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Methods to quantify avian airspace use in relation to wind energy development

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It is likely that there will continue to be a substantial increase in the number of wind turbines as we aim to meet global energy demands through renewable sources. However, these structures can have adverse impacts on airborne wildlife, such as posing a potential collision risk with the turbine structure. A range of methods and technologies have been applied to the collection of bird flight parameters, such as height and speed, to improve the estimation of potential collision compared to traditional visual methods, but these are currently not applied in a consistent and systematic way. To this end, a systematic literature search was conducted to (1) examine the methods and technologies that can be used to provide bird flight data to assess the impact of wind energy developments and (2) provide an updated framework to guide how they might be most usefully applied within the impact assessment process. Four empirical measurement methods were found that improve the estimation of bird flight parameters: radar, telemetry, ornithodolite and LiDAR. These empirical sensor-based tools were typically more often applied in academic peer-reviewed papers than in report-based environmental statements. Where sensor-based tools have been used in the report-based literature, their inconsistent application has resulted in an uncertain regulatory environment for practitioners. Our framework directly incorporates sensor-based methods, together with their limitations and data requirements, from pre-deployment of infrastructure to post-consent monitoring of impacts. This revised approach will help improve the accuracy of estimation of bird flight parameters for ornithological assessment of wind energy. Sensor-based tools may not be the most cost-effective. However, a precedent has been set for wind energy development consent refusal based on ornithological impact assessment, therefore the cost of collecting accurate and reliable flight data may be balanced favourably against the cost of development consent refusal.

Keywords: bird flight, collision risk, conservation, evidence-based, renewable energy.

Over the past century, an accelerating pace of industrialisation has led to increasing numbers of man-made structures, including renewable energy developments (Coates *et al.* 2011, Vas *et al.* 2015, Shepard *et al.* 2016), extending into and co-occupying the airspace with airborne wildlife (Lambertucci 2014). The collision and disturbance risks associated with wildlife interactions and renewable energy developments have the potential to affect species ecology and conservation (Martin 2011, Davy *et al.* 2017, Shamoun-Baranes *et al.* 2017, Thaxter, Buchanan, *et al.* 2017, Lambertucci and Speziale 2020).

Due to a number of high profile incidents (Orloff & Flannery 1992, Bevanger *et al.* 2009), collisions between birds and wind turbines have become a particular concern. As the industry continues to develop, with larger turbines being deployed and as costs fall to levels where government subsidies are negligible, wind energy will play a pivotal role in delivering global renewable energy targets (IRENA 2018, Committee on Climate Change 2019). Wind turbines are therefore increasingly commonplace in marine and terrestrial environments, raising the potential for negative avian interactions.

In the absence of an accurate, reliable and widely used means of collecting data on collision rates, particularly for offshore developments, estimates of the number of collisions between birds and turbines are usually predicted using collision risk models (CRMs; Masden & Cook 2016). CRMs form a key part of the pre-construction Environmental Impact Assessment (EIA) process in the UK and elsewhere (US Fish & Wildlife Service 2012, Jenkins *et al.* 2015). These models provide a means of estimating the probability of a bird colliding with a turbine blade (Masden & Cook 2016). This requires data on both bird and turbine characteristics, including, but not limited to, bird flight parameters, such as flight height and flight speed, and bird morphometrics, as well as turbine specifications such as rotor speed and turbine size. Collision estimates have been found to be sensitive to the bird flight parameters input into the model (Chamberlain *et al.* 2006, Douglas *et al.* 2012, Masden 2015) and, as a result, factors that affect the estimation of these flight parameters are likely to affect final collision estimates. It is therefore vital to ensure accurate and robust estimation of flight parameters during data collection for EIAs.

The need to collect data on flight height and speed is driven by guidance issued by statutory bodies (Atienza *et al.* 2011, Strickland *et al.* 2011, US Fish & Wildlife Service 2012, Jenkins *et al.* 2015, Santos *et al.* 2017, Scottish Natural Hertiage 2017). However, the current methods recommended for use in collecting bird flight data in relation to impacts of wind energy have changed little from those outlined initially (Orloff & Flannery 1992, US Fish & Wildlife Service 2003, Scottish Natural Hertiage 2005). Current guidance recommends flight height data are collected by observers visually estimating flight heights (Atienza *et al.* 2011, Strickland *et al.* 2011, US Fish & Wildlife Service 2012, Jenkins *et al.* 2015, Santos *et al.* 2017, Scottish Natural Heritage 2017). Flight speed data collection is not a requirement under current statutory guidance (US Fish & Wildlife Service 2012, Jenkins *et al.* 2015, Scottish Natural Hertiage 2017);

these data can be collated from existing values in the literature (e.g. Bruderer & Boldt 2001, Alerstam *et al.* 2007). However, from the initial issue of formal guidance (US Fish & Wildlife Service 2003, Scottish Natural Heritage 2005) to the present, a number of tools and technologies have emerged that are now routinely applied to the collection of bird flight data (Masden *et al.* 2009, Katzner *et al.* 2012, Shepard *et al.* 2016, Cook *et al.* 2018). Current guidance may therefore not reflect the most reliable methodologies with which to measure bird flight parameters.

The tools and technologies applied to the collection of bird flight data range from bird borne devices, such as GPS telemetry (Cleasby *et al.* 2015, Poessel *et al.* 2018) to remote-sensing approaches, such as radar (Stumpf *et al.* 2011, Hulka *et al*. 2013; Cook *et al.* 2018a). However, there is currently no guidance on how these methods can and should be applied to the collection of bird flight data in relation to quantifying impacts of wind energy, creating an uncertain regulatory environment for practitioners. Given that these methods are based on sensors that have been *adapted for* rather than *designed for* collecting bird flight data, the reliability of measurements may vary in response to the characteristics of the bird target (e.g. May *et al.* 2017, Cole *et al.* 2019), and/or the characteristics of the tracking environment (Kelly *et al.* 2009, May *et al.* 2017). Other limitations associated with logistics and with the sensor can also affect how useful a given tool is in accurately collecting bird flight data (Brookes 2009, Kelly *et al.* 2009, Cook *et al.* 2018, Cole *et al.* 2019, Péron *et al.* 2020).

Using sensor-based measurement methods to improve the accuracy of bird flight parameters can also refine how collision risk is calculated; from current calculations of species-specific collision risk to possible calculations of behaviour-specific collision risk. Currently, the collision-risk modelling process results in either a single value representing the likelihood of a species colliding with turbine blades (Band 2012), or a mean collision risk and associated confidence intervals per species (Johnston *et al.* 2014, Masden 2015, McGregor *et al.* 2018). However, bird flight height and flight speed are known to change as the behaviour of the bird changes (Cleasby *et al.* 2015, Fijn & Gyimesi 2018). As a result, it is likely that collision risk will vary between different behaviours and this has been shown to be the case both within (Stienen *et al.* 2008, Morinha *et al.* 2014) and between species (de Lucas *et al.* 2008, Thaxter *et al.* 2017). Calculating collision risk related to different species behaviours may therefore offer an improvement over current calculations. It is not possible, following current guidance and data collection recommendations, to partition flights into separate behaviours other than subjectively, but these can be defined empirically post-hoc from changes in measured flight parameters such as height, speed and trajectory (e.g. Pirotta *et al.* 2018).

At present, bird flight data collected to support EIAs often does not make use of the best methods available. Therefore, changes are required in the way data collection is approached in order to allow us to better estimate species-specific collision risk, and derive more use from the flight data collected, including estimates of behaviour-specific collision risk. A potential barrier to updating data collection guidance is the lack of understanding around how tools and technologies that currently exist could be applied in the context of flight data requirements for EIAs and CRMs. Here, we propose such an update in the format of a framework for data collection. This framework is constructed from a review of methods used to estimate bird flight parameters in relation to interactions with wind turbines. From this review, we aim to understand the different tools and technologies that have been applied to measuring flight parameters and, how they might be applied as part of baseline data collection for EIAs.

Current data collection process for EIA

The main goal of the EIA is to identify the potential negative effects of a development and eliminate, mitigate or compensate for those effects (Fig. 1). This begins with a scoping phase which is primarily a desk-based review of existing ornithological and habitat data of the area. During this phase, a level of value is established against which to measure impact based on, for example, designations, rarity and known sensitivity to effects of wind energy developments. Following scoping, observer-based surveys are used to collect data on bird species present, and their number, distribution and flight characteristics within the development area. These data are then entered into CRMs to predict potential collisions between birds of the area and the proposed turbines. It is during baseline data collection that using sensor-based methods could improve the estimation of bird use of the development area and therefore more accurately predict collision rates. Note that although Fig.1 is based on the UK EIA process, baseline data collection is a feature of the EIA process in many countries (Atienza *et al.* 2011, Strickland *et al.* 2011, US Fish & Wildlife Service 2012, Jenkins *et al.* 2015, Santos *et al.* 2017), meaning the suggestions for improvements to baseline data collection made here are applicable internationally.

METHODS

Data collection

In order to build a framework to improve collection of flight data during baseline surveys, we first carried out a systematic literature review to assess which methods have been applied to the collection of bird flight data in relation to impacts of wind farms. We searched Web of Science, Google Scholar, Google Search and the Tethys online database (www.tethys.pnnl.gov) for Environmental Statements (ESs), peer-reviewed publications, book chapters and theses and any references therein. Search terms were 'wind energy', 'wind farm' or 'wind turbine' in combination with 'bird flight' and 'bird collision', and further substituting 'bird' for 'avian' and 'ornithological'. This gave eighteen search term combinations all together. Literature searching was carried out until March 2019. Based on the recommendations by Haddaway *et al.* (2015), we focussed on the first 300 results from Google Scholar and our searches were limited to sources that were accessible online and written in English (see Supplementary Material S1).

Only documents quantifying bird flight in relation to interactions with wind energy (terrestrial and marine) were included and all phases of development (pre-construction, construction, post-construction) were considered. We excluded qualitative reviews, commentaries or other sources that did not include details of data collection methods. Simulation model-based analyses were included if they were parameterised with empirical data and the method was stipulated; if the study used other referenced data, that literature trail was followed. Where a study deployed more than one method for data collection, these were considered separately.

From the studies collated, we extracted information about the methods used, the flight parameters quantified, criteria of method selection, duration of data collection, goal of data collection, and if measurements were validated/calibrated prior to deployment of the method. Where data were collected by a cohort of sensors with overlapping deployment periods, as in Reid *et al*. (2015), the maximum deployment duration of an individual sensor was used. We classified studies as 'sensor' where a tool or technology was used to collect data remotely, e.g. via devices that transmit and receive signals that are reflected, refracted or scattered by the target object (e.g. radar) or are attached to the target object and transmit or receive signals produced by other technology (e.g. GPS tags). This definition results in two possible approaches to data collection; borrowing terminology from fluid dynamics: (1) Eulerian data collected at the site of the potentially impacted (wind farm) space (e.g. radar), and (2) Lagrangian data collected at the site of the potentially impacted bird, i.e. including telemetry (Cleasby *et al.* 2015) - see also Cole *et al.* (2019). Validation of measurements was considered to have been undertaken if testing was carried out to ascertain if the sensor's accuracy was in line with manufacturer guidelines. Calibration was defined as a test of how well the sensor performed and how the uncertainty in measurements varied over changing conditions. Methods that quantified horizontal and vertical bird movement and speed were considered capable of quantifying flight in 3D as these parameters are often crucial for distinguishing between flight activities or behaviours.

The use of observer-based data collection under current EIA protocols has the benefit of collecting both site-specific and species-specific data, but this may not be the case with the sensor-based methods considered here. As a result, we used the selection criteria that we extracted from the collated studies and the classification of the method as Eulerian or Lagrangian, in addition to limitations known to be associated with these methods elsewhere in the literature, to compile Table 1 and subsequently assess where each method could fit in to a framework for data collection.

RESULTS

Methods to quantify bird flight

A total of 308 applications of different methods, across 267 studies fulfilled the criteria outlined above (a number of studies deployed more than one method, see Supplementary material S1), out of a total of 393 studies reviewed, for which ten different methods were used (Table 1, Fig. 2). Following our definitions, radar, telemetry, LiDAR and ornithodolite (a pair of binoculars with inbuilt laser rangefinder, inclinometer and digital magnetic compass), and laser rangefinder paired with inclinometer represented sensor-based methods, while vantage-point surveys, boat-based transects, digital aerial surveys, acoustic methods and thermal animal detection system (TADS) paired with visual methods were considered non-sensor (Table 1). Although microphones for acoustic methods and cameras used in digital aerial surveys and TADS do use a kind of sensor to capture data and are therefore technically sensor-based methods, neither a microphone nor a camera are capable of directly measuring flight parameters. Microphone or camera based flight data must be back-calculated with a degree of observer subjectivity and as a result, they are included in Fig.2 and Table 1 with non-sensor methods. Further methods such as visual tracking (e.g. Perrow *et al.* 2006), whereby birds were tracked visually using a rigid-hulled inflatable boat (RHIB) provide data akin to telemetry for some metrics such as speed and are classified as such.

Significantly more studies referenced flight data for onshore than offshore wind energy developments (X^2_2 = 169.09, P < 0.001), 173 (65%), 93 (35%) respectively (one study quantified bird flight at both onshore and offshore locations). Visual based methods, encompassing onshore vantage point and offshore boat-based surveys, were used significantly more frequently than any other method (X^2_8 = 689.66, P < 0.001). However, across all studies there were 143 applications of sensor-based methods (53%). Five sensor-based methods were used overall (Fig. 2), with radar being used significantly more frequently than other sensor-based methods (X^2_4 = 133.05, P < 0.001). Sensor-based methods were typically deployed for longer durations and therefore likely collected a greater quantity of data to characterise the spatial and temporal variation in flight characteristics. Eighty-three of the 143 studies that deployed a sensor-based method gave information on the duration over which data were collected; of the 165 applications of non-sensor methods, 133 gave information on the duration of data collection. The duration of data collection was significantly different between sensor and non-sensor based studies based on the results of a Wilcoxon test, with median durations of 41 and 23 days respectively (z_{214} = -3.192, $P < 0.005$).

Flight parameters quantified

Of the five non-sensor-based methods, four collected data on multiple flight parameters (Fig. 3) but none collected data on flight speed and therefore were also incapable of collecting data in three-dimensions (Fig. 3). Of the five sensor-based methods identified in the literature search, all were used to collect data on multiple flight characteristics (see Fig. 3). Three (radar, telemetry and ornithodolite) were used to collect data on both bird flight height and speed and could therefore be used to improve collision risk estimates under species-specific collision risk calculations. All three methods were applied to the collection of three-dimensional flight data necessary for behaviour-specific collision risk calculations. LiDAR was not applied to the collection of flight speed and therefore neither to three-dimensional data, but the details of how this could be achieved were provided in the manuscript (Cook *et al.* 2018).

Although radar was the most common of the sensor-based methods used (Fig. 2), the prevalence of sensor-based methods varied markedly across the data time series (Fig. 4), with radar most common early on, and telemetry more prevalent later in the time series. This likely reflects the advancement of telemetry technology in availability, affordability and for use on smaller species. The overall diversity of methods available also increased later in the time series.

Building a framework

In Fig. 5, we inserted the three sensor-based methods applied to the collection of 3D flight data (Fig. 3) and LiDAR into the original EIA framework (Fig. 1), alongside additional limitations and logistical considerations identified for each method (Table 1). We suggest that the use of these methods in a given study be assessed in the context of the results of the scoping phase (Fig. 1) and a pre-deployment phase where the results of scoping can be verified and any logistical challenges in application be assessed. This approach ensures the most appropriate tool is selected to maximise the quantity and quality of the data collected. Ideally, Lagrangian data collection would follow Eulerian data collection, the latter being used to identify potential species at risk through site-wide collection of sensor-based flight data and the former being used to provide more species-focussed data collection based on the Eulerian survey data. However, such an approach may increase the typical two-year timescale in the UK or one year timescale elsewhere (Strickland *et al.* 2011, US Fish & Wildlife Service 2012, Jenkins *et al.* 2015, Santos *et al.* 2017), for undertaking pre-construction baseline data collection, and as a result the two are presented as distinct data collection options in Fig. 5. This also allows for the collection of Lagrangian-type data directly following scoping and pre-deployment surveys where known issues may have been identified.

Pre-deployment surveys

The logistical limitations of the sensor-based measurement tools (Table 1) may limit how effective a particular method is during baseline data collection. An understanding of the characteristics of the potential development site is therefore useful in order to select the most appropriate tool and can be gained through observer-based site surveys. Such surveys can identify physical site characteristics that may hinder data collection, such as the presence of a high density of non-bird objects in the tracking vicinity, i.e. clutter (Kelly *et al.* 2009, May *et al.* 2017). Species-specific qualitative data can also be gathered which may aid method selection at the site; for example, the number and species of birds at risk, their behavioural activity (e.g. foraging, migrating, roosting), and whether species from the site are potential designated features of nearby protected sites or have a notable conservation status, such classification as an Annex 1 species (EC Birds Directive 79/409/EEC). In this way, this data collection phase can be used to confirm the assumptions made during the literature-based scoping phase. Such a pre-deployment phase is a feature of the EIA process outside the UK (Strickland *et al.* 2011).

Baseline data collection

Following scoping and pre-deployment surveys, we recommend that bird flight data are collected using one of the sensor-based measurement methods. We suggest that Eulerian-based tools be used for site-wide data collection, to provide a quantitative measure of flight characteristics where use of the site by species can be relatively well described by individual flight parameters, e.g. birds commuting from roosting areas to foraging areas. Lagrangian-based tools, on the other hand, are most useful for species-specific data collection, to provide a quantitative measure of individual flight parameters where use or movement through the site results in complex flight patterns, e.g. birds foraging in the area. This reiterates the need for the pre-deployment survey phase outlined previously to aid in selecting the most appropriate tool.

Eulerian site-wide data collection: Framework stage 2a

As part of site-wide baseline data collection, empirical flight height and flight speed data may be needed for a range of bird species occurring in the potential development space. Eulerian type technologies which collect data from a fixed space, i.e. in this case the potential development site, can be used to collect this site-wide baseline data. From the literature search conducted here, three Eulerian type technologies have been applied to the collection of bird flight parameters in relation to interactions with wind energy (Table 1) and are capable of collecting both flight height and flight speed data (Fig. 3) *in situ* for better estimation of species-specific collision risk. Radar was the most frequently used method, likely due to its historical application within the field of ornithology and the availability of marine surveillance radars (Eastwood 1967, Hamer *et al.* 1995). Radar can collect both flight height and flight speed data, but requires separate horizontal and vertical arrays or a multi-array combination in order to do so. The main limitation of radar is the inability to distinguish between bird species using radar data alone (Rosa *et al.* 2016), necessitating that data be ground-truthed using an observer (Table 1). However, given radar can be operated nocturnally and in a wide range of weather conditions, this makes it a valuable tool for baseline data collection. By contrast, the other two Eulerian type methods (LiDAR and ornithodolite) cannot collect data in inclement weather or nocturnally, largely due to being manually operated. LiDAR and ornithodolite technologies are therefore likely to have useful supplementary value should radar deployment not be possible. For example, the ornithodolite is portable and may be used wherever is accessible to the operator; similarly, aircraft-mounted LiDAR can be operated far offshore where the use of radar may not be feasible.

Species-specific data collection: Framework stage 2b

As part of baseline data collection, information on flight height and speed may be required for key species that may be using the development site. Key species can be identified during scoping and pre-deployment surveys and subsequent discussion with stakeholders, linked to relevant legislation and an understanding of their life history traits. Lagrangian-type methods, represented in our framework (Fig. 5) as telemetry-based methods, are most useful in this case. Animal-attached telemetry tags have been applied to the collection of bird flight parameters in relation to quantifying interactions with wind farms and are capable of quantifying both flight height and speed for calculating species-specific collision risk estimates (Thaxter *et al.* 2017, Fijn & Gyimesi 2018). Particular attention should be given to the method of determining height from GPS sensors in telemetry tags. The inherent two-dimensional perspective of GPS devices relative to the satellites from which positional data are derived, means that GPS-derived height data can be subject to large inaccuracies (Péron *et al.* 2020), although precision of estimates increases with faster sampling schedules (e.g. Bouten *et al.* 2013, Thaxter *et al.* 2019). Other sources of error such as GPS dilution of precision (DOP) can also be incorporated into a modelled flight height distribution, using Bayesian approaches to account for inherent error (Ross-Smith *et al.* 2016). This method is useful for improving accuracy of flight height distributions, but not necessarily accuracy of individual flight height measurements. Alternatively, barometric altimeters may be incorporated into tags to quantify height, but these require continuous calibration to account for barometric drift, associated with spatial and temporal changes in atmospheric conditions (e.g. Cleasby *et al.* 2015). Field calibration may therefore not be feasible (but see Shepard *et al.* 2016, Borkenhagen *et al.* 2018), or may only likely be effective for a relatively short period of time (Péron *et al.* 2020). Deployment of telemetry devices should also consider any ethical consequences (Bodey *et al.* 2018), and the limitations associated with sample size and deployment duration (Thaxter *et al.* 2017) that may affect the use of the data collected for accurately determining collision risk.

Extension of the baseline

For collision risk estimates to better reflect the variability in bird flight characteristics with varying flight activity, we suggest an extension to baseline data collection (Fig. 5). Following on from Lagrangian species-specific data collection, it is also possible to calculate behaviour-specific collision risk estimates using behavioural states identified from the already collected telemetry data using, for example, movement modelling approaches (e.g. Pirotta *et al.* 2018). Using the flight parameter data associated with each behavioural state as separate inputs into CRMs, multiple collision risk estimates per species can be generated. Such an approach can help highlight when birds might be vulnerable to collision with turbines, e.g. when foraging or when commuting. Integrating this analysis with environmental co-variate data can help define the behavioural states, but can also provide a prediction of where birds might be vulnerable to collision. Such an approach could facilitate appropriate siting of the development and, depending on the resolution of the data, siting of individual turbines (de Lucas *et al.* 2012). Given the likely expansion in renewable energy worldwide, such an approach could be valuable at an early stage in the consenting process, enabling quick decision-making and conserving time and resources, as has already been demonstrated in the peer-reviewed literature (Péron *et al.* 2017).

In order to develop behaviour-specific collision risk estimates, three-dimensional flight data are required. This was theoretically possible with all four of the sensor-based methods and demonstrated for three of them (Fig. 3) identified in our literature search. However, in order to predict, spatially, where birds might be vulnerable, an equal measurement of space use across the bird's measured range is needed. This is not possible using Eulerian-based methods, which collect data from a fixed space. The resolution and precision with which flight data can be collected is reduced the further is the bird target from the Eulerian type device (May *et al.* 2017, Cole *et al.* 2019). Environmental variables and bird flight characteristics can also further influence the resolution and precision of data (May *et al.* 2017). As a function of their data collection approach, Eulerian and Lagrangian methods therefore differ in the resolution of the information they are capable of providing across a given range. Animal-attached telemetry devices are already routinely used to distinguish between flight behaviours using movement models or accelerometry (Shamoun-Baranes *et al.* 2012, Pirotta *et al.* 2018), whereas Eulerian devices such as radar more commonly provide quantitative measurements associated with individual flight characteristics (Masden *et al.* 2009, Mateos-Rodríguez & Liechti 2012, Pennycuick *et al.* 2013). However, in order to use telemetry data in defining behavioural states, it is necessary to collect data at a suitably high resolution. There is thus a possible trade-off between data resolution and battery life for telemetry data which may result in conflicting objectives, such as for understanding general space use and detailed flight behaviour, if data from telemetry devices are also to be used for species-specific collision risk estimates.

Post-consent data collection

Under current EIA guidelines, the need for post-consent data collection is assessed on a case-by-case basis and is not a requirement for all developments. However, by highlighting three different data collection goals (Fig. 5), we emphasise mandatory post-consent monitoring and highlight how the methods identified in our literature search and used in our framework can be used to meet these goals. Where a development is poorly sited, it may be necessary to attempt to mitigate potential collisions. This could be achieved by triggering intermittent shut down of turbines which is a proven effective measure for reducing bird mortality with little loss to overall energy generation (de Lucas *et al.* 2012). Sensor-based tools capable of automated detection, identification and tracking of birds as they enter the wind farm are likely most useful in triggering turbine shut down (McClure *et al.* 2018, but see Sheppard *et al.* 2015). In this regard, radar is likely the most useful tool and has been used to help mitigate bird collisions at wind farms (Marques *et al.* 2014, Tomé *et al.* 2017) and in other industries such as aviation (Ginati *et al.* 2010, Coates *et al.* 2011). Camera-based methods have also been trialled in mitigating collisions at wind farms (Birdlife International 2015). Non-real-time monitoring may involve use of further spatial planning approaches, which may bring in wider datasets and alternative methods beyond the scope of this review (e.g. Bradbury *et al.* 2014), but could also include Lagrangian data to map hotspots of sensitivity and vulnerability using information on flight behaviour (e.g. Thaxter *et al.* 2019).

A second goal of post-consent data collection would be to quantify if collision risk estimates generated using CRMs were accurate and, if not, identify the real impact of the development regarding bird collision rates. Quantifying collision rate requires observer input to identify birds using turbine searches with an understanding of searcher efficiency and bias, and potential scavenger removal (Morrison 2002, Smallwood 2007). Offshore monitoring requires automated detection of collision rates and has been trialled using Thermal Animal Detection System (TADS) and other sensors (Desholm *et al.* 2006, Skov *et al.* 2018).

Assessing if bird use of the site has been modified between pre- and post-construction is a useful goal for post-consent monitoring. Birds may be attracted to the development area by, for example, turbine structures which may provide roosting or perching opportunities (Osborn *et al.* 2000, Percival 2001, Barrios & Rodríguez 2004, Morris & Stumpe 2015), or, for offshore infrastructure, aggregation of prey species (Aurore *et al.* 2016). Visual-based surveys can confirm the occurrence of bird use of the development space post-construction and what species may be using the site in a manner similar to pre-deployment surveys. Given that any post-construction use of the development site is likely to be species-specific, Lagrangian data collection is likely to be most appropriate to determine three-dimensional use of areas (e.g. Thaxter *et al.* 2018), that may also help refine collision estimates as above (under baseline extension) by incorporating elements of behaviour. Alternatively, birds may avoid the development area post-construction. Avoidance rates are a key parameter used in CRMs and post-consent data collection can help confirm if avoidance rates used were accurate. As avoidance is based on measurements of flight data through the development area, the same approach outlined in the baseline data collection can be applied here. Eulerian-type methods can be considered for the larger spatial scales of avoidance and telemetry for finer-scales (May 2015, Cook *et al.* 2018). Using the same method to quantify avoidance post-construction as was used during baseline data collection (Fig. 5) ensures consistent methodology and means that baseline data act as reference data. Such a data collection design will further ensure that collision model predictions can be validated post-construction with actual avoidance incidents.

Validation and calibration of empirical methods

We evaluated and extracted information from the peer and non-peer reviewed literature on the methods applied to the collection of bird flight data in relation to interactions with wind energy (Fig 2, 3), the specific parameters quantified by these methods (Fig. 3) and the limitations and selection criteria associated with the use of these methods (Table 1), in order to provide an update to the current data collection guidance as part of ornithological impact assessment of wind energy developments (Fig. 5). In doing so, we highlighted how the use of sensor-based methods to collect bird flight data in relation to wind energy has evolved, likely reflecting the adaptation of technologies for collecting bird flight data generally (Fig. 4).

However, while developing a framework around sensor-based methods is likely to improve data accuracy and precision (Becker 2016, Fijn *et al.* 2018, Harwood *et al.* 2018), it is unlikely to be the most cost-effective means of data collection. This is likely to create challenges for the consenting process that may be overcome when such improvements in data accuracy and precision can be quantifiably demonstrated. This can be achieved when sensor-based methods are validated and calibrated. From the studies assessed here, however, the incidence of validation and/or calibration, according to our definition (see Methods) was low (Table 1). Rather, some studies opted to remove potentially erroneous data points (e.g. Poessel *et al.* 2018) or to restrict the data to within a certain range of the sensor (e.g. Welcker *et al.* 2017) or optimal sensor conditions (e.g. Brookes 2009, Cleasby *et al.* 2015), but such an approach may reduce amounts of potentially viable data for the consenting process.

Validation of device measurements can be achieved by quantifying the difference in measurement accuracy and precision with a known baseline. For example, Cole *et al.* (2019) used the known distance between ornithodolite operator and a building to test the precision of ornithodolite laser sensor in measuring distance. Alternatively, validation of a given device can be carried out using a second device that is already frequently used in quantifying bird flight. For example, Cook *et al.* (2018) validated measurements of flight height gained from LiDAR using unmanned aerial vehicles (UAVs) equipped with internal GPS or UAV height derived from photogrammetry. Calibrating a device establishes an understanding of how device measurements change specifically with the conditions likely to be experienced during deployment. For example, May *et al.* (2017) used a UAV to demonstrate that MERLIN avian radar detection was influenced by bird flight characteristics such as tortuosity, speed and height. Should calibrating devices to reflect all possible scenarios likely to be experienced during deployment not be possible, for example, as with atmospheric conditions and barometric altimeters attached to highly mobile species, possible post-hoc analytical solutions could be explored (e.g. Ross-Smith *et al.* 2016, Péron *et al.* 2020).

Validation and calibration of visual estimates is stipulated in current guidance (Scottish Natural Hertiage 2017), but evidence suggests this has been inconsistently undertaken. Where calibration was reported for visual-based studies, it was undertaken during the data collection surveys, using reference structures (e.g. Rothery *et al.* 2009), but few studies quantified the impact of changing environmental factors, such as topography or weather on estimates. Statutory guidance often stipulates that bird flight data should be collected in a range of weather conditions (e.g. Camphuysen *et al.* 2004, Scottish Natural Heritage 2017), therefore results of the calibration in these operational conditions should be provided. The subjectivity of visually-estimated quantities adds to the difficulty in validating and calibrating measurements. By contrast, sensor-based devices may provide data subject to errors that are more consistent and systematic, for example resulting from interference with bird detection from the environment. The more systematic the nature of discrepancies, the more feasible it is to quantify/ incorporate the effect of such discrepancies on the measurement of bird flight parameters. Where subjectivity might exist in determining the suitability of one sensor over another, Table 1, together with pre-deployment surveys, should provide contextual information to reduce such subjectivity.

While the increased cost of sensor-based methods likely deters statutory bodies from recommending the use of such methods, sensors offer improved accuracy in flight measurements in addition to an improved capacity to quantify the error and bias around such measurements. Such improvements may balance favourably against the increased cost of use given the potential economic cost of development consent refusal, consent delays, extended public inquiries or legal challenges based on inadequate data. A development in the UK has been refused consent based on estimates of bird collision mortality and uncertainty and disagreement around population mortality thresholds, with substantial economic cost to the developer (Broadbent & Nixon 2019). Such outcomes represent barriers to the development of renewable energy that can be, at least partially, overcome with collision estimates based on sensor-derived flight data.

Limitations and opportunities for further development

The guidance outlined in Fig. 5 is focussed on quantifying impacts from a single development. Cumulative impact assessment is a legislative requirement of EIA and has been highlighted as a concern for birds interacting with wind energy developments (Masden *et al.* 2010, Bastos *et al.* 2015, Brabant *et al.* 2015, Vasilakis *et al.* 2017, Kikuchi *et al.* 2019). Deploying technologies to quantify cumulative impacts would benefit from a network of sensors collecting data from the same individuals or life stages across multiple developments. On a large scale, such as for migrating life stages, networks of weather radars such as the currently used NEXRAD (Crum & Alberty 1993) and OPERA (Holleman *et al.* 2008) could be useful. A similar initiative has been set up using automated telemetry monitoring specifically for wildlife tracking (Taylor *et al.* 2017). However, such approaches are only currently operational for onshore developments and in a limited number of locations. For finer-scale information, such as individuals interacting with multiple developments within their home range, telemetry data has been found to be useful (Vasilakis *et al.* 2017), with further potential use as a spatial planning tool (Thaxter *et al.* 2019). There is also a need to consider the indirect, energetic consequences of multiple encounters with wind energy developments during flight and their impacts on survival and fecundity (Masden *et al.* 2010).

Conclusions

At present, bird flight data collected under EIA regulations often do not make use of the best methods currently available. Therefore, changes are required in the way data collection is approached and delivered in order to allow better estimation of species-specific collision risk, and derive more use from the flight data collected, such as behaviour-specific collision risk estimates. A potential barrier to updating data collection guidance is the lack of understanding around how tools and technologies that currently exist could be applied in the context of flight data requirements for EIAs and CRMs. Here, a framework is presented, building on that used within the existing EIA framework, to help guide the collection of bird flight data using sensor-based methods that have already been applied to the collection of bird flight data in relation to quantifying impacts of wind energy. Our framework incorporating these sensor-based devices will help stream-line decision-making for practitioners and ensure data collection is more accurate, consistent and standardised. Our framework is targeted to better quantify impacts of wind farms on birds, but is transferable to other situations where there is a need to quantify bird interactions with anthropogenic structures. Given the growing need to meet energy demands through renewable sources, and the concurrent challenges posed by the climate and biodiversity crises, it is necessary that decisions about wind energy development are made with the best available evidence regarding potential ecological impacts.

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Data availability statement

The data that support the findings of this study are available in the supplementary material of this article

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Table 1. Logistical factors that should be considered when deploying methods to collect bird flight data. 'Sensor' follows definitions of appropriate sensor-based data collection protocols (see Methods), 'Approach' refers to whether the data collection is Eulerian or Lagrangian (see Methods). 'Main selection criteria' represents the most frequently recorded reason across studies for selecting the method. 'Primary limitations' are those most frequently recorded across studies. NA is not applicable for a given method.

Method	Sensor-based (yes/no)	Approach	Number studies from peer/non-peer sources	Number of studies calibrated or validated	Main selection criteria	Deployed onshore/ offshore/ both	Mean duration of data collection (days)	Primary limitations
Radar	Yes	Eulerian	21/49	8	Nocturnal observations	Both	94	Lack of species-specific data
Animal-attached telemetry	Yes	Lagrangian	31/22	12	Species-specific data	Both	1080	Biases resulting from acceptable ratio of tag mass to bird body mass. Data collection restricted to times of the year

								when birds are accessible
LiDAR	Yes	Eulerian	0/1	1	Limitations of visual estimates	offshore	1[2]	Not deployable in inclement weather or nocturnally
Ornithodolite	Yes	Eulerian	3/8	1	Data quality/ species-specific data/ supplementary	both	71	Not deployable in inclement weather or nocturnally
Laser rangefinder + inclinometer	Yes	Eulerian	4/4	3	Site & species specific data/ data quality	Both	11	Doesn't provide 3D data
Vantage point survey	No	NA	28/86	21	Recommended by statutory bodies	onshore	65	Inaccurate relative to senor methods
Boat-based transect	No	NA	4/44	7	Recommended by statutory bodies	offshore	28	Inaccurate relative to sensor methods
Microphone	No[1]	NA	0/1	0	Nocturnal	onshore	246[2]	Microphone

array/acoustic					Observations			sensor does not measure flight parameters directly
Digital aerial surveys	No[1]	NA	0/1	0	Recommended by statutory bodies	offshore	20[2]	Camera sensor does not measure flight parameters directly
TADS + visual	No[1]	NA	0/1	0	Parameterize collision risk models	offshore	51[2]	Camera sensor does not measure flight parameters directly

1 Classed as non-empirical, given flight information cannot not be directly obtained (see text)

2 Based on a sample size of 1

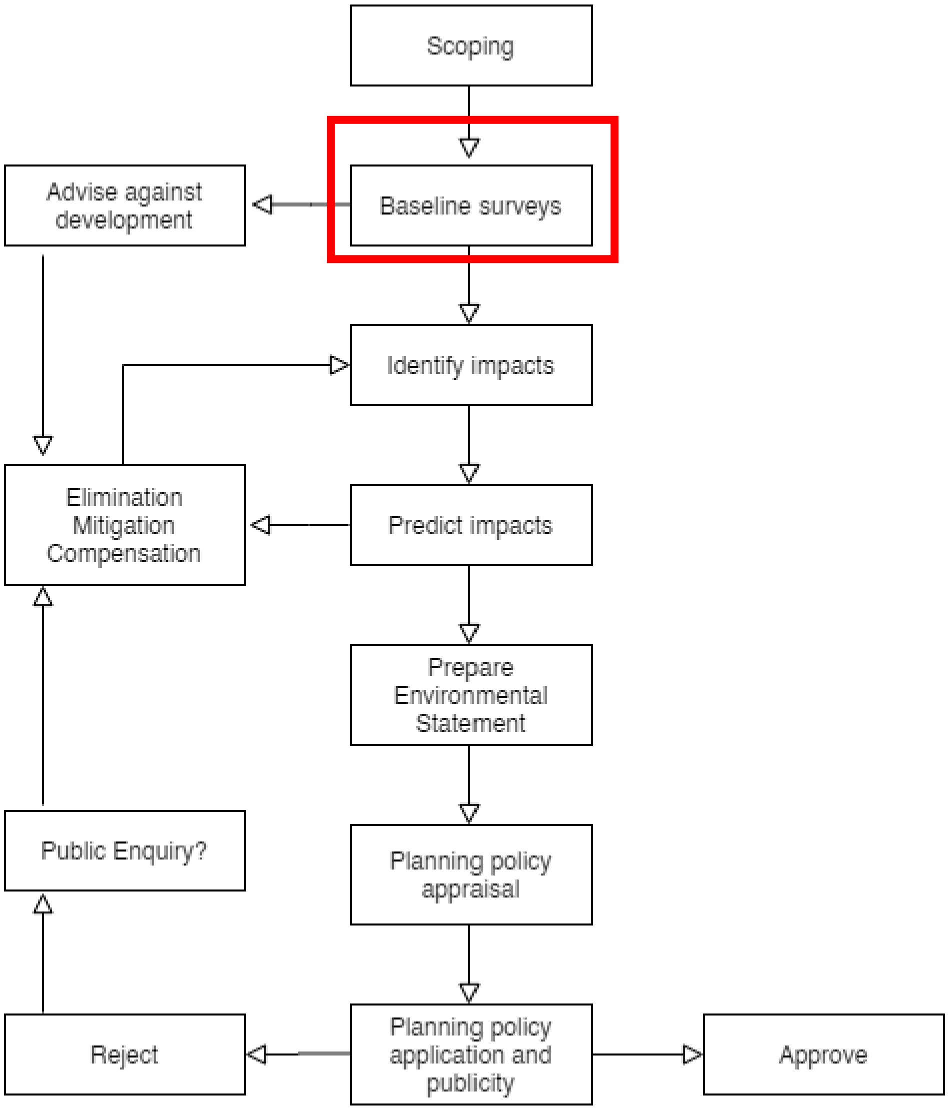

Figure 1. A framework outlining the EIA process (in the UK) with baseline data collection highlighted in red where sensor-based methods could provide bird flight data and where selection of sensor-based methods could be guided further by our framework.

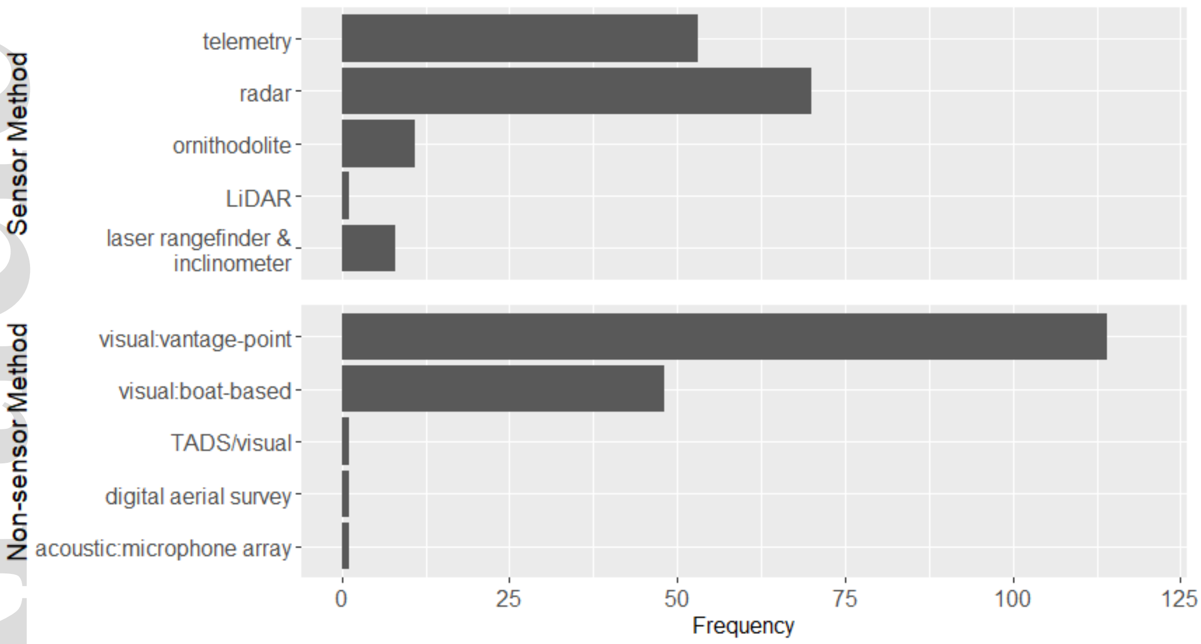

Figure 2. The frequency with which different methods were deployed to collect bird flight data to quantify impacts of wind energy developments based on a literature search of 308 applications. These studies were composed of peer-reviewed publications, grey literature and theses.

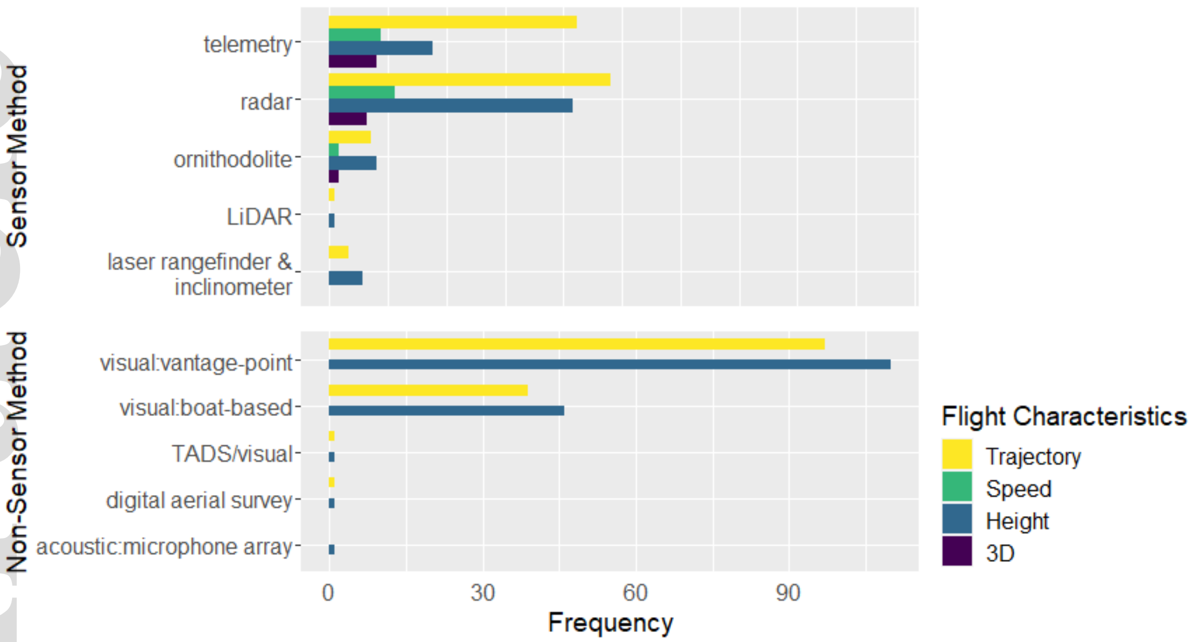

Figure 3. The frequency with which different methods were deployed to collect data on specific flight characteristics (trajectory, speed, height and flight in three-dimensions, meaning trajectory, speed and height data were collected concurrently) to quantify impacts of wind energy developments based on a literature search of 308 applications. These studies were composed of peer-reviewed publications, grey literature and theses.

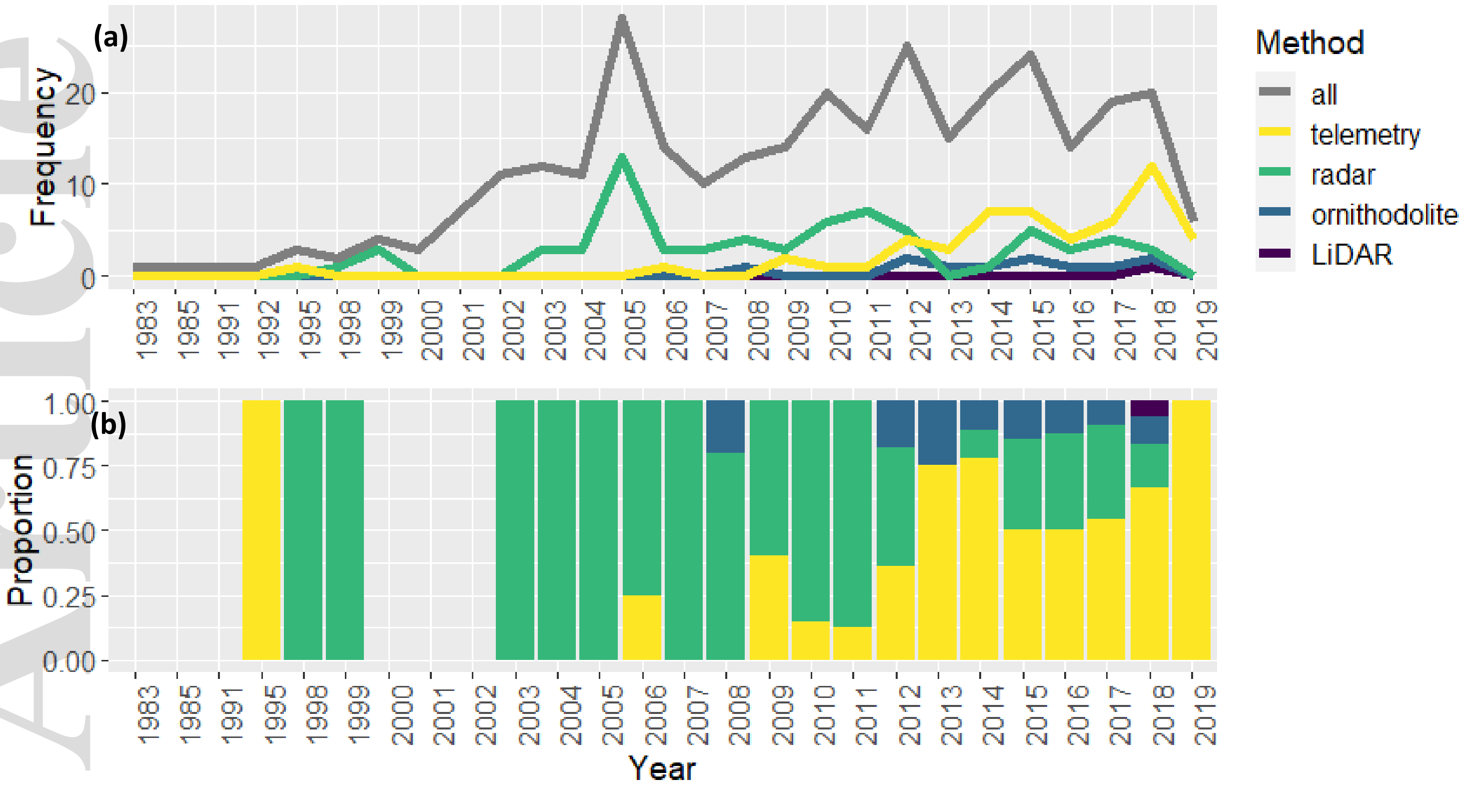

Figure 4. Variation in the frequency of studies using sensor-based methods (143 applications in total) over time presented as (a) total counts of each method (coloured lines) and total counts of all sensor and non-sensor studies (grey line, 308 applications in total); and (b) their proportional frequency relative to other methods for a given year. Years with no data are where our search criteria returned no studies using a sensor-based method.

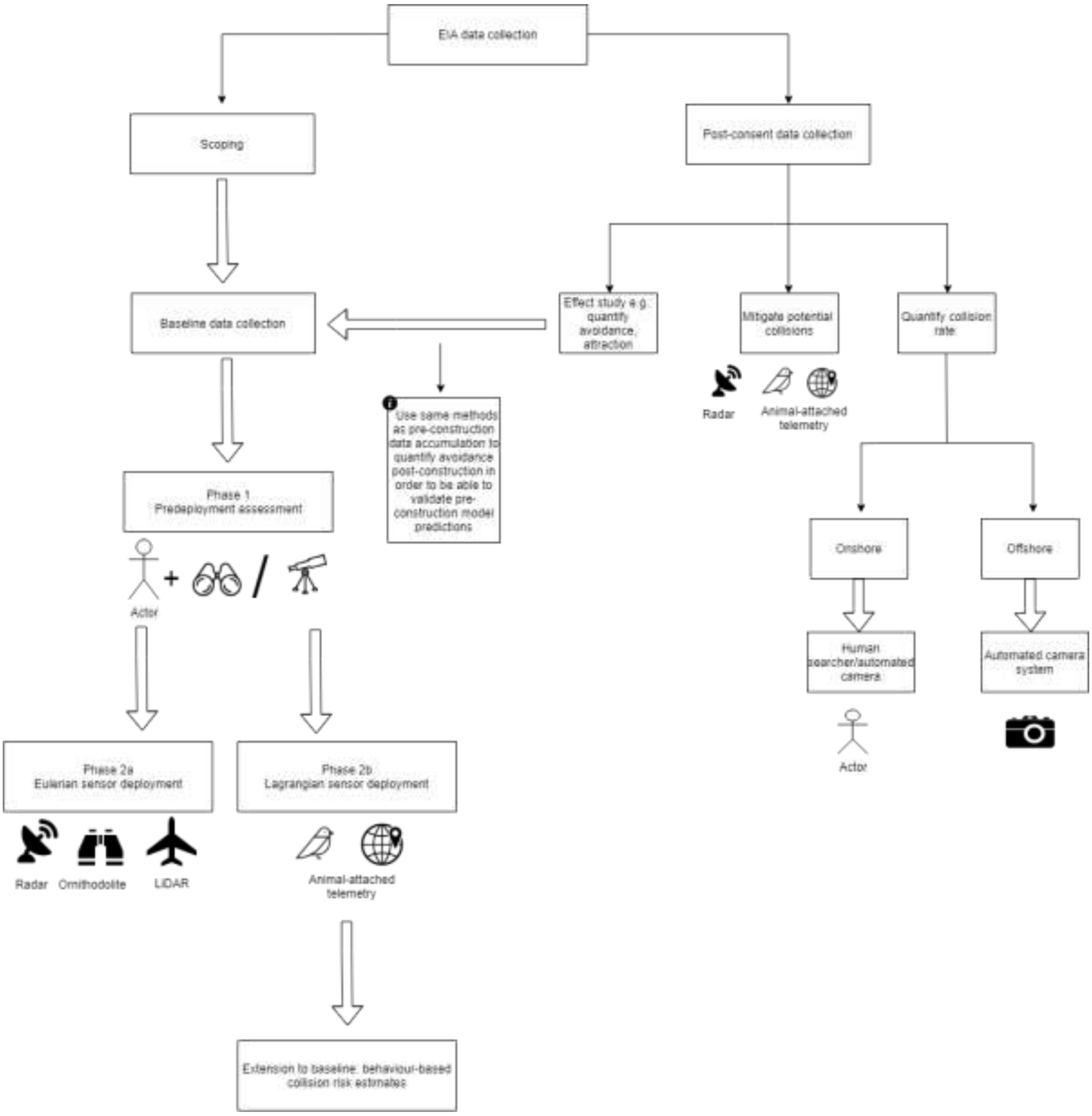

Figure 5. A framework for collecting flight data as part of EIA for wind energy, following a similar outline to the current EIA data collection framework (see Fig. 1), but including sensor-based measurement methods as primary baseline data collection methods. This framework includes a pre-deployment phase to better characterise the site of interest and includes an extension to the baseline for calculation of behaviour-specific collision risk estimates derived from telemetry data. We also better characterise the need for post-consent data collection and break this down into different data collection goals.