UAV IMAGES AS A SOURCE FOR RETRIEVAL OF MACHINE TRACKS AND VEGETATION GAPS ALONG CROP ROWS

MARK SPEKKEN [a], JOSÉ PAULO MOLIN [b]

[a] Founder-Director of SOMO solutions, Dept. Research & Development, Piracicaba-SP, Brazil

[b] Associate Professor, University of São Paulo, Dept. Biosystems Eng., Piracicaba-SP, Brazil

A paper from the Proceedings of the
14th International Conference on Precision Agriculture
June 24 – June 27, 2018
Montreal, Quebec, Canada

Abstract. *The trend of acquiring equipment and obtaining high resolution remote sensed images by Unmanned Aerial Vehicles (UAV) have been followed by sugarcane producers in Brazil, given its low cost. The images taken from fields have been used for retrieval of information like Digital Terrain Models (DTMs) from stereoscopy of overlapping images and spatial variance of biomass. In sugarcane production, driving deviations occur during planting because of manual steering inaccuracy, sliding of machines sideways on terrain slopes, side offset of planter-tractor along curves and GNSS errors. Given the accuracy of identification of vegetation, a demand was presented by parties in the sugarcane sector to identify and extract vectorized lines along the plant rows. These lines must present a degree of accuracy to be used as guidance reference, in order to keep these machines confined in tracks to avoid damages to parallel rows (strict CTF - Controlled Traffic Farming). In addition, it is important to retrieve the spaces along the rows with absent plants to estimate yield impacts and identify possible intervention (re-planting). A methodology was created and implemented to: (1) extract an approximate vegetation index from an RGB image and apply a filter to identify pixel values in the center of the plant-rows; (2) re-create lines (straight and curved) using a procedure of building line-segments along points for multiple parallel lines and adjustable offsets; (3) obtain a local thresholding classification from VI values and fragment the lines upon the classified pixel values. The methodology was implemented with the use of free software by the development of three small applications created in an open-source programming platform. RESULTS*

Keywords. *Object based identification, Automatic pilot, optimized processing, GIS*

Introduction

Data acquisition from agricultural fields is a laborious process and its collection traditionally requires covering the whole field by either walking or driving over it. UAVs (Unmanned Aerial Vehicles) have been spotted, for some time, as an alternative to the data gathering (Herwitz et al., 2004); and became recently an interesting option, considering its low purchasing and operating costs (Zhang & Kovacs, 2012). Upon such, applications were developed and studied to retrieve usable plant information (Sankaran et al., 2015).

Sugarcane producers (and service providers) in Brazil are following such trend by acquiring and flying their UAVs, aiming to retrieve an increasing amount of information from the data gathered. Among the information of interest by the sector are: the reconstruction of crop-rows into vectorized lines to be fed onto the interface of automatic pilot (AP) systems; and the identification, along these lines, of vegetation gaps caused by planting and sprouting failures (Souza et al, 2017).

Lines retrieved from images (properly georeferenced) have advantage to be acquired in regions where no AP was used while planting or, when used, no data was properly stored. Also, the lines obtained from images provide a more consistent spatial accuracy when compared to AP lines from the planting operation, because it overcomes: the sliding effect of machines-implements sideways on steep terrains; the tractor-planter offset along curves; GNSS errors while planting (ionospheric scintillation); and transversal deviations of the plant sprouting-emergence.

Early attempts made use of manual line reconstruction over images displayed on GIS software. Yet this fatigating and slow process could not deliver vectorized lines with consistent spatial accuracy, aside from its time, energy and financial costs. The development of Object Based Image Analysis (OBIA; Blaschke, 2010) searches to make possible automated detection of features on images based on shapes and patterns. Sanchez et al, (2015) proposed a method for automated recognition of vegetation in RGB cameras by testing Vegetation Indices with unsupervised thresholding. Peña et al. (2013) used OBIA methods for automated reconstruction of row-lines of maize crop, and afterwards to distinguish spatially the weeds by their location (in between the rows).

Souza et al. (2017) created an algorithm-method for automated extraction of rows and skips in sugarcane. The method uses OBIA for pattern recognition of crop-rows and applies a classification of vegetation based on on-row and between-row distinction. The work makes use of non-visible NIR bands for distinction of vegetation. Still, the procedures for row-crop reconstruction: do not give a clarity of steps; it mentions that the lines-output of the algorithm required some level of manual editing by the user, yet it does not mention the intensity of such process; and also the usability of the model (performance and hardware-software requirements) aren’t provided.

Majority of the data collected by UAVs, for practical purposes in filed, is currently retrieved by sequences of images captured in the visible spectrum and stored in RGB (Red-Green-Blue) bands format. In such context, this work presents an innovative methodology for row-crop reconstruction from UAV images capable to work with the common sources of images and presents a degree of resilience to process images in a range of radiometric and vegetation variance.

Methodology

A model was created and implemented in a computer algorithm aiming to reconstruct geographic vector-lines using the pixel data of geo-referenced images as source. The model is capable to reconstruct rows upon images with a flexible range of spatial resolution of pixels, plant-size, scarcity of vegetation coverage, row orientation (straight or curved), and some degree of radiometric variance.

Conceptual model

The methodology of the conceptual model of this work is explained after Figure 1, which identifies the data sources/outputs, the data flow, and the processes.

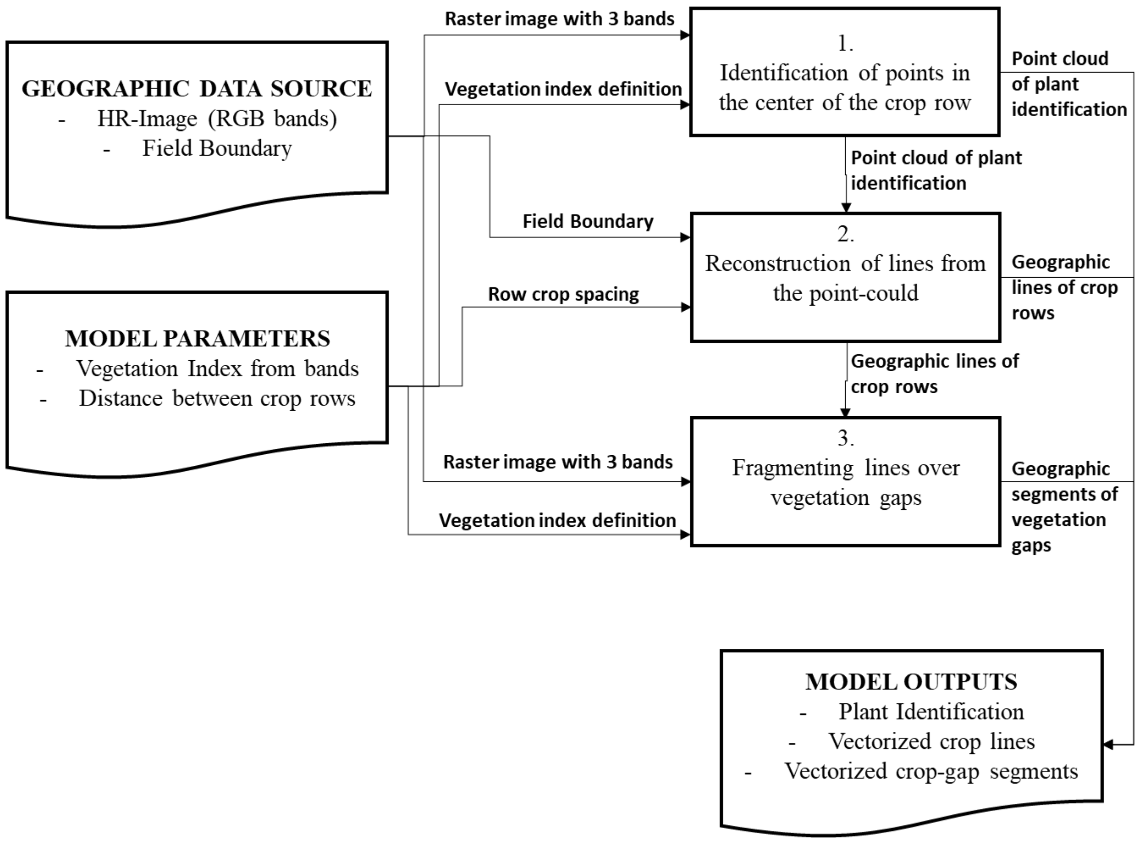

Fig 1. Structure, data flow and main parameters of the conceptual model.

Data Source

The Geographic data required by the model are:

- High-Resolution Image in with RGB bands. Is the mosaicked image composed by a minimum of 3 bands of 8 bits each (values ranging from 0-255), with a sufficient spatial resolution to safely separate vegetated rows (preferably below 0.15 m). Also, the plant size on the crop rows should present a minimum visible ground-floor in the inter-row space (e.g. Figure 2a).
- The Field Boundary should provide the accurate vertices of the polygons that compose the field (or subfields) overlapping accurately their respective field-limits on the image.
- The vegetation index witch is the equation that converts the band values into a single float value that aims for the best distinction of vegetation from other features in the image. The model, as implemented, already embodies a list of vegetation indices that can be used for distinct image and vegetation conditions.
- Distance between crop rows or the measure of width of the crop row, which guides an appropriate reconstruction of rows from the point-cloud.

The processes

1. Identification of points in the center of the crop-row

This process filters the image identifying the pixels that belong to the center row-crop as vectorized points. The output is a point-cloud that is significantly smaller (over 1000 times less) in the quantity of data in relation to the original image.

First, a vegetation index (VI) is obtained for each pixel by an equation among band-values. The VI seeks to obtain the greatest distinction between vegetation and non-vegetation features (Figure 2b). The model already embodies a number of VI equations already studied for RGB cameras (Sánches et al., 2014), and others tested herein. The user of the model can choose a more suitable option to achieve a better distinction.

In a moving window over the image, a neighboring operation analyses each pixel by a rotating cross with a range of half of the row-space. For each rotating step, the VI pixel-values below the cross are summed distinctively for the parallel and perpendicular directions. If the ratio of the summed values in parallel direction by the perpendicular direction does reaches a minimum threshold, the pixel location is considered to be on a crop-row. This location is then saved as a point in a list, along with the orientation of the rotating steps. If the threshold is not reached for any of the rotating steps, no point is saved.

After the list of points is obtained for the whole image, a local filtering procedure (modified after Spekken et al, 2013), is applied using the orientation attribute. Such procedure works ensuring that the neighboring points are consistent regarding: position upon row-crops, and same orientation. Afterwards, the procedure also averages the position of the remaining points located in a close range, to remove the effect of crop-rows with large width of vegetation and achieving a more accurate center of the row (Figure 2c).

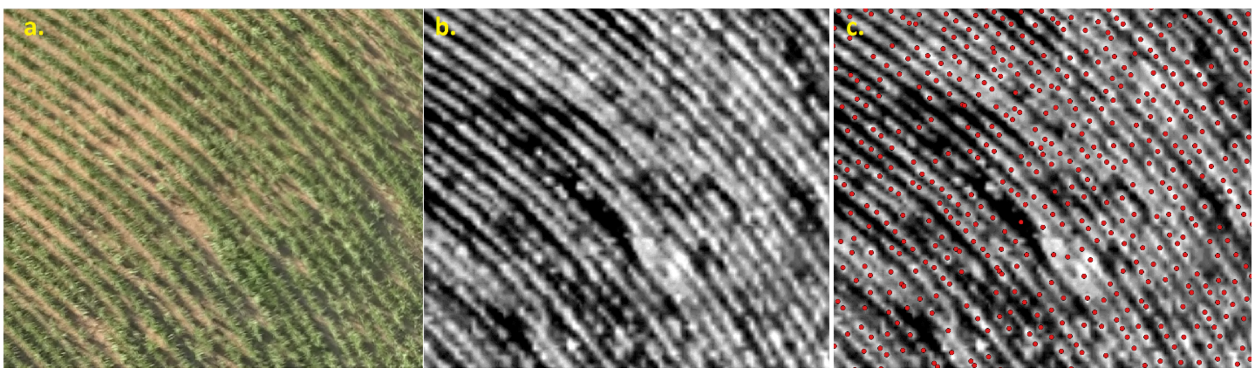

Fig 2. Subset of sugarcane ortho-image (in "a"); the Vegetation Index for the subset (in "b"); and the point cloud in the center of the crop-row obtained from process 1 (in "c").

At the end of this process, a point-cloud is obtained in a list and submitted to the next process for line-row reconstruction.

2. Reconstruction of lines from the point-cloud

The points retrieved by the previous process are spatially located in logic patterns of crop-rows, yet the points are not ordered in sequence of crop-rows. Thus, the reconstruction cannot happen by simply linking points in sequence in which they were identified.

The vector-line reconstruction upon the point cloud is done by two means: (1) creating a polyline from a segment patterns among points; and (2) creating offsets from a reference polyline that adjusts its shape over the surrounding points.

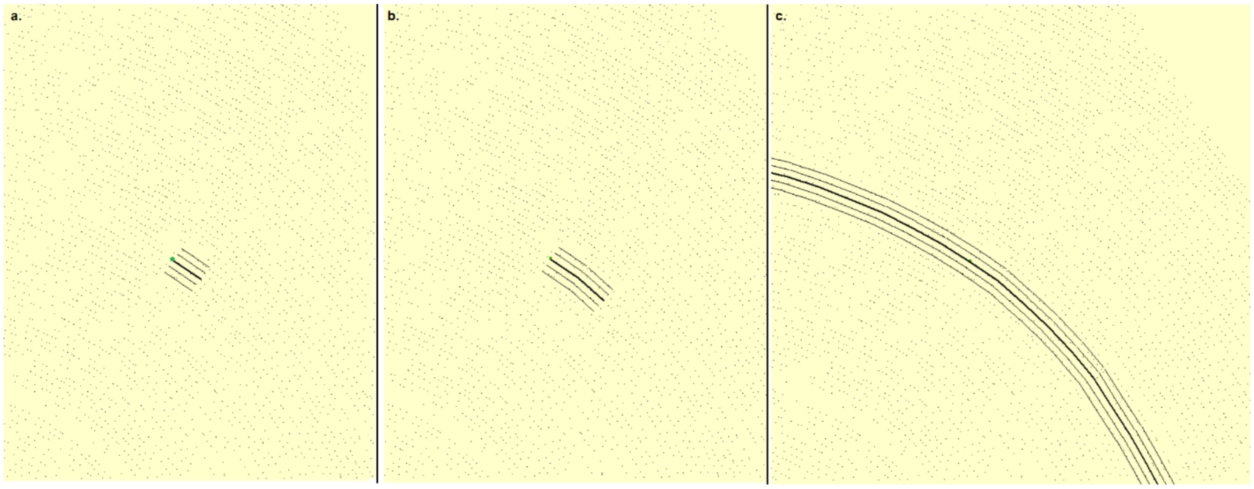

Fig 3. Steps of a single line-row reconstruction upon the point-cloud.

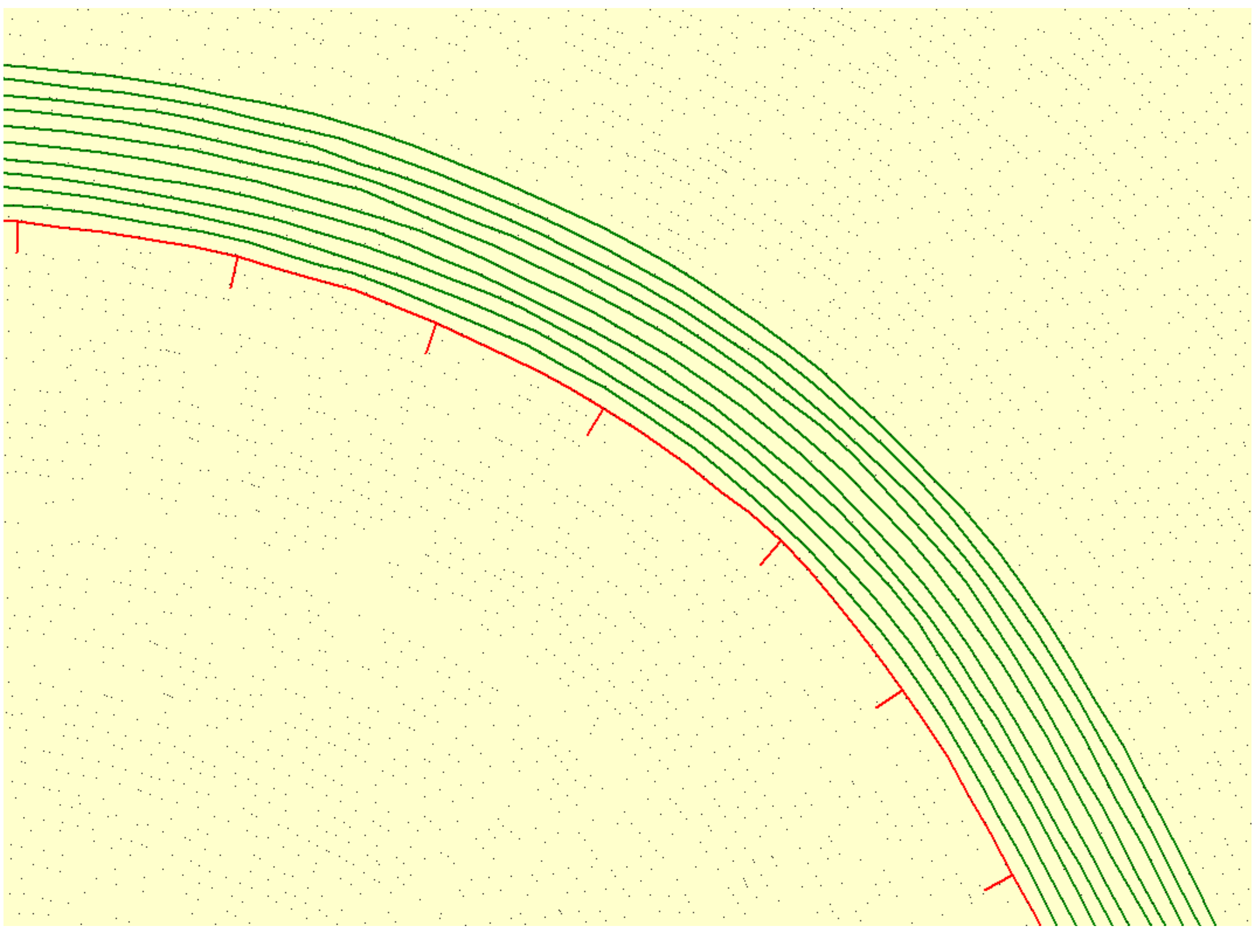

Fig 4. Offset lines (in green) from a reference line (in red) adjusted to their surrounding points.

The steps of this first method is explained by the sequence given in Figure 3, where:

- in "a", the user identifies one point (in green) and the model rotates parallel segments (separated by multiples of the row-spacing) around this point in a 360 degree search. The best fitting direction of these segments on the point cloud is the first segment of the line-row.
- In "b", the previous step is repeated in the edge of the first segment, yet in a narrower

angle range given by the direction of the first segment.

- In "c" the reconstruction of the line is obtained by recursively finding the segments on the edge of previous segment until reaching the field-border. The process resumes from the initial point selected in the opposing direction to complete the line-row until a field-border is reached on both sides.

The second method uses a full line reference, first offsetting it in a fixed distance given by the row-space value. The points surrounding this initial offset are sampled and one edge identified, afterwards they are linked by a nearest neighbor procedure and simplified in equidistant segments. Thus, the resulted adjusted line follows the original rows (Figure 4), regardless of the deviations of parallelism that it may present towards the original reference.

The offset method was implemented permitting that, in regions without any points-biomass, the offset-segments keep a fixed distance. Such approach permits the model to achieve full line reconstruction also in regions with scarcity of vegetation.

3. Fragmenting lines over vegetation gaps

The third process retrieves again a vegetation index on the raster-image to get distinction between vegetation and non-vegetation, in a similar procedure to Process 1. The user might select a vegetation index calculation that differs from the one used for extraction of the point-cloud, since the latter does not require a distinction in same level of accuracy as in Process 3 herein.

The resulting VI image is separated into smaller quadrants and each is submitted to clustering-based image thresholding using Otsu's algorithm (Otsu, 1979). The separation into smaller quadrants permits distinct thresholds to be found for images with different conditions that alter the greyscale-histogram over the image, like: variance in reflectance (time of day and clouds), presence of plant residues on the soil (straw), and variance in soil properties (sand brighter than clay).

For the entire length of the lines reconstructed, their segments are broken into points in an equidistance of 0.1 m. The points overlay the classified image sampling its respective spatial values. The sampling procedure already retrieves the local threshold identifying the ones that are vegetation or vegetation-gap.

Finally, sequences of a minimum number points classified and vegetation gaps are merged into line segments that identifies the presence and length of the gap.

Implementation of the model and usability

The model was implemented in 3 distinct algorithm-applications separated after the processes presented in this methodology. The algorithm was developed in Pascal within Lazarus-IDE platform (Free-Pascal initiative) and compiled into executable applications. The input and output vectorized files are in KML format, giving its simplicity of data storage and geodetic standards.

The algorithm was built independent of external libraries and packages. An internal spatial index structure was developed to be able to arrange the point cloud into defined quadrants to reduce the search-time for points for reconstruction of lines. The applications perform satisfactory in personal computers that operate in current and common hardware configurations.

Case study and discussion

One case study was processed by the model herein to provide assessment of the methods. A field grown with sugarcane with an area of 6.45 ha was subject to ortho-image retrieval from an UAV Phantom 4 Pro, 20 Megapixels camera. The pixel size was of 0.0519 m with RGB bands.

The sugarcane already subject to one harvest and the image was retrieved during its re-growth. Because of the sprouting variance from the ratoon over the field, it is difficult to provide accuracy for the emergency age, ranging around 100 days. The soil in between the rows was covered with straw and the rows were planted by manual steering. Figure 5a shows a full view of the field and some variance of biomass.

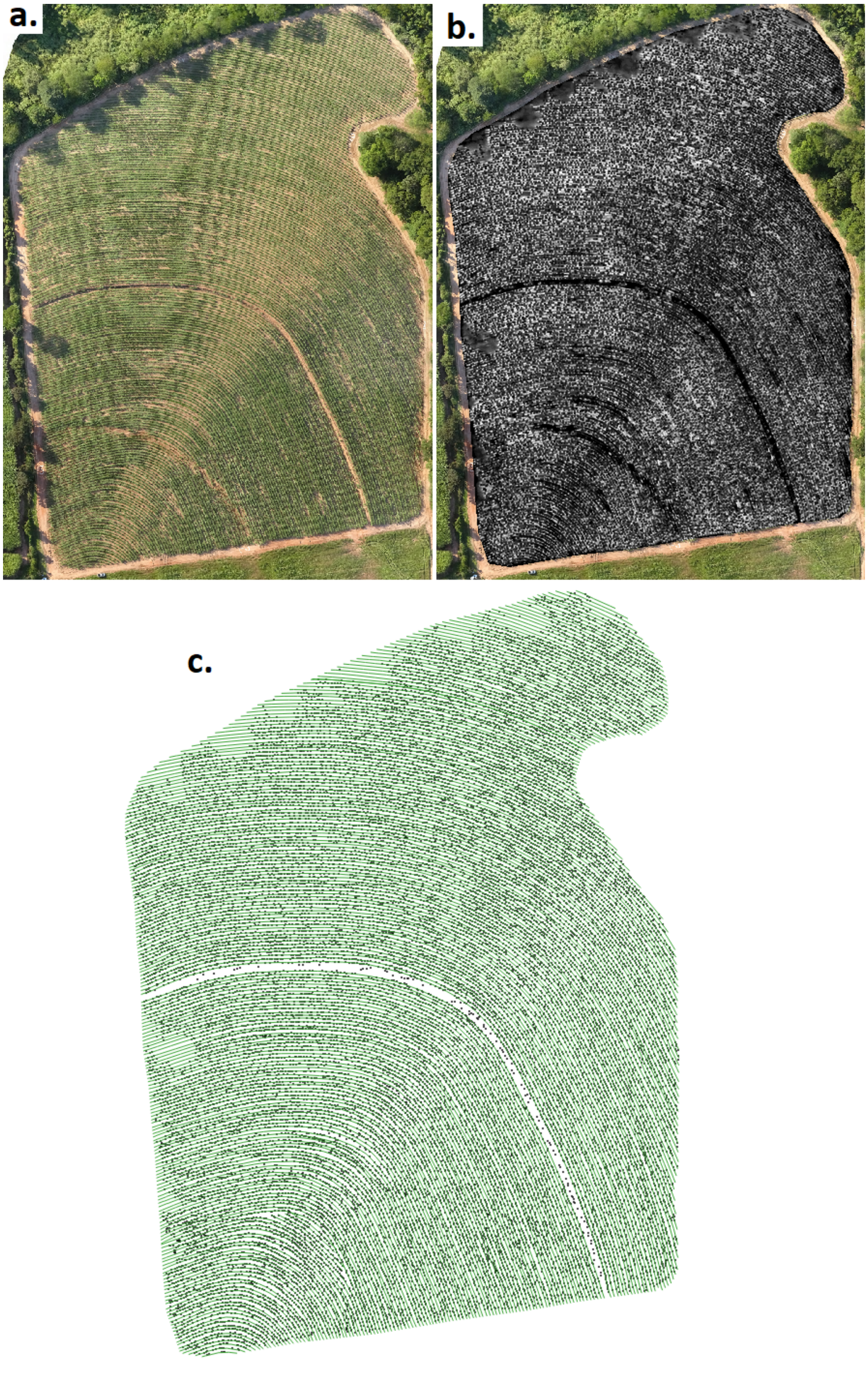

Fig 5. Steps and outputs of the first two processes of the model: point-cloud and line-rows.

Some shading effect from trees near to the field (north and west sides) leaded to a local decrease in the enhancement of the vegetation (Figure 5b) and in the identification of points (Figure 5c). The scarcity of points on these places was overcome by the offsetting procedure in the line reconstruction. A total of 43,297m of row length was retrieved by the model.

A view of the spatial accuracy of the lines upon the rows on its image can be observed in Figure 6. The red ellipses are locations where occurs noticeable deviations of the row parallelism (from when it was planted), yet still being captured by the adjusted offset procedure (Process 2). No lines generated by the model were subject to editing (or required it).

Fig 6. Subset of the case study showing overlay of the point-could and reconstructed lines upon the image.

The model was set for identifying vegetation gaps when these reach a length of 0.5m, which is a standard of the sugarcane sector defined by Stolf (1986). The gaps summed 868.76 m, which represents a fraction of nearly 2% of their field length. Figure 7 shows a subset of the identification on the original image, where blue segments represent the gaps.

Unfortunately, no in-field measurements were collected along the rows in this field for comparison/validation of the quantified values found. Some adjustments still are being applied to the model to compensate width of leaf canopy, which might lean over the gap masking the real length of the gap. Still, users of the model have showed favor towards the identification results.

The model-applications were registered and made available for commercial use. They are presently being use by sugarcane producers (and service providers), that are flying UAVs retrieving ortho-images. The extracted row-lines are being fed into the interface of automatic pilot systems, and gap-segments are being used as quantifiable indicators of field sanity and re-planting. A summed area over 150,000 hectares was already processed with the use of this algorithm. For other crops, successful tests were already performed using the applications for UAV corn images to individualize plants (Process 1), and rebuild the rows (Process 2) also measuring the distance between plants along these (to obtain plant distribution).

Fig 7. Identification of vegetation gaps along rows using the model

Conclusions

A model was hereby introduced that makes use of OBIA to spatially vectorize two information of interest from high resolution images: the crop-rows and the vegetation gaps. The model was designed to permit a level of resilience regarding variance in image inputs, being able to tolerate a range of variance in vegetative biomass, and image radiometric and contrast fluctuations. The concepts and implementation into algorithm were done in three main steps that work in sequence, each creating specific outputs. The usability was approved by the current user market, who showed acceptance of the results and is increasingly using it for applied field purposes.

References

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*. V. 65-1, 2-16.

Herwitz, S.R., Johnson, L.F., Dunagan, S.E., Higgins, R.G, Sullivan, D.V., Zheng, J., Lobitz, B.M., Leung, J.G, Gallmeyer, B.A., Aoyagi M., Slye, R.E., Brass, J.A. (2004). Imaging from an unmanned aerial vehicle: agricultural surveillance and decision support. *Computers and Electronics in Agriculture*. V. 44-1, 49-61.

Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE Trans. Sys., Man*. doi:10.1109/TSMC.1979.4310076

Peña, J.M., Torres-Sánchez J., de Castro, A.I., Kelly, M., López-Granados, F. (2013). Weed Mapping in Early-Season Maize Fields Using Object-Based Analysis of Unmanned Aerial Vehicle (UAV) Images. *PLoS ONE* 8(10): e77151. https://doi.org/10.1371/journal.pone.0077151

Sánchez, J.T., Peña, J.M., Castro, A.I., López-Granados, F. (2014). Multi-temporal mapping of the vegetation fraction in early-season wheat fields using images from UAV, *Computers and Electronics in Agriculture*, 103, 104-113.

Sankaran, S., Khot, L.R, Espinoza, C.Z., Sathuvalli, S.J.V.R., Vandemark, G.J., Miklas, P.N., Carter, A.H., Pumphrey, M.O., Knowles, N.R., Pavek, M.J. (2015). Low-altitude, high-resolution aerial imaging systems for row and field crop phenotyping: A review. *European Journal of Agronomy*, V. 70, 112-123.

Souza, C.H.W., Lamparelli, R.A.C., Rocha, J.V., Magalhães, P.S.G. (2017). Mapping skips in sugarcane fields using object-based analysis of unmanned aerial vehicle (UAV) images, *Computers and Electronics in Agriculture*, 143, 49-56.

Spekken M., Anselmi A.A., Molin J.P. (2013). A simple method for filtering spatial data. *In: Stafford J.V. (eds) Proceedings of the Precision agriculture '13*. Wageningen Academic Publishers, Wageningen. DOI https://doi.org/10.3920/978-90-8686-778-3_30

Stolf, R. (1986). Methodology for gap evaluation on sugarcane lines. *STAB*, V. 4. 12-20.

Zhang, C. & Kovacs, J.M. Precision Agric (2012) 13: 693. https://doi.org/10.1007/s11119-012-9274-5