Diagnostics of the WI345 Lake Trout Stock Assessment in Western Lake Michigan

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Table of Contents

INTRODUCTION

We applied statistical catch-at-age analysis (SCAA) to fishery and biological information on Lake Trout *Salvelinus namaycush* collected in western and southern waters of Lake Michigan to help improve population-level analyses of the species in Lake Michigan. One SCAA stock assessment was developed for Wisconsin waters that included statistical districts (see Smith et al. 1961) WM-3, WM-4, and WM-5 (to be referred to as WI345) and a second was developed for southern Lake Michigan that included Wisconsin, Illinois, Indiana, and Michigan waters. Both stock assessments were developed to estimate total abundance, biomass, growth, and mortality of Lake Trout that we could combine with the same quantities for fish management units in the 1836 Treaty-Ceded waters (see Caroffino and Lenart 2011; Truesdell and Bence 2016) to estimate prey consumption by Lake Trout in the main basin of Lake Michigan.

While SCAA is a powerful tool for estimating population demographics, integrating multiple data sources, specifying the most appropriate selectivity and catchability parameters, and discerning the best model fit to the data can make interpretation of output difficult (Carvalho et al. 2017). We adopted protocols established by the Modeling Subcommittee (MSC) of the Technical Fisheries Committee in the 1836-Treaty Ceded waters (Modeling Subcommittee, Technical Fisheries Committee 2018) for evaluating stability, bias, and reliability of the WI345 stock assessment. The MSC has not published a formal document that describes their protocols, but all their stock assessments must include an evaluation that addresses:

1. AD Model Builder (ADMB) output statistics
2. standard deviations for quantities appearing in the objective function
3. maximum effective sample size
4. selectivity and catchability functions
5. residual analysis
6. sensitivity of model output to starting values
7. retrospective analysis of SCAA output
8. Markov chain Monte Carlo (MCMC) posterior distributions of SCAA output
9. MCMC trace plots of SCAA output
10. MCMC auto-correlations for SCAA output

We used the MSC protocols to evaluate different versions of the WI345 stock assessment for Lake Trout. The biggest problem in WI345 was the lack of aged fish from the recreational harvest and the Lakewide Assessment Plan (LWAP) survey, which meant we could not estimate annual age compositions for catches, a prerequisite for developing a suitable SCAA. Therefore, we needed to find an alternative method to estimate age compositions. We decided to combine two other data sources for this purpose, samples of the lengths of fish caught in the recreational harvest or the LWAP survey and the recoveries of fish marked with coded-wire tags (CWTs) (Ebener et al. 2020). We applied these data in a different way to six versions of the WI345 stock assessment: 02-20-20, 03-09-20, 04-02-20, 09-21-20, 11-16-20, and 01-02-21. These versions represent the date (month-day-year) we completed modifications to each stock assessment.

Distinguishing features of the input and model structure for the six model versions tested are as follows.

1. <u>02-20-20 version</u>
    a. We used data for 1986-2017.
    b. We used one generic age-length key developed from all data collection methods across all years and aged from all structures available: fin clips, scales, otoliths, maxillaries, and CWTs. The age-length key gave the proportion of fish in each 10-mm length bin that were in each age group.
    c. The proportions in the age-length key were multiplied by numbers of unaged fish in each 10-mm length bin in the recreational harvest each year. The result was a matrix of the numbers by age and year for the unaged portion of the harvest, that was added to the numbers at age for the aged

portion of the samples to estimate the age composition of the entire sample. The proportions by age and year were then calculated for the entire sample (see Ebener et al. 2020). This matrix was used as the age composition by year for the recreational fishery in the model, but its effect on mortality estimates in the model was constrained as described below in 1.d. We recognize that this application of an age-length key makes a strong assumption that the probability distribution of age given length remains constant over all data sources the age-length key is applied to. This assumption is an issue for all subsequent model implementations and is one reason why we subsequently began considering model variants (not reported on herein) that are fit to length composition data, including models where dynamic processes are based on length.

d. A prior estimate of mean instantaneous total annual mortality rate (***Z***) for fully recruited fish of age 6+ was input along with a standard deviation (***sdZ***) for the natural logarithm of ***Z***, and these values were included in the objective function (see Truesdell and Bence 2016 for MM-67 assessment). This constrained the average annual ***Zs*** estimated in the model. In other words, the annual ***Zs*** in the model were estimated from both age composition data and the prior ***Z***. We estimated the prior from catch curves computed from recoveries of CWT-marked Lake Trout (Clark et al. 2021[1]). The CWT-based age data were adjusted for differences in annual collection effort (assumed to be proportional to annual sample size) and the initial number of tagged fish released for each cohort. The input values were ***Z*** = 0.2755 per year and ***sdZ*** = 0.0130.

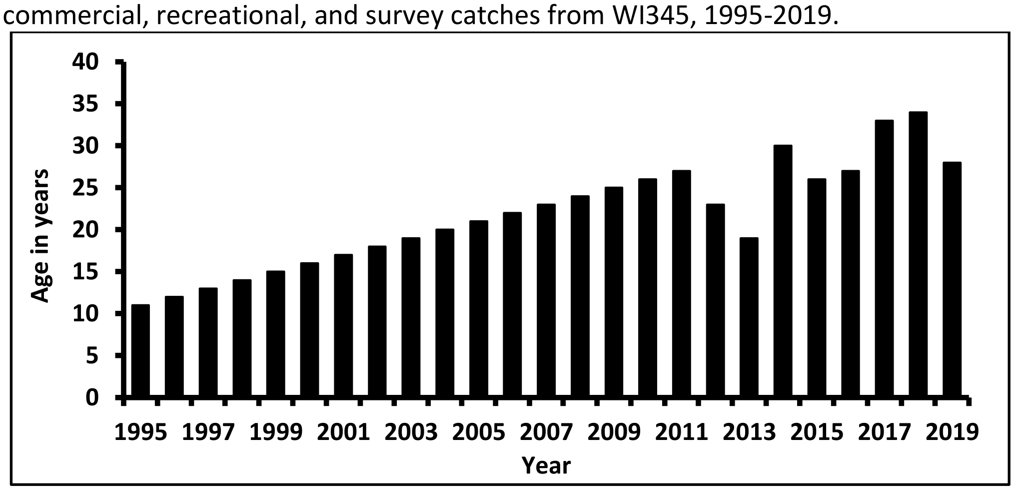
2. <u>03-09-20 version</u>
   a. We used data for 1986-2017.
   b. We suspected that mortality could have changed over time, so we calculated age-length keys for two time periods for this version. The first was from data pooled for 1986-2000 and the second was from data pooled for 2001-2017. We used data from all collection methods, but only used CWT ages for these keys. The age-length keys gave the proportions of fish in each 10-mm length bin that were in each age group.
   c. The proportions in the CWT derived age-length keys were multiplied by numbers of unaged fish in each 10-mm length bin in the recreational harvest for each year in the appropriate period. The results were two matrices of the proportions by age and year for the harvest. That is, the annual proportional age compositions of the harvest for 1986-2000 and 2001-2017 as described in 1.c. These matrices were used as the age compositions by year for the recreational fishery in the model.
   d. No constraints were placed on the model estimates of mortality, but an average ***Z*** and ***sdZ*** was estimated from CWT-based age composition data using catch curves. The CWT age composition data used in the catch curve was adjusted for the number of fish stocked for each year class and was used to estimate population abundance during 1966-1985.

3. <u>04-02-20 version</u>
   a. We used data for 1986-2017.
   b. We developed a single generic age-length key using data collected by all fishing and survey methods across all years (1986-2017) as described for the 02-20-20 version, except that we only used CWT ages. The matrix resulting from the application of this age-length key was used as the age composition by year for the recreational fishery in the model.
   c. No constraints were placed on the model estimates of mortality, but an average ***Z*** and ***sdZ*** was estimated from CWT-based age composition data using catch curves. The CWT age composition data used in the catch curve was adjusted for the number of fish stocked for each year class and was used to estimate population abundance during 1966-1985.

[1]Unpublished analyses in draft manuscript.

4. <u>09-21-2020 version</u>
    a. We added data for 2018 and 2019 to the 1986-2017 information.
    b. We developed a single generic age-length key using data collected by all fishing and survey methods across all years (1986-2019) as described for the 02-20-20 version, except that we only used CWT ages. The matrix resulting from application of this age-length key was used as the age composition by year for the recreational fishery in the model.
    c. We calculated the proportion of age-20+ fish in the age-length key only for years where they could exist. All previous versions of the generic age-length key estimated the proportional age composition through age 20+ for all years, but in years prior to 1986 there could not be any age-20+ fish because the 1966-year class was the first stocked in Lake Michigan. The maximum age of fish in any year was age 20 in 1986, age 21 in 1987, age 22 in 1988, age 23 in 1989 and so on. The sample size for each year used to estimate the proportion at age was the sum of the number at each age estimated from the age-length key from age 3 through the maximum age for that year. The oldest fish we observed in Lake Michigan was age 35 in 2019 in an adjacent management area, and the oldest age observed in WI345 was 34 in 2018. The maximum age observed for CWT-marked lake trout generally increased linearly through time in WI345 (Figure 1).

Figure 1. The maximum age of coded-wire-marked Lake Trout observed annually in commercial, recreational, and survey catches from WI345, 1995-2019.



    d. No constraints were placed on the model estimates of mortality, but an average ***Z*** and ***sdZ*** was estimated from CWT-based age composition data using catch curves. The CWT age composition data used in the catch curve was adjusted for the number of fish stocked for each year class and was used to estimate population abundance during 1966-1985.
    e. We reduced the Maximum Effective Sample Size (ESS) for both the recreational fishery and LWAP survey from 100 to 25 to increase model fit and achieve our convergence criterion.

5. <u>11-16-20 version</u>
    a. We used data for 1986-2019.
    b. We developed a single generic age-length key using data collected by all capture methods across all years (1986-2019) as described for the 02-20-20 version, except that we only used CWT ages. The matrix resulting from application of the age-length key was used as the age composition by year for the recreational fishery in the model. Proportional age composition for the recreational fishery was estimated as described in 1.c and 4.c.

c. We estimated age composition of the LWAP survey catch by applying an age-length key developed from CWT-recoveries by all capture methods in WI345 during 1986-2019 to the annual length distribution of fish captured in LWAP surveys during 1998-2019 (Ebener et al. 2020). Most ages of fish caught during the LWAP survey were determined from CWTs with lessor amounts from other aging structures and no fin-clipped fish were aged, although they dominated LWAP catches. In addition, over 90% of the 2004- to 2009-year classes were fin clipped but these year classes were not represented in our LWAP survey catch database as age 3, age 4, or age 5 but they were represented in catches as age 6+ (Ebener et al. 2020). Consequently, we felt the proportional age composition matrix for the LWAP survey in all previous versions was not appropriate, so we estimated age composition of the survey in the same manner as for the recreational fishery.
d. No constraints were placed on the model estimates of mortality, but an average ***Z*** and ***sdZ*** was estimated from CWT-based age composition data using catch curves. The CWT age composition data used in the catch curve was adjusted for the number of fish stocked for each year class and was used to estimate population abundance during 1966-1985.
e. We modified our methods for estimating the proportion wild for each year classes. In previous versions, we used catches of wild and stocked Lake Trout in LWAP, spawning surveys (SPAWN), and other surveys to estimate the contribution of wild fish to the population of age 3+ (Ebener et al. 2020). For the 11-16-20 version, we used only LWAP and SPAWN survey data. Further, sample sizes were very small for the 2014- and 2015-year classes, and in our opinion, the small sample sizes inflated proportion wild for the 2015-year class far beyond that of other year classes. Finally, there were no fish of the 2016-year class represented in LWAP or SPAWN surveys making it impossible to estimate abundance of wild age-3 fish in 2019. Consequently, we estimated proportion wild for the 1971–2013-year classes using the same the method as for all previous versions of the stock assessment (Ebener et al. 2020), but then fit a non-linear regression to the proportion wild data for all year classes and used the regression equation to project the proportion wild for the 2014-2016 year-classes (Ebener et al. 2020). The proportion wild for each year class was expanded to create a matrix of proportion wild at age by year (Ebener et al. 2020).
f. We modified our methods for estimating abundance of hatchery and wild Lake Trout at age 1. In previous versions, the assessment model itself did not use input data on proportion wild when fitting observational data, but instead we used these data after the model was fit to decompose the population into wild and hatchery portions. We used a movement matrix (Ebener et al. 2020) to estimate the number of stocked fingerlings and yearlings from each year class that moved into WI345 from other areas and then adjusted this estimate for reduced survival of fingerlings to estimate the number of hatchery yearling (age 1) equivalents (***Hatyearling_eq***) (Ebener et al. 2020). This number was used as the number of total age-1 fish in the population. After the stock assessment estimated abundance at age, we used the proportion wild (***pct_wild***) to estimate abundance of wild and hatchery fish as:

(1) $$Nwild_{i,j} = N_{i,j} * pct\_wild_{i,j}$$

(2) $$Nhat_{i,j} = N_{i,j} - Nwild_{i,j}$$

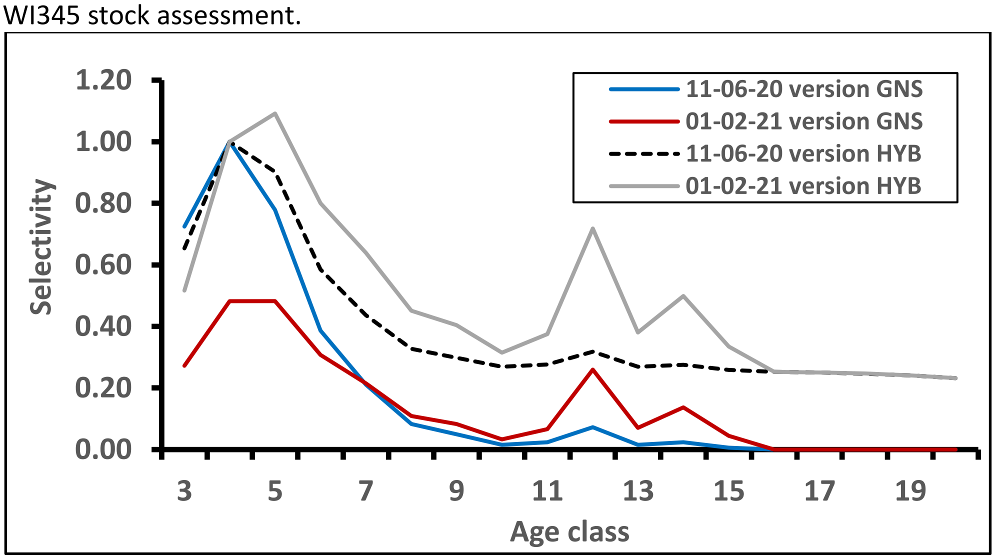
where ***N*** is total abundance, ***Nwild*** is wild fish, ***Nhat*** is hatchery fish, ***i*** is age class, and ***j*** is year. A problem with this implementation is that although additional wild recruitment can be accounted for by lowering early survival, this presupposes that a priori wild and hatchery recruitment would track, which really does not make sense. Before fitting the 11-06-20 version of the assessment model, we used proportion wild to expand ***Hatyearling_eq*** to represent the total abundance (wild plus hatchery; ***Totyearling_eq***) at age 1 for each year class (*i*) as:

(3) $$Totyearling\_eq_{i-2} = Hatyearling\_eq_{i-2} + \left\{\frac{Hatyearling\_eq_{i-2}}{(1.0-pct\_wild_{i,3})*pct\_wild_{i,3}}\right\}$$

Because the percentage wild matrix began at age 3, we applied our calculations to age-1 trout two year earlier with the code (***i-2***), thus there were not wild fish of the 2017-and 2018-year classes. The stock assessment then estimated a matrix of abundance at age by year, and we continued to also use the ***pct_wild*** at age matrix to allocate abundance at a given age between wild and hatchery fish as described in equations (1) and (2).

6. <u>01-02-21 version</u>
   a. We used data for 1986-2019.
   b. We modified commercial fishery selectivity to the stock assessment because previous versions had estimated selectivity of the small-mesh gill net fishery as being proportional to age composition of the population. We calculated age-specific selectivity of Lake Trout to the small-mesh gill net fishery by adjusting the age composition data by cumulative survival (Ebener et al. 2020). A comparison of the previous small mesh selectivity curve (versions 11-16-20 and earlier) and the selectivity adjusted for survival is shown in Figure 2.
   c. We developed a single generic age-length key using data collected by all fishing and survey methods across all years (1986-2019) as described for the 02-20-20 version, except that we only used CWT ages. The matrix resulting from application of this age-length key was used as the age composition by year for the recreational fishery in the model. Proportional age composition for the recreational fishery was estimated as described in 1.c and 4.c.
   d. We estimated age composition of the LWAP survey catch as described above in 5.c. for the 11-06-20 version.
   e. We used the same ***pct_wild*** data as for the 11-16-20 version.
   f. We used the same method as 5.e. to estimate abundance of age-1 wild and hatchery Lake Trout.
   g. No constraints were placed on the model estimates of mortality, but an average **Z** and **sdZ** was estimated from CWT-based age composition data using catch curves. The CWT age composition data used in the catch curve was adjusted for the number of fish stocked for each year class and was used to estimate population abundance during 1966-1985.

Figure 2. Small-mesh gill net (GNS) and hybrid (HYB) selectivity of age 3-20+ Lake Trout to the commercial fishery in the 11-06-20 and 01-02-21 versions of the WI345 stock assessment.



1.0 AD Model Builder Final Statistics

We used 11 components in the objective function (Objf) to fit the 02-20-20 version of the WI345 stock assessment and 10 components in all other versions. The Objf was estimated as the sum of the normal log likelihood (NLL) values for five data-based components plus the sum of lognormal likelihoods for five (6 in version 02-20-20) informative priors (NLP) (Brenden et al. 2011; Truesdell and Bence 2016). We applied likelihood component weighting factors of 1.0 to all the data-based components in the Objf (Table 1.0).

Table 1.0. Description of the quantities, parameters, likelihood weighting factors, and components of the objective function for six versions of the WI345 Lake Trout stock assessment.

Quantity or parameter description	Variable in SCAA	Likelihood weighting factor	Objective function component
Observed recreational catch	obs_r_C	1.0	NLL
Observed commercial catch	c_C	1.0	NLL
Observed survey CPUE by year	obs_lnCPE_Y	1.0	NLL
Observed proportion at age recreational fishery	obs_r_PA	1.0	NLL
Observed proportion at age LWAP[2] survey	obs_PAsv	1.0	NLL
Natural mortality age 1	M1		NLP
Random walk log catchability recreational fishery	ln_qrf_rw		NLP
Random walk deviations selectivity LWAP survey	rwdevsv_p1		NLP
Total average (over years) instantaneous mortality rate (02-20-20 only)	Z		NLP
Log natural mortality age 3+	lnmedM		NLP
Log natural mortality age 2	lnmedM2		NLP

[2]LWAP is the Lakewide Assessment Plan.

All versions of the WI345 stock assessment were able to run to completion and the maximum gradient was smaller than our convergence criterion (Table 1.1). The smallest Objf value was for the 03-09-20 version and largest was for the 11-16-20 version. For stock assessments prior to the 01-02-21 version, we were able to achieve convergence by narrowing the bounds on the age of the first inflection point (***p1*** value) for the selectivity function of the recreational fishery or LWAP survey, or by reducing the maximum effective sample size for the recreational or survey fishery.

Table 1.1. ADMB output for six versions of the WI345 Lake Trout stock assessment.

	WI345 assessment					
ADMB output	**02-20-20**	**03-09-20**	**04-02-20**	**09-21-20**	**11-16-20**	**01-02-21**
Number variables	141	141	141	149	149	149
Run complete	Yes	Yes	Yes	Yes	Yes	Yes
Number iterations	151	285	150	159	157	158
Convergence criterion	1.00e-004	1.00e-004	1.00e-004	1.00e-004	1.00e-004	1.00e-004
Maximum gradient	-4.53e-007	2.15e-005	4.53e-007	-4.16e-007	-1.06E-07	-2.12e-007
Objective function	5799.58	5706.51	5752.07	4121.42	12180.5	12127.5
Normal log likelihood	5915.68	5815.15	5861.97	4253.64	12321.2	12267.5
Lognormal prior	-116.103	-108.634	-109.895	-132.223	-140.618	-139.99

2.0 SCAA Output – Standard deviations

Inputs to the WI345 stock assessment include prior estimates for some parameters and an estimate of the standard deviation associated with the prior. We input priors for natural mortality rate of age 1 (***M_1***) and age 2 (***M_2***) based on data from Eck and Wells (1983) and Rybicki (1990), and age-3+ (***M***) and their standard deviations. The standard deviation for the natural logarithms of ***M_1*** (0.175) and ***M_2*** (0.10) were basically just guesses, and we assumed the standard deviation of the natural logarithm of ***M*** to be 0.5 because we wanted to give the stock assessment flexibility in estimating natural mortality. We also input standard deviations for the priors of commercial (0.15) and recreational (0.04) catch (Table 2.0).

Table 2.0. Standard deviation for quantities and parameters estimated for six versions of the WI345 Lake Trout stock assessment.

Parameter (prior)	Variance ratio	02-20-20	03-09-20	04-02-20	09-21-20	11-16-20	01-02-21
Sigma		0.083045	0.087744	0.086549	0.076562	0.071017	0.071393
M_1 (0.175)	3	0.249133	0.263231	0.259648	0.229686	0.213050	0.214179
Comml catch (0.15)	0.8	0.066436	0.070195	0.069239	0.061250	0.056813	0.057114
Recrl catch (0.04)	1	0.083045	0.087744	0.086549	0.076562	0.071017	0.071393
Ln_q recrl fishery	2.5	0.207611	0.219359	0.216373	0.191405	0.177542	0.178483
LWAP selectivity ***p1***	0.15	0.012246	0.013162	0.012982	0.011484	0.010653	0.010709

An overall common standard deviation (sigma) (Truesdell and Bence 2016) was estimated during the modeling fitting process as a bounded number and used to estimate the standard deviations of components used in the objective function. We input variance ratios for these components and multiplied the ratio by sigma to estimate their standard deviation. As the value for sigma varied in the modeling fitting process the standard deviations for the components also varied and the most likely values were those that resulted in the largest log likelihood value in the objective function. Sigma was highest for the 03-09-20 version and lowest for the 11-16-20 and 01-02-21 versions and subsequently so were the standard deviations of the other parameters (Table 2.0).

Standard deviations estimated during the model fitting process fell within guidelines established by the Modeling Subcommittee. The guidelines call for standard deviations of fishery catch to be less than 0.1 and our estimates for all versions ranged from 0.06 to 0.09. The guideline for catchability is to be less than 0.5 and our value for the recreational fishery was 0.21. There currently is no guideline for the standard deviation of selectivity but all our estimates were only 0.01 for the LWAP ***p1*** value.

3.0 Maximum Effective Sample Size

Maximum effective sample sizes (ESS) for the proportional age composition data were not estimated within any version of the WI345 stock assessment. The ESS is used as a weighting factor in multinomial composition data (Brenden et al. 2011; Truesdell et al. 2017). The ESS for age composition of the commercial and recreational fisheries and the LWAP survey was input to the data file, and within the stock assessment annual sample sizes greater than the ESS were set equal to the ESS (Table 3.0). The ESS value was 200 for the commercial fishery in all versions of the stock assessment but this is mute because the commercial age composition was not used in the Objf since data were missing for most years. We used an ESS of 25 for the recreational fishery in versions prior to 11-16-20 and 100 for the LWAP survey for the 02-20-20, 03-09-20, and 04-02-20 versions. For the 09-21-20 version, we used a ESS of 25 for both the recreational fishery and LWAP survey because the model was more stable, i.e., reached convergence criterion and ran to completion, at these lower ESS values than at ESS values used in previous versions.

Table 3.0. Maximum effective sample size applied to the proportional age composition of the commercial and recreational catch and the LWAP survey catch for six versions of the WI345 Lake Trout stock assessment.

Stock assessment	WI345 fishery type		
	commercial	recreational	LWAP
02-20-20	200	25	100
03-09-20	200	25	100
04-02-20	200	25	100
09-21-20	200	25	25
11-16-20	200	100	100
01-02-21	200	100	100

4.0 SCAA Output – Residual Analysis

We evaluated the WI345 models goodness-of-fit by plotting the standardized residuals (SRES) of fishery catch and age composition (Table 4.0). We examined the SRES for patterns and the degree of variation to test model assumptions (Carvalho et al. 2017). We did not estimate SRES for the commercial fishery because there were no observed harvest values for it after 1999. We calculated SRES based on stock assessment estimates for: 1) the annual recreational fishery catch; 2) the annual LWAP CPUE; 3) the proportions at age of the recreational fishery catch in the last year (2017 or 2019); 4) the proportions at age of the LWAP survey catch in the last year; 5) the proportion of the recreational fishery catch that was age 6; and, 6) the proportion of the LWAP survey catch that was age 6. We used age-6 fish for the SRES evaluation because it was the first age used in our catch curves and was highly selected by all fisheries.

Table 4.0. Quantities examined for residual analysis of six versions of the WI345 Lake Trout stock assessment.

Quantity	SCAA variable name	Description
Rec_fishery catch	res_r_C	SRES annual recreational fishery catch
Age comp rec_fishery last year	res_r_CA(j=2017 & 2019)	SRES recreational fishery age composition last year
LWAP survey lnCPUE	res_sv_cpe	SRES annual LWAP natural log CPUE
Age comp LWAP survey last year	res_sv_ac(j=2017 & 2019)	SRES LWAP survey age composition last year
Age 6 comp rec_fishery	res_r_CA(i=6)	SRES age-6 fish recreational fishery 1986 to last year
Age 6 comp LWAP survey	res_sv_ac(i=6)	SRES age-6 fish LWAP survey 1986 to last year

The SDRES for the recreational fishery catch and the LWAP CPUE (Table 4.0) were estimated as:

(4) $$SDRES = \frac{[\log(Obs+0.001)-\log(Pred+0.001]}{sd}$$

where log is the natural logarithm, ***Obs*** is the observed quantity, ***Pred*** is the predicted value from the stock assessment and ***sd*** is the predicted standard deviation for the quantity. A small constant of 0.001 was added to the observed and predicted CPUE values to avoid taking the natural logarithm of zero.

The SDRES for the age composition of the recreational and LWAP catch were estimated as multinomial functions, adjusted for the sample sizes up to the ESS, and estimated as:

(5) $$SDRES = \frac{(ObsP-PredP)}{\sqrt{PredP(1-PredP)/Nsamp}}$$

where ***ObsP*** is the observed proportion at age in the catch, ***PredP*** is the predicted proportion at age in the catch and ***Nsamp*** is the number of fish sampled from the recreational or LWAP catch.

The SDRES for each version of the stock assessment did not show sizable patterns but the variation was greatest for the age composition data, particularly age composition of the LWAP survey. The SDRES for the recreational fishery catch and the LWAP survey showed no patterns, and all values were between -2.0 and 2.0 (Table 4.1; Figure 4.1). The variance of the SDRES for the recreational fishery ranged from 0.55 to 0.61 for the 02-20-20, 03-09-20, and 04-02-20 versions and 0.68 to 0.79 for versions after 04-02-20. The variance of the SDRES values for the LWAP survey ranged from 0.20 to 0.24 for the 02-20-20, 03-09-20, and 04-02-20 versions and 0.67 to 0.73 for versions after 04-02-20. For the recreational fishery, the range and variance in composition of age-6 trout in the catch and age composition in the last year was larger for the 09-21-20, 11-16-20, and 01-02-21 versions than for versions prior to 09-21-20 (Table 4.1; Figure 4.1). The SDRES for the age composition of the LWAP survey did show some patterns and variation of the SDRES was quite large ranging from 2.5 to 6.2. Variation of the SDRES for the LWAP age composition data was more evenly distributed for the 11-16-20 and 01-02-20 versions than for previous versions after an age-length key was used to estimate age composition instead of using the actual age composition data. The predicted values for the age composition were nearly always underestimated (positive SDRES values). Plots of the SDRES for each quantity and each version of the WI345 stock assessment are shown in Figures 4.2 to 4.7.

Table 4.1. Minimum, maximum, mean, and variance of the standardized residuals (SDRES) for recreational fishery catch, catch-per-unit effort in the LWAP survey, age composition (comp.) of age-6 Lake Trout in the recreational and LWAP survey, and age composition (age 3+) in the last year for the recreational fishery and LWAP survey for six versions of the WI345 stock assessment for 1986-2019. Versions 02-20-20, 03-09-20, and 04-02-20 used data for 1986-2017 whereas versions 09-21-20, 11-16-20, and 01-02-21 used data for 1986-2019.

WI345 version	SRES statistic	Rec_fishery catch	Age comp. rec_fishery last year	LWAP survey lnCPUE	Age comp. LWAP survey last year	Age 6 comp. rec_fishery	Age 6 comp. LWAP survey
02-20-20	minimum	-1.69928	-0.73262	-0.69907	-1.49471	-1.09272	-2.95888
	maximum	1.64914	0.71768	1.10626	4.28796	1.45927	5.71957
	mean	0.00144	-0.02552	-0.14056	0.26752	-0.06013	0.83237
	variance	0.60954	0.14994	0.20881	2.50476	0.31247	6.15919
03-09-20	minimum	-1.56567	-0.81571	-0.76339	-1.29699	-1.07810	-2.83365
	maximum	1.51004	0.87983	1.09401	4.84727	2.48618	5.76752
	mean	-0.01191	0.13928	-0.13793	0.244987	0.15843	0.80642
	variance	0.55386	0.17930	0.2359	2.56443	0.65098	5.61282
04-02-20	minimum	-1.56633	-0.44309	-0.76741	-1.28882	-1.20256	-2.86435
	maximum	1.51410	1.11809	1.12446	4.62771	2.55750	5.79083
	mean	-0.00892	0.12167	-0.13849	0.23270	0.127815	0.785092
	variance	0.5702	0.14489	0.23797	4.03765	0.64826	5.61003
09-21-20	minimum	-1.83567	-0.59768	-1.32854	-0.80329	-1.07124	-1.70832
	maximum	1.6125	1.31854	1.84684	6.34165	1.77023	5.88414
	mean	-0.01836	0.16662	-0.02335	0.68022	0.05835	2.762084
	variance	0.68032	0.26249	0.66758	4.03765	0.40049	5.05060
11-16-20	minimum	-1.89895	-0.76834	-1.32868	-2.52312	-1.6287	-1.59126
	maximum	1.82054	2.79123	1.90206	4.05043	2.3802	7.09587
	mean	-0.02060	0.29734	-0.02091	-0.32839	0.31235	1.64043
	variance	0.79791	0.65210	0.72623	3.17626	0.81231	3.07358
01-02-21	minimum	-1.89385	-0.82903	-1.31913	-2.52082	-1.75535	-1.59161
	maximum	1.80180	2.69260	1.89645	4.03545	2.34662	7.09085
	mean	-0.02118	0.228475	-0.02070	-0.32847	0.264377	1.63337
	variance	0.78695	0.65278	0.71704	3.16066	0.81239	3.07115

Figure 4.1. Box and whisker plots of the standardized residuals for recreational catch, LWAP survey CPUE, and age composition of Lake Trout in the recreational and survey catches for six version of the WI345 stock assessment. Versions 02-20-20, 03-09-20, and 04-02-20 used data for 1986-2017 whereas versions 09-21-20, 11-16-20, and 01-02-21 used data for 1986-2019. For each box plot the mean is shown as an X, the grey horizontal line is the median, the grey box represents the interquartile range, while the vertical lines capped by horizontal lines demark 1.5 times the interquartile range, and the individual data points represent outliers. The dashed horizontal line represents a SDRES of 0.0.

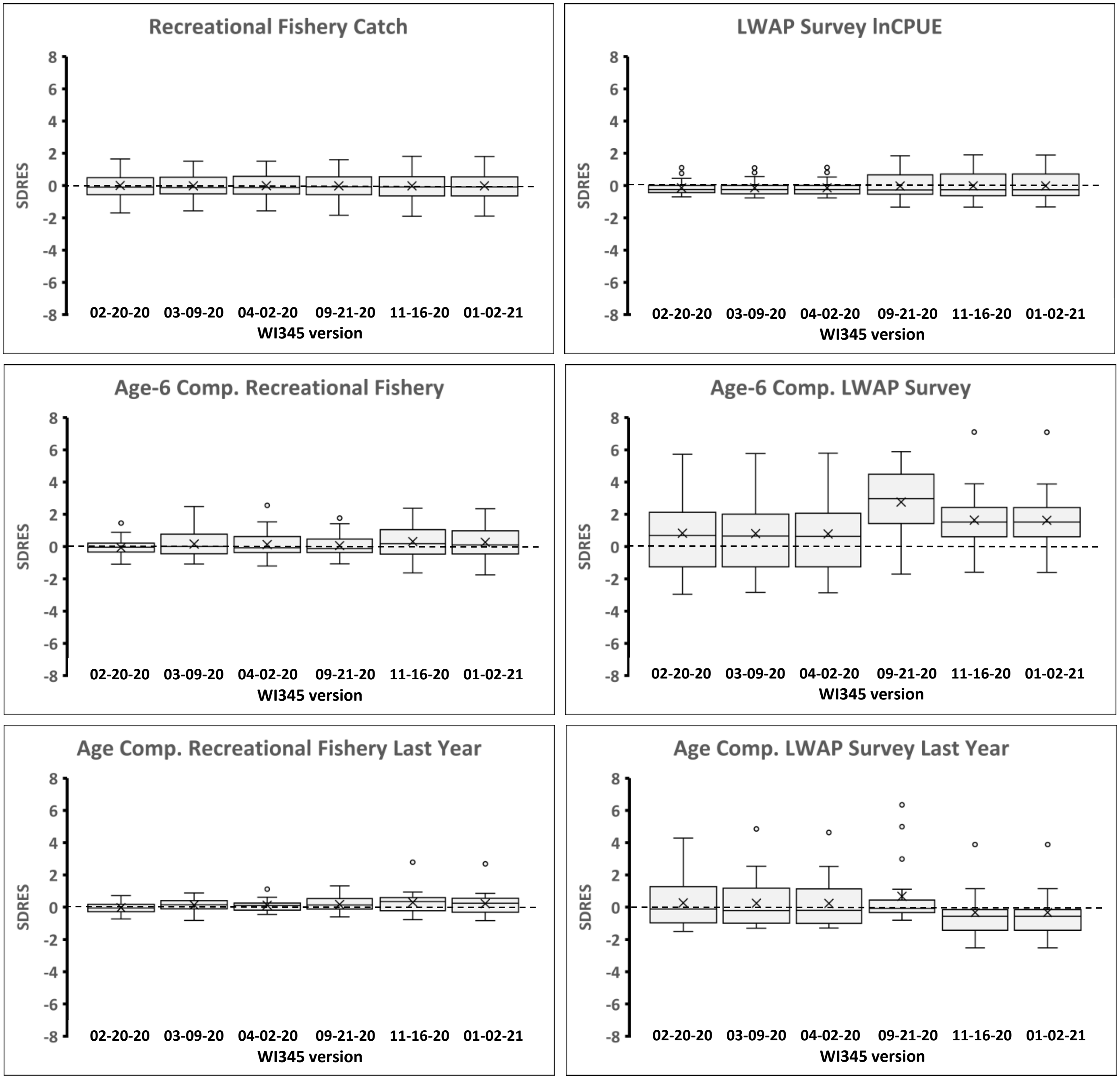


Figure 4.2. Residual plots WI345-02-20-20.

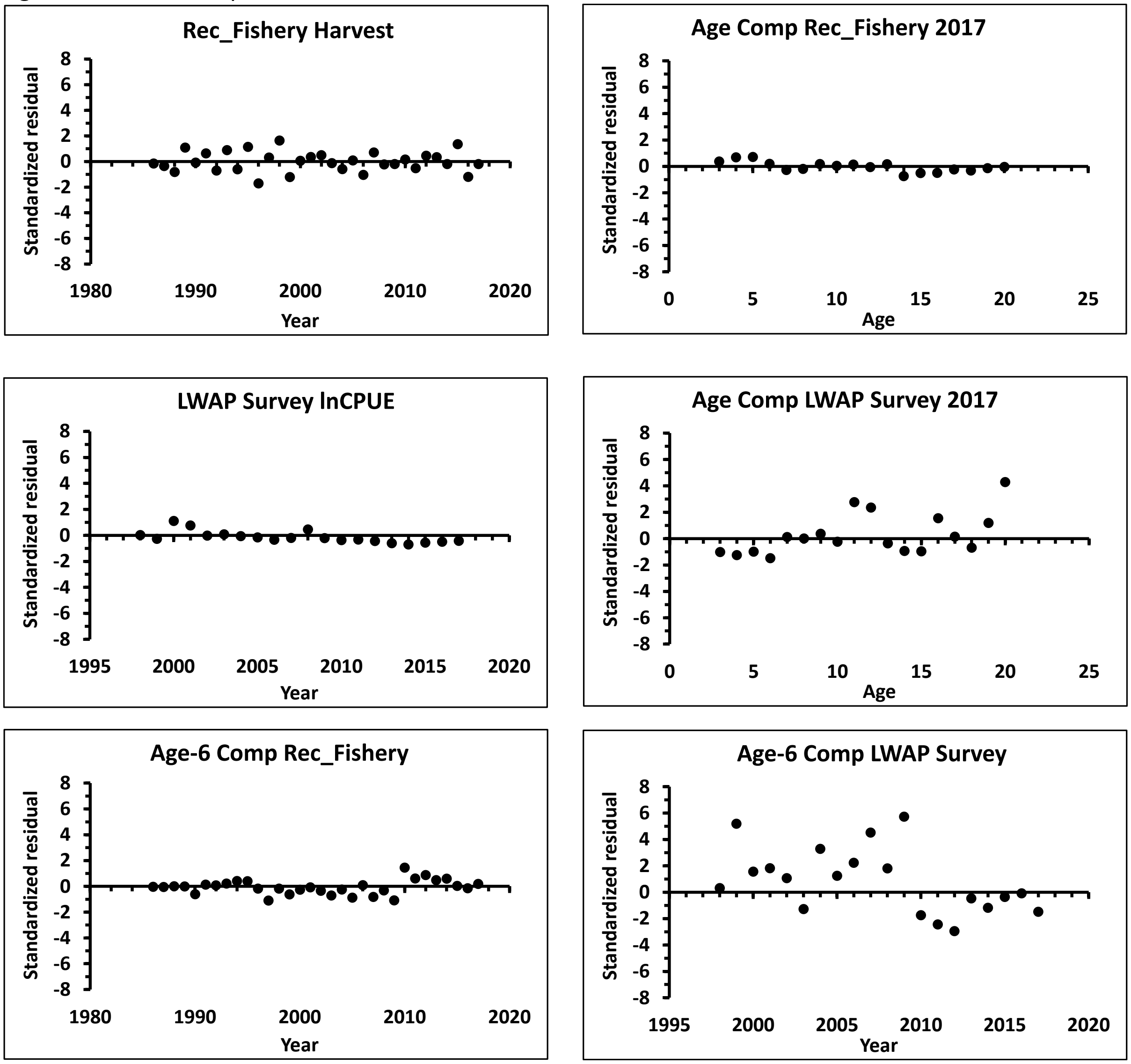


Figure 4.3. Residual plots WI345-03-09-20.

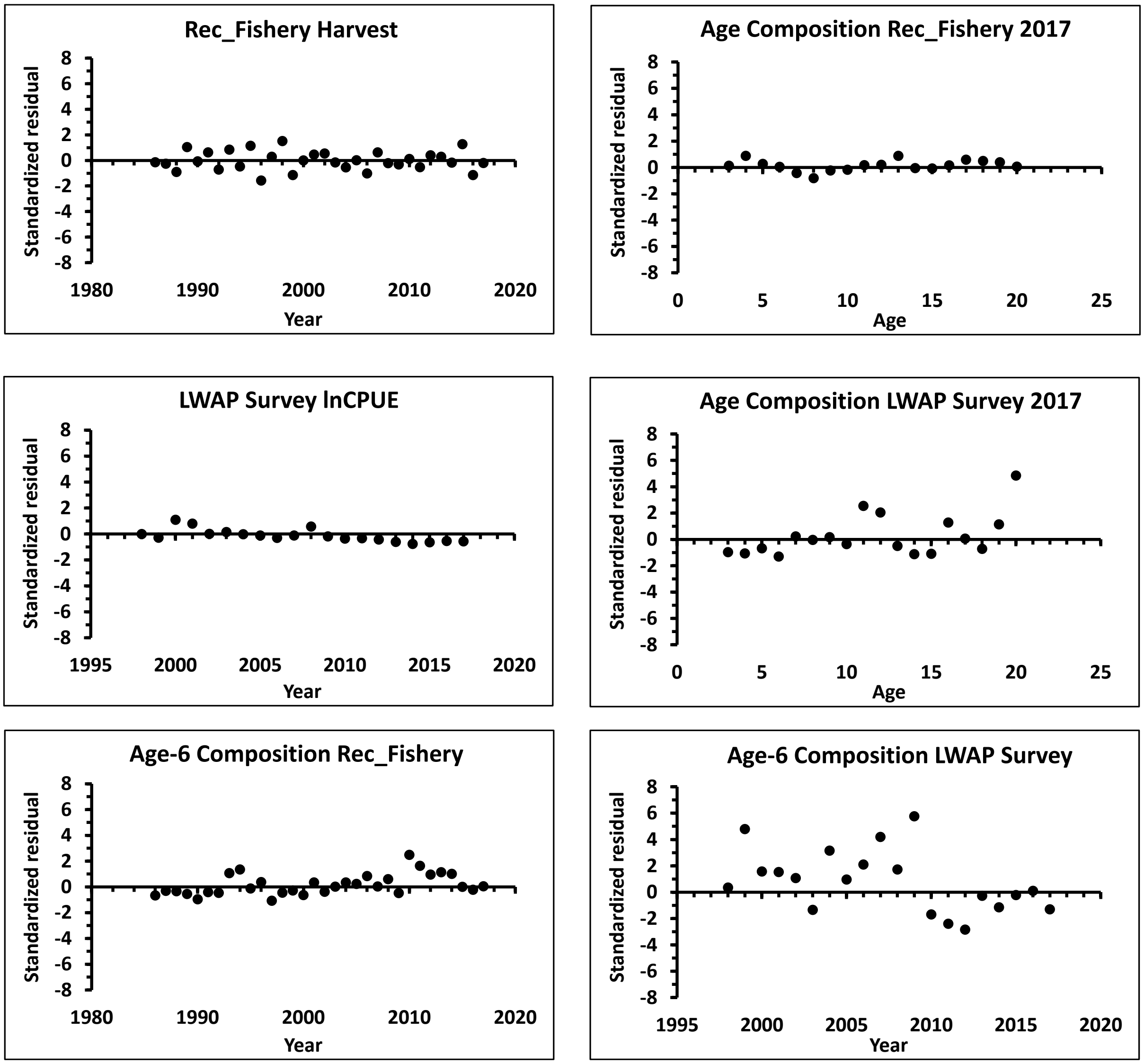


Figure 4.4. Residual plots WI345-04-02-20.

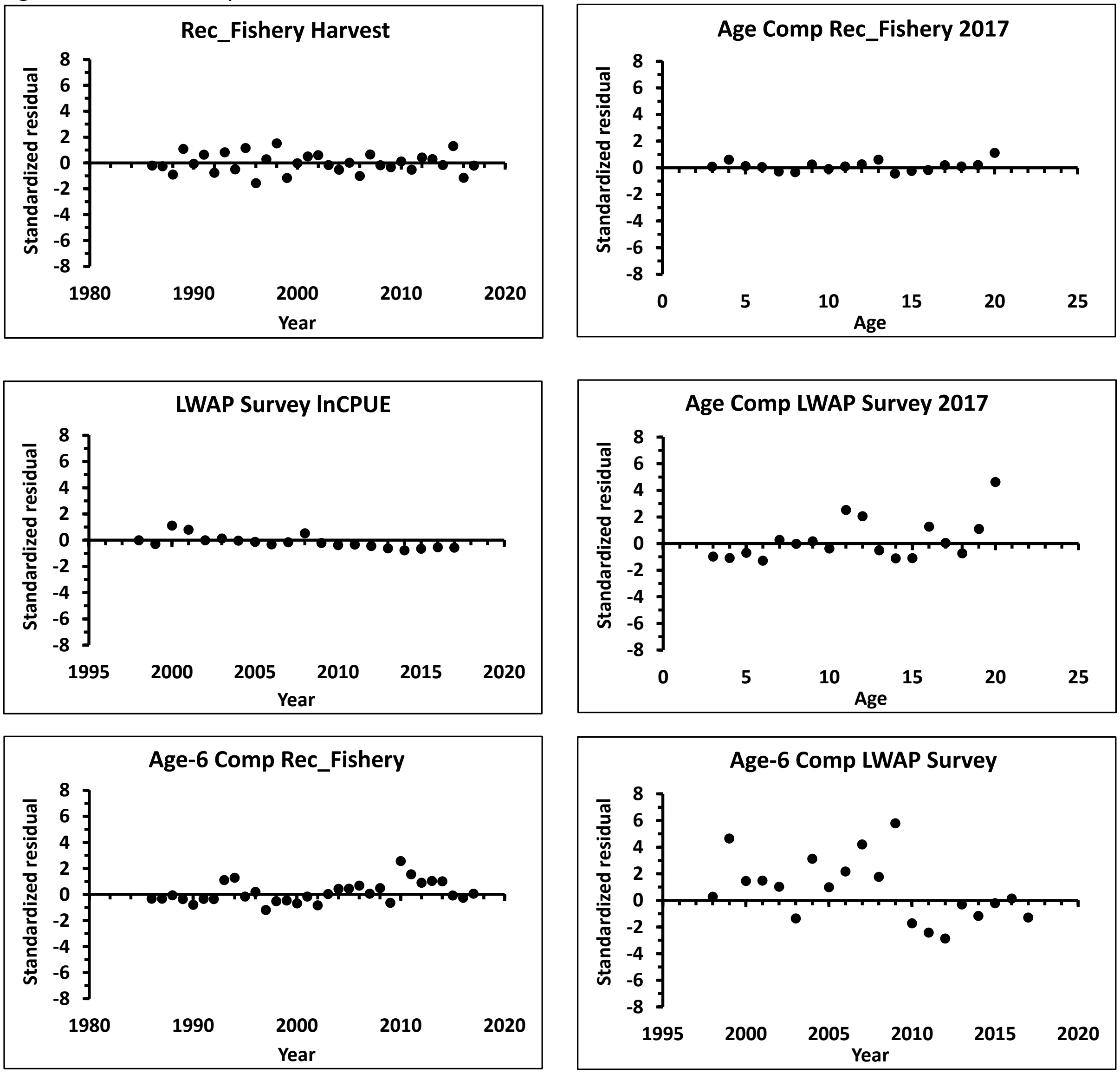


Figure 4.5. Residual plots WI345-09-21-20.

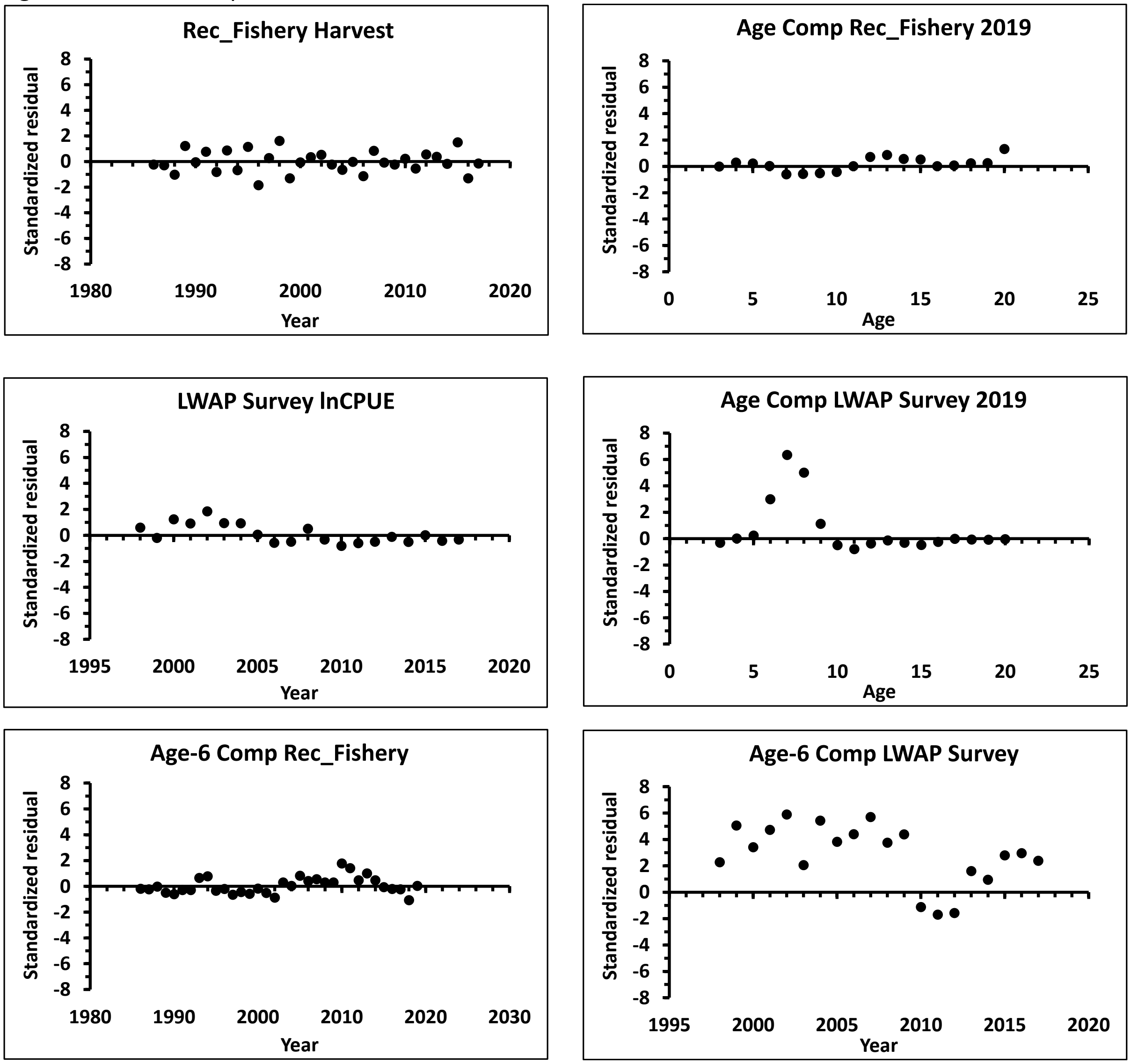


Figure 4.6. Residual plots WI345-11-16-20.

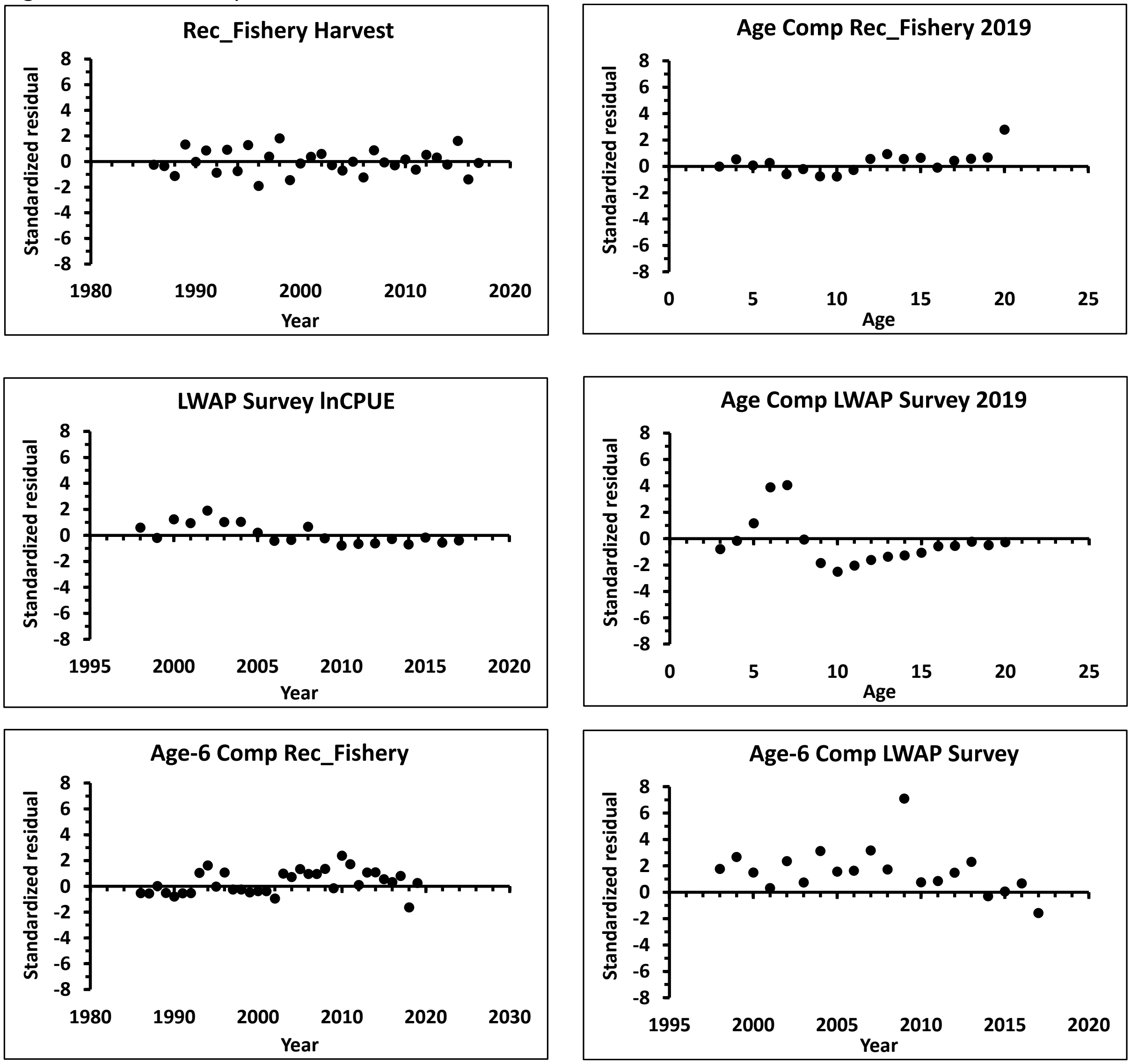
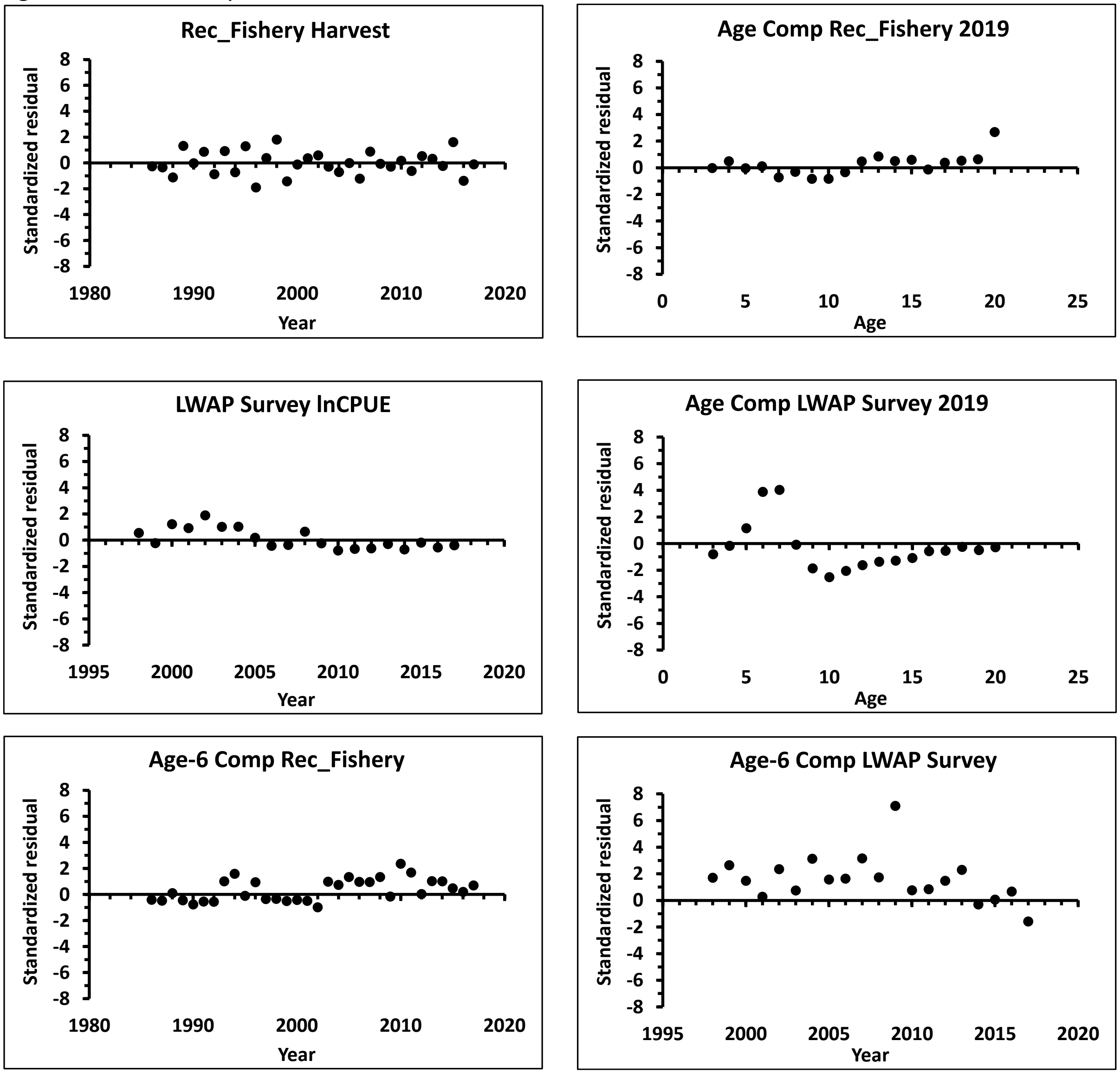


Figure 4.7. Residual plots WI345-01-02-21.



5.0 Selectivity and Catchability

Selectivity for the recreational fishery and the LWAP survey was estimated within the stock assessment fitting process (Truesdell and Bence 2016) but selectivity of the commercial fishery was not. We estimated selectivity of the recreational fishery by fitting a logistic function to the age composition data. For the LWAP survey we applied a random walk function that allowed the ***p1*** value of the selectivity curve to vary annually and fit a lognormal function to estimate age-specific selectivity (Truesdell and Bence 2016). Selectivity for the commercial fishery was input to the data file (Ebener et al. 2020) and described with a lognormal function.

Selectivity was not time varying for either the recreational or commercial fishery (Figure 5.1), but it was time varying for the LWAP survey (Figure 5.2). Except for the 02-20-20 version, there was little difference in selectivity of the recreational fishery between the different versions of the stock assessment, whereas modification of the commercial selectivity for the 01-02-21 version did increase selectivity for ages 5-15 (Figure 5.1). Annual differences in selectivity of ages 3-9 were smaller for the 11-16-20 and 01-02-21 versions than previous versions (Figure 5.2) after we used the age-length key to determine age composition of the LWAP survey (Ebener et al. 2020).

We did estimate time varying catchability for the recreational fishery and time varying fishing intensity for the commercial fishery because there is increasing evidence that catchability nearly always varies through time and is seldom constant (Wilberg et al. 2009). Catchability of the recreational fishery and fishing intensity of the commercial fishery were estimated as bounded parameters and a random walk was used to estimate catchability of the recreational fishery. Fishing intensity of the commercial fishery varied little between versions of the stock assessment. Catchability of the recreational fishery was similar for the 03-09-20 and 04-02-20 versions and the 11-16-20 and 01-02-21 versions and substantially lower for the 02-20-20 version than other versions, but all versions had the same temporal pattern (Figure 5.3). The largest divergence in catchability for the recreational fishery among all versions occurred during roughly 1991-2001 whereas after 2001 catchability was very similar among all versions except 02-20-20.

Figure 5.1. Age-specific proportional selectivity of the recreational and commercial fisheries for six versions of the WI345 Lake Trout stock assessment.

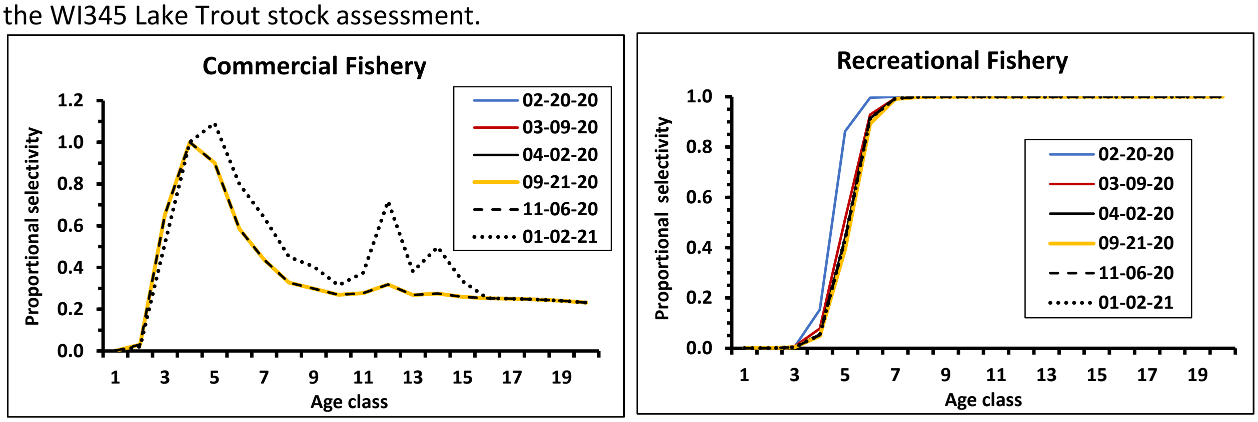


Figure 5.2. Age-specific proportional selectivity of the LWAP survey for six versions of the WI345 Lake Trout stock assessment. Each line represents selectivity for a given year.

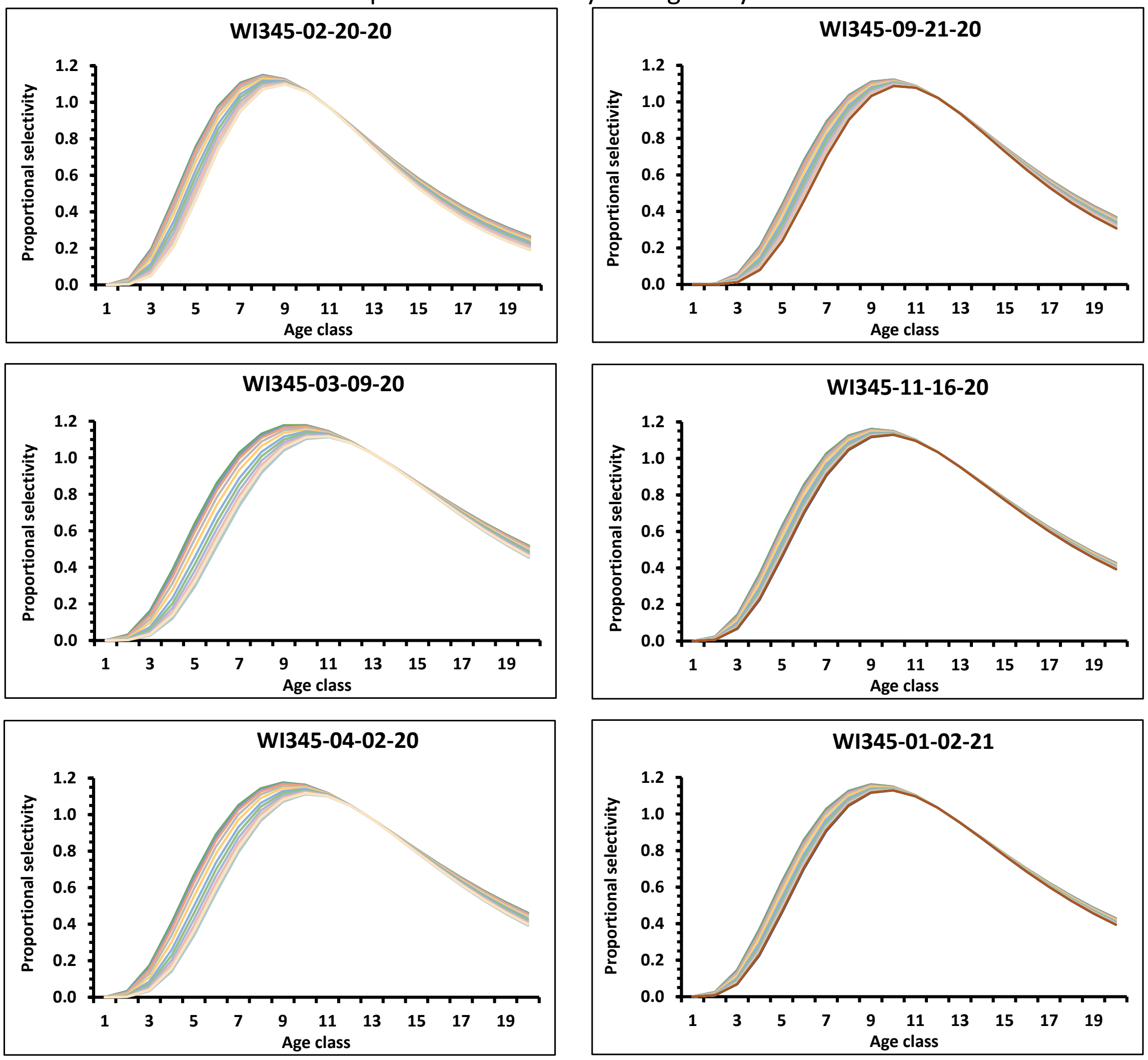
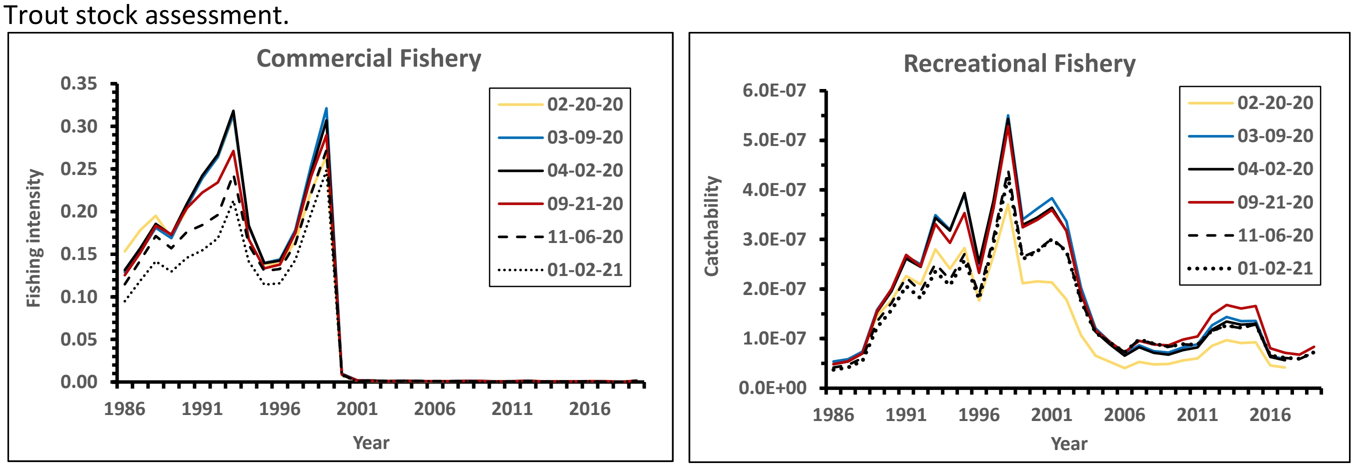


Figure 5.3. Commercial fishing intensity and recreational fishery catchability for six versions of the WI345 Lake Trout stock assessment.



6.0 SCAA Output – Starting Values

We tested the stability of our SCAA models by changing the starting values for the parameters of catchability or fishing intensity and selectivity for each fishery. We excluded evaluation of selectivity for the commercial fishery for all six versions because it was not estimated within the stock assessment. We illustrated effects of changing starting values on total population biomass. The starting value for each parameter in the INITIALIZATION_SECTION of the stock assessment is shown in Table 6.0.

Table 6.0. Starting values for selectivity and catchability parameters of the commercial and recreational fisheries and LWAP survey for six versions of the WI345 Lake Trout stock assessment. The middle starting value is the original for each version of the stock assessment.

Parameter	**SCAA variable & (starting values)**	**Description**
Commercial intensity	ln_qcf (-6,-3,3)	natural logarithm fishing intensity commercial fishery
Recreational catchability	ln_qrf_in (-30,-15,15)	natural logarithm catchability recreational fishery
Survey catchability	ln_qsv (-20,-10,10)	natural logarithm catchability LWAP survey
Recreational selectivity p1	lnselrf_p1 (-3,-1.5,1.5)	natural logarithm selectivity p1 value recreational fishery
Survey selectivity p1	lnselsv_p1 (-1.88,-0.94,0.94)	natural logarithm selectivity p1 value LWAP survey
Recreational selectivity p2	lnselrf_p2 (-1.44,-0.7,0.7)	natural logarithm selectivity p2 value recreational fishery
Survey Selectivity p2	lnselsv_p2 (-0.8,0.8,1.6)	natural logarithm selectivity p2 value LWAP survey fishery

We changed the starting values away from the initial values by a substantial amount since they are on the natural logarithm scale. If we made large-scale changes away from the initial starting values and the stock assessment still arrived at the same final estimates of biomass, then we considered the model to be stable and our estimates of the parameters was good. On the other hand, if final estimates of biomass were substantially different for different starting values of a parameter than we considered the model to be unstable. We changed starting values away from the original by first changing the sign and then doubling the value. For example, the starting value for commercial fishing intensity was -3 so we changed starting values to 3 and -6. We did not change more than one starting value at a time.

As the output below illustrate, our WI345 models always arrived at the same final annual estimates of population biomass given our range of starting values for selectivity and catchability (Figures 6.1 to 6.7). Consequently, we considered all versions of the WI345 stock assessment to be stable. We found that changing initial starting values was a good way to find problems with bounds on the parameters of interest.

Figure 6.1. Starting values WI345-02-20-20.

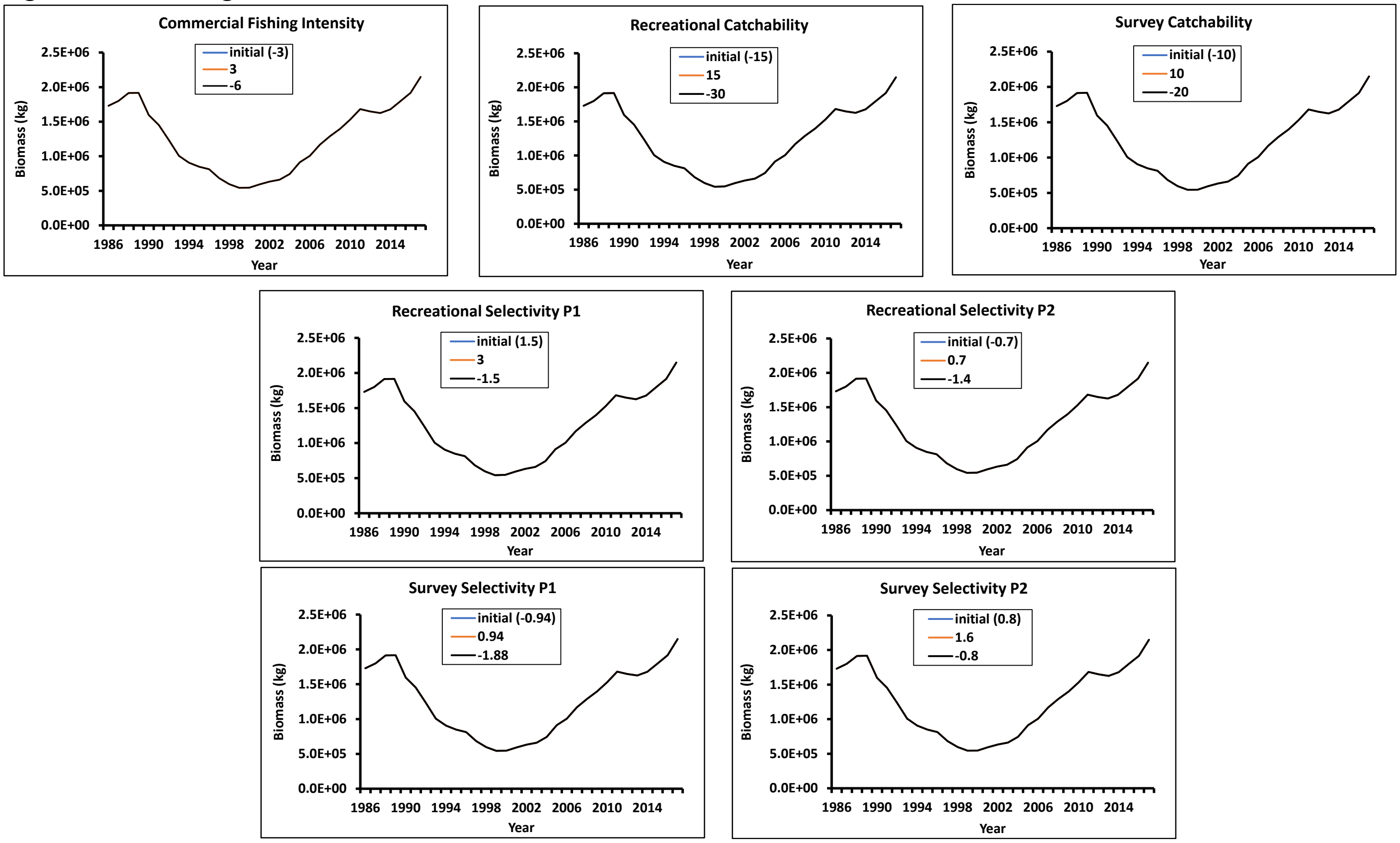


Figure 6.2. Starting values WI345-03-09-20.

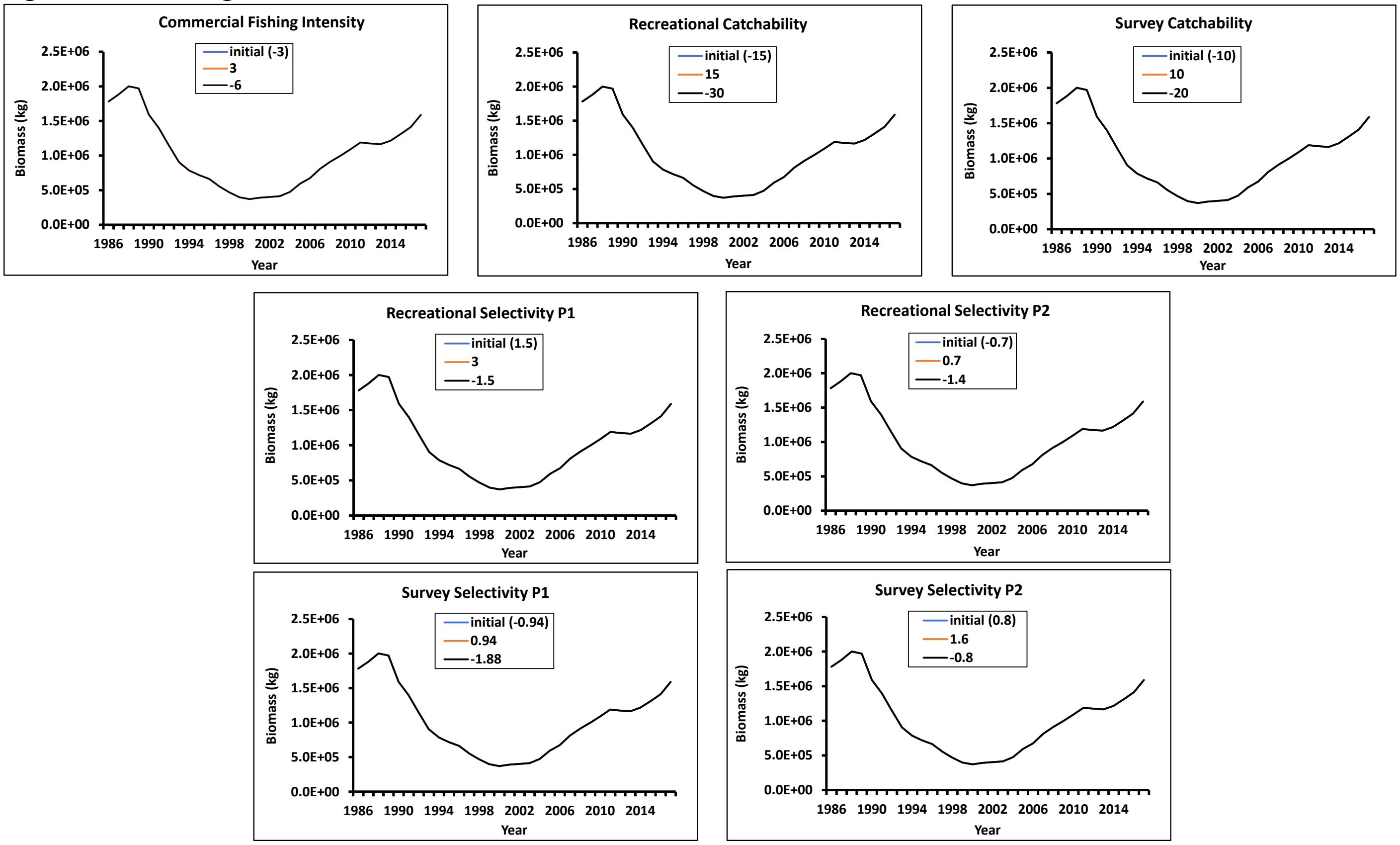


Figure 6.3. Starting values WI345-04-02-20.

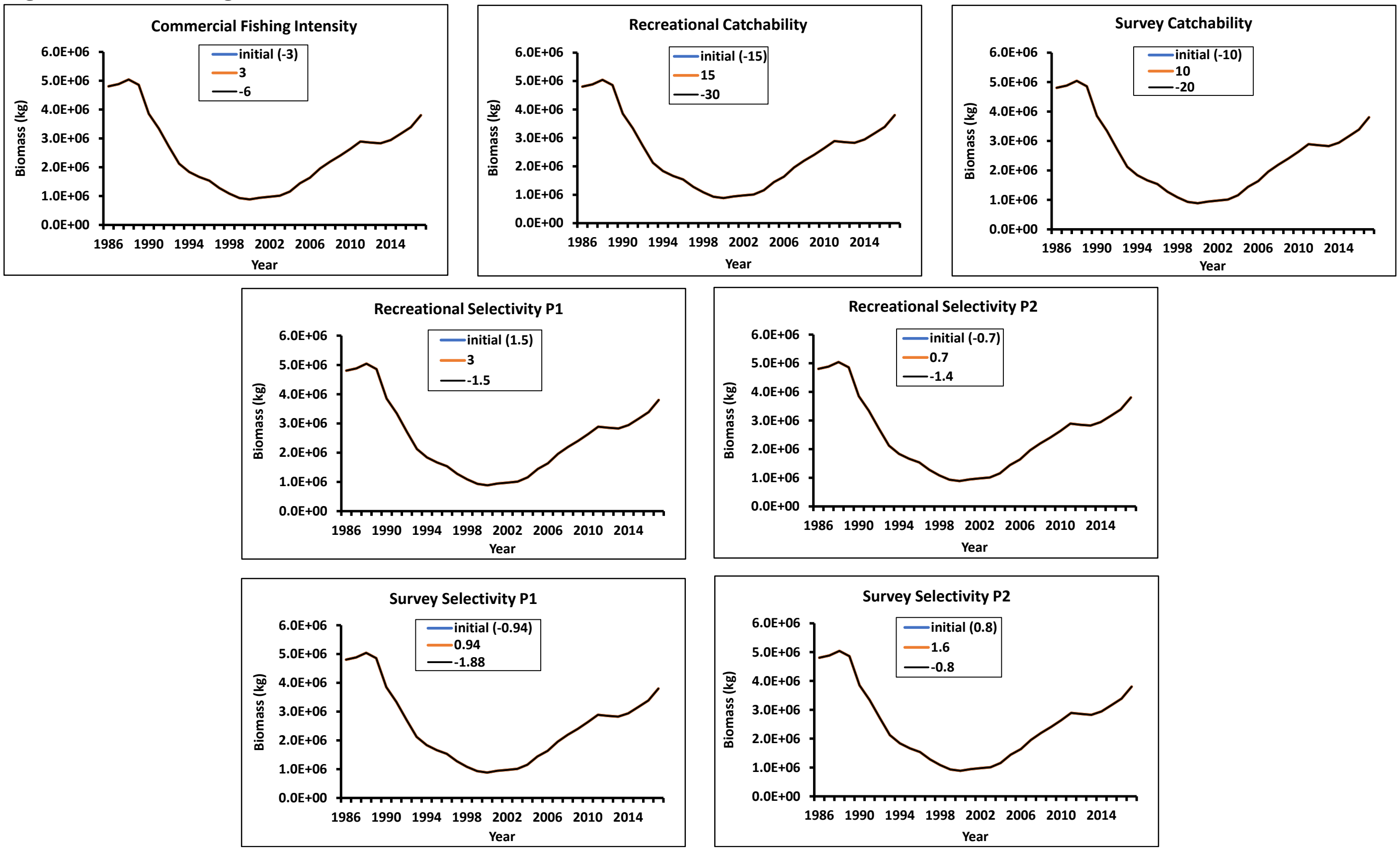


Figure 6.4. Starting values WI345-09-21-20.

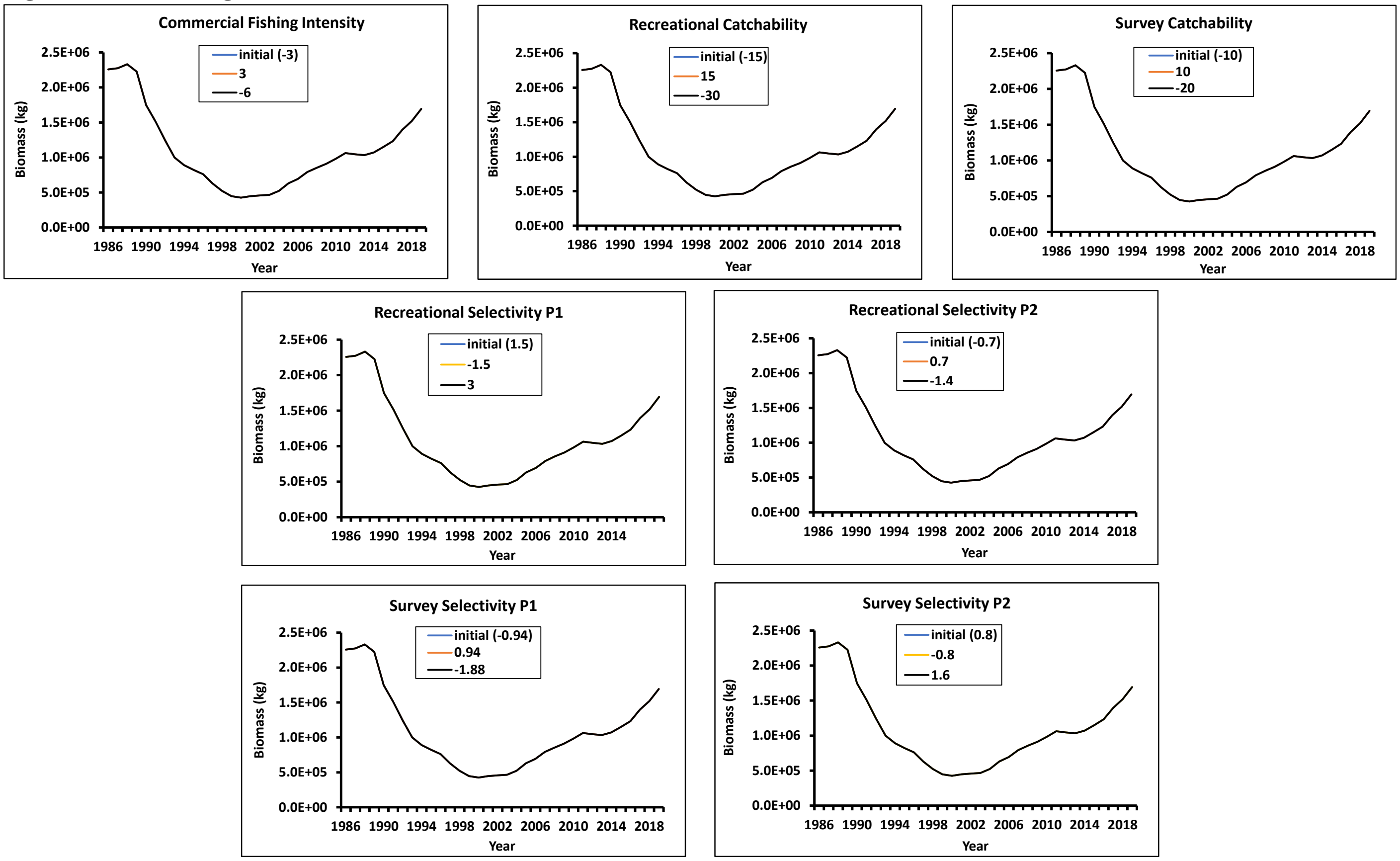


Figure 6.5. Starting values WI345-11-16-20.

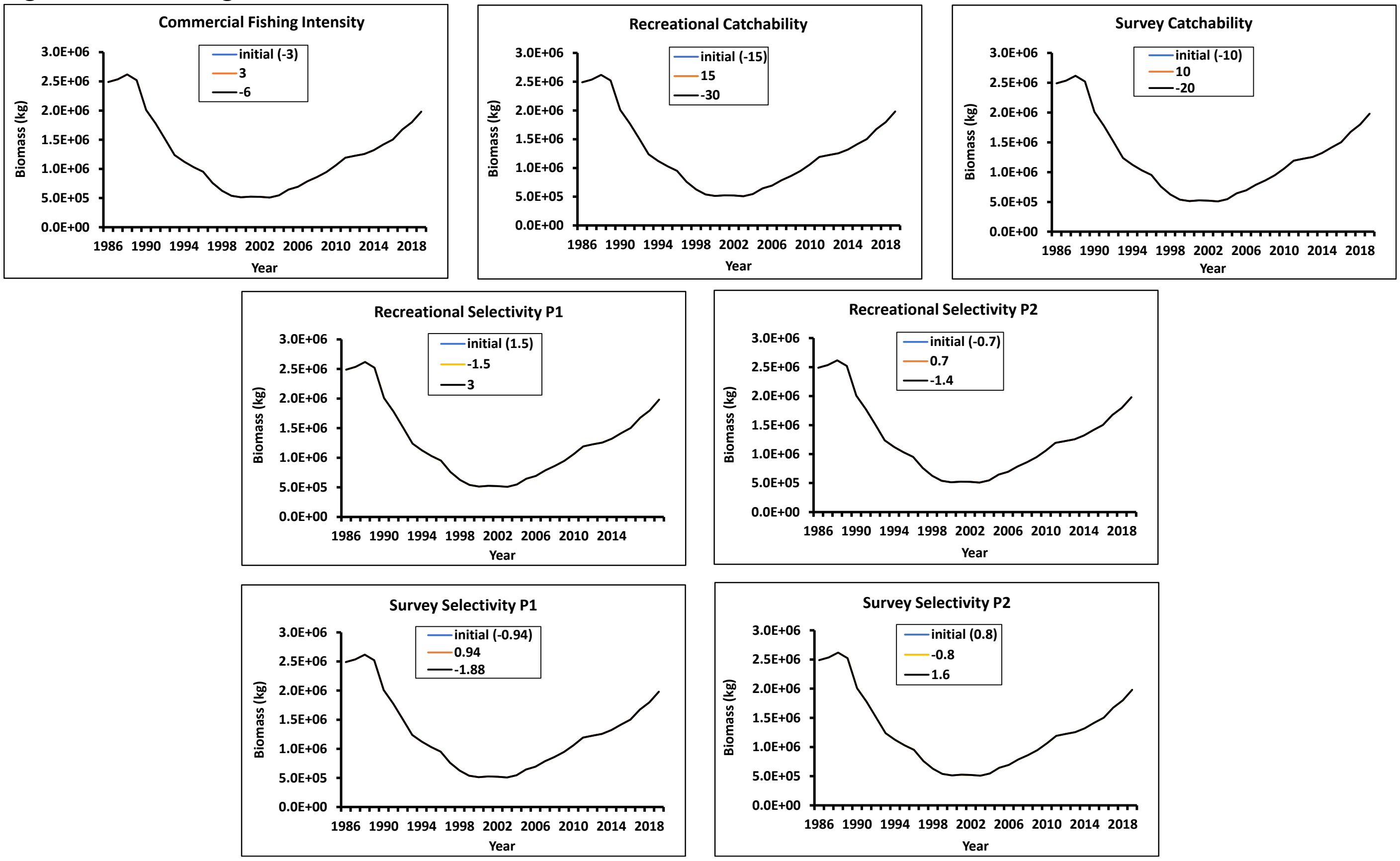
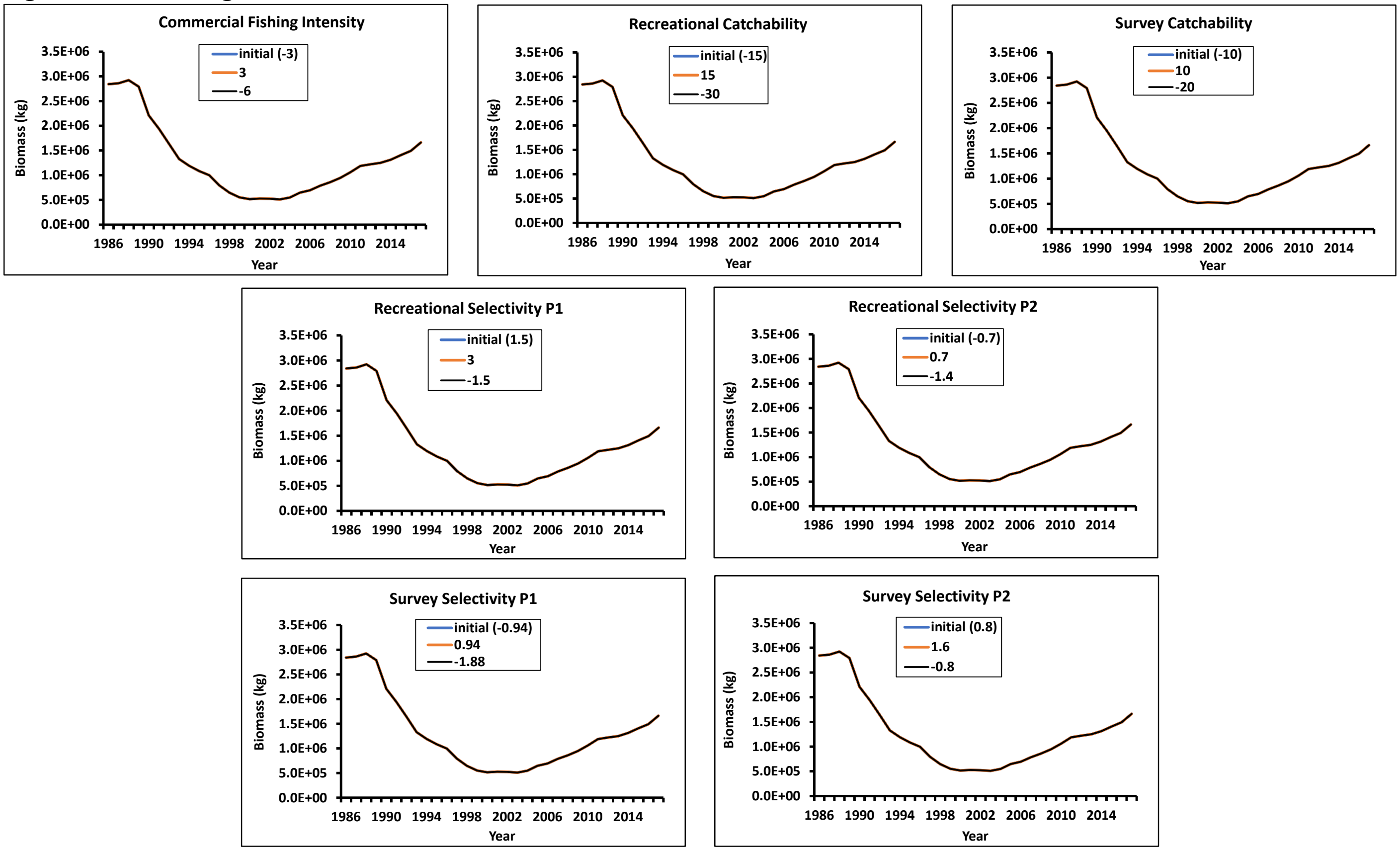


Figure 6.6. Starting values WI345-01-02-21.



7.0 Retrospective Analysis

We conducted retrospective analysis to evaluate whether estimated quantities from our SCAA analysis changed systematically or drastically as years of data were added or removed. A retrospective pattern is a systematic inconsistency among a series of estimates of population size, or related assessment variables, based on increasing periods of data (Mohn 1999; Legault 2009) that can be caused by missing data, increases in ***M***, changes in survey catchability, and time-varying processes that are not accounted for in the stock assessment (Mohn 1999; Legault 2009; Carvalho et al. 2017). Retrospective analysis involves fitting a stock assessment to a complete data set, then sequentially truncating (peeling off) data for the most recent year and fitting the stock assessment with the reduced data set (Legault 2009; Deroba 2014; Carvalho et al. 2017). Positive retrospective patterns occur when the values for a given quantity, biomass for example, increase as years are peeled off, while negative patterns occur when the quantity declines as years are peeled off (Deroba 2014). While it is not possible to know for certain that estimates near the end of a time series that change systematically as additional years of data are added were originally biased (rather than becoming less biased with additional years of data), this is quite plausible.

We evaluated retrospective patterns for eight quantities (Table 7.0). Total abundance, total biomass, and total mortality from our stock assessments will be used to forecast consumption by Lake Trout in Lake Michigan. For our estimates of consumption to be valid, these three quantities should be unbiased and without substantial error.

Table 7.0 Quantities evaluated with retrospective analysis for six versions of the WI345 Lake Trout stock assessment.

Quantity	SCAA variable	Description
Total abundance	totN	abundance age 1+
Total biomass	biomass	biomass (kg) age 1+
Biomass age 3+	biomass3	biomass (kg) age 3+
Spawning biomass	spbiomass	spawning biomass (kg)
Total mortality rate	ZbyY	average ***Z*** age 6+
Fishing mortality rate	FbyY	average ***F*** age 6+
Commercial fishing rate	F_CbyY	average commercial ***F*** age 6+
Recreational Fishing Rate	F_RbyY	average recreational ***F*** age 6+

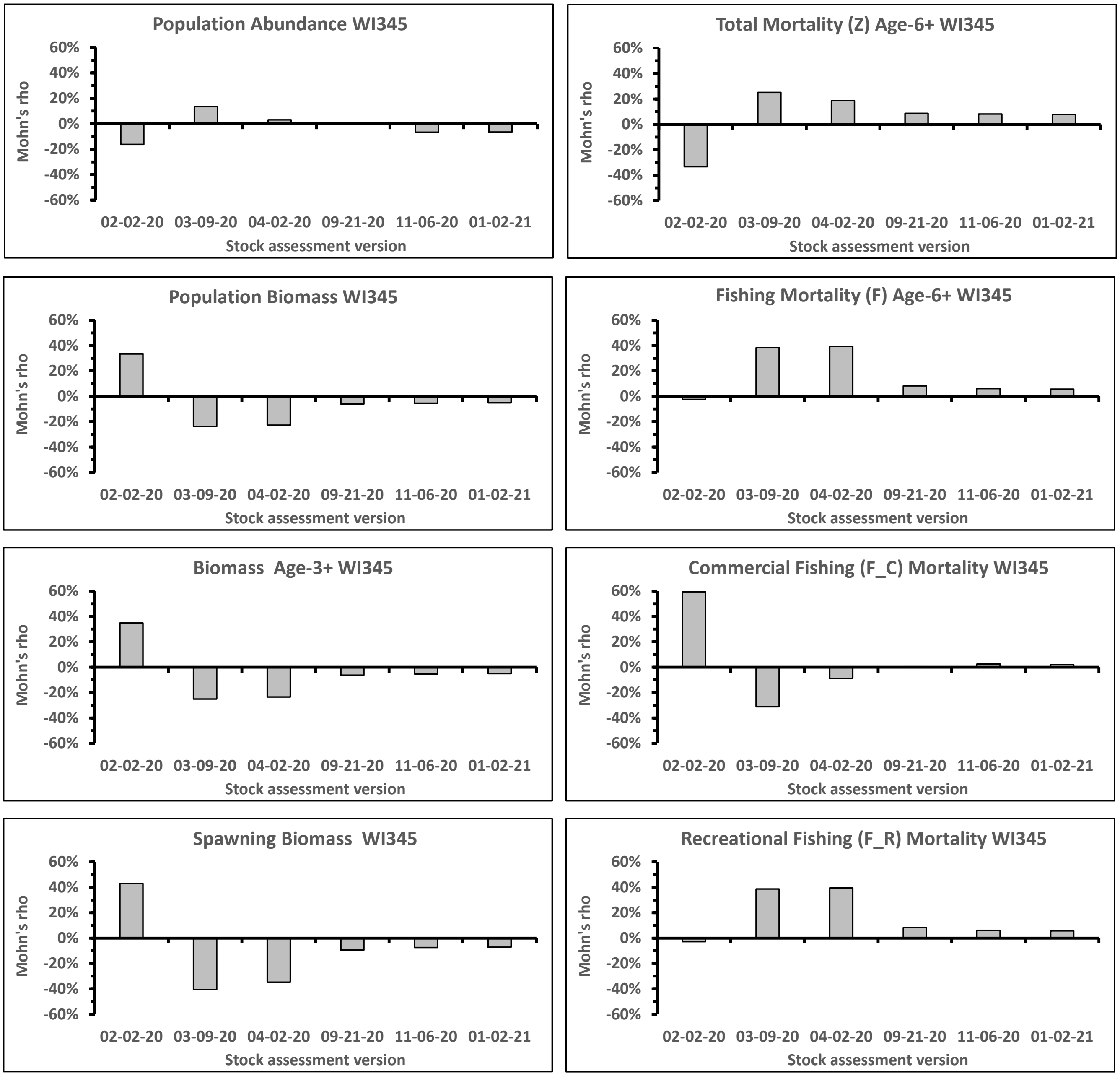
We used Mohn's rho (***ρ***) to evaluate retrospective patterns (Mohn 1999; Legault 2009; Deroba 2014; ICES 2020) for bias of model parameters or quantities for peels that included the years 2012-2016 for the first three versions or 2014-2018 for the last three versions. Mohn's rho allowed us to measure the magnitude of retrospective patterns (Deroba 2014) from the full assessment. To estimate ***ρ,*** the quantity (i.e., biomass) in a year for the stock assessment that includes all years (i.e., the full assessment) was subtracted from the quantity in the last year for a peel and then divided by the quantity for the full assessment. These proportional differences were then summed and divided by the number of peels to calculate ***ρ*** for each quantity as:

(6)
$$p = \sum_{y=1}^{npeels} \frac{X_{Y-y,tip} - X_{Y-y,ref}}{X_{Y-y,ref}}$$

where ***X*** represents a variable from the stock assessment, ***y*** is the year, ***npeels*** is the number of years that are dropped in succession and the assessment rerun, ***Y*** is the last year in the full time series, ***tip*** is the estimate in the last year from an assessment with a reduced time series, and ***ref*** is the assessment using the full time series (Legault 2009).

Some retrospective patterns were evident in all our estimated quantities but by refining estimates of the age composition of the LWAP survey and selectivity of the commercial fishery we were able to reduce the retrospective patterns (Figure 7.1). Retrospective patterns for all population demographic quantities were largest for the 02-20-20

Figure 7.1. Mohn's rho values for abundance, biomass, and mortality for six versions of the WI345 Lake Trout stock assessment.



03-09-20, and 04-02-20 versions and smallest for the 09-21-20, 11-16-20, and 01-02-21 versions. Mohn's rho values for the first three versions of the stock assessment were always smallest for total abundance and largest for biomass and mortality quantities. The values for ***ρ*** for population abundance declined from -16% for the 02-20-20 version to -0.2% for the 09-21-20 version and was 6.5% to 6.6% for the 11-16-20 and 01-02-21 versions (Figure 7.1). For population biomass, ***ρ*** ranged from -23% to 33% for the first three versions of the stock assessment and from -5% to -6% for the last three versions. For ***Z*** of age-6+ fish, ***ρ*** values ranged from -33% to 19% for the first three versions of the stock assessment to 8% to 9% for the last three versions. So, for the last three versions of the WI345 stock assessment there was less than a 10% positive bias for ***Z***, and a negative bias of about 6% for population abundance and biomass. Retrospective patterns for individual quantities for each version of the stock assessment are shown in Figures 7.2 to 7.7.

Figure 7.2. Retrospective plots WI345-02-20-20.

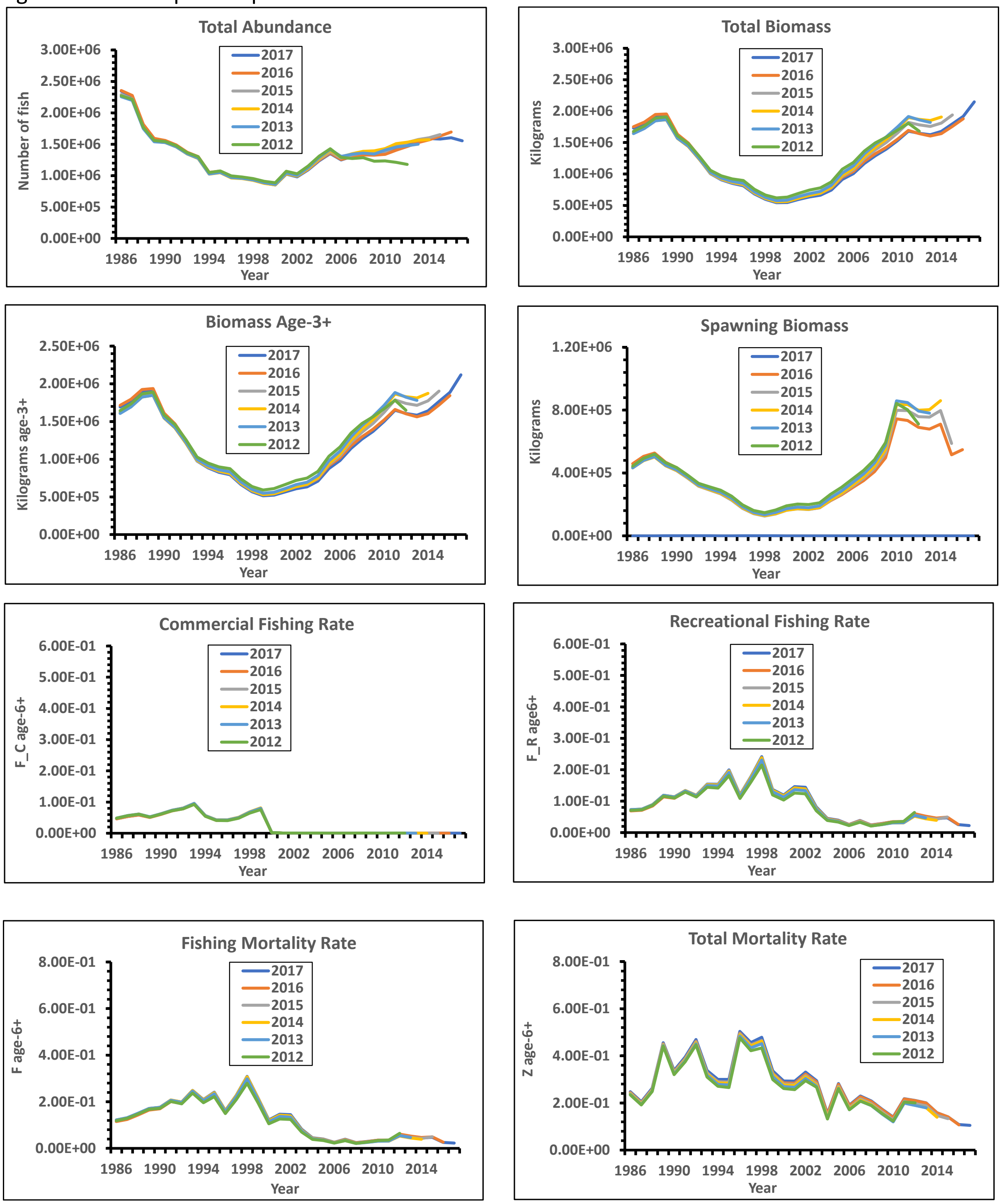
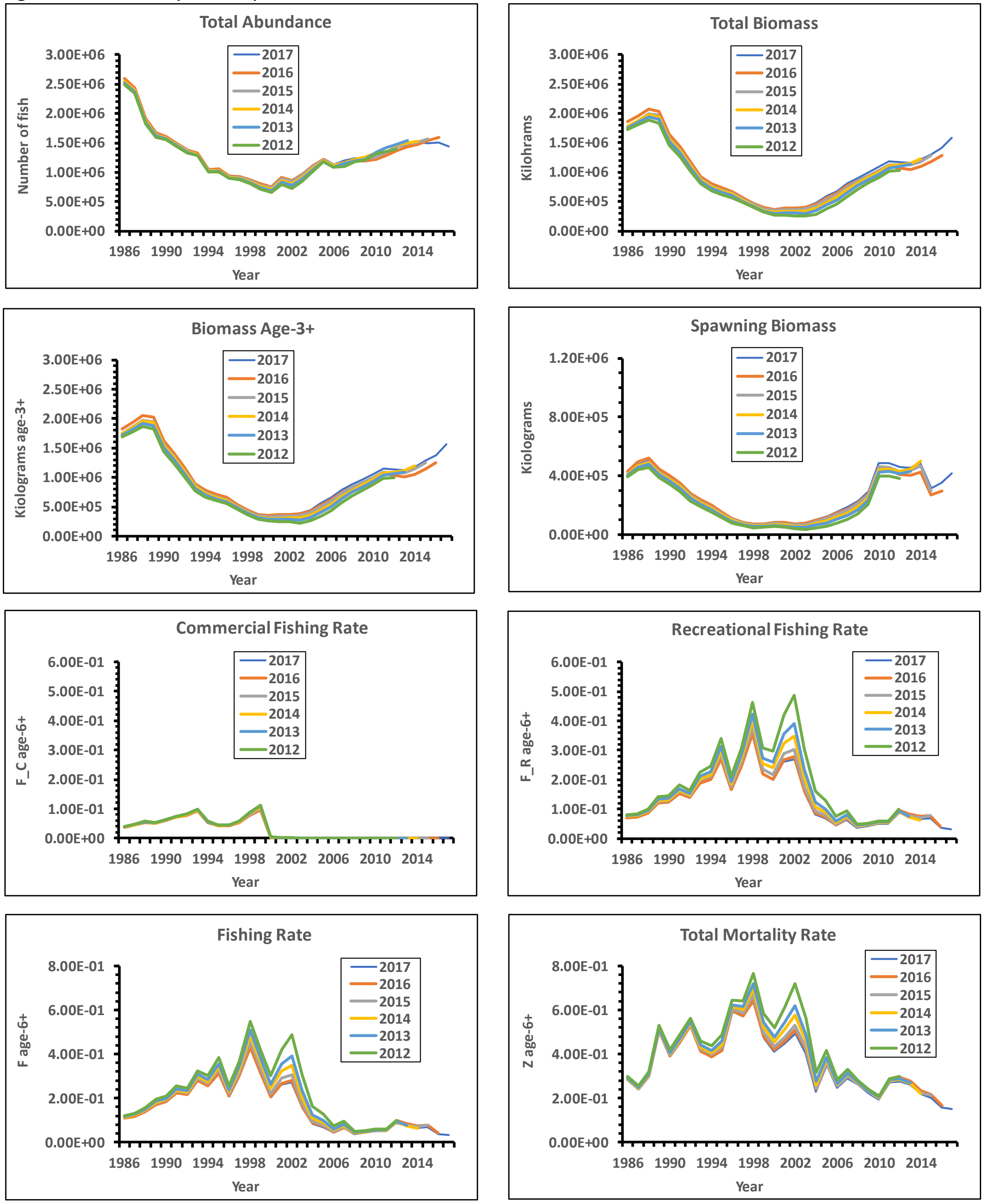
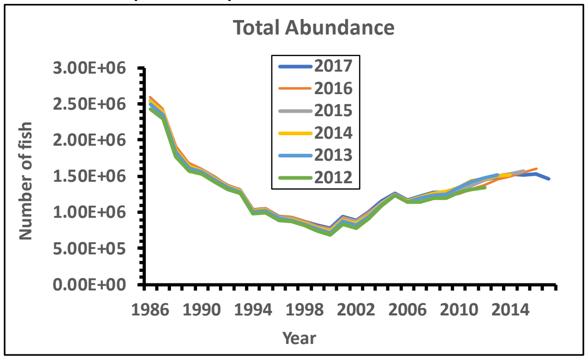
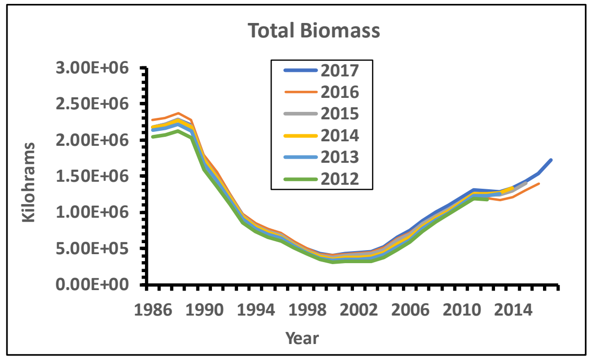


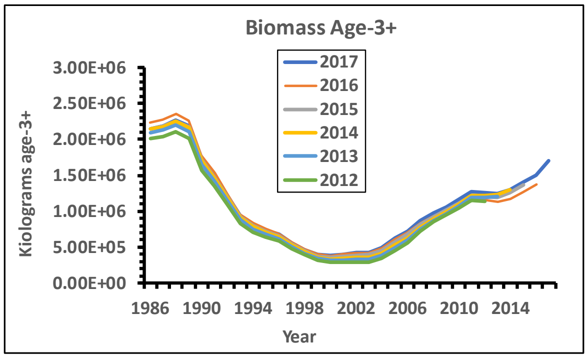
Figure 7.3. Retrospective plots WI345-03-09-20.

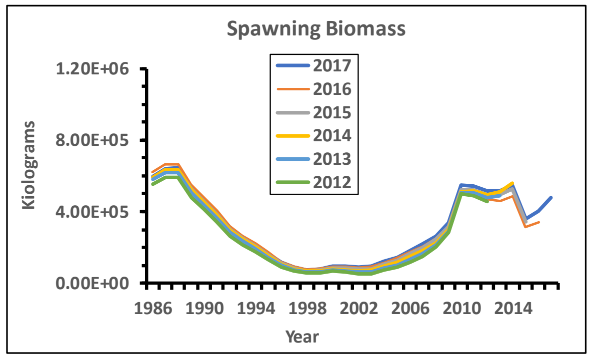


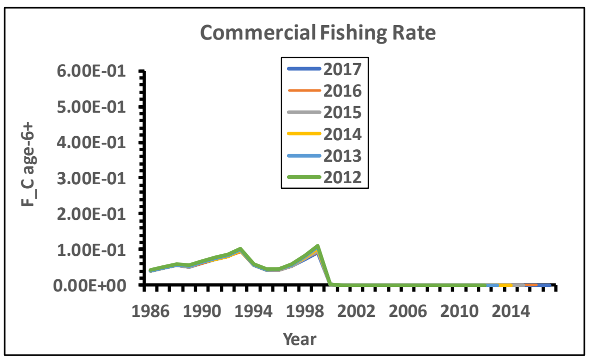
7.4. Retrospective plots WI345-04-02-20.

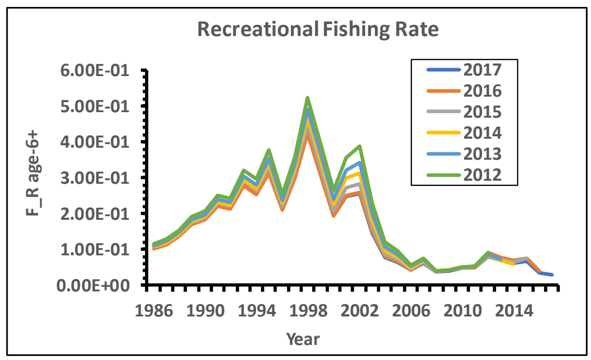


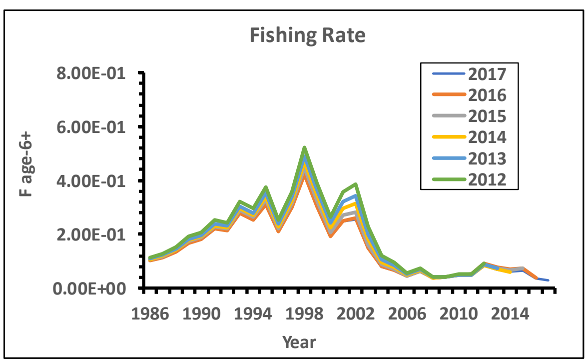


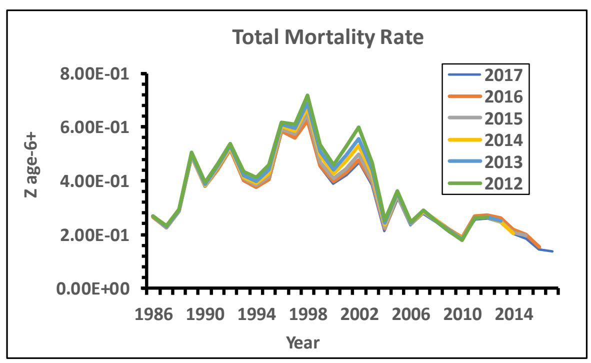




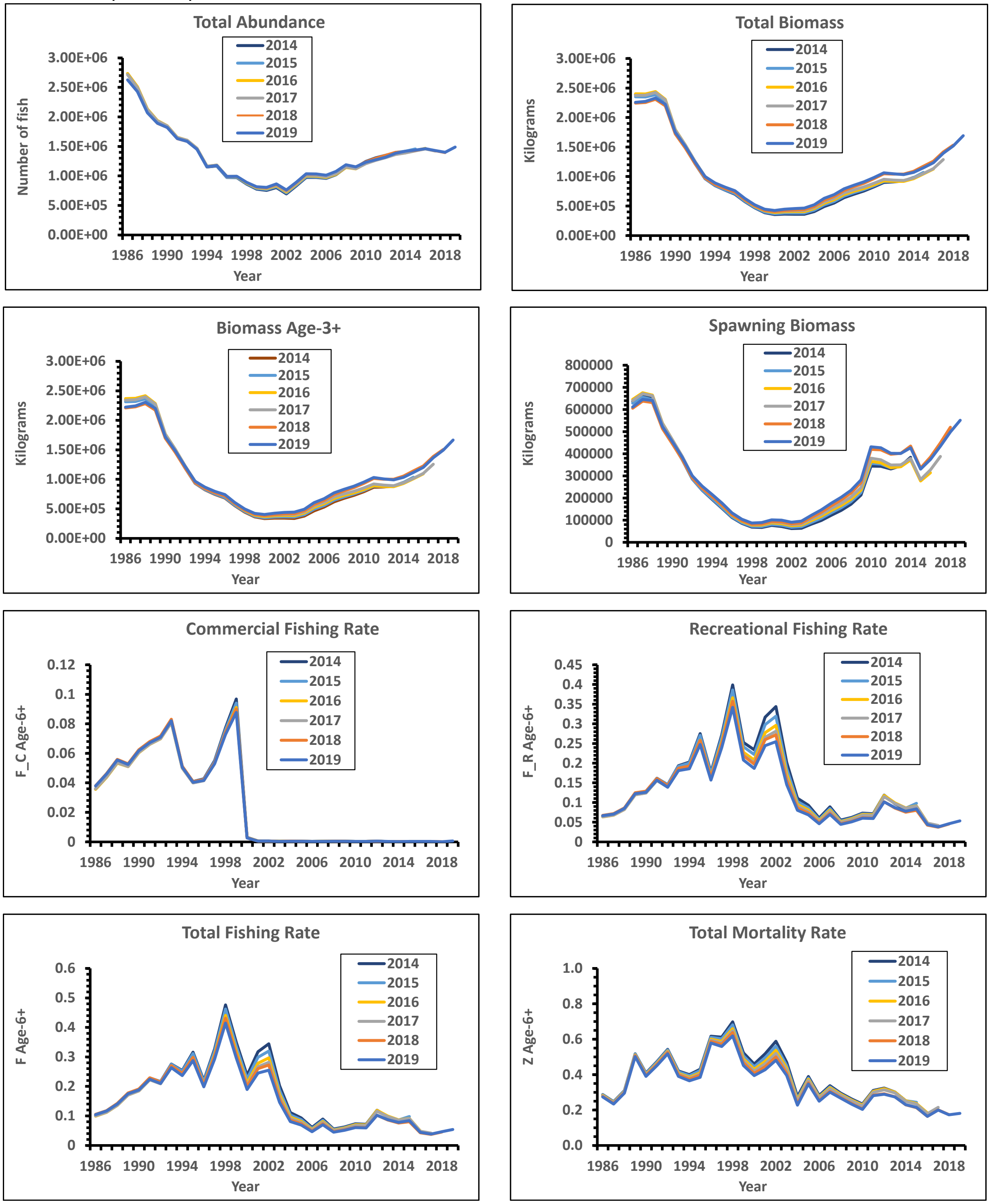




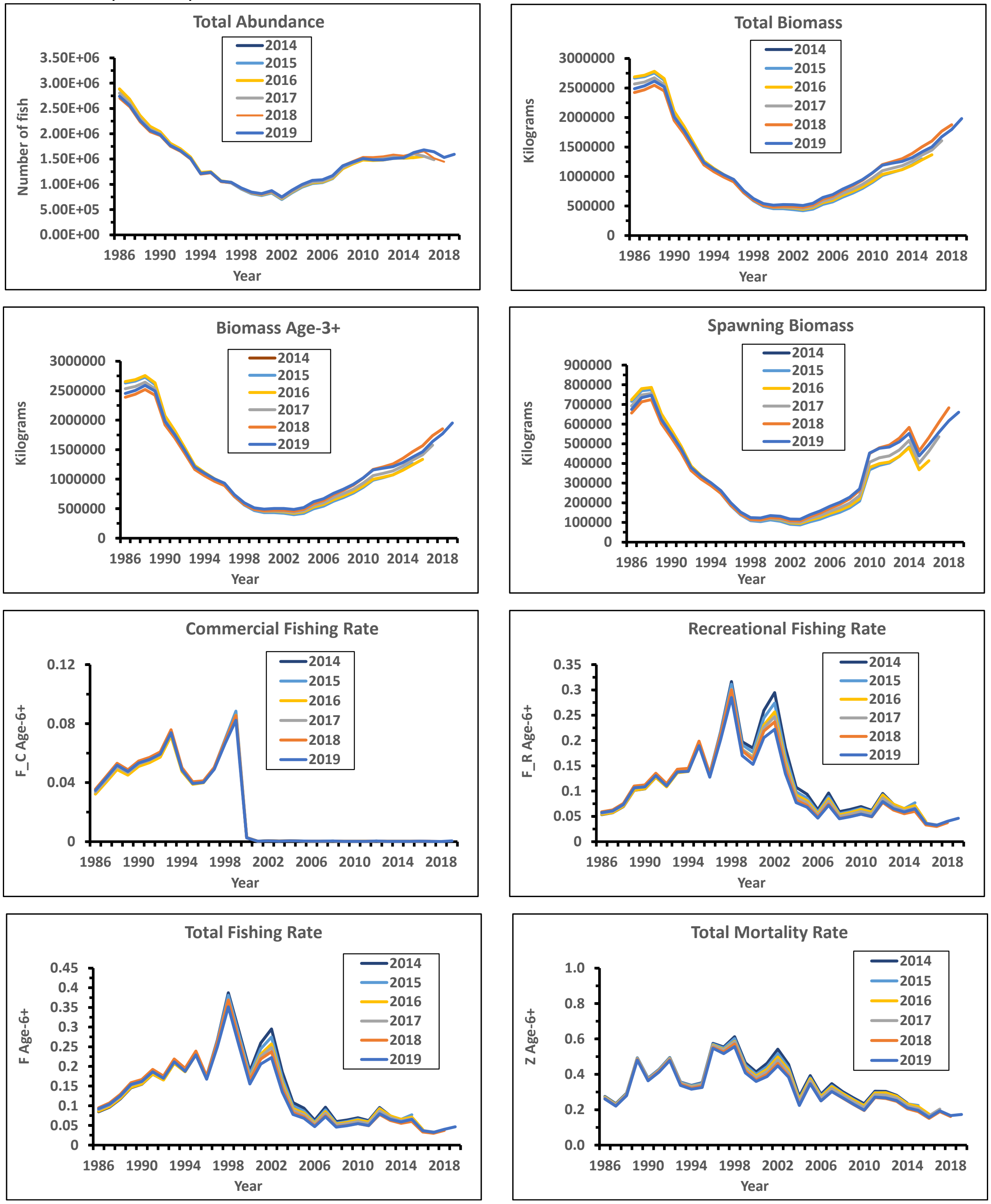




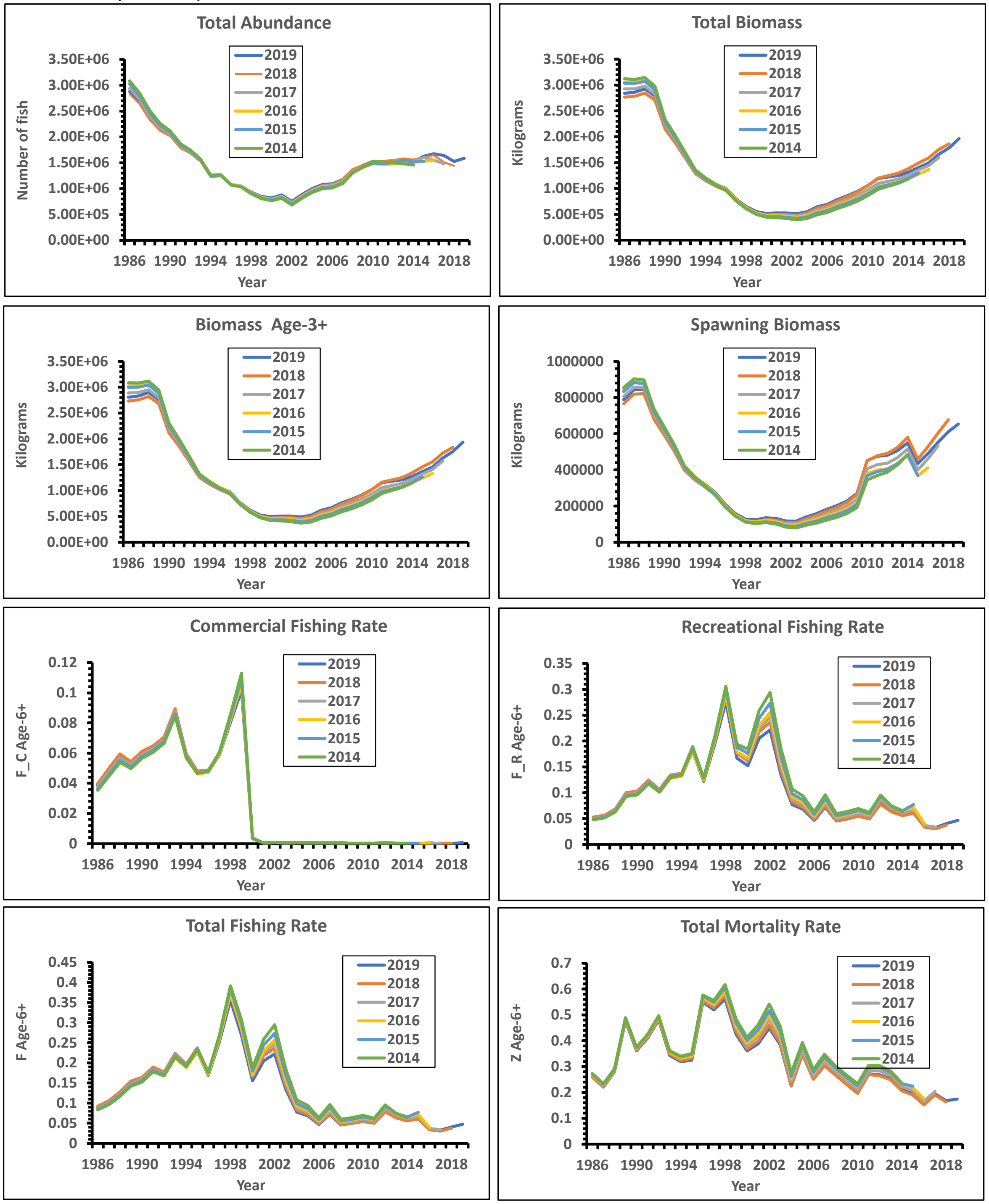
7.5. Retrospective plots WI345-09-21-20.



7.6. Retrospective plots WI345-11-16-20.



7.7. Retrospective plots WI345-01-02-21.



8.0 MCMC Simulations

We conducted Markov chain Monte Carlo (MCMC) simulations to estimate the likelihood profiles for quantities estimated in the WI345 stock assessment and to evaluate their bias. We ran one million MCMC iterations and saved every one hundredth iteration for 10 chains (Table 8.0). We ran simulations for the average total abundance and biomass estimated for the last ten model years and the average fishing and total mortality rates for age-6+ fish in the last three model years. We excluded the first 3,000 iterations in all MCMC simulations as the burn-in period, so our analysis illustrates iterations 3,001-10,000 for each chain. We used one *R*-script to read-in the "mceval" output generated from the MCMC simulations (Adam Cottrill, Ontario Ministry of Natural Resources and Forestry, Owen Sound, Ontario, personal communications) and a second *R*-script to plot the output (Michael Seider, U.S. Fish and Wildlife Service, Ashland, Wisconsin, personal communication) (see 11.0 Appendix - R-script for MCMC Analysis).

Table 8.0. Quantities for which one million Markov chain Monte Carlo simulations were run to evaluate bias in six versions of the WI345 Lake Trout stock assessment.

Quantity & SCAA variable	Description
Negative Log Likelihood (NLL)	sum of likelihood catch, survey CPUE, & age compositions
Objective Function (Objf)	NLL + NLP
Average Total Abundance (AvgN)	average abundance age 1+ last 10 model years
Average Total Biomass (AvgtotB)	average biomass (kg) age 1+ last 10 model years
Average Biomass Age 3+ (AvgB3)	average biomass (kg) age 3+ last 10 model years
Average Spawning Biomass (AvgB)	average spawning biomass (kg) last 10 model years
Average Total Mortality Rate (AvgZ)	average ***Z*** age 6+ last 3 model years
Average Fishing Rate (AvgF)	average ***F*** age 6+ last 3 model years
Average Commercial Fishing Rate (AvgF_C)	average ***F*** age 6+ commercial fishery last 3 model years
Average Recreational Fishing Rate (AvgF_R)	average ***F*** age 6+ recreational fishery last 3 model years

To put the MCMC simulations in perspective, we created a subjective scoring of the output to rank versions of the WI345 stock assessment. Plots of the quantities were ranked as 1 for poor, 2 for average, and 3 for good. The scores for each quantity were then summed for each version of the stock assessment. The characteristics for each of the ranking scores are given below.

Score	Trace Plot	Posterior Distribution	Autocorrelation
1	pattern, sticky, uneven	skewed, multiple maximum	decline to 50% or more
2	some pattern, some stickiness, uneven	small skew, single maximum	decline to 10-50%
3	no pattern, not sticky, even	no skew, single maximum	decline to <10%

Trace plots were, for the most part, without sizable trends but did exhibit some stickiness in all versions of the WI345 stock assessment (Figures 8.1 to 8.11). Objective function trace plots were nearly always bad and scored only 9 of 18 possible points, whereas trace plots for ***Z*** were nearly always good scoring 15 out of 18 points (Table 8.1). Trace plots for total abundance (13 points) and total biomass (14 points) were generally good and scored higher for all the last three versions than for the first three versions.

Likelihood profiles from all versions were generally normally shaped with a single peak but typically they were skewed to the right, or bumpy on the descending limb, or both. The Objf likelihoods were always poorly shaped and scored only 10 of 18 points, whereas total population biomass scored 15 of 18 points. Average total abundance and ***Z*** each ranked 13 of 18 points.

Auto-correlation plots did decline with lag and were generally 10% or less at the final log (Figures 8.2 to 18.12). The Objf scored only 9 of 18 points, whereas all population demographic quantities scored between 14 and 16 of 18 possible points. Auto-correlation did decline substantially from the 02-20-20 version to the 01-02-21 version (Table 8.1).

Overall, the 09-21-20 and 01-02-21 versions ranked the highest based on our scoring system, accumulating 78 out of 90 possible points. The 02-20-20 version ranked the lowest scoring 49 of 90 points. The 09-21-20, 11-16-20, and 01-02-20 versions all ranked substantially higher than the first three versions of the WI345 stock assessment. The sum of the trace plots, likelihood profiles, and auto-correlation scores for the last three versions of the stock assessment all improved by 16 to 20 points from the 04-02-20 version.

Table 8.1. Rankings of the MCMC trace plots (trace), posterior distributions (den.), and auto-correlation (corr.) for six versions of the WI345 Lake Trout stock assessments.

WI345	MCMC	Population quantity										
version	plot	Objf	NLL	AvgN	AvgtotB	AvgB3	AvgSSB	F_R	F_C	AvgF	AvgZ	Total
02-20-20	trace	1	1	1	1	1	1	2	2	2	2	14
	dens.	1	2	2	2	2	1	2	1	2	2	17
	corr.	1	2	1	2	2	2	2	2	2	2	18
03-09-20	trace	1	1	1	2	2	2	2	2	2	2	17
	dens.	1	3	1	2	2	2	1	2	1	2	17
	corr.	1	2	2	2	2	2	2	2	2	2	19
04-02-20	trace	1	2	2	2	2	2	2	1	1	2	17
	dens.	2	3	2	2	2	2	1	2	2	2	20
	corr.	1	2	2	2	2	2	2	3	3	2	21
09-21-20	trace	2	2	3	3	3	3	3	3	3	3	28
	dens.	2	2	2	3	2	3	2	2	2	2	22
	corr.	2	2	3	3	3	3	3	3	3	3	28
11-16-20	trace	2	2	3	3	3	3	2	2	2	3	25
	dens.	2	2	3	3	2	2	2	1	2	2	21
	corr.	2	2	3	3	3	3	3	3	3	3	28
01-02-21	trace	2	3	3	3	3	3	2	3	2	3	27
	dens.	2	2	3	3	2	2	2	2	2	3	23
	corr.	2	2	3	3	3	3	3	3	3	3	28

Figure 8.1. Trace plots and posterior distributions WI345-02-20-20.

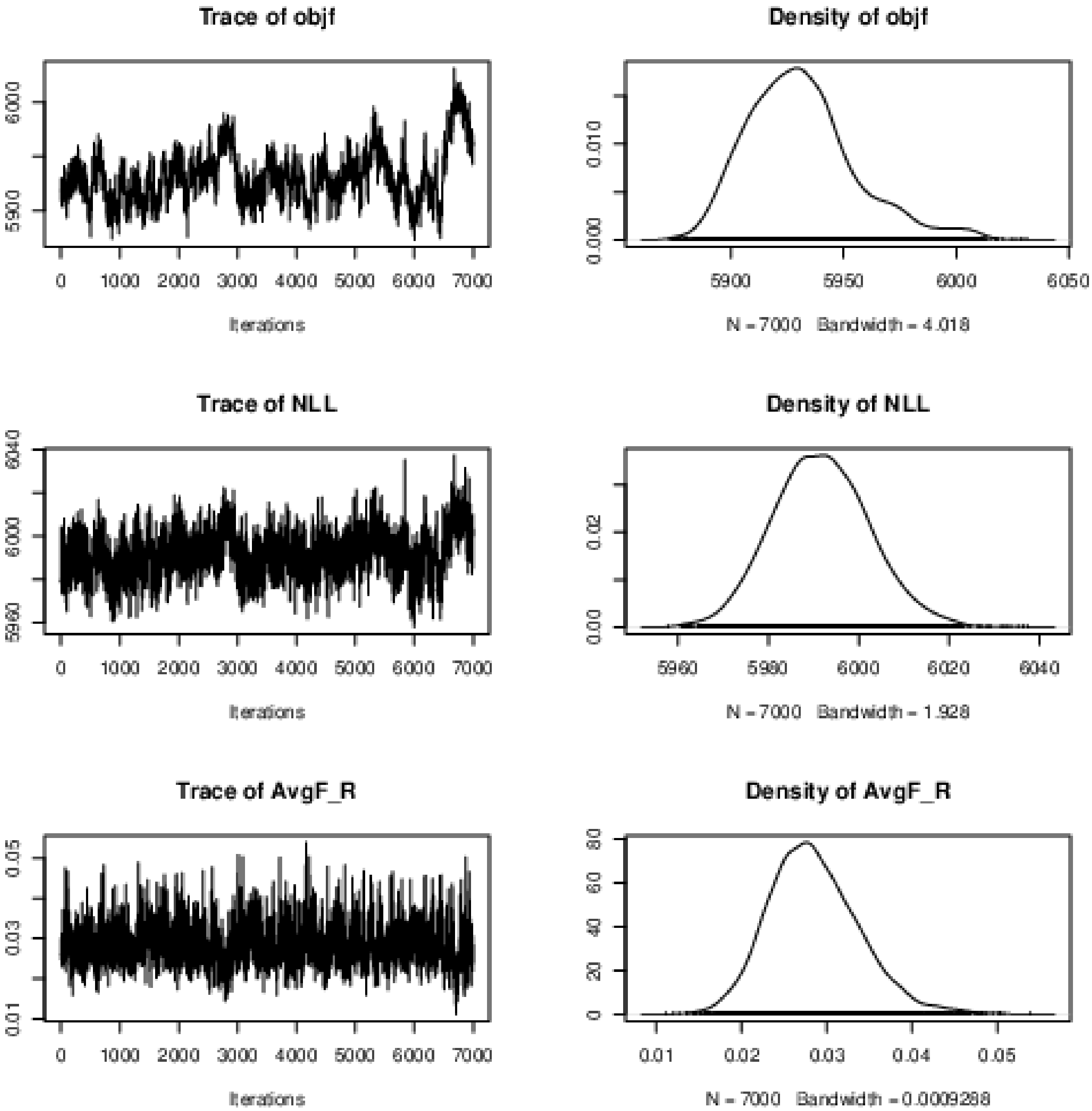


Figure 8.1 cont'd.

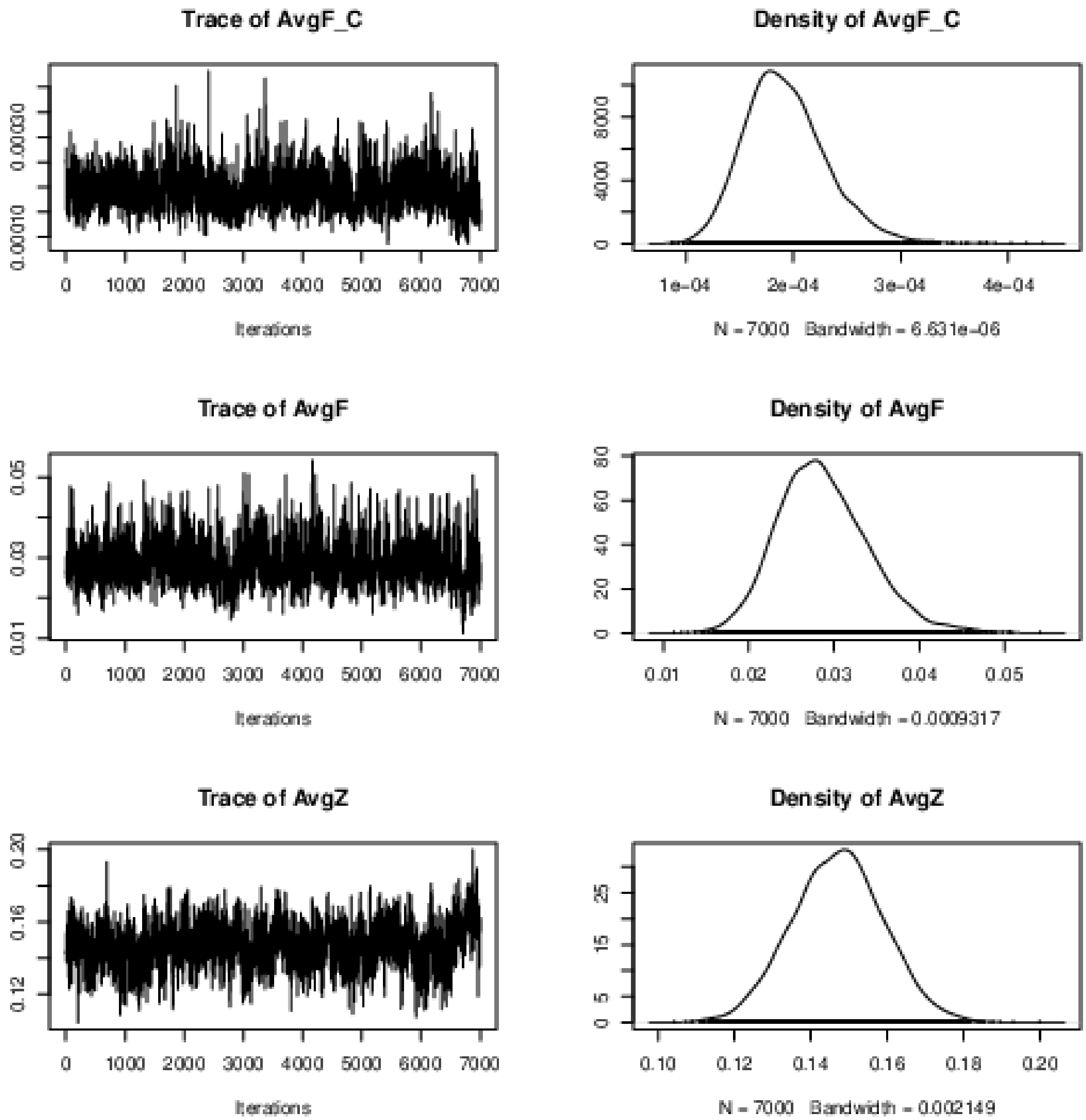


Figure 8.1 cont'd.

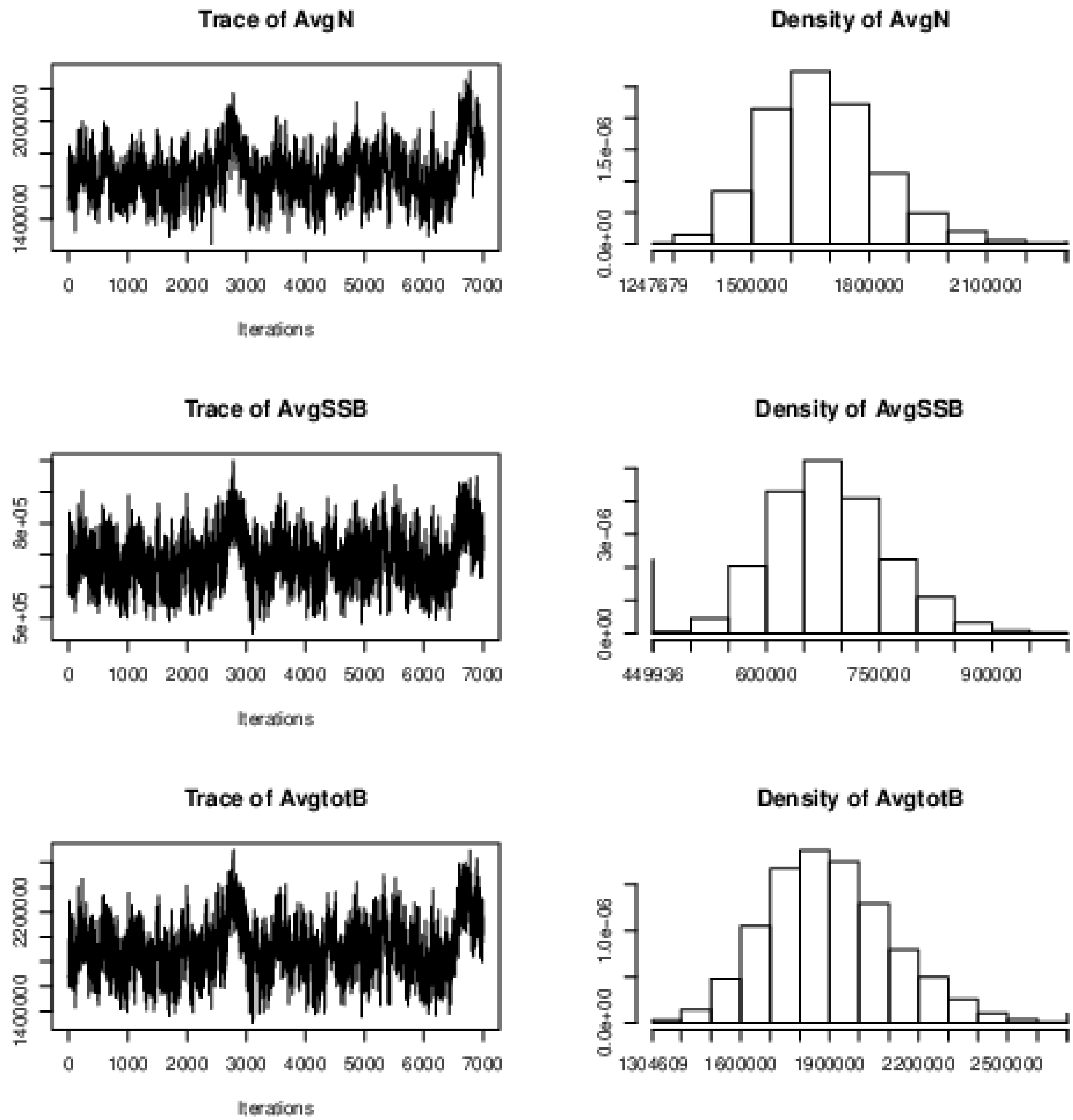
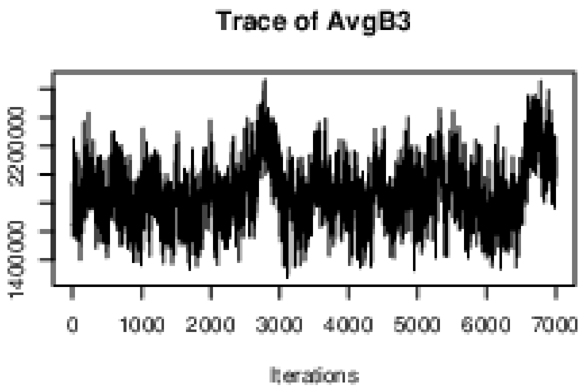
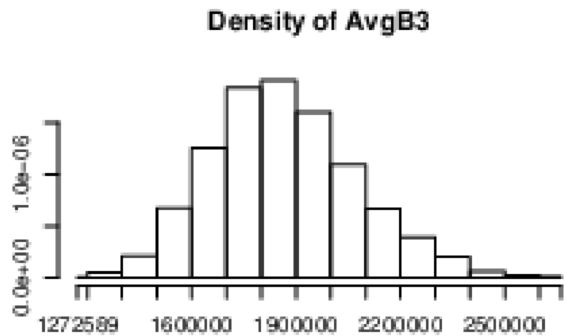


Figure 8.1 cont'd.





8.2 MCMC auto-correlations WI345-02-20-20.

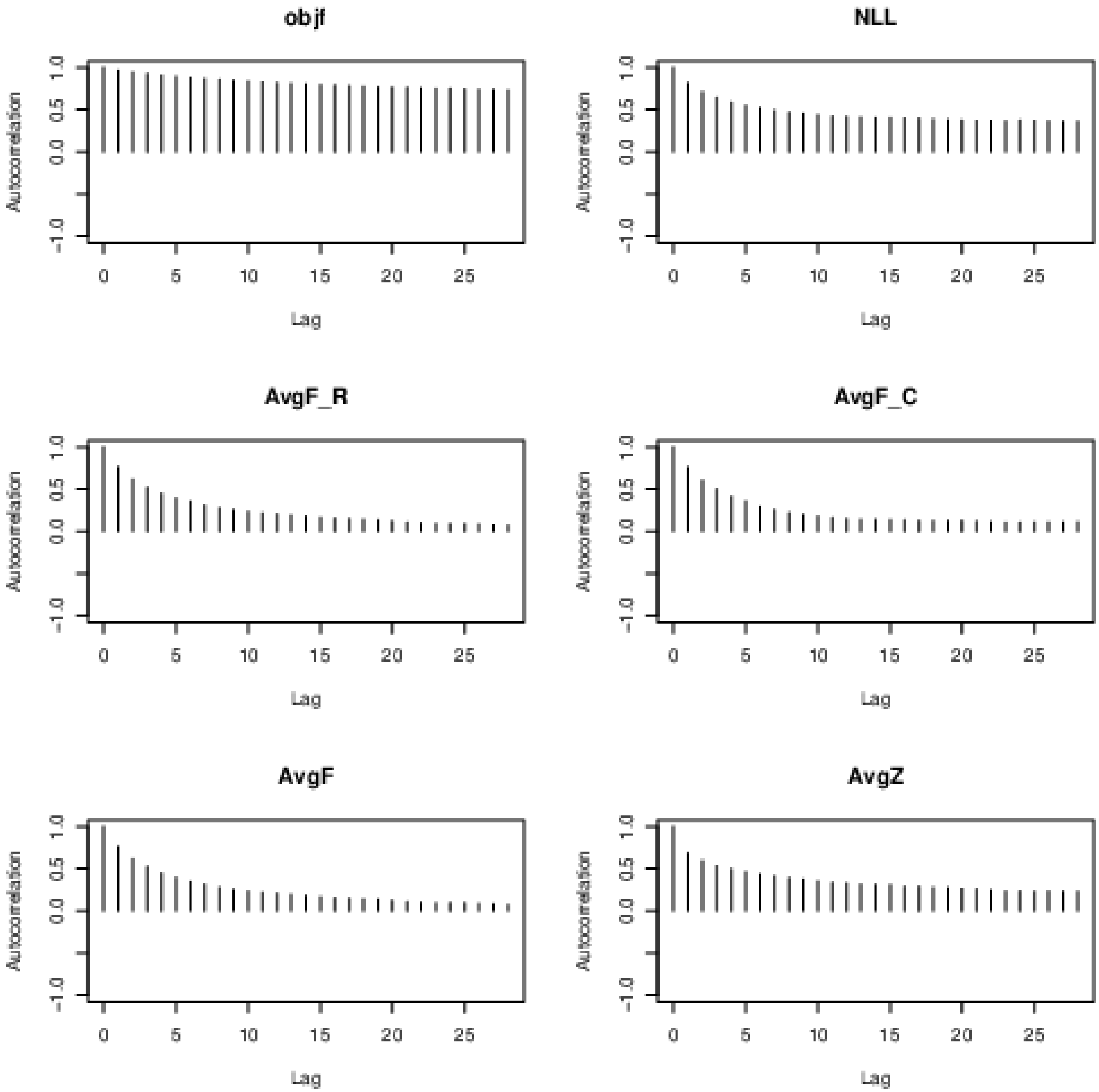
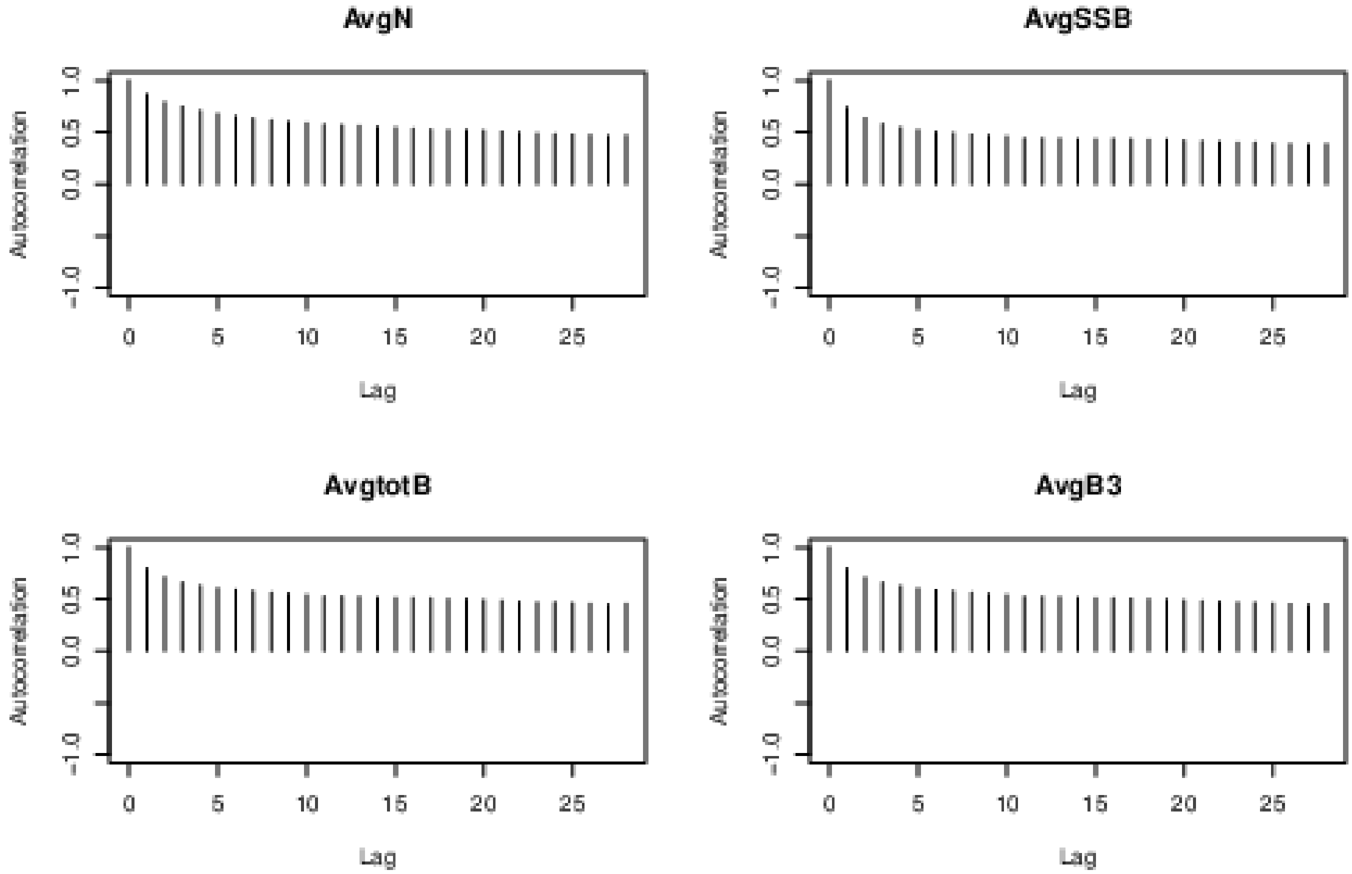


Figure 8.2 cont'd.



8.3. MCMC trace plots and posterior distributions WI345-03-09-20.

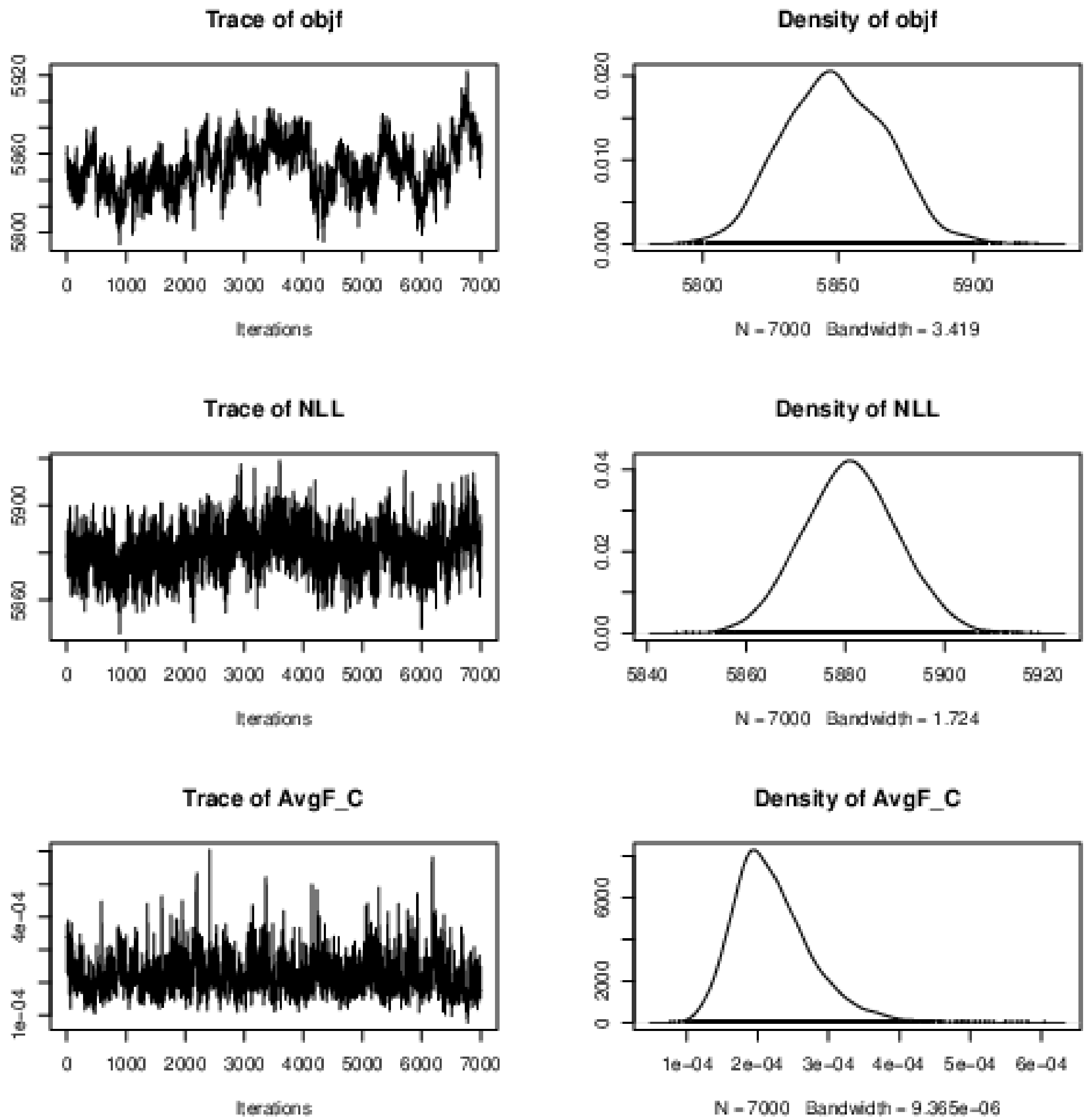


Figure 8.3 cont'd.

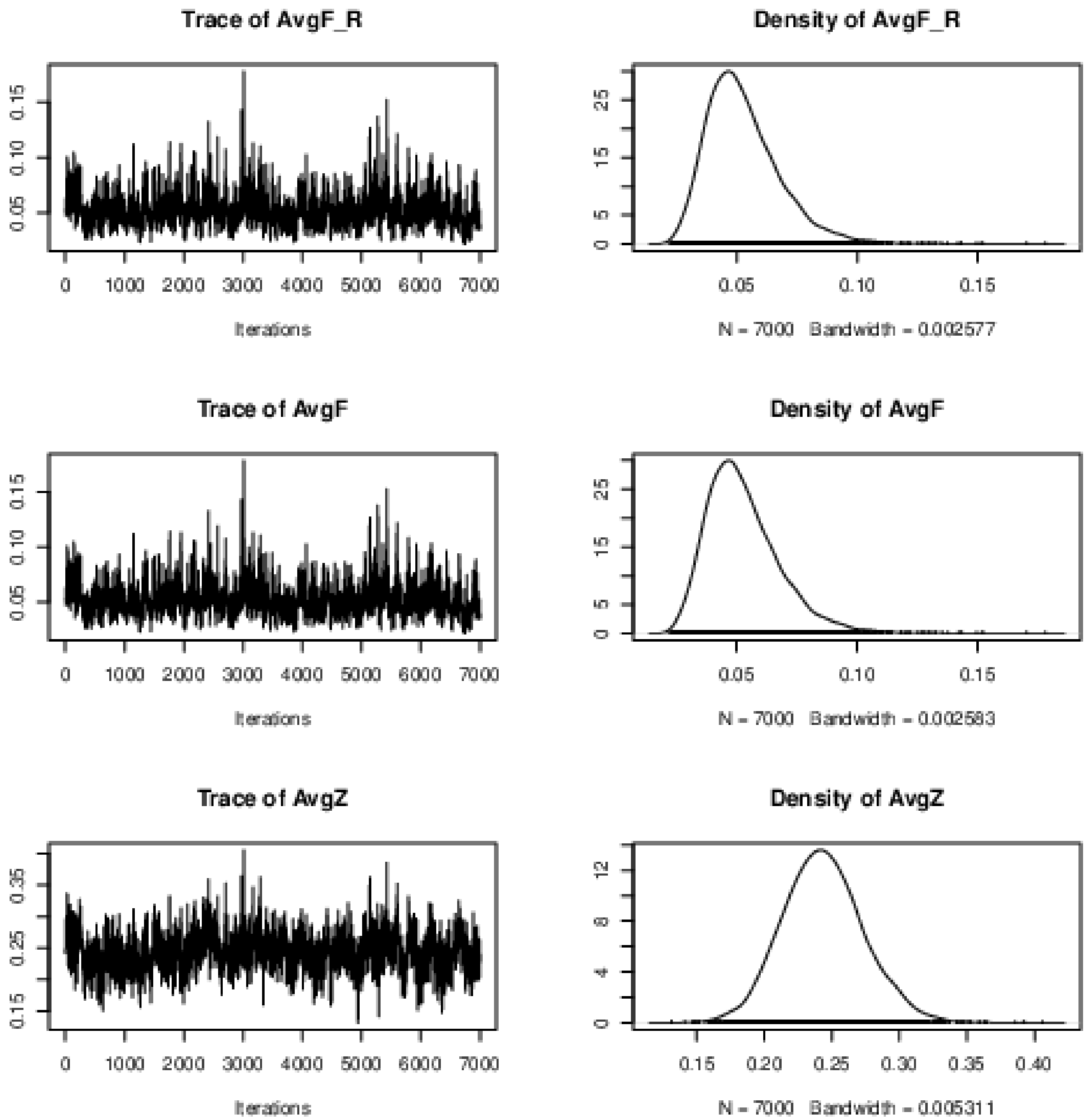
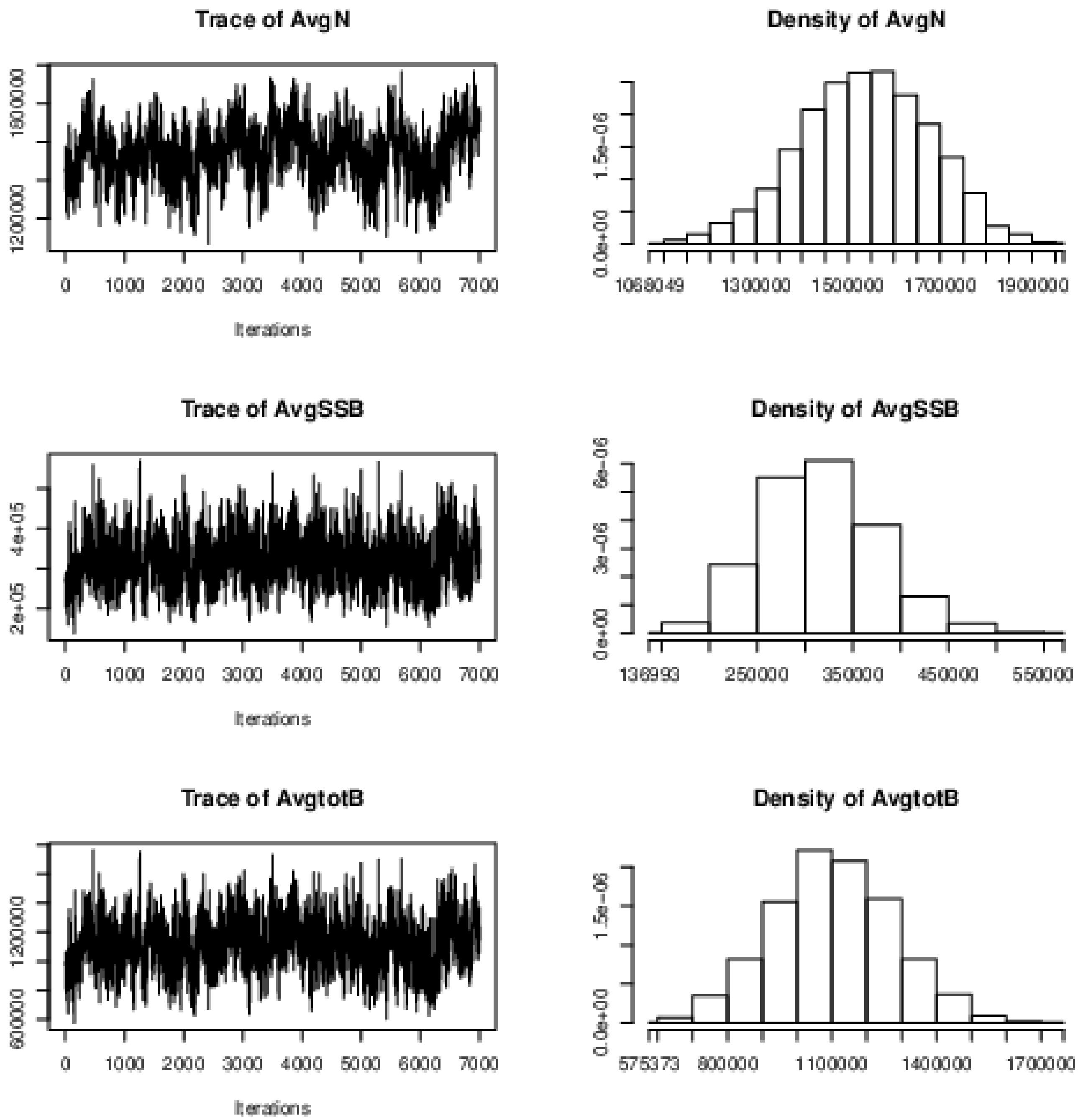


Figure 8.3 cont'd.



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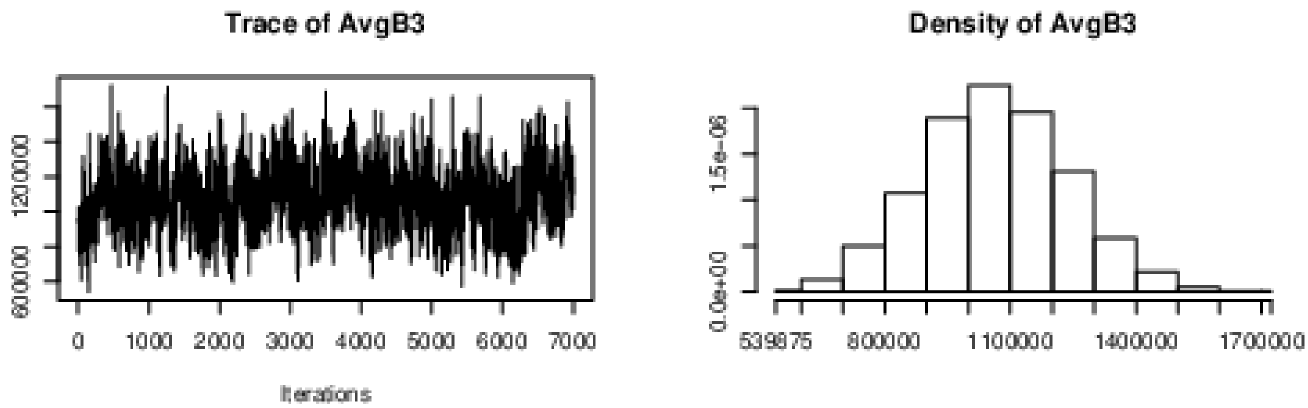


8.4. MCMC auto-correlations WI345-03-09-20.

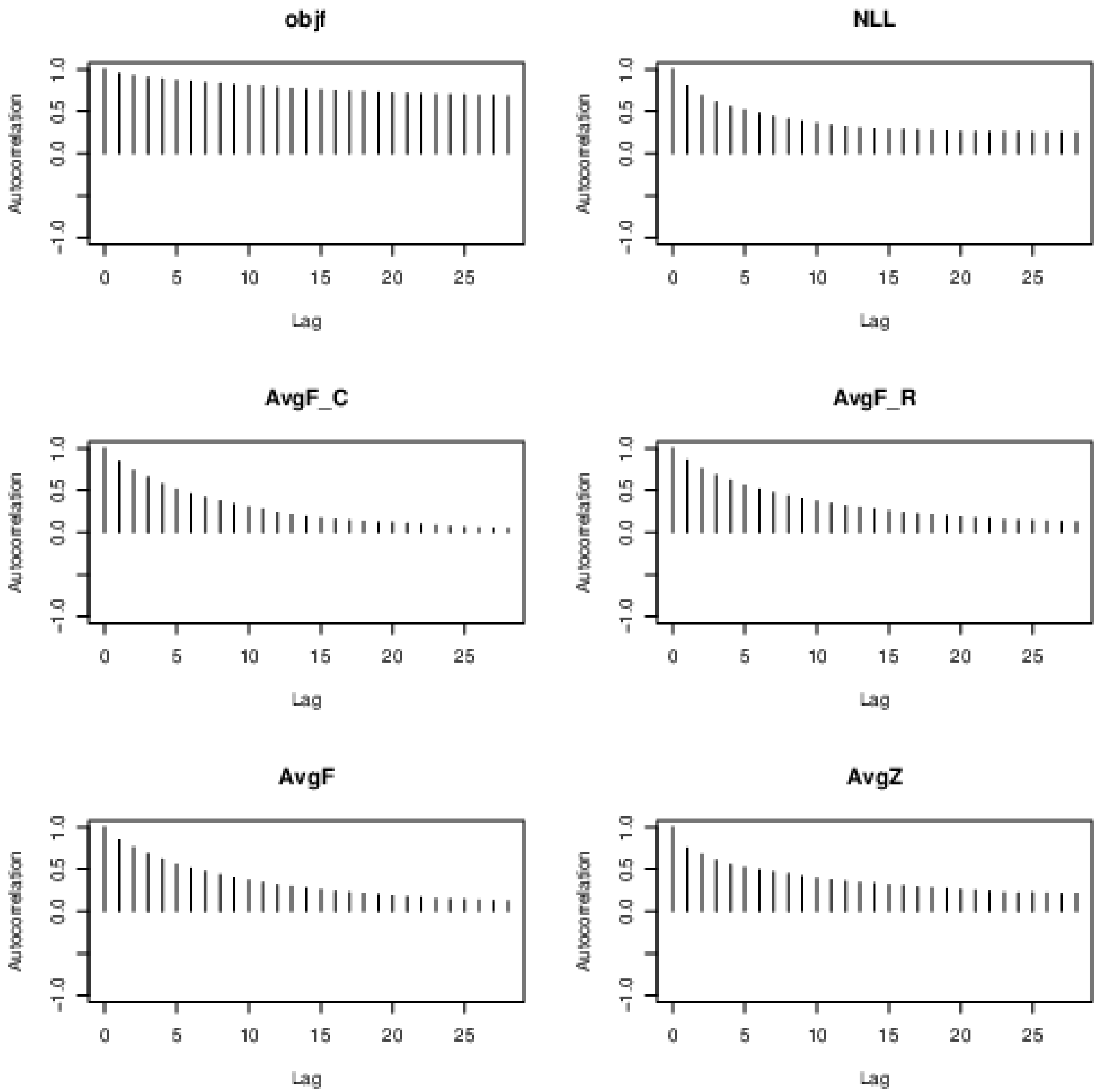
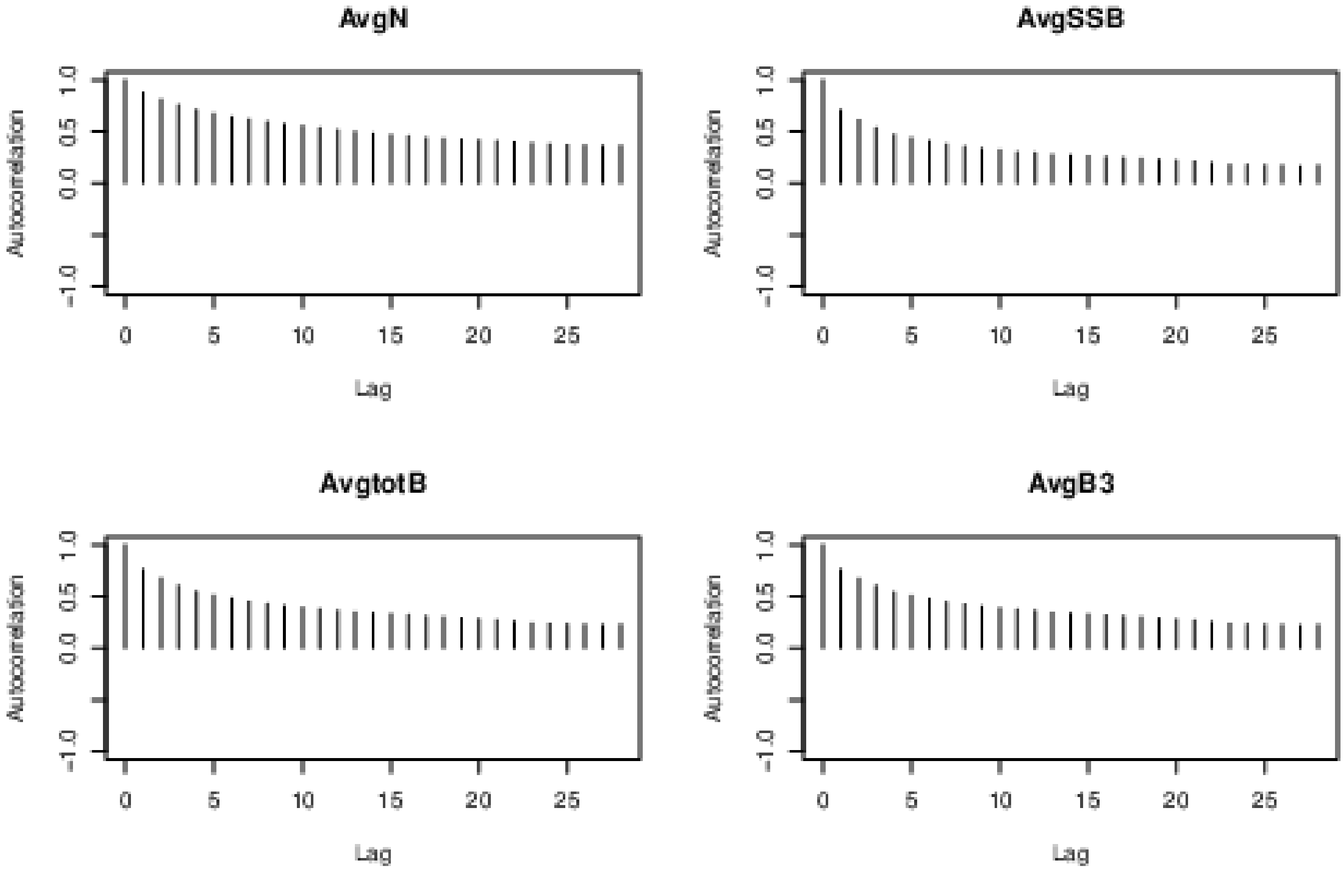


Figure 8.4 cont'd.



8.5 MCMC trace plots and posterior distributions WI345-04-02-20.

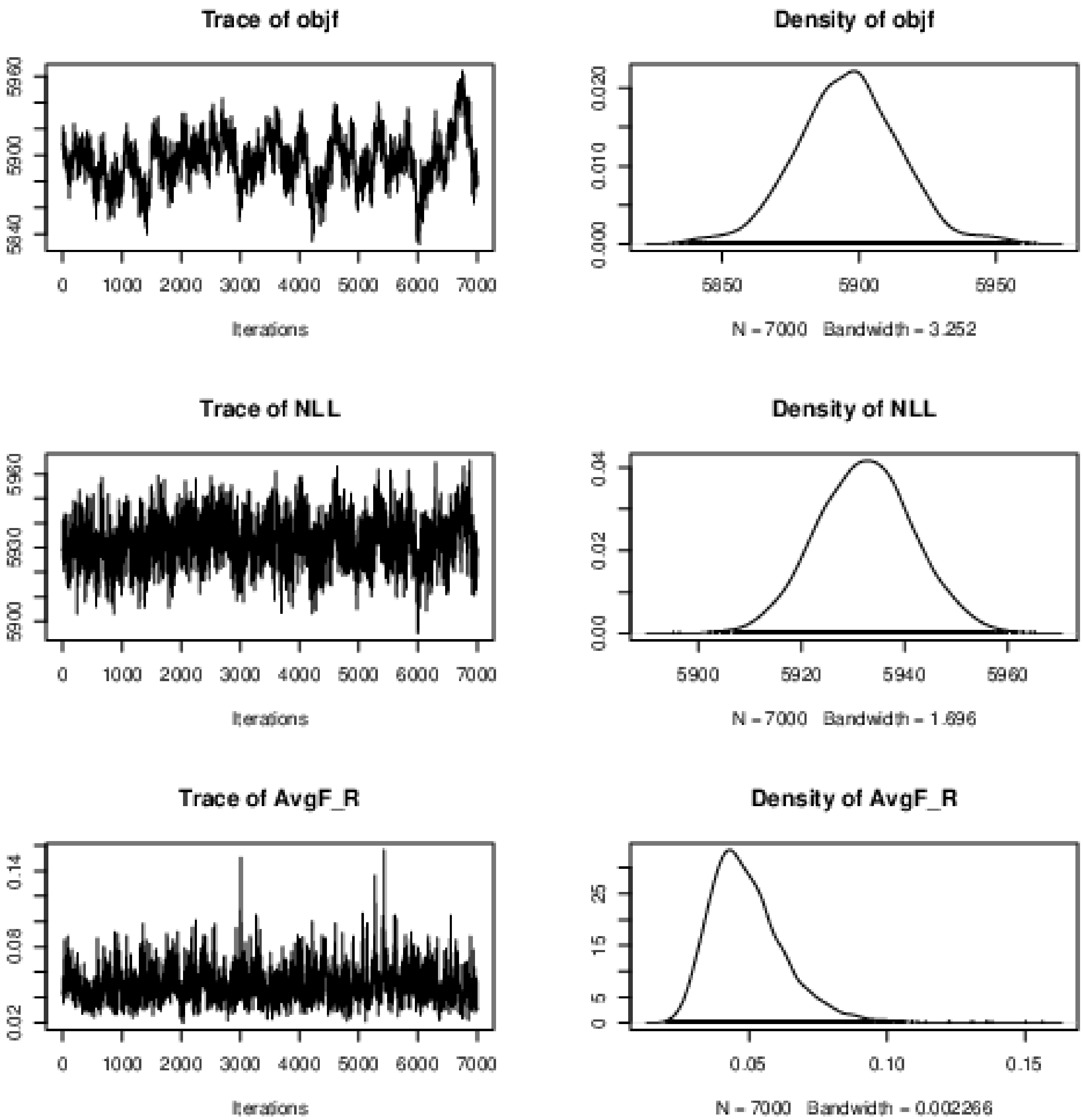


Figure 8.5 cont'd.

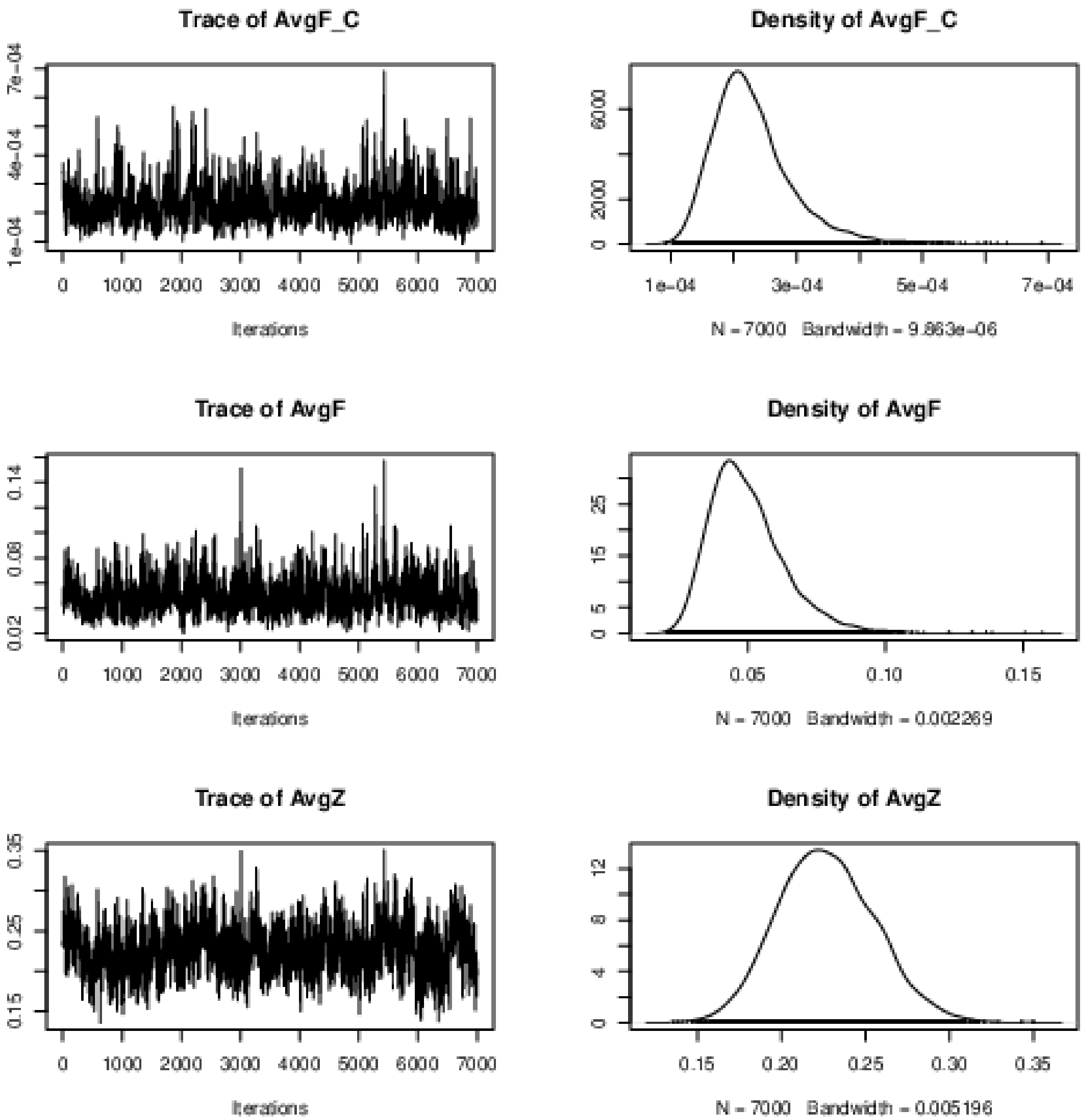


Figure 8.5 cont'd.

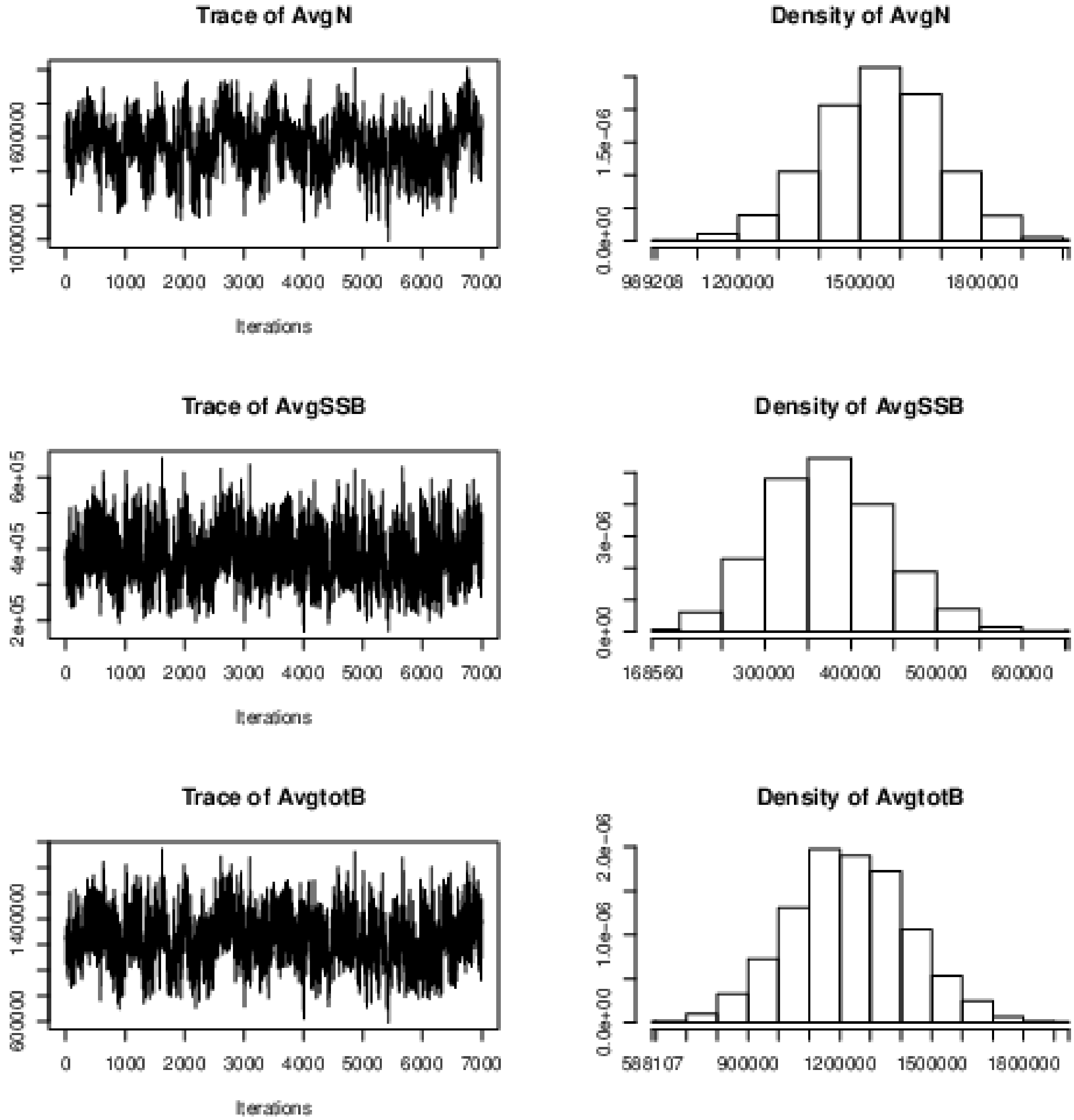
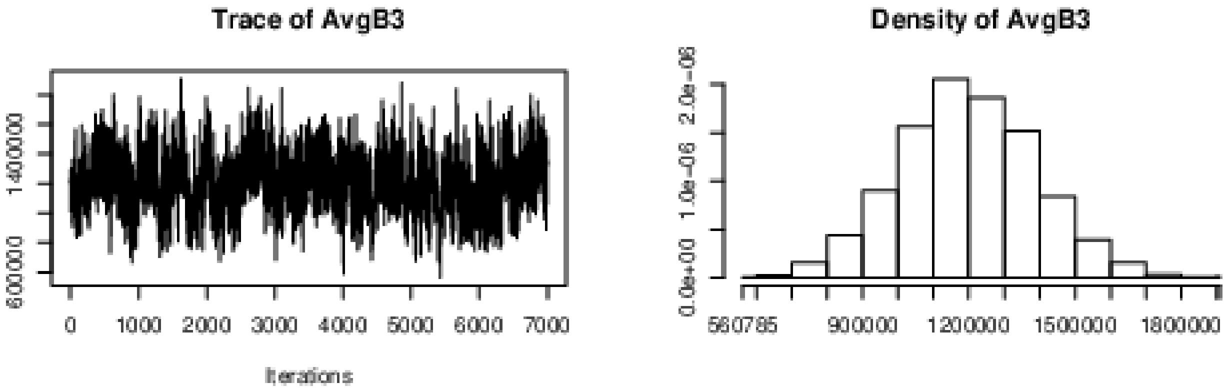


Figure 8.5 cont'd.



8.6 MCMC auto-correlations WI345-04-02-20.

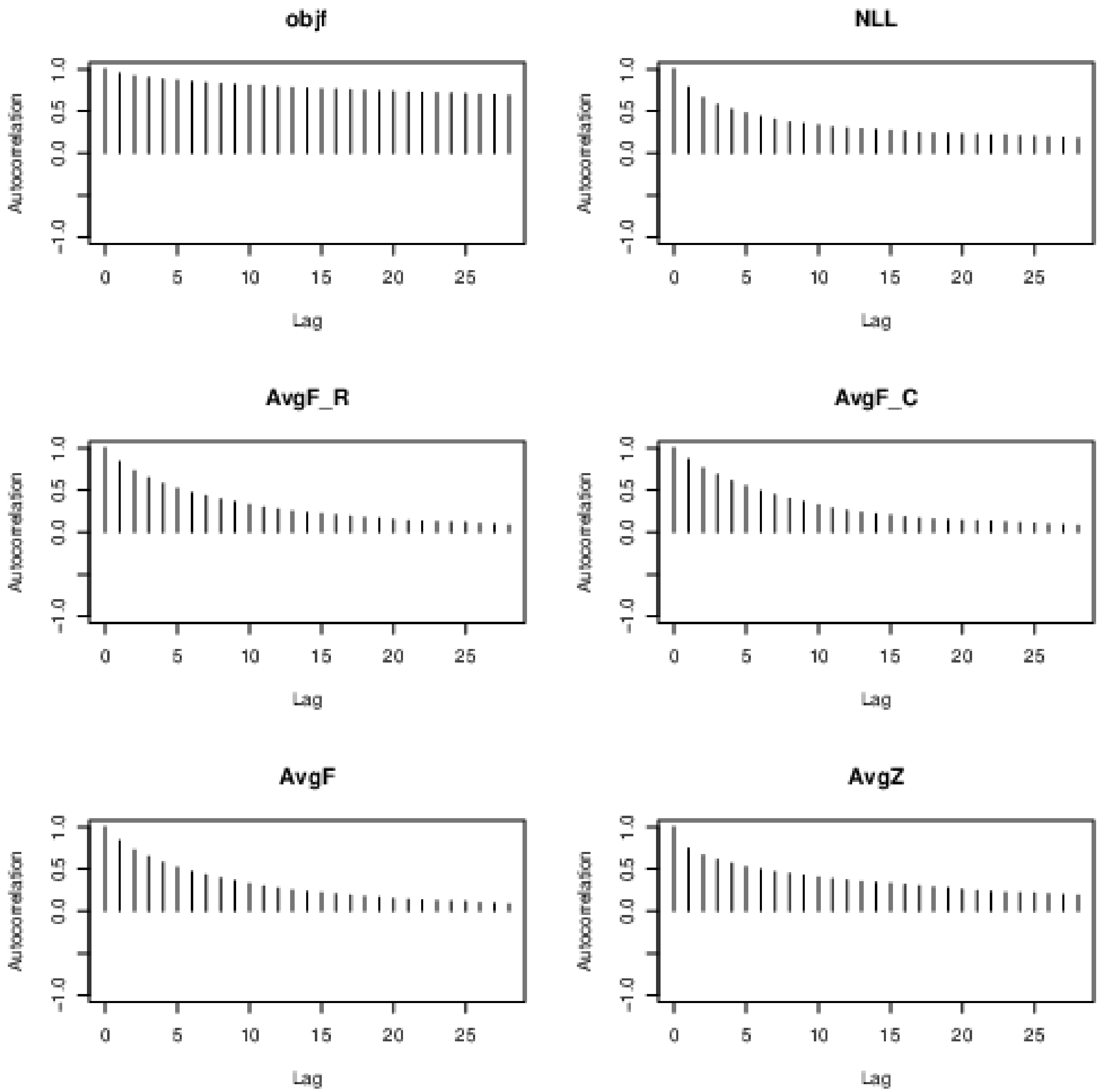
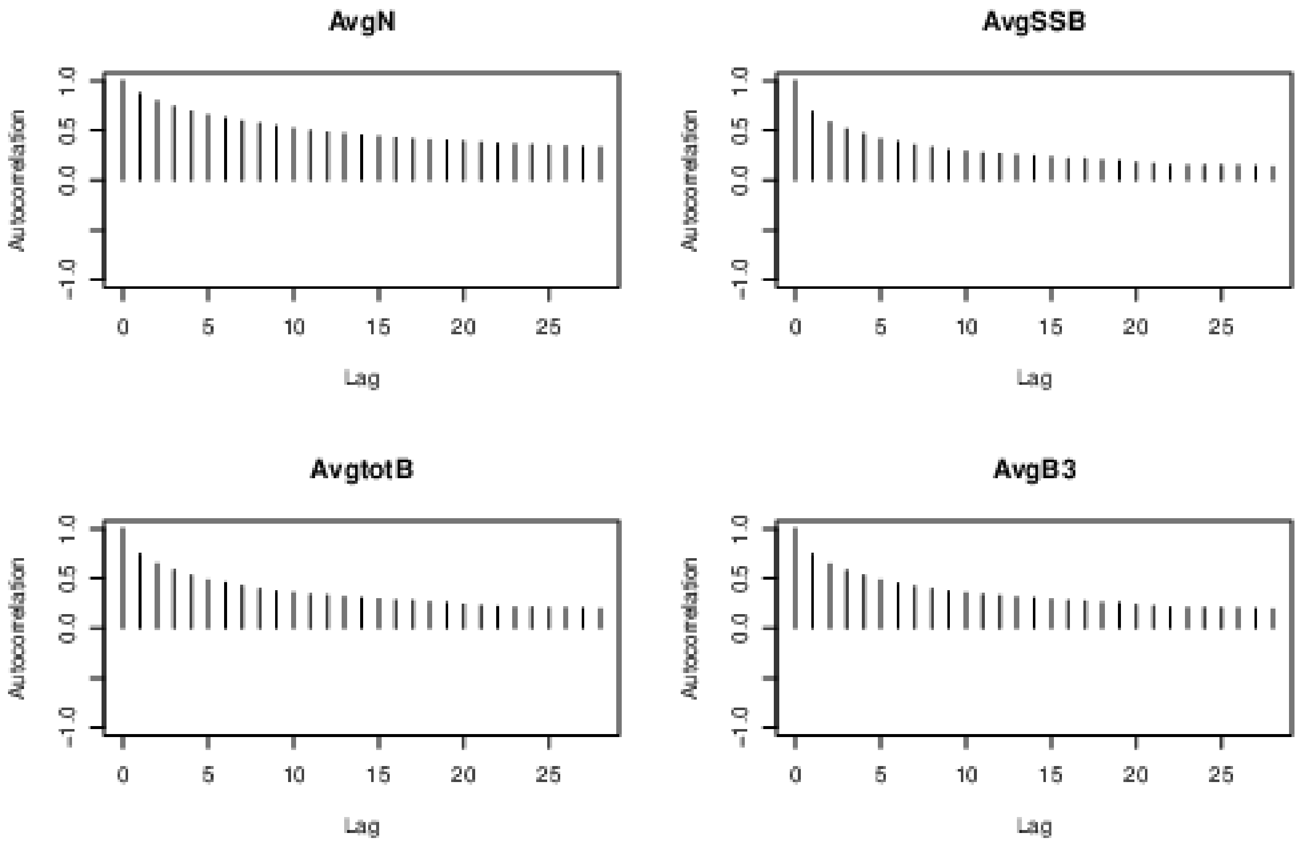


Figure 8.6 cont'd.



8.7 MCMC Trace plots and posterior distributions WI345-09-21-20.

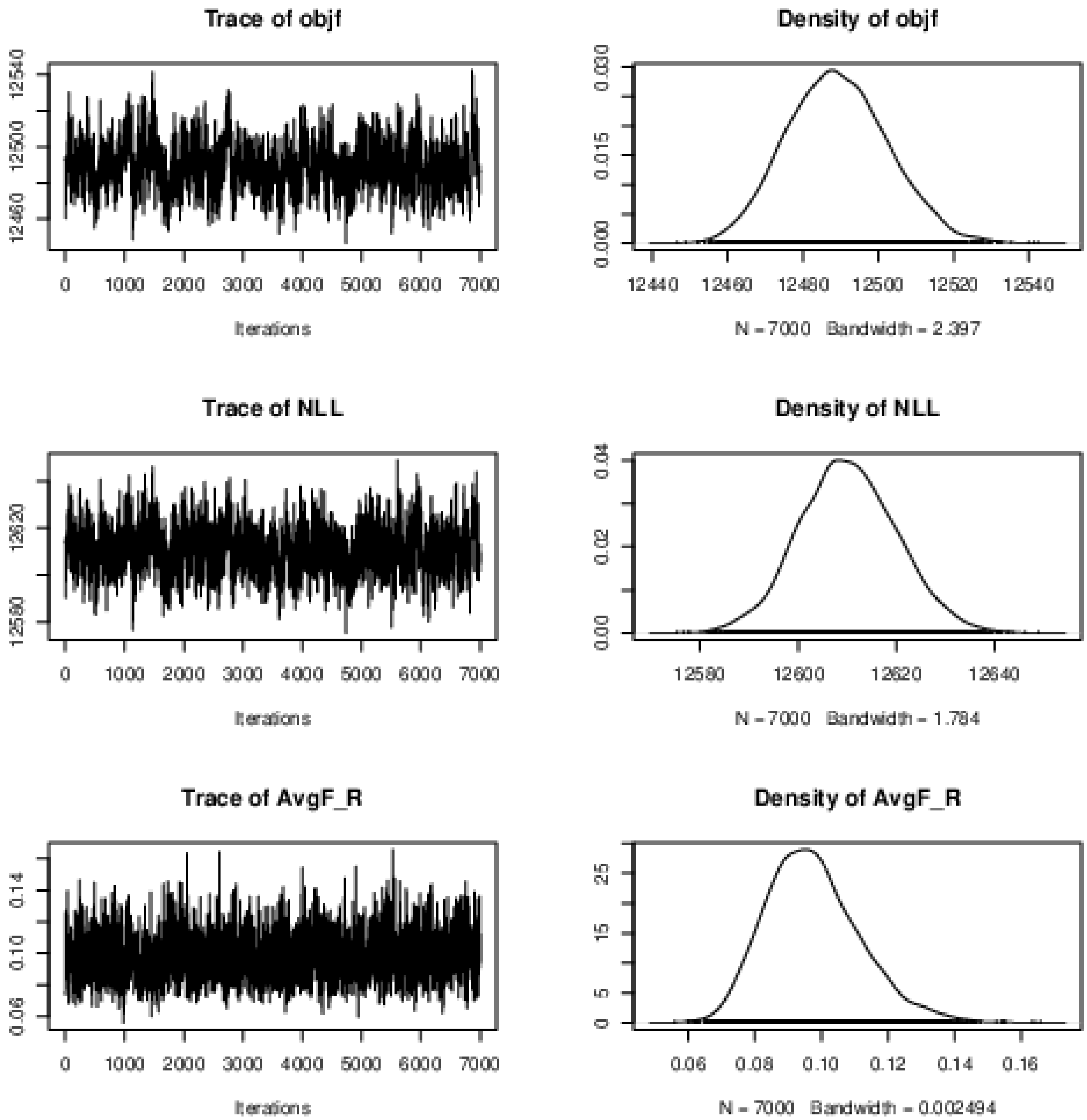


Figure 8.7 cont'd.

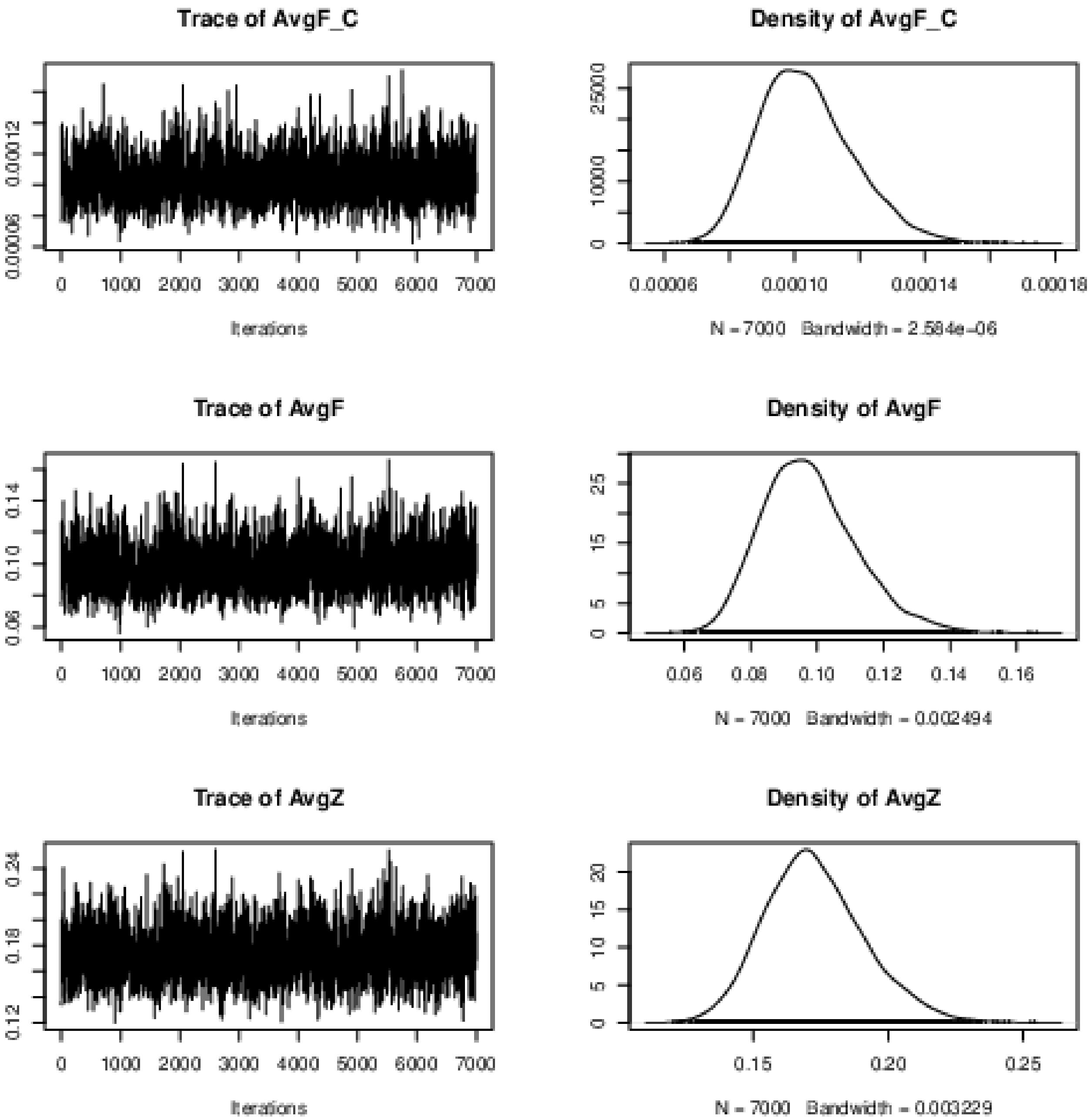


Figure 8.7 cont'd.

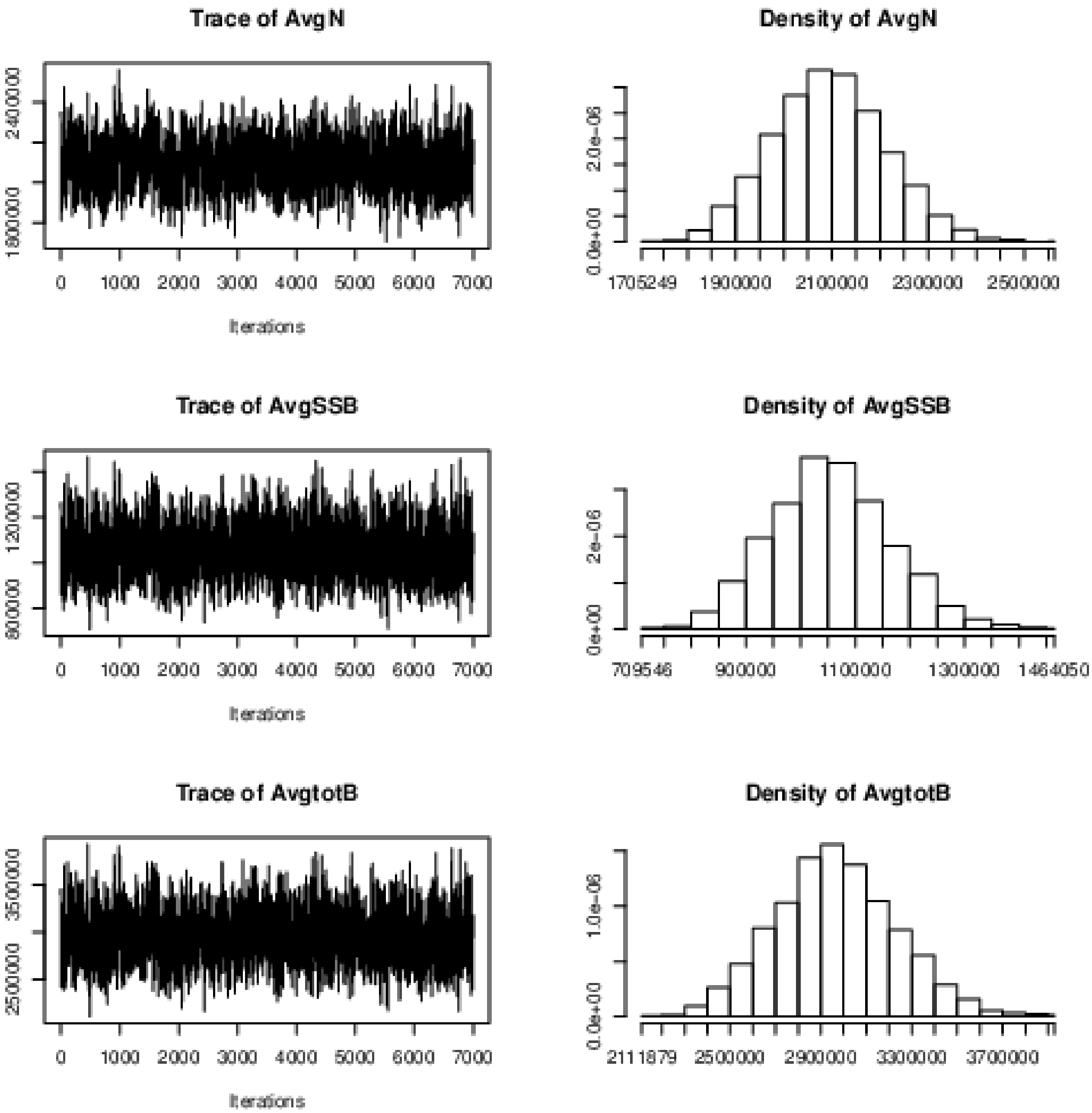
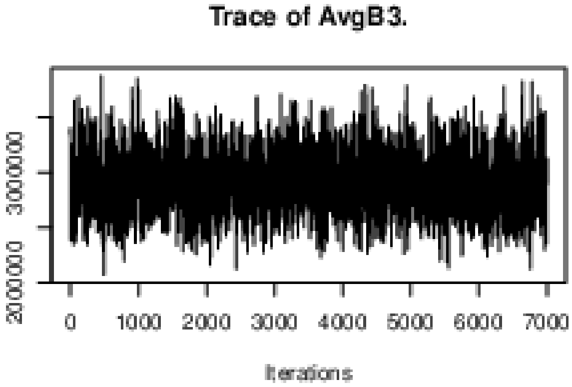


Figure 8.7 cont'd.



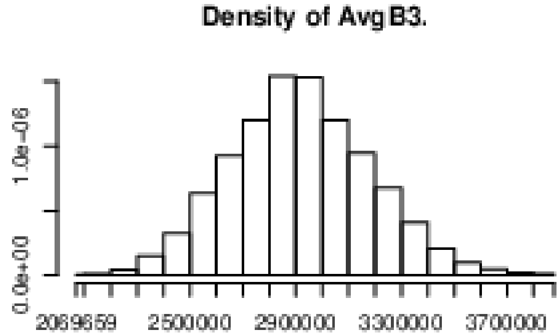


Figure 8.8. MCMC auto-correlations WI345-09-21-20.

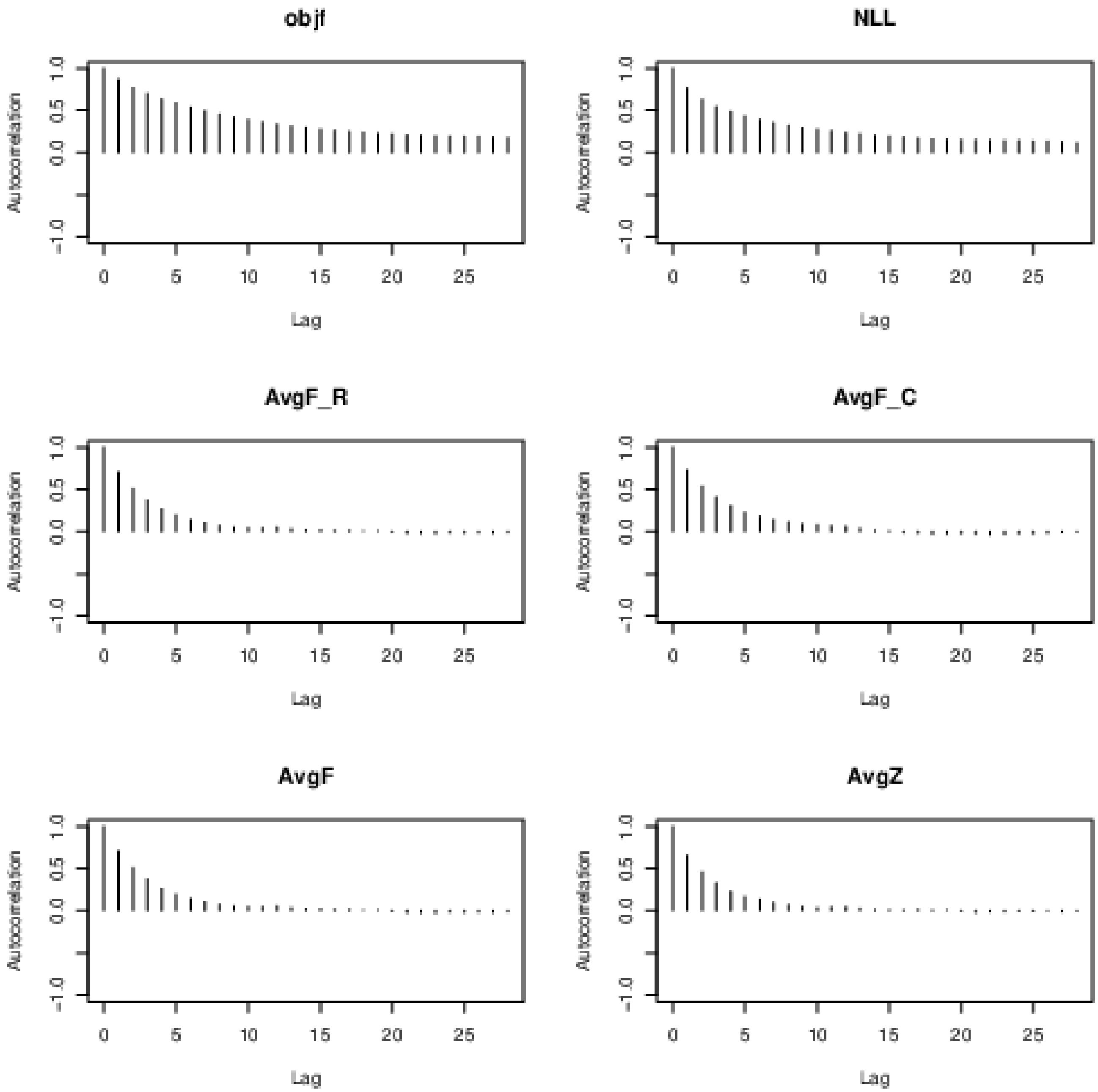


Figure 8.8 cont'd.

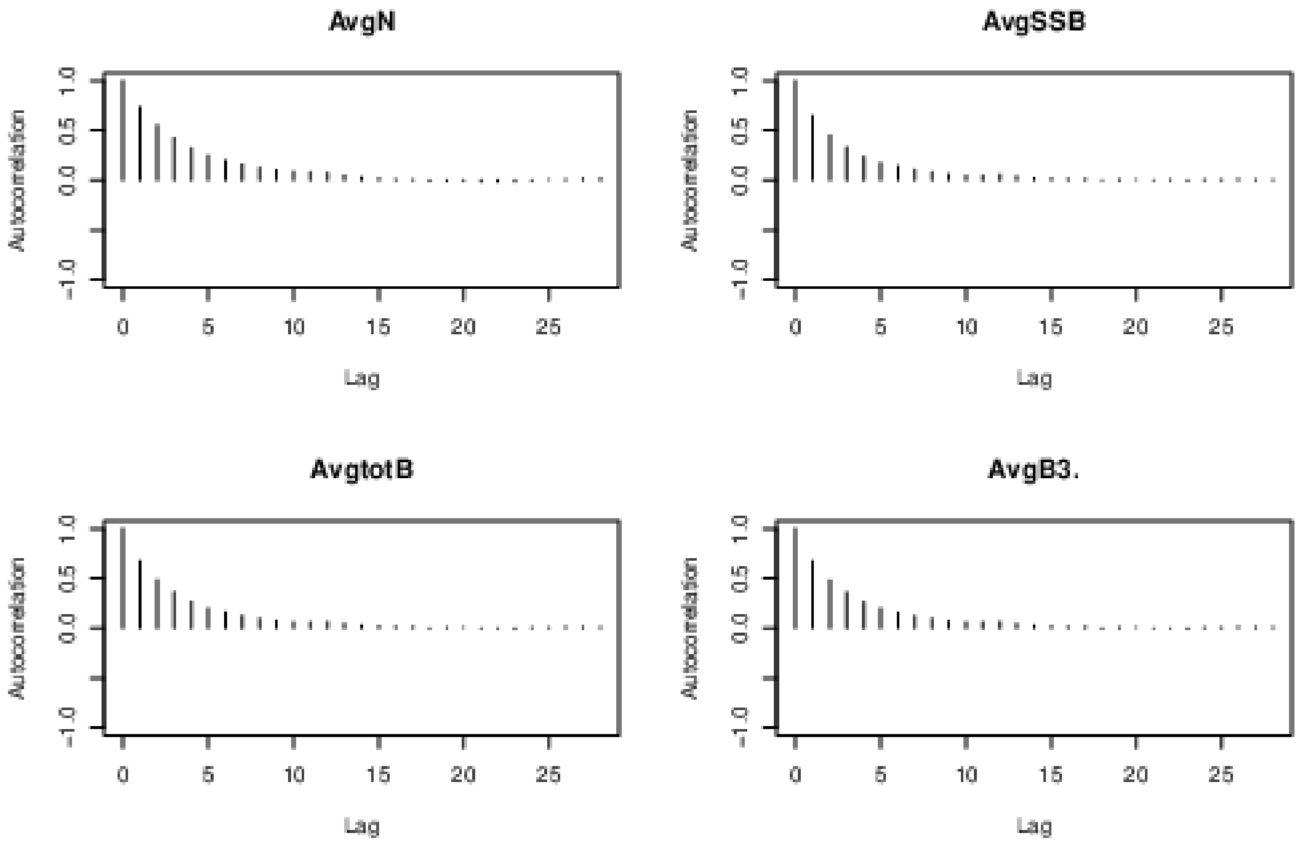


Figure 8.9. MCMC trace plots and posterior distributions WI345-11-06-20.

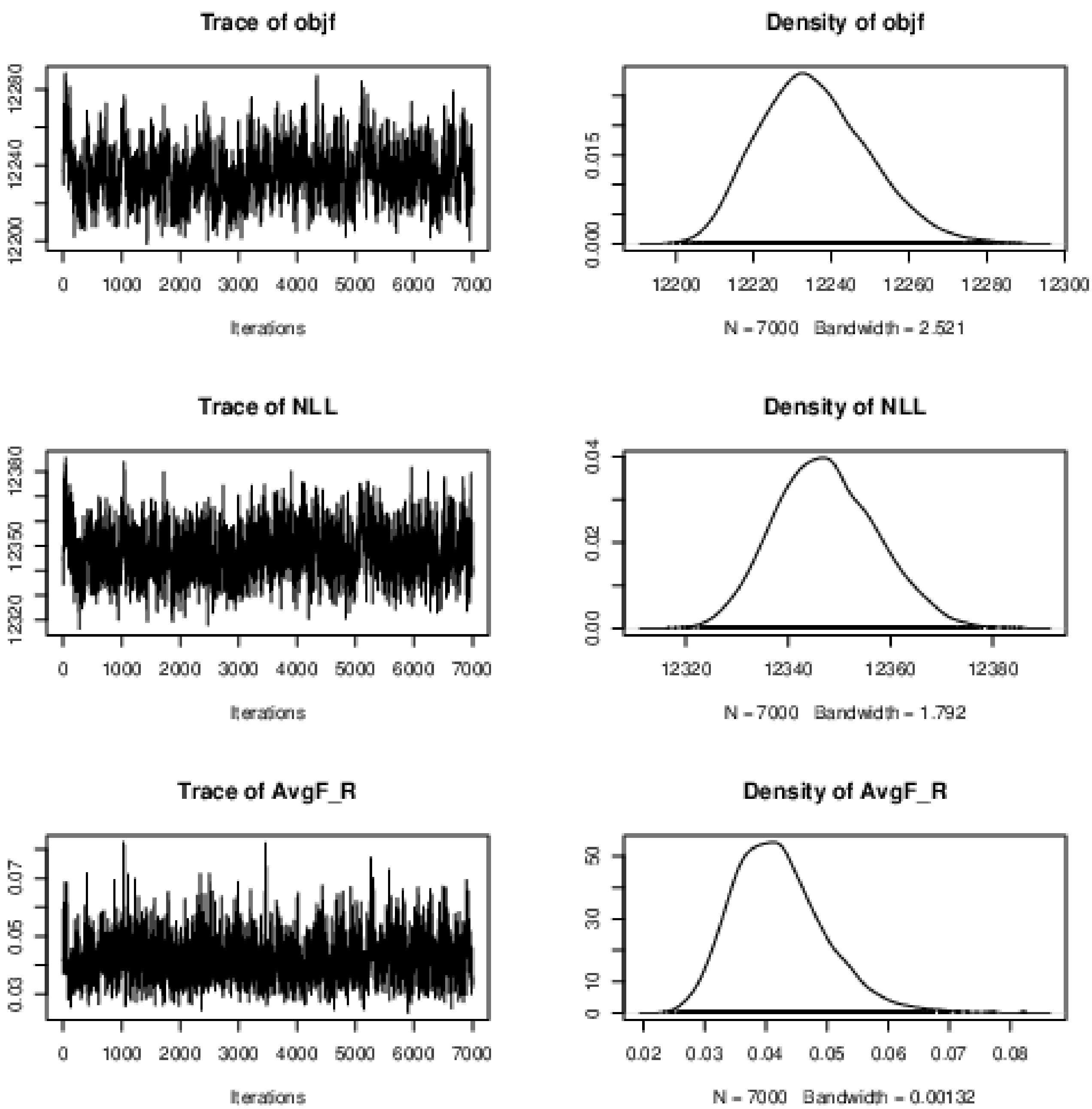


Figure 8.9 cont'd.

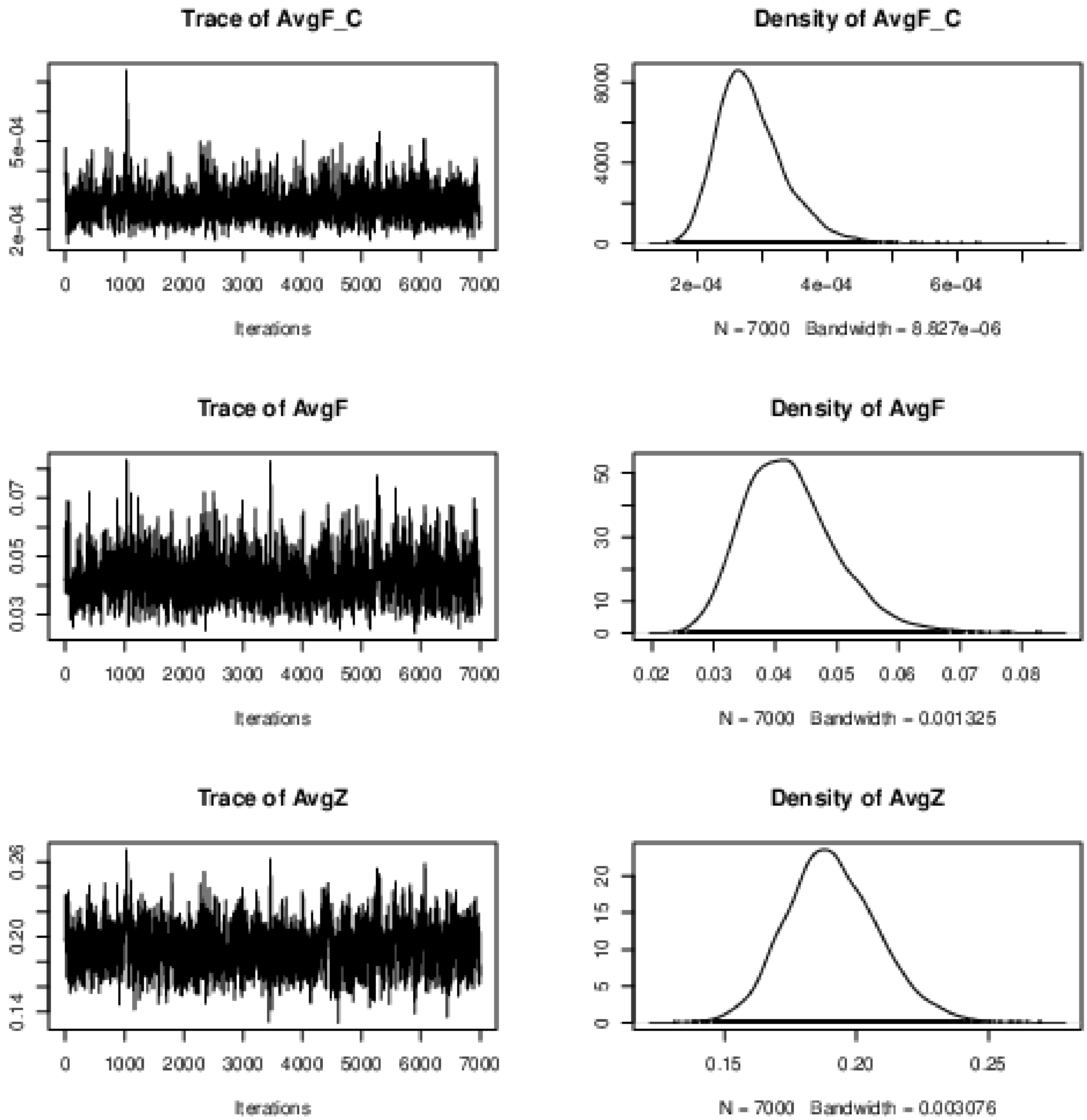


Figure 8.9 cont'd.

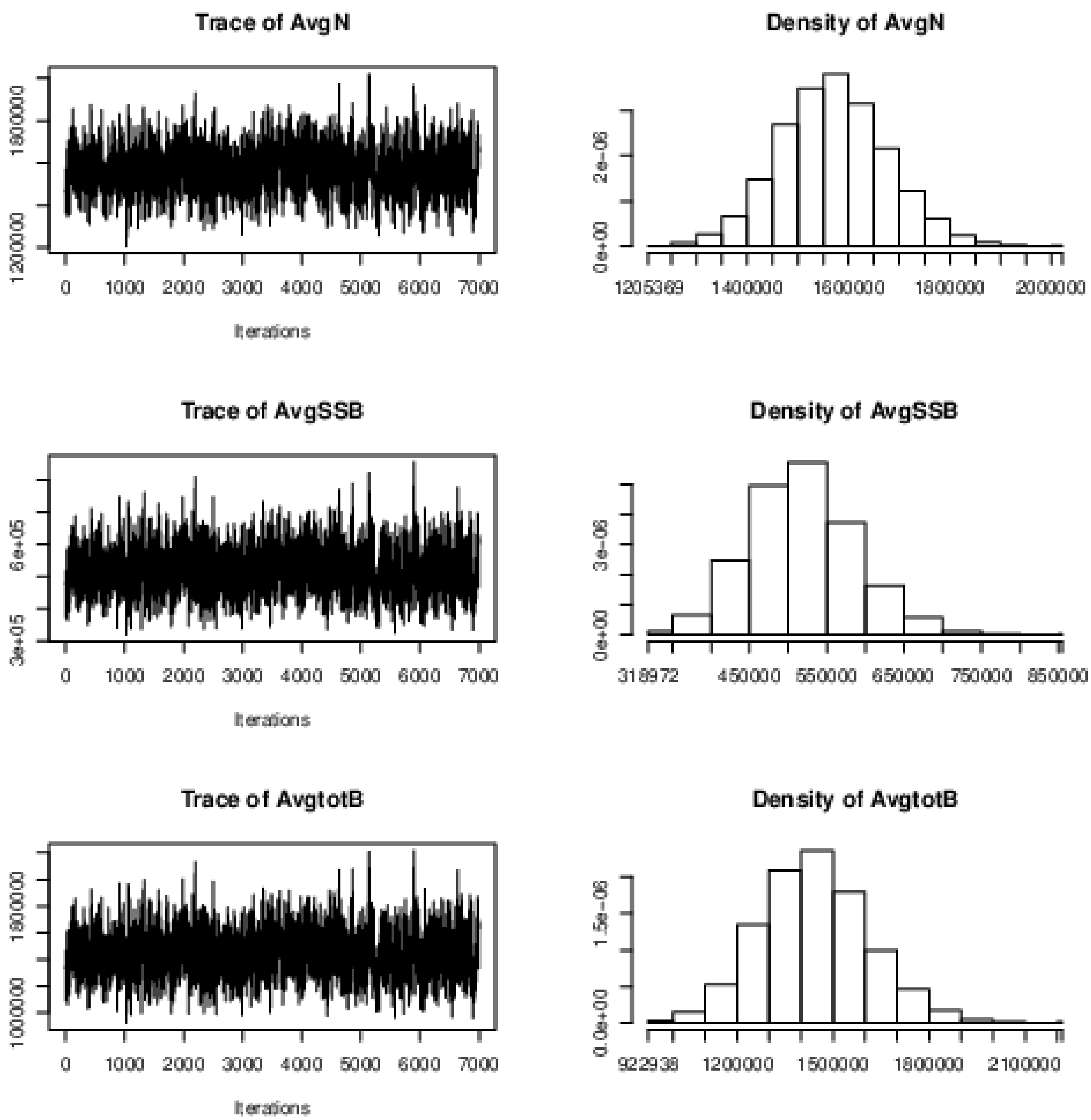
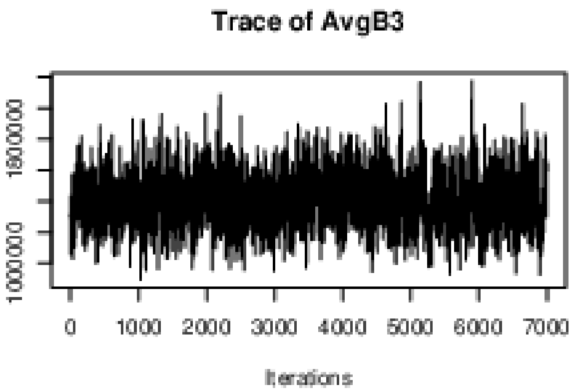
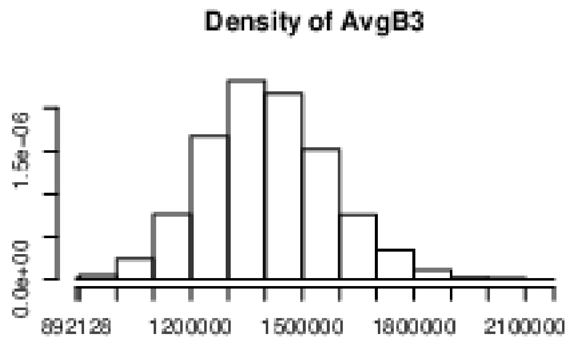


Figure 8.9 cont'd.





8.10. MCMC auto-correlations WI345-11-06-20.

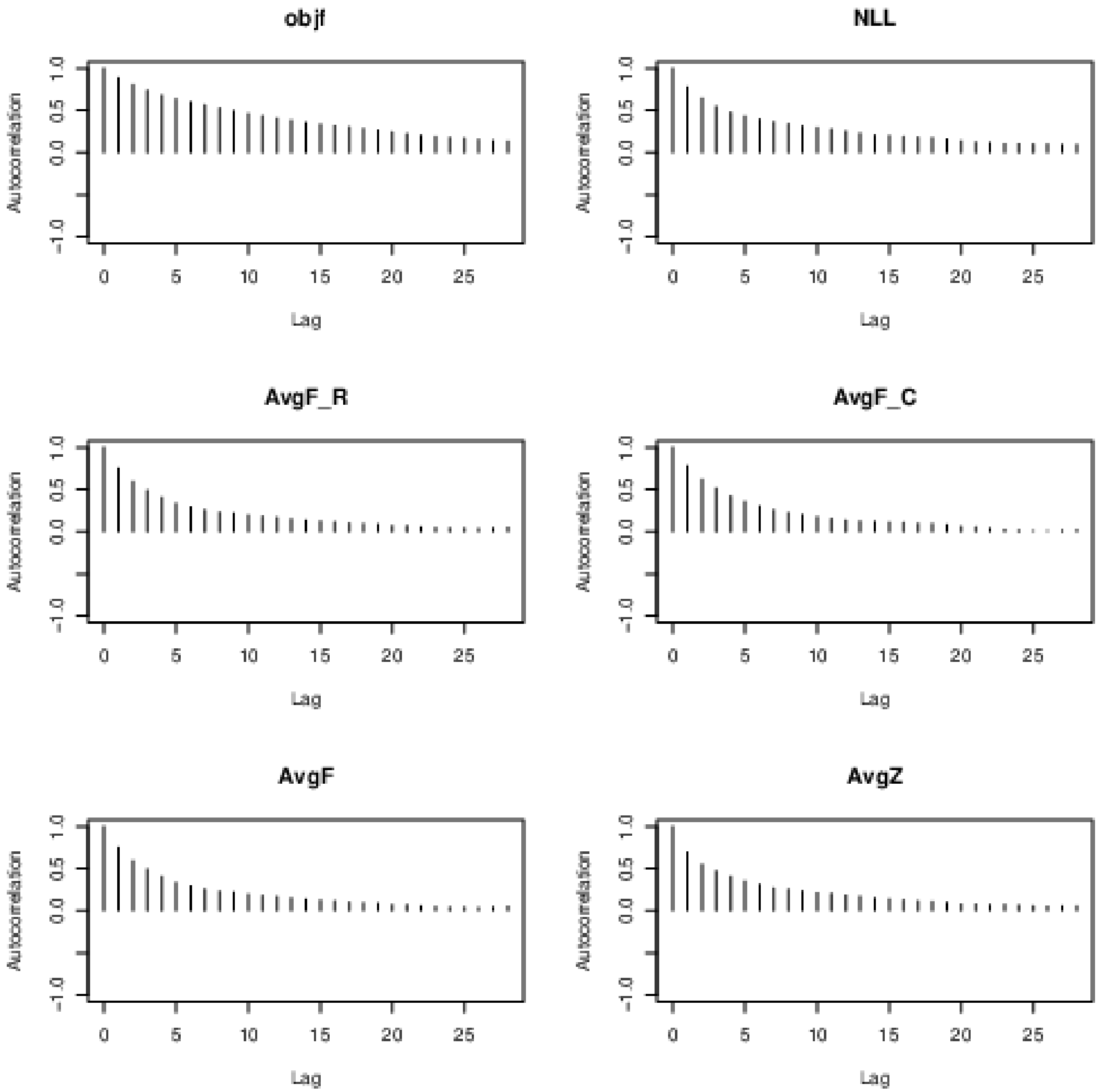


Figure 8.10 cont'd.

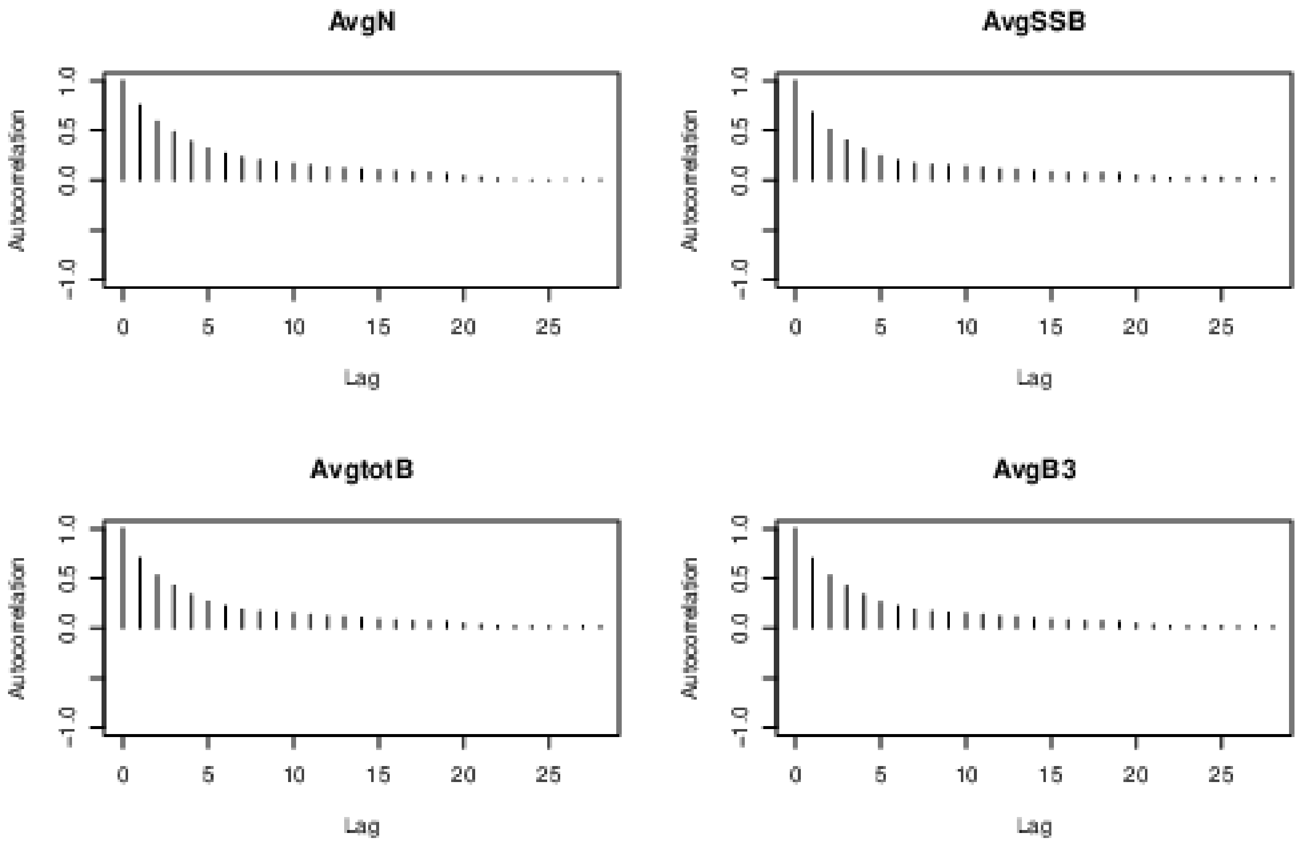


Figure 8.11. MCMC trace plots and posterior distributions WI345-01-02-21.

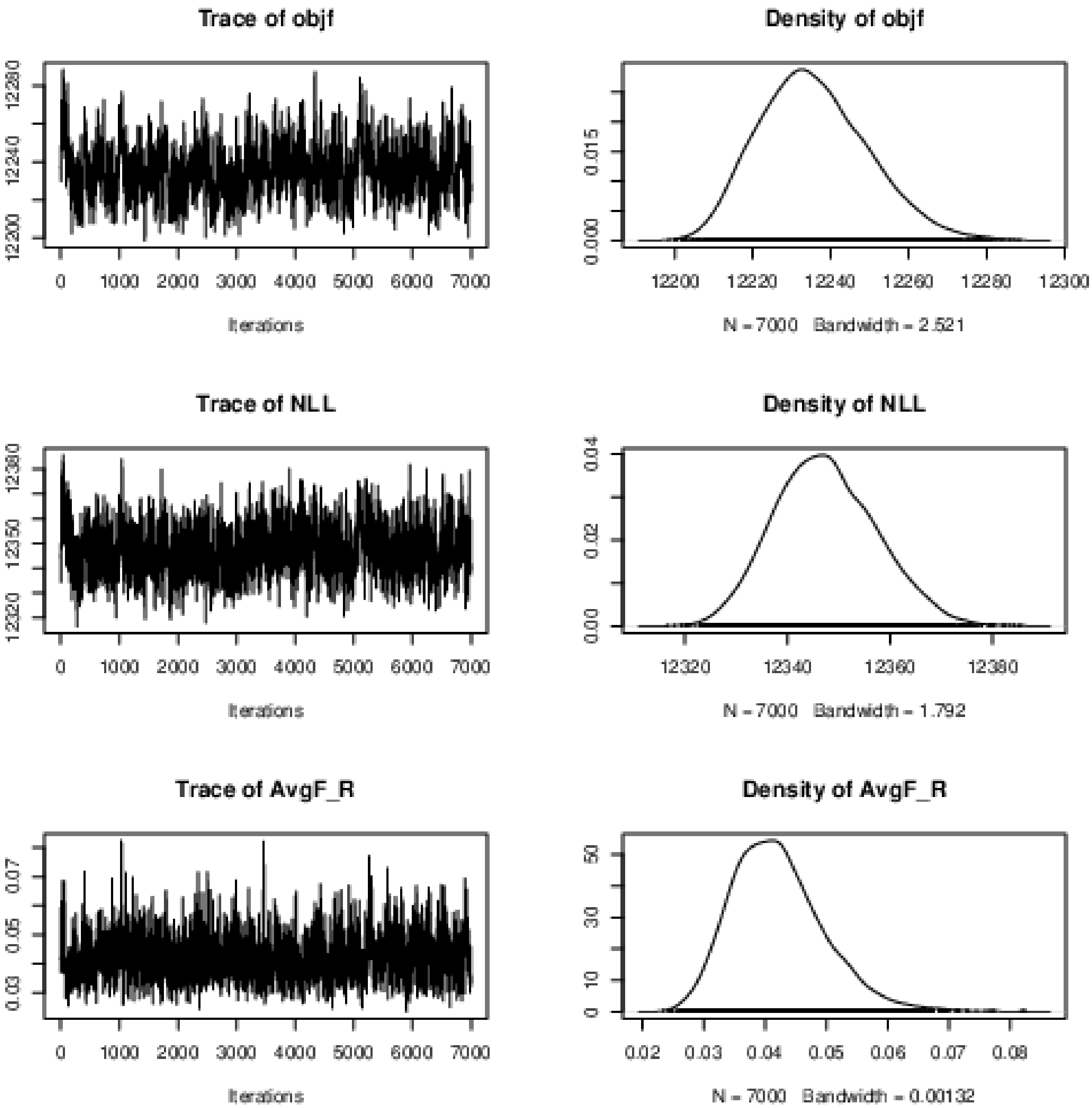


Figure 8.11 cont'd.

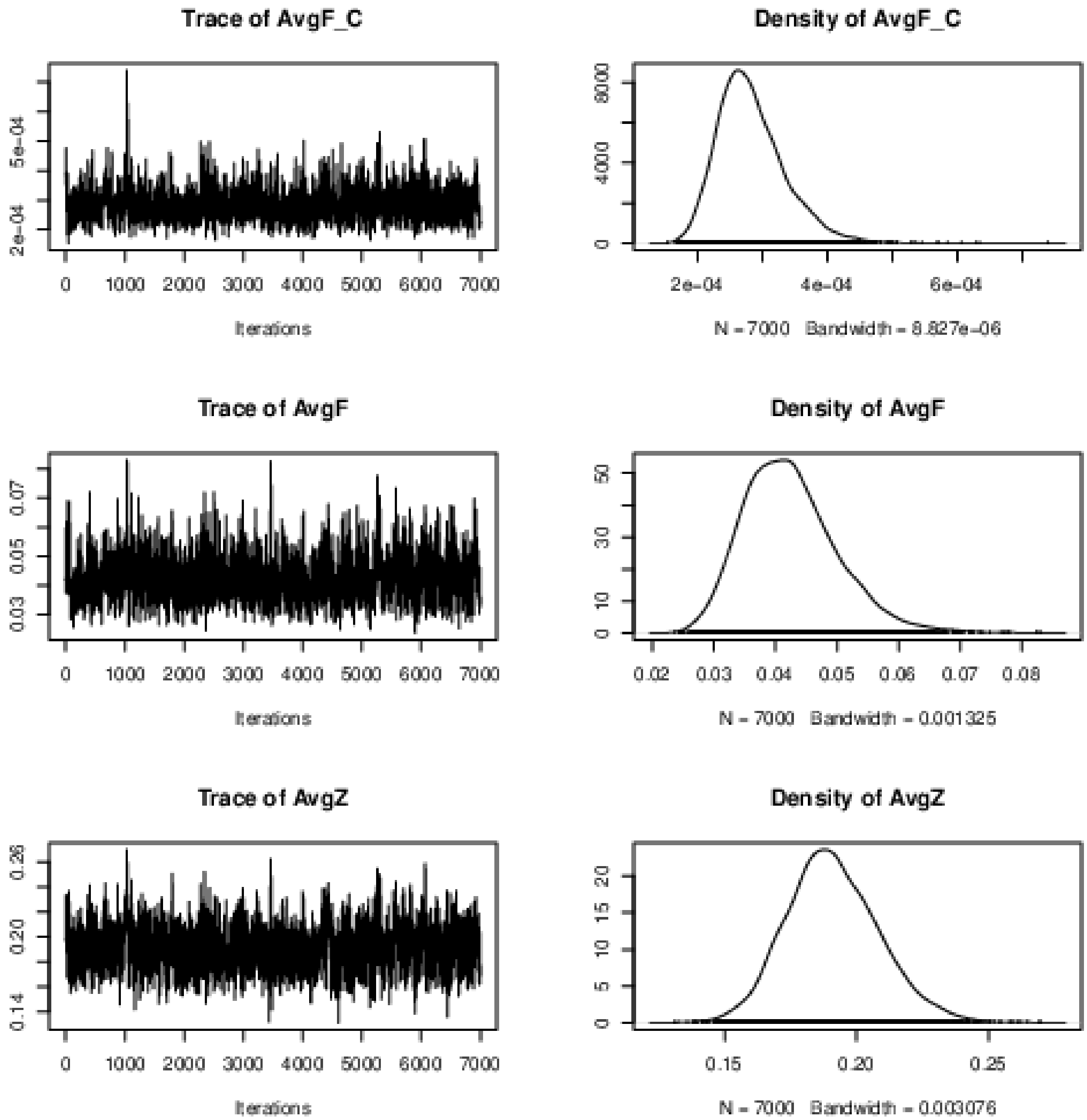


Figure 8.11 cont'd.

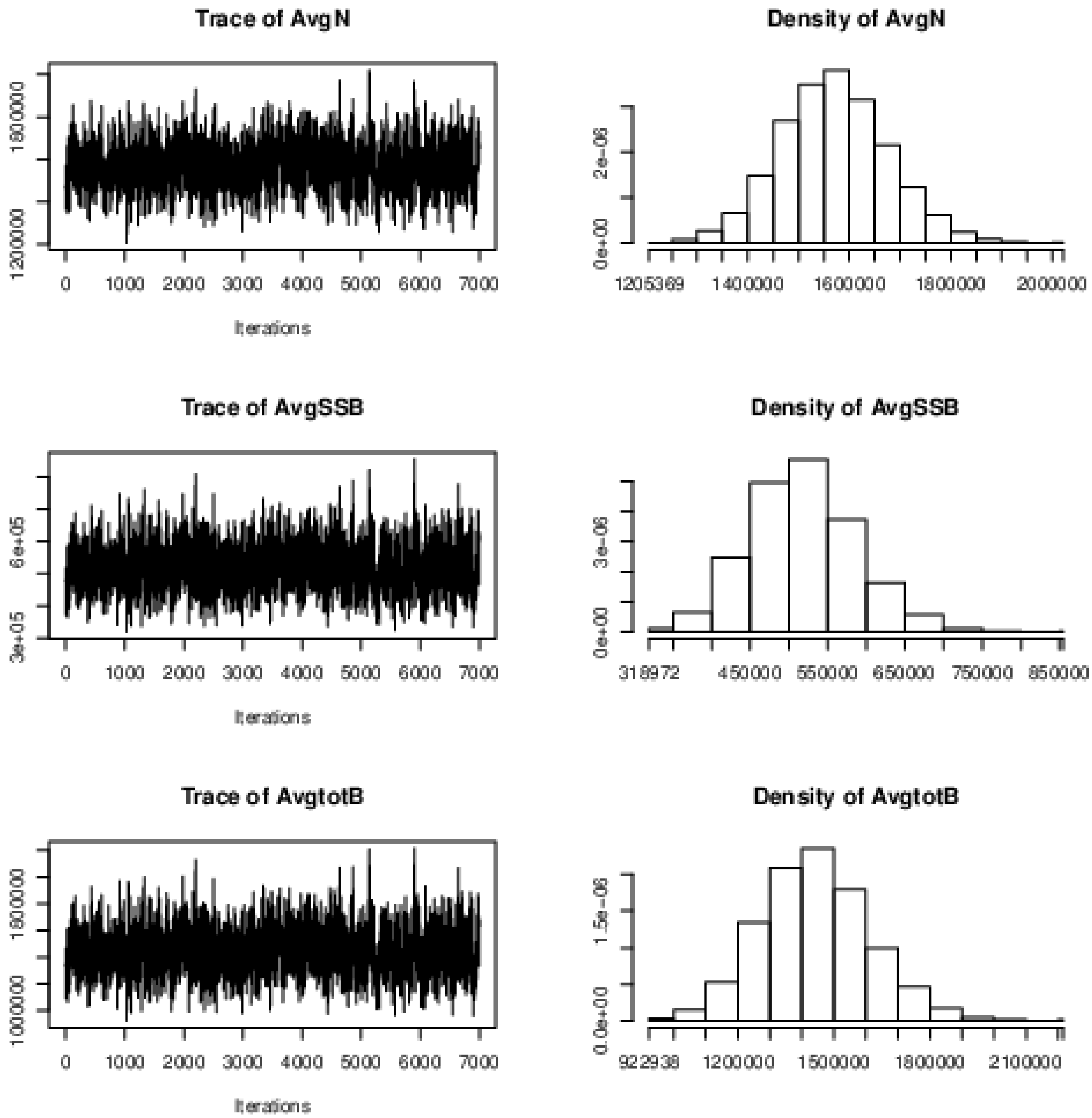


Figure 8.11 cont'd.

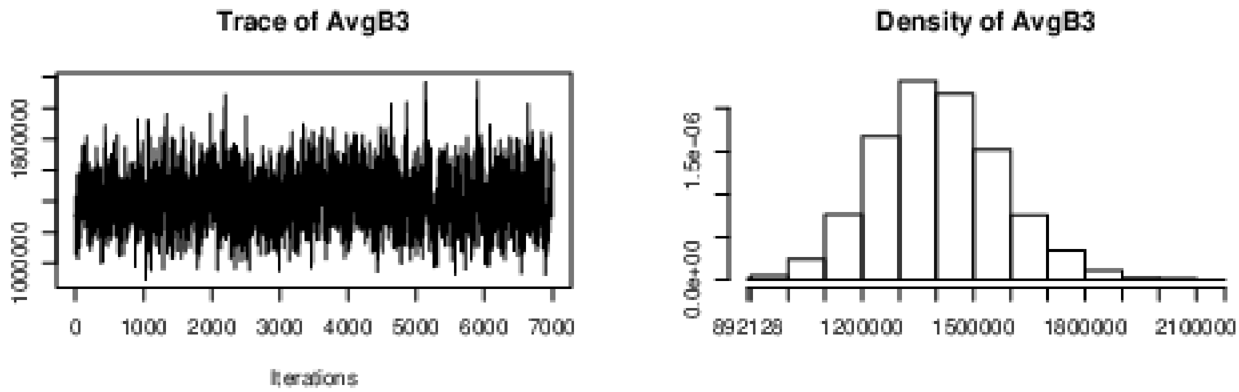


Figure 8.12. MCMC auto-correlations WI345-01-02-21.

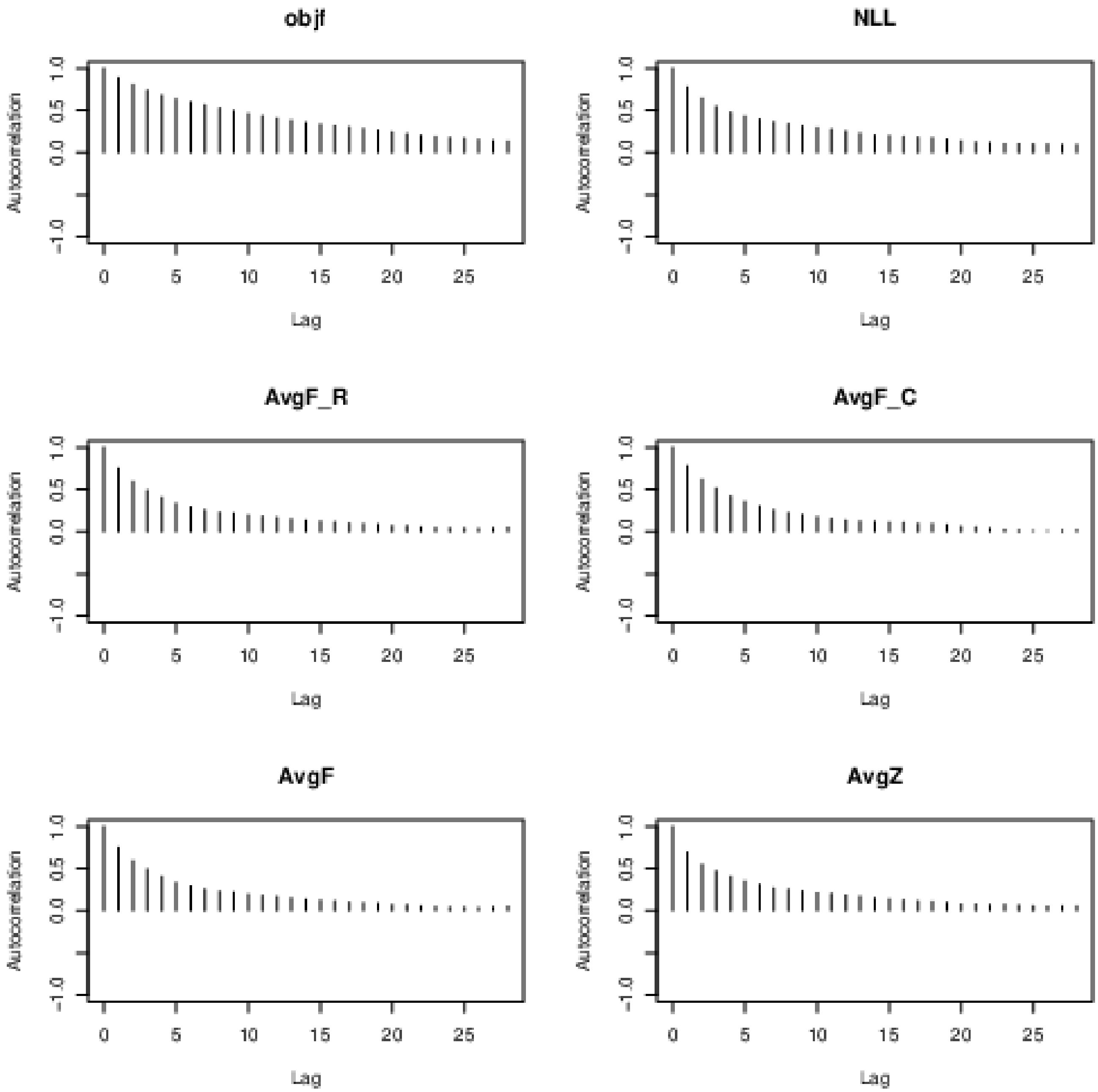
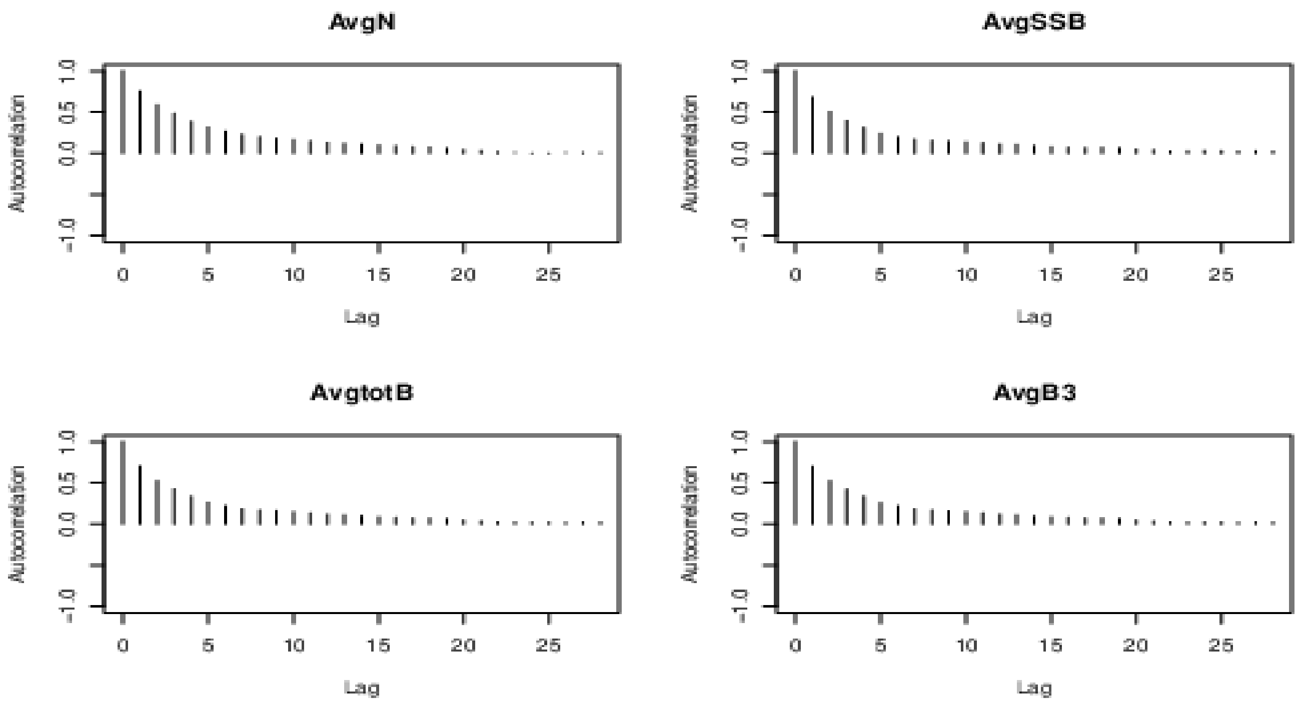


Figure 8.12 cont'd.



9.0 Summary

The structure of all six versions of the WI345 stock assessment were not fundamentally different. They varied in what aging structures were used to estimate age composition of the recreational fishery and LWAP catch, whether ***Z*** was estimated for the entire time series or split into two time periods, what values were used for commercial fishery selectivity, and whether yearling equivalents used as age-1 abundance inputs to the assessment were adjusted for contributions of wild fish. Selectivity for both fisheries was not time-varying in any version while selectivity of the LWAP survey was time-varying in all versions. Catchability was allowed to be time-varying for both fisheries. Consequently, determining the most appropriate model was not clear cut. All six versions ran to completion and their maximum gradients were less than our convergence criterion of 1.00E-04. Model-derived estimates of sigma were less than targets developed by the Modeling Subcommittee. All versions of the stock assessment were able to arrive at the same final estimates of biomass even at substantially different starting values for selectivity and catchability. The patterns and variations of the SDRES were similar for the recreational fishery catch and LWAP CPUE for all six versions and in each version age composition of the LWAP survey exhibited some patterns and larger variation than other quantities.

There were retrospective patterns for each version of the stock assessment but for the most part these patterns were small and declined from the first three versions to the last three versions. Retrospective patterns for abundance, biomass, and mortality quantities at the end of the time series were substantial ranging from 3% to 59% in the 02-20-20, 03-09-20, and 04-02-20 versions but declined to less than 8% in the 09-21-20, 11-16-20, and 01-02-21 versions. Our retrospective patterns for Lake Trout demographic quantities were substantially smaller than patterns reported by Brenden et al. (2011) in Lake Ontario where they also allowed catchability to vary as a random walk and they did not allow selectivity to be time-varying except to account for changes in recreational fishery size limits during three time periods.

MCMC simulations illustrated that the 02-20-20 version was the least reliable of all the versions of our WI345 stock assessment while the 01-02-21 version appeared to be the most reliable. Trace Plots, posterior distributions, and auto-correlations all improved from the 02-20-20 version to the 01-02-21 version. The lowest auto-correlations occurred for all versions after the 04-02-20 version. The use of all aging structures to estimate age composition of the recreational fishery, constraining estimates of ***Z*** in the objective function, and having two different generic age-length keys for estimating age composition of the recreational fishery all appeared to introduce bias in our stock assessment. It is imperative to have accurate estimates of the age composition of harvested fish for integrated stock assessments because aging errors can have sizable effects on their reliability (Catalano and Bence 2012). We believe the use of CWTs to determine ages of Lake Trout reduced our aging error to near zero compared to the 02-20-20 version which relied upon multiple, much less reliable, aging structures. However, substantial uncertainty and strong assumptions were added because of the necessity of applying age-length keys, based on data collected over multiple years. In theory this weakness could be addressed with sufficient collection and processing of CWT-marked fish annually from various data sources to generate annual age-length keys. Unfortunately, from an assessment perspective only, in addition to the challenge of obtaining adequate samples as recruitment of wild-born fish increases, reliance will have to be made on aging from natural structures. These current and growing uncertainties argue for considering assessment methods that do not require annual catch-at-age data (e.g., length-based methods).

We selected the 01-02-21 version as the most reliable of the six WI345 stock assessments based its small retrospective patterns, low Mohn's rho values, and MCMC simulations. All versions of the WI345 stock assessment achieved our convergence criterion, produced acceptable sigma values, arrived at the same final estimates of biomass regardless of the starting values for selectivity and catchability, and exhibited similar standardized residuals. Consequently, we used retrospective patterns and MCMC output to identify the 01-02-21 version as the most reliable.

One reason we developed the SCAA stock assessment was to aid in evaluating the influence of Lake Trout consumption on prey fish biomass in Lake Michigan. Predator abundance, biomass, and total mortality drive estimates of predator production and their consumption (Negus et al. 2008; He et al. 2015), so these quantities should have low levels of uncertainty. Our estimates of abundance and biomass for the 02-20-20 version exhibited sizable retrospective patterns and greater proportional differences of peels from the full assessment than other versions, thus it is the least reliable for projecting consumption of Lake Trout in Lake Michigan. Variability between retrospective peels of total abundance, biomass, and total mortality was smaller for the versions after 04-02-20, further pointing to the 01-02-21 version as the most acceptable stock assessment. Last, trace plots and auto-correlations produced for the 01-02-21 version scored better in our subjective ranking criteria than all but the 09-21-20 version, but we were using the wrong commercial selectivity in all but the 01-02-21 version.

10.0 Literature Cited

Brenden, T. O., J. R. Bence, B. F. Lantry, J. R. Lantry, and T. Schaner. 2011. Population dynamics of Lake Ontario lake trout during 1985-2007. North American Journal of Fisheries Management 31:962-679.

Catalano, M. J., and J. R. Bence. 2012. The sensitivity to assumed ageing error of the stock assessment used to recommend lake whitefish yield for 2008 from management unit WFH01 of Lake Huron. Quantitative Fisheries Center Technical Report 2011-01, Michigan State University, East Lansing, Michigan. Available from https://msu.dotcmscloud.com/qfc/publications/pdf-publications/2011-publications/The%20sensitivity%20to%20assumed%20ageing%20error_Catalano.pdf

Caroffino, D. C., and S. J. Lenart, editors. 2011. Statistical catch-at-age models used to describe the status of lean lake trout populations in the 1836-Treaty ceded waters of lakes Michigan, Huron, and Superior at the inception of the 2000 Consent Decree. Modeling Subcommittee, Technical Fisheries Committee. Available from https://www.michigan.gov/documents/dnr/LakeTroutLongReport_353000_7.pdf

Carvalho, F., A. E. Punt, Y. Chang, M. N. Maunder, and K. R. Piner. 2017. Can diagnostic tests help identify model misspecification in integrated stock assessments. Fisheries Research 192:28-40.

Deroba, J. J. 2014. Evaluating the consequences of adjusting fish stock assessment estimates of biomass for retrospective patterns using Mohn's rho. North American Journal of Fisheries Management 34:380-390.

Ebener, M. P., R. D. Clark, Jr., J. R. Bence, M. S. Kornis, T. Treska, and C. R. Bronte. 2020. Development of statistical catch-at-age data files of Lake Trout in western and southern Lake Michigan. Quantitative Fishery Center Technical Report T2020-01, Michigan State University, East Lansing, Michigan. Available from figshare DOI: 10.6084/m9.figshare.13495725.

Eck, G. W., and L. Wells. 1983. Biology, population structure, and estimated forage requirements of lake trout in Lake Michigan. United States Fish and Wildlife Service Technical Paper 111. Available from https://pubs.er.usgs.gov/publication/tp111.

He, J. X., J. R. Bence, C. P. Madenjian, S. A. Pothoven, N. E. Dobiesz, D. G. Fielder, J. E. Johnson, M. P. Ebener, R. A. Cottrill, L. C. Mohr, and S. R. Koproski. 2015. Coupling age-structured stock assessment and fish bioenergetics models: a system of time-varying models for quantifying piscivory patterns during the rapid trophic shift in the main basin of Lake Huron. Canadian Journal of Fisheries and Aquatic Sciences 72:7-23.

ICES. 2020. Workshop on catch forecast from biased assessments (WKFORBIAS; output from 2019 meeting). ICES Scientific Reports 2(28). 38 pp. Available from http://doi.org/10.17895/ices.pub.5997.

Legault, C. M. 2009. Report of the retrospective working group, January 14-16, 2008, Woods Hole, Massachusetts. Northeast Fisheries Science Center Reference Document 09-01, National Oceanic and Atmospheric Administration, U.S. Department of Commerce. Available from https://repository.library.noaa.gov/view/noaa/3611/noaa_3611_DS1.pdf.

Modeling Subcommittee, Technical Fisheries Committee. 2018. Technical Fisheries Committee administrative report 2018: status of lake trout and lake whitefish populations in the 1836 Treaty-Ceded waters of Lakes Superior, Huron and Michigan, with recommended yield and effort levels for 2018. Available from https://www.michigan.gov/documents/dnr/2018StatusStocksReport_631815_7.pdf.

Mohn, R. 1999. The retrospective problem in sequential population analysis: an investigation using cod fishery and simulated data. ICES Journal of Marine Science 56:473–488.

Negus, M. T., D. R. Schreiner, T. N. Halpern, S. T. Schram, M. J. Seider, and D. M. Pratt. 2008. Bioenergetics evaluation of the fish community in the western arm of Lake Superior in 2004. North American Journal of Fisheries Management 28:1649-1667.

Rybicki, R. W. 1990. Survival rates of 1- and age-2 year-old hatchery-reared lake trout in the west arm of Grand Traverse Bay, Lake Michigan. Michigan Department of Natural Resources, Fisheries Division Fisheries Research Report No. 1978. Available from https://www2.dnr.state.mi.us/Publications/pdfs/IFR/ifrlibra/Research/reports/1978rr.pdf.

Smith, S. H., H. J. Buettner, and R. Hile. 1961. Fishery statistical districts in the Great Lakes. Great Lakes Fishery Commission Technical Report 2, Ann Arbor, Michigan. Available from http://www.glfc.org/pubs/TechReports/Tr02.pdf.

Truesdell, S. B., and J. R. Bence. 2016. A review of stock assessment methods for lake trout and lake whitefish in 1836 Treaty waters of Lake Huron, Lake Michigan and Lake Superior. Quantitative Fisheries Center Technical Report T2016-01, Michigan State University, East Lansing, Michigan. Available from DOI: 10.6084/m9.figshare.3123949.

Truesdell, S. B., J. R. Bence, J. M. Syslo, and M. P. Ebener. 2017. Estimating multinomial effective sample size in catch-at-age and catch-at-size models. Fisheries Research 192:66-83.

Wilberg, M. J., J. T. Thorson, B. C. Linton, and J. Berkson. 2009. Incorporating time-varying catchability into population dynamic stock assessments. Reviews in Fisheries Science 18:7-24.

11.0 Appendix – *R*-script for MCMC Analysis

11.1 Script "read.mcmc.R"

```
##' Read in text files produced by AD model build's MCMC functions
##' and create an mcmc object that can be examined using R's built in
##' tools (Coda, mcmcplots ect).
##'
##' @title read.mcmc
##' @param mcmc.file - the name of or path to the ascii file that
##'    contains the output from admb.
##' @param header - a boolean value indicating whether or not names
##'    of the variables are included in the top row of the mcmc file.
##'    This may or may not be true depending on how tpl was
##'    structured and will have to be checked.
##' @param burnin - how many simulations should be discarded as the
##'    burnin period.  Any value less than or equal to the number of
##'    simulation is acceptable.
##' @param delimiter - this can be either whitespaces, tabs,
##'    semi-colons or commas.
##' @param names - this can either be a file name in the same directory
##'    as mcmc.file or a vector of character strings that correspond
##'    to the columns in the mcmc file.  This argument is maintained for
##'    flexibility.  Incorporating variable names into mcmc file when
##'    it is created and then using header==TRUE is the prefered approach.
##' @param ... - additional arguments to be passed to read.table().
##' @return an mcmc object
##' @author Adam Cottrill \email{adam.cottrill@@ontario.ca}
##' @keywords misc
##' @export

read.mcmc <- function(mcmc.file="mcmc.csv", header = TRUE, burnin=1000,
                delimiter=",", names=NULL,... ){

  require(coda)  #to convert text file to mcmc object

  mcmc.file <- gsub("[\\]", "/", mcmc.file)  #use slashes in paths
                              #rather than double back
                              #slashes
  #Check each of the arguments:
  #does the file exist?
  if(file.exists(mcmc.file) == FALSE){
    stop(paste("The file:'", mcmc.file, "' does not seem to exist."))}

  #delimiter can only be whitespaces, commas, or semi-colons
  match.arg(as.character(delimiter),c(" ",";",",","\t"))

  #make sure that header is boolean:
  match.arg(as.character(header),c("TRUE","FALSE"))
```

```
# first read in the mcmc file:
# if the delimiter is a space, the header isn't always read in
# correctly if the delimiter argument is supplied.
if(delimiter==' '){
  my.mcmc <- read.table(mcmc.file, header=header,...)
} else {
  my.mcmc <- read.table(mcmc.file, header=header, sep=delimiter,...)
}

#now we need to try and figure out what is going on with the names
#was a names argument provided? if not, then return option 4 from
#above:
if(header==FALSE){
  if(!is.null(names) & length(names)==1){
    #see if a 'names' is a file that exists
    #if not try pasting on the directory of the mcmc file and
    #test again, if this works re-assign names and read in the
    #files using the new, longer names argument.
    if(file.exists(names)==FALSE){
      if(file.exists(paste(dirname(mcmc.file),"/",names, sep=""))){
        names <- paste(dirname(mcmc.file),"/",names, sep="")
      } else {
        warning(paste(names, " could not be found.",sep=""))
      }
     }

     if(file.exists(names)){
       #if the file exists - read it in, check the number of elements
       #and apply them if possible, otherwise, issue a warning.
       my.mcmc.names <- read.table(names, sep=",")
       my.mcmc.names <- as.character(unlist(my.mcmc.names))
       if(length(my.mcmc.names)==ncol(my.mcmc)){
         #remove any trailing or leading whitespaces
         my.mcmc.names <-sub("^[[:space:]]*(.*?)[[:space:]]*$",
                    "\\1", my.mcmc.names, perl=TRUE)
         names(my.mcmc) <- my.mcmc.names
       } else {
         warning(paste("A file '", names,
           "' exists, but it contains the wrong number of elements (",
           length(my.mcmc.names), " instead of ", ncol(my.mcmc),
           "). \nNo names assigned to mcmc object."))
       }
     }
   } else {
     #if the number of names match the number of columns go ahead
     #and use them:
     if(length(names)==ncol(my.mcmc)){
        #remove any trailing or leading whitespaces
        names <-sub("^[[:space:]]*(.*?)[[:space:]]*$",
                    "\\1", names, perl=TRUE)
```

```
        names(my.mcmc) <- names
      } else if(length(names)>1 & length(names)!=ncol(my.mcmc)){
        warning ("'names' contains the wrong number of elements (",
          length(names), " instead of ", ncol(my.mcmc),
          "). \nNo names assigned to mcmc object.")
      } #else {
    }
  }

  #make sure that each column has a distinct name:
  if(length(names(my.mcmc)) != length(unique(names(my.mcmc)))){
    warn.txt <- "The names in mcmc object may not be unique."
    warning(warn.txt)
  }

  #make sure that burn in is a positive number
  if(!is.numeric(burnin) | burnin<0 | burnin > nrow(my.mcmc)) {
    warn.txt <-
    ("The burn in period must be a positive integer less than the number of rows in mcmc.file.")
    warn.txt <-
    paste(warn.txt,"\nNo 'Burn-in' period was removed from the mcmc simulations.",sep="")
    warning(warn.txt)
   } else {
    #discard the burn-in values from the mcmc chain
    my.mcmc <- my.mcmc[(burnin + 1):nrow(my.mcmc),]
   }

  #convert the matrix to an mcmc object so that coda functions can
  #work:
  my.mcmc <- try(coda::as.mcmc(my.mcmc), silent=TRUE)
  if(inherits(my.mcmc, what="try-error")){
    stop(my.mcmc[1])
  }

  #my.mcmc <- as.mcmc(my.mcmc)
  return(my.mcmc)
}
```

11.2 Script "MCMC_plotting.R"

```
##Plotting MCMC

#Source file for MCMC plotting functions
#Modify path to location of plotter/ source files
#source("C:/Users/MSeider/Documents/SCAA_Projects/R_plotter/Plotter
    Materials/Master_RPlotter_Files/read.mcmc.R")
source("C:/Users/tflwc/Desktop/datafiles/LAT Model Lake Michigan/Model evaluations WI345/read.mcmc.R")

#set location of your MCMC file
my.mcmc.file <- "C:/Users/tflwc/Desktop/datafiles/LAT Model Lake Michigan/Model evaluations WI345/WI345-04-
    02-20_mcmcout.txt"

#Run Cottrill's mcmc function (assumes column header is in file)
my.mcmc <- read.mcmc(my.mcmc.file, delimiter=" ", header=T, burnin=3000)

#Look at summary statistics
summary(my.mcmc)

#Set current date time for naming PDF
date.time <- format(Sys.time(), "%m.%d.%Y_%H_%M")

#Change name of MU
mu <- "WI345-04-02-20"

#Create pdf with output
pdf(file=paste0(dirname(my.mcmc.file),"/MCMC ",mu," ",date.time,".pdf"))
plot(my.mcmc)
autocorr.plot(my.mcmc)
graphics.off()
```