Journal of Environmental Management 417 (2026) 130885

Contents lists available at ScienceDirect

Journal of Environmental Management

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

Research article

Spatial redistribution of divers in response to offshore wind farms: A joint-likelihood Bayesian approach to assess seabird distribution changes

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1. Introduction

The global shift toward renewable energy has accelerated the development of offshore wind farms (OWFs) as a key source of sustainable energy. However, this expansion often targets relatively undisturbed areas, introducing new anthropogenic impacts to marine habitats and species. In Europe, the shallow waters of the North Sea provide an ideal setting for the installation of OWFs, making the region a global hotspot for offshore wind energy. Between 2010 and 2021, 20 OWFs have been constructed in the German North Sea, and significant growth is legally stipulated for the coming years (WindSeeG, 2016).

With the increase in OWF installations, concerns have been raised about their environmental impacts, particularly on marine fauna. Many bird populations rely on the North Sea as permanent or migratory habitats, making them especially vulnerable to habitat alterations and disturbances caused by wind farms (Welcker and Nehls, 2016). Effective spatial planning and conservation measures require robust assessments of these impacts, yet limitations in methodologies and spatial analyses present significant challenges (Dierschke et al., 2016; Furness et al., 2013). Current environmental impact studies often lack the spatial resolution and methodological consistency over the necessary long-term period required to capture the full extent of the impact of offshore wind farms on marine populations.

In Germany, mandatory five-year post-construction monitoring programmes aim to assess OWF impacts, including monthly, large-scale digital aerial surveys around each wind farm to survey seabirds and marine mammals with standardised methods (BSH, 2013). Hence, extensive monitoring data are available around each wind farm. While recent studies have begun to address OWF effects at broader spatial and temporal scales (e.g., Garthe et al., 2023; Vilela et al., 2021), significant gaps remain in understanding the spatial extent and variability of impacts, particularly for vulnerable species like divers. Red-throated (*Gavia stellata*) and Black-throated divers (*Gavia arctica*), which are part of the North-west European wintering population, are highly susceptible to OWF disturbances (Heinänen et al., 2020; Mendel et al., 2019). These species migrate through the German Bight and are most abundant during the spring migration (Mendel et al., 2008), overlapping spatially and temporally with OWF development.

Protective measures, such as the designation of the Special Protection Area (SPA Eastern German Bight) within the European Natura 2000 network, have restricted OWF development near critical habitats (BMU, 2009). Covering 3135 km^2, the SPA is surrounded by a defined main concentration area of 7000 km^2, established in 2009, which includes six offshore wind farm areas. Within this area, the development of new offshore wind farms is currently on hold to safeguard the ecological integrity of the region (BMU, 2009).

However, the displacement of divers due to OWFs and associated activities, such as ship traffic, remains a key concern. Avoidance behaviour has been widely documented in divers and, more recently, in auks, with reported displacement distances ranging from 1.5 to 16 km across studies (Heinänen et al., 2020; Allen et al., 2020; Vilela et al., 2021; Garthe et al., 2023; Peschko et al., 2024). These estimates, often derived from monitoring programmes around single or multiple wind farms, show high variability and depend heavily on the methods, spatial coverage, and temporal scales used (Mendel et al., 2014; Petersen et al., 2014; Webb and Nehls, 2019). This variability suggests that displacement responses are context dependent and may differ among wind farms and regions, reinforcing the need for long-term, regional-scale studies that encompass multiple developments and assess cumulative effects.

Individual divers have occasionally been observed within OWFs. While some studies, such as at the Kentish Flats wind farm, have suggested a possible reduction in displacement over time (Percival, 2014), this habituation pattern has not been consistently observed elsewhere, underscoring the need for analytical approaches that can be applied

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https://doi.org/10.1016/j.jenvman.2026.130885
Received 19 March 2025; Received in revised form 27 August 2026; Accepted 3 September 2026
Available online 7 September 2026

across broad spatial and temporal scales while retaining sufficient resolution to detect local and heterogenous responses.

Given the variability in displacement patterns and the methodological differences across studies, there is a need to explore and refine tools that can better address spatial complexity and data limitations in OWFs assessments. This study aims to address these challenges by employing a fully spatially explicit joint-likelihood Bayesian hierarchical approach to statistically estimate the extent and magnitude of *Gavia* spp. displacement during the spring season. Using a comprehensive dataset of monitoring flights conducted before (2001–2008) and after (2017–2021) OWF development in the German Bight, this study provides a robust framework for evaluating wind farm impacts.

This methodology not only provides a robust statistical framework for integrating spatial and temporal dependencies but also allows for a more accurate estimation of uncertainty by incorporating latent variables and hierarchical structures. By capturing both observed and unobserved variability in the data, it offers a comprehensive understanding of displacement patterns and their associated confidence levels, enhancing the reliability of the results.

Specifically, this study aims to.

1. Quantify changes in diver distribution before and after OWF construction using a fully spatially explicit joint-likelihood Bayesian hierarchical approach.
2. Estimate avoidance distances for different OWF clusters and evaluate spatial variability in displacement patterns.
3. Compare our approach and findings to existing displacement estimates for Gavia spp., highlighting the advantages and limitations of the applied modelling framework.

By integrating high-resolution spatial data collected over two decades with a novel modelling strategy that accounts for spatial autocorrelation and latent structures, this study provides a flexible framework for long-term, spatially explicit impact assessments that can be applied to a wide a wide range of species and ecological contexts.

Rather than proposing our framework as a universal standard, we present it as a complementary alternative to existing approaches used in offshore wind farm impact assessments. Bayesian spatial hierarchical models, such as the one used here, are increasingly recognised for their ability to handle complex ecological data, account for spatial and temporal structure, and propagate uncertainty in a principled way (Cressie et al., 2009; Cressie and Wikle, 2011; Hobbs and Hooten, 2015). While our approach offers important advantages, such as predictor-agnostic estimation and robustness to sampling design limitations, it also shares some challenges, particularly with respect to causal inference. We therefore frame it as one valuable addition to the toolbox for assessing spatial changes on species distributions.

The methods employed here offer a flexible and scalable approach that can be broadly applied in environmental impact assessments to evaluate changes in species distribution caused by human activities. We also critically examine how different analytical methods, spatial-temporal coverage, and study designs influence the estimation of OWF effects, highlighting the need for standardised approaches in future impact assessments.

2. Methods

2.1. Study area and time frame

This study utilises data from aerial surveys conducted between 2001 and 2021 over a large part of the German North Sea, covering an area of 28,625 km^2. The survey area encompasses all major offshore wind farm projects in the German North Sea, as well as additional monitoring programmes (Fig. 1).

The surveyed area includes a primary concentration zone for *Gavia* species (BMU, 2009), which extends over 7000 km^2 and shows the highest densities during spring, and a southern area, covering 13, 375 km^2 that mainly includes areas of low or medium densities. Additionally, data collected beyond the EEZ borders, extending into Denmark and the Netherlands, were included in the models. However, the prediction area was subsequently limited to within the EEZ border.

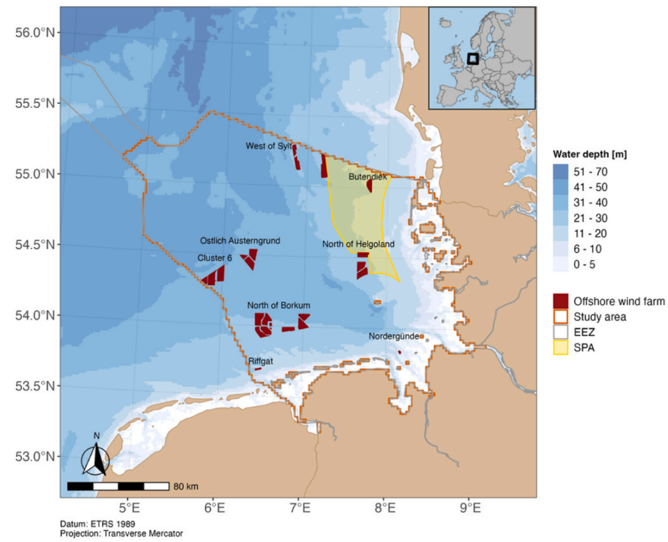

Fig. 1. Total prediction area in the German Bight (North Sea). Operational wind farms as of 2018 are shown in red; labels indicate the wind farm clusters defined for this study, not individual wind farm names. The grey line delineates the German Exclusive Economic Zone (EEZ), while the orange line indicates the limits of the study area. The Natura 2000 Special Protected Area (SPA) "Östliche Deutsche Bucht" (Eastern German Bight) is shown in yellow for reference.

All surveys included in this study were conducted during the species-specific spring season, from March 1st to May 15th, as defined by Garthe et al. (2007), representing the peak period of *Gavia spp.* abundance in the German Bight, when spring migrants' distribution overlaps most extensively with OWF footprints (Vilela et al., 2020). The mandatory monitoring programme (BSH, 2013) was also specifically designed to cover this seasonal peak. However, previous winter studies from UK sites are included in the discussion. Spatial survey coverage varied over time, being low to moderate between 2001 and 2005, and no spring data were available for 2006 or 2007. Coverage improved substantially between 2008 and 2015 and remained consistently high until 2021 (Fig. 2).

2.2. Species identification

Identification at the species level is rather difficult using aerial surveys. For both methods (digital and visual) a significant part of all individuals was only identified as *Gavia* spp. Analyses were therefore conducted including all individuals observed. However, it is known from previous studies (e.g. Mendel et al., 2008; Garthe et al., 2015) and from the wind farm monitoring projects that the majority of *Gavia* spp. (~90%) in this area are Red-throated divers.

Monitoring data from the baseline, construction, and operational phases of 20 different wind farm projects were included in the analyses (Fig. 2). To implement the joint-likelihood approach and estimate changes in the *Gavia* spp. density likelihood, we defined two survey periods of five years each. The first period, referred to as the "pre-OWF development" period, spanned from 2001 to 2008, although data were unavailable for 2006 and 2007. The second period, designated as the "post-OWF development" period, covered 2017 to 2021 and began after the completion of the last wind farm in the northern area (OWF Sandbank). Survey spatial coverage varied between years. Uneven sampling is handled directly by the model structure. As the model is fitted at the mesh nodes per year and method, each node only contributes data for

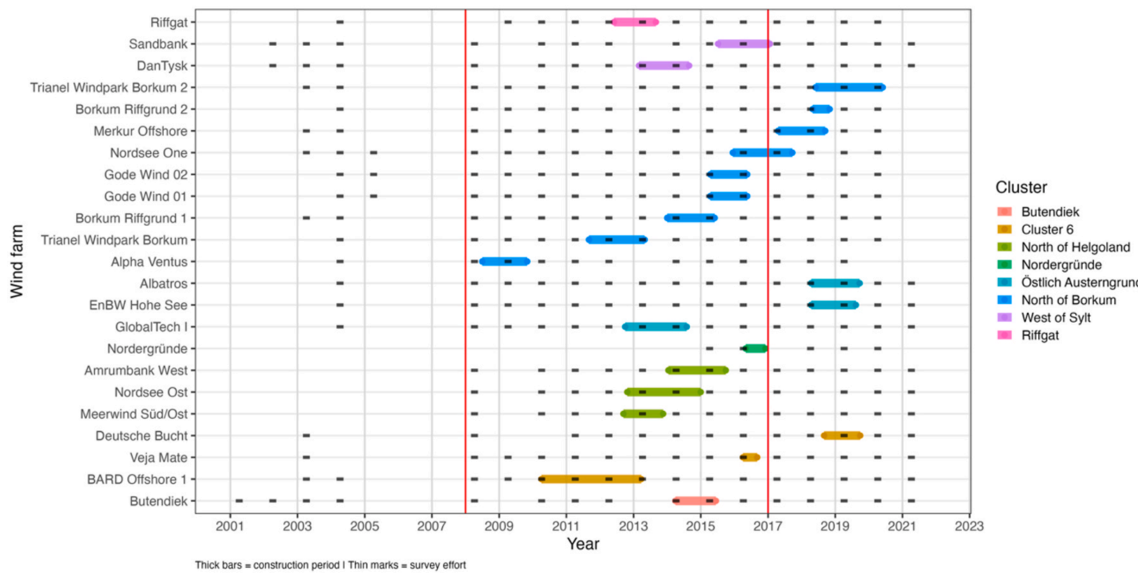

Fig. 2. Survey coverage (short black lines) and construction timeline for offshore wind farm projects in the German North Sea. Thick coloured bars indicate construction periods with colours denoting wind farm cluster assigned for each wind farm. Red lines delimit the "before" (pre-2008) and "after" (post-2017) time periods used in the analysis.

the years in which it was surveyed. Nodes covered in fewer years carry more uncertainty, which is reflected in the posterior estimates.

Although development of OWF continued after 2017 (see Fig. 2), all OWF built after that year were constructed in the southern area, within clusters that were already considered impacted.

2.3. Data collection methods

This study utilised exclusively aerial methods for data collection, following the protocols described by Vilela et al. (2021). These methods included visual aerial surveys and digital aerial surveys, with some temporal and spatial overlap between the two types. The flights were conducted on different dates depending on weather conditions, resulting in varying survey efforts across years. Data were subsequently pooled by year and data collection method.

Data from ship-based observations were excluded from the analysis due to their unsuitability for assessing displacement effects in these species. Divers are highly sensitive to approaching survey vessels, often responding by flying away or diving at distances of up to several kilometres (Bellebaum et al., 2006; Burger et al., 2019). This behaviour reduces the reliability of abundance estimates from ship surveys and makes it difficult to compare with aerial survey data.

Observer-based visual survey flights were primarily conducted as part of baseline monitoring from 2001 to 2013 and adhere to standards set by the German Federal Maritime and Hydrographic Agency (BSH, 2007). The probability of detection for conventional visual surveys was corrected using distance sampling techniques (Burt et al., 2014).

Starting in 2013, digital aerial surveys progressively replaced visual methods, following updated standards from BSH (2013). These surveys employed three different techniques: APEM, DAISI and HiDef. The APEM technique (Busch, 2015) utilises four cameras to capture simultaneous images with a resolution of ~3 cm (improved to 2 cm in January 2017) on the sea surface. Transect lines were spaced ~1.6 km. The DAISI technique (Coppack et al., 2015) uses two medium-format cameras with a resolution of 2 cm on the sea surface. Photos were taken at intervals of 1.5 s, resulting in ~48% overlap between frames. Transect lines were spaced 3-4 km apart. Finally, the HiDef technique (Weiβ et al., 2016) uses a high-resolution video camera system consisting of four independent cameras with a resolution of 2 cm on the sea surface. Camera angles are adjustable to minimise glare, with transect lines spaced ~3-4 km apart. This method served as the reference technique for digital surveys.

Surveys were conducted under favourable weather conditions, with sea states of less than 4 for visual surveys and less than 5 for digital surveys, and no clouds below flight altitude. Modelling the diver displacement.

To assess diver displacement accurately, we adopted a spatially explicit Bayesian modelling framework utilising Latent Gaussian Models (LGMs) and the Integrated Nested Laplace Approximation (INLA) with Stochastic Partial Differential Equations (SPDE) to account for spatial autocorrelation (Lindgren et al., 2011). This approach ensures proper handling of model error and acknowledges that observations collected at nearby locations are more correlated than those collected farther apart.

The INLA approach (Rue et al., 2009) was developed as a computationally efficient alternative to Markov Chain Monte Carlo (MCMC) methods (Robert and Casella, 2010; Brooks, 2011). LGMs are highly flexible models that have been successfully applied across diverse fields, particularly in ecological studies, thanks to the availability of the R-INLA package (Martino and Rue, 2008) and the more recent inlabru package (Bachl et al., 2019), specifically designed for modelling spatial distributions and changes in ecological survey data.

To incorporate spatial and spatio-temporal dependencies, we combined INLA with the SPDE approach proposed by Lindgren et al. (2011). The SPDE method represents a continuous spatial process, such as a latent stationary Gaussian Field (GF) with a Matérn covariance function, as a discretely indexed Gaussian Markov Random Field (GMRF; Rue and Held, 2005). This combination ensures computational efficiency while capturing spatio-temporal autocorrelation and dependencies, including latent variables that capture unobserved factors, making INLA-SPDE highly suitable for complex problems such as quantifying diver displacement caused by offshore wind farms (OWFs).

A refined Delaunay spatial mesh (Vilela et al., 2021) was constructed for the entire survey area with a maximum distance of 5 km between nodes. The mesh included a buffer zone beyond the prediction area to avoid boundary effects (Lindgren et al., 2011). Sightings and survey effort by season were aggregated at the mesh nodes, preserving information about the data collection method (HiDef, DAISI, APEM or Visual) and survey time-period.

For this before-after analysis, data from each time-period (before-OWF: 2001-2008; after-OWF: 2017-2021) were aggregated by method and grid node. A spatial model was developed to infer spatial distribution changes using a joint-likelihood spatial Gaussian Random Field (GRF) with a Matérn covariance to describe spatial and temporal dependencies. The data was fitted using a negative-binomial family distribution, where the intensity of the observed process was the primary driver of the posterior probability.

Conventional visual surveys were flown during the before period, while digital surveys dominated the after period, with a few visual flights remaining in the southern area during 2017 and 2018. Survey technique and period are therefore largely, though not entirely, coincident, and the overlap is too limited to estimate a technique effect from these data. Each observation was instead assigned the detection rate of the technique that produced it. HiDef was used as the reference, since a detection rate of 100% has been established for it (Mendel et al., 2018; Vilela et al., 2021). The remaining rates were taken from Vilela et al. (2021), who estimated them for this same survey programme using a year-by-year spatio-temporal model: 0.90 for DAISI, 0.67 for APEM and 0.80, for conventional visual surveys after distance-sampling correction. For each survey technique, the detection rate entered the model as a multiplicative offset on the exposure.

2.4. Model validation

The modelling framework used here was previously validated in Vilela et al. (2021) using the same dataset at an annual resolution. That work included year-by-year comparisons of observed and predicted distributions and cross-validation checks, confirming the model's robustness. As this study applies the same model structure to five-year periods, it builds on an already tested and reliable approach. Additionally, Vilela et al. (2021; Fig. 2 and Fig. S1) provides an overview of the spatial distribution of aerial survey effort across years, including both before and after periods, helping to contextualise data coverage and spatial consistency over time.

We assessed model adequacy using the deviance information criterion (DIC), the Watanabe–Akaike information criterion (WAIC), and leave-one-out cross-validation. The latter was used to calculate conditional predictive ordinates and probability integral transform values. Because the negative binomial response distribution is discrete, the ordinary probability integral transform (PIT) is not uniform even when the model is correctly specified. We therefore used the randomised PIT described by Czado et al. (2009), repeating the randomisation 20 times and pooling the resulting diagnostics. The design and results of these analyses are presented in Appendix A.

2.5. Joint-likelihood model

To assess changes in diver distribution, we implemented a joint-likelihood model in which observations from the before and after periods were analyzed simultaneously within a single hierarchical framework. Both datasets contribute to a joint likelihood and share a common latent spatial process, allowing consistent estimation of the underlying spatial field across periods.

Spatial differences between periods were estimated from the posterior change field of the joint model rather than by comparing separate model fits, allowing uncertainty from both periods to propagate into it. The model also included a separate intercept for each period to account for differences in overall density level. Separate single-period fits of the same model structure were used only to produce the period-specific density surfaces shown in Figs. 4 and 5 and to estimate abundance within the affected zones.

The detection factors for the conventional visual surveys were fitted by Vilela et al. (2021) using the *mrds* package (Laake et al., 2015), stratified by group size and sea state, and absolute numbers were derived with *MRSea* (Scott-Hayward et al., 2013); the corrected counts from that study are the input to the present analysis. The models presented here were fitted in R 4.5.2 (R Core Team, 2025) using *inlabru* 2.13.0 (Bachl et al., 2019) and R-INLA 25.10.19 (Rue et al., 2009), with fmesher 0.7.0, sf 1.1-0 and terra 1.8-93 for the spatial operations. The complete analysis is available as a documented script together with the input data (see Data availability).

2.6. Wind farm distance effect and diver displacement

Areas with strong evidence of negative change between the before and after periods, as identified by the joint-likelihood model, were used to estimate zones affected by OWF development. A location was counted as affected if the posterior probability of a decrease was at least 0.975, that is, if the entire 95% credible interval for the estimated change lay below zero (Fig. 3A).

Wind farms in the same cluster were merged into a single polygon, and average displacement distances were calculated only for the northern (West of Sylt and Butendiek) and southern (North of Borkum) clusters, where well supported declines were detected.

For each cluster, we kept only the adjacent area of decline. We then used a 1 km grid to calculate the distance from each boundary cell to the nearest wind farm within the cluster (Fig. 3B). Distances were summarised by their mean and 95% confidence interval, with their distribution shown in Fig. 7.

We also report the mean distance and the affected area for required probabilities from 0.975 down to 0.50, the latter being the zero contour of the change field, or the boundary at which a decrease and an increase are equally probable.

Statistical differences in displacement distances between wind farm clusters were evaluated using Welch's *t*-test, and effect sizes were quantified using Hedge's g. The estimated change in the number of individuals within each cluster was calculated by integrating the posterior mean density for each period over the affected zone and subtracting the after-period from the before-period abundance.

3. Results

The joint-likelihood model returned a DIC of 13,780.5 and a WAIC of 13,831.6. Leave-one-out cross-validation produced valid conditional predictive ordinates without failure for all 2666 observations. The mean log conditional predictive ordinate was −2.69 and was higher for the after period (−2.33) than for the before period (−3.35). The randomised probability integral transform (PIT) was approximately uniform, indicating good overall model calibration (mean = 0.503, SD = 0.298; Kolmogorov-Smirnov distance from uniformity of 0.025).

3.1. Diver distribution before offshore wind farm development

During 2001-2008, *Gavia spp*. distribution in the German Bight (Fig. 4) was concentrated in the north-eastern part of the study area, within the SPA (BMU, 2009), where the mean predicted density was 1.9 individuals per km^2, and the highest density anywhere in the study area, 8.2 individuals per km^2, also felt within it, driven by a strong aggregation observed during spring 2003 (Vilela et al., 2020). Across the study area, mean density was 0.5individuals per km^2.

Densities remained consistently under 1.8 individuals per km^2 in the area between the North of Helgoland, Nordergründe and North of Borkum clusters, and it was lowest around the North of Helgoland cluster, where mean density was 0.2 individuals per km^2 and no cell exceeded 0.8.

This distribution pattern highlights the variability in diver densities across the study area prior to the development of offshore wind farms.

3.2. Diver distribution after offshore wind farm development

Meaningful changes in *Gavia spp.* distribution were observed during the 2017–2021 period (Fig. 5). The population shifted away from the northern areas but continued to occupy the SPA, with a mean density of 1.7 individuals per km^2 and a maximum of 6.5.

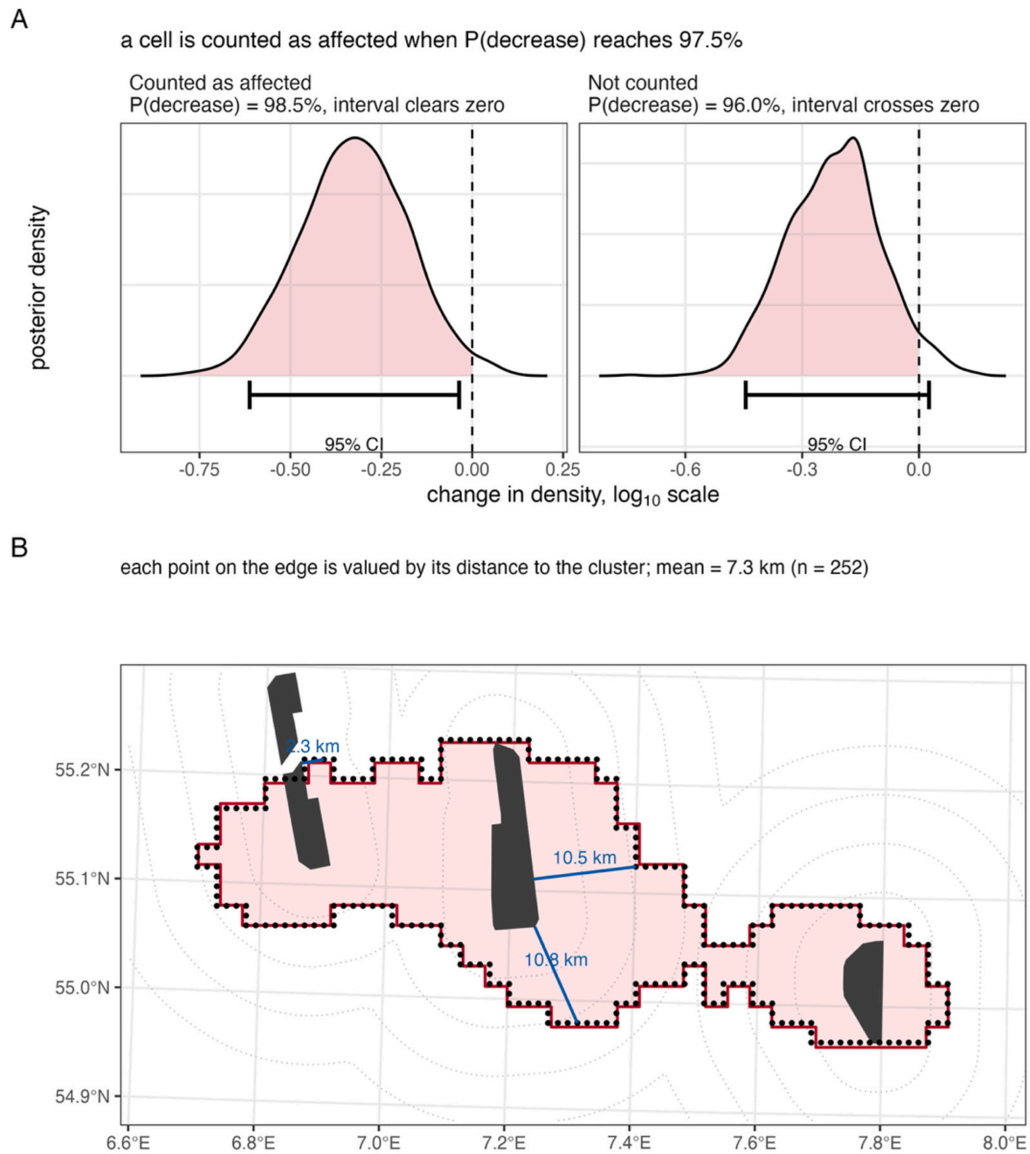

Fig. 3. Definition of the affected zone and measurement of the displacement distance. **(A)** Posterior distribution of the change in density at two cells of the prediction grid near the northern cluster; the bar below each curve is the 95% credible interval and the shaded area is the probability of a decrease. The left-hand cell meets the criterion and is counted as affected, while the right-hand one does not. **(B)** The shadowed area represents the resulting affected zone around the northern cluster, and black points mark the positions along its edge at which distances are measured. Three example measurements (blue) are shown as reference. The average effect is calculated as the mean distance from all points to the nearest OWF.

Densities increased north-east of Helgoland Island, and decreased close to the windfarm clusters. Together, these changes indicate a redistribution of divers across the study area following the development of offshore wind farms.

3.3. Estimated diver displacement effect due to the wind farms

Strong distribution changes were observed between the "before" and "after" distributions (Fig. 6). Areas of total gain were identified in the central region of the German Bight, particularly around the North of Helgoland cluster, in the southern area of the West of Sylt cluster, and on the cluster North of Borkum.

On the other hand, a well-supported decline was detected in the West of Sylt, Butendiek and North of Borkum clusters, as well as around the Riffgat OWF and north of Cluster 6.

3.4. Estimated displacement around wind farms

The average estimated displacement effect was 7.23 km ($CI_{95\%}$ [6.73, 7.73]) for the combined West of Sylt and Butendiek cluster, over an affected area of 1138 km^2, and 6.11 km ($CI_{95\%}$ [5.37, 6.84]) for the North of Borkum cluster, over 874 km^2. The difference in displacement distances between these two areas (Fig. 7) was statistically significant (Welch's $t = 2.49$, $p = 0.013$) with a small effect size (Hedge's $g = 0.26$). These mean distances summarise how far the boundary of the affected zone lies from the cluster; they are not the radius of a circular buffer, and the effect does not extend equally far in all directions.

No significant negative impact on population abundance was observed in the clusters North of Helgoland, and Cluster 6, or in the OWF Nordergründe. This interpretation should be viewed with caution for the OWF Nordergründe, where no sightings were available in the before period, resulting in higher uncertainty in the baseline distribution for that cluster.

It is important to note that the displacement effects in the West of

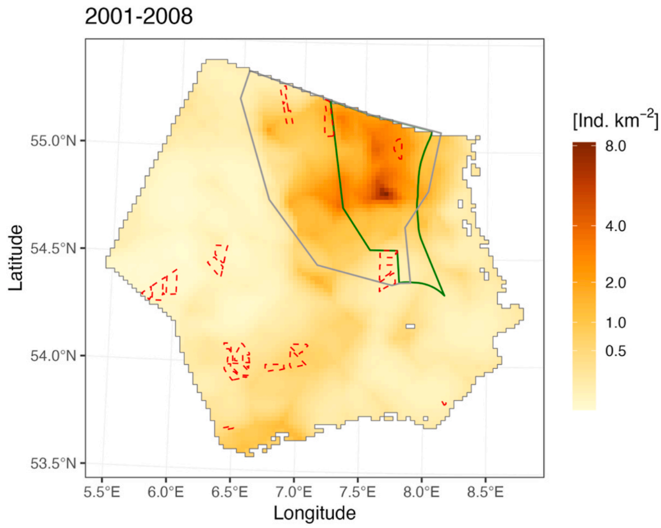

Fig. 4. Estimated posterior mean distribution of diver's density in the German Bight for time period 2001-2008, prior the development of Offshore Wind farms. Red dashed lines indicate future locations of the Offshore Wind farms. Map is in UTM projected coordinates. The colour scale is square-root transformed so that low densities remain distinguishable.

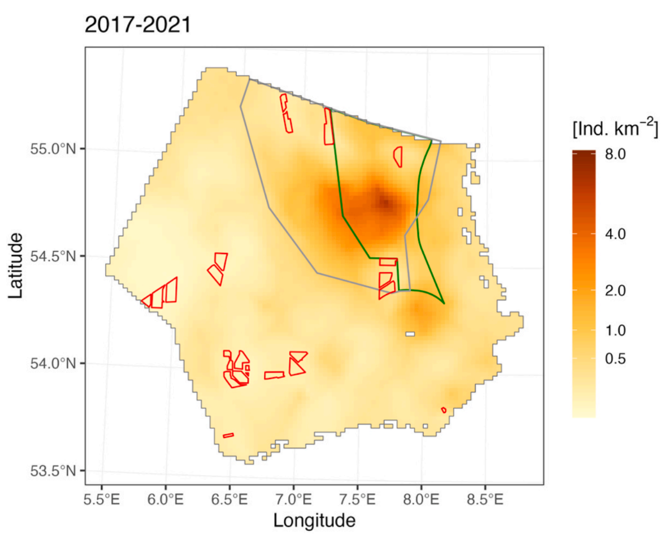

Fig. 5. Estimated posterior mean distribution of diver's density in the German Bight for the time period 2017-2021, after the development of OWFs. Red lines indicate locations of the already built OWFs. The colour scale is square-root transformed so that low densities remain distinguishable.

Sylt - Butendiek and North of Borkum clusters were highly asymmetric, and any single value for displacement should be considered a rough approximation of the overall cluster effect.

Because the affected zone is defined by how much evidence is required, its extent depends on where that requirement is set (Table 1). Lowering the required probability from 0.975 to 0.95 raises the northern estimate from 7.23 to 7.87 km and the southern one from 6.11 to 7.07 km. Below that, the two clusters behave differently. The northern zone grows smoothly, reaching 13.11 km at the zero contour, although by then 30% of its boundary lies on the edge of the prediction area (Fig. 6). The southern zone instead expands abruptly between 0.95 and 0.90: its area more than doubles, the mean distance jumps from 7.07 to 18.44 km, and a third of the boundary moves onto the edge of the prediction area. At and below 0.90, the southern zone is no longer a buffer around the cluster but becomes a diffuse region bounded by the

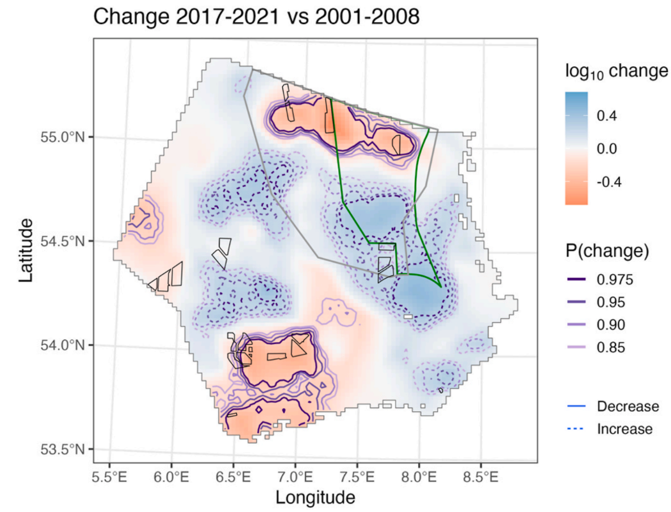

Fig. 6. Estimated net gain (blues) and loss (reds) in diver density estimated by the joint-likelihood model between the before OWF development period (2001-2008) and the after OWF period (2017-2021). Isolines show the posterior probability of a decrease (solid) and of an increase (dashed) at 0.975, 0.95, 0.90, 0.85. Black lines indicate locations of the OWFs. Diver main concentration area (BMU, 2009) in thick grey line, and SPA Eastern German Bight in green are shown as reference.

extent of the survey; distances derived from it can therefore no longer be interpreted as an effect range.

Integrating the posterior density over the two main areas enclosed by the 0.975 contour, which cover 1138 km^2 in the northern cluster and 874 km^2 in the southern cluster (Fig. 6), it was estimated a decline of 1523 individuals in the northern cluster, from 1994 in the before period to 471 in the after period, and 295 individuals in the southern cluster, from 396 to 101. These changes correspond to reductions of 76% and 75% respectively within the affected zones. Because the zones are defined as areas with strong support for a decline, the percentages represent the magnitude of the local change rather than a reduction in regional abundance. Previous studies suggest that total diver abundance in the German Bight has remained stable over the study period (Vilela et al., 2020, 2021), indicating that the birds were redistributed within the region rather than lost from it. As with the displacement distances, these estimates are lower bounds and increase as the evidential threshold is relaxed (Table 1).

4. Discussion

4.1. *Effects of distance to OWFs on Gavia spp*

The northern German North Sea consistently supports the highest densities of *Gavia* spp. during spring, (Garthe et al., 2007), making displacement in this area particularly significant in terms of individuals affected. Comparing pre-OWF (2001–2008) and post-OWF periods (2017–2021), while the Main Concentration Area (MCA) in the SPA remained the highest density zone, but post-construction patterns were more clustered. Such aggregation may reflect reduced habitat availability, leading to increased competition for resources within the remaining high-density areas (Furness et al., 2013; Busch and Garthe, 2016) and increased vulnerability to local environmental changes or anthropogenic pressures, such as fishing or shipping (Burger et al., 2019; Mendel et al., 2019). The reduced spatial extent of their distribution could also undermine population resilience, making it harder for individuals to relocate when disturbed (Dierschke et al., 2016).

Previous studies have confirmed displacement effects for *Gavia spp.* in the German Bight due to OWFs (Mendel et al., 2019; Vilela et al., 2021), even though overall population numbers have remained stable

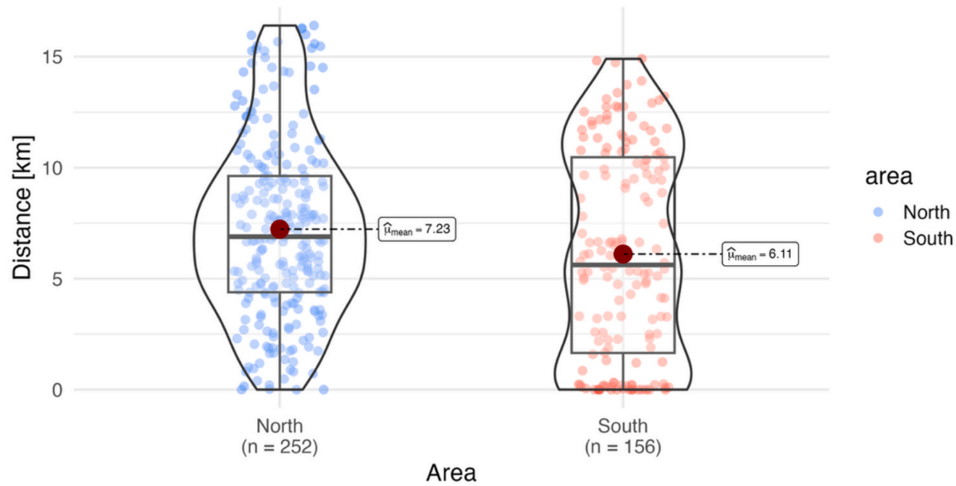

Fig. 7. Violin plot showing the estimated distance effect for each cluster area calculated as the distance between the OWFs boundaries and the boundaries of the zones with strong evidence of a decrease (north: affected area surrounding the OWF cluster West of Sylt and Butendiek; south: affected area surrounding the North of Borkum cluster). Each point represents every point of the boundary, valued by its distance to the cluster.

Table 1
Mean effect distance and area of the affected zone as a function of the posterior probability of a decrease required.

P(decrease)	North mean (km)	North area (km2)	South mean (km)	South area (km2)
0.975	7.23	1138	6.11	874
0.95	7.87	1387	7.07	1062
0.90	8.62	1669	18.44	2459
0.80	9.64	2026	21.67	3516
0.70	10.65	2318	24.20	4250
0.60	11.57	2539	25.80	4866
0.50 (zero contour)	13.11	2811	28.84	5538

across the 2001–2021 period despite fluctuations (Vilela et al., 2020, 2021). Our results extend these findings by revealing spatially heterogeneous and asymmetric patterns around OWF clusters. Displacement was more pronounced along the E-W axis in the West of Sylt-Butendiek clusters and along the N-S axis in the North of Borkum cluster, consistent with Garthe et al. (2023). Such asymmetry may be shaped by environmental gradients, such as currents, wind patterns, or prey availability (Skov and Prins, 2001; Kleinschmidt et al., 2019) or by OWF-specific factors including turbine layout and density, and nearby human activities such as fishing or shipping (Dierschke et al., 2016; Mendel et al., 2019).

OWFs may also indirectly enhance prey availability by acting as no-take zones and creating artificial reef habitat, increasing fish abundance, biomass, and diversity within turbine areas, with possible spillover to adjacent waters (Bergström et al., 2013; van Hal et al., 2017; Degraer et al., 2018; Coolen et al., 2020; Glarou et al., 2020). While it remains unclear whether these effects reflect true production or aggregation, they could help sustain diver populations outside OWFs even as distribution shifts occur. Low pre-construction survey coverage in some clusters (e.g., North of Helgoland) adds uncertainty to displacement estimates. Recent advances in spatial modelling, such as Gaussian random fields, can help integrate sparse baseline data with post-construction monitoring (Szostek et al., 2024; Grundlehner et al., 2025). Our approach incorporates before-impact data within the joint likelihood, enabling a spatio-temporal analysis that accounts for both baseline and post-construction conditions. Although the before and after periods span five years each, helping to reduce short-term natural variability, the before period includes fewer survey years in some areas, which may limit the ability to fully account for interannual fluctuations. This limitation is partially mitigated by the model's ability to incorporate data uncertainty and spatial structure, but results in these areas (e.g., North of Helgoland, Nordergründe, Riffgat) should be interpreted cautiously.

Cross-validation indicates adequate model calibration, with higher predictive performance during the after-construction phase, consistent with the more limited baseline coverage described above. The sensitivity analysis in Appendix A shows in detail the effect of this limitation. Displacement was detected in every subset of survey seasons that retained substantial coverage around a wind farm cluster, while the direction of the change and its location relative to the wind farms remained stable. However, the estimated extent of the affected zone generally decreased as survey coverage was reduced. The distances reported here should therefore be interpreted as lower bounds for two reasons: the evidential threshold used to define the affected zone the amount of available survey effort.

These findings also highlight the need for individual displacement assessments for each wind farm during the planning phase to account for natural population distribution and cumulative effects from neighbouring clusters.

4.2. *Limitations of current methods*

OWF displacement effect estimates vary depending on study design, spatial coverage, and assumptions. BACI (Before-After-Control-Impact) designs are widely used but rely on assumptions often violated in dynamic marine systems, such as homogeneous control areas and independence of effects (Petersen et al., 2014; Mendel et al., 2019). Confounding factors, including natural distribution shifts, population changes, hydrodynamic variability, and cumulative impacts, can bias BACI-based assessments (Skov and Prins, 2001; Vilela et al., 2021).

Distance-based models mitigate some BACI limitations by examining density gradients around OWFs (Vilela et al., 2021), but likewise, their accuracy depends on selecting the appropriate reference area. Ideally, this area should represent the natural, unaffected density that would occur in the OWF footprint in its absence. In practice, achieving this can be challenging: in single-OWF assessments, survey coverage may not extend far enough, while in regional studies, natural gradients, neighbouring OWFs and other pressures can influence potential reference areas. This is particularly problematic in highly variable habitats, where populations can change rapidly and surrounding areas may not be representative, especially when the OWF is in a particularly suitable habitat.

While these challenges are not unique to distance-based models and can also affect BACI approaches, they highlight the need for careful reference area selection and cautious interpretation of results considering potential biases. Other methods, such as first derivative curves (Mendel et al., 2019) or density comparisons across distance classes (Heinänen et al., 2020), can overestimate displacement effects if reference densities come from naturally high-density zones near OWFs, such as the surroundings of the SPA, where broader-scale shifts in bird population may exaggerate contrasts with impacted zones (Vilela et al., 2020, 2021). In this study, spatial contrasts are inferred through a latent spatial field rather than through predefined reference distances, which reduces sensitivity to naturally high-density areas far from OWFs when interpreting displacement patterns.

The distribution of *Gavia* spp. is influenced by dynamic factors such as hydrodynamic variability, food availability, and human activities, which are often overlooked in impact studies relying on fixed predictors. Daily variation in responses to OWFs and ecological gradients complicate displacement modelling (Skov and Prins, 2001; Dorsch et al., 2019). *Gavia* spp. may thus exhibit a spatially structured response to OWFs, balancing avoidance behaviour with the benefits of high-quality habitats. Accounting for these unknowns is essential for more accurate assessments.

Digital aerial surveys were used almost exclusively during the after period, so survey method and study period largely overlap in this analysis. To account for differences in detection among survey methods, we applied method-specific detection rates estimated for the same survey programme (Vilela et al., 2021). Separate intercepts for the before and after periods further capture any study-wide difference, whether it reflects a regional change in abundance or a uniform residual difference in detection. The spatial change field therefore contains only local variation relative to the overall change across the study area and provides the basis for the reported distance estimates.

4.3. Comparison with other studies

This study applies a spatially explicit joint-likelihood Bayesian hierarchical model based on a Log-Gaussian Cox Process (LGCP) implemented in INLA. By design, this approach integrates spatial autocorrelation, latent processes and cumulative effects (Underwood, 1994; Osenberg et al., 2006) while removing the need for control areas, addressing some specific structural assumptions of BACI designs. This is particularly valuable in dynamic marine systems, where such assumptions rarely hold (Liebhold and Gurevitch, 2002; Paradinas et al., 2015). The hierarchical Bayesian framework provides a spatially explicit estimation of change with coherent uncertainty propagation (Cressie et al., 2009; Cressie and Wikle, 2011; Pennino et al., 2017).

Compared with approaches that represent spatial patterns only through explicitly specified predictors, such as standard GAM formulations, the LGCP-INLA framework can also account for residual spatial-temporal dependence using latent fields.

No explicit environmental predictors were included. The covariates available at the required resolution, including bathymetry, seabed slope, distance to coast, substrate and habitat class, were static between periods and would therefore enter both linear predictors identically. Including them would redistribute baseline spatial structure between fixed effects and the latent field without altering the change field, a form of spatial confounding described by Hodges and Reich (2010).

We therefore adopted a covariate-agnostic formulation. This allows fine-scale patterns to be estimated without assuming or prespecifying responses to particular ecological gradients, providing a statistically robust and versatile tool for ecological studies and impact assessments. Neither OWF presence nor distance from an OWF was included as a predictor, so the correspondence between the estimated declines and OWF clusters arose from the estimated spatial pattern rather than being imposed by the model. However, this association does not indicate causality: any unmeasured driver that changed between periods is absorbed into the latent field and cannot be distinguished from the OWF effect. The resulting patterns are also conditional on the assumed spatial structure.

The cluster-specific avoidance distances estimated in this study (0 - 7.23 km) are lower than BACI-GAM estimates for the German North Sea (9 - 16 km; Mendel et al., 2019; Heinänen et al., 2020; Garthe et al., 2023). The displacement distances reported here are conservative lower-bound estimates, outlining the area within which the entire 95% credible interval for the change lies below zero and so describe where the decline is strongly supported rather than how far it reaches. This differs from Vilela et al. (2020), where displacement was summarised using posterior mean (median) estimates from a one-dimensional distance-based analysis. Despite these differences in reporting, the lower bounds of the 95% credible intervals in the present study are consistent with the lower credible limits reported in Vilela et al. (2020).

Our results are consistent with Vilela et al. (2020), who observed high spatial variability and no measurable effects at several wind farms, supporting the notion of asymmetric effects. This highlights the method's ability to capture subtle displacement patterns often overlooked in traditional analyses (Grundlehner et al., 2025). The Bayesian hierarchical framework further allows incorporation of prior probability distributions reflecting species behaviour (Blangiardo and Cameletti, 2015) and modelling spatial autocorrelation as a multilevel random effect. This allows for the inclusion of potential processes and spatially explicit factors that influence *Gavia* spp. distributions, resulting in a robust analysis of displacement effects. It also accounts for multiple sources of uncertainty in both observed data and underlying species distribution processes, leading to more reliable inferences and realistic predictions (Beguin et al., 2012; Pennino et al., 2017).

Using high-quality monitoring data within a standardised methodological framework, the LGCP-SPDE joint likelihood approach estimates continuous spatial patterns directly from the data and propagates uncertainty throughout. While not intended to replace all existing designs, it offers a scalable and flexible alternative, especially well-suited for regional-scale assessments with variable data coverage and where the underlying spatial structure of the process under study (e.g., species behaviour) is critical for interpretation. This approach refines our understanding of ecological impacts and supports the development of effective, evidence-based conservation and management strategies.

Importantly, it also underscores the value of comparing before and after data, an approach increasingly at risk in cost-driven monitoring programmes, particularly when species distributions and planned OWF developments may be spatially correlated, risking bias in post-hoc impact assessments without proper baselines. Garthe et al. (2025) further highlights the ecological risks posed by OWFs near marine protected areas, showing that such developments can lead to significant seabird displacement and compromise conservation targets.

Within the INLA-SPDE framework, different modelling choices may be appropriate for different contexts. For instance, previous studies such as Vilela et al. (2020) and Szostek et al. (2024) applied a one-dimensional spatial domain, modelling abundance as a function of distance to OWFs. While effective for localised avoidance gradients, this does not account for two-dimensional autocorrelation and may be less reliable in areas with complex spatial structure or uneven survey coverage. Nonetheless, such alternative approaches remain valuable when pre-construction data are scarce or unevenly distributed. The fully spatial LGCP-SPDE framework used here leverages the full resolution of aerial survey data, providing a more integrated view of distributional change.

Similarly, Grundlehner et al. (2025) proposed the EPIC design, combining a peripheral control area with Bayesian statistics to address seabird habitat loss around OWFs. This underscores ongoing methodological innovation and the need to match tools to data structure and conservation objectives. We emphasise that method selection should be guided by the specific objectives of the study, the nature and resolution of available data, and the spatial complexity of the system under investigation.

Different analytical strategies represent spatial structure in different ways. BACI-type approaches summarise observations within predefined spatial units, offering transparency but potentially increasing sensitivity to stochastic variation in heterogeneous systems. In contrast, LGCP-based models represent spatial structure explicitly through a latent field, allowing complex spatial patterns to emerge while quantifying uncertainty directly. However, while LGCP-based models offer flexibility and coherent uncertainty propagation, they are computationally demanding (Blangiardo and Cameletti, 2015), rely on assumptions about spatial smoothness (Illian et al., 2012), and require careful model specification, which may reduce transparency and accessibility compared with simpler approaches (Fuglstad et al., 2019). While BACI/BAGI designs and LGCP-based models differ conceptually, they should be viewed as complementary tools, with their relative suitability depending on the ecological question, spatial complexity, and data structure.

Taken together, these results demonstrate the value of combining high-quality, long-term monitoring data with flexible modelling frameworks to capture the spatially variable effects of OWFs on sensitive species. Spatially explicit Bayesian approaches can account for complex spatial responses, incorporate uncertainty, and reveal patterns often overlooked by conventional methods.

The five additional UK winter studies included in the updated Table 2 (APEM Ltd, 2015; APEM Ltd, 2021; Burt et al., 2017; Percival, 2013; Percival, 2014) provide important context for seasonal and geographic variability in displacement. UK winter studies consistently report shorter displacement distances or primarily within-OWF displacement (Percival, 2013: within-site only; Percival, 2014: up to ~3 km; APEM Ltd, 2015: within 500 m buffer) compared to German North Sea Spring estimates (5–12 km), with the notable exception of London Array where Natural England's interpretation supports displacement up to ~11.5 km in winter (APEM Ltd, 2021). Burt et al. (2017) further demonstrate that shipping activity compounds OWF effects in Liverpool Bay, highlighting cumulative disturbance as an important context-dependent factor. Overall, these studies confirm that displacement distances are highly site- and context-specific, varying with OWF size, turbine configuration, local oceanography, season, and survey methodology.

5. Conclusions and areas for future research

This study provides a spatially explicit assessment of long-term displacement patterns of divers (Gavia spp.) associated with OWF development in the German North Sea. By combining multiple before and after years within a joint-likelihood LGCP–INLA framework, the analysis reduces the influence of strong interannual variability and focuses on persistent spatial redistribution patterns.

Estimated displacement distances represent conservative, lower-bound effects, derived only from areas where negative responses are supported with high posterior probability. While the magnitude and spatial extent of displacement vary among wind farm clusters, results consistently indicate avoidance within several kilometres of OWFs, with effects extending farther in some cases but with increasing uncertainty.

The joint-likelihood approach estimates spatial responses from the data without prespecifying them, conditional on the assumed spatial model structure, and provides a robust basis for assessing long-term spatial effects in complex scenarios. The results are particularly relevant to inform strategic marine spatial planning and cumulative impact assessments at regional scales.

Future research could incorporate drivers that varied between periods, including period-averaged oceanographic conditions and prey distribution. Models could also allow responses to static variables, such as benthic habitat, to differ between periods, thereby testing whether habitat associations changed over time. Extending the framework to multi-species analyses and multi-driver cumulative impact assessments would further support regional-scale planning for offshore development and help assess how uncertainty in displacement estimates propagates into higher-level planning and management decisions.

Table 2
Overview of recent studies investigating displacement of divers in the North Sea showing significant displacement effects observed during the winter and spring seasons.

Study	Time frame	Study area/OWF	Spring	Winter	Data source/Method
Petersen et al. (2014)	2005-2007 2011-2012	Horns Rev 2, Denmark	5 - 6 km	—	Aerial/BACI
Webb et al. (2017)	2004-2016	Lincs, UK	8 km	—	Aerial/BACI
Heinänen et al. (2020)	2016	NE German North Sea	5 km	—	Aerial/Density gradient
Mendel et al. (2019)	2000-2013 2015-2017	NE German North Sea	9 km	—	Aerial and ship/BACI
Vilela et al. (2020)	2001-2018	German North Sea	From 5.2 to 7.3 km	—	Aerial/1D LGCP-INLA
Garthe et al. (2023)	2000-2017	German North Sea	9–12 km	—	Aerial and ship/BACI GAMs
Percival (2013)	2010-2013	Thanet, UK (Thames Estuary)	—	Within OWF only (~27% decline within site; no buffer effect)	Visual aerial/Buffer zones
Percival (2014)	2011-2013	Kentish Flats, UK (Thames Estuary)	—	95% within OWF; ~3 km	Boat counts/Buffer zones
APEM Ltd, 2015	2009-2014	London Array, UK (Thames Estuary)	—	Within OWF footprint (500 m buffer analysis)	Aerial grid/Buffer zones
APEM Ltd, 2021	2009-2019	London Array, UK (Thames Estuary)	—	~11.5 km (Natural England interpretation)	Aerial grid/Density modelling
Burt et al. (2017)	2004-2016	Liverpool Bay SPA, UK (Irish Sea)	—	Shipping + OWF effects modelled; no specific km threshold reported	Aerial/Distribution modelling
Current study	2001-2021	German North Sea	0 - 7.23 km (cluster dependent)	—	Aerial/Before-after Joint-likelihood LGCP-INLA

CRediT authorship contribution statement

Raul Vilela: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Formal analysis, Conceptualization. **Claudia Burger:** Writing – review & editing, Writing – original draft, Project administration, Investigation, Data curation, Conceptualization. **Ansgar Diederichs:** Writing – review & editing, Writing – original draft, Project administration, Funding acquisition, Conceptualization. **Lesley Szostek:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Anika Freund:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Alexander Braasch:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Georg Nehls:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition.

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

During the revision of this manuscript, the authors used Claude Opus 5 (Anthropic) to improve the language and readability of the revised passages, to check the internal consistency of the reported values against the analysis outputs, and to assist with debugging and documenting the analysis code. The original manuscript and analysis were developed by the authors, and all model specifications, analytical decisions and interpretations are their own. The complete code is openly available (see Data availability). The authors reviewed and edited the output as needed and take full responsibility for the content of the published article.

Declaration of competing interests

This study was funded by the Bundesverband der Windenergie Offshore e.V (BWO). We would like to thank Bundesamt für Naturschutz (BfN) at Vilm, Landesbetrieb für Küstenschutz, Nationalpark und Meeresschutz Schleswig-Holstein (*LKN*.SH), and the Forschungs-und Technologiezentrum Westküste (FTZ) which provided additional survey data for the analysis. This study would not have been possible without the work of the observers and technicians who collected and analyzed the data. Special thanks to Jochen Bellebaum, Brian Beckers and Werner Piper for their contributions during the inception of this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2026.130885.

Data availability

The analysis code and the input data are archived at Zenodo under DOI 10.5281/zenodo.22117556, and the working repository is at https://github.com/rvilp/OWF-displacement (code under MIT, data under CC BY 4.0). Counts are aggregated to the nodes of the spatial mesh; the 2001–2018 records were first released with Vilela et al. (2021), and the 2019–2021 records are released here for the first time.

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