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From parameter uncertainty to process simulation: rethinking collision risk models

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ABSTRACT

Collision Risk Models (CRMs) are central to environmental assessment for offshore wind but operate under data limitations and uncertain ecological assumptions. While stochastic extensions incorporate parameter uncertainty, the basic approach remains structurally unchanged, treating collision risk as a function of uncertain inputs rather than as the outcome of underlying behavioural and spatial processes. This paper argues for a shift from parameter estimation to simulation. Agent-based models (ABMs) provide a necessary extension to CRMs by simulating bird movement, behavioural responses, and interactions with turbine arrays. In this framework, collision risk emerges from generative processes rather than being imposed through fixed parameters such as avoidance rates. ABMs complement deterministic and stochastic CRMs, support scenario testing, generate synthetic data under data scarcity, and provide mechanistic insight into collision risk. ABMs have not been integrated into regulatory collision risk assessment but doing so would enhance the biological realism of collision modelling, offering a more robust basis for decision-making in offshore wind consenting.

1. Introduction

Collision risk from offshore wind is routinely estimated using Collision Risk Models (CRMs) within environmental impact assessments (EIA). These models are used to inform regulatory decisions, including thresholds for acceptable impact and the need for mitigation.

I argue that collision risk is currently mis-specified as a parameter estimation problem rather than as the product of underlying behavioural and spatial processes. This distinction matters because collision events are not generated by parameters, but by interactions: between individuals, their behavioural states, and the environments they move through. Treating risk as a function of uncertain inputs obscures these generative processes and limits the ability of models to explain variation across contexts, to represent adaptation, or to support scenario-based reasoning. In this sense, current CRMs exemplify a broader issue in ecological modelling, where uncertainty is addressed at the level of inputs while the underlying causal structure remains implicit and unexamined.

In this paper, I use collision risk modelling as a case to argue for a shift from parameter estimation to process simulation. I propose that agent-based models (ABMs) provide a complementary framework in which risk emerges from the interactions of individuals within spatially well-described environments. This approach does not simply refine existing estimates but reframes the modelling problem by making the generative mechanisms explicit and open to examination. As such this is an argument for revisiting the shared conceptualization of collision risk, which should be seen as a part of a cyclical modelling process in keeping with recent arguments for good practice (Jakeman et al., 2024).

The distinction between parameter uncertainty and process uncertainty has received little explicit attention in the collision risk context. The argument is not that existing CRMs should be replaced, but that their role should be reconsidered within this broader modelling framework. This has relevance beyond offshore wind, emphasizing the need for more explicit representation of generative processes in ecological modelling more generally, and I return to this in the concluding comments.

2. Collision risk models

The most commonly used model in onshore EIA work was developed by Band (Band et al., 2007) and later updated for offshore wind (Band, 2012; Cook et al., 2025). Band's offshore CRM represents collision risk through a set of aggregate parameters (e.g. density, flight height, avoidance), which substitute for the underlying behavioural processes that generate flight paths and interactions. Avoidance rates and flight height data are drawn down from prior observational work

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(e.g., (Cook et al., 2014, 2018)). A range of other variables are also included. All of this data is hard won and there is not enough of it (Skov et al., 2018). Moreover, data is collected using diverse methods that introduce the potential for errors and reduce the likelihood of a fully representative account of risk (Feather et al., 2025).

Band's models use fixed point estimates for parameters. These parameters are averages and thus reduce their probability distributions to a single value. This practice makes risk determination less biologically plausible and it is potentially overly cautious (Cook et al., 2025; Green et al., 2016). In response to this problem stochastic CRMs have been developed (Masden, 2015; McGregor et al., 2018) that run multiple Monte Carlo simulations of the CRM across the known probability distributions. This delivers an estimated probability range for collision risk. While the stochastic approach recognizes the uncertainty around inputs, this is still fundamentally the same CRM approach, with the same data collection issues.

By treating collision risk as a parameter estimation exercise fixed estimate and stochastic CRMs assume an idealized causal model without any explicit formulation or testing of that model. Current models pursue an optimization strategy which ignores dynamic emergence of risk under changing circumstances: Monte Carlo draws are not mechanisms; parameter distributions are not dynamics. Collision risk should be seen as a generative systems problem, focused upon the why and how of collision. Collisions are the result of interactions between bird behaviour, spatial properties of wind farms, and key environmental factors such as weather. CRMs cannot capture this interaction which means they are not sufficiently context sensitive, and they are unable to explain any variation.

3. Agent base models

An individual or agent-based model (henceforth ABM) is a simulation tool that allows the creation of an environment that can be populated with individual agents. Those agents can have purposes and capacities to deliver those purposes. The simulation will produce emergent properties, and the modelling process and data collection enables the understanding of key interactions that lead to these properties. ABMs help to model a dynamic space of agents interacting with one another, and with the environment.

Within the ABM community there is a clear move to shared good modelling practice though the use of the Overview, Design concepts and Details (ODD) protocol (Grimm et al., 2010, 2020). Grimm et al. (2010) note that ODD "promotes rigorous model formation" (p.2766) through a hierarchical process beginning with an explicit formulation of model purpose and then close attention to causal assumptions and mechanisms. This protocol allows straightforward ABM comparison, and Grimm and colleagues go on to suggest that the ODD protocol would be useful for other complex modelling approaches.

ABMs are not simply a more detailed modelling tool, but a different way of representing ecological systems. Rather than estimating outcomes from assumed relationships between variables, they generate outcomes from clearly specified processes (Grimm and Railsback, 2006; McLane et al., 2011). Given this, ABMs offer a way to understand the emergence of collision risk and yet they appear to play little role in consenting decisions in offshore wind. To my knowledge, the only published example of agent-based modelling directly linked to offshore bird collision risk assessment is that of Perrow and colleagues (Perrow et al., 2010). However, they used an ABM simulation to estimate exposure and flight activity before passing those parameters into a conventional CRM, where it was then deployed in a consenting decision (Cook and Masden, 2019). To this end the work remained embedded within the CRM framework rather than treating collision risk itself as an emergent property of agent-environment interactions.

Warwick-Evans and colleagues used an ABM to predict the impact of windfarms on northern gannet (*Morus bassanus*) body mass, productivity and mortality (Warwick-Evans et al., 2018). In this model, individual birds are represented as agents with dynamic states whose behaviour changed in response to internal condition and environmental context. Outcomes such as mortality and reproductive success emerged from these interactions rather than being specified a *priori*. The model was built using field data and it spatially described the area in which that data had been collected, adding key biological parameters drawn from the literature. Multiple simulations were run, including those with windfarms introduced into the foraging environment. The net result of this model was that wind farms seemed to make no significant difference to body mass, productivity and mortality.

This example of an ABM in the context of offshore wind does not deliver a collision risk estimate. It nonetheless shows how field data can be deployed in a simulation to experimentally test one possible impact of offshore wind and how this might be of central use to consenting processes. By grounding the ABM in real data, and sense checking base line simulations against known outcomes at the site, the modeler can move to manipulations and simulations to test future scenarios (Grimm and Railsback, 2006). This makes clear that current data collection for CRM delivery could be deployed in an ABM context. That data should include the full probability distributions, in keeping with recent stochastic innovations, and will enable the modelling of emergent collision risk under various changing scenarios (e.g., population densities, weather conditions, time of year, etc.) thereby explaining how collision risk is generated.

Sandhu and colleagues developed an ABM for golden eagles (*Aquila chrysaetos*) in an onshore wind farm context (Sandhu et al., 2022). The purpose of their model, following the ODD protocol, was to simulate regional eagle movements at turbine relevant scales with a particular focus upon orographic updrafts – those caused by wind interacting with local terrain – and their interaction with flight decisions. A key ambition of this project was to see if this model could assist with the siting of windfarms to reduce collision risk. With a focus upon low altitude flight, and seasonal data, Sandhu and colleagues were able to demonstrate the potential for conflict with turbines. Their model had several beneficial features, including the stochastic modelling of eagle decision behaviours around flight path and the use of publicly available atmospheric and topographical data. However, as Sandhu et al. noted, to improve the accuracy of their model local wind flow modelling for specific sites would be of value to improve the resolution of predicted flight behaviours. The model also excluded some flight modes, which would interact with other variables such as foraging behaviours and turbine avoidance behaviours. These elements would all require extra data collection. To this end, this model has not produced a formal collision risk estimate of the sort required in consenting, but as the authors state this provides a platform from which to build and demonstrates that practical ABM work is underway at least for onshore wind environments.

It is worth noting the validation of the model by Sandhu et al. (2022). Validation is a key component of the ODD protocol, and in this project a large amount of eagle telemetry data were deployed to achieve this. This data required significant effort to trap and tag eagles with solar powered GPS locators, and this was accompanied by the relevant technical infrastructure to make use of the data. The telemetry data allowed for a comparison between real and simulated eagle tracks. Whilst the model generally outperformed other methods the authors noted a degradation in performance at increasing altitude. As they commented, this is possibly because conditions become decoupled from terrain at higher altitudes and the focus of this project was upon orographic updrafts. Validation should be seen as a novel challenge for ABMs compared to CRMs that are typically evaluated through parameter uncertainty and sensitivity analyses. ABMs require assessment at multiple levels, including individual behaviour, movement patterns and emergent system outcomes (Grimm et al., 2010, 2020). As Sandhu et al. (2022) show, this adds empirical demands because observations are needed not only to estimate parameters but also to assess whether simulated agents reproduce known behavioural and ecological patterns. This may be viewed as the cost of pursuing greater biological realism through explicit representation of behavioural processes. However, such validation can provide stronger tests of causal assumptions than approaches that focus exclusively on uncertainty surrounding parameter estimates.

Key to the ABM approach is the introduction of better-defined behavioural data. This requires field work of a different kind to that traditionally associated with CRM development. Linder and colleagues produced a statistical model of the behavioural components of collision risk at an onshore wind farm (Linder et al., 2022). They investigated how flight data about head position, active flight, track tortuosity and track symmetry might influence collision risk in the context of key weather variables. Their analysis used field data collected and categorized using an artificial intelligence assisted camera system. The main finding was that low tortuosity was associated with higher collision risk, as was active flight. Whilst there will be challenges to deploying cameras in offshore wind environments it is not impossible (Skov et al., 2025). This would enable the generation of data about the proportion of time spent engaging in flight behaviours under specific conditions, which can further refine an ABM rendition of a stochastic CRM. Again, this is a novel cost to ABM development in comparison to CRM approaches and progressive model development – combining expert knowledge, targeted behavioural studies and new sensor technologies - is likely to be necessary before ABMs can be routinely applied across all consenting contexts.

4. A future for CRMs

As noted, CRMs do not make clear the causal assumptions they are built upon. CRMs idealize causation through their use of a limited array of behavioural and spatial parameters. However, rather than throw the baby out with the bathwater, the proposed ABM approach can be used to sense check extant CRMs by running their data in simulated environments, in this way allowing relevant stakeholders to develop context-sensitive causal understanding. This has the additional benefit of allowing historic CRMs to be repurposed, and for data pooling across CRMs to create increasingly sensitive models for simulation and scenario testing. In this way we can make best use of available data and develop a post collection standardization of data – another aspect of good modelling practice (Jakeman et al., 2024). Moreover, as ABM development continues, we will be able to better understand which variables are most crucial in any risk assessment, and focus upon collecting that data, which should have efficiency benefits. In essence this means that we could embed, or ground future CRM practices in ABMs.

From a management perspective, this means that ABMs should be viewed as complementary. The conventional CRMs are attractive because they are transparent, computationally efficient and currently incorporated into established consenting processes. Agent-based approaches are unlikely to displace these tools immediately, but they can provide additional decision support by identifying situations in which collision risk is particularly sensitive to behavioural responses, environmental conditions or wind-farm configuration. This creates crucial opportunities for scenario testing, including evaluation of alternative turbine layouts prior to development. In this way ABMs could improve both impact assessment and mitigation planning while allowing conventional CRMs to continue fulfilling their regulatory role. In this framework, ABMs could continue to develop and influence regulatory practice. By following the ODD protocol, and more general good modelling practice, a community of modellers could make much progress in improving our understanding of collision risk and how to reduce it.

5. Conclusion

This paper has been focused on parameter estimation-based collision risk models for birds in offshore wind settings. These models have been the focus of much research and development, seeking to determine relevant parameters (Cook et al., 2025) and the broader field is beginning to look beyond this approach. For example, trait based models have been proposed for bat collision risk (Crane et al., 2025). Crane and colleagues specifically used wing morphology as a predictor of collision risk within a qualitative risk framework but concluded that other traits including behaviours would improve the accuracy of modelling. This is promising, but this does not focus upon the processes that generate collisions. Agent Based Models are an underused tool in the wind industry. They can enable scenario testing, sensitivity analysis, and mechanistic interpretation of risk under conditions where empirical data are limited or absent.

The distinction between parameter and process uncertainty is not unique to collision risk modelling. Similar challenges arise in ecology wherever outcomes are inferred from aggregate parameters or empirical correlations rather than generated from explicitly represented mechanisms. This has been discussed extensively in fields such as species distribution modelling, where process-based approaches have been proposed to complement correlative models by incorporating physiology, demography, dispersal and species interactions (Evans et al., 2016; Peterson et al., 2015). The value of agent-based and other process-based modelling approaches lies in transparent causal assumptions, and the capacity to explore emergent outcomes and test ecological hypotheses under novel conditions. Achieving these benefits will require empirical investment beyond that traditionally associated with CRM development. Process-based models must be informed and validated using behavioural, movement and interaction data that allow assessment not only of parameter values but also of whether simulated agents reproduce observed ecological patterns. Even where ABMs are used primarily to sense-check or contextualize conventional CRMs, these additional data demands remain central because they provide the evidence needed to represent and evaluate the behavioural processes from which collision risk emerges. The argument advanced here should therefore be understood as part of a broader shift in ecological modelling towards explicit representation of mechanisms and the empirical programmes needed to support them. The strong recommendation of this paper, then, is that the offshore wind industry and its regulators, along with academic partners, should join with this shift of focus and invest both in the development of ABM approaches and in the collection of the behavioural and ecological data required to make those approaches effective complements to current CRM practices.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author used CoPilot to act as an editor to improve the flow of the prose and to check that all responses to the review process had been included. The author reviewed and edited the output as needed and takes full responsibility for the content of the published article.

CRediT authorship contribution statement

Thomas E. Dickins: Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

The author reports the following real or perceived competing interests: TD provides independent consultancy services to HM Government, U.K. and Shoney Wind Limited. Both organizations have active interests in offshore wind energy development and associated environmental impact assessments, including collision risk modelling. However, these organizations had no role in the study design, data collection, analysis, interpretation of data, or the writing of this manuscript.

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Data availability

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

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