CHAPTER
6

Drones for Good: UAS Applications in Agroecology and Organic Farming

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6.1. Introduction: Flying Robots on Agroecosystems

More than "flying robots". Drones. They are more properly defined as 'unmanned aerial systems' (UAS) and today, they embody different data acquisition tools and approaches together: geo-information and communication technologies (GeoICT), MEMs and sensors, robots, people, artificial intelligence, social intelligence, Internet of Things (IoT), Big Data. Today, small, low-cost quadcopters with 'special eyes' or mimetic bionic-birds fly almost everywhere: on river corridors, on forests, on the city, on farmlands (Pajares, 2015; Tang and Guofan, 2015; White *et al*., 2016; Baena *et al*., 2018; Merkert and James Bushell, 2020). Drones for civil and environmental applications – or Drones for Good – are becoming even more diffused, assuming a key role especially within the domain of agriculture by supporting actual challenges of increasing sustainability in cropping and agro-food production systems (Sylvester, 2018). In fact, UAS recently seduced and entered many fields of cropping systems, particularly through the framework of Agriculture 4.0, within the different declinations of precision agriculture, smart farming, and climate-resilient faming systems (Radoglou-Grammatikis, 2020; Tsouros *et al*., 2019). They are mainly deployed for monitoring crop yields, assessing nutrie nt and water stress, mapping weed distribution, and for pest management (Radoglou-Grammatikis, 2020).

The epoch of the 'flying robots' for agriculture and agro-environmental monitoring started a decade ago when drones 'slipped away' from the military

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aviation technologies fences, by entering into the domain of civil applications (Kim *et al*., 2019). Through a huge emphasis from the worlds of academy, national and international institutions, and agro-industries, drones rapidly broke into the 'collective imagery' as the flying robots which will make the difference in pursuing sustainability in agriculture. This emphasis is well synthetized by mainstream articles from *MIT Technology Review*, which enormously sponsored the forthcoming entrance of 'agricultural drones' (2014) and, later, highlighted the ways they are revolutionizing agriculture (2016). In fact, as reported by Goldman Sachs research (2021), the expansion of drones in agriculture seems to be confirmed also in terms of growth of drone industry and services; agriculture is the second one after construction sector, with a total addressable market worth USD 6,000 million. Globally, the drone market size was USD 4,400 million in 2018 and it is expected to grow to USD 63,600 million in 2025, with a compound annual growth rate of 55.9 per cent during such temporal range (*Market Insider*, 2021). It is estimated that agricultural drones will grow to about USD 32,400 million by 2050 which will represent almost 25 per cent of UAS global market (Kim and Kim, 2019). At present a wide range of UAS are available on the global market. If on one hand, different 'ready to fly' UAS are produced by big manufacturers (DJI, AGEagle, Parrot, Trimble Navigation, Precisonhawk); on the other, once UAS open hardware and open software notably increased, giving the opportunity to assemble and to build an operational drone for aerial surveys (Gayathri Devi *et al*., 2020).

This chapter will explore the world of UAS and their applications in different domains of agriculture; it is structured in the following sections:

- From the space to the near surface: UAS in agriculture
- Agricultural UAS: platforms, sensors, components
- UAS applications in sustainable agriculture and agroecology
- UAS for preserving spider monkey and agroecosystem management: experiences from tropical forests of Chocò (Ecuador)
- Opportunities and perspectives for the agroecology transition

6.2. From the Space to the Near Surface: UAS in Agriculture

In the past, GIScience was widely characterized by an increasing massive use of remote sensing technologies and platforms, mainly equipped on aircraft and satellites, to acquire spatial information about Earth surface processes through specific sensors (Goodchild, 2007). At present, a wide range of satellite-derived images are available: public aerospace programs, such as from USGS/NASA Landsat (US) and ESA Copernicus (European Union) or commercial satellites (WorldView, Planet among others). For a deeper understanding, see detailed explanations in Chapter 11.

However, due to their spatial resolutions – which usually range from 30 to 10m per pixel for public aerospace programs, or up to 0.2 m per pixel for commercial platforms – remotely-sensed data from satellite is generally scarcely suitable for application at agroecosystem or at a detailed scale (Tsouros *et al*., 2019). Moreover, satellite temporal resolution – or namely frequency of revisiting time over the same area of interest – may represent a critical constraint in terms of image acquisition. In fact, satellite platforms are not generally suitable to capture images in a required time-frame, as often needed for acquiring remotely sensed information from agroecosystem dynamics and cropping cycle (Kim *et al*., 2019; Zhang *et al*., 2021). Moreover, some environmental conditions, such as cloud cover and atmospheric factors, may drastically affect the quality of imagery, making difficult or, in some cases, impossible, to extract data and useful information (Kim *et al*., 2019).

Airborne cameras have a long track in the history of remote sensing; however, the use of aircraft for aerial surveys is at present economically onerous as it would require a strong coordination between farmers to acquire large portions of agricultural territory to make it cost-effective.

On the other hand, the lately rapid and extensive spreading of UAS is currently offering new opportunities for a deeper understanding of agroecosystem complexity and for supporting a paradigm shift in agriculture. In fact, according to specific national regulations, UAS can fly at much lower altitudes compared to aircraft/satellite, usually from few meters up to 120-600 meters above the ground (Zhang *et al*., 2021). Such flight altitude combined with the actual available technology of sensors considerably increases spatial resolution up to 0.01 m per pixel, or even higher. Some authors refer to this characteristic as the 'ultra-high' spatial resolution of UAS-derived images (Tsouros *et al*., 2019). Moreover, different UAS can be equipped with a wide range of image-acquisition devices, from optical to multi and hyper-spectral sensors (Kim and Kim, 2019).

One of the advantages of integrating UAS for spatial analysis in agriculture is related to the low latency represented by on-demand repeatability of acquisition flight, which makes ultra-high resolution aerial surveys more suitable for agroecosystem monitoring and management. In fact, drones may survey farmland every week, every day or even every hour, given the chance to perform on-demand multi-temporal time-series, able to detect changes, and to unveil new opportunities in agrosystem management (Radoglou-Grammatikis, 2020; Marino and Alvino, 2018). Therefore, direct control of temporal resolution of aerial surveys may give both to researchers and to farmers an integrated technical and operative support for studying ecosystem dynamics and for rapid interventions on the field.

6.3. Agricultural UAS: Platforms, Sensors, Components

This section describes aerial platforms and the main components of an UAS. UAS are structured in different components and elements interacting with each other. Key elements and components are five: i) one (or more) aerial platform (commonly named Unmanned Aerial Vehicles, UAV); ii) a payload constituted by one (or more) sensor for spatial data acquisition or mechanical devices; iii) an UAV remote controller combined with a ground control station; iv) a human operator; and v) a GIS-based software for image processing and output maps.

6.3.1. Aerial Platforms: Multi-rotors, Fixed-wing and Hybrids

Firstly, we refer to the term platform in relation to the underlying aerial-vehicle structure which is the physical support for mounting extra tools and peripherals, such as MEM, GPS, and sensors. At present, different typologies of aerial platforms are available and can be adopted for agricultural purposes, according to the specific aims, the operational conditions, and the context.

They include rotorcraft and fixed-wing aircraft on one side; aerostatic balloons, blimps, and kites on the other (Fig. 1). Even if, at present, the most diffused platforms for agrosystems monitoring and management are rotorcraft and fixed-wing aircraft, the adoption of the long-stand aerial photography represented by balloons or kites should not be excluded *a priori* for photogrammetry surveys, as they still represent important alternatives for particular contexts and needs (Bryson *et al.*, 2013; Lorenz and Scheidt, 2014).

In general, the main elements which characterize an aerial platform and, therefore, its operational functions and range, are the aerodynamic features represented by the wings. Indeed, there are two types of primary aerial platforms: rotary- and fixed-wing (Radoglou-Grammatikis, 2020).

Rotary-wing platforms are usually multi-rotor models which are classified according to the number of propellers. With the exception of the traditional unmanned helicopters (one propeller), multi-rotors platforms are divided in the following categories: tricopters (three propellers); quadcopters (four propellers); exacopters (six propellers); octocopters (eight propellers) (Kim and Kim, 2019; Radoglou-Grammatikis, 2020). Generally, increase in the number of propellers corresponds to largest payload capacity (up to 9.5 kg for octocopters) and size of UAS. Quadcopters and hexacopters are usually smaller and are adapted to carry a payload ranging above 1.25-2.6 kg (Hayat *et al.*, 2016; Vergouw *et al.*, 2016).

Major advantages of employing multi-rotor platforms in agriculture are the following: i) ease of use compared to fixed-wing platforms (no runaway is needed), ii) the capability of taking-off and landing vertically, and iii) the ability of hovering on a given area for detailed inspection (Chapman *et al.*, 2014; Hassler and Baysal-Gurel, 2019).

Fixed-wing platforms are similar, both in shape and in aerodynamics, to an airplane. They require a reserved space as runway or a catapult (i.e. Trimble UX5), according to their size (from 90 to 300 cm wingspan). The main advantages are related to their longer flight autonomy and faster velocity compared to multi-rotors platforms. In fact, they are capable of covering vast areas of land rapidly, and to support high temporal and spatial resolution data acquisition; in addition, some fixed-wing platforms can carry heavier payloads for extended routes (Hogan *et al*., 2017). However, they are not adapted for aerial survey in narrow spaces or for tasks which require operation of hovering or manoeuvring. They are generally preferred for application in wide field-mapping tasks for large portions of areas. With the exception of some assembled UAV (Moudrý *et al*., 2018), fixed-wing UAV are generally more expensive and in some countries they are limited due to internal regulation of keeping the aircraft in visual line of sight (VLOS) with the pilot (Torresan *et al*., 2017).

Finally, an interesting technological solution among modern platforms is represented by the hybrid-wing which integrates propellers for taking-off and landing, but also fixed-wing for large field-mapping tasks (Kim and Kim, 2019).

Aerial platforms vary in weight, size, flight autonomy, payload, and power. Aerial platforms are generally classified according to their weight, specifically named maximum take off mass (known as MTOM); hence, they are commonly divided in 'small' (≤15 kg), 'light' (≤7kg) and 'ultra-light' (≤0.250 kg) (Zhang *et al*., 2021).

A less explored opportunity for low-cost aerial surveys is today represented by aerostatic balloons, blimps, and kites (Lorenz and Scheidt, 2014). Different platforms, which do not integrate any propellers or electric engines, are at present available. Generally, they are more suitable for semi-static or punctual aerial surveys or data acquisition for small areas. They are adapted for different geographical contexts, especially for non-invasive aerial surveys in sensitive ecosystems (Bryson *et al*., 2013). Main characteristics and categories of aerial platforms are summarized in Table 1. It is worth noting that each typology of the above-mentioned aerial platforms presents the corresponding pros and cons.

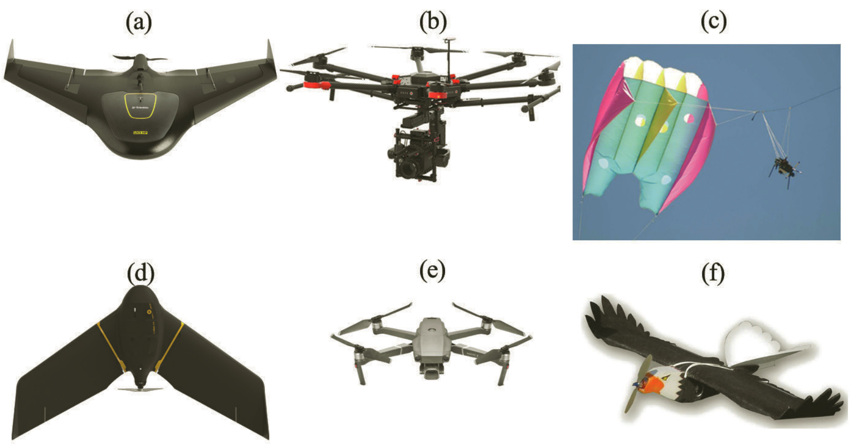


Fig. 1: Main typologies of unmanned aerial vehicles: (a) Fixed-wing UAV Trimble® UX5 (100 cm wingspan); (b) Multi-rotor hexacopter DJI® Matrice600; (c) Kite platform and camera; (d) Fixed-wing UAV EbeeSensfly® (115 cm wingspan); (e) Multi-rotor quadcopter DJI® Mavic Pro 2; (f) Bionic bird, Drone Bird®
(*Source*: Author's elaboration)

Table 1: Main Characteristics of Aerial Platforms for Agricultural Monitoring and Management (*Source*: Author's elaboration)

Aerial Platform Category	Advantages	Disadvantages
Rotary-wings (quadcopter, hexacopter, octocopter)	Ease of use Take-off/landing vertically Hovering on a specific spot Capture detailed images Suitable for narrow spaces	Low flight autonomy (15-25′) Limited payload Not suitable for extreme environments (tropical context, high temperatures)
Fixed-wings	High flight autonomy (20-40′) Data acquisition on vast areas Large payload	Runway or catapult for take-off Requirement of flight ability and control No hovering
Kite & balloon	Extremely low-cost Handmade assembly Limited legal regulations	Not suitable for large mobile mapping Limitations in stability Requirement of technical skills

6.3.2. Payload: Sensors and Peripherals

The component that gives 'special eyes' or other specific functions to UAVs is represented by the payload. Generally, it is constituted by different types of sensors for spatial data acquisition, but it could be implemented by other mechanical or electronic peripherals (grippers, discharger devices, biological and chemical sensors, weather sensors). By mounting these equipments, UAS are turning into powerful observation-and-sensing systems which may speed up a more comprehensive understanding of agroecosystem processes and functions, by interlinking ground sensors and stations based on IoT technologies (Gupta *et al*., 2015; Hayat and Yanmaz, 2016).

Kind and number of elements of payload that can be installed on a UAV depend on their size and weight; the main aspect to be considered is the UAV's payload lift capability. Therefore, every aerial platform will have a maximum payload which limits size and weight of equipment that can be adopted. Similarly, general performances of UAV, such as flight time, stability, and velocity are strongly affected by the payload. It is noteworthy that many UAV manufacturers, such as DJI or Parrots provide on-board sensors which comply with the mentioned characteristics (Kim and Kim, 2019; Easterday *et al*., 2019). UAS applications in agriculture usually require adoption of small and lightweight payload to ensure performance, both in data acquisition and flight range (Zhang *et al*., 2021).

Typically, UAV sensors can be classified in the following types:

- Visible light sensors (RGB)
- Multispectral sensors
- Hyperspectral
- Thermal sensors
- Light detection and ranging sensors (LiDAR)

6.3.2.1. Visible Light Sensors (RGB)

Undoubtedly, visible light sensors – or commonly named RGB cameras – are the most used optical devices integrated into UAVs. These cameras produce the image most typically recognized in photography, by using red, green, and blue bands (or channels) within the range of visible light for image composition. Different typology of RGB cameras are at present available for aerial surveys: from reflex to mirror-less, from bridge to compact cameras (Yonah *et al.*, 2018). They are generally capable of acquiring images from high to ultra-high spatial resolution, according to pixel count and sensor size. The main advantage of RGB cameras is the relative ease of use, both in terms of image acquisition and data processing, by using common photogrammetry software (Zheng *et al.*, 2018; Tewes and Schellberg, 2018). Moreover, aerial surveys can be performed in different skylight conditions, both with cloud cover or cloudiness; however, weather changes during the UAV survey time-frame may extremely affect the quality of mosaic composition, due to changes in light conditions and, therefore, the different image exposures (Roth and Streit, 2017).

Downsides of using only RGB cameras are mainly due to their incapability of detecting different parameters which are not included the visible range. Consequently, RGB cameras are often coupled with multispectral sensors (Gruner *et al.*, 2019; Hassler and Baysal-Gurel, 2019).

6.3.2.2. Multispectral Sensors

Multispectral sensors expand the capability to obtain information beyond the visible spectrum of human eyes. As vegetation absorbs and reflects light in a wider range of spectrum, a larger amount of information can be, therefore, derived from multispectral images. Particularly, this spectral information is essential to assess, to monitor, and to manage different components and dynamics of agroecosystems: from physiological, biological, and physical characteristics of vegetation, to biodiversity and water management (Patrick *et al.*, 2017; Iqbal *et al.*, 2018).

The most diffused use of multispectral sensors in agriculture is related to the generation of several vegetation indices by the use of combinations of specific bands, commonly located in the near infrared (NIR) region of spectrum, within 750 nm and 2,500 nm wavelength. Therefore, multispectral sensors are designed to acquire information in multiple channels of light spectrum (typically, from 4 to 12 bands) and they cover large wavelength ranges (from 50 to 100 nm wide). Undoubtedly, the most important and adopted vegetation index for analyses on vegetation is the normalized difference vegetation index (NDVI) (Zaman-Allah *et al.*, 2015; Zhang *et al.*, 2018; Hassler and Baysal-Gurel, 2019); however, many variants based on bands in the NIR region were developed to increase performances of multispectral analyses. It is worth noting that, as most of the vegetation has higher spectral response within a slight portion between Red and NIR, different sensors are implemented with a dedicated channel around 717 nm wavelength, called Red-Edge (Hassler and Baysal-Gurel, 2019).

Disadvantages of multispectral sensors are mainly linked to the complexity of data to be acquired and processed for deriving useful information. In fact, use of multispectral sensors requires corrections in different phases of the processing workflow: i) on site before the aerial survey for image acquisition (radiometric calibration); ii) during pre-processing (image enhancement and mosaicking); iii) during the calculation of vegetation indices (Zhang *et al.*, 2021).

In terms of accessibility, multispectral sensors for UAS are usually much more expensive as compared to RGB cameras. It is not rare that RGB cameras are hacked and modified by stakeholders to extend the capability to acquire information in NIR and Red-Edge as well. This improvement is technically possible by complete substitution of the original RGB optical filter with another one, turning the original camera into a multispectral sensor in NIR region. Commonly, the result from hacking the camera is a hybrid sensor which acquires invisible RGB and NIR together. Clearly, hacked sensor will no longer work in visible light acquisition mode; hence, the use of original RGB camera together with the modified NIR camera is documented in many cases (Zhang *et al.*, 2021).

6.3.2.3. Hyperspectral Sensors

Likewise multispectral cameras are capable of detecting information beyond the visible light spectrum. The main significant differences are related to the number of available bands and the bandwidths. In general, hyperspectral cameras can capture specific and independent spectral information by hundreds, or even thousands, of bands which cover narrow wavelength windows, ranging from 10 to 20 nm (Hunt and Daughtry, 2018). Detailed explanations of hyperspectral sensors and image-processing techniques are described in Chapter 4 of the present book.

The adoption of such cameras on UAS seems to be very promising in agriculture as they can be adopted for different purposes: mapping plant species and phytocenosys dynamics by detecting specific spectral signatures, measuring physiological processes of vegetation, plant phenotyping and modeling (Hunt and Daughtry, 2018; Tsouros *et al.*, 2019). Unfortunately, lightweight hyperspectral sensors which are suitable for UAS platforms are currently in full technological development and, therefore, they are still very expensive, both for public institutions and farmers; hence, they are not commonly adopted in agricultural applications.

In addition, these sensors require a huge amount of computational resources as hyperspectral imaging typically generates an enormous volume of data to be processed and managed.

6.3.2.4. Thermal Sensors

Thermal sensors are specific cameras which are able to detect the temperature of surfaces and objects. As all bodies with temperature > 0 K (–273°C - –459°F) have the physical property of emitting energy in the infrared spectrum, these sensors are capable of capturing and – after calibration processes – return an output in terms of thermal imaging (Hassel and Baisal-Gurel, 2019). They usually detect infrared energy within a wavelength range from 750 to 10^6 nm (REF). In general, thermal sensors are adopted for mapping and assessing spatial variability of evapo-transpiration rate of vegetation and water stress associated with other physical factors, such as morphology, pedology, and micrometeorology (Granum *et al*., 2015; Ribeiro-Gomes and Hernández-López, 2017).

The main constraint of thermal cameras is related to the low spatial resolution as compared to the other mentioned sensors (Ribeiro-Gomes and Hernández-López, 2017). This typology of sensors is not commonly adopted in agriculture as it is particularly expensive on one hand, and requires advanced skills and competences in data pre- and post-processing, on the other. Thermal sensors are often combined with RGB and multispectral sensors for UAS survey (Lioy *et al*., 2021).

6.3.2.5. Light Detection and Ranging Sensors (LiDAR)

Light detection and ranging (LiDAR) devices are active sensors which are able to acquire 3D information (x,y,z) by emitting a beam of light pulses which hit surfaces and objects; light is reflected back and recorded by the sensor as spatial information (Maltamo *et al*., 2014).

In general, LiDAR sensors are consolidated technologies commonly adopted as laser scanners for on-ground surveys. Since more than twenty years, airborne LiDAR is widely used for different environmental applications, such as geomorphological and topographic applications. High-resolution digital surface models (DSM) and digital terrain models (DTM) are the first-level output of using LiDAR data. By analyzing and integrating DSM and/or DTM with other information, it is possible to exploit LiDAR data in various applications (Vepakomma *et al*., 2004; Lombard *et al*., 2019).

Only recently, by the rapid advances in technology development, LiDAR sensors are integrated into UAS platforms, gaining even more attention in a wide range of applications. Due to their effective capability to accurately measure 3D structures, LiDAR technology provides different opportunities, especially in forest ecology, agriculture, soil and water management (Bagaram *et al*., 2018). Common applications in agroforestry refer to canopy height and density measurements, fractional vegetation coverage, above-ground mass estimations, and land mapping (Zhang *et al*., 2021).

The main constraint of deploying LiDAR survey is today represented by the extremely high costs of sensors which also may require an adequate UAV in terms of payload and safe aerial operations.

6.3.3. Ground Control Station and UAV Controller

To deploy an effective aerial survey, dedicated flight planning, a real-time flight control, and drone monitoring are required. The ground control station – commonly named GCS – is a computer (tablet, smartphone or laptop) by which the human operator is able to monitor, in real-time, UAV data acquisition during the flight (Kim and Kim, 2019). In addition, GCS continuously communicates to UAV controller, which is commonly the remote control device working in two-way data link for managing both flight operations and the autopilot system. With the UAV control system, different information acquired by the set of sensors integrated on to the drone allows control over important parameters, such as the flight altitude, the planimetric distance from the take-off/landing base (home point), the inside and outside temperature, the presence of obstacles, and air force (Kim and Kim, 2019). All the acquired information from UAV sensors is therefore displayed on the GCS which allows direct monitoring of the flight, both for real-time assessment of the aerial survey-data acquisition and for possibly performing recovery or safety operations.

Usually, GCS is based on dedicated proprietary software or applications provided by the UAV manufacturers or by other software houses, such as UgCS (universal ground control station), DroneDeploy; on the other hand, according to UAV hardware compatibility, different open-source software is available and is currently under development, such as mission planner ground station, MAV Pilot, APM Planner 2.0, MAVProxy, QGroundControl.

6.3.4. Human UAS Operator

The human control in UAS is crucial in all phases: from flight planning to the aerial survey. Firstly, it is necessary, and in most of countries mandatory by law, to pilot the UAV during the flight. Even if most of aerial surveys are performed automatically by the GCS by accomplishing the pre-planned flight for spatial data acquisition, a pilot is always required to assist all the aerial operations. Normally, a second operator is often required to support the pilot in all flight operations, in order to assist possible recovery manoeuvrings.

Beyond the UAV pilot, the human component is essential also in upstream and downstream phases of the aerial survey. In the preliminary phase, a geographical analysis of the area of interest by using GIS-based software is strongly recommended, in order to: (i) set up an optimized flight scenario which is able to maximize capability of data acquisition; (ii) identify possible physical limitations to flight (obstacles, accessibility, topography, infrastructures, sensitive places); (iii) examine critical factors that may affect data acquisition (water bodies, weather conditions, vegetation). In the post-flight phase, all data acquired by aerial survey must be processed, visualized, and analyzed.

6.4. UAS Applications in Sustainable Agriculture and Agroecology

Thanks to the wide range of UAS platform typologies, sensors, and possible interlinks with agro-environmental ground-based sensor networks, a broad set of applications in the domain of agriculture are at present experienced. Moreover, by considering the current speed of UAS technology development, areas of application may be further consolidated as well as other potential uses in the future will be tested and implemented (Hunt and Daughtry, 2017). However, UAS applications are mainly developed in different domains and sub-domains of farming, with particular emphasis within the Agriculture 4.0 framework: precision farming, smart farming, and sustainable agriculture (Hunter *et al.*, 2017). Unfortunately, scientific literature does not report UAS applications in the field of agroecology as such.

As an intrinsic function of most remote sensing technologies, land-cover mapping and classification are the main achievements of using UAS in agriculture. By the multi-scalar geometric resolution provided by UAS (from sub-meter to sub-centimeter resolution) which may fly at different altitudes, such information becomes crucial to understand spatial distribution, variability, and dynamic changes of land-cover features. Therefore, classification can be performed by discriminating, within large portions of surface, different land cover macro classes, i.e. forests, agricultural patches, grazing lands, bare soil and build-up areas; on the other hand, UAS ultra-resolution acquisition capability gives the opportunity to perform extremely detailed land cover/land use classification, enabling recognition of specific habitat types, phytochenosys, and individual plants (Ahmed *et al.*, 2017; Strong *et al.*, 2017; Librán-Embid *et al.*, 2020).

In addition, they might be exploited to produce high-resolution three-dimensional maps of forests or individual tree. This is made possible by photogrammetric elaborations, such as structure from motion techniques (known as SfM), by using stereoscopic images acquired by RGB cameras or LiDAR data.

In general, UAS applications help to obtain useful diagnostic information of different agroecosystem components and dynamics, derived from image acquisition and processing. It includes, among others: vegetation growth and yield, above-ground biomass, nutrients and chlorophyll contents, water stress, plant and animal diversity, plant species density, presence of pollinators, soil characteristics, soil water, and terrain morphology (Jay *et al.*, 2019; Cruzan *et al.*, 2016). Diagnostic information may be acquired in different phases of vegetation growth by different aerial surveys, making UAS a powerful tool for monitoring at multiple temporal and spatial scales. Continuous high-resolution monitoring gives to farmers the possibility to know where and when to deploy action during the growing period of vegetation (Nonni *et al.*, 2018).

One interesting approach to clarify and to summarize UAS applications which are diffused in precision agriculture is presented by Hunt and Daughtry (2017). This work proposes to divide UAS employments in three niches, according to the objectives and costs: 'scouting' for problems, monitoring to prevent yield losses, and planning agricultural management operations. Firstly, UAS can be used for 'praecox diagnosis' to rapidly detect emerging issues by real-time image acquisition and, therefore, to support decision making for interventions. Secondly, it can be employed for monitoring crop changes by advanced adoption of different sensors which require calibration, pre- and post-data processing from GIScientists or professionals. Finally, the third niche is related to the use of UAS for planning and management, which is today mainly oriented only for nutrient applications (2017).

As the most diffused applications are related to mapping, classifying, and monitoring land cover, we present common UAS employments simplified by areas of interest, which may have intersections at each other: vegetation, soil, agrosystems, and biodiversity.

6.4.1. Vegetation Monitoring

This activity represents the most diffused UAS applications to support agricultural practices. It usually combines the use of RGB cameras with multispectral sensors to identify possible critical issues on the land cover (Marcial-Pablo *et al*., 2019). The main purposes are to detect and to map, at a very detailed scale, the health status of plants by analyzing different vegetation stresses: nutrients deficits, water stress, and plant diseases (Zhang *et al*., 2021).

To perform these tasks, several vegetation indices based on multispectral bands have been adopted in remote sensing analyses, according to the specific objectives. Most common vegetation indices exploited in agriculture are the following: NDVI, difference vegetation index (DVI), enhanced vegetation index (EVI), ratio vegetation index (RVI), Red-edge vegetation stress index (RVTI), green normalized vegetation index (GNVI), chlorophyll absorption ratio index (CARI), nitrogen nutrition index (NNI), and photochemical reflectance index (PRI) (Liu *et al*., 2018; Galiano *et al*., 2012). It is worth noting that the combination of NIR with red bands is often adopted for above-ground biomass estimation, canopy structure, and calculation of the leaf area index (Gruner *et al*., 2019). A complete overview of vegetation indices, operating bands, and applications in agriculture is summarized by Padua *et al*. (2017) in Table 3.

Another emerging application is represented by exploiting the ultra-resolution of UAS images to identify individual or clustered specific plant species, commonly defined in conventional agriculture as weeds. This application has found notable interest in precision agriculture technology, by the site-specific weed management framework (Peña *et al*., 2013; Castaldi *et al*., 2017). This approach aims to control weed and to drastically reduce the use of herbicides within the crop by detecting weed in early stages and by deploying a strict site-specific herbicide distribution. To pursuit this goal, a detailed weed map is required for precise operations and actions. Spatial analysis can be performed, both by image photo-interpretation techniques and by automatic extraction for weed detection. The first choice does not require advanced skills or expertise but, according to the size of the surveyed area, it can be time-consuming; the second one is time-efficient but requires skills and competences in GIS-analyses and modeling. In the latter case, use of machine-learning techniques and computer -ision analyses are required. The most common automatic classification techniques are the following: object-based image analysis (OBIA), artificial neural network (ANN), and maximum likelihood classifier (MLL) (Tamouridou *et al*., 2017; De Castro *et al*., 2012; Bechtel *et al*., 2008). Generally, computer vision techniques are based on the use of both RGB and multispectral bands. However, RGB cameras can be used alone for automatic land-cover classification, simplifying calibration, and data processing (Ayhan and Kwan, 2020).

One promising application of automatic mapping specific plant species in organic farming and in agroecology is the use of low-cost commercial drones, equipped with a standard RGB camera. A representative case study in the framework of organic farming is reported by Mattivi *et al*. (2021). In this experimental research, a Parrot Anafi UAV was adopted to automatically extract presence of *Sorghum halepense, Chenopodium* and *Amaranthus retroflexus* in a maize-crop field. Results showed good performances of detecting weed by testing ANN, OBIA, and MLL (Figure 2). Moreover, this study also showed the feasibility of adopting a completely open-source workflow for RGB image processing (OpenDroneMap software) and automatic weed extraction by using open algorithms and packages available in SAGA and QGIS software (Mattivi *et al*., 2021).

It is noteworthy that even if weed mapping is mainly developed within precision farming, the use of such information offers to organic farming and agroecology the opportunity to scout farmers for geovisualizing components of biodiversity and for improving agrosystems management.

6.4.2. Soil Monitoring

Assessing general conditions and physico-chemical characteristics of soil system in agroecosystem is paramount. Soil texture, soil moisture contents (SMC), soil organic matter (SOM), soil water, soil temperature, electrical conductivity, and biological activity are the most important aspects that can be assessed by using UAS (Jorge *et al*., 2019; Sobayo *et al*., 2018; Krížová *et al*., 2018). To monitor soil-related characteristics, multi-spectral, hyper-spectral and thermal sensors are generally required, often combined together.

According to experimental studies of Wang (2016) and Guo *et al*. (2020), SOM, which is an important indicator of soil fertility, can be modeled and estimated by combining multi-spectral with hyper-spectral images. UAS equipped with thermal infrared sensor can be exploited to assess the spatial distribution of crop water deficit (Chisholm *et al*., 2013; Chen *et al*., 2019). In addition, thermal imaging can be also used for estimating the soil moisture, the water temperature comprehensive index, as well as the SMC, at different soil depths (Zhang *et al*., 2019;

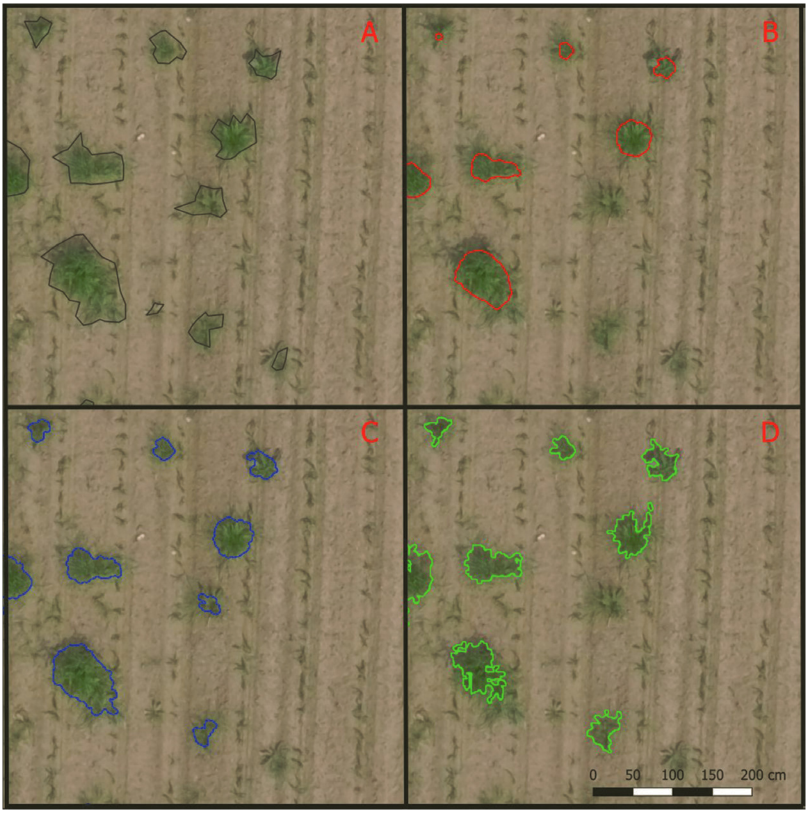


Fig. 2: Details of the weed map obtained with: (A) expert photo interpretation (reference data), (B) MLC method, (C) ANN method, and (D) OBIA method (Mattivi *et al*., 2021)

Zhang *et al*., 2021). To deploy such applications, usually adopted in the domain of precision agriculture, it is necessary to manage a set of specific hardware (UAV and sensors), dedicated software, and expertise which might represent critical elements that make scarcely accessible UAS to medium/small farms.

On the other hand, more user-friendly and affordable systems are at present adopted, especially for scouting farmers on a specific site and for supporting decision-making processes. It is the case of water stagnation in low-lying areas from intense precipitation, which is due to the lack of proper drainage or infiltration processes (Hunt *et al*., 2018). By using a small low-cost UAS equipped with RGB cameras it is possible to map in detail the flooded areas and to deploy rapid interventions.

In general, soil monitoring by the use of UAS and different kinds of sensors is mainly oriented to increase efficiency of water management and irrigation, in the framework of smart farming.

6.4.3. Agroecosystems and Biodiversity Monitoring

Only recently, some efforts and successful attempts to bring UAS technologies within an agroecological framework to manage agricultural lands and agroforest ecosystems were accomplished (Xavier *et al*., 2018; Padua *et al*., 2017; Libràn-Embid *et al*., 2020). The role of integrating biodiversity conservation with habitat management for agricultural-landscape diversification is widely documented. In fact, different strategies to improve and manage ecosystem services through agrobiodiversity, such as pollination and pest control, are at present experimented (Gurr *et al*., 2017; Landis, 2017). They substantially require a shift in geographic scales – from crop to farm and to landscape – in agroecosystem and natural-resources management. The main effort is oriented to consolidate the relationship between plant and animal diversity and to pursuit in beneficial effects on productivity of agroecosystems (Snyder and Tylianakis, 2012; Gurr *et al*., 2017; Libràn-Embid *et al*., 2020). These strategies include the use of UAS for different purposes: mapping plant diversity, detecting floral resources and animals, as well monitoring habitat changes (Padua *et al*., 2011; Libràn-Embid *et al*., 2020).

In this framework UAS is representing a promising technology to support agroecosystem and biodiversity monitoring and management. For instance, it was adopted to monitor and to assess the implementation of vegetative buffer strips, such as wildflowers, hedgerows or shrubs at (or within) the field margins, in order to increase useful biodiversity, such as beneficial organisms (Tschumi *et al*., 2017; Balzan *et al*., 2016).

One among the most common UAS applications is related to manual or automatic discrimination of flowers within agricultural landscapes in order to identify, to assess plant diversity, and to enhance biocontrol processes (Mullerova *et al*., 2017). For instance, some studies reported good accuracy in mapping and classifying *Heracleum mantegazzianum* (giant hogweed) (Michez *et al*., 2016), *Robiniapseudo acacia* (black locust) (Mullerova *et al*., 2017) and *Iris pseudacorus* (yellow flag iris) (Hill *et al*., 2017). In addition, by combining remote-sensing imaging techniques with ground agro-environmental data, emerging experimentations are showing the capability of using UAS for estimating arthropod populations and understanding agroecosystems dynamics (Carl *et al*., 2017; Xavier *et al*., 2018). Related to this, an interesting study, which adopted UAS for agrobiodiversity monitoring, was developed by Xavier *et al*. (2018) in South Georgia (USA). They used an DJI® M100 hexacopter equipped with an RGB ZenmuseX3 camera combined with ground data to monitor and predict the population-beneficial arthropod as pollinators, by mapping flower areas from high-resolution UAV imagery. Their results highlight concrete possible UAS applications for agroecosystem management by showing a positive correlation between greater areas of blooming flowers and higher numbers of pollinators (Xavier *et al*., 2018).

UAS technologies were also tested for different scopes within integrated agroforestry management (Padua *et al*., 2017). They were adopted to measure both ecological and structural properties, such as canopy gaps, floristic biodiversity, phytochemical features, and height metrics in forests, shrub, and grass ecosystem (Anderson and Gaston, 2013). Fixed-wing UAS is used to assess canopy gaps and floristic biodiversity in the forest under-storey, indicating that very-high spatial resolution is sufficient to reveal strong dependency between disturbance patterns and plant diversity (Getzin *et al*., 2012). In addition, by using SfM photogrammetry technique, UAS can be employed to assess growth, both on individual tree or groups of trees (Gatziolis *et al*., 2015). An important application is also related to forest-fires detection and monitoring by using multiple UAS equipped with infrared and RGB cameras and a central station (Merino *et al*., 2011).

As concealing food production with biodiversity conservation is one of the key elements of agroecology, some efforts at using UAS to monitor fauna in agricultural landscapes were deployed. By combining the use of RGB with thermal cameras, UAS provides a useful tool to detect and to track movement of many endothermic animals and environmental anomalies in temperatures as well (Costa *et al*., 2013). These tasks may be useful to quantify and to localize presence of animals in agricultural landscapes, reducing the unintentional kills, and increasing harvest efficiency (Libràn-Embid *et al*., 2020). Several studies reported important results in optimizing relationships between farming management and the presence of different species of fauna, such as *Circus pygargus* (Mulero-Pázmány and Negro, 2011), *Capreolus capreolus* (Cukor *et al*., 2019), *Vanellus vanellus* (Israel and Reinhard, 2017).

Only recently, other UAS applications to monitor and to assess animal biodiversity in agroecosystems are offering new opportunities for both optimizing harvests and valorising human-environment relationships. One ongoing experimental research is about detecting and assessing wasps' nests through the use of UAS thermal sensors (Lioy *et al*., 2021). As wasps' nests might play an important role as they are pest predators in many crops (Prezoto *et al*., 2019), their precise localization and assessment is essential. Other promising UAS applications are related to the localization and quantification of important vertebrate pollinators and seed dispersers, such as bats and hummingbirds. In fact, it has been demonstrated that their absence can drastically reduce fruit or seed production up to 60 per cent on an average (Ratto *et al*., 2018). Spatial distribution and behavior about vertebrate pollinators and seed dispersers may represent an important task for improving agroecosystem management and wildlife biodiversity conservation. In addition, the combined use of a multispectral sensor with thermal camera showed interesting performances in detecting birds and mammals, allowing UAS-derived counts and age of colony-nesting (Chretien *et al*., 2016; Weissensteiner *et al*., 2015). Hence, detection and tracking of certain species which have mobility in and around farmlands might make an important contribution to agroecosystem planning and biodiversity conservation (Libràn-Embid *et al*., 2020).

6.5. UAS for Preserving Spider Monkey and for Agroecosystem Management: Experiences from Tropical Forests of Chocò (Ecuador)

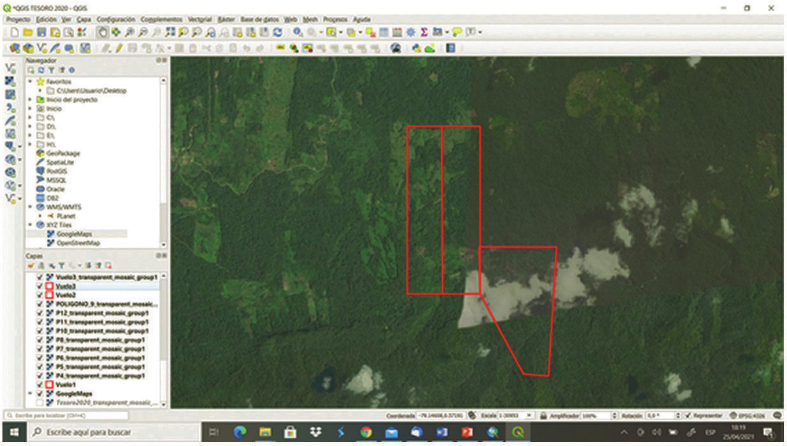
The present study is developed in the tropical forest ecosystems of Ecuador, under the Washu Project. The general framework of the project is to develop an integrated model by combining scientific investigation, environmental education, and community education to create empowered, strong, and independent communities for conservation practitioners and for their own forests.

One of the main tasks was to support management and rehabilitation of spider monkey (*Atelesfuscipes fuscipes*), which is one of 25 most threatened primates in the world, listed within the category Critically Endangered (CR) and included in Appendix II of CITES. Moreover, spider monkey is currently the most threatened primate in Ecuador, especially through illegal trafficking and habitat loss. They inhabit the northern and central region of the Ecuadorian coast, and the western foothills. They live in tropics and humid subtropics between 100 and 1700m a.s.l., both in continuous forest and forest patches – principally in primary and older secondary forests. Spider monkeys are vulnerable to ecosystem degradation as their diet is based on mature fruits; therefore, larger areas of healthy forest are required to acquire food. A group formed of 30 individuals occupies approximately 90 to 250 hectares. Their ecological role is crucial as they are, among neotropical primates, the best disperser species due to their digestive system and a mobility range of about 6 kms per day. Moreover, as umbrella species, conservation of spider monkey results in a wider protection of habitat also for other endangered animals, such as jaguars or the green macaws.

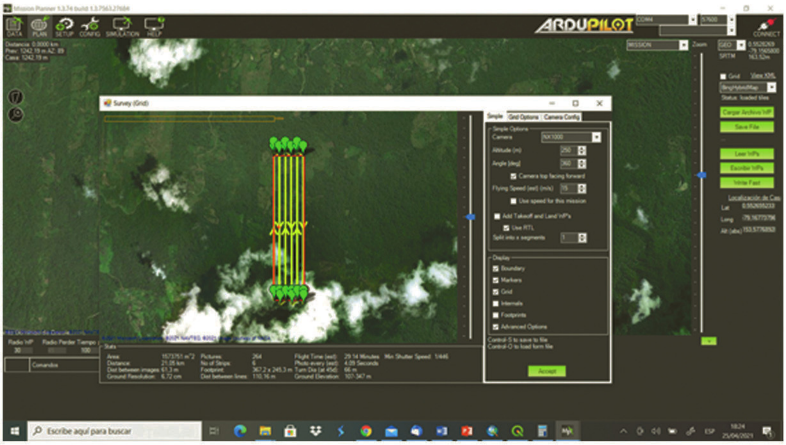
Main threats for spider monkeys are deforestation, unsustainable agricultural practices, cattle, and mining. A combination of such factors has led to the loss and fragmentation of spider monkey habitat and a severe reduction in the population size of this primate.

To support conservation programs for spider monkey and its ecosystems, a UAS-based monitoring plan was developed in 2014 by Drone & GIS enterprise (Quito). By considering context and resources, particular attention was dedicated to the hardware and software setup: a low-cost fixed-wing UAV was identified and adopted for aerial surveys (E384 by Event38); it was equipped with a low-cost RGB camera (Samsung NX1000, 16 mm lens). To perform aerial surveys as well spatial analyses, GCS Mission Planner and QGIS open-source software were used; Pix4Dmapper® was selected to perform SfM elaborations (Fig. 3).

In addition, to perform aerial surveys in a morphologically complex area, a DTM (30 m resolution) from the Shuttle Radar Topography Mission was integrated in the flight plans. By using QGIS, different areas of interests of about 500 ha each were analyzed and selected for UAV aerial surveys. Each area of 500 ha is completely covered by three UAV mission plans. For the flight plan, an altitude of 250 m a.s.l. and a speed of 15 m/s were set; to obtain reliable orthophotos



(a)



(b)

Fig. 3: Open-source software showing: (a) geographic analysis and definition of areas of interest in QGIS environment, and (b) specific parameters for UAV survey with Mission Planner

and DSM output by SfM, standard frame overlaps were configured for image acquisition during the flight (sidelap 70 per cent; overlap 75 per cent). By setting these parameters, three UAV surveys were performed obtaining about 6.7 cm of ground sampling resolution, during 30 minutes of flight. The main characteristics are summarized in Table 2.

Results from processing and analyzing UAV dataset allowed to clearly identify and to map important deforestation hotspots and important processes of ecosystem degradation within the study area (Fig. 4).

Table 2: Main Settings and Parameters for UAV Aerial Survey

	Flight 1	**Flight 2**	**Flight 3**
Ground resolution:	6.72 cm	6.72 cm	6.72 cm
Distance between images:	61.3 m	61.3 m	61.3 m
Pictures:	264	264	302
Flight time:	29:14 minutes	30:04 minutes	38:06 minutes
Photo interval (est):	4.09 sec	4.09 sec	4.09 sec

Fig. 4: High-resolution ortophoto obtained after photrammetric analysis, showing deforestation hotspots

Such results are paramount for spider monkey habitat conservation as well for agroecosystem management to be shared with local indigenous farmers. It is noteworthy that by using a fixed-wing UAV in favorable weather conditions, it was possible to perform 1,200 ha of data acquisition in one single day, at ultra-high spatial resolution imaging. On the other hand, by considering the weather conditions, such as cloud cover over tropical forests of Ecuador, usable high-resolution images (0.3 m) from commercial satellites are rare. Therefore, the use of a fixed-wing UAV capable of acquiring spatial data of a large portion of surface represents an opportunity for biodiversity and ecosystem monitoring.

6.6. Opportunities and Perspectives for the Agroecology Transition

Despite the recent and the actual proliferation of UAS for different applications in farming systems, it seems there are important further steps to globally fulfill, or to make substantial advances, in new pathways towards agroecological transition. At present, agricultural activities are drastically shaping about 37.4 per cent (56.1 M km^2) of all land surfaces on Earth (150 M km^2), making farmlands the widest human-modified ecosystem (FAO, 2016; 2017). Magnitude and extension of multi-scalar impacts of agriculture are widely documented in scientific literature: land use and land-cover changes, contamination and degradation of soil and freshwater systems, loss of genetic and functional diversity (biosphere integrity), alteration of global biogeochemical flows, and increase in anthropogenic greenhouse gases (Campbell *et al*., 2017; Kissinger *et al*., 2012; Shindell, 2016; Steffen *et al.,* 2016). To face the global challenges and to significantly increase sustainability of agriculture at different geographic scales – from ecosystem to landscape as far as the biosphere scale – dramatic changes to approach and to manage agrosystems are required. At present, a unique opportunity window for driving agriculture toward a sustainable model of farming and natural resources management is embodied by the agroecological approach (Altieri *et al*., 2017). It represents a paradigm shift of conceiving agriculture by adopting a holistic approach for food production, supporting and valorising ecological functions and processes, and bio-cultural diversity and socio-economic values of agroecosystems (Wezel, 2009; Altieri, 1989). By such a conceptual and applicative framework, agroecology is ever more marking new pathways for investigating complexity of agroecosystems worldwide, in order to increase functional diversity, to control biogeochemical fluxes into a close-loop system, and to pursue socio-economic sustainability of agricultural production as well (Altieri, 1989; Wezel *et al*., 2009).

In this framework, the systemic approach of geographical information science (GIScience) combined with the use of GeoICT and UAS offers a twofold opportunity for understanding ecological complexity and, therefore, to design and manage agroecosystems: firstly, it is able to integrate different biophysical, ecological, hydrological, anthropic, and socio-economic dynamics into spatially explicit analyses and modeling about the complex interactions of socio-environmental systems; secondly, it includes participatory methodologies which may represent powerful tools in supporting local community empowerment, public decision making processes, policy support, and planning in agroecosystem design and management (Walsh, S.J., Crews-Meyer, 2002; Goodchild, 2007; Goodchild *et al*., 2007).

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