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ARTICLE

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Developing an ecological risk-based approach to facilitate licensing offshore wind development

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Abstract

The increasing societal demands on the seabed due to the expansion of offshore wind energy highlight an urgent need to better understand the relationship between human activities and the structure and function of seabed ecosystems. In this paper, we propose an empirically derived approach to quantify relative ecological risk to benthic invertebrate assemblages from future offshore wind development. Using benthic data from over 22,000 seabed grab samples across the UK shelf and wider North Sea contained in OneBenthic, a freely available online data repository, we produce modeled raster layers for three biological criteria upon which we define ecological risk. These are (1) relative benthic sensitivity based on response traits expression, (2) benthic biodiversity, and (3) assemblage rarity. We create a holistic map based on these three layers and discuss how this information may be used, using a new online tool, to assist decisions regarding future offshore development to minimize potential impacts on benthic assemblages. Given the broad spatial coverage of our maps, our tool could help expedite the expansion of offshore wind in a large area of the northeast Atlantic, whilst the underlying methodology can be applied to other regions with extensive benthic survey data, thereby facilitating international commitments to reduce carbon emissions. We propose how the maps may be improved and discuss the future incorporation of extra criteria into the framework.

KEYWORDS
assemblage structure, benthic sensitivity, biodiversity, renewable energy, sustainable management

INTRODUCTION

We are currently witnessing significant global growth in renewable energy generation from offshore wind. In 2023, the industry added 11 GW, bringing the global total to over 75 GW. This represents a 24% year-on-year increase, marking the second-largest growth ever, despite challenges in key markets (Global Wind Energy Council, 2024). Demanding Governmental future targets are being set for many countries which is driving this expansion. For example, the UK Government in 2019 passed an Act (The Climate Change Act 2008 (2050 Target Amendment) Order 2019; http://www.legislation.gov.uk/uksi/2019/1056/contents/made) that set out a framework to reduce net emissions of greenhouse gases by 100% relative to 1990 levels by 2050, making the United Kingdom a "net zero" emitter. An increased reliance on offshore wind energy is expected to help meet this, with a targeted 50 GW from this sector alone by 2030 (UK Government, 2022). This situation is reflected in other European countries (Birchenough & Degraer, 2020; Korpinen et al., 2021) and countries across the globe (Galparsoro et al., 2022; Putuhena et al., 2023; Watson et al., 2024). Current and future offshore windfarm (OSW) arrays are situated in areas that often coincide with, or overlap, other seabed uses (e.g., demersal fishing, aggregate extraction, dredged material disposal), each imposing distinct direct and/or indirect impacts on the seabed (Goodsir et al., 2015; Guşatu et al., 2021; Palanques et al., 2014). The combined and cumulative effects resulting from the current increase in human activities, and the demands and pressures on marine resources resulting from multiple industrial sectors, significantly increase the potential to induce long-term and possibly permanent changes in marine ecosystem functions (Dannheim et al., 2020; Houde et al., 2014; Nogues et al., 2020). As such, there is a growing need to manage the demands associated with the expansion of offshore wind in a sustainable manner to ensure that the role the seabed plays in supporting important ecosystem services is safeguarded (Stelzenmüller et al., 2018; Watson et al., 2024).

Most marine ecosystems have been altered by human activities (Halpern et al., 2008, 2015). Indeed, as much as 41% of the World's oceans have been subject to multiple anthropogenic perturbations (Halpern et al., 2008), with coastal and shelf seas being particularly susceptible due to their proximity to the World's largest cities (Crain et al., 2008; Houde et al., 2014). The role the marine environment plays in supporting important ecosystem processes and in stemming further impacts associated with climate change is becoming increasingly understood (Ruckelshaus et al., 2013). Sedimentary benthic ecosystems, in particular, play an integral role in a number of important ecosystem services (Hope et al., 2019; Rife, 2018; Thrush et al., 2013), but their capacity to effectively provide such provisioning (e.g., pharmaceutical compounds) and supporting services (e.g., sediment stabilization, primary and secondary production) may be directly and/or indirectly altered by physical disturbances (Epstein et al., 2022; Tiano et al., 2019; Watson et al., 2024).

For many decades, the structural characteristics or qualities of benthic invertebrate assemblages have been described and quantified using a variety of approaches, from simple metrics describing specific features of the assemblage (e.g., total abundance, diversity, and evenness) to more involved, multivariate approaches which impart taxonomic identity into community descriptions (Boon et al., 2011; Reiss & Kröncke, 2005). The latter enables benthic assemblages to be classified into more discrete categories, or "biotopes," often defined according to their most abundant or characterizing taxa. All these approaches provide invaluable insights into how benthic assemblages vary, both with respect to natural environmental drivers (e.g., sediment type, depth, temperature) and in response to human activities. More recently, information regarding the behavioral, morphological, and life history characteristics of the individuals within the assemblage, or Biological Traits Analysis (BTA), has been used to provide additional insights into their potential ecological functioning (Beauchard et al., 2017; Bremner et al., 2006) or their response to human pressures (Bolam et al., 2014, 2023; van Denderen et al., 2015). Given this, the current challenge faced by applied marine scientists is how to assimilate this information into a meaningful, more unified manner that can be easily understood and adopted by the relevant sectoral practitioners and associated licensing authorities (Dannheim et al., 2020).

In this paper, using a "big data" (Peters et al., 2014) approach to the macrofauna (benthic invertebrates), we develop an ecological approach to identify spatial differences in marine benthic assemblages to their risk associated with future offshore wind development. Our method is based on modeling unique characteristics of benthic assemblages that we consider are relevant to, and thus should be included in, decisions regarding the location of future sites. The criteria we propose are (1) assemblage sensitivity; (2) assemblage biodiversity; and (3) assemblage rarity. Firstly, we apply BTA, using specific response traits that determine a species' response to a nonspecific, physical impact to the seabed, to define the relative sensitivity of benthic macrofauna. Secondly, we assess differences in macrofaunal biodiversity using an approach developed in a companion study (Cooper et al., 2023), which integrates alpha-, beta-, and gamma-diversity metrics. Finally, we identify assemblages that show low ubiquity (i.e., high rarity) across our study area of the UK continental shelf and the wider North Sea. We define areas of varying ecological risk based on each of these criteria in turn, then bring this information together into a holistic, composite map revealing relative risks from future OSW development. We present a novel, publicly accessible online tool wherein benthic ecological risk of any area of interest can be quantified. We discuss how our results, and potential future iterations, could inform OSW licensing by guiding developments away from areas where benthic assemblages show greater sensitivity, and/or highest biodiversity and/or to spatially rare assemblages. As our outputs describe inherent characteristics of benthic assemblages across large areas, they may assist in cross-sectoral decisions as part of national marine spatial planning approaches.

METHODS

The OneBenthic database

The empirical macrofaunal data used in this study are contained in the OneBenthic database (https://rconnect.cefas.co.uk/onebenthic_portal/). OneBenthic brings together publicly available disparate benthic datasets (macrofaunal abundance/biomass and sediment particle size) in a cloud-based PostgreSQL database. As of October 17, 2024, the database contained 53,705 samples collected between 1969 and 2023. However, ~94% of the selected dataset used in this analysis was collected between 2000 and 2023, ensuring that the majority of data reflect contemporary conditions. The spatial extent of the dataset spans UK shelf waters and regions of other northeast Atlantic countries such as France, Belgium, the Netherlands, Germany, Denmark, and Norway. The OneBenthic database incorporates taxonomic information from the World Register of Marine Species (WoRMS, see https://www.marinespecies.org/), allowing data to be outputted using standardized nomenclature. WoRMS data are accessed via the R package "worms," with each taxon uniquely identified by the aphiaID field. From the available dataset, we selected a subset of 37,925 samples (Figure 1) for which the data were considered comparable, that is, sampled using a 0.1-m^2 grab or core and processed using a 1-mm sieve and outside all seabed boundaries licensed for anthropogenic pressures (e.g., sediment extraction, disposal). Colonial taxa were included and given a value of one. A fourth-root transformation was then applied to the raw abundance data to downweigh the influence of highly abundant taxa. To mitigate spatial autocorrelation in the data, following a semi-variogram approach adopted by Cooper et al. (2019), samples less than 50 m apart were removed from the dataset, reducing the overall number to 22,814.

Figure 2 shows a schematic summarizing the steps from OneBenthic raw data to the production of our ecological risk layers (described in the *Quantifying the risk elements* section).

Quantifying the risk elements

Based on the abundance data in OneBenthic, the procedure to create 100% coverage maps of each of the three risk elements varied. The individual steps for each criterion are described below.

Sensitivity

A suite of seven biological traits, considered relevant to determine the potential sensitivity of macrofaunal taxa to the impacts associated with OSW, were selected (Table 1). Our seven traits relate to a species' response to the combination of physical disturbances associated with the main interacting, sector-specific impacts associated with OSW (e.g., abrasion, increased suspended solids, smothering) rather than to each of these in turn. The seven traits selected are similar to those adopted by Bolam et al. (2014) to define sensitivity to demersal trawling. Given that the largest spatial footprint impact associated with OSW relates to sediment scour and abrasion, these traits represent a good basis. Each of the seven traits was subdivided into several "modalities," chosen to encompass the range of possible attributes of all the taxa; for example, modalities for the mobility trait were swimming, burrowing, crawling, or sessile. A total of 31 modalities were established for the seven selected traits (Appendix S1: Table S1).

Trait information was obtained from Clare et al. (2022) wherein traits information, principally from published journal papers and books, and websites of various scientific institutions (e.g., http://marlin.ac.uk/biotic/) are available. The data source uses a fuzzy coding approach (Chevenet et al., 1994) that allows taxa to exhibit multiple expressions for the same trait, thus avoiding the obligate assignment of a taxon to a single category which can lead to inaccurate characterization of biological or ecological profiles (Usseglio-Polatera et al., 2000). Of the 3998 taxa within our dataset, traits information from Clare et al. (2022) was lacking for 1000 taxa, principally since many taxa within OneBenthic are at species level while the trait information of Clare et al. (2022) is based at the genus level or above. For these taxa, traits information was assigned based on traits for the most closely related taxa (mostly for genera within the same family). Taxa that were present in less than 0.1% of the samples and, where sampled, attained a mean abundance of less than 10 per sample were excluded.

Sample (assemblage) sensitivity values were derived using the approach outlined in Figure 3. Firstly, the 31 trait modalities were assigned a value for taxon modality sensitivity, ranging from 1 (low) to 10 (high), according to how expression of that modality governs a taxon's sensitivity to (or response from) the physical impacts associated with OSW construction and operation (see Table 1). These values were multiplied by trait modality fuzzy scores and then summed to generate individual taxon sensitivity values. The scoring of overall sensitivity of a particular taxon is governed by all seven traits on an equal basis.

The mean sample sensitivity value was calculated by multiplying square-root taxon-transformed abundances by their corresponding taxon sensitivity value—these were then summed and divided by the total untransformed sample abundance (Figure 3). In this manner, the traits

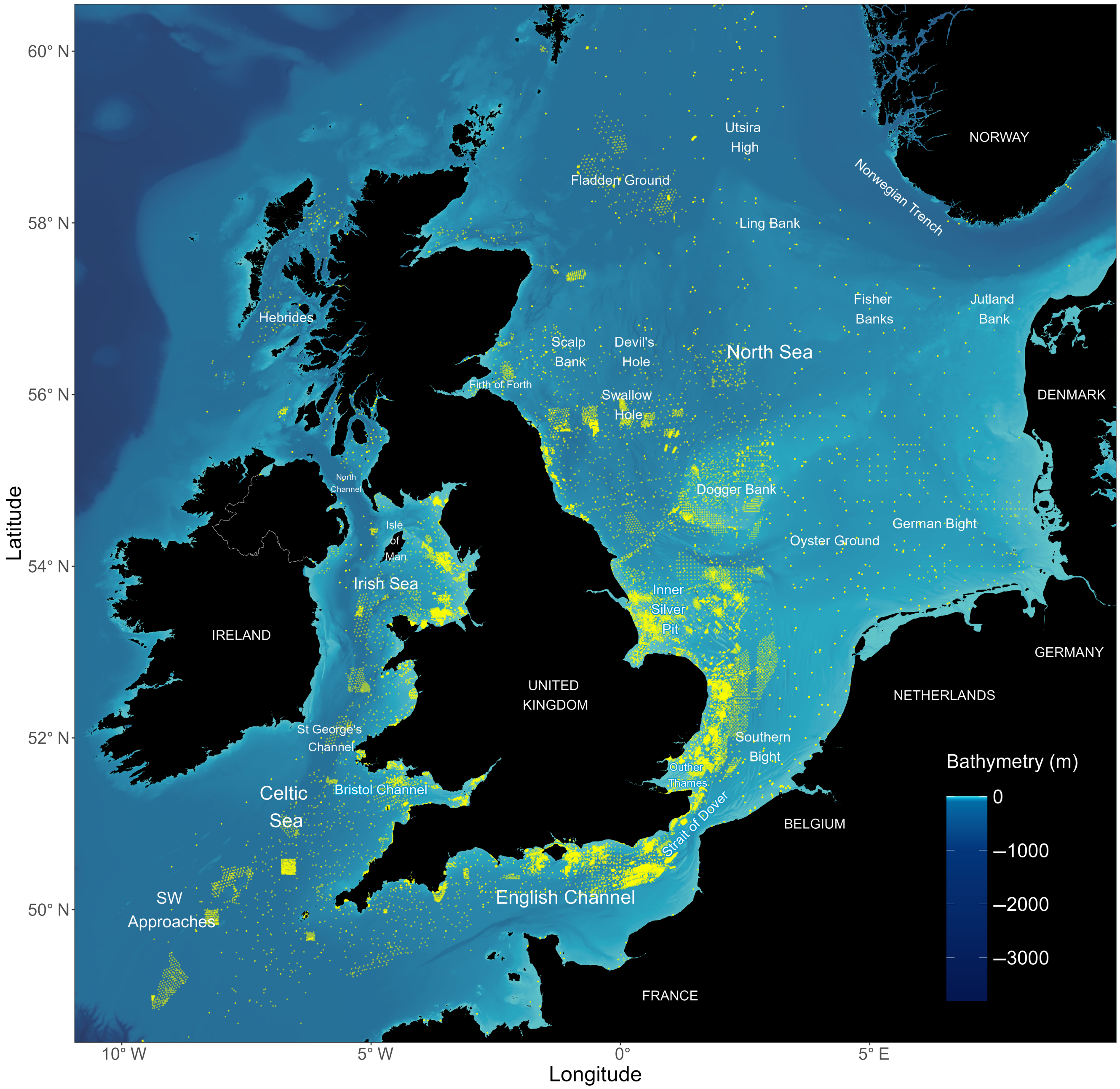


FIGURE 1 Locations of the 37,925 samples from OneBenthic. Background bathymetry from GEBCO Grid (GEBCO Compilation Group, 2023). Map lines delineate study areas and do not necessarily depict accepted national boundaries.

expressed by all species present in the sample contribute to the assemblages' relative sensitivity.

Using a Random Forest modeling approach based on regression trees (Breiman, 2001; Cutler et al., 2007), the sample sensitivity scores were used to create a 100% coverage sensitivity layer. Predictor variables used in modeling were selected by initially running single models to identify those with a good correlation with the response variable. A pairs plot was then used to remove covariates. Model performance was assessed using R^2 and root mean squared error (RMSE), both metrics based on a comparison of observed and predicted model outputs. Cross-validation, whereby the model was run 10 times using different subsets of the data, was performed to create the final model based on a mean of the 10 runs and a corresponding confidence (coefficient of variation, or "CV") layer.

Biodiversity

A heat map representing benthic biodiversity was produced in a parallel study (Cooper et al., 2026). Based on

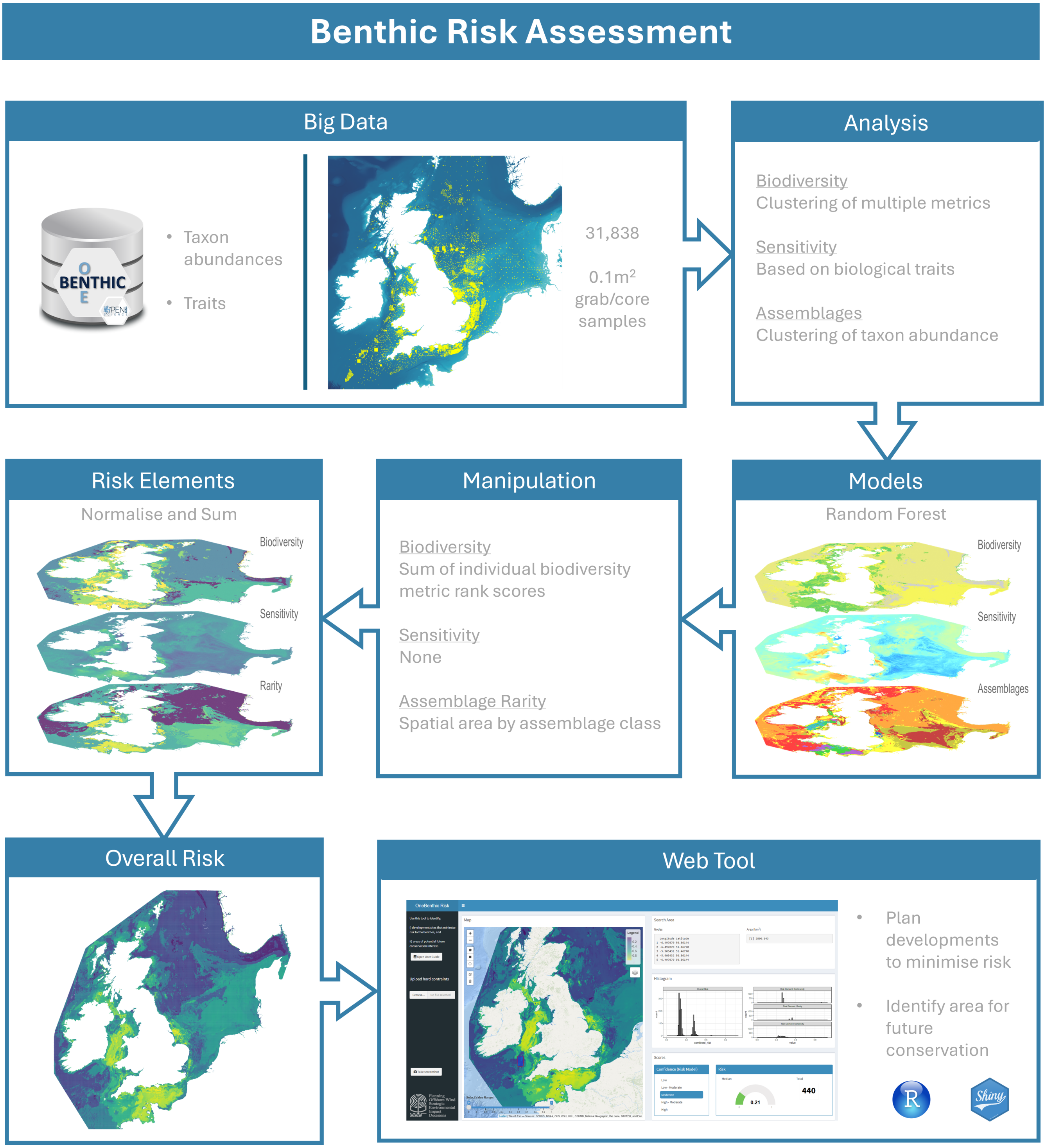


FIGURE 2 Schematic illustration summarizing the steps from OneBenthic raw data to the production of our ecological risk layers.

the same dataset used in the present study (see *The OneBenthic database*), Cooper et al. (2026) produced multiple maps revealing different aspects of biodiversity, based on metrics that give different weights to relative species abundance (Hill numbers 0, 1, and 2, and abundance) and assessed within the Whittaker (1972) framework (alpha-, beta-, gamma-diversity). These biodiversity metrics were then synthesized into a single map, based on *k*-means clustering (R function "kmeans") of the individual metrics followed by Random Forest modeling. The resulting map identifies eight biodiversity cluster groups, ranked according to the sum of cluster centers, and colored using a heat map color scale. In the present study, it was necessary to derive a numeric scale for biodiversity

TABLE 1 Trait modality sensitivity scores (values in square brackets) for the seven traits used to estimate relative sensitivity of macrofaunal taxa.

	Sensitivity		
Trait	**Low**	**Medium**	**High**
Morphology	Exoskeleton [1] Crustose [2] Cushion [3]	Tunic [4] Soft [7]	Stalked [9]
Living habit	Free living [1] Crevice/hole/under stones [2] Tube-dwelling [3]	Burrow-dwelling [4] Epi/endo zoic/phytic [7]	Attached to substratum [9]
Sediment position	Deep (>10 cm) [1] Mid-depth (5-10 cm) [3]	Shallow (0-5 cm) [7]	Surface [9]
Mobility	Swim [1]	Burrow [7]	Sessile [10] Crawl / creep / climb [8]
Longevity (years)	<1 [1] 1–2 [2]	3–10 [7]	>10 [9]
Larval development location	Planktotrophic [1]	Lecithotrophic [5]	Direct [9]
Egg development location	Eggs shed into water [1] Asexual/Budding [2]	Eggs laid on or attached to bed [5]	Eggs brooded by adults [10]

from the categorical values derived by Cooper et al. (2026). This was performed in the present study by substituting the categorical classes (1–8) with the summed *k*-means cluster center values for each cluster group (see Table 2). This method maintained the relative biodiversity similarities between cluster groups, allowing them to be translated onto a continuous scale.

Assemblage rarity

The macrofaunal abundance data from OneBenthic (see *The OneBenthic database*) were used to identify the spatial distribution of discrete faunal groups based on multivariate taxonomic structure, following the method adopted by Cooper and Barry (2017). Data were first subjected to a fourth-root transformation to ensure the appropriate weighting of colonial and rarer taxa in the analyses. Clustering was undertaken using the *k*-means (R function "kmeans") approach with the MacQueen (1967) algorithm. This clustering method works by choosing the cluster solution that minimizes the within-cluster sum of squares, summed over all variables and clusters. A *k*-means clustering approach was specifically chosen due to its utility for analyzing large datasets. The number of cluster groups was decided through reference to an "elbow plot," and it represents a balance between representing biological complexity and broader spatial patterns (Appendix S1: Figure S1).

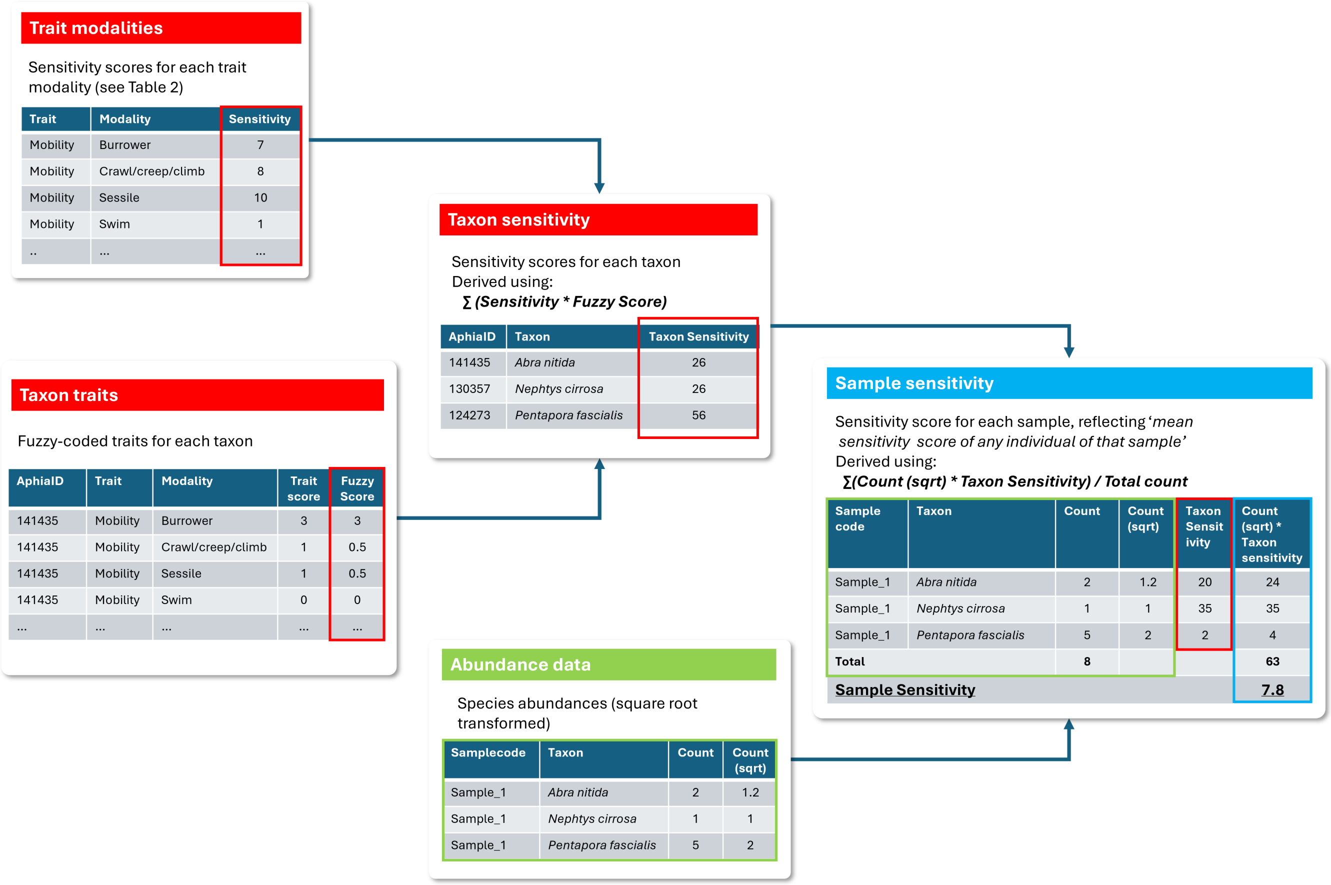
To establish the relationship (i.e., similarity/dissimilarity) between the different faunal cluster groups, the absolute distances between each of the cluster centers across all variables (R function "dist") were computed. The resulting dissimilarity matrix was then used to generate a dendrogram based on group average hierarchical clustering (R function "hclust"). Informed by the dendrogram (Appendix S1: Figure S1b), each group was assigned a code (and color) to show the relatedness of the groups. To allow an understanding of the biological characteristics of each macrofaunal group, we used both cluster centers and the SIMPER routine in Primer v7 (Clarke & Gorley, 2015) to identify characterizing taxa. In addition, mean univariate measures of taxon richness and total abundance of each were calculated, as well as the proportions of taxa by major phyla.

Random Forest modeling was then applied to produce a 100% coverage layer for macrofaunal assemblages (see *Modeling the risk elements*). The spatial extent of each categorical faunal assemblage cluster group was determined and subtracted from the total raster extent. In this way, assemblage groups with limited spatial extent have high scores, while groups that are widespread have lower scores, thus providing a measure of rarity. Cluster groups were substituted in the raster for their rarity scores, thus providing a numeric rarity layer.

Modeling the risk elements

Environmental predictors

Various raster predictor layers for environmental variables affecting marine benthic macrofauna were sourced



Trait modalities

Sensitivity scores for each trait modality (see Table 2)

Trait	Modality	Sensitivity
Mobility	Burrower	7
Mobility	Crawl/creep/climb	8
Mobility	Sessile	10
Mobility	Swim	1
..	…	…

Taxon sensitivity

Sensitivity scores for each taxon
Derived using:
*∑ (Sensitivity * Fuzzy Score)*

AphiaID	Taxon	Taxon Sensitivity
141435	*Abra nitida*	26
130357	*Nephtys cirrosa*	26
124273	*Pentapora fascialis*	56

Taxon traits

Fuzzy-coded traits for each taxon

AphiaID	Trait	Modality	Trait score	Fuzzy Score
141435	Mobility	Burrower	3	3
141435	Mobility	Crawl/creep/climb	1	0.5
141435	Mobility	Sessile	1	0.5
141435	Mobility	Swim	0	0
…	…	…	…	…

Sample sensitivity

Sensitivity score for each sample, reflecting '*mean sensitivity score of any individual of that sample'*
Derived using:
*∑(Count (sqrt) * Taxon Sensitivity) / Total count*

Sample code	Taxon	Count	Count (sqrt)	Taxon Sensitivity	Count (sqrt) * Taxon sensitivity
Sample_1	*Abra nitida*	2	1.2	20	24
Sample_1	*Nephtys cirrosa*	1	1	35	35
Sample_1	*Pentapora fascialis*	5	2	2	4
Total		**8**			**63**
Sample Sensitivity					**7.8**

Abundance data

Species abundances (square root transformed)

Samplecode	Taxon	Count	Count (sqrt)
Sample_1	*Abra nitida*	2	1.2
Sample_1	*Nephtys cirrosa*	1	1
Sample_1	*Pentapora fascialis*	5	2

FIGURE 3 Flow chart for calculation of sensitivity scores. For information regarding the final step ("Web Tool") please see *Web application*.

for use in modeling (Appendix S1: Table S2). These layers came from Bio-ORACLE (https://www.bio-oracle.org/; Assis et al., 2018; Tyberghein et al., 2012) and Mitchell, Aldridge, and Deising (2019). All Bio-ORACLE layers were obtained using the Download Manager with the following options: Dataset version: Bio-ORACLE v3; Period of layers = Present-day conditions [decade 2000–2010]; Depth of layers = Benthic layers; Layers to download = Mean and Range. Available layers from Mitchell, Aldridge, and Deising (2019) included data products (percent Mud, percent Sand, and percent Gravel; https://doi.org/10.14466/CefasDataHub.63), and associated predictor variables (i.e., Water Depth, Wave velocity, Current speed, Suspended inorganic particulate matter (summer, winter, and mean); https://doi.org/10.14466/CefasDataHub.62). Six additional environmental layers representing seafloor topography were derived from the bathymetry layer (water depth) using SAGA GIS tools for QGIS (v.3.2; Conrad et al., 2015). These included a variable combining topographic slope length and steepness (gradient over the length, the LS-Factor), and the relative location along the entire length of a discrete slope ranging from 0 to 1 from the bottom to the top of the slope (relative slope position [RPS], Böhner & Selige, 2006). Raster layers from Bio-ORACLE were cropped and resampled so that the spatial extent and pixel resolution matched those from Mitchell, Aldridge, and Deising (2019).

Response variables (sensitivity and assemblage rarity)

Our study required 100% coverage raster layers for each of our criteria. Whilst the layer for biodiversity was available from Cooper et al. (2026), it was necessary, in the current study, to produce corresponding spatial models for sensitivity and faunal assemblages. Full coverage maps for each of these layers were produced using Random Forest modeling, an ensemble method where a large number of decision trees (typically 500–1000) are built using random subsets of the samples and predictor variables (Breiman, 2001; Cutler et al., 2007). Regression trees were used for the continuous sensitivity variable, with predictions based on averages from all trees. In contrast, classification trees were used for the categorical

TABLE 2 Biodiversity values of each macrofaunal biodiversity cluster group (Cooper et al., 2023), derived from the ranked sum of cluster centers following a *k*-means clustering approach.

Biodiversity cluster group	Biodiversity value
Bio-A	4.83
Bio-B	4.34
Bio-C	4.27
Bio-D	4.06
Bio-E	3.85
Bio-F	3.28
Bio-G	3.14
Bio-H	2.39

assemblage clusters, with spatial predictions made either as class-specific probabilities, derived from the proportion of component trees predicting the class, or as the class with a majority vote. Random Forest was selected for its suitability in predicting numeric and factor-type response variables and its ability to account for multiple interactions and nonlinear relationships between the response and predictor variables (Rodriguez-Galiano et al., 2012). The models were built in R (R Core Team, 2024) using the "randomForest" implementation in the "randomForest" package (Liaw & Wiener, 2002) and were run with the default settings using 1000 trees. Preliminary single models using all environmental variables were initially run to select the best variables and remove those with high covariance. Variables were excluded from the models based on redundancy (high correlation with another variable) or a poorly defined relationship with the response variable. When addressing correlations between variables, the variable least likely to express a mechanistic link with biodiversity was removed. Covariance between environmental variables was investigated using values extracted for the sample locations from the predictor rasters. Correlation analysis (Appendix S1: Figure S2) was used to represent covariance and identify the main predictor variables. Although Random Forest models are not sensitive to covariance effects (Huang & Boutros, 2016), models with fewer predictor variables are simpler and easier to interpret. Additionally, the calculation of variable importance statistics is more accurate in models with fewer variables, as highly correlated predictor variables can mask the importance of other variables by being interchangeable in the component trees. Cross-validation via repeated subsampling was performed to evaluate the robustness of the model estimate and predictions for data subsetting. This also allowed additional information to be extracted from the model outputs to create maps of confidence in the predicted distribution (Mitchell et al., 2018). The cross-validation was done on 10 split sample datasets with 75% of the data used to train and 25% to test models, randomly sampled within the levels of the response variable to maintain the class balance. For numeric variables (i.e., sensitivity), the final model outputs were plotted as the mean of all 10 runs. A confidence map layer consisting of the CV (10-run SD/mean) was also produced. Model performance was evaluated using R^2. All accuracy statistics are presented as means and SDs of the scores from the 10 model runs. For the assemblage clusters, the final model output was plotted as the cluster class with the majority vote of all 10 model runs. Three confidence layers were also produced consisting of: (1) the frequency of the most common class, (2) the average probability of the most common class, and (3) combined confidence computed by multiplying the previous two. Model performance was assessed using multiple, commonly used accuracy statistics calculated from a confusion matrix. Sensitivity, specificity, and balanced accuracy (BA) were calculated both for individual classes and for the model overall. Thus, the final maps from the model presented consist of (1) the predicted distribution of each assemblage cluster class (derived from a majority vote of 10 model runs each indicating the most likely class) and (2) a confidence map layer (high values represent high confidence) calculated by multiplying the frequency of the most common class by its average probability over the 10 model runs.

Combined risk

Once the modeled risk layers were derived for each of our three risk elements (sensitivity, biodiversity, assemblage rarity), the values for each were normalized using a rescale function (value minus min value divided by max value minus min value) to bring their values onto a common scale from 0 (lowest) to 1 (highest). These three rasters were then "stacked" and summed to create a final continuous variable for risk (values from 0 to 3), with values again normalized to bring them on to a scale from 0 (least risk) to 1 (most risk).

Assessing model performance

The composite risk layer was generated by summing three input layers—sensitivity, biodiversity, and rarity—rather than modeling risk directly. As a result, no confidence surface was produced during its generation. To quantify confidence in the composite layer, we derived a composite confidence surface by combining the confidence information associated with each input.

For **sensitivity**, a CV raster was available from model outputs. Because higher CV values represent greater uncertainty, we transformed the raster into a confidence surface by subtracting CV values from 1. For **biodiversity** and **rarity**, confidence layers were originally derived from the categorical models. In our derivation of the risk layer, we substituted cluster groups for the raw biodiversity and rarity scores, but we retained the original confidence layers to quantify certainty. These layers were used directly without further transformation.

The three confidence surfaces were then averaged to produce the composite risk confidence surface:

$$\mathrm{Confidence}_{\mathrm{Risk}} = \frac{\mathrm{Confidence}_{\mathrm{sensitivity}} + \mathrm{Confidence}_{\mathrm{Biodiversity}} + \mathrm{Confidence}_{\mathrm{Rarity}}}{3}.$$

Higher values in $\mathrm{Confidence}_{\mathrm{Risk}}$ indicate greater confidence in the composite risk prediction. The resulting surface was classified into five ordinal levels (Low, Low–Medium, Medium, High–Medium, High) for visualization in the web application (see below).

Web application

To allow stakeholder utilization of our risk layers, we produced an R shiny web application (app) using the “shinydashboard” package (Chang & Ribeiro, 2021) which is shared using the Posit Connect software (see https://posit.co/products/enterprise/connect/). The app features a sidebar panel, leaflet map, and results boxes. The app allows the user to display rasters for the combined risk layer or for each of the risk elements layers (i.e., sensitivity, biodiversity, and assemblage rarity) separately. The app also allows a variety of relevant polygons to be displayed, either via the map “control panel” or via user upload of geoJSON files. Drawing tools available in the “leaflet map” allow users to easily create areas of interest (or polygons). Based on the map and underlying raster layers, the application outputs: (1) drawn polygon node coordinates, (2) median ecological risk values from the raster, and (3) a total ecological risk score based on a summation of all raster cell values within the area of interest. The app also shows histograms, created using the R “ggplot” package (Wickham, 2016), of the risk values of all the modeled cells within the area of interest for each individual risk element and one for the combined risk. The user-defined polygons can be moved or edited, and the application automatically updates the outputted risk values (1–3). The app also includes a screenshot facility that allows users to output results to a .pdf file.

RESULTS

Risk elements

Sensitivity

The macrofaunal sensitivity model (Figure 4a) had R^2 and RMSE values of 0.53 (±0.01) and 2.15 (±0.03), respectively, indicating acceptable performance. There are clear, large-scale patterns in macrofaunal sensitivity to offshore wind impacts across the study region. Areas of highest sensitivity include the English Channel, inshore regions of the east coast of England, mid Irish Sea area, and along the Norwegian Trench (see Figure 1 for location names). Areas of relatively lower macrofaunal sensitivity characterize the southern North Sea and parts of the northern and much of the west coast of Scotland.

Biodiversity

Differences between areas of seabed occupied by cluster groups 3 and 4 from the original model (Figure 4b) are much less apparent in the numeric model output, reflecting the minor differences in absolute biodiversity between these groups (Table 2). This similarity in biodiversity between cluster groups is also evident between groups 1 and 2. When placed onto a continuous biodiversity scale (Figure 4c), it is evident that the regions of greatest macrofaunal biodiversity occur across the whole of the English Channel, the eastern Celtic Sea, mid Irish Sea, Inner Hebrides (west coast of Scotland), and across inshore regions of the southern North Sea. Areas where macrofaunal biodiversity is relatively poor are located in the southern North Sea, mid-North Sea, and along certain areas off the west coast of Scotland.

Assemblage rarity

Model performance for macrofaunal assemblages was good, with an overall BA of 0.79 (see Appendix S1: Table S4). Spatial extent of assemblage cluster groups varies significantly from 892 km^2 (A2a) to 323,617 km^2 (D2b) (see Table 3), representing 0.1% and 35.8% of the study area, respectively. Assemblages with the most limited spatial extent are typically those with highest richness and abundance (see assemblage characteristics shown in Appendix S1: Table S3). These groups include A2a, found in patches off the east coast of England; A1, found at Inner Silver Pit and in the mid Irish Sea; and C1b, found in a variety of locations including coastal areas of the western English Channel and off the coast of

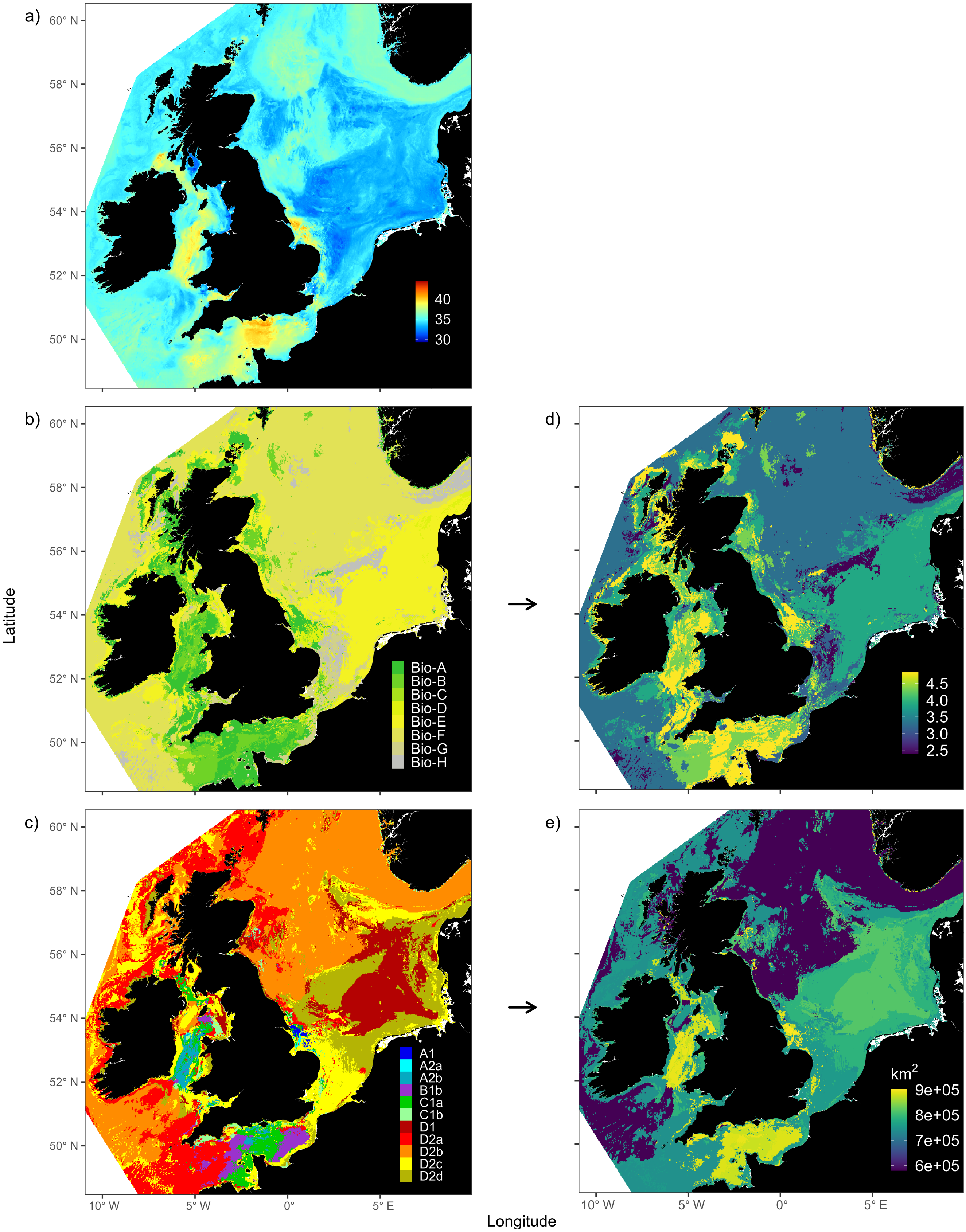


FIGURE 4 Risk element models for (a) sensitivity (numeric model), (b) biodiversity (categorical model from Cooper et al. (2026)), and (c) assemblages (categorical model), together with numeric derivatives for (d) biodiversity and (e) assemblage rarity.

TABLE 3 Spatial extents (in square kilometers and percentage of total) for faunal assemblage clusters.

Group	Area (km^2)	Percentage of total	Inverse area (km^2)
A2a	892	0.1	902,574
A1	1574	0.2	901,893
C1b	9638	1.1	893,828
A2b	11,276	1.2	892,190
B1b	17,456	1.9	886,010
C1a	26,593	2.9	876,874
D1	86,830	9.6	816,637
D2d	114,933	12.7	788,534
D2c	148,718	16.5	754,748
D2a	161,940	17.9	741,526
D2b	323,617	35.8	579,850
Total	903,466		

Note: The area not occupied values (in square kilometers: final column) are those used to directly reflect spatial rarity for the risk assessment. Groups are ordered according to increasing area.

North Wales. These assemblages, together with several others such as C1a and B1b which are found principally in the English Channel, form the main regions of highest ecological risk regarding assemblage rarity (Figure 4f). In contrast, other assemblage types are widespread and ubiquitously span larger regions of the study area. For example, the most spatially expansive group D2b dominates the majority of the northern North Sea and much of the southern Irish Sea, while the next ubiquitous assemblage, D2a, represents large parts of the southwestern part of the study area and much of the coast of Scotland, Northern Ireland, and the Republic of Ireland (Figure 4e).

Combined risk

Each of the three individual risk elements (Figure 4a,c,e) was used to create a holistic, combined ecological risk layer by summing each of the standardized risk values (Figure 5). The resulting overall ecological risk to OSW development raster map shows that spatial variations in benthic assemblage risk occur at different spatial scales for different regions of the study area. For example, large regions of the most southwestern part of the area and the northern North Sea are represented by homogenous areas of low relative ecological risk (values around 0.2) (Figure 5). Large parts of the southern North Sea (except the inshore areas of the English coast) show low, but slightly higher, ecological risk (risk values ~0.5). Meanwhile, the majority of the central English Channel, the mid Irish Sea and inshore areas of the eastern English coast, are dominated by assemblages portraying relatively high overall ecological risk to offshore wind. However, Figure 5 also reveals much smaller scale, regional variations in ecological risk occur. These areas of high patchiness in risk are found, for example, in the northern and southern Irish Sea, the east coast of Scotland and England, and the eastern English Channel (Figure 5).

Each of the three individual risk elements shows some degree of independence in their spatial pattern, meaning that some areas of high biodiversity risk (Figure 4c), for example, do not represent high sensitivity risk (Figure 4a). This example is observed off some parts of the southwest coast of England. Meanwhile, the macrofaunal assemblages in the region off the southeastern coast of England which are regarded as medium risk based on assemblage rarity (Figure 4e) are neither biodiverse nor sensitive to offshore wind development impacts and are concluded to have relatively low overall ecological risk to future development.

Confidence in the overall risk scores (Figure 6) reveals that risk confidence is relatively high for the majority of the North Sea, Celtic Sea, the southwestern Approaches, and the central parts of the Irish Sea. Lower model confidence values tend to occur around Ireland, to the west and north of Scotland, and outside of the UK EEZ off the coast of France and Denmark.

Web application

The Risk tool web application, available from https://rconnect.cefas.co.uk/OneBenthicRisk/, is principally intended to allow OSW practitioners to understand and identify variations in benthic ecological risk and to use this information to refine potential development sites to areas of reduced risk. The app represents a visual output of ecological risk based on the data and subsequent data analytical procedures outlined in the *Methods* section. In the illustrative example shown in Figure 7, area of interest site A results in an overall median risk score of 0.66 (and an associated total score of 159). Relocating the potential development area (area of interest box B) results in a reduced ecological risk median score of 0.17 (total score reduced to 67).

DISCUSSION

For the present study, we used three independent qualities of benthic invertebrate assemblages upon which to

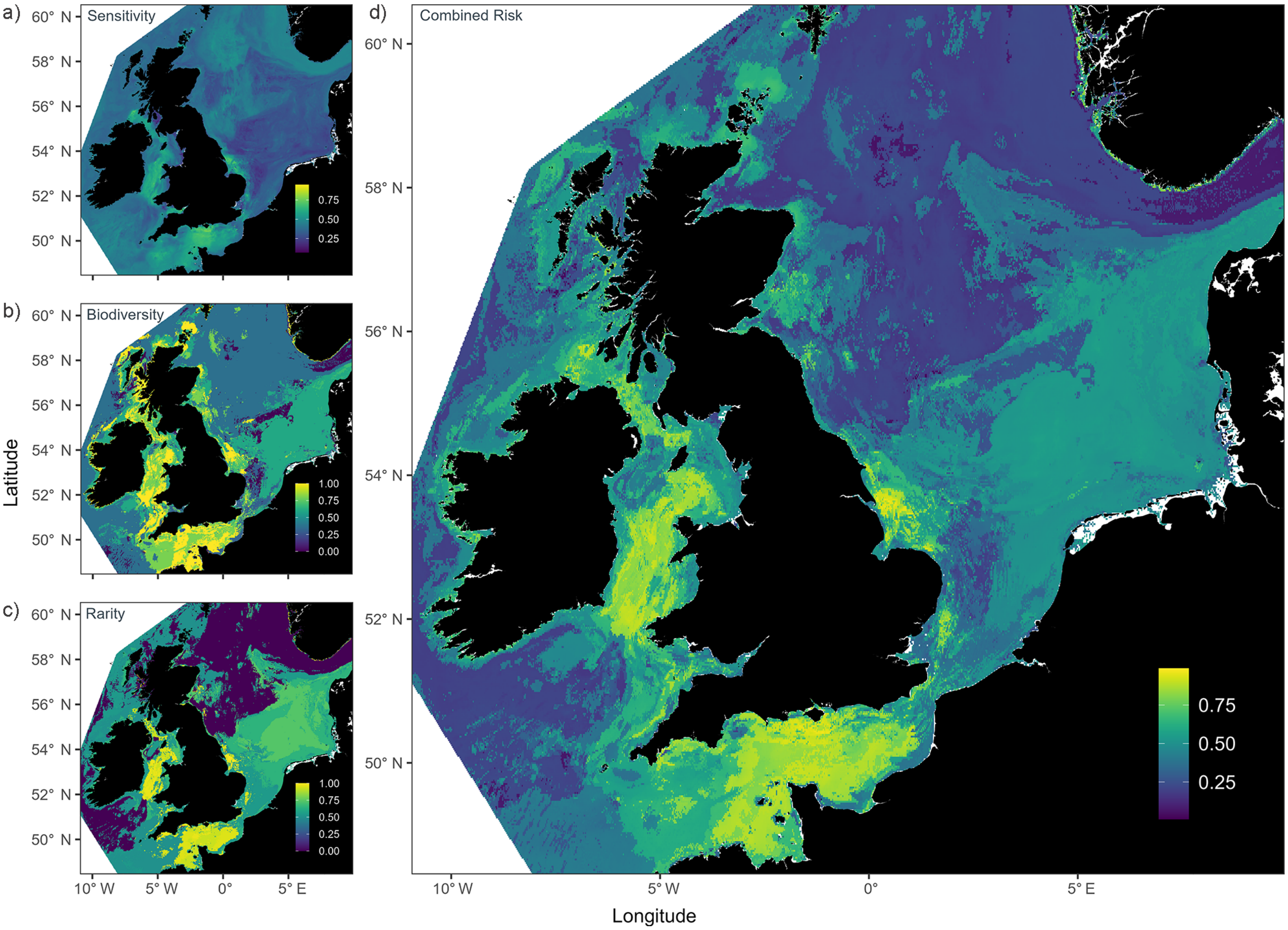


FIGURE 5 (a–c) Heat maps showing individual normalized risk element layers for (a) macrofaunal sensitivity to offshore wind, (b) biodiversity, and (c) assemblage rarity. (d) Heat map of the combined risk layer based on a summation and normalization of these three risk elements.

base informed decisions regarding the relative ecological risks associated with future offshore wind development. Firstly, we deemed the inclusion of relative sensitivity of invertebrates, founded on a biological trait-based approach, to be fundamentally important to include in decision-making. Given that how a species responds to either directly (damaged, killed) or indirectly (recovery via recolonisation processes) a physical impact is fundamentally governed by the inherent traits it expresses, this approach has gained widespread applicability for sensitivity assessments for both terrestrial (Böhm et al., 2016; González-Suárez et al., 2013) and marine species (Beauchard et al., 2021; Bolam et al., 2014; Gonzalez-Irusta et al., 2018) to a range of pressures. The traits selected in this study, broadly reflecting those adopted by Bolam et al. (2014) regarding benthic sensitivity to demersal trawling, are likely to represent a robust proxy for a range of physical pressures in the marine environment. That is, this suite of traits is theoretically likely to predispose any species to be affected by and/or recover from the various direct physical benthic pressures such as those associated with OSW construction and operation. For instance, soft-bodied (morphology trait), sedentary (mobility trait), and attached to substratum (living habit trait) would infer high sensitivity to the associated physical impacts such as abrasion/disturbance of the seabed surface, penetration or disturbance of the sediments, smothering, and physical change to another seabed type. Meanwhile, planktonic larval development will confer a greater potential for species recolonisation of the seabed regardless of the specific activity. The wealth of empirical experimental and observational demersal trawling impact studies conducted during the past two decades has provided a good understanding of the links between benthic invertebrate trait expression and sensitivity (Tillin et al., 2006; Kaiser et al., 2006; van Denderen et al., 2015). In contrast, there is a relative paucity of comparable offshore renewables impacts-specific data

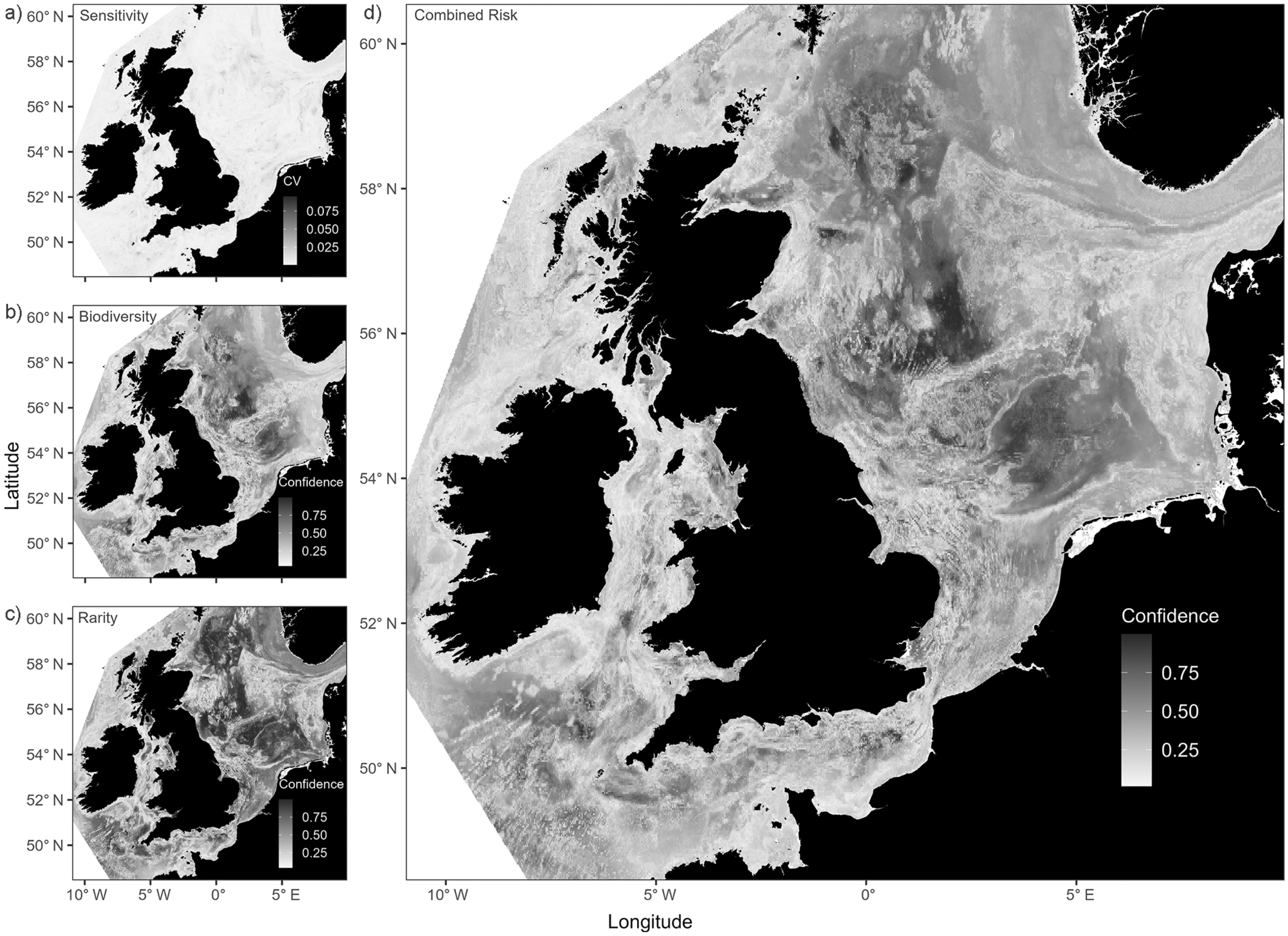
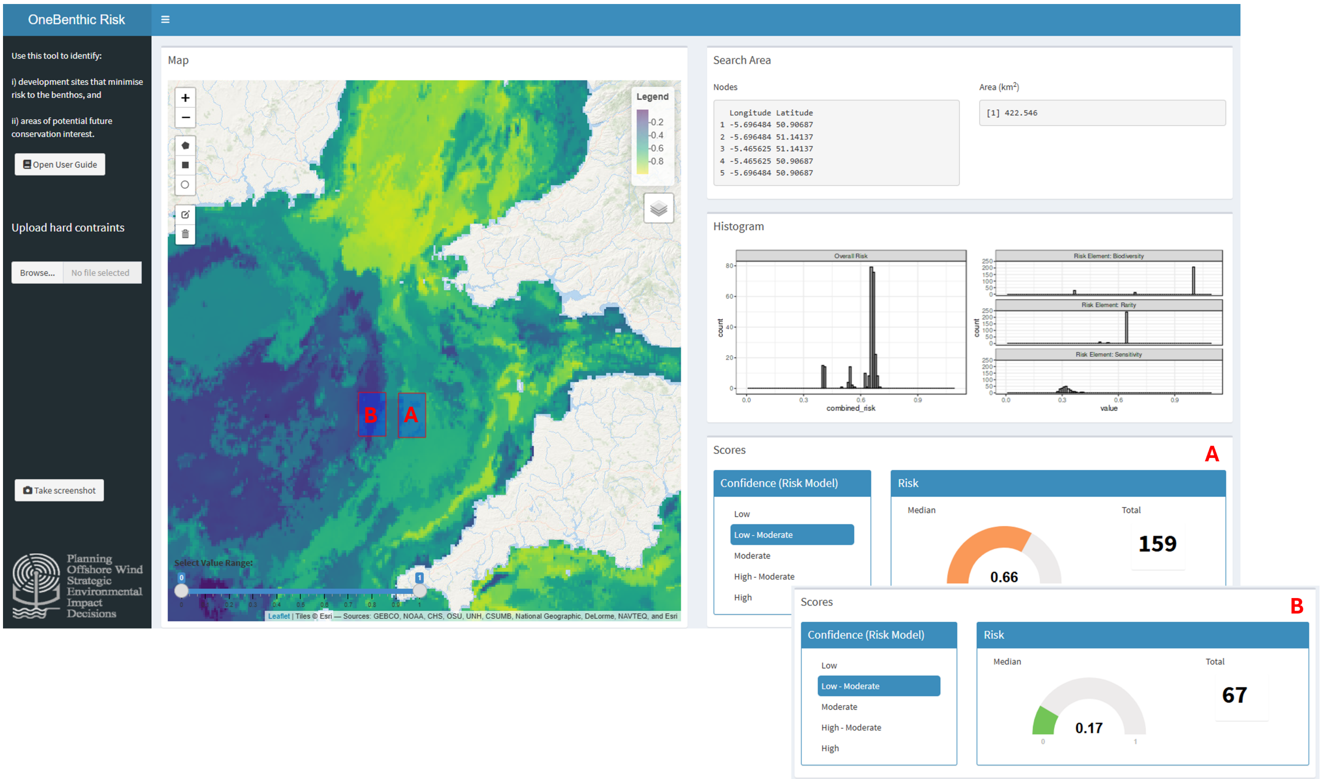


FIGURE 6 (a–c) Maps showing model performance of the individual risk element layers for (a) macrofaunal sensitivity to offshore wind, (b) biodiversity, and (c) assemblage rarity. (d) Model confidence values for the combined risk layer. Model performance scores range from 0 to 1 (biodiversity, rarity, and combined risk), with higher scores indicating higher confidence in the model. For sensitivity (CV), lower scores indicate higher confidence in the model.

and, consequently, a good understanding of which traits convey a tolerance to its associated impacts is currently lacking (Coolen et al., 2022; Galparsoro et al., 2022). Indeed, as Gasparatos et al. (2017) points out, there is an urgent need to identify and assess potential environmental impacts associated with offshore energy production to prevent or minimize negative effects at a very early stage of the OSW planning process. This future increased understanding should be used to improve our understanding of species responses and, thus, trait-based assessments of sensitivity to this sector.

Secondly, supporting the recent findings of Stranddorf et al. (2025), we advocate that benthic biodiversity is an important criterion which should be considered as part of planning future OSW development. High biodiversity not only represents a fundamental natural capital in the generation of marine ecosystem services (Tubío et al., 2021) but, in line with substantive theoretical support for the biodiversity-ecosystem functioning paradigm (Naeem et al., 1994; Loreau et al., 2001; Tilman et al., 1996), biodiverse habitats represent the most functionally important regions of the seabed. A large body of research shows that greater diversity leads to an increase in the number of expressed biological traits and greater effects on ecosystem functioning compared to less diverse assemblages that have poor functional expression (Reiss et al., 2009; Snelgrove et al., 2014). The policy requirement to safeguard important ecological function and associated ecosystem services is becoming increasingly pressing; thus, identifying and consequently protecting relatively biodiverse marine benthic assemblages is a key goal for policy-supporting science.

Thirdly, as identified by Cooper and Barry (2017), benthic assemblages vary not only in their taxonomic composition, that is, the compositional differences in the faunal cluster groups presented here, but also that these



Use this tool to identify:

i) development sites that minimise risk to the benthos, and

ii) areas of potential future conservation interest.

Nodes

```
  Longitude Latitude
1 -5.696484 50.90687
2 -5.696484 51.14137
3 -5.465625 51.14137
4 -5.465625 50.90687
5 -5.696484 50.90687
```

Area (km^2)

```
[1] 422.546
```

FIGURE 7 Screenshots from the ecological risk app (https://rconnect.cefas.co.uk/OneBenthicRisk/) showing results for two potential areas of interest, A and B. Inset shows risk scores for scenario B.

different assemblages can exhibit dramatic differences in their spatial extents (Table 3). Quantifying their relative spatial extents affords the opportunity to identify assemblages which are relatively rare, opening the opportunity to provide them with greater protection from future development. It is becoming increasingly evident that managing biological resources based on such assemblage-level groups, as opposed to species-based approaches, provides an improved basis upon which to help address biodiversity loss (Belitz et al., 2025). As O'Brien et al. (2022) pointed out, characterizing the diversity of distinct assemblages in marine ecosystems and their distribution is key to the successful implementation of regional conservation planning and marine spatial planning processes that collectively aim to maintain or restore biodiversity and ecosystem functions that underpin services and benefits to society.

Management of sectoral pressures inherently relies on empirical data and the information we glean from them. The individual ecological risk maps provided here, particularly when unified to a single composite raster layer (Figure 5), provide a meaningful backdrop against which the ecological impacts of future OSW developments can be assessed. The composite map provides an illustration of accumulated relative sensitivity, biodiversity, and assemblage rarity, facilitating the spatial examination of the potential for adverse cumulative effects. The associated tool we have developed based on these layers (Figure 7) offers a simple, user-friendly interface to allow a range of stakeholders (e.g., developers, licensing authorities, scientific advisers) to understand, visualize, and portray the relative ecological risks for any area of interest. Furthermore, easy signposting of which of the three criteria (i.e., sensitivity, biodiversity, assemblage rarity) is responsible for raising the risk for a particular area (i.e., histogram plots; Figure 7) allows the potential for early mitigation options to reduce ecological risk at the planning stage of an activity. We have witnessed that benthic assemblages may possess independent qualities of ecological risk, that is, highly biodiverse assemblages are not always sensitive to OSW development while, in contrast, other assemblages are sensitive but not biodiverse. This highlights the need to base licensing decisions on such a suite of characteristics as basing decisions on single or inappropriate criteria increases the risk of inadvertently and unnecessarily severely impacting benthic assemblages.

Our composite map (Figure 5) infers that the lowest ecological risk regions for future OSW development are found widespread across the northern North Sea (except inshore), some parts of the southern North Sea, the Irish Sea south of Ireland, and to the west of Ireland in the Atlantic Ocean. The majority of the Irish Sea, English Channel, and the inshore areas of the southern North

Sea, in contrast, represent areas of greatest relative ecological risk. Decisions regarding future development will inherently be heavily based on practical, logistical and financial factors, together with potential risks to other ecological (e.g., seabirds, marine mammals, fish), sectoral (e.g., other licensed activities), and societal (e.g., cultural interests) constraints. Proximity to the coast is a critical factor regarding suitability: Regions further offshore generally carry a higher ecological impact footprint and elevated costs to transfer the generated power to land. It must be noted that even areas identified as relatively high ecological risk based on our approach do not necessarily or automatically represent "exclusion areas" for future OSW development. They represent areas of greatest ecological risk based on sensitivity to the pressure, biodiversity, and assemblage rarity (or any two of these for medium risk areas), and by definition, the remaining regions reflect areas of low relative ecological risk. Inherently, this philosophy assumes that OSW development negatively impacts biodiversity and assemblage structure: Whether this is reflected in reality, given the complex interrelationships between OSW development with associated direct and indirect effects (e.g., potential exclusion or reduction in demersal trawling pressure, increased carbon delivery to the seabed resulting from epifaunal species on turbines), still largely remains to be established (Galparsoro et al., 2022).

Our approach may be augmented by additional criteria to the three presented herein, where considered necessary and/or appropriate. For example, areas of high conservation value as defined by legislation (e.g., marine protected areas or Annex I Habitats) can be included or uploaded into the app to augment our risk layers, creating a framework whereby both consenting and ecological risk considerations are brought together. Indeed, the online tool allows (and its associated guidance document promotes) the upload of a suite of additional layers to be used to assist with decisions regarding future development areas. Likewise, additional or alternative ecological layers may be used in the future depending on the context and what measure of benthic structure and/or function is to be safeguarded. For benthic assemblages, for example, estimated total secondary production (Bolam et al., 2010), bioturbation potential (Zhang et al., 2024), or effect trait-based maps (Bolam et al., 2023) currently offer the opportunity to include proxies of ecological function into this framework. As scientists are increasingly being asked by regulators and licensing authorities to protect marine ecosystem function and ecosystem services (in addition to routine structural-based metrics) (Causson & Gill, 2018), we envisage that, once sufficient data are available to provide more robust large-scale maps of such criteria, these metrics can also be included on an equal or even elevated priority over structural-based maps.

The approach presented here offers the basis for wide flexibility in application to facilitate early decisions regarding the suitability of future licensing activities. The holistic risk map presented here is based on an equal weighting to each of the three adopted criteria, while, alternatively, it may also be derived by varying the relative importance on any of the metrics. For example, it is entirely plausible to regard protection of biodiversity to preside over assemblage rarity or sensitivity. Meanwhile, for application to other marine-based activities or pressures where the present understanding of the inherent biological characteristics that predispose benthic invertebrates to being sensitive or nonsensitive is presently lacking, the relative influence of each metric within the final composite map can be refined (e.g., by reducing the relative influence of the sensitivity risk layer).

One noteworthy limitation of the present study relates to the fact that the layers presented were derived based on invertebrate data from grabs and cores from the OneBenthic data repository. As grabs and cores can only be successfully used to acquire benthic invertebrate data from sedimentary habitats, our modeling approach and thus the resulting layers assume that sediments occupy the whole of the study region when, in reality, there are known regions of the study area which possess coarser (cobbles, boulders) or even bedrock substrates. The invertebrate communities of such habitats and their sensitivity to OSW impacts are inherently different from those of sediment regions. During application, this limitation may be addressed through uploading raster layers of predicted rock habitats and, for example, placing less confidence on our predicted ecological risk values in areas of predicted rock habitat.

This study capitalizes on data across several decades. Some species' distributions will undoubtedly have changed due to climatic shifts or more localized changes due to changes in demersal fishing pressure during this time span. However, we believe this is likely to be a greater limitation for species distribution models than models of derived layers which encapsulate information from all the species within a sample as we have done here for our three independent layers. Cooper and Barry (2017) provided support for this, showing the spatial distribution of assemblages across the UK shelf remained comparable between 1976 and 2016. Moreover, as we are producing models based on the underlying relationships between the benthos (response variable) and environmental drivers (predictor variables), any climatic changes in species distributions are likely to manifest through a slightly poorer model performance as opposed to a less accurate spatial representation.

Based on a significantly large amount of empirically derived, quantitative observational data of benthic invertebrate assemblages contained within the OneBenthic repository, modeled using a suite of environmental predictor variables to produce maps of three ecological criteria we consider important for licensing decisions as part of OSW planning, our ecological risk map offers an alternative but complementary framework to the European Union Nature Information System (EUNIS) habitat approach that currently forms the basis of such planning decisions across Europe (Davies et al., 2004; Galparsoro et al., 2012). Our approach and the EUNIS framework represent bottom-up and top-down approaches respectively (Cameron & Askew, 2011; LaFrance et al., 2014; Shumchenia & King, 2010) and each have their own merits and offer useful insights to facilitate management decisions. While the latter (i.e., EUNIS) currently represents the statutory basis representing potential significance of impacts as part licensing assessments, and will undoubtedly continue to do so, insights from our bottom-up method should be used to augment those from a EUNIS habitat approach. Regions where disparity between the two approaches are identified should be given particular attention. Top-down and bottom-up approaches are fundamentally different and provide different insights for valid reasons. There are multiple, interacting benthic impacts associated with the construction and operation of OSW project (e.g., smothering, habitat change, abrasion) (Copping et al., 2020), each acting at various spatial and temporal scales and each varying in significance depending on the nature of the receiving environment and the design and construction methods adopted (Li et al., 2023). In view of the relative paucity of good monitoring data upon which we can utilize to more fully understand the implications of such impacts on the structure and function of benthic assemblages (Franco et al., 2015; Lindeboom et al., 2015), prudent management is required and decisions regarding future developments should be informed by harnessing the merits provided by each of these complementary approaches as opposed to a reliance on a single approach if we are to provide a more robust, ecological-based basis for future developments. The online tool developed here can and should be used by OSW practitioners as a means of obtaining instantaneous predictions regarding the ecological risks of any area of development interest. In doing so, areas subsequently identified as high risk may be avoided at an early stage, thereby expediting the expansion of the OSW sector and, ultimately, facilitating national net zero emission targets being achieved.

This study examines an ecological risk-based approach for determining future OSW locations. The methodology can also be adapted to other sectors including dredged material disposal and sediment extraction. Two of the three layers—assemblage rarity and biodiversity—characterize inherent qualities of the benthos that are equally relevant across all types of anthropogenic pressures. Although our trait sensitivity scoring approach is currently focused on (and scored to proxy) offshore wind, it could similarly be adopted for physical pressures related to other sectors. Insights from previous research, such as Bolam et al. (2016) pertaining to dredged material disposal, may assist in applying this method more broadly by identifying response traits pertinent to sector-specific sensitivities. In this respect, our study adds to a growing body of science aiming to understand and quantify risks associated with various anthropogenic activities to facilitate future licensing (Bolam et al., 2014; Kaikkonen et al., 2024; Kenny et al., 2018; Quemmerais-Amice et al., 2020).

AUTHOR CONTRIBUTIONS

S. G. Bolam and K. M. Cooper conceived the idea for the paper, designed the methodology, and collated the relevant data. S. G. Bolam managed the traits data for the taxa within OneBenthic. K. M. Cooper wrote the R script for the manuscript and shiny dashboard app, with contributions from A. -L. Downie (modeling). S. G. Bolam and K. M. Cooper both contributed to the writing of the manuscript, and all authors gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data and code (Cooper, 2025) are available from the Centre for Environment, Fisheries and Aquaculture Sciences (CEFAS) Data Hub: https://doi.org/10.14466/CefasDataHub.190. This record includes links to the primary datasets, associated R scripts, and an API for accessing the modeled layers. A small number of third-party datasets used under data-sharing agreements are not publicly available; summary information for these datasets is provided in Appendix S1: Table S5.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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