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Review Article

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A framework for improving treatment of uncertainty in offshore wind assessments for protected marine birds

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Governments worldwide are setting ambitious targets for offshore renewable energy development (ORD). However, deployment is constrained by a lack of understanding of the environmental consequences of ORD, with impacts on protected birds forming a key environmental consenting challenge. Assessing the impacts of ORD on marine birds is challenging, utilizing interlinked approaches to understand complex behavioural, energetic, and demographic processes. Consequently, there is considerable uncertainty associated with ORD assessments for marine birds, with current methods failing to quantify uncertainty in a scientifically robust, evidence-based manner. This leads to a high degree of precaution and a lack of confidence in the evidence used to inform ORD consenting decisions. We review the methods used to estimate ornithological ORD impacts in the UK, a country at the forefront of ORD. We identify areas in which uncertainty quantification could be improved through statistical modelling, data collection, or adaptation of the assessment process. We develop a framework for end-to-end quantification of uncertainty, integrating uncertainty estimates from individual stages of the assessment process. Finally, we provide research recommendations to better quantify and reduce uncertainty, to lower future ORD consenting risk. These recommendations extend beyond the UK and could improve impact assessments in other countries with different legislative frameworks.

Keywords: environmental variation, impact assessment, marine birds, offshore wind energy, precaution, seabirds, uncertainty.

Introduction

Ambitious targets for expansion of offshore renewable energy power generation are being set by governments in many countries around the world. Environmental policies in these countries require that this growth is delivered in a sustainable manner. At the heart of this sustainability goal is the need to quantify effects on protected wildlife and, in some regulatory contexts, demonstrate no adverse effect on populations of protected species, in particular top predators such as seabirds. For example, under the EU Birds Directive, Special Protection Areas (SPAs), classified for their nationally and internationally important aggregations of seabirds, require a Habitats Regulation Appraisal (HRA) where any planned development is deemed to potentially have an adverse effect on an SPA (https://www.gov.scot/policies/environmental-assessment/habitats-regulations-appraisal-hra/). Offshore renewable energy developments (ORDs) have the potential to affect protected seabird populations through collisions with turbine blades and through displacement from important habitat (Drewitt and Langston, 2006; Busch *et al.*, 2013; Thaxter *et al.*, 2015; Dierschke *et al.*, 2016; Welcker and Nehls, 2016). Seabirds are long-lived animals, meaning their populations are sensitive to small increases in adult mortality. Survival and productivity rates could be impacted by ORDs, and because these developments have long proposed lifespans spanning several decades, the potential population consequences of the developments on protected seabird populations could be significant.

Assessing the impacts of ORDs on protected marine bird populations requires the use of data from multiple sources and a range of modelling approaches to understand a set of complex behavioural, energetic, and demographic processes in the context of a dynamic marine environment. Inevitably, results from these assessments have considerable uncertainty associated with them (Masden *et al.*, 2015). Where scientific data do not exist or are incomplete and it is therefore not possible to complete a full evaluation of the possible risks an activity may cause to the environment, regulators in many countries implement the precautionary principle (De Sadelaar, 2009; RSPB, 2019). For example, the European Commission advises that "The implementation of an approach based on the precautionary principle should start with a scientific evaluation, as complete as possible, and where possible, identifying at each stage the degree of scientific uncertainty" (https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2000:0001:FIN:EN:PDF). However, the un-

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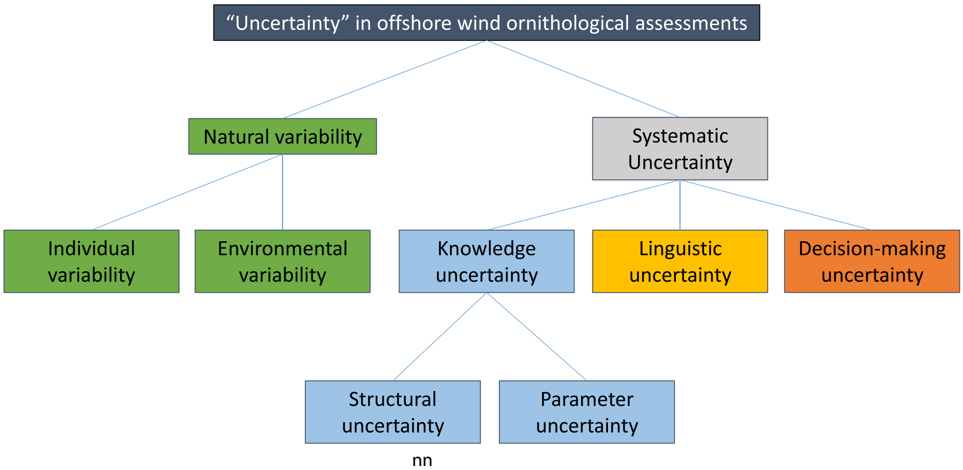

Figure 1. Summary of the sources of uncertainty affecting ornithological offshore windfarm assessments. Redefined from Masden *et al.* (2015).

certainty itself can be difficult to evaluate and propagate through the assessment process due to data paucity, the modelling of complex environments, and the limitations of statistical techniques. Current assessment processes do not quantify the overall uncertainty associated with the impacts of ORDs in a scientifically robust, evidence-based manner (Green *et al.*, 2016). In impact assessments, following the precautionary principle, the degree of precaution applied should be proportional to the extent of scientific uncertainty, but due to mistreatment of uncertainty, precaution may often be applied incorrectly. Approaches for quantifying uncertainty vary between different stages of the assessment process, and there is a lack of consensus on how uncertainty should be presented and interpreted. Historically, uncertainty has been viewed by the offshore wind sector as a feature of the process that can only be managed through additional empirical data collection. However, better statistical treatment of uncertainty and a holistic approach to managing uncertainty from the beginning to the end of the assessment process are likely to yield greater confidence in predicted impacts and quantitative estimates of uncertainty associated with them, thereby reducing the degree of precaution that needs to be applied in key policy mechanisms such as HRA. Ultimately, improved treatment of uncertainty in the assessment process will lead to better evidence use in decision making, and the first step in this process is acknowledging that uncertainty exists. Removing uncertainty is not the goal; rather, the objective is to make a good decision, which requires a robust assessment of the relevant uncertainties (Bickel and Bratvold, 2008).

Here, we review the relevant sources of uncertainty in ornithological offshore wind assessments and the current estimation and use of uncertainty in assessments. We use the UK as an example because it holds internationally important populations of marine birds (Mitchell *et al.*, 2004) and has recently set out plans to accelerate ORD power generation [British Energy Security Strategy (https://www.gov.uk/government/publications/british-energy-security-strategy)]. We provide a generic framework for the end-to-end propagation of uncertainty throughout the ORD assessment process, alongside a series of recommendations for improved quantification and reduction of uncertainty in future research.

Defining and identifying sources of uncertainty

When assessing environmental impacts, the level and form of uncertainty depend on the availability of relevant empirical data, data collection and sampling methodologies, analysis and modelling methods, the linguistics used by different stakeholders, and policy frameworks (Masden *et al.*, 2015). We redefine the framework developed by Masden *et al.* (2015) to recognize how understanding ecological processes relies on separating and quantifying the contributions and impacts of systematic uncertainty versus natural variability (Figure 1; see the Glossary for full definitions of key terms, Supplementary Material S1). Natural variability is a property of natural systems, which may have many causes. For seabirds, variability exists between individuals within a breeding colony relating to physiology, age, or sex (termed *individual variability*), between sub-colonies through social processes and local gene flow, between colonies due to differing habitat characteristics, and across years due to environmental conditions or other aspects of the ecosystem (termed *environmental variability*; Figure 1). As natural variability is a property of the ecological system, it cannot be reduced. However, it can be characterized and quantified through measurement, such as by including explanatory covariates used within models or analyses of ecological processes, ideally clearly separating its impacts from those arising from uncertainty. However, characterizing and quantifying natural variability to successfully differentiate it from uncertainty may require substantial data collection over long time periods, particularly for long-lived species such as seabirds.

Uncertainty is introduced due to limitations in describing, measuring, and representing an ecological system. This has been termed *knowledge uncertainty* (Masden *et al.*, 2015; Figure 1). Within ornithological offshore wind assessments, knowledge uncertainty arises from constraints in understanding and representing the ecological processes through which seabirds are affected by ORDs and in understanding their baseline dynamics. For example, in the UK, three types of seabird interactions are typically considered: displacement from habitat, barrier effects, and collision impacts. These categories capture many underlying behavioural mechanisms, some of which may be explicitly represented within the assessment process. However, many behaviours are currently

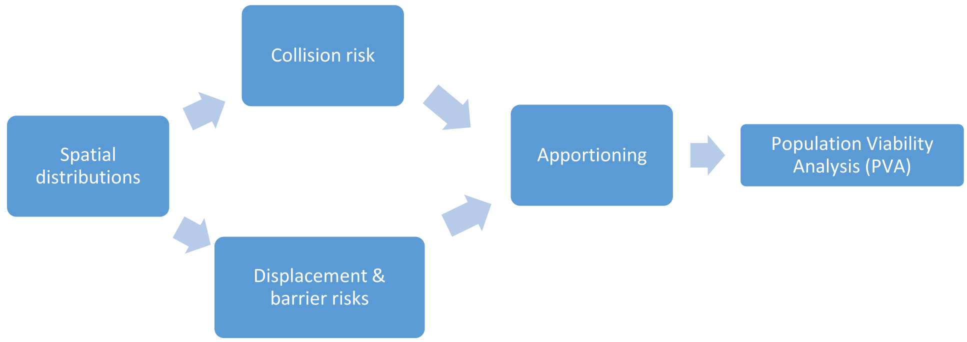

Figure 2. A schematic diagram summarizing the modelling tools involved in the ornithological offshore wind impact assessment process in the UK.

not included, such as habituation, impacts on other trophic levels affecting predator–prey interactions, and foraging site fidelity. Most of the underlying behavioural mechanisms can only be partially described and measured, resulting in knowledge uncertainty that affects ornithological assessment outcomes. Furthermore, all behaviours have energetic and fitness consequences for individuals, which translate to long-term effects on demographic rates for populations and can only partially be described and measured. These limitations all contribute to knowledge uncertainty in assessments.

Knowledge uncertainty is comprised of structural uncertainty and parameter uncertainty. *Structural uncertainty* depends on how fully the mathematical representation of a model captures ecological processes. Our definition of *parameter uncertainty* depends on the quality of the data used to parameterize the model so that measurement and sampling errors are adequately described (Figure 1). Although natural variability is often characterized as a component of parameter uncertainty, we decouple these definitions so that the treatment of each element can be considered in isolation. Better data collection through experimental design, improvements in data analyses, and more advanced statistical modelling approaches can reduce knowledge uncertainty, leading to more precise estimates.

Within ornithological impact assessments, uncertainty also arises through linguistic and decision-making processes. *Linguistic uncertainty* arises because language is vague and/or the precise meaning of words changes over time or between disciplines (Masden *et al.*, 2015). For instance, the use of the word "precautionary" within assessments was established to have a precise meaning and interpretation, yet it has a different interpretation for various stakeholders. Moreover, the term "precautionary" is often used with qualifiers such as "overly" or "excessive", further clouding the definition of the term and its use within decision-making. *Decision-making uncertainty* relates to how knowledge and predictions are interpreted, communicated, and used in the management and policy arenas (Masden *et al.*, 2015). Whilst important, we do not consider these two additional sources of uncertainty in depth within this review, instead focusing on knowledge uncertainty and environmental variability.

This paper focuses on how environmental variation and structural and parameter uncertainty are recognized, quantified, and propagated through the assessment process. These two processes—natural variability and knowledge uncertainty—are often confused by practitioners and can be difficult to disentangle, but conflating variability with uncertainty can lead to incorrect specification of error (see Supplementary Material S1 for an example). The complexities of natural systems and limitations of ecological data collection mean that uncertainty cannot be, in practice, either perfectly quantified or reduced to zero. Yet, its importance within impact assessment approaches results in a critical need for improvements aimed at both uncertainty quantification and reduction.

Review of current modelling tools and estimation of uncertainty: UK example

In the UK, the current modelling framework for the assessment process comprises interlinked modelling tools that address aspects of seabird ecology or ORD impact, including the spatial distributions of seabirds at sea, collision risk, displacement, and barrier risks, the apportioning of seabirds at sea to protected breeding colonies, and population viability analysis (PVA; Figure 2).

At-sea surveys and tracking data (e.g. from Global Positioning System tags, "GPS") as well as biotic (e.g. colony counts) and abiotic (e.g. environmental data) information are synthesized to define baseline spatial distributions of birds, potentially separated by behaviours such as flight or foraging, to produce continuous maps of mean density estimates with uncertainty (e.g. Johnston *et al.*, 2015; Waggitt *et al.*, 2018). The spatial distribution maps serve as inputs, along with energetic and growth information, prey data, windfarm-specific characteristics, and behavioural responses to ORDs, to estimate displacement and barrier effects in different seasons. The spatial maps are also combined with models of the behavioural responses to ORDs to provide estimates of collision risk in the breeding and non-breeding seasons. To understand the impacts of displacement, barrier, and collision risks of the proposed ORD on protected populations, most often in Special Protected Areas (SPAs), apportioning is used within the assessment process to attribute effects on seabirds in the breeding and non-breeding seasons to each candidate population. Finally, PVA produces predictions of long-term population consequences, which are the final outputs of this approach (Butler et al. 2020a). Below, we summarize the current methods used to estimate uncertainty within the ORD ornithological assessment process in the UK.

Spatial distributions

Spatial data are used in the assessment process at varying scales: broad-scale, offshore wind farm project-level, and breeding colony-level. Broad-scale data are usually based on offshore aerial or boat-based surveys, capturing spatial distributions of birds and providing insight into seasonal space use (Waggitt *et al.*, 2020), which may then be used for marine spatial planning. Project-level abundance data are collected through surveys of ORD footprints and analysed using either design- or model-based methods. Design-based methods use formulae for estimating the quantity of interest (e.g. mean abundance) directly from the raw data, based solely on the survey design used for data collection, without the need for a model. Design-based methods can be used for analysing project-level data because they are collected using a simple, standardized design (i.e. a systematic survey). Model-based methods instead use an explicit model and so rely on additional assumptions. In the context of project-level abundance data, this involves using spatial smoothers and covariates to estimate abundance in unobserved areas within the survey region (e.g. Mackenzie *et al.*, 2013). Simpler model-based approaches, such as generalized linear models (GLMs), could also be used, but the advantage of including a spatial smoother is that it can account for underlying spatial patterns that cannot be explained by the covariates. Whilst mean estimates of project-level abundance from spatial models are robust, the models perform poorly for species present in low numbers, so it is necessary to use design-based estimates with bootstrapping to obtain confidence intervals. In contrast, if missing data (e.g. transects missed due to weather conditions) mean that the data collection does not reflect the intended design, then design-based approaches are unlikely to be appropriate and model-based approaches will be needed. In many situations, it will be appropriate to apply both design-based and model-based approaches to investigate the causes of any substantive differences.

Finally, colony-level utilization distributions of birds in the breeding season are derived from tracking data (e.g. Wakefield *et al.*, 2017) and are used to provide spatial estimates of the space use and density of birds in the marine habitat around each breeding colony. Here, GLMs or their variants (GLMMs, GAMMs) are used to empirically describe the colony-specific spatial distributions of birds in relation to both accessibility (distance to the breeding colony) and environmental heterogeneity, although residual autocorrelation is typically not accounted for within these models and so uncertainty cannot be defensibly quantified.

Displacement and barrier effects

Quantifying the consequences of displacement by ORDs on a seabird population requires estimates of the proportion of birds displaced and the impact of that displacement on the population's demographic rates. Displacement is estimated through distributional changes in seabirds before and after the wind farm is built, usually based on comparisons of pre- and post-construction monitoring data (e.g. Vanermen *et al.*, 2015; Dierschke *et al.*, 2016). However, such changes could result from some other cause operating in parallel or from natural seasonal and yearly variability in space use. Therefore, this distributional approach suffers from the conflation of both natural variability and knowledge uncertainty. Until recently, accurately estimating the proportion of birds displaced has proved challenging (but see Heinänen *et al.*, 2020; Peschko *et al.*, 2020a, b, Peschko *et al.*, 2021), with natural variability in the marine environment compounding the difficulty in quantifying displacement rates. Historically, this problem has been exacerbated by inconsistent approaches, low statistical power (Maclean *et al.*, 2013), and poor design of post-construction monitoring studies (Marine Management Organization, 2014). However, more recently, the MRSea package in R (Mackenzie *et al.*, 2013) provides a more consistent approach to address some of these issues by defining and producing a range of outputs and metrics that are relevant to the estimation of displacement and by providing a modelling framework that can be used to derive these from project-level data. The spatial modelling approach used within MRSea is not the only statistical approach that could be used to estimate displacement. More sophisticated statistical approaches (e.g. R-INLA) and simpler approaches (e.g. GLMs or generalized additive models, GAMs) could also be used, and the application of these different approaches is context-dependent. However, MRSea has the advantage of being specifically tailored to the estimation of displacement and is widely known and accepted in the offshore renewable energy industry. Studies have also highlighted clear inter-specific differences in displacement rates. For example, divers, gannets, and to a lesser extent auks, show a consistent negative response to wind farms, whereas others, such as cormorants, show evidence of attraction, and several other species show no clear response (Dierschke *et al.*, 2016). This highlights the need for species-specific approaches to estimating displacement and barrier effects.

Having quantified the proportion of birds displaced from an ORD, it is necessary to consider the impact of this displacement on protected populations. At a population level, displacement may affect birds through a reduction in survival due to the energetic costs associated with losing an area used for commuting, foraging, or other essential behaviours and/or a reduction in breeding success due to the increased energetic costs of provisioning young or increased predation risk of eggs and chicks due to adults spending longer away from the nest. At present, there is little evidence with which to quantify the impacts of displacement on demographic rates, although biologging is increasing our understanding of the behaviour and energetics of marine birds (Dunn *et al.*, 2020; Duckworth *et al.*, 2022; Buckingham *et al.*, 2023) and enabling the effects of behavioural change arising from ORDs on demography to be estimated empirically. Studies that estimate these links will be critical because analyses suggest that increased energetic costs can have a more significant effect on adult survival than has been assumed in previous assessments (Searle *et al.*, 2020). Furthermore, life history theory predicts long lived species such as seabirds will prioritize their own survival over that of their dependent young. Evidence suggests that seabirds do attempt to buffer the impacts of increased energetic costs through reduced parental investment in chicks (Suryan *et al.*, 2006; Regular *et al.*, 2014), potentially reducing productivity.

Two methods have been used to estimate the demographic impacts arising from the displacement effects of ORDs: the "Displacement Matrix" approach (hereafter the *matrix approach*) and the use of individual-based models (IBMs). The two methods differ in terms of the complexity of the approach, the data required, the outputs, and the treatment of uncertainty. The matrix approach uses the density of birds within the wind farm footprint (and a buffer area around the wind farm where birds are predicted to be affected) estimated from local at-sea survey data multiplied by a displacement rate (percentage of adult birds within the footprint and buffer that are assumed to be displaced, ranging from 0 to 100%) and a displacement mortality rate (percentage of birds that are assumed to suffer mortality as a consequence of displacement, ranging from 0 to 100%; Joint-SNBC 2017). The resulting matrix approach table (i.e. proportion of birds potentially displaced or dying as a result of ORD development) provides a visual and qualitative consideration of uncertainty in displacement impacts. The matrix approach only considers the mortality of adult birds, with no consideration of potential effects on dependents and, therefore, breeding success. An alternative approach to estimating displacement is the use of stochastic IBMs (e.g. SeabORD, Searle *et al*., 2014, 2018). IBMs still require an input for displacement rates but improve the biological realism of displacement mortality rates by incorporating seabird behaviour, energetics, and demographic processes into the model, as well as providing estimates of impacts on both adult birds and their dependents. Current models include some quantification of uncertainty (e.g. impact of prey levels) and are relatively sophisticated in the way that variability (e.g. individual variation in body mass or susceptibility to displacement and choice of foraging location) is accounted for, and these are aggregated and represented in model output using confidence intervals (Searle *et al*., 2018). However, there are many other parameters within SeabORD for which temporal and inter-individual variability are not considered, largely due to a lack of available information on the level of variability that might plausibly be expected (Searle *et al.,* 2022a).

Collision risk

In the absence of empirical estimates of collisions that can be generalized to new locations, collision risk models are used in EIAs to estimate risk. Whilst there are a variety of collision risk models available (Masden and Cook, 2016), the most widely used of these is the Band *et al.* (2007) model, subsequently adapted for the offshore environment (Band, 2012), and then into a simulation tool to account for stochastic variation in parameters (the stochastic Collision Risk Model, sCRM; Masden, 2015, McGregor *et al*., 2018). Three sets of parameters are used in the model (McGregor *et al*., 2018): site-specific seabird data (monthly densities of birds in flight, site-specific or generic flight height distributions), generic seabird data (biometrics, flight characteristics), and turbine and wind farm data (rotor size, hub height, RPM, etc.). The model itself is highly sensitive to particular input parameters for which there is often limited empirical data, resulting in further uncertainty surrounding predicted impacts (Masden *et al*., 2021). This problem is exacerbated because there is often substantial natural variation in many of these parameters (e.g. flight speed and height), linked to underlying environmental conditions, and these relationships are not captured by existing models. Finally, alternative options are available for implementing the sCRM, which results in impact assessments presenting several alternative versions of the collision predictions, introducing additional complexity in interpretation.

Apportioning

Apportioning is currently used within the assessment process to identify individuals that are likely to be affected by an ORD and are part of a protected SPA population. In the UK, apportioning in the breeding season is currently based either on a simple distance–decay relationship (the NatureScot tool[1]), or on spatial models derived from GPS tracking data (Butler *et al*., 2020b; Wakefield *et al*., 2017). In both cases, the proportion of individuals originating from an SPA within a particular area of sea is assumed to be equal to the product of the estimated usage of the area of sea by individuals from the colony (based on colony-specific spatial models) and the colony size. Apportioning in the non-breeding season is currently based on a simpler regional approach, Biologically Defined Minimum Population Sizes (BDMPS; Furness, 2015), which accounts for individuals from non-UK as well as UK colonies. None of the current apportioning tools account for variability or uncertainty.

Population viability analysis

Population Viability Analysis (PVA) provides an established statistical framework for translating effects on annual demography into impacts on longer-term population trajectory (Soulé, 1986; Beissinger and McCullough, 2002). Population models are run forward in time for impacted and unimpacted populations and then compared against each other using a range of metrics (Cook and Robinson, 2016; Jitlal *et al*., 2017). Metrics used in assessments that provide relative comparisons of impacted and baseline simulations are preferred because they are less sensitive than absolute comparisons to misspecification of baseline demographic rates and initial population sizes (Cook and Robinson, 2016). Currently, these are the counterfactual of population size (CPS), which is the ratio of the final population size of the impacted population divided by the final population size of the unimpacted population, and the counterfactual of population growth rate, defined as the CPS raised to the power of the inverse of the number of years of impact. Key inputs to PVAs are the initial population size, the estimated combined annual impacts of the ORDs on demographic rates, and the baseline demographic rates (age-specific survival, productivity, and age at first breeding). PVAs used for impact assessments typically assume closed populations (no immigration or emigration), and some models incorporate forms of density dependence. However, PVAs do not usually include ongoing impacts such as projected changes to baseline demographic rates under climate or other environmental change (Horswill *et al*., 2022, Searle *et al*., 2022b).

Recommendations for improving treatment of uncertainty in the impact assessment process

Research prioritization

Decision-making in the face of uncertainty can be strengthened by recognizing which sources of uncertainty are "controllable", meaning they can be minimized and managed, and which are "important", having a significant and qualitative effect on management outcomes (Milner-Gulland and Shea, 2017). We have used these concepts to lay out a set of research priorities, identifying current evidence gaps that can be addressed by scientific approaches and that are likely to lead to positive management outcomes through better quantification and a reduction in uncertainty. The recommendations focus on future empirical data collection and the use of modern analytical methods to exploit information, mapping them to the current modelling framework. Quantifying uncertainty is as important as reducing it in the context of supporting the decision-making process (Milner-Gulland and Shea, 2017). Where uncertainty appears to be reduced but is not properly evaluated overall, the risk of unanticipated outcomes increases. Therefore, for each research priority, we provide a qualitative assessment of its contribution to the full quantification of uncertainty and to reducing uncertainty (high or medium; Table 1). In the remainder of this section, we make recommendations for a full evaluation of uncertainty across the framework, identify the added value of incorporating post-construction monitoring data, and set out future developments of statistical models that will help fill the evidence gaps. Research priorities are mapped to the main text through bold number referencing, e.g. (**1**).

Spatial distributions

Understanding the space use of birds, including behaviour-specific habitat preference, and how these vary between individuals and in response to environmental variation, is a key area in which uncertainty in assessments can be better quantified and reduced (Table 1). More data are being collected in relation to ORDs and spatial planning, with technological advances leading to new survey methods and data types becoming available: aerial and boat-based surveys (Hammond *et al*., 2002, 2013, 2018), drones (Rush *et al*., 2018), camera imaging on wind farms to assess collisions (Skov *et al*., 2018), biologging devices that track location and collect in-situ environmental information (Cleasby *et al*., 2015; Isaksson *et al*., 2021), movement through accelerometers (tri-axial movement) (Chimienti et al. 2016), and behaviour through time-depth records (Peschko *et al*., 2020, Duckworth *et al*., 2021). These advances in data collection present questions as to the best use of these varying data types. Data collected using different surveying techniques often has varying structures that require specific statistical analysis techniques to address intrinsic issues such as autocorrelation and replication. For example, boat-based observations generate information about the abundance of animals at a snapshot in time. By contrast, tracking data, generated from tags attached to individuals, provides spatial and temporal information for one animal. Greater knowledge will be gained, and hence uncertainty reduced, if at least some of these data types can be integrated (Matthiopoulos *et al*., 2022; Schaub and Kery, 2021). For effective integration, two criteria need to be met: data must overlap or align either spatially or temporally, and statistical methods must be developed to deal with intrinsic data issues and propagate uncertainty through the model. For example, data integration could advance seabird assessments by addressing the current failure to adequately consider the distribution of non-breeding birds during the breeding season, leading to differences between assessments based on tracking data and those based on at-sea surveys (Sansom *et al*., 2018; Searle *et al*., 2020). New year-round tracking datasets will allow this to happen (Merkel *et al*., 2016; Buckingham *et al*., 2022; Duckworth *et al*., 2022). Integrated modelling would allow the distribution of non-breeding birds to be estimated and the uncertainty associated with this component of the population to be quantified (**1**).

Movement models are used to predict behaviours (e.g. foraging, resting at sea, diving) and estimate activity budgets of seabirds fitted with biologgers to investigate flight paths with respect to collision risk, barrier effects, and displacement (Cleasby *et al*., 2015; Warwick-Evans *et al*., 2017; Peschko *et al*., 2020). A class of movement models used for analysing tracking data are hidden markov models (HMMs), which are state–space time series models that assume the observed (state-dependent) time series is driven by an unobservable (hidden) state process. They sequence behaviours (states) and can account for serial dependence between observations (Patterson *et al*., 2008; Langrock *et al*., 2012). Depending on the complexity of the behavioural states required, combining locational data with ancillary information such as accelerometers, time-depth recorders (TDRs), or environmental covariates can produce more plausible models. Using movement models in the context of assessments can improve the quantification and reduction of uncertainty because they can provide more information about how birds are using an area of sea, particularly if two current limitations can be addressed: model validation and propagating uncertainty. Typically, model validation is difficult to achieve because ground-truth data are generally unavailable. However, where animals have been fitted with a device that records Global Positioning System (GPS) and time-depth records (TDR), there is an opportunity to fit a movement model using only location data and use the depth information to validate the model's accuracy in determining behavioural states (Browning *et al*., 2018). Validating a location-only movement model could be useful in circumstances where only some individuals had TDRs and/or accelorometers but all had GPS functionality in the tag and a general movement model was required (**2**).

Typically, HMMs do not consider observation error on location but treat the state as part of a stochastic process (Patterson *et al*., 2008). Continuous-time Markov chain Monte Carlo models calculate velocity and momentum and allow for behavioural switching to occur continuously in time rather than at (discrete) observational times (Parton and Blackwell, 2017). They can account for observation error and for irregular observations. Using continuous-time models allows for uncertainty to be quantified and for more biologically realistic trips to be simulated (Blackwell, 2019). In this way, GPS and at-sea survey data could be integrated through sampling from a utilization distribution generated by the movement model (**1, 2**).

Non-breeding season distributions present a large component of current uncertainty within ORD assessments and should be prioritized for future research (**3**). Due to the ethical and logistical challenges of deploying GPS tags on marine birds for extended periods, non-breeding season utilization distributions are typically estimated from data from Geolocators (GLS), which are light-level data loggers. They are lightweight and long-lasting devices that can be attached to leg rings, meaning they are suitable for deploying on marine birds for extended periods. However, because a bird's position is estimated using ambient light intensities and elapsed time, GLS locations have relatively large locational uncertainties up to hundreds of km (Merkel *et al*., 2016), which hinders their use in assessments relative to the scale of individual offshore wind farms. Nevertheless, these data can offer insight into the long-distance movements and distributions of seabirds during the non-breeding season (Merkel *et al*., 2016; Buckingham *et al*., 2022; Duckworth *et al*., 2022) and will be particularly useful for reducing uncertainty in the apportioning methods used in the non-breeding season (**3**).

Species distribution or habitat preference maps that form the inputs to displacement and collision risk models are produced using spatial data (Wakefield *et al*., 2017, Waggitt *et al*., 2019). Habitat preference models associate animal space use with characteristics of their environment (Aarts *et al*., 2008). When these models are used to predict space use, choosing appropriate explanatory covariates is important; however, the marine environment is dynamic and mostly inaccessible, so

Table 1. Summary of research priorities for better estimating and reducing uncertainty in seabird offshore wind farm assessments, moving beyond current tools and methodologies.

	Research priorities and relevant stage of assessment	Contribution to quantifying uncertainty	Contribution to reducing knowledge uncertainty
1	Data integration from different sources and seasons for better knowledge of year-round distributions to quantify and reduce uncertainty ***Spatial distributions and apportioning***	High	High
2	Improving uncertainty quantification in movement models ***Spatial distributions and apportioning***	High	Medium
3	Better understanding and quantification of year-round distributions and impacts of displacement to quantify and reduce uncertainty ***Spatial distributions, displacement, and apportioning***	Medium	High
4	Better understanding and quantification of predator–prey interactions, relationship between prey density and availability, impacts of ORDs on prey distributions and availability to quantify and reduce uncertainty ***Spatial distributions, displacement, and collision***	High	High
5	Estimate link between displacement effects and changes in demographic rates (productivity and survival) to better quantify and reduce uncertainty ***Spatial distributions, displacement, and apportioning***	High	High
6	Effects of displacement on different age classes, e.g. immatures and non-breeders to better quantify and reduce knowledge uncertainty ***Displacement***	Medium	Medium
7	Improve uncertainty quantification within IBMs to better characterize and reduce structural and parameter uncertainty ***Displacement and collision***	High	Medium
8	Assess sensitivity of collision risk model outputs to variation in input and structural parameters; understand and quantify covariance between parameters used in collision risk models to better quantify and reduce structural and parameter uncertainty ***Collision***	Medium	Medium
9	Improve estimates of flight speed and height for species to better characterize and reduce parameter uncertainty, quantify influence of environmental conditions to better characterize natural variability, and understand how variation in flight speed and flight height is related to behaviour (e.g. commuting versus foraging) to reduce knowledge uncertainty ***Collision***	Medium	Medium
10	Improve estimates of avoidance rates and partitioned into micro-, meso-, and macro-avoidance to better quantify and reduce structural and parameter uncertainty; improve understanding of the influence of environmental conditions on avoidance to better characterize natural variability; improve understanding of the contribution of model error to predicted collision rates and the implications of this for estimates of avoidance rates ***Collision***	High	High
11	Improve estimates for abundance, productivity, adult and immature survival, carryover effects, and inter-colony movements (including uncertainty in rates) to better quantify and reduce parameter uncertainty ***PVA***	High	High
12	Empirical estimation of correlation in demographic rates and influence of environmental stochasticity to better characterize natural variability and improve quantification of structural and parameter uncertainty ***PVA***	Medium	High
13	Understand relationship between demographic rates and prey availability to better quantify and reduce knowledge uncertainty; improve estimates for interactions between demographic rates and climate and other environmental variables to include in population forecasts to better characterize natural variability ***PVA***	High	High
14	Integrated population modelling and model fitting methods to better quantify structural and parameter uncertainty by using all available abundance data to inform estimation of demographic rates; improved models of observation error for abundance estimates to support this ***PVA***	Medium	Medium
15	Sensitivity analyses for PVAs to help prioritize efforts to reduce structural and parameter uncertainty ***PVA***	Medium	Medium
16	Better understanding and quantification of density dependent processes in populations to reduce knowledge uncertainty ***PVA***	Medium	Medium

Priorities are grouped into "medium" and "high" contributions to (a) full quantification of uncertainty and (b) reduction of knowledge uncertainty. Note that the order of priorities within the table broadly follows their relevance to each stage of the assessment process (shown in bold), moving from estimating spatial distributions of birds and apportioning to quantifying displacement and collision impacts and comparison of impacts via population modelling and PVA. The assignment of each research category into "medium" or "high" was done by expert judgement—i.e. the authors' assessment for how much each proposed research priority would improve quantification of uncertainty, and reduce knowledge uncertainty, within the context of the UK assessment process.

collecting and defining appropriate covariates can be challenging. Currently, covariates that represent proxies for prey fields are used due to the paucity of information (Tremblay *et al.*, 2009; Johnston *et al.*, 2015; Waggitt *et al.*, 2018). Associating top predators with oceanographic covariates such as sea surface temperature amidst many complex biological and physical processes can make habitat association modelling difficult due to weak explanatory power where covariates do not adequately capture heterogeneity in environmental space (Skov *et al.*, 2016; Wakefield *et al.*, 2017; Waggitt *et al.*, 2018). However, impact assessments need to account for pre, during, and post-development activities, along with seasonal variation in seabird habitat use due to life history stages (pre-breeding, breeding, chick incubation, non-breeding, and migratory), as well as population response to environmental variability. An overriding issue is that a full understanding of the complexity of ORD impacts on seabird behaviour and activity budgets, as well as proper quantification of uncertainty, can only be achieved through the collection of good quality covariates from direct prey of seabirds. Using prey data (instead of proxies) accounts not only for environmental variability but also provides a direct link to the causal mechanisms of key drivers in seabird demographics. Information on prey fields can then be combined with oceanographic covariates to identify and characterize different scales of seabird distribution and the underlying mechanisms that drive change over space and time (**4, 5**).

Apportioning

Where apportioning is derived from habitat utilization models developed using GPS tracking data (e.g. Butler *et al.*, 2020b), more thorough statistical approaches are needed to properly address the intrinsic complexities of spatial and temporal autocorrelation associated with such data. Use of such approaches would mean that uncertainties around estimated habitat utilization distributions could be incorporated into assessments (**1, 2**). For species where colony-specific GPS tracking data are not yet available or are unobtainable due to difficulties in accessing birds for deployment, the rate of decay of utilization with distance can be estimated using foraging ranges derived from published distributions (e.g. Woodward *et al.*, 2019), rather than being fixed as a constant as is the current approach. Foraging ranges can also be disaggregated by population, region, or meta-population as appropriate (**2**), and the inter-population variability in foraging ranges is used to quantify uncertainty in apportioning percentages. Within the non-breeding season, models of geolocator data can, where available, be used as a basis for apportioning in place of the BDMPS, with these models accounting for the locational uncertainty associated with geolocator data (**3**).

Displacement and barrier risks

In the context of ORD displacement impacts, current IBMs have limited uncertainty quantification. Structural uncertainty within IBMs should also be addressed with future research prioritizing improved representation of: flight paths and estimated bird density maps (**2**); behaviour, energetics, and ORD interactions outside the chick-rearing period (**3**); overall prey availability and spatial heterogeneity in prey (**4**); the joint distribution between seabirds and prey spatio-temporal dynamics (**4**); and the relationship between adult mass at the end of the chick-rearing period and overwinter survival [(**5**); e.g. Daunt *et al.*, 2020]; and better understanding and incorporation of impacts on immatures and nonbreeders (**6**). Uncertainty estimates in IBMs can be improved by estimating parameters for which empirical data are not available, through calibration of the model against observed data (**7**). Standard calibration processes involve fitting against observed data to identify the sets of input parameters that provide the best match, according to some metric (e.g. sum of squared differences, deviance), to observed data on one or more of the model outputs. However, many commonly used calibration methods do not account for the uncertainty associated with calibration. Methods of likelihood-free inference, such as Approximation Bayesian Computation (ABC; Beaumont *et al.*, 2002; Marjoram *et al.*, 2003; Sisson *et al.*, 2007) do allow for uncertainty to be estimated but are infeasible in practice due to computational processing time. A potential solution is emulation, which approximates the IBM using a statistical model (Kennedy and O'Hagan, 2001). An emulator runs the IBM for a relatively small number of sets of input parameters and constructs a statistical model that describes how the key outputs of the mechanistic model vary in relation to the values of the input parameters (Oyebamiji *et al.*, 2017; Pietzsch *et al.*, 2020). Uncertainty associated with calibration can be quantified whilst accounting for the uncertainty that arises from the relatively small number of runs of the process-based model.

Collision risk

By incorporating stochasticity, the sCRM better accounts for parameter uncertainty than the deterministic model on which it is based. However, that underlying model remains unchanged and lacks what are likely to be important features of seabird behaviour, such as relationships with environmental conditions, variation across life history stages, and interactions with the turbines themselves, thereby contributing to structural uncertainty within the model. The current model also lacks explicit consideration of covariance in model parameters and its impact on model output (**8**). Tracking of flight paths in three dimensions through wind farms would benefit collision estimates by reducing structural uncertainty in how birds respond to turbines (**9**). This will require high-resolution GPS tags (e.g. Thaxter *et al.*, 2018; Johnston *et al.*, 2015, 2022), high-resolution cameras, and tracking algorithms or combinations of both (Skov *et al.*, 2018). Such technology is available but requires deployment on a large scale to obtain sample sizes sufficient to begin addressing the behavioural and interaction questions of interest and to enable robust assessment of potential device effects. Significant data collection is likely to be needed before any substantial reduction in this component of structural uncertainty within collision models can be achieved. Collision predictions from the sCRM are highly sensitive to assumptions about avoidance rates, and this is a critical focus for impact assessment purposes (**10**). Avoidance rates for the sCRM are estimated by comparing the number of collisions recorded at a wind farm to those that the model predicts would have occurred in the absence of any avoidance. As such, they combine the behavioural response of the birds to the wind farm or turbine with structural uncertainty arising from the simplified model assumptions and parameter uncertainty due to imperfect underpinning data. Current estimates are based on an amalgamation of data sources, very little of which has been collected at operational offshore wind farms due to the difficulty of undertaking long-term studies at these locations (Cook *et al.*, 2018).

Population viability analysis

We have identified three broad areas in which improvements can be made to better characterize and reduce uncertainty in PVAs: the representation of structural uncertainty and natural variability within PVA models, the validation and calibration of population models used in PVAs, and efforts specifically aimed at reducing structural uncertainty in PVA models.

First, PVA should improve methods for representing structural uncertainty and natural variability. Knowledge uncertainty and natural variability in initial population size could be accounted for through the development of a plausible statistical model of observation error for seabird count data (**11**). Most PVAs currently assume that stochastic variation in demographic rates is independent over time, and that variation in demographic rates (productivity and survival) are uncorrelated. Yet inter-annual variation in demographic rates is unlikely to be independent because the underlying drivers, such as climate, exhibit patterns of temporal dependence and because of carryover effects on demographic rates (Bogdanova *et al.*, 2017). Correlations between demographic rates are likely to arise because stochastic environmental effects act simultaneously on demographic processes (e.g. adults may prioritize their survival over productivity). Recent work has estimated correlations in seabird demographic rates for a single species breeding in the UK (Horswill *et al.*, 2021), and further work would improve uncertainty representation within PVAs (**12, 13**). In populations for which sufficient long-term data are available, this approach would produce more defensible annual estimates of both survival and productivity.

Second, validation and calibration of models underpinning PVAs should be progressed (**14**). Running PVA models retrospectively (using the initial population size from a past year) allows the resulting predicted trends to be compared against observed trends seen in the population abundance data. Discrepancies between predicted and observed trends indicate either errors in the values of PVA inputs and/or structural errors in the model underpinning the PVA. Statistical models have been developed that use this discrepancy to estimate poorly known demographic rates, which lack direct empirical data and may only be poorly constrained by inference from expert judgement, as is common for juvenile survival in most seabird species. Although these models have been used in some contexts (e.g. Freeman *et al.*, 2014), they have not been widely implemented. They are effectively a partial form of data integration that can be used to quantify, and often reduce, parameter uncertainty in parameters that are otherwise difficult to estimate and have a broader application than has currently been utilized within assessments.

Third, efforts should be made to reduce structural uncertainty within PVAs. The most substantive improvement for PVA models in resolving structural errors is making their underlying assumptions more biologically realistic. These include linking environmental stochasticity to prey availability and climate change (**12**), empirically parameterizing density-dependent processes (**16**), consideration of inter-specific interactions, inclusion of interactions between different ORD impacts (e.g. determining whether such impacts are synergistic or antagonistic), consideration of carry-over effects, and including dispersal, immigration, and emigration within the context of metapopulations (**11**). Prioritizing these extensions requires consideration of appropriate model complexity, the defensibility of additional model parameters underpinned by existing or new data, and the likely impact of the extension upon the PVA model outputs.

Synthetic approaches to adequately characterizing and reducing uncertainty

Sensitivity analysis

Sensitivity analysis is a valuable tool for examining components of a mathematical or statistical abstraction of a system. This is particularly true in the case of simulations with Monte Carlo treatment of uncertainties, such as those found within the sCRM, IBMs, and PVAs. A sensitivity analysis evaluates the practical importance of the various inputs to a model by perturbing these with resulting changes in outputs examined in practical terms (e.g. Cook and Robinson, 2016; Donovan *et al.*, 2017; Jitlal *et al.*, 2017). Sensitivity analysis is also informative about where research efforts can be focussed to reduce structural uncertainty. If the analysis suggests the model is sensitive to assumptions or parameters, then research to confirm the assumptions or increase the precision of the parameter estimates can be prioritized. Conversely, non-influential assumptions or parameters warrant lesser consideration because model outcomes are more robust to these inputs. Sensitivity analysis can be used to indicate which model inputs contribute most to the precision of outputs and thereby to develop a priority list for reducing uncertainties. This is likely to be particularly helpful in the context of collision models (**8, 10**), but is also relevant to all modelling components of impact assessment whose contribution to uncertainty cannot be easily evaluated by inspection. For instance, in PVA, commonly used counterfactual metrics (e.g. ratios of impacted to baseline population characteristics) are sensitive to inputs that relate to annual ORD impacts on demographic rates and comparatively insensitive to the values of inputs relating to conditions such as baseline demographic rates and initial population size (Cook and Robinson, 2016; Jitlal *et al.*, 2017). Further sensitivity analysis can be used to determine whether potential extensions to PVAs are likely to lead to substantive changes in key PVA outputs, and prioritizing which of these extensions will lead to substantial improvements in the application of PVA within ornithological assessments (**15**).

End-to-end propagation of uncertainty

The standard assessment process for estimating ORD impacts on seabirds uses outputs from a linked set of modelling tools to inform the decision-making process. The choice of which tools are linked together is dependent on the context of the impact assessment and subjective user judgements such as the choice of input data. Additional structural uncertainty may arise within the framework either if there are impacts other than those currently considered within the assessment process or if components between the tools interact. For example, displacement and collision risks are assessed independently and their impacts are added together, which ignores any biological interaction between the movement and the behavioural processes that underpin displacement and collision effects. At present, precaution can be magnified through this process, with precautionary outcomes from each stage of the assessment (Figure 2) compounded together. Therefore, it is important to address both the characterization of uncertainty within individual tools and the quantification of the propagated uncertainty within the framework where multiple tools are linked together, termed *end-to-end uncertainty*. The framework of linked tools can be considered as a meta-model within which inter- and intra-tool uncertainty can be quantified.

The simplest approach for linking uncertainties between tools is via simulation. Each simulation randomly generates the values of any inputs that contain uncertainty and/or any internal tool components that involve stochasticity. This approach can account for both uncertainty and variability within the common framework. The distribution of the assessment process outputs (e.g. PVA metrics) across simulations then quantifies the end-to-end uncertainty associated with the assessment process. The limitations of the approach are that: end-to-end uncertainty will only be meaningful if uncertainty within individual tools and inputs is comprehensive and statistically defensible; a large number of simulations are required to produce stable estimates of uncertainty; and the approach assumes independence between tools. All of these represent potentially substantive issues in the context of ORD assessments. The first issue can be resolved through improved quantification of uncertainty within the individual tools or within the input data to the tools, and the second through computational approaches (e.g. parallel computing) that allow sufficiently large numbers of simulations to be used. Solutions to the final issue are likely to be context-dependent but may need to involve restructuring the current models so that there can be feedback between them (effectively making them components of a larger, overarching model rather than separate models).

Use of post construction monitoring

The tools within the assessment process predict the likely impacts of future ORDs. As developments become operational, a potential mechanism for reducing uncertainty is through the incorporation of data that quantifies the impacts of existing ORDs. These data include at-sea monitoring such as density and distribution data, radar and camera data to detect collisions and micro-avoidance, and land-based/coastal monitoring of foraging patterns, provisioning and nest attendance behaviour, demographic rates, and colony counts, which can be used to retrospectively assess the impacts of ORDs upon seabird populations. The most obvious use of post-construction monitoring data is to refine the estimates of key input parameters, such as displacement rates, collision rates, and avoidance behaviour, for use in future assessments. As the amount of available data to be included in parameterizing models increases, knowledge uncertainty and, in particular, parameter uncertainty should be reduced. The other key role of post-construction monitoring data is in data validation to detect additional structural errors within the tools used for assessment. Incorporating post-construction monitoring data in this feedback mechanism may appear to increase uncertainty if uncertainty is currently being underestimated (e.g. properly accounting for natural variability). However, identifying structural errors and providing the empirical basis to resolve them would lead to more biologically realistic modelling tools and greater confidence in impact assessments. Broader-scale data (e.g. on population size and abundance) can also be used to detect whether the overall ORD impacts produced by assessments are consistent with the levels of change in demography and abundance that are seen after construction. However, these data are not able to distinguish the cause of any discrepancies—which components of the assessment process are introducing error—and are also likely to have low statistical power to detect differences (Cook *et al*., 2019). The primary focus of post-construction monitoring data collection should therefore be on informing and validating specific assumptions, inputs, and component tools used within the assessment process.

Summary

Strategies to reduce uncertainty and obtain a better understanding of the impacts of offshore wind development on the environment whilst ensuring the sustainability of the marine ecosystem are only feasible if the sources of uncertainty are first identified and properly quantified. We have identified a broad range of areas in which uncertainty quantification could be improved. Delivering the underpinning science to enable accurate, robust, and defensible ornithological ORD impact assessments requires developing and advancing a credible line of inference from our conceptual understanding of the ecological and behavioural processes involved through to quantitative impact estimates with uncertainty (Hobbs and Hooten, 2015). This involves representing our knowledge and understanding of the interactions between seabirds and ORDs with models and observations of the key processes shaping these responses, such as seabird spatial habitat use, displacement and barrier effects, and collision impacts. Many of the more substantial evidence gaps for which uncertainty could be reduced are ones that operate across large spatio-temporal scales. These should be addressed through strategic studies rather than at the level of individual offshore wind project post-construction monitoring studies. Administering such strategic studies through an advisory group with a core scientific remit and funding provided by the relevant stakeholders (wind farm developers/operators, regulators, and statutory agencies) would best facilitate the large-scale studies needed. Such an approach would benefit from cross-border and international research collaboration. All models, whether conceptual, theoretical, or statistical, are simplified abstractions of reality. We rely on the proper quantification of natural variability and uncertainty to bridge the gap between reality and our modelled representations to provide inference and to understand their validity for shaping decision-making and policy. Similarly, the data that we collect to inform a model will often only partially capture the true underlying state of the process we are trying to observe. A failure to recognize or quantify these uncertainties in models and data results in poorly informed decision-making where the rationale is unclear, rather than providing transparent, objective, evidence-based decision-making informed by proportionate risk assessment. It is therefore imperative that we undertake ornithological ORD impact assessments with properly quantified uncertainty to inform the appropriate degree of precaution.

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Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

Conflict of interest statement

The authors have no conflicts of interest to declare.

Data availability statement

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Author contributions statement

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