The Evaluation of High Resolution Aerial Imagery for Monitoring of Bracken Fern

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Abstract

The Royal Natal National Park and the Rugged Glen Nature Reserve are part of the uKhahlamba Drakensberg Park (UDP) World Heritage Site and have infestations of bracken fern (Pteridium aquilinum [L.] Kuhn). Prior image classification research on bracken fern were constrained by low resolution satellite imagery and the inability of hard classifiers to account for mixed pixels. Currently there are differing views on which season is best for mapping of bracken fern. To overcome these constraints high resolution aerial imagery of 0.5m spatial resolution and a soft classifier, fuzzy classification, were employed to identify bracken fern infestations. This study compared imagery captured in winter and spring to determine which season was better suited for the image classification of bracken fern. The winter and spring classified images produced overall accuracies of 81.4% and 94.4% with Kappa coefficients of 0.63 and 0.89 respectively. These results show that high resolution imagery in conjunction with fuzzy classification can be used to identify bracken fern and that spring is more suitable for monitoring of bracken fern as compared to winter.

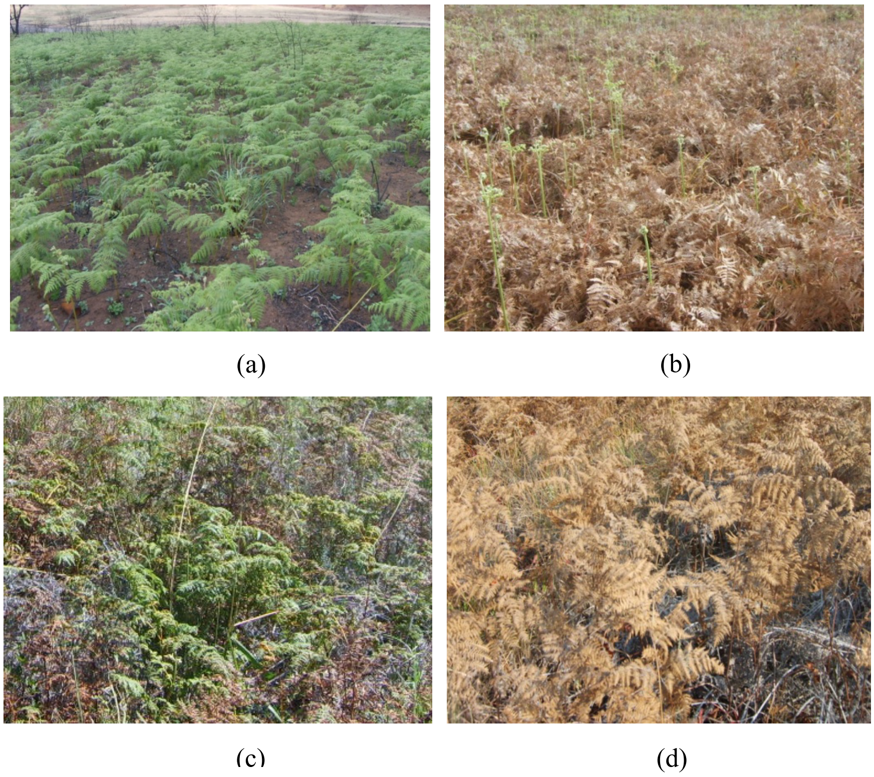
1. Introduction

Bracken fern is an aggressive, opportunistic and resilient invasive plant in South Africa, Mexico and United Kingdom (Bond *et al.*, 2007; Schneider and Fernando, 2010). There are significant infestations of bracken fern in the uKhahlamba Drakensberg Park (UDP) that could cause severe economic and ecological problems. Bracken fern can drive up the maintenance costs of the national parks (Goodall and Naudé, 1998). It interrupts the functioning of ecosystems that it infests and is a threat to biodiversity (Schneider, 2006; Bond *et al.*, 2007). The UDP is a hotspot of plant biodiversity with 13% of its flowering plants found nowhere else in the world (UDP WHS- IMP, 2011).

There are currently no classification maps delineating the bracken fern infestation in the UDP (Richert, personal communication, April 2013). Remote sensing can be used to monitor bracken fern as it is the only practical method to identify invasive plants over large areas (Holland and Aplin, 2013). Internationally research exists on image classification of bracken fern and which season would be favourable for its identification however such research has not been conducted in South Africa.

1.1 Bracken fern

Bracken fern has a distinct phenology that causes changes in its physical appearance, shown in Figure 1. Spring and summer are its growing seasons were young and fully developed fronds exhibit a distinct green colour. In autumn bracken fern decays and it exhibits a green/brown colour. In winter bracken fern dies back and it exhibits a brown/grey colour. The dead plant matter persists into the following spring and is partially obscured by new growth. In spring and summer bracken fern is visually distinctive from the surrounding vegetation however this is not so during winter.



(a) (b) (c) (d)

Figure 1. Phenology of bracken fern in the Royal Natal National Park and Rugged Glen Nature Reserve; (a) bracken fern fully grown, (b) bracken fern sprouting in early spring, (c) bracken fern in early autumn, and (d) bracken fern in early winter.

1.2 Recent image classification research

Mapping of bracken fern has been attempted using low spatial resolution imagery and hard image classification techniques however due to the errors caused by mixed pixels those methods are considered inappropriate for the classification of bracken fern (Pakeman *et al*., 1996; Holland and Aplin, 2013). The use of high resolution imagery in the image classification of bracken fern has led to an improvement of accuracy and reliability (Holland and Aplin, 2013). However, even with high spatial resolution imagery the problem of mixed pixels persists (Laba *et al*., 2008). Researchers have used soft classifiers to classify bracken fern (Schneider and Fernando, 2010; Schmook *et al*., 2011) which have been shown to be effective in addressing the problem of mixed pixels (Laba *et al*., 2008; Frazier and Wang, 2011; Schmook *et al*., 2011). Soft classifiers such as fuzzy classification have produced more accurate and reliable classified images than hard classifiers (Laba *et al*., 2008; Schmook *et al*., 2011). Fuzzy classification is an alternative approach to hard classification techniques that create discrete class ranges. It avoids using arbitrary sharp thresholds and that makes it suited to manage the uncertainties boundaries between heterogeneous land cover types that are not discrete (Benz *et al*., 2003; Jensen, 2005; Chaira and Ray, 2010). Boyd and Foody (2010) suggested that the problem of mixed pixels can be reduced by using either remotely sensed imagery with the finest spatial resolution possible or employ algorithms that focus on spectral un-mixing analysis. Therefore combination of high resolution aerial imagery and the fuzzy classification technique should suitably address the problem of mixed pixels by reducing their impact in the classified images. Table 1 shows recent research on image classification using soft classifiers and high resolution imagery.

There are differing views about which season is best for the image classification of bracken fern. The season in which imagery is captured is important because the phenology of bracken fern impacts the image classification results obtained. Spring (Laba *et al*., 2008 and Schmook *et al*., 2011) and summer (Mehner *et al*., 2004) were found to be effective in distinguishing between different types of vegetation due to vigorous plant growth that resulted in particularly high reflectance in the NIR band which might be expected. In contrast Holland and Aplin (2013) found bracken fern to be more distinct in winter due to the thick masses bracken fern formed when it died back which contrasted with other semi-natural vegetation and ever green grasses. While Schneider and Fernando (2010) research showed poor results using imagery captured in winter.

Table 1. Recent research on image classification

Research	**Remote Sensor and season of image capture**	**Spatial and spectral resolution**	**Image analysis techniques**	**Results** (Overall accuracy-OA, Kappa coefficient –Kc)
Holland and Aplin (2013)	**(a)** LANDSAT 5 TM [Early winter, 2005] **(b)** LANDSAT 7 ETM+ [Summer, 2006] **(c)** LANDSAT 7 ETM+ [Late winter, 2007] **(d)** IKONOS [Spring, 2005]	**(a, b & c)** 30 m, 6 visible, NIR and SWIR **(d)** 4 m, 3 visible bands and NIR	Supervised classification with the Maximum likelihood classifier	**(a)** OA: 57.8%. Bracken fern class; UA: 68.1 %, PA: 69.1 % **(b)** OA: 58.9 %. Bracken fern class; UA: 51.1 %, PA: 67.7 % **(c)** OA: 65.7 %. Bracken fern class; UA: 65.6 %, PA: 86.7 % **(d)** OA: 73.7 %. Bracken fern class; UA: 78.4 %, PA: 58.8 %
Schmook *et al.* (2011)	LANDSAT ETM+ [Spring , 2000]	30m; visible, NIR and SWIR	In-Process Classification Assessment (IPCA)	Bracken fern class: Kc: 0.72, UA: 73 %, PA: 90 %
Laba *et al.* (2008)	Quickbird Imagery [Spring, 2004]	**(a)** 0.61m & **(b)** 2.4 m, CIR & RGB	**(1)**Supervised Classification **(2)**Fuzzy Classification	**(a,1)** OA : 73.6%, **(b,1)** OA : 64.9%, **(a,2)** OA : 75% , **(b,2)** OA : 83%

2. Materials and Methods

This section covers a description of data, resources and the classification techniques employed in this study which are the: (i) study area, (ii) aerial imagery, (iii) image pre-processing, (iv) GPS field surveys, (v) fuzzy classification process, and (vi) accuracy assessment of the classified images.

2.1 Study Area

The Royal Natal National Park and Rugged Glen Nature Reserve are part of the UDP; a locality map is shown in Figure 2. The UDP situated in the province of KwaZulu-Natal in the Republic of South Africa and borders the Kingdom of Lesotho on its western boundary (Kruger *et al*., 2011; UNEP-WCMC, 2011). The Royal Natal National Park and Rugged Glen Nature Reserve are adjacent to each other and have an area of 80.94km^2 and 7.62km^2 respectively (UNEP-WCMC, 2011). The research areas are protected areas and are under the control the provincial conservation organisation, Ezemvelo KwaZulu-Natal Wildlife (EKZNW) (Krüger *et al*., 2011).

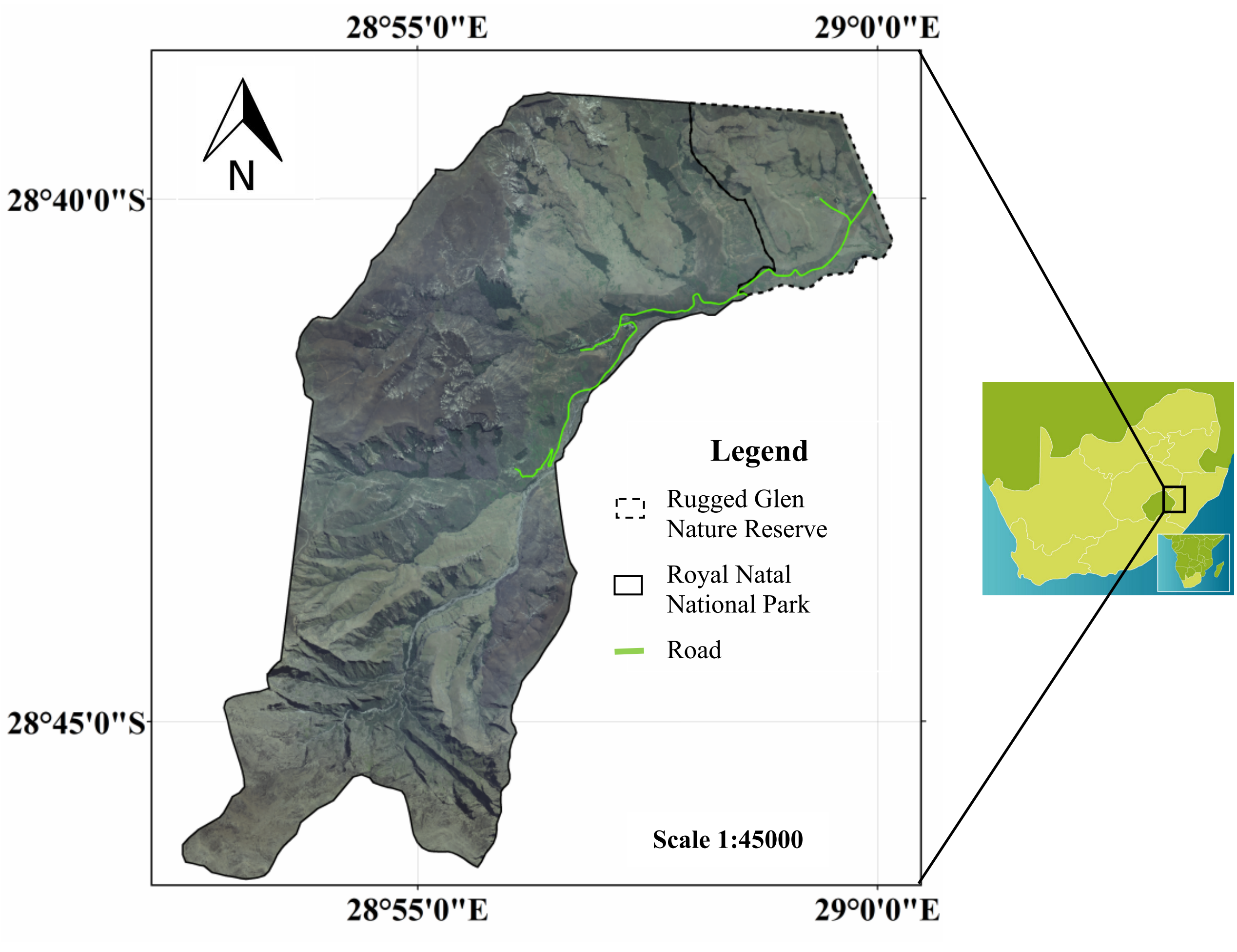


Figure 2. Locality map of Royal Natal National Park and Rugged Glen Nature Reserve

2.2 Aerial imagery

The Chief Directorate: National Geospatial-Information (CD: NGI) provides national coverage of digital multispectral aerial imagery with a ground sample resolution of 0.5m. Imagery available of the research areas was captured in 2009/07/13, mid-winter, and 2011/10/08, mid-spring. Imagery was captured with a Z/I Imaging Digital Mapping Camera (DMC) with a focal length of 12cm, pixel size of 12µm and an image size of 13824 x 7680 pixels. The average flying height is 5525m and 5730m above mean sea level for each epoch of imagery respectively. The CD: NGI performed image pre-processing to correct for radiometric distortions, then the imagery is geo-referenced but not orthorectified.

2.3 Pre-processing

At the time that this study was conducted, in 2012, the orthorectified mid-spring imagery was not yet available from the CD: NGI and due to time constraints it was decided to orthorectify the imagery. Image orthorectification was carried out using Leica Photogrammetric Suite (LPS) Project Manager. LPS Project Manager automatically extracted tie points from overlapping areas of the geo-referenced imagery as well as a single digital terrain model mosaic from the sensor parameters, interior orientation and triangulation data. The image orthorectification was based on: the WGS 84 ellipsoid, Hartebeesthoek 94 coordinate system and the Transverse Mercator projection system with a central meridian of 29˚. Bilinear resampling was used to resample the imagery to 0.5m and the rmse was less than half an image pixel.

2.4 GPS field surveys

The GPS field surveys were conducted in March and June 2012. GPS coordinates were recorded around clumps of bracken fern and other land cover features, occurring on differing slopes and altitudes, to form reference polygons. These reference polygons were used to assist the image classification process.

2.5 Fuzzy classification of bracken fern

A two land cover class classification system was employed, bracken fern and non-bracken fern. The Non-Bracken fern class was a hierarchy of other vegetation land cover types. The fuzzy classification process was a two-step process. Step one produced a classified image using the Maximum Likelihood Classifier (MLC) and the second step involved a fuzzy convolution procedure. The MLC was used in the fuzzy classification because it is a parametric decision rule that has produce accurate results in previous image classification research. This classification decision rule assumes that pixel values of a land cover type followed a normal distribution. It examines the probability of a pixel in relation to each defined land cover class and their mean reflectance (Jensen, 2005; Campbell, 2007; Lillesand *et al*, 2008). Equation 1 (Campbell, 2007) shows the calculation of the MLC.

$$D = \ln\left(a_c\right) - \left[0.5\ln\left(\left|Cov_c\right|\right)\right] - \left[0.5\left(X - M_c\right)^T\left(Cov_c^{-1}\right)\left(X - M_c\right)\right] \qquad [1]$$

D	-	Maximum likelihood distance
c	-	Class
X	-	Measurement vector of the candidate pixel
M_c	-	Mean vector of the sample of class c
a_c	-	Probability a candidate pixel is a member of class c
Cov_c	-	Covariance matrix of the pixels in the sample of class c
$\lvert Cov_c \rvert$	-	Determinant of covariance matrix of the pixels in the sample of class c
Cov_c^{-1}	-	Inverse of covariance matrix of the pixels in the sample of class c
ln	-	Natural logarithm function
T	-	Transposition function

The mid-winter and mid-spring classifiers were each trained using 70 reference sites, with 35 reference sites used per a land cover class. Data training of the classifier was an iterative process; the frequency distribution diagrams of the land cover types approximated a normal Gaussian distribution for each land cover type. Any bi-modal frequency diagrams of a land cover type were re-trained to create two sub classes for that same land cover type. This was done to better represent the land cover types that occurred which also reduced chances of possible misclassification. The training sites were taken from the reference polygons and directly from the imagery itself. This helped to minimise the effect of the time that passed between the capture of the mid-winter imagery and the ground truth survey on the image classification.

The fuzzy classification was carried out using the MLC. Therefore the fuzzy mean (u^*) and fuzzy covariance matrix (V^*) replace the conventional mean and covariance matrix of the conventional MLC algorithm. Equation 2 (Jenson, 2005) is the representation of the fuzzy classification using based on the MLC membership function for class c and Equation 3 (Jenson, 2005) shows the variables involved in a fuzzy classification based on the MLC.

$$f_c(x) = \frac{P_c^*(x)}{\sum_{i=1}^{m} P_i^*(x)} \qquad [2]$$

where

$$P_i^*(x) = \frac{1}{(2\Pi)^{\frac{N}{2}} \left| V_1^* \right|^{\frac{1}{2}}} \times \exp\left[-0.5\left(x - u_i^*\right)^T \left(V_i^*\right)^{-1} \left(x - u_i^*\right)\right] \qquad [3]$$

N	-	Dimension of pixel vectors
m	-	Number of classes

P_i* - MLC algorithm with the fuzzy mean and covariance matrix

u* - Fuzzy mean

V* - Fuzzy covariance matrix

$1 \leq i \geq m$

In step two the convolution operation produced a single classification layer using the multilayer MLC image and a distance file that was created in step one. This was done by calculating the total weighted inverse distance of all land cover classes within a window of pixels. Thereafter the convolution operation assigned the centre pixel of the window, in the class with the largest total inverse distance summed over the entire set of fuzzy classification layers (Erdas, 2010).

2.6 Accuracy assessment

The accuracy of classified images was evaluated using: ground truth surveys conducted in September 2012, error matrices to determine accuracy and Kappa coefficients (Kc) to determine reliability. Each classified image was validated independently using a different set reference sites from those used to train the classifiers, with an equal number of sites for each land cover class. The mid-spring classification was validated with more reference sites only because it had identified more areas as bracken fern compared to the mid-winter classification which needed to be tested. The difficult terrain made it unfeasible to travel to all parts of the research areas. Thus the sampling was restricted to the accessible grasslands, hillsides and hilltops. However this restriction did not introduce bias into the accuracy assessment because the classified images identified bracken fern occurring on grasslands, hillsides and on hilltops of varying altitude and degree of slope.

3. Results

This section covers the results of the mid-winter and mid-spring classifications with use of: (i) classification maps, (ii) error matrices and (iii) mean plot diagrams. The sites in which bracken fern was identified in the mid-winter and mid-spring are shown in Figures 3 and 4 respectively.

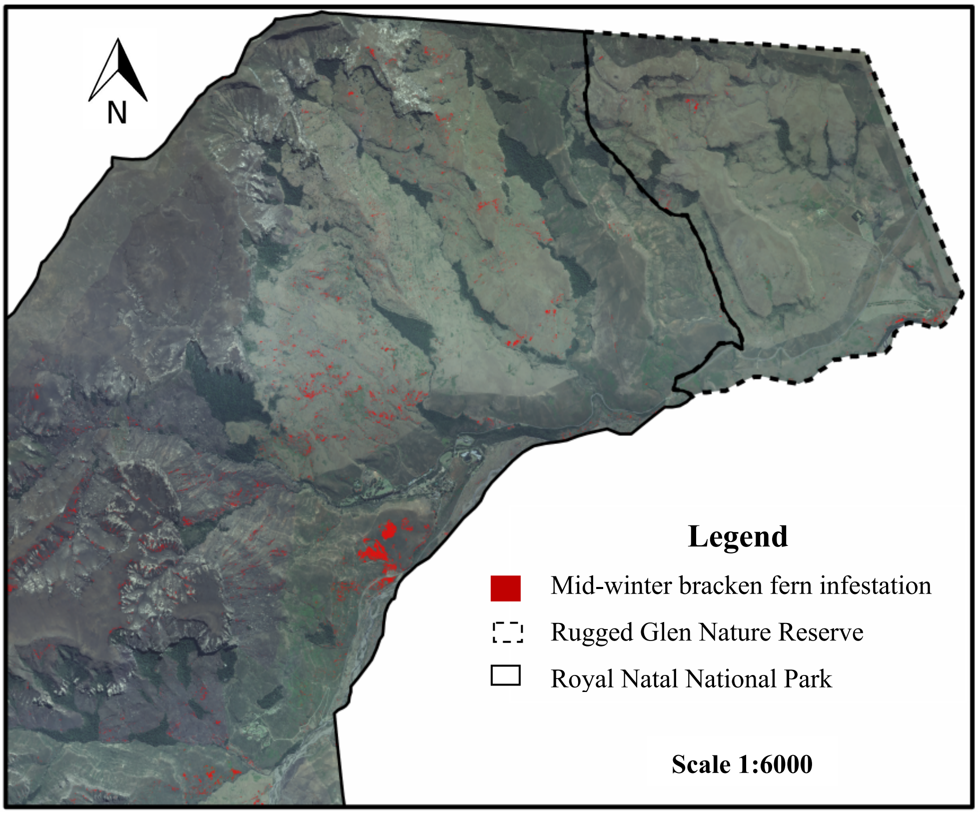


Figure 3. Classification map of bracken fern in mid-winter

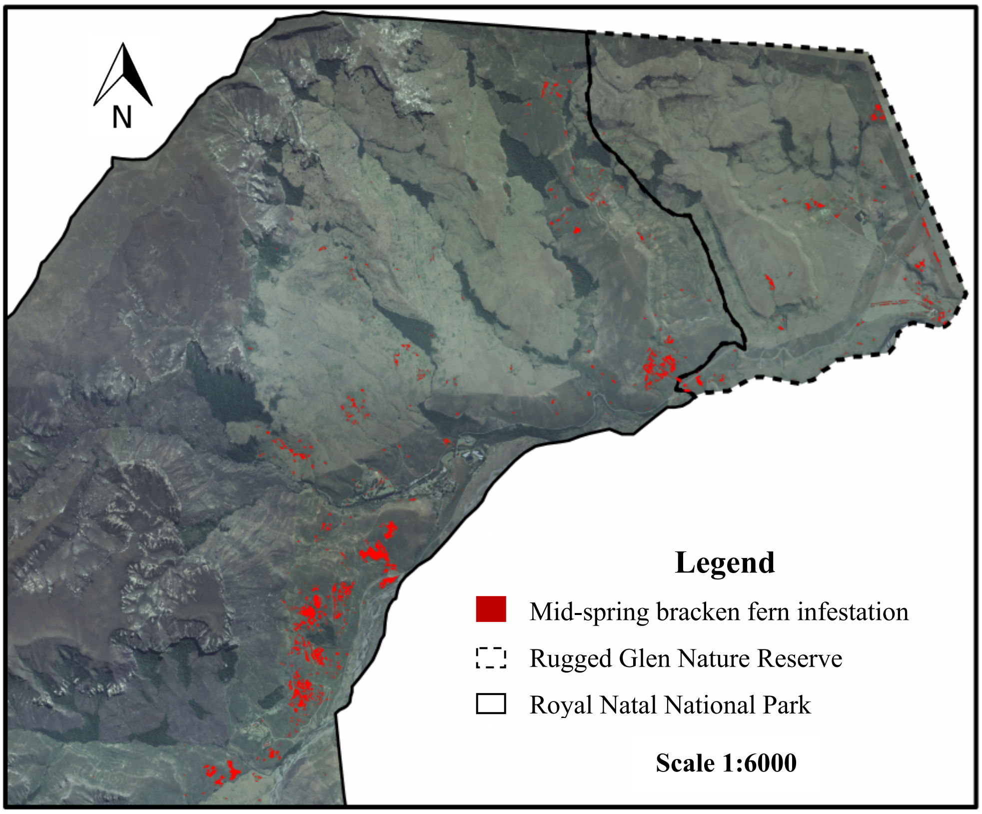


Figure 4. Classification map of bracken fern in mid-spring

The distribution of the bracken fern infestations in the Royal Natal National Park and Rugged Glen Nature Reserve is shown in Figures 3 and 4. To monitor any change of the bracken fern infestation accurate and reliable classification maps are needed. The error matrices for the mid-winter and mid-spring classifications are shown in Tables 2 and 3 respectively.

Table 2. Mid-winter fuzzy classification error matrix

Nos.	**Classes**	**Reference Data**						
		Bracken fern	**Non-Bracken fern**	**TOTALS**	**UA**	**EC**	**OA**	**Kc**
1	Bracken fern	24	11	35	68.6%	31.4%	81.43 %	0.63
2	Non-Bracken fern	2	33	35	94.2%	5.7%		
	TOTALS	26	44	70				
	PA	92.3%	75%					
	EO	7.7%	15%					

Table 3. Mid-spring fuzzy classification error matrix

Nos.	**Classes**	**Reference Data**						
		Bracken fern	Non-Bracken fern	TOTALS	UA	EC	**OA**	**Kc**
1	Bracken fern	41	4	45	91.1%	8.9%	94.44 %	0.89
2	Non-Bracken fern	1	44	45	97.8%	2.2%		
	TOTALS	42	48	90				
	PA	97.6%	91.7%					
	EO	2.4%	8.3%					

The mid-spring classified image has a lower error of commission and omission for bracken fern as compared to the mid-winter classified image. This may indicate that the classifier is less likely to confuse bracken fern as another vegetation type and vice versa in mid-spring than in mid-winter.

The spectral reflectance patterns of the land cover features included in the mid-winter and mid-spring classifications are shown in Figures 5(a) and 5(b) respectively. These mean plot diagrams were created using the mean reflectance values of each land cover type across the NIR, red, green and blue spectral bands.

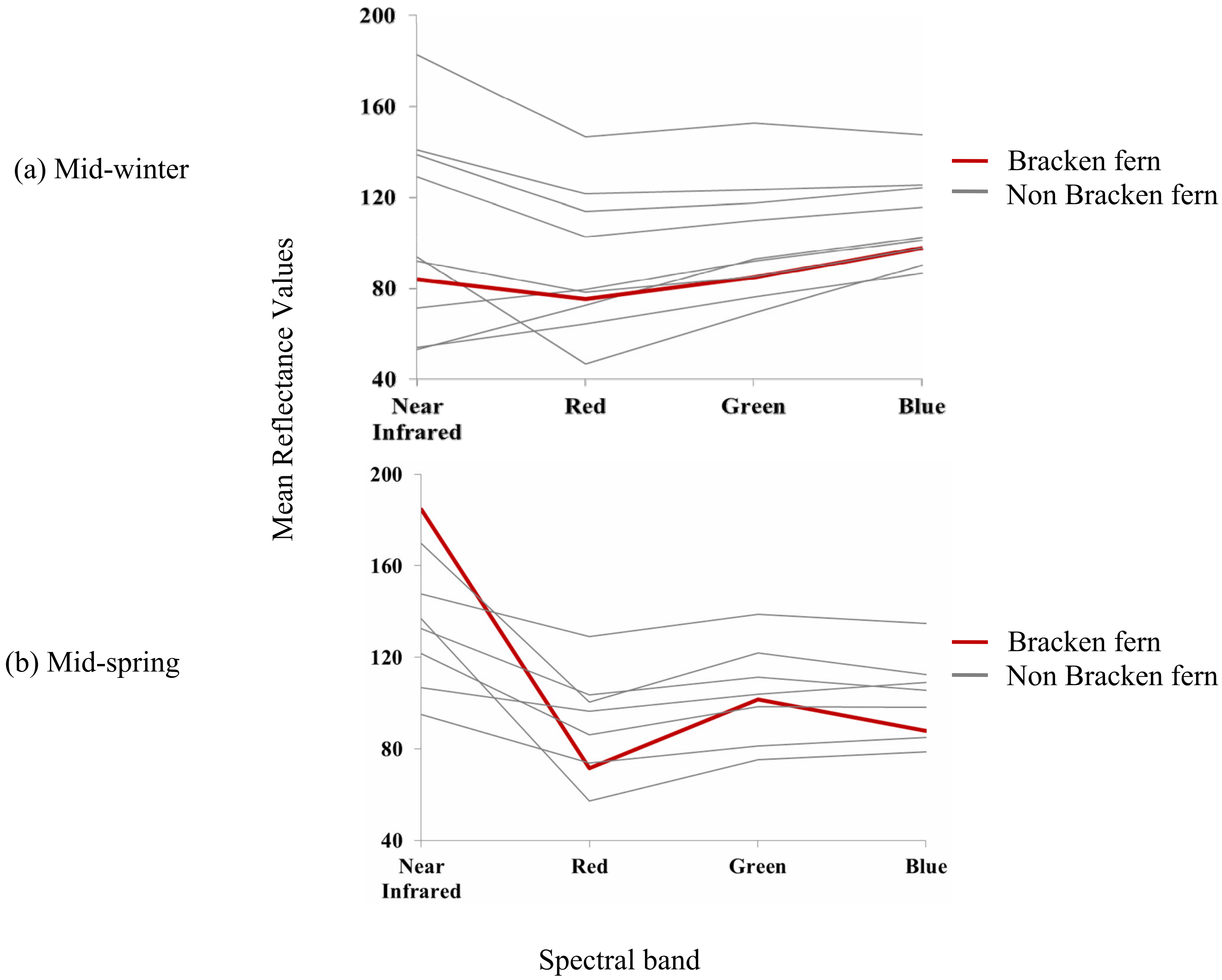


Figure 5. Mean spectral response of land cover features of fuzzy classification; (a) mid-winter classification, (b) mid-spring classification

The mean plot diagrams show that the spectral reflectance pattern of bracken fern varies from mid-winter to mid-spring. In Figure 5(b) the spectral reflectance value for bracken fern in the NIR band is unique and separable from the non-bracken fern class. While the spectral reflectance pattern of bracken fern and non-bracken class fern look similar in the RGB bands of the mid-spring imagery. Also the bracken fern and non-bracken class fern look similar in the mid-winter imagery. This suggests that it would be easier to identify bracken fern in mid-spring than in mid-winter.

4. Discussion

There were three factors that contributed to the image classification results obtained in this study and the ecological and managerial issues that the classification maps can address. These factors were: (i) spatial resolution, (ii) temporal resolution, and (iii) spectral resolution of the imagery used in the fuzzy classification process.

4.1 Spatial resolution

In this study the combination of the high resolution imagery together with soft classification were used and produced reliable and accurate classified images of bracken fern. This was due in part to the ability of high resolution imagery to identify small features accurately in a heterogeneous environment were discrete boundaries between vegetation types do not occur and the land cover gradually changes from one feature to another. On the periphery of bracken fern clumps were various groupings of vegetation occurred within a pixel the high spatial resolution assisted the soft classifier to address these mixtures.

4.2 Temporal characteristics

Previous research highlighted that the distinct phenology of bracken fern and the time of year in which imagery is captured as being significant factors in its detection (Mehner *et al*., 2004; Holland and Aplin, 2013). This research reaffirms that the distinct phenology of bracken fern impacts its physical appearance [refer to Figure 1] which in turn impacts the spectral reflectance pattern it exhibited. This research also showed that bracken fern was easier to identify in spring as compared to winter. In spring bracken fern consisted of bright green plants with their fronds fully unfurled (Bond *et al*, 2007) which contrasted with other types of vegetation. While in winter the physical state of bracken fern clumps consisted of dead and decaying plants which were spectrally similar to other land cover types.

The three year gap between the capture of the mid-winter imagery between the ground truth surveys may have impacted the results this study obtained as due possible seasonal weather variations. However since the bracken fern infestations were not monitored prior to this study the full extent of the impact on the mid-winter results are unknown.

4.3 Spectral resolution

Figure 5(a) showed that in mid-winter when bracken fern is decaying or dead it exhibits a similar spectral reflectance pattern to other vegetation features. This could be responsible for the relatively large error of commission seen in the mid-winter classified image error matrix as compared to the mid-spring classified image. During mid-spring bracken fern has the highest reflectance of all the land cover features in the NIR band due to the presence of chlorophyll (Campbell, 2007; Lillesand *et al*., 2008) in its fully developed fronds that makes bracken fern easier to detect in mid-spring than in mid-winter.

The similarity of spectral reflectance patterns of the bracken fern and non-bracken fern classes in the visible bands in Figure 5(a) and 5(b) suggest that classifications with the RGB imagery alone would include significant amounts of errors of omission and commission. The NIR band is slightly more effective in identifying bracken fern in mid-spring than the RGB bands [refer to Figure 5(b)]. The combination of visible and NIR bands was suitable for its identification.

4.4 Ecological and managerial relevance

This study showed that classification maps can be created to identify bracken fern. Given further epochs of imagery captured in mid-spring and considering the requirements outlined by Lu *et al*. (2004) and Lu and Weng (2007), it will be possible to conduct change detection analysis to monitor the bracken fern infestation. Change detection analysis would provide information on the extent and rate of the spread for the infestation over a long period (Lu *et al.*, 2004; Lu and Weng, 2007). This information could facilitate enforcement of control measures to preserve the biodiversity of the UDP and possibly save the EKZNW money on possible maintenance costs as highlighted by Goodall and Naudé (1998). The availability of this imagery opens the door for possible monitoring of various other invasive plant species in the UDP and the rest of South Africa's national parks in general.

5. Conclusion

This study has determined two pieces of information vital to the image classification of bracken fern in the Royal Natal National Park and Rugged Glen Nature Reserve. Firstly the combination of high spatial resolution imagery and soft classification does address the potential negative impact of mixed pixels in classified images. Secondly the spectral reflectance pattern exhibited by bracken fern made it easier to identify it in spring as compared to winter. This study also reaffirmed that the distinct phenology of bracken fern is a major factor in its identification. Now knowing this information it could be possible to monitor the change of the bracken fern infestation in the Royal Natal National Park and Rugged Glen Nature Reserve provided that there are multiple epochs of mid-spring imagery available.

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