A review on the use of drones for precision agriculture

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Abstract. In recent years, there has been a strong activity in the so-called precision agriculture, particularly the monitoring aspect, not only to improve productivity, but also to meet demand of a growing population. At a large scale, precise monitoring of cultivated fields is a quite challenging task. Therefore, this paper aims to propose a survey on techniques, applied to precision agriculture monitoring, through the use of drones equipped with multispectral, thermal and visible cameras. For each application, the main limitations are highlighted and the parameters to be considered before to perform a flight are reported.

1. Introduction

Farming is facing many economic challenges in terms of productivity and cost-effectiveness, and the increasing labour shortage partly due to the depopulation of rural areas, as well. Among such global challenges, it should be considered the population increase, the urbanization, an increasingly degraded environment, an increasing trend toward consumption of animal proteins changing in food preferences through aging population and migration, and, of course, the climate change [1, 2]. Furthermore, reliable detection, accurate identification and proper quantification of pathogens and other factors affecting both plant and animal health, are critical to be kept under control in order to reduce economic expenditures, trade disruptions and even human health risks. Thus, a more advanced agriculture needs to be set, characterized by the adoption of *ad hoc* production processes, technologies and tools derived from scientific advances, research and development activities.

Precision farming and measurements have already established paradigms in order to increase farm productivity and quality, as well as improving working conditions through reduction of manual labour. All these factors play an important role in making farming sustainable. Also, many modern farmers already use high-tech solutions, e.g., digitally-controlled farm plants and also unmanned aerial vehicles (UAVs) for monitoring and forecasting. Drones are available at affordable prices and are capable of imaging ground data with corresponding geographic locations. That helps the user to have a complete and clearer picture of the ground information. For instance, multispectral and RGB cameras equipped drones offer the advantage of imaging the near infrared portion of the electromagnetic spectrum over the crops, thus providing the crops health conditions [3].

Figure 1. Pre-programmed navigation trajectory for the soil assessment in the APM Planner open-source software.

Drone images and ground sensor data are so expected to play a crucial role in precision agriculture, providing wide room for scientific research and development [4]. Furthermore, several metrological aspects have to be considered for developing such platforms, from the sensors embedded on them up to the instrumentation and the calibration procedures for their testing [5].

Despite their effectiveness and usefulness, the main drawback lies on the fact that these systems are calibrated only for a specific task (e.g., classifying different kinds of vegetation, water bodies, urban, bare soil, etc.), without the ability of creating a holistic view of agricultural processes. This lack of interoperability causes additional work for the human operators, since they have to manually feed the output data from one system to another. For all such reasons, software modules, drones and other equipment are object of research in order to develop a common information middleware and application interface. The aim is to reduce monotonous and time consuming work [6].

In this paper, a review of the drone technology applied to the precision agriculture is presented. In particular, the drone architecture according to the sensors embedded on the payload for precision agriculture applications is reported. Then, the design of a drone in terms of measurements capabilities, power consumption and time of flight according to the application requirements is delineated. Emphasis is also placed in the control part of the drone, understanding its dynamic behavior and how to control it. In such a way, changes in the decision-making system and the mission planner can be made in a simpler way, facilitating the development of different control strategies compared to those already available and validating the effects of modifying the control architecture for complex missions. Finally, the main procedures needed for the calibration of the sensors embedded on drones are reported and an overview of the post-processing tools for extrapolating significant parameters of the monitored area are described.

The rest of the paper is organized as follows. An overview of the drone architectures and the payload sensors for precision agriculture together with its flight control system are reported in Sec. 2 and 3, respectively. Section 4 describes the use of drones for precise agriculture and, for each application, a review of the needed calibration procedures is carried out. Moreover, the main post-processing tools are described. Finally, Section 5 concludes the paper.

2. The architecture of a drone for precision agriculture

As reported in [7], the basic architecture of a drone, without considering the payload sensors, consists of: (i) frame, (ii) brush-less motors, (iii) Electronic Speed Control (ESC) modules, (iv) a control board, (v) an Inertial Navigation System (INS), and (vi) transmitter and receiver

Figure 2. Architectural overview of the Parrot Bluegrass.

modules.

In precision agriculture, as well as in disaster relief, building inspection or traffic monitoring, the employed drones are semi-autonomous. In that case, the drone has to fly according to the definition of a flight path in terms of waypoints and flight altitude. Thus, the drone has to embed on board a positioning measurement system (e.g., Global Navigation Satellite System, GNSS) for knowing its position with respect to the waypoints. Furthermore, it embeds an altimeter (e.g., barometer, laser altimeter, ultrasonic sensor) for flying at constant flight altitudes. An example of software for defining the mission trajectory is the APM Planner [8]. In Fig. 1, the user interface of this tool is depicted.

The payload of a drone includes all the sensors and actuators that are not used for the control of its flight (e.g., the gimbal with the RGB camera). In case of precision agriculture, the sensors embedded on drones are: multispectral camera, thermal camera, RGB camera and Light Detection and Ranging (LiDAR) systems.

Multispectral cameras are used for quantifying the state of the monitored vegetation in terms of: (i) chlorophyll content, (ii) leaf water content, (iii) ground cover and Leaf Area Index (LAI), and (iv) the Normalized Difference Vegetation Index (NDVI). Thermal cameras have demonstrated high potential for the detection of water stress in crops due to the increased temperature of the stressed vegetation.

For example, in [9], the authors propose a drone for vegetation monitoring using thermal and multispectral cameras. The thermal camera is the thermovision A40M, with 320×240 pixels and having a spectral response in the range of $7.5\,\mu m$ to $13\,\mu m$. Furthermore, each pixel has a resolution of 16 bits and a dynamic range of $233\,K$ to $393\,K$. The multispectral sensor is the six-band multispectral camera MCA-6 Tetracam. The camera consists of six independent image sensors and optics with user configurable filters, having center wavelengths at 490, 550, 670, 700, 750, and 800 nm, respectively.

RGB cameras and LiDAR systems are usually adopted to digitize the terrain surface to provide the Digital Terrain Model (DTM) or the Digital Surface Model (DSM) of the monitored area. The DSM represents the earth's surface and includes all the objects on it. On the other hand, the DTM represents the ground level of the soil without considering the vegetation height. For example in [10], the authors use the Swinglet CAM drone with embedded the compact camera Canon IXUS 220 HS for estimating the characteristics of a vineyard. They have performed a flight by acquiring the images related to a vineyard in several waypoints. By using the commercial tool Pix4Dmapper [11], the DSM and DTM are extrapolated. In particular, the differential model of the vine rows is obtained by subtracting the DTM from the DSM.

According to the previous examples, in order to use a drone for precision agriculture, at least the following capabilities are needed: (i) the drone has to fly according to waypoints definition,

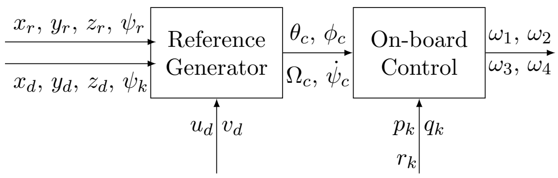

Figure 3. The control scheme. Subscript c indicates the commands, r indicates the references, d indicates the drone variables and k indicates the sensors and data fusion outputs.

(ii) the drone has to control its flight altitude, (iii) the drone has to sense and avoid obstacles during the flight, (iv) the drone has to land according to the state of the battery, automatically and (v) the acquired images have to be stabilized with a gimbal.

An example of drone that can be used for precision agriculture and fulfills the above mentioned requirements is the Parrot Bluegrass (see, Fig. 2). In particular, it can be driven according to preliminary defined waypoints and flight altitude values. Furthermore, it embeds a RGB camera, the Parrot Sequoia multispectral sensor and a sensor for measuring the environmental luminosity.

3. Flight control system

As a common rule in the literature [12, 13], the flight control system of semi-autonomous drones is split into two parts: a reference generator (*outer loop*), that takes into account the position to reach, expressed in terms of waypoint (x_r, y_r and ψ_r) and flight altitude (z_r), and generates the command signals ($\dot{\psi}_c$, Ω_c, θ_c and ϕ_c); and an on-board control system (*inner loop*), that uses such commands providing as output the motors speed ω_i (i from 1 to the number of propellers). They work together in a cascade control structure, where the inner loop (on-board) needs to regulate at a rate faster than the outer loop (that usually runs on a ground control station). Figures 3 and 5 describe the overall system and the on-board control architecture, respectively. The reference generator uses the drone position (x_d, y_d and z_d) and the orientation along z-axis (ψ_k) to compute the command signals ($\dot{\psi}_c$, Ω_c, θ_c and ϕ_c), where the drone position and velocity (u_d, v_d and w_d) come from the positioning measurement system. There are many approaches to carry out the references, from basic heuristic techniques to more advanced model based methods that exploit an accurate dynamical model of the plant. However also classical (and simple) Proportional Integral Derivative (PID) controllers might benefit from a detailed model. In any case, the dynamical model of the aircraft can be easily derived by introducing the so-called inertial (O_{FI}) and body (O_{ABC}) reference systems, as depicted in Fig. 4. Further details can be found in [12, 13].

The aim of the reference generator is to reach the position coordinates (x_r, y_r, z_r and ψ_r) by tuning the desired attitude (θ_c and ϕ_c), the heading velocity ($\dot{\psi}_c$) and the thrust (Ω_c) of the drone, later used as references for the on-board control system. Usually, it is not much complicated to design or modify the available control architecture. For example, in the case of the Parrot Bluegrass, the Software Development Kit (SDK) can be employed to implement a suitable position controller improving the performance of the existing one in the mission planner. Also, the on-board control is decomposed into two parts: the attitude and the rate controller, both illustrated in Fig. 5. The scheme integrates the state estimator that, starting from the accelerometer and gyroscope data, allows to estimate the attitude (ψ_k, θ_k and ϕ_k) and the angular velocities (p_k, q_k and r_k) of the drone, used by the on-board control loop. Usually, such control architecture is "closed", especially when using commercial applications. Therefore, it is not possible to make changes to either the control gains or the control loop (state estimator included). Thus, those drawbacks and limitations have to be considered when going to design a flight control system in a precision agriculture scenario. Disturbances rejection in adverse

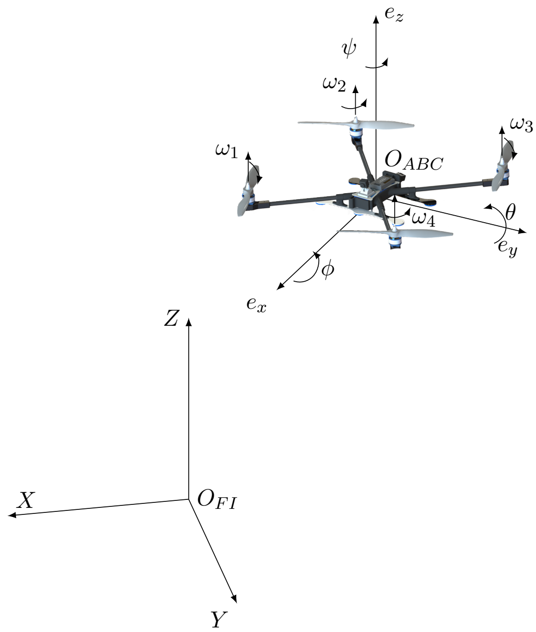

Figure 4. Drone in the body-frame (O_{ABC}) and the fixed-frame (O_{FI}) reference system. The forces, the spin direction and the propellers velocity, ω_i, from each rotor are also reported.

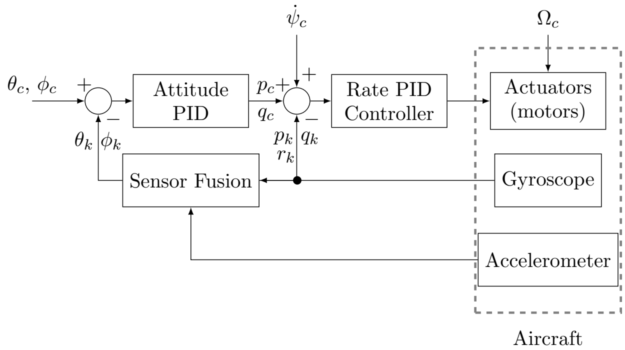

Figure 5. On-board control architecture of a semi-autonomous drone. Usually, the attitude controller runs at 250 Hz while the rate controller runs at 500 Hz.

weather conditions and robustness against model uncertainties are a key feature. Indeed, the aircraft has to be able to control its position under the influence of wind gusts. This is especially true when flying close to obstacles (e.g., threes or vineyards), since position errors due to a wind gust might cause a collision damaging the crops. Current position control methods, such as PID, do not perform well under the influence of gusts. Indeed, PID gust rejection properties scale with magnitudes of the gains, which is often limited by the positioning measurement system update frequency in outdoor scenarios. Moreover, the integrator term is generally slow in compensating persistent wind disturbances. Nowadays, there is much activity of the scientific research in this specific field [14, 15].

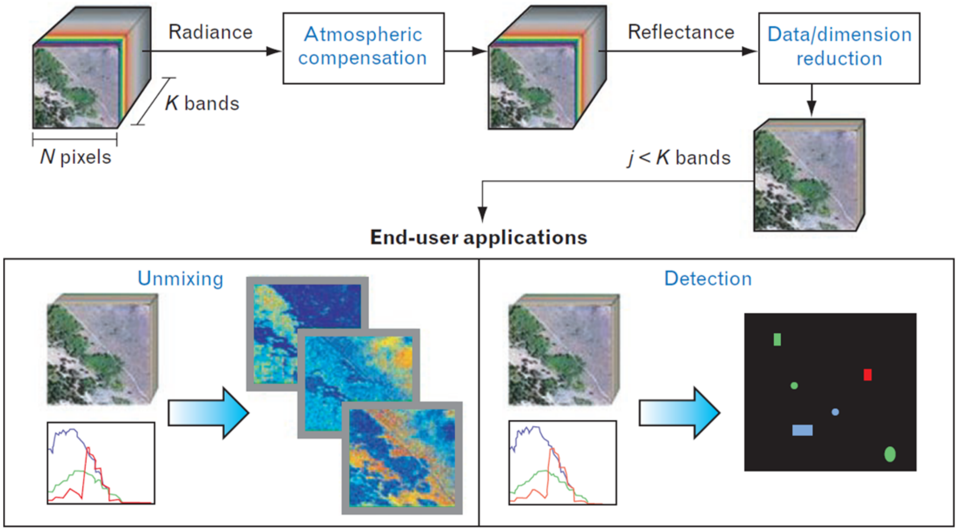

Figure 6. The post processing procedure for extrapolating information related to the state of the vegetation from the acquired multispectral images.

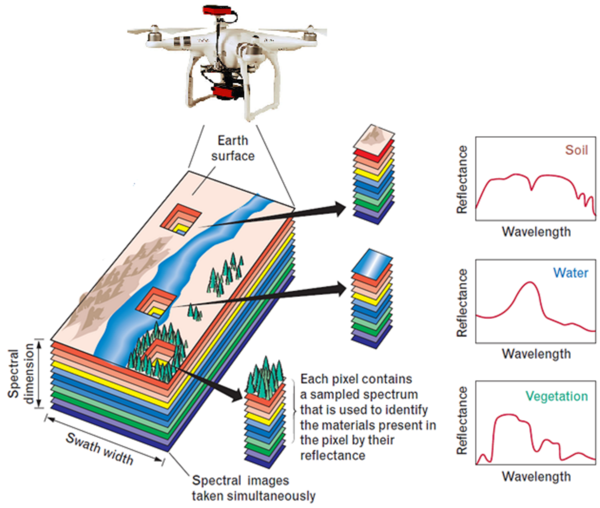

Figure 7. The monitoring operations of a crop by means of multispectral camera embedded on drone.

4. The use of drone for precision agriculture

Intensive agriculture has several negative impacts on the environment. It adds significant and environmentally detrimental amounts of nitrogen and phosphorus to terrestrial ecosystems [16]. Also, excessive fertilizers application can cause pollution risks for the environment, whereas insufficient fertilizer used to replace nitrogen and phosphorus lost through intensive cropping can lead to soil degradation and loss of fertility. Additionally, pollution of water courses and bodies, and consequent degradation of water-related ecosystems are rising due to agricultural chemicals seeping into nearby water. Furthermore, serious soil degradation, which threatens the productivity of the different soils, can be observed all over Europe [17].

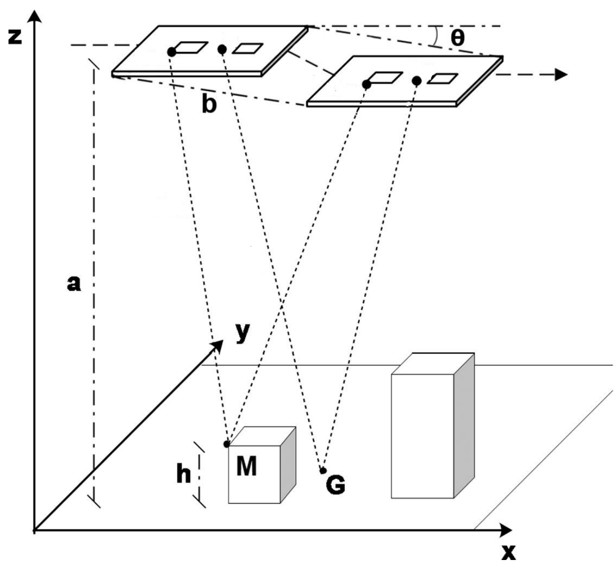

Figure 8. The 3D reconstruction process by considering two images acquired by drone in two waypoints [22].

In addition to the environmental impact, the health risk aspect of the use of chemicals in agriculture needs to be considered. Indeed, chemicals may threat farm workers, as well as families and possibly the inhabitants of the areas surrounding crops, vineyards and farming sites. Additionally, pesticides are absorbed by crop and natural resources (i.e., water and soil) and end up as concealed substances in the food chain, with the increasing risk for both livestock and humans, with huge negative impacts on the public health. Through autonomous precision farming, these effects can be mitigated since chemicals, such as fertilizer and pesticides, are only administered where needed instead of being applied over a large area.

In such a context, the use of drones in agriculture has recently been introduced for big areas inspection and smart targeted irrigation and fertilization [18, 19]. The possibility of detecting, by a drone and an infrared camera, the areas where a major irrigation is needed or where a foliage disease is spreading, can help agronomists to save time, water resources and reduce agrochemical products. At the same time, such advanced farming techniques may lead to increased crop productivity and quality.

Specifically, water deficiency, nutrient stress or diseases can be localized and measured and decision can be made to fix the problem. Many vegetation indexes have been developed which involve various data features, such as the NDVI. Special camera systems are able to acquire data from an invisible part of the electromagnetic spectrum called Near-Infraed (NIR) and extract quality information, such as the presence of algae in the rivers or oil spills near costs [20].

Current agriculture drones applications [21] are: (i) biomasses, crop growth and food quality monitoring, (ii) precision farming, such as to determine the degree of weeds for site-specific herbicide applications, (iii) harvesting and logistic optimization. All these applications require the processing of the images acquired from a camera embedded on the drone.

According to the sensors embedded on drones, it is possible to define three types of applications for precision agriculture: (i) applications based on multispectral and thermal cameras, and (ii) applications based on RGB cameras.

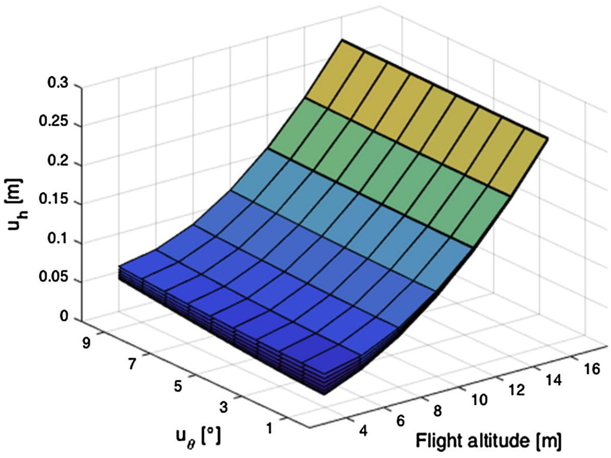

Figure 9. Height uncertainty value u_h vs flight altitude and pitch angle uncertainty value u_θ, for different uncertainty values related to the measurement of the distance between the two waypoints [22].

4.1. Applications based on multispectral and thermal cameras

Usually, for agriculture the terrain is scanned by using satellites with multispectral and thermal cameras. For precision agriculture, due to the needed high spatial resolution, drones are more suitable platforms than satellites for scanning. They offer much greater flexibility in mission planning than satellites.

The drone multispectral and thermal sensors simultaneously sample spectral wavebands over a large area in a ground-based scene (see, Fig. 7). After post-processing, each pixel in the resulting image contains a sampled spectral measurement of the reflectance, which can be interpreted to identify the material present in the scene. In precision agriculture, from the reflectance measurements, it is possible to quantify the chlorophyll absorption, pesticides absorption, water deficiency, nutrient stress or diseases.

There are four sampling operations involved in the collection of spectral image data: spatial, spectral, radiometric, and temporal. The spatial sampling corresponds to the Ground Sample Distance (GSD). The GSD is the distance in meters between two consecutive pixel centers measured on the ground. It depends on the sensor aperture and the flight altitude. The spectral sampling is performed by decomposing the radiance received in each spatial pixel into a finite number of wavebands. The radiometric resolution corresponds to the resolution of the Analog to Digital Converter (ADC) used for sampling the radiance measured in each spectral channel. Furthermore, the temporal sampling refers to the process of collecting multiple spectral images of the same scene in different instants.

Those four sampling operations have to be taken into account for the design of a flight mission and for choosing correctly the multispectral camera and the drone platform. The post-processing procedure required for extrapolating information from the acquired multispectral and thermal images is depicted in Fig. 6. In particular, the images acquired by drone provides measurements related to the radiance in each pixel. In order to measure the reflectance, image processing algorithm are applied to compensate the effects due to the atmosphere absorption and the spectrum of the solar illumination. From the reflectance values, it is possible to detect several materials and the state of the vegetation according to known spectral responses.

4.2. Applications based on RGB cameras

In precision agriculture, the images acquired by drones embedding RGB cameras are used for extrapolating DTM and DSM related to the surveyed area. To this aim, it is important to define the flight mission parameters according to the spatial resolution, and the measurement accuracy of the reconstructed DTM and DSM. As in case of multispectral and thermal cameras, the spatial resolution is defined in terms of GSD. According to the GSD that would be reached, the camera resolution and the flight altitude are chosen. The height measurements of the terrain and of the objects in the scene are obtained by taking two consecutive images from the camera in two different waypoints [22]. The two images have to overlap the same objects in scene (see, Fig. 8). Usually, an overlapping factor of the 70 % between the two images is adopted. From the two acquired images, by knowing the camera parameters, the position and the altitude of the waypoints, it is possible to extrapolate the heights of the objects in the scene.

In [22], the authors propose an uncertainty model for quantifying the accuracy related to the 3D reconstruction of a terrain or a surface by means of aerial photogrammetry. As reported in Fig. 9, they have modeled the uncertainty related to the height measurements for several flight altitudes according to the uncertainty on the measurements of the distance between two waypoints and the orientation of the second waypoint respect to the first one.

From that figure, it is possible to observe that the uncertainty on the height measurements at a flight altitude of 16 m is in the order of 30 cm. Furthermore, they have evaluated the uncertainty related to the commercial tool, Pix4Dmapper [11], adopted to provide DTM and DSM. In that case, at the flight altitude of 11 m, the measurement uncertainty is 30 cm.

From those analyses, it is highlighted that the accuracy related to a 3D reconstruction mainly depends on the accuracy of the drone position measurement system. Thus, according to the target accuracy, several techniques for localizing the drone during the flight can be adopted: (i) differential GPS systems, having a position accuracy in the order of 1 m, (ii) real-time kinematic (RTK) GPS, having an accuracy in the order of 2 cm, and (iii) simultaneous localization and mapping (SLAM) based techniques achieving a position accuracy in the order of 10 cm.

5. Conclusions

In this paper, a review on the use of drones for precision agriculture has been presented. In particular, the general architecture of a drone for multispectral/thermal sensing and DTM/DSM has been discussed. Some technical details about the control system architecture have been also provided. Furthermore, for both the applications, the main limitations and the parameters to take into account before performing a flight are described.

Future trends in this research field go toward the use of cheap commercial mini or micro drones. However, in doing so, the measurement accuracy specifications are challenging to be addressed and several problems arise. For example, for that drones the wind influence, the low GPS accuracy and the strong drift of the INS play destructing effects in flight stability and image acquisition [23].

6. Acknowledgements

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References

[1] Gnip P, Charvat K and Krocan M 2008 Analysis of external drivers for agriculture *World conference on agricultural information and IT, LAAID AFITA WCCA* 797–801

[2] Carpenter S R, Caraco N F, Correll D L, Howarth R W, Sharpley A N and Smith V H 1998 Nonpoint pollution of surface waters with phosphorus and nitrogen *Ecological Applications* **8** 559–568

[3] Reinecke M and Prinsloo T 2017 The influence of drone monitoring on crop health and harvest size *2017 1st International Conference on Next Generation Computing Applications* pp 5–10

[4] Murugan D, Garg A, Ahmed T and Singh D 2016 Fusion of drone and satellite data for precision agriculture monitoring *2016 11th International Conference on Industrial and Information Systems* pp 910–914

[5] Daponte P and Debei S 2018 Special issue on selected methods and instrumentation of metrology for aerospace *IEEE Aerospace and Electronic Systems magazine* **33**

[6] Fontanella R, Vetrella A R, Fasano G, Accardo D, Moriello R S L, Angrisani L and Girard R 2017 A standardized approach to derive system specifications for drones operating in the future UTM scenario *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems* pp 250–255

[7] Brzozowski B, Daponte P, De Vito L, Lamonaca F, Picariello F, Pompetti M, Tudosa I and Wojtowicz K 2018 A remote-controlled platform for UAS testing *IEEE Aerospace and Electronic Systems Magazine* **33** 48–56

[8] APM planner official web site `http://ardupilot.org/planner/` accessed: Sept. 2018

[9] Berni J A J, Zarco-Tejada P J, Suarez L and Fereres E 2009 Thermal and narrowband multispectral remote sensing for vegetation monitoring from an Unmanned Aerial Vehicle *IEEE Transaction On Geoscience and Remote Sensing* **47** 722–738

[10] Burgos S, Mota M, Noll D and Cannelle B 2015 Use of very high-resolution airborne images to analyse 3D canopy architecture of a vineyard *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* pp 399–403

[11] Pix4Dmapper official web site `https://pix4d.com/` accessed: Sept. 2018

[12] Bouabdallah S, Murrieri P and Siegwart R 2005 Towards autonomous indoor micro VTOL *Autonomous Robots* **18** 171–183

[13] Silano G, Aucone E and Iannelli L 2018 CrazyS: A software-in-the-loop platform for the Crazyflie 2.0 nano-quadcopter *2018 26th Mediterranean Conference on Control and Automation* pp 352–357

[14] Smeur E J J, de Croon G and Chu Q 2018 Cascaded incremental nonlinear dynamic inversion for mav disturbance rejection *Control Engineering Practice* **73** 79–90

[15] Oleynikova H, Taylor Z, Siegwart R and Nieto J 2018 Safe local exploration for replanning in cluttered unknown environments for microaerial vehicles *IEEE Robotics and Automation Letters* **3** 1474–1481

[16] Vitousek P M, Mooney H A, Lubchenco J and Melillo J M 1997 Human Domination of Earth's Ecosystems *Science* **277** 494–499

[17] Salmelin J, Pölönen I, Puupponen H H, Hämäläinen H, Karjalainen A K, Väisänen A and Vuori K M 2018 Hyperspectral imaging of macroinvertebrates—a pilot study for detecting metal contamination in aquatic ecosystems *Water, Air, & Soil Pollution* **229** 308

[18] Bacco M, Ferro E and Gotta A 2014 UAVs in WSNs for agricultural applications: An analysis of the two-ray radio propagation model *2014 IEEE SENSORS* pp 130–133

[19] Gago J, Douthe C, Coopman R, Gallego P, Ribas-Carbo M, Flexas J, Escalona J and Medrano H 2015 UAVs challenge to assess water stress for sustainable agriculture *Agricultural Water Management* **153** 9–19

[20] Manfredonia I, Stallo C, Ruggieri M, Massari G and Barbante S 2015 An early-warning aerospace system for relevant water bodies monitoring *2015 IEEE Metrology for Aerospace* pp 536–540

[21] Grenzdörffer G, Engelb A and Teichertc B 2008 The photogrammetric potential of low-cost UAVs in forestry and agriculture *The International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences* vol 37 pp 1207–1214

[22] Daponte P, De Vito L, Mazzilli G, Picariello F and Rapuano S 2017 A height measurement uncertainty model for archaeological surveys by aerial photogrammetry *Measurement* **98** 192–198

[23] Daponte P, De Vito L, Mazzilli G, Picariello F, Rapuano S and Riccio M 2015 Metrology for drone and drone for metrology: Measurement systems on small civilian drones *2015 IEEE Metrology for Aerospace* pp 306–311