

Application of SPOT Imagery for Landcover Mapping and Assessing Indicators of Erosion and Proportion of Bareground in Arid and Semi-arid Environment

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Abstract

Inappropriate land-use on a fragile ecological condition have greater impact on the natural state of rangelands making land degradation a common phenomenon. Usage of remote sensing has become an ideal choice for monitoring these natural resources. SPOT 5 imagery was used, in this study for characterizing land cover classes and mapping vegetation distribution in the North West Province, South Africa by employing the maximum likelihood classification technique. Regression technique was also used to assess relationship between rainfall distribution and proportion of bare ground. Water body, bare ground, indicators of erosion, built-up area, grass and shrubs were the LULC classes in the image classification. Except for indicators of erosion, all the land-cover classes were classified with higher accuracies (in average, >0.78 overall accuracies and 0.70 for Kappa). However, SPOT 5 imagery yielded low overall accuracy (<0.3) for indicators of erosion. Strong coefficient of determination ($r^2=0.80$) was detected between average rainfall and proportion of bare ground indicating that rainfall is the most important factor in controlling the spatial distribution of vegetation in the study sites.

Keywords: Bareground; Land use land cover; Indicators of erosion; Ecology

Introduction

Inappropriate land use and high population density in concurrence with fragile ecological conditions have greater influence on the natural state of rangelands in semi-arid and arid areas where land degradation and expansion of woody vegetation often further deteriorate the livelihoods of the impoverished people who directly depend on natural resources. In the North-West province, unpalatable trees and shrub encroachment, a wide spread form of rangeland degradation at the expense of palatable vegetation over long period of time as well as expansion of bare ground are major problems. This scenario is believed to be triggered and aggravated by climatic phenomena and livestock grazing [1,2]. Heavy livestock grazing considered being the main cause of vegetation degradation [1,3] particularly in the communal areas [4].

The proportion of bare ground is a relevant indicator of rangeland condition at a given region at a landscape level [5-8]. A normal hydrologic cycle leads to a healthy rangeland with greater potential of green biomass production with less bare ground cover. Disruption of hydrological cycle in rangelands can cause a desert like weather pattern [9] resulting into an increasing proportion of bare ground exposure. This scenario is a bigger challenge in most communal lands of South Africa. In areas where stocking rates are low, the way livestock use the rangelands may play an important role in triggering land degradation. For example, restriction of livestock movements at a confined locality can cause serious rangeland degradation even when the number of the livestock is smaller [10,11] indicated that despite an average reduction

of livestock, stocking rates in some regions of the world, the recent increase in livestock quantities per individual farms is causing higher land degradation around residential areas.

Assessment of the distribution and development of different biophysical phenomena in rangelands is hampered by lack of relevant data on soil, vegetation, topography and socio-economic conditions. Acquiring meaningful data on rangelands requires collection and evaluation of different patterns of biophysical factors over large areas [12,13]. Traditional field-based data is not enough to accurately assess rangeland conditions over large spatial extents outside of a sampling unit [14].

The application of remote sensing is an important technique for rangeland assessment and reducing the problems that are associated with the traditional field-based data collection. The spectral variation from the satellite image together with a field data can provide a guide to the surface characteristics and spatial distribution of distinctive features [13]. Multispectral satellite imagery can be used effectively for land cover classification and mapping of rangelands [15,16]. Beeri et al. indicated that remote sensing allows a quick, cost effective and systematic way of acquiring reliable and up-to-date information [17]. Many studies have shown that application of remote sensing have improved rangeland management and assessment processes by providing multiple means through its expanded temporal and spectral scales [8]. Vegetation mapping has been made using multispectral satellite imagery particularly SPOT 5 [18].

Vegetation mapping that shows environmental variations over extensive landscape is essential for rangeland management [8]. There is no comprehensive rangeland vegetation distribution and

characteristics mapping in the North-West province by taking into considerations the different rangelands management regimes regarding the application of spectral discrimination of land cover classes. Therefore, this study attempts to characterise the different land cover classes and mapping vegetation distribution and rangeland conditions using SPOT 5 imagery and explores the potential of SPOT 5 imagery for mapping vegetation cover, proportion of bare ground and indicators of erosion using a maximum likelihood classifier.

Study Area

The North-West province of South Africa is located between 22°39'21" E and 25°17'28" E and 24°43'36"S and 28°00'00"S (Figure 1).

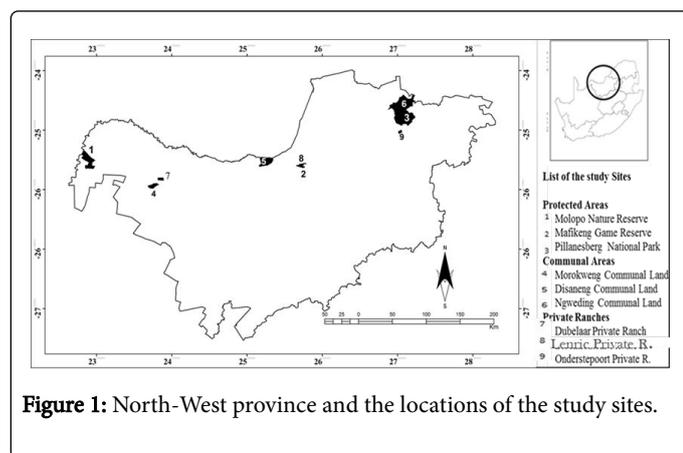


Figure 1: North-West province and the locations of the study sites.

According to Schultze [19] and FAO [20] annual rainfall distribution and climatic classification in South Africa, the North-West province can be classified into three major rainfall zones based on the average rainfall received, namely: arid (low rainfall zones (200-400 mm)), semi-arid (medium rainfall zones (401-600 mm)), and sub-humid (high rainfall zone (601-800 mm)). Rainfall varies from the more mountainous and wetter eastern region to the drier, semi-desert plains of the Kalahari in the west. Climatic conditions vary significantly from west to east. The far western region is arid (receiving less than 300 mm of rainfall per annum), encompassing the eastern reaches of the Kalahari Desert. The rainy season usually occurs from October to March which is summer season with more sunshine days and warm temperatures. Therefore, the area has a higher advantage for agricultural activity than the country's average. However, most parts of the province have not enough rainfall and surface water. Consequently, shortage of water affects the extent of soil fertility to sustain large scale crop production in the region [21,22].

Materials and Methods

Data types and sources

Satellite imagery: SPOT 5 imageries of the study areas were acquired from SANSA between February 28, 2014 and April 6, 2014 for use in this study.

Rainfall data: Mean growing season rainfall data and average temperature records from 1993-2014 of the study sites were sourced from the South African Weather Services. As rainfall is one of the climatic elements playing major roles in tropical and subtropical regions, analysing the amount and distribution of rainfall over time is

extremely important to assess the extent to which rangelands could recover through the natural process.

Field data: Field data was collected during the peak growing seasons of the study sites between February and April 2014 on two biophysical indicators such as proportion of bare ground and indicators of erosion (gullies, rills and dongas).

Assessing proportion of bare ground: Bare ground location was recorded from 177 sample points by taking differential GPS readings from the study sites. These GPS locations were identified on the satellite imagery and were used as training areas for image classification.

Indicators of erosion: Data on these indicators were collected during the assessment of the proportion of the bare ground from 177 points by measuring the width of gullies, rills and dongas. GPS positions of the locations of the erosion indicators were taken in order to identify them on the high resolution (pan-sharpened) SPOT satellite images. The sizes of these indicators on the images were determined and compared with field derived sizes.

Analysis of SPOT 5 data

Image pre-processing: SPOT 5 data were processed to top-of-the-atmosphere reflectance using the Cos(t) image-based correction method in ERDAS Imagine 2013 environment [23]. The images were then georectified (RMSE=7.6 m) using high resolution aerial photograph and projected into UTM (WGS 84) using a first order affine transformation and nearest neighbour resampling.

Image classification: One important part of digital image analysis is the identification of certain groups of pixels that have specific spectral characteristics and to establish the various features or land cover classes characterized by these groups [24]. Satellite image classification is the process of categorizing all the pixels in an image into a finite number of individual classes based on the spectral information and characteristics of these pixels. The classification result in a classified image is basically a thematic output of the original image. Remote sensing image data in this study was classified using maximum likelihood classification (MLC) which is a hard classification approach. The maximum likelihood classification method is derived from Bayes' theorem. This method is a popular method by which the population of the statistics such as variance and mean are estimated to maximize the likelihood or probability from a defined probability density function in the given feature space. Correct representation of a population can be achieved by selecting statistically unbiased sampling of training data from the population. The probability density in the maximum likelihood classification technique is selected to be a multiple normal distribution and this multiple normal distribution gives the mean and the variance-covariance matrix which is the maximum likelihood estimator.

Classification scheme: The maximum likelihood classification technique is exclusively based on spectral properties computed mathematically on a pixel basis. This classification algorithm entails training areas to be identified for every land cover class. These training areas were selected to represent the spectral behaviour within each class. Major attention was drawn to the basic ground cover types such as (i) water body, (ii) built up area, (iii) shrub-land and tree, (iv) herbaceous vegetation and grass, (v) bare ground and (vi) indicators of erosion. Primarily, these classes can be compared to ecological site descriptions that are used as benchmarks in monitoring rangeland ecosystems [9,25]. The classes shown in Table 1 were extracted as

thematic classes from the image and for which area statistics were generated.

Class Name	Description
Water Body	Area dominated by water bodies such as dams, wider rivers and ponds
Bare Ground	Area dominated by newly ploughed farm land, fallow fields and Bare soils
Indicators of erosion	Area dominated by indicators of erosion such as rills, gulley's and dongas
Built-up areas	Areas dominated by villages and inhabited areas
Grasses/Herbaceous vegetation	Areas dominated by grasses, herbs and pasture
Trees/Shrubs	Areas dominated by Acacia trees and other woody plants including scattered trees and shrubs

Table 1: Image interpretation classes used in the classification.

Spectral signatures for bare ground and the rest of land cover classes training sites were extracted from all satellite imagery layers and assessed for signature separability in order to determine appropriate decision rules. Maximum likelihood classification was performed from the extracted spectral signatures.

Classification accuracy assessment: Ground-truth sites were documented during field visits by getting GPS coordinates and photographs within the study region between February and April 2014. Each ground-truth site was digitized as area of interest (AOI) through visual selection of homogeneous areas close to collected GPS coordinates using a false colour and true colour image of SPOT 5 of March and April 2014 of the study sites. To minimize mapping errors during visual digitalisation of the ground-truth data, one hundred and fifty sampled grid values were computed from ground-truth AOI-mask for each land cover class from the ground truths from each protected area and communal lands in all rainfall zones but only ninety sampled points were computed from each private ranch in all rainfall zones. The resulting new mask was used to compute spectral index thresholds for each land cover class dataset. Additional information besides the ground truth-data was obtained from Google Earth, aerial photographs and topographic maps of the study sites to generate independent test sites as a basis for formal accuracy assessment of the final mapping result.

Accuracy of the classified images were analysed using the standard error matrix [26] that reported users' accuracy, producers' accuracy, overall accuracy and the Kappa coefficient of agreement statistics [27,28]. The Kappa coefficient) is a measure of classification accuracy which incorporates the off-diagonal elements as well as the diagonal terms to give a more reliable assessment of accuracy than overall accuracy [29].

SPOT 5 imageries of the study sites were used to determine major land-use land-cover classes. Visual interpretation of the images during land cover classification was improved by means of ground-based data. Land cover classification results are presented with a display of land cover maps. This is followed by a description of the characteristics of each classified land cover class. Related information portraying spatial extents and distribution of each classified land cover class has been highlighted.

Relationship between proportion of bare ground and rainfall

Spatial patterns of proportion of bare ground and spatial distribution of rainfall are highly correlated. Linear regression analysis was performed to assess the impact of spatial distribution of precipitation on the proportion of bare ground in the study sites.

Results

Land use/Land cover statistics

In this study, land cover classification was performed primarily to map major land cover classes and determine the capability of SPOT data to map land cover types, extent of bare ground and indicators of erosion. Table 2 presents the percentage coverage of each major land cover type and their corresponding areas. In the low rainfall area, of Morokweng communal lands, bare ground comprised the larger area coverage followed by grasses/herbaceous vegetation with the least extent of indicators of erosion.

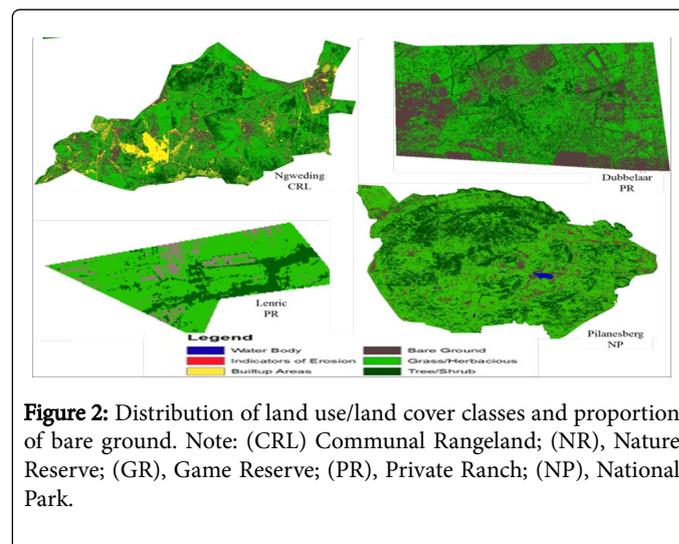


Figure 2: Distribution of land use/land cover classes and proportion of bare ground. Note: (CRL) Communal Rangeland; (NR), Nature Reserve; (GR), Game Reserve; (PR), Private Ranch; (NP), National Park.

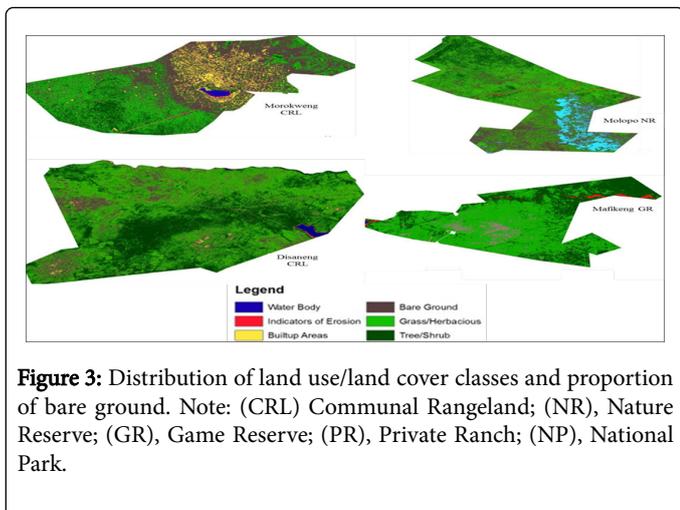


Figure 3: Distribution of land use/land cover classes and proportion of bare ground. Note: (CRL) Communal Rangeland; (NR), Nature Reserve; (GR), Game Reserve; (PR), Private Ranch; (NP), National Park.

The Molopo Nature Reserve and Dubbelaar private ranch in this region were largely dominated by grasses/herbaceous vegetation with relatively higher bare ground proportion (Figure 2). In the medium rainfall zone, bare ground coverage was lower comprising of 17% in the Dibaneng communal area (Figure 3), 8% Mafikeng Game Reserve and 10% in the Lenric private ranch. In the medium and high rainfall regions, grass/herbaceous vegetation cover comprised of the largest proportion. The bare ground in the Onderstepoort private ranch in the high rainfall region was 6%. Bare ground comprised the largest proportion in the communal areas and these areas are believed to be degraded [30,31] as compared to the protected areas and the private ranches. Communal areas are characterized by a high number of livestock, soil erosion, and the loss of palatable grazing species [30,31] causing over utilization of pasture lands beyond their carrying capacity. Shackleton [32] indicated that animal stocking rates in the communal areas are more than twice that of the neighboring commercial farms. Consequently, there is a general agreement that this land degradation is due to overgrazing [33,34].

Rainfall Zones	LRF ZONE						MRF ZONE						HRF ZONE					
	Morokweng CRL		MOLOPO NR		Dubbelaar PR		Dibaneng CRL		MHK_GR		Lenric PR		Ngweding CRL		Pillanesberg NP		O-PR	
Land Cover Classes	LC (%)	Area (Km ²)	LC (%)	Area (Km ²)	LC (%)	Area (Km ²)	LC (%)	Area (Km ²)	LC (%)	Area (Km ²)	LC (%)	Area (Km ²)	Area (Km ²)	LC (%)	Area (Km ²)	LC (%)	Area (Km ²)	
Cloud Cover	0	0	8	40	0	0	0	0	0	0	0	0	0	0	0	0	0	
Water Body	1	3	1	3	0	0	1	4	2	3	0	0	0	2	8	0	0	
Indicators of Erosion	1	2	2.5	3	1	2	0.6	1	1	1.4	0	0	1	0.4	3	0	0	
Builtup Area	11	23	0	0	0	0	1	3	0.5	1	0	0	143	0	0	1	0.7	
Bare Ground	43	102	26	128	37	42	17	81	8	15	10	1	325	19	327	9	6	
Grass/Herb	28	69	43	221	50	56	43	295	64	98	70	4	768	44	801	59	40	
Tree/Shrub	16	38	22	108	13	15	22	265	31.5	56	20	2	345	35	580	31	21	

Table 2: Percentage of land use land cover across the three rainfall zones of the study sites. Note: LRF, low rainfall; MRF, medium rainfall; HRF, high rainfall; CRL, communal rangeland; NR, nature reserve; PR, private ranch; GR, game reserve; NP, national park; LC, land cover.

Accuracy assessment

Accuracy was established empirically by selecting sample pixels from the image and verifying their labels against classes determined from reference data. The proportion of pixels from each class labelled in the image correctly by the classifier was estimated as well as the proportion of pixels from each class incorrectly labelled into every other class. These results were articulated in tabular form treated as the 'error matrix' [24]. The land cover classification accuracy is mainly

affected by: categorical resolution (number of land cover classes) and, spectral resolution (using a few spectral bands rather than all bands) [35].

In this study, maximum likelihood classification yielded an overall accuracy of 0.74 and 0.74 with overall Kappa index of agreement 0.66 and 0.80 in the Morokweng communal rangeland, and Molopo Nature Reserve respectively in the low rainfall area (Tables 3 and 4).

Land Use/Land Cover Classes	Water Body	Bare Ground	Indicators of Erosion	Built up Areas	Grass	Shrubs	No. of Classified Pixels	User Accuracy
Water Body	5	0	0	0	0	0	5	1.00
Bare Ground	0	21	0	2	3	3	29	0.72
Indicator of Erosion	0	2	3	0	1	2	8	0.38

Built up Areas	0	3	0	10	2	3	18	0.55
Grass	0	2	2	1	39	5	49	0.80
Shrubs	0	1	5	0	3	33	42	0.79
No. of Ground Truth Pixels	5	29	10	13	48	45	150	
Producers Accuracy	1.00	0.72	0.30	0.77	0.81	0.74	Overall Accuracy	0.74

Table 3: Error matrix for land cover classes in Morokweng communal rangeland. $\kappa=0.66$.

Land Use/Land Cover Classes	Water Body	Bare Ground	Indicators of Erosion	Cloud/Built up Areas	Grass	Shrubs	No. of Classified Pixels	User Accuracy
Water Body	1	0	0	0	0	1	2	0.50
Bare Ground	0	26	2	2	3	0	33	0.79
Indicator of Erosion	0	0	3	1	0	1	5	0.60
Cloud/Built up Areas	0	2	0	19	2	1	24	0.79
Grass	0	2	1	1	40	3	47	0.85
Shrubs	1	0	1	2	4	31	39	0.80
No. of Ground Truth Pixels	2	30	7	25	49	37	150	
Producers Accuracy	0.50	0.87	0.43	0.76	0.84	0.84	Overall Accuracy	0.80

Table 4: Error matrix for land cover classes in Molopo Nature Reserve. $\kappa=0.74$.

Land Use/Land Cover Classes	Bare Ground	Indicators of Erosion	Grass	Shrubs	No. of Classified Pixels	User Accuracy
Bare Ground	22	1	3	0	26	0.88
Indicator of Erosion	0	1	0	1	2	0.50
Grass	3	0	34	5	42	0.80
Shrubs	1	1	2	16	20	0.85
No. of Ground Truth Pixels	26	3	39	22	90	
Producers Accuracy	0.85	0.33	0.88	0.72	Overall Accuracy	0.81

Table 5: Error matrix for land cover classes in Dubbelaar Private Ranch. $\kappa=0.71$.

The overall accuracy 0.81, 0.77 and 0.76 with overall Kappa index of agreement 0.72, 0.66 and 0.62 was yielded in the Disaneng communal rangeland, Mafikeng Game Reserve and the Lenric private ranch around Mafikeng Game Reserve region respectively in the medium rainfall area (Tables 6-8).

Land Use/Land Cover Classes	Water Body	Bare Ground	Indicators of Erosion	Built up Areas	Grass	Shrubs	No. of Classified Pixels	User Accuracy
Water Body	8	0	0	0	0	0	8	1.00
Bare Ground	0	37	0	1	6	2	46	0.80
Indicator of Erosion	0	0	2	0	0	0	2	1.00

Built up Areas	0	1	0	2	0	2	5	0.40
Grass	0	3	0	0	44	6	53	0.83
Shrubs	0	1	2	2	5	26	36	0.72
No. of Ground Truth Pixels	8	42	4	5	55	36	150	
Producers Accuracy	1.00	0.88	0.50	0.40	0.80	0.72	Overall Accuracy	0.81

Table 6: Error matrix for land cover classes in Disaneng communal rangeland. $K=0.72$.

Land Use/Land Cover Classes	Water Body	Bare Ground	Indicators of Erosion	Built up Areas	Grass	Shrubs	No. of Classified Pixels	User Accuracy
Water Body	3	0	1	0	0	1	5	0.60
Bare Ground	0	13	0	1	6	2	22	0.59
Indicator of Erosion	0	1	3	0	2	1	7	0.43
Built up Areas	0	1	0	2	0	1	4	0.50
Grass	0	2	0	0	54	12	68	0.79
Shrubs	0	1	2	0	5	41	47	0.87
No. of Ground Truth Pixels	3	17	6	3	65	58	150	
Producers Accuracy	1.00	0.76	0.50	0.75	0.83	0.71	Overall Accuracy	0.81

Table 7: Error matrix for land cover classes in Mafikeng Game Reserve. $K=0.66$.

Land Use/Land Cover Classes	Bare Ground	Grass	Tree/Shrubs	No. of Classified Pixels	User Accuracy
Bare Ground	14	0	0	14	1.00
Grass	7	32	5	44	0.73
Shrubs	3	7	22	32	0.69
No. of Ground Truth Pixels	24	39	27	90	
Producers Accuracy	0.58	0.82	0.81	Overall Accuracy	0.76

Table 8: Error matrix for land cover classes in Lenric Private Ranch. $K=0.62$.

Land Use/Land Cover Classes	Bare Ground	Indicators of Erosion	Built up Areas	Grass	Shrubs	No. of Classified Pixels	User Accuracy
Bare Ground	26	0	3	3	2	34	0.76
Indicator of Erosion	0	2	0	0	1	3	0.67
Built up Areas	2	0	14	4	3	23	0.61
Grass	3	0	1	40	5	49	0.82
Shrubs	0	2	2	3	34	41	0.83
No. of Ground Truth Pixels	31	4	20	50	45	150	
Producers Accuracy	0.84	0.50	0.70	0.80	0.76	Overall Accuracy	0.77

Table 9: Error matrix for land cover classes in Ngweding Communal Area. $K=0.69$.

Land Use/Land Cover Classes	Water Body	Bare Ground	Indicators of Erosion	Grass	Shrubs	No. of Classified Pixels	User Accuracy
Water Body	12	0	0	0	0	12	1.0
Bare Ground	0	17	1	2	1	21	0.81
Indicator of Erosion	0	1	2	0	2	5	0.40
Grass	0	3	0	51	8	62	0.82
Shrubs	0	2	2	6	40	50	0.80
No. of Ground Truth Pixels	12	28	5	59	51	150	
Producers Accuracy	1.00	0.76	0.40	0.83	0.71	Overall Accuracy	0.77

Table 10: Error matrix for land cover classes in the Pillanesberg National Park. $K=0.73$.

The overall accuracy in the High Rainfall Zone was 0.77, 0.81 and 0.89 in the Ngweding Communal rangeland, Pillanesberg National Park and the Onderstepoort private ranch around the Pillanesberg National Park with overall Kappa index of agreement 0.69, 0.73 and 0.83 respectively (Tables 9-11).

Land Use/Land Cover Classes	Bare Ground	Built up Areas	Grass	Tree/Shrubs	No. of Classified Pixels	User Accuracy
Bare Ground	17	0	3	0	20	0.85
Built up Areas	0	1	0	1	2	0.5
Grass	2	0	32	4	38	0.73
Shrubs	0	0	2	29	31	0.83
No. of Ground Truth Pixels	19	1	37	33	90	
Producers Accuracy	0.89	1.00	0.83	0.73	Overall Accuracy	0.89

Table 11: Error matrix for land cover classes in Onderspoort Private Ranch. $K=0.83$.

All classes from all study sites resulted into producer accuracies higher than 70% except the built-up areas and indicators of erosion in almost all study sites which yielded producers accuracy of $\leq 50\%$. The low accuracy of the built-up areas and indicators of erosion in all the study sites might be attributed to the similarities of the spectral signatures of the land cover classes in the regions. In most of the study sites, built-up areas pixels were classified as bare ground and shrub. The misclassification of the built-up area to the bare ground could be attributed to the bare ground and built up areas have similar spectral reflectance and physical structure. Indicators of erosion was the most misclassified land cover class during this study probably because of lack of distinctive spectral reflectance of this land cover class. The producer's accuracy of indicators of erosion was 30% while the user's accuracy was slightly higher (38%). This means that although 30% of the indicators of erosion were correctly identified, only 38% of the areas labelled indicators of erosion were indicators of eroded areas, implying a significant misclassification of the pixels in that category in Morokweng communal area Table 8. Similarly, a user's accuracy of 40% and a producer's accuracy of 33% for the indicators of erosion in Disaneng communal area in the medium rainfall region was also one of the lowest accuracy levels acquired and this scenario was also seen in other study sites.

Some difficulties were detected also when spectrally separating the farmlands and bare ground; grass and herbaceous vegetation particularly in the low rainfall area. Therefore, the farm land and bare ground were combined into one single class (bare ground) and grasses and herbaceous vegetation were also classified into one class called grass/herbaceous. There was a massive presence of taller and greener trees around Disaneng village, north of Disaneng Dam. The spectral reflectance of the trees overshadowed the spectral reflectance of built-up areas and it was extremely difficult to extract and characterize the built-up areas independently. The low producer's (0.4) and user's (0.4) accuracies in this specific area might be related to these factors.

It was noted that there was a weakness in the methodology which was employed to classify the land cover classes from the SPOT 5 satellite imagery. Previous studies have shown that supervised classification techniques such as Maximum Likelihood Classification (MLC) algorithm could not express water erosion features at an acceptable level of accuracy due to the spectral similarities with other land cover features [36,37]. However, all classes from all study sites possess overall Kappa Index of agreement of above 60% indicating a moderate agreement with the ground truth.

Impact of rainfall distribution and management regimes on the proportion of bare ground

Rainfall distribution and the proportion of bare ground were negatively correlated ($r=-0.91$) with a high coefficient of determination ($R^2=0.80$, $P<0.001$) indicating that the distribution of rainfall had a significant effect on the proportion of bare ground in the study sites. The average proportion of bare ground for the entire study sites was 22% with a standard deviation of 11%. The highest average proportion of bare ground was 35% in the low rainfall area followed by 16% in the high rainfall area and the least average proportion of bare ground was found in the medium rainfall area (15%). As rainfall increased from the low rainfall areas to the high rainfall areas, the proportion of bare ground decreased significantly.

The proportion of bare ground in the low rainfall area was the highest (43%) followed by private (37%) and protected rangelands (26%). The protected rangelands in high rainfall areas and low rainfall areas were covered with 19% and 26% of bare ground, respectively. Communal rangelands had the highest proportion of bare ground

while protected areas had the least across all the rainfall zones. The proportions of bare ground in the high rainfall areas and the medium rainfall areas were low, comprising only 16% and 15% of the total areas of these respective rangelands. At low rainfall region, where the rainfall normally is below 400 mm, the proportion of bare ground was the highest. These arid and semi-arid regions are dynamic in nature where spatio-temporal variability of abiotic factors dictate the biotic factors particularly rainfall [38-40].

The distribution of rainfall has a major impact in overall abundance of vegetation across the study sites (Figure 4). The low and extremely erratic rainfall has a clear effect on the growth of vegetation in the low rainfall areas. In these areas, there is a closer similarity in terms of the proportion of bare ground among the three rangeland regimes indicating the stronger relationship between the rainfall distribution and conditions of vegetation rather than other factors such as management strategy. The nature of rainfall distribution can cause alteration of a stable state of rangelands resulting into a reduced biomass production [41].

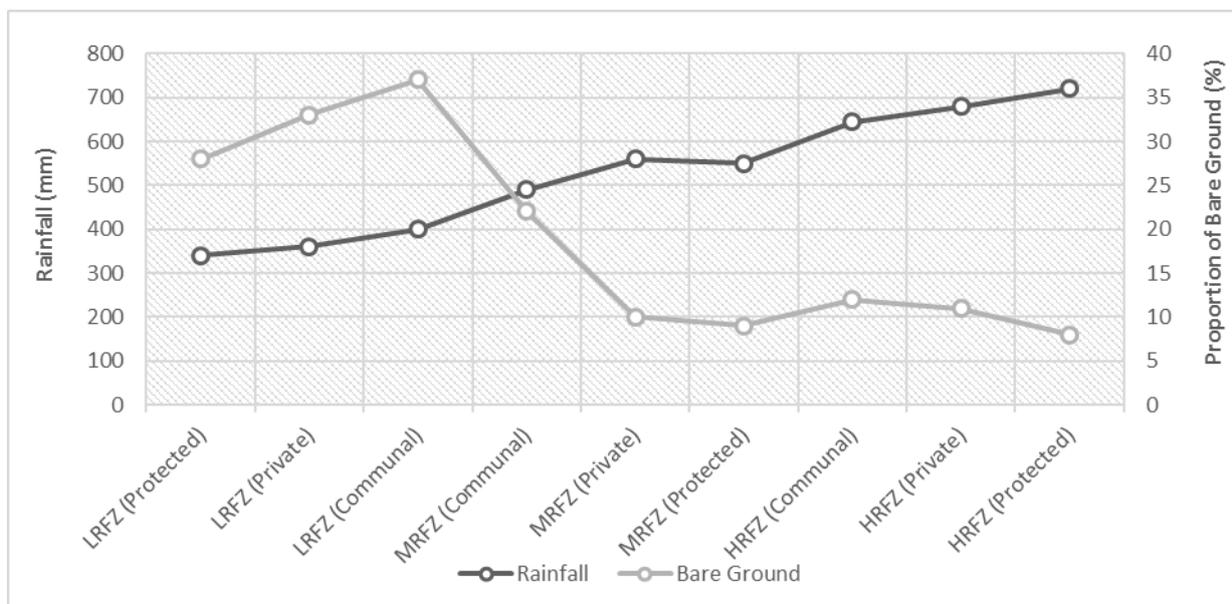


Figure 4: Relationship between rainfall distribution and proportion of bare ground across the study sites in the North West Province.

Continuous and unchecked grazing conditions resulted in communal rangelands losing vegetation cover, hence the higher proportion of bare ground with long term negative implications for the overall health of the rangelands [4,33]. Shrub encroachment and the replacement of perennial grasses by less palatable annual grasses are common phenomena around communal rangelands and are often considered as indicators of land degradation [42,43]. As a result of overgrazing and inappropriate management practices, *Acacia malifera* tree, which is unpalatable to livestock, is found encroaching into the communal grazing areas, especially in the low rainfall region at the expenses of the palatable herbaceous vegetation [44,45]. This condition increases rural poverty levels by creating situations where the long-term goal of sustainable rangeland use, and management is undermined by short-term needs of food security [46-48].

In addition, it was observed that the proportion of bare ground was higher around and near watering points in protected areas and around settlement areas in the communal rangelands. However, satellite imageries failed to show the extent and locations of smaller watering points (ponds less than 100 m²) in low and medium rainfall areas. Unpalatable and weaker sparse grass species characterize the zone in the immediate vicinity of watering points (0-100 m), whereas places farther away from the watering points were characterized by high abundance of highly desirable and palatable grasses. These findings agree with previous studies. For instance, areas that are closer to watering points in which grazing pressure is higher; palatable perennial plants decline in quantity and density and are replaced by less desirable forages or bare ground [49].

Vegetation cover is a crucial factor in reducing the effect of water soil erosion. If the area is covered by bare ground or very little

vegetation cover, soil erosion by water increases. Plant and residue cover protects the soil from rain drop and splashing impacts by slowing down the movement of surface runoff and allowing excess surface water to infiltrate. The effectiveness of a plant in terms of reducing the impact of soil erosion depends on the spatial extent and quantity of vegetation cover. The presence of vegetation residue that completely covers the soil and intercepts all falling rain drops at and closer to the surface are some of the most efficient factors in protecting the top soil from various types of erosion. Therefore, the results of this study suggest that low rainfall areas, which are characterized by higher proportion of bare ground, are the most vulnerable regions for higher level of erosion by water and wind. Moreover, these areas experience isolated heavy rainfall during summer seasons making them susceptible to land degradation due to loss of the fertile top soil. In particular, the communal areas in all rainfall zones are the most vulnerable rangelands because they are characterised by higher number of human and livestock population [4,50,51].

Conclusion

In this study, SPOT 5 imagery was used for mapping land cover features in the study sites and this data source was also assessed for its capacity for mapping different biophysical indicators of rangelands such as indicators of erosion and proportion of bare ground besides land cover classes using the maximum likelihood classification technique. The data was found to be highly useful for mapping and assessing rangeland land cover classes with acceptable accuracy particularly the proportion of bare ground which is a good indicator of rangeland health and other land cover classes such as water body, built up areas, grass/shrub and tree/shrubs in spite of some characteristic problems. However, SPOT 5 imagery was found to be irrelevant for assessing indicators of erosion such as gulleys, rills and dongas due to coarse 10 m × 10 m spatial and spectral resolution. The study sites are located in arid and semi-arid areas; the presence of indicators of erosion in most of the study sites is also limited because of low rainfall. More research focusing on reconciling field data and satellite imagery has to be carried out to improve results. Strong coefficient of determination ($r^2=0.80$) was detected between average rainfall and proportion of bare ground indicating that rainfall is the most important factor in controlling the spatial distribution of vegetation in the study sites.

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