The efficiency of drone technology vs. ground-based methodologies for evaluating the density and distribution of invasive alien vegetation

Figure 1. *Acacia Mearnsii* (left), the drone flying at the Lomond study site (middle), and *Acacia Saligna* (right)

Lauren Searle

Supervisor: Charl Deacon

Co-supervisors: Julia van Schalkwyk, Kirsten Watson, James Pryke

Department of Conservation Ecology, Stellenbosch University

9th November 2021

UNIVERSITEIT STELLENBOSCH UNIVERSITY

Abstract

Invasive alien plants (IAPs) pose a significant threat to indigenous biodiversity in the Cape Floristic Region (CFR). Recently, drones have been suggested to aid the mitigation of this threat as they allow for rapid and effective monitoring of IAP density. However, before drone technology can be integrated into IAP removal programs, some validation is required to understand how the interpretation of drone-imagery compares to traditional ground-based sampling techniques. Therefore, the overall aim of this study was to determine whether drone technology was more efficient at estimating IAP density compared to traditional ground-based sampling. To achieve this, across ten study sites, three IAP density estimates were compared: (1) density estimates calculated from stem counts and percentage area covered by IAPs during ground surveys, (2) density estimates calculated manually from drone imagery, and (3) density estimates calculated automatically by using the random forest classification algorithm. The results indicated that drone-based methods produced IAP density estimates more representative of the study sites compared ground sampling techniques. Furthermore, the results showed that automatic classification was the least time-consuming method, whereas manual digitization was the most time-consuming. The findings of this study indicated that field-based surveys require a considerable investment of time and effort, whilst producing relatively unreliable results. In contrast, drone technology can circumvent the disadvantages of ground-based surveys such as human error and biased data extrapolation, and produce accurate density estimates for IAPs. Additionally, the integration of drones into the toolkit of IAP removal programmes within the CFR region can lead to substantial savings regarding time, labour, and financial resources. Therefore, it is recommended that drone technology should be integrated into IAP removal programmes to improve the efficiency of alien plant removal.

Keywords: drone technology, invasive alien plants, unmanned aerial vehicle, random forest classification, vegetation mapping

---

1. Introduction

Invasive alien plants (IAPs) pose one of the greatest threats to native flora and fauna in South Africa. For instance, IAPs threaten native ecosystems by out-competing indigenous plant species thus changing the vegetation structure. Consequently, IAPs restrict native fauna from completing essential biological tasks such as creating nests, thermoregulating, migrating, and feeding (Clusella-Trullas and Garcia 2017). In turn, these changes alter ecosystem function and dynamics (Mostert et al. 2017; Ancin-Murguzur et al. 2020; Holmes et al. 2020). Through negatively impacting native ecosystems, IAPs degrade potential ecosystem goods, and reduce ecosystem service delivery (Gaertner et al. 2014; Holmes et al. 2020).

The issue of IAPs is extensive in South Africa, and invasions cover a local land area of 265000 ha in national parks and nature reserves alone (Holmes et al. 2020). A study of the Cape Floristic Region (CFR), falling within the most invaded province in the country, found that IAPs threaten more than 1000 native plant species (Cheney et al. 2019). To conserve the biodiversity of the CFR, effective IAP mitigation measures are urgently required. However, to mitigate the establishment and spread of IAPs, accurate information of their spatial distribution and density is mandatory (Royimani et al. 2019). This information is required to improve predictions of invasion and distribution patterns of IAPs for enhanced decision-making, optimal resource allocation, and overall effectiveness of control measures (Mararakanye et al. 2017; Royimani et al. 2019). Moreover, the earlier IAP populations are detected in the initial stages of invasion, the more cost-effective and efficient the removal process will be (Rejmánek 2000; Lehmann et al. 2017).

Conventionally, removal programmes use ground-based techniques to collect data on IAPs (Royimani et al. 2019). The most popular ground-based sampling techniques include quadrat sampling and line-transects. If done precisely, consistently and repeatedly, these techniques provide high-resolution data (Sutherland 2006; McNaught et al. 2018; Barnas et al. 2019). However, these laborious sampling techniques are often avoided due to time limitations, expenses, and resources required, especially for larger areas (Cheney et al. 2018). Furthermore, it can be logistically challenging to sample vegetation in remote or inaccessible areas (Barnas et al. 2019). These challenges may result in spatial variation in IAP data, as some areas cannot be surveyed (Barnas et al. 2019). Consequently, invasion processes and stages of invasions may be poorly defined, resulting in biased conclusions on trends of the spread and distribution of IAPs (Barnas et al. 2019).

A promising solution to these limitations of ground-based sampling and the requirements of IAP removal programmes is the dawn of drone technology (Anderson and Gaston 2013; Barnas et al. 2019). Drones are unmanned, remotely controlled aircrafts that can collect spatial data over large areas while using very little resources. In recent years, drones have become progressively popular in ecological research and conservation because of their ability to be easily deployed, their effortless operation, and high spatio-temporal resolution compared to remote sensing imagery (Müllerová 2019). They can complete vegetation surveys rapidly (Lehmann et al. 2017), allowing for the timely detection of IAPs, therefore, making monitoring and eradication efforts more efficient (Dvořák et al. 2015). Additionally, the flight paths that are created are repeatable, thus allowing users to conduct future surveys without introducing spatial variation (Lehmann et al. 2017). IAP species are ideal candidates for surveillance by drones as they are typically fast-growing species with a high biomass and reproduction rate, therefore forming large monospecific stands which are easily detected through aerial imagery (Leishman et al. 2007; Müllerová 2019).

The use of drones to detect and monitor IAPs is economical, flexible, and faster (Lehmann et al. 2017). However, according to Lehman *et al*. (2017), not many land managers are currently using drone technology due to high acquisition costs or a lack of ability in operating drone systems. Furthermore, South African drone flights are controlled by the South African Civil Aviation Authority (SACAA) who have established excessive barriers to the use of drones in ecological research. The SACAA have done this by creating numerous restrictions on how and where drone flights can take place, as well as made it expensive to become legally compliant with the restrictions. Another possible setback of utilizing drones is the complexity of detecting small individual invasive plant species from aerial images (Müllerová 2019). This is crucial from a management perspective as these undetected IAPs can act as dispersal foci in habitats (Müllerová 2019). Even though drone technology may solve the limitations put forth by ground-based sampling, it is evident that it still has its setbacks. Therefore, before drone technology can be integrated into the toolkit of IAP removal programs, a validation study is required to understand how the interpretation of drone-imagery compares to traditional ground-based sampling techniques.

Using a comparative approach, the overall aim of this study was to determine whether drone technology is more efficient in estimating IAP density and spatial distribution than traditional ground-based sampling. To achieve this, the following research questions were posed: (1) Which method (drone-technology vs. traditional ground-based sampling) provides the most reliable density estimation of IAP cover relative to one another, and (2) which of the two methods are more time-efficient in collecting data across the proposed survey areas?

Under the first research question, it was hypothesized that drone technology provides better estimations of IAP density, as drone imagery encompasses entire areas. This is relative to traditional ground-based sampling methods, such as quadrat surveys or line-transects, where only small portions of land are surveyed to make approximations for larger areas. Although ground-based sampling methods may provide detailed biological information on particular alien species, quadrats placed outside of areas with IAPs will cause the results to falsely indicate that there are no or fewer IAPs in the study area than truly present. Under the second research question, it was hypothesized that the use of drone technology is highly time efficient. Drones can be rapidly deployed and cover a great expanse more quickly. Unlike drone technology, ground-based sampling is time-consuming and requires more labour and comprehensive surveillance of the research area.

2. Methods:

2.1 Study area:

This study was conducted on Flower Valley Farm, Heidehof Farm, Fairfield Farm, and Lomond Farm where active IAP clearing programmes were taking place (Figure 2). These farms fall within the Agulhas Plain region, a lowland coastal region within the CFR at the Southern tip of South Africa (Figure 2). The region has an area of 2160 km^2 (Fourie et al. 2013) and is located amongst four inland (Elim, Bredasdorp, Napier, and Stanford) and five shoreside towns (Pearly Beach, Arniston, Struisbaai, Gansbaai, and Agulhas). Most of the region is privately owned and utilized for livestock or fynbos farms (Heydenrych 1999; Fourie et al. 2013). Only 9 % of the Agulhas Plain is formally protected by nature reserves (Conradie 2010; Fourie et al. 2013).

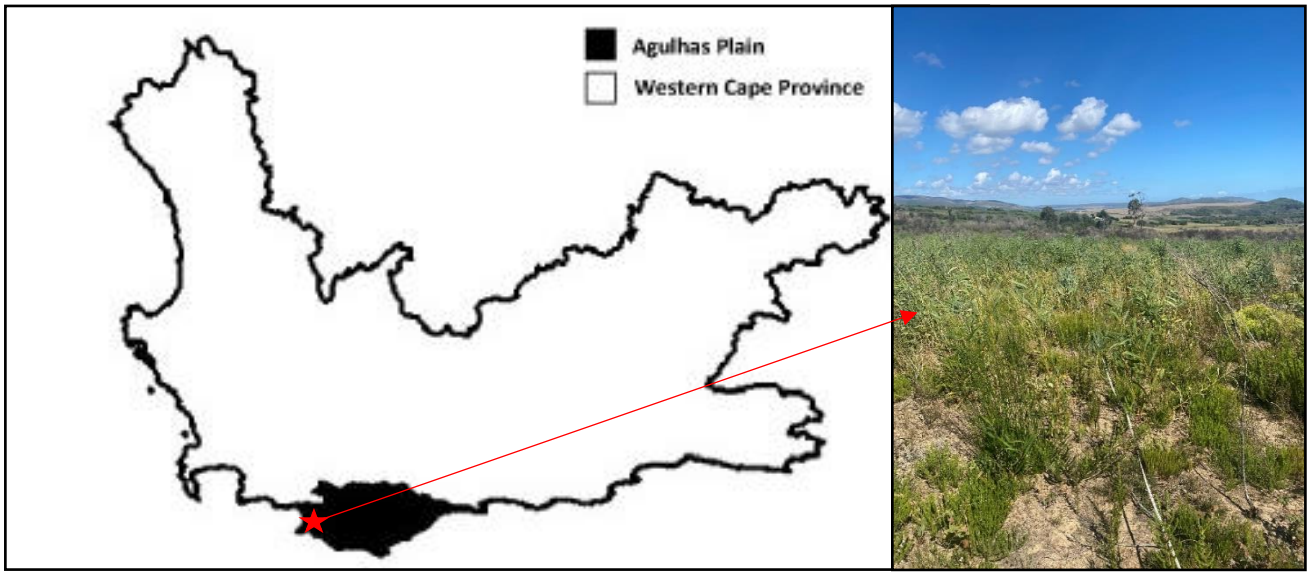


Figure 2. Left: The location of Flower Valley Farm and surroundings (red star) within the Agulhas Plain, Western Cape (Fourie et al. 2013). Right: Native and invasive plants of a site demarcated for IAP-removal on Flower Valley Farm.

As a result of the complex geology of the Agulhas Plain, the area is characterized by a wide variety of infertile soil types (Heydenrych 1999). There are many vegetation types in the region, such as Limestone Proteoid, Elim Asteraceous Fynbos, Restoid Fynbos, and Sand Proteoid vegetation types, which are considered highly threatened (Laubscher et al. 2009). These vegetation types prosper in the region's Mediterranean climate and are all prone to fire outbreaks (Fourie et al. 2013). Alien plant invasions and agricultural activities have altered much of the environment (Heydenrych 1999). The most common IAP species on the Agulhas Plain include *Acacia, Pinus, and Eucalyptus*. *Acacias* were initially introduced into the region as dune stabilizers, whereas *Eucalyptus* and *Pinus* were introduced for timber and plantations (Fourie et al. 2013). It is estimated that 31% of the Agulhas Plain has already been invaded by IAPs (Nowell 2011). As a result of the high plant endemism and prevalence of IAPs, the United Nation Development Programme describes the Agulhas Plain to have the greatest quantity of lowland threatened species within South Africa, thus, making it the highest priority for conservation (Laubscher et al. 2009).

2.2 Field sampling

To compare the effectiveness and time-efficiency between traditional ground-based methods and novel drone technology, three IAP density estimates were compared in this study: (1) density estimates calculated from ground surveys, further divided into density estimation through stem counts, and density estimation through percentage IAP cover, (2) density estimates calculated manually from drone imagery, and (3) density estimates calculated using an automatic classification algorithm. This study followed a similar protocol to Hill et al (2017), however, instead of the methods being conducted by separate teams, each method was performed by the same person to reduce user bias. Ten sites, each 1 ha in size, were selected based on where the IAPs were located, as well as where Flower Valley Conservation trust's IAP removal programmes were occurring. According to these criteria, five sites were chosen on Flower Valley farm, two sites on Heidehof farm, two sites on Lomond farm, and one on Fairfield farm. Field surveys and drone imagery collection took place simultaneously in January 2021.

Once the 10 sites were selected, DJI GSpro (SZ DJI TECHNOLOGY CO., LTD) was used to demarcate the sites remotely before going into the field. Following the demarcation of the sites, a flight path was designed to perform an aerial survey at each of the ten sites. The application also provided the coordinates of the site corners, which were used for the ground-based surveys.

2.2.2 Ground-based survey

In the field, a GPS was used to find the location of the sites; once identified, the corners were then marked to provide an outline of the study area. For each of the ten study sites, two 100m transects were laid down 30m from the right and left sides (Figure 3). Every 5m along the transects, and within a 50cm radius, the invasive alien plant species were identified, the stems of the IAPs were counted, and the percentage ground covered by vegetation as well as the percentage of alien plants were estimated. Furthermore, at each site, a description of the surrounding area (e.g., the texture of the soil or the presence of a slope), as well as any significant factors that influence the density of alien vegetation, were noted (e.g., noting that the site falls within a burn scar). These notes aided in obtaining a greater understanding of the surrounding environment that the data collected could not demonstrate. The data was recorded on a standard data sheet designed before the study was initiated (refer to Appendix A for datasheet template).

The information collected from ground surveys were then recorded onto a digital spreadsheet for further calculations. The density of the IAPs was calculated using the average stem count of each transect, whereafter these data were extrapolated to account for the entire sample site. The percentage

area covered by IAPs was calculated and extrapolated to account for the entire hectare study site to obtain the baseline density data.

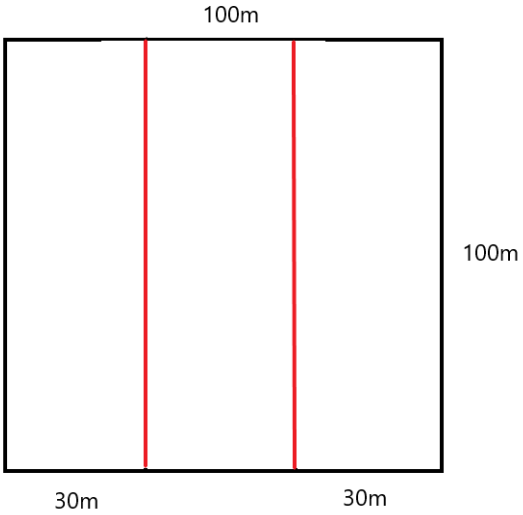


Figure 3. A schematic diagram showing the layout of a hectare study site (in black) with two line-transects for on-the-ground surveys (in red), 30m from each side.

2.2.1 Drone imagery collection

To map the vegetation cover of each survey site, drone flights were conducted using a multirotor DJI Phantom 4 Pro (diagonal size: 350mm, max speed: 72 km/h, Satellite positioning system: GPS/GLONASS). The Phantom 4 Pro is equipped with a 20-megapixel RGB camera. For each site, the drone followed the predefined flight plan designed in DJI GSpro (SZ DJI TECHNOLOGY CO., LTD). The standard settings for all flights can be found in Table 1. For each survey site, the drone took multiple photos along the flight plan (Figure 4). These orthophotos were then exported to the computer. Using the cloud-based drone imagery processing system Open Drone Map (webODM), the photos were then stitched together to produce red, green, and blue (RGB) colour composite orthomosaics of each site (Figure 5).

Table 1. The settings used for all drone flights for this study.

Parameter	Setting for drone Flight
Shooting angle	parallel to the main path
Capture mode	Hover & capture at point
Flight course mode	Inside mode
Speed	3.0 m/s
Height	60m
Front overlap ratio	75%
Side overlap ratio	75%

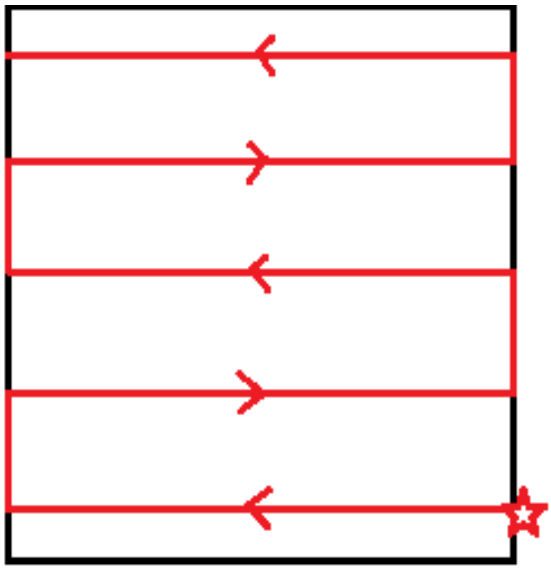


Figure 4. An example of a flight path plotted (red lines) within a study site (black). The red star indicates the starting position of the flight path.

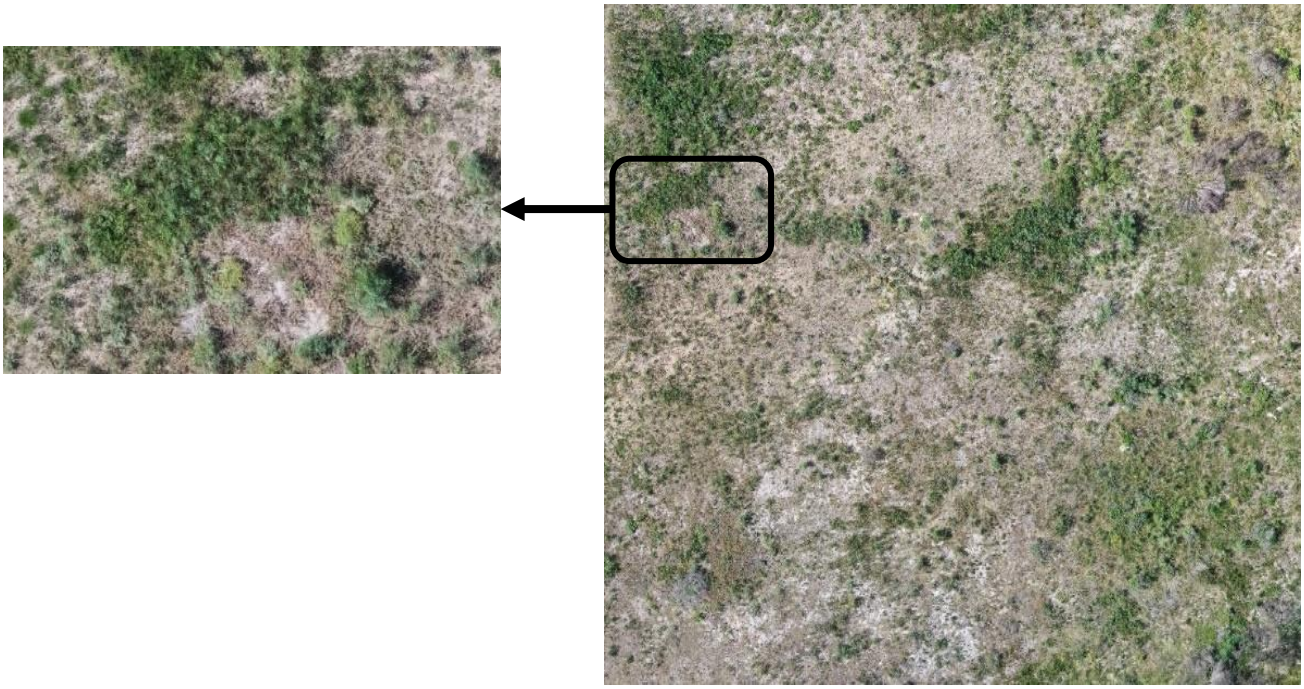


Figure 5. The orthomosaic produced from drone imagery of a study site on Flower Valley farm (right) with an example of the quality of the orthomosaic zoomed in (left).

2.2.3 Drone imagery manual classification

Firstly, the resulting orthomosaics from the drone surveys were used to manually identify the IAPs in the ten study sites. Because the IAPs form dense stands, they were easily visible on the 2cm resolution orthomosaic images (Figure 5). When a stand of IAPs was identified, its location was digitized by drawing spatial polygons in ArcMap version 10.7.1 (Redlands 2019). The polygons were drawn to encompass the leafy vegetation of the IAPs (Figure 6). Following this, the average IAP density in each site was calculated by adding the surface area measures of each polygon on each orthomosiac.

Figure 6. The first site on Flower Valley's orthomosaic post manual classification. The red indicates the outline of the polygon surrounding the IAP stands.

2.2.4 Drone imagery automated classification

All automatic classifications were performed in R (R Core Team 2021), using the *rgdal* (Bivand et al. 2021), *randomForest* (Liaw and Wiener 2002), *caret* (Kuhn et al. 2021), and *raster* (Hijmans et al. 2021) packages. To automatically classify the IAPs, a random forest classification algorithm was used. Random forest pixel-based classification is a non-parametric machine learning method that creates multiple decision trees to classify pixels based on their spectral information (Fu et al. 2017; Hill et al. 2017). This algorithm was chosen as it is easy to implement, it has been successfully applied to the classification of vegetation cover (Fu et al. 2017), and has proven to be one of the most effective algorithms in a benchmark study by Pirotti et al. (2016) on image classification algorithms (Hill et al. 2017; Oldeland et al. 2021).

The first step in the random forest algorithm was to create training data through manually classified polygons in ArcMap version 10.7.1 (Redlands 2019). These polygons were created by grouping similar landcover types and assigning them to their perspective classes via visual analysis. On average, 2% of the image was classified into training data which consisted of four land cover classes: i) IAPs, ii) brown

vegetation, iii) bare ground/dead plants, and iv) indigenous green vegetation (Table 2). Per class, seven to ten polygons were created on each orthomosaic. Following this, the training data and orthomosaics were imported into R (R Core Team 2021), where the random forest classification was performed. The output of this operation was a raster containing the four classes (Figure 7; Appendix B), and from these raster images, the surface area of the IAP class was calculated to generate a density estimate of the IAP cover.

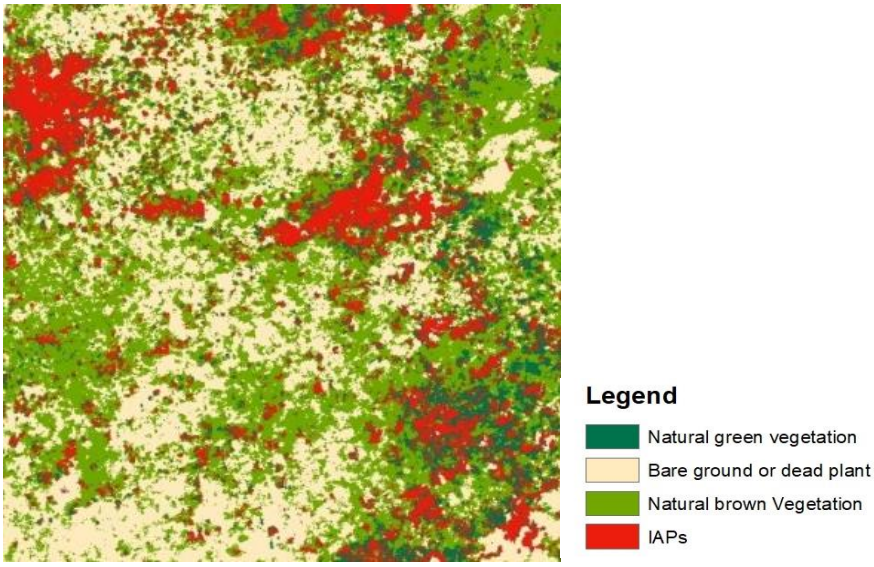


Figure 7. The output of the Random Forest Algorithm of the orthomosaic of the first site on Flower Valley farm. The legend (right) indicates the four classes used in the training data. For images of the other sites, refer to Appendix B.

Table 2. Description of the landcover classes used in the training data.

Land cover class	Description
Invasive Alien Plants (IAPs)	Non-native invasive plants, mainly consisting of *Acacia Saligna, Acacia Mearnsii, Leptospermum laevigatum, and Hakea sericea.*
Indigenous brown Vegetation	Native dull plants, mostly consisting of brown-coloured grasses.
Bare ground/ Dead vegetation	Areas where soil or rocks are exposed, as well as areas covered by dead plant material.
Indigenous green vegetation	Native fynbos vegetation that was green in colour and thus similar to IAPs

To determine which method was the most accurate estimate of IAP density, each method was individually compared to the baseline density data. This was achieved by creating generalized linear

models (GLMs) in R (R Core Team 2021) using the *lme4* package (Bates et al. 2015). Within these models, the response variable was the density estimation method, and the explanatory variable was the baseline density data. From these models, estimation and standard error values were obtained. To see how well the model fitted the observed data, a pseudo-R-squared value was calculated using the rsq() function from the *rsq* package (Zhang 2021). Following this, an ANOVA was performed to compare the reduction in deviance when the variable is dropped from the GLM model.

To increase the study's sample size following the data collection and to test whether the methods were more reliable for smaller sites, the study sites were divided into two. For instance, the orthomosaics created were split in half and were compared to the field data collected by the transect on that half. Consequently, 20 different sites were compared. The density estimation methods were then compared in a generalized mixed linear model in R using the *lme4* package (Bates et al. 2015). The generalized linear mixed model allowed the farm on which the survey took place to be considered as a random effect. This random effect allows for the hierarchical nature of the sampling design to be accounted for. Again, the pseudo-R-squared value was calculated using the r.squaredGLMM() function from the MuMIn package (Barton 2020), and an ANOVA was performed to detect pairwise differences.

2.3 Time Comparisons

To compare the time efficiency of the three methods, the time required by the surveyors to complete each method were recorded from beginning to end. The time taken to perform a ground-based survey was recorded at each site and the average of these times were calculated. To calculate the time taken for the manual digitization, the flight time of the drone to survey a site was recorded and combined with the time taken to digitize the IAPs in an orthomosaic. Similarly, the time taken for the automatic classification was calculated by adding the flight time of the drone survey to the time required to create the training data. The time taken for data processing within the automatic classification method was omitted as it ran unsupervised and therefore did not require any person-hours. In R (R Core Team 2021) using *nortest* (Gross and Ligges 2015), *car* (Fox and Weisberg 2019), *lattice* (Sarkar 2008), and *multcomp* (Hothorn et al. 2008) packages, the time of each method was compared using an ANOVA, then a post hoc TukeyHSD test was used to test for statistical differences between the groups. For a conceptual summary of the entire methodology, refer to Figure 8.

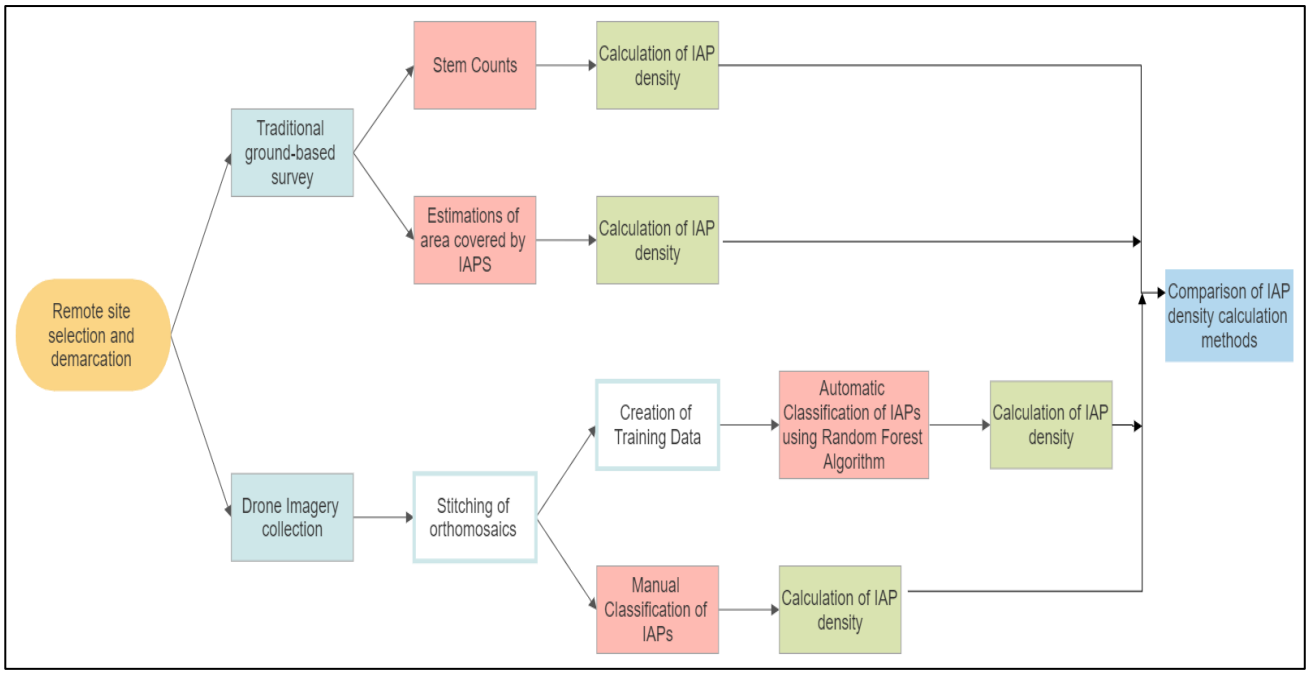


Figure 8. A conceptual framework of the methodology.

3 Results

The results are presented as follows: 1) the comparisons of different IAP density estimation methods of the large (1 ha sites), 2) comparisons of the different IAP density estimation methods for the smaller (0.5 ha sites) and, 3) the comparisons of the time taken per each method. This study found that drone technology produced the best estimates of IAP density and that the automatic classification of the drone imagery was most time efficient method.

3.1 Comparison of Density Estimation methods

Table 3. Results of a generalized linear model comparing the different estimation methods' data to the baseline density data. Pseudo R^2 of Automatic classification model = 0.84, pseudo R^2 value of Manual model = 0.94, the pseudo R^2 value of Stem Count model= 0.99.

	Estimate	Standard error	Chi-squared	P-value
Automatic method	-1.653e-06	6.677e-07	5.7916	0.01244
Manual method	-3.228e-06	1.026e-06	8.7487	0.00036
Stem Count	-2.187e-05	7.851e-06	10.031	0.00095

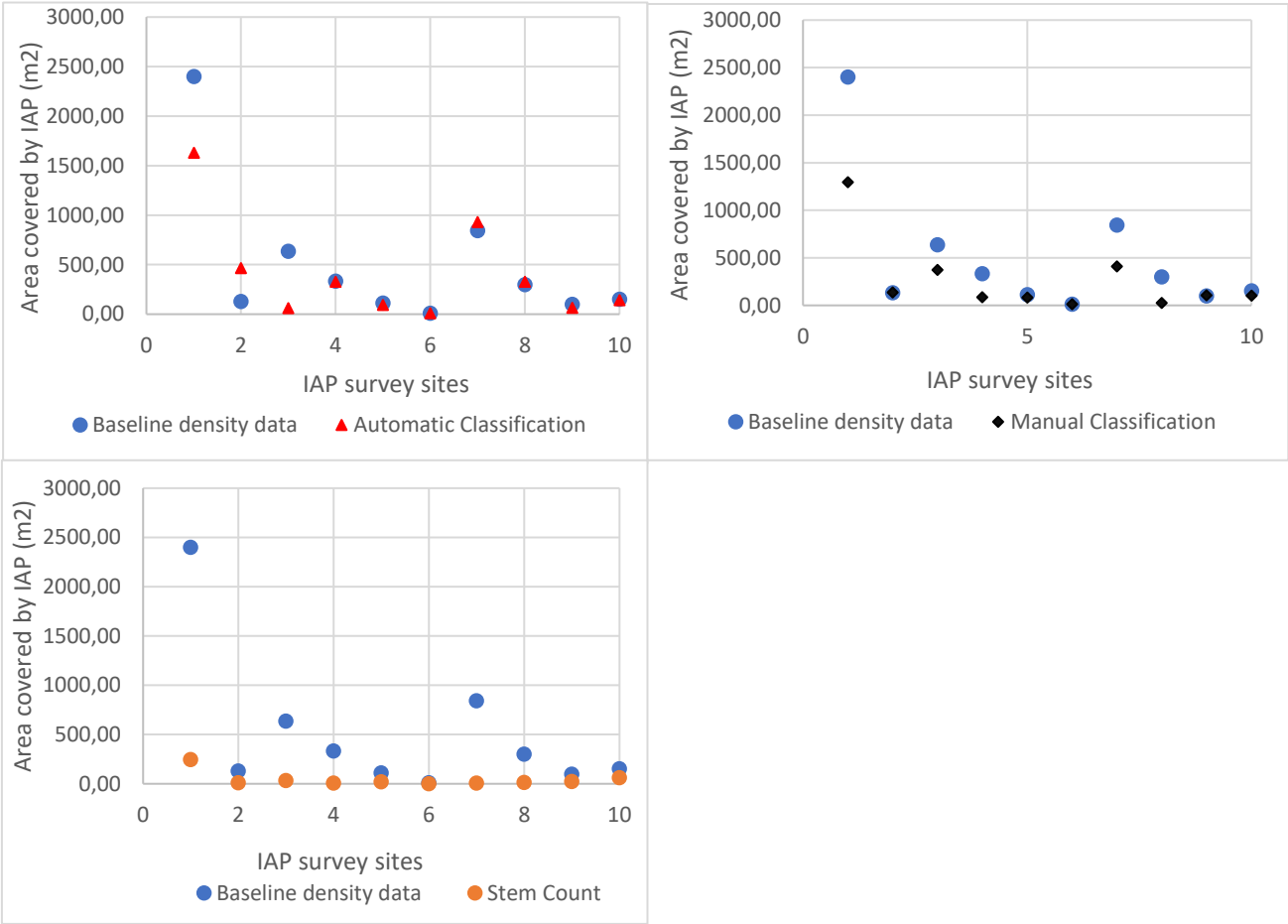


Figure 9. Comparisons between density estimates calculated from automatic classification vs. baseline density data (top left), estimates calculated by manual classification vs. baseline density data (top right), and stem count vs. baseline density data (bottom left).

There was a significant difference in the means of all the density estimation methods compared to the baseline density data (Table 3). The automatic classification model had an overall mean value closest to that of the baseline field measurements, although the difference between the means of the baseline density estimates and the automatic classification estimates was significant ($p < 0.05$). The mean values of manual digitisation and stem count were significantly lower compared to automatic classification ($p < 0.001$), and stem count produced the lowest overall mean values compared to the density estimates of the field-based method ($p < 0.001$).

The scatterplots (Figure 9) indicated that stem count produced estimates of area covered by IAPs which were significantly lower compared to that of the baseline field estimates, further supported by the significant p-value ($p < 0.001$) attained in the GLMs (Table 3). Overall, the estimates produced by manual digitisation were closer to field estimates compared to stem counts (Table 3). The manual digitisation method produced density estimate values that were similar to that of the baseline data for half of the study sites, while for the other half of the sites, manual digitisation produced significantly lower estimates of IAPs compared to the baseline density data. GLM results have shown that the automatic classification method generated values closest to that of the baseline density data, compared to the other two methods investigated here ($p < 0.05$; Table 3). It estimated the IAPs density to be the same for 7 out of 10 sites (Figure 9). Overall, for site 1, all the methods underestimated the density of IAPs compared to field estimations. For site 6, all methods produced the same estimates of IAP density compared to the baseline field data.

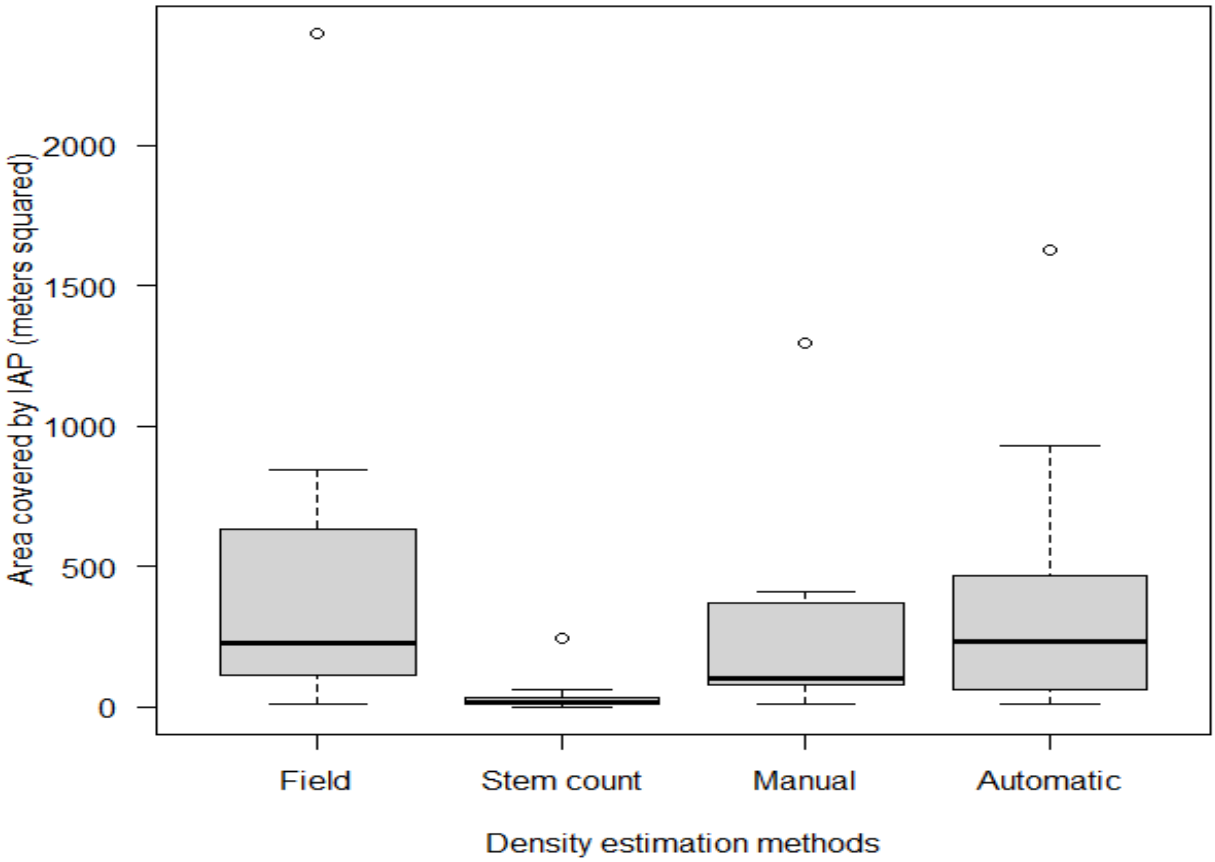


Figure 10. A comparison of boxplots representing the data collected by the density estimation methods per hectare site.

Overall, the values produced from the stem count had a much narrower inter-quartile range compared to the other density estimation methods (Figure 10). The median of the density estimates generated by the stem count was much lower than that of the field estimate, thus again indicating a substantial underestimation of IAP density. The manual method produced estimates with a narrower inter-quartile range compared to that of the baseline field data and automatic classification methods. The median

produced by the manual method is considerably lower than that of the baseline field data. Finally, the estimated density values produced by the automatic classification method had a wide inter quartile range compared to the other methods, yet narrower compared to that of field estimates. The median of the automatic classification data is most similar to the median of the baseline density data compared to the other two methods. Therefore, compared to the other density estimation methods, the automatic classification method produced IAP density sizes most similar to the field data for the 1 Ha sites.

3.2 Comparison of Density Estimation estimates of the halved study sites

Table 4. Results of a generalized linear mixed model comparing the different estimation methods' data to the field data of the halved data sites. Pseudo R^2 of Automatic classification model = 0.84, pseudo R^2 value of Manual model = 0.94, the pseudo R^2 value of Stem Count model= 0.99

	Estimate	Standard error	Chi-squared	P-value
Automatic method	0.012367	0.005336	244.08	0.01706
Manual method	0.013027	0.004995	227.64	0.01755
Stem Count	0.035382	0.006377	122.88	1.369e-09

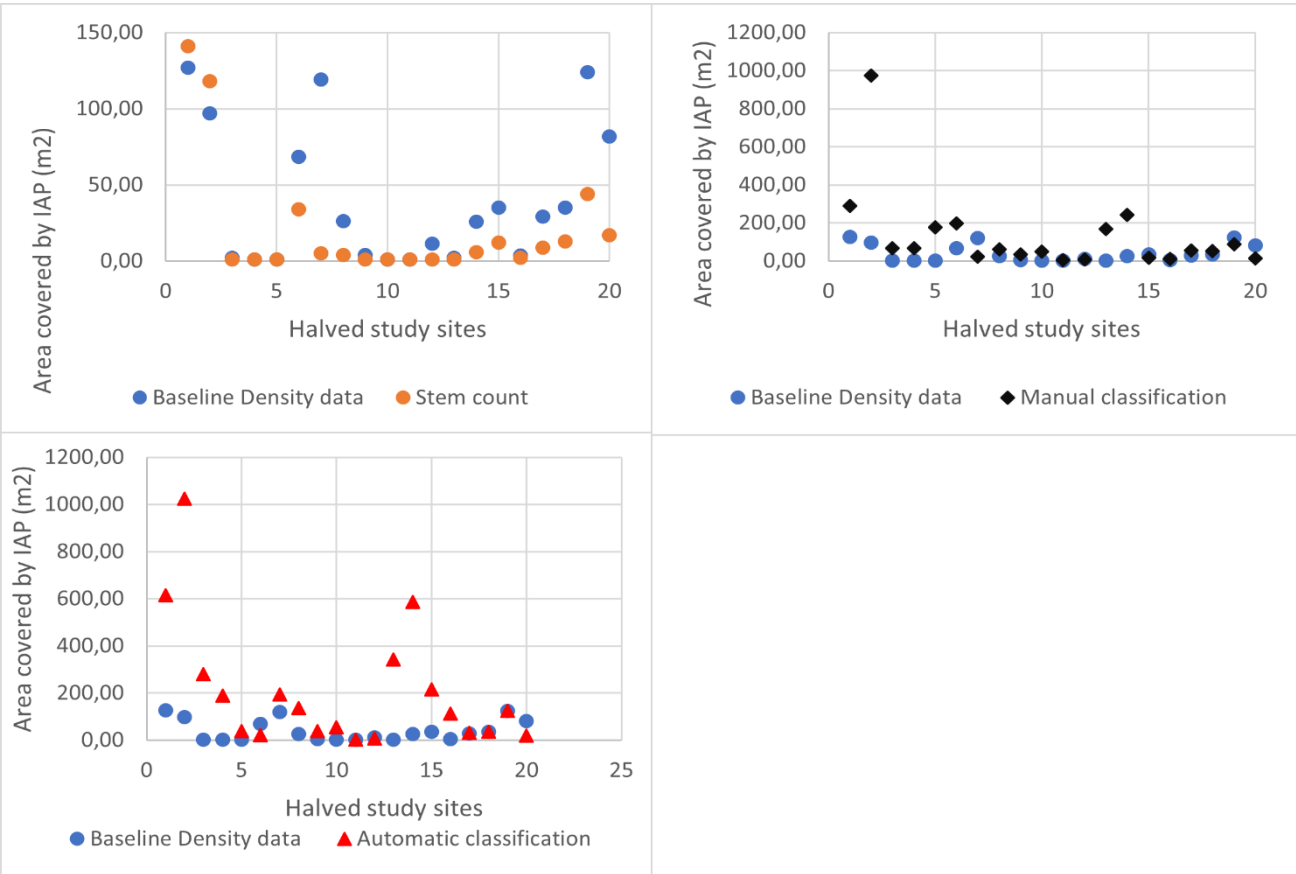


Figure 11. Scatterplots comparing density estimates for halved sites calculated from automatic classification compared to baseline density data (top left), estimates calculated by manual classification vs. baseline density data (top right), and stem count vs. baseline density data (bottom left).

Similar to the results of the full hectare sites, there was a significant difference in the means of all the density estimation methods compared to the baseline density estimates (Table 4). However, for the smaller sites, the manual classification produced an overall mean value closest to that of the baseline field measurements ($p < 0.05$), while stem count still had the lowest overall mean value ($p < 0.001$).

Stem count produces estimates similar to the baseline density estimates for 7 sites, however it underestimates the IAP density for 13 sites (Figure 11). The dissimilar values of IAP density for majority of the sites is supported by the significantly small p-value attained from the GLMMs ($p < 0.001$). The estimates produced by the automatic, and manual techniques were greater than that of the field data, thus indicating that these techniques could have overestimated the density of the IAPs. The manual digitisation produced similar IAP densities to the baseline field data for 13 sites and mainly overestimated the IAP density for 7 sites. The automatic classification method produced similar data for 10 sites, and for majority of the remaining sites it overestimated the IAP density. Overall, both manual and automatic classification methods overestimated the IAP density for site 2.

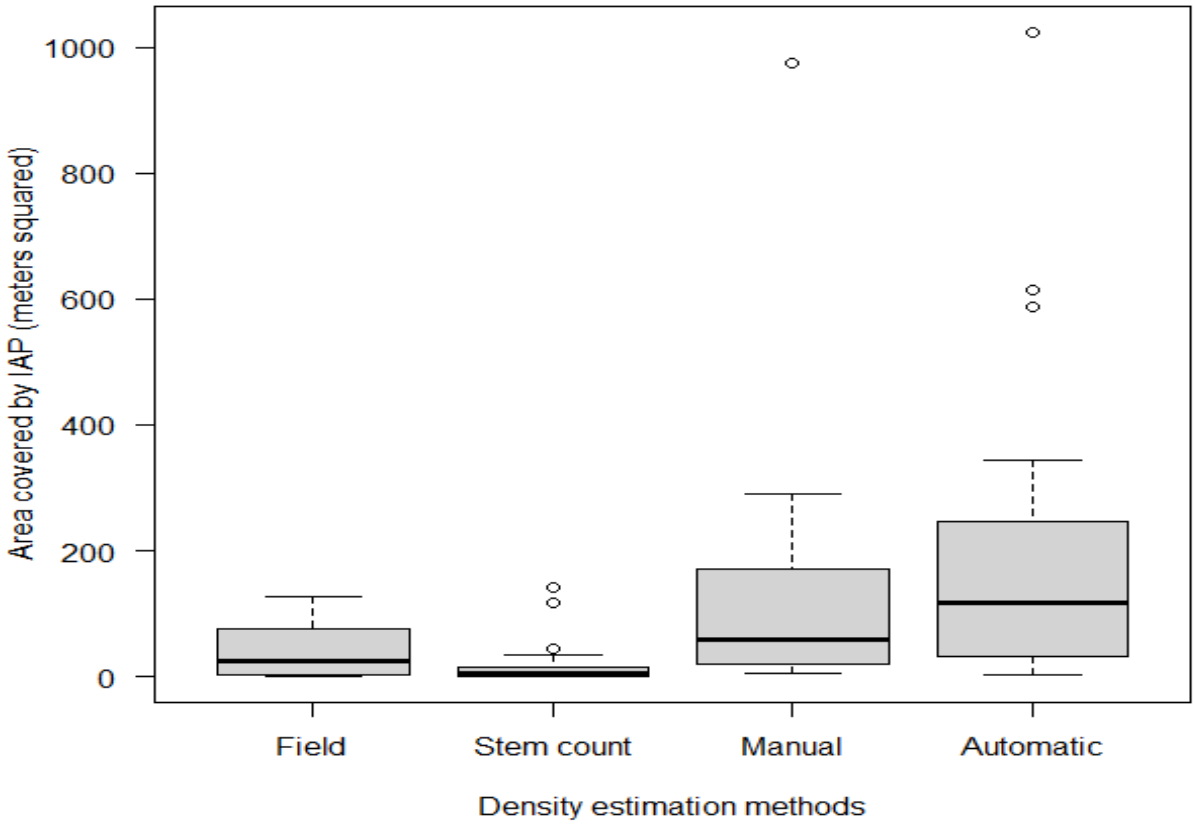


Figure 12. A comparison of boxplots containing the density estimates of the different methods for 5000m^2 sites.

Similar to the full hectare sites, the inter-quartile range of estimates produced by stem counts were very narrow (Figure 12). The median of the stem count data was also lower compared to that of the baseline field data. The manual digitization IAP density estimates had a wider inter-quartile range compared to that of the field estimates, but a median value that was close to that of the field estimates,

although slightly higher ($p < 0.05$). The automatic classification method produced the widest inter-quartile range of values as well as the highest median value. For the smaller sites (0.5ha), the manual classification method preformed slightly better than the automatic classification. Therefore, once again the digital methods provided the best estimates of IAP density.

3.3 *Comparison of time taken*

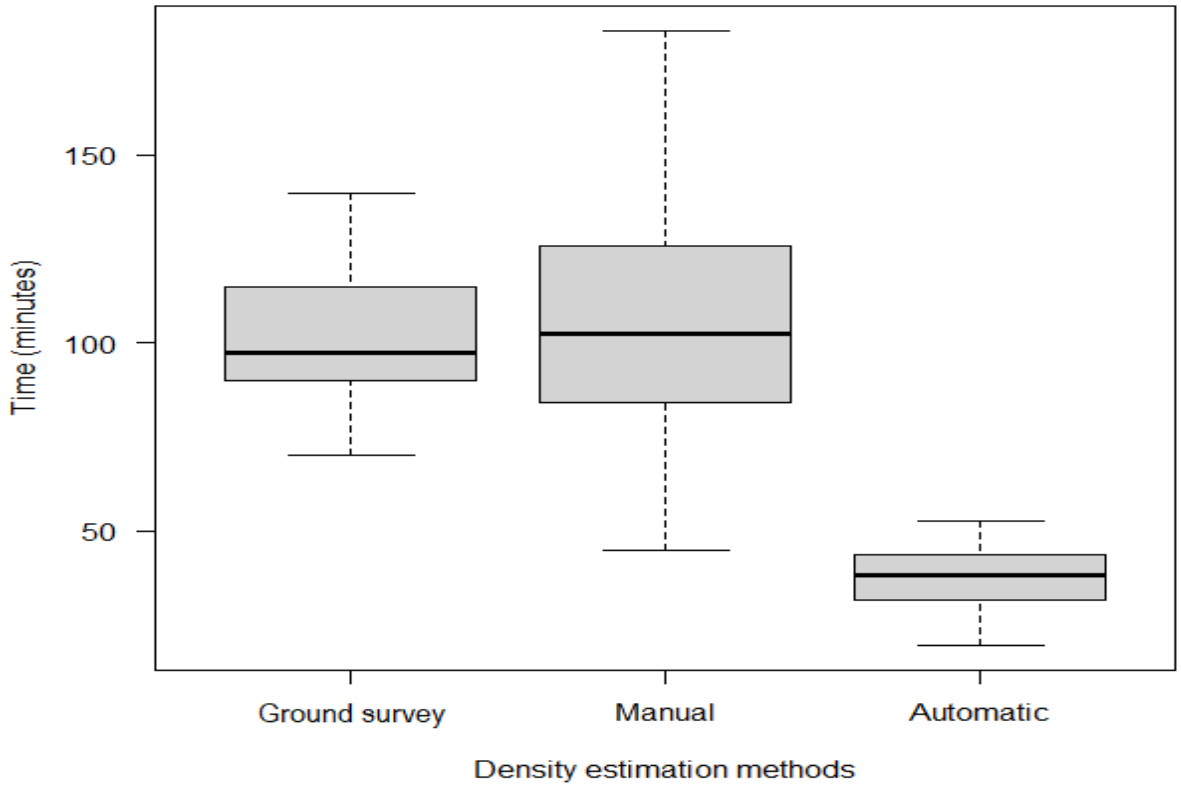


Figure 13. Boxplots of the amount of time taken to estimate the density of IAP by collecting field data (including both stem count and % density), through the manual classification method, and the automatic classification method.

Table 5. The results of the post hoc TukeyHSD test

Comparison	Difference	Lower	Upper	P- value
Field vs. Automatic	63.6	34.83	91.77	0.0000224
Manual vs. Automatic	70.8	42.33	99.27	0.0000040
Manual vs. Field	7.5	-20.97	35.97	0.7921289

The field survey of the 10 study sites required the effort of two field surveyors and took an average of 101 minutes per site. Both the manual and automatic classification methods required 5 minutes of drone flight time and required 1 person to monitor the drone. The manual image interpretation required an average of 109 minutes per site to analyze and digitize polygons by 1 person. In comparison, the automatic classification required an average of 33 minutes per site to create training data and 1 person. Therefore, the automatic classification was significantly quicker than the manual classification ($p < 0.001$) and the ground-based survey (Table 5; Figure 13). However, it did require an average of 691 minutes of unsupervised machine hours to run the random forest algorithm. The person-hours required to calculate the density of a hectare site was quickest using the automatic classification method, whereas it took the longest with the manual estimation method.

4 Discussion

Determining the extent of an area invaded by IAPs is essential for the adequate preparation and application of IAP control measures (Mararakanye et al. 2017). Over the past years, drones have been applied successfully in conservation biology for mapping vegetation and therefore could prove useful in removal programmes (Tay et al. 2018). However, before drone technology can be integrated into the toolkits of IAP removal programmes in South Africa, validation is required to understand how the interpretation of drone-imagery compares to traditional ground-based sampling techniques. Therefore, this study compared the efficiency of three methods in measuring the density of IAPs, namely ground-based surveying, automatic classification of drone images, and manual classification of drone images.

4.1 Which method provides the most reliable density estimation of IAP cover?

Under the first research question, it was hypothesized that drone technology would provide better estimations of IAP density. The results indicated that drone technology produced density estimates similar to, or slightly better than, the ground sampling techniques, thus supporting the hypothesis. The automatic classification technique provided the best results for the larger study sites (1 ha), whereas the manual classification provided better results for the smaller study sites (0.5 ha).

4.4.1 Larger sites vs. smaller sites

For the large study sites, the results indicate that the stem count consistently underestimated the density of IAPs, with very little variation in the data (Figure 9). The low similarity between the stem counts and baseline data could have resulted from the IAP's stems not falling within the quadrats and thus not being counted. Consequently, when this data was extrapolated for the entire study site, it significantly underestimated the density of IAPs. The miscalculation of IAP density was expected as other research also discovered that ground-based methods such as stem counts did not extrapolate data accurately to the entire study site, especially when the target species were irregularly distributed (Kerr and

Ostrovsky 2003; Tay et al. 2018). Additionally, ground surveys are susceptible to human errors such as researcher fatigue or limited knowledge in identifying IAPs, thus further contributing to the underestimation of IAP density (Barnas et al. 2019).

Compared to the stem count density estimates, the density data produced by the manual classification was slightly more similar to the baseline data. The results indicated that the manual classification produced similar densities for half of the large study sites, but consistently underestimated the IAP density for the other study sites. In contrast, other studies have found manual classification to produce very accurate density data (Hill et al. 2017). However, seeing as manual classification of vegetation is subjected to the knowledge and experience of the interpreter (Mararakanye et al. 2017; Rwanga and Ndambuki 2017) it is understandable that the results differed from other studies. Therefore, the underestimation of IAP density estimates were most likely the result of inexperience and thus human error. Furthermore, it was found that during the manual classification process, certain shrubby IAPs were difficult to classify as they looked similar to the indigenous fynbos. This may be the result of herbaceous alien shrubs (e.g., *Leptospermum laevigatum)* being more difficult to identify within the fynbos compared to the invasive alien trees (e.g., *Acacia saligna*). The *Leptospermum laevigatum* were common in the six underestimated sites. Therefore, it is possible that they were not classified, thus further contributing to the underestimation of IAP density.

The results indicated that the automatic classification produced IAP density data that was the most comparable to the baseline density data of the large study sites. The automatic classification produced the best results as it used an unmonitored algorithm to classify the IAPs, thus repressing the human error that the other two methods were subjected to. Although this method produced the best results overall, compared to the baseline density data it overestimated and/or underestimated the density of IAPs at the first three sites. It is challenging to determine which method is the most accurate, but under- or overestimation can result from vegetation with similar colours to the IAPs being misclassified (Tay et al. 2018). The similarity in colour between IAPs and indigenous vegetation can hinder the automatic classification algorithm as each pixel is classified depending on the colour. Yet, with few data outliers and a data range that is relatively narrow, the results shown here indicate that the automatic classification produced accurate and consistent estimates of IAP density.

Even for smaller sites, the stem count produced density estimates that were significantly different from the baseline data, thus indicating that this method is still not reliable for smaller areas. Again, the use of drone technology was more reliable for the smaller sites. However, in this instance, manual classification produced IAP density estimates that were slightly more similar to the baseline data than the automatic classification methods. These results agree with other studies that found the manual

classification method to be more efficient than automatic classification and traditional ground surveys (Hill et al. 2017).

The results indicate that, for larger sites, the automatic classification method is the most effective method to use, whereas, for smaller sites, manual classification may provide slightly better density estimates. The manual and automatic classification provided better density estimates as drones can provide a more inclusive view of a landscape than that of a ground-based surveyor (Hill et al. 2017). Therefore, inaccurate estimations produced from extrapolating data to account for an entire site is limited with drone technology. Although the drone methods produced better IAP density estimates, results from this study showed that they can sometimes overestimate or underestimated the densities of some sites. Errors in density estimation can propagate from image capture, as fast movements from wind turbulence can cause imagery blurring and partial distortion within the orthomosaics that are used for analysis (Lehmann et al. 2017). As a consequence of poor image quality, the training and reference data could be flawed (Graça et al. 2017). This can reduce the accuracy of the random forest algorithm and make it more difficult for the interpreter to classify different vegetation manually (Lehmann et al. 2017). Therefore, the use of a drone is limited to less windy days.

Although the % cover of IAP provided a good base to compare the drone and stem count data to, it must be acknowledged that the field baseline data could have also provided inaccurate density estimates. For instance, all three methods produced IAP densities lower than the baseline data for the first study site. This indicates that the site's baseline field data could be inaccurate and thus overestimated IAP density. Slight inaccuracies in the baseline field data was anticipated as previous research has found that field surveys have the ability to produce significant data errors (Hill et al. 2017). Therefore, it is suggested that all three methods may not have as severely underestimated the IAP density of this site, but rather the baseline field data was incorrect and overestimated the IAP density.

4.2 Which method was more time-efficient?

Although drone techniques can provide good estimates of IAP density, effective removal programmes will also be benefited by the rapid collection of density data. Before this study took place, it was hypothesized that drone technology would be the most time-efficient method in estimating the density of IAPs. This study proved that automatic classification was the least time-consuming method, whereas manual digitization proved to be the most time-consuming.

The results indicated that the ground-based surveys were the second most time-consuming method. This is owing to the fact that surveyors had to walk along transects through dense vegetation and unstable terrain. Additionally, large areas had to be covered by the surveyors. However, the presence

of surveyors in the field allowed for additional data, such as identifying indigenous plant species, the measurement of plant height, and the percentage of ground cover to be collected. Thus, simple ground-surveys that collect supplementary data on the study site may still play a vital role in vegetation surveys, especially with regards to confirming invasive species identity.

In comparison, the manual classification of drone images proved to be the least time-efficient process. Although the drone allowed for rapid data collection, the manual digitization of the data was very time-consuming. However, the time taken for the digitization process depends on the user's experience (Mararakanye et al. 2017), thus indicating that this process could have been more time-efficient with a more experienced user.

Automatic classification proved to be the most time efficient as the only time required was for data collection by the drone and time spent on creating training data. The time taken for data processing was not included as it was not supervised by a person. Nevertheless, even if the unsupervised hours were included, once the algorithm was trained to identify IAPs in a particular study site it, the same training data could be reapplied for surveys of that site, thus saving time in site revisits (Hamylton et al. 2020).

Furthermore, other studies found that the amount of computer processing power and time required would have increased with the image's resolution (Cruzan et al. 2016). Consequently, the scalability of drone technology in IAP removal programmes may be limited as larger survey areas require more data to process (Cruzan et al. 2016). However, the time to process data can be addressed by improving computer processing power (Hill et al. 2017).

4.3 Implications for Conservation and IAP removal programmes

This study showed that field-based surveys require a considerable investment of time and effort whilst still producing relatively unreliable results. Additionally, walking large areas, often in difficult terrain, is counterproductive and unviable in terms of practicality, budget and safety of the surveyors (Lehmann et al. 2017). Furthermore, field surveys are not able to provide spatially explicit information of large study sites. It was expected, unlike ground-based surveys, that the drones would not be able to identify individual IAP plants (Müllerová 2019). However, this was not the case with this study nor other studies (Müllerová 2019) which found that automatic classification algorithms were able detect individual IAP species, indicating that the resolution of the data was sufficient. Whereas, during ground-surveys the transects often missed small IAP plants and therefore they were not included in the stem count. Consequently, aerial images produced by drones are relevant for studying large areas, especially when the plant population is distributed heterogeneously (Tay et al. 2018).

Instead of drones, many studies have been using satellite remote sensing (RS) data to obtain aerial images of a study site. For instance, a study by Holden et al. (2021) found RS data produced by satellites to be useful in identifying IAPs within water towers in South Africa. Like drone technology, RS techniques capture data at large spatial extents whilst requiring little labour (Royimani et al. 2019). However, high-resolution RS imagery from satellites is very expensive to obtain and therefore is not feasible for small- to medium-scale IAP removal programmes but is rather used for large scale regional or country mapping (Müllerová 2019). Although free RS data is available, these open-source data sets (e.g., Google Earth) have coarse resolutions and thus restricted applications (Tay et al. 2018). Furthermore, the automated identification of a plant species from RS data can be challenging, particularly when the landscape is complex and has a heterogenous vegetation cover (Tay et al. 2018). In contrast, maps created from drone images offer higher spatial resolutions, are feasible, and are more flexible in data acquisition than open-source RS data (Lehmann et al. 2017; Müllerová 2019).

Although drones have proven to be the most applicable to IAP removal programmes than ground-based surveys and RS, there are many legal constraints for drone flights in South Africa. Drone flights are regulated by the South African Civil Aviation Authority (SACAA). The SACAA has placed numerous restrictions on drone flights, including where and how they can take place. The regulations specify that without a permit drones can only be used for private purposes without commercial outcome or gain. For commercial, corporate, and non-profit uses, drones have to be registered and can only be operated by qualified and licensed pilots. Therefore, it is costly and tedious to become legally compliant with these regulations. Additionally, drone flights are not allowed to occur near urban areas, thus prohibiting surveys of these often invaded places (Dvořák et al. 2015). These regulations are mainly concerned with protecting the privacy of the public. However, this is creating an excessive barrier to the potential advantages of utilizing drones for conservation in national parks and nature reserves where privacy concerns are irrelevant.

If the limitations of drone laws can be overcome, drones will be able to circumvent the limitations put forth by traditional ground-based surveys. Drones provide efficient and timely data on the density of IAPs and therefore can assist urgent management actions within the field, monitor the control efforts, and allow for revisitations of the infested sites. This revisitation is vital as it helps avert new IAPs from reaching maturity, restocking the seed banks and thus restoring the invasion process (Lehmann et al. 2017). Through this study and other studies, drones have proven to be flexible monitoring tools as they can be deployed with little planning (Koh and Wich 2012; Ancin-Murguzur et al. 2020). For instance, the drone flight can be started almost immediately after arrival at the study area, thus making it effective to use during weather conditions that may disturb the original fieldwork plans. Furthermore, the efficient IAP density estimates produced through drone technology will allow the managers to

acquire the right amount of pesticide and other materials for the IAP removal (Hill et al. 2017). Consequently, IAP removals will be more effective, thus requiring less follow up treatments and ultimately saving landowners money. In due course, the use of drones in IAP removal programmes will help mitigate the negative effects of IAPs, thus contributing to the conservation of endemic flora and fauna in the highly threatened CFR.

To further improve the impact that drones will have on conservation, future studies should take advantage of the flexibility of drones and conduct the aerial surveys during flowering time when the IAPs are producing prominent flowers. During the manual classification process it was difficult to identify IAP herbaceous species such as the *Leptospermum laevigatum* because they are similar in colour to the surrounding fynbos and have small discreet leaves. Furthermore, as the random forest classification classifies pixels based on colour, it is also likely that the similar colours between indigenous plants and IAPs hindered the automatic classification process. Therefore, some IAP species may be better detected at certain phenological stages when their flowers make them more conspicuous (Huang and Asner 2009; Somodi et al. 2012; Müllerová 2019), or by using other visual bands such as near-infrared (Buitrago et al. 2018). Additionally, while creating training data for the automatic classification algorithm, more vegetation classes could be specified thus allowing for similar-looking plants to be distinguished from one another (Shiferaw et al. 2019). However, it must be noted that a higher volume of training data will be more computationally demanding.

5 Conclusion

IAP removal programmes play a vital role in the conservation of rare biodiversity in the CFR. This study showed that drone technology has many advantages over traditional ground-based surveys and therefore can further improve IAP removal programmes. Drone technology has the ability to circumvent the disadvantages of ground-based surveys such as human error, and biased data extrapolation. The integration of drones into the toolkit of IAP removal programmes within the CFR can lead to substantial savings regarding time, labour, and financial resources. Additionally, it has the capacity to increase the efficiency of removal programmes as it enables prioritization of eradication efforts to the most invaded sites as well as facilitates site revisits. However, for drone technology to reach its full potential within South Africa, drone laws pertaining to conservation need to be urgently revised.

6 Acknowledgements

Firstly, I wish to express my appreciation to my supervisor, Dr. Charl Deacon who has been a tremendous mentor for me. His advice is invaluable and without his guidance this project would have not been possible. I would also like to thank my co-supervisors Julia van Schalkwyk and Kirsten Watson for their time and wisdom. To Flower Valley Conservation Trust for supporting this project by driving me to the invasion sites, assisting me with drone surveys, and providing me with accommodation during the research period. A big thanks to Dandi Kritzinger for taking time to assist me during the ground-surveys. Finally, I would like to thank my family and friends for their endless encouragement and support.

References[1]

Ancin-Murguzur FJ, Munoz L, Monz C, Hausner VH (2020) Drones as a tool to monitor human impacts and vegetation changes in parks and protected areas. Remote Sens Ecol Conserv 6:105–113. https://doi.org/10.1002/rse2.127

Anderson K, Gaston KJ (2013) Lightweight unmanned aerial vehicles will revolutionize spatial ecology. Front Ecol Environ 11:138–146. https://doi.org/10.1890/120150

Barnas AF, Darby BJ, Vandeberg GS, et al (2019) A comparison of drone imagery and ground-based methods for estimating the extent of habitat destruction by lesser snow geese (*Anser caerulescens caerulescens*) in La Pérouse Bay. PLoS One 14:1–19. https://doi.org/10.1371/journal.pone.0217049

Barton K (2020) MuMIn: Multi-Model Inference. R package version 1.43.17. Version 1:18

Bates D, Mächler M, Bolker BM, Walker SC (2015) Fitting linear mixed-effects models using lme4. J Stat Softw 67:. https://doi.org/10.18637/jss.v067.i01

Bivand R, Keitt T, Rowlingson B, et al (2021) rgdal: Bindings for the "Geospatial" Data Abstraction Library. R package version 1.5-27

Buitrago MF, Skidmore AK, Groen TA, Hecker CA (2018) Connecting infrared spectra with plant traits to identify species. ISPRS J Photogramm Remote Sens 139:183–200. https://doi.org/10.1016/j.isprsjprs.2018.03.013

Cheney C, Esler KJ, Foxcroft LC, et al (2018) The impact of data precision on the effectiveness of alien plant control programmes: a case study from a protected area. Biol Invasions 20:3227–3243. https://doi.org/10.1007/s10530-018-1770-8

Cheney C, Esler KJ, Foxcroft LC, van Wilgen NJ (2019) Scenarios for the management of invasive *Acacia* species in a protected area: Implications of clearing efficacy. J Environ Manage 238:274–282. https://doi.org/10.1016/j.jenvman.2019.02.112

Clusella-Trullas S, Garcia RA (2017) Impacts of invasive plants on animal diversity in South Africa: A synthesis. Bothalia 47:1–12. https://doi.org/10.4102/abc.v47i2.2166

[1] Biological Invasions Journal referencing style

Conradie B (2010) Farmers' views of landscape initiatives: The case of the Agulhas Plain, CFR

Cruzan MB, Weinstein BG, Grasty MR, et al (2016) Small Unmanned Aerial Vehicles (Micro-Uavs, Drones) in Plant Ecology. Appl Plant Sci 4:1600041. https://doi.org/10.3732/apps.1600041

Dvořák P, Müllerová J, Bartaloš T, Brůna J (2015) Unmanned aerial vehicles for alien plant species detection and monitoring. Int Arch Photogramm Remote Sens Spat Inf Sci - ISPRS Arch 40:83–90. https://doi.org/10.5194/isprsarchives-XL-1-W4-83-2015

Fourie H, De Wit MP, Van der Merwe A (2013) The role and value of water in natural capital restoration on the Algulhas Plain. Annu Rev Pharmacol Toxicol 41:145–174

Fox J, Weisberg S (2019) An R Companion to Applied Regression, 3rd edn. Sage Publications Ltd, Cananda

Fu B, Wang Y, Campbell A, et al (2017) Comparison of object-based and pixel-based Random Forest algorithm for wetland vegetation mapping using high spatial resolution GF-1 and SAR data. Ecol Indic 73:105–117. https://doi.org/10.1016/j.ecolind.2016.09.029

Gaertner M, Biggs R, Te Beest M, et al (2014) Invasive plants as drivers of regime shifts: Identifying high-priority invaders that alter feedback relationships. Divers Distrib 20:733–744. https://doi.org/10.1111/ddi.12182

Graça NLSDS, Mitishita EA, Gonçalves JE (2017) Use of UAV platform as an autonomous tool for estimating expansion on invaded agricultural land. Bullentin Geod Sci 23:509–519. https://doi.org/10.1590/S1982-21702017000300034

Gross J, Ligges U (2015) nortest: Tests for Normality. R package version 1.0-4. 1–10

Hamylton SM, Morris RH, Carvalho RC, et al (2020) Evaluating techniques for mapping island vegetation from unmanned aerial vehicle (UAV) images: Pixel classification, visual interpretation and machine learning approaches. Int J Appl Earth Obs Geoinf 89:102085. https://doi.org/10.1016/j.jag.2020.102085

Heydenrych BJ (1999) An investigation of land-use practices on the Agulhas Plain (South Africa), with emphasis on socio-economic and conservation issues

Hijmans RJ, Etten J Van, Sumner M, et al (2021) raster: Geographic Data Analysis and Modeling. R package version 3.5-2

Hill DJ, Tarasoff C, Whitworth GE, et al (2017) Utility of unmanned aerial vehicles for mapping invasive plant species: a case study on yellow flag iris (*Iris pseudacorus L.*). Int J Remote Sens 38:2083–2105. https://doi.org/10.1080/01431161.2016.1264030

Holden PB, Rebelo AJ, New MG (2021) Mapping invasive alien trees in water towers: A combined approach using satellite data fusion, drone technology and expert engagement. Remote Sens Appl Soc Environ 21:100448. https://doi.org/10.1016/j.rsase.2020.100448

Holmes PM, Esler KJ, van Wilgen BW, Richardson DM (2020) Ecological restoration of ecosystems degraded by invasive alien plants in South African Fynbos: Is spontaneous succession a viable strategy? Trans R Soc South Africa 1–29. https://doi.org/10.1080/0035919X.2020.1781291

Hothorn T, Bretz F, Westfall P (2008) Simultaneous inference in general parametric models. Biometrical J 50:346–363. https://doi.org/10.1002/bimj.200810425

Huang C ying, Asner GP (2009) Applications of remote sensing to alien invasive plant studies. Sensors (Switzerland) 9:4869–4889. https://doi.org/10.3390/s90604869

Kerr JT, Ostrovsky M (2003) From space to species: Ecological applications for remote sensing. Trends Ecol Evol 18:299–305. https://doi.org/10.1016/S0169-5347(03)00071-5

Koh LP, Wich SA (2012) Dawn of drone ecology: Low-cost autonomous aerial vehicles for

conservation. Trop Conserv Sci 5:121–132. https://doi.org/10.1177/194008291200500202

Kuhn M, Wing J, Weston S, et al (2021) caret: Classification and Regression Training. R package version 6.0-90

Laubscher CP, Ndakidemi PA, Bayat MS, Slabbert A (2009) Conservation and propagation of endangered Proteaceae on the Agulhas plain for sustainable ecotourism development. Sci Res Essays 4:374–380

Lehmann JRK, Prinz T, Ziller SR, et al (2017) Open-source processing and analysis of aerial imagery acquired with a low-cost Unmanned Aerial System to support invasive plant management. Front Environ Sci 5:1–16. https://doi.org/10.3389/fenvs.2017.00044

Leishman MR, Haslehurst T, Ares A, Baruch Z (2007) Leaf trait relationships of native and invasive plants: Community- and global-scale comparisons. New Phytol 176:635–643. https://doi.org/10.1111/j.1469-8137.2007.02189.x

Liaw A, Wiener M (2002) Classification and Regression by randomForest. R News 2:18–22

Mararakanye N, Magoro MN, Matshaya NN, et al (2017) Railway side mapping of alien plant distributions in Mpumalanga, South Africa. Bothalia 47:1–11. https://doi.org/10.4102/abc.v47i1.2130

McNaught I, Thackway R, Brown L, Parsons M (2008) A field manual for surveying and mapping nationally significant weeds - 2nd edition

Mostert E, Gaertner M, Holmes PM, et al (2017) Impacts of invasive alien trees on threatened lowland vegetation types in the Cape Floristic Region, South Africa. South African J Bot 108:209–222. https://doi.org/10.1016/j.sajb.2016.10.014

Müllerová JM (2019) UAS for Nature Conservation – Monitoring Invasive Species. In: Applications of Small Unmanned Aircraft Systems. pp 157–172

Nowell MS (2011) Determining the hydrological benefits of clearing invasive alien vegetation on the Agulhas Plain, South Africa

Oldeland J, Revermann R, Luther-Mosebach J, et al (2021) New tools for old problems — comparing drone- and field-based assessments of a problematic plant species. Environ Monit Assess 193:. https://doi.org/10.1007/s10661-021-08852-2

Pirotti F, Sunar F, Piragnolo M (2016) Benchmark of machine learning methods for classification of a Sentinel-2 image. Int Arch Photogramm Remote Sens Spat Inf Sci - ISPRS Arch 41:335–340. https://doi.org/10.5194/isprsarchives-XLI-B7-335-2016

R Core Team (2021) R: A language and environment for statistical computing

Redlands CESRI (2019) ArcGIS Desktop: Release 10.7,1

Rejmánek M (2000) Invasive plants: Approaches and predictions. Austral Ecol 25:497–506. https://doi.org/10.1111/j.1442-9993.2000.tb00055.x

Royimani L, Mutanga O, Odindi J, et al (2019) Advancements in satellite remote sensing for mapping and monitoring of alien invasive plant species (AIPs). Phys Chem Earth 112:237–245. https://doi.org/10.1016/j.pce.2018.12.004

Rwanga SS, Ndambuki JM (2017) Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS. Int J Geosci 08:611–622. https://doi.org/10.4236/ijg.2017.84033

Sarkar D (2008) No Lattice: Multivariate Data Visualization with R. Springer, New York

Shiferaw H, Bewket W, Eckert S (2019) Performances of machine learning algorithms for mapping fractional cover of an invasive plant species in a dryland ecosystem. Ecol Evol 9:2562–2574.

https://doi.org/10.1002/ece3.4919

Somodi I, Čarni A, Ribeiro D, Podobnikar T (2012) Recognition of the invasive species Robinia pseudacacia from combined remote sensing and GIS sources. Biol Conserv 150:59–67. https://doi.org/10.1016/j.biocon.2012.02.014

Sutherland WJ (2006) Ecological Census Techniques, 2nd edn. Cambridge University Press, Cambridge

Tay JYL, Erfmeier A, Kalwij JM (2018) Reaching new heights: can drones replace current methods to study plant population dynamics? Plant Ecol 219:1139–1150. https://doi.org/10.1007/s11258-018-0865-8

Zhang D (2021) rsq: R-Squared and Related Measures. R package version 2.2

Appendixes

Appendix A

The data collection sheet for ground-based surveys:

	Assessor:
	Date of Assessment:
	Farm name:
	NBAL ID/Block ID:
	GPS Coordinates S:
	GPS Coordinates E:
	Time Taken:

Quadrat	**Genus of dominant native plants**	**Alien Invasive species**	**Stem Count of Alien plants**	**% of Alien plants**	**% ground covered by all vegetation**	**Height of tallest dominant plant (cm)**
1						
2						
3						
4						
5						

6						
7						
8						
9						
10						
11						
12						
13						
14	-	-	-			
15				-	-	-
16						
17						
18						
19						
20						
21						
22						
23						
24						
25						
26						

27						
28						
29						
30						
31						
32						
33						
34						
35						
36						
37						
38						
39						
40						

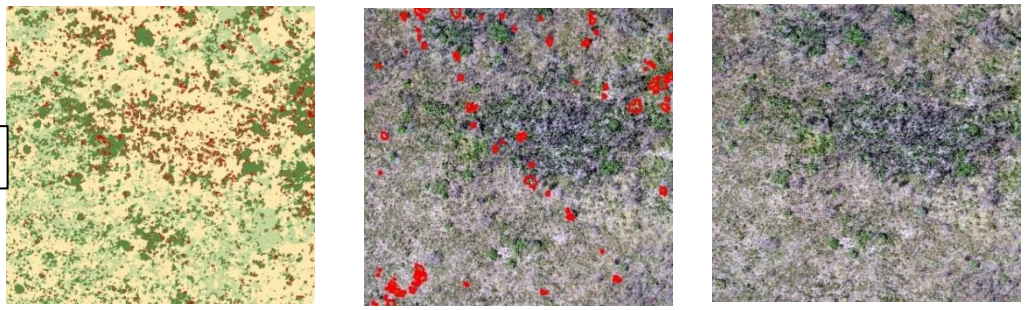
Appendix B

Legend

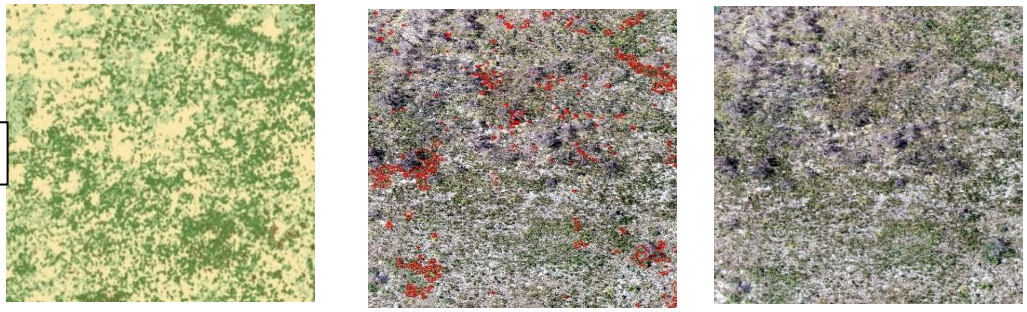
- Natural green vegetation
- Bare ground or dead plant
- Natural brown Vegetation
- IAPs

Flower Valley Site

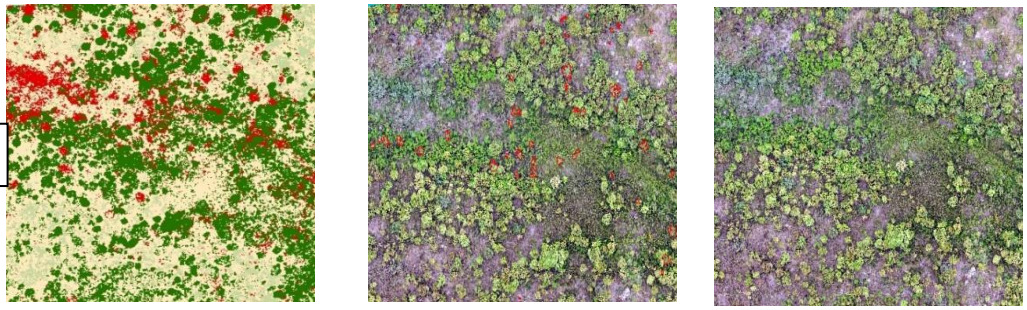
Flower Valley Site



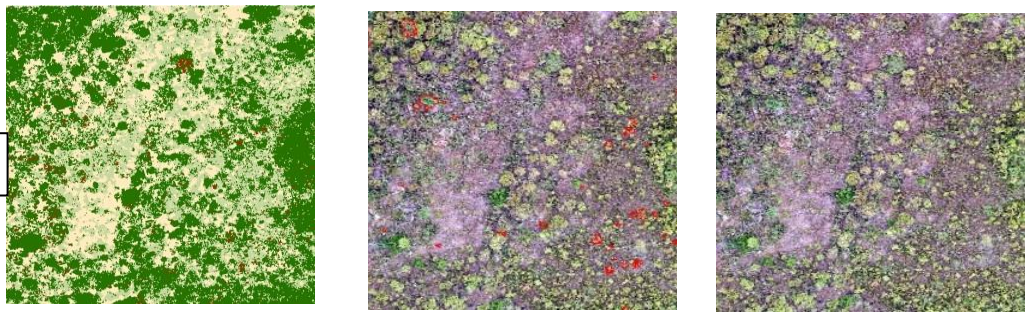
Flower Valley Site



Flower Valley Site



Flower Valley Site



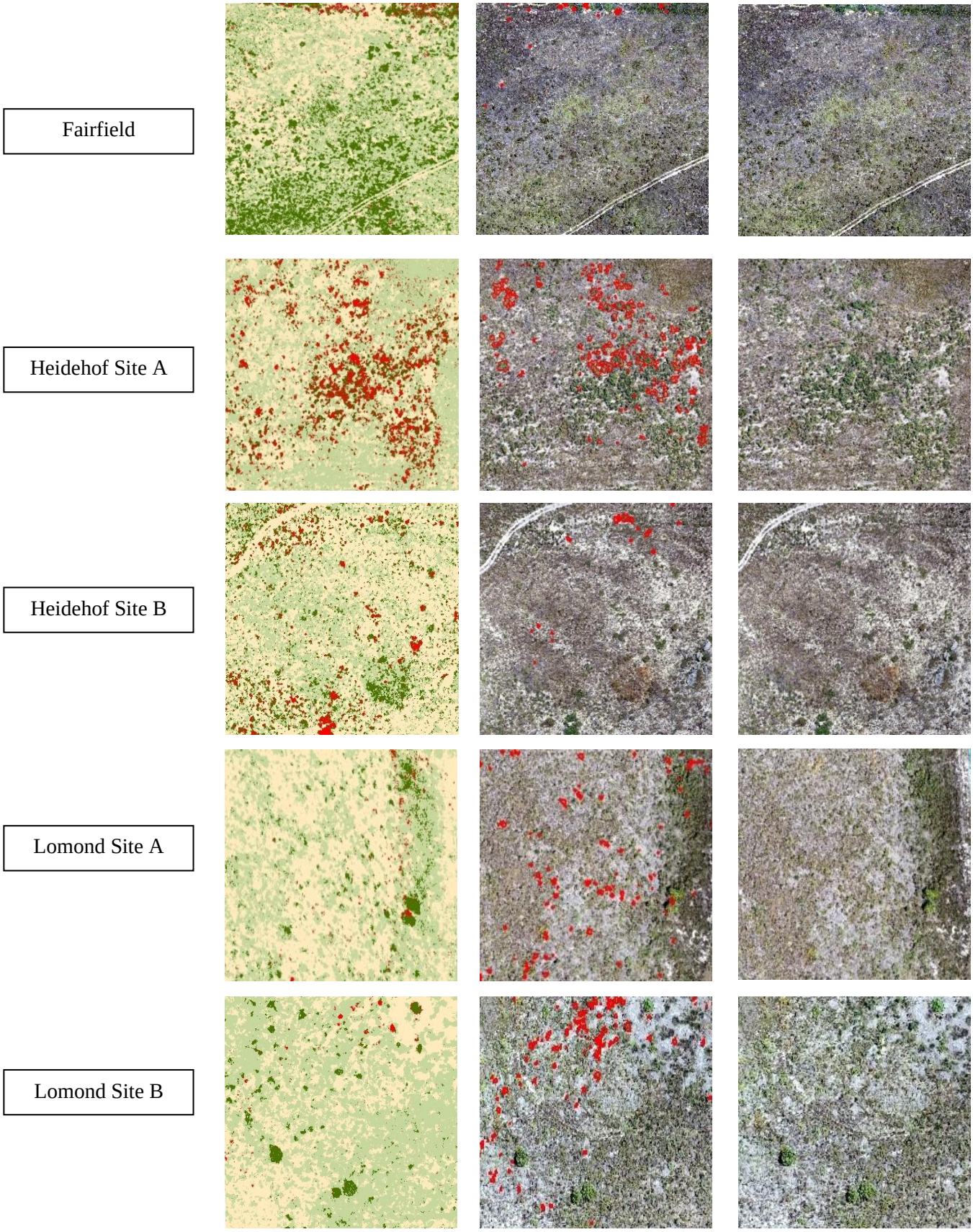


Figure B 1. The orthomosaics of each study site (far right) with the output of the automatic classification on the left, the output of the manual classification in the middle. The legend on the top left explains the different classes of the automatic classification.