DETECTING AND MAPPING INVASIVE ALIEN WATTLE IN KWAZULU-NATAL, SOUTH AFRICA

Romano Lottering & Kabir Peerbhay

Discipline of Geography, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, P/Bag X01, Scottsville, Pietermaritzburg 3209, South Africa
Email: lottering@ukzn.ac.za; peerbhaykabir@gmail.com

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ABSTRACT: Invasive alien wattle disturbs ecological and economic sectors in South Africa, which may lead to losses in biodiversity and ecosystem services. Remote sensing techniques utilized for early detection and mapping of invasive wattle are pivotal in the South African context, as the relevant decision-making processes need to be taken to eradicate and reduce invasion. In this study, we integrated image texture combinations computed from a SPOT-6 image with sparse partial least squares discriminant analysis (SPLS-DA) to detect invasive alien wattle and surrounding land cover classes. From the results, the texture combination model (OA = 74%; kappa statistic = 70) outcompeted the single band image texture model (OA = 68%; kappa statistic = 65) and vegetation indices (OA = 62%; kappa statistic = 59). The most significant texture parameters selected by the SPLS-DA model were correlation, second moment and homogeneity, which were predominantly computed from the red and NIR bands. The 5×5 moving window was the most frequently selected window for detecting and mapping invasive alien wattle. Overall, this study confirms the ability of image texture combinations integrated with SPLS-DA to detect and map the spatial distribution of invasive alien wattle.

1. INTRODUCTION

Wattle is a leading invasive alien plant (IAP) species in South Africa, and its increasing spatial distribution has invaded more indigenous environments. It has spread globally through wind, water and animal dispersal (Gwate et al., 2016), where large quantities have been found in the KwaZulu-Natal (KZN) province of South Africa. Invasive alien wattle has high water consumption, which results in rapid growth and proliferation rates into grassland and arable land (de Neergaard et al., 2005). Wattle may be defined specifically based on the various plant species that fall under its genera, such as *Acacia mearnsii* (black wattle) and *Acacia dealbata* (silver wattle). Young tree and shrub-like wattle display similar characteristics in appearance and growth, making it difficult to distinguish one species from another at early growth stages (de Neergaard et al., 2005). Therefore, this study collectively investigates wattle species as a general alien invader in KZN, where *Acacia mearnsii* and *Acacia dealbata* are the predominant wattle species found in the area.

Conventional methods of minimising the impacts of IAPs include biological, chemical and mechanical control measures, which are well documented in South African literature. This is due to the high demand for locating invasive species during early growth stages (Huang and Asner, 2009). However, these methods are expensive, subjective and impractical over large spatial scales, because the full distribution extent is unknown. Thus, remote sensing assists in detecting and mapping IAPs, where information can be utilised in decision-making to manage invasive alien wattle through efficient eradication measures. Using remote sensing for detection and mapping offers objective, inexpensive and spatially explicit data of ground surface processes that are beneficial in vegetation mapping (Lottering et al., 2019). Remote sensing of invasive wattle is minute in South Africa, as detection of IAPs is generally broad and not specific to a particular alien invasive species (Bradley, 2014) or genus. Therefore, it is imperative to utilise accurate and timeous methods of detecting and mapping IAPs, as the detection and mapping allow the necessary control methods to be implemented (de Neergaard et al., 2005).

Image texture is an effective scale-dependent remote sensing technique, which examines the local variance of a variation of grey image tones and can define the spatial arrangements of objects in high spatial resolution imagery (Franklin et al., 2001). For example, Lottering et al. (2020) successfully detected and mapped invasive bugweed and surrounding commercial forest species using image texture derived from WorldView-2 imagery. However, Lottering et al. (2019), Hlatshwayo et al. (2019) and Nichol and Sarkar (2011) have shown the significance of image texture combinations in improving the detection and mapping of spatial phenomenon.

Image texture combinations improve detection through its ability to simplify the structure of the canopy and reduce image errors such as atmospheric effects, sun angle effects and sensor angle effects (Lottering et al., 2019, Myneni et al., 1995). The various texture parameters can enhance the structure of vegetation on the earth's surface through the use of ratios that are formed by combining these parameters (Lottering et al., 2019). Different vegetation encompasses different textures due to their structural makeup, therefore are discernable in remotely sensed textural data. For instance, Hlatshwayo et al (2019) successfully mapped forest above-ground biomass using texture combinations computed from SPOT-6 pan-sharpened imagery. However, image texture combinations may be considered highly data dimensional and redundant, therefore requiring effective methods for feature extraction.

Therefore, we proposed using the SPLS-DA algorithm as it uses a sparsity solution and simultaneously performs variable selection and dimensionality reduction (Chun and Keleş, 2010). SPLS-DA is a multivariate technique based on the partial least squares approach. Lottering et al (2020) successfully detected and mapped bugweed using image texture and the SPLS-DA algorithm. The SPLS-DA algorithm was able to select the best texture variables and reduce data dimensionality within the dataset. However, to the best of our knowledge, no study has tested the utility of SPLS-DA and image texture combinations in effectively detecting and mapping invasive alien wattle.

As a result, this study aimed to investigate the potential use of image texture combinations computed from a 6 m SPOT-6 image integrated with the SPLS-DA algorithm to identify and map alien invasive wattle. In addition, the image texture combination model was compared to the single image texture bands and vegetation indices in detecting invasive alien wattle.

2. MATERIALS AND METHODS

2.1 Study Area

The study was conducted in the low-lying Midlands area (29°16'43"S; 29°48'15"E) (Figure 1) of KwaZulu-Natal, which lies adjacent to Mooi River and Escourt and stretches to the western KwaZulu-Natal border. The study site covers an area of approximately 606 km^2 and experiences hot, humid summers that are characterised by heavy rainfall and mild, dry winters. The area receives an average annual rainfall of 975.44 mm, which generally occurs in summer and spring. This area is dominated by the grassland biome, where invasive wattle has been pivotal in altering grassland on-site and influence rangeland production (Gwate et al., 2016). The landscape elevation ranges from 1130 to 1410 m above sea level, with temperatures ranging from 9.2°C to 37.2°C.

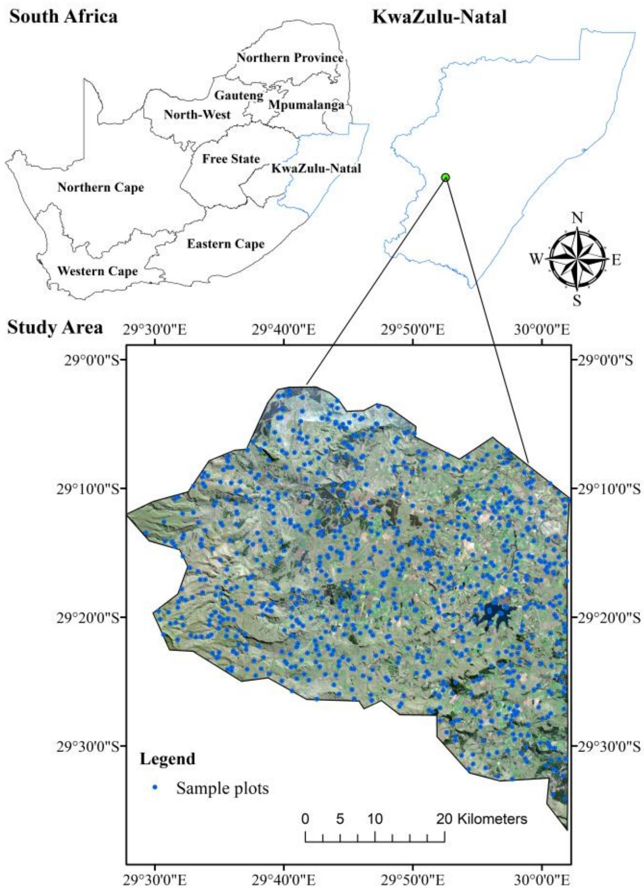

Figure 1: Location of the study area in KwaZulu-Natal, South Africa

2.2 Image Acquisition and Preprocessing

A SPOT-6 image was used to detect and map invasive alien wattle. This image has 5 spectral bands which image the earth at a 1.5 m spatial resolution for the panchromatic band, and 6 m spatial resolution of the multispectral bands. The image was freely available from the South African Space Agency (SANSA) on the 25th of May 2019, under cloudless conditions. The SPOT-6 image consisted of four bands ranging from the visible to near-infrared (NIR) region of the electromagnetic spectrum. These bands consist of the blue (0.455-0.525 µm), green (0.530 – 0.590 µm), red (0.625 – 0.695 µm) and near-infrared (0.760 – 0.890 µm). The image was ortho-rectified courtesy of SANSA and was radiometrically corrected by converting digital numbers to the top of atmosphere reflectance. The image was referenced using the Universal Transverse Mercator (UTM zone 36S) projection, which uses the WGS84 Geodetic system. ENVI 5.2 was used for preprocessing the SPOT-6 image.

2.3 Reference data

A field campaign was conducted on the 29th of May 2019, four days after the acquisition of the SPOT-6 image. A total of 150 random 5 x 5 m plots were generated by the Hawths tool in ArcMap 10.5 for each of the surrounding land cover classes namely: Built-up, Water, Grass, Agriculture and Bare soil. These plots were used to obtain image texture from the SPOT-6 image for each land cover class. The location of wattle was achieved using purposive random sampling. A total of one hundred and fifty 5 x 5 m plots containing wattle were then used to obtain image texture from the SPOT-6 image.

All sample plots were verified in field using a handheld TrimbleGeoHX6000 Global Positioning System (GPS) with sub-meter accuracy. Overall, a total of 900 sample plots were collected in field (Table 1). The mean texture values for each of the 900 sample plots were extracted from the SPOT-6 image using Zonal Statistics in ArcMap 10.5.

Table 1: Sample size of each class surveyed (n = 900)

Class	No. of Samples
Built-up	150
Water	150
Grass	150
Agriculture	150
Bare soil	150
Wattle	150

2.4 Image texture

Image texture is useful for detecting wattle and surrounding land cover classes, as these classes have distinct spatial structures, which can be discriminated using the texture of an image. This method is divided into the grey-level occurrence matrix (GLOM) and grey-level co-occurrence matrix (GLCM) (Lottering et al., 2019). GLOM does not account for the spatial relationships that exist between pixels and are computed based on the histogram of pixel intensity within a processing window (St-Louis et al., 2006). It consists of five filters to calculate texture, which includes; mean, variance, entropy, data range, and skewness. Conversely, a spatial dependent matrix of different tones of grey is used in GLCM to compute texture by calculating pairwise combinations of grey tones in a processing window (Haralick et al., 1973). It consists of 8 filters to calculate texture, namely; contrast, variance, dissimilarity, mean, homogeneity, correlation, entropy, and second moment. For a more detailed description of these texture parameters, please see Lottering and Mutanga (2012).

In this study, we only used GLCM combinations, as many studies have found that it was more superior than GLOM (Lottering and Mutanga, 2012; Hlatshwayo et al 2019). A co-occurrence shift of $x = 1$, $y = 1$ and $\theta = 45°$ was used to compute texture from the SPOT-6 image. These texture parameters were controlled using the 3x3, 5x5 and 7x7 moving windows. This resulted in a total of 96 texture parameters computed from the SPOT-6 image, which were subsequently combined to form texture combinations. Image texture was computed using ENVI 5.2 software.

2.5 Processing the SPOT-6 image

The SPOT-6 image was processed in three steps:

Step 1: Single image texture parameters computed from the SPOT-6 image were used to detect invasive alien wattle and surrounding land cover classes.

Step 2: All possible combinations of the eight image texture parameters of any two texture filters were used to detect invasive alien wattle and surrounding land cover classes. Each combination was exclusive to the spectral band and moving window size. Image texture combinations were derived using the following formula:

$$\frac{B1}{B2} \ldots (1)$$

Where B1and B2 are texture parameters

Step3: For comparison purposes, 15 vegetation indices computed from the SPOT-6 image were used to detect invasive wattle and surrounding land cover classes. These indices were generally dependent on the NIR and red band, as these regions are sensitive to vegetation (Barry et al., 2008).

2.6. Sparse partial least squares discrimination analysis (SPLS-DA)

SPLS-DA was used to determine the relationship between single image texture parameters or image texture combinations or vegetation indices with invasive alien wattle and surrounding land cover classes. This algorithm is multivariate and has adapted the partial least squares approach (Lê Cao et al., 2011), however, it differs by imposing sparsity to the solution. This eliminates insignificant variables by imposing an L_1 penalty, which assigns variables a score of zero. Also, SPLS-DA simultaneously performs variable selection and dimension reduction, which is important when dealing with high dimensional and redundant data such as image texture. This results in a few non-zero texture parameters that are then used to build latent components that show the most important discrimination among the land cover classes. The class association of each variable is subsequently coded using the reference cell coding. This assumes that the response matrix (Y) is one of the ($G + 1$) classes that is denoted 0, 1…G, where 0 is the control group. Then, the response matrix (Y) that is recorded is defined as n x (G + 1) matrix with the following elements:

$$y^{*}_{i,(g+1)} = I(y_i = g) \quad (1)$$

Where $i = 1, \ldots, n$ and $g = 0, 1, \ldots, G$, and where $I(A)$ are indicator functions of an event A.

A classifier is fitted, once the latent components are established (Chung and Keles 2010). Selecting a classifier from many classification methods is the final step required by the SPLS-DA algorithm, which is due to the sample size (n) usually being greater than the number of components (K). Therefore, for this purpose, linear classifiers are commonly used (Chung and Keles 2010). The SPLS-DA algorithm was run using the "splsda" function (Chun and Keleş 2010) in R statistical package version 3.1.3 (R Development Core Team 2015).

2.7. Model Optimisation

Using the ten-fold cross-validation method, the number of components were selected for successfully running the SPLS-DA model. This was achieved by systematically adding components to the SPLS-DA model, then calculating the error. The approach was repeated on the training dataset until a point was reached where additional components did not improve the model. Furthermore, the SPLS-DA model requires two parameters to be optimized, namely; 'eta' and 'k'. The former parameter represents the sparsity threshold that ranges from 0 to 1, while the latter parameter represents the number of hidden components. The latent components subsequently retain the most significant texture parameters for classification and a zero probability is obtained by insignificant texture parameters. After the SPLS-DA model is optimised using the training dataset it is then used to classify the test dataset.

2.8. Accuracy Assessment

The dataset (n = 900) was split into 30% test and 70% training. Using a confusion matrix, the classification results for the SPLS-DA model were calculated based on the test dataset. This process was run at 100 iterations, which accounted for variations in classification accuracies due to different test and training datasets (Fassnacht et al., 2014). The error matrix is built of the user and producer accuracies, where the user accuracy (UA) determines whether the class on the map is also present on the ground. In contrast, the producer accuracy (PA) shows the probability of a ground-class being correctly classified on the map during classification (Comber, 2013). The overall accuracy (OA) is expressed as a percentage, where it informs the degree of accuracy of the various samples and whether they were correctly mapped. Subsequently, the statistical test of the kappa coefficient can then be determined to evaluate how well the classification performed.

3. RESULTS

3.1. Optimising the SPLS-DA model

A tenfold cross-validation method was used to determine the components that produced the lowest error rate, which was based on the training (n = 630) dataset. The results show that the 7th (eta = 0.4; k = 7), 7th (eta = 0.3; k = 5) and 9th (eta = 0.2; k = 2) components had the lowest error rate for the image texture combination, single image texture and vegetation indices, respectively.

3.2. Classification using the SPLS-DA model

Table 2 provides evidence of the SPOT-6 image being successfully classified using the SPLS-DA model to detect invasive alien wattle and surrounding land cover classes using image texture combinations, single image texture and vegetation indices. The texture combinations proved superior over the single texture and vegetation indices, with an overall accuracy of 74% and a kappa statistic of 70.

Table 2: Accuracy assessment for the classification using image texture combinations, single image texture and vegetation indices computed from the SPOT-6 image

SPLS-DA Model	Class Name	UA (%)	PA (%)	OA (%)	Kappa Statistic
Texture Combinations	Built-up	71	72	74	70
	Water	74	75		
	Grass	76	79		
	Agriculture	73	70		
	Bare Soil	80	77		
	Wattle	69	67		
Single texture	Built-up	68	70	68	65
	Water	62	68		
	Grass	70	69		
	Agriculture	69	71		
	Bare Soil	73	70		
	Wattle	62	59		
Vegetation Indices	Built-up	63	66	62	59
	Water	58	55		
	Grass	64	60		
	Agriculture	66	68		
	Bare Soil	65	69		
	Wattle	55	58		

Furthermore, the change in overall classification accuracy produced by the SPLS-DA image texture combination, single image texture and vegetation indices models when running each model at 100 iterations for dividing the training and test datasets. The mean overall classification accuracy was 72% with a standard deviation of 2.15%, a mean overall classification accuracy of 65% with a standard deviation of 2.27% and a mean overall classification accuracy of 60% with a standard deviation of 3.04% for the SPLS-DA image texture combination, single image texture and vegetation indices models, respectively.

3.3. Frequency of significant variables simultaneously selected by the SPLS-DA model

The SPLS-DA image texture combination model yielded the highest overall classification accuracy and simultaneously selected a total of 35 significant variables. Figure 2 a. shows that correlation, second moment and homogeneity were the most frequent texture filters used to develop texture combinations and Figure 2 b. shows that these texture combinations were generally computed from the NIR and red bands of the SPOT-6 image. Thus, containing the majority of the invasive alien wattle and surrounding land cover class information. In addition, Figure 2 c. shows that the 5 × 5 moving window dominated the development of the SPLS-DA model.

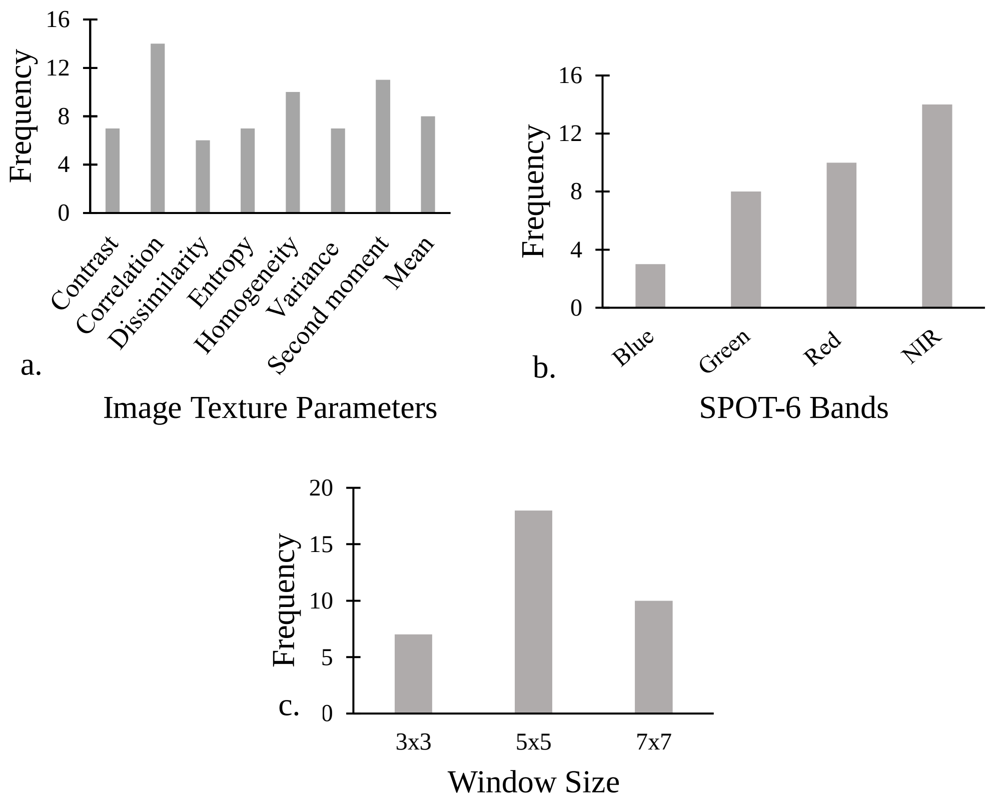

Figure 2: Frequency of selected a. Image texture parameters, b. SPOT-6 bands and c. Window size using the SPLS-DA algorithm

3.4. Mapping the spatial distribution of invasive alien wattle using SPLS-DA

A predictive map displaying the distribution of invasive alien wattle was subsequently developed, using the image texture combination model, as it yielded the highest overall accuracy. Since invasive wattle was the main focus of the study, we only displayed wattle distribution in the predictive map. This map was developed using the R statistical package version 3.1.3 (R Development Core Team 2015). Figure 3 represents the spatial distribution of invasive alien wattle over the study area.

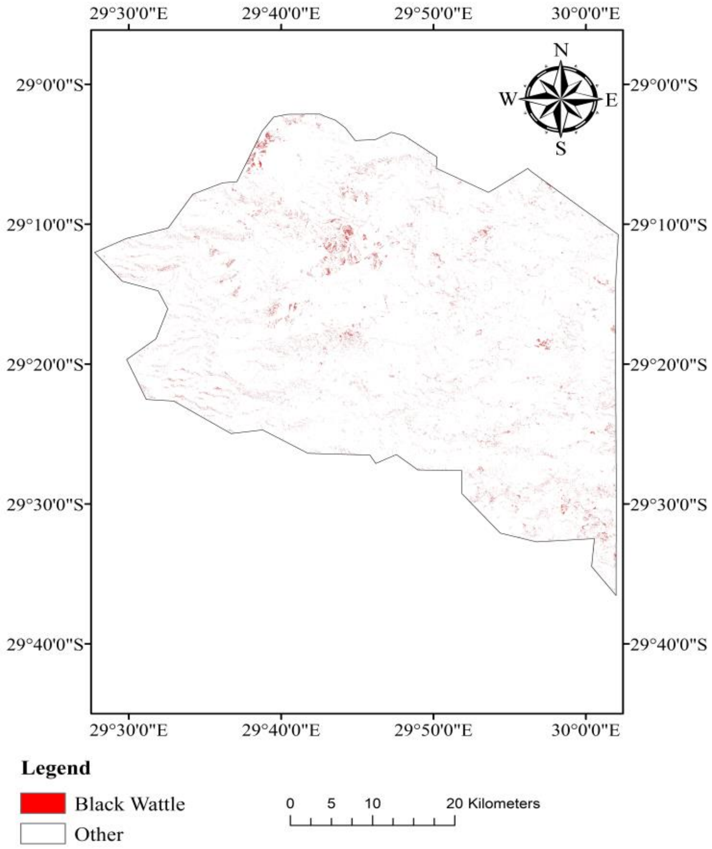

Figure 3: Spatial distribution of wattle in the low-lying Midlands area of KwaZulu-Natal

4. DISCUSSION

In this study, we investigated the ability of image texture combinations to detect invasive alien wattle and surrounding land cover classes. The results showed that the SPLS-DA model integrated with image texture combinations (OA = 74%; kappa statistic = 70) outperformed both SPLS-DA models integrated with single image texture bands (OA = 68%; kappa statistic = 65) and vegetation indices (OA = 62%; kappa statistic = 59). This could be due to two factors; firstly, image texture simplifies the structure of the invasive wattle and surrounding landcover classes and secondly, image texture band combinations may reduce background, sun angle and sensor angle effects (Nichol and Sarker, 2010), which may have improved the classification.

The SPLS-DA model integrated with image texture combinations generally selected ratios that were made up of correlation, second moment and homogeneity. According to Wood et al (2012), GLCM parameters such as correlation characterize horizontal vegetation structure. As a result, the horizontal growth of matured invasive wattle increased the frequency of correlation in the development of the texture combination model. In a separate study, Song et al (2015) found that homogeneity and second moment played a significant role in mapping forest cover change. The superior performance of these texture parameters was also identified in previous studies that examined vegetation within a remotely sensed scene, where these texture parameters contained most of the structural information (Hlatshwayo et al., 2019 and Lottering et al., 2019). Additionally, Zakeri et al. (2017) found that the addition of image texture improved land cover classification using polarimetric synthetic aperture radar imagery.

Image texture combinations were typically derived from the red and NIR bands of the SPOT-6 image.

These bands contain structurally relevant information, therefore played a significant role in detecting and mapping the spatial structure of invasive wattle and surrounding land cover classes. Equally, Lottering et al. (2019) found that image texture combinations derived from the NIR and red bands proved useful for detecting and mapping vegetation defoliation. In addition, the SPLS-DA model also predominantly selected the 5x5 moving window to detect and map invasive alien wattle. Small moving windows, such as 3×3, tend to exaggerate the differences within a particular window, which increases the noise content in the texture image (Chen et al., 2004). Larger moving windows, such as the 7×7, use more processing time and may result in eroding class boundaries (Jobanputra and Clausi, 2006).

The predictive map shows a relatively consistent distribution of wattle over the entire study area; however, wattle was prominent in small pockets in the northern border region and the central region. The northern area is characterised by open and bare spaces, which has resulted in dispersed wattle seeds invading these areas and proliferating. Furthermore, the dense presence of wattle in the central pocket is found adjacent and within a forested area. Lottering and Mutanga (2012) stated that IAPs occurs along forest margins such as access routes, which create pathways that allow for further invasion and spreading of IAPs into the forest regions. Additionally, alien invasive wattle was detected along riparian zones within the study area, more specifically in adjacent areas to the dam found in the study region. Poona (2008) and Witt (2005) stated that wattle has the characteristic of growing close to water sources due to its high water intake.

5. CONCLUSION

This study aimed to investigate the potential use of image texture combinations to effectively detect and map invasive alien wattle. The following conclusions were drawn:

- The image texture combination model was more effective in detecting alien invasive wattle and surrounding land cover classes, yielding the highest overall accuracy when compared to the single image texture model and vegetation indices.
- The distribution of invasive alien wattle over the low-lying Midlands study area was successfully mapped using the SPLS-DA model of image texture combinations, where alien invasive wattle occurred consistently over the entire study area.

Overall, this study was the first to use image texture combinations to detect and map invasive alien wattle. The results obtained are valuable in understanding the spatial distribution of alien invasive wattle in KZN, which may assist in effective resource management and eradication programmes.

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