

Land Use and Vegetation Density across Altitudinal Gradients in Sterkspruit Nature Reserve, South Africa: A Drone-Based Analysis

Utilisation des terres et densité de la végétation selon les gradients altitudinaux dans la réserve naturelle de Sterkspruit, Afrique du Sud : Analyse à partir d'images de drone

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Résumé

La croissance continue des populations humaines et de la consommation par habitant a entraîné une exploitation non durable de la biodiversité terrestre, aggravée par le changement climatique, l'acidification des océans et d'autres impacts environnementaux anthropiques. Les études sont essentielles pour classer les types de végétation, comprendre leurs différences et soutenir la recherche écologique, la préservation de la biodiversité et le suivi environnemental. La présente étude a examiné la classification de l'occupation du sol (Land Use and Land Cover, LULC) et la relation entre la densité de végétation et l'altitude dans la réserve naturelle de Sterkspruit (STNR), en Afrique du Sud, à l'aide de techniques de télédétection. Une classification supervisée a été réalisée sur des images aériennes en utilisant l'algorithme du maximum de vraisemblance (Maximum Likelihood Algorithm, MLA) avec 58 points de vérité terrain, aboutissant à quatre classes d'occupation du sol : zone boisée, zone rocheuse et sommet montagneux, sol nu et zone bâtie, et zone herbacée. La classification a obtenu une précision globale de 0,97 et une valeur Kappa de 0,96, indiquant un modèle hautement fiable. Pour évaluer la densité de la végétation, l'indice de végétation par différence normalisée (NDVI) a été calculé et analysé en fonction de

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l'altitude. Le coefficient de corrélation de Spearman de -0,157 a montré une faible association négative, tandis que la régression linéaire a révélé une légère relation négative statistiquement significative entre le NDVI et l'altitude ($p = 0,038$), bien que l'altitude n'explique que 2,1 % de la variance du NDVI. Ces résultats suggèrent que l'altitude influence la densité de la végétation, mais que d'autres facteurs environnementaux jouent probablement un rôle plus important. Cette étude démontre l'efficacité de la télédétection pour la classification de l'occupation du sol et apporte un éclairage sur les dynamiques de végétation dans les écosystèmes montagneux de la réserve naturelle de Sterkspruit.

Mots clés : Gradient altitudinal, réserve naturelle de Sterkspruit, couverture végétale, télédétection, Afrique du Sud

Abstract

The continued growth of human populations and per capita consumption has resulted in unsustainable exploitation of the Earth's biological diversity, exacerbated by climate change, ocean acidification, and other anthropogenic environmental impacts. Studies are crucial for classifying vegetation types, understanding their differences, and supporting ecological research, biodiversity preservation, and environmental monitoring. This study investigated Land Use and Land Cover (LULC) classification and the relationship between vegetation density and altitude in the Sterkspruit Nature Reserve (STNR) in South Africa, using remote sensing techniques. A supervised classification was conducted on aerial photography images using the Maximum Likelihood Algorithm (MLA) with 58 ground-truthed points, resulting in four land cover classes: wooded area, rock and mountain summit, bare soil and built-up area, and grassland. The classification achieved an overall accuracy of 0.97 and a Kappa value of 0.96, indicating a highly reliable model. To assess vegetation density, the Normalized Difference Vegetation Index (NDVI) was computed and analyzed against altitude. The Spearman correlation coefficient of -0.157 showed a weak negative association, while linear regression revealed a slight, statistically significant negative relationship between NDVI and altitude ($p = 0.038$), though altitude explained only 2.1% of NDVI variance. These findings suggest that altitude impacts vegetation density, but other environmental factors likely play a more significant role. This study demonstrates the effectiveness of remote sensing for land cover classification and provides insight into vegetation patterns in mountainous ecosystems in Sterkspruit Nature Reserve.

Keywords: Altitude gradient, Sterkspruit Nature Reserve, vegetation cover, remote sensing, South Africa

Introduction

Remote sensing involves gathering information about the Earth's land and water surfaces using overhead images (Campbell & Wynne, 2011). With the growing demand for geographic information, remote sensing is attracting major interest (Zhang *et al.*, 2017; Zhu *et al.*, 2019), especially due to its capacity to cover extensive areas quickly and repeatedly. This capability is particularly valuable for ecological monitoring, which is often unfeasible with ground-based methods (Mashala *et al.*, 2023; Senf, 2022). In the early years, remote sensing data were scarce and costly to obtain. With the launch of an increasing number of Earth observation satellites, particularly open-access ones like the Landsat (Wulder *et al.*, 2019) and Sentinel series (Carrasco *et al.*, 2019), accessing global remote sensing imagery has become both convenient and affordable. With this, online platforms such as Copernicus Sentinel Hub, Google Earth Engine (Gorelick *et al.*, 2017), and Earth Server (Baumann *et al.*, 2016) make it even easier to obtain imagery. Based on this technology, we can get critical data for urban planning, environmental management and biodiversity conservation (Turner *et al.*, 2015). Similarly, remote sensing is applied in precision agriculture, allowing farmers to monitor crop health and optimize practices through temporal data analysis (Zhang & Kovacs, 2012). This enables them to classify and map plant cover, estimate the biomass and volume of plants on site, and identify crops and agricultural yields. This can help detect trends such as deforestation, farmland expansion, or increasing urbanization.

Natural vegetation types are distributed variably across altitudinal gradients, potentially resulting in variations in ecosystem formation and diversity (Becker *et al.*, 2007; Liu *et al.*, 2019). In addition to vegetation type, plant cover is also influenced by altitude and temperature (Piao *et al.*, 2011). Both vegetation and altitude have an impact on mammal species composition and diversity and distribution patterns reflecting biogeographic affinities and the ability of grassland species to invade forest habitats (Caceres *et al.*, 2011). Anderson *et al.*, (2018) found that vegetation and microhabitats significantly influence microclimates along altitudinal gradients; in montane forests, at higher elevation, there is higher stem density and higher humidity, and cooler temperatures are moderated by vegetation type and habitat. However, evaluating human pressures and their effects on natural resources, both within and around protected areas, is critical for fully understanding the dynamics involved and for recommending protection strategies to inform public policy (Kokou *et al.*, 2023; Antonio, 2013). Vegetation studies must account for natural environmental factors, such as altitude, and anthropogenic factors, like agriculture, mining, and urban expansion, to fully understand the dynamics of ecosystem change and guide effective conservation strategies. For example, in South Africa's Mpumalanga Province, there was a change in land cover between 2010 and 2020, with a loss of 1.5% of areas in a natural state in 2010, to other land uses in 2020. According to von Staden *et al.* (2022) this loss was mainly due to mining (38.4%), agriculture (21.9%) and human settlements expansion (16.1%).

The Sterkspruit Nature Reserve (STNR), located in South Africa's high-altitude region, is characterized by its diverse ecosystems, which are under increasing pressure from anthropogenic activities such as agriculture and urban expansion. This study aims to compare and classify various vegetation types in Sterkspruit Nature Reserve through the application of remote sensing, especially of high-resolution aerial photography. This is very important given the ability of remote sensing to capture fine-scale spatial detail and monitor rapid environmental changes affecting the region. Specifically we seek to identify distinct vegetation types and their spatial distributions, facilitating a better understanding of ecological patterns and biodiversity within the reserve. Furthermore, it aims to analyze the temporal changes in vegetation cover over time, highlighting any shifts that may result from external pressures, including climate change and land use modifications.

Materials and Methods

Study area

The Sterkspruit Nature Reserve (STNR) is located at -25.154346° S, 30.548687° E in South Africa's Mpumalanga Province, and covers 2060 ha (Figure 1). The reserve was originally divided into a core zone and a buffer zone, but since this study focuses exclusively on the core zone, the area considered is split into two core sections. The predominant geological formations found in the area are primarily sedimentary in nature, composed mainly of quartzite with medium grains and layered shale (Bronkhorst & Bain, 2005). Additionally, substantial sections are covered by greyish-green andesitic lava. The reserve experiences an average annual rainfall of 862 mm, mainly received between October and March. The summers are characterized by mild temperatures, with an average daily mean of 21.6° C (ranging from 11° to 36° C). Winters are cold, with a mean average daily temperature of 9.6° C (-2° to 23° C). Frost is commonly observed during winter, and in exceptionally cold years, higher-elevation areas may receive snowfall (Bronkhorst & Bain, 2005).

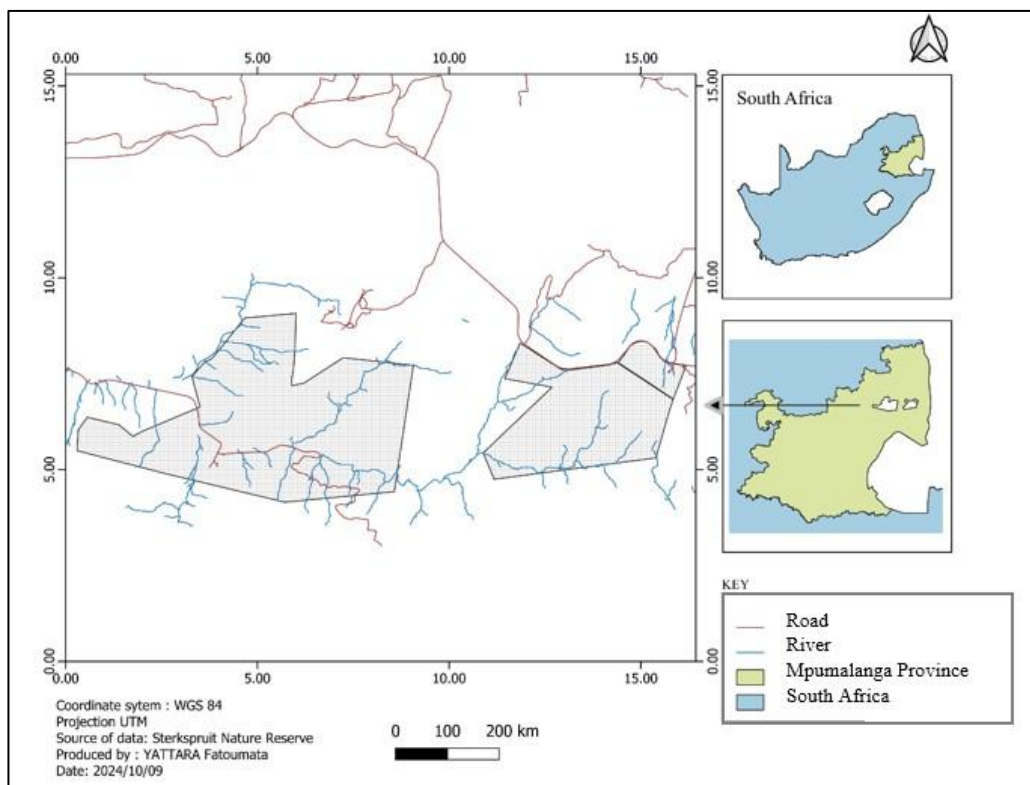


Figure 1. Nature Reserve in Mpumalanga Province, South Africa

Data collection

Land Use and Land Cover Classification with Supervised Maximum Likelihood Algorithm

The classification of the Sterkspruit Nature Reserve was made possible through aerial images obtained from the Southern African Wildlife College, taken in May 2023. These images were captured during the autumn season, and the field data used to validate the classification were collected in February 2024. The characteristics of these images are presented in Table 1 below.

Table 1: Sensor and aerial image characteristics

Sensor	Acquisition date	Image Resolution
Sony a7 RIV/Zeiss	02/03/2023	21,4 cm
Sonnar 55cmf/1.8		

We used GAIA GPS (v2524.2) a mapping and navigation mobile application to record field data, especially the geographical coordinates representing each land cover class, at 58 points. The data collected at these points, known as "ground control points", were used to assess and validate the classification of land use and different land cover classes (Koffi N'Dere *et al.*, 2019). Additionally, we used a notebook to record relevant information such as vegetation types, land cover class descriptions, altitude, land use activities, and notes on human activity or disturbance (e.g., evidence of mining, farming, or urban development). All the pre-processing of the image had already been carried out at the source.

The supervised classification based on the Maximum Likelihood Algorithm (MLA) was used. The decision to use MLA was justified by its widespread use and effectiveness in remote sensing studies (Richards, 2022). In many ways, it has become the benchmark against which subsequent algorithms are compared (Richards, 2022). MLA calculates the probability that a given pixel belongs to a particular class and assigns it to the class with the highest likelihood, making it particularly well-suited for multi-class classification problems where class separability is crucial (de Jong & Van der Meer, 2005). Moreover, studies have demonstrated that the algorithm achieves high classification accuracy for diverse tropical land covers, primarily due to the effective separation between class means in the decision space (Ahmad & Quegan, 2012). MLA is a robust technique with a very low chance of misclassification (Sisodia *et al.*, 2014).

Data analysis

Land use and land cover classification

A color composite was applied to better discriminate against the different classes, by using a combination of the spectral bands (3-1-2) for the Red, Green and Blue (RGB) primary colors. The Region of Interest (ROIs) were defined, and from there, we generalized the processing over the entire area of STNR. All classification steps were performed in the Semi-Automatic Classification Plugin (Congedo, 2021) using Quantum GIS 3.28.15. After classification, four occupancy classes were defined. We used the Kappa index to express the accuracy of an image classification (Foody, 2018).

$$K = \frac{(po - pe)}{(1 - pe)} \quad (1)$$

Where

- Po is the observed agreement, i.e., the proportion of times the raters agree.
- Pe is the expected agreement, i.e., the proportion of times the raters are expected to agree by chance.

In addition to the Kappa index, the user accuracy (Pu) and producer accuracy (Pr) are complementary tools in evaluating the performance of classification models. Together, they provide critical information about the reliability and sensitivity of the model, allowing researchers and practitioners to make informed improvements to classification systems (Chytrý *et al.*, 2011).

$$Pu = \frac{(TN + TP)}{(TN + FP + FN + TP)} \quad (2)$$

Where

- TN (True Negative) represents the number of negative cases correctly classified.
- TP (True Positive) represents the number of positive cases correctly classified.

- FP (False Positive) represents the number of negative cases incorrectly classified.
 - FN (False Negative) represents the number of positive cases incorrectly classified.
- $$Pr = \frac{TP}{(TP+FN)} \quad (3)$$
- Where:
- TP (True Positives) represents the number of pixels correctly classified as belonging to the class of interest.
 - FN (False Negatives) represents the number of pixels incorrectly classified as not belonging to the class of interest.

Vegetation density assessment as a function of elevation gradient

To evaluate vegetation density across the altitudinal gradient, we used two main variables. Firstly, we used the Digital Elevation Model (DEM) (Balasubramanian, 2017) and secondly, the Normalized Difference Vegetation Index (NDVI). It was calculated using the reflectance of the red (R) and Near-Infrared (NIR) channels measured in the visible band by sensors. This index is a simple numerical indicator and a powerful tool that can be used to assess spatio-temporal changes in green vegetation (Pettorelli, 2013). The calculation formula is (NIR-R) / (NIR+R). The characteristics of sensors and the aerial image used (Table 1) were taken from Wynand *et al.* (2024). Given the very fine resolution of the aerial imagery used, resampling was performed to adapt it to the DEM image for a fair comparison. Conversions of rasters to data frames were done using the Extractor plugin in QGIS (Gandaho, 2023). The Spearman rank correlation test was applied to the DEM and NDVI, since neither of these variables was normally distributed (Shapiro-Wilk test, $p < 0.05$) (Mishra *et al.*, 2019). The correlation coefficients range from -1 to +1, indicating the strength of association, with hypothesis tests and confidence intervals used to assess statistical significance and estimate relationship strength in the population (Schober *et al.*, 2018). To process and analyse the data, we used R version 4.1.1 (R Core Team, 2024). Database processing was done using the dplyr package (Wickham *et al.*, 2023), and the analysis and visualization were performed with the ggplot2 package (Wickham, 2016).

Results

Land Use Land Cover (LULC) classification

The LULC classification tasks were performed with data from 58 ground-truthed points, and the maximum likelihood algorithm yielded four classes (Table 2).

Table 2. Land cover classes obtained after supervised classification of images based on the MLA

Class	Description
Wooded area	Dense and open forests (mountain and surface), vegetation formations along rivers.
Grassland	The set of herbaceous areas (mountain meadows, rocky meadows).
Bare soil and built-up area	Housing, roads (dirt roads and paved roads), burned areas, infrastructure, and all areas devoid of vegetation.
Rock and mountain summit	Includes rocky areas and rock formations.

The classification of land use and land cover yielded an overall accuracy value of 0.97 and a Kappa coefficient of 0.96 (Table 3). The producer’s accuracy values were 97.41% for wooded areas, 98.33% for rock and mountain summits, 99.26% for bare soil and built-up areas, and 93.50% for grasslands. The user’s accuracy values were 99.61%, 96.99%, 94.37%, and 98.74% for the same respective classes.

Table 3. Land Use Land Cover Classification evaluation metrics

Reference data						
Classified data	Wooded areas	Rock and mountain summit	Bare soil and built-up areas	Grassland	Total	Pu (%)
Wooded areas	20.77	0.44	0.07	0.03	21.32	97.41
Rock and mountain summit	0.06	34.25	0.40	0.13	34.83	98.33
Bare soil and built areas	0.00	0.06	21.92	0.10	22.08	99.26
Grassland	0.03	0.56	0.83	20.36	21.77	93.50

Total	20.85	35.31	23.22	20.62	Overall accuracy	0.97
Pr (%)	99.61	96.99	94.37	98.74	Kappa	0.96

Figure 2 illustrates the spatial distribution of the four main land cover classes identified in the study area, namely wooded areas, rock and mountain summits, bare soil and built-up areas, and grasslands. The classification clearly distinguishes these land cover types based on their spectral and spatial characteristics. Wooded areas are mainly concentrated in the central and northern parts of the landscape, reflecting zones with dense vegetation cover. Rock and mountain summits appear as scattered patches in the elevated regions, while bare soil and built-up areas are predominantly located around settlements and along major roads. Grasslands occupy extensive portions of open terrain, particularly in the lowland zones. This spatial representation provides a clear overview of the land cover structure and forms the basis for further analysis of land use dynamics and ecosystem patterns within the study area.

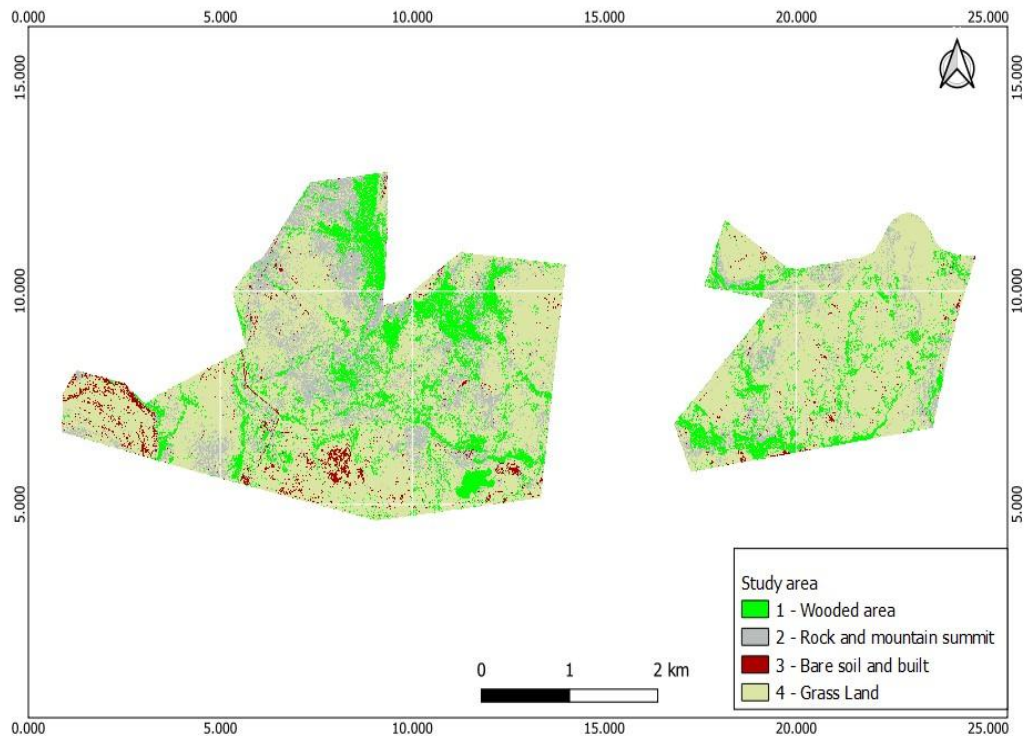


Figure 2. The four categories of Land Use and Land Cover over Sterkspruit Nature Reserve in Mpumalanga Province, South Africa.

3.2. Vegetation density assessment as a function of elevation gradient

The analysis revealed a weak negative relationship between NDVI and altitude (Figure 3). The Spearman correlation coefficient was -0.157, indicating a slight inverse monotonic association between the two variables. The linear regression model confirmed this trend, with an altitude coefficient of -0.0001267. The relationship was statistically significant (p -value = 0.038), although the explanatory power of the model was low (R^2 = 0.021), indicating that only 2.1% of the variation in NDVI is explained by altitude.

Discussion

The results indicate a high level of accuracy in the supervised classification of aerial photography images (Table 3). These performances are remarkable and demonstrate that the discrimination between land cover classes is highly reliable (Hajalalaina *et al.*, 2013). This means that the approach used to identify different land cover classes is statistically robust. Our results are comparable to those obtained in Togo in the classified forest of Amou-Mono and in Malawi, where the authors found similar results with overall accuracies of more than 95% (Koffi N'Dere *et al.*, 2023). The study revealed a weak but significant link between vegetation density (NDVI) and altitude. The Spearman correlation coefficient was -0.157, indicating a weak negative monotonic association between NDVI and altitude. Furthermore, the linear regression model showed that for each unit increase in altitude, NDVI decreased slightly. Although this relationship is statistically significant (p -value = 0.038), the effect size is small, showing that very little of the variance in NDVI was explained by altitude.

Accurate classification is crucial in landscape analysis, as it allows for the detection of variations in vegetation and other types of land cover with great reliability, which is essential for managing natural resources in a protected area like the Sterkspruit Nature Reserve.

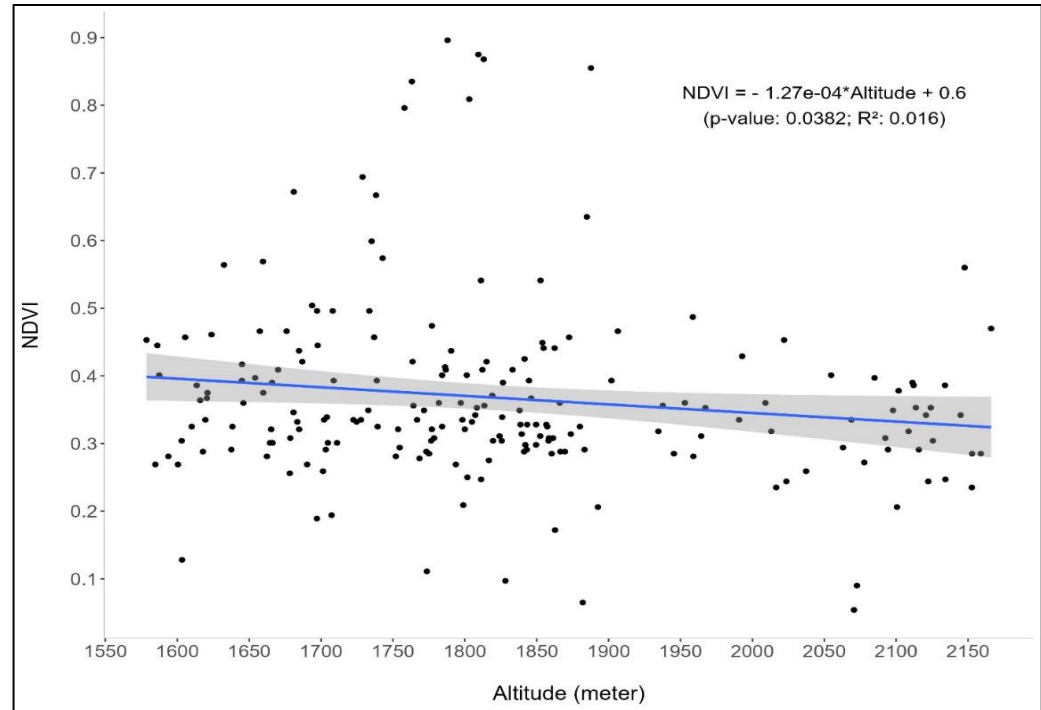


Figure 3. Relationship between NDVI and altitude at Sterkspruit Nature Reserve, South Africa

The study revealed a weak, although significant link correlation between vegetation density (NDVI) and altitude. These results suggest that while altitude has an impact on vegetation density, this effect is small and does not constitute the primary factor influencing NDVI in this area. Other environmental factors, such as soil composition, local climate, or human land use, may play a more determining role in the variability of vegetation at different altitudes (Argles *et al.*, 2022). The negative relationship between altitude and vegetation density (NDVI) could be linked to several ecological factors. As altitude increases, conditions generally become harsher for vegetation, with lower temperatures, stronger winds, and reduced nutrient availability in mountainous soils (Thakur & Chawla, 2019).

Conclusion

This study offers significant insights into land use dynamics and vegetation changes within the Sterkspruit Nature Reserve. It underscores the critical role of remote sensing as an analytical tool for managing and conserving mountainous ecosystems, while also highlighting the intricate relationships between vegetation and environmental factors like altitude. The findings demonstrated statistical reliability, with Kappa index scores surpassing 90%. The analysis using Pearson's correlation test revealed a decline in vegetation density in STNR with increasing altitude. These findings serve as a valuable foundation for future research, which could focus on how the vegetation in STNR is affected by climate change and other anthropogenic pressures.

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Authors' Contribution

Role of the contributor	Author’s name
Conceptualization, Methodology and editorial	Yattara F
Supervision - Validation	Kudakwashe M, Thompson L, Kamgang S A
Data Management, Formal Analysis	Yattara F, Gandaho S M
Revision	Kokou B K

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