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Very high resolution aerial data to support multi-temporal precision agriculture information management

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Abstract

The usage of small-sized unmanned aerial systems (UAS) has increased in the last years, in many different areas, being agriculture and forestry those who benefit the most from this relatively new remote sensing platform. Leaf area index, canopy and plant volume are among the parameters that can be determined using the very high resolution aerial data obtained by sensors coupled in unmanned aerial vehicles (UAV). This remote sensing technology affords the possibility of monitoring the vegetative development, identifying different types of issues, enabling the application of the most appropriated treatments in the affected areas. In this paper, a methodology allowing to perform multi-temporal UAS-based data analysis obtained by different sensors is proposed. A case study in vineyards and chestnuts is used to prove the benefits of continuous crop monitoring in its management and productivity of agroforestry parcels/activities.

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Keywords: UAS; vineyards; chestnuts; multi-temporal data analysis; precision agriculture

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1. Introduction

Remote sensing platforms in precision agriculture (PA) have been applied for several years by the usage of different platforms such as satellites or manned aircrafts. Lately with the appearance of Unmanned Aerial Systems (UAS), that can be remotely piloted or have a programmed route to perform autonomous flight, new possibilities are offered in the remote sensing field. Generally, UASs also requires a ground-control station, sensor suites and communication devices for carrying out flight missions[1]. PA is a concept based on observing, measuring and responding to inter and intra-field variability in crops. The goal of PA is to define a decision support system for farm management with the goal of optimizing returns on inputs while, at the same time, preserving resources[2]. To achieve this, a fast, reliable, cost-effective and easy method to scan the fields is required. The crop's condition can be assessed by the stage of ripening, water status, pest attacks and nutritional requirements. The remote sensing capabilities acquired by UAS can provide this necessary data, so that the farmer is able to identify problems in early stages and rapidly select the appropriated interventions[3]. PA relies on four main tasks: data acquisition; terrain variability mapping; decision making; and application of management practices[4]. Remote sensing can be used with great benefit in the first three tasks. Acquiring the necessary information is one of the key factors of PA to provide correct support in the decision-making process and recognition of temporal variations[5]. The use of Unmanned Aerial Vehicles (UAV) can help to determine parameters such as leaf area index (LAI), crop cover, volume or height. Providing a flexible access to crop parameters such as vegetative vigour, quality and yield estimation[6].

This study proposes a methodology capable of analysing very high resolution UAV-based data from different types of sensors in a multi-temporal perspective, focusing on two different crops of great economic impact in Portugal, vineyards (*Vitis vinifera* L.) and chestnut trees (*Castanea sativa* Mill.). Where considerable areas of these crops are present in the northern region of the country[7]. The commercial value of these plantations depends on several factors such as: the caste (vineyards), the plant quality, and the climatic conditions of the region. However, in both crops, there are problems that may interfere with their development, which makes effective detection and inspection techniques necessary to decrease the occurrence risk of those problems, thus enabling a viable and sustainable cultivation of these crops. Nowadays, direct ground observations are performed to assess the presence of issues. In the vineyard, there are diseases for which it is necessary to eliminate many plants from the parcel or in some cases, to eliminate the whole parcel[8]. Regarding chestnut trees, problems such as Chestnut ink and Chestnut blight are the main causes of its decline[9]. For all these reasons, the detection of problems in earlier stages becomes indispensable, allowing a quicker response capacity to apply the proper treatment, saving up crops and reducing maintenance costs.

UAVs appear as the ideal tool, allowing the monitoring of crops through the analysis of spectral signatures and its vegetative development. The proposed methodology allows evaluating the temporal evolution of these cultures, determining the probable causes of potential problems, from biotic and/or abiotic origins, thus allowing the application of the most appropriate measures to eliminate/mitigate the identified problems.

This paper is structured as following: a brief overview of the related work in UAVs applied to agroforestry with a major focus on studies that used time-series data and data generated by each flight mission is provided in section two; in section three, the data analysis process is present and described; the fourth section, presents some preliminary results from the application of the proposed methodology; finally, section five presents some conclusions and provides the next steps implementing the proposed methodology.

2. Background

The technological development lead to the emergence of affordable and easy to operate small-sized UASs[10], making this platform suitable to be applied in different areas[11]. UAS allows the acquisition of very high resolution data using different types of sensors, with a greater versatility and cost-effectiveness than satellites or manned aircrafts in small/medium-sized projects[12]. The possibility to survey considerable areas in shorter time, providing very-high spatial and temporal resolutions images, makes UAS an ideal platform for monitoring agroforestry parcels[13]. In this specific sector, the UAS applicability goes from crop monitoring[13,14], invasive weed mapping[15], irrigation management[16–18], biomass[19–21], chlorophyll[22,23], and nutrient estimation[21,24] to vegetation height maps[25,26], among others. Different types of sensors operating in different parts of the electromagnetic spectrum (*i.e.* visible, red edge, near infra-red, thermal) can be used[10].

The flexibility of UAS platforms increases its applicability to survey the same area over time. This approach was already applied in some studies, where UAVs and different sensors to acquire time series of data have been used with different purposes in different types of agricultural crops as barley[27], sunflowers[28], silage maize[29], rice[30] and vineyards[6]. In the aforementioned studies, time series allowed to reach results that, in some cases, were noticeable only after a certain vegetative cycle stage of the studied crops. Thus the use of time series among the same area bring great advantages, since they allow to assess the vegetation development in several phenological stages and to identify problematic areas, which will enable to analyse the response to the implemented mitigation measures in an effective way.

The usual system architecture for UAS-based data acquisition and processing follows two main components: the UAS responsible for acquiring field data and a processing unit composed by a high-performance workstation for storing, management and delivering the information to the user. The data acquisition is performed by the UAS, composed by an UAV, with sensors coupled to it, and a ground station. Each UAV, independently of the chosen configuration, which are fixed-wing or rotary-wing, is usually composed by a GNSS receiver (at least GPS receiver), a data acquisition sensor and a ground station along with a local storage to collect the acquired data. The acquired data passes through a photogrammetric processing stage where the data is unfolded into different outputs as: orthophoto mosaics, three-dimensional models, Digital Elevation Models (DEMs) and 3D point clouds[10]. Orthophoto mosaics provide imagery data that can be used in image processing algorithms. DEMs provide elevation data from the terrain's surface, which can contain elevation data from features present in the ground surface - Digital Surface Model (DSM) - or only from the ground - Digital Terrain Models (DTM)[31]. These models are computed considering the three-dimensional point clouds generated from the application of Structure from Motion (SfM) algorithms in the images acquired by the sensors on-board the UAV. From the subtraction of the DTM from the DSM, elevation models containing only information from objects above the ground - Digital Differential Model (DDM) or Canopy Height Models (CHM) - can be computed[19].

However, data generated by the photogrammetric software does not provide any valuable information to the final user and in a multi-temporal perspective: it must be analysed, and usually this type of analysis is performed manually. In the next section some directions on how to automatize such task are presented with the examples of vineyards and chestnuts. Digital image processing techniques applied to the outputs derived from UAS-based data allows, among others, to determine the area occupied by vegetation on a given land parcel. This enables the identification of areas with higher production, allowing, for instance, sowing optimization, diseases and/or pest detection, thus contributing to promote an efficient management.

3. Proposed data analysis methodology

This section specifies the proposed methodology that enables the processing of UAS-based data in agriculture crops, more specifically in vineyards and chestnuts. It presents the different phases, that ranges, from vegetation segmentation to the information obtained from the specifications provided by the user. Fig. 1 presents an overview of the processing pipeline, where the several outcomes from the photogrammetric processing are used as inputs. The crop's vegetation segmentation is performed, depending on the type of crop and/or parameters. Finally, time series analysis is performed to provide a comparison with the extracted parameters and to identify areas with possible biotic and abiotic issues reporting them to the user.

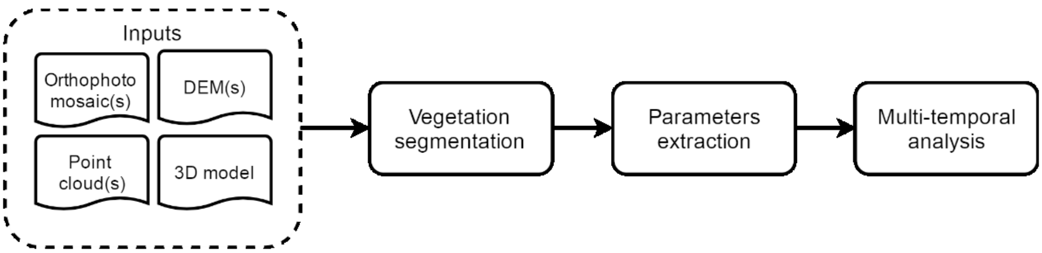

Fig. 1. The proposed methodology workflow, performing time series analysis to enable decision support in PA.

3.1. Crop's specific vegetation extraction

For multi-temporal analysis of agricultural crops, specific parameters need to be assessed to understand their influence in crops' development. These include the epoch of the year, the vegetative stage, the meteorological and soil conditions and the phytosanitary and nutritional status. Once the parameters are identified, they need to be transposed to the platforms and sensors, guiding their selection along with other variables. In addition, some of these conditions may mask the normal manifestation of specific problems, generating important relationships between variables, hence the importance of time series, since it allows reducing the inherent risks. The algorithms to be developed and implemented must be capable of dealing with each specific characteristic from both cultures. The algorithms should be capable of successfully accomplishing three different stages: crop's vegetation segmentation, extraction of parameters from a single flight and perform the multi-temporal analysis in the same area of interest.

Crop's vegetation segmentation can be performed in different ways, through global[32,33], or local[34] thresholding, using vegetation indices[32] or object-based image analyses[33]. In both cases, the algorithms should be capable of detecting crop's vegetation, separating it from the soil and non-vineyard and non-chestnut vegetation (*e.g.* roads, buildings, soil vegetation). To perform vineyard vegetation segmentation, some authors successfully applied different methods, based on Hough transform[34], skeletonization[35], machine learning methods, k-means and vegetation indices[36]. However, in this case and regarding vineyards, it is intended to automatically delimit each vineyard plot and to identify vine rows. In order to perform vineyard plot detection some authors used Fast Fourier Transform (FFT) and Gabor filters[37]. Regarding the chestnut tree, it is planned to individually detect each chestnut tree in several chestnut plots.

With the crop's vegetation properly segmented, it is possible to extract more valuable and accurate information from both cultures. In the vineyards, its volume, area and vegetative vigour are parameters that can provide general information about the vines state. Fig. 2 presents the proposed methods to perform the parameters extraction in vineyards, with the inputs from the pre-processed UAS-based data, the vineyard plot is identified and masked. In the vegetation segmentation stage, the soil vegetation is excluded to improve the reliability of the extracted parameters, after vegetation segmentation being performed different parameters can be extracted. With each vineyard plot being automatically detected, it is possible to compare the extracted parameters in a multi-temporal perspective.

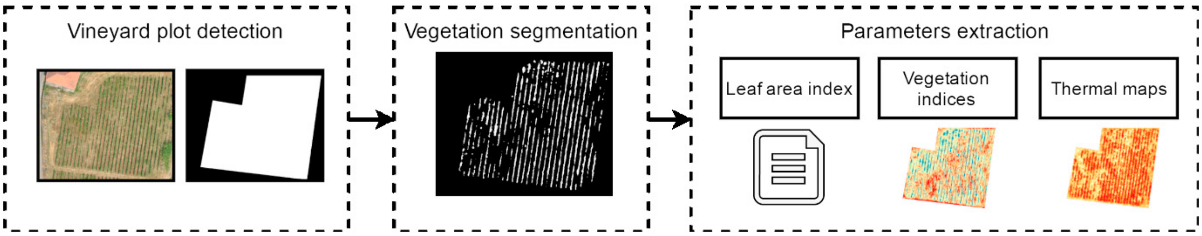

Fig. 2 Methodology to extract parameters from UAS-based data in vineyards. Different types of sensors can be applied in order to extract more and useful parameters.

Regarding chestnut trees, it is possible to identify and extract properties such as crown diameter and the height of tree present in a given image. Fig. 3 presents an example of the proposed methodology using data from several sources acquired in a small chestnut plot. The imagery data along with the digital elevation models are used as inputs and then the chestnut vegetation is segmented, making possible to obtain parameters as canopy cover area and height. These parameters extracted from a single set of data can be crossed with other sources of information in order to enhance the time-series analysis.

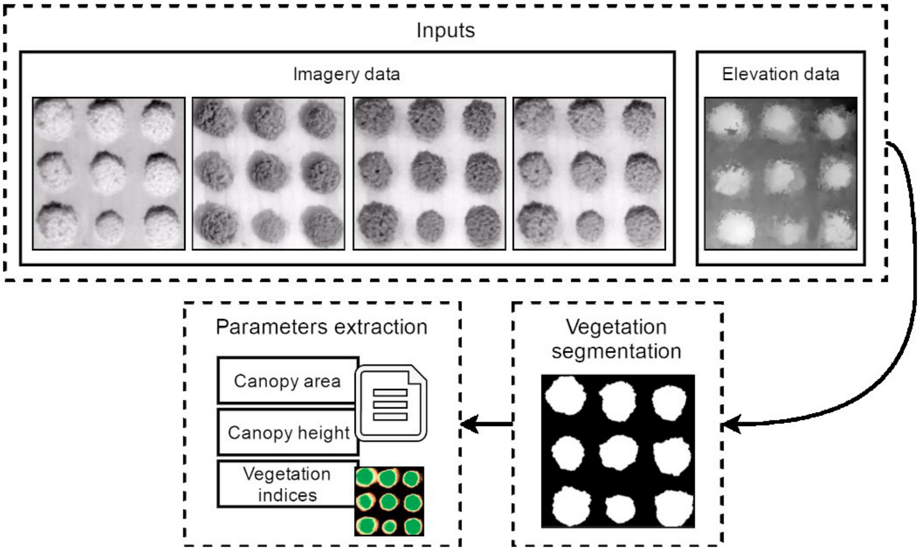

Fig. 3 Methodology to extract crop parameters from UAS-based data in chestnut plots using elevation and imagery data.

3.2. Multi-Temporal analysis

After processing the data collected from each individual flight, it is possible to analyse the same area and compare it with a previous campaign, in order to perform a temporal evaluation of a specific crop. In vineyard's specific case the comparison should be performed in a plot-to-plot scale. The vegetative status of the plants can be estimated by spectral vegetation indices, computed from multispectral or hyperspectral UAS-based data, or by thermal data.

For the chestnut tree case, after the detection of each tree in a given area, an individual tree assessment in a different dataset (different flight) can be performed, to compare parameters, such as crown height and area. From this comparison different scenarios can happen: (1) the tree is not identified, which means that it can be dead and/or it was cut-down; (2) a big area regression was found, which can be related with the presence of a phytosanitary problem and it must be inspected in the field; (3) the area is bigger or approximately the same, which represents that the development is in the correct path or the tree is in a controlled environment even if it is infected, meaning that any potential disease as not manifested itself. This way, it is possible to provide a clear overview of the behaviour of phytosanitary problems distribution and to provide an overview of the vegetation development. Table 1 presents the parameters extracted from the data of two flights over the same chestnut plot and the respective difference.

The obtained results from the temporal analysis can be compiled in a form of a report or maps, providing valuable information about the crop's conditions both in a global and in a local perspective. The application of this approach in comparison with traditional methods will reduce the time and human resources allocation to monitor and mitigate the occurrence and emergence of biotic and abiotic problems.

4. Proof of concept

This section presents the applicability of the proposed methods described in the previous section. Two cases are presented, regarding a chestnut area and a vineyard plot. The data were acquired using a fixed-wing UAV, the eBee (senseFly SA, Lausanne, Switzerland). In what regards chestnut area data, it is related with two flights from two different years 2014 and 2015. The vineyard data were acquired during 2016 in six different flights.

Table 1 presents the results from the canopy height and the area occupation of 9 chestnuts in the two acquisition epochs in an area of approximately 900 m^2. The occupation area was extracted from the segmented images of both flights and the canopy height was extracted from the DDM. Results demonstrate the possibility of the correct extraction of parameters from UAS-based data. The chestnut occupation area growth had an evolution of approximately 35 m^2 while the average height increase in the compared chestnut trees was of 0.15 m. Thus, results are considered normal, which means that there are no phytosanitary problems on the evaluated area.

Table 1. Comparison of the extracted parameters on the same chestnut area.

Tree number	Acquisition 1		Acquisition 2		Difference	
	Area (m^2)	Height (m)	Area (m^2)	Height (m)	Area (m^2)	Height (m)
1	56.6	6.6	54.2	7.0	-2.4	0.4
2	38.5	5.5	39.0	5.5	0.5	0
3	51.7	6.9	54.8	7.1	3.1	0.2
4	44.5	6.3	52.4	6.5	7.9	0.2
5	42.8	5.3	48.3	6.1	5.5	0.8
6	30.8	2.9	30.8	2.8	0	-0.1
7	37.2	6.6	43.0	6.1	5.8	-0.5
8	40.9	6.6	51.4	6.6	10.5	0
9	50.1	6.1	53.7	6.4	3.6	0.3

Regarding the vineyard parcel, Fig. 4 (a) represents the area occupied by the vine vegetation acquired in six flights. These flights address different phenological stages, from the fruit set - when the grape berries are forming - to the veraison stage, when grape clusters are ripening. The vineyard occupation area is presented in Fig. 4 (b). It can be noticed a vegetation increase in the first three flights and from this onwards, a decrease in vegetation up to the last flight when the harvest season is approaching.

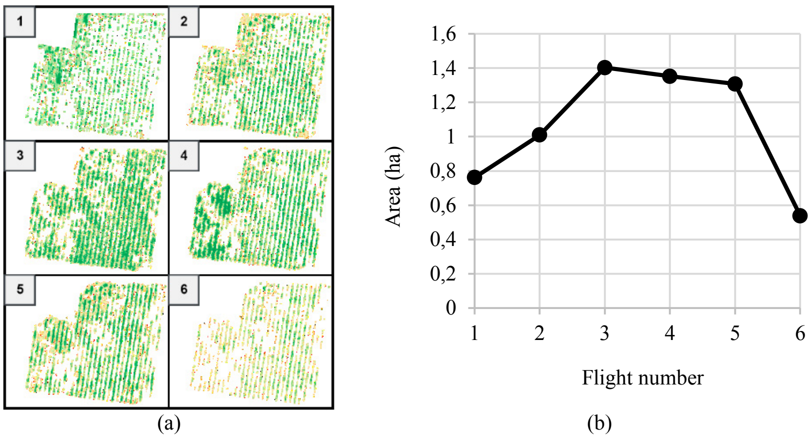

Fig. 4 Temporal evolution of a vineyard plot vegetation along six flights, (a) segmented vineyard vegetation, (b) vineyard vegetation area.

The multi-temporal analysis performed in this section validates the possibility to collect important information for both chestnut and vineyard areas. The presented results also demonstrate the validity of extracting parameters to estimate vegetative development.

5. Conclusions and future work

In this study a methodology to improve the UAS-based data analysis in PA is presented, with a major focus on vineyards and chestnut trees. The presented methodology is capable of monitoring the decline of chestnut trees and the vegetative development of vineyards from UAV-based data in a multi-temporal perspective. This methodology can be implemented in an agricultural management system to improve the support to the decision making process.

As future work, a suitable data acquisition methodology should be defined to ensure the correct timing according to the crop in analysis, given the phenological development among other conditions. The algorithms to be used in each step of the vegetation analysis must ensure a proper performance and, at same time, accurate results. The ability of the algorithms to automatically detect anomalous situations is a key factor to reduce the time required to perform interventions and to allocate the necessary human resources. The final goal will be a controlled monitoring of problems affecting the cultures, with the economic benefits that come from it, as well as the crops' vegetative development monitoring.

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References

1. Pappalardo J. Unmanned aircraft roadmap reflects changing priorities. Natl Def. 2003;87(392):30.
2. McBratney A, Whelan B, Ancev T, Bouma J. Future Directions of Precision Agriculture. Precis Agric. 2005 fevereiro;6(1):7–23.
3. George EA, Tiwari G, Yadav RN, Peters E, Sadana S. UAV systems for parameter identification in agriculture. In: 2013 IEEE Global Humanitarian Technology Conference: South Asia Satellite (GHTC-SAS). 2013. p. 270–3.
4. Zhang C, Kovacs JM. The application of small unmanned aerial systems for precision agriculture: a review. Precis Agric. 2012 Jul 31;13(6):693–712.
5. Lan Y, Thomson SJ, Huang Y, Hoffmann WC, Zhang H. Current status and future directions of precision aerial application for site-specific crop management in the USA. Comput Electron Agric. 2010 outubro;74(1):34–8.
6. Ballesteros R, Ortega JF, Hernández D, Moreno MÁ. Characterization of Vitis vinifera L. Canopy Using Unmanned Aerial Vehicle-Based Remote Sensing and Photogrammetry Techniques. Am J Enol Vitic. 2015 Jan 16;ajev.2014.14070.
7. Instituto Nacional de Estatística, I. P. Estatísticas Agrícolas 2015. Lisbon, Portugal: Instituto Nacional de Estatística, I.P.; 2016.
8. EFSA Panel on Plant Health (PLH), Jeger M, Bragard C, Caffier D, Candresse T, Chatzivassiliou E, et al. Risk to plant health of Flavescence dorée for the EU territory. EFSA J. 2016 Dec 1;14(12):n/a-n/a.
9. Martins L, Castro JP, Bento R, Sousa JJ. Monitorização da condição fitossanitária do castanheiro por fotografia aérea obtida com aeronave não tripulada. Rev Ciênc Agrár Soc Ciênc Agrár Port. 2015;38(2):184–90.
10. Pádua L, Vanko J, Hruška J, Adão T, Sousa JJ, Peres E, et al. UAS, sensors, and data processing in agroforestry: a review towards practical applications. Int J Remote Sens. 2017 maio;38(8–10):2349–91.
11. Jenkins D, Vasigh B. The economic impact of unmanned aircraft systems integration in the United States. Association for Unmanned Vehicle Systems International (AUVSI); 2013.
12. Matese A, Toscano P, Di Gennaro SF, Genesio L, Vaccari FP, Primicerio J, et al. Intercomparison of UAV, Aircraft and Satellite Remote Sensing Platforms for Precision Viticulture. Remote Sens. 2015 Mar 13;7(3):2971–90.
13. Berni JAJ, Zarco-Tejada PJ, Suarez L, Fereres E. Thermal and Narrowband Multispectral Remote Sensing for Vegetation Monitoring From an Unmanned Aerial Vehicle. IEEE Trans Geosci Remote Sens. 2009 Mar;47(3):722–38.
14. Turner D, Lucieer A, Watson C. Development of an Unmanned Aerial Vehicle (UAV) for hyper resolution vineyard mapping based on visible, multispectral, and thermal imagery. In 2011.
15. Gómez-Candón D, Castro AID, López-Granados F. Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture purposes in wheat. Precis Agric. 2013 Nov 8;15(1):44–56.
16. Baluja J, Diago MP, Balda P, Zorer R, Meggio F, Morales F, et al. Assessment of vineyard water status variability by thermal and multispectral imagery using an unmanned aerial vehicle (UAV). Irrig Sci. 2012 Aug 21;30(6):511–22.
17. Bellvert J, Girona J. The use of multispectral and thermal images as a tool for irrigation scheduling in vineyards. Erena M López-Fr Montesinos Berthoumieu JF 2012« Use Remote Sens Geogr Inf Syst Irrig Manag Southwest Eur Options Méditerranéennes Ser B Stud Res. 2012;(67):131–137.
18. Bellvert J, Zarco-Tejada PJ, Girona J, Fereres E. Mapping crop water stress index in a 'Pinot-noir' vineyard: comparing ground measurements with thermal remote sensing imagery from an unmanned aerial vehicle. Precis Agric. 2013 Nov 8;15(4):361–76.
19. Bendig J, Bolten A, Bennertz S, Broscheit J, Eichfuss S, Bareth G. Estimating Biomass of Barley Using Crop Surface Models (CSMs) Derived from UAV-Based RGB Imaging. Remote Sens. 2014 Oct 28;6(11):10395–412.
20. Bendig J, Yu K, Aasen H, Bolten A, Bennertz S, Broscheit J, et al. Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley. Int J Appl Earth Obs Geoinformation. 2015 Jul;39:79–87.

21. Pölönen I, Saari H, Kaivosoja J, Honkavaara E, Pesonen L. Hyperspectral imaging based biomass and nitrogen content estimations from light-weight UAV. In 2013.
22. Uto K, Seki H, Saito G, Kosugi Y. Characterization of Rice Paddies by a UAV-Mounted Miniature Hyperspectral Sensor System. IEEE J Sel Top Appl Earth Obs Remote Sens. 2013 Apr;6(2):851–60.
23. Zarco-Tejada PJ, González-Dugo V, Berni JA. Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera. Remote Sens Environ. 2012;117:322–337.
24. Caturegli L, Corniglia M, Gaetani M, Grossi N, Magni S, Migliazzi M, et al. Unmanned Aerial Vehicle to Estimate Nitrogen Status of Turfgrasses. PLOS ONE. 2016 Jun 24;11(6):e0158268.
25. Mathews AJ, Jensen JLR. Visualizing and Quantifying Vineyard Canopy LAI Using an Unmanned Aerial Vehicle (UAV) Collected High Density Structure from Motion Point Cloud. Remote Sens. 2013 May 7;5(5):2164–83.
26. Suomalainen J, Anders N, Iqbal S, Roerink G, Franke J, Wenting P, et al. A Lightweight Hyperspectral Mapping System and Photogrammetric Processing Chain for Unmanned Aerial Vehicles. Remote Sens. 2014 Nov 10;6(11):11013–30.
27. Bendig J, Bolten A, Bareth G. UAV-based Imaging for Multi-Temporal, very high Resolution Crop Surface Models to monitor Crop Growth Variability. PFG Photogramm Fernerkund Geoinformation. 2013 Dec 1;551–62.
28. Vega FA, Ramírez FC, Saiz MP, Rosúa FO. Multi-temporal imaging using an unmanned aerial vehicle for monitoring a sunflower crop. Biosyst Eng. 2015;132:19–27.
29. Castaldi F, Pelosi F, Pascucci S, Casa R. Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize. Precis Agric. 2017 Feb 1;18(1):76–94.
30. Willkomm M, Bolten A, Bareth G. NON-DESTRUCTIVE MONITORING OF RICE BY HYPERSPECTRAL IN-FIELD SPECTROMETRY AND UAV-BASED REMOTE SENSING: CASE STUDY OF FIELD-GROWN RICE IN NORTH RHINE-WESTPHALIA, GERMANY. Int Arch Photogramm Remote Sens Spat Inf Sci. 2016;41.
31. Hirt C. Digital Terrain Models. In: Grafarend E, editor. Encyclopedia of Geodesy [Internet]. Cham: Springer International Publishing; 2014. p. 1–6. Available from: https://doi.org/10.1007/978-3-319-02370-0_31-1
32. Meyer GE, Neto JC. Verification of color vegetation indices for automated crop imaging applications. Comput Electron Agric. 2008 outubro;63(2):282–93.
33. Torres-Sánchez J, López-Granados F, Peña JM. An automatic object-based method for optimal thresholding in UAV images: Application for vegetation detection in herbaceous crops. Comput Electron Agric. 2015 Jun;114:43–52.
34. Comba L, Gay P, Primicerio J, Ricauda Aimonino D. Vineyard detection from unmanned aerial systems images. Comput Electron Agric. 2015 Jun;114:78–87.
35. Nolan A, Park S, Fuentes S, Ryu D, Chung H. Automated detection and segmentation of vine rows using high resolution UAS imagery in a commercial vineyard. In 2015. p. 1406–12.
36. Poblete-Echeverría C, Olmedo GF, Ingram B, Bardeen M. Detection and Segmentation of Vine Canopy in Ultra-High Spatial Resolution RGB Imagery Obtained from Unmanned Aerial Vehicle (UAV): A Case Study in a Commercial Vineyard. Remote Sens. 2017 Mar 15;9(3):268.
37. Rabatel G, Delenne C, Deshayes M. A non-supervised approach using Gabor filters for vine-plot detection in aerial images. Comput Electron Agric. 2008 Jul;62(2):159–68.