Evaluation of Selected Vegetation Indices to Assess Rangeland Vegetation in Eastern Libya

Abdulsalam Al-Bukhari, Tim Brewer, and Stephen Hallett

Abstract Observation methods used at ground-based sites are widely used in studies assessing rangeland degradation. However, observations through time are often not integrated nor repeatable, making it difficult for rangeland managers to detect degradation consistently. Vegetation cover in the eastern Libyan rangelands has changed both qualitatively and quantitatively due to natural factors and human activity. This raises concerns about the sustainability of these resources, which play an important role in providing part of the food needs of large numbers of grazing animals, in turn providing food for human consumption. The aim of this research is to evaluate a range of vegetation indices derived from satellite imagery to identity those approaches best applicable for remotely assessing and monitoring vegetation cover in the semi-arid and arid rangelands. This approach was achieved through the utilization of medium resolution satellite imagery to classify vegetation cover. A number of vegetation indices applied in arid and semi-arid rangelands similar to the study area were assessed using ground-based colour vertical photography (GBVP) methods to identify the most appropriate index for classifying percentage vegetation cover. The Modified Soil Adjusted Vegetation Index (MSAVI2) was identified as the most appropriate as this had good correlation with ground data due to the mixture of soil background and vegetation reflectance in low-density vegetation cover areas. Even though the Normalized Difference Vegetation Index (NDVI) remains the most widely-used index, it has limitations as it does not adequately address the influence of the soil background. In arid and semi-arid areas, reducing the soil background noise offers a significant quantitative and qualitative enhancement. These results allow the application of these indices to images from different dates to detect changes in vegetation, allowing monitoring of change in this fragile environment in response to natural and anthropogenic processes.

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1 Introduction

Rangeland in Libya provides a significant pillar of support for the national economy, where it represents some 70% of the national landmass. Approximately half of the Libyan rangelands, estimated to be some five million ha in extent, are located in the east of Libya and they play an important role in providing part of the food needs of large numbers of grazing animals (Bayoumi et al. 1998), protecting the environment and conserving the soil from erosion by water and wind.

The eastern Libyan rangeland vegetation cover has changed both qualitatively and quantitatively over the past four decades in response to: decline in rainfall, frequent droughts, wind and water erosion, and human activities such as overgrazing, seasonal fire outbreaks and mismanagement by both pastoralists and rangeland managers (Omar Al Mukhtar University 2005). Managers of Libyan rangelands need effective monitoring systems to help them detect potential problems and to provide data to enable better decisions to be made for the future, to ensure sustainable rangeland management (Al-Bukhari et al. 2018). The accurate monitoring of vegetation condition in rangeland is important for demonstrating rangeland condition, characterizing land cover type and quantifying its extent (Meyer and Turner 1994).

Vegetation cover is frequently used as an indicator when utilising remote sensing data for land condition assessment. Vegetation indices are one of the most widely implemented applications of remotely sensed data for observing and evaluating vegetation by integrating reflectance measurements from two or more wavebands (Pickup et al. 1993; Bannari et al. 1995). Vegetation indices derived from remote sensing data have been widely applied in studies of arid and semi-arid areas at different scales to estimate vegetation cover (Pickup et al. 1994; Gilabert et al. 2002; Jiang et al. 2008). By using these indices, several vegetation parameters such as leaf area, biomass and physiological activities can be assessed (Baret and Guyot 1991; Verrelst et al. 2008), as these parameters are highly correlated to vegetation indices in the red and near infrared wavebands (Broge and Leblanc 2001). The implementation of these indices is generally straightforward and can be used to calculate surface properties when the vegetation canopy is not too dense (less than 50%) or too sparse as the density variation causes significant alteration to the indices as the amount of soil background signal varies (Huete 1988; Liang 2005).

The most widely implemented vegetation index is the Normalized Difference Vegetation Index (NDVI) (Tucker 1979) which has been applied successfully in many studies of arid and semi-arid rangelands (Al-Bakri and Taylor 2003; Jafari et al. 2007; Homer et al. 2012; Sant et al. 2014). However, the NDVI has limitations in areas affected by the soil background in sparsely vegetated areas (Huete 1988). The reflection of soil and sand are much greater than the reflection of vegetation in the red waveband and hence estimating vegetation cover is challenging. Therefore,

soil reflectance adjusted indices such as the Soil Adjusted Vegetation Index (SAVI) (Huete 1988), the Optimized Soil Adjusted Vegetation Index (OSAVI) and the Modified Soil Adjusted Vegetation Index (MSAVI2) (Qi et al. 1994), have been proposed to overcome this limitation (Gilabert et al. 2002; Shupe and Marsh 2004). The Soil and Atmospherically Resistant Vegetation Index (SARVI) (Kaufman and Tanre 1992) has also been developed to reduce the effect of the atmosphere in these regions. Overall, these indices tend to improve the differentiation between soil and vegetation while reducing the effects of illumination conditions (Baret and Guyot 1991). However, they have been identified as being sensitive to soil brightness effects (Huete 1988; Roujean and Breon 1995), particularly where the vegetation cover is low (Broge and Leblanc 2001).

Pickup et al. (1993) proposed the perpendicular distance vegetation index (PD54) to overcome this problem using visible green and red reflectance to separate vegetation cover from soil instead of red and NIR reflectance. They found that this index was less sensitive than red and NIR indices to differences in plant greenness. Although the PD54 index has been widely assessed with success in several Australian rangelands (Bastin et al. 1993; Pickup et al. 1994; McGregor and Lewis 1996), it was not the strongest predictor of perennial or total plant cover in the studied area. Also, it requires the subjective delineation of a soil line and vegetation dominated pixels in the spectral plot. This process needs considerable knowledge in image analysis, is subjective, and can result in a lack of consistency in the application of the index (Jafari et al. 2007).

Jafari et al. (2007) tested the stress related indices 1 and 4 (STVI-1, 4) to solve this problem in the southern arid rangeland in Australia in combination with 12 vegetation indices, comparing the results with measured vegetation cover at land system and landscape scale. They found that STVI-1 and 4 were highly to very highly correlated with vegetation cover at both scales. O'Neill (1996) in western New South Wales found similar results in a community dominated by chenopod shrublands. Barati et al. (2011) have analysed the vegetation cover fraction in sparsely vegetated areas near Esfahan, Iran, evaluating the relationships between 20 vegetation indices and vegetation cover fractions. Their results indicated that the Difference Vegetation Index (DVI) and Ratio Difference Vegetation Index (RDVI) were the most sensitive indices for assessing vegetation cover.

Although many vegetation indices have been proposed, it is obvious that much remains to be done to understand how these indices are implemented in various environments (Silleos et al. 2006) because the results from the studies are often at variance with each other. In addition, these indices cannot be applied to all arid and semi-arid areas as they do not have a standard universal value for the vegetation types found (Bannari et al. 1995).

Some studies have been conducted in Libyan rangeland that include remote sensing data resources for mapping vegetation cover. Mnsur and Rotherham (2010) mapped the change of land cover/land in selected areas of Al Jabal Alakhder from 1984 to 2005 using Landsat TM and Landsat ETM+ data applying a supervised classification method. Elaalem et al. (2013) applied supervised classification using SPOT 5 imagery for evaluating land cover/land use in the north-west region of the

Jeffara Plain. They found this approach led to the production of inaccurate land cover classes due to the limitations of the supervised classification adopted when classifying heterogeneous land cover/use classes. White et al. (2003) mapped changes in vegetation cover in the Wadi Al-Hayat in the south of Libya using NDVI derived from Landsat data. However, the techniques applied in these Libyan studies have limitations in arid and semi-arid areas where sparse vegetation causes increased reflectance response effects from the soil background.

However, a remotely sensed method still requires ground truth data to validate the results. The field-based digital photography method is gaining popularity for the purpose of cover estimation, as it can reduce field time and enable additional analysis in the future (Ko et al. 2017). High resolution, nadir photography can serve as a realistic ground plot. It is information rich, understandable to a broad base of people, and the unanalysed information can be archived for future use. High resolution imagery, of less than 1 cm, is being used by a number of researchers (Breckenridge et al. 2011; Cagney et al. 2011; Karl et al. 2012; Mirik and Ansley 2012). Using high resolution imagery, Pilliod and Arkle (2013) found that the photography-based grid point intercept (GPI) method in Great Basin plant communities was strongly correlated to the line intercept (LI) method but it was 20–25 times more efficient, identified 23% more plant species, and was more precise in determining percent cover. Furthermore, they found that GPI could precisely estimate cover of basic vegetation components when they exceeded 5–13% while LI cover estimates had to exceed 10–30% cover for equal precision. Detecting change when percent cover is low is very important in arid lands where land cover is typically sparse.

Richardson et al. (2001) indicated digital photography analysis was able to generate accurate results in much less time compared to the LI method. Another study which compared digital photo analysis and the point intercept (PI) method also suggested that the results between the two methods were similar when a sufficient number of plots were combined together (Booth and Tueller 2003). Analyzing digital images acquired from the field can be advantageous since the production of permanent images enables the researcher to reanalyze the data later on with more advanced methods and software (Boyd and Svejcar 2005). This method can be particularly helpful since it can drastically reduce time spent in the field and control surveyor-bias (Booth and Tueller 2003). The Sant et al. (2014) methodology has been demonstrated as being an appropriate method in the USA where ground-based photography has been used to assess the vegetation cover.

The aim of this study is not to review in general the use of vegetation indices, as intensive reviews have already been published (Bannari et al. 1995; Jensen 2000; Silleos et al. 2006; Jones and Vaughan 2010; Ren and Feng 2015) rather to evaluate the indices where the purpose is to solve the problem of assessing low vegetation cover in sparsely vegetated rangeland. The specific aim of this paper is to evaluate a range of vegetation indices derived from remote sensing data that have been implemented in other arid and semi-arid rangelands similar to the study area to identity those that are applicable for Libyan rangelands by comparing the performance of the selected spectral indices, using ground-based colour vertical photography (GBVP) to provide comparative ground based measurements of vegetation cover.

2   Materials and Methods

2.1   Study Area

The study area was located in the eastern Libyan rangeland (Fig. 1). This area, including Al Jabal Al Akhdar (the Green Mountain), contains more than 50% of the total number of Libyan floral species and represents one of the most important rangeland areas in Libya, especially during the winter months where the rainy season extends between October and March. The annual rates of rainfall lie between 50–200 mm, while the annual mean temperature is approximately 20 ° C (SWECO 1986).

   The study area was selected to best represent the diversity of eastern Libyan rangeland conditions. The boundary was the 300 mm rainfall line to the north, 23° longitude to the east, 21° longitude to the west, and the 50 mm isohyet to the south, as officially in Libya rangeland is located within land receiving annual precipitation between 50 mm to less than 300 mm.

2.2   Field Survey

The field data collection area (Fig. 1) was selected to include representative rainfall, soil and land management variation within the study area and was located between the 50–200 mm isohyet zones from south to north, comprising an area of
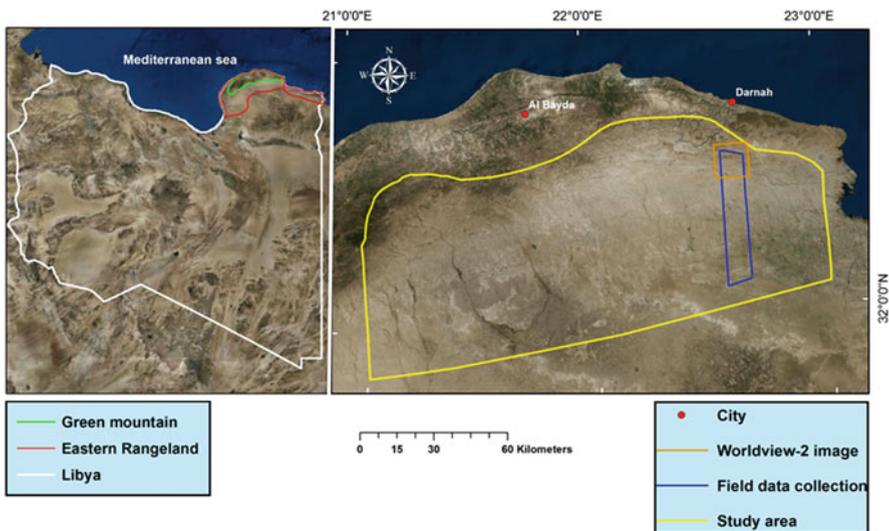

Fig. 1 The study area

approximately 500 km^2. A total of 100 sample sites were visited to allow for redundancy, with 50 samples used for training data and 50 as validation data. The sample locations were determined using the fishnet tool in ArcGIS (ESRI 2017) to give an even distribution of sites throughout the study area. The sites were greater than 650 m from each other to ensure independence based on semi-variance measurement of the spatial dependence among the observations as a function of distance (Karnieli et al. 2008). The optimum time for field and satellite data collection was based on advice from Libyan rangeland experts and analysis of MODIS NDVI data for the period 2012–2016 to establish the peak extent of vegetation cover.

Ground based vertical photography (GBVP) images (Sant et al. 2014) were taken at each sample site with a 24-megapixel, 10 mm focal length, Canon Digital D750 camera mounted on a portal boom (Fig. 2). Site location was recorded with a Garmin GPSMAP 64S GPS.

The GBVP image ground cover was calculated as follows (Avery and Berlin 1992) (Eq. 3.1):

$$\text{Image ground cover} = \frac{\text{SAW} \times \text{LH}}{\text{FL}} \quad (3.1)$$

Where SAW = sensor array width, LH = lens height and FL = focal length:

Fig. 2 GBVP image acquisition

The average lens height for each nadir image was 3.2 m at all sample locations with a standard deviation of +/− 0.05 m, and the area of the image footprint was 34.5 m^2 with a standard deviation of +/− 1 m^2. Additional high oblique images were taken from the centre point of the nadir image aligned to the four cardinal compass directions to provide additional vegetation cover context.

Adobe Lightroom and Photoshop software packages were used to manage the raw image data collected. The highest quality image at each sample location from the five replicates in each orientation was selected for the classification based on its histogram profile. Masking of the shadow from the portable boom was required for some images.

2.3 GBVP Image Classification

The GBVP nadir images were processed using a combination of the object based ENVI Feature Extraction tool (ENVI 2017) and ArcGIS to calculate the percentage vegetation cover. The objects were classified into three basic ground cover types: bare ground, shrub, and annual vegetation, as well as two additional categories: litter and shadow (Sant et al. 2014).

For each of the 100 GBVP images, a minimum of 15 samples for each ground cover type were digitised as polygons by visual interpretation. These polygons acted as training samples to classify the remaining image pixels. The ENVI Feature Extraction tool offers three methods of classification: K Nearest Neighbour (KNN), Support Vector Machine (SVM), and Principal Components Analysis (PCA). Each of these methods were applied and tested on 10 georeferenced GBVP nadir images, to determine the accuracy of each classification method by using 100 randomly located points in each GBVP image, created using the fishnet tool in ArcGIS. The 100 random points were visually interpreted and compared to each of the classified values from each of the three classification methods from which the most accurate classification method was determined (Congalton 1991).

The Support Vector Machine (SVM) method was identified as the most accurate classification method and was used to produce the percentage cover of shrub, annual vegetation, litter, shadow, and bare ground for each GBVP nadir image. These images were individually classified to overcome variances between images in terms of soil colour, degree of stone cover, and presence of a cryptobiotic cover (Sant et al. 2014). Shadow was classified for each image and was included as part of the % cover of the originating category of that shadow. Therefore, the percentage cover of shrub and annual vegetation (green cover) and any associated shadow were used to calculate the vegetation cover percentage from the satellite derived remotely sensed data.

3 Remote Sensing Data

Landsat 8 OLI images (C1 Level-1) were acquired in March 2017 (paths/ rows: 183/037, 183/038 and 182/038). This imagery was used to derive the vegetation map for the whole study area, represented by the yellow polygon outline in Fig. 1. A Worldview-2 image was also obtained from April 2017 (provided by Digital Globe Inc.) which covered part of the selected field data collection study area (Fig. 1). This image was used in an alternative processing method to evaluate the accuracy of the percentage vegetation cover classification for the selected vegetation index.

3.1 Landsat Image Classification

The ENVI software was used for pre-processing the Landsat 8 images to radiometrically correct, mosaic the three images and subset the study area. A comprehensive range of vegetation indices were selected for evaluation (Table 1). These indices were identified as being appropriate for measuring sparsely vegetated areas of arid and semi-arid rangelands as they have shown good performance in the literature.

Table 1 Vegetation indices selected for evaluation

Vegetation index	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$(NIR - RED)/NIR + RED)$	Tucker (1979)
Difference Vegetation Index (DVI)	NIR/RED	Tucker (1980)
Ratio Difference Vegetation Index (RDVI)	$NIR - RED/\sqrt{NIR + RED}$	Roujean and Breon (1995)
Soil Adjusted Vegetation Index (SAVI)	$[(NIR - RED)/NIR + RED + L)] \times (1 + L)$	Huete (1988)
Optimized Soil Adjusted Vegetation Index (OSAVI)	$(NIR - RED)/NIR + RED + 0.16$	Rondeaux et al. (1996)
Modified Soil Adjusted Vegetation Index 2 (MSAVI2)	$\frac{2NIR+1-\sqrt{(2NIR+1)^2-8(NIR-RED)}}{2}$	Qi et al. (1994)
Soil and Atmospherically Resistant Vegetation Index (SARVI)	$(1 + L)(NIR - RB)/NIR + RB + L$	Kaufman and Tanre (1992)
Stress Related Vegetation index -1 (STVI-1)	$(MIR \times RED)/NIR$	Thenkabail et al. (1994)
Stress Related Vegetation index -3 (STVI-3)	$NIR/(RED + MIR)$	Thenkabail et al. (1994)
Stress Related Vegetation Index -4 (STVI-4)	$NIR - (RED \times MIR)/(NIR + MIR)$	Jafari et al. (2007)
Mid-infrared-3 Vegetation Index (MSVI-3)	$NIR/(MIR + SWIR)$	Thenkabail et al. (1994)
Modified Triangulation Vegetation Index-1 (MTVI1)	$1.2 [1.2(NIR - GREEN) - 2.5 (RED - GREEN)]$	Haboudane et al. (2004)

The results from each index tested were compared to the GBVP nadir images to identify the most appropriate vegetation index to estimate vegetation cover data at the sample sites. The selected vegetation index from the GBVP image analysis was used to train the Landsat 8 image classification for the whole study area. Vegetation index threshold values were defined for the percentage vegetation cover classification to take into account the sensitivity of remote sensing data to vegetation cover and the minimum vegetation cover that could provide protection to the soil from erosion. The percentage vegetation cover classification boundaries were selected based on a previous study conducted in part of the study area (SWECO 1986): <10%, 10–35%, >35%. To calculate the accuracy of the percentage cover map, an error matrix was produced using the validation data generated from the GBVP images, to determine the overall accuracy, commission, and omission errors for each class. Kappa analysis was used to determine the agreement within the classification.

The accuracy assessment of the classified Landsat 8 image versus the nadir GBVP data gave a low classification accuracy, due to the very different resolutions and spatial extent of the two sets of imagery, ranging from 2 mm resolution for the GBVP nadir data to 30 m for the Landsat 8 imagery. The ground extent of each GBVP nadir image was approximately 4% of a single Landsat pixel and therefore the ground cover percentage of the GBVP image may not be representative of the averaged pixel response on the Landsat image. The four cardinal direction GBVP images were therefore used to obtain a wide area training dataset equivalent to a 30×30 m Landsat pixel. The wider area was classified based on visual assessment of what could be seen on the four cardinal images to estimate a vegetation cover value for the 30×30 m area. The wide area training dataset was applied to the Landsat 8 imagery and a new vegetation cover classification derived that was assessed for accuracy.

3.2 Worldview 2 Image Classification

An alternative method was tested to enhance the accuracy of the classification, using a multi-resolution approach applied by Simms et al. (2017) in Afghanistan where the core mapping was undertaken within a 1 km^2 segment at 1 m resolution and statistically expanded to enable classification of 32 m DMC imagery to enable regional classification of imagery. The selected vegetation index that had the highest correlation using the GBVP data was applied to the Worldview 2 imagery to create a vegetation index classification image at 2 m resolution and an accuracy assessment was undertaken. The threshold values from the vegetation index were identified to classify the Worldview 2 image into the three vegetation cover classes. A training dataset from the Worldview 2 vegetation cover classification was selected to train the 2017 Landsat 8 image. This produced a new vegetation cover classification to

investigate whether this enhanced the accuracy of the medium resolution data classification compared to classifying the medium resolution data directly using the GBVP images. An accuracy assessment was conducted on the new classification using the GBVP images to enable this comparison to be made.

4 Results and Discussion

4.1 Ground Based Vertical Photography (GBVP) Method

The results from five years of NDVI values across the study area showed that the peak of vegetation production was from February to April (Fig. 3) and was therefore the optimum time for ground survey. This also agreed with the views of Libyan rangeland experts consulted during the research and other authors (Tehrany et al. 2017). The field data collection for the GBVP therefore took place in March 2017 to correspond with the peak of vegetation greenness.

In the field, shadow was minimized by taking GBVP images between 9:00 a.m. and 4:00 p.m. At each sample location, GBVP nadir and cardinal azimuth (north, east, south, and west) images were captured five times. The total number of images captured were 500 GBVP nadir images and 2000 images for the four cardinal directions. The 100 'highest quality' GBVP nadir images (one for each sample location) and the 400 'highest quality' images for the four cardinal directions (one from each cardinal direction at each sample location) were selected for analysis to extract the vegetation cover.
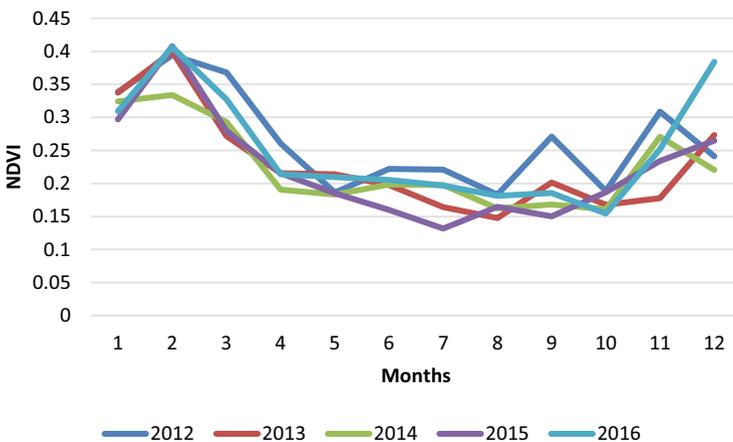

Fig. 3 Five-year trend of MODIS NDVI

4.2 GBVP Image Classification

In order to identify the most appropriate method for classifying the GBVP images, three methods of classification available in the ENVI Feature Extraction tool were tested. The K Nearest Neighbour (KNN) and Principal Components Analysis (PCA) did not perform well but the Support Vector Machine (SVM) was identified as the most appropriate method for classification with an overall accuracy of 85%, followed by K Nearest Neighbour (KNN) and Principal Components Analysis (PCA) with overall accuracies of 40% and 30%, respectively. The results of the classifications from the three methods can be seen in Fig. 4.
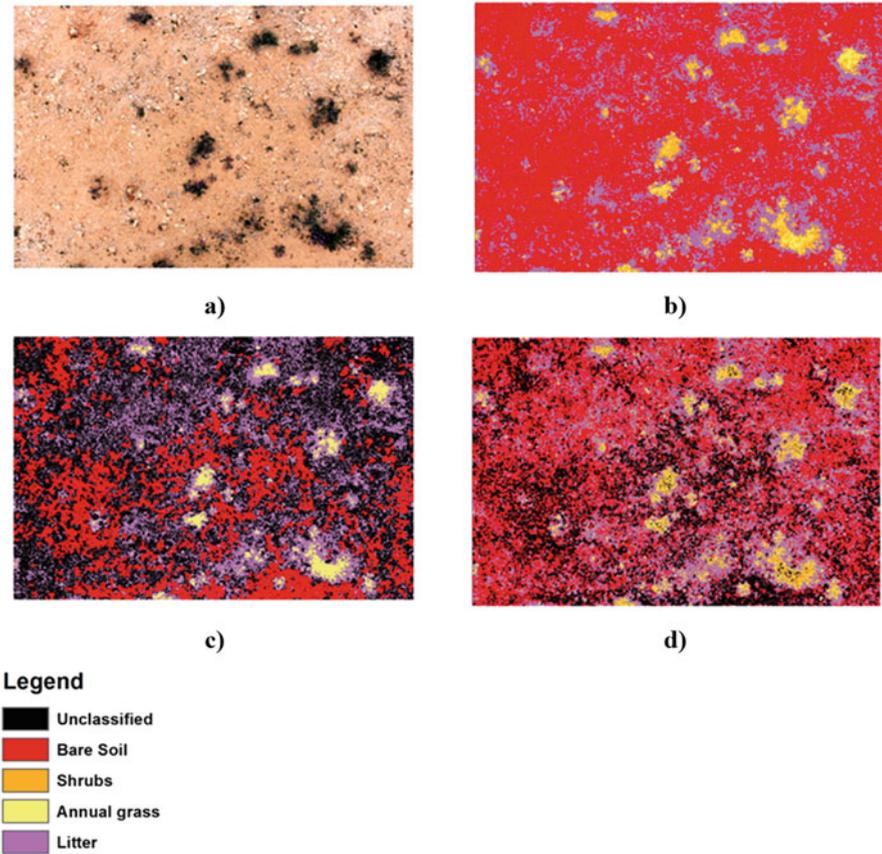
Fig. 4 Classification methods tested for GBVP images; (**a**) ground-based colour vertical, (**b**) support vector machine (SVM), (**c**) principal components analysis, and (**d**) k nearest neighbour (KNN)

4.3 Vegetation Indices Analysis Using GBVP Imagery

Twelve vegetation indices derived from the Landsat 8 imagery and the total vegetation cover extracted from the GBVP were analysed using simple linear regression. The results showed that all vegetation indices tested in this study were significantly and strongly correlated with the ground data (nadir image GBVP) with r values ranging from 0.653 to −0.821 (Table 2). STVI_1 was the most correlated index with ground measured vegetation cover extracted from the non-adjusted GBVP with r = −0.821 where a decreasing index value corresponds with increasing vegetation cover. This finding agrees with Jafari et al. (2007). The lowest correlation index was MSVI_3 with r = 0.653. This shows that the shortwave infrared index is less effective for predicting vegetation cover.

With the inclusion of visual interpretation from the four cardinal images, the results indicated that the correlation of all vegetation indices was enhanced. The correlations ranged from 0.697 to −0.894 (Table 3). STVI_1 remained the most correlated index to ground vegetation cover, and the correlation of STVI_1 increased from −0.821 to −0.894. Even though the most highly correlated index was STVI_1, it has a negative relation with vegetation cover as the index decreases with increasing vegetation influence making it harder to interpret compared to the indexes that have a positive correlation (Jafari et al. 2007). The MSVI_3 correlation was also enhanced, reaching 0.697 compared to 0.653.

The results demonstrated that the use of the shortwave infrared MSVI_3 index instead of the near infrared in the STVI_3 index reduced the accuracies of prediction as it had the lowest correlation. This finding agreed with Barati et al. (2011). Also, indices that integrate the green band, such as MTVI1, are among the well correlated indices. This result is similar to Baret and Guyot (1991) and Haboudane et al. (2004) but is inconsistent with other results using the green band conducted in similar

Table 2 The relationship between the vegetation indices and nadir GBVP image

Vegetation indices	Mean	Std.Dv.	r (X,Y)	r^2
NDVI	0.141794	0.04578	0.792676	0.628336
DVI	0.121312	0.02173	0.743858	0.553325
RDVI	0.130861	0.03171	0.788842	0.622272
SAVI	0.133665	0.03435	0.794053	0.630520
OSAVI	0.119144	0.03482	0.795596	0.632972
MSAVI2	0.131119	0.03187	0.788526	0.621774
SARVI	−0.046473	0.04785	0.710057	0.504181
STVI_1	0.425994	0.07041	−0.820685	0.673523
STVI_3	0.537347	0.04395	0.755061	0.570117
STVI_4	0.272397	0.04356	0.809562	0.655391
MSVI_3	0.507744	0.04024	0.653112	0.426555
MTVI1	−0.001471	0.06045	0.807264	0.651674

p-value is 0.0000 with all indices

Table 3 The relationship between the vegetation indices and the GBVP images using visual interpretation of the four cardinal direction GDVP images

Vegetation indices	Mean	Std.Dev.	r(X,Y)	r²
NDVI	0.141794	0.04578	0.870957	0.758566
DVI	0.121312	0.02173	0.835211	0.697577
RDVI	0.130861	0.03171	0.874532	0.764806
SAVI	0.133665	0.03435	0.879232	0.773050
OSAVI	0.119144	0.03482	0.877093	0.769292
MSAVI2	0.131119	0.03187	0.874669	0.765046
SARVI	−0.046473	0.04785	0.721251	0.520204
STVI_1	0.425994	0.07041	−0.894678	0.800449
STVI_3	0.537347	0.04395	0.814367	0.663194
STVI_4	0.272397	0.04356	0.877200	0.769480
MSVI_3	0.507744	0.04024	0.697431	0.486411
MTVI1	−0.001471	0.06045	0.887711	0.788032

p-value is 0.0000 with all indices

sparsely vegetated areas where a decrease in the sensitivity of the index gave a lower correlation with variations in vegetation cover fraction (Barati et al. 2011).

Moreover, the study indicates that SAVI, OSAVI, and MSAVI2 (soil adjusted indices) give similar correlations to NDVI; this result is similar to Ren and Feng (2015) but is not consistent with the findings of other work where soil-adjusted indices perform better than NDVI (Rondeaux et al. 1996; Huete 1988). However, NDVI does not cancel the noise caused by the soil background. In arid and semi-arid areas, reducing the soil background noise is a significant quantitative and qualitative enhancement (Silleos et al. 2006).

The optimised soil-adjusted vegetation index (OSAVI) is the same as SAVI with a soil adjustment factor of 0.16 rather than 0.5 that is based on vegetation cover density. However, since the vegetation cover was of relatively low density in the study area, the SAVI should result in better performance in a low-density vegetated area as it has a higher adjustment factor compared to OSAVI (Lawrence and Ripple 1998). For optimal adjustment of the soil effect, however, the L factor (a function of vegetation cover density) should vary inversely with the amount of vegetation present and ranges from 0 to 1. MSAVI2 replaces the constant L in the SAVI equation (Table 1) with a variable L function that is self-adjustable. This enhancement of the MSAVI2 minimises the soil background influences, resulting in greater vegetation sensitivity (Qi et al. 1994). The SAVI needs antecedent knowledge regarding densities of vegetation in terms of adopting an optimal L value while MSAVI2 does not require knowledge of vegetation cover to determine the L factor (Qi et al. 1994). The MSAVI2 was therefore selected and tested to map the vegetation cover within the eastern Libyan rangeland taking into account the soil background effect and also its designed correction with respect to how the non-modified SAVI index responds to vegetation.

4.4 Accuracy Assessment of Vegetation Cover

The accuracy assessment of the MSAVI2 derived percentage vegetation cover using the nadir only GBVP imagery indicated that the overall accuracy was 84% and the user's accuracy for the three vegetation cover classes were 92.5%, 33.33% and 57.14%, respectively (Table 4).

Whereas when the cardinal GBVP imagery was included, the accuracy assessment of the MSAVI2 derived percentage vegetation cover showed an overall accuracy enhancement. The overall accuracy was 94.7% and the user's accuracy for the three vegetation cover classes were 97.8%, 60% and 100%, respectively (Table 5 and Fig. 5).

## 4.5 Worldview 2 Image Classification

The result of using the Worldview 2 high-resolution image with GBVP to train the 2017 Landsat 8 image illustrated that the overall accuracy of the MSAVI2 derived percentage vegetation cover map decreased, but there was some enhancement in the

Table 4 Accuracy assessment of the percentage vegetation cover derived from Landsat 8 MSAVI2 using non-adjusted GBVP imagery

Reference data (ground data)						
Classified data (percentage vegetation cover)	Vegetation cover class	<10%	10–35%	>35	Total	User's accuracy
	<10%	37	2	1	40	92.5%
	10–35%	2	1	0	3	33.33%
	>35%	1	2	4	7	57.14%
	Total	41	4	5	50	
	Producer's accuracy	90.24%	25%	80%	Overall accuracy	84%

Table 5 Accuracy assessment of the percentage vegetation cover derived from Landsat 8 MSAVI2 using cardinal GBVP imagery

Reference data (ground data)						
Classified data (percentage vegetation cover)	Vegetation cover class	<10%	10–35%	>35%	Total	User's accuracy
	<10%	38	1	0	39	97.82%
	10–35%	1	3	1	5	60%
	>35%	0	0	6	6	100%
	Total	39	4	7	50	
	Producer's accuracy	97.82%	75%	85.71%	Overall accuracy	94.73%
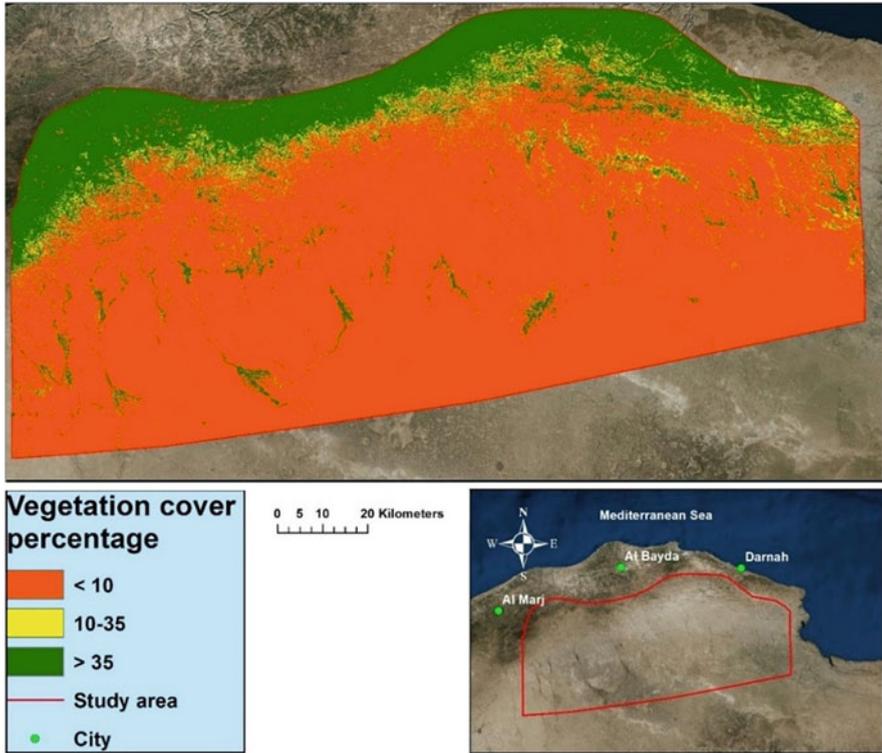
Fig. 5 Vegetation cover percentage derived from the MSAVI2 index using cardinal GBVP imagery

Table 6 Accuracy assessment of the percentage vegetation cover derived from Landsat 8 MSAVI2 using the Worldview 2 image

Reference data (ground data)							
Classified data (percentage vegetation cover)	Vegetation cover class	<10%	10–35%	>35%	Total	User's accuracy
	<10%	127	46	7	180	70.5%
	10–35%	38	372	108	518	71.8%
	>35%	5	90	480	575	83%
	Total	170	508	595	1273	
	Producer's accuracy	74.7%	70%	80.6%	Overall accuracy	76.9%

user and producer accuracies as indicated in Table 6. The overall accuracy was 76.9% and the user's accuracy for the three vegetation cover classes was 70.5%, 71.8% and 83%, respectively.

In addition, the kappa value indicted good agreement (K = 0.719) according to the rating criteria of kappa statistics described by Landis and Koch (1977) and Rwanga and Ndambuki (2017) when compared with K = 0.5079 when the

classification of vegetation cover from the Landsat 8 image was implemented using the nadir GBVP imagery. Whereas when the cardinal GDVP imagery was used the agreement in the classification increased to K = 0.8403.

Overall, using the very high-resolution Worldview 2 imagery with the GBVP images did not enhance the accuracy of the Landsat 8 image classification compared to classifying the data directly using the GBVP images. The reason could be that the ground survey design was established for the greater spatial extent of the Landsat 8 imagery whereas the Worldview image only covered a small part of the study area that led to a low number of sample points located within the Worldview image area. More investigation is needed but using high-resolution satellite imagery is not recommended at this time due to the extra cost involved in obtaining the imagery.

The advantages of the GBVP method are that the vegetation indices assessment is based on much more detailed ground data producing a training and verification dataset that is more closely allied to the data produced by the satellite sensor. It gives a better assessment of the amount of soil versus vegetation taking into consideration the soil background effect. The GBVP can also be reanalysed and classified in the future with more advanced techniques and software applications.

5   Conclusions

The vegetation index approach, supported by the use of ground data, allowed the measurement of the low vegetation cover density in the arid and semi-arid Libyan rangeland taking into account the influence of the soil background. Twelve vegetation indices were tested with the ground-based colour vertical photography (GBVP) and Landsat 8 imagery.

The MSAVI2 index was identified as the most appropriate to use due to the mixture of soil background reflectance with vegetation reflectance in low-density vegetation cover areas. Also, the resolution of the imagery (30 m resolution) did not match the resolution of the information collected on the ground. A further consideration is that successful remote sensing vegetation analysis assessments require a statistically designed survey in terms of the number of points, the distance between the points and the strata used to ensure a fully representative ground survey for all classification categories that are going to be generated from the image.

Even though the NDVI remains the most widely used index, it has limitations as it does not address the influence of the soil background. In arid and semi-arid areas, reducing the soil background noise offers a significant quantitative and qualitative enhancement. Other indices such as STVI_1 were also highly correlated. However, the correlations were either too complex, as in the case of the STVI_1 index where it has a negative relation with vegetation cover making it harder to interpret compared to other indexes that have a positive correlation, or they required more specific parameterisation which would be more difficult to apply by non-experts.

Availability of Data and Materials   The vegetation indices presented in this paper derive from open source remote sensing information, specifically Landsat and MODIS from: https:// earthexplorer.usgs.gov. A Worldview-2 image was provided by Digital Globe Inc.

Author Contributions   **Abdulsalam Al-Bukhari:** conceptualization, methodology, supervision, software, data curation, formal analysis, validation, investigation, writing-original draft, visualization, writing—review and editing. **Stephen Hallett:** supervision, review of analysis, writing—review and editing. **Tim Brewer:** supervision, review of analysis, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Competing Interests   The authors declare that they have no competing interests.

References

Al-Bakri J, Taylor J (2003) Application of NOAA AVHRR for monitoring vegetation conditions and biomass in Jordan. J Arid Environ 54:579–593

Al-Bukhari A, Hallett S, Brewer T (2018) A review of potential methods for monitoring rangeland degradation in Libya. Pastoralism 8(1):1–14

Avery TE, Berlin G (1992) Fundamentals of remote sensing and airphoto interpretation, 5th edn. Prentice Hall, London

Bannari A, Morin D, Bonn F, Huete A (1995) A review of vegetation indices. Remote Sens Rev 13: 95–120

Barati S, Rayegani B, Saati M, Sharifi A, Nasri M (2011) Comparison the accuracies of different spectral indices for estimation of vegetation cover fraction in sparse vegetated areas. Egypt J Remote Sens Space Sci 14:49–56

Baret F, Guyot G (1991) Potentials and limits of vegetation indices for LAI and APAR assessment. Remote Sens Environ 35:161–173

Bastin G, Sparrow A, Pearce G (1993) Grazing gradients in central Australian rangelands: ground verification of remote sensing-based approaches. Rangel J 15:217–233

Bayoumi MA, Al-Saadi OR, Awad JA (1998) The economic importance of rangeland. J Arts Sci Garyounis Univ Al Marj Libya:165–169. (in Arabic)

Boyd CS, Svejcar TJ (2005) A visual obstruction technique for photo monitoring of willow clumps. Rangel Ecol Manag 58:434–438

Booth DT, Tueller PT (2003) Rangeland monitoring using remote sensing. Arid Land Res Manag 17:455–467

Breckenridge RP, Dakins M, Bunting S, Harbour JL, White S (2011) Comparison of unmanned aerial vehicle platforms for assessing vegetation cover in sagebrush steppe ecosystems. Rangel Ecol Manag 64(5):521–532

Broge NH, Leblanc E (2001) Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. Remote Sens Environ 76:156–172

Cagney J, Cox SE, Booth DT (2011) Comparison of point intercept and image analysis for monitoring rangeland transects. Rangel Ecol Manag 64(3):309–315

Congalton RG (1991) A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens Environ 37:35–46

Elaalem MM, Ezlit YD, Elfghi A, Abushnaf F (2013) Performance of supervised classification for mapping land cover and land use in Jeffara Plain of Libya. In: International proceedings of chemical, biological & environmental engineering, vol 55

ENVI (2017) Feature extraction with example based classification tutorial ENVI 5.4.1. Exelis Visual Information Solutions, Broomfield

ESRI (2017) ArcGIS help, toolbox, ArcGIS desktop10.5. ESRI

Gilabert M, González-Piqueras J, Garcıa-Haro F, Meliá J (2002) A generalized soil-adjusted vegetation index. Remote Sens Environ 82:303–310

Haboudane D, Miller JR, Pattey E, Zarco-Tejada PJ, Strachan IB (2004) Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: modeling and validation in the context of precision agriculture. Remote Sens Environ 90:337–352

Homer CG, Aldridge CL, Meyer DK, Schell SJ (2012) Multi-scale remote sensing sagebrush characterization with regression trees over Wyoming, USA: laying a foundation for monitoring. Int J Appl Earth Obs Geoinf 14:233–244

Huete AR (1988) A soil-adjusted vegetation index (SAVI). Remote Sens Environ 25:295–309

Jafari R, Lewis M, Ostendorf B (2007) Evaluation of vegetation indices for assessing vegetation cover in southern arid lands in South Australia. Rangel J 29:39–49

Jensen J (2000) Remote sensing of environment: an earth resource. Prentice-Hall, Saddle River, p 526

Jiang Z, Huete AR, Didan K, Miura T (2008) Development of a two-band enhanced vegetation index without a blue band. Remote Sens Environ 112:3833–3845

Jones HG, Vaughan RA (2010) Remote sensing of vegetation: principles, techniques, and applications. Oxford University Press, Oxford

Karl JW, Duniway MC, Schrader TS (2012) A technique for estimating rangeland canopy-gap size distributions from high-resolution digital imagery. Rangel Ecol Manag 65(2):196–207

Karnieli A, Gilad U, Ponzet M, Svoray T, Mirzadinov R, Fedorina O (2008) Assessing land-cover change and degradation in the Central Asian deserts using satellite image processing and geostatistical methods. J Arid Environ 72:2093–2105

Kaufman YJ, Tanre D (1992) Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. IEEE Trans Geosci Remote Sens 30:261–270

Ko DW, Kim D, Narantsetseg A, Kang S (2017) Comparison of field-and satellite-based vegetation cover estimation methods. J Ecol Environ 41(2):34–44

Landis JR, Koch GG (1977) A one-way components of variance model for categorical data. Biometrics:671–679

Lawrence RL, Ripple WJ (1998) Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape: Mount St. Helens, Washington. Remote Sens Environ 64(1):91–102

Liang S (2005) Quantitative remote sensing of land surfaces. Wiley, Hoboken

McGregor K, Lewis M (1996) Quantitative spectral change in chenopod shrublands. In: Hunt LP, Sinclair R (eds) Focus on the future—the heat is on, Proceedings of the 9th biennial conference of the Australian Rangeland Society, Port Augusta, SA, pp 153–154

Meyer WB, Turner B (1994) Changes in land use and land cover. Changes. In: Meyer WB, Turner BL (eds) Land use and land cover. Cambridge University Press, p 549

Mirik MSAA, Ansley RJ (2012) Comparison of ground-measured and image-classified mesquite (Prosopis glandulosa) canopy cover. Rangel Ecol Manag 65:85–95

Mnsur S, Rotherham ID (2010) Using TM and ETM+ data to determine land cover land use changes in the Libyan Al-jabal Alakhdar region. In: Rotherham I. D., Agnoletti, M., Handley, C. (Eds.), End of tradition? Part 2 commons: current management and problems (cultural severance and commons present). Landsc Archaeol Ecol 8:32–38

O'Neill A (1996) Satellite-derived vegetation indices applied to semi-arid shrublands in Australia. Aust Geogr 27:185–199

Omar Al Mukhtar University (2005) Study and evaluation natural vegetation in Al Jabal Al Akhdar area, Final report, Al Bieda, Libya (in Arabic)

Pickup G, Chewings V, Nelson D (1993) Estimating changes in vegetation cover over time in arid rangelands using Landsat MSS data. Remote Sens Environ 43:243–263

Pickup G, Bastin G, Chewings V (1994) Remote-sensing-based condition assessment for nonequilibrium rangelands under large-scale commercial grazing. Ecol Appl 4:497–517

Pilliod DS, Arkle RS (2013) Performance of quantitative vegetation sampling methods across gradients of cover in Great Basin plant communities. Rangel Ecol Manag 66(6):634–647

Qi J, Chehbouni A, Huete A, Kerr Y, Sorooshian S (1994) A modified soil adjusted vegetation index. Remote Sens Environ 48:119–126

Ren H, Feng G (2015) Are soil-adjusted vegetation indices better than soil-unadjusted vegetation indices for above-ground green biomass estimation in arid and semi-arid grasslands? Grass Forage Sci 70:611–619

Richardson MD, Karcher DE, Purcell LC (2001) Quantifying turfgrass cover using digital image analysis. Crop Sci 41:1884–1888

Rondeaux G, Steven M, Baret F (1996) Optimization of soil-adjusted vegetation indices. Remote Sens Environ 55:95–107

Roujean JL, Breon FM (1995) Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. Remote Sens Environ 51(3):375–384

Rwanga SS, Ndambuki J (2017) Accuracy assessment of land use/land cover classification using remote sensing and GIS. Int J Geosci 8:611

Sant ED, Simonds GE, Ramsey RD, Larsen RT (2014) Assessment of sagebrush cover using remote sensing at multiple spatial and temporal scales. Ecol Indic 43:297–305

Shupe SM, Marsh SE (2004) Cover-and density-based vegetation classifications of the Sonoran Desert using Landsat TM and ERS-1 SAR imagery. Remote Sens Environ 93:131–149

Silleos NG, Alexandridis TK, Gitas IZ, Perakis K (2006) Vegetation indices: advances made in biomass estimation and vegetation monitoring in the last 30 years. Geocarto Int 21:21–28

Simms DM, Waine TW, Taylor JC (2017) Improved estimates of opium cultivation in Afghanistan using imagery-based stratification. Int. J. Remote Sens 38(13):3785–3799 https://doi.org/10.1080/01431161.2017.1303219

SWECO SC (1986) Final report, land survey, mapping and pasture survey for 250.000 hectares of South Jabel el Akhdar area, for Socialist People's Libyan Arab Jamahiriya Secretariat for Agricultural Reclamation and Land Development, Contract No. 17/90/81, Libya

Tehrany MS, Kumar L, Drielsma MJ (2017) Review of native vegetation condition assessment concepts, methods and future trends. J Nat Conserv 40:12–23

Thenkabail PS, Ward AD, Lyon JG, Merry CJ (1994) Thematic Mapper vegetation indices for determining soybean and corn growth parameters. Photogramm Eng Remote Sens (USA) 60:437

Tucker CJ (1979) Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens Environ 8:127–150

Tucker CJ (1980) A spectral method for determining the percentage of green herbage material in clipped samples. Remote Sens Environ 9:175–181

Verrelst J, Schaepman ME, Koetz B, Kneubühler M (2008) Angular sensitivity analysis of vegetation indices derived from CHRIS/PROBA data. Remote Sens Environ 112:2341–2353

White K, Brooks N, Drake N, Charlton M, MacLaren S (2003) Monitoring vegetation change in desert oases by remote sensing; a case study in the Libyan Fazzān. Libyan Stud 34:153–166

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