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Review

On the Use of Unmanned Aerial Systems for Environmental Monitoring

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Abstract: Environmental monitoring plays a central role in diagnosing climate and management impacts on natural and agricultural systems, enhancing the understanding hydrological processes, optimizing the allocation and distribution of water resources, and assessing, forecasting and even preventing natural disasters. Nowadays, most monitoring and data collection systems are based upon a combination of ground-based measurements, manned airborne sensors or satellite observations. These data are utilized in describing both small and large scale processes, but have spatiotemporal constraints inherent to each respective collection system. Bridging the unique spatial and temporal divides that limit current monitoring platforms is key to improving our understanding of environmental systems. In this context, Unmanned Aerial Systems (UAS) have

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considerable potential to radically evolve environmental monitoring. UAS-mounted sensors offer an extraordinary opportunity to bridge the existing gap between field observations and traditional air- and space-borne remote sensing, by providing not just high spatial detail over relatively large areas in a cost-effective way, but as importantly providing an entirely new capacity for enhanced temporal retrieval. As well as showcasing recent advances in the field, there is also a need to identify and understand the potential limitations of UAS technology. For these platforms to reach their monitoring potential, a wide spectrum of unresolved issues and applications specific challenges require focused community attention. Indeed, to leverage the full potential of UAS-based approaches, sensing technologies, measurement protocols, post-processing techniques, retrieval algorithms and evaluations techniques need to be harmonized. The aim of this paper is to provide a comprehensive general overview of the existing research on studies and applications of UAS in environmental monitoring in order to suggest users and researchers on future research directions, applications, developments and challenges.

Keywords: UAS; remote sensing; environmental monitoring; precision agriculture; vegetation indices; soil moisture; river monitoring.

1. Introduction

Despite the recent and rapid increase in the number and range of Earth observing satellites (e.g., Drusch et al, 2012; Hand, 2015), current high spatial resolution satellite sensors are generally too coarse in temporal resolution for many quantitative remote sensing applications, and are thus of limited use in detecting and monitoring dynamics of environmental processes. Recent advances in earth observation are opening new opportunities for environmental monitoring at finer scales. For instance, CubeSat platforms represent a promising satellite technology operating predominantly in the visible to near-infrared portion of the electromagnetic spectrum, but with very high temporal resolution (e.g., McCabe et al., 2017a, 2017b). Nevertheless, most of these satellites are operated by commercial organizations, so that, if short revisit times are required (i.e. for high frequency monitoring), the cost of image acquisition can become a limiting factor. While manned airborne platforms can in principle provide both high spatial resolution and rapid revisit times, in practice their use is routinely limited by operational complexity and cost. Their use becomes feasible only over medium-size areas and it is currently adopted by several commercial operators. Recent advances in Unmanned Aerial Systems (UAS) technology present an alternative monitoring platform that provides a low-cost opportunity to capture the spatial, spectral, and temporal requirements across a range of applications (Berni et al., 2008). They offer high versatility and flexibility compared to airborne systems or satellites, and the potential to be rapidly and repeatedly deployed to acquire high spatial and temporal resolution data (Pajares, 2015).

While UAS systems cannot compete with satellite imagery in terms of spatial coverage, they provide unprecedented spatial and temporal resolutions unmatched by satellite alternatives. Furthermore, they do so at a fraction of the satellite acquisition cost. For example, a newly tasked high resolution natural colour image (50 cm/pixel) from a satellite (e.g., GeoEye-1) can cost up to 3,000 USD. On the other hand, the initial outlay to acquire a UAS with a natural colour camera can be purchased for less than 1,000 USD, delivering datasets of high spatial resolution (several cm/pixel) and a temporal resolution limited only by the number of flights (and power supply). The costs for acquiring UAS imagery are usually derived from the initial investment, the processing software and the cost of fieldwork. However, after the initial investment, datasets can be delivered more often and at a higher resolution than any other earth observing system.

Beyond allowing the high spatial and temporal resolutions needed for many applications, UAS-mounted sensors have several additional advantages, which are key across a range of applications. First, they provide rapid access to environmental data, offering the near real-time capabilities

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required in many applications. The most mature of these is the capacity to share orthomosaic and elevation data, using both commercial and open-source alternatives (Schuetz, 2016). Second, UAS satisfy also safety requirements and accessibility issues for inspection of inaccessible sites or hazard monitoring (Watts et al., 2012). Third, the great advantage of UAS is their capacity to collect data in under the cloud conditions that would otherwise obscure remote retrieval. Analysis of meteorological data has shown that, even with daily re-visits of earth observation satellites, the probability of operating a monitoring service based on optical satellite imagery in rainy regions is about 20%, while the probability of obtaining a usable image with UAS is between the 45% and 70% (Wal et al., 2013). Finally, operations with UAS are not limited to specific hours (as with sun-synchronous satellite sensor), and thus UAS can be used for round-the-clock environmental monitoring.

Mentioned capabilities, together with the increasing variety and affordability of both UAS and sensor technologies, have stimulated an explosion of interest from researchers across numerous domains (Anderson and Gaston, 2013; Whitehead and Hugenholtz, 2014; Whitehead et al., 2014; Adão et al., 2017). Among others, Singh and Frazier (2018) provided a detailed meta-analysis on published articles highlighting the diversity of processing procedures used in UAS applications clearly identifying the critical need for a harmonization among the many possible strategy to derive UAS-based products.

Dynamic nature and spatial variability of environmental processes that are often happening at very fine scales generate need for high spatial and temporal resolution data. For successful and efficient monitoring, timely data are necessary, and high flexibility makes the UAS imagery ideal for the task. Specific timing and frequent acquisition of data at very fine scales enable targeted monitoring of rapid (inter-annual) changes of environmental features, among others plant phenology and growth, extreme events, and hydrological processes. For these reasons, environmental studies were among the first civil applications of the technology in 1990's. Thanks to the significant cost reduction of both vehicles and sensors, and recent developments in data processing software, the UAS applications expanded rapidly in last decade, stimulating a number of additional and complementary topics spanning full automation of a single or multiple vehicles, tracking and flight control systems, hardware and software innovations, tracking of moving targets, and image correction and mapping performance assessment. This growing interest in UAS applications is reflected in the number of UAS-based research papers published in the last 27 years, with a special interest to those using UAS technology for environmental monitoring (based on a search of the ISI-web of knowledge using the keywords "UAS" or "UAV", and "environment"), with a particularly prominent increase during the last five years (Figure 1).

In addition to the increasing availability of UAS, recent advances in sensor technologies and analytical capabilities are rapidly expanding the number of potential UAS applications. Increasing miniaturization allows multispectral, hyperspectral and thermal imaging, as well as Synthetic Aperture Radar (SAR) and LiDAR sensing to be conducted from UAS (e.g., Anderson and Gaston, 2013). As examples of recent UAS-based environmental monitoring applications, work has focused on: a*)* land cover mapping (e.g., Bryson et al., 2010; Akar, 2017); b*)* vegetation state, phenology and health (e.g., Bueren et al., 2015; Ludovisi et al., 2017), *c)* precision farming/agriculture (e.g., Zhu et al., 2009; Urbahs, 2013; Jeunnette and Hart, 2016), d*)* monitoring crop growth, and invasive species infestation (e.g., Samseemoung et al., 2012; Alvarez-Taboada et al., 2017), *e)* atmospheric observations (e.g., Witte et al., 2017), *f)* disaster mapping (e.g., Stone et al., 2017), *g)* soil erosion (e.g., Frankenberger et al., 2008; d'Oleire-Oltmanns, 2012;), h) mapping soil surface characteristics (e.g., Quiquerez et al., 2014; Aldana-Jague et al., 2016) and i*)* change detection (e.g., Niethammer et al., 2012).

The aim of this paper is to depict the state-of-the-art in the field of UAS applications for environmental monitoring, with a particular focus on hydrological variables, such as vegetation conditions, soil properties and moisture, overland flow and streamflow. This review provides a common shared knowledge framework useful to guide and address the future activities of the international research network being promoted by the recently funded HARMONIOUS COST Action. The Action is funded by the European Cooperation in Science and Technology (COST)

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programme, that supports networking activities to improve our current knowledge and disseminate research outcomes. The aim of the HARMONIOUS COST Action is to channel all competencies, knowledge, and technologies of a wide international network involving more than 90 scientists from different parts of the world. This challenge will be achieved by sharing and further developing the experience, data, tools and technology possessed by the numerous institutions involved in this Action. Using a common strategy and a continuous interaction, the HARMONIOUS Action will enhance the actual capabilities of environmental analysis and support the definition of optimized and standardized procedures for UAS-based applications.

We divide our review into three sections that focus on different aspects of UAS-based environmental monitoring: 1) data collection and processing; 2) monitoring natural and agricultural ecosystems; 3) monitoring river systems. We finish by summarizing issues, roadblocks and challenges in advancing the application of UAS in environmental monitoring.

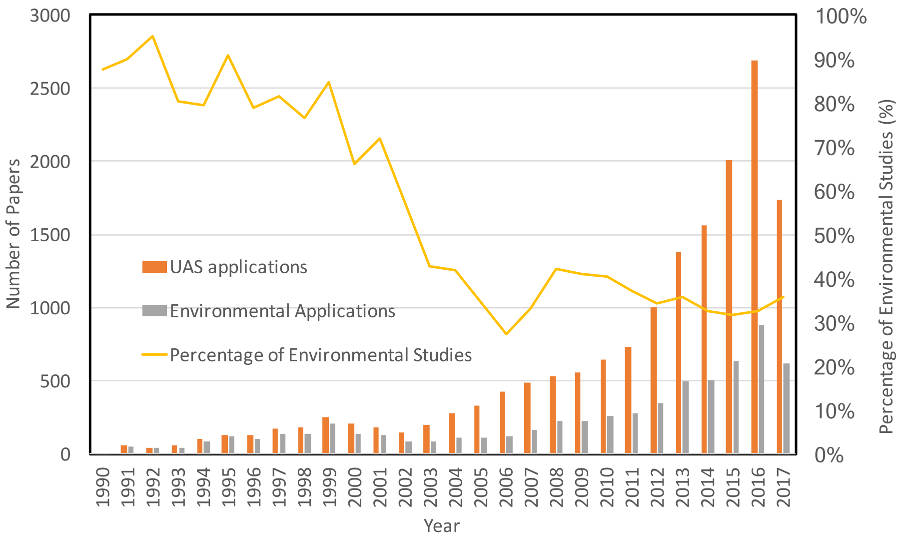

Figure 1. Number of articles extracted from the database ISI web of knowledge published from 1990 up to 2017 (last access 15/01/2018).

2. Data Collection, Processing and Limitations

While offering an unprecedented platform to advance spatiotemporal insights across the earth and environmental sciences, UAS are not without their own operational, processing and retrieval problems (Gay et al., 2009). These range from image blur due to the forward motion of the platform (Sieberth et al., 2016), resolution impacts due to variable flying height, orthorectification issues and geometric distortion associated with inadequate image overlap (Colomina and Molina, 2014), and the spectral effects induced by variable illumination during flight. These and other factors can all affect the subsequent quality of any orthorectified image and subsequently the derived products, as well described in a recent review paper by Whitehead and Hugenholtz (2014). As such, it is essential to consider best practice in the context of a) mission and flight planning; b) pre-flight camera/sensor configuration; c) in-flight data collection; d) ground control/ radiometric calibration and correction; e) geometric and atmospheric corrections; f) orthorectification and image mosaicking; and g) extracting relevant products/metrics for remote sensing application. Items a) and b) are pre-flight tasks, c) and d) are conducted in the field at the time of survey, and e) – g) are post-survey tasks. Together, these aspects can be considered as fundamentals of data acquisition and post-processing, which deliver the necessary starting point for subsequent application-specific analysis. However, despite the existence of well-established workflows in photogrammetry, manned aircraft, and satellite-based remote sensing to address such fundamental aspects, UAS systems introduce various additional complexities, which to date have not been thoroughly addressed. Consequently, best

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practice workflows for producing high quality remote sensing products from UAS are still lacking, and further studies that focus on validating UAS-collected measurements with robust processing methods are important for improving the final quality of the processed data (Rieke et al., 2011; Mesas-Carrascosa et al., 2014; Ai et al., 2015).

2.1. Pre-flight planning

Flight or mission planning is the first essential step for UAS data acquisition and has a profound impact on the data acquired and the processing workflow. Similar to other remote sensing approaches, a host of parameters must be considered before the actual flight, such as platform specifications, the extent of the study site (area-of-interest), ground sampling distance, payload characteristics, topography of the study site, goals of the study, meteorological forecasts and local flight regulations. UAS have additional aspects that require further consideration, including the skill level of the pilot, platform characteristics and actual environmental flight conditions: all of which affect the data characteristics and subsequent phases of processing.

Due to the proliferation of low-cost, off-the-shelf digital cameras, photogrammetry has been the primary implementation of UAS. James and Robson (2014) highlighted how unresolved elements of the camera model (lens distortion) can propagate as errors in UAS-derived DEMs, and how this can be addressed by incorporating oblique images. Other studies have highlighted the importance of flight line configurations (Peppa et al., 2014), as well as minimising image blur (Sieberth et al., 2016). There is a need to consolidate this evidence to develop best practice guidance for optimizing UAS SfM measurement quality, whilst maintaining ease of use and accessibility.

Accurate absolute orientation (georeferencing) is an important element for UAS surveys, and is fundamental for any multi-tempoal monitoring or comparison to other datasets. This task is often referred to as registration, and is conventionally dependent on establishing ground control points (GCPs) which are fixed by a higher order control method (usually Global Navigation Satellite System - GNSS survey). A number of studies have examined the effect of GCP networks (number and distribution) in UAS surveys, showing that significant errors are expected in SfM-based products where GCPs are not adopted (Eltner and Schneider, 2015; Peppa et al., 2016). Nevertheless, systematic DEM error can be significantly reduced by including properly defined GCPs (James et al., 2017a) or incorporating oblique images in the absence of GCP (James et al., 2014).

Best practice can also be drawn from manned aerial photogrammetry. Direct-georeferencing is standard practice in aerial photogrammetry, where the position and orientation of the platform is precisely determined using on-board survey-grade differential GNSS and inertial measurement unit (IMU) data combined through an inertial navigation system (INS) (Toth and Jóźków, 2016). This allows the camera station (exposure) position and orientation to be derived directly, thus eliminating or minimizing the need for ground control points. Therefore, as discussed by Colomina and Molina (2014), there is an increasing drive towards achieving cm-level direct-georeferencing for UAS using alternative GNSS/IMU configurations, precise point positioning (PPP) and dual frequency GNSS.

2.2 Sensors

The large availability of UAS equipped with visible (VIS) commercial camera (see Table 1) has been the main driver for several researches exploring the potential use of low cost sensors for vegetation monitoring (Geipel et al., 2014; Torres-Sanchez et al., 2014; Saberioon et al., 2014; Jannoura et al., 2015). Among the many available visible spectral indices, the Normalized Green-Red Difference Index - NGRDI, Excessive Green - ExG and VEG indices achieved the good accuracy in the vegetation mapping. Such vegetation indices may be a cost-effective tool for biomass estimation and establishing yield variation maps for site-specific agricultural decision-making.

Over the last five to eight years, near-infrared (NIR) multi and hyperspectral sensors have become more widely available for UAS. Modified off-the-shelf RGB cameras - initially very popular (e.g., Hunt et al, 2010) - have now started to be replaced by dedicated multispectral or hyperspectral cameras, as the latter have reduced in cost and weight. For instance, light weight hyperspectral sensors for UAS are now available from different vendors (e.g., SPECIM; HYSPEX; HeadWall). This progress offers more defined and discrete spectral responses than the modified RGB or multi-band camera. Multispectral cameras commonly employ multiple lenses, which introduces band-to-band offsets that should be adequately corrected in order to avoid artefacts introduced into the combined multi-band product (Laliberte et al., 2011; Jhan et al., 2017). Furthermore, radiometric calibration and atmospheric corrections are needed to convert the recorded digital numbers (DN) to surface reflectance values to enable reliable assessment of ground features, comparison of repeated measurements and reliable determination of spectral indices (Lu and He, 2017). Although DN are frequently utilized directly to derive vegetation indices (e.g., NDVI), illumination differences between (and within) surveys, and differing (and unknown) spectral responses between sensors make it difficult to utilize such data.

Radiometric calibration normally involves in-field measurement of reference natural or artificial targets with a field spectroradiometer (e.g., Brook and Ben-Dor, 2011; Zarco-Tejada et al., 2012; Lu and He, 2017) and requires significant additional effort. Some current multispectral cameras (e.g., Parrot Sequoia, MicaSense RedEdge) include a downwelling irradiance sensor and calibrated reflectance panel in order to address some of the requirements of radiometric calibration. This is beneficial, but it does not address the full complexity of radiometric calibration and artefacts will remain. Other aspects, such as bidirectional reflectance (modelled through the bidirectional reflectance distribution function (BRDF)) and image vignetting, introduce further uncertainties for image classification. While the most appropriate workflow for dealing with multispectral imagery to some extent depends on the complexity of the subsequent application (e.g., basic vegetation indices or reflectance-based image classification), the growing body of literature and recent sensor developments support the development of best practice guidelines for the environmental UAS community.

Hyperspectral sensors (Table 3) can be briefly mentioned as extensions of the discussion surrounding multispectral sensors above, and related considerations of radiometric calibration and atmospheric correction. Over the last five years, there has been increasing interest in hyperspectral imaging sensors (e.g., Lucieer et al., 2014; Honkavaara et al., 2017). While these are still more expensive than multispectral systems, they offer significant potential for quantitative soil vegetation and crop studies. UAS hyperspectral imagers typically offer contiguous narrow bands in the VIS-NIR portion of the spectrum. Existing cameras include pushbroom and more recently frame capture technology. Depending on the capture mechanism, there are typically artefacts related to non-instantaneous (time delay) capture across bands, or physical offsets between bands (Honkavaara et al., 2017). There has also been interest in (non-imaging) UAS-mounted (hyperspectral) spectrometers (e.g. Burkart et al., 2015).

In the hyperspectral domains, high radiometric accuracy and accurate reflectance retrieval are key factors to further exploit this technology (Ben-Dor et al., 2009). Accordingly, practices from the manned hyperspectral sensor can be adopted in UAS applications, such as the new super-vicarious calibration method suggested by Brook and Ben-Dor (2011, 2015). To this end, they used artificial targets to account for the radiometric accuracy and further to generate a high quality reflectance data-cube. Technology have recently introduced also light sensors in the SWIR region for UAS applications (HeadWall).

UAS broadband thermal imaging sensors (see Table 4) measure brightness temperature of the Earth's surface typically between 7.5–13.5 μm. Key considerations relate to spatial resolution and thermal sensitivity, with the latter now achieving 40-50 mK. Thermal UAS remote sensing also requires consideration of radiometric calibration and accounting for vignetting and other systematic effects, as discussed by Smigaj et al. (2017). An example of thermal image providing the surface temperature in Celsius degree obtained over a vineyard of Aglianico is given in Figure 2. Here, one can appreciate the high level of details offered by this technology in the description of a patchy vegetation cover.

LiDAR sensors (see Table 5) are also becoming more commonplace on UAS platforms, as increasingly lightweight systems become achievable (although <3 kg maximum take-off weight is

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still challenging). There is of particular interest in UAS LiDAR for forestry applications, particularly in relation to classifying and quantifying structural parameters (e.g., forest height, crown dimensions; Sankey et al., 2017).

A comprehensive review of the available cameras and sensors is given in the appendix to guide future studies and activities in this field.

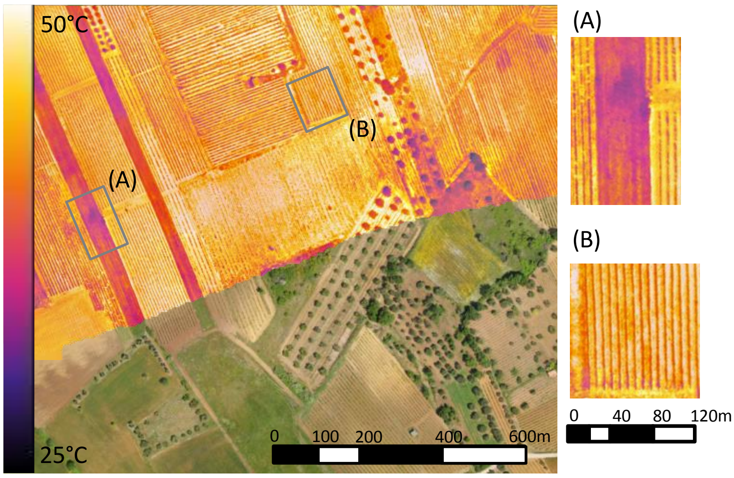

Figure 2. A thermal survey over an Aglianico vineyard in the Basilicata region (southern Italy) overlaying an RGB orthophoto obtained by a multicopter mounting both an optical and a FLIR Tau 2 camera. Insets A and B provides a magnified portion of the thermal map where is possible to distinguish pattern of vegetation and distribution of the surface temperature.

2.3. Softwares

Finally, alongside sensor technological developments, low cost and particularly open source software has been vital in enabling the growth in UAS for environmental and other applications. This includes proprietary structure-from-motion (SfM) software such as Agisoft Photoscan and Pix4D, which is significantly more affordable than most conventional photogrammetric software. In particular, photogrammetry has been the primary implementation of UAS.

UAS-based photogrammetry can produce products of a similar accuracy to those achievable through manned airborne systems (Colomina and Molina, 2014). This has been underpinned by the development of SfM software, which offers a user-friendly and low-cost alternative to conventional digital photogrammetric processing. While this has made photogrammetry more accessible to non-experts, quantification of uncertainty remains an ongoing challenge (James et al., 2017b). This is because SfM relaxes some of the conventional expectations in terms of image block geometry and data acquisition.

Cloud-based platforms such as DroneDeploy or DroneMapper offer the possibility to integrate and share aerial data, but also to derive orthomosaics with light processing workloads. Moreover, there has also been development of open source SfM software, including VisualSfM, Bundler, Apero-MicMac, OpenDroneMap, etc. Many open source GIS and image processing software (e.g. QGIS, GRASS, SAGA GIS, Orfeo Toolbox, ImageJ) support the subsequent exploitation of this data, including applications such as image classification and terrain analysis. All these offers the opportunity to develop high quality measures with low cost sensors and software that emphasized even more the potential number of applications of the available tools (Sona et al. 2014, Ouédraogo et al., 2014, Kaiser et al., 2014.)

3. Monitoring Agricultural and Natural Ecosystems

Natural and agricultural ecosystems are influenced by climatic forcing, physical characteristics and management practices that are highly variable in both time and space. Moreover, vegetation state changes may occur within short time (Manfreda and Caylor, 2013; Manfreda et al., 2017), due to

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unfavourable growing conditions or climatic extremes (e.g., heat waves, heavy storms, etc.). Therefore, in order to capture such features, monitoring systems need to provide accurate information over large areas with a high revisit frequency (Atzberger, 2013). UAS is one such technology that is enabling new horizons in vegetation monitoring. For instance, the high resolution of UAS-imagery has led to a significant increase in the overall accuracy in species-level vegetation classification, monitoring vegetation status, monitoring weed infestations, estimating biomass, predicting yields, detecting crop water stress and/senescent leaves, reviewing herbicide applications, and pesticide control.

3.1. Vegetation Monitoring and Precision Agriculture

Precision agriculture (Zhang and Kovacs, 2012) has been the most common environmental monitoring application of UAS. High spatial resolution UAS imagery enables much earlier and cost-effective detection, diagnosis, and corrective action of agricultural management problems compared to low resolution satellite imagery. Therefore, UAS may provide the required information to address farmers' needs at the field scale, enabling them to take better management decisions with minimal costs and environmental impact (Huang et al., 2013; Link et al., 2013; Zhang, 2014).

Vegetation state can be evaluated and quantified through different vegetation indices from images acquired in the visible, red edge and near-infrared spectral bands that display a strong correlation with soil coverage and Leaf and Green Area Index (LAI and GAI), Crop Nitrogen Uptake (QN), chlorophyll content, water stress detection, canopy structure, photosynthesis, yield, and/or growing conditions (e.g., soil moisture) (e.g., Shahbazi, 2014; Helman et al., 2015; Gago et al., 2015; Helman et al., 2017). These vegetation indices can be exploited to monitor biophysical parameters as an alternative to destructive *in situ* measurements.

Among the many available vegetation indices, the normalized difference vegetation index (NDVI) is one that is most widely used (Lacaze et al., 1996; Gigante et al., 2009; Helman 2018). UAS-NDVI maps can be at least comparable to those obtained from satellite visible observations, which is highly relevant for a timely assessment of crop health status with capacity to provide immediate feedback to the farmer. NDVI surveys performed with UAS, aircraft, and satellite demonstrated that low resolution images would fail in representing intra-field variability and patterns in fields characterized by small vegetation gradients and high vegetation patchiness (Matese et al., 2015). Moreover, UAS-derived NDVI showed a better agreement with ground-based NDVI observations compared to satellite-derived NDVI in several crop and natural vegetation types (Gay et al., 2009; Primicerio et al., 2012; McGwire et al., 2013; Hmimina et al., 2013). The significant difference between vegetation patterns observed by satellite and UAS can be observed in Figure 3 where a date-palm field is described. In particular, UAS-based observation can be considered comparable to field observations.

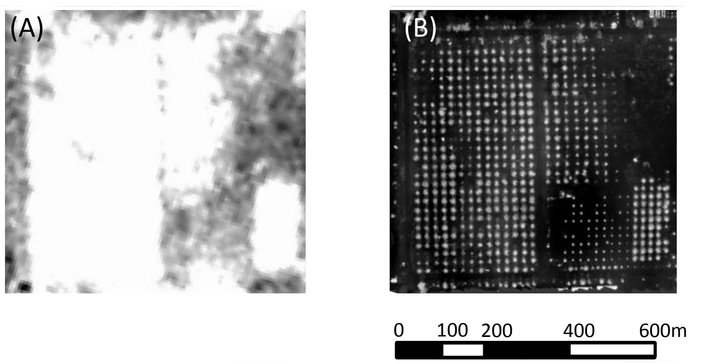

Figure 3. Comparison between a CubeSat NDVI map of a date-palm plantation at 3m of resolution (A) and a UAS-derived NDVI at 3cm of resolution (B).

In the last decade, particular attention has been given to the monitoring of vineyards with UAS because of their high economic value. Johnson et al. (2003) proposed one of the first applications

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where different sensors are used for determining measures related to: chlorophyll function and photosynthetic activity, LAI, and plant health status (among others variables) to map vigour differences within fields. More recently, Zarco-Tejada et al. (2012, 2013a, 2013b, 2013c) demonstrated the potential for monitoring specific variables such as crop water stress index, photosynthetic activity and carotenoid content in vineyards the using multispectral, hyperspectral camera and thermal camera.

Based upon the authors' experiences, farmers have expressed particular interest in monitoring crop conditions for the quantification of water demand, nitrogen status or infestation treatments. Several of the variables or indices described above may be used for rapid detection of crop pest outbreaks or to map the status of crops.

Monitoring soil water content is critical for determining efficient irrigation scheduling. Hassan-Esfahani et al. (2015) derived topsoil moisture content using RGB, NIR and thermal bands. The effective amount of water stored in the subsurface can be obtained by exploiting mathematical relationships between surface measurements and the root-zone soil moisture, such as the SMAR (Manfreda et al. 2014; Baldwin et al. 2017).

As an example, Sullivan et al. (2007) observed that the thermal infrared (TIR) emittance was highly sensitive to canopy response and can be used for monitoring soil water content, stomatal conductance, and canopy cover. TIR has similarly been used for the monitoring and estimation of soil surface characteristics such as microrelief and rill morphology (de Lima and Abrantes, 2014a), soil water repellency (Abrantes et al., 2017), soil surface macropores (de Lima et al., 2014b) and skin surface soil permeability (de Lima et al. 2014a). Another application is the use of TIR in surface hydrology for estimating overland and rill flow velocities by using thermal tracers (de Lima and Abrantes, 2014b; Abrantes et al., 2018).

More specifically, the TIR emittance displayed a negative co-relation with stomatal conductance and canopy closure, indicating increasing canopy stress as stomatal conductance and canopy closure decreased. An additional strategy is represented by the use of the crop water stress index (CWSI - Jackson et al., 1981; Cohen et al., 2017) calculated from leaf water potential that can be used to determine the required frequency, timing and duration of watering. In this regard, the CWSI, derived with a UAS equipped with a thermal camera, is frequently adopted to quantify the physiological status of plants, and more specifically leaf water potential in experimental vineyards (Zarco-Tejada et al., 2012; Baluja et al., 2012; Tejada et al. 2013b; Gago et al., 2014; Bellvert et al., 2014) and orchards (Gonzalez-Dugo et al., 2013; 2014). The derived CWSI maps can serve as important inputs for precision irrigation. Time-series of thermal images can also be used to determine the variation in water status (Santesteban et al, 2017).

Using the VIS-NIR (0.4-1.0µm) hyper spectral and multispectral analyses of simulated data have shown that soil attributes can be extracted from these spectral regions, particularly those most commonly used by the current UAS platforms (Ben-Dor and Banin, 1994, 1996; Soriano-Disla et al., 2014). These studies demonstrated that the VIS-NIR spectral region alone can open up new frontiers in soil mapping (as well as soil moisture content retrieval) using on-board multi and hyper spectral UAS sensors without using heavy-weight sensors of the SWIR (1-2.5µm) region. Aldana-Jague et al. (2016) mapped soil surface organic carbon content (<0.5 cm) at 12 cm resolution exploiting six bands between 450 and 1050 nm of low-altitude multi-spectral imaging. D'Oleire-Oltmanns et al. (2012) showed the applicability of UAS for measuring, mapping and monitoring soil erosion at 5 cm resolution with an accuracy between 0.009 and 0.027 m in the horizontal directions and 0.007 m in the vertical direction. Detailed information about soil erosion can enhance proper soil management at the plot scale (Quiquerez et al., 2014).

Such tools were further explored by Zhu et al. (2009), who investigated the ability to quantify the differences in-soil nitrogen application rates using digital images taken from an UAS in comparison with ground-based hyperspectral reflectance and chlorophyll content data. They suggested that aerial photography from UAS has the potential to provide input in support of crop decision-making processes minimizing field sampling efforts, saving both time and money, and enabling accurate assessment of different nitrogen application rates. Therefore, such information may

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serve as inputs to other agricultural systems, such as tractors or specific drones, that optimise fertilizer management.

Besides monitoring, UAS can also improve agronomical practices. Costa et al. (2012) described an architecture that can be employed to implement a control loop for agricultural applications where UAS are responsible for spraying chemicals on crops. Application of chemicals is controlled by the feedback obtained from the wireless sensor network (WSN) deployed on the crop field. They evaluated an algorithm to adjust the UAS route under changes in wind (intensity and direction) to minimize the waste of pesticides. Pena et al. (2013; 2015) explored the optimization of herbicide applications in weed-crop systems using a series of UAS multispectral images. The authors compute multiple data, which permits calculation of herbicide requirements and estimation of the overall cost of weed management operations in advance. They showed that the ability to discriminate weeds was significantly affected by the imagery spectral (type of camera) used as well as the spatial (flight altitude) and temporal (the date of the study) resolutions.

Among these technical advantages and constrains, the importance of the limitation of operational rules in using UAS in several countries needs to be highlighted. As an example, Jeunnette and Hart (2016) developed a parametric numerical model to compare aerial platform options to support agriculture in developing countries characterized by highly fragmented fields, but manned systems are still more competitive from an operational and cost/efficiency point of view because of the present limitations in altitude, distance and speed of UAS. In particular, UAS becomes cost-competitive when they are allowed to fly higher than 300m AGL. Nevertheless, all the applications described highlight the potential use of UAS in developing advanced tools for precision agriculture applications and for vegetation monitoring in general. With time, both technological advances and legislation will evolve and likely converge, further advancing the efficient use of such technologies.

3.2.Monitoring of Natural Ecosystems

As with agricultural ecosystems, the proliferation of UAS-based remote sensing techniques have opened also new opportunities for monitoring and managing natural ecosystems (Anderson and Gaston, 2013; Tang and Shao, 2015; Torresan et al., 2017; Ventura et al., 2017). In fact, drones provide options and opportunities to collect data at appropriate spatial and temporal resolutions to describe ecological processes and allow better surveying of natural ecosystems placed in remote, inaccessible or difficult and/or dangerous to access sites. As examples, some habitats (e.g., peat bogs) can be damaged through on-ground surveys, while drones positioned several meters above the surface can provide a near comparable level of information as that obtained through plot-based measurements (e.g., canopy cover by species). Drones are also useful for undertaking rapid surveys of habitats such as mangroves, where access is often difficult and plot-based surveys take far longer to complete (see Figure 4).

UAS therefore offer the potential to overcome these limitations and have been applied to monitor a disparate range of habitats and locations, including tropical forests (Paneque-Gálvez et al., 2014), riparian forests (Dunford et al., 2009; Dufour et al. 2013), dryland ecosystems (Cunliffe et al., 2016), boreal forests, and peatlands (Puliti et al., 2015). Pioneering researchers have been using UAS to monitor attributes such as plant population (e.g., Jones et al., 2006; Chabot and Bird, 2012); biodiversity and species richness (e.g., Getzin et al., 2012; Koh and Wich, 2012); plant species invasion (e.g., Michez et al., 2016; Müllerová et al., 2017a); restoration ecology (e.g., Reif and Theel, 2017); disturbances (e.g., Gonçalves et al., 2016; McKenna et al., 2017); phenology (e.g., Klosterman and Richardson, 2017; Müllerová et al., 2017b); pest infestation in forests (Lehmann et al., 2015; Minarik and Langhammer, 2016), and land cover change (e.g., Ahmed et al., 2017).

Many studies have focused on the retrieval of vegetation structural information to support forest assessment and management (e.g., Dandois and Ellis, 2013; Puliti et al., 2015). Information on the plant and canopy height can also be obtained from stereo images (Dittmann et al., 2017; Otero et al., 2018), which can be further used to estimate above ground biomass (see for example Figure 4). 3D

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maps of canopy can also be used to distinguish between trunks, branches and foliage and can be used by logging companies and farmers (Sankey et al., 2017).

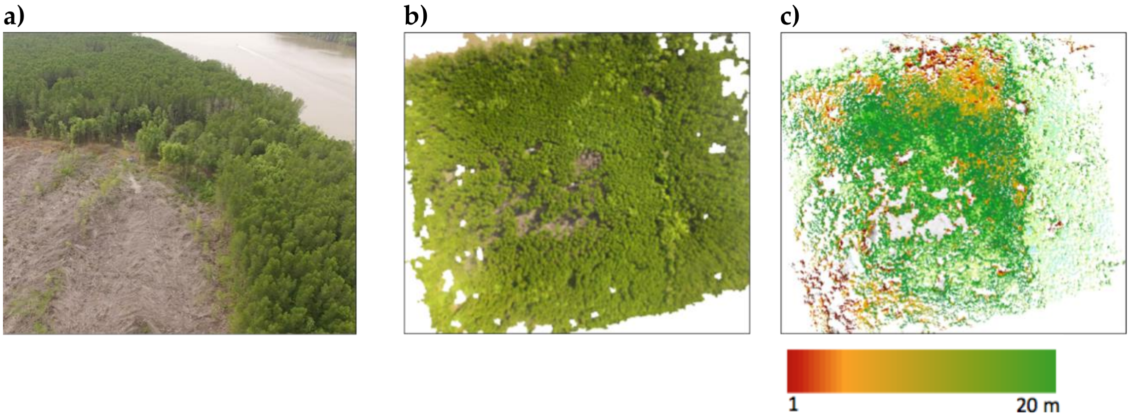

Figure 4. **a)** RGB image of mangrove forest clearances, Matang Mangrove Forest Reserve, Malaysia, as observed using an RGB digital camera mounted on a DJI Phantom 3, **b**) RGB orthoimage from which individual (upper canopy) tree crowns can be identified as well as different mangrove species and **c**) the Canopy Height Model (CHM) derived from stereo RGB imagery, with darker green colours representing tall mangroves (typically > 15 m).

UAS represents a promising option enabling timely, fast and precise monitoring important for many plant species, invasive ones in particular (Calviño-Cancela et al., 2014; Michez et al., 2016; Hill et al., 2017; Müllerová et al. 2017a). Flexibility of the data acquisition enabled by the UAS mean is very important since plants are often more distinct from the surrounding vegetation in certain time of their growing season (Müllerová et al. 2017b). Besides fast monitoring of newly invaded areas, the UAS methodology enables prediction/modelling of invasion spread that is driven by combination of many factors, such as habitat and species characteristics, human dispersal, and disturbances (Rocchini et al., 2015). Legal constrains limiting use of UAS to unpopulated areas can be especially problematic for invasive species that tend to prefer urban areas, still the UAS technology can greatly reduce costs of extensive field campaigns and eradication measures (Lehmann et al., 2017).

UAS are also revolutionizing the management of quasi-natural ecosystems such as restored habitats and managed forests. They have been used to quantify spatial gap pattern in forests in order to support planning common forest management practices such as thinning (Getzin et al., 2014) or to support restoration monitoring in uneven habitats at risk. For example, Quilter et al. (2000) used UAS for monitoring streams and riparian restoration projects in inaccessible areas on Chalk Creek (Utah). Knoth et al. (2013) applied a new mapping technique to support the monitoring of restored cut-over bogs using a UAS-based NIR remote sensing approach. TIR data were also used by Ludovisi et al. (2017) to determine the response of forest to drought in relation to forest-tree breeding programs and genetic improvement.

4. River Systems and Floods

Satellite data are widely used to monitor natural hazards (e.g. floods, earthquakes, volcanic eruptions, wildfire, etc.) at national and international scales (Tralli et al. 2005). This popularity is due to their wide coverage, spectral resolution, safety, and rate of update (Gillespie et al. 2007; Joyce et al. 2009). Nevertheless, UAS have also been widely used for rapid assessment following natural extreme events and in the context of humanitarian relief and infrastructure assessment (Stone et al., 2017). According to Quaritsch et al. (2010), UAS should be utilized as a component of a network of sensors for natural disaster management. Although, there are a number of technological barriers, which must be overcome before UAS can be utilized in a more automated and coordinated manner, their potential for disaster response is significant (Erdelj et al., 2017).

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An interesting example is given by the Hurricane and Severe Storm Sentinel (HS3) program launched by NASA (2015) that deployed different high-tech UAS to monitor hurricane formation and evolution. UAS "catch" data inside the storm (winds and precipitation) and in the surrounding environment using multiple sensors that include a radar scanner and wind LiDAR, multi-frequency radiometer, and a microwave sounder. Such technology may provide information never measured before on hurricanes.

Given UAS potentials, we expect significant advances in fields of hydrology and hydraulics where there is a significant potential for the use of UAS for monitoring river systems, overland flows or even urban floods.

2.1. Flow monitoring

River systems and stream flow can be monitored by remotely integrating the techniques of water body observation, vegetation mapping, DEM generation, and hydrological modelling. Satellite sensors in the visible, infrared, and microwave range are currently used to monitor rivers and to delineate flood zones (Syvitski et al. 2012; Yilmaz et al. 2010; D'Addabbo et al., 2016). These methods are generally used only over large rivers or areas of inundation in order to detect changes at the pixel level. UAS can describe river dynamics, but with a level of detail that is several orders of magnitude greater and can enable distributed flow measurements over any river system and in difficult-to-access environments.

In this context, the integration of UAS imagery and optical velocimetry techniques has enabled full remote kinematic characterization of water bodies. Optical techniques, such as Large Scale Particle Image Velocimetry (LSPIV, Fujita et al., 1997) and Particle Tracking Velocimetry (PTV, Brevis et al., 2011), are efficient yet non-intrusive flow visualization methods that yield spatially distributed estimations of the surface flow velocity field based on the similarity of image sequences. Proof-of-concept experiments have demonstrated the feasibility of applying LSPIV from manned aerial systems to monitor flood events (Fujita and Hino, 2003; Fujita and Kunita, 2011). More recently, videos recorded from UAS have been analysed with LSPIV to reconstruct the surface flow velocity field of natural stream reaches (Detert and Weitbrecht, 2015; Tauro et al., 2015). This allow to gain a detailed Lagrangian insight into river dynamics that is valuable in calibrating numerical models.

Most of these experimental observations entail a low-cost UAS hovering above the region of interest for a few seconds (the observation time should be adjusted to the flow velocity and camera acquisition frequency). An RGB camera is typically mounted on-board and installed with its optical axis perpendicular to the captured field of view to circumvent orthorectification (Tauro et al., 2016a). To facilitate remote photometric calibration, Tauro et al. (2016a) adopted a UAS equipped with a system of four lasers that focus points at known distances in the field of view. In several experimental settings, the accuracy of surface flow velocity estimations from UAS was found to be comparable to (or even better than) traditional ground-based LSPIV configurations (Tauro et al., 2016b). In fact, compared to fixed implementations, UAS enable capture of larger fields of view with a diffused rather than direct illumination. Such optical image velocimetry techniques can measure flow velocity fields over extended regions rather than pointwise, and at temporal resolutions comparable to or even better than ADV (Acoustic Doppler Velocimetry) based on the presence of detectable features on the water surface (Tauro et al., 2017).

Most platforms offer both piloted and GPS waypoint navigation up to 10 km range (even if this may be subject to national regulations) and are quite stable in windy conditions. In this context, UAS technology is expected to considerably aid in flood monitoring and mapping. In fact, flood observation is a considerable challenge for space-borne passive imagery mostly due to the presence of dense cloud cover, closed vegetation canopies, and the satellite revisit time and viewing angle (Joyce et al. 2009; Sanyal and Lu 2004). Although synthetic aperture radar (SAR) satellite sensors (e.g. Sentinel-1, TerraSAR-X, RADARSAT-2) can overcome these visibility limitations, they are unable to provide sub-metre level spatial resolution necessary for detailed understanding of flood routing and susceptibility. Applying UASs with an appropriate flight mode may overcome some of these issues

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allowing for rapid and safe monitoring of inundations and measurement of flood hydrological parameters (Perks et al., 2016). Moreover, hyperspectral sensor can also be used to extend the range of water monitoring applications. Examples are: sediment concentration, chlorophyll distribution, blooming algae status, submerged vegetation mapping, bathymetry and chemical and organic waste contaminations (Flynn and Chapra, 2014; Klemas, 2015).

4. Final remarks and challenges

UAS-based remote sensing provides new advanced procedures to monitor key variables, including vegetation status, soil moisture content and stream flow. A detailed description of such variables may increase our capacity to describe water resources availability and helping agricultural and ecosystem management. The present manuscript provides an overview of some of the recent applications in the field UAS-based environmental monitoring. The wide range of applications testifies the great potential of these techniques, but at the same time the variety of methodologies adopted is an evidence that there is still room for significant improvement. The variety of vehicles, sensors and specificity of the case study have stimulated the proliferations of a huge number of specific algorithms addressing flight planning, image registration, calibration and correction, derivation of specific indices or variables: but there is no evidence of comprehensive comparative studies able to selected the appropriate procedure for a specific need.

Despite the rapid development in software procedures, there is a huge need to standardize the workflow for operational use of UAS. High spatial resolution of UAS data generates high demands on data storage and processing capacity. Traditional procedures of collecting ground-truth data or ground-control points for satellite imagery do not show sufficient positional accuracy, especially in complex terrain (Müllerová et al. 2017b). Legal constrains restricting the UAS data acquisition can limit some potential applications, particularly in urban environment. There are also technical limits, such as weather constrains (wind, rain), high elevations or very hot environment that can be challenging for most of the devices/sensors (see e.g. Wigmore and Bryan, 2017).

Nevertheless, technology and scientific research have a clear path to follow that have been traced by manned aerial photogrammetry and earth observation from satellites. Such observational practices have already addressed several of the problems that UAS-based observations are facing. Miniaturization of technology and sensors will increase with time the reliability of UAS-observation reducing several of the limitations related to the use of UAS.

- The first and most critical limitation in the use of UAS is the limited flight time that affect directly the possible extent of the investigated area. This problem is currently managed by mission planning able to manage multiple flights, but the technology is offering new solutions that will extend the flight endurance up to several hours making more and more competitive the use of UAS. For instance, new development in the battery industry suggests that the relatively short flying time imposed by battery capacity will be significantly improved in the future (Langridge and Edwards, 2017). In this context, another innovation introduced in the most recent vehicles is an integrated energy supply system connected with solar panel on board that allows to extend typical flight endurance from the maximum of 40-50 minutes up to 5 hours.
- The second critical issue regards the impact of Ground Sample Distance (GSD) on quality of the surveys. This limitation can be solved implementing 3D flight paths that follows the relief in order to maintain uniform the observation's Ground Sample Distance (GSD). At the present, only few software (e.g., UgCS, eMotion 3) use digital terrain models to adjust the height path of the mission to the relief in order to maintain uniform GSD.
- The third critical issue regards the image registration, correction and calibration. Vulnerability of UAS to weather conditions (wind, rain) and the geometric and radiometric limitations of current lightweight sensors have stimulated the development of new algorithms for image mosaicking and correction. In this context, the development of open source and commercial SfM software allowed to properly address the mosaicking issue, but the radiometric correction

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and calibration is still an open question that may find potential solution in earth observations experiences.

- Vegetation can be measured in its state and distribution using RGB, multispectral, hyperspectral and thermal cameras. Each of these sensors allow to derive information with some sort of drawback. For instance, multispectral, hyperspectral and thermal camera can provide more appropriate description of the vegetation, but at the expenses of the spatial resolution and also with additional needs and requirements for the calibration. Also soil moisture and river flow can be measured using different sensors and algorithms, but a comprehensive assessment of the performances of each of these methods and procedures is strongly needed.
- The wide range of experiences described herein highlighted the huge variability in the strategies, methodologies and sensors adopted for each specific environmental variable monitored.
- Finally, UAS compared to satellite offer a similar complexity, but this sector has received much less resources to fill existing gaps in the technology. Nevertheless, this is also the reason why there is a lot of room for further improvements in the technology and use of such methods. The first and most important is also connected to the improvement of satellite techniques that may largely benefit from the use of high detailed UAS-data (see Figure 5).

There is a growing need to define harmonized approaches able to channel the efforts of all these studies and identify the optimal strategy for UAS-based monitoring. The aim is to define a clear and referenced workflow starting from the planning and acquisition of the data and the generation of maps. In particular, we envisage the need to stimulate a comparative experiment able to assess the reliability of different procedures and combination of algorithms in order to identify the most appropriate methodology for environmental monitoring in different hydroclimatic conditions.

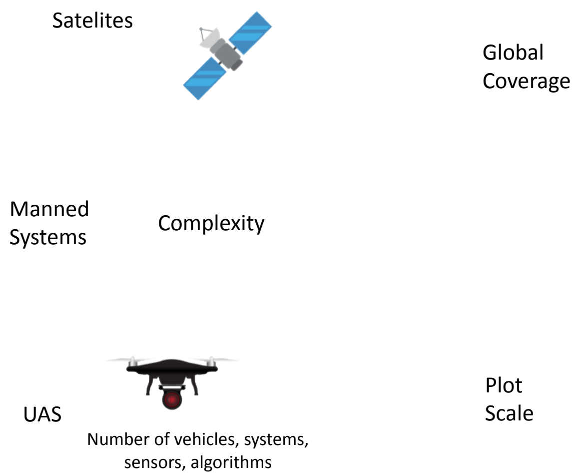

Figure 5. UAS vs satellite monitoring.

The recently funded COST Action entitled HARMONIOUS is aimed at stimulating joint activities to facilitate a more common strategy in environmental monitoring. This Action should enhance observational capabilities and also improve model parameterization across a range of fields. The Action is structured around five working groups (WGs) that will tackle different aspects in the use of UAS technologies, with the aim to identify the optimal strategy for data processing, monitoring the vegetation status, monitoring soil water content, monitoring river systems and discharge and finally harmonize the outcomes of these studies. The structure of the network with the responsible of each activity are shown in Figure 6. The aim is to stimulate, within the next few years, a number of field experiments oriented at benchmarking the existing procedures and algorithms for monitoring the variable of interest mentioned.

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In the coming four years, we will organize workshops and training courses, promote scientific missions and design cooperative experiments, that should address the following objectives:

- Establish standardized protocols for the necessary pre-processing of UAS (geometric correction of image orthomosaics, developing and integrating practical measures for radiometric correction and reflectance retrieval);
- Improve morphological representation of micro-topography, plots/fields, basins, parcels, and watercourses using UAS-based digital photogrammetry, and LiDAR surveys;
- Improve standard procedures for environmental monitoring to support precision agriculture and protection of ecosystems;
- Enhance soil property retrieval, with a major emphasis on soil moisture monitoring through combined use of thermal and VIS/NIR images and spectral based modelling;
- Understand how field measurements of vegetation properties and soil (moisture) scale up through UAS-based measurements to satellite estimates;
- Define a flow velocity and discharge monitoring procedure that provides stream flow measurements in open channels, creeks, rivers and floodplains;
- Identify a new standard procedure for hydrological monitoring that allows key river basin components to be monitored with a high level of detail that may help in the use of the most recent hydrological models.
- Endorse the UAS utilization chain from mission planning to a final product.

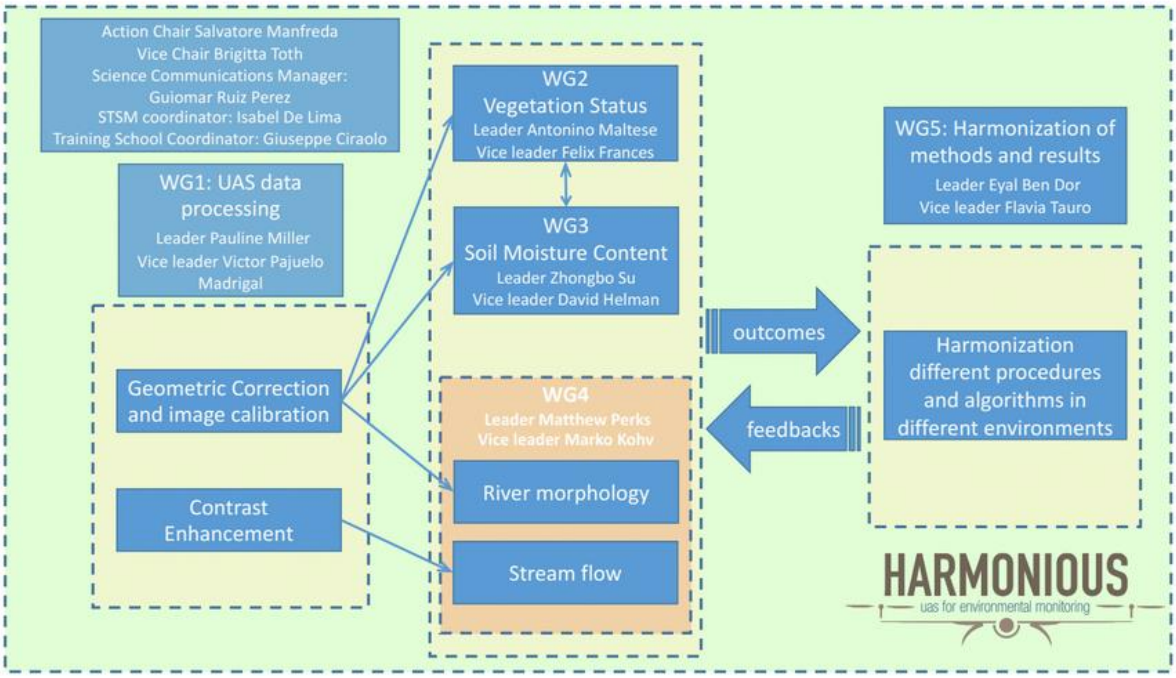

Figure 6. Structure and composition of the research network of the COST Action HARMONIOUS.

The integration of different techniques, including traditional instruments, fixed and mobile camera surveys, satellite observations, and geomorphological analyses, is anticipated to allow better characterization of river basins with a spatial and temporal coverage higher than that offered by traditional techniques, improving the knowledge of hydraulic, ecological and hydrological dynamics. Moreover, the definition of clear and specific procedures may also help the definition of new legislation at the European scale removing some of the actual restriction that limiting potential use of UAS in a wider range of contexts.

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Appendix A: Available sensors and cameras

Given the variety of sensor available for UAS applications, we consider extremely useful to provide an overview of the available cameras and sensors and their characteristics. In the following, we summarized the most common optical cameras (Table 1), multispectral cameras (Table 2), hyperspectral cameras (Table 3), thermal cameras and laser scanners (Table 5). The present tables expands the list of sensors provided by Casagrande et al. (2017).

Table 1. List of optical cameras suitable for UAS and their main characteristics.

Manufacturer and model	Sensor type Resolution (MPx)	Format type	Sensor size (mm²)	Pixel pitch (µm)	Weight (kg)	Frame rate (fps)	Max shutter speed (s⁻¹)	Approx. price ($)
Canon EOS 5DS	CMOS 51	FF	36.0 x 24.0	4.1	0.930	5.0	8000	3400
Sony Alpha 7R II	CMOS 42	FF MILC	35.9 x 24.0	4.5	0.625	5.0	8000	3200
Pentax 645D	CCD 40	FF	44.0 x 33.0	6.1	1.480	1.1	4000	3400
Nikon D750	CMOS 24	FF	35.9 x 24.0	6.0	0.750	6.5	4000	2000
Nikon D7200	CMOS 24	SF	23.5 x 15.6	3.9	0.675	6.0	8000	1100
Sony Alpha a6300	CMOS 24	SF MILC	23.5 x 15.6	3.9	0.404	11.0	4000	1000
Pentax K-3 II	CMOS 24	SF	23.5 x 15.6	3.9	0.800	8.3	8000	800
Canon EOS 7D Mark II	CMOS 20	SF	22.3 x 14.9	4.1	0.910	10.0	8000	1500
Panasonic Lumix DMC GX8	CMOS 20	SF MILC	17.3 x 13.0	3.3	0.487	10.0	8000	1000
Ricoh GXR A16	CMOS 16	SF	23.6 x 15.7	4.8	0.550	2.5	3200	650

Table 2. List of multispectral cameras available on the market for UAS and their main characteristics.

Manufacturer and model	Resolution (Mpx)	Size (mm)	Pixel size (µm)	Weight (kg)	Number of spectral bands	Spectral range (nm)
Tetracam MiniMCA-6	1.3	131 x 78 x 88	5.2 x 5.2	0.7	6	450-1000
Tetracam ADC micro	3.2	75 x 59 x 33	3.2 x 3.2	0.9	6	520-920
Quest Innovations Condor-5 ICX 285	7	150 x 130 x 177	6.45 x 6.45	1.4	5	400-1000
Parrot Sequoia	1.2	59 x 41 x 28	3.75 x 3.75	0.72	4	550-810
MicaSense RedEdge		120 x 66 x 46		0.18	5	475-840
Sentera Quad	1.2	76 x 62 x 48	3.75	0.170	4	400-825
Sentera High Precision NDVI and NDRE	1.2	25.4 x 33.8x 37.3	3.75	0.030	2	525-890
Sentera Multispectral Double 4K	12.3	59 x 41 x 44.5		0.080	5	386-860
SLANTRANGE 3P NDVI		146 x 69 x 57		0.350	4	410 - 950
Mappir	3.2	34 x 34 x 40		0.045	1-6	405-345

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680 **Table 3.** List of hyperspectral cameras for UAS and their main characteristics.

Manufacturer and model	Lens	Size (mm²)	Pixel size (µm)	Weight (kg)	Spectral range (nm)	Spectral bands and resolution
Rikola Ltd. hyperspectral camera	CMOS	5.6 x 5.6	5.5	0.6	500-900	40- 10 nm
Headwall Photonics Micro-hyperspec X-series NIR	InGaAs	9.6 x 9.6	30	1.025	900-1700	62 - 12.9 nm
BaySpec's OCI-UAV-1000/2000	C-mount	10x10x10	N/A	0.127/0.218	600-1000	100-5 nm/20-12-15nm
HySpex Mjolnir V-1240		25x17.5x17	0.27mrad	4.0	400 – 1000	200-3 nm
HySpex Mjolnir S-620		25.4x17.5x17	0.54 mrad	4.5	970 - 2500	300-5.1
Specim-AISA KESTREL	push-broom	99x215x240		2.3	600 - 1640	Up to 350 bands/3-8nm
Cornirg microHSI 410 SHARK	CCD/CMOS	136x87x70.35	11.7 µm	0.68	400 – 1000	300bands/2nm
Resonon Pika L		10.0x12.5x5.3	5.86	0.6	400-1000	281 bands/2.1 nm

681 **Table 4.** Representative thermal cameras suitable for UAS.

Manufacturer and model	Resolution (Px)	Sensor size (mm²)	Pixel pitch (µm)	Weight (kg)	Spectral range (µm)	Thermal Sensitivity (mK)
FLIR Vue Pro 640	640 x 512	10.8 x 8.7	17	<0.115	7.5-13.5	50
FLIR Vue Pro 336	336 x 256	5.7 x 4.4	17	<0.115	7.5-13.5	50
FLIR Tau2 640	640 x 512	N/A	17	<0.112	7.5-13.5	50
FLIR Tau2 336	336 x 256	N/A	17	<0.112	7.5-13.5	50
Thermoteknix Miricle 307 K	640 x 480	16.0 x 12.0	25	<0.170	8.0-12.0	50
Thermoteknix Miricle 110 K	384 x 288	9.6 x 7.2	25	<0.170	8.0-12.0	50/70
Workswell WIRIS 640	640 x 512	16. x 12.8	25	<0.400	7.5-13.5	30/50
Workswell WIRIS 336	336 x256	8.4 x 6.4	25	<0.400	7.5-13.5	30/50
YUNCGOETEU	160x120	81 x 108 x 138	12	0.278	8 - 14	< 50

682 **Table 5.** List of laser scanners for UAS and their main characteristics.

Manufacturer and model	Scanning pattern	Range (m)	Weight (kg)	Angular res. (deg)	FOV (deg)	Laser class and λ (nm)	Frequency (kp/s)
ibeo Automotive Systems IBEO LUX	4 Scanning parallel lines	200	1	(H) 0.125 (V) 0.8	(H) 110 (V) 3.2	Class A 905	22
Velodyne HDL-32E	32 Laser/detector pairs	100	2	(H)-(V) 1.33	(H) 360 (V)41	Class A 905	700
RIEGL VQ-820-GU	1 Scanning line	>1000	25.5	(H) 0.01 (V) N/A	(H) 60 (V) N/A	Class 3B 532	200
Hokuyo UTM-30LX-EW	1,080 distances in a plane	30	0.37	(H) 0.25 (V) N/A	(H) 270 (V) N/A	Class 1905	200

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Velodyne Puck Hi-Res	Dual Returns	100	0.590	(H)-(V) 0.1-0.4	(H) 360 (V) 20	Class A-903	
RIEGL VUX-1UAV	Parallel scan lines	150	3.5	0.001 °	330	Class A-NIR	200
Routescene – UAV LidarPod	32 Laser/detector pairs	100	1.3	(H)-(V) 1.33	(H) 360 (V) 41	Class A-905	
Quanergy M8-1	8 laser/detector pairs	150	0.9	0.03-0.2 °	(H) 360 (V) 20	Class A-905	

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