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Review

Characterizing vegetation complexity with unmanned aerial systems (UAS) – A framework and synthesis

Jana Müllerová [a,*], Xurxo Gago [b], Martynas Bučas [c], Jaume Company [d,e], Joan Estrany [d,e], Josep Fortesa [d,e], Salvatore Manfreda [f], Adrien Michez [g,h], Martin Mokroš [i,j], Gernot Paulus [k], Edvinas Tiškus [c], Maria A. Tsiafouli [l], Rafi Kent [m]

[a] Institute of Botany of the Czech Academy of Sciences, Průhonice, Czech Republic
[b] Research Group on Plant Biology under Mediterranean Conditions, Universitat de les Illes Balears (UIB), Institute of Agro-Environmental and Water Economy Research, INAGEA, Spain
[c] Marine Research Institute of Klaipeda University, Klaipėda, Lithuania
[d] Mediterranean Ecogeomorphological and Hydrological Connectivity Research Team, Department of Geography, University of the Balearic Islands, 07122 Palma, Spain
[e] Institute of Agro-Environmental and Water Economy Research, INAGEA, University of the Balearic Islands, 07122 Palma, Spain
[f] Dipartimento di Ingegneria Civile, Edile e Ambientale (DICEA), Università Degli Studi di Napoli Federico II, Napoli, Italy
[g] University Rennes 2 LETG (CNRS UMR 6554), CEDEX, 35043, Rennes, France
[h] TERRA Research and Teaching Center—Forest Is life, Gembloux Agro Bio-Tech, University of Liege, 5030 Gembloux, Belgium
[i] Technical University in Zvolen, Zvolen, Slovakia
[j] Czech University of Life Sciences Prague, Prague, Czech Republic
[k] Spatial Information Management, Carinthia University of Applied Sciences, Villach, Austria
[l] Aristotle University of Thessaloniki, School of Biology, Thessaloniki, Greece
[m] Independent Researcher, Bahan, Israel

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A B S T R A C T

Ecosystem complexity is among the important drivers of biodiversity and ecosystem functioning, and unmanned aerial systems (UASs) are becoming an important tool for characterizing vegetation patterns and processes. The variety of UASs applications is immense, and so are the procedures to process UASs data described in the literature. Optimizing the workflow is still a matter of discussion. Here, we present a comprehensive synthesis aiming to identify common rules that shape workflows applied in UAS-based studies facing complexity in ecosystems. Analysing the studies, we found similarities irrespective of the ecosystem, according to the character of the property addressed, such as species composition (biodiversity), ecosystem structure (stand volume/complexity), plant status (phenology and stress levels), and dynamics (disturbances and regeneration). We propose a general framework allowing to design UAS-based vegetation surveys according to its purpose and the component of ecosystem complexity addressed. We support the framework by detailed schemes as well as examples of best practices of UAS studies covering each of the vegetation properties (i.e. composition, structure, status and dynamics) and related applications. For an efficient UAS survey, the following points are crucial: knowledge of the phenomenon, choice of platform, sensor, resolution (temporal, spatial and spectral), model and classification algorithm according to the phenomenon, as well as careful interpretation of the results. The simpler the procedure, the more robust, repeatable, applicable and cost effective it is. Therefore, the proper design can minimize the efforts while maximizing the quality of the results.

1. Introduction

There are considerable gaps between field-based and remote sensing-based approaches as the field variables differ from those assessed by remote sensing techniques. Thanks to a very fine resolution, unmanned aerial systems (UASs), also called unmanned aerial vehicles (UAVs), remotely piloted aerial systems (RPASs) and informally drones, can help to upscale the point or plot field measurements into the landscape scale, and potentially to larger areas bridging the gap between field surveys and satellite data (Alvarez-Vanhard et al., 2020). UASs are increasingly

* Corresponding author.
E-mail address: jana.mullerova@ibot.cas.cz (J. Müllerová).

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used in the last decade, becoming an important tool for characterizing different aspects/components of vegetation in many ecosystems worldwide. The tool is ideal for both research experiments and targeted operational use; e.g., in nature protection (Gonzalez et al., 2016; Jiménez López and Mulero-Pázmány, 2019; Müllerová et al., 2017a). A wide choice of aircraft types (different types of copters or fixed-wings), sensors (multispectral, hyperspectral, Light Detection and Ranging - LiDAR), procedures and algorithms are available for the acquisition as well as the processing and interpretation of data (Colomina and Molina, 2014; Fig. 1). UAS surveys can thus be customized and designed for a variety of applications (Yao et al., 2019). In order to maximize the benefits of UAS, it is crucial to choose appropriate system settings, design of the field campaign, preprocessing of the data and the algorithms (Tmušić et al., 2020). Considering the research purpose and characteristics of the studied ecosystem shows to be likewise important.

Within vegetation studies, UAS tool is being used for a large variety of purposes, including mapping current vegetation state, studying processes at the level of ecosystem, community and individual, assessing and modelling the plant growth, monitoring and evaluating effects of human disturbances and natural disasters such as wildfires, torrential floods and insect outbreaks (Anderson and Gaston, 2013; Bailón-Ruiz et al., 2018; Calsamiglia et al., 2020; Estrany et al., 2019; Holman et al., 2016; Michez et al., 2016; Müllerová, 2019; Näsi et al., 2018). Considering the increasing use of the tool, and the important impact the design of the study has on results, many scientists and practitioners emphasize the need for standardization to assure harmonizing the UAS data acquisition and subsequent processing with the research goal (Manfreda et al., 2018). For such standardization, a great variety of UAS-based research in the field of vegetation science needs to be synthesized into an integrated framework, including the common grounds and challenges.

Here, we present a comprehensive synthesis aiming to categorize research and identify common rules that shape workflows applied in UAS-based studies facing complexity in ecosystems. Ecosystem complexity is regarded as an important driver of biodiversity and ecosystem functioning across taxa, biomes and spatial scales (Stein et al., 2014). The variety of UAS applications in the vegetation heterogeneity assessment is immense, and so are the procedures described in the literature. Irrespective of the ecosystem, similarities can be found according to the research aims (the ecosystem / community / individual property addressed). Vegetation properties encompass varying levels of heterogeneity in time and space, allowing classification into the following major components: (i) composition (covering a topic of biodiversity), (ii) structure (such as biomass and stand structure) and (iii) status (such as phenology stage and plant stress) (cf. Randlkofer et al., 2010). Following the concept of Essential Biodiversity Variables (EVB; Jetz et al. 2019), and remote sensing enabled EVBs (Reddy et al. 2021) these components could be translated into (i) compositional diversity (EVB groups of species populations & community composition), (ii) structural diversity (EVB group of ecosystem structure) and (iii) functional diversity (EVB groups of species traits & ecosystem function). All the components cover both static and dynamic processes, with different range and dimension of the dynamics. Still commonalities within these ecosystem components can be identified. Here, we present a synopsis as a general framework of UAS-based vegetation studies allowing us to design a UAS survey according to its purpose. We support the framework by detailed schemes of individual components, as well as examples of best practices of UAS studies covering each of the vegetation components and related applications.

2. General framework of UAS-based vegetation survey

The characterization of individual components within the framework of the vegetation complexity requires a specific survey design. The decision tree in Fig. 2 represents a general framework of vegetation surveys using UAS. The studies are divided according to the component of vegetation heterogeneity addressed: (1) species composition (parameters of biodiversity), (2) ecosystem structure (stand volume/complexity), (3) plant status (phenology and stress levels), and (4) dynamics (disturbances and regeneration) (see https://www.costharmonious.eu/characterizing-vegetation-complexity-with-uas/ and Supplement 1 for an interactive workflow). To reach the best quality results, the design of the survey including quality of the data and selection of the processing algorithms should be driven by the purpose of research and characteristics of the ecosystem property of interest. Information on abiotic conditions (not necessarily derived from UAS surveys) are often essential for the models. Many of the processes are dynamic, so the temporal aspects related to abiotic and biotic factors

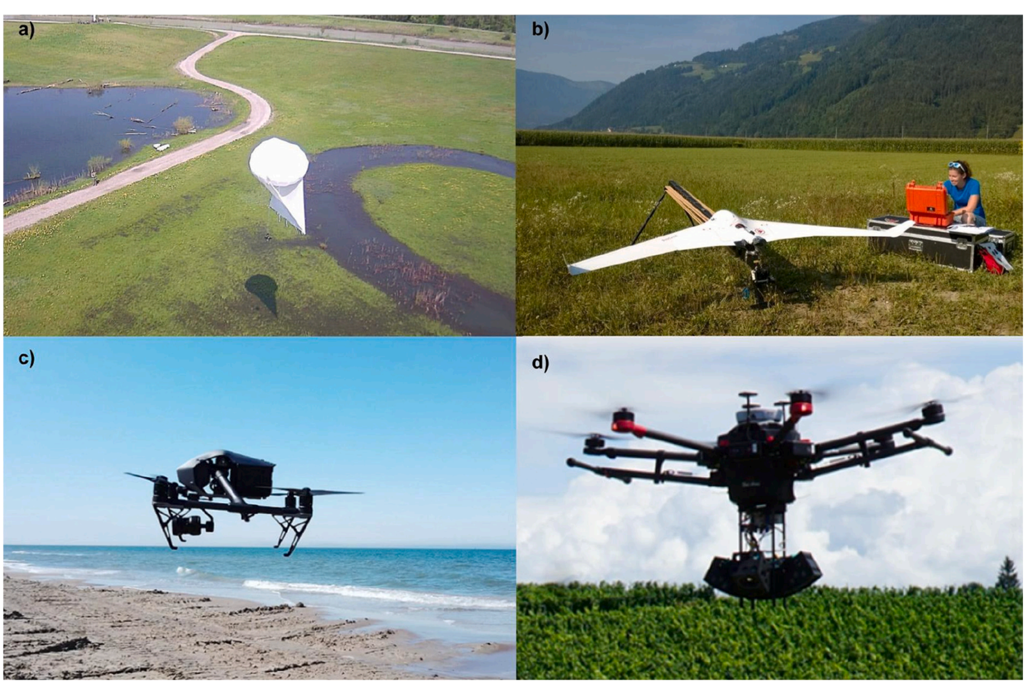

Fig. 1. Different platforms and sensors in UAS surveys; a) Lighter-Than-Air Helikite Balloon with Sony A7RII used for renaturation monitoring; b) BRAMOR ppk Fixed-Wing with Micasense Red Edge used for riparian vegetation monitoring; c) DJI Inspire 2 with zenmuse x5s RGB camera, used for shallow water vegetation and beach cast monitoring (Palanga, Lithuania), and d) Leica Aibot AX 20 with multidirectional sensor prototype (5 Sony ILCE-QX1 RGB sensors for capturing NADIR and 4 oblique images). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

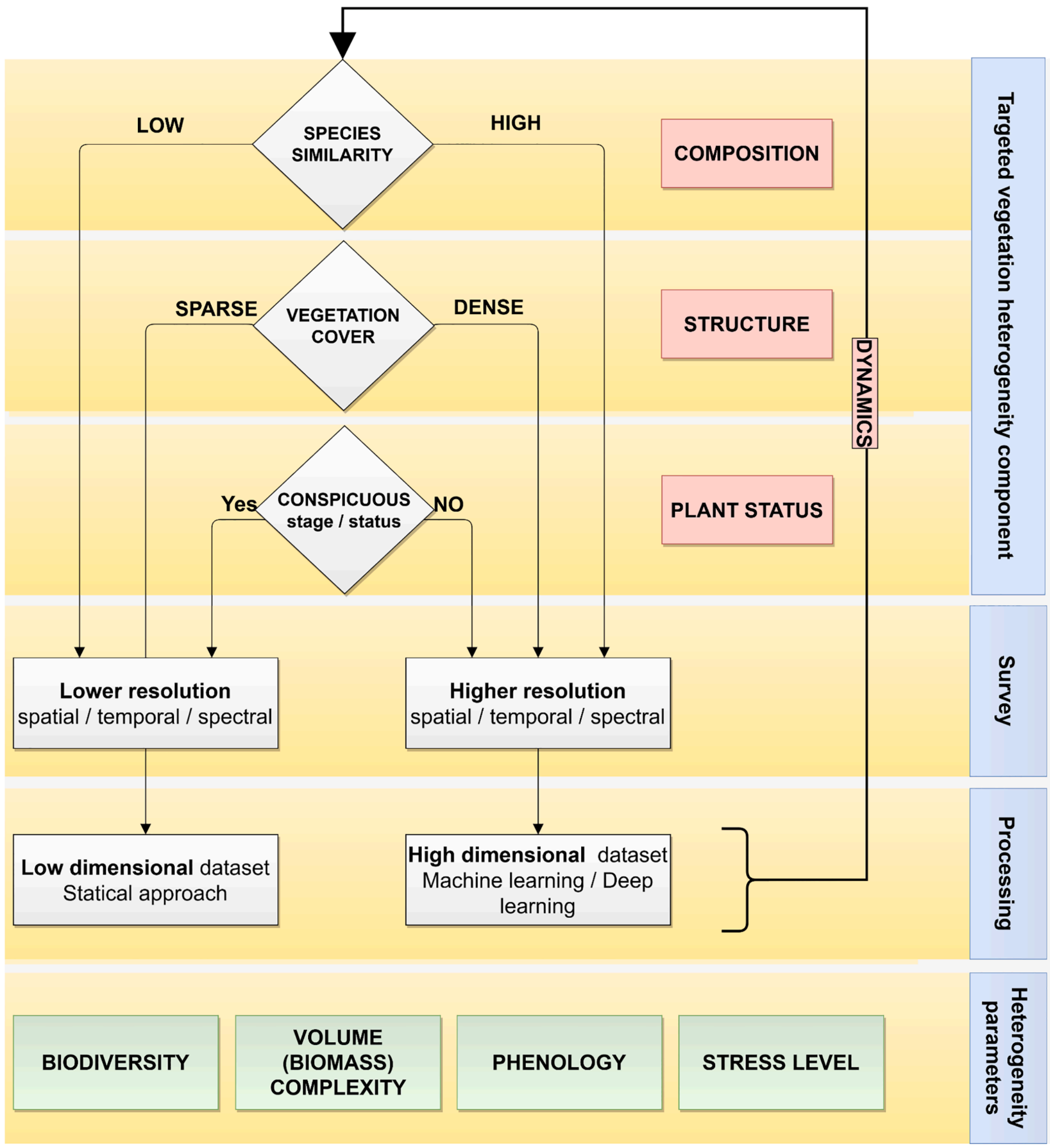

Fig. 2. Decision tree for designing the UAS-based vegetation survey according to the phenomenon/part of vegetation heterogeneity addressed. Details on each component of vegetation heterogeneity are explained in the following Figs. 3, 4 and 5, and in an interactive workflow at https://www.costharmonious.eu/characterizing-vegetation-complexity-with-uas/ and in the Supplement 1).

need to be added to describe the changes properly. In the Fig. 2., abiotic conditions, such as geomorphology, soil properties, climatic conditions and hydrology are not included, still they all play a significant role in shaping the vegetation heterogeneity and influence the survey design (Tmušić et al., 2020).

The resolution of the UAS survey has to be adjusted depending on ecosystem characteristics, i.e. according to species and individuals' similarity and targeted heterogeneity component. The resolution, as the similarity, is hereafter considered in the following dimensions: time, space and electromagnetic spectrum. For example, when characterizing vegetation composition for the purposes of biodiversity assessment, monitoring of rare and invasive species, or understanding the processes of species coexistence and succession, it is crucial to differentiate among the species. Such differentiation will depend on the way the species occupy space through time. Furthermore, their intrinsic morphological properties will produce specific morphological and spectral signatures that can be applied for either species identification or evaluation of their status using remote sensing techniques. In case the spectral/textural characteristics of co-occurring species are similar, differentiation would require higher spectral resolution to increase their spectral separation (Chadwick and Asner, 2016; Marvin et al., 2016). In general, the less distinct the feature is (e.g. species with a high degree of similarity to the surroundings), the more advanced sensors and the more complex methodology are required (Fig. 2). The same applies for assessing ecosystem structure, where for sparser ecosystems (e.g. sparse arid or semi-arid shrublands or tundra), photogrammetric point cloud can be sufficient, whereas for denser and more complex ecosystems such as forests, advanced LiDAR sensor becomes indispensable for most applications (Barbosa et al., 2016; Beland et al., 2019; Kent et al., 2015; Lefsky et al., 2002). The levels of conspicuousness and symptomaticity of the studied phenomenon (e.g. phenological stage and/or physiological status caused by stress) influence the required level of spectral/spatial/temporal resolution (Fahlgren et al., 2015; Ghosal et al., 2018; Singh et al., 2016) and, again, the sophistication of the analytical models. In case of asymptomatic physiological status at visible range, it is very difficult to reach satisfactory results unless additional advanced hyperspectral or thermal sensors are used (Gago et al., 2017).

Insufficiently coarse resolution can decrease the accuracy, still more detail does not automatically mean better results. Whereas very high spatial resolution can be extremely beneficial for detection of small patches or individual plants, it can tremendously increase the data complexity, processing time and data storage. Additionally, increasing spatial resolution from centimeters to millimeters can make classification extremely difficult, breaking individuals into a complex of branches and stems, green and dry leaves, individual flowers within the inflorescence, insects and soil background. Such extreme detail of UAS data also brings new challenges in the training and validation process (due to the precision limits of field Global Positioning System instruments, GPS), and proper matching of layers in case of change detection and canopy height models (Müllerová et al., 2017a). The three components of resolution, spatial, spectral and temporal, are interconnected, and certain trade-offs exist between them (Lisein et al., 2015; Michez et al., 2016). Thus, optimal resolution should be carefully chosen considering the purpose of the study as well as the target vegetation addressed.

3. The hands-on challenge: How to assess species composition, ecosystem structure and plant status by employing UASs?

3.1. Species composition: Highlighting biodiversity

Plant species composition varies along the axes of spatio-temporal heterogeneity (Lambers et al., 2008; Pugnaire and Valladares, 1999). Whereas at coarse scales it is defined by biogeographical zones and biomes, at finer scales, is determined by changes in composition as a function of abiotic conditions as well as inter-specific interactions with human management and co-occurring plant and animal species (Augustine and McNaughton, 1998; Fedele et al., 2017; Pugnaire and Valladares, 1999).

Examples where UASs have been used for specific vegetation/habitat types show that the challenges are to a certain extent case specific, depending mainly on natural characteristics. UASs were successfully applied in habitat mapping and monitoring for nature conservation purposes. Decisions on which methods and data to choose for UAS

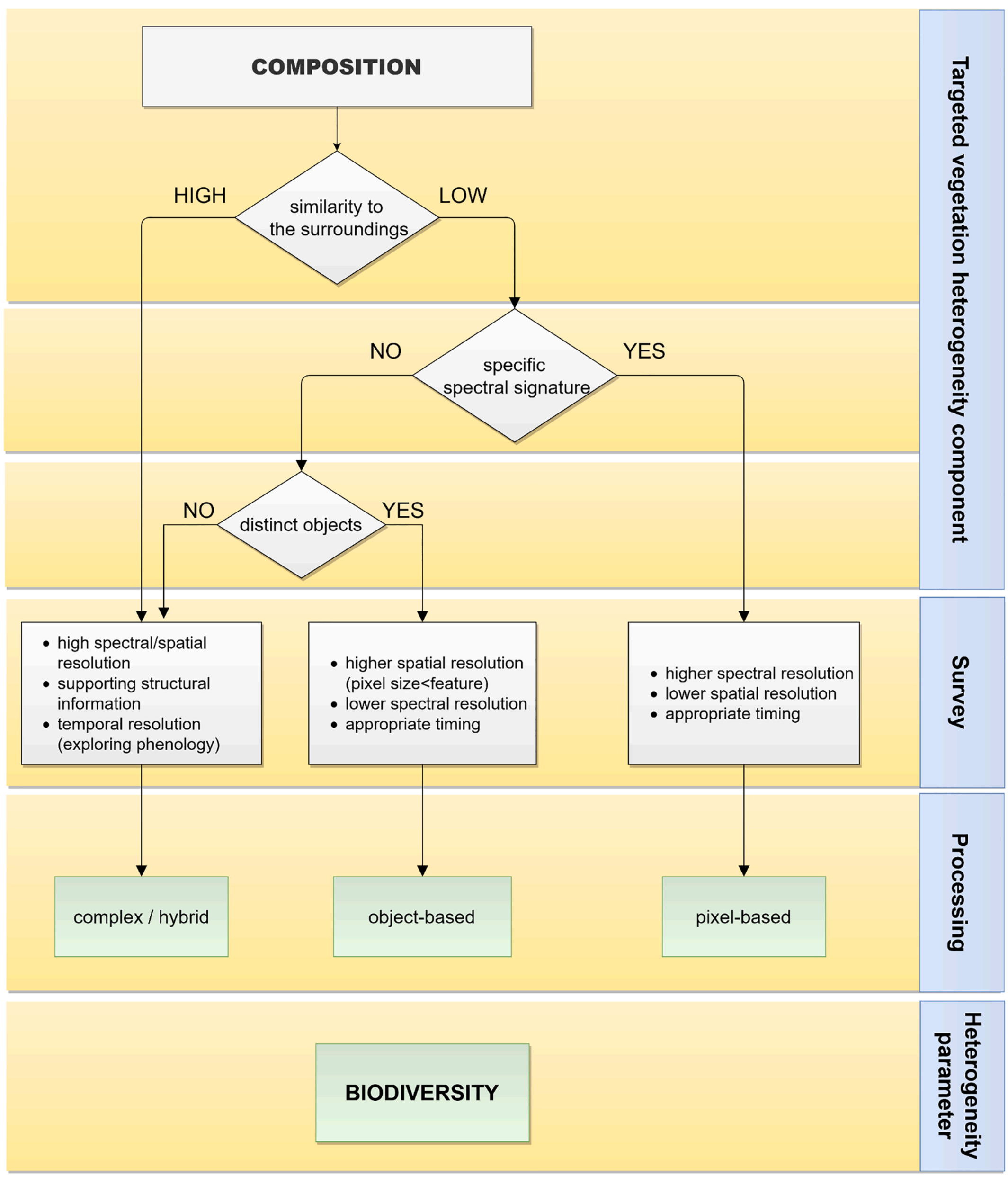

Fig. 3. Workflow for UAS-based detection of plant species composition (biodiversity, adapted from Müllerová, 2019).

assessment of plant composition shall be driven by the target species/vegetation characteristics. For species expressing low spectral and structural similarity to the co-occurring species, coarser resolution data combined with simple models would be sufficient; whereas for less distinct species, highly similar to their surroundings, a more complex approach must be applied (Müllerová, 2019). Accurate distinction between similar species is demanding in respect to the data resolution (spatial, temporal and/or spectral) and algorithms (using more complex or hybrid approaches); subtle differences in phenology or structure can help (Fig. 3).

For species that do not have a specific form (such as patchiness, and shape of individuals, inflorescences or the leaves) but are rather spectrally distinct from their surroundings, the pixel based approach might be appropriate (Müllerová et al., 2017a; Tamondong et al., 2020). Information on shape, texture and context can markedly improve precision of the species determination (Franklin, 2018; Gini et al., 2014). This is especially true for the species and/or vegetation types that have distinct shapes and/or form patches (Müllerová et al., 2017b), and for low cost digital Red-Green-Blue (RGB) cameras lacking near infrared band and with high intercorrelation of visible bands (Pande-Chhetri et al., 2017). In general, OBIA represents a powerful tool in UAS data processing that can to some extent reduce the noise and consequent “salt and pepper” effect caused by ultra high spatial resolution. However, the extreme detail leads to a large number of objects with varying spectral, morphological and proximity characteristics, which can be controlled by choosing the right spatial resolution (Yuba et al., 2021).

For complex vegetation patterns and species with a high degree of similarity, there is a need for higher spectral/spatial/temporal resolution data, multiple data sources, three-dimensional (3D) information on stand height and structure and/or advanced algorithms (e.g. Kattenborn et al., 2020; Martin et al., 2018; Michez et al., 2013). Machine and deep learning algorithms are particularly helpful to map complex vegetation, and can overcome the problem with laborious collection of training samples and ultra high spatial resolution (Liu et al., 2018).

To summarize, provided that the methodological workflow of the mision follows the species/habitat characteristics, UASs represent a powerful tool to be employed in biodiversity monitoring schemes, enabling assessment of species diversity and detection and mapping of individual species and/or habitat types. Thanks to very high spatial and temporal resolution, either repeatedly throughout the phenological season or using the optimal time window for the data acquisition, it is possible to map even the species that are difficult to distinct from the surroundings, especially in case information on 3D structure is added, several sensors combined and/or sophisticated algorithms of machine and deep learning deployed.

3.2. *Ecosystem structure: Measuring biomass, volume and stand complexity*

The structure belongs among the main drivers of resource variability. Particularly in forest environments, fine-scale information on canopy structure derived from UAS like canopy cover, gaps, vertical and horizontal structure and spatial aggregation are important since structure drives many ecological processes such as understorey diversity, seed establishment, and forest regeneration, and shapes important ecosystem services (Bagaram et al., 2018; Getzin et al., 2012; Kent et al., 2015).

Examples of assessing structure can be found for various ecosystems, such as shrublands (Cunliffe et al., 2016; Swetnam et al., 2018) and riparian areas (Meneses et al., 2018), but most UAS studies regard forests. In the latter, vegetation structure is addressed to analyse the stand complexity or quantify its volume/biomass (Fig. 4). 3D information is generated by different sensors and stored as point clouds for further processing. Normalization of ground using precise Digital Terrain Model (DTM) is greatly recommended (Aguilar et al., 2019). For 3D information, both passive (optical) and active (e.g. LiDAR) sensors can be used (Camarreta et al., 2020). While 3D information describing the upper

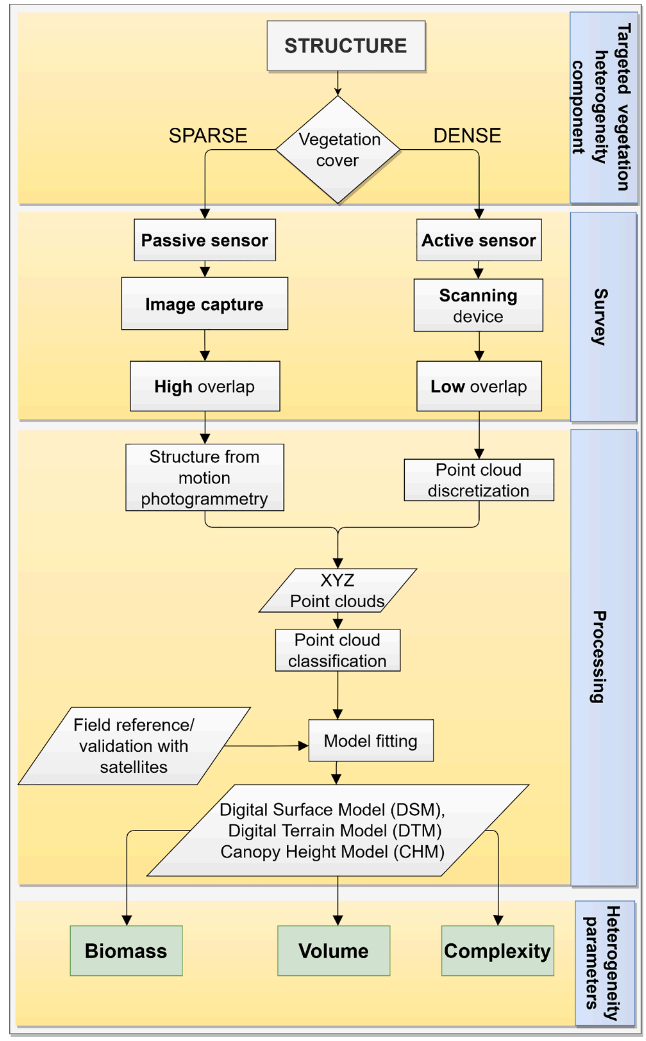

Fig. 4. Workflow for UAS-based ecosystem structure assessment.

most canopy layer can be acquired by various sensors, LiDAR sensors are necessary for the generation of DTM under the forest canopy and assessment of structural layers that is intrinsically related to the stand density and complexity.

Laser scanning provides the most accurate information on structural components including height, canopy dimensions, gaps, and biomass, and if mounted on UAS it can provide very high spatial details. However, its application is still limited due to the high costs and the fact that the sampled area is substantially smaller compared to the aerial LiDAR. In case of dense stands with complex multidimensional structure, active sensors (LiDAR) or DTM-independent approaches are an option (Giannetti et al., 2018), whereas passive sensors are not able to penetrate the canopy (especially during leaf-on season) to reach the inner structural layers and the ground (Kašpar et al., 2021). Still, for less dense and complex stands, passive optical sensors represent a low cost and simple solution to provide information on forest attributes including height, canopy dimensions, and biomass (Baltsavias et al., 2008; Dandois and Ellis, 2010; White et al., 2015). Photogrammetric point clouds are derived from overlapping imagery by using the digital imaging photogrammetry approach such as Structure from Motion (SfM) algorithm (Westoby et al., 2012), preferably with high overlap and lower flight altitudes (Seifert et al., 2019).

Still, many issues remain using passive instead of active sensors, especially related to closed or vertically complex canopy and shadows (Dandois and Ellis, 2013). Precision of results is also species specific;

while for evergreen single-stemmed tree species, photogrammetric products are comparable to LiDAR in capability to capture forest structure and estimate the biomass (especially for regularly designed forest plantations and open forests), it is less reliable for deciduous trees (especially during leaf-on period) and for canopy cover above 60 to 80% (Guerra-Hernández et al., 2017; Wallace et al., 2016). To overcome these problems, the data sources can be joined, such as adding spectral properties to LiDAR, or combining LiDAR-derived DTM and a series of photogrammetrically-derived DSMs to assess changes in the canopy (Lisein et al., 2013; Wallace et al., 2016). However, in such cases, precise co-registration is required. Alternatively, analyses of forest structure and gaps can be based solely on optical properties of UAS imagery, using the effect of darker objects (shaded gaps; Bagaram et al., 2018; Getzin et al., 2014). Nevertheless, such approach might bring even more imprecision with dense and/or highly vertically heterogeneous canopies.

As summarized in Fig. 4, from the examples proposed from different communities and environments, the choice of the sensor (active vs passive remote sensing) is particularly important for the structural assessment, and should respect the complexity of the stand to be sampled.

3.3. Plant status: phenology and plant stress

Plant status is driven by phenological stage and physiological status in response to endogenous (circadian and seasonal rhythms) and exogenous factors (abiotic stressors). High spatial and temporal resolution of UASs provide an unprecedented detailed insight into the ecosystem's response to (a)biotic stress (D'Odorico et al., 2020). Most of the papers using UASs to assess plant stress are performed in agricultural and forestry applications focusing only on a single species at a time, while for species rich natural ecosystems, such studies are largely lacking (but see e.g. Banerjee et al., 2020; Zhang et al., 2017).

Studied phenomena can range from distinct and well defined phenomena by spectral properties that can be assessed using relatively low spatial, temporal and spectral resolution, to the less conspicuous/ symptomatic phenomena, where the most sophisticated hyperspectral and thermal sensors coupled with complex modelling are needed (Fig. 5). In addition, even defining specific factors affecting the particular plant physiological status might be difficult due to the fact that the plant response to different types of stress is often indistinctive (Jones and Vaughan, 2010).

For example, UASs thermal imagery and the related leaf energy balance model estimations can be used to detect (a)biotic stress early since stomata are highly reactive to any stress, from abiotic stress such as drought (Gago et al., 2017) and herbivory attacks (Smigaj et al., 2019). In addition, stomata closure promotes general increase in canopy temperature that can be used as a physiological stress indicator (Smigaj et al., 2019). Very high spatial resolution of UAS data opens the opportunity to assess drought stress at individual level.

As for phenological stage, UASs provide both very high spatial detail and possibility of right timing of the data acquisition to capture a particular phenomenon, e.g. flowering (Carl et al. 2017; Müllerová

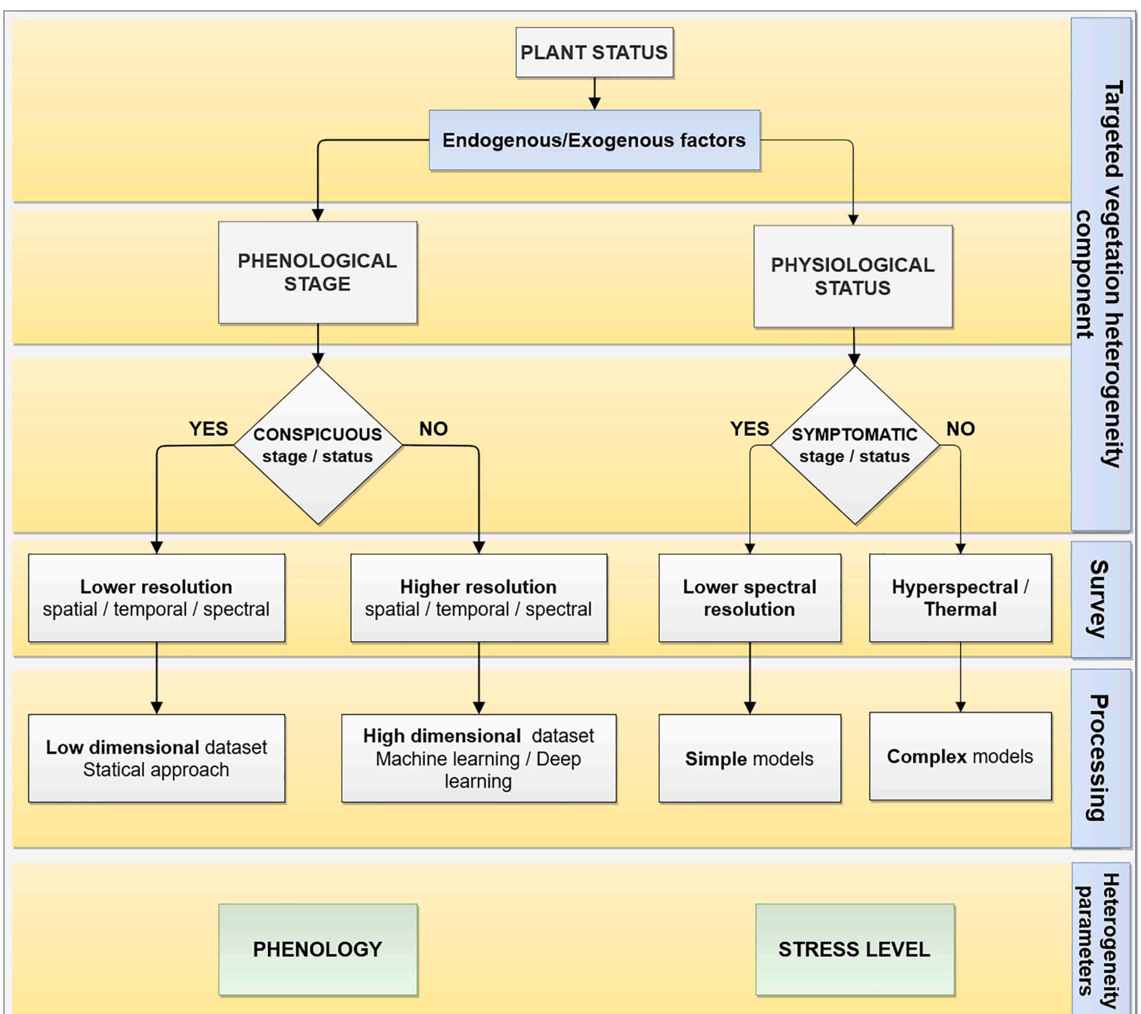

Fig. 5. Workflow for UAS-based assessment of plant status.

et al., 2017b; de Sá et al. 2018). Unlike the satellite data, UAS surveys allow data acquisition on demand and enable to zoom on individual plants within the stand, and therefore to study variation within plant populations and/or trace the very first or last individuals of particular phenophase (Fawcett et al., 2020). Improvements of sensor resolution and/or ability of UAS to fly very close to the canopies obtaining sub-cm resolution (such as for nano and micro-UASs) are still not widely employed even though the spatial information they provide is tremendous. For instance, ultra high spatial resolution enables the detection of flowering individuals without the need for higher spectral resolution sensors, opening a new opportunity to use micro-UASs to characterize ecosystem dynamics (Gago et al., 2020).

3.4. Ecosystem dynamics: Disturbances and regeneration

Many natural processes are dynamic, addressing plant composition, ecosystem structure or plant status from a temporal perspective. Whereas data collection itself follows the workflows suggested in previous sections depending on the type of ecosystem/phenomenon and heterogeneity addressed, a change detection approach is adopted for repeated UAS measurements to study the changes in time. Still, we have to bear in mind that for different components of heterogeneity (composition, structure and status), the dynamics can show different ranges and dimensions that must be reflected by the survey design.

To assess dynamic processes, such as phenological development or stress response, the temporal dimension is indispensable. Operational satellite data are the most commonly used for this purpose, however due to lower spatial resolution they are suitable mostly at global and landscape scales and for large homogeneous stands (Berra et al., 2019), and their temporal coverage is limited by their revisiting frequency. On the contrary, UAS can provide very high spatial and temporal resolution (revisiting time), and flexible, frequent and “ad hoc” data acquisition. Thus, UASs allow to explore the phenological cycle in unprecedented detail, e.g. individual-level phenological patterns and intraspecific variation (Fawcett et al., 2020; Park et al., 2019). Because of unprecedented fine scales, UAS are also very appropriate for dynamic ecosystems such as riparian areas and river ecosystems (Laslier et al., 2019; Michez et al., 2016).

In case of dramatic events, absence of data is common. Here, flexibility provided by UAS brings immediate revenues, since the surveys need to be conducted as soon as possible after the disturbance to support the decision-making and prevent further damage. Flights can be conducted immediately, eliminating the risk of injury linked to field surveys, such as in case of forest fires and windthrow (Mokroš et al., 2017; Yuan et al., 2015). UASs was also shown to assist in monitoring post-fire regeneration (Fernández-Guisuraga et al., 2018; Larrinaga and Brotons, 2019).

Insect disturbances in forests act at varying spatial and temporal scales, and understanding local dynamics as well as early detection of infestation onsets, which can be both facilitated by UAS, are very important (Senf et al., 2017). A variety of approaches and sensors were applied in UAS analyses of forest infestation dynamics; not only sophisticated hyperspectral sensors (Näsi et al., 2018) but also simpler sensors, such as multispectral or even low cost consumer grade cameras (Cardil et al., 2017; Minařík and Langhammer, 2016). UAS can also serve to study natural regeneration of forest after the outbreak (Röder et al., 2018). UAS assessment allows more cost-effective monitoring compared to the field surveys, and enables to acquire data at very high frequency providing observation data about the gradual spectral change after the attack. It can therefore be used to estimate the impacts of forest defoliation in spatial and temporal terms, for better assessing outbreak spread patterns and providing guidance in forest management programs. For possible extension of monitoring over larger areas, integration of UAS and satellite data is to be considered.

4. Research gaps and future perspectives

Exploring the capabilities of different statistical, spatial, temporal and textural settings, UAS represent a huge potential for assisted vegetation assessment. There is no doubt that recent technical advances significantly increase capabilities and accessibility of both platforms and sensors. One such example is the geometrical precision of UAS orthomosaics. Geometric distortions, particularly significant in forest or other complex environments (see Ludwig et al., 2020), can to a large extent deteriorate reproducibility, complicate the assessment of dynamic processes and decrease the power of change detection in general. Even though the number and design of ground control points are still an open debate in the scientific community (Padró et al., 2019), recent advances in affordable miniaturized GPS and on board UAS (such as Real-time kinematic - RTK) push the boundaries towards automation and increased geometric accuracy without (or with severely limited amount of) field work.

In addition, technological progress is opening brand new opportunities, such as extraction of meaningful information through standardized procedures without a need to be a specialist in the remote sensing field, mechanistic models and/or on-the-fly incorporation of ground and plant measurements to calibrate the remote sensing models, different flight modes (flying closer to the target, longer flights covering larger area, penetrating the forest canopy to assess the forest herb layer, Hyyppä et al. 2020; Ryddel et al., 2020), autonomous/real-time sensing (improving temporal resolution to assess plant stress, detection of non forested and eroded areas in tropical rainforest, Cruz et al. 2016), or targetless workflows to capture accurate reflectance values (Schneider-Zapp et al., 2019).

However, even though technological advances are expected to overcome many limits of current technologies and methodologies, some constraints will certainly remain, such as UASs regulations and restrictions. Recent harmonization of UASs regulations within the EU will definitely foster collaborative efforts and promote competitive development in the field.

5. Concluding remarks

UASs offer products and applications never imagined just a decade ago. However, optimizing the workflow is still a matter of discussion. In our review, we summarized and generalized the procedures of UAS-based vegetation research. Aiming to provide a framework for optimal workflow to characterize vegetation complexity with UAS, we divided it by the major components of vegetation complexity: biodiversity, structure and status, covering also the dynamic processes. We propose a general framework and detailed decision trees for each component including examples, and synthesize that any UAS survey must be built respecting the following steps: (i) get familiar with the phenomenon to be studied; (ii) choose suitable UAS and appropriate temporal, spatial and spectral resolution; (iii) select either simple or more sophisticated processing, classification algorithms and models depending on the complexity of the studied phenomenon; and (iv) carefully interpret the results considering the weaknesses and limits of UASs methods. During the process one must bear in mind that the simpler the procedure, the more robust, repeatable, applicable and cost effective it is; proper design minimizes the efforts and maximizes the best results, and appropriate temporal, spatial and spectral resolution are essential key-points. The experimental design must thus be adapted to the studied phenomenon and not the other way around. Still, even if UAS technology is capable and widely available, a combination of profound ecological background (Goddard et al., 2021) and robust knowledge on the limits of UAS technology are indispensable to avoid misinterpretation of the findings.

Declaration of Competing Interest

The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contribution

JM conceived and co-ordinated the writing, RK and XG supported formulation of the framework and the paper outline, and all authors took an active part in writing the paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2021.108156.

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