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Evaluating Several Vegetation Indices Derived from Sentinel-2 Imagery for Quantifying Localized Overgrazing in a Semi-Arid Region of South Africa

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Abstract: Rangeland monitoring aims to determine whether grazing management strategies meet the goals of sustainable resource utilization. The development of sustainable grazing management strategies requires an understanding of the manner in which grazing animals utilize available vegetation. In this study, we made use of livestock tracking, in situ observations and Sentinel-2 imagery to make rangeland scale observations of vegetation conditions in a semi-arid environment, to better understand the spatial relationships between vegetation conditions and sheep movement patterns. We hypothesized that sheep graze more selectively under low stocking rates—resulting in localized overgrazing. We also assessed the importance of image spatial resolution, as it was assumed localized effects of grazing will be best explained by higher resolution imagery. The results showed that livestock tend to congregate along drainage lines where soils are deeper. The findings demonstrate how the spatial analysis of remotely sensed data can provide a landscape-scale overview of livestock movement patterns. This study illustrates that high-resolution normalized difference vegetation index (NDVI) data can be used as a grazing management tool to determine the spatial variability of productive areas across the semi-arid Upper Karoo rangelands and identify preferred grazing areas.

Keywords: animal-landscape interactions; grazing management; livestock movement; NDVI; rangelands; Sentinel-2

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1. Introduction

One of the primary objectives of rangeland monitoring is to determine whether grazing management strategies meet the goals of sustainable resource utilization and to prevent rangeland degradation from taking place. Frequent assessments of livestock movements and the monitoring of vegetation conditions are essential for establishing whether management strategies are effective, especially within the context of prolonged droughts, grazing pressures, land-use changes and climate change. However, using traditional observation methods for monitoring vegetation conditions and animal movement is often difficult, time-consuming and costly, especially in extensive grazing environments [1,2]. Economically feasible monitoring methods are required, particularly in arid to semi-arid environments that are susceptible to degradation.

Small stock farms are typically subdivided into camps. Camps refer to a fenced grazing area where livestock are kept, also known as a paddock [3]. These camps are utilized in a rotational manner and the number of animals per camp is determined in terms of the relationship of animal to land area also referred to as stocking density [3]. High stocking density, is often regarded as the reason for localized overutilization of grazing areas [4,5]. This is supported by studies that have shown diversity in vegetation and vegetation cover can be significantly reduced by recurring overgrazing due to high stocking densities in fragile landscapes [6,7].

The Upper Karoo is characterised by an arid to semi-arid environment with low rainfall and extreme temperatures. Vegetation typically consists of a wide range of species dominated by perennial dwarf shrubs and therefore is known as the Karoo shrublands. Inequality, poverty, and hunger, as well as, unsustainable water supply, remain some of the key challenges that people face living and farming in the Upper Karoo. These challenges are interconnected with the impacts of a changing climate, environmental degradation, and population growth [8]. The incidence of perennial grasses is low, while short-lived grass species typically irrupt in response to rain events [9]. In this fragile ecosystem, it is important to understand how grazing pressures and grazing management strategies can influence vegetation dynamics when developing guiding principles for sustainable rangeland management [10,11]. Semi-arid environments typically experience high heterogeneity and temporal variability in precipitation, which results in variable vegetation productivity and forage availability [12–15].

It is critical that land users and managers have a good understanding of how this variability impacts the movement patterns of grazing livestock [1,12]. Overgrazing is one of the most important causes of rangeland degradation in the Upper Karoo [16,17]. Degradation results in a loss of biodiversity, a deterioration in rangeland productivity due to an increasing rate of soil erosion, and has a direct influence on the carrying capacity of the rangeland. This ultimately has an impact on the profitability of livestock farming [18–21]. Monitoring animal behaviour and vegetation attributes, such as species diversity and density, is pivotal to good rangeland management practices and for preventing degradation in semi-arid areas such as the Upper Karoo. Sustainable management intervention strategies can be developed by correlating the grazing patterns of livestock with the available resources [1,22,23]. Although remotely sensed data have been used extensively for rangeland monitoring [24–27], such data have not yet been used to characterize behavioural grazing patterns of livestock in the Upper Karoo.

Global navigation satellite systems (GNSS), such as the global positioning system (GPS), have been effective for tracking and monitoring animal behaviour [1,28–30], while advances in remote sensing (RS) technologies offer ever-increasing opportunities to assess and characterize land surface conditions over time and scale [12,31]. In particular, spaceborne RS sensors can be used to obtain landscape-wide snapshots at intervals ranging from months to minutes [32]. The recent availability of high temporal (5-day interval) and high spatial (10–60 m) resolution imagery from the Sentinel-2 satellite constellation [33] opened up new opportunities for monitoring temporal changes in vegetation conditions. Sentinel-2 imagery has been used since 2015 for applications ranging from vegetation classification [34–38], vegetation condition monitoring [36], yield estimation [39–41], mapping soil organic carbon in croplands [42–44], nitrogen status of crops [45,46] and monitoring water quality of inland waters [47].

Indices representing vegetation "vigour" or "greenness" are commonly used in Earth observation of vegetation. They have, for instance, been successfully used to map and monitor photosynthetically active and healthy vegetation [2], differentiate between weeds, crops and bare soil [48], and determine the chlorophyll content and plant biomass [49,50]. Commonly used indices include the normalized difference vegetation index (NDVI) [51], the green normalized difference vegetation index (GNDVI) [52] and the soil adjusted vegetation index (SAVI) [53], but the efficacy of a range of other indices has also been demonstrated [54–57]. Low-resolution ($\geq$250 m) NDVI data have been found to be useful for indicating grazing land productivity and evaluating vegetation activity across regional grazing systems [58–61].

Vegetation indices have been combined with GPS collar data to monitor animal movement patterns, habitat use and grazing preferences [1,12,62,63]. Using NDVI and GPS data, Handcock et al. [1] and Browning et al. [12] showed that changes in grazing vegetation conditions can be correlated with animal movement and grazing preferences. Apart from these pioneering studies, relatively little research has been done on using RS data to inform grazing management.

Ground-based behavioural sampling assessments often lack continuous observations over extended periods and normally only last a few days, are often limited to daylight hours and weather conditions could play a significant role [64–66]. For instance, observations could be affected by wind or rain where animals tend to lie down during adverse weather conditions. It is important to assess behavioural patterns across all four seasons of a year. For instance, animals' grazing and movement patterns on cold winter mornings are different compared to those of hot summer months. Due to limited funds, time, and observers, many studies are only carried out in one or maybe two seasons [64,67]. Another limitation of in situ (ground-based) observations is that observer proximity could alter the animals' grazing behaviour [65,68]. Therefore, techniques and technologies that can bridge the gap between ground-based assessments and longitudinal observations offered by remotely sensed data are of great importance for current and future monitoring purposes [69].

This study aims to evaluate the use of remotely sensed vegetation indices for rangeland management in semi-arid areas sensitive to overgrazing and degradation. GPS measurements and Getis-Ord Gi* hotspot analysis were used to map statistically significant hotspots of animal movement (i.e., gazing). The hotspots were then statistically compared to eight commonly used vegetation indices, extracted from Sentinel-2 imagery, to determine how growth vigour relates to animal movement. A secondary aim was to assess the value of high (10 m × 10 m) vs. lower (1000 m × 1000 m) spatial resolution imagery for monitoring vegetation conditions and for predicting sheep grazing behaviour. The findings are interpreted within the context of optimizing grazing management systems in a sustainable manner and reducing the risks of overgrazing and degradation in highly sensitive areas such as the semi-arid shrublands of South Africa.

2. Materials and Methods

2.1. Study Area

The study was undertaken at the Carnarvon Agricultural Research Station in South Africa (31.0086°S, 21.8939°E; 1310 m above sea level). The station is situated within the Western Upper Karoo vegetation type [70] (Figure 1), which forms part of the Nama-Karoo biome that covers much of the western interior of South Africa (>400,000 km^2) and extends into the south of Namibia [70]. The average rainfall received is 170 mm, though there is a gradient of increasing rainfall from the west (120 mm) to the east (220 mm) [71]. The Western Upper Karoo receives most of its rainfall during the autumn months, with the wettest month usually being March. The mainland use of the area is small stock farming [72].

The vegetation layer of the Upper Karoo consists primarily of small-leaved dwarf shrubs and shrubby succulents, typically comprising of *Pentzia* spp., *Eriocephalus* spp. and *Ruschia intricata*. Grasses may be present soon after good summer rains and comprise *Aristida* spp., *Enneapogon* spp. and *Stipagrostis* spp. [70,73].

This study forms part of a grazing trial established in 1988 by the Department of Agriculture to test the effects of stocking densities on vegetation conditions. Four stocking densities were set at a rate representing a high stocking density (4.0 hectares per small livestock unit (ha SSU^{-1})), a recommended (5.5 ha SSU^{-1}), a low (7.0 ha SSU^{-1}) and a very low stocking density (8.0 ha SSU^{-1}) [73] (Figure 2). The trial is managed on a three-camp rotational grazing management system, with twelve Afrino ewes per three-camp system. Additional information on the grazing trial and setup is available from Harmse and Gerber [73].

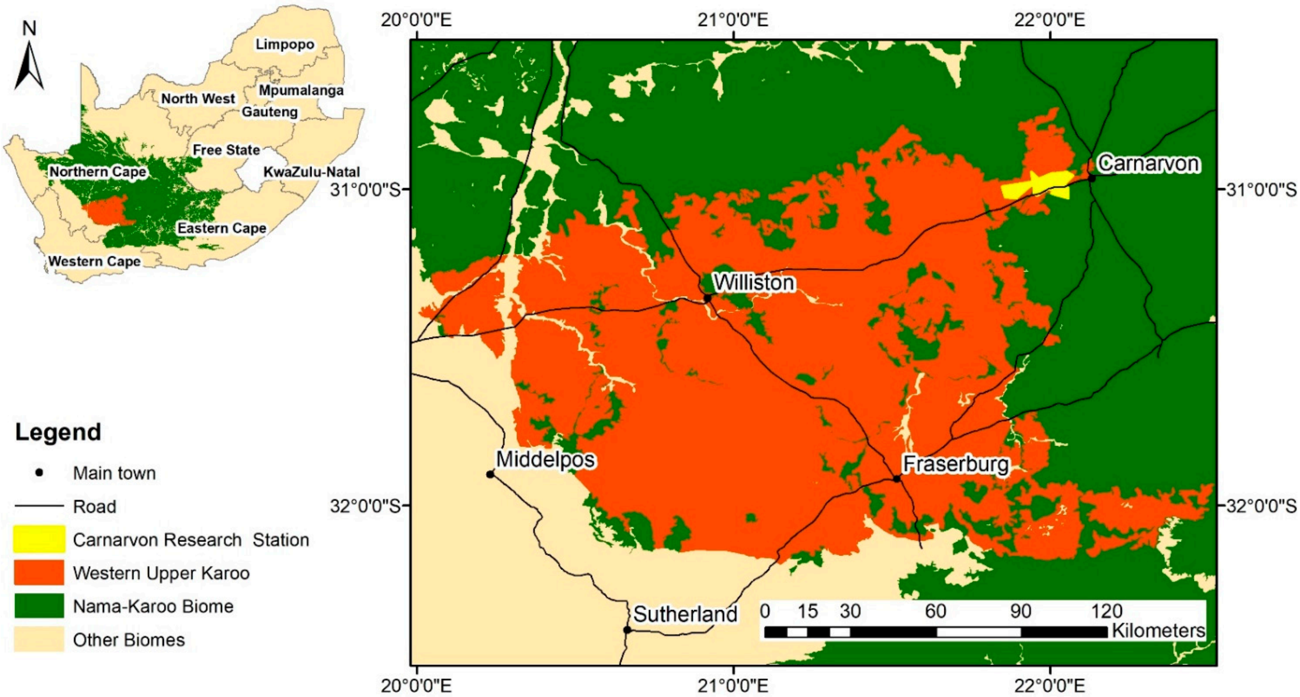

Figure 1. Location of the Western Upper Karoo region within the Nama-Karoo biome. Insert map shows the location within South Africa. The Carnarvon research station is indicated in yellow; the Nama-Karoo biome is indicated in green and the Western Upper Karoo vegetation type is indicated in orange.

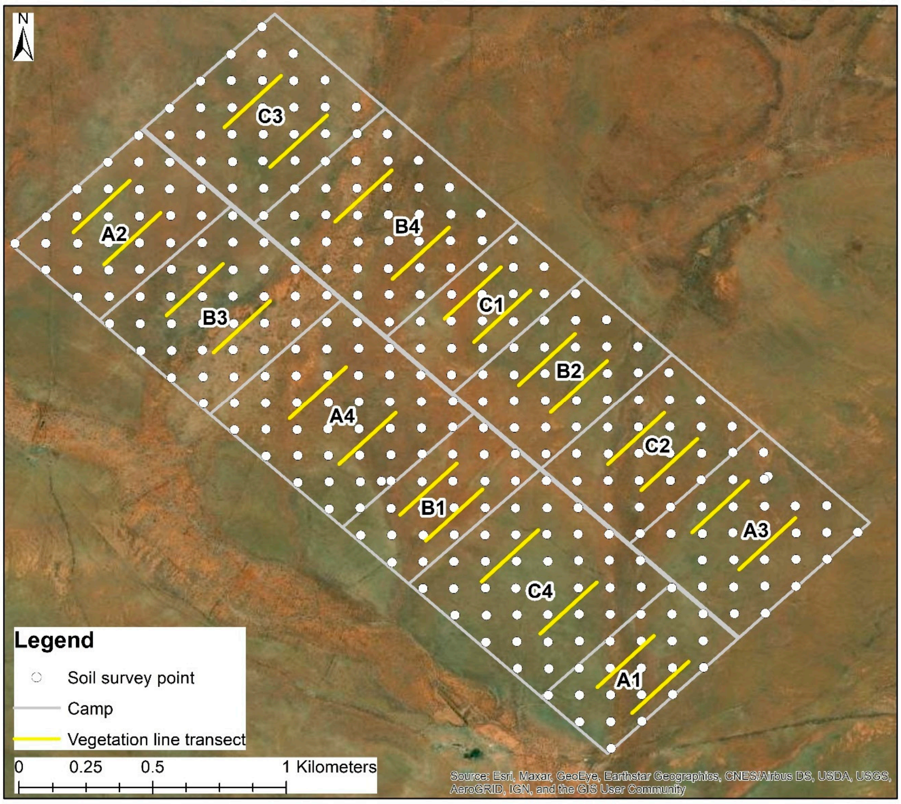

Figure 2. The stocking density trial layout with 12 camps, soil survey points (black filled circles) and vegetation line transects (yellow lines). High stocking density = camps assigned the numbers A1, B1 and C1; recommended stocking density = A2, B2 and C2; low stocking density = A3, B3 and C3; and very low stocking density = A4, B4 and C4.

2.2. Data Collection

GPS data collars were fitted to sheep to evaluate if camp scale variability in vegetation composition and condition affects grazing patterns of small stock. In situ vegetation and soil surveys were carried out across the entire study area to assist with the interpretation of the remotely sensed data. Spectral indices were calculated from the Sentinel-2 imagery to make rangeland scale observations of vegetation conditions with the aim of better understanding the spatial relationships between soil depth, vegetation composition and sheep movement patterns. The following subsections provide more detail about these data collection activities.

2.2.1. Vegetation and Soil Surveys

A soil survey was carried out on a 100 m $\times$ 100 m grid across the study site. A total of 334 soil sample points were surveyed. Soil profile pits were dug by using a peak and spate up to the point where bedrock was reached. Soils were classified according to the Taxonomic Soil Classification system for South Africa [74], together with the Field Book for the Classification of South African Soils [75]. Soil depth, along with limiting material (e.g., bedrock that restricts root penetration and limits the amount of water the soil can supply plants), were noted. A soil depth map was created from the surveyed samples (please see Appendix A, Figure A1). The Mann-Whitney test was used for soil depth comparisons.

A vegetation composition survey was conducted in May 2018, at the end of the rainy season. The vegetation layer in the deep and shallow sites was surveyed along twenty-four 200 m line transects (Figure 2). The vegetation surveys focused on both the perennial dwarf shrub and grass species and involved the identification of the nearest plant species at 1 m intervals along the line transects. The species composition, richness (i.e., the number of different plant species) and evenness were calculated. The latter was determined by calculating Simpson's measure of evenness (D) as $D = \Sigma(n/N)^2$, where n is the number of plants per given species and N is the number of plants for all species.

2.2.2. Animal Movement Data

During the summer, autumn or winter grazing period the sheep were allocated to only four of the twelve camps. All the sheep were in the C camps (Camps C1, C2, C3 and C4; Figure 3a) during the summer, then the sheep were moved to the A camps during autumn (Figure 3b) and from there to the B camps during the winter (Figure 3c). GPS/GSM data collars (Supplier: African Wildlife Tracking) were fitted to three randomly selected sheep from each of the four stocking density treatments between December 2017 and December 2019. All the collars were set to record GPS positions every hour over the three years. More than 200,000 GPS positions were recorded in this manner. Data recorded included the date, time, coordinate, movement speed and temperature of the collar. The movements of the three sheep represent the movements of the herd of which they are members. The Afrino is a breed of sheep that are cohesive and always graze together; individual sheep rarely leave the herd.

2.2.3. Satellite Imagery

Sentinel-2 imagery was acquired from the Copernicus Open Access Hub [76]. The Sentinel-2 constellation provides 13-band multispectral images at a 5-day interval. The experimental dataset contained 25 cloud-free Sentinel-2 images representing each month of the year from December 2017 to December 2019. Sen2Cor [77] was used to convert top-of-atmosphere radiance to surface reflectance values. The surface reflectance images were then used to generate eight spectral (vegetation condition and soil moisture) indices (Table 1), utilizing spectral bands 2, 3, 4, 8 (10 m spatial resolution), 9 (60 m spatial resolution) and 11 (20 m spatial resolution).

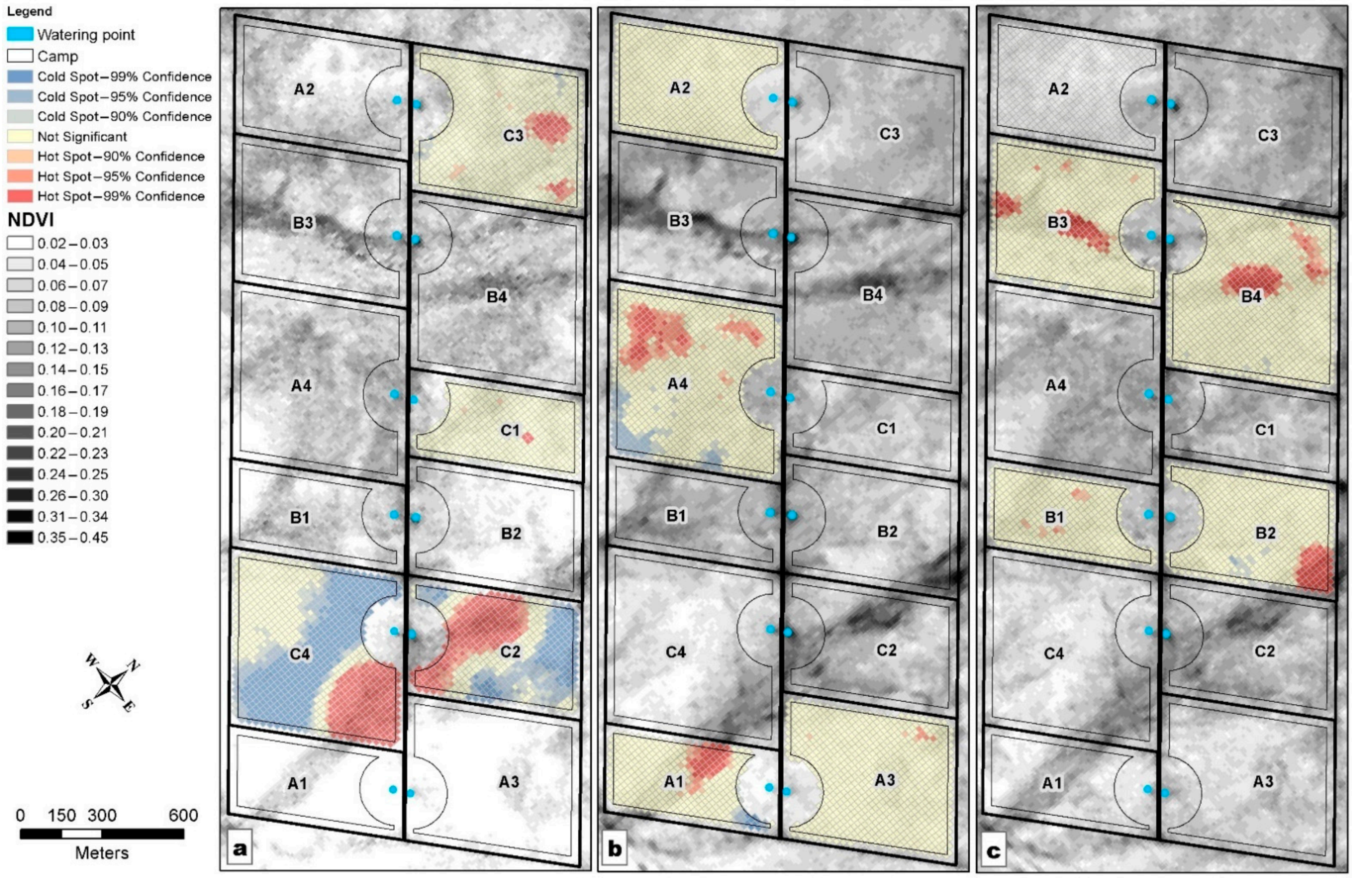

Figure 3. (**a**) NDVI values and locations of the grazing hotspots under all the stocking densities during the summer (December to February) of 2017/2018, (**b**) during autumn (March to May) of 2018, and (**c**) during winter (June to August) of 2018.

Table 1. Spectral indices generated for each Sentinel-2 A image.

Index	Formulation	Reference
Atmospherically resistant vegetation index	$\mathrm{ARVI} = \frac{(\mathrm{NIR})-(2\times\mathrm{Red})+(\mathrm{Blue})}{(\mathrm{NIR})+(2\times\mathrm{Red})+(\mathrm{Blue})}$	[78]
Bare soil index	$\mathrm{BSI} = \frac{(\mathrm{Red}+\mathrm{SWIR})-(\mathrm{NIR}+\mathrm{Blue})}{(\mathrm{Red}+\mathrm{SWIR})+(\mathrm{NIR}+\mathrm{Blue})}$	[79]
Green chlorophyll index	$\mathrm{GCI} = \frac{(\mathrm{NIR})}{(\mathrm{Green})} - 1$	[80]
Green normalized difference vegetation index	$\mathrm{GNDVI} = \frac{(\mathrm{NIR}-\mathrm{Green})}{(\mathrm{NIR}+\mathrm{Green})}$	[52]
Modified soil adjusted vegetation index 2	$\mathrm{MSAVI2} = \frac{2\times\mathrm{NIR}+1\sqrt{(2\times\mathrm{NIR}+1)^2-8(\mathrm{NIR}-\mathrm{RED})}}{2}$	[81]
Moisture stress index	$\mathrm{MSI} = \frac{(\mathrm{MidIR})}{(\mathrm{NIR})}$	
Normalized difference moisture index	$\mathrm{NDMI} = \frac{(\mathrm{NIR}-\mathrm{SWIR})}{(\mathrm{NIR}+\mathrm{SWIR})}$	[82]
Normalized difference vegetation index	$\mathrm{NDVI} = \frac{(\mathrm{NIR}-\mathrm{Red})}{(\mathrm{NIR}+\mathrm{Red})}$	[83]

2.3. Data Analysis

2.3.1. Hotspot Analysis

GPS point data (Section 2.2.2) representing sheep locations at 1-h intervals were used as incidents, while 20 m × 20 m regions, configured in a regular array (i.e., fishnet), were utilized as the aggregation polygons (zones). The camp boundaries were used to define the bounding polygon (i.e., where incidents are possible). Sheep tend to congregate around the watering points during prolonged periods of the day to rest. They also tend to move along the boundary of the camps to rest in the corners. Buffer zones within 10 m from camp boundaries and 30 m from watering points were consequently created and used to exclude non-grazing events (GPS records).

The Getis-Ord Gi* statistic, as implemented in the Optimized Hot Spot Analysis (OHA) tool of ArcGIS 10.7 [84], was used to identify statistically significant spatial clustering in the GPS data. Getis-Ord Gi* statistics have been shown to be superior to other clustering techniques such as kernel density estimation (KDE), which uses a kernel function to fit a smoothly tapered surface to each GPS point [85]. The GI* statistic considers each feature within the context of its neighbouring features. For a feature to be a statistically significant hot spot, it must have a high value and be surrounded by other features with similarly high values. The local sum for a feature and neighbours features is compared proportionally to the sum of all features. When the local sum is different from the expected local sum, and when that difference is too large to be the result of random chance, then a statistically significant z-score results [84]. The GI* statistic determines clustering intensity at high or low levels and provides statistical measures in the form of z-scores and *p*-values to indicate statistical significance. Zones were determined to be part of significant hotspots when the z-score was higher than 2 (at 95% confidence level), and for cold spots, when the z-score was lower than -2 (at 95% confidence level).

The OHA classified each zone in the grazing camp as either a statistically significant hot spot, cold spot or as not significant [86,87]. The OHA was conducted to characterize the monthly spatial distribution of sheep across the grazing camps by identifying areas within the camps that were most frequently visited by sheep (hot spots) and areas least visited (cold spots). This allowed for an examination of the underlying spatial processes that may be driving the hot and cold spot zones across the grazing camps. Maps depicting the hot and cold spots were created to visually (qualitatively) analyse GPS data. Data processing, spatial analysis and the making of maps were carried out using ArcGIS 10.7 software.

2.3.2. Statistical Comparisons between Hotspots and Spectral Indices

Linear and quadratic regressions were applied to compare sheep grazing behaviour (hotspots) with the spectral index values (Table 1) derived from the Sentinel-2 imagery. Index values were subjected to different transformations, i.e., logarithmic, reciprocal, square and square roots to find the best approximation to the normal distribution [88]. The normality of data distributions for all dependent and predictor variables was tested using normal quantile plots [89].

2.3.3. Spatial Resolution Comparison

The spectral indices with the strongest correlation with the hotspots were identified (Section 3.2) and resampled to 20 m, 30 m, 50 m, 100 m, 250 m, 500 m and 1000 m spatial resolution to evaluate the impact of spatial resolution. Optimum spatial resolution was determined using linear and quadratic regression analysis fitted to the GI* z-scores obtained from the optimized hotspot analysis.

3. Results

3.1. Hotspot Analysis

Hotspots were found to be prominent in camps with drainage lines (see Camps A1, B2, B3, B4, C2, and C4 in Figure 3). When the sheep were allocated to camps with no drainage lines (Camps A2, A3, A4, B1, C1, and C3), no significant clustering occurred. The season and time of year do not seem to influence when the animals congregate in drainage areas. Cold spots were mostly associated with low NDVI values outside of the drainage lines. The hotspots indicated that the sheep spent significantly more time grazing in a relatively small portion (17.3%) of available grazing land (Table 2). This finding could alter perceptions of the true impact of stocking density and possible overutilization of portions within camps.

Table 2. The area (ha and %) in each grazing camp that was identified as either hotspot, cold spot or not significant.

Camp Number	A1		A2		A3		A4		B1		B2		B3		B4		C1		C2		C3		C4		Ave	
	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%
Hot spot	2.7	15.9	0.0	0.0	0.3	1.0	6.6	16.0	0.6	3.4	2.6	10.3	3.4	10.3	4.6	11.2	0.2	1.4	9.0	35.8	2.2	6.4	8.4	20.4	**3.4**	**11.0**
Cold spot	1.0	5.9	0.0	0.0	0.0	0.	4.1	9.9	0.0	0.0	0.6	2.5	0.2	0.7	0.2	0.5	0.0	0.0	10.4	41.3	0.1	0.4	20.5	50.1	**3.1**	**9.3**
Not significant	13.2	78.2	25.7	100.0	32.2	99.0	30.4	74.1	17.0	96.6	22.1	87.2	29.8	89.0	36.3	88.3	17.2	98.6	5.8	22.9	31.3	93.2	12.1	29.5	**22.8**	**79.7**

3.2. Spectral Index Evaluation

A total of eight spectral indices were statistically compared to the Gi* z-score from the optimized hotspot analysis. Four indices, namely bare soil index (BSI), green coverage index (GCI), moisture stress index (MSI) and normalized difference moisture index (NDMI), were best described by linear models based on the Akaike information criterion [90], while atmospherically resistant vegetation index (ARVI), green normalized difference vegetation index (GNDVI), modified soil adjusted vegetation index 2 (MSAVI2) and normalized difference vegetation index (NDVI) were best described using quadratic models. Strong ($r^2 > 0.8$) models were achieved for GCI, MSAVI2 and NDVI, with the latter producing the strongest ($r^2 = 0.82$) model (Table 3). Figure 4 graphically shows the best performing regression models.

Table 3. Regression and test statistics of linear and quadratic regression analyses fitted to the Gi* z-score from the optimized hotspot analysis and the vegetation and soil moisture index scores.

Name	Regression Equation	Model	r^2	p	F_{1109}
ARVI	$y = 7927.8x^2 + 1111.7x + 38.489$	Quadratic	0.385	1.34×10^{-6}	26.22
BSI	$y = 0.0023x - 19.783$	Linear	0.197	1.19×10^{-6}	26.51
GCI	$y = 35.355x + 7.9429$	Linear	0.816	1.67×10^{-41}	479.05
GNDVI	$y = -421.94x^2 + 271.15x - 40.285$	Quadratic	0.672	5.37×10^{-26}	195.71
MSAVI2	$y = -168.49x^2 + 148.89x - 12.450$	Quadratic	0.818	1.06×10^{-41}	483.47
MSI	$y = 34.972x - 54.806$	Linear	0.446	1.54×10^{-15}	87.08
NDMI	$y = -116.86x - 25.755$	Linear	0.444	1.93×10^{-15}	86.28
NDVI	$\mathbf{y = -247.39x^2 + 197.60x - 11.920}$	**Quadratic**	**0.820**	$\mathbf{5.62 \times 10^{-42}}$	**491.01**

3.3. Impact of Spatial Resolution

A pixel comparison analysis was carried out to assess how image spatial resolution affects the relationship between Gi* z-score and image derivatives. This experiment was carried out only on NDVI, given that it outperformed the other spectral indices (see the previous section). NDVI values were resampled using the nearest neighbour technique from 10 m (native resolution) to 20 m, 30 m, 50 m, 100 m, 250 m, 500 m and 1000 m (Table 4). The strongest model ($r^2 = 0.87$) between Gi* z-score and NDVI was found to be at 100 m resolution. The strongest model at 100 m resolution was statistically stronger compared to the other spatial resolutions tested. This finding is supported by Figure 5 in which the drainage lines become undetectable at resolutions lower than 250 m. The weakest models ($r^2 < 0.2$) were produced for the largest pixel sizes at 500 m and 1000 m (Table 4).

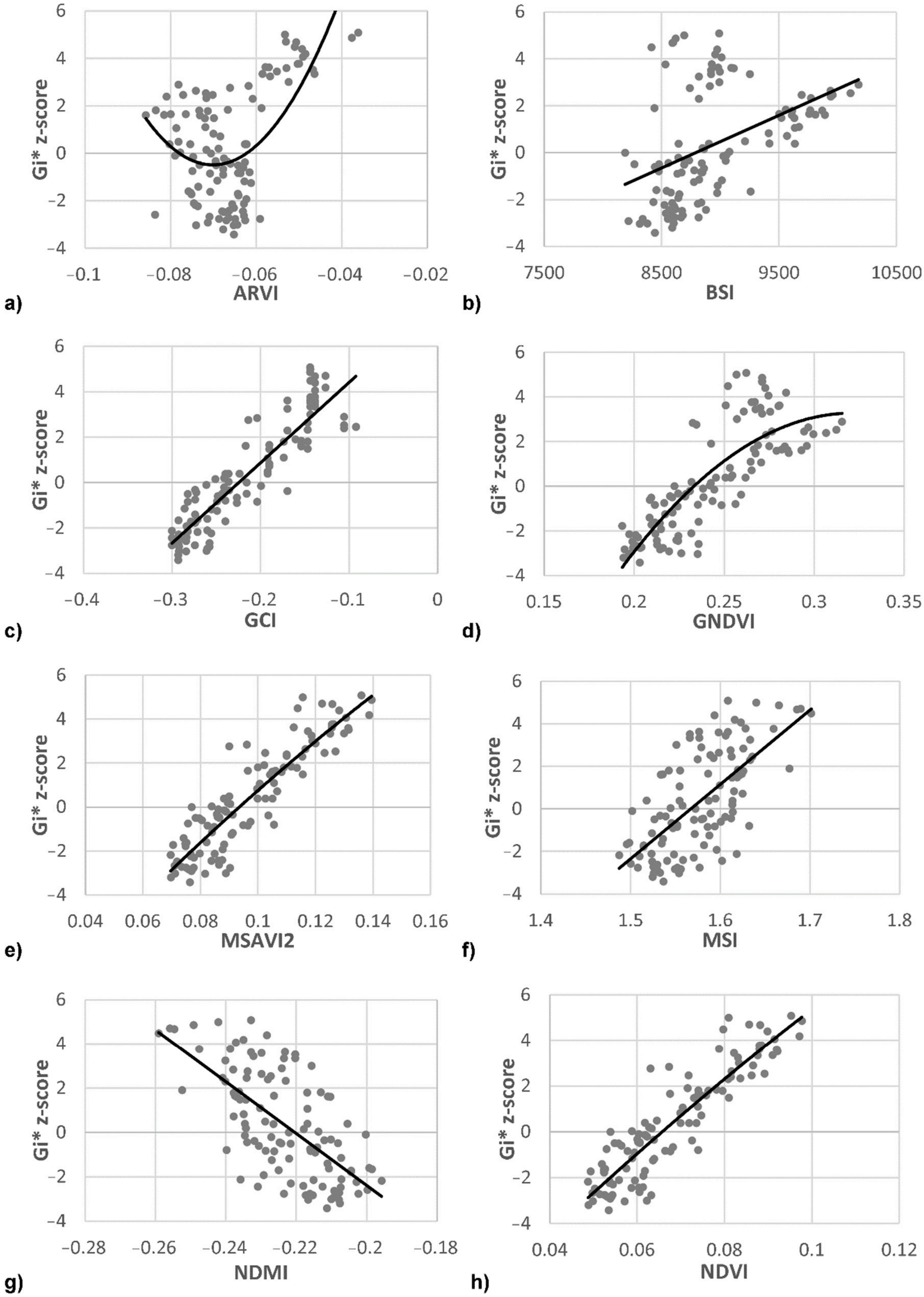

Figure 4. Regressions with untransformed data showing the relationship between the Gi* z-score from the optimized hotspot analysis and the following vegetation and soil moisture index scores: (**a**) ARVI, (**b**) BSI, (**c**) GCI, (**d**) GNDVI, (**e**) MSAVI2, (**f**) MSI, (**g**) NDMI, (**h**) NDVI.

Table 4. Regression and test statistics of linear and quadratic regression analyses fitted to the Gi* z-score from the optimized hotspot analysis and NDVI scores.

Spatial Resolution (Area)	Regression Equation	r^2	p	F_{1199}
10 m × 10 m (100 m^2)	$y = -1869.5x^2 + 567.62x - 23.703$	0.8187	1.48×10^{-53}	847.00
20 m × 20 m (400 m^2)	$y = -1870.6x^2 + 569.13x - 23.769$	0.8324	1.84×10^{-76}	922.68
30 m × 30 m (900 m^2)	$y = -2288.5x^2 + 626.32x - 25.7$	0.8212	2.98×10^{-73}	842.19
50 m × 50 m (2500 m^2)	$y = -2472.1x^2 + 643.45x - 26.0$	0.8214	1.34×10^{-73}	850.63
100 m × 100 m (10,000 m^2)	$\mathbf{y = 3235x^2 - 54.33x - 6.2795}$	**0.8684**	$\mathbf{2.73 \times 10^{-86}}$	**1210.24**
250 m × 250 m (62,500 m^2)	$y = -9350.8x^2 + 1523x - 53.774$	0.5977	1.45×10^{-38}	267.03
500 m × 500 m (250,000 m^2)	$y = -5 \times 10^{+06}x^2 + 582{,}888x - 18{,}363$	0.1809	0.00015	14.94
1000 m × 1000 m (1,000,000 m^2)	$y = 17.778x + 3.7778$	-2×10^{-16}	n/a	0.00

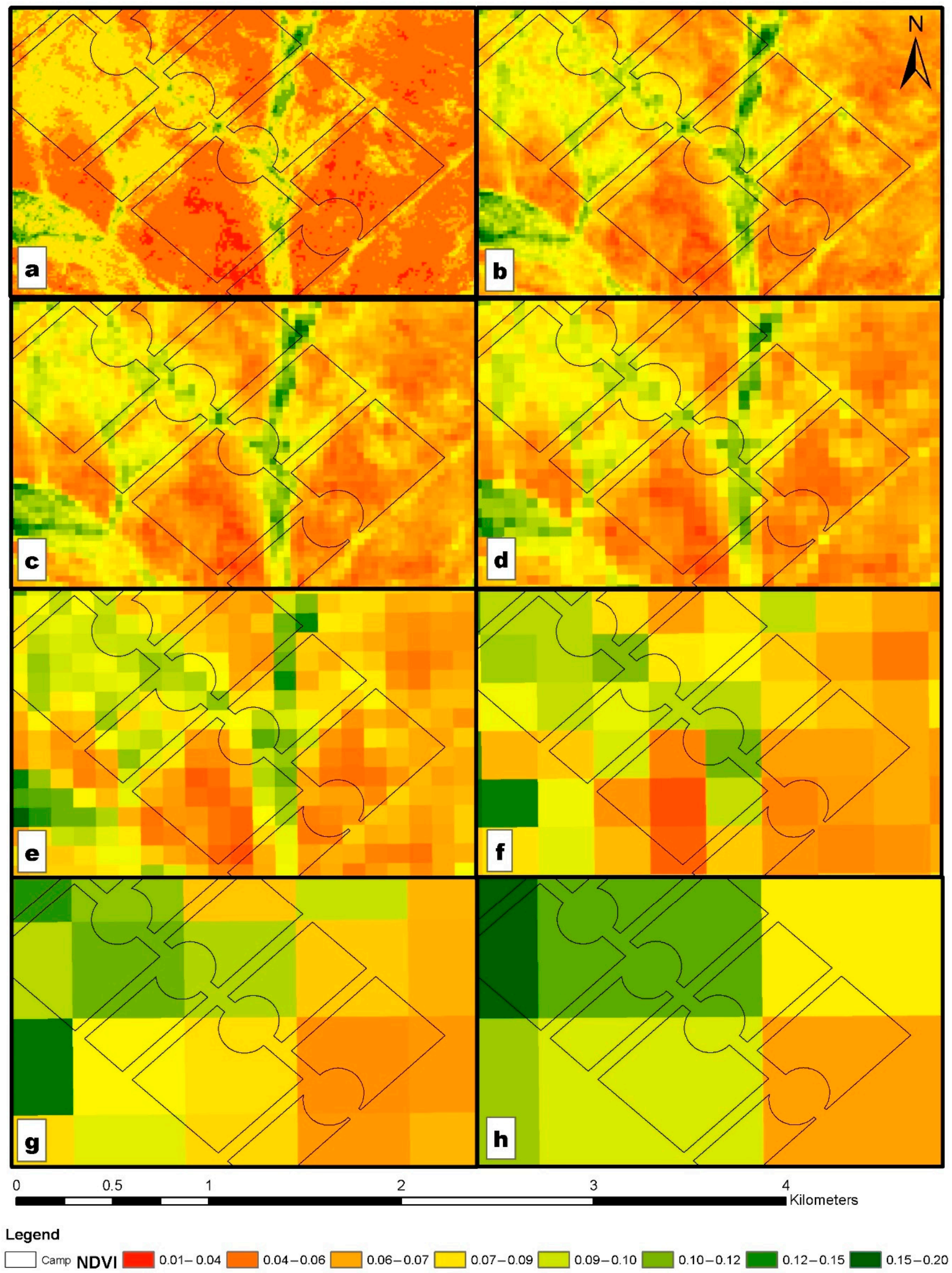

Figure 5. NDVI image pixel comparison at (**a**) 10 m, (**b**) 20 m, (**c**) 30 m, (**d**) 50 m, (**e**) 100 m, (**f**) 250 m, (**g**) 500 m and (**h**) 1000 m of the grazing stocking rate trial.

4. Discussion

4.1. Hotspot Analysis

The integration of GPS location data and RS imagery allows for spatiotemporal comparisons of sheep grazing preferences and vegetation conditions [1,23]. Previous research by Falú et al. [91] and Browning et al. [12] showed that livestock expand their daily feeding areas in response to low forage availability. This relationship between grazing behaviour and vegetation condition can be used to predict the movement of animals and their preferred grazing areas. It can also be used to predict the grazing behaviour of sheep (and other livestock) across farms. Access to such information would greatly improve grazing management strategies and ultimately protect areas and plant species sensitive to overgrazing [1].

In this study, six of the twelve grazing camps are bisected by drainage lines. The GPS data and hotspot analysis showed that the sheep prefer areas along drainage lines with higher vegetation vigour (higher NDVI), but expanded their foraging domain when placed in camps with less variability (no drainage lines). It was found that the drainage lines were utilized year-round by the sheep under all stocking densities and the sheep only utilized less than 20% of available grazing land when a drainage line is present. Drainage lines are therefore effectively exposed to higher stocking rates in comparison with the rest of the camp. The higher biomass in the drainage lines does not necessarily enable these areas to sustain selective overgrazing as this may harm the more palatable plant species, ultimately reducing the biodiversity [23,92,93].

Although the effect of rainfall events on vegetation conditions was not the focus of this study, previous work [94] found strong correlations between rainfall variability and vegetation indices and that such indices accurately reflect vegetation production potential and rain use efficiency in semi-arid environments. In our study, the high-resolution Sentinel-2 imagery confirmed variability in vegetation conditions across the study area and over time. For instance, higher NDVI values were recorded in the drainage line areas and these areas also responded more swiftly to rainfall events in comparison to the grazing areas outside the drainage lines. Early summer rain in January resulted in increased vegetation activity, which is reflected in the NDVI values. This was observed from 2017 to 2020, except for 2019, when lower than average rainfall was received. The NDVI values clearly portrayed differences in vegetation cover and plant vigour, likely driven by higher soil moisture content, which is in accordance with the findings of Archer [95], Xue and Su [96] and West et al. [97].

A possible explanation for the sheep clustering in the drainage lines is the in situ observed denser vegetation layer in these areas. The plants are also more palatable. This is most likely due to the soils being deeper along the drainage lines. During field visits, it was observed that selective defoliation of specific plant species occurs, which suggests that vegetation cover is not the only driver of grazing behaviour. Although a detailed comparison between the measured soil properties and vegetation composition is outside the scope of this paper, it is clear from preliminary analyses that vegetation composition and density impacted animal behaviour and grazing selection. More work is needed to investigate how species composition and soil conditions impact grazing behaviour. The use of remotely sensed imagery for species detection and mapping should also be investigated. Identifying and mapping more productive areas across rangelands should assist land users to fence off these areas to prevent overgrazing. Understanding how small stock utilize drainage lines could assist in the sustainable use of these areas through improved management strategies such as fencing off these preferred grazing areas. This should be considered during farm planning processes on a large scale, but also on a camp scale when stocking rate is considered.

4.2. Spectral Index Evaluation

From our results, it is clear that vegetation variability drives the grazing patterns of sheep and that fine-scale mapping of vegetation will aid farm planning and management activities, particularly in the Upper Karoo where vegetation is sparse. While widely used, NDVI is not the only remotely sensed spectral index used to assess vegetation conditions. For instance, SAVI has been used with great success in arid regions with low vegetation cover [2,95,98]. However, vegetation indices are affected by a range of biophysical factors [95] and it is often difficult to select the most appropriate index for livestock management.

In this study, eight spectral indices were compared to determine which index would best describe the grazing preference of sheep in the Upper Karoo. Three of the eight indices (i.e., GCI, MSAVI2 and NDVI) showed a strong relationship with the hotspot analysis Gi* Z-scores. Based on our data, NDVI was found to be the most suitable index for describing the grazing preferences of sheep. The strongest regression models were achieved with MSAVI2 and NDVI. It is interesting to note that these two indices are the only two that only utilize the NIR- and red bands. This agrees with previous work that the Red and NIR2 bands were among the three most important Sentinel-2 MSI bands to estimate fractional vegetation coverage (FVC) [99]. FVC is an important parameter to characterize land surface vegetation [100] and previous work has also noted that simple Vis, such as MSAVI 2 and NDVI that combines only the visible red- and NIR bands have enhanced sensitivity to detect green vegetation in sparsely vegetated areas [96,99].

4.3. Impact of Spatial Resolution

Vegetation indices such as NDVI are widely employed in rangeland management, but often used at relatively low (e.g., 250–1000 m) spatial resolutions to assess vegetation quality at landscape and regional scales [101,102]. To better understand the impact of using such low-resolution data for modelling grazing behaviour (and stock carrying capacity calculations), we statistically compared the observed grazing behaviour in the study area to a range of NDVI datasets extracted at different resolutions. The results showed that the relationship between the grazing behaviour (Gi* z-scores) and NDVI was strongest at 100 m resolution, but that the model fit deteriorated significantly as resolutions were reduced to beyond 100 m (Table 3). This is explained by the importance of drainage lines in our study area as sheep tend to congregate in such areas, as well as the fact that the average width of the drainage lines in the study area is 102 m. While the higher (e.g., 10 m) resolution imagery represents larger amounts of variability, the patchy nature of the vegetation [70] reduced the statistical relationships between grazing behaviour and NDVI. This finding has far-reaching implications as it shows that NDVI (and likely other indices) derived from imagery such as MODIS (250 m) and Sentinel-3 (300 m) will not adequately represent grazing conditions and behaviour in semi-arid environments such as the Upper Karoo [70]. Conversely, the results show high (e.g., 10–30 m) resolution imagery is not necessarily optimal for modelling grazing conditions as such high-resolution imagery is more sensitive to localized variations such as rocky outcrops or bare patches. However, the differences between using 10 m, 20 m, 30 m 50 m and 100 m imagery were marginal.

There exists a need to use RS data to advise sustainable management intervention strategies to prevent overgrazing from taking place [1]. From this study, it was shown that it can be achieved by having a good understanding of the spatiotemporal heterogeneity of vegetation across rangelands and within grazing camps. Modelling grazing hotspots across rangelands allows for the identification of areas that need to be fenced off, to protect certain palatable vegetation areas and ultimately prevent the loss of biodiversity and rangeland productivity. Such measures could increase the profitability of livestock farming by increasing stock numbers in areas with less variation in grazing hotspots and decreasing stock numbers in areas that are prone to overgrazing (as can be identified using NDVI imagery). Remotely sensed NDVI is ideal for monitoring vegetation attributes, such as plant density and -vigour, and for predicting grazing patterns of livestock [23]. It is cost effective, can be generated on a timely basis, and can be applied to monitor conditions throughout the year and over extensive periods. Clearly, it is important for supporting rangeland management and to prevent the degradation of delicate environments such as the Upper Karoo.

It is important to note that the dynamics of grazing behaviour of animals change over spatial scales [103,104]. In less arid environments where stocking rates are higher and the rainfall is more reliable, the effect of selective grazing in drainage areas may be less. More work is needed to better understand why the drainage lines in our study area had such a large influence on grazing patterns. The correlation between the remotely sensed vegetation conditions and livestock production potential should be investigated in future studies. Finally, replicating this study in similar semi-arid environments, but with different vegetation types (e.g., the succulent Karoo- and savanna biomes) will add much value to the current research.

5. Conclusions

The ability to identify areas in rangelands that are most productive is of great value for land users, as it may prevent overgrazing and assure the long-term sustainability of livestock farming. Without such information, selective grazing activities can unintentionally lead to a mosaic of overgrazed patches [105], especially under low stocking rates. Given the threat of climate change and desertification, unintentional overutilization of productive drainage lines can lead to the formation of bare patches and/or encroachment of alien species. Mapping of these productive areas and understanding their use by small stock could assist in the sustainable use of these areas through improved management strategies. Historically, the process of determining the grazing patterns of sheep in the semi-arid ecosystems of the Upper Karoo was extremely time-consuming and costly. This study demonstrated that high-resolution NDVI data can be used as a grazing management tool to determine the spatial variability of productive areas across the Upper Karoo rangelands and for identifying preferred grazing areas.

This study is the first to use a dense time series of Sentinel-2 data for rangeland monitoring in the semi-arid Karoo. The Sentinel-2 satellite constellation offers an unprecedented opportunity for frequent and long-term monitoring of vegetation conditions in the Upper Karoo and similar rangelands. By combining RS and GPS data, we can improve our understanding of sheep grazing patterns, which can ultimately lead to the optimization of production through precision farming.

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Appendix A

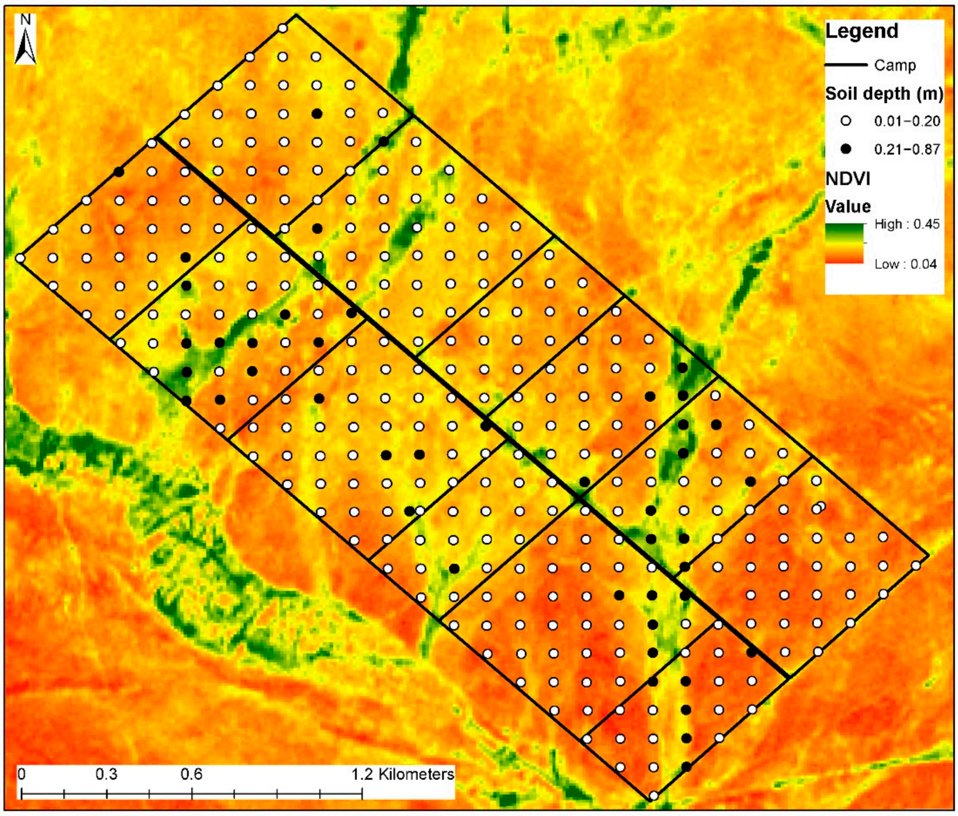

Figure A1. Soil depth classification and the average NDVI values across the camps of the stocking density trial area. The white circles show soil with a depth of 0.01 to 0.20 m and the black circles show soil with a depth of 0.21 to 0.87 m.

References

1. Handcock, R.N.; Swain, D.L.; Bishop-Hurley, G.J.; Patison, K.P.; Wark, T.; Valencia, P.; Corke, P.; O'Neill, C.J. Monitoring Animal Behaviour and Environmental Interactions Using Wireless Sensor Networks, GPS Collars and Satellite Remote Sensing. *Sensors* **2009**, *9*, 3586–3603. [CrossRef] [PubMed]
2. Vani, V.; Mandla, V.R. Comparative Study of NDVI and SAVI Vegetation Indices in Anantapur District Semi-Arid Areas. *Int. J. Civ. Eng. Technol.* **2017**, *8*, 559–566.
3. Allen, V.G.; Batello, C.; Berretta, E.J.; Hodgson, J.; Kothmann, M.; Li, X.; McIvor, J.; Milne, J.; Morris, C.; Peeters, A.; et al. An international terminology for grazing lands and grazing animals. *Grass Forage Sci.* **2011**, *66*, 2–28. [CrossRef]
4. Ash, A.J.; McIvor, J.G.; Corfield, J.P.; Winter, W.H. How Land Condition Alters Plant-Animal Relationships in Australia's Tropical Rangelands. *Agric. Ecosyst. Environ.* **1995**, *56*, 77–92. [CrossRef]
5. Kaine, G.; Tozer, P. Stability, resilience and sustainability in pasture-based grazing systems. *Agric. Syst.* **2005**, *83*, 27–48. [CrossRef]
6. Seymour, C.L.; Milton, S.J.; Joseph, G.S.; Dean, W.R.J.; Ditlhobolo, T.; Cumming, G.S. Twenty years of rest returns grazing potential, but not palatable plant diversity, to Karoo rangeland, South Africa. *J. Appl. Ecol.* **2010**, *47*, 859–867. [CrossRef]
7. Tessema, Z.; de Boer, W.; Baars, R.; Prins, H. Changes in soil nutrients, vegetation structure and herbaceous biomass in response to grazing in a semi-arid savanna of Ethiopia. *J. Arid Environ.* **2011**, *75*, 662–670. [CrossRef]
8. African Union. *Agenda 2063: The Africa We Want*; Report of the Commission on the African Union; African Union: Addis Ababa, Ethiopia, 2015.
9. O'Connor, T.G.; Roux, P.W. Vegetation Changes (1949–1971) in a Semi-Arid, Grassy Dwarf Shrubland in the Karoo, South Africa: Influence of Rainfall Variability and Grazing by Sheep. *J. Appl. Ecol.* **1995**, *32*, 612. [CrossRef]
10. Roth, R. *Karoo Veld: Ecology and Management*; Esler, K.J., Milton, S.J., Dean, W., Richard, J., Eds.; Briza Publications: Pretoria, South Africa, 2006.
11. Todd, S.W.; Hoffman, M.T. A fence line in time demonstrates grazing-induced vegetation shifts and dynamics in the semiarid Succulent Karoo. *Ecol. Appl.* **2009**, *19*, 1897–1908. [CrossRef]
12. Browning, D.M.; Spiegal, S.; Estell, R.E.; Cibils, A.F.; Peinetti, R.H. Integrating space and time: A case for phenological context in grazing studies and management. *Front. Agric. Sci. Eng.* **2018**, *5*, 44–56. [CrossRef]

13. Muller, K.; O'Connor, T.G.; Henschel, J.R. Impact of a severe frost event in 2014 on woody vegetation within the Nama-Karoo and semi-arid savanna biomes of South Africa. *J. Arid Environ.* **2016**, *133*, 112–121. [CrossRef]
14. Paruelo, J.M.; Lauenroth, W.K. Interannual variability of NDVI and its relationship to climate for North American shrublands and grasslands. *J. Biogeogr.* **1998**, *25*, 721–733. [CrossRef]
15. Peters, D.; Havstad, K. Nonlinear dynamics in arid and semi-arid systems: Interactions among drivers and processes across scales. *J. Arid Environ.* **2006**, *65*, 196–206. [CrossRef]
16. Roux, P.W.; Theron, G.K. Vegetation Change in the Karoo Biome. In *The Karoo Biome: A Preliminary Synthesis*; CSIR: Pretoria, South Africa, 1987; pp. 50–69.
17. Roux, P.; Vorster, M. Vegetation change in the karoo. *Proc. Annu. Congr. Grassl. Soc. S. Afr.* **1983**, *18*, 25–29. [CrossRef]
18. Berg, L.V.D.; Kellner, K. Restoring degraded patches in a semi-arid rangeland of South Africa. *J. Arid Environ.* **2005**, *61*, 497–511. [CrossRef]
19. Kraaij, T.; Milton, S. Vegetation changes (1995–2004) in semi-arid Karoo shrubland, South Africa: Effects of rainfall, wild herbivores and change in land use. *J. Arid Environ.* **2006**, *64*, 174–192. [CrossRef]
20. Biggs, R.; Simons, H.; Bakkenes, M.; Scholes, R.; Eickhout, B.; van Vuuren, D.; Alkemade, R. Scenarios of biodiversity loss in southern Africa in the 21st century. *Glob. Environ. Chang.* **2008**, *18*, 296–309. [CrossRef]
21. Visser, N.; Morris, C.; Hardy, M.; Botha, J. Restoring bare patches in the Nama-Karoo of South Africa. *Afr. J. Range Forage Sci.* **2007**, *24*, 87–96. [CrossRef]
22. Ganskopp, D.; Cruz, R.; Johnson, D. Least-effort pathways? A GIS analysis of livestock trails in rugged terrain. *Appl. Anim. Behav. Sci.* **2000**, *68*, 179–190. [CrossRef]
23. Bradley, B.A.; O'Sullivan, M.T. Assessing the short-term impacts of changing grazing regime at the landscape scale with remote sensing. *Int. J. Remote Sens.* **2011**, *32*, 5797–5813. [CrossRef]
24. Ludwig, M.; Morgenthal, T.; Detsch, F.; Higginbottom, T.; Valdes, M.L.; Nauß, T.; Meyer, H. Machine learning and multi-sensor based modelling of woody vegetation in the Molopo Area, South Africa. *Remote Sens. Environ.* **2019**, *222*, 195–203. [CrossRef]
25. Sankey, T.T.; Weber, K.T. Rangeland Assessments Using Remote Sensing: Is NDVI Useful? Final Report: Comparing Effects of Management Practices on Rangeland Health with Geospatial Technologies (NNX06AE47G). 2009, pp. 113–122. Available online: https://giscenter.isu.edu/Research/Techpg/nasa_intl/pdf/FinalReport-NNX06AE47G.pdf (accessed on 10 January 2022).
26. Palmer, A.R.; Samuels, I.; Cupido, C.; Finca, A.; Kangombe, W.F.; Yunusa, I.A.; Vetter, S.; Mapaure, I. Aboveground biomass production of a semi-arid southern African savanna: Towards a new model. *Afr. J. Range Forage Sci.* **2015**, *33*, 43–51. [CrossRef]
27. Numata, I.; Roberts, D.A.; Chadwick, O.A.; Schimel, J.; Sampaio, F.R.; Leonidas, F.C.; Soares, J.V. Characterization of pasture biophysical properties and the impact of grazing intensity using remotely sensed data. *Remote Sens. Environ.* **2007**, *109*, 314–327. [CrossRef]
28. Tomkins, N.; O'Reagain, P. Global positioning systems indicate landscape preferences of cattle in the subtropical savannas. *Rangel. J.* **2007**, *29*, 217–222. [CrossRef]
29. Ungar, E.D.; Henkin, Z.; Gutman, M.; Dolev, A.; Genizi, A.; Ganskopp, D. Inference of Animal Activity from GPS Collar Data on Free-Ranging Cattle. *Rangel. Ecol. Manag.* **2005**, *58*, 256–266. [CrossRef]
30. Moll, R.J.; Millspaugh, J.J.; Beringer, J.; Sartwell, J.; He, Z. A New 'View' of Ecology and Conservation through Animal-Borne Video Systems. *Trends Ecol. Evol.* **2007**, *22*, 660–668. [CrossRef]
31. Kennedy, R.E.; Andréfouët, S.; Cohen, W.B.; Gómez, C.; Griffiths, P.; Hais, M.; Healey, S.P.; Helmer, E.H.; Hostert, P.; Lyons, M.B.; et al. Bringing an ecological view of change to Landsat-based remote sensing. *Front. Ecol. Environ.* **2014**, *12*, 339–346. [CrossRef]
32. Kalluri, S.; Alcala, C.; Carr, J.; Griffith, P.; Lebair, W.; Lindsey, D.; Race, R.; Wu, X.; Zierk, S. From Photons to Pixels: Processing Data from the Advanced Baseline Imager. *Remote Sens.* **2018**, *10*, 177. [CrossRef]
33. European Space Agency (ESA). Sentinel-2 Web Page. Available online: https://sentinels.copernicus.eu/web/sentinel/home (accessed on 15 December 2021).
34. Wang, M.; Liu, Z.; Baig, M.H.A.; Wang, Y.; Li, Y.; Chen, Y. Mapping sugarcane in complex landscapes by integrating multi-temporal Sentinel-2 images and machine learning algorithms. *Land Use Policy* **2019**, *88*, 104190. [CrossRef]
35. Vuolo, F.; Neuwirth, M.; Immitzer, M.; Atzberger, C.; Ng, W.-T. How much does multi-temporal Sentinel-2 data improve crop type classification? *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *72*, 122–130. [CrossRef]
36. Macintyre, P.; van Niekerk, A.; Mucina, L. Efficacy of multi-season Sentinel-2 imagery for compositional vegetation classification. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *85*, 101980. [CrossRef]
37. Prins, A.J.; Van Niekerk, A. Crop type mapping using LiDAR, Sentinel-2 and aerial imagery with machine learning algorithms. *Geo-Spat. Inf. Sci.* **2021**, *24*, 215–227. [CrossRef]
38. Persson, M.; Lindberg, E.; Reese, H. Tree Species Classification with Multi-Temporal Sentinel-2 Data. *Remote Sens.* **2018**, *10*, 1794. [CrossRef]
39. Novelli, F.; Spiegel, H.; Sandén, T.; Vuolo, F. Assimilation of Sentinel-2 Leaf Area Index Data into a Physically-Based Crop Growth Model for Yield Estimation. *Agronomy* **2019**, *9*, 255. [CrossRef]
40. Hunt, M.L.; Blackburn, G.A.; Carrasco, L.; Redhead, J.W.; Rowland, C.S. High resolution wheat yield mapping using Sentinel-2. *Remote Sens. Environ.* **2019**, *233*, 111410. [CrossRef]

41. Gómez, D.; Salvador, P.; Sanz, J.; Casanova, J.L. Potato Yield Prediction Using Machine Learning Techniques and Sentinel 2 Data. *Remote Sens.* **2019**, *11*, 1745. [CrossRef]
42. Gholizadeh, A.; Žižala, D.; Saberioon, M.; Borůvka, L. Soil organic carbon and texture retrieving and mapping using proximal, airborne and Sentinel-2 spectral imaging. *Remote Sens. Environ.* **2018**, *218*, 89–103. [CrossRef]
43. Vaudour, E.; Gomez, C.; Loiseau, T.; Baghdadi, N.; Loubet, B.; Arrouays, D.; Ali, L.; Lagacherie, P. The Impact of Acquisition Date on the Prediction Performance of Topsoil Organic Carbon from Sentinel-2 for Croplands. *Remote Sens.* **2019**, *11*, 2143. [CrossRef]
44. Castaldi, F.; Hueni, A.; Chabrillat, S.; Ward, K.; Buttafuoco, G.; Bomans, B.; Vreys, K.; Brell, M.; van Wesemael, B. Evaluating the capability of the Sentinel 2 data for soil organic carbon prediction in croplands. *ISPRS J. Photogramm. Remote Sens.* **2019**, *147*, 267–282. [CrossRef]
45. Ramoelo, A.; Cho, M.A. Explaining Leaf Nitrogen Distribution in a Semi-Arid Environment Predicted on Sentinel-2 Imagery Using a Field Spectroscopy Derived Model. *Remote Sens.* **2018**, *10*, 269. [CrossRef]
46. Segarra, J.; Buchaillot, M.L.; Araus, J.L.; Kefauver, S.C. Remote Sensing for Precision Agriculture: Sentinel-2 Improved Features and Applications. *Agronomy* **2020**, *10*, 641. [CrossRef]
47. Ansper, A.; Alikas, K. Retrieval of Chlorophyll a from Sentinel-2 MSI Data for the European Union Water Framework Directive Reporting Purposes. *Remote Sens.* **2018**, *11*, 64. [CrossRef]
48. Torres-Sánchez, J.; Lopez-Granados, F.; Peña-Barragan, J.M. An automatic object-based method for optimal thresholding in UAV images: Application for vegetation detection in herbaceous crops. *Comput. Electron. Agric.* **2015**, *114*, 43–52. [CrossRef]
49. Hunt, E.R.; Daughtry, C.S.T.; Mirsky, S.B.; Hively, W.D. Remote Sensing with Simulated Unmanned Aircraft Imagery for Precision Agriculture Applications. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2014**, *7*, 4566–4571. [CrossRef]
50. Rasmussen, J.; Ntakos, G.; Nielsen, J.; Svensgaard, J.; Poulsen, R.N.; Christensen, S. Are vegetation indices derived from consumer-grade cameras mounted on UAVs sufficiently reliable for assessing experimental plots? *Eur. J. Agron.* **2016**, *74*, 75–92. [CrossRef]
51. Tucker, C.J.; Sellers, P.J. Satellite remote sensing of primary production. *Int. J. Remote Sens.* **1986**, *7*, 1395–1416. [CrossRef]
52. Gitelson, A.A.; Merzlyak, M.N.; Lichtenthaler, H.K. Detection of Red Edge Position and Chlorophyll Content by Reflectance Measurements Near 700 nm. *J. Plant Physiol.* **1996**, *148*, 501–508. [CrossRef]
53. Huete, A.R. A soil-adjusted vegetation index (SAVI). *Remote Sens. Environ.* **1988**, *25*, 295–309. [CrossRef]
54. Huete, A.; Didan, K.; Miura, T.; Rodriguez, E.P.; Gao, X.; Ferreira, L.G. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sens. Environ.* **2002**, *83*, 195–213. [CrossRef]
55. Gong, P.; Pu, R.; Biging, G.S.; Larrieu, M.R. Estimation of forest leaf area index using vegetation indices derived from hyperion hyperspectral data. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 1355–1362. [CrossRef]
56. Jiang, Z.; Huete, A.R.; Didan, K.; Miura, T. Development of a two-band enhanced vegetation index without a blue band. *Remote Sens. Environ.* **2008**, *112*, 3833–3845. [CrossRef]
57. Wu, W. The Generalized Difference Vegetation Index (GDVI) for Dryland Characterization. *Remote Sens.* **2014**, *6*, 1211–1233. [CrossRef]
58. Gong, Z.; Kawamura, K.; Ishikawa, N.; Goto, M.; Wulan, T.; Alateng, D.; Yin, T.; Ito, Y. MODIS normalized difference vegetation index (NDVI) and vegetation phenology dynamics in the Inner Mongolia grassland. *Solid Earth* **2015**, *6*, 1185–1194. [CrossRef]
59. Sun, B.; Li, Z.; Gao, W.; Zhang, Y.; Gao, Z.; Song, Z.; Qin, P.; Tian, X. Identification and assessment of the factors driving vegetation degradation/regeneration in drylands using synthetic high spatiotemporal remote sensing Data—A case study in Zhenglanqi, Inner Mongolia, China. *Ecol. Indic.* **2019**, *107*, 105614. [CrossRef]
60. Zhumanova, M.; Mönnig, C.; Hergarten, C.; Darr, D.; Wrage-Mönnig, N. Assessment of Vegetation Degradation in Mountainous Pastures of the Western Tien-Shan, Kyrgyzstan, Using EMODIS NDVI. *Ecol. Indic.* **2018**, *95*, 527–543. [CrossRef]
61. Yeganeh, H.; Khajedein, S.J.; Amiri, F.; Shariff, A.R.B.M. Monitoring rangeland ground cover vegetation using multitemporal MODIS data. *Arab. J. Geosci.* **2014**, *7*, 287–298. [CrossRef]
62. Swain, D.L.; Friend, M.A.; Bishop-Hurley, G.J.; Handcock, R.N.; Wark, T. Tracking livestock using global positioning systems—Are we still lost? *Anim. Prod. Sci.* **2011**, *51*, 167–175. [CrossRef]
63. Augustine, D.J.; Derner, J.D. Controls over the strength and timing of fire-grazer interactions in a semi-arid rangeland. *J. Appl. Ecol.* **2013**, *51*, 242–250. [CrossRef]
64. Venter, Z.S.; Hawkins, H.-J.; Cramer, M.D. Cattle don't care: Animal behaviour is similar regardless of grazing management in grasslands. *Agric. Ecosyst. Environ.* **2019**, *272*, 175–187. [CrossRef]
65. Agouridis, C.T.; Stombaugh, T.S.; Workman, S.R.; Koostra, B.K.; Edwards, D.R.; VanZant, E.S. Suitability of a GPS collar for grazing studies. *Trans. ASAE* **2004**, *47*, 1321–1329. [CrossRef]
66. Recio, M.R.; Mathieu, R.; Maloney, R.; Seddon, P.J. First Results of Feral Cats (*Felis catus*) Monitored with GPS Collars in New Zealand. *N. Z. J. Ecol.* **2010**, *34*, 288–296.
67. Manning, J.; Cronin, G.; González, L.; Hall, E.; Merchant, A.; Ingram, L. The Behavioural Responses of Beef Cattle (*Bos taurus*) to Declining Pasture Availability and the Use of GNSS Technology to Determine Grazing Preference. *Agriculture* **2017**, *7*, 45. [CrossRef]
68. Turner, L.W.; Udal, M.C.; Larson, B.T.; Shearer, S.A. Monitoring cattle behavior and pasture use with GPS and GIS. *Can. J. Anim. Sci.* **2000**, *80*, 405–413. [CrossRef]

69. Brandt, M.; Mbow, C.; Diouf, A.A.; Verger, A.; Samimi, C.; Fensholt, R. Ground-and Satellite-based Evidence of the Biophysical Mechanisms behind the Greening Sahel. *Glob. Chang. Biol.* **2015**, *21*, 1610–1620. [CrossRef] [PubMed]
70. Mucina, L.; Rutherford, M.C.; Palmer, A.R.; Milton, S.J.; Scott, L.; Lloyd, J.W.; van der Merwe, B.; Hoare, D.B.; Bezuidenhout, H.; Vlok, J.H.J. Nama-Karoo Biome. The vegetation of South Africa, Lesotho and Swaziland. *Strelitzia* **2006**, *19*, 324–347.
71. Harmse, C.J.; Du Toit, J.C.O.; Swanepoel, A.; Gerber, H.J. Trend analysis of long-term rainfall data in the Upper Karoo of South Africa. *Trans. R. Soc. S. Afr.* **2021**, *76*, 1–12. [CrossRef]
72. Hoffman, M.T.; Skowno, A.; Bell, W.; Mashele, S. Long-term changes in land use, land cover and vegetation in the Karoo drylands of South Africa: Implications for degradation monitoring. *Afr. J. Range Forage Sci.* **2018**, *35*, 209–221. [CrossRef]
73. Harmse, C.J.; Gerber, H.J. Effect of stocking density on vegetation and animal performance within the semi-arid shrublands of the Karoo, South Africa. *Afr. J. Range Forage Sci.* **2018**, *35*, 13–22. [CrossRef]
74. Group, S.C.W.; Macvicar, C.N. *Soil Classification: A Taxonomic System for South Africa*; Department of Agricultural Development: Pretoria, South Africa, 1991; ISBN 0621107840.
75. Le Roux, P.A.L.; du Plessis, M.J.; Turner, D.P.; van der Waals, J.; Booyens, H.B. *Field Book for the Classification of South African Soils*; South African Soil Surveyors Organization: Bloemfontein, South Afrca, 2013.
76. European Commission. Copernicus, 2 Copernicus Open Access Hub. Available online: https://Scihub.Copernicus.Eu/ (accessed on 5 January 2022).
77. Main-Knorn, M.; Pflug, B.; Louis, J.; Debaecker, V.; Müller-Wilm, U.; Gascon, F. Sen2Cor for Sentinel-2. In *Image and Signal Processing for Remote Sensing XXIII*; SPIE: Bellingham, WA, USA, 2017; p. 3.
78. Kaufman, Y.J.; Tanre, D. Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. *IEEE Trans. Geosci. Remote Sens.* **1992**, *30*, 261–270. [CrossRef]
79. Rikimaru, A.; Miyatake, S. Development of Forest Canopy Density Mapping and Monitoring Model Using Indices of Vegetation, Bare Soil and Shadow. In Proceedings of the 18th ACRS, Kuala Lumpur, Malaysia, 20–24 October 1997.
80. Gitelson, A.A.; Viña, A.; Ciganda, V.; Rundquist, D.C.; Arkebauer, T.J. Remote estimation of canopy chlorophyll content in crops. *Geophys. Res. Lett.* **2005**, *32*, L08403. [CrossRef]
81. Qi, J.; Chehbouni, A.; Huete, A.R.; Kerr, Y.H.; Sorooshian, S. A modified soil adjusted vegetation index. *Remote Sens. Environ.* **1994**, *48*, 119–126. [CrossRef]
82. Gao, B.-C. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sens. Environ.* **1996**, *58*, 257–266. [CrossRef]
83. Tucker, C.J. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sens. Environ.* **1979**, *8*, 127–150. [CrossRef]
84. ESRI. *ESRI ArcGIS Desktop: Release 10.5*; Environmental Systems Research Institute: Redlands, CA, USA, 2017; Volume 844, p. 845.
85. Alessa, L.; Kliskey, A.; Lammers, R.; Arp, C.; White, D.; Hinzman, L.; Busey, R. The Arctic Water Resource Vulnerability Index: An Integrated Assessment Tool for Community Resilience and Vulnerability with Respect to Freshwater. *Environ. Manag.* **2008**, *42*, 523–541. [CrossRef]
86. Ord, J.K.; Getis, A. Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geogr. Anal.* **1995**, *27*, 286–306. [CrossRef]
87. Getis, A.; Ord, J.K. The Analysis of Spatial Association by Use of Distance Statistics. *Geogr. Anal.* **2010**, *24*, 189–206. [CrossRef]
88. Quinn, G.P.; Keough, M.J. *Experimental Design and Data Analysis for Biologists*; Cambridge University Press: New York, NY, USA, 2002; ISBN 0-521-00976-6.
89. Sokal, R.R.; Rohlf, F.J. *Biometry: The Principles and Practice of Statistics in Biological Research*; W. H. Freeman: New York, NY, USA, 1995; pp. 451–554.
90. Akaike, H. A new look at the statistical model identification. *IEEE Trans. Autom. Control* **1974**, *19*, 716–723. [CrossRef]
91. Falú, E.M.D.; Brizuela, M.Á.; Cid, M.S.; Cibils, A.F.; Cendoya, M.G.; Bendersky, D. Daily feeding site selection of cattle and sheep co-grazing a heterogeneous subtropical grassland. *Livest. Sci.* **2014**, *161*, 147–157. [CrossRef]
92. Kothmann, M. Grazing Methods: A Viewpoint. *Rangelands* **2009**, *31*, 5–10. [CrossRef]
93. Bailey, D.W.; Brown, J.R. Rotational Grazing Systems and Livestock Grazing Behavior in Shrub-Dominated Semi-Arid and Arid Rangelands. *Rangel. Ecol. Manag.* **2011**, *64*, 1–9. [CrossRef]
94. Nicholson, S.; Farrar, T. The influence of soil type on the relationships between NDVI, rainfall, and soil moisture in semiarid Botswana. I. NDVI response to rainfall. *Remote Sens. Environ.* **1994**, *50*, 107–120. [CrossRef]
95. Archer, E. Beyond the "climate versus grazing" impasse: Using remote sensing to investigate the effects of grazing system choice on vegetation cover in the eastern Karoo. *J. Arid Environ.* **2004**, *57*, 381–408. [CrossRef]
96. Xue, J.; Su, B. Significant remote sensing vegetation indices: A review of developments and applications. *J. Sens.* **2017**, *2017*, 1353691. [CrossRef]
97. West, H.; Quinn, N.; Horswell, M.; White, P. Assessing Vegetation Response to Soil Moisture Fluctuation under Extreme Drought Using Sentinel-2. *Water* **2018**, *10*, 838. [CrossRef]
98. Almutairi, B.; El, A.; Belaid, M.A.; Musa, N. Comparative Study of SAVI and NDVI Vegetation Indices in Sulaibiya Area (Kuwait) Using Worldview Satellite Imagery. *Int. J. Geosci. Geomat.* **2013**, *1*, 50–53.
99. Wang, B.; Jia, K.; Liang, S.; Xie, X.; Wei, X.; Zhao, X.; Yao, Y.; Zhang, X. Assessment of Sentinel-2 MSI Spectral Band Reflectances for Estimating Fractional Vegetation Cover. *Remote Sens.* **2018**, *10*, 1927. [CrossRef]

100. Zhang, X.; Liao, C.; Li, J.; Sun, Q. Fractional vegetation cover estimation in arid and semi-arid environments using HJ-1 satellite hyperspectral data. *Int. J. Appl. Earth Obs. Geoinf.* **2013**, *21*, 506–512. [CrossRef]
101. Westinga, E.; Beltran, A.P.R.; de Bie, C.A.; van Gils, H.A. A novel approach to optimize hierarchical vegetation mapping from hyper-temporal NDVI imagery, demonstrated at national level for Namibia. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *91*, 102152. [CrossRef]
102. Arjasakusuma, S.; Yamaguchi, Y.; Nakaji, T.; Kosugi, Y.; Shamsuddin, S.-A.; Lion, M. Assessment of values and trends in coarse spatial resolution NDVI datasets in Southeast Asia landscapes. *Eur. J. Remote Sens.* **2018**, *51*, 863–877. [CrossRef]
103. Stears, K.; Shrader, A. Increases in food availability can tempt oribi antelope into taking greater risks at both large and small spatial scales. *Anim. Behav.* **2015**, *108*, 155–164. [CrossRef]
104. Larson-Praplan, S.; George, M.R.; Buckhouse, J.C.; Laca, E.A. Spatial and temporal domains of scale of grazing cattle. *Anim. Prod. Sci.* **2015**, *55*, 284–297. [CrossRef]
105. Barthram, G.T.; Duff, E.I.; Elston, D.A.; Griffiths, J.H.; Common, T.G.; Marriott, C.A. Frequency distributions of sward height under sheep grazing. *Grass Forage Sci.* **2005**, *60*, 4–16. [CrossRef]