Current Protocols

Nano & Micro-UAVs: a new grand challenge for precision agriculture?

Journal:	*Current Protocols*
Manuscript ID	CP-19-0253
Wiley - Manuscript type:	Overview
Date Submitted by the Author:	13-Dec-2019
Complete List of Authors:	Gago, Jorge ; Universitat de les Illes Balears, Biologia Estrany, Joan; Universitat de les Illes Balears, Geography Estes, Lyndon; Clark University, Geography Fernie, Alisdair ; Max Planck Institute of Molecular Plant Physiology, Central metabolism Alorda, Bartomeu; Universitat de les Illes Balears, Physics Brotman, Yariv; Ben-Gurion University of the Negev, Life Sciences Flexas, Jaume; Universitat de les Illes Balears, Biologia Escalona, Jose; Universitat de les Illes Balears, Biologia Medrano, Hipolito; Universitat de les Illes Balears, Biologia
Keywords:	Phenotyping, Remote Sensing, UAVs, NAVs, MAVs
Abstract:	By collecting data at spatial and temporal scales that are inaccessible to satellite and field observation, UAVs (unmanned aerial vehicles) are revolutionizing a number of scientific and management disciplines. UAVs may be particularly valuable for precision agricultural applications, offering strong potential to improve the efficiency of water, nutrient, and disease management. However, some authors have suggested that the UAV industry has over-hyped the potential value of this technology for agriculture, given that it is difficult for non-specialists to operate UAVs, as well as to process and interpret the resulting data. Here, we analyze the barriers to applying UAVs for precision agriculture, which range from regulatory issues to technical requirements. We then evaluate how new developments in the nano- and micro-UAVs (NAVs and MAVs, respectively) markets may help to overcome these barriers. Among the potential breakthroughs we identify is the ability of NAV/MAV platforms to directly quantify plant traits using methods (e.g. object-oriented classification) that require less image calibration and interpretation than spectral-index based approaches. We suggest that this potential, when combined with steady improvements in sensor miniaturization, flight precision, and autonomy, as well as cloud-based image processing, will make UAVs a tool that achieves much broader adoption by agricultural managers in the near future. If this wider uptake is realized, then UAVs have real potential to improve agriculture’s resource use efficiency.

Nano & Micro-UAVs: a new grand challenge for precision agriculture?

Jorge Gago[1,2*], Joan Estrany[3], Lyndon Estes[4], Alisdair R. Fernie[2], Bartomeu Alorda[5], Yariv Brotman[6], Jaume Flexas[1], José Mariano Escalona[1], Hipólito Medrano[1]

[1]-Grup de Recerca en Biologia de les Plantes en Condicions Mediterrànies, Departament de Biologia, University of the Balearic Islands (UIB) / Instituto de investigaciones Agroambientales y de la Economía del Agua (INAGEA), ctra. Valldemossa km. 7.5, 07122, Palma, Spain.
[2]-Central Metabolism Group, Molecular Physiology Department, Max-Planck-Institut für Molekulare Pflanzenphysiologie, 14476 Golm, Germany
[3]-Mediterranean Ecogeomorphological and Hydrological Connectivity Research Team, Department of Geography, University of the Balearic Islands / Instituto de investigaciones Agroambientales y de la Economía del Agua (INAGEA), E-07122 Palma de Mallorca, Balearic Islands, Spain. (http://medhycon.uib.cat)
[4]-Graduate School of Geography, Clark University, 950 Main Street, Worcester, MA 01610 USA
[5]-Department of Physics, University of the Balearic Islands, E-07122 Palma, Mallorca, Balearic Islands, Spain.
[6]-Department of Life Sciences, Ben Gurion University of the Negev, Beer Sheva, Israel.

* Corresponding author: J. Gago, e-mail: xurxogago@gmail.com

Abstract

By collecting data at spatial and temporal scales that are inaccessible to satellite and field observation, UAVs (unmanned aerial vehicles) are revolutionizing a number of scientific and management disciplines. UAVs may be particularly valuable for precision agricultural applications, offering strong potential to improve the efficiency of water, nutrient, and disease management. However, some authors have suggested that the UAV industry has over-hyped the potential value of this technology for agriculture, given that it is difficult for non-specialists to operate UAVs, as well as to process and interpret the resulting data. Here, we analyze the barriers to applying UAVs for precision agriculture, which range from regulatory issues to technical requirements. We then evaluate how new developments in the nano- and micro-UAVs (NAVs and MAVs, respectively) markets may help to overcome these barriers. Among the potential breakthroughs we identify is the ability of NAV/MAV platforms to directly quantify plant traits using methods (e.g. object-oriented classification) that require less image calibration and interpretation than spectral-index based approaches. We suggest that this potential, when combined with steady improvements in sensor miniaturization, flight precision, and autonomy, as well as cloud-based image processing, will make UAVs a tool that achieves much broader adoption by

agricultural managers in the near future. If this wider uptake is realized, then UAVs have real potential to improve agriculture's resource use efficiency.

Keywords: Phenotyping, remote sensing, UAVs, NAVs, MAVs

The rise of Unmanned Aerial Vehicles

In the last 10 years, Unmanned Aerial Vehicles (hereafter UAVs) have revolutionized several industrial applications and scientific disciplines, and even more rapid growth in the use of UAVs is anticipated over the next decade (Zaloga et al. 2015). For plant ecophysiology and precision agriculture research, these advances have opened new possibilities by enabling more frequent, highly detailed observations to be collected over large areas, thereby allowing individual plants within entire fields to be measured several times per day at sub-centimeter resolution (Gago et al. 2015).

This capability makes UAVs particularly useful for precision agricultural management, by offering the ability to more rapidly identify management problems and target interventions, such as the detection and treatment of pests and diseases and the application of fertilizer and irrigation treatments (Sankaran et al. 2015; López-López et al. 2016). Improving water management is a particular concern for agriculture, given the large share of production that occurs in semi-arid regions, where limited water availability and frequent droughts dramatically constrain agricultural productivity. These concerns are made more urgent by climate change, which is expected to exacerbate hydrological uncertainty (IPCC, 2013). The long-heralded "Blue Revolution" promotes the idea that agriculture can dramatically increase its "crop per drop" by leveraging new water management technologies. However, improving water use efficiency has been challenging, and will likely require considerable use of UAV technologies to make significant progress (Beer et al. 2009; Gago et al. 2014).

A wide variety of UAV platforms, including multi-copter and fixed-wing types, are available that can carry a range of sensors (RGB, multi-spectral, hyperspectral, and thermal cameras), which can be analysed to provide important information on crop status and health (Lelong et al. 2008; Berni et al. 2009; Zarco-Tejada et al. 2012; Díaz-Varela et al. 2015; Gago et al. 2017). However, these potential benefits may not be fully realized due to public concerns about the threats to safety and privacy posed by UAVs (Freeman and Freeland, 2015). Another barrier to the uptake of UAVs in agricultural management is the methods and expertise that are required to derive crop-relevant information from UAV-collected data. These challenges include complex aerial image processing and calibration requirements, and the complexity of interpreting the resulting bio-physical data (Berni et al. 2009; Zarco-Tejada et al. 2012; Gago et al. 2015; Freeman and Freeland, 2015). These combined factors represent significant hurdles that serve to limit the practical use of UAVs to researchers and specialized companies rather than lay users. Freeman and Freeland (2015) suggested that the UAV industry in the USA over-hyped the agricultural uses of UAVs, most likely in an effort to overcome negative social and political perceptions and to facilitate funding support. However, these same authors envisage that within the near-future, that further developments will make it possible for there to be a genuine increase in farm-based user of UAVs.

In recent years, numerous studies have reviewed the application of UAVs to a variety of fields, including ecology and plant ecophysiology (Gago et al. 2015; Sankaran et al. 2015; Pádua et al. 2017; Garret and Anderson, 2018). In this paper, we build on these previous efforts by reviewing the emergence of UAVs in the scientific literature and their agricultural applications, focusing particularly on the most recent advances and the obstacles that have prevented the use of these technologies by farm managers and other non-specialists. We hypothesize that the use of "very small" UAVs –called NAVs (nano-UAVs) and MAVs (micro-UAVs)– could boost the rapid adoption of this technology by the broader agricultural community in the coming years. Finally, we discuss the new challenges and opportunities posed by these miniature vehicles for precision agriculture and water stress assessment.

Big problems, small solutions

Remote sensing has generally been limited to manned aircraft and satellites. However, UAVs have "changed the rules of the game" by offering new opportunities and perspectives for data collection (Anderson et al. 2013; Gago et al. 2015). UAVs are generally low cost and can be operated without significant expertise or training (Anderson and Gaston, 2013; Hassanalian and Abdelkife, 2017).

This affordability and ease of use, both of which are expected to increase in the coming years (Garret and Anderson, 2018), has led to extensive use of UAVs by the general public, and in turn prompted increased regulation and concern regarding UAV-related threats to the safety of manned airspace, public health, and privacy (Nakamura and Kajikawa, 2018). In the US and EU, for example, it is necessary to obtain a Remote Pilot Certification to operate UAS for non-hobby use and other certificates in relationship to the aircraft and the operator, a factor that might hinder their uptake in agriculture.

Beyond any regulatory constraints, the ability to make use of UAV-collected data for agricultural applications also remains challenging. First, the large volume of images that UAVs collect to cover a relatively small area must be processed to create a single model covering the area of interest, a process which entails the creation of a 3-D model based on Structure From Motion technology (Westoby et al. 2012; Fonstad et al. 2013). Larger field sizes or finer spatial resolutions require concomitant increases in computational requirements and image processing time. Altogether, the image processing can be time-consuming and typically requires the use of expensive photogrammetric commercial software. For quantitative measures of plant status over multiple dates, it is also necessary to radiometrically calibrate the collected imagery (Berni et al. 2009; Zarco-Tejada et al. 2012; Zhang and Kovacs, 2012). Furthermore, UAV-derived measurements should be validated against ground-truth data (i.e. field-collected measurements on the related plant variables; for review see Gago et al. 2015).

Recent advances in UAV technology may help to mitigate the two aforementioned barriers to broader UAV use. One of these is the development, of very small, consumer-grade UAVs, which combine highly precise, autonomous flight capabilities with high-resolution (and, in some cases, gimbal-stabilized) imaging. UAVs are classified as “very small” based on military criteria related to size, flight endurance, and capabilities (Watts et al. 2012), but generally means UAVs weighing <2 kg. Beneath this weigh threshold very small UAVs are further sub-divided into nano- (NAVs, <200 g) and micro-UAVs (MAVs, 200-2000g), following weight criteria proposed by Brooke-Holland (2012). An extensive review of current drone classification criteria is provided by Hassanalian and Abdelkife (2017). As an illustrative example some MAVs and NAVs commercial models can be seen in Figure 1.

Since the earliest studies of Herwitz et al. (2003a, b), an analysis of the number of papers reporting UAVs investigations or associated methodologies published annually since the last 15 years in agriculture and plant sciences in the Web of Science® database, research using this technology have expanded greatly both in number and scope. Search was focused into original articles and reviews within the categories "ecology", "remote sensing", "imaging science photographic technology", "environmental sciences", "agricultural engineering", "forestry", "agriculture multidisciplinary" and "plant sciences". Both searches were manually revised to ensure that papers were directly related with any application in agriculture or plant sciences. The first search integrating all types of UAVs retrieved a total of 461 papers, meanwhile about MAVs or NAVs there was just 2 papers that accomplished our criteria (Fig. 1). Interestingly, from 2009 the number of papers describing UAVs applications to plant sciences started to grow exponentially (Fig. 1), probably related with the previous general release of commercial civilian UAVs by companies as DJI® or Mikrokopter® both funded in 2006. Intriguingly, only two papers are focused on directly application of very small drones to agriculture (Roldán et al., 2015; 2016) (Fig. 2).

Beyond personal uses (such as selfies), the small sizes of these aircraft make them less threatening from a health and safety perspective, which may help to alleviate the use restrictions established by the national aviation authorities. Indeed, in February 2018, the European Aviation Safety Agency (EASA) published their recommendations for new UAS regulations, factoring in these technology developments. According to these recommendations, UAVs <250 g in weight are exempted from registration (although must still be operated within acceptable airspace and safety limits), since they are considered to pose a much lower risk to public health and manned aviation. Risks related to privacy, security, and data protection are also limited, given that permissible flight distances are within 50 m of the pilot (EASA, 2018).

Smartphones and smartdrones?

Most existing articles focused on UAVs in agriculture describe two different hardware systems in the aerial platform. One system is dedicated to flight and navigation requirements, while the other is responsible for the capture and storage of data (Lelong et al. 2008; Zarco-Tejada et al. 2012; Gago et al. 2017). Larger sensors require UAVs with higher payload capacity. Payload capacity is a function of power consumption (provided by batteries), engines, and propeller type, which can in turn require larger airframes and thus heavier weights. A number of UAV-based precision agricultural studies have used advanced sensors, such as thermal and hyper-spectral cameras, which have required additional systems for data control and management that added considerable payload weight (Sugiura et al. 2005; Berni et al. 2009; Zarco-Tejada et al. 2012; Gago et al. 2017).

However, the recent advances in sensor miniaturization (thermal sensors/cameras <3 g size 20x20x15 mm with 80x60 pixel image resolution, or multi-spectral cameras < 72 g with size 59x41x28 mm 4608x3456 px resolution and 4 bands) and considering that NAV and MAVs are intrinsically linked to "smartphones", which provide the main hardware/software interface and thereby substantially reduce logistical and systems requirements. Open programming environments (distributed as Software Development Kits by the UAVs providers) are often available, making it possible to customize the interface for more advanced uses. This in turn increases the amount of hardware and software that is compatible with mobile apps. These not only allow the configuration and establishment of the UAV, but also the design of the flight planning, image capture, and image overlapping required to obtain an accurate DTM. As a result, some of these apps even allow images acquired during flight to be uploaded directly to cloud computing facilities, where the imagery is processed into the necessary geo-referenced mosaics, as well as basic analyses (e.g. foliar area, NDVI values) and retrieved within minutes after the flight is completed.

It is worth mentioning that the spatial precision of UAV-derived imagery that relies on the UAV's GNSS (Global Navigation Satellite System) still has fairly limited accuracy, primarily due to imprecision in the altitude axis and the GNSS positioning error. Spatial accuracy can be improved by correcting selected image coordinates using known ground control points (GCPs), particularly when a differential positioning (D-GNSS) station is used to correct the GCP coordinates (Woodget et al. 2014). A recent study employed real-time kinetics (RTK) and post-processing kinetics (PPK) with a ground station in real-time to improve spatial calculations based on both UAV- and satellite data (Fazeli et al. 2016). The open source program package for GNSS positioning project (http://www.rtklib.com) makes it possible to adjust the positioning error using a GNSS station to improve the accuracy of UAV spatial data. This approach could also be adapted to GSM networks, in order to improve flight precision as well as obstacle avoidance. Indeed recently, consumer grade UAVs equipment including RTK (Real-Time Kinematics) have being released, and it is expected that greatly facilitates the generation of precise georeferenced models.

NAVs and MAVs offer potentially new approaches for UAVs to navigate their environments via communication with on-the-ground sensors. For instance, Chakrabarty and Langelaan (2009) proposed a methodology to plan flights while factoring in atmospheric data related to wind (e.g. intensity, direction, and updrafts), in order to maximize flights distances and times of small UAVs. The effectiveness of this methodology requires access to real-time updates from wind sensors on the ground as well as current atmospheric models.

Beyond improvements in spatial accuracy and flight endurance, feeding data into UAVs from other ground-based sources can important for other aspects of precision agriculture. For example, data on incoming solar radiation must be employed to radiometrically correct multi- and hyper-spectra imagery so that reliable vegetation metrics can be derived (Sankaran et al. 2015). Similarly, air temperature, humidity, and other variables collected by nearby meteorological stations can be combined with UAV-collected thermal imagery to improve energy balance calculations and thermal stress indices (Monteith and Unsworth, 1990; Jones, 1999). Additionally, one of the most promising uses of UAVs is their potential capability to extrapolate ground sensor data into spatially continuous measurements, which requires accurate calibration of UAV-based data to sensor data. Real-time communication between ground sensor data and the UAV may facilitate this capability (Sheng et al. 2010), which is one the main challenges for future development of UAV technologies.

Flying closer to the target: NAVs and MAVs open new opportunities for precision agriculture and plant ecophysiology

In the last decade, several UAV-based agricultural management applications were proposed, including methods to monitor drought and nutrient stress (Berni et al. 2009; González-Dugo et al. 2013; Zaman-Allah et al. 2015; Severtson et al. 2016; Gago et al., 2017), to treat pests and diseases (Calderón et al. 2013, 2014; García-Ruiz et al. 2013, Jansen et al. 2014), and to measure productivity (Bendig et al. 2015; Holman et al. 2016; Maresma et al. 2016). Although these methods were developed for UAV-collected data, they required precise calibration in order to provide accurate information on plant status. For example, vegetation indices derived from multi-spectral UAV imagery are sensitive to variations in solar illumination, therefore the imagery must first be converted into surface reflectance before analysis, which generally requires calibration against reflectance targets (Sankaran et al. 2015). After calibration, the values derived from the images have to be further calibrated against plant-truth measurements, which requires additional expert knowledge that is usually not possessed by the lay UAV user (Berni et al. 2009; González-Dugo et al. 2013; Gago et al. 2017).

Although calibration is usually required, there are a number of biophysical parameters that may be measured with less calibration, including certain variables related to phenology, growth, leaf area, height, and biomass traits, that in turn correlate with productivity and yields (Swain et al. 2010; Granados et al. 2013; Díaz-Varela et al. 2015; Torres-Sánchez et al. 2015; Dempewolf et al. 2017; Chen et al. 2018). By flying closer to the plant, MAVs and NAVs increase the possibilities for measuring previously unseen variables that are important for precision agriculture and phenotyping, and in doing so further minimize calibration requirements. For instance, MAVs and NAVs can fly between vineyard rows and capture sideways-looking images of the vines (Fig. 3a). The resulting images can be analyzed using object-based image classification techniques to directly measure the size and number of grape bunches (Fig. 3b), thereby providing a direct measurement of yield. Although the efficacy of this approach requires the development of automated algorithms and substantial computing resources, it would have little need for spectral calibration, facilitating cloud-processing applications to obtain an end-product ready for the user as it is already developed by several private companies generating 3D ortho-models with multi-spectral vegetation indices.

For example, crop size will be among the new trait targets that can be monitored in precision viticulture applications using this new generation of UAVs (Fig. 3c). Similarly, such "between-the-row" data and classification methods could also be used to classify leaves, and thereby estimate leaf area and growth rates for an entire orchard. Flying very close to the crops will likely revolutionize both the type and quality of information that can be retrieved from agricultural fields.

Greenhouse crop production is rapidly increasing in Europe (now covering 405,000 ha, including 105,000 ha in South-East Europe), which has been combined with high-tech farming strategies to greatly increase the yields of some crops, such as tomato, which has seen 6-fold productivity gains in just a few years (FAO, 2017). The pioneering work of Roldán et al. (2015) showed how a MAV (AR.drone 2.0 of Parrot®) could fly inside a greenhouse to collect environmental data (including air temperature, humidity, CO_2 concentration and incident light radiation) and provide a map of greenhouse micro-environmental conditions. The same authors extended and improved this capability by combining the MAV data with wireless sensor networks and ground robots (Roldán et al. 2016).

Plant phenotyping within greenhouses is also an important topic, but has not yet been widely explored beyond the use of cameras in a permanent position or expensive automated robotic systems (Fiorani and Schurr, 2013). To our knowledge, there are no studies that demonstrate the use of UAVs for this purpose. UAVs flying inside a greenhouse are exempt from conventional drone regulations because they are not flying in public airspace. As another potential application of this technology, we provide the example of a phenotyping study of 300 different accessions of *Arabidopsis thaliana* (Fig. 4) grown in the greenhouses of the Max-Planck Institute of Molecular Plant Physiology in Potsdam (Germany). We used a NAV (Microdrone Parrot®) modified to carry a high-resolution micro-camera vertically and pointing downwards (Fig. 4a), which we used to determine canopy leaf area and relative growth rates between accessions (Fig. 4b). This example illustrates how this technology can be applied as a low-cost alternative to the more expensive conventional phenotyping systems. In another example, UAVs were recently employed as high-throughput phenotyping platforms, measuring the primary and secondary metabolic responses to drought in a Mediterranean vineyard with the physiological responses at leaf, stem and whole-plant level. This information can be highly useful for crop breeding strategies beyond experiments in greenhouses and pots (Gago et al. 2017).

Concluding remarks

The rapid increase and improvement of UAV technologies enabled a greatly increase both in the spatial and temporal resolution of agricultural measurements, individual plants or entire fields; thus, offering new opportunities for ecophysiology and precision agriculture. Nevertheless, it has also been suggested that we are currently inside a "cycle of hype", and that the real capacities of UAVs have been highly exaggerated (Freeman and Freeland, 2015). To demonstrate that UAVs provide more than hype for precision agricultural applications, the UAV industry and research community must now develop user-friendly technologies and methodologies for providing useful tools in the hands of farmers. In this respect, NAVs and MAVs hold more promise than larger UAVs carrying more complex sensors, and may be easily used by farmers for a range of precision farming and resource management applications. By flying much closer to their targets, MAVs and NAVs will also provide a new dimension of crop information—field-quality data collected rapidly over entire fields and orchards, with far less need for complex calibration steps.

If this potential is achieved, the use of UAVs will grow beyond the current group of higher specialized users (researchers and drone service providers). Such wider use of UAVs may be key to ushering in the long-heralded "Blue Revolution", wherein output is increased for much lower water and nutrient use, thereby improving the environmental sustainability of agriculture.

Acknowledgments

This work was supported by the national project AGL2014-54201-C4-1R (MINECO, Government of Spain) and the european project VITISMART (652615), ERA-NET CoFound FACCE Surplus PROGRAM (Food, Security, Agriculture and Climate Change) in the Horizon 2020 research program. Also, authors want to thank Raúl Santos of the Serveis Científicotécnics of the UIB for his help with the UAVs.

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Legends

Fig. 1. UAV papers published in plant sciences from 2003 to 2018 (black line), specific papers employing NAVs and MAVs are illustrated by red columns. The search was performed using Web of Science® database using the search field "topic", being the keywords, categories and criteria described in the main text.

Fig. 2. Different types of NAVs and MAVs: from upper left to right Microdrone Parrot ® modified with a HD RGB camera, customized racing-drone with X flight board, and the Spark and Mavic Pro from DJI®.

Figure 3. (a) MAVs DJI Mavic Pro flying between the rows of a vineyard; (b) aerial view of the vines row where grape clusters are clearly visible; and (c) detail of the previous image with a resolution allowing the direct count of clusters per vine.

Figure 4. (a) NAV Microdrone Parrot® modified to carry and support an external high-resolution camera pointing downwards; (b) the NAV flying over a phenotyping experiment of Arabidopsis thaliana ecotypes inside a greenhouse at the Max-Planck Institute of Molecular Plant Physiology (Potsdam, Germany), (c) orthophotography generated from the NAV, useful to estimate total leaf area (zenithally exposed) and growth thus characterizing the phenotypes.

Fig. 1.

1354x762mm (72 x 72 DPI)

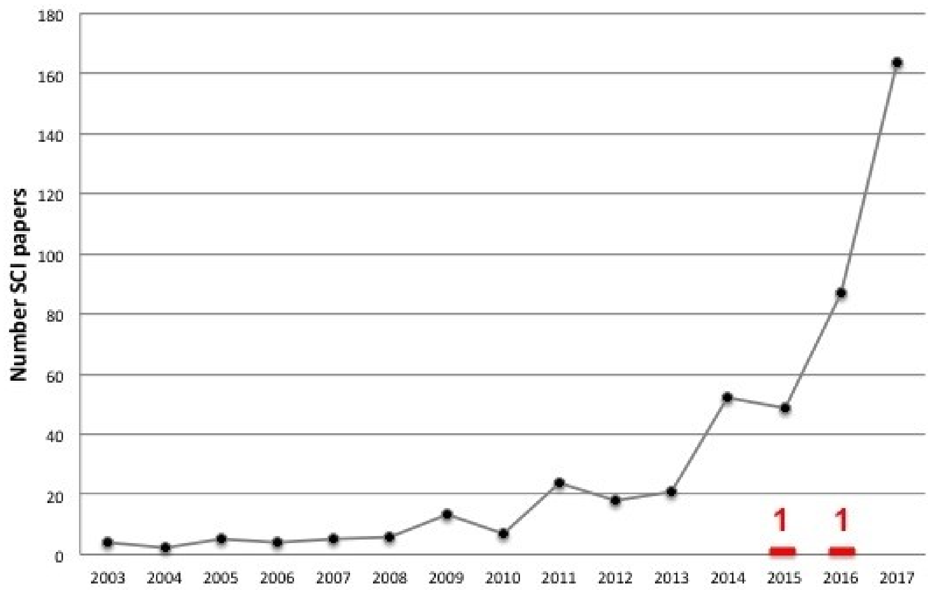

Fig. 2.

196x123mm (72 x 72 DPI)

Fig. 3.

256x340mm (72 x 72 DPI)

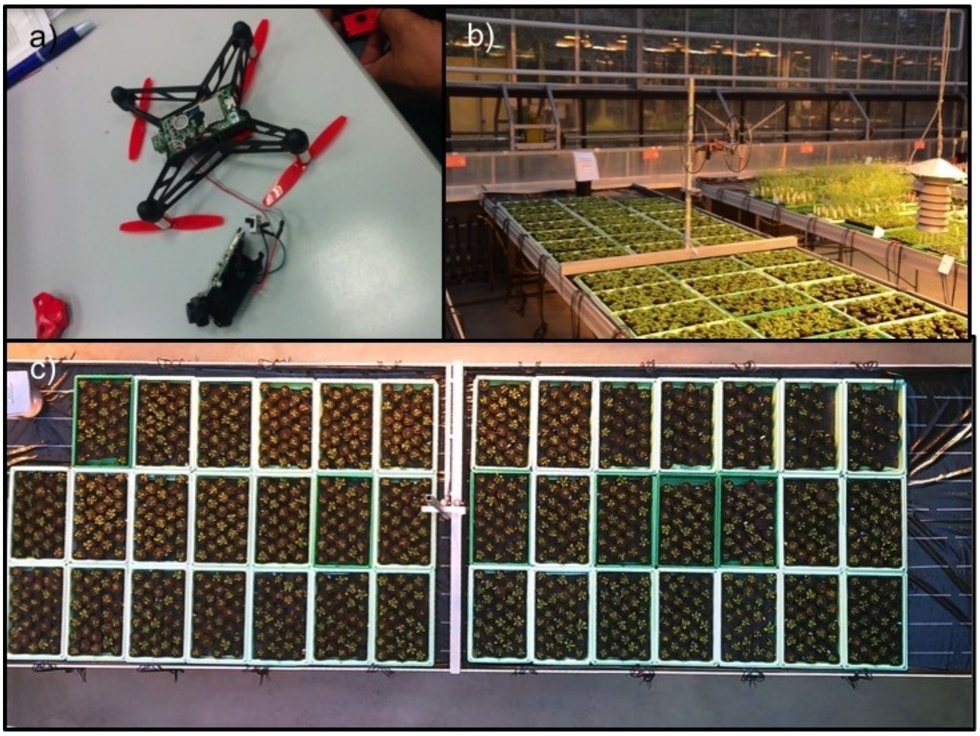

Fig. 4.

257x192mm (72 x 72 DPI)