Field grown apple nursery tree plant counting based on small UAS imagery derived elevation maps

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Abstract. *In recent years, growers in the state are transitioning to new high yielding, pest and disease resistant cultivars. Such transition has created high demand for new tree fruit cultivars. Nursery growers have committed their incoming production of the next few years to meet such high demands. Though an opportunity, tree fruit nursery growers must grow and keep the pre-sold quantity of plants to supply the amount promised to the customers. Moreover, to keep the production economical amidst rising labor shortages, the nursery growers are looking at incorporating technological advances on the horizon. Also to insure the young nursery seedlings from adverse winter weather, growers need to accurately know the tree inventory grown in the actual field environment. Therefore, objective of this study was to develop and validate robust field grown apple nursery plant counting algorithm that is based only on elevation pixel values of small Unmanned Aerial System (UAS) based low altitude RGB imagery data. The nursery field images were obtained using small UAS operated at 30 m above the ground level. Image processing was performed in a Geographic Information System (GIS) software, where the pipeline was defined focusing on the isolation of apple plants based on thresholds of pixel height in circular regions along the crop line. In the first step the Digital Elevation Model (DEM) was processed in order to extract the Digital Terrain Model (DTM); the height of the plants was estimated according to the Crop Surface Model (CSM), which is the difference between the DEM and DTM. In the second step, the center lines of crop rows were extracted. As a third step, inside each row line generated were the points with a fixed spacing of 25 cm and buffered circular regions with a diameter of 50 cm. Those buffer areas were classified aiming following the logistic that "only the circles with maximum height higher than 23 cm can be counted as plants". The proposed methodology presented satisfactory results, reaching an estimation with an accuracy of 95%.*

Keywords. *Tree fruit nursery, Plant inventory maps, Aerial imaging, Digital surface model, Zonal statistics.*

INTRODUCTION

Washington State tree fruit crop production is valued at about $5 billon with state leading in fresh market apple, pear and sweet cherry production with U.S. (WSDA, 2018). In recent years, growers in the state are transitioning to new high yielding, pest and disease resistant cultivars. Such transition has created high demand for new tree fruit cultivars. Nursery growers have committed their incoming production of the next few years to meet such high demands. Though an opportunity, tree fruit nursery growers must grow and keep the pre-sold quantity of plants to supply the amount promised to the customers. Moreover, to keep the production economical amidst rising labor shortages, the nursery growers are looking at incorporating technological advances on the horizon.

Also to insure the young nursery seedlings from adverse winter weather, growers need to accurately know the tree inventory grown in the actual field environment. This is different than ornamental nursery crops grown in containers. Manual counting is the only available and commonly used methodology to quantify nursery tree inventory. Typically, growers have to do laborious and time consuming inventory of nursery plants, about 4 times a year (i.e., every season). This operation carries long working days for already scares workforce in the field besides delay to obtain the final results. Furthermore, manual counting in the field environment does not ensure 100% counting accuracy, but gives an estimative with about an absolute error of 5%. Error can be due to the measurement error incurred when several field scouts carrying evaluations throughout the day for several days.

Technological alternatives like small unmanned aerial based remote sensing can be explored to improve the nursery inventory mapping processes. There are many research studies on plant-by-plant mapping of forests since the begging of remote sensing (Helsinki, 1955). Specific to nursery inventory mapping, prior studies have developed systems and algorithms suitable for seedlings planted in containers (Robbins et al., 2012; Ehsani et al., 2014; Leiva, 2014). To the best of our knowledge, nursery plants grown in the actual agricultural fields has been explored previously through use of small UAS based multispectral imaging, work of our group and developing an image-filtering pipeline (Quiros and Khot, 2016). Although promising, the number of data collection and analysis steps interdependencies hindered the repeatability of the methodology. For example, the illumination of plants under rapidly changing field environments create challenges to filter out the plant from weeds. Therefore, objective of this study was to develop and validate robust field grown apple nursery plant counting algorithm that is based only on elevation pixel values of small UAS based low altitude RGB imagery data.

MATERIALS & METHODS

The present work was conducted in the Washington state Columbia basin valley located in the center of the State surrounded by hills of 600 to 700 m above sea level (47° 9'39.23"N, 119°47'44.02"W). Data was collected mid-October of 2017 on a sunny day between 10 am and noon having solar radiation of approximately 10.29 MJ/m^2. The study covered an area of 600 m^2, with a plot of 12 x 50 m dimensions. Imaged were 6 crop lines planted at 2 m of distance between them with each line taken as a repetition to analyze the percentage of error in plant count (Figure 1).

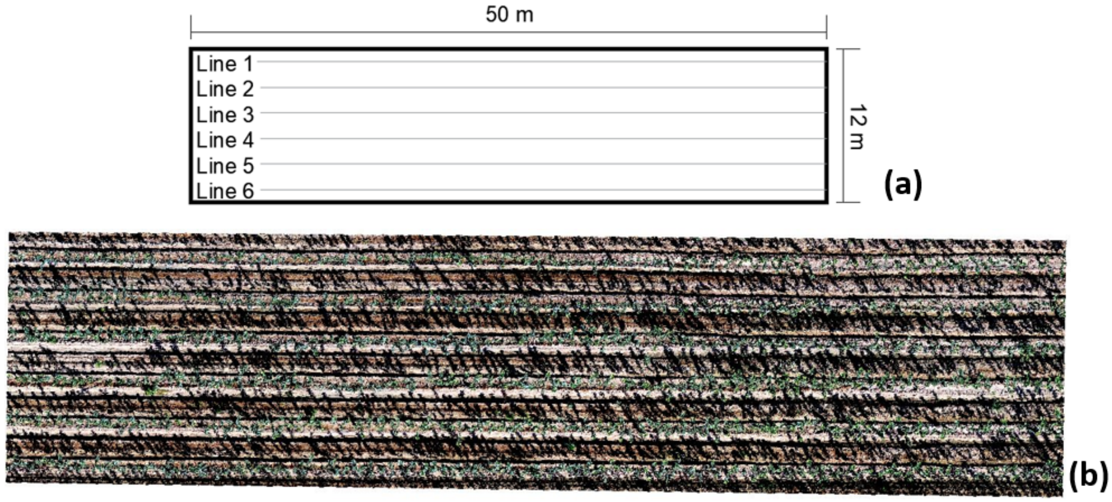

Figure 1. (a) Study plot dimensions and crop lines identification, and (b) mosaic image used for data processing.

For the collection of images, used was a small UAS (i.e., quadcopter) (DJI Phantom 4 Pro, China) equipped with a 12-megapixel Complementary metal–oxide–semiconductor (CMOS) RGB imaging sensor. Images were collected at ground surface distance (GSD) of approximately 0.023 m/pixel at a height of 30 m. The small UAS featured a Global Navigation Satellite System (GNSS) allowing the aircraft to execute a predefined flight plan developed using a mission planner (Drone Deploy, Pix4D, San Francisco, CA) software.

For the present work, images were acquired with a lateral and longitudinal overlap of 80%, guaranteeing the total coverage of the study area. After the flight, the collected images were processed in the Agisoft© (Photoscan Professional software ver. 2017, Agisoft LLC, St. Petersburg, Russia) which, through its own algorithms, allowed to orient the images, generate the orthomosatic and the digital terrain and surface models (DTM and DSM). The models were later analyzed in a GIS (Geographic Information System) environment.

The imagery analysis involved three major steps. Step 1 was to extract height of the plants using combination of a DSM, which represents the canopy vegetation, and the DTM, which represents the ground level (Bending et al., 2012). Subtracting the DTM from the DSM, obtained was the crop surface model (CSM) (Figure 2a). In step 2, the orthomosaic obtained from the aerial imagery was used for the generation of the 6 crop central lines (Figure 2b). From the central lines, generated were the points with fixed distances of 0.25 m in each line, totaling 846 points. The distance between points was determined from ground observations of the actual average spacing between the plants. The third step was then to create a buffer for each point with a diameter of 0.50 m to have 846 circular polygons covering an area of 0.196 m². From the CSM, the maximum height values were extracted for each circular polygon. With the maximum height values, the presence of plants was defined for those polygons with a maximum height above 0.23 m (Figure 2c). This threshold was taken from the average height of 5 plants noticeably smaller than the rest. In order to evaluate the efficiency of the automatic counting technique, the manual count obtained as ground reference was used as the real value.

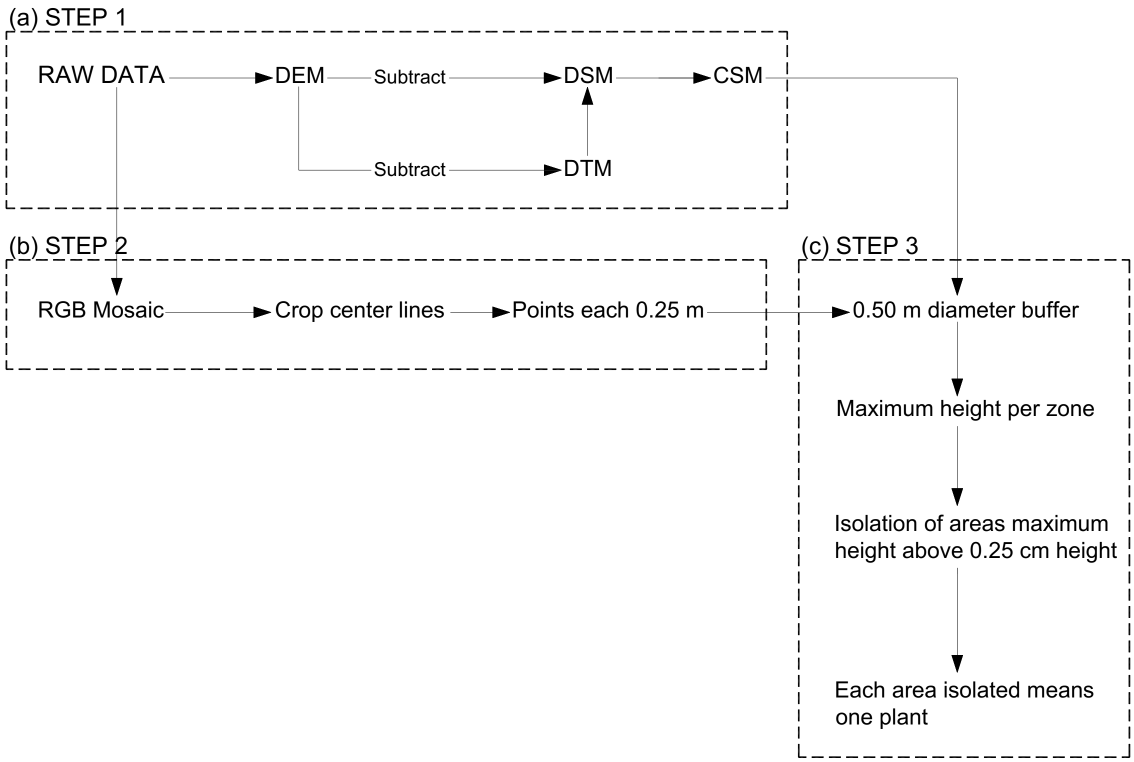

Figure 2. Flow chart resuming steps of the presented methodology.

RESULTS & DISCUSSION

An average error percentage of 5% was obtained from the 6 rows (lines) analyzed. In row 2 (line 2), the ground-reference and algorithm estimated plant count was identical; most likely due to the defined shape and regular spacing of plants. In all the other rows, the percentage of error was higher (see Table 1), tending to overestimate the number of plants.

Table 1. Difference between actual ground reference and algorithm estimated plant count and average error percentages for each of the six tree rows.

Row line	Ground reference plant count	Algorithm estimated plant count	Difference (Ground reference - Estimated)	Error (%)
1	122	133	-11	9
2	132	132	0	0
3	135	129	6	4
4	119	131	-12	10
5	124	129	-5	4
6	112	118	-6	5
			Average	5

Figure 3 shows the resulting image on each of the main steps of the algorithm implemented for plant counting. Even being close to each other, crop rows present differences between them regarding the height of plants (Figure 3a). In row lines 4, 5 and 6, wide gaps in the tree seedling lines as well as the punctual no-plant zones along the other lines were detected successfully by the algorithm (Figure 3d and e). The irregular shape of plants and canopy was minimized in the analysis as the algorithm considered only few pixels inside the sample area above the height limit to be counted as a plant. Besides plant height, developed algorithm considers many others factors such as seedling perimeter, size and the vector direction of the axes captured in the image. For a better understanding of how this methodology works, figure 4 presents a CSM derived3D reconstructed view, where pixels above 0.25 m are highlighted as plants (in yellow), and rest as places without plants (red spheres).

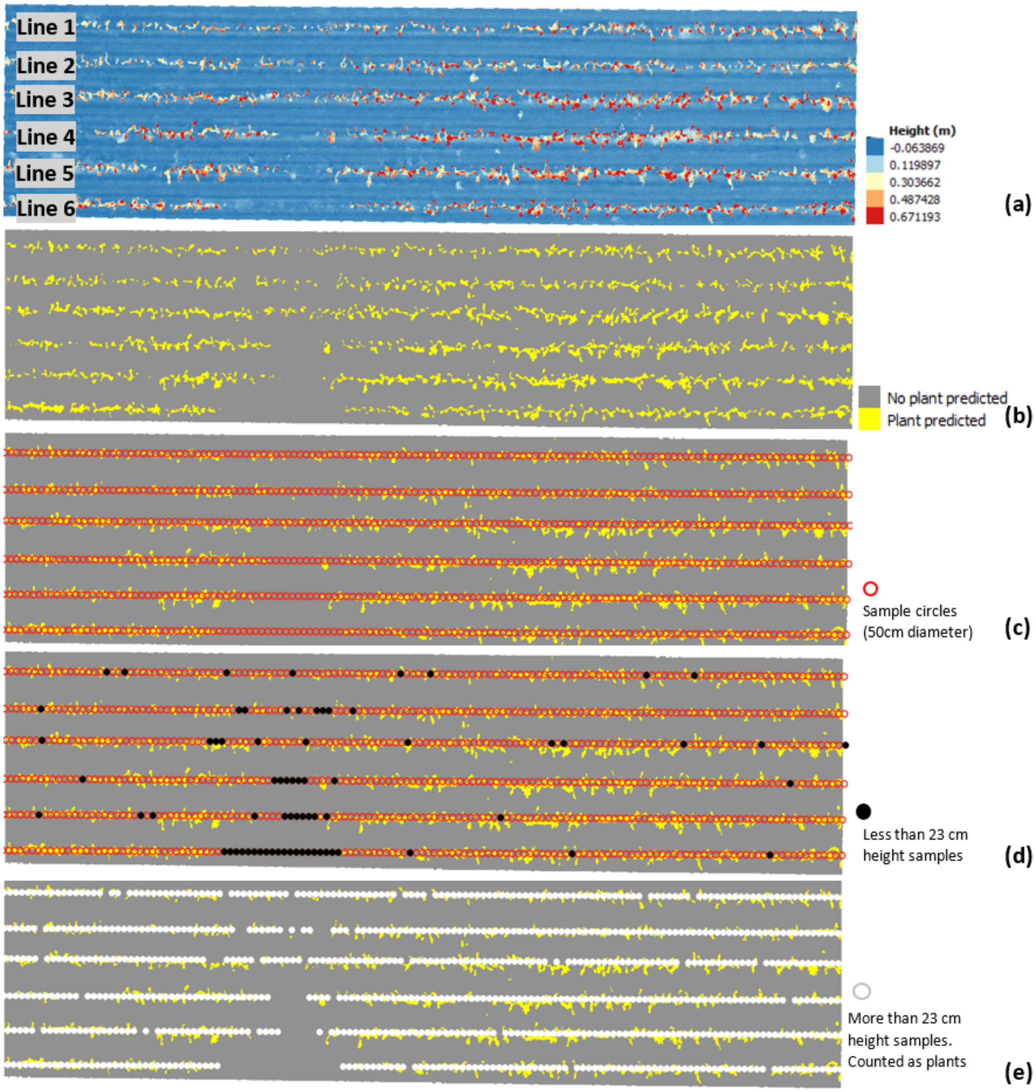

Figure 3. Resulting images from the main steps of the process: (a) DSM, (b) planted and non-planted areas binary image, (c) circular sample zones, (d) samples not counted as plants and (e) samples counted.

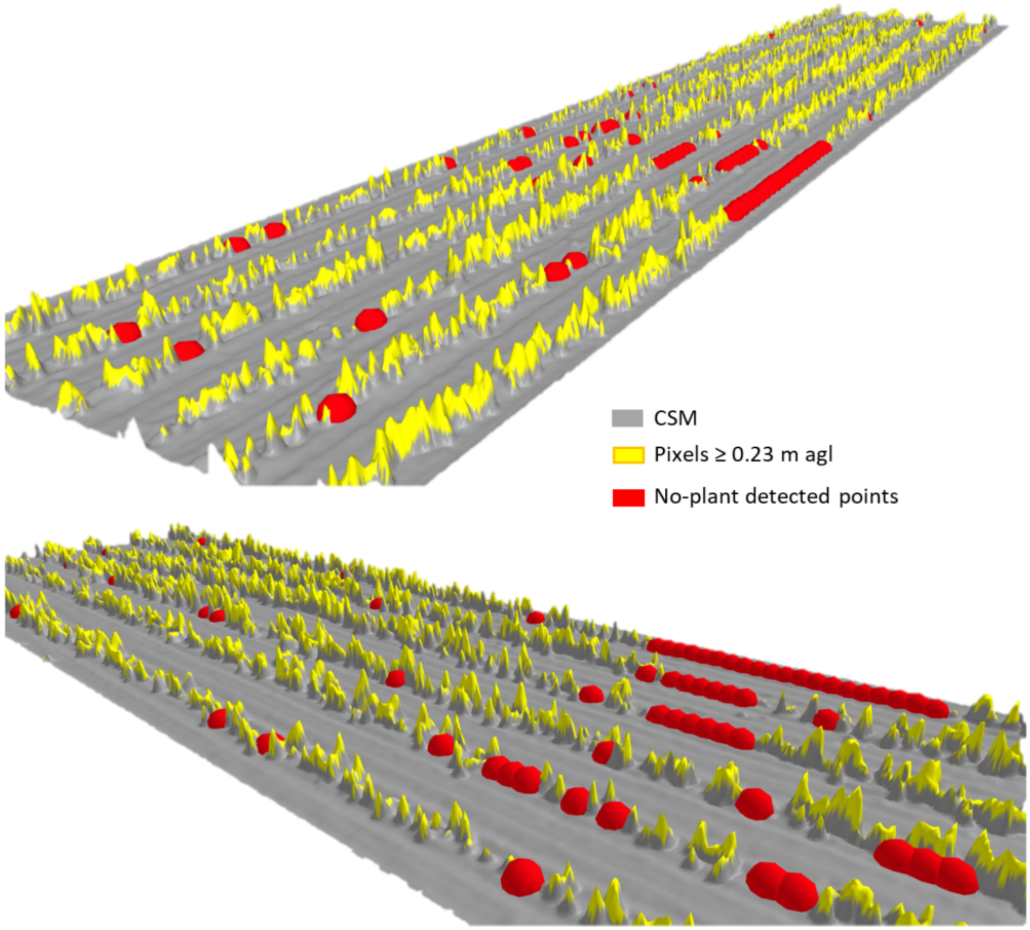

Figure 4. 3D view isolated regions above 0.23 m above ground level (yellow) and no-plant detected points over the CSM (red).

For the replication of the above methodology, the use of DTM is mandatory. Use of DEM alone to generate the height thresholds will lead to possible information loss depending on field weavings, while the CSM obtained from the subtraction of the DSM from the DTM will result in a multiplane smoothened 3D surface depicting actual field terrain characteristics (Figure 5).

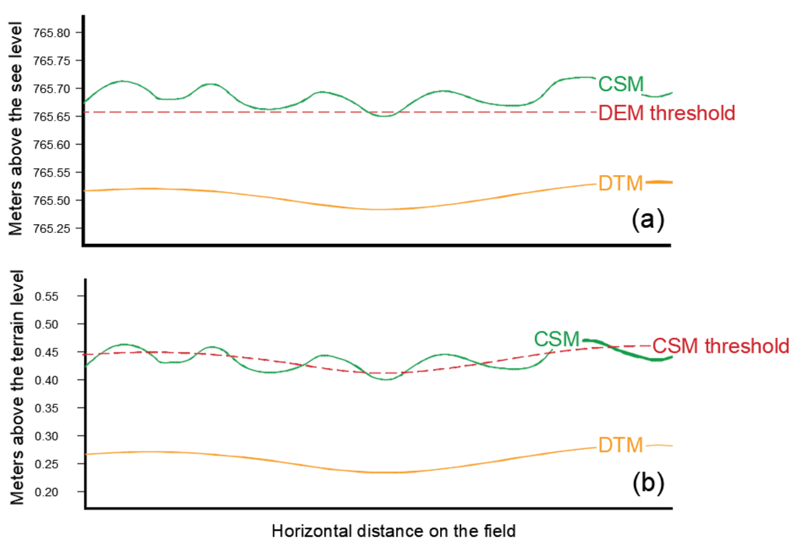

Figure 5. Effect of using directly the DEM (a) to create the plant height threshold, compared with using CSM (b).

In addition, using the technique presented in this study to threshold the apple seedling pixels in an image can avoid any distortion caused by shadows in the image. In Figure 6a and b, the effect of shadows can be noted, which confounds the identification of plants using only the reflectance information. Moreover, elevation data can also avoid interferences in the process caused by straw, rocks, weeds as founded by Quiros and Khot (2016). In Figure 6c and d, it is evident that once the algorithm outputs the binary image, all the background obstacles are removed and plants are simply identified as the circles with height values higher than 23 cm.

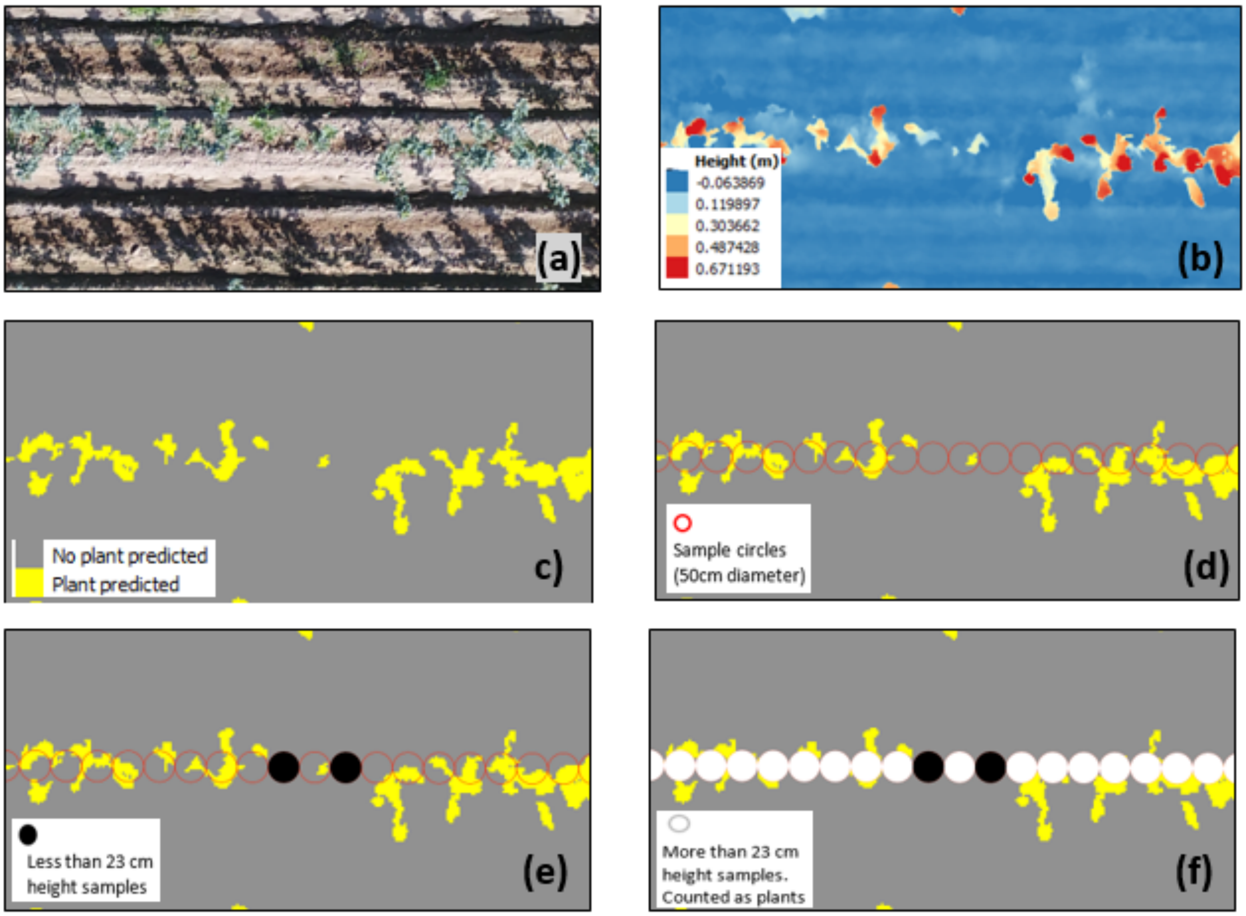

Figure 6. Example of processing steps from the original image (a) until the identification of plants (f), passing through CSM (b), binary image (c), sample regions (d) and thresholding (e).

Previous research on apple tree count reached similar accuracy but the algorithm needed to pass through many steps with several types of image enhancements and multiple color thresholds were required to separate plant from the background. Such processing increased the algorithm dependency on external factors like luminosity, and spatial and spectral resolution (Quiros and Khot, 2016). Thus, limiting potential use of such approach. On contrary, elevation data developed algorithms simplified plant counting algorithm. Therefore, it reduced the associated plant counting errors and making mapping and or atomization feasible in the long run.

Conclusion

The study results confirm the feasibility of using small UAS RGB imagery derived elevation map data for apple nursery plant counting with average errors of about 5%, common in manual counting approaches. Our future studies will validate the robustness of the proposed approach and developed algorithm on large acreage tree fruit nursery seedlings.

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References

Ehsani, R., Leiva, J.N., Owen, J. (2014). Applications of small UAV systems for tree and nursery inventory management.

Helsinki. (1955). On the estimation of growing stock from aerial photographs. Commun. Inst. For. Fenn. 46(01).

Leiva, J. (2014). Use of Remote Imagery and Object-based Image Methods to Count Plants in an Open-field Container Nursery. University of Arkansas. 123 pp

Quiros, J., Khot, L. (2016). Potential of low altitude multispectral imaging for in-field apple tree nursery inventory mapping. IFAC-PapersOnLine. 49(16), 421-425.

Robbins, J., Owen, J., Saraswat, D., Ehsani, R., Maja, J., Stoven, H., Landgren, C., Doane, S. (2012). Development of an inventory management tool using visual imagery from a multirotor aerial platform. SNA Research Conference. 57.

“Washington Annual Statistical Report”, USDA. (2014). United States Department of Agriculture, Washington.