Assessing the potential of remote sensing to discriminate invasive Asparagus laricinus from adjacent land cover types

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Abstract: The utility of remote sensing technique to discriminate Asparagus laricinus from adjacent land cover types using a field spectrometer data was explored in this study. Analysis made use of original spectra and spectra simulated based on Landsat and SPOT 5 bands. Comparisons were made at individual and plot levels using original spectra, and individual and group level using simulated spectra. The near-infrared region showed consistent significant differences between A. laricinus and adjacent land cover types at the individual level analysis. In particular, Landsat- and SPOT 5-simulated spectra showed significant differences in only the NIR band. The findings suggest the potential of upscaling field-based data into airborne or spaceborne remote sensing techniques with more emphasis on the NIR band. However, more studies need to be undertaken that will make up for the shortcomings encountered in this study. In this regard, improvements can be made using large number of samples, stratifying target plants according to phenologies, and taking spectral measurements at ideal times as much as possible. Furthermore, laboratory measurements would help in drawing up conclusive statements on the discriminability of the species.

Subjects: Biodiversity; Botany; Earth Sciences

Keywords: Asparagus laricinus; remote sensing; spectral reflectance; spectral bands; field spectrometer

1. Introduction
Invasive alien plants are a growing global concern (Richardson & Van Wilgen, 2004; Rouget, Hui, Renteria, Richardson, & Wilson, 2015; Schor, Farwig, & Berens, 2015; Vicente et al., 2013). These
plants hold special characters that make them outcompete and replace indigenous vegetation, and have the potential of spreading to other areas (Bradley & Marvin, 2011; Mgidi et al., 2007; Van Wilgen, 2006). As a result, they compromise ecosystem stability, delivery of ecosystem goods and services, and threaten biodiversity and economic productivity (van Wilgen, Reyers, Le Maitre, Richardson, & Schonegevel, 2008; van Wilgen et al., 2012; Van Wilgen, 2006). Mitigating these effects is costly; South Africa, for example, spends considerable amounts of money in programs such as the Working for Water (WfW) which is mandated to control invasive alien plants.

Most invasive plant control measures focus primarily on established invasions and less attention is given to new infestations (Mgidi et al., 2007). The success of this practice is unsatisfactory, since an effective management of invasive alien plants should depend on early detection and eradication (Mgidi et al., 2007). One method of achieving early detection of plant invasions is through the use of spatial and temporal maps that show the distribution of invasive plants (Dorigo, Lucieer, Podobnikar, & Čarni, 2012). Traditional methods can be used to provide spatial and temporal distribution of invasive plants, but the methods often rely on field inventories that are limited in spatial coverage, time-consuming, and relatively expensive (Dewey, Price, & Ramsey, 1991; Dorigo et al., 2012; Rodgers, Pernas, & Hill, 2014).

Remote sensing methods make up for most inefficiencies of the traditional mapping methods and are used to characterize the spatial and temporal distribution of plants (Alparone, Aiazzi, Baronti, & Andrea, 2015; Campbell & Wynne, 2011; Galvão, Epiphaniou, Breunig, & Formaggio, 2011; Jensen, 2014; Lillesand, Kiefer, & Chipman, 2015). Remote sensing is the science of deriving information from electromagnetic energy reflected from objects on the ground (Alparone et al., 2015; Campbell & Wynne, 2011; Jensen, 2014). The method differentiates earth features using varying sensitivity of ground objects to electromagnetic radiation often acquired within the visible, infrared, and microwave regions of the spectrum (Campbell & Wynne, 2011; Lillesand et al., 2015). Several studies have used a variety of remote sensing techniques to study invasive alien plants (e.g. Abdel-Rahman, Mutanga, Adam, & Ismail, 2014; Adam & Mutanga, 2009; Adelabu, Mutanga, Adam, & Sebego, 2014; Bentivegna et al., 2012; Berg, Kotze, & Beukes, 2013; Manevski, Manakos, Petropoulos, & Kalaitzidis, 2011; Martin, Barreto, & Fernández-Quintanilla, 2011; Mirik et al., 2014; Narumalani, Mishra, Wilson, Reece, & Kohler, 2009; Prasad & Gnanappazham, 2014).

Plants have been mapped using multispectral remote sensing techniques in a number of studies (e.g. Dronova, Gong, Wang, & Zhong, 2015; Johansen, Phinn, & Witte, 2010; Labo et al., 2008; Lemke, Hulme, Brown, & Tadesse, 2011; Vancutsem, Peckel, Evrard, Malaisse, & Defourny, 2009). This method is good particularly for large spatial area mapping purposes (Azong, Malahlela, & Ramoelo, 2015; Cuneo, Jacobson, & Leishman, 2009; Dronova et al., 2015; Vancutsem et al., 2009). In comparison, hyperspectral remote sensing offers better accuracy levels of vegetation characterization due to the high spectral resolution and continuous hyperspectral bands they possess (Alparone et al., 2015; Carroll, Glaser, Hunt, & Sappington, 2008; Gavier-pizarro, Kuemmerle, & Stewart, 2012; Huang & Asner, 2009; Jensen, 2014). For example, Bentivegna et al. (2012) detected invasive cutleaf teasel (Dipsacus laciniatus L.) in Missouri, USA using high spatial resolution (1 m) hyperspectral images (63 bands in visible to near-infrared spectral region). Mirik et al. (2013) explored the ability of hyperspectral imagery for mapping infestation of musk thistle (Carduus nutans) on a native grassland during the pre-and peak-flowering stages using support vector machine classifier in Friona, Parmer County, USA. Ouyang et al. (2013) used a field spectrometer data to find the most appropriate period for mapping invasive Spartina alterniflora by measuring its community and major victims at different phenological stages in Chongming Island, China. Similarly, Rudolf, Lehmann, Große-stoltenberg, Römer, and Oldeland (2015) developed a classification model to spectrally discriminate between invasive shrub Acacia longifolia from other non-native and native species using field-based spectra and condensed leaf tannin content in Portuguese dune ecosystems, Portugal.

However, discrimination of plant species using hyperspectral data often places emphasis on identification of the optimal specific bands for discrimination. These bands are narrow and cannot be
separated from within the broader bandwidth of multispectral data. Hyperspectral remote sensing has grown significantly in the past few decades. However, its application in operational characterization is rather limited. Although there is a promise to translate research efforts of hyperspectral remote sensing into operational tools, current advances in data availability show that multispectral remote sensing remains the most important source of information in vegetation monitoring. For example, DeVries, Verbesselt, Kooistra, and Herold (2015) monitored small-scale forest disturbances in a tropical montane forest of southern Ethiopia using Landsat time series. Gu and Wylie (2015) developed a 30-m grassland productivity estimation map for central Nebraska in USA using 250 m MODIS and 30 m Landsat 8 observations, United States. Johansen, Phinn, and Taylor (2015) mapped woody vegetation clearing in Queensland, Australia from Landsat imagery using the Google Earth Engine. Kennedy et al. (2015) described factors attributing to disturbance change from Landsat time-series in support of habitat monitoring in the Puget Sound region, USA. Therefore, research efforts involving hyperspectral remote sensing analysis need to consider extending the technique into multispectral remote sensing techniques.

This study uses a continuum of hyperspectral bands to identify best wavelength regions for discriminating *Asparagus laricinus* from adjacent land cover types. As such, it focuses on spectral regions rather than identifying individual bands in an attempt to simulate multispectral remote sensing systems. Specific objectives of the study are (1) determining whether or not *A. laricinus* can be differentiated from adjacent land cover types using a field spectrometer data and (2) to investigate the performance of spectra simulated according to Landsat and SPOT 5 images in discriminating *A. laricinus* from adjacent land cover types. There have been little or no studies that focused on discriminating *A. laricinus* from other vegetation or land cover types. *A. laricinus* is a plant belonging to the Asparagaceae family and occurs in different parts of South Africa. However, the plant is not indigenous in South Africa and has a status of “list concern” in the South African National Biodiversity Institute (SANBI) national Red List of South African plants (Foden & Potter, 2005). Knowledge on the spectral and spatial characteristics of the species assists the development of better management strategies in areas where it invades. Such maps can also help traditional health practitioners and pharmaceutical industries to locate stands of the plant for medicinal purposes, as it also has medicinal uses (Fuku, Al-Azzawi, Madamombe-Manduna, & Mashele, 2013; Mashele & Kolesnikova, 2010; Ntsoelinyane & Mashele, 2014).

2. Methods

2.1. Study area

The study was conducted in the Klipriviersberg Nature Reserve, in Johannesburg, South Africa (Figure 1). It covers an area of approximately 680 hectares in extent and is managed by the City of Johannesburg. The reserve lies in the Klipriviersberg area, a transition zone between the grass land and the savannah biome in the northern edge of the Highveld (Faiola & Vermaak, 2014). Climatic conditions experienced in the reserve vary from warm to hot summer (17–26°C) and cool to cold winter (5–7°C) (Kotze, 2002). Three geology types occur in the reserve, namely basalt and andesite volcanic rocks that underlay the reserve; quartzites and conglomerates of the upper Witwatersrand system underneath the lavas in north of the reserve; and dolomites of the Transvaal system south of the reserve (Kotze, 2002). The flora of the reserve is categorized into two broad vegetation types, the Andesite Mountain Bushveld and a section of Tsakane Clay Grassland at its flatter southern end (Faiola & Vermaak, 2014). There is relatively rich biodiversity with approximately 650 indigenous plant species, 215 bird species, 16 reptile species, and 32 butterfly species. Mammals that occur in the reserve include lesser spotted genet, African civet, zebra, red hartebeest, blesbok, springbok, duiker, black wildebeest, porcupines, meerkats, and otters (Faiola & Vermaak, 2014).

2.2. Field data

Field surveys were conducted between the 2 and 14 December 2014 during summer season of the area with the aim of characterizing the vegetation under relatively high vigor condition. *A. laricinus* is found extensively in one part of the reserve, while other occurrences are scattered in small spatial
extents. Such a rather limited distribution resulted in delineation of 10 plots of 15 m radius each (Figure 2). The plot size was chosen with the anticipation of extending the investigation to space-borne remote sensing techniques. Each plot therefore accommodates at least one pixel of Landsat imagery (30 m resolution) and a number of SPOT 5 imagery pixels (1.5–10 m resolutions). The center of each plot was recorded using GPS (Garmin GPSmap® 76) within 3 m accuracy. A total of 13 sample plants were taken randomly within the 15 m radius plot area. Although random, sampling was attempted to follow a systematic design as shown in Figure 2. Therefore, samples were taken at 5-m intervals along perpendicular transects that intersect at the center of plot (Appendix A). However, this was rarely achieved as it was difficult walking through the thorny and dense stands of *A. laricinus*, prompting use of random sampling. *A. laricinus* individuals varied between six and eight plants within each plot.
Spectral data were collected using Spectral Evolution® SR-3500 Remote Sensing Portable Spectroradiometer (Spectral Evolution Inc., Lawrence, MA, USA). The spectrometer has a 1.6-nm spectral resolution ranging between 340 and 2,503 nm. Target radiance in energy unit was converted into percent reflectance using a white reference measurement (Prospere, McLaren, & Wilson, 2014). Three spectral measurements were taken for each A. laricinus plant from different leaf canopy parts of the plant with all measurements taken at 5 cm above leaf canopy to mimic a remotely sensed data (airborne and spaceborne) viewpoint. The three spectral measurements were averaged to represent the reflectance spectra of each sample plant. Spectral measurements from adjacent land cover types were taken in a similar manner. These measurements should ideally be taken when the sun is overhead to acquire electromagnetic radiation reflectance optimally (Cho, Sobhan, Skidmore, & de Leeuw, 2008; Fernandes, Aguiar, Silva, Ferreira, & Pereira, 2013; Mansour, 2013; Olsson, van Leeuwen, & Marsh, 2011; Rudolf et al., 2015). However, time constraints did not necessarily allow the application of this protocol for all measurements.

2.3. Analysis of spectral reflectance per region
Analysis was limited to the regions that showed consistent spectral differences between A. laricinus and adjacent land cover types. In order to identify these regions an average spectrum was computed from the three spectral measurements taken from each target (A. laricinus and adjacent land cover type, respectively). The resultant average values were pooled per land cover type and averaged to generate “global” spectral curves representing A. laricinus and each adjacent land cover type in the study area as illustrated (Figure 3). The global spectra of A. laricinus was compared against each adjacent land cover types, as illustrated in an example comparing A. laricinus and grass in Figure 4. Please note, not all global comparisons are presented in here for the sake of brevity. The global spectra of adjacent land cover types were computed to determine the potential discrimination of A. laricinus from them, since the species can co-exist with a mixture of land cover types in a natural environment. Comparison using global pairs is deemed a better representation of the study area than comparison of individual pairs that most likely yields results that are unable to converge to a compromise generic conclusion.

A visual assessment of the global spectra was used to determine regions that were considered unnecessary for differentiating A. laricinus and adjacent land cover types. Two rules were used to determine these regions. The first rule included regions that returned random reflectance properties commonly known as atmospheric noise (A. laricinus vs. Grass: 1,873–1,954 and 2,351–2,503 nm; A. laricinus vs. Acacia: 1,821–1,956 nm and 2,282–2,503 nm; A. laricinus vs. Herbaceous: 1,838–1,942 nm and 2,272–2,503 nm; A. laricinus vs. mixture of herbaceous and bare ground: 1,831–1,970 nm and 2,351–2,503 nm). The second rule included regions that did not show spectral reflectance difference between A. laricinus and adjacent land cover types (A. laricinus vs. Grass: 340–343, 684–750 nm and 1,350–1,824 nm; A. laricinus vs. Acacia: 650–749 and 1,331–1,448 nm; A. laricinus vs. Herbaceous: 340–387, 641–748 nm and 1,316–1,448 nm; A. laricinus vs. Mixture of herbaceous and bare ground: 340–467, 685–745 nm and 1357–1,455 nm). These exclusions resulted in four discontinuous regions (Table 1, Figure 5) based on which spectra of individual targets (individuals of A. laricinus and adjacent land cover types) were used in further analyses.

Analysis involved comparison of reflectance between A. laricinus and adjacent land cover types at two levels, namely individual and plot levels. Individual level comparison was made between A. laricinus and adjacent land cover type at a sampling point within each plot. On the other hand, plot level comparison was made between plot level mean reflectance of A. laricinus against plot level mean reflectance of dominant adjacent land cover type. Differences at both levels were assessed graphically and using statistical tests such as the analysis of variance (ANOVA) and t-test (Weiss, 2012). All the tests were calculated using 95% confidence level (α = 0.05).

2.4. Simulation of Landsat and SPOT 5 imagery bands
Wavelength regions corresponding to Landsat and SPOT 5 bands were extracted from the original reflectance spectra for all A. laricinus and adjacent land cover types. This was an initial step to
testing the potential of upscaling field-based remote sensing information to airborne or satellite-based remote sensing. Only blue, green, red, and NIR bands were simulated or Landsat, while green, red, and NIR spectral bands were simulated for SPOT 5 imagery. These elected bands are widely used...
in the assessment of vegetation characteristics (e.g. Manevski et al., 2011; Mirik, Ansley, et al., 2013; Mirik, Emendack, et al., 2014). Five separate pools representing *A. laricinus*, grass, acacia, herbaceous, and mixture of herbaceous and bare ground were created. Reflectance comparisons were done at individual and group level. Individual level compared the pool of *A. laricinus* against separate pools of grass, acacia, herbaceous, and mixture of herbaceous and bare ground. The group level
compared *A. laricinus* pool against combined pool of adjacent land cover types. Spectral differences were assessed using ANOVA and t-test.

### 3. Results

Individual-level comparisons between *A. laricinus* and adjacent land cover types resulted in an overall significant difference in all spectral regions, based on ANOVA results. However, separate reflectance comparisons of each of the individuals per plot showed inconsistent significant differences. Distinct spectral separability between *A. laricinus* and adjacent land cover types was observed mostly in the NIR region (region 2), with seven of 10 plots. In contrast, only two in the ultraviolet–visible (region 1), three in the NIR–SWIR (region 3), and five in the SWIR (region 4) regions showed clear separation. These differences are illustrated in Figure 6 which show spectral reflectance differences between *A. laricinus* and grass of one plot. Significant differences are presented using different letters, whereas same letters represent insignificant differences. Distinct separation between *A. laricinus* and adjacent land cover types in the NIR region (region 2) is shown by higher reflectance of *A. laricinus* than other land cover types (Figure 6).

Grasses represented majority of land cover types at plot level analysis (7 of 10 plots), while Herbaceous, Acacia, and Mixture of ground and herbaceous were dominant in each of the remaining plots. Comparisons at this level resulted in significant differences in all plots based on t-test results as illustrated in Figure 7. In most cases, *A. laricinus* had higher reflectance than adjacent land cover types in the NIR region (region 2), with 8 of 10 plots. The species had higher reflectance in five plots in the ultraviolet–visible (region 1), six plots in the NIR–SWIR (region 3) and five plots in the SWIR region (region 4).

#### 3.1. Landsat simulation

Comparisons between *A. laricinus* and adjacent land cover types at the individual level resulted in an overall significant difference in all Landsat simulated bands (blue, green, red, and NIR), based on the ANOVA results. Individual pair comparisons using least significance difference (LSD) resulted in significant difference between *A. laricinus* and all land cover types, in most cases (Figure 8). Similarities were, however, observed between *A. laricinus* and grass in the blue and red bands, and between *A. laricinus* and herbaceous vegetation in the green band (Figure 8). *A. laricinus* had higher reflectance than other adjacent land cover types with exceptions of Acacia in the blue band, Acacia and herbaceous in the green and NIR bands, and Acacia and grass in the red band.
Figure 7. Plot-level mean reflectance of *A. laricinus* and adjacent land cover types.

Note: The comparisons are per region and per plot. (Mix. Ground & herb = Mixture of herbaceous and bare ground).
Figure 8. Mean reflectance of simulated Landsat bands per land cover type (individual level).

Note: The comparison is per spectral band. (Herb. & ground = Mixture of herbaceous and bare ground).
Figure 9. Mean reflectance of simulated Landsat bands per land cover type (Group level).

Note: The comparison is per spectral band.
Comparison of reflectance at the group level between *A. laricinus* and combined adjacent land cover types resulted in insignificant difference in the blue, green, and red bands, while the difference was significant in the NIR (Figure 9). *A. laricuns* had higher reflectance than combined adjacent land cover types in the green and NIR band, while it had lower reflectance in the blue and red bands (Figure 9).

### 3.2. SPOT 5 simulation

Reflectance comparisons of SPOT 5 simulated bands resulted in overall significant differences in all bands, based on ANOVA. Individual pair comparisons using LSD showed significant differences between *A. laricinus* and adjacent land cover types in all bands, except for comparison between *A. laricinus* and herbaceous vegetation in the green band as well as between *A. laricinus* and grass in the red band (Figure 10). *A. laricinus* had a relatively high reflectance in all bands. However, it had lower reflectance than Acacia plants in all bands and herbaceous vegetation in the green and NIR bands, and grass in the red band (Figure 10).

Group-level comparisons between *A. laricinus* and combined adjacent land cover types showed significant difference in only the NIR band (Figure 11). *A. laricinus* had higher reflectance than combined adjacent land cover types in the green and NIR bands, while it had negligible reflectance in the red band (Figure 11).

### 4. Discussion

The utility of a field-based spectral data to discriminate *A. laricinus* from adjacent land cover types was investigated in this study. Investigations were made using original spectra and spectra simulated based on bands of Landsat and SPOT 5 images. These simulations were intended to assess the potential of upscaling the technique to spaceborne remote sensing techniques. Analyses were done at individual and plot levels using original spectra, and individual and group level for the simulated spectra. Visual comparisons using global pair reflectance of *A. laricinus* and each adjacent land cover type showed differentiation in the ultraviolet–visible (region 1), NIR (region 2), NIR–SWIR (region 3), and SWIR (region 4) spectral regions, but the difference was considerable in the NIR region (e.g. Figure 5). *A. laricinus* had high reflectance in NIR (region 2) and NIR–SWIR (region 3) and low reflectance in ultraviolet–visible region (region 1) and SWIR region (region 4) when compared with grass. *A. laricinus* reflectance was high in all regions when compared with herbaceous, while it was high in
ultraviolet–visible (region 1), NIR (region 2), and NIR–SWIR (region 3) when compared with mixture of bare ground and herbaceous plants, but it was low in all regions when compared with Acacia. All these wavelength regions are considered best at characterizing vegetation types (e.g. Manevski et al., 2011; Mirik, Ansley, et al., 2013; Mirik, Emendack, et al., 2014). The far-SWIR region on the other hand is considered best at discriminating between photosynthetic, non-photosynthetic vegetation components, and ground due to spectral absorption attributable to presence of cellulose in healthy vegetation (Daughtry et al., 2006; Guerschman et al., 2009; Nagler, Daughtry, & Goward, 2000; Serbin, Daughtry, Hunt, Reeves, & Brown, 2009).

The overall significant differences observed for individual-level comparisons per plot are not attributable to reflectance difference between A. laricinus and adjacent land cover types. This is because significant differences were observed even within individuals of same land cover types, based on pairwise comparisons using LSD. There were further inconsistent significant differences when comparing individuals per plot separately. As such, distinct separation between A. laricinus and adjacent land cover types was mostly achieved in the NIR region, for 7 of 10 plots, while only a few plots showed clear separation in the ultraviolet–visible region, NIR–SWIR, and SWIR regions (Figure 6). Consistent significant difference observed in the NIR region was somewhat expected, given the distinct reflectance differences between A. laricinus and adjacent land cover types from the global spectra comparisons (e.g. Figure 5).

The plot-level differences between A. laricinus and dominant adjacent land cover types were considerable particularly between A. laricinus and grass as well as A. laricinus and mixture of herbaceous vegetation and bare ground (e.g. Figure 7). The differences were somewhat expected given different global reflectance patterns of A. laricinus, grass, and mixture of herbaceous vegetation and bare ground (Figure 3). In contrast, the differences between A. laricinus and herbaceous were lower, although they were significant in the visible, NIR, and lower end of SWIR regions. This can as well be explained by the global reflectance resemblance of A. laricinus and herbaceous (Figure 3). Another noteworthy observation at the plot level was the fact that the magnitude of reflectance of A. laricinus was greater than for herbaceous vegetation in the ultraviolet–visible (regions 1), NIR region (region 2), and SWIR (region 4), and smaller in NIR–SWIR (region 3). This is the opposite of what were observed in comparisons between A. laricinus and grass as well as A. laricinus and a mixture of herbaceous vegetation and bare ground. This dissimilarity can be attributed to the relatively heterogeneous species composition of herbaceous plants within a plot. In contrast, grass and bare ground can be comparatively considered homogenous land cover types, respectively, having marked spectral difference with A. laricinus.

The significant difference between A. laricinus and adjacent land cover types using the Landsat-and SPOT 5-simulated bands achieved at the individual-level analysis (Figures 8–11) was anticipated, given the distinct homogeneous setup of A. laricinus and adjacent land cover types. This setting does, however, occur rarely in an ideal natural environment where plant of different species co-exist. Unlike individual level analysis which showed significant differences in all bands (Figure 8 and 9), only the NIR band showed significant difference at group level (Figure 10 and 11). These results showed the potential of discriminating A. laricinus from adjacent land cover types using this band which is available in most remotely sensed data. This agrees with a study that classified Asparagus officinalis (a species that belongs to the same family as A. laricinus) successfully using Landsat imagery (Tatsumi, Yamashiki, Canales Torres, & Taipe, 2015).

The NIR band was most useful in discriminating between A. laricinus and adjacent land cover types. This is not surprising as the band has been widely used in discriminating between plant species in a number of studies. For example, A. officinalis was successfully identified using NIR reflectance spectroscopy by Perez and Sanchez (2001). This region was used in studies on plants not related to A. laricinus, too, such as by Xu, Yu, Fu, and Ying (2009) who successfully discriminated between two tomato varieties in China using visible–near-infrared reflectance spectroscopy.
bands as well as vegetation indices that best characterize, classify, model, and map the world’s main agricultural crops. Bentivegna et al. (2012) detected cutleaf teasel (D. laciniatus) with hyperspectral imagery using visible–NIR spectral region along Missouri Highway, USA. Calvini, Ulrici, and Amigo (2015) tested sparse methods for classifying Arabica and Robusta coffee species using near-infrared hyperspectral images.

5. Conclusion
This study aimed at determining the potential of discriminating between A. laricinus and adjacent land cover types in the Klipriviersberg Nature Reserve using a field spectrometer data. Analysis of spectral reflectance was done at individual and plot levels using the original spectra. Although different spectral wavelength regions showed the ability to differentiate the species from other land cover types, the NIR region was found to be the most consistent of all. This finding is in line with other vegetation studies, although such studies on asparagus are rare.

A comparative similarity between A. laricinus and herbaceous plants was noteworthy. This similarity can make identification of the plant challenging in such co-existence. In contrast, the species can be discriminated from grass and mixed land cover (ground and herbaceous vegetation) at relative ease. The separability from grass is particularly important if the species favors to co-exist more with grass than with other species (7 of 10 plots were dominated by A. laricinus and grass in this study). The ability to discriminate these species from mixed land cover types that include bare ground, among others, is useful since it enables early detection in sparsely vegetated areas. Further studies are however needed to determine the relative contribution of different land cover types in the mixture to spectral reflectance.

Analysis of spectra simulated based on Landsat and SPOT 5 imagery bands showed the NIR to be consistent in discriminating A. laricinus from other land cover types. This finding is encouraging in that it shows the potential of upscaling the application to airborne and spaceborne remote sensing that mostly include the NIR region of electromagnetic energy. This study, however, used limited number of samples and thus should rather be considered a preliminary indicator that needs further studies. Future studies should attempt to utilize large number of samples. Such sample size can be achieved with the use of small sampling units and high spatial resolution imagery (e.g. SPOT 5, 6/7), particularly in areas where the spatial extent of invasion is small relative to imagery with lower spatial resolution (e.g. Landsat). In addition, limiting spectral measurements within ideal time frames when there is enough illumination would need to be considered. Furthermore, it is vital to profile the biochemical contents of the species so that relationships can be built between the inherent contents of the plant and their effects on spectral signatures. In connection to this, it is important to take into consideration spectral properties at different phenological stages of the species.

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**Appendix A**

Center coordinates of sample plots used in the analysis

| Plots | Latitude   | Longitude |
|-------|------------|-----------|
| 1     | −26.30169  | 28.01205  |
| 2     | −26.30117  | 28.01164  |
| 3     | −26.30085  | 28.01121  |
| 4     | −26.30076  | 28.01141  |
| 5     | −26.3002   | 28.01127  |
| 6     | −26.30018  | 28.01058  |
| 9     | −26.30063  | 28.01058  |
| 8     | −26.30148  | 28.01138  |
| 9     | −26.30257  | 28.01096  |
| 10    | −26.30291  | 28.01106  |