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Modelling approaches and data requirements for a spatio-temporal index-based assessment of longfin eels

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The longfin eel *Anguilla dieffenbachii* supports important commercial, customary, and recreational fisheries in New Zealand and is a key species in freshwater ecosystems. To effectively manage this resource and maintain its cultural and ecological roles requires knowledge of stock size and the pressures that affect it. An international review in 2013 of information about longfin eel trends and status recommended the development of a comprehensive longfin eel population assessment to support eel management.

However, eel population assessment models developed with conventional methods are problematic because the complex life-history and stock structure of eels do not meet model assumptions. Perhaps the biggest barrier to freshwater eel stock assessments is the derivation of reliable indices of abundance for species that do not move between catchments and do not mix well within catchments. A 2016 review of potential approaches recommended development of a spatially distributed modelling approach (SDM) that would integrate information from multiple sources and predict female spawning biomass across the country.

To produce a suitable index of abundance for longfin eels, this project identified and co-funded development of an SDM approach for stream networks. VAST is a modeling tool developed by the US National Oceanic and Atmospheric Administration (NOAA) to implement a spatial delta-generalised linear mixed model (delta-GLMM) to standardise time series of spatial observations. VAST estimates spatial and temporal variation, habitat associations, and correlations among categories. However, standard approaches based on latitude and longitude (Euclidean space) poorly represent systems where fish attributes follow the stream network. Through a related project funded by the Ministry of Business, Innovation, and Employment Endeavour Fund ('Cultural Keystone Species', C01X1616) and in collaboration with NOAA, the VAST developers added methods for modelling stream networks.

The eel model developed under the current project uses as a proxy for female spawning biomass the density of eels larger than 50 cm (which are mostly female), predicted across the spatial framework. Local predictions are based on relationships with environmental factors, such as distance to coast, upstream elevation, and access, as well as spatio-temporal models of density with spatial correlations across the network.

Details of model development and application of the model to encounter/non-encounter data from the Waikato and Waitaki catchments are described in the research report titled "Spatiotemporal models in stream networks, with application to New Zealand longfin eels" supplementary to this report. In the body of the report a model was developed for the Waikato catchment based on encounter/non-encounter and density data in two size categories, sensitivity of the model to each of the parameters was explored, and a simulation study was used to provide an overview of future sampling requirements for ongoing and improved estimates of these model parameters.

The new methods improve on previous approaches by: 1) generating time series of predictions rather than static estimates; 2) improving the statistical spatial modeling methods to provide more accurate predictions; 3) including information relevant to size and sex composition, so that the estimates more

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closely approximate female spawning biomass; 4) modeling the influence of instream barriers and the time since their introduction; and 5) estimating the sampling required to identify population trends at catchment scale.

The models in general performed well at estimating trends. As expected, the precision of the estimates was considerably greater with longer time series of sampling data. An annual sample size of 30 was large enough to reliably detect a 2.5% density decline per year over 9 years, whereas 15 was not. A similar rate of decline over 20 years was reliably detected with either 15 or 30 samples per year.

Further simulation work is recommended to explore additional issues which include a wider range of sample sizes, trend scenarios, time periods, and size ranges; the potential to increase precision with more or better covariate information; the potential to share information among catchments to increase statistical power; and comparison between the stream network model and standard VAST with its Euclidean assumptions about spatial correlations.

1. INTRODUCTION

The longfin eel *Anguilla dieffenbachii* is a key species in freshwater ecosystems and supports important customary, commercial, and recreational fisheries in New Zealand. To effectively manage this resource while maintaining its cultural and ecological keystone species role requires knowledge of stock size and the pressures influencing the biomass and the productivity of the fishery. It is not known if the current management approach for longfin eels is sustainable. Longfin eel stocks have been affected by commercial, customary, and recreational catches, eel extermination campaigns promoted by acclimatisation societies from the 1930s to 1950s (Williams et al. 2017), habitat destruction and modification, barriers to upstream fish passage, and direct mortality through the effects of hydro-electric turbines, flood control schemes, and drain clearance activities.

The need for knowledge on stock size and the processes structuring longfin eel populations was emphasised in 2013 during an international review of information relating to longfin trends and status (Haro et al. 2013). The review panel recommended the development of a comprehensive longfin eel population assessment in New Zealand, which could then be used to help manage these longfin eel stocks sustainably under the Quota Management System (QMS). Specifically, the information could be used to estimate the current status of the population and/or exploitation rates, and thereby assess the impact of future catches on the population.

Longfin eel population assessment models cannot easily be developed using conventional fisheries assessment methods, because eels have a complex life-history pattern and stock structure that does not meet the assumptions of those models (Dunn et al. 2009). Eel stocks during their freshwater phase are distributed fractally, with diverse growth rates, sex ratios, and length and age compositions, at many spatial scales, and low rates of mixing (Hoyle 2016). A recent review of stock assessment methods for longfin eels (Hoyle 2016) recommended the development of a spatially distributed modelling approach to integrate information from multiple sources, and to predict the female spawning biomass of longfin eels across the entire country—thus providing a reliable series of relative abundance. Applying this population assessment will require integration of ongoing fisheries datasets, as well as information from fishery independent datasets. The fishery independent datasets are required because fished areas are likely to have different population structures from unfished areas, with the majority of female spawning biomass supported by unfished areas. Estimating spawning biomass in both fished and unfished areas is one of the key goals for an informative population assessment of longfin eels (Hoyle 2016).

To help develop and implement an effective spatial-temporal modelling approach, project EEL201701 funded the attendance of the lead author at the CAPAM mini-workshop on spatio-temporal modelling of fishery CPUE data in La Jolla, CA, USA, 26 February–2 March, 2018. Discussions canvassed various alternative methods for modelling fishery data, including several tools for fitting spatial autoregressive models. These approaches usually represent data on a grid or lattice (Ver Hoef et al. 2018), but have also been adapted for application to stream networks (Ver Hoef et al. 2006, Peterson et al. 2013, Hocking et al. 2018).

One of the methods presented at the CAPAM meeting was a spatio-temporal modelling methodology based on the R package VAST (Thorson & Barnett 2017). VAST (Vector Autoregressive Spatio-Temporal model) is an R package for implementing a spatial delta-generalised linear mixed model (delta-GLMM) for multiple "categories" (e.g. species, size, or age classes) when standardising time series of spatially referenced observations of catch rates or other density-related data. VAST is designed to estimate spatial and temporal variation in responses, while incorporating habitat associations and correlations among categories, and estimating the aggregate response for a target category in one or more years. It accounts separately for covariates affecting density and catchability. The model can include sub-models such as encounter probability and positive catch rates. In the density estimation context, both components incorporate variation in density among years (as a fixed effect) and can incorporate variation among samplers as a random effect that may be correlated among categories (see https://github.com/James-Thorson/VAST). Charsley (2019) showed that the standard version of VAST using Euclidean distance models was able to predict probability of capture better than a previous

approach based on regularised random forests (Crow et al. 2014). VAST has an established user base in fisheries and is becoming widely used as a tool for spatial-temporal modelling and development of abundance indices (e.g., Grüss et al. 2019, Maunder et al. 2020).

Through a related NIWA project funded by the Ministry of Business, Innovation, and Employment Endeavour Fund ('Cultural Keystone Species', C01X1616) and in collaboration with the National Oceanic and Atmospheric Administration (NOAA), the VAST developers were funded to add methods for modelling stream networks to VAST. This development, the application of which is described by Rudd et al. (in press), combined the advantages of VAST with the ability to model correlations along a dendritic stream network. This approach to modelling stream networks was originally applied in a stand-alone model (Hocking et al. 2018), but its integration into VAST provides considerably more functionality. Standard approaches based on the usual two dimensions of latitude and longitude (Euclidean space) poorly represent stream networks, because fish attributes follow the network rather than across the intervening land (Ver Hoef et al. 2019).

The VAST stream network model can be used for both estimation and prediction. The model uses as a proxy for female spawning biomass the density of eels larger than 50 cm (which are mostly female), predicted across the spatial framework.

Local predictions are based on estimated relationships between population variables and relevant environmental factors, such as distance to coast, upstream elevation, and access, as well as spatio-temporal models of density with spatial correlations across the network. It should be noted that these analyses apply to rivers and streams, but not to lakes.

The sensitivity of the model to each of the parameters is explored and a simulation study provides an overview of future sampling requirements for ongoing and improved estimates of these model parameters.

2. METHODS

Details of the VAST stream network model structure and methods are provided by Rudd et al. (in press). The following section gives an overview of these modelling methods. Details are given for how these methods were adapted to estimate female spawning biomass, and for the simulation testing methods used to identify sampling needs. Supplementary tables are provided in Appendix 1.

2.1 Spatial framework

The River Environment Classification (REC) network database (version 2.4) was used as the basis of the spatial framework. The REC is based on a digital drainage network that was derived from a digital elevation model (DEM) with a spatial resolution of 50 m (Snelder & Biggs 2002). The digital network represents New Zealand's rivers as *ca.* 600 000 segments (bounded by upstream (parent) and downstream (child) nodes or confluences) and their corresponding catchments. The digital network is stored in a geodatabase that applies a unique identifier to each segment (nzsegment). The georeferenced segments and catchments facilitate analyses of upstream-downstream connectivity and accumulation of catchment characteristics (e.g., land areas with different geological or land cover categories) in the downstream direction.

In developing the framework, two catchments were chosen as case studies: the Waikato and the Waitaki, with the primary focus for spawning biomass estimation on the Waikato.

From the REC database, eight habitat covariates were chosen to examine in the stream network spatio-temporal models. Covariates determined to be important in recent studies of stream networks around New Zealand (Crow et al. 2014) were selected, including the mean flow in cubic metres per second (cumecs), distance from coast (km), local elevation (m), coefficient of variation of annual rainfall, average January air temperature (°C × 10), years since the dam was completed (the Karapiro dam was

completed in 1947 and the Waitaki dam in 1935), and years squared since the dam was completed. The habitat information was mostly constant through time and represented average values across time for each stream segment. Only the dam-related variables were time-varying. VAST can model annually varying habitat covariates, but fine-scale annual data were unavailable. Therefore, it was assumed that static habitat information over time adequately reflected the drivers of population dynamics.

All the observations described in Sections 2.2 and 2.3 were matched to the network using the 'nzsegment' identifier. The length of the stream was sampled to 150 m (Joy et al. 2013), assuming constant stream width.

2.2 Environmental data

Environmental data were collated from two main sources: the REC database which provided time-constant data, and site-level covariates measured at habitat sampling sites by the Waikato regional council (WRC) environmental monitoring team. Regional council habitat sampling sites were a subset of the eel count sampling sites. The number of habitat sampling records per year is reported in Table 1.

Table 1: Number of habitat samples per year.

Year	Samples
2010	5
2011	15
2012	30
2013	39
2014	34
2015	29
2016	36
2017	21

For simulation work, a subset of eight habitat covariates was originally selected from a larger set of covariates. This selection was done because VAST, like any regression method, is sensitive to correlated continuous covariates (Dormann et al. 2013). A variance inflation factor analysis (James et al. 2013) was performed to carry out the selection of the eight habitat covariates (Shannan Crow, personal communication).

The eight selected habitat covariates included: *Dist2Coast*, *us_elev*, *Total.fishing.time*, *Boulder*, *Small.Gravel*, *Sand*, *Large.Wood*, *SBHB.Q9..Periphyton*, *Channel.Width.average*, *SBHB.Q6..Sediment.Deposition*, *SBHB.Q8.Abundance.and.Diversity.of.Habitat*, and *Temp*. These covariates are described in Table 2. However, only the three covariates distance from coast (km), local elevation (m), and years since the Karapiro dam was completed were available in the REC database at all river segments across the stream network. Therefore, only those three above-mentioned covariates were ultimately employed for the simulation work. The environmental data collected by WRC had very low sample sizes per sampling year (see Table 1) which was too sparse to be useful for estimation and prediction. Additionally, the three above-mentioned selected REC covariates tended to result in a converged model.

Table 2: Covariate labels and definitions for the habitat covariates collected by Waikato Regional Council.

Covariate label	Definition
Dist2Coast	The downstream distance to the coast (km).
us_elev	The upstream mean elevation above sea level of the watershed or basin (m).
Total.fishing.time	The total time spent fishing for eels (mins).
Boulder	Index for the % coverage of boulders at a sampling site.
Large.Wood	Index for the % coverage of large wood at a sampling site.
Periphyton	Index for the % coverage of periphyton at a sampling site.
Width	The average channel width (m) of a sampling site.
Sediment.Deposition	Index for the % coverage of sediment deposition at a sampling site as defined by Stark et al. (2001).
Diversity.of.Habitat	Unitless index for the overall abundance and diversity of the habitat at a sampling site as defined by Stark et al. (2001).
Temp	The water temperature (°C) at the time of sampling.

2.3 Eel population data

The REC network was populated with fishery information to develop the longfin eel population model. These data include information on encounter/non-encounter, density, and size structure, as well as environmental conditions. Originally, it was also planned to include information on growth rates, sex ratio, and length at maturation based on the recommendations from Hoyle (2016); however, methods that could be applied without requiring these data were later identified.

Encounter/non-encounter and density information were collated from information held by NIWA, the New Zealand Freshwater Fish Database (NZFFD), and other research partners. The NFFFD (Crow 2017) provided observations of encounter or non-encounter of longfin eels across New Zealand. The following NZFFD columns were selected: 'nzsegment' (segment identification), 'fishmeth' (fishing method), 'angdie' (whether or not longfin eels were observed during a sampling event), 'upcoodY', 'upcoordX', 'downcoordY', and 'downcoordX' (the easting and northing coordinates of the stream segment's child and parent nodes), 'year' (the sample year), and 'org.groups' (the sampling agency).

Other data were included from a study specific to the greater Waikato River region that recorded, for each sampling event, the number of longfin eels observed and each eel's length. This study used electrofishing to sample longfin eels over an area swept of 150 m. This dataset included 274 sampling events over nine years, across 116 locations spanning 30 catchments. The dataset observed and measured 3261 eels over the nine years; these eels ranged from 60 mm TL to 1350 mm with a median of 222 mm.

For encounter/non-encounter analyses, the Waikato Regional Council data were combined with the NZFFD dataset by converting observations specific to the Waikato River catchment from counts to encounter/non-encounter data.

For length-based analyses focused on the greater Waikato river region, raw length data were grouped into counts of individuals per 10-mm length bin and sampling event. In preliminary models described in Appendix 1, four different options were used for length categories, but the analyses presented here used a different approach for the length categories, described in section 2.4.

2.4 Estimation models for spawning biomass

The approach, as recommended by Hoyle (2016), provides an index via a time series of female spawning biomass estimates. The data in the NZFFD largely report encounters (encounters/non-encounters), which is a useful proxy for biomass but lacks information on the composition of large females that represent potential female spawning biomass.

To estimate a proxy for female spawning biomass we categorised lengths as above and below 500 mm. Mean length at migration for males has been estimated as 620 mm (Hoyle & Jellyman 2002). Eels at least 500 mm long would include some males but are more likely to be female than male.

Density data were calculated as counts per segment length because models fitted to count data consistently failed to converge. This assumed that segment length was an indicator of the extent to which the river has been sampled in terms of length and width. That means the abundance indices are only indicators of the true abundance because the area in which it is estimated is incorrect.

The estimation model was fitted with a Poisson-link delta model (Thorson 2018), rather than the delta-lognormal used for the encounter/non-encounter analyses and the zero-inflated Poisson used for length category analyses (Rudd et al. in press). The delta-lognormal and zero-inflated Poisson approaches failed to reliably converge for models with densities in two size categories; and the zero-inflated Poisson approach is appropriate for discrete dependent variables like counts, but not for continuous dependent variables like catch rates. The Poisson-link delta model uses log-links for both numbers-density and biomass per number (ObsModel = c(2,1)).

The three REC covariates distance from coast (km), local elevation (m), and years since the Karapiro dam was completed were included in the model. The version of VAST used here assumes by default that covariate effects are linear, although recent developments of the software mean that future studies could model non-linear covariate effects. Spatial and spatio-temporal components were included in the numbers-density component and the biomass per number component (FieldConfig = c(1,1,1,1)).

2.5 Determining sampling needs and time frames to estimate fishing indicators at alternative levels of precision.

To estimate the sampling needs to detect population trends, the greater Waikato estimation model for counts and lengths was set up as an operating model (OM) to conduct a simulation experiment. This OM was used to simulate a collection of randomised datasets that could then be refitted in estimation models.

Two versions of the OM were established, one for a period of 9 years 2009–2017, and the other for 20 years 2009–2028. A separate 20-year model was made because the data did not span a 20-year period. Therefore, random effects were needed in the temporal variability terms in order to project into the future (Thorson 2019).

In the 9-year operating model, the annual temporal intercept terms were estimated as fixed effects (RhoConfig[1:2] = (Beta1 = 0, Beta2 = 0)), and spatio-temporal terms were estimated as random effects which were autoregressive among years (RhoConfig[3:4] = (Epsilon1 = 2, Epsilon2 = 2)). In the 20-year operating model, years without data could not be estimated using fixed effects, so the temporal intercept terms were estimated as random effects, independent among years (RhoConfig[1:2] = (Beta1 = 1 and Beta2 = 1)), and spatio-temporal terms were estimated as in the 9-year model.

The 20-year OM lacked habitat data for the years 2018–2028. The covariates distance to coast and upstream elevation do not change among years and were therefore kept static for this time period. The covariate for the years since the Karapiro dam was completed was extended over the additional years. The operating model was set up with dummy values for observations in the simulated year-site strata. These dummy data were used in the predictive probability but not in the likelihood. Locations to be simulated were selected as follows:

a. Prioritise the network segments considered more likely to be sampled. These were Waikato network segments with a high probability of capture for longfin eels. Initial probability of capture estimates were obtained from a regularised random forest (RRF) model (Crow et al. 2014). The 69 segments not included in that study were omitted. High probability of capture was deemed to be greater than 0.6760, which was the upper quartile of probability of capture in the Waikato. This left 817 segments to sample.
b. Select 60 of these segments at random in each year. Thus, in the 9-year OM an extra 540 locations were added, and in the 20-year OM an extra 1200 locations were added.
c. Build the OM with the Waikato data and habitat covariates.

Two trend scenarios were considered: either no change in the trend (tre = 0), or a declining trend to 50% lower density over 20 years (tre = 1). When tre = 0, the trend parameter (temporally varying intercept, $\beta_1(\mathrm{f},\mathrm{t})$ and $\beta_2(\mathrm{f},\mathrm{t})$) was left unchanged from its estimate in the OM. When tre = 1, the trend parameter was changed to values between 1.5 and 0.75 over 20 years in all factors *f*. Therefore, in the 9-year OM, the overall decline was less substantial given the shorter time period. These values were selected because they produced indices for longfin eel abundance that reflected an approximate 50% decline in abundance over 20 years. However, this decline estimate was only approximate because other temporal parameters such as the spatio-temporal terms and density covariates changed year-to-year.

Two dataset sample sizes were considered, with either n = 15 or n = 30 sampling locations (reaches) per year. Where each sampling location contained one count record for eels less than 500 mm in length and one count record for eels greater than 500 mm in length.

Simulation involved the following steps, repeated for each combination of factors: trend scenario (tre = 0, tre = 1), data set size (n = 15, n = 30), and OM (years = 8, years = 20):

a. Set the trend parameters.
b. Randomly select *n* of the 60 sites per year.
c. Simulate the data using the fitted TMB object, conditional on the fixed and random effects estimated.
d. Save the simulated data.

Steps c and d were repeated 100 times, i.e., 100 data sets were simulated. Figure 1 gives the mean simulated abundance indices under all scenarios, data set sizes, and OMs.

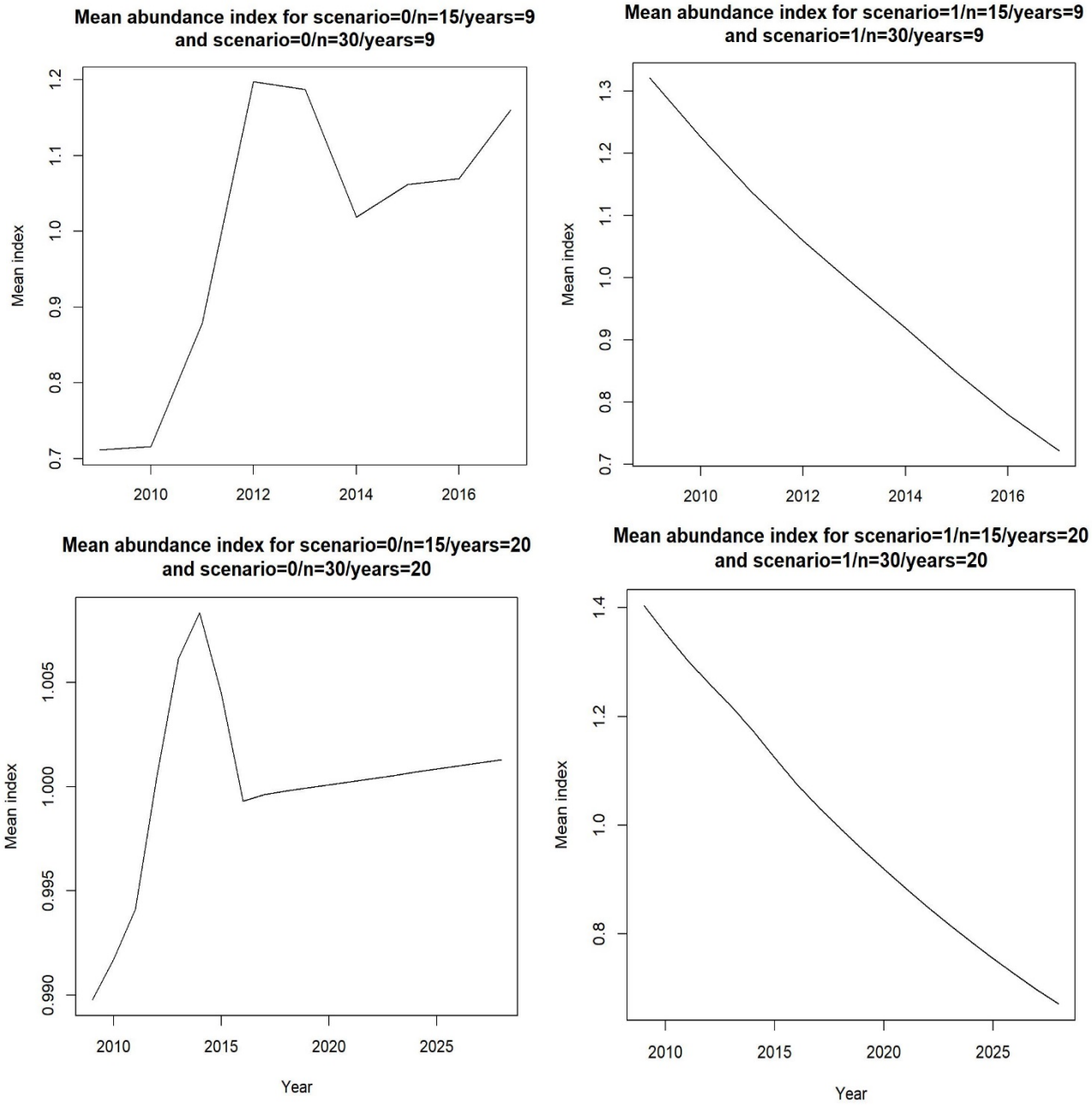

Figure 1: The mean simulated abundance index from the 9-year OM (top) and 20-year OM (bottom) with no declining trend (left) and a 50% declining trend over 20 years (right).

2.6 Estimating models (EM)

The 9-year and 20-year EMs were set up in the same ways as their respective OMs except that in the 20-year model the trend (time-varying intercept) parameter was modelled as a random effect sampled from a normal distribution with a mean defined as a random walk. This meant that an intercept did not need to be estimated yearly, which reduced the number of estimated parameters in the model. A temporal random effect was needed to make estimates in years without any sampling data (2018–2028).

In some models, particularly when the sample sizes were low (e.g., n = 15 in the 9-year model), models still failed to converge. This was due to two main issues: parameters were non-identifiable (high gradients, local minima, etc.), or the Hessian matrix was not invertible.

For these, the models were refitted without habitat covariates, to reduce the number of estimated parameters and to improve identifiability.

The following metrics were reported from the simulation study:

- Percentage of missing indices: the models that failed to converge and produce an index for abundance for longfin eels. Two percentages are given, before and after rerunning the failed models with reduced settings.
- The reliability of the trend: for each simulation, the difference between the slope coefficients from regressions of log(Est)~year and log(True)~year.
- Coverage: for each simulation, the percentage of years that included the true abundance index value within its $(1-\alpha)$ confidence interval. $(1-\alpha)$ was set as:
  - 0.95
  - 0.80
  - 0.50
- Absolute bias: the estimated index minus the true index, by year.
- Relative bias: the absolute bias divided by true index, by year.
- Root mean square error:, which is given by (Stow et al. 2009):

$$\mathrm{RMSE_i} = \sqrt{\sum_t^{\mathrm{n_t}} (\hat{y}_t - y_t)^2 / n_t},$$

  where n_t is 9 or 20 years and $i = 1, \ldots, 100$ repetitions.

3. RESULTS

3.1 Model fits 1

The fit to the data of the 9-year operating model was examined via the residuals. Spatial and temporal patterns (Figure 2) were difficult to interpret due to the sparseness of the data, but no anomalous patterns were observed. VAST generates goodness of fit plots using the DHARMa package (Hartig 2020) which produces the expected distribution by simulating from the fitted model. The diagnostic plots in Figure 3 indicate a small amount of under-dispersion, with observations on average closer to expected values than assumed by the model.

Diagnostics for the 20-year model are similar to the 9-year model for both the spatial-temporal (Figure 4) and DHARMa diagnostics (Figure 5).

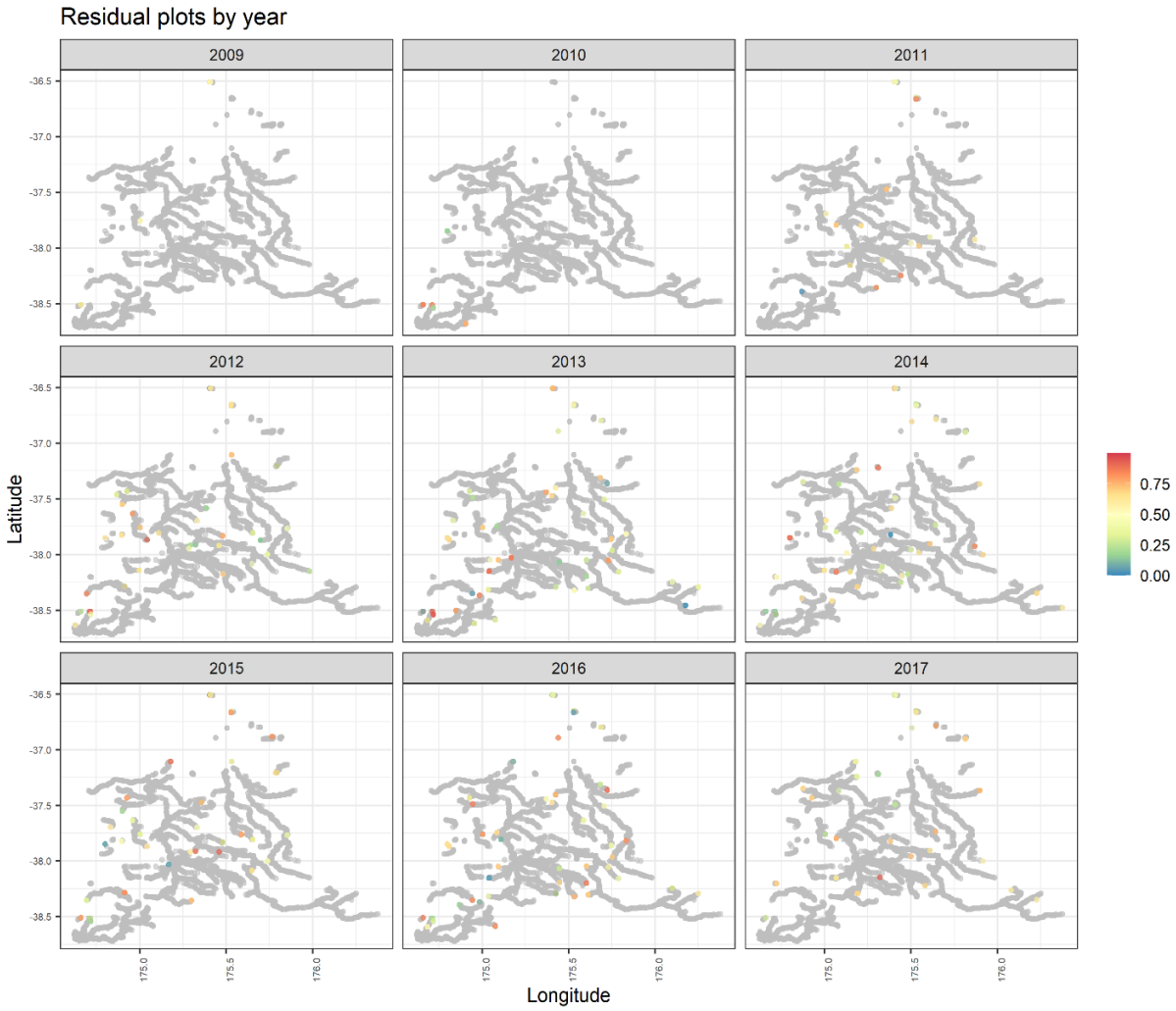

Figure 2: Standardised residuals across time and space for the 9-year operating model (OM).

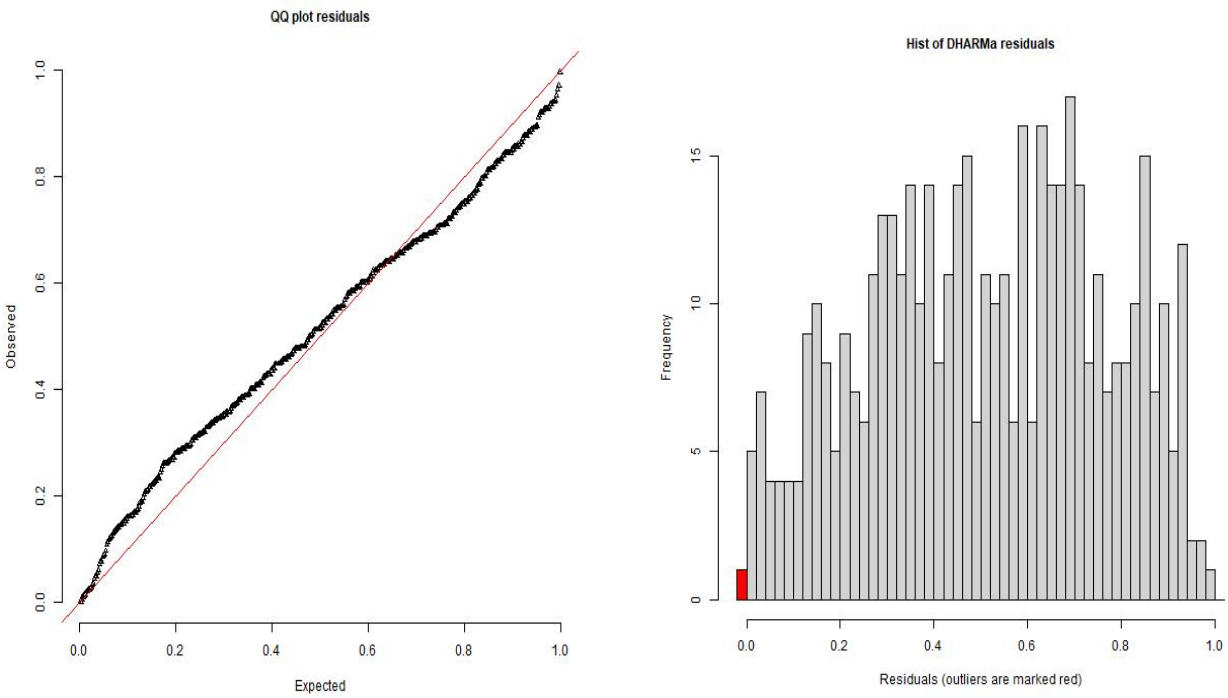

Figure 3: QQ plot and histogram of standardised residuals for the 9-year operating model (OM).

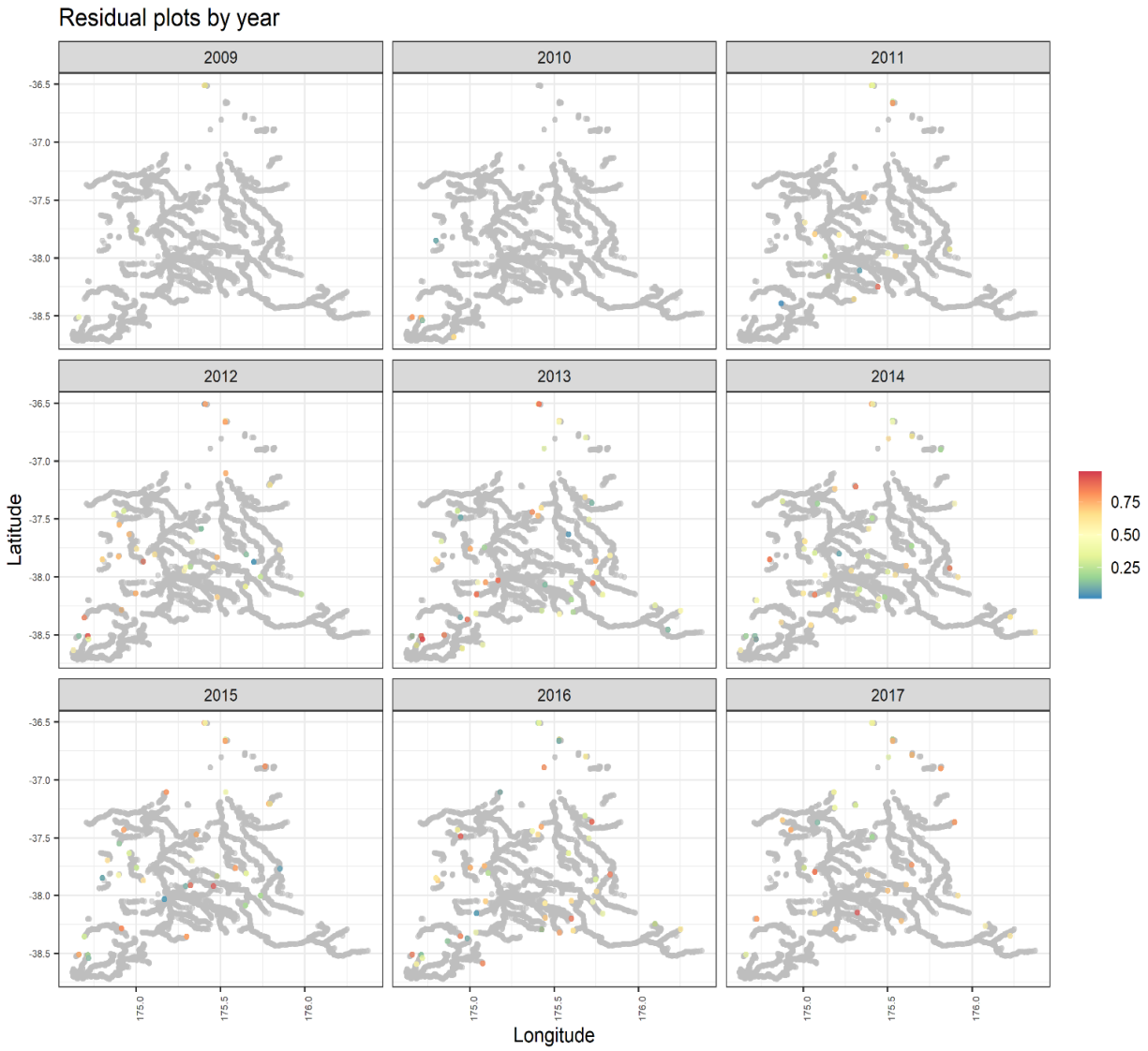

Figure 4: Standardised residuals across time and space for the 20-year operating model (OM).

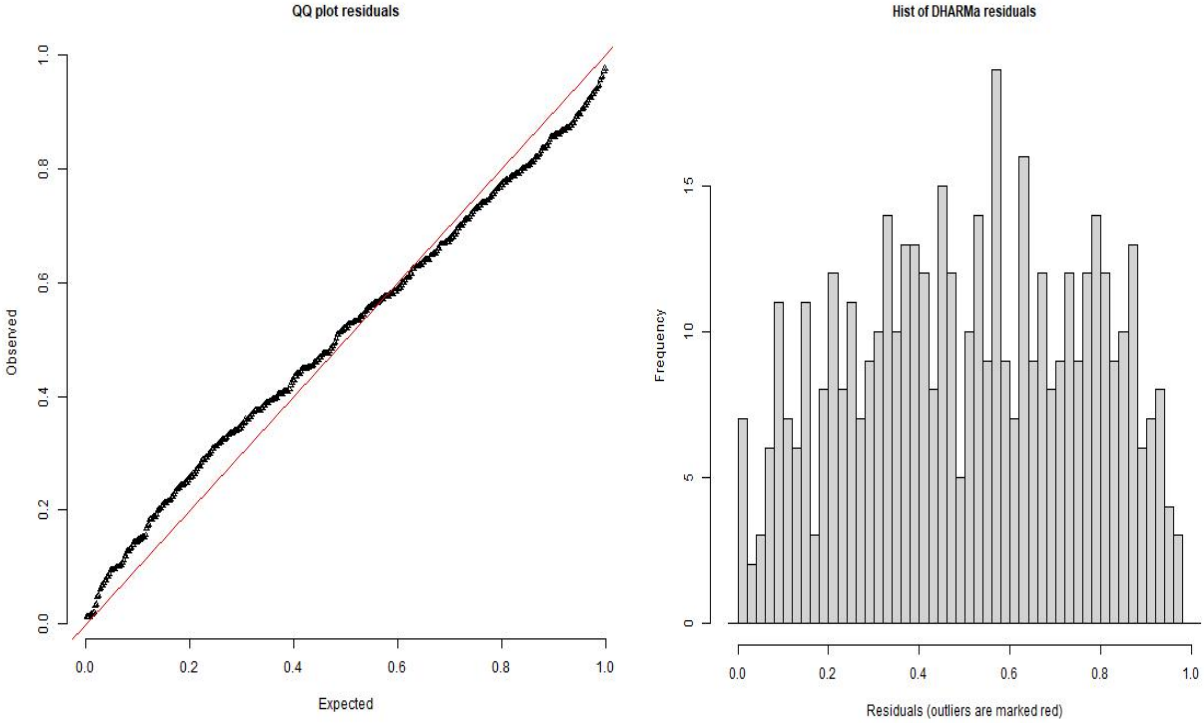

Figure 5: QQ plot and histogram of standardised residuals for the 20-year operating model (OM).

3.2 Model results

The model estimated temporal trends for the two size categories in the 9-year model (Figure 6), with the density of eels over 500 mm estimated to have increased after about 2010 before stabilising. Eels less than 500 mm showed no clear trends in density through time. Plots of the spatial distribution of density suggested that density increases for the larger size category were widely distributed (Figure 7).

Results for the 20-year model, in contrast, showed no clear trends through time for both size categories (Figure 8). Very little variation was estimated between years, and estimated uncertainty levels were large. Similarly, little change through time was apparent in the spatial distribution of the large size category (Figure 9).

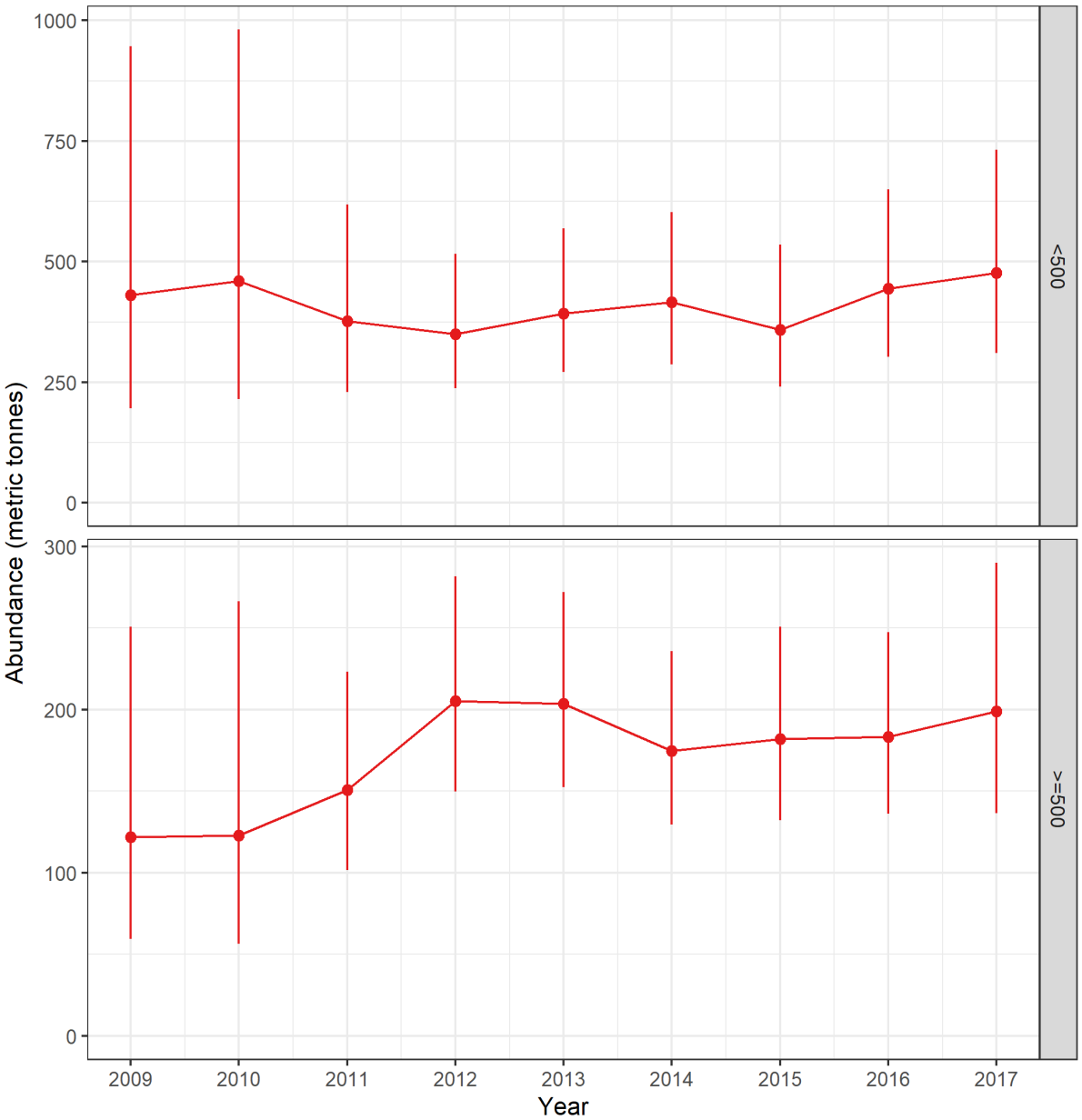

Figure 6: Predicted abundance (biomass) for longfin eels less than 500 mm (top panel) and at or greater than 500 mm (bottom panel) in the Waikato region from the 9-year operating model (OM).

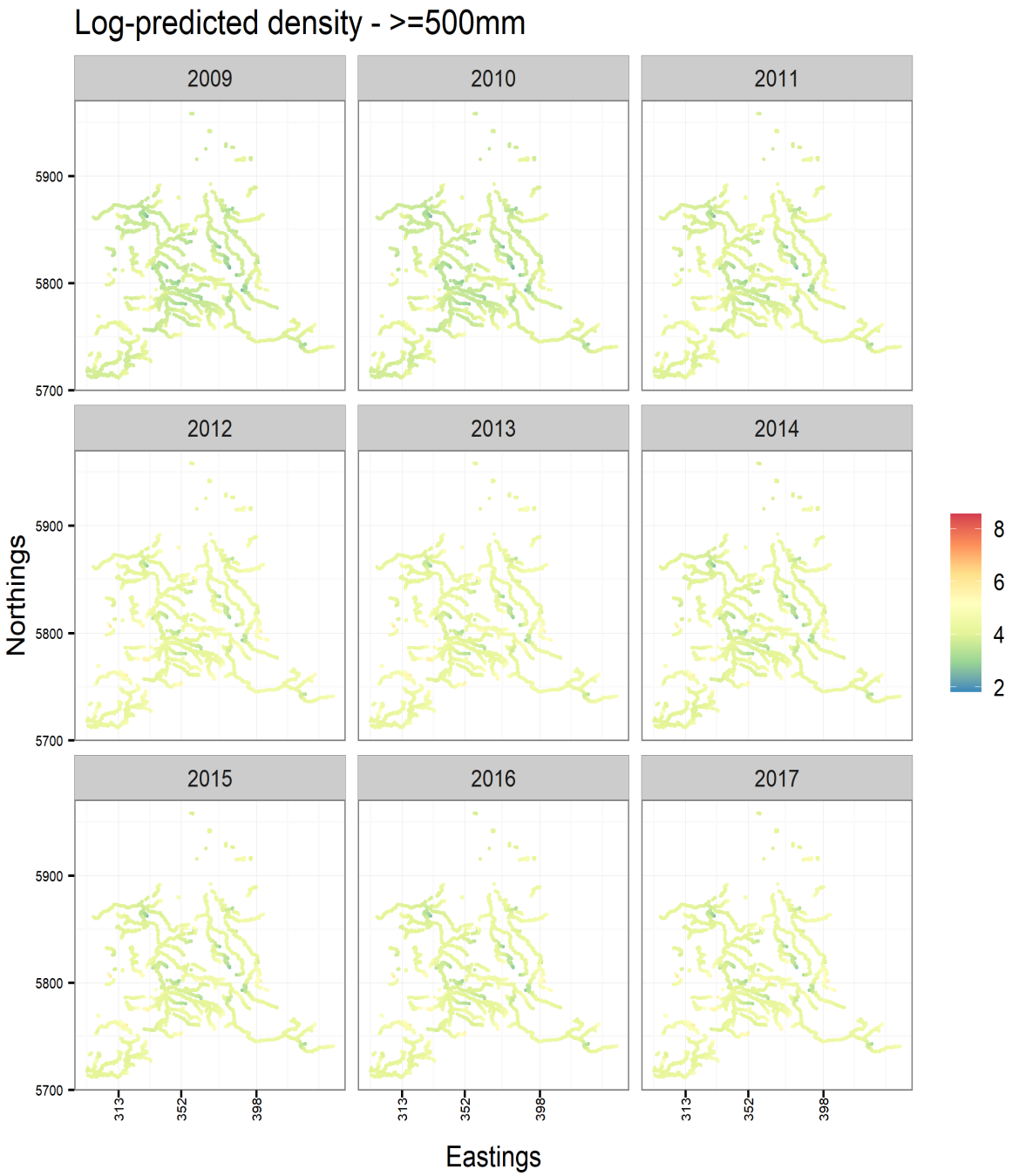

Figure 7: Log predicted density for longfin eels in the Waikato region from the 9-year operating model (OM).

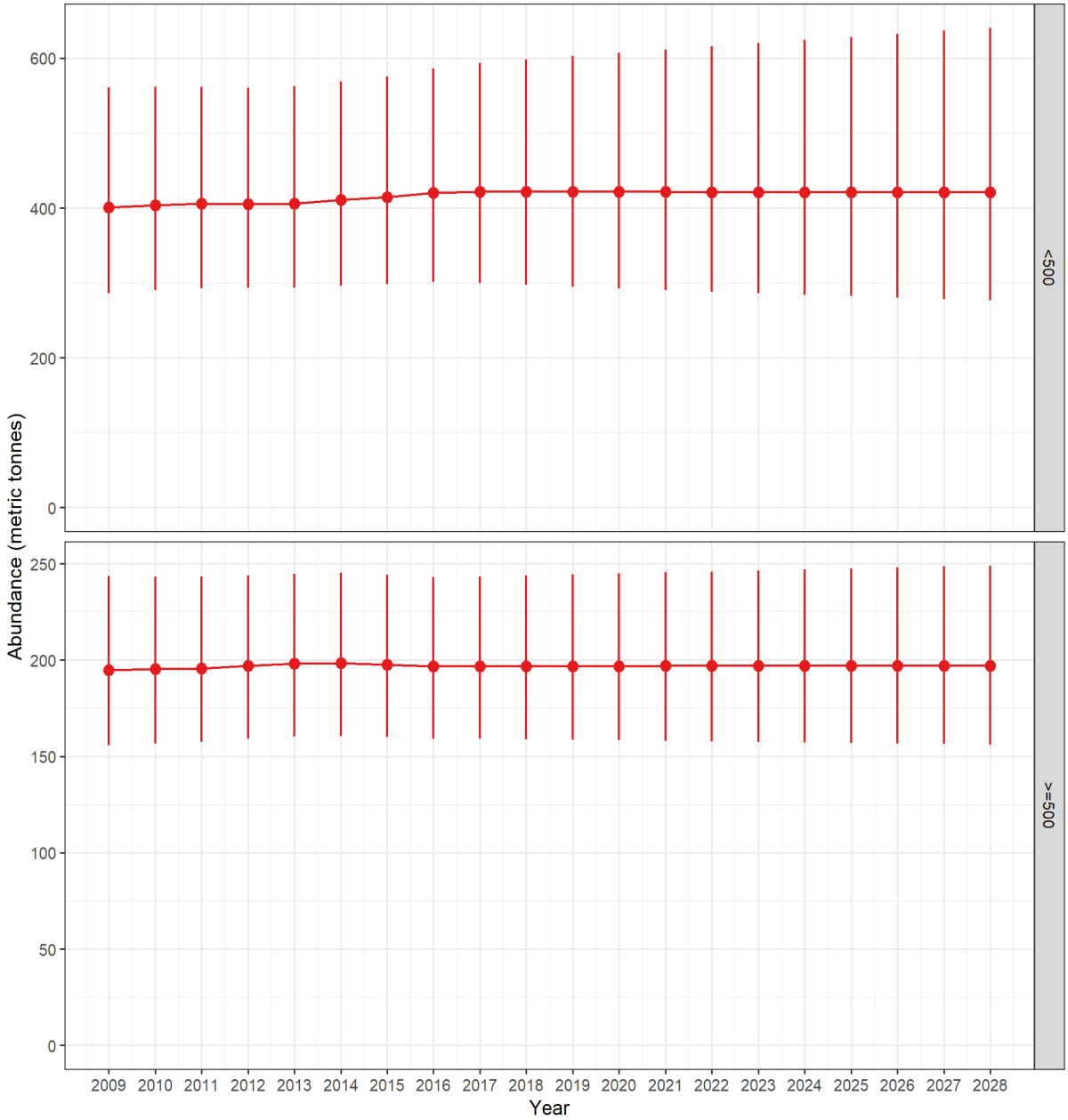

Figure 8: Predicted abundance (biomass) for longfin eels less than 500 mm (top panel) and at or greater than 500 mm (bottom panel) in the Waikato region from the 20-year operating model (OM).

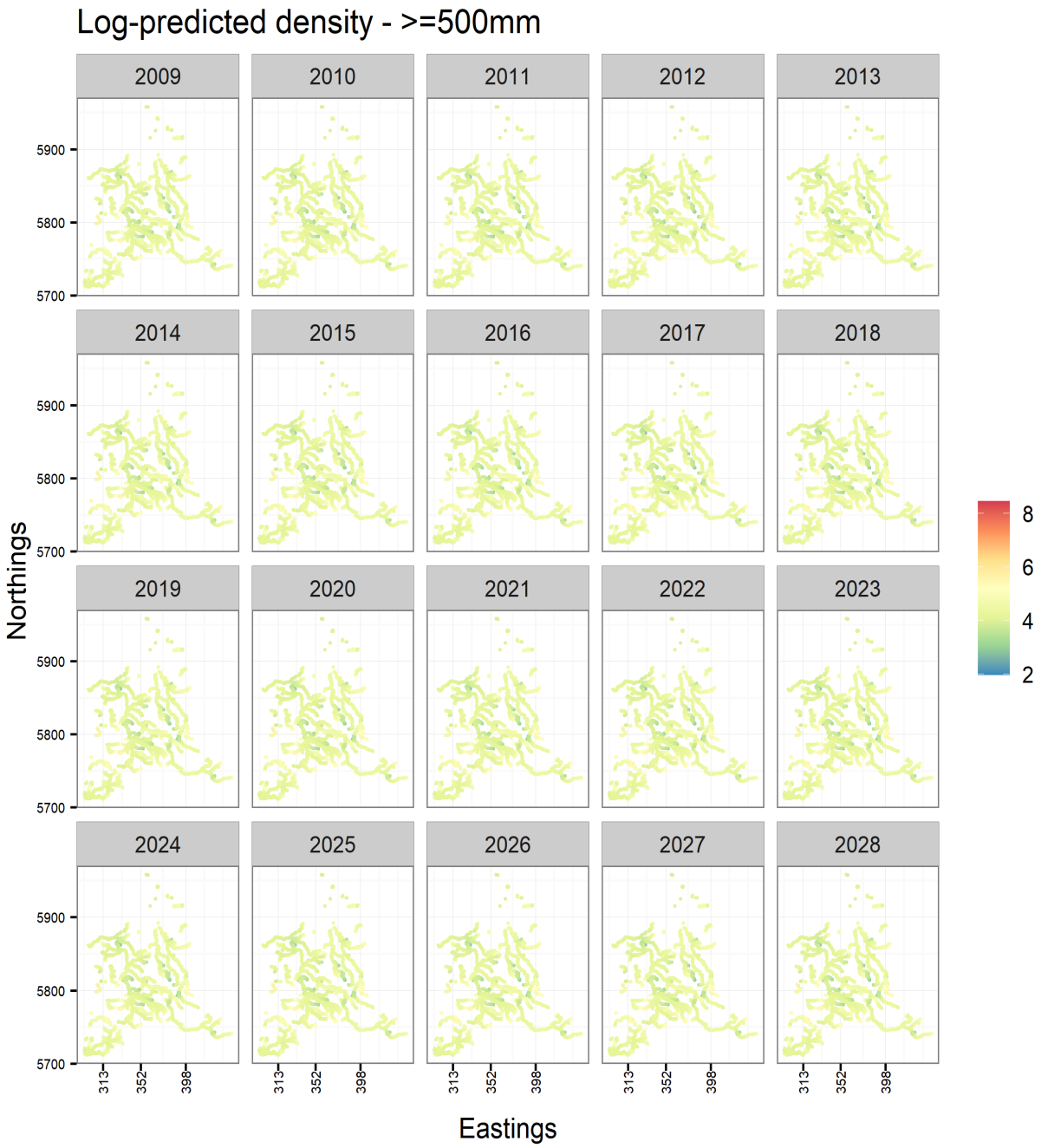

Figure 9: Log predicted density for longfin eels in the Waikato region from the 20-year operating model (OM).

3.3 Simulation results

Simulations were carried out to test the ability of the model to estimate trends under different scenarios of assumed trends, time series lengths, and rates of data collection.

Although most models were able to successfully converge (Table 3), a small proportion of models failed to fit the 9-year time series, particularly at the lower rate of 15 sample locations per year.

For the 9-year simulations, the trend estimates generally appeared unbiased, though there was a suggestion of some positive bias for the declining scenario (50% over 20 years, or 0.025 per year) with 15 samples per year, with the median slope approximately 0.01 per year (Figure 10). For the trend scenarios, uncertainty in the trend estimates was similar at the same sample size, but with considerably more precision at sample size of 30 per year than at 15 per year.

The coverage of the true relative density by annual estimates of relative density was well above the nominal level for simulations from the 9-year OM (Figures 11 to 14), suggesting that the confidence interval estimates were too wide. These coverage estimates assume that the density estimates are independent of one another, which is not true due to spatio-temporal correlation in the model. Estimates for the scenario with declining population density and 15 samples per year showed evidence of bias in the trend estimate, but this bias was absent from the equivalent scenario with 30 samples per year.

For the 20-year simulations the trend estimates appeared largely unbiased (Figure 15), though with slight positive bias for the scenarios with declining trend and 15 or 30 samples per year (Figures 16 to 19). Coverage was above the nominal level for all types of confidence interval. Some positive bias was evident in the trends of relative error estimates for scenarios with both 15 and 30 samples per year.

Table 3: Percentage of simulations missing indices.

		Operating model	
Trend scenario	Sample size scenario	9-year OM	20-year OM
0	15	4%	0%
0	30	1%	0%
1	15	8%	0%
1	30	2%	0%

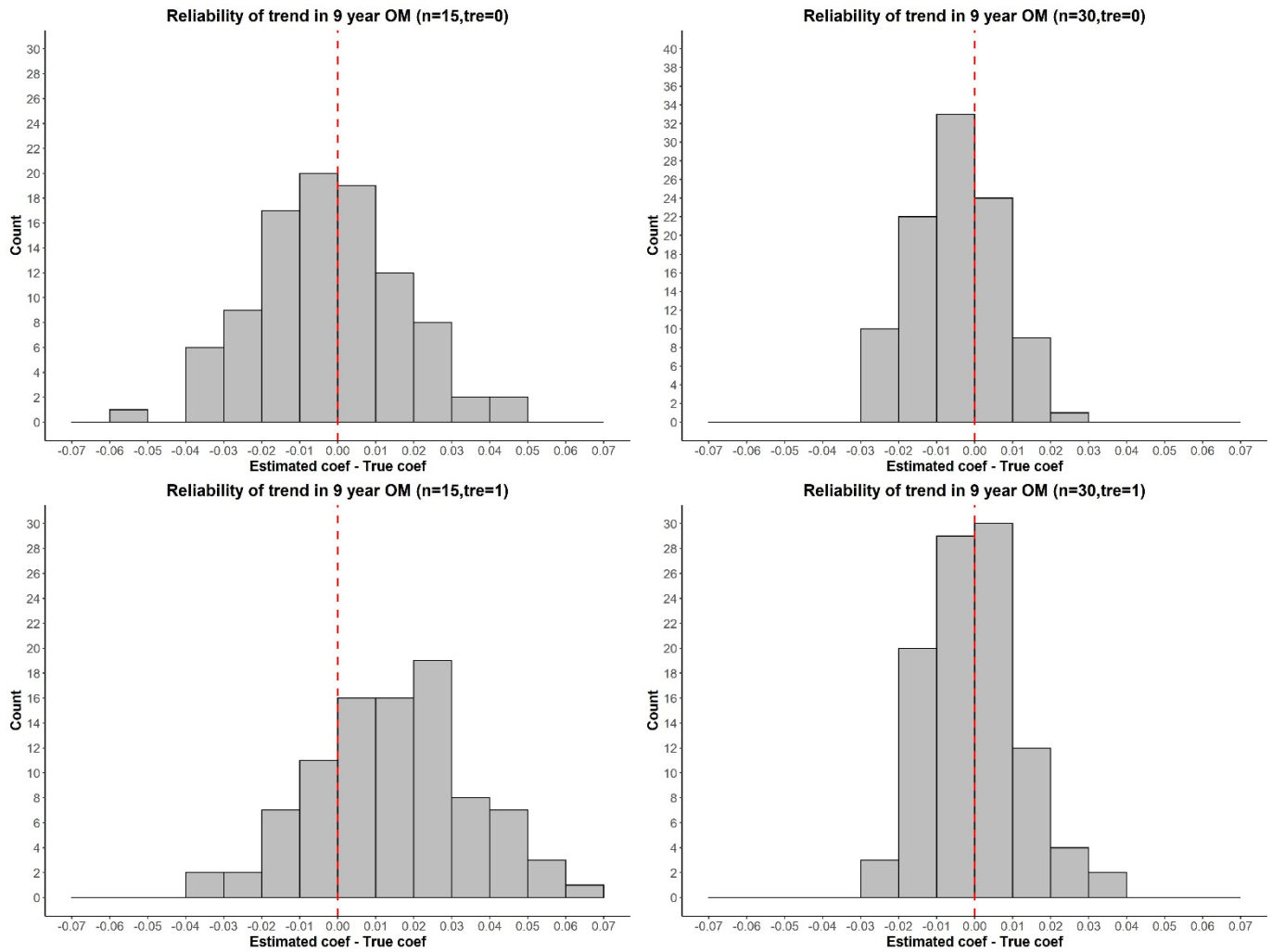

Figure 10: Reliability of trend for the 9-year operating model, with a sample size of 15 per year (left) and 30 per year (right), with trend parameters unchanged (above) and with 50% decline over 20 years (i.e., 0.025 per year) (below).

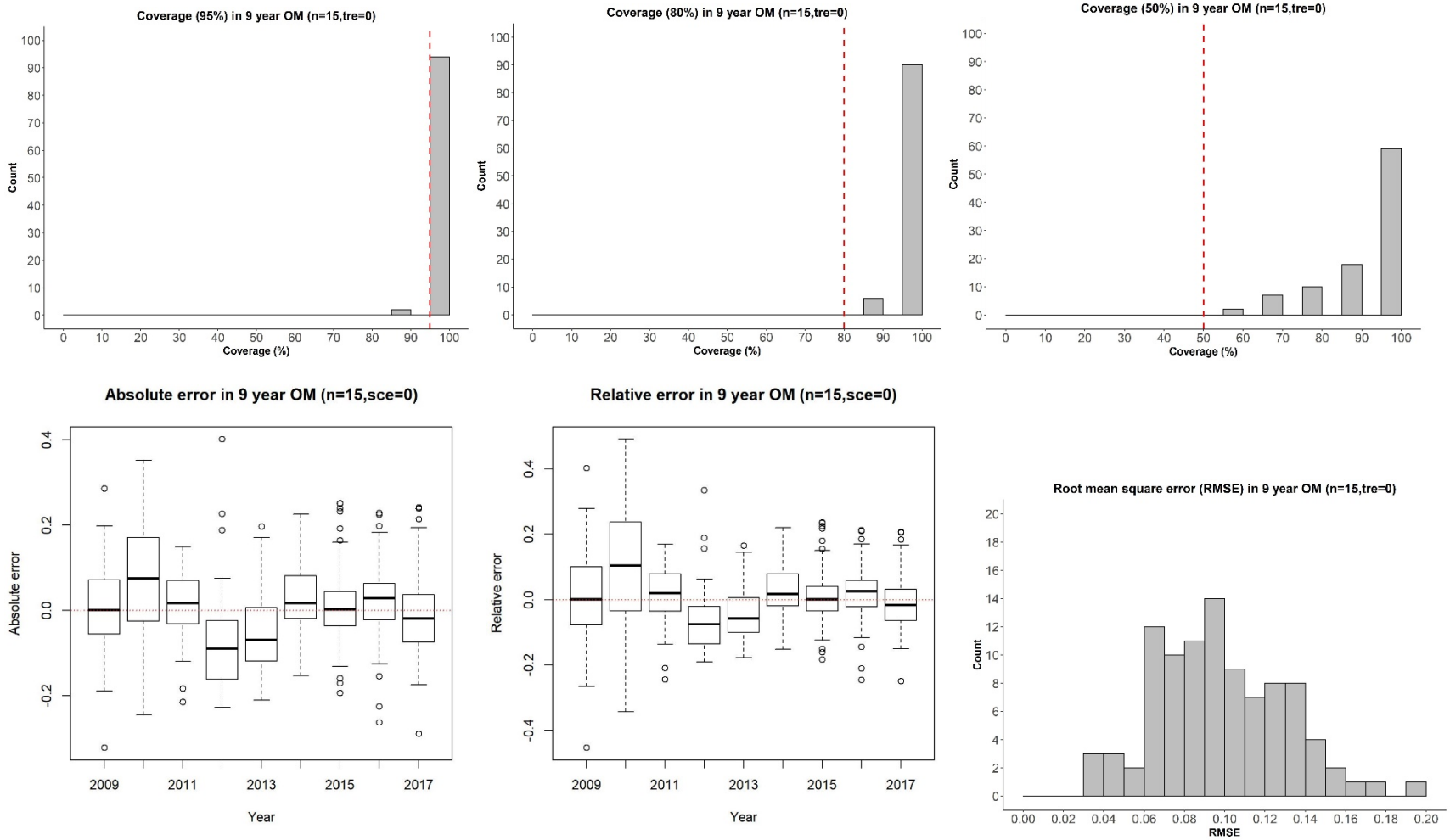

Figure 11: Results for 9-year operating model, with a sample size of 15 per year and trend parameters unchanged.

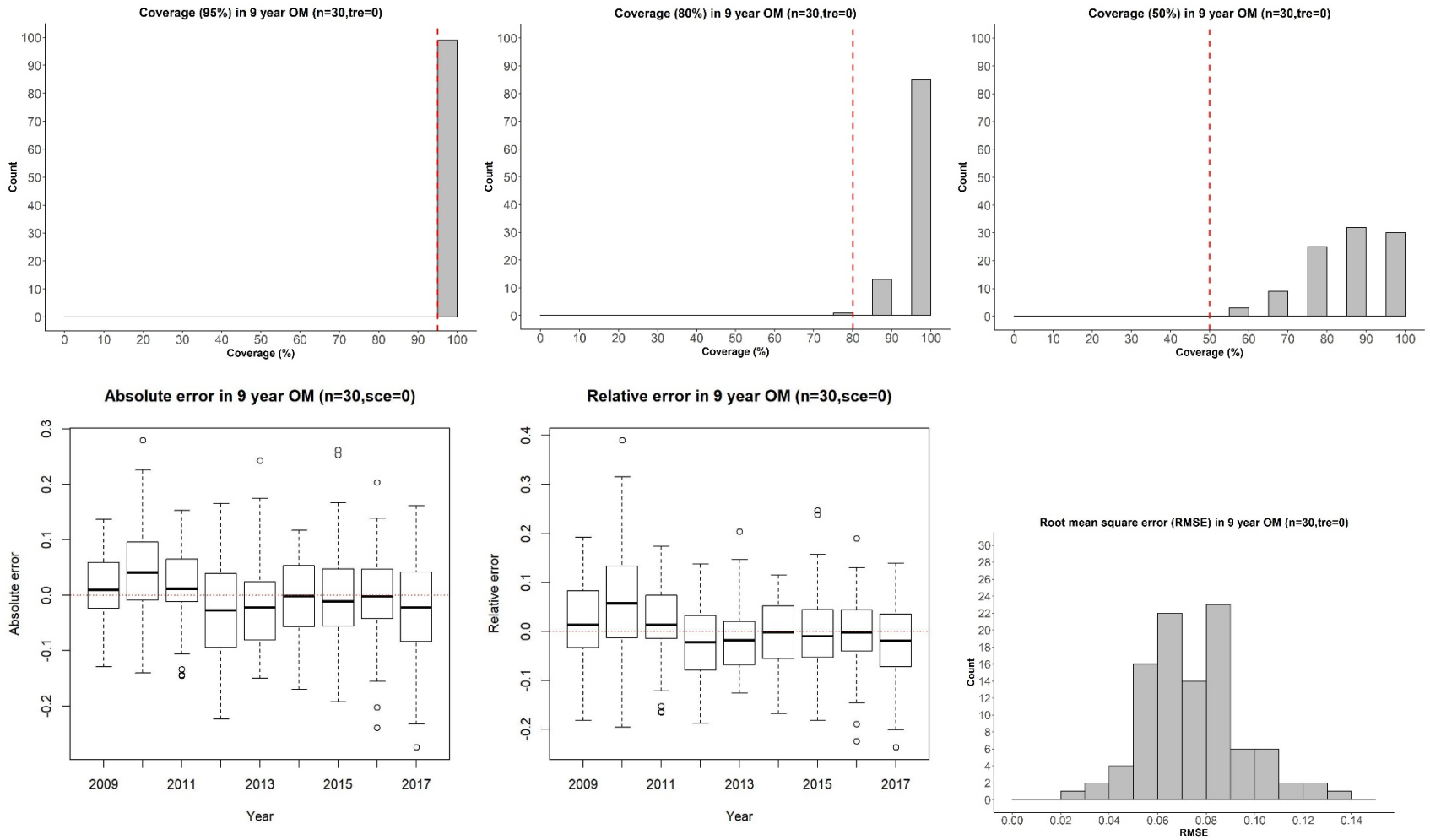

Figure 12: Results for 9-year operating model, with a sample size of 30 per year and trend parameters unchanged.

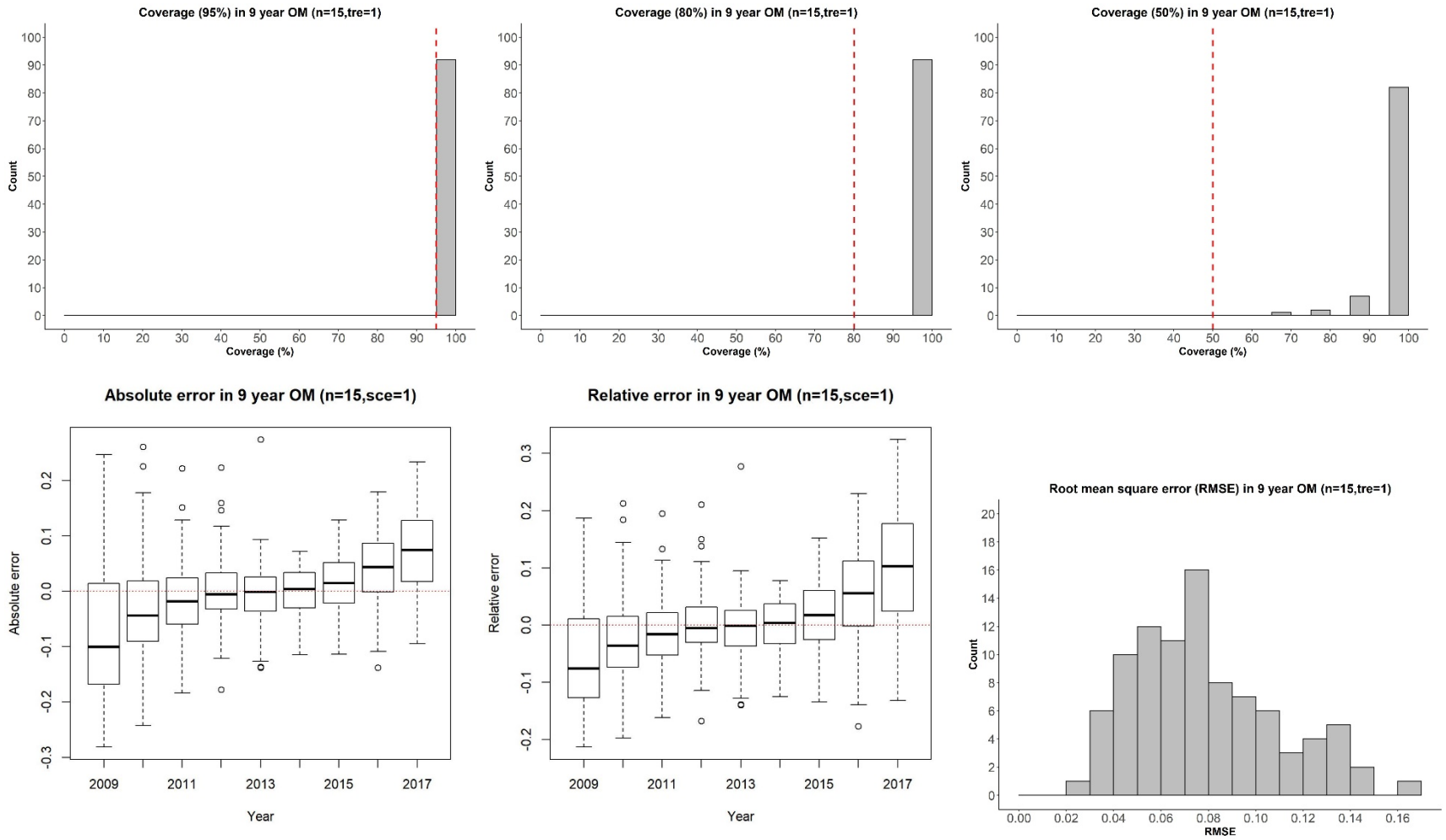

Figure 13: Results for 9-year operating model, with a sample size of 15 per year and an assumed 50% decline over 20 years.

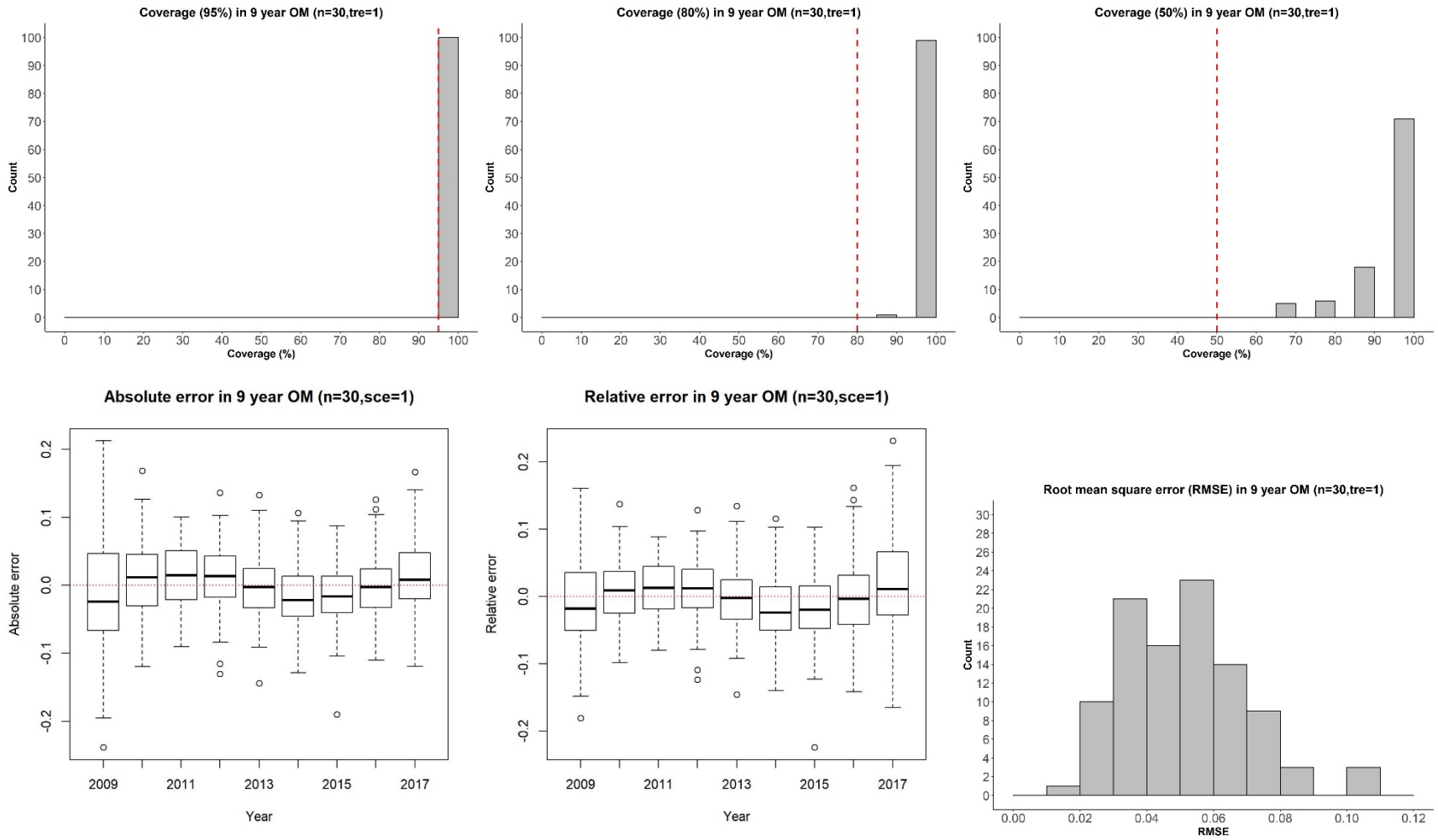

Figure 14: Results for 9-year operating model, with a sample size of 30 per year and an assumed 50% decline over 20 years.

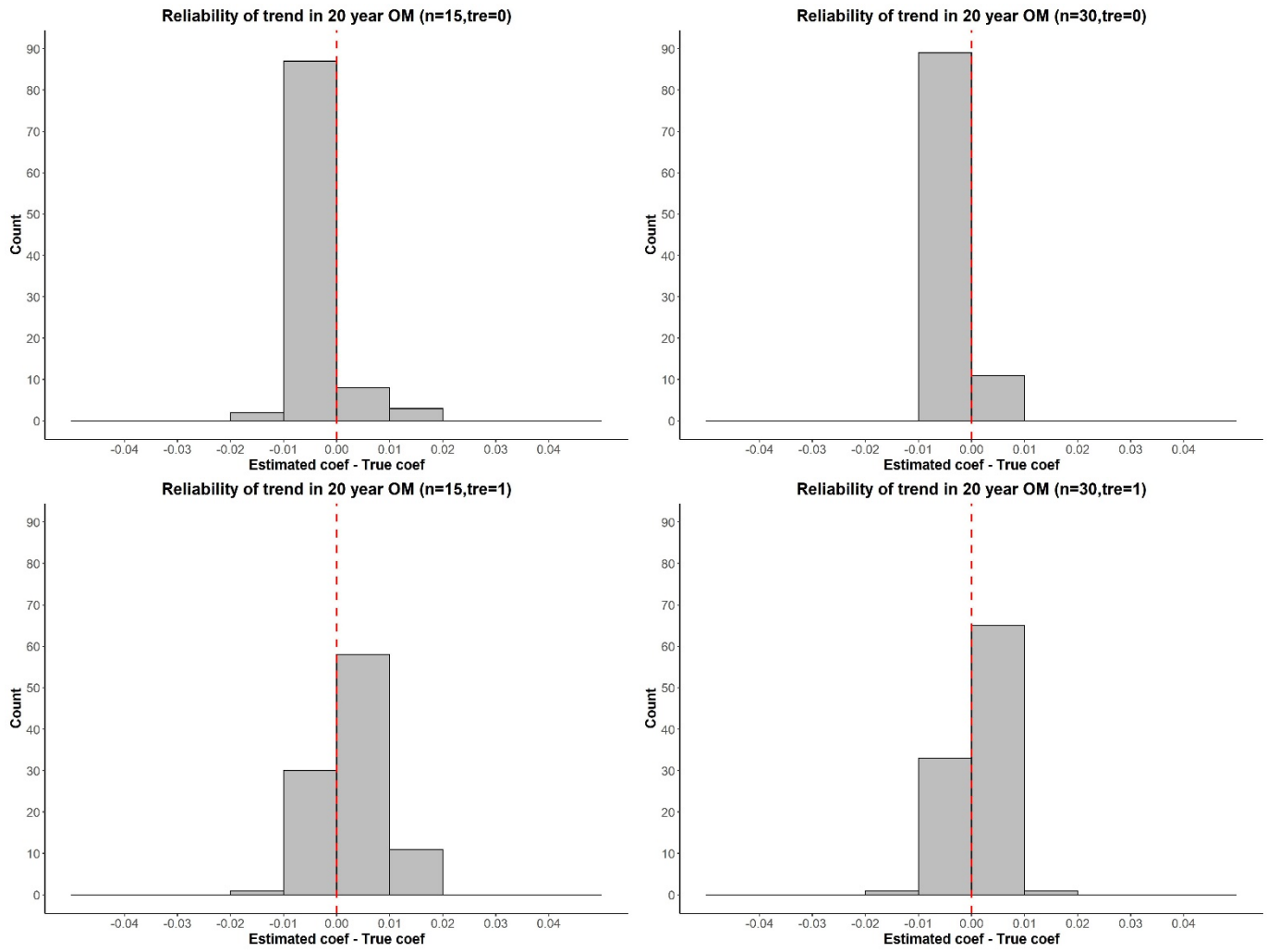

Figure 15: Reliability of trend for the 20-year operating model, with a sample size of 15 per year (left panels) and 30 per year (right panels), when trend parameters are unchanged (top panels) and when a 50% decline over 20 years is assumed (bottom panels).

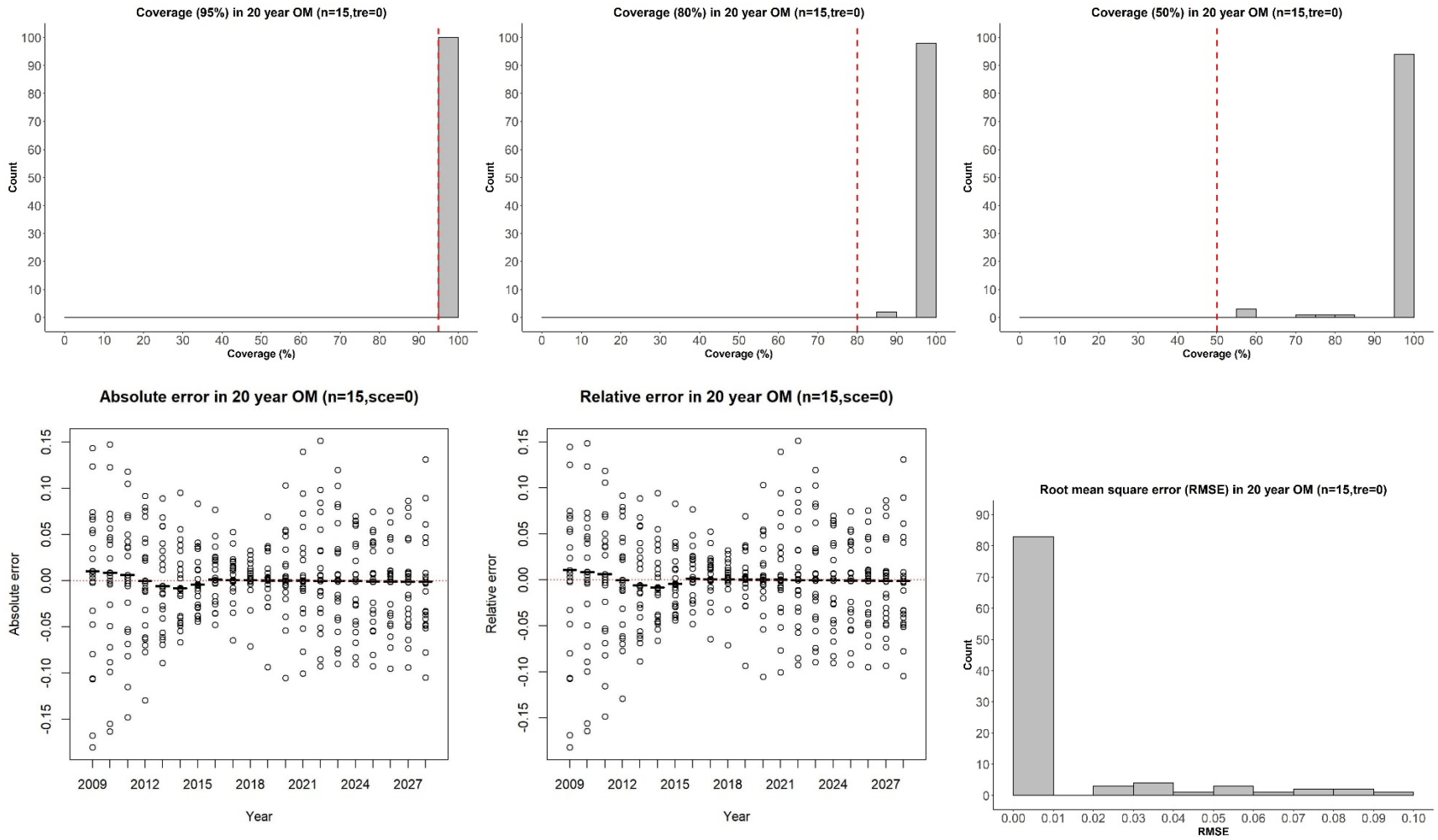

Figure 16: Results for 20-year operating model, with a sample size of 15 per year and trend parameters unchanged.

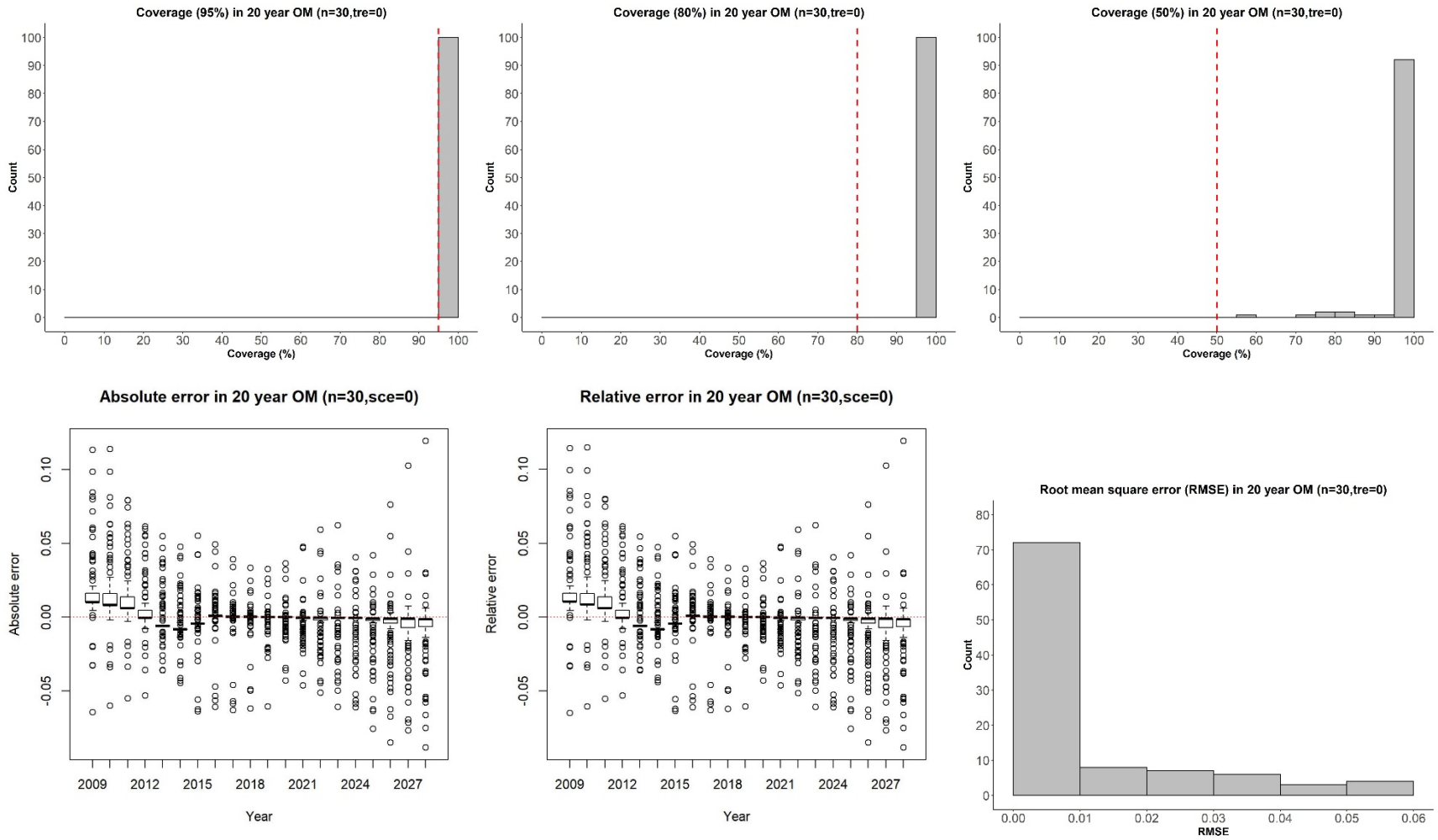

Figure 17: Results for 20-year operating model, with a sample size of 30 per year and trend parameters unchanged.

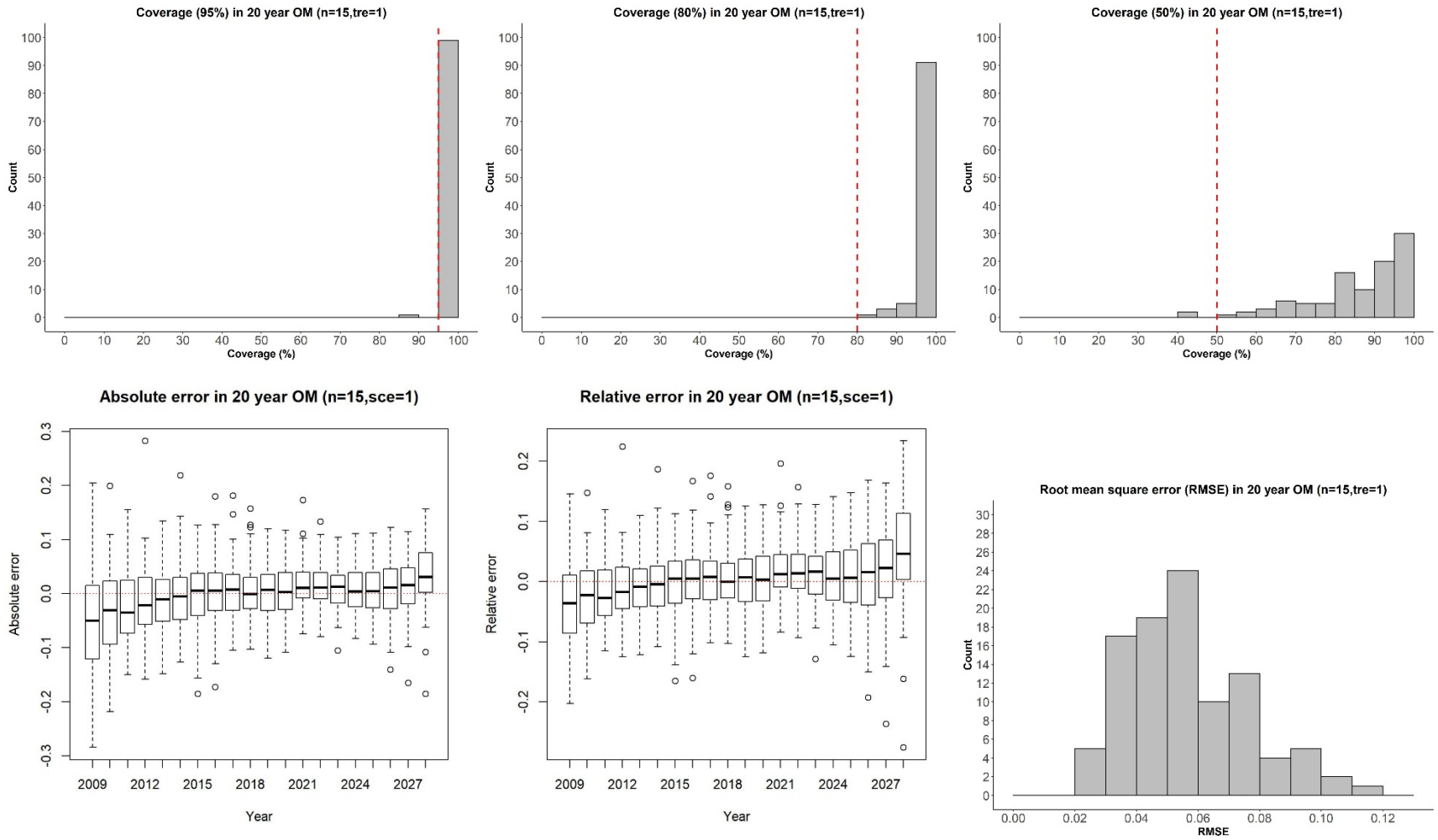

Figure 18: Results for 20-year operating model, with a sample size of 15 per year and an assumed 50% decline over 20 years.

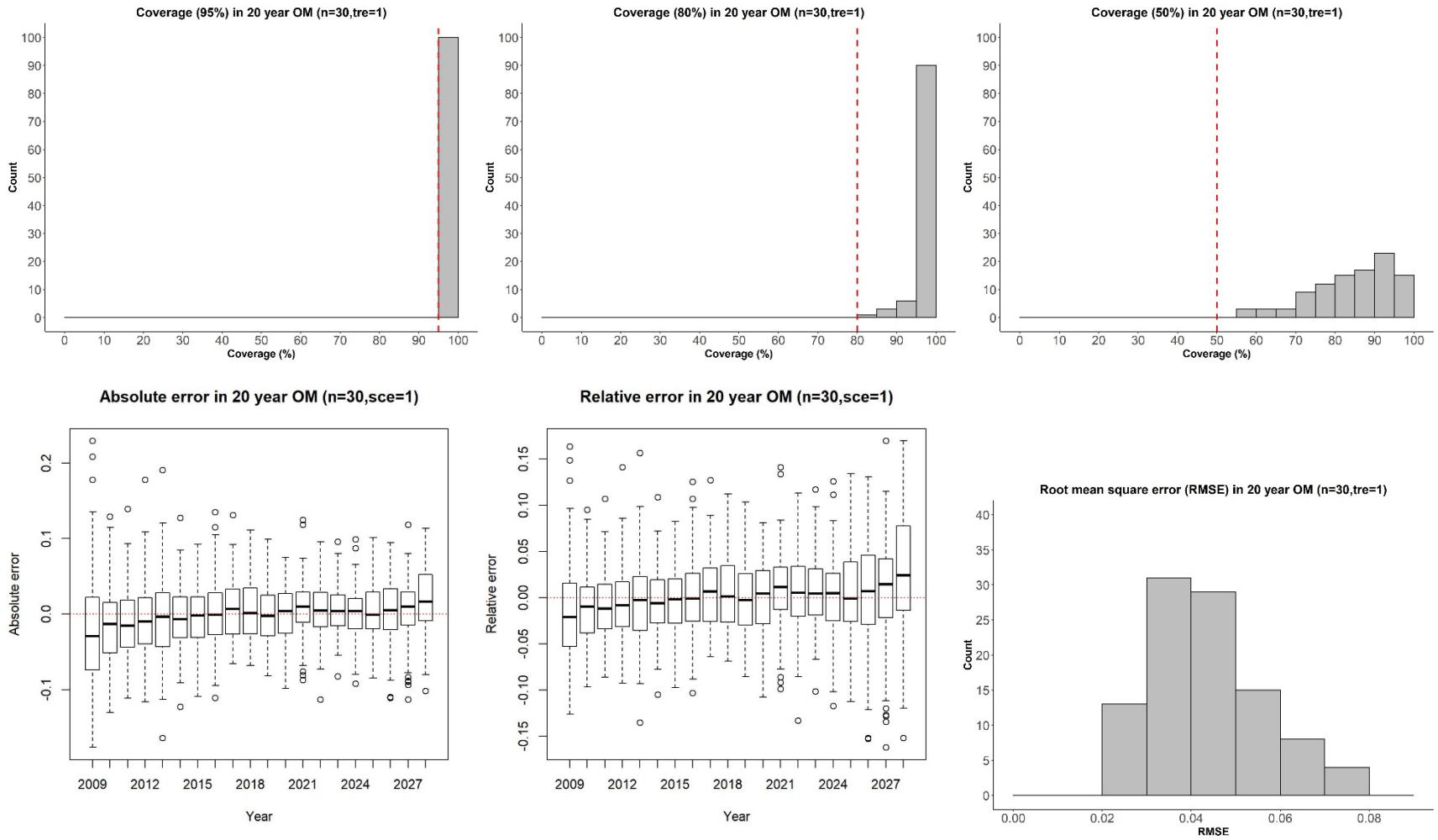

Figure 19: Results for 20-year operating model, with a sample size of 30 per year and an assumed 50% decline over 20 years.

4. DISCUSSION

Previous analyses (Leathwick et al. 2008, Crow et al. 2014) used data from the NZFFD to provide estimates of longfin eel distribution. The present work and related projects have improved those estimates in the following ways: 1) by generating time series of predictions; 2) by updating and improving the statistical spatial modelling methods, resulting in more accurate predictions; 3) by including information on counts, lengths, and sex composition, so that the index estimates more closely approximate female spawning biomass; 4) by modelling the effect of instream barriers and the time since their introduction; and 5) by estimating the sampling required to identify population trends at catchment scale.

The ability of VAST models to provide a time series is a key advantage over machine learning methods such as RRF. VAST also provides maps of estimated abundance both for the current state and over time, which are particularly useful for stakeholders and managers. VAST models in Euclidean space have previously been shown to predict more reliably than RRF methods (Charsley 2019). Another advantage of VAST is that it can estimate relationships between response variables and covariates and provide information about those covariate relationships. Machine learning methods may have more ability to deal with nonlinear relationships, correlations, and interactions among covariate effects, although analysts must take care to guard against overfitting. However, machine learning methods tend to be more of a black box and make it difficult to characterise the relationships. Moreover, capacities have recently been introduced in VAST to model non-linear covariate effects using splines (Arnaud Grüss, NIWA, personal communication); these new capacities will allow for a more realistic representation of the impacts of continuous covariates on longfin eel encounter probability and density and will also hopefully result in VAST models for longfin eels with better predictive capability.

The model fits to catch rate data at various sites based on spatial effects, temporal effects, spatio-temporal effects, and covariate relationship effects. Covariates may be classified as either catchability covariates or density covariates. To predict abundance across the entire time series and stream network, the model uses the combined spatial, temporal, and spatio-temporal effects and the density covariate effects. Catchability covariate effects are not required for prediction. Such prediction using covariate effects is only possible for covariates that are available for all times and sites. This limits the use of covariates to a) density covariates that are available across the whole spatio-temporal domain, and b) catchability covariates that are available for every catch rate observation.

The simulations presented here show a small amount of bias but in general the models perform well at estimating trends. As expected, the precision of the estimates was considerably greater with longer time series of sampling data. In the simulations, an annual sample size of 30 locations was large enough to reliably detect a 2.5% density decline per year over 9 years, whereas sample size of 15 locations was not. A similar rate of decline over 20 years was reliably detected with either 15 or 30 samples per year.

Only a limited range of simulation scenarios could be explored in the present study, and further simulation work is recommended. Issues to explore include a wider range of sample sizes, trend scenarios, time periods, and size ranges; the potential to increase precision with more or better covariate information; the potential to share information among catchments to increase statistical power; and comparison between the stream network model and standard VAST with its Euclidean assumptions about spatial correlations.

The simulations presented here sample preferentially from areas with above average probability of capture of eels, based on the assumption that these areas are more likely to be sampled in reality. Future simulations should explore alternative sampling schemes to identify whether there are approaches that avoid bias and give higher precision. Trends from a binomial model will likely be easier to estimate when the mean is closer to 0.5 (Nam 1987).

The simulation presented here only addresses information obtained by sampling. There is potential to obtain additional information about factors that substantially affect eel abundance, such as instream

barriers, which might considerably improve estimates from the models. The current study assumes that barriers have been in place since the construction of the Karapiro dam in 1947. However, other barriers in the Waikato may have been constructed earlier or later than this. Information on the years since a barrier has been constructed can be informative about eel distributions and abundance given their migratory biology; instream barriers are important because each eel generation must migrate upstream from the sea.

There is also potential to further improve the modelling approaches. Modelling population densities using these approaches is new and there is considerable potential. One possible improvement is in covariate selection. This might start with a null model containing no habitat covariates, and then add covariates incrementally. Models could be compared and selected using Akaike Information Criterion (AIC). This has the potential to reduce the number of non-converged estimating models and provide more accurate indices for the tre=0.

Indices were derived from predictions made for the stream network spatial domain for the Waikato region. Due to computational restrictions a reduced stream network was used. More realistic predictions would be made when using a full stream network of the Waikato region. Clusters of computation (supercomputers) could be accessed to make these predictions.

VAST has the ability to incorporate data from various sources. Models have been shown to improve by incorporating multiple data types (Grüss & Thorson 2019). Encounter/non-encounter data could be incorporated into the model from the NZFFD. The NZFFD is a very extensive source of longfin eel encounter/non-encounter data which spans the Waikato region spatially and temporally. The addition of these data could improve the estimation of spatial, spatio-temporal, and temporal model terms.

5. MANAGEMENT IMPLICATIONS

The models in general performed well at estimating trends over longer time scales. This approach therefore has potential for estimating trends in spawning biomass at the catchment scale and the national scale. Managers may wish to consider developing long-term monitoring that supplements current levels of sampling with additional targeted sampling.

Further simulation work is recommended to explore issues that include: a wider range of sample sizes, trend scenarios, time periods, and size ranges; the potential to increase precision with more or better covariate information; the potential to share information among catchments to increase statistical power; and comparison between the stream network model and standard VAST with its Euclidean assumptions about spatial correlations.

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APPENDIX 1: Supplementary Tables

Table 1.1: Estimates of fixed effects parameters for the 9-year OM. (Continued on next page)

Parameter	Estimate (3dp)	Standard Error (3dp)
$\beta_1(< 500, 2009)$	1.851	2.378
$\beta_1(\geq 500, 2009)$	3.994	1769.353
$\beta_1(< 500, 2010)$	0.750	1.229
$\beta_1(\geq 500, 2010)$	0.478	0.840
$\beta_1(< 500, 2011)$	1.989	0.658
$\beta_1(\geq 500, 2011)$	2.453	0.582
$\beta_1(< 500, 2012)$	2.454	0.453
$\beta_1(\geq 500, 2012)$	2.894	3.160
$\beta_1(< 500, 2013)$	2.456	0.409
$\beta_1(\geq 500, 2013)$	2.497	0.307
$\beta_1(< 500, 2014)$	2.909	0.442
$\beta_1(\geq 500, 2014)$	2.556	0.317
$\beta_1(< 500, 2015)$	2.180	0.449
$\beta_1(\geq 500, 2015)$	2.337	0.395
$\beta_1(< 500, 2016)$	2.657	0.453
$\beta_1(\geq 500, 2016)$	2.574	0.355
$\beta_1(< 500, 2017)$	3.049	0.501
$\beta_1(\geq 500, 2017)$	2.119	0.411
$\beta_2(< 500, 2009)$	3.032	2.185
$\beta_2(\geq 500, 2009)$	-0.143	1769.353
$\beta_2(< 500, 2010)$	4.186	1.087
$\beta_2(\geq 500, 2010)$	3.376	0.614
$\beta_2(< 500, 2011)$	2.733	0.600
$\beta_2(\geq 500, 2011)$	1.602	0.548
$\beta_2(< 500, 2012)$	2.182	0.448
$\beta_2(\geq 500, 2012)$	1.463	0.306
$\beta_2(< 500, 2013)$	2.287	0.406
$\beta_2(\geq 500, 2013)$	1.841	0.274
$\beta_2(< 500, 2014)$	1.879	0.456
$\beta_2(\geq 500, 2014)$	1.623	0.287
$\beta_2(< 500, 2015)$	2.455	0.440
$\beta_2(\geq 500, 2015)$	1.886	0.366
$\beta_2(< 500, 2016)$	2.187	0.465
$\beta_2(\geq 500, 2016)$	1.659	0.314
$\beta_2(< 500, 2017)$	1.863	0.496
$\beta_2(\geq 500, 2017)$	2.196	0.317
$\gamma_1(< 500, Dist2Coast)$	-0.968	0.301
$\gamma_1(\geq 500, Dist2Coast)$	-0.845	0.226
$\gamma_1(< 500, Elevation)$	1.061	0.373
$\gamma_1(\geq 500, Elevation)$	1.148	0.276
$\gamma_1(< 500, Dam)$	-0.276	0.290
$\gamma_1(\geq 500, Dam)$	-0.458	0.219
$\gamma_2(< 500, Dist2Coast)$	0.327	0.293
$\gamma_2(\geq 500, Dist2Coast)$	0.707	0.200
$\gamma_2(< 500, Elevation)$	-0.875	0.363
$\gamma_2(\geq 500, Elevation)$	-0.912	0.264
$\gamma_2(< 500, Dam)$	0.210	0.266
$\gamma_2(\geq 500, Dam)$	0.489	0.173
$L_{\epsilon 1}(< 500)$	-0.102	0.096

Parameter	Estimate (3dp)	Standard Error (3dp)
$L_{\epsilon 1}(\geq 500)$	-0.145	0.096
$L_{\epsilon 2}(< 500)$	0.135	0.100
$L_{\epsilon 2}(\geq 500)$	-0.056	0.052
$L_{\omega 1}(< 500)$	0.988	0.153
$L_{\omega 1}(\geq 500)$	0.712	0.114
$L_{\omega 2}(< 500)$	0.135	0.100
$L_{\omega 2}(\geq 500)$	-0.056	0.052
$log(\kappa_1)$	-2.062	0.510
$log(\kappa_2)$	-4.329	0.876
$log\left(\sigma_M^{(1)}\right)$	-0.754	0.104
$log\left(\sigma_M^{(2)}\right)$	-0.813	0.110

Table 1.2: Estimates of fixed effects parameters for the 20-year OM.

Parameter	Estimate (3dp)	Standard Error (3dp)
$mean(\beta_1(< 500))$	2.608	0.211
$mean(\beta_1(\geq 500))$	2.535	0.174
$mean(\beta_2(< 500))$	2.164	0.244
$mean(\beta_2(\geq 500))$	1.785	0.158
$L_{\beta_1}(< 500)$	-1.058×10^{-24}	0.066
$L_{\beta_1}(\geq 500)$	-8.885×10^{-25}	0.080
$L_{\beta_2}(< 500)$	1.982×10^{-25}	0.059
$L_{\beta_2}(\geq 500)$	-1.867×10^{-20}	0.076
$\gamma_1(< 500, Dist2Coast)$	-0.851	0.247
$\gamma_1(\geq 500, Dist2Coast)$	-0.733	0.240
$\gamma_1(< 500, Elevation)$	0.872	0.301
$\gamma_1(\geq 500, Elevation)$	1.024	0.288
$\gamma_1(< 500, Dam)$	-0.243	0.308
$\gamma_1(\geq 500, Dam)$	-0.442	0.249
$\gamma_2(< 500, Dist2Coast)$	0.208	0.250
$\gamma_2(\geq 500, Dist2Coast)$	0.628	0.223
$\gamma_2(< 500, Elevation)$	-0.684	0.295
$\gamma_2(\geq 500, Elevation)$	-0.805	0.278
$\gamma_2(< 500, Dam)$	0.185	0.287
$\gamma_2(\geq 500, Dam)$	0.466	0.206
$L_{\epsilon 1}(< 500)$	-0.068	0.120
$L_{\epsilon 1}(\geq 500)$	-0.075	0.126
$L_{\epsilon 2}(< 500)$	-0.113	0.079
$L_{\epsilon 2}(\geq 500)$	0.039	0.048
$L_{\omega 1}(< 500)$	1.002	0.145
$L_{\omega 1}(\geq 500)$	0.717	0.105
$L_{\omega 2}(< 500)$	-0.606	0.171
$L_{\omega 2}(\geq 500)$	0.226	0.104
$log(\kappa_1)$	-2.051	0.524
$log(\kappa_2)$	-4.503	0.869
$log\left(\sigma_M^{(1)}\right)$	-0.715	0.085
$log\left(\sigma_M^{(2)}\right)$	-0.709	0.085