Identification of gaps in sugarcane plantations using UAV images

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Abstract.
Global climate change is a highly quoted issue nowadays. Therefore, actions related to rational and efficient use of cultivated lands, which is the main goal of precision agriculture, are required. Sugarcane culture provides an energetic alternative to achieve lower greenhouse gas emissions. In this study we present preliminary results of a methodology for detecting gaps in sugarcane crop, from images acquired using an Unmanned Airborne Vehicle (UAV). The study area is located at Iracemápolis, country side of São Paulo State, Brazil. Results demonstrated that very high resolution UAV optical images can efficiently detect gaps in sugarcane plantations. Our methodology identified 20,90% of exposed soil areas resulting of planting and/or growing flaws. This information allows producers to repair the flaws in planted lines, consequently intensifying and increasing crop productivity. Moreover, the quantification of the area affected by gaps can directly improve estimates of sugarcane production. This study confirmed that UAVs are excellent tools for gathering very high resolution spatially explicit optical remote sensing information over agriculture crops. The planting/growing gaps were significantly large for justifying the need of producers' intervention, through new planting or fertilizing the area. Nevertheless, we point out the necessity for improving UAVs flight parameters, such as flight high and line distances between imagery, once the sensor viewing angle may cause false vegetation density, masking exposed soil areas.

Key words: precision agriculture, remote sensing, image processing, pattern recognition.

1. Introduction

Global climate change has dominated scientific discussions in the last few decades, demonstrating that humanity faces a great challenge ahead for mitigating or adapting to its impacts. The main consequences of climate change are the increased frequency of extreme

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climate events, leading to more intense and longer droughts, increase of heavy precipitation events, more rigorous winters and much warmer summers as well as changes in oceanic dynamic processes (IPCC, 2014). Besides all these alterations, there is also the loss of crops due to such changes, including food crops, and lack of new cultivars adapted to this new climate configuration (EMBRAPA, 2014).

Carbon dioxide (CO_2) is the most important greenhouse gas, mostly generated from production and consumption of fossil fuels (IPCC, 2014). The substitution of fossil fuels by biofuels, such as ethanol produced from sugarcane, may help reducing greenhouse gas emissions as well as the impact of climate change (NASS et al., 2007). However, the energy matrix needs to be adapted for ensuring that the growing demand for biofuels would not increase deforestation or land use change from food crops to sugarcane crops (MAPA, 2006). Improving and intensifying productivity of sugarcane cultivated areas should reduce the risk of sugarcane expansion over other areas.

Geotechnologies are fundamental tools for consolidating areas with high agricultural production, as these techniques can increase the accuracy for estimating planted and harvested areas as well as managing soil use, such as the identification of plantation gaps and the detection of erosive processes (EMBRAPA, 2014). For the future vision of the worldwide agriculture, EMBRAPA (Brazilian Agriculture Research Corporation) highlights that geotechnologies such as unmanned airborne vehicles (UAVs) and laser technologies, will help to establish strategies for minimizing negative impact of economic activities on the environment and to suggest solutions for a better potential use of all natural resources during different time horizons (EMBRAPA, 2014).

According to Gebbers and Adamchuck (2010), precision agriculture has a multidisciplinary characteristic, as it consists of a set of technologies (sensors and algorithms), machines and crop managing techniques. In order to achieve high productivity and natural resources conservation, precision agriculture uses remote sensing data and instruments, coupled with image processing and pattern recognition algorithms.

Due to the acquisition of very high spatial resolution images, UAVs are being used in precision agriculture (Honkavaara et al., 2013), as it is not affected by cloud cover. The use of UAVs for agronomic purposes has shown good results as demonstrated by Candón et al. (2013), with weed infestations on wheat crops studies, and by Honkavaara et al. (2013), estimating wheat and barley biomass.

The objective of this study is to present a methodology for the detection and quantification of gaps formed during planting or growing of sugarcane crops. The use of UAV images for precision agriculture is relevant because it brings new possibilities for improving crop’s productivity by feeding the producer with highly accurate data about the crop status.

2. Materials and Methods

The study area consists of a sugarcane field of approximately 6 ha (Figure 1), located at Iracema Mill in Iracemápolis city (São Paulo state), 220km distant from the state capital. The sugarcane plants studied were on their second sprout, two months old, (they were harvested on December of 2015).

The high resolution images from the sugarcane plot were acquired in February 16th, 2016, using a GYRO 200 OCTA 355 UAV (octocopter), equipped with a Sony RX100II camera of 20.2 megapixels and a CMOS Exmor R® sensor (blue, red and green). A gimbal was used to allow the camera to remain horizontal regardless of the motion of the UAV. In one flight, 135 photographs were obtained at nadir viewing, at 80 meters high from the ground, with 2.14 cm spatial resolution. An overlapping of 80% (longitudinal) and 60% (side) was used. The flight route was divided into 5 lines of 400m length and 200m width each (Figure 2).

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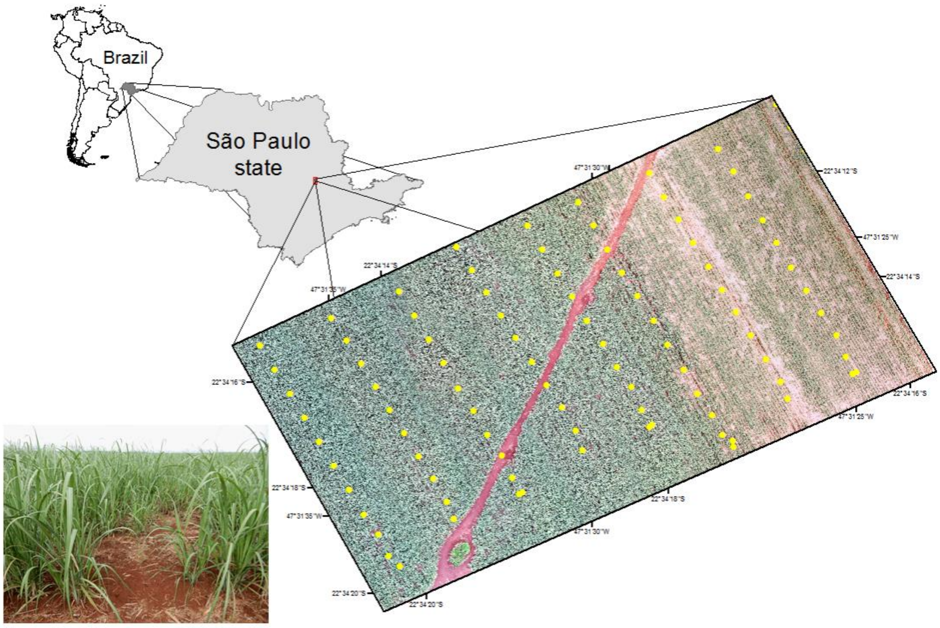

Figure 1: Sugarcane plot selected as study area.

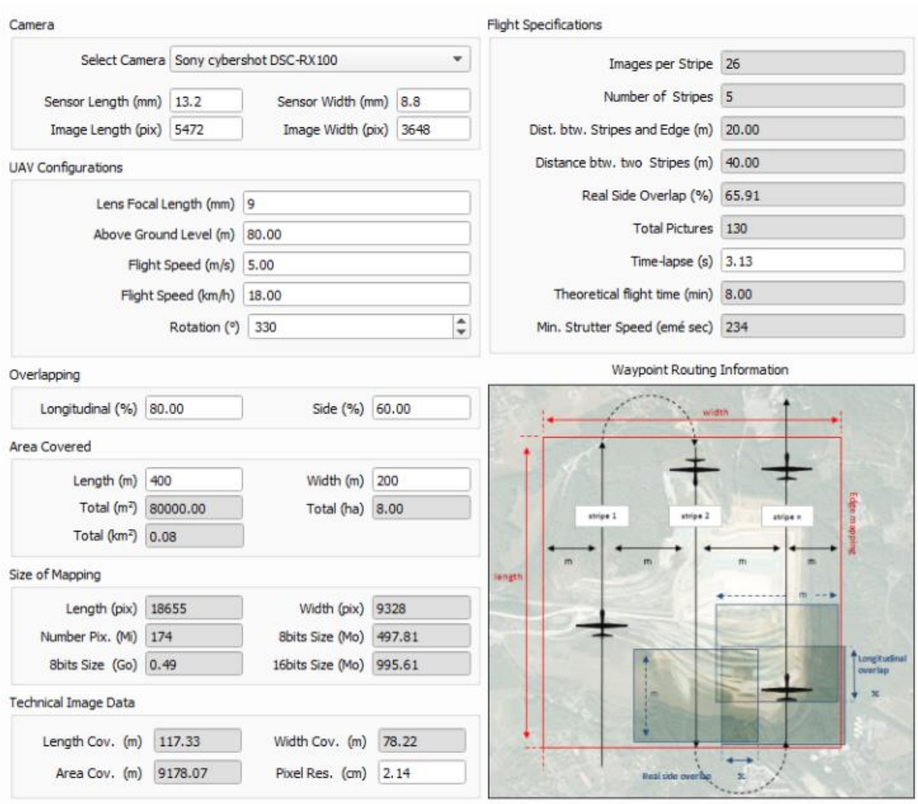

Figure 2: The UAV flight parameters.

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The software Pix4D (Pix4D, 2016) was used for mosaicking the images; since each image owned its own pair of central coordinates, the software processed the data automatically. However, we noticed a difference in the pixels values near the nadir viewing geometry (waypoints) of the image in comparison with more distant pixel (between waypoints). According to the acquisition geometry of the images and the architecture of the vegetal canopy, each image presented a higher presence of soil on its center in relation to more distant pixels. These center distant areas in the image are observed in an oblique way by the sensor, which means that due to the planting lines, one plant overlaps the other. In order to correct this error, we calculated the pixels average value in relation to the distance of the central point of each image that forms the mosaic.

From the orthomosaic, we applied a band math, obtaining the *Green-Red Vegetation Index* (GRVI), proposed by Motohka et al. (2010), according to equation 1.

$$GRVI = \frac{\rho Green - \rho Red}{\rho Green + \rho Red} \tag{1}$$

According to Motohka et al. (2010), the GRVI index is used as a phenological indicator for depicting seasonal vegetation and soil surface changes. The choice of the bands used in the index is related to photosynthetic activity of vegetation, which absorbs radiation at red wavelengths (~645nm) and reflects the radiation at green wavelengths (~540nm).

The GRVI values vary from -1 to +1, where negative values represent higher presence of soil, and positive values represent higher presence of vegetation.

Once the camera manufacturer does not release the filter sensor function used for the conversion of digital numbers into reflectance values, we used the digital values obtained from the camera directly in the equation for the GRVI calculation. The resulting GRVI values were, then, reclassified to generate a binary map, where negative values were transformed into 0 (zero) and positive values into 1 (one) in order to classify the crop into two classes: exposed soil and plantation.

3 Results and Discussion

We primarily obtained an orthomosaic, which is presented on Figure 3. The very high resolution images (mosaic) allowed a leaf level analysis and a direct interpretation over the crop conditions. It is possible to visualize exposed soil and problems with crop development analyzing the leaf coverage density. The analysis of the orthomosaic allowed the quantification of the area of exposed soil, and consequent impact on crop productivity. Moreover, the image processing workflow previously described, allowed quantifying and spatialize gap area in the study site. These are essential elements for decision making aiming to correct the gaps, through planting new sprouts or applying larger amounts of fertilizers.

Based on the GRVI values, it was possible to quantify the areas with vegetation and the ones with exposed soil. Also, the index generation reduces the information dimensionality, forming one single image from the mosaic with three bands retaining the most important elements for analysis.

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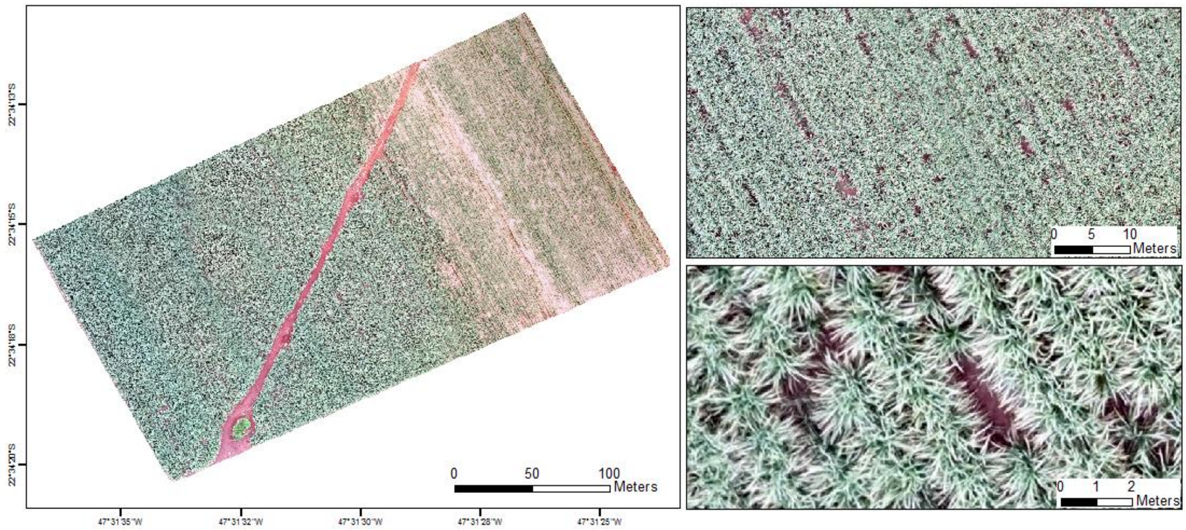

Figure 3: Orthomosaic (left) and spatial high resolution detail (right).

The acquisition geometry effect was corrected as we attributed different weights to each pixel value with a linear function accounting for the distance from the central point of each photograph that forms the mosaic. Figure 4 displays the variation of the average index values of GRVI in relation to distance of the image center. The parameters of equation derived from this observed variation was used to establish the correction weights.

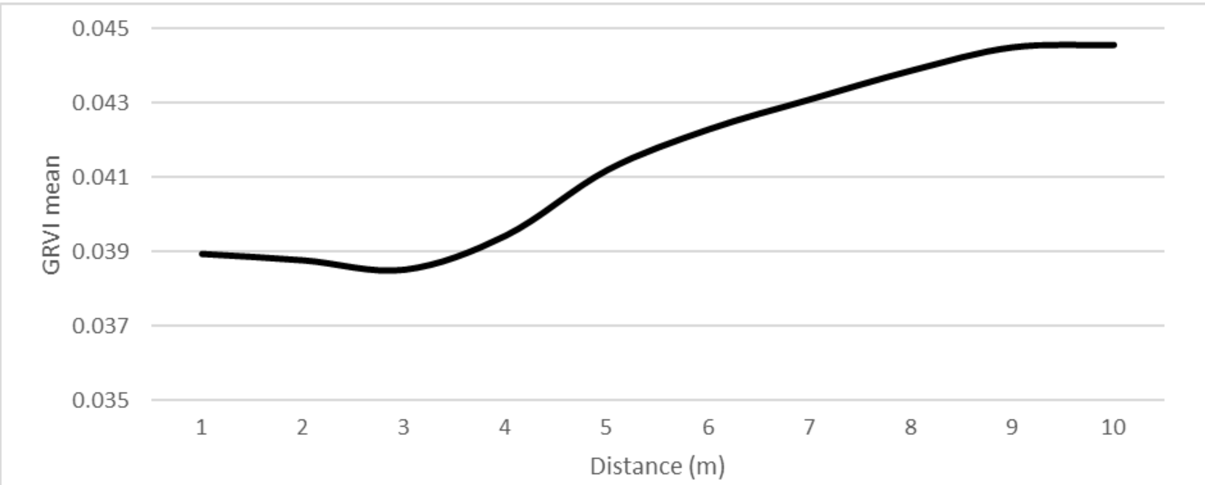

Figure 4: Linear function of the GRVI average in relation to the distance of the image center.

Figure 5a displays the map with the index generated without correction, where it is possible to identify stripes of dark green areas, caused by the acquisition geometry. Figure 5b displays the stratified distance related to the images center, where it is possible to visualize higher distances between flight lines. Figure 5c shows pixels weights defined accordingly the distance. Figure 5d illustrates the corrected GRVI map, which shows stripes of less green tonalities when compared with Figure 5a.

There was also a small difference between the results of exposed soil and vegetation area sizes calculated from the binary images generated from GRVI and corrected GRVI (Table 1). It is important to point out that the road (the red line crossing the sugarcane plot in Figures 5a and 5d) was not considered on the calculation (Figure 6).

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Table 1: Crop area and crop failure area calculated based on the GRVI map before and after the index correction.

	Crop failure	Crop
With correction	21,70%	78,30%
Without correction	20,90%	79,10%

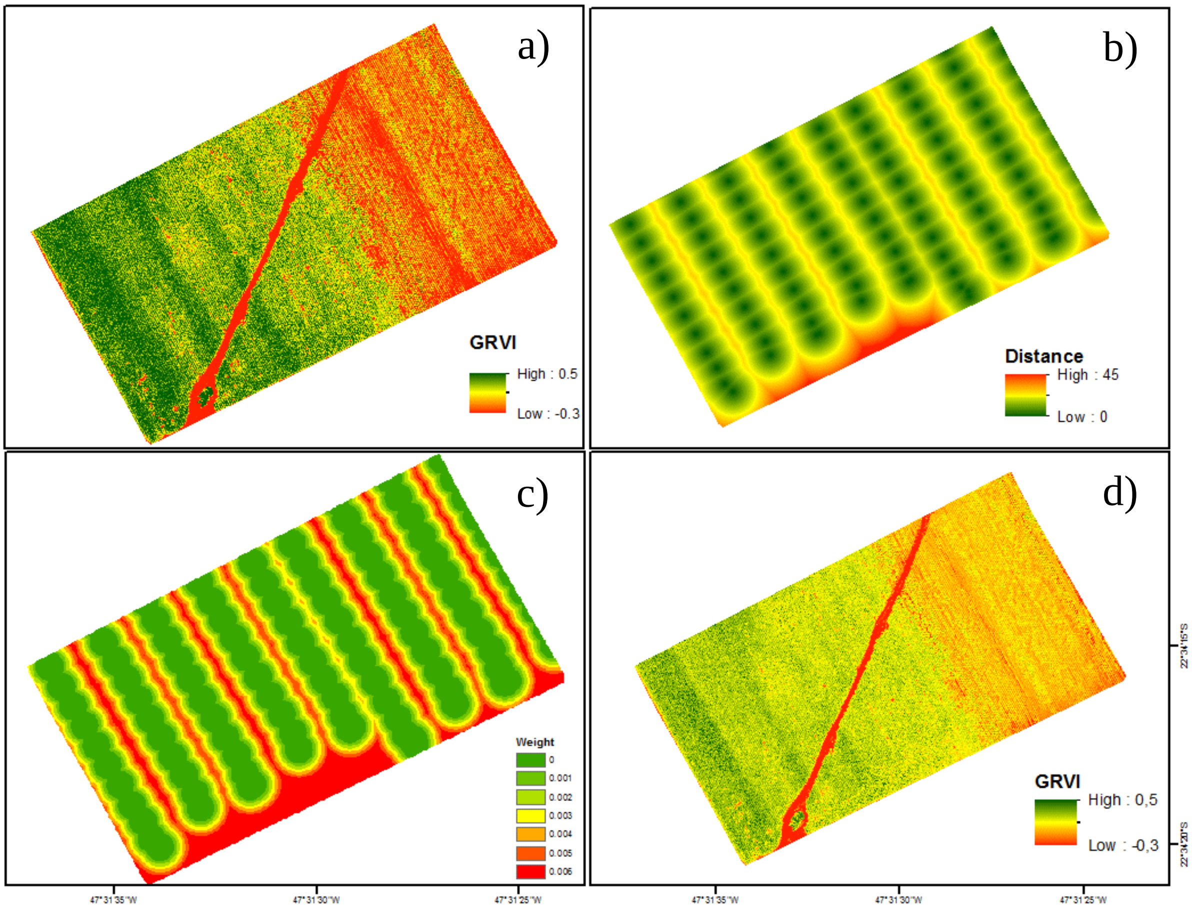

Figure 5: a) GVRI index values without correction; b) Variation of pixels distance to the center of the image, in meters; c) Stratified weight values in relation to distance; and d) Corrected GRVI index values.

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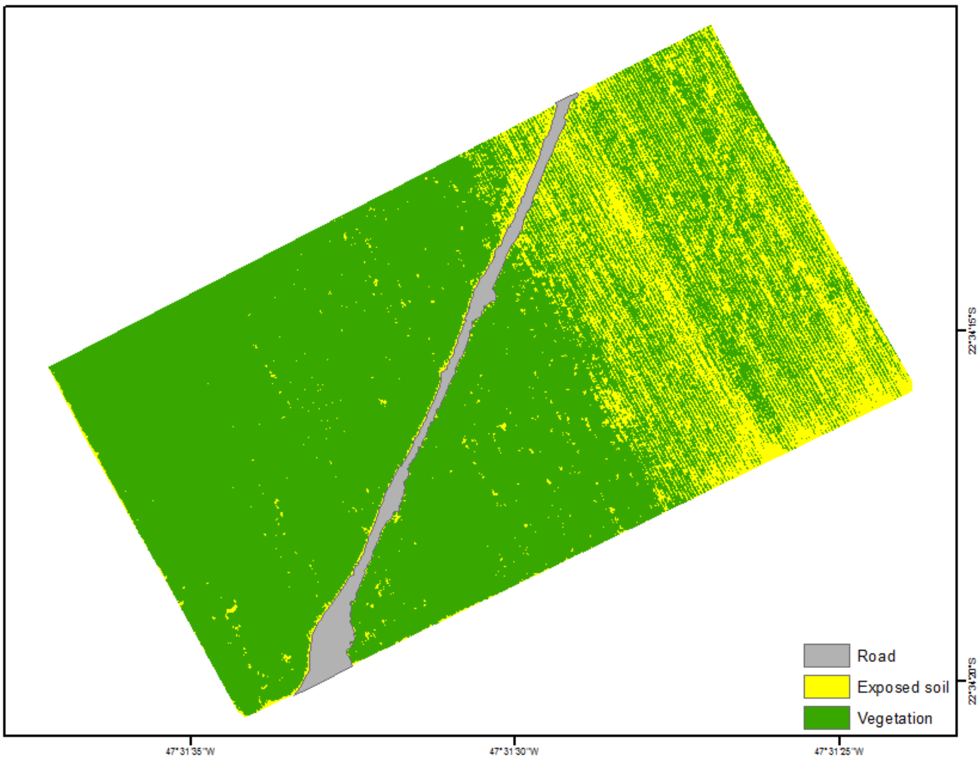

Figure 6: Stratified map with exposed soil coverage.

The mean sugarcane production for Sao Paulo state is 80 ton/ha, according to IBGE (2016). Based on this information, we calculated that the area exposed to gaps could have a potential production loss of 103.1 t, due growing or planting problems. The difference between GRVI with and without correction was 0.8%, representing approximately 4 t. This may be a small difference, however with the increase in biofuels demand it can become significant, motivating further studies related to UAV distortion images used on precision agriculture.

4. Conclusions

Our results demonstrated that the use of UAVs for image acquisition in precision agriculture is an appropriate tool for crops information collection. From simple image processing techniques, such as, mosaic, bands math and weighed threshold, it is possible to acquire crucial information about crop's development.

Regarding the sugarcane field, we found a significant loss of production related to the planting/growing flaws quantified in the images, which justifies the need of intervention, planting new sprouts or increasing the amount of fertilizers.

Also, we have seen that it is important to improve UAVs flight parameters, such as high and distance between image lines, as the viewing angle of the sensor may cause false vegetation concentration, covering exposed soil areas.

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