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Testing and Validating Metrics of Change Produced by Population Viability Analysis (PVA)

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Testing and validating metrics of change produced by Population Viability Analysis (PVA)

Mark Jitlal, Sarah Burthe, Stephen Freeman and Francis Daunt

Centre for Ecology & Hydrology
NATURAL ENVIRONMENT RESEARCH COUNCIL

Table of Contents

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Executive Summary

- The aim of this research project was to review the use of Population Viability Analysis (PVA) metrics in the context of assessing the effect of offshore renewable developments on seabirds and to test PVA metric sensitivity to mis-specification of input parameters. The most useful metrics in this context are those that are least sensitive to such mis-specification, enabling more robust assessment of offshore renewable effects.
- Recent work has tested PVA metric sensitivity using a simulation approach. To complement these findings, the objective in this project was to test metric sensitivity using real-world data. This approach is useful where one wishes to understand a specific region where real data are available, or where one wishes to address generic questions with real data. If the same metrics show low sensitivity in models of real world data as in simulation models, then this would provide re-assurance that these metrics are the most appropriate for use in assessments.
- Five study species were selected: black-legged kittiwake *Rissa tridactyla*; common guillemot *Uria aalge*; razorbill *Alca torda*; herring gull *Larus argentatus* and European shag *Phalacrocorax aristolelis*. Of these, the first four were considered in population modelling in the Forth/Tay region in a previous Marine Scotland Science project (Freeman *et al.* 2014). Similar models have, in the interim, also been fitted for shags in this region so this species was also considered. The SPAs considered in this report were Buchan Ness to Collieston Coast SPA, Fowlsheugh SPA, Forth Islands SPA and St Abb's Head to Fastcastle SPA.
- Data on abundance, survival and productivity were collated from a variety of sources. Regular or sporadic counts were available from all sites, based on whole colony or plot counts. Productivity was available from all four SPAs for kittiwakes, and for European shags at two SPAs, otherwise data on demographic rates was limited to the Isle of May in the Forth Islands SPA.

- All models were fitted using a Bayesian approach in the software R/WinBUGS. Model fitting was in 'state-space' form, which allows for 'observation error' and environmental stochasticity simultaneously within the same model. Models forecasted the population size for each species at each SPA, for 25 years from 2016 to 2041. Adult survival was set to decline by one of a range of specified rates equating to offshore renewable effects, namely 0% (i.e. no change), 0.5%, 1%, 2% and 3%. Annual productivity was set to decline by 0%, 1%, 2%, 3% and 5%.
- Previous work has indicated that ratio PVA metrics are less sensitive than probabilistic PVA metrics. Accordingly, we tested the sensitivity of six PVA metrics, comprising two ratio metrics (median of the ratio of impacted to un-impacted annual growth rate; median of the ratio of impacted to un-impacted population size); two metrics related to the ratio metrics (median difference in impacted and un-impacted annual growth rates; median difference between impacted and un-impacted population size) and two probabilistic metrics (probability of a population decline exceeding 10%, 25% or 50%; centile for un-impacted population which matches the 50th centile for the impacted population).
- Sensitivity of the six PVA metrics was assessed in relation to mis-specification of input parameters. We considered adult mortality (the complement of survival, since survival is high in seabirds and % increases are limited by the constraint of lying below a survival rate of 1) and productivity to differ from those of the baseline by: -30%, -20%, -10%, 10%, 20% and 30%. We then assessed sensitivities in relation to population status, combining data from all species/SPAs for which we achieved model convergence. Finally, we assessed PVA sensitivities in relation to scenarios of change resulting from the renewables development (i.e. the effect size).
- The state-space modelling approach proved extremely powerful in forecasting population sizes, in particular where censuses were regular. Even in cases where censuses were sporadic, the models generally performed well, though for three species/SPA populations the models would not converge successfully.
- The two ratio metrics were least sensitive to mis-specification in input parameters. They performed well in populations of different status, and under different scenarios of change. The two difference metrics were not readily interpretable, but proved useful when growth rates or population size estimates were small. The probabilistic metrics were more sensitive to mis-specification to input parameters than the ratio PVA metrics. The 'probability of a population decline' metric has been widely used in assessments but proved highly sensitive to mis-specification. The metric representing the

centile from the un-impacted population size equal to the 50th centile of the impacted population size at the end of the wind farm showed moderately low sensitivity to mis-specification of survival and productivity. It performed considerably better than the other probabilistic metric with markedly lower sensitivity to mis-specification, population status and renewables effect size. However, it was more sensitive than ratio metrics, and in some cases showed unstable sensitivity which was less apparent in ratio PVA metrics.

- We recommend that those undertaking assessments consider the relative performance of different metrics with respect to sensitivity to mis-specification of input parameters. Of the two ratio and two probabilistic metrics, the ratio metric 'median of the ratio of impacted to un-impacted annual growth rate' was least sensitive, followed by the ratio metric 'median of the ratio of impacted to un-impacted population size' and then the probabilistic metric 'centile for un-impacted population which matches the 50th centile for the impacted population'. If these are used in assessments in future, we recommend that interpretation should factor in their relative sensitivities. Furthermore, a priority for future research would be to analyse the probabilistic metric using simulations, to assess whether the same results are found as in this study. The probabilistic PVA metric 'probability of a population decline' was much more sensitive than the other three and is not recommended for use in this context. Finally, we recommend that the two PVA metrics related to the ratio metrics (median difference in impacted and un-impacted annual growth rates; median difference between impacted and un-impacted population size) are used since they are estimable when ratios are being calculated and are useful in some circumstances.

1. Introduction

1.1 Policy Context

The Scottish Government has set a target of 100% of Scottish demand for electricity to be met by renewable sources by 2020. The Scottish Government has a duty to ensure that offshore renewable developments are achieved in a sustainable manner. Scottish Ministers have consented offshore renewable energy sites under Section 36 of the Electricity Act 1989. A licensing process was followed that included the examination of Environmental Statements (ES) which consider the potential impacts and mitigation strategies of the proposed developments.

Offshore renewable developments have the potential to impact on seabird populations that are protected by the EU Birds Directive [2009/147/EC], notably from collisions with turbine blades and through displacement from important habitat (Drewitt & Langston 2006; Larsen & Guillemette 2007; Masden *et al*. 2010; Grecian *et al*. 2010, Langton *et al*. 2011, Scottish Government 2011). Other factors of concern are barrier effects to the movement of migrating or commuting birds, disturbance during construction and operation, toxic and non-toxic contamination and negative effects of developments on the distribution and abundance of prey. Set against these, positive effects may be apparent, in particular if developments result in downstream changes to the physical environment that increase biomass of lower tropic levels (Inger *et al*. 2009). Further, they may act as Fish Aggregating Devices (FADs) creating foraging opportunities for seabirds (Inger *et al*. 2009), though attracting seabirds may increase their vulnerability to other effects such as collision and noise (Scottish Government 2011). Species differ in the sensitivity to disturbance, with auks of intermediate vulnerability and gulls and terns of low vulnerability (Garthe & Hüppop 2004; Langston 2010; Furness *et al*. 2013). These potential effects are predicted to be particularly important for breeding seabirds that, as central place foragers, are constrained to obtain food within a certain distance from the breeding colony (Daunt *et al*. 2002; Enstipp *et al.* 2006).

To aid the future development of offshore renewables, Marine Scotland have developed draft Sectoral Marine Plans for offshore Wind, Wave and Tidal Energy (Scottish Government 2013b) that have involved identifying the available resources and key constraints at a national and regional level, then applying social, economic and environmental assessments to inform the development of plan options. These plans have been subject to a Sustainability Appraisal and public consultation exercise (Scottish Government 2013e) and are underpinned by detailed technical assessments including a Strategic Environmental Assessment (SEA; Scottish

Government 2013d), Habitats Regulations Appraisal (HRA; Scottish Government 2013a) and Socio-economic Assessment (Scottish Government 2013c).

The above analyses have synthesised the potential sensitivities of internationally important seabird populations in Scotland and recognised areas of uncertainty associated with these effects. Therefore, in order to evaluate potential interactions between offshore renewables and marine wildlife in future, Marine Scotland believes that further marine science is required to continue to reduce uncertainty and apply the appropriate level of precaution.

Population Viability Analysis (PVA) provides a robust framework that uses demographic rates to forecast future population levels, either under baseline conditions or under scenarios of change resulting from, for example, an offshore development (Maclean *et al.* 2007; Freeman *et al*. 2014). A sensitivity analysis of PVA metrics to variation in demographic parameters would enable regulators and their advisers to assess the utility of each of these metrics in determining whether a predicted effect is unacceptably large. Demonstrating the validity of these metrics would also ensure that PVA outputs are presented and interpreted in the most suitable way. The outcomes could then be fed back into designing future monitoring requirements. Furthermore, the outputs could inform the establishment of thresholds of acceptable change by regulators, although such an approach has been heavily criticised (Green *et al*. 2016). Finally, they could improve assessments of risk and uncertainty with respect to population viability in environmental assessments and help to ensure that the level of precaution applied is appropriate.

1.2 Project Objectives

An important component of consenting of proposed offshore renewable developments is an assessment of the population consequences on seabirds. Population Viability Analysis (PVA) provides a robust framework that uses assumed or estimated demographic rates (principally survival and productivity) in a mathematical model to forecast future population levels of a wild animal population, either under currently prevailing circumstances or as a consequence of some perturbation to the system (Maclean *et al*. 2007; Freeman *et al*. 2014). Stochastic PVA models are run many times selecting from a distribution of input parameters, resulting in outputs representing the mean, confidence intervals and all quantiles including the 50% (median).

The range of PVA metrics which have the potential to describe the magnitude of a predicted effect on a population include population size by some target date, change in size or growth rate between pairs of consecutive years, trend in population size, counterfactual/ratio of population size or growth rate, probabilities of population decline to below a specific level or a specific percentage of the starting population size, excess probabilities of population decline to below a specific level or a specific percentage of the starting population size, population level predicted to be exceeded with predefined probability (e.g. 'as likely as not', Mastrandrea *et al*. 2010) and posterior probabilities (or quantiles derived from them) for any of the above.

This PVA framework allows the sensitivity of these metrics to changes in demographic parameters, notably due to estimation error, to be estimated. This is important as all demographic parameters are estimated with uncertainty, and population change and PVA metrics are disproportionately affected by changes in the magnitude of each. Accordingly, the aim of this project is to review the range of metrics available in PVA analysis and evaluate the sensitivity of these metrics in the context of decision making frameworks.

The report will first review the literature regarding the range of metrics available for use by PVA analysis in the context of renewable assessment frameworks of seabirds. It will then examine the relative sensitivity of a subset of these metrics to mis-specification of input parameters (adult survival and productivity) using PVAs developed on protected seabird populations at SPAs in the Forth/Tay region. It will also assess the impact of mis-specification in the context of population status and effect size of offshore renewable development. Finally, the project will make recommendations on the usefulness and application of the range of metrics within an assessment framework, and make recommendations to inform future assessments that use PVA analysis based on the conclusions of the study.

2. Literature Review

2.1 Introduction

Population Viability Analysis (PVA) uses life-history or population growth rate data to parameterise a mathematical population model to estimate population size and extinction risk of a species into the future (Norton 1995; Beissinger & Westphal 1998; Boyce 2001). Specifically, PVAs have been used for several purposes including predicting the future size of an animal population, estimating the probability of a population going extinct over time, evaluating management strategies most likely to maximise population persistence or exploring how different assumptions consequently alter the viability of small populations (see (Coulson *et al.* 2001)). PVAs have been widely used in conservation biology and wildlife management, aided by the development of intuitive, widely available and user-friendly software packages, particularly to forecast risks of extinction for species of conservation concern (Ludwig 1999). PVAs are a valuable tool because they facilitate the predictive modelling of animal populations under alternative environmental, management or harvesting scenarios and hence can be used to evaluate the effectiveness or consequences of different management decisions. Thus, PVAs can be considered to be a type of risk assessment of the long-term viability of animal populations.

A wide range of models can be considered to be PVAs (Ralls *et al*. 2002). However, in its most common form, PVA utilises life-history parameters (for example growth rates, juvenile and adult mortality, adult fecundity rates etc.) for individuals in a population projection matrix to estimate population size into the future (Boyce 1992). Models can either be deterministic (demographic rates such as survival and reproduction are constant or are determined in a predictable manner) or stochastic (vital rates vary unpredictably over time). Stochastic PVA models, can include demographic stochasticity (e.g. variation between individuals that affects whether a bird survives a given year) and environmental stochasticity (environmental change that would affect all individuals in a group), and hence the variability in the parameters is important, not just the mean values (Maclean, Frederiksen & Rehfisch 2007). PVAs have been developed for a wide range of species from different taxa, including plants (Maschinski *et al.* 2006), invertebrates (for example, sea-urchins (Pfister & Bradbury 1996) and insects (Bauer *et al.* 2013)), amphibians (Pickett *et al.* 2016), reptiles (Enneson & Litzgus 2009), fish (Sweka & Wainwright 2014), birds (Wootton & Bell 2014) and mammals (Pertoldi *et al.* 2013). Although difficult to assess due to the term "PVA" or "Population Viability Analysis" not commonly being included as a keyword, birds appear to be the taxonomic group where PVAs have most commonly been applied. A crude search of Web of Science including the search terms “PVA AND Population Viability Analysis” plus the group (e.g. “mammal”) returned 25 citations for plants; 15 for fish; three for reptiles; 38 for birds and 20 for mammals. PVAs have been extensively used in conservation and management with studies focusing on a broad range of topics including: investigating risk of extinction and population viability in small populations (Grayson *et al.* 2014); assessing the impact of different harvesting levels (York *et al.* 2016), predicting population sizes after reintroductions and enhancements (Halsey *et al.* 2015), assessing impacts of threats such as habitat loss (Naveda-Rodriguez *et al.* 2016), climate change (Marrero-Gomez *et al.* 2007) and disease (Haydon, Laurenson & Sillero-Zubiri 2002), assessing effectiveness of alternative management strategies (Ferreras *et al.* 2001); establishing conservation status and strategies (Bevacqua *et al.* 2015); establishing the effectiveness of conservation strategies under a fixed budget (Duca *et al.* 2009); and evaluating which demographic parameters population growth is sensitive to in order to inform management (Mortensen & Reed 2016). As a crude indication, a search in Web of Science found the most published references for the search term “*PVA and management*” (320 references), followed by “*PVA and conservation*” (247), “*PVA and population size*” (167), with few references for “*PVA and renewable energy*” (7) or “*PVA and wind farm(s)*” (2, both on terrestrial wind farms; but note that the majority of studies on PVAs and wind farms are undertaken as part of the planning process e.g. Habitats Regulation Assessments (in Scotland, the law in England and Wales calls them Assessments) and are not published in peer-reviewed journals but within so called “grey- literature”).

The outputs of PVAs consist of a predicted population trajectory through time. A suite of metrics have been used to predict the changes in the population of the focal species, both for conservation purposes and as a result of a particular threat or management scheme. Note that the term “metric” is not widely used outside the sphere of PVAs for seabirds and wind farms, where it has broadly been defined (Cook & Robinson 2016a, 2016b) as any value or rule upon which a decision about whether or not a population level effect associated with the impacts of an offshore wind farm is deemed acceptable. We consider the metric to be a value or unit of measurement, and not a rule, and hence cannot be used as an effective search term. A review of the model outputs from general literature in the last five years found that many studies simply reported estimated population sizes or population growth rate for particular time periods (Lopez-Lopez, Sara & Di Vittorio 2012; Wootton & Bell 2014; Naveda-Rodriguez *et al.* 2016). A commonly reported metric was that of quasi-extinction or extinction thresholds, whereby a probability is given for a population declining below a particular threshold (e.g. 10%) after a certain time (e.g. 10 years) or the predicted time to extinction (Blakesley *et al.* 2010; Alemayehu

2013; Hu, Jiang & Mallon 2013; Beissinger 2014; Robinson *et al.* 2016). The difference in extinction probability under different scenarios was reported when comparing management regimes e.g. management Scenario 1 resulted in an X% higher extinction probability than Scenario 2 (Bazzano *et al.* 2014). Susceptibility to quasi-extinction (SQE) has been used to assess whether or not a population is at risk of declining to a specified level (quasi-extinction threshold), a metric which supposedly integrates both parameter uncertainty and stochasticity. This method uses parametric bootstrapping to determine 95% confidence limits of quasi-extinction and then the SQE is defined as the proportion of the bootstrap that indicates a high probability of quasi-extinction (set arbitrarily as >= 0.9 in this paper; Snover and Heppell (2009)).

There are a number of sources of uncertainty that are incorporated within stochastic PVA models (Boyce 1992). There are two main components of uncertainty in time series of demographic variables or population counts: observation and process uncertainty (also called observation and process error or variation). Observation uncertainty (or sampling uncertainty) describes noise in the data that arises due to imprecise or biased empirical data collection methods, for example detection difficulties due to terrain, weather conditions or observer experience and human error. Process uncertainty describes noise that is related to the real variation in the parameter and comprises the real drivers of population fluctuations that are of interest (Bakker *et al.* 2009; Ahrestani, Hebblewhite & Post 2013). Methods for incorporating uncertainty are continuing to advance, including methods for separating out parameter uncertainty and process variation e.g. Heard *et al.* (2013). Therefore, the results of such PVAs are probabilistic, for example risks, probabilities or likelihoods of population decline or extinction. Sensitivity analysis, which determines the amount of change in the model results in response to changes in model parameters, is an important component of PVAs (Saltelli & Annoni 2010; Aiello-Lammens & Akçakaya 2016). Sensitivity analysis can be used to prioritise and inform empirical data collection by establishing the importance of parameters with imperfect knowledge and parameters where improved precision would enhance model predictions. Sensitivity analysis also facilitates understanding and identification of life-history parameters that are highly influential on population size and future viability in order to inform and prioritise conservation or management strategies. Sensitivity analysis is achieved by perturbing the life-history parameters either via a local (one at a time) or global sensitivity analysis (see Mccarthy, Burgman & Ferson (1995); Wisdom, Mills & Doak (2000); Cross & Beissinger (2001); Naujokaitis-Lewis *et al.* (2009); Aiello-Lammens & Akçakaya (2016) for details). Global sensitivity analysis is considered superior to local, because varying local analysis fails to account for the influence of interactions between parameters, but has rarely been applied in part due to computational difficulties and difficulties in quantifying interactions between parameters (Naujokaitis-Lewis *et al.* (2009); Coutts and Yokomizo (2014); but see Aiello-Lammens & Akçakaya (2016)).

Despite the wide application of PVAs to inform and make predictions including the impacts of management or developments, there have been a number of criticisms of their use and how well models can be used to inform management decisions, including how estimates of uncertainty are utilised (Coulson *et al.* 2001; Ellner *et al.* 2002; Reed *et al.* 2002; McCarthy, Andelman & Possingham 2003; Green *et al.* 2016). The quality of the life-history data used to parameterise models may determine how effectively PVAs are able to predict population changes, and for model predictions will only be valid at predicting extinction if the distribution of life-history parameters between individuals and years is stationary in the future (Coulson *et al.* 2001). There is a need to determine and understand how accurately PVAs can predict population size change but the predictions from PVAs are rarely tested against empirical data in the future to establish how well models performed. Criticism has been levied about how the model results can be difficult to understand, assess and interpret by stakeholders (Knight *et al.* 2008; Pe'er *et al.* 2013). Due to uncertainty and variability amongst the input parameters for the PVA models and hence uncertainty associated with the final metrics produced, decision makers may lack confidence in and may misinterpret model predictions (Addison *et al.* 2013; Green *et al.* 2016). Thus, it is critically important that steps are made to solve these challenges where possible (Masden *et al.* 2015; Green *et al.* 2016), since PVAs remain one of the most widely used tools for evaluating the impacts of anthropogenic developments, wildlife management or conservation strategies on focal populations.

2.2 Seabird PVAs and Marine Renewable Developments

One application of PVAs is as a tool to understand the likely impacts of offshore wind farms on seabird populations. The development of offshore wind farms has the potential to be an important anthropogenic intervention into marine habitats. The UK supports nationally and internationally important breeding and wintering populations of seabirds and the UK government has legal obligations to evaluate the effects such developments may have on such populations. The development of offshore wind farms may negatively impact seabird populations by increased mortality associated with direct collisions with turbines, by displacement of birds from suitable foraging areas; and by impeding movements of commuting or migrating birds (Garthe & Huppop 2004; Drewitt & Langston 2006; Everaert & Stienen 2007; Masden *et al.* 2009; Furness, Wade & Masden 2013; Searle *et al.* 2014; Cleasby *et al.* 2015; Vanermen *et al.* 2015; Busch & Garthe 2016). In the UK, a wide number of reports have used PVAs to assess the impact of wind farm developments on seabird populations and to inform the consenting process for approval of these wind farm developments (see Table 1 for examples). It should be noted that details of PVAs for evaluating the impacts of wind farms are largely available through so called “grey literature” (reports and assessments) rather than ISI published papers. PVAs have aimed to either compare the predicted population trajectory into the future with the wind farm development to that without the development, or to quantify the risk that the development poses by establishing probability of future population declines. Both deterministic and stochastic PVA models have been used for evaluating the impacts of wind farms and it has been argued that deterministic models are a more “honest” approach where there is significant uncertainty around demographic parameters because the presented confidence limits from stochastic models imply an unjustified level of precision in the underlying data (WWT 2012). However, stochastic models are more conservative (Lande, Engen & Sæther 2003) and deterministic models do not produce a distribution of results and hence cannot employ probabilistic metrics. A number of different metrics from the PVAs, for example the increase in the probability of a population decreasing by a fixed amount over time, have been used to provide assessments of the impact of wind farms on seabird populations. Metrics have been criticised for being sensitive to uncertainties both in the life-history parameters used to build the models and in the size of the impact of wind farms on the population (Masden *et al.* 2015; Green *et al.* 2016). Uncertainty in the demographic rates used to parameterise models can lead to uncertainty in whether the predicted magnitude of the impact (e.g. increased mortality or reduced productivity) will lead to an adverse effect on the focal population size (Masden *et al.* 2015). Uncertainty in the size of the impact of the wind farms on the population arises due to lack of empirical data on collision risk, displacement or barrier effects on seabird populations. Thus, there is concern that the metrics may not enable accurate predictions and good understanding of the impacts of offshore wind farms on seabird populations (Cook & Robinson 2016a; Green *et al.* 2016). This uncertainty has therefore led to a precautionary approach to assessments (see Thompson *et al.* (2013) for details).

A broad range of metrics have been derived from PVA population models in order to assess the population level effects of wind farm development on seabird populations (Cook & Robinson 2016a). Cook & Robinson (2016a, 2016b) identified 11 metrics that had been derived from population models as part of HRA undertaken for offshore wind farms that were within the planning process. These metrics were summarised from reports from 27 proposed sites at which the population level impacts of offshore wind farms on seabirds had been considered during assessment: Aberdeen Offshore Wind Farm, Beatrice, Burbo Bank Extension, Docking Shoal, Dogger Bank Creyke Beck A, Dogger Bank Creyke Beck B, Dogger Bank Teesside A, Dogger Bank Teesside B, Dudgeon, East Anglia One, Fife Wind Energy Park, Galloper, Hornsea Project One, Inch Cape, London Array Phase II, MORL (MacColl, Stevenson, Telford), Navitus Bay, Neart na Gaoithe, Race Bank, Rampion, Seagreen Alpha, Seagreen Bravo, Triton Knoll 3, Walney I & Walney Extension. The metrics derived from PVAs were split into two broad categories: i) probabilistic approaches (e.g. the probability of the population declining); or ii) ratio approaches (e.g. the ratio of the population size in the presence and absence of the wind farm). Cook & Robinson (2017) builds on this work, but for a reduced set of metrics from the reports, focusing on two PVA metrics (declines in probability difference for both growth rate and population size, equivalent to Metrics 4 and 7 in Table 2; and counterfactual of impacted and un-impacted populations for both growth rate and population size, equivalent to Metrics 2 and 3 in Table 2) and one rule (Acceptable Biological Change) derived from a PVA metric (Metric 15 in Table 2).

2.3 Review Aims

This review builds on the recent report from Cook & Robinson (2016b), which reviewed 11 metrics derived from population models used as part of the HRA undertaken for assessing the impacts of offshore wind farms on seabird populations, by considering a further range of published reports that did not form part of HRAs (see Table 1).

The purpose of our review was to:

1. Provide details of the metrics produced by PVAs;
2. To summarise any evaluations of how sensitive the metrics were to variation in the input parameters in order to recommend which metrics would be useful to pursue further.

In total we review 15 metrics, of which 11 were previously identified in the Cook & Robinson report (2016b). The four additional metrics that we identified were the difference in population growth rate, the difference in population size, the odds ratio of a decline and the centile for un-impacted population which matches the 50th centile for the impacted population (see No's.s 12-15 in Table 2). It should be noted that for stochastic models comparing impacted and un-impacted scenarios, metrics are derived using a "matched runs" approach (WWT 2012; Green *et al*. 2016). Stochasticity is applied to the population, but the same survival and productivity rates are incorporated for both the impacted and un-impacted populations at each time step prior to any impact from an offshore wind farm being applied.

Table 1

Additional reports reviewed for PVA modelling metrics which were recommended by the project steering group and were not included in the Cook & Robinson reviews (2016a and 2016b). N.B. population growth rate is defined as being the mean rate of growth across the period of interest (ratio of the population in year i+1 to that in year i; also known as the population multiplication rate).

Reference	Species considered	Metrics used	Equivalent metric No. and description if already included in Cook & Robinson 2016b (Table 2 in this report). Metrics in bold are not included.
Mackenzie, A. & Perrow, M.R. (2009) Population viability analysis of the north Norfolk Sandwich tern *Sterna sandvicensis* population. Report for Centrica Renewable Energy ltd and AMEC Power & Process. Mackenzie, A. & Perrow, M.R. (2011) Population viability analysis of the north Norfolk Sandwich tern *Sterna sandvicensis* population. Report for Centrica Renewable Energy ltd and AMEC Power & Process JNCC & NE (2012) Defining the level of additional mortality that the North Norfolk Coast SPA Sandwich tern population can sustain. JNCC & NE.	• Sandwich tern	• Probability of population decline: the probability of the simulated population falling below thresholds compared to the starting population • Change in probability of decline: the difference in probability of decline between impacted and un-impacted populations (also known as the Counterfactual of the probability of population decline; CPD)	• No. 7: Probability of a 10, 25 or 50% population decline • No 8: Change in probability of a 10, 25 or 50% population decline
Trinder, M. (2014) Flamborough and Filey Coast pSPA Seabird PVA Final Report: Appendix N to the response submitted for deadline V. Report for SMart Wind.	• Gannet • Kittiwake • Guillemot • Razorbill • Puffin	• Population growth rate • Predicted change in population growth rate i.e. the reduction in growth rate between un-impacted and impacted populations • Probability of population decline • Change in probability of population decline	• No. 1: Population growth rate • **Not included in Cook & Robinson** but similar to No 2: Ratio of median impacted to un-impacted growth rate • No 7: Probability of a 10, 25 or 50% population decline • No 8. Change in probability of a 10, 25 or 50% decline • No 7: Probability of a 10, 25 or 50% population decline (but considered in the final year)

Reference	Species considered	Metrics used	Equivalent metric No. and description if already included in Cook & Robinson 2016b (Table 2 in this report). Metrics in bold are not included.
		• Probability the population size in the final year for the impacted population will be less than a range of percentages of the un-impacted population size • Change in the probability of the population size in the final year for the impacted population will be less than a range of percentages of the un-impacted population size	• No. 8: Change in probability of a 10, 25 or 50% decline (but considered in the final year)
Trinder, M. (2015) Flamborough and Filey Coast pSPA Seabird PVA Report: Appendix M to the response submitted for deadline IIA. Report for SMart Wind.	• Gannet • Kittiwake • Guillemot • Razorbill • Puffin	• Predicted change in population growth rate i.e. the reduction in growth rate between un-impacted and impacted populations • Ratio of the impacted to un-impacted population size (Counterfactual of population size) at 5 year intervals up to 25 years	• **Not included in Cook Robinson** but similar to No 2: Ratio of median impacted to un-impacted growth rate • No. 3: Ratio of the impacted to un-impacted population size
Inch Cape Offshore Limited (2011) Inch Cape Offshore Wind Farm Environmental Statement: Appendix 15B Population Viability Analysis.	• Kittiwake • Guillemot • Razorbill • Puffin	• Change in probability of a population decline	• No. 8: Change in probability of a 10, 25 or 50% decline
Freeman, S., Searle, K., Bogdanova, M., Wanless, S. & Daunt, F. (2014) Population dynamics of Forth and Tay breeding seabirds: review of available models and modelling of key breeding populations. Final Report to Marine Scotland Science.	• Kittiwake • Guillemot • Razorbill • Puffin • Herring gull	• Probabilities of population decline to threshold percentages (25, 50, 75 and 100%) below the baseline in 2015 • Excess probabilities of population decline compared to that predicted by baseline in 2015 for threshold percentages (25, 50, 75 and 100%) i.e. probability of a decrease in the impacted population minus that for the un-impacted population	• No. 7: Probability of a 10, 25 or 50% population decline • No 8: Change in probability of a 10, 25 or 50% population decline

Reference	Species considered	Metrics used	Equivalent metric No. and description if already included in Cook & Robinson 2016b (Table 2 in this report). Metrics in bold are not included.
Moray Offshore Renewables Ltd (2013) Environmental Statement: Ornithology population viability analysis outputs and review.	• Gannet • Kittiwake • Guillemot • Razorbill • Puffin • Fulmar	• Probabilities of the population dropping below threshold percentages (quasi-extinction) of the baseline population size during the lifespan of the project (25 years or 25 years plus 10 year recovery) • Change in probabilities of the population dropping below threshold percentages (quasi-extinction) of the baseline population size during the lifespan of the project (25 years or 25 years plus 10 year recovery)	• No. 7: Probability of a 10, 25 or 50% population decline • No. 8: Change in probability of a 10, 25 or 50% population decline

Table 2

Description of metrics used to assess population responses to impacts of offshore wind farms. For each metric an indication is given of the scale over which the metric operates and a description of the metric. This table is adapted from Table 1 in Cook & Robinson 2016b and includes an additional four metrics (two based on our additional review of the reports listed in Table 1 and two requested to be included by Marine Scotland Science; additional metrics are numbers 12-15).

No.	Ratio or probabilistic	Can be used to distinguish wind farm effects?	Metric	Scale and meaning (N.B. the scale of 0-1 generally only applies if the impact of the wind farm is negative relative to the un-impacted scenario)	Description	Included in Cook & Robinson 2016b
1	**Neither**	**No**	**Population growth rate**	• Value of 1 indicates a stable population • <1 indicates a declining population • >1 indicates an increasing population	Calculation of population growth rate (calculated as mean rate over the study period; Final population size/Initial population size)$^{1/Nyears}$) in the presence of the wind farm enables evaluation of whether the population will remain stable, increase or decrease through the life time of the project.	Yes
2	**Ratio**	**Yes**	**Ratio of median impacted to un-impacted growth rate (counterfactual of population growth rate)**	• Scale from 0 – 1 • Value of 1 indicates the impacted population growth rate is the same as the un-impacted growth rate (no population-level consequence) • Values close to 0 indicate a large proportional difference between the impacted and un-impacted population growth rates (a strong population-level consequence)	Considering only the growth rate of a population (as in No. 1 above) in the presence of an offshore wind farm enables an assessment of whether the population will remain stable, increase or decrease over time, but it does not make it possible to quantify the impact of the wind farm on that growth rate. However, this is possible if the growth rate of the population in the presence of a wind farm is compared to that expected in the absence of a wind farm. This ratio is also known as the **COUNTERFACTUAL OF POPULATION GROWTH RATE**	Yes
3	**Ratio**	**Yes**	**Ratio of impacted to un-impacted population size (counterfactual of population size)**	• Scale from 0 – 1 • Value of 1 indicates the impacted population size is the same as the un-impacted size (no population-level consequence) • Values close to 0 indicate a large proportional difference between the impacted and un-impacted population size (a strong population-level consequence)	PVA models can be used to estimate population size through time both with and without the offshore wind farm. Comparing the ratio of these two population sizes gives a statistic that can be used to assess the population level impact of the offshore wind farm. Cook and Robinson state that the ratio could be derived either from a simple deterministic model or taken from the mean or median values simulated using a more complex stochastic model. We advocate that the ratio should be obtained from the median of x simulations of matched pairs; or in a Bayesian context the median will come from the posterior distribution of	Yes

No.	Ratio or probabilistic	Can be used to distinguish wind farm effects?	Metric	Scale and meaning (N.B. the scale of 0-1 generally only applies if the impact of the wind farm is negative relative to the un-impacted scenario)	Description	Included in Cook & Robinson 2016b
					the ratios. The ratio of population sizes could be estimated either at a fixed point in time, for example at the end of a project, or at a series of intervals throughout the life time of a project. This ratio is also known as the **COUNTERFACTUAL OF POPULATION SIZE (CPS).** For example,CPS_{25} = Predicted population size at 25 years (with wind farm)/ predicted population size at 25 years (no wind farm)	
4	**Probabilistic**	**No**	**Probability that growth rate <1, 0.95, 0.8**	• Scale from 0 – 1 • 0 indicates that none of the simulations from a stochastic model result in a growth rate <1 (decreasing population) • 1 indicates that all of the simulations from a stochastic model result in a growth rate <1	Calculated from a stochastic model based on the proportion of simulations where the population declines (has a growth rate <1). The probability of a population declining is typically assessed over the lifetime of the project, but other time scales could be selected. The metric could consider the probability of the growth rate being below other values (e.g. 0.95 or 0.8) which could be selected with reference to the status of the population concerned. Referred to as the Decline Probability Difference (DPDλ) in Cook & Robinson (2017)	Yes
5	**Probabilistic**	**Yes**	**Change in probability that growth rate <1, 0.95, 0.8 (linked to No. 4)**	• Scale from 0 – 1 • 0 indicates that there is no likely change in the probability of the growth rate being <1 between impacted and un-impacted populations (no population-level consequence) • values approaching 1 indicate there is an almost certainly change in the probability of the growth rate being <1 between the impacted and un-impacted populations (i.e. a population-level consequence)	Quantifying the probability of a population decline in the presence of an offshore wind farm may not be meaningful if simulations show that the population may already be at risk of declining in the absence of a wind farm, for example if >50% of simulations have a growth rate <1. To assess the population level impact of a wind farm it is necessary in this case to determine how much greater the probability of a decline is in the presence of an offshore wind farm than in the absence of an offshore wind farm. This can be done either at a single fixed point in time, or at intervals throughout the life time of the project.	Yes
6	**Probabilistic**	**No**	**Probability that population is below initial size at any point in time**	• Scale from 0 – 1 • 0 indicates that none of the simulations from a stochastic model result in a population below its initial size at any point in time • 1 indicates that all of the simulations	After an initial impact, environmental stochasticity and density dependence may mean a population is able to recover throughout the life time of a project. This recovery would mean that over 25 years the final population size may not be smaller than starting population size.	Yes

No.	Ratio or probabilistic	Can be used to distinguish wind farm effects?	Metric	Scale and meaning (N.B. the scale of 0-1 generally only applies if the impact of the wind farm is negative relative to the un-impacted scenario)	Description	Included in Cook & Robinson 2016b
				from a stochastic model result in a population below its initial size at any point in time		
7	**Probabilistic**	**No**	**Probability of a 10, 25 or 50% population decline**	• Scale from 0 – 1 • 0 indicates that none of the simulations from a stochastic model show the impacted population declining by a given magnitude (no population-level consequence) • 1 indicates that all simulations show the impacted population declining by at least the given magnitude • The probability thresholds are also known as quasi-extinction or pseudo-extinction thresholds	A metric to assess the population level impact of a development could be derived by estimating the proportion of simulations for a population in the presence of a wind farm in which a decline of a given magnitude was recorded. Referred to as the Decline Probability Difference (DPDn) in Cook & Robinson (2017)	Yes

No.	Ratio or probabilistic	Can be used to distinguish wind farm effects?	Metric	Scale and meaning (N.B. the scale of 0-1 generally only applies if the impact of the wind farm is negative relative to the un-impacted scenario)	Description	Included in Cook & Robinson 2016b
8	**Probabilistic**	**Yes**	**Change in probability of a 10, 25 or 50% decline (Linked to No. 7; also known as Counterfactual of the probability of population decline)**	• Scale from 0 – 1 • 0 indicates that there is no likely change in the probability of the population decreasing by a given magnitude between the impacted and un-impacted populations (no population-level consequence) • Values approaching 1 indicate there is a large change in the probability of the population decreasing by a given magnitude between the impacted and un-impacted populations (a population-level consequence)	Seabird populations are already declining at many UK colonies (JNCC 2013). Hence, the presence of a wind farm may not substantially increase the probability of the population size at these colonies being <1, if all simulations from the baseline scenario already have a population size less than the starting population size. However, the presence of the wind farm may cause a further reduction in population size. It may, therefore, be more meaningful to consider the change in probability of population size decreasing by a given magnitude, for example a X% increase in the probability of a Y% decline. Also referred to as the Counterfactual of the probability of population decline (CPD), for example the $CPD_{25,10}$ is the difference in the probability of a decline from the starting population size of 10% occurring 25 years after the wind farm construction between impacted and un-impacted populations. CPD can be calculated relative to the change from the starting population after a set time, or relative to the median population. Risk to the population concerned based on the changes in probability can be assessed using IPCC based likelihoods (see Mastrandrea *et al*. 2010). Such likelihoods simply convert the probabilities of the population dropping below the starting population into more accessible language for stakeholders according to boundaries	Yes
9	**Probabilistic**	**Yes**	**Probability of a population being a given magnitude below the median size predicted in the**	• Scale from 0 – 1 • 0 indicates that none of the simulations from a stochastic model show the impacted population size being a given magnitude below the un-impacted population size (no population-level consequence)	The metric to assess the population level impacts of a wind farm may be derived by estimating a median size for a population in the absence of an offshore wind farm and calculating the proportion of simulations for a population in the presence of a wind farm which were either below this median population size, or a given magnitude below this median population size.	Yes

No.	Ratio or probabilistic	Can be used to distinguish wind farm effects?	Metric	Scale and meaning (N.B. the scale of 0-1 generally only applies if the impact of the wind farm is negative relative to the un-impacted scenario)	Description	Included in Cook & Robinson 2016b
			absence of an impact	• 1 indicates that all simulations show the impacted population is a given magnitude below the un-impacted population size (population level consequence)		
10	**Probabilistic**	**Yes**	**Probability that impacted population growth rate is 2.5, 5 or 10% less than un-impacted growth rate**	• Scale from 0 – 1 • 0 indicates that none of the simulations from a stochastic model show the impacted population growth rate being a given magnitude below the un-impacted population growth rate (no population-level consequence) • 1 indicates that all simulations show the impacted population growth rate is a given magnitude below the un-impacted population growth rate (population level consequence)	With growth rates simulated from stochastic models, it may be desirable to estimate a mean or median value for the un-impacted population and calculate the proportion of simulations in which the growth rate of the impacted population is lower, or a given percentage lower, than this value. This approach has the advantage of allowing a probabilistic forecast of the impact of the offshore wind farm on a population, e.g. there is a 50% chance that the wind farm will reduce the population growth rate by 10%.	Yes
11	**Probabilistic**	**Yes**	**Overlap of Impacted and Un-impacted Populations**	• Scale from 0 – 1 • 0 indicates that none of the simulated population sizes after 25 years from the stochastic model of the impacted population overlap with the simulated population sizes after 25 years from the un-impacted population • 1 indicates that all of the simulated population sizes after 25 years from the stochastic model of the impacted population overlap with the simulated population sizes after 25 years from the un-impacted population	Using stochastic models, the population size at a fixed point in time (i.e. at the end of a project lifetime e.g. 25 years) may be expressed as a distribution. In these circumstances, it may be desirable to compare the distributions of the impacted and un-impacted populations. Where there is greater overlap between the two populations, impacts may be deemed less significant.	Yes
12	**Closely related to ratio approaches**	**Yes**	**Difference in population growth rate i.e. the reduction in growth rate between un-**	• Similar to No. 2 (Ratio of median impacted to un-impacted growth rate) but absolute not ratio values (one growth rate subtracted from the other) • The magnitude of the value relates to the magnitude of the difference	Considering only the growth rate of a population (as in No. 1) in the presence of an offshore wind farm enables an assessment of whether the population will remain stable, increase or decrease over time, but it does not make it possible to quantify the impact of the wind farm on that growth rate. However, as with No. 2, this is possible if the growth rate of the population in	No; closely related to No. 2

No.	Ratio or probabilistic	Can be used to distinguish wind farm effects?	Metric	Scale and meaning (N.B. the scale of 0-1 generally only applies if the impact of the wind farm is negative relative to the un-impacted scenario)	Description	Included in Cook & Robinson 2016b
			impacted and impacted populations	between the two growth rates	the presence of a wind farm is compared to that expected in the absence of a wind farm.	
13	**Closely related to ratio approaches**	**Yes**	**Difference in population size i.e. the reduction in population size between un-impacted and impacted populations**	• Similar to No. 3 (Ratio of impacted to un-impacted population size) but absolute not ratio values (one population size subtracted from the other) • The magnitude of the value relates to the magnitude of the difference between the two population sizes	PVA models can be used to estimate population size through time both with and without the offshore wind farm. Comparing these two population sizes by looking at the difference between them enables assessment of the population level impact of the offshore wind farm. As with No 3, the metric of population sizes could be estimated either at a fixed point in time, for example at the end of a project, or at a series of intervals throughout the life time of a project.	No; closely related to No. 3
14	**Probabilistic**	**Yes**	**Odds Ratio of a threshold population decline comparing impacted to un-impacted populations**	• An odds ratio of 1 implies that the presence of the wind farm has no effect on the probability of an event (e.g. a threshold population decline) • An odds ratio >1 implies that the wind farm leads to an increase in the probability of the event	Odds ratios are a way of quantifying the odds of an event happening and provide an additional way of reporting the impacts of a wind farm on seabird populations. However, we did not find any instances where odds ratios were used as metrics for PVAs associated with wind farms in the literature examined in Table 1. The odds ratio essentially provides a summary of the difference between the probabilities for impacts and un-impacted populations so is an alternative way of quantifying the difference between the raw probabilities. For example: - If a decline of 50% in the population (N.B. the level of the decline is not actually relevant to the calculation of the odds ratio) has been estimated to have a probability of 0.2 in the absence of a wind farm, but 0.5 when the wind farm is present - then the odds ratio for the effect of the wind farm is: (0.5 / (1 - 0.5)) / (0.2 / (1 - 0.2)) = 4 - the wind farm has the effect of multiplying the odds of the event (a 50% decline) by four.	No; closely related to No. 8

No.	Ratio or probabilistic	Can be used to distinguish wind farm effects?	Metric	Scale and meaning (N.B. the scale of 0-1 generally only applies if the impact of the wind farm is negative relative to the un-impacted scenario)	Description	Included in Cook & Robinson 2016b
15	**Probabilistic**	**Yes**	**Centile for un-impacted population which matches the 50th centile for the impacted population**	• Related to No. 11 • Values between 0 and 100	This metric is the centile for the un-impacted population which matches the 50th centile of the impacted population. The centile values are taken from the distributions of the impacted and un-impacted populations. The metric from which Acceptable Biological Change (Marine Scotland 2015) is derived.	No; closely related to No. 11

2.4 Sensitivity of PVA Metrics

The second aim of our review was to **summarise any evaluations of how sensitive the metrics were to variation in the input parameters in order to recommend which metrics would be useful to pursue further.** Metrics have been criticised as being sensitive to uncertainties in the demographic parameters used in the modelling process and in the magnitude of the impact predicted on populations (Green *et al.* 2016). In order to evaluate this, Cook & Robinson (2016b) conducted analyses to quantify how sensitive the conclusions drawn from each model were to uncertainty in the demographic parameters used in the population models, the structure of the population models used to derive the metrics and the magnitude of the impact considered. Cook & Robinson (2017) built on this sensitivity analysis by comparing model sensitivity for the counterfactual metrics (No's.s 2 and 3 in Table 2) between models run using a matched runs approach and those without (i.e. where base demographic rates within a stochastic population model vary between un-impacted and impacted populations).

Overall, Cook & Robinson evaluated the metrics according to whether the metric responses were **clear** (the metric shows a noticeable change in response to impacts of increasing magnitude) and **consistent** (the shape of the relationship between the metric and the magnitude of the impact was linear). A clear response would make it easier to distinguish between population level changes associated with differing magnitudes of the impact. Thus, if metrics are not clear then it may be difficult to distinguish impacts arising as a result of the wind farm from natural variation in the population. The shape and consistency of the response are also important because if the response is consistent then it is easier to understand and predict the relationship between the metric and the population level impacts and to understand the consequences of under- or over-estimating the magnitude of impacts. Curved relationships between metrics and the magnitude of the impact are more difficult to interpret than linear relationships because the effects on the population will depend on the magnitude of the impact and hence conclusions are more vulnerable to mis-specification of model parameters. Cook & Robinson concluded that none of the 11 metrics they considered showed both a clear and consistent response to impacts of increasing magnitude, and that none of the probabilistic approaches gave responses that were clear or consistent. Of the 11 metrics, population growth rate, ratio of impacted to un-impacted population growth rate and ratio of impacted to un-impacted population size were the most promising (see Cook & Robinson 2016b; Cook & Robinson 2017). Population growth rate and ratio of impacted to un-impacted population growth rate were promising because of a consistent linear relationship with the magnitude of the impact. However, due to overlap in the confidence limits for these metrics and the range over which they operate, distinguishing population level effects with and without the wind farm would be difficult unless the magnitude of the impact was very large. The ratio of impacted to un-impacted population size was promising because it was the only metric that showed a clear response to the range of impacts considered in the analysis.

Cook & Robinson specifically tested sensitivity to the following:

1. **Population trend**: whether the metric was sensitive to the population trend prior to wind farm construction increasing, decreasing or being stable.
2. **Mis-specification of the demographic parameters:** whether the metrics are sensitive to changes in the demographic parameters (i.e. a large change in the metric arises from a small change in the demographic parameter; for:

    i. Adult survival;
    ii. Immature survival;
    iii. Chick survival;
    iv. Productivity.

3. **Density dependence:** whether the metric is sensitive to inclusion of density dependence on productivity and breeding adult survival in the models.
4. **The form of density dependence:** whether the metric is sensitive to the form of density dependence in the models i.e. how quickly the adult survival rate changes as the population approaches or moves away from the carrying capacity (rather than whether this is compensatory i.e. population growth rate will reduce with increasing density or depensatory i.e. population growth rates will reduce with decreasing density).
5. **Whether stochastic or deterministic:** whether the metric is sensitive to the inclusion of stochasticity (i.e. is modelled from input parameters over a range of values rather than a fixed value).

The most promising metrics for use in assessing the population level effects of wind farms on seabirds were considered to be the ratio of impacted to un-impacted population growth rate (No. 2 in Table 2) and the ratio of impacted to un-impacted population size (No. 3 in Table 2). Cook & Robinson (2017) recommended that stochastic models using a matched run approach are used because this is likely to reflect the most precautionary approach. The median values of the decision criteria predicted for the counterfactual metrics (Metrics 2 and 3) were greater when a matched run approach was used than when models were run without (see Cook & Robinson 2017). See Table 3 for a full summary of sensitivity of all metrics to the five criteria listed above and a summary of how clear and consistent the metrics were. Table 4 summarises the main strengths and weaknesses of each metric and how the metric should be used and interpreted if being used to assess the impacts of wind farms.

Table 3

Sensitivity of metrics used to determine the impacts of offshore wind farms on seabird populations to variation in the input parameters (adapted from Table 5 in Cook & Robinson (2016b)). Shading indicates how well each metric performs: light grey indicates good, dark grey moderate and black poor performance. The two main criteria (highlighted with a thick black line) are whether there was a clear and consistent relationship between the magnitude of the effect and the metric. N.B. probabilistic metrics cannot be calculated from deterministic models, so the comparison between stochastic and deterministic models is not applicable. No's.12-14 from Table 2 were not included as these were not included in the sensitivity analysis from Cook & Robinson (2016b).

No.	Metric	**Clear** • **Green**: clear difference between metrics for impacts of increasing magnitude • **Amber**: metric varies over a very narrow range • **Red**: the metric reaches an asymptote with impacts of increasing magnitude	**Consistent** • **Green**: linear relationship • **Amber**: non-linear curved relationship • **Red**: stepped relationship	**Insensitive to population trend** • **Green**: identical regardless of population trend • **Amber**: <10% change in metric in relation to population trend • **Red**: >10% change in metric in relation to population trend	**Insensitive to adult survival** • **Green**: sensitivity to misspecification <1% for 10% impacts on survival or productivity • **Amber**: sensitivity to misspecification <5% for 10% impacts on survival or productivity • **Red**: sensitivity to misspecification >5% for 10% impacts on survival or productivity	**Insensitive to immature survival** • **Green**: sensitivity to misspecification <1% for 10% impacts on survival or productivity • **Amber**: sensitivity to misspecification <5% for 10% impacts on survival or productivity • **Red**: sensitivity to misspecification >5% for 10% impacts on survival or productivity	**Insensitive to chick survival** • **Green**: sensitivity to misspecification <1% for 10% impacts on survival or productivity • **Amber**: sensitivity to misspecification <5% for 10% impacts on survival or productivity • **Red**: sensitivity to misspecification >5% for 10% impacts on survival or productivity	**Insensitive to productivity** • **Green**: sensitivity to misspecification <1% for 10% impacts on survival or productivity • **Amber**: sensitivity to misspecification <5% for 10% impacts on survival or productivity • **Red**: sensitivity to misspecification >5% for 10% impacts on survival or productivity	**Insensitive to incorporation of density dependence** • **Green**: median values the same with or without density dependence • **Amber**: <10% change with density dependence vs independent • **Red**: >10% change with density dependence vs independent	**Insensitive to the form of density dependence incorporated** • **Green**: straight line regardless of shape of density dependence or max value of pructivity/adult survival • **Amber**: wavy line • **Red**: clear relationship with density dependence	**Insensitive to stochastic/deterministic model** • **Green**: median values same for both model types • **Amber**: <10% change between models • **Red**: >10% change between models
1	Population growth rate										
2	Ratio of median impacted to un-impacted growth rate										
3	Ratio of impacted to un-impacted population size after 25 years										
4	Probability that growth rate <1										
5	Change in probability that growth rate <1										
6	Probability that population is below initial size at any point in time										
7	Probability of a 25% population decline										
8	Change in probability of a 25% decline										
9	Probability of a population being 50% below un-impacted population										
10	Probability that impacted population growth rate is 2.5% less than un-impacted growth rate										
11	Overlap of Impacted and Un-impacted Populations										

Table 4

Overview of the strengths and weaknesses of the different metrics and information on how the metric should be used to assess the impacts of wind farms. Table adapted from Table 6 in Cook & Robinson (2016b) with the addition of numbers 12 and 13 which were not included in the sensitivity analysis from Cook & Robinson (2016b). We have not included metrics 14 or 15 since sensitivity of these metrics to input parameter specification has not been assessed, so it is not possible to synthesise their strengths and weaknesses.

No.	Metric	Strengths	Weaknesses	How to use and interpret the metrics
1	**Population growth rate**	• Easy to interpret • Consistent relationship between metric and magnitude of impact: easier to make predictions about likely impacts • Relatively insensitive to misspecification of the input parameters	• On its own can't be used to assess wind farm impacts due to lack of comparison with un-impacted population • Variability around the estimates mean it can be difficult to distinguish between variation in the baseline population growth rate and the impacts from the wind farm	• Not a meaningful metric on its own- need to compare the population growth rate of the un-impacted population with that of the impacted population in order to understand then population level effect associated with a wind farm • Lack of a significant difference between impacted and un-impacted populations does not necessarily mean that there would be no population level consequences of the wind farm (due to overlapping confidence intervals)
2	**Ratio of median impacted to un-impacted growth rate**	• Consistent relationship between metric and magnitude of impact: easier to make predictions about likely impacts • Insensitive to misspecification of the input parameters and relatively insensitive to uncertainty in parameter estimates • Insensitive to population trend: metric reflects impact of wind farm and not population status	• Metric varies over a limited range, with the overlapping confidence limits this makes it hard to determine likely population level effects from different magnitudes of effect • Hard to assess effects of the wind farm in a population context due to this limited range	• Metric can be used regardless of population status or trend • Metric should be presented as a median value with 95% confidence limits • Thresholds for determining a wind farm impact are subjective but could be set in reference to the status or trend of the population • Models should be run with a matched run approach
3	**Ratio of impacted to un-impacted population size**	• Easy to interpret in context of a population effect • Clear relationship between metric and magnitude of impact: easier to make	• Sensitive to population declines • More sensitive to misspecification of the demographic parameters than population growth rate or ratio of impacted to un-	• Metric can be used for stable or increasing populations on its own • May be useful context for the ratio of impacted to un-impacted population

No.	Metric	Strengths	Weaknesses	How to use and interpret the metrics
	after 25 years	predictions about likely impacts • Relatively insensitive to uncertainty in the demographic parameters	impacted population growth rate	growth rate regardless of trend • Metric should be presented as a median value with 95% confidence limits • Thresholds for determining a wind farm impact are subjective but could be set in reference to the status or trend of the population • Models should be run with a matched run approach
4	**Probability that growth rate <1**	• Easy to understand, intuitive	• On its own can't be used to assess wind farm impacts due to lack of comparison with un-impacted population • Sensitive to misspecification of adult survival rate • Sensitive to population trends: if population is stable/declining then metric only varies over limited range and so it is difficult to identify population level effects associated with different impacts • True variation in parameters and that based upon observation error are usually not distinguished • Measures are sensitive to any change in conditions in the future	• Not a meaningful metric on its own- need to compare the population growth rate of the un-impacted population with that of the impacted population in order to understand then population level effect associated with a wind farm • Can only be used when the population was increasing prior to the wind farm construction • Requires robust measures of site-specific adult survival • Thresholds for determining a wind farm impact are subjective but could be set in reference to the status or trend of the population
5	**Change in probability that growth rate <1**	• Easy to understand, intuitive: metric quantifies the change in probability of a population declining as a result of a wind farm	• Sensitive to population trend • Sensitive to misspecification of demographic parameters • True variation in parameters and that based upon observation error are usually not distinguished • Measures are sensitive to any change in	• Should not be used when the populations were declining prior to wind farm construction where the change in probability of growth rate is already close to 1 • Requires robust, site specific data on demographic parameters

No.	Metric	Strengths	Weaknesses	How to use and interpret the metrics
			conditions in the future	• Thresholds for determining a wind farm impact are subjective but could be set in reference to the status or trend of the population
6	**Probability that population is below initial size at any point in time**	• Accounts for the fact that populations may recover over the lifetime of the wind farm	• On its own can't be used to assess wind farm impacts due to lack of comparison with un-impacted population • Sensitive to population trends prior to wind farm construction • Sensitive to misspecification of the demographic parameters • True variation in parameters and that based upon observation error are usually not distinguished • Measures are sensitive to any change in conditions in the future	• Not a meaningful metric on its own - need to compare the population growth rate of the un-impacted population with that of the impacted population in order to understand then population level effect associated with a wind farm • Can only be used when the population was increasing prior to the wind farm construction • Requires robust measures of site-specific adult survival • Thresholds for determining a wind farm impact are subjective but could be set in reference to the status or trend of the population
7	**Probability of a 25% population decline**	• Easy to understand • Can be related to established conservation assessments (e.g. (Eaton *et al.* 2015)	• On its own can't be used to assess wind farm impacts due to lack of comparison with un-impacted population • Sensitive to population trends prior to wind farm construction • Sensitive to misspecification of the demographic parameters • True variation in parameters and that based upon observation error are usually not distinguished • Measures are sensitive to any change in conditions in the future	• Not a meaningful metric on its own - need to compare the population growth rate of the un-impacted population with that of the impacted population in order to understand then population level effect associated with a wind farm • Can only be used when the population was increasing prior to the wind farm construction • Requires robust measures of site-specific adult survival • Thresholds for determining a wind farm impact are subjective but could be set in reference to the status or trend of the population

No.	Metric	Strengths	Weaknesses	How to use and interpret the metrics
8	**Change in probability of a 25% decline**	• Easy to understand, intuitive: metric quantifies the change in probability of a population declining by 25% as a result of a wind farm	• Sensitive to population trends prior to wind farm construction • Sensitive to misspecification of the demographic parameters • True variation in parameters and that based upon observation error are usually not distinguished • Measures are sensitive to any change in conditions in the future	• Should not be used when the populations were declining prior to wind farm construction where the change in probability of growth rate is already close to 1 • Requires robust, site specific data on demographic parameters
9	**Probability of a population being 25% below un-impacted population**	• Easy to understand, intuitive comparison of impacted and un-impacted populations • Can be related to established conservation assessments (e.g. (Eaton *et al.* 2015)	• Some sensitivity to population trends prior to wind farm construction • Sensitive to misspecification of the demographic parameters • True variation in parameters and that based upon observation error are usually not distinguished • Measures are sensitive to any change in conditions in the future	• The 25% threshold is subjective and may not be appropriate. Consideration needs to be given to whether to whether alternative thresholds may be more appropriate considering the status and importance of the focal population • Requires robust, site specific data on demographic parameters • Sensitivity to the form and inclusion of density dependence means that models with density dependence should only be used where there is robust evidence for it occurring within the population
10	**Probability that impacted population growth rate is 2.5% less than un-impacted growth rate**	• Relates the impacted population growth rate to that of the un-impacted population	• Difficult to understand in a population context • May be statistically difficult to detect a 2.5% difference in growth rate. Could use higher levels of change but more severe impacts would be required to detect them • Sensitive to population trends prior to wind farm construction • Sensitive to misspecification of the demographic parameters • True variation in parameters and that based upon observation error are usually	• Should not be used when the populations were declining prior to wind farm construction where the change in probability of growth rate is already close to 1 • Requires robust, site specific data on demographic parameters • Sensitivity to the form and inclusion of density dependence means that models with density dependence should only be used where there is robust evidence for it occurring within the population

No.	Metric	Strengths	Weaknesses	How to use and interpret the metrics
			not distinguished • Measures are sensitive to any change in conditions in the future	
11	**Overlap of Impacted and Un-impacted Populations**	• Straightforward comparison that looks at how similar the model outputs are for impacted and un-impacted populations	• Sensitive to population trends prior to wind farm construction • Sensitive to misspecification of the demographic parameters • Sensitive to estimates of uncertainty surrounding the demographic parameters • Value can depend on the number of simulations used in the modelling to obtain the metric • True variation in parameters and that based upon observation error are usually not distinguished • Measures are sensitive to any change in conditions in the future	• Sensitive to population trends means the metric should only be used where there is good understanding of the status of the focal population • Requires robust, site specific data on demographic parameters and the uncertainty surrounding them • Sensitivity to the form and inclusion of density dependence means that models with density dependence should only be used where there is robust evidence for it occurring within the population • Needs careful analysis to ensure enough simulations are used in the models
12	**Difference in population growth rate i.e. the reduction in growth rate between un-impacted and impacted populations**	• consistent relationship between metric and magnitude of impact: easier to make predictions about likely impacts • Insensitive to misspecification of the input parameters and relatively insensitive to uncertainty in parameter estimates • Insensitive to population trend: metric reflects impact of wind farm and not population status	• Metric varies over a limited range, with the overlapping confidence limits this makes it hard to determine likely population level effects from different magnitudes of effect • Hard to assess effects of the wind farm in a population context due to this limited range • Provides absolute values of difference between population growth rate rather than ratios and may need to be interpreted also in the context of No. 2	• Metric can be used regardless of population status or trend • Metric should be presented as a median value with 95% confidence limits • Thresholds for determining a wind farm impact are subjective but could be set in reference to the status or trend of the population
13	**Difference in population size i.e. the reduction in size between un-impacted and**	• consistent relationship between metric and magnitude of impact: easier to make predictions about likely impacts • Insensitive to misspecification of the input parameters and relatively insensitive to	• Provides absolute values of difference between populations rather than ratios and may need to be interpreted also in the context of No. 3	• Metric can be used regardless of population status or trend • Metric should be presented as a median value with 95% confidence limits • Thresholds for determining a wind farm

No.	Metric	Strengths	Weaknesses	How to use and interpret the metrics
	impacted populations	uncertainty in parameter estimates • Insensitive to population trend: metric reflects impact of wind farm and not population status		impact are subjective but could be set in reference to the status or trend of the population

2.5 Criticisms of PVA Metrics in Assessing Wind Farm Impacts

A number of criticisms have been levied against using the metrics derived from PVAs to assess the impact of wind farms (Cook & Robinson 2016a; Green *et al.* 2016). The main criticisms (some of which e.g. No. 1 are equally applicable to broader modelling contexts) were as follows:

1. Lack of empirical data to provide robust estimates and associated confidence limits of collision, barrier and displacement effects on seabirds.
2. Due to this lack of robust estimates of impact levels, probabilistic methods for assessing the risk of population impacts from wind farms are not scientifically robust or defensible - this includes metrics from PVAs that estimate e.g. the difference in probability of a decline between impacted and un-impacted populations.
3. Thresholds are subjective and it should not be claimed that these have been set based on scientific evidence.

Green *et al.* 2016 makes a number of recommendations for providing a scientifically robust and defensible method of assessing population-level impacts of wind farms on seabirds. In the context of PVA modelling the ratio of the expected population size with the wind farm to that without it (No. 3 in Table 2; also termed the so-called Counterfactual of Population size (CPS)) is recommended as a robust metric because this metric is relatively insensitive to uncertainties about demographic rates because they apply to both impacted and un-impacted scenarios. Cook & Robinson (2016b) also advocate the use of this metric, which in conjunction with the ratio of population growth rate (No. 2 in Table 2), is considered to score well in the assessments of sensitivity in Table 3. However, it should be noted that the ratio of impacted to un-impacted population size was sensitive to incorporation and the form of density dependence (see Table 3). Uncertainty can be incorporated, as in Cook & Robinson 2016b, if metrics are derived from a stochastic model or across a range of impact levels. Bayesian approaches, such as those utilised by Freeman *et al.* (2014) and a potential method for conducting Global Sensitivity Analysis developed by Aiello-Lammens & Akçakaya (2016) show promise in being able to separate out the uncertainty associated with input parameter values used in the modelling with that from scenarios of impact on a population (for example different levels of collision mortality or displacement risk), and thus have potential to help address the criticisms levied by Green *et al.* (2016). It has been highlighted that the strength of PVAs lies not in predicting absolute values of viability or costs of management but rather in evaluating the relative effects of different management scenarios (Perkins, Vickery & Shriver 2008). Green *et al.* (2016) is highly critical of interpreting effects based on arbitrary boundaries, which includes probabilistic approaches including probabilities and changes in probabilities of population declines below quasi-extinction thresholds (No. 7 and No. 8 in Table 2), and interpretation of such boundaries advocated for species conservation using IPCC based approaches detailed in Mastrandrea *et al.* (2011) where, for example, an effect is considered to be 'moderate-high' if there is a > 5 % increase in the likelihood of a 20 % population reduction.

2.5.1 Density Dependence

Green *et al.* (2016) also recommends that PVAs should be constructed using density-independent matrix models because such models would be more precautionary in their assessments of population impacts than models including density dependence (as compensatory density dependence, widely assumed to be the most common form, would tend to reduce the impact on population size). However, density-dependent processes may be depensatory, thus slowing the rate of population growth at lower population densities rather than at high densities. Establishing whether compensatory or depensatory density-dependent processes are occurring for species that are the focus of PVAs for wind farms is important: if depensatory processes are operating and are ignored in PVAs then a population decline arising from a wind farm could have larger consequences on the population than are predicted by the models, accelerating population decline and delaying population recovery. Recent work has identified depensation occurring due to increased anti-predator vigilance or colonial defence decreasing rates of productivity in smaller populations in eight species of seabird and seaduck, including species that have been the focus of PVAs for wind farms (Arctic skua, kittiwake, black-headed gull, sandwich tern, common tern, guillemot, puffin and herring gull; Horswill & Robinson 2015; Horswill *et al.* 2016). Indeed, depensation was reported almost twice as often as compensation as a mechanism regulating productivity rates and the authors highlight that this positive feedback mechanism on population size has the potential to be highly destabilising. However, density-dependent effects can vary significantly between colonies in relation to local conditions. Cook & Robinson (2016b) concluded from their sensitivity analyses that density dependent processes operating on the population would mitigate any impacts arising from the wind farm and hence that assuming no density dependence is present is likely to be the most precautionary approach unless depensatory density dependence is known to be operating. Furthermore, Cook & Robinson (2016a) recommend that density-dependence could be incorporated within models where careful consideration has deemed this appropriate, but that density independent models are likely to represent a more precautionary approach in many cases.

2.5.2 Consideration of the Time-Span used to Assess Impacts

Consideration needs to be given to the time-span over which metrics are used to determine whether the wind farm is likely to have an impact on seabird populations, for example whether the assessment is made at time increments from the construction period of the wind farm or at the end of the wind farm operating period e.g. 25 years. The time period selected needs to consider that there will be increasing uncertainty for both impacted and un-impacted scenarios with extrapolation in to the future and hence increased risk of false conclusions on the predicted magnitude of population level effects, but conversely short time windows do not reflect the duration of the lifespan of the wind farm licence (typically 25 years).

2.6 Knowledge Gaps

Cook & Robinson (2016b) adopted a conventional PVA approach whereby they assumed values for demographic parameters (specifically survival, varying between ages, and productivity) and projected simulated population predictions forward in time from a specified starting point (typically at an 'equilibrium' age-structure). No data were directly used, so no models were fitted and the results could be assumed valid for any species with demography approximately similar to that adopted in the simulations. With such an approach, since values appropriate for a given species will often be unknown with accuracy, a range of values tend to be considered, and this is the approach the BTO adopted. The advantage of this approach is that since no data fitting is required, there is a considerable reduction in computational demands. The second advantage is that it is possible to model a range of seabird life history strategies. As such, one can construct an analysis that is potentially relevant to all species and regions. However, this approach is less desirable where one wishes to understand a specific region where real data are available, or where one wishes to address generic questions with real data. One example of the latter is the need for a generic solution to the common situation where there are non-local empirical data that are relevant to the focal colony which itself lacks data. Another feature of these models is that the confidence intervals can be unrealistically narrow. A further consideration is that although the Cook & Robinson (2016b) sensitivity analysis undertook a comprehensive assessment of metric sensitivity using simulation approaches, a key knowledge gap is that metric sensitivity has not been comprehensively examined using real data. A project that focussed on this would be complementary to the work undertaken by the BTO. If the same metrics show low sensitivity in models of real world data as in simulation models, then this would provide re-assurance that these metrics are the most promising. Furthermore, such an approach would enable generic questions to be addressed with real data. One example which is very common with UK seabird populations is where data are absent from the focal colony but available from an adjacent colony, thereby offering a natural, informative prior. We would recommend that such approaches are undertaken so that sensitivity of metrics can be tested using real-world data.

2.7 Recommendations from Literature Review

- The two metrics that have been recommended for use in establishing the impact of a wind farm on seabird populations are the **Ratio of median impacted to un-impacted growth rate** and the **ratio of impacted to un-impacted population size (also known as counterfactual of population size).**
- The two metrics of the **difference in population growth rate between impacted and un-impacted populations** and the **difference in population size** should also be considered as these may be more useful if the growth rates or population size estimates being compared are small (ratios may be misleading in this context).
- Metrics should be obtained from stochastic models using a matched run approach because this is likely to reflect the most precautionary approach.
- Should probabilistic metrics be used, based on the rationale that they have been widely used in the past within published conservation science literature, and may still be used extensively in the future, it should be acknowledged that these have received criticism in Green *et al.* (2016) and Cook & Robinson (2016b).
- Density dependence should only be included where there is evidence that this may be occurring in the population of interest, otherwise use of density-independent models, or a range of density dependent structures, is advised.
- Global Sensitivity Analysis approaches detailed in Aiello-Lammens & Akçakaya (2016) and Bayesian approaches utilised by Freeman *et al.* (2014) to separate model outcome uncertainty that arises due to uncertainty in the parameter estimates used to build the models from the uncertainty in the effects of the management action (in this case wind farms) should be considered.

3. Population Modelling: Methods

3.1 Modelling Approach

A key early decision by the Steering Group was to agree which population modelling approach to use. Conventionally, PVA have been applied by assuming values for demographic parameters (specifically survival, varying between ages, and productivity) and projecting simulated population predictions forward in time from a specified starting point (typically at an ‘equilibrium’ age-structure). No data are directly used, so no models are fitted and the results can be assumed valid for any species with demography approximately similar to that adopted in the simulations. In practice, since values appropriate for a given species will rarely be known with much accuracy, a range of values tend to be considered. The advantage of this approach is that since no data fitting is required, there is a considerable reduction in computational demands. The second advantage is that it is possible to model a range of seabird life history strategies. As such, one can construct an analysis that is potentially relevant to all species and regions. This approach is less desirable where one wishes to understand a specific region where real data are available, or where one wishes to address generic questions with real data. One example of the latter is the need for a generic solution to the common situation where there are non-local empirical data that are relevant to the focal colony which itself lacks data (see next section). Another feature of these models is that the confidence intervals can be unrealistically narrow.

In the previous population modelling contract CEH undertook for Marine Scotland Science, we fitted state-space models using Bayesian techniques via WinBUGS to data from four SPAs for five species in the Forth/Tay region (Freeman *et al.* 2014). Here, no parameter values were specified beforehand; all were estimated from the data prior to projecting the population predictions forwards to beyond the period of the data. In these models, the population is assumed to change stochastically (the ‘state process’) and the counts to be equal in expectation to the population level (or part of it), subject also to sampling variability (the ‘observation process’). Using this method, sampling co-variances of parameter estimates are naturally accommodated. In Freeman *et al.* (2014), demographic parameters were assumed to vary about a mean value, with a specified variance, where these were estimated from models applied at sites with more substantial data (generally the Isle of May). While the need for defining parameter configurations *a priori* are reduced in such models, the results are dependent upon the data used (precision, for example, will depend in part upon the likely representativeness of the data from the well-studied colony). One advantage of this approach is in the case where there is interest in specific colonies/study areas, thereby providing a rationale for fitting the model to real data. Of the various methods that can be used to fit models to data, we consider this approach to be the most robust because of greater realism in the estimating of credibility intervals, in particular due to the partitioning of observation and process error, in cases where there are empirical data (counts and/or demography data) or informative priors (see Freeman *et al.* 2014 for a discussion of this). A second advantage of this approach is in addressing generic questions with real-world data. One example has been addressed above that we think is particularly relevant in this context, where data are absent from the focal colony but available from an adjacent colony, thereby offering a natural, informative prior. However, considerable thought is required before adopting this approach since information from another colony cannot automatically be assumed to apply elsewhere, to other species and/or regions, and any assumptions should be clearly specified. Two more advantages arise from this approach within the specific context of this project: a) Cook & Robinson (2016) have undertaken a comprehensive sensitivity analysis of PVA metrics using simulations in a traditional framework, so there would be a benefit in testing the performance of the same suite of metrics in an empirical analysis, with confidence gained if the same metrics perform well using both approaches; b) there is continuity with the previous report (Freeman *et al.* 2014). The main disadvantage of this approach is the analytical and computational demands. Furthermore, if there is no interest in specific colonies/regions, or if the generic questions that can be addressed using real-world data, then a simulation approach is the logical way forward.

The Steering Group decided that there was such interest, and that it would be complementary to the recent work by Cook & Robinson (2016), so this was the method that was undertaken. Further, the decision was to focus on the three main issues emerging from past work and stakeholder interest: sensitivity in a range of PVA metrics including a comparison of ratio and probabilistic types, effect of population status on sensitivity, and effect of renewables effect size on sensitivity. Finally, it was agreed following consideration of the literature that density dependence would not be included in the models (see literature review).

3.2 Modelling Methods

3.2.1 Input Data

Five study species were selected: black-legged kittiwake, common guillemot, razorbill, herring gull and European shag. Of these kittiwake, guillemot, razorbill and herring gull were considered in Freeman *et al.* (2014). As similar models have, in the interim, also been fitted for shags we also consider this extra species. We accumulated data sets on abundance, survival and productivity from four SPAs (Buchan Ness to Collieston Coast SPA; Fowsheugh SPA; Forth Islands SPA; St Abb's Head to Fastcastle SPA).

New data were added up to 2016 where available (Freeman *et al.* 2014 modelled data up to 2012). Data include colony counts, in full if possible but often such data are available only in a limited number of years, or else have been made only in smaller parts of the main colony (i.e. plots). Demography is estimated from ringing data (survival) or nest record data (productivity per nest/pair). Such data have long been gathered by CEH at the Isle of May in the Forth Islands SPA, but are often missing elsewhere in the region. Data availability and sources for the species considered are given in Tables 5 and 6, respectively.

Counts and demographic parameter estimates can be found in Appendix 1.

Table 5

Data availability for each species at each SPA. Regular census means annual or near-annual. Sporadic census is less regular – typically every four to seven years. Sources: [a]Seabirds Monitoring Programme online database; [b]Vicky Anderson/Edward Grace, RSPB, pers comm; [c]Roddy Mavor, JNCC pers comm.; [d]Harris *et al.* 2009, 2013; [e]Frederiksen *et al.* 2004 updated; [f]Lahoz-Monfort *et al.* 2011, 2014; [g]Newell *et al.* 2012; [h]Lahoz-Monfort *et al.* 2013; [i]BTO ringing and recovery data, purchased for Freeman *et al.* 2014

Species	**SPA**	**Counts**	**Survival (Adult birds)**	**Productivity**
Kittiwake	Forth Islands	Regular census[a]	Regular survey[e]	Regular census[a,g]
	St Abb's Head	Regular census[a]	No	Regular census[a]
	Fowlsheugh	Sporadic census[a]	No	Regular census[a]
	Buchan Ness	Sporadic census[a]	No	Regular census[a]
Guillemot	Forth Islands	Regular census[a]	Regular survey[f]	Regular census[a,g,h]
	St. Abb's Head	Sporadic census [a] Regular sub-plot survey[a]	No	No
	Fowlsheugh	Sporadic census[a] Regular sub-plot survey[b]	No	No
	Buchan Ness	Sporadic census[a] Sporadic sub-plot survey[c]	No	No
Razorbill	Forth Islands	Regular census[a]	Regular survey[f]	Regular census[a,g,h]
	St Abb's Head	Sporadic census[a] Regular sub-plot survey[a]	No	No
	Fowlsheugh	Sporadic census[a] Regular sub-plot survey[b]	No	No
Herring gull	Forth Islands	Regular census[a]	Historical survey[i]	Regular census[a]
	St Abb's Head	Regular census[a]	No	No
Shag	Forth Islands	Regular census[a]	Regular survey[a]	Regular census[a]
	St Abb's Head	Regular census[a]	No	Regular census[a]
	Buchan Ness	Sporadic census[a]	No	No

Table 6

Data source for each species at each SPA.

Species	SPA	Counts	Adult survival	Productivity
Kittiwake	Forth Islands	Forth Islands	Isle of May	Isle of May
	St Abb’s Head	St Abb’s Head	Isle of May	St Abb’s Head
	Fowlsheugh	Fowlsheugh	Isle of May	Fowlsheugh
	Buchan Ness	Buchan Ness	Isle of May	Buchan Ness
Guillemot	Forth Islands	Forth Islands	Isle of May	Isle of May
	St. Abb’s Head	St. Abb’s Head	Isle of May	Isle of May
	Fowlsheugh	Fowlsheugh	Isle of May	Isle of May
	Buchan Ness	Buchan Ness	Isle of May	Isle of May
Razorbill	Forth Islands	Forth Islands	Isle of May	Isle of May
	St Abb’s Head	St Abb’s Head	Isle of May	Isle of May
	Fowlsheugh	Fowlsheugh	Isle of May	Isle of May
Herring gull	Forth Islands	Forth Islands	Isle of May	Isle of May
	St Abb’s Head	St Abb’s Head	Isle of May	Isle of May
Shag	Forth Islands	Forth Islands	Isle of May	Isle of May
	St Abb’s Head	St Abb’s Head	Isle of May	St Abb’s Head
	Buchan Ness	Buchan Ness	Isle of May	Isle of May

3.2.2 Population Models

The models adopted for these data are as described in Freeman *et al.* (2014) and we provide only a brief overview here. A state-space model for the annual counts was adopted, with the expected number of breeding pairs of a population in year *t* given by N_t, where, for a species such as shag that begins breeding at age three is:

$$N_t = Nr_t + Na_t$$

$$Nr_t \sim Poisson\left(N_{t-3}\left(\frac{f_{t-3}}{2} \times \varphi_{j,t-3}\varphi_{j,t-2}\varphi_{j,t-1}\right)\right)$$

$$Na_t \sim Binomial\left(N_{t-1}, \varphi_{a,t-1}\right)$$

Where Nr_t and Na_t are respectively the numbers of new recruits, and survivors of the previous breeding population, in year *t*. The model is straightforwardly amended to accommodate those species that do not begin breeding until aged five or six. Juvenile survival probabilities $\varphi_{j,t}$ are assumed to take a constant value φ_j , unknown but estimable from the data; those for adults $\varphi_{a,t}$ are assumed normally distributed mean values and variance estimated from a set of ringing data at the Isle of May. Completing the model the annual numbers of chicks per pair f_t are estimated with means and variance from nest record data gathered at the site in question, where available, or using the data from the Isle of May where site-specific productivity data are unavailable. Due to the paucity of kittiwake counts at Fowlsheugh and Buchan Ness to Collieston Coast, these were modelled simultaneously in a single (multivariate) state-space model, with a common juvenile survival rate. As in Freeman *et al.* (2014) there were problems modelling the Kittiwakes at the Forth Islands SPA; this was due to low counts in 1994, which subsequently recovered for a few years, and so the 1994 counts were omitted from the data that informed the state space model.

Models were fitted using Bayesian techniques using the software JAGS (Plummer 2013). As in Freeman *et al.* (2014), multiple projections for 25 future years (2016 to 2041) of wind farm impact under various scenarios (given below) are made by repeatedly sampling from the distributions above, effectively generating posterior distributions for the abundance in future years. Using the model above, we thus produce 'baseline' predictions, under the assumption that prevailing conditions apply in future years. We then produced a series of alternative 'impacted' population trajectories assuming that adult survival, productivity or both were negatively affected by some 'perturbation', equating to the effect of an offshore wind farm. This enables a comparison of future predictions following perturbation with those under the 'status quo' assumptions, known as the baseline. In consultation with the Steering Group, adult survival was set to decline by one of a range of specified rates, namely 0% (i.e. no change), 0.5%, 1%, 2% and 3%. Declines in annual productivity were set to 0%, 1%, 2%, 3% and 5%. Finally, combined effects of survival and productivity were set to, respectively, 0%/0%, 1%/1%, 2%/2%, 3%/3% and 0.5%/5%. Note that these are percentage point changes, as requested by the Steering Group, which differs from the approach taken in Cook & Robinson (2016b) where percentage changes were investigated. In all models, an additional five years were projected with no change in survival or productivity, representing a post-wind farm decommissioning period.

3.3 PVA Metric Sensitivity

The above modelling framework allowed us to examine the population changes under various levels of impact upon the demographic parameters, given that these take the values of the model. It is, of course, plausible that the average values of adult survival and productivity experienced by the populations may differ from those implied by the demographic data used, especially where these are 'borrowed' from adjacent sites for those without such data of their own (for survival, this is all sites apart from the Forth Islands; even there, all ringing data are from a single study at the Isle of May). Therefore, we also repeated the entire procedure with demographic parameters "mis-specified" to varying degrees. Specifically, we considered median adult mortality (the complement of survival, since survival is generally high in seabirds and percentage increases are greatly limited by the constraint of lying below a survival rate of one) and productivity to differ from those of the baseline by, in turn -30%, -20%, -10%, 10%, 20% and 30%. The consequences of uncertain adoption of demographic parameters could then be examined by plotting a suite of PVA metrics against this rate of mis-specification, under a range of renewables effect sizes.

The Steering Group, having considered the findings of the literature review, requested that we examine the sensitivity of five PVA metrics, and Marine Scotland Science requested that we include a sixth metric (PVA F):

1) Median of the ratio of impacted to un-impacted (=baseline) annual growth rate (PVA A; Metric No. 2 in Table 2).
2) Median of the ratio of impacted to un-impacted population size after 25 years (PVA B; Metric No. 3 in Table 2).
3) Median difference in impacted and un-impacted annual growth rates (PVA C; Metric No. 12 in Table 2.)

4) Median difference between impacted and un-impacted population size after 25 years (PVA D; Metric No. 13 in Table 2).
5) Probability of a population decline over 25 years exceeding a) 10% b) 25% and c) 50% (PVA E1, E2 and E3 respectively; Metric No. 7 in Table 2).
6) Centile for un-impacted population which matches the 50th centile for the impacted population after 25 years (PVA F; Metric No. 15 in Table 2).

PVAs A and B are ratio metrics, PVAs C and D are metrics related to ratio metrics and PVAs E and F are probabilistic metrics. All of these metrics are readily estimable from the repeated simulations above, with posterior distributions of the ratios/differences arising from a “matched runs” approach, as recommended (WWT 2012; Green *et al.* 2016; Cook & Robinson 2017) i.e. the parameters defining the expected annual counts in each replicate are identical, except insofar as the expected impacted figures are adjusted to reflect the level of the impact. Plotting these metrics against alternative levels of adult survival or productivity used gives a visual assessment of the sensitivity of these metrics to the choice of demographic parameters.

Note that for the models of razorbills at Fowlsheugh, two of the thirteen models exhibited formal warnings via the Brooks-Gelman statistic values regarding convergence for juvenile survival. However, the estimates of the PVA metrics from these models appear to be consistent with the pattern as shown by other species/SPAs and so these are retained in the plots.

However, for three species/SPA combinations there were inherent problems with the “baseline” model (with no mis-specification). This was for shags at Buchan Ness, having a baseline model which “converged”, but not to anything sensible (the observation error was greater than the counts) and for herring gull at both sites, which had problems with the convergence of key parameters, adult survival and juvenile survival. Therefore, we considered these three species/SPAs to be unreliable and did not use them in the assessment of the sensitivity of the PVA metrics.

3.4 Structure of the Results

The Steering Group requested that we examine the sensitivity of these PVA metrics to mis-specification in adult mortality and productivity, and investigate to what extent this sensitivity varied with predicted population status and size of renewables effect. Accordingly, the results section is split into three parts.

First, we provide the full results of population modelling, including retrospective data fitting, population forecasts and PVA sensitivities for one species/SPA population: kittiwakes at Forth Islands. It was considered by the Steering Group necessary to show this comprehensive output for one population only, although models presented were undertaken on all populations. Combining the mis-specifications in adult mortality or productivity with the scenarios of annual decline in adult survival or productivity provides four graphical outputs:

1. Mis-specification in adult mortality with scenarios of renewables-induced change in productivity;
2. Mis-specification in adult mortality with scenarios of change in adult survival;
3. Mis-specification in productivity with scenarios of renewables-induced change in productivity;
4. Mis-specification in productivity with scenarios of change in adult survival.

Second, we present PVA sensitivities in relation to population status, combining data from all species/SPAs for which we achieved model convergence. We estimated the projected population growth rate as follows:

$$\lambda = \left(\frac{Estimated\ median\ total\ population\ in\ 2041}{Estimated\ median\ total\ population\ in\ 2016}\right)^{1/25}$$

Lambda is calculated for the baseline model and takes the values for the various species/SPA combinations shown in Table 7. Populations were classed as increasing (lambda > 1) or decreasing (lambda < 1). Of the four combinations outlined above, we only show results from the analysis of mis-specification in adult mortality with the maximum scenario of change in adult survival (3%), to maximise clarity.

Third, we present PVA sensitivities in relation to scenarios of change resulting from the renewables development (i.e. the effect size). Of the four combinations outlined above, we only show results from the analysis of mis-specification in adult mortality with scenarios of change in adult survival.

Table 7

Projected population growth rates over the period 2016-2041 for Species/SPA populations.

Species/SPA population	**Lambda**
Kittiwakes:	
Forth Islands	0.964
St Abb's Head	0.937
Fowlsheugh	0.969
Buchan Ness to Collieston Coast	0.967
Guillemots:	
Forth Islands	1.012
St Abb's Head	1.018
Fowlsheugh	0.997
Buchan Ness to Collieston Coast	1.022
Razorbills:	
Forth Islands	1.023
St Abb's Head	0.991
Fowlsheugh	1.040
Shags:	
Forth Islands	1.004
St Abb's Head	0.980

4. Population Modelling: Results

4.1 Population Modelling and PVA Sensitivity in Forth Islands Kittiwakes

The data available for Forth Island kittiwakes, the population for which we present the full set of outputs, ranges from 1984 to 2016. The annual variation in the median adult survival and productivity as well as the posterior distribution of juvenile survival and the observation error are given in Figure 1. The latter two parameters approximate a normal distribution, with a mean juvenile survival of 0.685. The model suggests that Kittiwakes at the Forth SPA have declined from an initial abundance of just over 10,000 to about 4,000 in 2016. Future projections indicate further declines (Figures 2a-c), though note the wide credible intervals, broadening as time passes, as uncertainty increases in these estimates.

For the sensitivity analysis, the median population size after 25 projected years (2041) was estimated under a range of mis-specifications in adult mortality or productivity and scenarios of annual decline in adult survival or productivity (Figure 3). The estimated population size when adult survival or productivity does not change and there is no mis-specification in the Bayesian model results in an estimate of approximately 1,300 birds. As expected, population size under all effect size scenarios declines with increasing mortality and increases with increasing productivity (Figure 3). These relationships are non-linear, and different scenarios of annual decline diverge as the overall effect of mis-specification strengthens, because percentage point changes in mis-specification have a relative, not absolute effect on population size.

The outputs of PVA metric sensitivity can be found in Figures 4a-h for PVA A, B, C, D, E1, E2, E3 and F, respectively (see Section 3.3 of the methods for a definition of each metric). We estimated the PVA metrics using seven model runs for changes in adult mortality (-30% to +30% at 10% increments) and seven runs for productivity (-30% to +30% at 10% increments). The model run of no change in adult mortality or productivity is shared by both, hence a total of thirteen models were run.

The ratio of impacted to un-impacted annual growth rate (PVA A; Figure 4a) was very close to one for the full range of scenarios and, matching theory and past evidence using simulations, was insensitive to mis-specification in demographic parameters. One possibility for the low sensitivity of PVA A is the scale of values, with all values being close to one, and, therefore, sensitivity potentially appearing low in a visual assessment even in cases where it is not. However, we show that this is not the case in Appendix 2, where we consider a 25 year growth rate, whereby lines deviate markedly from one and low sensitivity is still apparent.

Estimates for the ratio of impacted to un-impacted population size after 25 years (PVA B; Figure 4b) showed a range of values with respect to scenarios of change in productivity and, in particular, mortality, but it was also insensitive to mis-specification in demographic parameters. The PVA metric representing the difference in impacted and un-impacted growth rates (PVA C; Figure 4c) was also comparatively insensitive. In contrast, the PVA metric representing the difference in impacted and un-impacted population size (PVA D; Figure 4d) was considerably more sensitive, and showed non-linear patterns of change which were dependent on the effect size scenario, associated with the relationship between absolute and relative changes in population size (as with Figure 3).

As regards the probabilistic metrics, the metric presenting the probability of a population decline over 25 years exceeding 10%, 25% and 50% (PVAs E1, E2 and E3; Figure 4e, f and g respectively) showed high sensitivity to mis-specification both in mortality and reproduction. Each shows a non-linear pattern of change in line with expectations and past use of these metrics, including the expected variation between PVAs E1, E2 and E3 in relation to the stated exceedance thresholds of 10%, 25% and 50%. In contrast, the metric representing the centile for un-impacted population which matches the 50% centile for the impacted population after 25 years (PVA F; Figure 4h) showed moderately low sensitivity to mis-specification of survival and productivity. It was less sensitive than PVA E with and more sensitive than ratio metrics PVA A and B.

Graphical presentation of sensitivity of PVA metrics for all 13 species/SPA combinations can be found in Appendix 3.

Figure 1: Diagnostics plot from the Bayesian state space model for adult survival, productivity, juvenile survival and observation error.

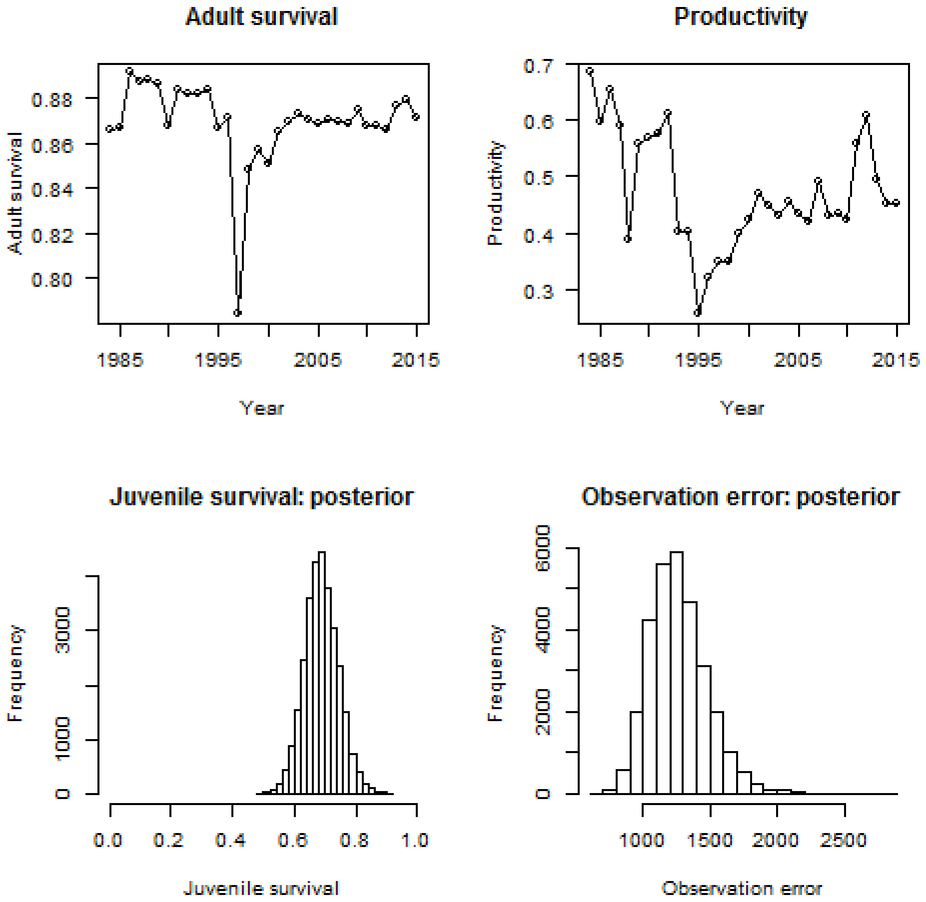


Figure 2a: Estimated total abundance from 1984 to 2016, with an additional 25 years of projections with various declines in productivity and a final five years of projections with no decline in productivity.

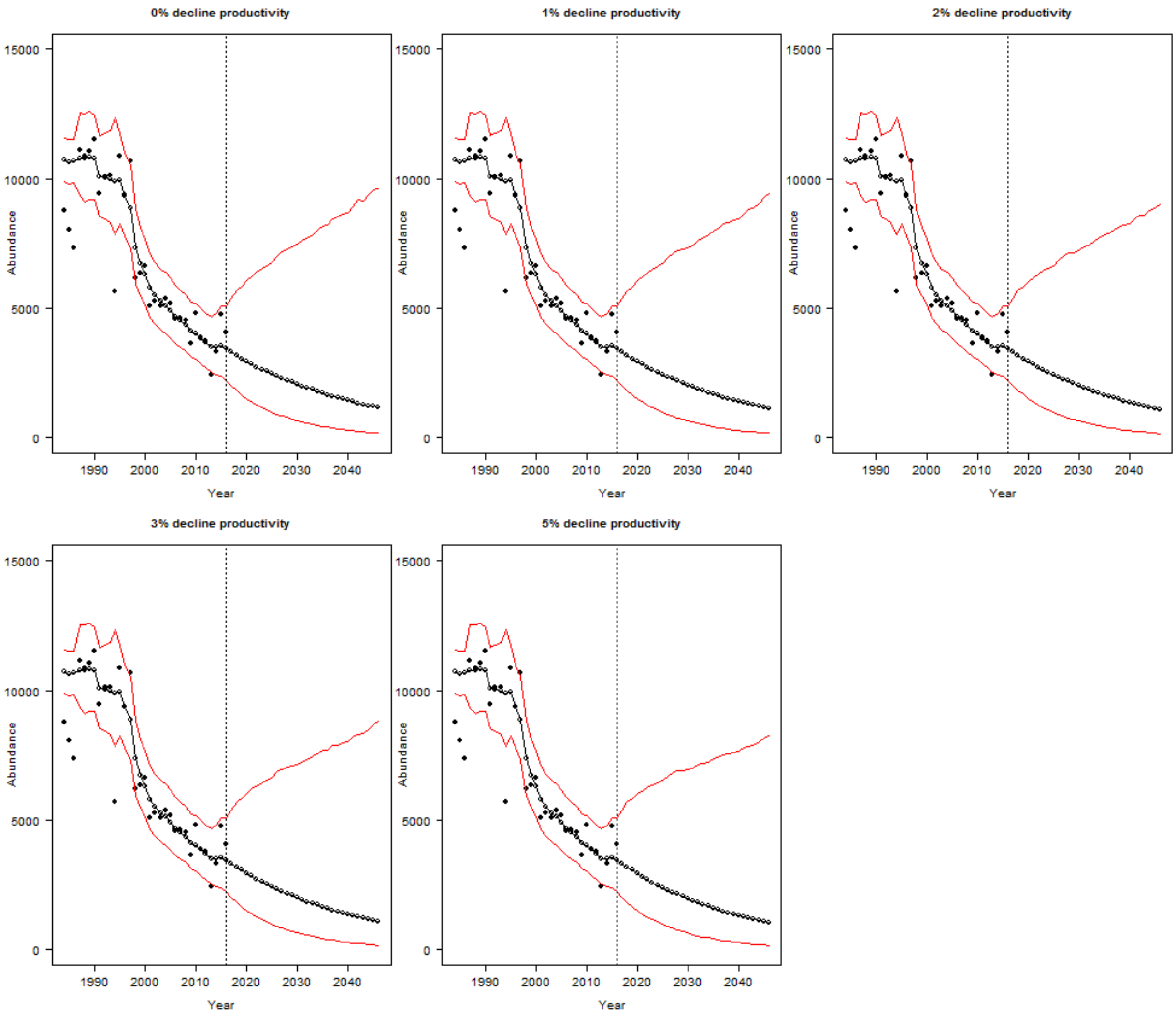


Figure 2b: Estimated total abundance from 1984 to 2016, with an additional 25 years of projections with various declines in adult survival and a final five years of projections with no decline in adult survival.

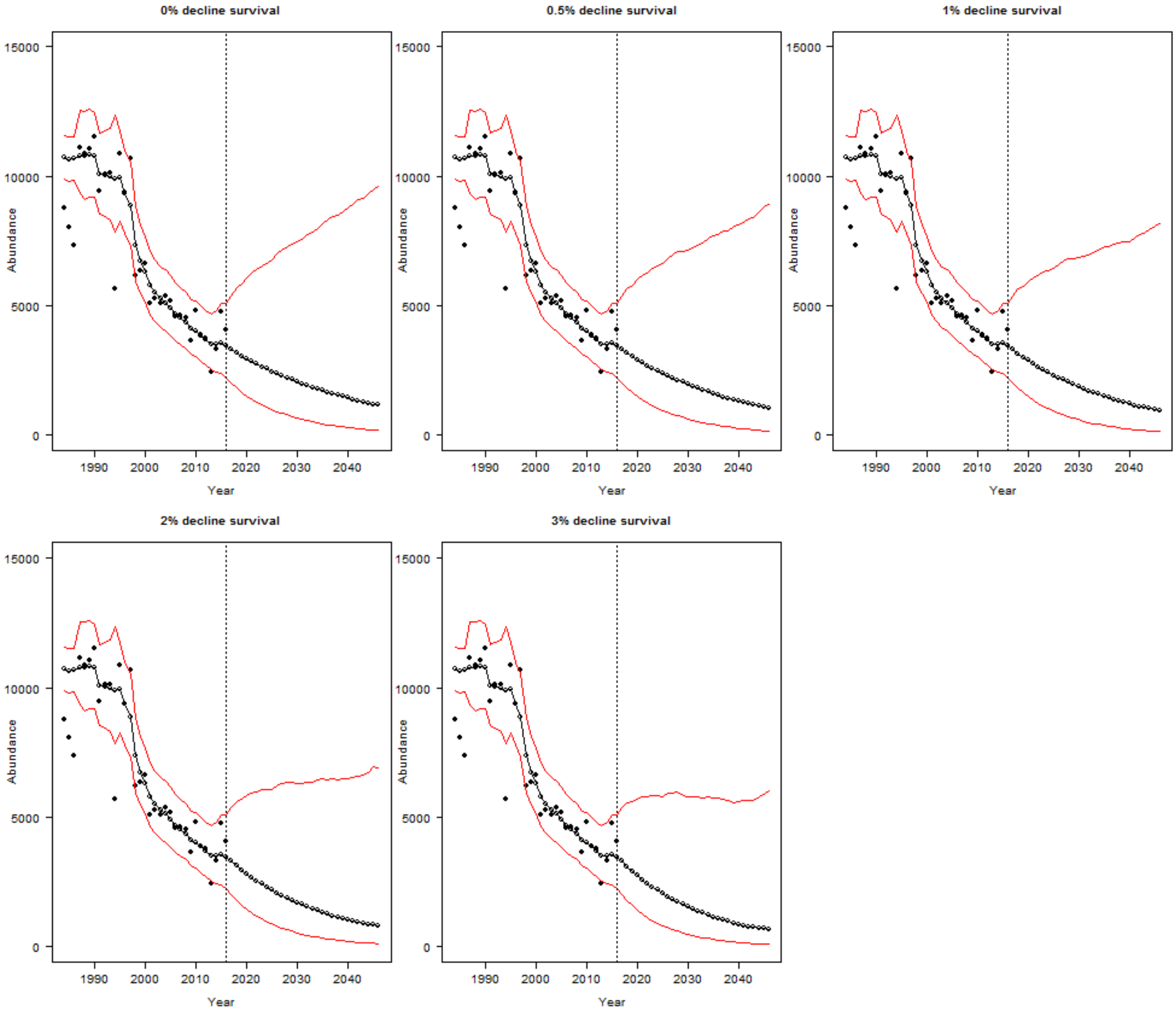


Figure 2c: Estimated total abundance from 1984 to 2016, with an additional 25 years of projections with various declines in both productivity and adult survival and a final five years of projections with no decline in either productivity or adult survival.

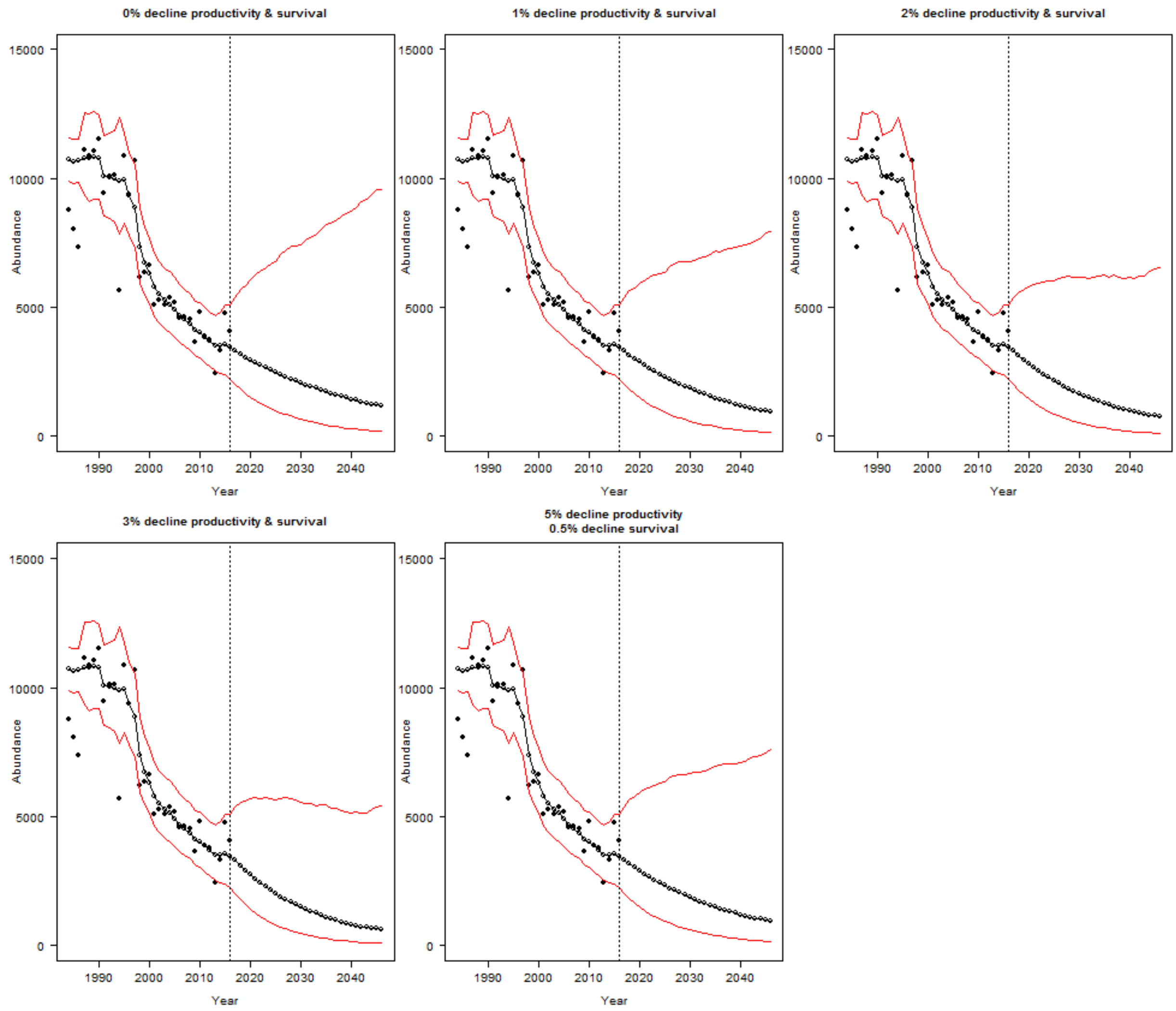


Figure 3: Median impacted population size after 25 years of projections under various scenarios of mis-specification in productivity and adult mortality. Adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2016-2041).

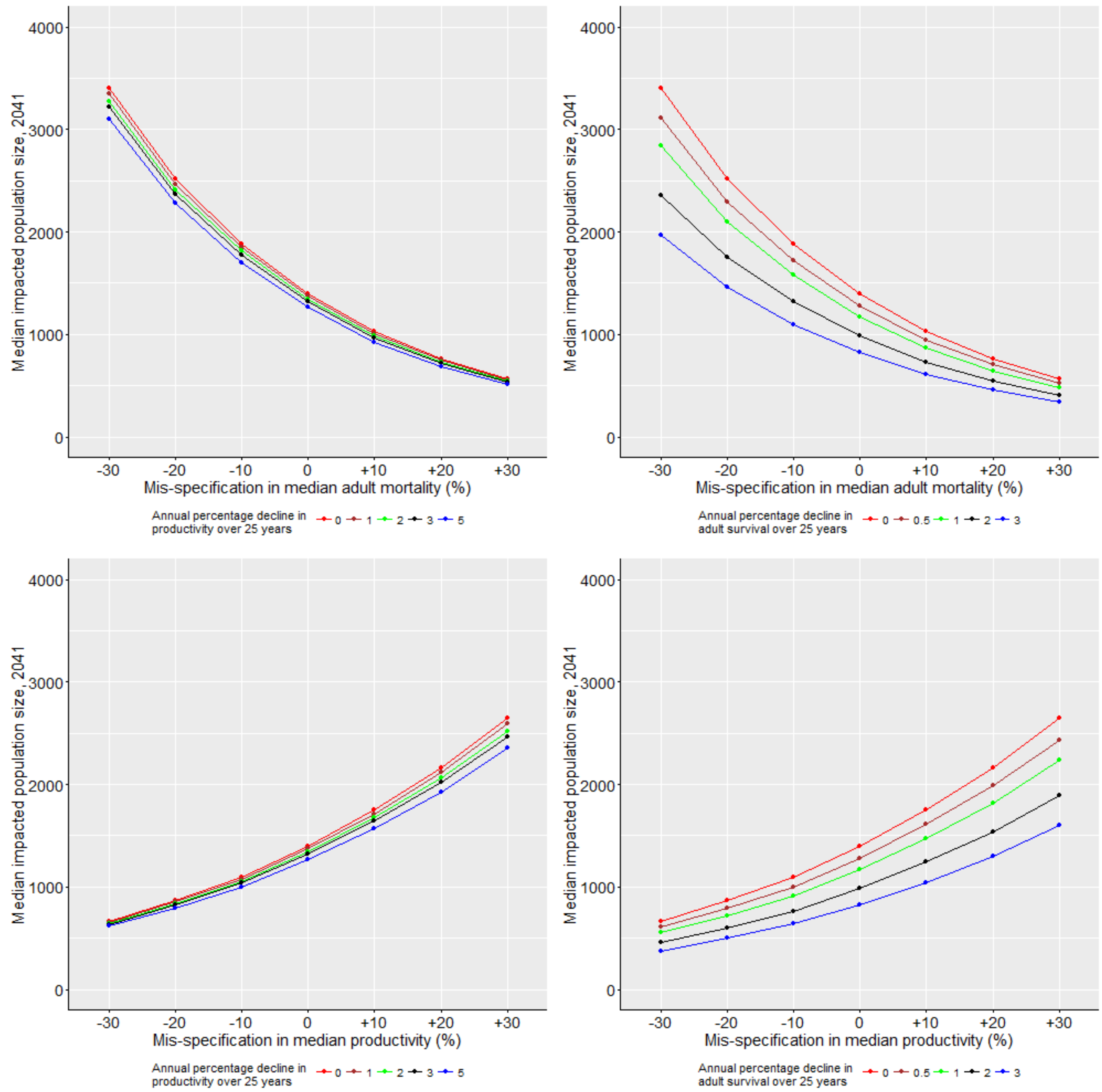


Figure 4a: PVA Metric A – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population. Adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2016-2041).

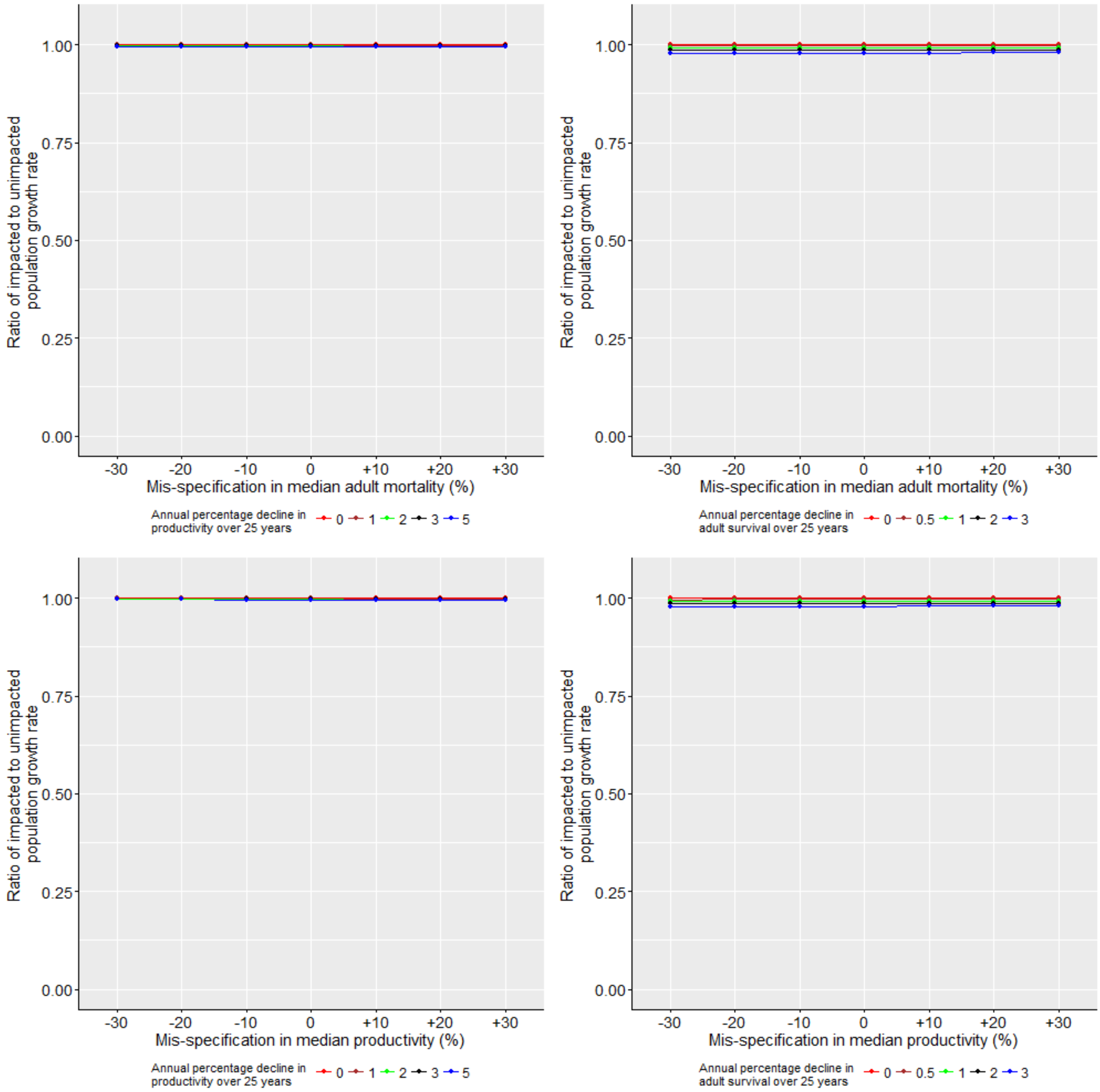


Figure 4b: PVA Metric B – ratio of population size at 2041, comparing impacted population vs. un-impacted population. Adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2016-2041).

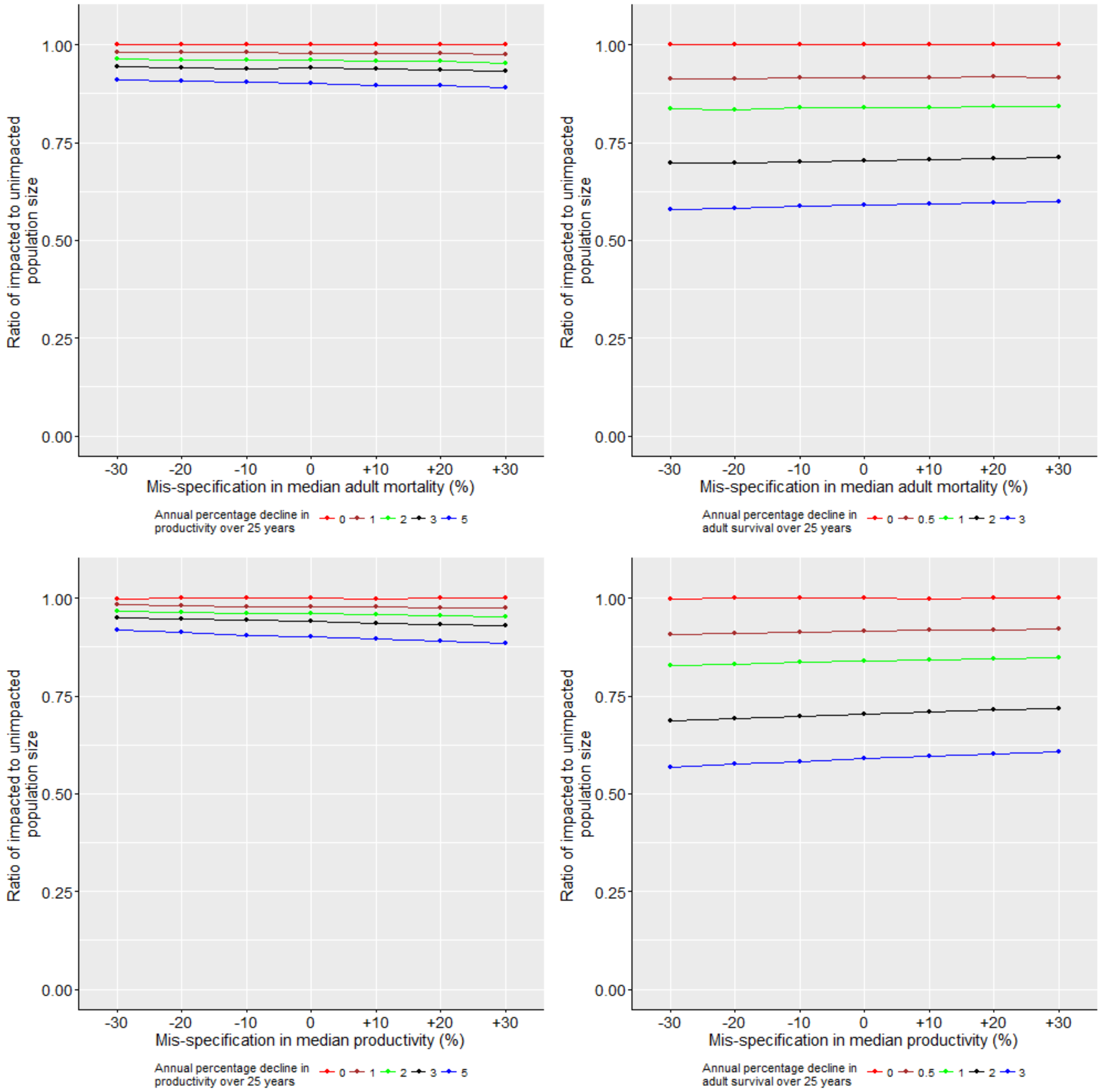


Figure 4c: PVA Metric C – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population. Adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2016-2041).

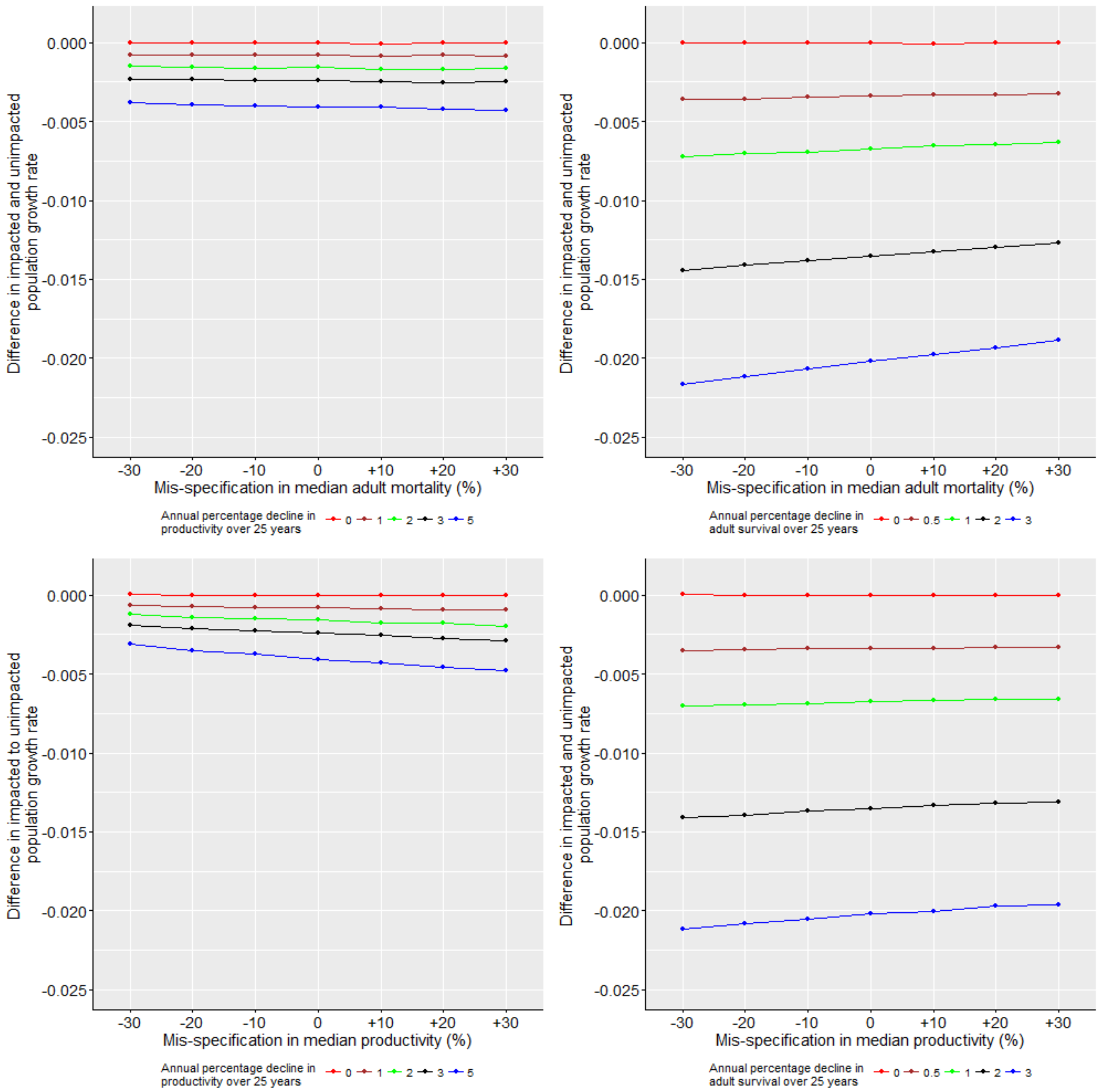


Figure 4d: PVA Metric D – difference in population size at 2041, comparing impacted population vs. un-impacted population. Adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2016-2041).

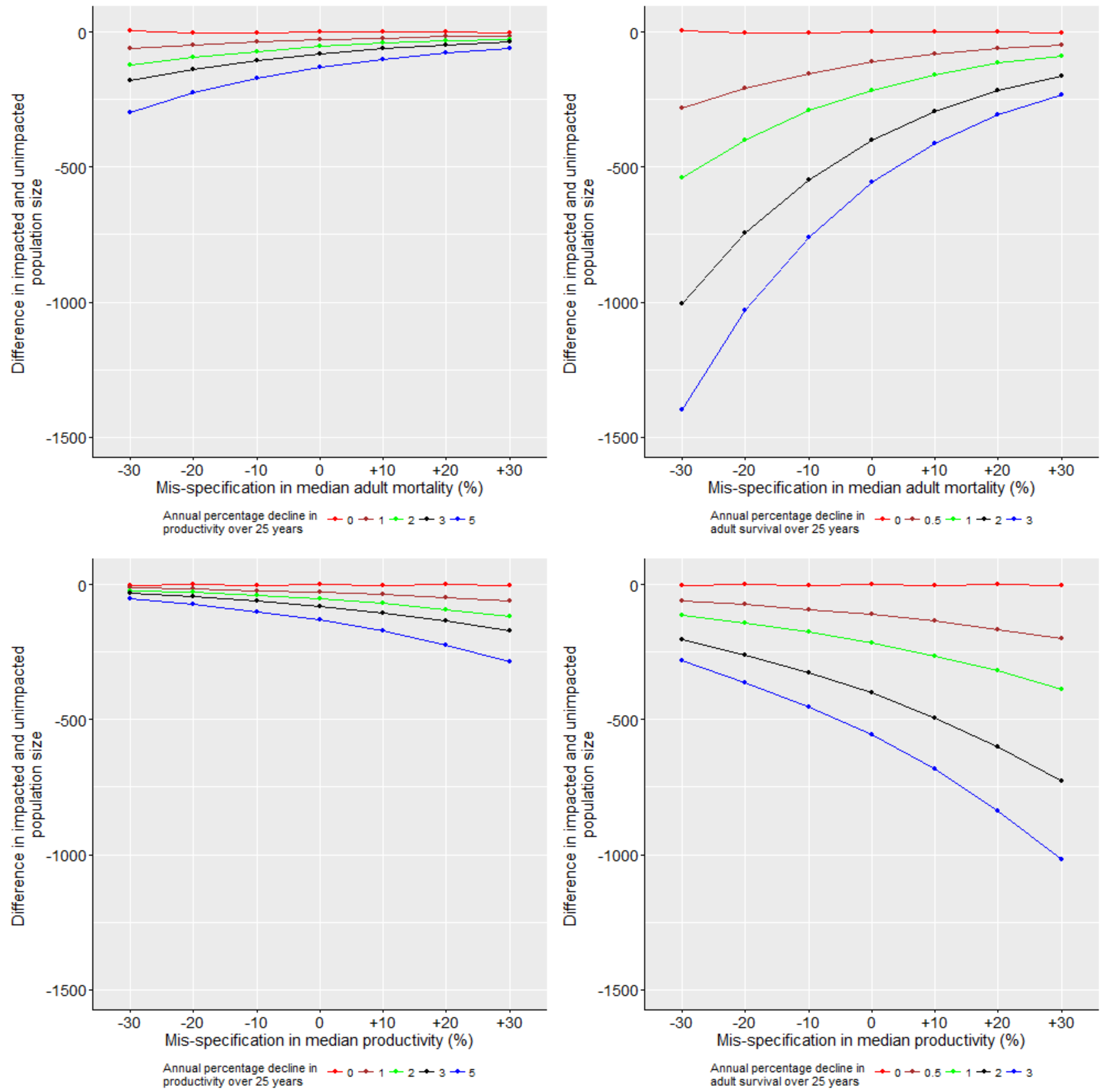


Figure 4e: PVA Metric E1 – probability of population decline greater than 10% from 2016-2041. Adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2016-2041).

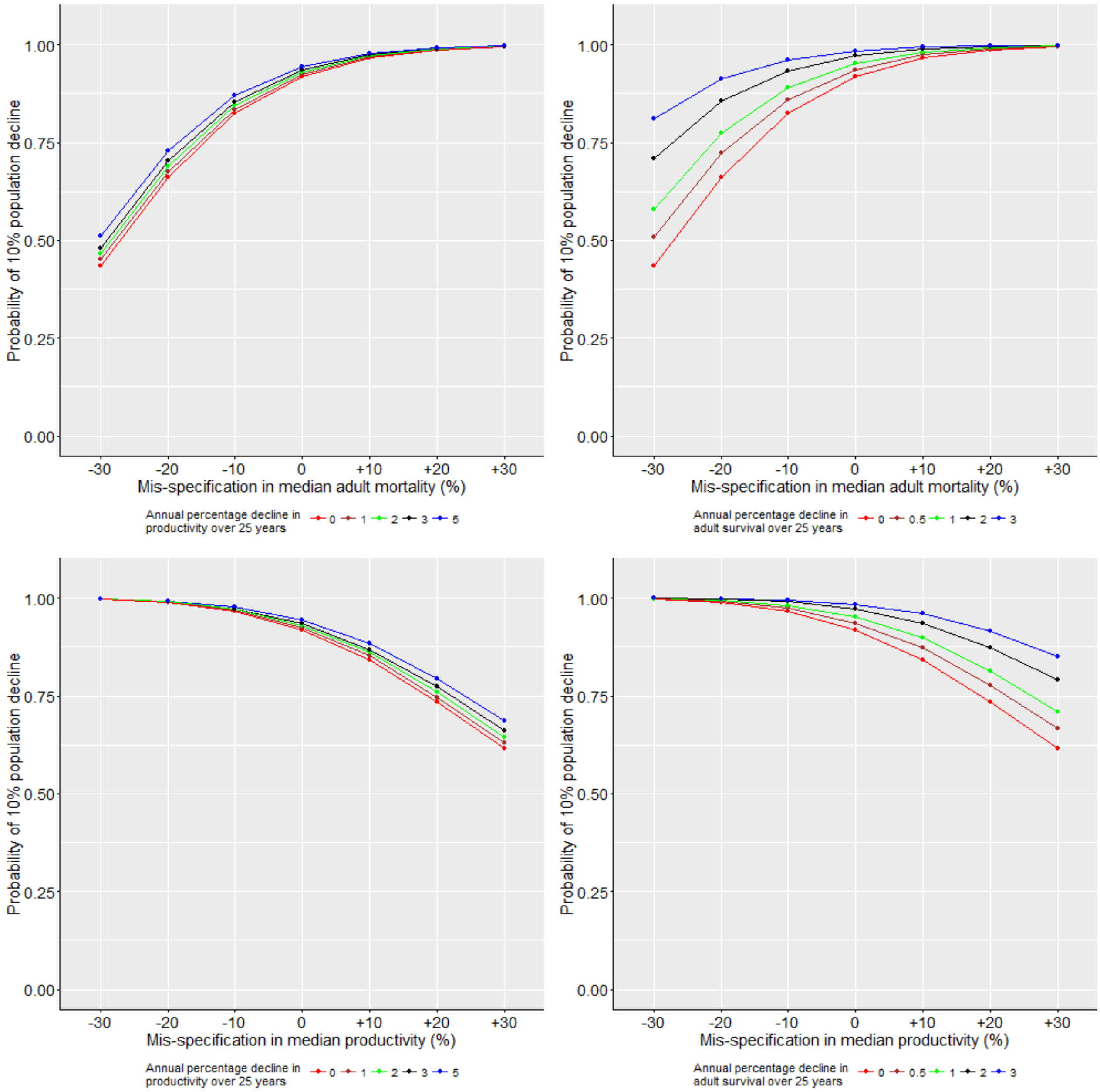


Figure 4f: PVA Metric E2 – probability of population decline greater than 25% from 2016-2041. Adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2016-2041).

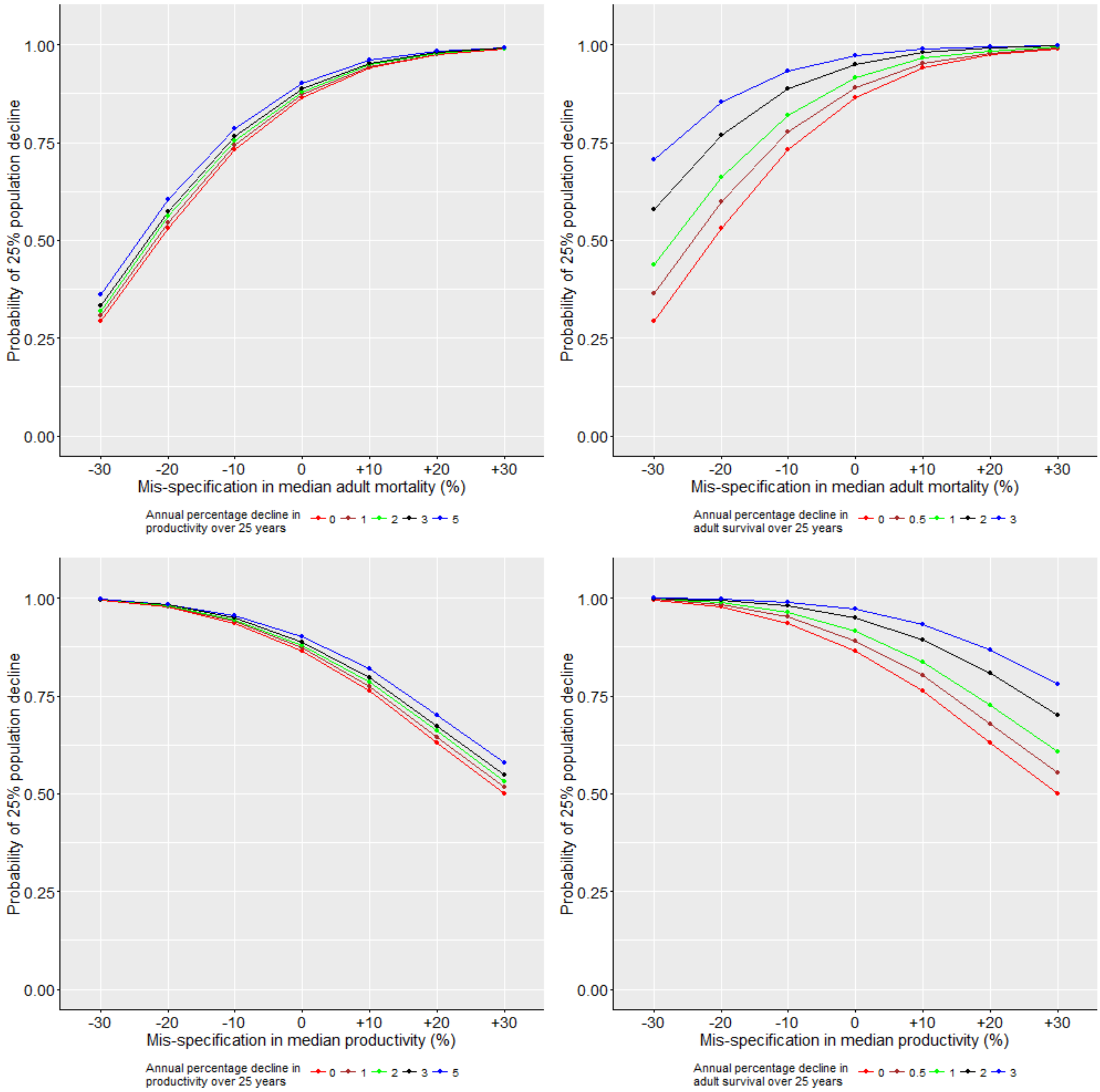


Figure 4g: PVA Metric E3 – probability of population decline greater than 50% from 2016-2041. Adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2017-2041).

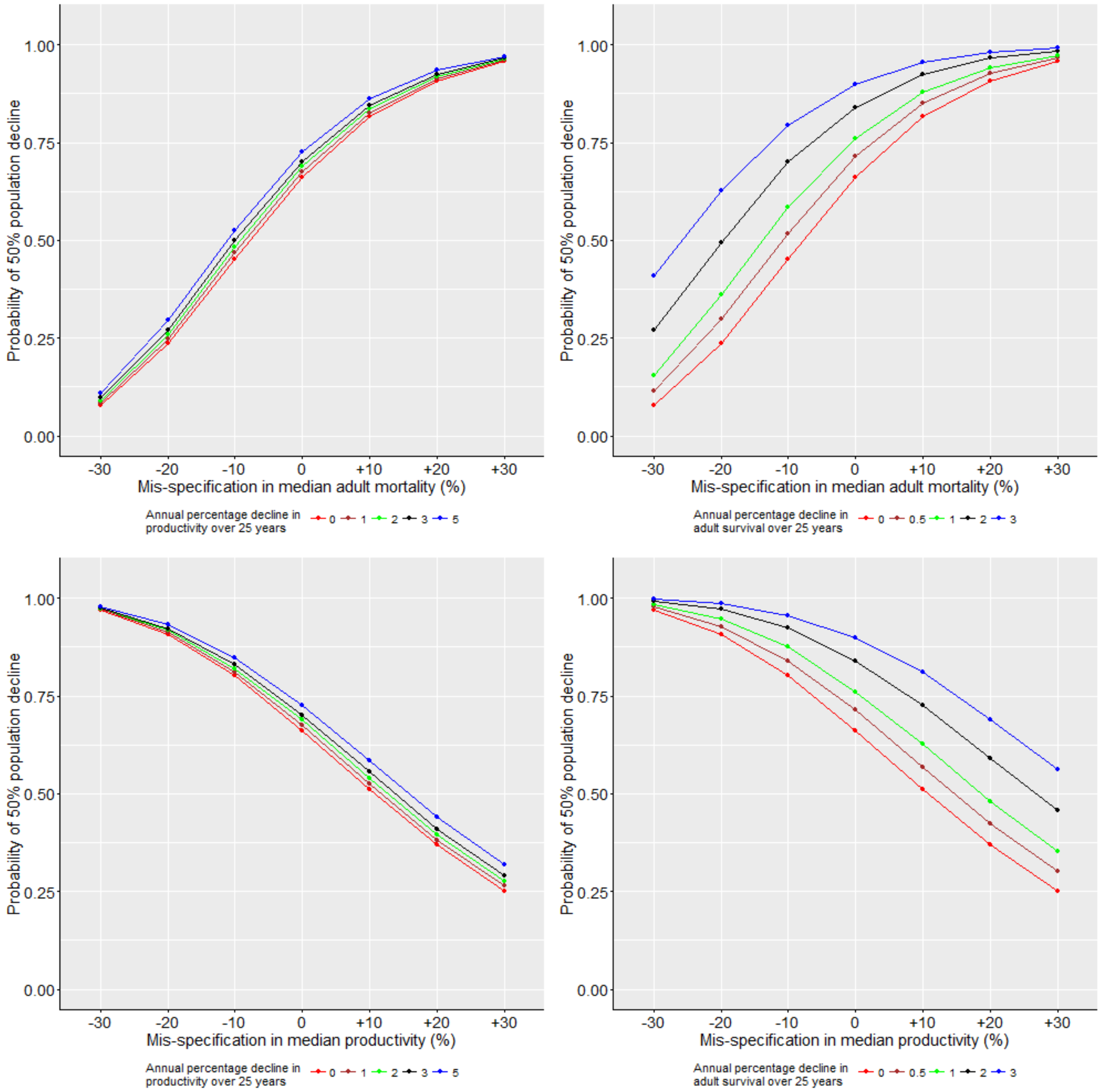
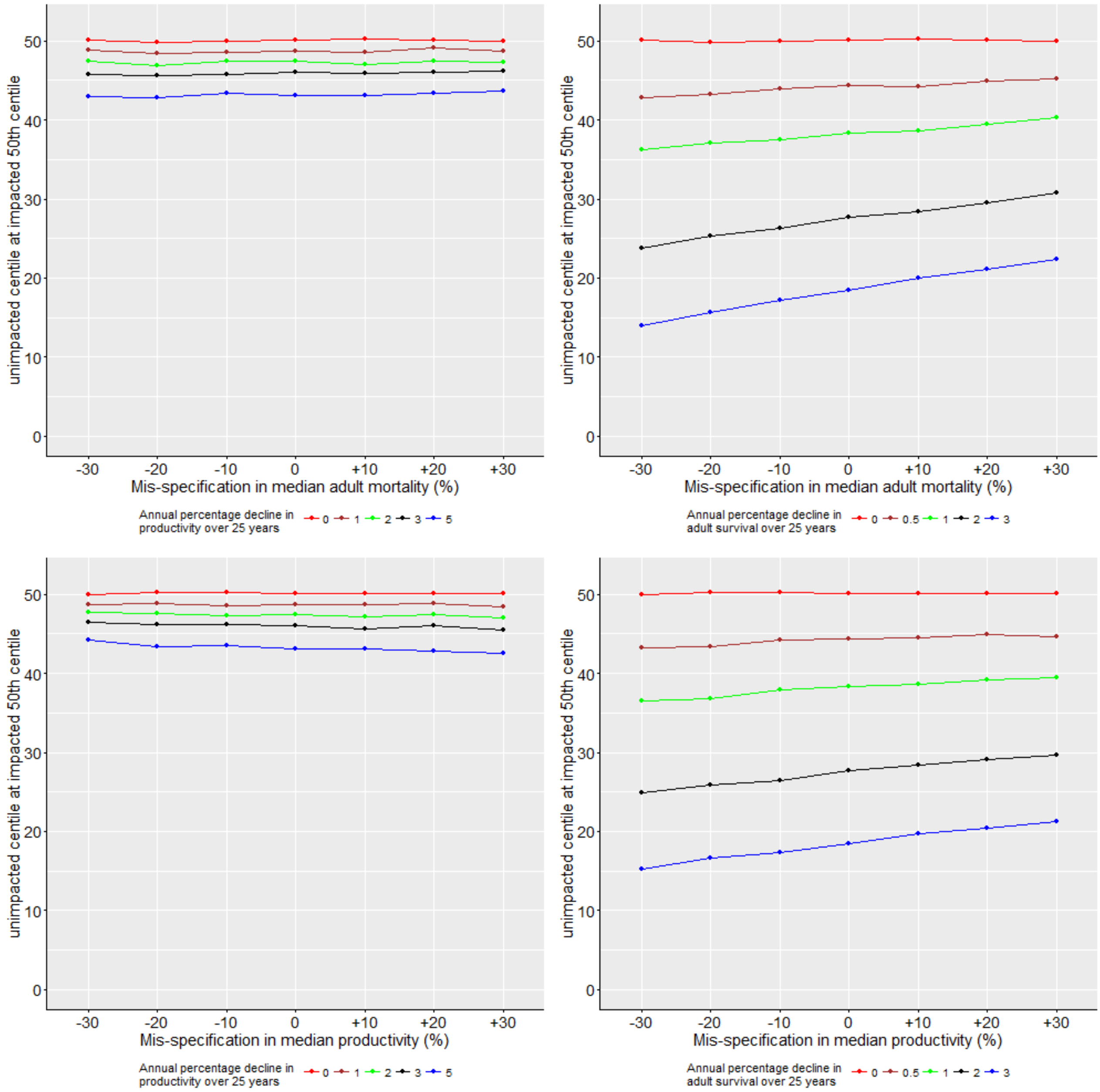


Figure 4h: PVA Metric F – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041. Adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2016-2041).



4.2 PVA Sensitivity in Relation to Population Status and Renewables Effect Size

To examine the effects of population status and renewables effect size, we integrated the results for the 13 SPA species/combinations for which we had good model convergence at the time of writing:

- Kittiwakes: Forth Islands; St Abb's Head; Fowlsheugh; Buchan Ness to Collieston Coast
- Guillemots: Forth Islands; St Abb's Head; Fowlsheugh; Buchan Ness to Collieston Coast
- Razorbills: Forth Islands; St Abb's Head; Fowlsheugh
- Shags: Forth Islands; St Abb's Head

Six of the thirteen indicated increasing abundance over time. These are guillemots at Forth Islands, St Abb's Head and Buchan Ness to Collieston Coast, razorbills at Forth Islands and Fowlsheugh and shags at Forth Islands, while the remainder showed a decrease (Table 7), providing a comparatively even balance facilitating this comparison. Results for differences in sensitivity in decreasing and increasing populations can be found in Figures 5a-h for PVA A, B, C, D, E1, E2, E3 and F, respectively. These plots show results from the analysis of mis-specification in adult mortality with the maximum scenario of change in adult survival (3%).

We present PVA sensitivities in relation to scenarios of renewables effect size in Figures 6a-h for PVA A, B, C, D, E1, E2, E3 and F, respectively. Of the four combinations shown in Figures 3 and 4, we only show results from the analysis of mis-specification in adult mortality with scenarios of change in adult survival, with effect sizes of 0.5%, 1%, 2% and 3%.

For PVA A, values approximate one (range 0.977-1) and there was no discernible difference in sensitivity between decreasing and increasing populations or with respect to renewables effect size (Figures 5a and 6a). Note that although annual growth rates are close to one, 25 year growth rates will show a discernible difference. For example, an annual growth rate of 0.977, results in a 25 year growth rate of 0.559.

For PVA B, there was also no discernible difference in sensitivity between decreasing and increasing species (Figure 5b). There was an increase in sensitivity with increasing effect sizes, with slopes flatter at 0.5% effect size compared with 3%

effect size, though the effect was small and the metric can be considered comparatively insensitive to all scenarios of effect size (Figure 6b).

PVAs C and D had higher sensitivity than PVAs A and B overall, but showed a similar response to population status and renewables effect size to PVA B, such that there was no clear difference between decreasing and increasing species in slope (Figure 5c and 5d), and a slight increase in gradient with increasing effect size from 0.5% to 3% (Figure 6c and 6d).

For PVA E, increasing populations showed greater sensitivity to probability of population decline greater than 10% than decreasing populations (Figure 5e), whereas the converse was true for a probability of population decline greater than 50% (Figure 5g). Similar sensitivities were apparent at 25% (Figure 5f). These differences reflect the pattern of probabilities of thresholds of change in population size relative to population status, with mis-specification having a smaller effect on probability of a smaller change in population size (10%) in a decreasing population since probability of this outcome is very high in most circumstances, and a smaller effect on probability of a larger change in population size (50%) in an increasing population (where probability of this outcome is very low in most circumstances). There was no clear difference in sensitivity with respect to renewables effect size, being comparatively high and variable in all scenarios at all three thresholds (Figures 6e-g).

PVA F showed a similar response to PVAs A, B, C and D with respect to population status and effect size. Thus, there was no clear difference in sensitivity between decreasing and increasing species in slope, with sensitivity overall being moderately low, higher than ratio metrics but lower than PVA E (Figure 5h). Sensitivity was also comparatively unaffected by effect sizes (Figure 6h).

Figure 5a: PVA Metric A – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population, for changing adult mortality and a 3% decrease in adult survival, across decreasing populations and increasing populations.

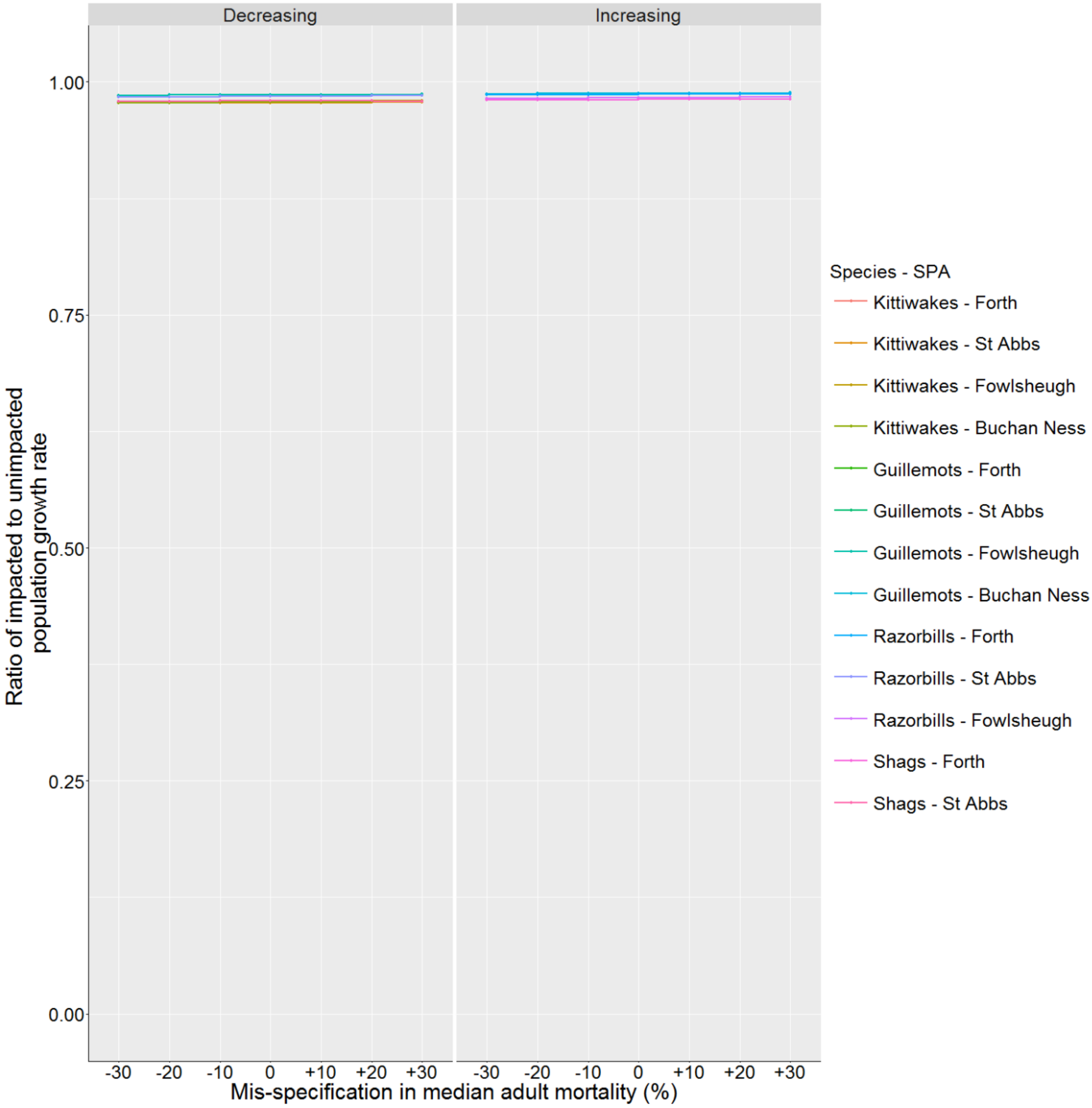


Figure 5b: PVA Metric B – ratio of population size at 2041, comparing impacted population vs. un-impacted population, for changing adult mortality and a 3% decrease in adult survival, across decreasing populations and increasing populations.

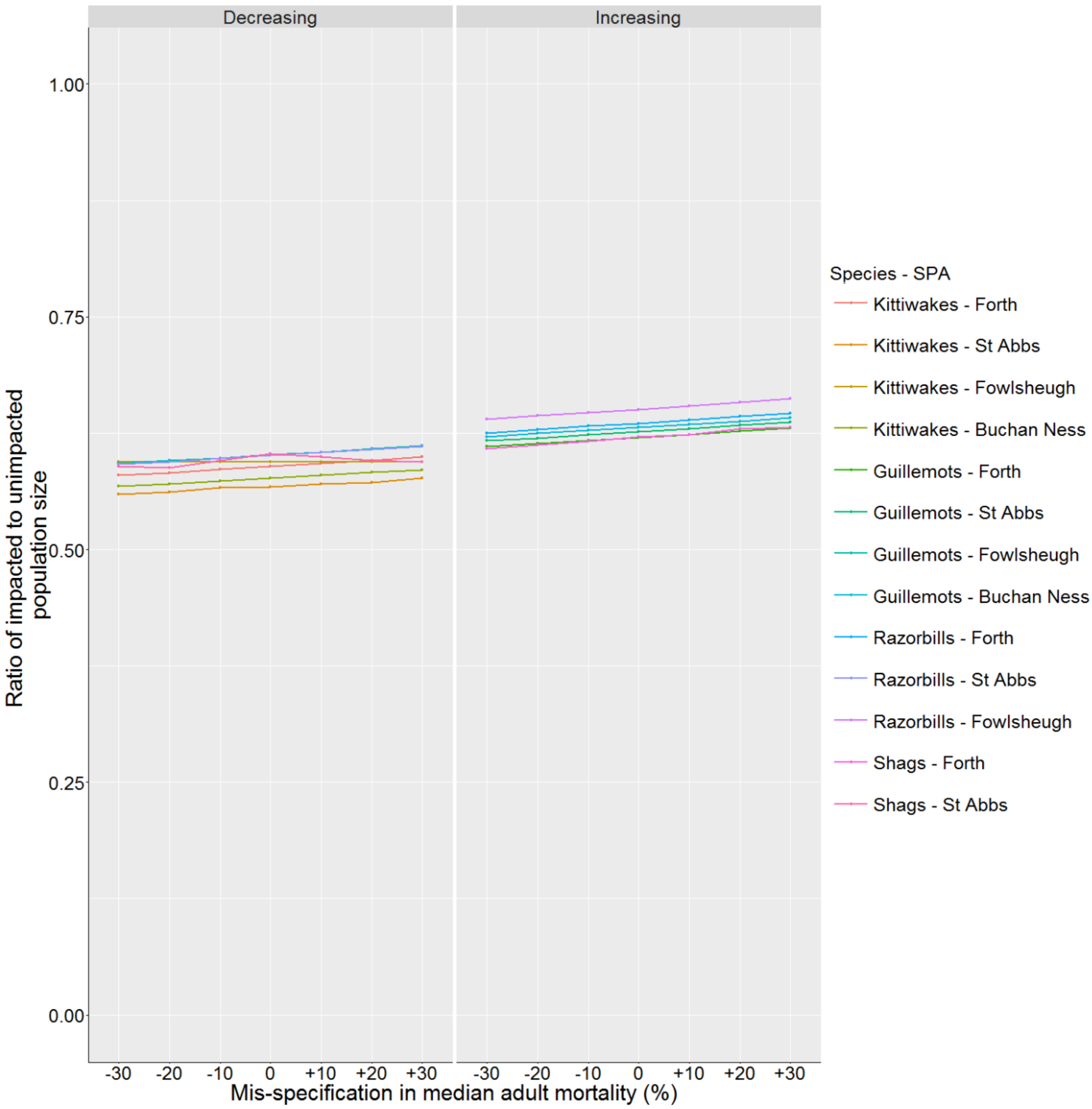


Figure 5c: PVA Metric C – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population, for changing adult mortality and a 3% decrease in adult survival, across decreasing populations and increasing populations.

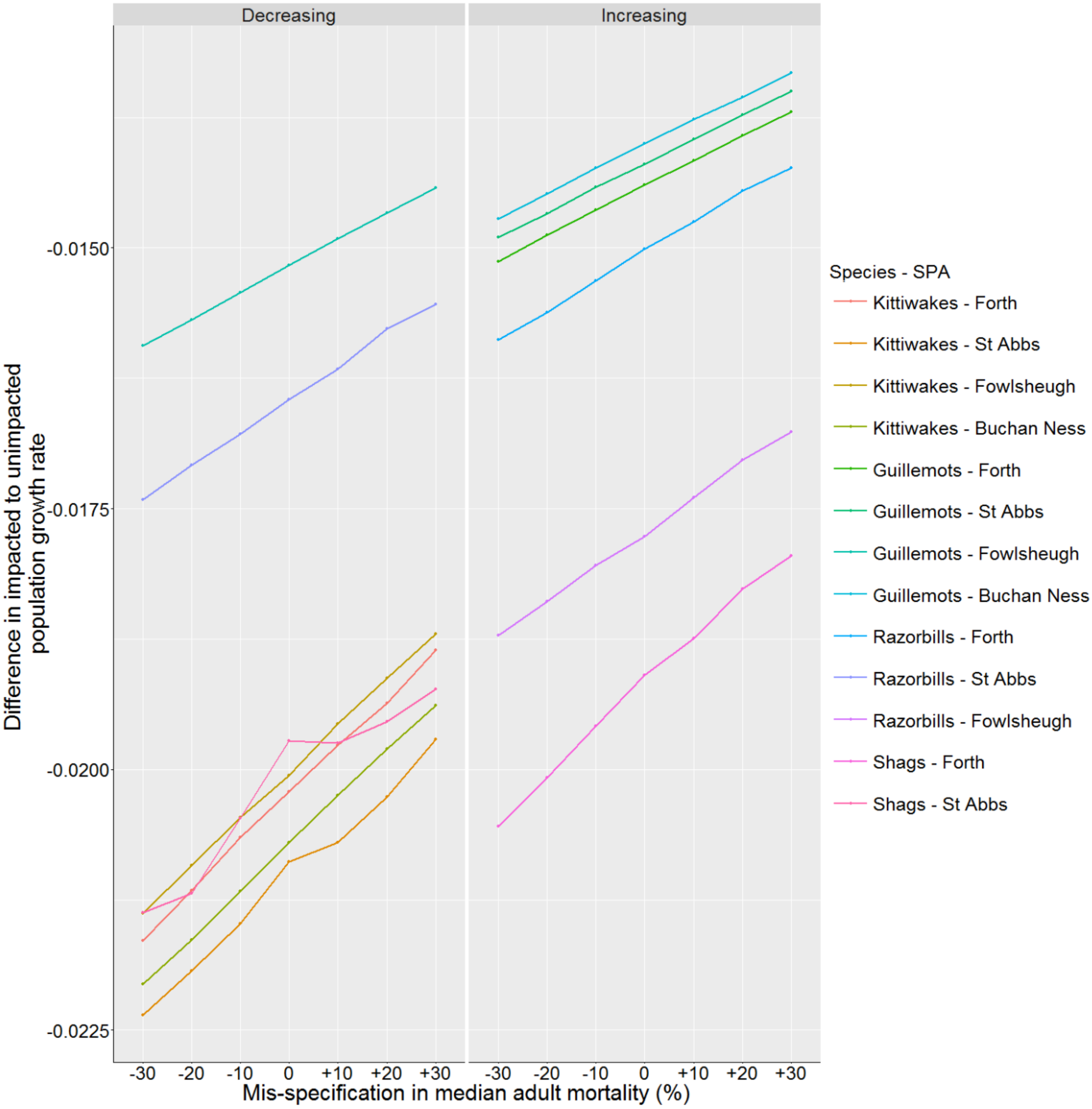


Figure 5d: PVA Metric D – difference in population size at 2041, comparing impacted population vs. un-impacted population, for changing adult mortality and a 3% decrease in adult survival, across decreasing populations and increasing populations.

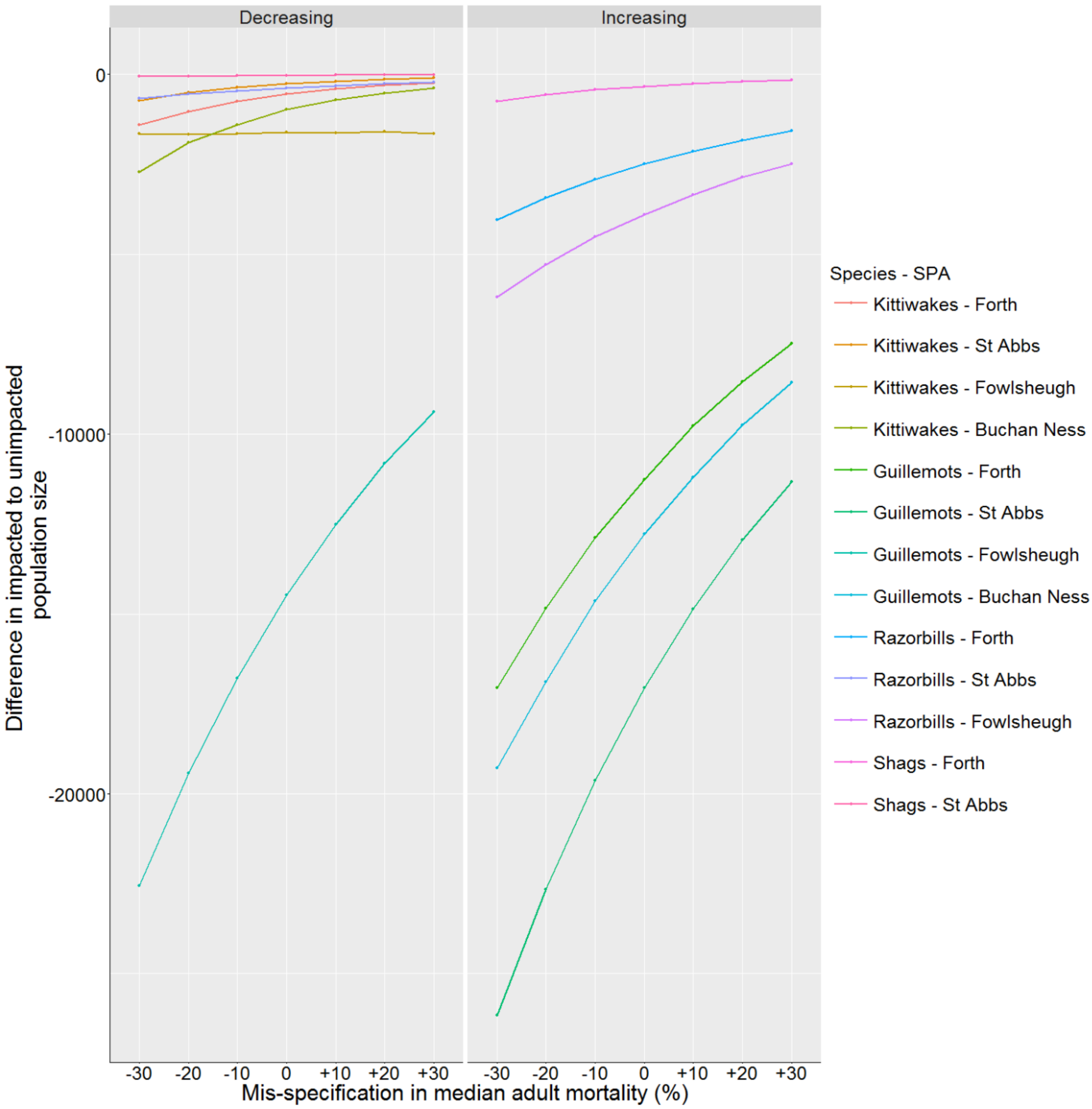


Figure 5e: PVA Metric E1 – probability of population decline greater than 10% from 2016-2041, for changing adult mortality and a 3% decrease in adult survival, across decreasing populations and increasing populations.

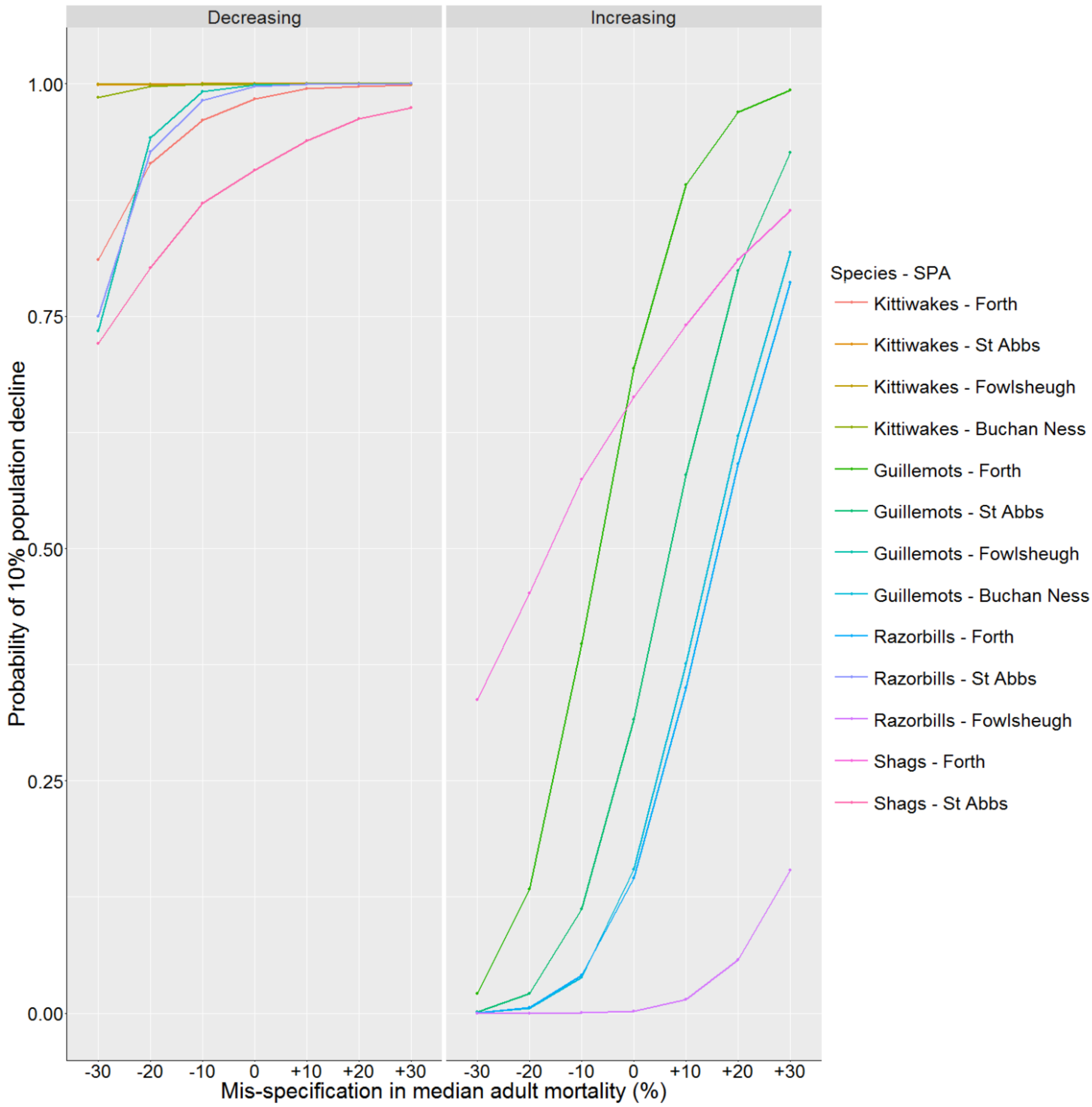


Figure 5f: PVA Metric E2 – probability of population decline greater than 25% from 2016-2041, for changing adult mortality and a 3% decrease in adult survival, across decreasing populations and increasing populations.

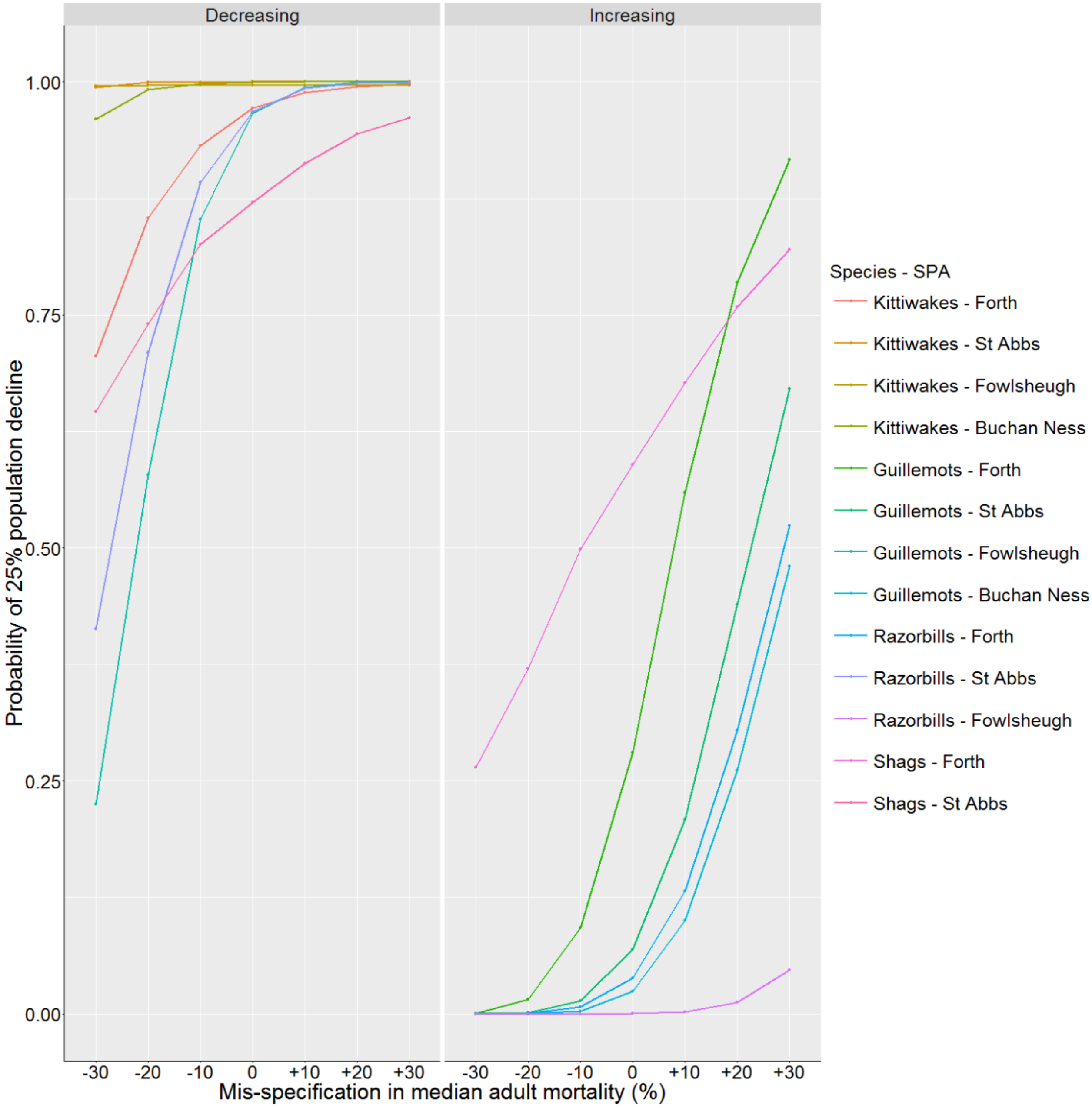


Figure 5g: PVA Metric E3 – probability of population decline greater than 50% from 2016-2041, for changing adult mortality and a 3% decrease in adult survival, across decreasing populations and increasing populations.

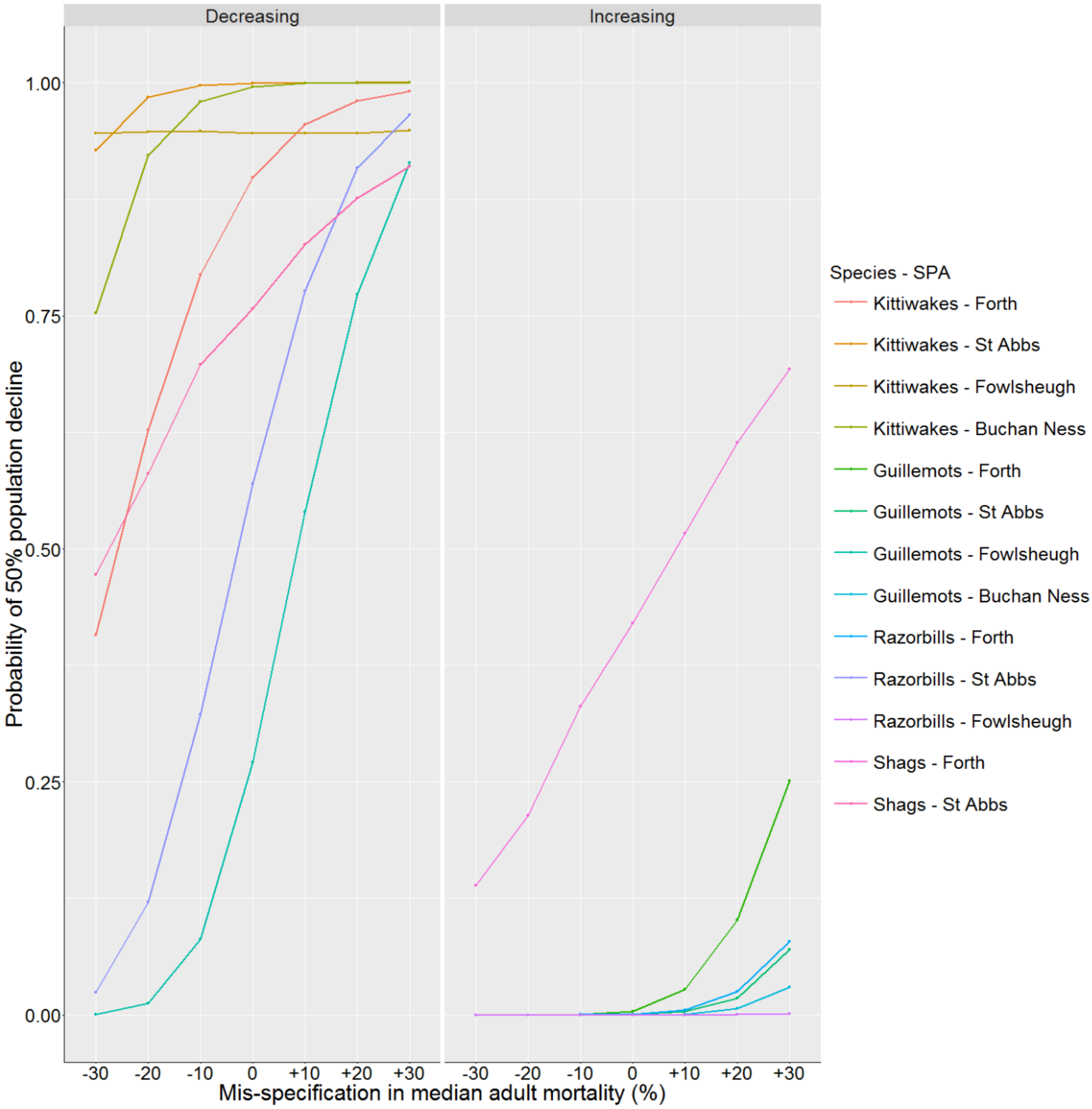


Figure 5h: PVA Metric F – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041, for changing adult mortality and a 3% decrease in adult survival, across decreasing populations and increasing populations.

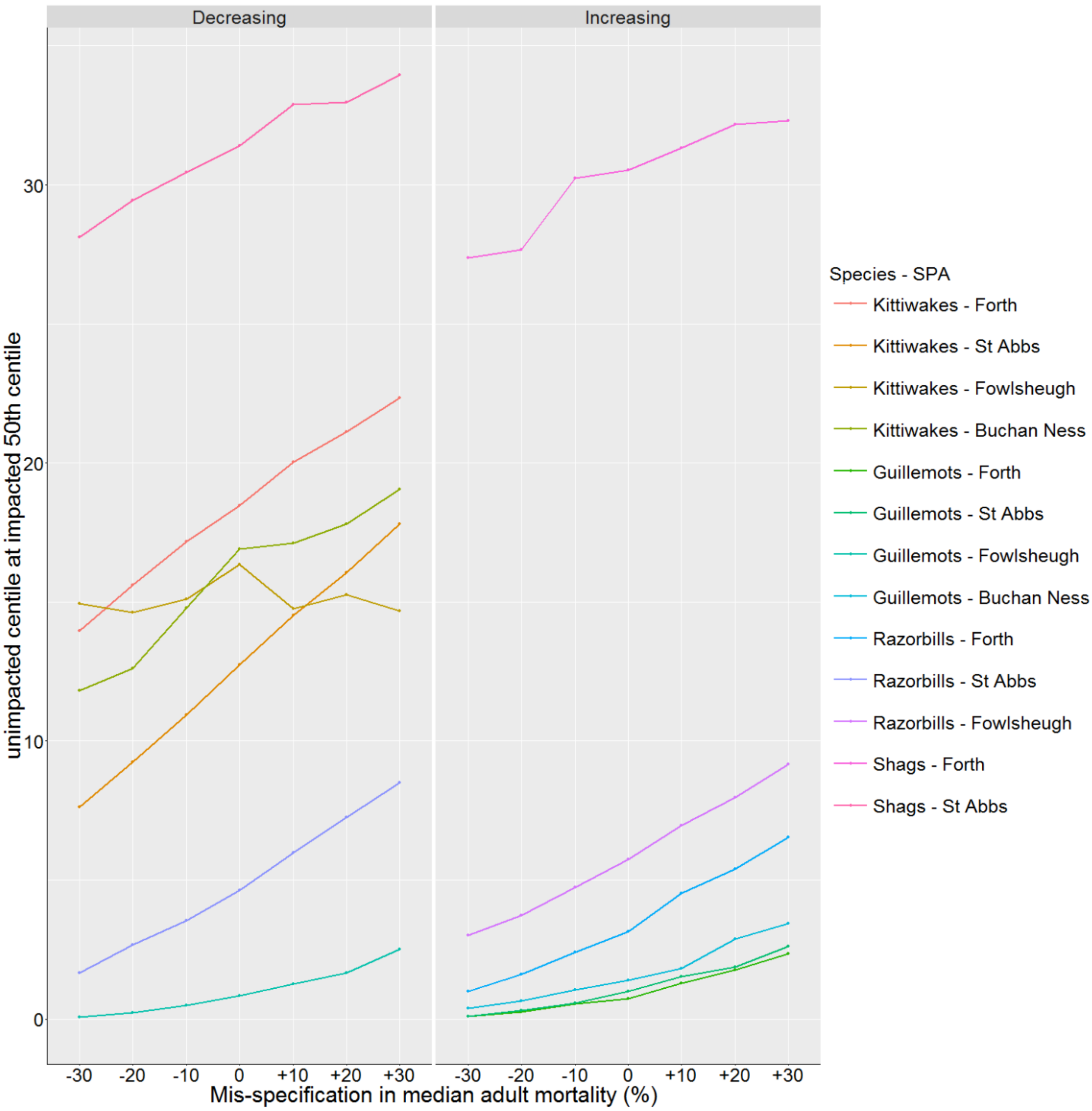


Figure 6a: PVA Metric A – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population, for changing adult mortality and various decreases in adult survival, across all populations.

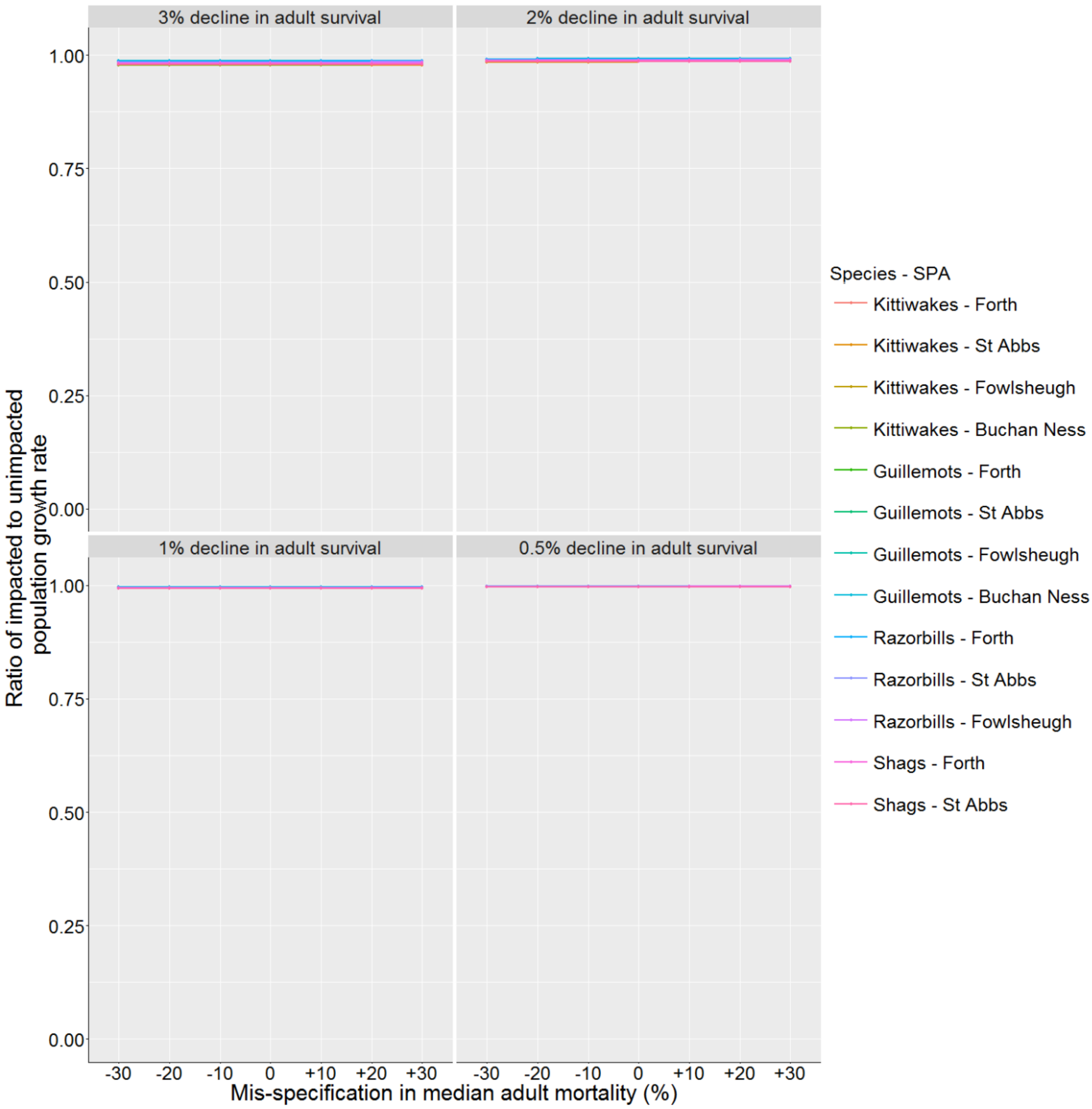


Figure 6b: PVA Metric B – ratio of population size at 2041, comparing impacted population vs. un-impacted population, for changing adult mortality and various decreases in adult survival, across all populations.

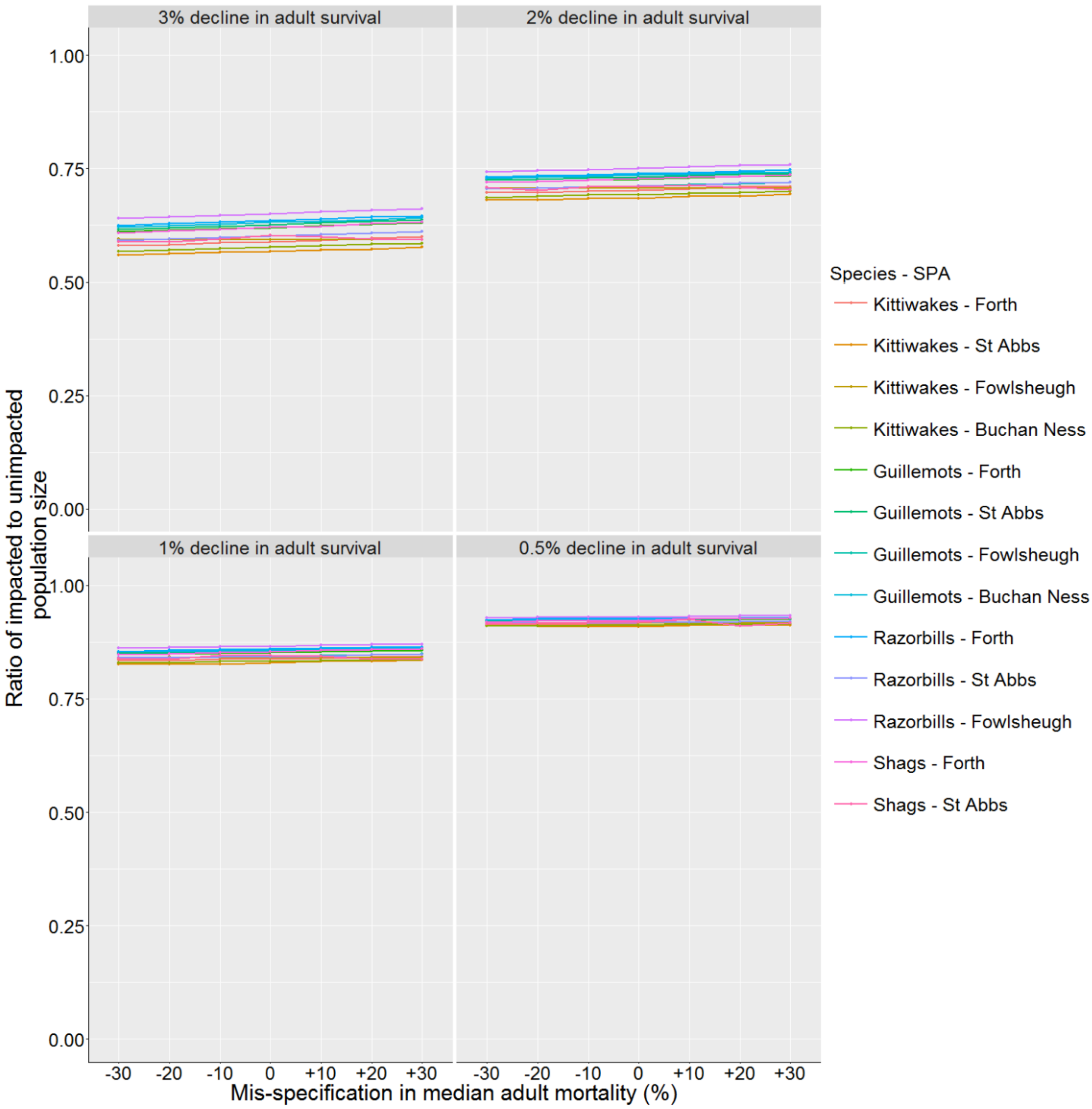


Figure 6c: PVA Metric C – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population, for changing adult mortality and various decreases in adult survival, across all populations.

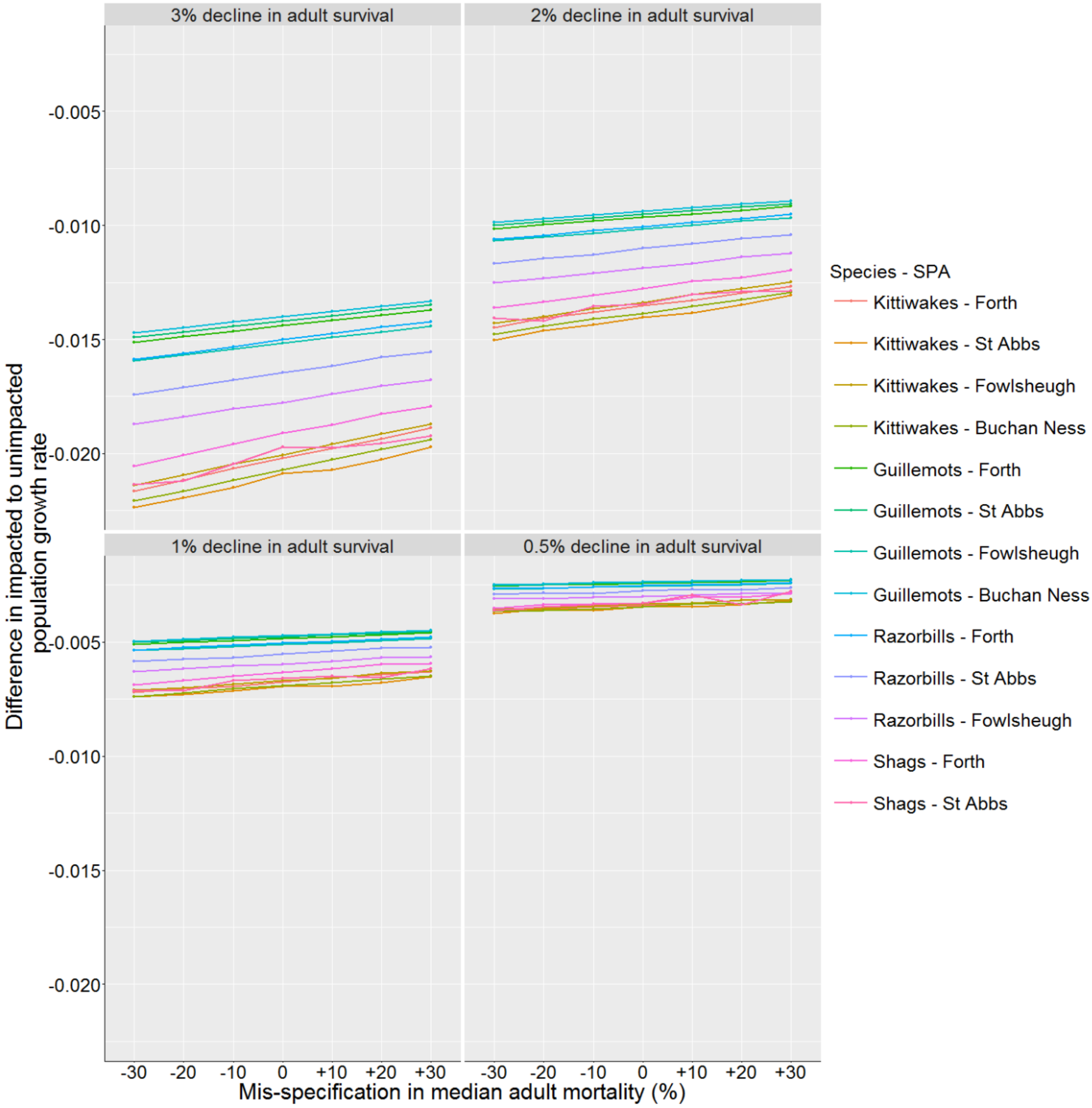


Figure 6d: PVA Metric D – difference in population size at 2041, comparing impacted population vs. un-impacted population, for changing adult mortality and various decreases in adult survival, across all populations.

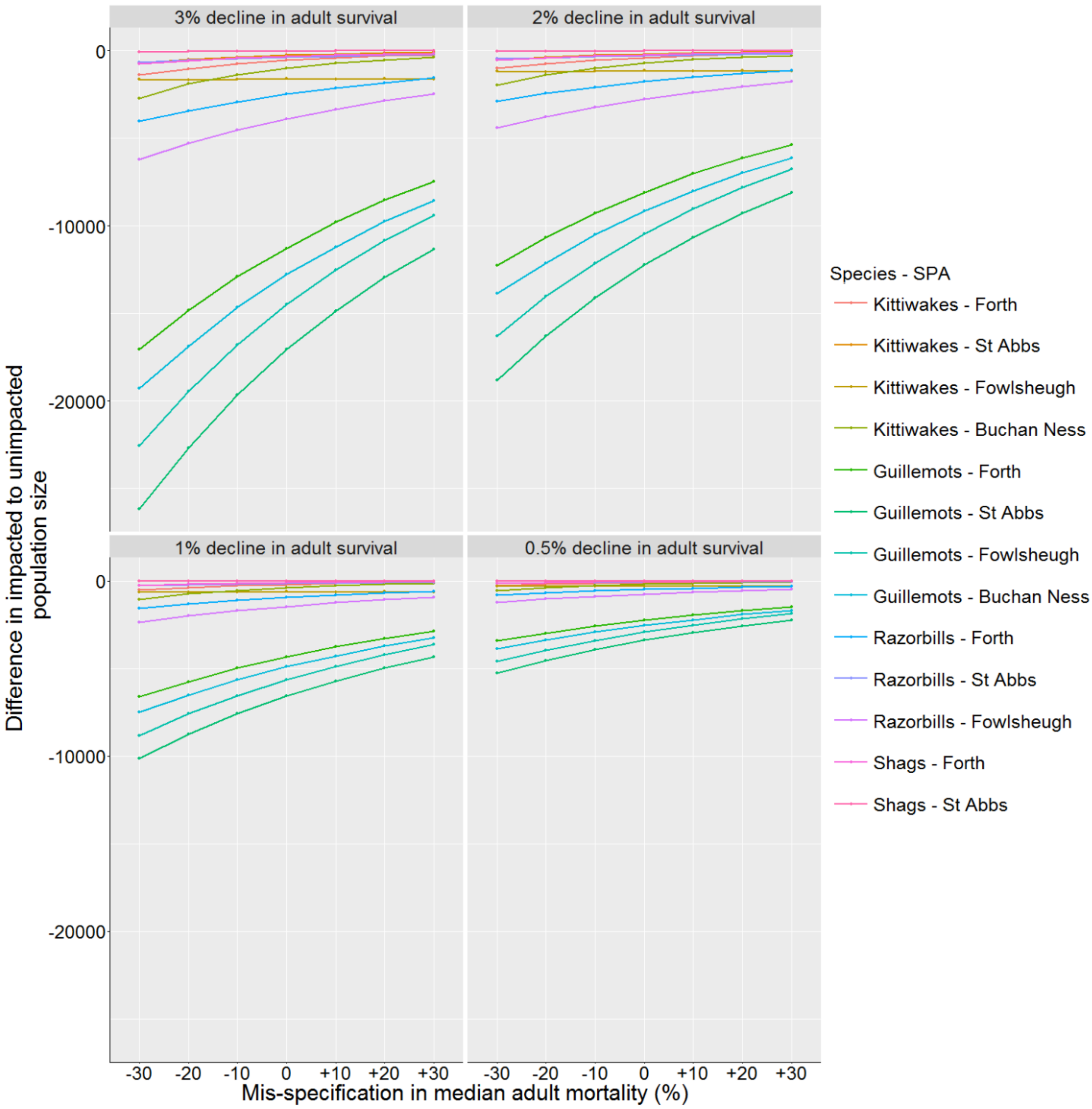


Figure 6e: PVA Metric E1 – probability of population decline greater than 10% from 2016-2041, for changing adult mortality and various decreases in adult survival, across all populations.

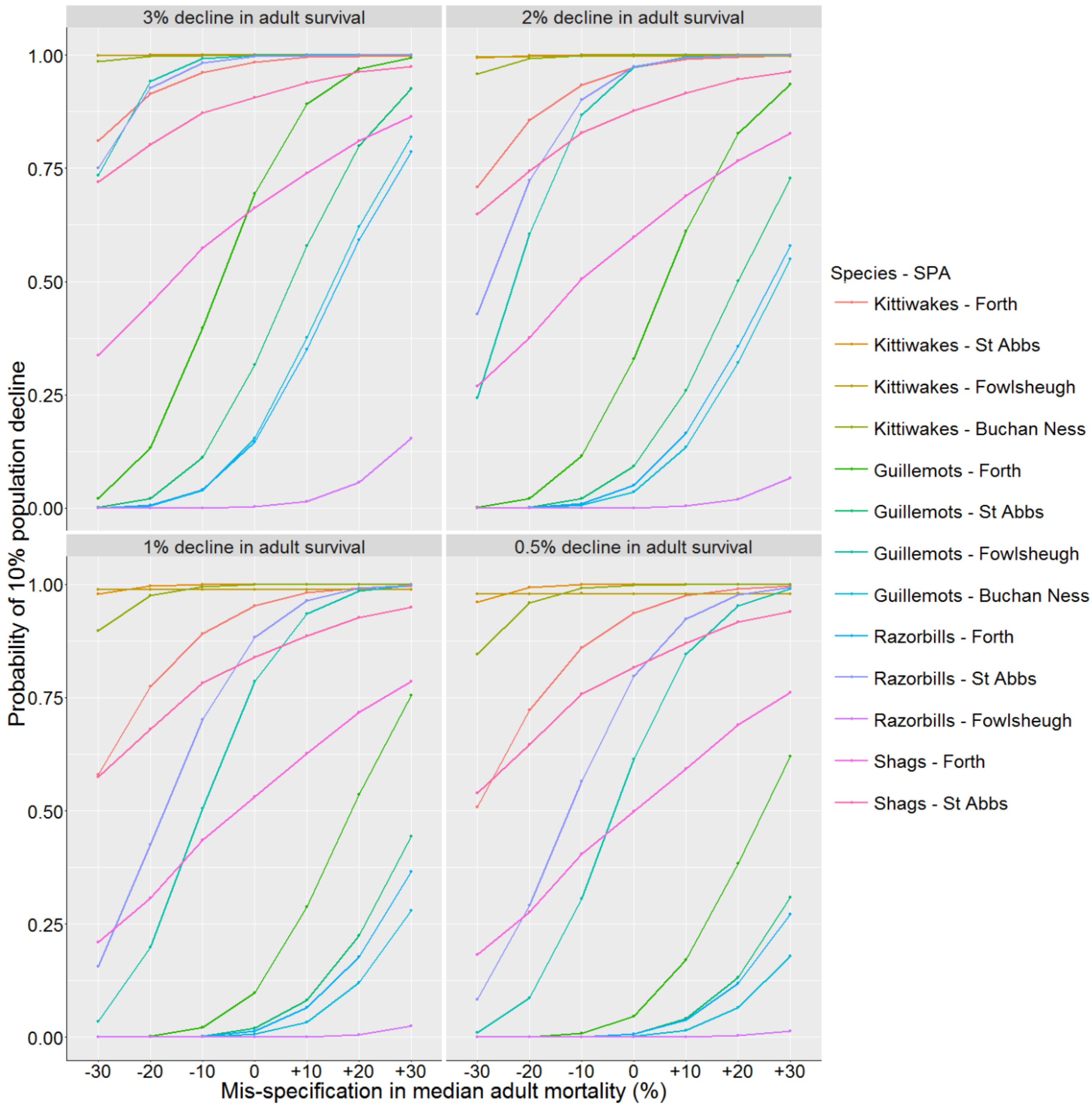


Figure 6f: PVA Metric E2 – probability of population decline greater than 25% from 2016-2041, for changing adult mortality and various decreases in adult survival, across all populations.

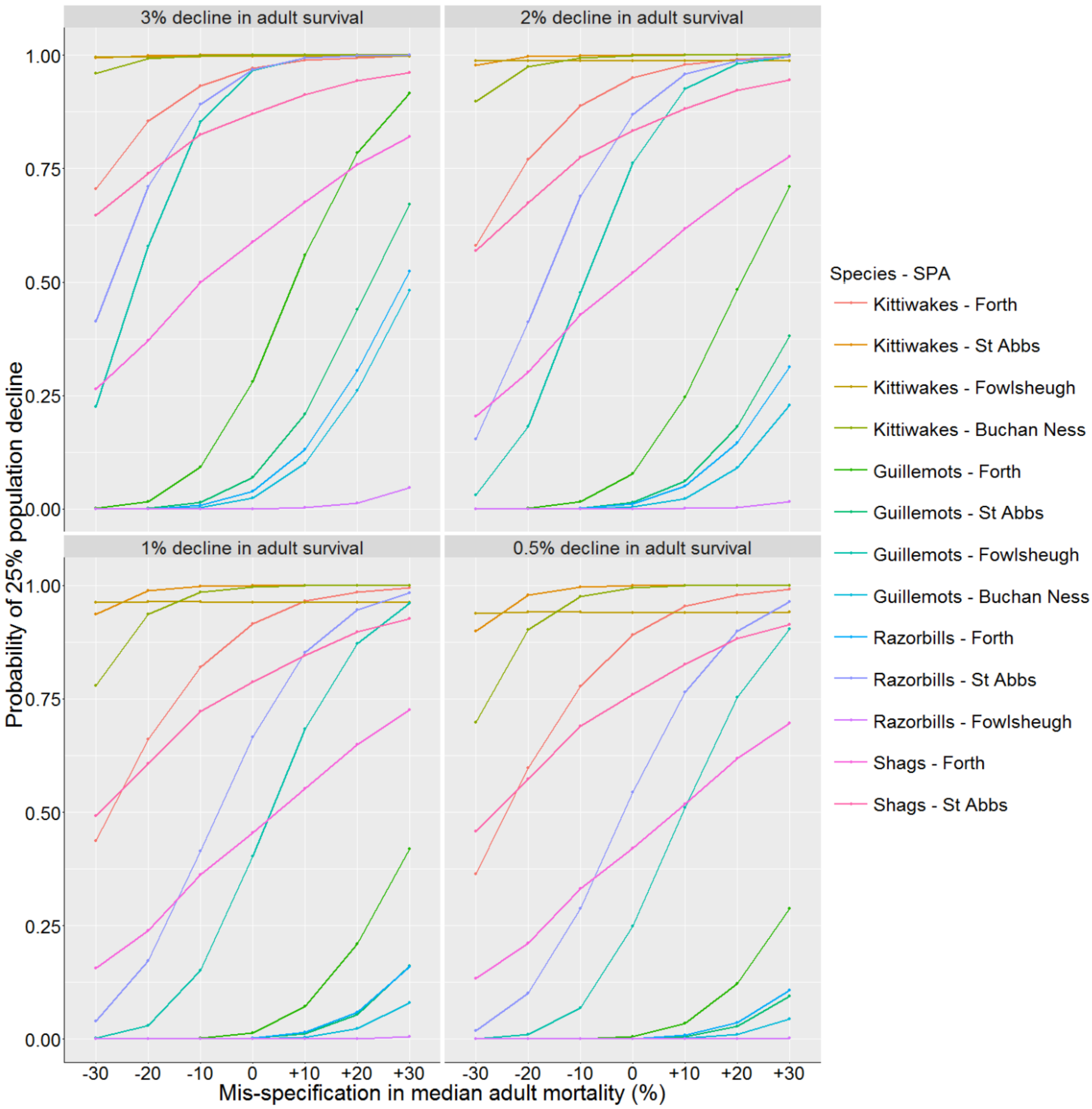


Figure 6g: PVA Metric E3 – probability of population decline greater than 50% from 2016-2041, for changing adult mortality and various decreases in adult survival, across all populations.

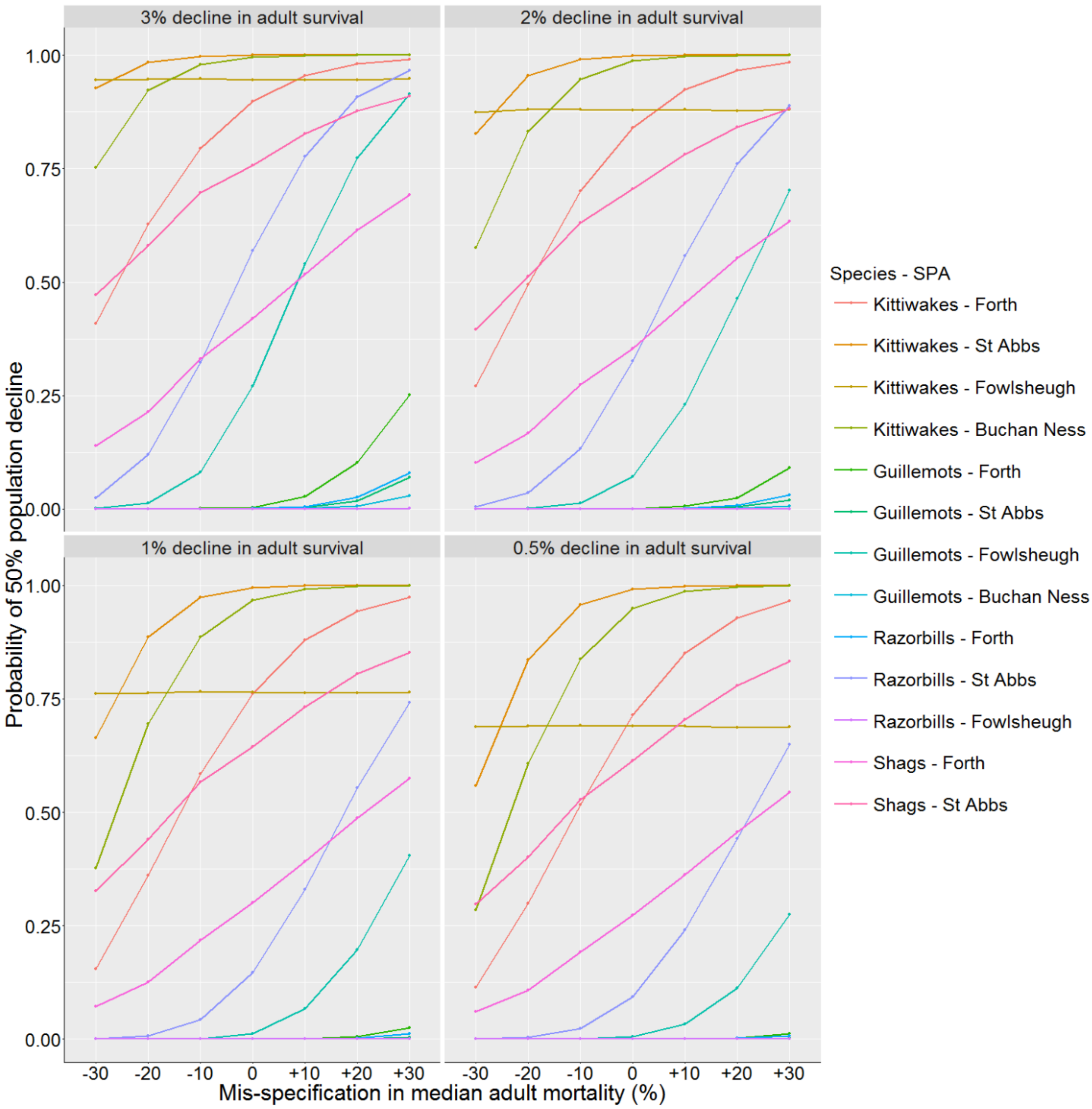
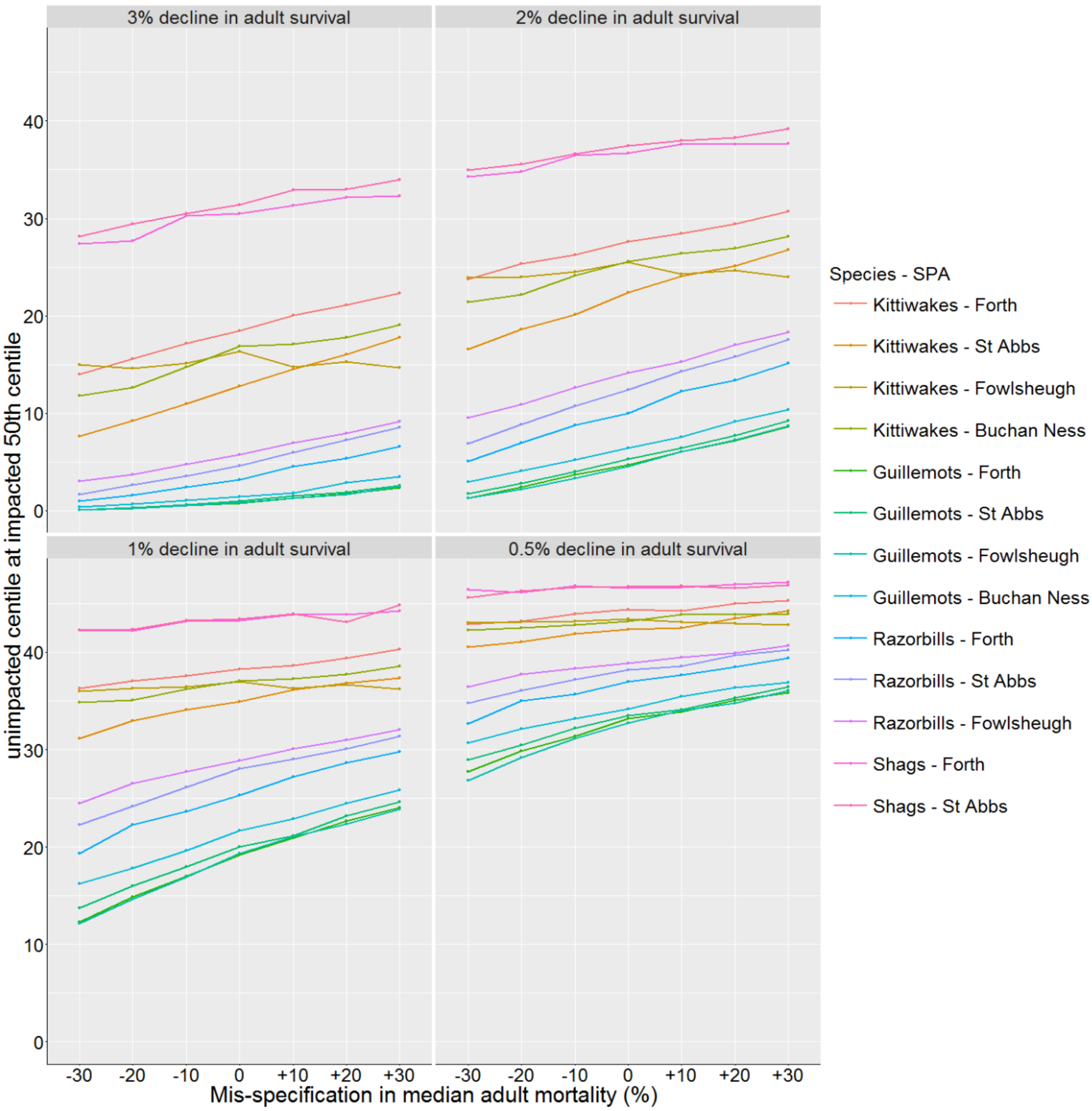


Figure 6h: PVA Metric F – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041, for changing adult mortality and various decreases in adult survival, across all populations.



5. Discussion and Recommendations

5.1 PVA Metric Sensitivity

This study represents the most comprehensive assessment of PVA metric sensitivity to mis-specification of demographic rates in relation to population status and perturbation effect sizes in the seabird/marine renewable context using real-world data. Using available data on abundance, survival and productivity in a well-studied region of the UK and Bayesian population modelling approaches, we compared the sensitivity to mis-specification of input demographic parameters of six PVA metrics, comprising two ratio metrics (PVAs A and B), two metrics related to ratio metrics (PVAs C and D) and two probabilistic metrics (PVAs E and F).

By undertaking an analysis of real-world data sets, our work provides a useful complement to recent work on sensitivity of PVA metrics to input parameter uncertainty using simulation modelling of generic seabird species with varying life histories (Cook & Robinson 2016b, 2017). The close accordance in findings provides confidence on choice of PVA metrics that are least sensitive to such mis-specification, and, therefore, most suitable for use in wind farm assessments.

5.2 Recommendations on PVA Metrics

The two ratio metrics performed best among the six metrics considered with respect to sensitivity to mis-specification in input parameters. The ratio of impacted to un-impacted annual growth rate (PVA A) and ratio of impacted to un-impacted population size after 25 years (PVA B) both showed low sensitivity to demographic input mis-specification, in accordance with findings from other studies (Green *et al.* 2016; Cook & Robinson 2016b, 2017), with PVA A performing consistently better than PVA B.

The calculations of difference in impacted and un-impacted annual growth rates (PVA C) and between impacted and un-impacted population size after 25 years (PVA D) were not so readily interpretable but they are useful when growth rates or population size estimates are small.

In keeping with other work, we found that the probability PVA metric (PVA E) was highly sensitive and we, therefore, caution against using it in this context, in accordance with recommendations by other authors (Green *et al.* 2016; Cook & Robinson 2016b, 2017). We were not tasked with testing the sensitivity of counterfactual probabilistic metrics, in particular Metric 8 in Table 2 ("Change in probability of a 10, 25 or 50% decline", also known as "Counterfactual of the probability of population decline", and linked to Metric 7 in Table 2/PVA E in this report), a metric that has been used frequently in assessments, often in association with PVA E. However, a visual examination of the figures presenting PVA metric E shows in almost all cases, a clear divergence between the lines across the range of values of mis-specification, and this change in the difference between values across effect sizes represents sensitivity to mis-specification of demographic rates in the excess probability referred to here. Good examples where this is clear are Figure 4e (all four panels) and Figure 4f (all four panels). It is not clear in all cases – see for example Figure 4g (top left panel). However, overall we can conclude that this counterfactual is comparatively more sensitive to mis-specification than ratio metrics.

Finally, the metric representing the centile from the un-impacted population size equal to the 50th centile of the impacted population size at the end of the wind farm (PVA F) showed moderately low sensitivity to mis-specification of survival and productivity. It performed considerably better than the other probabilistic metric (PVA E - probability of a population decline) with markedly lower sensitivity to mis-specification, population status and renewables effect size. However, it was more sensitive than ratio metrics, and in some cases showed unstable sensitivity which was less apparent in PVA metrics A and B (see Figures 5 a, b and h; Figures 6 a, b and h).

We recommend that those undertaking assessments consider the relative performance of different metrics with respect to sensitivity to mis-specification of input parameters. To summarise, of the two ratio and two probabilistic metrics considered here, the order with respect to sensitivity to mis-specification of input parameters was PVA A; PVA B; PVA F; PVA E. PVA E was much more sensitive than the other three and is not recommended for use in this context. If the first three are used in assessments in future, we recommend that interpretation should factor in their relative sensitivities. We also recommend that PVA metrics (C and D) are used since they are estimable when ratios are being calculated.

Note that we do not make recommendations on appropriate thresholds in relation to the above metrics, which is a societal choice and a matter for regulators.

5.3 Recommendations on PVA Analysis in Assessments of Renewables on Seabirds

We believe that Population Viability Analysis is a robust framework for forecasting future population change of seabirds under baseline conditions and under conditions of varying perturbations on demographic rates caused by renewable developments.

Furthermore, we believe that Bayesian state-space models have considerable potential in Population Viability Analysis using real data. Forecasts are made straightforward by the adoption of this approach, since posterior distributions are naturally generated. Furthermore, these methods do not suffer from the same criticism aimed at traditional methods that confidence intervals are unrealistically narrow. In addition, the study region has some of the most comprehensive demographic data available on seabirds in the UK, collected by CEH at their long term field site on the Isle of May, which has proved extremely valuable in carrying out this work. However, the restricted availability of high quality data left us with no alternative but to use these data on other populations where no such data exist. Despite this, the models of these other populations generally performed well. Exceptions were where population counts were sparse and variable, a particular issue at the Buchan Ness to Collieston Coast SPA.

5.4 Future Research and Monitoring Priorities

A fruitful avenue for future research would be extension to more complex models that incorporate environmental covariates or density dependence. Although there remains a lack of empirical evidence linking environmental covariates and seabird demography (Daunt *et al.* 2017), examples do exist (e.g. Frederiksen *et al.* 2004) and could form the rationale for future modelling including covariates. Evidence for density dependence in UK seabird populations is emerging (Horswill *et al.* 2016) and could be included where there is strong evidence for its occurrence including, crucially, whether the form of density dependence is compensatory or depensatory.

It would also be beneficial to estimate PVA metric sensitivity across a broader range of real world examples, comprising more species with differing life histories than we could consider here. This approach would enable a more comprehensive assessment of ratio and probabilistic metrics. Furthermore, it would be useful to test PVA F using a simulation modelling approach (Cook & Robinson 2016b, 2017) to establish whether a similar sensitivity to mis-specification of input parameters was apparent using that method. Another future priority would be to test sensitivity of different metrics using different population modelling methods: in addition to

Bayesian state-space models, other methods that may be more suited to sparse data could be incorporated, such as age-structured population growth models.

It is encouraging to note the value of plot counts, since these can be maintained on an annual or near- annual basis much more readily than full colony counts. However, we would recommend that full counts continue to be undertaken regularly to ensure that plots continue to be representative. Local data on survival and productivity add significantly to the ability to model populations effectively. However, our study demonstrates that PVA metrics, and their sensitivity to mis-specification, can be estimated where data are absent from the focal colony but available from an alternative, ideally nearby colony, thereby offering a natural, informative model prior. However, considerable thought is required before adopting this approach since information from another colony cannot automatically be assumed to apply elsewhere to other species and/or regions.

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Appendix 1

Input Parameters to the Bayesian State Space Models

This appendix details the input values for the population models.

Input parameters for adult survival and productivity are provided at two scales. In the Bayesian models, they are on the logit or the log scale (Table A1.1). However, these can be somewhat difficult to understand, so we have back transformed those that are on the log scale (productivity for kittiwakes and shags), using the mean and variance on the log scale to estimate the mean and variance of the untransformed productivity, which is log-normally distributed; these estimates can be verified with simulations. The two approaches matched. We, therefore, ran simulations for the parameters on the logit scale and estimate the mean and variance for the remaining untransformed survival and productivity parameters (Table A1.2).

Population counts are provided for all populations that were successfully modelled in this project in Tables A1.3 (kittiwakes), A1.4a and A1.4b (guillemots), A1.5a and A1.5b (razorbills) and A1.6 (shags).

Table A1.1

Input parameters into the Bayesian state space models for kittiwakes, guillemots, razorbills and shags at Forth Island, St Abbs, Buchan Ness and Fowlsheugh SPAs. Note that adult survival is on the logit scale and productivity is on the log scale for kittiwakes and shags, and on the logit scale for guillemots and razorbills (see Table A1.2 for values on the untransformed scale).

Species	SPA	Adult survival: mean (sd)	Productivity: mean (sd)
Kittiwake	Forth Islands	1.875 (0.546)	-0.790 (0.898)
	St Abb's Head	1.875 (0.546)	-0.615 (0.679)
	Fowlsheugh	1.875 (0.546)	-0.313 (0.492)
	Buchan Ness to Collieston Coast	1.875 (0.546)	-0.678 (0.699)
Guillemot	Forth Islands	2.705 (0.634)	1.041 (0.583)
	St Abb's Head	2.705 (0.634)	1.041 (0.583)
	Fowlsheugh	2.705 (0.634)	1.041 (0.583)
	Buchan Ness to Collieston Coast	2.705 (0.634)	1.041 (0.583)
Razorbill	Forth Islands	2.494 (0.685)	0.552 (0.350)
	St Abb's Head	2.494 (0.685)	0.552 (0.350)
	Fowlsheugh	2.494 (0.685)	0.552 (0.350)
Shag	Forth Islands	2.147 (1.215)	-0.052 (0.637)
	St Abb's Head	2.147 (1.215)	0.170 (0.590)

Table A1.2

Input parameters into the Bayesian state space models for kittiwakes, guillemots, razorbills and shags at Forth Island, St Abbs, Buchan Ness and Fowlsheugh SPAs. Note that adult survival and productivity are on the untransformed scale.

Species	SPA	Adult survival: mean (sd)	Productivity: mean (sd)
Kittiwake	Forth Islands	0.855 (0.067)	0.679 (0.755)
	St Abb's Head	0.855 (0.067)	0.681 (0.521)
	Fowlsheugh	0.855 (0.067)	0.825 (0.432)
	Buchan Ness to Collieston Coast	0.855 (0.067)	0.648 (0.515)
Guillemot	Forth Islands	0.927 (0.045)	0.725 (0.111)
	St Abb's Head	0.927 (0.045)	0.725 (0.111)
	Fowlsheugh	0.927 (0.045)	0.725 (0.111)
	Buchan Ness to Collieston Coast	0.927 (0.045)	0.725 (0.111)
Razorbill	Forth Islands	0.910 (0.058)	0.631 (0.080)
	St Abb's Head	0.910 (0.058)	0.631 (0.080)
	Fowlsheugh	0.910 (0.058)	0.631 (0.080)
Shag	Forth Islands	0.847 (0.145)	1.163 (0.823)
	St Abb's Head	0.847 (0.145)	1.410 (0.909)

Table A1.3

Kittiwake breeding population sizes used in population models for each SPA. Values represent number of breeding pairs.

SPA	Forth Islands	Forth Islands	Forth Islands	Forth Islands	Forth Islands	St Abbs to Fast Castle SPA	Fowlsheugh SPA	Buchan Ness to Collieston Coast SPA
Site	**Bass Rock**	**Craigleith**	**Fidra**	**Isle of May**	**The Lamb**	**St Abb's Head NNR**	**Fowlsheugh**	**Boddam to Collieston**
1981				6115				
1982								
1983								
1984				6012				
1985				5510				
1986		725	532	4801	167	13940	22051	19498
1987	2400		726	6765	214	15182		
1988		770	610	7638	175	16200		
1989		840	705	7564	250	19066		
1990		850	598	8129	187	17642		
1991			494	6535	106	16183	23522	
1992			489	6916	223	16524	34872	
1993		1028	452	7009	84	15268		
1994		564	330	3751	160	13007		
1995		951	435	7603	210	13670		24957
1996	2142	509	314	6269	143	13437		
1997	3044	714	298	6518	119	13393		
1998			243	4306		8044		
1999	1307	511	225	4196	115	9576	18800	
2000	1000	539	343	4618	132	11077		
2001	670	440	243	3639	117	8028		14091
2002	774	383	315	3666	139	8890		
2003	910	450	273	3335	124	6642		
2004	660	501	217	3876	126	6239		13330
2005	563	492	257	3790	94	7239		
2006	505	444	275	3167	202	6288	11140	
2007	377	508	244	3424	96	6463		12542
2008	323	513	222	3354	110	5298		
2009	425	594	237	2316	82	4616	9454	
2010	440	600	232	3422	133	4744		
2011	313	542	204	2685	140	4688		
2012	395	620	191	2465	95	4314	9388	
2013	270	293	128	1712	47	3403		
2014	324	300	167	2464	84	3625		
2015	441	537	275	3433	99	4209	9655	
2016	325	468	259	2912	101	2779		

Table A1.4a

Guillemot breeding population sizes used in population models for Forth Islands SPA. Values represent number of breeding pairs. Counts of individuals were converted to pairs using k-values from the Isle of May (Harris *et al.* 2015a, updated). Count type WCC = whole colony count.

SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA
Site	**Bass Rock**	**Craigleith**	**Fidra**	**Isle of May**	**The Lamb**
Count type	**WCC**	**WCC**	**WCC**	**WCC**	**WCC**
1981				11250	
1982					
1983				14750	
1984				13000	
1985				13000	
1986		1404	126	13700	1967
1987	1797		53	11680	572
1988		969	88	11223	1604
1989		1181	101	12736	2502
1990		1167	67	12632	1807
1991			134	11440	1631
1992			161	11511	2136
1993		981	143	12418	2287
1994		1400	219	13843	2309
1995		1263	172	15326	1887
1996	1911	1112	153	14500	2163
1997	2682	507	173	17340	2829
1998			207	17384	2063
1999	1890	1333	293	16933	2935
2000	2373	1913	427	17979	1677
2001	2395	2087	448	18442	1431
2002	2452	1291	506	20185	820
2003	2057	1546	434	19519	1449
2004	1966	1549	492	20332	1517
2005	1547	1208	583	18858	1313
2006	2346	1215	333	15578	1268
2007	1030	1058	541	15536	1283
2008	1402	1347	353	15036	2541
2009	2136	1512	439	14143	1842
2010	1329	919	429	15029	1806
2011	1906	1625	316	14955	1944
2012	1328	1371		14100	
2013	1546	1347	372	13349	2224
2014	1759	2498	550	14248	2403
2015	2385	2254	467	15945	2289
2016	1562	1798	325	16132	2150

Table A1.4b

Guillemot breeding population sizes used in population models for St Abbs Head to Fast Castle SPA, Fowsheugh SPA and Buchan Ness to Collieston Coast SPA. Values represent number of breeding pairs. Counts of individuals were converted to pairs using k-values from the Isle of May (Harris *et al.* 2015a, updated). Count type WCC = whole colony count; PC = mean of plot means.

SPA	**St Abbs to Fast Castle SPA**	**St Abbs to Fast Castle SPA**	**Fowlsheugh SPA**	**Fowlsheugh SPA**	**Buchan Ness to Collieston Coast SPA**	**Buchan Ness to Collieston Coast SPA**
Site	**St Abb's Head NNR**	**St Abb's Head NNR**	**Fowlsheugh**	**Fowlsheugh**	**Boddam to Collieston**	**Boddam to Collieston**
Count type	**WCC**	**PC**	**WCC**	**PC**	**WCC**	**PC**
1981						
1982						
1983						
1984		142		198		
1985		119		209		
1986	16443	157	37453	173	9225	
1987	17775	156		208		
1988	18667	143		194		
1989	21394	165		232		
1990	21790	172		206		
1991		174				
1992		167	39381	240		126
1993	20036	180		217		
1994		190		216		
1995		199		237	16602	137
1996		177		244		
1997		240		244		
1998	26254	219		234		148
1999		232	48651	295		
2000		272		234		
2001		248		253	19286	185
2002		318				
2003	29502	264		296		
2004		255		300		202
2005		283		243		
2006		238	39370	216		
2007		270		225	17876	153
2008	29079	252		305		
2009		304	42339	244		
2010		229		240		163
2011		299		285		
2012		232	37277	233		
2013	29828	253		221		158
2014		265		199		
2015		223	40979	236		
2016		236		201		194

Table A1.5a

Razorbill breeding population sizes used in population models for Forth Islands SPA. Values represent number of breeding pairs. Counts of individuals were converted to pairs using k-values from the Isle of May (Harris *et al.* 2015b, updated). Count type WCC = whole colony count. Unrealistic k-values were recorded in 2005 so population counts were excluded.

SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA
Site	**Bass Rock**	**Craigleith**	**Fidra**	**Isle of May**	**The Lamb**
count type	**WCC**	**WCC**	**WCC**	**WCC**	**WCC**
1988		79	120	1903	26
1989		74	91	2075	33
1990		38	48	1508	21
1991		70	79	1425	28
1992		34	53	1909	30
1993		41	44	2052	9
1994		56	62	2227	26
1995		79	59	3108	34
1996	165	64	65	2989	64
1997	138	66	81	2719	19
1998			86	3126	
1999	71	114	147	3429	92
2000	65	157	86	3105	68
2001	111	111	72	3346	78
2002	180	131	111	2844	90
2003	64	117	63	2233	81
2004	128	138	82	2677	85
2005					
2006	169	175	123	2975	62
2007	119	181	128	2735	77
2008	85	147	95	2591	80
2009	70	117	127	2400	70
2010	63	136	123	2557	42
2011	94	185	108	2705	70
2012	106	157	70	3068	66
2013	105	129	109	2879	59
2014	124	110	170	2987	65
2015	144	193	139	3202	46
2016	91	186	122	3570	82

Table A1.5b

Razorbill breeding population sizes used in population models for St Abbs Head to Fast Castle SPA and Fowsheugh SPA. Values represent number of breeding pairs. Counts of individuals were converted to pairs using k-values from the Isle of May (Harris *et al.* 2015b, updated). Count type WCC = whole colony count; PC = mean of plot means.

SPA	**St Abbs to Fast Castle SPA**	**St Abbs to Fast Castle SPA**	**Fowlsheugh SPA**	**Fowlsheugh SPA**
Site	**St Abb's Head**	**St Abb's Head NNR**	**Fowlsheugh**	**Fowlsheugh**
count type	**WCC**	**PC**	**WCC**	**PC**
1988	1343	21		
1989	1398	23		
1990	1072	18		
1991		29		
1992		24	6827	
1993	1187	21		
1994		25		
1995		29		
1996		23		
1997		33		
1998	1793	29		
1999		28	5808	
2000		30		
2001		26		
2002		32		
2003	1595	20		
2004		15		9
2005		29		
2006		20	3341	20
2007		21		19
2008	1262	18		
2009		23	3696	18
2010		18		14
2011		24		
2012		23	4883	21
2013	1269	22		14
2014		20		18
2015		16	5180	22
2016		18		20

Table A1.6

Shag breeding population sizes used in population models for each SPA. Values represent number of breeding pairs.

SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA	Forth Islands SPA	St Abbs to Fast Castle SPA	Buchan Ness to Collieston Coast SPA
Site	**Bass Rock**	**Craig-leith**	**Fidra**	**Inch-mickery**	**Isle of May**	**The Lamb**	**St Abb's Head NNR**	**Boddam to Collieston**
1973		164	17		1076	244		
1974		225	27		933	255		
1975	180	214	25		644	233		
1976	213	201	20	8	497	210	187	
1977	201	186	18	12	921	156	193	
1978	202	208	23	14	769	143	134	
1979	188	215	25	14	966	160		
1980	191	198	25	11	1041	143		
1981	154	252	43	14	1163	220		
1982	194	344	59	22	1425		209	
1983	170	356	66	42	1567	283		
1984	193	379	64	22	1639	284		
1985	101	345	55	29	1524	303	268	
1986	75	388	67	24	1310	301	364	440
1987	162	465	64	24	1916		396	
1988	93	435	86	24	1290	250	318	
1989	111	544	124	29	1703	286	366	
1990	121	522	116	28	1386	290	338	
1991		646	242	33	1487	305	463	
1992		665	255	36	1634	318	450	
1993	20	155	88	28	715	65	300	
1994	13	106	73	10	403	36	115	
1995		171	84	20	503	81	173	223
1996	47	159	81	18	512	77	175	
1997	41	180	107	28	502	65	160	
1998			86	25	621		196	
1999	30	131	61	33	259	76	165	
2000	28	208	123	32	541	46	233	
2001	39	237	139	41	734	99	300	415
2002	25	233	186	52	676	102	296	
2003	24	197	254	70	968	124	365	
2004	46	324	272	78	687	111	369	594
2005	18	131	115	52	281	49	131	
2006	36	118	198	57	485	65	162	
2007	28	199	169	57	399	73	132	331
2008	22	133	146	55	427	97	131	
2009	15	200	159	54	465	75	138	
2010	16	207	204	55	492	114	157	
2011	25	281	191	62	540	66	160	
2012	11	258	172	71	648	77	171	
2013	31	117	153	59	322	44	94	363
2014	12	137	162	65	338	49	107	

Appendix 2

Ratio of Impacted to Un-Impacted 25 Year Population Growth Rate

One possibility for the low sensitivity of PVA metric A (median of the ratio of impacted to un-impacted annual growth rate) is the scale of values, with all values being close to one, and, therefore, sensitivity potentially appearing low in a visual assessment even in cases where it is not. However, here we consider a 25 year growth rate, where lines deviate markedly from 1 and sensitivity is more discernible. This analysis shows that low sensitivity is still apparent (Figure A2.1).

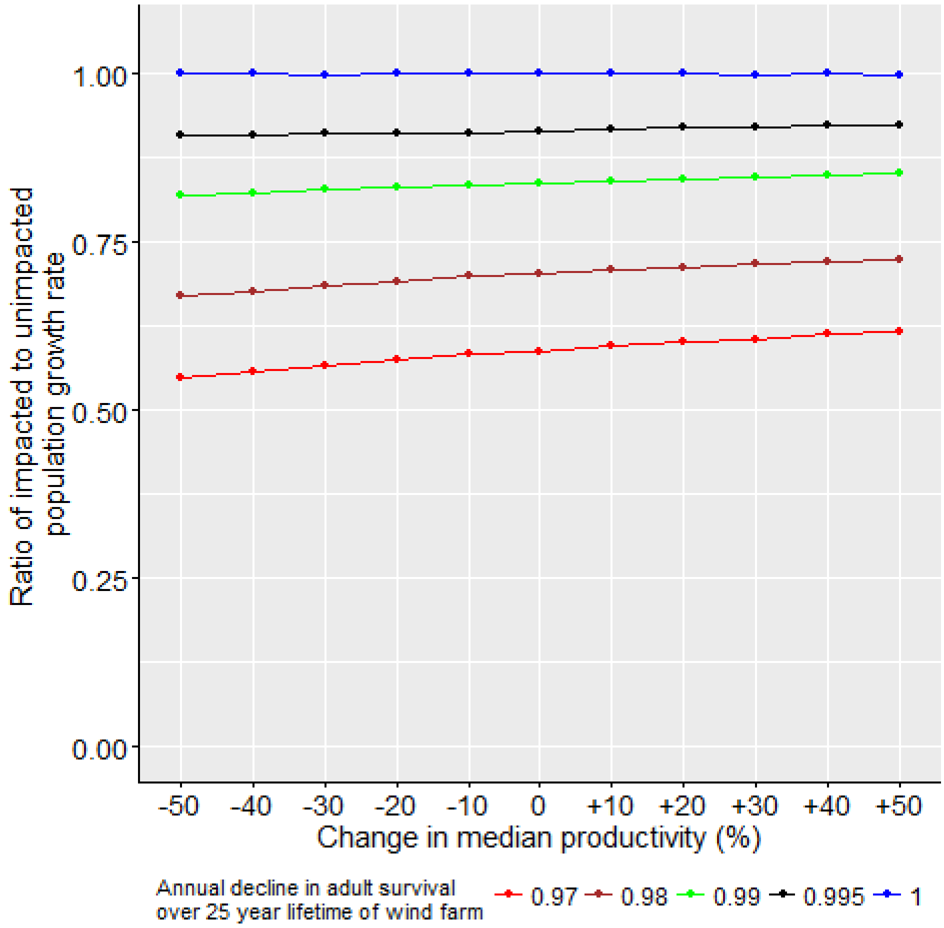


Figure A2.1: PVA Metric A – ratio of 25 year population growth rate, comparing impacted population vs. un-impacted population, showing productivity mis-specification varied from -50% to +50% (with 0% representing no mis-specification) in Forth Islands kittiwakes. The five coloured lines represent the different levels of potential impact on annual adult survival.

Appendix 3

PVA Metric Sensitivity for all Populations

This Appendix presents graphical output of PVA metric sensitivity for the 13 populations considered in this project. For each species, the sequence of figures is as presented in Figure 4 of the main report for Forth Islands kittiwakes. For completeness, we include Forth Islands kittiwakes here.

In all figures, adult mortality mis-specification is illustrated in the upper panels and productivity mis-specification in the lower panels. Mis-specification was varied from -30% to +30% (with 0% representing no mis-specification). The five coloured lines represent the different levels of potential impact on annual productivity (left panels) or annual adult survival (right panels) over the hypothetical 25 year lifetime of the wind farm (2017-2041).

1. **Kittiwakes at Forth Islands SPA**:

Figure A2.1a: PVA Metric A for Forth Kittiwakes – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

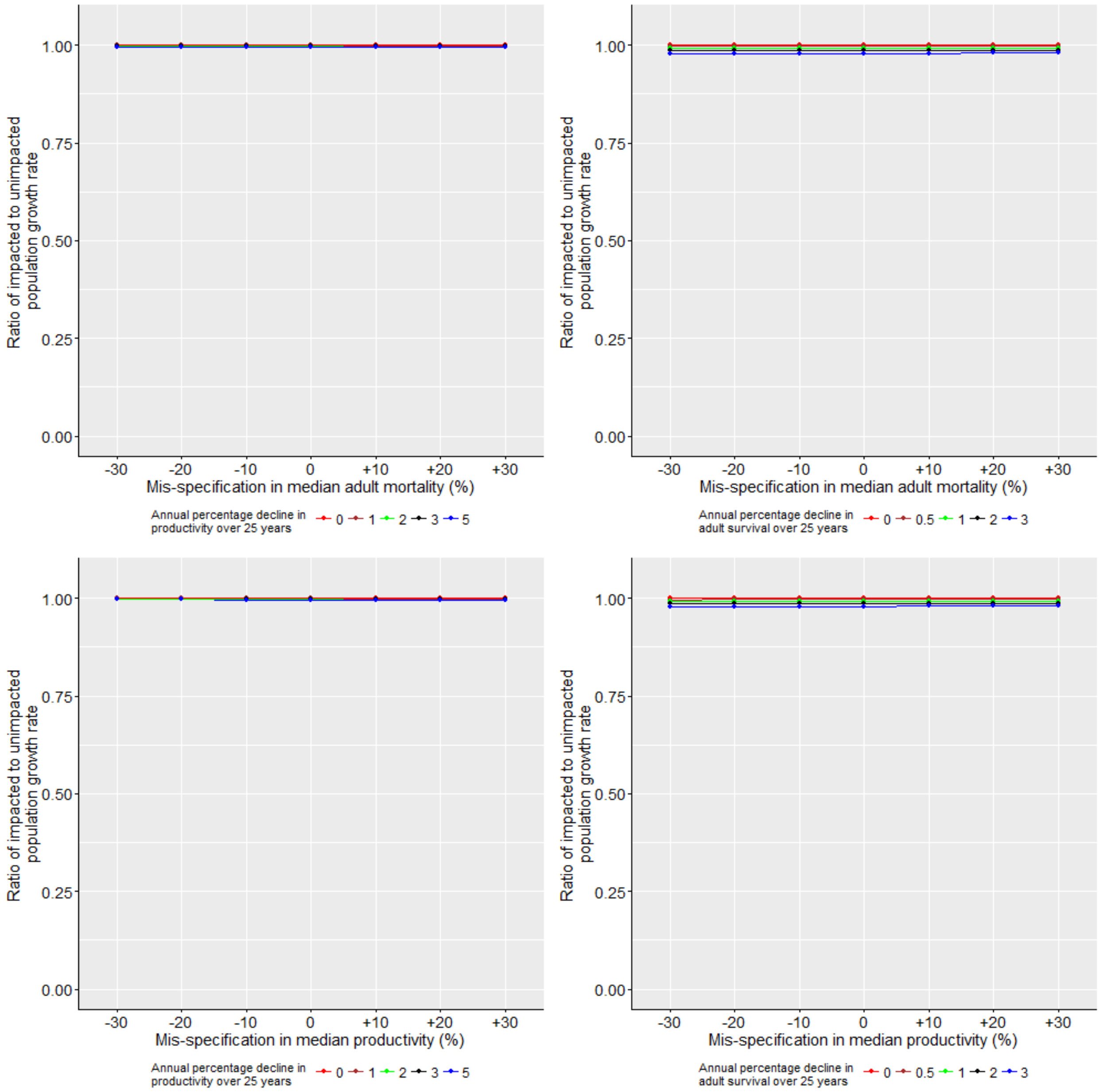


Figure A2.1b: PVA Metric B for Forth Kittiwakes – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

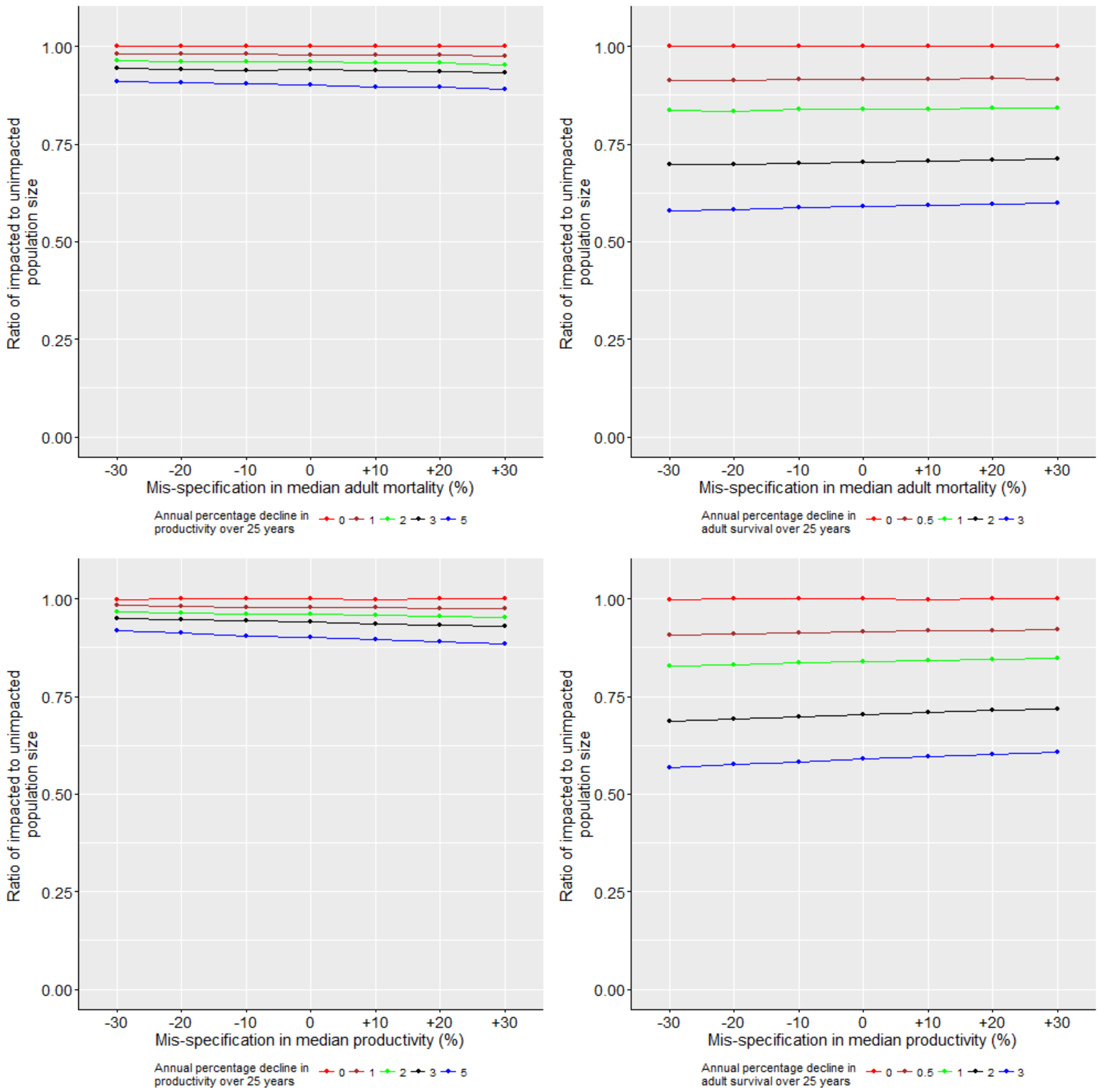


Figure A2.1c: PVA Metric C for Forth Kittiwakes – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

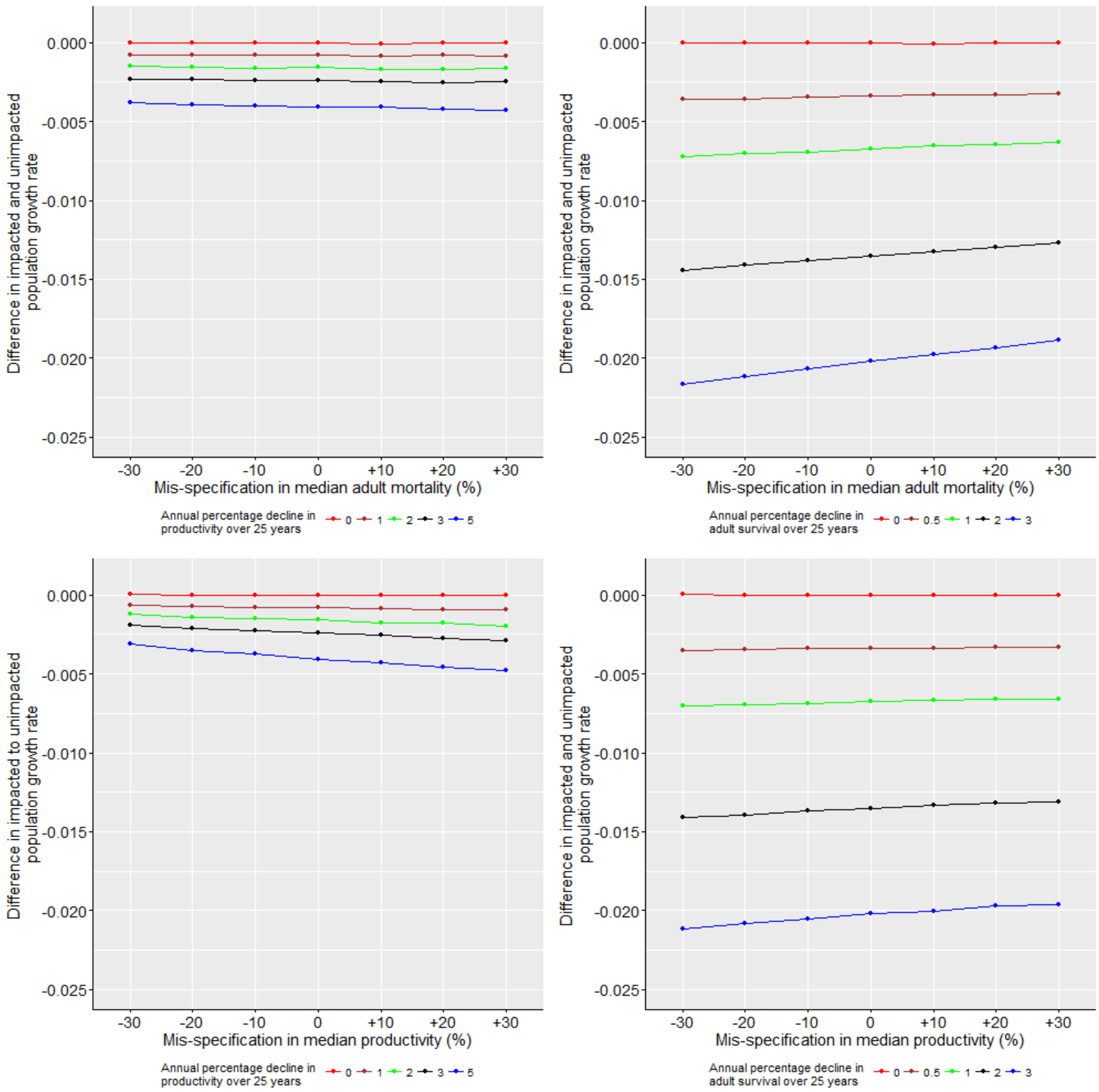


Figure A2.1d: PVA Metric D for Forth Kittiwakes – difference in population size at 2041, comparing impacted population vs. un-impacted population.

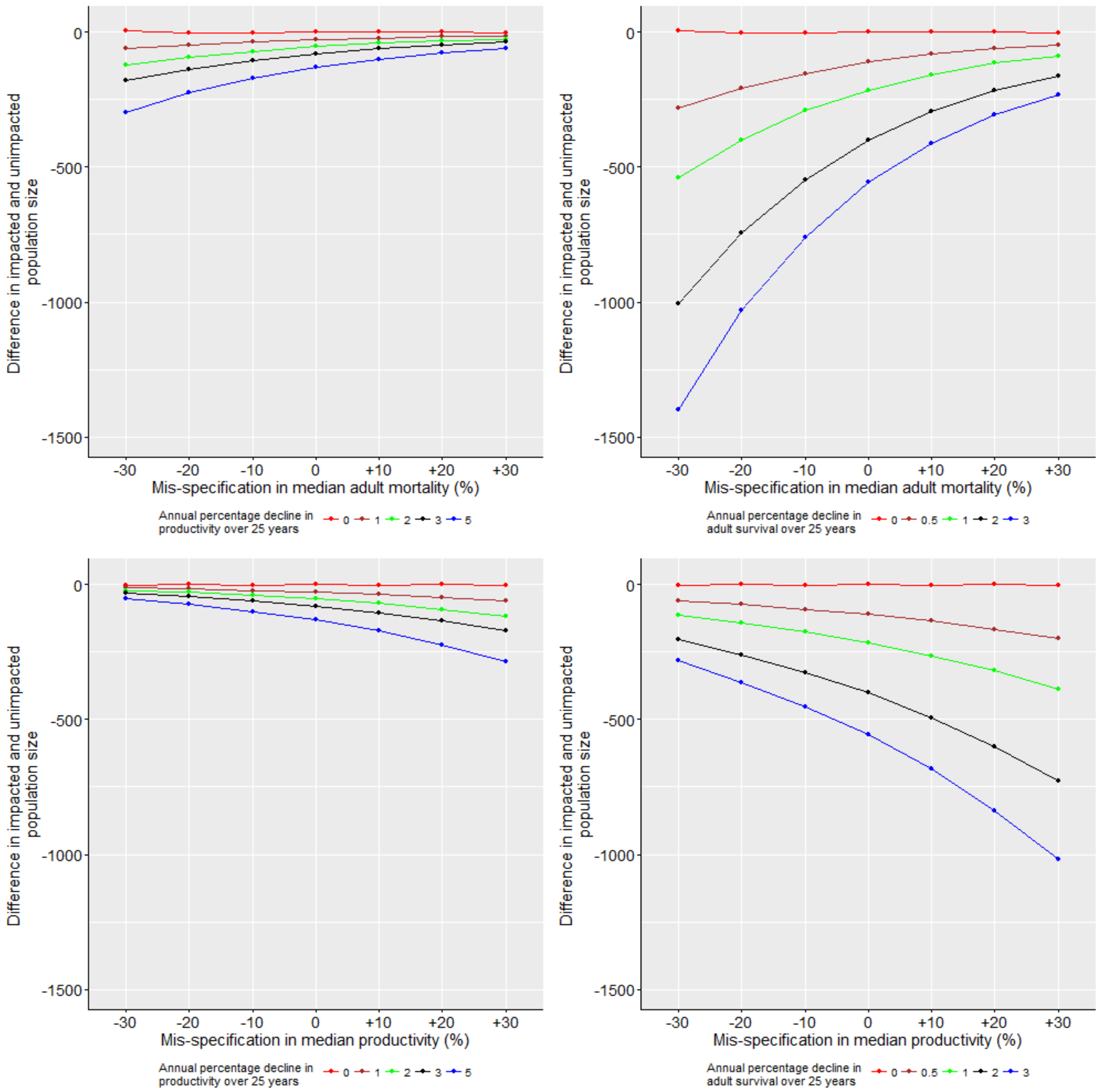


Figure A2.1e: PVA Metric E1 for Forth Kittiwakes – probability of population decline greater than 10% from 2016-2041.

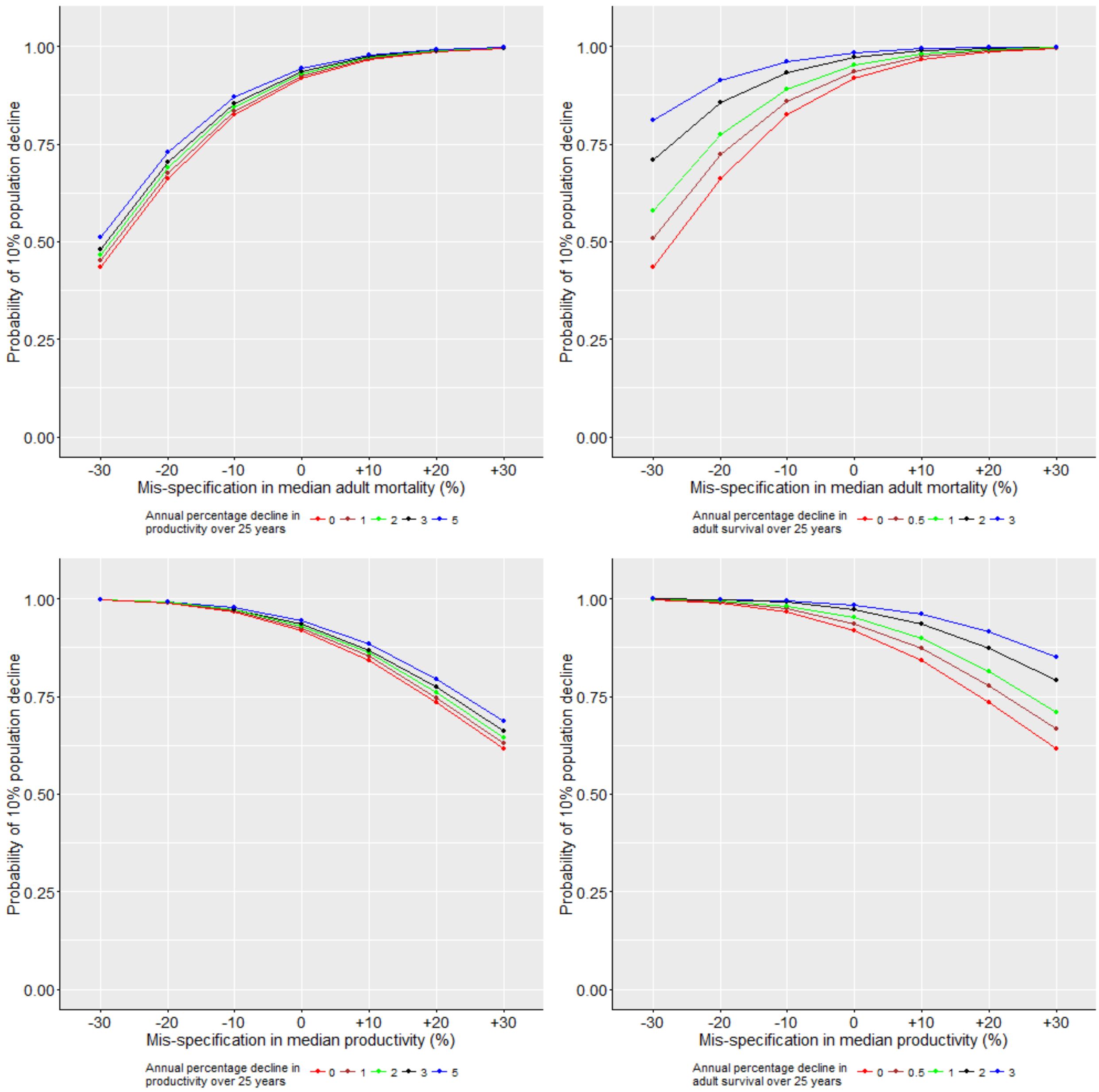


Figure A2.1f: PVA Metric E2 for Forth Kittiwakes – probability of population decline greater than 25% from 2016-2041.

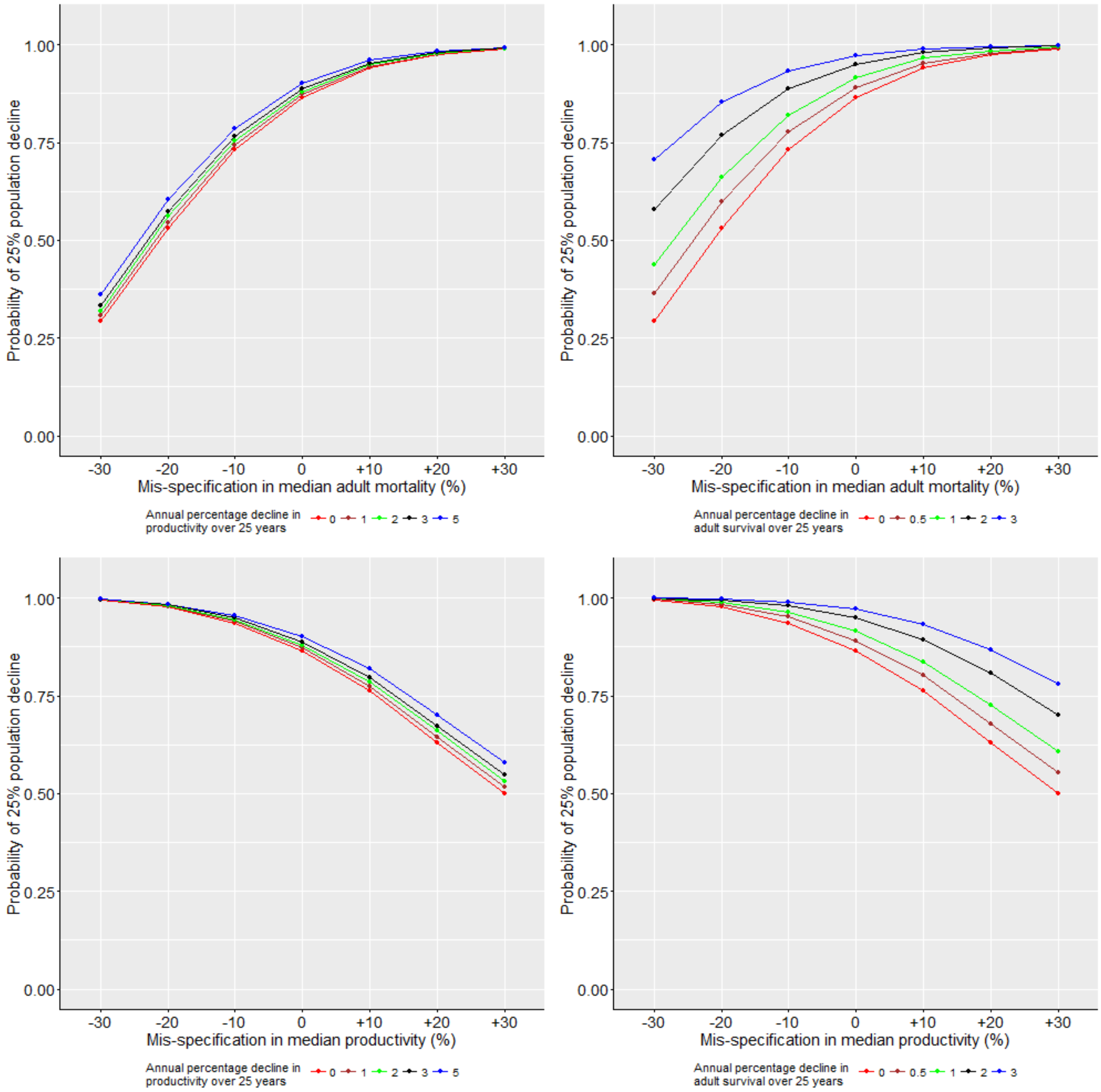


Figure A2.1g: PVA Metric E3 for Forth Kittiwakes – probability of population decline greater than 50% from 2016-2041.

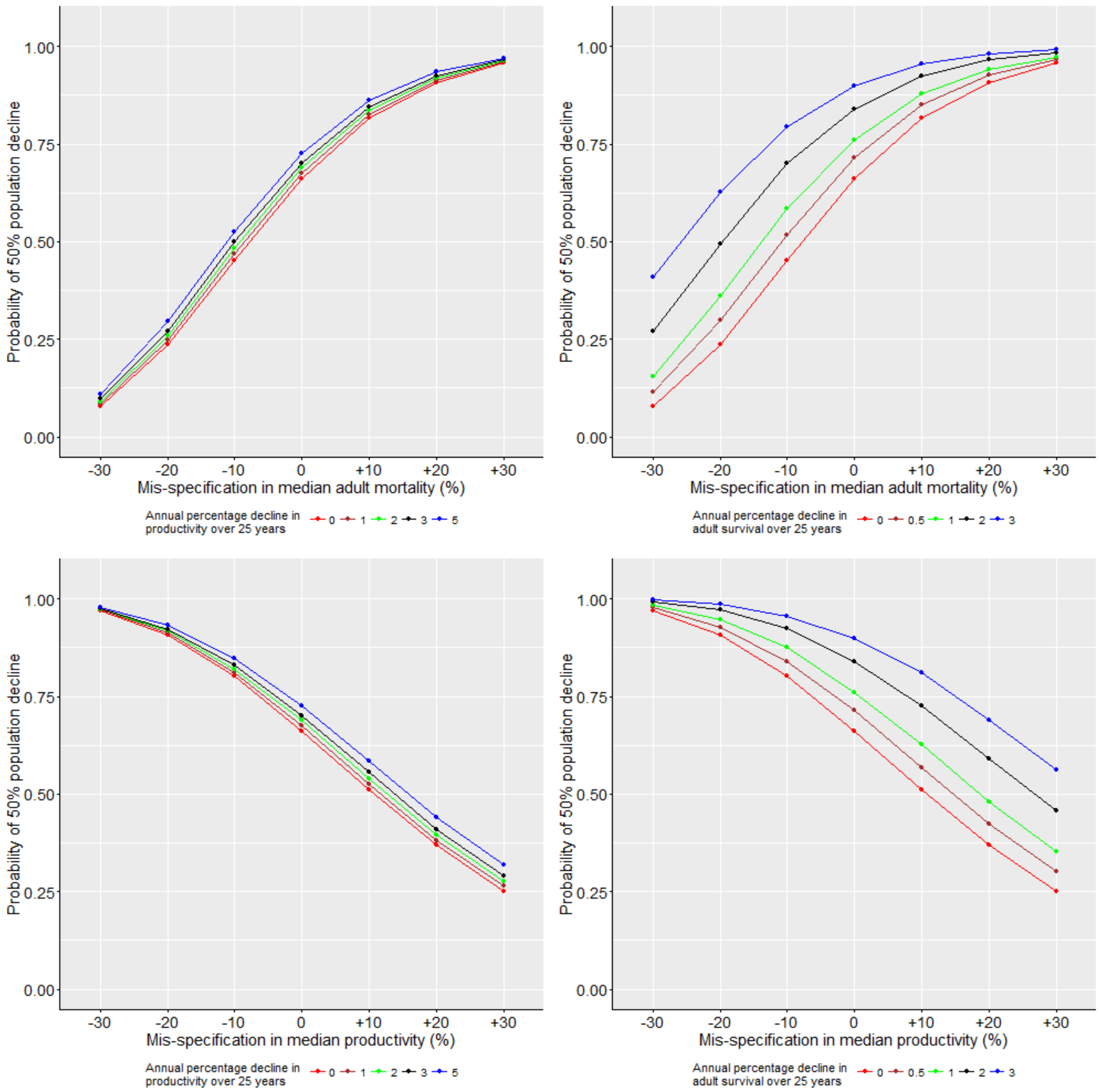
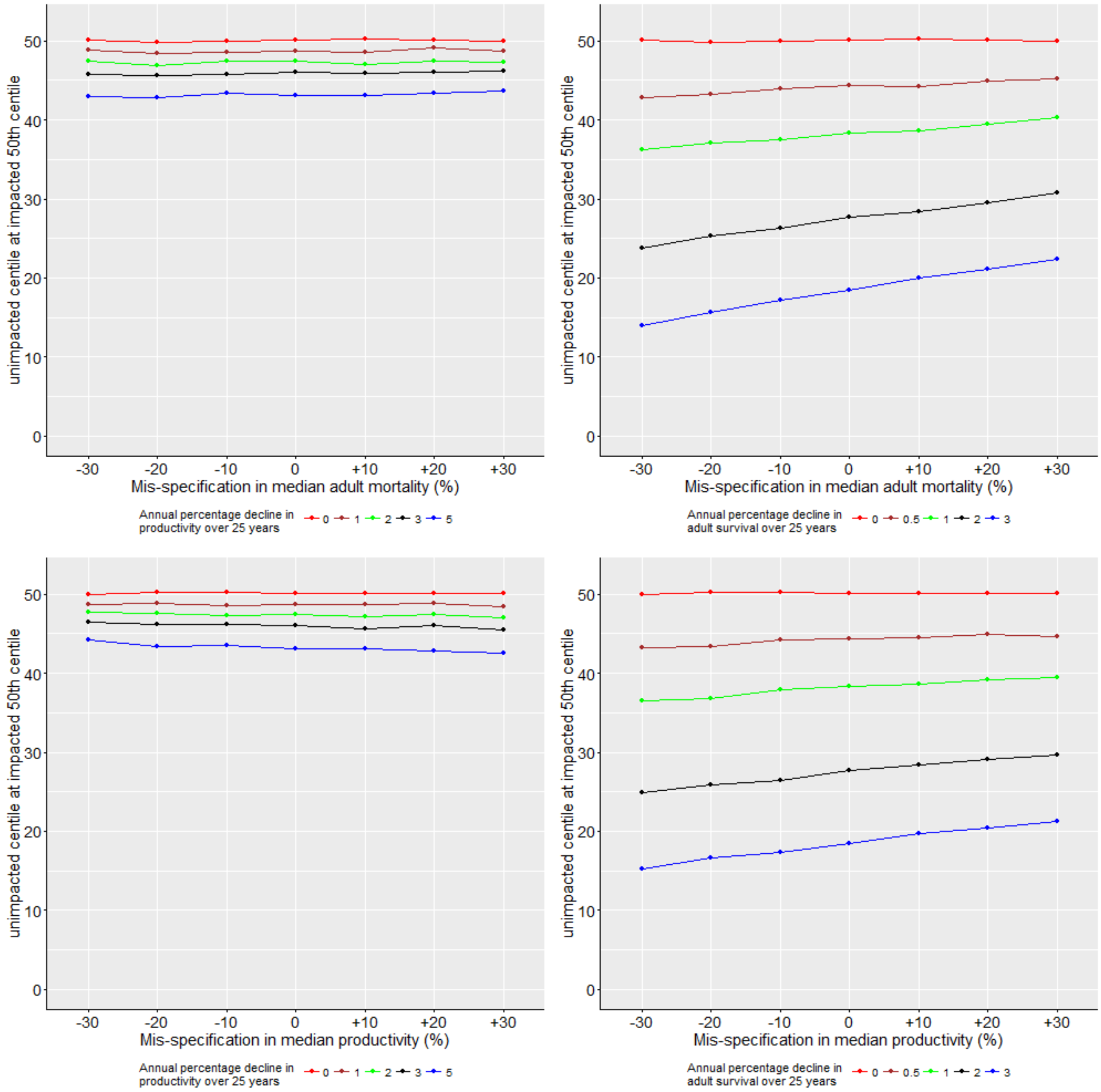


Figure A2.1h: PVA Metric F for Forth Kittiwakes – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



2. **Kittiwakes at St Abb's Head SPA**:

Figure A2.2a. PVA Metric A for St Abb's Kittiwakes – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

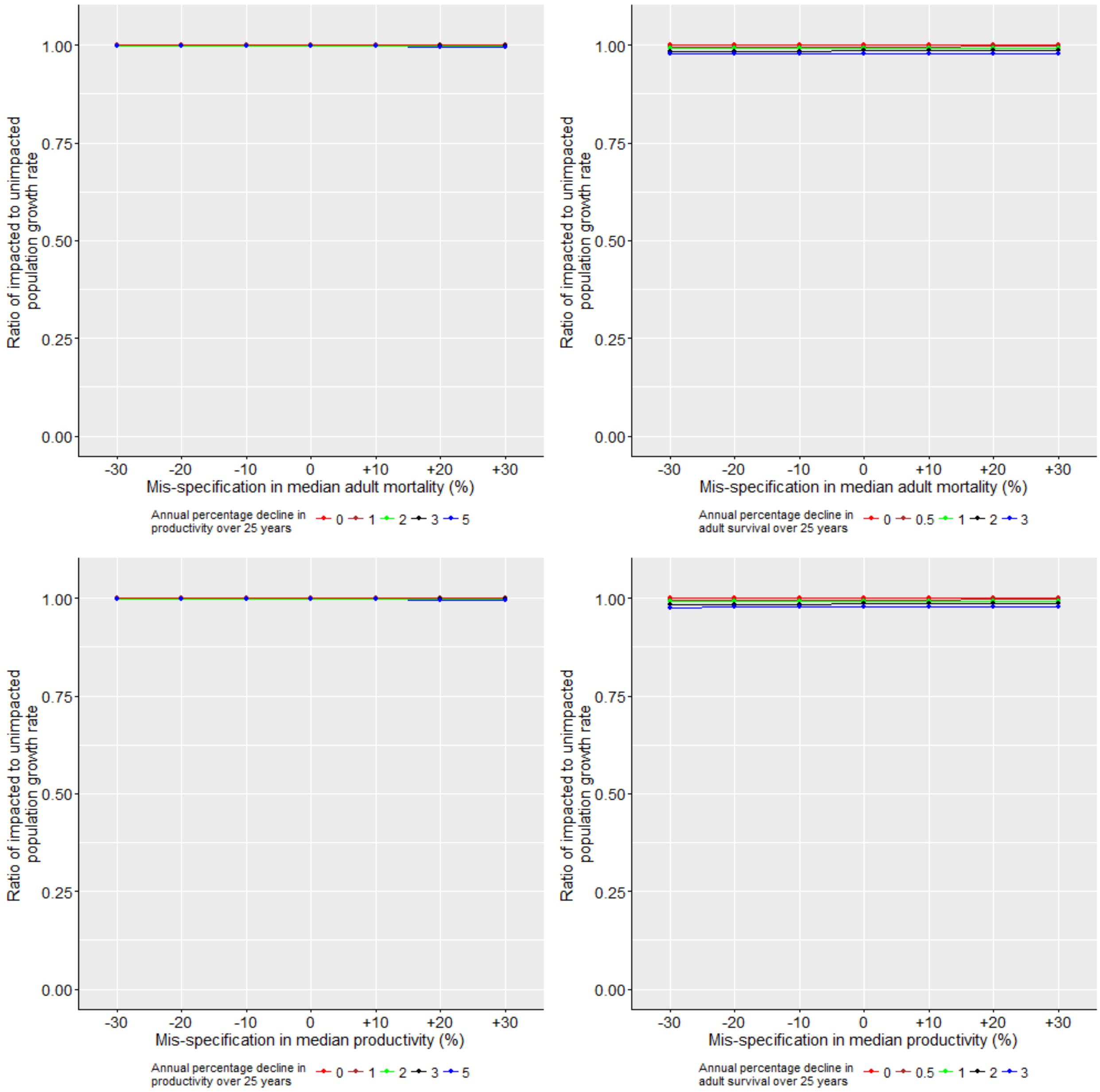


Figure A2.2b. PVA Metric B for St Abb's Kittiwakes – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

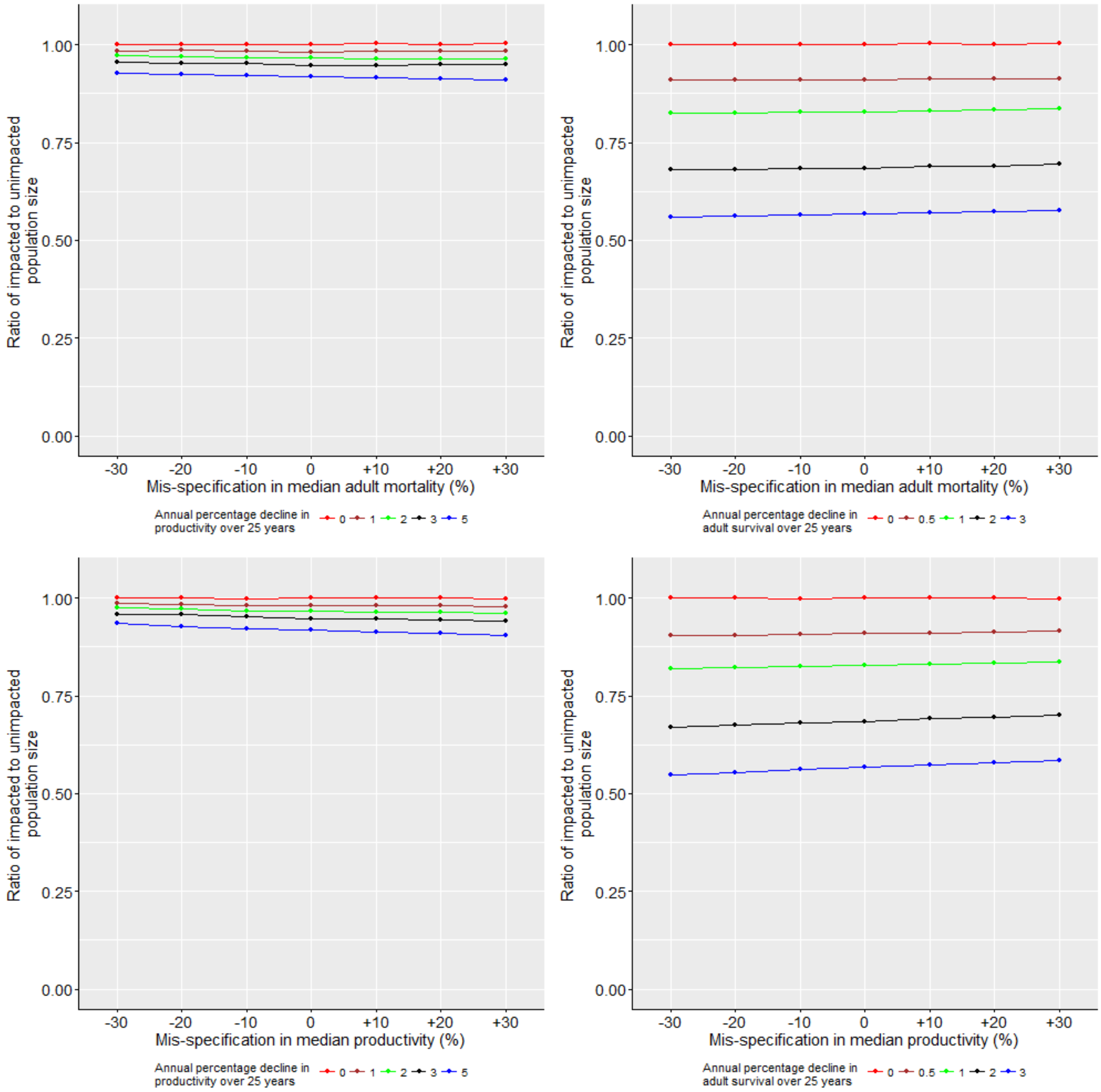


Figure A2.2c. PVA Metric C for St Abb's Kittiwakes – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

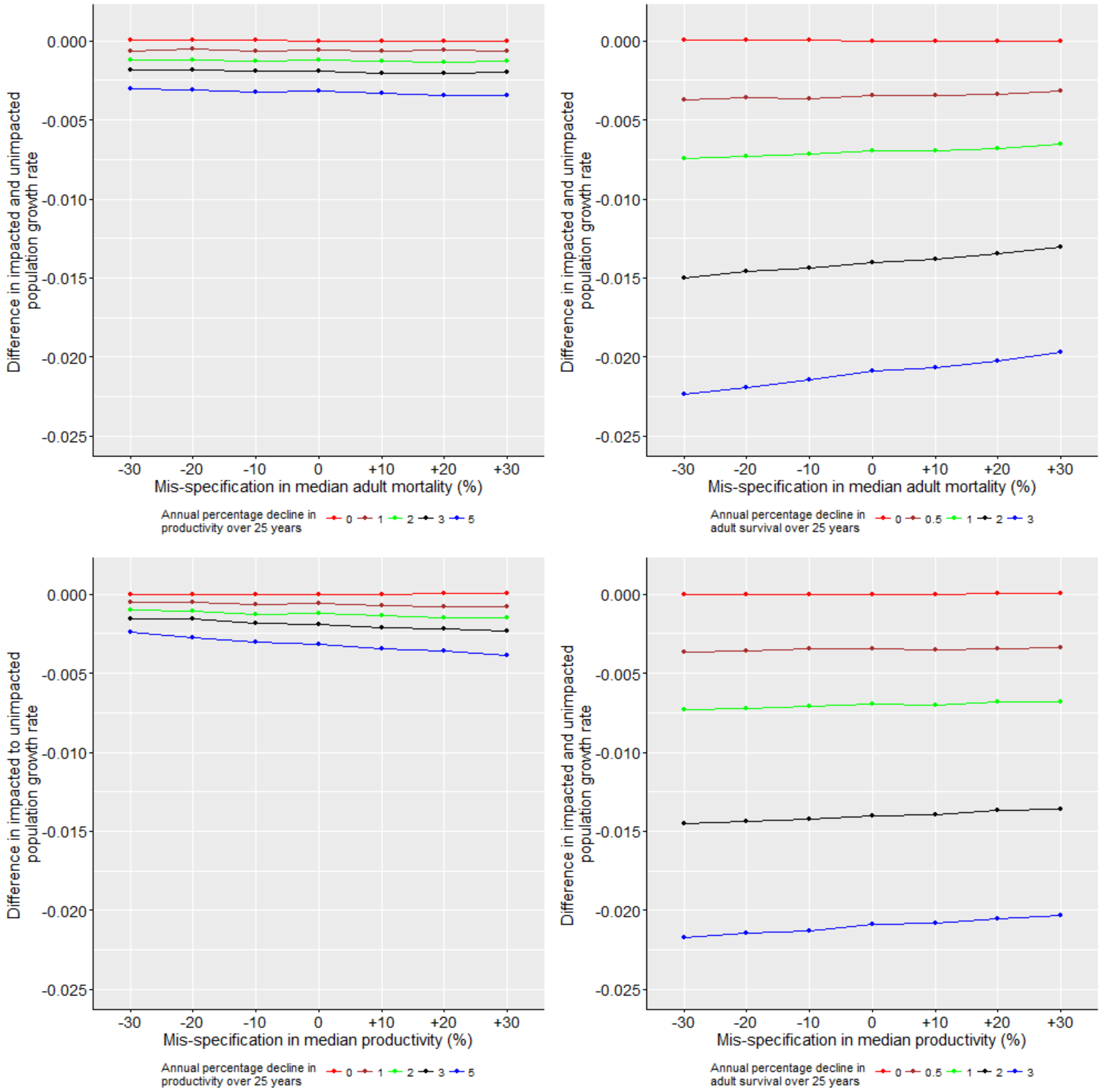


Figure A2.2d. PVA Metric D for St Abb's Kittiwakes – difference in population size at 2041, comparing impacted population vs. un-impacted population.

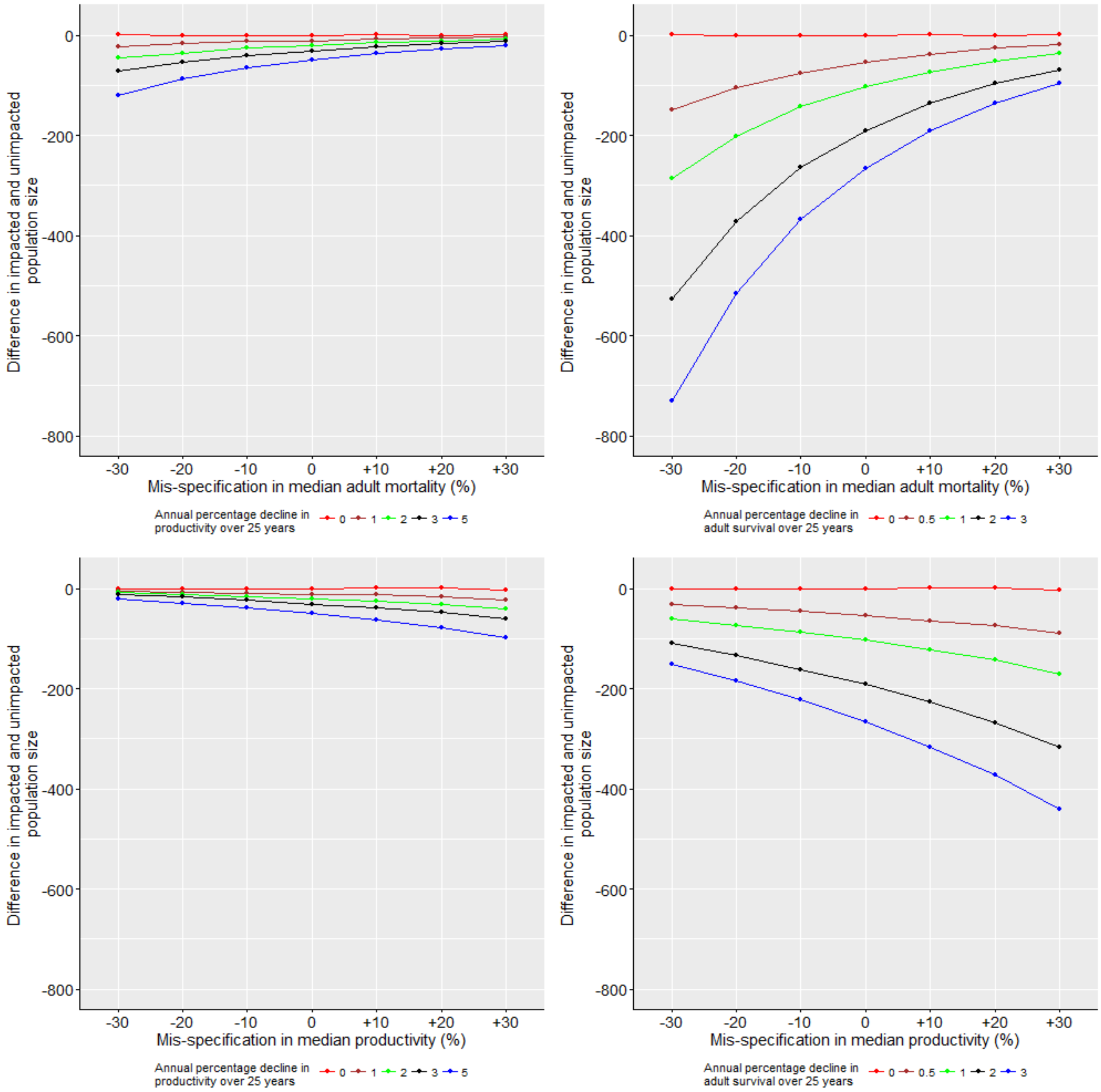


Figure A2.2e. PVA Metric E1 for St Abb's Kittiwakes – probability of population decline greater than 10% from 2016-2041.

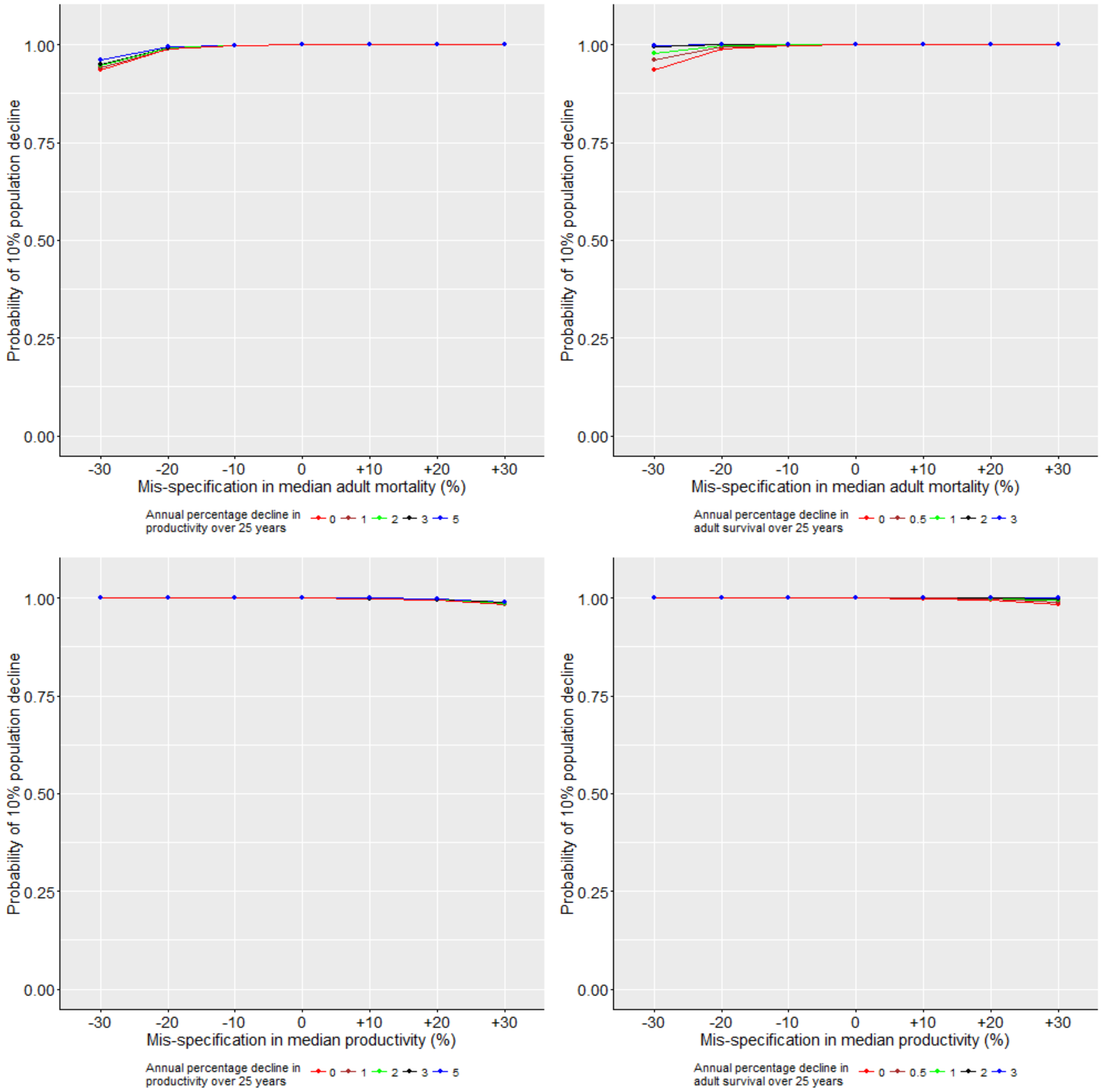


Figure A2.2f. PVA Metric E2 for St Abb's Kittiwakes – probability of population decline greater than 25% from 2016-2041.

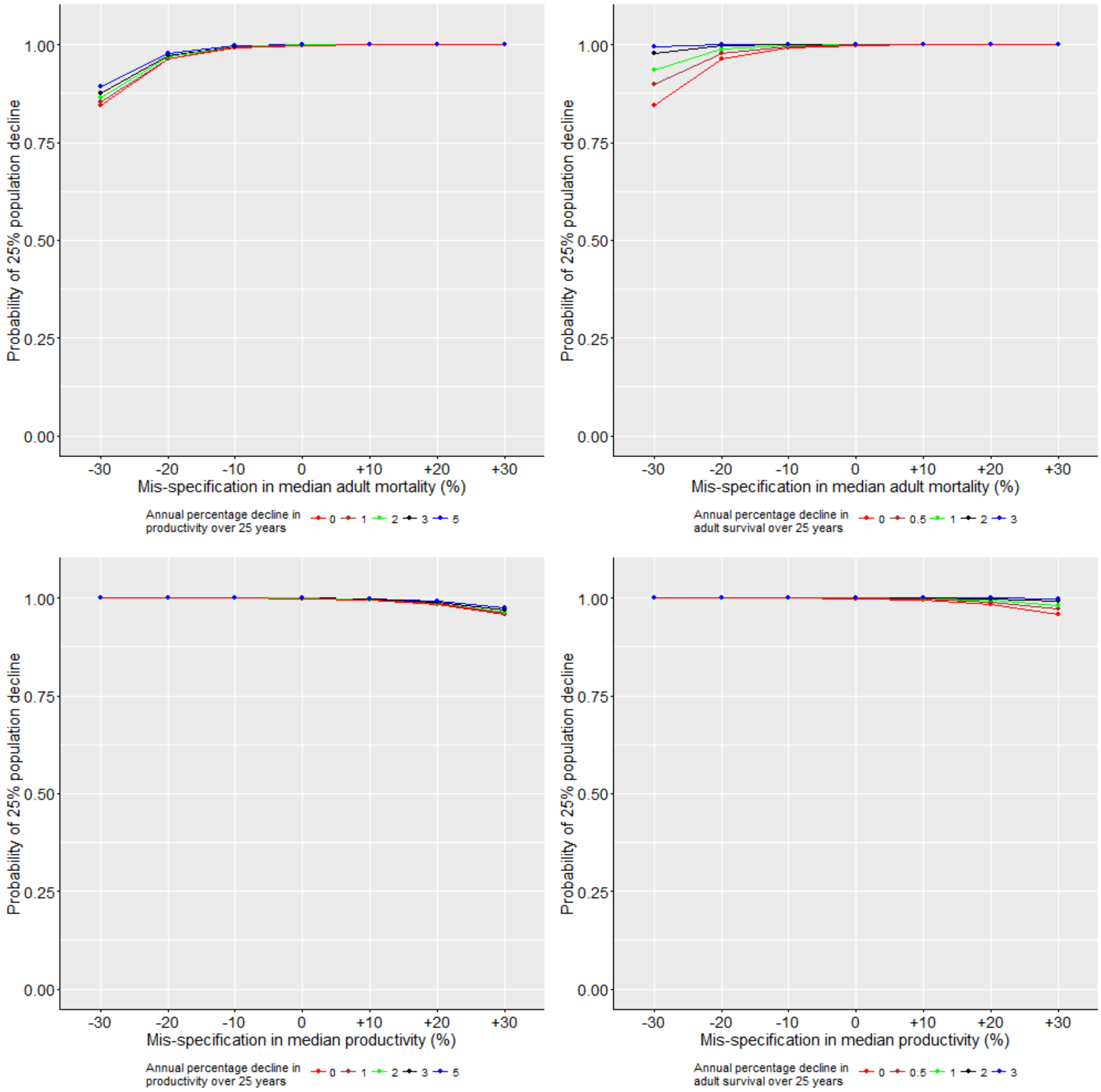


Figure A2.2g. PVA Metric E3 for St Abb's Kittiwakes – probability of population decline greater than 50% from 2016-2041.

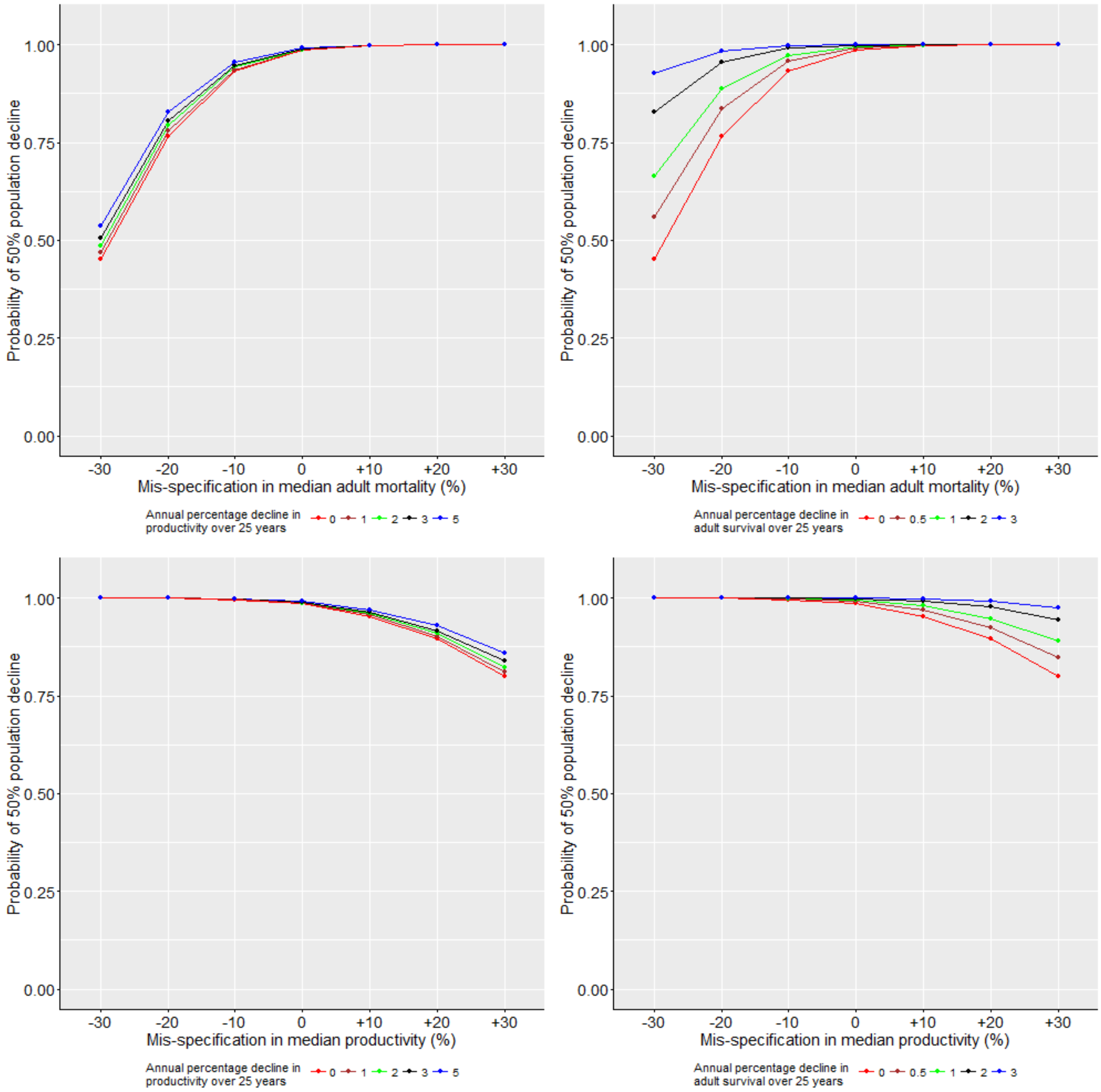
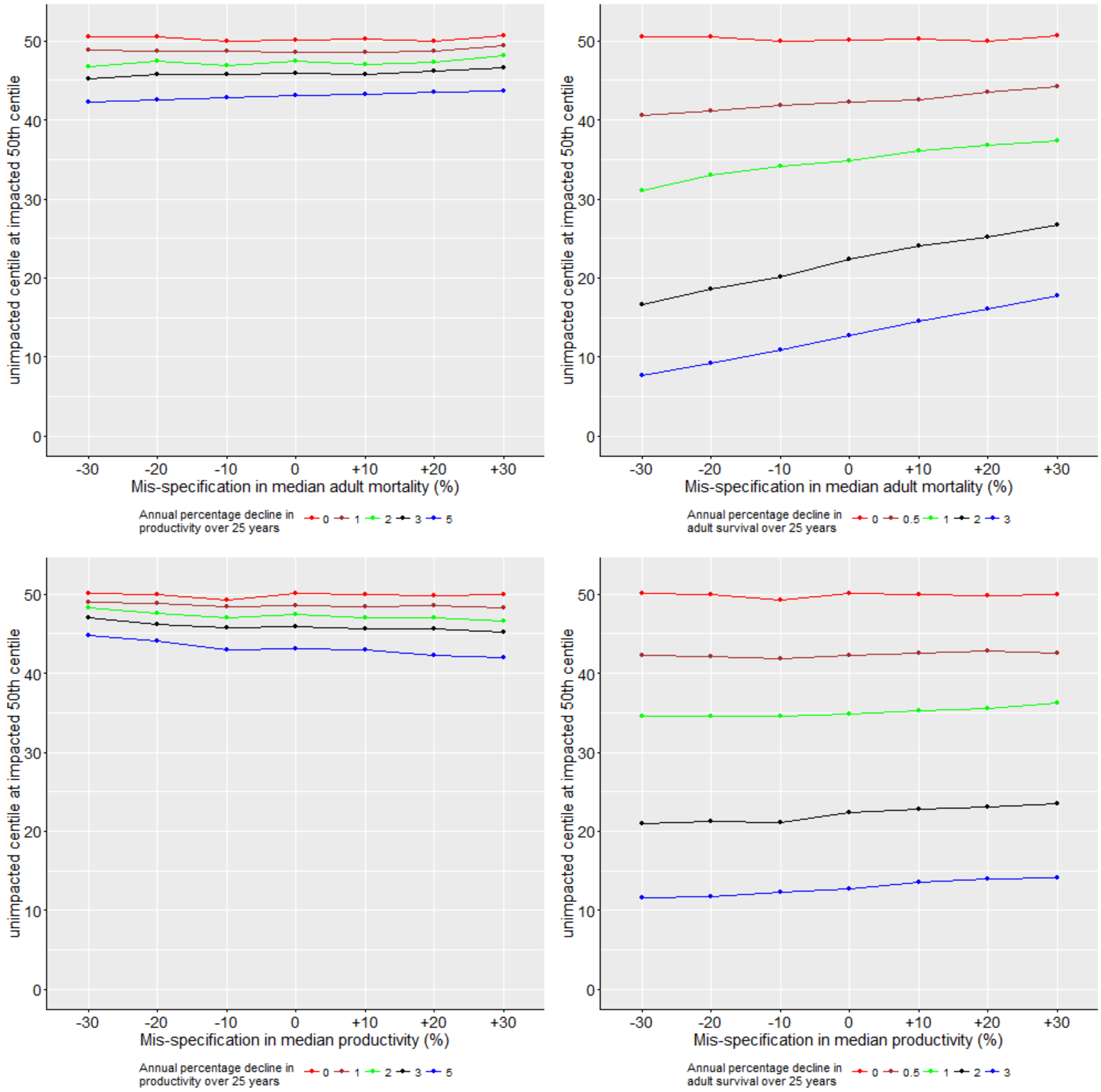


Figure A2.2h. PVA Metric F for St Abb's Kittiwakes – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



3. **Kittiwakes at Fowlsheugh SPA**:

Figure A2.3a. PVA Metric A for Fowlsheugh Kittiwakes – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

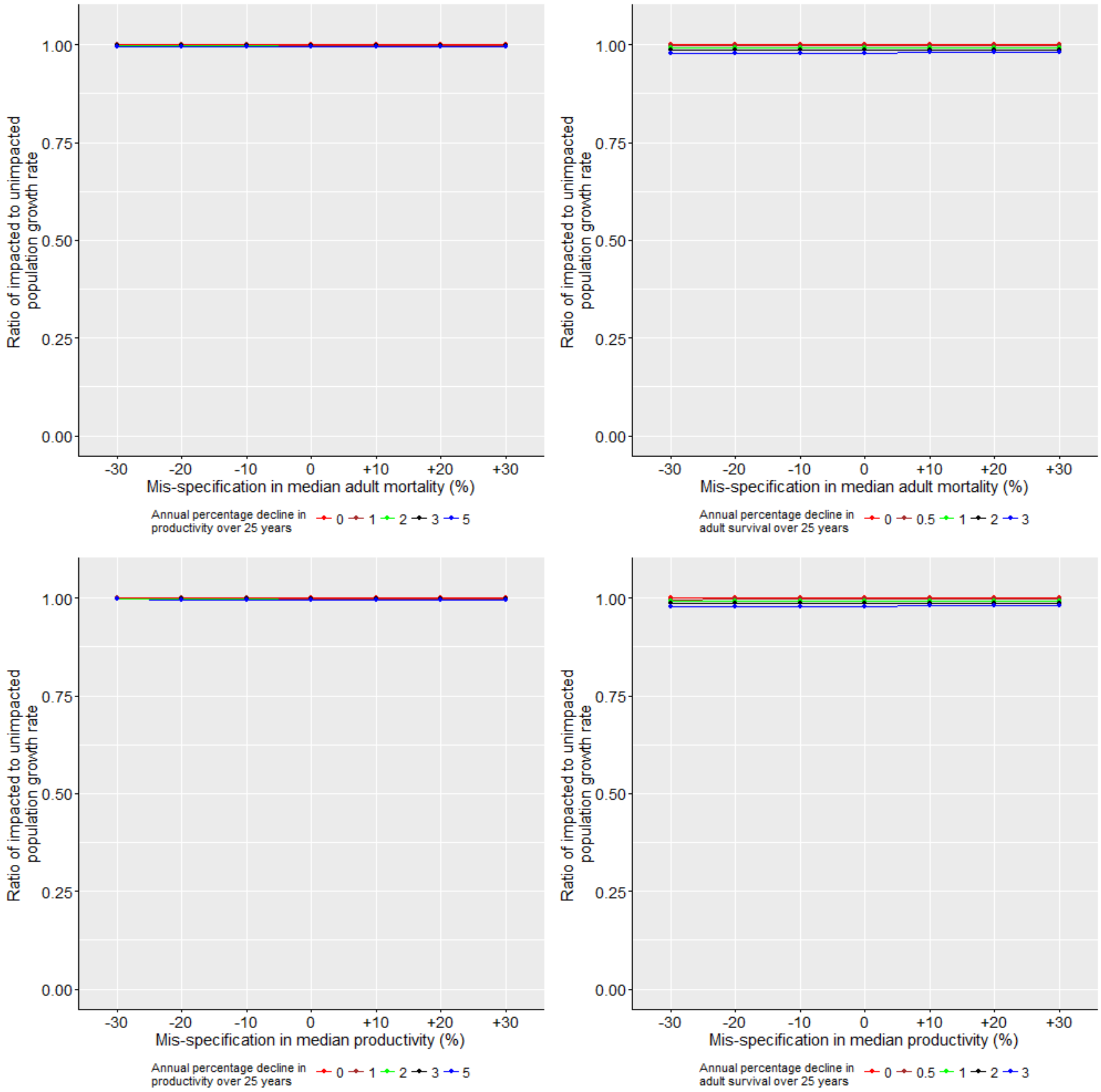


Figure A2.3b. PVA Metric B for Fowlsheugh Kittiwakes – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

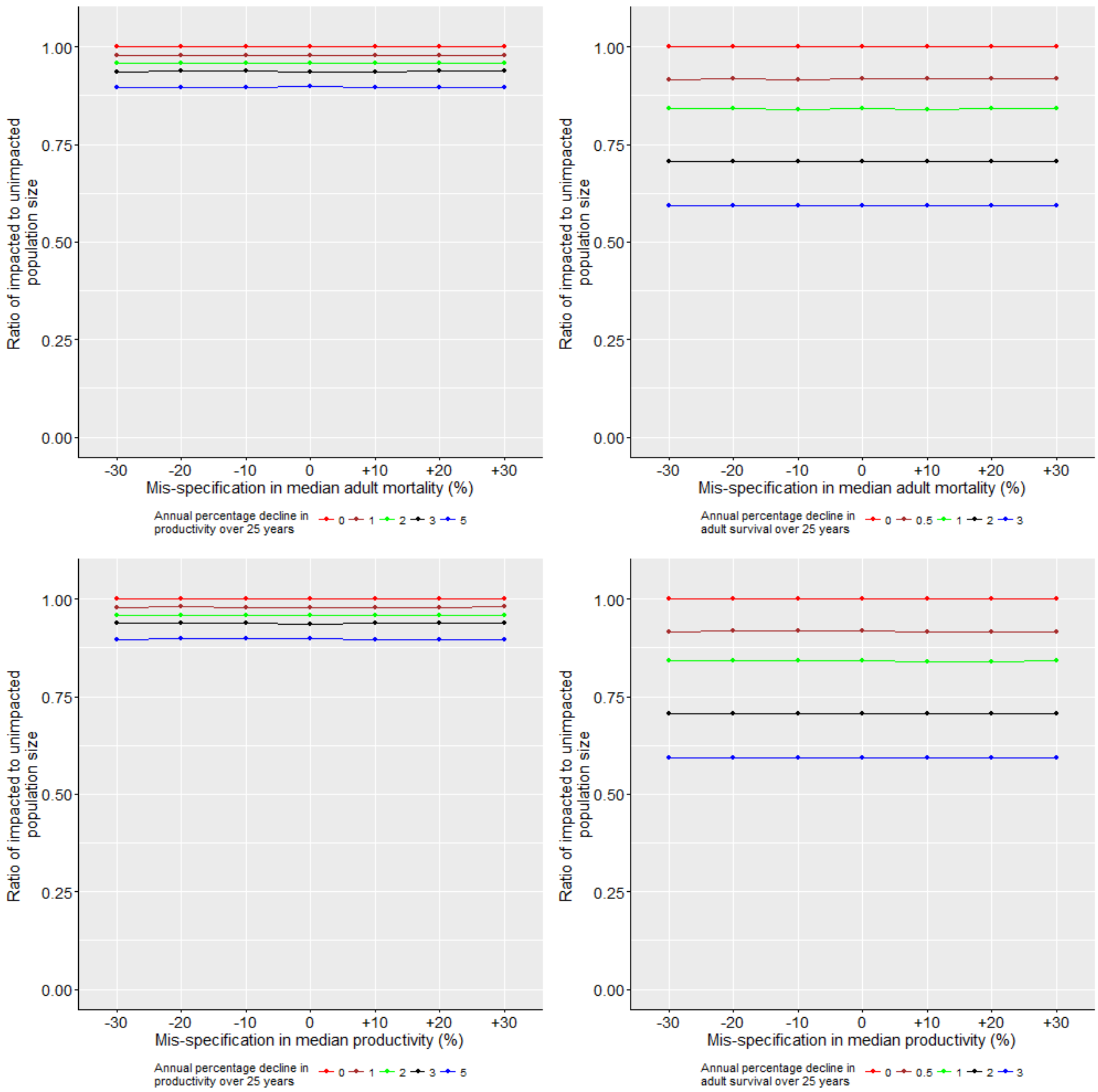


Figure A2.3c. PVA Metric C for Fowlsheugh Kittiwakes – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

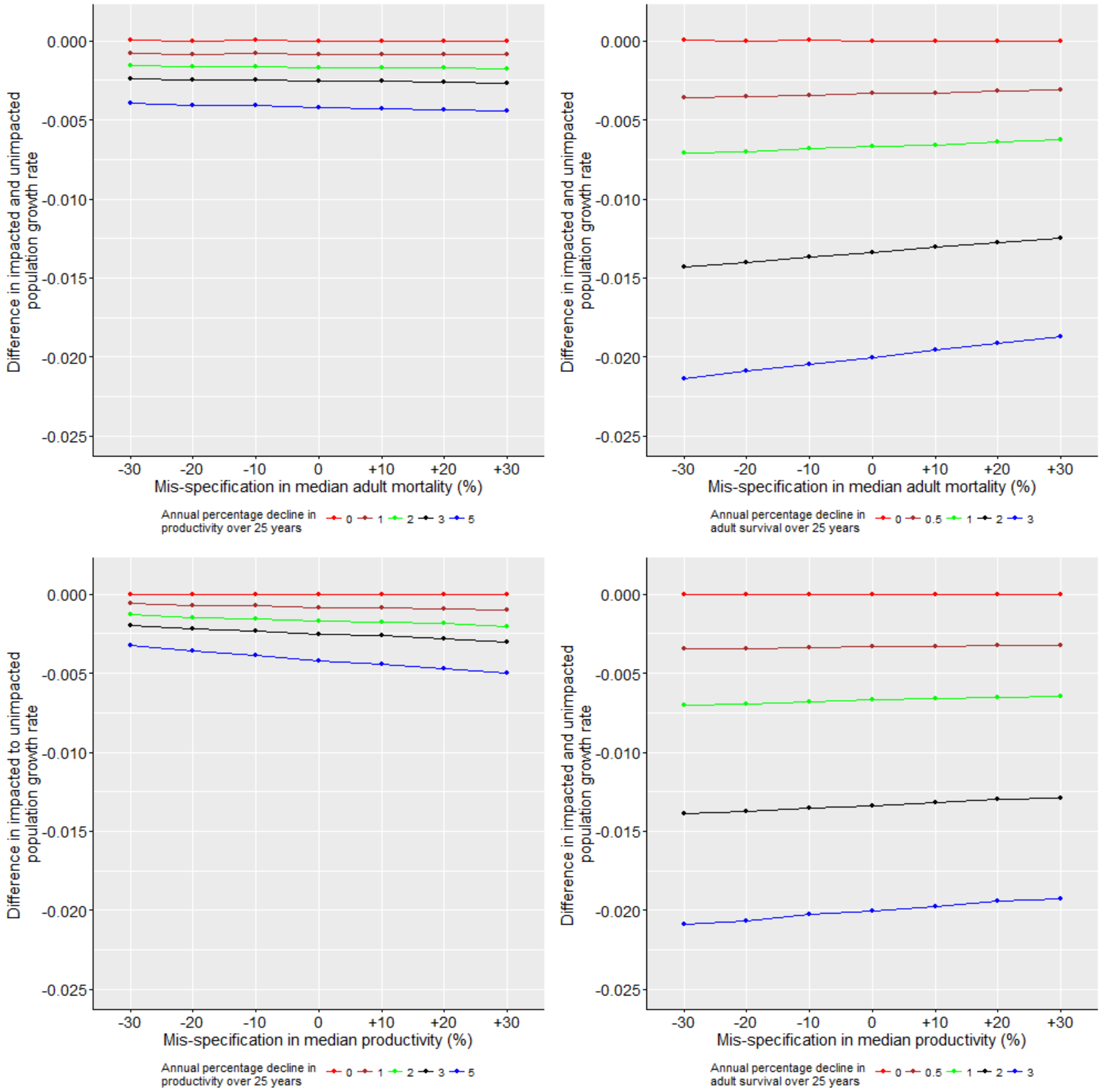


Figure A2.3d. PVA Metric D for Fowlsheugh Kittiwakes – difference in population size at 2041, comparing impacted population vs. un-impacted population.

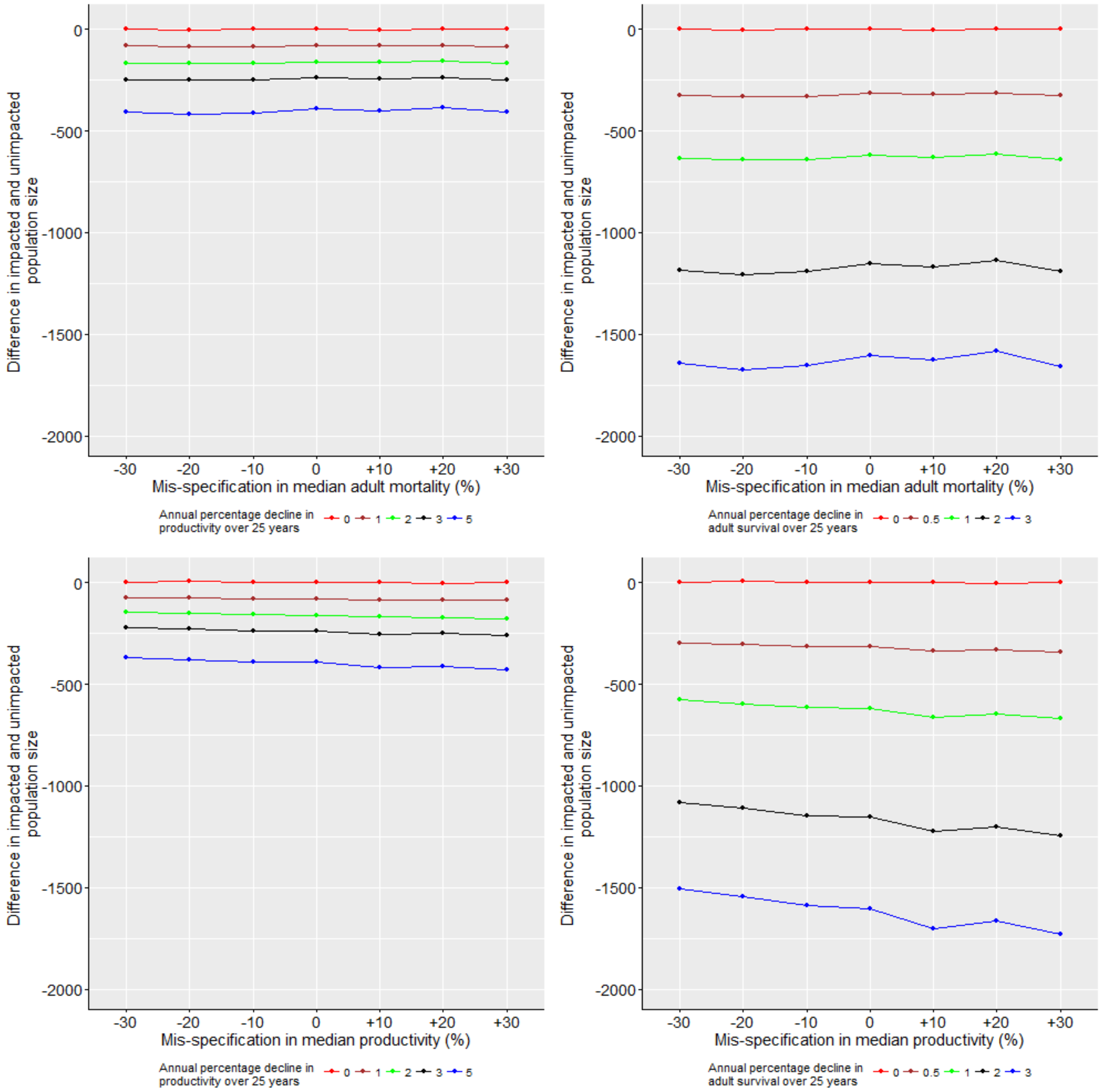


Figure A2.3e. PVA Metric E1 for Fowlsheugh Kittiwakes – probability of population decline greater than 10% from 2016-2041.

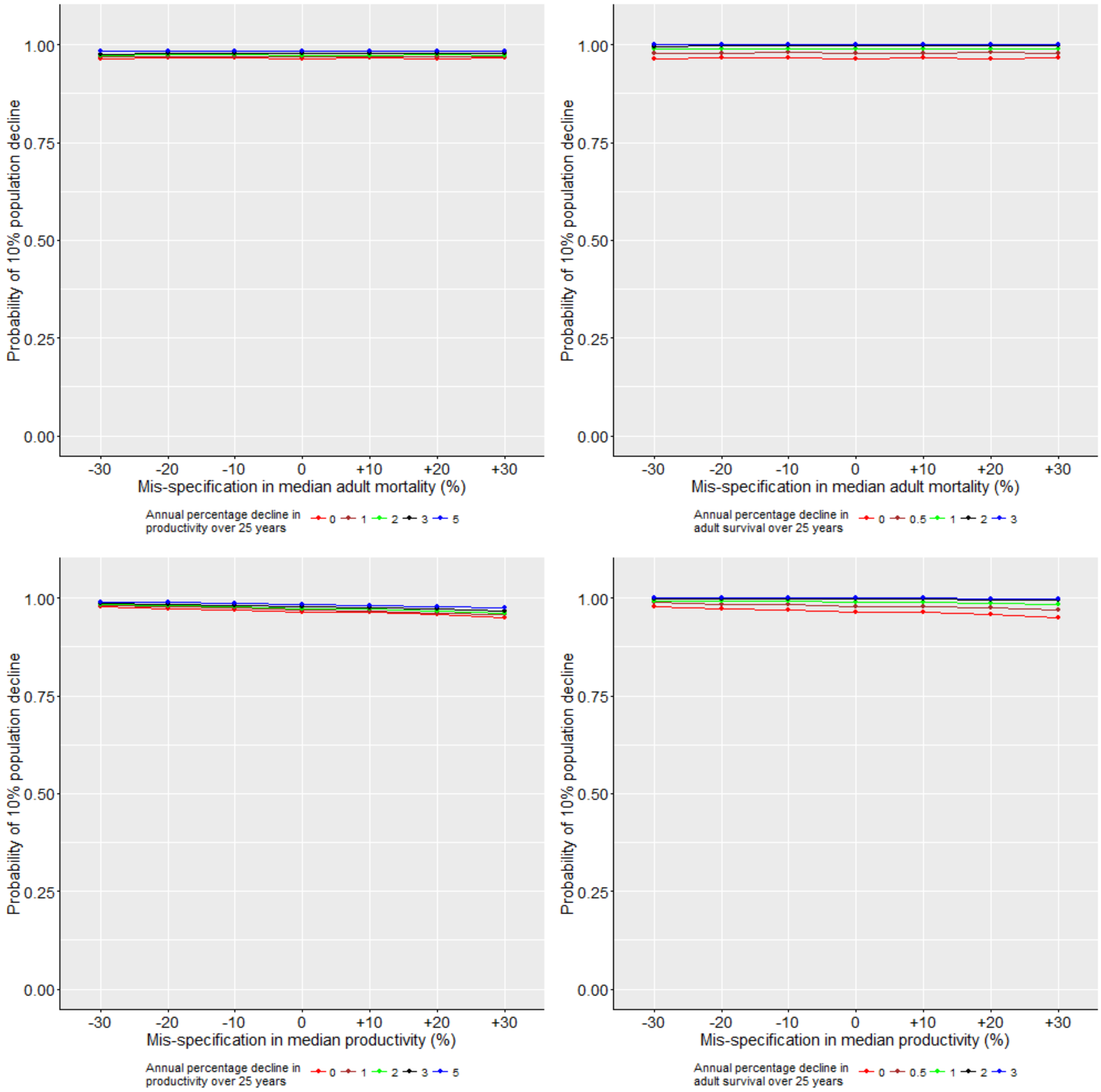


Figure A2.3f. PVA Metric E2 for Fowlsheugh Kittiwakes – probability of population decline greater than 25% from 2016-2041.

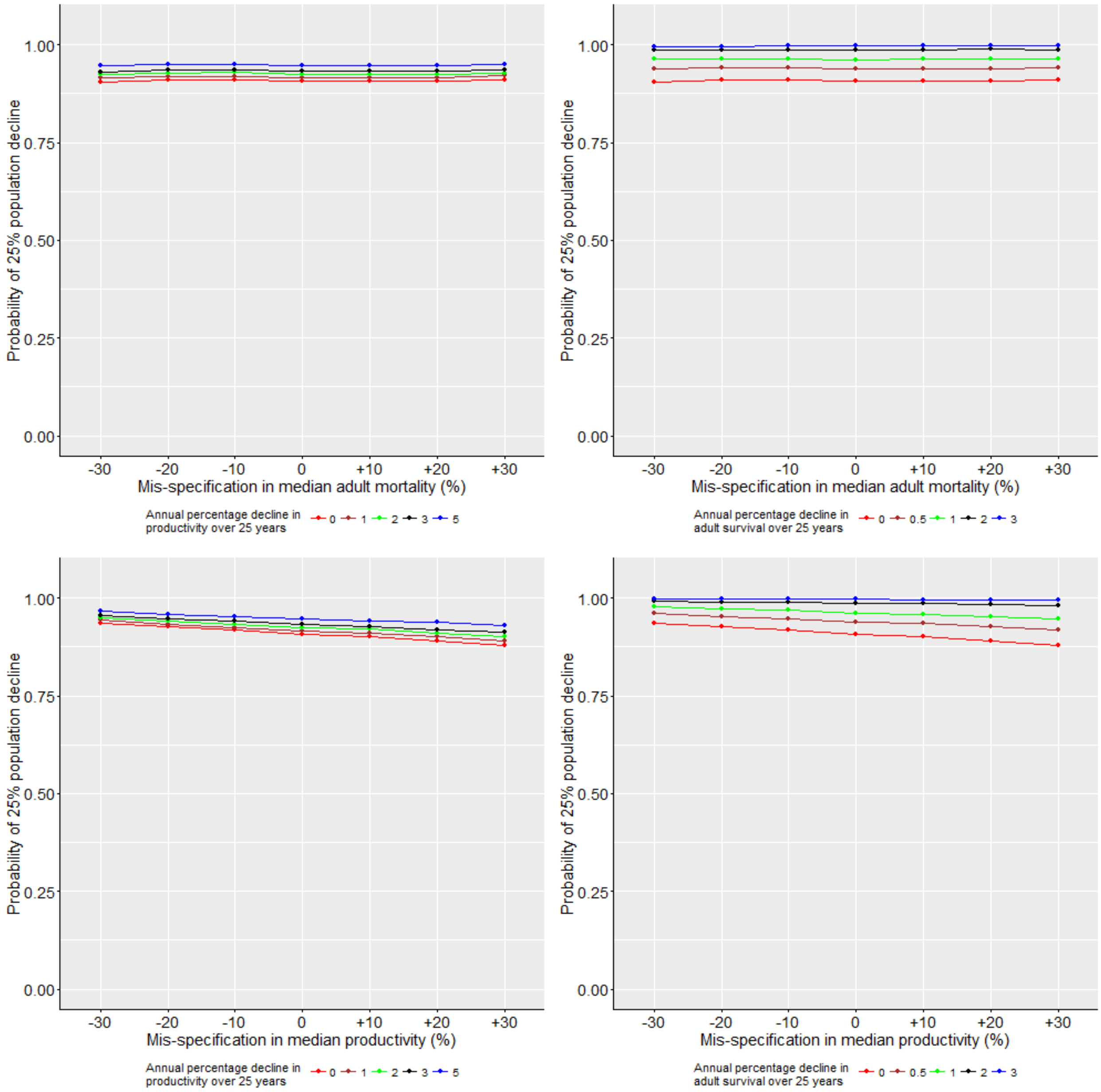


Figure A2.3g. PVA Metric E3 for Fowlsheugh Kittiwakes – probability of population decline greater than 50% from 2016-2041.

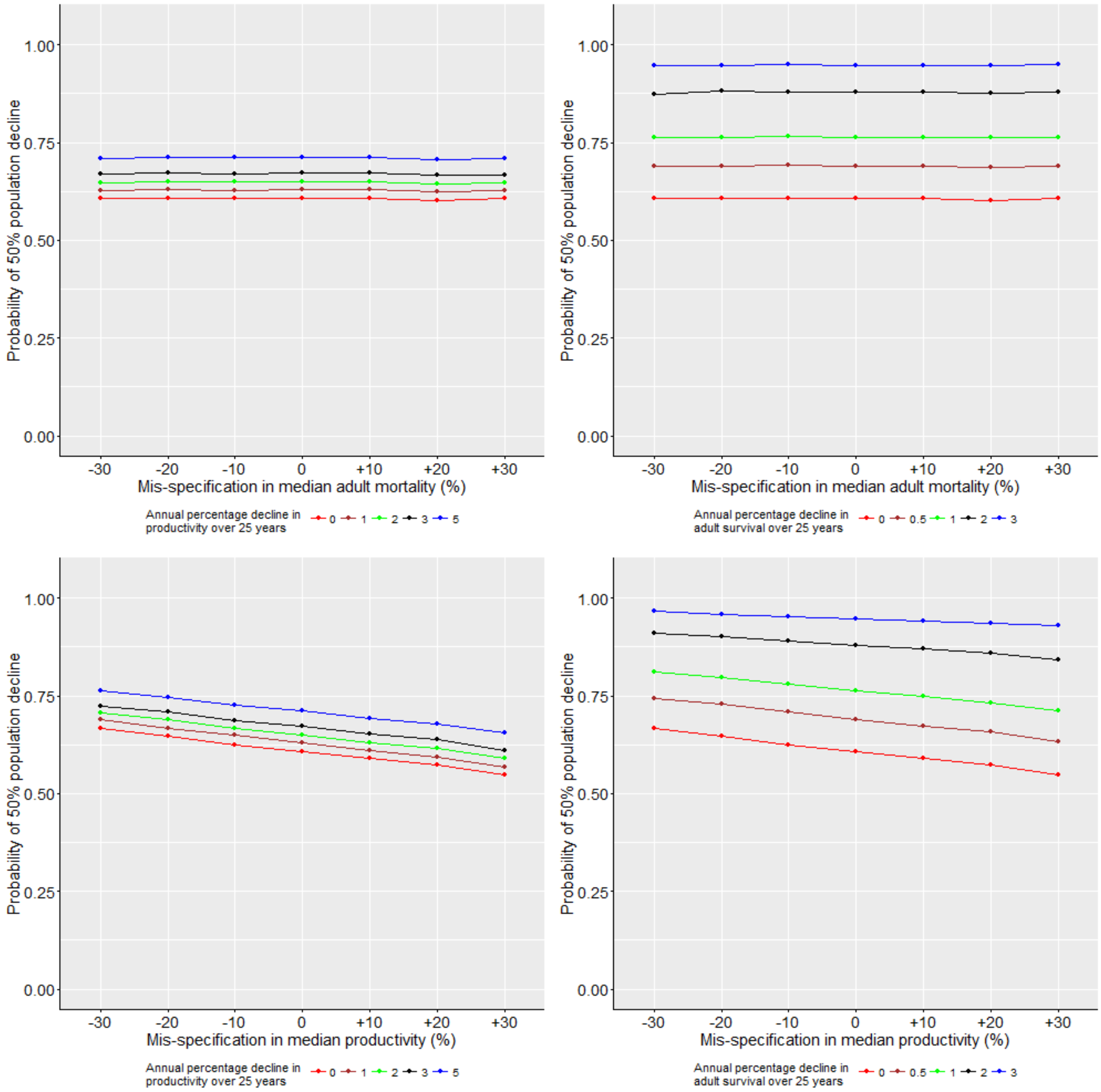
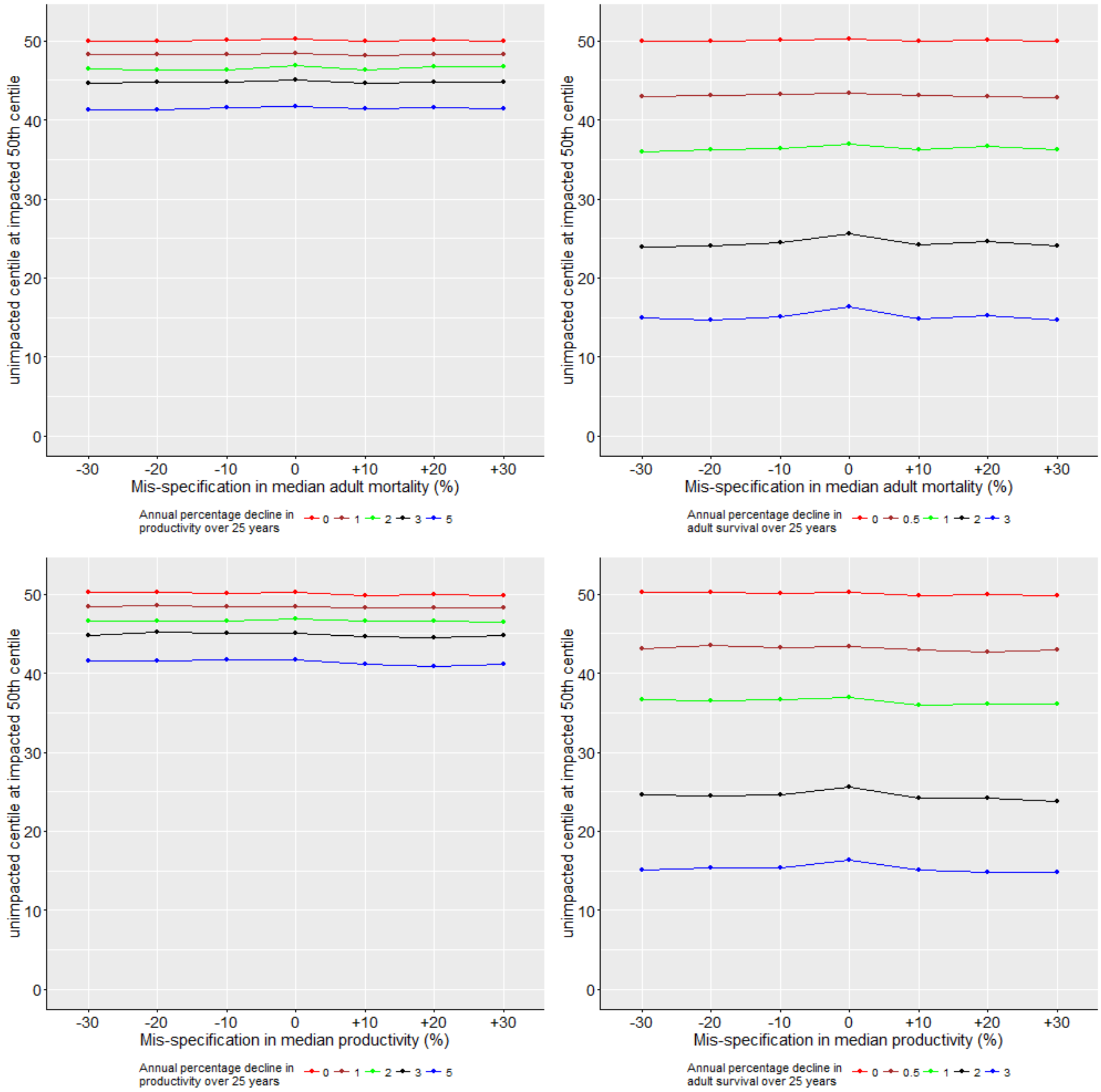


Figure A2.3h. PVA Metric F for Fowlsheugh Kittiwakes – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



4. **Kittiwakes at Buchan Ness to Collieston Coast SPA**:

Figure A2.4a. PVA Metric A for Buchan Ness Kittiwakes – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

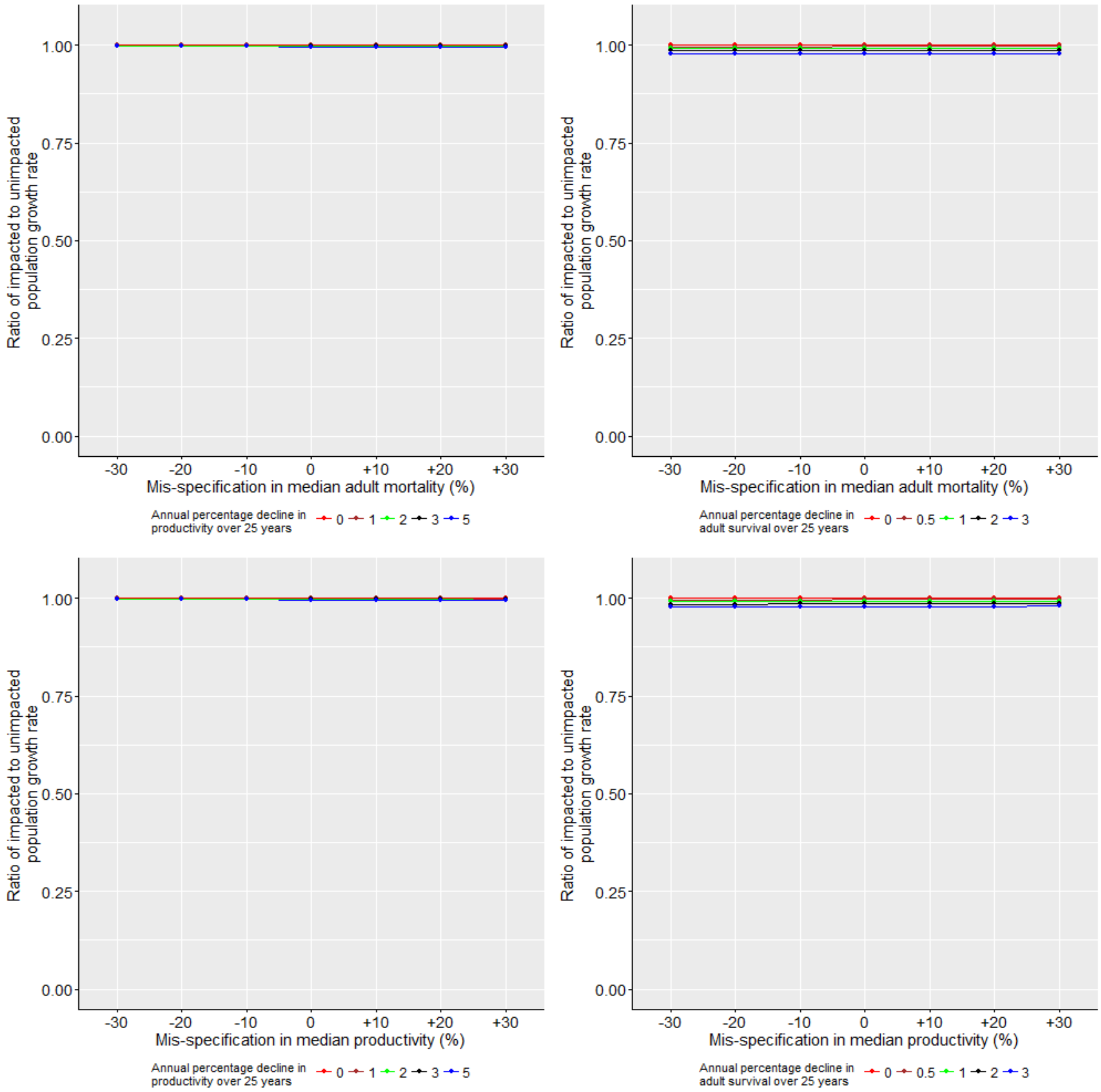


Figure A2.4b. PVA Metric B for Buchan Ness Kittiwakes – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

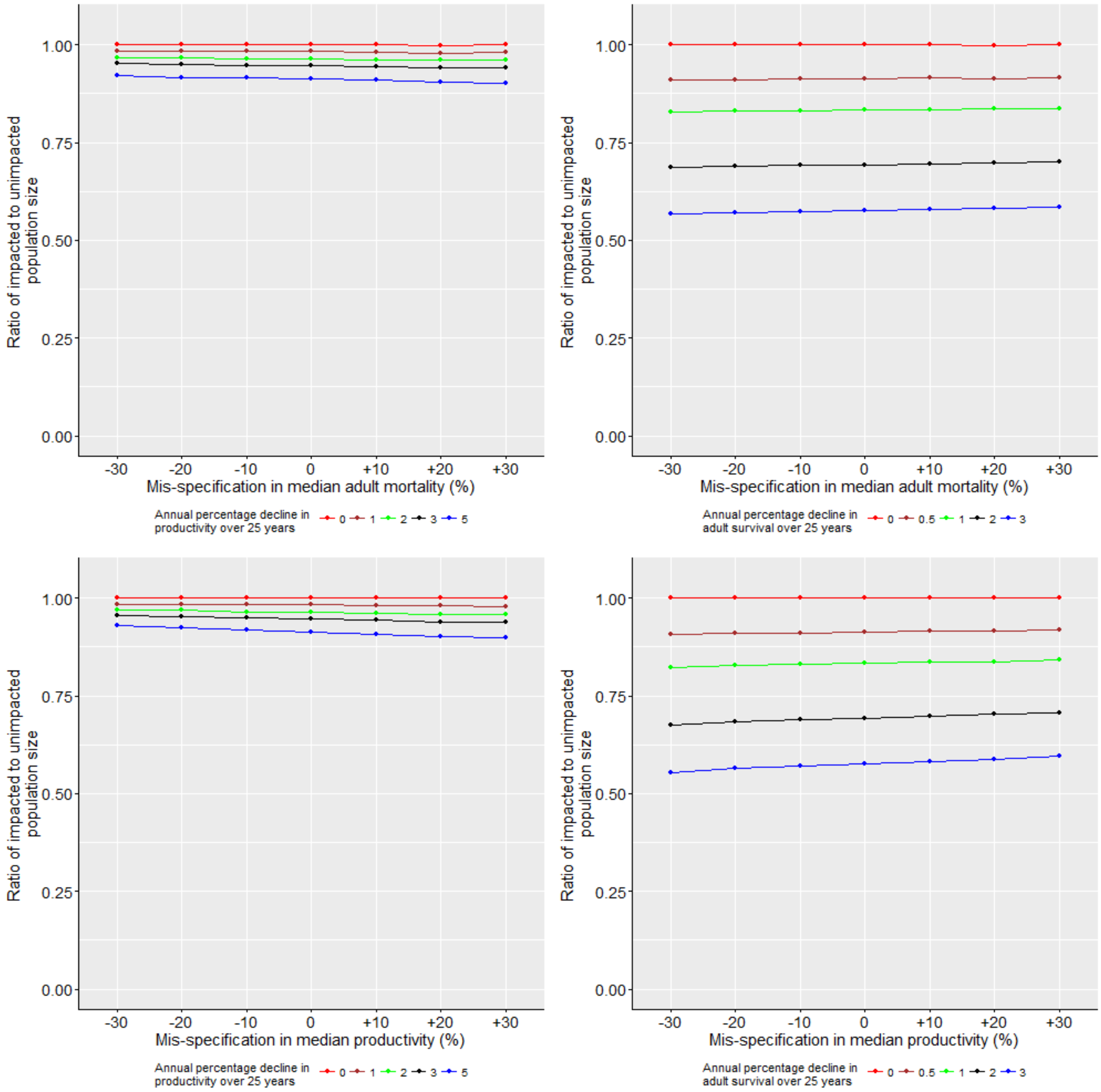


Figure A2.4c. PVA Metric C for Buchan Ness Kittiwakes – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

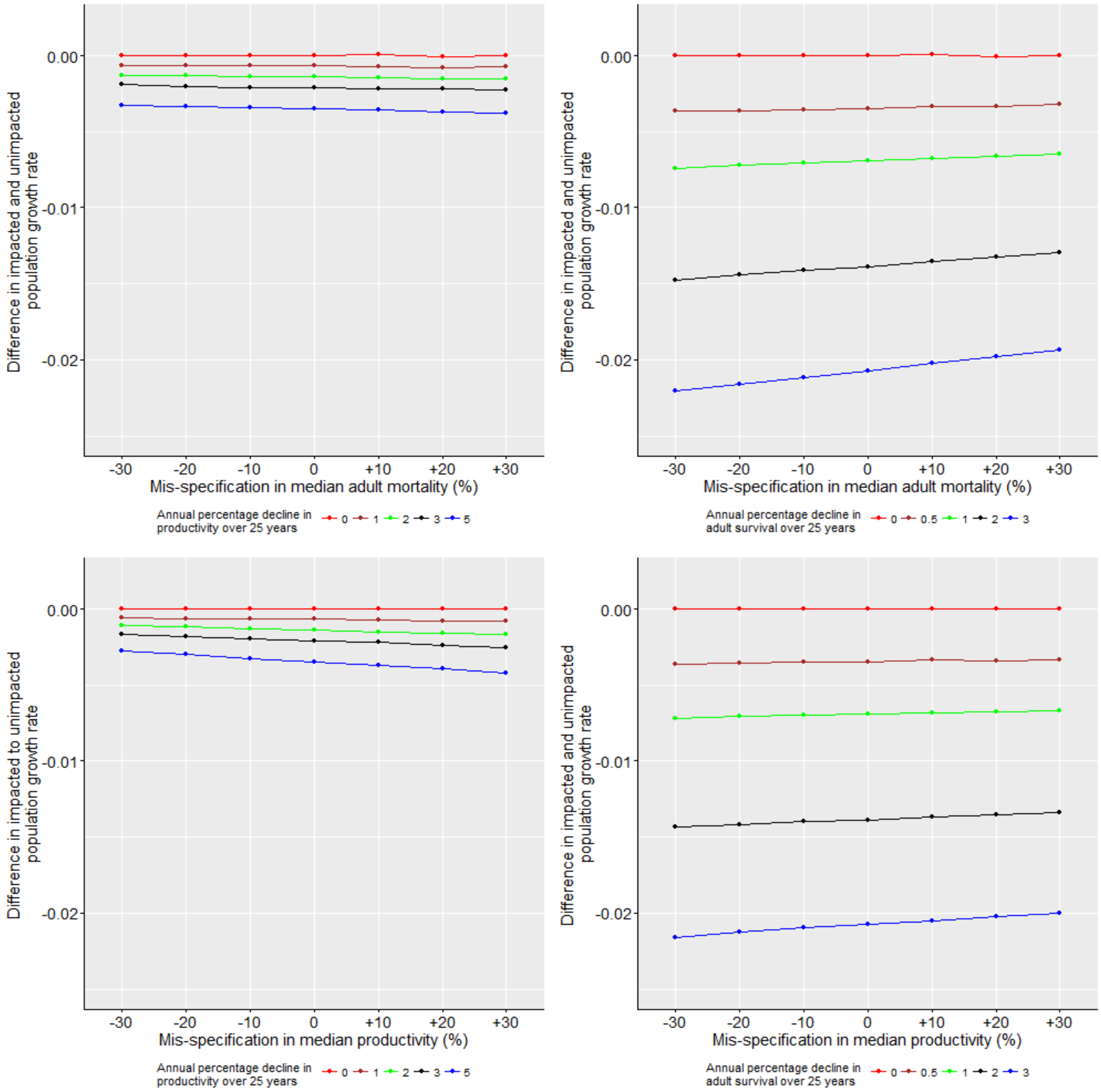


Figure A2.4d. PVA Metric D for Buchan Ness Kittiwakes – difference in population size at 2041, comparing impacted population vs. un-impacted population.

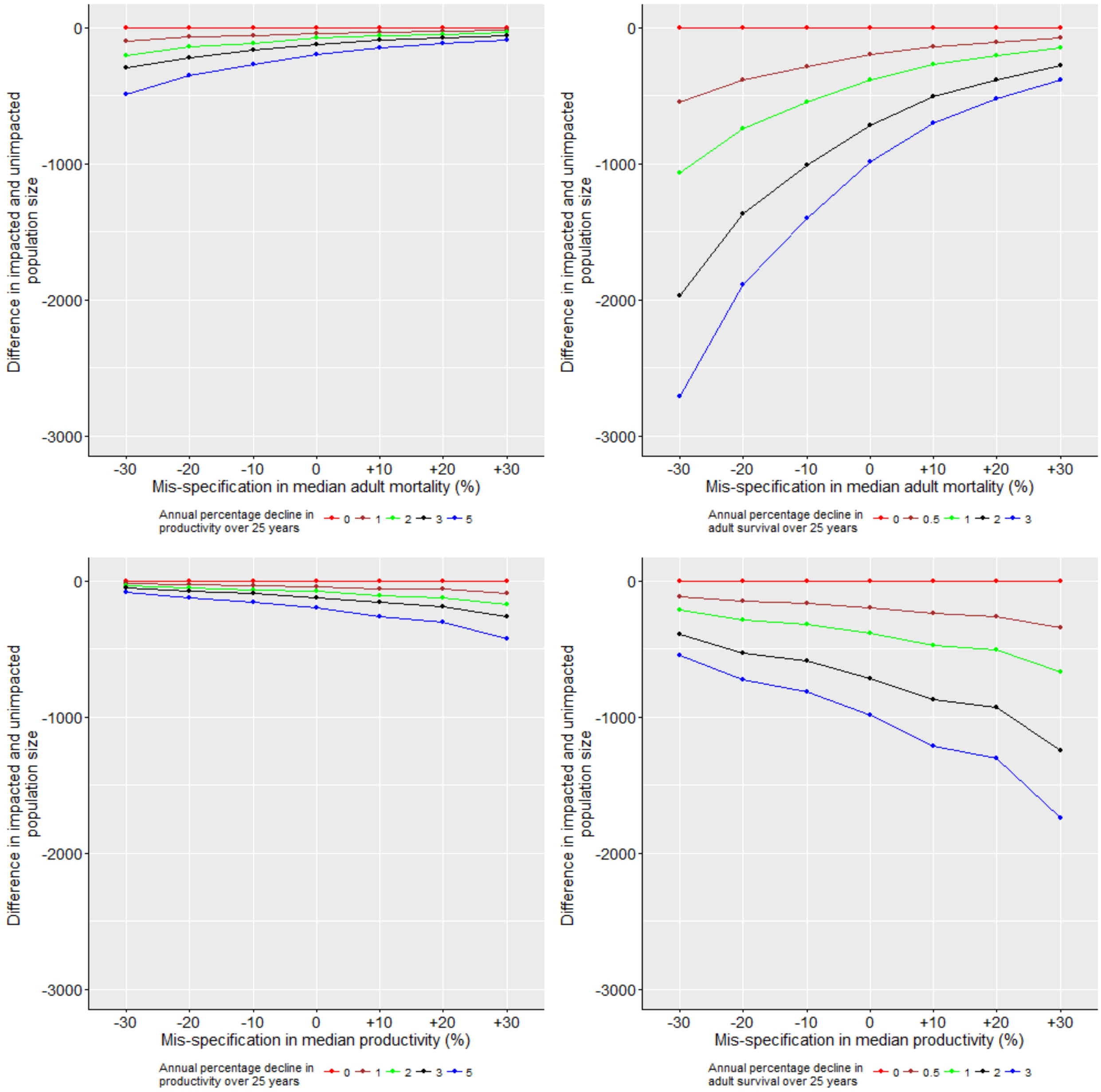


Figure A2.4e. PVA Metric E1 for Buchan Ness Kittiwakes – probability of population decline greater than 10% from 2016-2041.

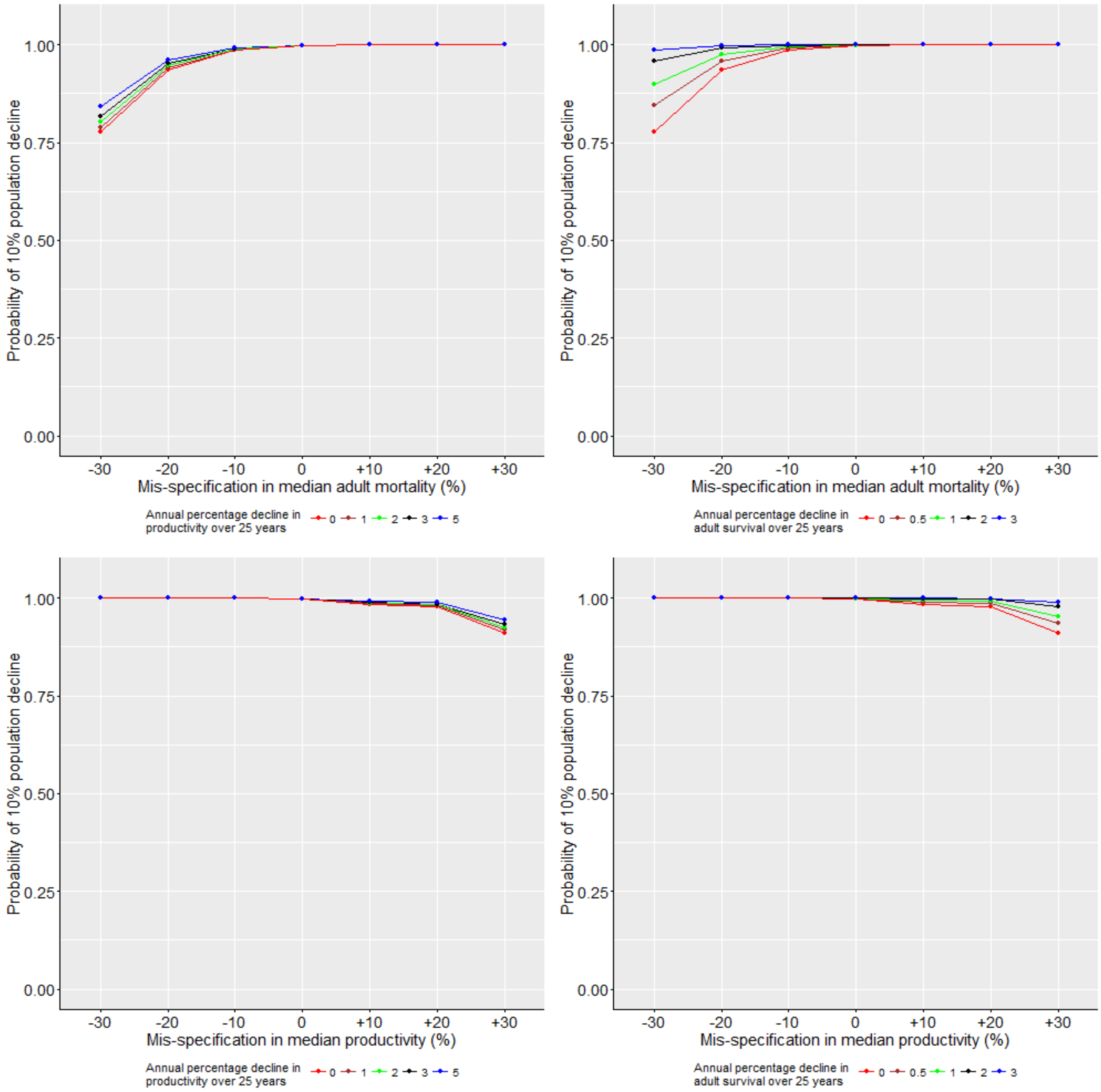


Figure A2.4f. PVA Metric E2 for Buchan Ness Kittiwakes – probability of population decline greater than 25% from 2016-2041.

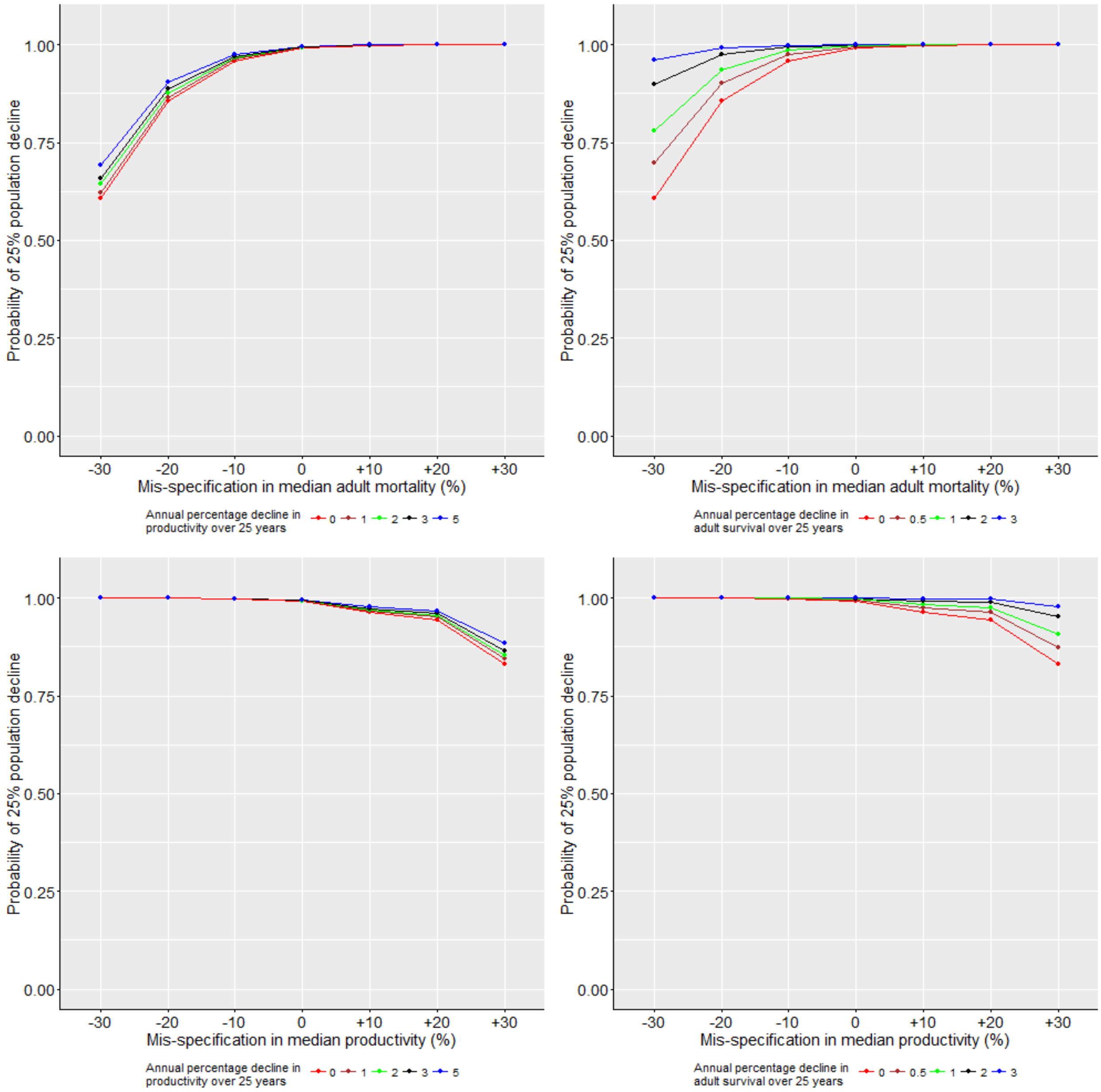


Figure A2.4g. PVA Metric E3 for Buchan Ness Kittiwakes – probability of population decline greater than 50% from 2016-2041.

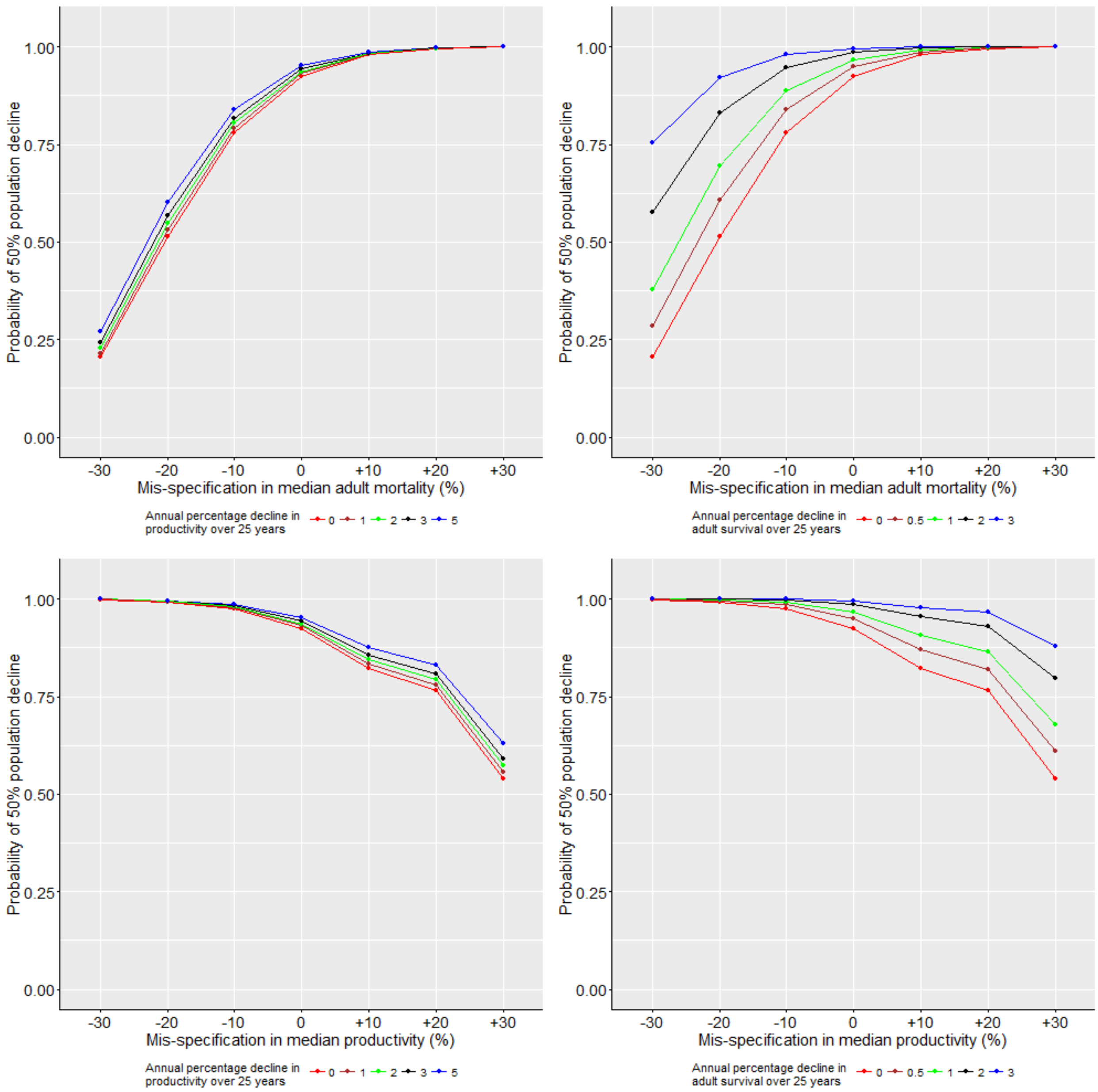
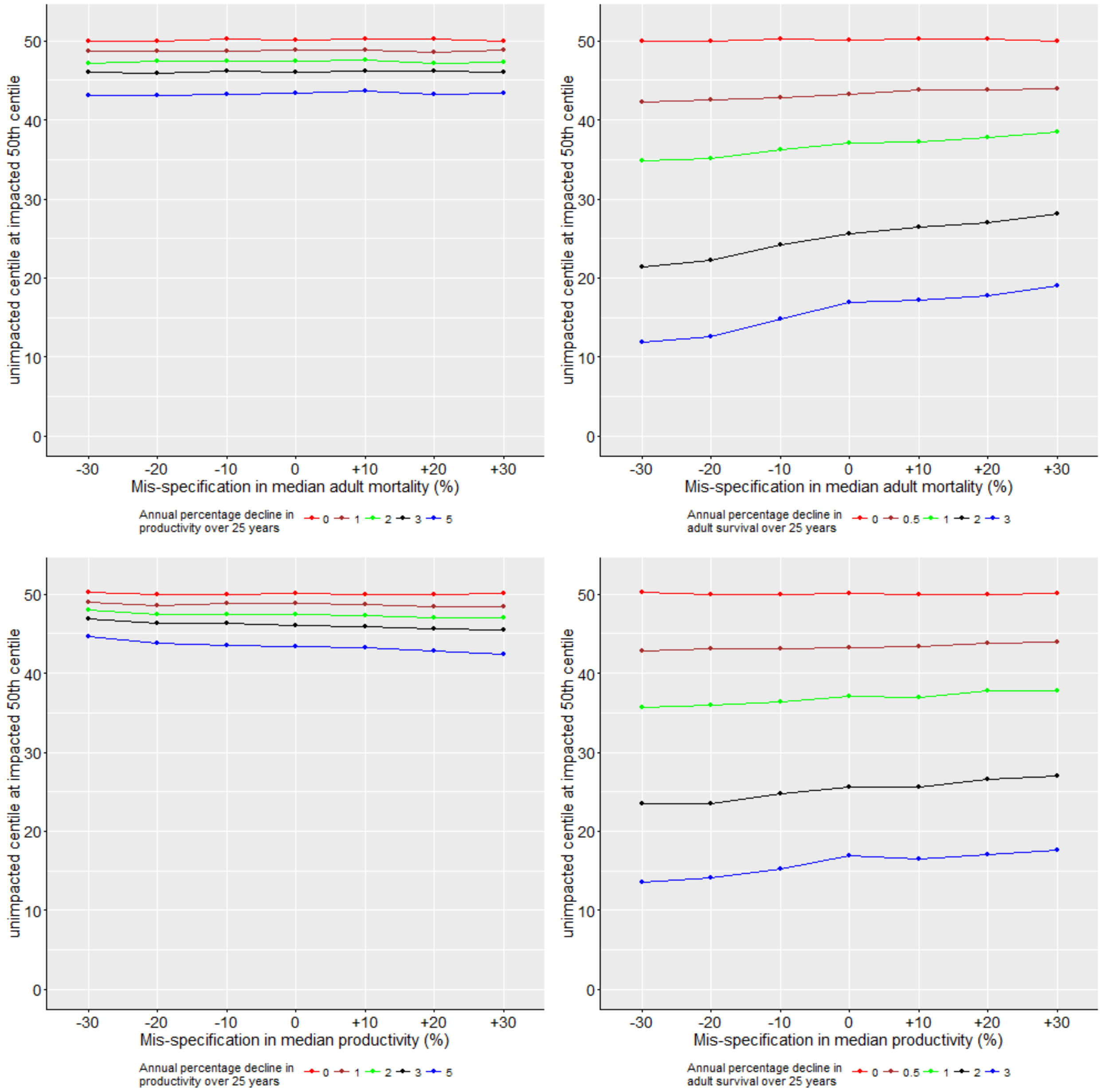


Figure A2.4h. PVA Metric F for Buchan Ness Kittiwakes – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



5. **Guillemots at Forth Islands SPA**:

Figure A2.5a. PVA Metric A for Forth Guillemots – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

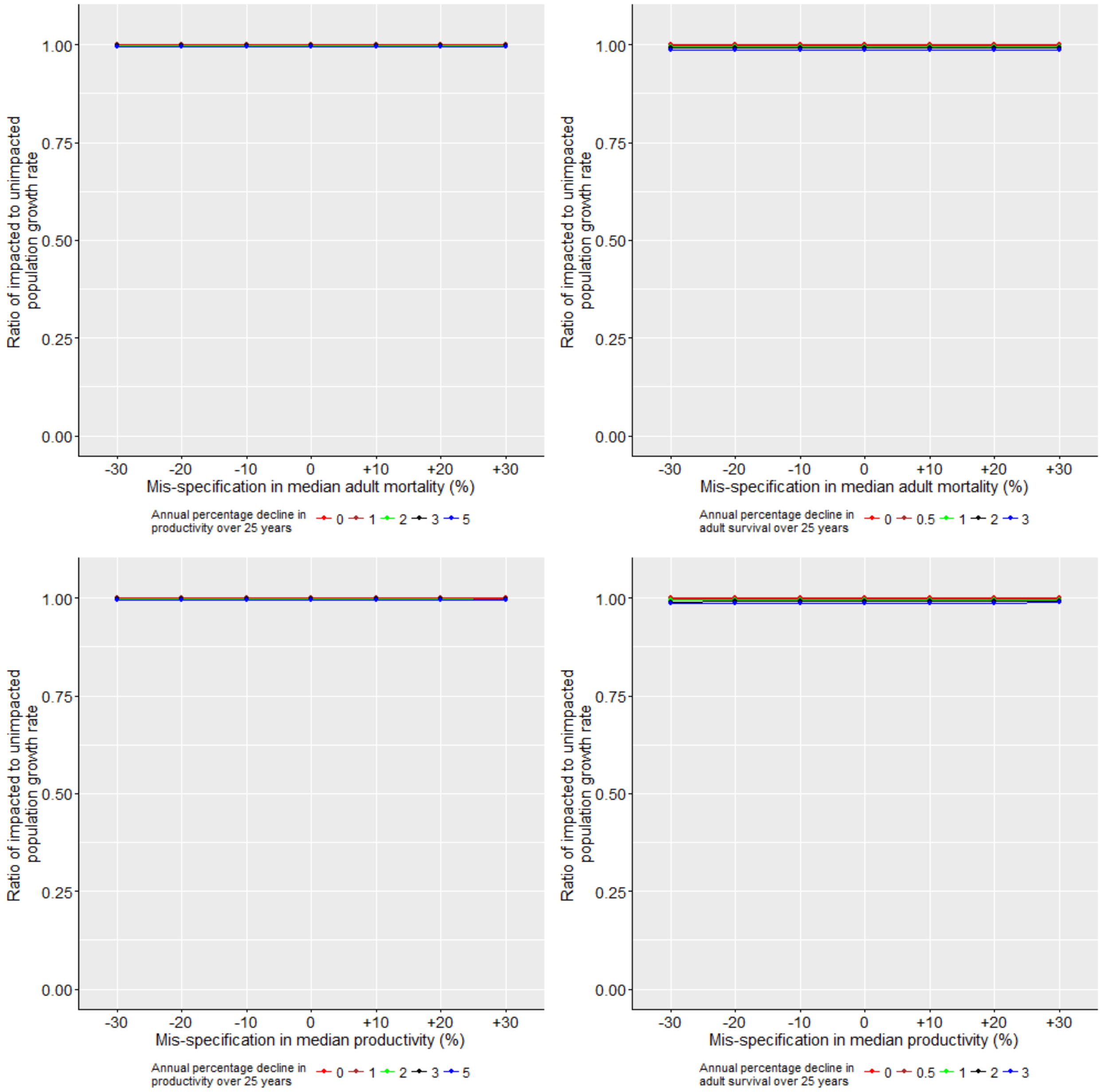


Figure A2.5b. PVA Metric B for Forth Guillemots – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

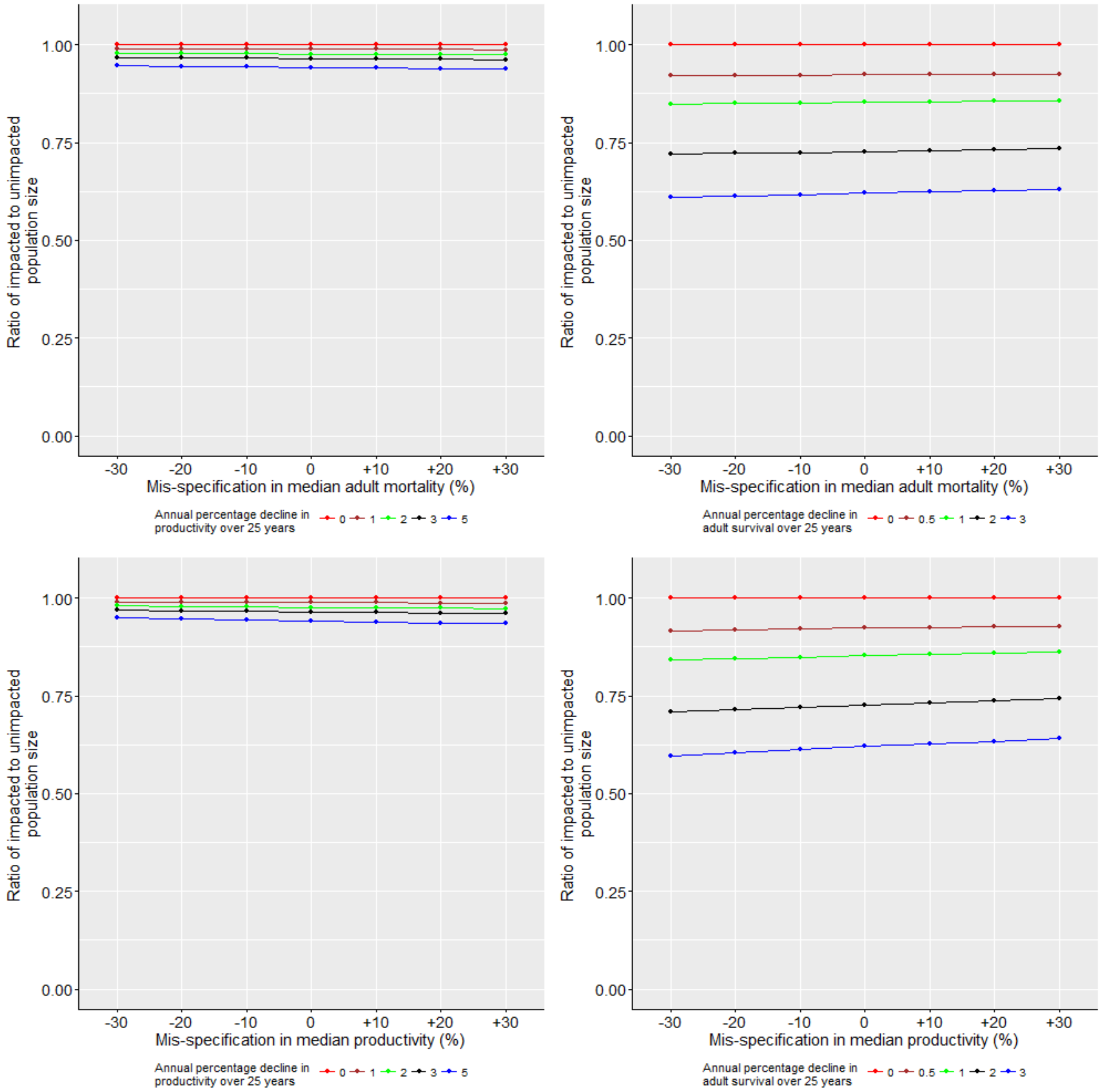


Figure A2.5c. PVA Metric C for Forth Guillemots – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

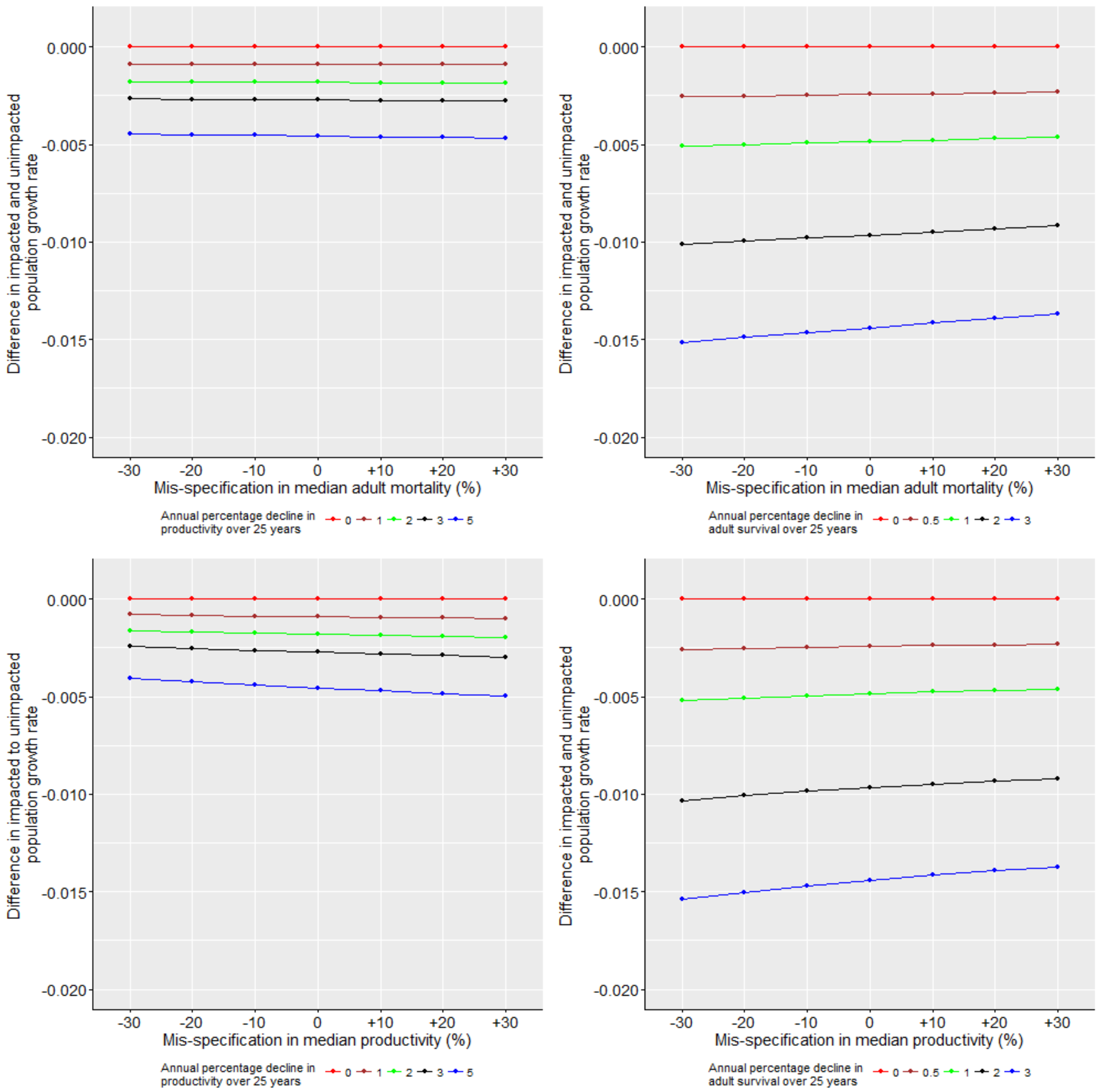


Figure A2.5d. PVA Metric D for Forth Guillemots – difference in population size at 2041, comparing impacted population vs. un-impacted population.

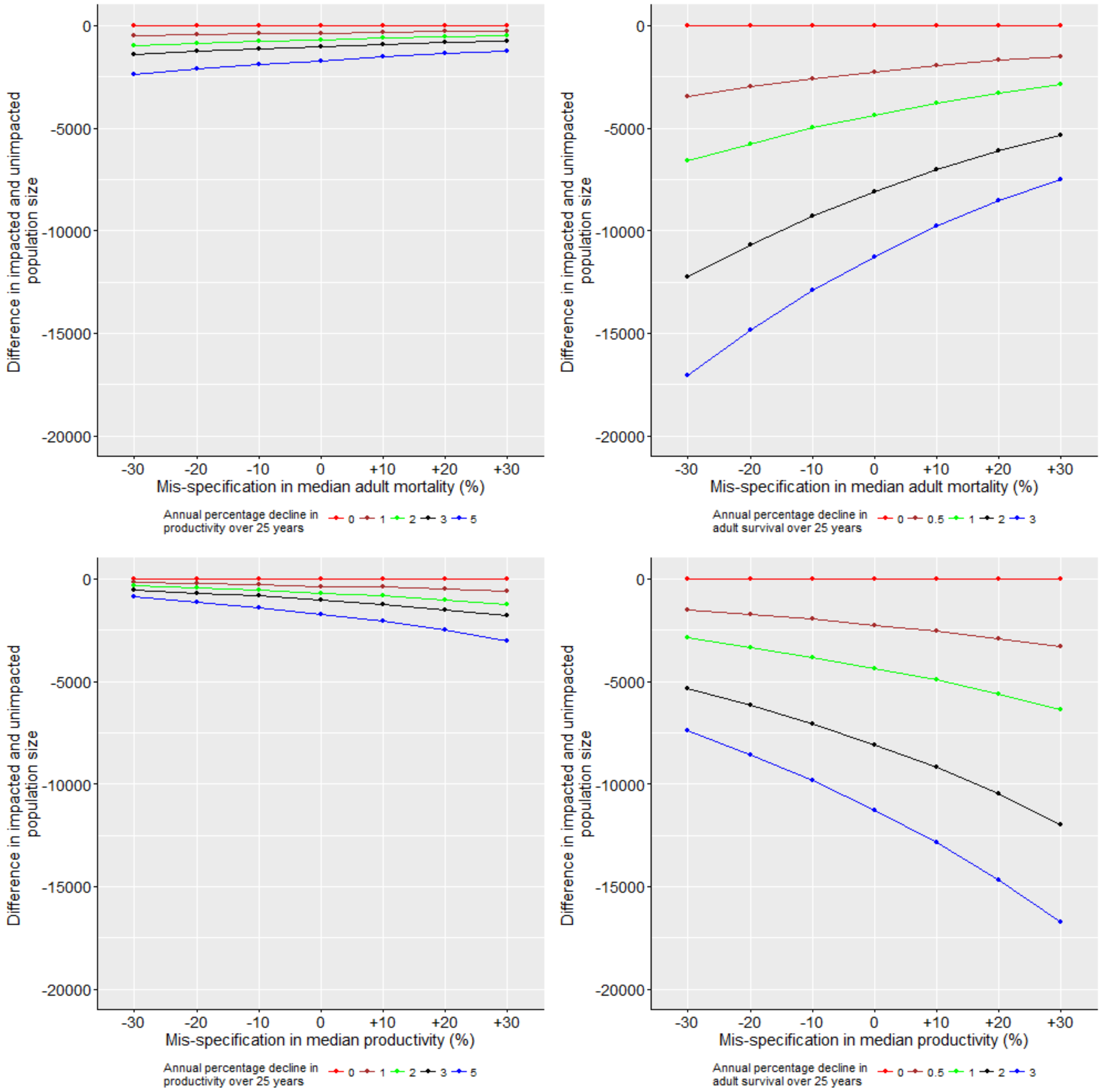


Figure A2.5e. PVA Metric E1 for Forth Guillemots – probability of population decline greater than 10% from 2016-2041.

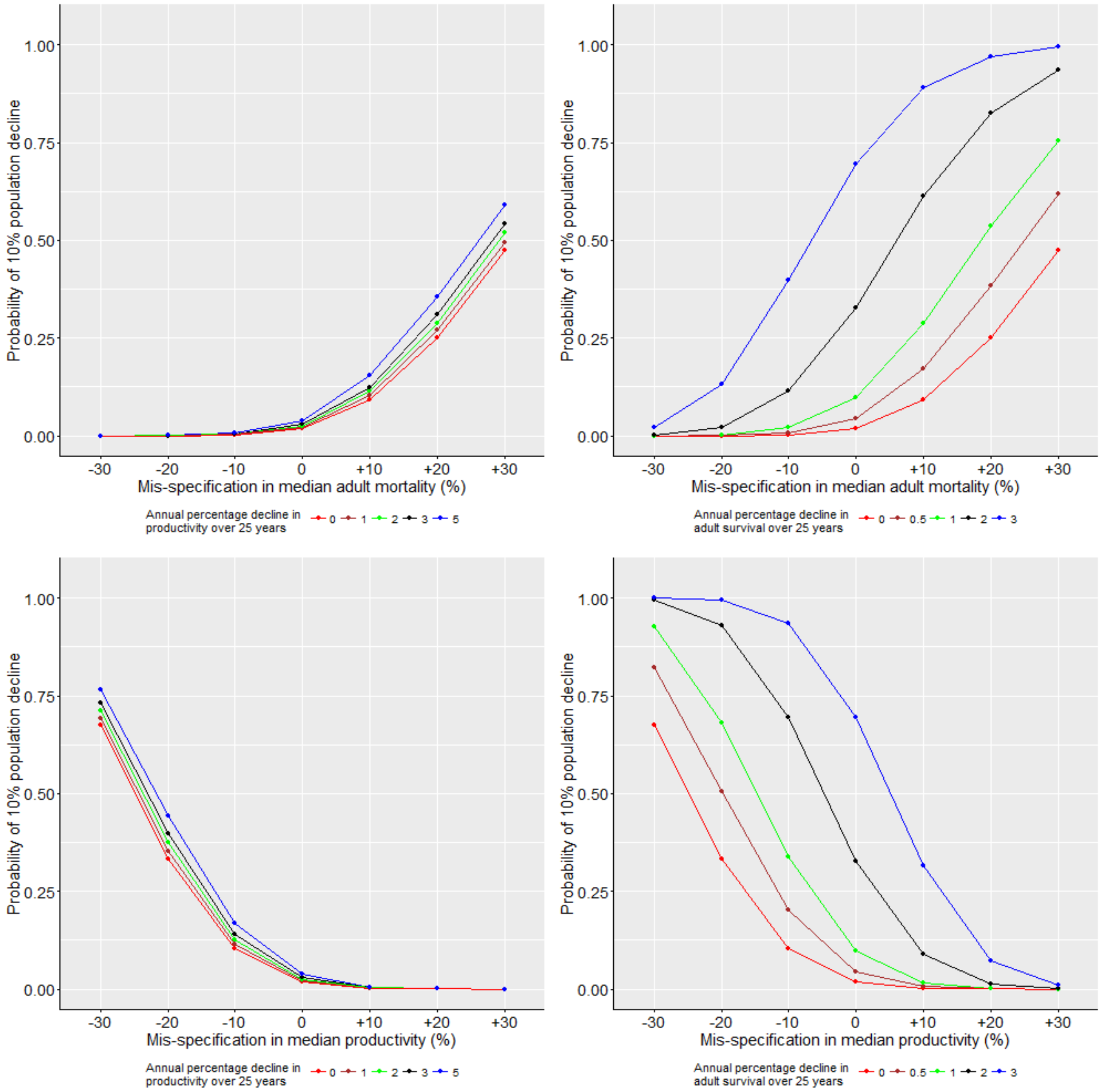


Figure A2.5f. PVA Metric E2 for Forth Guillemots – probability of population decline greater than 25% from 2016-2041.

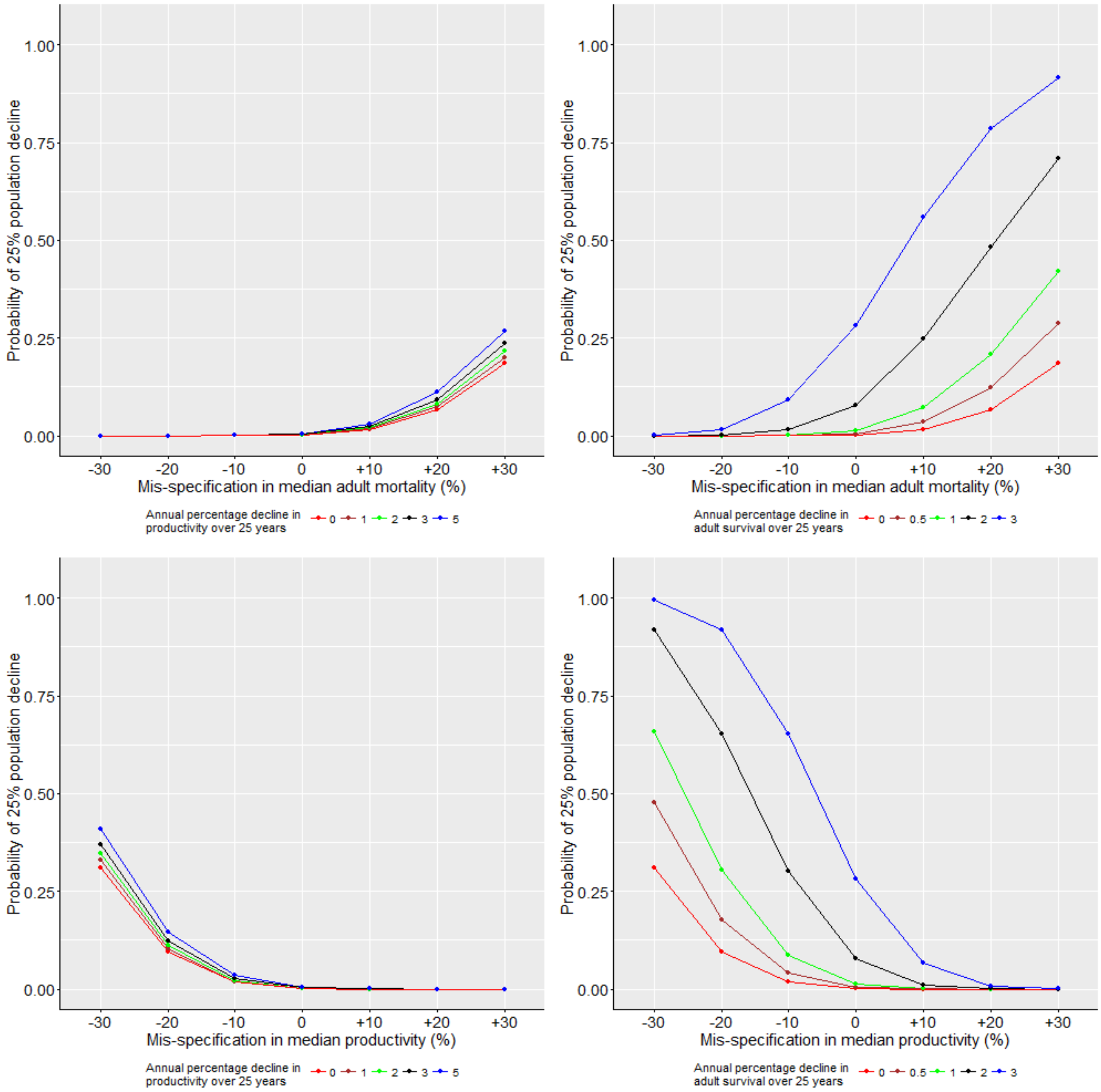


Figure A2.5g. PVA Metric E3 for Forth Guillemots – probability of population decline greater than 50% from 2016-2041.

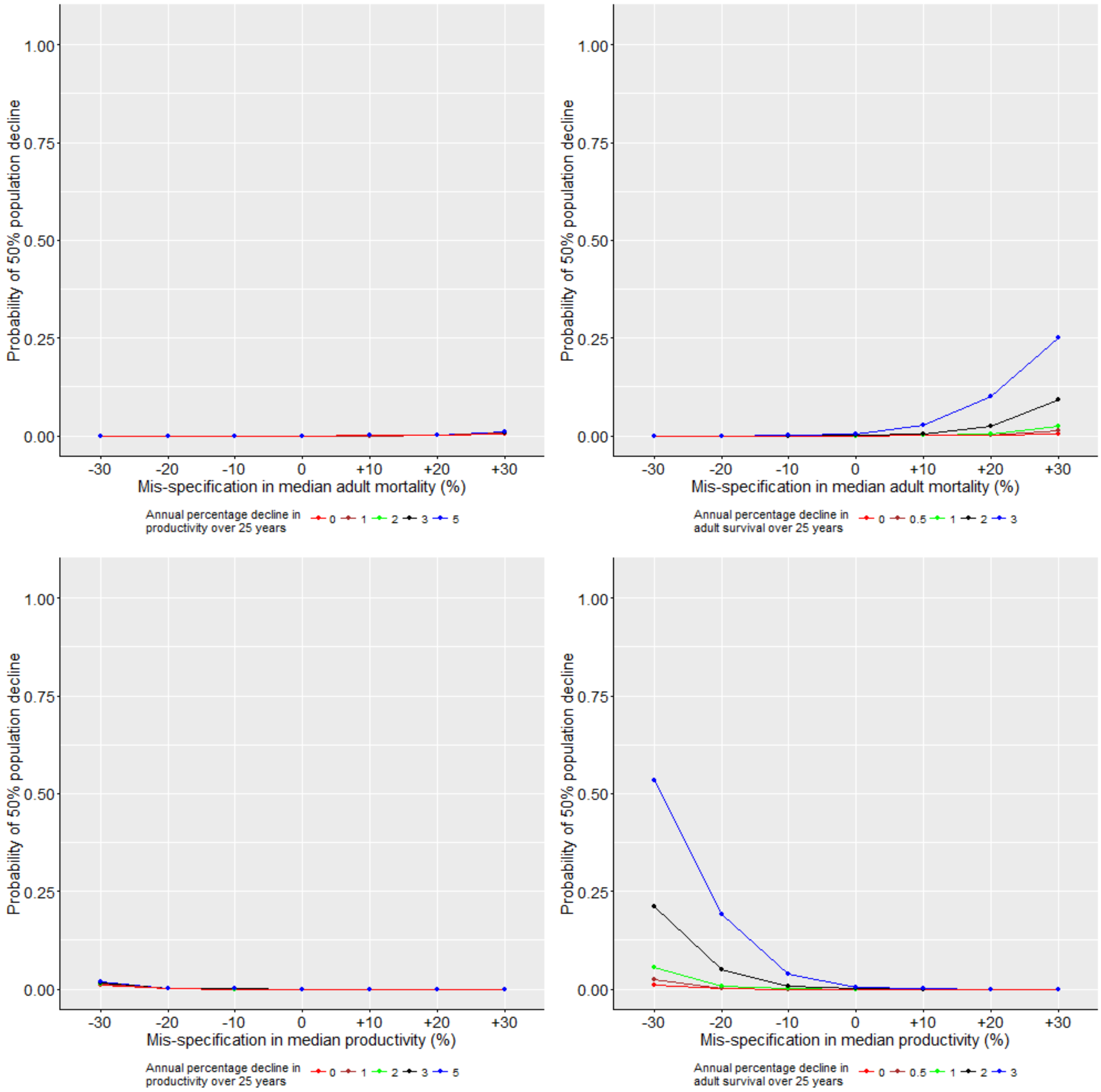
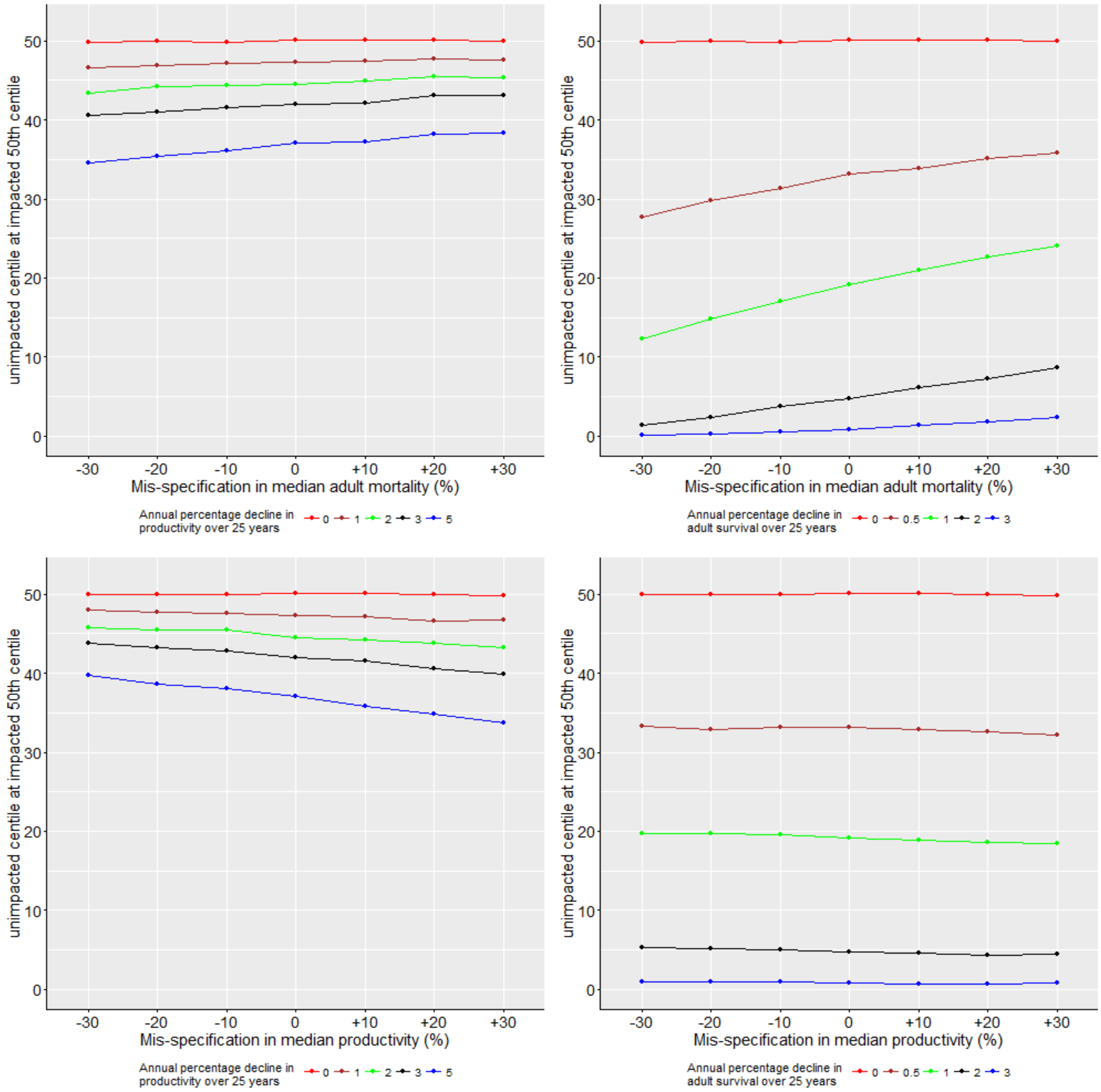


Figure A2.5h. PVA Metric F for Forth Guillemots – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



6. **Guillemots at St Abb's Head SPA**:

Figure A2.6a. PVA Metric A for St Abb's Guillemots – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

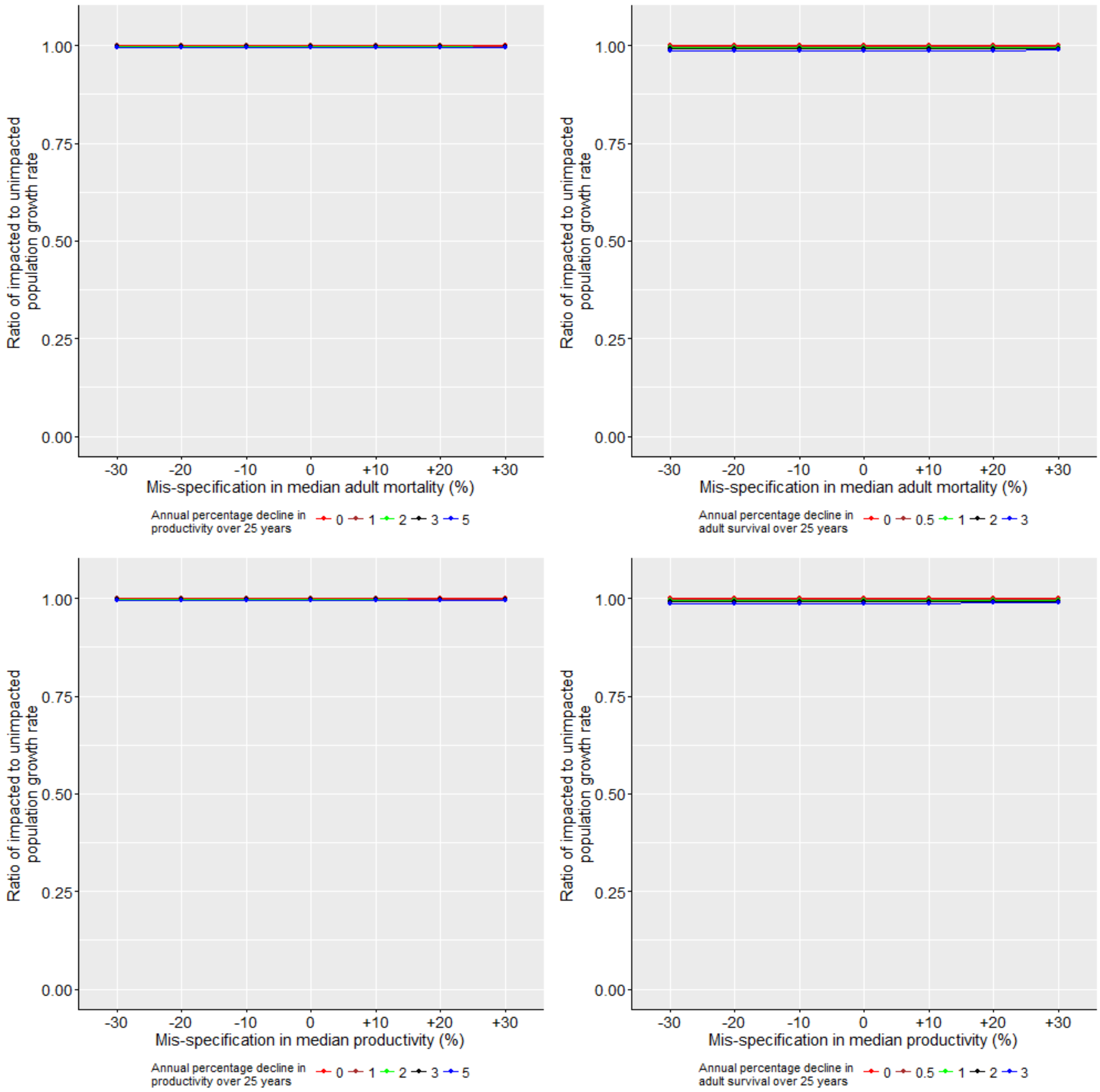


Figure A2.6b. PVA Metric B for St Abb's Guillemots – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

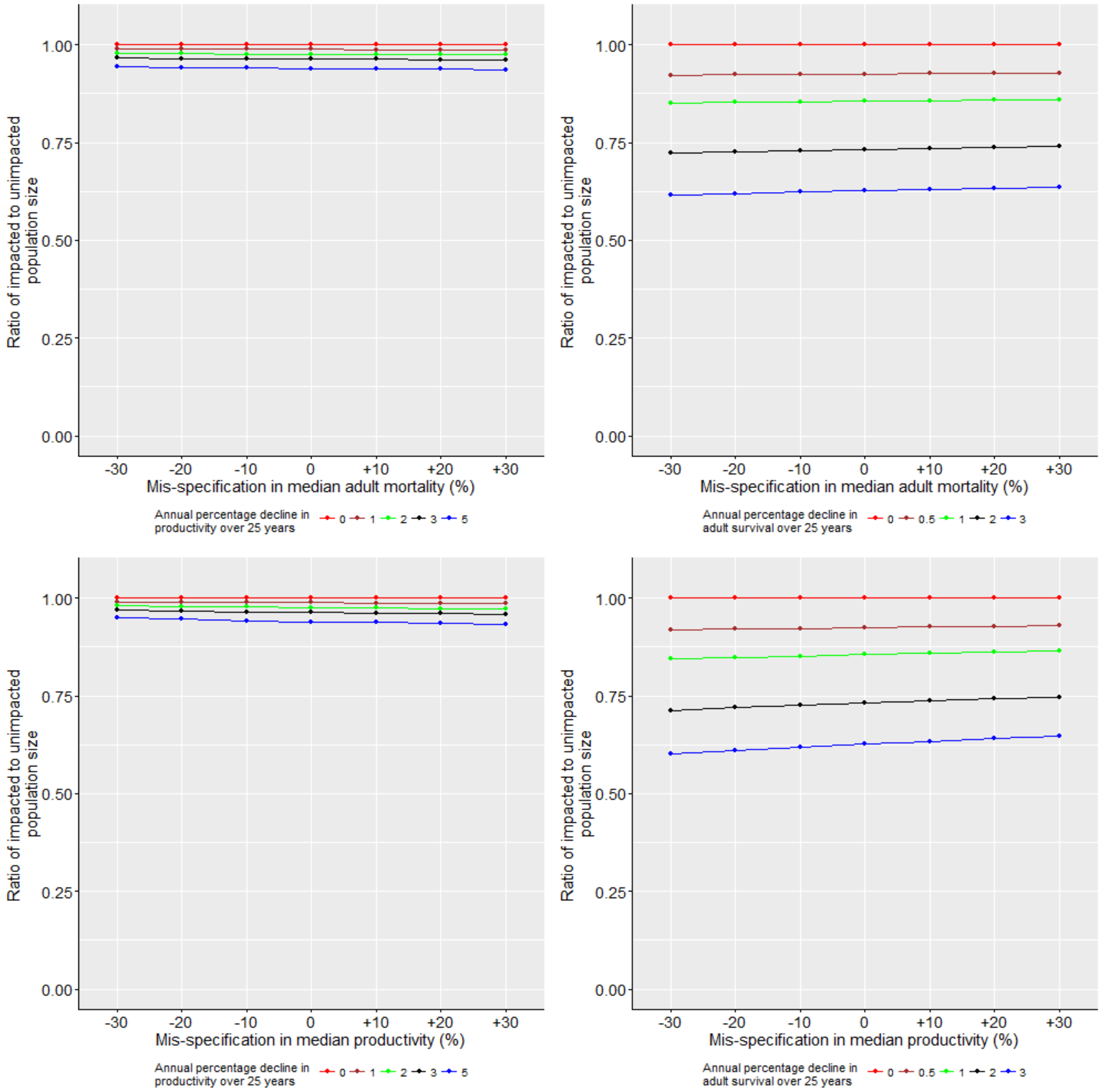


Figure A2.6c. PVA Metric C for St Abb's Guillemots – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

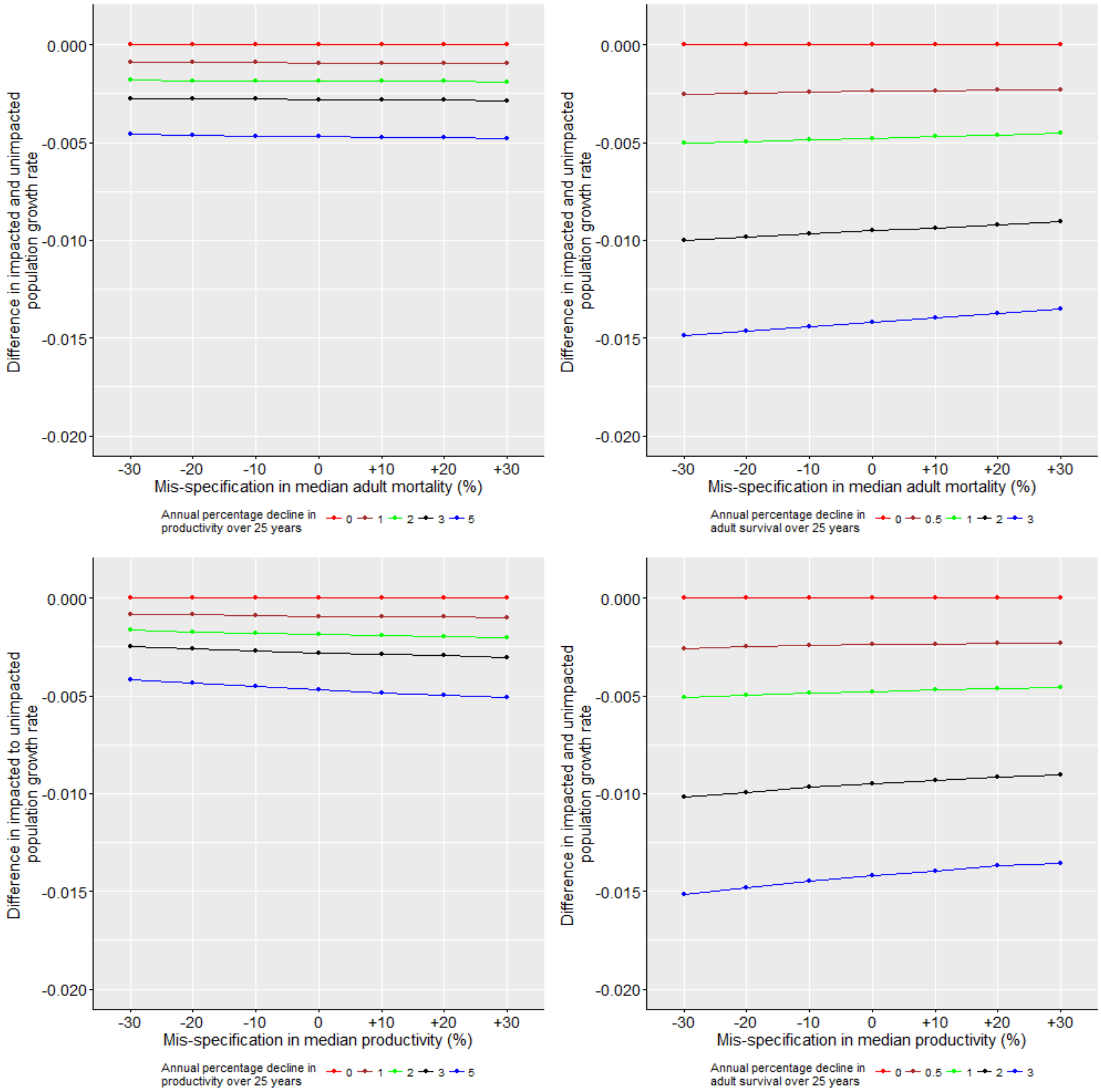


Figure A2.6d. PVA Metric D for St Abb's Guillemots – difference in population size at 2041, comparing impacted population vs. un-impacted population.

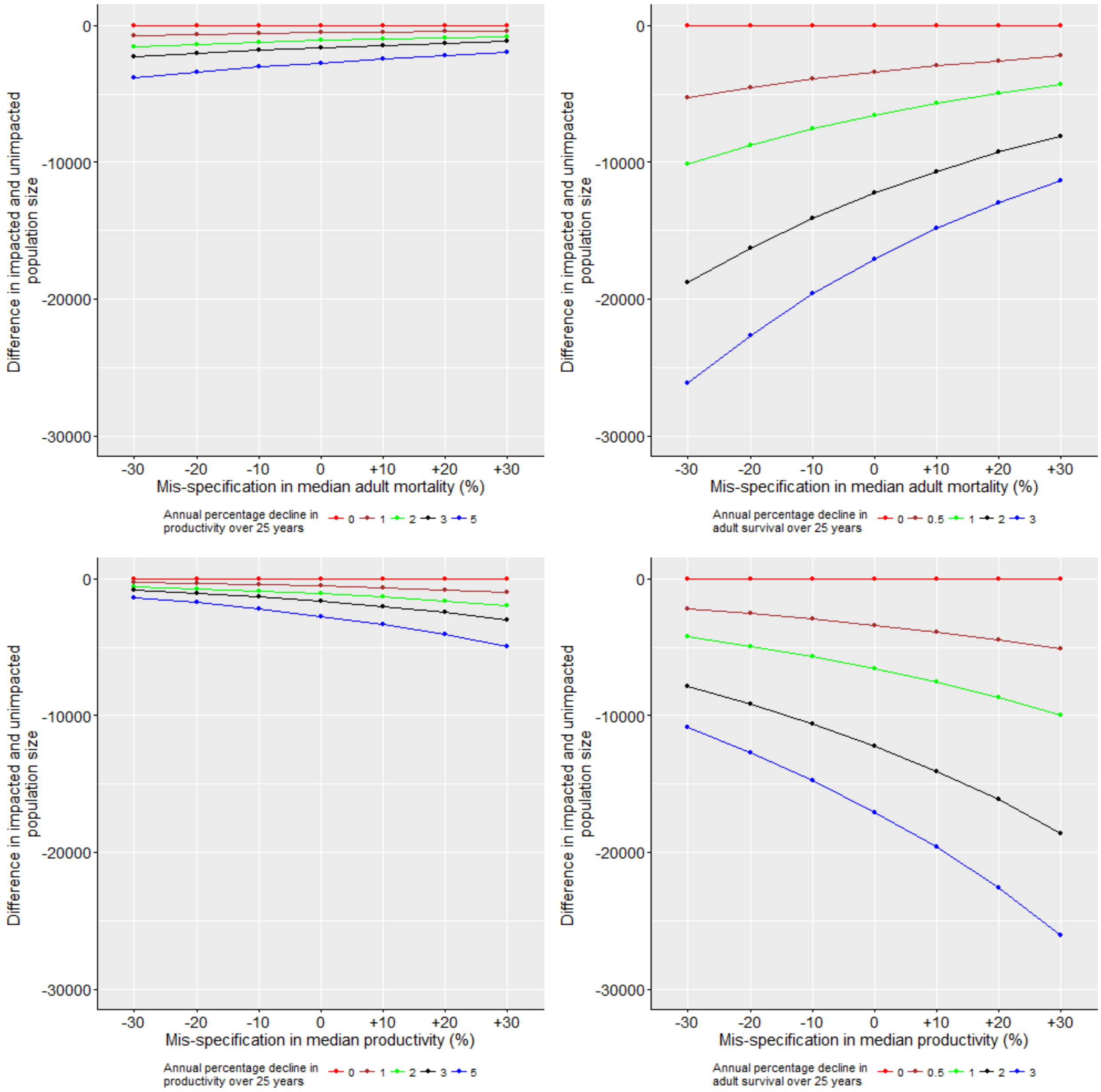


Figure A2.6e. PVA Metric E1 for St Abb's Guillemots – probability of population decline greater than 10% from 2016-2041.

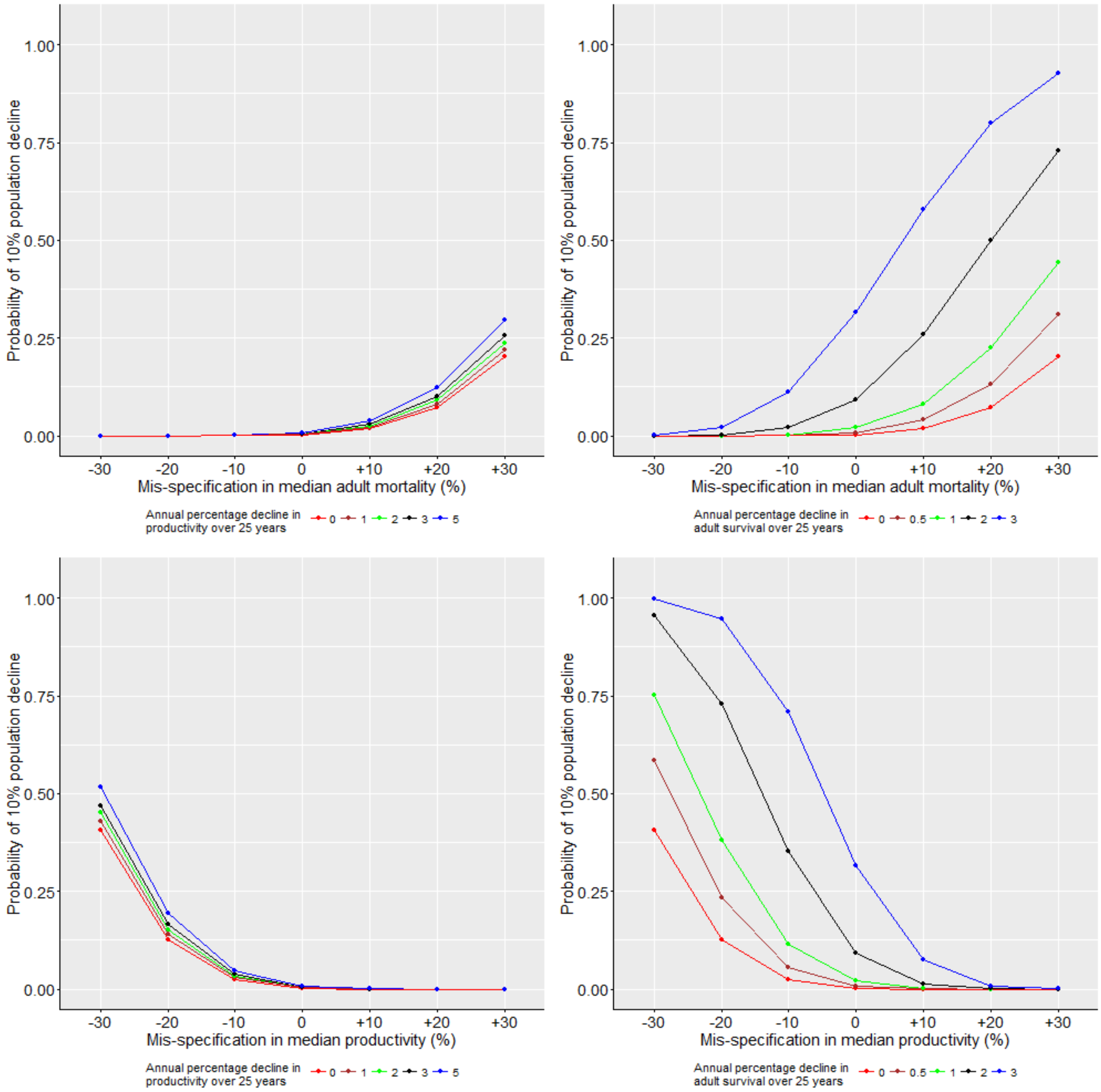


Figure A2.6f. PVA Metric E2 for St Abb's Guillemots – probability of population decline greater than 25% from 2016-2041.

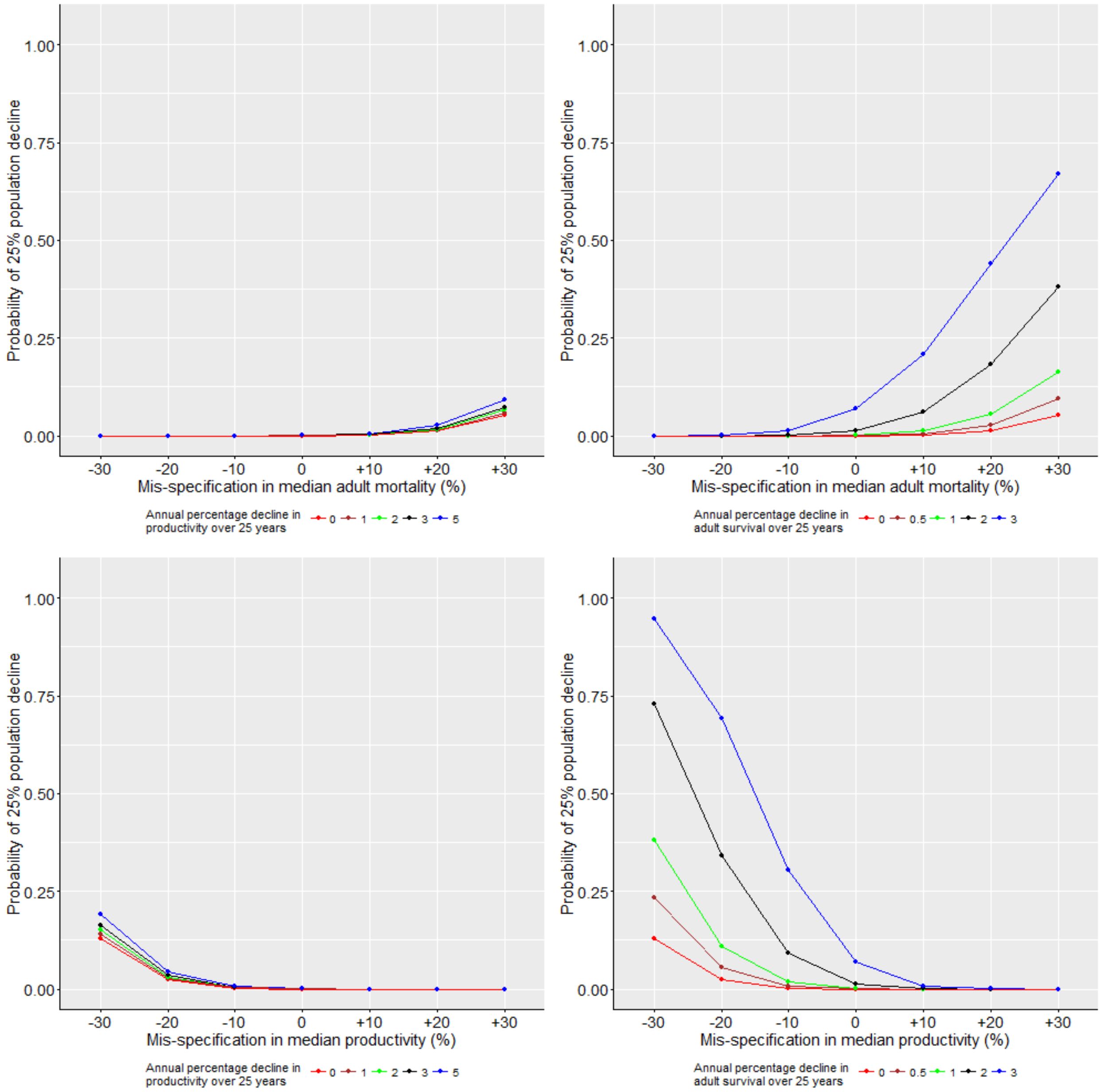


Figure A2.6g. PVA Metric E3 for St Abb's Guillemots – probability of population decline greater than 50% from 2016-2041.

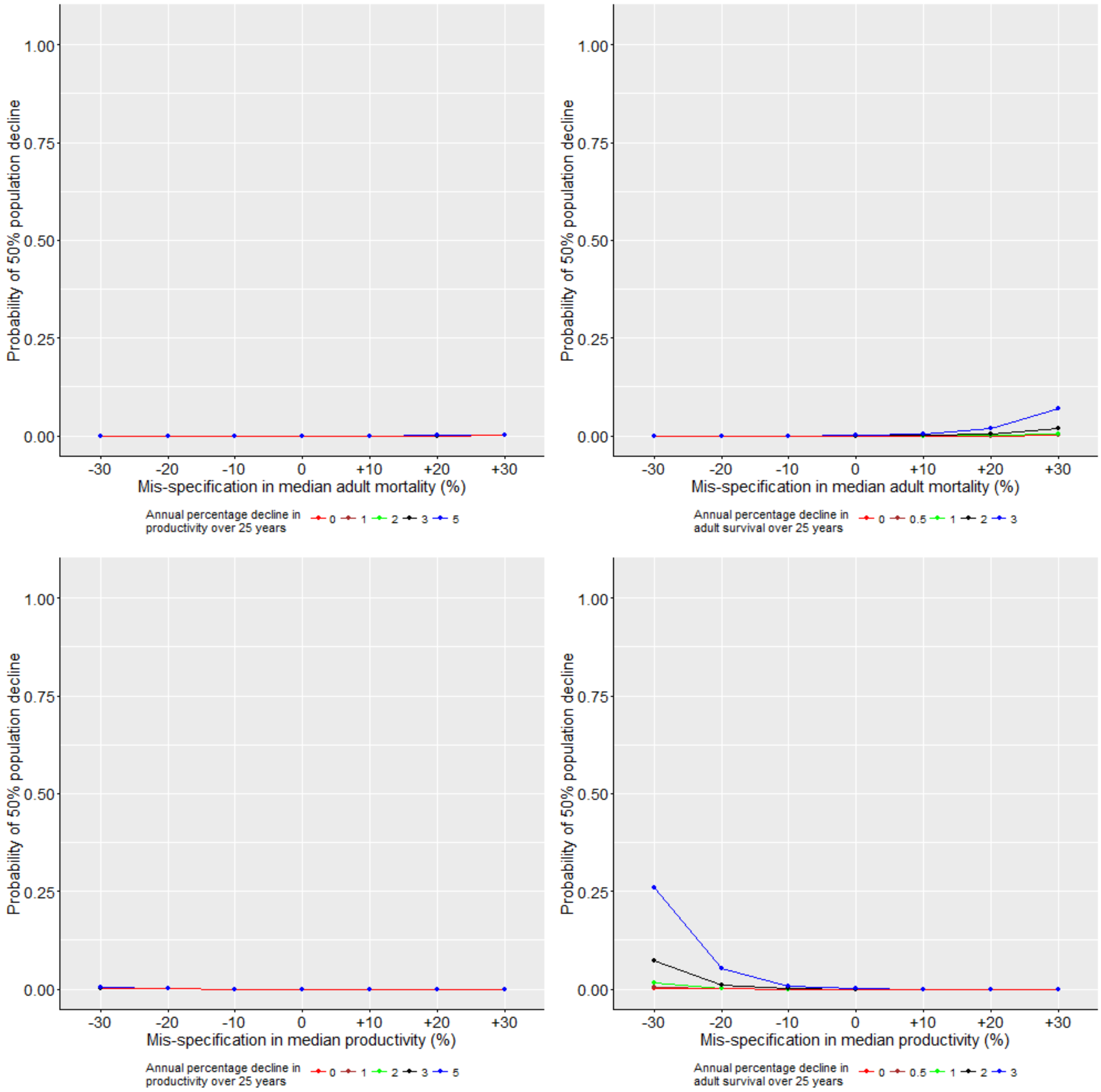
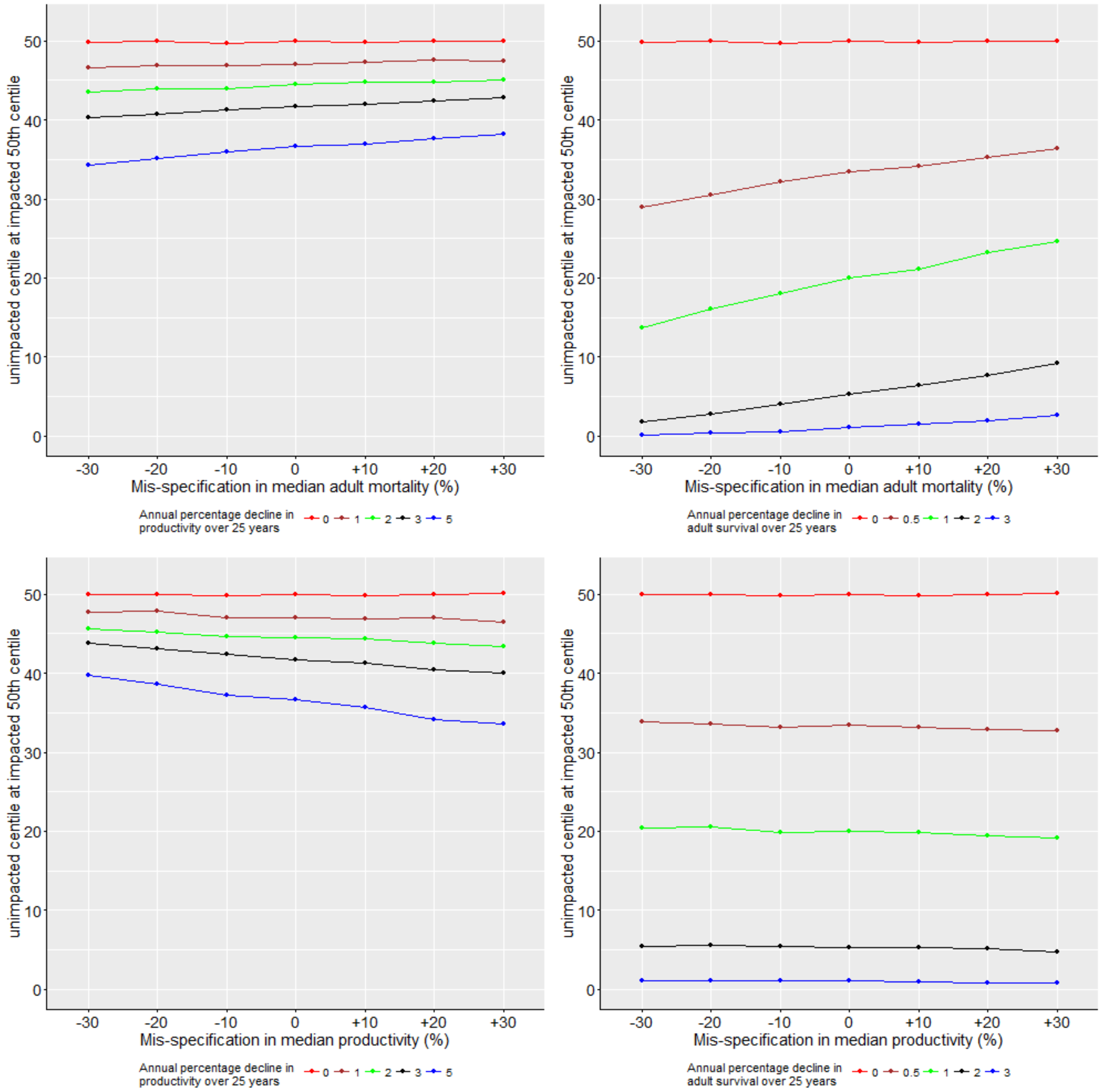


Figure A2.6h. PVA Metric F for St Abb's Guillemots – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



7. **Guillemots at Fowlsheugh SPA**:

Figure A2.7a. PVA Metric A for Fowlsheugh Guillemots – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

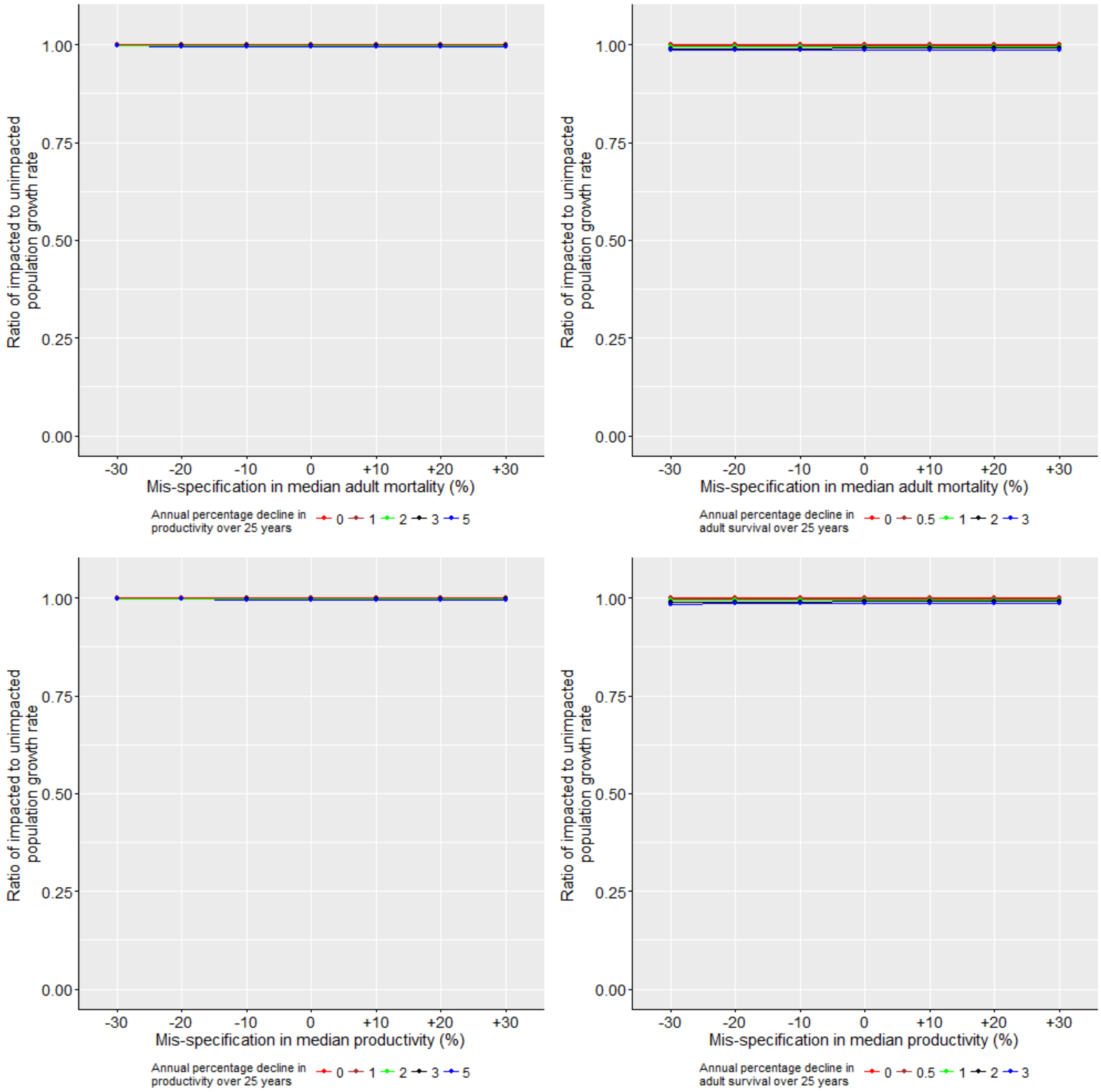


Figure A2.7b. PVA Metric B for Fowlsheugh Guillemots – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

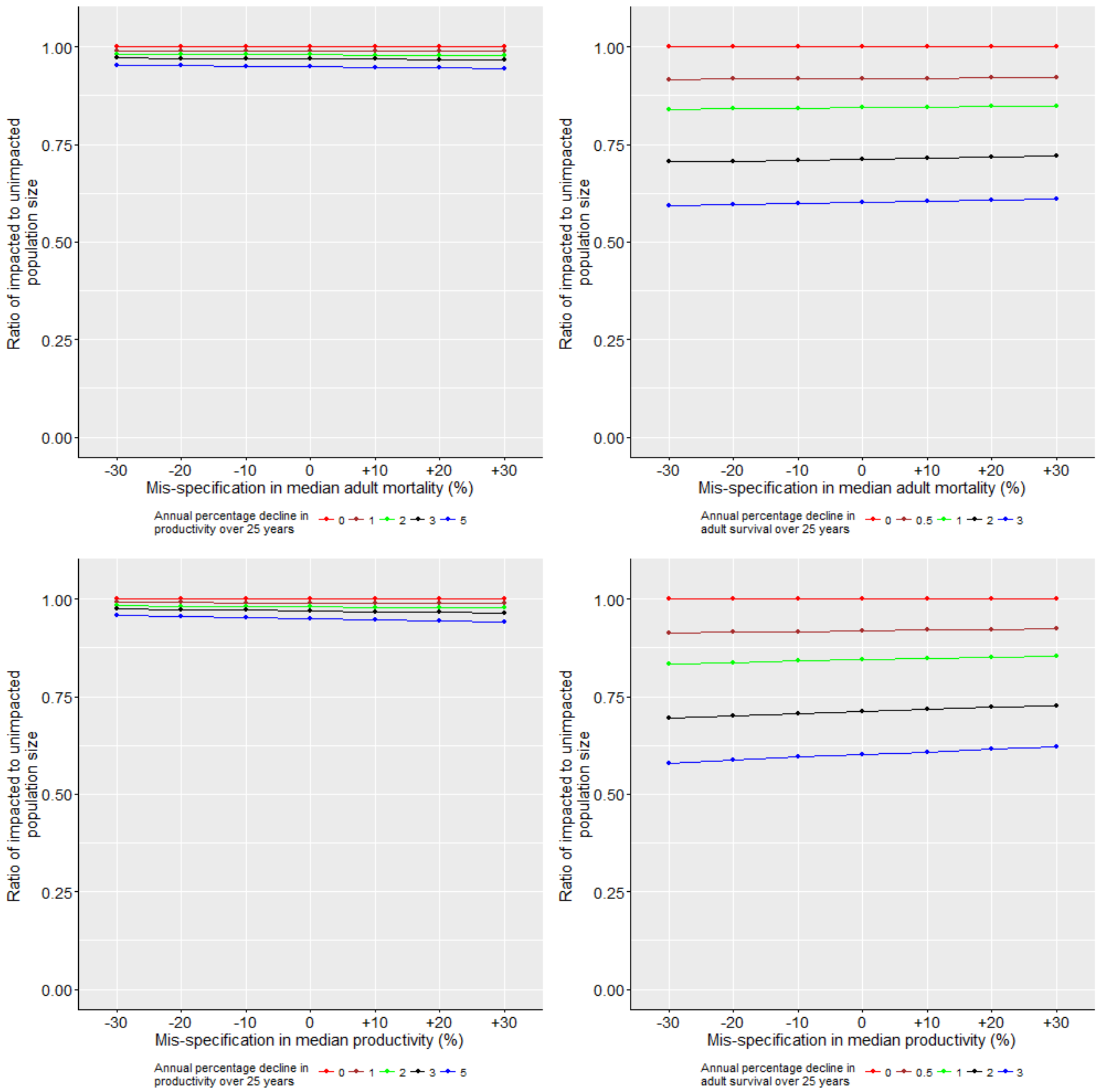


Figure A2.7c. PVA Metric C for Fowlsheugh Guillemots – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

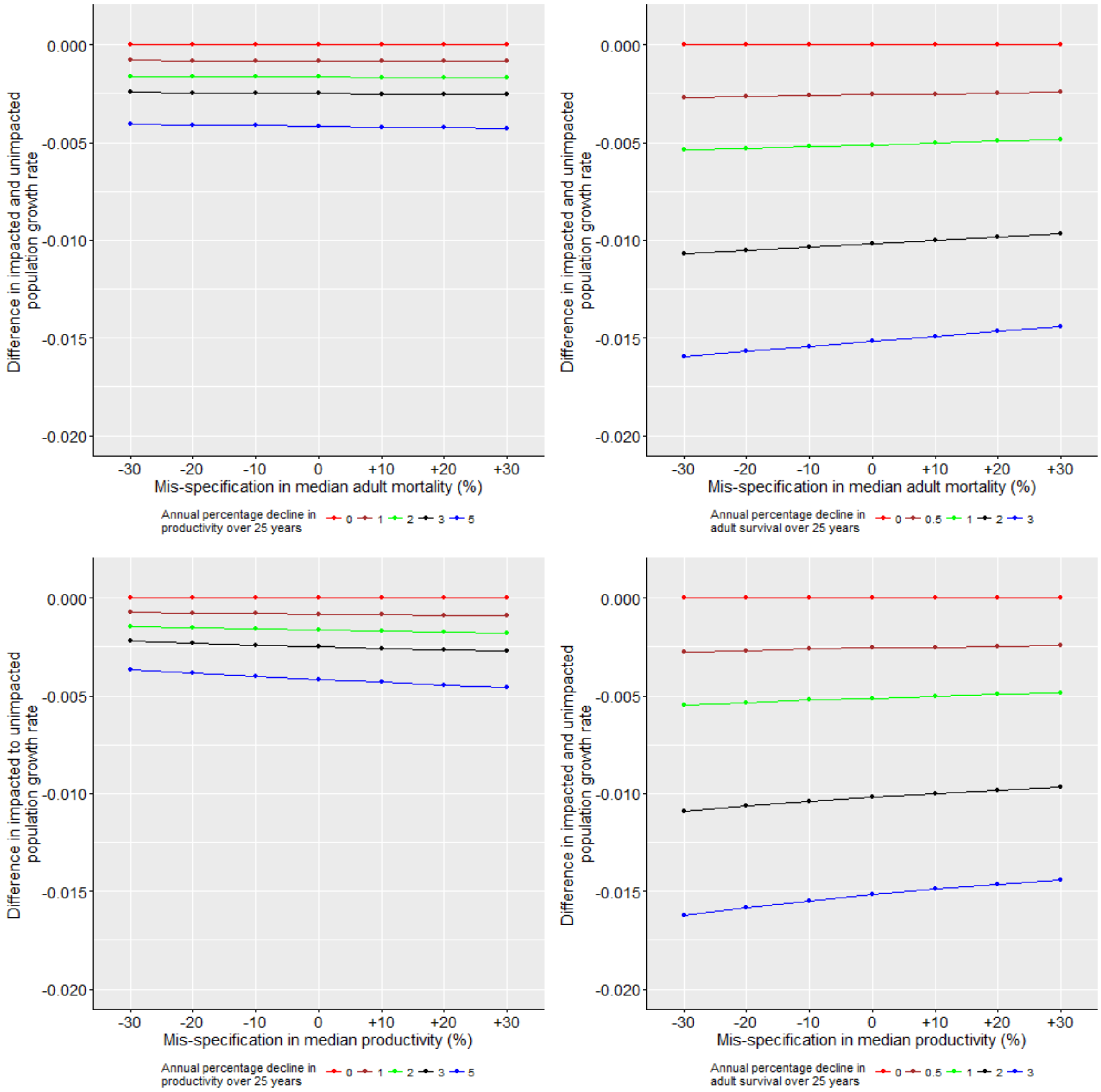


Figure A2.7d. PVA Metric D for Fowlsheugh Guillemots – difference in population size at 2041, comparing impacted population vs. un-impacted population.

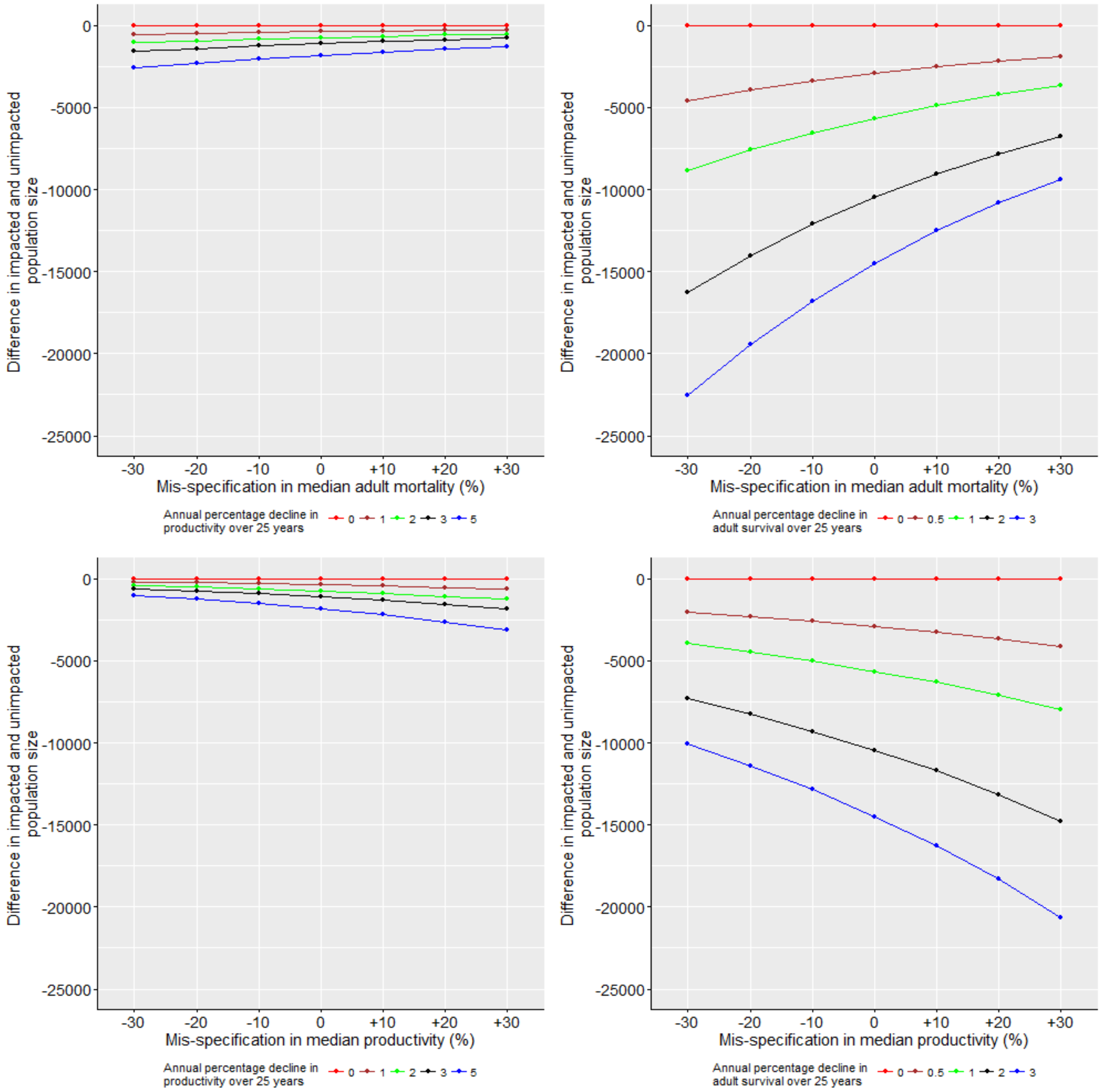


Figure A2.7e. PVA Metric E1 for Fowlsheugh Guillemots – probability of population decline greater than 10% from 2016-2041.

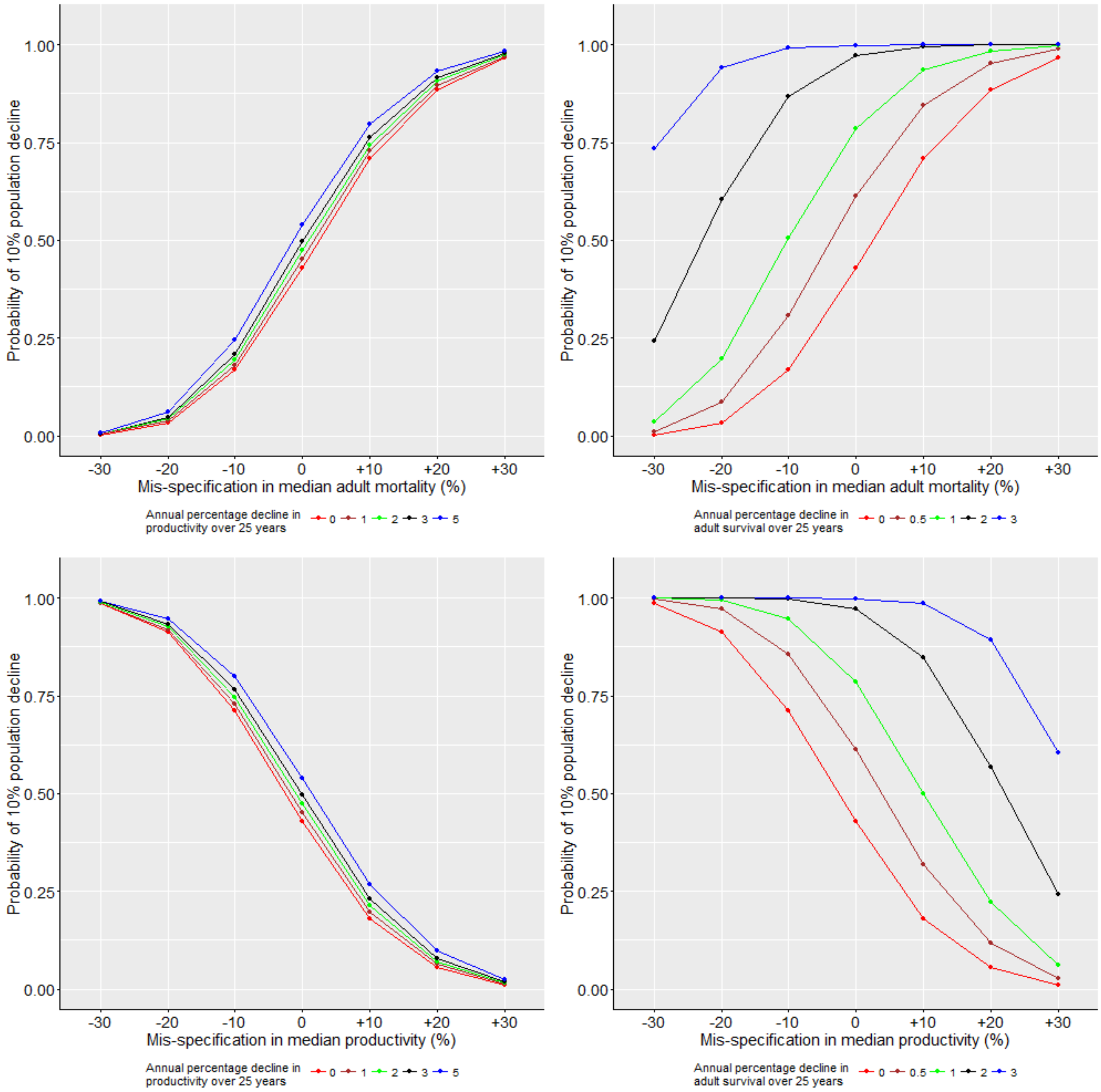


Figure A2.7f. PVA Metric E2 for Fowlsheugh Guillemots – probability of population decline greater than 25% from 2016-2041.

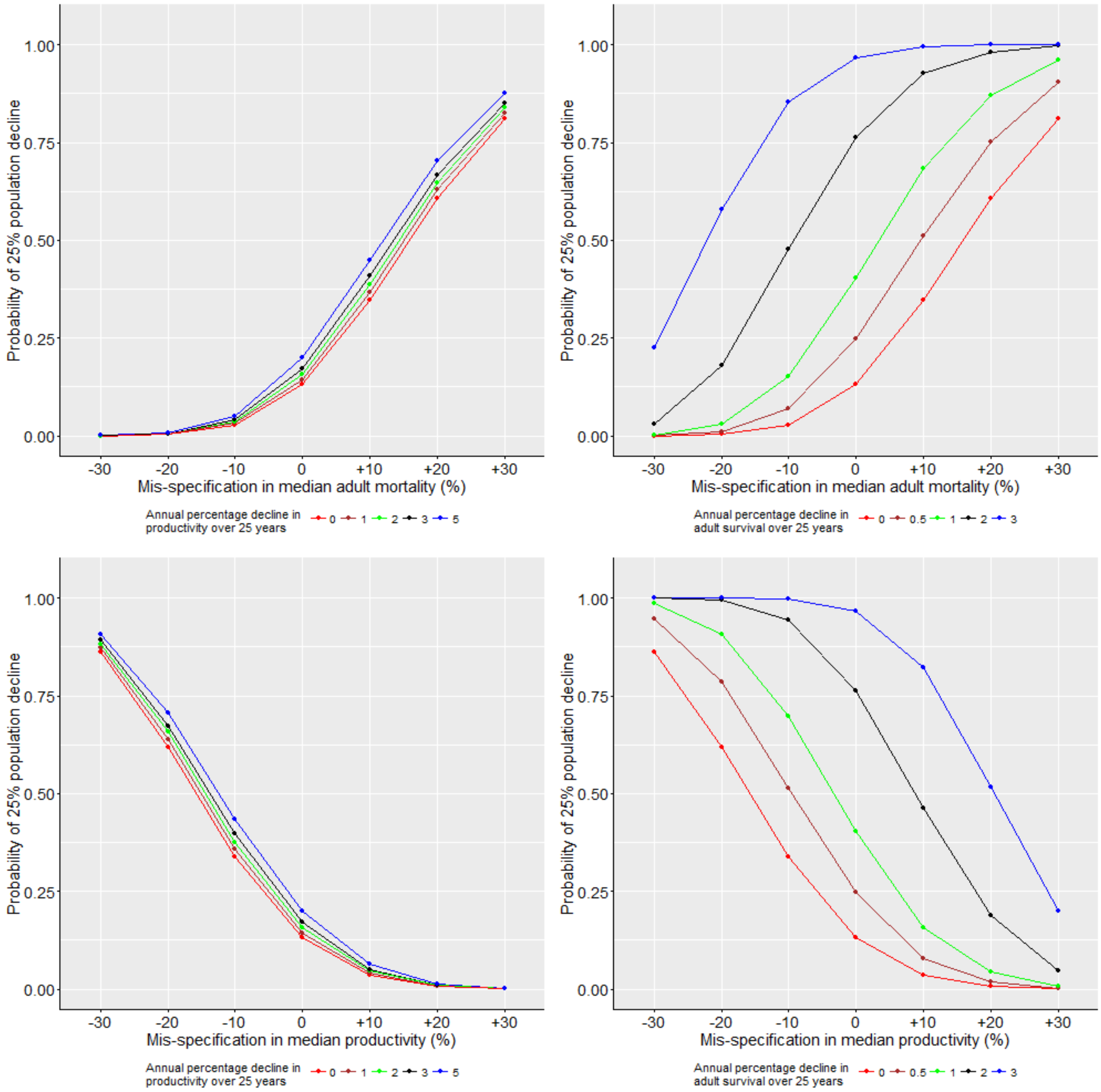


Figure A2.7g. PVA Metric E3 for Fowlsheugh Guillemots – probability of population decline greater than 50% from 2016-2041.

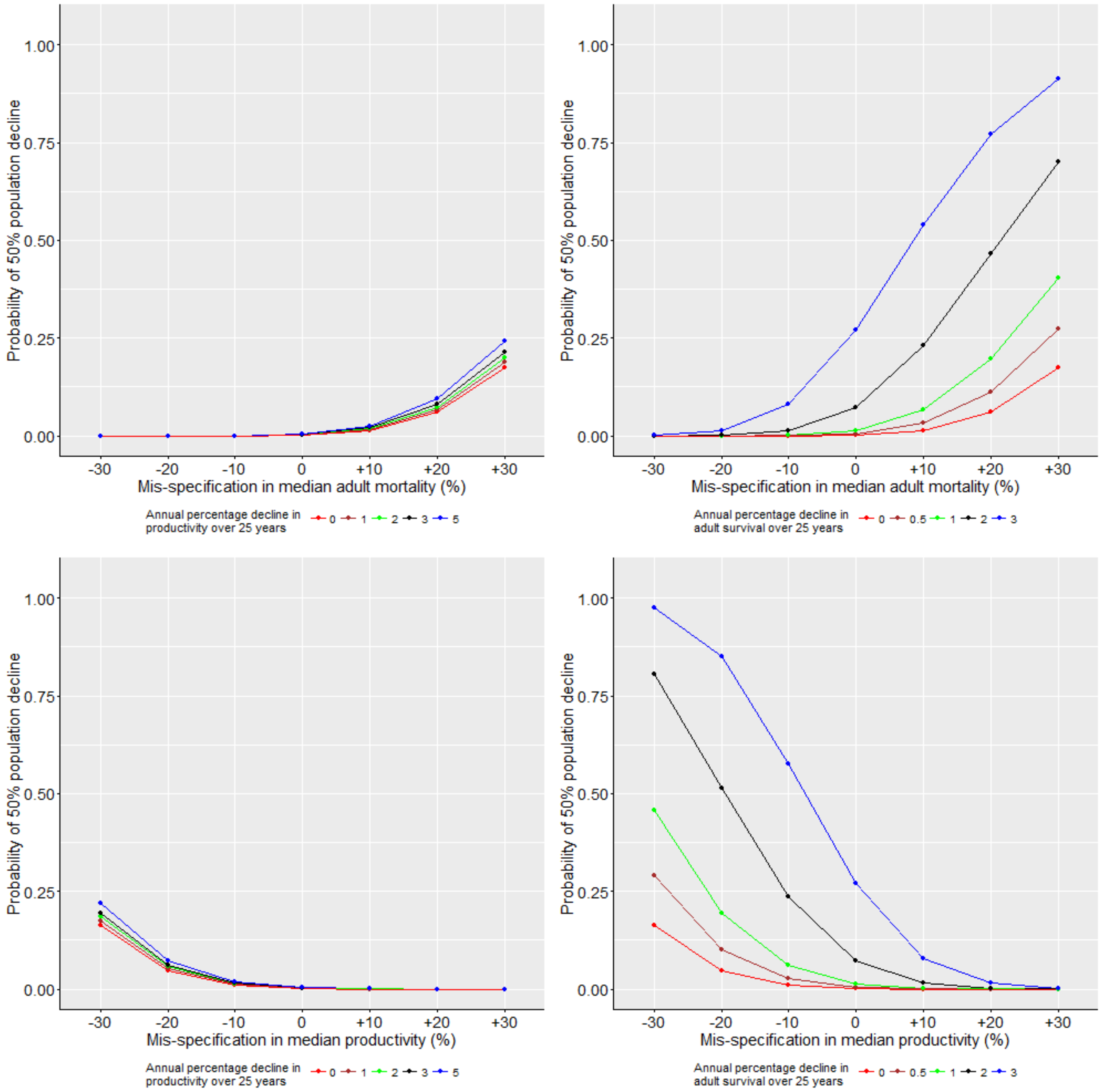
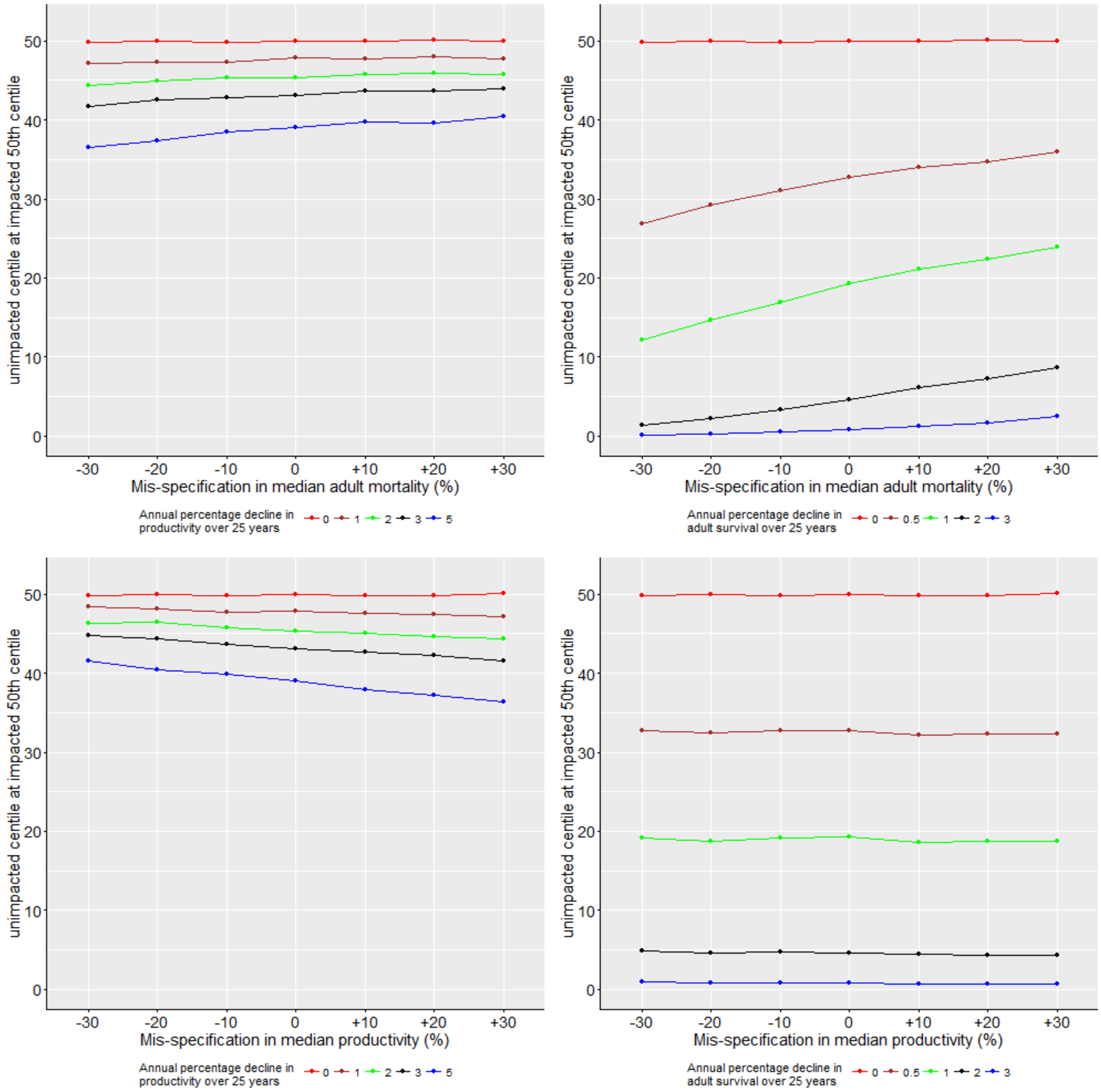


Figure A2.7h. PVA Metric F for Fowlsheugh Guillemots – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



8. **Guillemots at Buchan Ness to Collieston Coast SPA**:

Figure A2.8a. PVA Metric A for Buchan Ness Guillemots – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

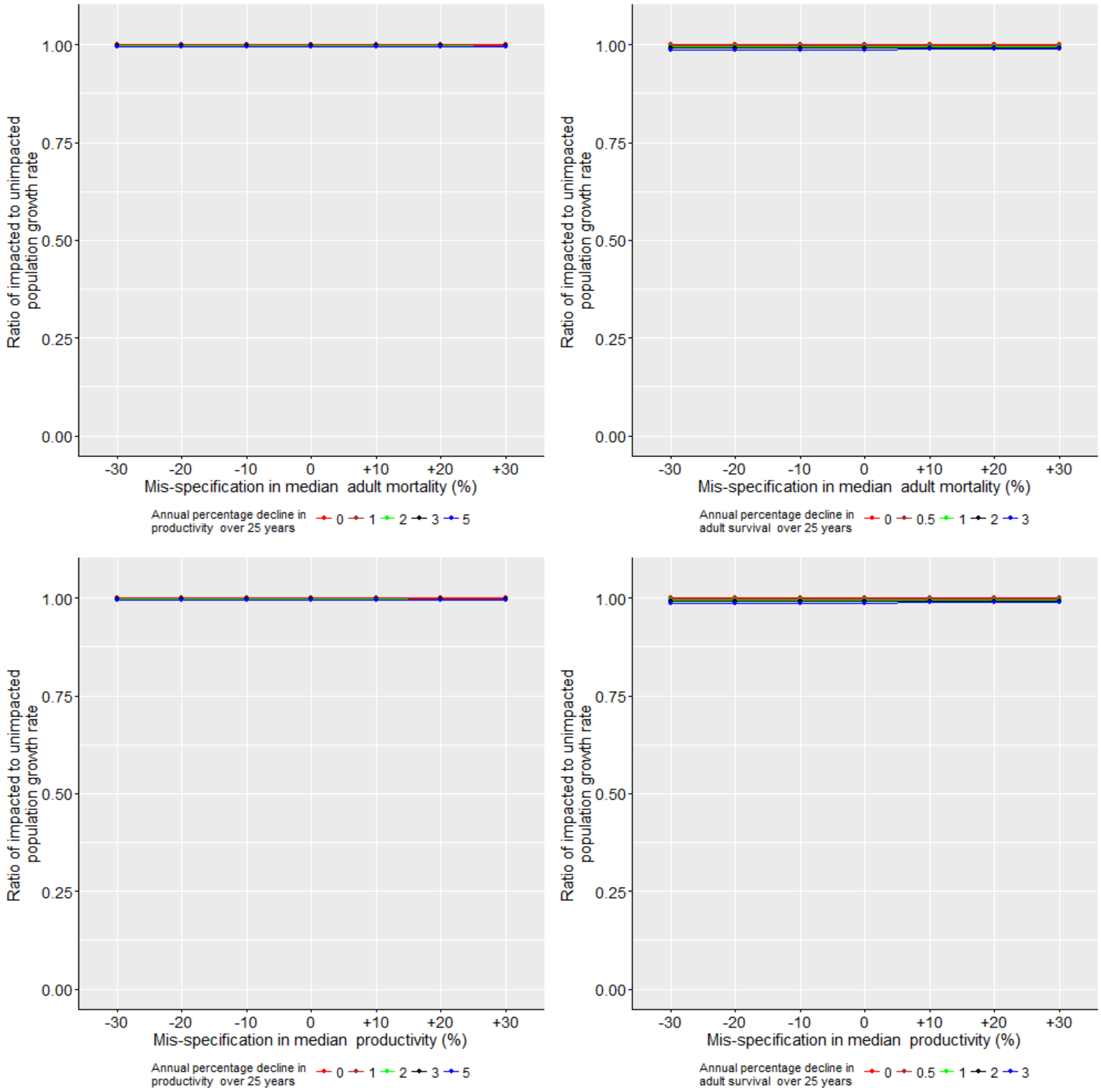


Figure A2.8b. PVA Metric B for Buchan Ness Guillemots – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

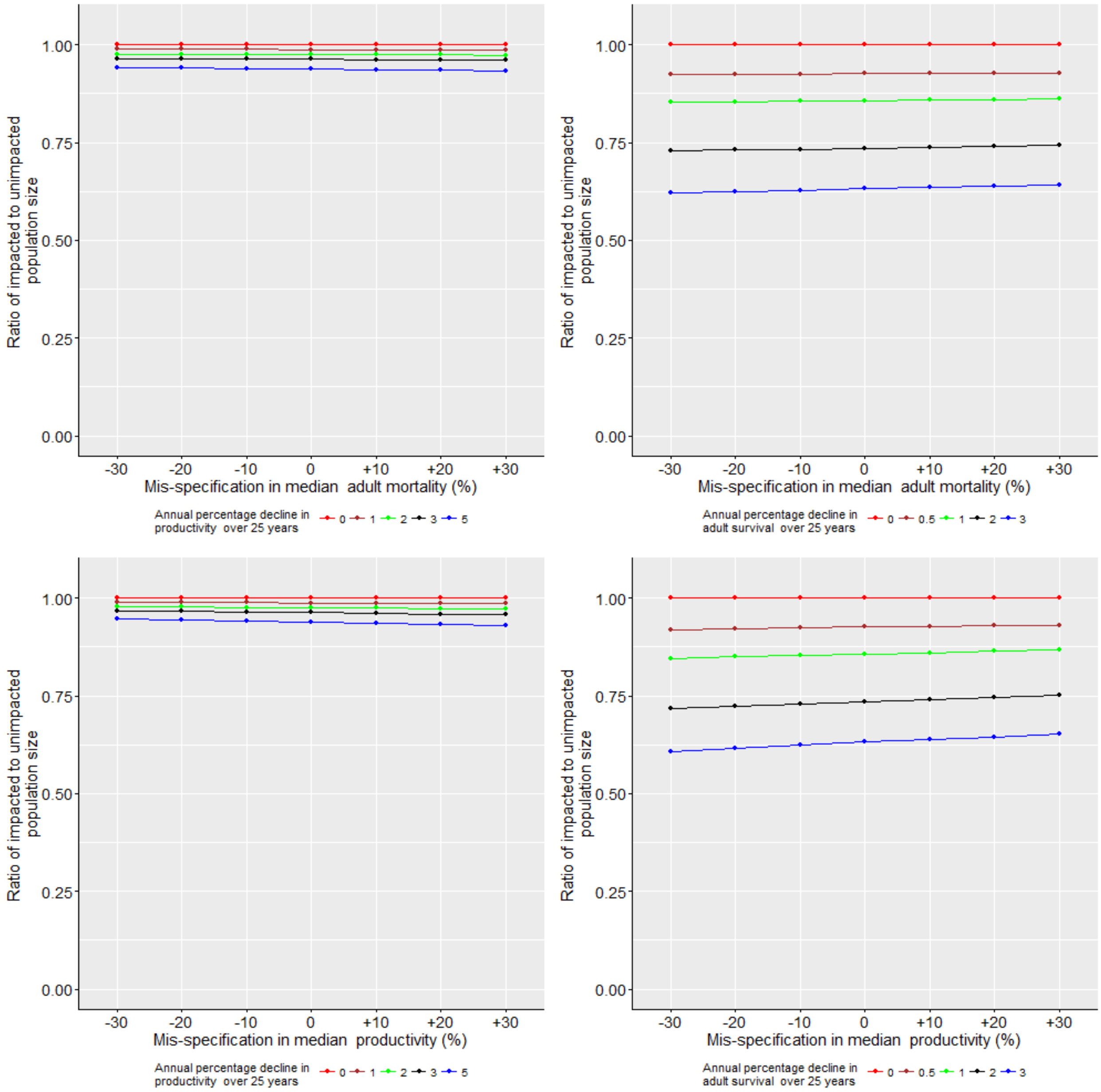


Figure A2.8c. PVA Metric C for Buchan Ness Guillemots – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

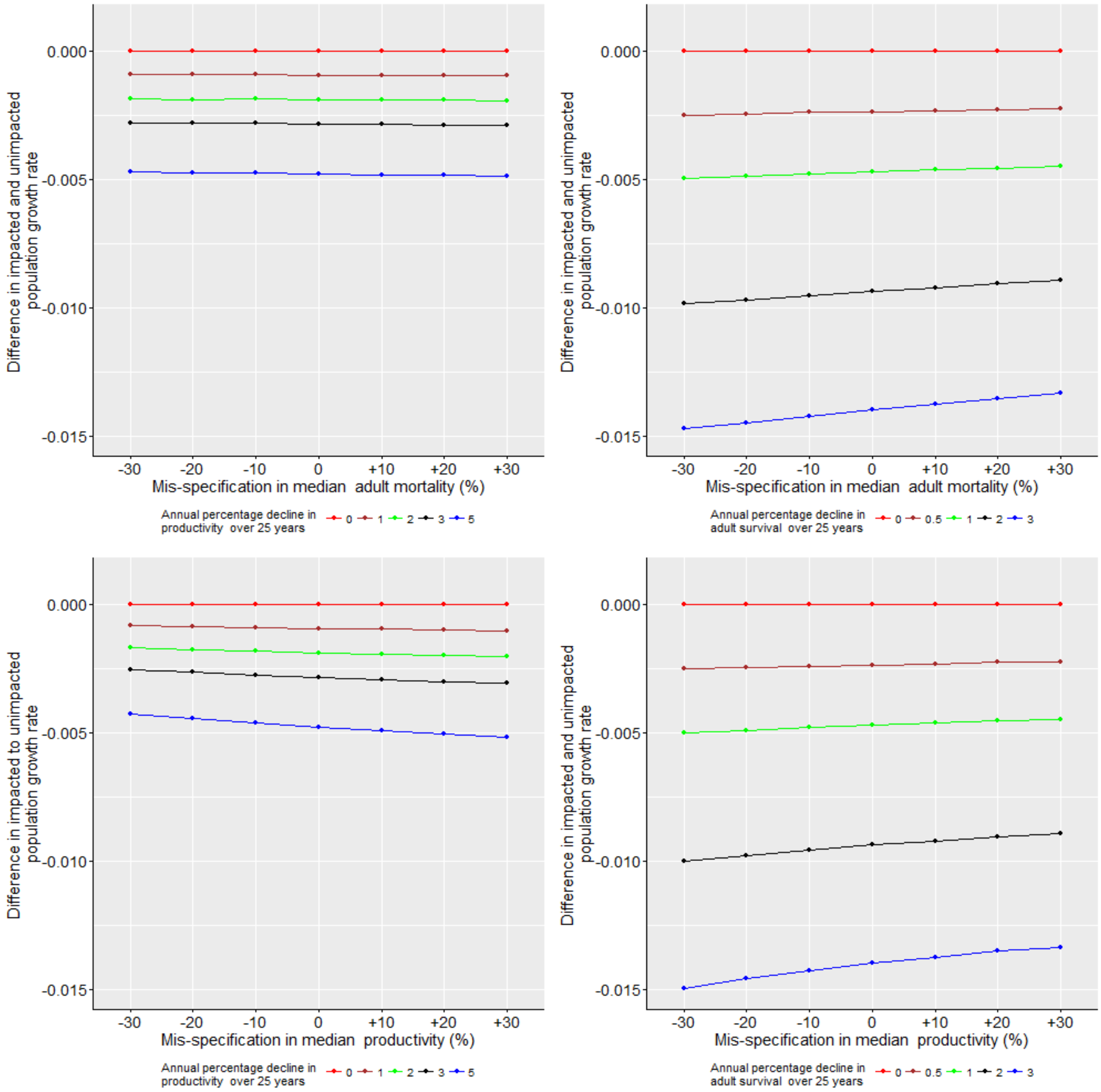


Figure A2.8d. PVA Metric D for Buchan Ness Guillemots – difference in population size at 2041, comparing impacted population vs. un-impacted population.

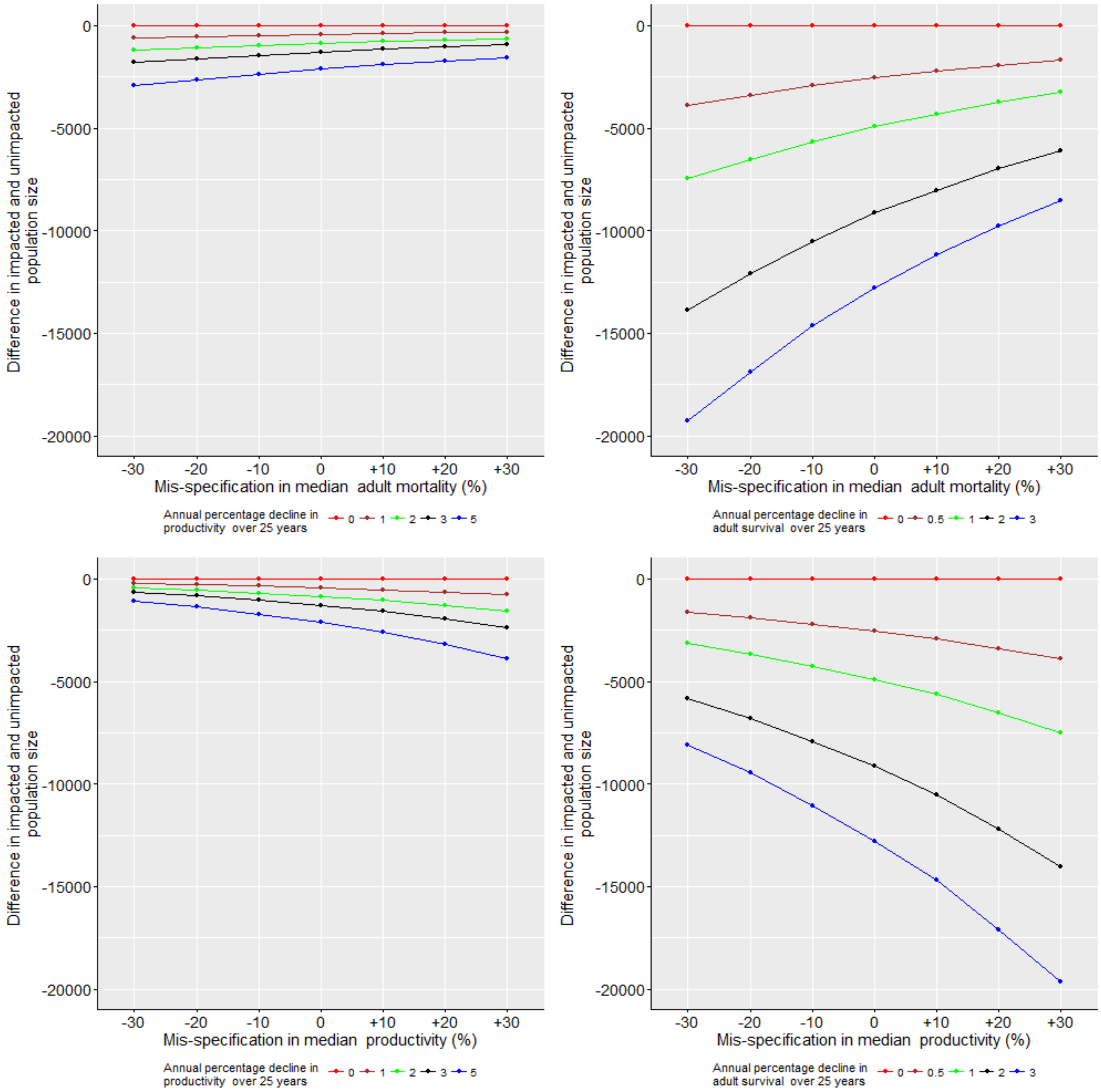


Figure A2.8e. PVA Metric E1 for Buchan Ness Guillemots – probability of population decline greater than 10% from 2016-2041.

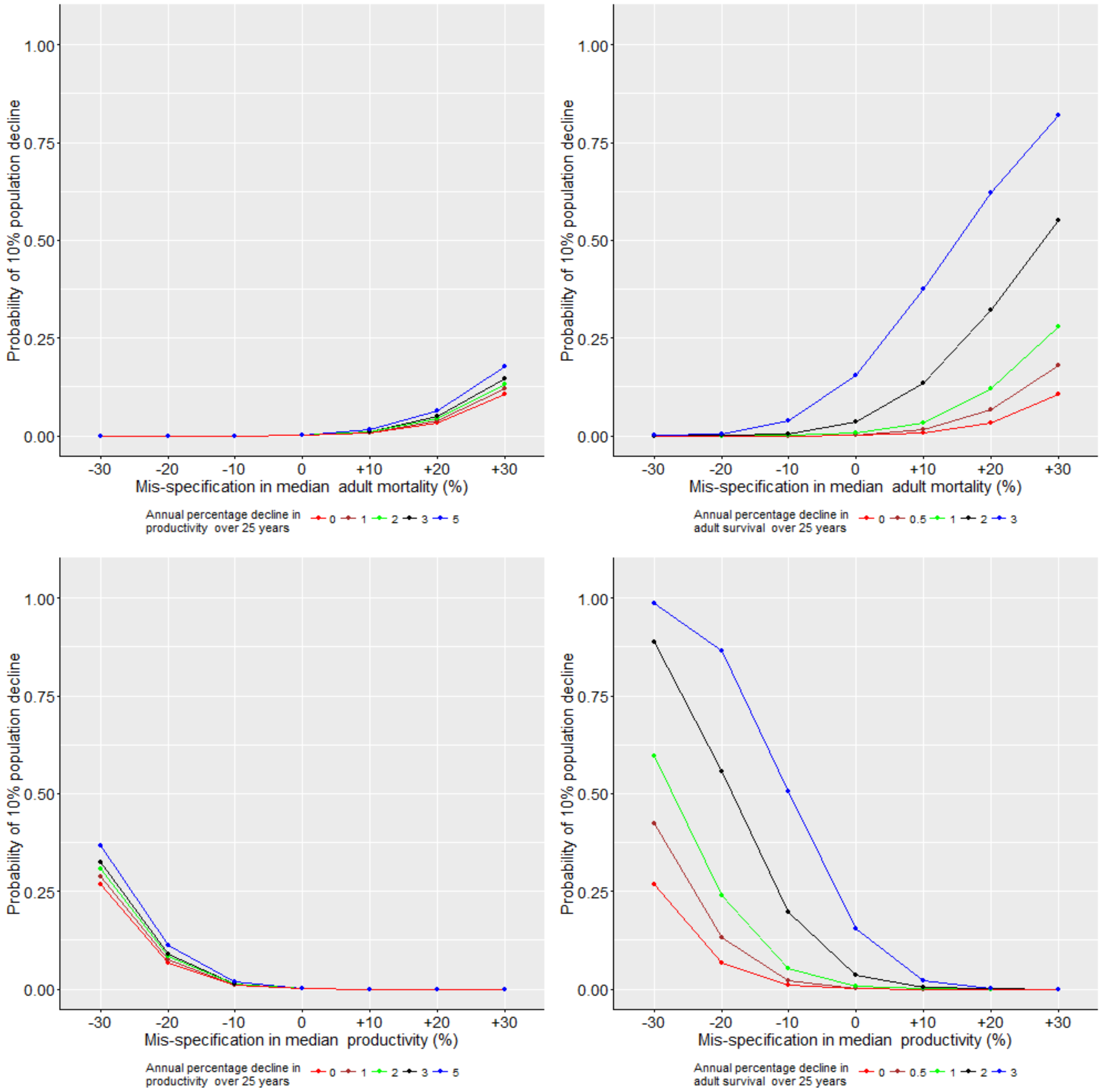


Figure A2.8f. PVA Metric E2 for Buchan Ness Guillemots – probability of population decline greater than 25% from 2016-2041.

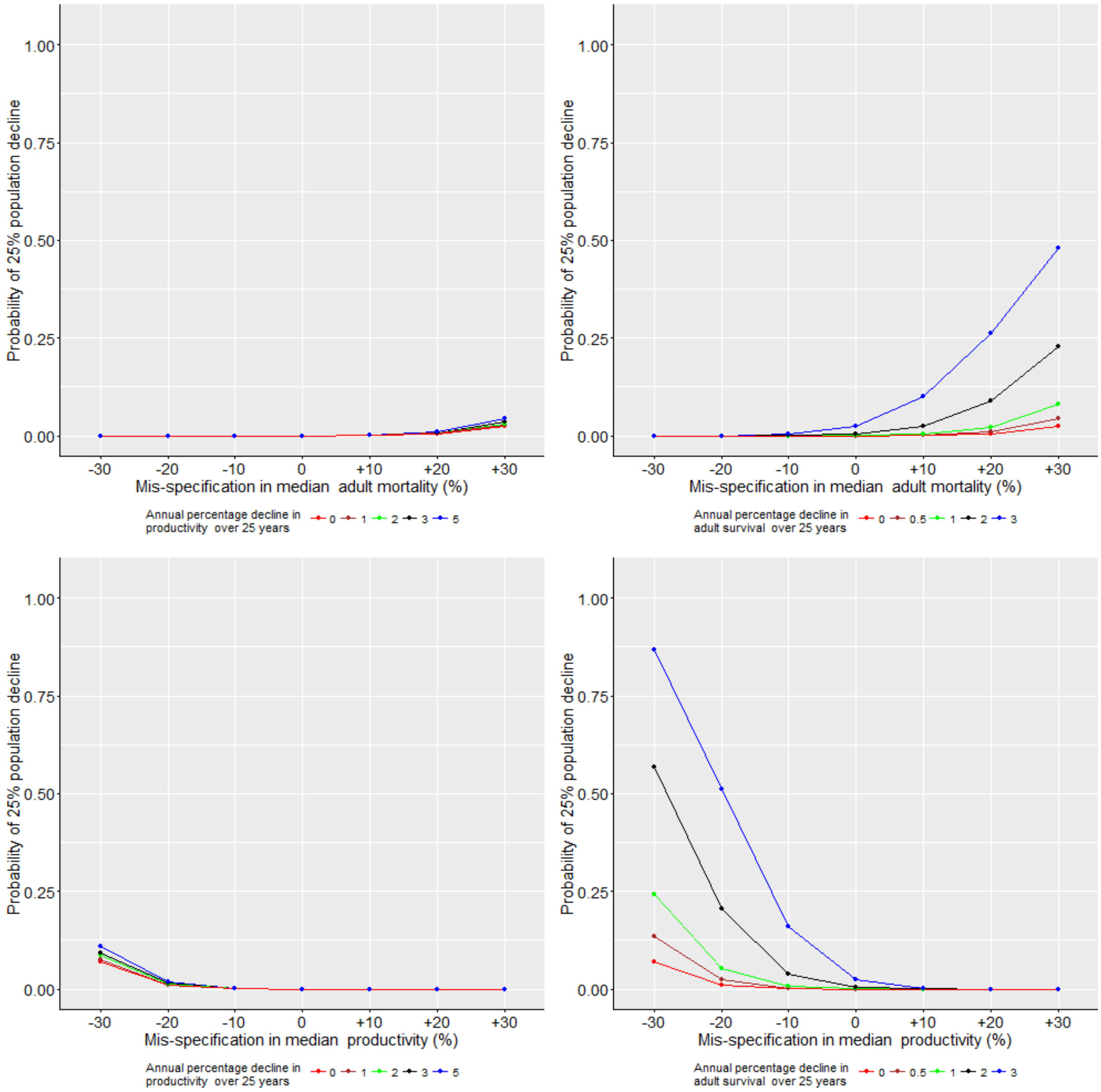


Figure A2.8g. PVA Metric E3 for Buchan Ness Guillemots – probability of population decline greater than 50% from 2016-2041.

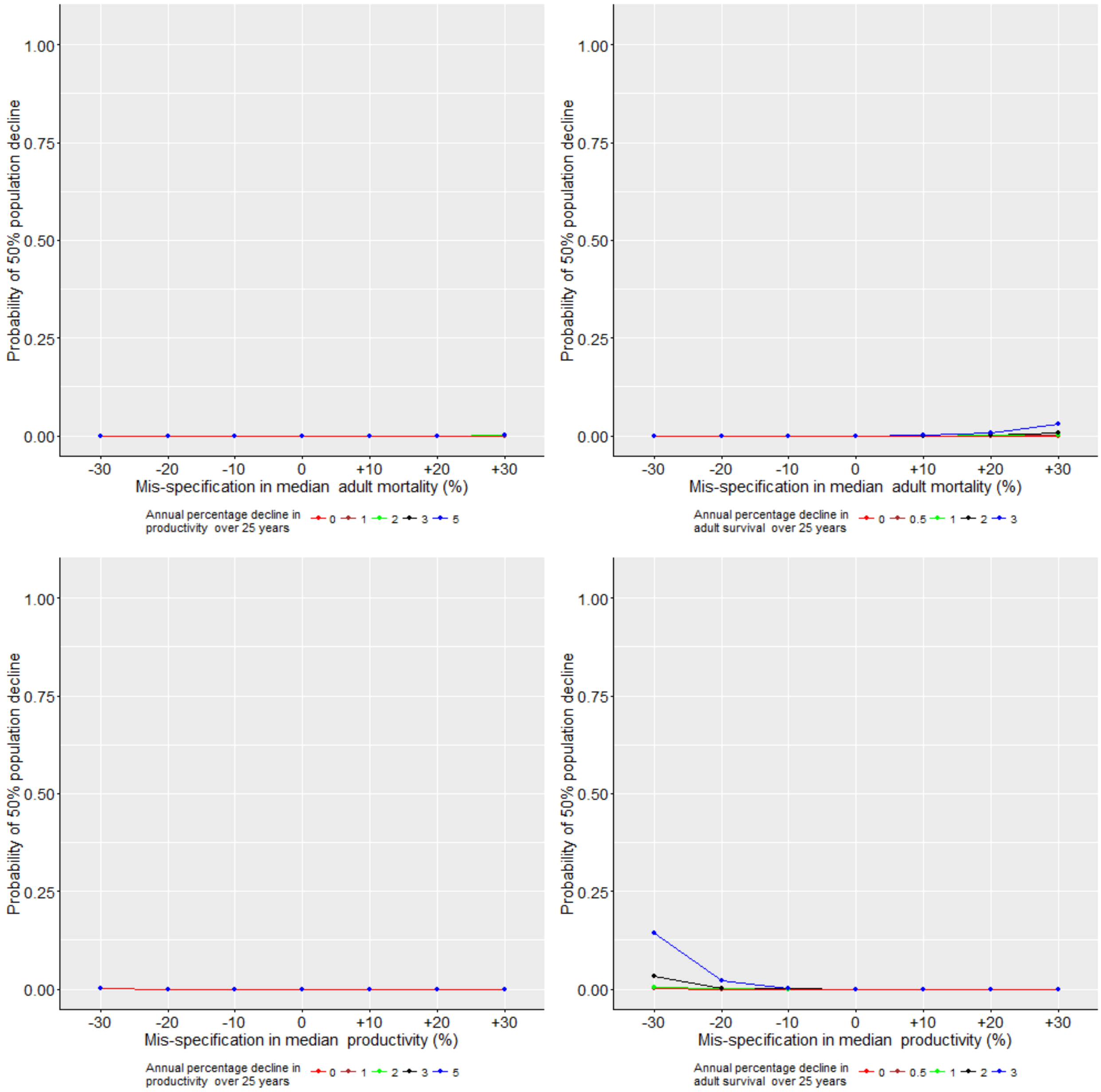
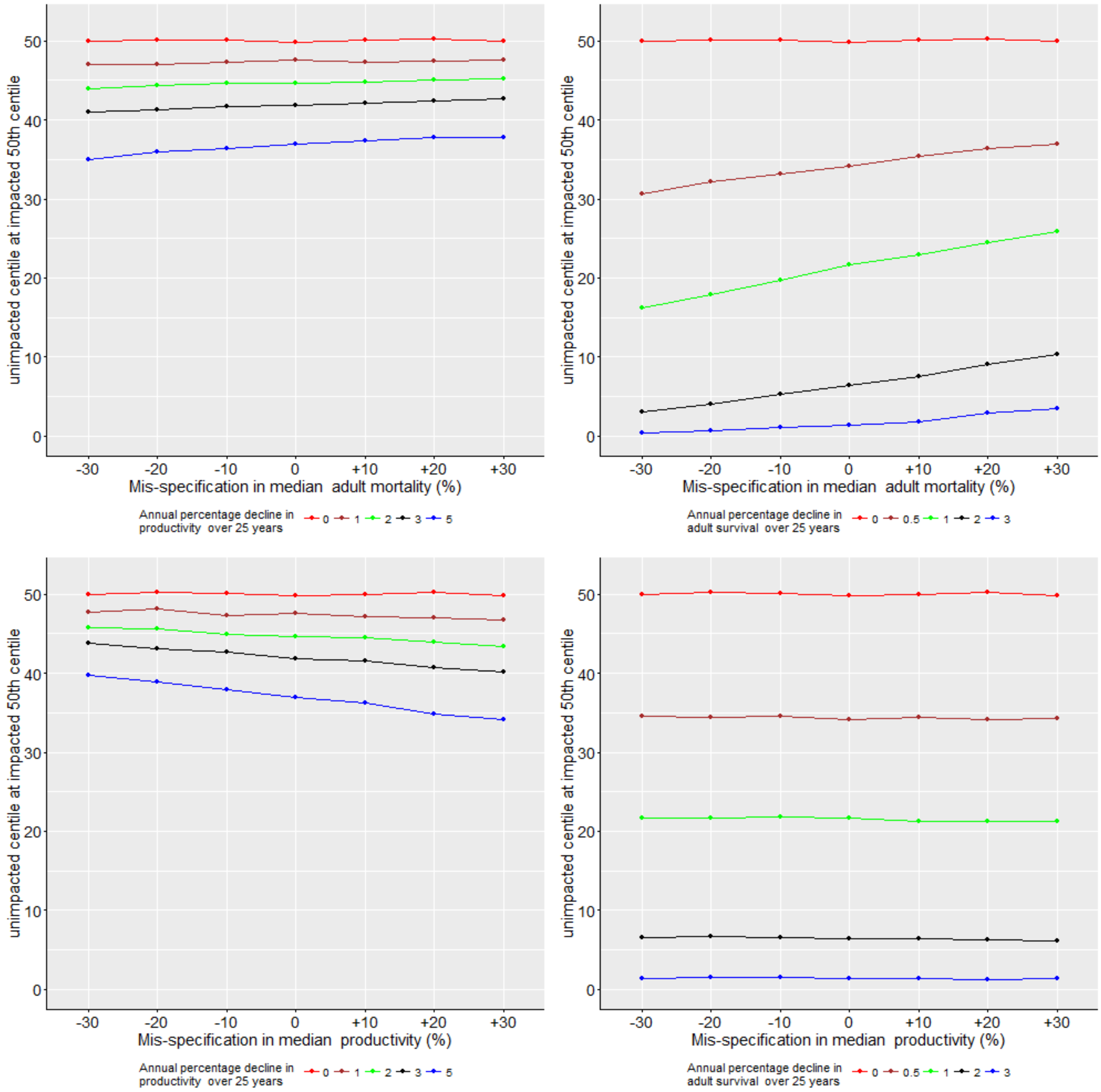


Figure A2.8h. PVA Metric F for Buchan Ness Guillemots – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



9. **Razorbills at Forth Islands SPA**:

Figure A2.9a. PVA Metric A for Forth Razorbills – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

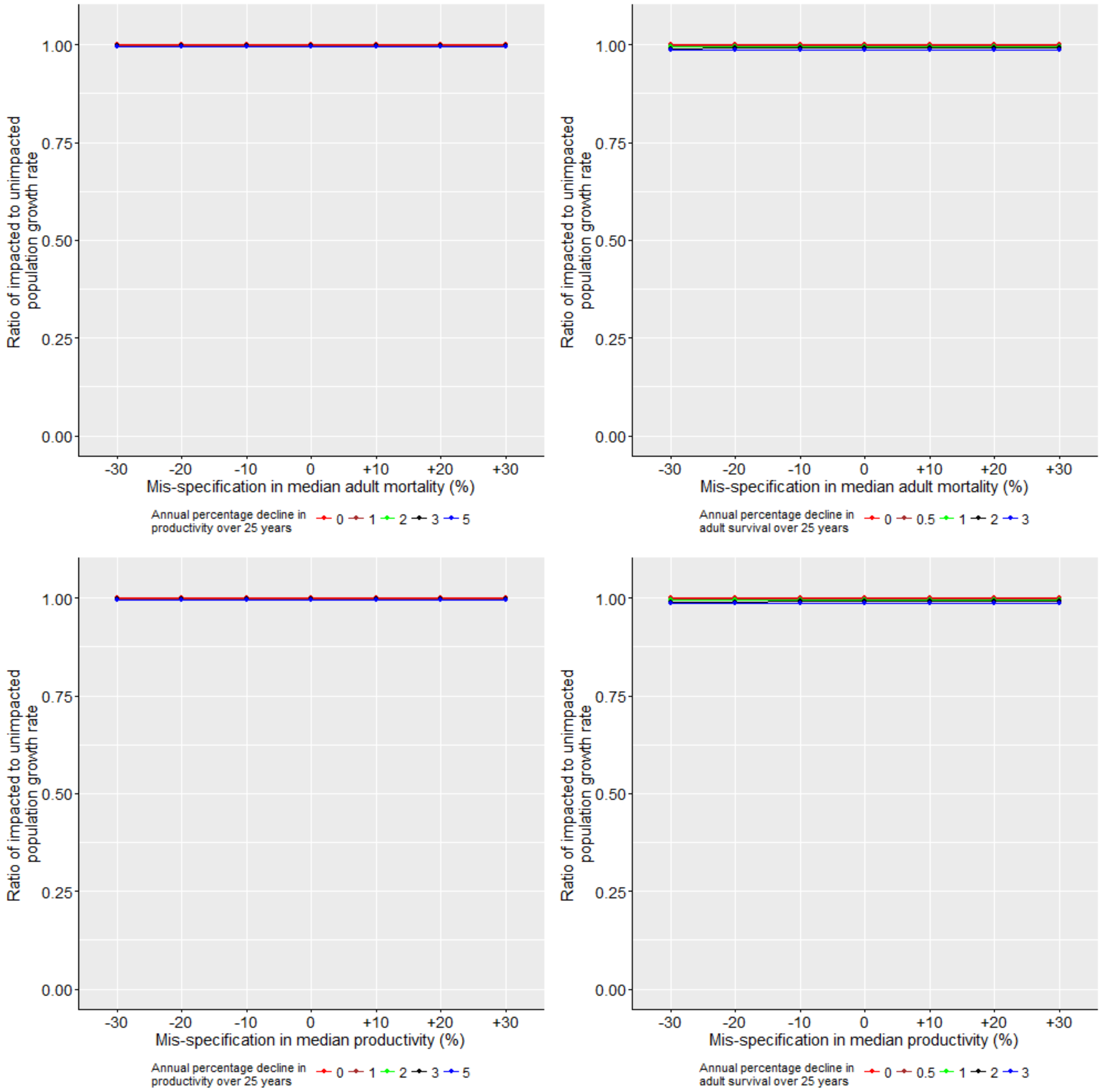


Figure A2.9b. PVA Metric B for Forth Razorbills – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

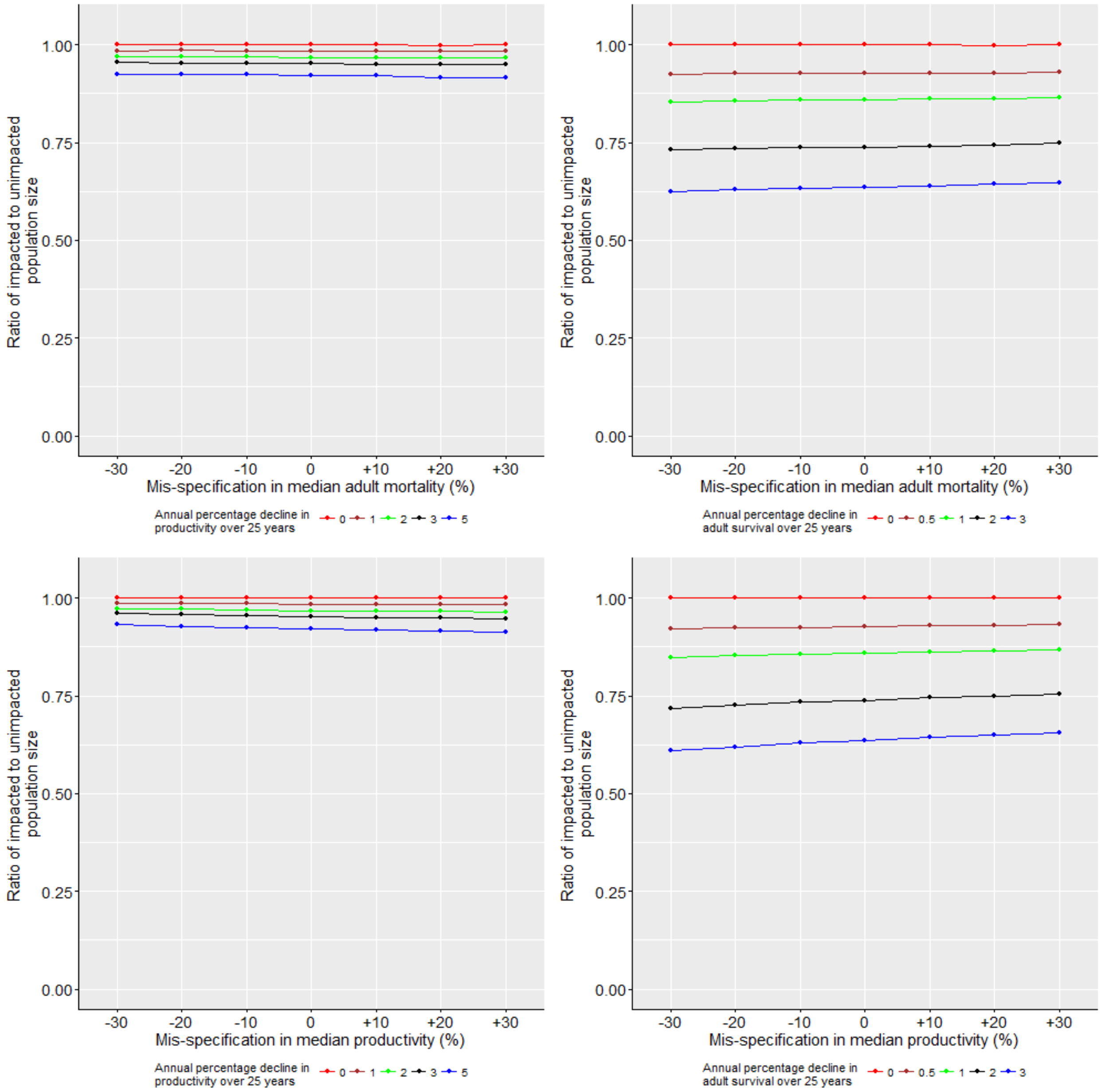


Figure A2.9c. PVA Metric C for Forth Razorbills – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

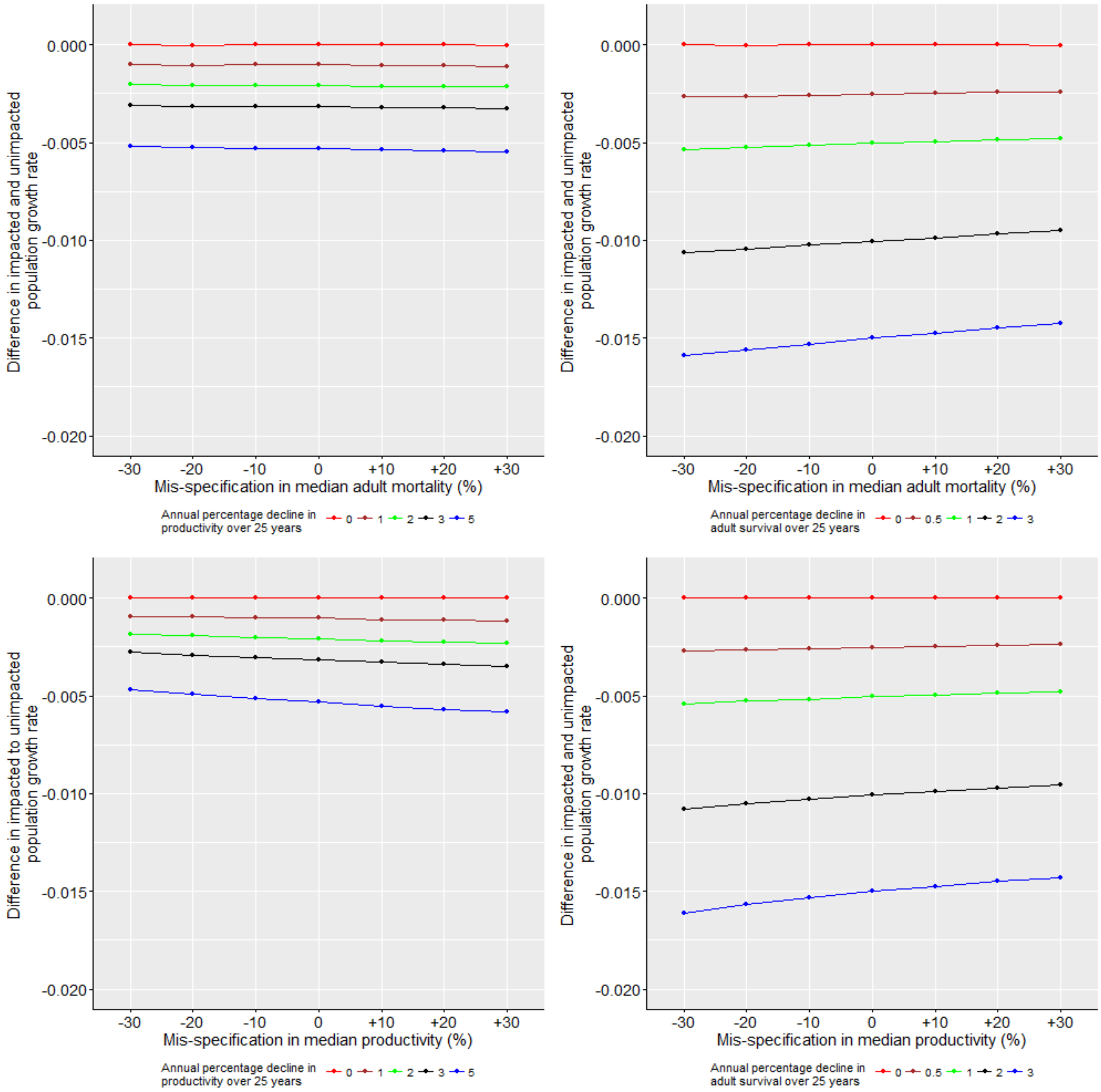


Figure A2.9d. PVA Metric D for Forth Razorbills – difference in population size at 2041, comparing impacted population vs. un-impacted population.

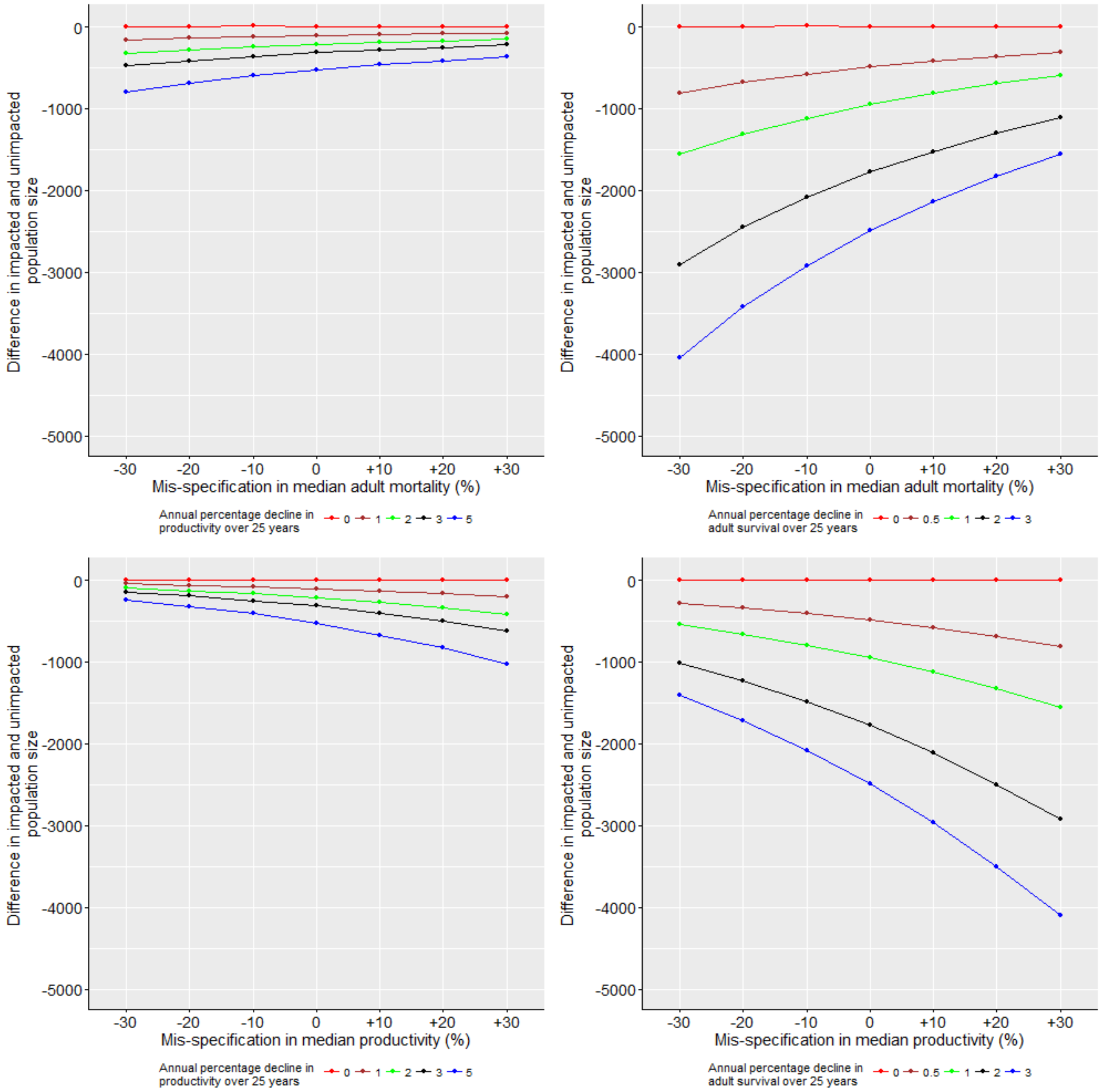


Figure A2.9e. PVA Metric E1 for Forth Razorbills – probability of population decline greater than 10% from 2016-2041.

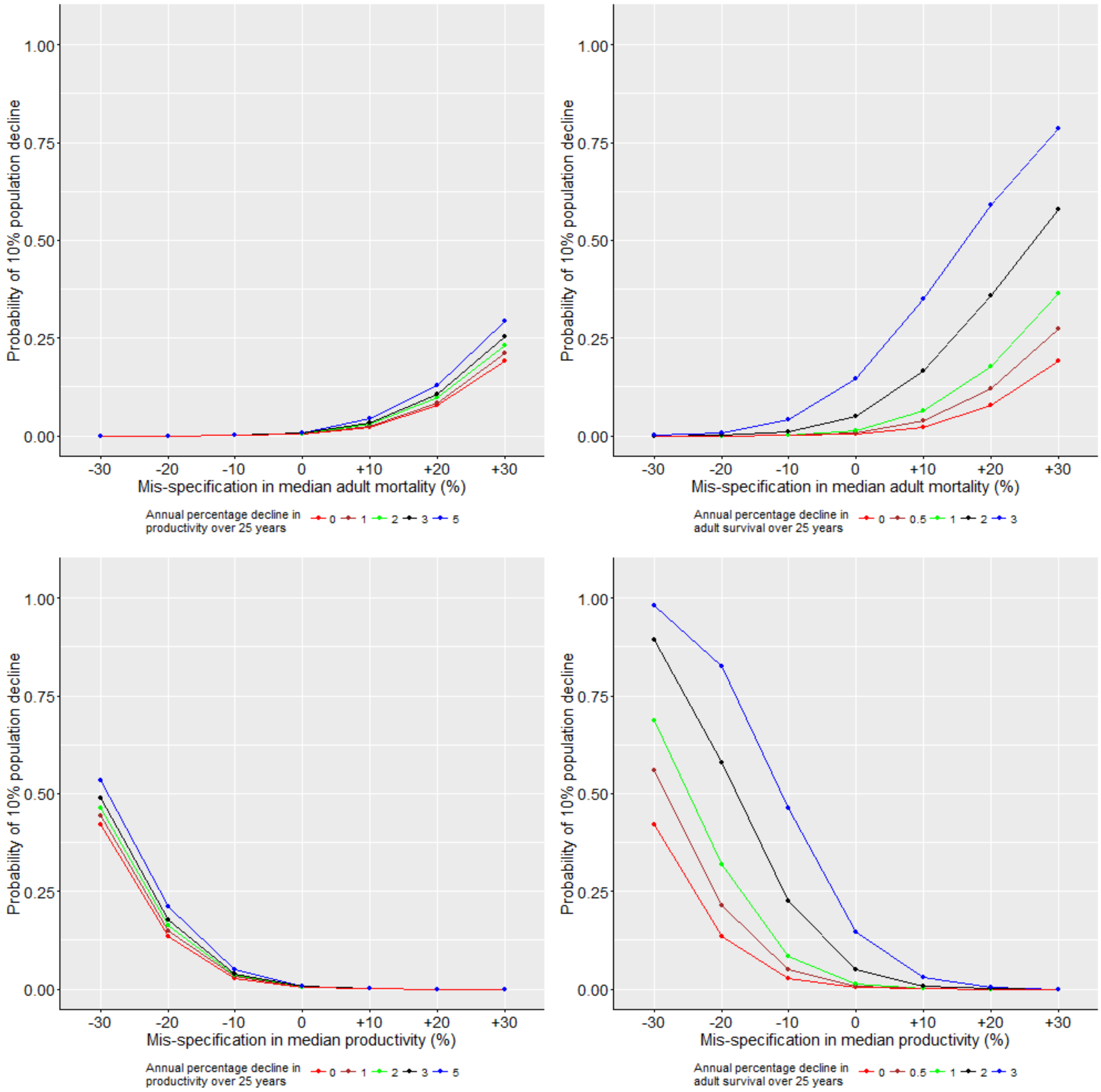


Figure A2.9f. PVA Metric E2 for Forth Razorbills – probability of population decline greater than 25% from 2016-2041.

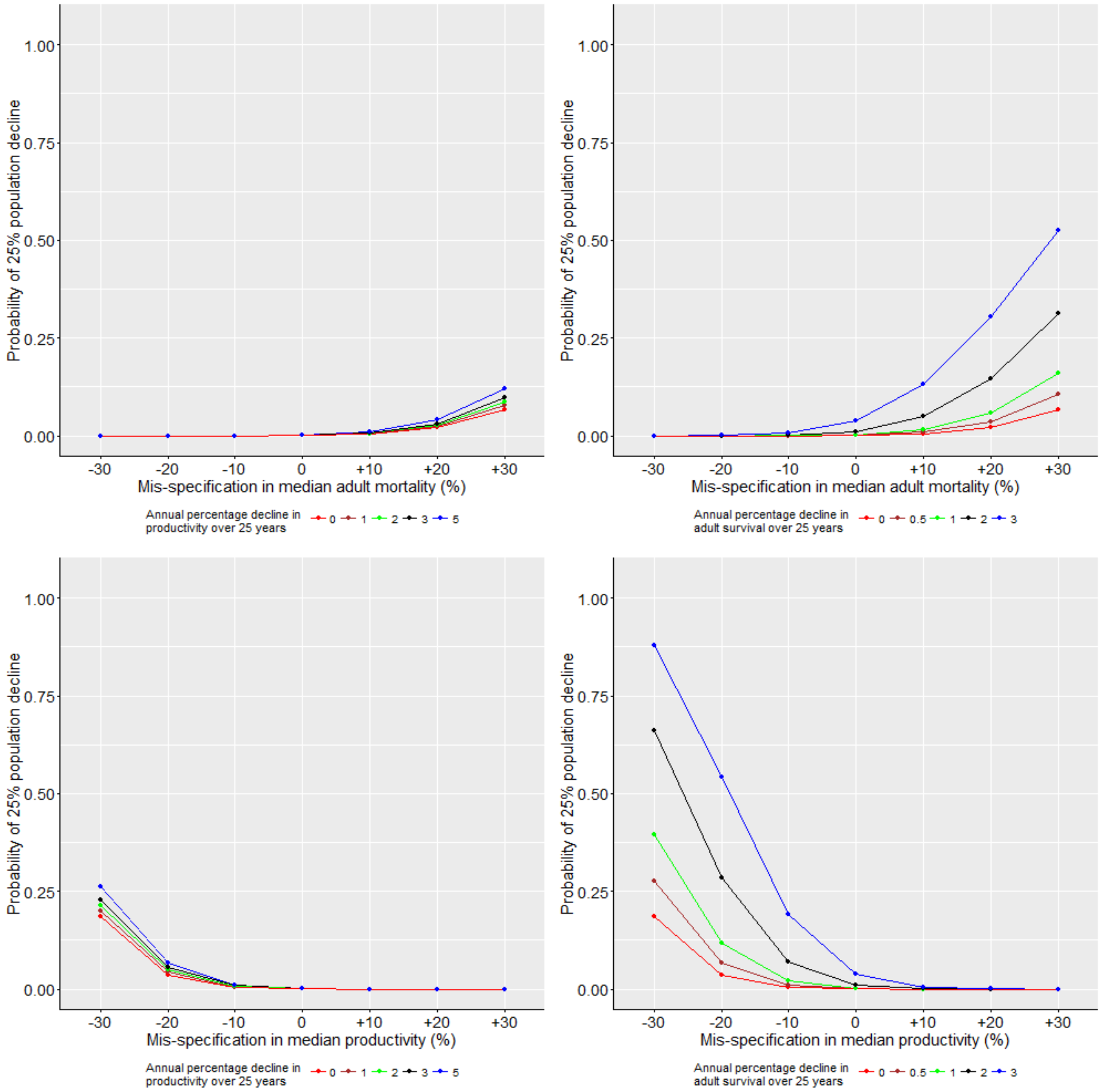


Figure A2.9g. PVA Metric E3 for Forth Razorbills – probability of population decline greater than 50% from 2016-2041.

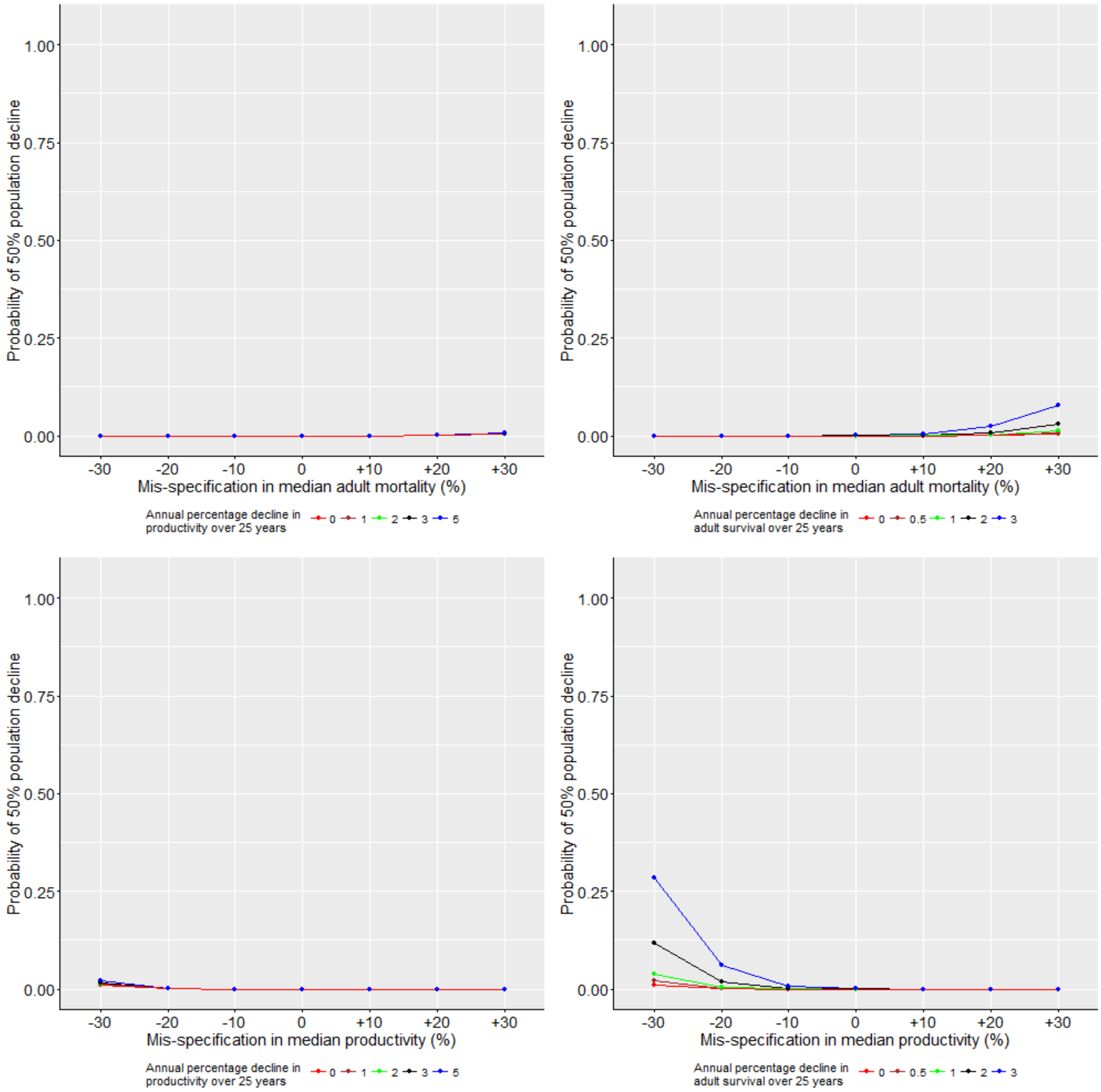
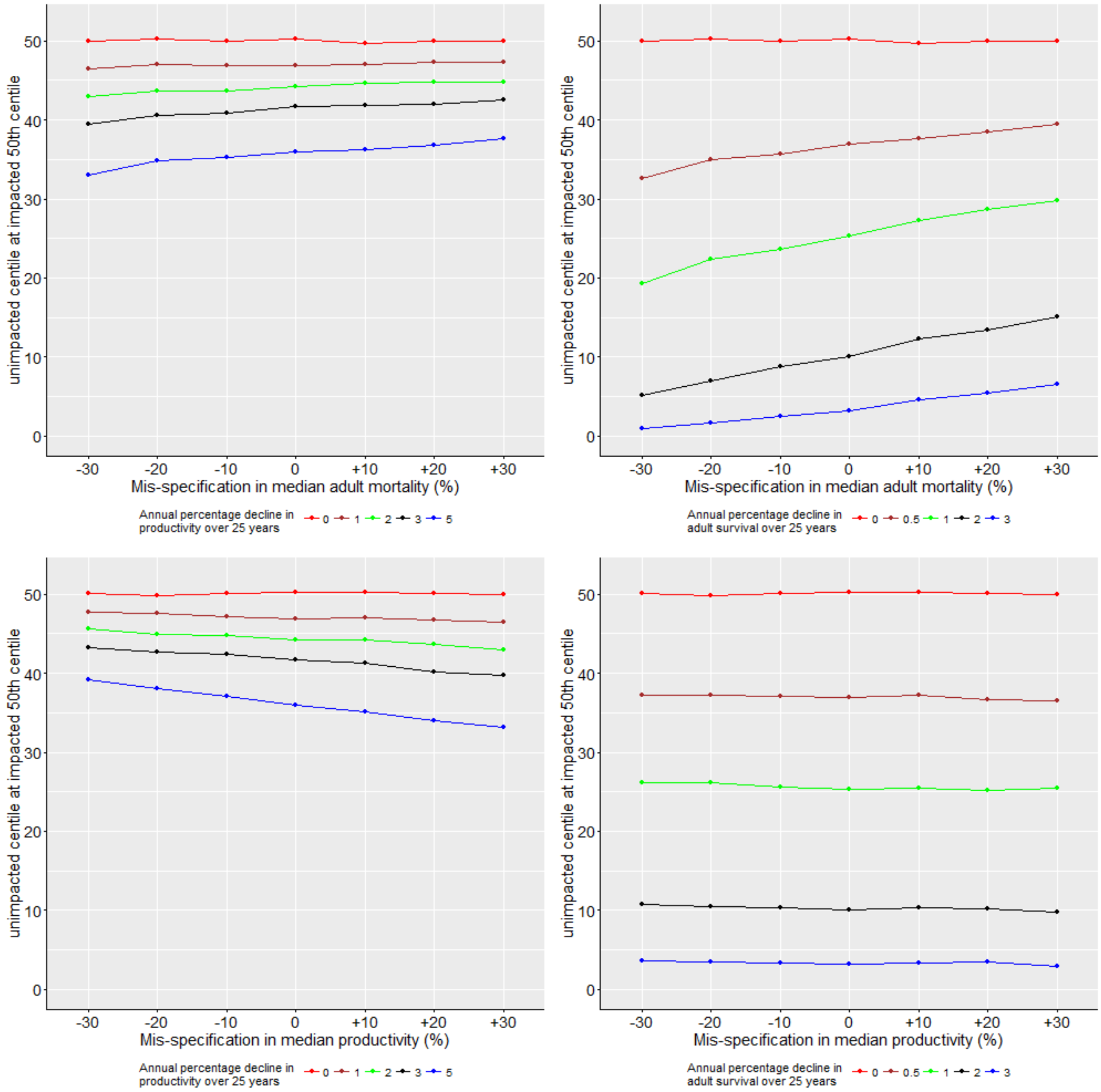


Figure A2.9h. PVA Metric F for Forth Razorbills – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



10. **Razorbills at St Abb's Head SPA**:

Figure A2.10a. PVA Metric A for St Abb's Razorbills – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

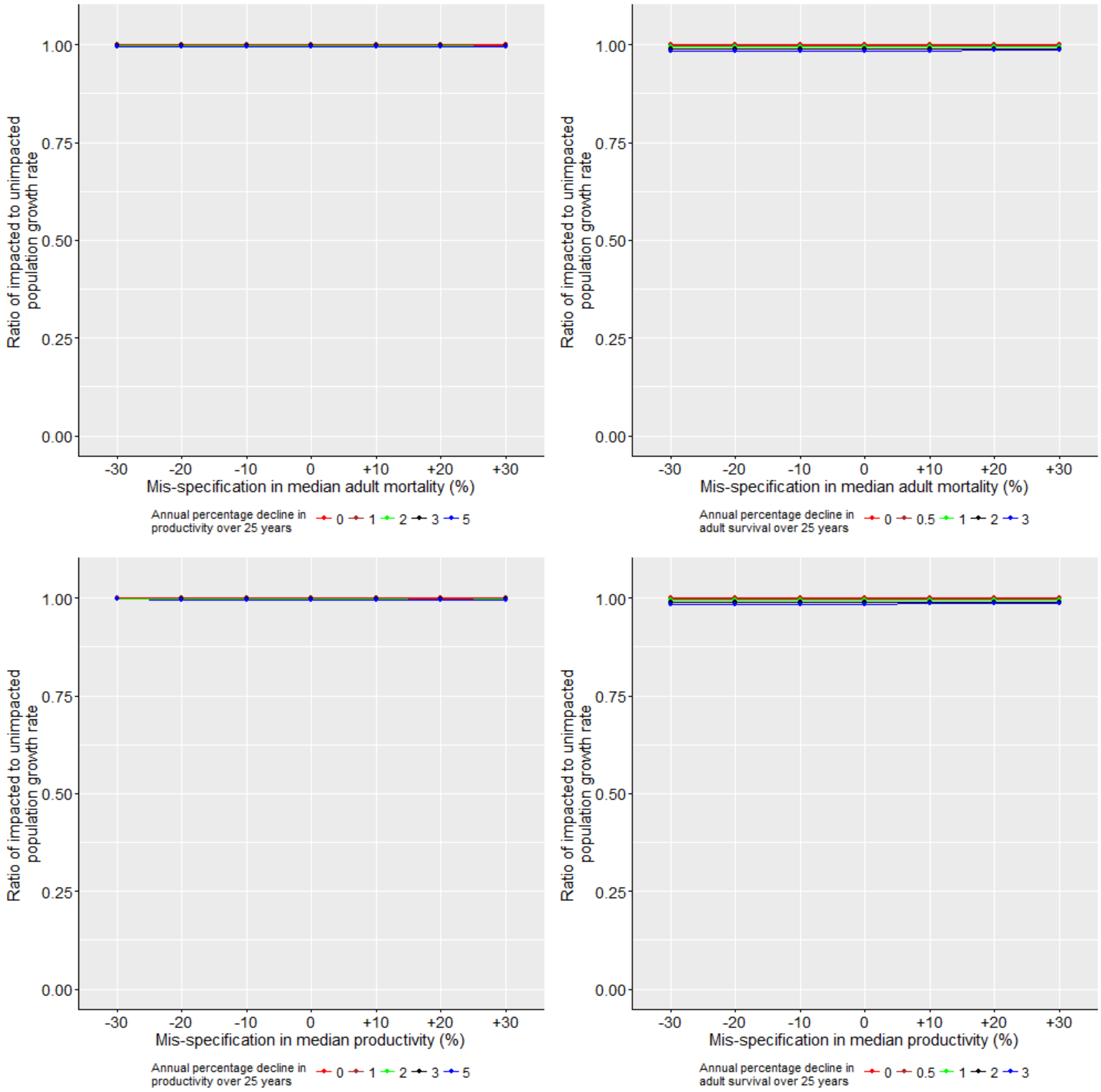


Figure A2.10b. PVA Metric B for St Abb's Razorbills – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

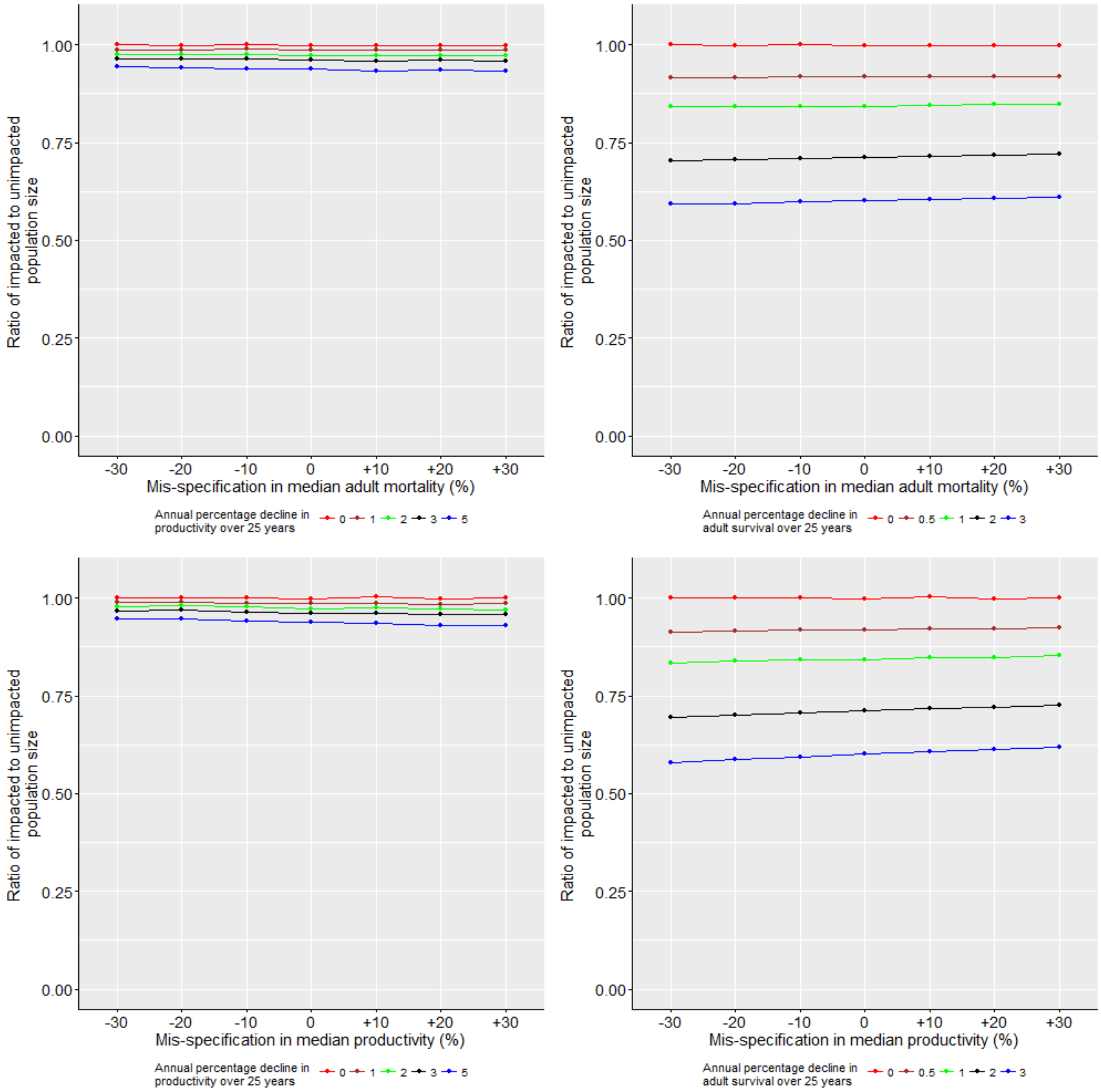


Figure A2.10c. PVA Metric C for St Abb's Razorbills – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

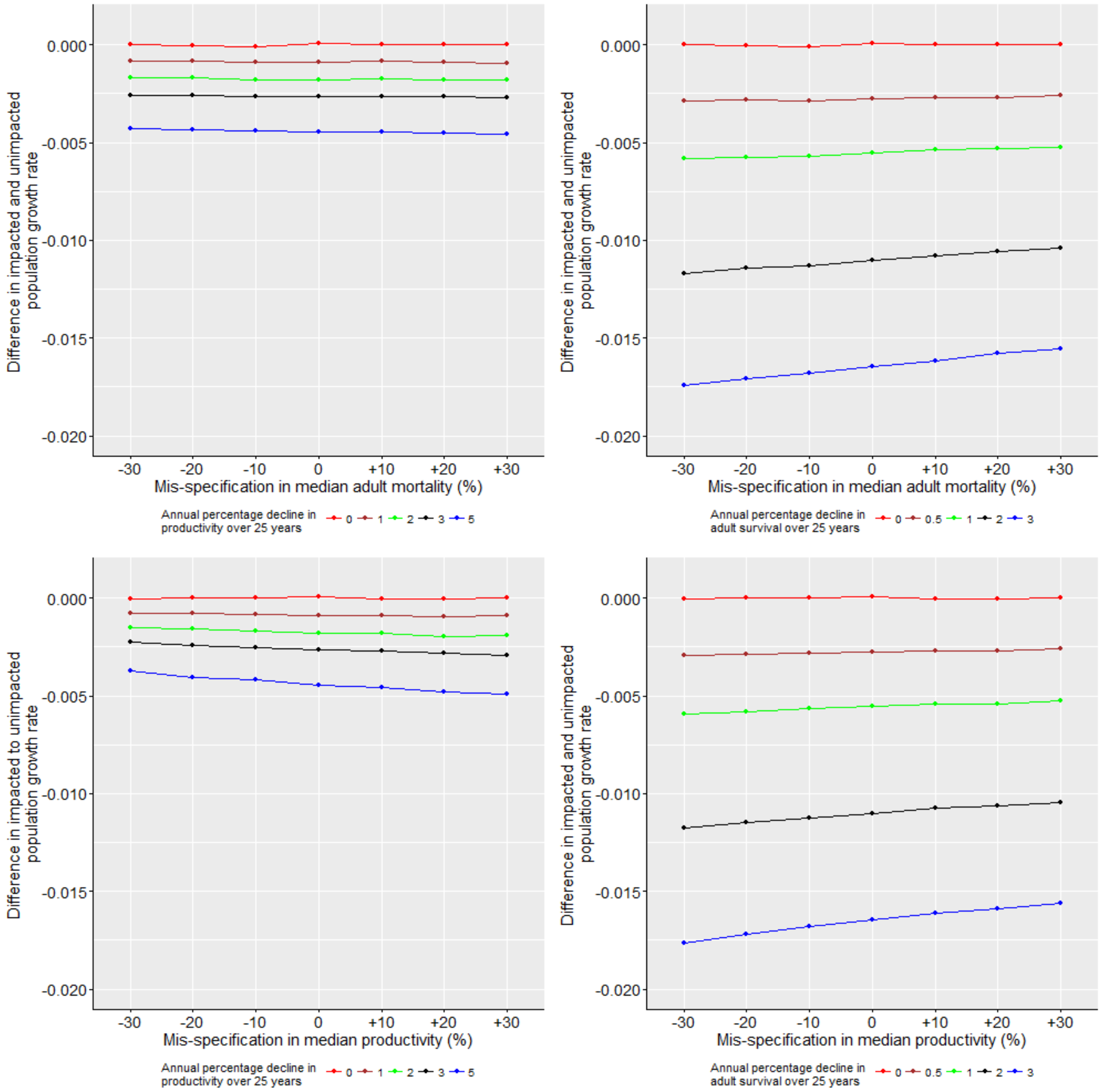


Figure A2.10d. PVA Metric D for St Abb's Razorbills – difference in population size at 2041, comparing impacted population vs. un-impacted population.

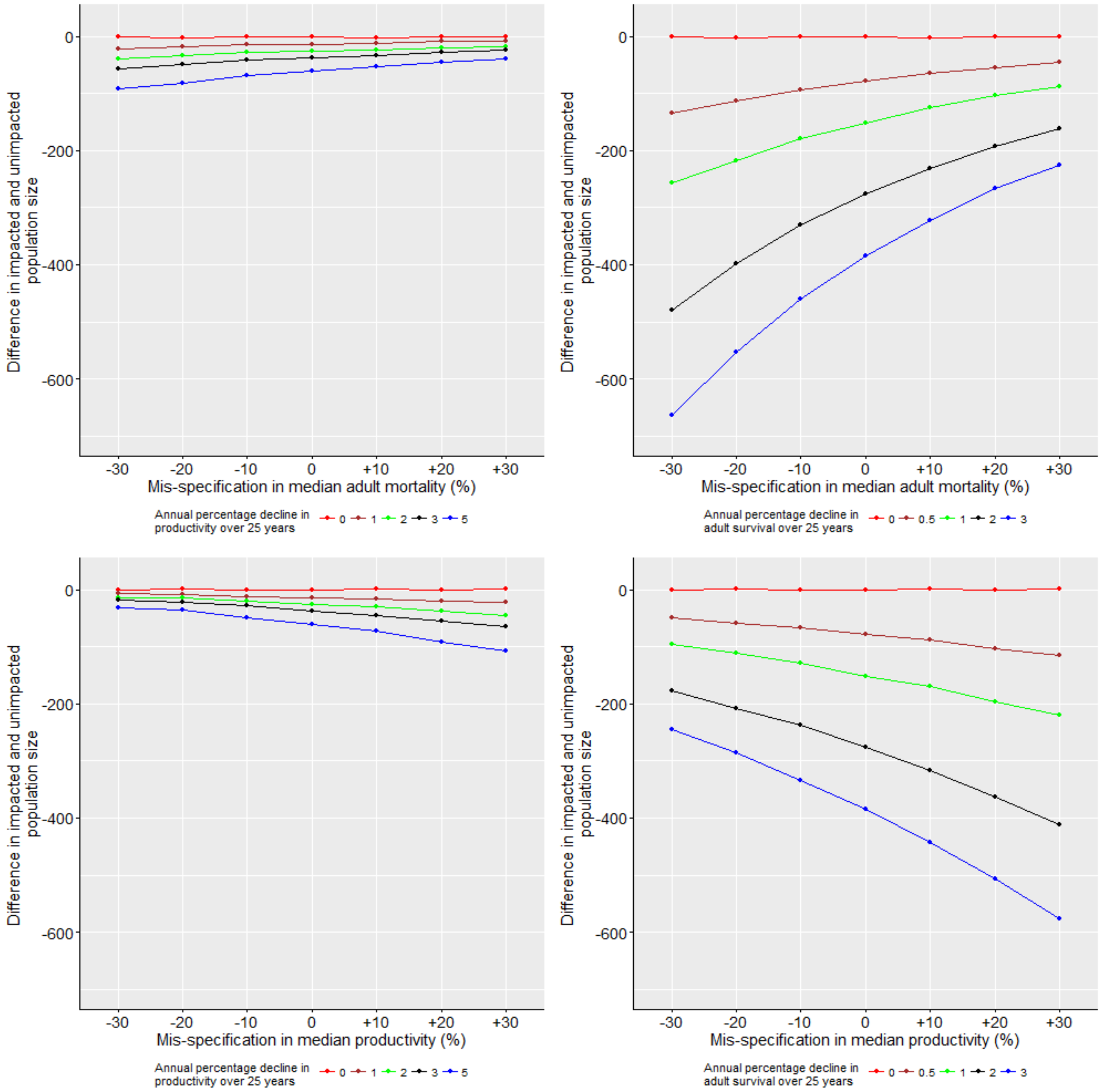


Figure A2.10e. PVA Metric E1 for St Abb's Razorbills – probability of population decline greater than 10% from 2016-2041.

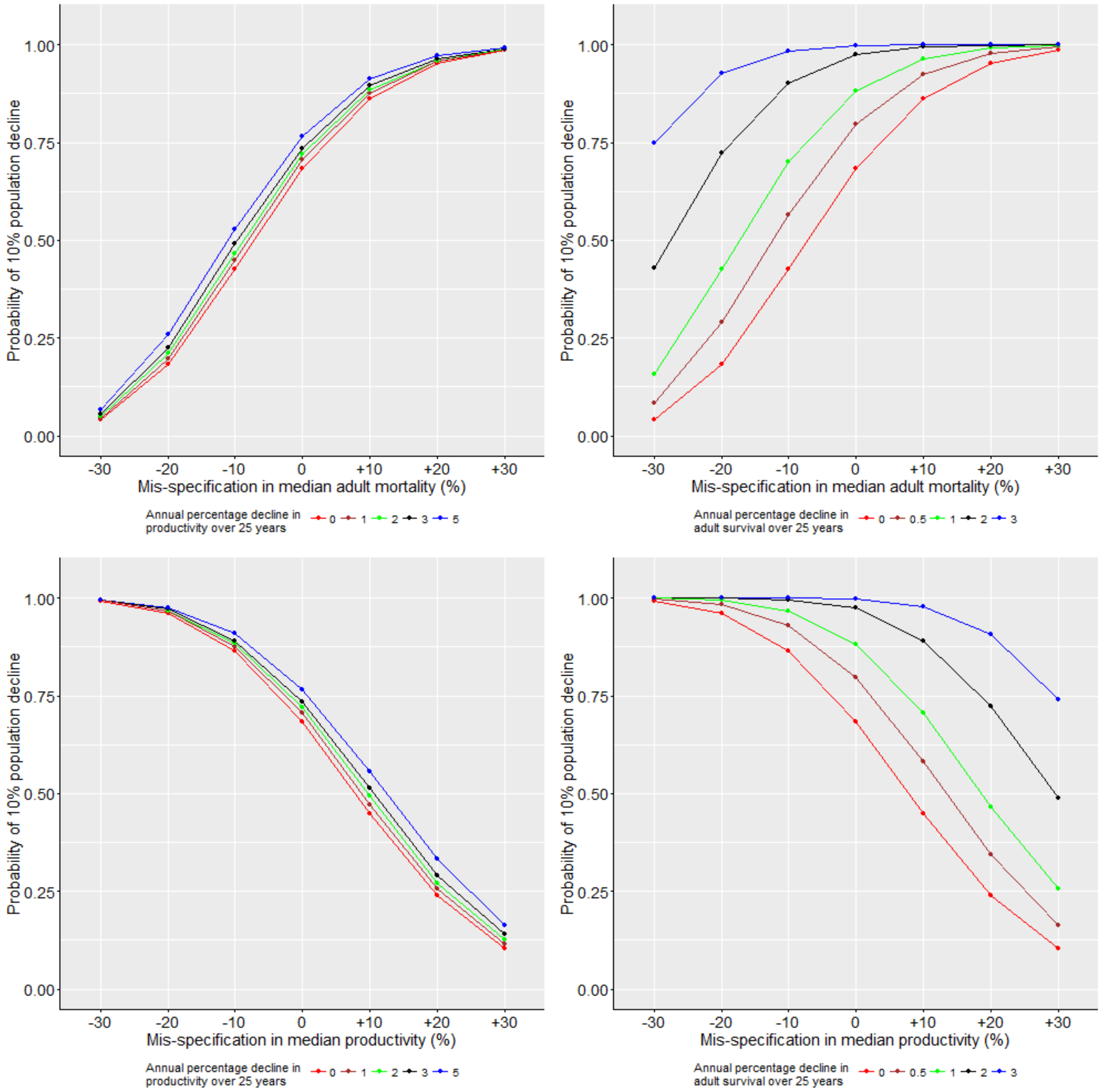


Figure A2.10f. PVA Metric E2 for St Abb's Razorbills – probability of population decline greater than 25% from 2016-2041.

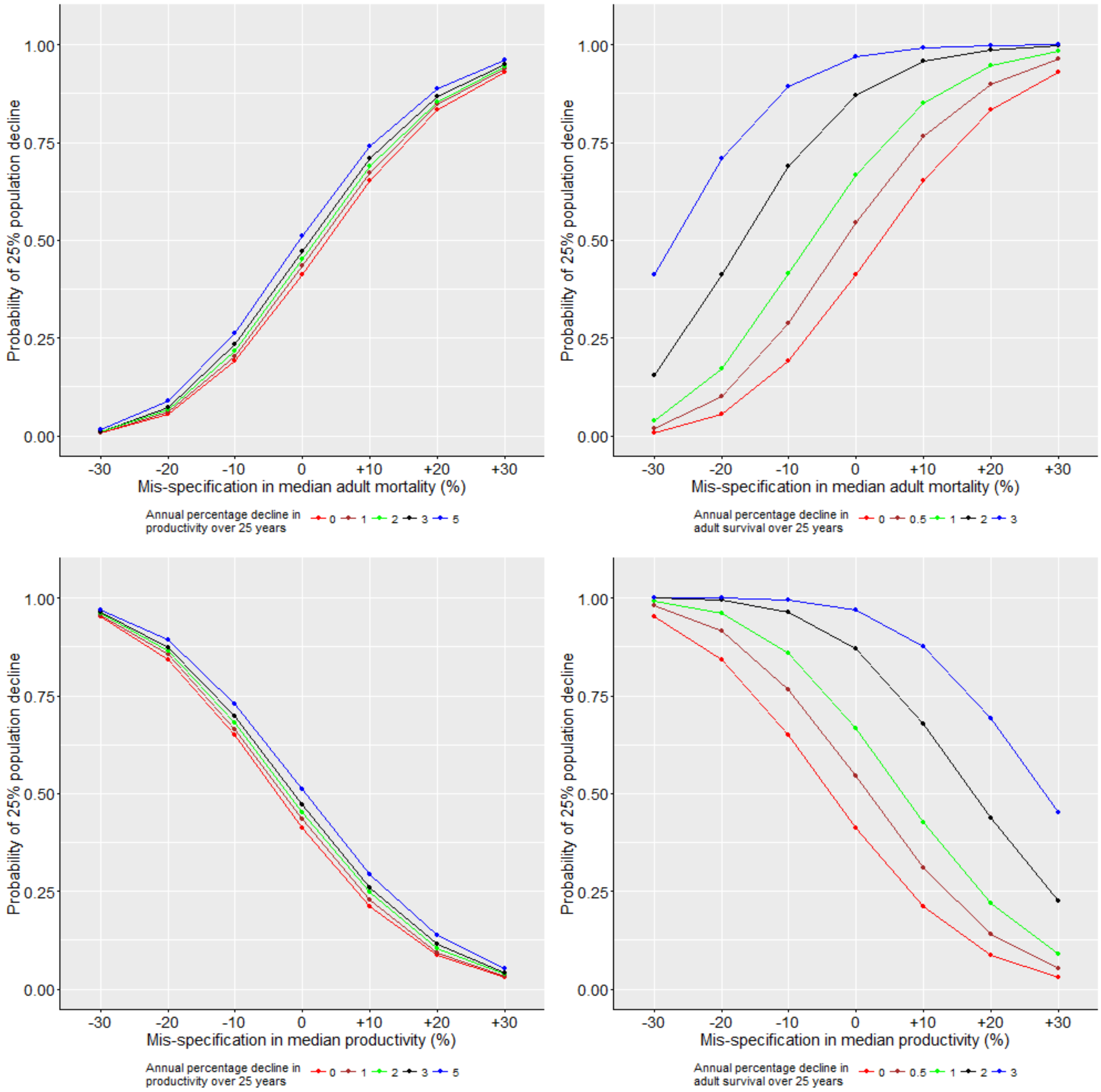


Figure A2.10g. PVA Metric E3 for St Abb's Razorbills – probability of population decline greater than 50% from 2016-2041.

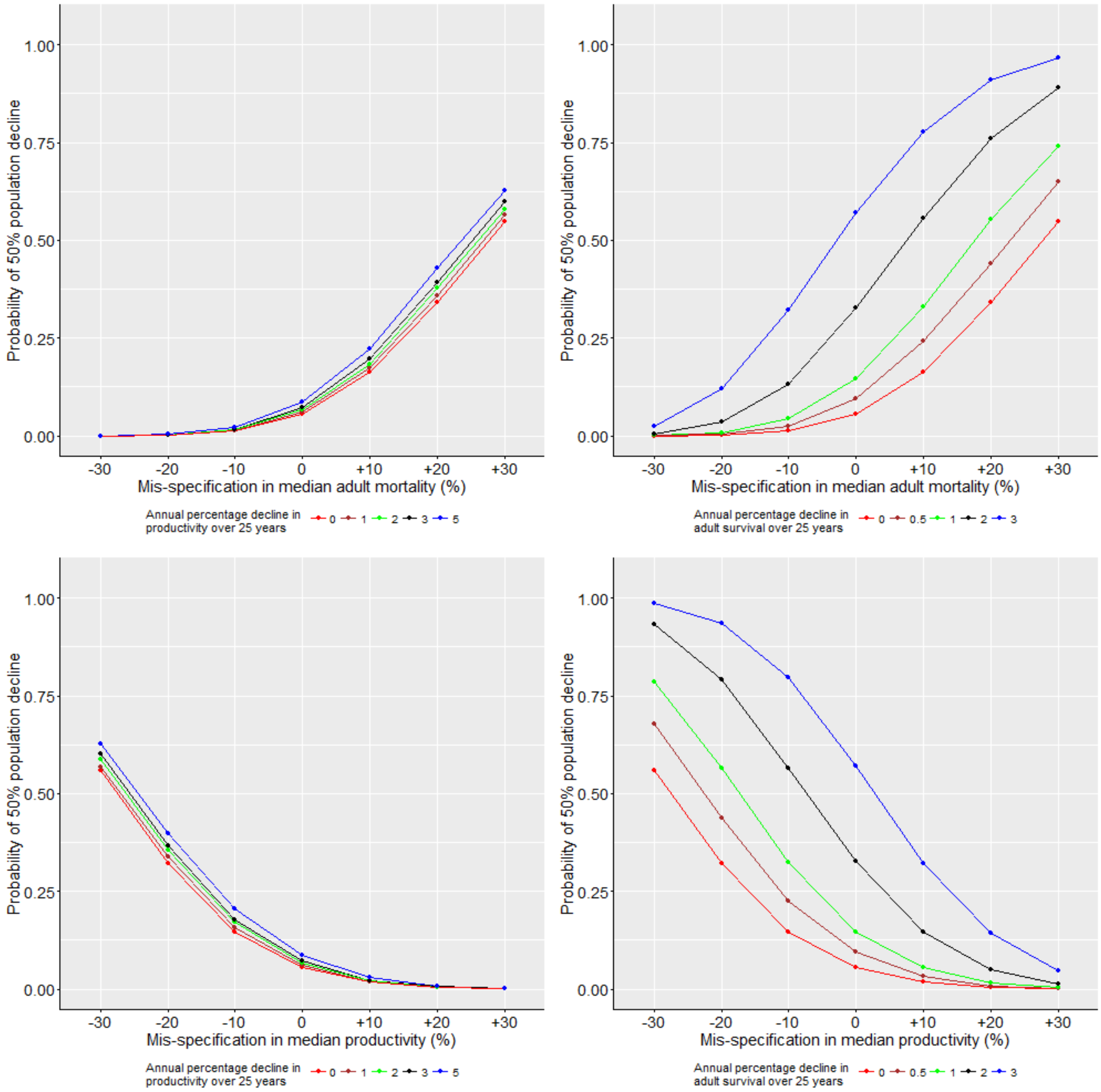
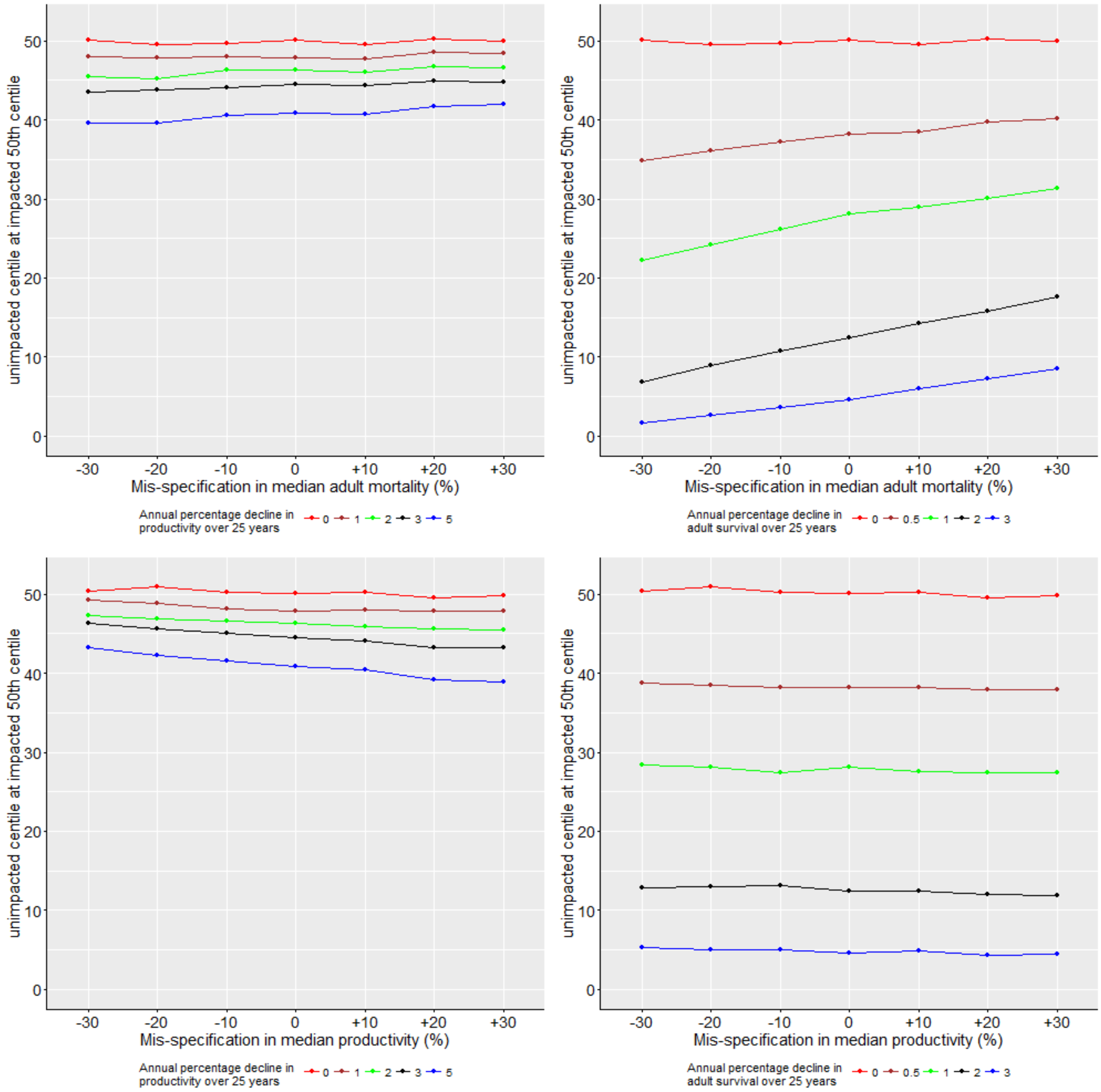


Figure A2.10h. PVA Metric F for St Abb's Razorbills – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



11. **Razorbills at Fowlsheugh SPA**:

Figure A2.11a. PVA Metric A for Fowlsheugh Razorbills – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

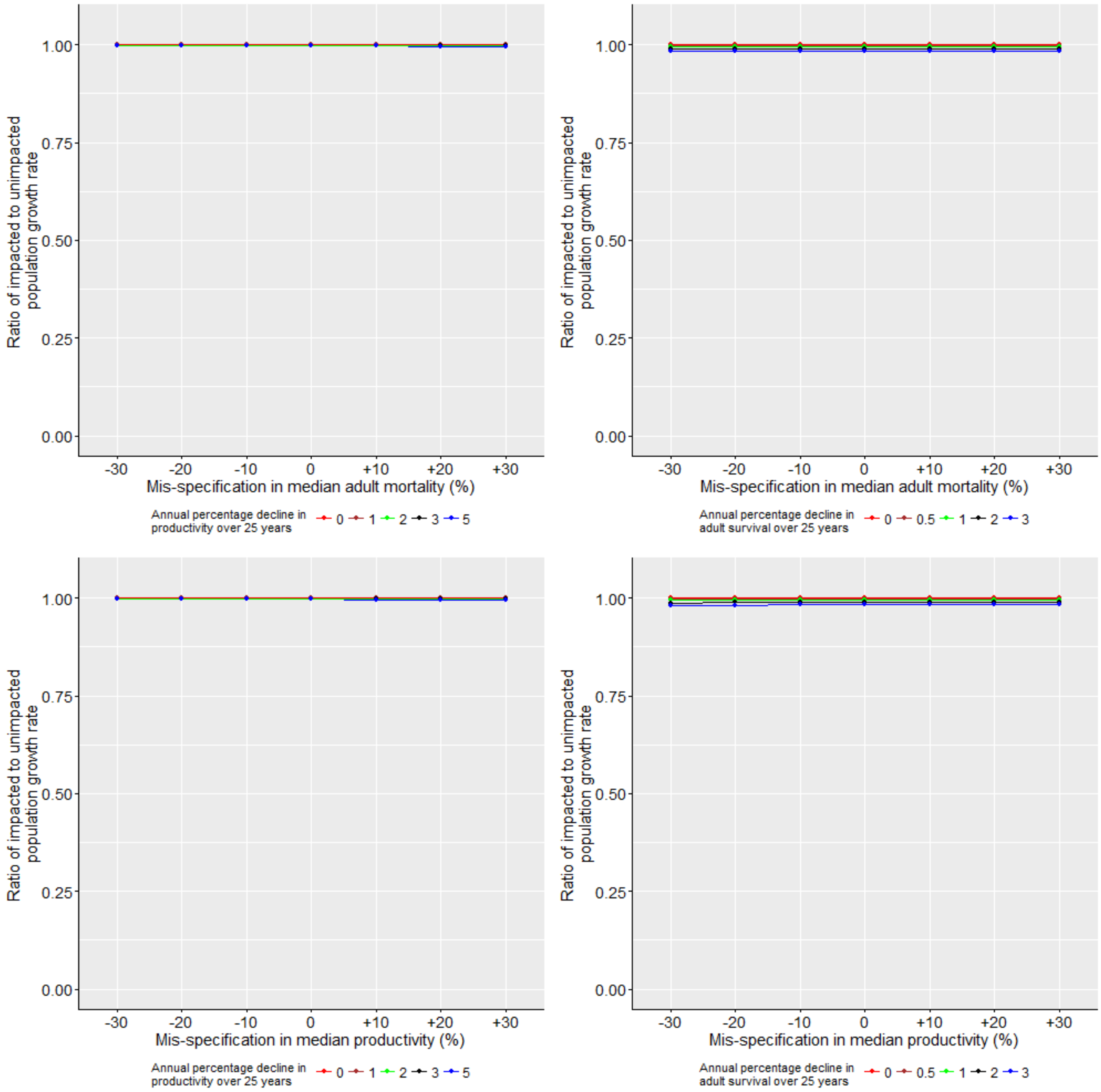


Figure A2.11b. PVA Metric B for Fowlsheugh Razorbills – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

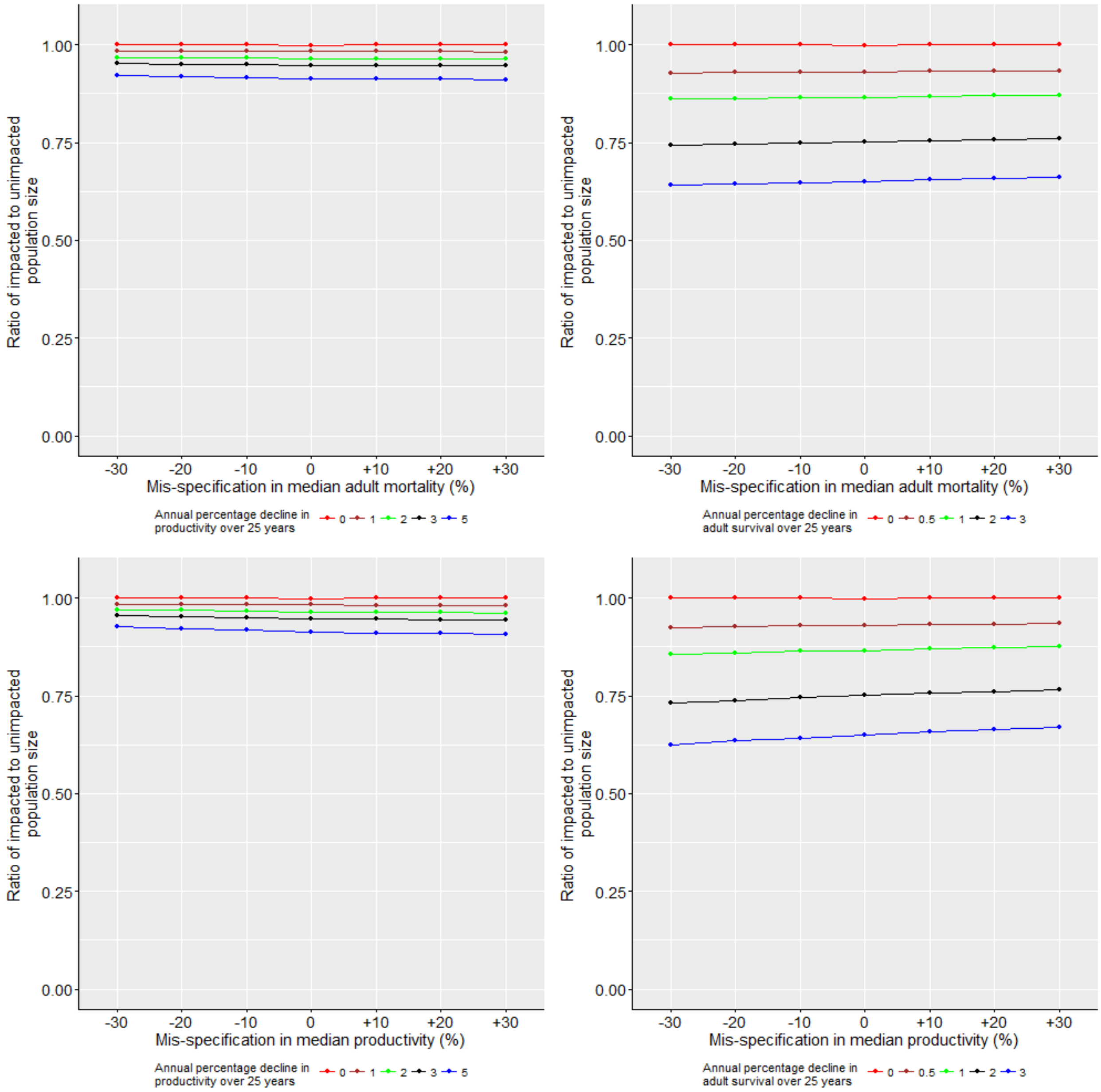


Figure A2.11c. PVA Metric C for Fowlsheugh Razorbills – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

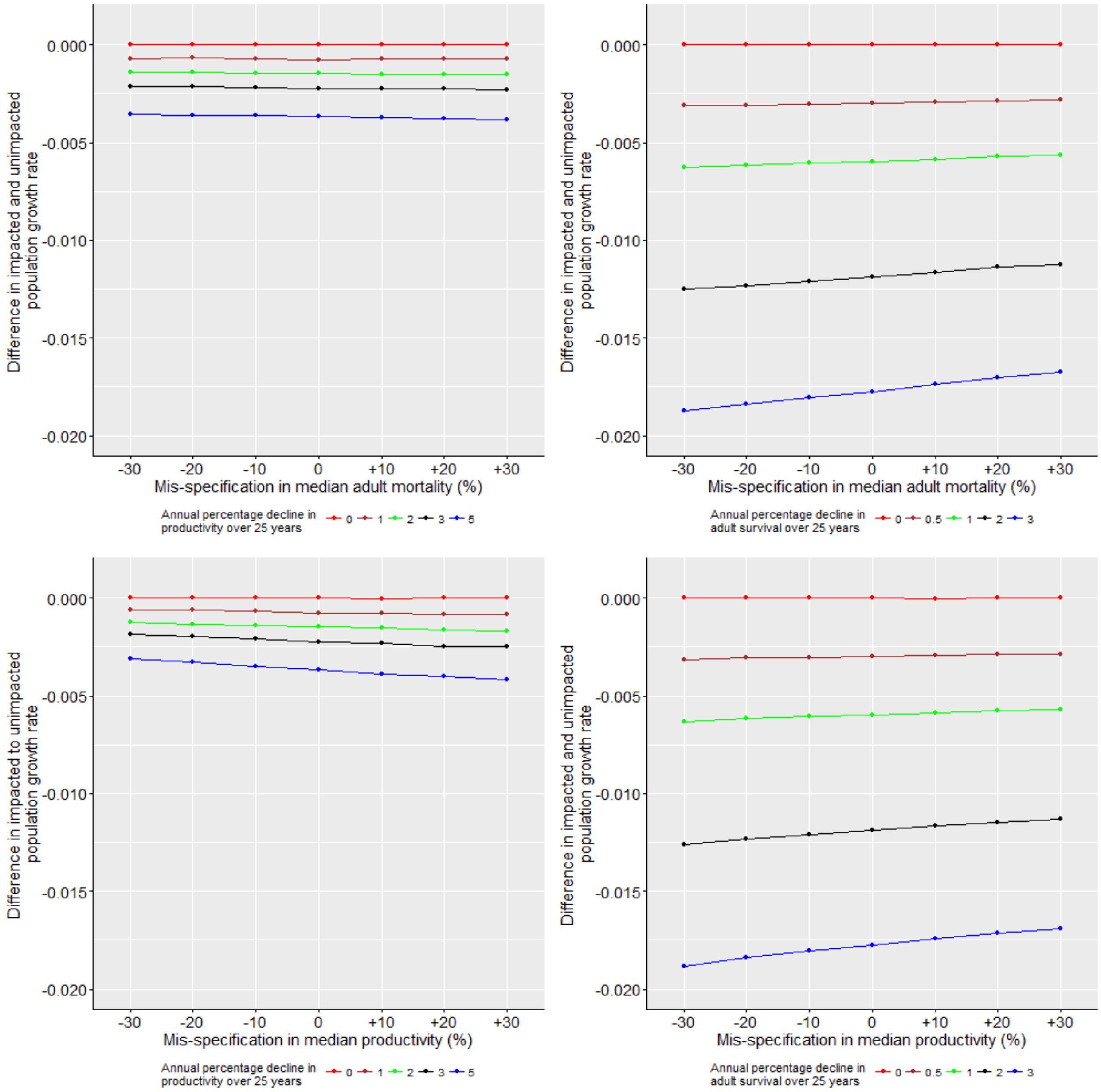


Figure A2.11d. PVA Metric D for Fowlsheugh Razorbills – difference in population size at 2041, comparing impacted population vs. un-impacted population.

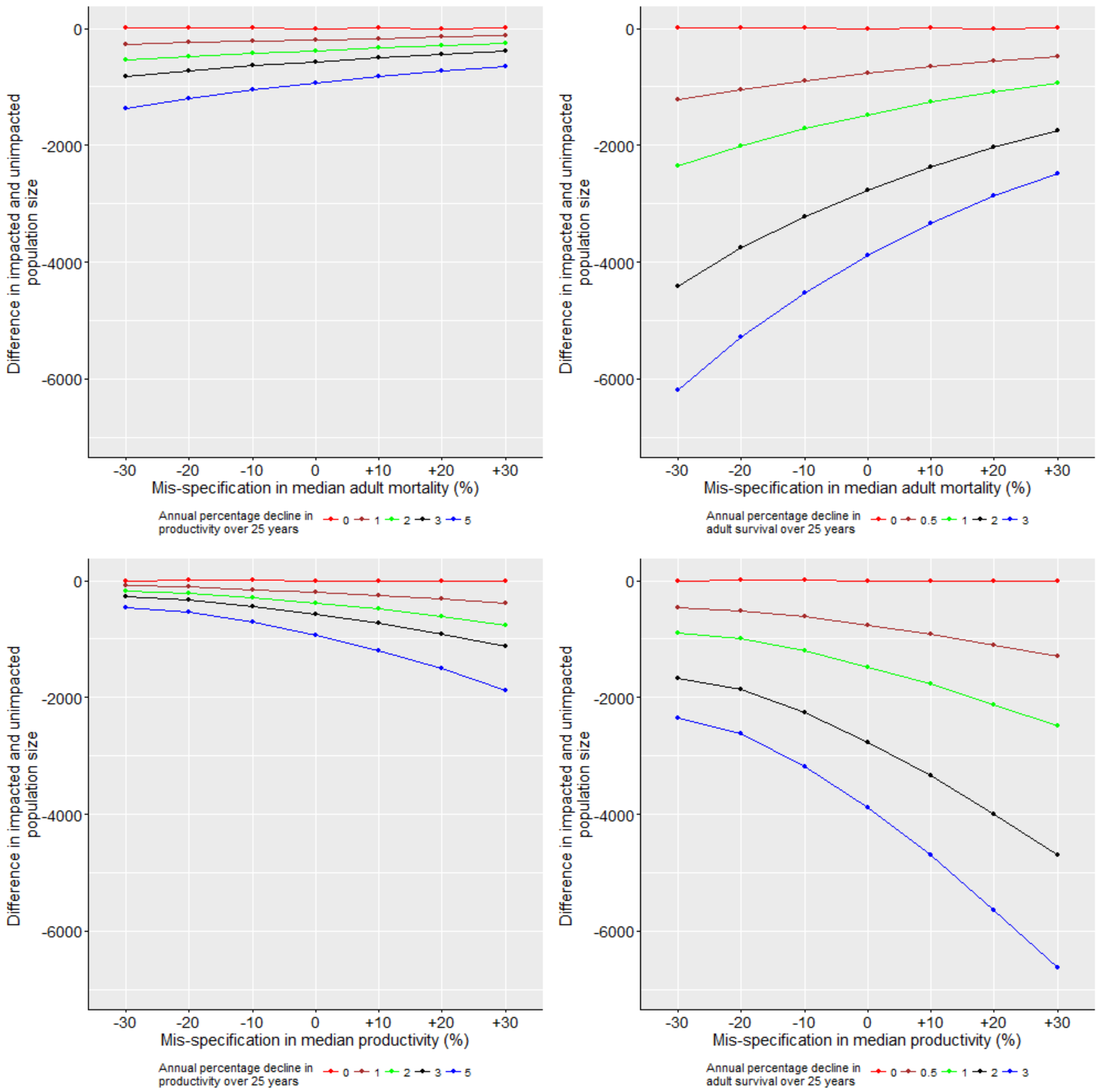


Figure A2.11e. PVA Metric E1 for Fowlsheugh Razorbills – probability of population decline greater than 10% from 2016-2041.

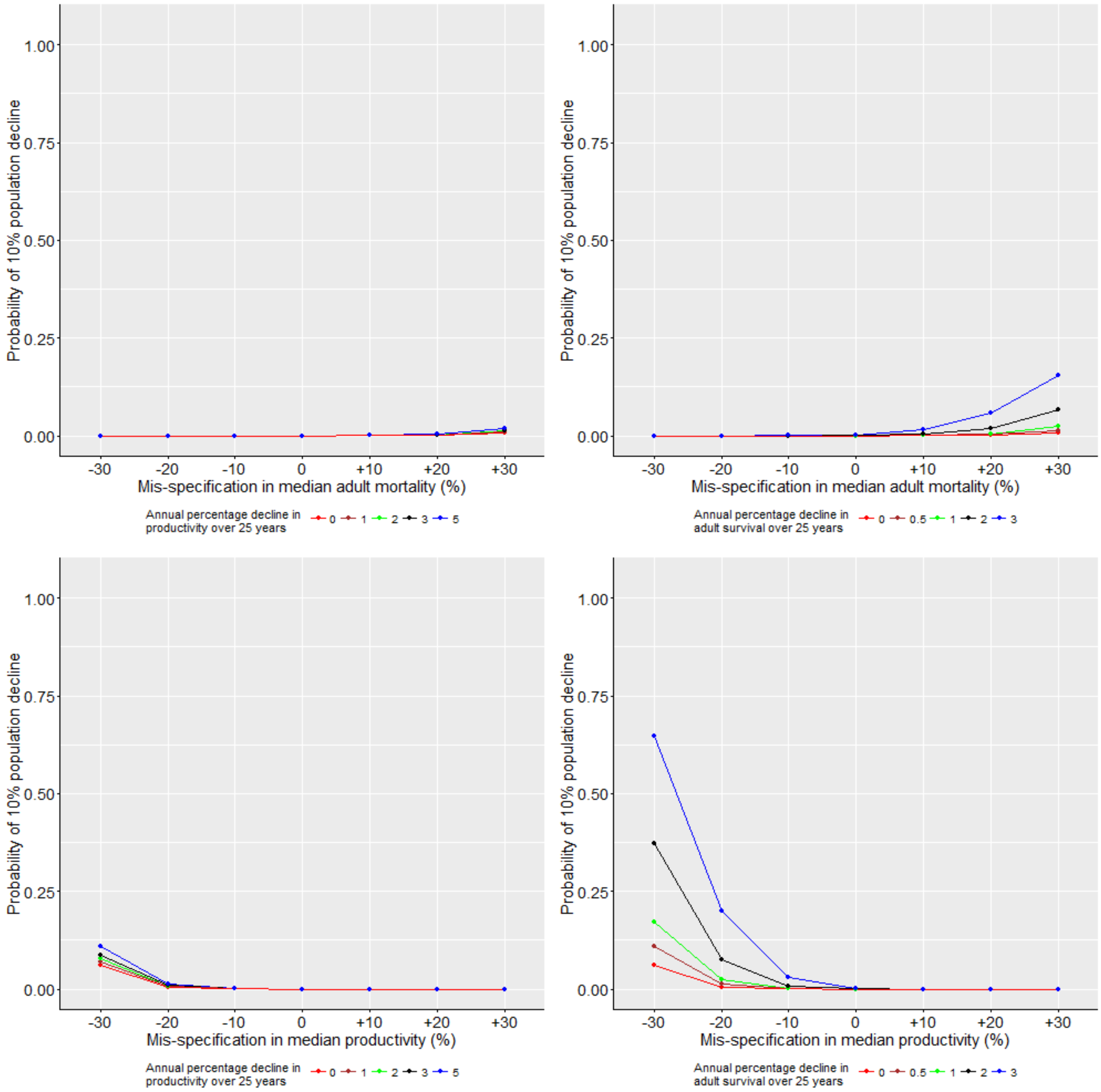


Figure A2.11f. PVA Metric E2 for Fowlsheugh Razorbills – probability of population decline greater than 25% from 2016-2041.

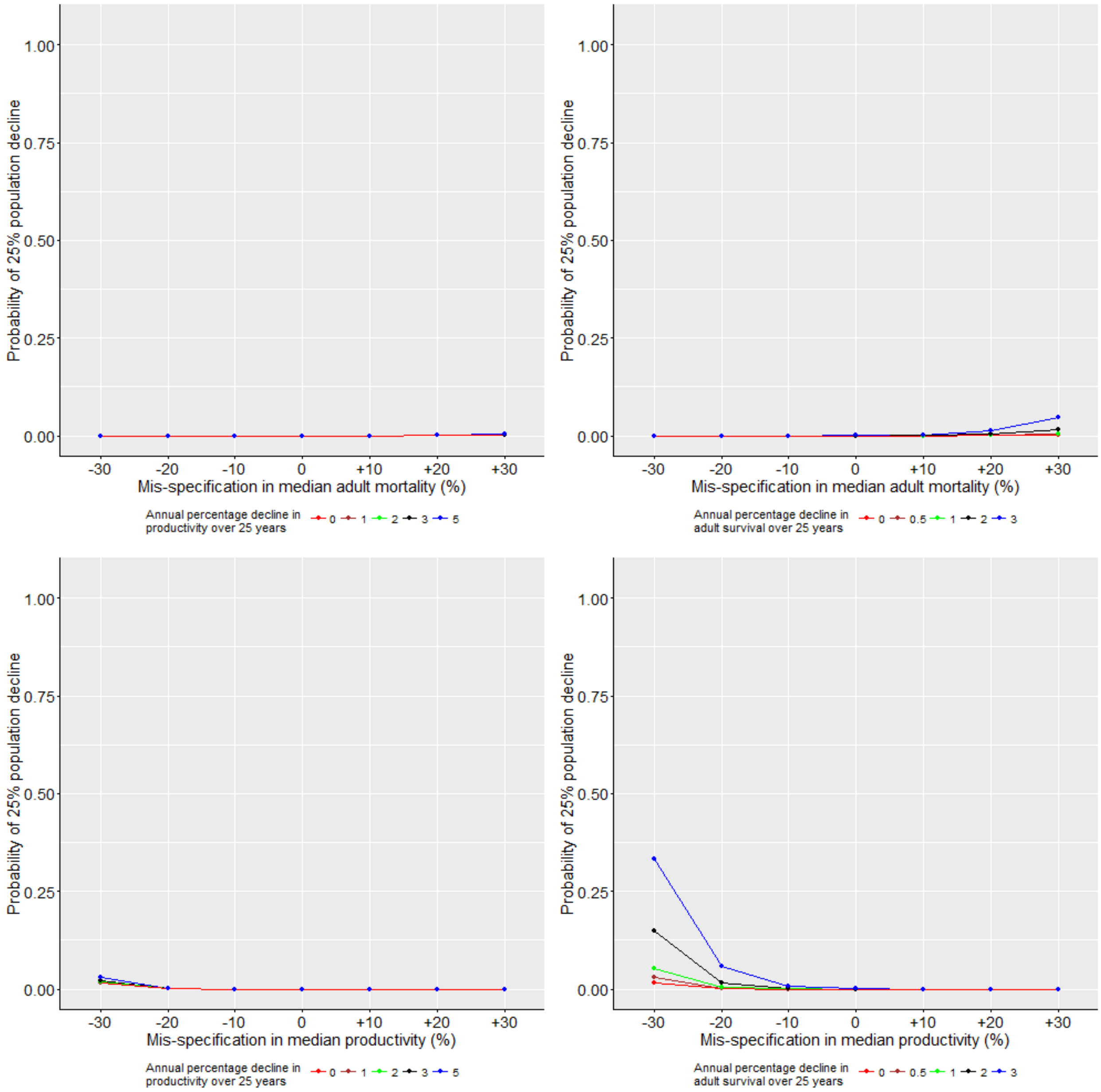


Figure A2.11g. PVA Metric E3 for Fowlsheugh Razorbills – probability of population decline greater than 50% from 2016-2041.

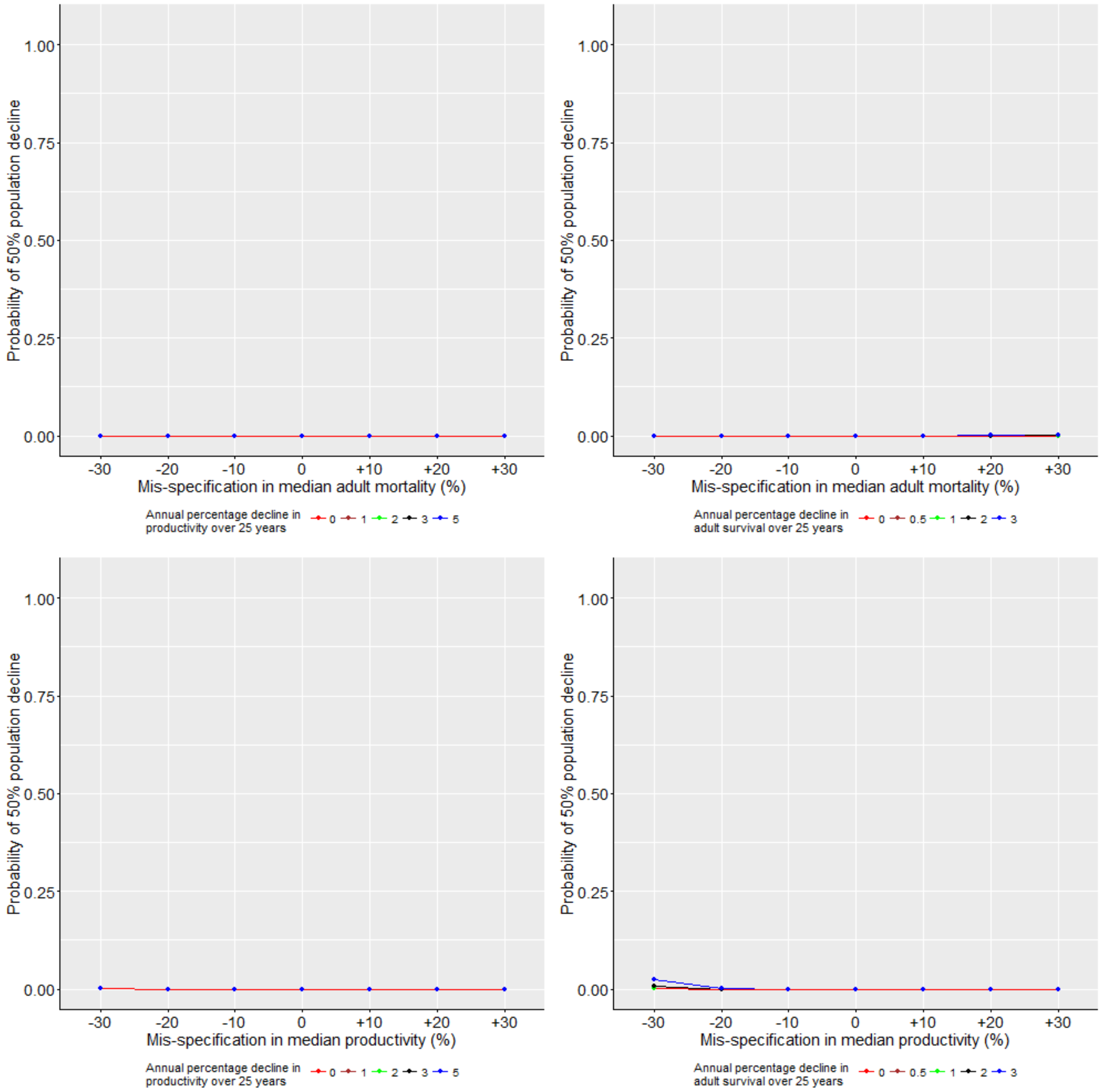
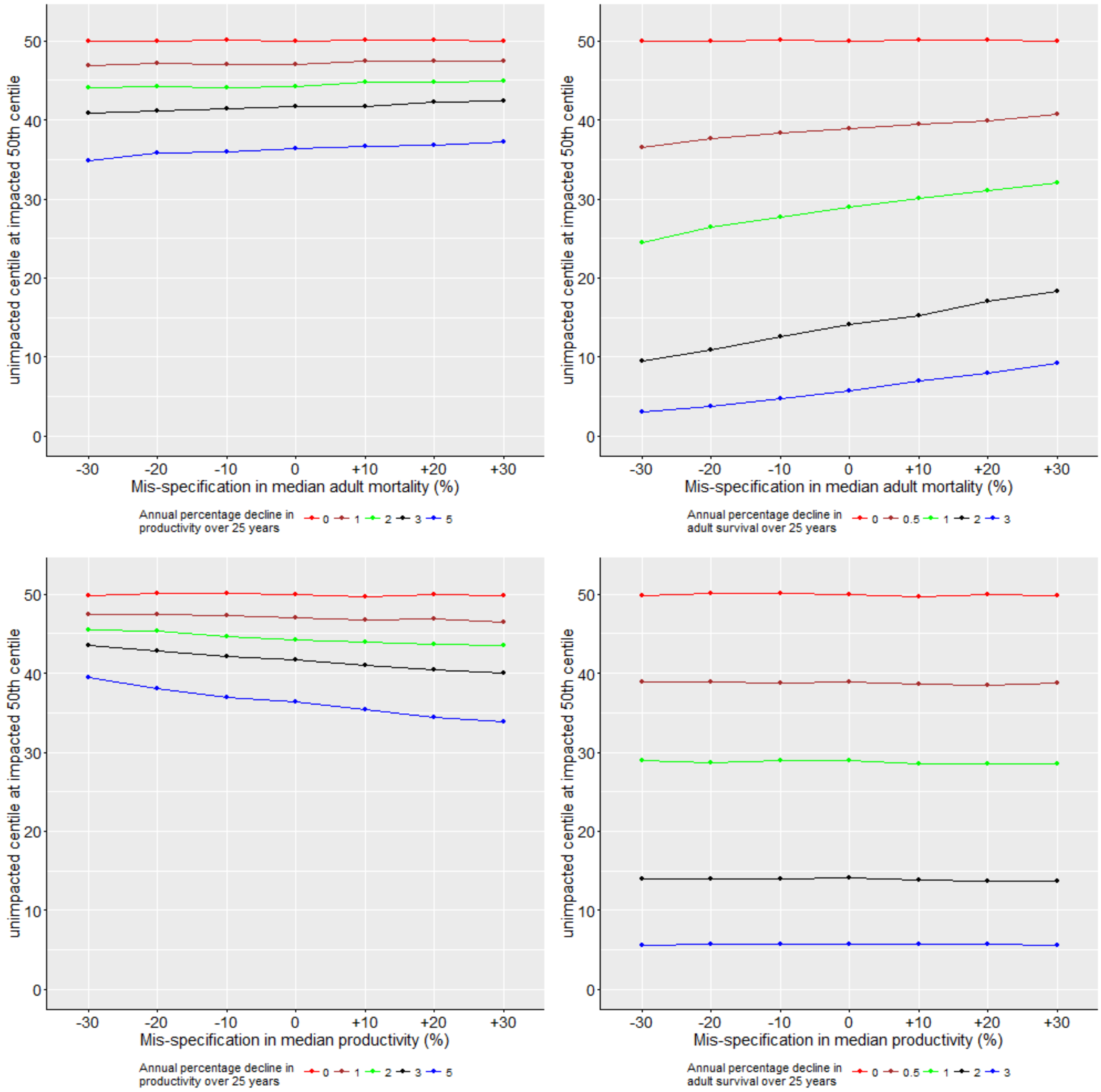


Figure A2.11h. PVA Metric F for Fowlsheugh Razorbills – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



12. **Shags at Forth Islands SPA**:

Figure A2.12a. PVA Metric A for Forth Shags – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

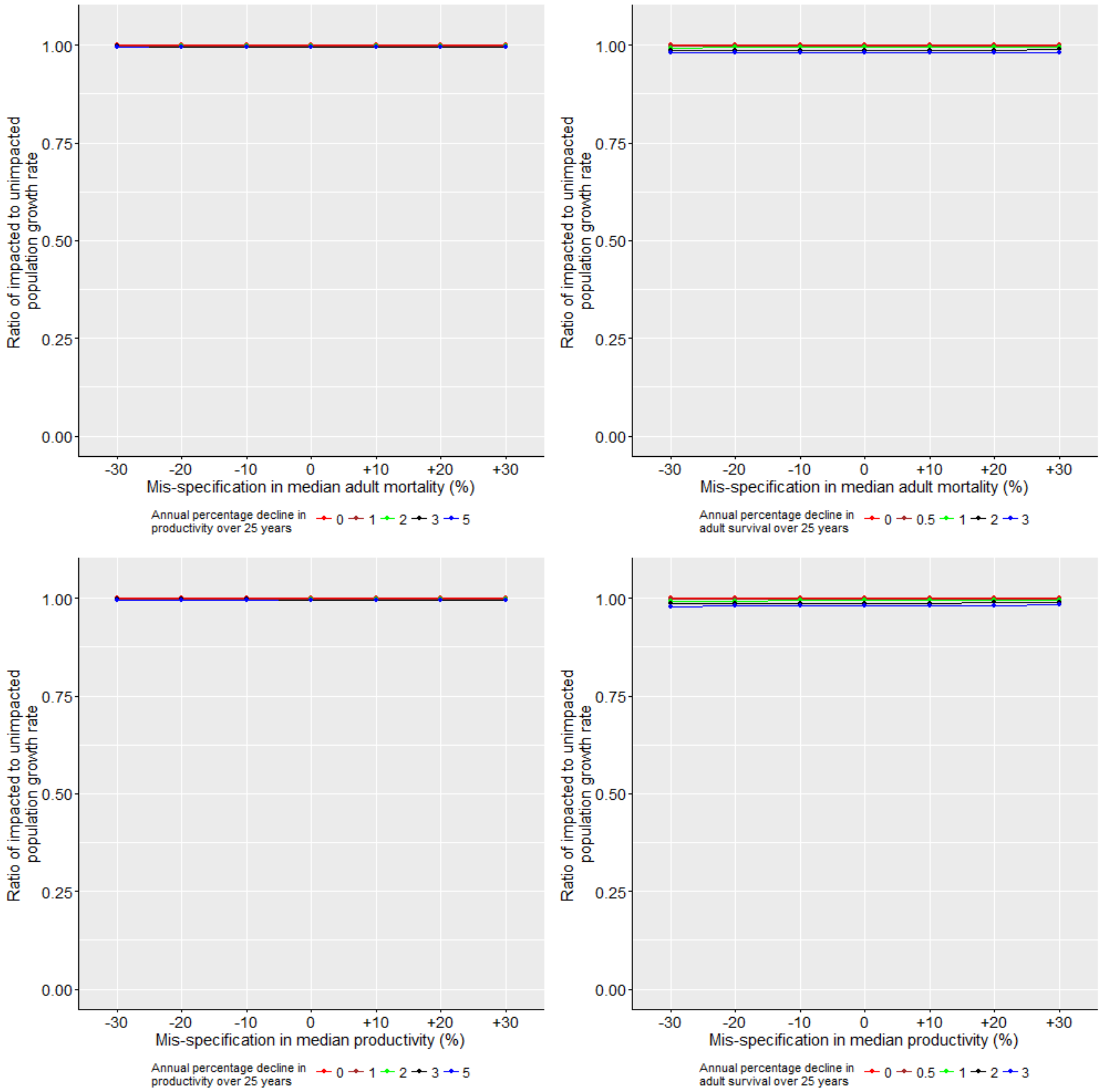


Figure A2.12b. PVA Metric B for Forth Shags – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

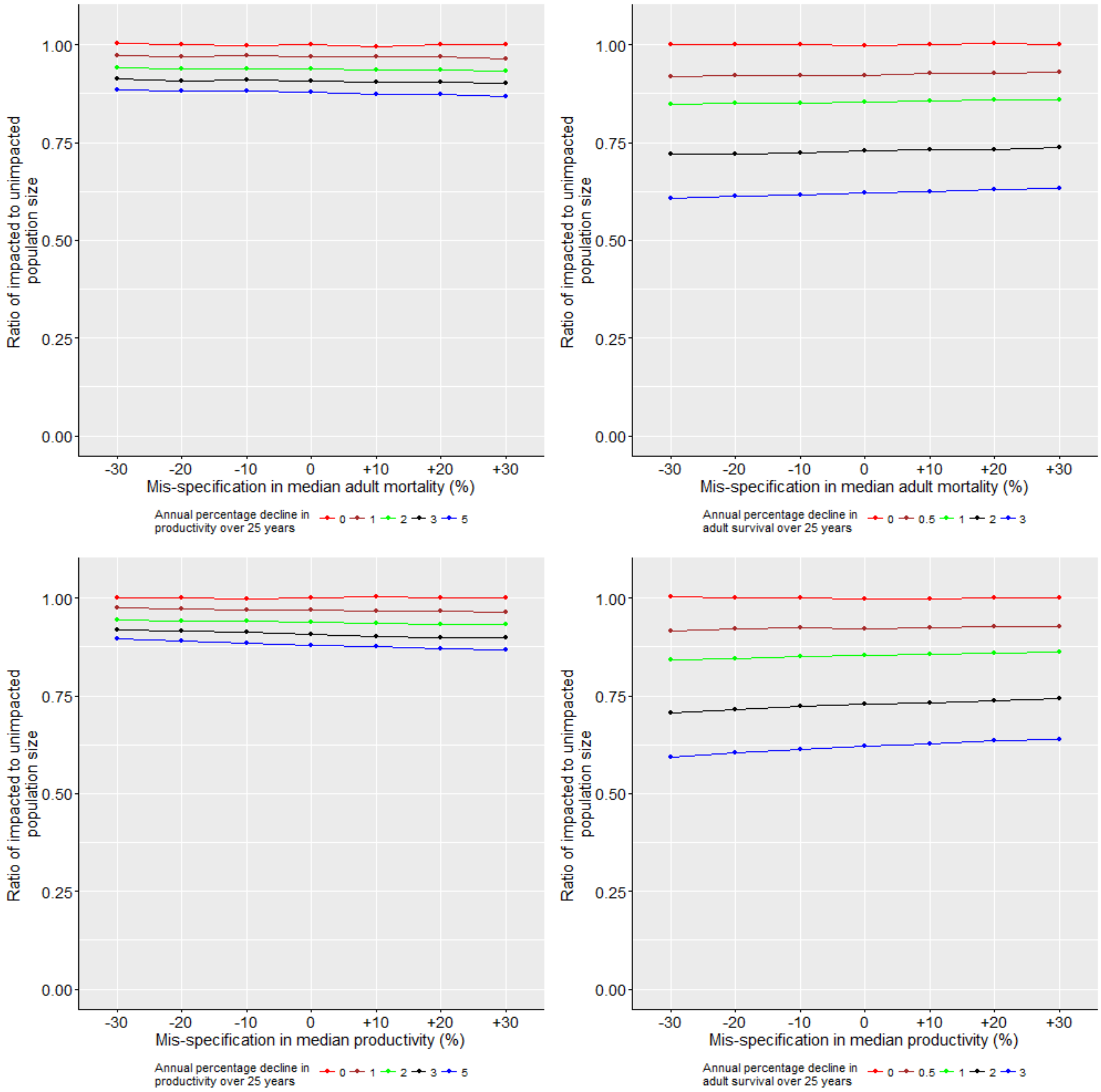


Figure A2.12c. PVA Metric C for Forth Shags – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

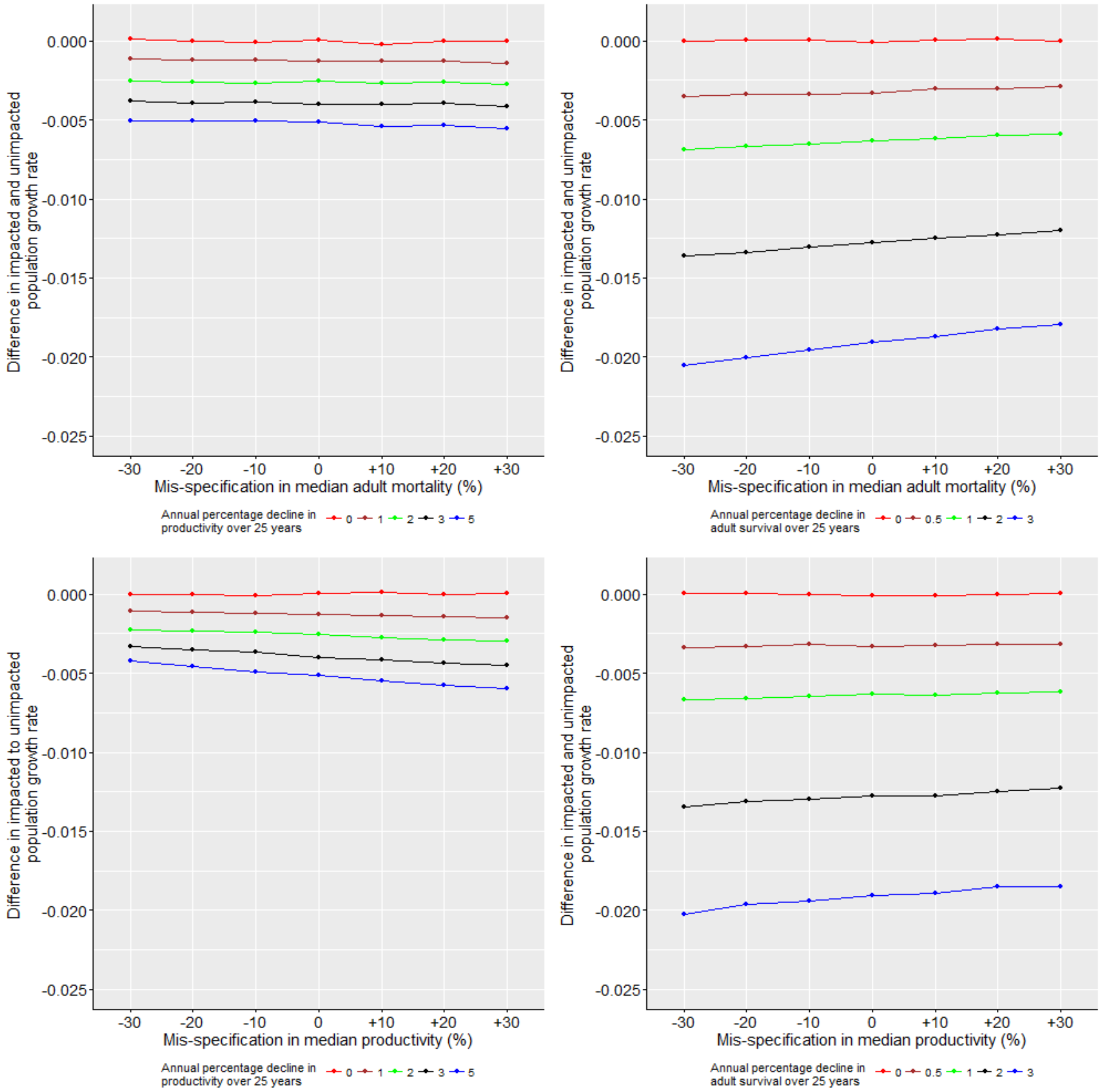


Figure A2.12d. PVA Metric D for Forth Shags – difference in population size at 2041, comparing impacted population vs. un-impacted population.

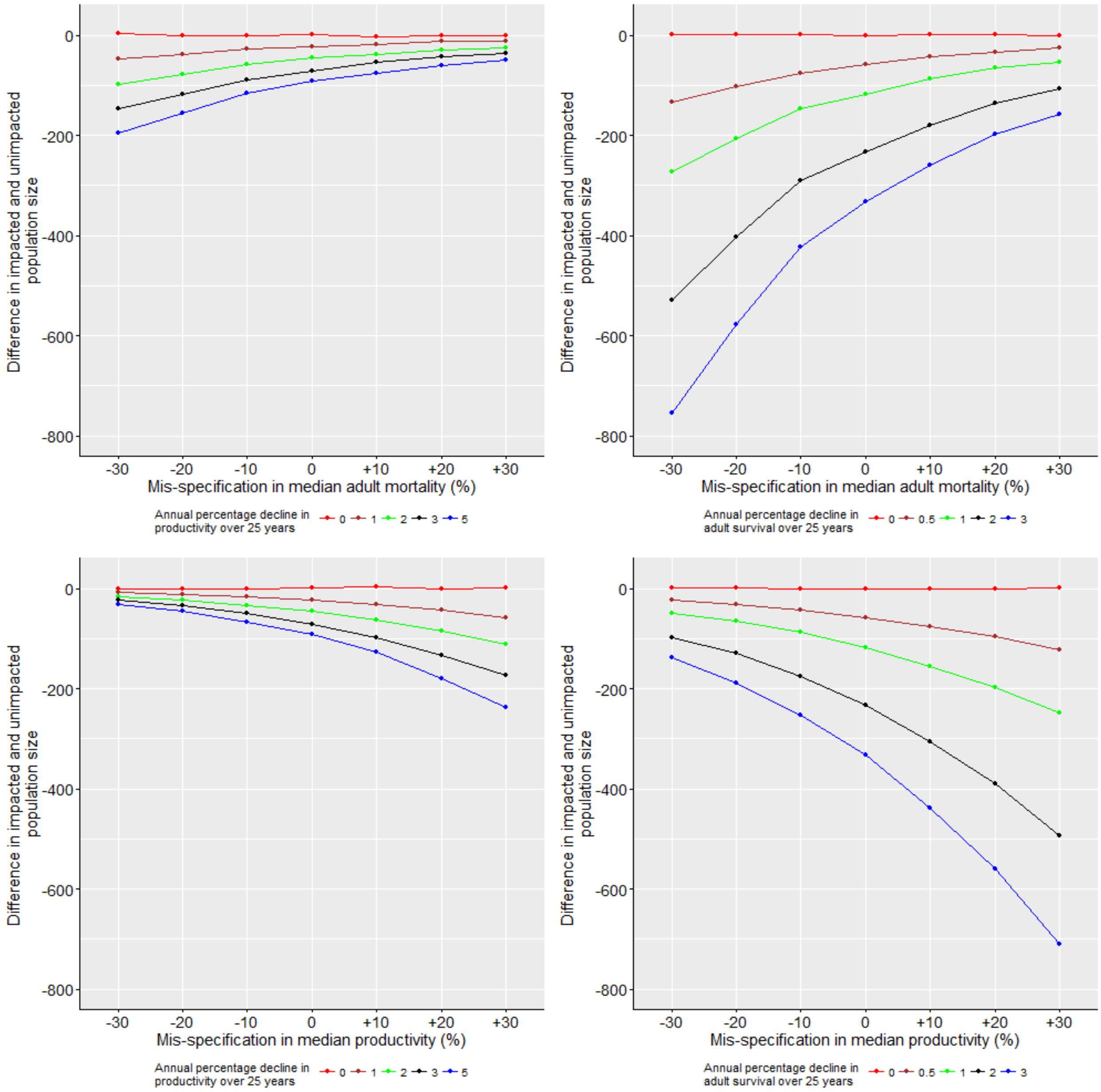


Figure A2.12e. PVA Metric E1 for Forth Shags – probability of population decline greater than 10% from 2016-2041.

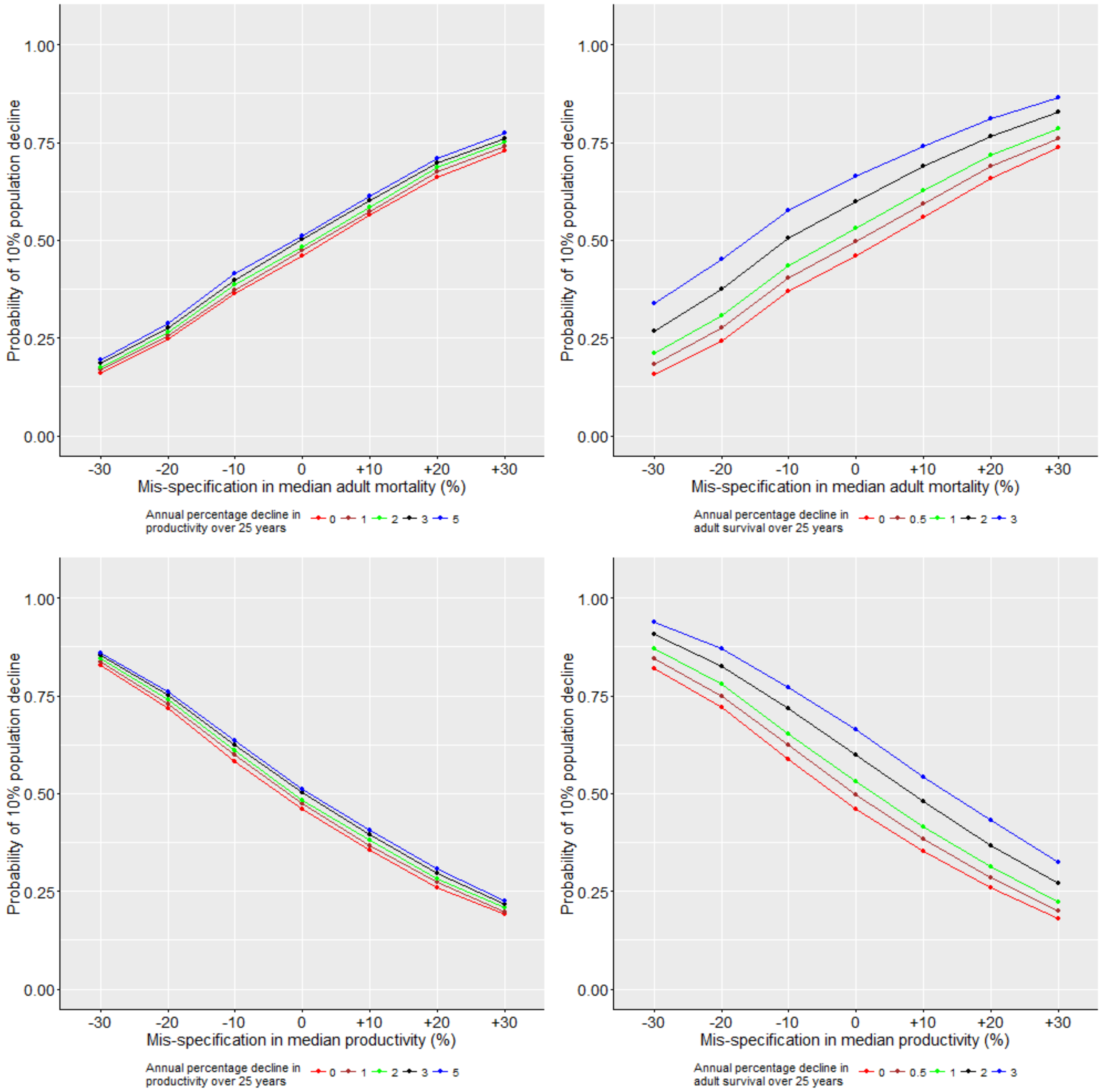


Figure A2.12f. PVA Metric E2 for Forth Shags – probability of population decline greater than 25% from 2016-2041.

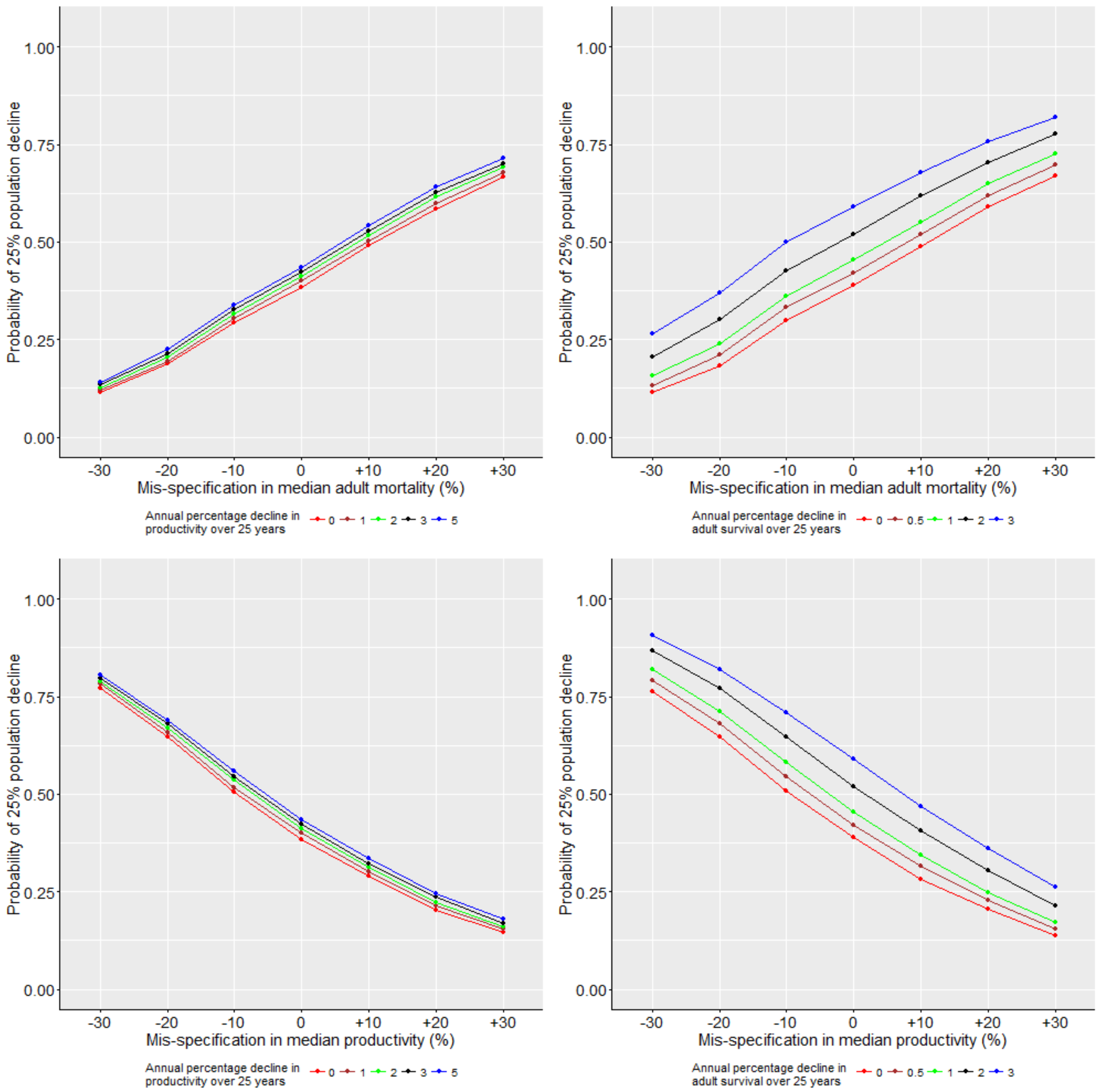


Figure A2.12g. PVA Metric E3 for Forth Shags – probability of population decline greater than 50% from 2016-2041.

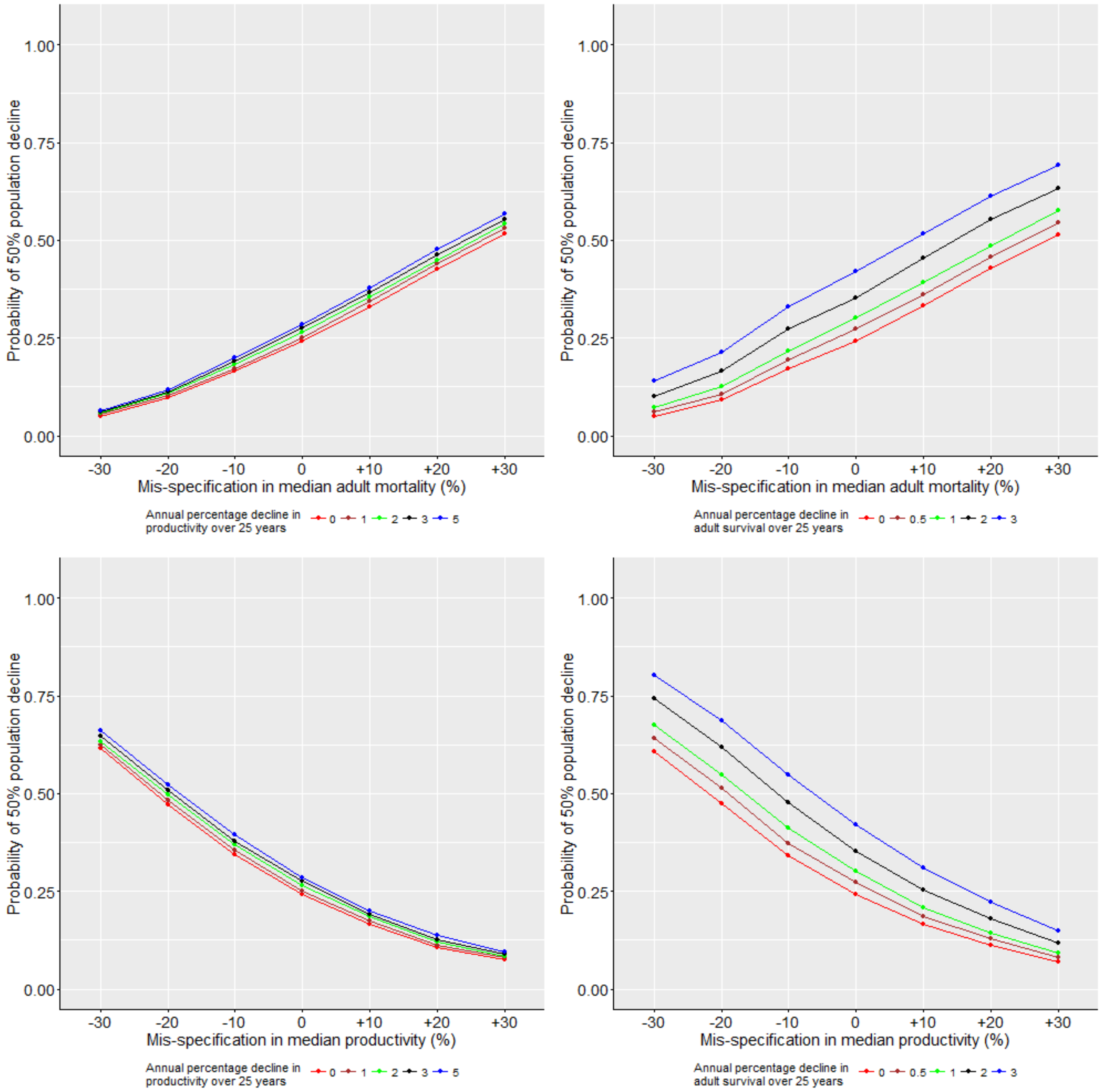
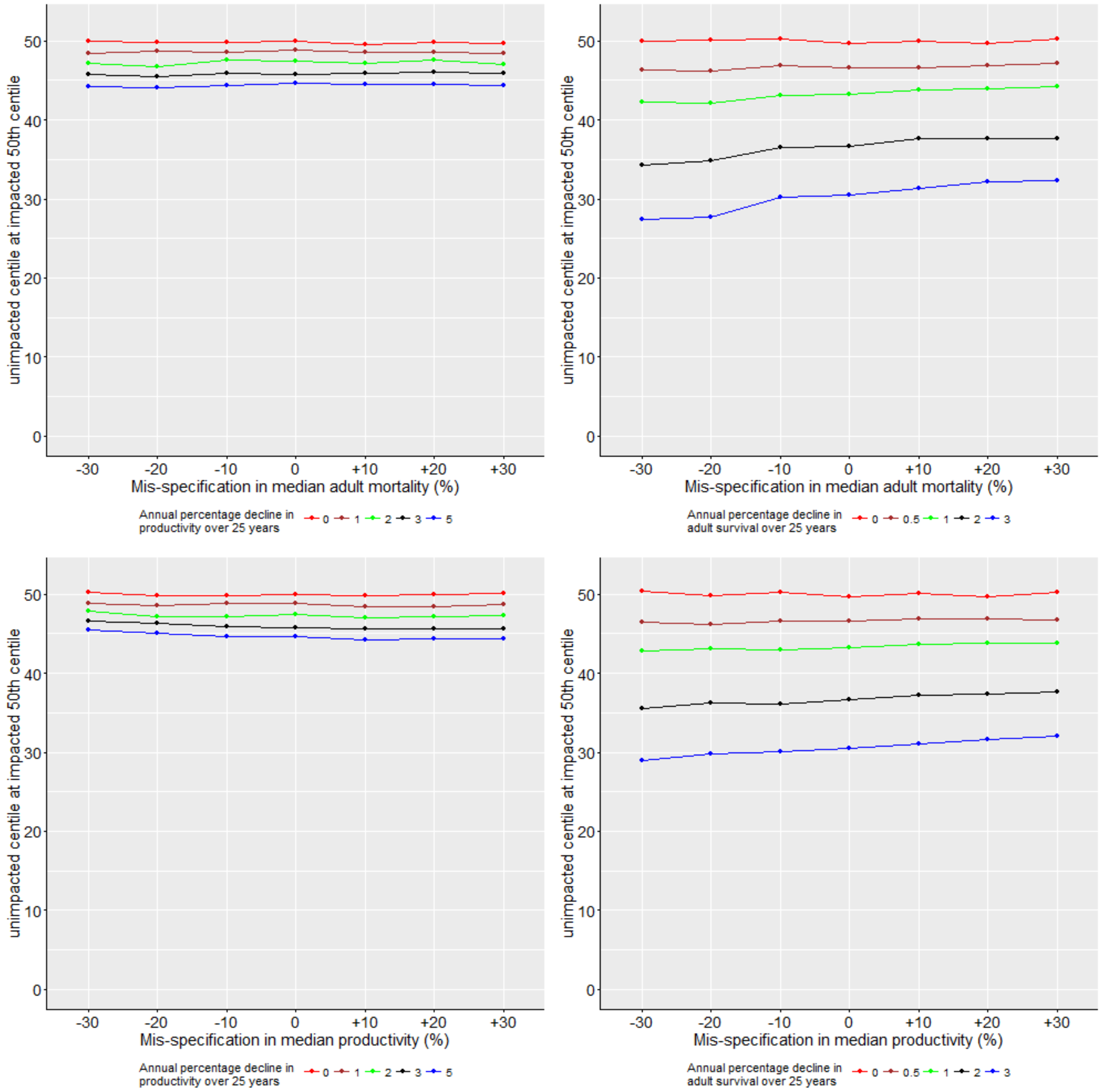


Figure A2.12h. PVA Metric F for Forth Shags – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



13. **Shags at St Abb's Head SPA**:

Figure A2.13a. PVA Metric A for St Abb's Shags – ratio of population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

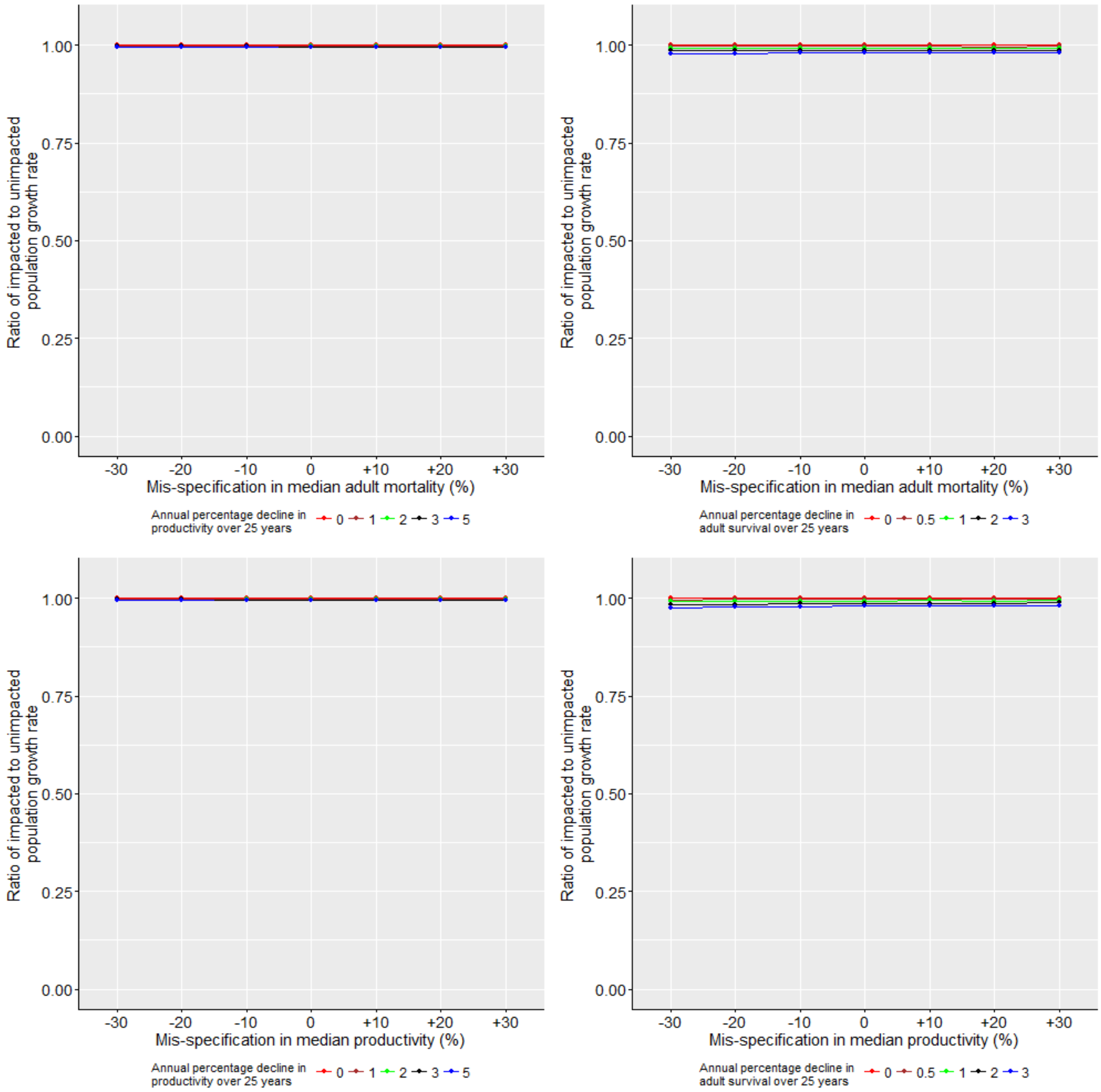


Figure A2.13b. PVA Metric B for St Abb's Shags – ratio of population size at 2041, comparing impacted population vs. un-impacted population.

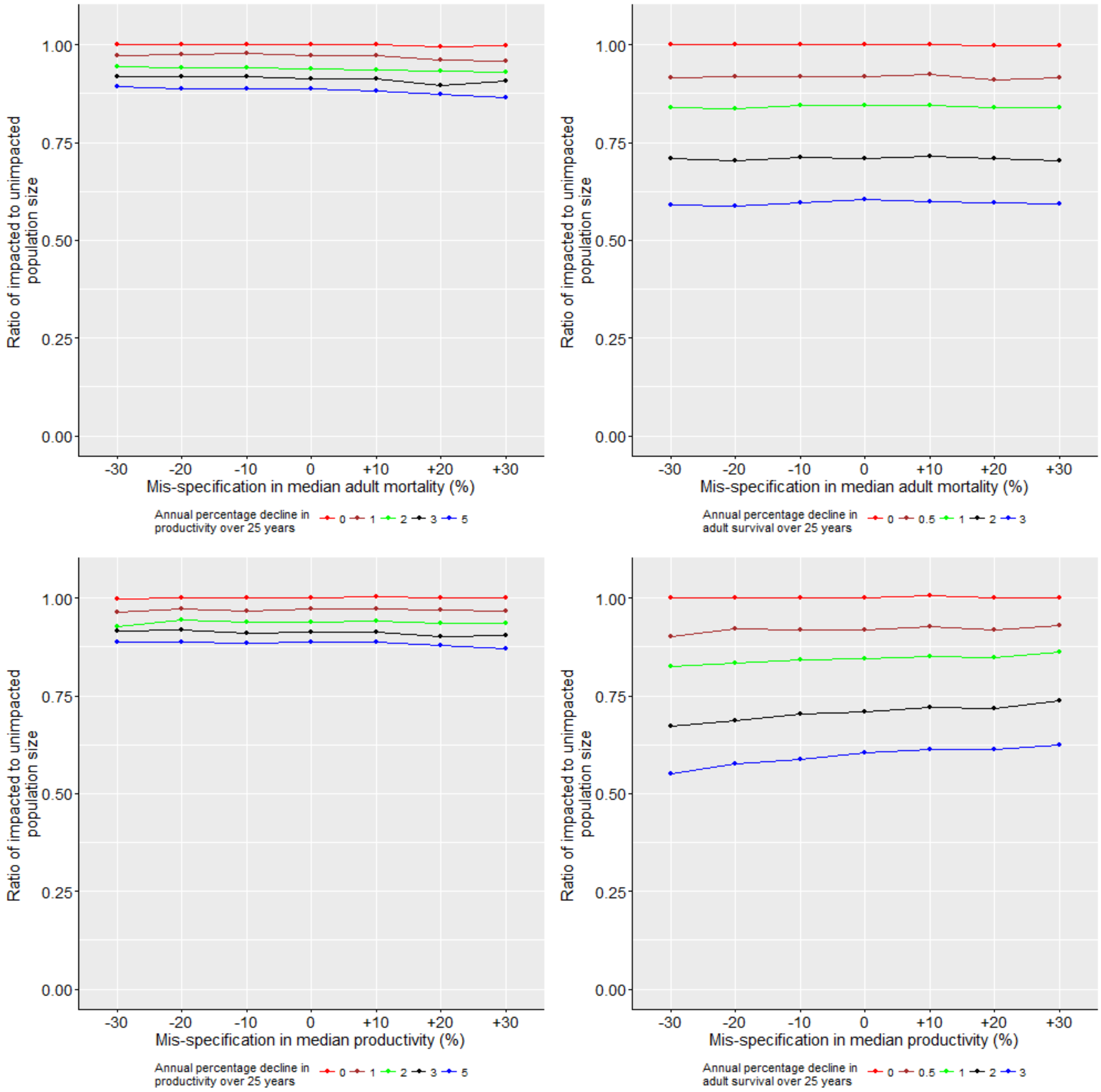


Figure A2.13c. PVA Metric C for St Abb's Shags – difference in population growth rate from 2016-2041, comparing impacted population vs. un-impacted population.

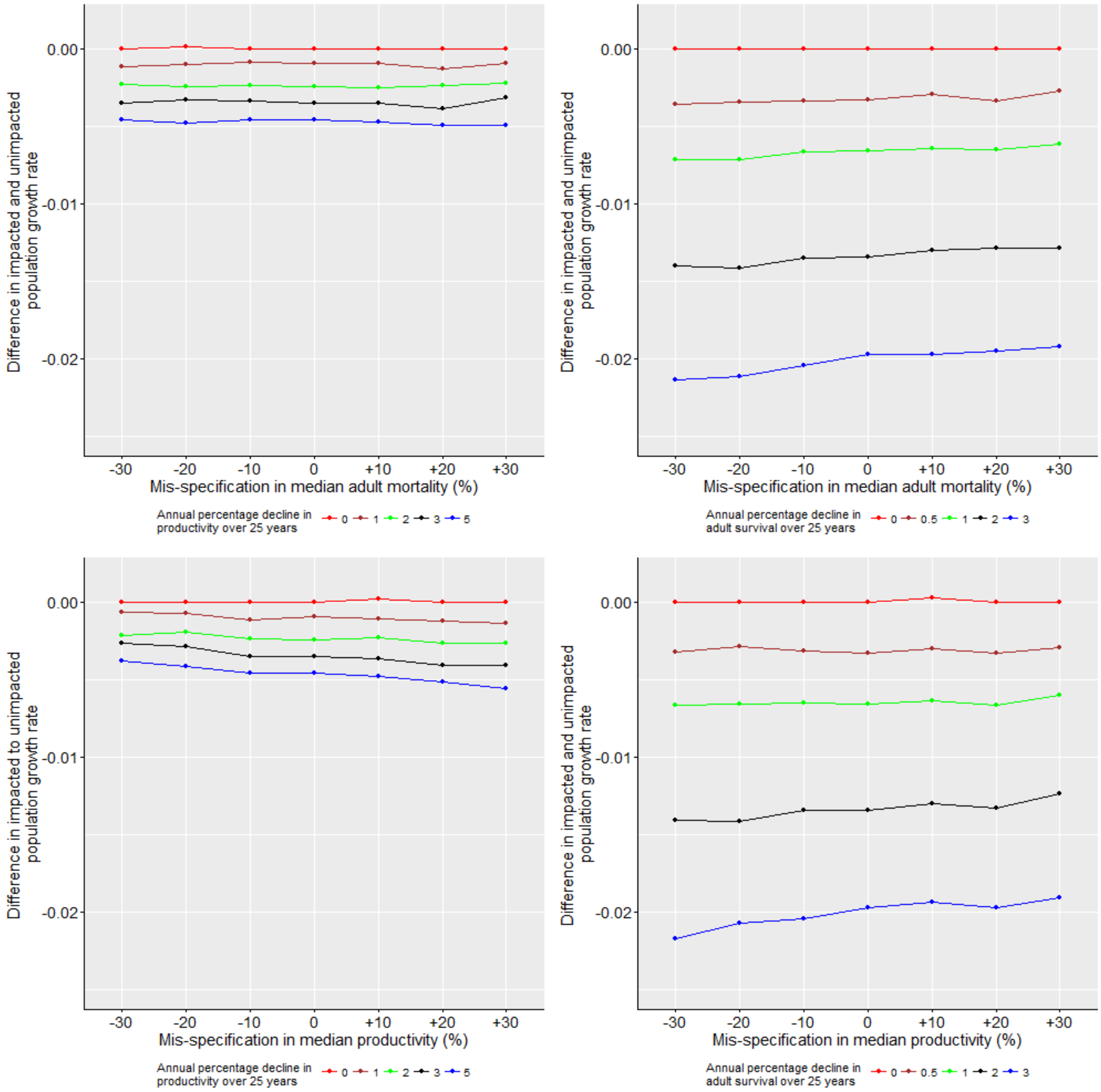


Figure A2.13d. PVA Metric D for St Abb's Shags – difference in population size at 2041, comparing impacted population vs. un-impacted population.

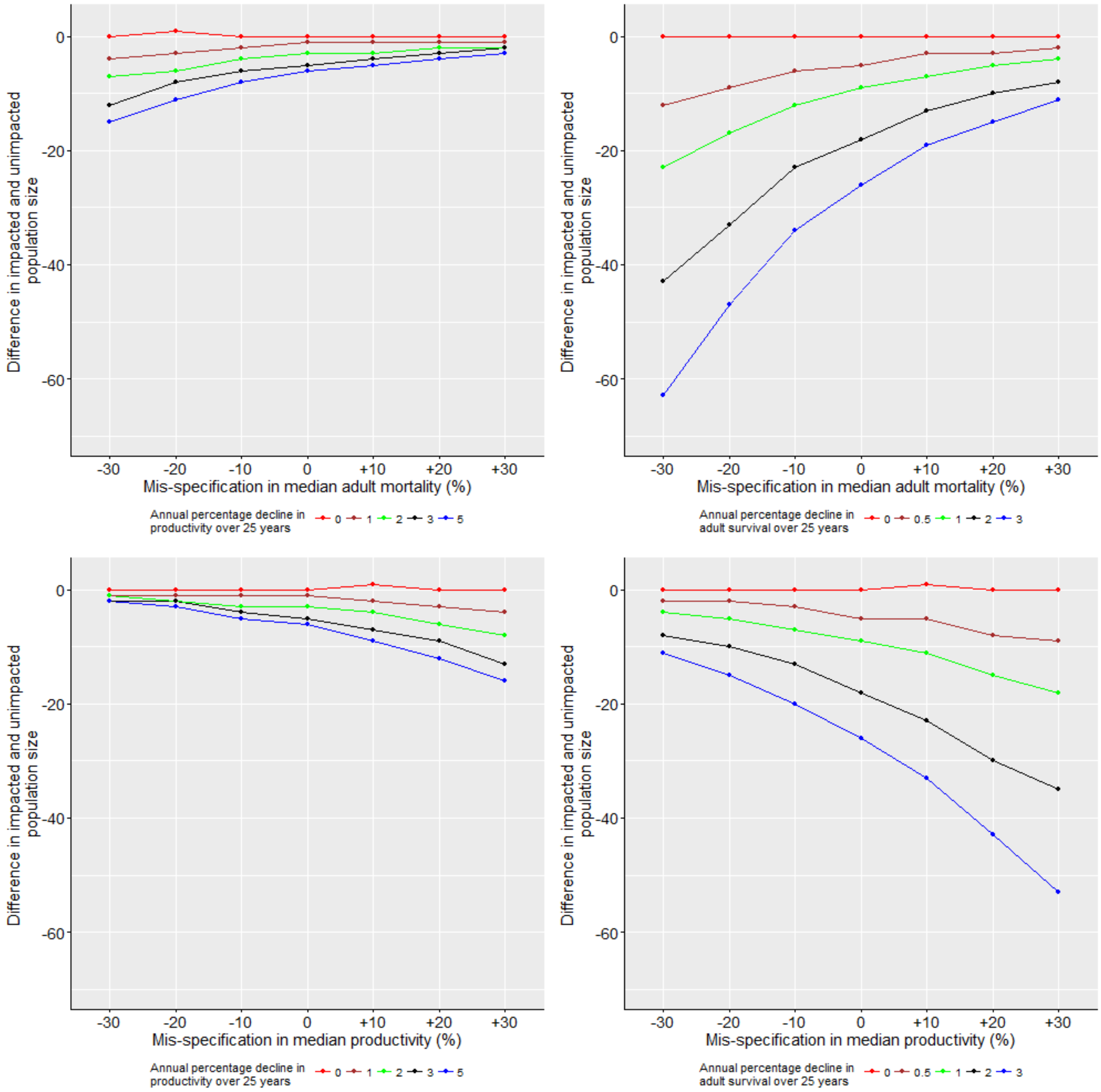


Figure A2.13e. PVA Metric E1 for St Abb's Shags – probability of population decline greater than 10% from 2016-2041.

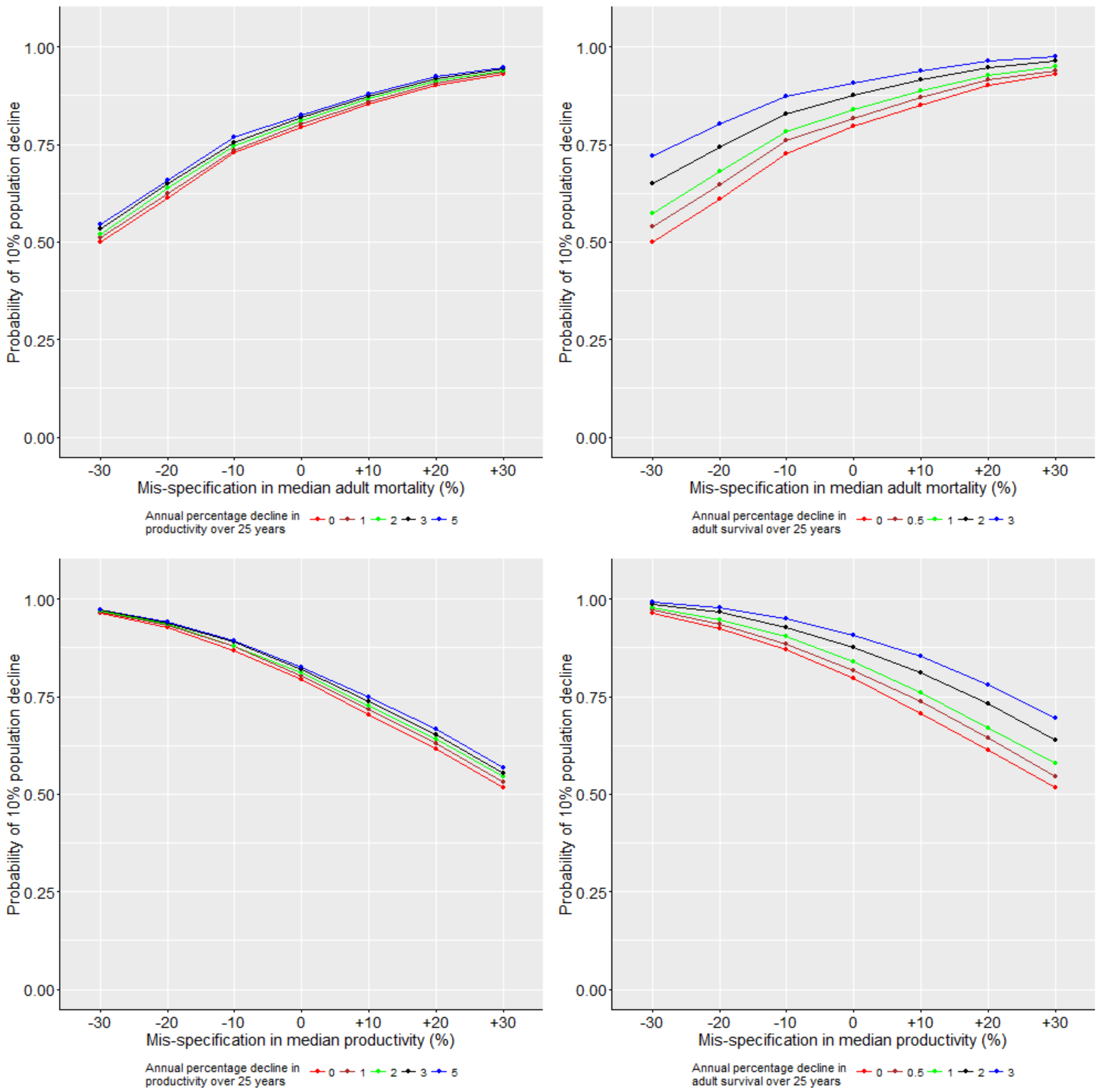


Figure A2.13f. PVA Metric E2 for St Abb's Shags – probability of population decline greater than 25% from 2016-2041.

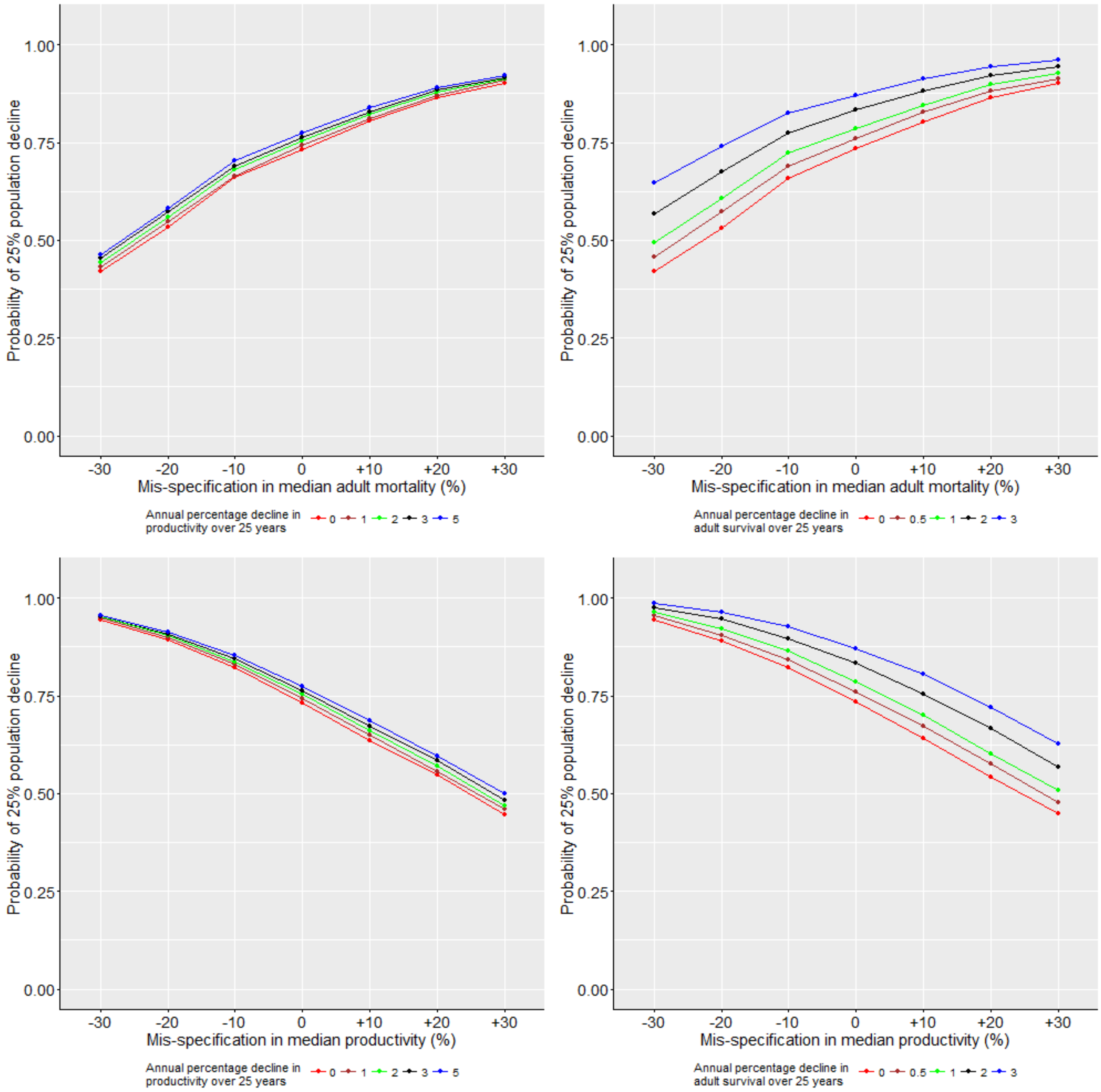


Figure A2.13g. PVA Metric E3 for St Abb's Shags – probability of population decline greater than 50% from 2016-2041.

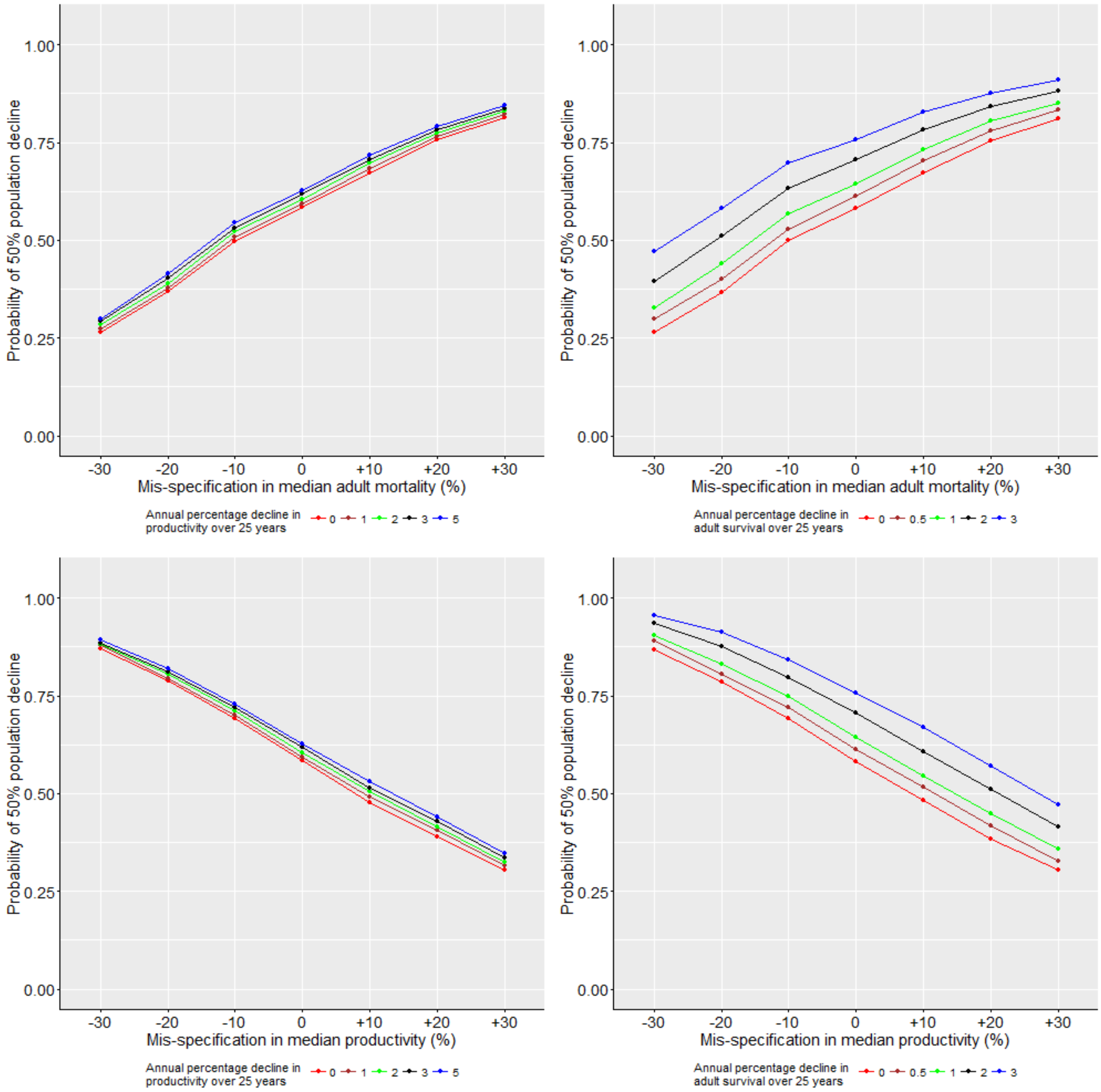
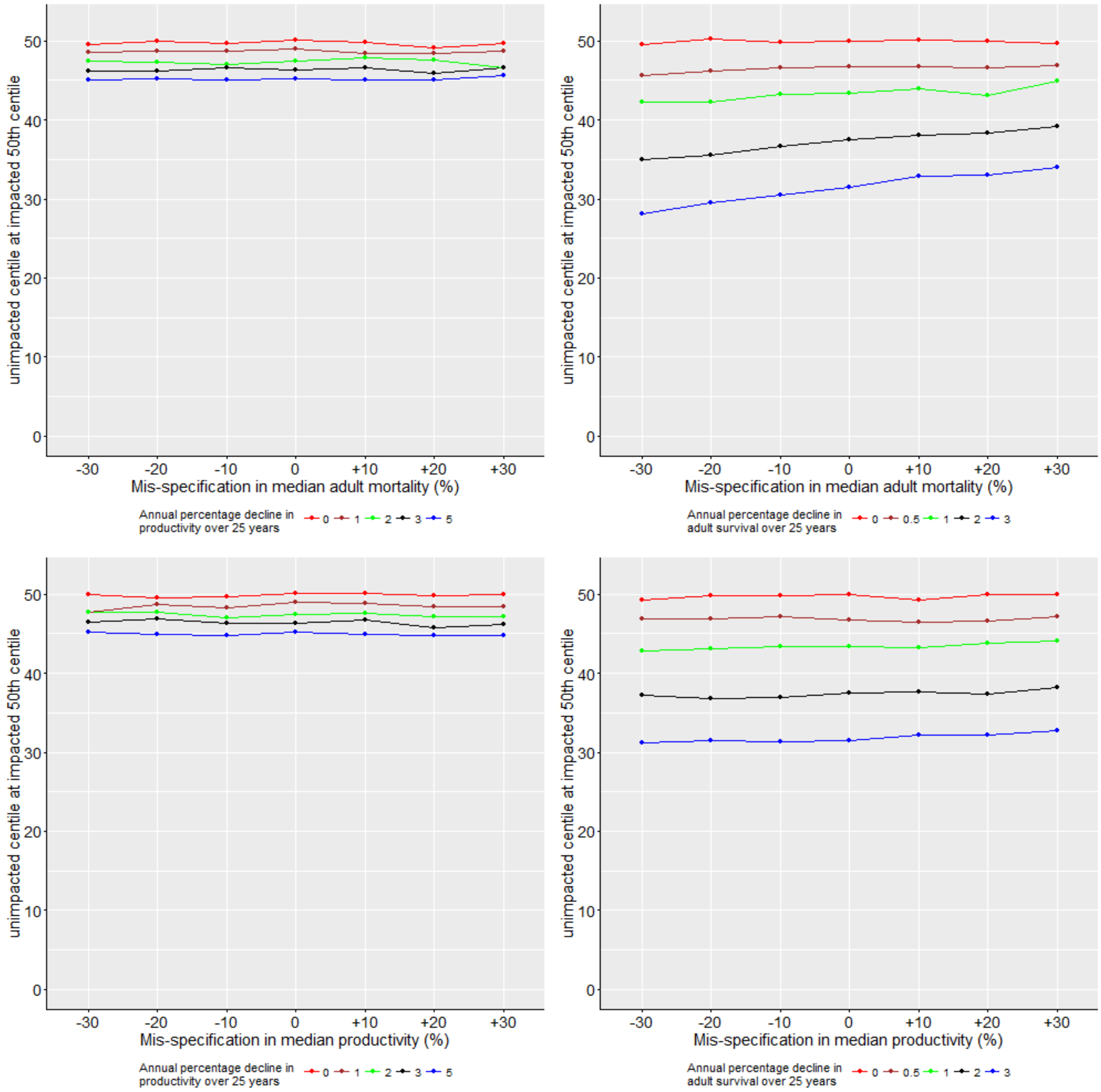


Figure A2.13h. PVA Metric F for St Abb's Shags – centile from un-impacted population size equal to the 50th centile of the impacted population size, at 2041.



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