Coffee crop coefficient prediction as a function of biophysical variables identified from RGB UAS images

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Abstract. Because of different Brazilian climatic conditions and the different plant conditions, such as the stage of development and even the variety, wide variation may exist in the crop coefficients (Kc) values, both spatially and temporally. Thus, the objective of this study was to develop a methodology to determine the short-term Kc using biophysical parameters of coffee plants detected images obtained by an Unmanned Aircraft System (UAS). The study was conducted in Travessia variety coffee plantation. A UAS equipped with a digital camera was used. The images were collected in the field and were processed in Agisoft PhotoScan software. The data extracted from the images were used to calculate the biophysical parameters: leaf area index (LAI), leaf area (LA) and Kc. GeoDA software was used for mapping and spatial analysis. The pseudo-significance test was applied with $p < 0.05$ to validate the statistic. Moran's index (I) for June was 0.228 and for May was 0.286. Estimates of Kc values in June varied between 0.963 and 1.005. In May, the Kc values were 1.05 for 32 blocks. With this study, a methodology was developed that enables the estimation of Kc using remotely generated biophysical crop data.

Key words: *Coffea arabica* L., drone, irrigation, leaf area, uav (unmanned aerial vehicle).

INTRODUCTION

Brazil produces a significant share of coffee beans, contributing 63.4% of the world production, with 10.5 million tons in the 2018/2019 crop (USDA, 2019). It is the largest Arabica coffee producer, accounting for 46.9% of the world Arabica coffee production, and is the second-largest Robusta coffee producer, contributing 16.5% of its world production (USDA, 2019).

Some improvements in coffee management and production systems, such as irrigation, have led to the development of the crop, enabling the crop to be introduced in areas that were not previously suitable for coffee production. In addition, irrigation has provided an increase in productivity (Bonomo et al., 2008). Even in traditional areas for coffee crop production, irrigation can help reduce the effects of prolonged droughts

during critical periods of water requirement by coffee (Silva et al., 2005; Lima et al., 2010; Vicente et al., 2015).

For a better quantification of the amount of irrigation to be applied, the coffee water intake is estimated mainly by the use of climatological variables, with the crop coefficient (Kc) being determined by the relationship between crop evapotranspiration (ETc) that is evaluated experimentally; by reference evapotranspiration (ETo), obtained by lysimeters or by the use of estimation models (Doorenbos & Kassan, 1979); or still, by adapting the soil water balance (Camargo & Pereira, 1994).

In addition to being an indicator of great physical and biological significance, the Kc reflects the local climate and crop characteristics (Doorenbos & Pruitt, 1997), and it depends on the architecture, plant cover, and plant transpiration (Sato, 2007; Oliveira et al., 2007).

However, due to the different Brazilian climatic conditions, variation in the Kc values exist in the literature. Notably, the adoption of a single Kc value may lead, according to Silva et al. (2011), depending on the time of year, to over- or underirrigation, both of which are detrimental to the crop. In addition, according to Oliveira et al. (2007), several varieties of coffee, planting systems, and sizes exist; therefore, a single value of Kc should not be established, and agronomic experiments are needed. Thus, Kc values should be determined for the different phases of the coffee phenological cycle, plant age, local climatic conditions, and crop management adopted (Oliveira et al., 2007). However, agronomic experiments are time-consuming and laborious.

The development of Unmanned Aircraft Systems (UAS) in the last decade has enabled the acquisition of remote sensing images with a high spatial and temporal resolution, as well as providing information with vegetation details and an observation angle different from field observations. With this type of image, general mosaics are possible, as well as Digital Elevation Models, Digital Terrain Models, and 3D Models of the crop. Thus, the acquisition of plant biophysical data and information through remote images from UAS could replace field sampling and agronomic experiments.

Thus, it is believed that it is possible to determine the Kc of a coffee crop from high-spatial-resolution images obtained by UAS. Therefore, the present study aimed to develop a methodology for estimating the crop coefficient (Kc) in the short term by using relationships between Kc and biophysical parameters of coffee plants (leaf area, plant density, and weed management); this was achieved by using data already available in the literature and comparing it to Kc determined from RGB (Red, Green, Blue) UAS image data and from field data.

MATERIALS AND METHODS

The study was conducted in June 2017 and May 2018 in a 0.4 ha Travessia cultivar coffee plantation, which was a remnant of an earlier experiment, whose treatments are described by Caldas et al. (2018). This plantation is located in the city of Lavras, Minas Gerais, Brazil (21°13'33"S, 44°58'17"W, altitude 936 m) (Fig. 1). The plantation was established in February 2009 with 2.60×0.60 m spacing and is irrigated by drip irrigation.
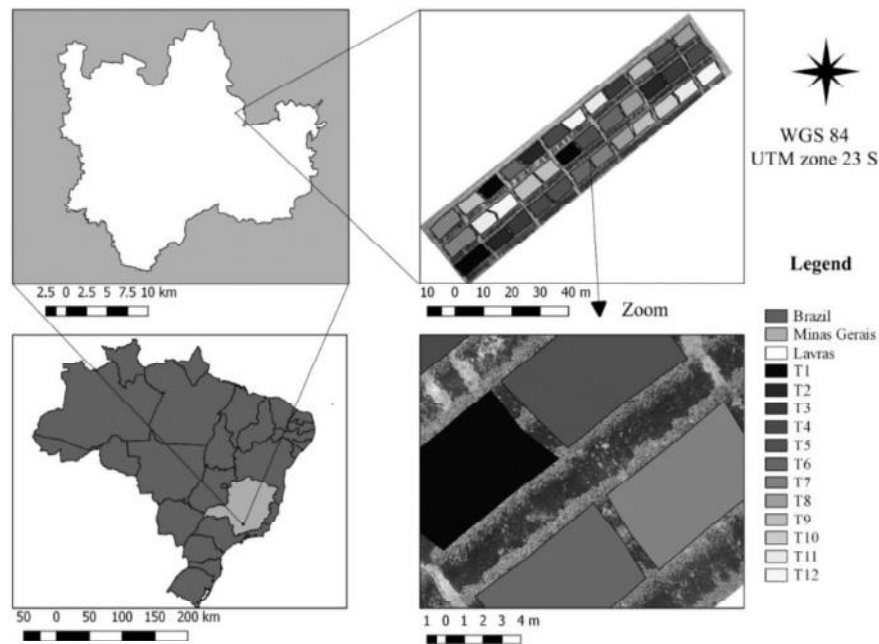
Figure 1. Study area location and treatment delimitation.

According to the Köppen classification, the regional climate is Cwa type, characterized by a dry season in the winter and a rainy season in the summer. The average annual rainfall is 1,460 mm, and the average annual temperature is 20.4 °C, with a minimum temperature of 17.1 °C in July and a maximum of 22.8 °C in February (Dantas et al., 2007). For the UAS image bank, six ground control points (GCPs) were evenly distributed throughout the field (Santos et al., 2019). The positions of the GCPs and the sampled plants were taken using a differential global positioning system (DGPS; Trimble Navigation Limited, Sunnyvale, California, USA), model SP60, with horizontal and vertical precision of 0.07 m. Later, the GCPs were identified in the images and used for georeferencing.

UAS-based data collection

The processing of images acquired by a UAS consists of a semiautomatic workflow, in which most of the software uses a similar workflow, following the process of calibrating the camera, aligning the images, and generating point clouds to generate the digital surface models (DSM) and the digital terrain model (DTM) (Hugenholtz et al., 2013; Nex & Remondino, 2014).

The software Agisoft PhotoScan Professional Edition version 1.2.4 (Agisoft LLC, St. Petersburg, Russia) was used to create the orthomosaic and to generate the DSM and DTM. This software identifies homologous points in the image and creates a continuous region by using stereoscopy to generate a point cloud.

The classification of the point cloud was performed to obtain the DSM and DTM, following the methodology described by Panagiotidis et al. (2016) and Surový et al. (2018); the parameters defined were maximum angle (deg) = 15, maximum distance (m) = 0.1, and cell size (m) = 40.

The DSM, DTM, and orthomosaic created in PhotoScan software were exported in a GeoTiff file from Quantum GIS software ver. 2.16.3 (QGIS Development Team, Open Source Geospatial Foundation); georeferenced in the Universal Transverse Mercator (UTM) coordinate system as WGS 84 zone 23 S datum, according to the coordinates of the control points collected in the study area; and used to draw a polygon of the area of interest in the shapefile (.shp) format.

To obtain the plant height, the methodology proposed by Panagiotidis et al. (2016) was used, in which a canopy height model (CHM) is obtained by subtracting the DSM from the DTM. For the correct extraction of plant height values, the Focal Statistics tool of ArcGIS version 10.5 (ESRI, Redlands, California, USA) was used, which identifies the highest pixel value in the CHM tree canopy, while avoiding lower or larger pixel values in the tree canopy. The plug-in Point Sampling Tool of QGIS software was used to obtain the plant height data already tabulated.

The crown diameters of the plants were extracted from the orthomosaic using the QGIS measurement tool.

All processing was performed for the 2 months of data obtained through the UAS.

Field measurements

The tree height measurement (hm) data and the crown diameter measurement (dm) data were collected in the same period of image acquisition, June 2017 and May 2018, with the aid of a measuring tape in 1.0 cm increments, with a maximum length of 2.50 m. We selected 144 plants, following the sampling methodology proposed by Ferraz et al. (2017).

All plants sampled were georeferenced using a DGPS receiver.

Statistics and data analysis

For the calculation of the biophysical parameters, Eq. (1) for the Leaf Area Index (LAI) was used, as reported by Favarin et al. (2002). This parameter was calculated using field data and data extracted from the UAS images.

$$LAI = 0.0134 + 0.7276 \times D_c{}^2 \times h \qquad (1)$$

where Dc – crown diameter (m) and h – plant height (m).

To calculate the biophysical parameter Leaf Area (LA), Eq. (2) was used:

$$LA = LAI \times (DR \times DP) \qquad (2)$$

where DR – Distance between rows (m) and DP – Distance between plants (m).

For the estimation of the crop coefficients (Kc), Eq. (3) was used, as proposed by Villa Nova et al. (2002):

$$Kc = 0.347 \times LA \times \left(\frac{Np}{10,000}\right) + kcd \times \left(1 - \frac{0.785D_c{}^2}{DP \times DR}\right) \qquad (3)$$

where Np – Number of plants (0.641 plants ha[-1]); LA – Leaf Area; D_c – Crown diameter (m); DR – Distance between rows (m); DP – Distance between plants (m), and kcd –Crop coefficient representative of the plant cover between rows ($kcd = 1$ in the presence of transpiring vegetation cover, and $kcd = 0.5$ absence of transpiring vegetation cover).

To create the Kc map, the average of the four plants of each block was used for the months of June and May. Electronic spreadsheets were used to calculate Kc and organize the data, and the GeoDA free software was used for the spatial analysis (Anselin, 2006).

To estimate the spatial variability of the data from the study area, the spatial weight matrix was calculated using GeoDA, using the 'queen' criterion; that is, second-order neighbors are considered. Thus, $W_{ij} = 1.0$ if the i-th block shares at least one side with the j-th block; otherwise, $W_{ij} = 0$. The pseudo-significance test was applied with $p < 0.05$ to validate the statistic.

Moran's global autocorrelation Index (I) proposed by Bailey & Gatrell (1995) describes the spatial arrangement of objects given by Eq. (4):

$$I = \frac{n}{W} \times \frac{\sum_i \sum_j W_{ij} z_i z_j}{\sum_i z_i^2} \ \forall \ i \neq j \tag{4}$$

where n − number of observations; W_{ij} − element of the neighborhood matrix for pair i and j; W − sum of the weights of the matrix; z_i and z_j − deviations from the mean $(z_i\text{-z})$, $(z_i\text{-z})$, and z − mean.

According to Ponciano & Scalon (2010), the i ranges from 0 to 1.0, indicating positive direct autocorrelation, and from 0.0 to −1.0, indicating indirect and negative autocorrelation.

The regression and correlation of the Kc data obtained in the field and by the UAS were performed using the average of the four plants from each block. To evaluate whether the estimates were significant at $p < 0.05$, a t-test was applied. The Root Mean Square Error (RMSE) were also calculated. The descriptive statistical analyses were performed in the statistical software R (R Core Team, Vienna, Austria).

RESULTS AND DISCUSSION

The Kc data obtained by the UAS images, on average, were lower than the data obtained in the field; that is, the values obtained by the UAS images were underestimated for June 2017 and May 2018. However, the correlation was strong, with Pearson correlation coefficient with R equal to 0.85, coefficient of determination (R^2) equal to 0.73 was found for the Kc values in June 2017. In May 2018 Pearson correlation coefficient with R equal to 0.89, the coefficient of determination (R^2) equal to 0.79 was found for the Kc values (Fig. 2).
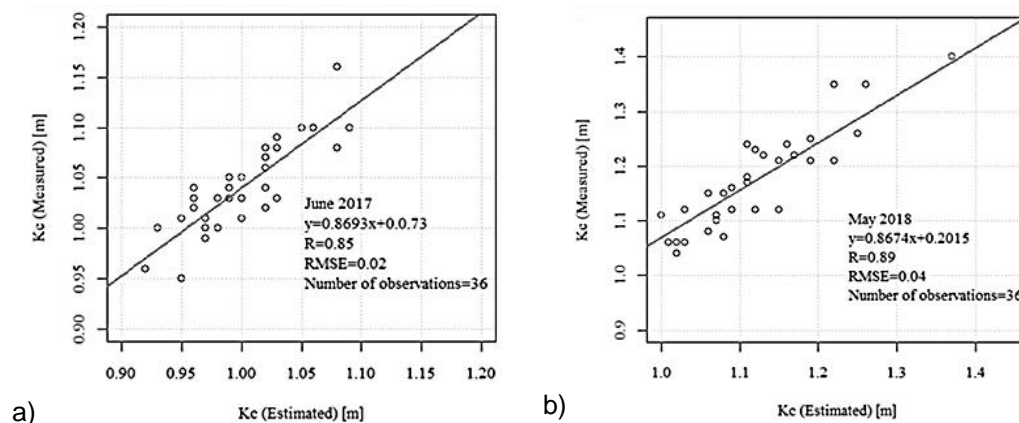
Figure 2. Regression between Kc data measured in the field and obtained by the UAS: a) of June 2017 and b) of May 2018.

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Through linear regression, Eq. (5) is proposed to correct the coffee Kc data estimated from the UAS image, with the correlation of 72 numbers of observations, with an R value equal to 0.93 and a coefficient of determination (R^2) equal to 0.86. According to Eq. (5), it is possible to estimate the Kc of the coffee plant from Kc data obtained by the aircraft. This type of equation has practical relevance since it provides an indirect way of obtaining crop data.

$$Kc_m = 0.9618 \times Kc_e + 0.0879 \tag{5}$$

where $Kc_m - Kc$ measured (m) and $Kc_e - Kc$ estimated by the UAS (m).

The Kc measured in the field and that obtained from the UAS image were significantly different, with a *p value* < 0.02.

Kc map (Fig. 3) was proposed based on the biophysical characteristics of the coffee plants, following the methodology proposed by Villa Nova et al. (2002) and using UAS data.
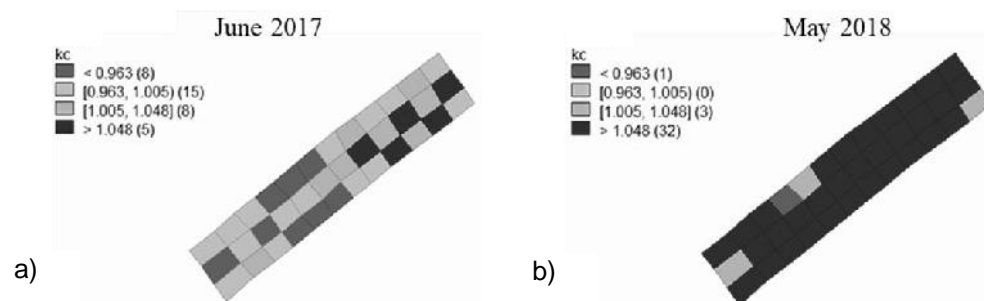
Figure 3. Kc map for the months (a) of June 2017 and (b) May 2018.

The Kc differed significantly between months; that is, the null hypothesis was rejected, and the Kc spatial autocorrelation in the blocks was considered; this autocorrelation increased with time. In June 2017, a I = 0.228 was observed, and in May 2018, I = 0.286.

As observed in Fig. 3, most of the blocks at the beginning of the experiment, in June 2017, when the coffee plants were in the vegetative period during the flower maturation stage, showed Kc values between 0.96 and 1.0. This variation is dependent on the plant height and crown diameter. For the month of May 2018, when the plants were in the reproductive period during the fruiting phase, the Kc values were 1.05 for 32 blocks, indicating a homogeneous Kc. According to Oliveira et al. (2007), in the period of crop establishment, the Kc curve has low values, and when the crop reaches a maximum canopy, the curve tends to stabilize with close values, a trend consistent with the data found in this study.

Some studies on Kc recommend values according to coffee crop development, such as Doorenbos & Pruitt (1997), who proposed a mean Kc value between 0.9 and 1.1 for adult coffee trees at all stages of development, without specifying the location and conditions under which these values were obtained. Those values are within a range greater than that found and recommended in this study (0.96 to 1.05), which is due to the variety and/or the method used for obtaining Kc.

Arruda et al. (2000) found Kc values equal to 0.73 and 0.75 in the first years of coffee production and Kc values of 0.87 and 0.93 for coffee plants 7 and 8 years of age, respectively. The present study found Kc values consistent with the values from that study, considering that mean Kc values between 0.96 and 1.05 were obtained for coffee plants 9 and 10 years of age, respectively.

For coffee plants with adequate management and heights of 2.0 to 3.0 m, in a sub-humid climate, Allen et al. (1998) proposed a Kc between 0.90 and 0.95 and for soil without plant cover and in the presence of weeds, they proposed a Kc between 1.05 and 1.10, respectively, with reference evapotranspiration estimated by the Penman-Monteith method - FAO. Those results were slightly higher than those found in the present study because the maximum Kc value found herein was 1.05, with weeds present in the interrows; this slight difference in the results can also be attributed to the method used for obtaining the Kc values.

Villa Nova et al. (2002), for Mundo Novo coffee crops, observed Kc values between 0.5 and 1.2 and between 0.9 and 1.2, without weeds and with weeds, respectively, with a density of 4,000 plants ha^{-1}. Despite using a different cultivar, that study obtained a Kc range close to that found in the present study, when considering the Kc results with weeds in the interrow.

As observed, the Kc values obtained herein were consistent with the literature, with some variations according to the stage, age, and variety. Furthermore, the method used to obtain the Kc values takes into account the plant biophysical characteristics, showing the sensitivity and consistency of the data, thus confirming its efficiency and adoption for rational irrigation management in coffee crops (Villa Nova et al., 2002).

Notably, the generated Kc map followed the equation proposed by Villa Nova et al. (2002), and it was developed for a specific variety. This equation may not represent Kc for all varieties; however, this methodology is feasible for generating Kc maps using biophysical data obtained remotely, which would be very useful in irrigation management.

According to the literature, studies for the quantification of Kc for coffee crops were performed using agronomic experiments. The advantage of using the methodology proposed herein is the ability to obtain biophysical parameters of coffee crops remotely, which is an indirect and nondestructive method of data collection. In addition, it is necessary to quantify the Kc at the different phases of the phenological cycle of coffee plants of different ages, which is difficult to do in the field. Thus, using remotes methods to obtain data from coffee plants allows the collection of crop data in almost real-time, determining the spatial variability of the crop data, and creating a historical series, thus favoring more efficient and assertive management.

CONCLUSIONS

This study developed a methodology for estimating Kc using biophysical data obtained remotely. It is an indirect methodology to obtain data in a non-destructive way.

The estimative showed a strong correlation, R of 0.93, so it is possible to estimate the Kc of the coffee plant from the Kc data obtained by the aircraft. In addition, the Kc values found in the study ranged from 0.96 to 1.0 in the vegetative period and from 1.05 in the reproductive period.

The data found were consistent with the literature; thus, this method is useful for estimating Kc and for assisting in irrigation management of coffee crops.

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