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Unmanned Aerial Vehicles (UAVs) in environmental biology: a review

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ABSTRACT

Acquiring information about the environment is a key step during each study in the field of environmental biology at different levels, from an individual species to community and biome. However, obtaining information about the environment is frequently difficult because of, for example, the phenological timing, spatial distribution of a species or limited accessibility of a particular area for the field survey. Moreover, remote sensing technology, which enables the observation of the Earth's surface and is currently very common in environmental research, has many limitations such as insufficient spatial, spectral and temporal resolution and a high cost of data acquisition. Since the 1990s, researchers have been exploring the potential of different types of unmanned aerial vehicles (UAVs) for monitoring Earth's surface. The present study reviews recent scientific literature dealing with the use of UAV in environmental biology. Amongst numerous papers, short communications and conference abstracts, we selected 110 original studies of how UAVs can be used in environmental biology and which organisms can be studied in this manner. Most of these studies concerned the use of UAV to measure the vegetation parameters such as crown height, volume, number of individuals (14 studies) and quantification of the spatio-temporal dynamics of vegetation changes (12 studies). UAVs were also frequently applied to count birds and mammals, especially those living in the water. Generally, the analytical part of the present study was divided into following sections: (1) detecting, assessing and predicting threats on vegetation, (2) measuring the biophysical parameters of vegetation, (3) quantifying the dynamics of changes in plants and habitats and (4) population and behaviour studies of animals. At the end, we also synthesised all the information showing, amongst others, the advances in environmental biology because of UAV application. Considering that 33% of studies found and included in this review were published in 2017 and 2018, it is expected that the number and variety of applications of UAVs in environmental biology will increase in the future.

KEYWORDS

Plant conservation, wildlife monitoring, UAS, drone, ecology, aerial survey, remote sensing;

INTRODUCTION

Environmental biology is a part of environmental science, an academic field integrating also other empirical sciences such as chemistry, physics, geography, soil science, atmospheric science and others. One of the main characteristics that can describe environmental biology is interdisciplinarity. Thorough studies of biological phenomena and processes are not possible without having the detailed information about the surrounding environment. Acquiring information about the environment is a key step during each study in the field at different levels, from an individual through species to community and biome. Such information may be extremely useful in assessing environmental threats caused by human activity or natural processes. However, obtaining information about the environment is frequently difficult because of, for example, the phenological timing, spatial distribution of a species or the limited accessibility of a particular area to the field survey. Moreover, remote sensing technology, which enables the observation of the Earth's surface and is currently very common in environmental research, has many limitations such as insufficient spatial, spectral and temporal resolution; a high cost of data acquisition or downloading cost from commercial providers; and the dependence on the cloud cover at the time of the acquisition (Müllerová et al., 2017). Consequently, since the 1990s, researchers have been exploring the potential of different types of unmanned aerial vehicles (UAVs) for monitoring Earth's surface, including the science of environmental biology (e.g. Nyquist, 1997; Quilter and Anderson, 2001; Hardin and Jackson, 2005; de Sá et al., 2018). In the recent years, many review articles showed applications of UAV in different fields of environmental studies. For example, Jones et al. (2006) and Chabot and Bird (2015a) assessed the usefulness of small UAV in wildlife monitoring. Anderson and Gaston (2013) presented

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UAV applications in population ecology, vegetation dynamics and ecosystem processes. Baena et al. (2018) described how the UAVs are applied in plant conservation. The increase in the visibility and usefulness of UAV in environmental biology was confirmed by a thorough scientific literature search performed in this study. First, we selected keywords that were then used to search Google Scholar inventories (date of search: 15 November 2018) for scientific papers dealing with environmental biology and using UAVs. We also searched for environmental biology papers using general remote sensing techniques to show the comparison of trends in the number of publications. For counting UAV papers, the following keywords were used: environmental biology, unmanned aerial system, unmanned aerial vehicle, drone. For counting traditional remote sensing papers, we used the following keywords: environmental biology, remote sensing, satellite, Landsat (as the example of commonly used satellite data). Then, the publication counts in years 2000–2018 were compared and charted. The analysis revealed that the use of general remote sensing techniques in environmental biology has been stabilised since 2013. In contrast, the number of environmental biology papers dealing with UAVs has continuously increased in the past 20 years. Interestingly, 2011 was the inflection point on the UAV paper trend line, and after that year, the number of environmental biology UAV papers per year has been rapidly increasing (Figure 1).

Because the number of applications of UAV in environmental science rapidly increased in the recent years, we focused primarily on papers published after 2010 in this review. From all the papers included (cited) in this study, 33% were published in the past 2 years, which reflects the general trend of increasing numbers of UAV applications in environmental biology (Figure 2).

Taking into account the increasing impact of UAV applications on environmental studies, the main purpose of this study was to review the current state of the literature dealing with the use of UAVs in environmental biology. Specifically, the review focused on the origins, functions, relationships, interactions and natural history of living populations, communities, species and ecosystems in relation to dynamic environmental processes. Moreover, the advantages and limitations of using UAVs as well as future perspectives were summarised in the final part of this work. The present study is the first complex review of UAV technology in the field of environmental biology and is divided into the following parts: (1) technical notes and classification of UAVs; (2) detecting, assessing and predicting threats on vegetation; (3) measurements of biophysical parameters of plant communities; (4) quantifying the dynamics of plants and habitats; and (5) population and behaviour studies of animals. This layout results from the specificity of using UAVs to acquire information about selected groups of organisms and environmental threats. Owing to the animal mobility, or the need for precise mapping of plant species or plant diseases,

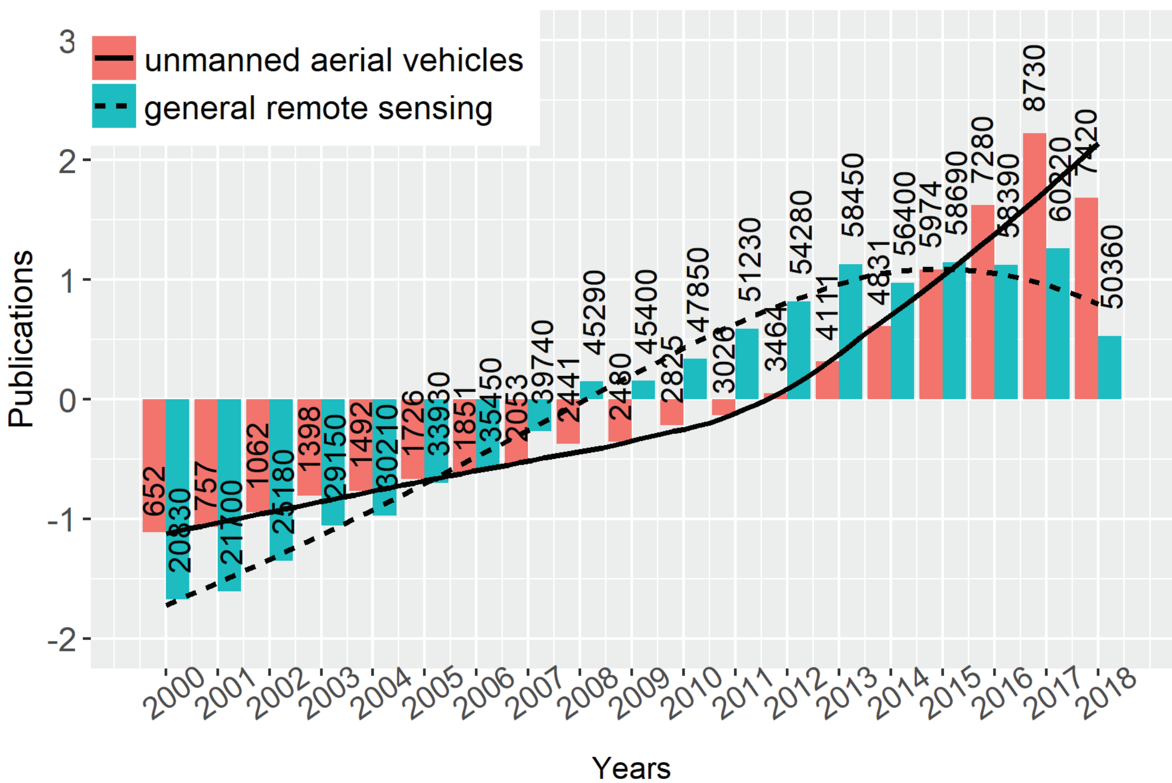

Figure 1. Comparison between the number of environmental biology publications using general remote sensing techniques and those using unmanned aerial vehicles (UAVs). As the number of UAV paper is generally low in comparison to general papers, the results were centred and scaled (red and blue bars). The real number of general and UAV papers per year is given at the top of a particular bar. The trend lines were calculated using local polynomial regression (loess) methods using R software and ggplot2 package (R Core team 2018, Wickham 2009).

various types of drones, sensors or methods of the remote sensing material treatment are used. Therefore, the next section describes the technical aspects of using UAVs.

1. TECHNICAL NOTES AND CLASSIFICATION OF UAVS

UAVs, also known as unmanned aerial systems (UASs), or commonly called drones, can be classified according to multiple criteria. Two categories can be distinguished by methods of lift (airframe type): (1) fixed-wing and (2) rotor-based vehicles. Another substantial feature of UAVs is their size, which greatly determines their operating range and the payload they are able to carry. Anderson and Gaston (2013) have proposed classification of UAVs based on the above-mentioned criteria. Large- and medium-sized UAVs are able to operate within a range of up to 500 km. Owing to their size, large-sized UAVs resemble small manned aircrafts (e.g. NASA Ikhana) and require a long runway for take-off and landing, full aviation clearance and ground maintenance as conventional planes. They are able to carry a payload of hundreds of kilograms, to fly at high altitudes of up to 20 km and even stay in the air for 2 days. These advantages of large-sized UAV are frequently balanced by high costs of set-up, running and maintenance. In turn, medium-sized UAS are able to operate for up to 10 h at altitudes lower than 4 km. Their payload can usually reach up to 50 kg. However, overall costs and space to take-off of medium-sized UAVs are lower than those for a large UAV. Small-sized and mini UAVs have an operational range of up to 10 km, fly at much lower altitudes (<1 km) and normally operate up to 2 h. The small ones can carry up to 30 kg, whilst the mini UAVs carry only 5 kg. Whilst large-sized and medium-sized UAVs generally have fixed-wing airframes, smaller drones can frequently be rotor-based aircrafts. The latter require little space for take-off and landing, which is a great advantage in complex terrain. They can be controlled remotely through radio, or their route (mission) can be planned beforehand. Micro and nano drones have similar features as those in the small and mini class. However, they are in flight for a maximal of 1 h, at an attitude of up to 250m and can carry <5 kg. UAVs from small to nano size are much cheaper than large- and medium-sized ones, thus their popularity has increased in the recent years as well as in scientific research (Anderson and Gaston 2013). Each platform should have the following instruments on board to provide a correct and accurate position of the aircraft, which is crucial for a successful and safe flight: inertial measurement unit (IMU), satellite navigation receiver, baro-altimeter and compass (Colomina and Molina, 2014).

A proper choice of UAV type is important in planning a research survey but equally important are the sensors the aerial platform is supposed to carry. UASs are usually deployed for experiments using remote sensing techniques and telemetry tracking. For observations using a visible range of light,

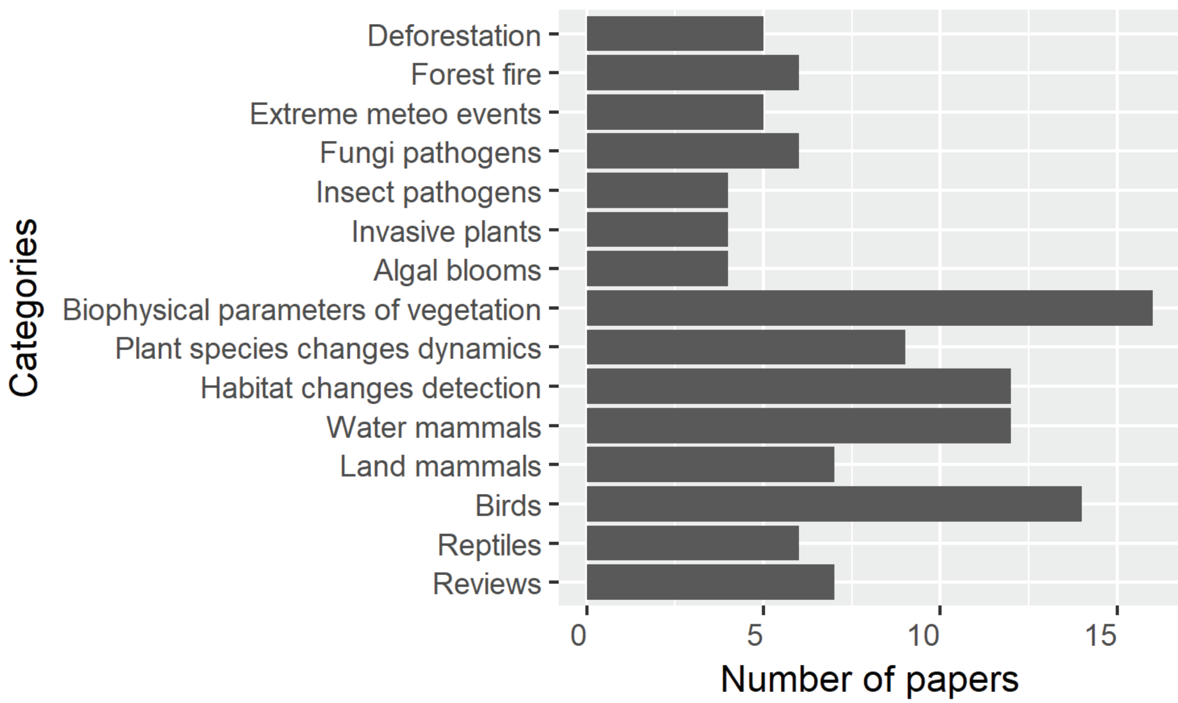

Figure 2. Number of papers dealing with UAV applications in environmental biology since 2010 that were reviewed in this study. The chart was produced using R software and ggplot2 package (R Core Team 2018, Wickham 2009).

many different easily available RGB (red, green, blue) cameras or even smartphones can be installed on UAVs (Colomina and Molina, 2014). Some off-the-shelf UAVs have already integrated cameras that are capable of taking photos as well as videos. Those cameras are often used in beyond line of sight (BVLOS) flights, facilitating the UAV navigation. For some applications, generally connected with vegetation monitoring, infrared (IR) or short-wave infrared (SWIR) radiation should be sensed. Therefore, more sophisticated filters and sensors are needed. Multispectral sensors have the capability to register an image in several different spectral ranges, for example, RGB, NIR (near-infrared) and SWIR. Combination of images obtained within different spectral ranges allows for detecting features that are not visible to the human eye. Markedly more precise, hyperspectral cameras produce images using many narrow spectral ranges. However, these cameras are frequently heavy (cause low UAV operation time), are more expensive than multispectral cameras and require more specialised knowledge to properly maintain them. Even thermal imagery, nowadays, can be obtained using drones. Also airborne laser scanning (ALS) technology, light detection and ranging (LiDAR), that normally uses manned aircraft platforms can be installed on a UAV. To carry this sensor, a UAV has to have enough power to lift large payloads, so this technology still needs some improvements. Apart from the sensor spectral resolution, spatial and radiometric resolution should also be taken into account. Choosing resolution is important for further processing of data, and it should be adjusted to the scale and characteristics of the phenomenon or object we are trying to investigate. Spectral resolution determines what kind of information we will be able to retrieve, whereas spatial or radiometric resolution specifies the scale and accuracy.

A key step after UAV imagery acquisition is the image calibration and processing. At this stage, it is important to have correct data on image orientation and camera calibration. There are many examples of software that enables processing of UAV-captured data. Amongst licensed desktop software, we shall mention Pix4Dmapper, Agisoft PhotoScan, Autodesk ReCap, Reality Capture, PhotoModeler, 3DF Zephyr and licensed cloud computing solutions such as DroneDeploy or PrecisionMapper. There are also open-source, free of charge projects such as OpenDroneMap and Regard3D. Most of the software uses a photogrammetric technique called structure from motion (SfM), which is based on multiple views of an object captured in different positions of the camera in relation to a given object. A scale invariant feature transform (SIFT) is used to identify common feature points across the image set, which are sufficient in establishing the spatial relationships between the original image location in an arbitrary 3D coordinate system (Micheletti et al., 2015). On the basis of SfM methodology, the following data sets could be produced: orthophotomaps, point clouds, digital elevation models (DEMs), digital surface models (DSMs), 3D models of objects and vegetation canopy.

2. DETECTING, ASSESSING AND PREDICTING THREATS ON VEGETATION

Threats affecting plant communities can be divided into different categories. This study proposed to distinguish the following groups: (1) uncontrolled or illegal logging, (2) fire damage assessments and prediction, (3) extreme meteorological events, (4) fungal pathogens, (5) insect pathogens, (6) invasive species and (7) harmful algal bloom.

One of the first thoughts about the threats affecting vegetation is uncontrolled, illegal logging of rainforests. Large rainforest areas, full of precious tree species and difficult to access on the ground, are also difficult to monitor and, therefore, are severely affected by illegal logging. In the recent years, UAV have become more and more common in forest monitoring and they can also be applied to logging detection as several examples are given in Paneque-Gálvez et al. (2017). Messinger et al. (2016) pointed out that drones can also be used to detect deforestation connected with illegal gold mining that occurs in rainforests in Brazil. Not only forests but also farmlands can be wilfully grabbed by mining and palm oil companies. In Indonesia, palm oil companies have to obtain permission from the government and also from local community to start planting palm trees, but they are frequently able to win by promising some benefits such as roads and higher income to local community. This frequently leads to land-owning-related conflicts. Local community is able to regain the rights to the land when they prepare high-resolution UAV-based maps (Radjawali and Pye, 2017). However, there are some limitations of such actions because the residents are mostly not able to operate the drone or perform the post-processing of the images. Other problems are the lack of electricity that is available only in major cities, and therefore, some advantages of using drones are lost. Nevertheless, more and more technological advances are being introduced in forestry and UAVs will become more common and more easily operatable in the future. Surely, best results in detecting changes in forest structure can be obtained when UAV-derived data are combined with other data sources such as terrestrial laser scanning (Rosca et al., 2017). The authors revealed that these two data sources are complementary and higher accuracy in detecting gaps and changes in the canopy can be obtained when using both simultaneously because the laser scanning increases the sensitivity to gaps in the canopy. However, to drastically diminish the costs of the study, it would be reasonable to rely only on UAV data. Using a low-cost UAV equipped with standard, commercially available RGB camera is also sufficient to monitor forest recovery and changes in dynamics (Zahawi et al., 2015). There are even entire UAV-based surveillance systems proposed, which allow for low-cost acquisition, processing, visualisation and assessment of changes occurring in forests (Saadat and Sharif, 2017).

Yuan et al. (2015) conducted a comprehensive review on using UAV in forest fire monitoring and detection. However, since 2016, at least 2660 new studies have been published based on Google Scholar search using keywords, 'forest fire UAV'. Amongst these new papers, Fraser et al. (2017) used octocopter UAV equipped with a 24-megapixel camera to assess the forest damage due to the fire and distinguish the fraction of remaining and regenerating green vegetation as well as charred organic material. They compared aggregated UAV-based results to well-established Landsat spectral indices such as d-NBR and post-NBR and obtained satisfactory results recommending the use of UAV to assess the forest damage over smaller areas. Sankey et al. (2017) were able to detect even subtle changes in tree canopy cover and density resulting from experimental thinning or burning in parts of research plots. The authors indicated that UAV equipped with a hyperspectral sensor and a LiDAR scanner performed better in classification of individual species and accurate detection of burned areas but suggested that these analyses are restricted to small areas because of the short operation time. In contrast, a fixed-wing UAV with multispectral camera provides satisfactory results with much longer operation time. Although assessing the effects and severity of forest fires using UAV is important for management, the crucial issue is to detect forest fire at the very beginning to protect the uncontrolled spreading of fire. For example, Cruz et al. (2016) worked out the new Forest Fire Detection Index (FFDI) that uses UAV imagery and is based on vegetation classification methods adapted to detection of the tonality changes on flames and smoke. The FFDI incorporates a simple, commonly used Excess Green Index that enables vegetation to be extracted from the background and relies on normalised values in three separated visible bands (red, green and blue). This index alone can also be used to measure fire severity from UAV (McKenna et al., 2017). Post-fire monitoring by using UAV is becoming more and more popular, and recently, it has been revealed that it is more precise to use UAV with multi-spectral camera (Parrot SEQUOIA) than using high-resolution satellite, World-View-2 (Fernández-Guisuraga et al., 2018). The valuable results were achieved despite the occurrence of undesirable issues such as the horizontal banding noise, inhomogeneous radiometry across the image and problems with irradiance sensor connections.

Not only fire threats but also the effect of extreme meteorological events can be detected using UAV. Inoue et al. (2014) detected fallen trees after hurricane events using high-spatial-resolution UAV-helicopter-derived photographs (0.5–1.0 cm/pixel) taken by a consumer-grade camera. The authors were able to detect up to 90% of fragments of fallen trees that were longer than 10 m or wider than 0.3 m in diameter but missed many smaller tree parts. However, this could probably be overcome by using a multispectral camera. In coastal areas, such hurricane events may also cause other damages to vegetation that can also be assessed remotely by UAV. High velocity wind can increase the salinity of the ground water available for plant roots as well as expose the aerial parts of the trees to salt spray. These stress conditions can cause damages called vegetation browning (Bernardes et al., 2017). In the latter study, three drones were simultaneously used to collect high overlapping RGB images at 1inch/pixel resolution. In addition, a five-band multispectral camera was used to better detect vegetation affected by browning. The results were later scaled up to the resolution of Sentinel 2 and Landsat images to show the limitations of orbital systems in detecting vegetation browning. Not only extreme wind but also the effects of other exceptional meteorological phenomena, such as hail, can be monitored using UAV. Zhou et al. (2016) simulated hail events of different severity on two varieties of potato at three different growth stages. A multispectral camera with red, green, blue and NIR bands installed underneath the octocopter was set to collect imagery at different time points (0–60 days) after the damage occurred. Although crop yield and spectral indices after hail events were detected to be decreased, both potato varieties recovered relatively well and damages could be detected only up to 10 days after the event. This indicates how important it is to obtain the information about damages timely, and for such cases, the UAVs are a perfect solution. Extreme droughts or water stress in plants can also be assessed using multispectral cameras mounted underneath the drone. For example, *Vitis vinifera* (grape vine) sensitivity to water stress was assessed using UAV-derived 10-cm resolution imagery from MCA-6 six narrow bands centred at 530, 550, 570, 670, 700 and 800 nm (Baluja et al., 2012). More information about using UAVs in the assessment of the effects of droughts on vegetation are described in Gago et al. (2015) and references therein.

Apart from fire threats, a relatively important threat for vegetation is fungi that negatively affect different parts of plants. Many examples can be given on agricultural plants, such as vines, that can be a host for *Fomitiporia mediterranea* (causing wood decay) and *Phaeomoniella chlamydospora* (causing grape vine leaf stripe disease), reducing the production and quality of grapes and causing a high rate of yearly death of grapes. The assessment of how much a grape population is affected by these fungi can be performed using an octocopter UAV system containing a Tetracam ADC-lite camera that enables sensing in red, green, and NIR spectra (Di Gennaro et al., 2016). The authors calculated Normalised Difference Vegetation Index (NDVI) using high spatial resolution of imagery (pixel size = 5cm); this was enough to estimate the vine infection level in different places of the vineyard. Thanks to the specially designed UAV, it is possible to investigate the presence and airborne loads of pathogenic fungi at higher altitudes (100 m above ground level) and, therefore, assess the possibility of long distance transport of *Fusarium* spores in this case (Lin et al., 2014). *Fusarium* species cause scab or *Fusarium* head blight disease that manifest through decreasing plant yield, discolouring crop kernels, reducing seed quality and contaminating yields with mycotoxins harmful for humans. Lin et al. (2014) used fixed-wing UAV with aerobiological samplers installed in the front of the wings and compared the concentration of *Fusarium* spores with ground-level standard Burkard volumetric sampler. It turned out that in specific situations, such as early afternoon or during the winter, spore concentration was greater at higher altitudes, which suggests that *Fusarium* spores can fly high enough to be transported over long distances. Techy et al. (2010) used two synchronised UAV to detect fungi-like *Phytophthora infestans* (causing potato late blight) sporangia in the atmosphere several tens of meters above the infected potato crop. It was revealed that it is possible to achieve a reasonable accuracy and comparability using two UAVs sampling the air simultaneously at different heights (25 and 45 m above ground level). Moreover, viable sporangia were detected even at higher altitude, which supports the previously mentioned possibility of pathogen transport by wind. Another species of *Phytophthora* (*Phytophthora alni*) is responsible for defoliation symptoms in *Alnus glutinosa* (black alder), and these symptoms were detected with high accuracy (81.0–90.6%) using two, RGB and modified RGNIR, cameras installed aboard fixed-wing UAV flying between 100 and 400 m above ground level (Michez et al., 2016a). The high level of classification (healthy to unhealthy) accuracy was also reached because of the frequent flights in different times during the year. This is evidence that taking images at different phenological phases increases the accuracy of classification. Damages caused by another plant pathogen, *Alternaria* species, were assessed using a hyperspectral camera installed on UAV (Dijkstra et al., 2017). The authors concluded that the damaged-healthy pixel classification error only slightly increased when the number of bands was substantially reduced (from 28 to 3), which is important because of UAV payload and costs. Another example can be family-specific fungal pathogens *Uredo rangelli* (myrtle rust) that affect around 50% of species from Myrtaceae family in Australia. Sandino et al. (2018) detected paper bark tea trees infected with *U. rangelli* with an accuracy of 94.72%. This high performance resulted from applying an integrated system that classifies and maps affected trees using UAVs, hyperspectral sensor and machine learning techniques. The hyperspectral camera was able to sense up to 274 narrow bands in a wavelength range of 385–1000 nm.

Another important group of plant pathogens are insects that can act directly, causing, for example, the defoliation of trees, and also indirectly – when an insect acts as a vector transmitting bacteria or virus pathogens. European spruce bark beetle (*Ips typographus*) infections have been detected in *Picea abies* (Norway spruce) forests by using a small-sized UAV platform equipped with an imaging hyperspectral sensor. This sensor operated in a range of 500–900 nm and was sufficient to detect three classes of spruce individuals, healthy, infected and dead, with an accuracy of 75% (Näsi et al., 2015). Also, in Bulgaria, forest areas infected by bark beetle were detected. However, Stoyanova et al. (2018) used only a 5-channel multispectral camera and did not classify trees as infected or uninfected but only evaluated NDVI values in the study area. Despite the simplicity of the analysis, the authors were able to clearly delineate patches where NDVI was lower and attributed this decrease to the infection with *Ips* species. Early detection of Huanglongbing (HLB) (a bacterial disease transmitted by vector) is also possible using UAV-derived hyperspectral images. This motile bacterium causes chlorosis of the leaf veins, entire leaf or branch, and the fruit from infected plants grow deformed, is bitter and is not suitable for selling to consumers. This pathogen is transferred by a psyllid *Diaphorina citri*, which acts as a vector. Garcia-Ruiz et al. (2013) used a hexacopter with a Tetracam camera sensing six narrow bands that could be configured in different ways by centring a particular band at different wavelengths to detect infected orange trees. The authors found that images acquired at 710 nm and NIR–red difference index were significantly different between healthy and HLB-infected trees. The same camera placed in a hexacopter UAV was used to detect damages caused by *Leptinotarsa decemlineata* on 16 *Solanum tuberosum* (potato) plots. Additional insects in different numbers (low, medium and high) were placed into the plots, and the difference in NDVI was recorded after 1 day (Hunt and Rondon, 2017). However, this difference was not consistent when three different methods were used, and probably, using a more sophisticated vegetation index or longer interval between two subsequent acquisitions, the differences would be more specific.

A common threat for native vegetation is invasive plant species. They can frequently and easily settle in non-native areas because of the lack of natural enemies and may reach large sizes and adapt well to conditions met in new areas. This causes a competition between native and invasive plants, and the latter, most frequently, win, which leads to limiting the ecological niche of the native species. In the most severe cases, equivalent native species can be entirely eliminated from a particular area. Therefore, detecting, mapping and monitoring invasive species are highly recommended to protect the local biodiversity. Such actions can be successfully undertaken using UAV systems (Müllerová et al., 2017). For example, Michez et al. (2016b) used a fixed-wing UAV with two cameras (RGB and RGNIR) to detect and map three invasive riparian taxa: *Fallopia japonica*, *Fallopia sachalinensis* (Japanese knotweed), *Impatiens glandulifera* (Himalayan balsam) and *Heracleum mantegazzianum* (giant hogweed). The authors obtained the UAV imagery at particular phenological phases, which increased the probability of the plant detection. Large, white, inflorescences allowed them to obtain almost perfect results (92% accuracy) in detecting *Heracleum mantegazzianum* in the flowering stage. This result is sufficient to use with the proposed method directly in monitoring this invasive species. However, for the remaining two taxa, the results were significantly worse, and this was attributed to the time-window selection as well as the mixing of *I. glandulifera* with the native plants. Müllerová et al. (2017) confirmed that *H. mantegazzianum* can be successfully detected using UAV-derived imaging data (up to 100%). The authors emphasised that such a perfect result was possible only when the images were taken during the flowering stage in July. When images were taken at fruiting or later, the detectability reached maximally 60%. In the mentioned study, it was also possible to reasonably detect *Fallopia* sp. (up to 79% accuracy) in November images, when these plants senescence and are distinctly brown-reddish in colour. The general conclusion of Müllerová et al. (2017) was that taking images at appropriate phenological stage is the most important for increasing UAV-based image classification accuracy. In Portugal, de Sá et al. (2018) monitored *Acacia longifolia* (long-leaved wattle) flowering, an invasive shrub species, using two cameras, RGB and colour-infrared (CIR), changeably placed at a UAV for examining the effect of a biocontrol agent (*Trichilogaster acaciaelongifoliae*). This Australian wasp parasitises on the invasive shrub *A. longifolia* flowers successfully limiting the dispersal and fit of the plant. de Sá et al. (2018) assessed flowering cover at different time points during the season and showed that a smaller area covered by flowers is detected in the senescence period than in the peak flowering period. They attributed this difference to a hypothetical effect of the introduction of *T. acaciaelongifoliae*, proving the suitability of UAV multispectral imagery in the assessment of the effects of the biocontrol agent on flowers. The next *Acacia* species, *Acacia mangium* (black wattle), is one of the most aggressively invasive trees in the savanna-type ecosystems in Brazil named Mussununga. Because *A. mangium* is substantially higher than native vegetation, this species has negative effects on the biodiversity conservation, agriculture and land reclamation in Brazil. However, the range and rate of *A. mangium* invasion can be assessed using a low-cost, fixed-wing UAV equipped with RGB and CIR cameras. This, together with open-source, laptop-based ground station, allowed for reaching an 82.7% accuracy in the classification of the invasive tree (Lehmann et al., 2017). Also, Chabot et al. (2018) prepared a relatively easy to apply system to monitor invasive *Stratiotes aloides* (water soldier) in Canada, both emergent and submerged plants, with high accuracy regardless of the classification of UAV-derived imagery that was performed by the producer or the user. The authors pointed out three necessary steps to reach reliable results, that is, obtaining radiometrically calibrated multispectral imagery with NIR band, performing segmentation to distinguish above-water and submerged plant parts and performing semi-automated classification of features using machine-learning classifier.

The last topic in this section is the detection and assessment of harmful algal blooms (HAB) in water ecosystems. HAB are known to negatively affect vascular plants and macrophytes growing in the water, for example, by decreasing their biomass (Twilley et al., 1985), but algae can be successfully controlled by macrophytes (Wang et al., 2012). Therefore, HAB detection by UAV is treated here as a benefit to animals and humans rather than other plants. For example, Shang et al. (2017) detected *Phaeocystis globosa* in Zhangjiang River estuary, Weitou Bay and Taiwan Strait based on radiometric measurements of downwelling irradiance and upwelling radiance recorded by a spectroradiometer mounted on a fixed-wing airframe. The radiances were also measured *in situ* and showed very similar results to the values measured by the instruments installed at the UAV, proving that UAVs of this type can also be used over sea areas. Also, a recent study from the Yellow Sea confirms the possibility of using UAVs to detect and even calculate biomass of green algae that are attaching to the rafts with a red algae *Porphyra yezoensis* and are negatively affecting the *P. yezoensis* aquaculture. Xu et al. (2018) showed that using normalised green-red difference index was the best algorithm that allows for the detection of green algae in aquaculture. Moreover, the authors proposed a method combining UAV-derived images, field survey and Sentinel-2 satellite data that were suitable for green algae detection and biomass estimation. Recently, HAB detection and algae biomass estimation are possible using UAVs. Interestingly, Jung et al. (2017) invented a complex system containing autonomous surface vehicle and UAV that is designed for removing algae blooms and reducing their negative effects on the environment. They used electrocoagulation and flotation technique, reaching an almost perfect removal (98.53%) of cyanobacteria. Much more and up-to-date reading on UAVs role and support in HAB research can be found in Kislik et al. (2018) and references therein.

3. MEASURING THE BIOPHYSICAL PARAMETERS OF VEGETATION

Remotely sensed data allow to measure different properties of land cover features determining their height, width, circuit, volume or density. Whilst artificial surfaces generally do not vary during the year, the nature continuously changes because of the passing through of different phenological/developmental stages or succession processes. Therefore, frequent acquisitions of remote sensing images to properly assess the vegetation changes are needed. However, conventional remote sensing technologies, such as planes and satellites, suffer from some limitations such as low temporal and spatial resolutions of images. These limitations may be successfully overcome by UAVs – they are independent on the revisit time, and the pixel size is usually markedly lower because of the lower operation altitude. Consequently, UAVs seem to be perfectly suitable for measuring the dynamics of vegetation and its biophysical parameters. In this field, taking photographs is a primary source of information. For example, Dandois and Ellis (2013) used automated UAV image acquisition techniques and high-spatial resolution multispectral 3D data sets/point clouds to assess structural dynamics of forest canopy and to repeatedly predict the forest aboveground biomass and carbon content. This study was performed in two temperate deciduous forest sites in Maryland (USA). The authors have shown a new UAV remote sensing system enabling routine and inexpensive aerial 3D measurements of canopy structure and spectral attributes (e.g. vertical canopy profiles, tree heights, tree volume). The results were similar to those obtained from LiDAR but with RGB spectral attributes for each point derived from SfM computer vision algorithms, enabling high-frequency observations within a single growing season. The use of UAV for image acquisition in forest canopy structure monitoring was also applied by Getzin et al. (2014) to quantify small spatial gap patterns in forests and by Zahawi et al. (2015) for subtropical forest recovery mapping. Puliti et al. (2015) used UAV-derived data to develop models estimating mean height, dominant height, stem number, basal area and stem volume for forest inventory information at a local scale, whereas Zhang et al. (2016) used it for long-term forest monitoring. In turn, UAV photographs were used in beech forests to estimate the canopy cover, foliage clumping and leaf area index (Chianucci et al. 2017) as well as mapping forest canopy gaps (Bagaram et al. 2018). Rossi et al. (2018) delineated forest cover and testing plots after mixed-severity fires combining SPOT6 image and UAV Imagery, whereas Saarinen et al. (2018) assessed biodiversity in boreal forests by predicting their structural diversity.

Measuring the height of plant communities is needed to assess the biomass and also the internal structure of a community. It is also helpful in estimating yields, for example, from olive orchards (*Olea europaea L.*) (Zarco-Tejada et al., 2014). This task can be completed using RGB/CIR images obtained using UAV. Also wild plants, and not necessarily trees but even herbaceous plants of a proper size, such as *Phragmites australis*, can be measured using SfM-derived point clouds from UAV (Meneses et al., 2018). Vegetation measurements are possible based on images taken from different angles – oblique photographs. For example, Lin et al. (2015) used oblique photos to detect individual trees in an urban area. A new parameter synthesising the common feature parameters of texture and RGB brightness was proposed in the mentioned study. As the UAV technology continues to develop and gains new applications, there is an increasing demand for validation and testing of UAV-based products. Therefore, Fraser et al. (2018) tested the impact of flying height on SfM image processing and assessed discrepancies in outputs obtained by using different software packages and the effects caused by processing parameter settings. From the numerous results, it is worth mentioning that amongst flying heights of 50, 100 and 120 m above the woodland area, it turned out that the 100-m height was the optimal solution regardless of the software tested.

At present, besides image acquisition by UAV for measuring vegetation parameters, the LiDAR acquisitions become less expensive over time and more easily accessible. One of the first examples showing the potential of UAV-borne LiDAR for use in the forestry research was provided by Jaakkola et al. (2010). Using high-resolution data set from rotor-based UAV, it was possible to improve the methodology for mapping individual trees. Wallace et al. (2012) illustrated how an octocopter UAV-LiDAR system could be applied to tree-crown structural measurements of tree location and height. It was presented that a UAV-borne LiDAR system can be relatively low cost and light and simultaneously able to collect spatially dense, accurate and repeatable measurements for forest inventory applications. The LiDAR-hyperspectral image fusion method based on high-resolution LiDAR, hyper- and multispectral data taken from UAVs was used to measure structural characteristics (e.g. individual tree canopy height and diameter, number of trees) of individual tree crowns in a ponderosa pine forest (Pinus ponderosa) and its ecotone. This complex method was also used for classifying vegetation at the species level following eight different cover types including tree, shrub and herbaceous species in 12-cm resolution hyperspectral data (Sankey et al., 2017).

4. QUANTIFYING THE DYNAMICS OF CHANGES IN PLANTS AND HABITATS

One of the main objectives of using UAVs in plant ecology and conservation is mapping the distributions of individual plant species and vegetation types at a fine spatial scale (Anderson and Gaston, 2013). UAV monitoring of health conditions and ecological succession dynamics of plant communities is also of increasing importance. The increasing availability of UAVs and their automation of use enabled the first attempts to detect dynamics of plant species and habitats based on data acquired by sensors placed on the UAV.

One of the applications of the UAVs (in Central Europe) in the remote detection of tree taxa was the project of Będkowski and Stereńczak (2012) aimed to apply a new quasi-object-based method (a combination of multispectral classification and object-based classification) for tree species classification using UAV multispectral images. The images were taken in October – in the final phase of the vegetation season with changes in colouring of different tree species: *Pinus sylvestris* (Scotch pine), *Quercus petraea* (sessile oak), *Betula verrucosa* (birch) and *Quercus rubra* (eastern red oak). It was emphasised that the acquisition of images in Autumn, under non-standard light conditions, may provide valuable information that facilitates species detection. A similar approach considering phenological differences was conducted to monitor the length of the individual tree growing season by identifying the autumn phenophases of *Q. petraea* (sessile oak) using multispectral aerial images acquired from UAV (Będkowski and Stereńczak, 2013). UAV images were taken in RGB and red, green and NIR channels by two cameras and were used to recognise the deciduous riparian forest species (Michez at al., 2016b). The authors generated the orthophoto and computed the Canopy Height Model (CHM) based on image-derived DSM and LiDAR data as DEM. The data was then used to perform *object-based image analysis* (OBIA) and multi-resolution image segmentation by taking into account the phenological differences of the following species: *Alnus glutinosa* (black alder), *Fraxinus excelsior* (common ash), *Acer pseudoplatanus* (sycamore maple) and *Picea abies* (Norway spruce).

Although smaller, herbaceous (weed) plant species can also be detected using a UAV. Peña et al. (2013) prepared a map of *Amaranthus blitoides* (broad-leaved weed) and *Sorghum halepense* (grass weed) in an experimental maize field in Spain. The authors used 2-cm spatial resolution UAV imagery with green, red and NIR bands to perform OBIA classification of the weeds. Moreover, Hung et al. (2014) proposed an alternative learning-based approach for invasive weed detection using feature learning to minimise the effort required for weed detection. Specifically, they aimed to optimise the UAV flight altitude and image spatial resolution to reach possibly high classifier performance for following weed species: *Eichhornia crassipes* (water hyacinth), *Solanum viarum* (tropical soda apple) and *Nassella trichotoma* (serrated tussock). Another grass species (*Alopecurus myosuroides*) is considered to be one of the major weeds of cereal crops because this annual plant releases many seeds and develops resistance to a variety of herbicides. Using a UAV, this species can be detected and mapped and its density can be estimated in winter wheat crops (*Triticum aestivum L.*) (Lambert et al. 2017). The authors acquired images in a range of 670–750 nm and RGB bands. In turn, Lu et al. (2017) investigated spatio-temporal variation of species composition in grassland. It is an essential step during the evaluation of grassland sensitivity to stress factors, the understanding of evolutionary processes of the local ecosystem and the development of grassland management strategies. As an alternative to space-borne remote sensing images (e.g. MODIS, Landsat, Quickbird), the authors have used UAV with a modified digital camera (NIR, green and blue bands) to explore species composition in a tall grassland at different times of the growing season to assess spatio-temporal variations in species composition. Object-based plant classification was performed for the following classes: *Bromus inermis* (dense), *B. inermis* (sparse), *Asclepias* species, *Solidago* species, *Festuca* species with *B. inermis* and senesced grass. An interesting example of the UAV use is the mapping of aquatic vegetation. Husson et al. (2013) evaluated the use of a UAS for surveying emergent, floating-leaf and riparian vegetation in three boreal freshwater systems. Using RGB images acquired from UAV, the vegetation stands were visually and manually defined as homogenous patches that differed from surrounding vegetation patches in colour, texture and shape. Husson et al. (2016) also tested the possibility of using UAV images in the visible spectrum (380–750 nm) for automatic mapping of helophytes (*Equisetum fluviatile*, *Schoenoplectus lacustris*, *P. australis*, *Carex rostrata*) and Nymphaeides *(Nuphar lutea, Potamogeton natans, Sparganium spp., Nymphaea alba ssp. candida, Nuphar pumila*). The automated classification of aquatic species was based on OBIA performed using two classification methods: threshold classification and random forest.

One of the first purposes of using aerial photography acquired from UAV in habitat dynamics was the monitoring of rangelands. Quilter and Anderson (2001) evaluated the potential utility of low altitude and large scale UAV imagery (RGB and NIR spectrum) in assessing the changes in biomass of *Ceriotoides lanata* (winterfat) shrub. This shrub species was an example of assessing the quality and state of pastures. Hardin and Jackson (2005) used a UAV for taking imagery of rangelands as an alternative to the high-cost aircraft surveys and time-consuming field work. They designed and built a small, radio-controlled UAV from inexpensive, off-the-shelf components that could be used for imaging rangelands at low altitudes and confirmed its feasibility as a rangeland research tool by assessing its flight characteristics. Getzin et al. (2012) used a 7-cm pixel-size RGB photography acquired from UAV to assess the floristic biodiversity by detecting canopy gaps that are related to the floristic biodiversity of a forest understory. Thanks to a UAV, Chabot et al. (2014) captured RGB images that were used for habitat quality measurement, important for *Ixobrychus exilis* (least bittern). This is the example of how UAV-based imagery can contribute to the knowledge about the distribution of migratory bird species placed at IUCN Red List (least concern status in this case). The wetlands habitat classes (e.g. water, floating vegetation, cattail and bur-reed) can be distinguished and mapped using RGB imagery taken from fixed-wing UAV and performing the supervised pixel-based spectral classification (Chabot and Bird 2013). Interestingly, small rotor-based UAVs can be used even in extremely cold climates, for example, in Antarctica (Lucieer et al. 2014). Despite the substantial decrease in operation time, the authors were able to successfully collect low-altitude aerial photographs to map moss beds, the dominant plant in East Antarctica. The SfM technique was applied to derive ultra-high-resolution 3D models of moss beds. A 2-cm DSM and 1-cm orthophoto mosaic were derived from the 3D model and aerial photographs. Finally, a terrain surface modelling technique based on the DSM was used to obtain a proxy for water availability from snowmelts, one of the key environmental factors affecting moss fitness. UAVs showed their suitability to also assess the spatial changes in habitats over dry areas. Vegetation structure was described in a semi-arid transition zone between grass and shrub area using 3D models (DEM, DSM, CHM) produced using SfM methodology applied to RGB UAV imagery (Cunliffe et al., 2016). This approach yielded ultra-fine (<1 cm) spatial resolution canopy height models, which could be used to estimate the volume of individual grass tussocks. Vegetation types included in this project were the following: grass-dominated (*Bouteloua eriopoda*), grass-shrub (*B. eriopoda* and *Larrea tridentata*), shrub-grass (*L. tridentata* and *B. eriopoda*), shrub-dominated (*L. tridentata*), shrub-grass (*B. eriopoda*, *Pinus edulis* and *Juniperus monosperma*), grass-shrub (*B. eriopoda*, *Pinus edulis* and *Juniperus monosperma*), grass-shrub (*B. eriopoda* and *L. tridentata*). On the basis of the orthomosaic, DSM generated from UAV RGB imagery and R software, Cruzan et al. (2016) manually and automatically classified habitats in upland prairie distinguishing the following classes: trees, shrubs, swales, hummocks and *Lasthenia californica* (California goldfields) individuals at peak flowering phase. UAV imagery can also be used for degradation monitoring of littoral vegetation. Ballari et al. (2016) explored the potential of UAV images in the Galapagos Islands by calculating NDVI and conducting the OBIA for the identification of vegetation presence and its fitness. Imagery was captured using RGB and NIR cameras. An interesting example of the application of UAV to study water habitats is the monitoring of intertidal reefs performed by Murfitt et al. (2017). A quadcopter UAV survey (<1-cm resolution data) provided estimates of dominant canopy-forming algae and geomorphic variables showing elevation and distance to seaward reef edge. Coastal ecosystems belong to the most transformed areas and are particularly vulnerable to human activity. Such areas require a high-resolution mapping of sensitive marine habitats (Ventura et al., 2018). In the mentioned study, RGB imagery from a lightweight quadcopter and OBIA were used to demonstrate that UAV are suitable for mapping varied coastal environments such as *Posidonia oceanica* (seagrass meadow), a rocky coast with nurseries for juvenile fish and sandy areas with reefs formed by a polychaete species *Sabellaria alveolata*. Wetlands have a positive impact on the environment, for example, they attenuate floods, accumulate nutrients and stabilise water regimen. UAVs with RGB camera can also be helpful over this kind of habitat serving to assess the changing vegetation fitness and biomass (Boon and Tesfamichael 2017). SfM methodology can be used to produce ultra-high-resolution point clouds, orthophotos, DEM and DSM. These UAV imagery-based products may serve in the detailed assessment of wetland quality. Similarly, estuarine wetlands can be monitored by UAV that enable a detailed habitat mapping immediately after storms and human disturbances and at different sea levels (Gray et al. 2018). UAV-derived images may enhance the Support Vector Machine (SVM) classifier performance on WorldView-3 and RapidEye satellite data, which was tested in Rachel Carson Reserve in North Carolina, USA. In this case, different vegetation indices, texture layer and LiDAR-derived DEM were used as independent variables in the model. It was emphasised that estuarine environments were hardly accessible for fieldwork and, moreover, it would be not possible without disturbing or destroying precious and sensitive habitats. Therefore, remotely controlled UAVs seem to be extremely suitable to obtain the information about the ecosystem structure or processes occurring on the studied estuarine environments.

5. POPULATION AND BEHAVIOUR STUDIES OF ANIMALS

One of the main applications of UAV technology in environmental biology is also the observation of animals, autonomous wildlife telemetry tracking as well as monitoring and assessment of animal habitats (Chabot and Bird 2015a). Wich and Koh (2018) indicated that UAVs can also be applied in surveillance for monitoring illegal activities, such as poaching, in protected areas and towards endangered species. Application of UAVs in animal research is becoming more common because some habitats can be hardly accessible from a ground level and animals themselves might be dangerous in close proximity (Chabot and Bird, 2015a). Many examples of using UAVs can be found in animal research, but the majority of studies are limited to vertebrates: mammals, birds and reptiles. Most surveys on animals are carried out using RGB cameras and the obtained imagery is examined manually by observers. However, computer vision methods and techniques have rapidly increased in popularity in animal conservation fields in the recent years.

Mammals living in the water belong to some of the most examined species using UAVs. This is because many of these species are vulnerable to changing environment and often are an object of whaling and poaching. Cetaceans are especially interesting not only for researchers but also for the public and economy. Particularly, estuaries and, generally, coastal areas are potentially liable to animal-economy-related conflicts. Such situations occurred in St. Lawrence Seaway where radar signals emitted by ships were disorienting and, therefore, caused harm to sea mammals. Detecting whale species by UAV-based imagery (multispectral camera) was the primary step in studying this phenomenon. It turned out that *Delphinapterus leucas* (beluga whale) was the easiest to detect using an airborne sensor, as it appeared in high contrast to surrounding water on the photos (Schoonmaker et al., 2008). Durban et al. (2015) had surveyed the length of *Orcinus orca* (killer whales) off the coast of Vancouver Island (British Columbia, Canada) using photogrammetric images obtained with UAV, which were controlled from a vessel. Ferguson et al. (2018) had used fixed-wing UAV for cetacean (Cetacea) research near the shore of the northernmost point of Alaska (USA). Collected data were used to assess the density of marine mammals, where *D. leucas* (beluga whales) and *Balaena mysticetus* (bowhead whales) have been observed from both UAV and manned aircraft flying over the same area. Afterwards, photos were inspected by analysts, who observed that bowhead whale density estimates derived from UAS images were higher than those from airplane observations. In contrast, the beluga whales were observed more frequently from the airplane. It resulted from the fact that the flights were not carried out simultaneously and cetaceans were changing their position within the study area. Also, the health of whales (*Megaptera novaeangliae*, humpback whales) was assessed in non-invasive and innovative approach using UAV. UAV equipped with a sterile Petri dish sampled respiratory vapour to estimate the diversity and abundance of microbiota of a whale's respiratory tract (Pirotta et al. 2017). Usually, such research would be harmful and stressful for an animal or not be possible at all, because of its direct nature.

Another example of using UAVs for surveying marine mammals can be found in research on pinnipeds, a clade within Carnivora order. Similar to cetaceans, this group contains many species requiring constant monitoring and attention of scientists. Animals from this clade are susceptible to changing climate and often are victims of sealing. Goebel et al. (2015) and Krause et al. (2017) studied *Hydrurga leptonyx* (leopard seals) in the Antarctic to measure body size of those mammals. Thanks to photogrammetric data obtained from drones, they were able to determine the body dimensions and weight of seals. Authors compared UAV data with ground survey and revealed that, in some cases, ground surveys were even less accurate than remote sensing data. These results are very promising for future research on pinnipeds, because aerial surveys are less invasive than traditional ones carried out on the ground with direct contact with animals. Gooday et al. (2018) attempted to detect a pinniped species (*Arctocephalus forsteri*, fur seals) using thermal imagery in a coastal forest in New Zealand. It turned out that thermal imagery performed better than standard RGB in the mornings only, because of the temperature of the ground that was significantly lower than the bodies of the animals. Also, when seals had just come out of the water, their fur was wet, so, as a consequence, on the thermal imagery, there was a water mask on their fur and they weren't as visible. Other pinniped species, *Phoca largha* (spotted seal) and *Histriophoca fasciata* (ribbon seal), were observed using UAV and a manned helicopter on sea pack ice on the Bering Sea (Moreland et al. 2015). It was documented that seals were less concerned about the presence of a UAV than other bigger aircrafts. The UAV was deployed from a ship; therefore, it could operate farther from shore than the manned aircrafts used in the study. The UAV and the manned aircraft imagery were also compared in a population survey and an assessment of the moulting stage in a *Halichoerus grypus* (grey seal) (Johnston et al. 2017). The difference between the two data sources in population surveys were very small (adults: 1%; juvenile: 3.7%). It was suggested that a multicopter UAV was the most useful for moult-stage assessment in comparison with fixed-wing aircraft.

Body size (length) and lifestage of the Florida manatee (*Trichechus manatus*: family Trichechidae, order Sirenia) individuals were assessed using a tethered airship (aerostat), which is a cheaper alternative of a UAV (Flamm et al., 2000). Moreover, Martin et al. (2012) proposed UAV-based models to detect manatees based on their behaviour, habitat characteristics and environmental gradient. Also *Dugong dugon* (Sirenia order) individuals were remotely counted using a fixed-wing UAV flying over Shark Bay in Australia. It was possible to distinguish the species from sharks and dolphins and to estimate the number of adults and calves.

There are also many examples of using UAV to study animals living on land , primarily in the context of species and ecosystem conservation. *Capreolus capreolus* (roe deer) fawns are often hidden between grass-covering meadows whilst waiting for their mother to come back. As meadows are being mowed and fawns are hard to detect, there is a danger of killing them by mowing machines, which is a problem from not only a perspective of animal conservation but also a contamination of gathered crops. Israel (2011) proposed a method of detecting fawns hidden in the vegetation using UAV and thermal imagery, because their body has a higher temperature than the surrounding vegetation. The survey was conducted during 15 days over an area of >70 ha during different time points of the day, weather and insolation conditions. This method needs further examination, because bare ground or roads can have higher temperature than vegetation, so it can cause mistakes. African savanna is full of open vegetation such as shrubs and trees, usually with a flat landscape that make it suitable for aerial surveys. Vermeulen et al. (2013) detected elephants using fixed-wing UAV flying at 100-m altitude in Burkina Faso. However, smaller animals such as buffon's kob or baboons were not visible from that height.

Despite this, there are later studies showing the possibility of detection of mammals smaller than elephants. Mulero-Pázmány et al. (2014) monitored *Ceratotherium simum* (white rhinoceros) in South Africa to assess the usefulness of UAVs against poaching. It was even possible to detect people with dogs on the UAV photographs and the authors suggested that they might have been poachers. However, there was no opportunity to distinguish the state of a wire fence, and video data were proposed as better suited for surveillance purposes than images. Rey et al. (2017) developed a semi-automatic animal-detection system based on machine learning. The system was trained with crowd-sourced annotations provided by volunteers who manually interpreted sub-decimetre resolution colour images. The system achieves a high recall rate, and a human operator can then eliminate false detections with limited effort. Animals detected using this method were *Equus quagga burchellii* (Burchell's zebra), *Giraffa camelopardalis giraffa* (Nubian giraffe) and *Struthio camelus australis* (ostrich). The data from this study were used by Kellenberger et al. (2018) who proposed another semi-automatic detection system using convolutional neural networks (CNNs), which are one of the deep learning algorithms. Barasona et al. (2014) studied a spatial distribution of tuberculosis amongst ungulates in Doñana National Park (south-western Spain). The authors modelled species host abundance, thanks to data gathered with a UAV. Great apes are a subfamily of species that are vulnerable to changing environment because of human activity. Those endangered animals are living mostly in tropical and subtropical rainforests, which are difficult to study, although UAVs can still be useful in such places. Wich et al. (2016) compiled an orthomosaic based on UAV imagery to later visually detect nests of *Pongo abelii* (Sumatran orangutan). It turned out that the number of nests detected from the ground was much higher than from aerial survey because of the variability of canopy openness. However, nest density analysis showed that nests detected from the ground and from UAV imagery have similar locations.

Bats are mostly active nocturnally, which makes them more difficult to be detected using passive remote sensing techniques. In most cases, bats are surveyed using microphones and thermal imagery. These methods were used by Fu et al. (2018) to measure echolocation signals and how the *Tadarida brasiliensis* (Brazilian free-tailed bat) bats avoid collisions in the air. The authors used a studied, custom-modified UAV equipped with microphone and thermal imaging camera. They had to overcome constraints that were noises emitted by the drone itself. The conclusion was that bats weren't disturbed by the UAV, but they were behaving towards it similar to any other object.

Birds are generally smaller than mammals but may form large colonies. UAVs were applied to assess the size of such colonies, and data obtained by drones give promising results in performing bird population censuses. Chabot et al. (2015b) counted nests of *Sterna hirundo* (common tern) and prepared a population census of this species in one of the biggest breeding colonies in North America. The results were validated by ground counting and showed some difficulties in accurate estimation of the number of individuals because of the colour similarity with surrounding vegetation and varying light conditions during the flights. In contrast, counting of *Fregata ariel* (frigate bird), *Thalasseus bergii* (crested tern) and *Eudyptes schlegeli* (royal penguin) individuals in different environments (polar and tropical) based on UAV imagery was more accurate than ground observation counting (Hodgson et al. 2016). An interesting approach to frequent UAV flights was applied to study the breeding activity of *Chroicocephalus ridibundus* (black-headed gull) (Sardà-Palomera et al. 2012). A fixed-wing UAV equipped with RGB camera took many images of the same area, and it was possible to indicate periods when the nests were active by comparing the images. Authors pointed out that birds from the studied colony were very sensitive to disturbances during ground survey, whilst when the flights were performed, they didn't seem to notice the presence of the UAV.

Many studies also incorporate the information about habitat that offers the possibility of modelling the distribution of a particular species based on habitat features. A complex study on *Larus canus* (common gull) combined automatic detection of birds, counting clutches and colony habitat assessment based on UAV images (Grenzdörffer 2013). The habitat was mainly characterised by morphological features and the height and structure of the vegetation. Chabot et al. (2014) studied habitat quality of the water bird (*I. exilis*, least bittern) by estimating the abundance of birds in artificial wetlands, also recording different habitat parameters.

Drones are often used to study penguins. The abundance of *Pygoscelis papua* (gentoo penguin) and *Pygoscelis antarctica* (chinstrap penguin) estimated using UAV was compared with previous ground-observed abundance on South Shetland Islands (Goebel et al. 2015) and Falkland Islands (Ratcliffe et al., 2015). Delord et al. (2015) used a kite to obtain imagery of *Eudyptes chrysocome* (macaroni penguin), *Aptedonytes patagonicus* (king penguin) and *Phalacrocorax bougainvillii* (Guanay cormorant) colonies, showing that the kite may be a cheaper alternative to UAVs to study penguin population density.

UAVs were also used for raptor research, mainly for observing nests and chicks, because these species are rather individual in their behaviour. Potapov et al. (2013) carried out long-term research on *Haliaeetus pelagicus* (Steller's sea eagle) in Magadan State Reserve, Russia, since 1992 using various equipments. In 2012, they also used UAV for observation of these raptors. This is an example that the use of UAV can be complementary to other research methods. Junda et al. (2015) studied nests of four species of birds of prey: *Pandion haliaetus* (osprey), *Haliaeetus leucocephalus* (bald eagle), *Buteo regalis* (ferruginous hawk) and *Buteo jamaicensis* (red-tailed hawk) in Montana, USA, and Saskatchewan, Canada. The authors used rotor-based UAV with GoPro cameras for recording videos and capturing photos of nests. It was pointed out that at least two persons were needed for this type of survey: a UAV pilot and an observer of bird behaviour towards a UAV. It was very important because birds, especially ospreys, were aggressive towards the aircraft. It even happened that a drone was knocked down by an individual. The nests and nestling of *Corvus cornix* (hooded crow) were classified according to a survey carried out using UAV and by climbing trees. Weissensteiner et al. (2015) pointed out that buying an off-the-shelf drone is less expensive than full climbing gear for two persons. It was observed that, in certain nests, the number of nestlings decreased between drone survey and climbing. Authors suggested that it is most likely due to nest predation, rather than UAV imagery inaccuracy. In general, nesting can be determined with high reliability. Moreover, the use of UAV gives more possibilities for surveying, because it is independent from size and shape of a tree or nest location.

Apart from optical surveys, UAVs can be used for radio-tracking birds. Tremblay et al. (2017) used this technique on small forest birds: *Catharus bicknelli* (Bicknell's thrush) and *Catharus ustulatus* (Swainson's thrush). The UAV equipped with radio-receiver was able to detect 50% of tagged birds during a flight at 50-m altitude, where the signal was stronger and more constant in comparison with ground-based signals. There was no significant interference of signal with UAV electronics. It was pointed out that aerial radio-tracking survey might give better results than the ground ones, although there is a need to perform longer and faster flights by drones. Rodríguez et al. (2012) used UAVs and GPS data loggers for study on *Falco naumanni* (lesser kestrel) and their habitat selections. They tracked birds using data loggers and then surveyed the area with UAV to take images to document flight paths of kestrels.

The last vertebrate class that was recently broadly investigated using drones is reptiles. Primarily, the research deals with endangered species and UAVs are helpful mainly in counting individuals. However, observing reptile behaviour is also possible by UAVs, and this particularly can lead to action on the matter of conservation. Bevan et al. (2015) used UAVs equipped with a GoPro camera to study the behaviour of *Lepidochelys kempii* (Kemp's ridley turtle), particularly their nesting, hatching and foraging at the nesting beach at Rancho Nuevo, Mexico. Videos were taken with satisfactory quality despite the turbid water in the research area. However, this study showed that the light UAV (in this case weight = 1,336 g) was susceptible to stronger winds. Therefore, in the later study, Bevan et al (2016) used a heavier drone (weight = 2,870 g) to observe reproductive behaviour (courtship and mating) of *Chelonia mydas* (green turtle). Another sea turtle (*Lepidochelys olivacea*, olive ridley turtle) was counted by observers on photos obtained from fixed-wing UAV (with NIR camera) on nesting sites located at Ostional National Wildlife Refuge in Costa Rica (Sykora-Bodie et al. 2017). The authors also used graphical software that allowed for reducing glare and generally improving the quality of the images as well as automated counting.

The second interesting group amongst reptiles are crocodiles. Similar to the turtles, their size is promising when considering to monitor these animals from the air. Evans et al. (2015) used fixed-wing UAV to search for nests of *Crocodylus porosus* (estuarine crocodiles) in Kinabatangan River in Sabah, Malaysian Borneo. Aerial photographs were then examined by observers who found three crocodile nests, but after validation in the field, it turned out that there were only two nests, as the unconfirmed one was an area of dead grass. The population density of other crocodiles, *Gavialis gangeticus* (gharial) and *Crocodylus palustris* (mugger), was assessed based on fixed-wing UAV-derived images taken by a GoPro camera in Babi River, Bardia National Park, Nepal (Thapa et al 2018). Also the most known crocodile, *Crocodylus niloticus* (Nile crocodile*) was counted using UAV imagery at* Lake Nyamithi, Ndumo Game Reserve in South Africa (Ezat et al. 2018). UAV images allowed for counting 20% more individuals than those obtained during simultaneous ground survey. Apart from the number of individuals, the crocodile body length was also estimated in the mentioned study.

6. FINAL CONSIDERATIONS AND PERSPECTIVES

The present study reviews recent scientific literature dealing with the use of UAV in environmental biology. From numerous papers, short communications and conference abstracts, we selected 110 study examples of how UAVs can be used in environmental biology and which organisms can be studied in this manner. We attempted to group papers included in this study according to their scope. A subjective separation of categories resulted from the varying purposes and differences in obtaining research material on plants and animals. The main application of UAVs related to animals is to count them, and using UAVs frequently proved to be a better method than surveys at the ground level. To observe behaviour or to count animals, it is enough to use a consumer-grade RGB camera that is able to take images and videos. In contrast, there are many different purposes of vegetation analysis, from assessing stress factors through biomass and morphometry to phenological timing of allergenic plants, which is important for human exposure to allergenic pollen. Frequently, there are no visible differences between healthy and infected trees on RGB photographs. Therefore, a thorough vegetation analysis requires much more sophisticated sensors such as multispectral or hyperspectral cameras. These devices are able to reveal features that are not visible to the human eye. As a result, we differently distinguished categories: animals were grouped according to their taxonomy and plants according to the purpose of the study. We found that most of the 'plant' studies dealt with measuring biophysical parameters of vegetation (14.5%) and time changes in vegetation at ecosystem levels (10.0%). Amongst 'animal' studies, birds (12.7%) and water mammals (10.9%) were mostly examined using UAVs. We also could indicate a category that gathers studies of interactions between different groups of organisms. Mainly, these studies involve plant pathogens, and in this work, we emphasised the role of UAV in monitoring damages to plant caused by fungi and insect pathogens (Figure 3).

Conventional remote sensing techniques such as different satellite imagery, for example ,Terra, Aqua, Landsat and Sentinel series, Proba-V, Ikonos, World View-2 or aerial imagery, revolutionised the monitoring of the Earth's surface in different spatial scales. What's more, the data from most of them are freely available to every user. Terra and Aqua satellites are equipped with, amongst others, a MODIS sensor that is able to sense radiation in many narrow bands (above 30 bands: high spectral resolution). Together, Aqua and Terra satellites take an image of a particular area two times during daylight hours and two times at night (high temporal resolution). However, the MODIS sensor has a very low spatial resolution and the pixel size is at least 250 m × 250 m (Vermote et al., 2015). In contrast, Landsat or Sentinel 2 satellites are able to acquire imagery with a spatial resolution of 30 m or even 10 m. In turn, these satellites have lower spectral resolution (approximately 10 bands) and much lower temporal resolution. Owing to the narrow path that could be sensed on a particular day, it takes 16 days to take a Landsat image in the same place (ESA 2015, USGS 2018). Therefore, each satellite sensor has its own advantages that are simultaneously balanced by the shortcomings. Moreover, none of the publicly available satellites with free data reach the spatial resolution of images lower than 1 m. Satellites cannot

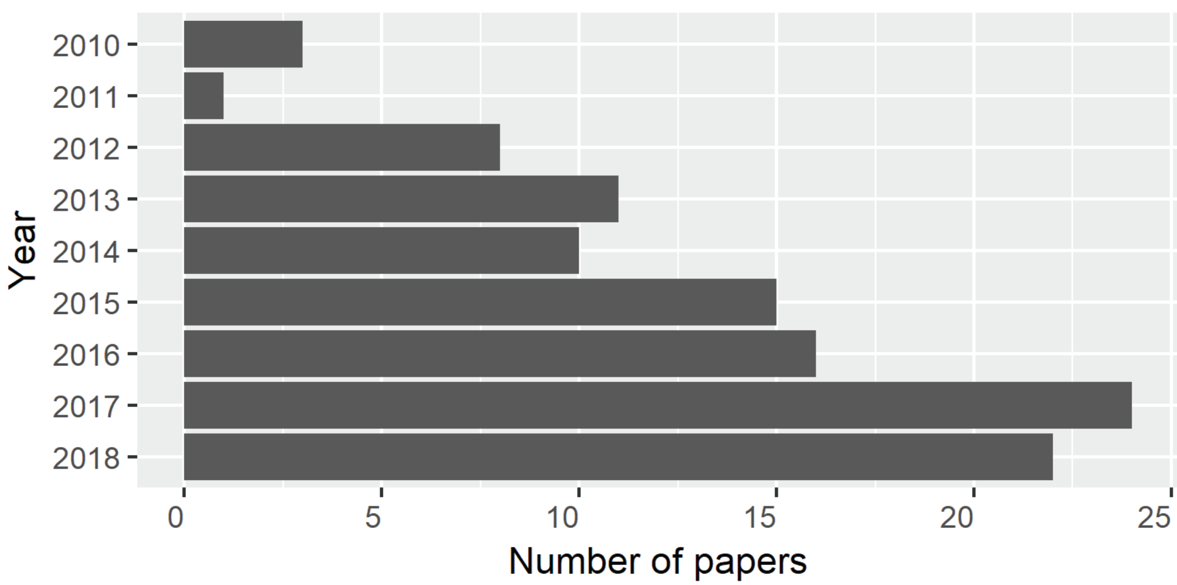

Figure 3. Number of publications dealing with UAV applications in environmental biology separated into categories proposed in this review. Category Reviews contains other review papers that describe the applications of UAV in different narrow fields within environmental biology. The chart was produced using R software and ggplot2 package (R Core Team 2018, Wickham 2009).

change their schedule for taking imagery when clouds cover the sensor field of view. What is more, none of the satellites have a hyperspectral camera aboard that is able to sense 200 narrow bands that could be adjusted in the spectral range. These limitations may be partially overcome by using manned airplanes. However, it generates high costs that have to be spent on fuel, hiring a pilot with a professional aviation licence and the camera operator. Also, a plane has to be adjusted to taking photos and also the frame for the camera has to be properly installed. Moreover, such manned planes are not manoeuvrable when there is a need to operate over smaller areas. A nearby airport, as well as fulfilment of all aviation procedures, is also needed, which increases the effort put into the survey. However, UAVs offer possibilities to overcome many limitations that are mentioned above. These devices are expected to substantially contribute to the technological and methodological advance in environmental biology in the future.

Amongst many advantages of UAVs that outperform conventional remote sensing techniques, some of the most important features should be mentioned. These advantages are usually broadly described in almost every paper with UAV applications; thus we only summarise them here. Considering the economical aspect, UAV operation costs are much lower than maintaining satellites or conventional planes. Even if we take into account UAV construction costs, staff training and certification, the costs will be affordable not only for universities but also for private people. Another aspect is the resolution of the information obtained. Owing to UAVs low altitude of flights, there is the possibility to sense the Earth's surface with much smaller pixel size (high spatial resolution) than in the case of satellites. UAVs are also perfect for monitoring small objects and areas but with high frequency. Satellites have their fixed revisit time but drones can be used even several times a day over the area of interest (high temporal resolution). Performing such frequent flights by manned airplanes would be very expensive, and considering the small objects, they may not have enough place to manoeuvre. The possibility of frequent flights is very important in temperate or equatorial climates where a dense cloud cover prevents from correct radiation recording. Taking into account the Landsat satellite, there is a probability that only several clear-sky images are available for a particular area per year. In contrast, drones fly under clouds and can be used even when the dense clouds entirely cover the sky. What is more, small-sized rotor-based UAVs do not require much space to take off because they are taking off vertically and this is useful in a difficult terrain. Drones are widely used in studies based on optical remote sensing, but there are many other applications. We shall mention acoustic surveys, where it was able to record sound using a microphone, although sound emitted by drone engines and its computer may interfere. Apart from remote sensing, there are also possibilities of direct surveys. For example, we should mention meteorological surveys (measuring temperature, humidity) that are very useful in environmental biology as well as gathering airborne biological samples, such as fungal spores or plant pollen, for their transport and human exposure assessment.

Despite the fact that UAVs have plenty of applications and overcome many limitations of traditionally used remote sensing products in environmental biology, they also have weak points. It is not always easy to obtain imagery of a high quality and issues such as horizontal banding noise or inhomogeneous radiometry across the photograph can occur. The quality of data also depends on UAV types and sensors; in other words, it depends on available funding. There are also some limitations related to survey object, for example, the target plant under dense tree canopy, a wild bee hive located at the top of a tree or the mobility of animals. In such cases, UAV-derived data should still be validated by ground surveys, which increases the effort put into the study. Another weak point is the operation time, but this mainly concerns the rotor-based UAVs. At present, the drone must be rather light to possibly extend the operation time. On the other hand, this limited power capacity forces the operators to install possibly light sensors on the drone. When the drone is equipped with a more sophisticated sensor, it has a very short operation time (Dijkstra et al., 2017). The use of drones is also diminished in research areas with limited access to electricity (Radjawali and Pye 2017). Similar to any other man-made object, UAVs have an impact on nature. There are cases that documented the interaction of UAVs and animals, mainly by modifying their behaviour by a flying drone. In most research on wildlife, the impact on animals was not observed, but some studies confirmed that mammals (Ditmer et al., 2015; Pomeroy et al., 2015) and birds (Weissensteiner et al., 2015; Vas et al., 2015; Junda et al., 2015; Chabot et al., 2015b) show signs of disturbance; however, those might not be seen externally by an observer. Thus, when planning such surveys, we need to consider whether our research won't cause more harm than good to animal species. Moreover, quality of data acquired by UAVs results from operator skills working in different environments such as marine, mountain and forest area and in different meteorological conditions. Another factor negatively affecting the possibility of data acquisition by UAVs is national or regional administrative regulations on legal drone flights. There are many legal restrictions for UAV operations such as maximum altitude and speed, daylight operations over uninhabited areas and within visual line of sight and prohibition or restriction for using UAVs over national parks and reserves. Often, the crew of a UAV must consist of a pilot and ground-level observer, both with some degree of experience, certification and licence.

In this article, we demonstrated that UAV technology by flying slowly at low altitudes makes it possible to acquire detailed information about the environment being applicable in studies of many fields in environmental biology. Nevertheless, it is expected that the NIR and SWIR thermal, hyperspectral sensors and laser scanners will be more adapted (by decreasing costs and complexity of use) for UAV applications. However, it must be noted that the demands for both spatial and spectral resolution depend largely on the purpose of the study – for example, good results can be achieved with substantially lower resolution if the vegetation is sampled at the most characteristic phenological phase (Müllerová et al., 2017). In turn, high spatial resolution can often compensate (to some extent) the lower spectral resolution. Furthermore, different environmental variable measurements such as sound, light, air temperatures, humidity and air pollution will be more accessible using UAVs. It is also expected that advanced future UAV constructions such as gimbal (pivoted support) or the oblique images acquisition will become more common in environmental biology. Moreover, the performance of image post-processing and spatial analysis will be increasingly automated. It should also be underlined that software user interfaces will become more readable and understandable for users inexperienced in image processing. In addition, cloud computing will be more popular within the field of photogrammetry and, probably, more companies will be offering such services or hybrid services of desktop software and cloud, which won't require advanced hardware or software. Finally, future UAV-based solutions that may be applied in environmental biology will be connected with using different data sources and multi-point of view approach. New sensors and samplers will be installed in several synchronised UAVs flying at different heights and sampling the biological air content. Furthermore, UAV-derived remote sensing data will be combined with multi-satellite remote sensing data. Considering that images from high-resolution commercial satellites (such as World View 4, spatial resolution 0.31 m; Pleiades, 0.5 m; SPOT 6 and 7, 1.5 m) will be less expensive, the UAV-satellite data fusion will be a possibility to obtain more up-to-date and accurate information about the biological part of the environment.

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