OFFSHORE RENEWABLES JOINT INDUSTRY PROGRAMME (ORJIP) FOR OFFSHORE WIND

Summary report of sensitivity analysis (WP2)

AssESs: Assessing the extent and significance of uncertainty in offshore wind assessments

December 2025

orjip working to accelerate offshore consenting

ORJIP Offshore Wind

The Offshore Renewables Joint Industry Programme (ORJIP) for Offshore Wind is a collaborative initiative that aims to:

Fund research to improve our understanding of the effects of offshore wind on the marine environment.

Reduce the risk of not getting, or delaying consent for, offshore wind developments.

Reduce the risk of getting consent with conditions that reduce viability of the project.

The programme pools resources from the private sector and public sector bodies to fund projects that provide empirical data to support consenting authorities in evaluating the environmental risk of offshore wind. Projects are prioritised and informed by the ORJIP Advisory Network which includes key stakeholders, including statutory nature conservation bodies, academics, non-governmental organisations and others.

The current stage is a collaboration between the Carbon Trust, EDF Energy Renewables Limited, Ocean Winds UK Limited, Equinor ASA, Ørsted Power (UK) Limited, RWE Offshore Wind GmbH, Shell Global Solutions International B.V., SSE Renewables Services (UK) Limited, TotalEnergies OneTech, Crown Estate Scotland, Scottish Government (acting through the Offshore Wind Directorate and the Marine Directorate) and The Crown Estate Commissioners.

For further information regarding the ORJIP Offshore Wind programme, please refer to the Carbon Trust website, or contact Žilvinas Valantiejus (zilvinas.valantiejus@carbontrust.com) and Ivan Savitsky (ivan.savitsky@carbontrust.com).

Acknowledgements

This document was produced on behalf of ORJIP Offshore Wind by Biomathematics and Statistics Scotland (BioSS), MacArthur Green (part of SLR Consulting) and UK Centre for Ecology and Hydrology (UKCEH). The report was authored by Dr. Adam Butler (BioSS), Prof. Jason Matthiopoulos (MacArthur Green, part of SLR Consulting), Dr. Altea Lorenzo-Arribas (BioSS), Dr. Kate Searle (UKCEH), Ms. Katie Delacombe (BioSS) and Esther Jones (BioSS).

Annex A was authored by Prof. Jason Matthiopoulos (MacArthur Green, part of SLR Consulting).

We thank all of the stakeholders who contribute to the stakeholder engagement activities within Section 2 and attended the workshop in September 2024.

We thank Scottish Government Marine Directorate (SGMD) for permission to use code from the Cumulative Effects Framework, funded by SGMD and the European Maritime and Fisheries Fund.

The project was advised by the ORJIP Offshore Wind Steering Group and the AssESs Project Expert Panel. We would like to thank the following organisations for their advice and support of the project via participation on the Project Expert Panel:

Department for Environment, Food and Rural Affairs (Defra)

Joint Nature Conservation Committee (JNCC)

Natural England

NatureScot

Royal Society for the Protection of Birds (RSPB)

Scottish Government Marine Directorate

This report was sponsored by the ORJIP Offshore Wind programme. For the avoidance of doubt, this report expresses the independent views of the authors.

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Citation

Butler, A., Matthiopoulos, J., Lorenzo-Arribas, Searle, K., Delacombe, K. and Jones, E.L. *Summary report of sensitivity analysis (WP2). AssESs - Assessing the extent and significance of uncertainty in offshore wind assessments*. The Carbon Trust. December 2025

Annex A should be cited as:

Matthiopoulos, J. *Investigated investigation of uncertainty in assessment tools: Annex A to Summary report of sensitivity analysis (WP2). AssESs - Assessing the extent and significance of uncertainty in offshore wind assessments*. The Carbon Trust. December 2025

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List of Abbreviations

AssESs	Assessing the extent and significance of uncertainty in offshore wind assessments (ORJIP)
BDMPS	Biologically Defined Minimum Population Scales
BioSS	Biomathematics and Statistics Scotland
CEF	Cumulative Effects Framework
CI	Confidence Interval
CPS	Counterfactual Population Size Ratio
CRH	Collision Risk Height
CRM	Collision Risk Model
DD	Density Dependence
EmodNET	European Marine Observation and Data Network
GAM	Generalised Additive Models
GPS	Global Positioning System
HPAI	Highly Pathogenic Avian Influenza
HRA	Habitat Regulations Assessment
INTaS	Integration of tracking and at-sea survey data (ORJIP)
JNCC	Joint Nature Conservation Committee
MERP	Marine Ecosystems Research Programme
NE	Natural England
NERC	Natural Environment Research Council
ORD	Offshore Renewable Development
ORJIP	Offshore Renewables Joint Industry Programme
OSG	ORJIP Steering Group
OWF	Offshore Wind Farm
PEP	Project Expert Panel
ProcBe	Procellariiform Behaviour and Demographics (JNCC)

PVA	Population Viability Analysis
QuMR	Improving quantification of mortality rates associated with displacement within the assessment process (ORJIP)
SA	Sensitivity Analysis
ScotMER	Scottish Marine Energy Research
sCRM	Stochastic Collision Risk Model
SD	Standard Deviation
SeabORD	SeabORD (Searle et al., 2018) is a tool to help estimate the cost to individual seabirds due to displacement and barrier effects from offshore renewable developments (ORDs)
SG	Scottish Government
SGMD	Scottish Government Marine Directorate
SNCB	Statutory Nature Conservation Body
SPA	Special Protection Area
WP	Work Package

Executive Summary

A. Assessments of the ornithological impacts of offshore wind are undertaken using a range of **quantitative tools** that quantify annual mortalities from collision and displacement, apportion impacts to protected populations, and use population models to evaluate longer-term consequences.

B. Within this project we quantify **current levels of uncertainty** across the assessment process, and **sensitivities** of estimated impacts to different sources of uncertainty.

C. We evaluate the extent to which key impact assessment outputs, such as metrics associated with Population Viability Analysis (PVA), are **sensitive to uncertainties in inputs**, and to **assumptions around model structure and correlation between parameters.**

D. We assess sensitivity to inputs (Section 3), with uncertainty ranges and distributions derived through **stakeholder engagement** (Section 2) and based on the outcomes of the **review of evidence** around the estimates and associated uncertainties for key parameters used within assessment tools (WP1).

E. Outputs from this analysis demonstrate particular sensitivity of key output metrics to parameters that have a **linear relationship with mortality** (for displacement) and flux (for collision), with lower sensitivity to parameters describing bird morphology and baseline demography.

F. Uncertainty in outputs is strongly influenced by parameters, particularly **avoidance and displacement rate**, for which (a) the output metrics are sensitive to the parameter values and (b) the parameter values contain substantial uncertainty.

G. Uncertainty in outputs is also heavily driven by **treatment of variation in density data**, particularly in the context of displacement, where impacts are highly sensitive to the mean-maximum density value used by the displacement matrix (itself highly sensitive to the characteristics of the raw density data).

H. We illustrate the potential value in **propagating uncertainty from collision and displacement models into PVA models,** as a way of capturing uncertainty across the assessment process without needing to run models under large numbers of distinct scenarios.

I. Substantial **structural uncertainties** (i.e. uncertainties that arise because models are an imperfect representation of reality) are present as current assessment approaches and tools make simplifying assumptions, and omit biological features, and the systems-based sensitivity analysis (Section 4) investigates whether a **holistic modelling** of the uncertainties in the assessment process can lead to a robust representation of the sensitivities in the system.

J. We examine whether the **inclusion of biological processes which are currently not considered within assessments**, such as the inclusion of an explicit relationship between population size and foraging range, lead to significant divergence of risk estimates, and contract or inflate uncertainty in predictions of population viability.

K. This exploratory, forward-looking investigation of uncertainty **helps inform which biological features currently omitted from assessments need to be introduced**, and which of the existing features may be simplified without loss in accuracy or precision.

L. Results show that **correlations between parameters in models can generate unexpected bias and loss of precision** if they are not properly accounted for within the modelling.

M. We suggest that a key feature that is likely to improve precision and accuracy is the inclusion of **predicted future population size in relation to impact on seabird distribution** and exposure to risk.

1. Introduction

The AssESs project (Assessing the extent and significance of uncertainty in offshore wind assessments), funded by the Offshore Renewables Joint Industry Programme (ORJIP) for Offshore Wind, aims to improve the treatment of uncertainty within the assessment process for ornithological impacts, to reduce risks and delays to the consenting of offshore wind developments.

A key motivation for the project is an urgent need to quantify current levels of uncertainty across the assessment process, and sensitivities of estimated impacts to different sources of uncertainty. This is delivered through a review of existing approaches to the treatment of uncertainty within assessments, and of the evidence basis that informs these approaches, which is then used to structure a quantitative evaluation of the sensitivity of key metrics of impact to uncertainty in parameter values and model assumptions. The second key motivation for the project is a need to improve, via stakeholder engagement, the ways in which information on uncertainty is translated into decision-making within the context of a precautionary approach.

Within this work package (WP2) we assess the extent to which key impact assessment outputs, such as metrics associated with Population Viability Analysis (PVA), are sensitive to uncertainties in inputs, and to assumptions around model structure. Uncertainty ranges and distributions are derived from the WP1 review (**AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**) wherever feasible, supplemented by information obtained through stakeholder engagement. We also assess sensitivity to the ways in which uncertainty is treated within assessment tools, considering different scenarios for the use of uncertainty that reflect current practice and feasible alternatives that do not consider uncertainty in each step of the assessment process in isolation but instead allow for uncertainty to be propagated between stages. These comparisons helped to inform stakeholder discussions in WP3 (**AssESs – Summary report of stakeholder engagement (WP3)**) around the way that uncertainty is interpreted in relation to precaution. The sensitivity analysis (SA) also informs WP4 recommendations (**AssESs – Recommendations and roadmap (WP4)**) around future data collection and research, and treatment and interpretation of uncertainty in relation to precaution within the assessment process.

Uncertainty ranges and distributions considered within the sensitivity analysis, and scenarios that capture current practice around the use of these ranges within assessments, have been agreed following consultation with stakeholders (Defining scenarios with stakeholders)) to ensure relevance of the results. Using existing tools, and approaches to link these tools developed within the Scottish Marine Energy Research (ScotMER) Cumulative Effects Framework (CEF), we have evaluated the sensitivity of key metrics of impact to uncertainties in inputs across multiple assessment tools (Uncertainty in relation to inputs)). This task has also evaluated the sensitivity of outputs to alternative scenarios around the treatment of uncertainty within the process, maximising the ability of the SA to structure stakeholder discussions around decision-making in WP3.

Structural uncertainties arise from the fact that current assessment approaches and tools make simplifying assumptions, and omit biological features. Systems-based Sensitivity Analysis) investigates whether a holistic modelling of the uncertainties in the assessment process can lead to a robust representation of the sensitivities in the system. We therefore aim to examine whether the types of system interdependencies in the seabird/renewables interaction, that are currently not considered within assessments, lead to significant divergence of risk estimates, and over/under-precautionary predictions of population viability. This forward-looking investigation of uncertainty, although purely exploratory at the present time, will help us determine which biological features currently omitted from assessments need to be introduced, and which of the existing features may be simplified without loss in accuracy or precision.

2. Defining scenarios with stakeholders

It is crucial that the scope of the sensitivity analysis is relevant to stakeholder needs, since initial results of the sensitivity analysis are used to structure and facilitate discussions around uncertainty and precaution at the stakeholder workshop in **AssESs – Summary report of stakeholder engagement (WP3)**, and because results of the sensitivity analysis also contribute directly to the production of recommendations in **AssESs – Recommendations and roadmap (WP4)**. The detailed remit of the sensitivity analysis (especially in relation to parameter estimates, uncertainty ranges, scenarios of existing practice) was agreed in consultation with the ORJIP Steering Group (OSG) and Project Expert Panel (PEP) to ensure relevance of the results to the assessment process. The key part of the consultation – a workshop, held in September 2024 – also included additional expertise and perspectives not already represented on the OSG or PEP.

Stakeholder engagement, informed by the outcomes of the WP1 review, was crucial in determining:

- Tools, parameters, species, projects and populations to consider so as to maximise relevance of the SA results to the current assessment process.
- The most appropriate "reference" estimates to use for each parameter – sensitivity is then evaluated by looking at the impact of varying each parameter away from this "reference" estimate.
- Levels of uncertainty to consider for each parameter, especially those for which multiple sources of evidence are available (WP1) or for which information of uncertainty is missing.
- Appropriate ways of capturing uncertainty – e.g. uncertainty ranges, or, in situations where it is not plausible to assume that the parameter is uniformly distributed, through the parameters of probability distributions.
- Current approaches to the propagation of uncertainty between tools.

2.1. Initial engagement

The draft set of tools to consider within the sensitivity analysis was agreed at the start of the project, in conjunction with the review of existing tools within **AssESs – Summary report of uncertainty and**

approaches to evaluating uncertainty review (WP1), allowing background work on the development of code to run the sensitivity analyses to begin. It was necessary to constrain the scope of the sensitivity analysis to ensure that it could be completed within the timeframe and resources of the project. Given the importance of HRA in the breeding season, and the widespread use of the NatureScot apportioning tools, we initially envisaged the scope being focused on three pathways - (a) NatureScot Apportioning Tool (NatureScot, 2018), Stochastic Collision Risk Model (sCRM) (McGregor et al, 2018) and Natural England (NE) /Joint Nature Conservation Committee (JNCC) PVA Tool (Searle et al., 2019), (b) NatureScot Apportioning Tool, Displacement Matrix and NE/JNCC PVA Tool, and (c) SeabORD and NE/JNCC PVA Tool. Note that SeabORD would not be re-run as part of the sensitivity analysis, but would (when considering uncertainty in relation to inputs in Section 3) exploit existing SeabORD runs done as part of existing sensitivity analyses in the ORJIP Improving quantification of mortality rates associated with displacement within the assessment process (QuMR) project.

2.2. Stakeholder workshop

A two-hour online stakeholder workshop on the scope of the sensitivity analysis (SA) took place on 26 September 2024, following the completion of the draft review for WP1. The workshop aimed to reach consensus around six key elements of the scope of the sensitivity analysis:

1) Species, projects and populations to focus on in the SA,
2) Levels of uncertainty to consider for inputs to the tools being used within the SA (e.g., using evidence from the review in WP1),
3) Approach(es) that the SA needs to consider when propagating uncertainty between different tools so as to capture current practice,
4) Key impact assessment outputs (e.g., PVA metrics) to focus on in the SA,
5) Correlations between parameters,
6) Choice of probability distributions to best reflect uncertainty in inputs,

with the primary focus of the workshop being around the first three of these elements. The workshop also sought feedback on the draft review of tools and parameters within WP1.

2.2.1. Attendees

The workshop involved (Table 1) members of the Project Team, Project Expert Panel and ORJIP Steering Group, as well as Carbon Trust and two additional external experts.

Table 1: Workshop participants

Workshop participants	
Project Team	
BioSS	UKCEH
MacArthur Green	James Hutton Institute
Project Expert Panel and ORJIP Steering Group	
NatureScot	Ørsted

Workshop participants	
Equinor	Ocean Winds
ScotGov	Shell
SSE	Crown Estate Scotland
Natural England	NatureScot
Ørsted	Defra
RSPB	RWE
Additional Experts	
MacArthur Green	Waardenburg Ecology
Carbon Trust	

2.2.2. Structure

The workshop involved a two-hour online session. The workshop began, following introductions, with a presentation by Dr Adam Butler (Biomathematics and Statistics Scotland (BioSS)) on the overall objectives of the project and the purpose of the workshop. This presentation emphasised the role of the sensitivity analysis within the project, and the way in which the outputs from the sensitivity analysis would feed into the stakeholder workshop around uncertainty and precaution in early December (**AssESs – Summary report of stakeholder engagement (WP3)**. He emphasised that the role of the meeting was to agree a scope for the sensitivity analysis, to ensure the inputs and scenarios that are considered produced outputs that are relevant to stakeholder needs. This was followed by a presentation by Prof Bob Furness (MacArthur Green) on the results of the review of tools and parameters within WP1, outlining the evidence base around the data underpinning assessments and guidance, for different species. There was a particular focus on quantification of uncertainty, and the aim of the presentation was to inform and stimulate subsequent discussions. Following the presentations there was a Q&A session around the presentations, and then a structured set of discussions around the scope of the sensitivity analysis.

2.2.3. Summary of Q&A on presentations

Note: the names of the two presenters (Adam Butler (AB), Bob Furness (BF)) are included for clarity, since this part of the discussion was a Q&A session, but the discussion is otherwise summarised and anonymised.

Definitions of uncertainty and precaution: there was discussion around the distinction between precaution and uncertainty, the definitions of each term, and whether precaution should be applied to inputs or outputs. Advantages of applying precaution to outputs, so as to avoid multiplying precaution in the inputs, were highlighted – it was noted, for example, that the seasonal peak can be substantially higher than the mean (up to 5 times higher in the project-level data collated for WP1) due to aggregation of birds. AB confirmed that there will be more detailed discussion of the interpretation of uncertainty in relation to precaution, and definitions of precaution and uncertainty, both in the **AssESs – Summary report of stakeholder engagement (WP3)** stakeholder workshop and subsequent stakeholder engagement, and that the sensitivity analysis will inform this by comparing quantitative results that arise from different approaches to the treatment of uncertainty in relation to precaution.

Ground versus air speed: there was discussion around the points in the WP1 presentation on air and ground speed, and in particular why ground speed is less than air speed. BF clarified that seabirds fly at minimum power cost to preserve energy, and that air speed is therefore influenced by the wind (e.g., a headwind takes up more effort, so leads to a higher airspeed, whilst a tailwind uses less energy leading to a lower airspeed, but both of these would have the same ground speed). It was noted that wind speeds and wind directions will influence the height at which birds fly, that it is important to consider flux both upwind and downwind from the windfarm, and that foraging areas will depend on wind direction and speed.

Avoidance: there was discussion on the impact of age and individual-level variation on avoidance. It was noted that individuals feeding chicks will feel more pressured to forage, and that the more experienced, older breeders/birds may have learned knowledge on avoidance tactics. There was agreement around the importance of avoidance, and it was noted that for sensitivity analyses involving avoidance rate it is important to work with (1 – avoidance rate), because without doing this the importance of avoidance can be artificially overstated.

Summarising density data: it was noted that uncertainty in project-level densities may not be well represented by using standard deviations, because the assumption of normality will not necessarily be plausible.

2.2.4. Summary of discussion around SA scope

The remaining discussion sought to reach consensus around (1) species, projects and populations to focus on in the SA, (2) levels of uncertainty to consider for inputs to the tools being used within the SA (e.g., using evidence from the review in **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**), (3) approach(es) that the SA needs to consider when propagating uncertainty between different tools so as to capture current practice, (4) key impact assessment outputs (e.g., PVA metrics) to focus on in the SA, and, insofar as feasible, (5) correlations between parameters & choice of probability distributions to best reflect uncertainty in inputs. The five discussion topics were arranged in descending order of importance in relation to stakeholder involvement in initial decision making, so that the initial topics were those for which stakeholder discussion was regarded as essential to ensure relevance, whilst the later, more technical topics, were regarded as those for which the project team could formulate a proposed approach and seek written feedback. In practice, time pressures meant that the first three topics were discussed, and elements of the fifth topic were also discussed as part of the discussion around these topics. The fourth topic was not discussed at the workshop, but was resolved in written correspondence following the meeting.

Selection of species, projects and populations

There was discussion around the selection of species, projects and populations for inclusion in the SA, noting that the selection of species and projects will necessarily be heavily influenced by data availability and that it would be infeasible within the timelines of the project to source additional data in time to use it within the SA. Discussion focused in particular on the question of whether the SA should use data from real Offshore Wind Farms (OWF) or alternatively should use synthetic or hypothetical data. It was noted that if hypothetical data are used then they need to reflect reality, so the process of generating the data is critical. The difficulties of using actual OWF data were also highlighted. There was a general consensus around using synthetic but plausible OWF data: either hypothetical (simulated) data or else anonymised / perturbed versions of real data. In relation to the selection of species for inclusion in the SA it was noted that the density data collated in the WP1 review were based on site characterisation of OWFs and that there may be species not included there. It was also noted that these are only daytime, and so do not include nocturnal activities, providing an additional source of uncertainty. It was noted that it would be interesting to include Storm Petrel and Manx Sheerwater but data are limited for these species. West coast tagging of petrels on the West Coast is feeding into the JNCC Procellariiform Behaviour and Demographics (ProcBe) project, and it was noted that the link to ProcBe should be highlighted. Consideration of in-combination assessments was discussed, but it was noted that uncertainty in existing OWF impacts was not currently captured within in-combination assessments.

Levels of uncertainty for inputs

The next discussion focused on agreeing levels of uncertainty to consider for inputs to the tools in the SA, including (a) baseline density/abundance (for use in Collision Risk Model (CRM) and Displacement Matrix), (b) displacement rate, displacement mortality rate (for use in Displacement Matrix), (c) avoidance rate and other collision risk inputs (for use in CRM), (d) foraging range (for use in breeding season apportioning), (e) baseline demographic rates (for use in Population Viability Analysis). It was noted that it is not necessarily possible or necessary to agree in detail the level of uncertainty to consider for every input individually, so the remit of the discussion was to agree on the approach to setting these levels, especially where information is sparse/lacking. Key points raised in the distribution were:

- Empirical distributions of project-level density (abundance) values from at-sea surveys are not well captured by commonly used probability distribution models: rather, they are typically bimodal, reflecting substantial inter-annual differences and the fact that two years of data are usually collected. The use of Tweedie distributions (e.g., in recent work in the Netherlands) was highlighted.
- The use of NERC (Natural Environment Research Council) Marine Ecosystems Research Programme (MERP) data to characterise densities was discussed, but it was noted that the properties of these will differ from the characteristics of monthly project-level density data used in assessments.
- It was noted that a project is currently underway to update demographic rates, which will be published soon.
- It was noted that the way foraging range enters into apportioning calculations varies between England and Scotland, and that foraging range is typically used to screen Special Protection Areas (SPAs) for inclusion in a Habitat Regulations Assessment (HRA).
- The impact of Highly Pathogenic Avian Influenza (HPAI) on foraging ranges was identified
- Seasonal definitions were highlighted as a key issue – e.g., in relation to sensitivity of outputs to the specification of the duration of breeding season.

Approaches to propagation of uncertainty

This discussion focused on agreeing the approaches that the SA needs to consider when propagating uncertainty between different tools so as to capture current practice. It was noted that the key thing here is for the Project Team to understand how uncertainty is currently handled in situations where more than one tool is being used, to make sure the SA includes scenarios that reflect this. Within this context one "scenario" could, for example, be to feed uncertainty information into assessments by always taking the upper limit of the uncertainty range for every parameter. The scenarios of existing practice used in the SA will be designed to capture those approaches that are either recommended in guidance or widely used in practice, to ensure relevance of the SA results to the existing assessment process. The outputs from this part of the SA fed into stakeholder workshop discussions (**AssESs – Summary report of stakeholder**

engagement (WP3) around different ways and points in the process at which uncertainty/precaution is applied – e.g., to inputs or outputs. Key points from the discussion were that:

- Multiple scenarios may be run within the context of an assessment, so there is both uncertainty within each scenario, and uncertainty between scenarios;
- Bootstrap densities, rather than summary statistics of density, are increasingly being used as inputs for collision models;
- Quantitative uncertainties in outputs within a scenario are often captured using SDs and confidence intervals;
- The way in which, and extent to which, uncertainty is presented can vary between graphs and the associated text;
- Variation in practice between SNCBs needs to be taken into account within the SA.

2.3. Follow-up engagement

There was follow-up engagement via email and written documents to (a) capture input relevant organisations and individuals that could not be represented at the meeting, (b) get feedback around issues that could not, because of time constraints, be covered in the meeting (e.g., selection of impact metrics), and (c) follow up with individuals who had raised specific points at the meeting that could not be fully explored within the discussions. Note that the focus of the discussions and subsequent follow-up engagement was only on reaching a consensus around the scope of the SA, to ensure relevance, not on reaching a consensus around what should be done in assessments: WPs 3 and 4 will go on to consider the wider context around the use of uncertainty within the assessment process.

One key element that was not discussed at the workshop, due to time constraints, but for which input was sought via follow-up engagement, was in relation to the key metrics of impact (outputs) to consider within the sensitivity analysis. Stakeholder engagement was used to ensure that the metrics used in SA are relevant to those used in practice in assessments. It was highlighted, when seeking stakeholder input, that it is not necessary to decide on a single metric, if there are multiple metrics that would be useful to consider within the SA.

A detailed proposed scope of work for the evaluation of sensitivity in relation to inputs (Section 3) - involving specification of tools, parameters, species, windfarm characteristics and parameter estimates to be considered, and an explanation of the approach to quantifying impact of variation and uncertainty in these parameters - was formulated following the stakeholder engagement workshop (Section 2.2), and circulated to the Project Expert Panel and Steering Group. The scope was then revised to account for this feedback. Interim results from the sensitivity analysis in relation to inputs (Section 3) were used to inform and structure the stakeholder engagement workshop on 6th Dec (**AssESs – Summary report of stakeholder engagement (WP3)**). The tight timelines associated with this meant that the scope of work for this part of the sensitivity analysis was necessarily highly constrained. The analysis was, however, modified and extended following the workshop to incorporate additional stakeholder feedback (e.g., through inclusion of additional species).

3. Uncertainty in relation to inputs

The first part of the sensitivity analysis focuses on quantifying uncertainty in key metrics of impact in relation to uncertainties in parameters using the sets of tools and parameters agreed within the stakeholder engagement (Section 2), informed by the outputs of the review in **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**. The specific objectives of this part of the sensitivity analysis were to:

1. Investigate the impact of different approaches to the propagation of uncertainty between tools;
2. Investigate how varying the values of parameters by an amount that is common for all parameters (eg., -10% / +10%) translates into variation in key outputs;
3. Investigate how the advised/published levels of uncertainty in parameter values translate into variation in key outputs;
4. Evaluate the impact of changing qualitative modelling options within the tools.

The scope of this work goes beyond previous sensitivity analyses for specific tools by considering the impacts of uncertainty in parameters to multiple tools upon a single set of outputs (PVA metrics) and by considering the propagation of uncertainty between tools. Scenarios of existing practice and guidance involve a separate interpretation of uncertainty in relation to precaution for each tool. We consider alternative, more statistically defensible, scenarios in which uncertainty is propagated between tools and the interpretation of precaution is made in relation to the final outputs (uncertainty is propagated and so uncertainty can be captured that arises in earlier steps within the assessment process). These alternative scenarios represent potential mechanisms for modifying the way precaution is interpreted in relation to uncertainty in assessments and preliminary results from these comparisons helped to inform discussions in WP3 (through the stakeholder workshop).

3.1. Methods: selection of tools

When collision is being considered we use the stochastic collision risk model (sCRM, McGregor et al., 2018) - which, where relevant, is also used to run the deterministic Band model by setting all standard deviations equal to zero - to quantify annual mortality from collision and then, via code from the CEF, feed the outputs of this tool into the CEF extension to the NE/JNCC PVA tool. When displacement is being considered we use the Displacement Matrix to quantify annual mortality from collision and then (via code from the CEF) feed the outputs of this tool into the CEF extension to the NE/JNCC PVA tool.

SeabORD provides an alternative tool for quantifying breeding season impacts of displacement, and we also undertake a small additional piece of work involving SeabORD and the NE/JNCC PVA tool, utilising existing SeabORD runs from the ORJIP QuMR project. The ORJIP QuMR project considered sensitivity of key SeabORD outputs to variation in key input parameters. Rather than duplicating this analysis, we link the outputs from the ORJIP QuMR sensitivity analysis to the JNCC/PVA Tool, to understand the implications of uncertainty and sensitivity in SeabORD for uncertainty and sensitivity in PVA metrics.

The sensitivity analysis described within this section focuses on evaluating the sensitivity of key metrics of impact to uncertainties in inputs across multiple assessment tools. Development of the capacity to run such evaluations, which rely upon linkage of assessment tools, was one of the key motivations for the development of the Cumulative Effects Framework (CEF), commissioned by the Scottish Government

(SG) ScotMER programme, so the work here exploits this functionality in order to generate large number of runs of linked tools in a relatively automated way. The Cumulative Effects Framework (CEF) is designed to link together existing assessments tools and data – including the main tools that are currently used for apportioning, PVA, displacement risk and collision risk - in a transparent way, so it provides a natural mechanism to use for assessing the sensitivity of outputs to inputs. The inputs to the CEF are, in essence, the inputs to the individual assessment tools (with a small number of additional inputs to control the linkages between tools), so using the CEF for the sensitivity analysis allows uncertainty to be considered across multiple assessment tools. The CEF has a user-friendly interface with underlying functionality provided by a suite of R functions. We directly ran the R functions that sit behind the CEF, rather than the user-friendly interface, to ensure transparency and reproducibility, and to provide a relatively fast and automated approach to produce a large number of runs of assessment tools.

We have, as far as possible, used existing tools, and only used new functionality created within the CEF project where this is necessary to the aims of this work. The workflow used by the CEF in the context of the tools considered here (aside from SeabORD) is straightforward, and, aside from consideration of alternative approaches to propagation of uncertainty, designed to replicate the approach currently taken within assessments:

1. Depending on the impact mechanism being considered, either monthly collision risk is quantified using the sCRM and summed to seasonal level, or seasonal displacement risk is quantified using the Displacement Matrix;
2. The resulting estimate of mortality is apportioned to the population of interest by multiplying by an "apportioning proportion"; this value is assumed to include a conversion from "all birds" into "breeding adults";
3. The estimated mortality is converted into an impact on annual survival rate by dividing the number of breeding adults in the population (e.g., number of breeding pairs x 2);
4. The impact on immature survival rate is assumed to be a fixed multiple of the impact on adult survival, and (direct) impacts on productivity rates are assumed to be zero;
5. These are then used as inputs to the PVA.

The key element of functionality that we have exploited from the CEF is the extension of the NE/JNCC PVA tool to allow simulation-based estimates of annual effects to be used as inputs – this allows, for example, the simulation-based outputs from the sCRM to be fed directly (after conversion into impacts on demographic rates) into the NE/JNCC PVA tool, allowing us to consider alternative ways of propagating uncertainty between tools. We use test examples to check that the NE/JNCC PVA tool and the CEF version version of the PVA tool produced identical results in situations where either could be used (e.g. where simulation-based inputs are not being used within the PVA).

We consider the proportion of birds that can be apportioned to the population of interest as one of the parameters to include in the sensitivity analysis, but it was decided not to consider the apportioning tools that generate these values. This is because none of the three apportioning tools currently used in assessments and included in the CEF are controlled by user-modifiable parameters: Biologically Defined Minimum Population Scales (BDMPS) and the GPS-based apportioning method (using Wakefield *et al.*, 2017), at least as currently implemented, do not contain user-modifiable parameters. The distance-decay approach ("NatureScot Apportioning") depends on the foraging range, but the stakeholder meeting (Section 2) noted that this dependence is complex, as the foraging range is primarily used to determine the set of populations to consider within the assessment, rather than to directly determine apportioning proportions. Consideration of the set of populations to consider is beyond the scope of this work, so we do not consider the impact of foraging range on apportioning within this sensitivity analysis. Note that alternative apportioning methods and tools are being developed (e.g., within the ORJIP INTaS (Integraton of tracking and at-sea survey data) project and in Niven et al., 2025) and will be relevant to future assessments, but the focus here is upon those tools that have commonly been used in assessments to date.

3.2. Methods: selection of species

The selection of species to include in the SA, and the impact mechanisms (collision / displacement) to consider for each species, were determined by a combination of stakeholder feedback and data availability. Only species for which quantitative estimates can be used to directly provide values for all of the parameters needed for running the relevant tools were included in the sensitivity analysis. In particular, species were only included if they were both (a) included in the MERP density maps (Waggitt et al., 2020) (since the MERP maps were used to generate scenarios of project-level densities) and (b) included in the NE/JNCC PVA tool (since reference values of demographic rates were specified based on default values within the NE/JNCC PVA tool). These criteria led to the exclusion of great skua (*Stercorarius skua*) and red throated diver (*Gavia stellata*; not included in the NE/JNCC PVA tool), arctic skua (*Stercorarius parasiticus*, not included in MERP maps), common gull (*Larus canus*), black-headed gull (*Chroicocephalus ridibundus*) and arctic tern (*Sterna paradisaea*; not included in either MERP maps or NE/JNCC PVA tool).

The initial position was to consider species and impact mechanisms for which all of the required "reference" parameter values data can be taken from the **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)** report (or, for baseline demographic rates, from the NE/JNCC PVA tool defaults), but following stakeholder feedback around appropriate reference values to use this list was extended to include northern fulmar (collision) and sandwich tern (collision, displacement). Based on these criteria the final set of species considered was:

Collision: northern gannet (*Morus bassanus*), black-legged kittiwake (*Rissa tridactyla*), great black-backed gull (Larus marinus), lesser black-backed gull (Larus fuscus), herring gull (Larus Argentatus), sandwich tern (*halasseus sandvicensis*), northern fulmar (*Fulmarus glacialis*).

Displacement: northern gannet (*Morus bassanus*), black-legged kittiwake (*Rissa tridactyla*; Scotland only), Sandwich tern (*halasseus sandvicensis*), common guillemot (*Uria aalge*), razorbill (*Alca torda*), Atlantic puffin (*Fratercula arctica*).

Note that for those species for which displacement and collision will be considered they will be treated separately – to keep the scope of work feasible (given the timelines) we do not consider combined impacts of displacement and collision here.

3.3. Methods: reference parameter values and uncertainty ranges

The starting point for the sensitivity analysis in relation to inputs is to produce a "reference" run for each species for each impact (collision or displacement, as relevant for each species). The sensitivity analysis then varies the values of parameters used within this "reference" run, to assess sensitivity to input values and to evaluate the impact of uncertainty in inputs. The sensitivity analysis also considers the impact of varying model assumptions.

Note that the “reference runs” are intended to represent *plausible* scenarios, but are not intended to reflect any specific set of developments, and are not intended to be representative. As such, they are intended to be useful as a basis for comparison (in relation to variation in parameter values), but are not intended to be used to provide an indication of absolute risk (or to, e.g., be used for the comparison of risk between species).

The selected set of tools determines the set of input parameters that need to be considered when running the tools. Table 2 summarises the input parameters for the tools being considered here, and how uncertainty is represented within each of these within the assessment tools.

Table 2: Parameters used in assessment tools/workflow considered within the sensitivity analysis.

* including impact of density dependence if a density-dependent model is being considered;
** functionality added explicitly within the CEF project

Parameter	Varies by windfarm/population (in CEF input)	How uncertainty is represented (in CEF input)
Species-specific inputs to sCRM (only relevant to scenarios involving collision risk)		
Density within project (no buffer)	Windfarm, month	Mean, SD **OR** Simulated
Body Length	None	Mean & SD
Wingspan		
Flight speed		
Avoidance rate		
Nocturnal activity		
Flight height	Windfarm	Value only (proportion at collision risk height) **OR** bootstrapped
Turbine/windfarm inputs to sCRM (only relevant to scenarios involving collision risk)		
Number of turbines	Windfarm	Value only – uncertainty not relevant as design-related parameters
Turbine model		
Windfarm latitude		
Windfarm width		
Number of blades		

Parameter	Varies by windfarm/population (in CEF input)	How uncertainty is represented (in CEF input)
Blade width		
Hub height		
Rotor radius		
Pitch		Mean & SD
Rotation speed		Mean & SD
Proportion of upwind flights		Value only
Tidal offset		Value only
Inputs to Displacement Matrix (only relevant to scenarios involving displacement risk)		
Mean seasonal peak density within project (with buffer)	Windfarm, month	Mean, SD **OR** Simulated
Displacement rate	*None*	Value **OR** Simulated**
Displacement mortality rate	*None*	
Parameters needed to link collision/displacement effects to PVA tool inputs		
Apportioning proportion	Population, windfarm, season	Value only
Population size (to standardise impact)	Population	Value only
Immature survival ratio**	Windfarm	Value only
Baseline parameters needed for PVA Tool		
Population size (to initialise PVA)	Population	Value only
Baseline productivity *	Population	Mean & SD*
Baseline adult survival *	Population	Mean & SD*
Baseline immature survival *	Population	Mean & SD*
Maximum brood size	*None*	Value only
Age at first breeding	*None*	Value only

These parameters generally represent input parameters for the individual tools: sCRM, Displacement Matrix and the NE/JNCC PVA Tool. Impact-related parameters for the NE/JNCC PVA Tool do not need to be specified, as these are derived from annual mortality estimates derived from the sCRM or Displacement Matrix.

The CEF introduced (following stakeholder feedback within that project) an explicit parameter to control the magnitude of the impact on immatures in relation to the impact on adults. The approach taken in the CEF is to assume that impacts on immature survival rates are a fixed multiple of impacts on adult survival rates, where the user specifies the multiplier used in converting impacts on adult survival into impacts on immature survival. This functionality is primarily included to allow sensitivity of assumptions around the treatment of impacts on immatures to be assessed.

3.3.1. Types of parameters

We divide the parameters required by the tools into three types, which we treat in distinct ways within the sensitivity analysis:

Fixed parameters, which do not depend on the species or population under consideration and are assumed fixed throughout. These parameters relate primarily to operational characteristics of turbines and windfarms (number of turbines, turbine model, windfarm latitude, windfarm width, number of blades, blade width, hub height, rotor radius, pitch, rotation speed, tidal offset). The focus of this work is on understanding uncertainty, so as these parameters relate to design they are not of direct interest. We therefore keep them fixed throughout the sensitivity analysis.

Species-specific parameters, being considered for uncertainty and sensitivity. These include almost all of the parameters considered in the **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**, apart from bird density: Body Length, Wingspan, Flight speed, Avoidance rate, Nocturnal activity, Flight height, Proportion of upwind flights, Displacement rate, Spatial scale of displacement, Displacement mortality rate, Baseline adult survival, Baseline productivity. Two parameters relating to the PVA, maximum brood size and age at first breeding, are specific-specific, but not considered in the uncertainty and sensitivity analyses.

Scenario-specific parameters that vary between windfarm and/or population scenarios: density/abundance in project (with/without buffer), population size, apportioning proportion, and ratio of immature to adult impacts. Different scenarios are constructed, to ensure that results of the SA are relevant to a range of situations. Sensitivity to the value used within each scenario is also assessed.

3.3.2. Values of parameters relating to windfarm/turbine characteristics

The discussion from the stakeholder meeting (Section 11), and subsequent feedback, indicated that there was a preference for using hypothetical rather than real windfarm information. The discussion did, however, emphasise the importance of the windfarm characteristics being plausible. The focus in specifying windfarm and turbine-related parameter values is therefore to ensure that they capture the sorts of situations encountered in practice in the context of assessments, but not necessarily to capture the exact range of inputs used in current assessments. Sensitivity analysis focuses upon relative results in any case (e.g. the impact of changes in inputs upon changes in outputs), so for this reason, and because the windfarm characteristics considered are hypothetical rather than real, for the purpose of the SA it is only necessary for the inputs to be plausible and relevant to assessments, not for them to be fully representative/comprehensive of actual assessments.

Values relating to turbine and windfarm characteristics (turbine model, number of blades, rotor radius, air gap, blade width, rotation speed, pitch, number of turbines, monthly operational time, latitude, windfarm width) are treated as fixed through the sensitivity analysis, since these are design-related parameters. Values are based on realistic values, comparable to projects in English waters, provided by Natural England. Three sets of generic values were provided ("Generic R4 OWF Irish Sea", "Generic R4 OWF Southern North Sea", "Generic R2 OWF Southern North Sea"), and the median of these is used to specify the value for each parameter. This results in considering a hypothetical windfarm with 50 turbines, latitude 53.2 degrees, width 10km, and turbines with 3 blades, rotor radius of 110m, mean air gap of 25m, blade width 7m, mean rotation speed of 7 rpm (SD = 0), mean pitch of 10 degrees (SD = 0), tidal offset of 2.5m, wind availability of 89-95% (depending on month), and zero maintenance downtime. Turbine power was assumed to be 5MW (based on median values from the relevant dataset in the CEF Data Store). Rotor speed and pitch were specified via probability distributions, rather than a relationship with wind speed, and a large array correction was not used.

3.3.3. Reference values of species-specific parameters

For each species-specific parameter, for each species for which it is relevant, we base the "reference run" on current SNCB guidance, where available, and perform all other comparisons against this "reference" run. This allows the impact of varying parameter values, and incorporating information on uncertainty in parameters, to be evaluated.

The reference parameter values for species-level collision risk model parameters (avoidance rate, flight speed, nocturnal activity factor, proportion of upwind flights, flight heights, wingspan, body length) were based on values recommended in the 2024 joint Statutory Nature Conservation Body (SNCB) advice note (JNCC et al., 2024), as summarised in Tables 2-4 of the WP1 report. The only exceptions were in those situations where values were not explicitly listed in JNCC et al. (2024): (a) flight speed values for northern fulmar were based on Pennycuick (1987) as listed in Table 31 of the WP1 report; (b) body length and wingspan for sandwich tern and northern fulmar were based on values from Snow & Perrins (1998) provided by Natural England; (c) proportion upwind values for northern Fulmar were assumed to be 0.5; (d) nocturnal activity values for norther Fulmar and sandwich tern were assumed to be [0.5, 0.75] and [0, 0.05] respectively, based on assuming about a crude conversion of values of 4 and 1 in Garthe & Hüppop (2004) into numeric values. Reference runs using CRM Model Option 2, with values for flight heights, are based directly on the bootstrap samples stored as data within the stochLAB R package that underpins that sCRM.

Separate Scottish and English reference runs are conducted for displacement, reflecting variations in the advice regarding species and rates. Scottish reference values for displacement rates and displacement mortality rates are based on values from NatureScot (2023h), as described in **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**, whilst English reference values are based on:

Displacement rate: a range from 30-70% for guillemot and razorbill, 60-80% for gannet.

Displacement mortality rate: range from 1-10% including 2% and 5% for guillemot and razorbill.

Reference values of baseline demographic rates (adult survival, productivity, maximum brood size, age at first breeding) are based on the default values for the NE/JNCC PVA Tool. Specifically:

- Defaults for adult and immature survival rates within the tool are derived from Horswill & Robinson (2015): we use the "national"-level values as the "reference" values, and using other values listed by Horswill & Robinson (2015) as "alternative" values.
- Defaults for productivity are based on aggregating Seabird Monitoring Programme productivity data – we use the national-level rates as "reference values".

3.3.4. Reference values of scenario-specific parameters

The final set of parameters relate to the specific windfarm(s) and/or populations being considered.

As noted earlier, the discussion from the stakeholder meeting (Section 11), and subsequent feedback, indicated that there was a preference for using hypothetical rather than real windfarm information. The discussion did, however, emphasise the importance of the windfarm characteristics being plausible. The focus in considering the values to use for key windfarm/population related parameters is therefore to ensure that a plausible range of scenarios are considered, that capture the sorts of situations encountered in practice in the context of assessments, but not necessarily to capture the exact inputs used in any specific assessment(s). As noted earlier, sensitivity analysis focuses upon relative results in any case (e.g., the impact of changes in inputs upon changes in outputs), so for this reason, and because the windfarm characteristics considered are hypothetical rather than real, for the purpose of the SA it is only necessary for the inputs to be plausible and relevant to assessments, not for them to be fully representative/comprehensive of actual assessments.

Reference values for project-level bird densities are derived from MERP species-level spatial distribution maps. Densities are calculated for each windfarm polygon within the European Marine Observation and Data Network (EmodNET) dataset contained in the CEF Data Store (https://cefrmwk-librarybook.datalabs.ceh.ac.uk/ord.html#ordpolygonsandpoints). For collision, monthly values are extracted for each polygon using the "on water" maps, and the reference density values (per km^2) are based on the project with the overall median density. For displacement, monthly values (aggregate totals) are extracted for each polygon using "all behaviours" (e.g. combining the "on water" and "in flight" maps), and the reference density values based on the same projects are for collision. For displacement maximum values across months within the "MERP period of colony association" are calculated, and for collision monthly values within this period are used. All calculations using the MERP maps are performed separately on each bootstrap sample, and mean and Standard Deviations (SDs) (across bootstrap samples) extracted at the end of each calculation. Note that the MERP maps are not year specific, so the averaging across years usually used in calculating mean seasonal peak values for the Displacement Matrix is not relevant here.

Modelled density surfaces, such as the MERP maps, are products estimated from modelling and will not reflect the survey-to-survey variation seen in empirical at sea survey data and captured in the mean seasonal peak values considered in assessments. The **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)** report noted that the level of variation can be very substantial. This variation is particularly important for displacement, where the empirical mean seasonal peak value is used. Variability in the MERP maps (e.g., between months) was compared against the wind farm data collated with WP1, and a simple adjustment applied to the densities derived from the MERP maps to ensure that variability is representative of the characteristics of actual density data (and that scenarios of density are consistent with the range of density values found in windfarm footprints). Specifically, our reference value density value (mean and SD of project-level seasonal mean peak abundance with buffer) is therefore based on

Seasonal mean value from MERP * Empirical ratio of seasonal peak to seasonal mean

where the peak-to-mean ratio is averaged across the four projects (Awel y Mor, Berwick Bank, Dudgeon and Sheringham Extensions, Hornsea Four) considered in the WP1 report.

The remaining reference values for scenario-based parameters are:

- Population size: based, for each species, on the median SPA population size, averaged across SPAs for which the species is a feature, using the "Master SPA summary table" from the Seabirds Count dataset; an adjustment factor of 0.67 is applied to counts for common guillemot and razorbill in order to derive an estimate of the number of breeding pairs.
- Proportion of birds to apportioning to population of interest: a reference value of 0.02.
- Ratio of impacts on immatures to impacts on adults: a reference value of zero, implying no impact on immatures.

3.4. Methods: variation and uncertainty in inputs

We assessed the impacts of varying input parameters, and explicitly account for quantified levels of uncertainty in these parameters, by using a set of "local" sensitivity analyses, in which each parameter is changed separately, for each combination of species and scenario. Although there would be advantages to a "global" sensitivity analysis (especially in relation to capturing interactions between the effects of different parameters), the timelines and the complexity of the inputs involved meant that this was not feasible to use here (for the sensitivity analysis in relation to inputs described in this section); the results of the "local" sensitivity analysis are also likely to be easier to interpret, which is important in this context as the sensitivity analysis was primarily used as a tool to facilitate stakeholder discussion in the stakeholder workshop within **AssESs – Summary report of stakeholder engagement (WP3)**.

3.4.1. Reference model runs and approaches to propagation of uncertainty

We ran the tools for each species, impact and (for displacement) administration using the "reference" parameter values. We focus on running tools using scenarios of current practice that were determined via stakeholder engagement described in Section 2 whilst exploiting the new functionality available within the CEF to propagate uncertainty between existing tools. Specifically, for each set of reference parameter values we implement three possible ways of quantifying and propagating uncertainty between assessment tools (Table 3).

Table 3: Approaches considered to the propagation of uncertainty between assessment tools within the sensitivity analysis

Approach to quantification and propagation of uncertainty	Implementation for collision	Implementation for displacement
Use average values	Use mean mortality from sCRM as annual effects in the PVA	Use median displacement rate and displacement mortality rate (where a range is specified)

Approach to quantification and propagation of uncertainty	Implementation for collision	Implementation for displacement
Use upper values	Use 97.5% quantile (upper 95% CI) from sCRM as annual effects in the PVA	Use upper end of range for displacement rate and displacement mortality rate
Propagate uncertainty between tools	Use simulated values from sCRM as annual effects in the PVA	Simulate displacement and displacement mortality rate uniformly within range, run displacement matrix for each set of simulated rates, and use simulated mortalities as annual effects in the PVA

The first two approaches are designed to represent the sorts of scenarios that are currently used. Because current approaches use multiple scenarios, and narrative judgement to interpret these, these approaches are illustrative of the types of scenarios that are currently used, rather than a definitive representation of current approaches. This is not intended to suggest that narrative judgement is inappropriate or unimportant, but rather reflects the fact that it cannot feasibly be used within the current context of a large-scale, multi-species, sensitivity analysis.

The final approach utilises extensions of the NE/JNCC PVA tool (and implementation of a "simulation-based" Displacement Matrix approach) within the CEF project, and provides the approach to propagation within the live CEF. (a) and (b) are not available via the live CEF, but can be implemented directly via the underlying CEF code, and are designed to replicate simpler approaches to propagating uncertainty.

3.4.2. Sensitivity to varying parameters by a fixed amount

We consider the impact of varying each of the species-specific and scenario-specific parameters in turn by a common fixed amount: -10% and +10%. For avoidance rate and baseline survival rate we apply this to (1 – avoidance rate) and (1 – baseline survival rate), given the recognised issue that varying avoidance rate, or any parameter that is close to one and constrained to be no greater than one, by a fixed percentage is not meaningful.

The ORJIP QuMR sensitivity analysis focused on kittiwake at the Forth Islands SPA and involved a "reference" set of model runs, together with 13 "alternative" sets of model runs. Within each of the 13 alternative model runs one of four possible parameters ("adult mass KG" = initial adult mass, "BM adult abdn" = threshold for proportion of initial adult mass at which abandonment of chicks occurs, "BM chick mortf" = threshold for proportion of chick mass at which chick mortality occurs, and "unattend max hrs" = time period after which unattendance leads to chick mortality) is varied by -10%, -5%, +5% or +10%. The prey level within SeabORD is recalibrated in each case. Note that there are 13 rather than 4 x 4 = 16 sets of alternative models runs because re-calibration was impossible (i.e. there was no prey level value that yielded values of baseline mass change and baseline productivity within acceptable ranges) when BM_adult_abdn was varied by -10%, +5% or 10%. Reference values for PVA parameters are as in previous aspects of the sensitivity analysis.

3.4.3. Comparison against alternative sources of information on parameter values

In addition to evaluating the impact of varying parameters by a fixed amount, we also compare outputs obtained using the "reference" value against potential "alternative" values for the parameter that arise either from (a) other SNCB guidance or (b) values in the scientific literature, building on the review in **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**.

Wherever the WP1 report listed parameter values other than those used to specify "reference values", we evaluate the impact of switching the relevant parameter from the "reference value" to this alternative value. Alternative values related to versions of SNCB guidance other than those used for setting reference values (e.g. SNCB, 2014; SNCB, 2017; Natural England, 2022; SNCB, 2022b) are considered, whenever these are listed in Tables 1-4 or (for displacement) in the **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)** text and differ from the corresponding value in JNCC et al. (2024). Alternative values derived from the published literature, that are listed in rows within tables in the **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)** report, are also considered where available. Specifically, alternative literature-based values are considered for:

- Avoidance rate by considering each source listed within Tables 8 (Northern gannet), 11 (black-legged kittiwake), 14 (great black-backed gull), 20 (lesser black-backed gull), 17 (herring gull)
- Flight speed by considering each source listed within Tables 23 (Northern gannet), 24 (black-legged kittiwake), 27 (great black-backed gull), 25 (lesser black-backed gull), 26 (herring gull), 28 (sandwich tern)
- Displacement rate by considering each source listed within Tables 38 (common guillemot), 39 (razorbill), 41 (sandwich tern) and in the text (northern gannet). Values from tables 40 (Atlantic puffin) and 37 (black-legged kittiwake) would also have been considered but are exactly equal to zero

Note that these table numbers refer to tables in **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**.

3.4.4. Comparison against alternative scenarios for parameter values

We also modify each of the scenario-based parameters, in turn, to have alternative parameter values, in order to evaluate how sensitive outputs are to the characteristics of the windfarm and population

For project-based density values, relating to either displacement or collision, the reference values are derived for the project with median (50% quantile) of overall mean density. We also consider alternative "low density" and "high density" values, based on the projects with the 10% and 90% quantile, respectively, of overall mean density. Similarly, for population size we consider three different scenarios per species (e.g., small, medium, high values) based on the distribution of SPA-level values within Seabird Count data for each species, so that different sizes of population are considered. The reference value for population size is based on the median (50% quantile) population size calculated across those SPAs for which the species is a designated feature, whilst alternative ("small colony" and "large colony") scenarios are constructed in the same way using 10% and 90% quantiles. For apportioning we also use different scenarios, to capture variations between populations and windfarms: the reference value is 0.2, with alternative values of 0.02 and 1 considered. Finally, the reference value for the ratio of immature to adult impacts is zero (implying no direct impacts on immatures), with alternative values of 1 (implying that impacts on adult and immature survival rates are equal).and 1.5 (implying that impacts on immatures are greater than impacts on adults) considered.

3.4.5. Impact of removing uncertainty in individual parameters

We next consider the impact of removing uncertainty from each of the parameters, in turn, for which uncertainty is quantified. For most parameters we do this by setting the standard deviation associated with the input parameter equal to zero. For flight height the reference model runs use bootstrap distributions of flight heights and CRM Model Option 2. When removing uncertainty in this case we switch to CRM Model Option 1 and use the values on proportion at collision risk height data from Table 21 of the **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)** report.

3.4.6. Investigating impact of variation in qualitative model options

As well as parameters, the tools considered here also contain a range of qualitative inputs that determine the model structure, and we also consider the impact of varying these options. Note that we only focus here on those inputs that are inherently qualitative – tools also contain options that appear qualitative, but are, in practice, just used to simplify the ways that users provide quantitative inputs (e.g., the PVA tool contains a “split immature rates?” option, but this is just a mechanism to allow users to rapidly fix immature and adult survival rates to the equal if they wish to do so). We also exclude options that are difficult to implement in a generalisable way (e.g., CRM model option 4, and the calculation of rotor speed and pitch for the sCRM using wind speed data).

In practice, this leads us to vary qualitative model options relevant to the PVA (Table 4).

Table 4: Reference and alternative specifications for qualitative model options within the PVA

Qualitative input	Reference value	Other options considered
Is demographic stochasticity considered?	No	Yes, with productivity modelled as binomial and maximum value constrained by maximum brood size
		Yes, with productivity modelled as a Poisson distribution and maximum value unconstrained
Model of environmental stochasticity	Stochastic (beta distribution, except gamma distribution for productivity is unconstrained), variation not matched across year	Deterministic
		Stochastic, variation matched across years
Model of density dependence (DD)	None (density independence)	Log-linear, positive or negative
		Linear, positive or negative

Qualitative input	Reference value	Other options considered
		Weibull (shape parameter 0.25, 0.5, 1.5 or 2), positive or negative

Where density dependent models are being used, the parameter value for the magnitude of density dependence in each demographic rate (productivity and adult survival) is selected, via numerical optimisation, such that the demographic rate is 0.05 greater (positive DD) or lower (negative DD) when the population size is doubled from the initial population size.

3.4.7. Alternative approaches to treatment of density data

For the displacement matrix, the "reference" values of project-level abundance (mean and SD) are based on adjusted seasonal peak values. We also consider seasonal mean values, and unadjusted seasonal peak values, derived directly from the MERP maps.

3.5. Methods: output metrics

We focus upon the PVA metrics produced by the NE/JNCC PVA Tool, which were derived via a process of stakeholder engagement, and which can readily be extracted from the existing tool. Specifically, we report the first five of the six metrics produced by that tool, together with an additional metric (M0) that was included following feedback.

M0. Impacted population size (mean, median, SD) at the end of 30 years of operation.

M1. ratio of impacted to unimpacted final population size (mean, median, SD) at the end of 30 years of operation.

M2. The ratio of impacted to unimpacted growth rate (mean, median, SD) at the end of 30 years of operation.

M3. Quantile for unimpacted population which matches the 50th centile for the impacted population at the end of 30 years of operation.

M4. The probability of impacted population size being lower that the baseline population size at the end of 30 years of operation.

M5. The probability of quasi-extinction at the end of 30 years of operation. We assume, somewhat arbitrarily (but to ensure consistency when comparing species/populations), that "quasi-extinction" relates to a population size of 10 breeding pairs, or less.

The final metric produced by the PVA tool (M6) relies on having a "target population size", which is difficult to meaningfully specify in a usefully generalizable way, so is not considered here.

Mathematical definitions of the metrics used are given in Appendix 1. Definitions of PVA metrics).

One important point to note is that metrics M1 and M2 are (for paired impact and baseline runs, and assuming comparison is against the year immediately prior to impact, as used in the PVA tool) deterministically related to each other, with M1 being equal to M2 to the power of the number of years of impact. For comparative purposes it is therefore equivalent to consider M1 or M2.

3.6. Results

We focus here on showing sensitivity in relation to one specific metric of impact, the ratio of impacted to unimpacted population size at the end of a 30-year period (M2). We focus on this metric because it, and a metric that is deterministically related to it (ratio of impact to unimpacted annual population growth rate), are widely used in practice. Within the associated github repository we will provide full results including all output metrics, and the exact parameters used within each of the runs considered in the sensitivity analysis, along with the code used to pre-process the inputs and to generate the model runs.

One general point in relation to all of the results is that environmental stochasticity appears to introduce very little uncertainty into the results. Environmental stochastic is known to be important (Lande, 1993), so the relatively minimal impact of environmental stochasticity in this context arises from (a) the far that the key PVA impact metrics being considered are relative comparisons of impacted and baseline scenarios and (b) because the stochastic simulations of year-to-year variation are matched between baseline and impacted scenarios. Additional simulations were undertaken in order to check that these results are consistent with the behaviour of the PVA tool (Appendix 2. Additional checks on PVA outputs)).

3.6.1. Collision

Within Figures 1-6 we illustrate the results relating to collision risk for a single species, kittiwake, but full results for all species are shown in Appendix 3: Sensitivity to Inputs – Additional Results) and we interpret results in relation to all species. Note that the absolute values of impact vary considerably between species, but that this should not be taken as indicative of variations in absolute risk between species, because the reference values are designed to be plausible, but not necessarily to be representative. As such, the model runs used in the SA are designed to be used to compare the relative importance of different input parameters, and the consequences of varying the values of these parameters, but are not designed to provide a defensible absolute estimate of species-level impact.

Increasing or decreasing the values of individual parameters by 10% gives an indication of the relative sensitivity of key model outputs, such as Counterfactual Population Size Ratio (CPS), to each of the parameters (Figure 1). The CPS values consistently show the highest levels of uncertainty to the avoidance rate (or, more specifically, one minus avoidance rate), the apportioning proportion, flight height, mean density and population size. It is credible that all of these parameters will be highly influential: annual impacts are directly proportional to the apportioning proportion, and flux within the sCRM is directly proportional to (1 – avoidance rate), to density, and will (depending on the sCRM model option) be approximately proportional to the proportion of the flight height distribution that lies within the rotor swept area. Population size is important because it determines the denominator used in translating impacts from the sCRM (which are based on density data) into inputs to the PVA tool. Note that, in practice, the role of population size is closely related to that of apportioning proportion, and the calculation of apportioning proportion will use information on population size, so the sensitivity to population size is essentially just a reflection of sensitivity to apportioning proportion. Results are moderately sensitive to the ratio of immature-adult impacts, and the proportion of upwind flights, and show low sensitivity to baseline productivity, baseline survival, body length and wingspan. Relative results are generally consistent regardless of the approach used to transfer values from the sCRM into the PVA, but nocturnal activity is an exception, with greatest sensitivity seen when simulated values are used than when mean or upper 95% Confidence Interval (CI) values are used.

PVA outputs were largely insensitive to removal of uncertainty from individual parameters (Figure 2), with the exception of flight height, where it led to a substantial change in the estimated level of impact, although no substantive change in the level of associated uncertainty in the output. In most cases uncertainty in the input parameter was removed by setting the standard deviation associated with the parameter to zero, but as flight height is specified as a bootstrap distribution of values rather than mean and SD (for CRM Model Option 2) in this case uncertainty was removed by switching from CRM Model Option 2 to CRM Model Option 1 and using the "proportion at collision risk height" values from the **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**. The apparent insensitivity to removal of uncertainty in most parameters is likely to reflect the fact that there is uncertainty in a number of different parameters, with the result that removal of uncertainty in any single parameter does not markedly alter the overall level of uncertainty in the outputs. The sensitivity of the *mean* level of impact to the removal of uncertainty in flight height may reflect the fact that, for this parameter, the approach to "removal of uncertainty" involves amending the CRM model option, which also alters the turbine specifications associated with proportion of birds at collision risk height.

In Figure 3 we look at sensitivity to the source (guidance or published literature) used to specify each parameter. Outputs are particularly sensitive to variation in the sources used to specify the value of the avoidance rate (Figure 3). This presumably represents a combination of the Band model being sensitive to this parameter (as, e.g., seen in Figure 1) and a high level of variation in published estimates of avoidance (**AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**). Sensitivity to different sources of rates on flight speed is rather lower, perhaps reflecting less variation, in absolute terms, in the published estimates of this parameter (**AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)**). Only one alternative source was considered for nocturnal activity, and outputs for this source were very similar to those obtained using the reference value.

Sensitivity of outputs to switching to "alternative scenarios" for project-specific parameters (mean density, apportioning proportion, population size, immature: adult impact ratio) was highest for the apportioning proportion, intermediate for mean density, and lowest for population size and immature:adult impact ratio (Figure 4). This partly reflects the inherent sensitivity of the models to different parameters, but also reflects the alternative scenarios considered. There is greater sensitivity to apportioning proportion than mean density, for example, in part just because the scenarios considered for apportioning proportion are more variable than those for mean density. This may, to some extent, be an artefact of the fact that we have used MERP maps: as derived products, created using statistical models that assume smooth relationships and static distributions across time, the spatial variation in abundance from MERP maps is likely to be lower than spatial variation in abundance at a specific point in time. It also reflects the fact that the alternative scenarios are defined and constructed in rather different ways for each parameter – e.g., those for apportioning proportion and immature:adult impact ratio were agreed through stakeholder discussion, whilst scenarios for mean density and population size were derived from MERP maps and Seabird Count data respectively.

Inclusion of demographic stochasticity into the PVA leads to a substantial increase in the level of uncertainty seem in estimated impacts (Figure 5). This partly reflects the importance of demographic stochasticity, and partly the fact that demographic stochasticity is not, currently at least, completely matched between impacted and unimpacted scenarios within the PVA tool. Additional simulations were undertaken in order to verify that these results are consistent with the behaviour of the PVA tool (Appendix 2). The increase is higher with an unconstrained rather than a constrained model of productivity, presumably because the inclusion of an upper limit on productivity helps to reduce uncertainty around baseline conditions, and hence also around impacts. Removal of environmental stochasticity, or switching environmental stochasticity to be match rather unmatched across years, has a negligible impact, presumably because environmental stochasticity already has little impact on the outputs (see above).

Switching from a density independent model to a density dependent model with positive density dependence increases the magnitude of impact (Figure 6), whilst switching to a model with negative density dependence reduces the level of impact (reflecting Merrall et al., 2024). The increase in the former case is of markedly greater magnitude than the reduction in the latter case. These general results hold regardless of the density dependence model used, although the increase in impact with positive density dependence is lower for a Weibull model with shape parameter 0.25 than for other density dependence models.

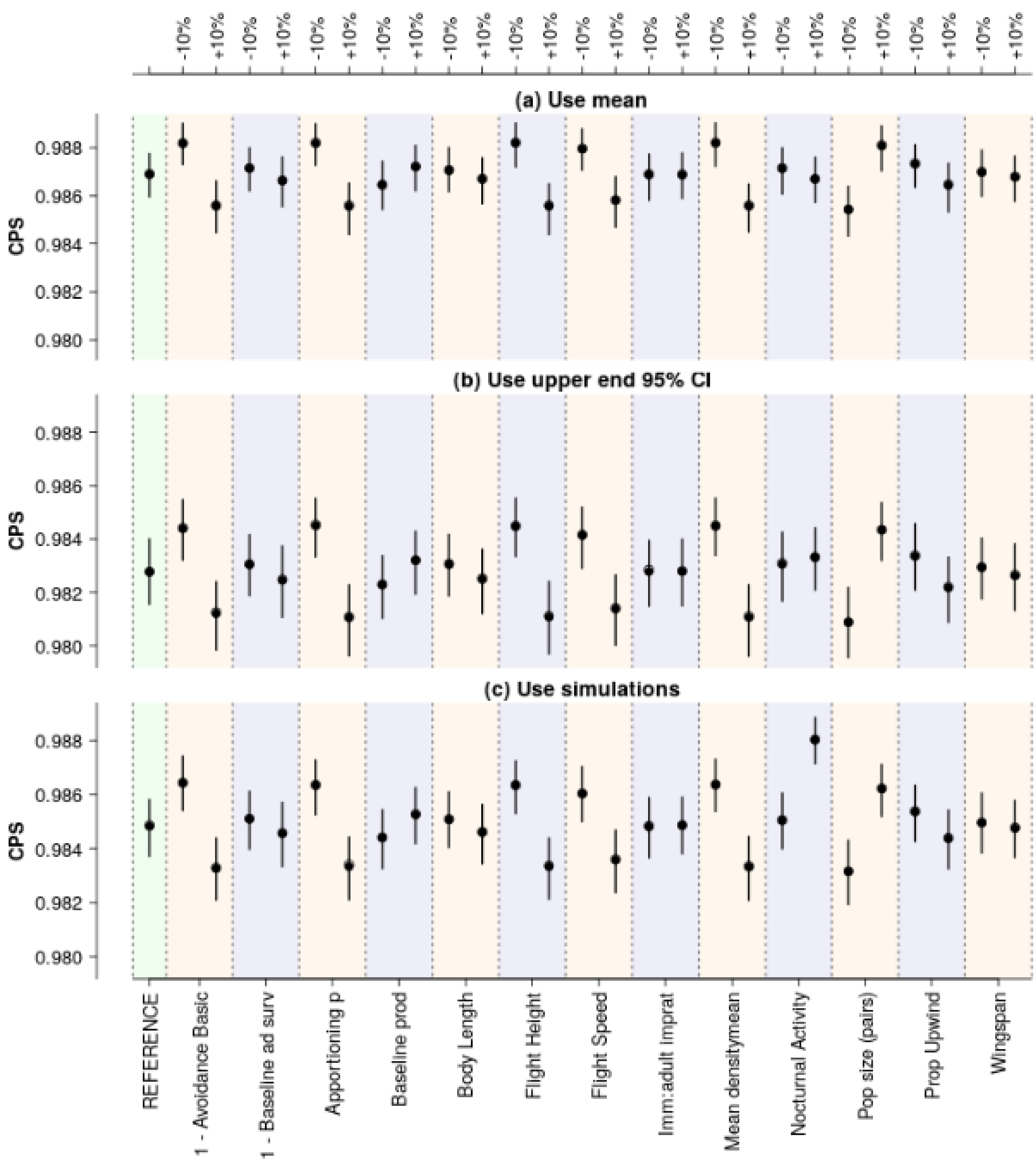

Figure 1: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for kittiwake after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

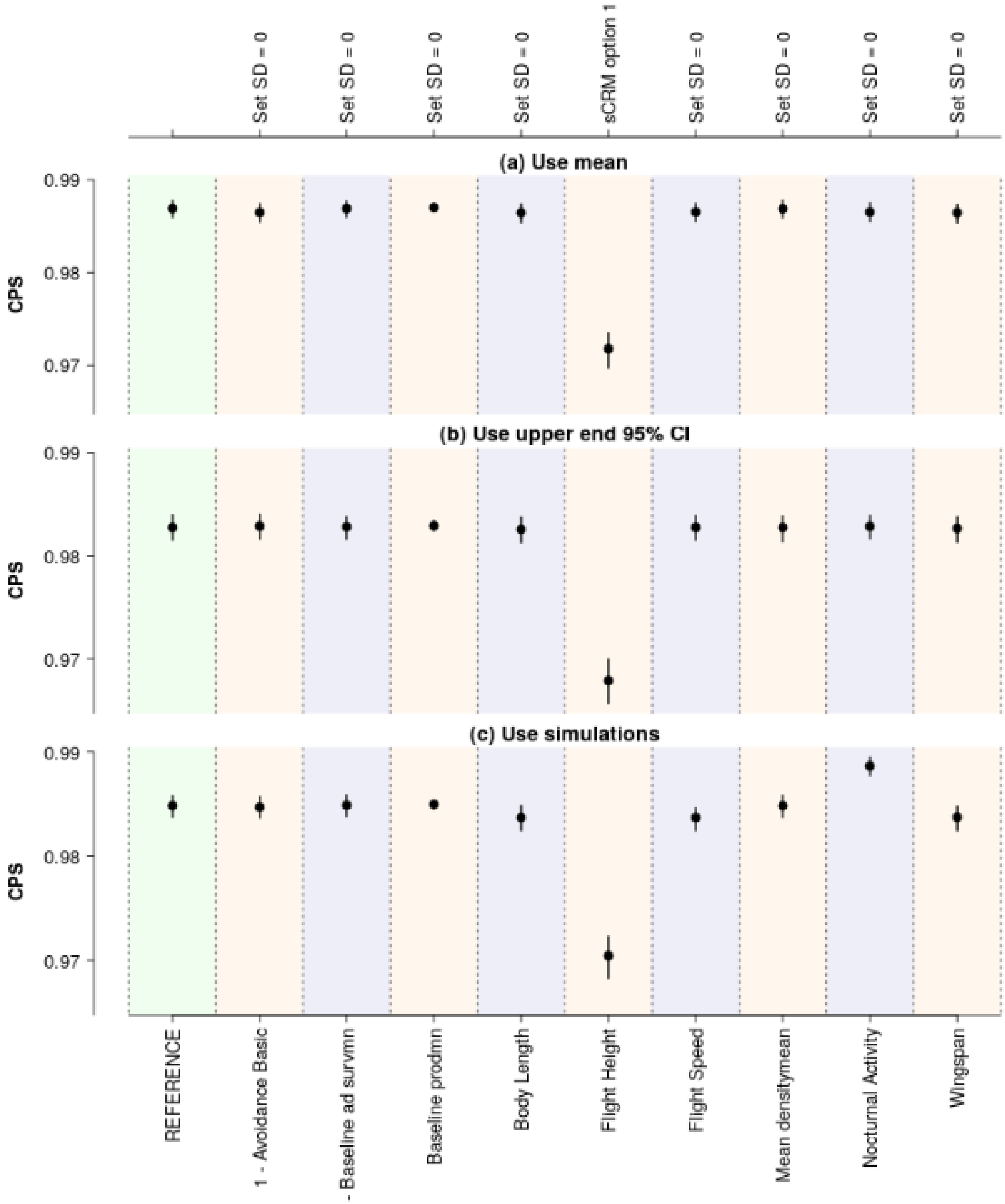

Figure 2: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for kittiwake after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

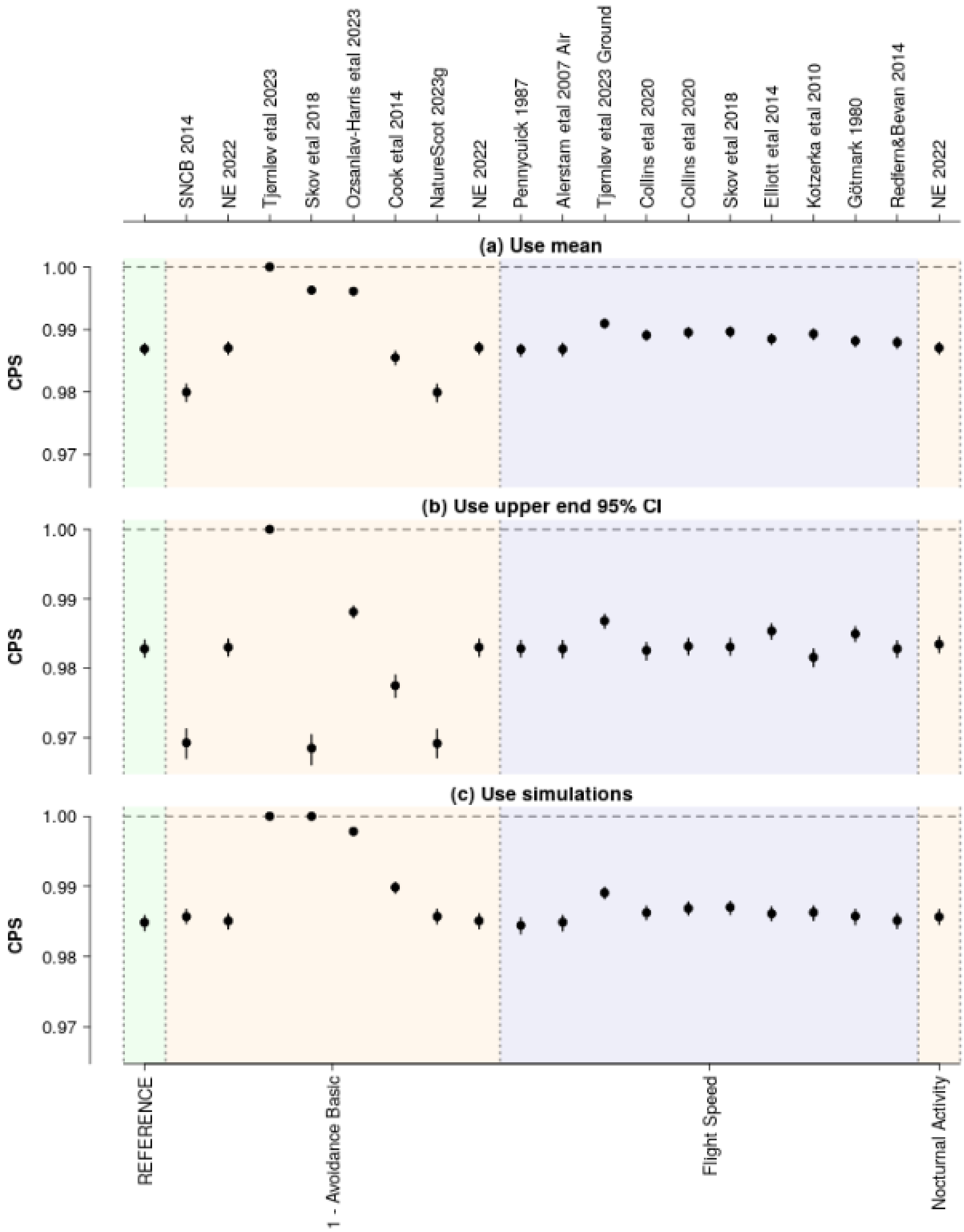

Figure 3: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for kittiwake after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in WP1 (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

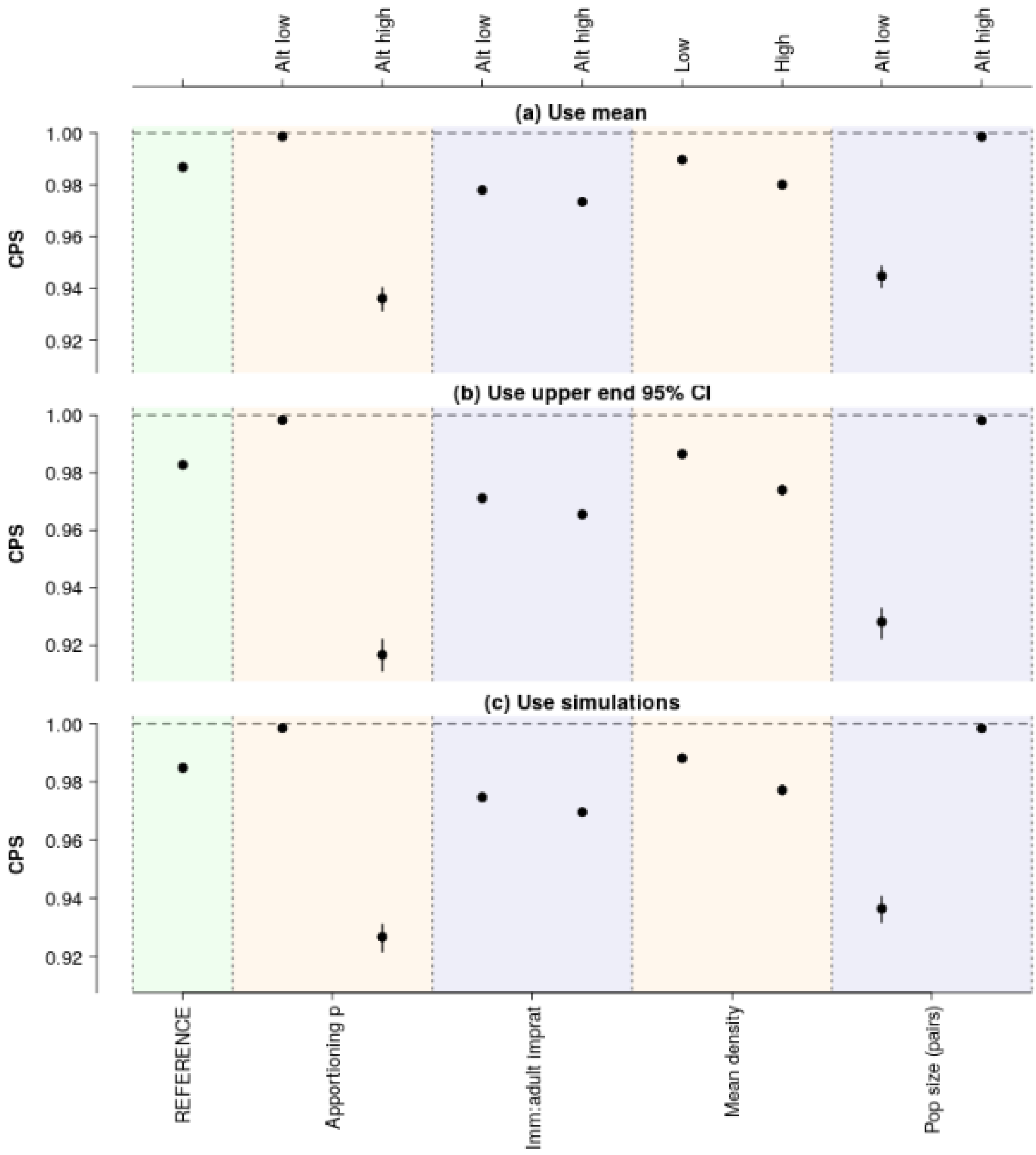

Figure 4: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for kittiwake after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

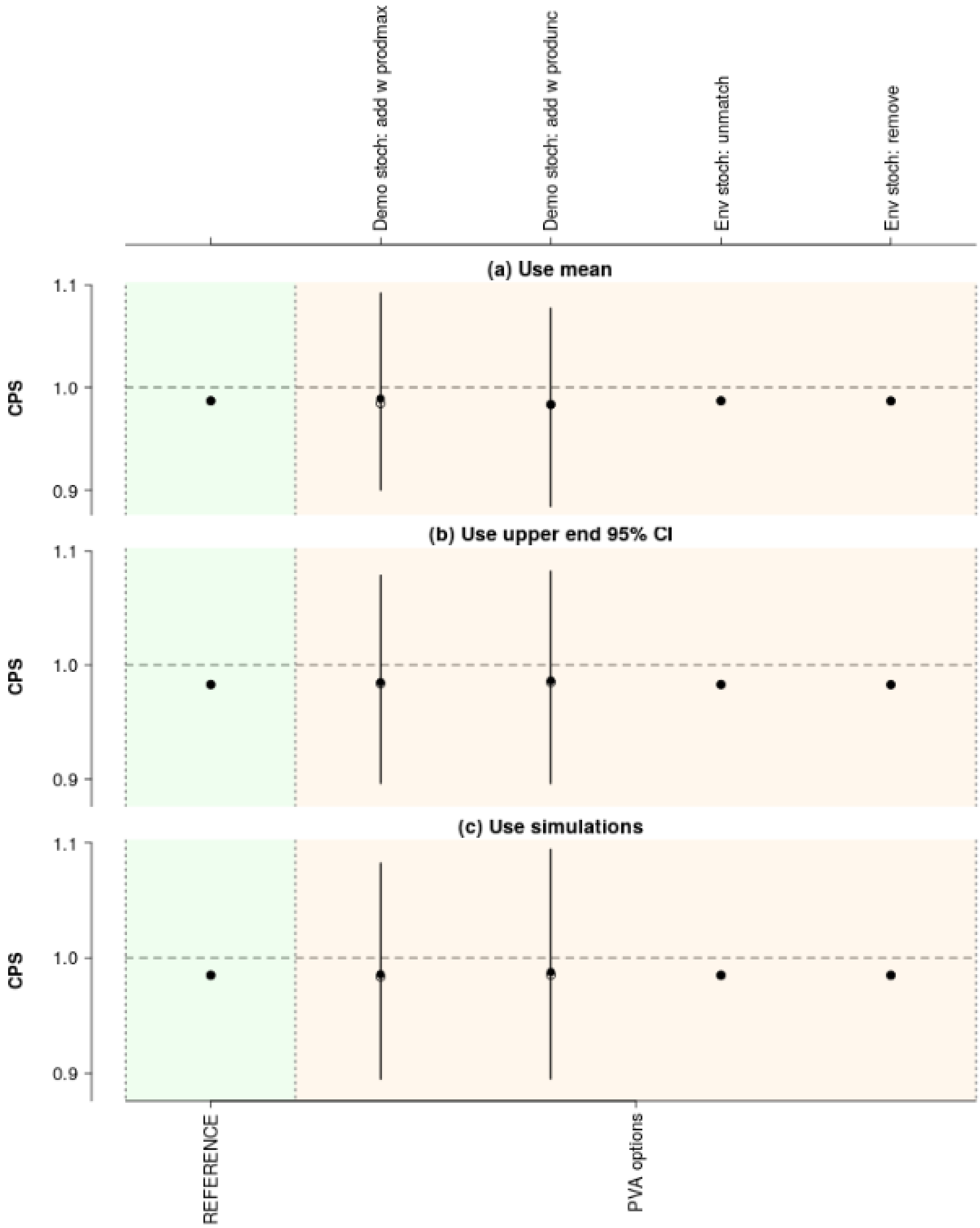

Figure 5: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for kittiwake after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

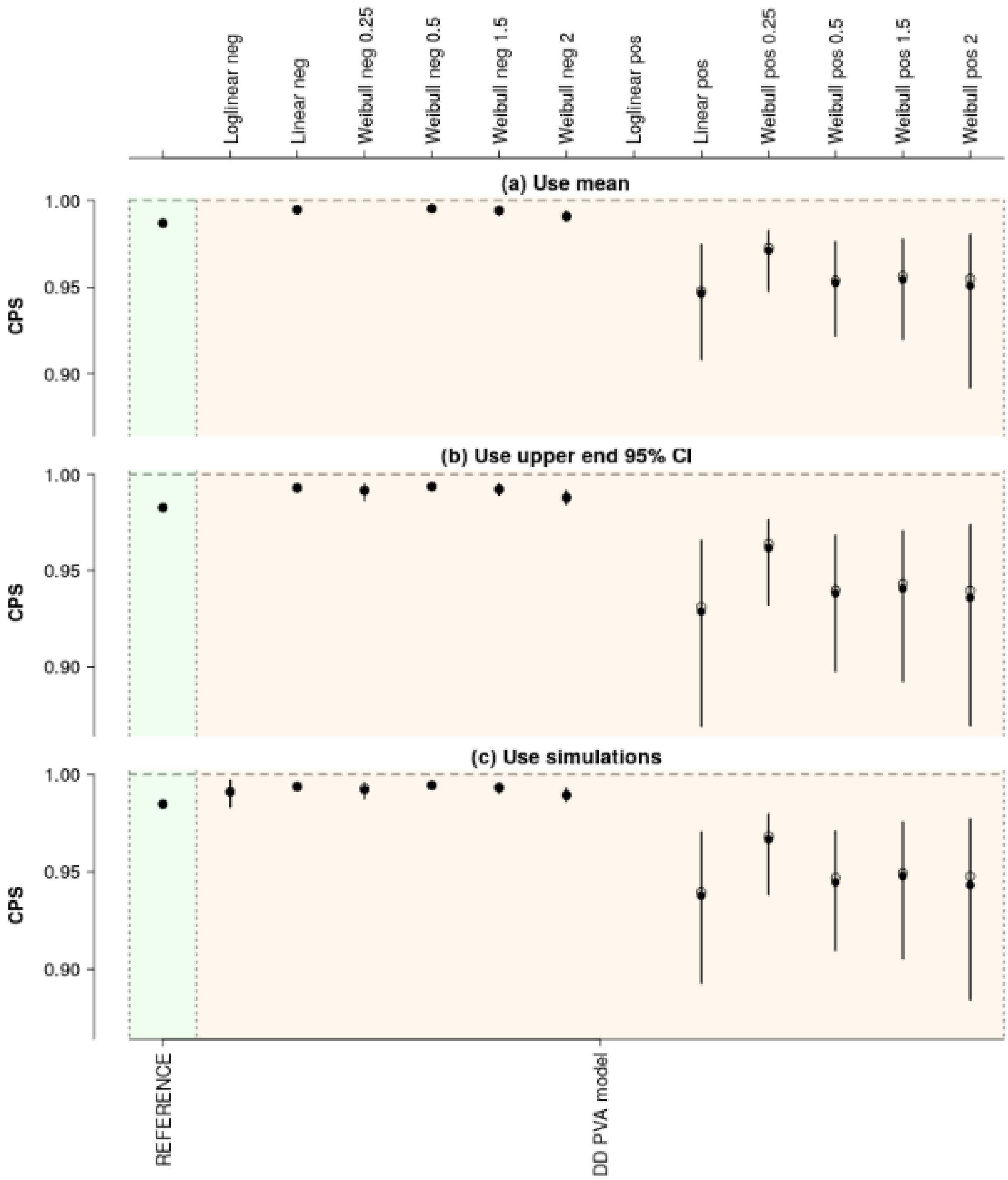

Figure 6: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for kittiwake after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

3.6.2. Displacement via displacement matrix

Figures 7-12 show equivalent comparisons to Figures 1-6, in the context of displacement. Again, the figures focus on one species, common guillemot, as an illustrative example, but the full range of outputs is included in the electronic supplementary material.

In the context of displacement, through Figures 7-12, we show results in relation to three different ways of calculating seasonal density: using the seasonal mean from the MERP maps, using the seasonal maximum from the MERP maps, and using the seasonal maximum from the MERP maps but adjusting for the fact that the max : mean ratio is much lower for the MERP maps than for the observed project-level density data that were considered in **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)** and which are typically used in practice.

It can be seen from the results in Figures 7-12 that the approach taken in treating the density data consistently has a substantial effect on the results, with the impacts for adjusted maximum values being greater than for MERP maximum values, which are in turn greater than the impacts for MERP mean values. This highlights the importance, as identified in WP1, of considering the approach that is taken when identifying the seasonal value to use within the Displacement Matrix.

Figure 7 shows the impact of varying each parameter by -10% or +10%. As for collision the parameters that have the greatest impact are generally those that directly relate to annual mortality (displacement rate, displacement mortality rate, density, population size, apportioning value), with less sensitivity for parameters relating to baseline demography. Figure 8 shows the impact of removing uncertainty from each parameter in turn – as for collision, the effect of removing uncertainty appears to be minimal. Figure 9 shows the impact of switching to alternative sources of information in order to specify the rates, and shows considerable variation in results in relation to the source used for specifying the displacement rate – reflecting both the importance of this parameter, and the fairly substantial variation in estimates of this rate between different sources. Figure 10 shows the impact of switching to alternative scenarios for key parameters, and we see that there is substantial (and broadly similar) variation from switching to alternative scenarios for the apportioning proportion, density values, and population size, but less impact in switching to alternative scenarios for the immature:adult ratio of impacts. Figure 11 shows the impact of including demographic stochasticity, and of modifying the form of environmental stochasticity. As for collision, the inclusion of demographic stochasticity substantially increases overall uncertainty, and the extent of this is greater when productivity is unconstrained than when it is constrained, whilst changes to the form of environmental stochasticity have a minimal impact. Figure 12 shows the effect of switching from density independent to density dependent models, and shows that, as for collision, the effect of positive DD is to increase the magnitude of the OW impact whilst the effect of negative DD is to decrease the magnitude of the OW impact.

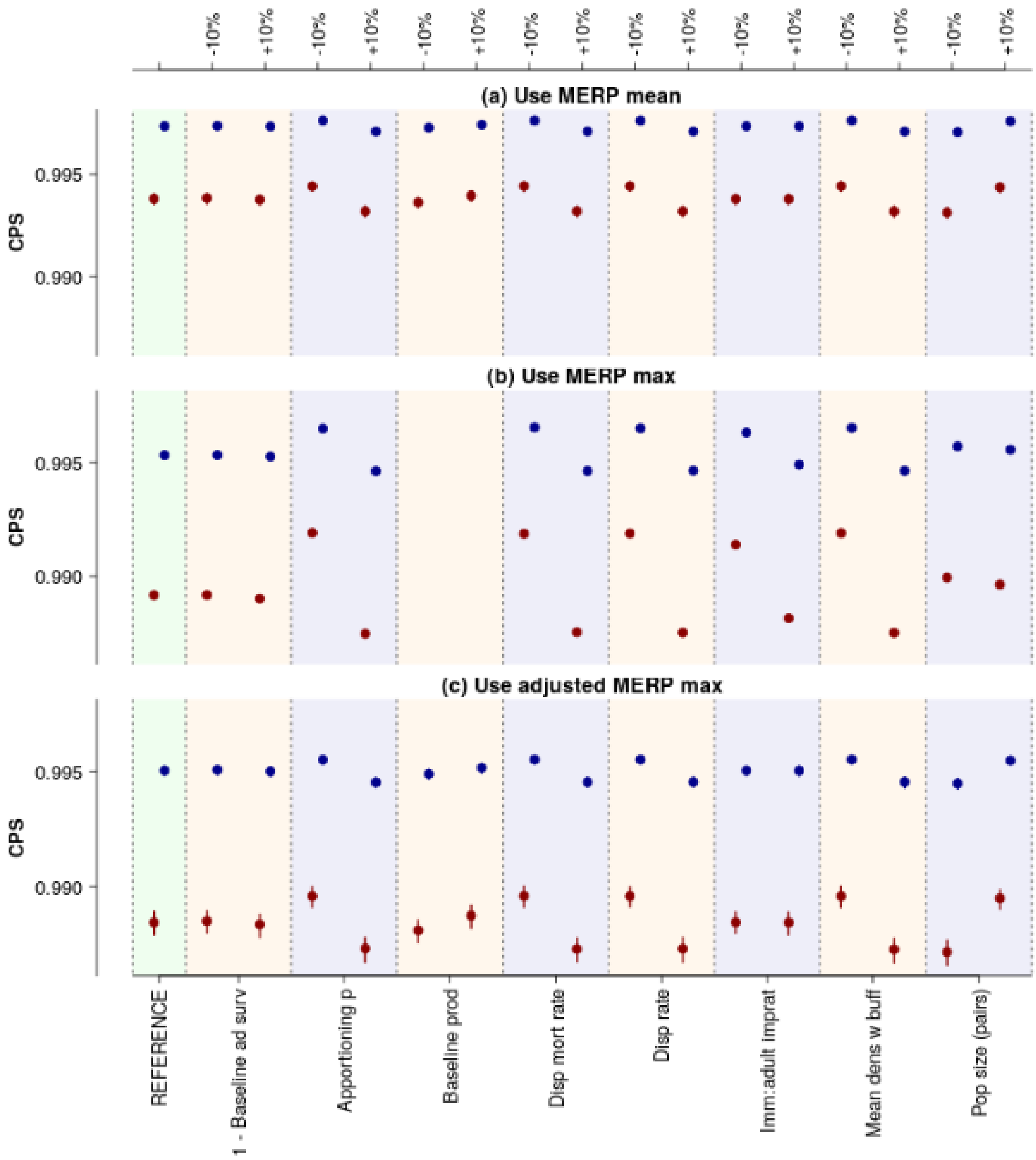

Figure 7: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

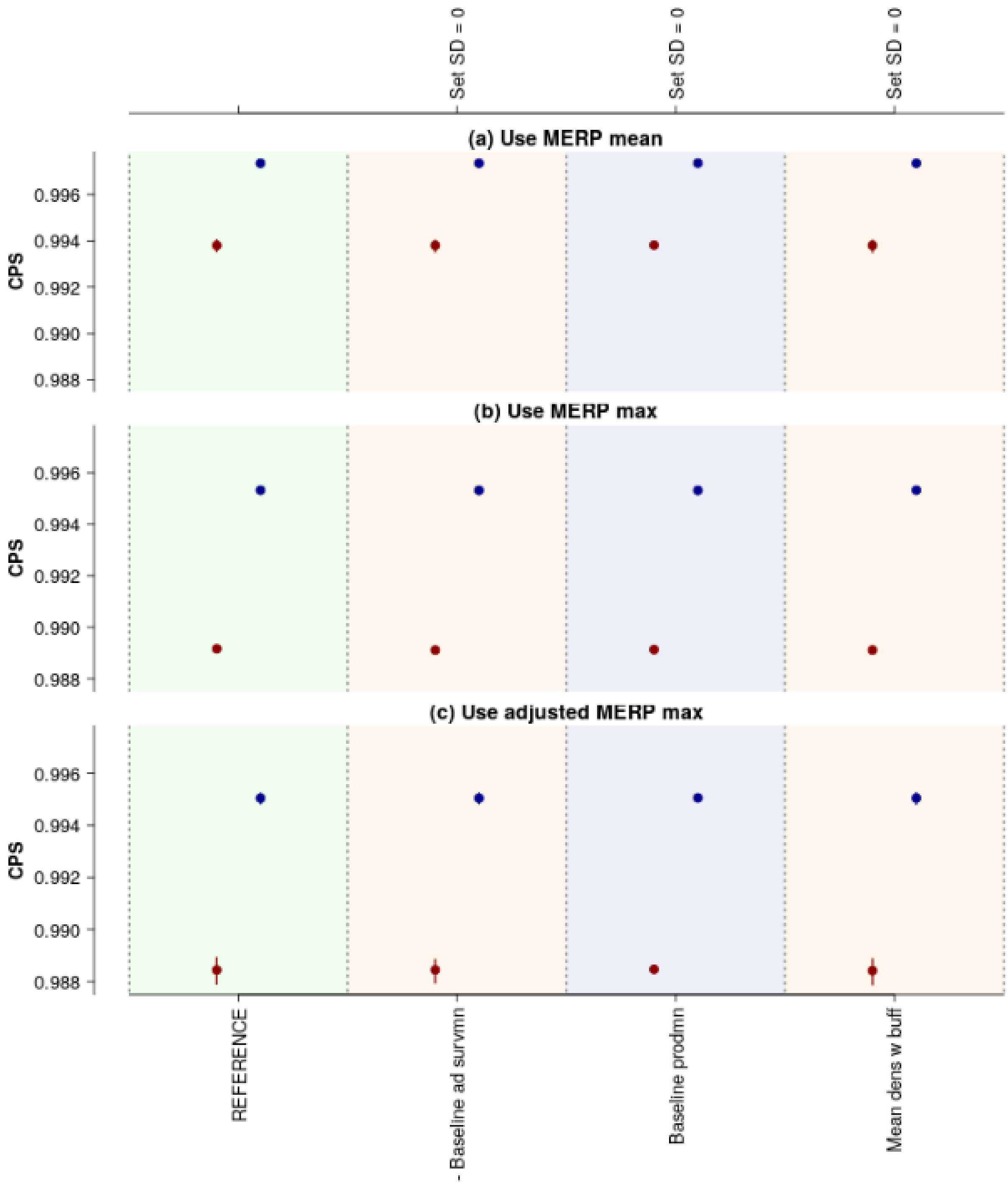

Figure 8: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

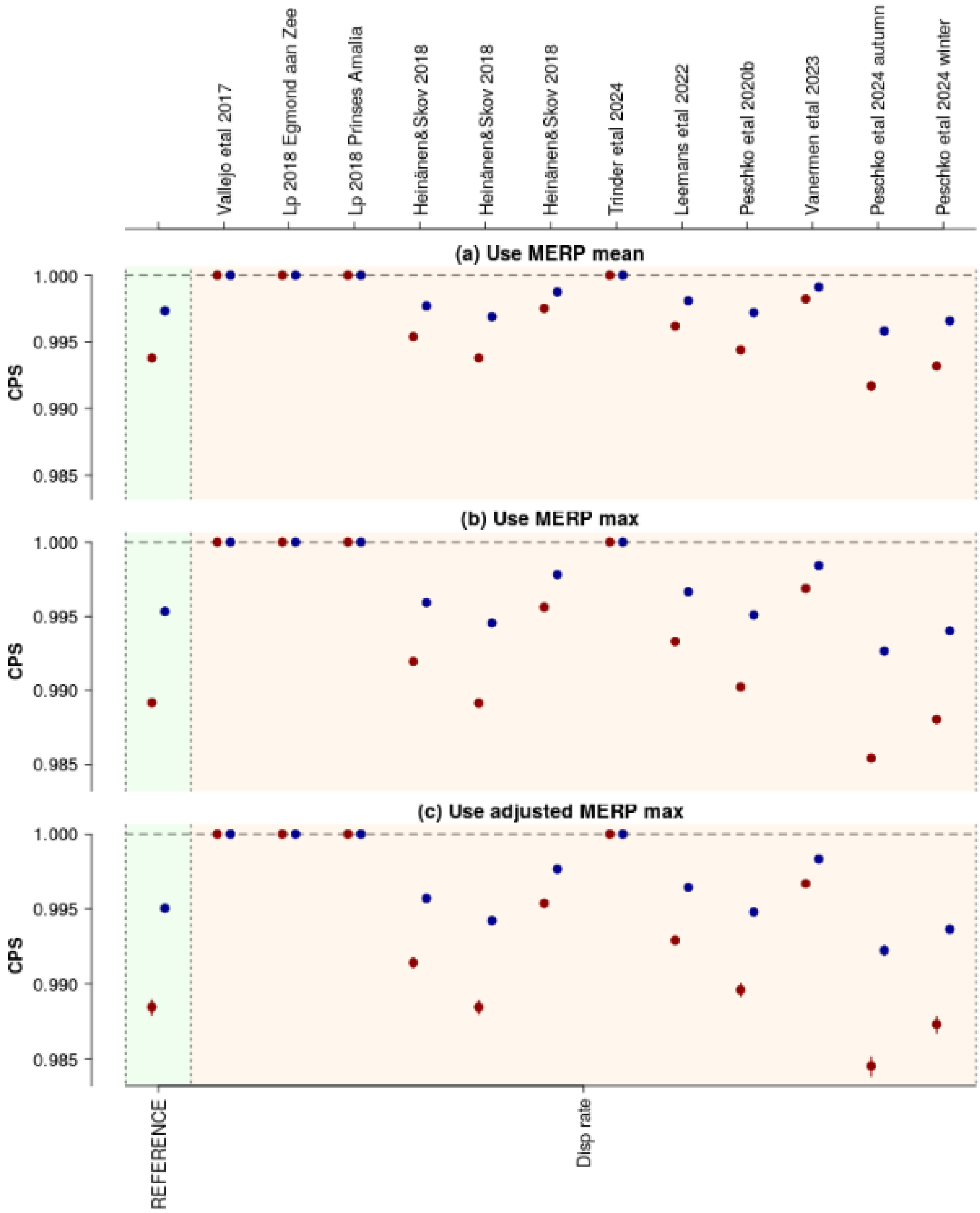

Figure 9: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in WP1 (as shown on y-axis). Displacement Matrix uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

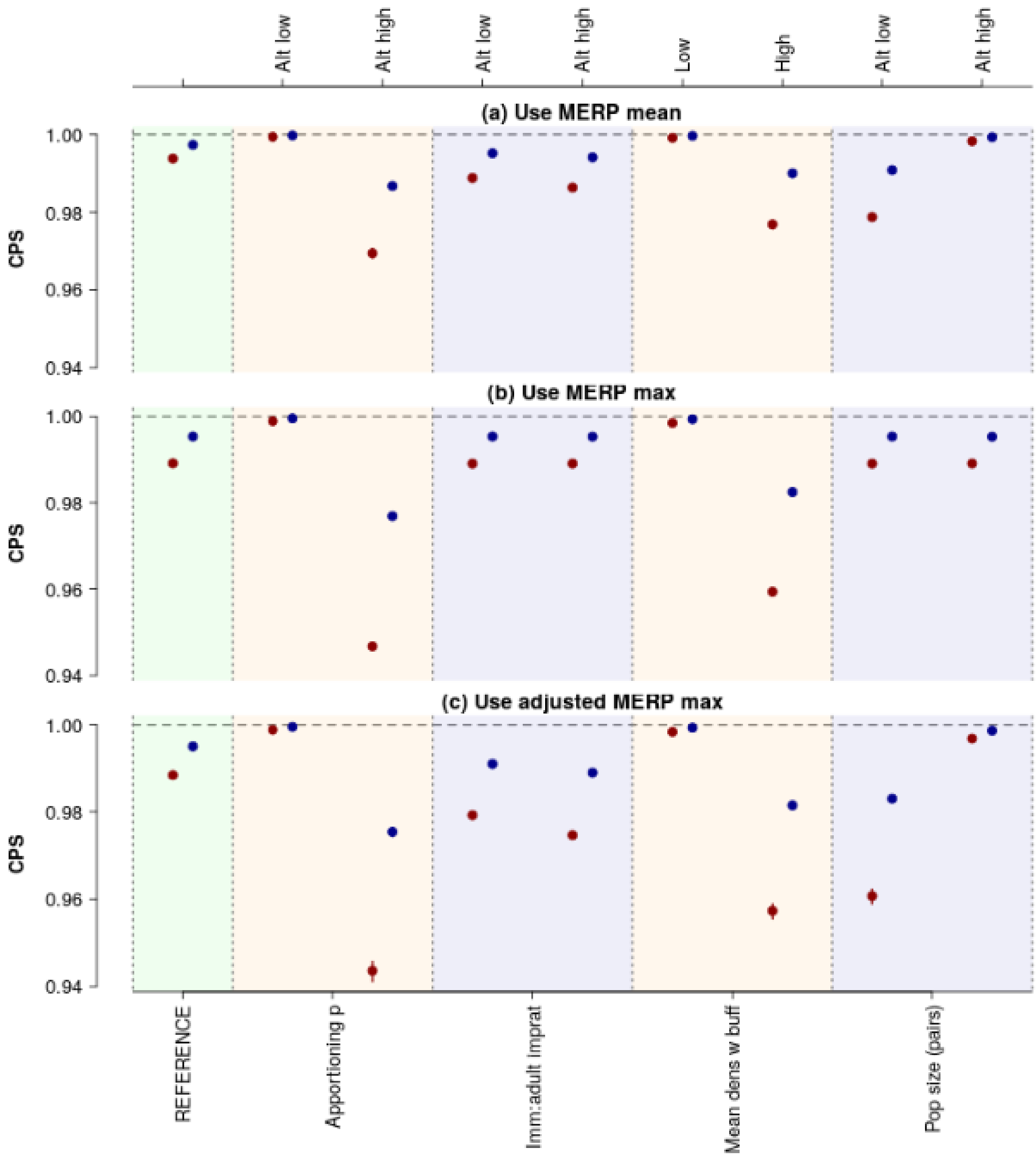

Figure 10: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

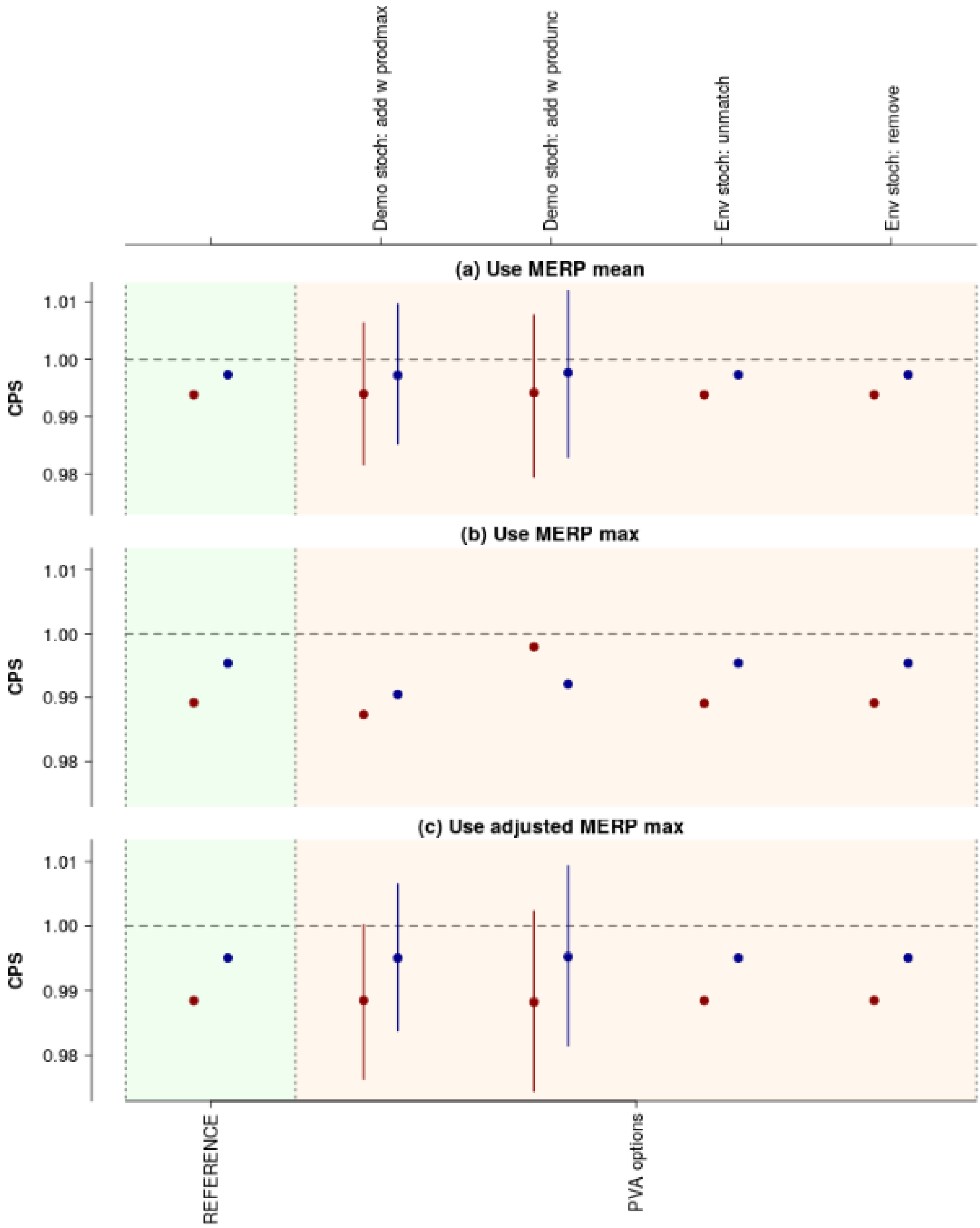

Figure 11: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity, remove environmental stochasticity, or match environmental stochasticity across years Displacement Matrix uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

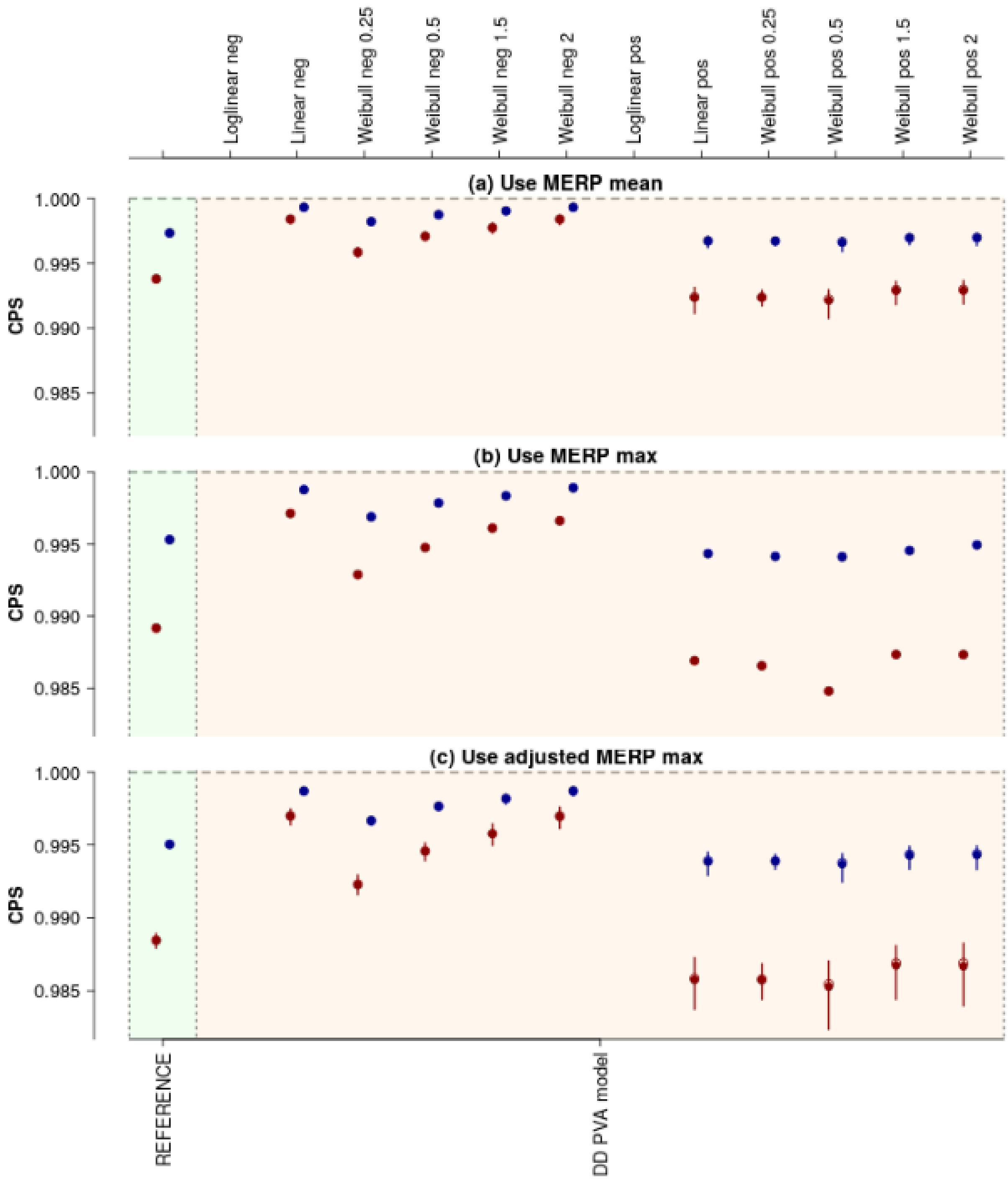

Figure 12: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

3.6.3. Displacement via SeabORD

We conducted a sensitivity analysis on four key parameters in the IBM SeabORD. We varied these parameters to assess how this variation affects model outputs for ORD impacts on seabird productivity and survival, and then used altered rates within the PVA to consider impacts of parameter sensitivity on PVA metrics. Sensitivity to the following model parameters was assessed:

- **adult_mass_KG** - Energy density of the bird's tissue (kJ g−1) - this parameter affects adult mass change in relation to energy gain
- **BM_adult_abdn** - Critical mass below which adult abandons chick thereby resulting in chick death
- **BM_Chick_mortf** - Critical mass below which chick is dead
- **unattend_max_hrs** - Critical time threshold for unattendance at nest above which a chick is assumed to die through exposure or predation

Each parameter was varied across a percentage range of the current default value in SeabORD, e.g., +10% +5% or -5%, -10%, in intervals comprising four different values (Figure 13 shows the impact on CPS after 30 years of impact of varying four key SeabORD parameters by these fixed amounts -10%, -5%, +5%, +10%).

Absolute magnitudes of impact are much higher than for other elements of the sensitivity analysis, but this will at least partly because the windfarm/population scenario considered here differs from the scenarios used elsewhere in the SA, since in this case we are utilising SeabORD runs that were already generated in the ORJIP QuMR project and relate specifically to the Isle of May. Note that calibration targets for the model could not be met when one of the parameters, *BM_adult_abdn* (Critical mass below which adult abandons chick thereby resulting in chick death), was varied by -10%, +5% and +10%. The inability to calibrate the model to more extreme variations of this parameter is to be expected. SeabORD is calibrated by varying one input value (total prey) to generate desired output values for two model outputs (baseline adult mass loss and baseline productivity). In general, we would expect that for any plausible model (and sensible choices for parameter and model output) calibrating one parameter against one model output should be possible. However, in this case where a single parameter is varied to try and calibrate against two different quantities there is no guarantee, in general, that it will be possible to calibrate a single model parameter in such a way as to match more than one model output (e.g., the model is "under-parameterised", containing less complexity, in terms of number of parameters, than there is data to support). In addition, because SeabORD was designed to capture key mechanisms relating to seabird behaviour, mass and breeding state, it is not surprising that any extreme variation in a key parameter relating to adult mass change and breeding state (and therefore subsequent breeding success) causes the model to produce outputs that are incompatible with empirical data.

The sensitivity analysis showed that adult mass loss during chick-rearing, and therefore subsequent adult survival, was somewhat sensitive to variation in the adult mass at which the breeding attempt fails (*BM_adult_abdn*) and to the energy density of bird tissue (*adult_mass_KG*), however there was considerable noise around these impacts, with all confidence intervals including zero. In contrast, this output was not sensitive to variation in the mass at which chicks die, nor the time threshold for unattendance relating to chick death. These results are as expected – the energy density of bird tissue affects the way in which adult mass change relates to energy acquisition in the model, and the adult mass at which the breeding attempt fails also affects adult mass change over chick-rearing due to changes in behaviour (primarily a relaxation in central place foraging constraints and provisioning of food to chicks). Similarly, for breeding success, the sensitivity analysis revealed little impact of parameter variation on chick survival (breeding success), with all confidence intervals including zero. This is likely because chick survival is represented within the model with more complex mechanisms than for adult mass change, where chicks are dependent upon the behaviour and state of their parents, as well as their own energetic and mass state. This introduces more noise in the relationships between single parameters and subsequent model output for chick survival, which is reflected in the sensitivity analysis results.

Therefore, when these impacts on breeding success and survival are implemented within the PVA, relatively low sensitivity is revealed (Figure 13). Using either all simulation values, the midpoint impact value, or the upper impact value in the PVA produced changes in the CPS metric as expected, with overall stronger reductions in impacted population sizes derived from the upper impact value, and overall smaller reductions in impacted population sizes resulting from the midpoint impact value (Figure 13). Broadly, the PVA CPS metrics did not differ strongly between the four parameters that were varied in the sensitivity analysis (Figure 13).

Overall, these results are consistent with expectations around the use of model calibration when parameter values are varied. The use of calibration serves to constrain the sensitivity of model output to parameter variation. This is due to known and acknowledged high levels of dependence between the prey parameter and many other parameters within the model.

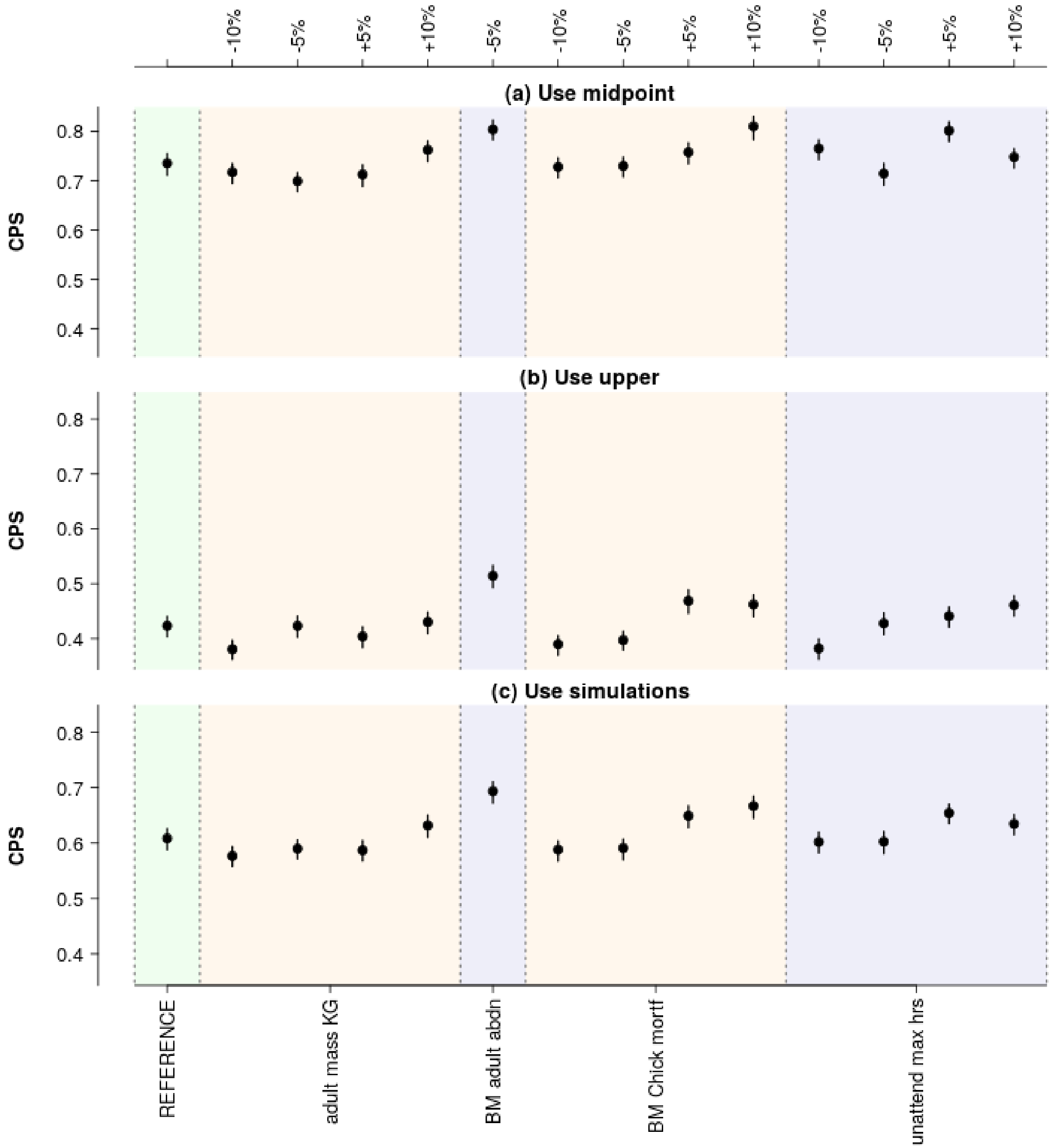

Figure 13: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for kittiwake after 30 years of displacement impact simulated via the SeabORD and PVA tool, based on SeabORD model runs from the ORJIP QuMR project that involved modifying each of four SeabORD model parameters by -10%, -5%, +5% and +10% from reference values.

3.7. Conclusions

The results of varying parameter values by a fixed amount indicate that key PVA outputs are particularly sensitive to those parameters that are directly proportional to annual displacement or collision mortality: (1 – avoidance rate), flight speed, displacement rate and displacement mortality rate. Sensitivity to bird wingspan and body length is much lower, as is sensitivity to baseline demographic parameters. In part, insensitivity to baseline demography results from the focus on relative metrics of impact, such as CPS (Jitlal et al., 2017), and is one of the key reasons that such metrics are a focus within assessments.

Estimates of impact differ between density independent and density dependent models, and, when there is density dependence, on the sign of the density dependence effect (with positive DD leading to higher impacts than density independence, and negative DD leading to lower impacts than density independence). There is less variation between DD models, although (a) the effect of positive DD is lower in the Weibull model with a shape parameter of 0.25 than in other DD models (b) PVA runs via the log-linear model with positive density dependence frequently failed (as might be anticipated, since this model can easily generate an explosion in the population size).

Demographic stochasticity has a very substantial effect on levels of uncertainty in PVA impact metrics, but environmental stochasticity has much less effect. Environmental stochastic is known to be important (Lande, 1993), so the relatively minimal impact of environmental stochasticity in this context arises from (a) the far that the key PVA impact metrics being considered are relative comparisons of impacted and baseline scenarios and (b) because the stochastic simulations of year-to-year variation are matched between baseline and impacted scenarios. As a result, whilst environmental stochasticity will have a substantial impact on baseline population sizes it can have a minimal impact on the relative difference between impacted and baseline population sizes. Note that the NE/JNCC PVA tool (and the CEF extension of this tool) fully match for the effect of environmental stochasticity – i.e. the simulations of environmental stochasticity are assumed to be exact identical for baseline and impacted runs – whereas demographic stochasticity is not completely matched between baseline and impacted runs, so to some extent the greater magnitude of uncertainty associated with demographic than environmental stochasticity that we see in the results of the sensitivity analysis may be a consequence of this. This highlights that there would be value in evaluating the extent to which stochastic decisions associated with baseline and impacted runs are currently matched against each other within existing assessment tools, and the extent to which this could be revised in future.

The impact of removing uncertainty in any individual parameter upon uncertainty in key PVA outputs appears to be minimal, potentially because there is substantial uncertainty in a range of key model inputs and only one parameter had uncertainty removed in each scenario.

There is an extensive literature around avoidance and displacement rates, and flight speeds, as outlined in the **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)** review. Outputs are highly sensitive to the source used in specifying avoidance and displacement rates, and to a lesser extent flight speeds, reflecting (a) the importance of these parameters within collision risk models and the Displacement Matrix and (b) considerable variation in the values of published displacement and avoidance rates.

Unsurprisingly, results indicate that impacts are systematically higher when upper uncertainty limits from collision and displacement models (e.g., upper end of 95% CI for collision outputs, upper limits for displacement and displacement mortality rates) are considered than when mean or median values are used. The sensitivity analysis demonstrates the potential to propagate the entire set of simulated values from the collision / displacement modelling through into the PVA, building on an extension of functionality on the NE/JNCC PVA Tool as part of the CEF project. Propagating uncertainty in this way enhances the potential to apply decisions around conservatism / precaution to model outputs, in a way that reflects the uncertainties associated with multiple stages of modelling.

As noted in the **AssESs – Summary report of uncertainty and approaches to evaluating uncertainty review (WP1)** report, the ratio of the mean seasonal peak to the seasonal mean can be large. Results of the sensitivity analysis suggest that, as a direct consequence of this, the magnitudes of impacts from displacement are highly sensitive to the treatment of monthly density data.

4. Systems-based sensitivity analysis

This part of the sensitivity analysis involves a holistic, systems-based investigation of uncertainty in ornithological assessments, looking ahead at how the incorporation of key biological feedbacks that are not currently considered within assessments can contract or inflate prediction uncertainty at different points of the assessment process.

The investigation of uncertainty is referred to as "holistic" because it includes all forms of variability that can affect the results: Observation uncertainty (resulting from observation methods and sample size, demographic stochasticity (intrinsic variation in vital rates, mortality events and migration events and environmental stochasticity (interannual fluctuations in mean vital rates as a result of covariates both extrinsic and intrinsic – such as might be caused by density dependence. However, a final source of uncertainty comes from model misspecification, the inevitable problem that the real world does not behave exactly as the model assumes. In many cases, such mismatches are caused by assumed functional forms (i.e. the nature of how model outputs depend on model inputs that may be inaccurate, or they may be the result of ignored dependencies between different aspects of the model. Density independent population models, for example, exclude the possibility of correlation (a relationship between population size and demography. If we assume density independence, but this assumption is in reality unrealistic, then the model will have been mis-specified. Correlations that exist between inputs or parameters of models, but are not accounted for within those models, could lead to inaccurate estimates of overall uncertainty, or make some stages of the modelling more/less sensitive to uncertainty.

We thereby examined whether correlations between parameters and inputs to the models used within assessments that are not currently captured by the models within the assessment process, can, when not accounted for, lead to significant divergence of risk estimates, and over or under-estimate uncertainty in predictions of population viability. This forward-looking investigation of uncertainty, although purely exploratory at the present time, will help us determine which biological features of the model (e.g. processes, mechanisms and assumptions that are currently omitted from assessment tools and approaches should be introduced in order to better represent uncertainty, and also determine the extent to which existing models may be simplified without loss in accuracy or precision.

The models used within assessments are based on mechanistic assumptions around behaviour, demography and population dynamics. It is therefore most appropriate to consider the impact of correlation by including the mechanistic processes that would induce correlation within the models (e.g. density dependence, rather than assuming arbitrary levels of correlation between model inputs. These structural correlations are better tied to biological understanding and can be parameterised more readily as a result. We extend the models to include an explicit link between population size and foraging range, for example, rather than simply assuming that there is correlation between these parameters. Using the actual assessment tools for this investigation was consequently not feasible, both for computational reasons and because it would need functionality (e.g., mechanistic features of models) that have not yet been implemented within either the CEF or the individual tools used in assessments. We therefore took as our starting point a system-level representation of the quantitative elements of the assessment process that necessarily includes simplifications (e.g., in assuming collision risk probabilities, rather than incorporating an explicit collision risk model) but which, crucially, incorporates the four key stages of 1) spatial utilisation of windfarm region by species of interest, 2) displacement of animals due to OWF operation, 3) collision mortality and avoidance secondary effects and 4) population viability assessment for a given future horizon. This abstracted, system-level model of the assessment process has considerably shorter running times than actual assessment tools, and can be used to approximate their essential functions. This allows the examination of adding currently missing features (e.g. the lack of relationship between population size and foraging range) that introduce connections and feedbacks between different inputs and outputs within the stages of an assessment.

The framework used within this part of the sensitivity analysis included different types of correlations and feedbacks that may be generated by biological inputs and outputs of each stage, going beyond the functionality currently considered within assessments. We first investigated the full parameter space available to such a model. Principally, this covered the specification of the life history of the species, the richness of its environment, the location and size of the OWF and the particular impacts it may have on breeding success and mortality of foraging birds. After extracting metrics of impact (the same PVA metrics as considered in Section 3), we explored the ability of flexible, empirical models (Generalised Additive Models (GAM)) to capture the responses of the system to the introduction of wind farms. We then explored simplified versions of the systems-level framework by using different representations of the full systems-level model to bring it to the level of dynamic complexity that currently exists in the tools and approaches used for impact assessment. By running both versions (full & simplified) we compared the influence of different mechanistic features that are not currently accounted for in assessments in causing bias or imprecision in the estimates of impact.

Full details of the approach and results are described in Annex A: Integrated investigation of uncertainty in assessment tools, which provides a Technical Report outlining the methods and results for the systems-based sensitivity analysis, but the key findings were that:

1. For the parameter space examined here, impacts were found to be relatively small. However, the selection of parameter values is designed to be plausible rather than representative, so this analysis provides a basis for undertaking comparisons of different models and assumptions, rather than to provide an absolute estimate of risk.

2. Correlations between model parameters can generate unexpected bias and loss of precision, if they are not properly accounted for within the modelling.

3. Statistical approximations to the models had limited explanatory power (deviance explained, never exceeded 50%), hence indicating that the quantitative approaches used in assessments cannot easily be eschewed via these computationally more expedient routes.

4. Bias and imprecision are not exclusive characteristics of either the full or simplified model. There were measurable but small differences in bias and imprecision that mostly depended on the rate of

growth of a species, the strength of density-dependent regulation, collision mortality rates and the size/distance of the OWF in relation to a colony.

5. We suggest that a key feature that is likely to improve both precision and accuracy is the inclusion of predicted future population size in relation to its impact on seabird distribution and exposure to risk i.e., coupling and iterating the calculation of exposure on an annual basis for PVA projections across several years.

5. Conclusions

The sensitivity analyses have built upon the review of current practice and evidence within WP1, and will, in conjunction with the stakeholder engagement in WP3, help to inform the development of recommendations within WP4. Specifically:

1. The outcomes of the WP1 review, and sensitivity analysis in relation to inputs (Section 3), will help in prioritising those parameters for which future research (data collection, analyses of existing data) and subsequent translation of evidence into updates to SNCB guidance would be most valuable in reducing uncertainty within assessments.

2. The sensitivity analyses help to illustrate the potential for technical improvements to the treatment of uncertainty within assessments, particularly through (a) greater use of simulation-based approaches to propagation of uncertainty between tools, (b) refinements to the Displacement Matrix to align with this simulation-based approach, allowing overall uncertainty within the assessment process to be quantified in a consistent way regardless of the impact mechanism(s) – collision and/or displacement – being considered; and (c) refinements to the treatment of variation in density data when using the Displacement Matrix.

3. Draft outcomes from the systems-based sensitivity analysis were used to stimulate discussion within the stakeholder engagement workshop in **AssESs – Summary report of stakeholder engagement (WP3)**, and so were used in informing the structure of the stakeholder engagement in WP3.

4. Within WP4 we demonstrate how the technical improvements to the treatment of uncertainty within assessments highlighted in this report can enable and support the implementation of recommendations that emerged from stakeholder engagement in WP3. In particular, stakeholder engagement in WP3 highlighted an urgent need to move away from the evaluation of precaution in relation to inputs towards the evaluation of precaution in relation to outputs, so that there is a more explicit and transparent link between precaution and uncertainty in key outputs, and in WP4 we outline how improvements to the propagation of uncertainty and to the implementation of the Displacement Matrix (used in analyses within this report) can help to underpin this transition.

5. The analyses within the systems-based sensitivity analysis help to inform future research, and changes to the assessment process, by identifying key biological processes that output metrics are sensitive to but that are not current accounted for within assessments – in particular the inclusion of a relationship between population size and seabird distribution.

6. The analyses within the systems-based sensitivity analysis also demonstrate that correlations between parameters in models can generate unexpected bias and loss of precision, indicating the importance of improved quantification of correlations as a key topic for future research and practice.

Development of recommendations will integrate evidence from across the review, sensitivity analyses and stakeholder engagement.

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Appendix 1. Definitions of PVA metrics

We provide mathematical definitions of the PVA metrics generated by the NE/JNCC PVA Tool and considered here.

Notation

For each of $i = 1, \dots, n$ simulations of annual population size from a population model, involving paired "impacted" and "baseline" runs, let:

- x_{ij} = i-th simulation of baseline (unimpacted) population size after j years of impact
- y_{ij} = i-th simulation of baseline impacted population size after j years of impact
- $x_{i0} = y_{i0}$ = i-th simulation of population size in year immediately prior to start of impact

In addition, we define thresholds as:

- u_e = quasi-extinction threshold
- u_t = target population size

Metrics

We define, after j years of impact:

M0: Impacted population size, y_{ij}, summarised across simulations i (e.g. via median, mean, SD, quantiles)

M1. Ratio of impacted to unimpacted population size, y_{ij}/x_{ij}, summarised across simulations

M2. Ratio of impacted to unimpacted annual growth rate, $y_{ij}^{1/j}/x_{ij}^{1/j}$, summarised across simulations

M3. Quantile for unimpacted population which matches the median impacted population,

$$\frac{1}{n}\sum_{i=1}^{n} \mathbf{I}\left(x_{ij} \le Q_{50}(y_{ij})\right)$$

M4. Quantile for impacted population which matches the median unimpacted population,

$$\frac{1}{n}\sum_{i=1}^{n} \mathbf{I}\left(y_{ij} \le Q_{50}(x_{ij})\right)$$

M5. Probability of quasi-extinction

$$\frac{1}{n}\sum_{i=1}^{n} \mathbf{I}(y_{ij} \le u_e)$$

M6. Probability that the population has recovered to target level

$$\frac{1}{n}\sum_{i=1}^{n} \mathbf{I}(y_{ij} \ge u_t)$$

where **I**(.) denotes the indicator function and $Q_{50}(.)$ the median.

Appendix 2. Additional checks on PVA outputs

We ran additional simulations in order to verify that two key results were reproducible and did not indicate a bug: (a) the finding that levels of environmental stochasticity are typically low in absolute terms and (b) the finding that levels of demographic stochasticity are much higher than levels of environmental stochasticity.

Methodology

We implemented these additional simulations by running the PVA tool for gannet, guillemot and kittiwake with the baseline demographic rates and the median population size used within the main simulations for each of these species. We then imposed standardised scenarios of impact: we assume that the magnitude of impact was either “low” (“0.2%”, corresponding to 0.002) or “high” (“2%”, corresponding to 0.002), and that the level of uncertainty relative to the magnitude of impact was either “low” (SE = 0.1 * mean) or “high” (SE = mean).

The purpose of the simulations was to establish the behaviour in relation to environmental and demographic stochasticity within the PVA tool in situations where the level of impact was standardised. We used three species, rather than a single species, in order to capture variations between species in population size and baseline demography.

For each scenario, we apply eight different PVAs, based on all possible combinations of three elements; (a) whether or not demographic stochasticity is considered, (b) whether or not environmental stochasticity is considered, and (c) whether uncertainty in impact is considered (when it is not considered the SE is set equal to 0.000001, a value so small that it is effectively equivalent to zero). As in the main simulations we focus on counterfactual population size ratio (CPS) after 30 years of impact. A burn-in period of 5 years is used.

Results

The results are shown in Figure 14.

When environmental stochasticity is the only form of stochasticity being considered (option DSD) then the resulting level of uncertainty in the output metric is consistently very low.

Including demographic stochasticity alone (option SDD) results in higher levels of uncertainty, but the magnitude of uncertainty, relative to that from including just environmental stochasticity, varies considerably between species – the increase is very substantial for kittiwake (which has the smallest median population size of the three species) but more modest for the other two species.

The relative importance of uncertainty in impact depends, unsurprisingly, on both the size of impact and the relative amount of uncertainty around that impact. When the ratio of SE to mean for the impact is 1 uncertainty in impact dominates the effect of demographic stochasticity in all cases except kittiwake with an impact of 0.2% (where the magnitude of demographic stochasticity and uncertainty in impact are broadly similar). When the ratio of SE to mean for impact is 0.1 the relative importance of the two sources upon uncertainty the output metric is quite variable.

These results show that the relative importance of different sources of uncertainty within the PVA is context-specific, but reinforce the finding that the effects of environmental stochasticity are generally low. Note that, crucially, this reflects the nature of the output metric being considered – e.g. because the metric quantifies the difference between impacted and baseline simulations, and both contain environmental stochasticity.

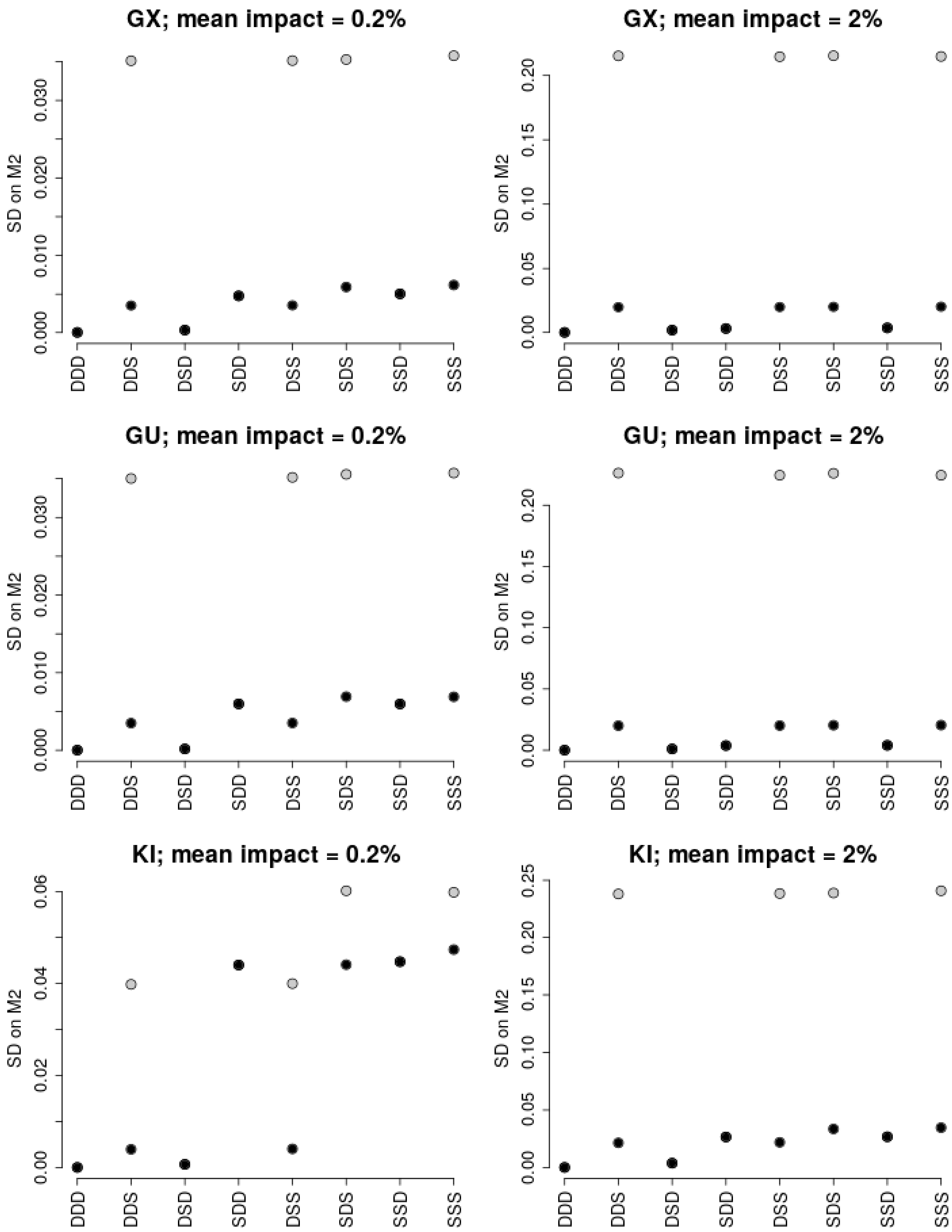

Figure 14: Standard deviation of counterfactual population size ratio (CPS) after 30 years of impact, for three species (GX = gannet, GU = guillemot, KI = kittiwake), based on an impact of either 0.002 (left) or 0.2 (right) and an SE to mean impact ratio of either 0.1 (black) or 1 (grey). Eight different ways of applying uncertainty within the PVA are considered, based on whether it is deterministic (D) or stochastic (S) in (a) demographic stochasticity, (b) environmental stochasticity and (c) uncertainty in impact. A code of "SDD" on the horizontal axis indicates, for example, that demographic stochasticity is included but environmental stochasticity and uncertainty in impact are not.

Appendix 3: Sensitivity to inputs – additional results

This supplementary information contains graphs (S1-S120 that correspond to those in the main WP2 report, but:

- are for all species considered for collision and displacement (the main report just presents results for a single species)
- are, for the Displacement Matrix, based on three different ways of using information on displacement rates and displacement mortality rates: using upper values, using mean values, or using simulated values. Only upper values are considered in the main report.

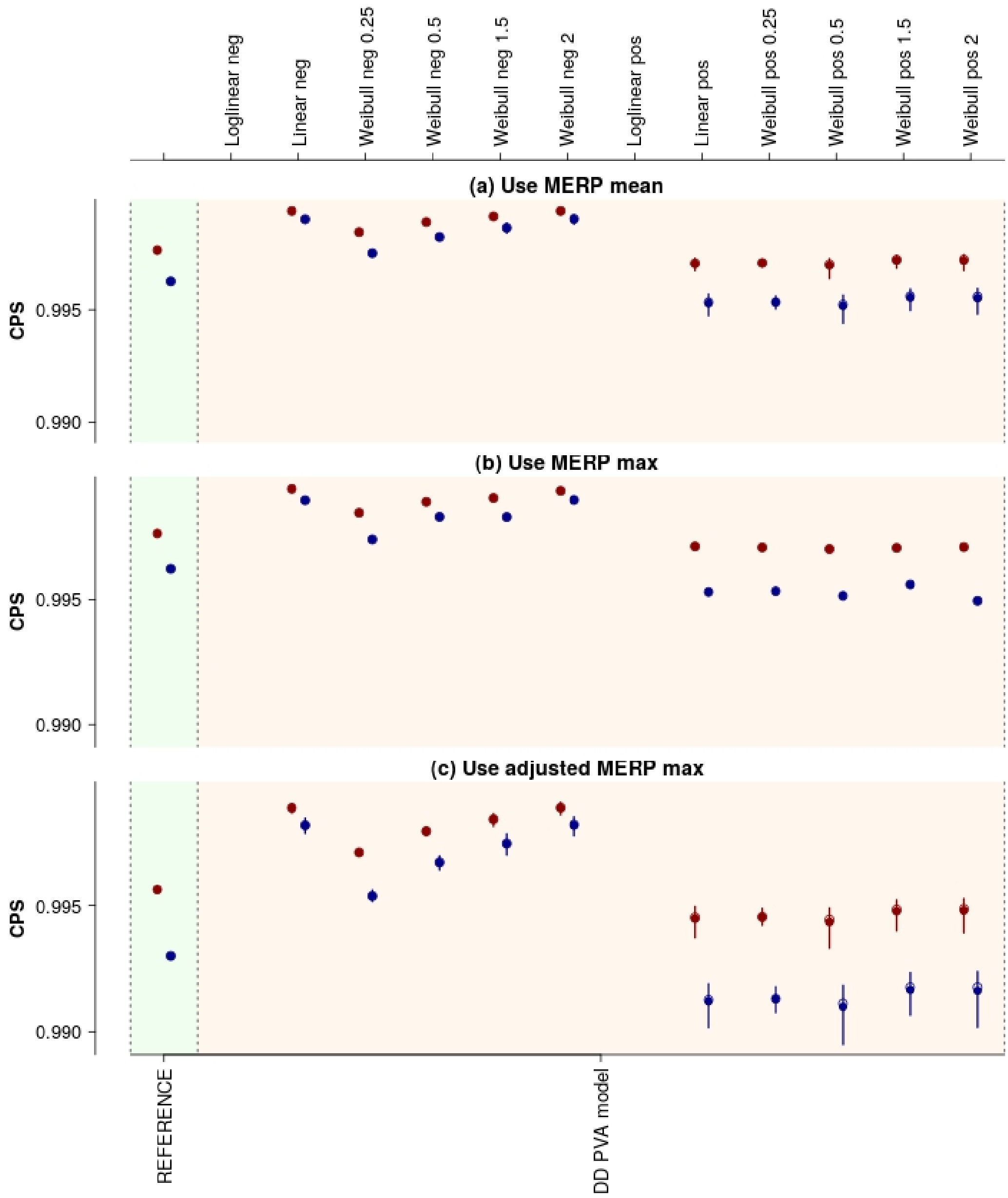

Figure S1: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

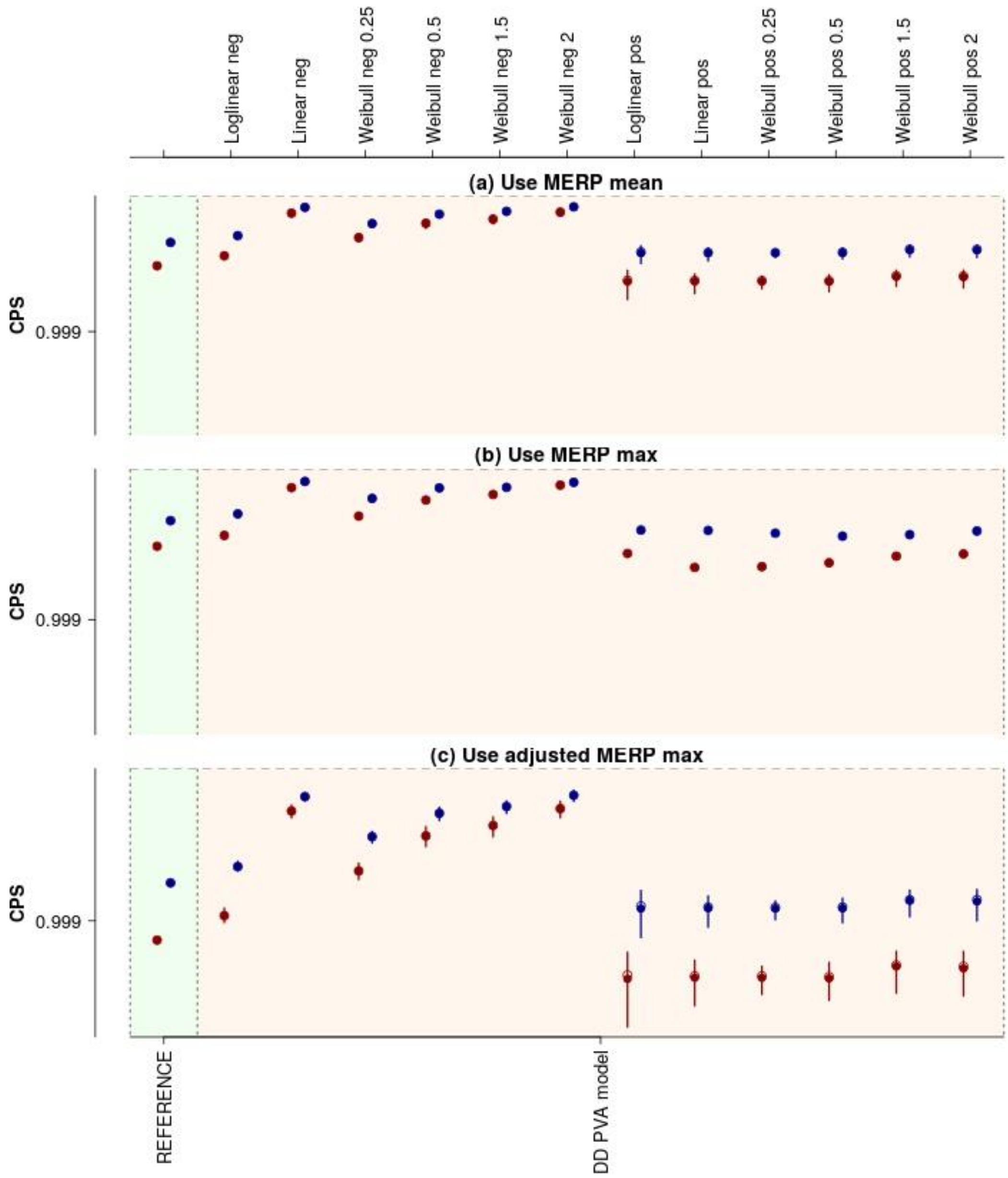

Figure S2: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

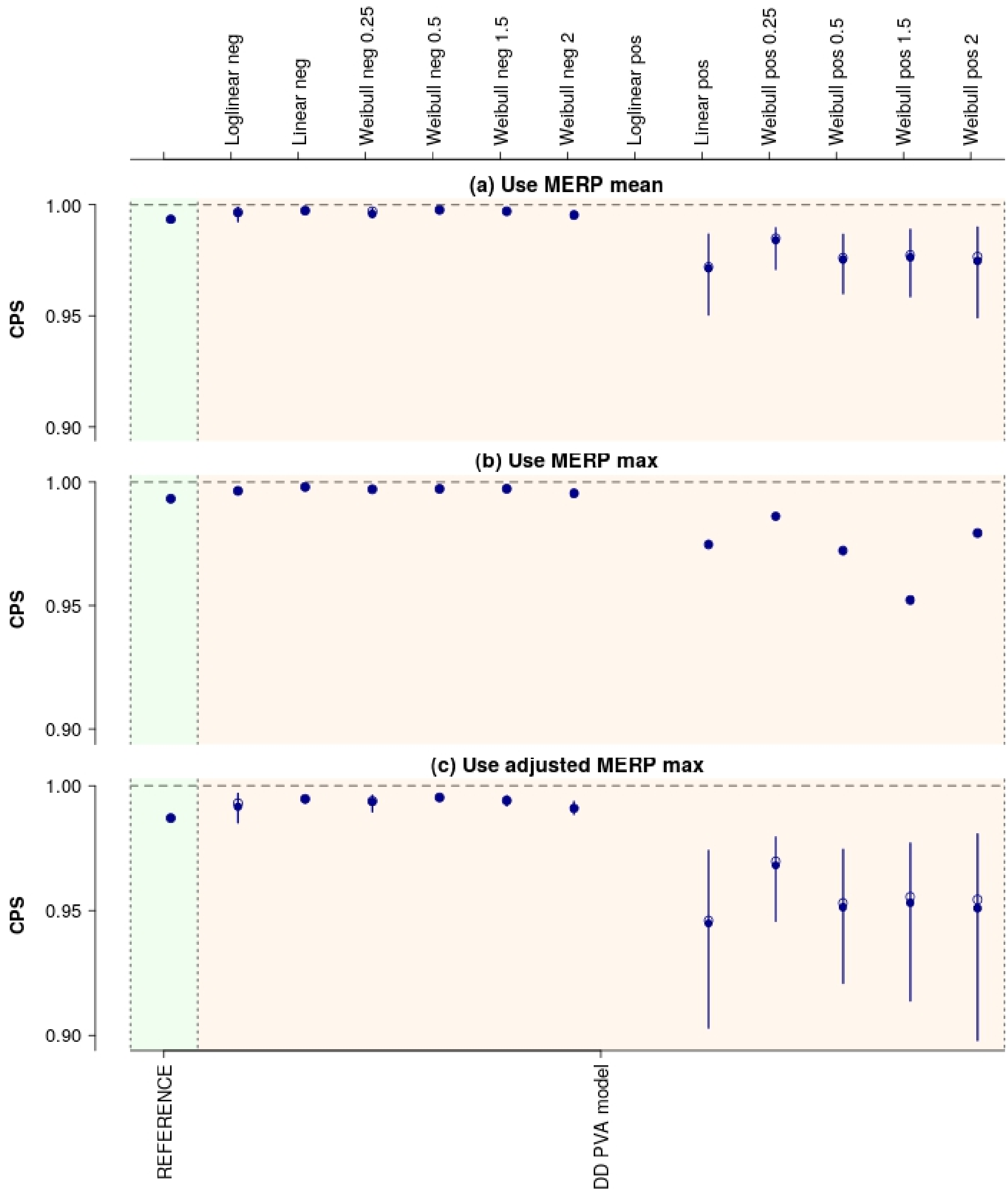

Figure S3: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

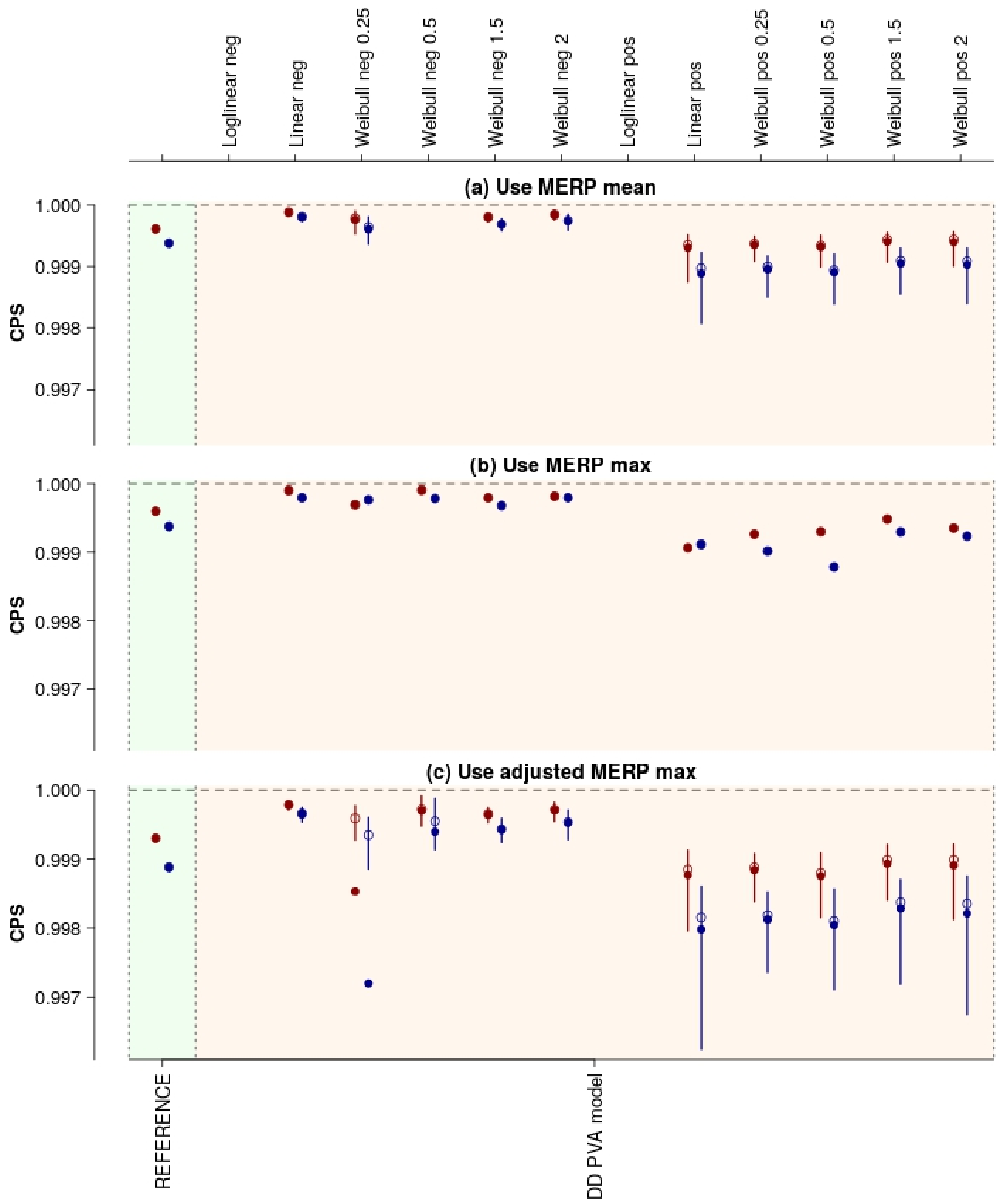

Figure S4: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

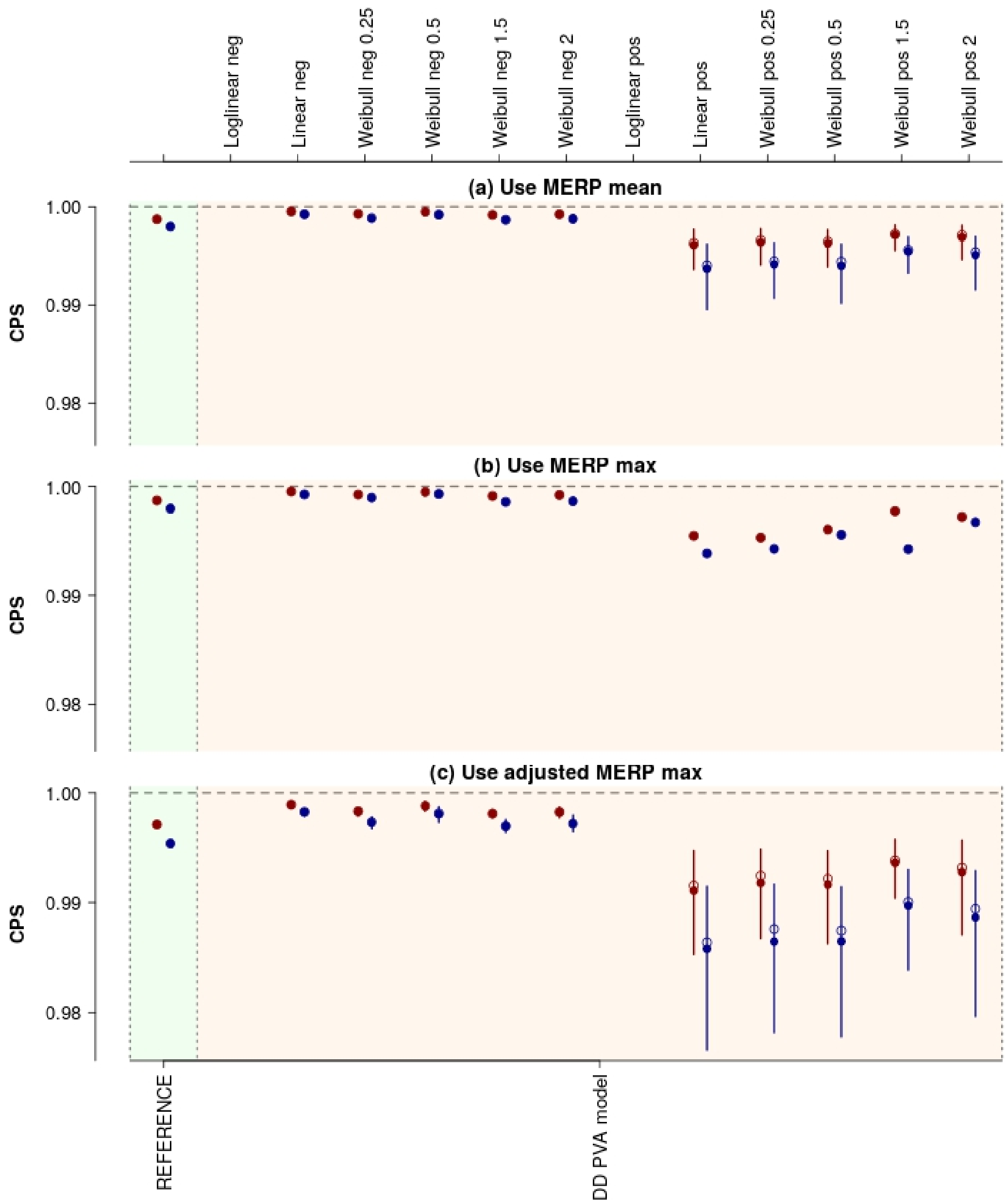

Figure S5: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

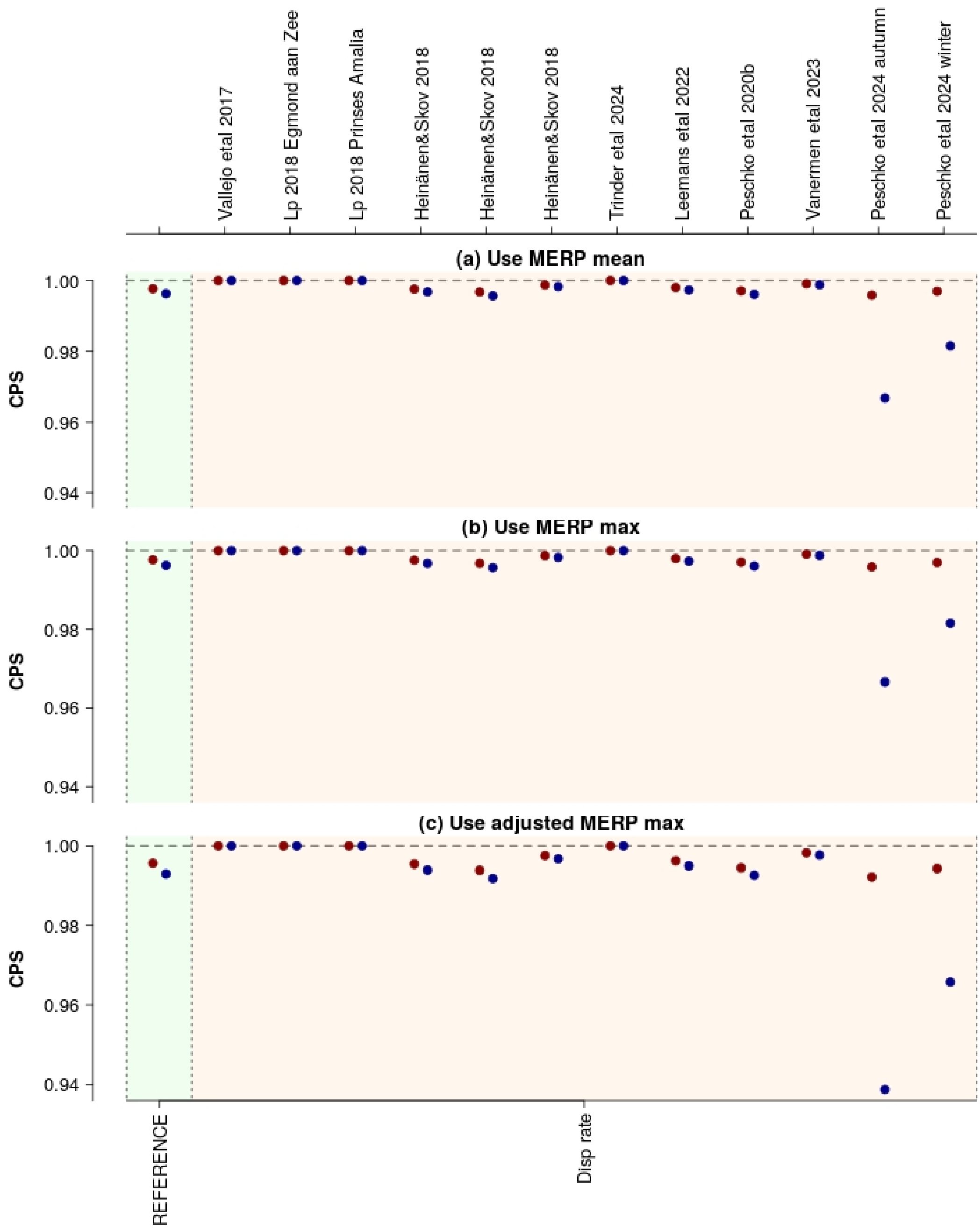

Figure S6: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

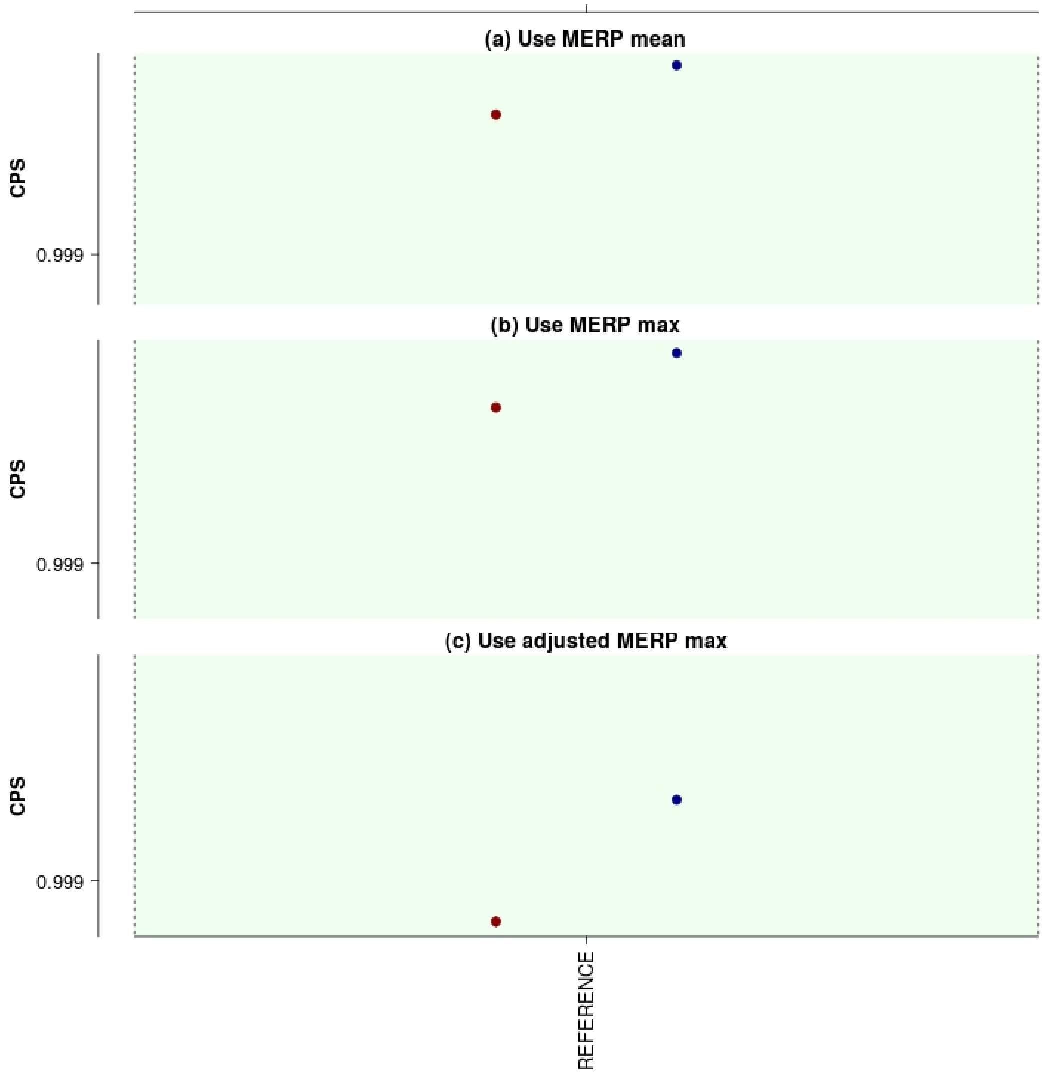

Figure S7: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

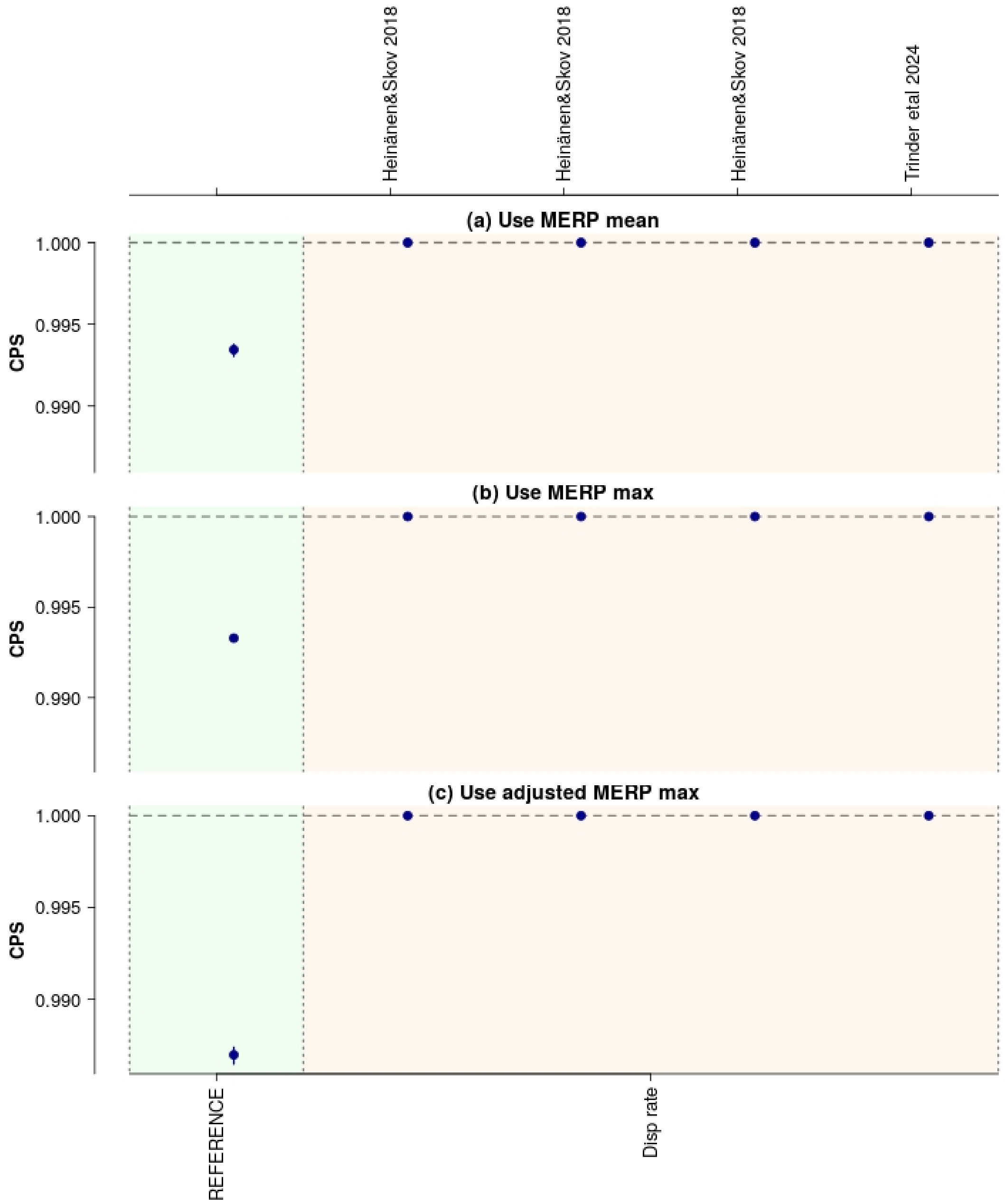

Figure S8: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

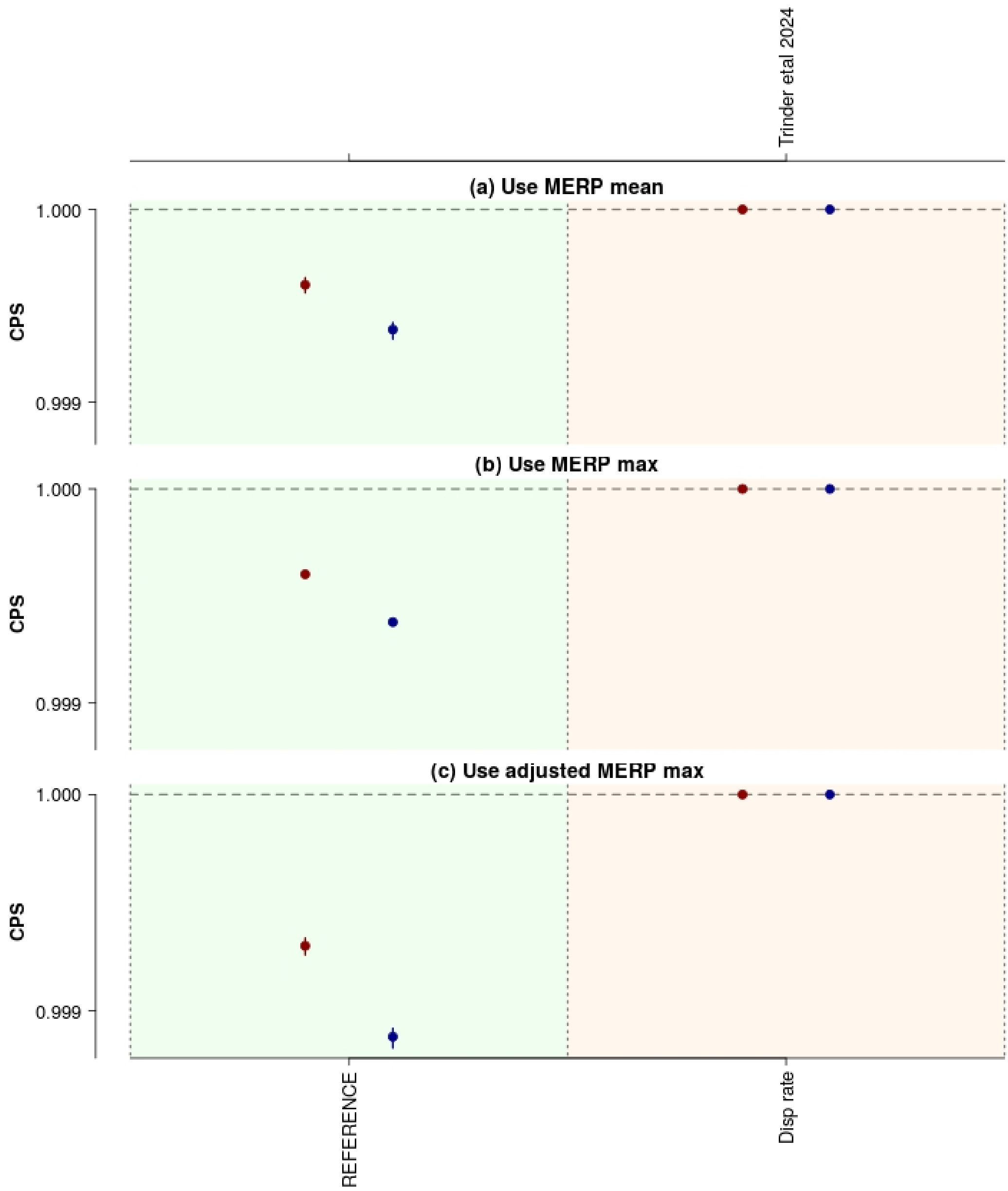

Figure S9: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

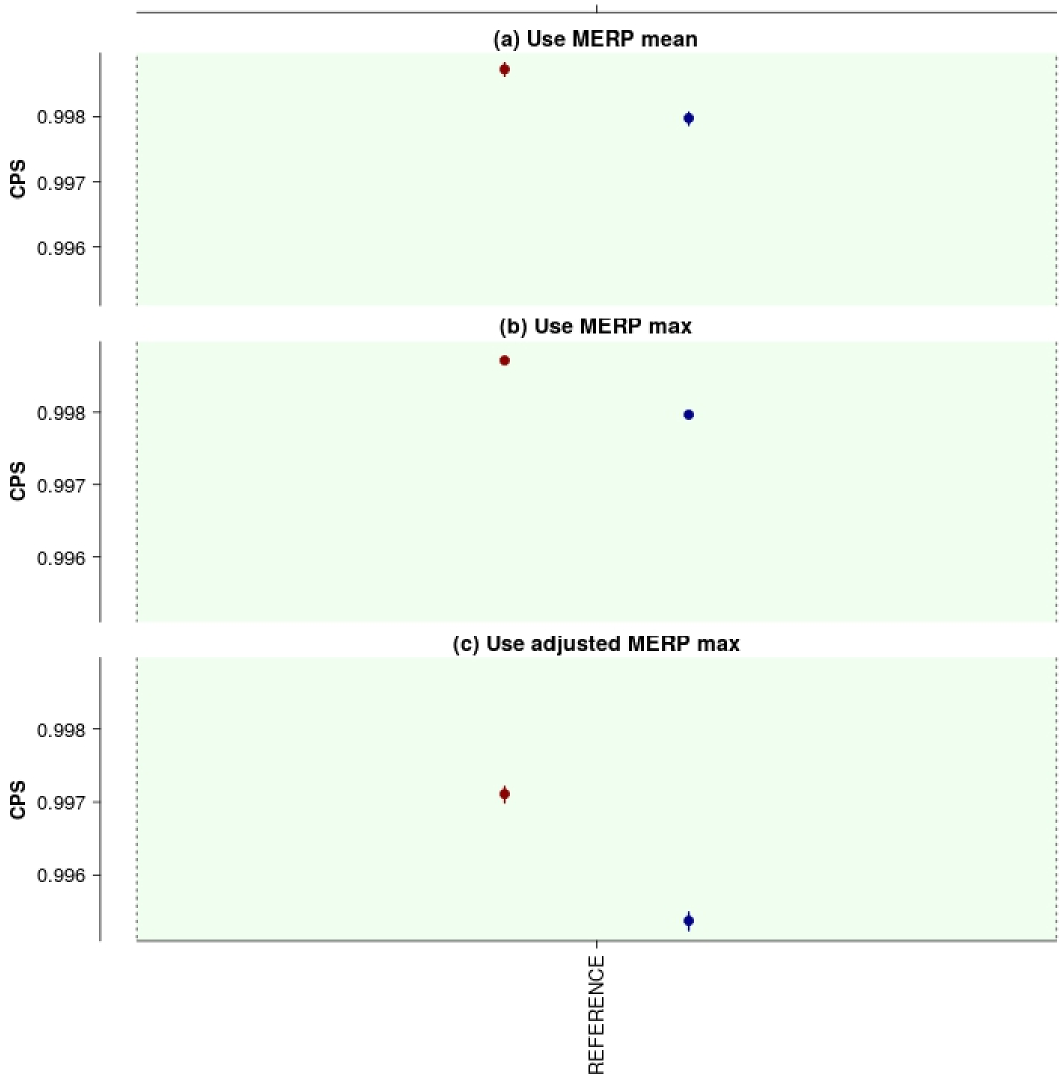

Figure S10: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

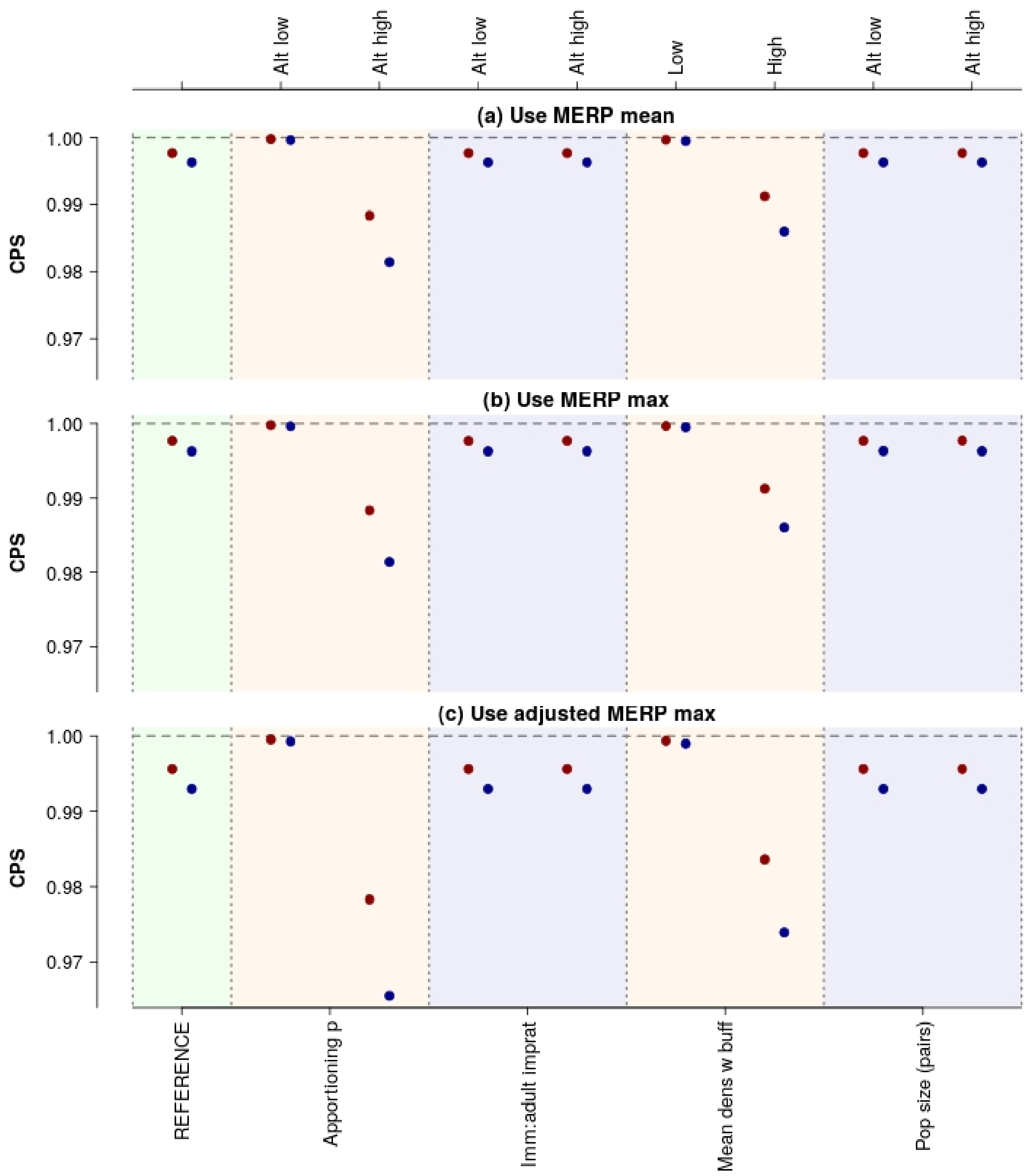

Figure S11: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

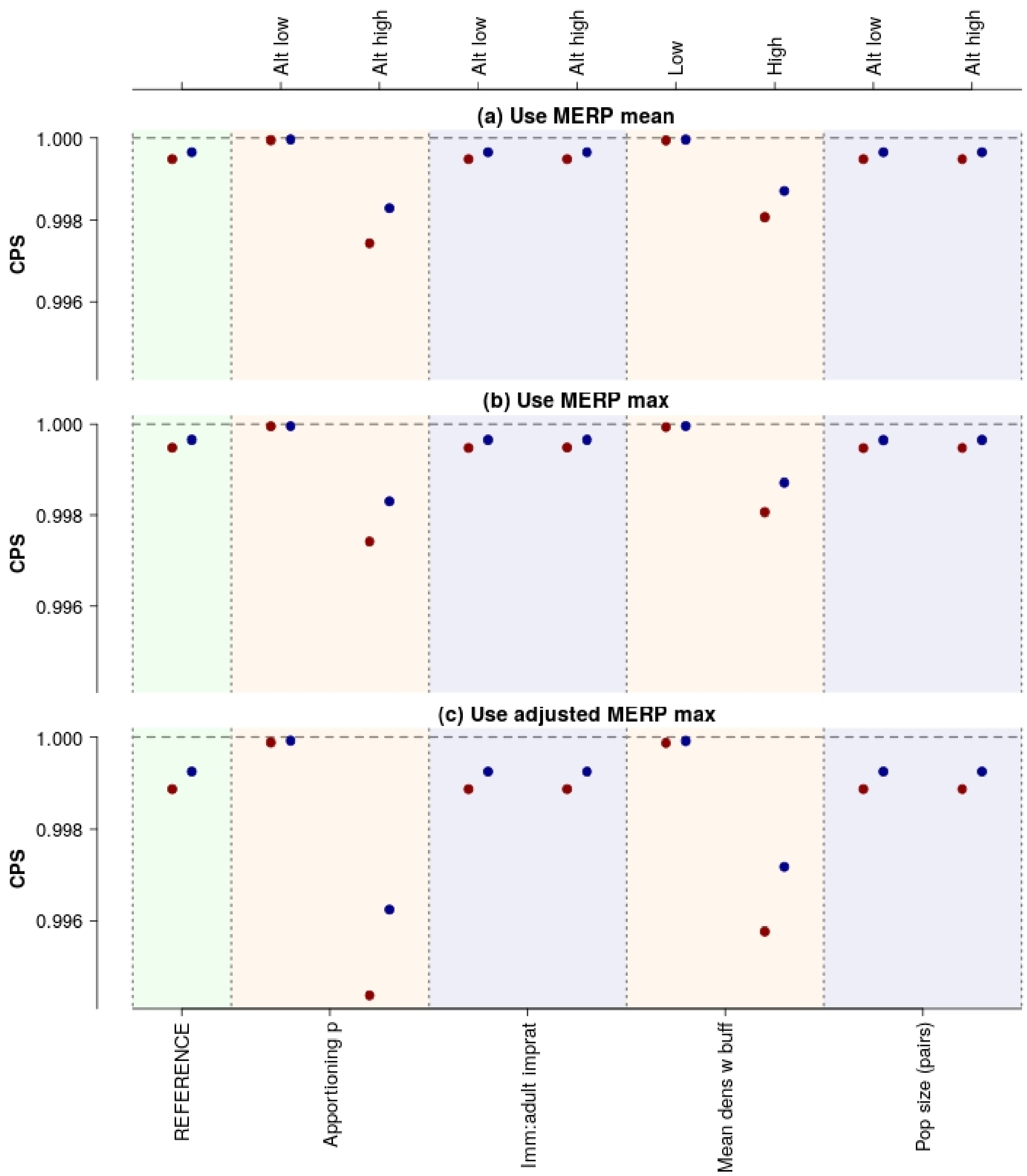

Figure S12: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

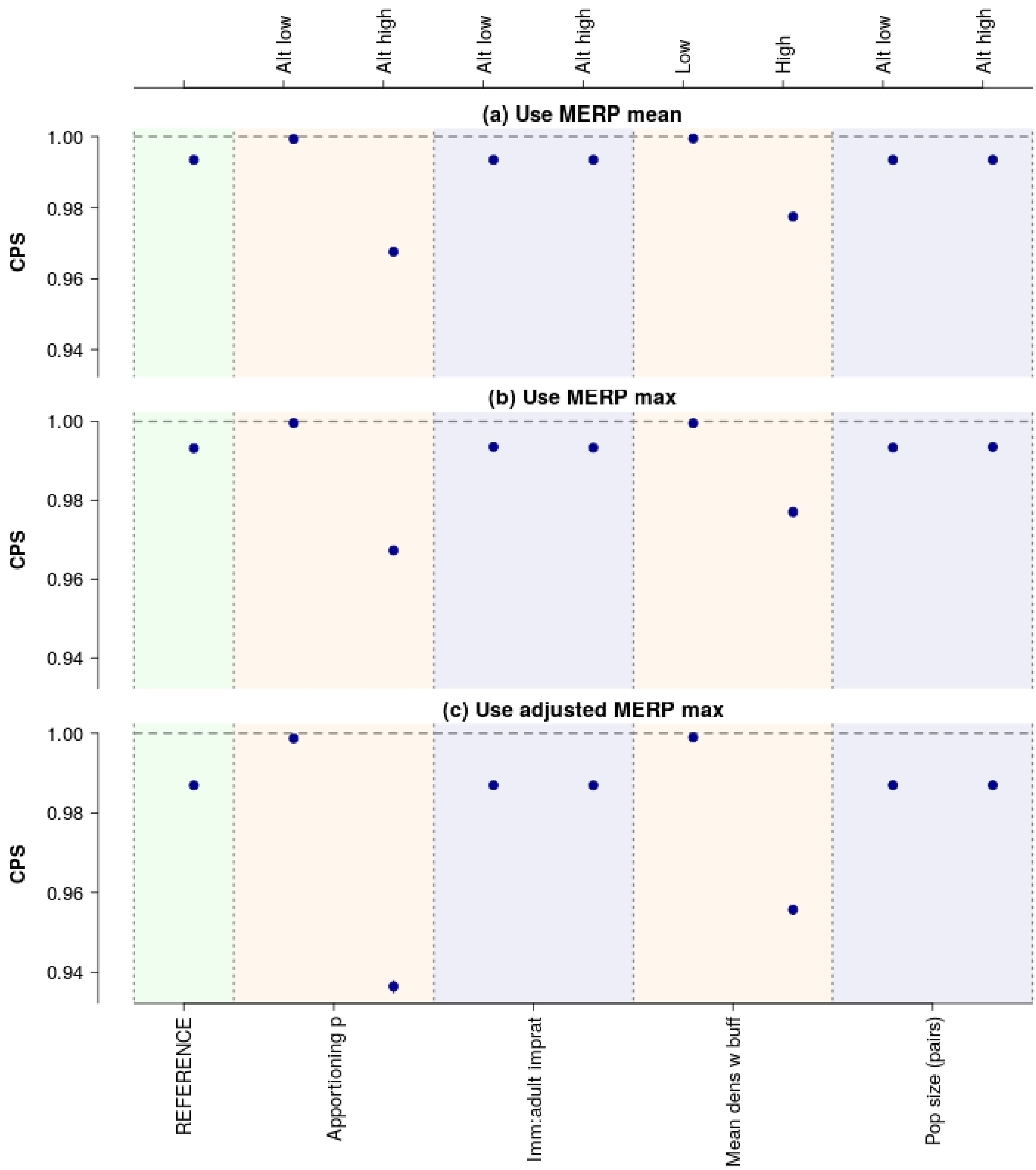

Figure S13: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

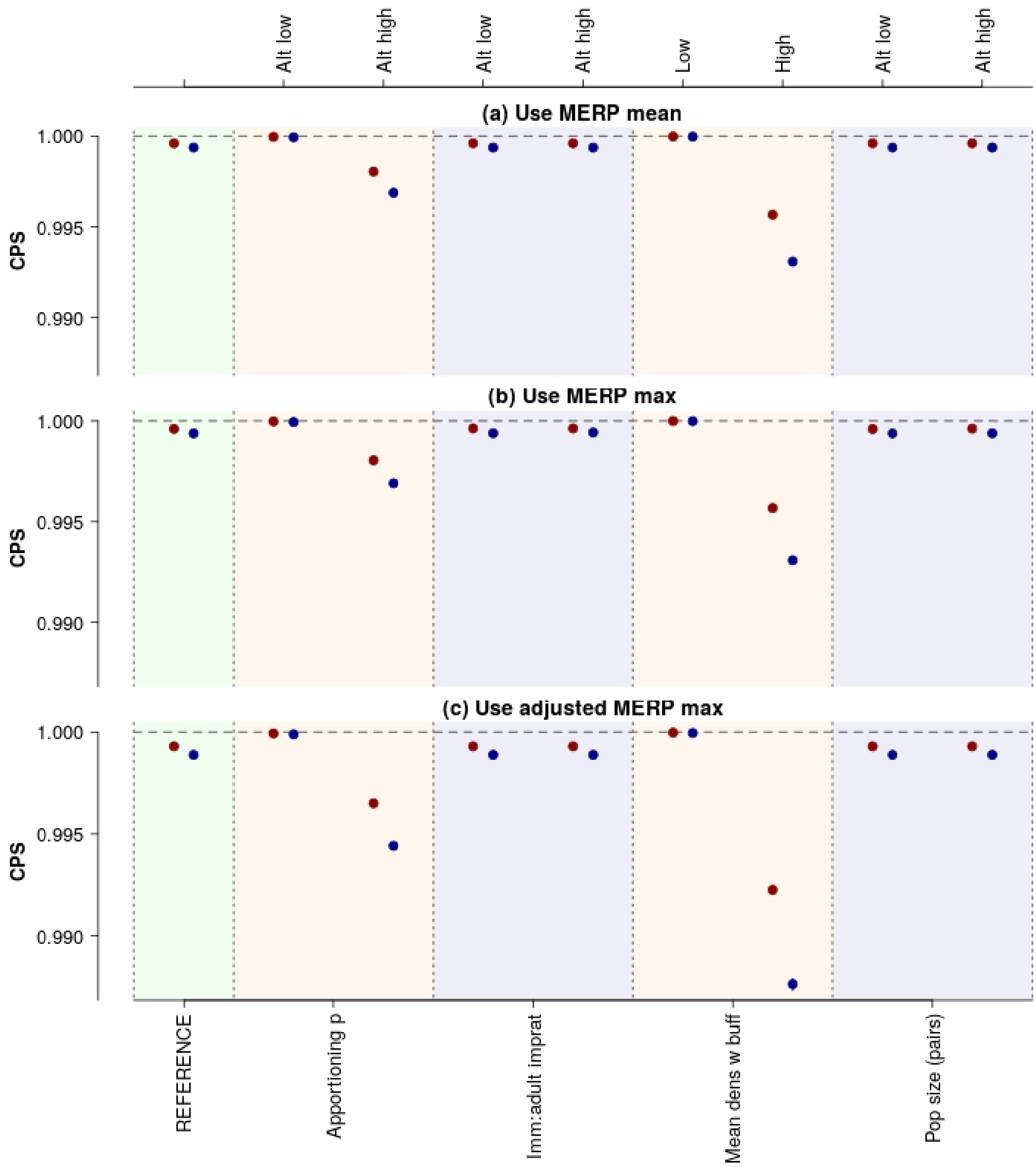

Figure S14: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

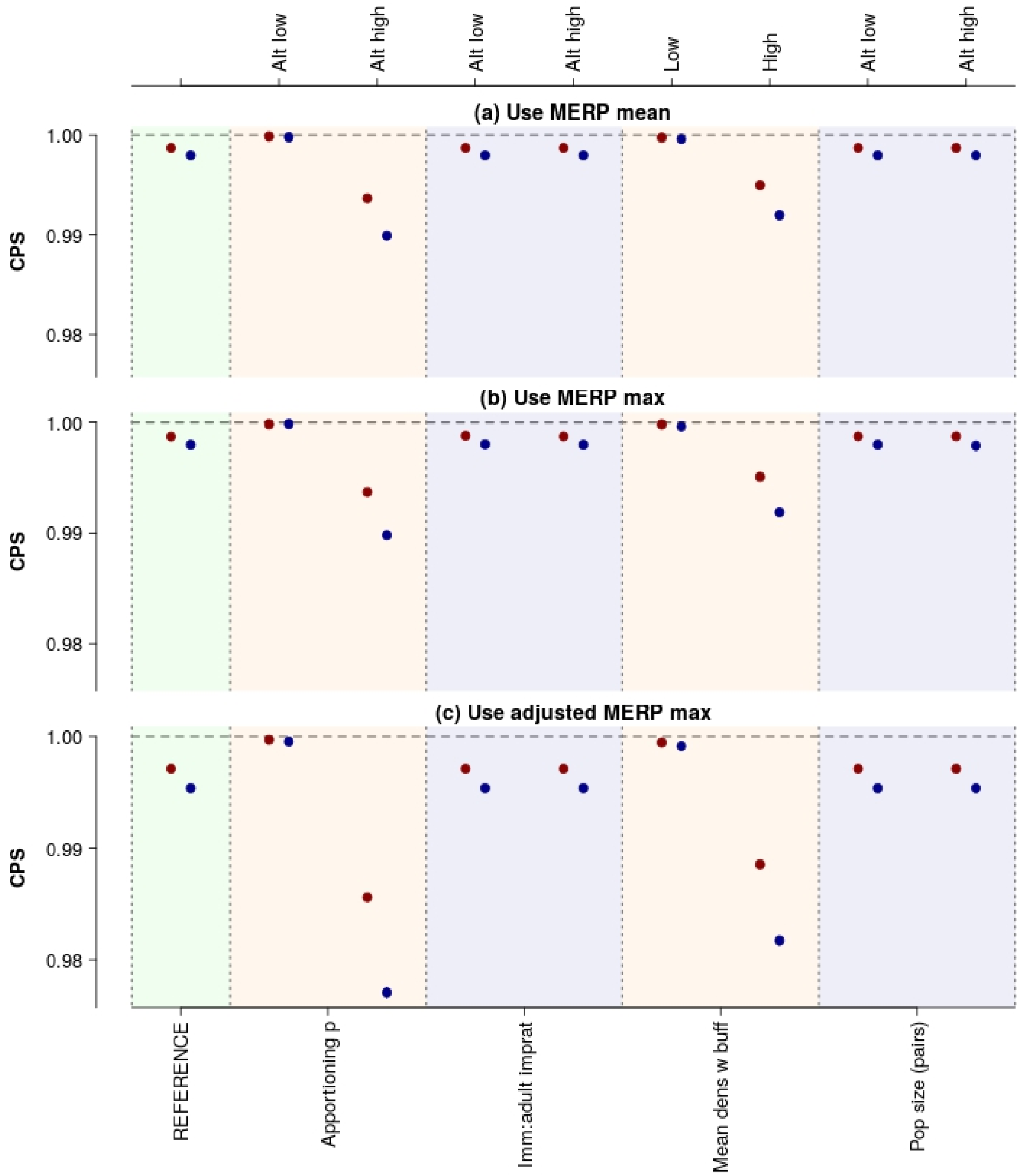

Figure S15: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

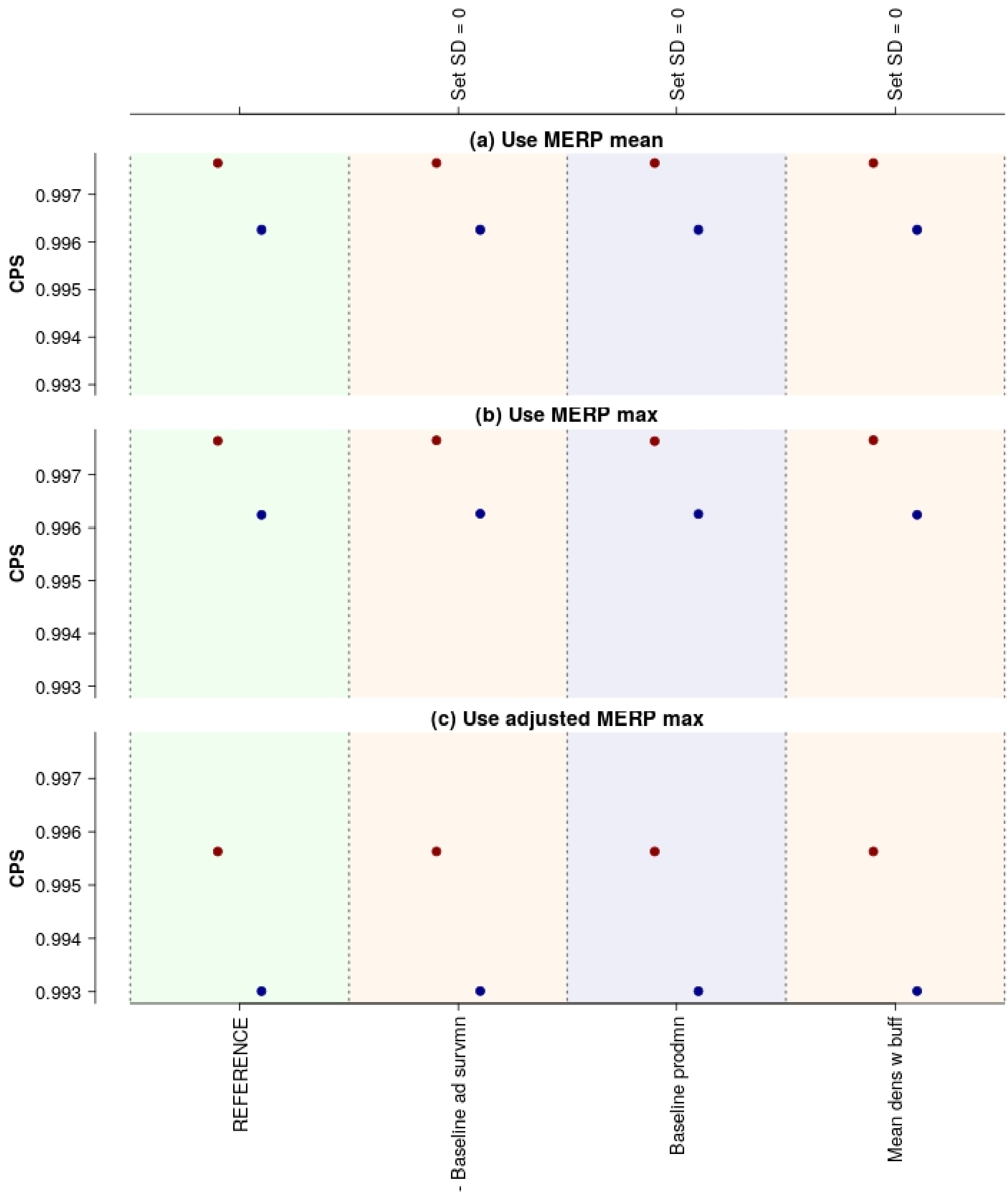

Figure S16: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

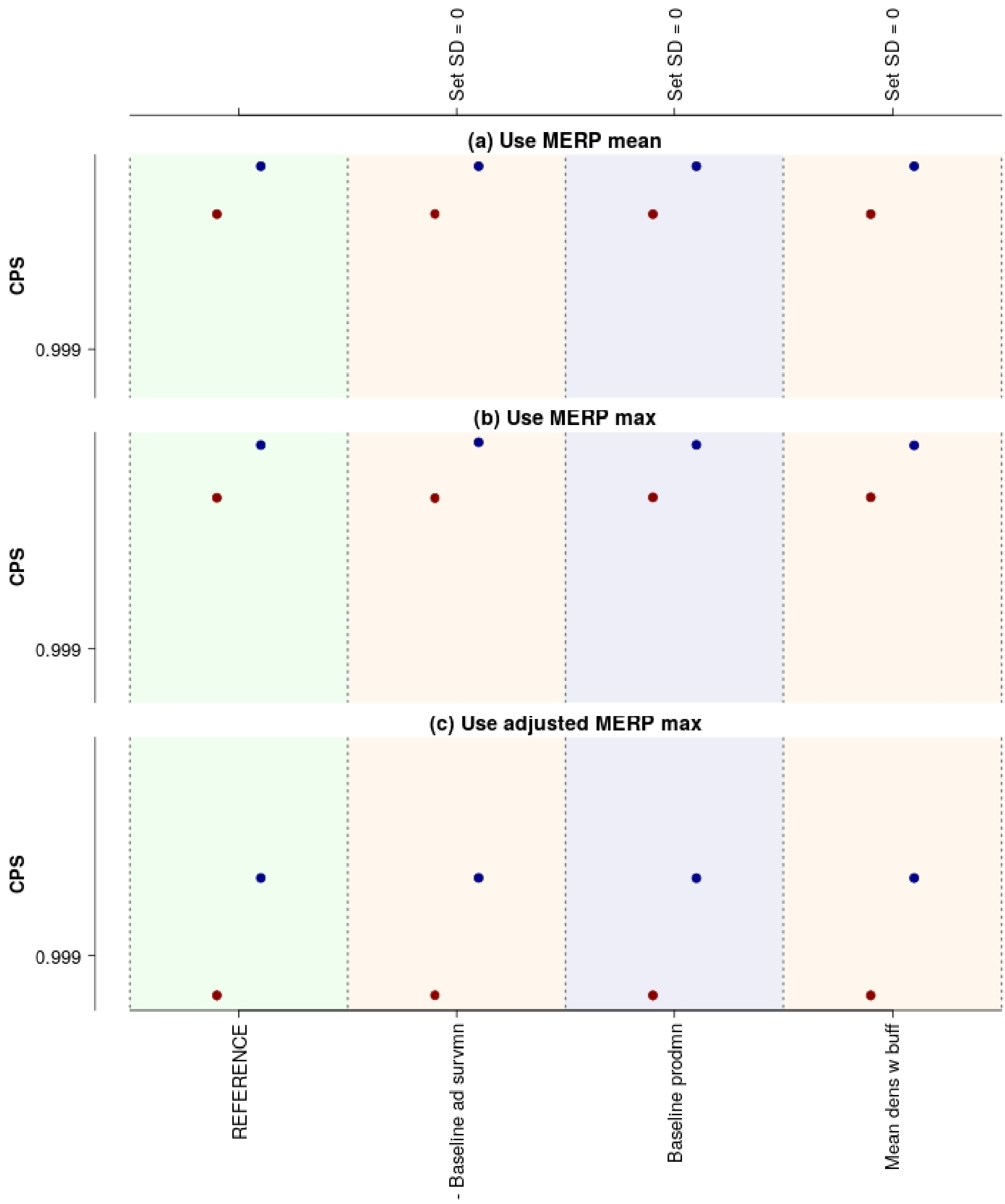

Figure S17: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

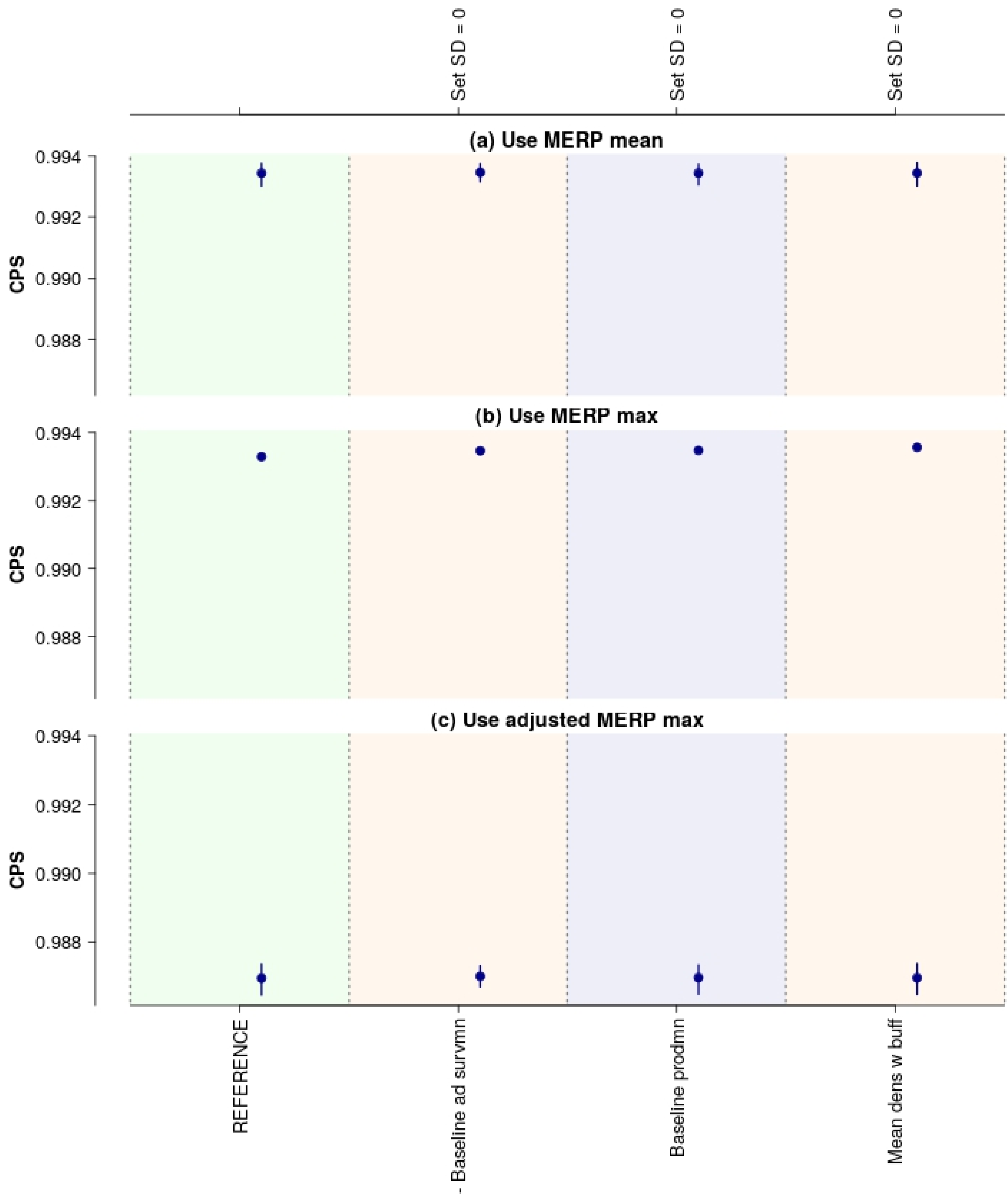

Figure S18: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

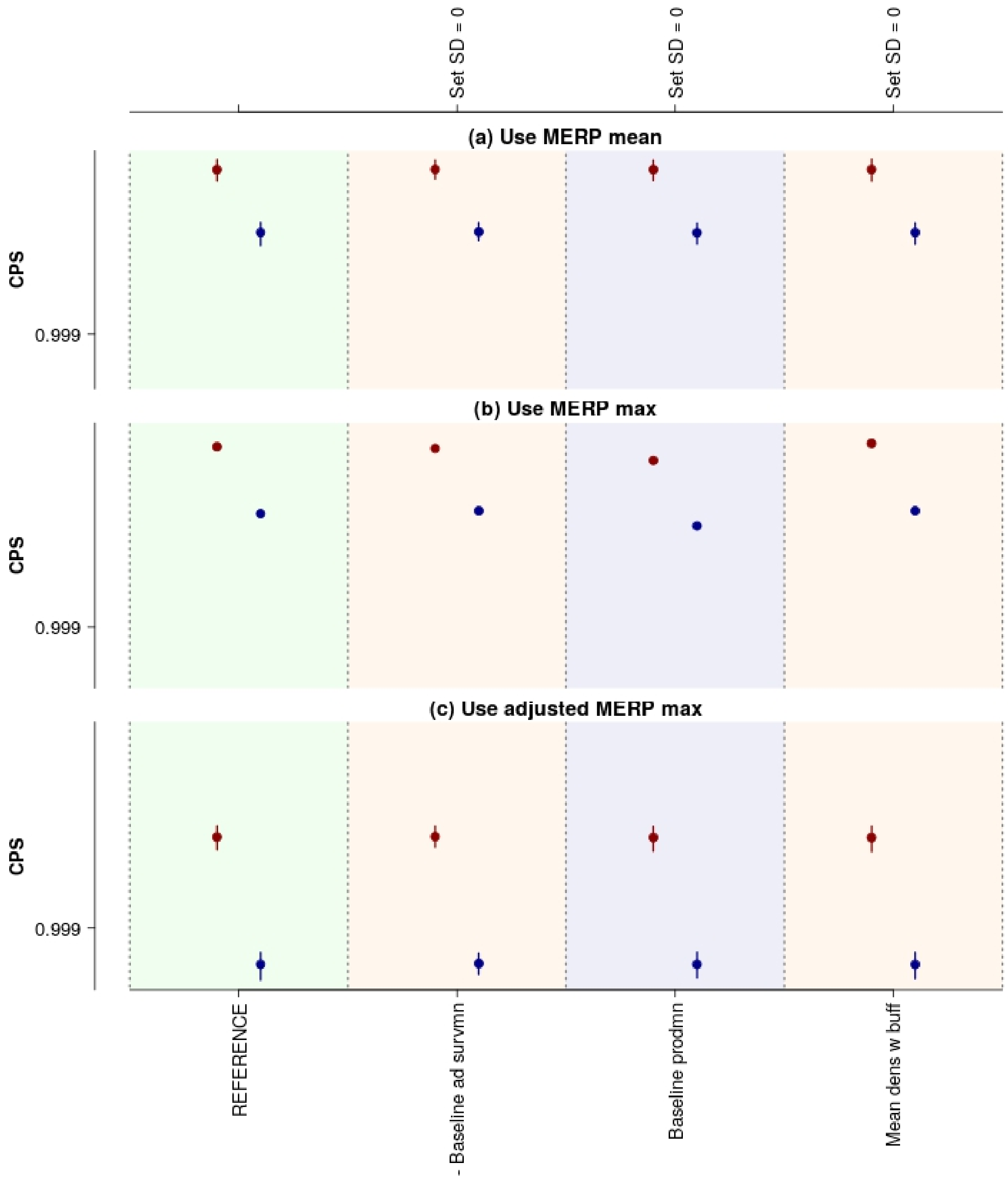

Figure S19: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

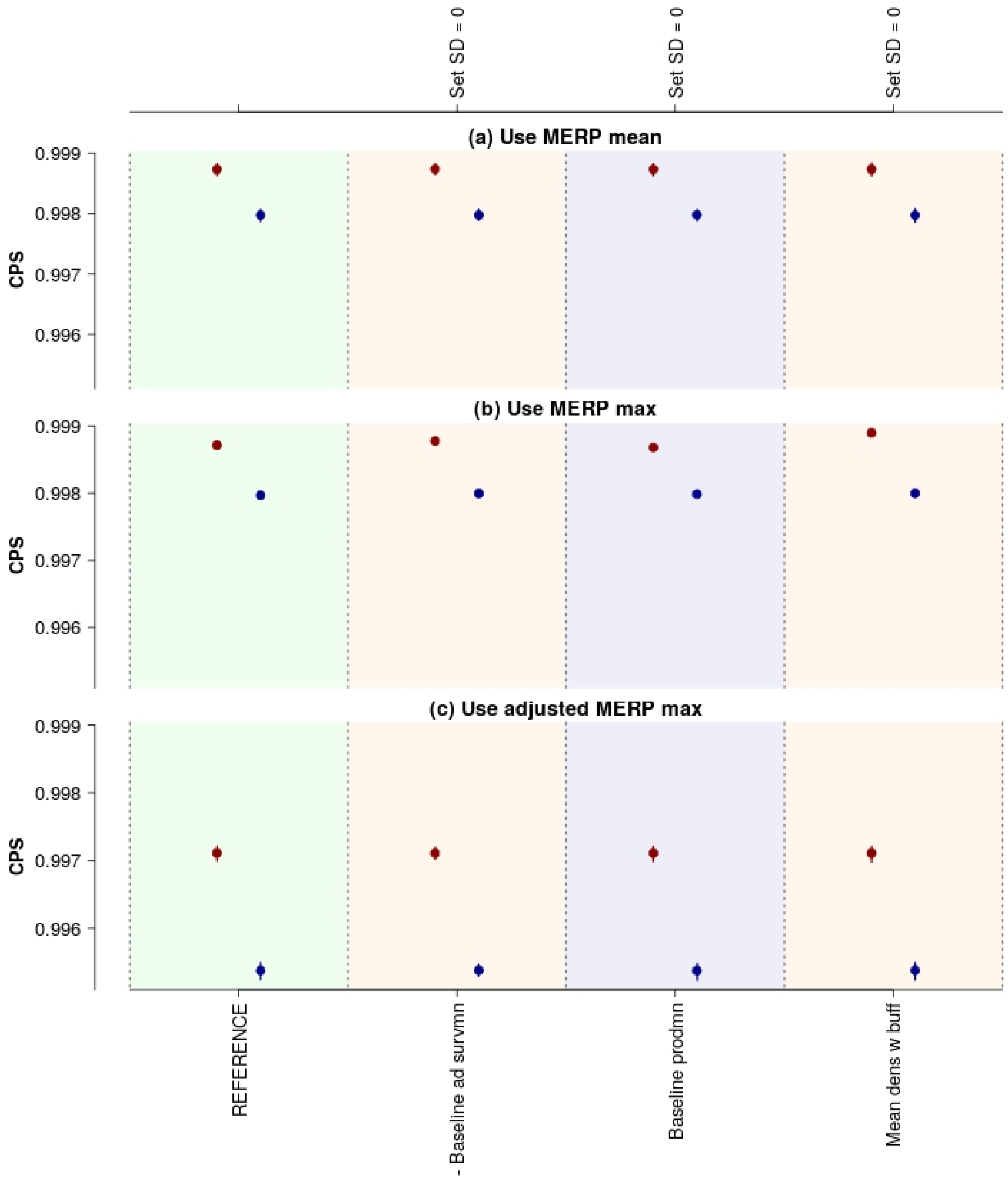

Figure S20: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

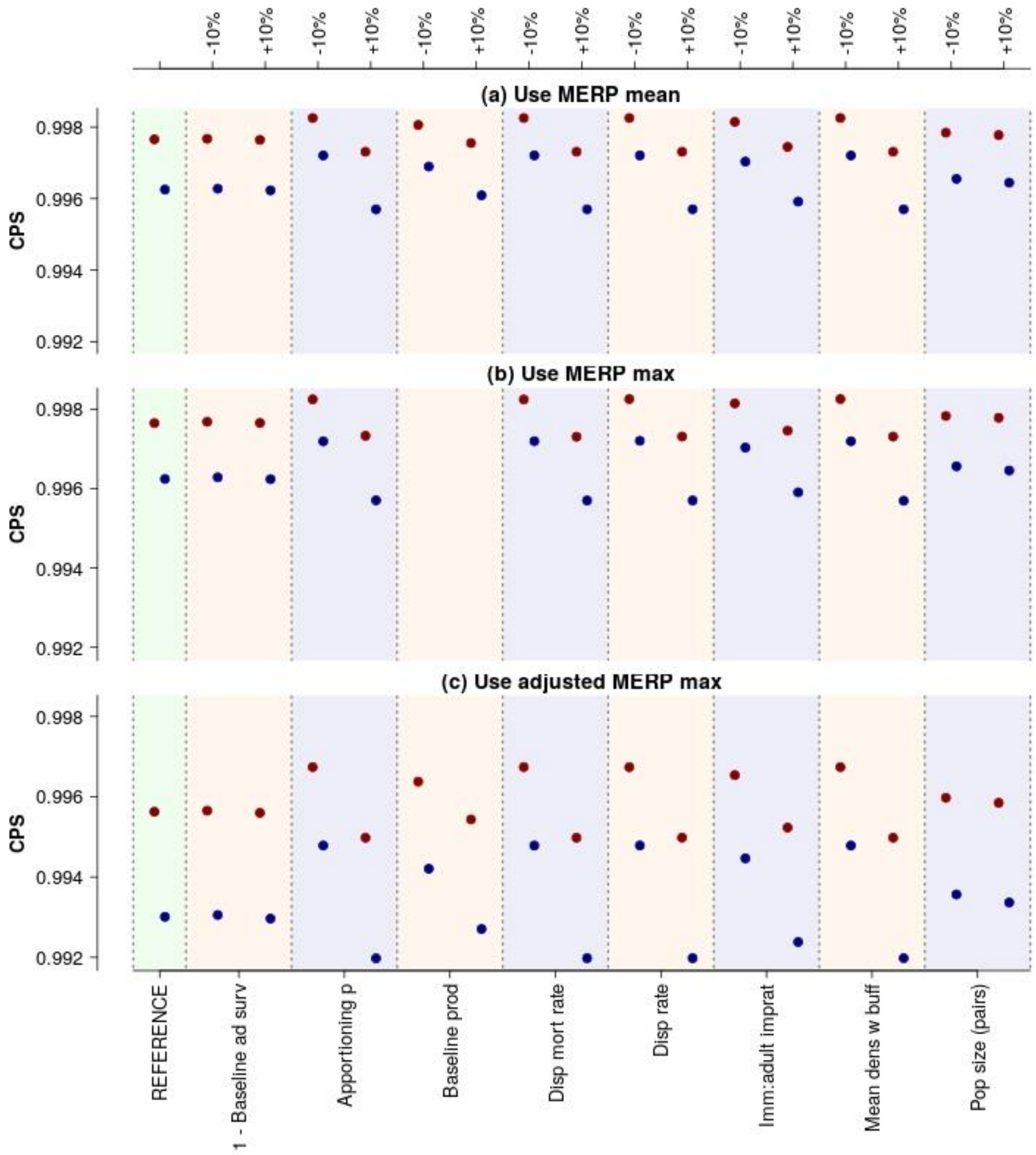

Figure S21: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

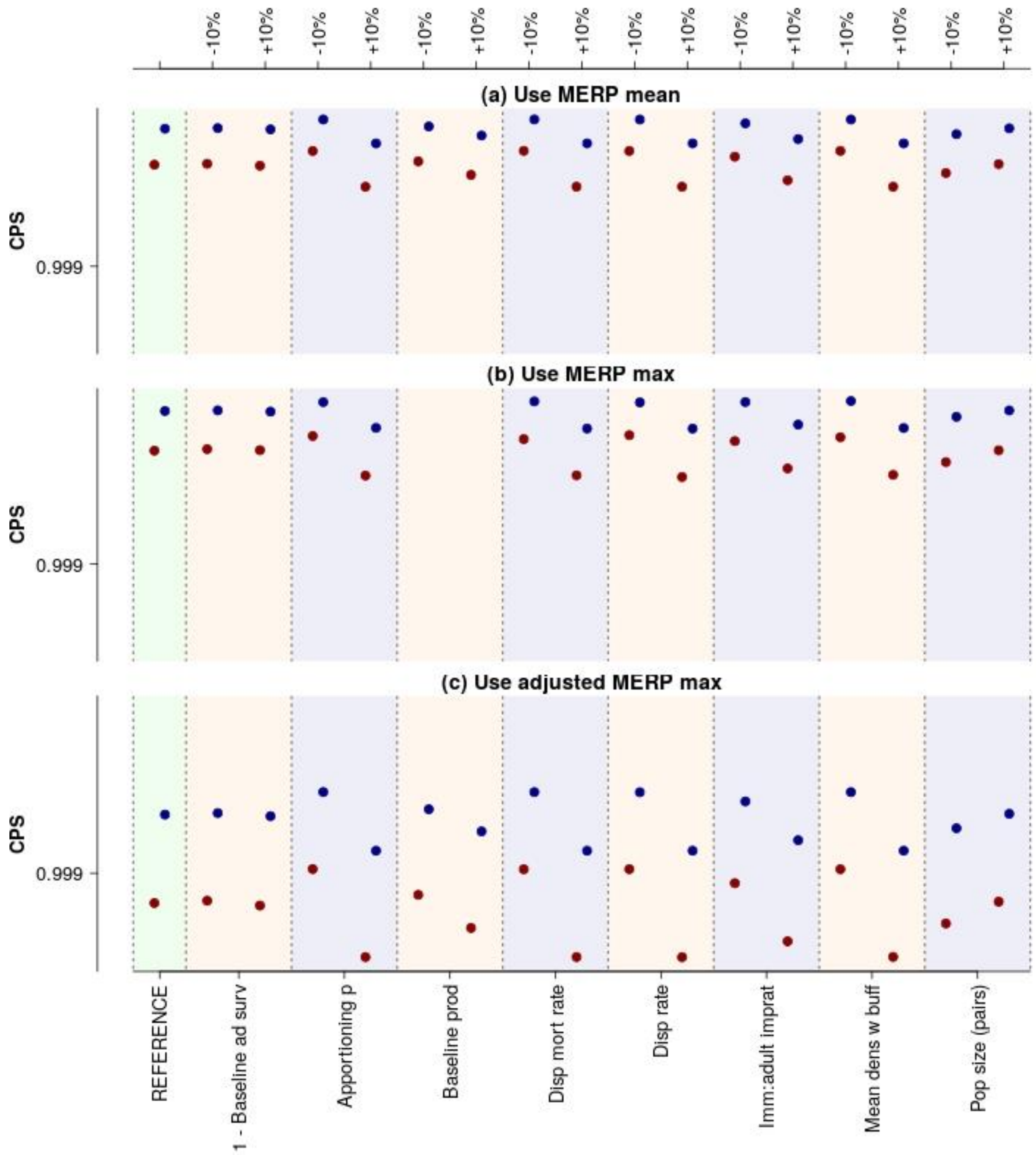

Figure S22: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

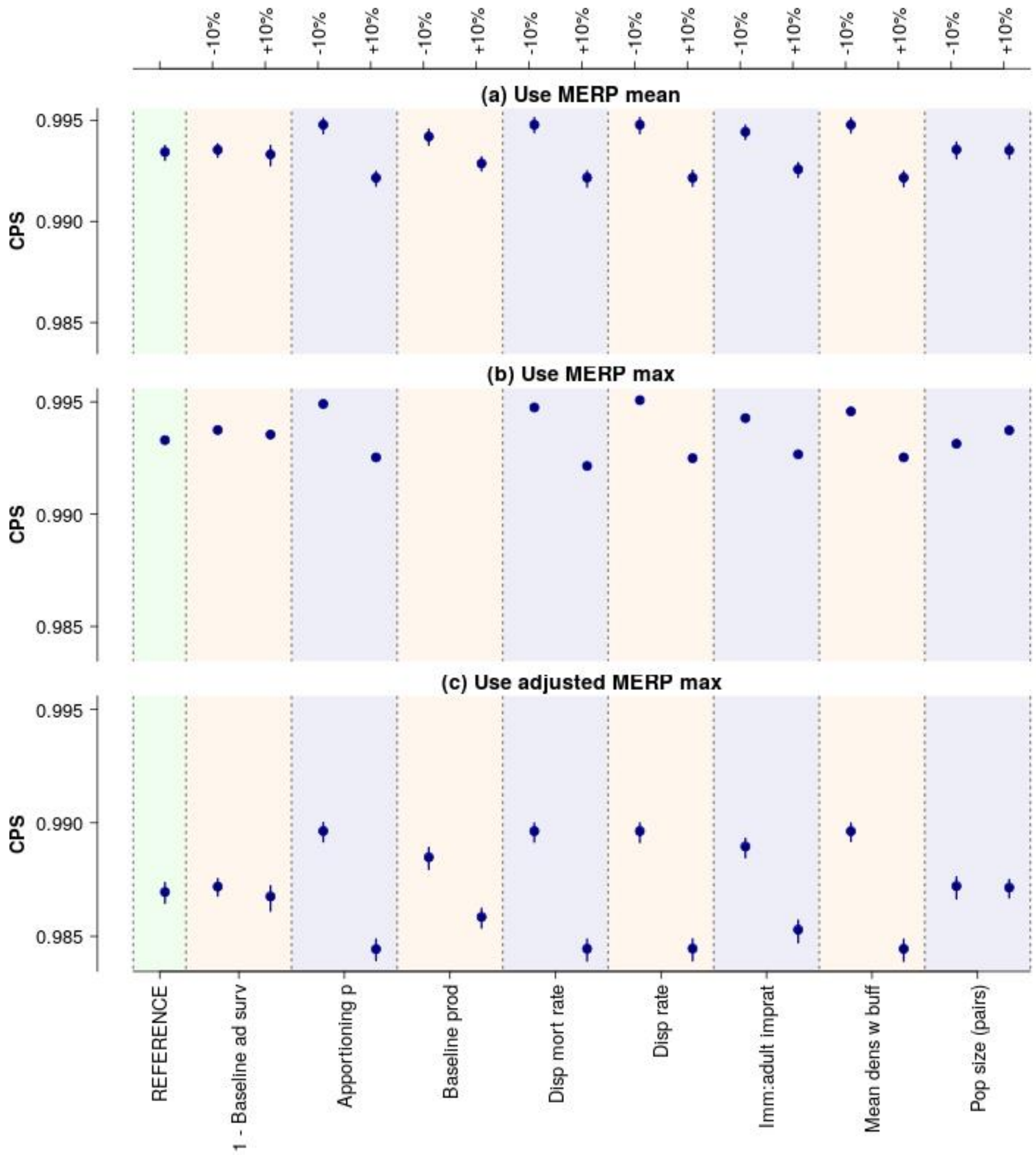

Figure S23: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

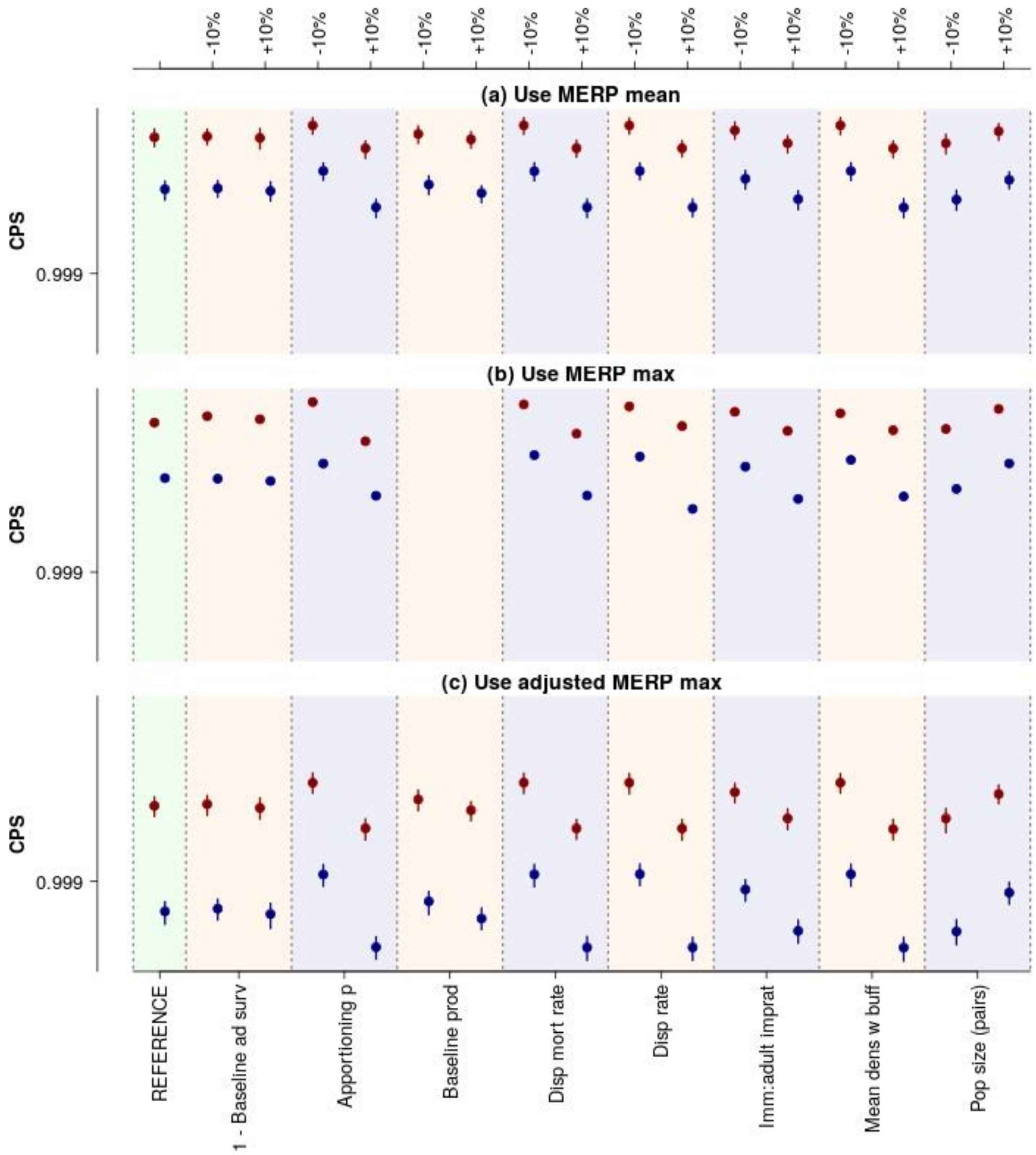

Figure S24: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

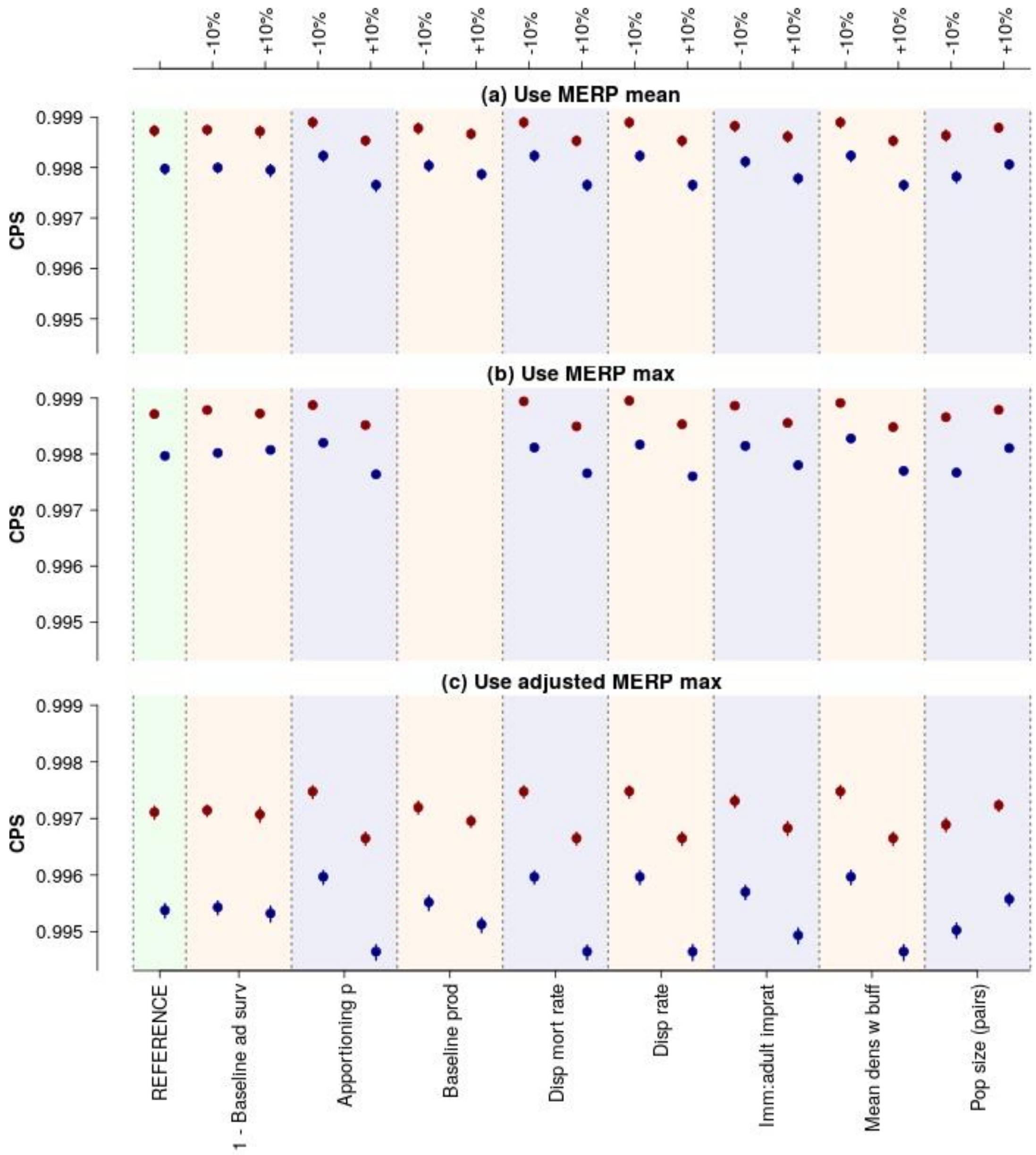

Figure S25: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

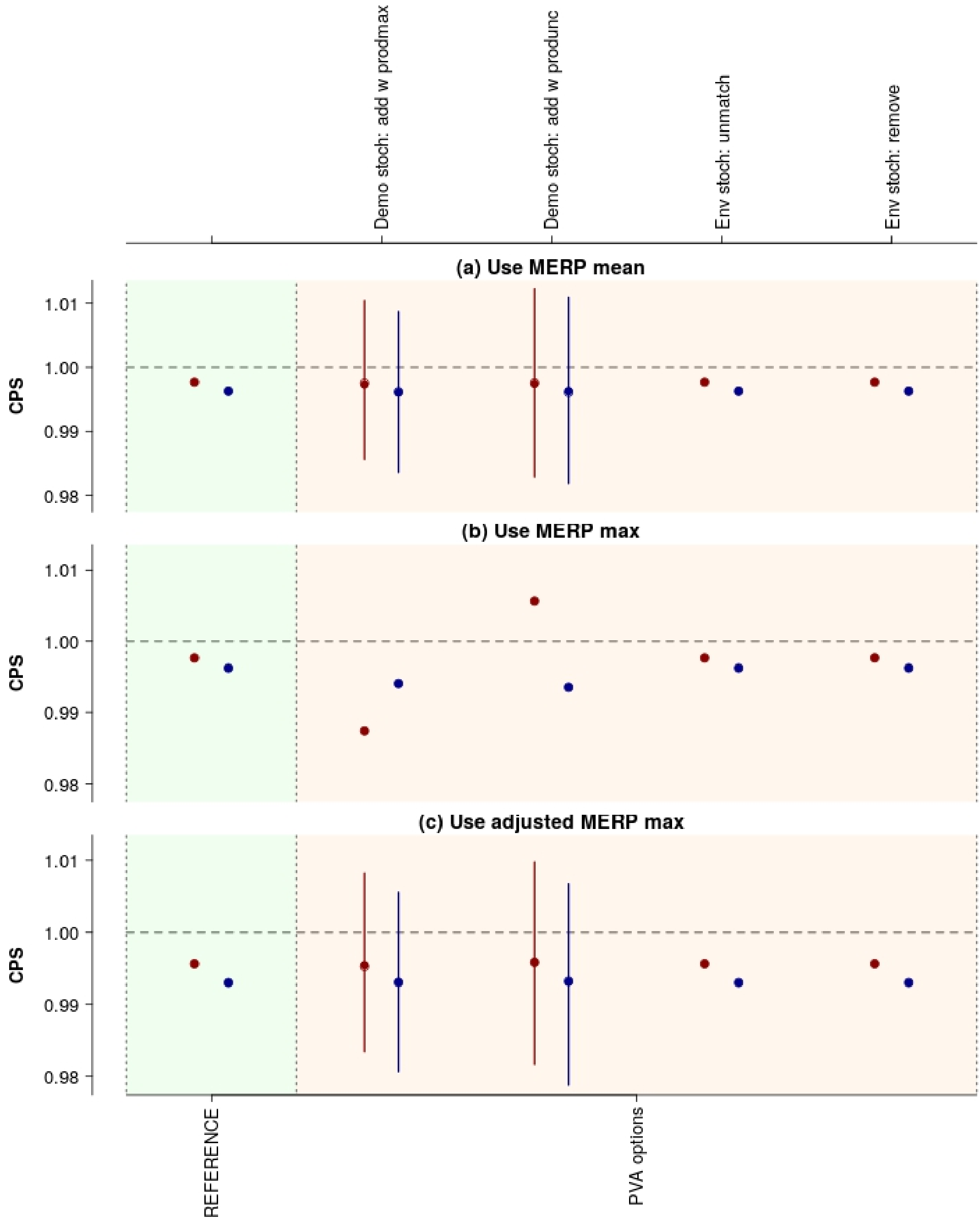

Figure S26: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

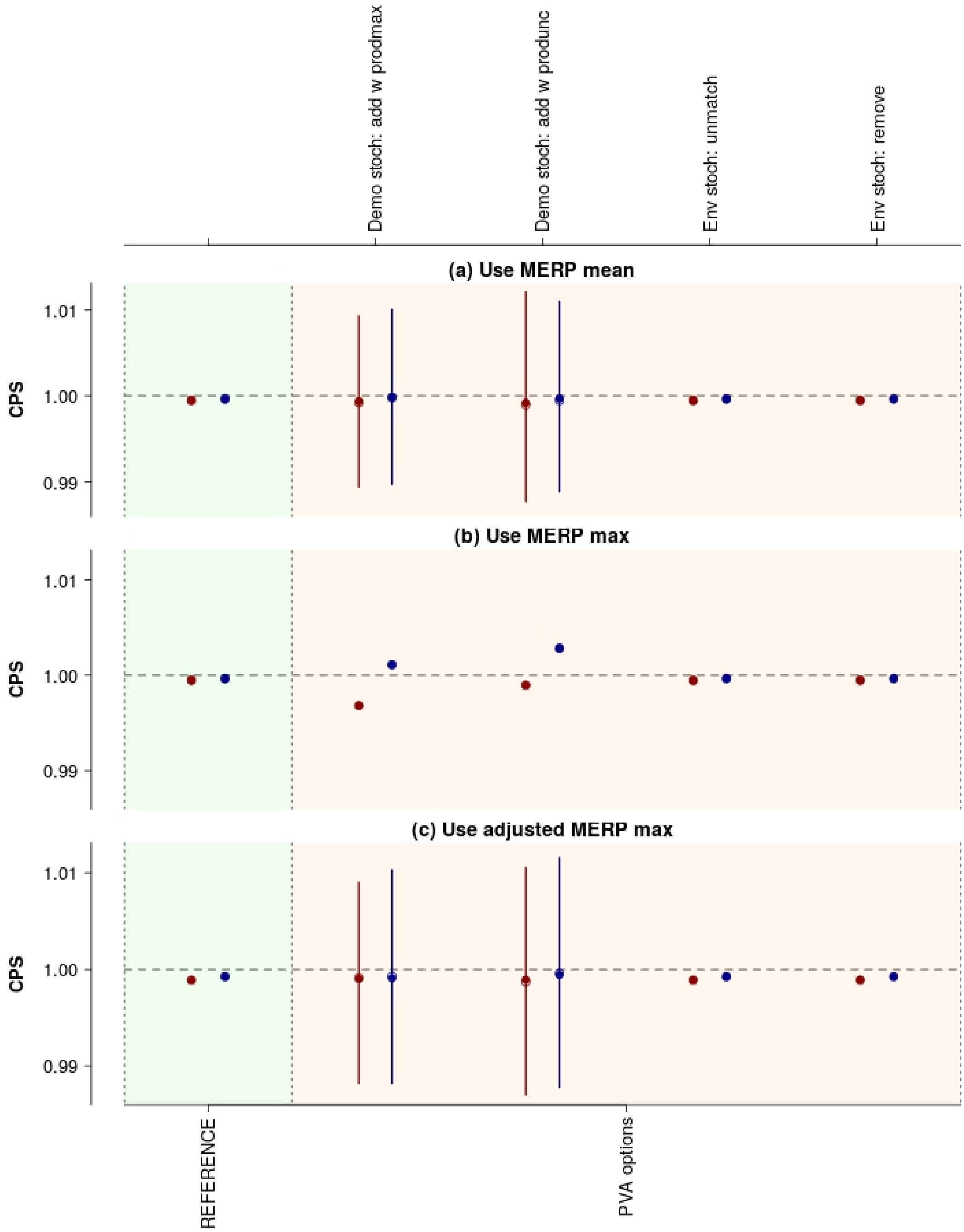

Figure S27: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

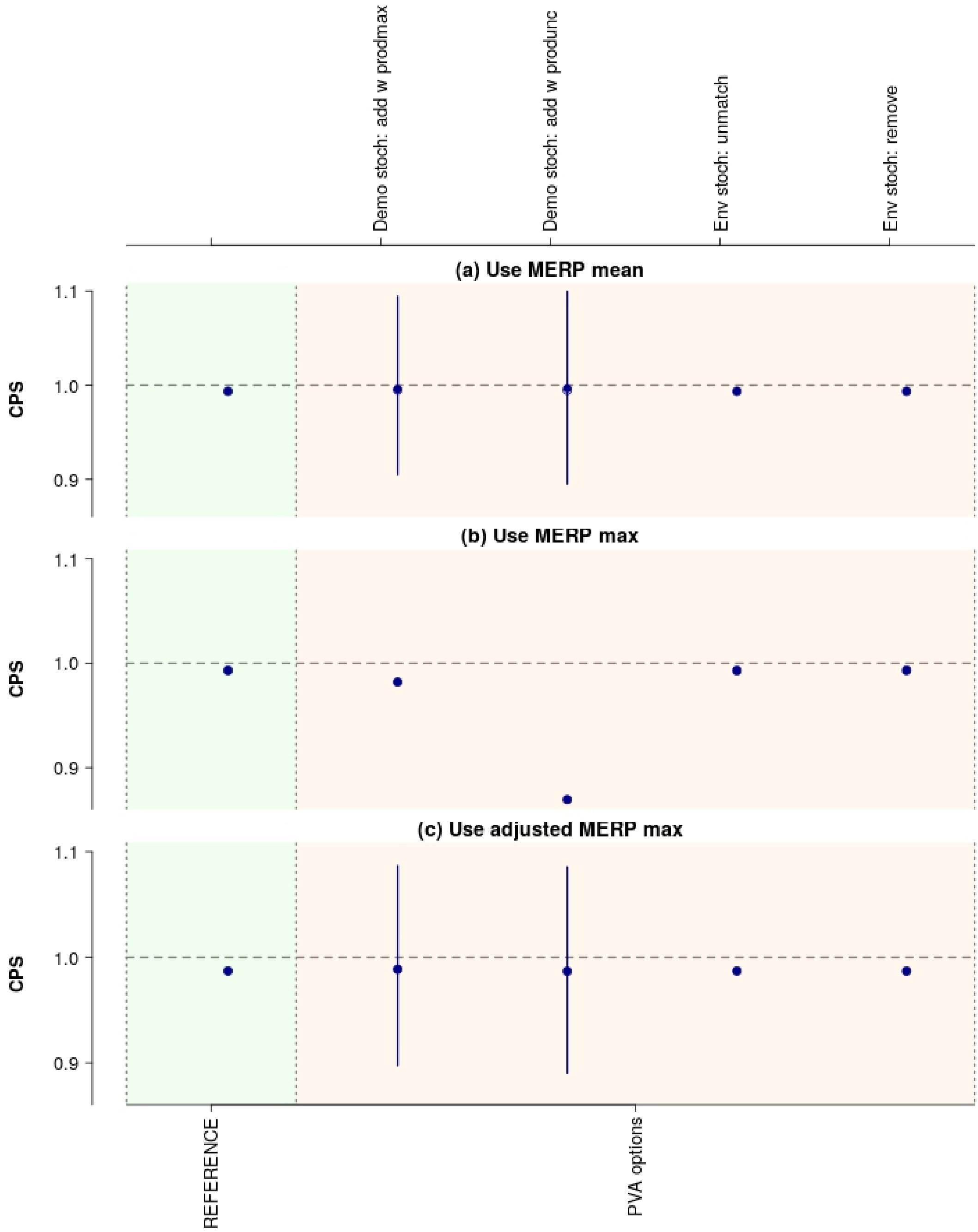

Figure S28: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

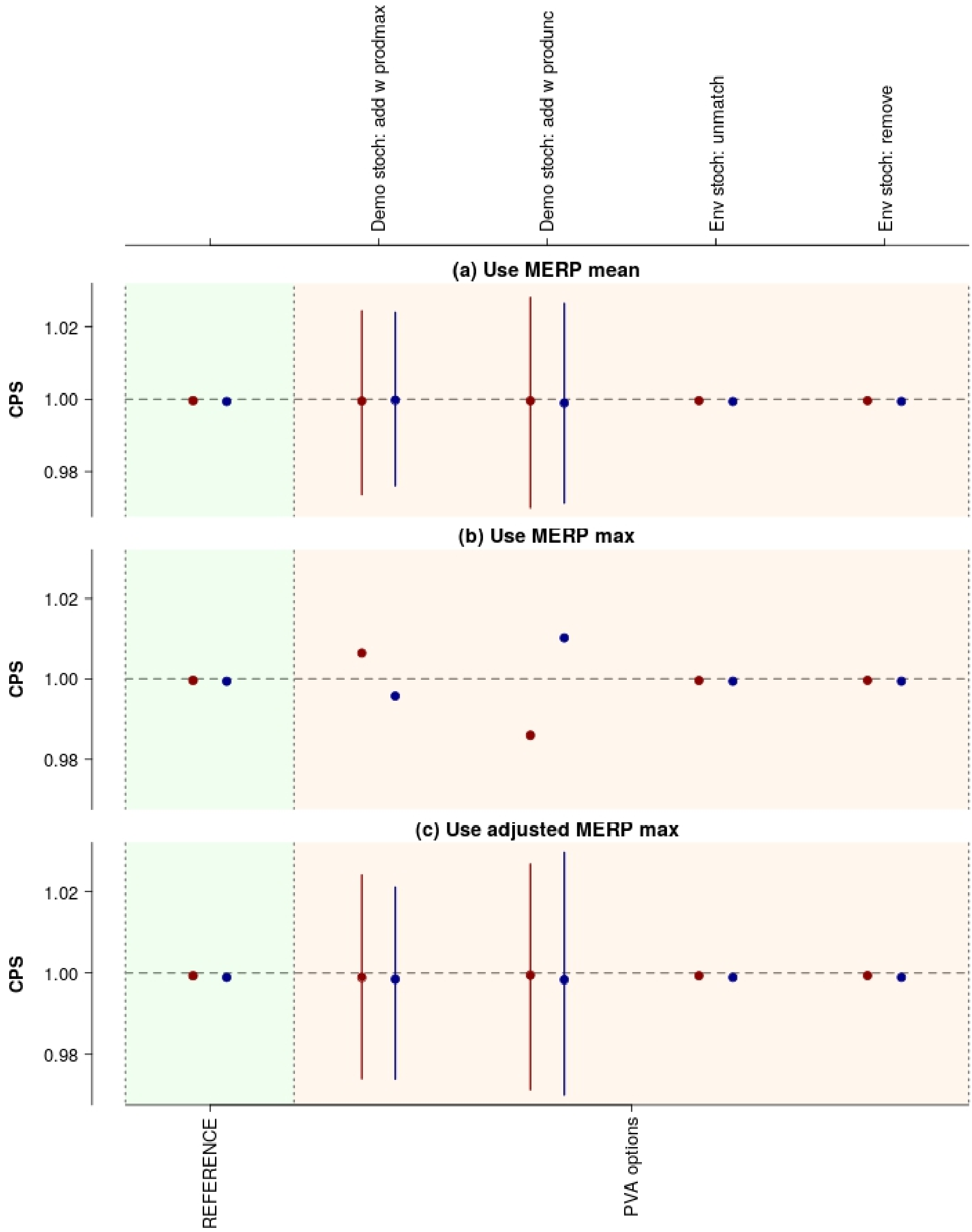

Figure S29: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

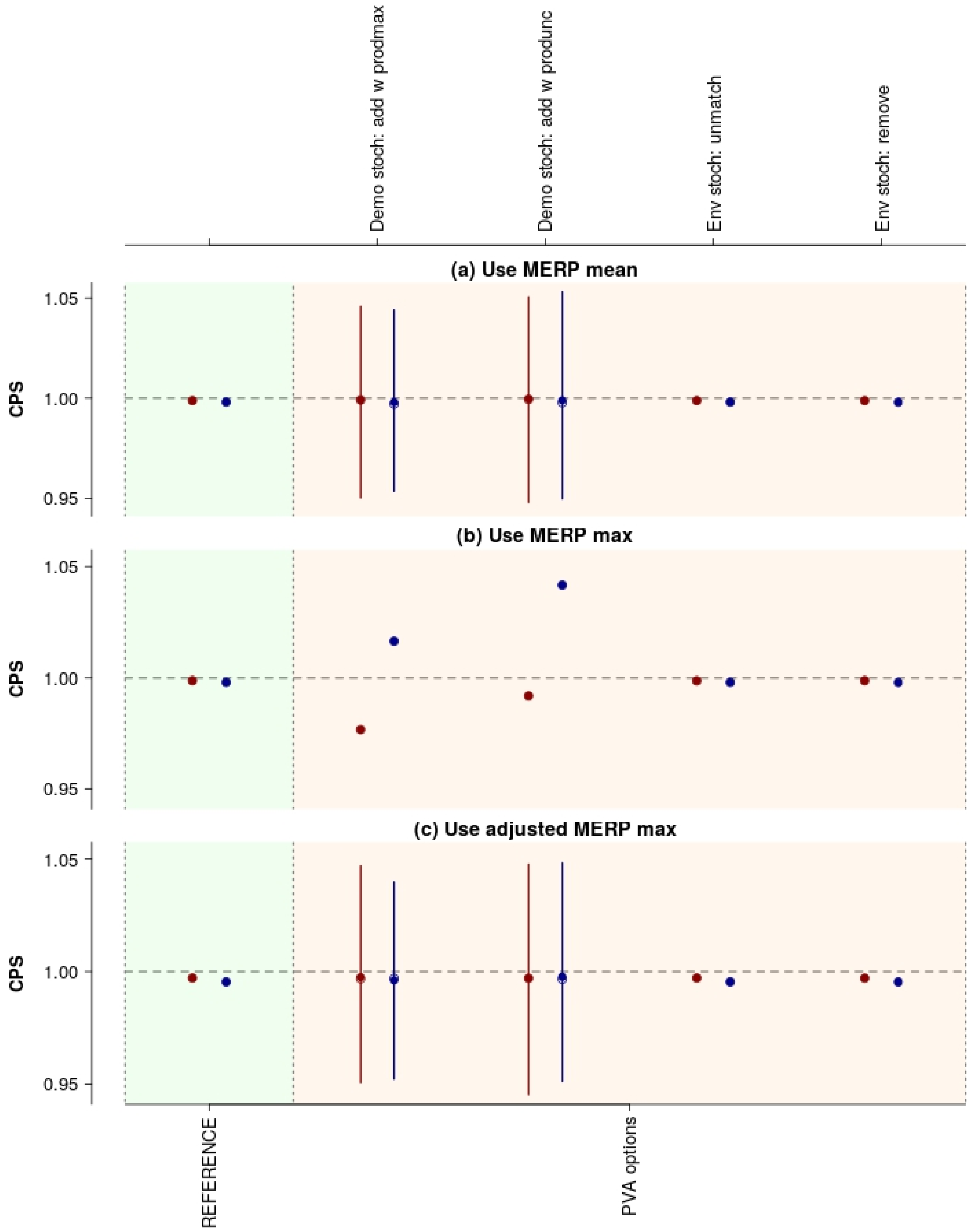

Figure S30: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix based on median values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

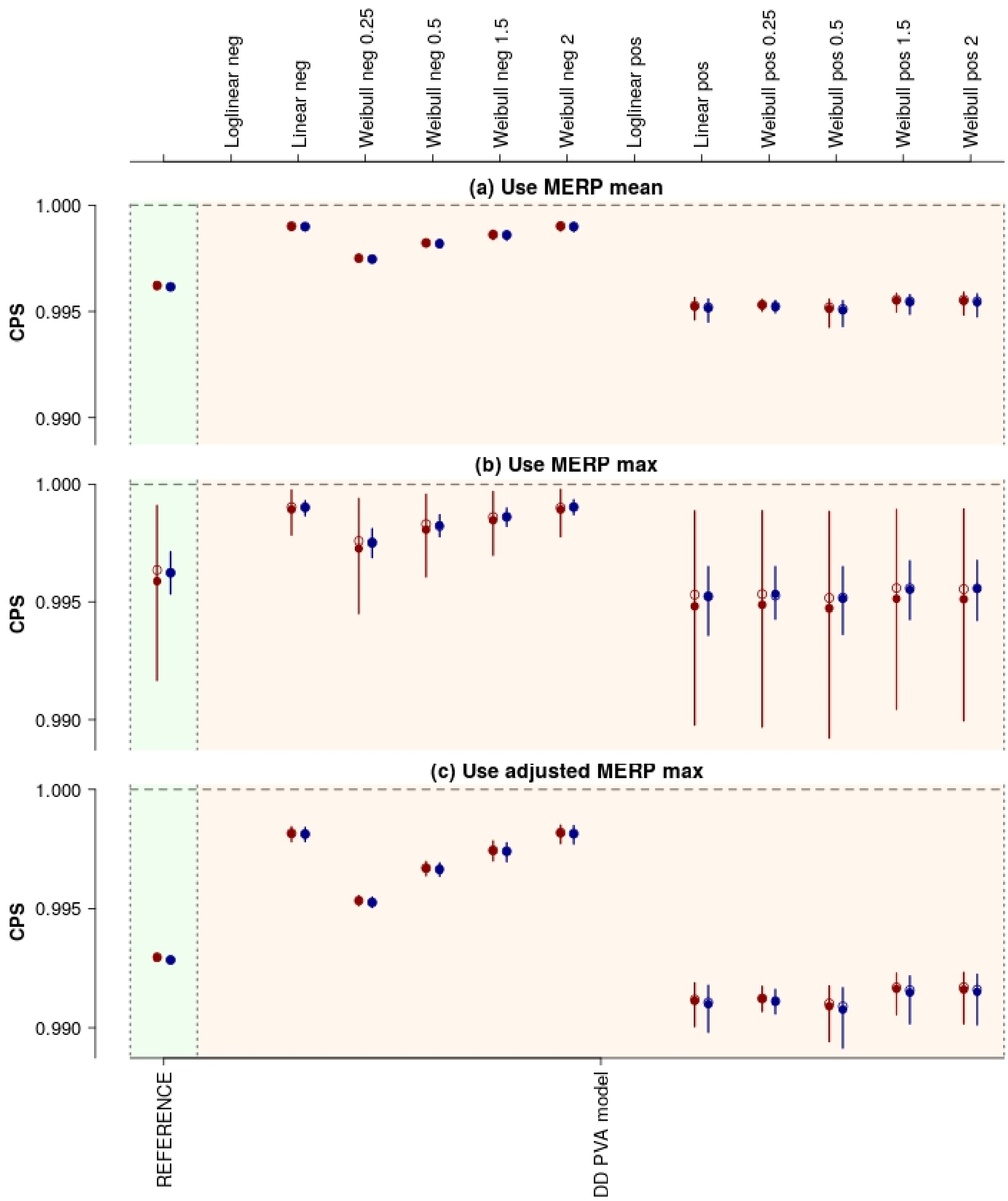

Figure S31: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

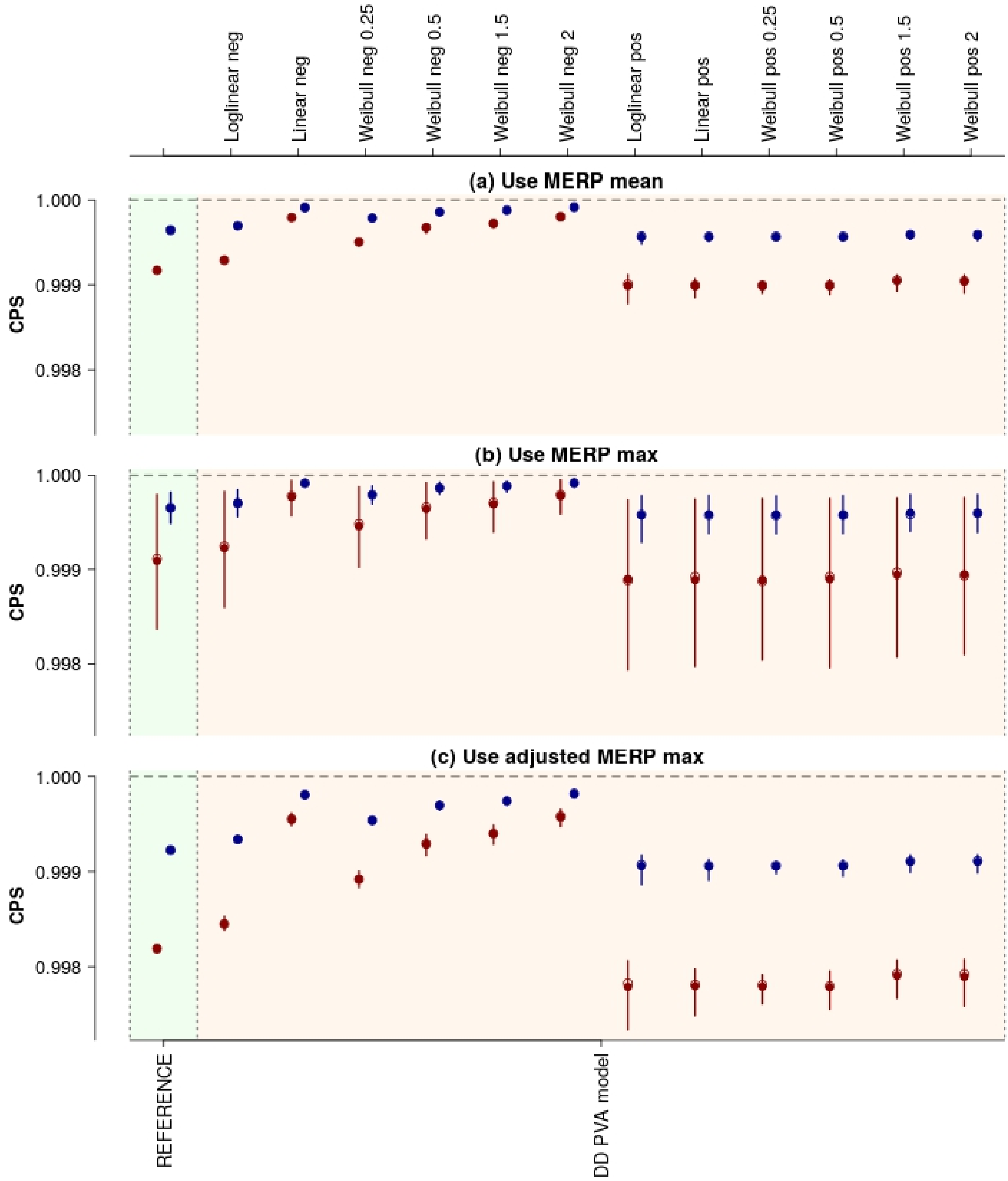

Figure S32: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

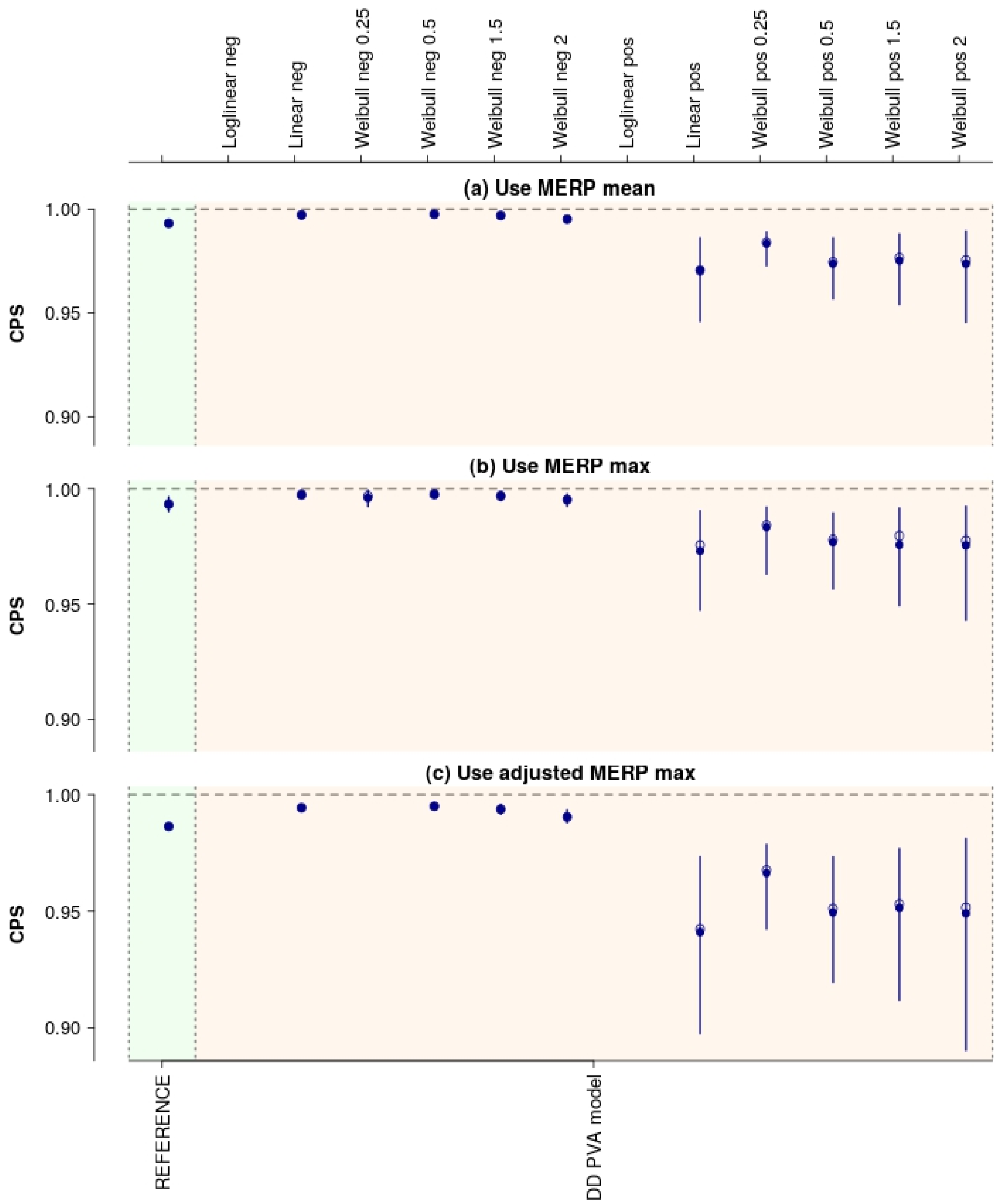

Figure S33: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

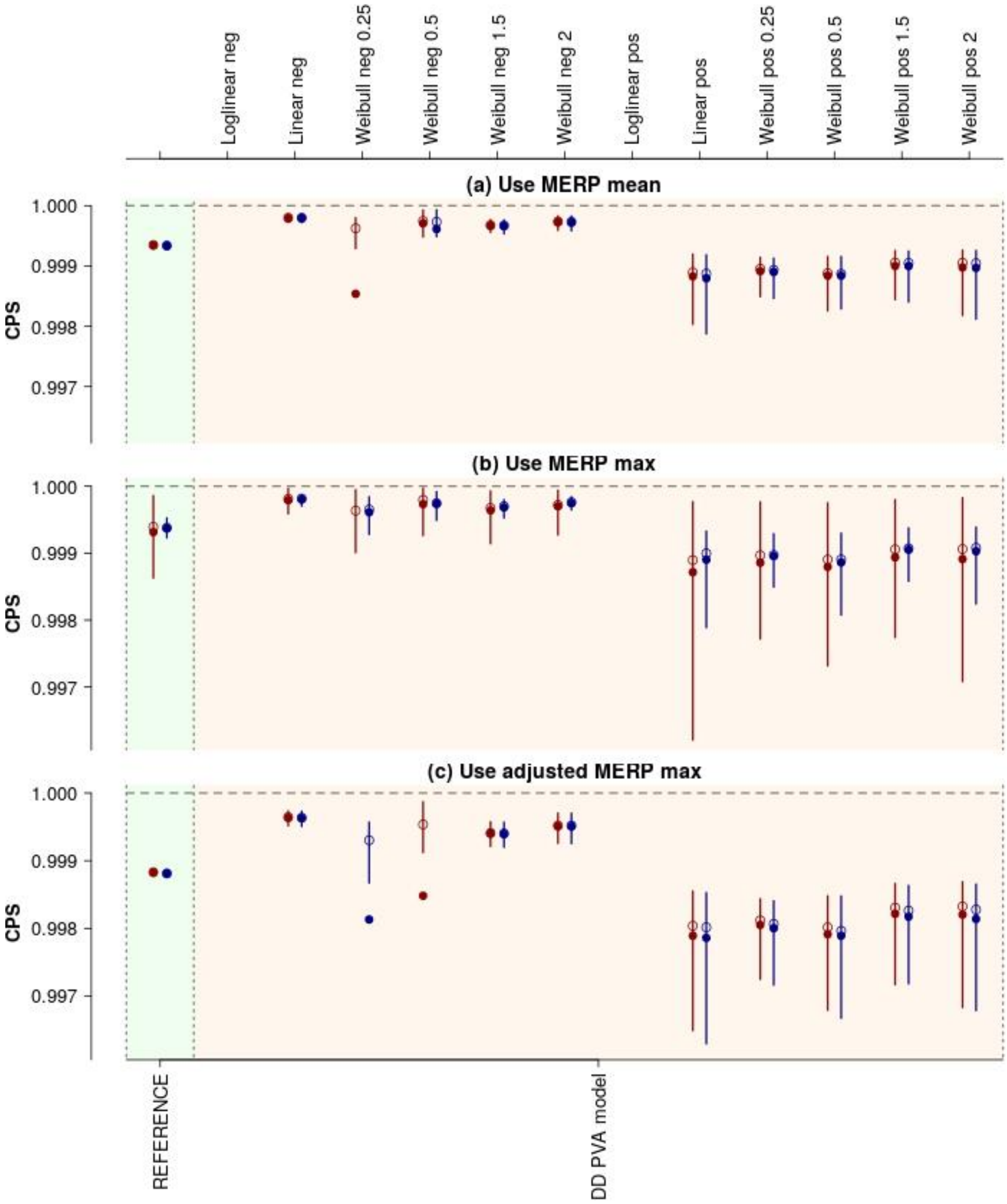

Figure S34: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

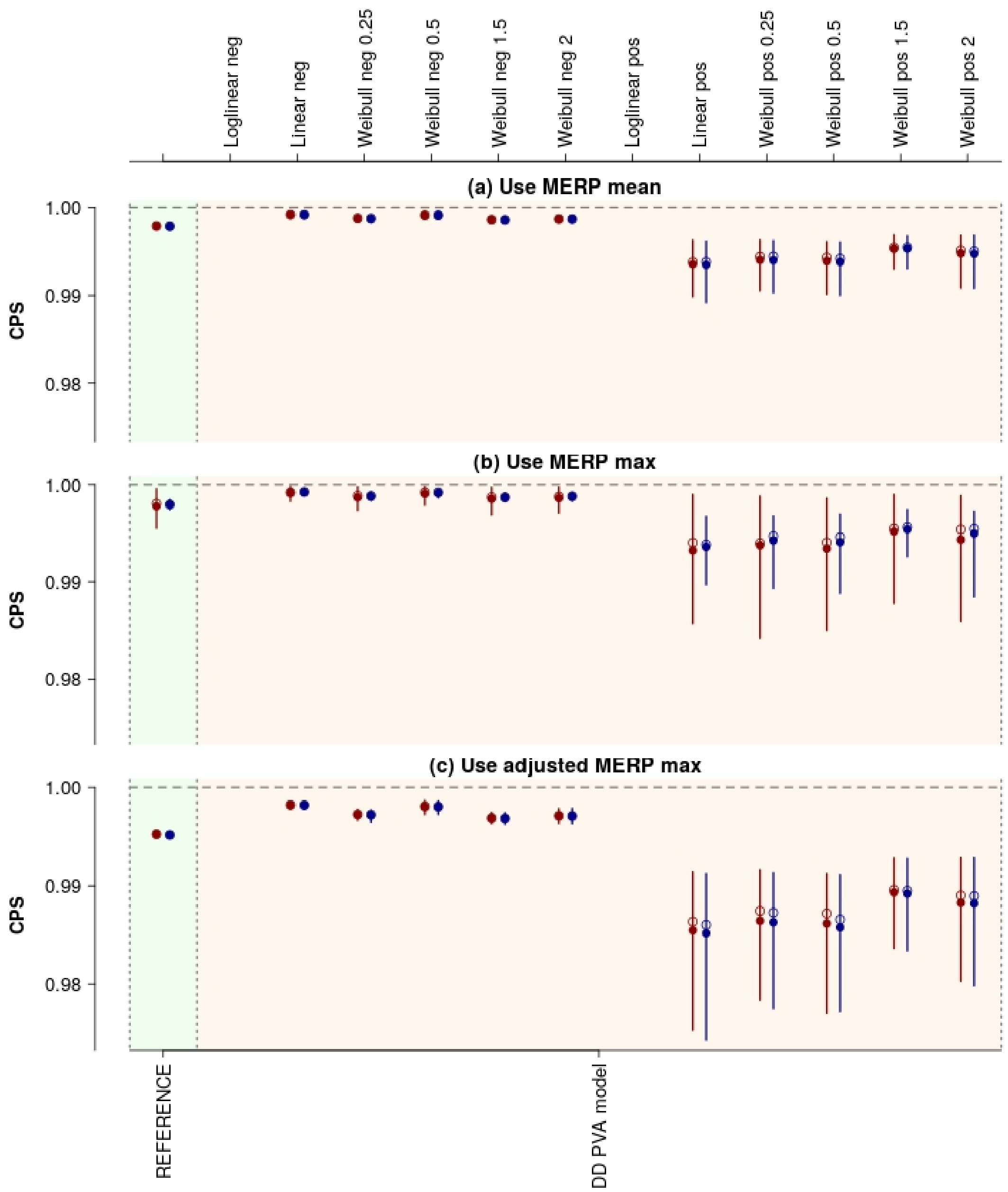

Figure S35: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

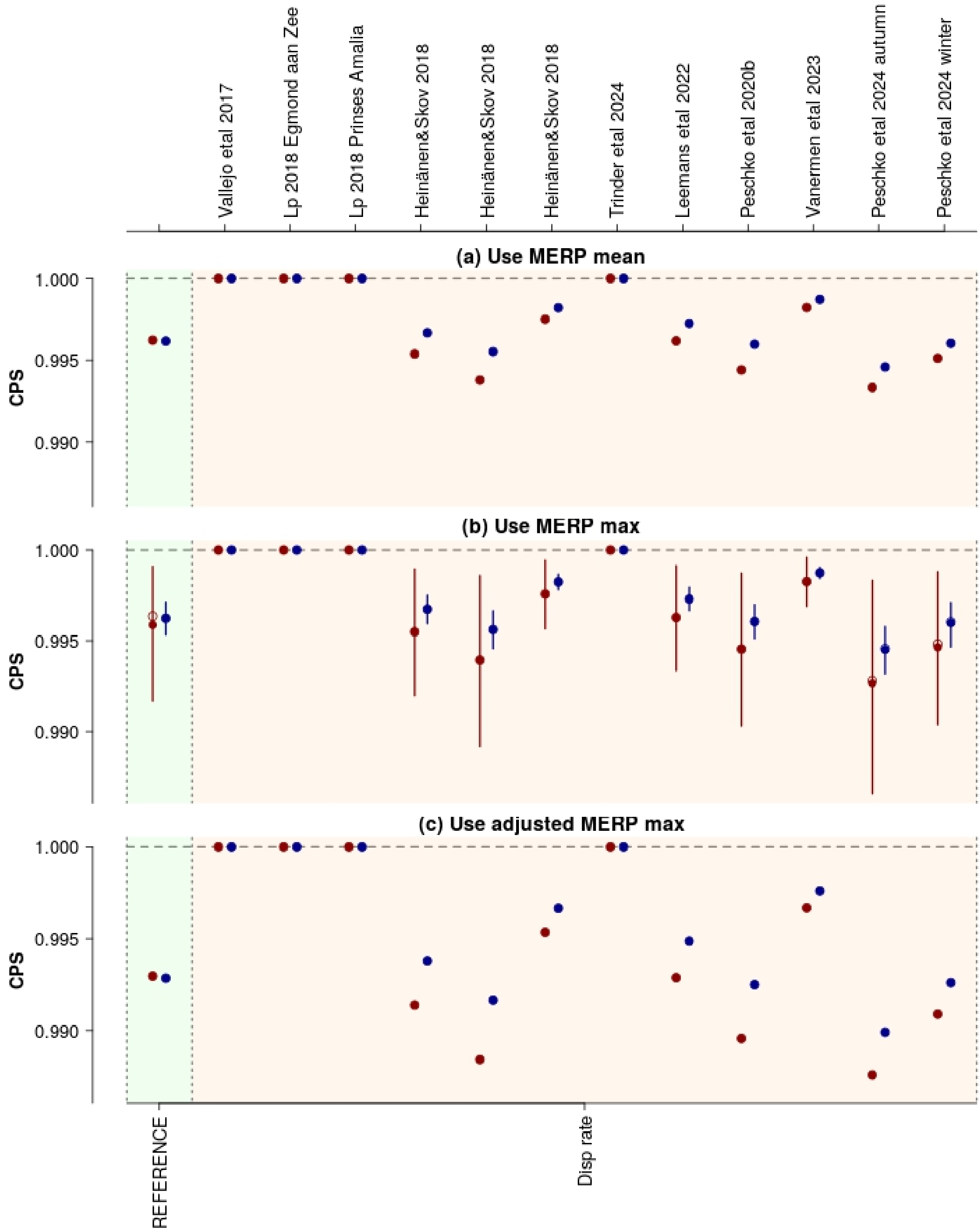

Figure S36: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

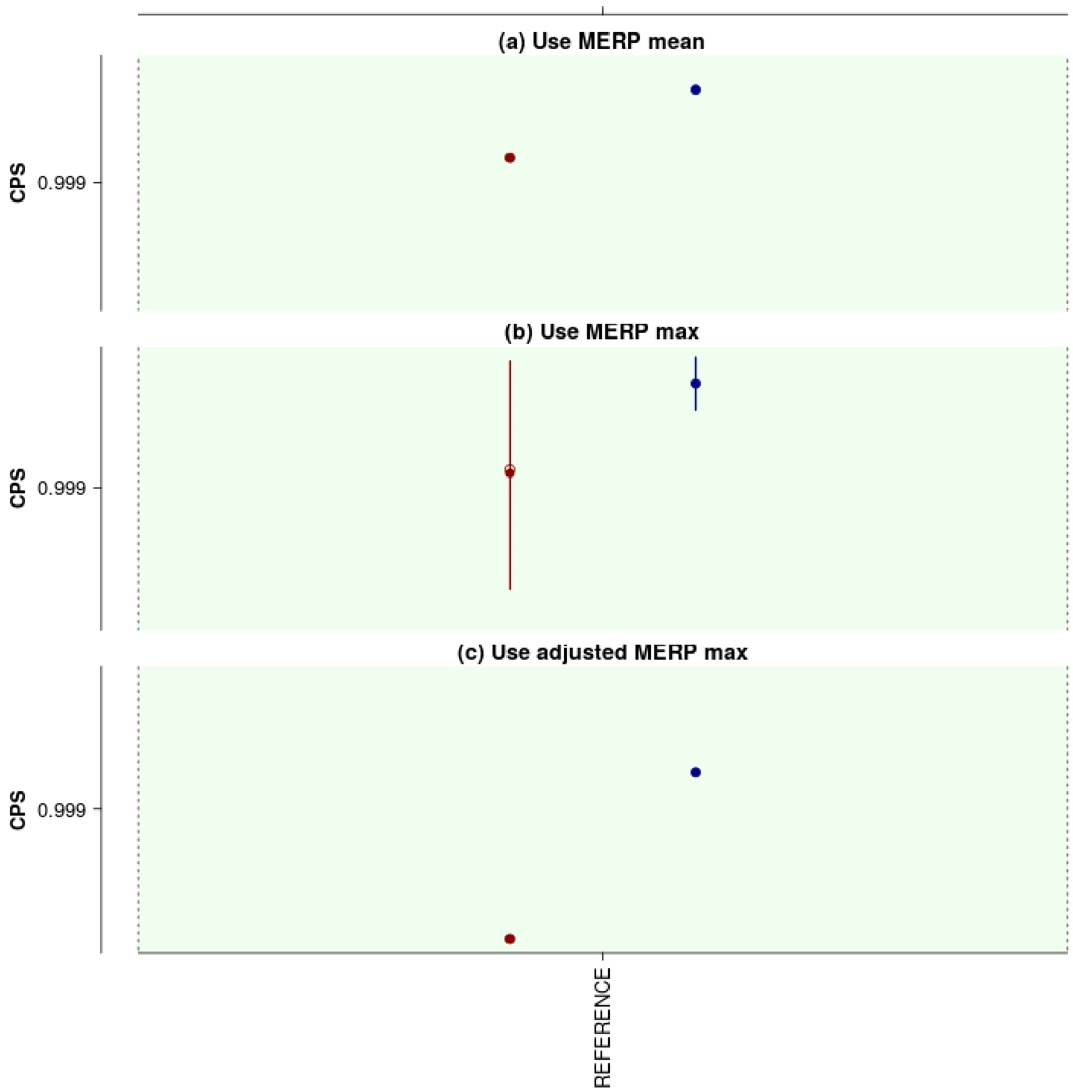

Figure S37: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

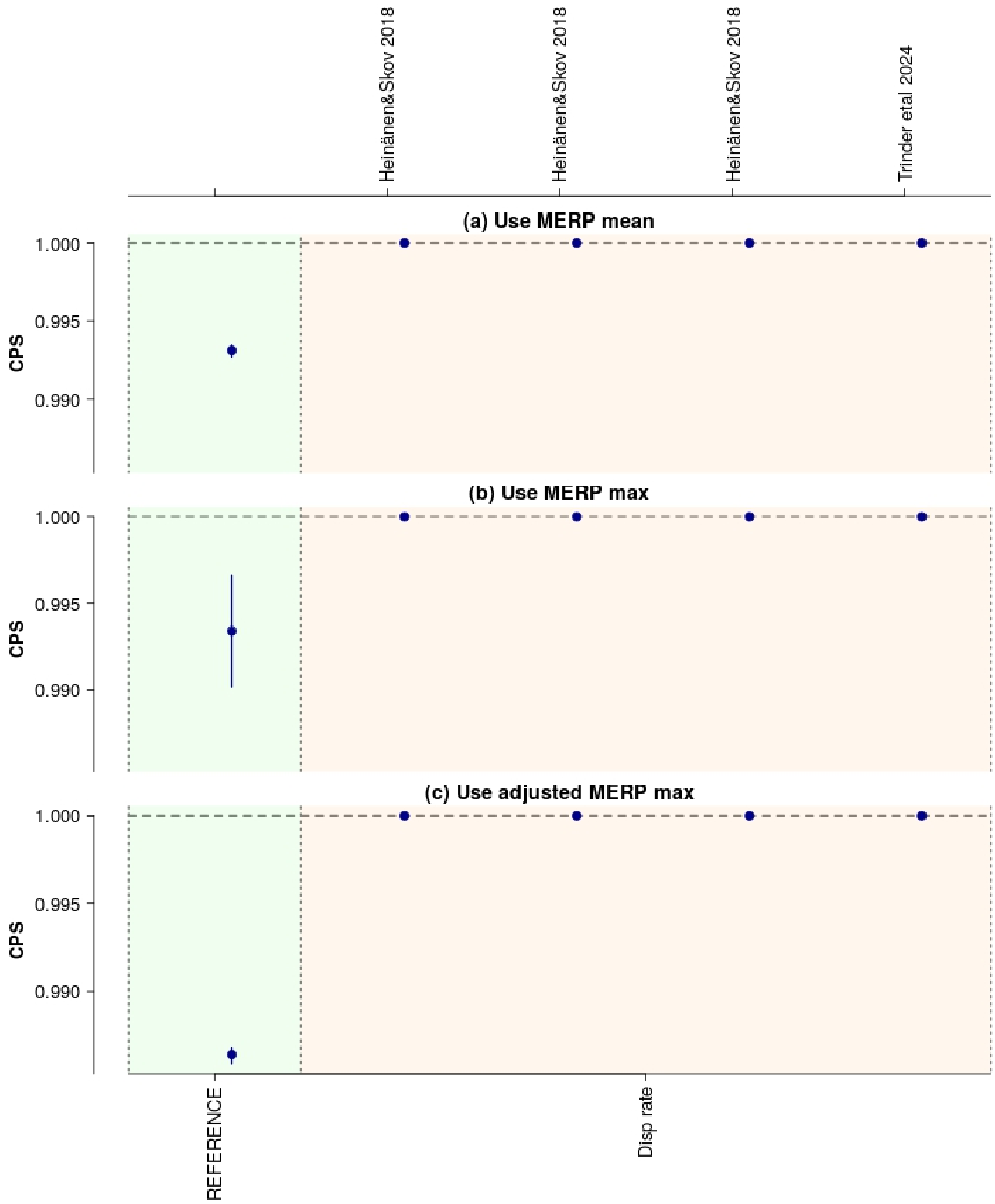

Figure S38: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

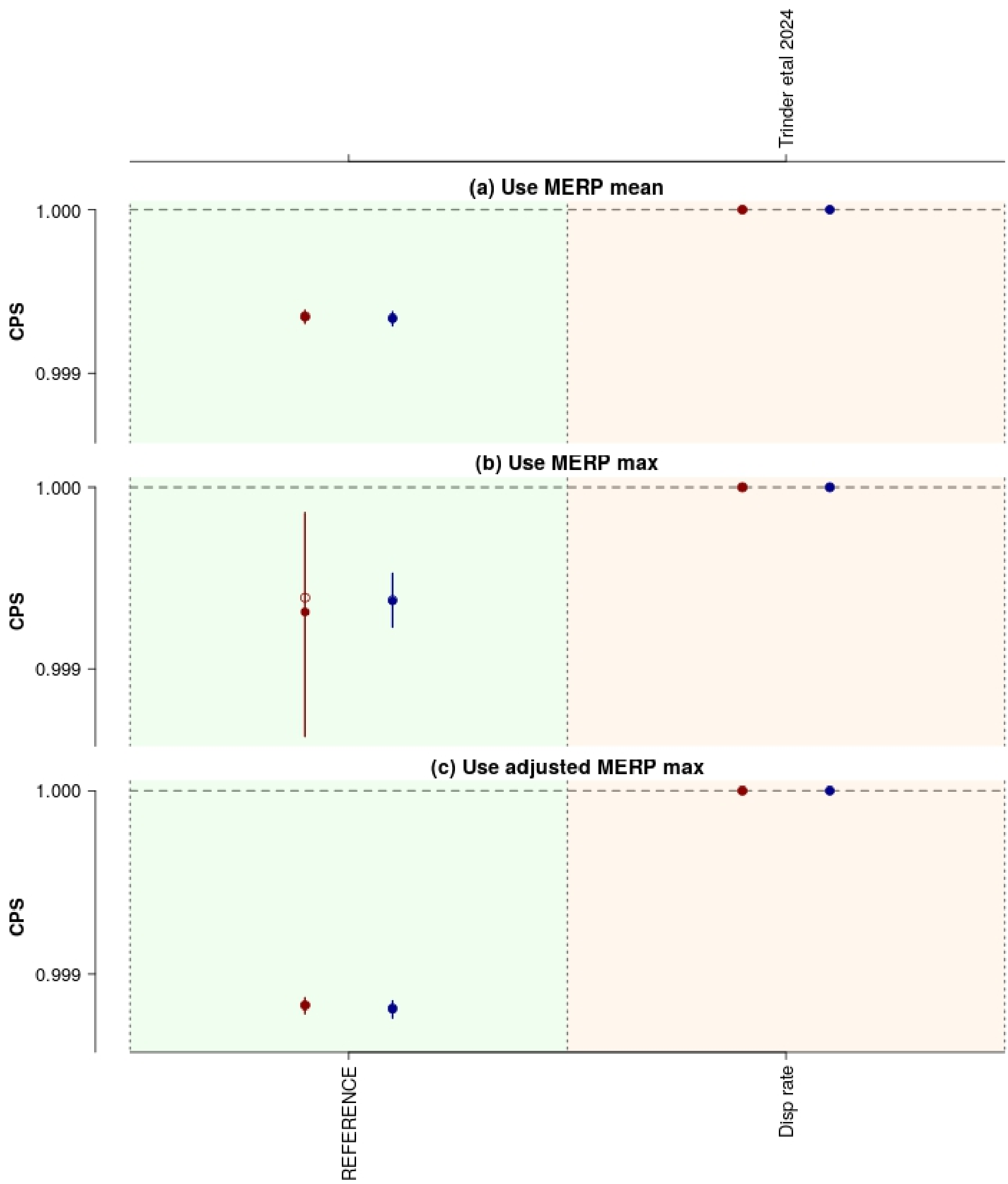

Figure S39: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

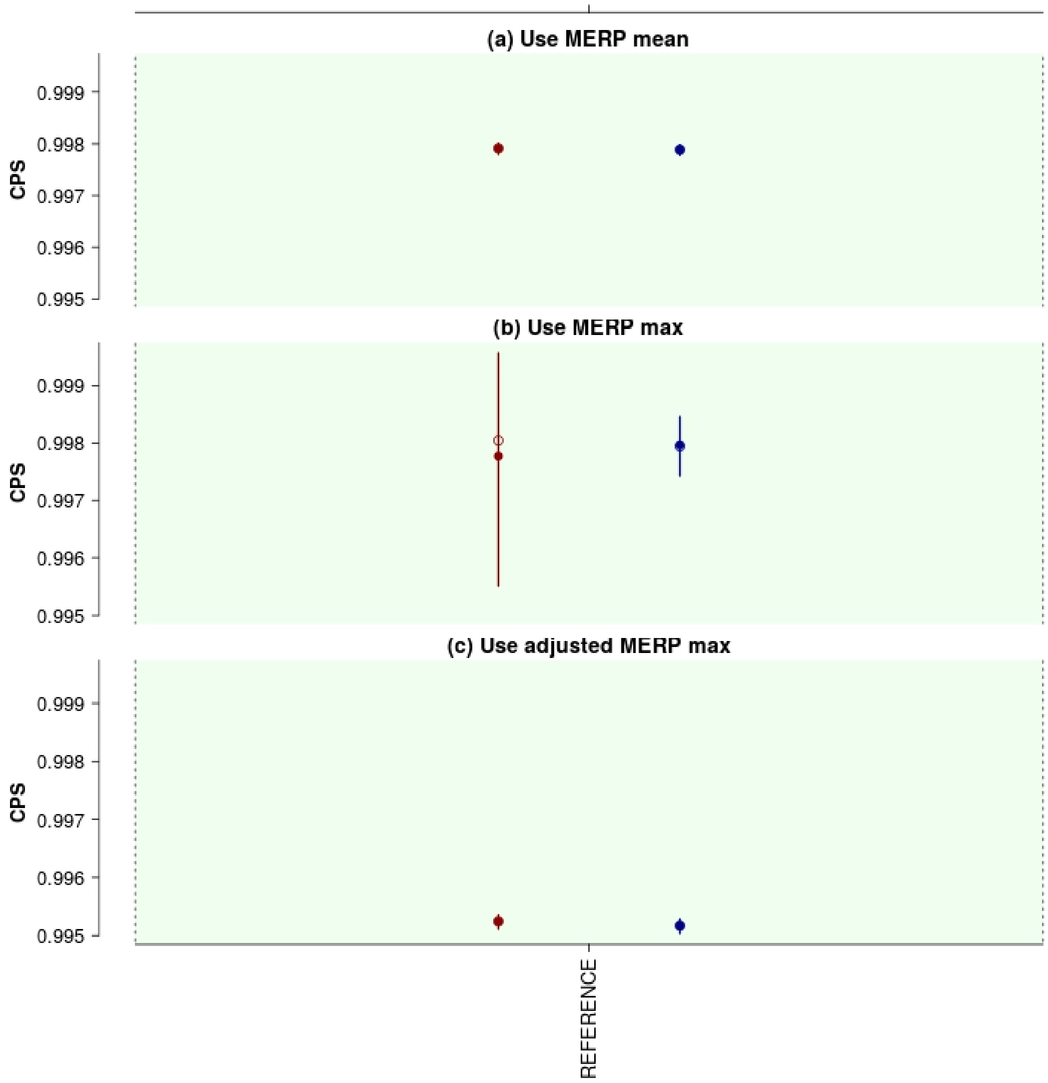

Figure S40: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

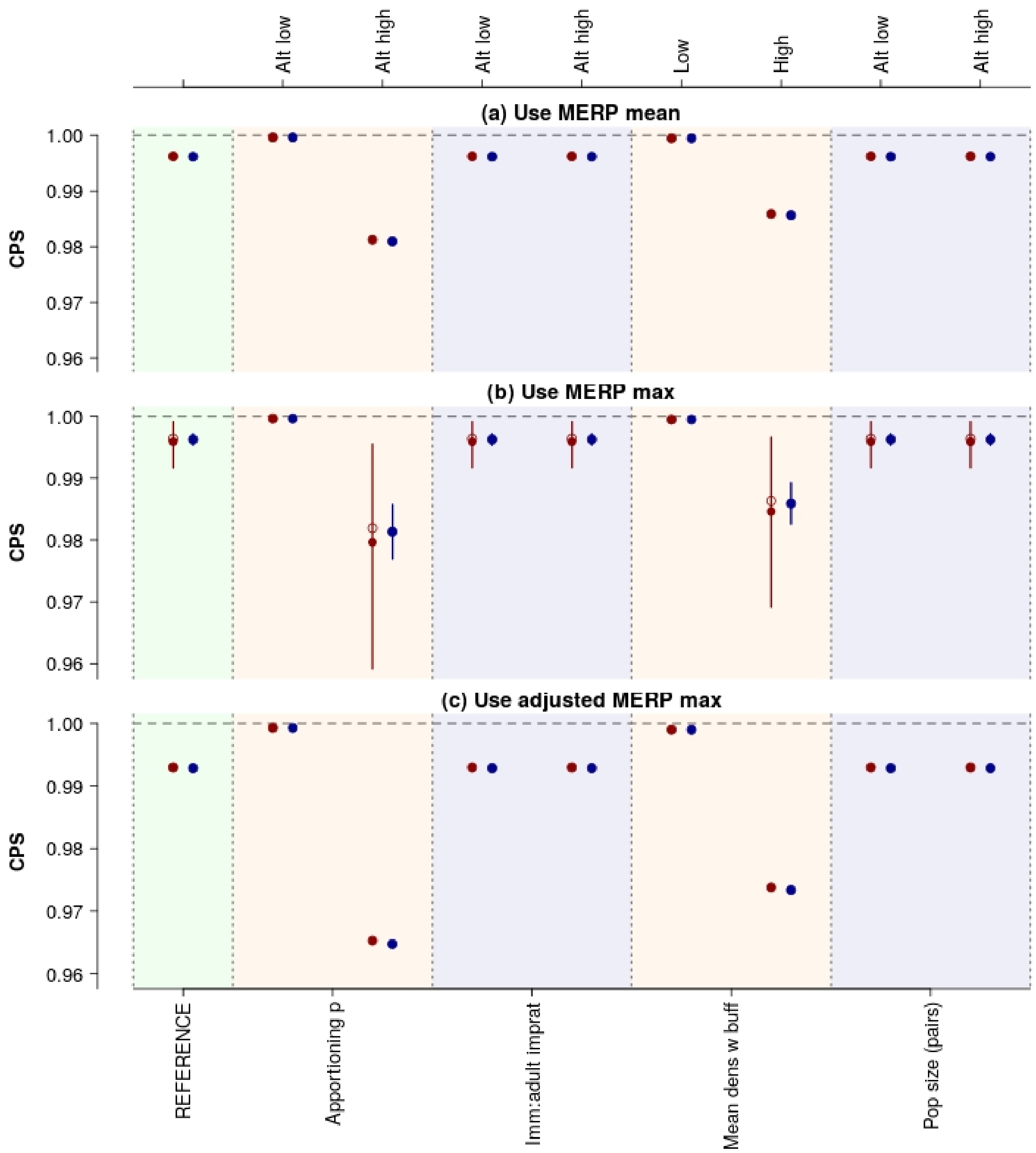

Figure S41: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

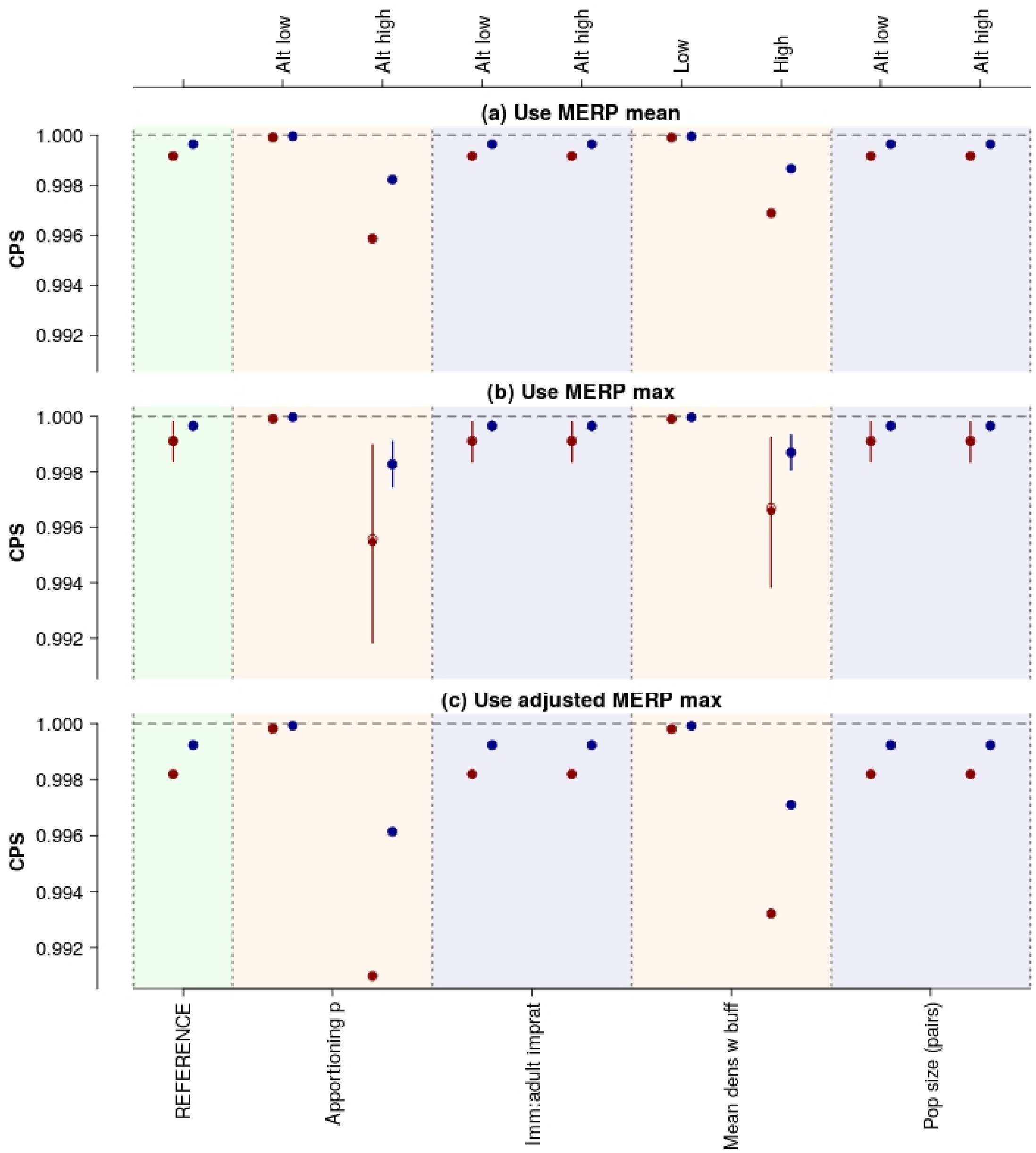

Figure S42: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

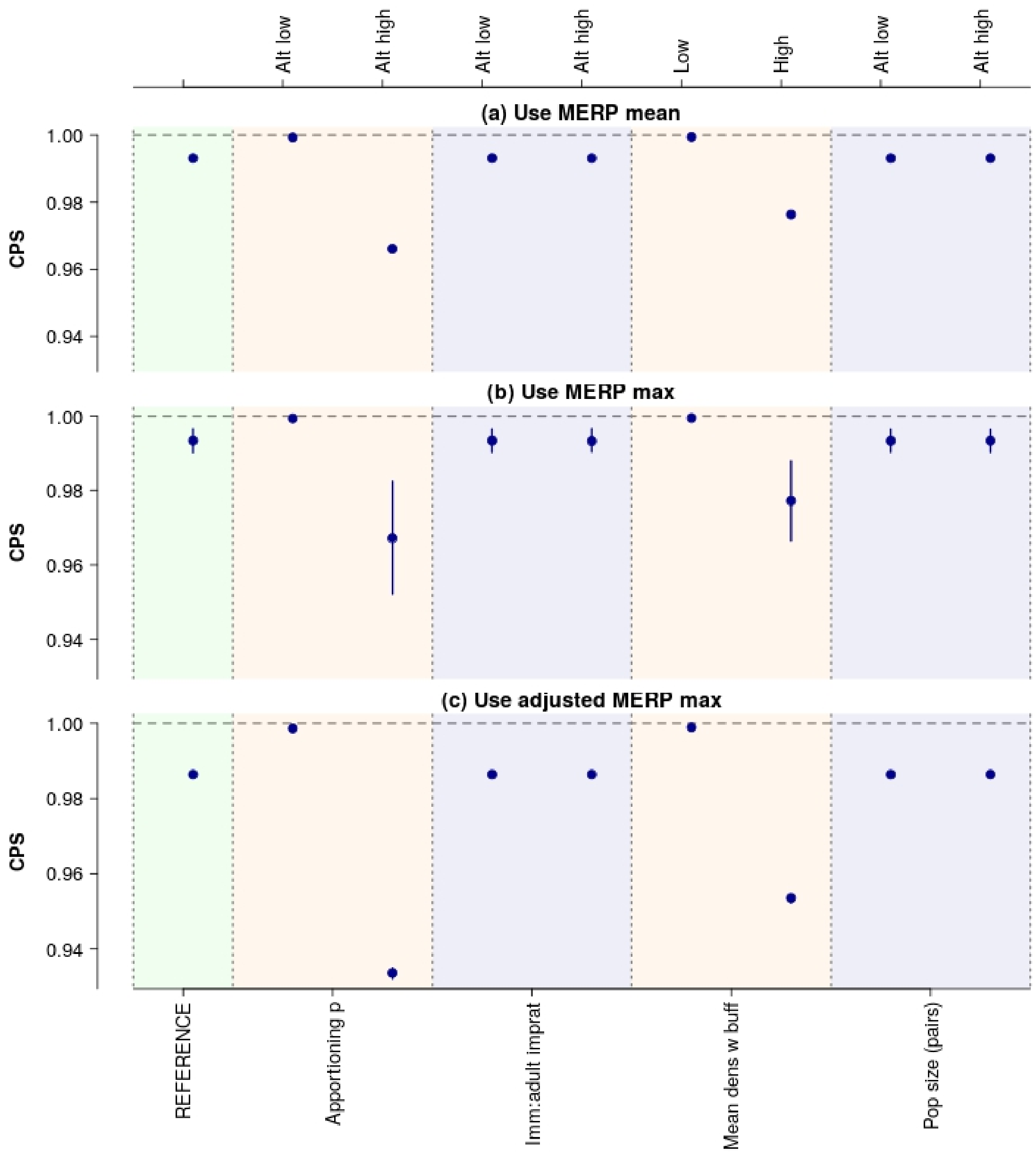

Figure S43: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

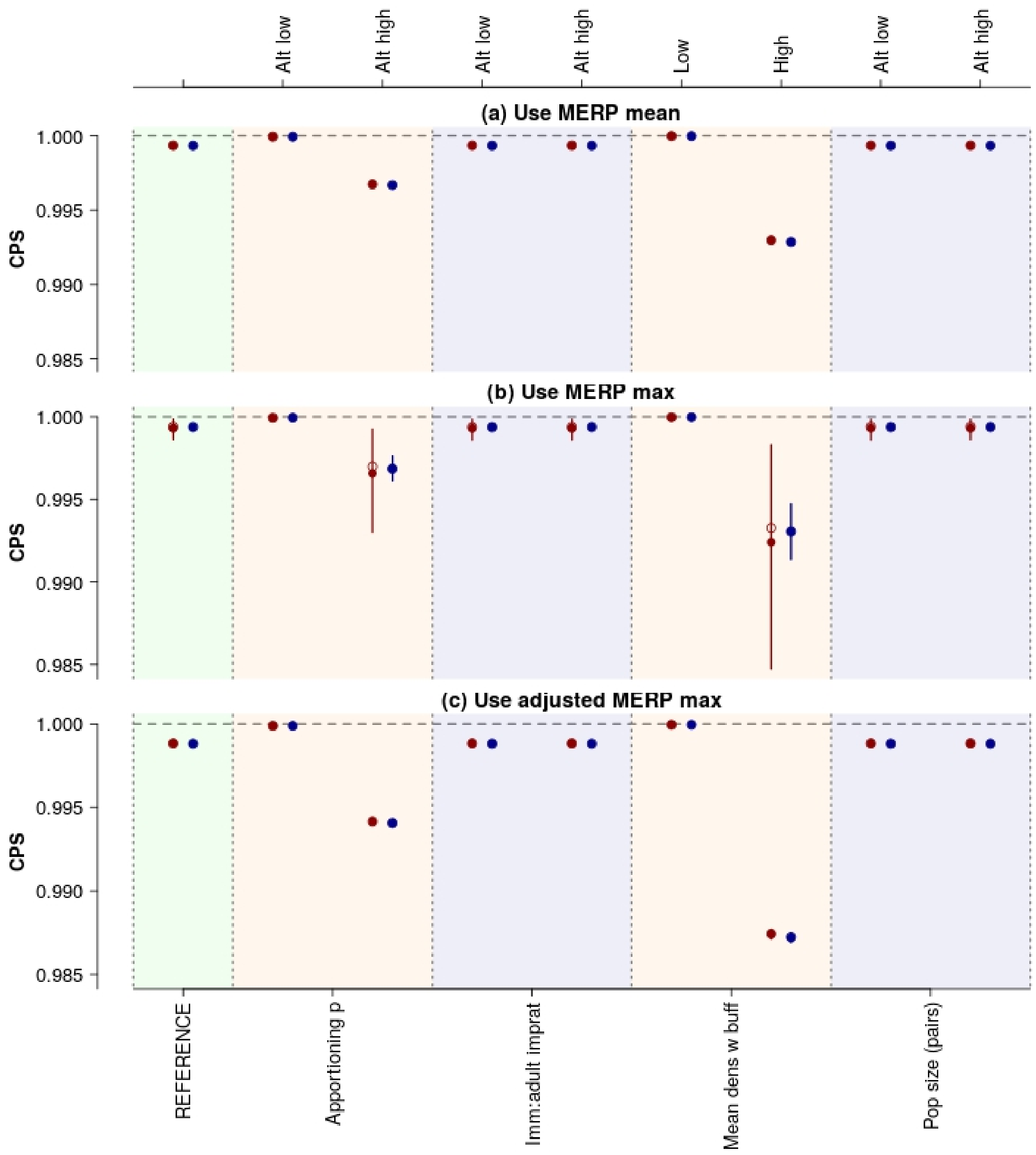

Figure S44: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

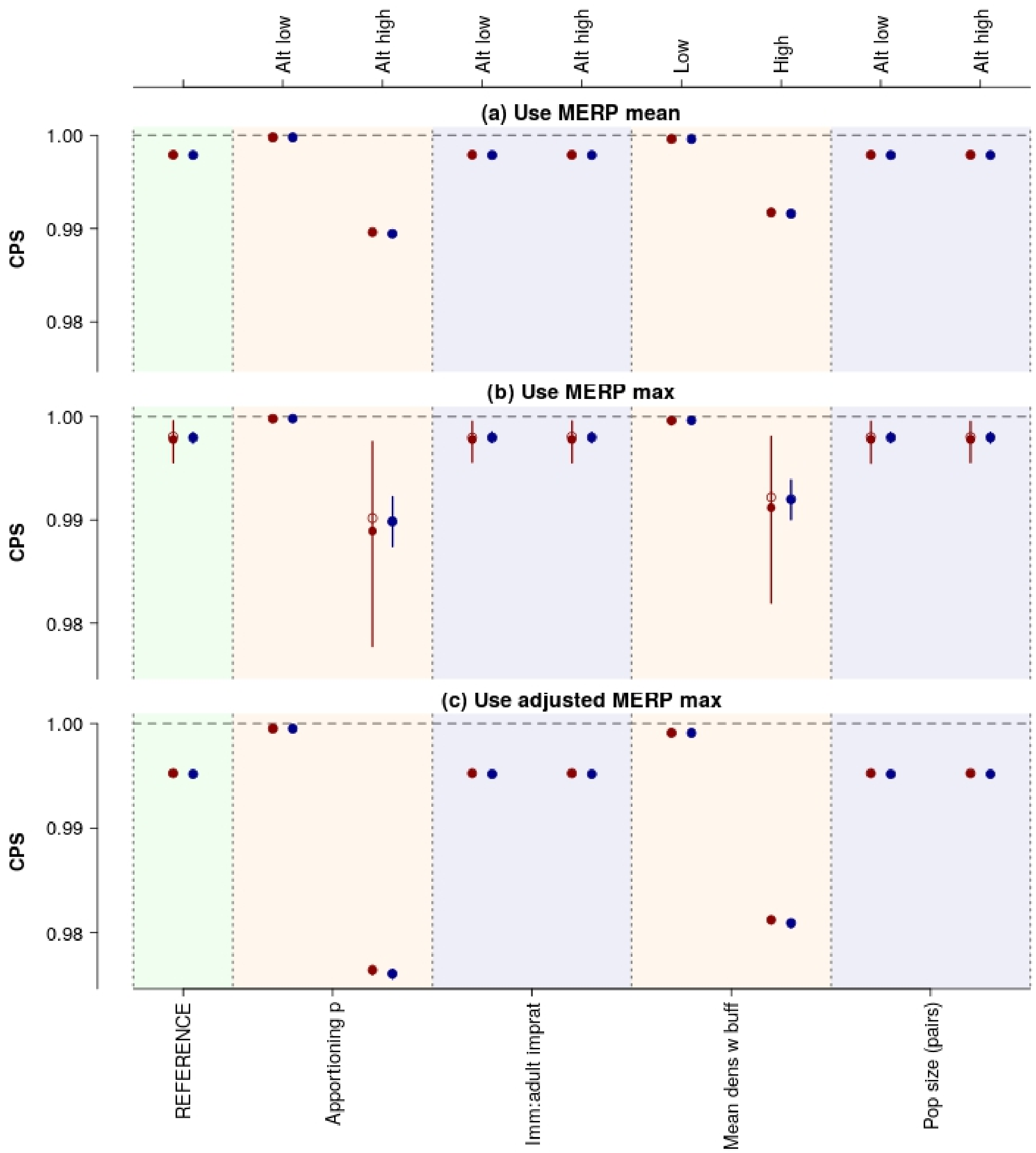

Figure S45: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

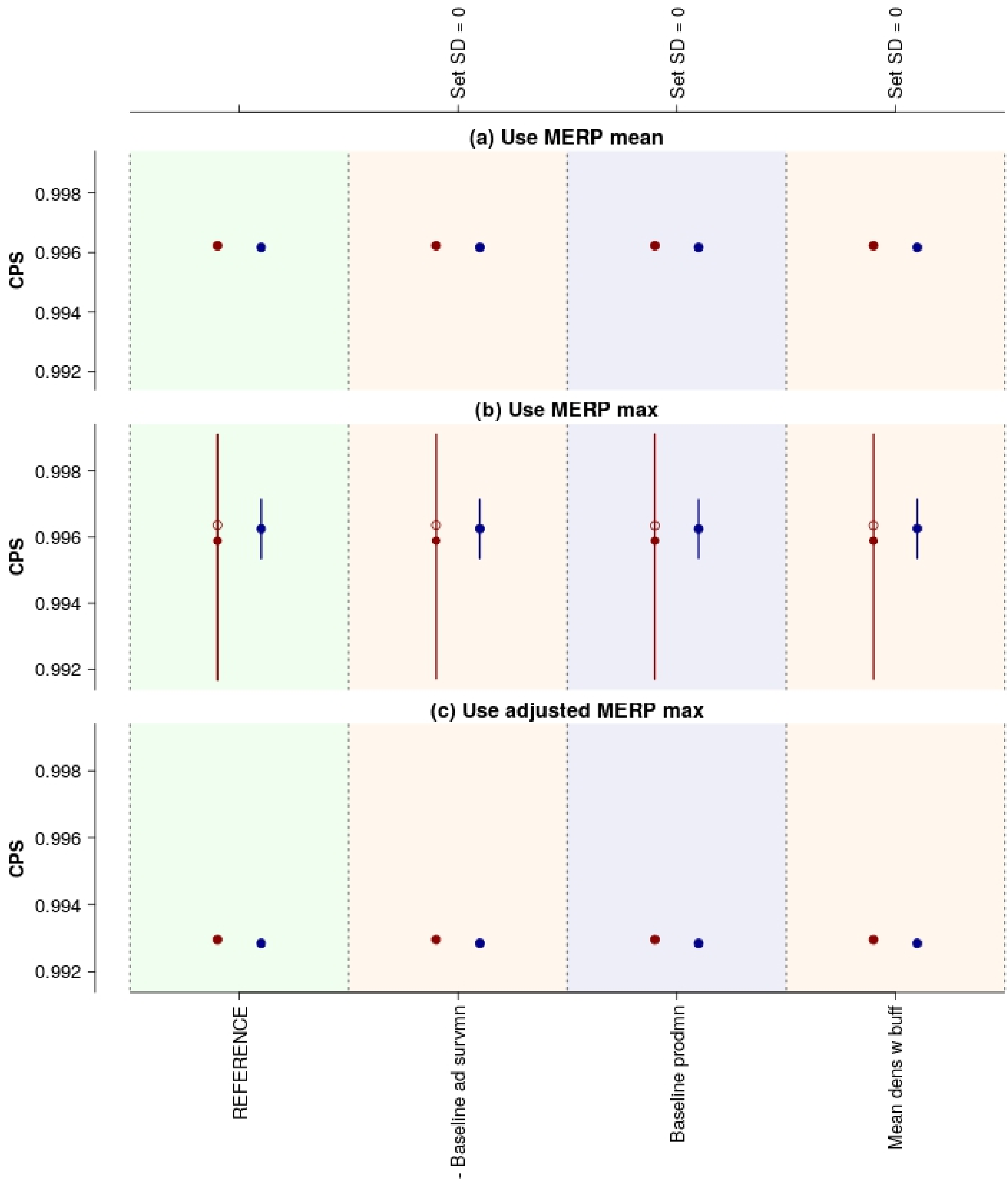

Figure S46: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

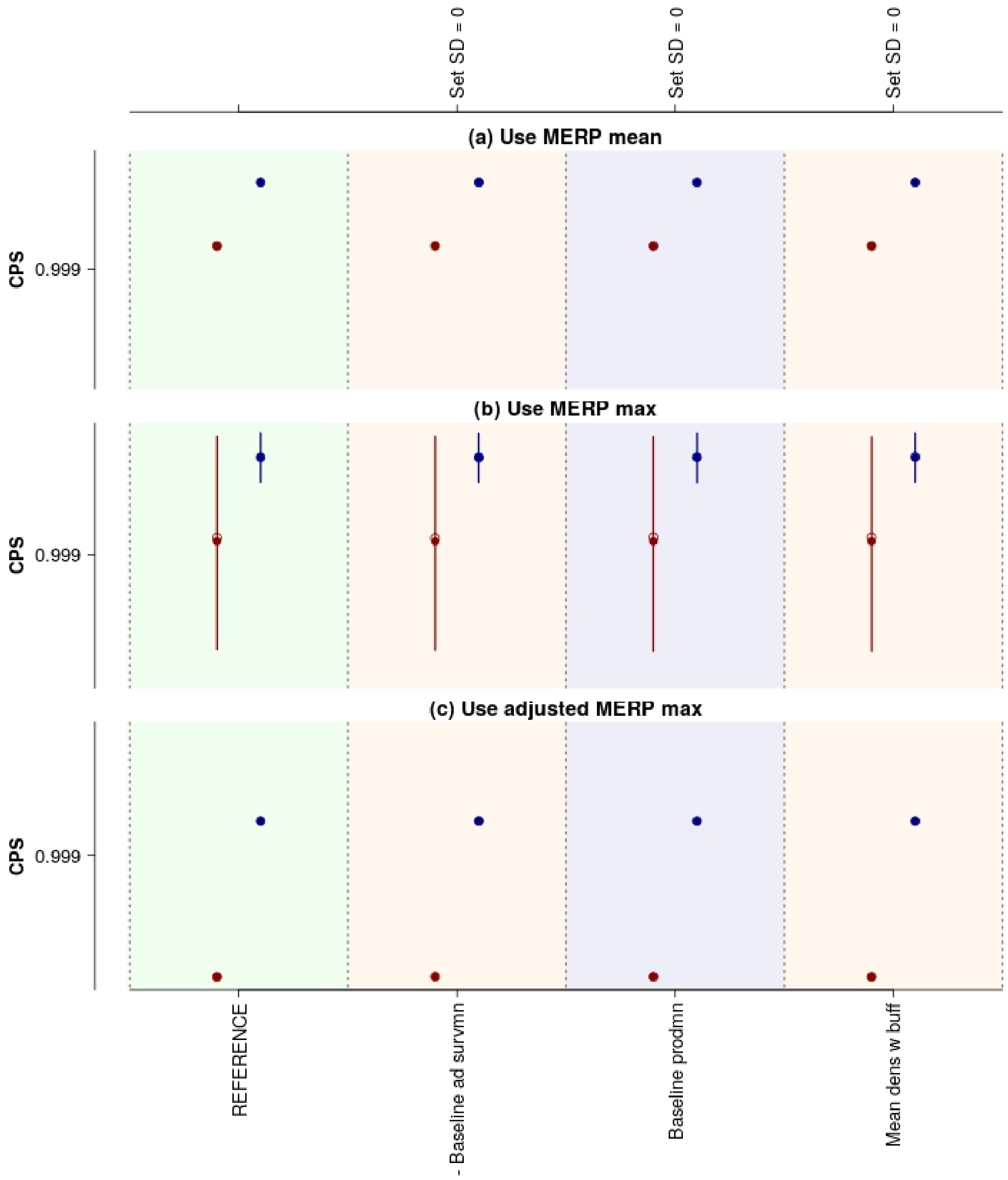

Figure S47: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

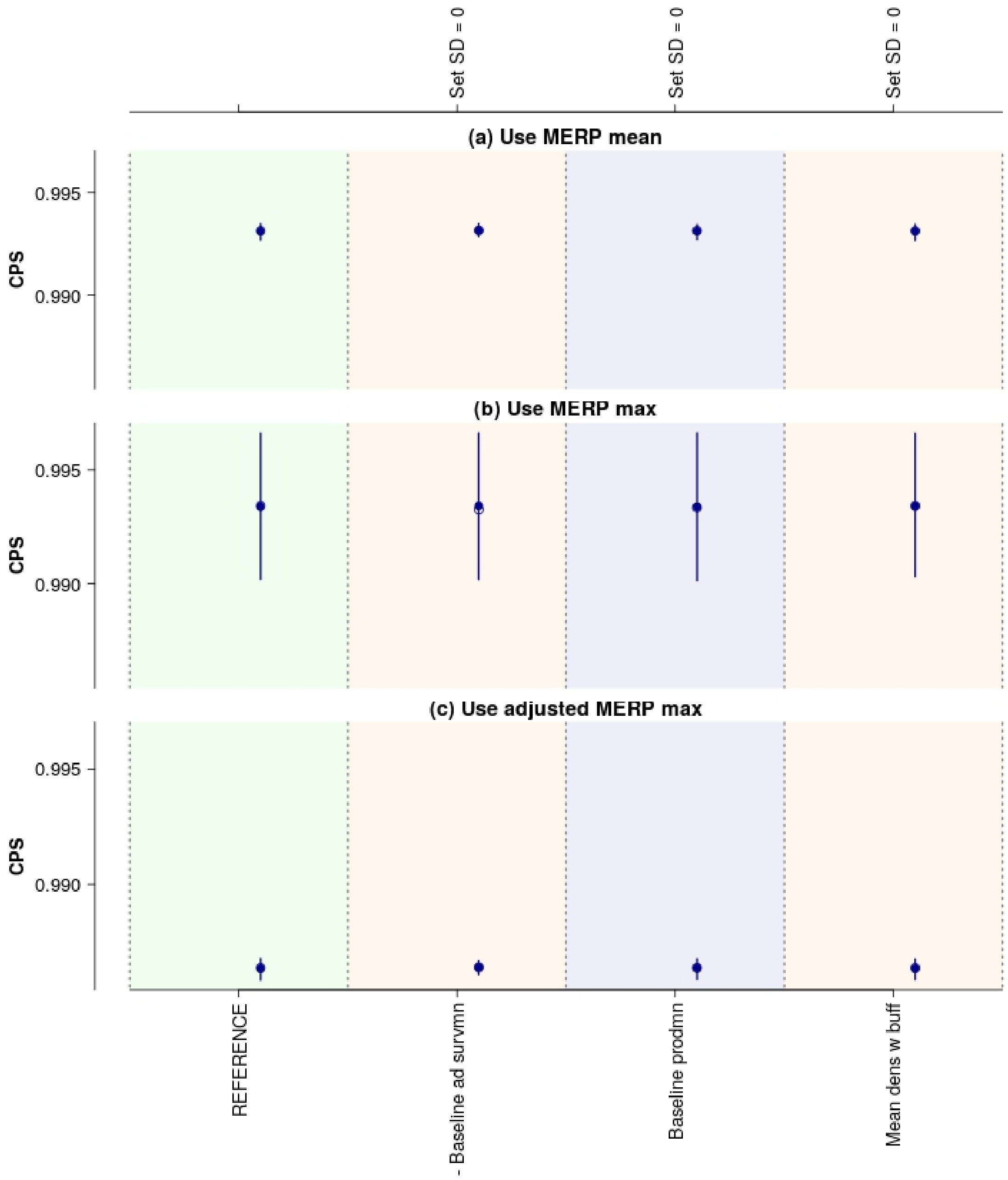

Figure S48: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

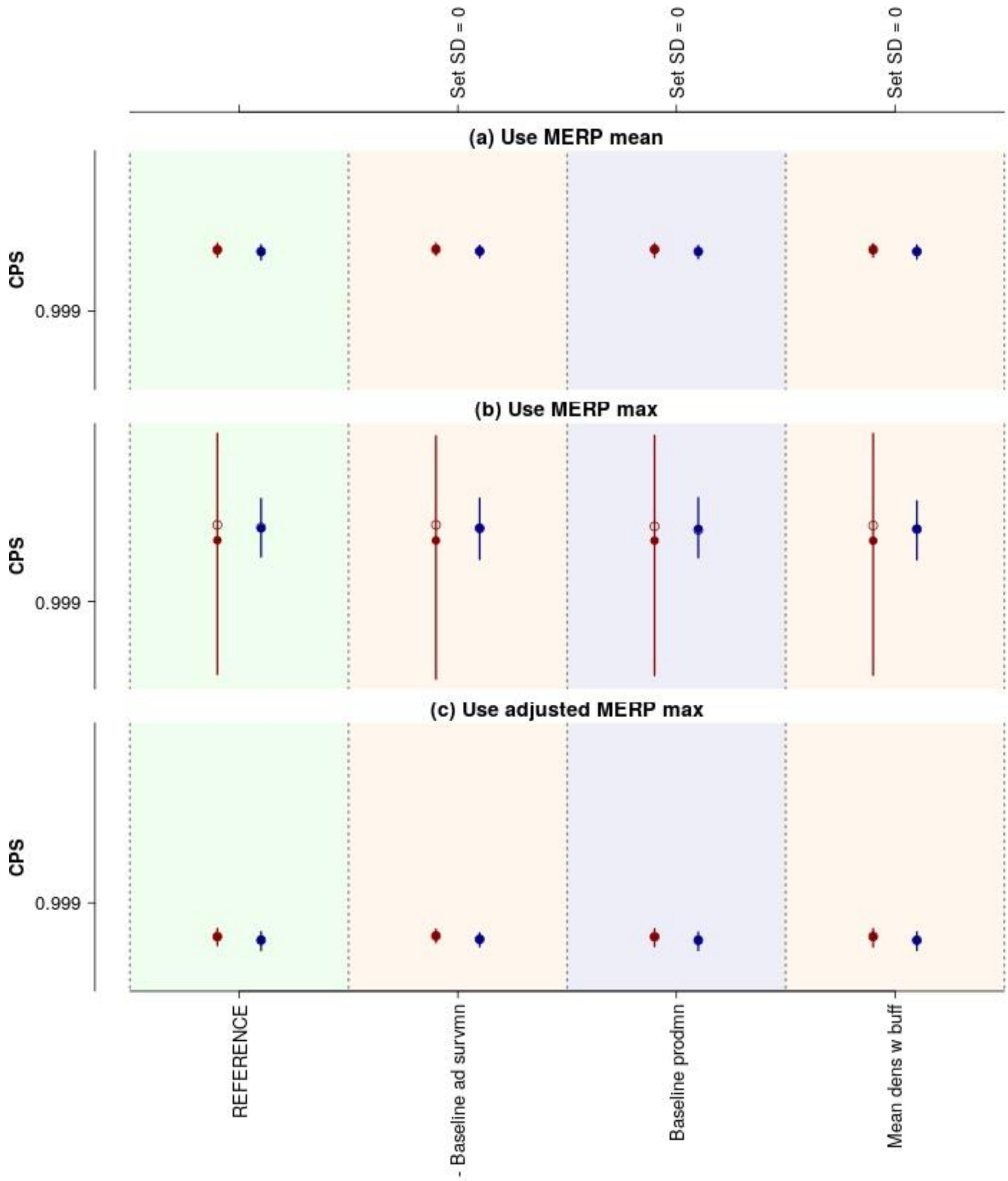

Figure S49: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

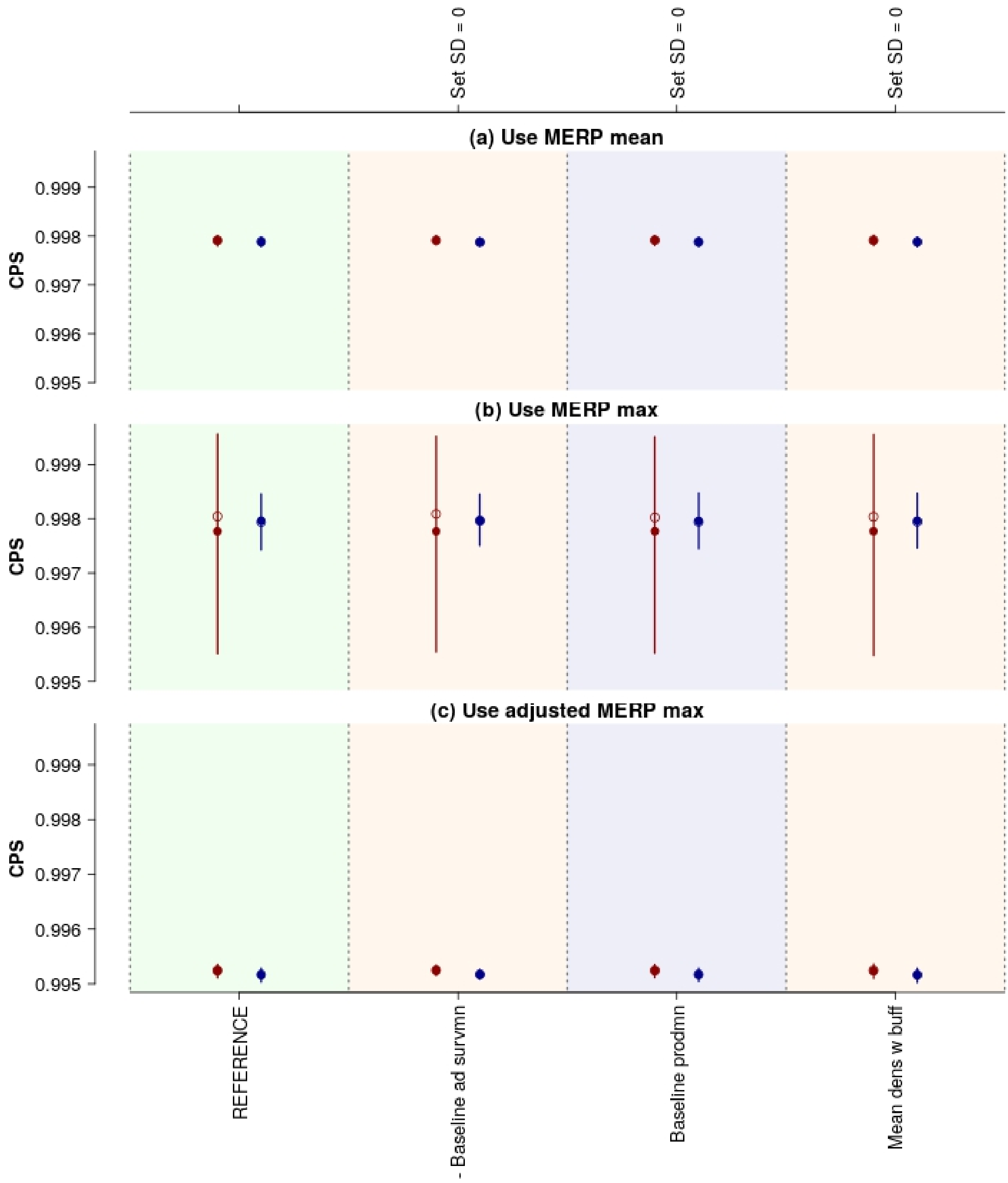

Figure S50: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

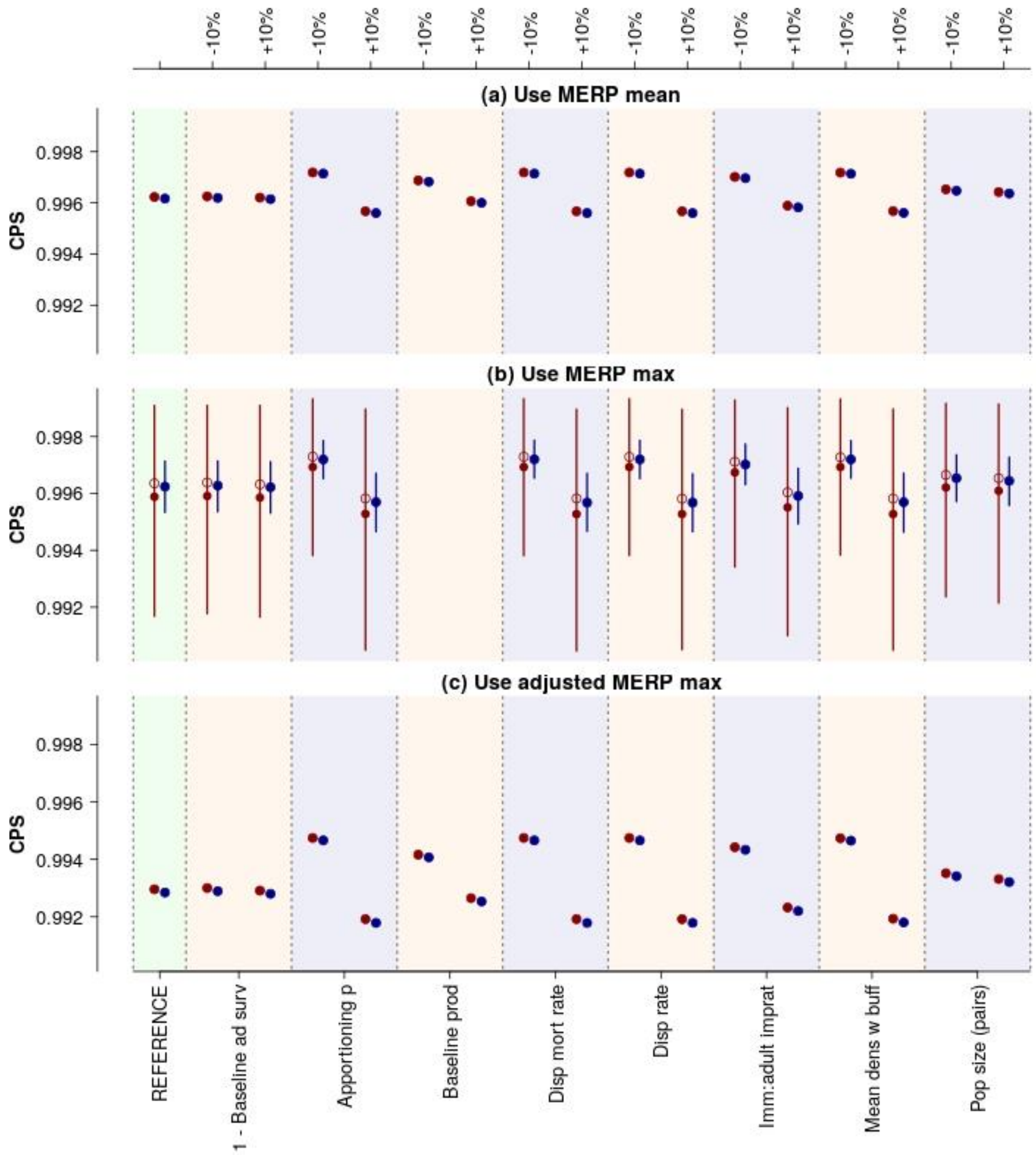

Figure S51: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

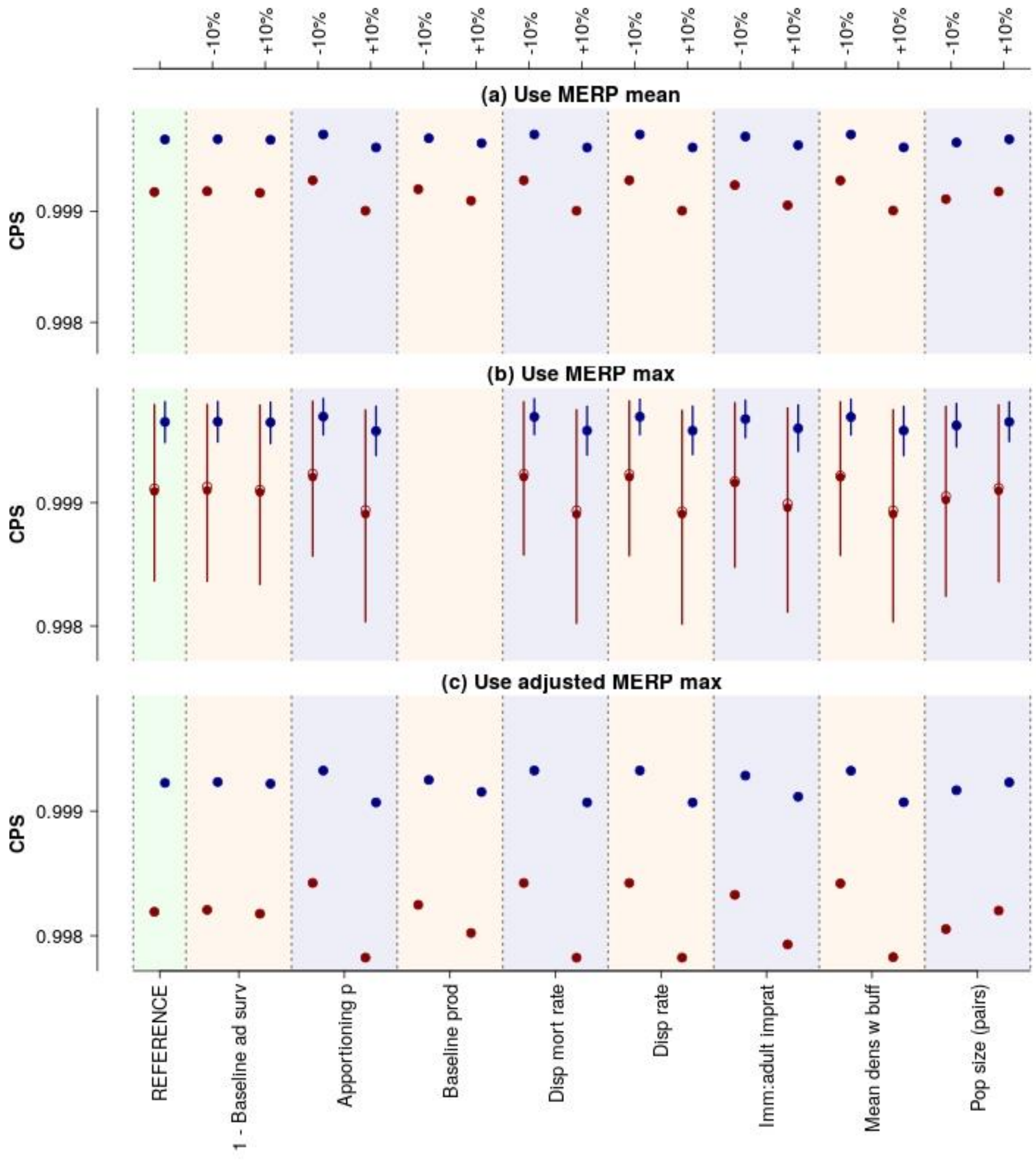

Figure S52: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

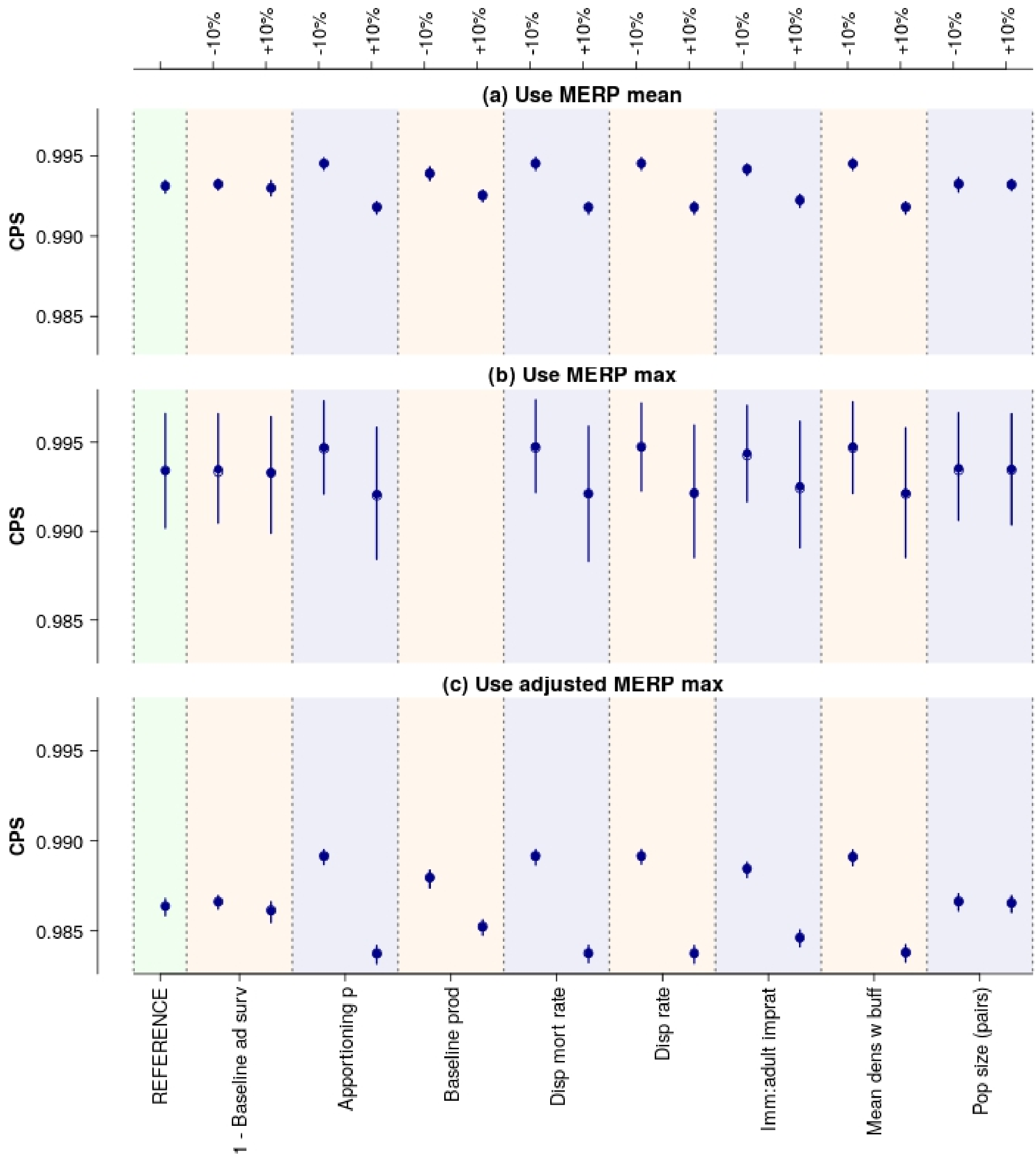

Figure S53: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

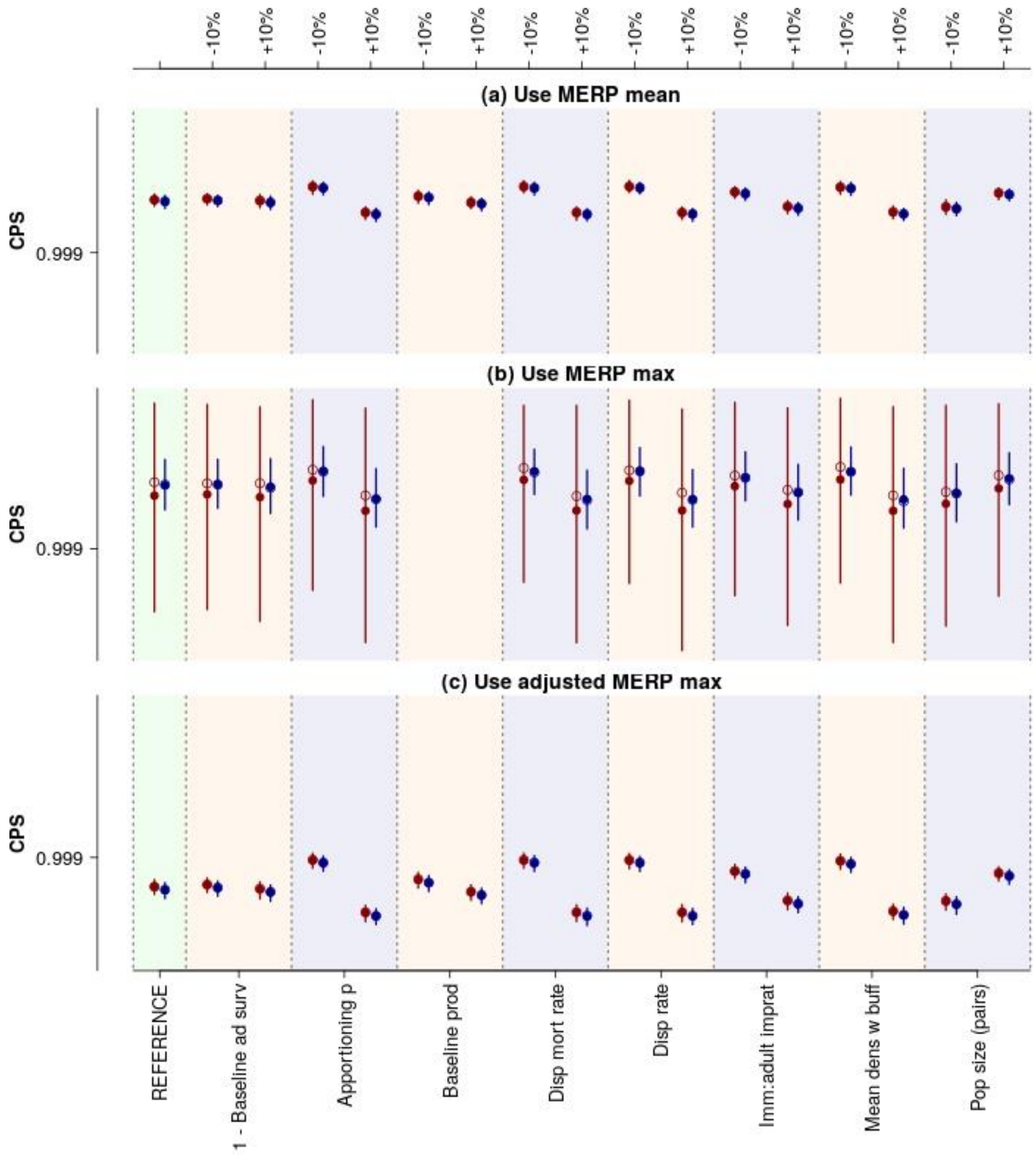

Figure S54: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

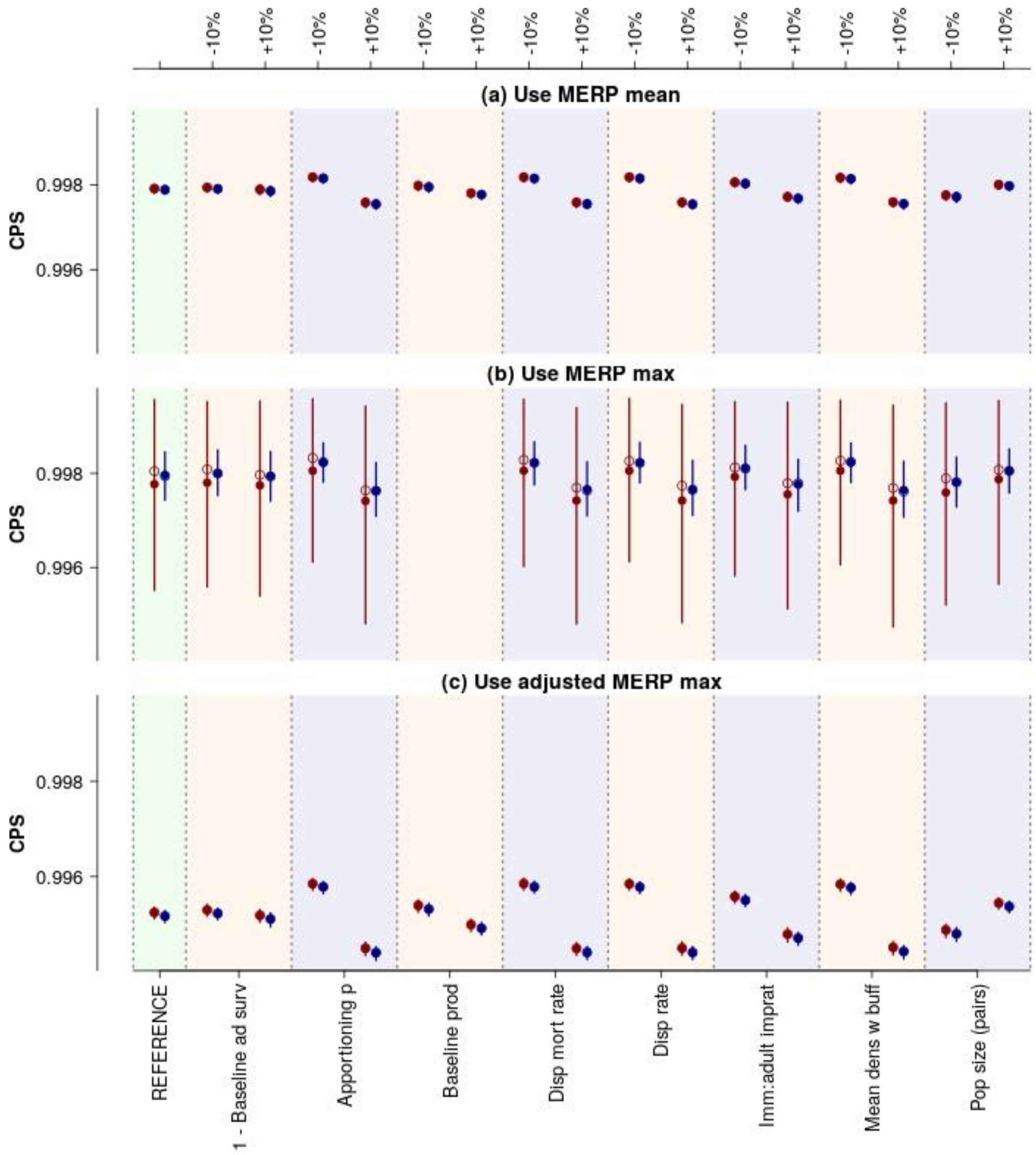

Figure S55: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

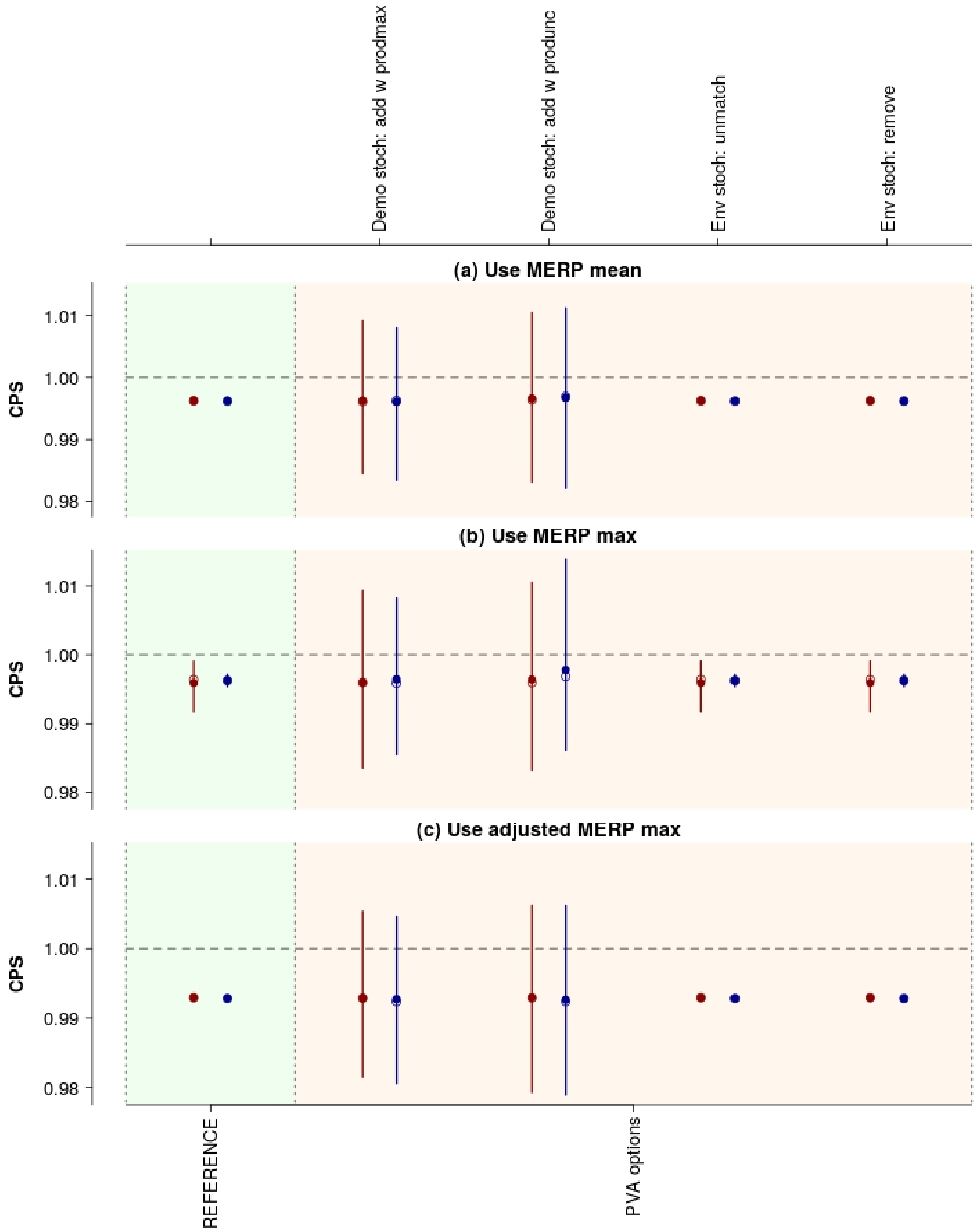

Figure S56: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for common guillemot after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

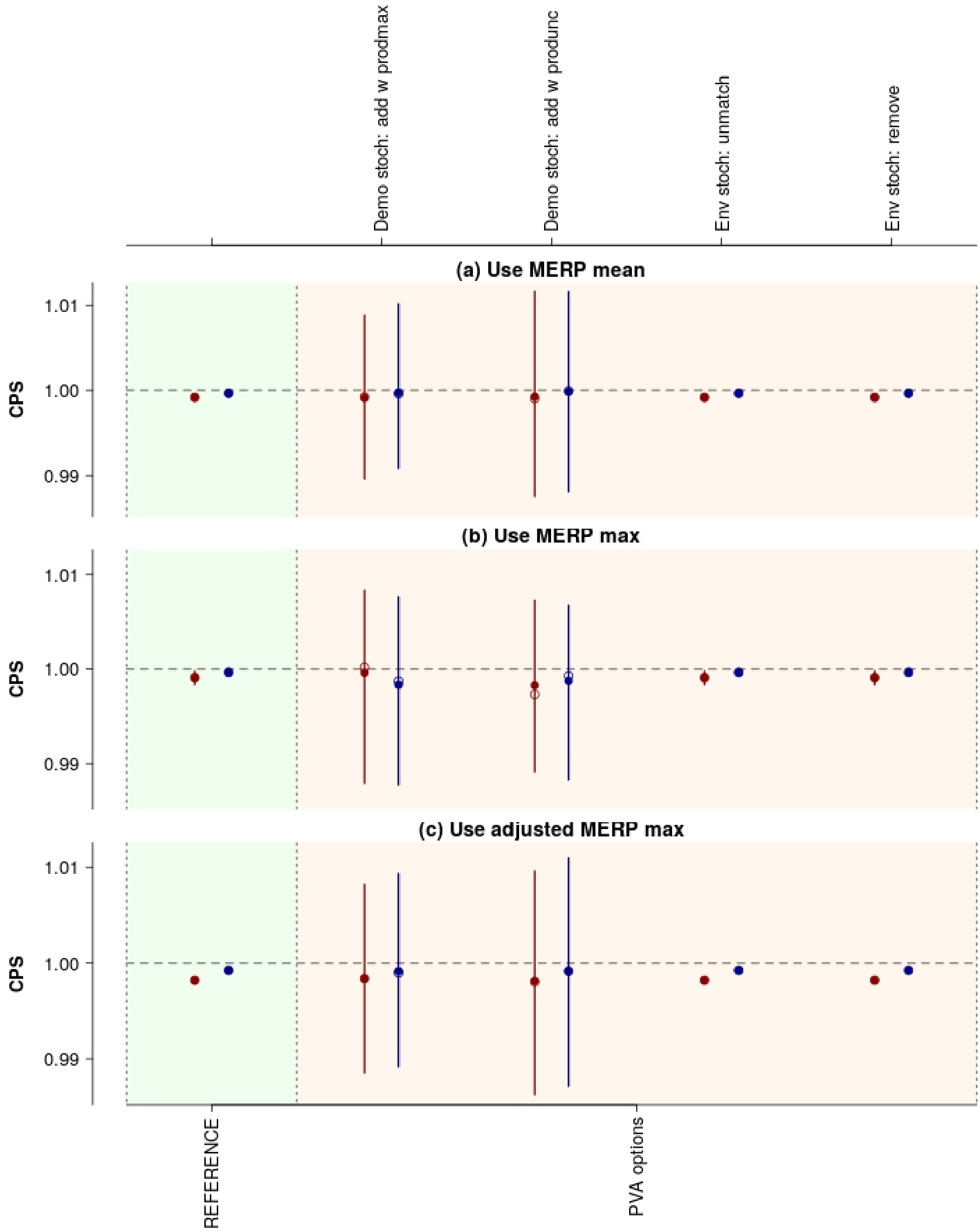

Figure S57: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

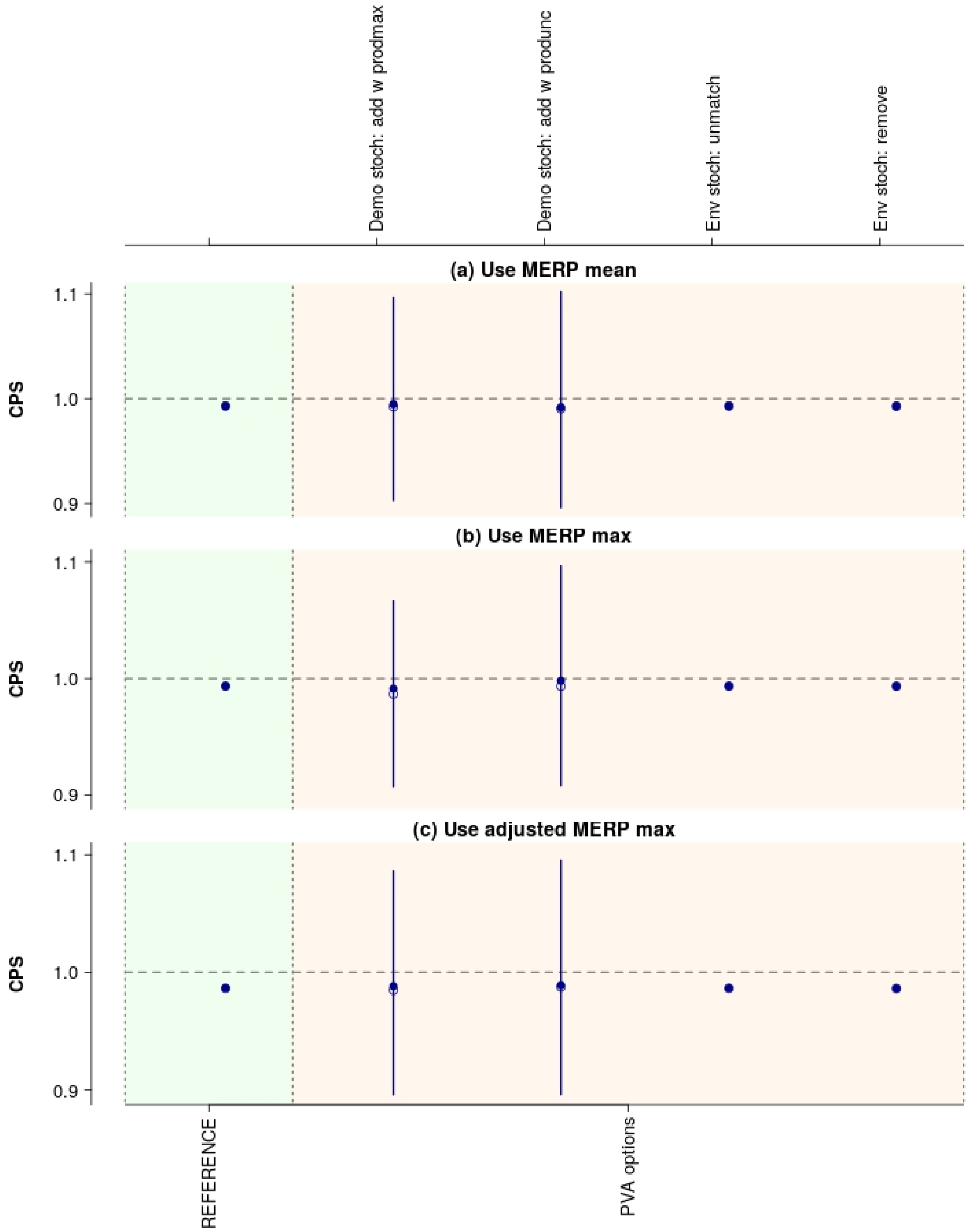

Figure S58: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

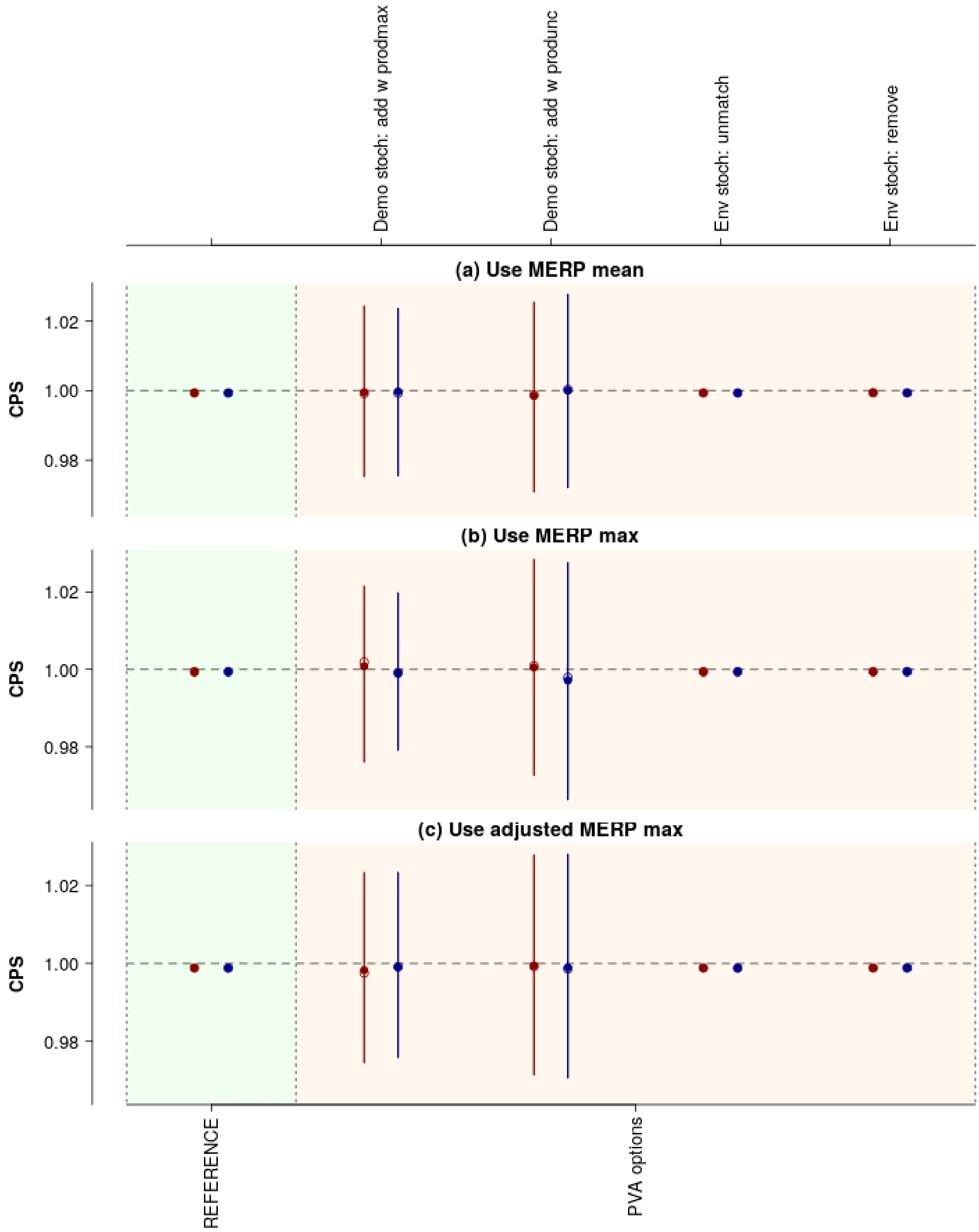

Figure S59: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

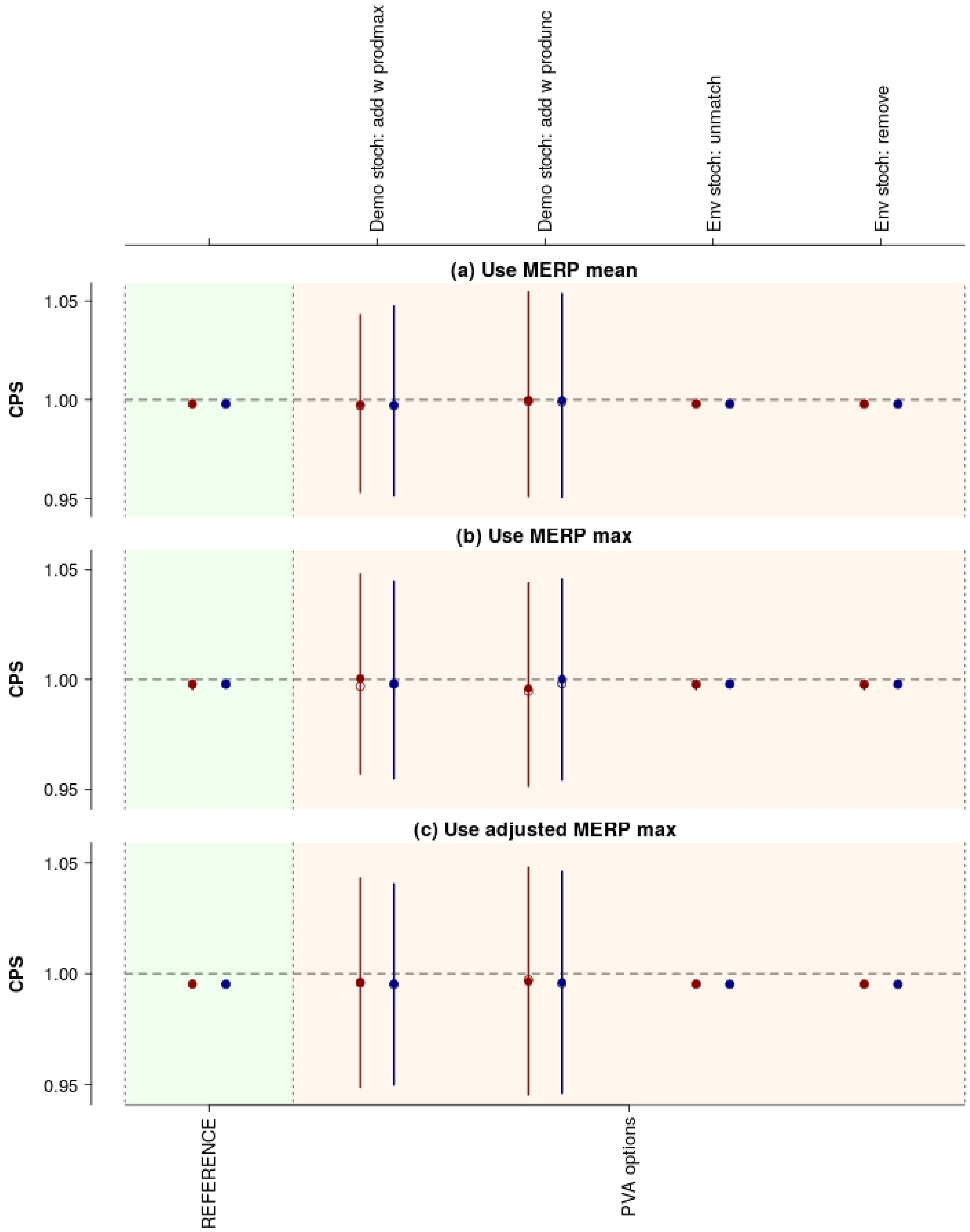

Figure S60: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix uses simulated values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

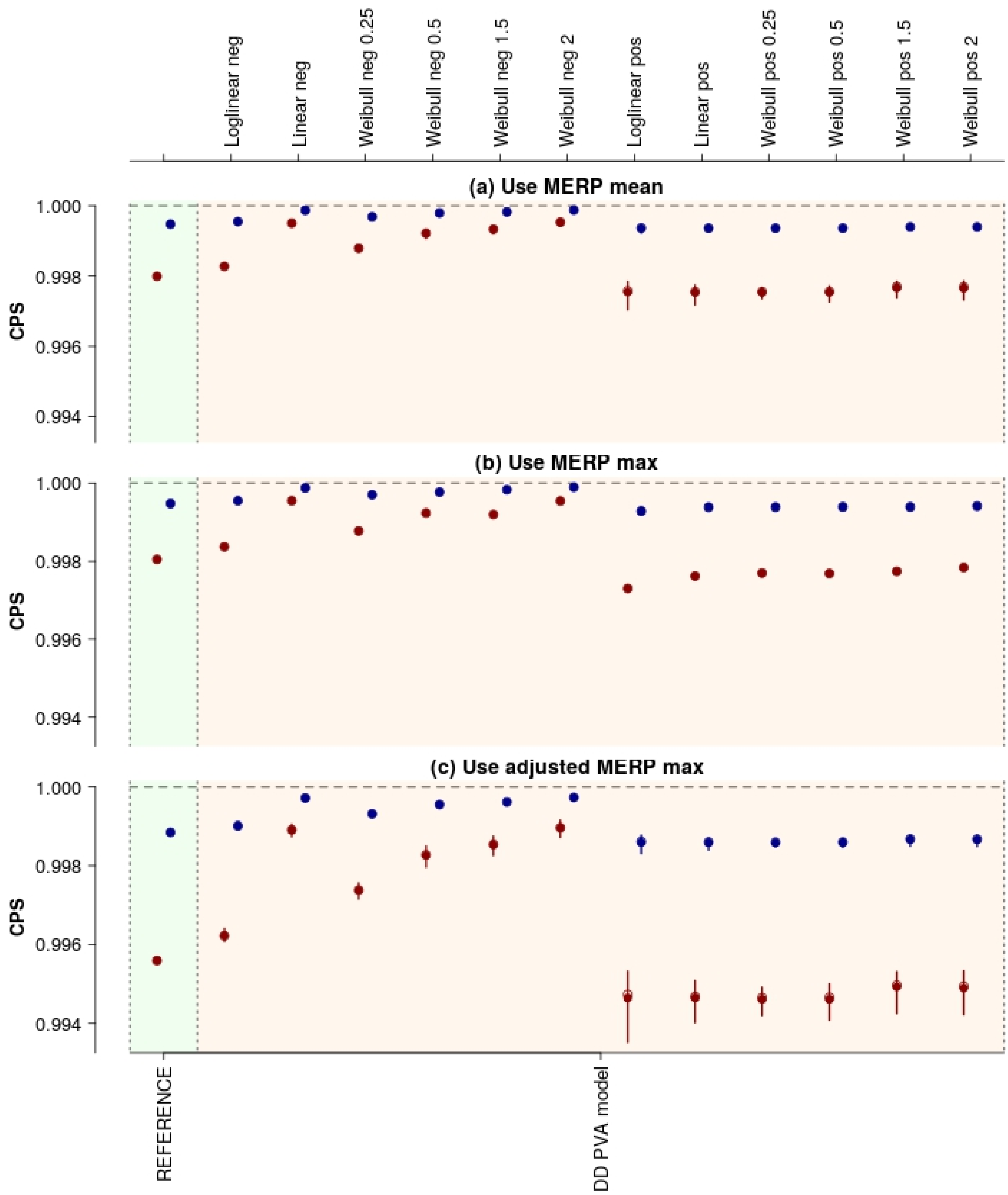

Figure S61: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

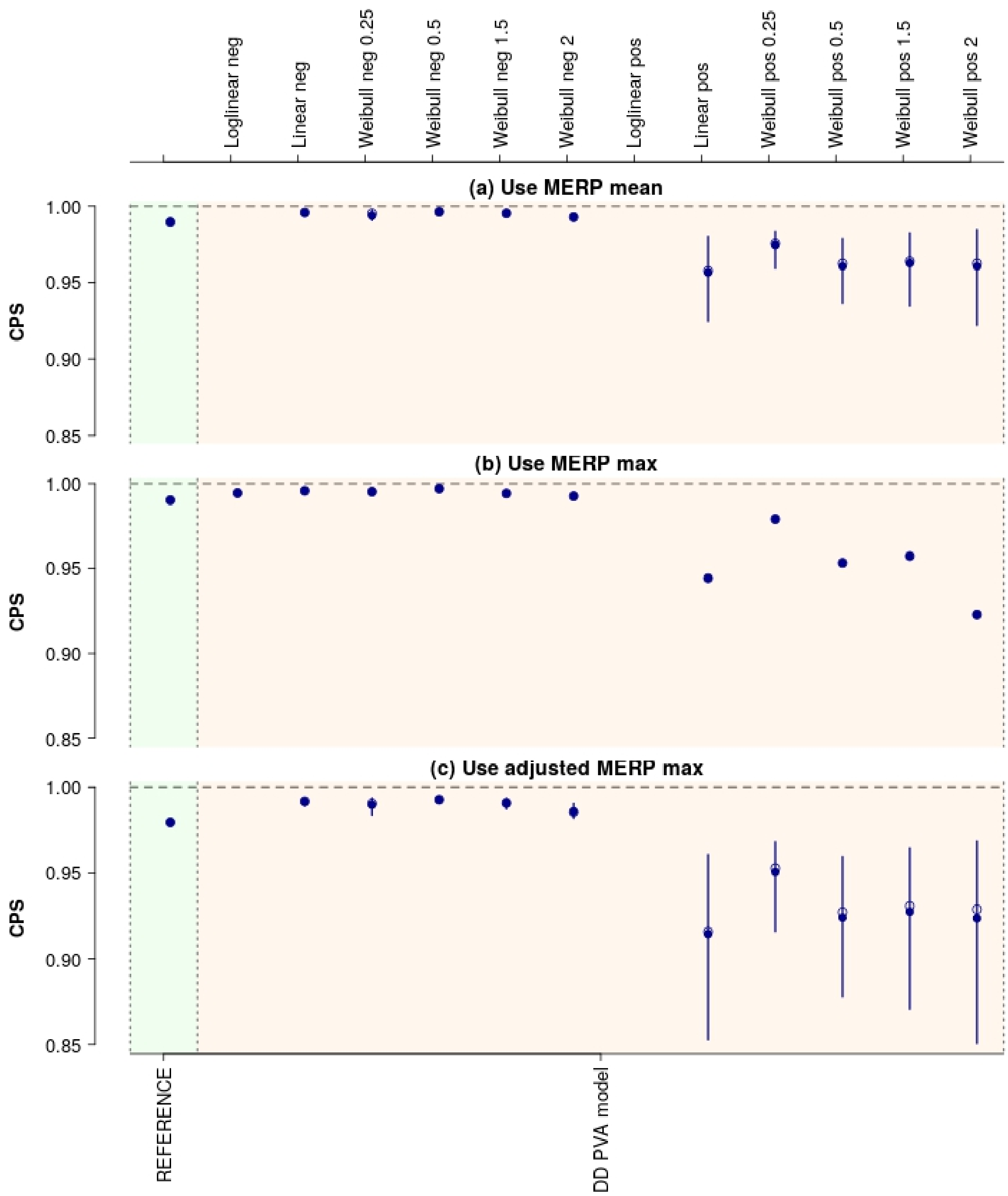

Figure S62: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

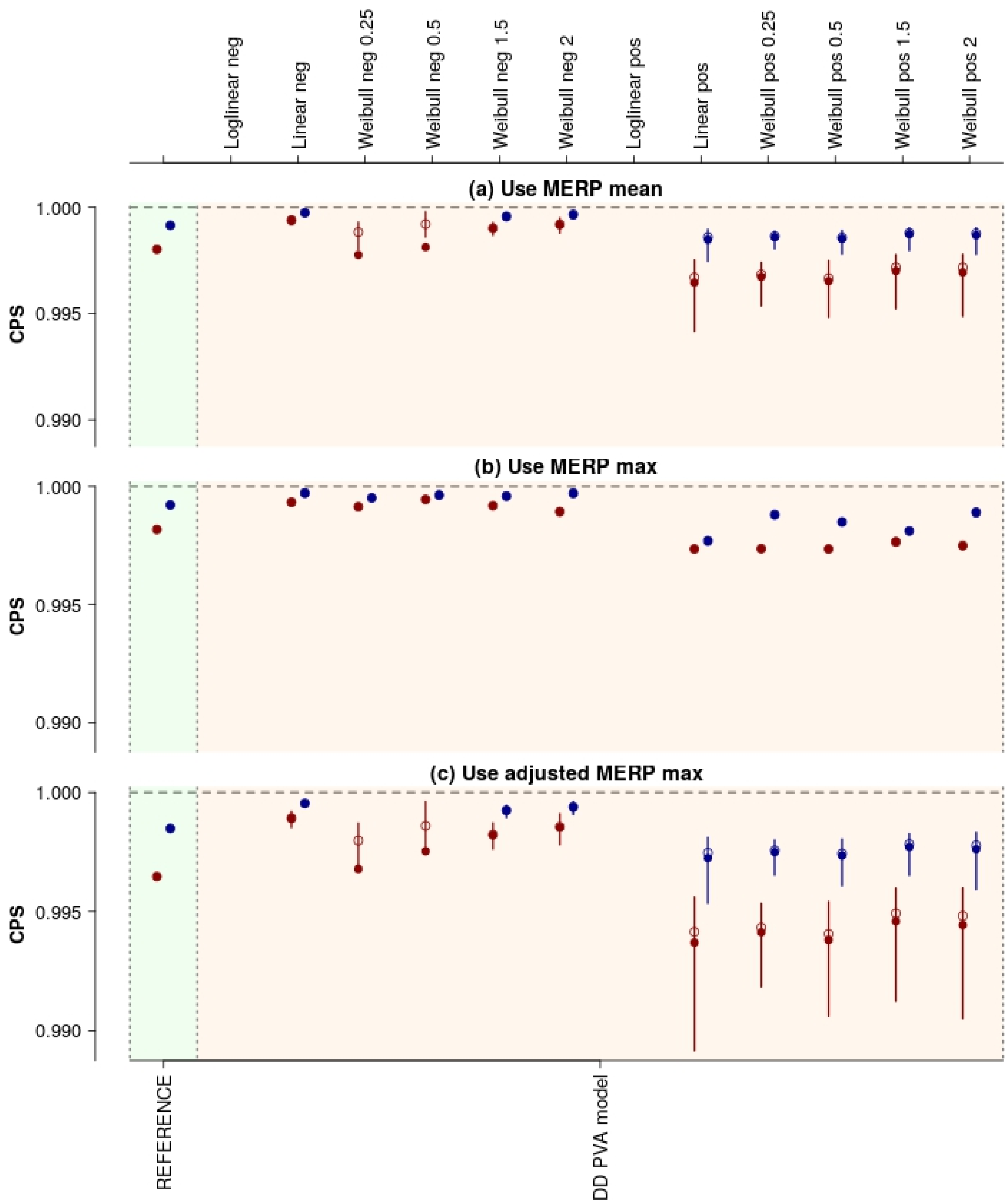

Figure S63: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

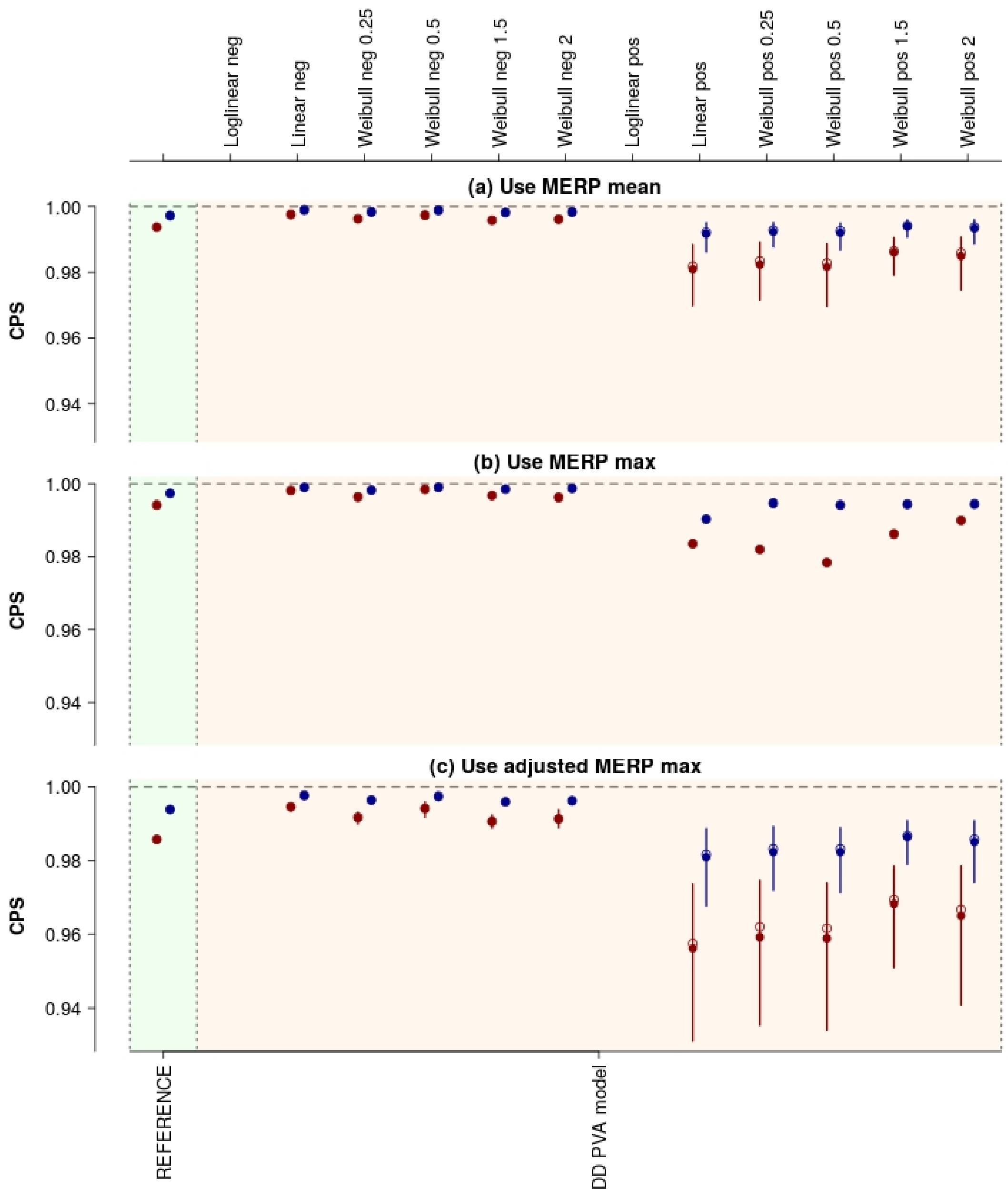

Figure S64: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

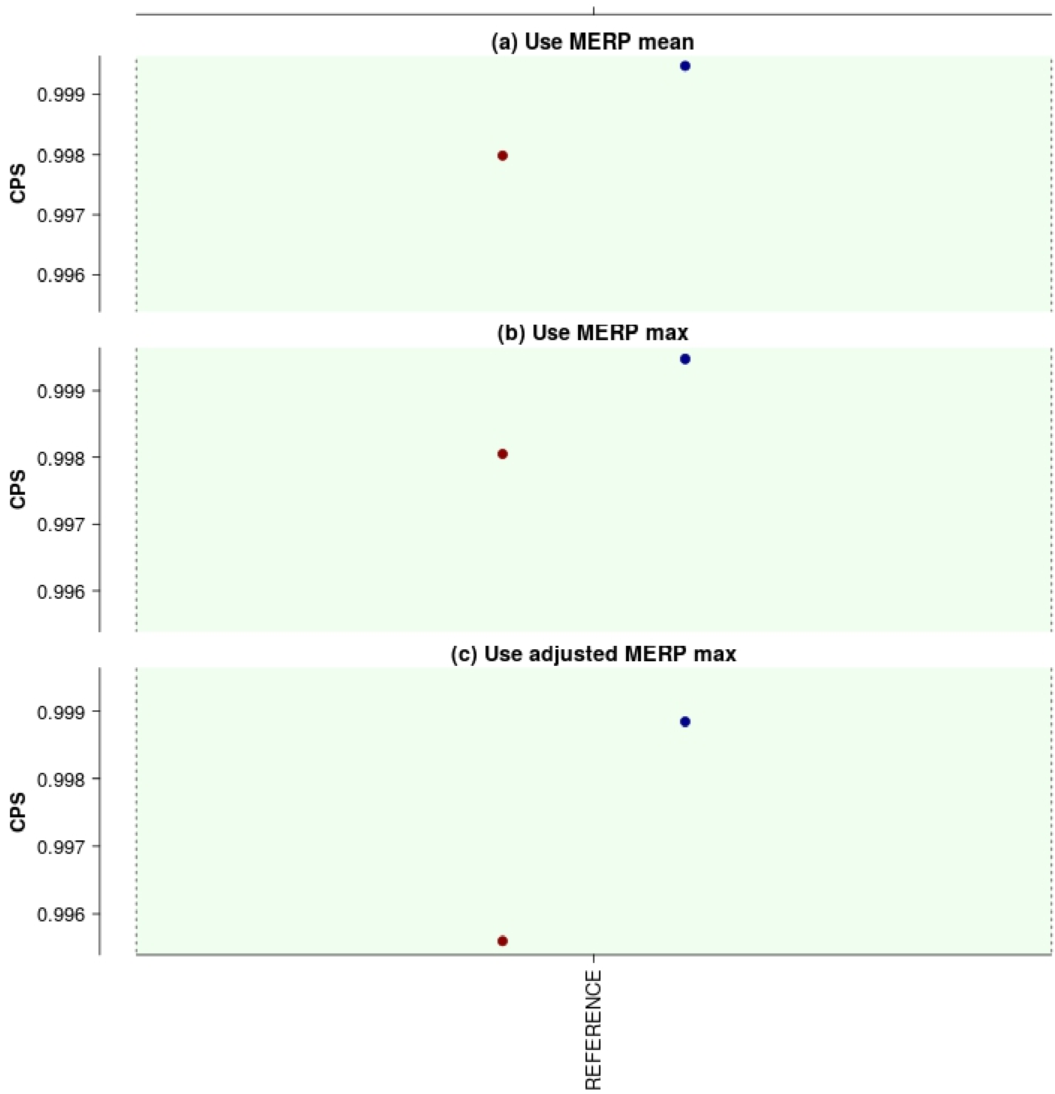

Figure S65: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

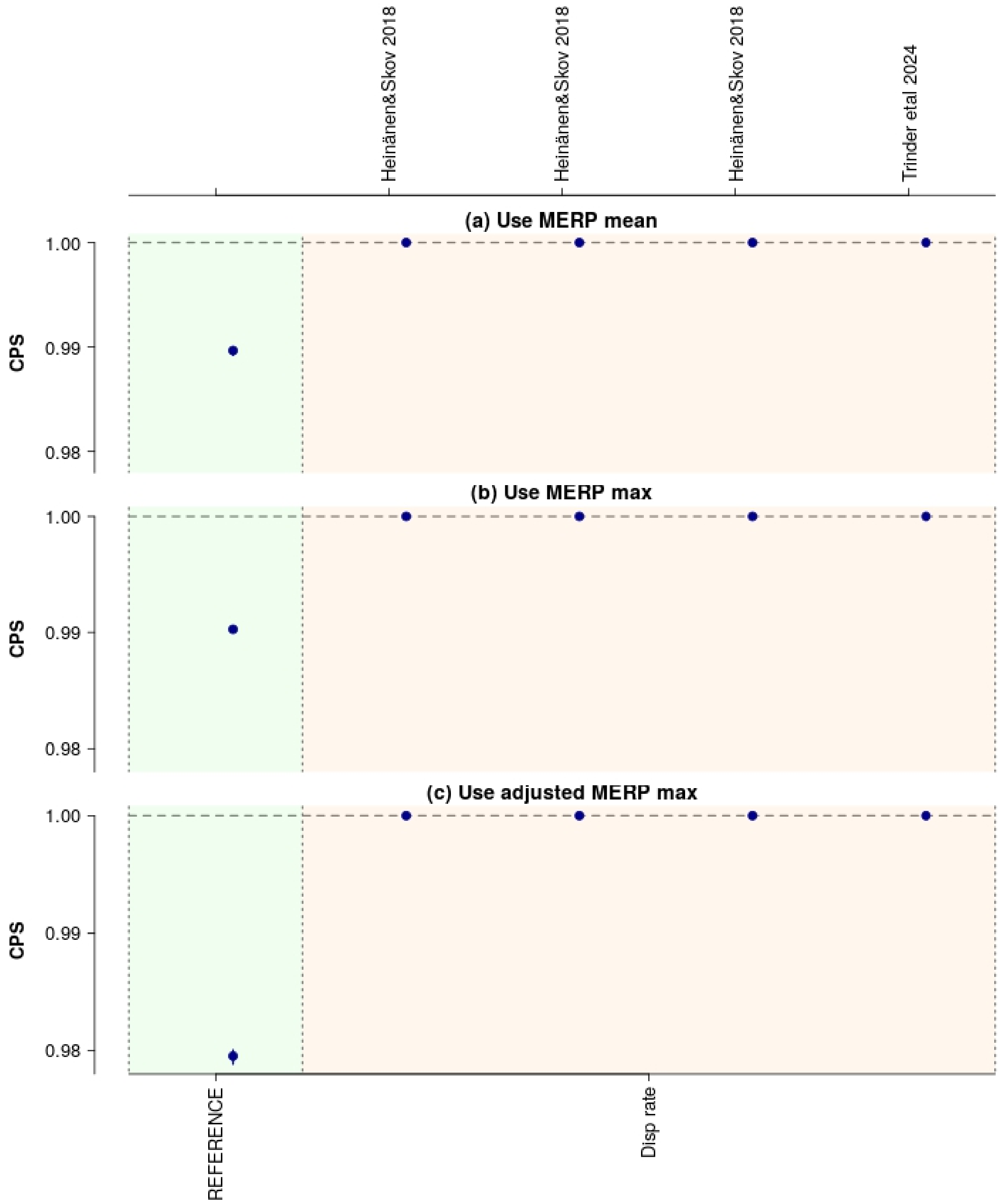

Figure S66: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

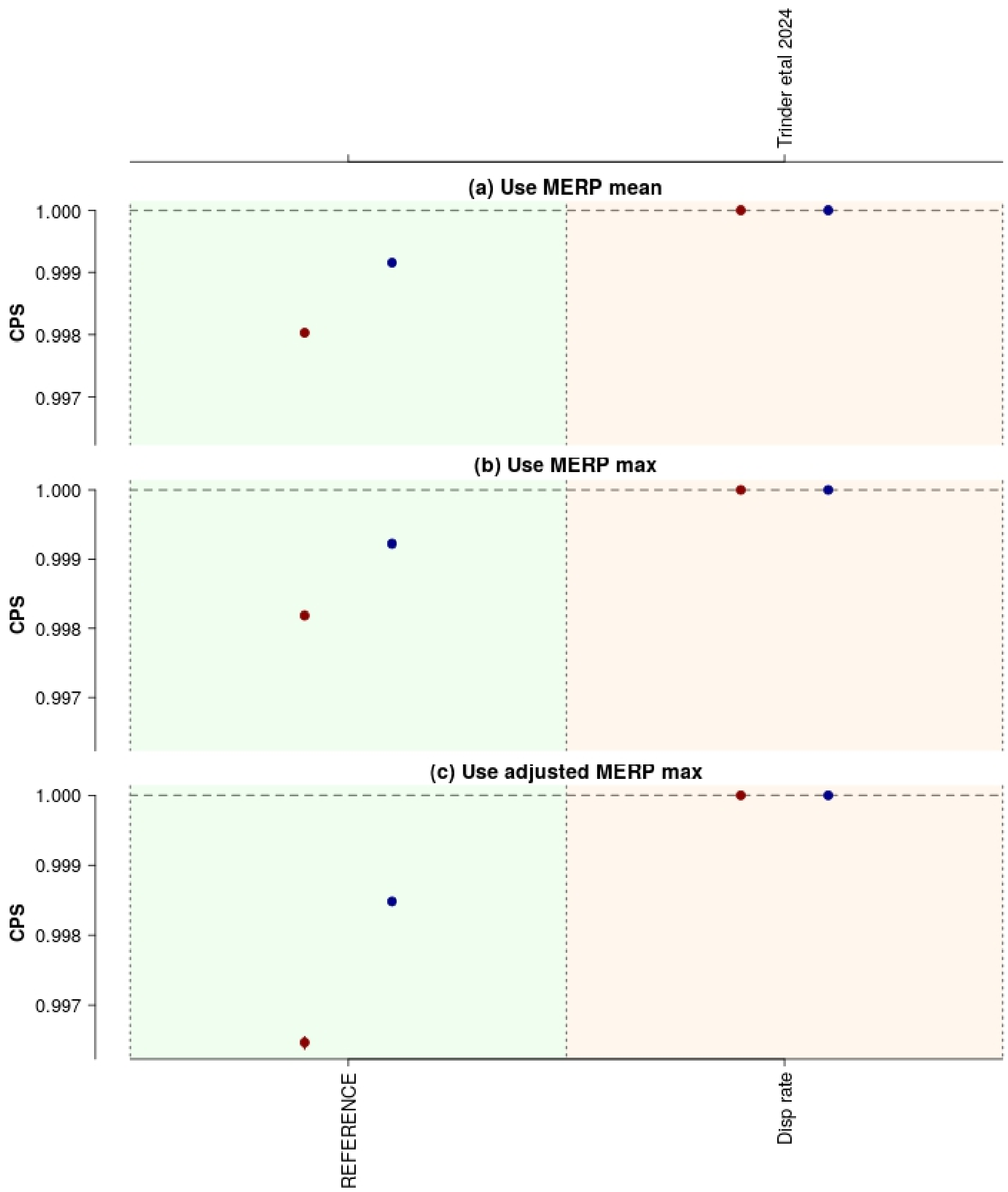

Figure S67: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

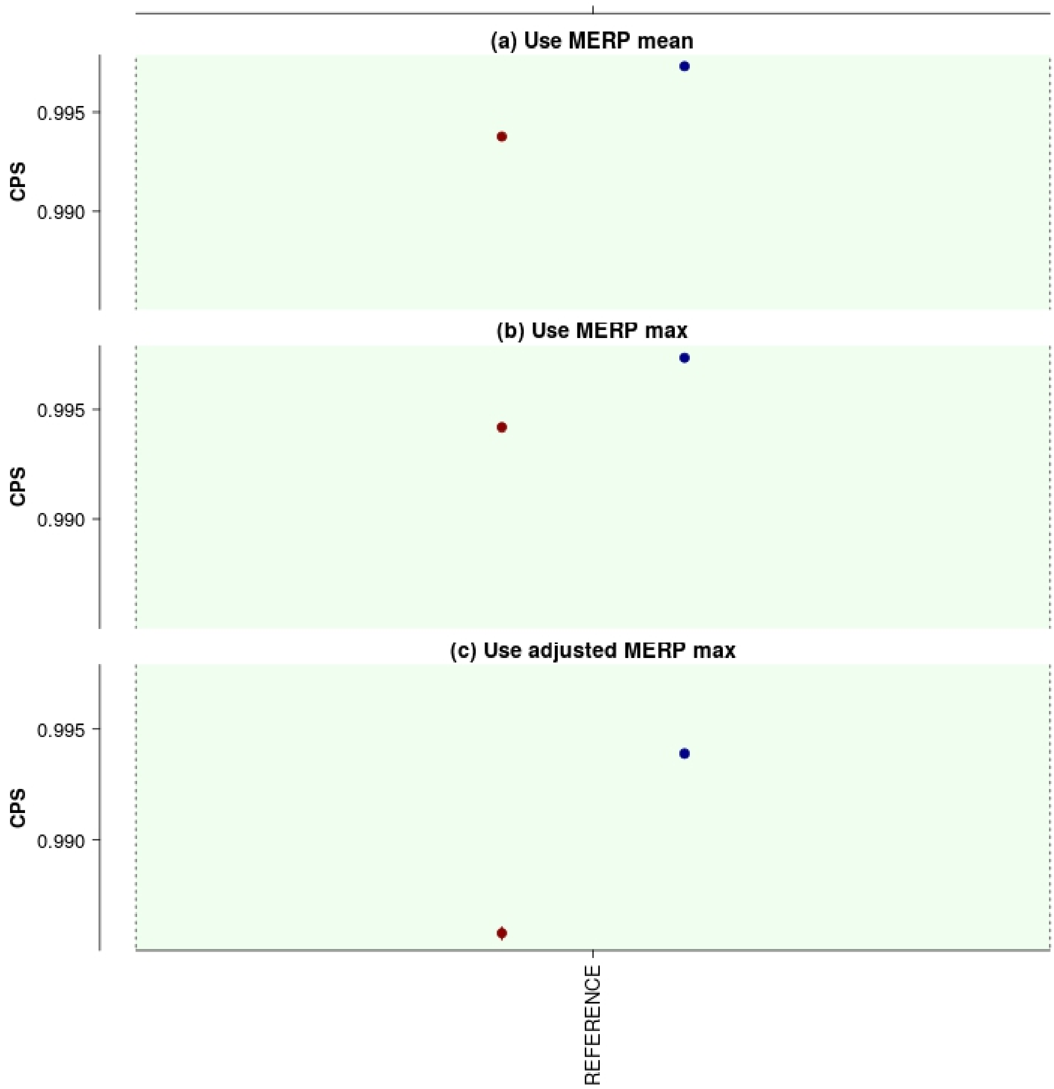

Figure S68: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

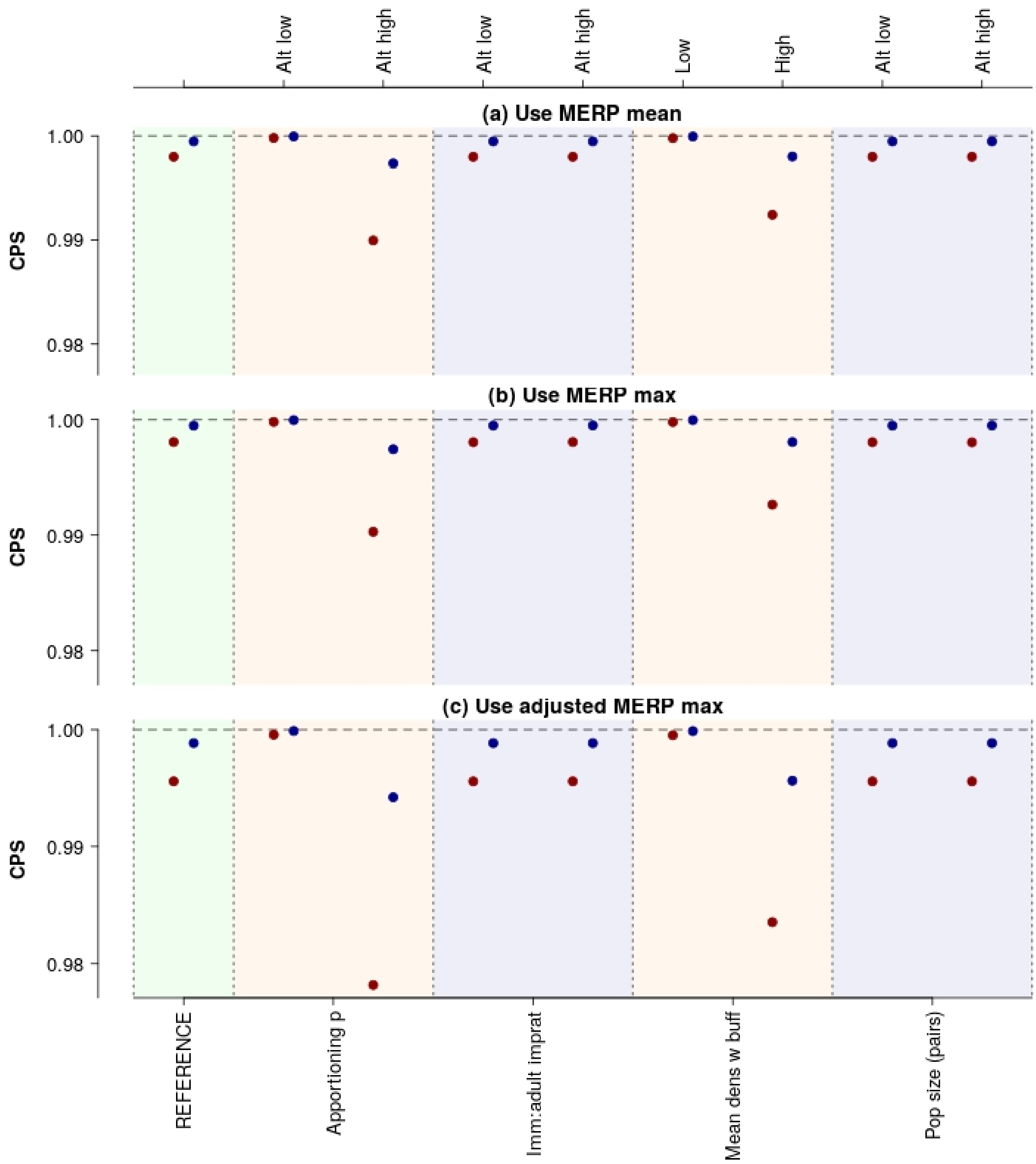

Figure S69: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

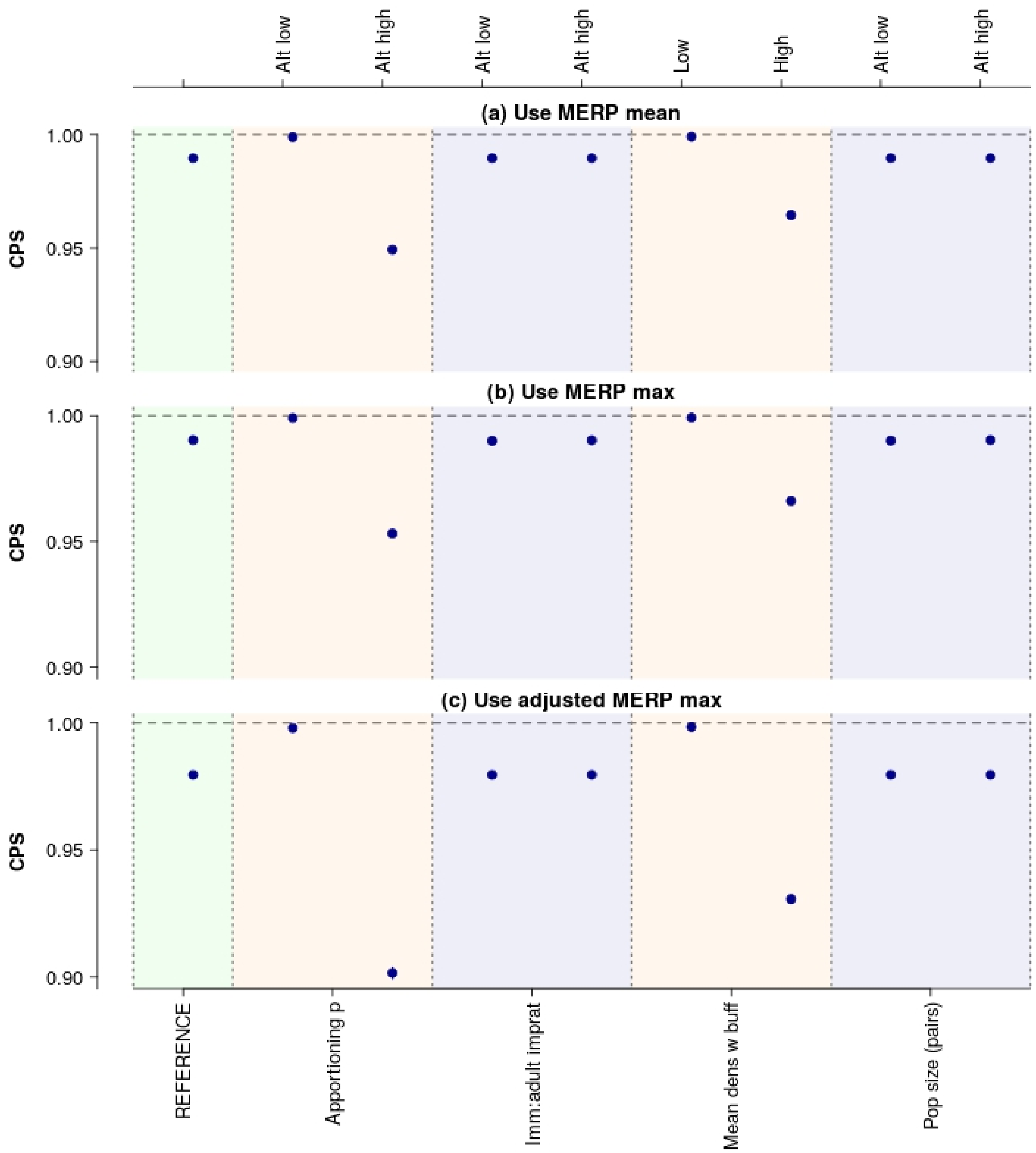

Figure S70: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

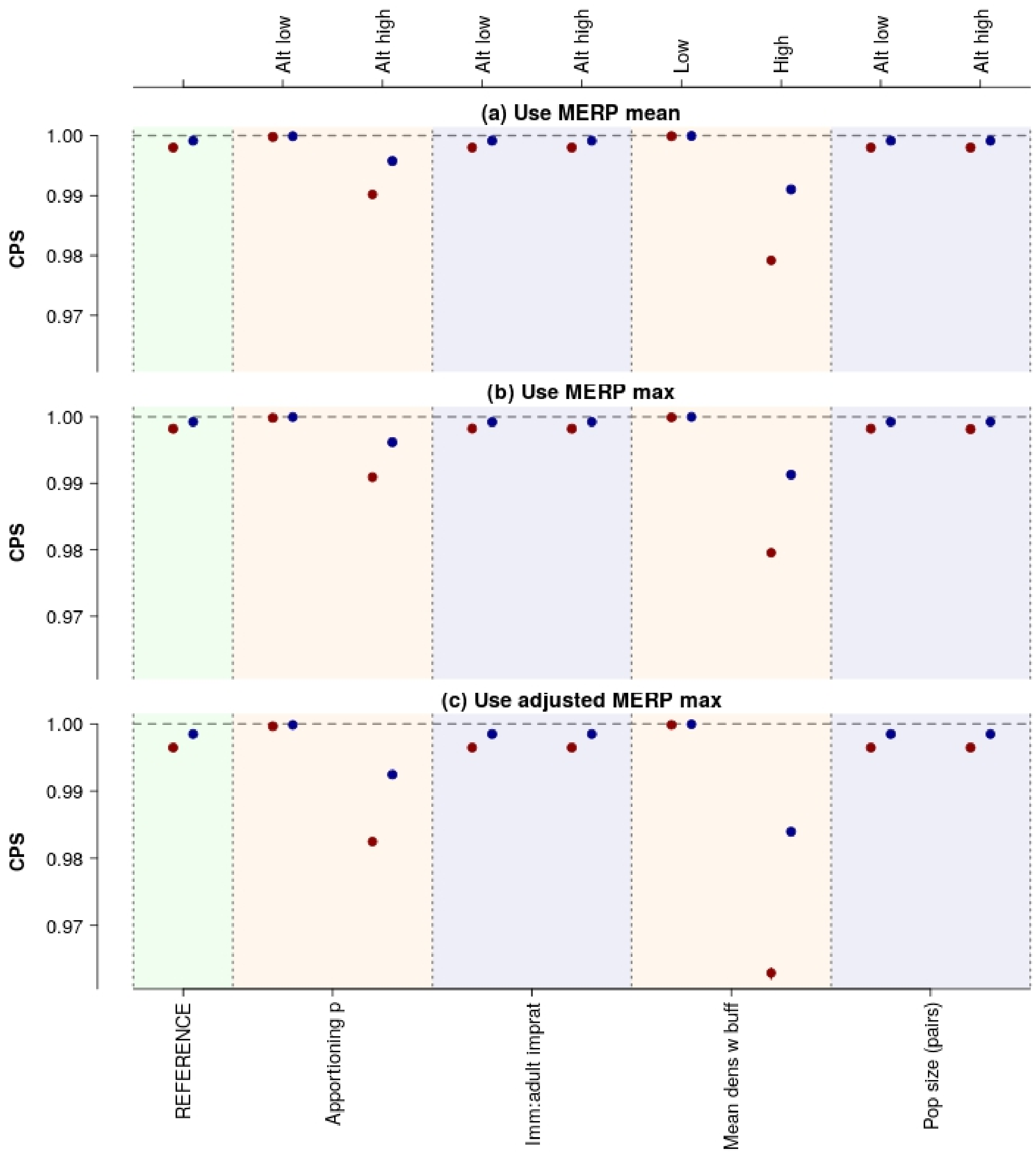

Figure S71: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

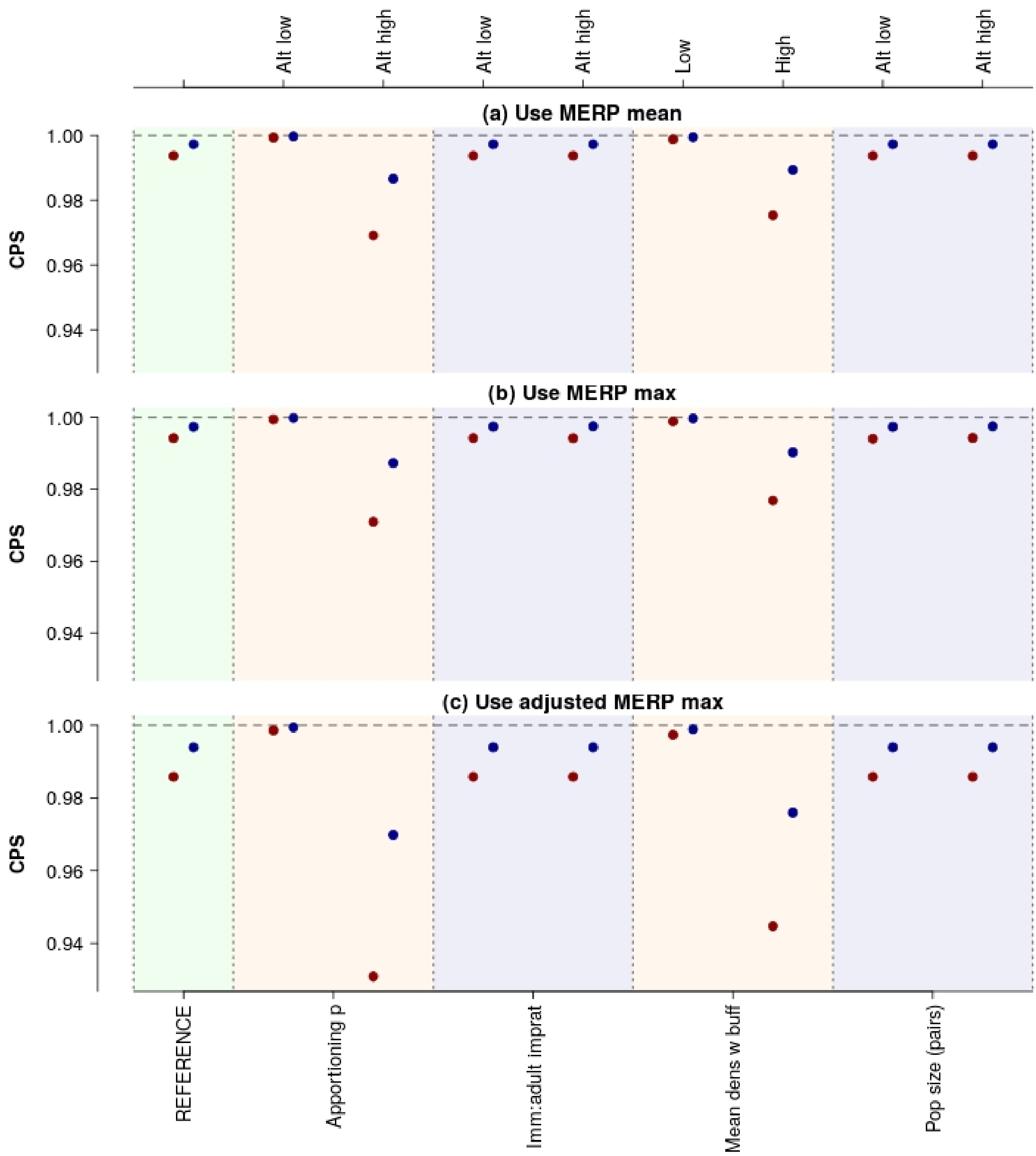

Figure S72: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

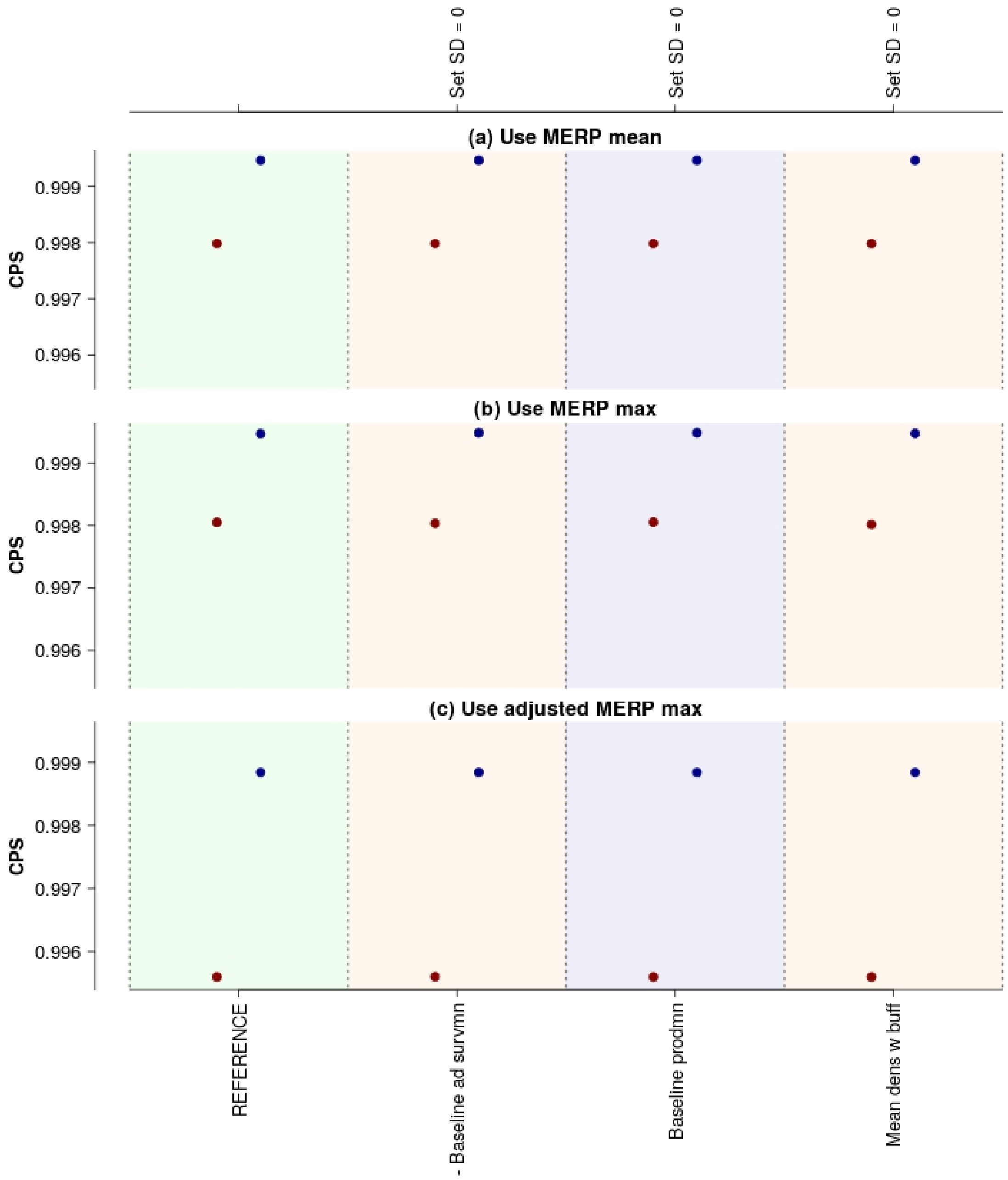

Figure S73: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

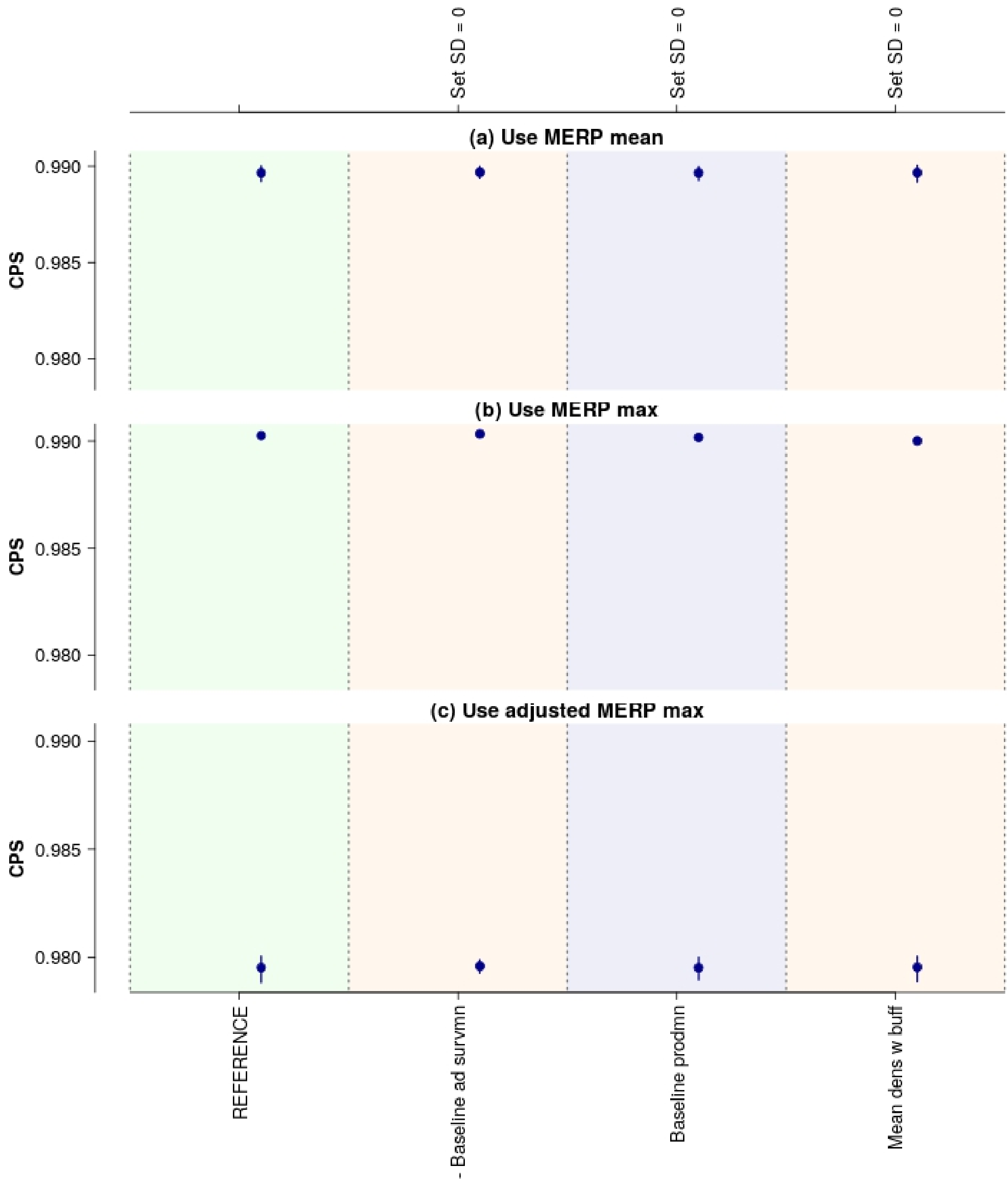

Figure S74: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

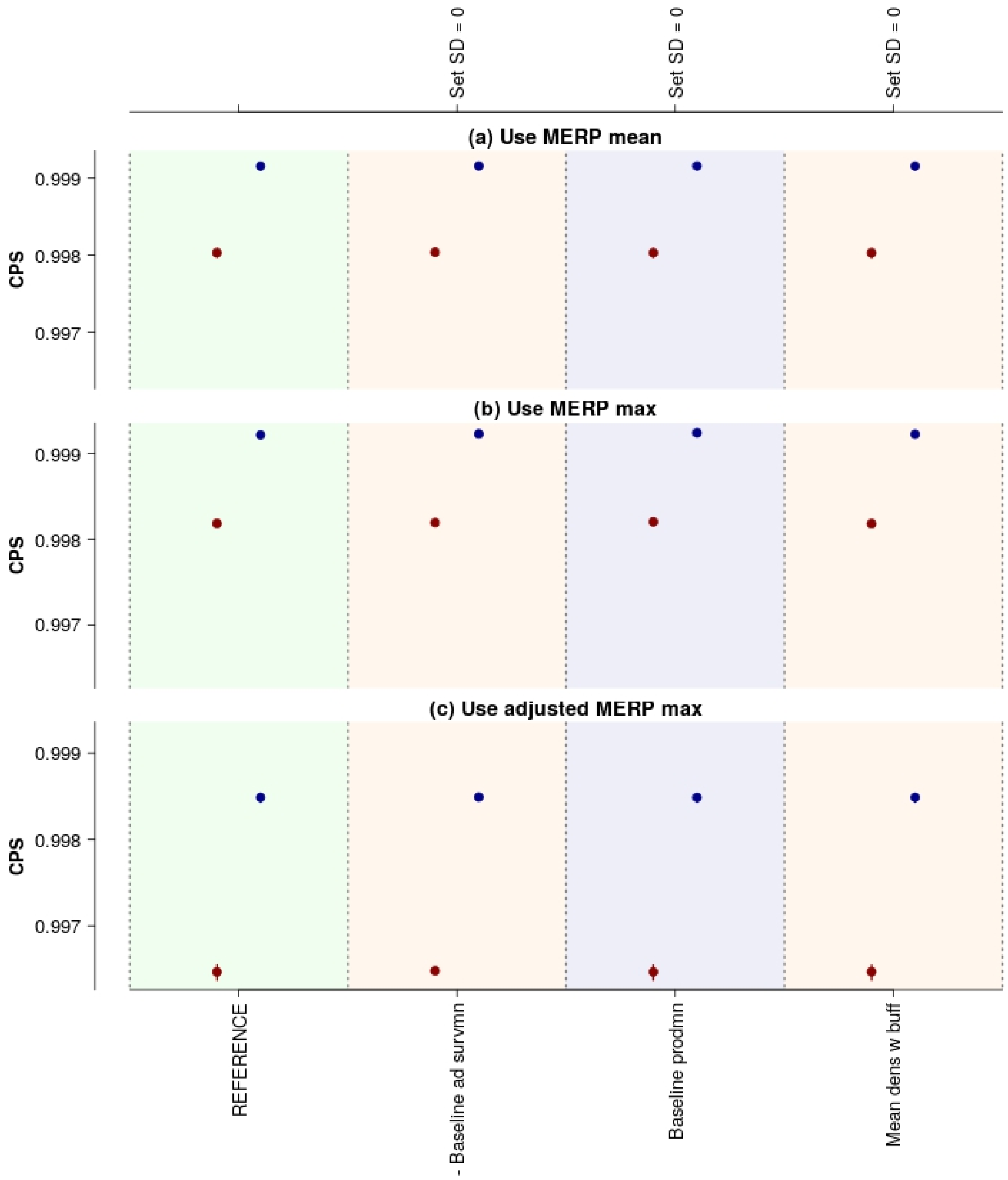

Figure S75: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

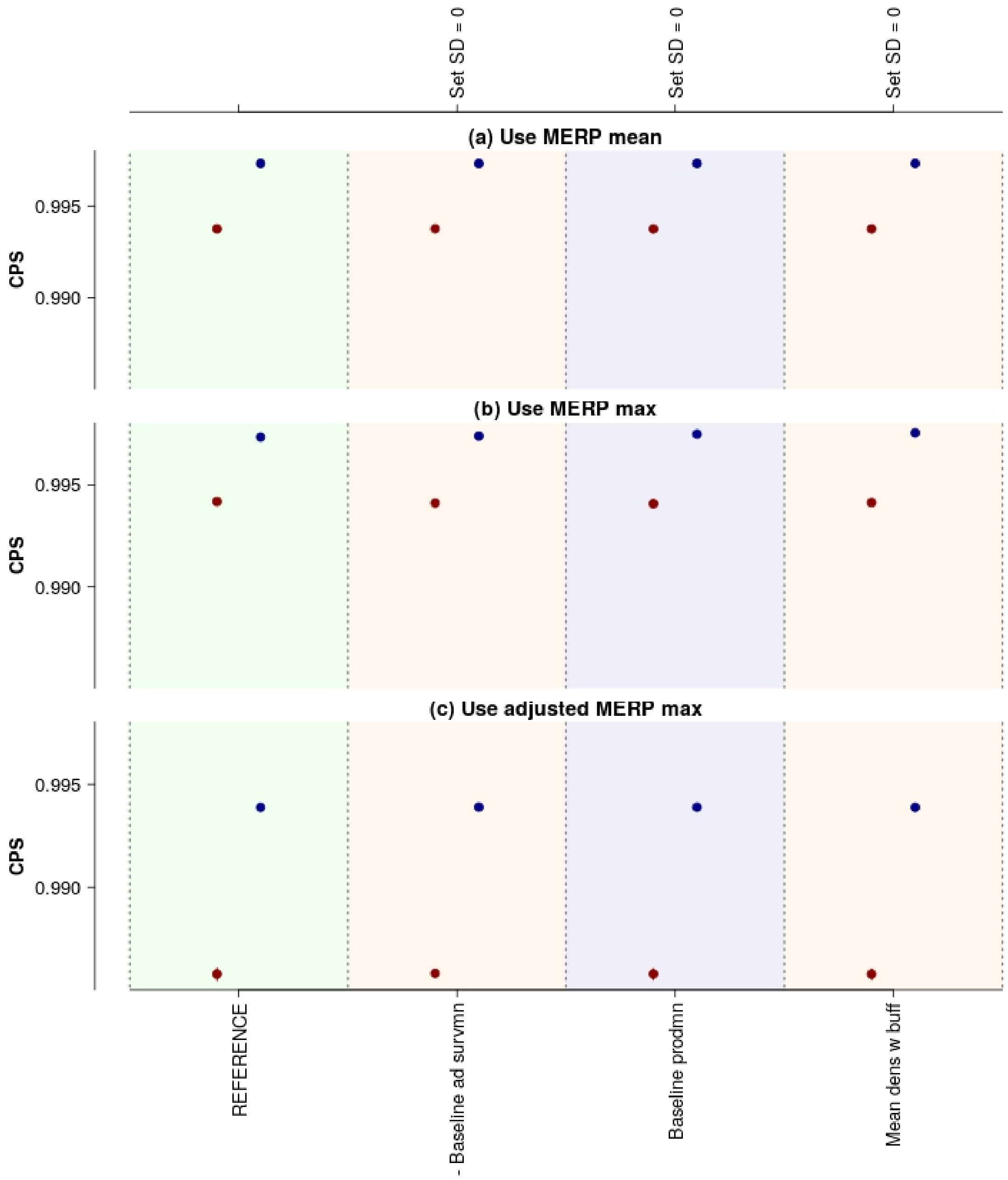

Figure S76: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

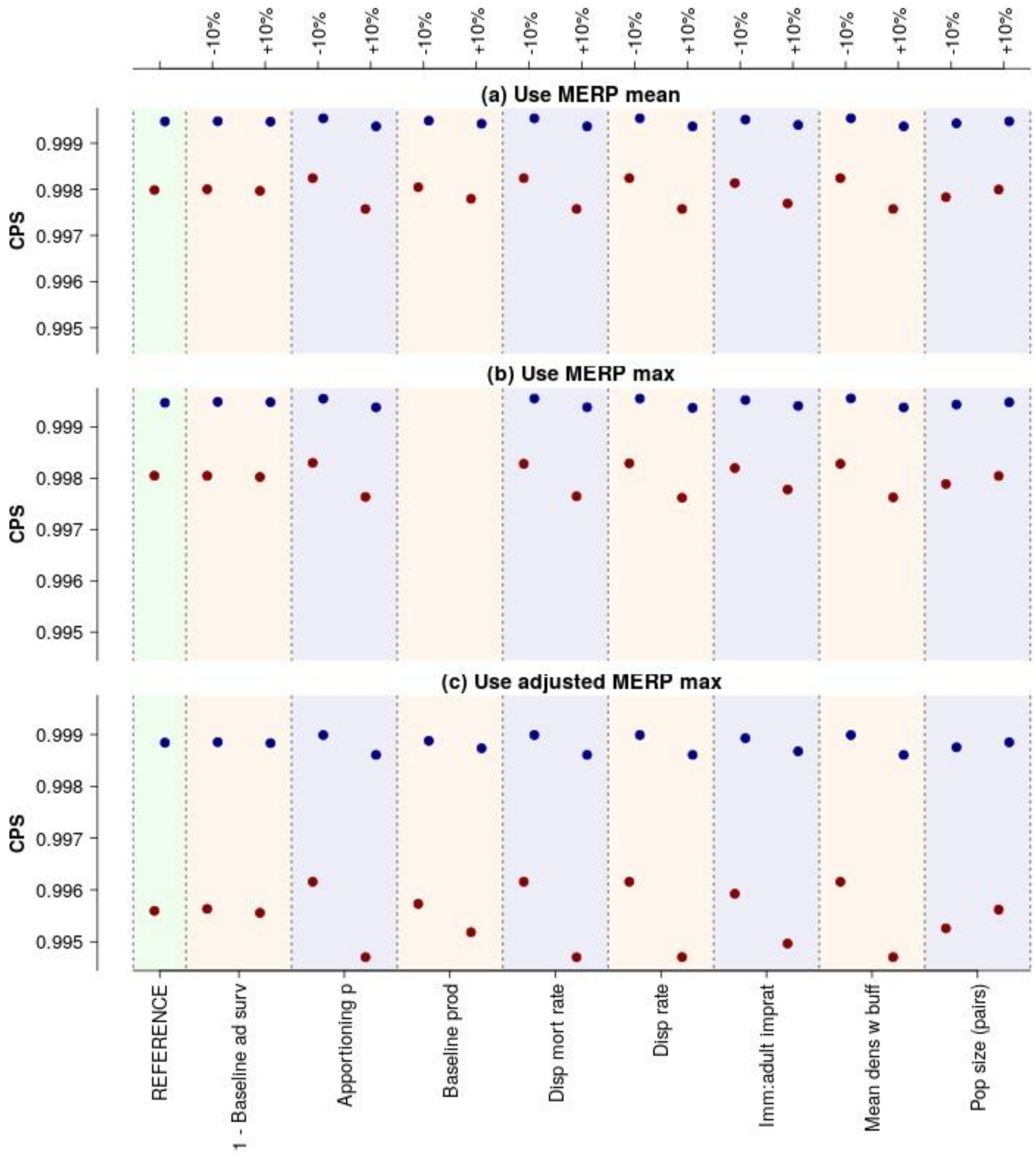

Figure S77: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

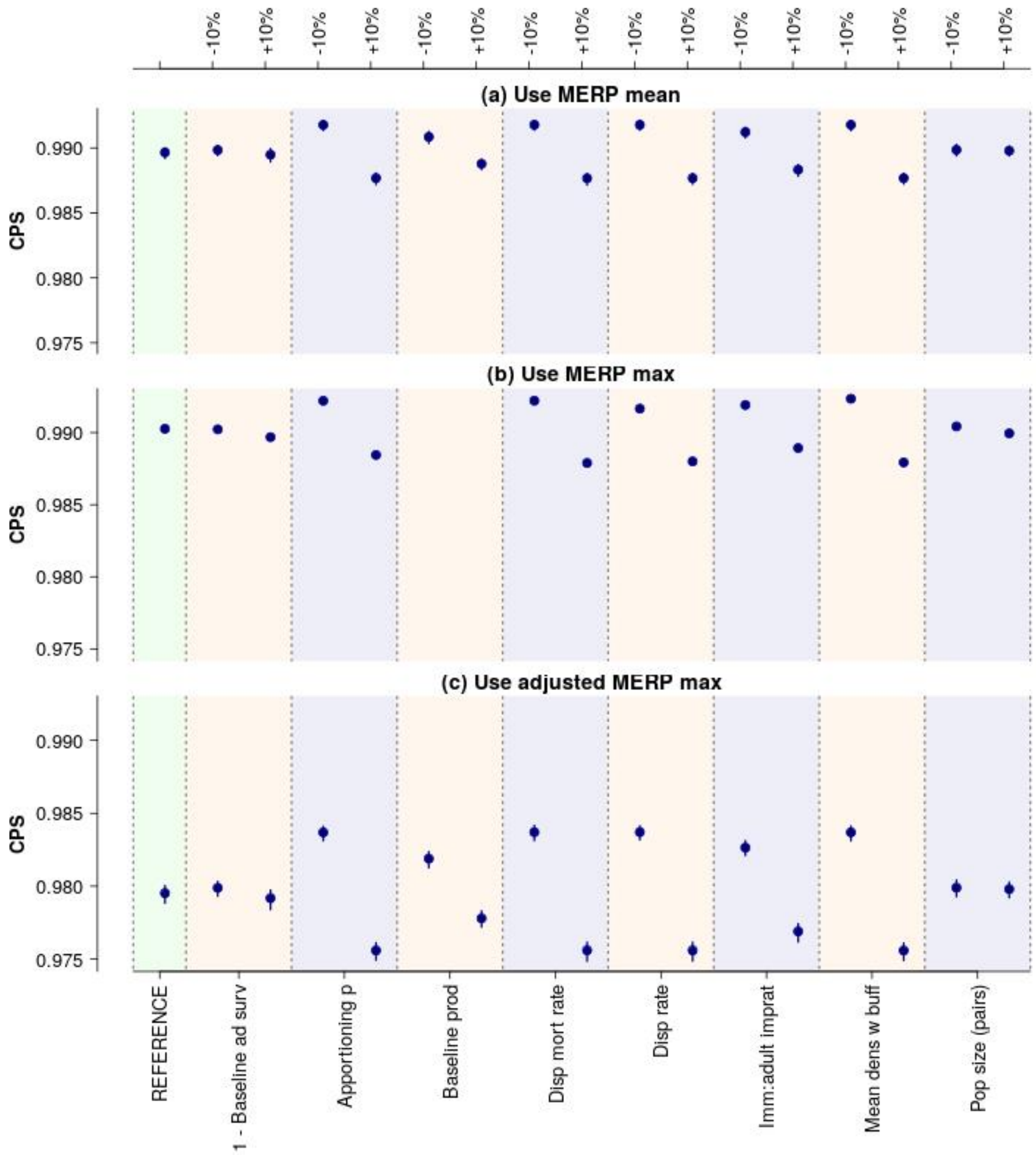

Figure S78: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

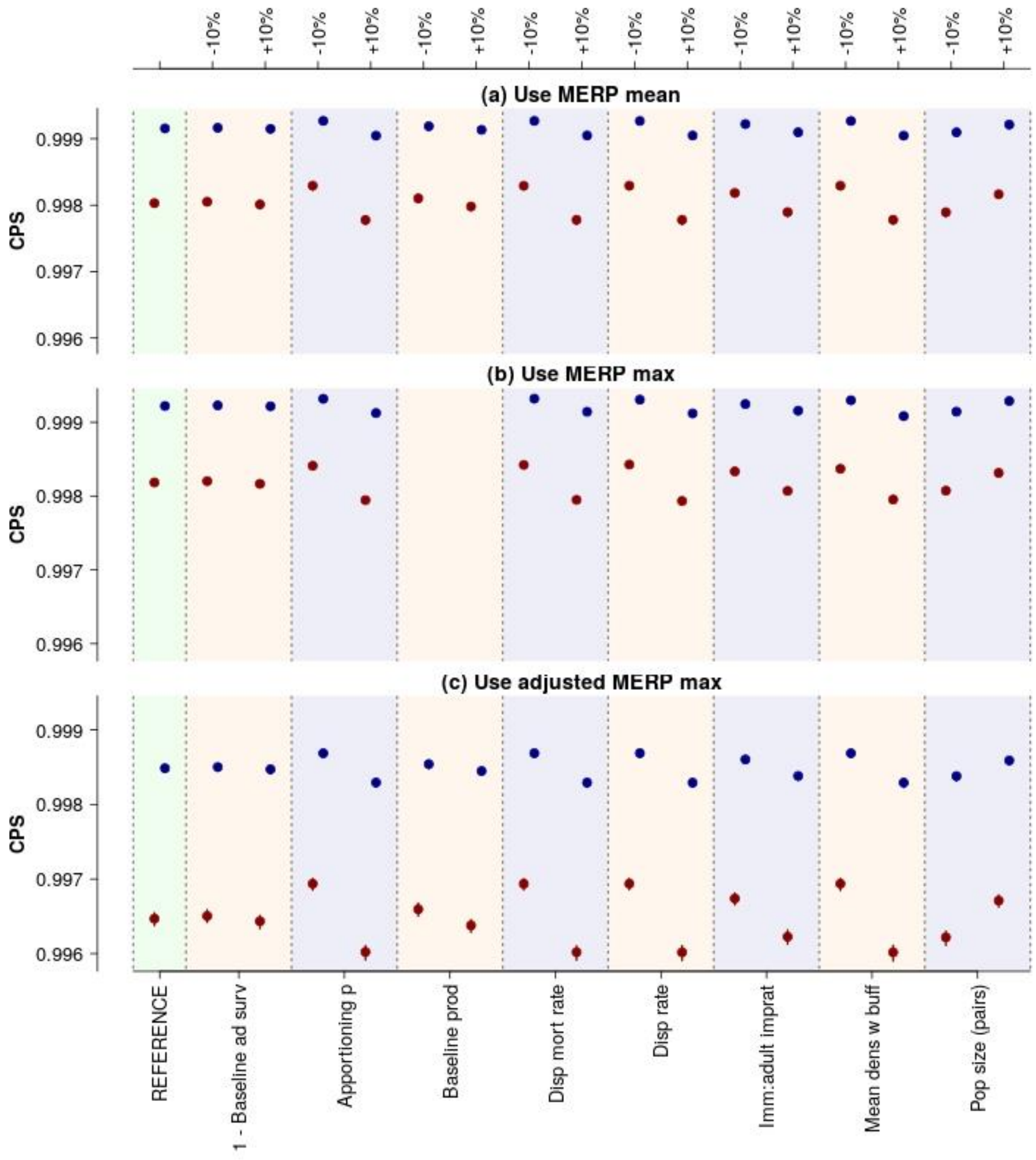

Figure S79: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

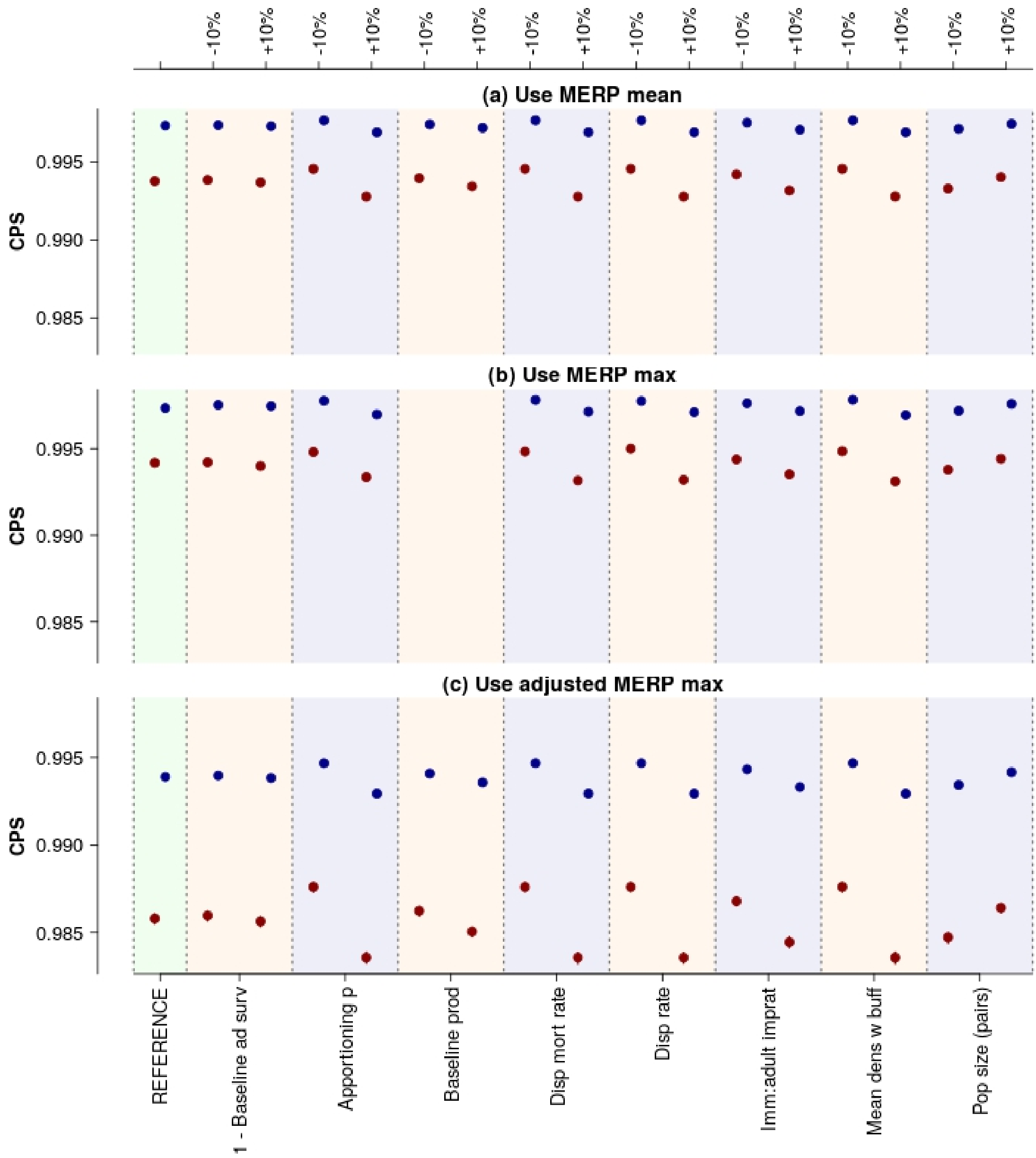

Figure S80: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

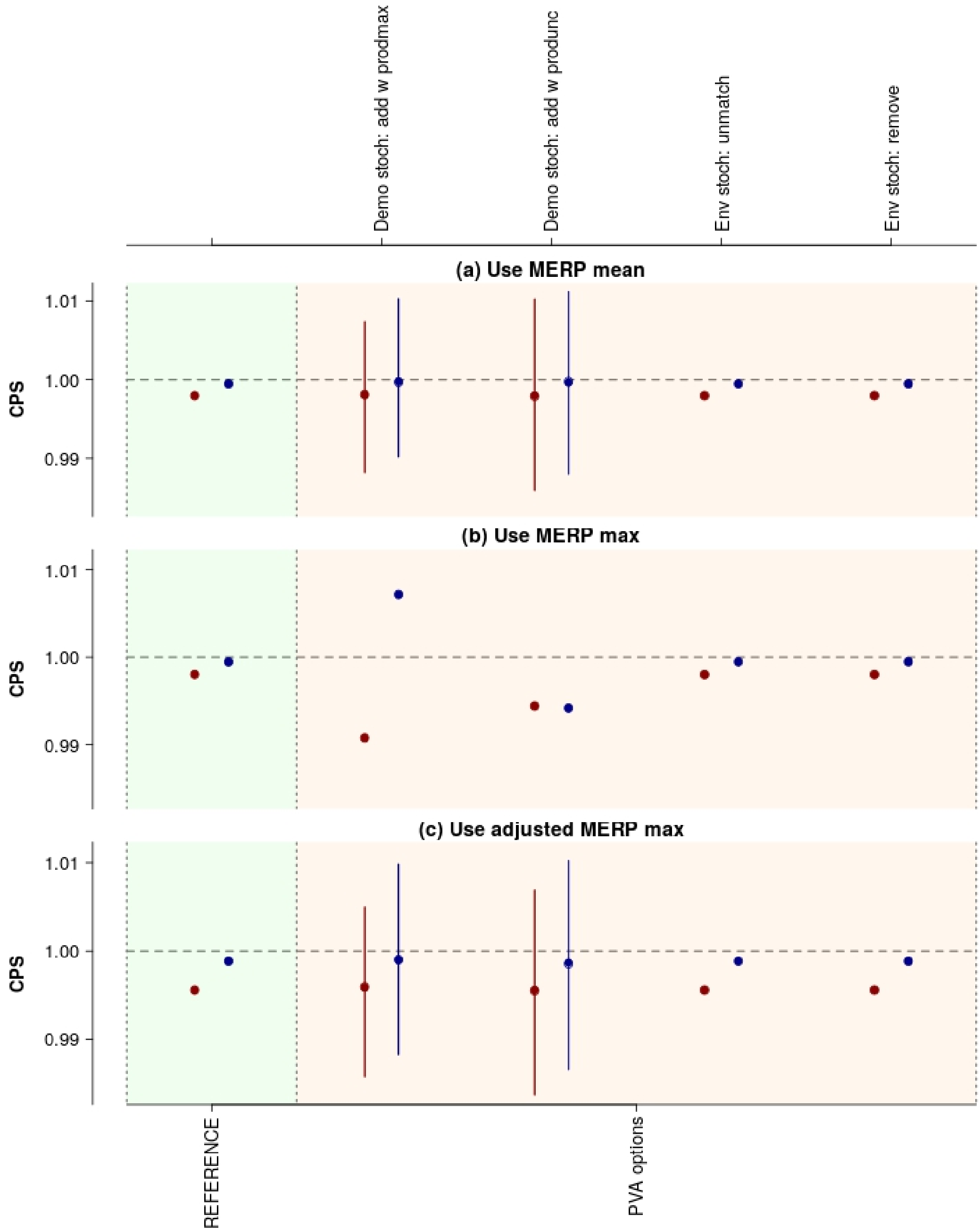

Figure S81: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

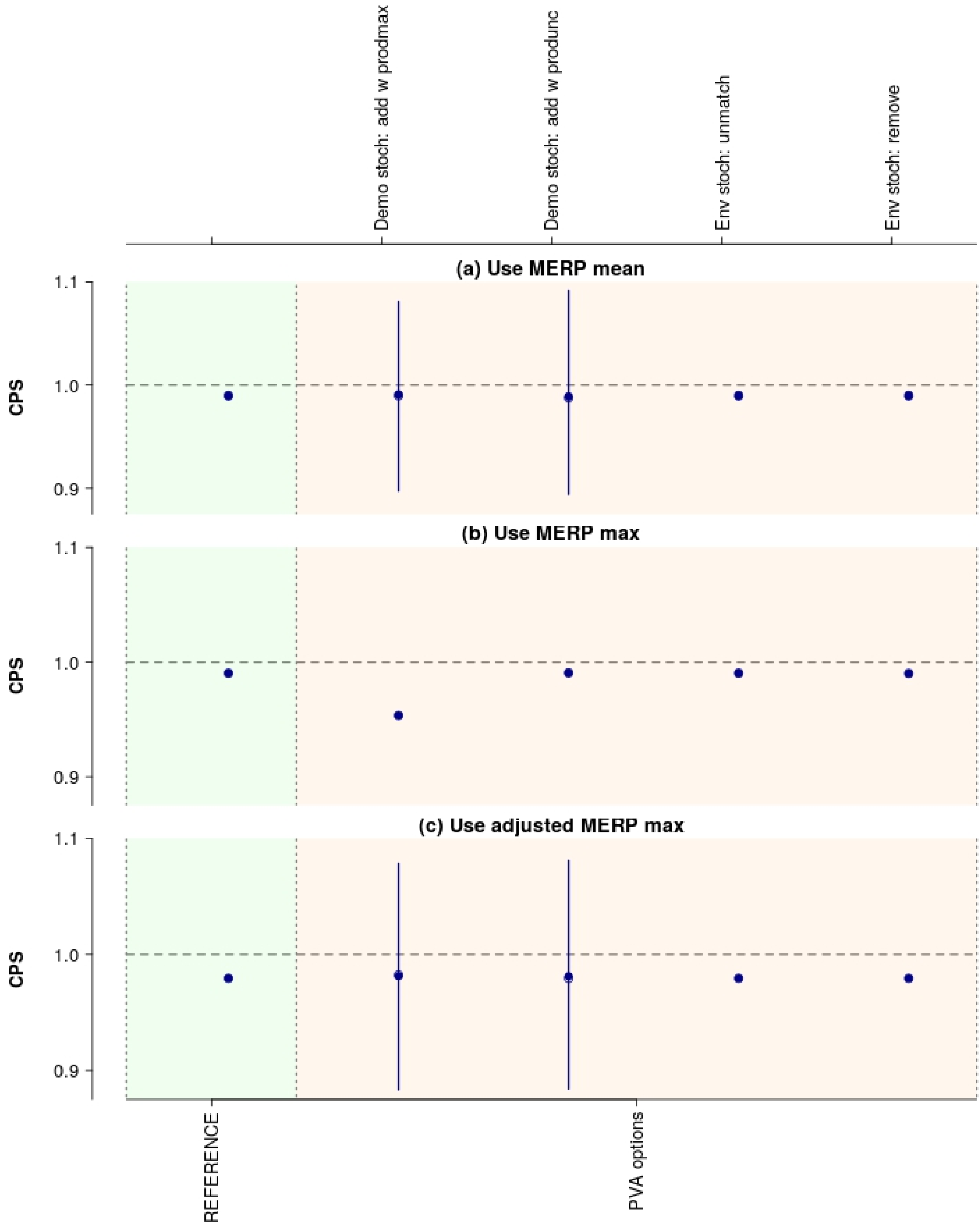

Figure S82: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for black-legged kittiwake after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

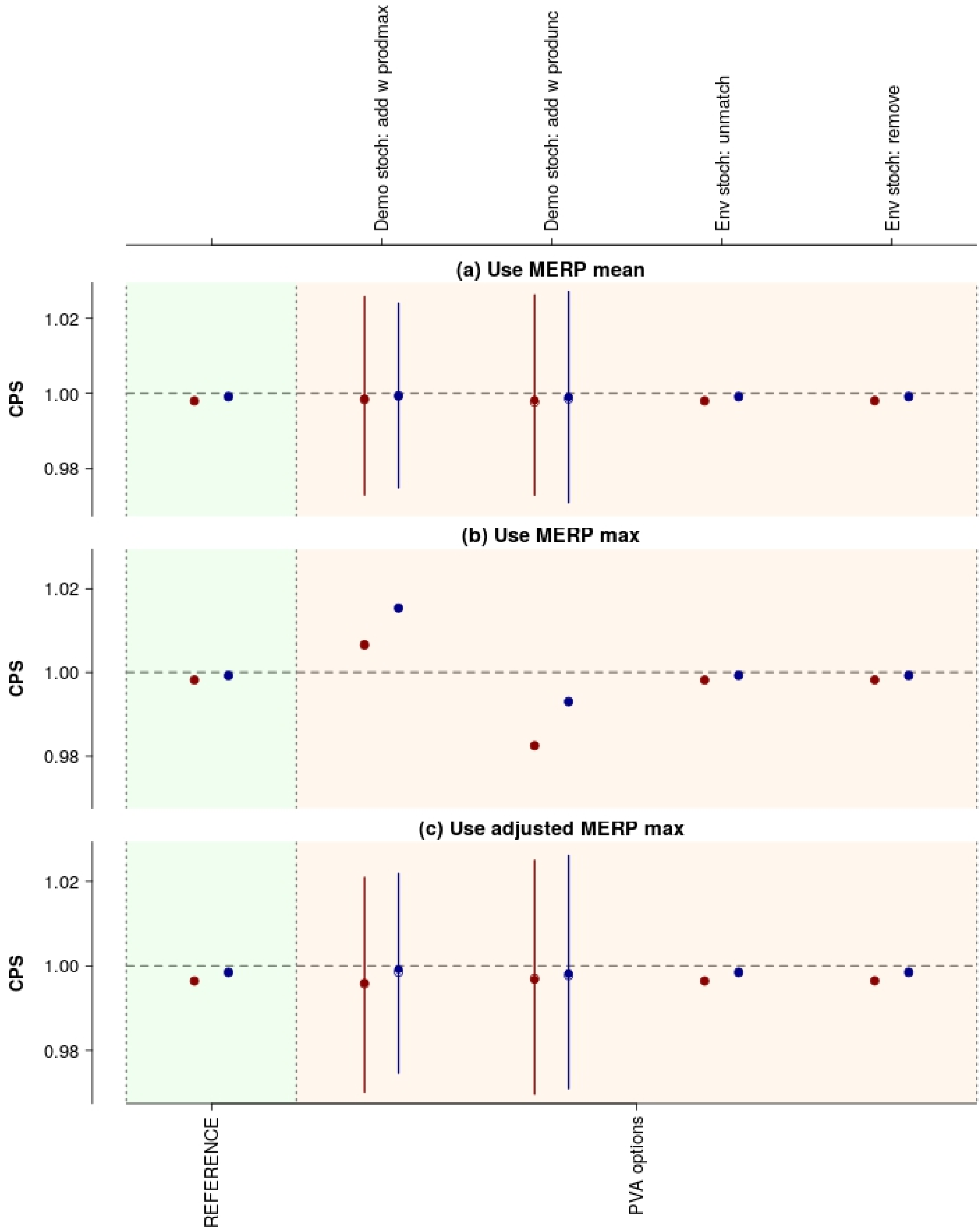

Figure S83: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for Atlantic puffin after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

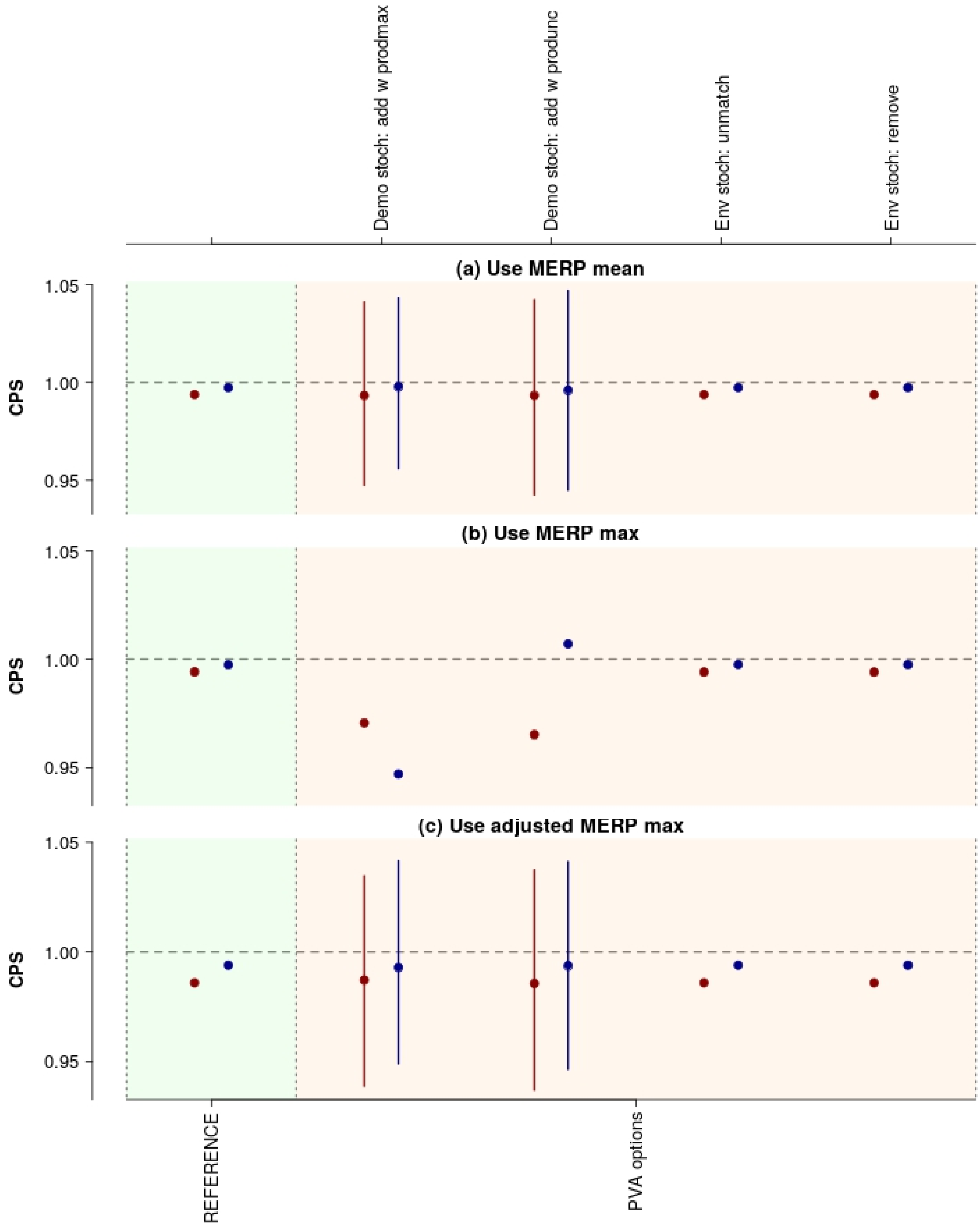

Figure S84: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for razorbill after 30 years of displacement impact simulated via the Displacement Matrix and PVA tool, with all parameters based on reference values for Scotland (red) or England (blue) and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. Displacement Matrix based on upper values for displacement rate and displacement mortality rate, and uses (a) mean MERP density, (b) maximum MERP density or (c) adjusted maximum MERP density.

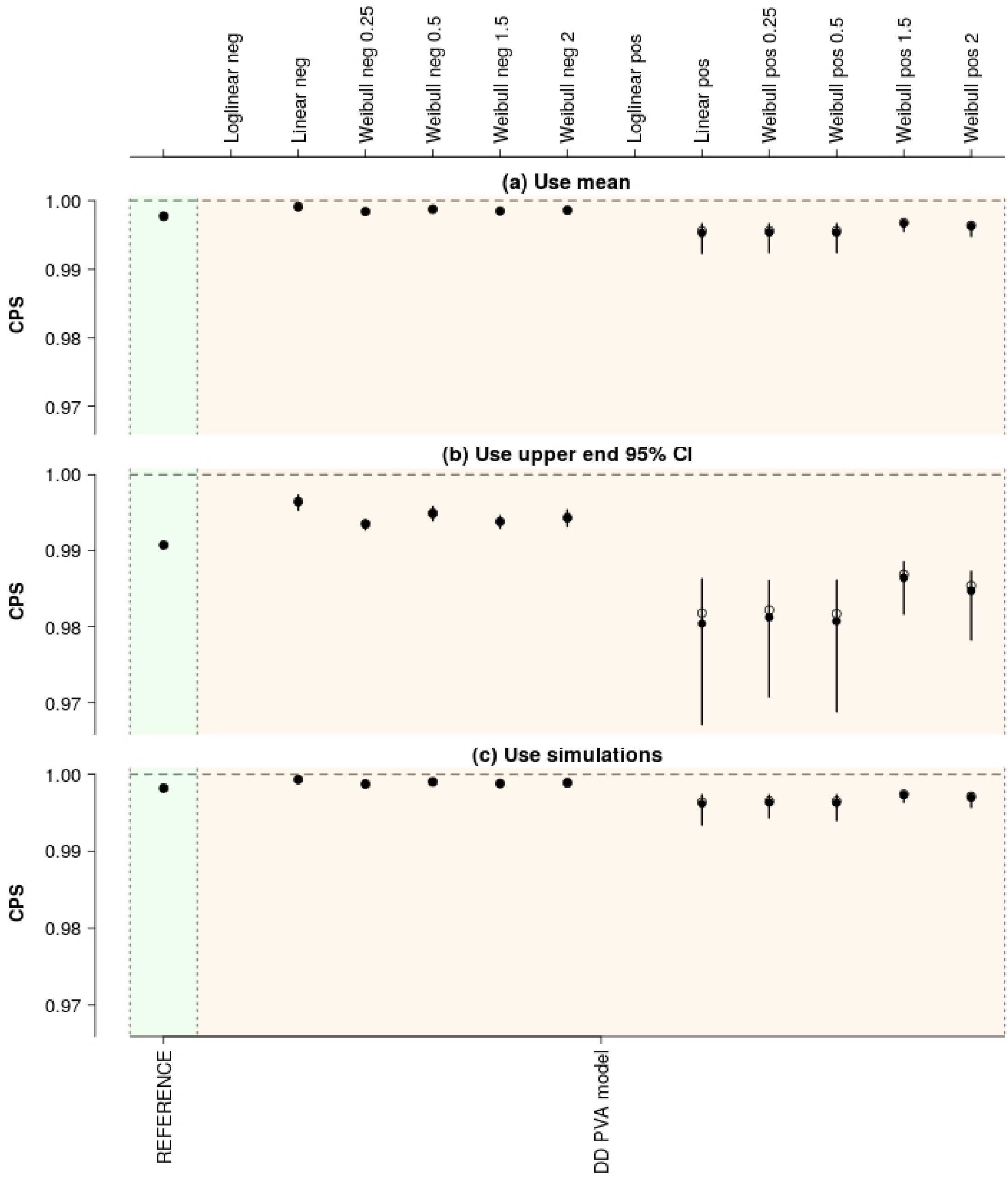

Figure S85: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern fulmar after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

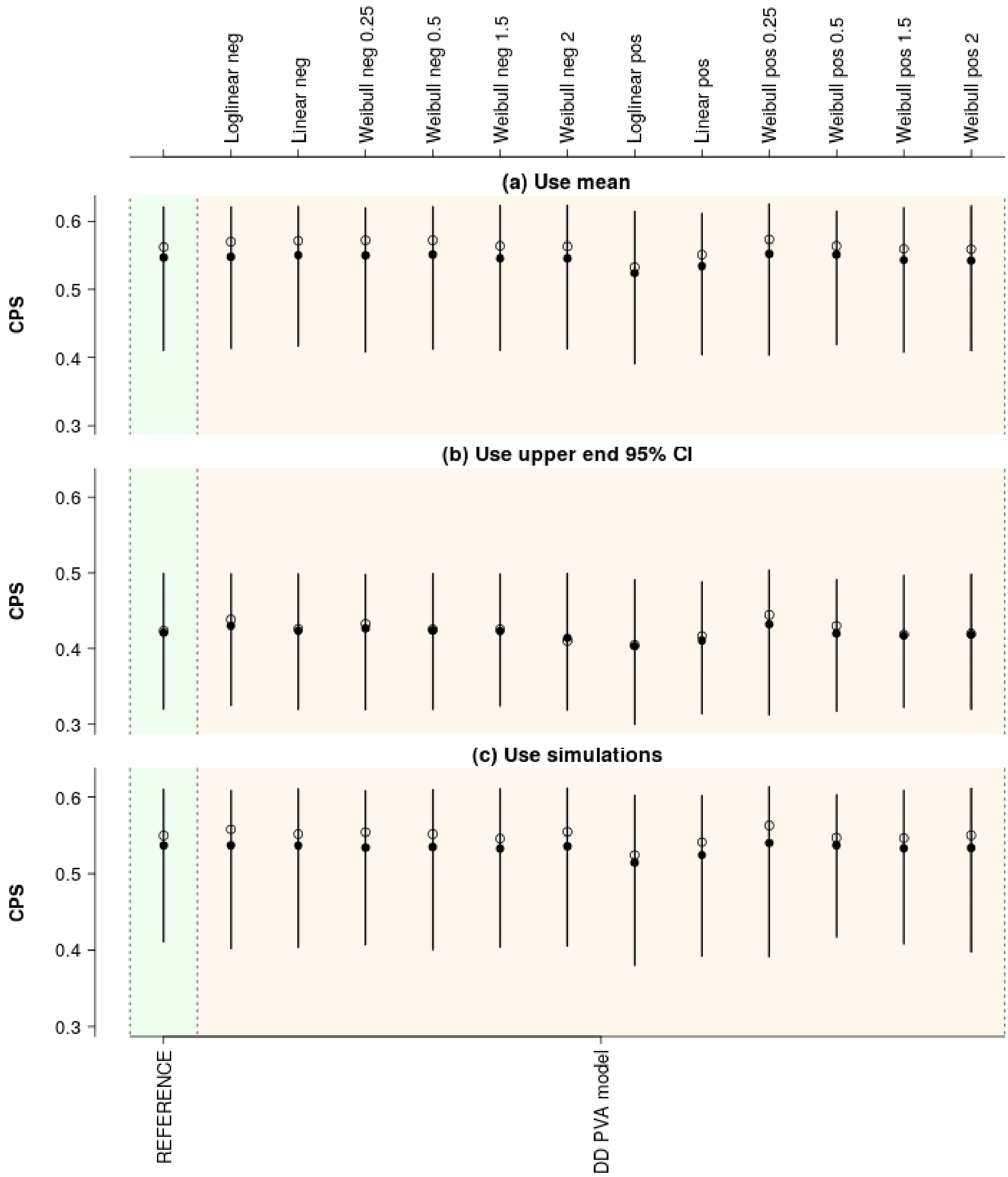

Figure S86: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for great black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

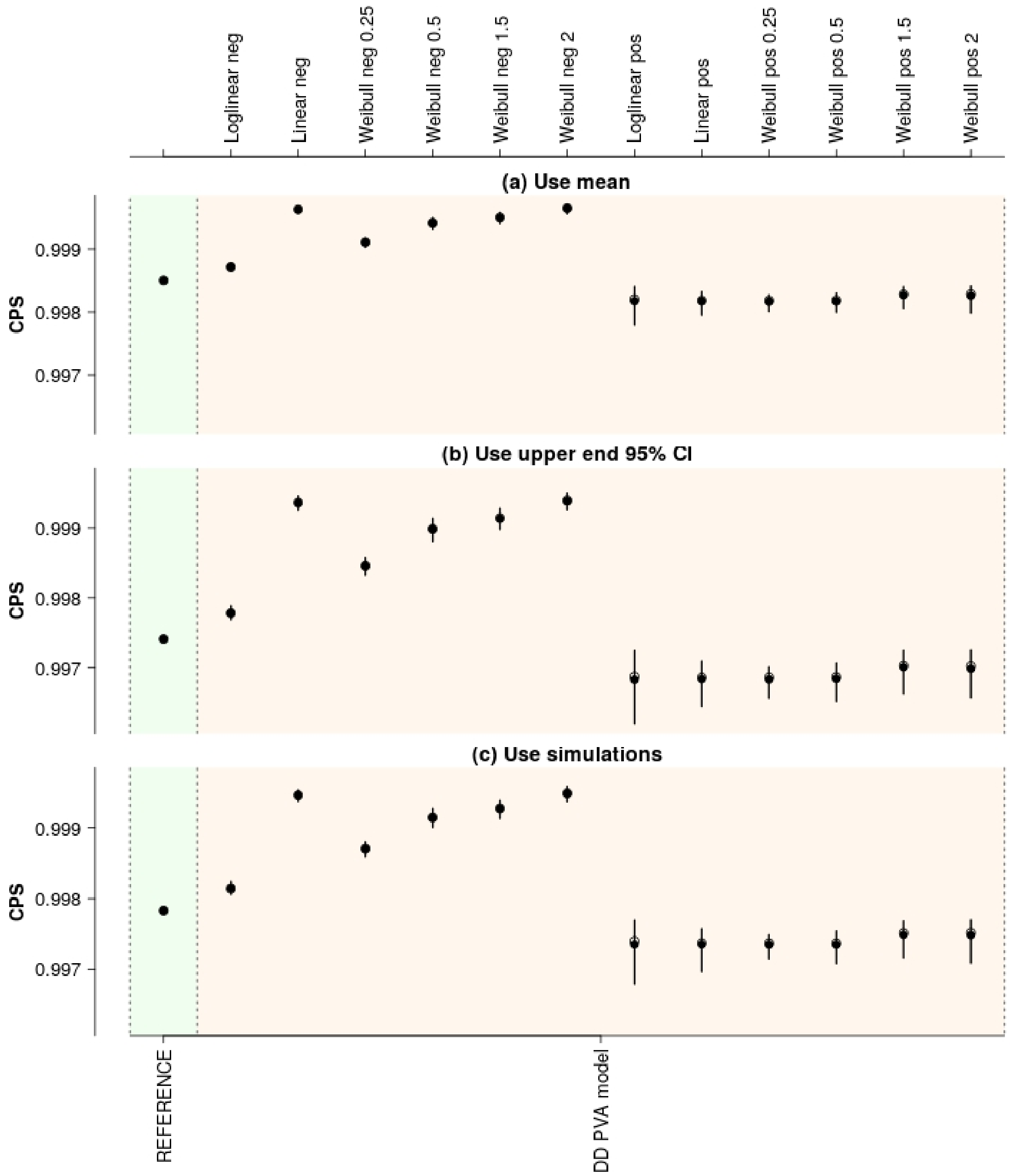

Figure S87: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

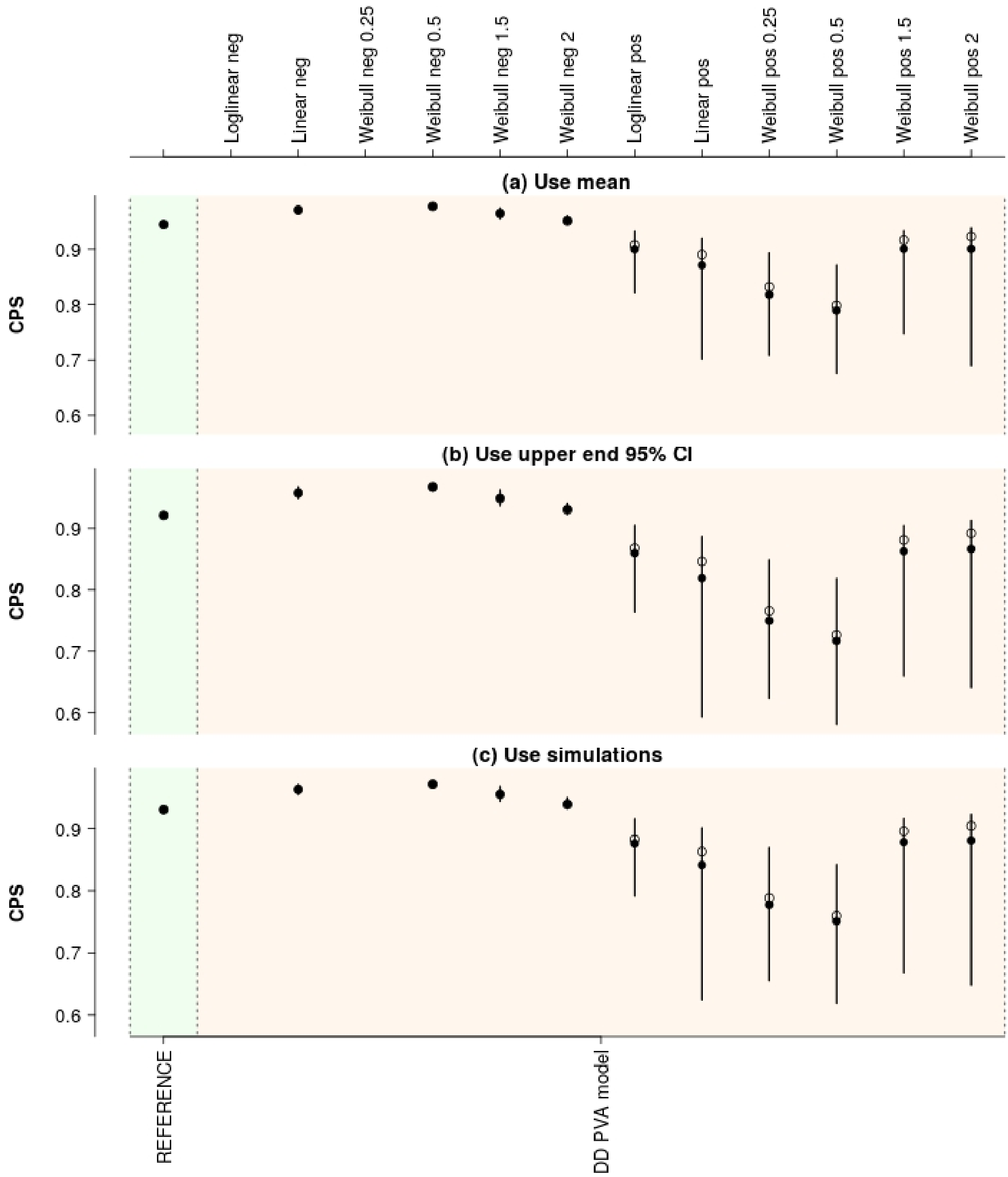

Figure S88: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for herring gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

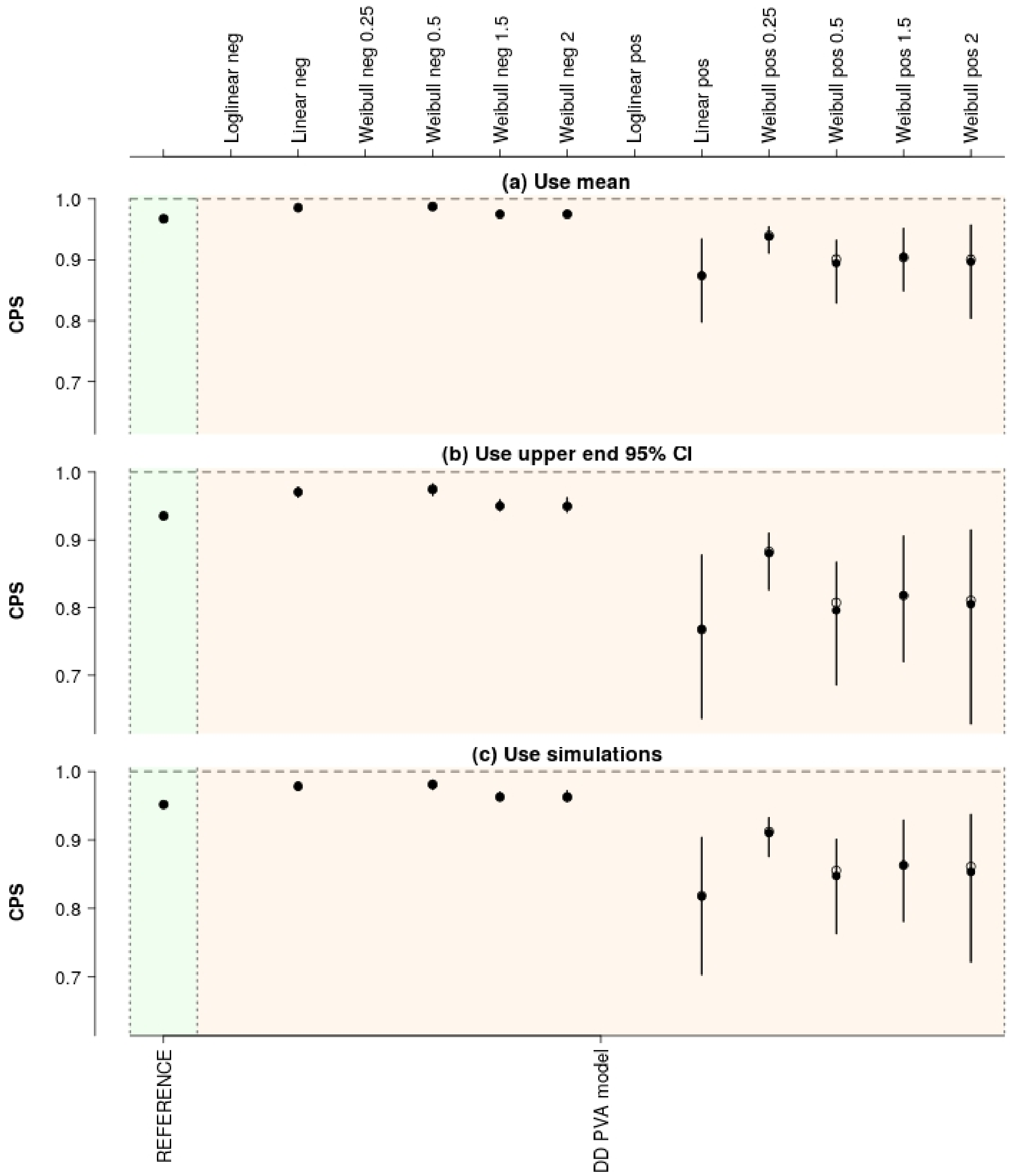

Figure S89: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for lesser black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

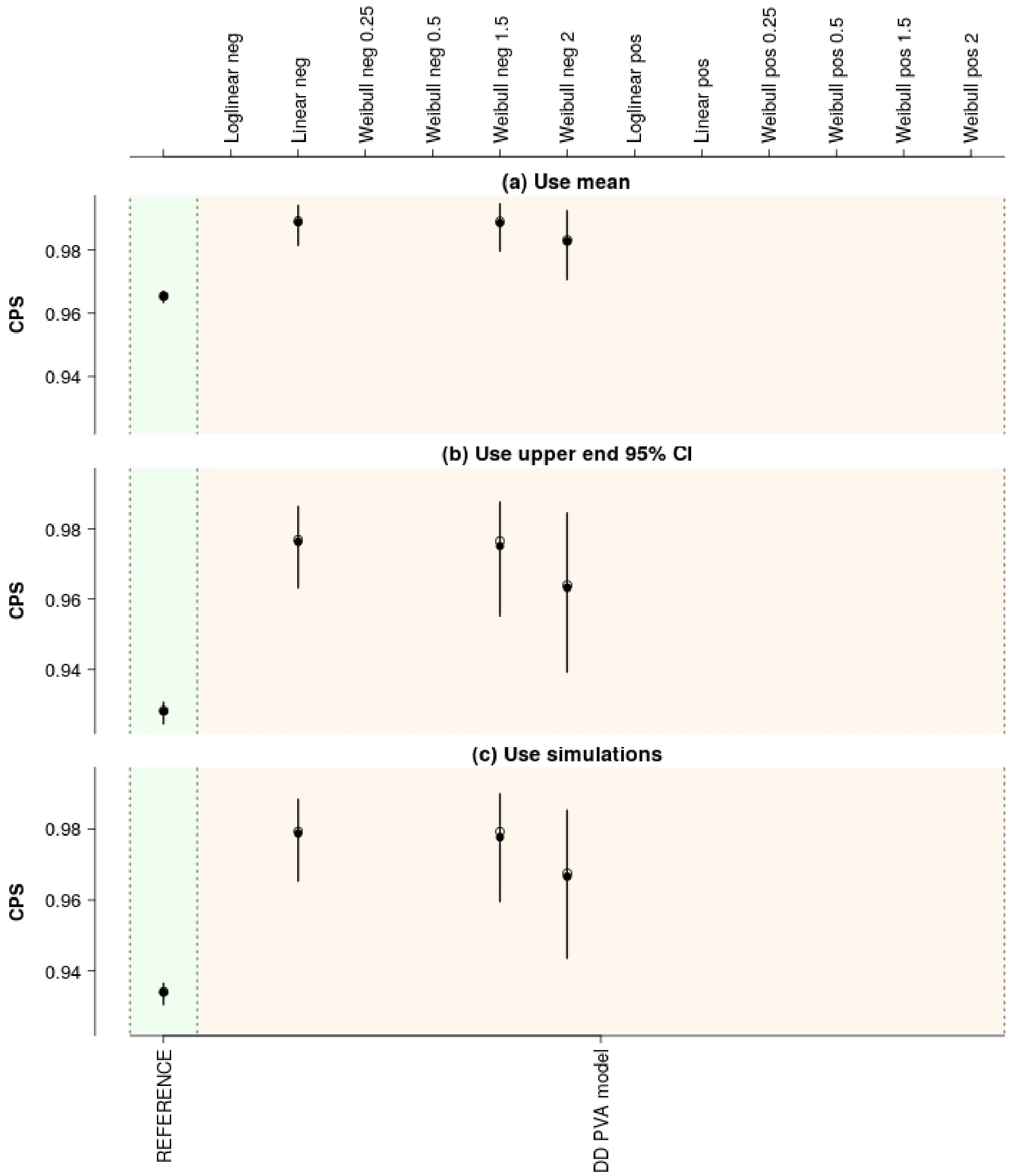

Figure S90: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for sandwich tern after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to include a range of models for negative (neg) or positive (pos) density dependence: linear, log-linear, Weibull (with shape parameter 0.25, 0.5, 1 or 2). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

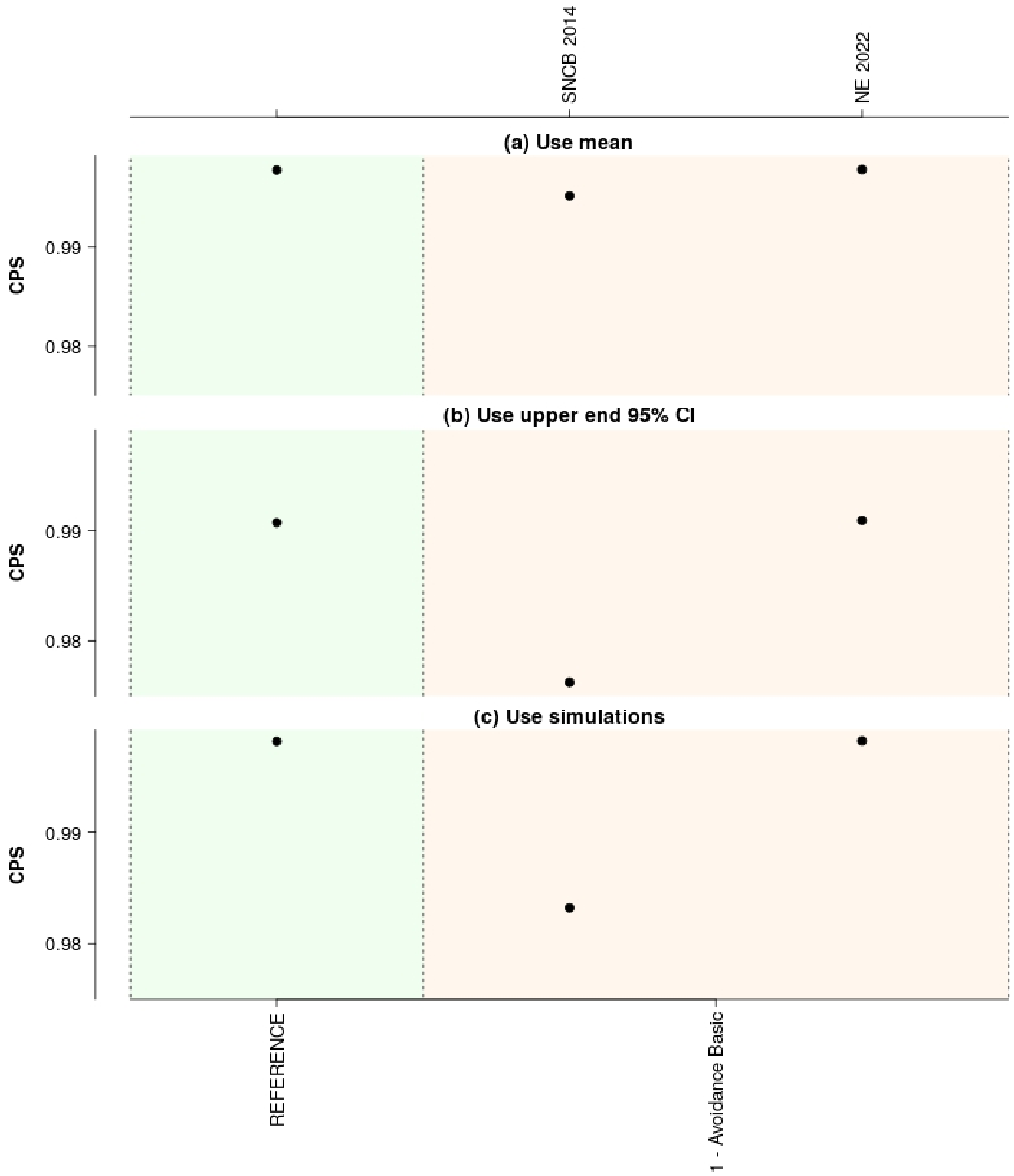

Figure S91: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern fulmar after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

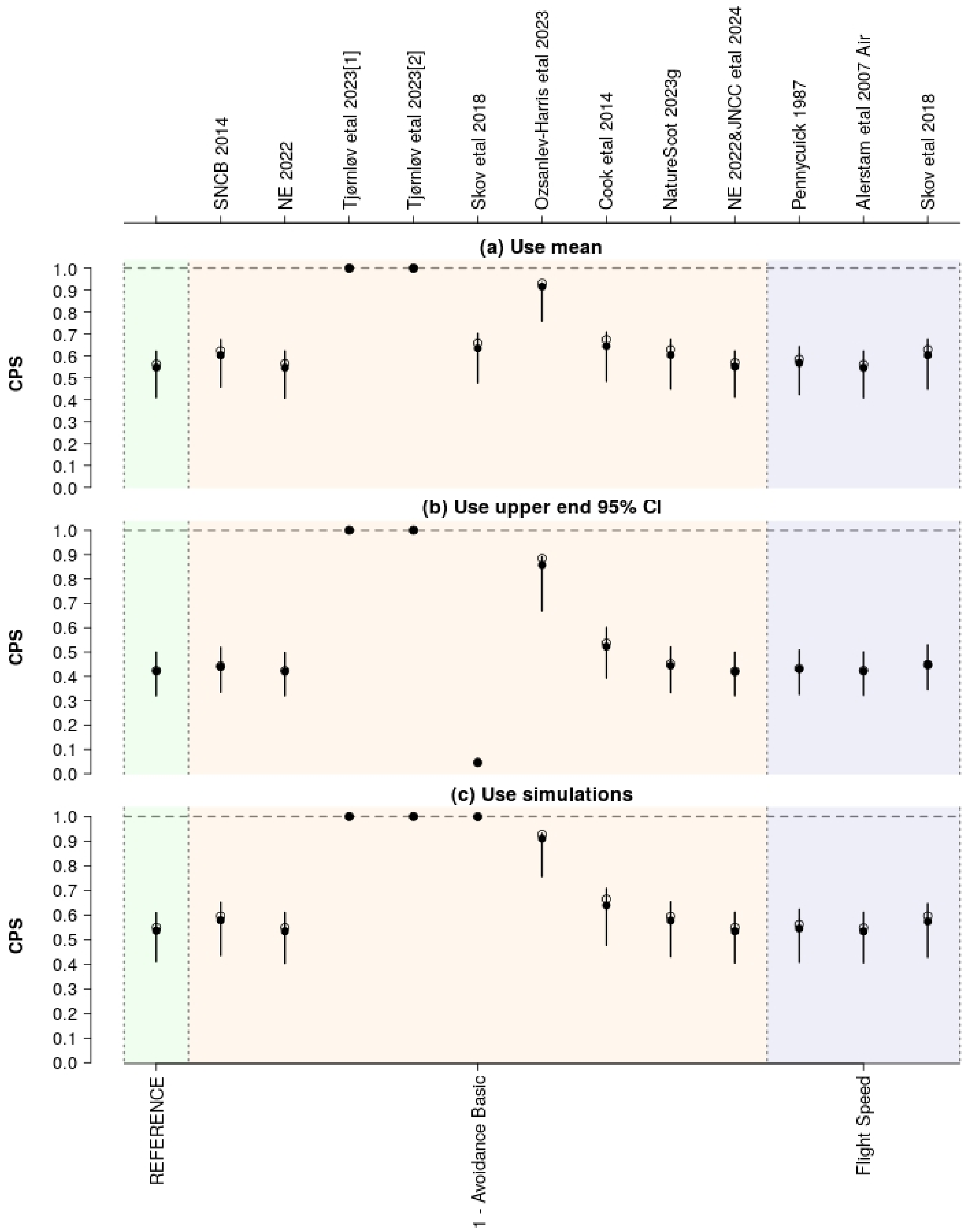

Figure S92: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for great black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

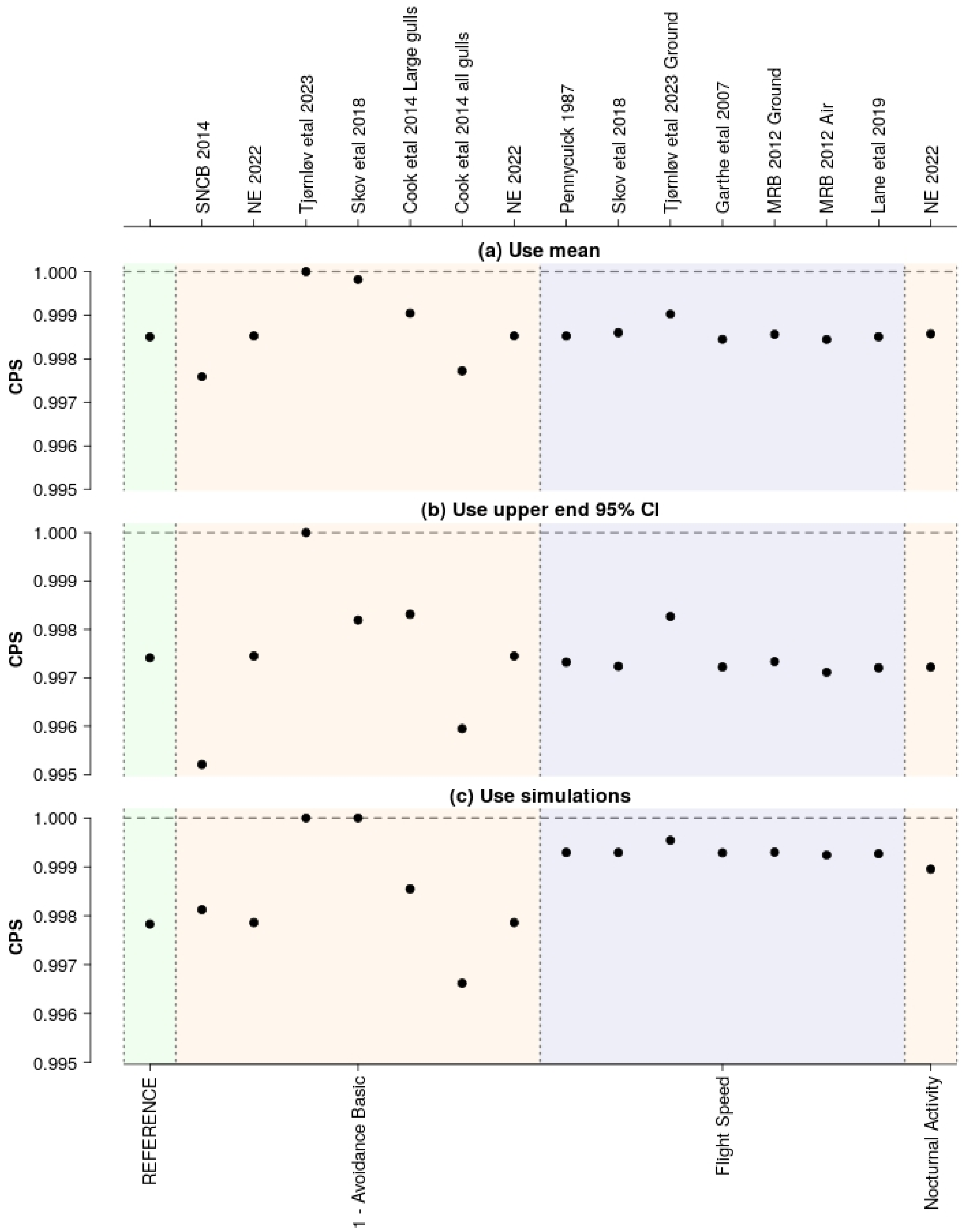

Figure S93: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

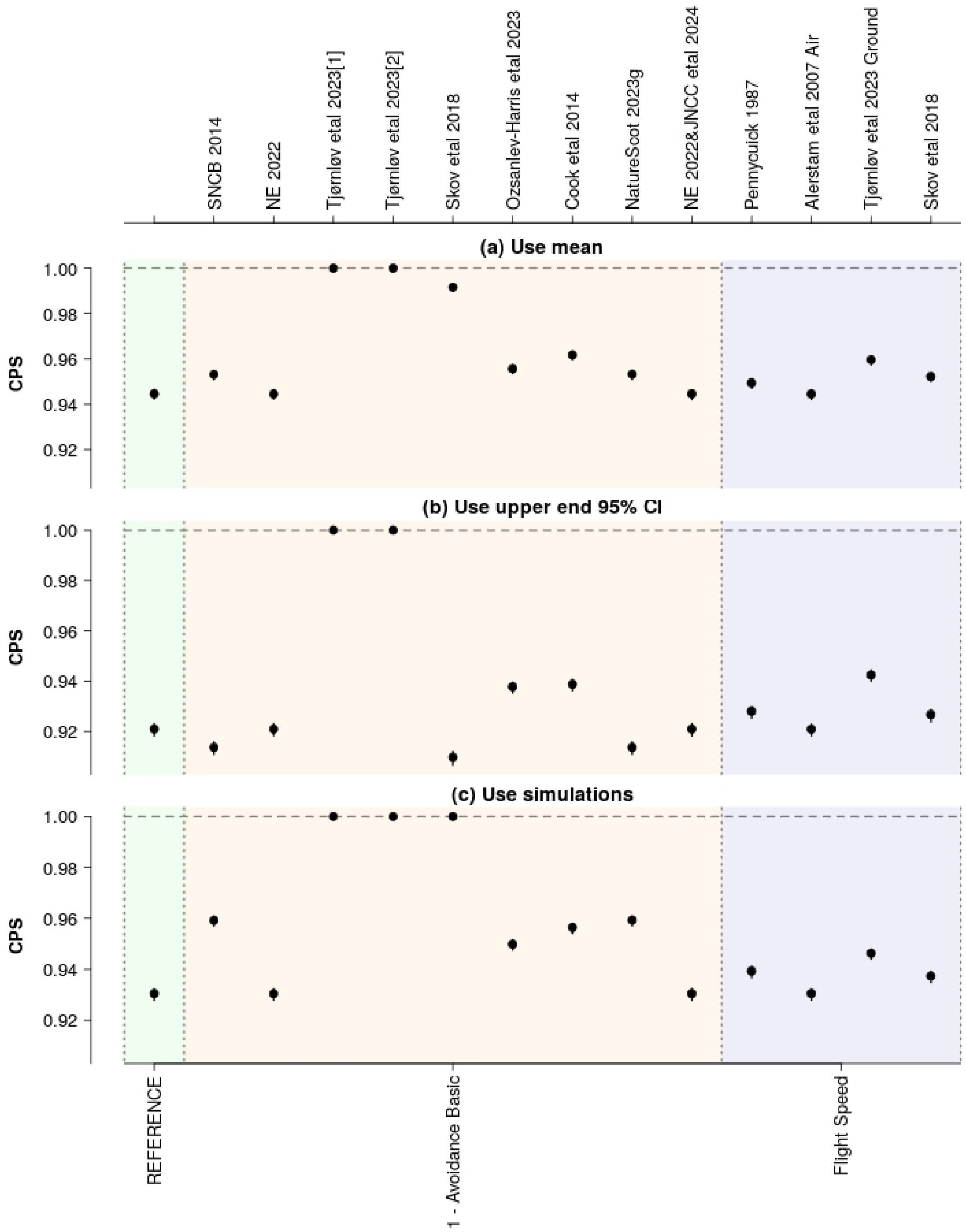

Figure S94: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for herring gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

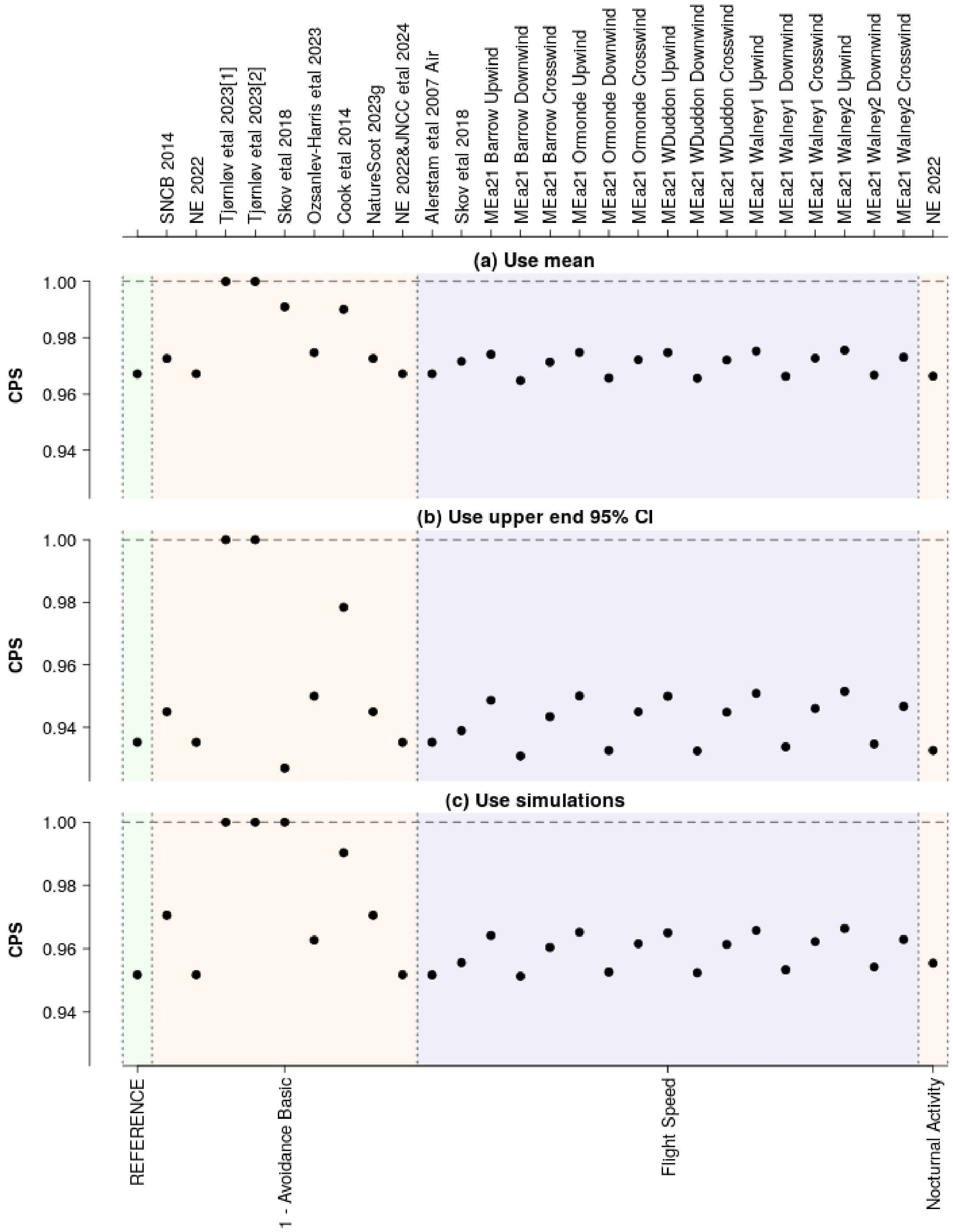

Figure S95: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for lesser black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

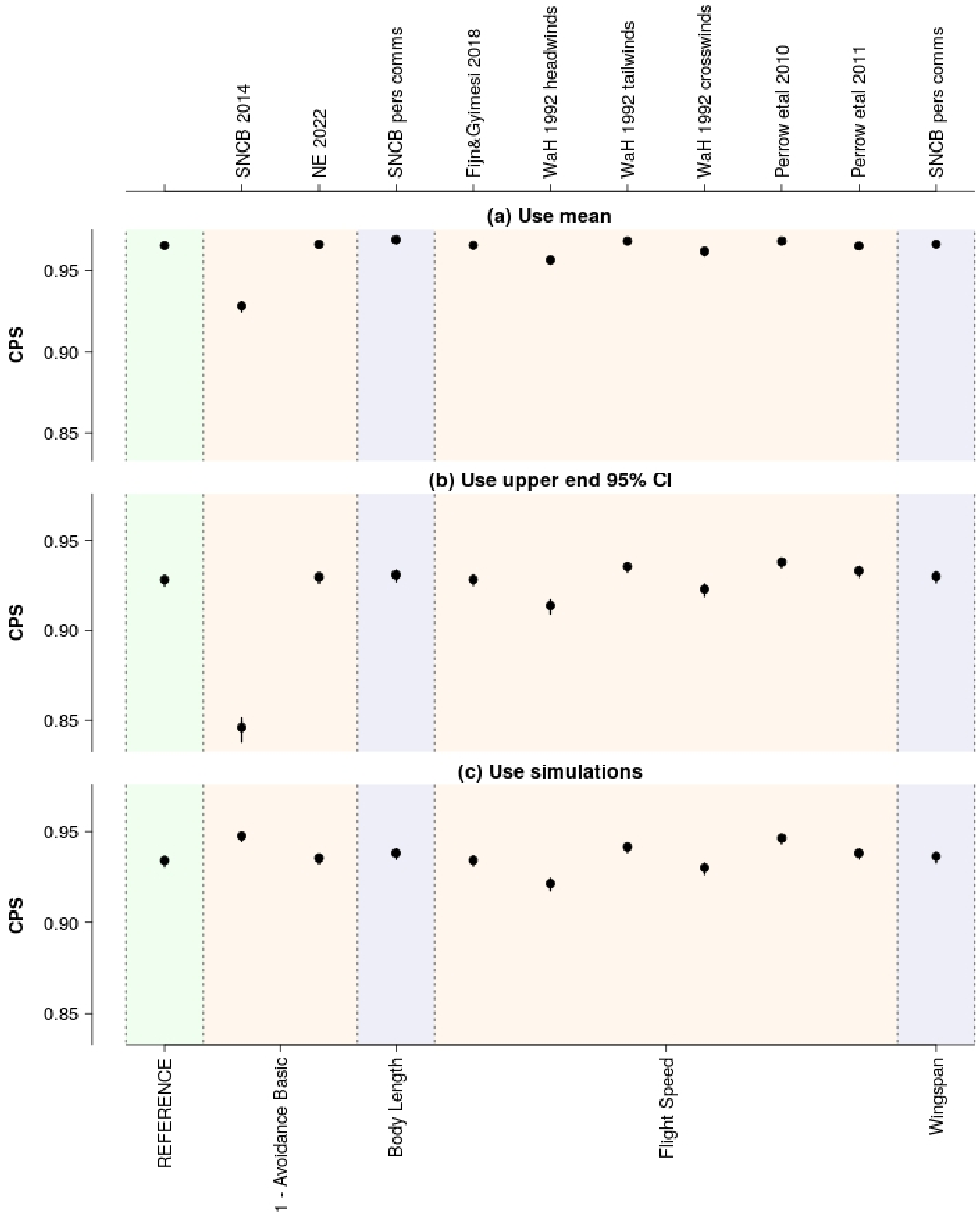

Figure S96: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for sandwich tern after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative data sources from the review in Task 1.2 (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

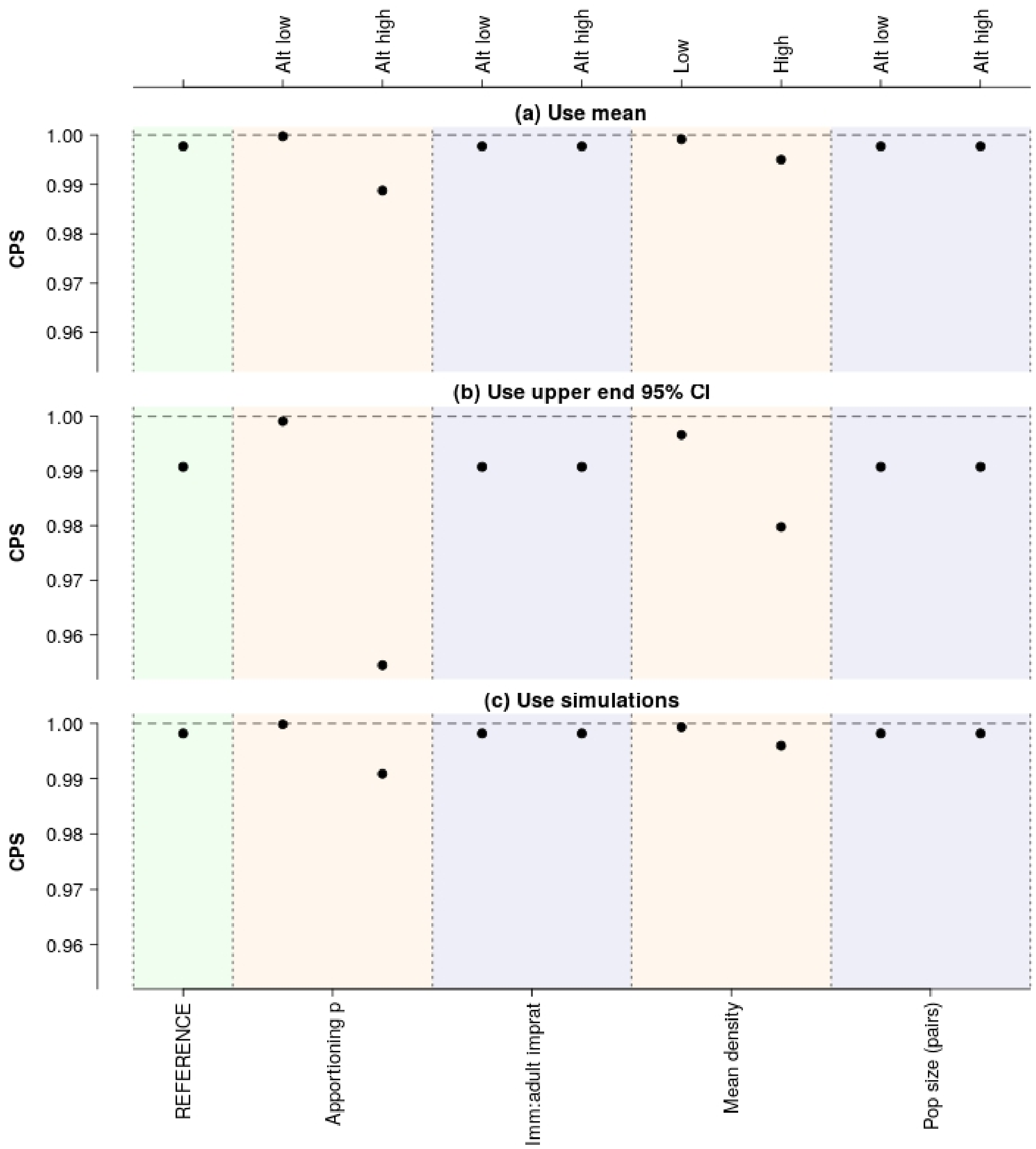

Figure S97: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern fulmar after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

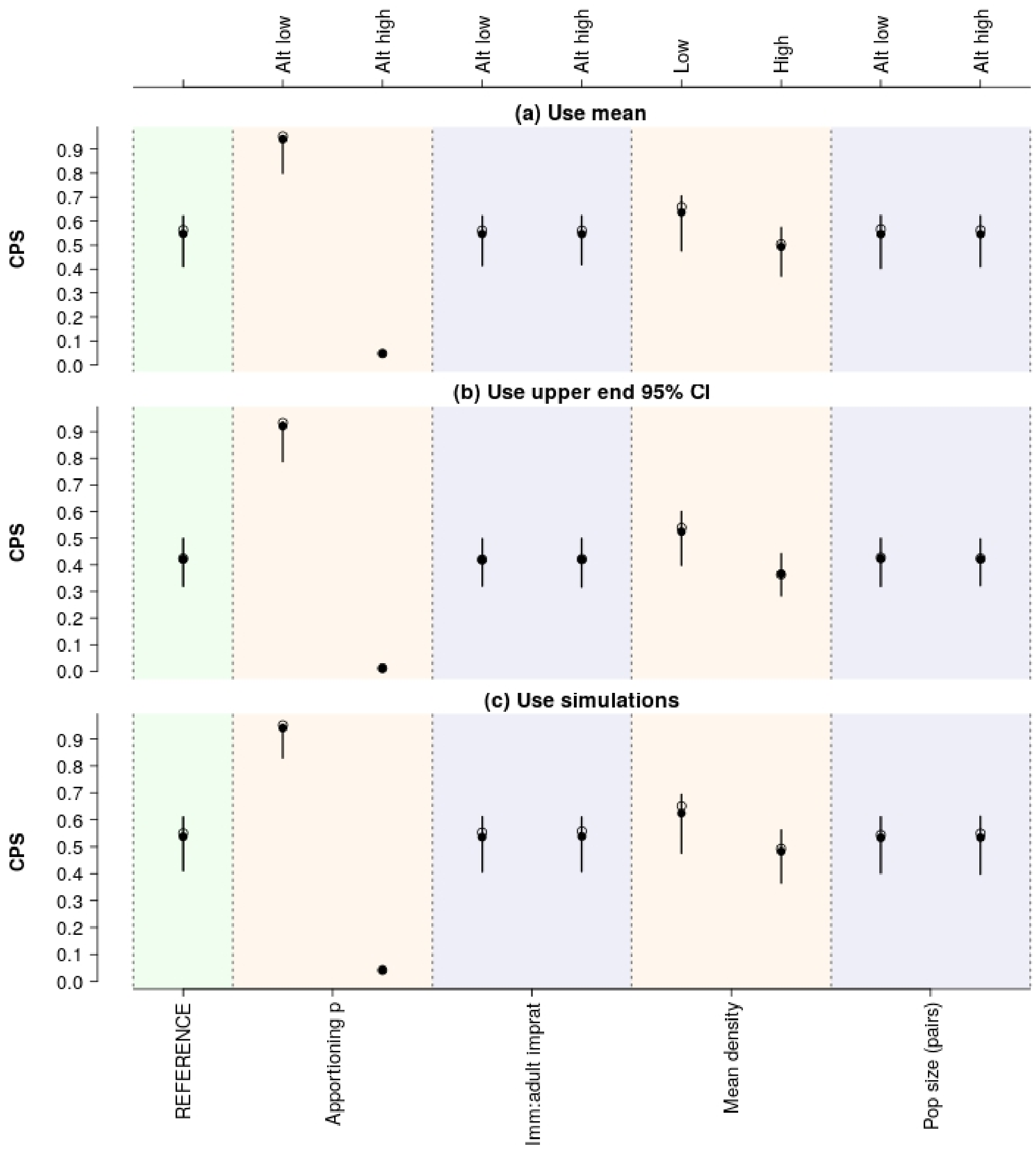

Figure S98: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for great black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

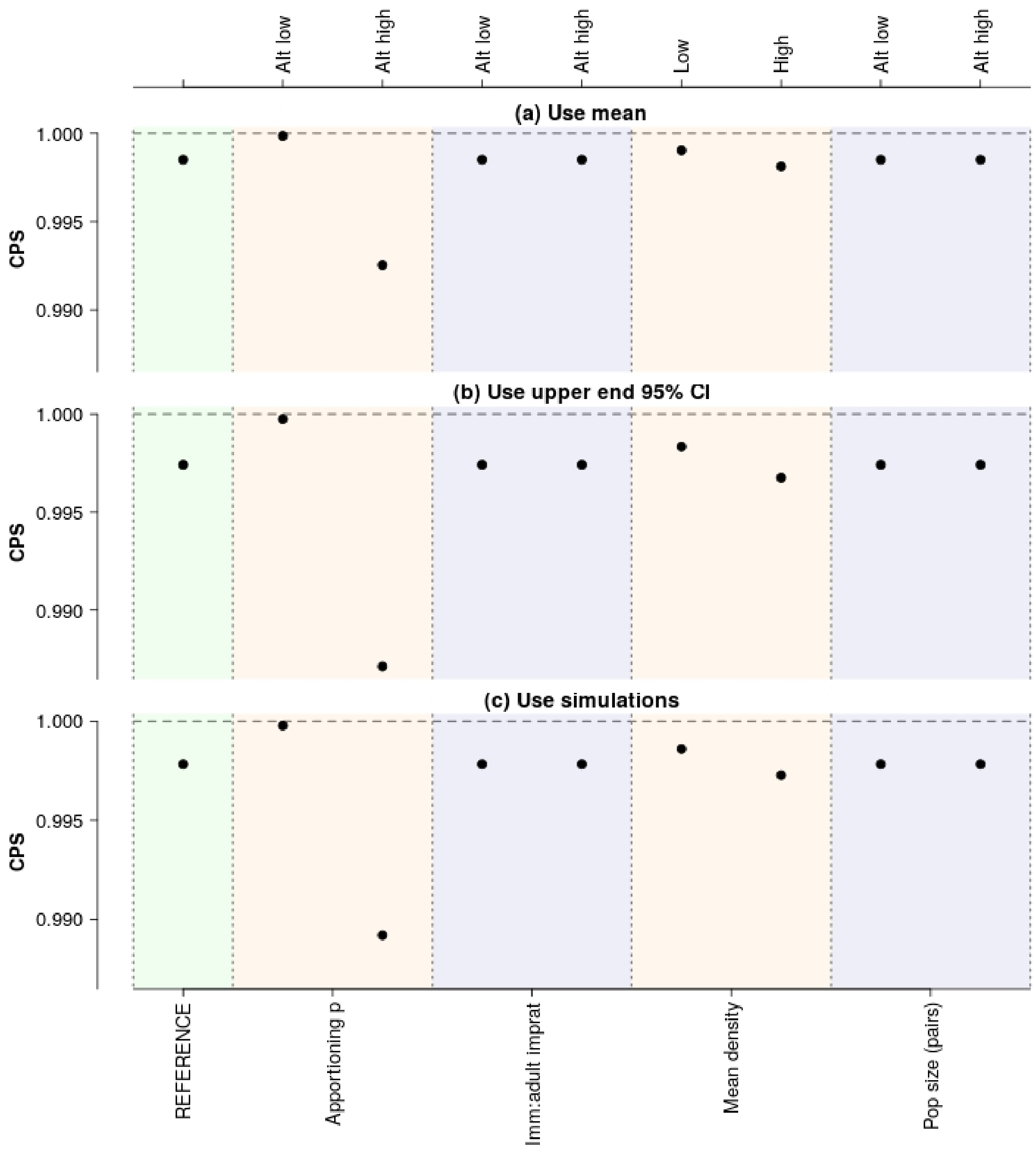

Figure S99: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

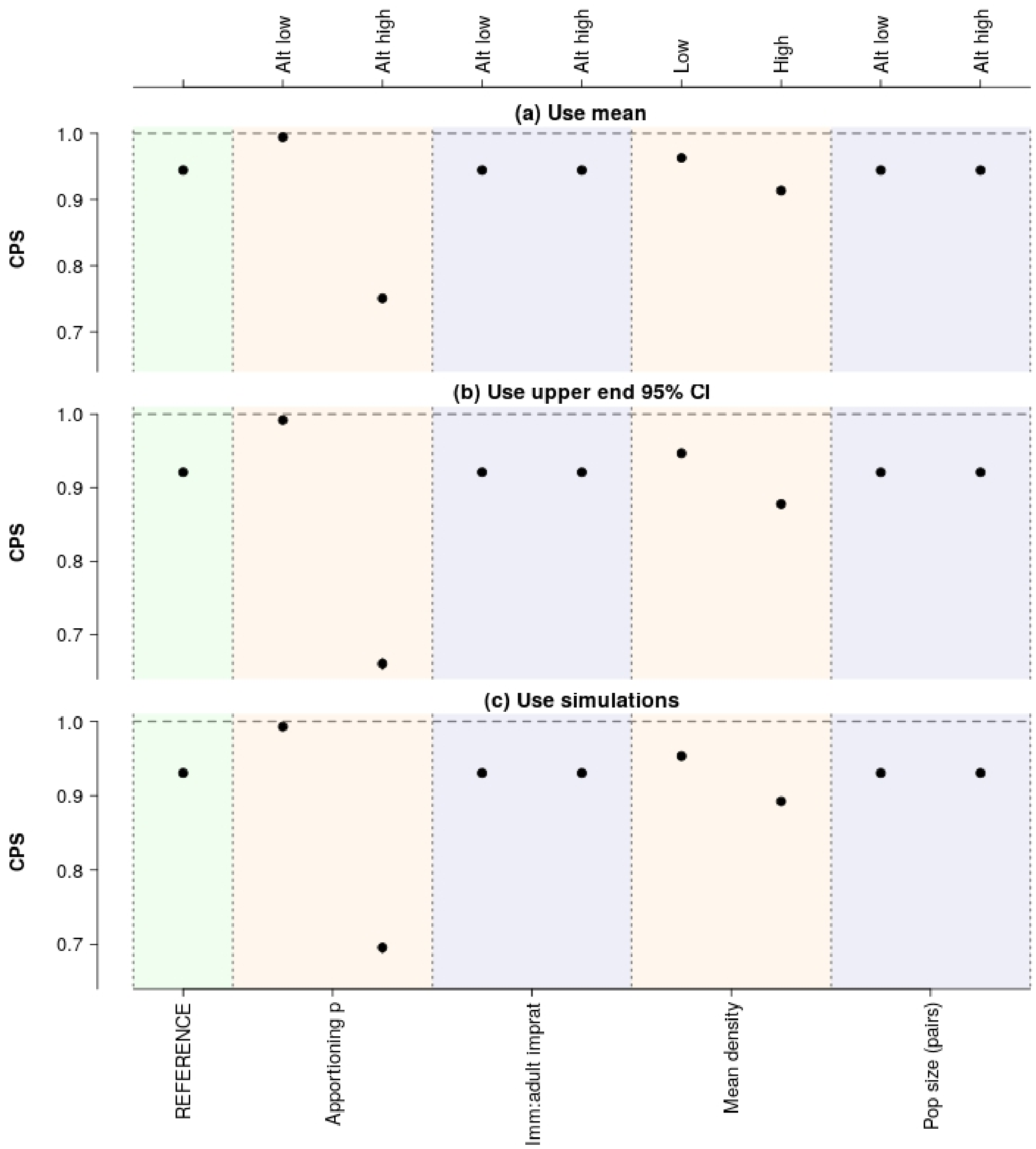

Figure S100: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for herring gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

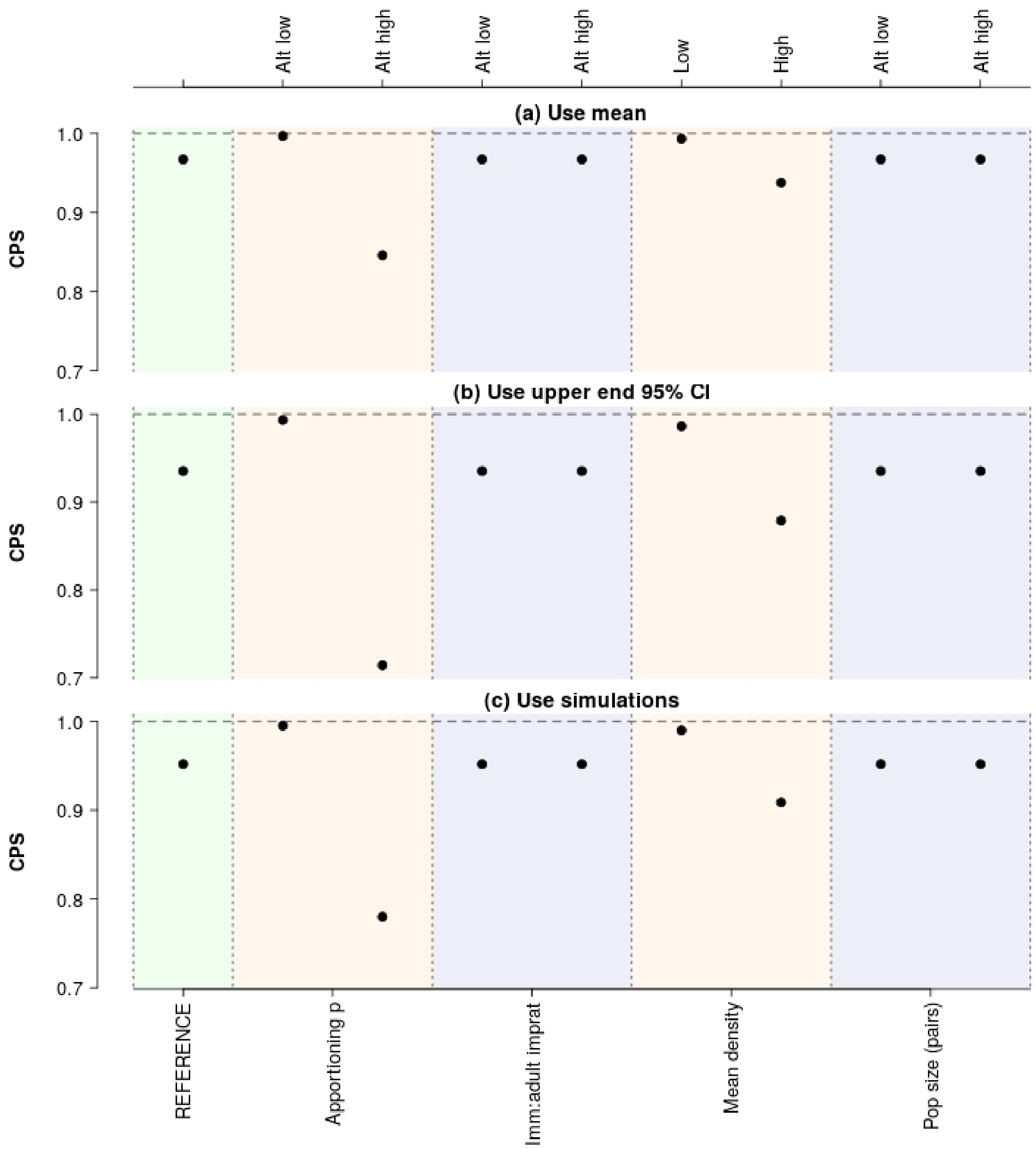

Figure S101: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for lesser black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

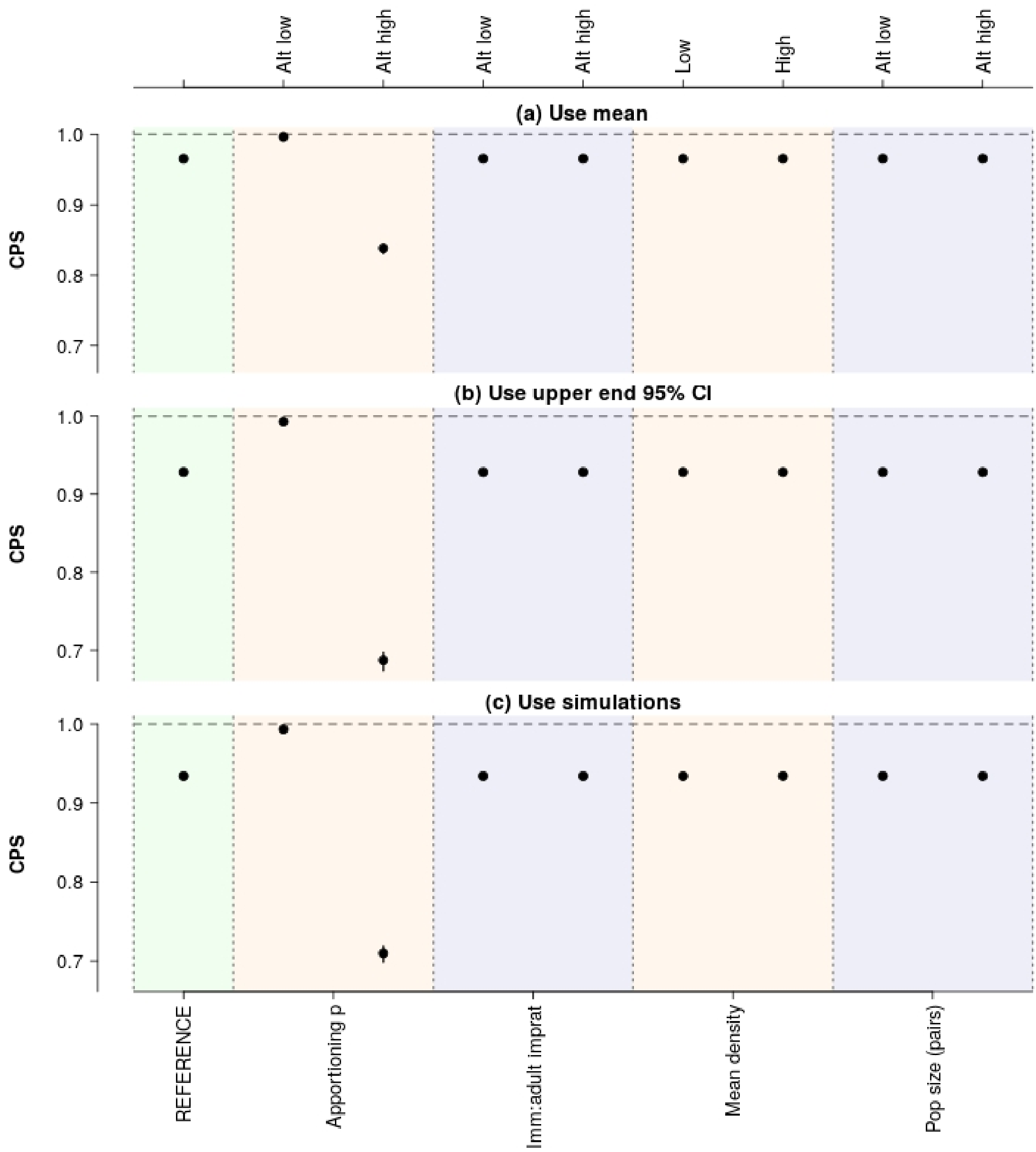

Figure S102: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for sandwich tern after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified to use alternative scenarios (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

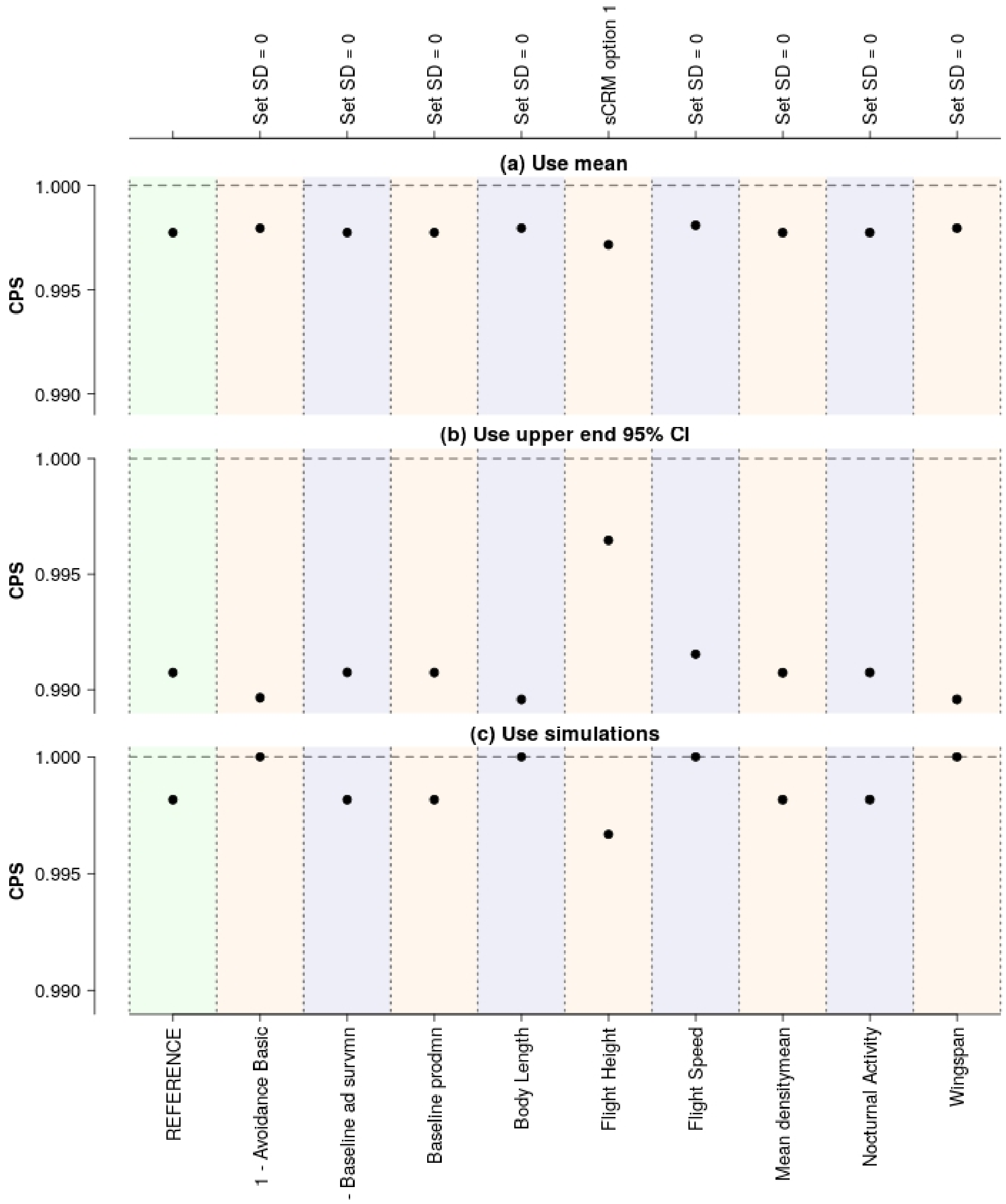

Figure S103: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern fulmar after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

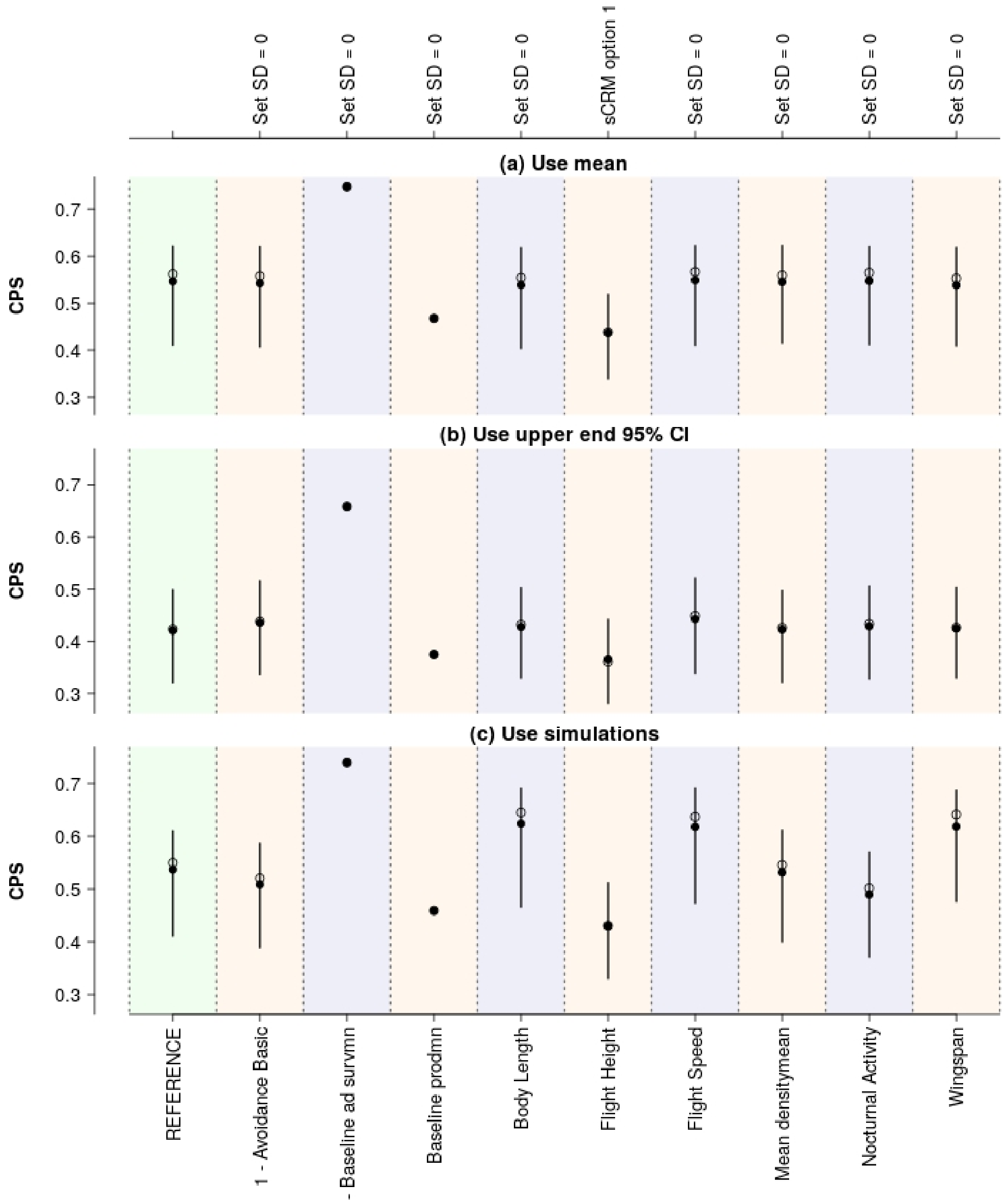

Figure S104: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for great black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

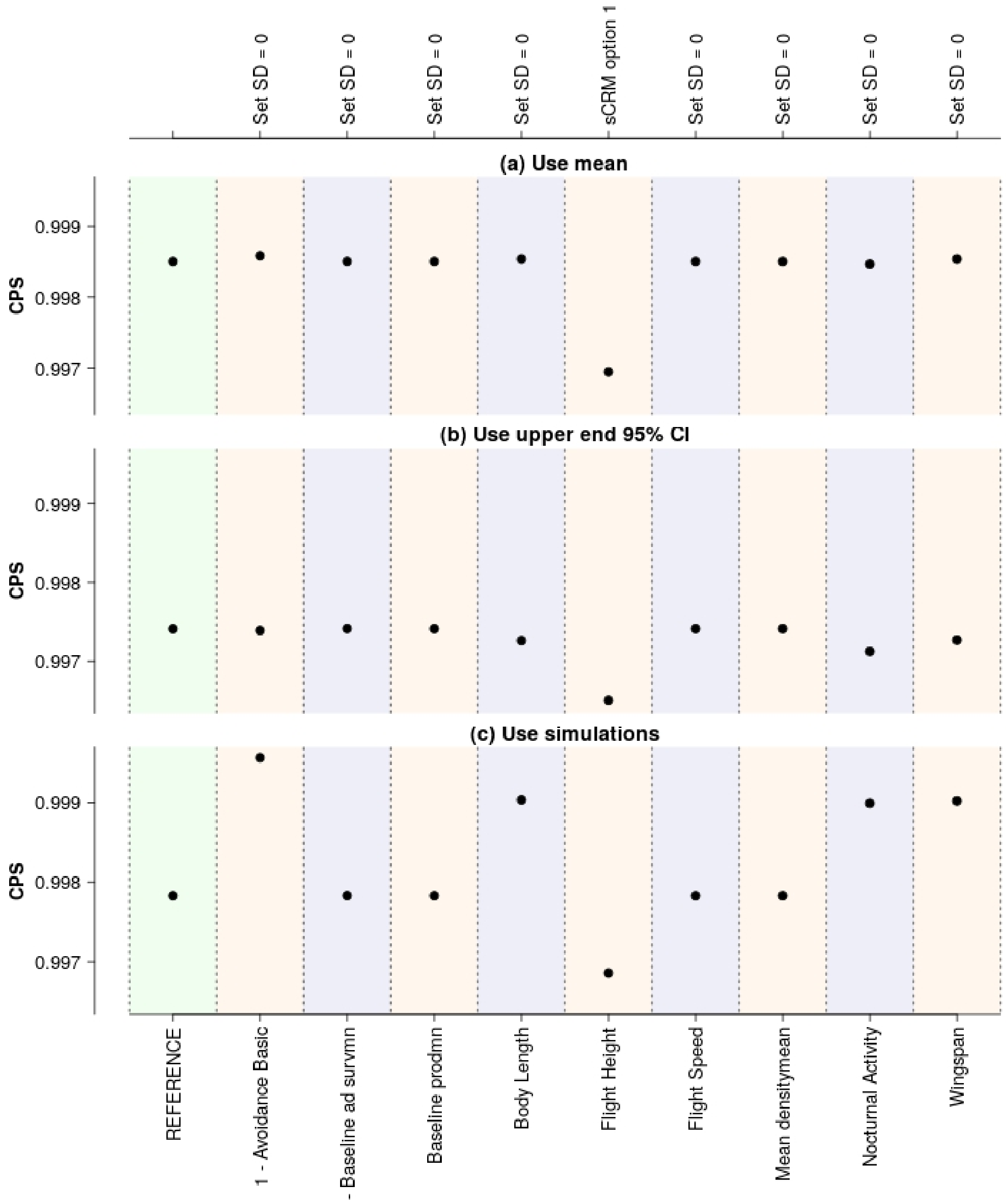

Figure S105: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

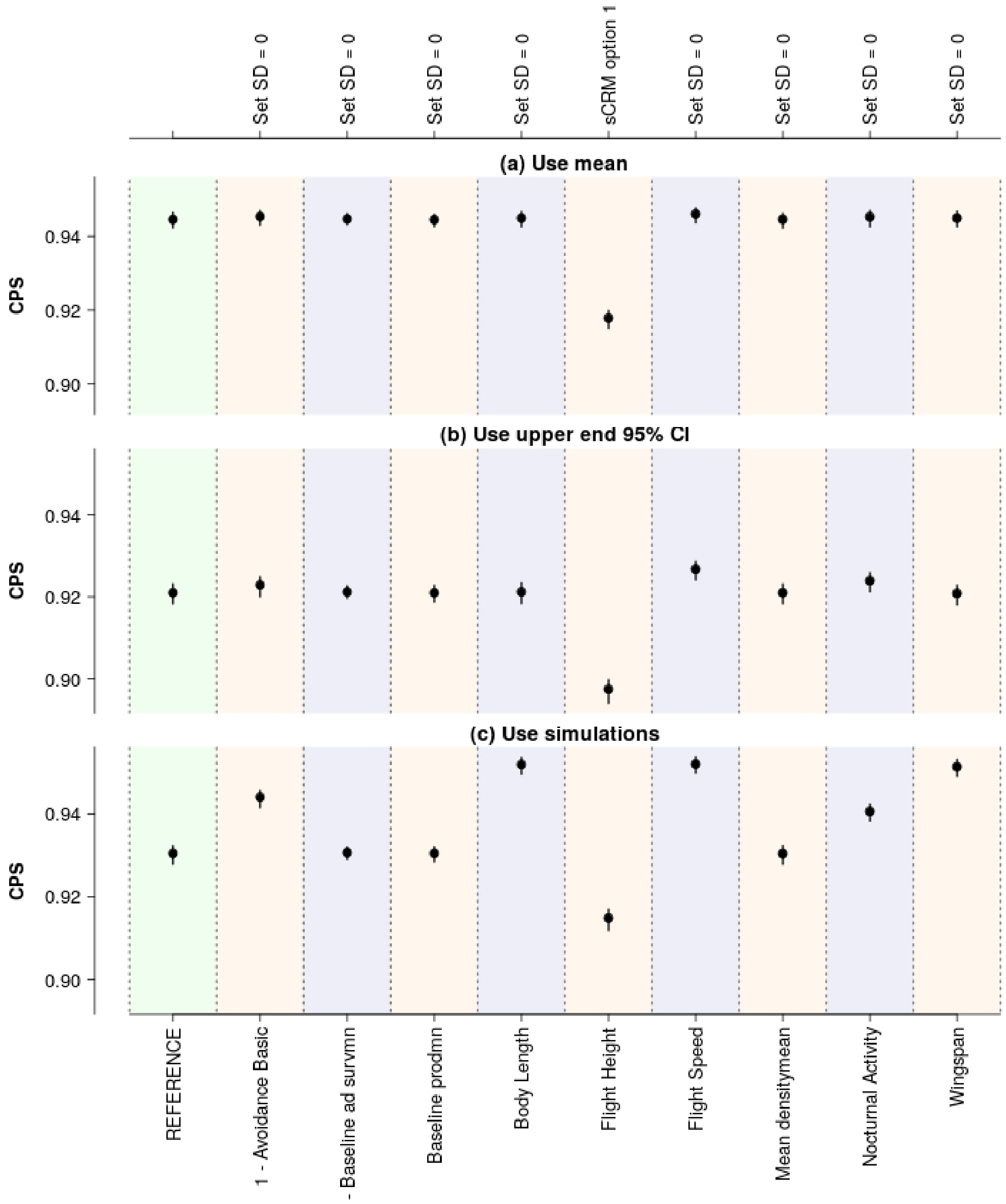

Figure S106: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for herring gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

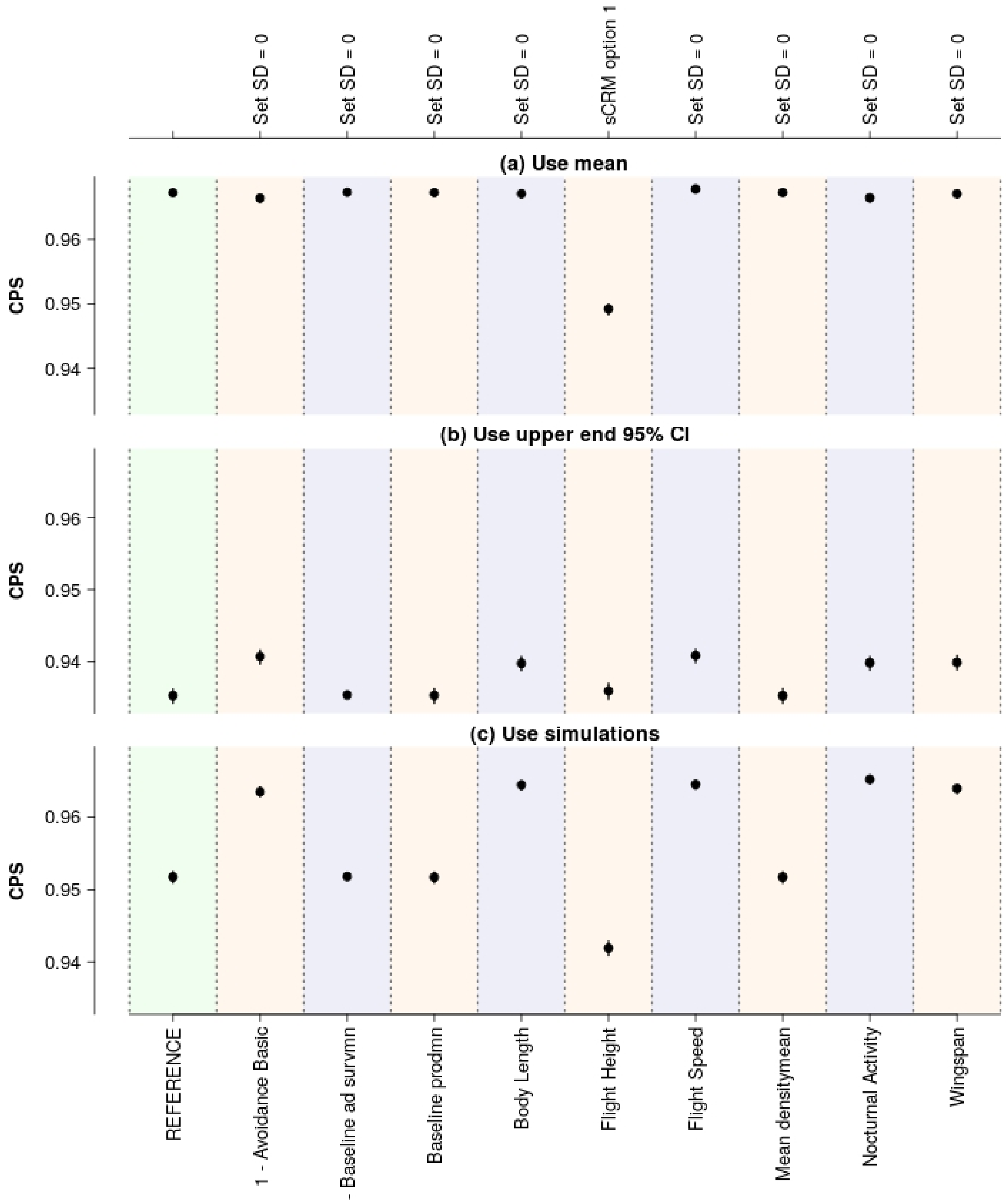

Figure S107: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for lesser black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

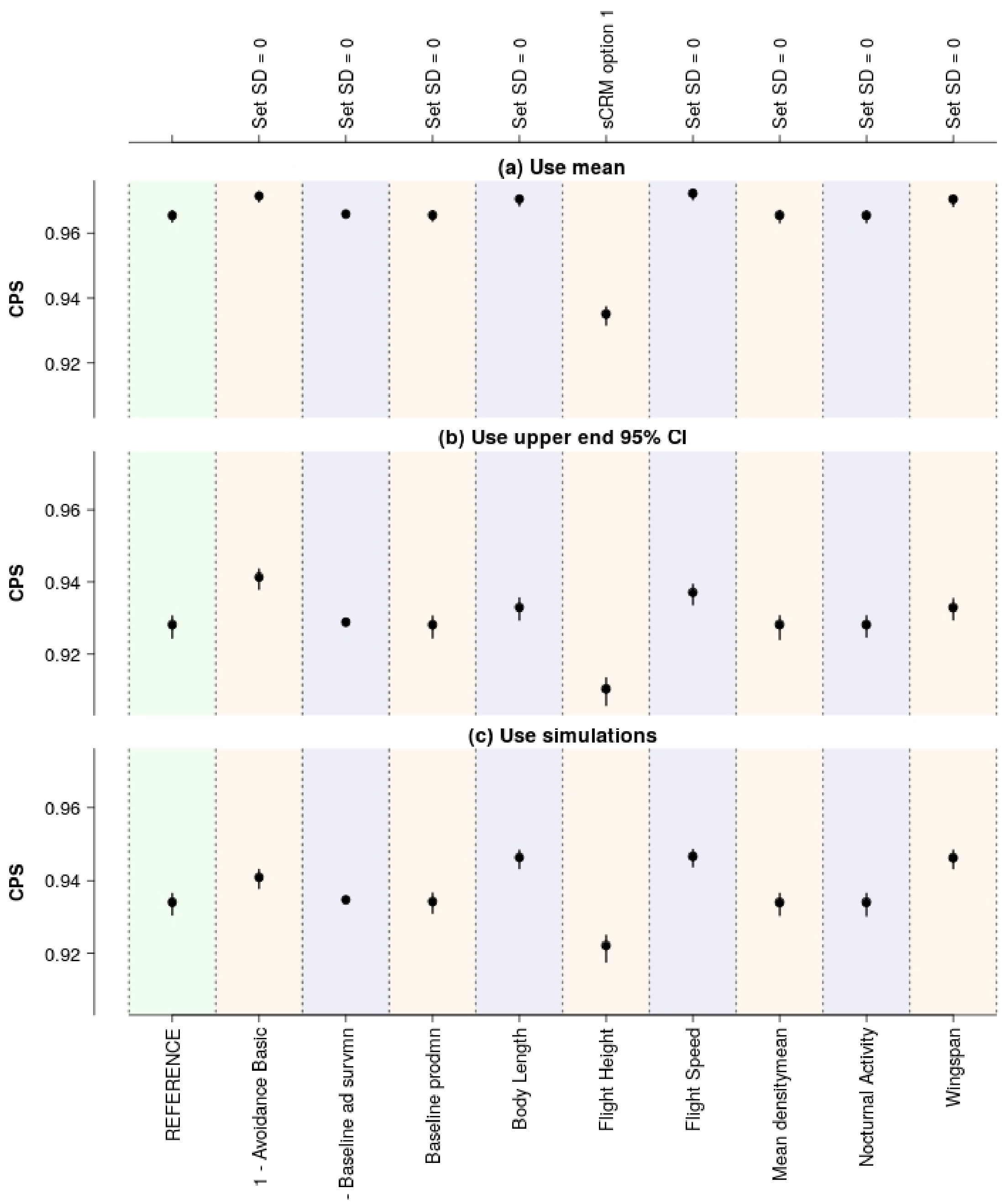

Figure S108: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for sandwich tern after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by removing uncertainty (as shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

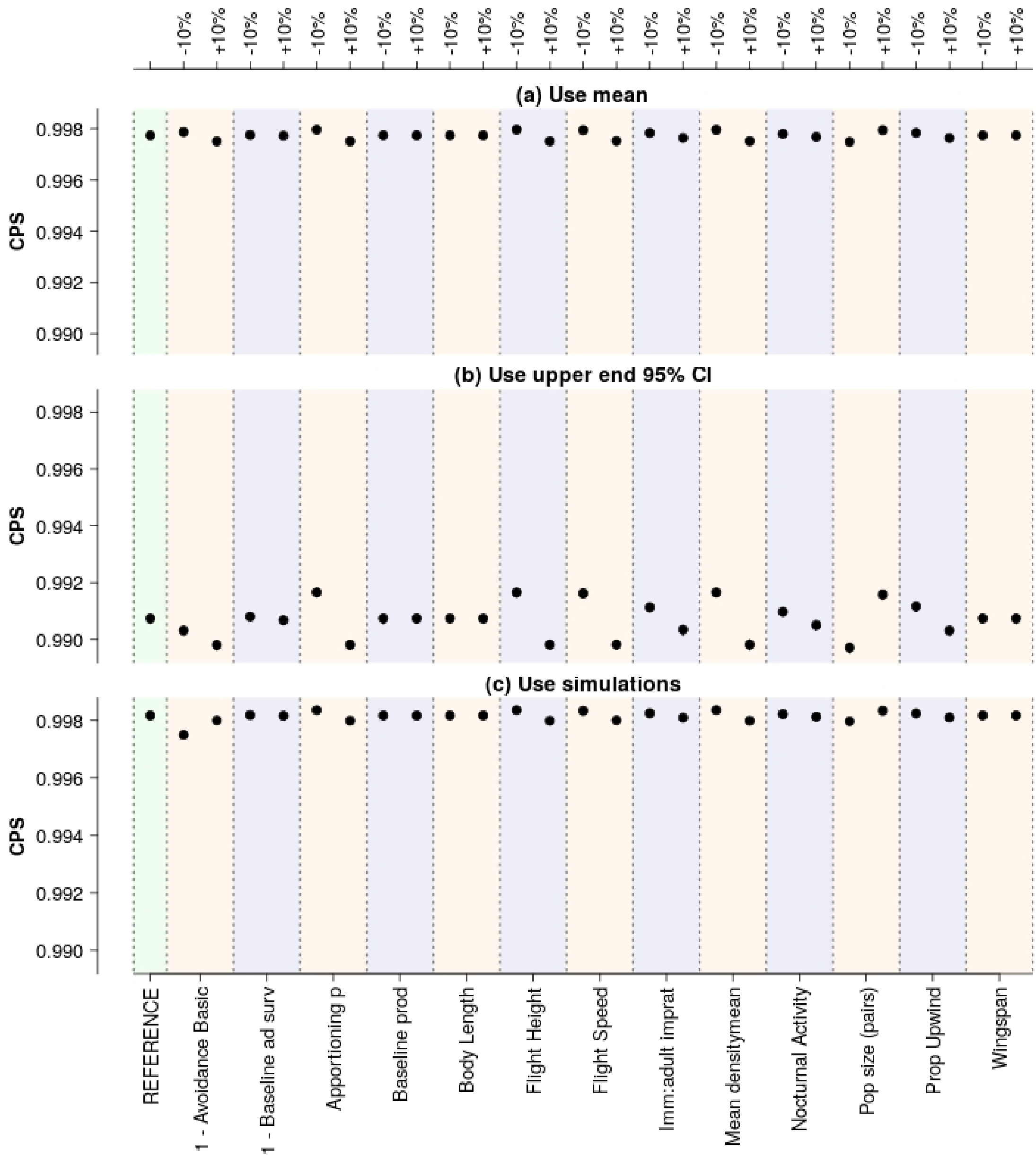

Figure S109: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern fulmar after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

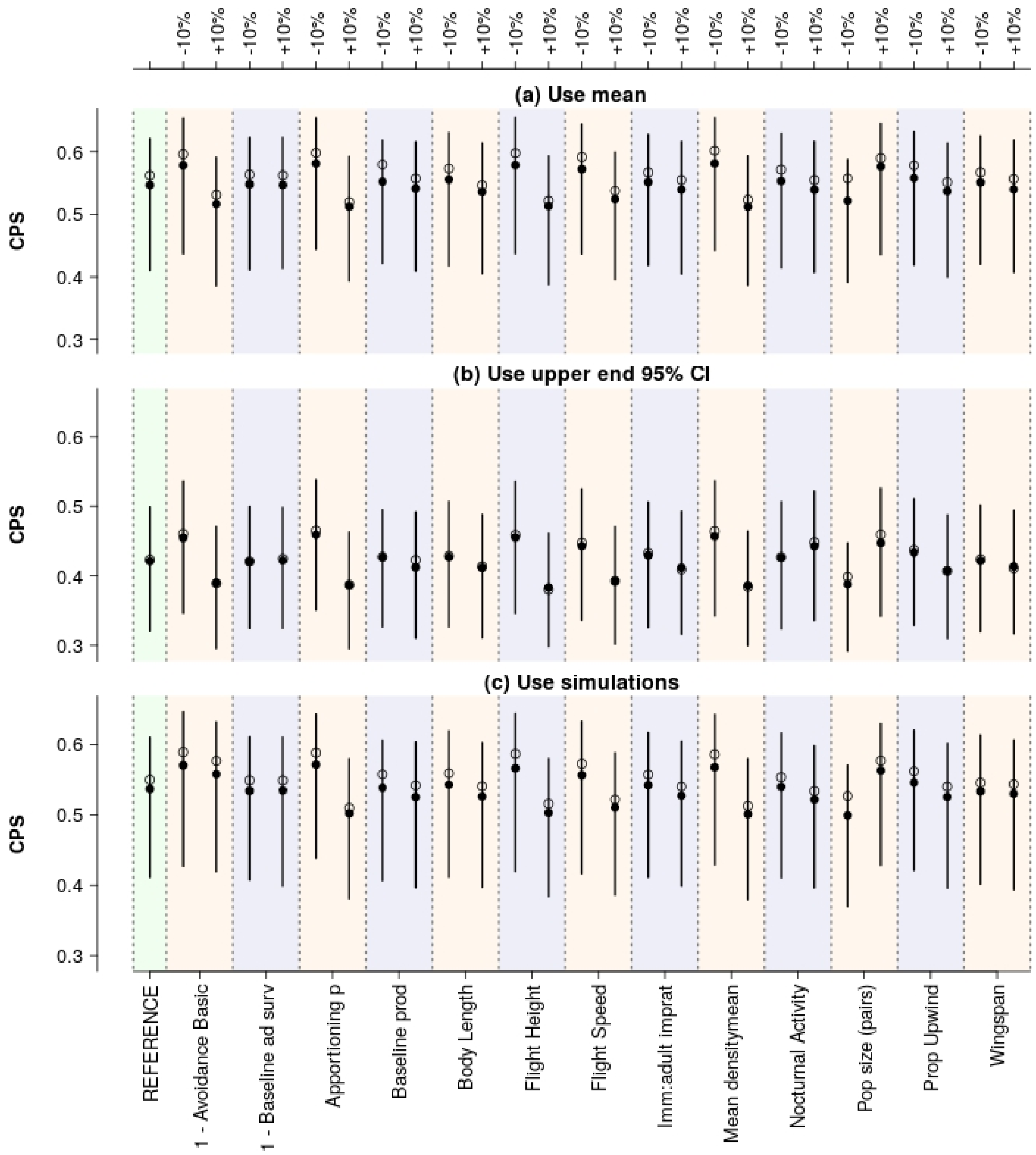

Figure S110: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for great black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

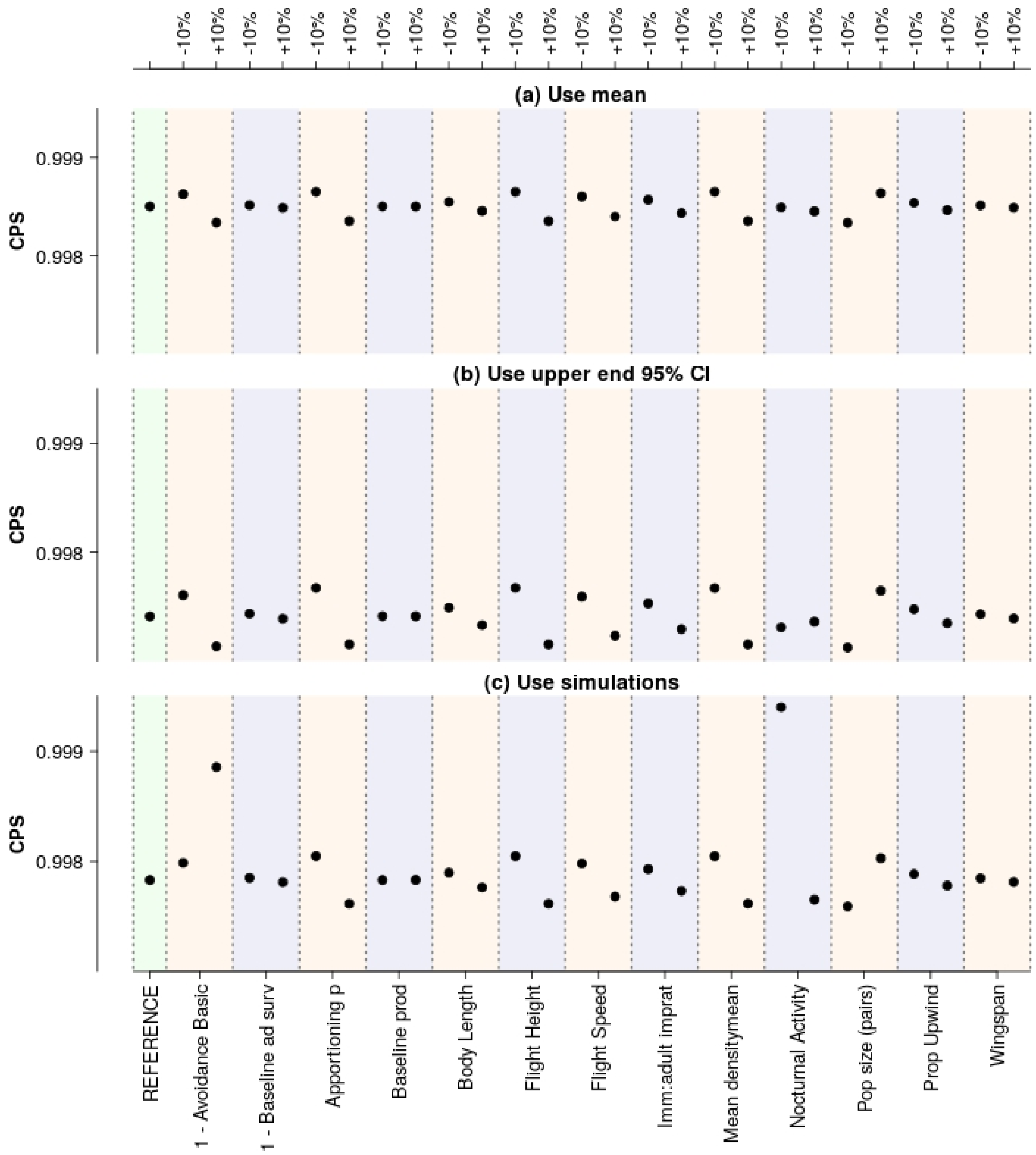

Figure S111: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

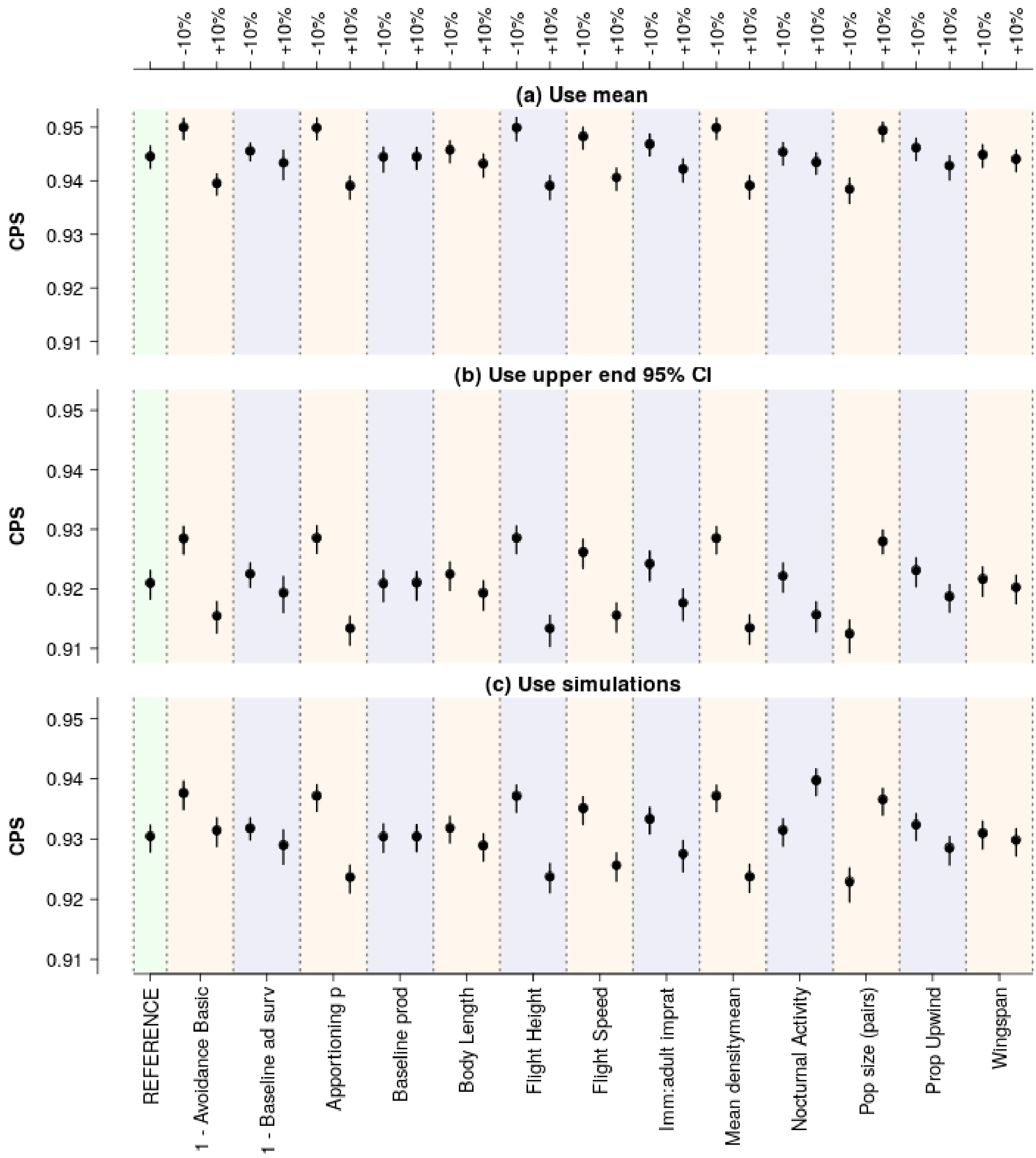

Figure S112: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for herring gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

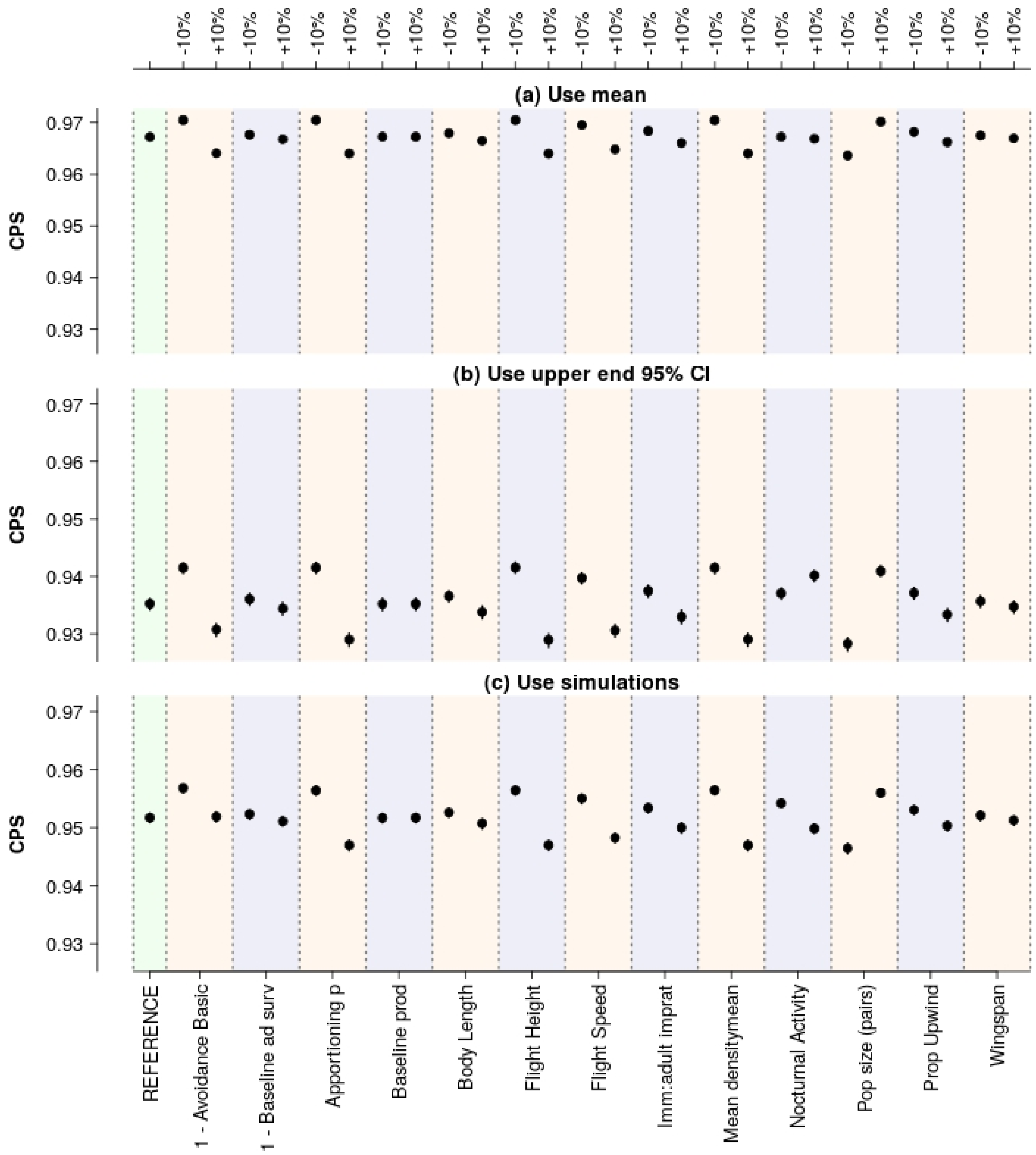

Figure S113: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for lesser black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

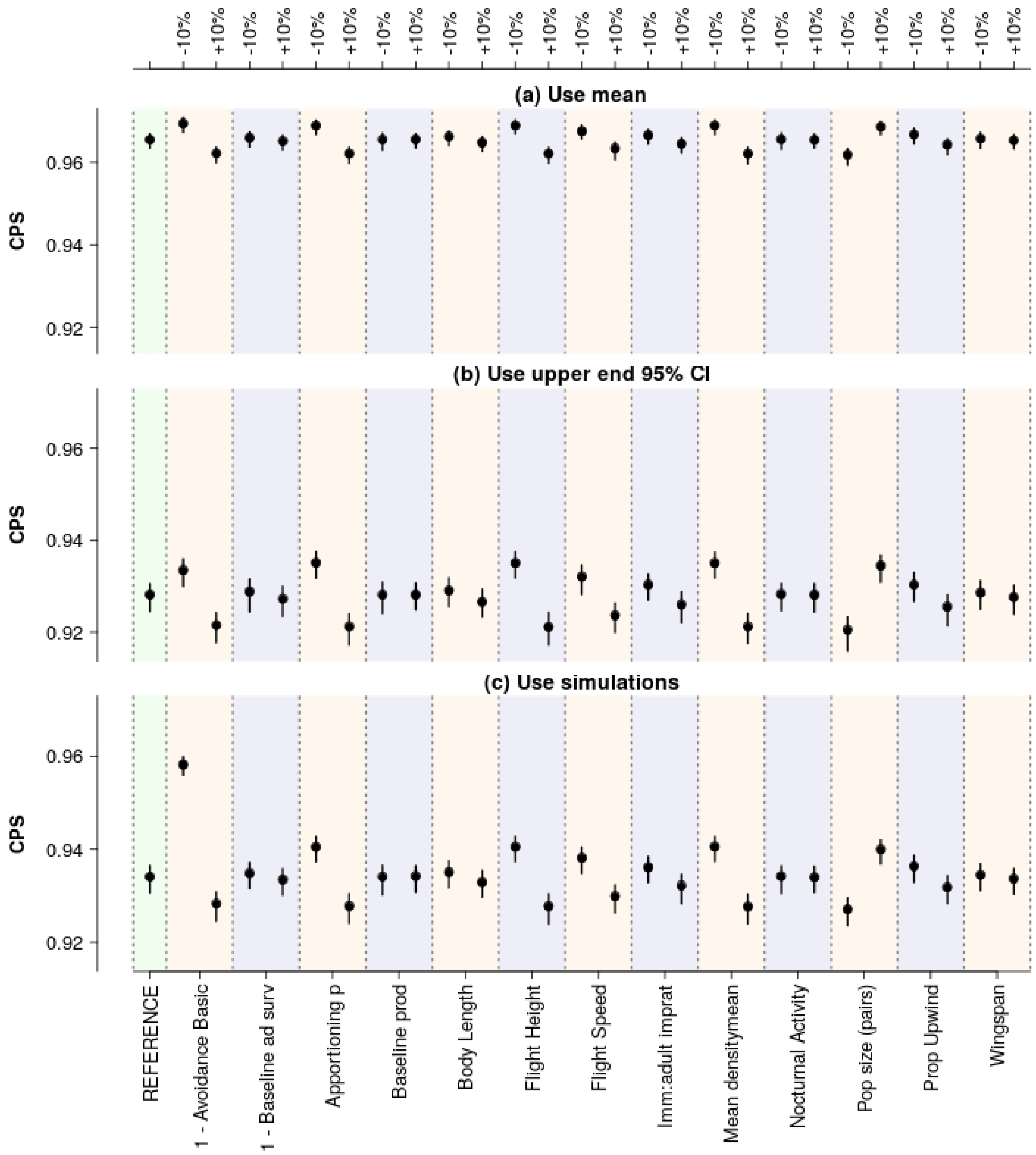

Figure S114: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for sandwich tern after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and with individual parameters (shown on x-axis) then modified by -/+10% (shown on y-axis). PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

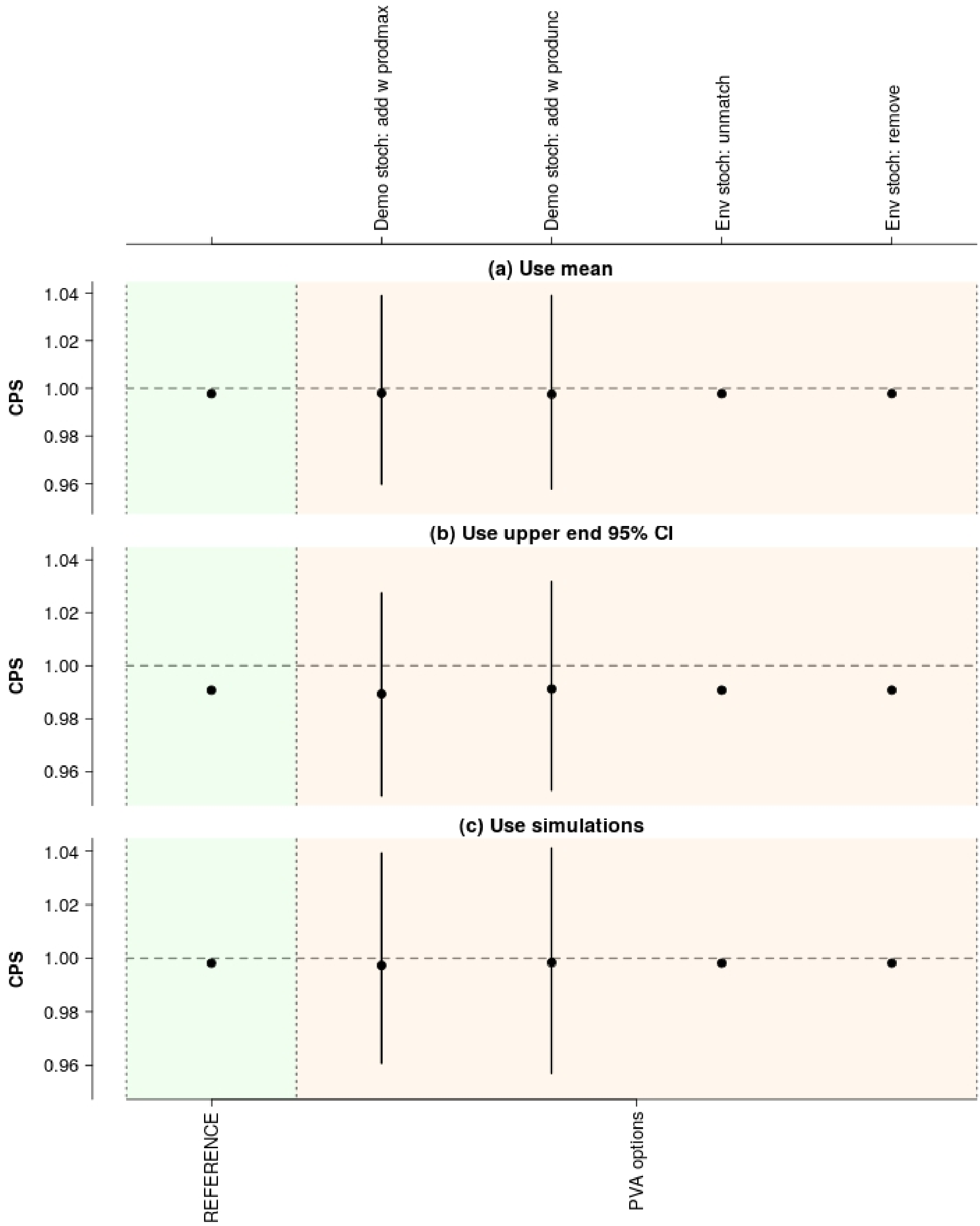

Figure S115: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern fulmar after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

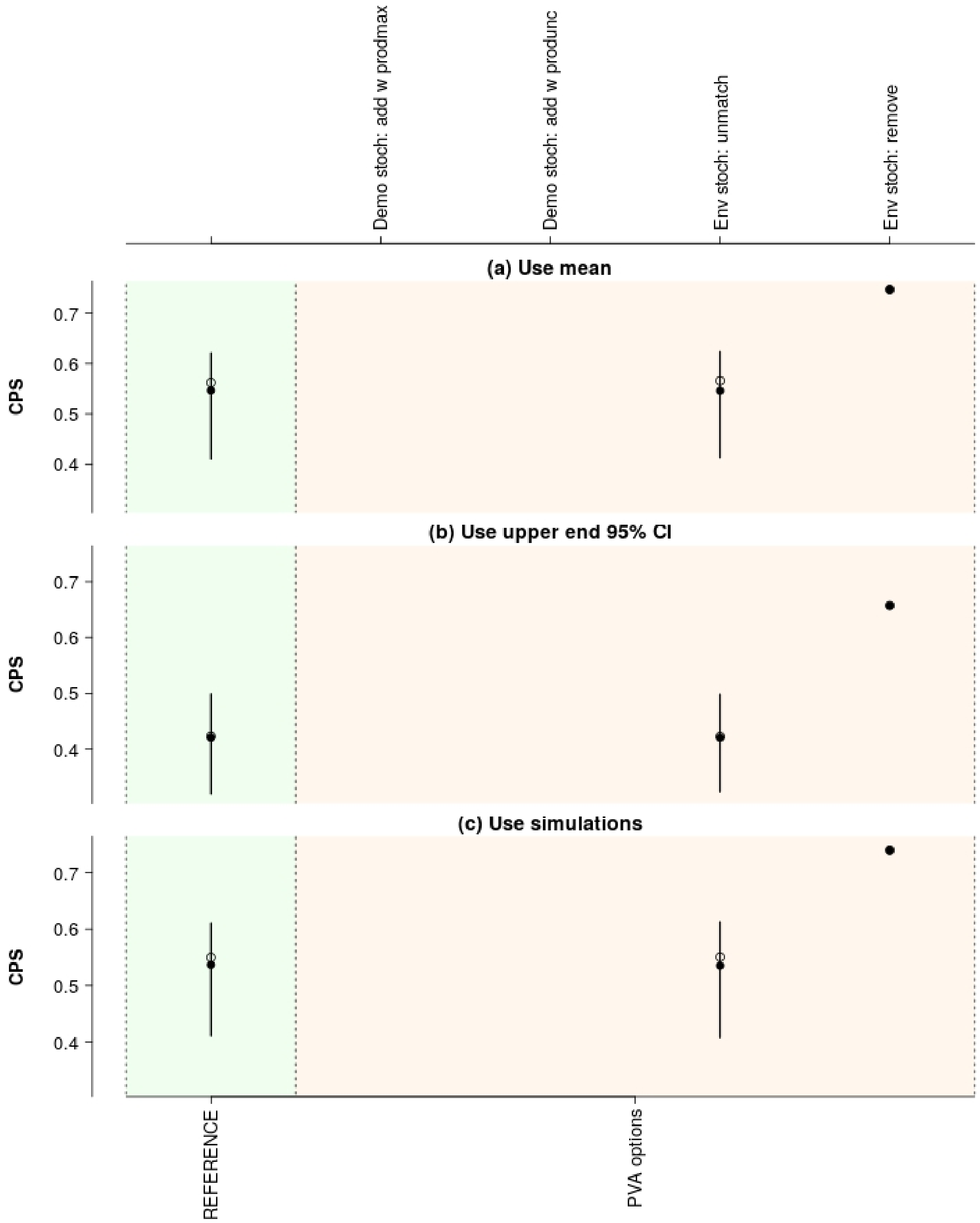

Figure S116: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for great black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

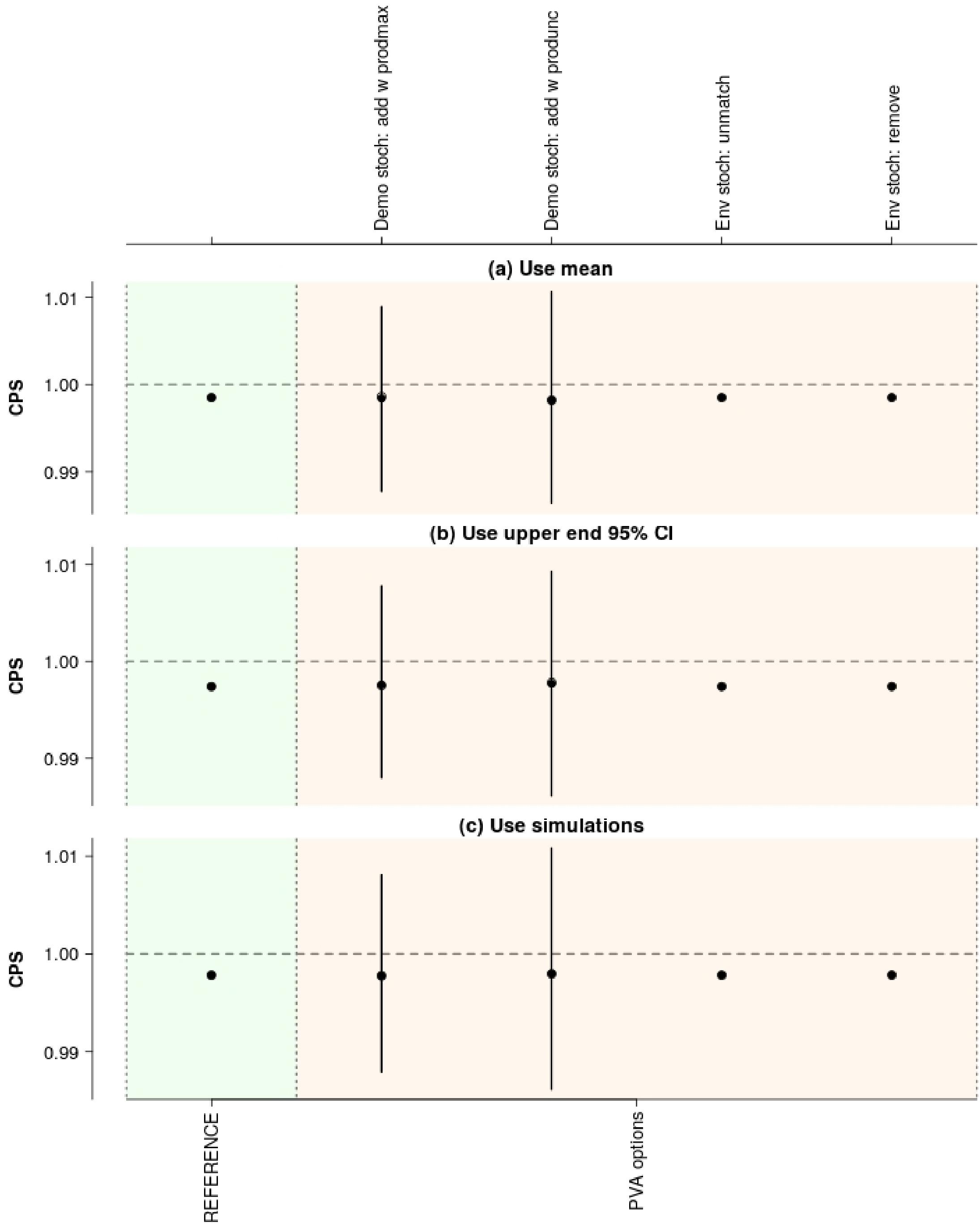

Figure S117: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for northern gannet after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

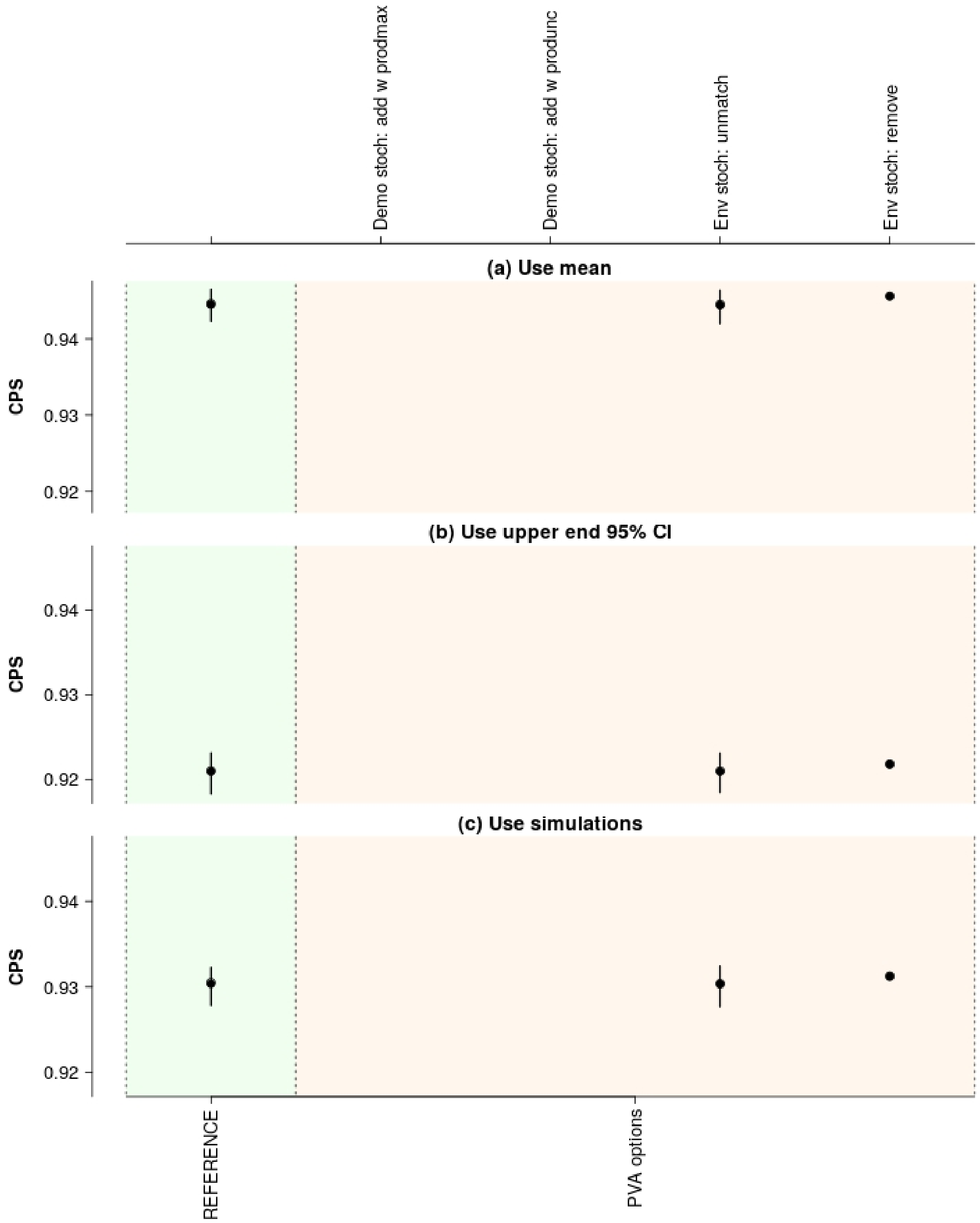

Figure S118: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for herring gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

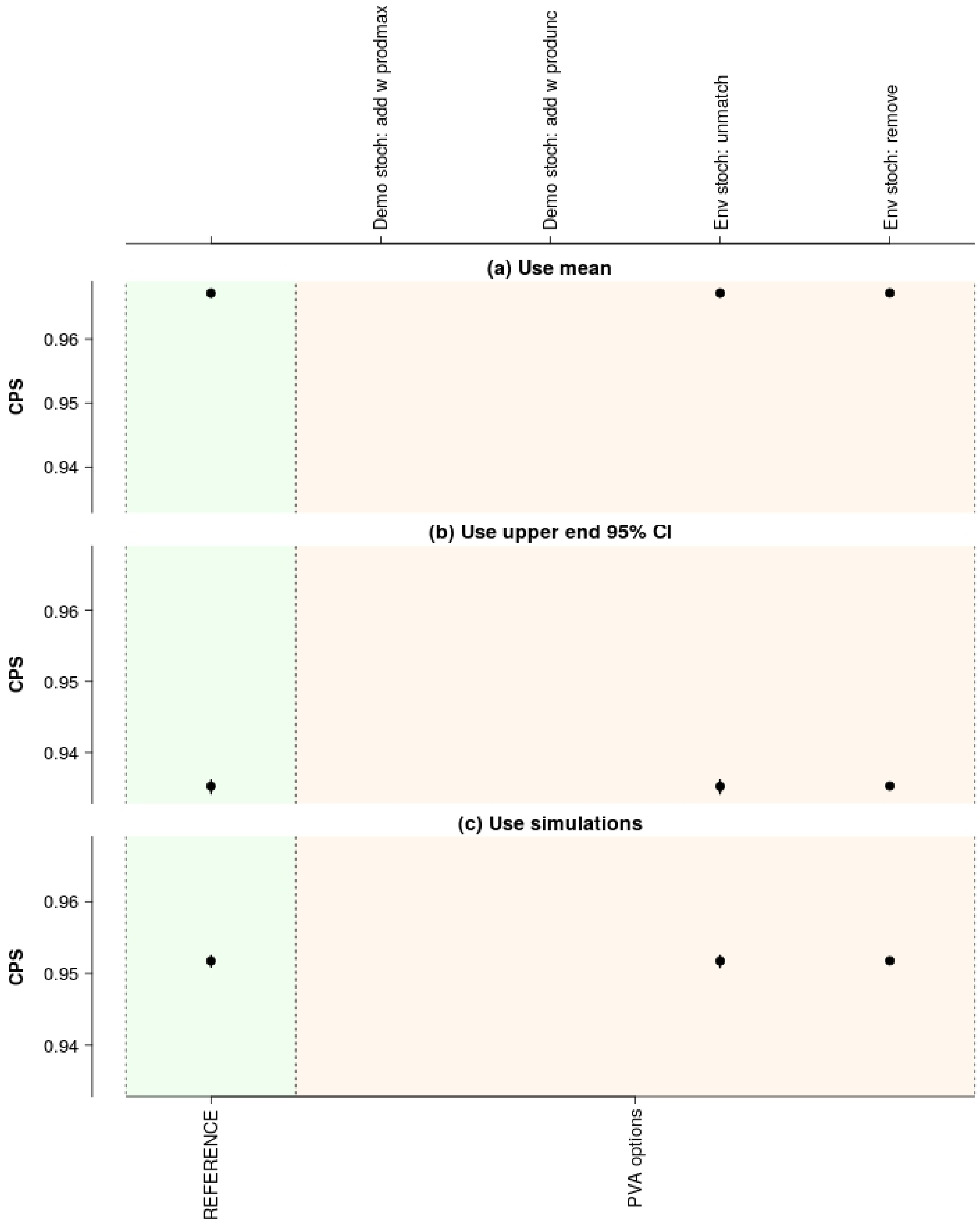

Figure S119: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for lesser black-backed gull after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

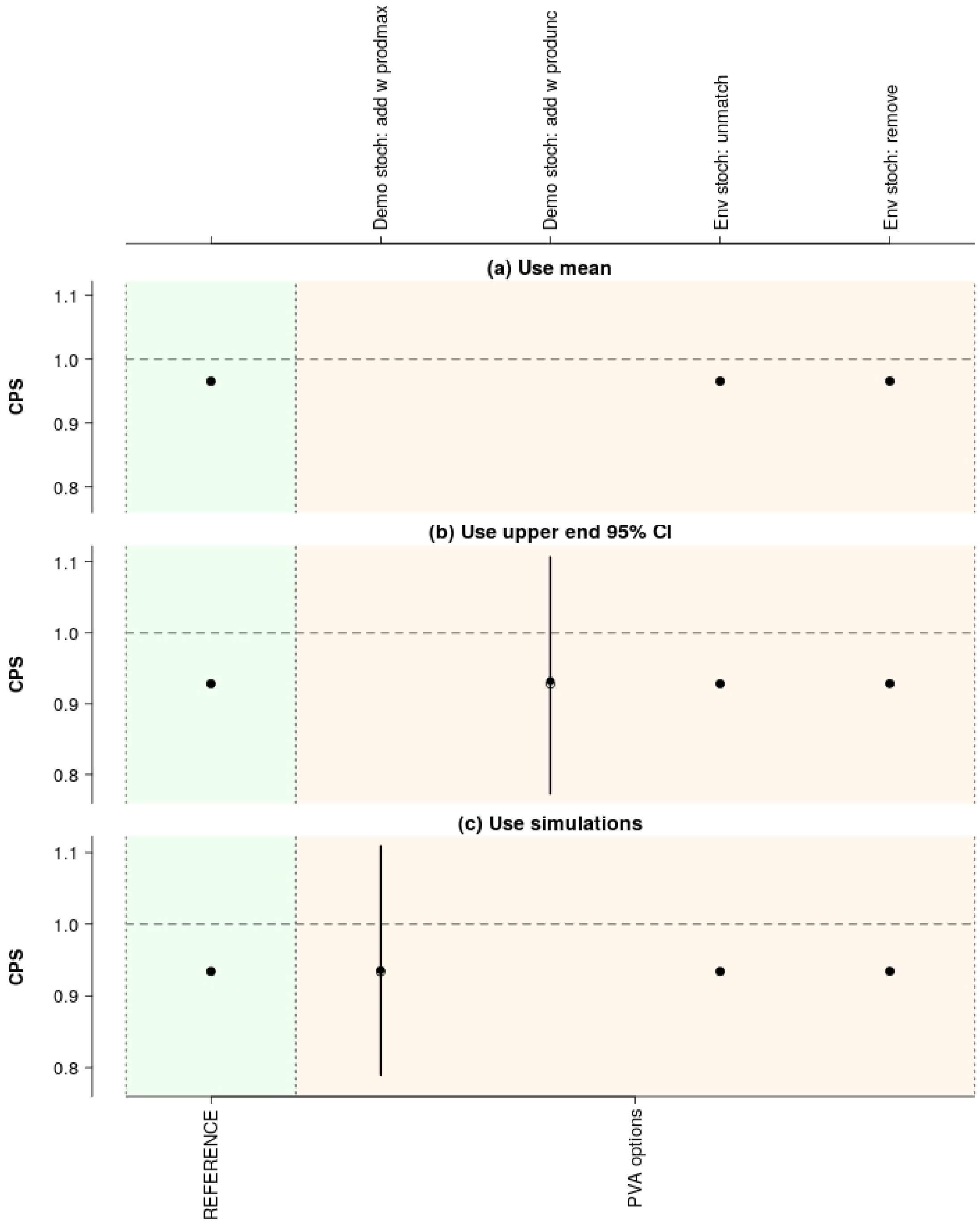

Figure S120: Mean (dot) and 95% CI (line) for counterfactual population size ratio (CPS) for sandwich tern after 30 years of collision impact simulated via the sCRM and PVA tool, with all parameters based on reference values and PVA options then modified (as shown on y-axis) to add demographic stochasticity (with or without a constraint on productivity), remove environmental stochasticity, or match environmental stochasticity across years. PVA uses either (a) mean from sCRM, (b) upper 95% CI from sCRM or (c) simulated values from sCRM.

Annex A: Integrated investigation of uncertainty in assessment tools

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List of Abbreviations

AssESs	Assessing the extent and significance of uncertainty in offshore wind assessments
AOS	Apparently Occupied Sites
GAM	Generalised Additive Model
GLM	Generalised Linear Model
IPS	Impacted Population Size
IQ	Impacted Quantile
ORJIP	Offshore Renewables Joint Industry Programme for Offshore Wind
OWF	Offshore Wind Farm
PVA	Population Viability Analysis
RGR	Ratio of Average Growth Rates
RPS	Ratio of Impacted to Baseline Size
UQ	Unimpacted Quantile
WP	Work Package

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Citation

Matthiopoulos, J. *Investigated investigation of uncertainty in assessment tools: Annex A to Summary report of sensitivity analysis (WP2). AssESs - Assessing the extent and significance of uncertainty in offshore wind assessments*. The Carbon Trust. December 2025

Abstract

This work package performs a holistic investigation of uncertainty in the impacts assessment process, looking ahead at how the incorporation of key biological feedbacks can contract or inflate prediction uncertainty at different points of the assessment. Using the full implementation of the assessment would make this computationally impossible. We therefore took as our starting point a maximal specification of the assessment (enhanced assessment, or eAssess), re-coded to incorporate the four key stages of 1) spatial utilisation of windfarm region by species of interest, 2) Displacement of animals due to Offshore Wind Farm (OWF) operation, 3) collision mortality and avoidance secondary effects and 4) population viability assessment for given future horizon. This framework included different types of correlations and feedbacks that may be generated by biological inputs and outputs of each stage. We first investigated the full parameter space available to such a model. Principally, this covered the specification of the life history of the species, the richness of its environment, the location and size of the OWF and the particular impacts it may have on breeding success and mortality of foraging birds. Using the same metrics of impact as in WP2, we explored the ability of flexible, empirical models (Generalised Additive Models) to capture the responses of the system to the introduction of wind farms. We found that these models had limited explanatory power, hence indicating that the assessment cannot easily be eschewed via these computationally more expedient routes. We then explored 5 simplified versions of the assessment (baseline assessment, or bAssess) by using different simplifications of our eAssess model, that could bring it to the level of dynamical complexity currently existing in the version of the impact assessment. By running both versions (bAssess & eAssess), we compared the influence of different assessment mechanistic features in causing bias or imprecision in the estimates of impact. We found that bias and imprecision are not exclusive characteristics of either eAssess or bAssess. There were measurable but small differences in bias and imprecision that mostly depended on the rate of growth of a species, the strength of density-dependent regulation, collision mortality rates and the size/distance of the OWF in relation to a colony. We suggest that a key feature that is likely to improve both precision and accuracy is the inclusion of predicted future population size and its impact on seabird distribution and exposure to risk.

1. Background

The assessment process comprises several interconnected modules. A key input is the distribution of species of interest and the locations/outlines of proposed or existing marine developments. The assessment's output is the long-term impact of these developments for the viability of the species. Although there can be variations on how these inputs/outputs are provided/produced, the assessment is fundamentally a mathematical/computer operator, mapping spatial arrangements of wildlife and human developments to simulated long-term population impacts.

The objective of this work package is to investigate whether a holistic modelling of the uncertainties in the assessment can lead to a robust representation of the sensitivities in the system. We therefore aimed to examine whether the types of system interdependencies in the seabird/renewables interaction, that are currently not part of the simpler versions of the assessment, lead to significant divergence of risk estimates, and over/under-precautionary predictions of population viability. This forward-looking investigation of uncertainty, although purely exploratory at the present time, will help us determine which biological features currently omitted from the assessment need to be introduced, and which of the existing features may be simplified without loss in accuracy or precision.

The words "holistic" and "robust", above, need some explanation. For our purposes here, a *holistic* investigation of uncertainty includes all forms of variability that can affect the results. We consider three sources of variability (Figure . The first is observation uncertainty, which relates to observation methods and sample size, and leads to parameter uncertainty. More data and more effective observation methods may reduce this. Other sources of uncertainty come from intrinsically stochastic aspects of the system: demographic stochasticity and environmental stochasticity. The simple classification in Figure ignores two complicating aspects of modelling: First, is the possibility of model misspecification, the inevitable problem of the real world not behaving exactly as the model assumes. Second, is the possibility of ignored dependencies between different aspects of the model. These dependencies could represent correlations between intermediate products of the assessment. A correlation between inputs or parameters in the model could fundamentally alter the net variability in results, or make some stages of the modelling more/less sensitive to uncertainty.

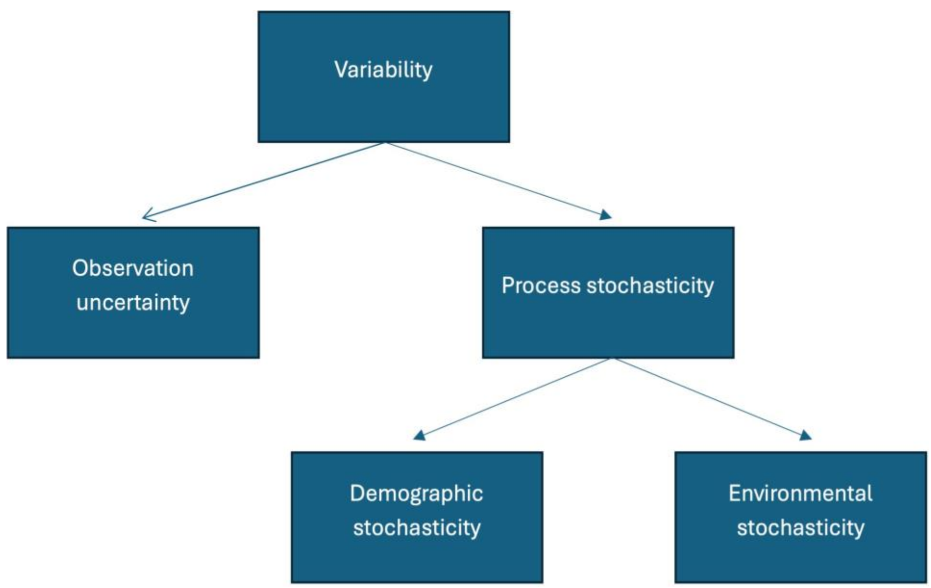

Figure 1: A classification of the types of variability considered in this analysis

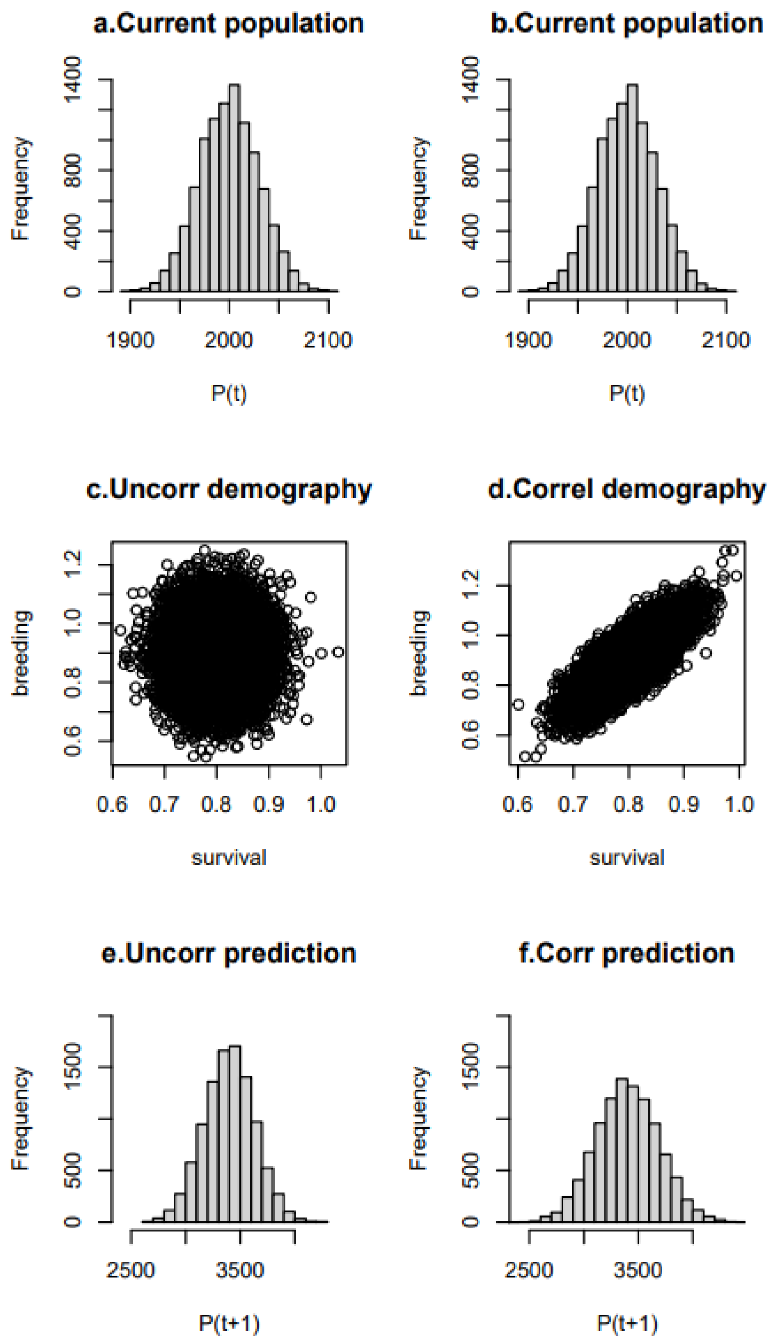

Figure 2: Illustration of predictions of population size in a simple, single-year PVA. The uncertainty in current population size is depicted by the distributions in (a) and (b). Using these as input, we predict population size under the assumptions of independent (c) and correlated (d) demographic parameters for breeding and survival. The corresponding predictions from those are shown in (e) and (f).

The effect that correlation may have on uncertainty estimates can be illustrated with a simple example of a single-year PVA. Let's assume that we have a prediction for the current population size of a colony (P_t), shown in Figure 2a&b (which are identical). We want to generate a prediction for next year's population size (P_{t+1}), by propagating the current population estimate and variability therein, through a simple demographic model in which the population size is determined as an unconstrained growth whose per-capita rate depends on adult survival (*s* and annual fecundity (*b*.

$$P_t + 1 = (s + b)P_t \qquad (1)$$

Note that there are no assumptions regarding density dependence or age structure and delayed breeding here, an ostensibly oversimplified model of demography for any seabird. In the first instance (Figure 2c) we assume that b and s have interannual variability but are uncorrelated. In the second instance (Figure 2d), we recognise that different years may be particularly good/bad for both survival and fecundity, so we permit some correlation between the demographic rates. We note that the corresponding predictions (Figure 2e&f), for just one year ahead have the same mean but different variances: Allowing demographic correlation takes the 95% CIs from (2948, 3853) in the uncorrelated case, to (2848, 3974), in the correlated one. This may seem like a small inflation of 13%, but compounded over several years, it could lead to considerable differences in final projections. This is an example where ignoring correlations in the process may lead to counter-precautionary (i.e., misleadingly overprecise) estimates. But the opposite is also possible: Structural correlations may reduce uncertainty, or they may have no impact at all. We cannot know what the outcome is, especially in a model as complicated as the assessment, until we have examined the effects of such correlations in all aspects of a system.

This work package aims to develop such a holistic investigation of uncertainty, to determine whether the predictions of a model that accounts for all these features are a) different and b) more robust than the results of a simpler version of the assessment.

2. Approach

In general statistical terms, *robustness* relates to models that are both accurate and precise. The ability to minimise bias and maximise precision is prized, because these two attributes often trade-off against each other in statistical estimation. This is usually considered in comparison to an underlying truth, often (especially in a frequentist setting) a single value about which the estimator is calculated. In this project, we will not have a true value for population viability, so we will need to compare the predictions of an assessment model with and without structural correlations. We frame this as a comparison between a baseline version, or bAssess, that captures key features of current practice, with an enhanced version, or eAssess, that is made more realistic by the addition of structural correlations. The term *structural* here is important because if correlations are introduced in phenomenological way, then they may not necessarily increase model realism. However, if correlations are added structurally, via the inclusion of real biological mechanisms that are missing from the bAssess, then we are better able to approach this as a comparison between current-practice and potential gold-standard.

This comparison may conclude one of three things:

i) the structural correlations make no difference for the assessment projections,

ii) the current approach is over-precautionary, or,

iii) the current approach is misleadingly precise (under-precautionary).

The first outcome would permit us to continue using bAssess, i.e. the simpler (and computationally cheaper) versions of the risk assessment. The other two outcomes would indicate cause for concern. If bAssess is over-precautionary (outcome ii), this would indicate that licences for marine developments may be withheld unnecessarily. On the other hand, under outcome iii, where the bAssess is unrealistically precise, we would risk omitting population outcomes more extreme than those we would be currently considering.

The issues of model misspecification and correlations are connected. It is notable that the problem of model misspecification can arise from the exclusion of correlations between parameters or components of the assessment. Conversely, many of the correlations in the system arise from mechanistic features of the biological system that may be assumed away by simpler versions of the assessment, either inadvertently, or for computational expedience.

For the above reasons, the issue of correlations is best approached by relaxing the mechanistic assumptions in the bAssess that are known or suspected to be unrealistic. The approach followed in this part of the project therefore is to list and evaluate these simplifying assumptions and to arrive at a more holistic version of the assessment by relaxing them. At that point, a comparison between the bAssess and the eAssess will indicate whether the particular structural correlations emerging within the system reveal the current practice to be precautionary or not. The bAssess is a minimal specification making the following assumptions:

1. The utilisation of the area around the windfarm is derived directly from data.
2. The abundance of the birds in the area remains constant in time and as the colony changes size.
3. All birds that move in that area enter the windfarm, and therefore, there is no displacement.
4. If displacement is considered, then no indirect effects on fecundity are assumed.

We look at the modules of the assessment along four stages (Figure 3), from the calculation of exposure to the long-term predictions of the Population Viability Analysis (PVA). We extend the processes examined in the eAssess to include windfarm avoidance and displacement effects (light green boxes in Figure 3). In the sections that follow, we consider what are the important features that might generate correlations within or between stages in the assessment.

A key principle of our approach is that the enhanced versions of the assessment modules contain the simpler versions as special cases (i.e., the basic version of the assessment can be retrieved from the enhanced version by setting parameters to particular values). In the following sections, we will highlight how this can be done for each of the four stages examined.

3. Model development: Basic v enhanced versions of the assessment

3.1. Stage 1: Exposure

Exposure in this context is defined as the expected number of birds in the vicinity of the windfarm. The basic version of the assessment receives this number as an input, from an assumed dedicated aerial survey.

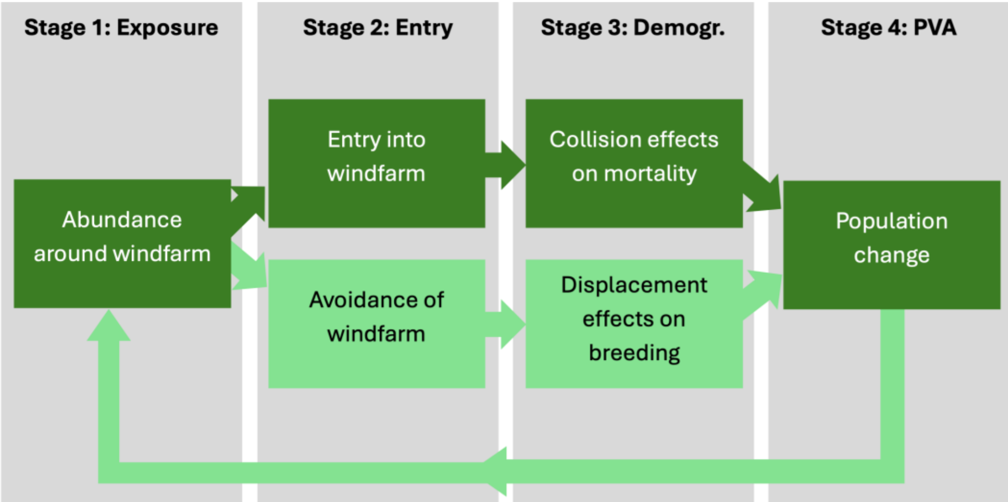

Figure 3: Overview of the four stages of an assessment considered in this work-package. The boxes represent a stage of computation (an assessment module) feeding information into other boxes as indicated by the arrows. Dark green boxes exist in both the basic and enhanced versions of the assessment, light green boxes and connections only exist in the extended version.

There may or may not be an uncertainty estimate accompanying the mean number, and this uncertainty may only incorporate observation uncertainty, rather than natural fluctuations in the utilisation of the area. A more pertinent assumption however, given the connection of the assessment to long-term PVA projections is that the density of birds does not change with colony size or is calculated as a fixed proportion of the colony size. In reality, exposure may be both constant and density dependent at different stages of colony growth, and will almost certainly also be responsive to variations in resource distribution (both inside and outside the windfarm polygon) as well as seasonal effects.

Our notation is detailed in Table .

The expected usage amounts are additive

$$U_F(s,P_t) + U_C(s,P_t) = U(s,P_t) \tag{2}$$

We will derive each of those components separately, but to do so, we need to quantify the range (R) of a colony. Although the range determines both foraging and commuting, it is mostly driven by foraging concerns. It is well known that increasing colonies will tend to expand their foraging range due to local depletion of resources (Lewis et al., 2001). For very large and growing colonies, where animals forage far away, the range will ultimately be capped by a balance between productivity and commuting costs, or commuting distances and time away from the colony (Charnov, 1976; Ollason, 1980), and such limits can be imposed onto our model, but we mainly focus here on colonies that have yet to face these constraints. As a colony grows (or declines), depending on the distance (d) between the colony and the windfarm, exposure may increase with an expanding home range which begins to include the farm polygon. Once the polygon is entirely within the range and the colony continues to grow, the density of birds using that area will stabilise as the exploitation of resources equilibriates with the local productivity of the area. Therefore, exposure due to foraging will initially be zero, increasing in proportion to colony size, only to stabilise at a maximum value (α) once the windfarm is completely included in the colony's range. For a circular home range

Table 1: Notation used in the Exposure calculation (Stage 1 of the model)

Class	Symbol	Rescription
State variable		
	$U_F\ (s, P_t)$	Expected usage of the windfarm area for foraging
	$U_C\ (s, P_t)$	Expected usage of the windfarm area for commuting
	$U\ (s, P_t)$	Total expected usage of the windfarm area
Function		
	$R(P_t)$	Range of the colony
	$U_f\ (d, P_t)$	Exp. foraging in land-masked annulus at distance d from colony
	$U_c(d, P_t)$	Exp. commuting in land-masked annulus at distance d from colony
Input Variable		
	Pt	The population size in year t
	I	Proportion of available marine space around colony
	A	Total area of the windfarm
	d	Distance of windfarm centroid from the colony
	S	Spatial location of windfarm
Constant		
	w_F	Proportion of time animals spend foraging
	w_C	Proportion of time spent commuting (noting that $w_F + w_C < 1$)
	δ	Measurement unit for length
	a_C	Decay of commuting usage with distance from colony
	a_F	Regulates abruptness of foraging range's outer boundary
	α	Maximum usage of a unit area inside the home range

whose area is masked to some proportion by land, the proportion of available marine area will be $l \in [0, 1]$. E.g., for a colony found on a long, straight coastline, this will be close to 0.5, while for a colony established on a small, remote island this will be close to 1. More complicated coastlines will introduce a dependence between l and R, which can be easily calculated using GIS, but will not concern us here as a complication. Then, α, the maximum amount of usage in the windfarm, is the ratio of total foraging usage ($w_F\ P_t$) over total home range area ($l\pi R^2$), which solves to the following expression for home range:

$$R = \sqrt{\frac{w_F P_t}{l \pi \alpha}} \tag{3}$$

An additional point on exposure relates to the relative balance between adults and sub-adults. It is possible that the home ranges of birds of different ages are also different (with non-breeders generally having broader-ranging movements). The complication from such an assumption would be that the two types of home ranges would need to be solved as a system of simultaneous equations, that would change dynamically as the age structure in the population changed. Here, we have chosen not to examine this complication, because currently, it is difficult to apportion exposure by bird age in aerial surveys.

The foraging utilisation may now be defined in a step-wise manner as

$$U_F(s) = \begin{cases} \alpha A & \text{if } d < R \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Continuous formulations are also possible, for instance, based on a logit function, we can obtain

$$U_F(s) = \frac{\alpha A}{1 + \exp\left(-a_F\left(1 - \frac{d}{R}\right)\right)} \tag{5}$$

This curve has an inflection point at the range value R and the coefficient aF regulates the steepness of the curve at the inflection point, so that as $a_0 > 100$ the continuous function approximates a stepwise function. It essentially generates a disc around the colony with graduating edges. Using this continuous version, and noting the range $R$is a function of population size, we can obtain a model for $U_F(s)$

$$U_F(s) = \frac{\alpha A}{1 + \exp\left(-a_F\left(1 - d\sqrt{\frac{l\pi\alpha}{w_F P_t}}\right)\right)} \tag{6}$$

Commuting usage will be a decaying function of distance, because of the radial nature of this problem (i.e. the same number of birds travelling outward and inward to the colony generate more traffic close to the colony than further away), but also because commuting costs increase with distance. We assume exponential decay for commuting utilisation-at-distance:

$$U_c(d) \propto \exp(-a_C d) \qquad d \in [0, R] \tag{7}$$

This needs to be normalised to 1, and scaled by commuting population size (i.e., multiplied by $w_C P_t$). The normalisation constant is $K = \int_0^R exp(-a_C r)dr$. Collectively, we get:

$$U_c(d) = \frac{a_C w_C P_t \exp(-a_C d)}{1 - \exp(-a_C R)} \tag{8}$$

We can move from $U_c(d)$ to $U_C(s)$ the use of unit area at the distance $d$by dividing by the area of the incomplete (masked) unit annulus at that distance:

$$U_C(s) = \frac{a_C w_C P_t A \exp(-a_C d)}{l\pi(\delta^2 + 2d\delta)((1 - \exp(-a_C R))} \qquad (9)$$

Therefore, the collective utilisation of the area A is:

$$U(s) = \frac{\alpha A}{1 + \exp\left(-a_F\left(1 - d\sqrt{\frac{l\pi\alpha}{w_F P_t}}\right)\right)} + \frac{a_C w_C P_t A \exp(-a_C d)}{l\pi(\delta^2 + 2d\delta)\left(1 - \exp\left(-a_C\sqrt{\frac{w_F P_t}{l\pi\alpha}}\right)\right)} \qquad (10)$$

Plotting this expression for fixed d against P_t (Figure 4a) and for fixed P_t against d (Figure 4b), makes it clear that even under some of our simplifying assumptions, the dependence between exposure and distance-to-farm/colony size has a non-trivial shape.

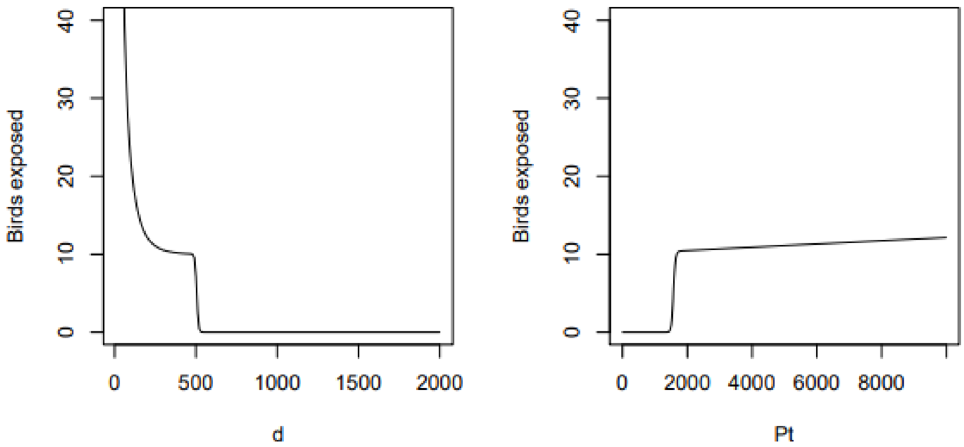

Figure 4: Behaviour of the exposure model for fixed distance and a growing population (a) and fixed population and increasing distance of the windfarm from the colony

Note that for particular combinations of distances and population sizes the impact is zero, because the windfarm is outside the range of the colony. Dynamically, this will have important consequences, because it implies that a declining population may benefit from a reprieve from any windfarm mortality, as its range contracts.

For every stage of the eAssess developed here, it will be important to determine how the final mathematical model (e.g., eq. (10)) can be simplified to the basic version of the assessment. If the initial aerial survey estimates of seabird abundance around the windfarm are used as a constant number in the assessment, then eq. (10) would be required to be a constant function. We can do this by assuming that l, d and P_t are all fixed, effectively leading to a function of the form

$$U(s) \propto A \qquad (11)$$

The output from this stage of the enhanced or basic assessment will be a number of animals that annually entered the region of the wind farm. We can model this as a Poisson process with overall rate $U_{(s)}$, which was partitioned across the classes of animals in the population

$$N_{1,i,t} \sim \text{Poisson}(U(s)\frac{P_{i,t}}{P_t}) \quad (12)$$

We use the subscript 1 in the above notation $N_{1,i,t}$ to denote the number of birds in the i^{th} age class, estimated as the output of stage 1 of the assessment.

Overdispersion in this process can be introduced via uncertainty in the inputs of the exposure model (e.g., interannual variability in environmental productivity can be captured by having a stochastic version of the a parameter).

3.2. Stage 2: Avoidance and entry

The second stage of the assessment, currently not always included in the basic analysis, is a branching between birds that enter the wind farm and birds that choose to circumnavigate it. Displacement effects are a key existing feature of risk assessment (Searle et al., 2018). Let us denote by $\pi \in [0, 1]$ the proportion of birds that enter the farm. There are two biological questions worth asking here:

1) Is π a constant number or could it vary with density of birds in the area of the windfarm, or with the time that the birds have had to become accustomed to the presence of the farm? For instance, if some sort of habituation process takes place, then, either birds learn to better navigate crossing the farm (so that π might go up), or they work out foraging routes that avoid it (so that π might go down).

2) Is there any difference between π for adults and sub-adults? Presumably, the foraging activity of provisioning adults may have time constraints, so they may not have the luxury of circumnavigating the wind farms.

In the absence of broad, cross-species evidence for habituation, we will proceed with just the second of these possibilities, by allowing a proportion (π_A) for breeding adults and a different proportion (π_J) for all other animals. In the simulation, we applied these probabilities via a binomial process, to determine the number $N_{2,i,t}$ of "crossers" in each class.

3.3. Stage 3: Demographic effects

We assume a proportionate survival effect (m_1) on the number of birds that cross the wind farm, as calculated by the current collision risk models (Furness, Wade, and Masden, 2013) and a displacement impact (m_2) on the breeding success of adult birds that circumnavigate the wind farm (Searle et al., 2018). Expected survivals $(s'_{i,t})$ across the adult and sub-adult populations will be weighted averages of birds affected and not affected by the windfarm.

$$s'_{i,t} = s_i\left(m_1\frac{N_{2,i,t}}{P_{i,t}} + \frac{(P_{i,t} - N_{2,i,t})}{P_{i,t}}\right) \quad (13)$$

These additional components of mortality and reductions in breeding success can be translated to the broader population by giving us the realised numbers of survivors as follows:

$$N_{3,i,t} \sim \text{Binom}(P_{i,t}, s'_{i,t}) \tag{14}$$

Similarly, for the breeding success effect we have

$$b'_t = b\left(m_2 \frac{N_{1,A,t} - N_{2,A,t}}{P_{A,t}} + \frac{(P_{A,t} - N_{1,A,t} + N_{2,A,t})}{P_{A,t}}\right) \tag{15}$$

The number of chicks $N_{3,1,t}$ produced by the population, incorporating the windfarm effects, is considered an output of stage 3 of the assessment and is modelled as a Poisson process:

$$N_{3,1,t} \sim \text{Poisson}(P_{A,t} b'_t) \tag{16}$$

Overdispersion can be introduced in this process via annual or colony specific variations of the survival rate b_t.

3.4. Stage 4: Population viability

Population Viability Analysis (PVA), has been an integral tool for seabird risk assessment. Within the assessment, it is the platform on which stages 1-3 are embedded. For instance, consider a closed population of a particular species whose size can be modelled by a stage-structured approach. On the assumption that breeding populations comprise apparently occupied sites (AOS) by pairs of seabirds, we focus on modelling the female population only. For any year *t* we consider three classes of animals: adults ($P_{A,t}$), floaters ($P_{F,t}$) and juveniles ($P_{i,t}$).

$$\begin{aligned} P_{A,t+1} &= N_{3,A,t} + R_t \\ P_{F,t+1} &= N_{3,F,t} - R_t + N_{3,n,t} \\ P_{i,t+1} &= N_{3,i-1,t} \\ P_{1,t+1} &= N_{3,1,t} \end{aligned} \tag{17}$$

In this formulation, the class of surviving adults is boosted by recruitment from the surviving floaters, according to a density-dependent recruitment rate r_t:

$$\begin{aligned} \text{logit}(r_t) &= \rho_0 - \rho_1 P_{A,t} \\ R_t &\sim Binom(N_{3,F,t}, r_t) \end{aligned} \tag{18}$$

The class of floaters acts as a buffer of potentially adult or near adult birds that may be unable to obtain a nest on the colony. Their survival is treated as identical to juveniles'. The class of juveniles comprises the surviving chicks born *n* years ago, the characteristic age to maturity for the species.

4. Population impacts

The first main comparison in this WP regards the population-level effects of OWF and is therefore conducted between impacted and unimpacted populations. We employ the same metrics of impact as the rest of the broader project.

4.1. Metrics of impact

For the purposes of sensitivity analysis, several iterations of the PVA will need to be run, both under identical and altered parameterisations, to capture systematic stochasticity and parameter uncertainty, respectively. The key output for each of these iterations is a set of impact metrics that rely on a comparison between impacted and baseline runs (baseline runs can also be thought of as controls, or counterfactuals). For each of $m = 1, \ldots, M$ iterations we consider the following notation:

- P_{A,t_0} : Population size before impact is introduced
- $\hat{P}_{A,t_1}$: Impacted population size at a given time horizon ($\Delta t = t_1 - t_0$) after the impact is introduced
- P_{A,t_1} : Baseline population size at a given time horizon ($\Delta t = t_1 - t_0$) after the time of impact introduction
- U_e: Quasi-extinction threshold
- U_{t_1} : Target population size

The average growth rate of a population over a given time horizon can be defined as

$$W_{\Delta t} = \left(\frac{P_{A,t_1}}{P_{A,t_0}} \right)^{\frac{1}{t_1 - t_0}}$$

Consistently with previous work packages, we will record the following metrics:

1. **Impacted population size (IPS)**: The value of $\hat{P}_{A,t_1}$
2. **Ratio of impacted to baseline size (RPS)**: The value $\hat{P}_{A,t_1}/P_{A,t_1}$
3. **Ratio of average growth rates (RGR)**: The ratio $\frac{\hat{W}_{\Delta t}}{W_{\Delta t}} = \left(\frac{\hat{P}_{A,t_1}}{P_{A,t_1}} \right)^{\frac{1}{t_1 - t_0}}$
4. **Unimpacted quantile (UQ)**: The quantile of the unimpacted population that matches the median impacted population.
5. **Impacted quantile (IQ)**: The quantile of the impacted population that matches the median unimpacted population.
6. **Probability of quasi-extinction** $p_{QE} = p(\hat{P}_{A,t_1} < U_e)$
7. **Probability of recovery (pRE)**: The probability $p_{RE} = p(\hat{P}_{A,t_1} > U_{t_1})$ that the population has recovered to a given target within the time horizon.

4.2. Using the eAssess for impacts sensitivity analysis

Because of its high computational efficiency (it is a highly abstracted version of the full assessment implementation), it is possible to use the eAssess as an exploratory tool for sensitivity analysis of impacts. To illustrate this capability,

Table 2: Parameter space ranges, explored by randomisation, as part of sensitivity analysis

Category	Par. Name	Definition	Min Value	Max Value
Species Parameters	RecrAge	Years to maturity	2	6
	AdSurv	Adult Survival	0.85	0.95
	JuSurv	Juvenile Survival	0.75	0.85
	BrSucc	Breeding Success	0.8	2
	pForage	Prop time spent foraging	0.1	0.8
	pCommut	Prop time spent	0	1-pForage
	DDLand	commuting	10^{-10}	10^{-1}
	DDSea	Density-dependent recruitment	10^{-10}	10^{-1}
		Maximum density per unit area		
OWF parameters	ColisionMort	Annual Collision Mortality	0.01	0.99
	FecundLoss	Proportional loss of fecundity	0.01	0.99
	d	OWF distance from colony	0	1000
	OWFArea	Area of windfarm footprint	100	1000
	AdCrossers	Crossing proportion of adults	0	1
	JuCrossers	Crossing proportion of juveniles	0	AdCrossers

we implemented a randomised exploration of parameter space, within the ranges listed in Table 2. The parameter space explored species characteristics as well as possible OWF spatial configurations, to identify which of those specifics have the greatest impact on the metrics of the previous section. For each parameter combination, we calculated the seven metrics and stored the combination of input parameters and output metrics into a dataframe for later analysis. A total of 10^5 parameterisations were examined, each replicated 100 times, so that a total of 10^7 eAssess runs were performed (computation time of 6 hours).

Each run was specified as follows: An initial simulation of the eAssess without the effects of OWF was run for 25 years, to make sure that the population had settled to its trajectory. Then, using the endpoint of the 25 years as the initial conditions, two counterfactuals were run for another 25 years, corresponding to futures with, and without the specified OWF.

From the resulting dataframe, we explored the capability of statistical models (GLMs and GAMs) to capture the population effects as a function of the species specifics and the OWF scenario specification (i.e., the parameters in Table 2). GAMs generally led to higher levels of explanatory power

(% deviance explained), but even the most flexible models were limited in their capacity to capture the behaviour of the system across parameter space. To try an mitigate this, we offered two constructed covariates to these models, based loosely on the type of mechanisms that connected the raw eAssess parameters to the metrics of impact.

The first constructed covariate Evalues was the dominant eigenvalue of a population projection matrix containing the baseline survival and fecundity values of the simulated species. This is equal to a population's intrinsic growth rate given its demographic rates and age to maturity (Caswell, 1989) and therefore a compact summary of four parameters into a biologically coherent value. We expected that the intrinsic growth rate of a population will influence its ability to recover and resist external mortality of a fixed intensity. In our statistical analyses below we found that unrealistically high intrinsic growth rates led to extreme and unpredictable outliers for impacts. We therefore filtered demographic parameter combinations to a set of eigenvalues lower than 1.15 (Evalues<1.15), based on published literature (Cortés, 2016; Horswill and Robinson, 2015).

The second constructed covariate dA was calculated as the ratio between the area of the OWF and the square of its distance from the colony. This ratio is proportional to the amount of area occupied by the windfarm relative to the area of a disc approximating a foraging home range that reaches up to the OWF. We expected bigger windfarms, closer to the colony, to have a greater impact.

The distribution of values for the seven metrics (Figure 5), can be compared to simulations conducted with the fully specified version of the assessment in previous work packages.

The first model examined the impacted population size (IPS):

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## IPSmu ~ s(Evalues) + s(pForage) + s(pCommut) + s(DDLand) + s(DDSea) +
##      s(ColisionMort) + s(FecundLoss) + s(dA) + s(AdCrossers) +
##      s(JuCrossers) ##
## Parametric coefficients:
##      Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11190.38      91.25  122.6  <2e-16 *** ## ---
## Signif. codes:      0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                     edf      Ref.df          F       p-value
## s(Evalues)         5.337     6.491     580.132      < 2e-16   ***
## s(pForage)         1.000     1.000       1.864      0.17223
## s(pCommut)         1.000     1.000       2.338      0.12625
## s(DDLand)          8.984     9.000     498.110      < 2e-16   ***
## s(DDSea)           1.380     1.659       0.419      0.72034
## s(ColisionMort)    1.000     1.000       0.316      0.57376
## s(FecundLoss)      1.000     1.000       0.415      0.51930
## s(dA)              3.676     4.026       4.589      0.00101   **
## s(AdCrossers)      1.000     1.000       2.771      0.09599   .
## s(JuCrossers)      1.000     1.000       0.553      0.45695
## ---
```

Signif. codes: 0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
R-sq.(adj) = 0.46 Deviance explained = 46.2%
GCV = 8.2229e+07 Scale est. = 8.2009e+07 n = 9849

This impact metric IPS does not contain a comparison with an unaffected version of the population, so it is likely to be mainly a result of population growth covariates such as the population’s intrinsic growth rate Evalues and the density dependence limitations at the colony DDLand, which mainly drives the population’s carrying capacity in this model. The model explained 46% of the deviance in the data.

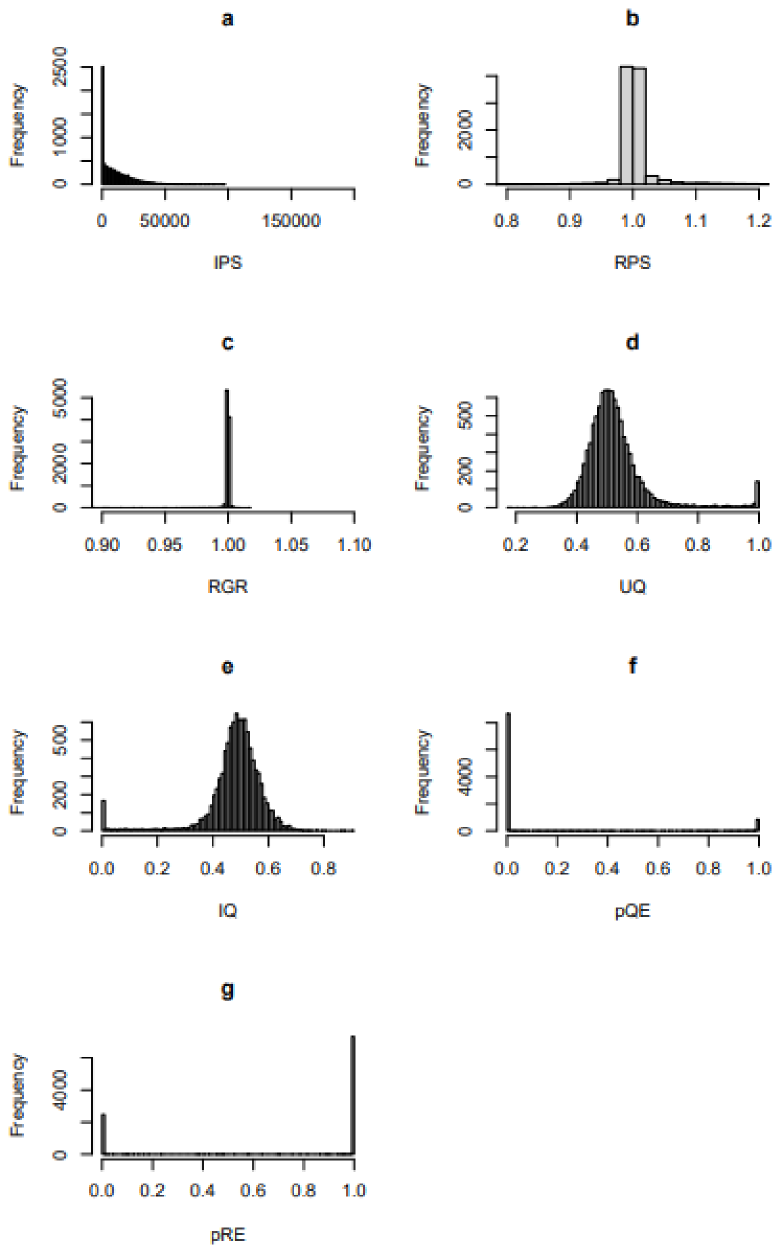

Figure 5: Raw distributions of the seven impact metrics used in this project (explained in Section 4.1)

The model for the mean ratio of impacted to baseline size (RPS), ratio of average growth rates (RGR), unimpacted and impacted quantiles (UQ, IQ), all explained moderate (<50%) percentages of deviance, indicating that the impacts of the eAssess cannot easily be captured by empirical models, albeit flexible ones, such as our GAMs. Nevertheless, these modelling exercises indicated that impacts were less dependent on demography but rather, mainly driven by the characteristics of the windfarm (distance, area, mortality).

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## RPSmu ~ s(Evalues) + s(pForage) + s(pCommut) + s(DDLand) + s(DDSea) +
##     s(ColisionMort) + s(FecundLoss) + s(dA) + s(AdCrossers) +
##     s(JuCrossers)
##
## Parametric coefficients:
##     Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.0031070    0.0003871    2591   <2e-16 ***
## ---
## Signif. codes:    0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                     edf     Ref.df        F      p-value
## s(Evalues)          1.000   1.000      5.205    0.0225    *
## s(pForage)          6.570   7.702      1.718    0.0816    .
## s(pCommut)          5.183   6.324      7.745    <2e-16    ***
## s(DDLand)           7.960   8.710    484.093    <2e-16    ***
## s(DDSea)            1.000   1.000      1.926    0.1653
## s(ColisionMort)     2.051   2.561     15.350    <2e-16    ***
## s(FecundLoss)       2.458   3.062      1.068    0.3698
## s(dA)               8.789   8.979    471.299    <2e-16    ***
## s(AdCrossers)       1.960   2.447      2.805    0.0414    *
## s(JuCrossers)       1.000   1.000      6.081    0.0137    *
## ---
## Signif. codes:    0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =      0.469  Deviance explained = 47.1%
## GCV = 0.0014818        Scale est. = 0.0014759      n = 9849
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## RGRmu ~ s(Evalues) + s(pForage) + s(pCommut) + s(DDLand) + s(DDSea) +
##     s(ColisionMort) + s(FecundLoss) + s(dA) + s(AdCrossers) +
##     s(JuCrossers)
##
## Parametric coefficients:
##     Estimate Std. Error t value Pr(>|t|)
## (Intercept) 9.997e-01    2.863e-05    34918 <2e-16 ***
## ---
```

```
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## Approximate significance of smooth terms:
##                     edf   Ref.df         F    p-value
## s(Evalues)        1.000    1.001     1.547    0.21363
## s(pForage)        1.681    2.091     0.676    0.53912
## s(pCommut)        1.000    1.001    19.817   8.79e-06  ***
## s(DDLand)         4.999    6.073    20.636    < 2e-16  ***
## s(DDSea)          1.001    1.001     1.140    0.28575
## s(ColisionMort)   2.741    3.413    10.755   2.22e-07  ***
## s(FecundLoss)     1.000    1.001     0.015    0.90231
## s(dA)             8.756    8.975   593.258    < 2e-16  ***
## s(AdCrossers)     1.000    1.001     7.363    0.00667  **
## s(JuCrossers)     1.000    1.001     2.811    0.09364  .
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## R-sq.(adj)  =   0.36   Deviance explained = 36.2%
## GCV = 8.0934e-06       Scale est. = 8.0727e-06     n = 9849

##
## Family: gaussian
## Link function: identity
##
## Formula:
## UQ ~ s(Evalues) + s(pForage) + s(pCommut) + s(DDLand) + s(DDSea) +
##     s(ColisionMort) + s(FecundLoss) + s(dA) + s(AdCrossers) +
##     s(JuCrossers) ##
## Parametric coefficients:
##     Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.531358    0.000847    627.4  <2e-16 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## Approximate significance of smooth terms:
##                     edf   Ref.df         F    p-value
## s(Evalues)        1.001    1.002     0.020    0.88896
## s(pForage)        4.725    5.786     1.065    0.31667
## s(pCommut)        4.173    5.174    22.200    < 2e-16  ***
## s(DDLand)         4.826    5.878    18.814    < 2e-16  ***
## s(DDSea)          2.509    3.093    15.184    < 2e-16  ***
## s(ColisionMort)   1.001    1.002    96.894    < 2e-16  ***
## s(FecundLoss)     1.757    2.191     1.505    0.23125
## s(dA)             8.996    9.000   493.140    < 2e-16  ***
## s(AdCrossers)     1.001    1.001    24.158   1.26e-06  ***
## s(JuCrossers)     1.001    1.002     9.606    0.00194  **
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## R-sq.(adj) =   0.332  Deviance explained = 33.4%
## GCV = 0.0070883          Scale est. = 0.0070653     n = 9849
##
## Family: gaussian
## Link function: identity
##
## Formula:
```

```
## IQ ~ s(Evalues) + s(pForage) + s(pCommut) + s(DDLand) + s(DDSea) +
##       s(ColisionMort) + s(FecundLoss) + s(dA) + s(AdCrossers) +
##       s(JuCrossers) ##
## Parametric coefficients:
##       Estimate Std. Error t value Pr(>|t|)

## (Intercept) 0.4841385     0.0008516     568.5  <2e-16 ***
## ---
## Signif. codes:     0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                     edf      Ref.df          F        p-value
## s(Evalues)          1.000    1.001       0.003       0.95853
## s(pForage)          5.869    7.026       1.661       0.11130
## s(pCommut)          4.213    5.222      20.819       < 2e-16    ***
## s(DDLand)           7.857    8.654     101.105       < 2e-16    ***
## s(DDSea)            2.561    3.157      12.212       < 2e-16    ***
## s(ColisionMort)     1.000    1.000     109.528       < 2e-16    ***
## s(FecundLoss)       2.121    2.646       2.333       0.11444
## s(dA)               8.996    9.000     498.453       < 2e-16    ***
## s(AdCrossers)       1.423    1.731      15.887       1.27e-05   ***
## s(JuCrossers)       1.001    1.001      11.468       0.00071    ***
## ---
## Signif. codes:     0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =       0.369  Deviance explained = 37.1%
## GCV = 0.0071702               Scale est. = 0.0071433        n = 9849
```

The remaining two models looking at the probability of quasi-extinction and probability of recovery had high explanatory power, driven mainly by the intrinsic capacities of simulated species (Evalues and DDLand), rather than aspects of the OWF specification. This finding should not be interpreted as generalisable since both the probabilities of quasi-extinction and recovery were defined with regard to an arbitrary population threshold (pQE below 50 individuals, and pRE above 1000).

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## pQE ~ s(Evalues) + s(pForage) + s(pCommut) + s(DDLand) + s(DDSea) +
##       s(ColisionMort) + s(FecundLoss) + s(dA) + s(AdCrossers) +

##       s(JuCrossers)
##
## Parametric coefficients:
##       Estimate Std. Error t value Pr(>|t|)

## (Intercept) 0.103096      0.000793      130     <2e-16 ***
## ---
## Signif. codes:     0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                         edf           Ref.df              F        p-value
```

```
## s(Evalues)        1.788   2.248       0.932   0.410909
## s(pForage)        1.000   1.000       0.057   0.810794
## s(pCommut)        4.156   5.148       1.003   0.408921
## s(DDLand)         8.990   9.000   14537.835    < 2e-16 ***
## s(DDSea)          1.000   1.000       0.469   0.493562
## s(ColisionMort)   5.586   6.735       1.313   0.243100
## s(FecundLoss)     1.000   1.000       0.020   0.887533
## s(dA)             2.031   2.203       8.025   0.000178 ***
## s(AdCrossers)     1.735   2.154       0.992   0.412690
## s(JuCrossers)     1.641   2.036       0.759   0.459866
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =     0.93   Deviance explained =     93%
## GCV = 0.0062131         Scale est. = 0.0061942   n = 9849
##
## Family: gaussian
## Link function: identity
##
## Formula:
## pRE ~ s(Evalues) + s(pForage) + s(pCommut) + s(DDLand) + s(DDSea) +
##     s(ColisionMort) + s(FecundLoss) + s(dA) + s(AdCrossers) +
##     s(JuCrossers) ##
## Parametric coefficients:
##     Estimate Std. Error t value Pr(>|t|)

## (Intercept) 0.745398    0.001738    428.8  <2e-16 ***
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

## Approximate significance of smooth terms:
##                   edf     Ref.df         F   p-value
## s(Evalues)        8.721   8.977     30.973   <2e-16 ***
## s(pForage)        1.568   1.939      0.476   0.6175
## s(pCommut)        1.000   1.001      0.759   0.3839
## s(DDLand)         8.998   9.000   5788.243   <2e-16 ***
## s(DDSea)          1.002   1.003      0.100   0.7529
## s(ColisionMort)   1.001   1.002      5.153   0.0231 *
## s(FecundLoss)     1.001   1.001      1.371   0.2414
## s(dA)             8.305   8.814     14.717   <2e-16 ***
## s(AdCrossers)     1.001   1.003      0.038   0.8478
## s(JuCrossers)     2.790   3.490      1.633   0.1638
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =     0.843  Deviance explained = 84.3%
## GCV = 0.029872 Scale est. = 0.029762      n = 9849
```

5. Comparing accuracy and precision changes between bAssess and eAssess

The second comparison, unique to this WP, regards the change in accuracy and precision in going from the bAssess to the eAssess. We first simplified the eAssess by considering the features that could be removed in order to obtain a more basic version of the model, and then examined which of these features led to bias and imprecision in the final results.

5.1. Specifying the baseline assessment (bAssess).

There are three key features of the eAssess that can be rolled back to what may be considered a more basic version (bAssess):

1. The density of birds around the windfarm may be considered constant, regardless of whether the population is growing or declining.
2. It may be assumed that there may be no avoidance of the OWF, only crossing through it.
3. It may be assumed that there are no secondary effects to displacement, as opposed to allowing losses in fecundity.

Using these assumptions, we constructed five bAssess models, described as follows:

- bAssess 1: No secondary effects of avoidance
- bAssess 2: No avoidance, only crossing
- bAssess 3: No feedback of population growth
- bAssess 4: No feedback, no secondary effects
- bAssess 5: No feedback, no avoidance

During the sensitivity analysis simulation one of these five versions was selected at random and compared with the eAssess results. We focused on RPS, the ratio of impacted to unimpacted population size, mainly because this metric results in measures of centrality (mean and median) as well as spread (standard deviation). This allowed us to quantify which set of assumptions had the biggest impact on accuracy and precision, respectively.

5.2. Accuracy comparison between bAssess and eAssess

Assuming that the eAssess is the more accurate model compared to any of the bAssess versions, we defined accuracy in three different ways. First, as the difference between the mean RPS of the enhanced and baseline models

$$\Delta\mu_{RPS} = \mu_{eRPS} - \mu_{bRPS}$$

Second, as the ratio between the mean RPS of the baseline and enhanced models

$$R\mu_{RPS} = \frac{\mu_{bRPS}}{\mu_{eRPS}}$$

as the proportional difference between the RPS of the enhanced model (eRPS) and the RPS of the baseline model (bRPS).

$$\delta\mu_{RPS} = \frac{\mu_{eRPS} - \mu_{bRPS}}{\mu_{eRPS}}$$

To these response variable, we fitted a flexible model using all the available covariates, with the addition of the indicator variable for the particular bAssess examined for each covariate combination. The model with the simple difference $\Delta\mu_{RPS}$ had the highest explanatory power. The histogram of differences (Figure 6a), indicated that the bias in impact predictions is not necessarily skewed in the positive or negative direction. In other words, the baseline model is not consistently precautionary, nor is it overoptimistic. Looking at more detail at zoomed box-plots of the potential bias characterising each of the five bAssess models, we see consistently symmetric forms of bias (Figure 6b).

To investigate these differences in more depth, we looked at the flexible gam model comprising bAssess type and eAssess parameterisation as explanatory variables. The summary of this model indicates that, on average, bAssess models 3,4, and 5 tend to have increased impact bias, hinting therefore that omission of the feedback feature between population growth and exposure will tend to underestimate impacts. The marginal plots of the three most influential model terms of the model (Figure 7) suggest that the bAssess models are likely to be overoptimistic (therefore, not precautionary) for slow-growing species, that have intermediate strength of density dependence and for which the placement and size of an OWF takes up a small proportion of the colony's home range (i.e. the impact of small or distant farms may be underestimated).

```
DRPSmuMod<-gam(DRPSmu~bAssess+s(Evalues)+s(pForage)+s(pCommut)+s(DDLand)+s(DDSea)+
   s(ColisionMort)+s(FecundLoss)+s(dA)+s(AdCrossers)+s(JuCrossers),
data=impactDat)
```

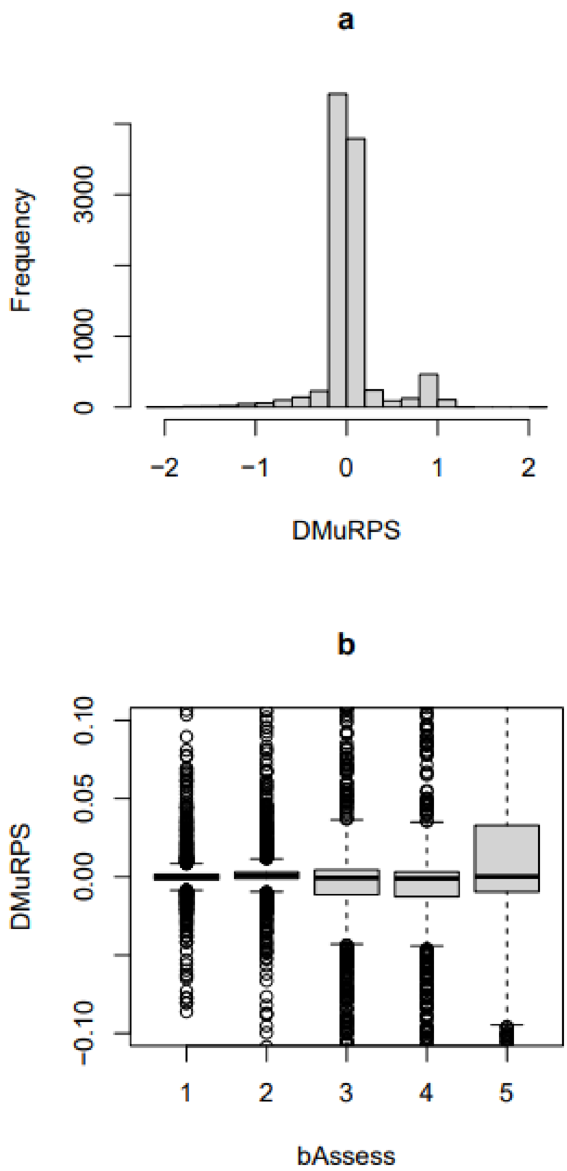

Figure 6: Histogram of bias in RPS metric under the baseline and enhanced models. Positive values indicate that the enhanced model predicted greater impact (hence, current assessment is likely to be overoptimistic), negative values indicate that baseline model predicted greater impact (and hence bAssess is likely to be precautionary). Aggregate differences are seen in (a), boxplots of differences according to each of the five versions of bAssess are seen in (b)

```
summary(DRPSmuMod)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## DRPSmu ~ bAssess + s(Evalues) + s(pForage) + s(pCommut) + s(DDLand) +
```

```
##      s(DDSea) + s(ColisionMort) + s(FecundLoss) + s(dA) + s(AdCrossers) +
##      s(JuCrossers)
##
## Parametric coefficients:
##                   Estimate   Std. Error   t value    Pr(>|t|)
##      (Intercept)  0.001880   0.005662     0.332       0.740
##      bAssess2     0.009310   0.008018     1.161       0.246
##      bAssess3     0.050548   0.007902     6.397    1.66e-10  ***
##      bAssess4     0.055479   0.007982     6.950    3.88e-12  ***
##      bAssess5     0.055916   0.007874     7.101    1.32e-12  ***
##      ---
## Signif. codes:    0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## Approximate significance of smooth terms:
##                      edf     Ref.df          F     p-value
## s(Evalues)         1.861     2.344      49.806      <2e-16  ***
## s(pForage)         1.000     1.000       0.906      0.3413
## s(pCommut)         1.000     1.000       0.573      0.4491
## s(DDLand)          8.486     8.924     569.589      <2e-16  ***
## s(DDSea)           1.000     1.000       0.166      0.6835
## s(ColisionMort)    1.000     1.000       2.772      0.0960  .
## s(FecundLoss)      1.000     1.000       0.767      0.3812
## s(dA)              5.656     6.328       8.828      <2e-16  ***
## s(AdCrossers)      1.000     1.000       3.357      0.0669  .
## s(JuCrossers)      1.572     1.951       0.760      0.4094
## ---
## Signif. codes:    0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## R-sq.(adj) =      0.354  Deviance explained = 35.6%
## GCV = 0.061533 Scale est. = 0.061355         n = 9849
```

5.3. Precision comparison between bAssess and eAssess

We defined precision in three different ways. First, as the difference between the standard deviation in RPS of the enhanced and baseline models

$$\Delta\sigma_{RPS} = \sigma_{eRPS} - \sigma_{bRPS}$$

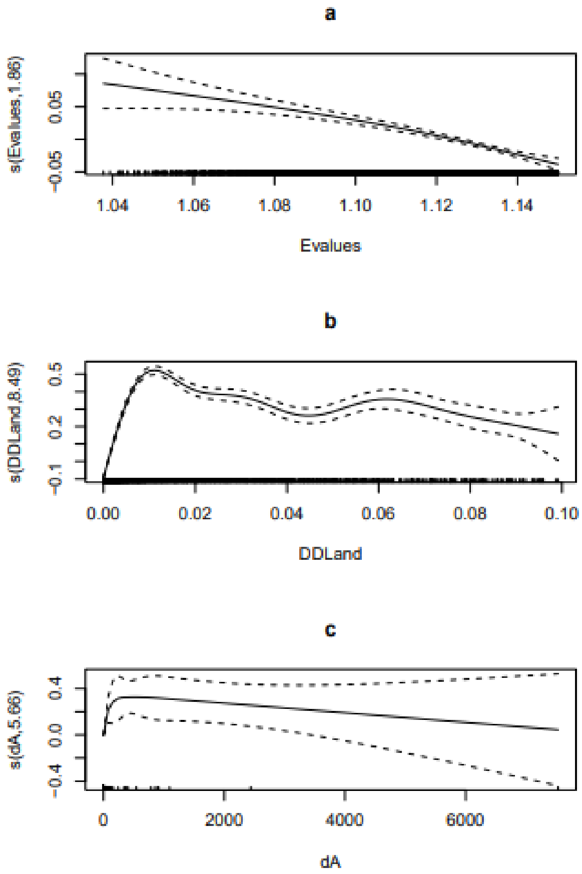

Figure 7: Marginal plots of the influential terms in the model looking at the difference between mean impacts. The units on the y-axes are relative measures of bias. High values indicate that the bAssess is overoptimistic, low values that it is precautionary.

Second, as the ratio between the st devs RPS of the baseline and enhanced models

$$R\sigma_{RPS} = \frac{\sigma_{bRPS}}{\sigma_{eRPS}}$$

as the proportional difference between the st dev in RPS of the enhanced model (eRPS) and the RPS of the baseline model (bRPS).

$$\delta\sigma_{RPS} = \frac{\sigma_{eRPS} - \sigma_{bRPS}}{\sigma_{eRPS}}$$

To these response variable, we fitted a flexible model using all the available covariates, with the addition of the indicator variable for the particular bAssess examined for each covariate combination. The model with the simple difference $\Delta\sigma_{RPS}$ had the highest explanatory power. The histogram of differences (Figure 8a), indicated that precision in impact predictions is neither necessarily lost nor gained in going from bAssess to eAssess. Looking at more detail at zoomed box-plots of the potential precision loss/gain characterising each of the five bAssess models, we see that this pattern is mostly preserved across different bAssess models (Figure 8b).

To investigate these differences in more depth, we looked at the flexible gam model comprising bAssess type and eAssess parameterisation as explanatory variables. The summary of this model indicates that, on average, bAssess models 3, 4, and 5 tend to have increased uncertainty, hinting therefore that omission of the feedback feature between population growth and exposure will tend to underestimate the variability in possible impacts. The marginal plots of the four most influential model terms of the model (Figure 9) suggest that bAssess models are likely to be overprecise (hence, not precautionary) for slow-growing species that experience only intermediate levels of colony density dependence and low collision mortality, and for which the placement and size of an OWF takes up a small proportion of the colony's home range (i.e. the impact of small or distant farms may be more variable than predicted by bAssess).

```
DRPSsdMod<-gam(DRPSsd~bAssess+s(Evalues)+s(pForage)+s(pCommut)+s(DDLand)+s(DDSea)+
   s(ColisionMort)+s(FecundLoss)+s(dA)+s(AdCrossers)+s(JuCrossers),
data=impactDat)

summary(DRPSsdMod)
```

```
##
## Family: gaussian
## Link function: identity ##
## Formula:
## DRPSsd ~ bAssess + s(Evalues) + s(pForage) + s(pCommut) + s(DDLand) +
##      s(DDSea) + s(ColisionMort) + s(FecundLoss) + s(dA) + s(AdCrossers) +
##      s(JuCrossers)
##
## Parametric coefficients:
##                  Estimate    Std. Error    t value    Pr(>|t|)
## (Intercept)     1.074e-03    1.360e-03      0.790       0.43
```

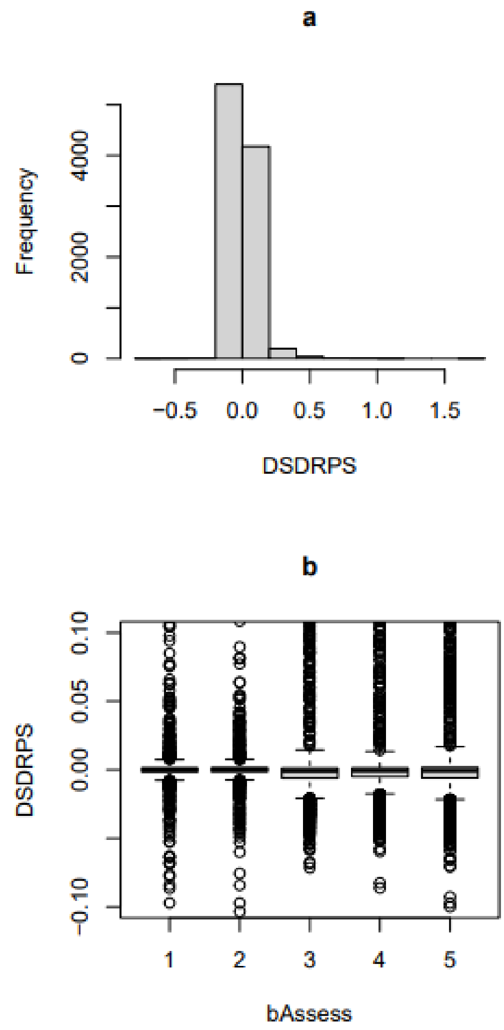

Figure 8: Histogram of change in precision in RPS metric under the baseline and enhanced models. Positive values indicate that the enhanced model predicted more uncertain impacts (hence, current assessment is likely to be overprecise), negative values indicate that baseline model predicted more uncertain impacts (and hence bAssess is likely to be imprecise). Aggregate differences are seen in (a) and boxplots of differences according to each of the five versions of bAssess are seen in (b)

```
## bAssess2      -4.712e-05   1.927e-03   -0.024      0.98
## bAssess3       1.357e-02   1.898e-03    7.146   9.56e-13   ***
## bAssess4       1.612e-02   1.918e-03    8.404    < 2e-16   ***
## bAssess5       1.541e-02   1.892e-03    8.143   4.32e-16   ***
##                      ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                    edf     Ref.df        F   p-value
## s(Evalues)       1.000      1.001   10.187   0.00142   **
## s(pForage)       1.001      1.003    0.043   0.83849
## s(pCommut)       2.300      2.891    1.526   0.15719
```

```
## s(DDLand)        8.934    8.999  440.227   < 2e-16   ***
## s(DDSea)         1.003    1.005    0.285   0.59584
## s(ColisionMort)  1.000    1.001    5.217   0.02237   *
## s(FecundLoss)    2.711    3.375    1.497   0.19874
## s(dA)            7.331    8.110   11.631   < 2e-16   ***
## s(AdCrossers)    1.000    1.001    0.020   0.88881
## s(JuCrossers)    1.901    2.386    1.262   0.30691
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 ##
## R-sq.(adj) =   0.301        Deviance explained = 30.3%
## GCV = 0.003552   Scale est. = 0.00354      n = 9849
```

6. Conclusions

- Correlations between parameters in models can generate unexpected bias and loss of precision.
- It is difficult to assume arbitrary forms and magnitudes of correlation in a model such as the assessment which is rich in mechanistic features of behaviour, demography and population dynamics.
- Correlations must therefore emerge from modelled interdependencies between mechanistic features of the model. These structural correlations are better tied to biological intuition and can be parameterised more readily as a result.
- Abstracted versions of the assessment process, with considerably shorter running times can be used to approximate its essential functions. This allows the examination of adding currently missing features that introduce connections and feedbacks between different inputs and outputs in the assessment stages.
- Examination of OWF impact metrics in response to the parameters characterising a seabird-OWF interaction indicates that impacts cannot readily be captured by correlational models, even reasonably flexible ones (deviance explained, never exceeded 50%). This indicates that abstraction of the assessment pipeline, and certainly, its replacement by simple empirical models are risky endeavours.
- For the parameter space examined here, impacts were found to be relatively small.

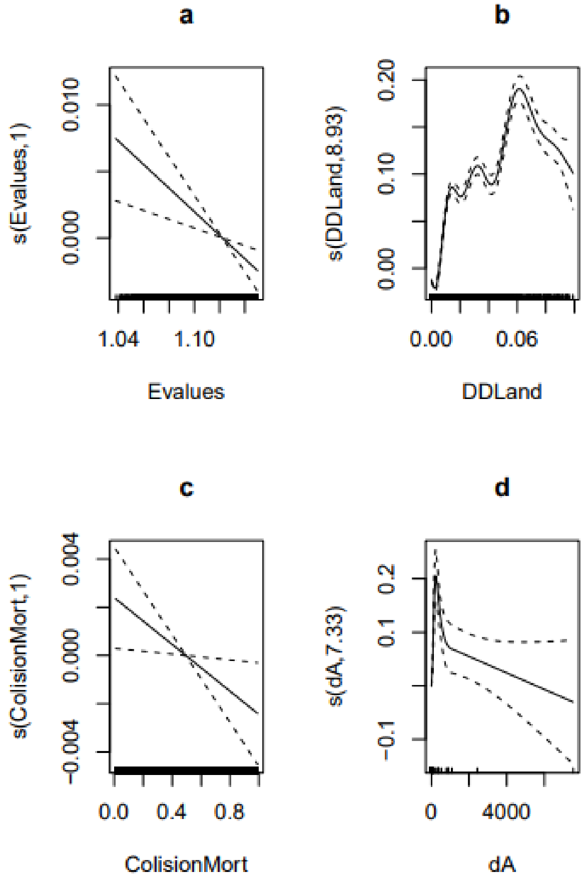

Figure 9: Marginal plots of the influential terms in the model looking at the difference between precision of impacts. The units on the y-axes are relative measures of difference in uncertainty. High values indicate that the bAssess is misleadingly precise, low values that it is precautionary.

- Comparison of the enhanced and basic versions (eAssess. bAssess) of assessment indicates that bias and imprecision are not exclusive characteristics of either eAssess or bAssess.
- There are measurable but small differences in bias and imprecision, and the bAssess (essentially, a mock of the currently used assessment methods) is neither certain to be precautionary nor overoptimistic.
- The accuracy and precision appear, within the context of the abstracted models considered here, appears to depend most on the rate of growth of a species, the strength of density regulation, collision mortality rates and the size/distance of the OWF in relation to a colony.
- A key feature that is likely to improve both precision and accuracy is the inclusion of predicted future population size and its impact on seabird distribution and exposure to risk.

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Appendix A: Code for enhanced assessment model

```
################# 1. FUNCTIONS

############ Exposure function
# Inputs:
# al: Maximum density of animals at unit of area inside home range
# A: Total area of windfarm
# aF: Abrubtness of home range boundary
# aC: Decay of commuting usage with distance from colony
# l: Proportion of available marine area in circle buffer
# delta: Unit of length
# wF: Proportion of time spent foraging
# wC: Proportion of time spent commuting
# d: Distance of windfarm from colony
# Pt: Current total population size
# Output:
# Expected usage of windfarm

expose<-function(al,A,aF,aC,l,delta,wF,wC,d,Pt)
{
  R<-sqrt((wF*Pt)/(l*pi*al))
  UF<-al*A/(1+exp(-aF*(1-d/R)))
  UC<-ifelse(d>R, 0,
             aC*wC*Pt*A*exp(-aC*d)/(l*pi*(delta^2+2*d*delta)*(1-exp(-aC*R))))
  return(UF+UC)
}



############ Population Viability Analysis
# Inputs:
# initPs: A vector of initial sizes for the population classes
#         (Adults, Floaters, Juvs 1-n)
# tmax: Duration of PVA in years
# su: Collected baseline survivals for all classes (Adults, Floaters, Juvs 1-n)
# al,A,aF,aC,l,delta,wF,wC,d: See function `exposure`
# piA,piJ: : See function `displace`
# b: Baseline fecundity
# m1: Survival from collision
# m2: Fecundity scaling for displacement
# rho0: Baseline recruitment
# rho1:  Density-dependent attrition to recruitment
# Pexp: Population feedback for exposure
#       Pexp=1: Corresponds to full eAssess model
#       Pexp=2: Only uses the initial population size for exposure
```

```
pva<-function(initPs, tmax, al,A,aF,aC,l,
              delta,wF,wC,d,piA,piJ, su,
              b, m1, m2, rho0, rho1, Pexp=1)
{
  nn<-length(initPs)-2 # Number of years to maturity
  # Data structures for pop. sizes and survivors
  P<-Surv<-Surs<-matrix(0, nrow=nn+2, ncol=tmax)
  # Data structures for births, recruitment and recruits
  births<-rec<-r<-rep(0,tmax)
  P[1:(nn+2),1]<-initPs # Initialisation
  # Probability vector of crossing/displacement for pop classes
  pv<-c(piA,rep(piJ,nn+1))


  for(t in 1:(tmax-1))
  {

    ##############  assessment Stage 1: Exposure
    texp<-t
    if(Pexp==2) texp<-1
    Ptot<-sum(P[1:(nn+2),texp])
    # Expected number of animals exposed
    u<-expose(al,A,aF,aC,l,delta,wF,wC,d,sum(P[,t]))
    # Animals exposed
    N1<-pmin(P[,t],rpois(nn+2, u*P[,t]/sum(P[,t])))

    ##############  assessment Stage 2: Displacement


    # Vector of birds crossing
    N2<-rbinom(nn+2,N1,pv)

    ##############  assessment Stage 3: Demography

    # Expected survival of classes
    Surv[,t]<-su*((P[,t]-N2)+m1*N2)/P[,t]
    Surv[is.na(Surv[,t]),t]<-0

    # Survivors
    Surs[,t]<-rbinom(nn+2,P[,t],Surv[,t])

    # Breeding success
    Bi<-b*((P[1,t]-N1[1]+N2[2])+m2*(N1[1]-N2[1])) # Birth rate
    births[t]<-rpois(1,Bi) # Births

    # Recruitment
    r[t]<-1/(1+exp(-(rho0-rho1*Ptot))) # Recruitment probability
```

```
    rec[t]<-rbinom(1,Surs[2,t],r[t]) # Number of recruits

    P[1,t+1]<-Surs[1,t]+rec[t] # Adult class
    P[2,t+1]<-Surs[2,t]-rec[t]+Surs[3,t] # Floater class
    P[3:(1+nn),t+1]<-Surs[4:(nn+2),t] # Sub-adult classes
    P[2+nn,t+1]<-births[t] # 1st year class
  }

  return(P)
}
```

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Published in the UK: 2025