Simulation of methods of dealing with age-based movement in PBF stock assessment

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Abstract

Spatial patterns in the distribution of age-classes are often the result of movement. The data needed to include movement in stock assessment models typically do not exist, and modelers use areas-as-fleets approach. In an attempt to better understand the effect of the age-based movement, this study used simulation methods and a factorial design with modeling movement, ignoring movement, modeling with substitute process, increasing observation error to reduce effect of un-modeled movement, and aggregated fleet structure. Two different states of nature governing the movement process are explored. Only the inclusion of the correct spatial structure along with estimation of movement rates produces unbiased and precise estimates of derived quantities, although some management quantities are less biased in non-spatially explicit models.

Introduction

Integrated models are the current state of the art for data-rich stock assessments. These models link diverse types of data via observation processes to underlying population dynamics which are controlled by system processes. Both system and observation processes are governed by parameters that can be estimated or specified. Estimation of parameters is done statistically using maximum penalized likelihood methods. The integrated approach allows for the use of many different types of data as long as the sampling processes linking the data to the population can be defined. Integrated models, in theory, allow for the estimation of system processes not directly informed by data.

Misspecification of either the observation or systems processes can result in lack of fit and model bias. Considerable attention being paid to some observation model processes (e.g. selectivity, Maunder *et al.* 2014) and some system model processes (e.g. natural mortality, Brodziak *et al.* 2011; growth, Maunder *et al.* 2015). The method of treating other system model processes such as movement remains uncertain but important. Due to the linkage of all data via the dynamics, misspecification on one process can have adverse consequences for other seemingly unrelated data sets.

Pacific bluefin tuna show a pattern of movement of age-1 fish from natal waters in the Western north Pacific Ocean (WPO) to feeding grounds in the productive Eastern Pacific Ocean (EPO). Return of juveniles to western Pacific waters appears to be related to maturation and pre-spawning. However, incorporation of this understanding into a spatially explicit integrated stock assessment model is difficult due to a lack of appropriate tagging studies. Movement is generally thought to be an age-based process, so ignoring or mis-specifying this process can impact selection (via availability) and mortality estimation.

Due to a lack of direct data on movement rates, the 2014 stock assessment of Pacific bluefin tuna assumed an instantaneously mixed population and incorporates regional selection patterns and catchability coefficients to account for spatial effects (areas-as-fleets). This study uses simulation methods to evaluate relative performance of different modelling approaches to deal with age-based movement for a Pacific bluefin tuna-like population. We conduct a series of simulation experiments using factorial design with modeling movement, ignoring movement, modeling with substitute process, increasing observation error to reduce effect of un-modeled movement, and aggregated fleet structure. We also explore two different states of nature governing the movement changes over time (annually random parameter value, or driven by cyclic environmental factor). The impact of the modelling approaches given the uncertainty of the states of nature on management quantities and derived quantities of interest are used to offer guidance on modeling choices.

Materials and Methods

1. Overview of study

We simulated synthetic populations using spatially explicit stochastic population dynamics (two areas) to evaluate different modeling approaches to structure movement aspects. The methods are explained (Figure 1) starting with 1) the simulation of the PBF-like synthetic populations, 2) two different states of nature governing the movement process, 3) different modelling approaches to deal with age-based movement tested, and 4) comparison of derived quantities of interest.

2. Simulation of PBF-like population

We used the commonly used stock assessment model, Stock Synthesis (Methot and Wetzle 2013) as simulation framework to create the 500 synthetic populations. Stock Synthesis is a widely used forward simulating integrated population dynamics model capable of fitting a wide variety of data types. The model keeps track of numbers at age by area and can transform the sampled age distribution into the equivalent length-at-age and overall length distribution. We used it to create synthetic populations based on stochastically generated parameters controlling the systematic and fishery processes governing the population dynamics (movement, recruitment, and exploitation histories).

Our study was based on the 2014 Pacific bluefin tuna assessment. The bluefin assessment integrated various types of data (abundance indices and size compositions) consisting of 14 individual fleets: 3 fleets with observations of abundance indices, and 11 fleets with size compositions. Fleets without observations of the length compositions were assumed to share a selectivity pattern with a similar fleet.

To evaluate the impact of modeling movement in simulations, a simplified version of the stock assessment model was developed as a basis of operating model (Table 1). The operating model maintained the key data components (abundance indices and size compositions), biological assumptions (growth, reproduction, natural mortality), and the model structure (quarterly) from the assessment. Taking these components into considerations, the model then 1) explicated the spatial movement with two areas (one WPO and one EPO); 2) reduced the fleet dimension to six: one WPO longline fleet represents adult fleet, one WPO troll & pole-line fleet represents age-0 fleet, three WPO surface fleets (small pelagic purse seine, tuna purse seine, and set net fisheries) represent age 1-5 fleets, and one EPO surface fleet represents age 1-3 fleet; and 3) fixed log unfished recruitment, initial fishing mortality, and selectivity patterns at the previous estimates from the assessment.

The key system process parameters (movement and recruitment) were generated at random from distributions described in Table 1. In order to avoid potential bias from patterns in the recruitment residuals from the assessment, recruitment deviates with the same variability as assumed in the assessment were randomly generated. Also, to reflect incomplete knowledge about movement, some aspects of movement were randomly generated. Age-based movement rates from WPO area to EPO area were determined by fraction of fish out of WPO to EPO at their earliest age 1 and at their latest age $A_{\mathrm{max\_WPO \rightarrow EPO}}$ (Methot and Wetzel 2013), where WPO area is recruitment settlement and spawning area containing majority of age classes and EPO area is a feeding area containing mostly age 1-3 fish (Figure 2). $A_{\mathrm{max\_WPO \rightarrow EPO}}$ was generated stochastically. The fraction of fish from WPO to EPO at age 1 was assumed to vary over time with mean rate at 40%, whereas the fraction of fish from WPO to EPO at age $A_{\mathrm{max\_WPO \rightarrow EPO}}$ was fixed at 0.1% to indicate nil fish move from WPO to EPO at $A_{\mathrm{max\_WPO \rightarrow EPO}}$. Movement rates between age 1 and age $A_{\mathrm{max\_WPO \rightarrow EPO}}$ were linearly interpolated after logarithmic transformation.

As for fish returning to spawning area, age-based movement rates from EPO area to WPO area were determined by fraction of fish out of EPO to WPO at their earliest age 1 and at their latest age $A_{\mathrm{max\_EPO \rightarrow WPO}}$. $A_{\mathrm{max\_EPO \rightarrow WPO}}$ was also generated stochastically. The fraction of fish from EPO to WPO at age 1 was fixed at 5% to reflect few fish move from EPO to WPO at age 1, whereas the fraction of fish from EPO to WPO at age $A_{\mathrm{max\_WPO \rightarrow EPO}}$ was fixed at 99.9% to indicate no fish above age $A_{\mathrm{max\_WPO \rightarrow EPO}}$ remain in the EPO area. Movement rates between age 1 and age $A_{\mathrm{max\_WPO \rightarrow EPO}}$ were linearly interpolated after logarithmic transformation.

Two different states of nature governing the movement time-varying process were considered (Figure 3). The force behind movement rates from WPO to EPO at age 1 over time could be random or environmentally driven. The former assumes that annual movement rates from WPO to EPO at age 1 is a random event within the uniform distribution from 10% to 70%. The latter assumes that annual movement rates from WPO to EPO at age 1 is a covariate with pan-Pacific decades-long climate variability (Pacific Decadal Oscillation, PDO; Latif and Barnett 1996; Hare 1996; Zhang 1996).

The fleet component of the operating model included: 61 years of simulated population dynamics with fishing that started from non-equilibrium population as assessment, and 5 fleets from WPO and one fleet from EPO removing catches with same length-based selection gear as assessment. Among these fleets, observation errors on abundance indices were assumed to the same as assessment, and size data assuming a multinomial error structure with variance described by the quarterly sample size were assumed to be equally precise (effective sample size at 50). A variety of mean fishing mortality trajectories were simulated with noise for each fleet based on trend and mean fishing mortality from the assessment, that increased at the start of the time series then remained constant, and increased or decreased after being harvested for 38 years given the uncertainty of exploitation histories (Figure 4; Carruthers *et al.* 2012). Catchability coefficient was assumed to be constant over time for each fleet.

The median of terminal spawning stock biomass relative to its maximum sustainable yield and to its unfished level for 500 PBF-like synthetic populations were 0.36 (± SD=0.13) and 0.09 (± SD=0.03), respectively (Figure 6).

3. Alternative estimation models

Five alternative estimation models were evaluated.

CS) The **Correctly Specified model** included two spatial areas and estimation of movement rates for movement nodes fixed at the correct ages, time invariant length-based selection patterns estimated, and data given the correct sample weights.

TI) The **Time Invariant model** was a single area (areas-as-fleets) model with separate time invariant length-based selection patterns estimated for each fleet and data given the sample weights. The time invariant model is the most similar to the current assessment model.

TV) The **Time-Varying model** was a single area (areas-as-fleets) model with separate time invariant length-based selection patterns for non EPO fleets, time-varying length-based selection estimated for the EPO fleet, and data given the sample weight.

DW) The **Down-Weighted model** was a single area (areas-as-fleets) model with separate time invariant length-based selection patterns estimated for each fleet and size data given the 10% of the sample weights for non-CPUE fleets.

AG) The **Fleet Aggregated model** was a single area (areas-as-fleets) model that combined catch and composition data for non-CPUE fleets, where composition data were weighted by their catch in numbers. The fleet aggregated model was estimated using time-varying age-based selection and a time invariant length-based selection. Fleets with CPUE were fit with a time invariant length-based selection pattern. All data were given sample weights.

4. Comparison of model results

We evaluated the performance of the estimation models based on the distribution of relative errors in the quantities of interest. Relative error (RE_d^j) is defined as the percentage of difference between estimated values (Est_d^j) and true value ($True^j$) divided by true value for quantity (*j*) for a given simulation run (*d*).

$$RE_d^j = \frac{Est_d^j - True^j}{True^j} \times 100$$

Bias was expressed as a percent and precision of the method was described by the distribution of relative error for method.

Results

1. Bias, precision, and percent converged models by method

CS (spatially explicit model estimating movement) was the best performing model for both management quantities and derived statistics under both movement hypotheses (Figure 6 and 7). The difference between the Correctly Specified Model and the other models was magnified when movement was assumed to have a PDO (low frequency) forcing function. Percentage of converged models was inversely related to the number of parameters, although this convergence issue is substantially reduced when a penalized likelihood approach is used for time-varying deviations (see below).

2. Cause of apparent bimodality

An apparent bimodality was displayed in some derived terminal year quantities (Figure 7) from the areas-as-fleets models with time-invariant selection patterns and PDO movement. The apparent bimodality was related to the movement rate near the terminal end of the model (Figure 8). The bimodality is an artifact of the proportion simulated datasets with high, medium, or low movement (Figure 9). High and low movement rates result in negative or positive biases in terminal biomass, while intermediate movement results in estimates of derived quantities that lie between. In our simulation with PDO type movement, more high or low terminal movement rate scenarios were generated than intermediate resulting in the bimodal distribution for some quantities.

3. Precision of time-varying selection models (TV and AG)

TV and AG can be improved with a penalized likelihood approach to the time-varying selection deviations. Penalized likelihood approach improves the convergence percentage to >99%. However, constraining the deviations is unlikely to resolve bias associated with either high or low movement rates at the end of the series.

Discussion

The spatially explicit model with estimated movement is the only approach that will lead to precise and unbiased estimates of some quantities of interest even when movement is not random. Models using alternative model process (selectivity) or down-weighting composition data are unlikely to be effective at accounting for movement when the movement is not random. However, some management quantities appear more robust than terminal year estimates, and these values may be more reliable if an areas-as-fleets approach is used.

A correctly specified model will need to be based on a complete understanding of the system and likely requires direct observations on the process of movement (such as tagging). More research needs to be done to determine if a constrained use of movement parameters (to make the deviation parameters more estimable), even without direct observation of movement, is better than ignoring movement. The use of time-varying selection to account for movement is not demonstrably better than down-weighting composition data and entails the use of considerably more parameters. We demonstrate that constraining the deviations via a penalty results in better convergence and performance (Martell and Stewart 2014).

This study was done with the sole purpose of comparing alternative models parameterizations that could be used to account for age-based movement. This study does not deal with the very real issues of misfit of the size composition in the current assessment due to sampling processes, combination of fleets with different selectivities, seasonal movements, and changes in the contact selectivity through time (Martel and Stewart 2014). Those issues need to be dealt with to prevent the composition data misfit from having undue influence on model results (Francis 2011). It is likely that adding more flexible selection patterns, including time-varying and non-parametric forms would be appropriate for those purposes, even if it does not successfully deal with un-modeled movement. Aggregating the non-CPUE fleets as in AG would likely benefit this approach by having only one fleet needing this detailed model structure.

The stock assessment needs be spatially explicit to correctly account for spatial patterns due to movement (Hurtado-Ferro *et al*. 2014). It may be that this goal is not attainable in the near future due to data limitation. Lacking a correctly specified model, special emphasis will need to be placed on how the inevitable composition misfit is affecting model performance (Sampson 2014). The influence of composition misfit should be reduced wherever possible (Francis 2011). Our suggestion for the next assessment is to include two levels of data resolution: 1) fleet disaggregation and 2) aggregation of non-CPUE fleets into a single fleet with flexible (Thorson and Taylor 2014) and time-varying selection. Models representing both levels of data complexity should be brought forward for review.

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Table 1. Data types used and parameters estimated in the stock assessment model and in the operating models. In the operating models, sampling distributions of the parameters and variables that were used to develop each simulated population and derive all catch, CPUE and length observations. All parameter values (except for recruitment deviations and fishing mortality, *F*) were drawn once from the distribution to produce a single simulated population. Annual recruitment deviations and *F*'s were drawn from the appropriate distribution for each year of the simulation. Uniform random variables are represented by Uniform(minimum bound, maximum bound) and Gaussian random variables are represented by Normal(mean, standard deviation).

	Stock assessment model	Operating models
Data		
Dynamics calculated	1952-2012, Quarterly	1952-2012, Quarterly
Number of area	1	2
Number of fleets	14	6
Number of tuned indices	5 (3 JPN LL, 1 TWN LL, 1 JPN toll)	6 (3 JPN LL, 1 JPN troll, 2 EPO)
Number of fleets with length data	11	6
Parameter estimated		
<u>Movement</u>		
Fraction of fish move from WPO to EPO at age 1 (1952-2011)	None	State 1: Uniform (0.1, 0.7) State 2: Generated (See Figure 3)
Maxima age with 0.1% of fish move from WPO to EPO ($A_{\mathrm{max\_WPO}\rightarrow\mathrm{EPO}}$)	None	Uniform (3, 4)
Fraction of fish move from EPO to WPO at age 1	None	Fixed at 0.05
Maxima age with 99.9% of fish move from EPO to WPO ($A_{\mathrm{max\_EPO}\rightarrow\mathrm{WPO}}$)	None	Uniform (3, 4)
<u>Recruitment</u>		
Log unfished recruitment ln(R_0) ('000's fish)	Estimated	Fixed at 9.09
Standard deviation for recruitment in log space (σ_R)	Fixed at 0.6	Fixed at 0.6
Spawner-recruit steepness	Fixed at 0.999	Fixed at 0.95
Recruitment deviations (1953-2011)	Estimated	Normal (0, σ_R=0.6)
<u>Mortality</u>		
Natural morality (age-specific *M*, yr^{-1})	Fixed (1.6 at age 0; 0.386 at age 1; 0.25 at age 2 above)	Fixed (1.6 at age 0; 0.386 at age 1; 0.25 at age 2 above)
Fishing mortality (*F*, yr^{-1}) for each fleet	Estimated	Generated (See Figure 4)
Initial fishing mortality	Estimated	Fixed at estimates from stock assessment
<u>Growth</u>		

Length at age 0 (L_0, cm)	Fixed at 21.5	Fixed at 21.5
CV of length at age 0	Fixed at 0.262	Fixed at 0.262
Length at age 3 (L_3, cm)	Fixed at 109.194	Fixed at 109.194
CV of length at age 3	Fixed at 0.05	Fixed at 0.05
Growth coefficient (K)	Fixed at 0.157	Fixed at 0.157
Reproduction		
Maturity at age	Fixed (0.2 at age 3, 0.5 at age 4, 1 at age 5 above)	Fixed (0.2 at age 3, 0.5 at age 4, 1 at age 5 above)
Selectivity patterns	Estimated (Length-based, asymptotic and domed shapes, time-invariant)	Fixed at estimates from stock assessment

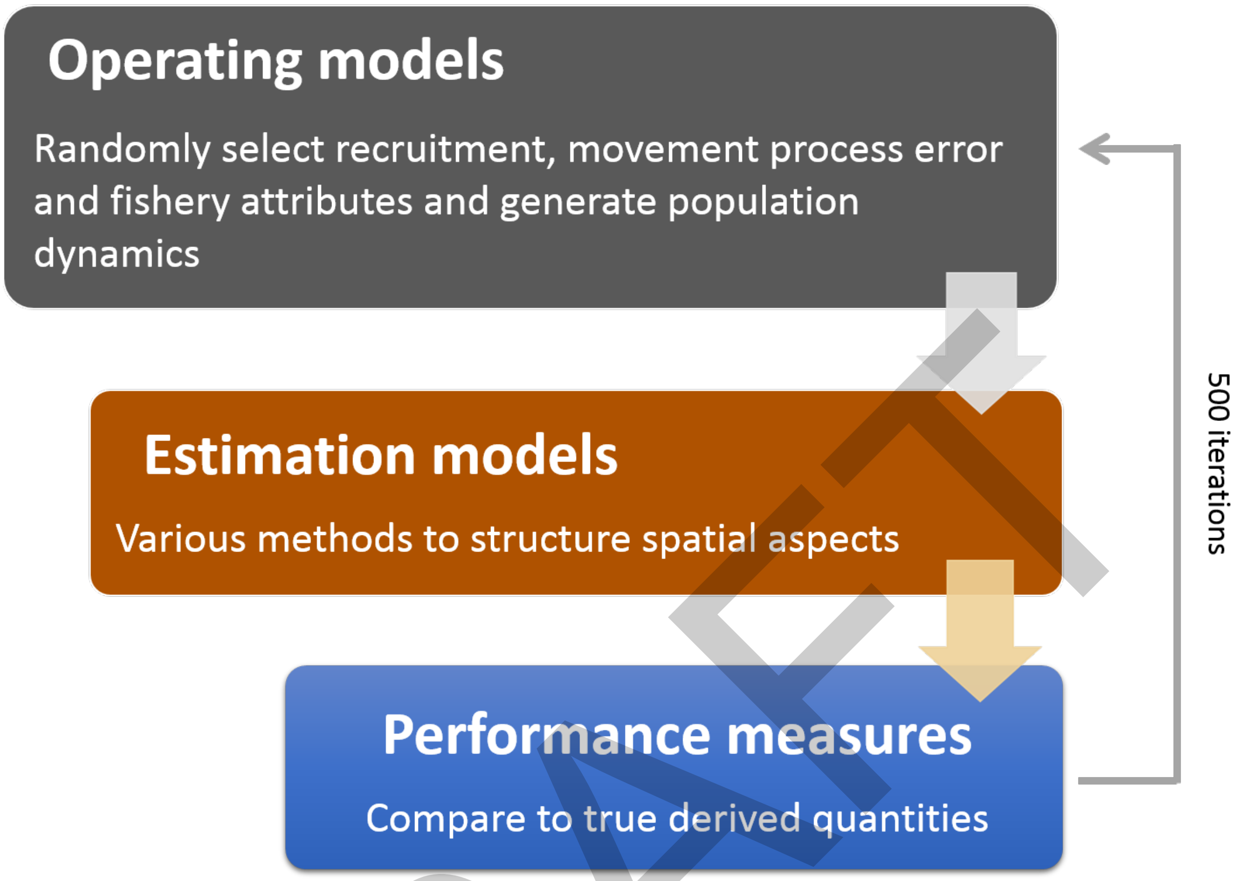


Figure 1. Diagram of the simulation steps used to test age-based movement.

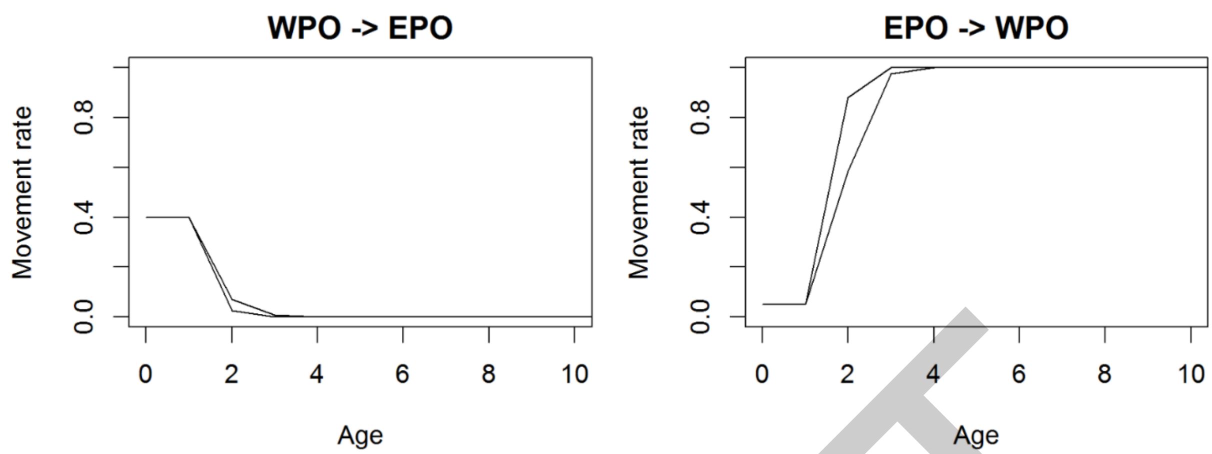
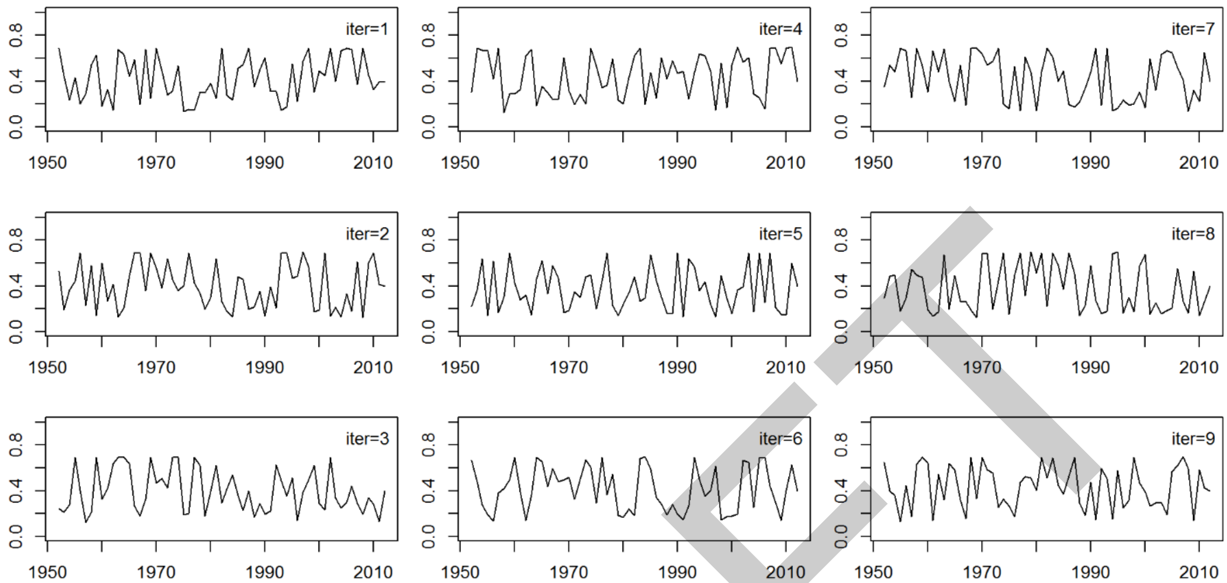


Figure 2. Age-based movement rate assumed in the simulation analyses. The fraction of fish from WPO area to EPO area at age 1 was assumed to be time-varying with mean rate at 40%.

a) Uniform



b) PDO-like

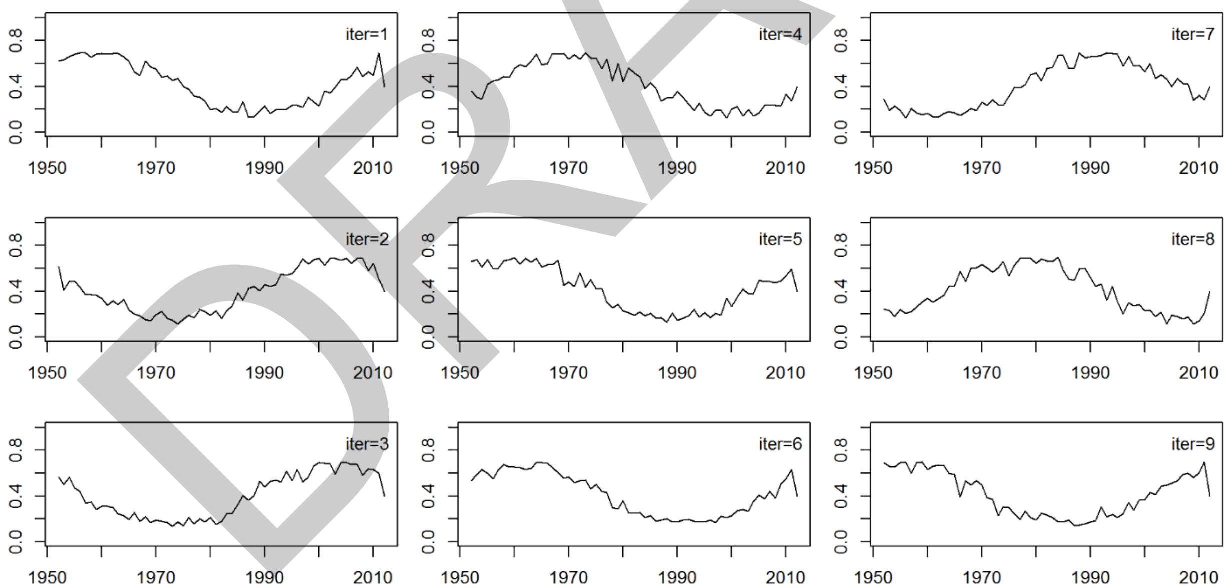


Figure 3. Nine examples of the time-varying movement rates for two states of nature in simulations, uniform (upper panel) and PDO-like (lower panel), where in each panel represents a single simulation (iteration). 500 simulated time-varying movement rates for each states of nature were generated in the study.

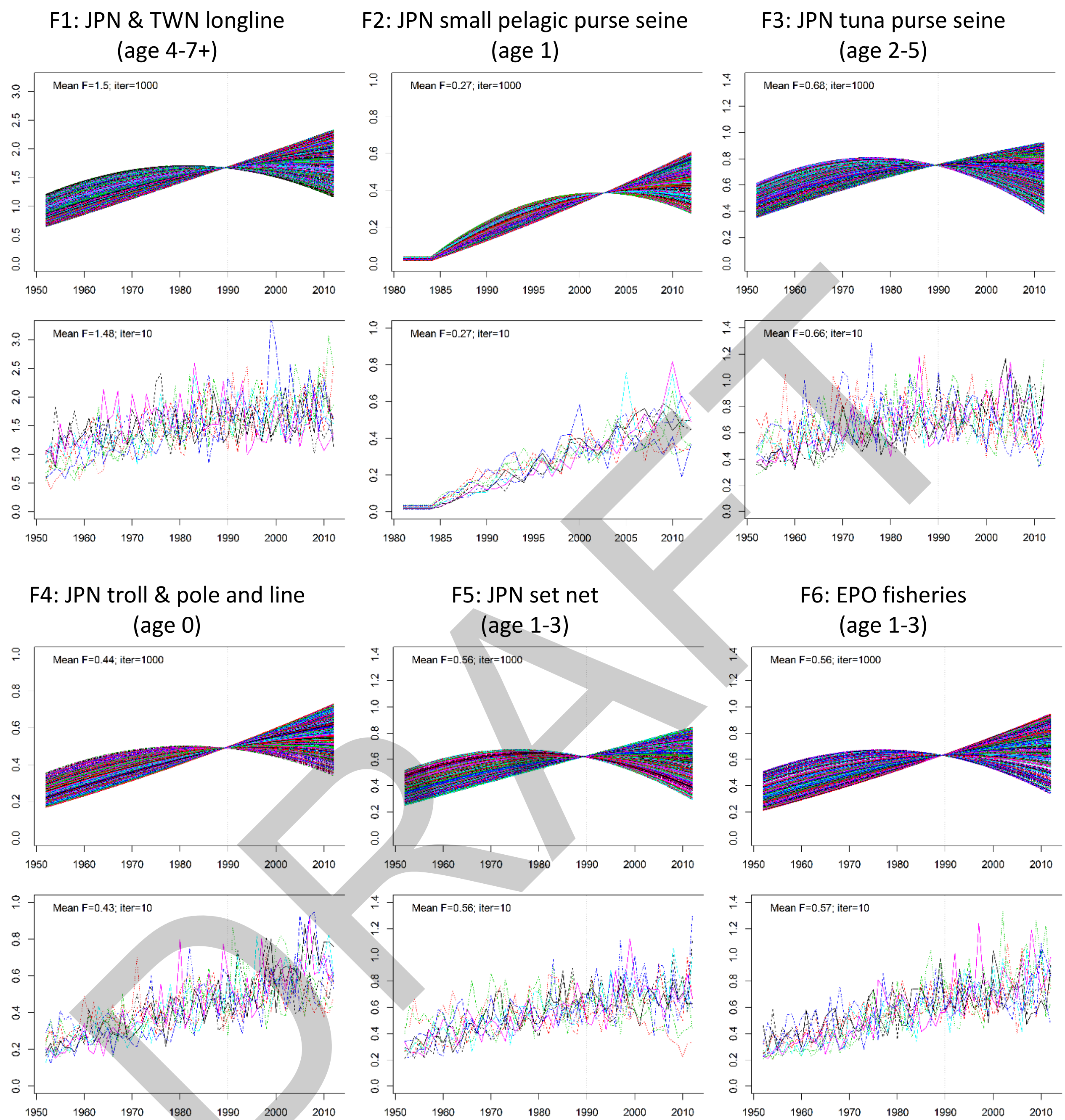


Figure 4. Examples of simulated fishing mortality trends for each fishery, where upper panel indicates 1,000 smooth trends of simulated fishing mortality and lower panel indicates 10 trends of simulated fishing mortality with noise for illustration purposes. 500 simulated fishing mortality trends with noise were generated for each states of nature in the study.

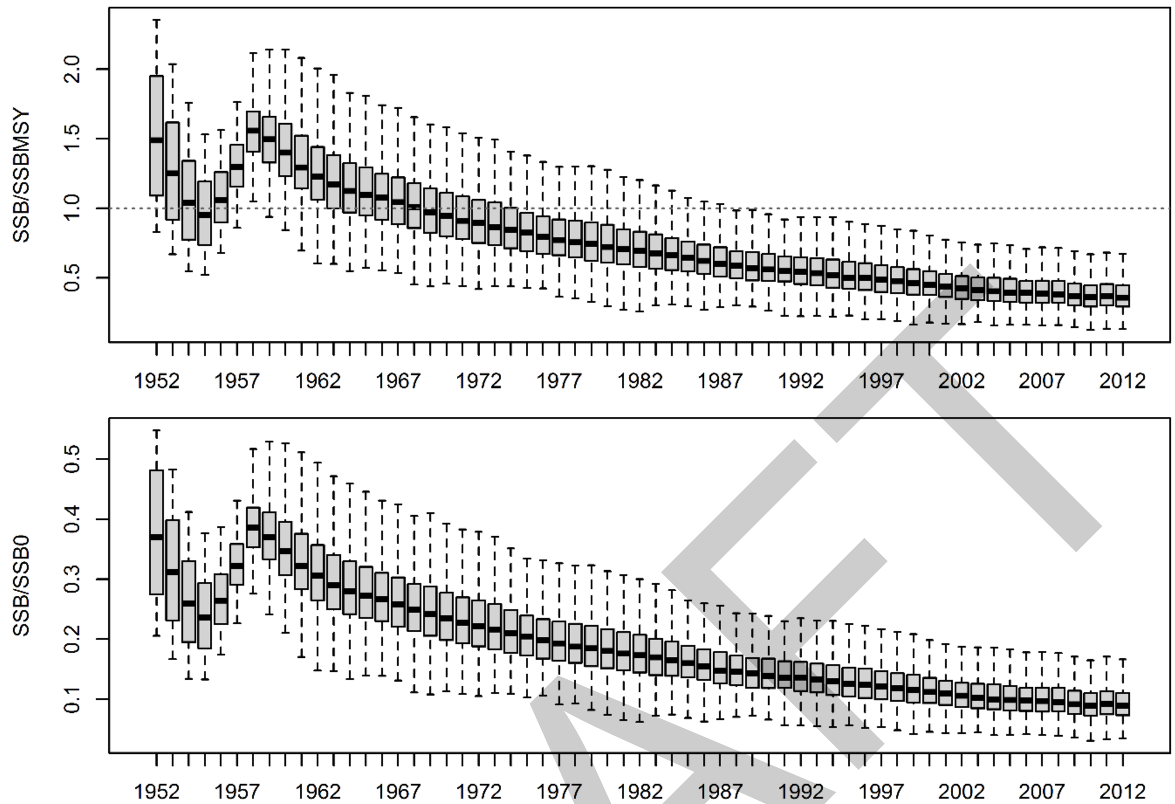


Figure 5. Box plot illustrating the distributions of spawning stock biomass relative to its maximum sustainable yield (MSY)-based reference points (upper panel) and spawning stock biomass relative to its unfished level (lower panel) from 500 synthetic populations for each states of nature. The horizontal line in the box represents median of the quantities, the box represents the lower and upper quartiles (25% and 75%), and the whiskers extend 1.5 times the inter-quartile range.

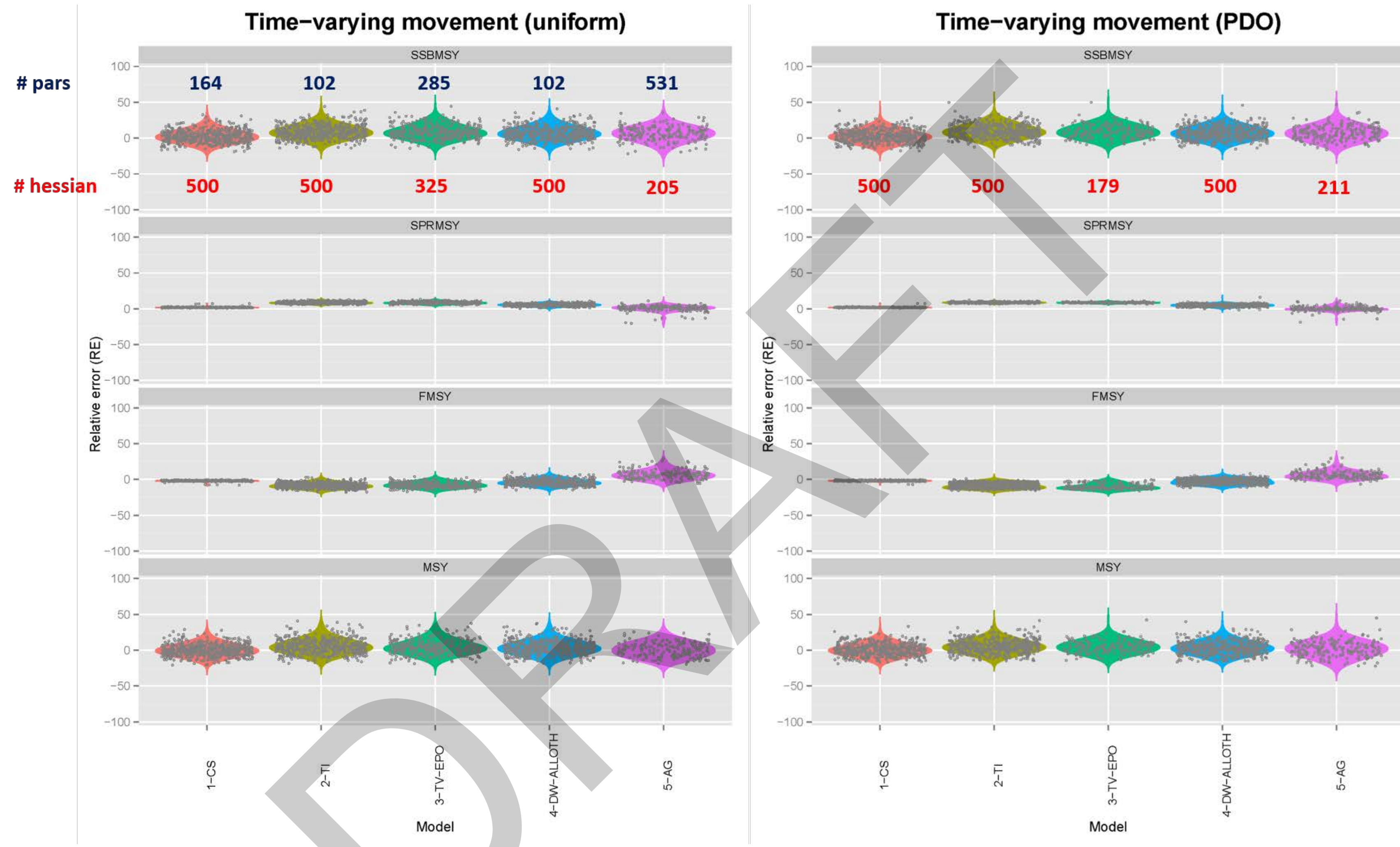


Figure 6. Violin plots illustrating the relative errors of estimated maximum sustainable yield (MSY)-based reference points for five estimation models applied to simulated populations for two states of nature, uniform (left panel) and PDO-like (right panel), where the dots indicate runs with invertible hessian, violin indicate kernel probability density of runs with invertible hessian, and number of runs with invertible hessian and number of active parameters estimated are shown.

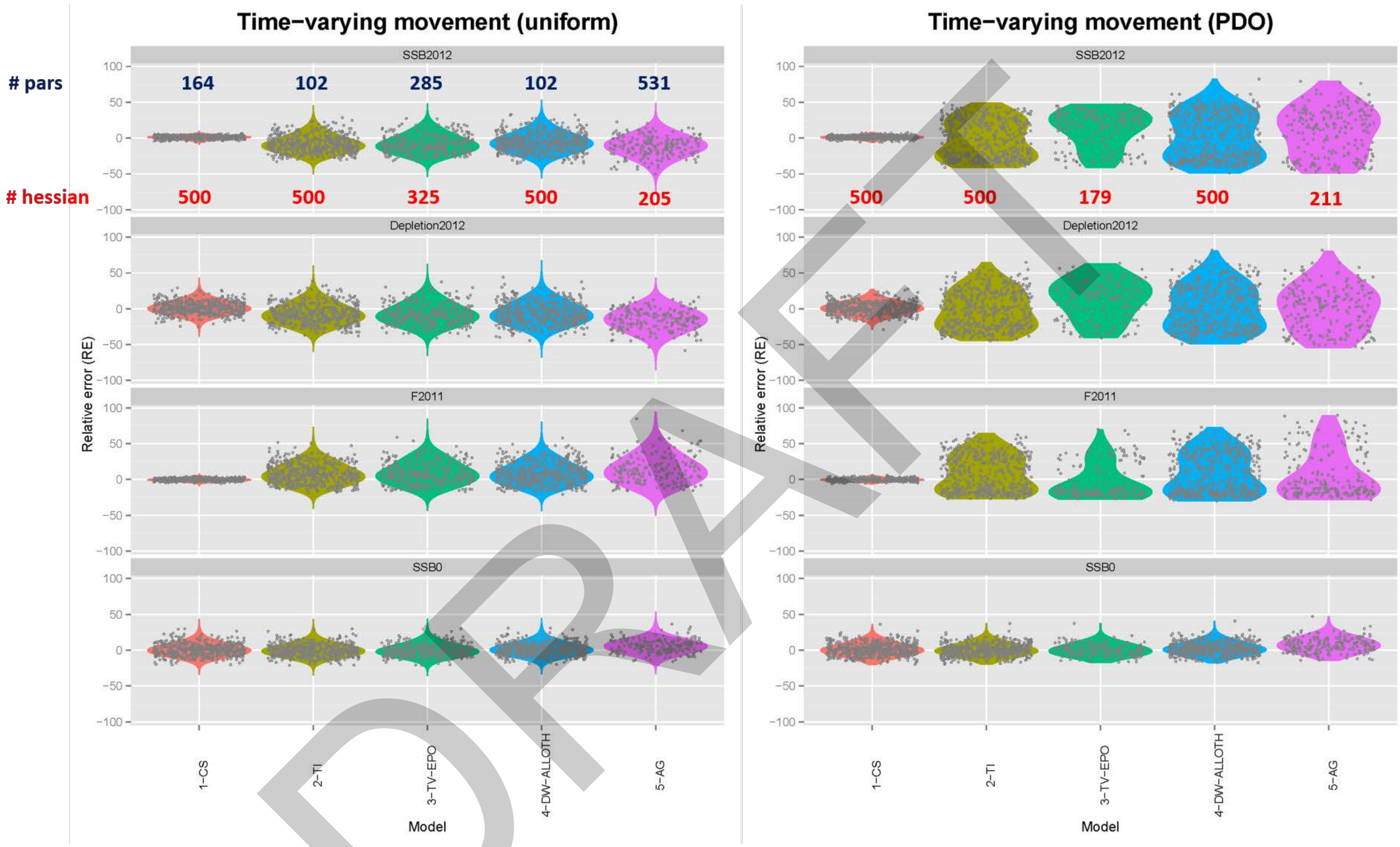


Figure 7. Violin plots illustrating the relative errors of estimated quantities of interest for five estimation models applied to simulated populations for two states of nature, uniform (left panel) and PDO-like (right panel), where the dots indicate runs with invertible hessian, violin indicate kernel probability density of runs with invertible hessian, and number of runs with invertible hessian and number of active parameters estimated are shown.

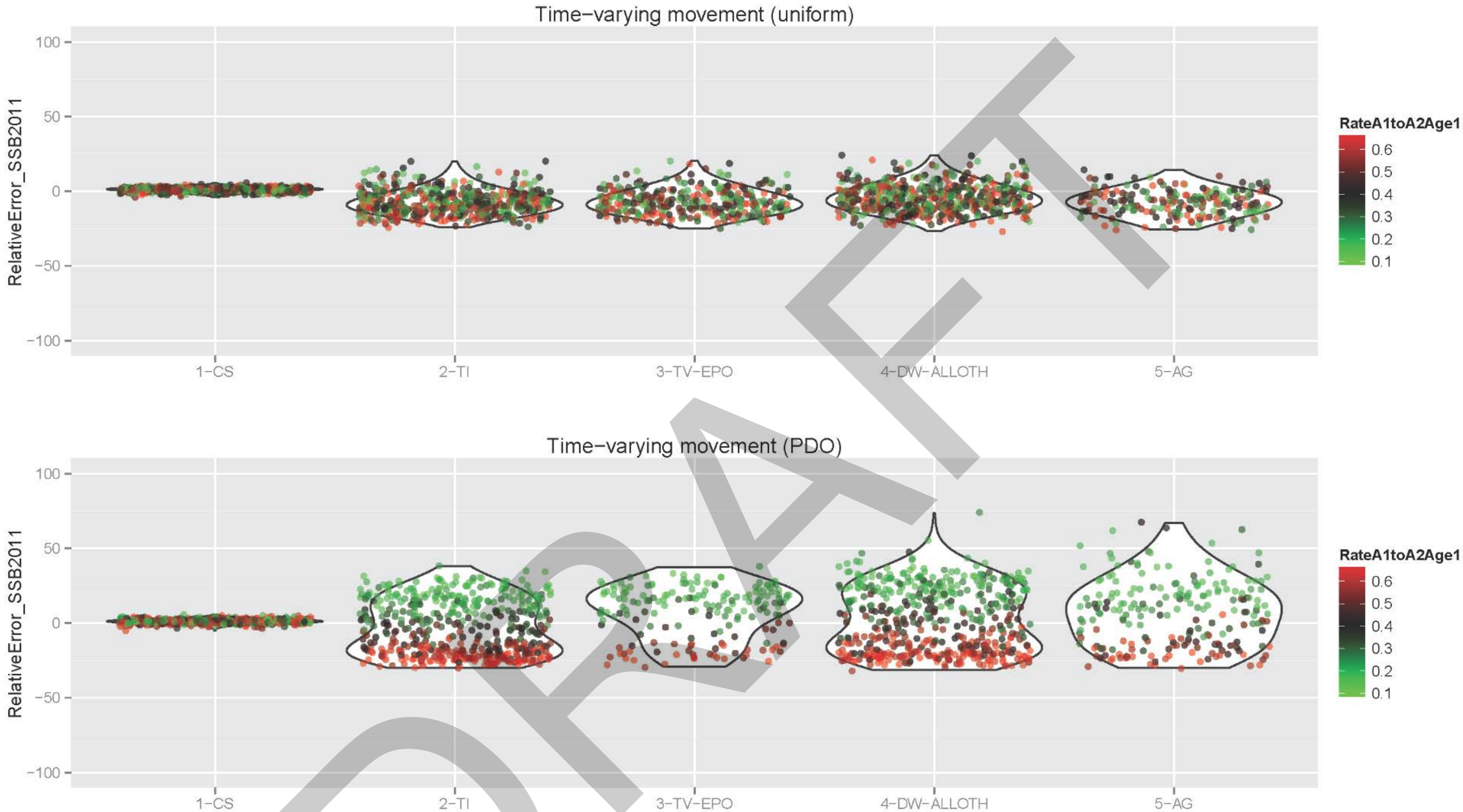


Figure 8. Violin plots illustrating the relative errors of estimated 2011 spawning stock biomass for five estimation models applied to simulated populations for two states of nature, uniform (upper panel) and PDO-like (lower panel), where the dots indicate runs with invertible hessian and violin indicate kernel probability density of runs with invertible hessian. Dots are categorized by fraction of fish move from WPO to EPO at age 1 in 2011.

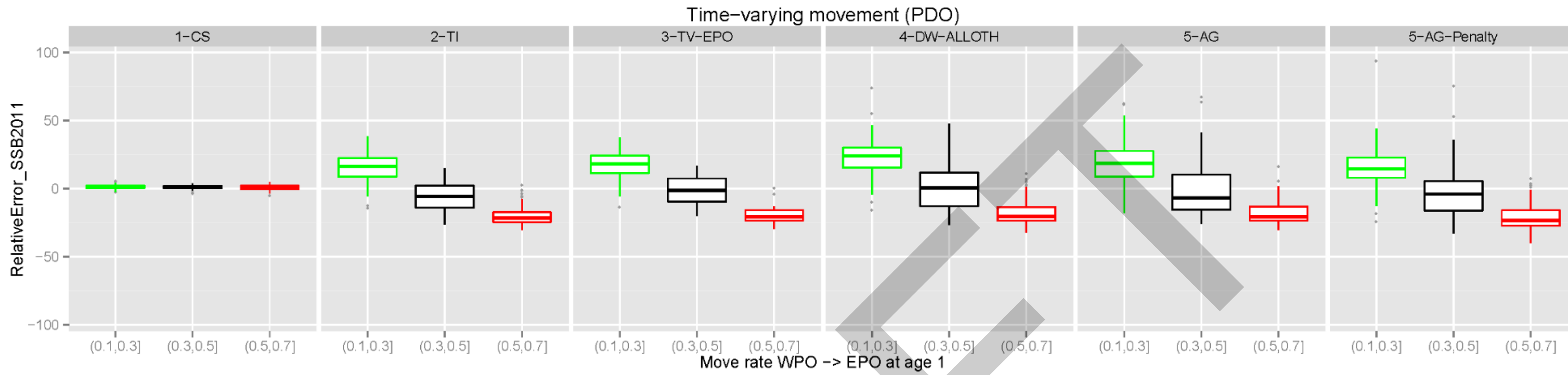


Figure 9. Box plots illustrating the relative errors of estimated 2011 spawning stock biomass for five estimation models applied to simulated populations with PDO-like movement. M6 is M5 with an arbitrary penalty on the time-varying deviations of selectivity. Plots are categorized by fraction of fish move from WPO to EPO at age 1 in 2011.