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Mapping invasive alien trees in water towers: A combined approach using satellite data fusion, drone technology and expert engagement

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ABSTRACT

Operationalising advances in remote sensing for invasive alien plant management remains a major challenge, despite its proven value globally. There is also a lack of detailed remote sensing studies in water towers, for example the southwestern Cape of South Africa, where invasive alien trees threaten water security. There is a need for cost-effective, easy to use, inclusive and repeatable approaches to map invasive alien plants to inform management. We use a novel, transdisciplinary approach, combining Google Earth Engine's processing power, freely available Sentinel imagery (fusion of Sentinel-1 and -2), expert engagement (including researchers, managers and decision makers), drone technology and field trips, to provide an accurate and up-to-date understanding of the occurrence and density of invasive alien trees in an important water tower for the southwestern Cape of South Africa at a 20 m resolution. We explored the efficacy of combining bands and indices with the highest alien tree discriminatory power based on a statistical spectral analysis of 10 of the 13 Sentinel-2 bands and 39 relevant indices with various other data inputs (e.g. Sentinel-1, topographic information) in six classifications using robust and advanced non-parametric image classifiers. All six classifications performed well, with invasive alien trees discriminated from surrounding shrublands with 89-92% accuracy, and alien tree groups discriminated with 74-84% accuracy. Data fusion of Sentinel-1 and -2 and inclusion of topographic information (elevation and landform) marginally improved the accuracy statistics. However we caution against over-reliance on accuracy statistics given the relatively small sample sizes typically used in multispectral classifications. The rich spectral information contained in the red edge and shortwave infrared parts of the spectrum were critical for alien tree discrimination as the key traits distinguishing these alien trees from indigenous shrubland vegetation are differences in biomass and water usage. Discrimination between different types of alien trees and discriminating alien trees from native vegetation with high water use (e.g. wetlands and mountain forests) remained a challenge for the given spatial and spectral resolutions of Sentinel-2 imagery, despite reasonable accuracy statistics. Though the results present a significant advance for the region, given currently available out-dated maps, engagement with decision makers showed that managers require even more detailed products for alien tree management.

1. Introduction

The application of remote sensing to the detection and management of invasive alien plants has become increasingly relevant during the last two decades as a result of rapid technological advancements (Huang and Asner 2009; Royimani et al., 2018; Paz-Kagan et al., 2019; Vaz et al., 2019). Improvements include a wider availability of free multispectral satellite imagery with ever-increasing spatial and temporal resolutions, such as Landsat-8 and Sentinel-2 (Royimani et al., 2018; Vaz et al., 2018). For example, the Sentinel-2 satellites have been shown to be particularly useful for vegetation classification because of the rich spectral information collected from the visible, red edge, near-infrared and shortwave-infrared wavelengths (Bolyn et al., 2018; Grabska et al., 2019; Immitzer et al., 2019). Similarly, the mainstreaming of drone technology affords cheap ground-truthing opportunities, especially in remote areas or challenging terrain (Dvořák et al., 2015; Müllerová et al., 2017; Kattenborn et al., 2019).

Despite advances in remote sensing technology, there have been

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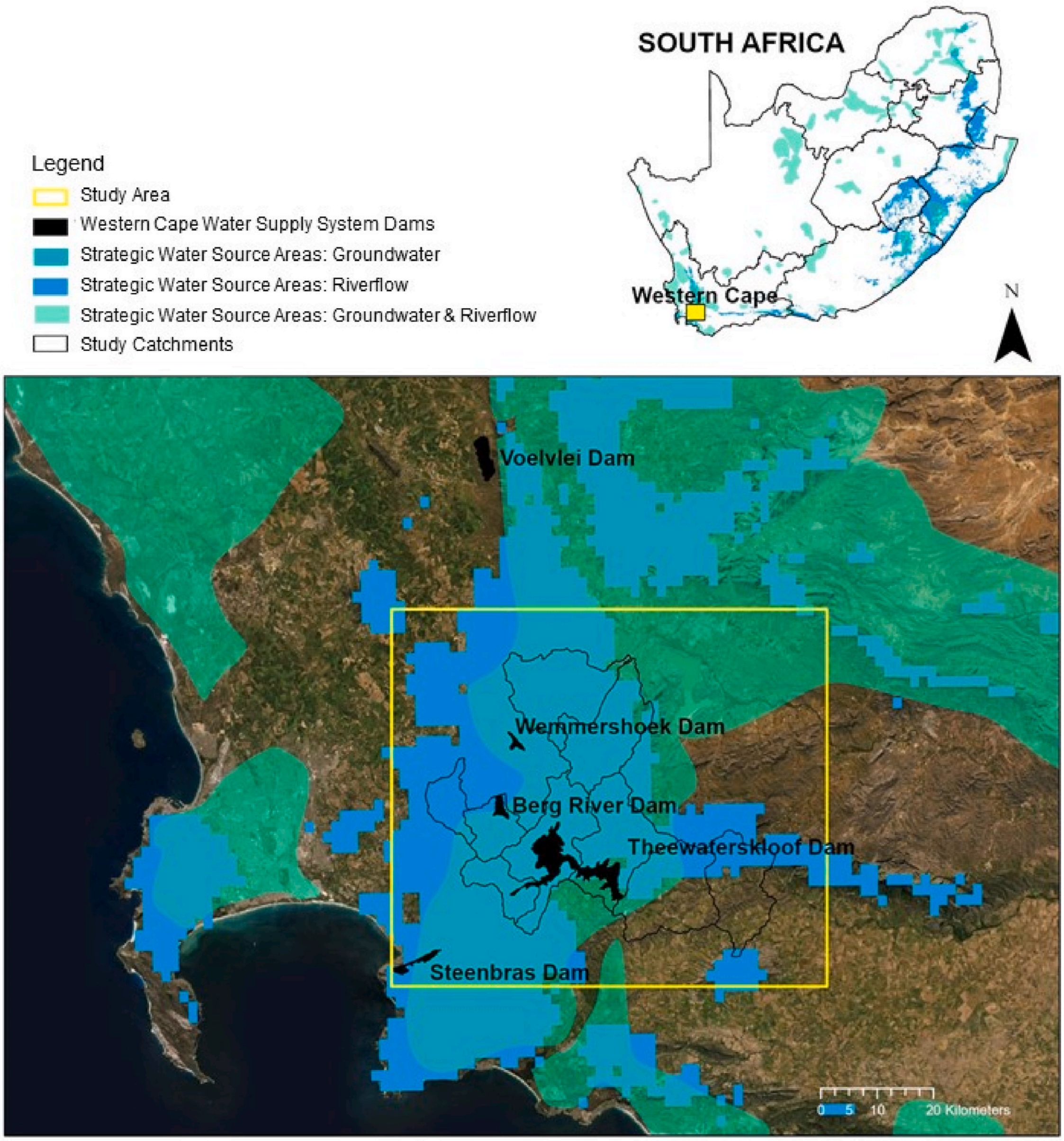

Fig. 1. The study area (yellow bounding box) and study catchments (black outlines) of the upper Berg and Breede catchments in the Western Cape of South Africa. The groundwater and surface water strategic water source areas are indicated on the map including areas of overlap. The five major dams of the Western Cape Water Supply System, a system of five large interconnected water impoundments are overlain in black. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

relatively few studies using multispectral satellite imagery for invasive alien plant mapping, especially in data poor regions (e.g. developing nations). Existing multispectral studies have tended to focus on distinguishing a single invasive alien plant species from native vegetation (Royimani et al., 2018). The few examples of this single species approach include American Bramble (*Rubus cuneifolius*) (Ndlovu et al., 2018; Rajah et al. 2018, 2019, 2020), Lantana (*Lantana camara*) (Oumar 2016) and Maritime Pine (*Pinus* pinaster) (Forsyth et al., 2014). Furthermore, a review by Royimani et al. (2018) on multispectral approaches for identifying invasive alien plants emphasised several research needs for supporting long-term and large-scale mapping considering financially constrained countries. These included, firstly, the need to investigate the benefits of multisource datasets (i.e. data fusion) for the detection of invasive alien plants (Royimani et al., 2018; Rajah et al., 2019). Secondly, that the capabilities of improved spatial and spectral resolution multispectral datasets should be explored jointly with robust and advanced machine learning algorithms such as Random Forest (RF) and Support Vector Machine (SVM) classifiers (Mountrakis et al., 2011; Royimani et al., 2018). Lastly, that vegetation indices should be integrated with optical reflectance bands for improving the capability for distinguishing among different invasive alien plant species (Royimani et al., 2018; Rajah et al., 2020).

There is also an urgent need to integrate technological and research advances into invasive alien plant management and decision making. For example, the limited research and associated methodologies focused on the detection and mapping of invasive alien plants using multispectral remote sensing have not yet been well integrated into alien vegetation management (Vaz et al., 2018; Foxcroft et al., 2020). Major barriers are cited as: lack of time for managers to read scientific papers, or issues with access to scientific papers, lack of expertise, poor relationships or collaboration with researchers, lack of clear workflows in scientific papers, and low applicability of research for managers (Matzek

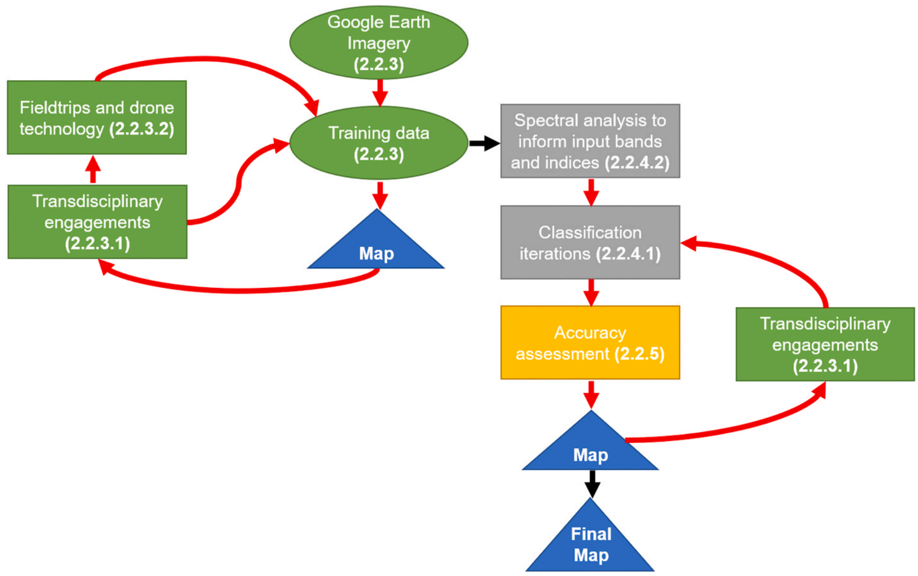

Fig. 2. Conceptual framework of how the methdology formed an iterative, non-linear, and adaptive process. Numbers in brackets are linked to method sections described below. Variables/data are given in circles, processes in rectangles and results in triangles. The arrows in black indicate transitions to the next stage of the framework after the transdisciplinary engagements cycles are complete.

et al., 2014; Kuebbing and Simberloff 2015; Foxcroft et al., 2020). Therefore, although the importance of engaging managers upfront and throughout the research process has been emphasised in the field of sustainability science, it is yet to be embedded in invasive alien plant remote sensing studies (Knapp et al., 2019).

Alien species have a significant impact on biodiversity loss (Paz--Kagan et al., 2019) and on economies (Van Wilgen et al., 2001; Pratt et al., 2017). In water scarce regions, invasive alien trees in particular are a problem, depleting already stretched water resources and increasing fire risk (Le Maitre et al., 2002; Van Wilgen et al., 2008). Invasion of mountainous regions and wetlands by alien trees is of great concern, as they provide disproportionately more water-related ecosystem services in relation to the surface area that they cover. These areas have been called 'water towers' for the disproportionate amount of run-off they produce globally (Viviroli et al., 2007). The combined impacts of anthropogenic climate change and water loss through invasive alien trees could be magnified in water towers, disproportionately reducing water supply, with associated socio-economic consequences likely to reach far beyond the mountain regions (Viviroli et al., 2011; Fort 2015). Therefore, alien trees in water towers represent a serious threat to water security in the future through the impact on increasing drought risk.

South Africa makes a good case study for these issues, being a water-scarce nation with a long and complex alien tree invasion history, with high native species richness and having made significant financial investment into its alien control programmes (ZAR 15 billion since 1995) (Van Wilgen et al., 2014; van Wilgen and Wannenburgh 2016; Foxcroft et al., 2020). Few, if any, of these programmes make use of the advances made in remote sensing applications for prioritization and monitoring of invasive alien clearing efforts (Ntshotsho et al., 2015; van Wilgen and Wannenburgh 2016; Cheney et al., 2018; Foxcroft et al., 2020). Sources of data to estimate the abundance of invasive alien plant species in the Western Cape are extremely coarse and between 10 to 20 years out of date (Van Wilgen and Wilson 2018). Despite uncertainty around current distributions, alien plants have spread prolifically, and were estimated in 2000 to cover 3 727 392 ha of the Western Cape, or, 28.82% of the province (Le Maitre et al., 2000). In spite of leveraging new funding opportunities and efforts being ramped up to clear invasive alien trees in water towers of the region in response to the recent multi-year drought (2015–2017), clearing efforts struggle to keep apace with invasion (Otto et al., 2018; Stafford et al., 2018). There is also anticipation for future drying in the region with strong drying signals across climate model projections for the area (Altwegg et al., 2014), and therefore the water-related impacts of these trees may be amplified in the future.

The water towers of the Western Cape of South Africa, the Upper Berg and Breede catchments, form part of the Western Cape Water Supply System, supplying the metropolis of Cape Town with water (New 2002). There is a particular need for an approach to detect and map invasive alien trees in this region that is cost effective, easy to use, inclusive (following a transdisciplinary approach), and repeatable. It is critical that this approach be repeatable due to high rates of spread and a dynamic fire regime. Towards this goal, we combine three types of affordable inputs (free satellite imagery, drone technology and expert engagement) in three affordable platforms (Google Earth Engine, Google Earth and transdisciplinary workshops) to develop a novel approach that could be easily applied and repeated in other data scarce regions.

2. Methods

2.1. Study region

The southwestern Cape of South Africa is a water scarce region that has a mean annual precipitation of ~380 mm/a (Water Resources 2012). It has a Mediterranean-type climate characterised by summer drought and winter rainfall, usually as a result of cold fronts. The geology of the region is dominated by the quartzitic sandstone mountains of the Cape Supergroup (Midgley et al., 2003; Manning and Goldblatt 2012), which are highly fractured and contain major aquifers, including the Table Mountain Group Aquifer (Blake et al., 2010). The indigenous vegetation is mainly fynbos, which is a highly biodiverse, fire-adapted shrubland, dominated by sclerophyllous, evergreen shrubs and graminoids, with no tree element except in fire-protected ravines where Afromontane Forest pockets are found (Manning and Goldblatt 2012). The fynbos covered mountains in the region are the most important strategic water source areas, particularly for riverflow, in the southwest of the country. The upper Berg and Breede catchments are extremely mountainous (highest elevation 2016 m) and form important water towers for the region, providing both large volumes of surface flow, as well as being important zones for groundwater recharge (Le Maitre et al., 2018a, b). These mountains generate much of the water resources for the Western Cape Water Supply System, an integrated system of five large water impoundments which supply the City of Cape Town metropolis, amongst other smaller towns, agriculture and industry (New 2002).

For this paper, we concentrate on nine sub-catchments in the Upper Berg and Breede catchments which are critically important for water supply to two of the five large dams in the Western Cape Water Supply System (Fig. 1). In the upper Berg and Breede catchments, one of the major threats to water security is invasive alien trees. As a legacy of forestry plantations and agriculture in the region, invasive alien trees have spread along riparian zones and into the mountains (Hoffmann et al., 2011; Van Wilgen and Richardson 2014). The species of major concern in the Western Cape are *Acacia mearnsii*, *Acacia saligna*, *Eucalyptus* spp., *Hakea* spp., and *Pinus* spp. (Meijninger and Jarmain 2014). In the upper Berg and Breede, the major issues are *Pinus* spp. in the mountains, and *Eucalyptus* spp. and *Acacia mearnsii* in the riparian zones. Quantifying the extent of alien tree infestations in these catchments is of urgent priority to decision makers so that they can adequately prioritise funding for clearing efforts to increase the resilience of the water supply to the City of Cape Town (Stafford et al., 2018). To help design our outputs to suit user needs we adopted a transdisciplinary approach, including decision makers and stakeholders from inception through the iterative refinement of our classifications (Fig. 2).

2.2. Invasive alien tree mapping

We explored the efficacy of combining bands and indices with the highest alien tree discriminatory power based on a statistical spectral analysis of 10 of the 13 Sentinel-2 bands and 39 relevant indices with various other data inputs (e.g. Sentinel-1, topographic information) in six classifications using robust and advanced non-parametric image classifiers. We harnessed the processing Google Earth Engine, also freely available, to run all classification iterations. The JavaScript API of Google Earth Engine makes the process relatively transparent and repeatable. Both the invasive alien trees and species of the fynbos biome are evergreen. Therefore, in an attempt to provide an up-to-date account of invasive alien trees in the region, we used the most recent image possible for the region that was aligned to our training data collection while also considering major fire events for the area.

We used an iterative, non-linear and adaptive process to collect and revise training data between January and December 2019 drawing on transdisciplinary engagements, field trips and drone technology. We needed an initial classification result to engage managers and decision makers (stakeholders) in the mapping process (Fig. 2). For this initial classification we used a SVM classifier trained on an initial training data set collected from Google Earth Imagery (January to February 2019). Using the input from stakeholders (either training points, or suggestions of where to obtain training points for various classes) along with field trips and drone imagery, we revised the training data. Once we had the final improved training dataset (in November 2019), we ran a series of six classifications varying input bands and indices (see section 2.2.4).

We describe our methods and the process followed in six subsections: 2.2.1 Land cover classes and invasive alien tree types, 2.2.2 Datasets, 2.2.3 Training data, 2.2.4 Classification iterations based on spectral analyses of bands and indices, 2.2.5 Accuracy assessment, and 2.2.6 Comparison with existing invasive alien tree datasets used by managers and decision makers in South Africa.

2.2.1. Land cover classes and invasive alien tree types

We classified sixteen different land cover/land use classes, including three different genera of invasive alien trees and a fourth lumped category representing "other invasive alien tree genera". The focal three invasive alien tree genera were: i) *Acacia* sp. (commonly known as wattles or acacias); ii) *Eucalyptus* sp. (commonly known as gums); and iii) *Pinus* sp. (commonly known as pines). These three were selected due to being the most pervasive and problematic in the study area (Meijninger and Jarmain 2014). The "other invasive alien tree genera" category included other invasive alien trees problematic in the area but with much lower occurrence and densities, such as poplars (*Populus* sp.), oaks (*Quercus* sp.), alders (*Alnus* sp.), and willows (*Salix* sp.). The motivation for including this additional category is that these trees, although not making up large areas of the catchment, do not fall into any of the native or other land cover/land use classes. We wanted to make provision for trees that were neither native forest, nor one of the three dominant alien tree classes. The additional 12 land cover/land use classes comprised: i) indigenous forest; ii) open water; iii) shrubland low density; iv) shrubland high density; v) burnt area; vi) bare ground; vii) wetland; vii) shade; ix) rock; x) dryland agriculture; xi) irrigated agriculture; and xii) urban/settlements.

2.2.2. Datasets

2.2.2.1. Sentinel-2 imagery. The most recent cloud free image was filtered from the Copernicus Sentinel-2 mission MultiSpectral Instrument (MSI) Level-2A data product (European Space Agency) on the Google Earth Engine catalogue. The Sentinel-2 satellites carry a MultiSpectral Instrument (MSI), which delivers Level-1C Top-of-atmosphere reflectances typically every 15–30 days over Europe and Africa. These are then processed to Level-2A surface reflectances, requiring no further atmospheric correction. Sentinel-2 has 13 spectral bands ranging from the visible and near infrared to shortwave infrared. Four of the bands (2, 3, 4, and 8) have a 10 m spatial resolution, six (5, 6, 7, 8 A, 11 and 12) have a 20 m spatial resolution and three (1, 9 and 10) have a 60 m spatial resolution (Table S1). For this study, the full target area was covered by a single Sentinel-2 tile, and the scene selected was dated January 6, 2019.

2.2.2.2. Sentinel-1 synthetic aperture radar imagery. Google Earth Engine's catalogue includes Sentinel-1 Synthetic Aperture Radar imagery (from the Copernicus programme of the European Space Agency) which has been pre-processed using the following steps: thermal noise removal, radiometric calibration and terrain correction. Sentinel-1 data contains co-polarization backscatter components, captured in a vertical polarization sending and vertical polarization receiving band (VV) and a vertical polarization sending and horizontal polarization receiving band (VH). It also contains dual band polarization images (VV and VH or HH and HV). We filtered the Sentinel-1 imagery to find a date as close as possible to the chosen Sentinel-2 scene date. Only single co-polarization images aligned with the existing Sentinel-2 scene date. This included four images for VV and seven for VH dating between 02/01/2019–9/01/2019 and 02/01/2019–21/01/2019, respectively. A median composite image was generated for both VV and VH bands. To reduce the speckle noise and thus increase the quality of the images, we applied a focal median filter to the pixels. Once processed, these bands were added to the Sentinel-2 image for use in the classifications.

2.2.2.3. Elevation and terrain landforms data. The Advanced Land Observation Satellite (ALOS) dataset provides landform classes by combining the Continuous Heat-Insolation Load Index and the multiscale Topographic Position Index based on a 30 m JAXA ALOS digital elevation model. There are 15 different landform classes in the dataset including variations of: peak/ridge, cliff, upper slope, lower slope, and valley classes. We added the landform for each pixel, as well as the elevation for each pixel, as bands for use in the classifications.

2.2.3. Training data

Initial training data were collected based on the authors' knowledge of the area and Google Earth imagery in January 2019. This included 270 points per land cover/land use class, a total of 4320 points for the 16 classes. These points were used to run an initial classification in order to have an initial invasive alien tree map to critique with stakeholders from the region. To improve the training data we used two main methods: i) transdisciplinary engagement, including engagement with researchers, managers and decision makers in critiquing existing training data and an initial invasive alien map; and ii) a combination of fieldtrips where we collected GPS coordinates and photos for each land cover/land use class and drone technology for remote and inaccessible ravines and mountainous areas, and lowland areas not easily accessible.

2.2.3.1. Transdisciplinary engagement. At the outset of the research, we spent two weeks informally engaging with 16 managers and decision makers working in or coordinating work on invasive alien tree management or prioritization in the upper Berg and Breede. From these meetings it was evident that the first priority was obtaining a fine-scale and up-to-date map of invasive alien trees for the study region to assist with conservation and management planning and implementation.

Once we had a first product to share with relevant stakeholders, we set up two contact sessions. The first, in April 2019, focused specifically on a range of 27 researchers and implementers working in the region. These stakeholders overlapped with the original 16 engaged at the beginning of the project. The second session, in May 2019, focused on 20 conservation and fire managers specifically working in the study area. We used two different approaches during the contact sessions.

For the first session, we engaged with stakeholders to critique hard copies of an initial invasive alien tree map for the area obtained by our first set of training data. Stakeholders were asked to highlight over- and under-classified areas, with a focus on the different alien tree groupings. For the second session, we aimed for a social learning exercise and used a digital approach for the engagement. We asked stakeholders to compare their existing management datasets to the initial invasive alien tree map developed through classifying the Sentinel-2 scene using overlays of both datasets on google earth imagery. We also asked managers to compare the two datasets to their own estimates based on field-based knowledge of the area. Next, we asked them to capture specific coordinates of invasive alien tree stands and indigenous forested areas that we could incorporate into our final training dataset.

Lastly in November 2019, we had a fourth and final engagement with 28 stakeholders. At this session, we presented examples of the final mapping products and provided training on how to create invasive alien maps using freely available imagery and software. Additionally we workshopped what would be required in a map and mapping process to make it repeatable and operational in future. Participants listed items in response to four main questions: i) what is needed in a map? ii) who needs the map? iii) for what purposes is a map needed? and iv) what technology would be required to assist the process? We collated information and ranked the importance of aspects based on the frequency of occurrence of participant responses.

2.2.3.2. Fieldtrip and drone technology. We used a combination of field trips (GPS and geolocated photos) and drone technology to ground-truth the original training data and the new points and areas received from local stakeholders. For each land cover/land use class we completed targeted flights, especially in areas that were unreachable on foot or by vehicle (Fig. S1). Furthermore, all focal river channels were flown, to check for riparian infestations. We used a Mavic 2 Pro quadcopter drone. The Mavic 2 Pro is equipped with a 12 mega-pixel RGB camera (DJI FC2204 with a 4 mm focal length) and is a capable of shooting 4 K video at 24 frames per second. We used a combination of images and videos, noting that oblique photographs were particularly helpful in aiding identification of vegetation (as opposed to aerial photographs). The flights were performed between May to November 2019. We did not use a standard flying height above ground and thus acquired various spatial resolutions dependent on the land cover/land use class. We used the drone imagery and videos to edit and remove existing training points and to capture new training data across the land cover/land use classes.

2.2.4. Classification iterations based on spectral analyses of bands and indices

We trained a SVM classifier with a randomly selected 70% of the final training data set to classify the Sentinel-2 scene (leaving 30% for validation for accuracy assessment). We kept this randomly selected sample of training data constant for all subsequent classifications to ensure comparability.

SVM is a non-parametric supervised machine learning algorithm which uses n-dimensional space to find the hyper-plane that differentiates between classes, and has been successfully used in vegetation classifications, particularly in retrieving biophysical information (Braun et al., 2010; Mountrakis et al., 2011; Royimani et al., 2018). Also useful for vegetation classifications is Random Forest (RF), which is a non-parametric machine learning method, but where multiple trees are grown (many classification trees are combined) and used to classify new objects based on attributes (Cutler et al., 2007; Tian et al., 2016; Royimani et al., 2018).

We selected the SVM classifier as it achieved high classification accuracy while the classification results aligned best with our ecological knowledge of invasive alien tree extents in the region compared to four other classifiers (RF, Decision Trees (CART), Maximum Entropy and the Minimum Distance classifiers). The RF classifier also had similar invasive alien tree accuracy results, however, did not provide as ecologically meaningful results as the SVM classifer in terms of distribution and extents. Superior accuracies of SVM and RF classifiers found in our study are in line with assessments of the capabilities of classifiers in remote sensing applications (Mountrakis et al., 2011; Royimani et al., 2018). We therefore ran most of our classifications using the SVM classifier (four in total), but use the RF classifier for two classifications, as RF allows for the easy estimation of probabilities.

2.2.4.1. Classification iterations. We ran four iterations of the classification using the SVM classifier, varying input bands and indices. For the **first classification** we used Sentinel-2 bands 5, 6 and 7 and the Normalized Difference Vegetation Index (NDVI), and Chlorophyll Green Index (Chlogreen), testing the assumption that these bands and indices commonly used in vegetation classification would provide adequate classification results (Bolyn et al., 2018). This result was used for the first stage of our stakeholder engagement.

For the **second classification**, we used Sentinel-2 bands 5, 6, 11, 12 and the following derived indices: Red-Edge pPak Area (RededgePeakArea) and Red – SWIR Bands Difference (RedSWIR1). These bands and indices were selected using a statistical approach (see section 2.2.4.2). The **third classification** involved data fusion, where we added bands from Sentinel-1 (see section 2.2.2.2) to the inputs used in classification 2, in an attempt to capture information on vegetation structure and biomass. The **fourth classification** investigates the value of including ALOS landscape information in the classification. We used the same inputs as for classification 2 but added bands with elevation and landform unit values (see section 2.2.2.3).

To establish whether information on the probability of occurrence of invasive alien trees would be useful (as opposed to presence/absence results), we explored the use of the RF classifier because SVM does not directly provide probability estimates. For the **fifth classification**, we used a RF classifier on the same inputs as for classification 2. For the **sixth classification**, we grouped all alien classes together and lumped all non-aliens and reran with the same inputs as classification 5. We extracted the probability that each pixel contained invasive alien trees and used these probabilities as a proxy for the density of invasive alien tree cover.

2.2.4.2. Spectral statistical analyses of bands and indices. To inform which bands and indices should be used in the classification iterations,

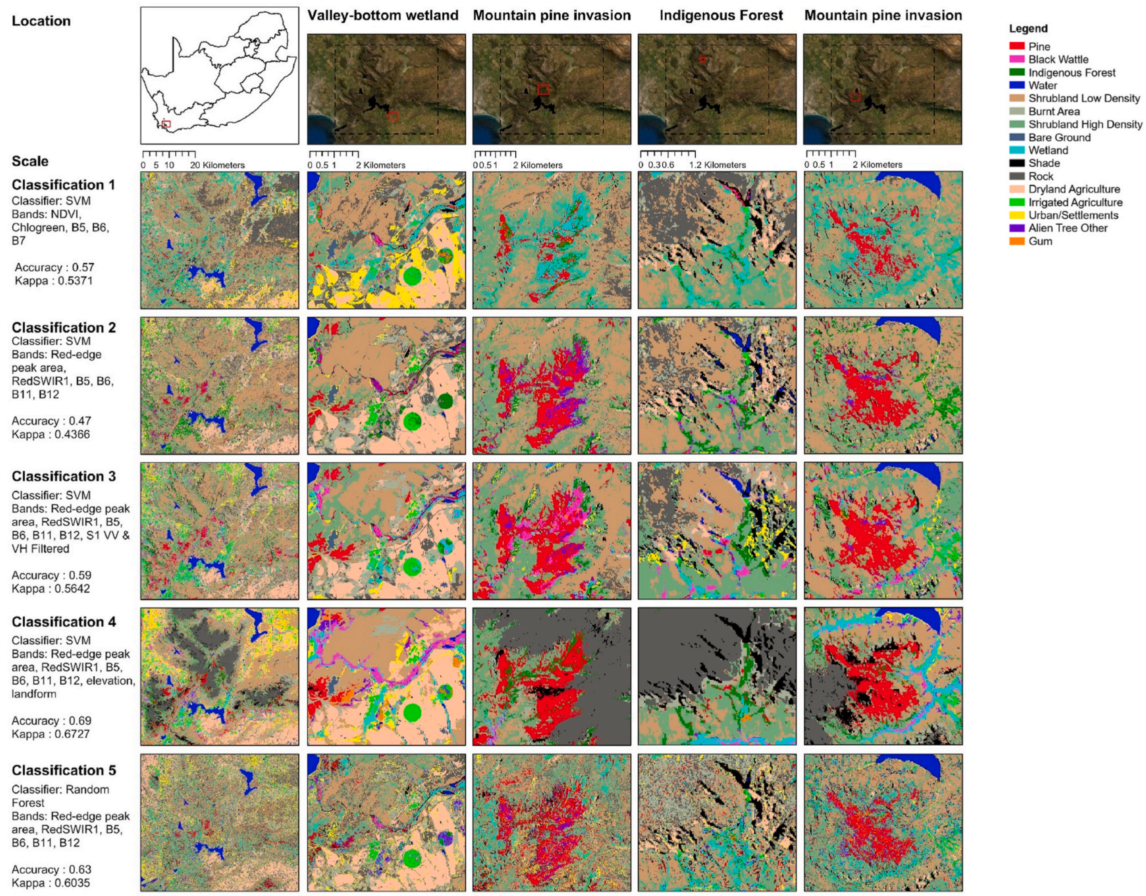

Fig. 3. The full classification result and statistics (overall and Kappa Statistic) for 16 landcover classes. The panels provide a comparison of five different classification results (rows 2–6) displayed spatially for the whole scene (column 1), and for four areas of alien infestations in: a valley-bottom wetland (column 2), the mountains upstream of the Theewaterskloof Dam (column 3), the fire-protected gorges of the Molenaars River (indigenous forest) (column 4), and the mountains upstream of the Berg River Dam (column 5). The location and scale of each scene (or column) is shown above (row 1). The Accuracy and Kappa statistics are for the validation results (30% of training data).

we performed statistical comparisons of the reflectance and index values extracted for each training data point across the 16 land cover/land use classes for each of the 10 Sentinel-2 bands that are useful for vegetation classification (out of 13 bands) and 39 derived indices (Tables S1 and S2) (Belgiu and Drăguţ 2016). We were interested in determining which combination of bands and indices would be useful in distinguishing the invasive alien tree species from each other as well as from the other 12 land cover/use classes.

We performed the spectral analysis on the full training dataset (i.e. total of 4320 points) as these are pure pixels that have been ground-truthed through field trips and drone flights. Specifically, for each of our 4320 training data points, we extracted the reflectance and index value, respectively, for all bands and indices. This resulted in 43 200 (10 $\times$ 4320) reflectance values and 168 480 (39 $\times$ 4320) index values i.e. in all cases 270 reflectance and index values for each of the 16 land cover/land use classes.

We performed a non-parametric Kruskal-Wallis test in R, due to normality being violated in most land cover/land use classes, to determine whether the differences in reflectance and the value between land cover/land use classes were significant for each band, and for each index, respectively (Holland and Wolfe 1973). We also performed Dunn's test for pairwise multiple comparisons for each band and all the indices (Dunn 1964; R Core Team 2016; Kassambara 2019). We present the results of the analyses using box-and-whisker plots for all calculated indices and Sentinel-2 bands for each of the key vegetation land cover/land use classes generated for the training data (270 points per class). We also show the range and mean of spectral signatures for all land cover/land use classes. We present the H statistics in Table S3 and Table S4.

We compared the results of our approach to that of another feature selection technique: the M-statistic (Kaufman and Remer, 2002), and the results were similar, therefore we only present the results of our approach here. The M-Statistic is calculated by dividing the difference of the means of spectra of the two LULC groups being compared, by the sum of their standard deviations (Kaufman and Remer, 2002). There was good agreement on the results for the bands, so we did not repeat this for all the indices and continued with our approach (Table S5).

2.2.5. *Accuracy assessment*

An independent validation dataset was generated by randomly splitting the training data into 70% for training and 30% for validation. A confusion matrix was generated for each classification iteration. We present total accuracy, the Kappa statistic and producer and consumers accuracy for the six different classification iterations described in 2.2.4.1. for: (a) all land cover/land use classes, and total accuracy and Kappa statistic for: (b) woody invasive alien plants (IAP) versus all other classes lumped together (IAP Accuracy), and (c) among these invasive alien tree classes (Intra IAP Accuracy) (Table S6 and Table S7).

2.2.6. *Comparison with existing invasive alien tree datasets used by managers and decision makers in South Africa*

We compare the classification results with two existing datasets with regional coverage which are currently used for prioritising funding and implementation of alien clearing efforts. These are the national scale

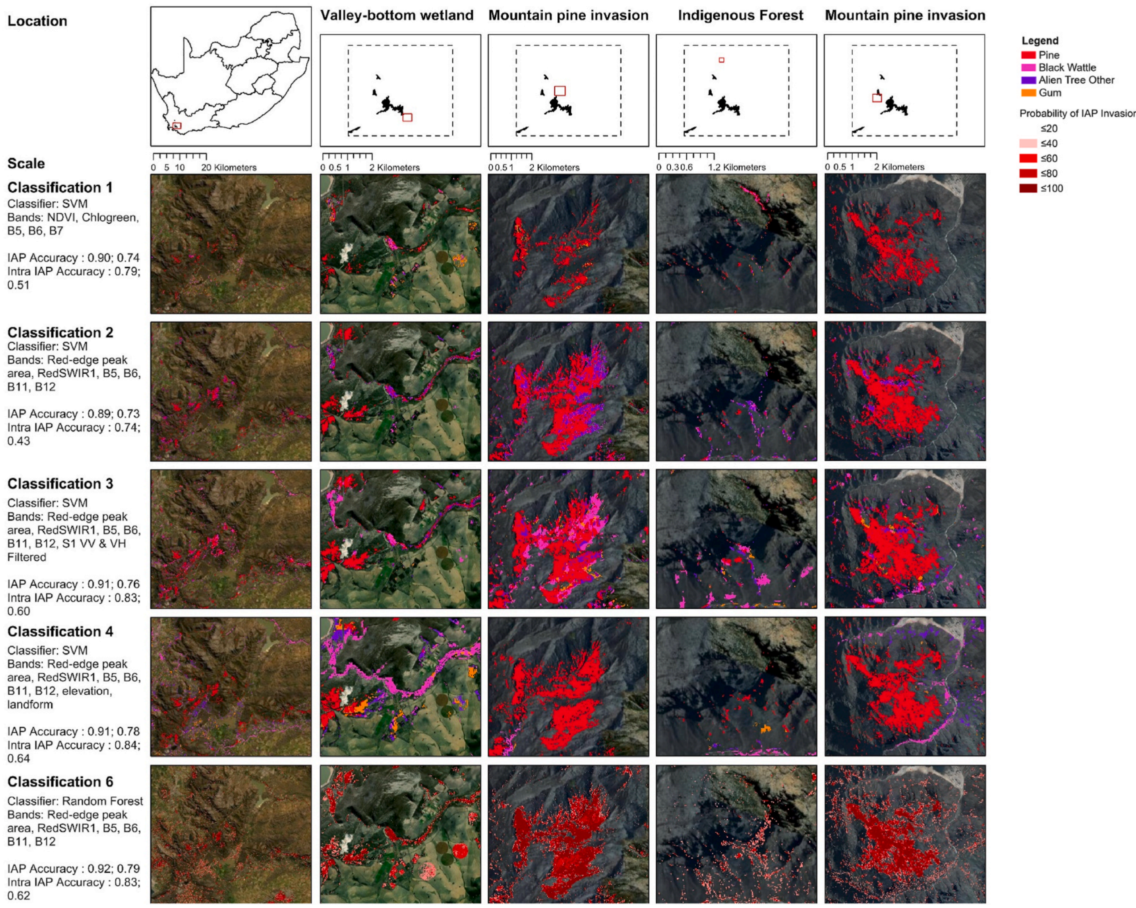

Fig. 4. The classification results for invasive alien trees only (4 classes). The Accuracy and Kappa statistics are indicated for the validation results (30% of training data) for discrimination ability among woody invasive alien plants (IAP) and all other land cover/land use classes ('IAP Accuracy'), and discrimination ability among woody invasive alien plants classes ('Intra IAP Accuracy') respectively. The panels provide a comparison of five different classification results (rows 2–6) displayed spatially for the whole scene (column 1), and for four areas of alien infestations in: a valley-bottom wetland (column 2), the mountains upstream of the Theewaterskloof Dam (column 3), the fire-protected gorges of the Molenaars River (indigenous forest) (column 4), and the mountains upstream of the Berg River Dam (column 5). The location and scale of each scene (or column) is shown above (row 1). For the Random Forest classification, this time the probability of infestation is shown (for all invasive alien trees) to provide an additional level of comparison, and not presence/absence for the four classes, therefore Classification 5 is not shown, but rather Classification 6.

alien tree map dating from 2008 with a spatial resolution of 250 m × 250 m (Kotzé et al., 2010) and the Natural Biological Alien Land-cover Attribute (NBAL) datasets, which are defined management units for which managers make annual estimates of the density of alien tree infestations. The NBAL dataset has a similar date to the classification results (i.e. the NBAL estimates are from 2018 and the Sentinel-2 imagery date is January 2019), the Kotzé et al. (2010) estimates are from 2008. We compare results visually with the three best performing classifications: 3, 4 and 6, and quantitatively with the best result (both in terms of statistics and a visual assessment), classification 3.

We compared these three alien tree datasets by aggregating the results to the coarsest mapping unit, in this case the managers dataset (NBAL polygons). This was done in both cases (for the national alien map and our classification 3 results) by summarising the raster units within polygons (taking the mean density). Imperfect overlap between the raster grids and the polygons may lead to some error in the results, however given the other sources of error in the other datasets, this should be sufficient for comparison. The national alien map results are given as average densities, however the classification results from this study are not. Therefore, to be able to compare results, an assumption was made that the presence/absence classification results could be averaged within polygons to obtain an indicator for density (%). Given that the classification results output is presence (1)/absence (0), this is not true density within the polygon (i.e. there may be 100% of pixels with >50% likelihood of being an invasive alien tree, and therefore 100% density would be calculated, when it is really 100% coverage at 50% density). Therefore there may be a slight overestimation of alien tree density at medium densities and high coverage, and slight underestimations at low densities and low coverage, but in most other instances the assumption holds well.

This analysis was performed for 898 polygons. The summary statistics were calculated: (a) overall for all polygons, (b) for low density invasions according to our classification results (zero invasions or <20% density recorded), and (c) for high density invasions according to our classification results (>60% and >80% density). The two existing datasets were compared to the classification 3 results using Pearson correlations (r).

3. Results

The results are presented in four sections, each addressing specific questions: 3.1 Can sentinel imagery be used for land cover/land use mapping in this region? 3.2 Can Sentinel imagery be used to discriminate invasive alien trees? 3.3 How do the results compare with existing datasets? and 3.4 What is important for operationalising remote sensing efforts into management and decision-making?

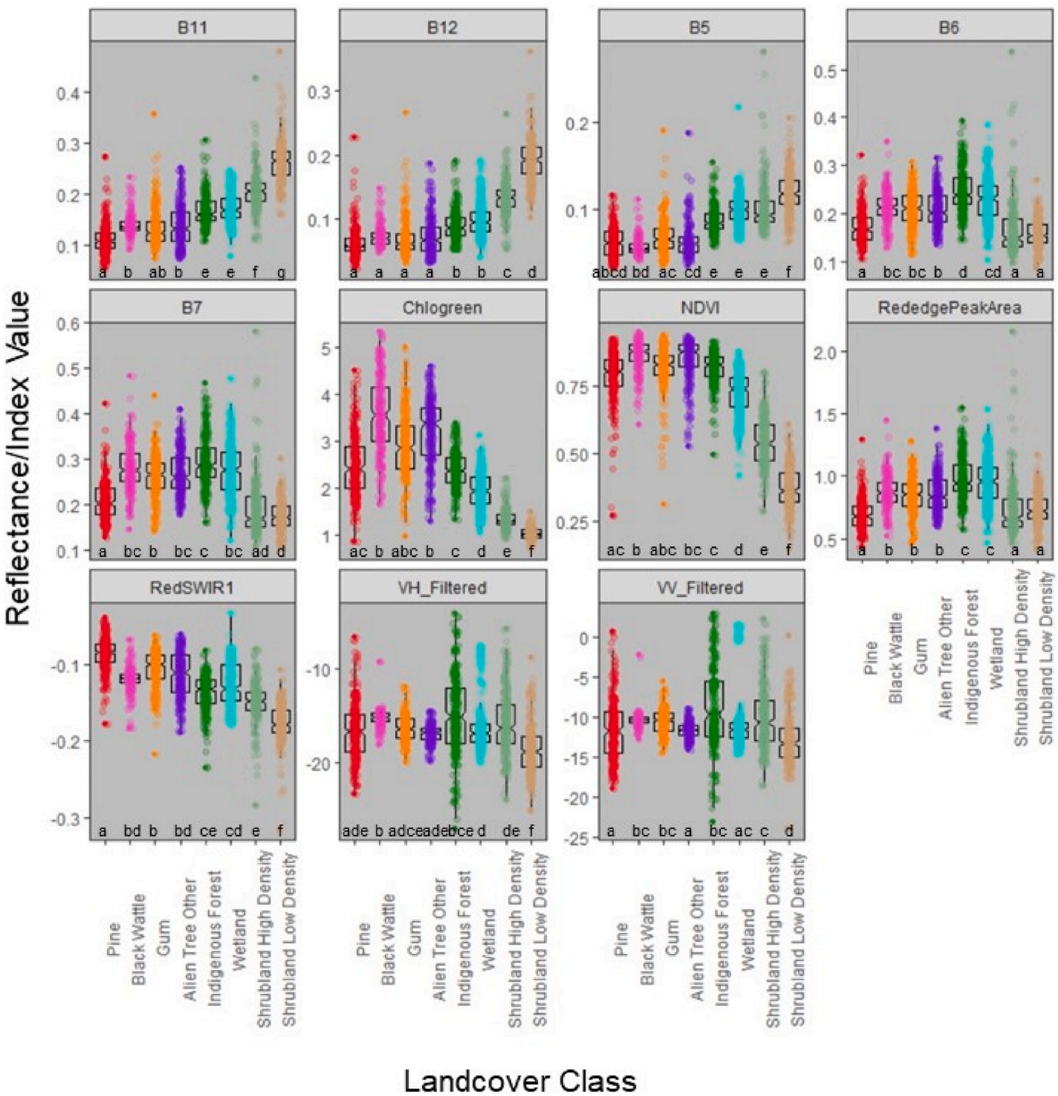

Fig. 5. The range and box-and-whisker plots for all bands and indices included in the classification iterations. Plots are shown for each of the key vegetation land cover/land use classes generated for the training data (270 points per class) for the Sentinel-2 scene acquired for January 6, 2019. The key vegetation land cover/land use classes are four alien tree classes: Pine, Black Wattle, Gum, Alien Tree Other, and four indigenous vegetation classes: Indigenous Forest, Wetland, and Shrubland Low and High Density. Land cover/land use classes that do not share a letter within each index (facet) are significantly different at $p < 0.05$ based on multiple comparisons (For full names of indices see Table S2, and Table S4 for H statistics). See Figures S4, S5 and S6 for the full results for all bands and indices.

3.1. Can Sentinel imagery be used for land cover/land use mapping in this region?

The first classification appears to have under-classified invasive alien trees, both in the mountains and in the wetlands (Fig. 3). This combination of bands and indices do not successfully discriminate indigenous forest from alien trees, particularly pines. This classification separates shade from water well, but over-estimates wetlands and urban/settlements. The second classification, using statistically selected bands and indices, appears to better discriminate alien invasion in the mountains, though perhaps underestimating invasion in the wetlands. Classification 2 outperforms classification 1 in mapping wetlands, and in separating urban/settlements from dryland agriculture, however it does not succeed in discriminating indigenous forest from irrigated agriculture. Classification 2 also fails to detect the uniform pine infestations in the mountains, identifying part of the infestation as ‘Alien Tree Other’. Whether this is a result of different age classes of pines in the mountain, or other factors, is not clear.

The results of the third classification, which takes into account biomass or vegetation density through fusion of synthetic aperture radar data, produces less ecologically sensible results, with a much patchier output. For example: wetland, indigenous forest and irrigated agriculture within one central pivot, which should just be irrigated agriculture, or urban/settlements being confused with rock in the mountains. Another issue is the false classification of Black Wattle in the mountains, instead of pine. In reality, Black Wattle is almost exclusively confined to riparian zones. Both classifications 2 and 3 perform well at detecting Black Wattle in the wetlands, though the third classification does better at detecting the wetlands adjacent to the Black Wattle. Classification 4 incorporates topographic information and produces an interesting effect, limiting urban/settlements in the mountain, with much less mixing of classes (more aggregated and distinct spatial arrangements). This approach works well for detecting Black Wattle in the riparian zones, and pines on the mountains, as well as discriminating water and shade from mountain cliffs. It makes less sense for dominant indigenous vegetation types, such as shrubland high density and low density as well as Rocks, the latter two classes which are over-classified. Classification 5, using the Random Forest (RF) classifier, is also extremely patchy, but overall invasive alien trees appear to be well discriminated.

Classifications 6, 3 and 4 perform best in discriminating invasive

Table 1
A comparison of the density (%) of invasive alien tree (IAT) cover for the three available alien tree datasets for the Berg and Breede catchments, South Africa, the National Biological Alien Land-cover Attribute (NBAL) management dataset from 2018, the national-scale invasive alien plant map from 2008 (Kotzé et al., 2010)), and classification results from 2019 (Classification 3). Summary statistics are given overall for all NBAL polygons, for low density invasions according to classification results (zero invasions or <20% density recorded), and for high density invasions according to classification results (>60% and >80% density). Colour scales are shown for mean values, from green (0%) to red (100%).

	Summary Statistics	Kotze IATs	NBAL IATs	SEBEI IATs
	Date of dataset	2008	2018	2019
Overall	Mean	11.4	17.7	19.7
	Max	72.6	90.0	100.0
	Min	0.0	0.0	0.0
	StDev	12.0	19.2	24.8
For low densities (zero)	Mean	12.0	13.4	0.0
	Max	47.4	70.0	0.0
	Min	0.0	0.0	0.0
	StDev	10.7	18.8	0.0
For low densities (<20%)	Mean	12.0	15.7	4.9
	Max	72.6	90.0	19.9
	Min	0.0	0.0	0.0
	StDev	12.9	18.4	5.5
For high densities (>60%)	Mean	9.1	29.3	76.5
	Max	16.0	77.0	100.0
	Min	0.0	0.0	60.7
	StDev	7.1	21.9	12.5
For high densities (>80%)	Mean	8.1	32.8	91.2
	Max	16.0	75.0	100.0
	Min	0.0	1.0	82.5
	StDev	7.5	20.8	5.8

alien trees from the other 12 classes (92%, 91%, and 91% respectively) (Fig. 4). Discriminating between alien tree classes is less successful in terms of accuracy results, however the same three classifications perform best, yielding accuracies of 84%, 83%, 83% for classifications 4, 3, and 6 respectively.

3.2. Can Sentinel imagery be used to discriminate invasive alien trees?

We compared the spectral signatures of the four invasive alien tree classes to that of indigenous vegetation and each other for ten Sentinel-2 bands, two Sentinel-1 bands and 39 indices. We also compared the spectral signatures between the four invasive alien tree classes.

At first glance, the spectral signatures for the invasive alien tree classes seem similar to indigenous vegetation, especially indigenous forest and wetland (Fig. 5, Fig. S2; Fig. S3), however there are some important differences, notably the Red Edge Peak Area and Red – SWIR Bands Difference indices have high discriminatory power (Fig. S4) as well as bands 5, 6, 11, 12 (Fig. S5). There is higher intra-class variation in the spectral signatures than inter-class variation for the four invasive alien classes and shrubland high density and low density, indigenous forest and wetland which weakens the possibility of discrimination. None of the Sentinel-1 bands appeared particularly useful for discrimination (Fig. S6).

None of the bands or indices were able to totally separate the four invasive alien classes. Pines were more easily discriminated from the other three invasive alien classes which are generally quite similar spectrally. For the bands or indices that pines were separable from one or more of the other three invasive alien classes, they were not separable from either indigenous forests or wetlands. This made these bands or indices not suitable in general for intra-alien class discrimination.

3.3. How do the results compare with existing datasets?

Both existing datasets (the NBAL 2018 map and the 2008 national invasive alien plant map) have higher invasive alien tree density than the classification results at low densities, and have lower invasive alien tree density at high densities (Table 1, Fig. 6), and are poorly correlated with the classification results ($R^2 = 0.06$ and $= 0.006$ respectively). The national invasive alien plant map, now ten years out of date, has the lowest densities of invasive alien trees in the Berg-Breede region overall (Kotzé et al., 2010). The discrepancies between the classification results and the recent NBAL dataset may be due to the coarse spatial scale at which the NBAL density estimates are summarised. For example, the average NBAL polygon size is 1.06 km^2 (range: 0.003 km^2–16.15 km^2) in comparison to 0.0001 km^2 grid resolution used for the classifications in this study (Table 1).

3.4. What is important for operationalising remote sensing efforts into management and decision-making?

Stakeholder engagements revealed that i) understanding of how the alien map product was generated; and ii) involvement in the validation using their local knowledge; led to increased expressed confidence in the product. Stakeholders recommended that ground-truthing results be presented with the final product in a way that the output could also be evaluated by users. Stakeholders found fine-scale drone imagery to be a suitable replacement approach when in-field methods were not feasible (Fig. 7).

Our final engagement with local and regional managers, co-ordinators, and decision makers in the study region was to compile a ‘wish-list’ for an invasive alien plant map. From this engagement, it emerged that providing presence-absence spatial data is just a small step

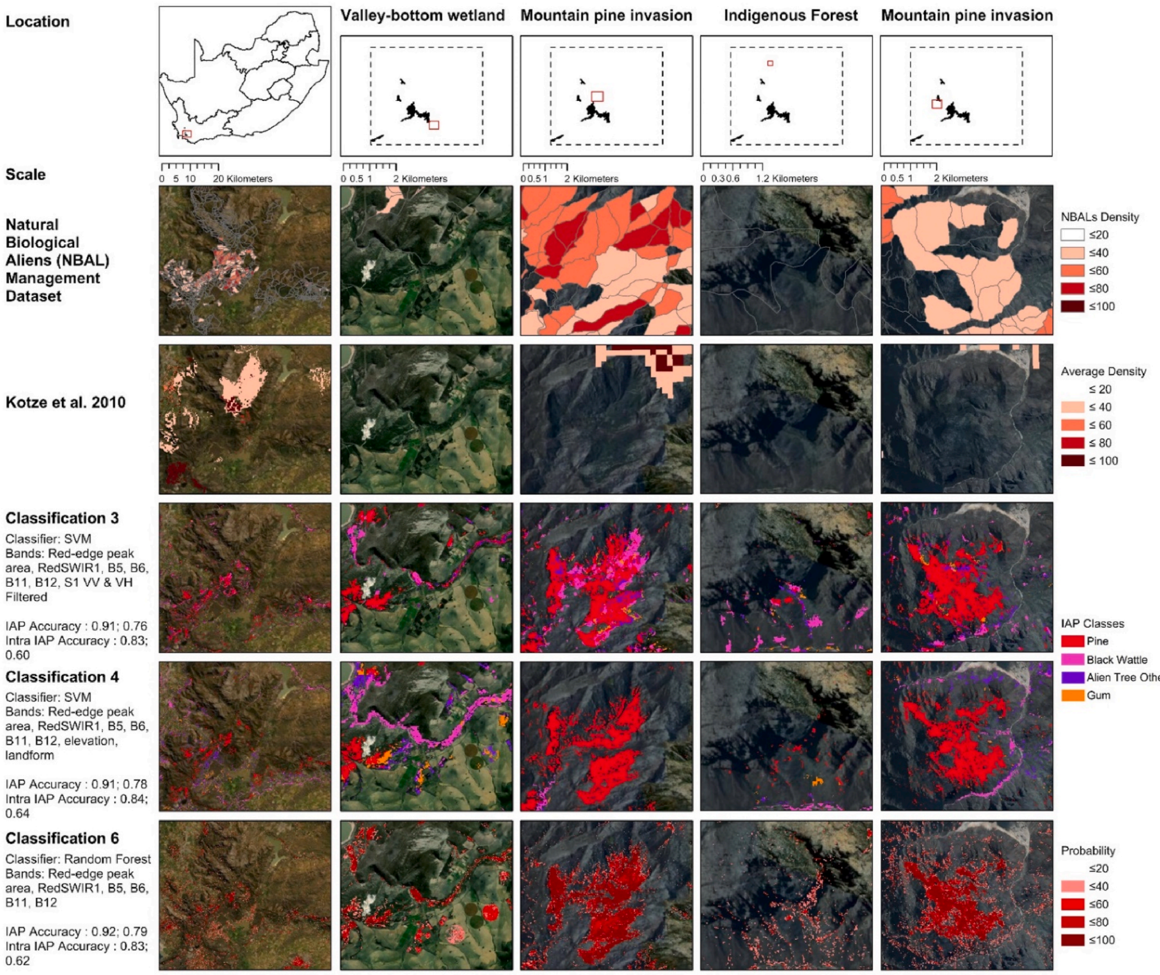

Fig. 6. A comparison of the three best classification outputs (Fig. 4) with the two existing datasets for managers and decision makers: The Natural Biological Alien Land-cover Attribute (NBAL) dataset, and the Kotze et al., (2010) national alien map. The locations are the same as in Figs. 4 and 5, in the Berg and Breede catchments of South Africa. The first two rows are densities of invasive alien trees, the second two rows are presence/absence from the four classes, and the final row is probability of invasive alien tree occurrence.

forward in what is required to inform managers' implementation and coordination efforts (Table S8). Information on species, age and density classes were highlighted as some of the most important information needed in a map, as it informs management decisions (e.g. type of intervention, whether herbicide is appliedor not and the type of team and equipment required). The most important users were identified as managers and landowners, and the primary purpose that was considered the most important was that of monitoring and evaluation, with prioritization and costing identified as the next most important. Drone technology was considered by stakeholders to be the most promising method to assist the process of operationalising remote sensing products in management (Fig. 7). Lastly, repeatable workflows, that could provide a way for managers and decision makers to update remote sensing products were seen as critical in the process of operationalising remote sensing research in the management of alien species in the region. The lack of access to other spatial datasets also emerged as a limit for the region (e.g. information on slope, cadastral information, and distance from roads).

4. Discussion

This study highlights the potential of using Sentinel-2 imagery for discriminating between invasive alien trees and indigenous shrubland vegetation in areas of strategic water importance in the southwestern Cape of South Africa.

Repeatable landscape scale mapping covering large areas is a priority for managers and decision makers in South Africa faced with the challenge of allocating limited resources (Royimani et al., 2018). Multispectral satellite sensors provide larger coverage areas, higher revisit times, are easier to process, and have more available archived images in comparison to manned or unmanned aircraft approaches (Paz-Kagan et al., 2019). The processing power of Google Earth Engine enables users to access, view and process multiple images for repeatable, long-term and largescale mapping of invasive tree coverages (Vaz et al., 2019). Incorporating drone technology using a low cost approach emerges as a successful strategy for improving user confidence in remote sensing processes and products by managers and decision makers (Kattenborn et al., 2019). Using drones for targeted locations within a larger area for collecting and ground-truthing training data significantly reduces costs and logistics when compared to the use of drones for systematic landscape scale mapping. The classification results can further be used as a guide for management, for targeted drone or other high resolution imagery acquisition.

According to accuracy statistics, selecting bands based on our analysis of spectral signatures did not improve the classification results. The accuracy statistics may be misleading, however, as visual interpretation of the findings reveal that the classification informed by the analysis of spectral signatures performs far better in capturing the full, known, spatial extent of invasive alien trees in the mountains. This highlights the critical importance of ecological knowledge in interpreting remote

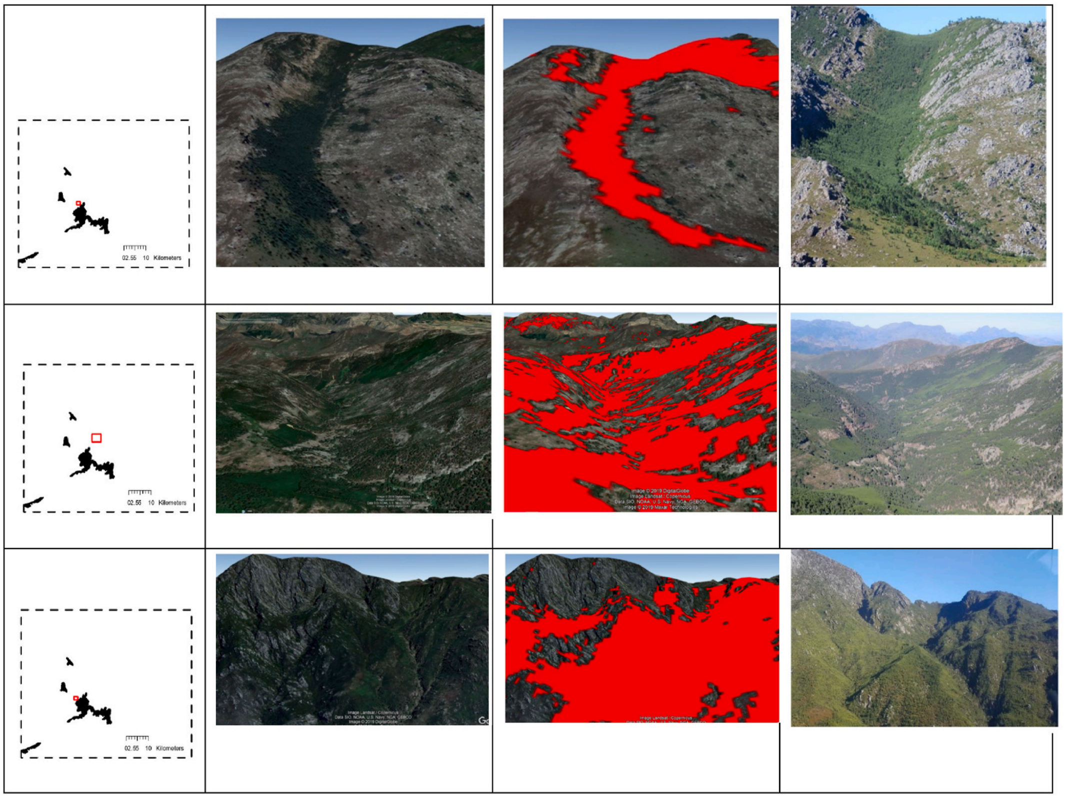

Fig. 7. Comparison of classification results with Google Earth Imagery and drone footage for three locations in the Berg and Breede catchments, South Africa. Drone footage (far right panel) inspired confidence in the classification results amongst stakeholders. The location is given relative to the Western Cape Water Supply System (see Fig. 1 for reference).

sensing results for vegetation mapping, and cautions against over-reliance on accuracy statistics considering the relatively small sample sizes typically used in multispectral classifications. Including backscatter inputs from Sentinel-1 did improve classification results, especially for the overall classification, but not for invasive alien trees. Adding topographic information as bands was one of the most effective techniques according to the accuracy statistics, especially for the overall classification. However, both Sentinel-1 and topographic information did not significantly improve the ability to discriminate between classes of invasive alien trees. In this study we used a univariate statistical approach along with visual and ecological interpretation for feature selection. Future work could consider exploring alternative feature selection approaches, such as multivariate linear discriminant analyses, amongst others (Belgiu and Drăguţ 2016).

According to the spectral analysis, the part of the spectrum that was the most useful to distinguish between invasive alien trees and indigenous shrubland vegetation was the red edge and shortwave infrared regions. The potential of these bands for distinguishing between forest species has been shown by recent European studies (Grabska et al., 2019; Immitzer et al., 2019). The rred edge region of the spectrum is known to be useful in distinguishing tree types, and traits such as biomass, leaf area index, amongst others (Hunt et al., 2016). The shortwave infrared region corresponds to the major known water absorption features of the spectrum, which suggests that these land cover/land use classes have significantly different water content and therefore water use characteristics (Seelig et al., 2008; Thenkabail et al. 2013, 2015; Ali et al., 2019). Sentinel-2 bands 5 and 6, which were also useful in discriminating invasive alien trees, are mainly associated with variations in chlorophyll content (Filipponi 2018). Other recent studies have also successfully shown that using Sentinel-2, sometimes combined with other creative inputs such as vegetation traits, Sentinel-1 backscatter, or temporal aggregation, results in highly accurate vegetation maps (Clerici et al., 2017; Van Tricht et al., 2018; Carrasco et al., 2019; Mudereri et al., 2019). Another study investigating the value of Sentinel-2 and Sentinel 1 imagery in vegetation classifications concluded that the spectral (Sentinel-2) data outperform synthetic aperture radar data (Kattenborn et al., 2019).

4.1. Operationalisation of remote sensing into invasive alien tree management

Using a transdisciplinary approach is one of the most widely reported ways to successfully connect scholars to society and translate research into action (Knapp et al., 2019). The findings from our study highlight that the type of engagement and materials used and provided to stakeholders is of critical importance to build confidence in the process and final products. The importance of building trust between researchers and stakeholders has been shown to be essential in facilitating knowledge transfer in university-industry partnerships (De Wit-De Vries et al., 2019). We highlight the importance of ongoing engagement between researchers and stakeholders from the start. We found that drone imagery provides a useful tool for managers and decision makers to evaluate classification outputs and management datasets . Therefore, we propose that drone technology is not only useful for improving the training data for running classifications (Kassambara 2019), it also plays a major role as a tool in transdisciplinary engagement with stakeholders. The value of drone imagery was in its ability to provide footage at an oblique angle (i.e. a side view of alien tree infestations), which aided species identification. Despite only obtaining drone imagery for key points in the area of interest, showing the drone imagery and enabling managers and decision makers to compare it to the 20 m satellite imagery data and Google Earth imagery, built confidence in the process and product.

The resulting maps of this study are a substantial improvement to the

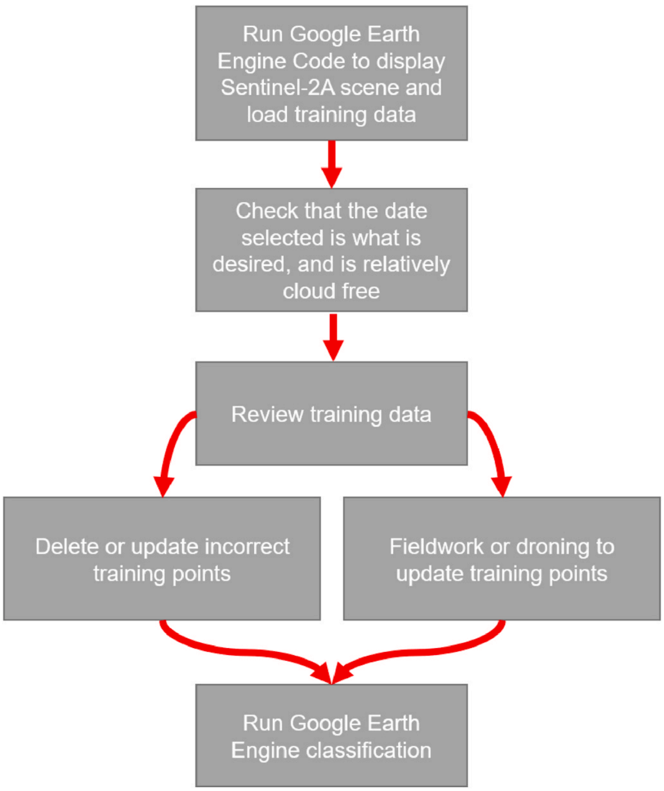

Fig. 8. Suggested workflow to ensure that the invasive alien tree map for the Berg-Breede region of South Africa is a repeatable, and up-to-date process rather than a static map. The code and training data needed are made available (Table S9 and Table S10).

existing datasets used by stakeholders in the region in both spatial resolution and date. The top performing classifications generated in this study mostly had higher values of invasion in comparison to existing management datasets and were poorly correlated with them. These existing management datasets may also be overestimating invasive alien trees in places, and underestimating them in densely infested areas. This is similar to findings of comparisons made between these existing management datasets and systematic plot surveys in a neighbouring national park (Cheney et al., 2018). Using probability instead of presence/absence adds extra information that could be used as proxy for density of invasive alien trees, but more research is needed to validate this assumption.

One of the aims of this research was to develop an approach to detect and map invasive alien trees in the Berg-Breede region, in the southwestern part of South Africa, that is cost effective, easy to use, inclusive, and repeatable. One of the major limitations to uptake of remote sensing applications into practice in South Africa has been identified as lack of available workflows in the literature (Foxcroft et al., 2020). To this end we provide a simple workflow that managers can use that wraps the static 2019 invasive alien map into a repeatable framework (Fig. 8). We provide the necessary code and training data (Table S9 and Table S10). Firstly, code should be run in Google Earth Engine to display the desired Sentinel-2 scene and to load the collected training data. The imagery is filtered by a cloud cover function, and therefore it is important that stakeholders check that the date produced is useful for their specific purpose, particularly if the interest is an updated map following a fire event or another major land cover/land use change.

Once the desired image has been identified and displayed, the training data can be overlaid as points. These training data should be systematically reviewed, using the updated imagery, on a point-by-point basis, paying careful attention to changes in the landscape, especially as a result of fires, or alien clearing efforts. We recommend that this be done in a geographic information system, so that attribute data can be updated, however it can also be done in Google Earth Engine if stakeholders do not have access to other software. All points that have changed should be deleted or updated to the correct land cover/land use (i.e. if a fire has burnt through a region, or if a field has been allowed to lie fallow, then these training data are no longer correct). Particular care should be taken at the edges of invasions of alien trees, due to spreading into adjacent natural areas over time. Once changed points are all deleted or updated, good practise would suggest that any lost training data needs to be collected again to total 270 points per land cover/land use class, or another selected even number per class. When this has been done, the full classification can be run in Google Earth Engine using the code provided.

5. Conclusion

We show the importance of using a transdisciplinary approach along with freely available satellite imagery and Google Earth Engine processing power for operationalising remote sensing in the management of alien tree invasions in key water towers of South Africa. Due to high spatial resolutions, drone technology provides a way to build confidence in the mapping process and outputs by managers and decision makers. This research provides a major improvement to existing mapping processes and products in the region. We also provide a simple, repeatable framework for users to update mapping products after disturbance or change in the region. Further efforts are required to achieve seamless integration of remote sensing processes and products into management of invasive alien plants. This requires an active learning process that engages researchers, managers and decision makers, which will not happen unless funding and time is made available for transdisciplinary, applied remote sensing research.

CRediT author statement

Alanna Rebelo & Petra Holden: Conceptualization, Methodology, Data curation, Writing- Original draft preparation, Visualization, Analysis, Reviewing and Editing.

Mark New: Supervision, Reviewing.

Ethical statement

The authors declare that all ethical practices have been followed in relation to the development, writing, and publication of the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2020.100448.

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