

African swine fever and detection dogs for wild boar carcasses

This is part of a broader study on the possibilities for deploying detection dogs to locate wild boar carcasses in the event of an outbreak of African swine fever (by Hilde Vervaecke and Manon De Meester, Odisee University of Applied Sciences, Belgium; steering committee members: Uta Kielau, Ellen Van Krunkelsven, Kristof Baert, and Arno Thomaes).



Eyes on the target

The use of drones to detect wild boar carcasses in the control and prevention of African swine fever

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Summary

First and foremost, an extensive literature review was carried out on the deployability of drones (UAV, UAS) with a view to applying this technology as a complementary tool for detecting wild boar carcasses in combination with search dogs. The first part of the literature review on drones examines the use of drones for monitoring live wild animals. Based on the literature studied within this theme, information could be gathered on the use of drones in forested environments and their impact on the welfare of wild fauna. In addition, it was possible to explore in more depth the use of cameras, including RGB and infrared cameras in densely vegetated areas, as well as the use of artificial intelligence models for automatically identifying animals in these camera images. Information on environmental factors that influence deployability could also be collected through this literature.

The second part of the literature review on drones focuses explicitly on the deployment of drones during the search for carcasses/bodies. For this purpose, literature from forensic sciences and archaeology was used, among other things, due to the animal models and the application of spectroscopy, LiDAR, photogrammetry and infrared imagery. The emergence of artificial olfactory gas sensors is also discussed.

This is followed by a summary of the most relevant information on legislation relating to the operation of drones. After this summary, the results of the surveys are discussed. Three different surveys were drawn up: one survey with more practical questions about the flight operation itself, one survey with questions about the different sensors, and one survey with questions concerning data processing. The aim was to gather qualitative information from the experiences and knowledge of experts in these fields. In addition, in-depth interviews were conducted by email and in person during an excursion to the TCRH training centre in Mosbach. The financial cost is also discussed, using information provided by respondents, including drone distributors. Finally, a discussion follows on the feasibility, strengths and pitfalls of this technology in relation to the objective (detection of wild boar carcasses).

Introduction

African swine fever is a problematic virus that is spreading within wild boar populations in Eastern Europe and is also circulating in Germany. It is deadly and highly contagious for suid species, and it carries significant economic consequences that should not be underestimated, such as major losses in pig farms during outbreaks and high costs associated with control measures (Cwynar et al., 2019). It is therefore extremely important to be well prepared for an infection within Belgium's wild boar populations so that rapid action can be taken to prevent further spread and infections in pig farms.

During a crisis situation, it is essential that all carcasses, carcass parts and bones of wild boar — in other words, potentially contaminated animal material — are located, removed and destroyed. However, finding them is a difficult task. Until now, Belgium has mainly relied on human search lines for this task, in which people comb an area on foot, visually and tactually using a stick (Draaiboek voor preventie en bestrijding van Afrikaanse varkenspest bij wild zwijn in het Vlaamse Gewest, 2024 and report TCRH Mosbach, 2025). The efficiency of this search technique, however, is questionable. A faster and more accurate way of screening areas is needed.

In this document, we therefore discuss the following: Would drones be capable of detecting wild boar carcasses? What are the pitfalls and strengths of this technology? And what is the overall feasibility?

Literature review on the deployability of drones:

Using drones to monitor wildlife

UAVs (unmanned aerial vehicles), also known as drones, originated in the military and were first introduced in 1916 for military applications (Cook, 2007). Today, drones are also used by civilians and are deployed across various fields for a wide range of purposes thanks to the development of machine learning models and artificial intelligence. For example, they can help in mapping traffic congestion, monitoring pollution, analysing crop growth in the agricultural sector, and tracking pest species (Al-Emadi et al., 2019; Singh et al., 2020; Yang et al., 2024).

In addition, drones have become increasingly interesting for ecologists and are used for environmental and ecological monitoring (Koh & Wich, 2012; Mulero-Pázmány et al., 2014), wildlife population monitoring and research (Christie et al., 2016; Linchant et al., 2015), fine-scale mapping (Zweig et al., 2015), vegetation studies (Getzin et al., 2012), and even for collecting biological samples, including exhaled blow from whales (Acevedo et al., 2010). They are also used for gathering animal behaviour data (Fiori et al., 2020; Graving et al., 2019), anti-poaching surveillance (Mulero-Pázmány et al., 2014), and much more.

Drones are being used increasingly for wildlife monitoring and censuses (Vermeulen et al., 2013) and have already been applied to various taxa, including fish (Kiszka et al., 2016), reptiles (Ezat et al., 2018), birds (Chabot & Bird, 2012), and both terrestrial and aquatic mammals (Hodgson et al., 2013; Witczuk et al., 2018).

Impact on wildlife welfare

When deploying drones for monitoring animal species, or when drones are operated in nature-rich areas, the potential impact on animal welfare must be taken into account. In several countries, drones are banned in nature reserves due to concerns about their impact on wildlife following repeated reports of drone misuse (Baltrus, 2014; Duporge et al., 2021). Drones can have a stress-inducing effect on animals, although the degree of this effect varies between individuals and between species (Bennitt et al., 2019; Chabot & Bird, 2012; Larsen et al., 2023; Wilson et al., 2022). Differences in reaction and stress levels between individuals of the same species can be influenced by environmental factors. For example, animals living closer to village or city boundaries are more quickly habituated to unfamiliar objects or sounds (Tablado & Jenni, 2017). Differences in responses between species may be related to variation in sensitivity to sound (Bennitt et al., 2019; Bracha, 2004). This sensitivity to sound includes not only the intensity (decibels) but also the frequency (hertz). Different species show varying sensitivities to specific frequencies. Elephants, for instance, are particularly sensitive to the sound of bees, and therefore drones producing similar frequencies are discouraged in elephant research (King et al., 2007). These species-specific sensitivities to frequencies must be better understood in order to optimise drone use for the target species, while also accounting for the fact that some species are sensitive to ultra- and infrasound (Heffner & Heffner, 1982).

To reduce the effect of drone noise on the stress levels of wild animals, it should be taken into account that the sound is perceived as loudest when the drone flies directly above the animal (Duporge et al., 2021; He et al., 2020). In addition to sensitivity to sound, species-specific adaptations (including those of rodents) to flying predators may also play a role in their response to drones (Mesquita et al., 2021). For example, a study found that martens and hares (not rodents, but species that are alert to birds of prey) did react to drones flying at heights of 109 m and 116 m, respectively, whereas a badger showed no reaction when the drone flew 60 m above it. However, none of these animals fled (Larsen et al.,

2023). In several studies, no behavioural changes were observed during drone overflights. This was the case for moose (McMahon et al., 2021), elephants (Vermeulen et al., 2013) and penguins (*Pygoscelis* spp.) (Goebel et al., 2015). In contrast, Eld's deer showed clear signs of stress and fled when the drone flew 10 m above them, while showing no response at 20 m altitude. Hog deer were less inclined to flee and only showed signs of noticing the drone when it flew at 10 m altitude, yet they did not flee (Nath Tripathi et al., 2024). Although flight behaviour and alertness signals can be good indicators of stress, it should not be forgotten that stress may also be present without being visibly apparent, as has been observed in bears (Ditmer et al., 2015). It is therefore important not to fly closer to animals than is necessary to collect data. Moreover, approaching animals intermittently rather than continuously tracking them can help to reduce stress. It is also recommended to avoid flying over the same animal more than once (Hodgson & Koh, 2016; Nath Tripathi et al., 2024).

Using cameras (RGB and thermal) and identifying species in images

Drones are often equipped with colour cameras (also known as RGB cameras) and infrared / thermal cameras. Colour cameras record visible light reflected by objects, while thermal cameras detect the part of the light spectrum emitted by heat sources such as (endothermic) animals, in contrast with a cooler environment. This contrast is therefore a requirement for generating clear thermal images (Garner et al., 1995; McCafferty et al., 2015). The use of infrared cameras is considered an effective method for monitoring wild animals, particularly due to their advantage over RGB cameras in detecting animals that are otherwise difficult to observe because of their camouflage, their nocturnal activity, or their tendency to hide quickly under trees or shrubs (Haroldson et al., 2003; Howell et al., 2021; Rahman et al., 2020; Shewring & Vafidis, 2021). On the other hand, very dense, interwoven tree canopies or other thick vegetation can limit detection with infrared cameras (Dunn et al., 2002; Kissell & Nimmo, 2011). Knowledge of the behaviour of the target species, including foraging behaviour such as seeking open grasslands to graze, can help in planning flights at locations and times when the likelihood of detection is highest (De Kock et al., 2022). This is usually just before sunrise and just after sunset. These times also have the added benefit that the thermal contrast between the animals and their surroundings is greater. During midday on warm days, the “hot crown effect” can occur, where heated treetops become almost indistinguishable from animals on thermal imagery or can completely obscure them (Frąckowiak & Goraj, 2023). A disadvantage of infrared cameras compared with RGB cameras is that animals appear very small in the images and the images are generally of low resolution. This can complicate identification (Lyu et al., 2024). To reduce this problem, it is recommended to fly directly above the target animal and film vertically downwards so that only the dorsal part of the animal is visible in the image. This prevents distortions of proportions caused by filming from different angles (Larsen et al., 2023; Nath Tripathi et al., 2024). When all observed animals are filmed in this manner, they can be distinguished from one another based on body length and body proportions. For this, however, a reference measurement visible in the environment and on the images is needed. The shape and characteristic thermal signature of the species can also be used to differentiate between species (Larsen et al., 2023).

The more similar animal species are to one another, the more difficult it becomes to distinguish them. In addition, manually screening and analysing the images is an intensive and time-consuming task. Deep learning models are currently being developed to address these issues and to achieve reliable automatic species identification (Wäldchen & Mäder, 2018). A distinction is made between pixel-based methods and region-based methods for recognising objects in images. Pixel-based methods consist of a multi-stage process: data preprocessing, digital segmentation (splitting the image into segments based on certain properties, with these segments then represented in different colours), object recognition, feature extraction, feature selection and object classification. It is up to experts to select

unique characteristics of animals—such as colour, contrast, shape or texture—for which a threshold value is then determined for each species. When a pixel exceeds this threshold value, an algorithm will use this information in identification and differentiation (Lyu et al., 2024; Zou et al., 2023). HOG (Histogram of Oriented Gradients) is an example of a pixel-based method with which deep learning models can be trained to identify animal species (Rangdal & Hanchate, 2014). Region-based methods analyse and process images at a more conceptual level and make use of convolutional neural networks (CNNs). Examples include Faster R-CNN and YOLO (Lyu et al., 2024; Ren et al., 2016). From R-CNN, for instance, a detection model can be constructed to identify deer in thermal images captured by drones, as in the study by Lyu et al. (2024). To construct a reliable model, an extensive collection of images is required in which the target animal is visible from the perspective of drones. These images are then used to train the deep learning model (Hey et al., 2020).

Training artificial intelligence to recognise animal species is more efficient with colour images (RGB images) than with thermal images. This is because colour images contain more pixels, are therefore sharper, and can be enlarged or zoomed in more effectively. Thermal images have a limited resolution, making it harder to locate animals in the image, which is less of an issue with RGB images. In addition, colour images (RGB) naturally have a wider colour spectrum, allowing colour to be used as an additional feature for identification (Lyu et al., 2024). However, capturing RGB images is not always possible due to dense vegetation or well-camouflaged species. Therefore, training deep learning models on thermal images is recommended. Other factors that limit the training of artificial identification models include morphological differences between sexes, differences between animals at various life stages, and the different postures that animals assume. Although they belong to the same species, these factors create shape variations that can impede recognition by the model or complicate its training (Dawson et al., 2021; Lindenfors et al., 2007; Marti & Ryser-Degiorgis, 2018). In addition to these intraspecific differences, some external factors also negatively affect detection and identification, such as background movement, weather conditions (fog blurs the image, and hot days cause the “hot crown effect”) (Frąckowiak & Goraj, 2023), and variations in altitude. If the drone is forced to change altitude frequently due to hills, mountains, or uneven tree heights, significant scale variation can occur, which can further complicate the artificial learning process (Lyu et al., 2024). Background elements such as rocks or tree stumps can also be disruptive, as they may be confused with animals of similar colour or shape in RGB images. On hot days, when these elements emit thermal radiation after heating, they can also interfere with thermal images (Dunn et al., 2002; Garner et al., 1995). Despite these challenges, the potential of deep learning models for object recognition is enormous, and future studies will likely determine how these limitations can be overcome.

Operationality and factors that can influence deployability:

When deploying drones during field research, several factors need to be considered. One of the most important factors is the weather, which can significantly influence drone operability. Although fixed-wing UAVs have already been successfully tested in extreme weather conditions, such as those in Antarctica, turbulence and gusts of wind generally remain a concern (Goraj, 2014; Rodzewicz et al., 2018). The reason it is advised against flying drones in strong winds is that wind undermines the stability of the drone, increasing the risk of losing directional control and causing collisions with objects such as trees. Such incidents can have disastrous consequences for the drone (Weissensteiner et al., 2015). Additionally, turbulence and high wind speeds can cause network connectivity issues, which may also be caused by electromagnetic interference from nearby power lines during the flight. Frequent signal loss limits the distance the drone can cover and the speed at which the mission can be completed (Nath Tripathi et al., 2024). Because wind affects drone stability, gusts also result in blurry and unclear images and video footage, especially for thermal (TIR) images (McMahon et al., 2021). Not

only wind but also fog and rain negatively affect the quality of infrared images, with rain carrying the added risk of water damage to equipment (Burke et al., 2018; Duffy et al., 2017; Gordon et al., 2007). For capturing clear thermal images, flying on cloudy days is preferred. Clouds are beneficial because sunlight can be a very disruptive factor when identifying animals. Warm days reduce the contrast between the animal and its background in thermal images, and solar radiation can heat other objects, making them appear as thermal hotspots that may be misidentified as animals (Chrétien et al., 2016; Dunn et al., 2002; Lethbridge et al., 2019). Cold, overcast winter months, particularly following snowfall, are therefore ideal for detecting animals, provided wind speeds are low. The lack of foliage and the increased contrast with the cold ground produce clearer images. When the distribution of the species is not a examined factor of the study, feeding sites can also be used during this period to facilitate detection, as food is scarce in winter (McMahon et al., 2021).

One factor that determines the suitability of a drone for a mission is the distance the UAV can cover and the time required to do so. Below are some examples of multirotor models from various wildlife monitoring studies. The DJI Matrice 300© equipped with an infrared camera was able to survey 4 km² during its battery life, which lasted 45 minutes (Larsen et al., 2023). With the DJI Inspire 2 quadcopter© fitted with a FLIR infrared camera, a shorter battery life of approximately 20 minutes was observed due to hardware limitations (McMahon et al., 2021). The DJI Mavic 2 Enterprise Dual©, equipped with both a TIR (thermal infrared) and VIS (visual image sensor), had a flight time of 31 minutes and a maximum range of 2.3 km (Nath Tripathi et al., 2024). In general, the flight time for smaller multicopters is around 30 minutes, while larger fixed-wing drones can remain airborne for up to 24 hours. Considering fixed-wing models, the distance drones can cover ranges from approximately 3 km to 6,000 km. Due to this wide variety, it is important to conduct a thorough preliminary study to select the model that best meets the needs of the research (Christie et al., 2016). Multirotor drones, with rotating wings, are very suitable for low-altitude flights in hard-to-reach areas due to their ability to move slowly and take off and land vertically. When there are few obstacles, these drones can easily perform their tasks at an altitude of 15–20 m. They are ideal for collecting detailed data, a benefit further enhanced by their ability to hover in place. However, flying too high can reduce stability due to increased wind speed at higher altitudes. At heights of 90 m, warning signals are often issued, and it is advised not to maintain or exceed this altitude. The disadvantage of this height limitation is that the survey area is reduced because less distance can be covered within the battery's flight time. Conversely, fixed-wing drones are ideal for covering longer distances at higher altitudes and surveying larger areas. They are used to collect a large quantity of images, in contrast to the higher quality data collected by multirotors, and are ideal for mapping the distribution of species with large habitats and heterogeneous dispersal patterns (Chabot & Bird, 2015; Nath Tripathi et al., 2024; Povlsen et al., 2022).

Comparing drones with other monitoring methods

This section provides a comparison between the use of UAVs for monitoring wildlife and several traditional methods with the same goal, highlighting the advantages of UAVs compared to these other approaches. A comparison with detection dogs is not included here, as a separate document is dedicated to this comparison (Search dogs and drones as a method for detecting wild boar carcasses: A comparison and exploration of their complementarity; 2025). Traditional census methods include ground counts such as the sample plot method. This involves systematically searching an area on foot, with people walking in long rows to flush animals from a selected section of land so that they can be counted. Although this method is commonly used, it has many disadvantages. Firstly, a large number of people (more than 50) is needed to conduct the survey properly, and it is very time-consuming. This work is often carried out by volunteers, but recruiting enough participants and maintaining their commitment is challenging. When paid personnel are employed, costs quickly rise. Additionally, this

method is highly invasive and significantly impacts the welfare and stress levels of wildlife. It also poses risks for the personnel conducting the survey, especially on uneven, difficult-to-navigate terrain or when there is a possibility of encountering dangerous species or aggressive individual animals. Furthermore, this method is ineffective for counting animals that are camouflaged, hidden, or active at night (Chabot & Bird, 2015; Ditmer et al., 2019; Frąckowiak & Goraj, 2023; Larsen et al., 2023). To address this, lamps are often used during nocturnal ground surveys. When light from these lamps shines on the tapetum lucidum (the reflective layer in the eyes of many animals), the eyes become clearly visible as points of light, facilitating the count. However, it has been observed that the use of infrared sensors produces better results than lamps for effectively detecting and identifying animals at night (Collier et al., 2007).

Another method for monitoring animals is by capturing individuals and fitting them with a transmitter. This approach is often used for young animals, such as calves of ungulates. However, it is highly invasive for the animals involved and causes significant stress for both the mother and the offspring. This stress can have serious consequences, such as the mother abandoning her young, potentially resulting in calf mortality (Del Giudice et al., 2015; Livezey, 1990). In a study by Del Giudice et al. (2015), 18.4% of moose calves were abandoned by their mothers within 42 hours following human handling. The stress caused by human approach and handling of wild animals could be avoided with drones, provided they are operated ethically and a wildlife-friendly distance is maintained (McMahon et al., 2021). Additionally, it has been noted that deploying a drone can be less expensive than employing a large number of people for ground-based surveys if all personnel require payment for their working hours. Another advantage of UAVs is that they can be equipped with sensors such as high-resolution RGB cameras and (forward-looking) infrared sensors (FLIR), which greatly enhance the detection of animals. Moreover, drones can perform additional tasks, such as remote tranquilisation and sample collection (Chabot & Bird, 2012; Christie et al., 2016; Witczuk et al., 2018).

Manned aircraft, such as helicopters, have traditionally been used to study species distribution. However, this practice is gradually being replaced by the use of drones for several reasons. Drones are less disruptive to wildlife as they are quieter and less visible (Colefax et al., 2019; Mulero-Pázmány et al.; Yang et al., 2019). They are also much safer than manned aircraft. Wildlife monitoring operations that require low-altitude manned flights are among the leading causes of fatal accidents for professionals working in the wildlife sector (Sasse, 2003). UAVs can fly much lower and slower than manned aircraft and are remotely operated, which limits risk (Anderson & Gaston, 2013). Another advantage is that multirotor UAVs can take off and land easily in many locations and are not constrained by cloud cover. They are also much cheaper than manned aircraft and more logistically feasible (Chabot, 2009; Linchant et al., 2015; Vermeulen et al., 2013). The purchase cost of manned aircraft can exceed \$60,000 depending on the model, and operational costs range from \$300 to \$6,000 per hour. By comparison, UAVs start at around \$300 for the cheapest commercial basic model (Christie et al., 2016). When monitoring moose calves, manned aircraft with visual observation proved less effective (61% chance of detection) than drones equipped with a TIR sensor for capturing thermal images (85% chance of detection) (Del Giudice, 2018; McMahon et al., 2021).

Although drones are a promising technology, they are not without drawbacks. Many of these disadvantages have already been discussed in this literature review, such as their potentially stressful effect on wildlife and their dependency on weather conditions during flights (Hodgson & Koh, 2016; Weissensteiner et al., 2015). Another drawback is the relatively limited range of multirotor drones due to their short battery life and regulations that may require the drone to remain within the operator's line of sight (Watts et al., 2010). Drones are most effective for wildlife monitoring when equipped with an infrared sensor. However, these sensors also have limitations. The resolution is often very low,

making identification not always possible. Additionally, there is the previously discussed issue of heated objects under strong sunlight, which can cause false positives. Capturing large amounts of imagery also makes post-flight analysis very time-consuming. Automatic identification models are under active development but are not yet always reliable or available for the intended purpose (Frąckowiak & Goraj, 2023; Lyu et al., 2024).

Limitations and capabilities of different sensors in combination with UAVs and their potential contribution to finding carcasses

Searching for wildlife carcasses is closely related to monitoring wildlife with drones. It involves detecting a specific target that may be concealed by vegetation, where the use of cameras with sensors to capture images—subsequently analysed, either manually or automatically using algorithms and deep learning models—is optimal. The main difference is, of course, that carcasses are dead. They no longer move and no longer emit heat. In addition, animals that are dying tend to seek shelter (Morelle et al., 2019). This makes detecting a carcass a particularly challenging task. Because the literature on this specific issue is very limited, research from forensic sciences is also consulted. This field often uses animal models, such as domestic pigs, which is relevant to detecting wild boar carcasses. Archaeological and anthropological literature is also examined, as these disciplines similarly focus on detecting hidden objects (including bones) and structures, often in densely vegetated areas. In addition to applying the previously discussed infrared sensors, including thermal imaging, other techniques that may be promising for carcass detection are considered. These include imaging spectroscopy using hyperspectral or multispectral imaging spectrometers, distance measurements through photogrammetry and LIDAR lasers, and the use of artificial olfaction.

Use of infrared cameras

When an endothermic organism dies, its body begins to cool. In the case of wild boar carcasses, this cooling process occurs at a rate of approximately 0.5 to 1 °C per hour. Consequently, it is possible to detect very recently deceased animals using infrared sensors. However, between one and two days post-mortem, the body has generally cooled too much for infrared sensors to be effective. Even though the body itself no longer produces heat, these sensors can still be used to detect carcasses if deployed at the right time and in the right place. This is because, during the decomposition process—starting between the third and seventh day after death—necrophagous invertebrates and microbes colonise the carcass in sufficient numbers to eventually emit heat visible in thermal imagery (Hohmann et al., 2021; Sandor et al., 2025). This effect is most pronounced with fly species from the Calliphoridae family, which lay their eggs in the carcass. Once the eggs hatch, the larvae feed on the tissue, producing metabolic heat. The larger the larval mass, the more heat is emitted. This phenomenon is known as the “larval mass effect” (Charabidze et al., 2011; Slone & Gruner, 2007). The amount of heat produced varies depending on the stage of decomposition and can range from 3 °C to 25 °C above ambient temperature, taking into account variations in ambient temperature. These findings differ between studies and are influenced by multiple factors, which will be discussed in more detail later.

The presence of larvae accelerates the decomposition process, meaning that advanced decomposition is reached more quickly when larval numbers are high. This is the stage where temperatures are highest and, consequently, detection probability is greatest (Amendt et al., 2017; Butters et al., 2021; Des, 2014; Descalzi, 2019; Lee et al., 2018; Nigam, 2018). For example, in a study by Rietz et al. (2023), a significant difference was observed between the temperature of wild boar carcasses in the putrefaction stage and in the advanced decomposition stage. Temperatures during the putrefaction stage were considerably lower, resulting in a much lower probability of detection, approximately 16%. It is only during the decomposition phase that larval numbers and activity increase and other detritivores begin

to colonise the carcass. The number and activity of invertebrates continue to rise, peaking during the advanced decomposition stage before declining. As the temperature rises with the increasing number of invertebrates, the difference between the carcass and its surroundings reaches its maximum. In the study by Rietz et al. (2023), this difference was more than 6.4 °C above ambient temperature (not mentioned in the study), increasing detection probability to between 50% and 80% (Rietz et al., 2023). According to Hohmann et al. (2021), the mean temperature of the carcasses ranged from 9 °C to 18 °C above an ambient temperature of 14–21 °C. Their study indicated that this temperature difference persisted from day 12 to day 21 post-mortem (Hohmann et al., 2021).

The large variation in detection probability within the advanced decomposition stage (specifically, the 50%–80% range reported by Rietz et al., 2023) indicates that not only the stage of decomposition determines the likelihood of detection; other factors also play a role. Moreover, the variation in the temperature difference between the environment and the heat emitted by the carcass (as previously discussed, ranging from 3 °C to 25 °C above ambient) is influenced by more than just the decomposition stage. Environmental factors such as weather and habitat are equally important in determining this difference and, consequently, the detection probability. For example, detection probability is much higher in open habitats such as grasslands (>70%) than in densely wooded areas. When canopy cover exceeded 29.3%, detection probability dropped below 25%. A positive correlation was thus observed between openness and detection probability (Rietz et al., 2023). Beyond the direct effect of the environment on the detection potential of drones equipped with infrared sensors, the environment also indirectly affects detection probability through its influence on decomposition. The environment provides the habitat for invertebrates and the thanatomicrobiome; therefore, the species composition and abundance of these organisms depend on the environmental conditions. Factors such as plant species, relatively high humidity, soil type, and degree of shelter can determine the diversity of necrophagous insects and other detritivorous or saprophagous (micro)organisms, which in turn affect the decomposition process (Babcock et al., 2020; Baz et al., 2014; von Hoermann et al., 2020).

Temperature, in addition to moderate humidity, is also critical for decomposition. In general, higher temperatures accelerate decomposition due to increases in microbial and invertebrate activity, resulting in more metabolic heat (Carter et al., 2009; Meyer et al., 2013; Probst et al., 2020; Santos et al., 2016). A temperature above 3 °C is necessary for many necrophagous invertebrates and microbes to survive and reproduce. Consequently, detection probability is highest on warmer days, whereas at air temperatures below 3 °C, it drops to less than 25%. When searching on warm days, the limitations of infrared sensors under strong solar radiation must be considered; detection is therefore recommended during warm but cloudy conditions (Rietz et al., 2023). Conversely, excessively high humidity or extreme temperatures can slow or even halt decomposition entirely. For instance, adipocere formation (“corpse wax”) can occur in overly moist, low-oxygen environments, and mummification can occur in excessively hot and dry environments (Carter et al., 2010; Fiedler & Graw, 2003).

Carcass size also affects the heat emitted and thus detection probability. Smaller carcasses attract fewer blowflies and provide less food for larvae, resulting in a smaller “larval mass effect.” Additionally, smaller carcasses are more easily moved, hidden, buried, or entirely consumed by scavengers such as corvids, foxes, or even carrion beetles (Silphidae) (Henry et al., 2021; Santos et al., 2016; Spicka et al., 2011; Trumbo & Sikes, 2021; Zhou, 2011). Finally, the health of the animal before death influences the rate of decomposition. Dehydration or pre-existing haemorrhages can reduce microbial dispersal throughout the body, and essential proteins for initiating the putrefaction phase may be lacking, delaying decomposition. Conversely, wounds facilitate insect entry, allowing blowflies to lay eggs more rapidly in the carcass (Sandor et al., 2025; Zhou, 2011).

Use of imaging spectroscopy with hyper- and multispectral images

Spectroscopy is the science of studying substances based on their electromagnetic spectrum. Radiation, such as light, can be split into bundles of colours using a diffraction grating or prism, with each colour corresponding to a different wavelength. This principle is useful for identifying elements because atoms can emit light when heated. When electrons transition from a higher to a lower energy level, the atom loses energy in the form of photons. The wavelengths of these photons differ for each element, giving each element a unique emission spectrum. The opposite is the absorption spectrum, which shows the colour spectrum of radiation directed at the atom minus the wavelengths absorbed by the atom itself (Op-Tec, 2008). An imaging spectrometer utilises the full electromagnetic spectrum and is based on the principle of spectroscopy, whereby substances can be identified according to the wavelengths they emit, absorb, or reflect. The system captures images, and each pixel is coloured according to the material visible at that pixel based on its characteristic reflective and emitted spectrum (Krekeler et al., 2023). Imaging spectrometers can be mounted on UAVs, provided that their weight does not exceed the allowable payload. Very lightweight spectrometers have already been designed to address the limitations of payload capacity (Burkart et al., 2014). Little is known about the use of spectrometers for detecting wild boar carcasses or the ASF (African Swine Fever) virus. However, spectrometers are being investigated for applications in forensic science, such as detecting blood on fingerprints and determining its age (Cadd et al., 2018), or finding gunshot residue (De Carvalho et al., 2018). They have also been explored for locating hidden graves. In these controlled experiments, animal carcasses were used as substitutes for human bodies, including pigs, rabbits, and cattle (Kalacska & Bell, 2006; Kalacska et al., 2009; Leblanc et al., 2014; Ruotsala, 2020; Silván-Cárdenas et al., 2017).

A carcass serves as a source of nutrients for nearby plants. Phosphorus, magnesium, potassium, calcium, and nitrogen are examples of nutrients required for plant growth, which are released into the soil during the decomposition of a body (Hunt Jr et al., 2011; Silván-Cárdenas et al., 2021). Chlorophyll is a nitrogen-containing compound, so plants need nitrogen to form chloroplasts. The amount of nitrogen—or nutrients in general—absorbed by a plant is positively correlated with the quantity present in the soil. Therefore, the more nitrogen present in the soil, the more the plant will absorb (Hunt Jr et al., 2011; Netto et al., 2005). Light reflected at wavelengths between 530 and 630 nm (yellow-green) and around 700 nm to 960 nm (red to near-infrared) is positively correlated with the concentration of chloroplasts and nitrogen in the plant. This wide range of characteristic spectral wavelengths arises from the great variability among plant species, so the spectral characteristics are species-specific. Using a spectrometer, the nitrogen concentration in plants can be determined, which is noticeably higher in areas where a carcass is hidden or has already decomposed (Benninger et al., 2008; Carter et al., 2007; Hopkins et al., 2000; Yoder & Pettigrew-Crosby, 1995). The elevated nitrogen concentration can persist for a long time after decomposition begins, in some cases even for years. On the other hand, it takes months for the increased nitrogen concentration to become visible in the vegetation surrounding the carcass or grave—typically 2 to 4 months—depending on the rate of decomposition, which in turn is influenced by temperature, weather, soil type, and the presence of saprophytic and necrophagous species (Brabazon et al., 2020; Silván-Cárdenas et al., 2021; Silván-Cárdenas et al., 2017).

By enabling the detection of subtle differences in light reflection from vegetation, spectrometers mounted on drones are used not only in forensic research but also in archaeology. In the search for archaeological sites, images of the canopy are captured using satellites, helicopters, or UAVs. These images are then analysed for abnormalities in vegetation to uncover hidden structures. This technique is known as “crop marks photography” (Aqduş et al., 2012; Lehmann et al., 2015; Peña-Villasenín et al.,

2024). Small variations in plant health can indicate unusual structures or elements in the soil, or the presence of bones. Such differences can be detected with spectrometers, and by analysing these hyperspectral images, anomalies can be identified (Beck & Cowley, 2011; Cavalli et al., 2007; Doneus et al., 2015). Analysing these images is not straightforward, as it requires extensive knowledge of spectrometry and specialised software to obtain reliable results. It is also essential to have a reference library so that each pixel can be interpreted correctly. Additionally, the large volume of data generated during a flight poses a challenge, requiring substantial storage capacity, which is often limited or unavailable. It has been suggested to install a small onboard computer to manage this, but doing so can exceed the maximum allowed payload of the drone (Aasen et al., 2018; Krekeler et al., 2023; Lasaponara & Masini, 2012; Opitz & Herrmann, 2018). Manually screening and analysing these images is extremely time-consuming. The question remains whether, similar to infrared imagery, artificial intelligence models could be trained to automate and accelerate these analyses; however, this also requires substantial training data. Further research is needed to assess the efficiency of this approach.

Spectroscopy is a promising technique, and imaging spectrometers have already been successfully applied to a variety of purposes beyond forensic research and archaeology, including geological mapping (Cracknell & Reading, 2014), petroleum exploration (Allen & Krekeler, 2011), hydrocarbon detection (Hörig et al., 2001), identification of plant diseases or water stress in orchards (Calderón et al., 2013; Zarco-Tejada et al., 2014), studies on the effects of carbon dioxide and nitrogen oxides on climate (Aumann et al., 2005), and detection of invasive plant species (Ustin et al., 2002). Although no literature was found on the use of drones equipped with spectrometers for the detection of wild boar carcasses and African swine fever (ASF), these studies demonstrate the potential of this technology. Further research on spectroscopy in the context of ASF control is required to determine its feasibility.

Satellite-based hyperspectral imagery has already been used to map the locations of crops, beech trees, and European oaks, as well as to assess the condition of crops such as maize. Based on this information, the habitat and distribution of wild boar could then be predicted with a certain probability (Bergmann et al., 2023). This can be useful for identifying smaller target areas from these images in order to plan drone flights equipped with, for example, infrared sensors.

Use of photogrammetry and LIDAR

Infrared, RGB, multispectral, and hyperspectral imaging sensors use two-dimensional images, which can then be interpreted either with the help of algorithms or by a trained professional eye. To obtain additional or different information, such as measurements, a three-dimensional image can be generated. There are two ways to achieve this: through photogrammetry (including the Structure from Motion technique) or by using Laser Imaging Detection and Ranging (LIDAR). We will discuss both techniques, but first focus briefly on photogrammetry.

Photogrammetry:

Photogrammetry is a coordinate-measuring technique that uses photographs to generate three-dimensional images. This technique relies on triangulation, based on the principle that all properties of a triangle can be calculated if only some are known. In photogrammetry, at least two photographs of a location are taken from two different positions. “Lines of sight” or “rays” are lines from the camera’s focal point to points on the object or site being photographed. From these lines, three-dimensional coordinates can be calculated. Photogrammetry is essentially a combination of photography and metrology (Ganci, 2017). The technique is used to detect or study objects, which can also include animals. Photogrammetry has been applied to measure elephants (Shrader et al., 2006), marine mammals (Pinnipedia) (Meise et al., 2014), hippopotamuses (Inman & Leggett, 2022), and deer (Smith et al., 2021). When used with a drone, this provides a safer and more animal-friendly alternative

to capturing, sedating, and handling animals to obtain the same information (Inman & Leggett, 2022; Linchant et al., 2015).

Beyond wildlife monitoring, photogrammetry is also applied in forensic searches for hidden graves. It can be used to construct a digital surface model with precise relief from photographs. Algorithms can then detect relief abnormalities that may indicate previous ground disturbances, such as excavations (Batson et al., 1975; Silván-Cárdenas et al., 2021). Algorithms such as Faster R-CNN, RetinaNet, Cascade R-CNN, and YOLOv4 are also suitable for automatic object detection and recognition with high efficiency. However, their effectiveness decreases when objects are hidden under vegetation, such as tree canopies or shrubs (Huang et al., 2024; Martinez-Esteso et al., 2025; Paulin et al., 2024). Detecting small objects, such as bones, has also proven unsuccessful with photogrammetry (Urbanová et al., 2017). The same problem arises in wildlife monitoring studies when measuring animals partially obscured by vegetation. One solution is to use multiple imputation, where plausible values are derived from the distributions and relationships of observed variables in the dataset. These generated values are then used to fill in missing data (Inman & Leggett, 2022; VanBuuren, 2018; VanBuuren & Groothuis-Oudshoorn, 2011). In earlier studies, average measurements of other animals were used to supplement missing data (Poolea et al., 1980), or animals that were partially obscured and lacked complete data were excluded from the dataset (Inman et al., 2019; Taylor et al., 1977).

As previously noted, forensic research has explored the use of imaging spectroscopy and infrared cameras. If these images have a sufficiently high resolution, they can be used to create a 3D model via photogrammetry. This may potentially increase the detection probability of hidden objects, although very dense vegetation remains a challenge (Nègre et al., 2025; Turner et al., 2020). One advantage of photogrammetry over LIDAR is its lower cost (Burdziakowski, 2018; Silván-Cárdenas et al., 2021). LIDAR, however, also has advantages over photogrammetry. The application of LIDAR is discussed below.

Laser Imaging Detection And Ranging (LIDAR)

LIDAR is similar to radar in that it emits a signal and then receives a reflection. The difference, however, is that the LIDAR signal consists of laser/light pulses rather than radio waves. The time between emission and reception is converted into distance data, which is used to generate a three-dimensional spatial skeleton. For drone-mounted LIDAR, a flight pattern is pre-planned, which the drone automatically follows at a pre-set speed and altitude during its flight (Martinez et al., 2020; Nègre et al., 2025; Podest, 2021; Pringle et al., 2012). LIDAR on drones has already contributed to detecting hemi-parasitic invasive plants (Barbosa et al., 2016), invasive rainbow trout (Roddewig et al., 2018), and studying archaeological structures (Silván-Cárdenas et al., 2021). Additionally, LIDAR can be used to detect hidden graves after decomposition, as the soil around the body shifts during the decay process, creating terrain changes detectable with LIDAR (Corcoran, 2016). Follow-up studies, however, found that detection is only possible for graves containing three or more bodies; a single body is insufficient to create a detectable difference. There was a positive correlation between the number of bodies in a grave, the terrain alteration, and detectability (Blau et al., 2018; Corcoran et al., 2018). Overgrown vegetation, disturbance of the soil surface by wildlife, and the accumulation of loose objects such as litter or animal faeces above the grave hinder detection (Silván-Cárdenas et al., 2021).

Other researchers recommend LIDAR for search missions where the target object is heavily concealed. LIDAR could potentially detect objects in forested areas because the laser can penetrate through the canopy between individual leaves and reach the ground. However, success depends on the quality and condition of the sensor, the density of vegetation, and the tree species (Hu et al., 2020; Masini et al., 2022). Another advantage is that LIDAR sensors can be effective at any time of day or night. This is because their functionality does not rely on the sun's position or sunlight reflection, as LIDAR provides its own light and is therefore considered an "active sensor" (Masini et al., 2022). Although LIDAR can

be used at night, it is still recommended to plan flights during the day so that obstacles are visible (Phillips et al.).

One disadvantage of LIDAR is its limitation in measuring highly reflective materials, such as metal or mirrors, and transparent materials like glass (Koopman et al., 2025). However, this limitation is not very relevant for our objective: detecting wild boar carcasses. Another drawback is the difficulty in interpreting the data collected by LIDAR. It is not always clear whether “ground points” are actually measured down to the ground. Small shrubs or tall grass can be mistakenly interpreted as ground, and although algorithms exist to remove trees, these do not yet work for low vegetation. This poses a problem when using LIDAR to examine terrain or search for unusual objects or structures on the ground surface in areas with low vegetation. Moreover, the number of ground points that LIDAR can record in locations with dense canopy, such as forests, is rather limited because the laser cannot penetrate everywhere. This increases the likelihood of false-negative errors (Corcoran, 2016; Hu et al., 2020; Koopman et al., 2025). Despite this, LIDAR is more effective than photogrammetry for searching for objects under a canopy, although it is financially more expensive (Ruffell & McKinley, 2005; Salo, 2011).

Use of artificial olfactory sensors and drone-based gas sensors:

Artificial olfactory sensors

Although various senses have already been successfully replicated artificially, research into artificial olfaction is progressing more slowly. This is due to the complexity of both the sense itself and the properties of the stimulus: a complex mixture of different volatile molecules. For example, humans have three receptors for perceiving colours, but no fewer than 400 olfactory receptors, with which we can detect tens of thousands of different smells. Because of the large number of olfactory receptor neurons, the odour patterns in the olfactory bulbs (bulbus olfactorius), and the brain regions responsible for odour perception, these components can be distinguished and can evoke memories (Gilad et al., 2003; Kim et al., 2022; Menini et al., 2004; Niimura & Nei, 2007). Artificial olfactory sensors, including e-noses, are systems modelled on a biological nose. They contain a sensor array with various nano gas sensors such as a metal oxide semiconductor sensor (MOS), a conducting polymer sensor (CP), a quartz crystal microbalance sensor, a surface acoustic wave sensor (SAW), an electrochemical sensor, a colorimetric sensor, and organic dyes. Each sensor has its own advantages and disadvantages, making the multi-sensor array widely applicable and adaptable to the target odour and requirements. In addition, an e-nose includes a pattern-recognition system based on artificial intelligence, and future analytical possibilities are very promising thanks to advances in deep learning (Röck et al., 2008; Sanaeifar et al., 2017).

A major advantage of an e-nose compared with a biological nose is that an e-nose does not become fatigued, whereas the biological sense of smell requires a great deal of energy and becomes tired quickly. Despite this major advantage, e-noses are not yet widely used in environmental search operations due to the lack of standardisation, the detection limits of the system itself, and operational limitations in poor environmental conditions (Bourgeois et al., 2003; Kim et al., 2022; Nicolas et al., 2008; Van Harreveld, 2003). However, several studies have already investigated their use, such as detecting carbon monoxide and hydrocarbons in vehicle exhaust (Wang et al., 2010), detecting variations in volatile organic compounds during lung cancer development (Thirumani et al., 2018), including a study reporting a diagnostic success rate of 75% and a classification success rate of 86% (Lee et al., 2021), and identifying ovarian carcinomas using breath samples with a specificity of 100% (Amal et al., 2015). Rheumatoid arthritis, schizophrenia, and viral infections such as COVID-19 can also be identified using VOC gas signatures (El Kazzy et al., 2021; Shan et al., 2020; Turner & Magan, 2004).

In general, it can be stated that artificial olfaction can analyse the chemical components of VOC traces and map both their quantitative and qualitative properties. As such, the e-nose is highly versatile, for example in medical diagnostics, food screening, environmental monitoring, and safety assessments such as gas leak detection. It is a promising technology because of its non-invasive nature, rapid analyses, and the possibility of real-time screening (Kim et al., 2022). For the time being, the analysis of VOCs in gases relies mainly on gas chromatography and mass spectrometry (the GC/MS system). Although this technique is extremely accurate, it is not easily deployable. It is expensive and requires a skilled expert. In addition, the technique is very time-consuming: the chromatographic run itself takes between 20 and 100 minutes, and the subsequent analysis can take more than 20 hours. These disadvantages could potentially be overcome with artificial olfactory sensors (Arshak et al., 2004; El Kazzy et al., 2021; Gouma & Sberveglieri, 2004).

The specificity of olfactory sensors is generally very high. Sensitivity, however, still requires improvement. This is therefore the main focus of many scientists researching artificial olfaction. Since the gas to be analysed almost always contains different types of gas molecules in different concentrations that can react with one another, and since the ratios between individual molecules also tend to vary constantly, it is very difficult to train neural networks to achieve high sensitivity (Albert et al., 2000; Peris & Escuder-Gilabert, 2009; Röck et al., 2008; Sung et al., 2024). Performance differences therefore depend not only on the type of gas that must be analysed, but equally on the setup of the e-nose and the choice of sensors used (Wang et al., 2021; Ye et al., 2021; Zhang et al., 2017). Another pitfall, in addition to issues with differentiation, is the problem of “sensor drift” (the gradual change in output even when the qualitative and quantitative input remains the same). This can be caused by ageing or changes in the environment, such as temperature or humidity. Algorithmic issues related to discretisation, as well as interference problems when unwanted input enters the system and alters the output, also occur (Vergara et al., 2012; Verma et al., 2016; Yan & Zhang, 2016; Zhang et al., 2018).

Drone-based gas sensors

Artificial olfactory sensors such as e-noses fall under the category of multi-gas sensors. Simple gas sensors usually contain only one type of sensor and do not rely directly on deep learning, but instead operate with threshold values. As a result, their capabilities are more limited, and they are mainly used to measure the concentration of a particular gas rather than to recognise complex VOC patterns. A simple gas sensor can therefore be regarded more as a highly sensitive and specific real-time measuring instrument than as an artificial biosensor. (Multi-)gas sensors are used on drones to detect gas leaks with great accuracy (Gallego et al., 2015; Kowadlo & Russell, 2008; Neumann et al., 2017; Yuan et al., 2019). Due to advances in deep learning, real-time data processing is now faster and more accurate than ever. A study using a CNN model showed that acetone and methanol could be detected in a gas sample within 30 seconds, and ethanol and NO₂ were detected within 10 seconds (Lee et al., 2022; Noh & Oh, 2025). In another study, only a minimum time of 1 second was needed to detect CO with 98% accuracy (Kang et al., 2022). Another study equipped a drone with an e-nose containing as many as 21 chemical sensors to analyse odours from wastewater treatment plants with real-time data processing (Burgués et al., 2022; Burgués et al., 2021).

One issue in drone-based gas sensing is the so-called “downwash effect”, which occurs when the drone’s rotors dilute and disperse the gas plume (Brinkman et al., 2020; Burgués & Marco, 2020; Sarghini & De Vivo, 2017). This can be mitigated by using a long tube through which gas samples are collected. The distance between the tube opening and the drone’s rotors can then be made sufficiently large to reduce this effect. Since such tubes may interfere with take-off, landing, and manoeuvring, flexible tubing is recommended. Another observed issue was that sensors quickly became saturated, and thus so did the signal. Recovery could take several minutes, making it necessary to “clean” the

sensors with fresh air (Kaliszewski et al., 2021). Another drawback is that sensors can be affected by fluctuating temperatures, or by temperatures that are too high or too low. Humidity can also cause signal disturbances. It is therefore recommended to take weather conditions into account and/or make hardware adjustments (Ayaz & Topuk, 2021; Mahdavi et al., 2021; Noh & Oh, 2024; Sitar et al., 2024). The combination of the downwash effect, weather dependency, and the relatively lower sensitivity during outdoor field missions—due to the large variation in VOCs as well as dilution and displacement by wind—means that drone-based multi-gas sensors and e-nose searches have mostly taken place in greenhouses and buildings, or in very close proximity to the likely target, such as flying along pipelines to detect gas leaks (Kaliszewski et al., 2021; Noh & Oh, 2025). Although research on deploying drones with gas sensors to detect and localise target gases during outdoor field missions is limited, some studies show promising results (Yuan et al., 2019).

Legislation

In Commission Implementing Regulation (EU) 2019/947 of 24 May 2019, the rules and procedures concerning the operation of unmanned aircraft are set out. This regulation describes, among other things, the differences in conditions between the “open”, “specific”, and “certified” categories. These are three different categories into which drone flights are classified based on the level of risk they pose to privacy, safety, and the environment. In addition, the importance and implications of geographical UAS zones are also considered (European Commission, 2019). In this chapter, only Implementing Regulation (EU) 2019/947 is consulted in order to maintain clarity in references. Every mention of an Article and Paragraph therefore relates to this implementing regulation. Where necessary, general references will be made to Delegated Regulation (EU) 2019/945 or Implementing Regulation (EU) 2019/946. Further information is provided at the end of this chapter.

Category “open”

The “open” category applies to flights that pose the lowest level of risk. For these flight operations, no standard procedures from aviation legislation need to be applied. No operational declaration needs to be submitted for a planned flight, nor is a prior operational authorisation required. However, the UAV classes within this category (C0, C1, C2, C3, C4) must be taken into account. These are defined in Commission Delegated Regulation (EU) 2019/945 (Implementing Regulation (EU) 2019/946 “on the rules and procedures for the operation of unmanned aircraft”). In addition, it is mandatory to register the UAV if it has a take-off mass of more than 250 g. Several conditions must be met before a flight can be classified under the “open” category. For example, the maximum take-off mass must be less than 25 kg (Article 4, §1, point b), and the drone may not be flown beyond VLOS (visual line of sight). One exception is when the drone is flying in follow-me mode. Another exception applies when a second person is deployed as an observer (Article 4, §1, point d). It is also prohibited to fly higher than 120 metres (measured from the nearest point on the earth’s surface) (Article 4, §1, point e). With regard to safety, it is stipulated that flights in the “open” category may not transport dangerous goods, nor may they drop any material (Article 4, §1, point f), and they must keep a safe distance from people. Moreover, flying over assemblies of people is prohibited for flights under this category (Article 4, §1, point c).

The minimum age for remote pilots in this category is 16 years (Article 9, §1). Only in subcategory A1, when the pilot is using a class C0 UAV, is no minimum age required, as drones in this category are considered “toys” (Article 9, §2). UAV operators conducting flights in the “open” category must register themselves if the UAV is equipped with a sensor capable of accessing personal data, or if the maximum permitted take-off mass exceeds 250 g. Even when the maximum permitted take-off mass is lower, operators must register if, upon impact with a person, kinetic energy of more than 80 J could be

transferred (Article 14, §5, point a). For the “open” category, both the UAV operator and the UAV remote pilot are expected to act responsibly and possess the necessary skills to ensure that a flight operation proceeds safely and correctly. Annex A of Implementing Regulation (EU) 2019/947 outlines what these responsibilities entail.

The responsibilities of the UAV operator include the following: developing appropriate procedures for flight operations; ensuring that the appropriate use of the radio spectrum is maintained during flights and that no harmful interference occurs (Annex A, UAS.OPEN.050, §1 & §2). They must select competent remote pilots for the flight operations and ensure that these pilots are familiar with both the manufacturer’s manual of the UAV being used and the procedures drawn up by the UAV operator. In addition, they must ensure that pilots have all relevant information regarding geographical zones that are applicable to the planned flight operation (Annex A, UAS.OPEN.050, §3 & §4: points a, b & c). The UAV operator must also ensure that all administrative matters falling under their responsibility are in order. This includes, among other things, ensuring that the UAV has an EU declaration of conformity referring to the class in which the UAV is categorised, and that the UAV is marked with a label indicating this class (Annex A, UAS.OPEN.050, §6: points a & b). Finally, it is important that the operator informs all involved persons of the associated risks (Annex A, UAS.OPEN.050, §7). Not only the UAV operator but also the UAV remote pilot has responsibilities. First of all, the pilot must hold a certificate of competency in accordance with the requirements of the subcategory in which the flight will take place. The pilot must also carry out checks prior to the flight to minimise risks. For example, the pilot must inspect the area for uninvolved persons, assemblies, and obstacles, and must also check the UAV for damage or technical faults. Additionally, the pilot must ensure that the payload does not exceed the prescribed maximum take-off mass (Annex A, UAS.OPEN.060, §1: points a, c, d & e).

When the flight operation can begin, it is essential that the remote pilot is capable of conducting the flight safely. This means the pilot must not be under influence (of medication, alcohol, drugs, or otherwise), overly fatigued, ill, or physically impaired, and must be able to maintain control of the aircraft at all times, except in cases of unforeseen loss of connection or pre-programmed autonomous flight. The remote pilot must comply with the rules regarding geographical zones and may not fly in areas where emergency services are active unless permission has been granted. The remote pilot must remain within VLOS (visual line of sight) unless an observer is used—someone who supports the pilot by maintaining visual contact with the UAV and by communicating with the pilot (Annex A, UAS.OPEN.060, §2: points a, b, c, & §3, §4). The “open” category consists of three subcategories. The division is based on the technical requirements of the UAV, the limitations relating to the flight operations, and the requirements the remote pilot must meet. These subcategories are A1, A2, and A3 (Annex A, UAS.OPEN.010, §1).

Subcategory A1

To fall under subcategory A1 within the “open” category, the following conditions must be met: persons who are not involved in the flight operation may not be overflown, unless the drone belongs to class C0 or C1 and has a maximum take-off mass of less than 250 grams. However, assemblies of people may never be overflown within this class (Annex A: UAS.OPEN.020, §1, §2 & §5). To operate a UAV of class C1, the remote pilot must have completed an online training course and passed the associated examination organised by the competent authority (Annex A: UAS.OPEN.020, §4, point b).

Subcategory A2

To fall under subcategory A2 within the “open” category, the following conditions must be met: as in the previous category, uninvolved persons may not be overflown. There must be a minimum distance of 30 metres between the flight operation and any uninvolved persons. Exceptions are possible if the

low-speed mode is activated and weather conditions allow it. When the UAV's performance has also been assessed and the area has been checked for obstacles, this minimum distance may be reduced to 5 metres. The pilot must always know and follow the user manual and the instructions provided by the drone's manufacturer. In addition, the pilot must hold a competency certificate recognised in the Member State in which the UAV operator is registered (Annex A: UAS.OPEN.030, §1 & §2).

Flights in subcategory A2 may only be carried out with UAVs belonging to class C2, and these must be equipped with systems for remote identification such as Remote ID (technology that allows the drone to be identified via signal transmission and reception, enabling the operator number and registration number to be known) and geo-awareness (a system that provides real-time information on the zone in which the drone is operating and whether that zone constitutes restricted airspace) (Annex A: UAS.OPEN.030, §3).

Subcategory A3

To fall under subcategory A3 within the "open" category, the following conditions must be met: the flight operation may not pose any danger to uninvolved persons and must remain at least 150 metres away from residential, industrial, recreational, or commercial areas (Annex Part A: UAS.OPEN.040, §1 & §2). The remote pilot must have completed an online training course and passed the corresponding exam, just as in subcategory A2. In this subcategory, flight operations are carried out using UAVs from classes C2, C3 or C4, or with a maximum take-off mass of less than 25 kg if the drone is home-built by private individuals (Annex Part A: UAS.OPEN.040, §3 & §4). The requirements for classes C2, C3 and C4 are defined in Delegated Regulation (EU) 2019/945.

Category "specific"

The "specific" category applies to flight operations that pose a higher risk than those falling under the "open" category. Before a flight can take place, a thorough risk assessment is required. This assessment determines which safety requirements and measures must be imposed (Implementing Regulation (EU) 2019/947 "on the rules and procedures for the operation of unmanned aircraft"). If the conditions required to operate under the "open" category cannot be met, the UAS operator must first apply for an operational authorisation in order to fly under the "specific" category. This application must be submitted to the competent authority together with a risk assessment and the proposed risk-mitigating measures (Article 5, §1, 2 & 3). The authority then determines whether the measures proposed by the UAS operator to mitigate the risks are sufficient (Article 12, §1).

Remote pilots flying in the "specific" category must, as stated in §2 of Article 8, meet the competency requirements described in Appendix 1 of the Annex to Implementing Regulation (EU) 2019/947, the standard scenarios or the LUC (Light UAS Operator Certificate), or the competency requirements defined in the operational authorisation as established by the competent authority (Article 8, §2). Skills such as applying operational procedures, managing the flight path of the UAV, UAV automation, situational awareness, coordination, problem-solving, teamwork, leadership, autonomy, decision-making, aviation communication management and communication transfer are the minimum requirements for performing operations in the "specific" category, as also listed in Article 8, §2. The minimum age for remote pilots conducting flights in this category is 16 years (Article 9, §1). In this category, UAS operators must always register, regardless of the mass of the aircraft (Article 14, §5 point b). Registration must also take place in the Member State where the operator resides, and they cannot be registered in multiple Member States at the same time (Article 14, §6).

LUC (Light UAS-operator Certificate)

Within the “specific” category, it is possible to obtain a LUC. This is a certificate that grants the holder greater freedom and removes the requirement for every risk assessment to be approved by an authority beforehand. UAS operators holding a LUC do not need an operational authorisation and do not have to submit an application. This applies only when the competent authority has approved the documents submitted during the LUC application and has clearly specified the conditions for obtaining the privileges associated with a LUC (Article 5, §6 point a and Annex Part C, UAS.LUC.060). In this case, the UAS operator is a legal person rather than a natural person. Only a legal person is eligible for a LUC. A legal person is a legal construct referring to a type of organisation. A UAS operator holding a LUC therefore comprises multiple natural persons. When applying for a LUC, the organisational structure, management system and the names of the personnel must therefore be provided (Annex Part C, UAS.LUC.010, §1 & 2). The LUC holder must also maintain a record for a period of at least three years, which includes the operational risk assessments, the measures taken to mitigate risks, and the qualifications and experience of the personnel involved (Annex Part C, UAS.LUC.020, §5). In addition, a safety management system and a safety policy must be established, and responsibilities and liabilities within the organisation must be clearly defined (Annex Part C, UAS.LUC.030, §1 & §2: points b and c).

Category “certified”

The “certified” category concerns flight operations in which both the operator and the aircraft must be certified, and the remote pilots must hold a licence, in accordance with Delegated Regulation (EU) 2019/945. This also applies when the UAV poses a risk to the environment, safety or privacy (Implementing Regulation (EU) 2019/947 “on the rules and procedures for the operation of unmanned aircraft”). The conditions for belonging to this category are as follows: the aircraft must be correctly certified in accordance with Article 40(1)(a), (b) and (c) of Delegated Regulation (EU) 2019/945, and the operations must involve risks due to flying over assemblies of people or because dangerous goods are being transported (Article 6, §1). Furthermore, if the competent authority concludes, based on the risk assessment, that the risks cannot be adequately mitigated, the operation will fall under this category and certification is required (Article 6, §2). The operator is also obliged to register the aircraft (Article 14, §7). The UAS operator must affix the registration number to UAVs with a maximum take-off mass of more than 250 g or those capable of transferring more than 80 joules of kinetic energy during a collision with persons. Registration is also required when the UAV poses a risk to the environment, safety or privacy (Article 14, §8).

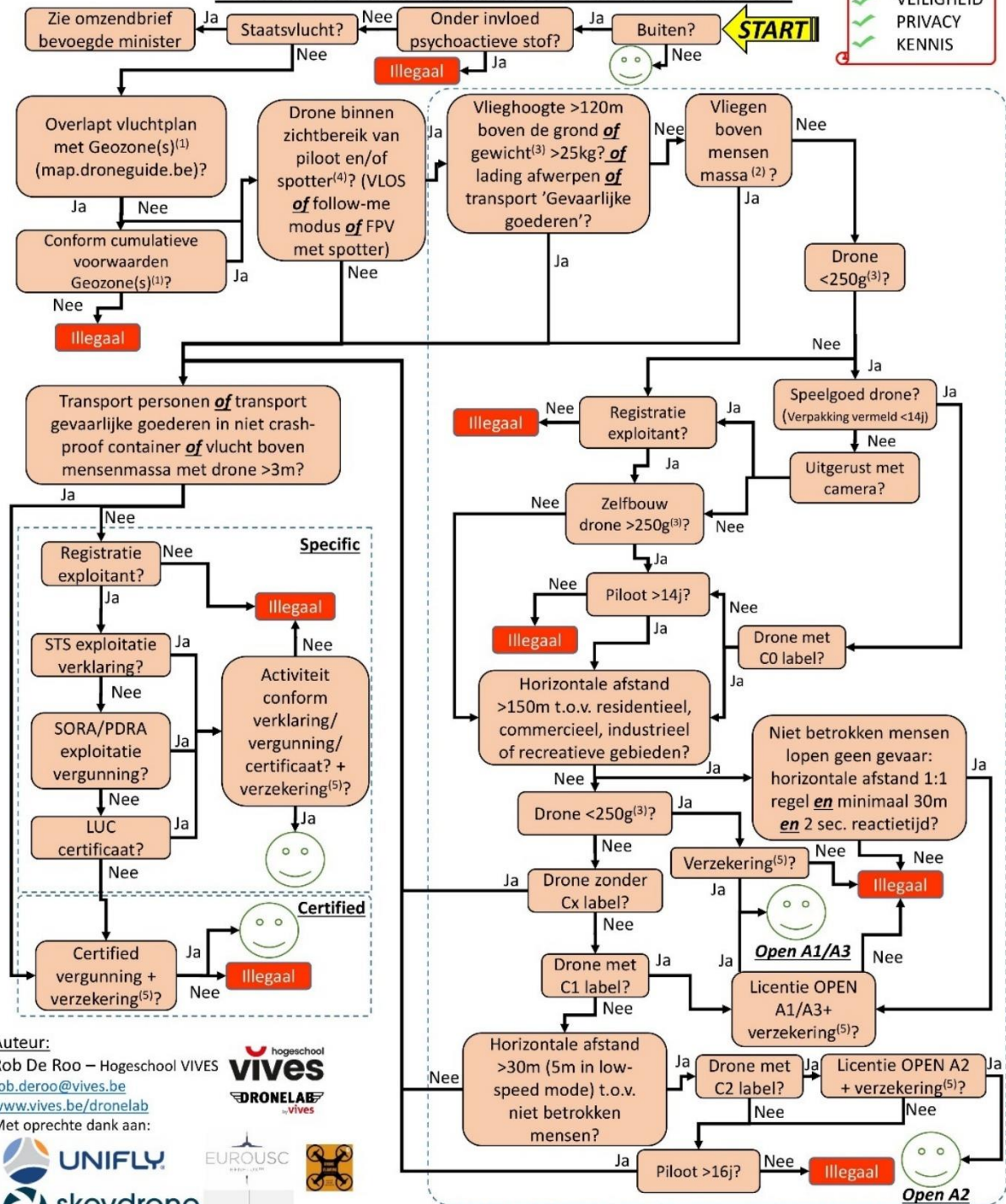
Geographic UAS zones

With regard to safety, privacy, or the environment, EU Member States may designate and delimit geographical UAS zones within which they may impose environmental standards, prohibit certain flights, allow access only to specific UAV classes, impose special conditions, require operators to apply for a permit prior to the flight operation, and/or grant access only to UAVs with specific technical features such as geo-awareness systems (Article 15, §1). Once these zones have been established, it is the responsibility of the EU Member States to make information about these zones, as well as the period for which they apply, publicly available and to share it in a common, unique digital format (Article 15, §2). The website of E.A.S.A Europe (<https://www.easa.europa.eu/en/domains/civil-drones/naa>) refers to the Belgian website <https://map.droneguide.be> to stay informed about the zones in Belgium (E.A.S.A; Skeyes & F.P.S).

Drone legislation flowchart

To obtain a comprehensible and clear overview of drone legislation, a public flowchart was created in 2023 by Rob De Roo, lecturer in drones at Vives University of Applied Sciences (BE), which is presented here in Dutch. This flowchart is a summary of the complete E.A.R (Easy Access Rules), an output of the EASA eRules project aimed at making information on drone legislation more accessible to citizens. These “Easy Access Rules” can be found via a link to a PDF file on the EASA website. A direct link is included here: <https://www.easa.europa.eu/en/document-library/easy-access-rules/easy-access-rules-unmanned-aircraft-systems-regulations-eu>. The E.A.R 2024 is a revision of the E.A.R 1998 (E.A.S.A, 1998, 2024).

FLOWCHART CIVIELE UAS OPERATIES



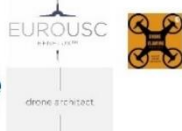
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Met oprechte dank aan:



Dit document bevat de belangrijkste evaluatie criteria om een legale civiele operatie uit te voeren. Er moet altijd voldaan worden aan alle vereisten van de relevante wetgevingen.

V23 21 Dec 2023

⁽¹⁾ Geozone = zone volgens MB 21/12/2020 inclusief luchtruim met bijzonder statuut: (CTR, P, D, R, LFA, HTA, TSA, TRA, ...), lucht/zeehavens, UAS testzones, ...

⁽²⁾ Bijeenkomsten waar zoveel mensen aanwezig zijn, dat het niet mogelijk is uit de weg te gaan

⁽³⁾ Gewicht = maximale opstijggewicht

⁽⁴⁾ Spotter staat naast piloot met duidelijke en effectieve communicatie tussen piloot en waarnemer

⁽⁵⁾ OPEN gewicht⁽³⁾ <20kg = BA voor derden / EG 785/2004 indien OPEN gewicht⁽³⁾ >20kg of SPEC of CERT

Results of qualitative surveys and in-depth interviews

The purpose of the surveys and in-depth interviews was to gather qualitative information. This concerns the respondents' experiences, personal knowledge, expertise and opinions. Despite the subjective nature of some responses, the information is valuable and may be important when making decisions in situations where scientifically substantiated information is insufficient in this relatively unfamiliar field.

Disclaimer: All information that is mentioned below is knowledge acquired from these surveys and interviews. Sometimes it is in line with the literature, and sometimes it is not. No exact sources (names) are mentioned as the surveys could be completed anonymously (which many respondents did) and due to privacy laws.

Challenges during flight operations

Challenges in wooded areas

Several drone pilots were consulted regarding their experience and observations when flying drones in wooded/forested areas or regions with tall obstacles. Most of them considered it too risky for the drone to fly lower than 5 metres above the treetops and strongly advised against flying between the trees, especially in conditions of increased wind speed. Detecting small branches is extremely difficult, even with obstacle detection systems, particularly towards the evening, which increases the likelihood of collisions that may have disastrous consequences for the drone. For this reason, the use of automated flight-planning software was discouraged in wooded environments, as full manual control of the aircraft should be maintained. Even when flying above the canopy, this is not always deemed advisable, as there may be significant variations in tree height, and in many forests — such as those in the Ardennes or Hoge Kempen — changes in terrain relief can create substantial elevation differences that cannot always be accurately calculated or detected in advance. When the terrain is relatively even and no tall trees or other obstacles protrude above the canopy, automated flight-planning software *can* be used and may even be very advantageous. Such software increases the likelihood that every metre of the predefined area is scanned and ensures that images are captured at a consistent altitude, which prevents scale distortion when comparing images. During flights and image acquisition, an overlap of 70% to 80% is recommended. The greater the overlap, the better identification models can detect and recognise objects. Furthermore, high overlap is essential when the images are used for photogrammetric applications.

Another issue experienced by some drone pilots when operating in areas with trees or other obstacles is the legal requirement to keep drones within the *visual line of sight* (VLOS). In theory, they note, this prohibits flying behind obstacles. Furthermore, concerns exist regarding sensor use in forested areas. RGB sensors cannot penetrate the canopy, and even infrared sensors struggle in dense vegetation, particularly on warm, sunny days when treetops exhibit hotspots (the “hot-crown effect”). According to some pilots, the penetration issue could be partially mitigated using LIDAR; however, altitude plays a critical role, as there is a negative correlation between flight height and accuracy. The altitude at which LIDAR accuracy becomes insufficient is currently unknown to pilots and requires further investigation. For drones equipped with gas sensors or advanced e-noses, forested environments present additional challenges because wind directions become unpredictable due to airflow disruption by the canopy. As a result, tracing an odour from above the treetops to its source becomes difficult, especially under stronger winds. More generally, for all sensors, higher flight altitudes result in reduced resolution or accuracy, which poses a significant limitation in areas with tall trees.

Another concern is the presence of (nesting) birds in the target natural areas. Raptors, in particular, could pose a threat by attacking the drone. Finding a suitable take-off location in vegetated areas is also challenging. Adequate free space (approximately 10 m²) is required for safe take-off. Given that drones have limited range due to battery constraints and the VLOS requirement, the take-off location is critical. Additional concerns include potential connectivity issues, particularly GPS signal loss, and difficulties in coordinating with site managers. As an additional note regarding the limitations of obstacle detection, a respondent mentioned that new models are being introduced that incorporate LIDAR for obstacle detection, which may eventually allow drones to fly beneath the canopy. While promising, this remains to be tested and studied.

Weather challenges

Weather also poses significant challenges. Nearly all respondents noted that wind is a major concern for many drone pilots. Pilots operating lightweight drones or flying in areas with many obstacles consider even slight wind problematic. Heavier drone models are generally more resilient, although turbulence can still affect image quality. For most drones, flying is feasible up to around 3 Beaufort. Heavier drones can operate safely in winds up to 4 Beaufort. However, even for these more stable models, wind speeds of 4 to 6 Beaufort make it impractical to capture clear images, whether using RGB cameras, infrared, gas sensors, or LIDAR. The maximum permissible wind speed for flight is specified in the drone's manual. While some respondents indicated that slight deviations may be tolerated, they emphasised the importance of following the manufacturer's instructions. Excessive wind makes safe take-off and landing impossible. During flight, strong winds reduce the pilot's control over the drone's direction, posing risks both to the drone and to surrounding property or people. Wind also accelerates battery depletion due to increased energy consumption. Furthermore, drones are more easily displaced from their intended positions, which not only has safety implications but also affects operations that require maintaining a constant altitude or following a preplanned flight path with adequate image overlap.

Rain presents additional challenges. It can cause ice to form on propellers, which is damaging to the drone. Most drones are not fully waterproof, and rain can cause motor corrosion. Rain also interferes with camera operations (RGB, infrared, thermal), and LIDAR is effectively unusable in wet conditions. Even light rain, mist, or drizzle can severely hinder image-capturing missions. Large variations in light intensity (e.g., partly cloudy conditions) can also interfere with visual operations, and strong sunlight can negatively affect image quality. Excessive sunlight and heat are particularly problematic for thermal imaging. Consequently, weather is a critical factor for successful drone operations. That said, several respondents noted that newer, more advanced drones are increasingly resilient to adverse weather conditions.

Challenges regarding legislation

Another challenge that can hinder operations is the legal framework. Many respondents consider this a major obstacle. Most highlighted the legislation concerning Visual Line of Sight (VLOS), which stipulates that drones must always remain within the operator's line of sight unless a special permit or authorisation (BVLOS) is obtained. This rule has significant implications, making it very difficult to fly in areas with varying terrain, obstacles, or buildings. Respondents also mentioned the need to comply with active geographical UAS zones, such as helicopter training areas (HTA), controlled traffic regions (CTR) in military zones, airports, and Natura 2000 protected sites, which can severely restrict flight operations. Maintaining a safe distance from people and buildings during certain flights was also reported as challenging. Some respondents noted the maximum flight altitude of 120 metres as a limiting factor. For flights conducted under the "specific" or "certified" categories, each mission

requires extensive preparation and paperwork. Several respondents viewed the organisation and administration of these flights as burdensome, particularly the time required to process the necessary applications.

Choice of drones and sensors and the financial costs

From the survey asking which drones respondents would recommend for detecting wild boar carcasses, several models were suggested. However, the basis for these choices was largely the same across respondents. They generally recommend a sturdy multirotor drone that is heavy enough to withstand some wind and stable enough to capture clear imagery. Preferably, the drone should be waterproof and equipped with powerful motors. It should be capable of carrying sensors such as RGB, thermal, and/or LIDAR. Thermal sensors were most frequently recommended, followed by LIDAR and RGB cameras with telephoto lenses. Gas sensors capable of detecting the VOCs from wild boar carcasses were also suggested, especially for searching in densely forested areas where thermal sensors may be less effective. These gas sensors were recommended to be used in combination with LIDAR so that, when the “scent” is detected, LIDAR can help penetrate the tree canopy and pinpoint the target. However, it is unclear whether respondents have practical experience with this method or if it was recommended based on theoretical feasibility. Obstacle avoidance systems with 360° sensors were also advised, ideally with sensors based on LIDAR. GPS was considered an indispensable tool by the respondents. The recommended models vary significantly in price, which naturally correlates with stability and sensor accuracy — the more expensive the drone, the more stable and precise it tends to be. The most frequently mentioned models are listed below (information from the surveys has been supplemented with details from www.dronepot.be):

- ➔ **DJI Matrice 4 Thermal©** – A drone priced at approximately €7,000, including a thermal sensor, with a maximum flight duration of 45 minutes. It is equipped with an infrared sensor, a telephoto camera, and a wide-angle camera.
- ➔ **DJI Matrice 30T©** – A smaller version of the DJI Matrice 300 RTK©. It features a stable infrared camera, wide-angle camera, and telephoto camera. Maximum wind resistance is 15 m/s and 12 m/s during take-off and landing. The drone is water-resistant and GPS-equipped. It weighs 3.8 kg with a maximum take-off weight of 4 kg and can reach speeds of 23 m/s. The price is approximately €12,500, including the thermal sensor and extra batteries.
- ➔ **DJI Matrice 300 or 350 RTK©** – A large drone with a maximum flight duration of 55 minutes, which reduces to around 43 minutes when carrying a DJI Zenmuse H20T© (thermal camera). The drone weighs 6.3 kg with a maximum take-off weight of 9 kg. It is highly stable, can reach a maximum speed of 23 m/s (82.8 km/h), and has a transmission range of 8 km in FCC mode. It can carry three payloads simultaneously with 360° sensors. The drone is waterproof and has obstacle avoidance features. Base price ranges from €8,500 to €14,000, excluding the DJI Zenmuse H20T© camera (~€12,000). Depending on payloads and extras, the total cost can exceed €20,000.
- ➔ **DJI Matrice 400©** – A large drone with a maximum flight time of 1 hour including payload. Integrated with a LIDAR sensor and mm-wave radar for obstacle detection. Maximum speed is 25 m/s, with wind resistance up to 12 m/s. Maximum take-off weight is 15.8 kg. It can carry up to 6 kg of payload, allowing combinations of various sensors, which are not included in the base price of €10,600–€14,500 (including batteries and charger). The H20 sensor series© is not compatible, but the Zenmuse H30T© thermal camera (~€5,000) is compatible. According to a respondent, total cost including sensors and extras can range from €20,000 to €50,000.
- ➔ **DJI Mavic 3 Enterprise series©** – Recommended to a lesser extent, including:
 - **DJI Mavic Enterprise©** with RGB sensor (€3,000–€4,000)

- **DJI Mavic 3T©** with thermal sensor (€5,000–€6,000)
 - **DJI Mavic 3 Multispectral©** with multispectral sensor (€4,500–€5,000)
 - Since most respondents stressed that a thermal sensor is essential, only the **DJI Mavic 3T©** meets this requirement. It has a flight time of 45 minutes and wind resistance up to 12 m/s, but it is not waterproof. It is worth noting that most respondents have limited experience with multispectral sensors and may therefore underestimate their potential contribution to detection.
- ➔ **LIDAR-equipped drones** – Estimated cost (drone and sensor) according to respondents: €16,000–€30,000.
 - ➔ **Hyperspectral sensor drones** – Estimated cost (drone and sensor) according to one respondent: €50,000.
 - ➔ **Multispectral sensor drones** – Estimated cost for the sensor alone: €1,000–€5,000.

In addition to the purchase cost of the drone and its sensors, several other expenses must be considered. These include the acquisition of extra batteries, a battery charger, and optional accessories or gadgets, which can range widely in price. Maintenance costs also play a role, as drones have limited lifespans that vary by model. Also, intensive use or adverse weather conditions can lead to part replacements and repairs. The hourly rate for drone pilots should also be factored in, along with potential costs for the UAV operator (who may not be the same as the drone owner or as the pilot) and an additional assistant or observer. According to survey responses, the hourly rate for drone pilots ranges between €70 and €150. However, most respondents left this question open, suggesting that rates can vary greatly depending on the assignment, drone model, and pilot. This may also indicate that rates are considered a sensitive subject or potentially high (SOURCE: Survey responses).

According to the chairman of the BRH organization (and also a drone pilot), whom we interviewed at TCRH Mosbach, large drone companies may charge up to €4,000 per day. These pilots are allowed to fly above the European maximum height of 120 meters. Using such drones, an area of up to 60 hectares can be screened within one hour if there are no obstacles or excessive wind. In Germany, thermal drones were successfully used to locate live wild boars, allowing hunters to better estimate populations and facilitate culling. Drones can also be used to herd animals toward hunters, especially in areas where thermal drones have a clear view, such as fields and maize plantations. Hunters often severely underestimate wild boar numbers per hectare—for example, estimating 4–5 animals when drones detected 40. Thus, drones provide significant added value not only in searching for carcasses but also in monitoring live animals for African swine fever control. While hunter deployment costs are not strictly part of the drone expenses, they can be considered part of the overall drone operation team in such cases (SOURCE: Interviews at TCRH Mosbach).

Other significant costs include training and certification, which can be expensive. Additionally, when large amounts of data are collected, the time required for data analysis—or the purchase of an AI detection model to reduce processing time—must also be taken into account (SOURCE: Survey responses).

Feasibility

Most respondents agree that searching for carcasses in relatively open areas is a difficult task. They are also almost unanimous in stating that searching for carcasses in a forest or densely vegetated area becomes virtually impossible. The concerns that arise are:

- Is a carcass detectable at all with thermal sensors?

- Significant limitations arise when the carcass is under the canopy for almost all sensors. From April to October, the canopy is considered restrictive. RGB and infrared cannot see through dense vegetation. LIDAR might help penetrate the treetops, but loses accuracy when there is a lot of low vegetation (ferns, bramble bushes). If the carcass is beneath this low vegetation, LIDAR is no longer effective. The longer the laser distance, the lower the accuracy. Very tall trees are also problematic.
- Concerns regarding the legislation around visual line of sight (VLOS).
- Difficulties in obtaining permission to fly where needed. Wild boars are becoming bolder and increasingly approach buildings and humans. Laws about flying over private property and near buildings or people could therefore pose a problem. Additionally, accounting for active geographic UAS zones, especially when these include forests and fields, can be very restrictive. Obtaining permits is therefore a must. Building the risk assessment, implementing measures, handling other administrative tasks, and waiting for approvals are all obstructive in this regard (SOURCE: Interviews at TCRH Mosbach).
- Difficulties finding suitable take-off and landing sites due to dense vegetation, inhabited areas, or poor signal coverage.
- Limitations of obstacle avoidance technology and the presence of unexpected obstacles. Good preparation and reconnaissance of the area are necessary to reduce risk to the drone. A site survey can help with this.
- High dependence on weather. Sun, rain, fog, snow, and wind all limit both drone operation and data collection. Weather can also be unpredictable and change even during a flight.
- Good training is very important, as well as practical exercises before the mission.
- Problems when flying between trees is expected. One respondent put it this way: “No operator with common sense does that.”
- Respondents with knowledge of the larval mass effect on thermal images expressed doubts about the effectiveness of thermal sensors for detecting small carcasses (young piglets), individual body parts, recently deceased bodies, or carcasses already in the “dry” stage of decomposition (bones). Additionally, there were concerns about search tactics during cold months when few flies—and thus larvae—are present.
- Concerns about limited reception and poor satellite connectivity. The advice was to avoid electricity poles and take off from a location with good signal.
- Another potential problem is the large volume of data collected. Post-flight data analysis can be very time-consuming and consequently expensive. AI detection models are recommended to reduce analysis time. However, there are currently no models specifically for the thermal signature of a wild boar carcass with larval mass or the specific VOC composition of gases unique to a decaying wild boar. A question raised in the interviews was: is such specificity necessary? Would simply detecting “carcass” be enough for gas sensor data? Perhaps a model exists from forensic science for finding missing deceased persons? Models have also been developed for the thermal signatures of humans and fawns. Developing a model for the thermal signature of larval mass is therefore not that far-fetched.
- A few respondents expressed concern that using drones to detect wild boar carcasses is still too little researched to be applied in practice, and that there might be other methods with more evidence of effectiveness and efficiency.
- When asked about the potential use of different sensors to detect carcasses in forested areas, the results were as follows:
 - Can a carcass beneath a leafy tree canopy be detected using multi- or hyperspectral imaging? → “Yes, but very difficult” to “not possible.”

- Can a carcass infected with the virus be distinguished from non-infected carcasses using spectroscopy with hyperspectral sensors (possibly handheld)? → Mostly “no idea.” A few respondents think it is not possible.
- Can a carcass beneath a leafy tree canopy be detected with LIDAR if it is also under low vegetation such as brambles or ferns? → “Yes, but very difficult” to “not possible.” Those who answered “yes” noted that the data can only be analyzed post-flight and not in real-time.
- Can carcasses be distinguished from sun-warmed objects (plants, soil, stones, etc.) or other heat sources (living animals, etc.) on thermal images? → There was significant disagreement. Responses ranged from “yes, but not very easy” to “almost impossible.” According to respondents, much depends on the trained eye of the drone pilot or data analyst and the use of detection models based on machine learning. The learning curve of these models is also very influential.
- Can thermal sensors detect carcasses beneath dense leafy tree cover or dense low vegetation? → Most respondents agreed this is almost impossible. Responses ranged from “very difficult” to “not possible.”
- Can drones with e-noses or other multi-gas sensors detect carcasses from a considerable height? → The few respondents with experience in gas sensors considered this possible but not easy. The rest reported having no knowledge in this area.
- Can drones with e-noses or other multi-gas sensors pinpoint carcasses? → Most respondents had no knowledge about this. A few considered it difficult but possible. These respondents had previously recommended combining LIDAR with gas sensors. It is unclear whether their estimate relies on this previous suggestion, with pinpointing being done by LIDAR rather than the gas sensors.

Additionally, some tips and advice were provided. Things can always go wrong during a flight, so good preparation is very important. It was recommended to create a checklist before each flight. Check the drone and the environment. Ensure that all administration, registrations, permissions, applications, certifications, etc., are in order beforehand. Make sure the pilot is well-trained, familiar with the drone being used, and experienced in a similar environment. If the pilot has no experience in the intended environment, extensive practice should be done first. A skilled pilot is the most important factor—someone who is not only adept at manoeuvring the drone but also has a trained eye to recognize thermal signatures of wild boar carcasses in real time, or can identify the correct anomalies during post-flight data processing, with or without AI, that are characteristic of the target, possibly also using sensors other than thermal.

Discussion and conclusion on the use of drones for detecting wild boar carcasses

After reviewing the literature study, surveys, and interviews, several conclusions can be drawn. First and foremost, drones are a promising technology, and recent developments in more robust models, various sensors, and artificial intelligence continue to expand their potential. Although drones are already being applied in various sectors for different purposes, knowledge about using drones specifically for detecting wild boar carcasses was limited and difficult to find and collect. This was why the literature study required a broad, cross-sectoral foundation. After a visit to the TCRH training centre in Mosbach, it became clear that the advanced technology was being used there in combination with

detection dogs to locate carcasses. The experience and expertise gained from this was extremely helpful, together with the survey results, in forming a picture of drone deployment for this purpose. This expertise, combined with the knowledge from the literature study, now provides a clear understanding of both the strengths and pitfalls of using drones for detecting wild boar carcasses.

Drones have a major advantage over humans or dogs because they literally have an overview, which increases both effectiveness and efficiency. This advantage, however, disappears when searching in densely forested areas. Even after reviewing the many different types of sensors that could be useful, the conclusion is that drones are not effective enough to locate carcasses under tree canopies, according to the literature as well as the survey responses and in-depth interviews at TCRH Mosbach (Dunn et al., 2002; Kissell & Nimmo, 2011; Silván-Cárdenas et al., 2021). This is especially true because the forest floor is often overgrown with low vegetation, which even LIDAR cannot penetrate, as the number of ground points the sensor can acquire in such environments is too limited (Corcoran, 2016; Hu et al., 2020; Koopman et al., 2025). According to the survey responses, a carcass lying under dense, low vegetation is effectively invisible to a drone. A study by Silván-Cárdenas et al. (2021) also showed that low, dense vegetation makes LIDAR results unreliable (Silván-Cárdenas et al., 2021). Only gas sensors could, in principle, detect the VOCs (volatile organic compounds) emitted by carcasses (Yuan et al., 2019). However, it remains unclear whether these VOCs can be detected above the tree canopy in dense vegetation and whether they can be traced back to their source. Odor particles are heavier than air and move less freely in dense vegetation. This problem has also been observed in tracking with dogs (Leigh & Dominick, 2015; Snovak, 2004; Syrotuck, 1972). Dogs can move between vegetation and reach these “passive odor plumes,” something drones cannot do. How far drones with gas sensors can reach these relatively localized odor particles remains unclear. The surveys, interviews, and the lack of literature specifically addressing this issue indicate that knowledge and experience are too limited to draw conclusions.

In areas with less dense vegetation, the possibilities are broader. Thermal sensors can see through small openings in light vegetation, and LIDAR can more easily find gaps to acquire ground points (Hu et al., 2020; Masini et al., 2022; Rietz et al., 2023). According to experts at TCRH Mosbach, as well as various survey respondents, RGB sensors are less successful because carcasses are too well camouflaged. Literature also confirms that infrared sensors are preferred over RGB for monitoring wildlife and detecting wild boar carcasses (Haroldson et al., 2003; Howell et al., 2021; Rahman et al., 2020; Rietz et al., 2023; Shewring & Vafidis, 2021). Whether hyperspectral imaging could help detect carcasses through anomalies in the chemical composition of plants is uncertain but worth further study, particularly for detecting bones or buried carcasses (Aqduş et al., 2012; Beck & Cowley, 2011; Cavalli et al., 2007; Doneus et al., 2015; Peña-Villasenín et al., 2024).

In areas without dense tree canopies, thermal sensors appear most efficient, partly because of their real-time results. In grasslands, fields, or maize crops, carcasses with large larval masses are detectable, both according to literature and the experience of respondents and the drone expert at TCRH Mosbach (Rietz et al., 2023). This technique has been successfully applied at TCRH Mosbach. Wild boars that have been dead for 1 to 3 days, completely cooled but without larval colonization, are difficult to detect with infrared sensors, as are bones or small carcass parts (data from interviews and literature) (Hohmann et al., 2021; Rietz et al., 2023; Sandor et al., 2025). In these relatively open areas, hyperspectral sensors, artificial olfactory sensors, and LIDAR could potentially be used to detect such remains. Bones might be detectable via hyperspectral sensors and LIDAR, as shown in experimental studies in archaeology and forensic sciences (Brabazon et al., 2020; Corcoran, 2016; Silván-Cárdenas et al., 2021; Silván-Cárdenas et al., 2017). Piglets and small body parts might also be detected via artificial olfactory gas sensors (Yuan et al., 2019). However, outside of a few experimental studies, there is

insufficient information available in this context. Relying on these technologies to detect wild boar carcasses during a crisis outbreak still seems premature.

The combination of drones with thermal and RGB sensors for screening open or lightly vegetated areas (forest edges, sparsely wooded areas with little undergrowth, maize fields) is considered the most feasible by most survey respondents and is already applied in Germany, as confirmed by the drone experts at TCRH Mosbach. It is an efficient way to screen, particularly with the use of automated flight software. Logistics are relatively straightforward in open areas, and only a few people are required (one pilot, an additional observer, and possibly someone analysing the data on a separate computer). However, thorough administrative preparation is necessary due to legislation regarding geographic UAS zones, flight licenses, permissions, exceptions to the VLOS rule, risk assessments, etc. (E.A.S.A, 2024; E.A.S.A; EU Commission, 2019). Early preparation is essential.

A major drawback of drones is weather dependency. During a crisis, searching must occur daily over weeks. It is problematic if flights are cancelled due to excessive sun, heat, wind, rain, snow, or fog (Burke et al., 2018; Chrétien et al., 2016; Duffy et al., 2017; Dunn et al., 2002; Gordon et al., 2007; Lethbridge et al., 2019; McMahon et al., 2021; Weissensteiner et al., 2015). While almost all survey respondents highlighted this problem, some also note that increasingly wind-stable and water-resistant drones and sensors are being developed. The price of these modern drones is high, and the disruptive effects of fog, rain, and heat on infrared imaging remain. This raises the question of whether detection dogs can fill the biggest gaps of drone detection: ineffectiveness in forest searches and weather limitations. Can dog search teams operate in dense vegetation? Are they accurate under varying weather conditions? What are the pitfalls of search dogs? And can drones compensate for these? If so, detection drones and search dogs could form the “dream team” that is being sought.

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