https://doi.org/10.29326/2304-196X-2025-14-2-123-132

Artificial intelligence-integrated drones used for detection of live wild boars, wild boar carcasses and remnants in the context of African swine fever control

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ABSTRACT

Introduction. Effective measures for African swine fever outbreak prevention and early detection are required in view of global spread of African swine fever, fatal viral hemorrhagic disease of domestic pigs and wild boars. Wild boar population managing and search for the wild boars died of African swine fever and being the virus source are considered priority measures for the disease control in wildlife.

Objective. Generalization of currently available knowledge about advanced technologies for the use of unmanned aerial vehicles (drones) in combination with artificial intelligence-based methods in the wild.

Materials and methods. Analytical research methods including search in the following databases were used: PubMed, Springer, Wiley Online Library, Google Scholar, CrossRef, Russian Science Citation Index (RSCI), eLIBRARY, CyberLeninka.

Results. Potential of using unmanned aerial vehicles (drones) and artificial intelligence (neural network) for detection of wild boars and their remnants in the context of combating African swine fever is described in the review. The role of wild boars in the disease spread and the need for wild boar population regulation are discussed in detail. Also, the importance of timely wild boar carcass removal and use of modern technologies for wild boar population recording and its density estimation are underlined. Data on the use of drones equipped with various technical devices for study of large animal populations in the wild are analyzed, advantages and peculiarities of unmanned aerial vehicle use are indicated. Experience gained in using neural networks-based techniques for automatic processing of animal images acquired from drones is also summarized.

Conclusion. Artificial intelligence-integrated unmanned aerial vehicles appear to be a key tool for managing wild boar populations and the rapid detection of African swine fever dead wild boars that allows improvement of overall effectiveness of the measures taken against this disease.

Keywords: review, wild boar, African swine fever, animal recording techniques, monitoring, aerial photography, unmanned aerial vehicles, UAVs, drones, artificial intelligence, neural network

Acknowledgements: The study was supported by the Ministry of Education and Science of the Russian Federation within the state assignment for the Federal Research Center for Virology and Microbiology (No. FGNM-2022-0004). The authors thank the reviewers for peer reviewing of this paper.

For citation: Bespalova T. Yu., Korogodina E. V., Mikhaleva T. V. Artificial intelligence-integrated drones used for detection of live wild boars, wild boar carcasses and remnants in the context of African swine fever control. *Veterinary Science Today*. 2025; 14 (2): 123–132. https://doi.org/10.29326/2304-196X-2025-14-2-123-132

Conflict of interests: The authors declare no conflict of interests.

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УДК 619:639.1.053:616-036.22:639.111.14:623.746.4-519:004.8

Интеграция применения дронов и искусственного интеллекта для обнаружения диких кабанов, туш и их останков в связи с африканской чумой свиней

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РЕЗЮМЕ

Введение. Глобальное распространение африканской чумы свиней, смертельно опасного вирусного геморрагического заболевания домашних свиней и диких кабанов, диктует необходимость применения эффективных мер предупреждения и раннего выявления вспышек. Контроль численности популяции, а также поиск туш диких кабанов, погибших от африканской чумы свиней и являющихся источником передачи вируса, считаются приоритетными мерами в управлении заболеванием в дикой природе.

Цель исследования. Обобщение имеющихся в настоящее время знаний о передовых технологиях применения беспилотных летательных аппаратов (дронов) в условиях дикой природы в сочетании с методами искусственного интеллекта.

Материалы и методы. При выполнении работы применялись аналитические методы исследований с использованием баз данных PubMed, Springer, Wiley Online Library, Google Scholar, CrossRef, РИНЦ, eLIBRARY, CyberLeninka.

Результаты. В данном обзоре рассматривается возможность применения беспилотных летательных аппаратов (дронов) и искусственного интеллекта (нейронных сетей) для обнаружения диких кабанов и их останков в контексте борьбы с африканской чумой свиней. Подробно обсуждается роль диких кабанов в распространении заболевания и необходимость контроля их популяции, значение своевременного удаления трупов кабанов, при этом подчеркивается важность использования современных технологий для учета численности и плотности популяции дикого кабана. Проанализирована информация о применении дронов, оснащенных различными техническими средствами, при изучении популяций крупных видов животных в условиях дикой природы, отмечены преимущества и особенности использования беспилотных летательных аппаратов. Также обобщен опыт применения нейронных сетей в контексте автоматической обработки полученных с помощью дронов изображений животных.

Заключение. Интеграция беспилотных летательных аппаратов и искусственного интеллекта, вероятно, может стать ключевым инструментом в контроле популяции дикого кабана и быстром обнаружении туш кабанов, погибших вследствие африканской чумы свиней, что в целом позволит повысить эффективность мер, направленных на борьбу с данным заболеванием.

Ключевые слова: обзор, дикие кабаны, африканская чума свиней, методы учета животных, мониторинг, аэрофотосъемка, беспилотные летательные аппараты, дроны, искусственный интеллект, нейронная сеть

Благодарности: Работа выполнена при поддержке Минобрнауки России в рамках Государственного задания ФГБНУ «Федеральный исследовательский центр вирусологии и микробиологии» (тема № FGNM-2022-0004). Авторы благодарят рецензентов за их вклад в экспертную оценку данной работы.

Для цитирования: Беспалова Т. Ю., Корогодина Е. В., Михалева Т. В. Интеграция применения дронов и искусственного интеллекта для обнаружения диких кабанов, туш и их останков в связи с африканской чумой свиней. *Ветеринария сегодня.* 2025; 14 (2): 123–132. https://doi.org/10.29326/2304-196X-2025-14-2-123-132

Конфликт интересов: Авторы заявляют об отсутствии конфликта интересов.

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INTRODUCTION

African swine fever (ASF), deadly viral hemorrhagic disease affecting both domestic pigs (*Sus scrofa domestica*) and wild boars (*Sus scrofa*), remains a critical global threat to pig industries [1]. Wild boars are now commonly recognized as key reservoirs and vectors for ASF transmission; infected migratory populations have been found to introduce the virus to multiple European countries [2, 3, 4, 5]. Monitoring of Eurasian wild boar populations – including assessments of population size, density, and dynamics – constitutes a critical component of ASF management strategies for the disease outbreak containment in wild populations. Early outbreak detection including systematic searching for carcasses, a primary source of direct and indirect ASF virus transmission, represents one of the most effective measures for ASF eradication in the wild. Rapid detection and safe disposal of dead wild boars can prevent further infection spread, since the virus is found to persist in ASF dead wild boars for several months [6, 7, 8, 9]. Searching for wild boar carcasses and remnants is a laborious and time – consuming work, which strongly depends on the outbreak size, season, terrain, vegetation density as well as other factors. According to researchers, most of the wild boar carcasses are often missed by traditional ground-based walking methods [10]. Therefore, alternative modern methods and technologies are required for reliable wild boar population size and density assessment and optimization of the process of searching for wild boar carcasses and remnants.

Currently, unmanned aerial vehicles (UAVs), known as unmanned aircraft system, copters, or drones controlled by one or more pilots using communication channels at remote piloting points (ground control stations), are becoming increasingly popular. Unmanned aerial vehicles are widely used in absolutely different fields, including wildlife monitoring. Moreover, various UAV systems, together with developing artificial intelligence (AI) technologies, are used for wild animal censusing, animal behaviour and movement analysis [11, 12, 13]. In the last decade, numerous studies of populations and natural habitats of both wild birds [14, 15, 16] and various wild large animal species (primates, elephants, hippos, ungulates) were carried out using drones as a part of environmental protection measures [17, 18, 19, 20, 21, 22, 23]. However, there are almost no data on their use for wild boar searching and for wild boar population size assessment in peer-reviewed sources. UAVs are one of the promising options to be added to the set of traditional monitoring methods. Some studies have shown that drones allow for more rapid and accurate estimation of wild animal populations in vast territories as compared with ground-based methods (walking monitoring, camera traps, etc.) [17, 24]. Previously, large-scale aerial photography of wildlife was carried out using manned aircrafts, but use of UAVs for aerial photography is much cheaper. UAVs can work under cloud cover in contrast to satellites [25]. Artificial intelligence and machine learning (ML) are revolutionizing wildlife monitoring by improving data quality for population estimates, streamlining data collection, and automating routine data processing. Neural networks – trained on extensive datasets from drone imagery, camera traps, and video cameras – can now achieve species-level identification and even distinguish individual animals. ML algorithms process visual data orders of magnitude faster than manual analysis, with demonstrated capability to filter tens of thousands of files in minutes to select animal-containing images, dramatically increasing research efficiency [18].

Given the ongoing ASF panzootic, testing of modern UAV-based approaches, firstly, as an observational tool for wild boar population size and density assessment, and, secondly, as a tool for efficient searching for wild boar carcasses and their remnants is of importance for the infection management in the wild. A review of published literature identified a critical research gap: no comprehensive studies exist on the UAVs application for searching for live wild boars and wild boar carcasses. Our review of AI-integrated UAV systems successfully deployed for other animal species appears to be helpful for their adaptation to programs on wild boar population monitoring.

This review synthesizes current knowledge on advanced AI-integrated UAV (drone) technologies applied for wildlife monitoring. The review addresses the following aspects: role of wild boar in ASF spread and importance of prompt removal of dead wild boars; use of UAVs and neural networks for wild large animal population monitoring with focus on drone-based approach advantages and features as compared to traditional methods.

MATERIALS AND METHODS

Analytical methods and searching in the following databases: PubMed, Springer, Wiley Online Library, Google Scholar, CrossRef, RSCI, eLIBRARY, CyberLeninka were used for the work.

ROLE OF WILD BOARS IN ASF EPIZOOTY

Since genotype II ASF virus detection in Eastern Europe (2007) the disease has spread to many European countries and far beyond its borders (to Asia, America and Oceania). According to the World Organization for Animal Health, ASF has been reported in 64 countries, more than 934 thousand pigs and more than 31 thousand wild boars have been infected over the past three years. Eurasian wild boars are believed to play the main role in the disease spread in Europe where more than 19 thousand outbreaks have been reported in wild boar population[1]. In most European countries, ASF spread has been facilitated for many years by factors potentially associated with wild boar ecology, infection management strategies in the wild (for example, an efficient search for dead wild boars), as well as with the long-term ASF virus persistence in animal carcasses and in the environment [1]. Monitoring of wild boar populations in Europe shows a steady increase in the population size and expansion of the population habitat over the past decades that hampers ASF management in the infected areas [26]. In Central European countries, Eurasian wild boar population density is high, 1.15–5.31 animals per 100 ha [27, 28]. The population density is known to be one of the important factors associated with ASF spread among wild boars, the higher the density, the higher the probability of pathogen transmission by direct contact [29]. For example, in Poland, ASF cases were reported mainly in the areas where the wild boar population was more than 1 animal per 1 km^2, but statistical and mechanistic models did not show a clear and consistent effect of wild boar density on ASF epizootology [1, 30]. Wild boars living in close proximity to both private and commercial farms pose a risk of ASF outbreaks in domestic pigs that becomes higher with the relatively high number of wild boars [31]. Therefore, ASF management requires the most reliable information on wild boar population size and density in each region in the context of various measures. However, it is actually quite difficult to obtain data close to absolute ones. This is the most challenging for remote areas and vast territories.

When studying the wild boar population in the context of ASF control, it is important to take into account their biological behaviour peculiarities, seasonal and landscape factors, as well as the virus persistence in the environment. Recently, a lot of studies has been carried out to examine various factors that ultimately affect the effective search for wild boars, their carcasses and remnants. The search can be improved by target searching for preferred habitats for both healthy and infected animals. Wild boars are known to be very mobile, hide in dense vegetation, and to be predominantly nocturnal with peak activity in the late evening (at sunset), at midnight and in the morning hours at sunrise throughout most of the year. Reduced activity at temperatures above 15 °C is their behavioural adaptation mediated by physiological characteristics. Wild boars are less active in the forest than in open areas, and they choose reeds in swampy areas as a safe resting place [32, 33]. ASF-diseased wild boar preferences should be taken into account to find the places where they die. Such animals display changes in their behaviour, they prefer solitude with sufficient shelter, silence, coolness, and plenty of water, which is associated with the condition caused by the infection (depression, fever, dyspnoea) [34]. During the studies, the vast majority (71%) of infected carcasses were found in forests, especially in young woodlands, as well as in places remote from roads and settlements, in places of transition from woodlands to sparsely wooded areas and shrubs, near trails, waterbodies and forest edges with tall grass [34, 35, 36]. The space-time clustering in detected ASF-positive wild boar carcasses was most prominent at a distance of 2 km and within 1 week after the outbreak reporting [37]. Moreover, seasonal features of ASF spread should be considered when planning carcass search activities. In most European countries there was an evident seasonality in ASF incidence in wild boars that increased in winter (December – February) and peaked in summer (July). According to Russian researchers, ASF outbreaks in wild boars reported in the Russian Federation regions in 2007–2022 also occurred mostly in November – December and February, with peaks in the summer months (July – August) [38, 39].

Natural behaviour of wild boars – digging roots, rolling on the ground and exploring various objects – may be a risk factor for the infection if they live in the virus-infected environment. Some researchers have shown that ASF virus transmission in wild boar habitats can occur not only through direct contact with infected conspecifics, but also through indirect contact with carcasses, secretions, soil, water, grass, or agricultural crops [28, 40, 41], while physical contact with pathogen-positive carcasses or the substrates beneath them poses an equal risk of ASF virus infection [42]. The carcass and remnant (bones and skin) decomposition sites remain attractive to wild boars for a long period of time [40]. The carcass decomposition process depends on the season and can take several days in summer to several months in winter [43]. ASF dead wild boars are a permanent source of infection for other animals, as the virus is highly resistant to environmental conditions and persists for a long time in various organs, tissues and secretions. It has been reported that a frozen carcass

[1] WOAH. African swine fever. https://www.woah.org/en/disease/african-swine-fever/#ui-id-2

can maintain infectious ASF virus for several months enabling the virus to overwinter and to initiate a new outbreak when the defrosted carcass is visited the following spring by a susceptible wild boar [37]. In the study carried out in Germany, it was noted that wild boars rummaged on decomposition sites, sniffing and poking on the conspecifics' carcasses, chewing on their bare ribs, the contact was observed in 30% of all visits by wild boars to such sites and the wild boars were especially "interested" in rooting on the soft soil that had formed under and around decomposed carcasses [8]. Later, it was found that more than 50% of cases of transmission in Eastern Poland were associated with indirect contact with infected carcasses that contributed to ASF virus persistence in wild boar populations [44]. In a recent study in the Czech Republic, a two-year monitoring using camera traps was conducted to assess the attractiveness of wild boar carcasses to their live conspecifics. It was shown that the number of visits by wild boars to the sites with experimentally placed carcasses during the year was more than five times higher than to control sites (without carcasses). Wild boars found the carcass relatively quickly, on average in 2 days in spring and summer, 6 days in autumn and 8 days in winter. The earliest visits were recorded in the spring, when the decomposition process was accompanied by a strong odour. Also, number of direct contacts with the carcass that varied depending on the season was determined. In autumn, wild boars came into direct contact with the carcass during 340 out of 541 visits (62.8%), in spring – during 71.2% of visits, in summer – during 74.5% of visits. The largest number of direct contacts was recorded in winter – 84.1% [33]. These findings are of great importance, since infected tissues (muscles, skin, subcutaneous fat) and organs of decomposing carcasses can be sources of ASF infection for several months, especially at low temperatures [9, 45]. Stability of the pathogen in the soil depends on the temperature: under experimental conditions at +4 °C, the virus retained its infectivity for up to 112 days [46], in the soil under the carcass – up to 2 weeks [47, 48]. The virus survival rate is found to depend on the soil type and pH level: the virus persists for a week in the forest and meadow soils, for 3 days in the soil of swampy areas, for at least 3 weeks in sand, and quickly dies in acidic forest soils [49].

Wild boars are omnivorous animals, just like domestic pigs, they are characterized by cannibalism. Tissues of other animals, including their conspecifics, were found in the stomach contents of wild boars [50]. In the study performed by J. Cukor et al. [51], direct contact of wild boar with carcasses was observed in 81% and cannibalism was observed in 9.8% of all reported visits of wild boars. Therefore, deliberate or accidental consumption of carcasses (cannibalism) or invasive contact with carcasses (with infected blood, tissues, or biological materials) can be considered as decisive factors in the chain of ASF virus transmission among wild boars [52]. Furthermore, infected carcasses can also maintain indirect virus spread by potential vectors – arthropods [42], as well as scavengers. According to J. Rietz et al. [53], some scavengers, in particular foxes, do not consume wild boar carcasses on site, but can move (scatter) their remnants over rather long distances in 6–10 days. Carcass parts are scattered over 400 m in 75% of cases, and maximum over 1.2 km. This should be considered for effective carcass searching as a part of ASF outbreak management. At the same time, such remnants scattering distances make a ground search by humans almost impossible.

Thus, wild boar carcasses and the surrounding soil are a reservoir for the long-term ASF virus persistence, and therefore early, rapid and effective search for potentially infected carcasses and their timely and safe removal from the environment are extremely important for minimization of the risk of the disease spread in the population. In ASF endemic areas the special attention should be paid to these measures using the accumulated knowledge about diseased wild boar behaviour and environmental factors that increase the likelihood of carcass detection.

For the purpose of ASF control wild boar population should be regulated and its density should be maintained at the lowest possible level in each region [6]. Existing methods of animal censusing are based on their direct counting during direct field observation with naked eye or binoculars, as well as on-site images obtained at fixed points using camera traps, as well as sampling, surveying, or analysis of various indirect evidence of animal life [54, 55]. The methods differ in the territory coverage, counting techniques, objects to be counted, used technical devices, etc. For example, the widely used method of winter route counting determines the correlation between the number of animals detected in a selected area (along the route), the number of tracks (left during one day) and the daily animal movement length (provided that the snow cover is appropriately thick). Today, this basic method is considered simple and universal, it is relatively low cost since used technical tools are cheap, but it is not suitable for censusing of elusive animals [55]. The significant disadvantages of conventional methods for wild animal censusing (complete snow cover, low accuracy, dependence on weather conditions, etc.) dictate the need for improvement of monitoring technologies. Combined methods are more useful for obtaining reliable data on the animal population size and migration. Currently, simultaneous use of several methods with specialized equipment, such as camera traps, video or infrared (IR) cameras, has been proven effective. However, according to some researchers, aerial monitoring is the most effective method of animal censusing as compared with field methods [19, 54, 55, 56].

USE OF DRONES FOR WILDLIFE MONITORING

Remotely piloted aircraft systems (UAVs) – commonly known as drones – have been gaining increasing popularity worldwide over the past few years. UAV system includes three main components: the aircraft itself (drone), which performs tasks in the air; the ground station where the drone takes off and lands and where the communication and control equipment is installed; and the operator who directly controls the drone during flight. UAVs have many advantages that make them a powerful tool for exploring wildlife. Until the past decade, it has been challenging to gather data on number of the animals located in particular area and at particular time because aircraft missions and satellite images are expensive, and ground-based surveys in many cases are limited by accessibility to sites, the areas that could be covered [11]. UAVs now provide transformative capabilities for field research, dramatically decreasing manpower demands, survey durations, and project expenditures. UAVs can be successfully used in remote areas and under harsh climate conditions. The selection of the UAV for wild animal monitoring and

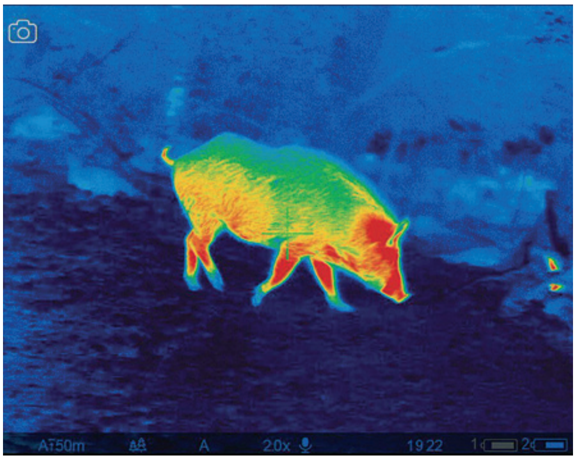

Fig. 1. Thermal image of a wild boar (https://pulsarvision.com/journal/calm-alert-hungry-getting-to-know-animals-through-thermal)

Fig. 2. Wild boar monitoring using drone technology (AI-generated image)

animal population size estimation critically depends on its payload specifications and installed sensors. UAV systems may incorporate machine vision sensors and AI-powered analytical capabilities. AI coupled with neural networks facilitates population census, real-time spatial monitoring as well as migratory pattern analysis and automated species classification [17, 57]. UAVs equipped with advanced electronic payloads – including digital sensors, night/thermal imaging cameras, communication systems, and GPS/GLONASS (Global Navigation Satellite System, GNSS) positioning units – exhibit significantly enhanced operational capabilities. Sensors based on machine vision enable visual perception of the UAV environment by creating a captured scene image, for example, a thermal imaging camera captures and registers IR radiation emitted by surrounding objects. There are practically no hard-to-reach places for UAVs with photo and thermal imaging cameras. Infrared cameras facilitate biotic/abiotic differentiation while maintaining diurnal/nocturnal operational capacity under varying environmental conditions. Their ability to detect thermally distinct targets enables wildlife monitoring through dense canopy cover and during crepuscular/nocturnal periods. In thermal IR waves, an animal looks like a bright object, provided that the animal's body temperature is higher than the ambient temperature (with a difference of up to 30–40 °C). Thermal images of the best quality are obtained at sunrise, late evening and at night (Fig. 1) [19, 54, 55, 57, 58].

Current UAV capabilities demonstrate significant potential for search for wild boars, their carcasses and remnants. Drones are capable of flying slowly at low altitudes, exploring areas that are hard-to-reach during ground-based surveys, such as dense forests or wetlands, as well as detecting moving and stationary objects without risk to humans (Fig. 2). The latter is important when searching for both living individuals at rest and animal carcasses. It has been found that images of the area covered by one frame made at altitude of 150 m are optimal for accurate counting of large groups of animals.

UAVs offer apparent advantages over traditional manned aircraft, owing to lower operational costs with minimal space requirements for their taking off. In addition, drones are relatively quieter than the latter, they may present less disturbance risk to animals due to noise, and could reduce the risk of biased counts because animals are less likely to flee and hide [20]. Regarding search for wild boar carcasses and remnants with UAVs, it should be taken into account that experiments have shown the high attractiveness of the places with wild boar carcasses and remnants for their fellow wild boars [33]. Since drones can easily detect live wild boar gatherings in these areas, this technology can also be used for wild boar remnant searching. Moreover, UAV thermal imaging can directly detect wild boar remnants by capturing heat signatures from fly larvae clusters and/or microbial activity during carcass decomposition. The heat generated by feeding larvae can be detected during their peak activity – between the 6th and 29th day of carcass decomposition – at ambient temperatures of 15–27 °C, when insect populations on the remnants are highest. Analysis of image resolution at varying flight altitudes revealed that thermal contrast between remnants and background was highest in noon recordings at 4 m altitude. A 15 m altitude proved optimal for balancing survey speed and detection efficacy during long-term monitoring, and objects became frequently overlooked beyond 30 m. All these factors should be taken into account when planning flights in order to maximize the chances for the remnant detection [59, 60].

UAV systems are continuously improving. Computer vision-integrated drone systems providing new capabilities and expanding UAV functionality are increasingly applied for object detection and recognition. Using computer vision, drones can autonomously process visual information, identify objects and make environment-dependant decisions. Currently, modern advanced technologies include the so-called FPV drones (First Person View) with Betaflight software and real-time video transmission. These systems enable high-speed, precise spatial data acquisition and long-range video signal transmission. FPV drones differ from conventional GPS drones in their smaller size and weight, which makes them easy to maneuver and move quickly (flight speeds can reach 100 km/h or more). FPV drones equipped with high-resolution cameras and video transmitters allows the user to see the real-time image on special glasses or monitor, feel the effect of their own presence in the airspace and remotely control the drone movements while adjusting the speed, altitude and angle of inclination of the device to control flight over a given

Fig. 3. Hugging-wing robot [62]

terrain. For the purpose of the environment monitoring, FPV drones, like other UAVs, are used to collect data and explore vast, new or remote territories, detect and track moving objects, wildlife habitats, and provide high-quality geo-referenced images[2] [61]. Also, application of universal robotic systems, hugging-wing robots, that can both hover in the air and perch on vertical supports such as tree trunks and poles is one of the promising methods for wild animal behaviour monitoring and collecting data on their habitats (Fig. 3). Remote autonomous navigation enables precise landing site determination for such robotic systems, achieving positioning accuracy within several meter ranges [62].

When planning UAV operations, some critical factors must be taken into account as they significantly impact both data quality and collection efficiency. These factors include: low resolution of the camera or sensor image, battery charge duration (which therefore determines the range and area covered in a single drone flight), weather conditions (strong wind, rain, snow), operator's control skills and experience, etc. [21]. Drone management and maintenance require special training for ground operators and compliance with security measures. In our country, use of any UAV is allowed only upon obtaining all required official documentation and permits in compliance with unmanned aerial vehicle regulations in place in the Russian Federation.

SOFTWARE AND ARTIFICIAL INTELLIGENCE USED FOR PROCESSING OF THE DATA COLLECTED BY DRONES

Conventional methods include visual analysis of photographs but manual photo analysis becomes increasingly labor-intensive and time-consuming when processing large photographic datasets. This method is inherently susceptible to human error factors including fatigue, inattention, etc. This disadvantage can be minimized by involving several specialists in the work or using software enabling automatic information processing [58]. Images obtained by UAV-mounted sensors are typically stitched together into an assembled digital map by using software programs. This digital map can then be uploaded into GIS (Geographic Information System) software, which can be geographically referenced using GPS data automatically gathered by the UAV in flight. When a UAV lack an on-board GPS, geographic coordinates can be manually obtained by reference to Ground Control Points (physical landmarks with known coordinates). Image processing of the digital map may be performed manually by the user, or automatically by image processing software that classifies objects. Digital files associated with drone images may be very large (up to 70 terabytes), particularly with the high resolution required for accurate object recognition [63]. Currently, domestic and foreign researchers use various software programs for processing data collected during wildlife monitoring [17, 58]. Longmore S. N. et al. [64] combined astronomical detection software with existing ML algorithms for automatic decrypting thermal images of animals, this pipeline contributed to effective detection of animals in the images. Currently, up to 30 software programs are being developed in Russia for different animal species identification, which count the number of animals both in a single image and in a series of images, some of software programmes enable simultaneous processing of thermal images and video materials[3] [55]. For example, the Thermal Infrared Object Finder (TIOF) software developed on the Python platform is capable of processing a large amount of infrared image data for specific animal identification [65].

Convolutional neural networks (CNNs) represent a state-of-the-art approach facilitating animal detection and counting in aerial imagery. CNNs are one of the main types of neural networks used for image recognition and classification that are composed of two main parts: feature extraction and classification. Feature extraction is aimed at creating maps of objects through utilizing processes called convolutions. CNN model contains three types of layers: convolutional layer, pooling layer and fully connected layer. The first two perform feature extraction, and the fully connected layer displays the extracted features and performs classification. Deep learning models offer a significant advantage in processing accuracy over conventional classification methods when trained and tested with large datasets, so the use of neural networks enables creation of accurate models of animal populations, tracking migration routes, and estimating population size [17]. Neural network-based flight control expands the UAVs capabilities. Neural networks demonstrate dynamic adaptability through continuous learning from operational data, enabling real-time optimization of both flight parameters and image acquisition settings in response to unpredictable environmental variables. They can combine data from various sensors mounted on the drone to improve perception and situational awareness, which allows the drone to make more informed

[2] https://sky-space.ru/blog/fpv-dron (in Russ.)

[3] https://ru.rt.com/qo5p (in Russ.)

decisions. In addition, neural networks allow UAVs to move autonomously, easily maneuver around obstacles during flight and that is very important for monitoring remote territories. Neural networks can optimize trajectories for drones, which is useful for the applications such as aerial photography or surveillance, where certain trajectories must be followed for optimal data collection [61]. The use of neural network algorithms minimizes the time required for task implementation (from a few seconds to several minutes), but the neural network training can take tens of hours. At the same time, the user should have programming skills in environments such as Python or Java, and the computer on which the ML will be performed must be equipped with appropriate equipment [15].

Outcomes of AI application for animal monitoring are presented in some studies and reports posted on the Internet resources. Zhou M. et al. tested two deep learning neural network models: CNN and deep residual networks (ResNet), for their efficacy for the classification of four animal species: cattle (*Bos taurus*), horses (*Equus caballus*), Canadian geese (*Branta canadensis*) and white-tailed deer (*Odocoileus virginianus*). The results have showed that visible images collected at a distance of 60 m or less are sufficient for accurate classification, and that the most effective algorithm can be the ResNet model with 18 layers (ResNet 18), since the overall accuracy rate for animal identification was 99.18% [66]. The experiment conducted by D. Marchowski on counting populations of 33 waterfowl species demonstrated successful use of AI-integrated UAVs in 96% of 343 cases. ImageJ/Fiji software and ML methods with neural network algorithms such as DenoiSeg were used for automated counting [15]. Krishnan B. S. et al. used fusion approach for ML, combining several pairs of thermal and visible images acquired from drones. It was interesting that for white-tailed deer, which were typically cryptic against their backgrounds and often in shadows in visible images, the added information from thermal images improved detection and classification in fusion methods from 15 to 85%. It has been found that image fusion in combination with two models of deep neural networks is ideal for photographing animals that are cryptic against the background [23]. Combining images were taken from 75 and 120 m above ground level, a faster region-based CNN (Faster R-CNN) was trained using annotated images labelled "adult caribou", "calf caribou" and "ghost caribou" (animals moving between images and blurring individuals during processing of photogrammetric data). The model accuracy, precision, and repeatability was 80, 90, and 88%, respectively [17]. In Hortobágyi Nemzeti Park (Hungary), AI technologies are used for preservation of endangered Asian wild Przewalski horses. Researchers are using drones to monitor the horse herd behaviour. The acquired high-resolution footage is processed on the Microsoft Azure platform and analysed using AI, which is able to distinguish horses from other animals[4]. The first tests of the software developed by specialists of the Moscow Institute of Physics and Technology in cooperation with the Ministry of Natural Resources and Environment of the Russian Federation were conducted in the Land of the Leopard National Park (Primorsky Krai, Russia). The software program enables recognition of Amur leopards, Amur tigers and other wild animals[5]. Also, AI-based wild animal recognition system developed by NtechLab company is currently tested in Russia. The system is currently integrated with videos containing bear images, but in the future it is planned to expand its functionality to cover other wild animal species[6]. The Ministry of Natural Resources and Environment staff-members are performing aerial surveys using drones and neural networks in some Russian regions to search for ungulate aggregations[7].

Finally, it is worth noting that in 2024, a team of American researchers created the Aerial Wildlife Image Repository (AWIR), which is a dynamic interactive database with annotated images acquired from drones equipped with conventional and thermal imaging cameras. AWIR provides the first open-access repository for users to upload, annotate, and curate images of animals acquired from drones. The AWIR also provides benchmark datasets that users can download to train AI algorithms to automatically detect and classify animals. The AWIR contains 6,587 animal objects in 1,325 visible and thermal images of predominantly large birds and mammals [67].

CONCLUSION

Reliable data on population size and density are required for ASF spread prevention in wild boars and risk assessment. Animal carcass searching serves as a critical tool for early ASF detection. The combination of modern UAVs with neural network algorithms is a highly effective method of obtaining accurate and timely information about the natural environment, which, in particular, opens up new opportunities in the field of wild boar population monitoring. In the era of the active AI development and widespread UAVs use, application of innovative technologies in combination with traditional methods appears to contribute to enhancing the efficiency of searching for live wild boars and their carcasses as well as the reliability of the obtained data, that can improve animal health control as a part of ASF management strategies. Close cooperation of programmers, wildlife researchers and veterinarians are required for successful implementation of such approaches. Since AI-integrated UAV is a cutting-edge technique used in wildlife research field, it requires ongoing evaluation.

REFERENCES

1. EFSA, Boklund A. E., Ståhl K., Miranda Chueca M. Á., Podgórski T., Vergne T., et al. Risk and protective factors for ASF in domestic pigs and wild boar in the EU, and mitigation measures for managing the disease in wild boar. *EFSA Journal*. 2024; 22 (12):e9095. https://doi.org/10.2903/j.efsa.2024.9095

2. Pejsak Z., Truszczyński M., Niemczuk K., Kozak E., Markowska-Daniel I. Epidemiology of African swine fever in Poland since the detection of the first case. *Polish Journal of Veterinary Sciences*. 2014; 17 (4): 665–672. https://doi.org/10.2478/pjvs-2014-0097

[4] https://habr.com/ru/companies/microsoft/articles/567406 (in Russ.)

[5] https://www.mnr.gov.ru/press/news/uchyenye_natsparka_zemlya_leoparda_v_primore_ispytali_iskusstvennyy_intellekt_dlya_raspoznavaniya_ti/ (in Russ.)

[6] https://360.ru/news/obschestvo/dikih-zhivotnyh-v-rossii-nachnut-otslezhivat-s-pomoschju-iskusstvennogo-intellekta-smi/?from=inf_cards (in Russ.)

[7] https://nsknews.info/materials/drony-i-neyroset-schitayut-dikikh-zverey-v-novosibirskoy-oblasti/ (in Russ.)

3. Oļševskis E., Guberti V., Seržants M., Westergaard J., Gallardo C., Rodze I., Depner K. African swine fever virus introduction into the EU in 2014: Experience of Latvia. *Research in Veterinary Science.* 2016; 105: 28–30. https://doi.org/10.1016/j.rvsc.2016.01.006

4. Nurmoja I., Schulz K., Staubach C., Sauter-Louis C., Depner K., Conraths F. J., Viltrop A. Development of African swine fever epidemic among wild boar in Estonia – two different areas in the epidemiological focus. *Scientific Reports.* 2017; 7:12562. https://doi.org/10.1038/s41598-017-12952-w

5. Sauter-Louis C., Forth J. H., Probst C., Staubach C., Hlinak A., Rudovsky A., et al. Joining the club: First detection of African swine fever in wild boar in Germany. *Transboundary and Emerging Diseases.* 2021; 68 (4): 1744–1752. https://doi.org/10.1111/tbed.13890

6. Sauter-Louis C., Conraths F. J., Probst C., Blohm U., Schulz K., Sehl J., et al. African swine fever in wild boar in Europe – A review. *Viruses.* 2021; 13 (9):1717. https://doi.org/10.3390/v13091717

7. Chenais E., Ståhl K., Guberti V., Depner K. Identification of wild boar-habitat epidemiologic cycle in African swine fever epizootic. *Emerging Infectious Diseases.* 2018; 24 (4): 810–812. https://doi.org/10.3201/eid2404.172127

8. Probst C., Globig A., Knoll B., Conraths F. J., Depner K. Behaviour of free ranging wild boar towards their dead fellows: Potential implications for the transmission of African swine fever. *Royal Society Open Science.* 2017; 4 (5):170054. https://doi.org/10.1098/rsos.170054

9. Fischer M., Hühr J., Blome S., Conraths F. J., Probst C. Stability of African swine fever virus in carcasses of domestic pigs and wild boar experimentally infected with the ASFV "Estonia 2014" isolate. *Viruses.* 2020; 12 (10):1118. https://doi.org/10.3390/v12101118

10. EFSA Panel on Animal Health and Welfare. Scientific opinion on African swine fever. *EFSA Journal.* 2015; 13 (7):4163. https://doi.org/10.2903/j.efsa.2015.4163

11. Gonzalez L. F., Montes G. A., Puig E., Johnson S., Mengersen K., Gaston K. J. Unmanned aerial vehicles (UAVs) and artificial intelligence revolutionizing wildlife monitoring and conservation. *Sensors.* 2016; 16 (1):97. https://doi.org/10.3390/s16010097

12. Schad L., Fischer J. Opportunities and risks in the use of drones for studying animal behavior. *Methods in Ecology and Evolution.* 2023; 14 (8): 1864–1872. https://doi.org/10.1111/2041-210x.13922

13. Petso T., Jamisola R. S. Jr. Wildlife conservation using drones and artificial intelligence in Africa. *Science Robotics.* 2023; 8 (85):eadm7008. https://doi.org/10.1126/scirobotics.adm7008

14. Hodgson J. C., Baylis S. M., Mott R., Herrod A., Clarke R. H. Precision wildlife monitoring using unmanned aerial vehicles. *Scientific Reports.* 2016; 6:22574. https://doi.org/10.1038/srep22574

15. Marchowski D. Drones, automatic counting tools, and artificial neural networks in wildlife population censusing. *Ecology and Evolution.* 2021; 11 (22): 16214–16227. https://doi.org/10.1002/ece3.8302

16. Demmer C. R., Demmer S., McIntyre T. Drones as a tool to study and monitor endangered grey crowned cranes (*Balearica regulorum*): Behavioural responses and recommended guidelines. *Ecology and Evolution.* 2024; 4 (2):e10990. https://doi.org/10.1002/ece3.10990

17. Lenzi J., Barnas A. F., ElSaid A. A., Desell T., Rockwell R. F., Ellis-Felege S. N. Artificial intelligence for automated detection of large mammals creates path to upscale drone surveys. *Scientific Reports.* 2023; 13:947. https://doi.org/10.1038/s41598-023-28240-9

18. Brickson L., Zhang L., Vollrath F., Douglas-Hamilton I., Titus A. J. Elephants and algorithms: a review of the current and future role of AI in elephant monitoring. *Journal of the Royal Society.* 2023; 20 (208):20230367. https://doi.org/10.1098/rsif.2023.0367

19. Witczuk J., Pagacz S., Zmarz A., Cypel M. Exploring the feasibility of unmanned aerial vehicles and thermal imaging for ungulate surveys in forests – preliminary results. *International Journal of Remote Sensing.* 2018; 39 (15–16): 5504–5521. http://doi.org/10.1080/01431161.2017.1390621

20. Linchant J., Lhoest S., Quevauvillers S., Lejeune P., Vermeulen C., Semeki Ngabinzeke J., et al. UAS imagery reveals new survey opportunities for counting hippos. *PLoS ONE.* 2018; 13 (11):e0206413. https://doi.org/10.1371/journal.pone.0206413

21. Semel B. P., Karpanty S. M., Vololonirina F. F., Rakotonanahary A. N. Eyes in the sky: Assessing the feasibility of low-cost, ready-to-use unmanned aerial vehicles to monitor primate populations directly. *Folia Primatologica.* 2019; 91 (1): 69–82. https://doi.org/10.1159/000496971

22. Baldwin R. W., Beaver J. T., Messinger M., Muday J., Windsor M., Larsen G. D., et al. Camera trap methods and drone thermal surveillance provide reliable, comparable density estimates of large, free-ranging ungulates. *Animals.* 2023; 13 (11):1884. https://doi.org/10.3390/ani13111884

23. Krishnan B. S., Jones L. R., Elmore J. A., Samiappan S., Evans K. O., Pfeiffer M. B., et al. Fusion of visible and thermal images improves automated detection and classification of animals for drone surveys. *Scientific Reports.* 2023; 13:10385. https://doi.org/10.1038/s41598-023-37295-7

24. Corcoran E., Denman S., Hamilton G. Evaluating new technology for biodiversity monitoring: Are drone surveys biased? *Ecology and Evolution.* 2021; 11 (11): 6649–6656. https://doi.org/10.1002/ece3.7518

25. Hvala A., Rogers R. M., Alazab M., Campbell H. A. Supplementing aerial drone surveys with biotelemetry data validates wildlife detection probabilities. *Frontiers in Conservation Science.* 2023; 4:1203736. https://doi.org/10.3389/fcosc.2023.1203736

26. Tack J. Wild boar (*Sus scrofa*) populations in Europe: A scientific review of population trends and implications for management. Brussels: European Landowners' Organization; 2018. 56 p. https://wildbeimwild.com/wp-content/uploads/2023/08/12-Tack-J-Wild-Boar-Population-Trends-in-Europe-2018.pdf

27. Carpio A. J., Apollonio M., Acevedo P. Wild ungulate overabundance in Europe: contexts, causes, monitoring and management recommendations. *Mammal Review.* 2021; 51 (1): 95–108. https://doi.org/10.1111/mam.12221

28. Chenais E., Depner K., Guberti V., Dietze K., Viltrop A., Ståhl K. Epidemiological considerations on African swine fever in Europe 2014–2018. *Porcine Health Management.* 2019; 5:6. https://doi.org/10.1186/s40813-018-0109-2

29. Podgórski T., Borowik T., Łyjak M., Woźniakowski G. Spatial epidemiology of African swine fever: Host, landscape and anthropogenic drivers of disease occurrence in wild boar. *Preventive Veterinary Medicine.* 2020; 177:104691. https://doi.org/10.1016/j.prevetmed.2019.104691

30. Śmietanka K., Woźniakowski G., Kozak E., Niemczuk K., Frączyk M., Bocian Ł., et al. African swine fever epidemic, Poland, 2014–2015. *Emerging Infectious Diseases.* 2016; 22 (7): 1201–1207. https://doi.org/10.3201/eid2207.151708

31. Boklund A., Dhollander S., Chesnoiu Vasile T., Abrahantes J. C., Bøtner A., Gogin A., et al. Risk factors for African swine fever incursion in Romanian domestic farms during 2019. *Scientific Reports.* 2020; 10:10215. https://doi.org/10.1038/s41598-020-66381-3

32. Johann F., Handschuh M., Linderoth P., Dormann C. F., Arnold J. Adaptation of wild boar (*Sus scrofa*) activity in a human-dominated landscape. *BMC Ecology.* 2020; 20:4. https://doi.org/10.1186/s12898-019-0271-7

33. Cukor J., Faltusová M., Vacek Z., Linda R., Skoták V., Václavek P., et al. Wild boar carcasses in the center of boar activity: crucial risks of ASF transmission. *Frontiers in Veterinary Science.* 2024; 11:1497361. https://doi.org/10.3389/fvets.2024.1497361

34. Morelle K., Jezek M., Licoppe A., Podgorski T. Deathbed choice by ASF-infected wild boar can help find carcasses. *Transboundary and Emerging Diseases.* 2019; 66 (5): 1821–1826. https://doi.org/10.1111/tbed.13267

35. Cukor J., Linda R., Václavek P., Šatrán P., Mahlerová K., Vacek Z., et al. Wild boar deathbed choice in relation to ASF: Are there any differences between positive and negative carcasses? *Preventive Veterinary Medicine.* 2020; 177:104943. https://doi.org/10.1016/j.prevetmed.2020.104943

36. Rogoll L., Schulz K., Staubach C., Oļševskis E., Seržants M., Lamberga K., et al. Identification of predilection sites for wild boar carcass search based on spatial analysis of Latvian ASF surveillance data. *Scientific Reports.* 2024; 14:382. https://doi.org/10.1038/s41598-023-50477-7

37. Allepuz A., Hovari M., Masiulis M., Ciaravino G., Beltrán-Alcrudo D. Targeting the search of African swine fever-infected wild boar carcasses: A tool for early detection. *Transboundary and Emerging Diseases*. 2022; 69 (5): e1682–e1692. https://doi.org/10.1111/tbed.14504

38. Coelho I. M. P., Paiva M. T., da Costa A. J. A., Nicolino R. R. African swine fever: spread and seasonal patterns worldwide. *Preventive Veterinary Medicine.* 2025; 235:106401. https://doi.org/10.1016/j.prevetmed.2024.106401

39. Zakharova O. I., Blokhin A. A., Burova O. A., Yashin I. V., Korennoy F. I. Risk factors for African swine fever spread in wild boar in the Russian Federation. *Veterinary Science Today*. 2024; 13 (1): 64–72. https://doi.org/10.29326/2304-196X-2024-13-1-64-72

40. Probst C., Gethmann J., Amler S., Globig A., Knoll B., Conraths F. J. The potential role of scavengers in spreading African swine fever among wild boar. *Scientific Reports.* 2019; 9:11450. https://doi.org/10.1038/s41598-019-47623-5

41. Nuanualsuwan S., Songkasupa T., Boonpornprasert P., Suwankitwat N., Lohlamoh W., Nuengjamnong C. Persistence of African swine fever virus on porous and non-porous fomites at environmental temperatures. *Porcine Health Management*. 2022; 8:34. https://doi.org/10.1186/s40813-022-00277-8

42. Tummeleht L., Häkkä S. S. S., Jürison M., Vilem A., Nurmoja I., Viltrop A. Wild boar (*Sus scrofa*) carcasses as an attraction for scavengers and a potential source for soil contamination with the African swine fever virus. *Frontiers in Veterinary Science.* 2024; 11:1305643. https://doi.org/10.3389/fvets.2024.1305643

43. Probst C., Gethmann J., Amendt J., Lutz L., Teifke J. P., Conraths F. J. Estimating the postmortem interval of wild boar carcasses. *Veterinary Sciences.* 2020; 7 (1):6. https://doi.org/10.3390/vetsci7010006

44. Pepin K. M., Golnar A. J., Abdo Z., Podgórski T. Ecological drivers of African swine fever virus persistence in wild boar populations: insight for control. *Ecology and Evolution*. 2020; 10 (6): 2846–2859. https://doi.org/10.1002/ece3.6100

45. Davies K., Goatley L. C., Guinat C., Netherton C. L., Gubbins S., Dixon L. K., Reis A. L. Survival of African swine fever virus in excretions from pigs experimentally infected with the Georgia 2007/1 isolate. *Transboundary and Emerging Diseases.* 2017; 64 (2): 425–431. https://doi.org/10.1111/tbed.12381

46. Prodelalova J., Kavanova L., Salat J., Moutelikova R., Kobzova S., Krasna M., et al. Experimental evidence of the long-term survival of infective African swine fever virus strain Ba71V in soil under different conditions. *Pathogens.* 2022; 11 (6):648. https://doi.org/10.3390/pathogens11060648

47. Carlson J., Fischer M., Zani L., Eschbaumer M., Fuchs W., Mettenleiter T., et al. Stability of African swine fever virus in soil and options to mitigate the potential transmission risk. *Pathogens*. 2020; 9 (11):977. https://doi.org/10.3390/pathogens9110977

48. Mazur-Panasiuk N., Woźniakowski G. Natural inactivation of African swine fever virus in tissues: Influence of temperature and environmental conditions on virus survival. *Veterinary Microbiology.* 2020; 242:108609. https://doi.org/10.1016/j.vetmic.2020.108609

49. Blokhin A. A., Burova O. A., Toropova N. N., Zakharova O. I., Iashin I. V., Korennoy F. I. Monitoring ASF in wildlife: virus survival in wild boar carcasses and disinfection methods (review). *Veterinariya.* 2022; (3): 14–21. https://doi.org/10.30896/0042-4846.2022.25.3.14-21 (in Russ.)

50. Merta D., Mocała P., Pomykacz M., Frąckowiak W. Autumn-winter diet and fat reserves of wild boars (*Sus scrofa*) inhabiting forest and forest-farmland environment in south-western Poland. *Folia Zoologica.* 2014; 63 (2): 95–102. https://doi.org/10.25225/fozo.v63.i2.a7.2014

51. Cukor J., Linda R., Václavek P., Mahlerová K., Šatrán P., Havránek F. Confirmed cannibalism in wild boar and its possible role in African swine fever transmission. *Transboundary and Emerging Diseases.* 2020; 67 (3): 1068–1073. https://doi.org/10.1111/tbed.13468

52. Sánchez-Cordón P. J., Lean F. Z. X., Batten C., Steinbach F., Neimanis A., Le Potier M. F., et al. Comparative evaluation of disease dynamics in wild boar and domestic pigs experimentally inoculated intranasally with the European highly virulent African swine fever virus genotype II strain "Armenia 2007". *Veterinary Research*. 2024; 55:89. https://doi.org/10.1186/s13567-024-01343-5

53. Rietz J., Ischebeck S., Conraths F. J., Probst C., Zedrosser A., Fiderer C., et al. Scavenger-induced scattering of wild boar carcasses over large distances and its implications for disease management. *Journal of Environmental Management*. 2024; 365:121554. https://doi.org/10.1016/j.jenvman.2024.121554

54. Hyun C.-U., Park M., Lee W. Y. Remotely piloted aircraft system (RPAS)-based wildlife detection: a review and case studies in maritime Antarctica. *Animals.* 2020; 10 (12):2387. https://doi.org/10.3390/ani10122387

55. Prosekov A. Yu. Characteristics and key limitations of traditional methods for accounting hunting

animals and digital technologies for solving the existing problems (review). *Agricultural Science Euro-North-East*. 2020; 21 (4): 341–354. https://doi.org/10.30766/2072-9081.2020.21.4.341-354 (in Russ.)

56. Prosekov A., Kuznetsov A., Rada A., Ivanova S. Methods for monitoring large terrestrial animals in the wild. *Forests*. 2020; 11 (8):808. https://doi.org/10.3390/f11080808

57. Tubis A. A., Poturaj H., Dereń K., Żurek A. Risks of drone use in light of literature studies. *Sensors*. 2024; 24 (4):1205. https://doi.org/10.3390/s24041205

58. Ivanova S., Prosekov A. Hunting resource management by population size control by remote sensing using an unmanned aerial vehicle. *Nature Environment and Pollution Technology*. 2024; 23 (1): 391–399. https://doi.org/10.46488/NEPT.2024.v23i01.033

59. Lee M. J., Voss S. C., Franklin D., Dadour I. R. Preliminary investigation of aircraft mounted thermal imaging to locate decomposing remains via the heat produced by larval aggregations. *Forensic Science International*. 2018; 289: 175–185. https://doi.org/10.1016/j.forsciint.2018.05.028

60. Butters O., Krosch M. N., Roberts M., MacGregor D. Application of forward-looking infrared (FLIR) imaging from an unmanned aerial platform in the search for decomposing remains. *Journal of Forensic Sciences*. 2021; 66 (1): 347–355. https://doi.org/10.1111/1556-4029.14581

61. Peksa J., Mamchur D. A review on the state of the art in copter drones and flight control systems. *Sensors*. 2024; 24 (11):3349. https://doi.org/10.3390/s24113349

62. Askari M., Benciolini M., Phan H. V., Stewart W., Ijspeert A. J., Floreano D. Crash-perching on vertical poles with a hugging-wing robot. *Communications Engineering*. 2024; 3:98. https://doi.org/10.1038/s44172-024-00241-0

63. Mechan F., Bartonicek Z., Malone D., Lees R. S. Unmanned aerial vehicles for surveillance and control of vectors of malaria and other vector-borne diseases. *Malaria Journal*. 2023; 22:23. https://doi.org/10.1186/s12936-022-04414-0

64. Longmore S. N., Collins R. P., Pfeifer S., Fox S. E., Mulero-Pázmány M., Bezombes F., et al. Adapting astronomical source detection software to help detect animals in thermal images obtained by unmanned aerial systems. *International Journal of Remote Sensing*. 2017; 38 (8–10): 2623–2638. https://doi.org/10.1080/01431161.2017.1280639

65. Prosekov A., Vesnina A., Atuchin V., Kuznetsov A. Robust algorithms for drone-assisted monitoring of big animals in harsh conditions of Siberian winter forests: recovery of European elk (*Alces alces*) in Salair mountains. *Animals*. 2022; 12 (12):1483. https://doi.org/10.3390/ani12121483

66. Zhou M., Elmore J. A., Samiappan S., Evans K. O., Pfeiffer M. B., Blackwell B. F., Iglay R. B. Improving animal monitoring using small unmanned aircraft systems (sUAS) and deep learning networks. *Sensors*. 2021; 21 (17):5697. https://doi.org/10.3390/s21175697

67. Samiappan S., Krishnan B. S., Dehart D., Jones L. R., Elmore J. A., Evans K. O., Iglay R. B. Aerial wildlife image repository for animal monitoring with drones in the age of artificial intelligence. *Database*. 2024; 2024:baae070. https://doi.org/10.1093/database/baae070

Received 28.02.2025
Revised 08.04.2025
Accepted 05.05.2025

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Contribution of the authors: All authors contributed equally to this work at all stages as well as to paper text writing.

Вклад авторов: Авторы внесли равный вклад на всех этапах работы и написания статьи.