

## D.1 ANALYSIS

This bridging analysis provides documentation of the transition from the catch-age model code and assessment approach developed in 2011 (Martell et al. 2012) and used from 2011-2016, to an updated version of the assessment model platform used for the current Herring assessment (V2). The new platform has been used in recent stock assessments (e.g., Grandin and Forrest 2017). The detailed bridging analysis is presented for the Strait of Georgia stock only, as the relative results did not differ among stocks areas. Summary results for all five stocks are included where informative. Sensitivity analyses included in this bridging analysis are limited to the key steps used to develop the base case for the 2017 assessment. We refer to the original 2011 model platform as V0, modifications to V0 as V1, and the new updated platform as V2.

Results presented for each bridging step are maximum posterior density (MPD) estimates. The first step (1A and 1B) was to re-run the 2016 assessment model code (V0) to reproduce results from 2016 (DFO 2016). Before proceeding, the estimation phases for the variance parameters rho ( $\rho$ ) and kappa ( $\kappa$ ) were modified to estimation phases 3 and 4, respectively. These parameters were estimated in phases 3 and 3, respectively, in 2016. Steps 7 and 8 below include descriptions and equations for rho and kappa.

The V1 model code also includes the following update to the estimation of the variance structure. Variance components of the model implemented within the *ISCAM* modelling framework (e.g., Grandin and Forrest 2017) were partitioned using an errors-in-variables approach. The key variance parameter is the inverse of the total variance  $\phi^{-2}$  (i.e., total precision, *varphi*). The total variance is partitioned into observation and process error components by the model parameter  $\rho$  (*rho*), which represents the proportion of the total variance that is due to observation error (Punt and Butterworth 1993, Deriso et al. 2007).

In the 2011 stock assessment (Martell et al., 2011), *varphi* was parameterized as the total standard deviation of the process error, rather than the total variance, i.e., V0 model code (2011-2016)

$$\tau = \frac{1 - \rho}{\text{varphi}}$$

$$\sigma = \frac{\rho}{\text{varphi}}$$

In the review of the 2011 stock assessment (DFO 2012), reviewers noted that the errors-in-variables approach should have been parameterized as a function of total variance (or its inverse precision). This change was made in subsequent versions of the software (e.g., Forrest et al., 2015; Grandin and Forrest 2017). However, the change was not implemented for the Pacific Herring assessment at the time, and for consistency has not been implemented in subsequent iterations of the assessment.

Given the recommendation of the reviewers in 2011 and to bring the assessment in line with best practices, the current assessment will update the errors-in-variables approach to represent partitioning of the total precision, i.e.,

$$\tau = \sqrt{1 - rho} * varphi$$

$$\sigma = \sqrt{rho} * varphi$$

where  $varphi$  now represents the inverse of the total variance, not total standard deviation. Therefore, to be able to compare results from model V0 to model V2, a hybrid version of V1 was developed, which used the above definition of tau ( $\tau$ ), sigma ( $\sigma$ ) and  $varphi$  ( $\varphi^{-2}$ ).

Of relevance to the bridging analysis is that this change to partitioning of the total variance impacts model estimates of leading parameters and unfished biomass ( $SB_0$ ). Table D.1 and D.2 summarizes MPD estimates of relevant leading parameters and  $SB_0$  from V0 model code used from 2011-2016, the updated V1 model code and V2 for AM1 (Table D.1) and AM2 (Table D.2). After making this one change, results from models V1 and V2 are nearly identical (Table D.1), indicating that any differences between V0 and V2 can largely be explained by the update to the errors in variables approach.

For all stocks, MPD estimates of  $SB_0$  using the updated model equations (V1 and V2) are numerically larger than those calculated using the previous equation (V0), with the largest differences occurring for SOG and PRD stocks. V0, V1 and V2 estimates of  $SB_0$  for HG are within 160 tonnes of each other. Trends are similar between AM1 and AM2 parameterizations of  $q$ .

Each bridging analysis step is described in Table D.3 and is carried out for both AM1 and AM2 model configurations. Following the convention of DFO 2016, the model cases are denoted AM1 for the case where surface (1951-1987) and dive (1988+) survey catchability parameters are estimated using a prior distribution and AM2 for the case where the surface survey catchability is estimated and the dive survey catchability is fixed at  $q_2 = 1$ .

### **Steps 1 and 2: Reconstruction of previous assessment with fixed parameters.**

The first step was to ensure that both V1 and V2 models produce output values that are identical to input values when all estimation procedures are turned off. Leading parameter initial values for V1 and V2 were set equal to MPD estimated values from the 2016 assessment (DFO 2016). With the estimation of all leading parameters turned off, both V1 and V2 produced model estimates identical to the initial leading parameters indicating that both models are working correctly and not estimating parameters when estimation procedures have been turned off (Table D.4).

### **Steps 3 and 4: All parameters estimated except $M$**

In Steps 3A, 3B, 4A, and 4B, parameter estimation is turned on for both V1 and V2, and model estimates are compared to examine similarities between estimated parameters and time series trends. Here, estimated natural mortality is assumed to be constant over time. Estimated values differ from initial leading parameter values, as expected, however they vary minimally between V1 and V2 (Table D.5). Model fits to the survey data and time series estimates of spawning biomass, recruitment deviations, depletion, and estimated natural mortality show near-identical trends (Figure D.1). Comparisons using AM2 (Steps 3B and 4B) show the same results thus these figures are not included for this step.

### **Steps 5 and 6: All parameters estimated, including $M$**

The estimation of time varying natural mortality within the age-structured model was first introduced to the herring stock assessment model in 2004, where instantaneous natural mortality is assumed equal over all ages but varies over time (Fu et al. 2004). The current parameterization of natural mortality ( $M$ ), where annual deviations in  $M$  are estimated using a random walk process was introduced in 2006 (Haist and Schweigert 2006). Support for inclusion of time varying  $M$  includes reduction in the magnitude of retrospective patterns and improved coherence between assumed and empirical fits to the spawn survey index. This parameterization of  $M$  has continued to be implemented in annual stock assessment of BC Pacific Herring.

Steps 5A, 5B, 6A, and 6B reexamine model outputs and time series trends described in Steps 3 and 4, with the addition of estimated time varying natural mortality. Model fits to the survey data and time series estimates of spawning biomass, recruitment deviations, depletion, and estimated natural mortality show near-identical trends when comparing V1 and V2 (Figure D.2). Comparisons using AM2 (Steps 5B and 6B) show the same trends as AM1 thus these figures are not included. Figure D.3 compares V2 constant  $M$  and time varying  $M$  model runs for AM1 (Steps 4A vs. 6A). The addition of time varying  $M$  results in improved model fits to the spawn index, particularly from 2010-2016 (Figure D.3b). Differences in the parameterization of  $M$  also impact estimates of  $SB_0$  where

$SB_0\_constantM$  is numerically larger than  $SB_0\_timevaryingM$  (Figure D.3c- see dots on far left side of the figure), and in deviations in recruitment (Figure D.3d). Steps 4B and 6B compare constant  $M$  and time varying  $M$  model runs for AM2, showing similar improvements to model fits in the spawn index (Figure D.4b). With AM2, differences in estimated values of  $SB_0$  are less pronounced than with AM1 (Figure D.4c vs. D.3c), likely attributed to more pronounced differences in  $q_1$  (Figure D.4g vs. D.3g).

### **Steps 7 and 8: Process and observation error: Investigating sensitivities to variance parameters for rho and kappa.**

The key variance parameter in the errors-in-variables approach is the inverse of the total variance  $\phi^{-2}$  (i.e., total precision,  $varphi$ ). The total variance is partitioned into observation and process error components by the model parameter  $\rho$  ( $\rho$ ), which is the proportion of the total variance that is due to observation error (Punt and Butterworth 1993, Deriso et al. 2007). In *ISCAM*, standard deviations in process error (tau,  $\tau$ ) and observation error (sigma,  $\sigma$ ) are related and modelled using the following equations for kappa ( $\kappa$ ) and rho ( $\rho$ ):

$$kappa = \left( \frac{1}{\sqrt{\sigma^2 + \tau^2}} \right)^2$$

$$rho = \sigma^2 \left( \frac{1}{\sqrt{\sigma^2 + \tau^2}} \right)^2$$

Since the introduction of *ISCAM* V1 in 2011, the model has been parameterized to estimate both kappa and rho. Steps 7 and 8 investigate the sensitivity of V2 (AM1 and AM2) to different fixed kappa values while estimating rho with constant  $M$  (Step 7A) and time varying  $M$  (Step 8A), and to different fixed rho values while estimating kappa with constant  $M$  (Step 7B) and time varying  $M$  (Step 8B). All combinations are described in Table D.6. Steps 7C and 8C present the status quo to date: estimating both kappa and rho, under constant  $M$  (Step 7C) and time varying  $M$  (Step 8C). When both rho and kappa are estimated (Steps 7C, 8C), the choice of initial value for rho and kappa does not impact estimated model parameters. This is the same for AM1, AM2 and both parameterizations of  $M$ . Figure D.5 shows model estimates of spawning biomass ( $SB_t$ ), demonstrating there are no changes in  $SB_t$  regardless of initial values when both rho and kappa are estimated (figures of model fits to spawn index, recruitment deviations, depletion, natural mortality and  $q$  are not shown). For all scenarios that include estimating rho while fixing kappa and estimating kappa while fixing rho, for AM1, AM2, and both parameterizations of  $M$ , the largest difference is in model estimates of  $SB_0$  and hence estimated depletion ( $SB_t/SB_0$ ). Figure D.6 presents (a) through (g) for Step 7A, Figure D.7 summarizes differences in  $SB_t$  and  $SB_t/SB_0$  for Step 7A (AM1 and AM2), and

Figure D.8 summarizes differences in  $SB_t$  and  $SB_t/SB_0$  for Step 7B (AM1 and AM2). Figures D.9 and D.10 present AM1 results only.

### **Step 9: Sensitivity to prior on $q$**

Estimates of current spawning biomass and one-year projections were presented for both AM1 and AM2 parameterizations of spawn survey  $q$  in 2014, 2015 and 2016 due to concerns around the choice of  $q$  prior and interactions with the harvest control rule. In the 2016 Science Response, the Herring Technical Working Group described in detail analytical concerns with both AM1 and AM2 parameterizations of  $q$  (Table A.1, DFO 2016). The bridging analysis considers 6  $q$  prior scenarios, differing by distribution (informative or uninformative) and mean prior  $q$  value, described in Table D.7, as well as additional scenarios to explore tightening and broadening of  $q$  prior by changing the standard deviation of the  $q$  prior while keeping the mean constant (Table D.8).

Under the constant  $M$  scenario, model estimates of  $q_1$  and  $q_2$  estimated using an uninformative prior (scenario 1) were near-identical to values estimated by AM1 (scenario 3, Figure D.11g). These scenarios produced near-identical estimates of  $SB_0$  and time series of spawning biomass (Figure D.11c). Further investigation of the sensitivity of model estimates to tightening and broadening of the standard deviation of the uninformative prior is presented in Figure D.12. With an uninformative  $q$  prior and standard deviation between 0.5 and 3.0, model estimates of  $q_1$ ,  $q_2$ ,  $M$ , and model estimates of spawning biomass are very similar (Figure D.12). In contrast, when the standard deviation on  $q$  prior is reduced to 0.1 (scenario 1d),  $q_1$  and  $q_2$  estimated to be considerably larger than scenarios 1, 1a – 1c, estimated  $M$  is numerically lower, and the time series of  $SB$  for all years after 1965 is numerically lower.

Figures D.13 and D.14 explore the same scenarios for time varying  $M$ . Interactions between estimating time varying  $M$  and estimating  $q$  are such that the lowest  $q$  prior value (scenario 2) results in the highest overall estimates of time varying  $M$  (Figure D.13f) and the highest estimates of spawning biomass (Figure D.13c). The uninformative prior (scenario 1) produced estimates similar to the mean  $q$  prior of 0.75 (scenario 4), and the highest  $q$  values and lowest biomass values occur with scenario 6 (AM2). As was the case with the constant  $M$  scenario, tightening and broadening the  $q$  prior by changing the standard deviation for the uninformative prior, scenario 1, estimates  $q$  values in the range of 0.75 for standard deviations between 0.5 and 3.0. The uninformative prior with a standard deviation of 0.1 results in lower estimates of time varying  $M$  and lower spawning biomass estimates relative to the other scenarios.

### **Step 11: Test V2 model with 2016 input data for remaining 4 major stocks**

V2 model successfully reproduced V1 model estimates from 2016 input data for AM1 and AM2 under scenarios of estimated constant  $M$  and estimated time varying  $M$  (Steps

3 – 6). Steps 3, 4, 5 and 6 were repeated for the remaining 4 stocks, AM1 and AM2, to ensure V2 would run for all stocks and to diagnose any issues related to model convergence or local minimas. Results from these model runs are not included in the bridging analysis.

### **Step 12: Summarize conclusions and determine base parameterization for V2**

1. 2016 V2 model estimates of  $SB_0$  differ from 2016 V1 estimates due to changes to the model code describing variance structure for process and observation error.
2. Parameter estimates and biomass trajectories compared between V1 and V2 were near identical, supporting the adoption of V2 model code for the 2017 herring assessment.
3. Based on the results from the sensitivity analyses presented in Steps 7, 8 (for rho and kappa for AM1, AM2 and constant and time varying  $M$ ) and Steps 9, 10 (for  $q$  prior and standard deviation in  $q$  prior), we recommend continuing with 2016 parameterization of rho, kappa, and natural mortality ( $M$ ) for AM1 and AM2 model runs. The sensitivity analysis was inconclusive with respect to supporting or eliminating a particular  $q$  parameterization over another. Resolution between AM1 and AM2 parameterization of  $q$  will require simulation-evaluation. Sensitivity analyses alone are insufficient for understanding the complex interplay between estimating rho, kappa,  $q$ , steepness ( $h$ ), and time varying processes such as  $M$  and selectivity and the implications for estimating biological references points such as unfished biomass.

We recommend defining two Base cases for each of the 5 major herring stocks: AM1 and AM2, and we recommend using V2 with the same assumptions and parameter settings as were used in 2016.

### **Step 13: Add 2017 data to V2 base for each stock area**

V2 model successfully fitted to the 2017 input data for AM1 and AM2 for all 5 major herring stocks.

## D.2 TABLES

Table D.1. Comparison of MPD estimates of leading parameters and unfished biomass,  $SB_0$ , given changes to the estimation of the variance structure for process and observation error (AM1).

<i>Parameters</i>	<i>Model Version</i>	<i>AM1</i>				
		<i>SOG</i>	<i>PRD</i>	<i>HG</i>	<i>CC</i>	<i>WCVI</i>
<i>SB<sub>0</sub></i>	V0	146.46	53.47	32.17	57.89	54.53
	V1	160.90	57.82	32.33	60.69	57.69
	V2	160.81	57.83	32.15	60.71	57.60
<i>R<sub>0</sub></i>	V0	3215.71	328.34	453.88	504.45	903.93
	V1	3226.89	348.43	450.05	511.89	927.31
	V2	3208.58	350.83	446.51	510.40	921.13
<i>steepness, h</i>	V0	0.76	0.73	0.81	0.82	0.75
	V1	0.74	0.72	0.81	0.82	0.76
	V2	0.74	0.72	0.81	0.82	0.76
<i>M (average)</i>	V0	0.57	0.45	0.40	0.47	0.65
	V1	0.56	0.44	0.40	0.47	0.65
	V2	0.56	0.44	0.40	0.46	0.65
<i>rbar</i>	V0	2731.60	235.92	306.18	372.23	724.75
	V1	2356.01	229.35	296.02	355.45	672.04
	V2	2336.29	231.15	294.38	354.40	666.99
<i>rinit</i>	V0	813.05	286.36	40.82	324.64	415.03
	V1	649.46	265.54	39.40	302.57	409.04
	V2	628.30	262.62	39.06	298.70	404.87
<i>tau</i>	V0	0.48	0.66	0.81	0.69	0.54
	V1	0.67	0.75	0.83	0.76	0.68
	V2	0.67	0.75	0.83	0.76	0.68
<i>sigma</i>	V0	0.32	0.45	0.47	0.35	0.40
	V1	0.39	0.51	0.51	0.41	0.46
	V2	0.37	0.49	0.49	0.39	0.44

Table D.2. Comparison of MPD estimates of leading parameters and unfished biomass,  $SB_0$ , given changes to the estimation of the variance structure for process and observation error (AM2).

<b>AM2</b>						
<b>Parameters</b>	<b>Model Version</b>	<b>SOG</b>	<b>PRD</b>	<b>HG</b>	<b>CC</b>	<b>WCVI</b>
<b><math>SB_0</math></b>	V0	110.71	53.24	23.90	51.35	42.76
	V1	130.38	57.55	24.10	54.12	46.50
	V2	130.84	57.83	23.99	54.18	46.51
<b><math>R_0</math></b>	V0	1453.11	285.63	285.87	346.47	529.33
	V1	1535.98	310.20	286.15	367.04	573.06
	V2	1537.69	350.83	284.25	367.10	569.73
<b>steepness, <math>h</math></b>	V0	0.80	0.73	0.80	0.83	0.73
	V1	0.77	0.72	0.80	0.83	0.74
	V2	0.77	0.72	0.80	0.83	0.74
<b><math>M</math> (average)</b>	V0	0.50	0.44	0.38	0.45	0.59
	V1	0.46	0.43	0.38	0.45	0.59
	V2	0.46	0.44	0.38	0.44	0.59
<b><math>rbar</math></b>	V0	1206.88	201.61	185.27	247.32	389.91
	V1	1082.17	201.04	182.97	249.08	387.38
	V2	1079.78	231.15	182.38	249.25	385.18
<b><math>rinit</math></b>	V0	393.27	263.67	34.43	269.29	272.43
	V1	294.20	250.58	33.99	255.38	273.78
	V2	285.98	262.62	33.82	252.29	270.02
<b><math>tau</math></b>	V0	0.48	0.67	0.84	0.72	0.58
	V1	0.67	0.75	0.85	0.78	0.70
	V2	0.67	0.75	0.85	0.78	0.70
<b><math>sigma</math></b>	V0	0.34	0.45	0.49	0.37	0.42
	V1	0.42	0.51	0.53	0.43	0.47
	V2	0.40	0.49	0.51	0.41	0.45

Table D.3. Bridging analysis steps.

<b>Bridging Step</b>	<b>Description</b>
1A	V1 (AM1): Set leading parameter initial values equal to the estimated MPD values from 2016 AM1 assessment. All estimation OFF.
1B	V1 (AM2): Set leading parameter initial values equal to the estimated MPD values from 2016 AM2 assessment. All estimation OFF.
2A	V2 (AM1): Set leading parameter initial values equal to the estimated MPD values from 2016 AM1 assessment. All estimation OFF.
2B	V2 (AM2): Set leading parameter initial values equal to the estimated MPD values from 2016 AM2 assessment. All estimation OFF.



<p><i>All subsequent steps include parameter estimation.</i>  <i>Steps 3A-4B estimate natural mortality as constant over time.</i></p>	
3A	V1 (AM1): Set leading parameter initial values equal to the estimated MPD values from 2016 AM1 assessment. Estimate all parameters.
3B	V1 (AM2): Set leading parameter initial values equal to the estimated MPD values from 2016 AM2 assessment. Estimate all parameters.
4A	<b>V2</b> (AM1): Set leading parameter initial values equal to the estimated MPD values from 2016 AM1 assessment. Estimate all parameters.
4B	<b>V2</b> (AM2): Set leading parameter initial values equal to the estimated MPD values from 2016 AM2 assessment. Estimate all parameters.
<p><i>Steps 5A-6B estimate time varying natural mortality.</i></p>	
5A	V1 (AM1): As per 3A, with time varying $M$ .
5B	V1 (AM2): As per 3B, with time varying $M$ .
6A	<b>V2</b> (AM1): As per 4A, with time varying $M$ .
6B	<b>V2</b> (AM2): As per 4B, with time varying $M$ .
<p><i>All subsequent steps involve <b>V2</b> model only.</i></p>	
7A	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): Investigate model sensitivity to different fixed values of kappa while estimating rho (constant $M$ )
7B	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): Investigate model sensitivity to different fixed values of rho while estimating kappa (constant $M$ )
7C	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): Investigate model sensitivity when both kappa and rho are estimated (constant $M$ )
8A	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): As per 7A, with time varying $M$ .
8B	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): As per 7B, with time varying $M$ .
8C	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): As per 7C, with time varying $M$ .
9A	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): Investigate model sensitivity to prior on MEAN $q$ (including uninformative and informative priors), with constant $M$ .

9B	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): Investigate model sensitivity to standard deviation of prior distribution on $q$ , with constant $M$ .
10A	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): Investigate model sensitivity to prior on MEAN $q$ (including uninformative and informative priors), with time varying $M$ .
10B	Sensitivity analysis ( <b>V2</b> , AM1 and AM2): Investigate model sensitivity to standard deviation of prior distribution on $q$ , with time varying $M$ .
11	<b>V2</b> : Test V2 model with 2016 input data for remaining 4 major stocks.
12	Summarize conclusions and determine base parameterization of <b>V2</b>
13	Add 2017 data to <b>V2</b> base for each stock area

Table D.4. Initial and estimated leading parameters for Steps 1A, 1B, 2A, and 2B.

Leading Parameters	All parameters fixed							
	1A		1B		2A		2B	
	Initial	Estimated	Initial	Estimated	Initial	Estimated	Initial	Estimated
<i>log_ro</i>	7.28	7.28	7.28	7.28	7.28	7.28	7.28	7.28
<i>steepness,h</i>	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
<i>log.m</i>	-0.69186	-0.69186	-0.69186	-0.69186	-0.69186	-0.69186	-0.69186	-0.69186
<i>log_avgrec</i>	7.09	7.09	7.09	7.09	7.09	7.09	7.09	7.09
<i>log_recinit</i>	5.97	5.97	5.97	5.97	5.97	5.97	5.97	5.97
<i>rho</i>	0.413297	0.413297	0.413297	0.413297	0.413297	0.413297	0.413297	0.413297
<i>kappa</i>	1.22062	1.22062	1.22062	1.22062	1.22062	1.22062	1.22062	1.22062
<i>sig</i>	0.58189	0.58189	0.58189	0.58189	0.58189	0.58189	0.58189	0.58189
<i>tau</i>	0.69330	0.69330	0.69330	0.69330	0.69330	0.69330	0.69330	0.69330

Table D.5. Initial and estimated leading parameters for Steps 3A, 3B, 4A, and 4B.

Leading Parameters	Estimate all parameters; estimated natural mortality is assumed constant over time							
	3A		3B		4A		4B	
	Initial	Estimated	Initial	Estimated	Initial	Estimated	Initial	Estimated
<i>log_ro</i>	7.28	8.27	7.28	7.61	7.28	8.27	7.28	7.59
<i>steepness,h</i>	0.8	0.7	0.8	0.7	0.8	0.7	0.8	0.7
<i>log.m</i>	-0.69186	-0.29550	-0.69186	-0.46059	-0.69186	-0.29431	-0.69186	-0.45374
<i>log_avgrec</i>	7.09	7.89	7.09	7.19	7.09	7.89	7.09	7.21
<i>log_recinit</i>	5.97	7.56	5.97	6.84	5.97	7.56	5.97	6.87
<i>rho</i>	0.413297	0.318488	0.413297	0.319655	0.413297	0.298097	0.413297	0.324913
<i>kappa</i>	1.22062	1.43411	1.22062	1.37875	1.22062	1.47583	1.22062	1.41208
<i>sig</i>	0.58189	0.47125	0.58189	0.48150	0.58189	0.44943	0.58189	0.47968
<i>tau</i>	0.69330	0.68936	0.69330	0.70246	0.69330	0.68964	0.69330	0.69143

Table D.6. Description of rho and kappa scenarios, including initial values for rho ( $\rho$ ), kappa ( $\kappa$ ), sigma ( $\sigma$ ), tau ( $\tau$ ) and the total variance.

rho and kappa scenarios	rho	kappa	$\sigma$	$\tau$	total variance
1	0.50000	0.50000	1.00	1.00	1.41421
2	0.05882	1.47059	0.20	0.80	0.82462
3	0.33166	2.89287	0.34	0.48	0.58794
4	0.41330	1.22062	0.58	0.69	0.90513
5	0.80000	0.80000	1.00	0.50	1.11803

Table D.7. Description of each  $q$  prior scenario, including prior type, mean, and standard deviation. The uninformative prior is modelled as a uniform distribution (mean, SD) and the informative prior is modeled as a normal distribution (mean, SD).

q prior scenario	q1			q2		
	Type	Mean	SD	Type	Mean	SD
1	Uninformative	1	1	Uninformative	1	1
2	Informative	0.25	0.274	Informative	0.25	0.274
3 (AM1)	Informative	0.566	0.274	Informative	0.566	0.274
4	Informative	0.75	0.274	Informative	0.75	0.274
5	Informative	1	0.274	Informative	1	0.274
6 (AM2)	Uninformative	1	1	Informative	1	0.01

Table D.8. Description of each  $q$  prior scenarios, including prior type, mean and standard deviation. This table differs from Table x.7 in that additional different standard deviation levels are explored.

q prior scenario	q1			q2		
	Type	Mean	SD	Type	Mean	SD
1	Uninformative	1	1	Uninformative	1	1
1a	Uninformative	1	3	Uninformative	1	3
1b	Uninformative	1	2	Uninformative	1	2
1c	Uninformative	1	0.5	Uninformative	1	0.5
1d	Uninformative	1	0.1	Uninformative	1	0.1

### D.3 FIGURES

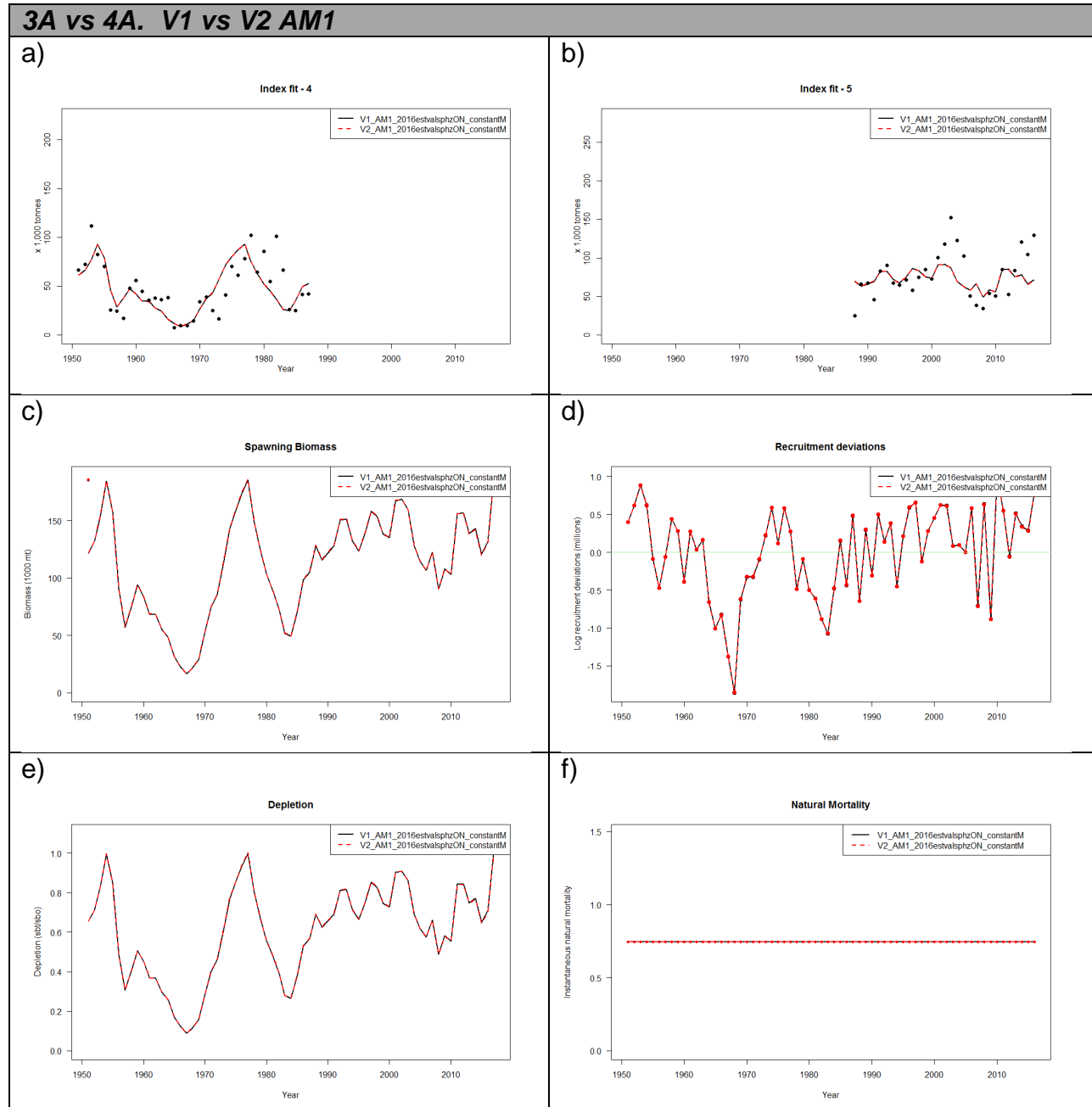


Figure D1. Comparison of V1 and V2 model outputs for Steps 3A and 4A: (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as a circle at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB/SB_0$ ); and (f) natural mortality. AM1 results only.

## 5A vs 6A. V1 vs V2 AM1

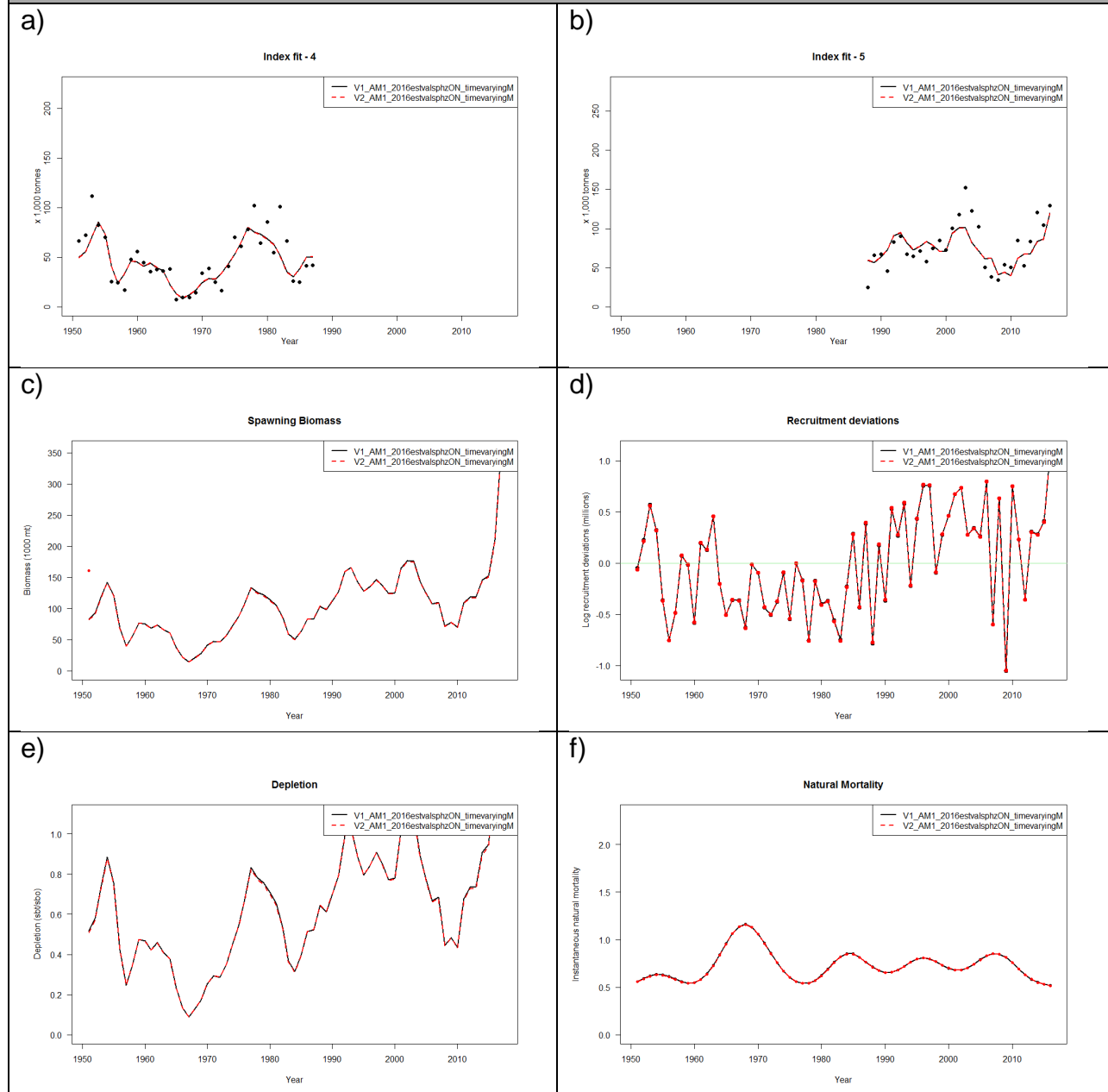
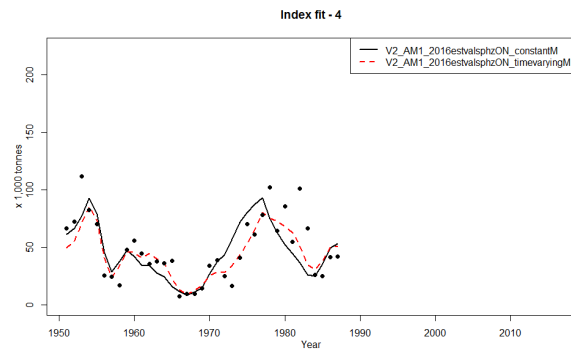


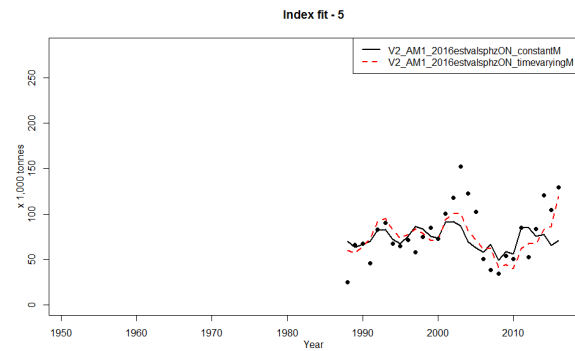
Figure D2. Comparison of V1 and V2 model outputs for Steps 5A and 6A: (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as a circle at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); and (f) natural mortality. AM1 results only.

## 4A vs. 6A. V2\_AM1 Constant M vs. time varying M

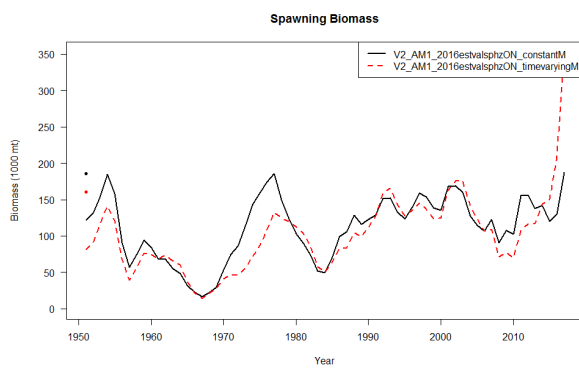
a)



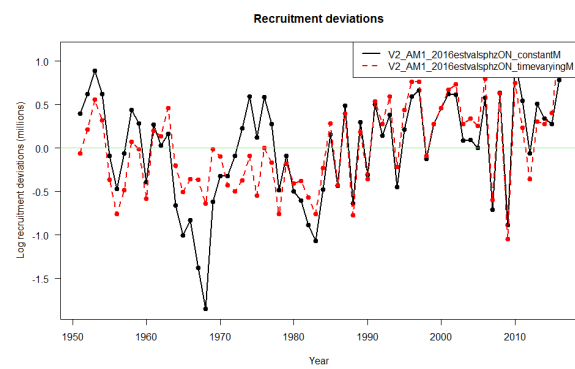
b)



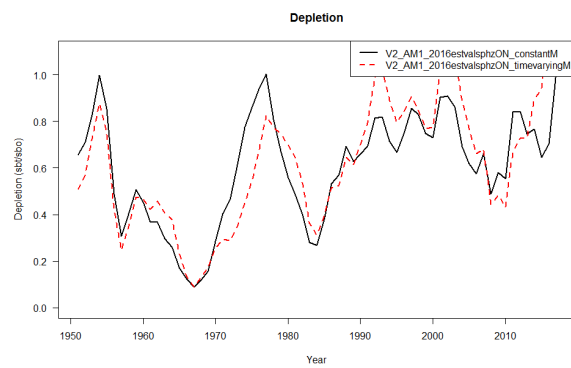
c)



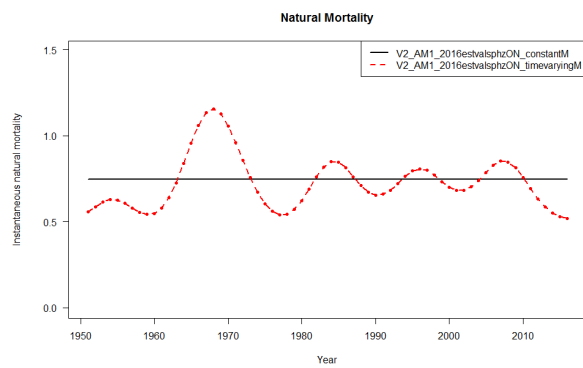
d)



e)



f)



g)

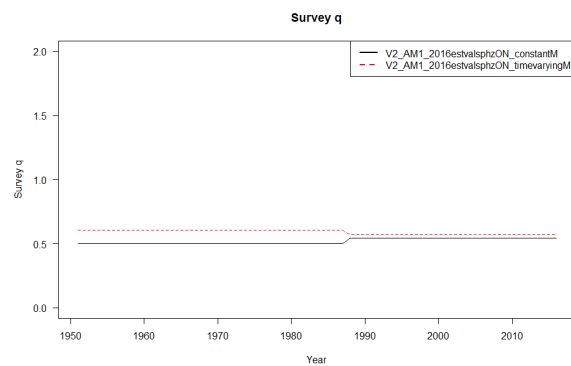
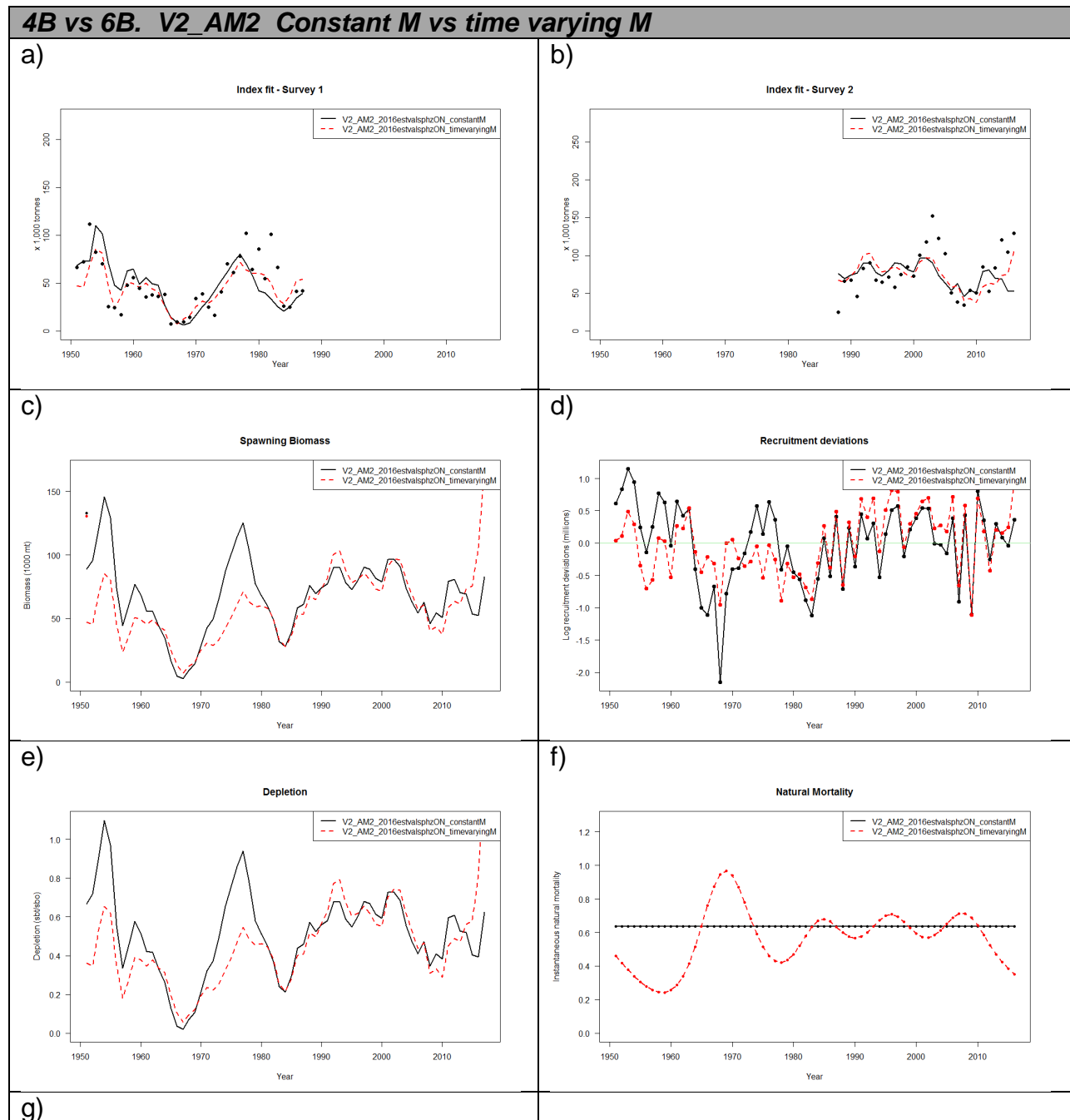


Figure D3. Comparison of V2 model outputs for Steps 4A (constant  $M$ ) and 6A (time varying  $M$ ): (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as a circle at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); (f) natural mortality, and (g) survey  $q$ . AM1 results only.



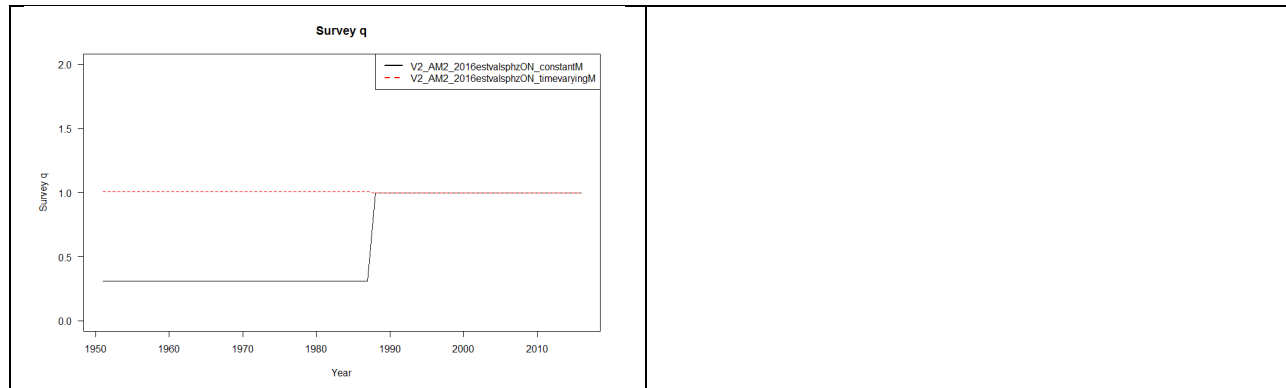
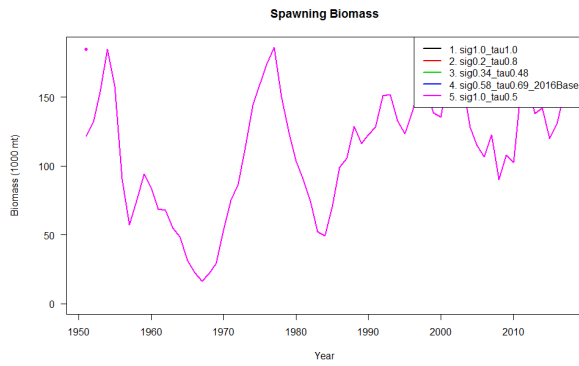


Figure D4. Comparison of V2 model outputs for Steps 4B (constant  $M$ ) and 6B (time varying  $M$ ): (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as circles at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); (f) natural mortality, and (g) survey  $q$ . AM2 results only.

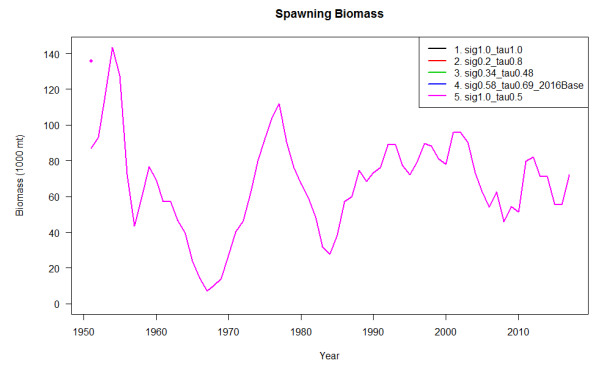


**7C and 8C (AM1 and AM2):  $V2\_kappaestimated\_rhoestimated$  with constant  $M$  and time varying  $M$ .**

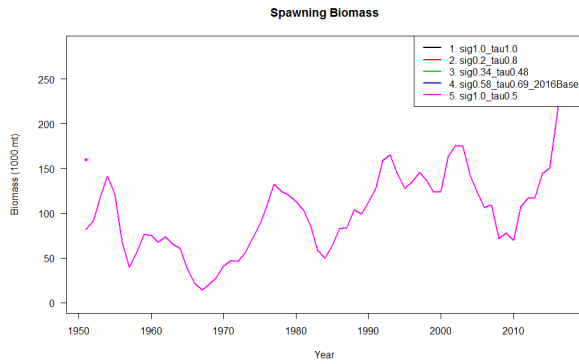
a) 7C\_AM1\_constantM



b) 7C\_AM2\_constantM



c) 8C\_AM1\_timevaryingM



d) 8C\_AM2\_timevaryingM

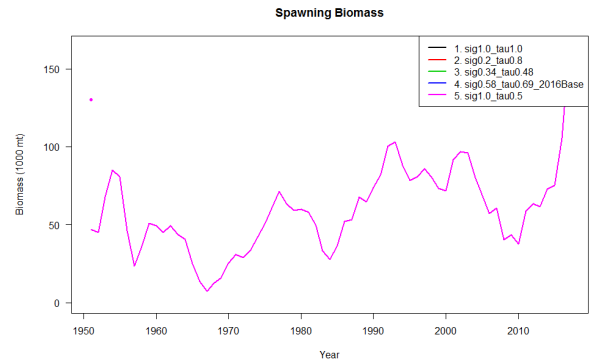
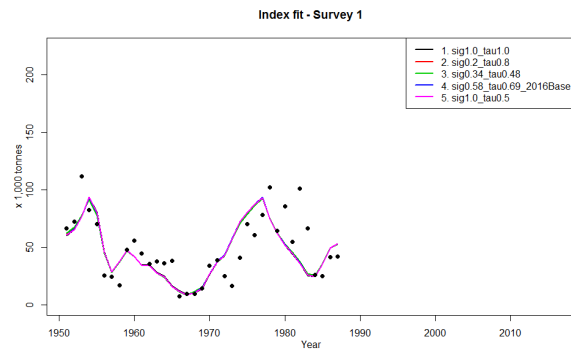


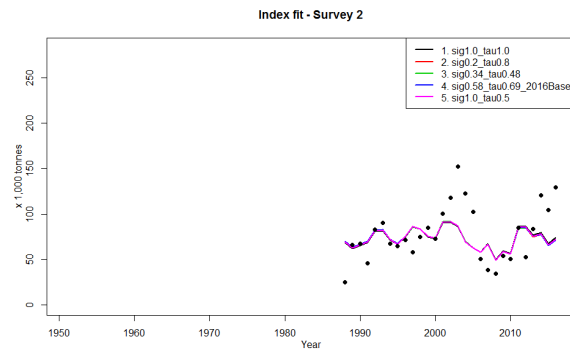
Figure D5. Comparison of  $V2$  estimated spawning biomass ( $SB_t$ ) when estimating both  $\rho$  and  $\kappa$  under constant  $M$ , Step 7C: AM1 (a) and AM2 (b), and time varying  $M$ , Step 8C: AM1 (c) and AM2 (d). Note y-axis scales differ for (a) – (d).

# 7A-AM1. V2\_AM1\_kappafixed\_rhoestimated with constant M

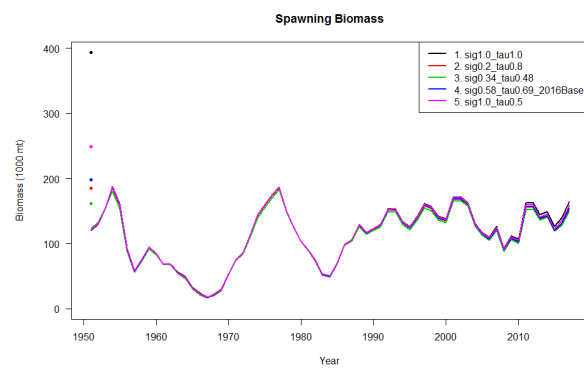
a)



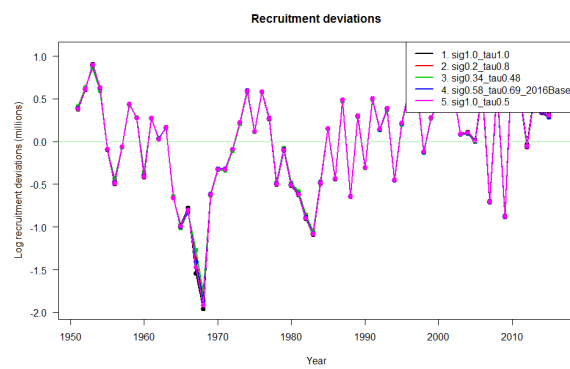
b)



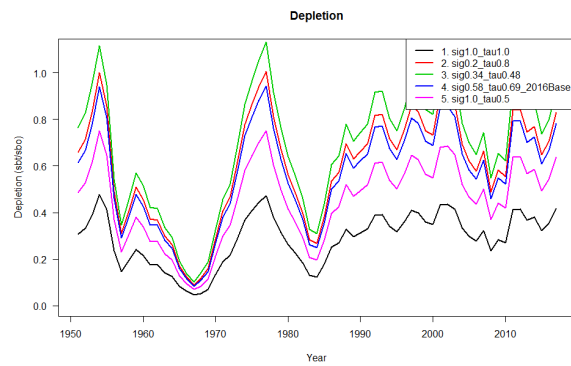
c)



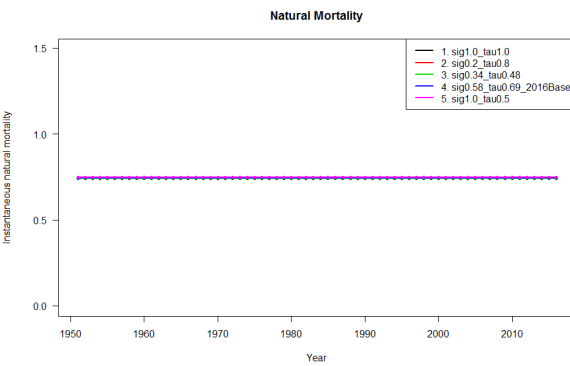
d)



e)



f)



g)

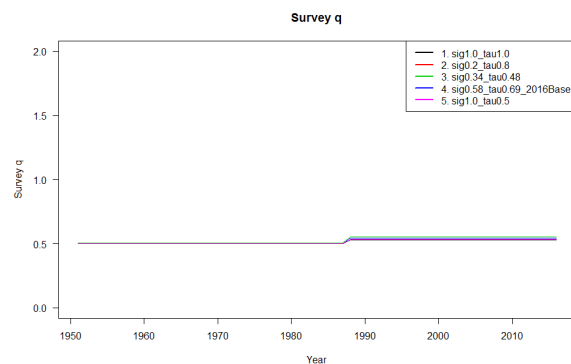


Figure D6. V2 model outputs for Step 7A\_AM1 for 5 different fixed kappa values (estimating rho, constant  $M$ ): (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as circles at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); (f) natural mortality, and (g) survey  $q$ . AM1 results only.

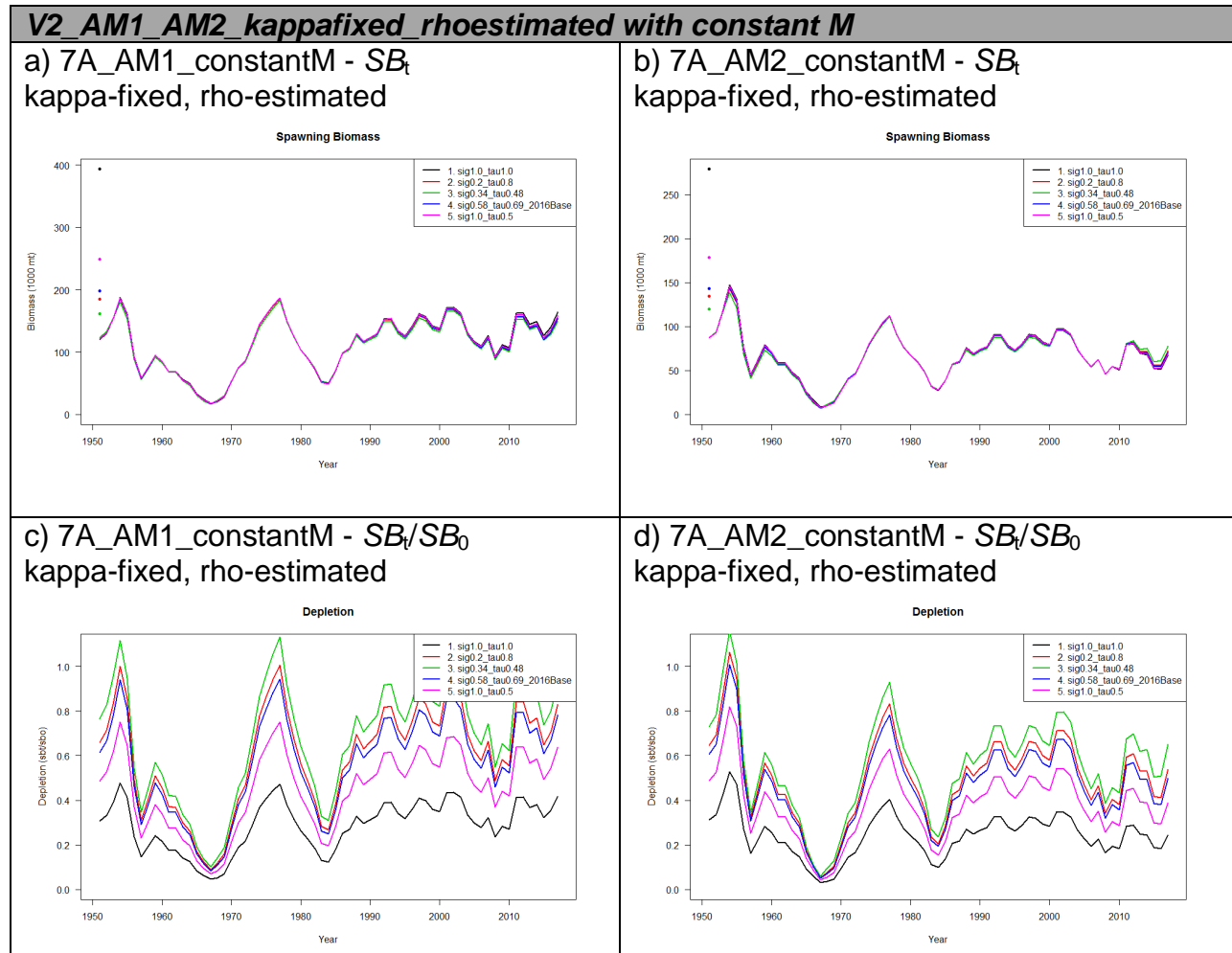
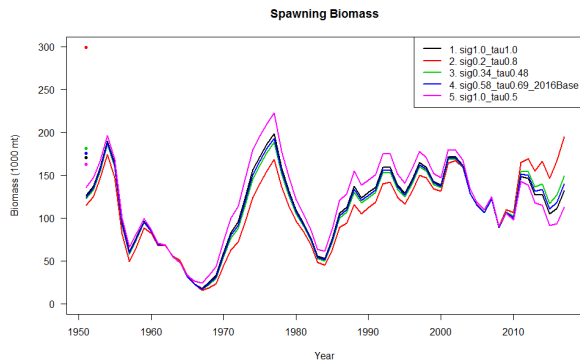


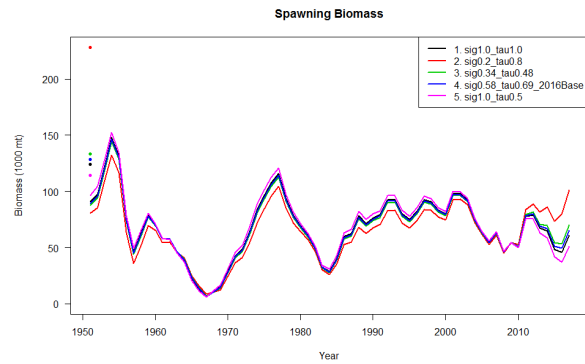
Figure D7. V2 estimates of spawning biomass ( $SB_t$ ) and depletion ( $SB_t/SB_0$ ) for Step 7A (fix kappa, estimate rho), AM1 and AM2. Constant  $M$  only.

### V2\_AM1\_AM2\_rhofixed\_kappaestimated with constant M

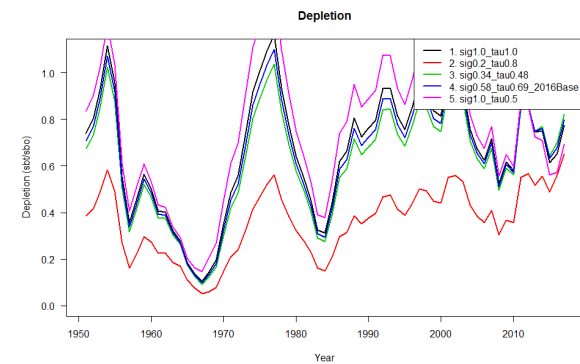
a) 7B\_AM1\_constantM -  $SB_t$   
rho-fixed, kappa-estimated



b) 7B\_AM2\_constantM -  $SB_t$   
rho-fixed, kappa-estimated



c) 7B\_AM1\_constantM -  $SB_t/SB_0$   
rho-fixed, kappa-estimated



d) 7B\_AM2\_constantM -  $SB_t/SB_0$   
rho-fixed, kappa-estimated

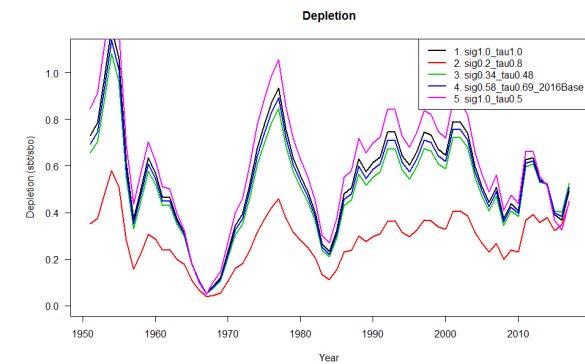
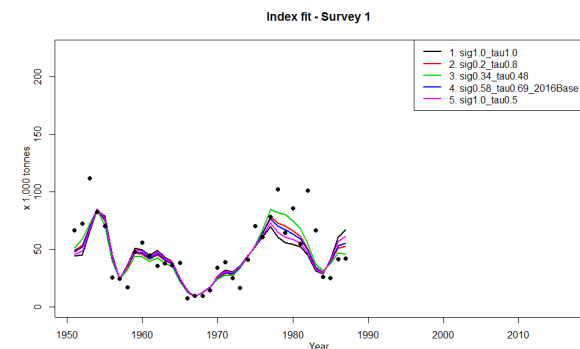


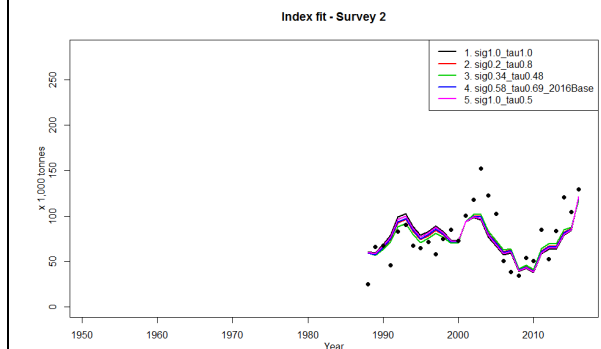
Figure D8. V2 estimates of spawning biomass ( $SB_t$ ) and depletion ( $SB_t/SB_0$ ) for Step 7B (fix rho, estimate kappa), AM1 and AM2. Constant  $M$  only.

### 8A-AM1. V2\_AM1\_kappafixed\_rhoestimated with time varying M

a)



b)



c)

d)

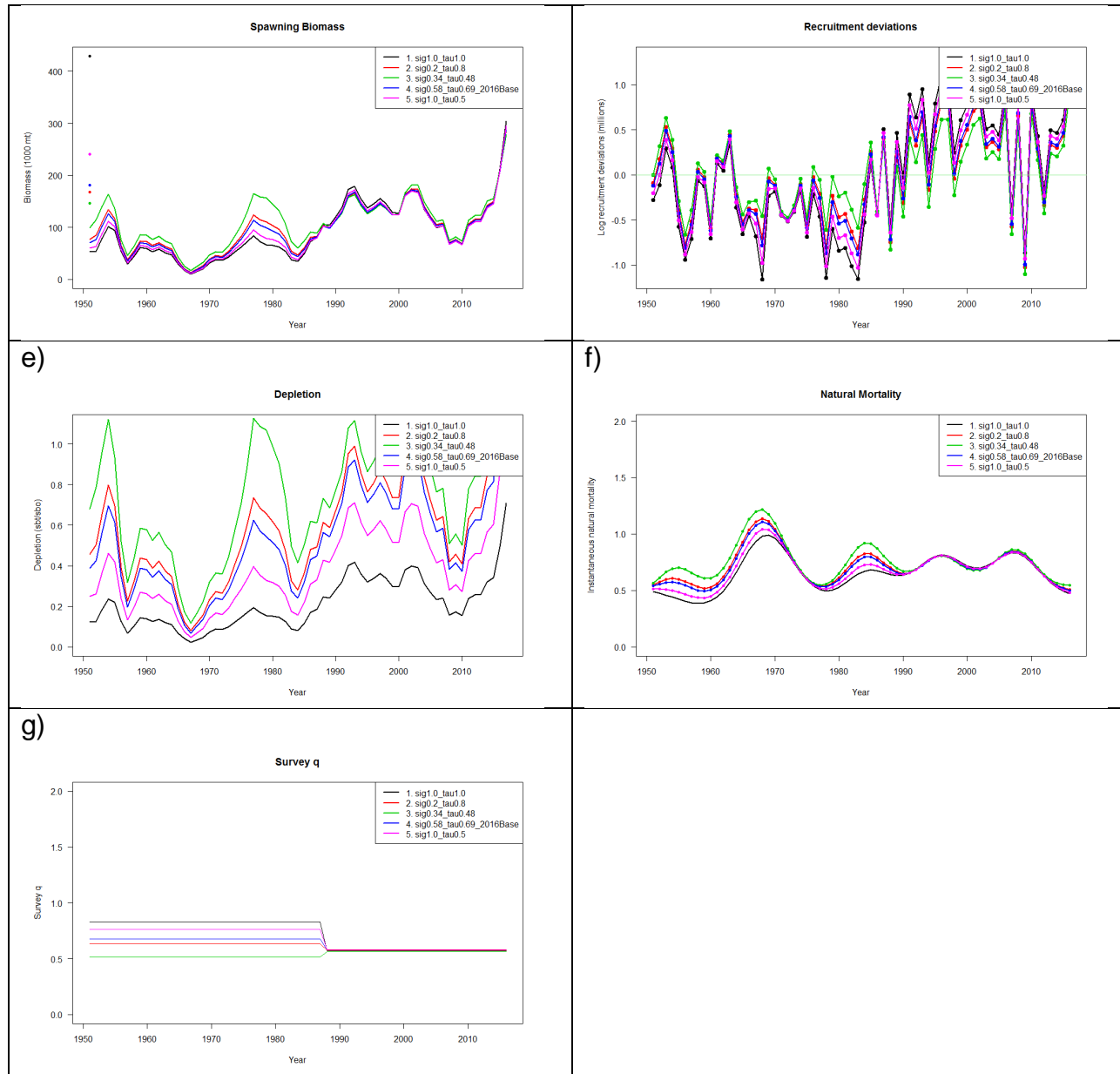
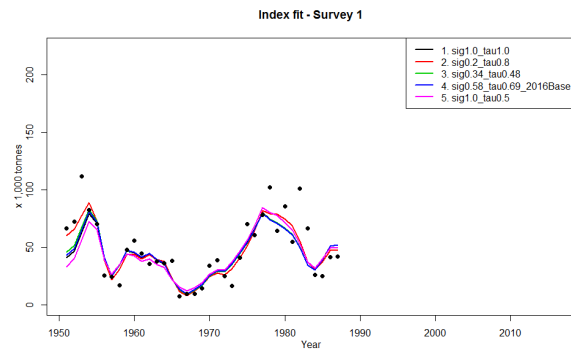


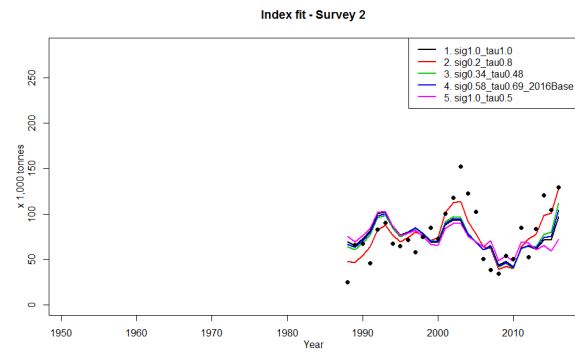
Figure D9. V2 model outputs for Step 8A\_AM1 for 5 different fixed kappa values (estimating rho, time varying  $M$ ): (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as circles at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); (f) natural mortality, and (g) survey  $q$ . AM1 results only.

## 8B-AM1. V2\_AM1\_rhofixed\_kappaestimated with time varying M

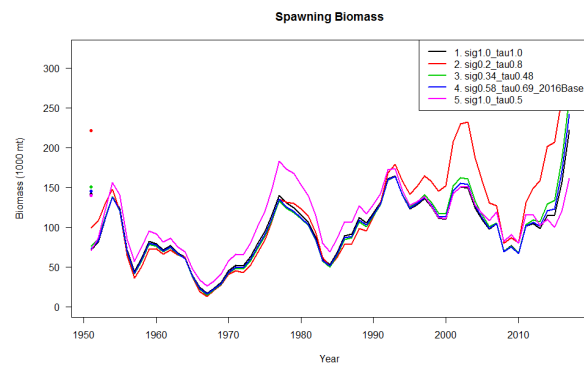
a)



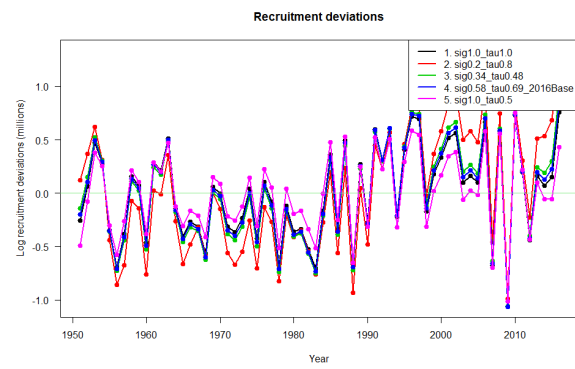
b)



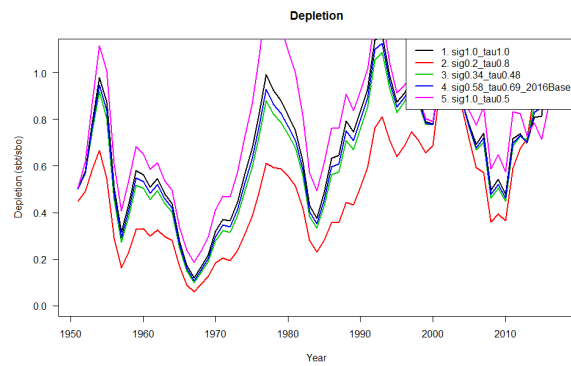
c)



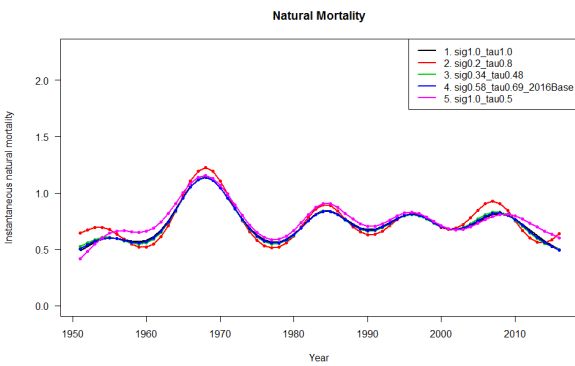
d)



e)



f)



g)

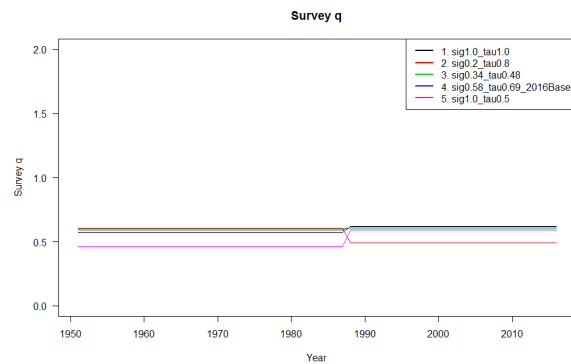
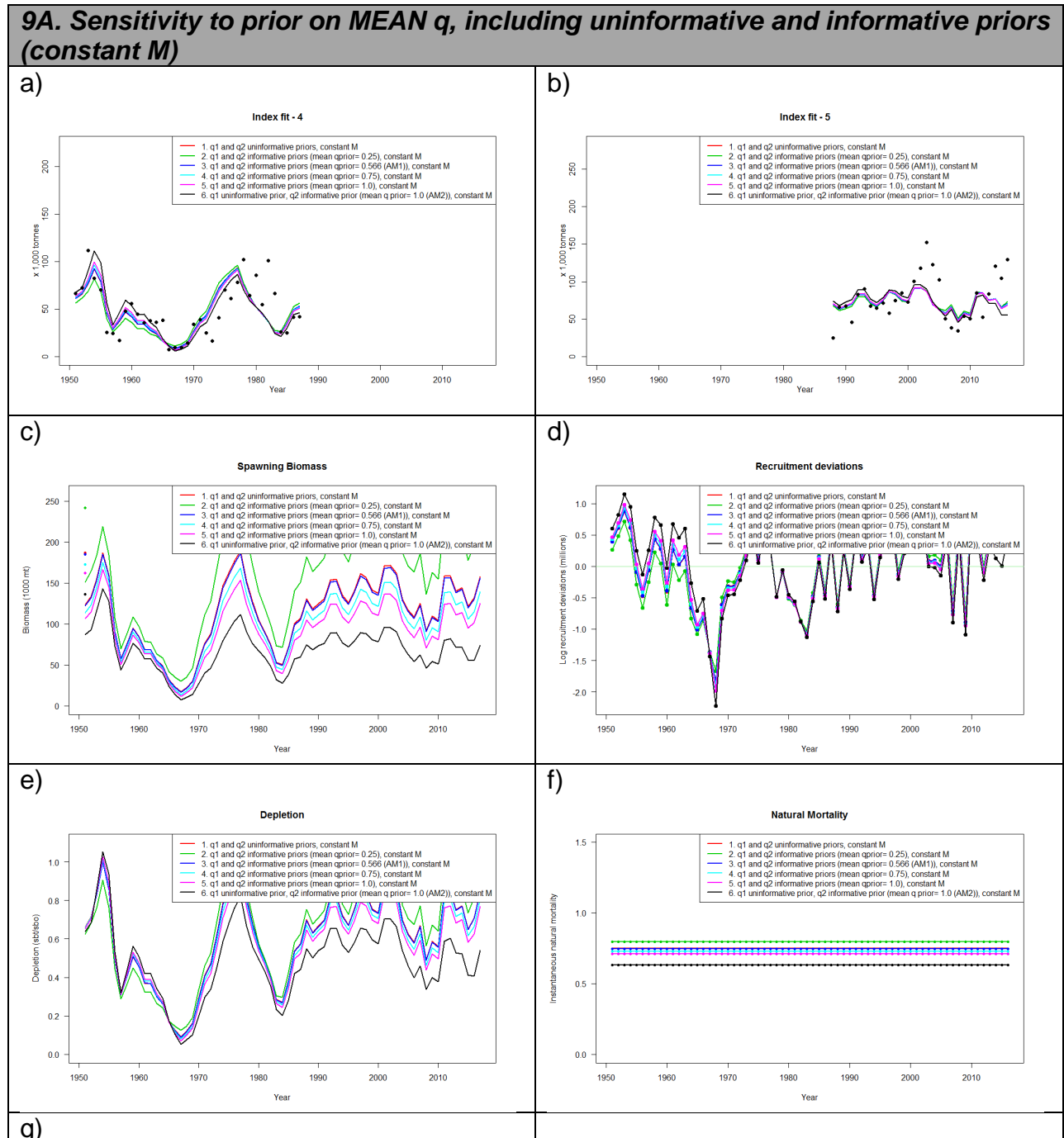


Figure D10. V2 model outputs for Step 8A\_AM1 for 5 different fixed rho values (estimating kappa, time varying  $M$ ): (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as circles at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); (f) natural mortality, and (g) survey  $q$ . AM1 results only.



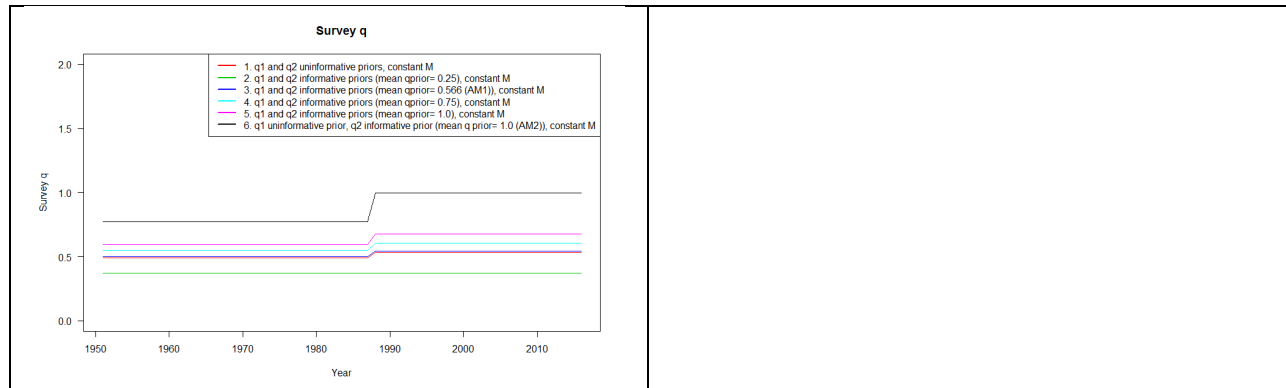
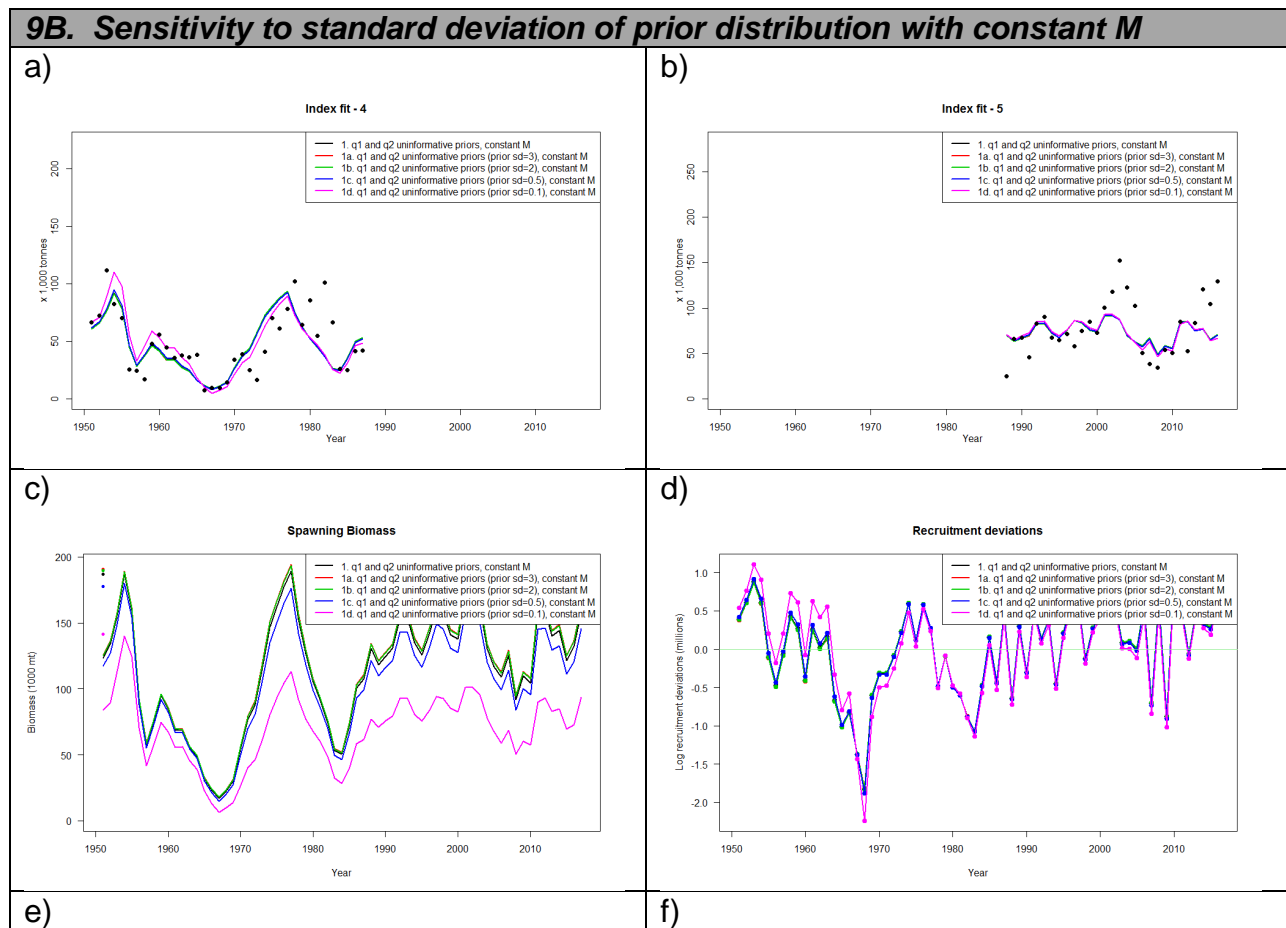


Figure D11. V2 model outputs for Step 9A for 6 different  $.q$  prior scenarios as described in Table D.7 with constant natural mortality: (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as circles at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); (f) natural mortality, and (g) survey  $q$ .





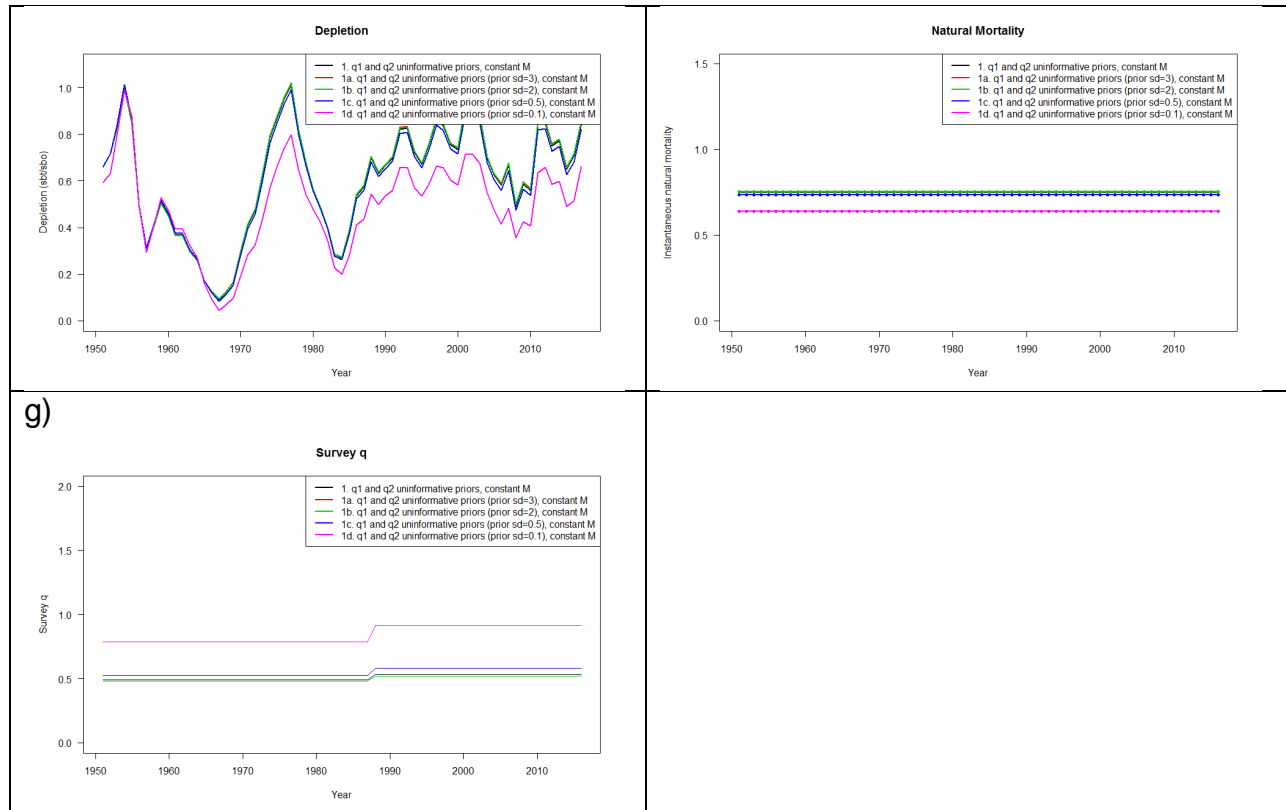
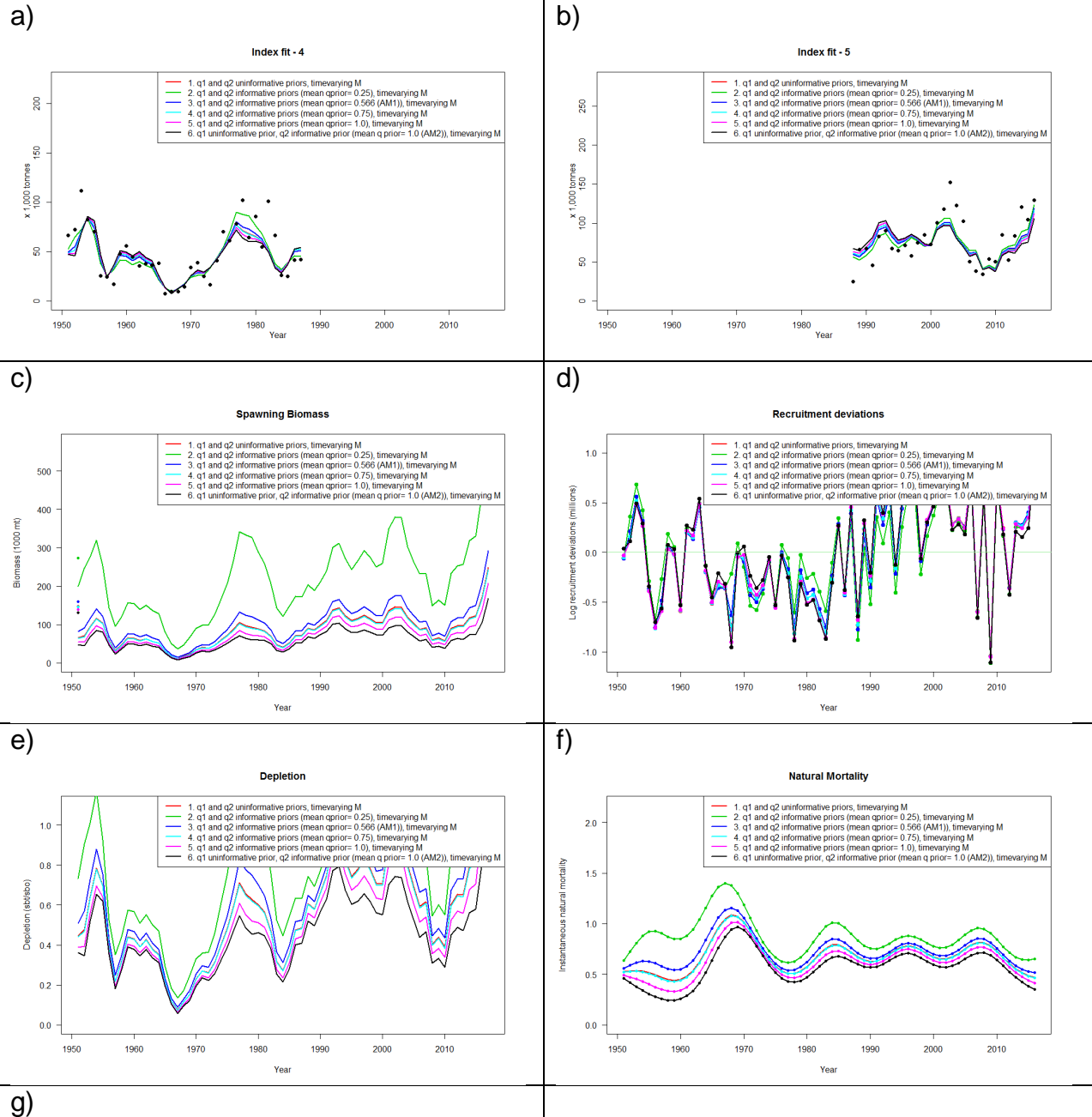


Figure D12. V2 model outputs for Step 9B for  $q$  prior scenario 1 with 5 different prior standard deviations as described in Table D.8. with constant natural mortality: (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as circles at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); (f) natural mortality, and (g) survey  $q$ .

# 10A. Sensitivity to prior on MEAN q, including uninformative and informative priors (with time varying M)



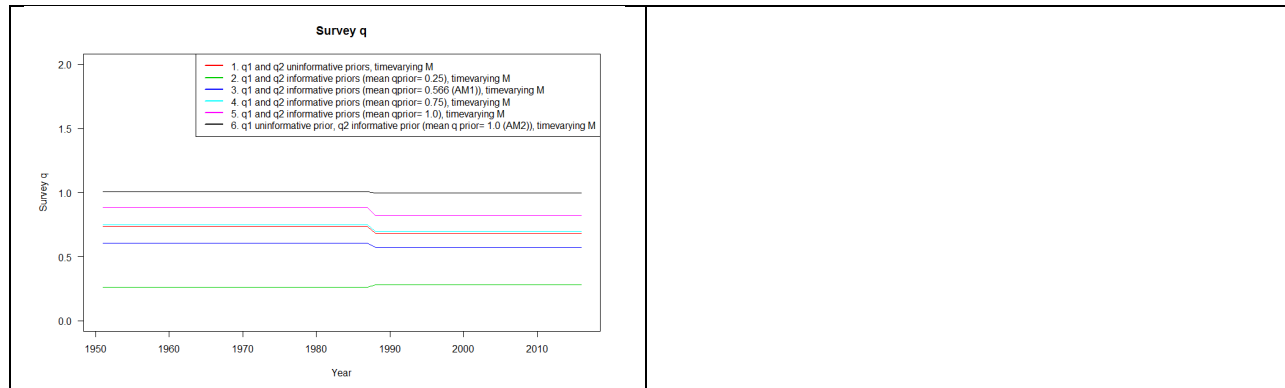
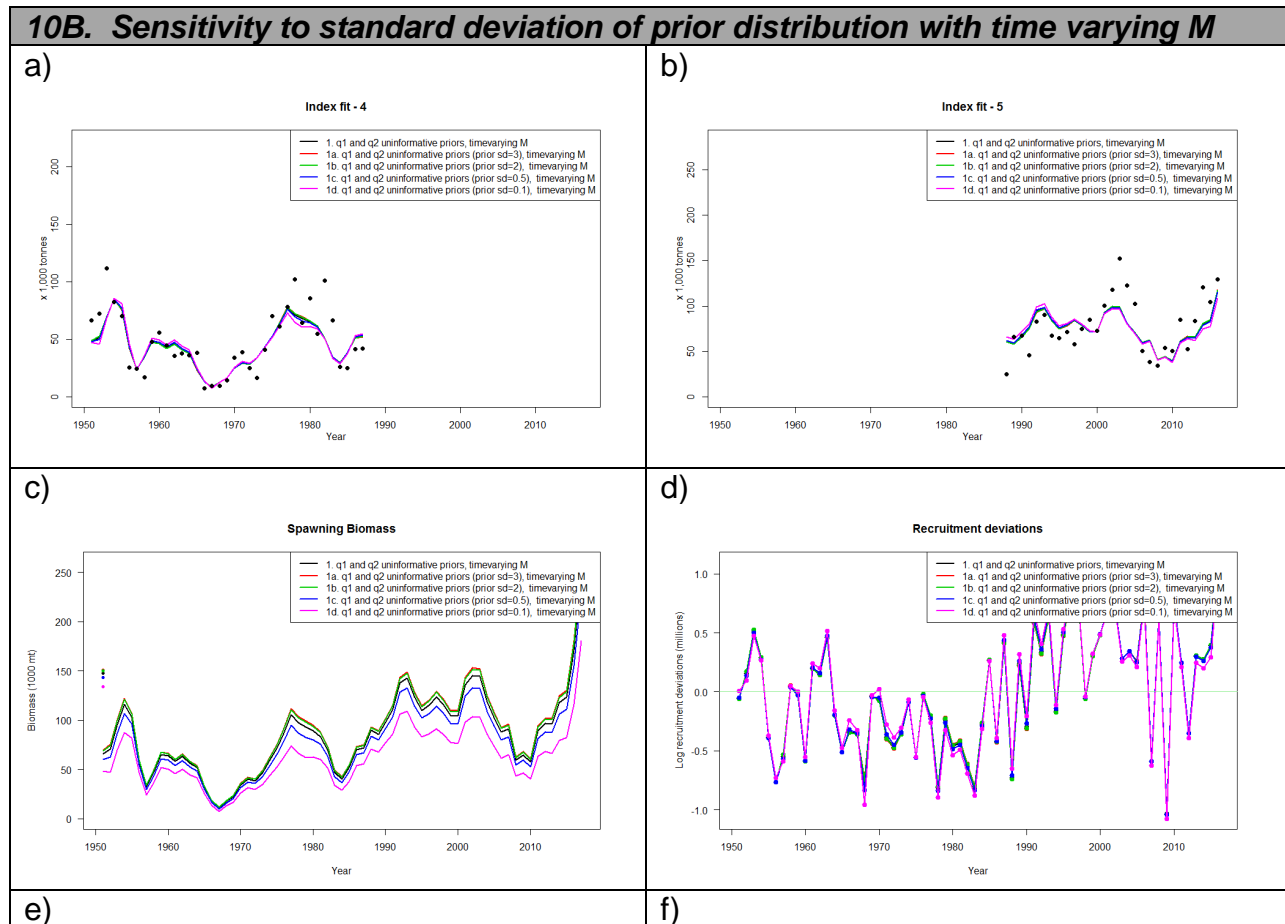


Figure D13. V2 model outputs for Step 10A for 6 different  $.q$  prior scenarios as described in Table D.7 with time varying natural mortality: (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as circles at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); (f) natural mortality, and (g) survey  $q$ .



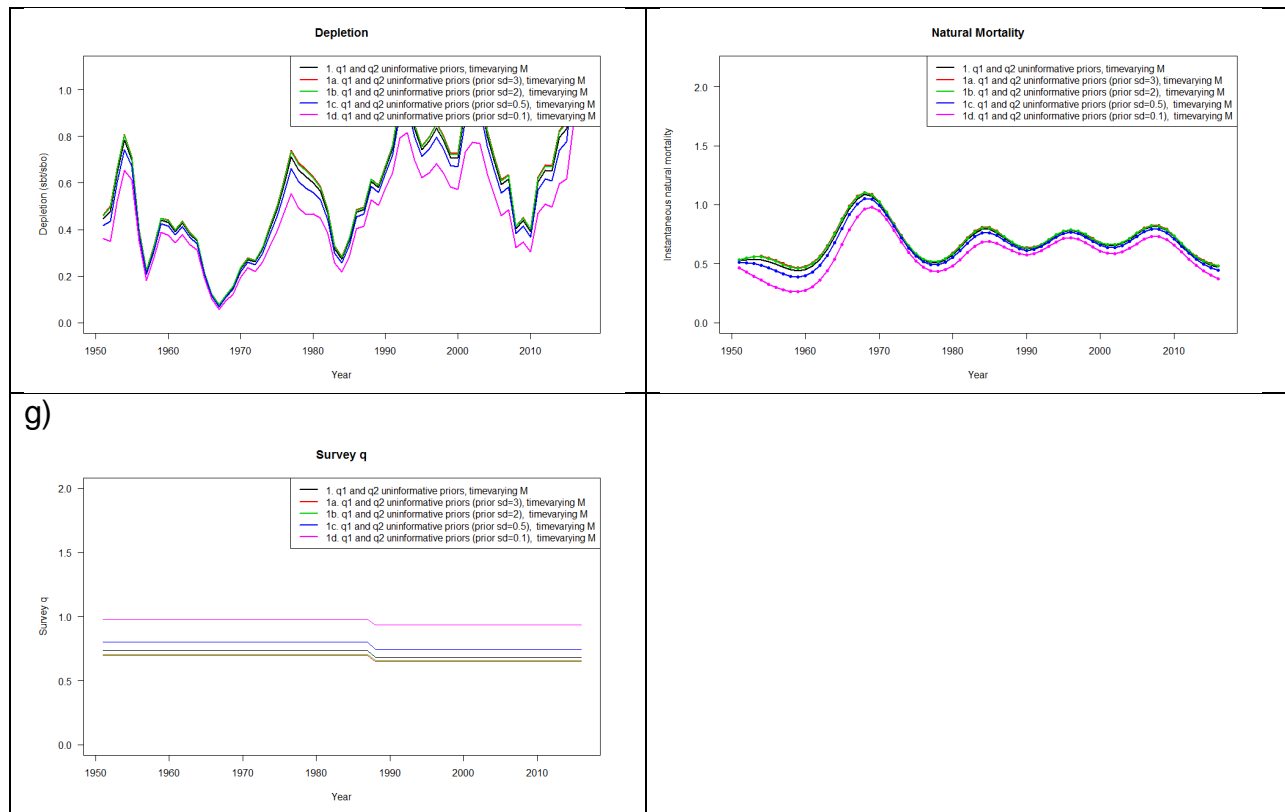


Figure D14. V2 model outputs for Step 10B for  $q$  prior scenario 1 with 5 different prior standard deviations as described in Table D.8. with time varying natural mortality: (a, b) model fits to the survey index, scaled by  $q$ , for the surface (a) and dive (b) survey time series; (c) time series of estimates spawning biomass, with unfished spawning biomass ( $SB_0$ ) shown as circles at 1951; (d) time series of estimated log recruitment deviations; (e) depletion ( $SB_t/SB_0$ ); (f) natural mortality, and (g) survey  $q$ .

## D.4 REFERENCES

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(5CD) and Queen Charlotte Sound (5AB) in 2013. DFO Can. Sci. Advis. Sec. Res. Doc. 2015/052. xii + 197 p.

Fu, C., Schweigert, J., and Wood, C.C. 2004. An evaluation of alternative age-structured models for risk assessment of Pacific herring stocks in British Columbia. DFO Can. Sci. Advis. Sec. Res. Doc. 2004/011. ii + 55 p.

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