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Use of remotely sensed data to estimate tree species diversity as an indicator of biodiversity in Blouberg Nature Reserve, South Africa

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ABSTRACT

We use remotely sensed data to estimate species diversity in Blouberg Nature Reserve (BNR) in the Limpopo province, South Africa to understand the state of biodiversity since communities' involvement in conservation initiatives. To achieve this objective, Landsat series data collected before and after community involvement in biodiversity conservation were used in conjunction with selected diversity indices i.e., Shannon-Wiener Index (H') and Simpson Index (D). Thirty 15 m × 15 m field plots were selected and all trees within each plot were identified, with the help of Botanists. Further, we applied regression analysis to determine the relationship between satellite derived tree species diversity and field observations. The results of the study demonstrated a significant ($p < 0.5$) variation in tree species diversity between 1990 and 2019. The highest relationship was obtained between H' and the combined remotely sensed spectral data and as well as Indices (VIs) when compared to other derived satellite data. Further, the results showed positive significant relationship ($p < 0.05$) between the combined remotely sensed data and observed H' index with $r^2 = 0.36$ and $r^2 = 0.34$ for the period before and after involving local communities in biodiversity conservation, respectively. Thus, the findings of the study indicate that the ecological condition of the reserve was slightly affected by the involvement of local communities in biodiversity conservation, for instance, volunteering in bush-encroachment eradication and decision-making. Overall, findings of the study underscore the relevance of remotely sensed data in assessing the ecological condition of protected areas and this information can help in decision-making.

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ecological status; mapping; species diversity; satellite data; statistical analysis; spatial characterization

1. Introduction

Tree diversity plays an important role in the functioning of an ecosystem and productivity (Cleland 2011; Arekhi et al. 2017). Tree species form the basis of the food chain, providing the food base and habitat, which boost ecological diversity (Xie et al. 2008; Cleland 2011). However, tree species diversity loss and disturbance are accelerating worldwide due

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to human disturbance (Cleland 2011; Marcon 2013; Thant 2017) and global climate change (Khare and Ghosh 2016; Li et al. 2018). Tree species loss could threaten the stability of the ecosystem services on which humans depend (Cleland 2011). Among the main human threats to biodiversity loss, deforestation (Li et al. 2018), bush encroachment, pollution (Thant 2017) and management practices are the key drivers (Oli and Subedi 2015; Paudel and Sah 2015). Landscape patterns related to disturbance, fragmentation and land cover change affect the abundance of rare and endangered species as well as biodiversity. Functional diversity loss, habitat loss, population declines and species invasions are among other indicators for tree species loss (Wang and Gamon 2019).

This ongoing biodiversity and ecosystem loss instantly requires assessment techniques that could quickly identify and monitor degradation hotspots (Krishnaswamy et al. 2009; Khare and Ghosh 2016; Rocchini et al. 2019) especially in Protected Areas (PAs). PAs are the cornerstone of global conservation efforts, therefore, requires long-term monitoring in order to maintain species integrity value (Vodouhê et al. 2010; Seiber et al. 2013). A halt of biodiversity loss is one of the Sustainable Development Goals of the United Nations' (Rocchini et al. 2019). Thus, to plan, manage and reduce biodiversity loss in an effective and sustainable way, it is essential to understand tree species diversity and composition of the ecosystems (Arekhi et al. 2017).

Traditionally, biodiversity has been monitored using field surveys, literature reviews, map interpretation and collateral as well as ancillary data analysis (Xie et al. 2008). Traditional monitoring of biodiversity is usually costly and time consuming (Krishnaswamy et al. 2009; Arekhi et al. 2017; Rocchini et al. 2019; Wang and Gamon 2019). Additionally, in most cases it is temporally limited (Rocchini et al. 2019). Moreover, species sampling in the field have several challenges, amongst them, observer bias, spatial errors, and historical bias on species distribution records (Rocchini et al. 2013).

Some studies that applied remote sensing in biodiversity estimation mostly focussed on mapping habitat through land cover classification without providing detailed verification of the habitat or tree diversity. For instance, the study by Arraut et al. (2018) produced vegetation structure map of Hwange National Park in Zimbabwe, using Landsat 8 data. Similarly, Bailey et al. (2016) measured land-cover change surrounding protected areas in the Maputaland-Pondoland-Albany Biodiversity hotspot from the 1980s whereas, Brink et al. (2016) assessed the land-use and land-cover for the Udzungwa Mountains National Park and its surroundings (20 km buffer) in Tanzania over a 20 year period (1990–2010) Thus, the recent development of satellite sensors provide opportunities to determine species diversity at large spatial extents (Nagendra et al. 2010; Rocchini et al. 2016; Arekhi et al. 2017; Thamaga 2018; Shoko et al. 2019). Remote sensing techniques provide an advanced, effective and practical method of obtaining accurate information on tree species diversity in a range of ecosystems (Wang and Gamon 2019) and their changes over time (Rocchini et al. 2019).

Comparatively, remote sensing can cover a large area over a short period whereas field based methods are restricted to small areas (Rocchini et al. 2019). In addition, the emerging remote sensed data allows spatial representation of species diversity, which could not be achieved using other methods. It permits the assessment of species diversity through tree characters or spectral information content (Wang and Gamon 2019). Remotely sensed data has also been used to understand the distribution of biodiversity to better identify high priority areas for conservation (Marcon 2013; Araújo et al. 2019; Rocchini et al. 2019), help maintain essential ecosystem goods and services (Wang and Gamon 2019) and ecological restoration efforts (Champagne et al. 2004). Furthermore, derived tree diversity maps from remote sensing data play an outstanding role in effective management and decision-making for vegetation patterns (Zhang et al. 2013; Arekhi et al. 2017), especially in data scarce regions of Southern Africa.

The current advancements in satellite technologies and their free availability provide new avenues for spatial explicit biodiversity monitoring and assessment in data-limited areas of Southern Africa. For instance, in South Africa, numerous PAs have been established to enhance biodiversity conservation; however, knowledge on biodiversity status in these areas remains rudimentary (South Africa's fifth national report to the Convention on Biological Diversity 2014; Hamer and Slotow 2017). In this study, we therefore, estimate tree species in the Blouberg Nature Reserve (BNR) in South Africa. The BNR was established in 1983 and involves local communities in biodiversity conservation. The BNR is endowed with variety of fauna (LEDET 2013) of which depend on the tree species for habitat. On the other hand, literature has shown that people likely to practice illegal activities in PAs that do not take their needs and aspiration into consideration (Vodouhê et al. 2010; Andrade and Rhodes 2012). The BNR, therefore, provides an appropriate case study and the experimental site for tree diversity estimation as a proxy for biodiversity assessment and monitoring in PAs. So far, there is a limited work that focussed on the tree species diversity in PAs especially that involve local communities in biodiversity conservation. The findings of the study will help to inform biodiversity conservation and management in BNR as well as practitioners in these data limited environments. Premised on this background, this study seeks to estimate species diversity in the Blouberg Nature Reserve in the Limpopo province, South Africa to understand the state of tree species diversity since local communities' involvement in biodiversity conservation initiatives. Further, we compared the derived species diversity results with bioclimatic data to establish whether the observed trends were a function of change in these factors or indirectly due to community involvement.

2. Materials and methods

2.1. Study area

The study was carried out in Blouberg Nature Reserve situated within latitudes of S 23° 01′ 04″ and longitudes of E 29° 04′ 09″. The BNR is located within the Blouberg Local Municipality, administered by Capricorn District Municipality of Limpopo Province, South Africa. It covers a total area of approximately 9 348 hectares. It is located approximately 34 km from R521, south-west of the Langjan Nature Reserve (LEDET 2013). The reserve was established in 1983 (Constant 2014) and started involving local communities in biodiversity conservation in 1992. The climate of the area is characterized by warm summer months, with temperatures ranging from 16 °C to 40 °C and mild winter months, with temperatures between 12 °C and 22 °C (Mostert 2006). The area receives an average annual rainfall of 410 mm per year, with the highest rainfall received during the summer months of December (LEDET 2013). The area experiences an orographic rainfall due to the east west positioning of the Soutpansberg Mountain (Mostert 2006).

Tree species within the reserve include Soutpansberg Summit Sourveld, dominated by *Combretum molle* and *Englerophytum magalismontanum*; Limpopo Sweet Bushveld, dominated by *Acacia robusta* and *Dichrostachys cinerea*; Roodeberg Bushveld, dominated by *Sclerocarya birrea* subsp and *Kirkia accuminatum*; and Soutpansberg Mountain Bushveld, with *Acacia karroo* and *Ziziphus mucronata* being the most dominant species. The reserve is endowed with variety of animal species; about 50 reptiles amongst them include Bibron's Stiletto Snake and Southern African Python. The reserve also have about 25 species of amphibians and amongst others include Northern Pigmy Toad. 21 Bat were also

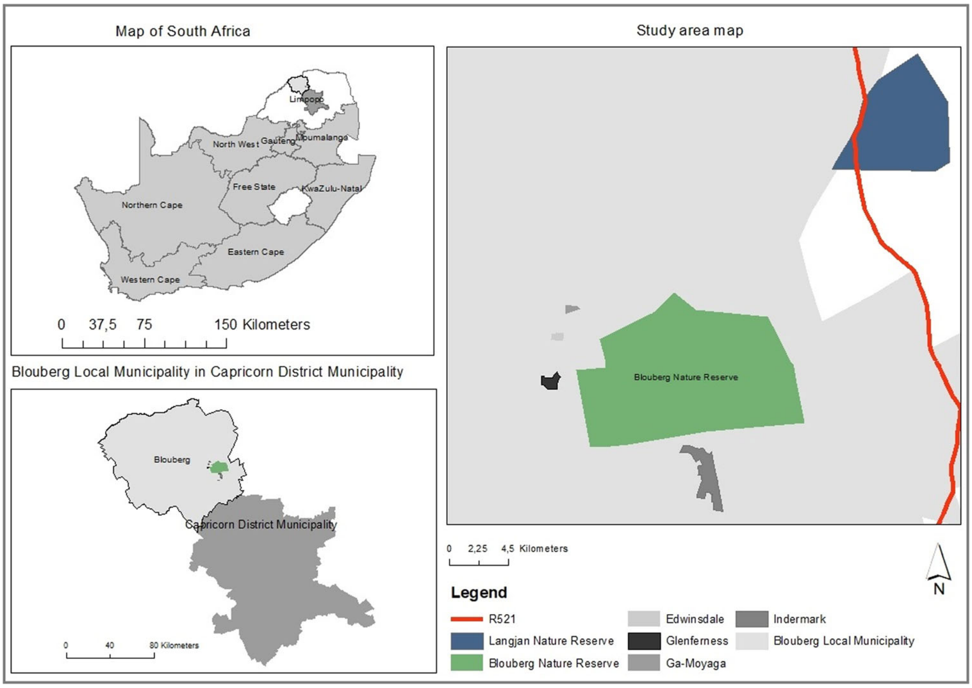

Figure 1. Blouberg Nature Reserve and surrounding villages in Limpopo, South Africa.

identified within the reserve (LEDET 2013; Constant 2014). The reserve is rich with Avifauna species (128), of which some of them (16) occur on IUCN Red List of Threatened Species like Cape Vulture, Lanner Falcon, and Saddle-billed Stork which are either vulnerable or endangered. Moreover, the BNR hosts one of the largest Cape Vulture breeding colonies in the world (LEDET 2013). The reserve also supports a variety of mammals including grazers such as bushbuck, mixed feeders such as Impala and browsers such as Giraffe (Constant 2014). Geologically, the area is dominated by variety of geological formations, which in conjunction with soil type underlie the spatial distribution of vegetation in the BNR. The area is associated with rocks such as gneisses, meta sediments and meta volcanics and soils including calcrete and limestone layers in the part of Limpopo Sweet Bushveld. In the Southpansberg Mountain Bushveld, the area is associated with rocks such as sandstone, quartzite, conglomerate, basalt and siltstone, and soils including acidic dystrophic to mesotrophic sandy to loamy. In the Rooderberg Bushveld, the area is associated with rocks such as sandstone, conglomerate, siltstone and shale, and mesotrophic soils, whereas rocks such as sandstone, quartzite and shale and extremely shallow, leached, acidic, coarse sand of the Glenrosa and Mispah soil forms in the Soutpansberg Summit Sourveld (LEDET 2013). Furthermore, villages including, Edwinsdale, Indermark, Ga-Moyaga, and Glenfernes surround the reserve (Figure 1).

2.2. Remote sensed data acquisition and pre-processing

Four Landsat satellite image scenes accessed from the United States Geological Survey (USGS) via the https://earthexplorer.usgs.gov web link were used (Table 1). These images were acquired in different years in order to examine the change in diversity within the reserve since local communities were involved in biodiversity conservation. Out of four

Table 1. Landsat-8 (OLI) spectral bands description.

Landsat-8 Sensor	Band number	Band name	Wavelength (μm)	Resolution
	1*	Coastal/ Aerosol	0.43–.45	
	2*	Blue	0.45–0.52	
	3*	Green	0.53–0.60	
	4*	Red	0.63–0.68	
	5*	Near Infra-red (NIR)	085.–0.89	
	6*	Short-wave Infra-red (SWIR)1	1.56–1.66	
	7	Short-wave Infra-red (SWIR)2	2.10–2.30	30
	8	Panchromatic	0.50–0.68	15
	9	Cirrus	1.36–1.39	30
Thermal Infra-red Sensor (TIRS)	10	Long-wave Infra-red (LWIR) 1	10.30–11.30	
	11	Long-wave Infra-red (LWIR) 2	11.50–12.50	
				100
Landsat-5 Sensor	Band number	Band name	Wavelength (μm)	Resolution
	1[a]	Visible Blue	0.45–0.52	
	2[a]	Visible green	0.52–0.60	
	3[a]	Visible Red	0.63–0.69	
	4[a]	Near Infra-red (NIR)	0.76–0.90	
	5[a]	Short-wave Infra-red (SWIR)1	1.55–1.75	30
	6	Thermal	10.40–12.50	120
	7[a]	Short-wave Infra-red (SWIR)2	2.08–2.35	
				30

[a]Used spectral bands.

collected Landsat satellite images, three were Landsat-5 Thematic Mapper (Landsat-5 TM) captured in 1990, 1996 and 2009 whereas one was Landsat-8 OLI captured in 2019. The choice of these years was determined by the availability of cloud free imagery from Earth Explorer. The collected Landsat-5 TM and Landsat-8 OLI images have a spatial resolution of 30 m and a revisit aptitude of 16 days. Overall, Landsat data is freely available, and it has the ability to provide large volumes of observations than other satellite data products. These datasets have been used for mapping land and vegetation cover changes and it continues to be commonly used in ecology (Cohen and Goward 2004). The images were atmospherically corrected, using the Dark Object Subtraction (DOS1) model under Semi-Automated Classification (SCP) in Quantum GIS (QGIS) version 3.0 software, which masks out clouds and shadows, among other non-target effects.

Furthermore, spectral reflectances from Landsat images for different years were then extracted corresponding to each plot coordinates points. The extracted spectral reflectances were then used to calculate selected Vegetation Indices (VIs) (Table 2). The VIs were used in this study were selected based on their well performance of compensating soil background influences and atmospheric effects in biodiversity conservation. Remote sensed variables in conjunction with field based diversity indices were then used to develop a model to estimate tree species diversity, using simple and multi-linear regression analysis. The developed model was then used to estimate tree species diversity across different years in a GIS environment.

2.3. Tree species data

2.3.1. Field sampling protocol and tree species data collection

The tree species sampling for data collection purposes was performed in 30 plots of 15 m × 15 m each. Work by Mutowo and Murwira (2012) and Mapfumo et al. (2016), have shown that sampling plot sizes widely used ranges between 25 and 200 m^2 in tall

Table 2. Vegetation indices used in the study and their equations.

Vegetation Index	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR-RED}{NIR+RED}$	Rouse et al. (1974)
Soil-adjusted vegetation index (SAVI)	$SAVI = \frac{NIR-RED}{(NIR+RED+L)}*(1+L)$	Huete (1988)
Enhanced Vegetation Index (EVI)	$EVI = G*((NIR - RED)/(NIR + C1*RED - C2*BLUE + L))$	Huete et al. (1999)
Simple Ratio Index (SRI)	$SRI = \frac{NIR}{RED}$	Tucker (1979)

L is a soil fudge factor that varies from 0 to 1 depending on the soil the coefficients adopted in the MODIS-EVI algorithm are; L = 1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5.

shrub communities and 200-25000 m^2 for trees in woods and forests. The statement guided the selected plot size for this study and it falls within the range. Simple random sampling was used to define the placement of sampling plots (Oli and Subedi 2015), with a minimum separation of 200 m to avoid overlapping sampling plots (Paudel and Sah 2015). All tree species type with 1.5 m per plot were identified and recorded. The centre coordinates of each plot were recorded, using Global Positioning System (GPS). 488 tree species belonging to 19 families were recorded. The collection of tree species data was conducted in April 2019.

2.3.2. Measuring diversity of tree species

In this study, we used the most frequently used diversity indices to quantify diversity in each plot i.e., Shannon-Wiener Diversity Index (H') and Simpson Diversity Index (D) (Table 3). Madonsela et al. (2018) and Peng et al. (2018) confirmed that H' and D, are the frequently used diversity indices in ecological literature. H' is a qualitative measure that reflects different types of species within a community or sample, and how common or rarely are they from each other (Mutowo and Murwira 2012; Ifo et al. 2016; Mapfumo et al. 2016; Madonsela et al. 2018). H' ranges between 0 and 5, usually between 1.5 and 3.5 but reaches 4 in rare cases (Türkmen and Kazanci 2010). D is generally influenced by the abundance in the distribution of tree species (Mutowo and Murwira 2012). It ranges between 0 and 1 where high scores, i.e., close to 1 indicate high diversity whereas low scores, i.e., close to 0 indicate low diversity (Türkmen and Kazanci 2010; Mapfumo et al. 2016). These indices were used in this study because they consider both species richness and abundance when measuring species diversity (Madonsela et al. 2018). Furthermore, H' is less affected by the presence of rare species (Dogan and Dogan 2006; Mapfumo et al. 2016; Rocchini et al. 2016). H' and D were calculated as indicated in Table 3.

2.4. Relationship between tree species diversity indices and remote sensed data

The relationship between species diversity indices as a response variable and spectral data as predictor variable was investigated using simple and multi-linear regression analysis techniques to determine species diversity. The relationship was determined between most commonly used diversity indices (Table 3) and remote sensed data. The Root Mean Square Error (RMSE), Coefficient of determination (r^2) and corrected Akaike's Information Criterion (cAIC) of the linear regression guided the selection of the most appropriate model to map tree species diversity.

Developed model for 2019 was having: 1. the smallest RMSE and cAIC, and 2. the highest r^2. The RMSE measures how close the model could predict field measurements; r^2 measures the proportion of the variance in the dependent variable that is predicted from the independent variable, whereas cAIC estimates the quality of each model, relative to

Table 3. Summary of diversity index and their expression.

Species diversity index	Equation	Reference
Shannon-Wiener Diversity Index (H′)	$H' = -\sum_{i=1}^{S} Pi \ln Pi$	Shannon and Wiener (1949)
Simpson Diversity Index	$D = 1 - \frac{\sum_{i=1}^{n} ni(ni-1)}{N(N-1)}$	Simpson (1949)

Where, H′ is index of species diversity, *Pi* is the proportional abundance of *i*th species is the number of individuals of all the species, ln is natural logarithm, *ni* = number of individuals of each species, *N* = total number of individuals of all species.

each of the other models. Peng et al., (2018) added that the objective of cAIC is to select the best approximating model.

Further, to investigate normality of the data in order to fulfil the requirements of linear regression analysis the Shapiro Wilk test was used. According to Mutowo and Murwira (2012), linear regression requires that data are normal distributed. In addition to normality, Pearson's correlation coefficients were used to evaluate the correlation between the variables. Moreover, we checked for the significance of the correlated variables using P-values.

2.5. Environmental variables

In addition to diversity indices and remote sensed data, environmental variables such as rainfall, temperature, Digital Elevation Model (DEM) and evapotranspiration were used in this study (Table 4) since they are known to affect species diversity pattern (Zhang et al. 2013; Imani et al. 2016; Sainge et al. 2019; Shoko et al. 2019). Rainfall, evapotranspiration and temperature were averaged annually. A DEM at a spatial resolution of 30 m was also used to derive the relief of a surface. To understand tree water use patterns, evapotranspiration data was considered to determine how it also influenced species diversity (Silva et al. 2017; Li et al. 2019). Further, according to Liu and El-Kassaby, (2018), Species richness is best predicted by climatic variables such as evapotranspiration and asserted that evapotranspiration may greatly impact tree growth patterns since it is uniquely linked to water, energy, and carbon cycle. Data were used to show the general pattern of the used environmental variables variations and how they might likely have affected the diversity within the study area. Thus, the relationship between species diversity and environmental variables was also explored based on tree species data collected from the field. The selected environmental variables were used in this study because they are amongst the most significant factors affecting species diversity and the woody vegetation (Nguyen et al. 2015).

3. Results

3.1. Tree species in BNR

Four hundred and eighty-eight tree species belonging to 19 families were recorded within 6750 m^2 of the BNR. Predominant tree species are from Fabacea, followed by Malvaceae and Boraginaceae with tree species of 200, 126 and 50 respectively. Malvaceae, Fabacea, Combretaceae and Rubiaceae are the only families with more than one type of tree species (Table 5). The most predominant species identified in the BNR include *Combretum molle, Englerophytum magalismontanum; Acacia robusta, Dichrostachys cinerea, Sclerocarya birrea subsp, Kirkia accuminatum; Acacia karroo and Ziziphus mucronata.*

Table 4. Environmental variables that were used in this study.

Variable	Definition	Source
Rainfall	Mean annually total, in millimetres (mm)	https://wapor.apps.fao.org/catalog/1
Evapotranspiration	Mean annually total, in millimetres (mm)	
Temperature	Mean annually total, in degrees Celsius (°C).	
DEM	Relief in metres (m)	http://srtm.csi.cgiar.org/

Table 5. Tree species lists and their frequencies of the study area.

Family		Names	Number of trees	Total
1.	Malvaceae	*Grewia flava*	80	126
		Grewia flavascenes Juss	46	
2.	Phyllanthaceae	*Pseudolachnostylis maprouneifolia*	43	43
3.	Burseraceae	*Commiphora Jacq. tree*	3	3
4.	Asteraceae	*Tarchonanthus camphoratus L.*	3	3
5.	Fabaceae	*Philenoptera violacea (Klotzsch) Schrire*	9	200
		Dichrostachys cinerea (L.) Wight & Arn		
		Acacia nigrescens	119	
		Acacia Nalatica	38	
			34	
6.	Rubiaceae	*Vangueria infausta Burch. subsp. Infausta*	4	13
		Plectroniella armata (K. Schum.) Robyns		
			9	
7.	Loganiaceae	*Strychnos spinosa Lam.*	6	6
8.	Anacardiaceae	*Sclerocarya birrea*	7	7
9.	Combretaceae	*Combretum imberbe Wawra*	5	9
		Terminalia prunioides M.A.Lawson		
			4	
10.	Brassicaceae	*Boscia albitrunca (Burch.) Gilg & Gilg-Ben.*	5	5
11.	Kirkiaceae	*Kirkia acuminata Oliv.*	2	2
12.	Euphorbiaceae	*Spirostachys africana Sond.*	6	6
13.	Ebenaceae	*Euclea undulata Thunb.*	12	12
14.	Phyllanthaceae	*Flueggea virosa (Roxb.ex Willd.) Voigt*	1	1
15.	Solanaceae	*Lycium ferocissimum Miers*	3	3
16.	Boraginaceae	*Ehretia rigida (Thunb.) Druce*	25	50
		Cordia grandicalyx		
			25	
17.	Rhamnaceae	*Ziziphus mucronata Willd. subsp. mucronata*	7	10
		Berchemia zeyheri (Sond.) Grubov		
			3	
18.	Combretaceae	*Terminalia sericea Burch. ex DC.*	4	4
19.	Burseraceae	*Commiphora mollis (Oliv.) Engl.*	5	5
Total				488

The tree species varied in few plots across the study area. The lowest value obtained from the used diversity indices was from plot 25 with (H' = 0.15; D = 0.29) whereas the highest value was obtained in plot 3 (H' = 3.14) and plot 11 (D = 0.88). Plot number 25 was noted with lowest tree species diversity, with the lowest richness of two amongst other plots. The number of tree species found in each plot mostly influenced the results. The information on tree species, therefore, can provide baseline information for conservation of the biodiversity particularly in PAs.

Table 6. Correlation between H′ and remote sensed data.

	2019	
	Correlation to H′	P-value
Band 1	−0.10	**0.02***
Band 2	−0.12	**0.01***
Band 3	−0.22	**<0.0001***
Band 4	−0.30	**<0.0001***
Band 5	−0.08	0.07
Band 6	−0.36	**<0.0001***
Band 7	−0.38	**<0.0001***
Band 9	0.14	**0.002***
NDVI	0.17	**0.0001***
SAVI	0.07	0.13
EVI	0.09	**0.04***
SRI	0.20	**<0.0001***

3.2. Correlation between H′ and VIs, and spectral data

In this study, correlation between the variables was evaluated using Pearson where H' for 2019 demonstrated negative correlation with spectral bands except with band 9 and all VIs. Overall, VIs had a positive correlation with H' over period when compared to the use of the raw Landsat derived spectral data (Table 6). To fulfil the linear regression, normality for the data was tested using Shapiro Wilk test. The findings of the study indicated that data does not follow normal distribution curve for all used years with $p = < 0.0001$. The findings of the study demonstrated negative correlation between H' and Landsat spectral data over period. The correlation was significant over the study period except for the year 1996 (Table 6).

3.3. Simple and multi-linear results in predicting species diversity

A series of simple linear regressions were performed, regressing diversity indices (H' and D) against each of the Landsat spectral bands and VIs, over period. Simple linear models based on Landsat spectral bands and VIs with H' did not perform well when compared to multiple linear regression. H' and band 7 (SWIR-2) for 2019 had slightly better relationship of ($r^2 = 0.14$) and (RMSE = 0.73) amongst other remote sensed data over period, but this was slightly better than band 6 (SWIR-1) with $r^2 = 0.12$ and RMSE = 0.74. Then, model based on the 2019 data was then used to estimate the tree species diversity for all years. Furthermore, both H' and D showed the lowest relationship with VIs (Table 7b). In this regard, the model for estimating tree species diversity was derived from the H' and combined Landsat spectral bands and VIs for all years (Figure 2).

In general, H' demonstrated better relationship with combined Landsat spectral bands and VIs than with individual remote sensed data. Consequently, the model (regression equation) with lowest RMSE and cAIC, and highest r^2 was derived from combined spectral bands and VIs and used to estimate diversity in the study area across different years. Obtained model equation was used to calculated diversity map in GIS environment. Consequently, H' species diversity maps of the study area were derived (Figure 2).

Figure 2 shows the great decrease in species diversity from 1990 to 1996. The species diversity then slightly increased from 1996 to 2009. Furthermore, species diversity decreased from 2009 to 2019. The highest diversity value was obtained in 2019 as compared to other period, however, only small portion of the study area was highly diverse, whereas 1996 obtained lower highest value than other period, but the diversity was distributed all over the area. High diversity was observed along the river as well as at the base of Soutpansberg Mountain, nonetheless, the diversity varies per period. The

Table 7. Relationship observed between two common measures of tree species diversity (H′ and D) and a. combined VIs and Landsat spectral bands, b. VIs and c. Landsat spectral bands.

Year	Index	R^2	RMSE	AIC
a.				
2019	H′	0.34	0.65	−407.33
	D	0.24	0.10	2236.89
b.				
2019	H′	0.14	0.73	−296.21
	D	0.08	0.11	−2161.93
c.				
2019	H′	0.21	0.71	−327.78
	D	0.17	0.10	−2206.98

Soutpansberg Mountain ranges from the east to the southwest whereas the river flows from the east to the south of an area.

In addition, to explain the variation in species diversity, remote sensed data and diversity indices as well as environmental variables were also integrated in this study (Figure 3). Mean annual temperature, rainfall and evapotranspiration over the BNR varied between a minimum of 1°C in 2015, 198 mm/year in 2015, 500 mm/year in 2012 and maximum of 17 °C/year in 2017, 380 mm/year in 2016, 666 mm/year in 2015, respectively. The increase in mean annual temperature was observed in 2013, 2016 and 2017, whereas the decrease in temperature was observed from 2010 to 2012; 2013 to 2015 and 2017 to 2019. In terms of rainfall, the decrease was observed from 2010 to 2012, 2013 to 2015 and 2016 to 2018; nevertheless great increase was observed in 2013 and 2016. Additionally, an increase in evapotranspiration rate was observed from 2009 to 2010 and 2012 to 2015, whereas the decrease was observed in 2012 and 2018. Further, the highest elevation was observed on the top of Soutpansberg mountain ranges, then medium at the most north, east, south of the study area and low at the bottom of Soutpansberg mountain ranges. The results showed strong positive significant correlation ($p < 0.05$) between H’ and annual evapotranspiration in all years. Furthermore, it was evapotranspiration in 2018 which had the highest relationship with H’ ($r^2 = 0.17$) than other years. In addition, H’ had negative insignificant relationship with annual rainfall across all years ($p > 0.05$).

4. Discussion

The BNR is one of the most important PAs in Limpopo province that incorporates local communities in biodiversity conservation. The reserve is endowed with a wide range of vegetation and wild animals that have the potential to contribute greatly to economic growth through tourism (Blouberg Municipality 2017). It is, therefore, important to ensure that tree species diversity in the area is frequently monitored and assessed to ensure sustainable conservation. Thus, the understanding of the tree species diversity status before and after involving local communities in biodiversity conservation is crucial as it provides reserve management with the necessary baseline information about tree species distribution within the reserve, which is essential in planning and management of the reserve.

4.1. Variation in tree species diversity

The results of this study demonstrated a significant ($p < 0.5$) variation in tree species diversity from 1990 to 2019. The high species diversity observed at the base of the Soutpansberg mountain might be attributed to favourable conditions such as humid and warm temperatures, whereas along the river might be attributed to the high wetness from the water in the

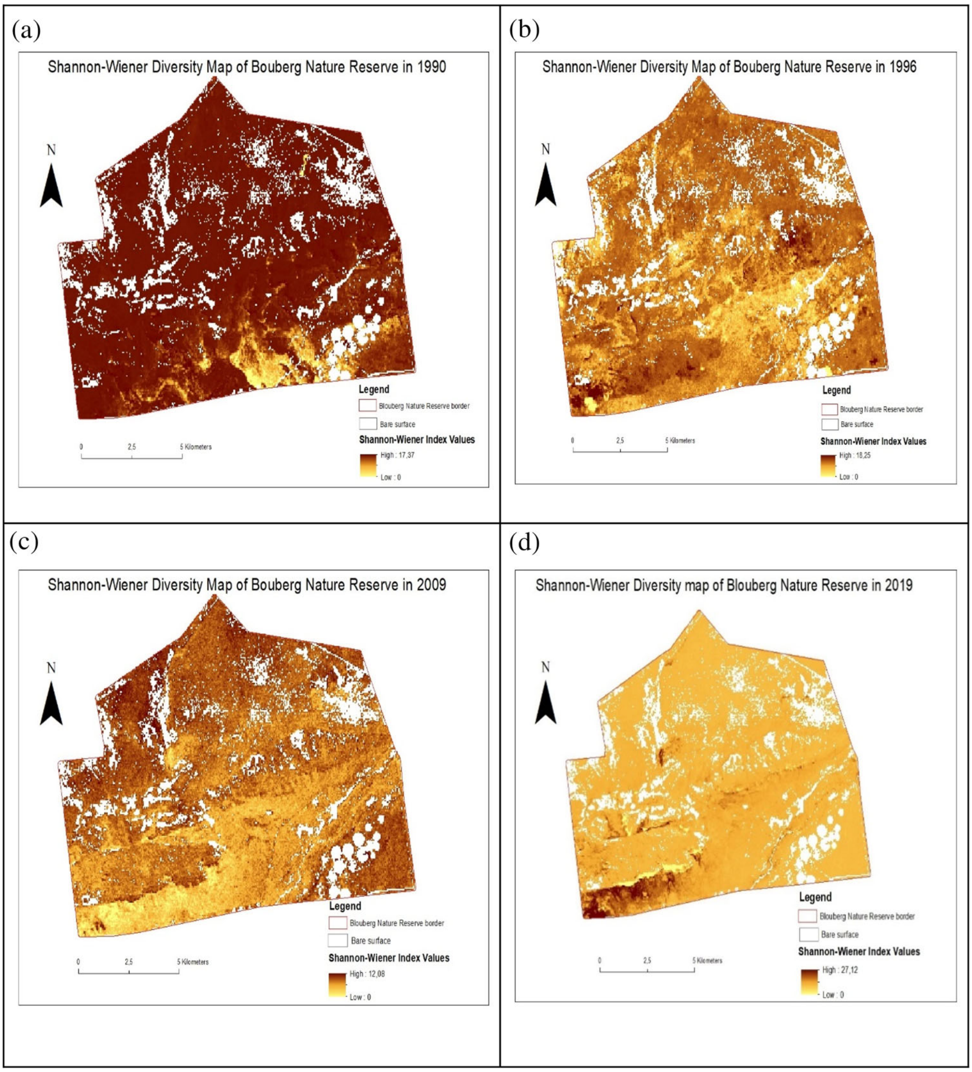

Figure 2. Tree species diversity thematic maps derived from H′, and combined VIs and Landsat spectral data over the period a. 1990, b. 1996, c. 2009 and d. 2019.

river. For instance, Li et al. (2019) observed high diversity of Salicaceae plants in warm and wet areas than other regions in China. The increased in rainfall might also be defined by the high species diversity along the river in 2019. For instance, Shoko et al. (2019) found that the high production of C3 AGB favours environments with high soil moisture. In addition, the high rate of evapotranspiration at the area might be attributed to the solar radiation of an area. According to Li et al. (2019) and Shoko et al. (2019), solar radiation is one of the primary sources of energy that regulates physical, chemical and biological processes of terrestrial ecosystems. Thus, the rate of evapotranspiration defines the species diversity (Silva et al. 2017; Li et al. 2019). In terms of elevation, the results of the study illustrate the decrease in species diversity in increasing elevation.

The results of the study are similar with of Gwali et al. (2010) and Imani et al. (2016) where they found that species diversity decreases with increasing altitude in semiarid savannah woodland in central Uganda and Kahuzi-Biega National Park and its

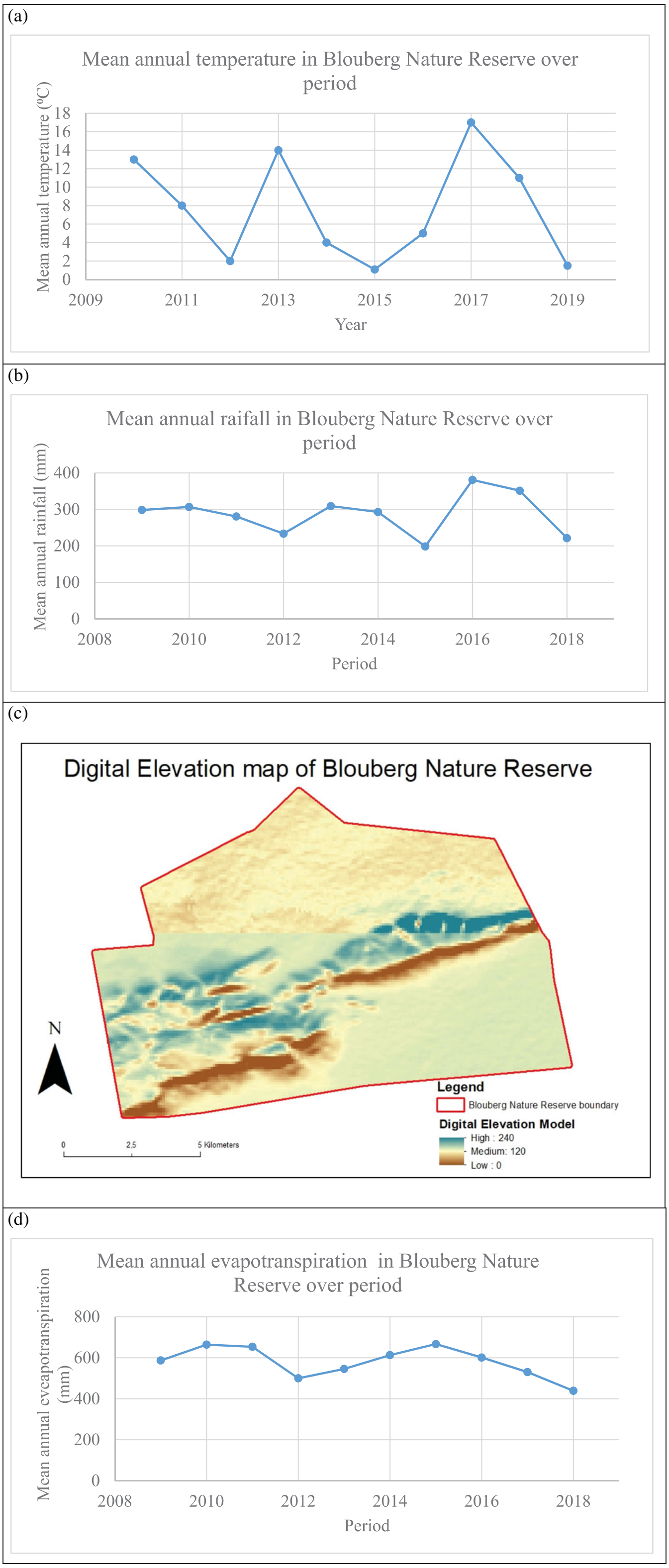

Figure 3. Environmental variables: a. temperature, b. rainfall, c. DEM, and d. evapotranspiration.

surroundings forest parks, and the Democratic Republic of Congo respectively. Similarly, Toledo-Garibaldi and Williams-Linera (2014) and Pandey et al. (2018) reported that species richness decreased unimodally with elevation gradient in Mountains of Eastern Mexico, and Khangchendzonga National Park, Sikkim respectively. Low diversity at the top of the mountain might be attributed by the rough and rocky terrain-giving rise to only competitive species. Additionally, their moderately drained surfaces offered by plateau (Phil-Eze 2012). The results of the study contrast with of Zhang et al. (2013) and Kanagaraj et al. (2017) who found highest species diversity appeared in the middle elevation in the Baihua Mountain Reserve, Beijing, China and Pachamalai Reserve Forest, Tamil Nadu respectively. Overall, the variation in tree species diversity in some areas such as at the base of the Soutpansberg Mountain and along the river remain almost stable throughout the period. This therefore ascertain assumption that vegetation structure and composition are also influenced strongly by elevation (Imani et al. 2016; Sainge et al. 2019), evapotranspiration, temperature and rainfall (Li et al., 2019).

Our results demonstrated that tree species diversity in BNR can be successfully predicted by H' in conjunction with Landsat variables. These findings imply the potential of using freely available emerging sensors for monitoring species diversity. On the other hand, from the findings of the study, we deduce that the multi-linear regression result in better model that can improve the prediction of tree species diversity. The findings of the study revealed that environmental variables had an influence on tree species diversity over time.

4.2. The performance of simple and multi-linear regression

It was found that H' in conjunction with remotely sensed variables could better determine tree species diversity when compared to D. H' was the better diversity index to define species diversity. This is because it considers both abundance and richness of the community (Dogan and Dogan 2006; Arekhi et al. 2017; Madosela et al. 2018). Moreover, Madonsela et al., (2018) added that species diversity indices that is both species richness and abundance like H' and D usually have better relationship with Landsat-8 spectral variables. However, in this case H' might be useful since the study does not focus only to determine the dominant species. Nevertheless, in some plots, the diversity was very low and this could be explained by the fact that they were dominated by few types and total number of species besides other abiotic and biotic factors as ascribed by the H'. This finding is approximately consistent with those of Shah, (2013) who observed lowest value of H' of 0.79 at site I to the highest of 3.95 at site III of Wular Lake, Kashmir Himalaya.

The relationship between H' and combined remote sensed data were explained better when compared to individual remote sensed data over the period. Furthermore, the relationship between H' and individual remote sensed data for 2019 is better than other years used. This could be explained by the fact that Landsat-8 OLI is recently launched with advanced properties than the previous Landsat data. Landsat-8 OLI has shown to be complex and vibrant compared to previous Landsat images like Landsat-5 TM (Poursanidis et al. 2015). For instance, Poursanidis et al. (2015) found that classification results from Landsat-8 OLI provide more accurate results of over 80% compared to the Landsat-5 TM.

In addition, in simple linear regression, H' showed a better significant positive relationship with VIs when compared to Landsat spectral bands. Our study further shows that H' has a better positive significant relationship with NDVI and SAVI with (r^2 = 0.05) and (RMSE = 0,772; 0,770), respectively when compared to other VIs over period. This might be because the used VIs were calculated using NIR which has been suggested for discriminating species diversity (Arekhi et al. 2017; Peng et al. 2018). Additionally, according to

Fajji et al. (2017) different VIs are computed from the combinations of two or more spectral bands, assuming that multi band analysis would provide further information than a single one. Furthermore, the results of the study could be attributed to the sensitivity of the VIs to variability in vegetation characteristics i.e., shape and size of the tree, water content, and associated background. Hence, this might be influence the results of this study. The same, the results might be attributed to the environmental factors such as amount of rainfall and temperature received in the study area.

This finding is consistent with those of Arekhi et al. (2017) where they found NDVI having the highest significant positive correlation with H' calculated from basal area (3×3 Shannon Index Basal Area (SIBA)) with $r = 0.685$ in June in the Gönen dam watershed area in Turkey. Furthermore, Peng et al. (2018) confirmed that the combination of NDVI and H' used to estimate species richness. In addition, Gaitán et al. (2013) study also showed a strong correlation between NDVI and species richness in steppes and ecosystems respectively. According to Madonsela et al. (2018) the differences in sensitivity to vegetation characteristics could be explained by the different measurement scales of VIs. For, instance in this study, the VIs which had better relationship with H' (NDVI and SAVI) have a measurement scale which ranges from -1 to 1.

Regarding the influence of environmental factors, Shoko et al. (2019) found that increase with *Themeda triandra* (C4) aboveground biomass (AGB) in March was marked with an increase in temperature with the highest significant positive relationship ($r^2 = 0.82$, $p < 0.005$) within the Drakensberg area in KwaZulu Natal. Similarly, Mapfumo et al. (2016) observed the linear relationship between H' and NDVI in wet part of Zambia ($r^2 = 0.68$; $p = 0.017$) and assumed that it could be explained by the fact that wet ecosystems receive high rainfall above 1000 mm leading to high diversity which facilitates high Coefficient of Variation in the NDVI. Overall, our study demonstrated lower relationships when compared to other studies, this might have attributed to the fact that other studies are using derivatives (Madonsela et al. 2018), commercial satellite images (Mutowo and Murwira, 2012), they were considering seasons (Mapfumo et al. 2016; Arekhi et al. 2017) that might have improved their predictions of species diversity.

Better relationship between H' and SWIR region of Landsat-8 could be attributed to the improved soil moisture content and vegetation of an area. In line with Jakubauskas and Price (1997) observation, biophysical properties of forest canopy are best explained by a combination of spectral information in the SWIR regions of Landsat-7 Enhanced Thematic Mapper (ETM). Additionally, Madonsela et al. (2018) also confirmed that the Landsat programme gathers crucial spectral information in the SWIR region, which is related to tree properties. The negative significant relationship between H' and spectral bands could be attributed to the amount of vegetation cover. Madonsela et al. (2018) made an assumption that positive correlation in the visible region indicates high spectral signal reflectance across all bands and this is typical of dry vegetation due to the background effect as it had dropped its foliage cover and vice versa. This ascertains our results since the area has a diverse tree species.

4.3. Implications to biodiversity conservation

Deducing from the results of this study, the use of remote sensing on estimating tree species diversity to understand state of tree species diversity since the local communities' involvement in biodiversity conservation plays an important role in conservation management. The results also imply that remote sensing explained the variation in species diversity better when integrated with environmental variables as they are also known to influence natural resources (Silva et al. 2017; Shoko et al. 2019) such as species diversity. Moreover, this demonstrates how ecological knowledge and satellite-based information can be effectively combined to address a wide range of current natural resource management.

5. Conclusion

We conclude that tree species diversity can be estimated using H' and combined Landsat spectral bands and VIs. Moreover, NDVI and SAVI results confirmed their reported ability in estimating vegetation diversity. Further, we conclude that the species diversity in the area varies over the period. However, changes in species diversity over time were not the same across the study area since some areas showed rapid changes, whereas those situated along the rivers and at the base of Soutpansberg Mountain appeared to be nearly stable with time. Overall, we conclude that the results of this study indicate that remote sensing can be successfully used to predict tree species diversity and to track the changes in species diversity in PAs. Additionally, the findings of the study indicate that the ecological condition of the nature reserve was slightly affected since the involvement of local communities in biodiversity conservation.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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