Effect of plant canopy shape and flowers on plant count accuracy using remote sensing imagery

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Abstract: Separate experiments were conducted to evaluate the effect of plant canopy shape and presence of flowers on counting accuracy of container-grown plants. Images were taken at 12 m above the ground. Two species of juniper (Juniperus chinensis L. 'Sea Green' and Juniperus horizontalis Moench 'Plumosa Compacta') were selected to evaluate plant shape and Coral Drift ® rose (Rosa sp. 'Meidrifora') was used to evaluate the presence of flowers on plant count. Counting algorithms were trained using Feature Analyst (FA). Total counting error, false positives and unidentified plants were reported. There was no difference between all variables measured when an algorithm trained with an image displaying regular or irregular plant canopy shape was applied to images displaying both plant canopy shapes even though the canopy shape of 'Sea Green' is less compact than 'Plumosa Compacta'. There was a significant difference in all variables measured between images of flowering and non-flowering plants when non-flowering 'samples' were used the train the counting algorithm in FA; total counting errors and unidentified plants was greater for flowering plants. In this specific case, applying an algorithm that did not include a training set displaying flowers, resulted in a less accurate count. Algorithms developed using FA appears to be fairly robust under these conditions.

Keywords: nursery plants, vegetation, inventory, feature analyst

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1 Introduction

In general, the nursery industry lacks an automated inventory control system (Harkess, 2005). The process of collecting inventory data in a nursery is labor intensive involving the physical counting of thousands of plants. Due to the time involved in manually counting plants, forest tree and nursery growers often count only a portion of their crop (Hale, 1985; S. Doane, personal communication, 8 May, 2008). In the last few years some improvements have been made in the inventory process such as the adoption of computers, software (Hodges et al., 2008; USDA, 2013), and mobile personal digital assistants (Brownsberger et al., 2001). While these technologies have helped in the processing of inventory data, the data are still mostly collected manually. Other technologies such as radio frequency identification (RFID) and bar codes are helping with the collection of inventory data but they have limitations such as the need for line-of-sight, signal transmission errors (Janam Technologies, 2011; Saraswat and Robbins, 2011), plant damage produced by tags (Luvisi et al., 2010), and adaptability into large nurseries (Schuch and Klein, 1996).

Aerial images combined with image processing software have been used to identify tree species composition (Hájek, 2006), crops and vegetation monitoring (Hunt et al., 2005; Furfaro et al., 2007; Shank, 2009; Bumgarner et al., 2012; Lebourgeois et al., 2012), and land cover classification (Akasheh et al., 2008; Dunford et al., 2009; Miller et al., 2009; Tombre et al.,

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2010). Both technologies have been used to detect a variety of individual objects such as bats (Hamilton et al., 2009), cattle and horses (Terletzky and Ramsey, 2014), marine birds (Groom, et al., 2013), and forest tree crowns (Wulder, 1998; Wulder et al., 2000; Pitkänen, 2001; Pouliot et al., 2002; Leckie et al., 2003; Tiede et al., 2005; Bunting and Lucas, 2006). Additionally, algorithms have been developed to count citrus trees (Ayyalamayajula et al., 2009), olive trees (Karantzalos and Argialas, 2004) and corn plants (Shrestha and Steward, 2003). This technology could be used for counting plants in nurseries.

Several factors contribute to the complexity of imagery used for plant inventory analysis including plant characteristics (plant color, species, plant size and shape, canopy cover, plant health), ground/surface characteristics (bare soil, gravel, ground cloth), and environmental factors (sunlight/shadows). Because these factors could influence the analysis of data obtained from remote-sensing images, these conditions must be accounted for when using these images. Since nurseries grow a wide range of plants, this may require several counting algorithms. This study was designed to evaluate the effect of plant canopy shape and presence of flowers on counting accuracy of container-grown plants.

2 Materials and methods

2.1 Canopy shape

2.1.1 Camera

A Sony Alpha NEX-7 (Sony Corporation of America IR, San Diego, CA), 24.3 megapixels color digital frame camera, with an 18-55 mm lens was used as the sensor. The shooting mode was set as manual with an ISO of 200, shutter speed of 1/250 seconds, and an f value of 8. Autofocusing and aspect ratio of 3:2 were fixed. Flash, object tracking, and face detection were turned off. Images from this camera contain three bands: red, green and blue (RGB).

2.1.2. Experimental design

Container-grown plants were spaced in staggered rows with a canopy separation of 5 cm between canopy edges. Two species of juniper (*Juniperus chinensis* L. 'Sea Green' and *Juniperus horizontalis* Moench 'Plumosa Compacta') growing in #2 black polyethylene containers (height: 21.6 cm, top diameter: 22.9 cm, and bottom diameter: 19.7 cm) (Plastics Inc., Jacksonville, TX) were used in the study since they were available in large numbers and the foliage, texture, and color was visually similar (Figure 1). Plants were pulled from nursery production blocks. Henceforth, the canopy for 'Plumosa Compacta' will be referred as 'regular' and 'Sea Green' canopy as 'irregular'. For each canopy shape treatment, a set of 64 containers (8 × 8) was established outdoors on black polypropylene fabric ground cover (Lumite, Inc., Alto, GA) on 13 November, 2013 at Greenleaf Nursery, Park Hill, OK (35.779098, -94.904323). Treatment sets were replicated five times in a randomized complete block design (RCBD) for a total of 10 sets. Two additional sets of 49 containers (7 × 7), one with 'Sea Green' juniper and the other with 'Plumosa Compacta', were positioned adjacent to the treatment sets and were used to train the algorithm using Feature Analyst (FA), and henceforth referred to as training sets (Figure 2). The number of plants used in training and treatment sets was determined based on preliminary experiments. Four plants per set were used for plant measurements. These were the corner plants of each set. Shoot height was measured from the substrate surface to the top of the plant. Average shoot height was 40 and 27 cm for 'Sea Green' and 'Plumosa Compacta' junipers, respectively. Average shoot diameter was determined by taking two measurements at 90^{o} from each other. Average shoot diameter was 49 and 39 cm for 'Sea Green' and 'Plumosa Compacta', respectively. A rule set within eCognition (Trimble®, Westminster, CO) was run to calculate RGB mean values from an aerial image at 0.15 cm/pixel spatial resolution, resulting in 81±51, 84±50, 53±43 for 'Plumosa Compacta', 60±45, 72±47, 41±36 for 'Sea

Green', and 15±17, 20±16, 31±14 for the black fabric used as ground cover. The image was taken using the same camera used for all images with an f value of 8 and a shutter speed of 1/250 seconds. Other camera settings were the same as previously described.

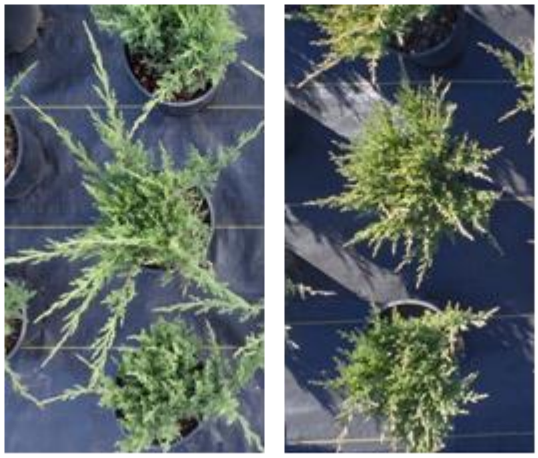

Figure 1 Two species of juniper evaluated. Left: *Juniperus chinensis* L. 'Sea Green' (irregular shape), right: *Juniperus horizontalis* 'Plumosa Compacta' (regular shape)

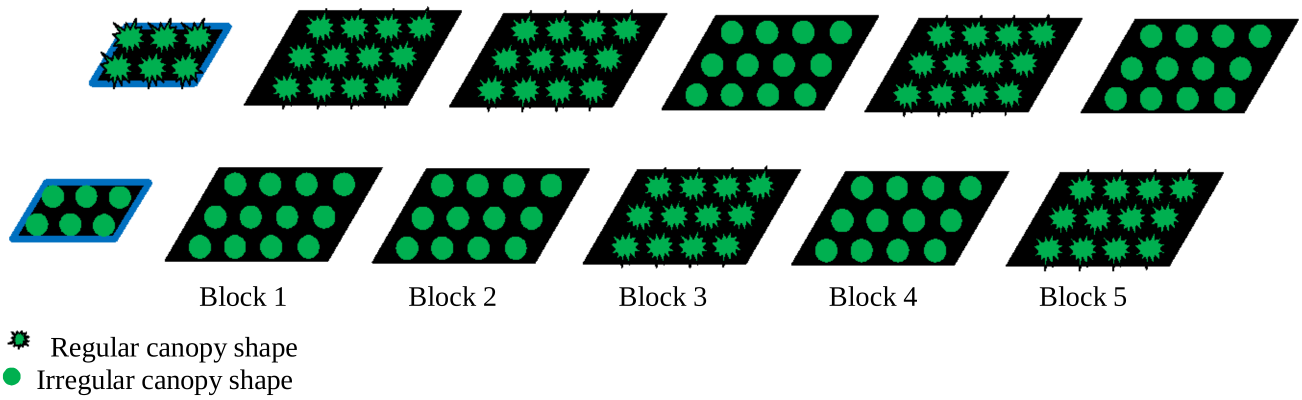

Figure 2 Illustration of the experimental design. Training sets used in Feature Analyst® are the two smaller sets on the left, the remainders are treatment sets

2.1.3. Data collection

Images were obtained by extending a Bil-Jax 3632T boom lift (Haulotte Group, Archbold, OH) to 12 m above ground level. To obtain images centered over blocks required moving the boom lift. Each time the boom was re-positioned, sensor height relative to the ground was determined using a measuring tape. The sensor, which was handheld, was positioned over the center of every block resulting in both sets for that block being included in the image (e.g. both treatment sets, within each block, were captured in the same image as is shown in Figure 2). Image spatial resolution was calculated based on 20 cm square white boards positioned around the treatment blocks, resulting in 0.15 cm/pixel. Two images of each plant set were taken and then used for algorithm evaluation.

2.1.4. Variables

Three variables were measured using the final count and output image as follows:

Total counting error: total software count-ground count. Total counting error is also presented as percentages based on the ground count from the set.

False positives: counts that do not represent a target plant (e.g. multiple counts, weeds or other objects within the ground cover that could be counted as a plant).

Unidentified: target plants that were not counted.

Means were separated using an analysis of variance followed by a student's t-test based on the experimental design described above using SAS 9.3 (SAS Institute Inc., Cary, NC).

2.1.5. Environmental parameters

Environmental parameters including light intensity (140 LUX), relative humidity (24.4%), temperature (15.6 ℃), and ground wind speed (0-4 km/h) were measured using a Mini Environmental Quality Meter (Sper Scientific, Scottsdale, AZ) before images were collected (10:20h). A subjective estimate of cloud cover was determined to be less than 5%.

2.1.6. Algorithm training using Feature Analyst®

In order to decrease image processing time, images were cropped and rotated using Adobe Photoshop Elements 6 (Adobe System Incorporated, San Jose, CA) leaving only the set of interest for that particular image. A total of two algorithms were trained, one for each canopy shape. Each algorithm was applied to all images regardless of canopy shape type. The general process used to train an algorithm is described as follows. Images were added into ArcMap™ Version 10.1 (ESRI, Redlands, CA) in JPEG format. Circular shapes ('samples') were digitized over individual plants. Several shapes can be used to digitize samples; however, circles were used since they require less user input than customizable polygons, making the process faster and more reproducible. The initial number of circular shapes digitized was based on user experience, and their position within the image was selected in order to capture variability of the target plants. For all algorithms, the initial number of digitized circles was eight and their positions were selected in order to capture distortion within the image which tends to be more variable at the edge of the images. A first segmentation based on the digitized samples was run using a supervised learning approach with the following parameters: a nature feature selector, no resample factor, Manhattan input representation, and vector as the output format. All three color bands were used for algorithm training. Based on the results from the first segmentation, pattern width of the input representation and/or number, size, and position of digitized circles might be modified until a uniform segmentation was obtained; a similar procedure was used by Hamilton et al. (2009), Miller et al. (2009), and Gasch et al. (2011) in wildlife, urban application, and rhizotron measurements, respectively. Following this, a number of procedures were applied to the image. These procedures included: conversion from raster to vector and vector to raster formats, aggregation, erosion, dilation, opening, smoothing, calculation of vector metrics, and conversion from polygons to points. Some of these procedures were applied more than once. Parameters for those procedures were fixed according to the images used for training. After a procedure is applied, FA creates an automated feature extraction model (AFE) that stores training set data and all procedures applied, Figure 3 shows an example of a final AFE model. Finally, the AFE model was applied to all images regardless of canopy shape. The AFE model was applied to the respective treatment set images using the batch processing tool. Parameters used to train the algorithm were based on user experience and a subjective analysis of the output files after procedures were applied. Parameters such as the number of cycles that a procedure is applied were changed several times by the operator until the final plant count accuracy no longer improved for that specific training image. This may be a source of error since different users might consider different procedures, order of procedures, and parameters.

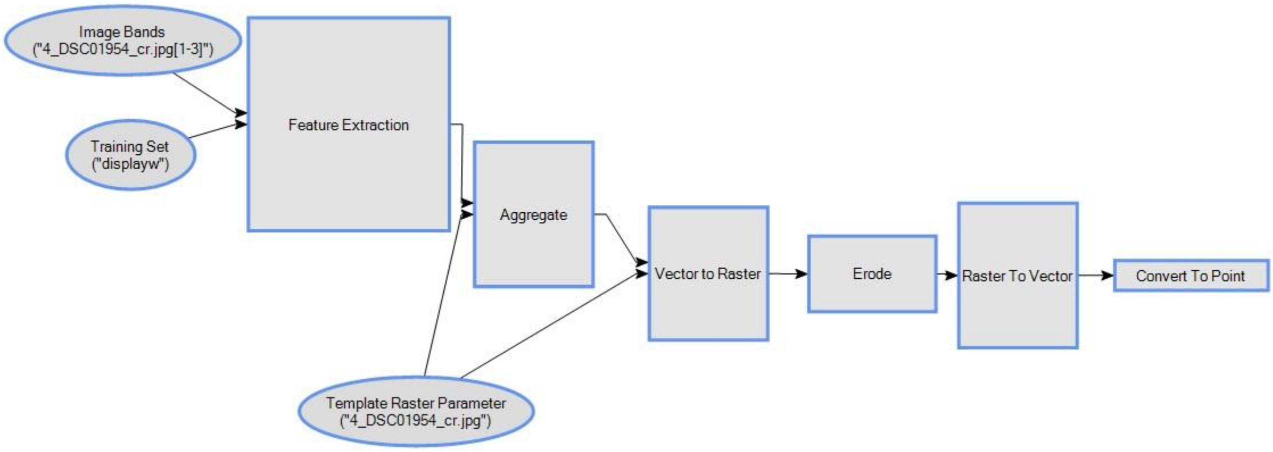

Figure 3 Graphic representation of an Automated Feature Extraction (AFE) model using Feature Analyst®.

2.2 Presence of flowers

2.2.1 Camera

A Sony Alpha NEX-7 (Sony Corporation of America IR, San Diego, CA), 24.3 megapixels color digital frame camera, with an 18-55 mm lens was used as the sensor. The shooting mode was set as manual with an ISO of 200, shutter speed of 1/250 seconds and an f value of 8. Autofocusing and aspect ratio of 3:2 were fixed. Flash, object tracking, and face detection were turned off.

2.2.2 Experimental design

Container-grown plants were spaced in staggered rows with a canopy separation of 5 cm between canopy edges. Coral Drift® rose (*Rosa* sp. 'Meidrifora') growing in true #1 yellow/green polyethylene containers (height: 17.8 cm, top diameter: 19.7 cm, and bottom diameter: 15.9 cm) (Nurseries Supplies Inc., Chambersburg, PA). Plants were pulled from nursery production blocks. Two treatments were evaluated: 1) roses with coral flowers and 2) roses without flowers; for the latter, flowers were removed manually (Figure 4). For each treatment, a set of 64 containers (8 × 8) was established outdoors on black polypropylene fabric ground cover on 13 November, 2013 at Greenleaf Nursery, Park Hill, OK (35.779098, -94.904323). Treatment sets were replicated five times in a randomized complete block design (RCBD) for a total of 10 sets. Two images of each set were taken and then used for algorithm evaluation. Two additional sets of 49 containers (7 × 7), one containing plants with flowers and the other without flowers were positioned adjacent to the treatment sets and were used to train the FA algorithm, and henceforth, referred to as training sets (Figure 5). Four corner plants per set were used for plant measurements. Shoot height was measured from the substrate surface to the top of the plant. The average shoot height was 25 cm. The average shoot diameter was determined by taking two measurements at 90^{o} from each other. The average shoot diameter was 30 cm. RGB mean values were calculated from an aerial image at 0.15 cm/pixel spatial resolution, under sunny conditions using eCognition (Definiens Imaging GmbH, Germany) for plant canopy and ground covers resulting in 139±62, 115±55, 99±55 for roses with flowers, 131±53, 122±52, 98±51 for roses without flowers, and 125±43, 128±42, 139±39 for the black fabric. The image used to calculate RGB mean values was taken using the same camera used for all images with an f value of 8 and a shutter speed of 1/250 seconds. Other camera settings were the same as previously described.

Figure 4 Coral Drift ® rose plant with flowers (left) and without flowers (right)

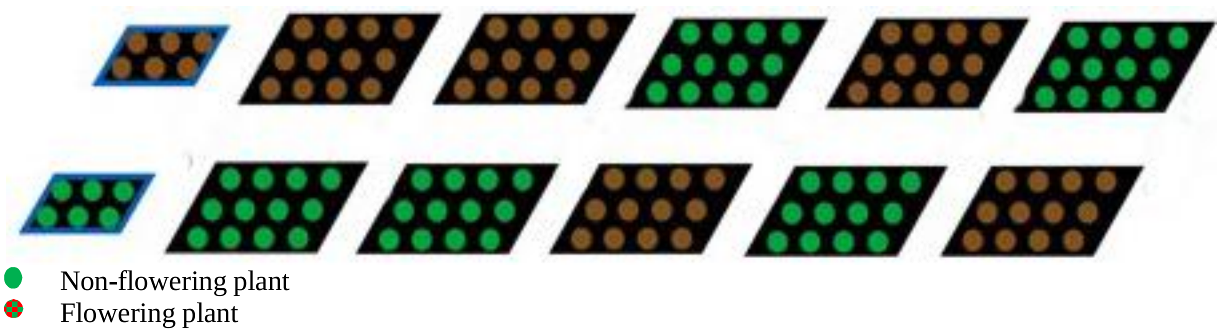

Figure 5 Illustration of the experimental design. Training sets used in Feature Analyst® are the two smaller sets on the left, the remainder are treatment sets

Data collection, variables measured and image selection parameters are the same as those described in the canopy shape experiment.

2.2.3 Environmental parameters

Environmental parameters including light intensity (140 LUX), relative humidity (24.4%), temperature (15.6 ℃), and ground wind speed (0-4 km/h) were measured using a Mini Environmental Quality Meter at the beginning of image collection (13:00 h). A subjective estimate of cloud cover was determined to be less than 5%.

2.2.4 Algorithm training

Algorithm training procedures using FA were similar to those described previously. A total of two algorithms were trained, one for plants with flowers and another for plants without them. Each algorithm was applied to all images regardless of presence of flowers.

3 Results and discussion

3.1 Canopy shape

3.1.1 Algorithm trained using images displaying plants with regular canopy shape

An algorithm was trained using a training image displaying junipers with a regular canopy shape using FA and then applied to images displaying junipers with regular and irregular canopy shapes. There were no significant differences between canopy shape treatments for total counting error ($F=0.30$, $p=0.6013$), false positives ($F=2.25$, $p=0.1679$), and unidentified plants ($F=0.54$, $p=0.4817$) when the data were analyzed using FA (Table 1). It is possible that some branches overlapped causing minor conflicts for the algorithm to resolve, resulting in small counting errors (i.e. two or more plants counted as one, generating unidentified plants).

Table 1 Count accuracy for container-grown junipers with regular (*Juniperus horizontalis* 'Plumosa Compacta') and irregular (*Juniperus chinensis* L. 'Sea Green') canopy shapes when training an algorithm with images displaying junipers with regular canopy shape using Feature Analyst®

Canopy shape	Total counting error		False positives		Unidentified plants	
	No.[z]	%[y]	No.[x]	%	No.	%
Regular	-2	-3%	0	0%	2	3%
Irregular	-1	-2%	0	0%	1	2%

Note: [z]Total counting error: total software count – ground count. Total counting errors are based on a ground count of 64.
[y]Variables expressed as percentages; variable/ground count ×100.
[x]False positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were count as a plant).

3.1.2 Algorithm trained using images displaying plants with irregular canopy shape

An algorithm was trained using a training image displaying junipers with an irregular canopy shape and then applied to images displaying junipers with regular and irregular canopy shapes. There were no significant differences between canopy shape treatments for total counting error (F=0.12, p=0.7337), false positives (F=3.27, p=0.0872), and unidentified plants (F=0.01, p=0.9165) when data were analyzed using FA (Table 2).

Table 2 Count accuracy for container-grown junipers with regular (*Juniperus horizontalis* 'Plumosa Compacta') and irregular (*Juniperus chinensis* L. 'Sea Green') canopy shape when training an algorithm with images displaying junipers with irregular canopy shape using Feature Analyst®

Canopy shape	Total counting error		False positives		Unidentified plants	
	No.[z]	%[y]	No.[x]	%	No.	%
Regular	-1	-2%	0	0%	1	2%
Irregular	-1	-2%	0	0%	1	2%

Note: [z]Total counting error: total software count – ground count. Total counting errors are based on a ground count of 64.
[y]Variables expressed as percentages; variable/ground count ×100.
[x]False positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were count as a plant).

When data were analyzed with FA, there was no difference between variables measured when an algorithm trained with an image displaying regular or irregular plant canopy shape was applied to images displaying either of the plant canopy shapes. Even though the canopy shape of 'Sea Green' is less compact than 'Plumosa Compacta', visible individual lateral branches are eliminated when applying the erosion procedure, thus making FA algorithm performance similar. The erosion procedure reduces object size by determining if pixels are enclosed within an object (Richards, 2012). Another explanation for the similarity in counting results between the two scenarios is that although the RGB values for both cultivars are not identical, FA segmented them similarly due to the wide range in RGB values.

When using FA, one set of training samples was selected by the user from one training image and then the training set was used to analyze different images. Since different users would likely pick different training sets, expectations were that this user input was going to increase experimental error, however, if there is an effect related to this process, it appears to have a minimal effect on count accuracy for juniper plants.

3.2 Presence of flowers

3.2.1 Algorithm trained using images displaying plants with flowers

An algorithm was trained using an image displaying plants with flowers and then applied to images displaying plants with and without them. Total counting error (F=0.60, p=0.4617), false positives (F=0.00, p=1.00), and unidentified plants (F=0.60, 0.4617) means generated with FA indicate no significant differences for flowering and non-flowering treatments (Table 3).

Table 3 Count accuracy for container-grown Coral Drift ® rose (*Rosa* sp. 'Meidrifora') with and without flowers placed on a black fabric ground cover, when training an algorithm with images displaying flowering roses using Feature Analyst®

Treatment sets	Total counting error		False positives		Unidentified	
	No.[z]	%[y]	No.[x]	%	No.	%
Flowering	-1	-2%	1	2%	2	3%
Non-flowering	-2	-3%	1	2%	3	5%

Note: [z]Total counting error: total software count – ground count. Total counting errors are based on a ground count of 64.
[y]Variables expressed as percentages; variable/ground count ×100.
[x]False positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were count as a plant).

When training samples were digitized using plants with flowers in FA, pixels from leaves/stems and flowers were included. This approach works well to extract plants without flowers since the sample included pixels representing leaves. Count accuracy may also be high since there were small differences in RGB mean values between treatments (139±62, 115±55, 99±55 for roses with flowers, 131±53, 122±52, 98±51 for roses without flowers).

3.2.2 Algorithm trained using images displaying plants without flowers

FA was trained using an image displaying plants without flowers and then applied to images displaying plants with and without flowers. There was a significant difference in total counting error (F=11.54, p=0.0274), false positives (F=4.85, p=0.0450) and unidentified plants (F=8.94, p=0.0403) between images of flowering and non-flowering plants when images were analyzed with FA (Table 4). When expressed as percentages, total counting errors and unidentified plants were greater for flowering plants. This may be explained by the lack of a representative training set that excludes pixels representing coral flowers, resulting in a less consistent extraction. Even though RGB mean values between plants with and without flowers were fairly similar, FA may require a more representative training sample for this scenario.

Table 4 Total count accuracy for container-grown Coral Drift ® rose (*Rosa* sp. 'Meidrifora') with and without flowers placed on a black fabric ground cover, when training an algorithm with images displaying non-flowering roses using Feature Analyst®

Treatment	Total counting error		False positives		Unidentified	
	No.[z]	%[y]	No.[x]	%	No.	%
Flowering	-6 a[w]	-9%	1 a	2%	7 a	11%
Non-flowering	0 b	-0%	2 b	3%	2 b	3%

Note: [z]Total counting error: total software count – ground count. Total counting errors are based on a ground count of 64.
[y]Variables expressed as percentages; variable/ground count ×100.
[x]False positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were count as a plant).
[w]Means followed by the same letter within the same column are not significantly different based on a Student's t-test (p≤0.05).

4 Conclusion

Based on our results, canopy shape did not significantly affect counting results when using FA. In developing the algorithm using FA, the settings are flexible enough to account for the differences in canopy shape and foliage color between these junipers. Other plant species with a difference in canopy shape should be evaluated to determine the robustness of FA.

The experiment comparing images from flowering and non-flowering plants highlighted the importance of selecting a representative training set. The algorithm developed using FA did not appear to run a successful segmentation due to the lack of pixels representing flowers in the training set.

Under the conditions which these experiments were conducted this methodology demonstrated that aerial images and FA could be used to automate plant count in open-field situations, however, further research needs to be conducted.

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