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Research article

A standardized protocol for assessing the performance of automatic detection systems used in onshore wind power plants to reduce avian mortality

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ABSTRACT

While wind power plants are an important contribution to the production of renewable energy to limit climate change, collision mortality from turbines is a danger for birds, including many protected species. To try to mitigate collision risks, automatic detection systems (ADSs) can be deployed on wind power plants; these work by detecting incoming birds using a detection/classification process and triggering a specific reaction (scaring off the bird or shutting down the turbine). Nonetheless, bird fatalities still occur at ADS-equipped wind power plants, which raises the question of the performance of these tools. To date, the lack of a transparent, peer-reviewed experimental process to compare the performance of types of ADS has meant there is no robust protocol to assess these systems.

With the aim of filling this gap, we developed two standardized protocols that provide objective and unbiased assessments of the performance of different types of ADS, based on their probability of detecting/classifying birds at risk of collision. Both protocols rely on precise 3D tracking of wild birds by human observers using a laser rangefinder, and the comparison of these tracks with those detected and recorded by an ADS. The first protocol evaluates a system's general performance, generating comparable data for all types of ADS. In this protocol, detection/classification probability is estimated conditional on several abiotic and biotic environmental factors such as bird size, distance from the target, the flight angle and azimuth of the bird, as well as weather conditions. The second protocol aims to verify that the performance of an ADS installed on a given wind power plant complies with its regulatory requirements. In this protocol, detection/classification probability is specifically estimated for a given target species at a given regulatory detection distance. This protocol also estimates the proportion of time an ADS is functional on site over a year, and the proportion of reaction orders successfully operated by wind turbines. These protocols have been field-tested and made publicly available for use by government agencies and wind power plant operators.

1. Introduction

The development of renewable energy is a cornerstone of the global energy transition aiming to decrease fossil fuel consumption in order to limit climate change (Chum et al., 2011; Teske, 2019). In this context, wind power plants as well as photovoltaic power plants are emerging all over the world (Tinsley et al., 2023). The downside is that the large-scale development of renewable energy sites, in particular wind energy, has negative consequences on the environment and on biodiversity that are well documented (Drewitt and Langston, 2006; Durá-Alemañ et al., 2023; Katzner et al., 2019; Kuvlesky et al., 2007). Birds and bats are the main taxonomic groups impacted by this infrastructure (Refoyo Román et al., 2020; Thaxter et al., 2017). For these taxa, wind power plants are a source of both habitat loss and fatality due to collisions with turbines

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(Gómez-Catasús et al., 2018; Marques et al., 2014). At the deadliest wind power plants, up to 26.9 birds and 15.5 bats *per* turbine may be killed by collision each year (Ferrer et al., 2012; Loss et al., 2013; Zimmerling et al., 2013; Zimmerling and Francis, 2016). These fatalities impact animal populations, potentially affecting their viability. This can have a particularly negative impact on long-lived species such as large raptors or bats, which often have small populations and population dynamics that are highly sensitive to **additional mortality** (Beston et al., 2016; Carrete et al., 2009; Duriez et al., 2023; Watson et al., 2018).

In Europe and North America, mitigating the risk of bird collision when wind turbines are operating is mandatory when protected bird species frequent wind power plants (European Commission, 2020; USFWS, 2013). Two main mitigation measures are currently implemented. The first relies on the passive curtailment of wind turbines during sensitive periods of a bird's annual cycle (i.e., during breeding or migration periods), during farming operations that may attract birds around wind turbines, and/or during weather conditions that increase the risk of collision (i.e., rain, wind, low visibility, etc.) (see e.g., Arnett and May 2016; Barrios and Rodríguez, 2004; Smallwood et al., 2007; Smallwood and Bell, 2020). Such mitigation measures may, however, lead to significant energy production losses, as curtailment is implemented even when there is no bird around the turbine (this also applies to curtailment for bats, see Hayes et al., 2019).

An alternative mitigation method relies on the installation of a detection–reaction system, called an automatic detection system (ADS), inside or close to a wind power plant. Unlike the passive curtailment method, these devices actively trigger a reaction only when a bird is near a turbine and considered at risk of collision (Gradolewski et al., 2021; Hanagasioglu et al., 2015; May et al., 2012; McClure et al., 2021). These systems work by (1) detecting birds that are approaching a turbine (i.e., birds at risk of collision), and (2) sending an order to prevent the collision, e.g., to **shutdown** the turbine or to emit a visual or auditory signal to scare the bird (Gradolewski et al., 2021; May et al., 2012; McClure et al., 2021). As these actions only occur when a bird is considered at risk of collision, in theory they should reduce the frequency and duration of turbine shutdowns, and thus reduce energy production loss (de Lucas et al., 2012). In this way, an ADS provides an appealing trade-off between reducing bird mortality and maintaining energy production.

Three main families of ADS currently exist: (i) Two-dimensional (2D) optic systems, (ii) Three-dimensional (3D) optic systems, and (iii) radar technology. The first family, 2D optic systems (e.g., DT Bird®, Safewind® or Probird®), uses optical cameras and relies on detection of pixel variations to identify birds at risk of collision up to a few hundred meters away (Harvey et al., 2018; KNE, 2020; May et al., 2012). These ADSs generally analyze changes in pixel contrast between successive images to detect a moving object, and then use the size of the object to classify it as either a relevant target (i.e., a bird with a wingspan of over 50 cm) or not.

The second family, 3D optic systems (e.g., Identiflight®, Bioseco®), combines a stereoscopic camera and a 2D optical camera to assess 3D trajectories of flying objects. This combination enables a more accurate assessment of the distance between the ADS and the detected object. These 3D systems can detect objects up to around 1 km under ideal conditions (Gradolewski et al., 2021; McClure et al., 2018). Both 2D and 3D optical systems mainly rely on manually programmed algorithms or artificial intelligence algorithms (machine learning or deep learning) to classify an object as being at risk or not. Classification rules for some of these ADSs are based on the size of the target (i.e., the number of pixels); actions are then usually triggered only for large species that can be detected at a high distance (Gradolewski et al., 2021). Alternatively, some systems classify certain species via artificial intelligence training (Duerr et al., 2023; Identiflight® website, n.d.; McClure et al., 2018).

The third family of ADSs, radar technology (e.g., 3DFlightTrack®), uses the reflection of radio waves by objects to detect them (Nilsson et al., 2018; Schmaljohann et al., 2008). Successive echoes from a given object are concurrently analyzed to determine if the object's trajectory could be deemed risky and whether or not it requires triggering a reaction (Górecki et al., 2023). Such technology is not yet able to classify a flying object at species level, but can determine an approximate size class. It is sometimes able to classify an object into an approximate species group (passerine, raptor, etc.) using wingbeats (Nilsson et al., 2018; Pavón-Jordán et al., 2020; Schmaljohann et al., 2008). Compared to optical systems, radar systems have a much larger detection range (up to 10 km), but detection may be hampered by landscape characteristics such as topography, trees or wind turbine structures themselves (Gerringer et al., 2016; Krijgsveld et al., 2011; Nilsson et al., 2018).

Although they have different technologies, all types of ADS are based on the same principles. They aim to detect and identify individual birds at risk of collision inside a given area around a wind turbine, generally a sphere-shaped area with the rotor at its centre. The radius of the risk sphere usually depends on the target bird species, as the time needed to reach the wind turbine depends on avian flight speed (Fluhr and Duriez, 2021; EolDist web application, 2021). This radius also depends on the wind turbine characteristics (mainly size), which influence their shutdown time. When an object considered to be a bird of interest enters the risk sphere, the ADS triggers a reaction.

Yet despite the installation of ADS in a number of wind power plants worldwide, bird mortality is still recorded there (see e.g., McClure et al., 2022, 2021), raising the question of the **effectiveness** of these systems in reducing collisions. To our knowledge, no global and robust investigation has been conducted to assess the ability of the different types of ADS to concretely reduce fatality rates. Only one peer-reviewed article dealing with the effectiveness of a single type of ADS is currently available (Identiflight®, McClure et al., 2021), and its results are controversial (Huso and Dalthorp, 2023). One reason for this lack of studies is that studying the efficacy of an ADS presents ethical issues. Indeed, to measure the success of an ADS, it is necessary to compare the fatality rates occurring several years before and after the installation of the ADS; as well as to compare results obtained from several equipped and unequipped sites (Before After Control Impact (BACI) type protocols: Huso and Dalthorp, 2023; Smallwood and Bell, 2020). Such methods would involve delaying the installation of an ADS at sites where collisions are expected or occur and thus allowing further mortality at unequipped wind power plants (control sites) for several years.

While this ethical issue makes effectiveness difficult or impossible to assess, a first step could be to assess their **performance,** i.e. their capacity to (i) detect and classify a bird potentially at risk of collision and (ii) trigger an appropriate reaction in time. Although performance and efficacy are not necessarily perfectly correlated, an ADS cannot be effective if it is not at least performant. As far as we are aware, ADS performance has been evaluated in independent, peer-reviewed, published studies for only one type of ADS: Identiflight® (see results published in peer-reviewed international scientific journals: Duerr et al., 2023; McClure et al., 2018). The performance of other types of ADS has been assessed by ADS suppliers themselves or by environmental consulting companies commissioned by wind power plants operators; as such, they are not independent and often not even publicly available (we were only able to find a few, e.g., Aschwanden et al., 2014; Gradolewski et al., 2021; Hanagasioglu et al., 2015; Harvey et al., 2018; May et al., 2012). From these few publicly available references, no general conclusion about ADS performance can be clearly drawn, mainly due to a lack of standardization of the assessment methods used. These evaluations are based on a wide variety of experimental protocols, often with variability in the measured response variables, as well as in the technical approach used to record them. These tests have also mainly been conducted under optimal detection conditions (e.g., on a sunny day when visibility was >800 m, McClure et al., 2018), which means they evaluate only the upper range of performance.

With the rise in the number of wind power plants, there is a corresponding increase in ADS deployment. While an ADS seems at face value a relevant solution to reduce bird fatality by wind turbines, it is problematic that the performance of these systems, which are expensive to implement, remains largely unknown. To help address this gap, we developed a robust, objective and standardized protocol to evaluate the performance of different types of ADS. In addition, we tested the operationality of this protocol in the field. Assessing ADS performance is crucial both to (i) help regulatory agencies and wind power plants operators to select the most appropriate ADS for a specific installation based on the site topography and the bird species present, and (ii) evaluate if the performance of an ADS installed on a given wind power plant complies with local regulations and/or wind power plant operators' expectations. However, because these two objectives are independent and mutually exclusive, we designed a protocol for each case. The relevant protocol could be used by ADS suppliers, government agencies or environmental consulting companies. Below we describe these two protocols and the choices made during their design and optimization. Importantly, this manuscript does not intend to present evaluation of the ADSs performances. The technical details related to the protocols' field procedure are not presented here, but can be consulted on the MAPE project website for more information (this study was carried out in the framework of the MAPE project - Reduction of Avian Mortality in Operating Wind Farms, MAPE project website: scientific valorization, 2021).

2. How to assess ADS performance?

The four following operational requirements (or stages) (Fig. 1) are involved in the performance definition of an ADS.

(1) Function: An ADS must be functioning, i.e., show good temporal and spatial coverage. Temporal coverage is the fraction of time, quantified in a fixed time interval (e.g., *per* month), during which the system is operational. Temporal coverage mainly depends on the frequency of ADS failures. Spatial coverage is the fraction of space included in the risk sphere that is effectively covered by the ADS. Spatial coverage decreases due to blind spots, potential blind angles, camera failures and depends also on the ADS's maximum detection distance for a given species (specific to each ADS model).

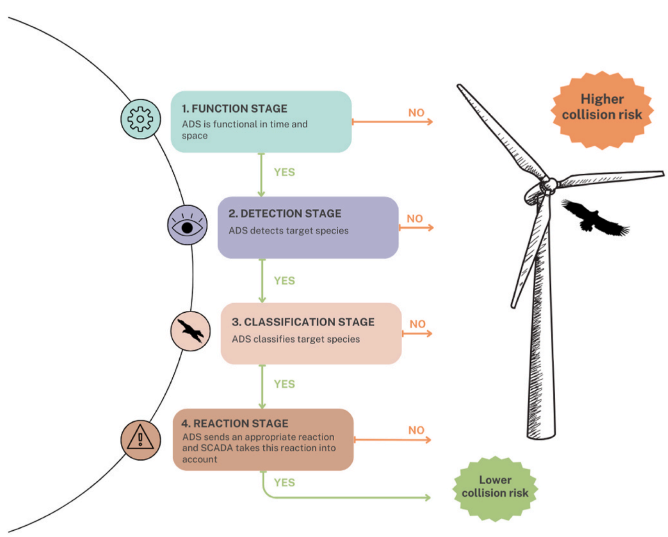

Fig. 1. The stages that must be assessed to evaluate ADS performance. The 'wind power plant' protocol requires evaluating all stages from 1 to 4, while the 'supplier' protocol only requires evaluating stages 2 and 3. Stage 1 is to estimate ADS functioning probability by analyzing its temporal and spatial coverage. Stage 2 is to estimate ADS detection probability. Stage 3 is to estimate ADS classification probability. (Stage 1 and 2 are generally merged because they cannot be easily separated.) Stage 4 involves evaluating reaction probability.

(2) Detection: An ADS must have a 'high rate' of target detection. Detection rate corresponds to the capacity of the ADS to identify a potential object of interest. As detailed above, the detection method used depends on the type of ADS (pixels of an image for optical systems, target echo for radar technology).

(3) Classification: An ADS must have a high rate of accurate classification. Classification combines all the steps involved in processing the information collected on a mobile target, from its detection by the ADS (size, speed, etc.) to the decision to trigger a reaction or not.

(4) Reaction: An ADS must react adequately in response to an identified risk. Reaction is defined as the ADS response following the detection and the accurate classification of a target bird at risk of collision. Two types of reaction are generally used: scare signals and turbine shutdown. The aim of visual or sound signals emitted by the ADS is to scare birds away from the turbine by alerting them to the danger (Aschwanden et al., 2014). Shutting down the wind turbine aims to slow the speed of the blades to reduce the risk of collision when the bird passes by. This second type of reaction requires communication between the ADS and the Supervisory Control And Data Acquisition (**SCADA**) nerve center of the turbine. An appropriate reaction is an ADS order that triggers a scare signal or turbine shutdown when a bird is at risk.

Good overall performance of an ADS is achieved when each of these four operational requirements is performed well.

As ADS suppliers and operators can have different evaluation objectives, a separate protocol is required for each, as mentioned above. We thus designed two protocols. The protocol aimed at ADS suppliers (hereafter referred to as the 'supplier' protocol) is designed to inform a general audience about the general performance of a specific ADS available on the market. This protocol only assesses detection and classification performance, as these do not depend on the specific characteristics of a wind power plant (i.e., surrounding landscape and technical characteristics of the turbines). Detection and classification performance must be assessed under various conditions of different influencing factors: distance between the bird and the ADS, size class of the species, background behind the bird, visibility, rainfall, solar radiation, luminosity, and solar incidence angle. These can then be used to fill in a generic performance grid for any type of ADS (Table 1).

The second protocol is intended for wind power plant operators (hereafter referred to as the 'wind power plant' protocol) and is designed to assess *in situ* all four operational requirements of ADS performance (function, detection, classification and reaction). In this protocol, detection/classification probability is estimated for the species of interest in a given wind power plant before a certain distance from the turbine (see e.g., EolDist web application, 2021) in order to define the minimal ADS detection distance needed according to the flight speed of the species and the characteristics of the wind turbines. Because this protocol aims to determine the average probability of detection and classification of targets before a certain distance by the ADS within a specific wind power plant, no environmental variable is considered in the statistical approach (Table 2).

2.1. *Evaluation of functioning performance ('wind power plant' protocol only)*

Functioning performance is here defined as the probability of the system being operational at any point in time and space during its deployment. This is defined by two components: the spatial and temporal coverage of the ADS. The absence of exhaustive spatial coverage of the ADS generally constitutes a **partial failure**. These partial failures are difficult, if not impossible, to measure, so they are not examined in this stage of the protocol, but are included in the detection/classification performance assessment (see below). Indeed, a lack of detection due to partial failure will negatively impact the detection/classification

Table 1
Final grid model of estimated performance for each ADS using the 'supplier' protocol.

'Supplier' protocol		Small/medium/large birds		
		Detection probability	Lower CI (95%)	Upper CI (95%)
Distance (m)	0–100			
	100–200			
	200–300			
	300–400			
	400–500			
	500–600			
	600–700			
	700–800			
	800–900			
	900–1000			
Bird's azimuth (°)	0–60			
	60–120			
	120–180			
	180–240			
	240–300			
	300–360			
Bird's vertical angle (°)	(-75)–(-45)			
	(-45)–(-15)			
	(-15)–15			
	15–45			
	45–75			
	75–105			
Rainfall (mm/10min)	0–0.58			
	0.58–1.25			
	>1.25			
Global radiation (J/cm^2/1h)	0–70			
	70–140			
	140–210			
	210–280			
	280–350			
Sun azimuth (°)	0–90			
	90–180			
	180–270			
	270–360			
Sun incidence (°)	(-20)–10			
	10–40			
	40–70			
Background	Sky			
	Vegetation			
Visibility (m)	0–200			
	200–400			
	400–600			
	600–800			
	800–1000			
Luminosity (lx)	0–24,000			
	24,000–48,000			
	48,000–72,000			
	72,000–96,000			
	96,000–120,000			

Table 2
Final grid model of estimated performance for each ADS using the 'wind power plant' protocol.

'Wind power plant' protocol	Probability	Lower CI (95%)	Upper CI (95%)
ADS function (time coverage)			
ADS detection/classification before the threshold distance specified in the regulations in force (m)			
ADS reaction			
Overall performance			

probability and is thus considered in the overall performance probability through the second step of performance assessment (see 2.2 Evaluation of detection and classification performance (both protocols)). Therefore, no specific measurement is required at this early stage, as such information might introduce redundancy afterwards. It should be noted that spatial coverage is generally verified by the supplier when the ADS is installed on a wind power plant. They might employ drones to detect potential blind spots and correct these by adapting the orientation of the equipment used to detect the targets.

Temporal coverage corresponds to the percentage of time during which the ADS is operational, i.e., is not experiencing a **complete failure**. Field observations can be conducted to estimate this by performing random visits in wind power plants and recording if and when the system does not react when a target crosses the risk sphere. Yet, as complete ADS failures are likely to be one-off occurrences, obtaining unbiased estimates for this parameter would require a very high number of field visits (typically 100 or more) and thus entail very high financial and time costs. Alternatively, the frequency of complete failures can be evaluated by assessing the number of days with a complete absence of detection/classification on a random selection of recorded data over hundreds of days. The functioning performance can then be expressed by the daily probability of the ADS not being in complete failure.

It should be noted that this method for estimating complete failure implies that the fieldwork procedure used to estimate detection/classification probability (see below) should be conducted during periods with no complete failure occurrence.

2.2. *Evaluation of detection and classification performance (both protocols)*

2.2.1. *Parameters to be estimated*

To estimate the detection probability of an ADS, it is necessary to know whether the target has been detected and its detection distance from the ADS. This can be done by comparing detections by an independent monitoring system with detection data from the ADS. To estimate the classification probability, we need information about how the ADS classified the target and what the target actually is. This can be done through identification of the targets that the ADS has classified, by viewing the video data, or by comparing the identification in the field with that recorded by the ADS (Duerr et al., 2023; McClure et al., 2018).

Since our method is intended to be applicable to all systems in a comparable way, both the 'supplier' and 'wind power plant' protocols focus on the combination of ADS detection/classification performance. This is because an ADS is continuously detecting moving targets and classifying them almost instantaneously as relevant or not for triggering a reaction. Some types of ADS can, on request, record information about all detected events, regardless of their classification or whether they triggered a response or not (personal communication from suppliers). However, extracting this data can represent a considerable amount of work and require large storage capacity, as some systems detect several tens of thousands of events in a single day such as the movement of trees, clouds or insects in the ADS environment, due to their high movement sensitivity. Moreover, not all ADSs are able to provide classification information independently from detection data, even on request. Aside from this, the separate evaluation of detection and classification would not provide any relevant information for potential users of these systems. Indeed, it is the result of both aspects that determines whether or not the system is making the right decision to trigger a reaction.

Bird trajectory data offer key variables for estimating detection/classification probability. The average distance between a bird and the ADS at first detection/classification is a common measure to indicate how well the system detects/classifies birds at a certain distance (Gradolewski et al., 2021; McClure et al., 2018). Although perfectly understandable by everyone, this parameter is actually not relevant to estimate ADS performance, as it gives no information about the proportion of trajectories correctly detected/classified as 'at risk' by the ADS out of those really at risk. In both our protocols, we defined the parameter to assess detection/classification performance as the probability of detecting/classifying a bird as being 'at risk' before it reaches the risk-sphere distance threshold (Fig. 2). It is the ability to detect/-classify before this distance that indicates that the ADS will potentially be able to prevent collisions by triggering a reaction early enough.

Concretely, for the 'supplier' protocol, detection/classification capability is assessed over 100-m steps ranging from a distance of 0–1000 m from the ADS (Table 1). For the 'wind power plant' protocol, a unique distance between the bird and the wind turbine is defined according to the flight characteristics of the target species present around the studied wind power plant (Table 2).

2.2.2. The choice of third-party methods to estimate detection/classification probability

Estimating the combined detection/classification probability before a certain distance from the turbine requires having (i) data related to events that have been detected and classified by the ADS and (ii) geolocation data of birds recorded by a reliable and robust independent system. The performance is assessed by comparing known target trajectories with the ADS detection/classification events of a given target to estimate the proportion of available targets that have been correctly detected/classified before a certain distance by the ADS. According to the available literature, target trajectories have been recorded using drones (Gradolewski et al., 2021), falconry birds (Brighton et al., 2017), human observers (McClure et al., 2018), or wild birds tracked with Global Positioning System (GPS) tags (Khosravifard et al., 2020) (Fig. 3).

The first of these methods, drones, has been used to mimic birds approaching wind turbines (Gradolewski et al., 2021). At first sight, the use of drones with onboard 3D geolocation would seem to be an accurate approach to determine ADS performance. This method does enable a large amount of data to be acquired in a short period of time, ensuring precise estimates through large sample size. It also ensures almost full control of the trajectory of the flying target, allowing some flight characteristics to be repeated for all trials. However, drones present several crucial limitations, which prevent robust evaluation of the combined detection/classification probability of an ADS (Fig. 3). First, they are a poor proxy for birds, in terms of size, shape, reflectance and type of trajectory and flight pattern. Such differences mean that the ADS classification algorithms may not have the same detection/classification rates for both drones and birds. Furthermore, the increased use of artificial intelligence as part of the classification algorithms will be more likely to exclude drones as relevant target objects at risk as a result of their recognition training (the use of drones will then lead to a negative bias in ADS performance estimates).

Falconry birds, i.e., trained birds, can also be used to mimic the presence of target birds in the ADS environment in a controlled manner

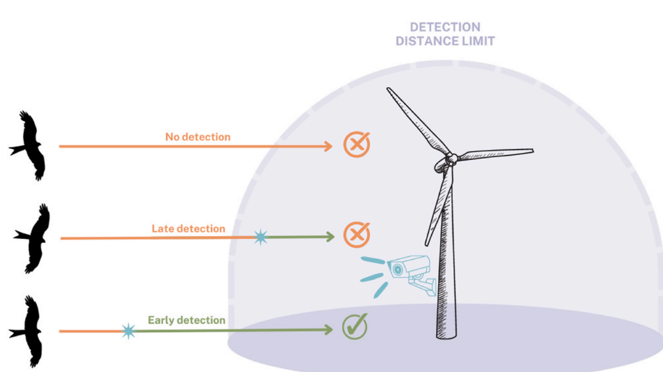

Fig. 2. Modelling the combined detection/classification probability before a certain distance (dotted line: risk sphere) based on trajectories recorded in the field. The time of detection/classification is represented by a blue star. The trajectory takes the value '1' if it is detected/classified before this distance (green tick), and '0' if it is not detected/classified before this distance (orange cross). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

(by teaching the birds to fly between trainers or to follow specific routes within the wind power plant). As it uses real birds, this approach has the advantage of providing realistic trajectories and flight patterns with true wingbeats. These birds can also be equipped with GPS tags, which record the 3D position of the bird every second, allowing a detailed analysis of the detection/classification performance of the ADS by comparing geographical positions and their times with those obtained by the ADS. In terms of the 'supplier' protocol, experimental falcon flights can also be organized to acquire 3D geolocations over most of the gradient of all abiotic influencing variables (Table 1) and in a variety of weather conditions (range of temperatures from winter to summer conditions; with moderate rain; in light fog; at wind speeds of up to 27.8 m/s). However, interviews with professional falconers revealed limitations for using this approach in the evaluation of combined detection/classification probability (Fig. 3). First, even with so-called '**high-flying' species**, falconry birds are generally not trained to fly at heights greater than 10 m (while the zone at risk of collision, i.e., the rotor of the turbines, is usually located between heights of 30 and 150 m). Furthermore, these birds are trained to fly in a straight line and at a relatively constant speed (between ~60 and 90 km h^{-1}, depending on the species) towards their trainer or a lure. Therefore, it is rarely possible to generate varied and unpredictable trajectories like those of wild birds. These differences in flight behavior/patterns between trained and wild birds may significantly affect their detection/classification by an ADS (Fig. 3). In addition, experimental flights at dusk and dawn, important since low luminosity may affect ADS performance while some birds may be active at these hours (see Table 1), are also impractical due to the risk that a bird unfamiliar with the test site may be unable to return to its falconer in the low light/visibility conditions of these periods.

Another method, equipping wild birds that regularly and naturally fly over the area of interest with high-resolution GPS tags, may allow the passive acquisition of a large quantity of geolocation data at a very fine time scale (longitude, latitude and altitude every second). This can then be compared with ADS detection/classification data. However, deploying this type of technology requires the capture of individuals and therefore the involvement of ornithologists with special authorizations that may be difficult to obtain. Moreover, even if several birds are equipped on a site, it may be challenging and take a long while before enough trajectories of these birds over the wind power plant are available for robust analysis. Because of these limitations, we did not include this approach in our protocols, although we think it remains highly relevant in terms of the quality of the data it can provide (Fig. 3) (Sassi et al., 2023).

Currently, the most robust, standardized and relevant approach for evaluating the combined detection/classification probability of an ADS is to record 3D positions of wild birds occurring at a wind power plant by one observer equipped with a laser rangefinder, preferentially assisted by a second observer. This method is not perfect: neither ADS nor human observers are exhaustive in the detection of birds near wind power plants, and some high-risk trajectories may be missed by both types of observation systems. Yet, the proportion of trajectories detected by ADS out of those detected by observers results in an unbiased estimate of the detection probability of the ADS, as long as the detection probability of the observers is independent of that of the ADS (Fig. 3) (this condition is not always respected: see the section 'Field testing of the protocols').

The use of binoculars with integrated laser rangefinders and a 3D compass is crucial in this approach. Most currently available ADSs on the market do not measure the distance between the detected object and the ADS. These binoculars, by providing the distance and azimuth between the target object and the laser rangefinder, allow an accurate 3D trajectory of the object to be drawn. For this to work, the clocks of the ADS and the observer/binoculars must be well synchronized, and only one bird should be present at any time in the study area. This approach also has its limitation: it is time consuming. For the same amount of time invested, it yields fewer trajectories on average than with drones or falconry birds, which makes this method less accurate. Its advantage is

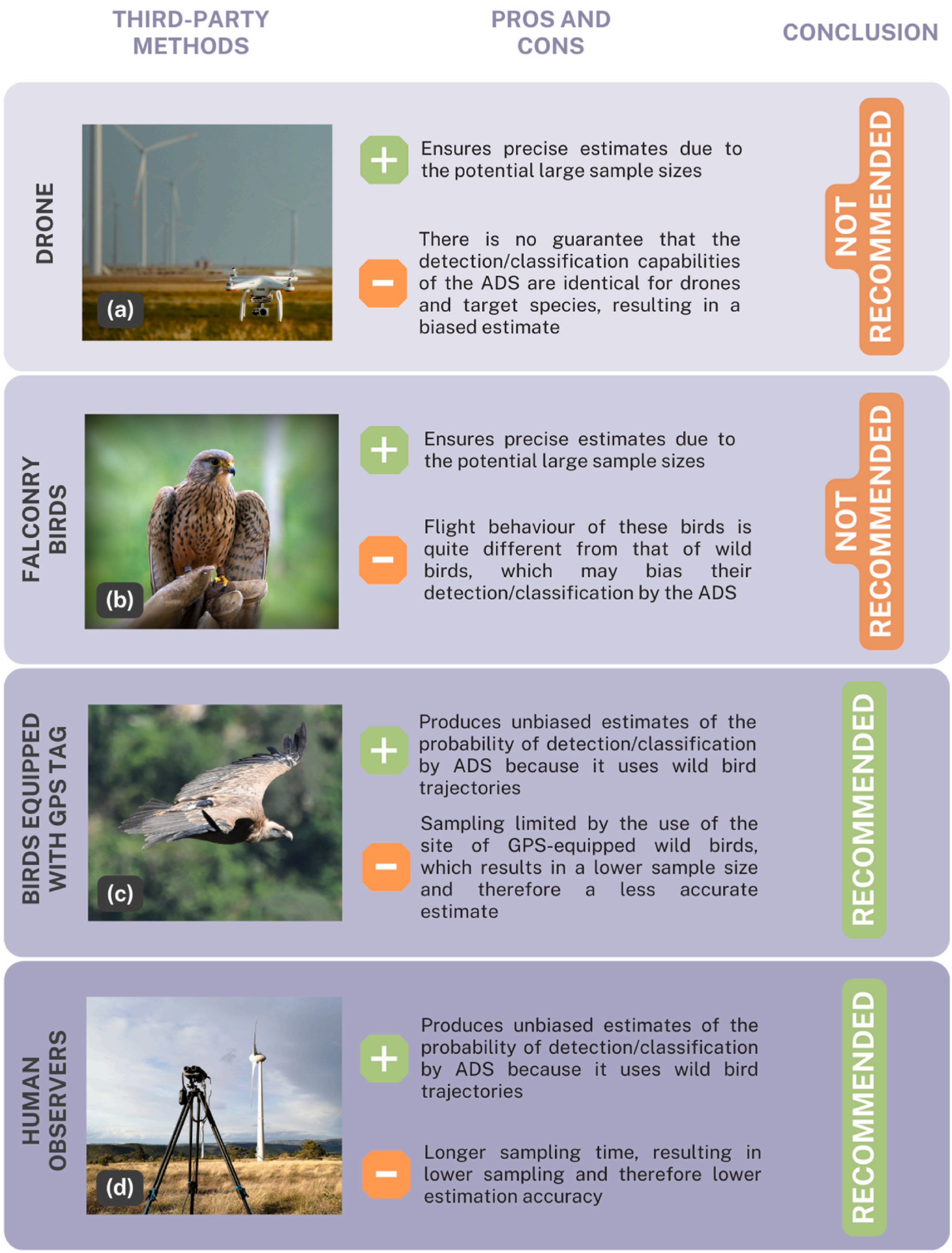

Fig. 3. The choice of third-party methods. The chosen approach must enable bird geolocations to be recovered in a way that is independent of the ADS, unbiased and accurate. No approach satisfies all three conditions. In such a situation, unbiased methods should be prioritized over biased ones, even if they are slightly less accurate. (a) Ana Sibler from Pixabay©, (b) Josep Monter Martinez from Pixabay©, (c) Olivier Duriez©, (d) Cyrielle Ballester©.

that it provides unbiased estimates in contrast to the other approaches (Fig. 3).

2.3. Evaluation of reaction performance ('wind power plant' protocol)

Reaction is defined as the ADS response following the detection/classification of a target object at risk of collision. In our 'wind power plant' protocol, we focus only on the shutdown of wind turbines and not on the emission of scare signals. This is because not all types of ADS produce these signals, but they all incorporate wind turbine shutdown. Reaction performance is assessed by estimating the probability of the ADS–SCADA coupling to correctly react, i.e., the probability that the

ADS sends the correct order and that this order is activated by the SCADA (Table 2). No fieldwork is needed to estimate this probability. It can be acquired by comparing data recorded by both the ADS and the SCADA, notably the daily number of shutdowns generated by the ADS and the number of shutdowns triggered by the SCADA, over hundreds of days.

It should be noted that our protocol does not consider the deceleration time of wind turbines after a shutdown order, since this is not a performance criterion of the ADS *per se*. This deceleration time depends essentially on the characteristics and settings of the wind turbines. However, it is important for operators to know/measure this deceleration time to define the threshold distances to be considered at risk (see (EolDist web application, 2021)).

3. Assessment of overall ADS performance

The three probabilities (function, detection/classification and reaction) characterizing ADS performance can be estimated from the data collected as described above by using generalized linear models (GLMs) with binomial distribution and the logit link function. Estimating the overall ADS performance on a specific wind power plant ('wind power plant' protocol) will allow verification that an ADS is performing well on that site. Local regulations may require different performance levels for different wind farms (e.g., requirements for only one of the performance aspects). The verification of ADS performance compliance will therefore be wind power plant dependent. The overall performance probability of an ADS is obtained by multiplying each of the three conditional probabilities of function, detection/classification and reaction (Table 2). The accuracy of the overall performance can be obtained using a **parametric bootstrap**.

As function and reaction probabilities can be estimated using a large number of days, this should make them very precise. The overall probability accuracy will thus largely depend on that of detection/classification probability, which primarily varies with the number of trajectories recorded by the observers. For example, with a detection/classification probability of 0.50 and 50 trajectories, the confidence interval will be [0.36; 0.64], while with a detection/classification probability of 0.50 and 100 trajectories, the confidence interval will be [0.40; 0.60], and with a detection/classification probability of 0.90 and 50 trajectories, the confidence interval will be [0.80; 0.98]. The expected precision given the number of trajectories and mean probability is easily obtained through the binomial distribution. The 'supplier' protocol involves modelling the effect of several explanatory variables on the combined detection/classification probability before a certain distance. As a result, the measurement effort will have to be greater to obtain a precise estimate over the entire gradient of explanatory variables.

4. Field testing of the protocols

We tested the protocols in the field from July 18, 2022 to October 21, 2022 on all three technologies that currently exist (2D cameras, 3D cameras and radar). The data was collected at five wind power plants located in different regions of France, each hosting different species of concern. Because these tests were performed under an agreement of confidentiality with private wind power plant operators, we cannot explicitly mention the precise site locations, the ADS brand and model tested, or the exact performance results obtained. The wind power plant operators gave their agreement on the condition that these experiments aimed to check the applicability of the protocol to be sure it was operational and not to assess ADS performance on their wind power plant.

To conduct the tests, observations were carried out at each wind power plant over three five-day periods separated by at least two weeks. We opted for the approach of two human observers equipped with binoculars with an integrated laser rangefinder monitoring a sphere with a radius of 1 km. This enabled us to assess performance with real flight behavior and site frequentation (unbiased). We targeted all possible birds with laser rangefinders, from pigeons (wingspan of ~0.5 m) to vultures (wingspan ~2.7 m). These measurements were carried out between sunrise and sunset (there is currently no robust solution for assessing an ADS in night-time conditions). This allowed us to test the relevance of the protocol for different species sizes and flight patterns, across various wind conditions, low light situations, backlight conditions, cloudy weather and light rain. A guide to the deployment of protocols for evaluating ADS performance is available on the MAPE website (MAPE project website: scientific valorization, 2021).

We found that the geographical location of the wind power plant had the greatest impact on sampling, while the time of year and weather conditions were found to have a lesser influence. The average number of trajectories obtained with the laser rangefinder varied considerably between wind power plants. For small birds (wingspan $<$ 1m), the average number of trajectories *per* day for all wind power plant combined was 13$\pm$ 11 (min = 0; max = 57). For medium-sized birds (wingspan between 1 and 1.5 m), the average number of trajectories collected *per* day was 13$\pm$ 11 (min = 0; max = 50). For large birds (wingspan >1.5 m), we obtained an average of 18$\pm$ 24 trajectories (min = 0; max = 92) *per* day.

A few limitations were noted during these tests. First, there were challenges with the laser rangefinder when tracking a bird against a background with vegetation. In this case, the distance measured was often that between the observer and the background and not between the observer and the bird of interest. It is possible that an ADS may also have difficulty detecting/classifying when birds are against a vegetation background (as several suppliers confirmed us). In this situation, the observer's detection capability is not entirely independent from that of the ADS, while our protocol's modelling approach assumes detection independence between the observer and the system. This non-independency could potentially result in an overestimation of the ADS's detection capability. There is unfortunately no statistical solution to this problem. The observers must try to minimize the occurrence of these situations in the field by making a judicious choice of observation points so that they are not too elevated in order to avoid measurements of birds against vegetation (Fig. 4).

Another difficulty found in this test phase concerns groups of birds passing through the wind power plant. If an ADS collects information on the position or azimuth of a detected bird, it is easy to determine whether the observer and the ADS have detected and tracked the same bird, provided that the different birds available to detection are coming from different directions. But some ADSs do not collect information on

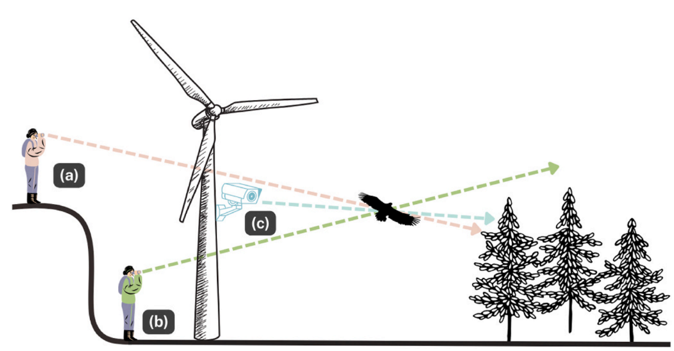

Fig. 4. Background of the same bird according to the position of the observer: the human observer (a) targets a bird against a background of vegetation, which may lead to measurement errors by the laser rangefinder; the observer (b) monitors a bird against a background of sky, leading to less measurement errors by laser rangefinders; the ADS (c) targets a bird against a background of vegetation. If the ADS is less performant when birds are against a background of vegetation, then using data from observer (a) will lead to an overestimation of ADS performance, as some observer-recorded trajectories of birds against the background will be removed from the dataset.

the geographical position or azimuth of a detected bird. For these systems, it is thus impossible to know whether the bird tracked with the laser rangefinder is the one detected by the ADS when several birds are present simultaneously in the risk area. This means that trajectories measured when groups of birds are present have to be excluded from the ADS evaluation. It is therefore essential to have two observers on the ground to ensure overall monitoring of the wind power plant area and to note the presence of groups of birds while using the laser rangefinder.

5. Conclusions

This study allowed us to determine the best approach for a standardized and robust protocol to assess the performance of any ADS deployed on a wind power plant to mitigate collision fatalities of birds. The field tests of the protocol confirmed that it was operational and identified specific situations that need to be taken into account either in the field or prior to data analysis. Such standardized assessment of ADS performance is crucially needed, both to reinforce the trust in these systems and to help government agencies and wind power plant operators select the most suitable ADS for a wind power plant. The protocols we suggest – one for ADS suppliers and another for wind power plant – should help improve transparency regarding ADS effectiveness and contribute to ensuring that the development of renewable energy is not at the expense of biodiversity.

CRediT authorship contribution statement

Cyrielle Ballester: Writing – original draft, Validation, Investigation, Formal analysis, Data curation, Conceptualization. **Sophie M. Dupont:** Writing – review & editing, Methodology, Conceptualization. **Alexandre Corbeau:** Writing – review & editing, Methodology, Conceptualization. **Thierry Chambert:** Writing – review & editing. **Olivier Duriez:** Writing – review & editing, Supervision, Conceptualization. **Aurélien Besnard:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Glossary

Additional mortality: We consider that mortalities resulting from wind turbine collisions are supplementary to mortality – natural or anthropogenic – already occurring in the population

Shutdown: When a turbine shutdown is initiated, the rotor motor stops, but a residual rotor speed remains, which effectively means that the blades slow down up to a residual speed rather than completely stop.

ADS effectiveness: Their capacity of the ADS to actually reduce fatality rates. Measuring this requires comparing the number of fatalities occurring before and after the installation of the system as well as in equipped sites vs control sites (BACI experimental setup: Smallwood and Bell, 2020)

ADS performance: The ability of the automatic detection system (ADS) to detect/classify/react to the arrival of a target in a risk sphere, as well as its degree of operability over time.

SCADA: SCADA is a control system architecture used in wind turbines that gathers and analyses data to monitor and control systems

Partial ADS failure: This occurs when only one of the components of a wind power plants ADS fails. This may be a failure lasting a few hours or the failure of a single camera. These failures are hard to identify by only looking at the data recorded by the ADS because this may contain partial-day detections or only pertain to specific cameras, making it difficult to detect a failure

Complete ADS failure: This is defined as a situation when the entire ADS of a wind power plant has failed for at least 24 h. In some cases, the wind power plant may automatically shut down when such a failure occurs. These failures are readily identifiable either by contacting the wind power plant operator or by analyzing the ADS data and identifying the days when no detections/classifications were recorded on the wind power plant

High-flying species: High-flying falconry birds include the peregrine falcon and the golden eagle. They should be distinguished from 'low-flying' species such as the goshawk, saker falcon or Harris's hawk

Parametric bootstrap:: This involves randomly sampling in a known distribution of a parameter of interest (usually estimated using a specific model)