Coupling state-of-the-art modelling tools for better informed Red List assessments of marine fishes

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Acknowledgments

We thank very much Romain Frelat for assisting us in preparing survey data. We are very grateful to José de Oliveira and Jim Ellis for their expert review and to Olaf Jensen, the Editor (Tadeu Siqueira), the Associate Editor (Caren Barceló) and three anonymous reviewers for their comments, which all considerably improved the quality of the manuscript. We also thank very much Lydia Groves for all of her assistance during the reviewing and production processes. Reference to trade names does not imply endorsement by the National Marine Fisheries Service, NOAA. The scientific results and conclusions, as well as any views or opinions expressed herein, are those of the author(s) and do not necessarily reflect those of NOAA or the Department of Commerce.

Conflict of interest statement

None of the authors have a conflict of interest.

Authors' Contributions

Arnaud Grüss, Henning Winker and James T. Thorson conceived the study; Arnaud Grüss, Henning Winker, James T. Thorson and Nathan Pacoureau developed the models; Arnaud Grüss and Aurore Maureaud compiled the data; Arnaud Grüss, Nicola D. Walker and Nathan Pacoureau compared the results for the application to results from previous assessments and studies; Arnaud Grüss, Henning Winker, James T. Thorson, Nicola D. Walker, Aurore Maureaud and Nathan Pacoureau analysed and discussed the results and contributed to the manuscript.

Data availability statement

Data are available from the Figshare Digital Repository https://doi.org/10.6084/m9.figshare.22596799.v1 (Grüss, 2023). R codes are available from the Zenodo Digital Repository https://doi.org/10.5281/zenodo.10565146 (Grüss, 2024).

Abstract

1. In the face of biodiversity loss worldwide, it is paramount to quantify species' extinction risk to guide conservation efforts. The International Union for the Conservation of Nature (IUCN)'s Red List is considered the global standard for evaluating extinction risks. IUCN criteria also inform national extinction risk assessments. Bayesian models, including the state-of-the-art JARA ("Just Another Red List Assessment") tool, deliver probabilistic statements about species falling into extinction risk categories, thereby enabling characterisation and communication of uncertainty in extinction risk assessments.

2. We coupled the state-of-the-art VAST ("Vector Autoregressive Spatio-Temporal") modelling tool and JARA, for better informed Red List assessments of marine fishes. In this framework, VAST is fitted to scientific survey catch rate data to provide indices to JARA whose uncertainty is propagated to JARA outcomes suggesting extinction risk categories (under the population reduction criterion). In addition, VAST delivers a valuable habitat assessment to better understand what may be driving extinction risk in the study region. Here, we demonstrate the coupled VAST-JARA modelling framework by applying it to five contrasting North Sea species, with or without a quantitative stock assessment and with different conservation statuses according to the latest global Red List assessments.

3. The North Sea application coupled with previous assessments and studies suggest that, among the three elasmobranchs, starry ray is in most need for urgent research (and conservation actions where appropriate), followed by spurdog, whilst lesser-spotted dogfish is increasing in biomass. Moreover, both the VAST-JARA modelling framework and previous research indicate that, while European plaice is not of conservation concern, cod has likely met the IUCN criteria for being listed as Endangered recently.

4. *Synthesis and applications*. The predictions of the VAST-JARA modelling framework for North Sea species, including JARA output and VAST habitat assessment, constitute valuable

supporting information to make interpretations based on Red List guidelines, which will help decision-makers in their next North Sea Red List assessment. We foresee applications of the modelling framework to assist Red List assessments of numerous marine fishes worldwide. Our modelling framework has many potential advantageous uses, including informing resource management about climate change impacts on species' extinction risks.

Keywords: Red List assessments, state-space models, VAST, JARA, habitat assessment, survey data, fishes

Introduction

In the face of biodiversity loss worldwide, it is paramount to quantify species' extinction risk to guide conservation efforts (Hoffmann et al., 2008; Butchart et al., 2010). The International Union for the Conservation of Nature (IUCN)'s Red List of Threatened Species ("Red List") is considered the global standard for evaluating species' extinction risks (Mace et al., 2008; Regan et al., 2013). IUCN criteria also inform national assessments of species' conservation status and extinction risk, such as the Committee on the Status of Endangered Wildlife in Canada (COSEWIC)'s assessment of endangerment under the Species at Risk Act (COSEWIC, 2019). Red List assessments are currently widely used to assess progress towards United Nations Sustainable Development Goals and to set Biodiversity Targets of the Convention on Biological Diversity. Following IUCN criteria, Red List assessments classify species into extinction risk categories: Critically Endangered (CR), Endangered (EN), Vulnerable (VU) (threatened categories), Near Threatened (NT), or Least Concern (LC). It is important to note that numerous species are also classified as Data Deficient (DD), i.e., that the extinction risk of numerous species cannot be assessed due to a lack of data yet many of those non-assessed species may be threatened (IUCN, 2023).

Although there exist five IUCN criteria (A to E; IUCN, 2023), Criterion A (the rate of population reduction scaled by generation length) is the most frequently and, often, the only criterion employed for the Red List assessments of marine fishes (d'Eon-Eggertson et al., 2015; Rueda-Cediel et al., 2018). This is primarily because Criterion A generally matches the population statuses predicted by stock assessments (Davies & Baum, 2012; Pacoureau et al., 2021). Different tools are available for assisting the Red List assessments that are based on Criterion A, including very rapid and easy-to-use approaches. However, misclassifying populations on the Red List can have substantial impacts on the prioritisation of conservation efforts and, consequently, on our ability to optimally counter biodiversity loss (Ale & Mishra, 2018; Rueda-Cediel et al., 2018). Therefore, analysts should seek to carry out the Red List assessments that are based on Criterion A (henceforth simply "Red List assessments") with tools that adequately characterise and communicate uncertainty around extinction risk.

Bayesian models represent powerful tools to evaluate extinction risks as they deliver probabilistic statements about species falling into extinction risk categories, thereby improving the characterisation and communication of uncertainty in extinction risk assessments (Boyd et al., 2017; Post et al., 2022). Currently, Red List assessments for marine fishes are generally supported by Bayesian state-space models implemented with the JARA ("Just Another Red List Assessment") platform, because of JARA's capacity to incorporate process error and uncertainty into the assessments (Sherley et al., 2020; Winker et al., 2020). One major advantage of JARA is that it is less sensitive to outliers (due to process and observation error) than simpler regression approaches and, therefore, more accurately captures rates of population change (Sherley et al., 2020; Winker et al., 2020). One of JARA's main utilities is an easy-to-interpret graphic showing the probability of population decline against Red List categories. This graphic, along with other JARA products, provides practitioners with valuable insights into the weight of evidence that supports their Red List assessment (Winker et al., 2020). JARA has been employed to assist Red List assessments for around 100 elasmobranchs worldwide and other taxa including demersal bony fishes (da Silva et al., 2019; Sherley et al., 2020; Dulvy et al., 2021; Pacoureau et al., 2021, 2023).

JARA inputs include abundance data and an estimate of generation length (the average age of breeding individuals). For marine fishes, abundance data can come in the form of the abundance trajectories predicted by stock assessment models or indices of relative abundance (henceforth simply "indices") derived from scientific survey catch rates or fisheries catch rates (Winker et al., 2020), where abundance is either abundance in numbers or abundance in biomass (henceforth simply "biomass"). Because most fish species worldwide do not have a stock assessment (Ovando et al., 2021; RAM Legacy Stock Assessment Database, 2021), indices are the most utilised data for JARA for marine fishes. Moreover, when available, indices estimated from survey catch rates are preferred to indices estimated from fisheries catch rates, because the stratified sampling design and well-defined sampling protocol (in terms of methods and effort) of most surveys result in catch rates that are more representative of the fish populations (National Research Council, 1998; Dennis et al., 2015). Indices are generated from catch rates via a catch rate standardisation procedure using regression models (Maunder & Punt, 2004).

Whilst numerous different models are available for catch rate standardisation (Hoyle et al., 2024), there is increasing recognition of the critical role of spatial structure in species' dynamics, extinction risks and recovery potential (Wilson et al., 2023). In this context. spatio-temporal models, regression models that account for spatial and spatio-temporal structure, are increasingly preferred for catch rate standardisation (Thorson et al., 2020). Spatio-temporal models represent spatial variation (latent variation that is constant over time) and spatio-temporal variation (latent variation that varies among years) at a very fine scale and, therefore, result in very precise estimates via the borrowing of information across adjacent locations and years (Shelton et al., 2014; Thorson et al., 2015). Simulation experiments also indicate that, compared to simpler regression models, spatio-temporal models generally produce more accurate estimates and/or better characterise uncertainty around these estimates (Grüss et al., 2019b; Brodie et al., 2020). One major advantage of spatio-temporal models is that, in addition to generating indices, they shed light on the spatio-temporal density patterns and patterns of distribution shifts and range expansion/contraction of fishes (Thorson et al., 2016). Thus, spatio-temporal models can deliver a habitat assessment (e.g., information about changes in species' range) that complements JARA outputs for better informed Red List assessments, as JARA informs only about species' extinction risks in relation to population trends. One of the most widely used spatio-temporal modelling approaches is the VAST ("Vector Autoregressive Spatio-Temporal") state-space modelling tool (Thorson, 2019), which is now commonly employed worldwide for the standardisation of the survey catch rates of fishes (e.g., Hodgdon et al., 2020; O'Leary et al., 2020; Adams et al., 2021).

Here, we couple the state-of-the-art VAST and JARA state-space modelling tools for better informed Red List assessments of marine fishes. VAST is fitted to survey catch rate data to provide indices to JARA, but also density maps and other habitat information to better understand what may be driving extinction risks in the study region. We demonstrate our coupled VAST-JARA modelling framework by applying it to five contrasting North Sea species.

Materials and methods

VAST

The VAST generalised linear mixed modelling platform was originally developed to standardise fish catch rate data, which generally include many zeros (Thorson et al., 2015). As such, VAST was designed as a delta modelling platform, that is a framework that combines together the encounter probabilities estimated by a first linear predictor and the positive catch rates estimated by a second linear predictor (Lo et al., 1992).

VAST delta models fitted to survey catch rate data estimate two linear predictors at each site and in each year in the logarithm scale, as a function of: (1) year intercepts treated as fixed effects; (2) spatial variation terms treated as random effects; (3) spatio-temporal variation terms treated as random effects; and, potentially (4) density covariates and/or catchability covariates (covariates related to sampling). The product of the two linear predictors is equal to density, d. The spatial and spatio-temporal variation terms represent the core of VAST models and account, respectively, for latent static and latent dynamic variables that influence fish densities (Shelton et al., 2014; Thorson et al., 2015). Details about the estimation and evaluation procedures of VAST models can be found in Appendix S1 in Supporting Information.

The densities predicted by VAST models at each site *s* and in each year t, $d(s,t)$, can be summed up over space to produce indices, $I(t)$, which can then be provided as input to JARA. However, VAST model predictions can also be processed to deliver a habitat assessment for the species of interest (Thorson et al., 2016; Grüss & Thorson, 2019; Han et al., 2021; Grüss, Moore, et al., 2023): (1) density maps can be generated; (2) annual centres of gravity (COGs) can be computed, to shed light on distribution shift patterns; and (3) changes in effective area occupied and population boundaries over time can be evaluated, to determine patterns of range expansion/contraction (Appendix S1). Eastward and northward COGs represent, respectively, the weighted mean longitude and weighted mean latitude of the species of interest in a given year, where each location of the modelled domain is weighted by the species' biomass at that location in that year (Thorson et al., 2016). As such, COGs contribute to highlight locations where species are faring well versus locations where this is not the case; e.g., a substantial distribution shift to the east suggests the species is undergoing depletion in some westernmost locations. Habitat assessments are not used as inputs in JARA yet constitute valuable complementary information for Red List assessments to better understand what may be driving species' extinction risk.

JARA

JARA is a generalised Bayesian state-space modelling tool that analyses one or several indices simultaneously, to determine in which Red List category species are likely to fall (Winker et al., 2020). In JARA, posterior distributions are estimated using Markov Chain Monte Carlo simulation. Uninformative priors are employed for all estimable parameters so that all the information on which inferences are based come from the indices considered and their associated uncertainty. For simplicity, we consider only the cases where one single VAST index is used in JARA.

In JARA, the trend of the indices is assumed to follow a Markovian process such that the index in year t, $I(t)$, is conditioned upon the index in year $t-1$, $I(t-1)$. A conventional exponential growth is assumed for the trend of the underlying population, such that the process equation on the log scale is:

$$\mu(t) = \mu(t-1) + r(t-1) \qquad \text{eqn 1}$$

where $\mu(t) = \log\big(I(t)\big)$; and $r(t) = \log\big(\lambda(t)\big)$ is the annual rate of change, with $\lambda(t)$ being growth rate in year t, and is considered to follow a random walk:

$$r(t) = \bar{r} + \eta(t) - 0.5\sigma_\eta^2 \qquad \text{eqn 2}$$

where $\bar{r}$ is the estimable mean rate of change; and $\eta(t)$ is the process error following a zero-centered normal distribution with standard deviation σ_η^2.

The observation equation corresponding to equation 1 is:

$$\log\big(y(t)\big) = \mu(t) + \varepsilon(t) \qquad \text{eqn 3}$$

where $y(t)$ is the relative abundance observation in year t; and $\varepsilon(t)$ is the log-normal observation error in year t. The observation variance is given by the sum of the inputted squared standard error estimates for the abundance index (here from VAST) and additional variance estimated by JARA. The Bayesian implementation of the state-space model and the diagnostics employed to evaluate it are described in Appendix S2.

The posterior of the population trajectory predicted by JARA, $\hat{I}(t) = \exp\big(\mu(t)\big)$, is used to calculate a posterior probability for the percent change in the fish population (%C). If $\hat{I}(t)$ spans more than three generation lengths (GLs), %C is estimated as the difference between the three-year median around the final year of $\hat{I}(t)$, denoted T, and the three-year median around the year corresponding to $T - (3 \times GL)$ (Sherley et al., 2020). To diminish the impact of short-term fluctuations, JARA always projects the year $T + 1$ to produce a three-year median around T. When $\hat{I}(t)$ represents a time span smaller than three GLs, forward projections are conducted in JARA; specifically, additional years without observations are provided to JARA until $\hat{I}(t)$ spans a period greater than $(3 \times GL) + 2$. Projections are based on the posterior of the median of $r(t)$ over all T years (Sherley et al., 2020).

JARA's main outcome is a graphic displaying the posterior distribution for %C over three GLs against the thresholds for Red List categories under IUCN Criterion A2 (Appendix S2). Another useful JARA outcome is retrospective analyses, where the terminal years of the index $I(t)$ are sequentially removed and forward projections are subsequently carried out to attain three GLs. These retrospective analyses allow for the identification of years in which %C traversed new Red List categories (Winker et al., 2020).

COUPLING JARA WITH VAST

We demonstrate the benefits of coupling the state-of-the-art VAST and JARA modelling tools through an application for five North Sea species. In particular, we show how VAST, in addition to delivering an index (and its associated standard errors) to JARA, also provides a habitat assessment that helps better interpret JARA outcomes. The five study species represent contrasting fish populations: starry ray (*Amblyraja radiata*) and lesser-spotted dogfish (*Scyliorhinus canicular*), elasmobranchs without a quantitative assessment and which latest global Red List assessments found to be VU and LC, respectively; spurdog (*Squalus acanthias*), an assessed elasmobranch species which latest global Red List assessments found to be LC; and cod (*Gadus morhua*) and European plaice (*Pleuronectes platessa*), assessed bony fishes which latest global Red List assessments found to be VU and LC, respectively. (Table 1). The VAST models were fitted to the data that were collected by the North Sea International Bottom Trawl Survey (NS-IBTS), which were retrieved from the

International Centre for the Exploration of the Sea (ICES) on their DATRAS platform (DATRAS, 2023) to be made available in the FISHGLOB database (Maureaud et al., 2024) (Appendix S3). None of the VAST models included density or catchability covariates. The GLs used in JARA were those employed in the most recent Red List assessments for the study species or were obtained from R package *FishLife* (Thorson, 2020) when not available in Red List assessments (Appendix S4).

Our North Sea application using FISHGLOB showcases this large international collaborative effort. FISHGLOB integrates scientific bottom trawl survey data collected worldwide that are pre-processed and homogenised (Maureaud et al., 2024). Here, we focus on the NS-IBTS survey data collected in Quarter 1 (January-March; NS-IBTS Q1) between 1983–2020 (DATRAS, 2023) that are available in the FISHGLOB database (Grüss, 2023), while acknowledging some limitations of the NS-IBTS Q1 survey for some of the study species (Appendix S4).

The authors of the present study did not conduct the research surveys themselves and, therefore, ethical approval did not apply to the present study. All of the R codes developed for the application are publicly available (Grüss, 2024).

Results

STARRY RAY

VAST predicted that starry ray relative biomass significantly decreased between 1983–2020 in the North Sea (Fig. 1). More specifically, VAST predicted that the starry ray population increased until 1993 and sharply declined afterwards (Figs 1 and 2). VAST predicted a dramatic habitat shrinkage for starry ray in the North Sea over the period 1983–2020: the COG of starry ray was predicted to significantly move eastwards and its effective area occupied to significantly diminish (Fig 1). VAST predicted that, in 2020, starry ray density hotspots became concentrated in the east of the North Sea, particularly in the Skagerrak Strait (Fig. 2).

JARA provided a percent change in the fish population (%C) estimate over three GLs for starry ray of -88.3%, with 97% of the posterior falling in CR (Fig. 3 and Table 1). Retrospective analyses with JARA suggested that starry ray switched from the CR status to the EN status in the last two years of the period 1983–2020 (Appendix S4).

COD

VAST predicted a significant decrease in cod relative biomass between 1983–2020 (Appendix S4). More precisely, the cod population was predicted to considerably dwindle until 2006, increase until 2016, and substantially decline again afterwards. VAST also estimated that the COG of cod significantly moved northwards (as well as westwards) between 1983–2020 and that the effective area occupied by the species significantly diminished. Consequently, VAST predicted that, while cod high-density areas were found throughout the North Sea in 1983, they tended to concentrate in the north of the region in 2020, particularly in the area between Shetland Islands and Scandinavia.

JARA provided a %C over three GLs for cod of -69.3%, with 100% of the posterior falling in EN. The drop in cod relative biomass worsened in the most recent GL of 1983–2020 (Appendix S4). Retrospective analyses with JARA suggested that increases in the cod population between 2006 and 2016 resulted in cod becoming LC in 2016, but that the large decline in cod relative biomass afterwards led the threshold for the EN status to be exceeded again in 2019–2020 (Fig. 4).

SPURDOG

VAST predicted an overall decline in spurdog relative biomass between 1983–2020 (Appendix S4). More precisely, the spurdog population was predicted to increase until 1990, dwindle until 2010, and slightly increase afterwards. Its COG significantly moved northwards between 1983–2020. The extent of spurdog high-density areas varied over time in response to changes in population size. While spurdog density hotspots were located primarily around Orkney Island in 1983, they were also found on the Fladen Ground and in the north of the Skagerrak Strait in 2020.

JARA provided a %C estimate over three GLs for spurdog of -52.6%, with 53% of the posterior falling in EN. Retrospective analyses with JARA suggested that increases in the spurdog population after 2010 have resulted in spurdog switching from the CR status to the EN status in 2013 (Appendix S4).

LESSER-SPOTTED DOGFISH

VAST predicted a very significant improvement in lesser-spotted dogfish relative biomass between 1983–2020 (Appendix S4). The increase in relative biomass started from 1999 and accelerated after 2010. VAST also predicted that the effective area occupied by lesser-spotted dogfish significantly diminished in 1983–2020 and that its COG significantly moved southwards and eastwards. Thus, VAST predicted that the highest lesser-spotted dogfish densities in 2020 were located in the eastern English Channel and southern North Sea. JARA estimated that the lesser-spotted dogfish population was LC with a 100% probability (Appendix S4).

EUROPEAN PLAICE

VAST predicted a significant improvement in European plaice relative biomass between 1983–2020 (Appendix S4). More precisely, VAST predicted an increase between

2005 and 2015 followed by a decrease. VAST predicted that plaice COG significantly moved westwards between 1983–2020 and that its density hotspots depended on the population trajectory. JARA estimated a %C over three GLs for European plaice of +55.5%, with 100% of the posterior falling in LC.

Discussion

Here, we showed the benefits of coupling the VAST and JARA modelling tools for better informed Red List assessments of marine fishes. One primary advantage of the VAST-JARA modelling framework is its adequate characterisation and communication of uncertainty around extinction risks with the Bayesian JARA model, which is paramount for making and prioritising conservation decisions. Moreover, VAST not only delivers indices to JARA whose uncertainty is propagated to JARA outcomes, but also provides a habitat assessment for each species which complements JARA outputs. We illustrated those two advantages with an application to five North Sea species.

The North Sea application coupled with previous assessments and studies (Appendix S4) suggest that, among the three study elasmobranchs, starry ray is in most need for urgent research and management action where deemed appropriate (noting that it has been listed as either a species not to be retained or a prohibited species on European Union fishing regulations since 2014), followed by spurdog, whilst lesser-spotted dogfish is increasing in biomass. We hasten to caveat that the NS-IBTS Q1 survey only partially covers the distribution area of the stock of spurdog in the North Sea, which is considered to occupy the whole of the Northeast Atlantic (ICES, 2022), and that some caution may therefore be required when interpreting our results for spurdog. As the NS-IBTS Q1 survey does not fully cover the spurdog stock and other stocks (e.g., the cod stocks as of 2023) that are considered by ICES, we encourage the integration of data from different sources (collected by different surveys and/or observer programs) in VAST in future applications of our VAST-JARA modelling framework for North Sea species. The major issue with a survey that does not fully cover stock units is that it does not allow for an accurate habitat assessment for those stock units (Grüss, Charsley, et al., 2023). Integrating different data sources in VAST will allow for improved habitat assessments, as well as for the generation of indices for JARA likely to have reduced uncertainty and interannual variability and to cover a longer time period (Grüss, Charsley, et al., 2023; Grüss, Thorson, et al., 2023). Data integration could be done with seasonal VAST models allowing for the sharing of information not only across locations, years and data sources, but also across seasons, to seek to further improve the quality of the indices estimated with VAST (Thorson et al., 2020).

Moreover, both the VAST-JARA modelling framework and previous research (Appendix S4) indicate that, while European plaice is not of conservation concern, cod has likely met the IUCN criteria for being listed as Endangered (EN) recently. However, we hasten to note that our data were for 1983–2020 and that a new stock assessment is upcoming for cod at the time of the present study (in 2023), which will consider a new definition of the Northern Shelf cod stocks and may provide different insights into the status of those stocks (ICES, 2023).

The population trends estimated by JARA were supported by the patterns of spatial density and distribution shifts predicted by VAST. The density maps and annual centres of gravity produced with VAST help distinguish between the areas of the study region where the species of interest is faring well from the areas where the species is undergoing depletion. Such information is invaluable for guiding spatial management efforts, including the design of marine protected areas (Grüss et al., 2019a; Paradinas et al., 2022). To further understand the patterns of spatial density and distribution shifts predicted by VAST and better exploit this information, we recommend research to determine the relative importance of fishing, environmental variables, and multispecies interactions in explaining changes in density and distribution shifts in starry ray and cod, noting that both are boreal species that may have responded to increasing sea temperatures (Dulvy et al., 2008).

VAST also provided insights into the patterns of range expansion/contraction of the study species, by predicting annual changes in effective area occupied and population boundaries. The effective area occupied metric estimated by VAST is similar to the metrics employed in the Red List assessments that relate species' range size and extinction risk (i.e., based on Criterion B), namely the Area of Occupancy and the Extent of Occurrence (Keith et al., 2018). However, here, the population trend estimated with JARA did not always concur with the changes in effective area occupied in VAST. Thus, while the effective area occupied of the declining starry ray and cod was predicted to significantly diminish, the effective area occupied of the thriving lesser-spotted dogfish was not predicted to increase but rather to significantly decrease. Based on the above-mentioned results, we encourage research to improve understanding of the relationship between range changes and population trends in marine fishes and develop optimal IUCN range reduction thresholds for classifying population declines based on species' range loss. This research will be important to uncover the risks of misclassifying IUCN conservation status when Criterion B (geographic range) is used instead of Criterion A (population change).

While the VAST-JARA modelling framework constitutes a robust tool that adequately characterises uncertainty, we caution against unequivocally accepting its outcomes. We recommend that specialists of Red List assessments and the fish population of interest should be involved in any application of the modelling framework. VAST indices and JARA settings should be proofed and verified by experts, including both fish ecologists and survey scientists. Importantly, the VAST-JARA modelling framework is designed as a decision-support tool and its output should not be taken as a final classification of extinction risk (Sherley et al., 2020). Instead, predictions from the VAST-JARA modelling framework, including JARA output and VAST habitat assessment, should be seen as supporting information to make interpretations based on Red List guidelines before a decision on the final Red List assessment outcome can be made (Lee et al., 2019; Sherley et al., 2020).

The predictions of the VAST-JARA modelling framework for North Sea species will help decision-makers in their next Red List assessment for the North Sea. We foresee applications of the VAST-JARA modelling framework to assist Red List assessments of numerous other marine fishes worldwide. In addition to the utilisation of multiple data sources in VAST, we also envision several avenues for future research including, among others, the use of VAST indices for different regions in JARA to derive weighted global %C estimates, the consideration of several species simultaneously in VAST and/or JARA, and investigations of climate change impacts on species' extinction risks with the VAST-JARA modelling framework (Appendix S5). The VAST-JARA modelling framework can be implemented with only a few years of monitoring data, but requires a fair number of encounter monitoring observations per year for VAST models for individual species. The consideration of multiple species simultaneously in VAST would allow for the borrowing of information across locations and years but also across species, thereby allowing for the estimation of VAST indices and JARA extinction risks for data-limited Red List species for which this is not possible with the current VAST-JARA modelling framework.

Acknowledgments

We thank very much Romain Frelat for assisting us in preparing survey data. We are very grateful to José de Oliveira and Jim Ellis for their expert review and to Olaf Jensen, the Editor (Tadeu Siqueira), the Associate Editor (Caren Barceló) and three anonymous reviewers for their comments, which all considerably improved the quality of the manuscript. We also thank very much Lydia Groves for all of her assistance during the reviewing and production processes. Reference to trade names does not imply endorsement by the National Marine Fisheries Service, NOAA. The scientific results and conclusions, as well as any views or opinions expressed herein, are those of the author(s) and do not necessarily reflect those of NOAA or the Department of Commerce.

Conflict of interest statement

None of the authors have a conflict of interest.

Authors' Contributions

Arnaud Grüss, Henning Winker and James T. Thorson conceived the study; Arnaud Grüss, Henning Winker, James T. Thorson and Nathan Pacoureau developed the models; Arnaud Grüss and Aurore Maureaud compiled the data; Arnaud Grüss, Nicola D. Walker and Nathan Pacoureau compared the results for the application to results from previous assessments and studies; Arnaud Grüss, Henning Winker, James T. Thorson, Nicola D. Walker, Aurore Maureaud and Nathan Pacoureau analysed and discussed the results and contributed to the manuscript.

Data availability statement

Data are available from the Figshare Digital Repository https://doi.org/10.6084/m9.figshare.22596799.v1 (Grüss, 2023). R codes are available from GitHub at https://github.com/agruss2/VAST-JARA-modelling-framework and Zenodo at https://doi.org/10.5281/zenodo.10565146 (Grüss, 2024)

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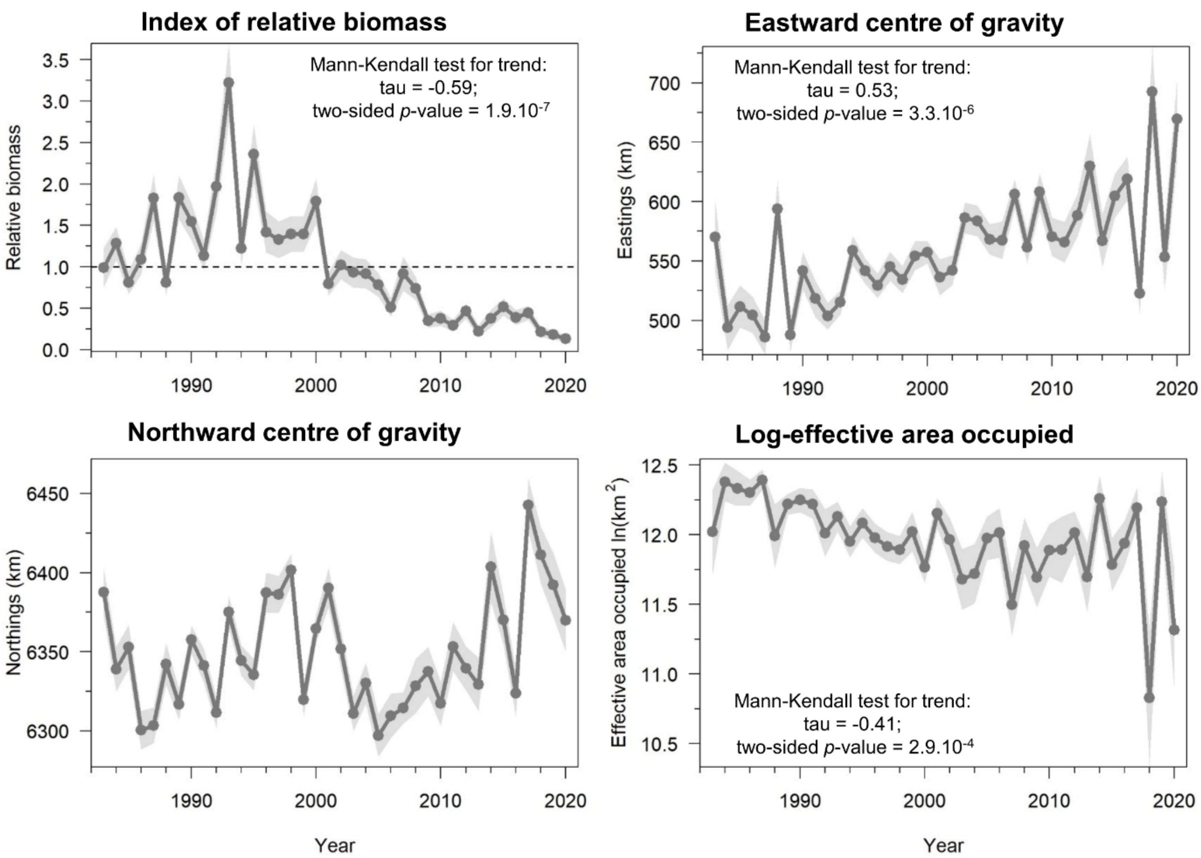
Figures

Fig. 1. Results of the VAST model for starry ray (*Amblyraja radiata*). Shaded areas represent 95% confidence intervals.



634 **Fig. 2.** Spatial patterns of log-density (in log(kg.km^{-2})) in select years of the period 1983-2020 predicted by the VAST model for starry ray. Spatial patterns of log-density in each year are shown only for those areas where log-density is greater than 1% of the maximum expected log-density over the entire period 1983-2020. For each year, the areas where log-density is less than 1% of the maximum expected log-density over the entire period 1983-2020 are highlighted in light grey.

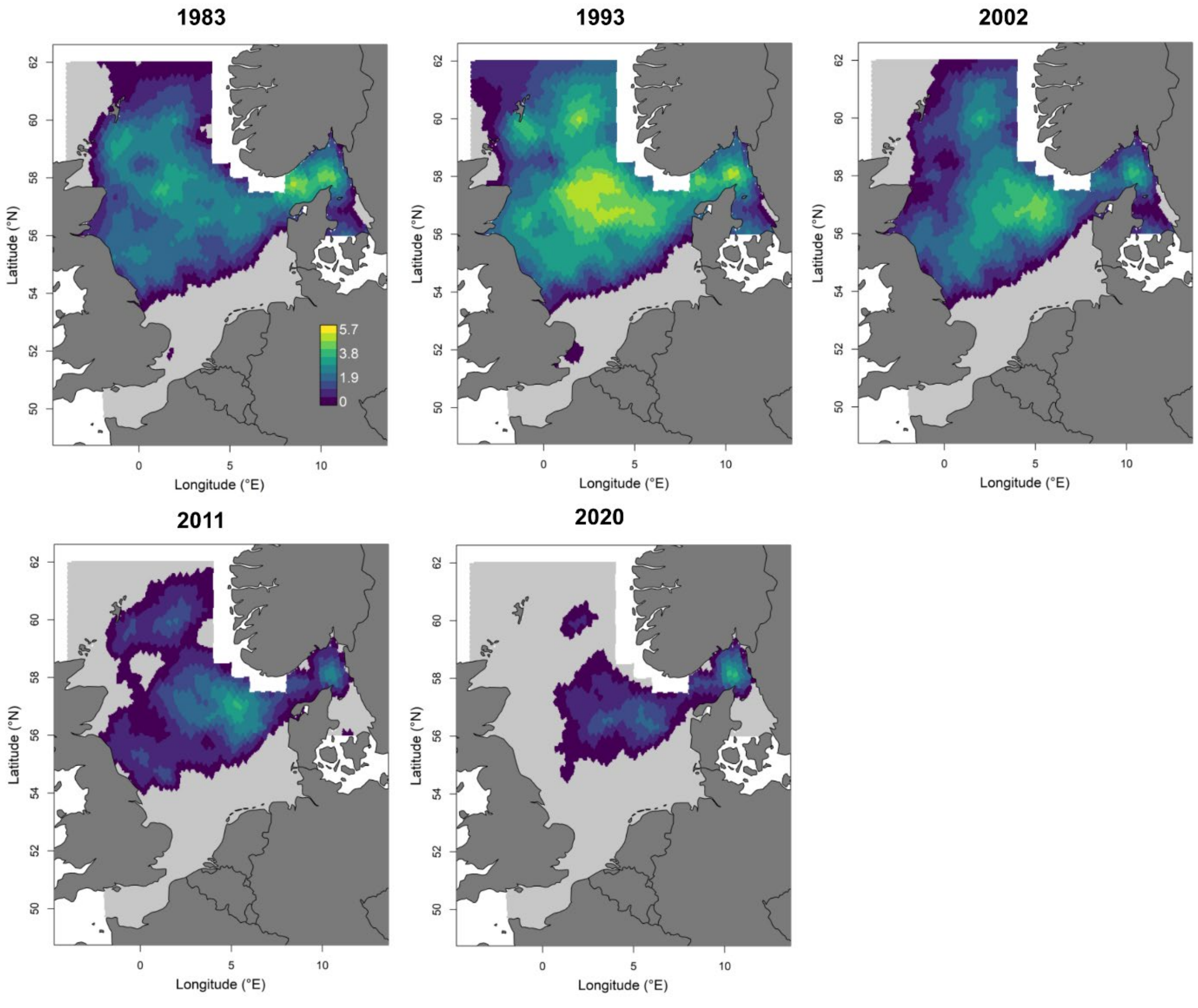


Fig. 3. Results of the JARA model for starry ray: (A) overall JARA fit (black line) to the VAST time-series and projected (dashed orange line) population trajectory over three generation lengths (GLs), and their 95% credible intervals (shaded areas); (B) the median and posterior probabilities for the percent annual change in the fish population (%C) calculated from all VAST years (in black), from the last 1 GL (in blue), from the last 2 GLs (in green) and from the last 3 GLs (in red), displayed relative to a stable population (with a %C of 0%; dotted line); (C) probabilities for %C over three GLs to fall within the International Union for the Conservation of Nature Red List categories under Red List Criterion A2 (also provided is the median %C over three GLs).

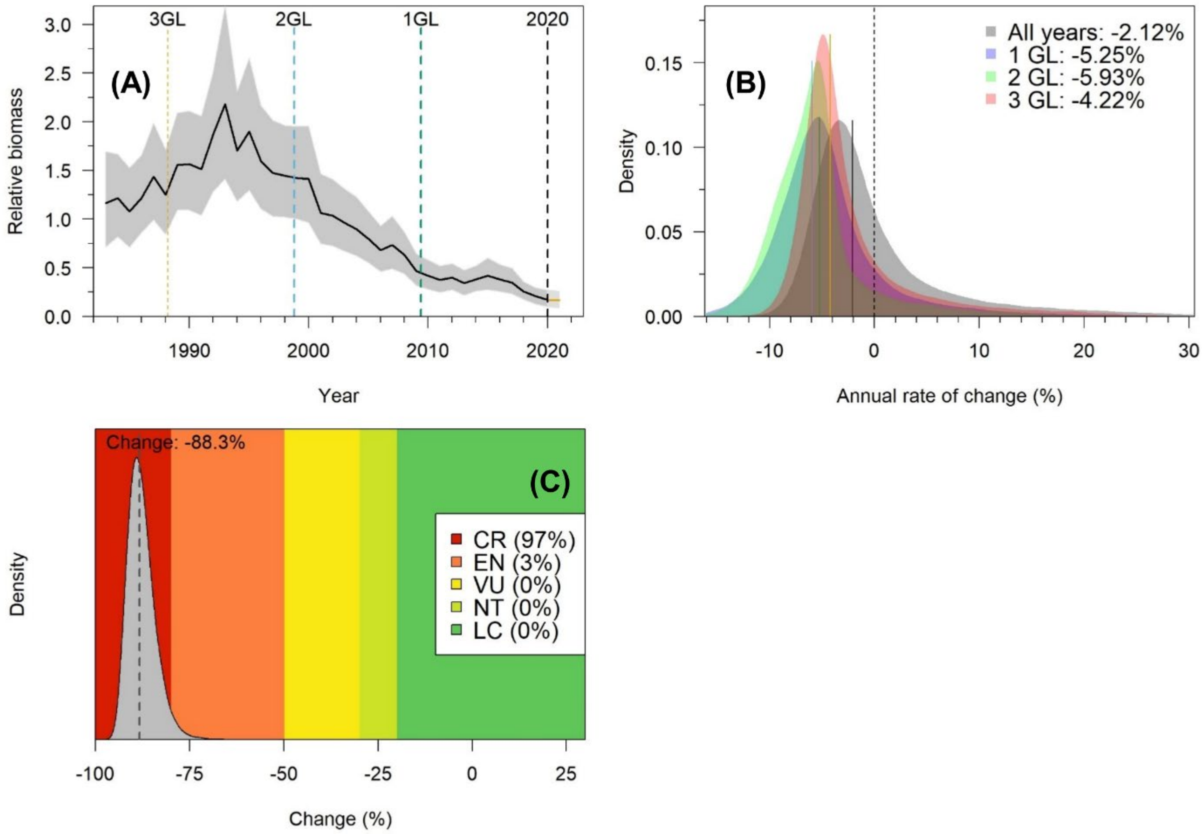
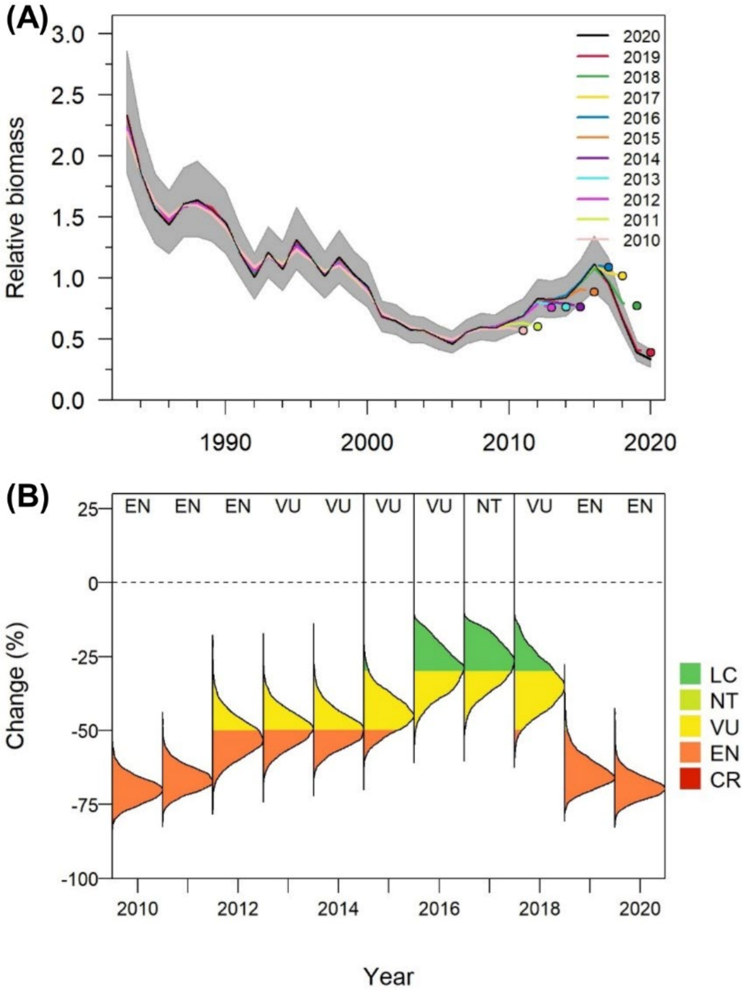


Fig. 4. Results of the retrospective analysis with JARA for cod (*Gadus morhua*): (A) retrospective pattern of relative biomass obtained through sequential removal of terminal years and subsequent forward projections to attain three generation lengths (GLs); and (B) corresponding retrospective status posteriors of change over three GLs – coloured according to the International Union for the Conservation of Nature Red List categories under Red List Criterion A2.



Tables

Table 1. Study species: regional (North Sea) name, International Union for the Conservation of Nature (IUCN) name, stock assessment information, and Red List category according to the most recent global Red List assessment and this study.

Species	**IUCN species name**	**Has a quantitative stock assessment?**	**Red List category according to the most recent global Red List assessment**	**Red List category in this study**
Starry ray (*Amblyraja radiata*)	Thorny Skate	No	VU	CR (97%), EN (3%)
Cod (*Gadus morhua*)	Atlantic Cod	Yes	VU	EN (100%)
Spurdog (*Squalus acanthias*)	Spiny Dogfish	Yes	VU	CR (2%), EN (53%), VU (26%), NT (7%), LC (12%)
Lesser-spotted dogfish (*Scyliorhinus canicula*)	Smallspotted Catshark	No	LC	LC (100%)
European plaice (*Pleuronectes platessa*)	European Plaice	Yes	LC	LC (100%)