Biological Conservation 311 (2025) 111449

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

Perspective

New frontiers in wind-wildlife monitoring systems

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A R T I C L E I N F O

Keywords:
Minimization
Monitoring
Sensor fusion
Technology
Wildlife

A B S T R A C T

Effective minimization of negative effects of wind energy on wildlife is an iterative process whereby direct observations of wildlife effects inform and validate mitigation strategies. Yet, the full implementation of this adaptive management has been hindered by a lack of appropriate data. The accurate, high-resolution data required exceeds the capacity of most current monitoring approaches (human observers or monitoring technologies applied in isolation). Current applications of monitoring technologies struggle to harness their full potential by failing to capitalize on opportunities for integration with additional technologies and/or by having limited temporal and spatial resolution. At the emergence of this new frontier of wildlife monitoring, we review the elements of a robust wind-wildlife monitoring system and highlight sensor fusion principles that facilitate effective implementation and integration of multiple monitoring technologies. We also illustrate how sensor fusion solutions can generate high resolution data on collision and displacement effects on terrestrial wildlife across complex spatial and temporal scales.

1. Introduction

Land-based wind energy is a critical component to global energy production yet continues to have unintended negative effects on wildlife (Allison et al., 2019; Schuster et al., 2015). Primary effects of concern are collision, whereby wind turbine blades make lethal contact with wildlife (Arnett et al., 2008; Marques et al., 2014), and displacement, whereby the presence of wind turbines causes wildlife to redistribute across the landscape—resulting in functional loss of habitat (Dohm et al., 2019; Lloyd et al., 2022). To balance the tradeoff between wind energy production and wildlife conservation goals, we must monitor effects (i.e., mortality, displacement), correlates of effects (i.e., individual behaviors at multiple scales), and the effectiveness of minimization approaches.

Most post-construction wildlife monitoring programs focus only on quantifying collision effects through ground-based carcass surveys performed by human observers (U.S. Fish and Wildlife Service, 2012). Human-based post-construction mortality surveys are resource intensive (e.g., surveyor labor and maintenance associated with clearing vegetation from survey plots) and often generate mortality estimates too uncertain to effectively validate or improve minimization measures. Further, these post-construction wildlife monitoring programs cannot collect real time data on wind and wildlife interactions that could inform species vulnerability and risk models used to guide wind turbine and wind farm siting and operation decisions. To overcome the limitations of human-based post construction monitoring surveys, there is a growing need to leverage sensor technologies capable of collecting high-quality data required to generate accurate estimates of effects and limit model parameter uncertainty (Chadès et al., 2015; Searle et al., 2025).

Species affected by wind farms are often highly cryptic and/or mobile species, and accurate observations of such species require resolution that exceeds the ability of human observers or sensors applied in isolation. As such, effectively monitoring wind-wildlife interactions requires a suite of integrated sensor technologies. Multiple integrated sensors surpass the capabilities of any one sensor. Accomplishing critical monitoring tasks will require one or more sensors to be effectively fused into the same system. The sensor fusion framework, borrowed from the computer science and engineering fields (Elmenreich, 2002), provides language to frame the discussion of how sensors can be combined to best address wind-wildlife monitoring goals at a variety of spatial scales.

There are three distinct categories of sensor fusions: competitive fusion, complementary fusion, and cooperative fusion (Fig. 1). Competitive fusion, or 'back-up' fusion, is designed to add redundancy and accuracy to a system by using 2 or more independent sensors that each collect data on the same landscape feature(s) or biological phenomenon. Monitoring with multiple units of the same sensor is an effective way to ensure data reliability by limiting the number of data gaps incurred via non-operational sensors. This redundancy is

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https://doi.org/10.1016/j.biocon.2025.111449
Received 9 September 2024; Received in revised form 17 June 2025; Accepted 17 August 2025
Available online 30 August 2025

particularly important when operators are not able to receive real-time system operation updates remotely and allows sensors to be offline for repairs without disruption to data collection. Complementary fusion occurs when multiple sensors collect independent but related data that can be combined to give a more comprehensive picture of the phenomenon. This type of fusion is particularly important as it can extend the spatial resolution when greater coverage of the wind turbine or wind farm is needed. Finally, cooperative fusion uses data from two or more independent sensors to derive emergent metrics. This type of cooperative fusion is commonly applied in single sensor – multi-unit configurations (i.e., two or more of the same sensor). For example, when two overlapping sensors can derive 3-dimensional (3D) movement.

In the following sections, we describe how sensor technologies—often integrated with sensor fusion techniques—are used to collect data for assessing collision and behavioral effects, parameterizing vulnerability and risk models, and informing minimization models. We also present a case study illustrating how sensor fusion systems can generate high-resolution data across complex spatial and temporal scales. We use this example to further explore how these data are used to address parameter uncertainty for collision-risk models and, when combined with automated processing and real-time feedback design elements, can be used to implement a curtailment minimization measure. Finally, we expand on our case study to demonstrate how an effective wind-wildlife monitoring system can be used iteratively in an adaptive management process to guide a hypothetical collision minimization measure.

2. Evaluate: observe effects

2.1. Collision monitoring

Collision with wind turbine blades has become a major anthropogenic cause of mortality for certain species of raptors and migratory bats (Arnett et al., 2008; Marques et al., 2014). Traditional carcass monitoring is ground-based and conducted by humans or dogs who regularly search a portion of the ground surrounding a subset of wind turbines for carcasses (Table 1). The raw counts from ground-based carcass survey data are converted to mortality rates using estimators such as GenEst (Dalthorp et al., 2018) that account for methodological variability (e.g., plots vs. roads and pads, human vs. dog team searchers, and cleared vs. uncleared plots). These estimators additionally account for variability associated with carcass persistence, searcher efficiency, and carcasses that fall outside of the search area (Dalthorp et al., 2018). Through standard analysis approaches and continuing efforts to standardize mortality databases, ground-based survey approaches continue to improve in generating metrics that characterize the cumulative mortality from wind energy (e.g., fatalities per turbine, fatalities per MW).

Carcass surveys are limited by inherent "partial observability" uncertainty. Human surveys are unlikely to directly observe collision events in real time because collisions are relatively rare events, not all wind turbines are monitored, and most carcass surveys are conducted during the day while collisions for bats and nocturnal migratory birds occur at night. These limitations result in a temporal gap between the moment of collision and the carcass discovery. This lag can be further exacerbated by survey schedules where 2- to 7- day gaps may exist between searches.

Sensors allow for continuous monitoring of wind turbine blades, thereby limiting temporal data gaps. Exchanging intermittent ground surveys with continuous technology-driven monitoring can maintain or improve the ability to estimate total wind turbine mortality, while simultaneously providing greater spatial and temporal survey resolution. Recent advances in computer vision have resulted in camera-based sensor systems that can directly observe collision events and subsequent tracks (i.e., movement of the carcass directly from the wind turbine blades to the ground) (Table 1). Visible light camera-based systems are useful for diurnal species whereas nocturnal species can be monitored with thermal or near infrared camera-based systems. Light Detection and Ranging (LiDAR) sensors can provide high-resolution 3-dimensional information on targets. The data can be used to track individual birds and bats within the field of view although LiDAR is not able to distinguish among broad taxonomic groups. Further, sensors can provide metrics of exposure rates (e.g., activity per unit of operational time) as a low-cost proxy for collision events. For example, Peterson et al. (2021) found that bat exposure, quantified as ultrasonic vocalizations per unit time wind turbines were operational, was highly correlated with mortality rates calculated from ground-based surveys. Activity rates derived from camera data and/or LiDAR data may also be informative, provided they are validated to correlate with fatality rates.

Sensor systems could also offer additional insights into specific risky flight behaviors such as attraction. This is particularly true for bats, whose patterns of activity and mortality suggest they may be attracted to wind turbines (Goldenberg et al., 2021). For example, bats have been observed approaching wind turbines and making multiple passes through the rotor swept zone suggesting that individuals are not coincidentally struck when their flight path happens to intersect a moving blade (Horn et al., 2008; Cryan et al., 2014; Goldenberg et al., 2021). At larger scales, attraction may present as increased activity within a development footprint compared to surrounding areas or increased

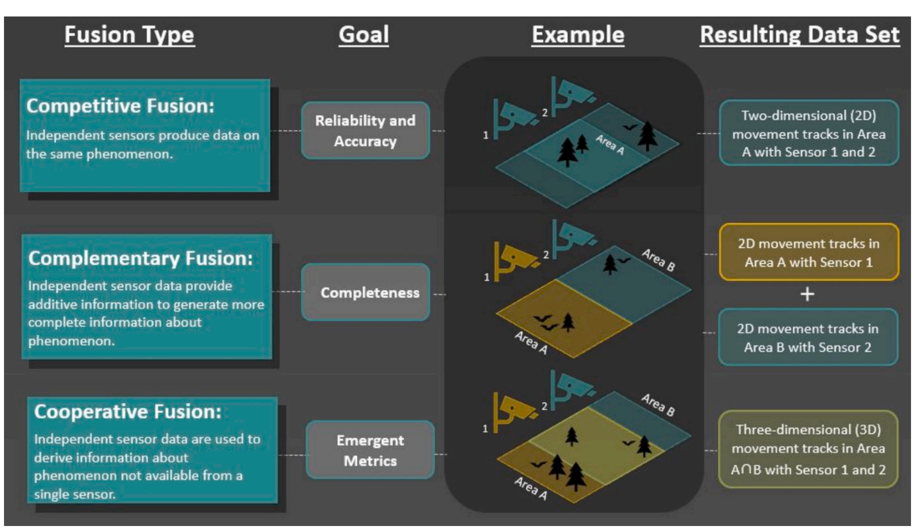

Fig. 1. Hypothetical example of three different sensor fusion scenarios applied to a 2-video camera system tasked with monitoring bats on a landscape.

Table 1
Technologies applicable to monitoring different priority effects of wind energy on wildlife. Implementation measures may incorporate any number of the listed metrics depending on the minimization strategy. Xs assigned to matrix even when capabilities are partial, e.g., species ID is possible with acoustics for some but not all species.

Data need for monitoring task	Human survey	Blade impact sensor	Camera (ground or turbine)	Camera (aerial)	3D camera (ground/ turbine	Acoustics	2D radar	3D radar	Lidar	RF tags	GPS tags
Enumerate fatalities[a]	x	x	x	x	x						
Exposure risk (fatality proxy)[a]			x		x	x	x	x	x	x	x
Species ID[a,b]	x		x	x		x				x	x
Annual distribution overlap with wind farm[a,b]			x	x	x	x				x	x
Density/activity rates (e.g., passes per time interval)[a,b]			x		x	x	x	x	x	x	x
Time within the rotor-swept area[b]	x				x			x	x	x	
Flight activity budgets[b]	x		x		x		x	x	x	x	x
Micro attraction/avoidance[b]					x				x		
Meso attraction/avoidance[a,b]							x	x			
Macro attraction/avoidance[a,b]							x			x	x
3D flight path (height, direction, speed, micro attraction/ avoidance)[b]					x			x		x	x
Flux rates[a,b]	x		x		x		x	x	x		

[a] Evaluate: observe effects.
[b] Parameterize: observe drivers of effects.

activity following construction (Hein et al., 2013; Solick et al., 2020). Disentangling the mechanisms of attraction is crucial because it has direct implications for collision risk and identifying the drivers of risk is key to developing effective mitigation strategies or interventions.

Camera-based mortality monitoring has several potential limitations. The spatial coverage or field of view (FOV) of a single camera oriented upward is unable to visualize the entire rotor-swept area with adequate resolution for small targets. In some contexts, it may be necessary to use complimentary sensor fusion to increase the spatial coverage. Second, thermal and infrared camera systems as well as LiDAR sensors have limited taxonomic resolution. Recent advances in camera-based computer vision algorithms can classify targets as non-biological or biological and further classify biological targets into broad categories of bat, bird, or insect. However, differentiation from thermal video alone remains challenging due to limitations in resolving body size and distance (Matzner et al., 2015). Camera-based systems that are complementary fused with acoustic detectors may allow for species identification for individuals crossing the detection threshold of both sensors (Willmott et al., 2023). Further, with video datasets that are annotated with species identifications obtained with acoustics, it may be possible to use machine learning techniques to gain even better taxonomic resolution with camera-based systems alone. In addition, LiDAR can be used in competitive fusion to provide a backup to camera datasets as well as cooperative fusion application to provide higher resolution information on target size, and 3D flight dynamics.

Collision detection systems can be mounted on wind turbine blades and use sound or vibration sensors to record the exact timing of collision events. This technology limits the amount of processing required to analyze video footage from several feeds by providing an accurate time stamp and perhaps offers an efficient standardization approach for generating mortality rate estimates. Though capable of categorizing subjects that strike the wind turbine blade into size/weight classes, collision sensors also have limited taxonomic resolution unless coupled with human observers to visit sites and retrieve carcasses, or via complementary sensor fusions with camera systems and acoustic detectors.

2.2. Displacement monitoring

Functional habitat is determined not only by the suitability of local biotic and abiotic conditions, but also by whether suitable habitat is accessible through movements (Van Moorter et al., 2023). When organisms no longer perceive habitat as suitable (e.g., perceived predation risk is too high) or suitable habitat is no longer accessible (e.g., impassable dam across a river), individuals are displaced and forced to redistribute across the landscape. When animals perceive the presence of novel anthropogenic structures such as wind turbines as risk factors indicating habitat unsuitability or as impassable barriers between suitable habitat, individuals may avoid habitat around a wind farm (macro avoidance) or wind turbines (meso avoidance) (Fig. 2). In some situations, these behavioral responses can result in displacement effects (May, 2015). While grouse have been a major focus of land-based wind energy displacement studies (LeBeau et al., 2023; Londe et al., 2022), displacement can affect many species, including pronghorn and reindeer (Milligan et al., 2023; Skarin et al., 2018), raptors (Dohm et al., 2019; Garvin et al., 2011), songbirds (Lehnardt et al., 2024), and bats (Ellerbrok et al., 2022). Displacement is also a concern for seabirds at offshore wind farms (Masden et al., 2010).

Monitoring displacement effects is challenging because unlike lethal collisions that occur in discrete events, displacement is a sublethal effect that varies in time and space. Identifying displacement requires disentangling natural changes from anthropogenic ones (Christie et al., 2019). Therefore, quantifying displacement requires long-term monitoring and careful study design to account for spatial and temporal variation in species presence, activity rates, habitat use, and/or movement patterns (often quantified as movement track densities) between pre-construction and post-construction conditions. To draw statistically robust inference about displacement effects, researchers most frequently consider avoidance within the framework of Before-After-Control-Impact (BACI) studies (Mendel et al., 2019; Peschko et al., 2020). A BACI framework emphasizes the importance of consistent monitoring from pre-construction through the post-construction phases of the project. However, study designs may vary by site and organism, such that After-Impact or After-Impact-Gradient (AIG) studies may be adequate to infer displacement via differences in species' activity rates or direct observations of individual avoidance or attraction behavior (Welcker and Nehls, 2016; Skov et al., 2018; Ellerbrok et al., 2022; Gaultier et al., 2023; Tjørnløv et al., 2023).

Acoustic detectors are a reliable option for continuously monitoring species activity rates (e.g., vocalizations per night) for species that regularly vocalize, such as echolocating bats and some migratory songbirds (Table 1). Despite a limited viewshed (40 m), the low cost of acoustic detectors means many units can take advantage of complementary fusion techniques to cover large spatial areas. Long-term acoustic surveys may be used in a BACI framework to detect

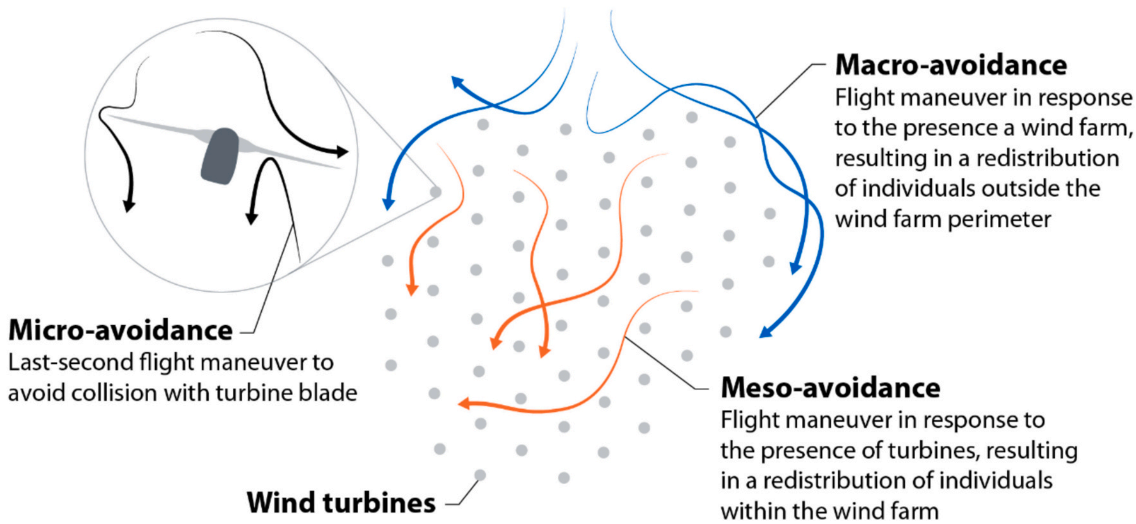

Fig. 2. Hypothetical example of three different spatial scales of avoidance metrics derived from datasets that can be generated from video (micro scale), radar (meso and macro scale), and or high-resolution radio frequency (RF) or GPS tags (meso and macro scale).
Modified from Skov et al. (2018) and Leemans et al. (2022).

differences between pre- and post-construction activity rates for one or more species (Solick et al., 2020) and are also ideal for monitoring along a gradient (e.g., from a monopole out to 1 km or more; Gaultier et al., 2023). However, acoustic detectors are ineffectual for species that do not vocalize frequently. Further, when interpreting acoustic data, it is important to recognize that single-microphone acoustic detectors are unable to determine whether a set of multiple vocalizations from the same species were produced by multiple individuals or a single individual making multiple approaches past the detector microphone, as would be expected if a bat was foraging. To address this limitation for bats, ultrasonic detectors may leverage cooperative fusion by comparing microsecond differences in arrival time of vocalizations at multiple microphones. This approach can assign calls to individual bats and may be able to reconstruct flight paths for several individuals simultaneously. However, distinguishing between specific individuals that move in and out of range of the detector remains challenging (Koblitz, 2018).

X-band radar has a viewshed of 1 km–10 km or more, depending on the biological target size and context (Nilsson et al., 2018) such that at the meso and sometimes macro scale, radar is the most effective way to quantify the flux rates and total amount of biomass using a site throughout the season. Cryan et al. (2014) showed such conditions, with a passage rate of 3 to 4 million animals, but only a small proportion of that biomass was ever detected by thermal cameras and acoustic detectors that were monitoring the micro scale over the same time period. Radar technologies can be an effective way to monitor displacement effects by quantifying habitat use in a BACI framework or along a gradient (Skov et al., 2018). X-band vertical-looking radar, and x-band 3D radar can track multiple individuals to generate passage rate metrics (Tjørnløv et al., 2023) and individual continuous tracks of larger bodied, volant species at the meso and macro spatial scales. Flight tracks can be used to quantify avoidance rates for a species or species group by deriving flight track densities within the wind power project's footprint compared to track densities outside the project (Skov et al., 2018; Box 1). Though radar is capable of tracking targets across a large viewshed, there are currently constraining target size limitations as well as ground clearance limitations (i.e., targets must be in flight to avoid ground interference) As such, for terrestrial applications, radar has mostly been used to monitor larger raptors. Radar classification software is quickly developing so that targets can be categorized as nonbiological, insect, bird, or plane (Werber et al., 2023), but species identification remains limited. Complementary fusion between radar and high-resolution ambient-light cameras is a progressing technique that allows some morphologically distinct avian targets to be identified by species (Lagerveld et al., 2020). A further limitation of radar monitoring is that terrestrial wind power projects, unlike most offshore wind plants, are often not uniformly distributed into grids. This makes After-Impact studies difficult because the delineation between inside and outside the project may not be discrete. In such cases, complementary fusion between several radar units may be appropriate to ensure adequate spatial coverage.

For certain species, behavioral studies may require tracking long-term individual movements with tagging technologies such as radio-frequency (RF) telemetry tags or GPS tags (Table 1) affixed to wildlife. Although tagging requires that researchers overcome the challenges associated with capturing and handling wildlife, the data acquired from tagging efforts can reveal previously unknown aspects of a species' life history (Weller et al., 2016). RF tags emit radio signals at a specific frequency that can be identified and tracked by specialized receivers, while GPS tags use satellite signals to determine the exact position of an individual. RF tags are generally smaller and less expensive, making them particularly valuable for tracking small-bodied organisms such as temperate bat species (McGuire et al., 2014; True et al., 2023) and migratory songbirds (Brown and Taylor, 2017; Morbey et al., 2018) that have too little mass to carry heavier high-resolution GPS tags. RF tags may also serve as lower-cost options for larger bodied organisms. The Motus network is a large-scale effort to track individuals through a coordinated open-source system of radio-telemetry arrays. This network may be valuable for investigating large-scale movement patterns of individuals tagged at a focal wind plant or tagged by researchers from other regions studying wind-wildlife interactions (Lamb et al., 2023; Loring et al., 2020) or movement ecology more generally. For tracking organisms within the wind farm, it may be possible to set up an array of receivers to recreate high-resolution movement tracks or establish several receiver stations as part of the Motus network. GPS tags are ideal when organisms have a large enough mass to support high-resolution solar-powered tags without impeding mechanical movements, such that data can be retrieved from satellites more frequently, for long periods of time, and can be remotely transmitted without tag retrieval. GPS tags have been used successfully to recreate the movement tracks of ungulates (Tsegaye et al., 2017), the flight tracks of multiple raptor species including white-tailed eagles (May et al., 2013), and several wading bird species during coastal breeding and migration (Loring et al., 2020). GPS tags are also important in monitoring the landscape-scale movements of grouse species (LeBeau et al., 2023). Pilot studies are exploring the application of very small, low-power communication tags that connect to alternate terrestrial networks to track bat migration (Hurme et al., 2025; Wild et al., 2023).

To quantify interactions with wind energy infrastructure, movement tracks collected with tags are analyzed similarly to those produced by radar. RF and GPS tags make it additionally possible to compare the usage of the landscape during pre-construction conditions to post-construction conditions, or to compare movement activity within the wind power project to activity outside the project. These comparisons help researchers understand how individuals respond to wind farms and wind turbines over the course of several weeks to months, using RF tags (the temporal duration is limited by battery and adhesive ability), or multiple years using GPS tags (LeBeau et al., 2023). Tagging efforts leverage both competitive and complementary fusion, in that each new tag deployed increases the likelihood of retrieving usable data and that each new tagged individual increases the spatial extent of our understanding about the movement dynamics of the population. While opportunities for sensor fusions with tags are less established, one promising avenue of exploration is competitive fusion with tagged individuals and radar. Identifying radar tracks of tagged individuals can provide researchers with high-accuracy training datasets of tracks from known species, which will improve radar classification by enabling more accurate species identification. Additionally, known tagged individuals could support species identification in other camera-based sensor systems.

2.3. Parameterize: observe drivers of effects

2.3.1. Monitoring to parameterize vulnerability and collision risk models

Vulnerability models are used to quantitatively assess if a population is susceptible to displacement or collision effects and are critical to effectively implementing mitigation frameworks (Croll et al., 2022). Vulnerability models consider population status and demography (e.g., population size, adult survival and reproduction, and conservation threat status) as well as collision and displacement-specific risk parameters such as flight activity rates and flight height (Furness et al., 2013; Kelsey et al., 2018. Though wind and wildlife monitoring systems may help inform population status and demographic parameters, we consider those metrics to be better suited for coordinated landscape-level monitoring systems (e.g., NABAT; Loeb et al., 2015) and therefore secondary to onsite monitoring systems. Species populations that are highly vulnerable to collision are unlikely to persist at wind farms because unsustainable mortality rates reduce populations. These species are expected to exhibit low avoidance rates; have low flight maneuverability; spend a large proportion of time in flight; and have characteristic flight speeds, heights, and durations within the rotor-swept area. Additionally, the turbulent environment of wind farms may interfere with flight (Shepard, 2025). Differences in visual perception can also contribute to collision vulnerability; many collision prone bird species have reduced visual capability when looking ahead (Martin and Banks, 2023). In contrast, displacement-vulnerable species are those that are unlikely to occupy the same space with wind plants because they are affected disproportionally by barrier effects or functional habitat loss. Such species are expected to exhibit low habitat flexibility (informed by natural history, not wind-wildlife monitoring systems) and high macro and meso avoidance rates of wind turbines (Kelsey et al., 2018).

For volant species, collision-risk models are versatile and can be used to predict risk at multiple spatial scales, including the wind farm, a set of wind turbines, or a single wind turbine (Masden and Cook, 2016). Collision-risk models may be used during pre-construction to estimate the expected mortality rates of a proposed project, or can be used to assess risk at an existing wind farm in an iterative process to improve predictive models of mortality rates, or to better understand collision probability (i.e., drivers of collision, when and why collisions occur). Over the past two decades researchers have explored a variety of approaches to collision-risk modeling (Masden and Cook, 2016). Despite extensive development, collision risk models fail to predict risk for certain species (Lintott et al., 2016) and the outputs remain sensitive to certain parameters such as flight speed (Masden et al., 2021) requiring increased efforts to collect high resolution species-specific flight data.

Both vulnerability and risk models are species-specific and rely on metrics of individual movement, including characteristic flight speed; flight height; flight duration within the rotor swept area; and measures of macro, meso, and micro avoidance and/or attraction. High-resolution movement tracks for ground-based species (e.g., grouse) and species-specific 3D flight tracks are necessary to properly parameterize models. In certain cases, when species-specific data is unavailable, surrogates are used given that they closely match the characteristics of the species of interest.

There are several approaches to acquiring high-quality 3D flight and movement behaviors data. It depends on the target taxa and the spatial scale and temporal resolution required to derive metrics (e.g., micro avoidance vs macro avoidance). 3D flight tracks are most cost-effectively acquired via cooperative thermal or ambient light camera sensor fusions. Two calibrated cameras, with known distances from each other, and a defined viewshed allow researchers to quantify flight direction, speed, and height. From these primary metrics it is possible to further derive a measure of micro avoidance and exposure time (i.e., amount of time the target flies within the rotor-swept area). Species identification with video alone is still in development for non-raptor species of birds and bats. Several video classification algorithms have demonstrated proficiency in identifying a biological target from a non-biological target and rudimentary ability to broadly classify biological targets into size-based bird, bat, and insect categories, but species identification has not been successfully implemented with these classification algorithms. Ambient light cameras oriented toward the rotor-swept area can acquire data of high-enough quality that human observers are able to classify targets during post-analysis. Under clear, daylight conditions, they are often able to accurately identify insects, birds, and diurnally flying bats to the family and often species level. However, monitoring biological targets during the nocturnal period when visual identification is unfeasible will most often require complementary fusions with acoustic detectors that can identify species or species groups.

While tracking via tagging technology, such as RF and GPS tags, continues to be the most common way to acquire movement data for large-bodied ground birds, traditional applications of these sensors may not provide the spatial resolution required to improve modeling efforts. Typical radio telemetry applications are effective at providing the position of a tagged individual but contain varying measures of error. Combining multiple antennas into an x, y, z array via complementary fusion techniques may provide much higher resolution movement data for individuals as they move through an entire wind farm footprint for both ground-based and volant species alike.

2.3.2. Modeling to parameterize minimization models

Operators may use real-time data to trigger curtailment when collision risk is highest. For example, wind speed data collected onsite is frequently used as an indicator of bat collision risk, with risk modeled as a decreasing function of wind speed with operators curtailing turbine operations when wind speed drops below a designated threshold (e.g., 5.0 m/s) (Whitby et al., 2021). Further, real-time wind speed data has been combined with bat acoustic activity rates to refine collision-risk probability models and subsequent minimization measures (e.g., curtail when wind speed is less than 5.0 m/s and a bat ultrasonic call is detected) (Hayes et al., 2019). Yet we still lack a detailed understanding of the abiotic and biotic drivers of risk, limiting our ability to improve current minimization techniques. Sensor technologies that can help us understand the drivers of attraction to turbines and elucidate the relationship between attraction and collisions are critical. Understanding how and under what conditions bats are attracted to turbines will help inform future sensor placements as well. For example, if the majority of bats or birds are attracted to the rotor swept zone from the ground level, then using ground based sensors to inform curtailment may be an effective and less costly way to inform a real-time activity based curtailment system. Further, thermal cameras and/or collision-impact sensors that can pinpoint the exact timing of a collision event, present additional opportunities to collect data, which can be used to parameterize site and species-specific collision probability models helping operators optimize the tradeoff between mortality reduction and energy production (Machado et al., 2024).

2.4. Supporting an iterative minimization framework with a robust wind wildlife monitoring system

An iterative minimization framework is critical to achieving the goal of limiting effects on wildlife until some performance criteria are met (e.g., no net loss of biodiversity). Specifically, this adaptive management approach supports decision making by iterating between modeling and empirically testing minimization measures (Fig. 3, A). The success and utility of this iterative process is contingent on the inclusion of high-quality data. This cycle of modeling and empirical testing must be supported by a robust wind-wildlife monitoring system that can: 1) monitor effects to assess the efficacy of an implemented mitigation measure (e.g., quantify mortality), and 2) monitor the drivers of effects to parameterize vulnerability and risk models (e.g., collision-risk models) (Fig. 3, B) (Runge, 2011). Designing and implementing a wind-wildlife monitoring system capable of accomplishing both monitoring goals requires integrating several design elements (Fig. 3, C), including sensor fusion principles, to increase system capacity (Fig. 3, D).

To further illustrate the use of such a system (one that leverages several sensor technologies integrated with sensor fusion techniques) consider a hypothetical scenario where a wind power project is planned to accomplish three goals with its monitoring system: 1) assess bat collision effects, 2) use metrics of bat activity rates to trigger real-time curtailment measures, and 3) gather data that reduces collision-risk model parameter uncertainty. While there are many suites of technology fusions that could potentially accomplish this goal, in this example, researchers have deployed nacelle-mounted ultrasonic detectors and upward-facing monopole-mounted thermal cameras.

Ultrasonic detectors are inexpensive and robust sensors that can be applied to record spatiotemporal activity patterns of echolocating species at spatial scales up to 40 m. Mounting these detectors on the nacelle will collect data from individuals flying near the wind turbine. Competitive fusion principles should be applied to the spatial deployment of these detectors to ensure continuous data collection is achieved. Sensors should also be monitored by humans periodically to assess functionality and avoid disruptions to data collection. When integrated with the SCADA system, activity rate data obtained in real time (acoustic calls per time interval) are used to inform collision-risk probability and to trigger curtailment (Hayes et al., 2019, Wildlife Acoustics).

Thermal cameras are deployed to gather high-quality data about microscale bat and wind turbine interactions. Thermal cameras can monitor collisions and provide information about the behaviors and conditions that are associated with increased collision probability. Collisions are directly detected with a 2-thermal camera system that can be mounted on the monopole facing upwards. The cameras are integrated with complementary fusion to generate 3D flight tracks and increase the spatial coverage to include the entire rotor-swept area (∼125-m rotor diameter). New data analysis tools are being explored to allow analysis in near real time (Matzner et al., 2020; Corcoran et al., 2021). Initial observations of collisions should be verified by human observers until the system demonstrates certain site-specific performance criteria and can identify collisions autonomously with high confidence.

In this example, as it relates to the iterative framework (Fig. 3), imagine an initial state of wind turbine operations with no minimization measures enacted. During facility operations, thermal cameras are used to directly assess collision effects. If collision effects exceed some agreed-upon threshold, operators may leverage data gathered on drivers of collision probability (e.g., flight dynamics prior to the collision event) from both the thermal cameras and acoustic detectors to parameterize collision-risk models. The outputs of such models can guide a site-specific minimization measure. Implementing a minimization measure may rely on using data collected in real time from acoustic detectors or thermal cameras, depending on which metric(s) is/are being used as an indicator of collision risk, to trigger the minimization measure (e.g., curtailment). This process of measuring effects, parameterizing models, updating minimization measures, and using real-time sensor data to implement a minimization measure should continue in an iterative process until stakeholder goals are achieved.

While the previous use case is valuable, both ultrasonic detectors and thermal cameras operate only at the microscale. There is a pressing need for greater exploration of individual behavior at the meso scale before

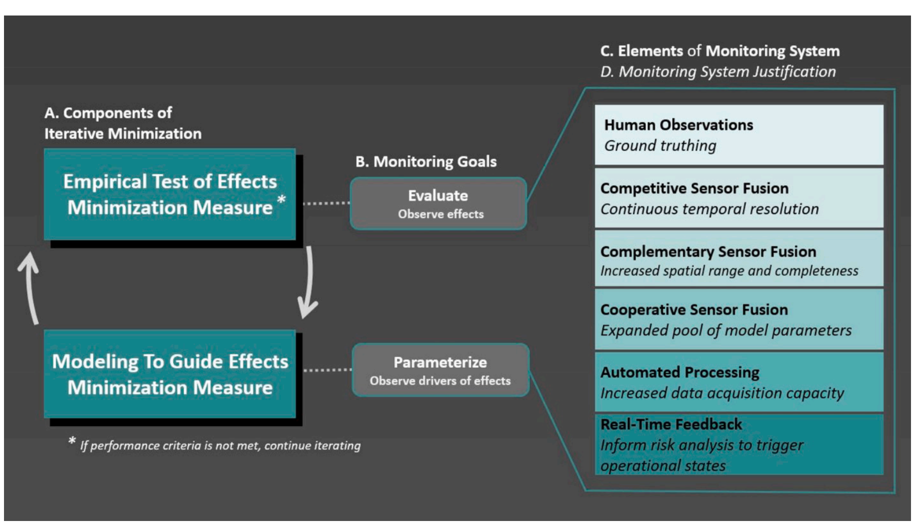

Fig. 3. To iterate between modeling mitigation measures and empirical validating mitigation measure decisions (A), an effective technology-driven wind and wildlife monitoring system must be capable of accomplishing two monitoring goals: 1) observe effects (e.g., quantify mortality) to assess minimization performance and 2) observe drivers of effects (e.g., flight height, avoidance, or use of real-time data to implement mitigation such as curtailment) to parameterize (B). Accomplishing the monitoring goals requires that we integrate several monitoring system design elements (C) each providing additional monitoring system capacity (D).

individuals approach the wind turbine (Fig. 4). A deeper understanding of bat behavior at the meso scale (within the project's footprint) is a critical missing element in the current suite of wind-wildlife monitoring tools. Obtaining this understanding will require a sensor with the capability to monitor movement of multiple-size targets at increasing spatial scales to parameterize models. To date, vertical-looking radar and 3D radar are capable of continuous tracking for larger subjects (e.g., raptor species.) but have not yet been validated for high-resolution target identification and tracking of smaller-bodied avian and bat species (5–150 g) (Nilsson et al., 2018). The application of radar for smaller targets is limited by a lack of radar datasets containing known targets and their extracted metrics (e.g., wing beat and/or flapping frequency) that can be used to train radar classification tools across different regions and conditions (Werber et al., 2023). Such a dataset could be achieved through competitive sensor fusion techniques whereby captured bats are tagged with high-resolution RF tags and monitored with a 3D receiver array or hand released and monitored with thermal cameras within the viewshed of radar systems. Once 3D radar is capable of effectively tracking these smaller targets at a meso scale, individual flight characteristics and population-level flux rates can be integrated into the iterative monitoring framework and used to reduce collision-risk model parameter uncertainty.

3. Concluding remarks

As we transition from human-based to technology-based wind-wildlife monitoring solutions, several benefits are expected. These benefits include increased temporal resolution of collision events, which should lead to more comprehensive characterizations of the abiotic and biotic drivers of collision risk; reduced parameter uncertainty, which should result in better vulnerability and risk model performance; and real-time processing and feedback that can be easily integrated into wind plant system controls for more cost-effective minimization strategies.

Despite the potential benefits, it is necessary to understand and articulate the limitations of technology-driven monitoring solutions, including hardware malfunctions, substantial data storage requirements, and high upfront costs. In many cases, these limitations can be overcome by combining multiple technologies or by using the higher-quality system outputs, e.g., more effective curtailment results in greater energy production, thereby offsetting upfront cost of installation. However, it is important for technology providers, researchers, and wind energy developers to engage early and often regarding the proper use and integration of technologies at the wind farm. This includes understanding where the technologies will be located on the wind turbine or within the project, how the technology will be powered, and how data will be collected onsite or transmitted to an offsite location. Additionally, the exact technical requirements of any monitoring system will vary based on the species of interest and the priorities of the operator.

Widespread adoption of technology-driven wind-wildlife monitoring systems may be hampered if monitoring technologies cannot be more effectively integrated as part of system digitization efforts, and as part of socio-technical-economic- political (STEP) co-design considerations (Aziz et al., 2022). Initial steps toward better consideration of environmental monitoring may include development of upstream (turbine manufacturer-level) technology and/or data flow, engaging with the community to foster excitement and acceptance, and demonstrating to regulators a more industry-wide commitment to advancing our knowledge about wind and wildlife interactions.

The application and development of technologies that more effectively quantify wildlife behavior allows for rebalancing of monitoring resources and for removing a critical barrier to a fully functional adaptive management framework (Månsson et al., 2023). The concept of a more expansive and technology-driven wildlife monitoring system has already benefited from interdisciplinary collaborations whereby in recent years engineers and computer scientists have more frequently worked with wildlife biologists to apply the tools of their trade to the wind energy and wildlife domain. As such, it has become increasingly common to deploy a range of sensor technologies and novel sensor fusion techniques at wind farms during pre- and post-construction periods to address questions at a variety of temporal and spatial scales. Several studies have explicitly leveraged sensor fusion techniques to support monitoring goals at wind facilities (Cryan et al., 2014; Lagerveld et al., 2020; Willmott et al., 2023), and future studies will benefit from identifying their monitoring goals and sensor fusion techniques when designing their monitoring systems.

Though not the focus of this review, there is great value in continuing to acquire baseline data collection that can be used to increase our understanding of landscape level distributions and abundance of species. Ultimately, monitoring species population health via long-term baseline metrics (e.g., population growth rates) is critical to understanding landscape-level impacts of the wind energy industry. However, assessing such impacts often requires coordinated monitoring efforts beyond the spatial extent and temporal bounds of a single wind plant. And so, at the wind farm level, monitoring the proximate collision and displacement effects remains the priority.

Target audience

Wind-wildlife practitioners, wind farm developers/operators, and conservation scientists.

Acknowledgement of financial and institutional support

This work was authored in part by NREL for the U.S. Department of Energy (DOE), operated under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Wind Energy Technologies Office. The

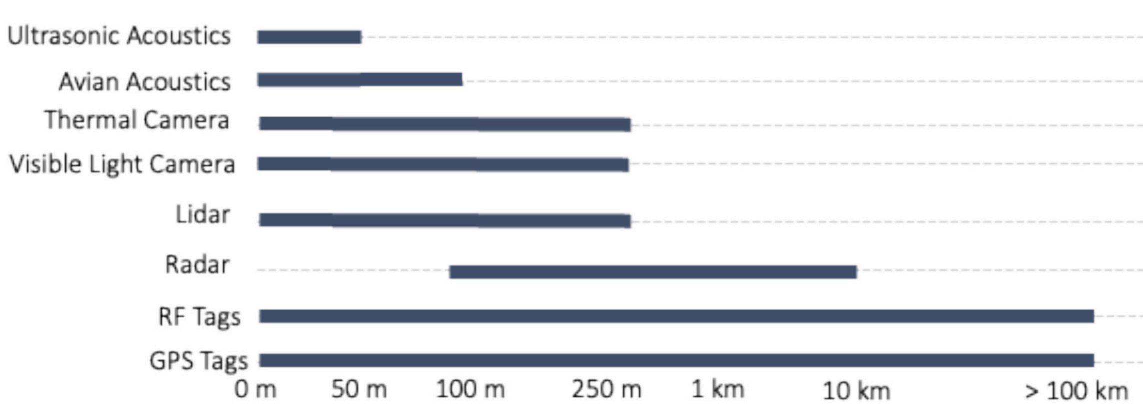

Fig. 4. Spatial range of common wind and wildlife monitoring technology sensors. X-axis on log scale.

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CRediT authorship contribution statement

Laura Dempsey: Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Jeff Clerc:** Writing – review & editing, Writing – original draft, Investigation. **Cris Hein:** Writing – review & editing, 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

No data was used for the research described in the article.

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