ALMOND ORCHARD MANAGEMENT USING MULTI-TEMPORAL UAV DATA: A PROOF OF CONCEPT

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IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium | 978-1-6654-2792-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/IGARSS46834.2022.9883370

ABSTRACT

In the last decade Unmanned Aerial Systems (UAS) have become a reference tool for agriculture applications. The integration of multispectral sensors that can capture near infrared (NIR) and red edge spectral reflectance allows the creation of vegetation indices, which are fundamental for crop monitoring process. In this study, we propose a methodology to analyze the vegetative state of almond crops using multi-temporal data acquired by a multispectral sensor accoupled to an Unmanned Aerial Vehicle (UAV). The methodology implemented allowed individual tree parameters extraction, such as number of trees, tree height, and tree crown area. This also allowed the acquisition of Normalized Difference Vegetation Index (NDVI) information for each tree. The multi-temporal data showed significant variations in the vegetative state of almond crops.

Index Terms**—** Almond crops monitoring, UAV multi-temporal data analysis, tree parameters extraction, vegetation indices, precision agriculture

1. INTRODUCTION

Almond (*Prunus dulcis*) is an important crop due to the health benefits provided by Mediterranean diet [1]. In terms of production, California is the most important region, accounting for roughly 80% of global supply. However, almond production is increasing globally, mainly in Mediterranean countries [2]. In the last decade, several studies using Remote Sensing platforms have been conducted in almond orchards, namely studies related to water stress management [3],[4]. Although, most of these studies present stand level analysis. According to the precision agriculture concept, monitoring and measuring processes need to consider the variability within the crops [5]. Thus, tree-level analysis, based on individual tree parameters extraction [6], are crucial for the characterization and monitoring of almond orchards [7].

Considering the importance of crop management at the tree level, essential in a context of climate change [8],[9], in this study we present a proof of concept of a methodology based on multi-sensor imagery data acquired by an Unmanned Aerial Vehicle (UAV) to automatically identify individual trees in almond orchards and extract different parameters for each one. As case study, an almond orchard was surveyed in two different epochs. The individual tree parameters, along with the Normalized Difference Vegetation Index (NDVI) information, extracted in the two different epochs, for each tree, are compared and analyzed. The proposed methodology aims to assess the potential of tree level analysis.

2. MATERIAL AND METHODS

2.1. Study area and UAV data acquisition

The experiment was carried out in a 0.53 ha almond orchard, without irrigation (Fig.1), composed of 173 trees. The orchard is located in São Salvador, Bragança, Portugal (41°25'55.7"N, 7°08'06.7"W, 342 m altitude).

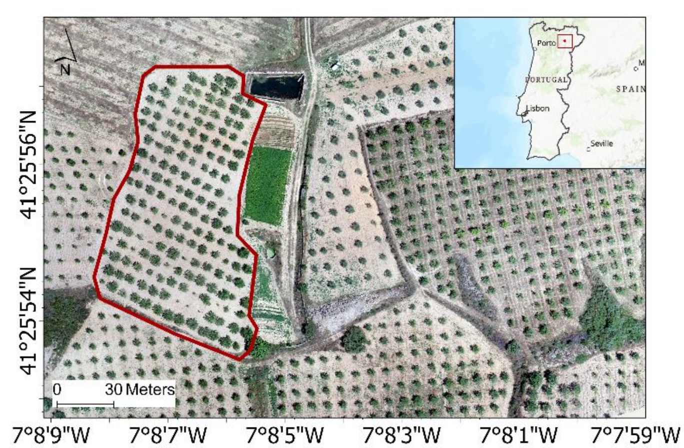

Fig. 1. Aerial overview of the analyzed almond orchard.

UAV data were acquired using a multi-rotor Phantom 4 (DJI, Shenzhen, China). To collect georeferenced RGB imagery, the camera is equipped with a CMOS sensor (12.4 MP resolution) set in a 3-axis gimbal. Multispectral imagery was captured with the Parrot SEQUOIA (Parrot SA, Paris, France). Sequoia is composed of four sensors allowing to capture four separate bands at a resolution of 1.2 MP: green, 550 nm (40 nm bandwidth); red, 660 nm (40 nm bandwidth); red edge, 735 nm (10 nm bandwidth) and near infrared, 790 nm (40 nm bandwidth). Irradiance data is collected during the flight and reflectance data is collected using a radiometric calibration target.

The flight missions were carried out on June 29th, and August 5th, 2021, at 60 meters flight height and with a longitudinal imagery overlap of 80% and 70% lateral overlap. The data collection period was Summer, which is characterized by a dry and hot climate with low precipitation values [10].

2.2. Data Processing

The data processing was based on three main steps (Fig.2): (1) photogrammetric processing; (2) tree crown segmentation; and (3) individual tree parameters extraction.

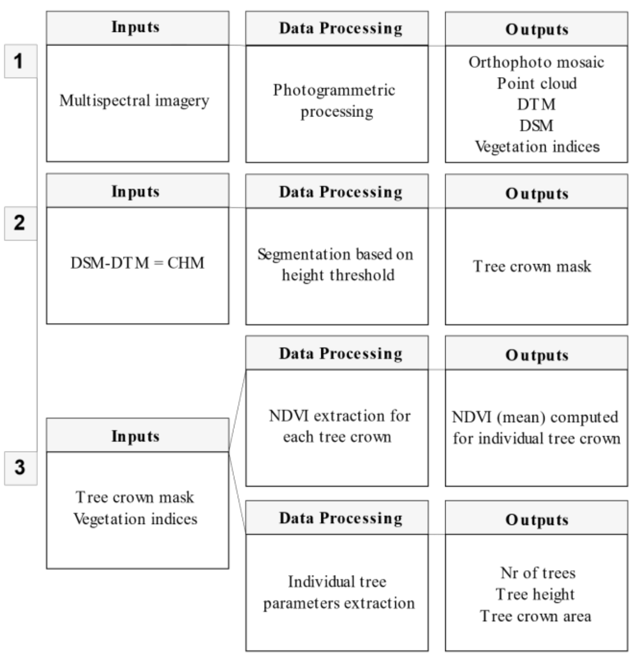

Fig. 2. Data processing workflow.

The Photogrammetric processing was performed using the Pix4Dmapper Pro (Pix4D SA, Lausanne, Switzerland). This software was used to process RGB and multispectral imagery. Several orthorectified raster outputs were computed, such as orthophoto mosaics, Digital Terrain Model (DTMs), Digital Surface Model (DSMs) and, after radiometric calibration, vegetation indices. Data was properly aligned during photogrammetric processing by using common points, in the imagery from both sensors and epochs, throughout the area. The Canopy Height Model (CHM) was created in QGIS software using a high-resolution DSM (pixel size: 1.6 cm) and DTM (pixel size: 7.8 cm).

The CHM was used as input in individual tree crown detection and segmentation process. In the binarization process, a threshold of 0.5 meters was applied, this value revealed to be effective since it completely removed existent lowland vegetation and the shadows casted by the tree crowns. From this procedure resulted a binary mask that is then vectorized to obtain the polygons for each detected tree crown.

In the last data processing procedure, the segmented tree crowns were used to obtain the mean NDVI [11] value for each tree crown and to extract other parameters such as tree height (derived from CHM), tree crown area and the number of trees.

3. RESULTS

3.1. Individual tree crown mean NDVI

Following the described data processing methodology, the acquired RGB and multispectral imagery was subjected to photogrammetric processing, and the individual tree crown detection was performed. This way, it was possible to obtain the mean NDVI value, computed for each tree crown on June 29^{th}, 2021 (Fig. 3a.), and August 5^{th}, 2021 (Fig. 3b.).

In Fig. 3 (a) and Fig. 3 (b), the mean NDVI values are presented in three classes: low, values below 0.53; medium, values between 0.53 to 0.59; and high, values above 0.59. Considering the results obtained on the different dates, contrasts on NDVI values are identified in all classes, showing a significant increase in the lower values of NDVI, between June 29^{th}, 2021, and August 5^{th}, 2021. According to these results, about 28% (48 trees) of low NDVI points remained in the lower class, about 27% (46 trees) changed from medium to low, and approximately 19% (33 trees) of trees with high NDVI values remained stable. These values prove the increase of water stress in the almond orchard, which over several years will lead to lower vigor.

Variations in the distribution of NDVI at higher and lower values are shown in Fig. 3 (d). In general, on June 29th, 2021, the values are higher (mean tree crown value of 0.56) when compared with the distribution on August 5th, 2021 (mean tree crown value of 0.49).

The obtained results also highlight differences within the almond trees on the two dates, as the trees at the plain areas with deeper soil exhibit lower water stress than the trees distributed at hillside areas with shallow soil (DTM presented in Fig. 3c.). This variation can be explained due to the greater accumulation of water from precipitation in plain areas along with a larger accumulation of organic matter in the soil. On the other hand, in the hillside areas, there is a greater flow of water, which hinders the accumulation and infiltration of water.

3.2. Individual tree parameters extraction

In tree parameters extraction, 173 trees were detected on both dates using the applied methodology. Regarding tree height, Fig. 4 shows that 53 trees have heights bellow 2.65 meters, 60 trees have heights between 2.65 to 3.01 meters and 60 trees have heights between 3.01 to 4.67 meters.

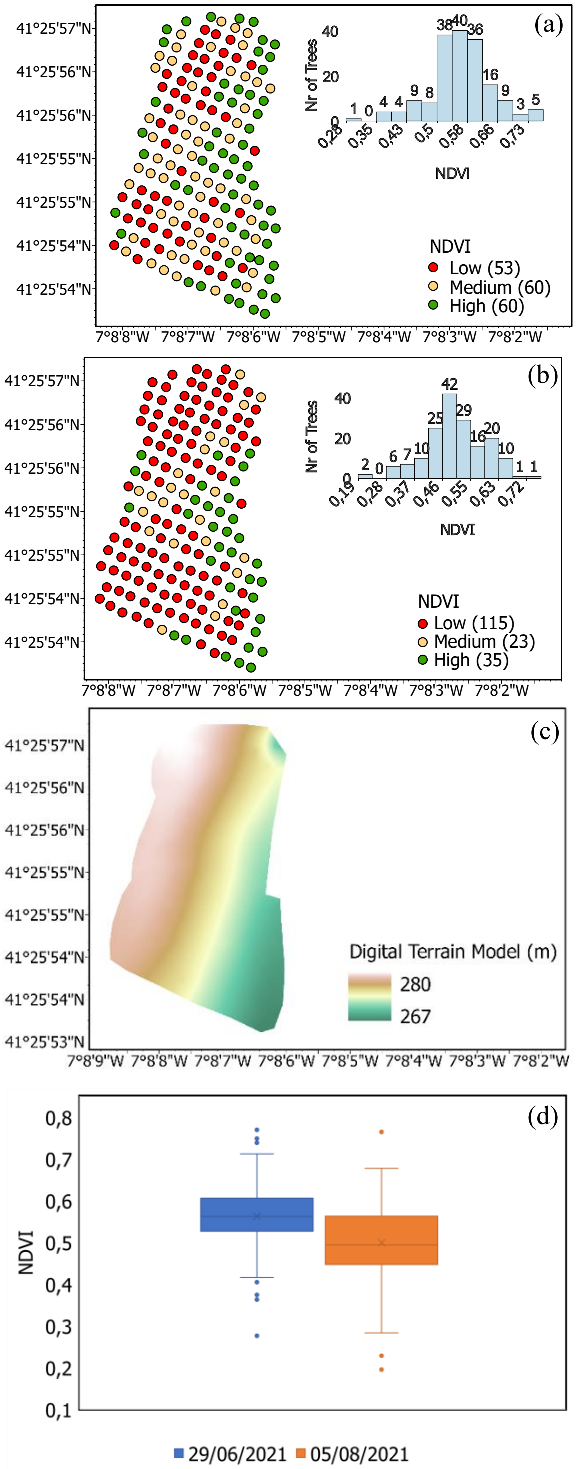

Fig. 3. Results of data processing workflow. (a) mean NDVI for individual tree crown on 29/06/2021; (b) mean NDVI for individual tree crown on 05/08/2021; (c) DTM of the study area; and (d) boxplot distribution with the mean tree crown NDVI on 29/06/2021 and 5/08/2021.

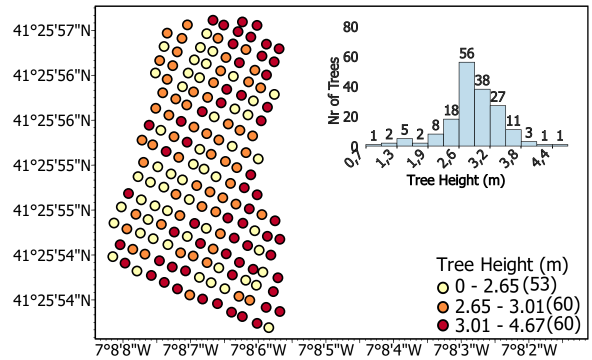

Fig. 4. Tree height distribution.

Concerning the tree crown area, about 66% (115 trees) showed a decline between the two dates.

4. CONCLUSIONS

The methodology presented in this study enables to obtain several tree-related parameters in almond orchards. The experimental results shown the feasibility to monitor the temporal vegetative decline, when analyzing different epochs. The extraction of height and tree crown area permits to evaluate the growth over time, enabling to assess individual tree growth for each tree and to implement field measures to potentially affected trees or areas. In the same manner, other metrics can also be estimated as tree volume, as well as, other vegetation indices and data from other sensors. As future work, the vegetative development of almond orchards within the growing season will be addressed by using multi-temporal UAV-based data and the inclusion of imagery data from other sensors is considered, as thermal infrared and hyperspectral sensors.

ACKNOWLEDGMENTS

The author acknowledges the financial support provided by the FCT-Portuguese Foundation for Science and Technology (UI/BD/150727/2020), under the Doctoral Programme “Agricultural Production Chains – from fork to farm” (PD/00122/2012) and under the project UIDB/04033/2020.

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