An indicator for assessing the status of marine-bird habitats affected by multiple human activities: A novel statistical approach

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ABSTRACT

We present an integrative statistical approach for estimating the current conditions of marine-bird habitats affected by human activities. We first estimated the influence of multiple human offshore activities on the species of interest using integrative regression techniques. We then used these models to predict the distribution and abundance of the species throughout the study area, in both the current situation, with human activities, and in a hypothetical situation without the effects of the studied human activities. We finally developed different measures related to the comparison between these two scenarios. The presented approach allows the integration of bird-count data from different sources and sampling schemes, thus maximizing the underlying database. It also provides a local metric highlighting critical regions where locally high abundance is co-localized with large declines in abundance due to human activities, as well as a global metric quantifying the overall condition of the marine-bird habitat in the study area in relation to human disturbance. This approach allows us to assess the cumulative influence of several anthropogenic pressures. We exemplarily applied the above approach to four different species and two different sea regions, namely European herring gulls and long-tailed ducks in the German section of the Baltic Sea, and European herring gulls, red-throated loons, and common murres in the German–Dutch–Belgian part of the North Sea. The considered activities were offshore wind farms, bottom-trawling fishery, and ship traffic. The results confirmed the avoidance of and attraction to human activities by marine bird species found in previous studies. These results show that the methods developed here can be used to provide indicators for inclusion in bird assessments under OSPAR and HELCOM conventions, and MSFD Article 8, criterion D1C5 (habitat for the species). The resulting indicator can be used to inform programmes of measures under MSFD Article 13.

1. Introduction

The environmental status of European marine waters is gaining increasing attention, at least partly due to their increased use for human activities. International efforts to achieve or maintain a good environmental status for these marine areas is reflected in the European Union (EU)'s Marine Strategy Framework Directive (MSFD, European Union, 2008), the new EU Biodiversity Strategy, and in the conservation strategies of the Regional Sea Conventions (e.g. OSPAR, 2010; State of the Baltic Sea, 2018; GES). The environmental status of the marine areas is usually assessed using indicators. Marine birds qualify as good indicators of changes in marine ecosystems (Paleczny et al., 2015) because they play an important role in marine food webs, often as top predators. However, thematic assessments of sea birds in Europe have largely been restricted to their abundance, distribution, and/or demography (OSPAR, 2017; UNEP-MAP, 2017; State of the Baltic Sea, 2018), despite MSFD and status assessments of the Regional Sea Conventions aiming to build assessments on a broader basis (Dierschke et al., 2021). For example, in
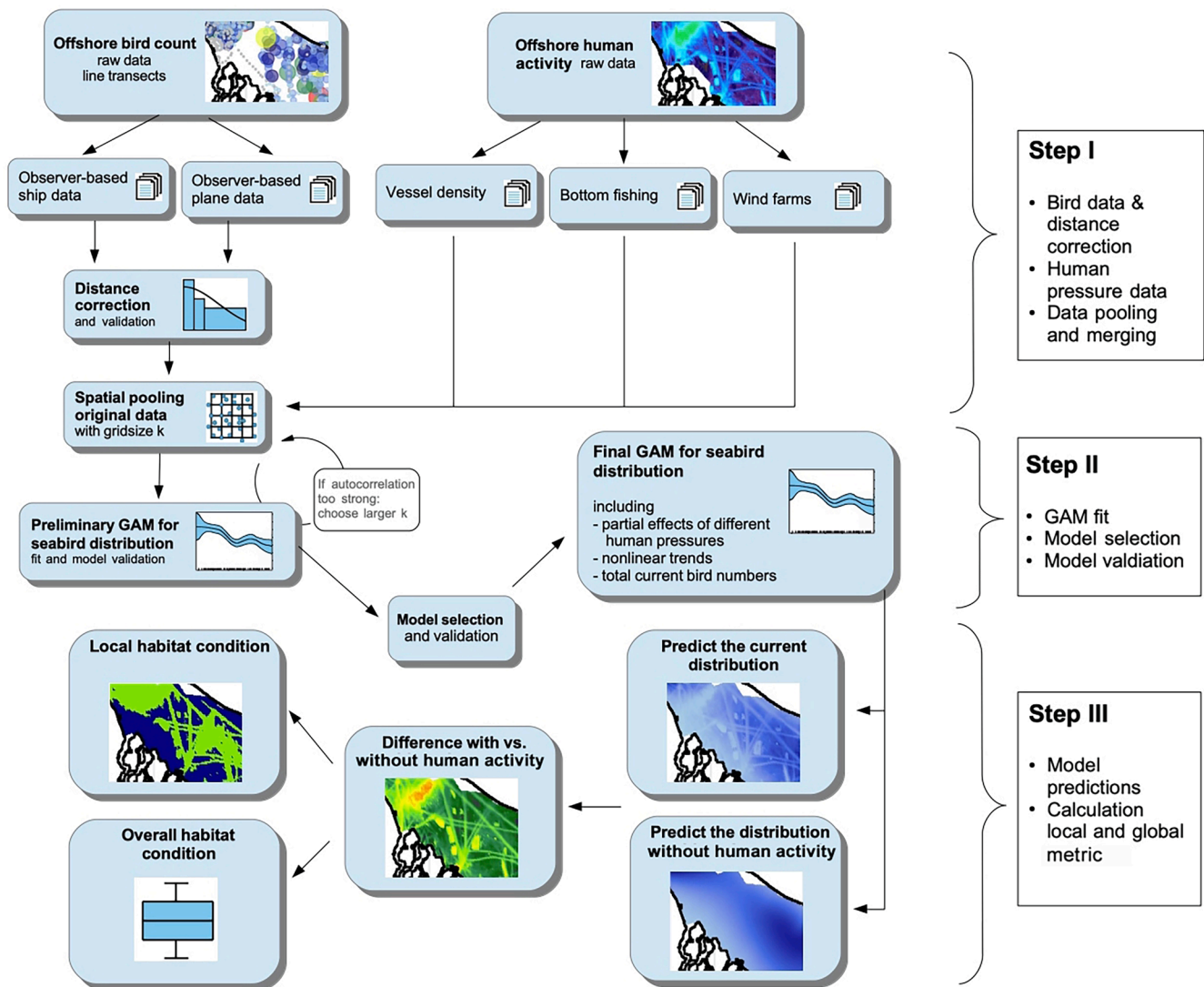
Fig. 1. Diagram of the developed approach applied to raw data for offshore bird counts and human pressures, using regression models to produce local and global metrics of marine-bird habitat conditions.

addition to the above criteria, the MSFD suggests that seabird assessments should also address bycatch mortality and habitat quality (Commission Decision (EU), 2017); however, indicators for these criteria are currently not available or are still under development (ICES, 2018, 2020).

The MSFD habitat quality criterion is formulated as "the habitat for the species has the necessary extent and condition to support the different stages in the life history of the species". It thus not only considers biological features, such as food availability, and structural features, such as water depth, but can also express the degree of disturbance from human activities. Although important sites for breeding, moulting, wintering, and migrating birds are often protected by national or international law, EU marine protected areas provide limited protection in practice (European Court of Auditors, 2020) because most disturbing activities such as fishing and shipping are not forbidden or are only slightly reduced. However, the extent of protection may vary among species, because different species react differently towards specific human activities, and because the spatial and temporal overlaps between the distributions of birds and these activities varies. Disturbance from human activities can range from escape flights caused by passing ships, to avoidance of large areas due to the presence of offshore wind farms (OWFs) (Dierschke et al., 2016; Fliessbach et al., 2019), while activities may also have indirect effects on the birds' food supply, e.g.,

by damage to the benthic fauna as a result of bottom-trawling fisheries.

Using the example of wintering marine bird species, we aimed to develop a method to assess habitat quality in relation to anthropogenic disturbance. By comparing the recently observed distribution with a modelled reference distribution based on predictive modelling without human activities, we estimated the cumulative influence of several activities on marine bird species. This effect was evaluated both locally (resulting in maps qualifying relative disturbance) and throughout the entire study area. The developed method thus allowed the extent and intensity of habitat disturbance to be assessed. This information can then contribute to status assessments of different species, and subsequently of the marine environment.

Estimates of marine-bird population numbers, trends, and distributions have been obtained using different survey techniques (Gibbons et al., 2004; Buckland et al., 2015) and statistical methods (Fewster et al., 2000; Paleczny et al., 2015; Schwarz, 2015; Soldaat et al., 2007). Offshore marine-bird distribution data are frequently based on different survey methods, such as observer-based ship- and aerial surveys, as well as digital-based aerial surveys (Mercker et al., 2021). However, all three methods have a strongly related sampling design: they generate count data (evaluated per unit area) and assess approximately similar spatio-temporal scales, so that data integration methods are relatively straight forward (Miller et al., 2018). A comprehensive statistical

Table 1
Human-activity data used in this study.

Sea	Human activity	Units	Temporal resolution	Source
Baltic Sea	ships (all types)	N ships crossing $1 km^2$ grid cell	2006–2016	HELCOM
Baltic Sea	wind turbines	distance to operating turbine	2006–2016	HELCOM
Baltic Sea	bottom-trawling	AIS signals/ km^2	2014–2015	JEODPP
North Sea	wind turbines	distance to operating turbine	2006–2019	OSPAR ODIMS and NGR Nationaal Georegister
North Sea	bottom-trawling	swept area ratio (subsurface)	2016	OSPAR ODIMS
North Sea	ships (all types)	hours per km^2 per month	2017	EMODnet

framework for analysing such data was recently developed (Mercker et al., 2021) to overcome the complex interactions among sampling and analytical techniques (Gibbons et al., 2004). In particular, here, estimates are based on joint-likelihood methods, i.e., multiple data sources are integrated into a single estimator (Miller et al., 2018). However, due to computational advantages, the applied estimator does not consider distance-dependent imperfect detection, which is instead evaluated in a separate step prior to the final regression analysis (Mercker et al., 2021) rather than modelling a thinned spatial point process within one single estimator (Miller et al., 2018). The approach of Ref. Mercker et al. (2021) allows the reliable estimation of trends, spatial distribution, and total bird numbers. In particular, this approach synchronously accounts for different challenges associated with marine-bird count data, building on previous regression methods used for trend estimates (e.g., Paleczny et al., 2015; Parsons et al., 2006; Robinson et al., 2015; Soldaat et al., 2007), census estimates (e.g., Clarke et al., 2003; Miller et al., 2013; Kazianka and Pilz, 2011; Anderson, 2007), and distance-sampling methods (e.g., Thomas et al., 2010; Buckland et al., 2015).

In the current study, we modified and extended the regression approach of Ref. Mercker et al. (2021) in several ways: first, we included additional covariates related to human activities, i.e., ship traffic, bottom-trawling, and OWFs. This allowed quantification of the partial effects of different human activities on species-specific local abundances, while simultaneously estimating (and thus distinguishing between) the effects of different natural covariates. Second, we used these regression models to assess both current spatial distributions and total bird numbers (as in Ref. Mercker et al. (2021)), as well as using the model to predict the spatial distribution and total bird numbers in a hypothetical situation ('counterfactual situation') without human activities. We then compared the results of both these scenarios to develop new metrics assessing local and global impairments of marine-bird habitats as a result of human activities.

2. Materials and methods

A synopsis of the presented approach is given in Fig. 1. We want to point out that several technical details e.g., with respect to imperfect detection, data pooling, and regression analyses are only summarized below; a more detailed description can be found in Ref. Mercker et al. (2021).

2.1. Count data and processing

2.1.1. Raw bird-count data

The following study was based on German offshore data from various Seabirds-at-Sea (SAS) projects with respect to the Baltic Sea, and German, Dutch, and Belgian offshore data from the European Seabirds at

Sea Partnership (ESAS) database for the North Sea. All bird-count data were based on internationally standardized line transect counts (Camphuysen et al., 2004), where birds were counted at high temporal resolution from aircraft (1 s) or ships (1 min), at various locations and times of year. The survey methodology included distance-sampling techniques, i.e., classifying counted birds into different distance classes perpendicular to the transect line (the number and size of the distance classes differed between ship- and aircraft-based counts). This enabled us to correct the counts for overlooked birds depending on the distance to the observer (Buckland et al., 2001, 2015); the consideration of imperfect detection on the transect line in contrast is considered with the final regression and prediction analysis (more details are given below). The analysis was restricted to winter data obtained in December, January, and February. The Baltic Sea data were collected in 2006–2016 and North Sea data in 2006–2019.

2.1.2. Raw human-activity data

Data regarding human activities were obtained from various sources (Table 1).

With respect to the Baltic Sea, data on yearly average ship densities and wind turbine locations (and year of commissioning) were obtained from HELCOM (link). These data were spatially merged with the bird-count data on a yearly basis, given that these variables (particularly wind turbine data) may change dramatically from year to year (example bird data merged with ship signal data from the Baltic Sea are shown in Fig. 8). Here, ship densities represent the density of all International Maritime Organization-registered ships crossing a 1 x 1 km grid cell. A map of European bottom-trawler Automatic Identification System (AIS) data (evaluated from October 2014 until September 2015, presented as numbers of AIS signals per km^2) was taken from the JRC Big Data Platform (JEODPP) (link). These data were only merged spatially (instead of spatiotemporally) with the bird-count data because the yearly resolution was not given. With respect to ship densities, "all ship types" was selected, and the densities thus included fishing vessels, particularly bottom-trawling fishery vessels. Notably, bottom-trawling only accounts for a small fraction of all ship data, and collinearity between both variables is assumed to be minor; however, both variables target qualitatively different types of impact: ship density represents the visual interaction between birds and the presence of ships, while "bottom-trawling" describes the interaction of that fishery with the sea floor.

With respect to the North Sea, data on wind turbine locations were obtained from OSPAR ODIMS (link) and NGR Nationaal Georegister (link) where commission dates for several wind park clusters were merged from various online sources (e.g., Wikipedia). Bottom-fishing intensity data from OSPAR ODIMS were also included (link). In particular, we used the variable "fishing intensity – subsurface", which represents the ICES response to an OSPAR request to support the development of common and candidate OSPAR biodiversity indicators for benthic habitats, given as fishing intensity/pressure per gear type for subsurface abrasion ("swept area ratio"; SAR). This "subsurface" category also includes surface abrasion. We included data from 2016 (only spatially merged with bird-count data), but these data are in principle available for other years. It was difficult to obtain data on vessel densities for the North Sea, and the only free source we were able to find was from EMODnet, which only included AIS-based vessel densities (given in hours per km^2 per month) for 2017 (link). Because of the lack of a temporal component, these data were also only merged spatially with the bird-count data. These data were not available for the outermost south-western corner of the Belgian North Sea, and the value was therefore set to zero for this region; however, given that this only accounts for small part of the study area and a single human-activity predictor, we assumed that the corresponding bias would be small.

Marine-bird data and data on human activities (as well as on natural covariates such as water depth and minimal distance to the coast) were merged at the level of raw count data to prevent information loss.

2.1.3. Spatio-temporal data pooling

Using raw bird-count data directly in complex spatio-temporal regression approaches leads to unfeasible computation times due to intense spatial and temporal autocorrelation within model residuals. Furthermore, this would lead to mean count values close to zero, which prohibits the use of Penalized Quasi Likelihood techniques in mixed regression models (Bolker et al., 2009) and could require the application of more complex models considering zero-inflation (Martin et al., 2005; Zuur et al., 2009; Korner-Nievergelt et al., 2015). After applying the distance-dependent detection correction (c.f., below), we thus pooled the data spatio-temporally based on a pre-defined regular rectangular spatial grid of side length *k* (c.f. Fig. 1) (for more technical details see Ref. Mercker et al. (2021)). The optimal grid cell side length *k* is not known *a priori* and needs to be evaluated during data analysis to find the optimal compromise between a high local spatial resolution (favouring small cells), and a manageable amount of autocorrelation and data size (favouring large cells). We tested $k = 30, 15, 10$, and 7 km.

2.2. Imperfect detection

The detection of birds by observers is usually imperfect, and the detection probability frequently decreases with increasing distance from the observer (Buckland et al., 2001; Buckland et al., 2015). We corrected for this by distinguishing between distance-dependent and distance-independent detection probabilities, as detailed in Mercker et al. (2021).

2.3. Species distribution models (sdGAMs)

2.3.1. Temporal covariates

Trend estimates can be deduced from the appropriate covariates during regression analyses (Schwarz, 2015; Fewster et al., 2000; Schwarz, 2015; Soldaat et al., 2007). If relatively short time frames are considered, population development can often be approximated by a simple (log-) linear trend. However, population changes over longer periods can be highly nonlinear, and pure (log-) linear regression models appear to be inappropriate or may show strong temporal autocorrelation. Generalized additive models (GAMs) (Wood, 2017; Fewster et al., 2000) or techniques based on Kalman-smoothing (Harvey, 1989; Soldaat et al., 2007) offer possible alternative methods. In the present study, we considered long-term trends (at least 10 years), and we therefore integrated the variable "year" as a possibly nonlinear term $s(year)$ using GAM techniques, where the optimal smoothness was estimated based on generalized cross-validation (GCV) methods (Wood, 2017).

2.3.2. Environmental/spatial covariates

We considered smooth terms of the variables *dist_land* (nearest distance to the mainland excluding the small offshore island of Helgoland) and *depth* (mean water depth) as environmental covariates. The aim was to further reduce the unexplained variance and thus increase the power and quality of trend estimates and predictions in the final regression models.

2.3.3. Human activities

We used *ships* (all vessel types), bottom-trawling fishery (*bottom_trawling*), and nearest distance to an operating wind turbine (*OWF*) as human-activity variables. Because significant avoidance effects have been found up to a distance of approximately 10 km from OWFs (Mendel et al., 2019; Garthe et al., 2018), we restricted the latter variable to 10 km by setting all values larger than 10 km to 10 km. This allowed a better statistical estimation of the effect because the scale of this variable was restricted to the scale of its possible influence. All three human activity variables were tested using the original scale and on a log-scale (e.g., *log_OWF=log(1+OWF)*) during model selection (c.f., below). The log-based transformation weights smaller values of the corresponding variable more strongly, and is thus particularly appropriate for small-

scale reactions, such as species only avoiding the footprints of the human activities. Alternatively, dependency on human activities could be modelled using smooth terms; however, we omitted this to allow the straightforward interpretation of regression coefficients.

2.3.4. Unexplained spatial inhomogeneities

We accounted for additional spatial abundance heterogeneities not explained by the other considered covariates (such as distribution of food availability, which was not considered in the models), by introducing a 2D-spatial smooth predictor in two alternative variants during model selection: as a thin plate regression spline, and as a tensor-product spline, both depending on *longitude* and *latitude* (Wood, 2017). Because 2D thin plate splines are optimized for variables on the same scale (Wood, 2017), we rescaled the geographical coordinates to kilometres before the analysis. However, the spatial smooth was *a priori* restricted to a large-scale spatial resolution (by setting the number of knots to 16) to prevent collinearity with the relatively small-scale variables of human activities. The optimal amount of smoothing for all the above smooth terms was determined based on GCV methods (Wood, 2017).

2.3.5. Detection-related covariates

Distance-independent detection-related covariates were given by the two variables *method* and *sea_state*. Estimates of population numbers strongly depend on these two variables, and their correct and stable estimation is thus of great importance. To facilitate a robust estimation, we omitted interaction terms between these variables to produce fewer but more stable estimated parameters. We also merged the former levels 0 and 1 for the variable *sea_state* into a single "1", and merged all levels ⩾4 into level "4", such that the final variable *sea_state* did not contain levels with sparse data.

Count data are often spatially and/or temporally strongly autocorrelated (Field et al., 2012; Zuur et al., 2007, 2009; Korner-Nievergelt et al., 2015; Zuur et al., 2017). Temporal autocorrelation may occur at two different time scales: first, data are probably autocorrelated between subsequent years, especially if a nonlinear population development is approximated by a log-linear term; and second, subsequent sampling units may also be strongly spatiotemporally autocorrelated, especially if they consist of subsequent parts of the same transect. We appropriately considered both types of temporal autocorrelation, as described in Ref. Mercker et al. (2021), and additionally adjusted the underlying spatial grid size *k* to make the spatio-temporal autocorrelation manageable.

2.3.6. General sdGAM structure

The "most complex" sdGAM (not yet pruned regarding its predictors, as described below) is given by

$$
\begin{aligned}
log(y_j) = \quad & \beta_0 + method_j + sea\_state_j + s(year_j) \\
& + s(depth_j) + s(dist\_coast_j) \\
& + f(ship_j) + f(bottom\_trawling_j) + f(OWF_j) , \\
& + g(latitude_j, longitude_j) \\
& + lag_1 + lag_2 + lag_3 \\
& \qquad + \text{offset}(log(area_j)) + \epsilon_j
\end{aligned}
\tag{1}
$$

with $\epsilon_j \sim N(0, \sigma^2)$ normally and independently distributed. Here, y_j is the vector of bird numbers, where the index *j* refers to the sampling unit number. β_0 is the fixed intercept, and $s(.)$ depicts a cubic regression spline (with the optimal number of knots estimated via GCV). $f(x)$ depicts either the main effect *x* or the log-transformed value $log(1 + x)$, and $g()$ describes either a regression spline $s()$ or a tensor-product spline $te()$. Because survey effort varied per sampling unit, the logarithm of the area surveyed was included as an offset (Zuur et al., 2007; Korner-Nievergelt et al., 2015). The terms lag_1, lag_2, lag_3 refer to the potential autocorrelation on a small temporal scale. The probability distribution and optimal subset/formulations of predictors were selected based on Akaike Information Criterion (AIC) analysis (Akaike, 1973) (c.f., section "Model selection and validation").
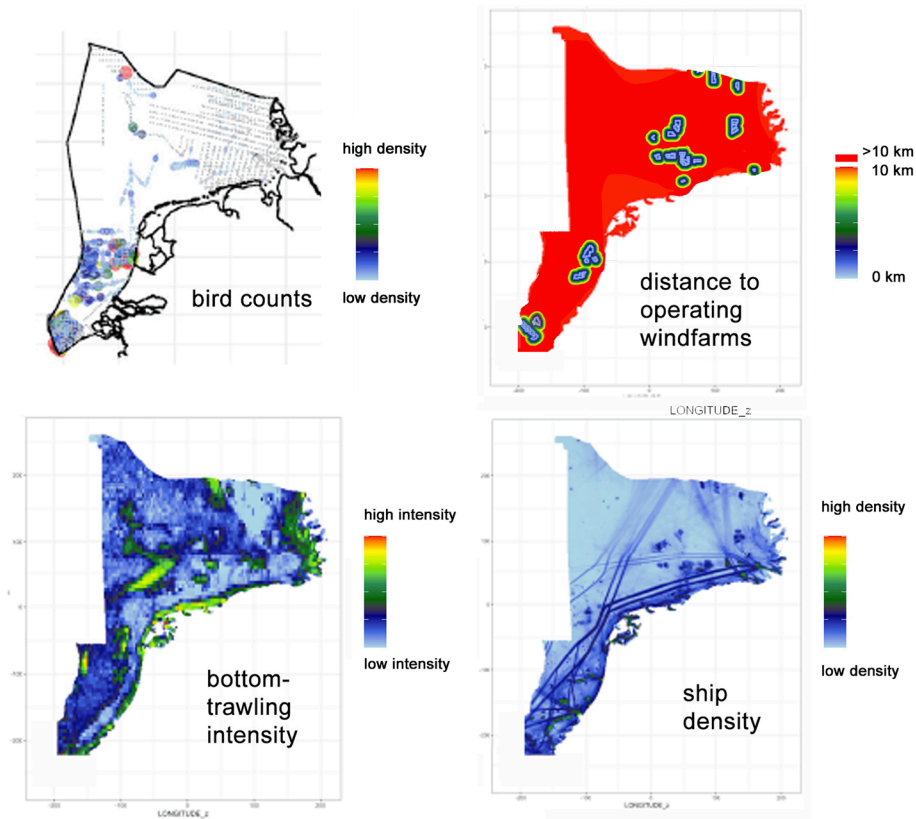
Fig. 2. Example plots of (pooled) raw bird-count data and (possibly log-transformed) raw data for different human activities in the German–Dutch–Belgian part of the North Sea.

2.3.7. Predicted bird distribution and population size

Trend estimates can be extracted directly from GAM regression results, but the calculation of predicted population distributions and sizes is less straightforward. We used the final fitted sdGAM to predict bird densities on a prediction map of the investigated area. Prediction-map data had a resolution of $1\ km^2$ and included values for all relevant environmental and anthropogenic covariates. Detection-related covariates (*method* and *sea_state*) are not given naturally, and have to be chosen/set. Here, we determined which *method–sea_state*-combination led to the highest predictions, and subsequently used the corresponding factor levels within all sdGAM-based predictions. This was based on the assumption that, for at least one *method–sea_state*-combination, detected bird numbers (after distance-correction) were close to the actual bird numbers, i.e., detection on the transect line was assumed to be close to 100%. Human activity-related covariates were either set to the most recent values available (2016 for the Baltic Sea and 2019 for the North Sea) to predict the current bird distribution, or to zero (respectively 10 km for the variable *OWF*) to predict the human activity-free situation.

2.4. Model selection and validation

Different model selection and validation steps were performed separately for each species–sea combination to select the most appropriate probability distribution, choose the most reasonable combination and formulations with respect to the fixed-effect predictors, and validate the several assumptions (such as linearity, homogeneity, or independence) underlying a regression model. In particular, we modified the selection and validation strategies as described e.g. by Ref. Zuur et al. (2010, 2009) and Zuur (2012). Further technical details are given in Ref. Mercker et al. (2021).

2.5. Habitat-quality metrics

2.5.1. Local habitat-condition metric D_{local}

This metric aims to define spatial regions where the habitat quality is poor as a result of human activity. This is reflected by a high predicted local abundance in the absence of the considered human activities, and a strong negative effect of the activities on the predicted abundance. It is therefore necessary to first define a measure for the (undisturbed) local abundance, which is optimally comparable between different species, e. g. approximately scaled between 0 and 1. This could easily be achieved by predicting the abundance in the undisturbed state and dividing the values by the maximal abundance in the entire area; however, this would be a non-robust approach, given that the scaling would be strongly affected by high abundances in individual cells. A more appropriate approach thus involves dividing by the α-percentile of the predicted abundance values (in the following we used $\alpha = 0.99$). If X now represents this local (undisturbed) abundance (ranging between 0 and approximately 1) and Y represents the strength of human-pressure-related decline ($Y = 1$ equals 100% decline, $Y = 0.5$ equals 50% decline, $Y = 0$ equals 0% decline, and $Y < 0$ equals an increase due to human activities),

$$D_{local} = XY \tag{2}$$

represents a measure that is high (e.g., $D_{local} > 0.5$) at high local abundance, with a strong decline due to co-localized human pressure. For example, if X is close to 1 (high local abundances in the undisturbed scenario), a value of $D_{local} = 0.2$ indicates a 20% reduction due to pressure from human activities in this area. The same value of $D_{local} = 0.2$ would be obtained if the natural density was only $X = 0.5$ (i.e. half-maximal) but the reduction due to activities was 40%, or if the natural density was small ($X = 0.2$), but there was a 100% reduction. This metric is thus a continuous measure, which is higher where high

Table 2

Summary of positive and negative effects of different human activities on different species–sea combinations. For ship- and bottom-trawling-related variables, a negative regression coefficient β indicated avoidance and a positive one indicatedattraction, while the opposite was true for offshore wind farm (OWF)-related variables, because distance to the OWF was considered. The choice of which human-activity variables were used in which combination and which manner (e.g., untransformed vs. log-transformed) was based on AIC-guided model-selection techniques (performed separately for each species–sea combination).

Sea	Species	Activity	β	p-value	Interpretation
OWFs:					
North Sea	red-throated loon	log_OWF	0.81	< 0.05	significant avoidance
North Sea	herring gull	NA	NA	NA	not selected
Baltic Sea	herring gull	OWF	0.08	< 0.001	significant avoidance
North Sea	common murre	log_OWF	0.26	0.11	not significant
Baltic Sea	long-tailed duck	OWF	-0.03	0.06	not significant
Ships:					
North Sea	red-throated loon	log_ships	-0.34	< 0.01	significant avoidance
North Sea	herring gull	ships	0.001	0.56	not significant
Baltic Sea	herring gull	NA	NA	NA	not selected
North Sea	common murre	log_ships	-0.22	< 0.001	significant avoidance
Baltic Sea	long-tailed duck	ships	-0.0002	< 0.001	significant avoidance
Bottom trawling:					
North Sea	red-throated loon	bottom_trawling	-0.20	< 0.01	significant avoidance
North Sea	herring gull	bottom_trawling	0.19	< 0.001	significant attraction
Baltic Sea	herring gull	log_bottom_trawling	0.36	< 0.001	significant attraction
North Sea	common murre	NA	NA	NA	not selected
Baltic Sea	long-tailed duck	bottom_trawling	-0.015	< 0.05	significant avoidance

abundance and high human activity-related decline are co-localized, and which is zero if either the local abundance or local human activity-related decline is zero. Finally, a negative value of D_{local} would indicate a local attraction to human activities. D_{local} is comparable between species and can be interpreted directly: as shown in the graphical analyses in the Results section, D_{local} (if positive) is approximately proportional to the decline in total bird numbers due to human pressures for each species (because high total declines can only be achieved if naturally high total numbers co-localize with strong declines due to human pressures).

2.5.2. Global habitat-condition metric D_{global}

This metric aims to define the overall habitat condition (i.e., in the entire study area) related to human activities by integrating D_{local} over the entire area and rescaling it by the overall abundance. A straightforward definition of this metric is thus given by

$$D_{global} = \frac{\sum_{i \in A}(X_i \times \max(0, Y_i))}{\sum_{i \in A} X_i}, \tag{3}$$

where D_{global} is weighted by the local abundance, i.e., cells with high local abundance influence this measure more strongly than areas with low abundance. In particular, i is an index referring to all 1 x 1 km grid cells throughout the study area A. The metric also confirms the intuition that assuming no reduction due to human activities (i.e., $Y = 0$ everywhere), it follows $D_{global} = 0$ corresponding to 0% reduction in the overall population. In contrast, if we consider a 100% reduction everywhere ($Y = 1$), it follows $D_{global} = 1$ corresponding to 100% reduction in the overall population, and for a reduction of 50% everywhere, $D_{global} = 0.5$. Importantly, the above formula means that grid cells with zero abundance are not considered, because when $X = 0$, the product also becomes 0. Grid cells with low abundances thus only have a minor influence on D_{global}.

Notably, this metric (in contrast to D_{local}) only considers negative effects (i.e. avoidance and not attraction) of human activities. We account for this by considering $\max(0, Y_i)$ instead of Y_i, such that in the event of negative Y_i-values (i.e. local abundance increase due to human activities), 0 is considered instead. If this is not done, D_{global} would reflect the overall change in population size with vs. without the considered human activities. Based on the above re-definition, D_{global} is equal to or

larger than the percentage population size change due to these activities (because local negative effects are not balanced by local positive effects in other parts of the assessment area). D_{global} thus "sums up" or "averages" only the negative local effects of human activities on marine-bird abundance. This metric is also comparable between species, since $D_{global} \in [0, 1]$.

2.6. Software

All statistical analyses, validation procedures, and visualizations were performed using the statistical software R (R Core Team, 2016) with the following packages: *sp*, *raster*, and *gstat* (Pebesma, 2004, 2005) for spatial analyses and visualizations; *ggplot2* (Wickham, 2009) for all other visualisations and plots; *Rmisc* (Hope, 2013) and *matrixStats* (Bengtsson, 2016) for different functions regarding data analysis and utility operations, *MASS* (Venables and Ripley, 2002), *pscl* (Jackman et al., 2008), and *mgcv* (Wood, 2017) for regression analyses, and *Distance* (Thomas et al., 2002; Thomas et al., 2010; Buckland et al., 2015; Miller et al., 2013) for distance sampling-related procedures.

3. Results

3.1. Validation of implementation of human pressures

We used several plots to validate the implementation of the different human-activity variables, because this step is crucial for the following analyses. The plots indicated no problems. Some examples of raw data for human activity are given for the North Sea in Fig. 2, and examples of human-activity data merged with bird-count data are given for the Baltic Sea in the Appendix in Figs. 8 and 9.

3.2. Species-specific reactions to human activities

Relative changes in local abundance as a result of different human activities can be extracted directly from the regression coefficients of the final (species-specific) sdGAMs. An overview is given in Table 2. Generally, most human activities had a negative influence on most of the species considered: 7 of the 15 sea–species–activity combinations showed a significant or highly significant negative influence on local abundance, while no significant relationship was detected or the activity
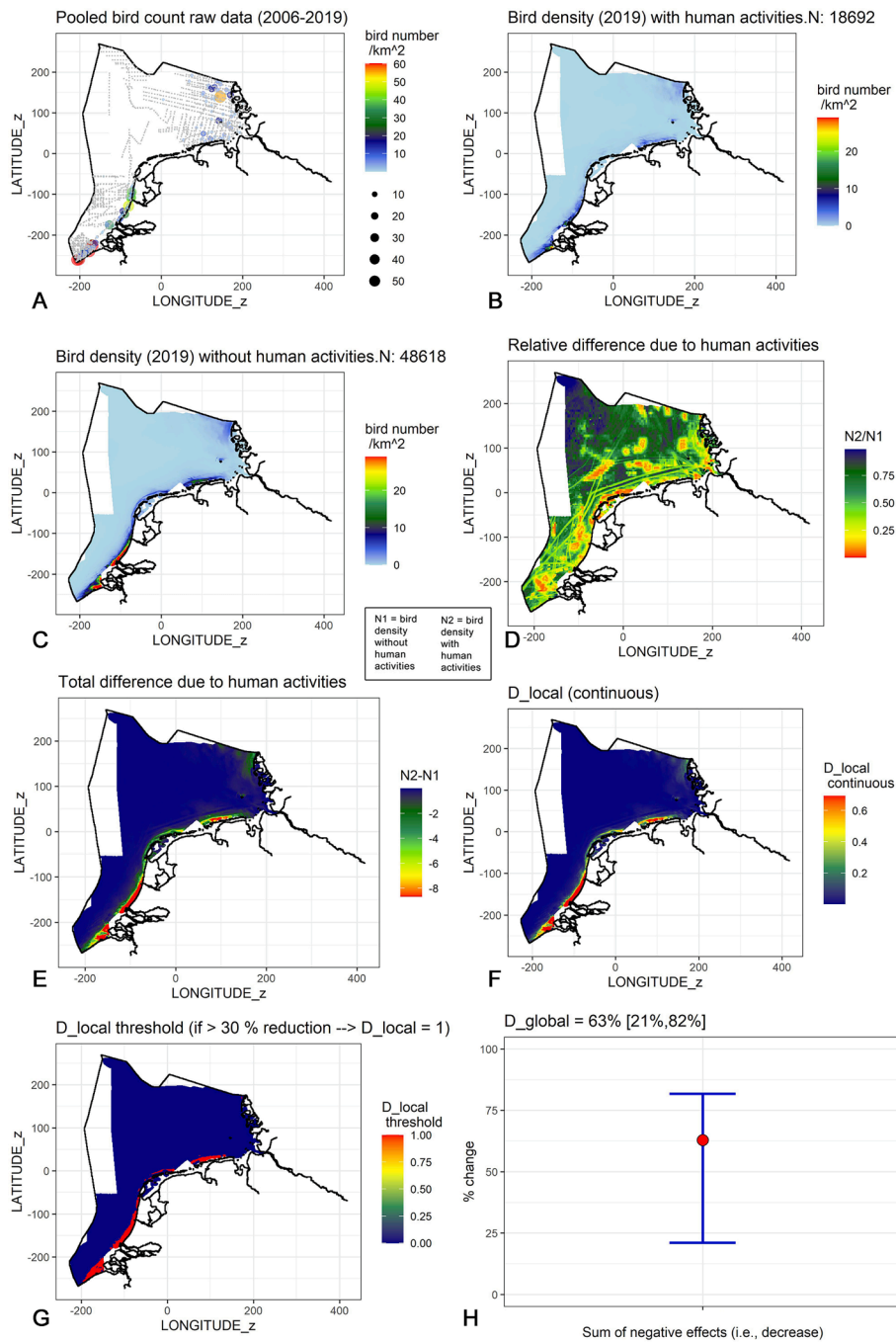
Fig. 3. Summary results for red-throated loons in the Belgian–German–Dutch North Sea. Pooled raw count data (A) were used to fit species distribution models (sdGAMs) leading to estimated current bird distributions with (B) and without (C) human activities. (D) Relative and (E) total differences in bird density due to human activities. (F) The distribution of the newly developed metric D_{local} was high if local high abundance and strong human-related decline co-localized. (G) D_{local} discretized using an example threshold of 30%. (H) Newly developed metric D_{global} summarizing/averaging D_{local} over the entire study area, but considering only human-related activities with a negative influence. If only negative pressures exist, D_{global} equals the percentage change in total bird numbers due to the pressures. The variables *LONGITUDE_z* and *LATITUDE_z* are centered spatial coordinates rescaled to units of kilometers.

was not selected as an explaining variable in the model for 6 cases. European herring gull (herring gull hereafter) was the only species that was significantly attracted by human activities (namely bottom-trawling in both seas).

Based on the regression coefficients, it is also possible to extract 'critical species-specific values' for each of the variables (e.g., the distance to OWFs below which the abundance falls below a certain threshold - data not shown), while the metrics D_{local} and D_{global} only evaluated the joint effect of all considered activities.

3.3. Predicted abundances, numbers, and metrics

The summarized results with respect to predicted abundances (with vs. without the considered human activities), relative and absolute changes due to these activities, corresponding predicted bird numbers,

and spatial patterns of D_{local} and an estimate for D_{global} for different species–sea combination are given in Figs. 3–7. In each case, the metrics D_{local} and D_{global} were calculated for the most recent year for which data were available (2016 in the Baltic Sea and 2019 in the North Sea). However, the entire time series (i.e., from 2006) was used to estimate the relationships between human activities and local bird abundance.

The most strongly affected species was the red-throated loon in the North Sea (Fig. 3) (D_{global} = 63%; Fig. 3 H). This suggests that the habitat is disturbed for 63% of red-throated loons (modelled for an undisturbed scenario) by the cumulative effects of the three activities (all negative effects; Table 1), while only 37% of the red-throated loons expected to winter in the North Sea from Belgium to Germany were unaffected. As explained above, this can also be interpreted as a total population loss of 63% due to the considered human activities. However, given that loon numbers may increase in undisturbed parts of the study area due to
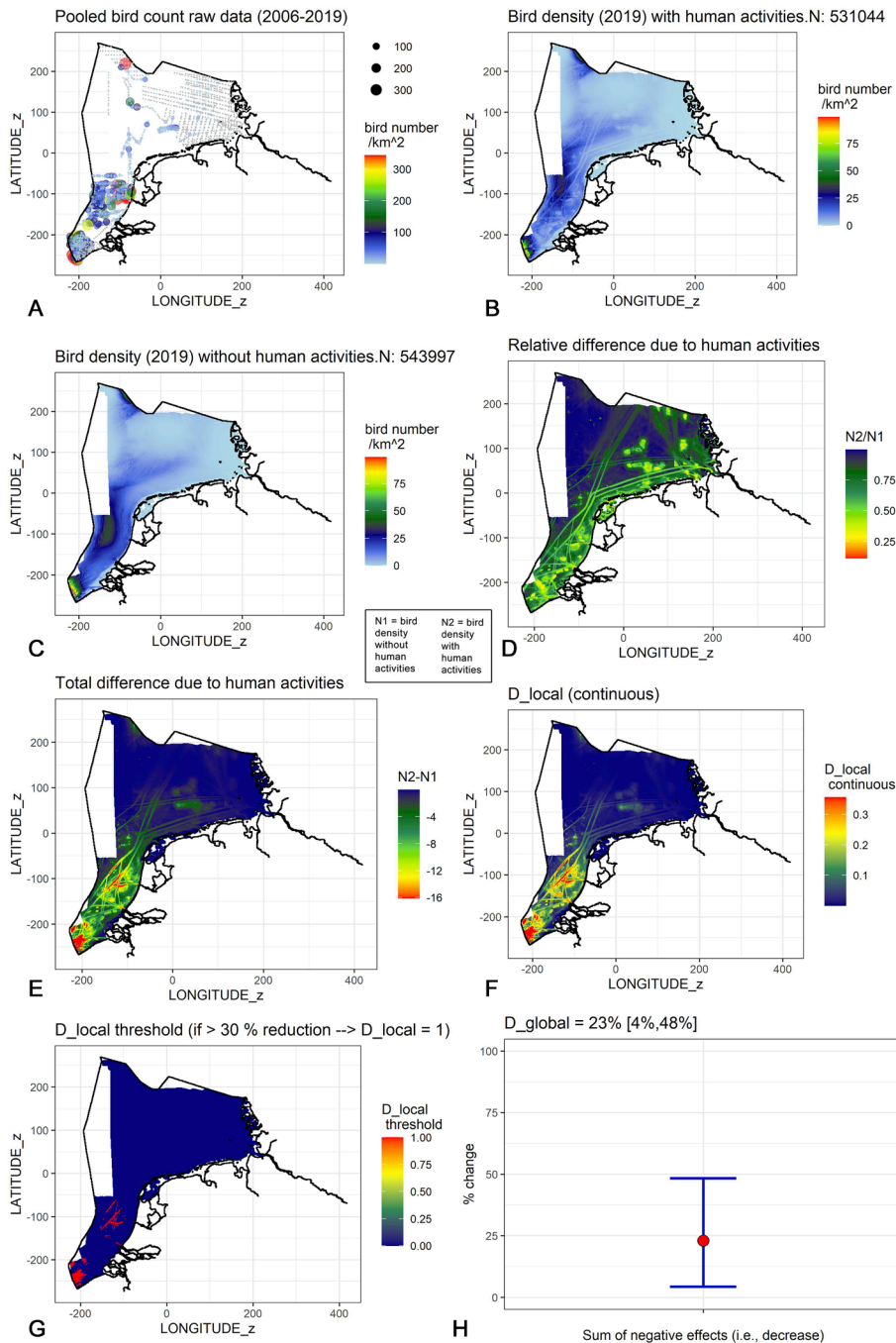
Fig. 4. Summary results for common murres in the Belgian–German–Dutch North Sea. For details see Fig. 3.

displacement, or the winter distribution may shift to areas outside the study area, the actual decrease in the population size may be less than 63%. The coastal distribution of this species during winter means that coastal areas, mainly restricted to the south-western part of the study area, are critical (Fig. 3E–G).

The second most-negatively affected species was common murres in the North Sea (Fig. 4) (D_{global} = 23%; Fig. 4H). The D_{global} value and the percentage overall population decline (calculated from relative difference in total numbers with vs. without the considered human activities; Fig. 4B–C) matched well, given that this species showed a significant negative reaction to shipping and a nearly significant negative reaction to OWFs (c.f., Table 2).

In contrast, although long-tailed ducks in the Baltic Sea avoided some areas with ship passages and bottom-trawling (c.f., Table 2), they

were generally only weakly affected by human activities (Fig. 7). In particular, D_{global} was only 6% (Fig. 7 H), indicating only minor changes in the overall population size due to human activities (total numbers in Fig. 7B–C). Indeed, regions with high abundance (such as the east of the study area) were largely unaffected by ship activity and bottom-trawling (Fig. 7B,D–F).

Herring gulls were strongly attracted to human activities in both the North Sea (Fig. 5) and the Baltic Sea (Fig. 6). D_{global} was only 1% in the Baltic Sea (due to some negative impact of OWFs - c.f., Table 2) and was 0% in the North Sea; however, the overall numbers in the disturbed scenario are distinctly higher in both seas compared to the undisturbed scenario (c.f., Fig. 5B–C and Fig. 6B–C). Importantly, the avoidance of OWFs by herring gulls may be an artefact, because gulls are often observed inside OWFs (Dierschke et al., 2016), but can be drawn away
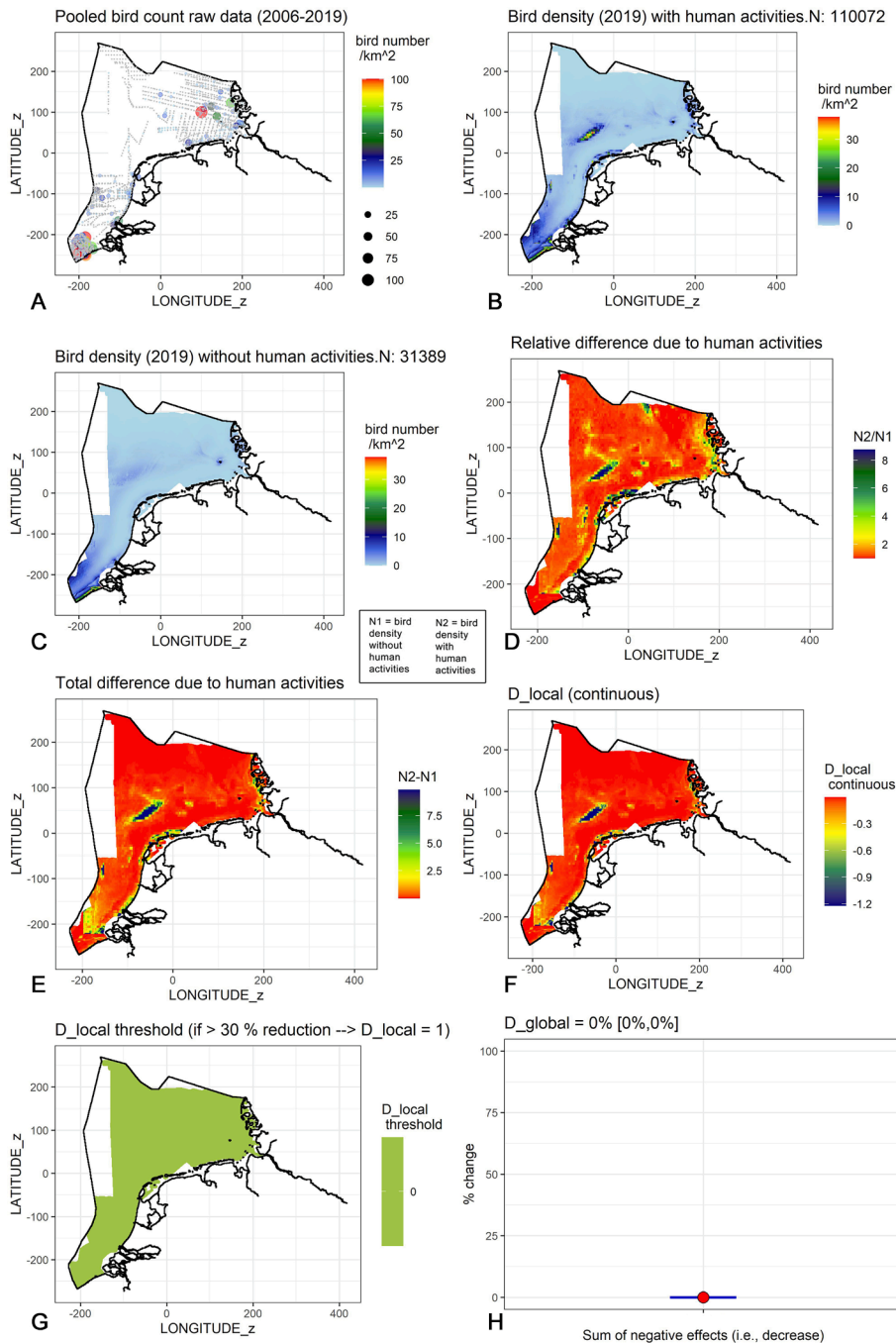
Fig. 5. Summary results for herring gulls in the Belgian–German–Dutch North Sea. For details see Fig. 3.

from OWF footprints by fishing vessels, which are not usually allowed to enter OWFs (Leopold et al., 2011).

4. Discussion

In this study, we assessed the influence of human activities on marine birds in the North Sea and Baltic Sea using a novel statistical approach, by comparing observed distribution patterns with what-if scenarios in the absence of human activities. This method was shown to provide a useful tool for assessing the status of marine birds and deriving appropriate measures for their protection.

4.1. Assessing habitat quality for marine birds

The results of our exemplary application of the novel approach supported the results of previous studies of the reactions of marine birds to human activities. Red-throated loons and common murres were previously shown to avoid the footprints of OWFs (Dierschke et al., 2016; Heinaenen et al., 2020; Peschko et al., 2020). Although the results for common murres were not significant in the current study, for this species, the second strongest OWF avoidance was measured, and the p-value of p = 0.11 nevertheless strongly suggests an existing influence. Furthermore, it must be taken into account that there is an additional negative effect from OWF-associated ships for this species, which would have to be added in order to consider all effects associated with the OWFs (Mendel et al., 2019). The derived order of magnitude for red-
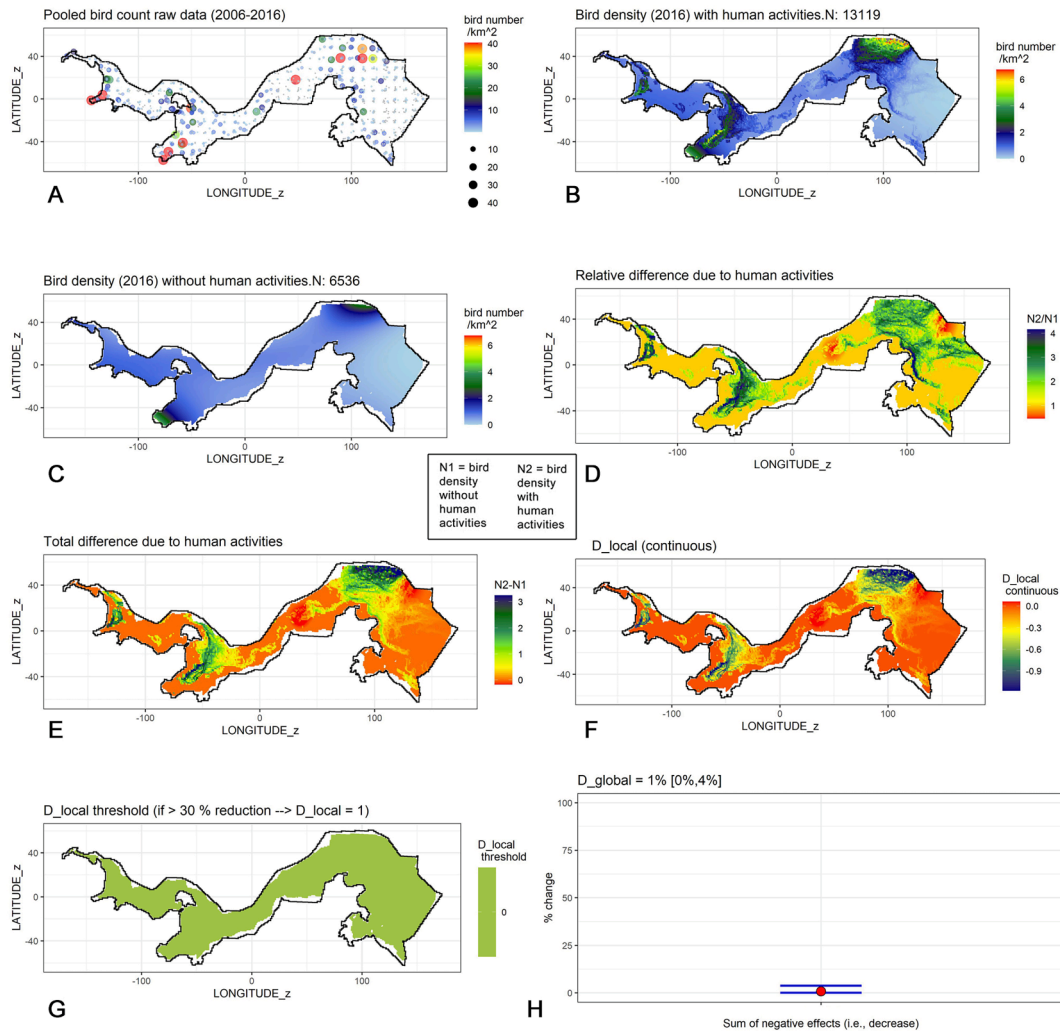
Fig. 6. Summary results for herring gulls in the German Baltic Sea. For details see Fig. 3.

throated loons (which can be estimated based on regression coefficients) matched the disturbance effects estimated e.g. by Ref. Garthe et al. (2018). Recent studies demonstrated that red-throated loons concentrated locally in the North Sea as a result of spatial constraints imposed by OWFs (Mendel et al., 2019; Garthe et al., 2018), possibly leading to higher local abundances than those observed without these constraints. This may have introduced some bias in our model by predicting higher bird densities in the undisturbed scenario. However, given that the considered non-OWF areas were much larger than the OWF-impacted areas, we assumed that this bias would only be minor.

Although previous studies showed avoidance by long-tailed ducks elsewhere (Petersen et al., 2011), this was not confirmed by the current study, probably because only one small wind farm is currently operating close to the wintering sites for that species in the German Baltic Sea. With respect to herring gulls, the avoidance of wind farms shown in our study was assumed to be an artefact, and the gulls did not avoid wind farm structures (in fact they have been shown to use them for roosting, Vanermen and Stienen (2019)), but were distracted away from the wind farm footprint to follow fishing vessels, which are not allowed to operate between the turbines (Leopold et al., 2011).

In accordance with our results, shipping has previously been shown to disturb wintering long-tailed ducks, red-throated loons, and common murres (Schwemmer et al., 2011; Burger et al., 2019; Fliessbach et al., 2019). In contrast, our results suggest that herring gulls do not avoid ships (Camphuysen et al., 1999), and are even attracted to ships in areas used for bottom-trawling, corresponding to their frequent aggregations

around fishing vessels associated with the feeding opportunities offered by bycatch discards (Garthe and Hüppop, 1994). Disturbance from these vessels alone was apparently not enough to significantly displace common murres from bottom-trawled areas. In contrast, long-tailed ducks, as the only benthic feeders in this study, were significantly and negatively affected by bottom-trawling, possibly due to a combined effect of disturbance from the vessels and reduced food availability caused by physical damage to the seafloor and its benthic fauna (Schröder et al., 2008). The negative response of red-throated loons to bottom-trawling was most likely caused by the presence of the fishing vessels.

The additive value of this study was the ability to assess the cumulative effects of different human activities, rather than just considering the effects of individual activities. Our approach showed the total impact of the considered human activities as stressors, regardless of whether their effects were additive, antagonistic, or synergistic (Folt et al., 1999). However, it is still possible to identify which individual activities contributed to the disturbance of a species, and this could be further improved if the metric D_{global} is broken down into contributions by the individual activities in future studies. The results thus indicate where management measures might be needed (e.g., with respect to MSFD Art. 13), and which human activities need to be addressed by these measures. This habitat quality-assessment tool and resulting indicator not only support the status assessments of marine bird species (MSFD Art. 8), but can also help to achieve good environmental status (MSFD Art. 9) and the environmental targets (MSFD Art. 10). However, the reliable assessment of the contribution of individual stressors is a complex task
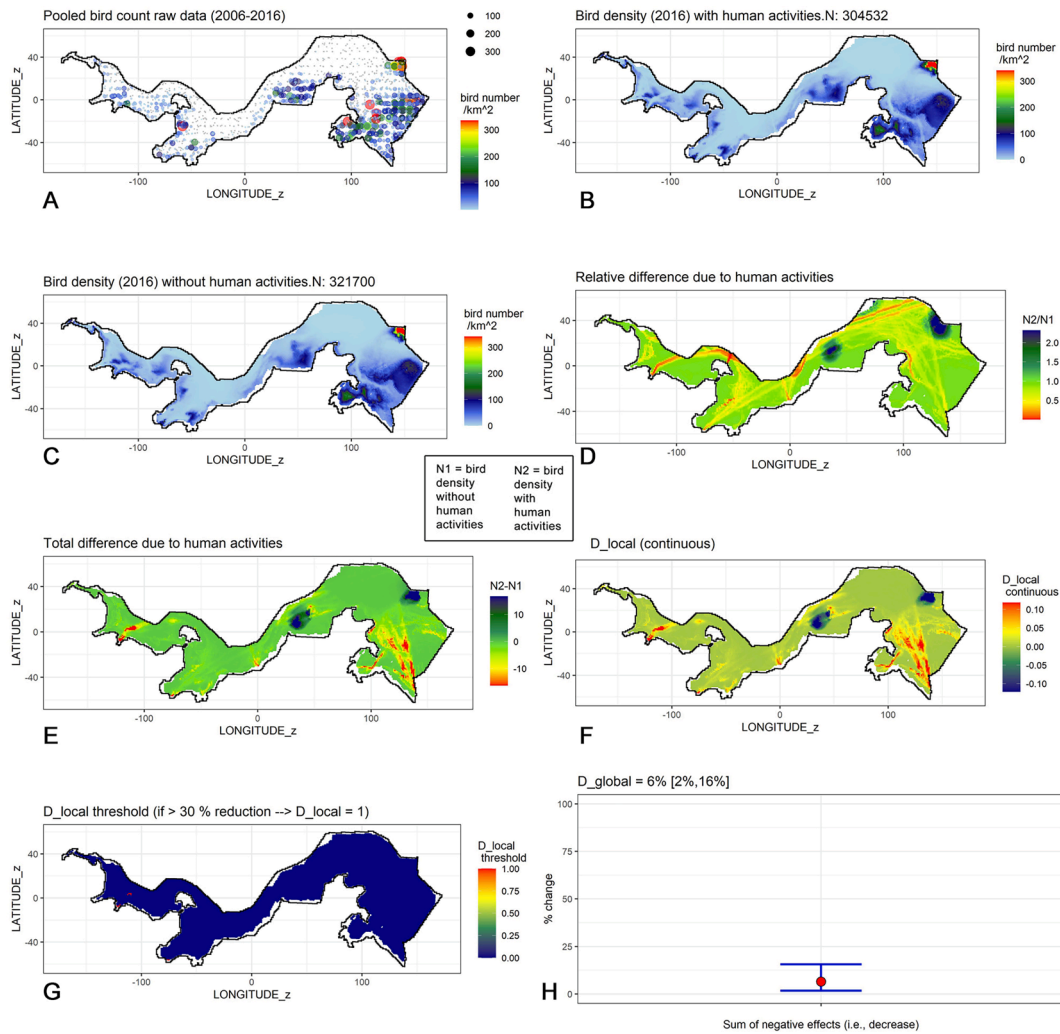
Fig. 7. Summary results for long-tailed ducks in the German Baltic Sea. For details see Fig. 3.

and further work has to be done, e.g., integrating additional natural and anthropogenic covariates, as well as a thorough evaluation of appropriate predictor formulations (e.g., considering nonlinear dependencies or appropriate spatio-temporal scales).

Importantly, the reference (what-if) scenario used in the current study did not reflect a purely natural state because the marine areas considered have been used by humans for centuries, and the birds have thus had to compromise between their optimal and available habitat requirements. Nevertheless, for important wintering areas such as the Pomeranian Bay, it was possible to show how important it is that certain activities such as shipping take place here only on a small scale. In these areas, activities should not further increase. The disturbed areas will thus continue to be used by the affected species without our knowing the biological population consequences. For example, the disturbances could lead to higher mortality or lower reproduction of the affected individuals due to reduced body condition. A similar problem exists for species that change their large-scale distribution patterns by moving to sub-optimal but less-disturbed areas, which cannot be assessed by the presented approach. These factors suggest that the provided estimates of disturbance are likely to be conservative.

The extent of disturbed habitat or the proportion of individuals disturbed in their habitat is reflected in our indicator by the D_{global}-value. But at which numerical value is Good Environmental Status (GES) achieved? In other words, at which D_{global}-value is the objective of the MSFD criterion "*the habitat for the species has the necessary extent and condition to support the different stages in the life history of the species*" no

longer met? In contrast to indicators that directly assess population sizes or their change through increased mortality or reduced reproduction, the extent of disturbed habitat cannot be directly translated into consequences for the development of population size. This is due to complex relationships in the density dependence of resource use and carry-over effects, which are not sufficiently known in the case of marine birds. A threshold might therefore only be set artificially. For example, there could be an egreement among experts on which value of D_{global} represents GES. It is also conceivable that GES is related to the confidence limits of the estimate, e.g., GES could be achieved when the confidence interval contains the value zero, i.e., when it is within the realm of possible that no habitat disturbance occurs at all. It needs to apply the indicator on a broader basis in order to arrive at a reasonable and applicable result here, taking into account further bird species, more marine regions and additional human activities.

4.2. Extending the power and scope of the tool

The basic approach presented here can be extended in various ways.

First, the analytic power of the tool could be enhanced by the inclusion of more or spatio-temporally better-resolved variables influencing the distribution of marine birds, particularly variables that better explain the spatial heterogeneities in abundance. For example, further information on trawler and ship densities (particularly with respect to the North Sea) should be used. Further, additional information on more human activities suspected or proven to cause disturbances could also be
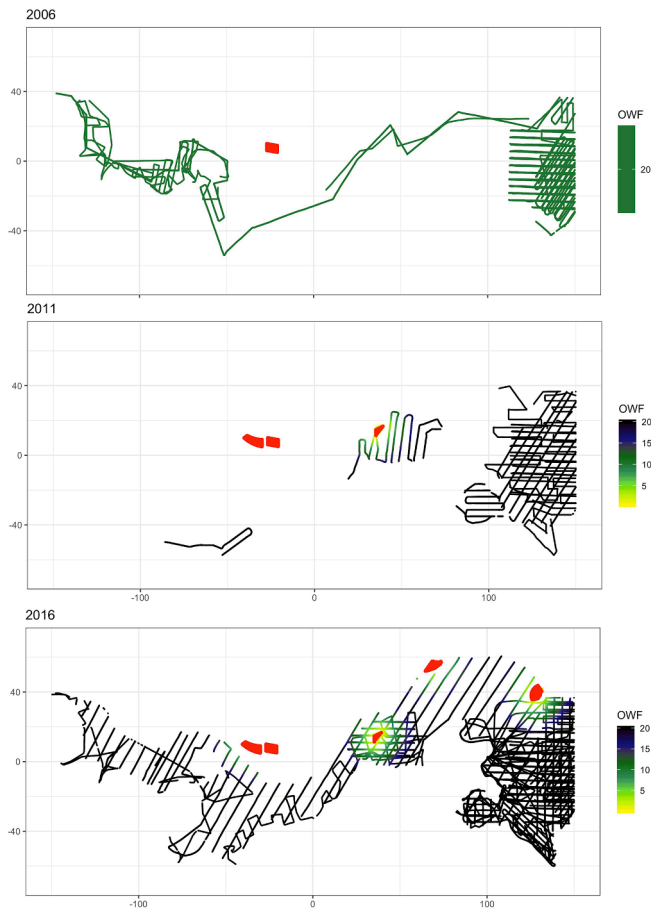
Fig. 8. Example validation of OWF-related activity variable for different years in the German Baltic Sea. Red polygons: operating OWFs (in sdGAMs used to calculate the variable "OWF"); lines: raw transect data, green/yellow: distance to nearest operating OWF (in sdGAMs the variable "OWF"). Note that distances > 10 *km* were set to 10 *km* (matching the definition of the variable *OWF*).
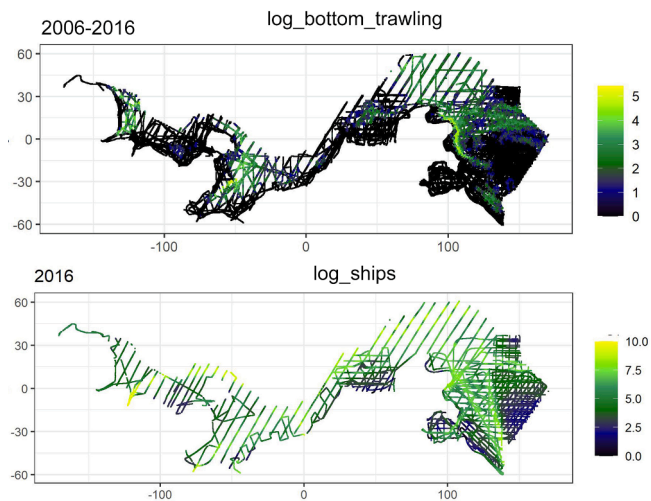

Fig. 9. Example validation of human activity variables 'log_ships' and 'log_bottom_trawling' in the German Baltic Sea.

included, such as aggregate extraction, drilling platforms, and recreational activities. Moreover, the robustness of the results would be increased by considering more environmental variables, including general variables such as productivity (e.g., chlorophyll A content of the

water, likelihood of frontal structures), and environmental characteristics closely related to the individual species. For example, the availability of benthic prey species or harvestable, ingestible, and digestible size classes (Kube and Skov, 1996) could be entered into the analyses if the data are available. In contrast to variables better explaining spatial distribution patterns, additional covariates explaining the observed year-to-year fluctuations and trends of the birds (such as yearly varying prey availability) would most probably not distinctly increase the precision of the estimated metrics. The reason is that they would not contribute to a better spatial prediction of the birds, and temporal heterogeneities are already covered by a (possibly nonlinear) phenomenological trend within the applied model. Further, D_{local} and D_{global} are calculated based on predicted spatial patterns for only the most recent year in the data, and thus do not directly depend on total yearly bird numbers (because abundance is rescaled for each species).

Second, seasons other than the wintering period for marine birds need to be considered to provide a more comprehensive picture of habitat quality. Possible important seasons could be the moulting period for seaducks in the summer, or the spring staging of various species before their long-distance migratory flights to Arctic breeding grounds; e.g., the German North Sea is much more important for red-throated loons as a spring staging site than in the winter (Mendel et al., 2019), and moulting seaducks are prone to disturbance from leisure activities (Petersen et al., 2017). However, to demonstrate the tool, we limited the current analysis to a single season and a small number of species.

Third, this study was tailored to marine birds that linger offshore, and the indicator could potentially be extended to birds living in coastal waters, either during the non-breeding period (e.g. some species of ducks and grebes) or when foraging during the breeding season.

Fourth, statistical methods for data integration and spatio-temporal ecological data are rapidly evolving (Miller et al., 2018; Zuur et al., 2017) and the presented approach could possibly benifit from these developments. For example, instead of applying a two-step-procedure (similar to Ref. Mercker et al. (2021)), a thinned point process model could be used instead to simultaneously analyse all detection and abundance related processes (Miller et al., 2018). Furthermore, survey data from other sources (such as bird counts from the shoreline) could possibly also be integrated; corresponding methods are e.g. presented in Mercker et al. (2021) and Miller et al. (2018). Finally, the recently developed integrated nested Laplace approximation (INLA) makes it possible to fit complex hierarchical Bayesian models within feasible computation times (Zuur et al., 2017). These approaches may provide a more straight forward separation between observation methods and the (latent) abundance process common across the different datasets.

4.3. Conclusion

The statistical approach developed here was able to integrate and assess the cumulative effects of different human activities on marine-bird habitat quality in terms of disturbance. This tool may therefore contribute to status assessments of marine birds in their environment. In conjunction with other indicators of bird abundance and reproductive rate (and possibly mortality in the future), this novel habitat indicator can help to identify problems in the marine environment and thus support measures to remedy them. This habitat indicator may thus be a valuable component of marine-assessment frameworks, such as those carried out in relation to Regional Sea Conventions or the MSFD.

CRediT authorship contribution statement

Moritz Mercker: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing - original draft. **Volker Dierschke:** Conceptualization, Writing - original draft, Supervision, Funding acquisition, Validation, Methodology, Writing - review & editing. **Kees Camphuysen:** Validation, Methodology, Writing - review & editing. **Axel Kreutle:** Validation, Methodology, Writing - review & editing,

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Appendix A

Further figures validating the implementation of data regarding human activities.

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