Assessing the synergistic potential of Sentinel-2 spectral reflectance bands and derived vegetation indices for detecting and mapping invasive alien plant species

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Abstract

Grassland biomes are valuable socio-economic and ecological resources. However, the invasion of grasslands by alien plant species has emerged as one of the biggest threats to their sustainability, management and conservation. Timely, cost-effective and accurate determination of invasive alien plant spatial distribution is paramount for mitigating the adverse effects of alien plants on natural grasslands. Whereas literature on use of optical bands for invasive alien plants detection and mapping is abound, there is paucity in literature on the integration of Vegetation Indices (VIs) and optical reflectance bands in invasive species mapping. Specifically, there is need to test the efficacy of improved and freely available sensors like Sentinel-2 in understanding landscape invasion. Hence, this study sought to assess the efficacy of Sentinel-2's optical bands and VIs for improving the mapping of American Bramble (Rubus cuneifolius) within a grassland biome. Variable Importance in the Projection (VIP) was used to identify the most influential reflectance bands and VIs, which were then fused at a feature level to determine Bramble spatial distribution. To determine the optimal season for Bramble mapping, seasonal classification accuracies were executed in Support Vector Machine (SVM) learning algorithm and accuracies for Spring, Summer, Autumn and Winter seasons compared. Results show that although the highest overall accuracy was achieved using only optical bands, fused imagery increased overall classification accuracies during spring and autumn i.e. 70% to 73% and 63% to 65%, respectively. However, the fused imagery failed to improve on the benchmark of optical imagery during summer and winter. Findings from this study underline the efficacy of complementing VIs and optical bands in determining the distribution of invasive species within grasslands at specific seasons. Furthermore, this study advocates for the adoption and fusion of freely available new generation satellite imagery such as Sentinel-2 as a cost effective option in landscape mapping.

Keywords: *Invasive alien plant, Grassland biome, Sentinel-2, Vegetation Indices, Spectral reflectance, Support Vector Machine (SVM).*

1. Introduction

Invasive alien plant species are regarded as the second most severe threat to global biodiversity after anthropogenic habitat destruction (Driver *et al*., 2012). Globally, invasive species are known to adversely affect the natural environmental, in turn affecting socio-economic systems (Richardson and van Wilgen, 2004; Davies and Johnson, 2011). In South Africa, Nel et al. (2005) notes that approximately 10 million hectares of land has been invaded by alien invasive plants, while Carbutt and Martindale (2014) note that infestations by invasive species have led to irreversible transformation of between 60-80% of the country’s natural grassland. Specifically, the American Bramble has adverse impacts on natural grazing lands, along roadsides and in riparian zones (Shezi and Poona, 2010). Generally, Bramble is known to adversely affect nutrient cycling, increase soil erosion, reduce animal carrying capacity, hinder natural plant succession, reduce quality and quantity of water production and promote changes in fire patterns and behaviour. Furthermore, the establishment of Bramble patches is known to have negative effects on specialist grassland species. The species is believed to be one of the most devastating invasive plant in the cool and moist KwaZulu-Natal mist-belt region and has significantly compromised ecological sustainability and socio-economic well-being (Erasmus, 1984).

The adoption of passive remote sensing imagery for mapping invasive species is increasingly becoming popular (Gil *et al*., 2013). Whereas the currently used imagery are known to generate reliable spatial distribution outputs (Walsh, 2018), their high cost per unit area is commonly a major concern, particularly for mapping large spatial extents. Additionally, their small swath, cloud cover and limited spatial resolution remain an impediment in invasive species mapping. Hence, recent developments in freely available sensors with larger swath as well as improved spatial, temporal and spectral resolutions (e.g. Landsat 8 and Sentinel-2) offer unprecedented prospects for large scale cost-effective invasive species mapping.

In addition to the above, recent studies have focused on exploiting inherent species characteristics such as reflectance variability arising from phenological evolution. The seasonal phenological characteristics may include differences in biophysical and biochemical properties from indigenous species, as well as spatial extents and patterns of dispersal (Dorigo *et al*., 2012). Invasive species are commonly typified by unique phenological characteristics that facilitates superior exploitation of ecological niches in their invasive range. McNairn *et al* (2009) notes that seasonal variability in leaf pigmentation as well as water content and structure significantly influence leaf reflectance, useful for invasive species mapping (Bradley, 2014).

There has been an increased use of satellite derived vegetation indices for increased accuracy in mapping invaded environments (Levin *et al*., 2007). According to Basso *et al* (2004), vegetation indices are more sensitive to vegetation parameters, compared to individual spectral bands, hence more useful when used as surrogates for vegetation and non-vegetation cover. Spectrally derived vegetation indices are particularly valuable as they significantly reduce the effects of soil, topography and satellite view angle (Hunt *et al*., 2013). Hence, indices have demonstrated ability to accurately quantify vegetation related spatial heterogeneity in complex landscapes (Benayas and Scheiner, 2002). Additionally, indices have been shown to vary across seasons and space, making them useful for detection within-field and intra and inter annual variability (Gobron *et al*., 2000).

The recent launch of the European Space Agency (ESA) Sentinel-2 (S2) multispectral satellite has availed new opportunities in remote sensing applications. Sentinel-2 is characterized by 13 bands spanning the visible/near-infrared, and short wave infrared spectral range and captures images at 60m, 20m and 10m spatial resolutions (Immitzer *et al*., 2016). Coupled with a 290km wide swath width and a five day temporal resolution, Sentinel-2 offer new opportunities for both local and regional scale vegetation mapping. The sensor's unique spectral resolution allows for the derivation of numerous vegetation indices that cannot be derived from other freely available multispectral satellites such as Landsat 8 and Moderate Resolution Imaging Spectroradiometer (MODIS). Sentinel-2 also has three vegetation red-edge spectral bands, currently not available in the freely available multispectral sensors (Cho *et al*., 2012). These unique and progressive features, coupled with the sensor's economic viability offer unprecedented opportunities in the discrimination and mapping of invasive alien plant species.

Analysis based on phenological variability is imperative in optimal detection and mapping of vegetation species. According to Verbesselt *et al* (2009), seasonal changes influence plant phenology and foliar chemistry; characteristics that can be exploited to determine optimal mapping seasons. According to McNairn *et al* (2009), invaders often exploit empty niches within a landscape and have distinct seasonal phenological characteristics from the surrounding native species, characteristics useful for increased seasonal discrimination. Sentinel-2's high temporal resolution (5 days), and consequently high data volume is a valuable asset that could be used to exploit these seasonal phenological variabilities. Hence, this study sought to determine the *efficacy* of fusing the most influential Sentinel-2 spectral reflectance bands and vegetation indices in mapping the American Bramble within a grassland biome at different seasons.

2. Methodology

2.1. Study area

The Ukhahlamba Drakensberg Park (UDP) (-29.380018°S; 29.539746°E) borders the eastern escarpment of Lesotho and stretches along the western border of the KwaZulu-Natal Province (Figure 1). The crescent shape of the UDP has an approximate length of 158km and a width of 28km at its widest point. The mountainous terrain of the UDP ranges in altitude from 1200m to 3408m above sea level, with mean annual temperatures approximately 16° Celsius. Mean annual precipitation varies from the foothills of the mountain (1000m) to the escarpment (1800m) (Kruger *et al*., 2011).

2.1.1. Target species

The American Bramble (*Rubus cuneifolius*) has been identified as a major threat to native flora and fauna within the South African grassland biome. A sprawling shrub species belonging to the

Rosaceae family, Bramble is known to thrive in a diverse range of habitats (Bromilow, 2010). Originally from North America, Bramble is believed to be one of the most harmful invasive alien plants in South Africa, specifically across the KwaZulu-Natal Province, where the cool and moist climatic conditions favour its growth. Its growth in bush clumps is directly responsible for its adverse effects on biodiversity. According to Henderson *et al* (2001), the impacts of Bramble infestation include a reduction in rangeland carrying capacity, alterations in nutrient cycling, increased soil erosion, changes in fire regimes and behavior and the disruption of hydrological process. Generally, Bramble is considered a severe threat to natural resources and sustainability and its effective management or eradication is of paramount importance.

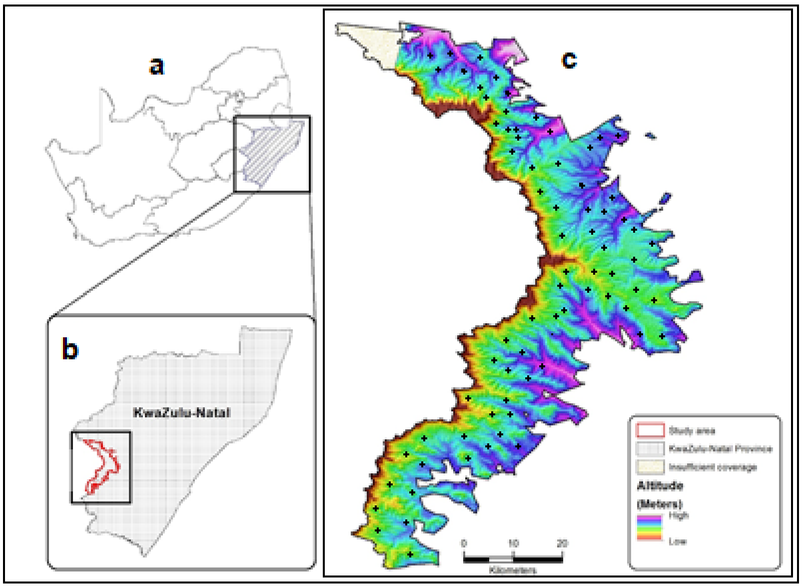

Figure 1: The uKhahlamba Drakensberg Park (UDP) (c), located within the KwaZulu-Natal Province (b) of South Africa (a). (The black dots are field point collected for training and validation).

2.1.2. Field data collection

Four major land cover classes (Bare rock, Bramble, Forest and Grassland) were considered for this study. Ground validation GPS points of the four land cover classes were collected using the purposive sampling technique. Ground validation points were collected during spring and summer of 2016, as these seasons coincide with Bramble flowering (ATLAS, 2014). Hence, data collection during these seasons was preferred as Bramble patches were easily discernable while in field. A GeoXT Trimble GPS was used to record ground validation data. Bramble ground validation points were recorded as close to the centroid of the respective Bramble patch as possible. In order to compensate for sensor spatial resolution, and to ensure collected Bramble ground validation points fell within the sensor pixels and are associated with the unique spectral reflectance, all recorded Bramble patches were spatially independent and ranged from 15m x 15m to 50m x 50m in size. Owing to the steep and mountainous terrain of the UDP, which restricted access, Bramble patches accessible by foot were considered for training and validation data. Additionally, aerial photographs at a 0.5m spatial resolution captured in 2016 were used to supplement and verify selected land cover ground truth points.

2.2. Image acquisition

2.2.1. Optical imagery

Four seasons (spring, summer, autumn and winter) Sentinel-2 imagery were acquired from the Copernicus open access hub (https://scihub.copernicus.eu/). The Sentinel-2 level 1-C raw products (radiance) were converted to level 2-A Sentinel-2 products (surface reflectance) using the default parameters of Sen2Cor plugin within the ESA SNAP toolbox 3.0. All Sentinel-2 level 2-A products were corrected for topographic effects of shadow commonly associated with mountainous regions such as the UDP. Topographic correction based on a local Digital Elevation Model (DEM) was conducted using the System for Automated Geoscientific Analyses SAGA (2.1.2) plugin within a Quantum GIS environment (QGIS), using the SAGA terrain analysis lighting tool on a band by band basis.

2.2.2. Vegetation indices

Sixty-five vegetation indices selected from the online Index DataBase (IDB) (www.indexdatabase.de) were calculated from level 2A Sentinel-2 multi season optical imagery. Indices were selected on the basis of being specific to Sentinel-2 and recognition by the IDB as effective and accurate measures of various vegetation parameters such as vigor, greenness and seasonal influences. The IDB is a tool developed to provide a simple overview of satellite specific vegetation indices that are useable from a specific sensor for a specific application (Henrich *et al*., 2012). All indices were calculated within a Python 2.7.13 environment using listed formulas from the IDB and spectral reflectance Sentinel-2 bands.

2.3. Variable selection

The Variable Importance in the Projection (VIP) method was implemented within a Python 2.7.13 environment. The VIP is a commonly used filter method first proposed in 1993 by Wold et al. (1993). The VIP is determined using projection information from **X** and **y** as:

$$VIP_j = \sqrt{d \sum_{k=1}^{h} v_k \left(w_{kj}\right)^2 / \sum_{k=1}^{h} v_k} \quad (1)$$

Where d is the number of variable and h the number of latent variables in the PLS model. VIP is the proportion of the fraction of the explained variance of X expressed by $v_k = c_k^2 t_k{}' t_k$ weighted by covariance between X and y, represented by w_{kj}, for each variable j over latent variables. The term c_k is obtained for each colum of the PS score T for the predicted response y (k) in equation (2)

$$x = \frac{t_{y}{}'\mathrm{y(k)}}{\mathrm{t}_k{}' t_k} \quad (2)$$

As the average of sums of squares of the VIP is equal to 1, the VIP scores >1 rule is typically adopted as a threshold (Wold et al. 1993).

The VIP method selected the 15 most influential bands across Sentinel-2 optical bands and derived Sentinel-2 vegetation indices. Selected VIP bands were used for data fusion and consequently formed the fused images used for image classification. Variable Importance in the Projection can serve to improve classification accuracy by efficiently identifying a subset of all initial variables that if combined, could enhance classification accuracies with parsimonious representation (Farrés *et al*., 2015). VIP measures the importance of each variable (Sentinel-2 optical bands and vegetation indices) with regard to the influence it would have on increasing the classification accuracy. For example, a variable that scores closer to or greater than 1 was considered to be important, hence included in the image classification process, whereas a variable scoring significantly less than 1 was considered less important, hence excluded from the classification process.

2.4. Image fusion: Optical bands and Vegetation Indices

Feature level image fusion was adopted to merge the 15 most influential VIP bands. As vegetation indices were calculated from optical bands, selected VIP optical bands and vegetation indices were all calculated at a spatial resolution of 20m. VIP bands were fused using the composite bands tool within an ArcMap 10.4 environment, resulting in four fused images, each representing a single season. The extraction of ground truth points was conducted on an individual basis for VIP optical bands and vegetation indices. The feature level fusion of VIP optical bands and vegetation indices ensured that the corresponding optical spectral reflectance was used for the vegetation index value. Fused optical bands and vegetation indices were then used for image classification.

2.5. Image classification

Image classification was conducted using the Support Vector Machine (SVM) algorithm within a Python environment. The SVM is a supervised statistical learning technique that was developed to deal with binary classifications (Vapnik, 1979). SVM seeks to identify a hyper-plane that can clearly distinguish input dataset into a predefined discrete number of classes that are consistent with training data (Mountrakis *et al*., 2010). Several evaluations of SVM have shown that the algorithm is capable of classifying/separating several classes with limited support vectors as training data, without ultimately compromising classification accuracies (Foody and Mathur, 2004). Ground truth points were used to extract spectra for the four major land cover classes (Bare rock, Bramble, Forest and Grassland) in the study area. Extracted fused VIP spectral reflectance with vegetation indices measurements were used in the SVM classification process.

2.6. Spatial distribution map and accuracy assessment

Support Vector Machine classification maps were generated for each seasonal image within a Python environment. Fused (VIP optical and vegetation indices) training data (70%) of all four considered land cover classes were used as the input for the multi-season Bramble spatial distribution maps. The respective test data set (30%) was then used to assess classification accuracies for each season. A confusion matrix was generated from the SVM process and user and producer accuracies used to quantify the reliability of resultant Bramble spatial distribution maps. Producer's accuracy means that for each class, the probability that a randomly chosen point in the field has the same class value on the map while User's accuracy means that for each class, the probability that a randomly chosen point on the map has the same class value in the field (Sammut and Webb, 2017).

3. Results

3.1. Optical and Vegetation Indices VIP band selection

A total of 15 most influential optical bands and vegetation indices were selected per season and considered for further analysis. The Sentinel-2 SWIR1 (11) and SWIR2 (12) bands were the most influential optical bands as they were selected for spring, summer and winter imagery. The narrow infrared optical band (8a) was only selected for spring and summer imagery. From all analyzed vegetation indices, the TM5/TM7, Simple Ratio 520/670 (SR520/670), Simple Ratio 800/550 (SR800/550) and Simple Ratio MIR/Red Eisenhydroxid-Index (SRMIR/Red) were the only indices selected across all seasonal imagery. The Simple Ratio 860/550 (SR860/550) and Renormalized Difference Vegetation Index (RDVI) vegetation indices featured across both spring and summer, while the Datt2 index featured across both autumn and winter. Other vegetation indices that featured in multiple seasons include Simple Ratio NIR/MIR (SRNIR/MIR) (spring and autumn), Simple Ratio672/550 (SR672/550) (summer and winter), Simple Ratio 800/470, Pigment specific simple ratio C2 (PSSRc2) (summer, autumn and winter), Simple Ratio Red/Green Red-Green Ratio (RGR) (spring and winter), SIPI3 (Structure Intensive Pigment Index 3) (spring and winter) and Chlorophyll IndexRedEdge (CIrededge) (summer and autumn).

3.2. Multi-seasonal reflectance bands and fused data classification accuracies

3.2.1. S2 reflectance bands

Seasonal classification using only Sentinel-2 reflectance bands resulted in overall accuracies ranging from 61-77% (Table 1). Summer exhibited the highest overall accuracy while winter produced the lowest. Stand-alone Sentinel-2 reflectance band results were used as a benchmark to investigate the potential synergistic properties of Sentinel-2 optical bands fused with vegetation indices to increase the accuracy of detection and mapping of Bramble.

Table 1: S2 reflectance band Support Vector Machine (SVM) seasonal confusion matrices. Where BR = Bare rock; BBL = Bramble; FR = Forest; GR = grassland; PA= Producers accuracy; OA= Overall accuracy and UA = Users accuracy.

	BR	BBL	FR	GR	UA (%)	BR	BBL	FR	GR	UA (%)
	(a) Spring					(b) Summer				
BR	31	0	0	15	67	32	2	0	12	69
BBL	0	28	0	44	39	0	24	0	29	45
FR	0	0	56	3	94	1	1	54	3	91
GR	1	13	3	70	80	2	3	7	94	88
PA (%)	96	68	94	53		91	80	88	68	
OA (%)	**70**					77				
	(c) Autumn					(d) Winter				
BR	30	0	0	16	65	34	0	0	12	73
BBL	0	20	1	47	30	0	22	1	69	24
FR	1	0	55	3	93	1	0	53	5	89
GR	1	30	0	60	66	0	15	1	51	76
PA (%)	93	39	98	48		97	59	96	37	
OA (%)	**63**					61				

3.2.2. *Fused VIP S2 reflectance bands and Vegetation Indices*

Seasonal classification accuracies ranged from 61% to 73% (Table 2), with spring imagery producing the highest overall accuracy and winter imagery producing the lowest overall accuracy.

Table 2: Fused VIP S2 optical bands and Vegetation Indices Support Vector Machine (SVM) seasonal confusion matrices. Where BR = Bare rock; BBL = Bramble; FR = Forest; GR = grassland; PA= Producers accuracy; OA= Overall accuracy and UA = Users accuracy.

	BR	BBL	FR	GR	UA (%)	BR	BBL	FR	GR	UA (%)
	(a) Spring					(b) Summer				
BR	31	0	16	0	65	31	2	5	3	67
BBL	0	42	0	14	75	0	34	1	28	54
FR	17	0	35	0	63	10	0	44	0	79
GR	0	15	0	56	78	0	14	0	44	75
PA (%)	64	73	69	80		75	68	78	59	
OA (%)	**73**					70				
Autumn	(c) Autumn					(d) Winter				
BR	32	0	4	2	72	30	0	1	5	80
BBL	1	27	5	25	43	3	30	1	19	56
FR	11	0	39	0	75	17	3	29	0	49
GR	0	31	0	48	58	0	16	15	45	56
PA (%)	73	47	69	57		50	61	52	65	
OA (%)	**65**					61				

Spring results showed high producers and users accuracies for Bramble (73% and 75%) and grassland (78% and 80%) land cover classes. The classification map resulting from spring imagery showed a significant overestimation of the grassland land cover class and an underestimation in the bare rock and forest classes (Figure 2a). Although Bramble users and producers accuracies were high, a slight overestimation with regard to classification of Bramble patches was evident. Summer results produced the second highest overall classification accuracy (68%) across all seasonal imagery.

Summer Bramble users (54%) and producers (68%) accuracies decreased as compared to spring results. An underestimation in the bare rock and forest land cover classes was observed, while an overestimation in the Bramble and grassland classes were observed when summer classification results were mapped (Figure 2b).

Autumn imagery produced an intermediate classifcation accuracy (60%) across all seasonal imagery. Bramble users (43%) and producers (47%) accuracies resulting from autumn imagery were the lowest across all seaons. The resulting autumn classificaton map overestimated Bramble and grassland landcover spatial extent (Figure 2c), while underestimating the spatial extent of the bare rock and forest landcover classes (Figure 2c). Winter imagery resulted in the lowest overall classification accuracy across all seasons (57%). An overestimation of the grassland and Bramble landcover class was observed in the resulting winter classification map, while an underestimation of the bare rock and forest landcover classess was observed (Figure 2d).

Generally, overall classification accuracies decreased with seasonal chronological order, starting with Spring, resulting in varying users and producers accuracies across all seasonal imagery. In assessing the results obtained from fused imagery, although the highest overall accuracy was achieved using only optical bands, fused imagery increased overall classification accuracies during spring and autumn, while failing to improve on the benchmark of optical imagery during winter.

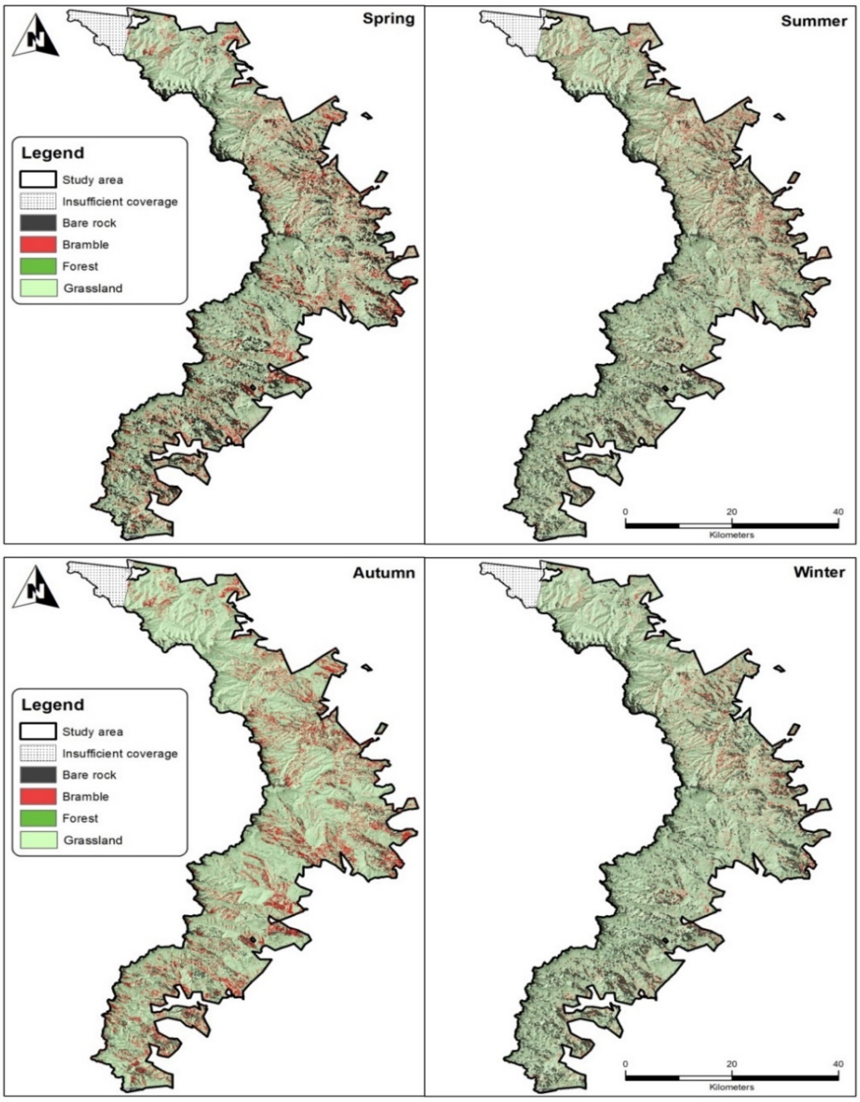

Figure 2: Multi-season classification maps produced using VIP selected optical bands and vegetation indices during Spring, Summer, Autumn and Winter.

4. Discussion

This study sought to determine if the synergistic properties of new generation optical imagery and derived vegetation indices have the potential to increase the discrimination and mapping of American Bramble (*Rubus cuneifolius*) from surrounding native vegetation. In addition, this study sought to determine the optimum season for the detection and mapping of Bramble. Generally, overall accuracies across the wet season (spring and summer) were greater, with spring achieving the highest accuracy (73%) across all seasons. Dry season (autumn and winter) detection and mapping of Bramble was poor, with winter resulting in the lowest classification accuracy (61%) across all seasons. Wet season overall accuracies suggest that the combination of new generation optical imagery bands and vegetation indices derived from these bands have sufficient potential for mapping and detecting Bramble. Sentinel-2 has three SWIR optical bands; two among the three were considered to be important variables (VIP) for spring, summer and winter seasonal imagery. Indices using the Shortwave Infrared (SWIR) optical band are known to be robust and provide an additional axis for potential vegetation discrimination (Kandwal *et al*., 2009). These unique characteristics of SWIR optical bands coupled with the increased Sentinel-2 spectral resolution within the SWIR region, known to be sensitive to foliar water content (Kim *et al*., 2012), could have contributed to the elevated accuracies seen for spring and summer seasonal imagery.

Simple ratio vegetation indices were repeatedly selected as a result of the VIP process and subsequently utilized in multi-season classification. According to Xue and Su (2017), the simple ratio combination of visible and Near Infrared (NIR) bands significantly improves the ability to distinguish between varying vegetation phenological parameters. This could explain the increased overall classification accuracies experienced during spring and summer as opposed to autumn and winter. Bramble is known to start flowering from early to mid-spring, resulting in white inflorescence (Denny, 1990), an important phenological feature that could have been responsible for the superior performance of vegetation indices during spring. This finding is in agreement with Evangelista *et al* (2009) who similarly compared time series imagery and derivative spectral analyses to map invasive alien species, where similar seasonal classification trends were observed in the respective case studies.

Gilmore *et al* (2008) notes that vegetation spectral properties and consequently species separability is dependent on several variables that include leaf pigmentation, leaf water content and leaf structure and size. The red-edge region of the electromagnetic spectrum is known to accurately detect subtle differences between the above-mentioned variables (Cho *et al*., 2012). Although Sentinel-2 possesses an unprecedented three red-edge bands, none of them were deemed to have a substantial effect as a stand-alone variable on overall classification accuracy. In this instance, the red-edge 1 band was selected as a standalone variable for autumn imagery, which produced the second lowest (65%) overall classification accuracy. However, numerous vegetation indices that incorporated red-edge bands were commonly selected as VIP bands across all seasons. This finding is in agreement with Delegido *et al* (2013), who developed a unique red-edge normalized vegetation index and successfully validated it against field data, noting it as an integral variable in determining vegetation physiological parameters.

The reduced classification accuracies in the autumn and winter imagery could be closely linked to similarities between the phenological life cycle of Bramble and surrounding native grass and shrub species. Bramble is known to flower during spring and senesce just before autumn and winter (Denny, 1990), thus in syncrony with the inter-annual growth patterns of dominant native grass and shrub species found within the UDP. Successful detection based on phenological characteristics depends on seasonal variability or inter seasonal growth pattern of the target species from surrounding native vegetation (Bradley, 2014). Hence, as Bramble follows the same inter-seasonal growth pattern of surrounding native vegetation, there is an increased probability of misclassification between the target species and surrounding native vegetation (Evangelista *et al*., 2009). This became evident when attempting to detect and map Bramble using autumn and winter Sentinel-2 imagery.

In comparison to benchmark results achieved by Rajah *et al* (2018), who solely utilized Sentinel-2 spectral reflectance bands to detect and map Bramble, the synergistic nature of spectral reflectance bands and vegetation indices only increased overall classification accuracies during specific seasons (spring and autumn). Using fused S2 optical imagery and vegetation indices, the optimum season for the detection and mapping of Bramble was determined to be spring. Even though results from this study differ from those of the benchmark, the synergistic nature of fused imagery has reasonable potential to advocate further research within the field of data fusion for invasive alien plant detection and mapping.

5. Conclusion

The primary aim of this study was to determine the potential of combined Sentinel-2 spectral bands and vegetation indices in increasing the discrimination and mapping accuracy of American Bramble (*Rubus cuneifolius*). An additional aim was to determine the optimal season for the most effective and accurate Bramble detection and mapping. Results obtained from this study allude to the practical and operational potential within the synergistic properties of combining Sentinel-2 spectral bands and vegetation indices. Furthermore, the optimum season for Bramble detection and mapping was spring, with the highest overall accuracy (73%) across all seasons. In addition to these practical advantages, free availability, wide swath width and short re-visit time of Sentinel-2 are particularly attractive traits that offer unprecedented opportunity for invasive alien mapping at a regional scale.

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