40808-019-00660-5.

Xiao D, Chen M, He X, Nie Y, Jiang N, Zhang W, Hu P, Wang K. 2023. Soil nutrients and vegetation along a karst slope gradient affect arbuscular mycorrhizal fungi colonization of roots rather than bulk soil AMF diversity. Plant Soil. 489(1-2):139–154. doi: 10.1007/s11104-023-06004-8.

Yang J, El-Kassaby YA, Guan W. 2020. The effect of slope aspect on vegetation attributes in a mountainous dry valley, Southwest China. Sci Rep. 10(1):1–11. doi: 10.1038/s41598-020-73496-0.

Yates CJ, Robinson T, Wardell-Johnson GW, Keppel G, Hopper SD, Schut AGT, Byrne M. 2019. High species diversity and turnover in granite inselberg floras highlight the need for a conservation strategy protecting many outcrops. Ecol Evol. 9(13):7660–7675. doi: 10.1002/ece3.5318.

Zhang W, Cheng L, Xu R, He X, Mo W, Xu J. 2023. Assessing spatial variation and driving factors of available phosphorus in a hilly area (Gaozhou, South China) using modeling approaches and digital soil mapping. Agriculture (Switzerland). 13(8):1541. doi: 10.3390/agriculture13081541.

Zhang Z, Wang X, Zhang Y, Gao Y, Liu Y, Sun X, Zhi J, Yin S. 2023. Simulating land use change for sustainable land management in rapid urbanization regions: a case study of the Yangtze River Delta region. Landsc Ecol. 38(7):1807–1830. doi: 10.1007/s10980-023-01657-3.

Zhou W, Beck BF. 2008. Management and mitigation of sinkholes on karst lands: an overview of practical applications. Environ Geol. 55(4):837–851. doi: 10.1007/s00254-007-1035-9.

Zhu J, Wu W, Liu HB. 2018. Environmental variables controlling soil organic carbon in top- and subsoils in karst region of southwestern China. Ecol Indic. 90:624–632. doi: 10.1016/j.ecolind.2018.03.073.