Diagnostics of the WIIM Lake Trout Stock Assessment in Southern Lake Michigan

Quantitative Fisheries Center Technical Report T2021-02

DOI: 10.6084/m9.figshare.16862446

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December 2021

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INTRODUCTION

We applied statistical catch-at-age analysis (SCAA) to fishery and biological information on Lake Trout *Salvelinus namaycush* collected in southern and western waters of Lake Michigan to help improve population-level analyses of the species in Lake Michigan. One SCAA stock assessment was developed for southern Lake Michigan that included Wisconsin, Illinois, Indiana, and Michigan waters (herein referred to as WIIM) and a second that included statistical districts WM-3, WM-4, and WM-5 (Smith et al. 1961) in Wisconsin that we named WI345 (Ebener et al. 2020). 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 WIIM 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 autocorrelations of SCAA output

Herein, we used the MSC protocols to evaluate six versions of the WIIM stock assessment for Lake Trout. WIIM is a combination of statistical districts WM-6, ILL, and IND, and MM-8 in Lake Michigan (Smith et al 1961; Ebener et al. 2020). The biggest problem with the WIIM stock assessment was the lack of ages for Lake Trout caught by the recreational fishery, which meant we could not estimate annual age compositions, which is generally 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 in the recreational harvest and recoveries of fish marked with coded-wire tags (CWTs) (Ebener et al. 2020, 2021). We applied these data in a different way to six versions of the WIIM stock assessment: 02-18-20, 03-04-20, 04-02-20, 09-21-20, 10-09-20, and 11-11-20. 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 model versions tested were as follows.

1. <u>02-18-20 version</u>
    a. We used data for 1985-2017.
    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*** = 0.180 per year and ***sdZ*** = 0.500.

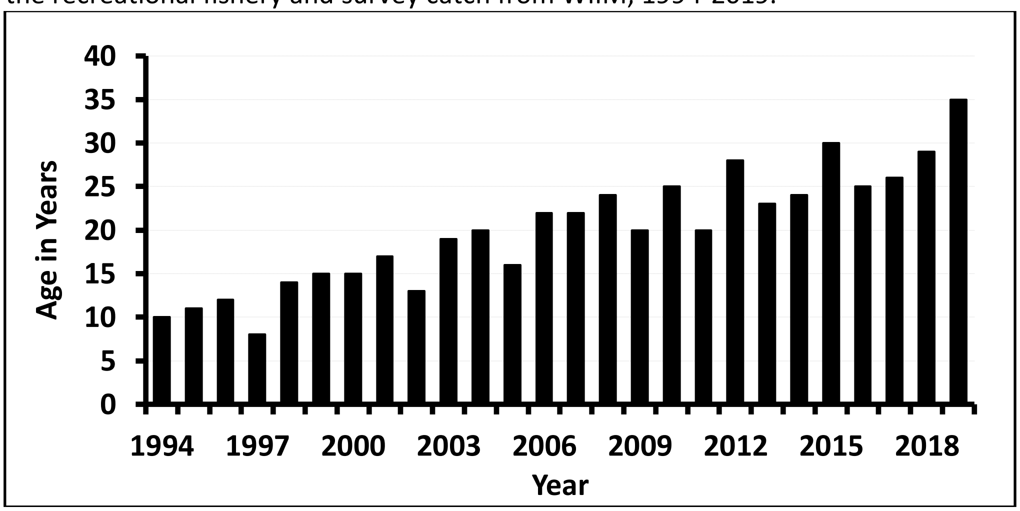
2. <u>03-04-20 version</u>
   a. We used data for 1985-2017.
   b. We suspected that mortality could have changed over time, so we calculated age-length keys for two time periods for this version. The first was from data pooled for 1985-2000 and the second was from data pooled for 2001-2017. We used 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 1985-2000 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 1966-1984.

3. <u>04-02-20 version</u>
   a. We used data for 1985-2017.
   b. We developed a single generic age-length key using data collected by all fishing and survey methods across all years (1985-2017) as described for the 02-18-20 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 the population abundance during 1966-1984.

[1]Unpublished analyses in draft manuscript.

4. 09-21-20 version
    a. We added data for 2018 and 2019 to the 1985-2017 information.
    b. We developed a single generic age-length key using data collected by all fishing and survey methods across all years (1985-2019) 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 ages 20 and older 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-19 in 1985, 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 and it was collected from WIIM in 2019. The maximum age observed for CWT-marked lake trout increased linearly through time in WIIM (Figure 1). Figure 1 suggests that the total mortality rate must be low for CWT-marked fish and age 35 must be well below the maximum age for CWT-marked fish, because if it wasn't, the trend in maximum age would have reached an asymptote.

Figure 1. The maximum age of coded-wire-marked Lake Trout observed annually in the recreational fishery and survey catch from WIIM, 1994-2019.



    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 1966-1984.

5. 10-09-20 version
    a. We used data for 1985-2019.
    b. We developed a single generic age-length key using data collected by all capture methods across all years (1985-2019) as described for the 02-18-20 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. 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 the population abundance during 1966-1984.

d. 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 10-09-20 version, we used only LWAP and SPAWN survey data. The proportion wild for each year class was expanded to create a matrix of proportion wild at age by year (Ebener et al. 2020).

e. 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 WIIM 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 10-09-20 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 begins at age 3, we used the percentage at this youngest age in the ***i-***th year and applied it in the calculations to obtain the total age-1 trout two years earlier (year ***i-2***). Thus, the 2017- and 2018-year classes of hatchery fish could not be expanded to account for wild fish. 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).

f. We increased the Maximum Effective Sample Size (ESS) for the recreational fishery from 25 to 100 because we felt more confident in the age composition data.

6. <u>11-11-20 version</u>
   a. We used data for 1985-2019.
   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 10-09-20 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 (1985-2019) as described for the 02-18-20 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 used the same ***pct_wild*** data as for the 10-09-20 version.
e. We used the same method as 5.e. to estimate abundance of age-1 wild and hatchery Lake Trout.
f. 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 each year class stocked and was used to estimate the population abundance from 1966-1984.

Figure 2. Proportional age-specific selectivity of Lake Trout to the commercial small-mesh gill net fishery in the 10-09-20 and earlier versions and the 11-11-20 version of the WIIM stock assessment.

1.0 AD Model Builder Final Statistics

We used 11 components in the objective function (Objf) to fit the 02-18-20 version of the WIIM 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 02-18-20) 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).

All six versions of the WIIM stock assessment were able to run to completion and the maximum gradient was smaller than our convergence criterion (Table 1.1). The smallest Objf was for the 02-18-20 version and the largest was for the 11-11-20 version, although there was little difference in the value of the Objf between the 10-09-20 and 11-11-20 versions (Table 1.1).

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

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[1] 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 (02-18-20 only)	Z		NLP
Log natural mortality age 3+	lnmedM		NLP
Log natural mortality age 2	lnmedM2		NLP

[1]LWAP is the Lakewide Assessment Plan.

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

	WIIM Assessment					
ADMB output	**02-18-20**	**03-04-20**	**04-02-20**	**09-21-20**	**10-09-20**	**11-11-20**
Number variables	144	144	144	152	152	152
Run complete	Yes	Yes	Yes	Yes	Yes	Yes
Number iterations	153	152	152	161	162	162
Convergence criterion	1.00e-004	1.00e-004	1.00e-004	1.00e-004	1.00e-004	1.00e-004
Maximum gradient	-1.94e-006	-8.30e-006	-3.38e-005	-6.41e-005	2.32e-005	1.12e-005
Objective function	5152.41	5318.87	5303.69	5929.3	12384.7	12385.8
Normal log likelihood	5277.36	5448.85	5433.29	6069.34	12529.6	12350.4
Lognormal prior	-124.954	-129.578	-129.600	-140.047	-144.859	-144.639

2.0 SCAA Output – Standard deviations

Inputs to the WIIM stock assessment include prior estimates for some parameters and an estimate of the standard deviation associated with the prior. We input these prior parameters for natural mortality rate of age 1 ($\boldsymbol{M_1}$) and age 2 ($\boldsymbol{M_2}$) based on data from Eck and Wells (1983) and Rybicki (1990), and age-3+ ($\boldsymbol{M}$) and their standard deviations. The standard deviation for the natural logarithms of $\boldsymbol{M_1}$ (0.175) and $\boldsymbol{M_2}$ (0.10) were basically just guesses, and we assumed the standard deviation of the natural logarithm of $\boldsymbol{M}$ 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).

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* declined slightly from the 02-18-20 to the 11-11-20 version and consequently so did the standard deviation for the other parameters (Table 2.0). The smallest *sigma* was estimated for the 10-09-20 version.

Table 2.0. Estimates of the standard deviation for quantities and parameters estimated for six versions of the WIIM Lake Trout stock assessment.

Parameter (prior)	Variance ratio	02-18-20	03-04-20	04-02-20	09-21-20	10-09-20	11-11-20
Sigma		0.069889	0.069016	0.068948	0.068526	0.06546	0.06561
M_1 (0.175)	3	0.209666	0.207048	0.206843	0.205580	0.19638	0.19684
Comml catch (0.15)	0.8	0.055911	0.055213	0.055158	0.054821	0.05237	0.05249
Recrl catch (0.04)	1	0.069889	0.069016	0.068948	0.068526	0.06546	0.06561
Ln_q recrl fishery	2.5	0.174722	0.172540	0.172369	0.171316	0.16362	0.16403
LWAP selectivity ***p1***	0.15	0.010483	0.010352	0.010342	0.010279	0.00982	0.00984

Standard deviations estimated during the model fitting process fell within guidelines established by the Modeling Subcommittee. The Modeling Subcommittee guidelines call for standard deviations of fishery catch to be less than 0.1, and our estimates for all versions ranged from 0.05 to 0.07. The guideline for catchability is less than 0.5 and our value for the recreational fishery was 0.16-0.17. There currently is no guideline for the standard deviation of selectivity but all our estimates were 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 WIIM 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 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. The ESS for the recreational fishery was 25 for all versions prior to 10-09-20 and 100 thereafter.

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

Stock assessment	WIIM Fishery Type		
	commercial	recreational	LWAP
02-18-20	200	25	100
03-04-20	200	25	100
04-02-20	200	25	100
09-21-20	200	25	100
10-09-20	200	100	100
11-11-20	200	100	100

4.0 SCAA Output – Residual Analysis

We evaluated the WIIM models goodness-of-fit by plotting the standardized residuals (SDRES) of fishery catch and age composition (Table 4.0). We examined the SDRES for patterns and the degree of variation to test model assumptions (Carvalho et al. 2017). We did not estimate SDRES for the commercial fishery because there were no observed harvest values for it after 1999. We calculated SDRES 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 SDRES 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 WIIM Lake Trout stock assessment.

Quantity	SCAA variable name	Description
Rec_fishery catch	res_r_C	SDRES annual recreational fishery catch
Age comp rec_fishery last year	res_r_CA(***j***=2017 & 2019)	SDRES recreational fishery age composition last year (***j***)
LWAP survey lnCPUE	res_sv_cpe	SDRES annual LWAP natural log CPUE
Age comp LWAP survey last year	res_sv_ac(***j***=2017 & 2019)	SDRES LWAP survey age composition last year
Age-6 comp rec_fishery	res_r_CA(***i***=6)	SDRES age-6 fish (***i***) recreational fishery 1985 to last year
Age-6 comp LWAP survey	res_sv_ac(***i***=6)	SDRES age-6 fish (***i***) LWAP survey 1985 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) $$SDRES = \frac{(ObsP-PredP)}{\sqrt{PredP(1-PredP)/Nsamp}}$$

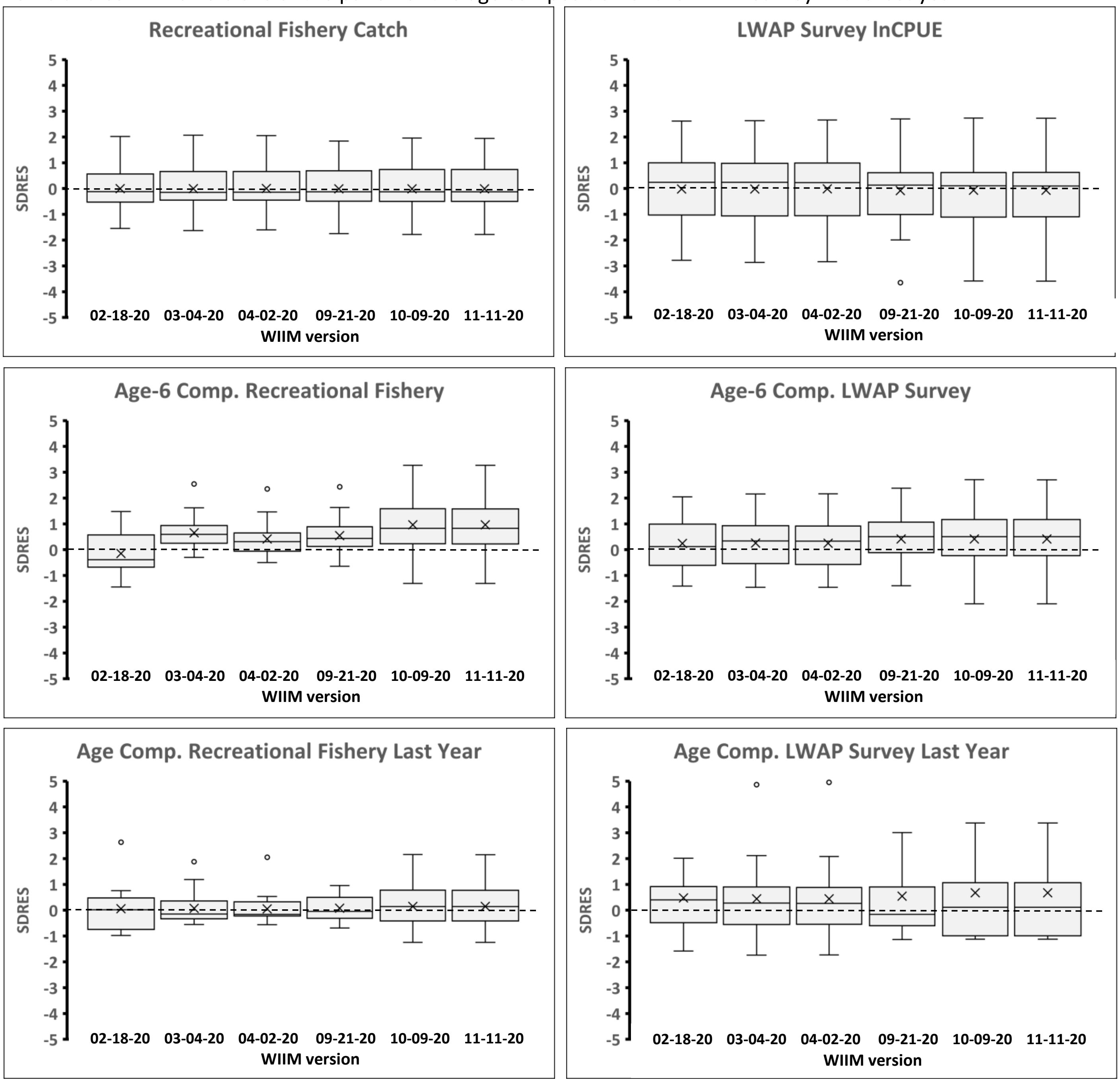
where ***ObsP*** is the observed proportion at age in the catch, ***PredP*** is the predicted proportion at age in the catch and ***Nsamp*** is the number of fish sampled from the recreational or LWAP catch.

The SDRES for each version of the stock assessment did not show sizable patterns but the variation was greater for versions after 09-21-20. The SDRES for the recreational fishery catch showed no patterns, and all values were between -2.0 and 2.0 (Table 4.1; Figure 4.1). The variance of the mean SDRES for the recreational fishery catch ranged from 0.54 to 0.60 and was slightly higher for the 10-09-20 and 11-11-20 versions (0.58-0.60) than the four previous versions (0.54-0.56). The SDRES for the LWAP CPUE also showed no patterns but the variance was larger for the 09-21-20, 10-09-20 and 11-11-20 versions than for versions prior to 09-21-20 (Table 4.1; Figure 4.1). The SDRES for the age composition data also showed no sizable patterns but the variation in the SDRES were larger for the last two versions of the stock assessment than for the first four versions. Composition of age-6 fish in the recreational fishery did show a slight positive pattern in the SDRES (Figure 4.1) unlike those of other quantities. Plots of the SDRES for each quantity and each version of the WIIM stock assessment are shown in Figures 4.2 to 4.7.

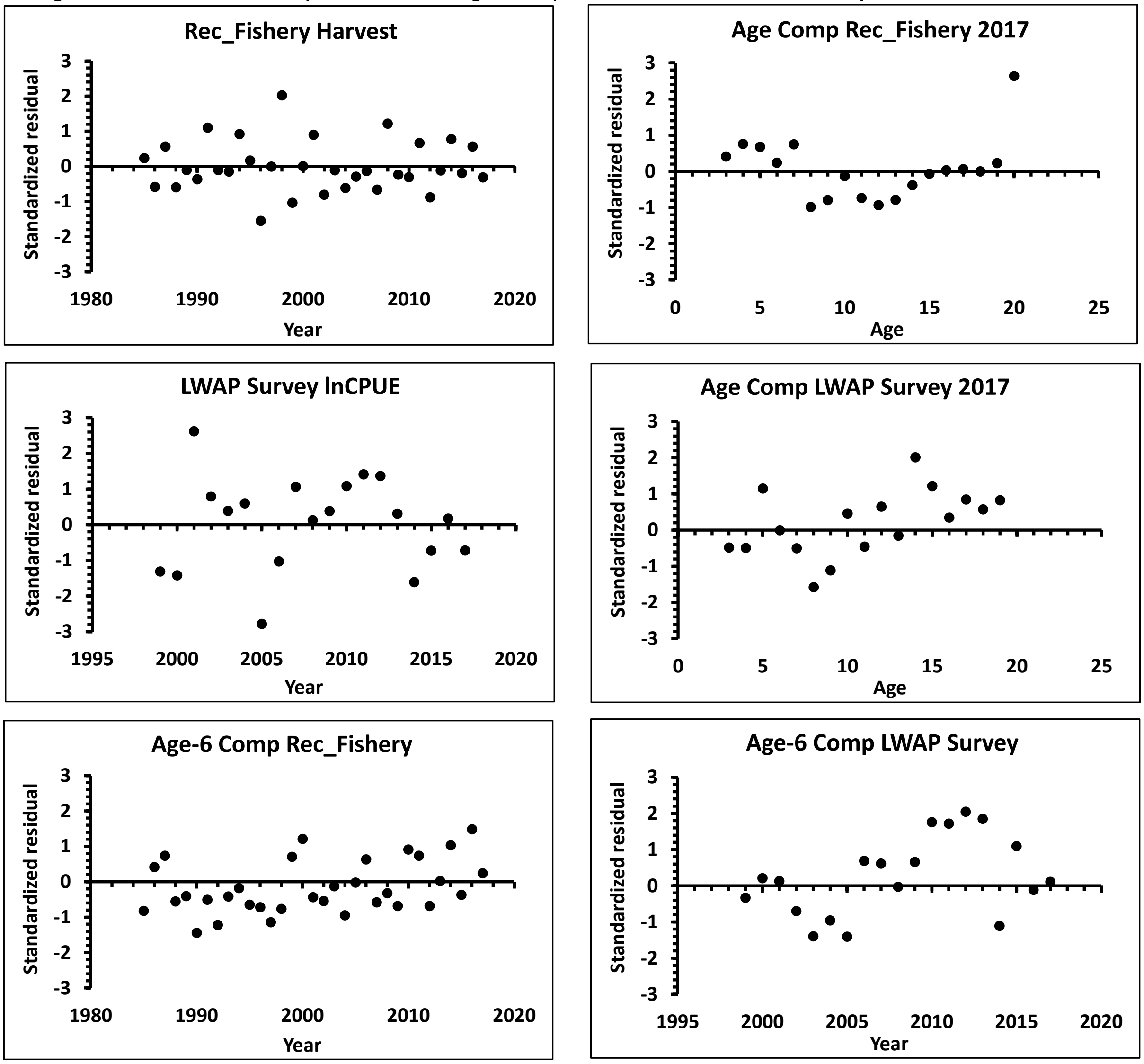
Table 4.1. Minimum, maximum, mean, and variance of the standardized residuals (SDRES) for recreational fishery catch, catch-per-unit effort in the LWAP survey, age composition (comp.) of age-6 Lake Trout in the recreational and LWAP survey, and age composition (age 3+) in the last year for the recreational fishery and LWAP survey for six versions of the WIIM stock assessment for 1985-2019. Versions 02-18-20, 03-04-20, and 04-02-20 used data for 1985-2017 whereas versions 09-21-20, 10-09-20 and 11-11-20 used data for 1985-2019.

WIIM version	SDRES 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
02-18-20	minimum	-1.54576	-0.97996	-2.78361	-1.58073	-1.44385	-1.40628
	maximum	2.02256	2.63619	2.69870	5.30535	1.48051	2.04727
	mean	0.00217	0.05614	-0.01549	0.47637	-0.16589	0.24099
	variance	0.53686	0.73822	1.66721	2.23952	0.55591	1.14348
03-04-20	minimum	-1.62678	-0.55303	-2.86460	-1.73835	-0.29706	-1.45882
	maximum	2.07124	1.88247	2.62745	4.86615	2.54226	2.15706
	mean	-0.00261	0.07509	-0.01430	0.44569	0.66342	0.25803
	variance	0.56377	0.38273	1.69286	2.08507	0.32607	1.20341
04-02-20	minimum	-1.60233	-0.55619	-2.83881	-1.72993	-0.49683	-1.45837
	maximum	2.05413	2.05178	2.65587	4.95002	2.35494	2.16679
	mean	-0.00187	0.05222	-0.01345	0.44189	0.41689	0.24725
	variance	0.56167	0.34671	1.69992	2.11184	0.33917	1.21744
09-21-20	minimum	-1.74563	-0.69055	-3.64798	-1.13544	-0.64290	-1.39461
	maximum	1.84477	0.95968	2.69640	8.09355	2.43704	2.38227
	mean	-0.01629	0.08207	-0.07581	0.54482	0.55904	0.41327
	variance	0.53687	0.26742	1.97090	4.74925	0.37457	1.13975
10-09-20	minimum	-1.77959	-1.24535	-3.58086	-1.12385	-1.30839	-2.09829
	maximum	1.95720	2.15470	2.73385	8.94537	3.26579	2.70965
	mean	-0.01440	0.14708	-0.06692	0.67596	0.97877	0.41811
	variance	0.58352	0.69522	2.09594	5.85594	0.88822	1.48502
11-11-20	minimum	-1.77973	-1.24627	-3.58844	-1.12330	-1.30997	-2.09856
	maximum	1.94693	2.15345	2.72309	8.94408	3.26577	2.70808
	mean	-0.01211	0.14712	-0.06768	0.67659	0.96258	0.41752
	variance	0.59848	0.69389	2.09949	5.85664	0.91076	1.48466

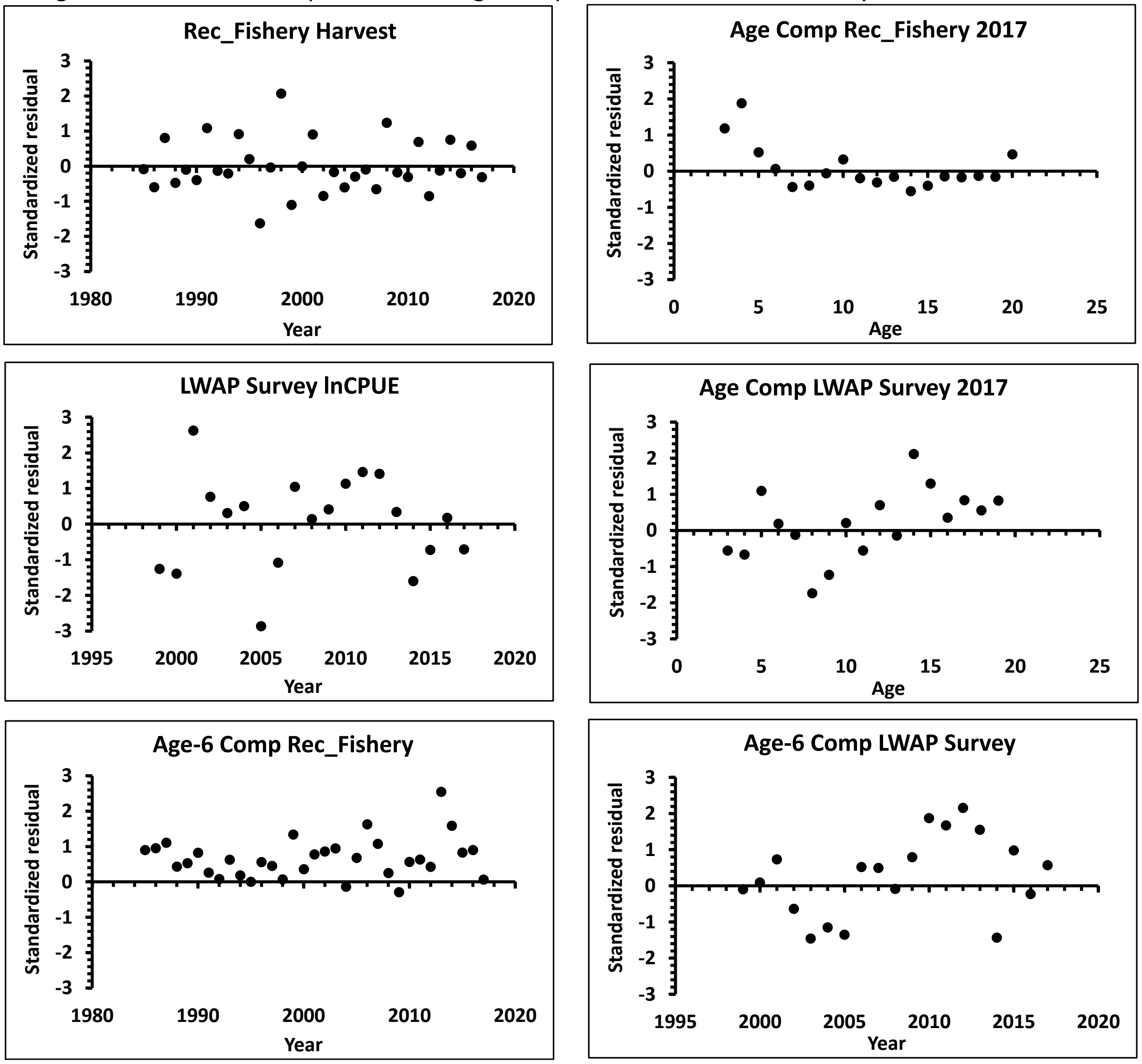
Figure 4.1. Box and whisker plots of the standardized residuals (SDRES) for recreational catch, LWAP survey CPUE, and age composition of Lake Trout in the recreational and survey catches for six versions of the WIIM stock assessment. Versions 02-18-20, 03-04-20, and 04-02-20 used data for 1985-2017, whereas versions 09-21-20, 10-09-20 and 11-11-20 used data for 1985-2019. 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. There was one positive outlier outside the range of plotted values for each of the 02-18-20 and 09-21-20 versions of the panel for the age composition of the LWAP survey in the last year.



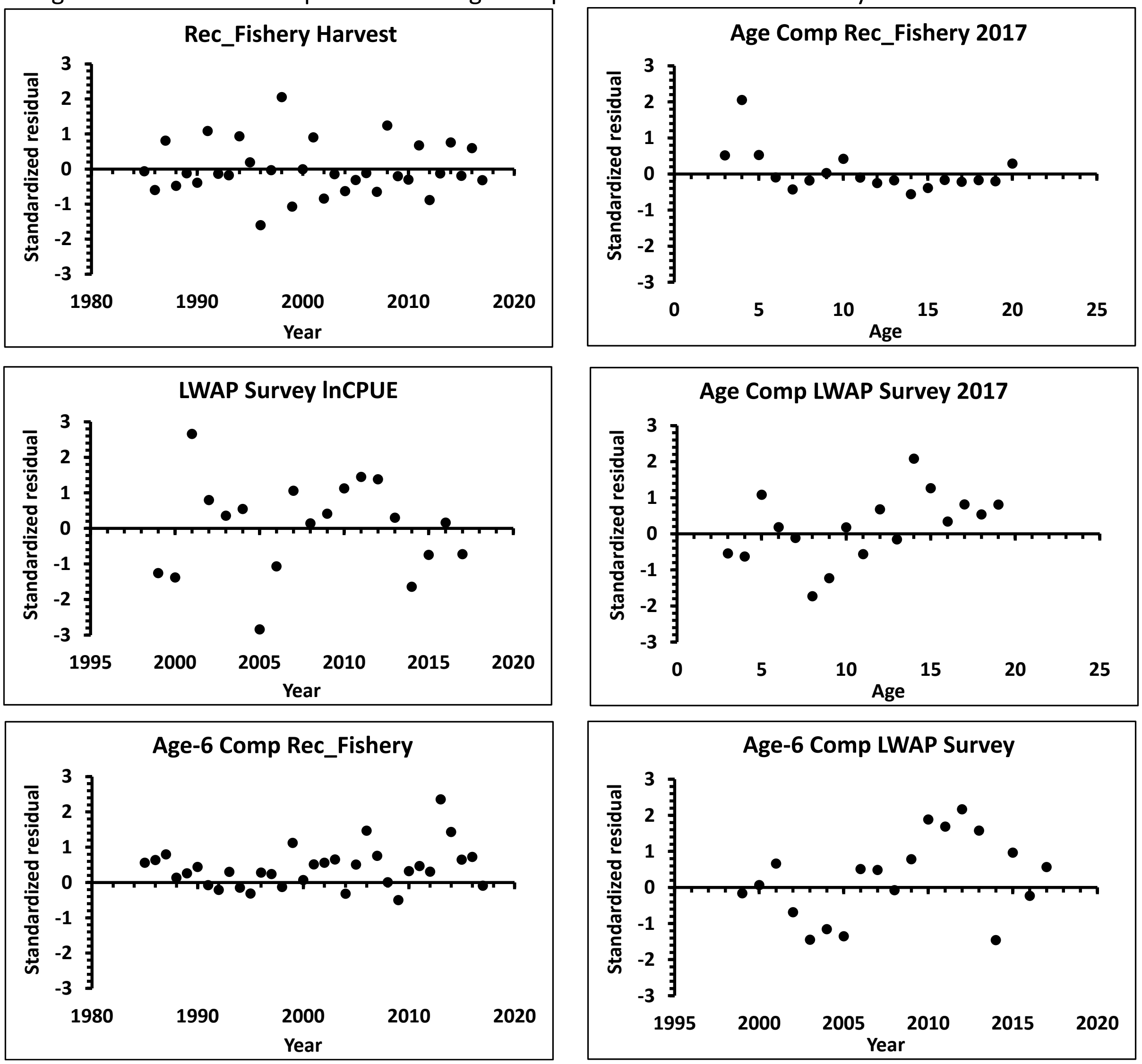
4.2 Residual plots WIIM-02-18-20. There was one outlier (SDRES=5.3) outside the range of plotted values for age 20 and older in the panel for the age composition of the LWAP survey in 2017.



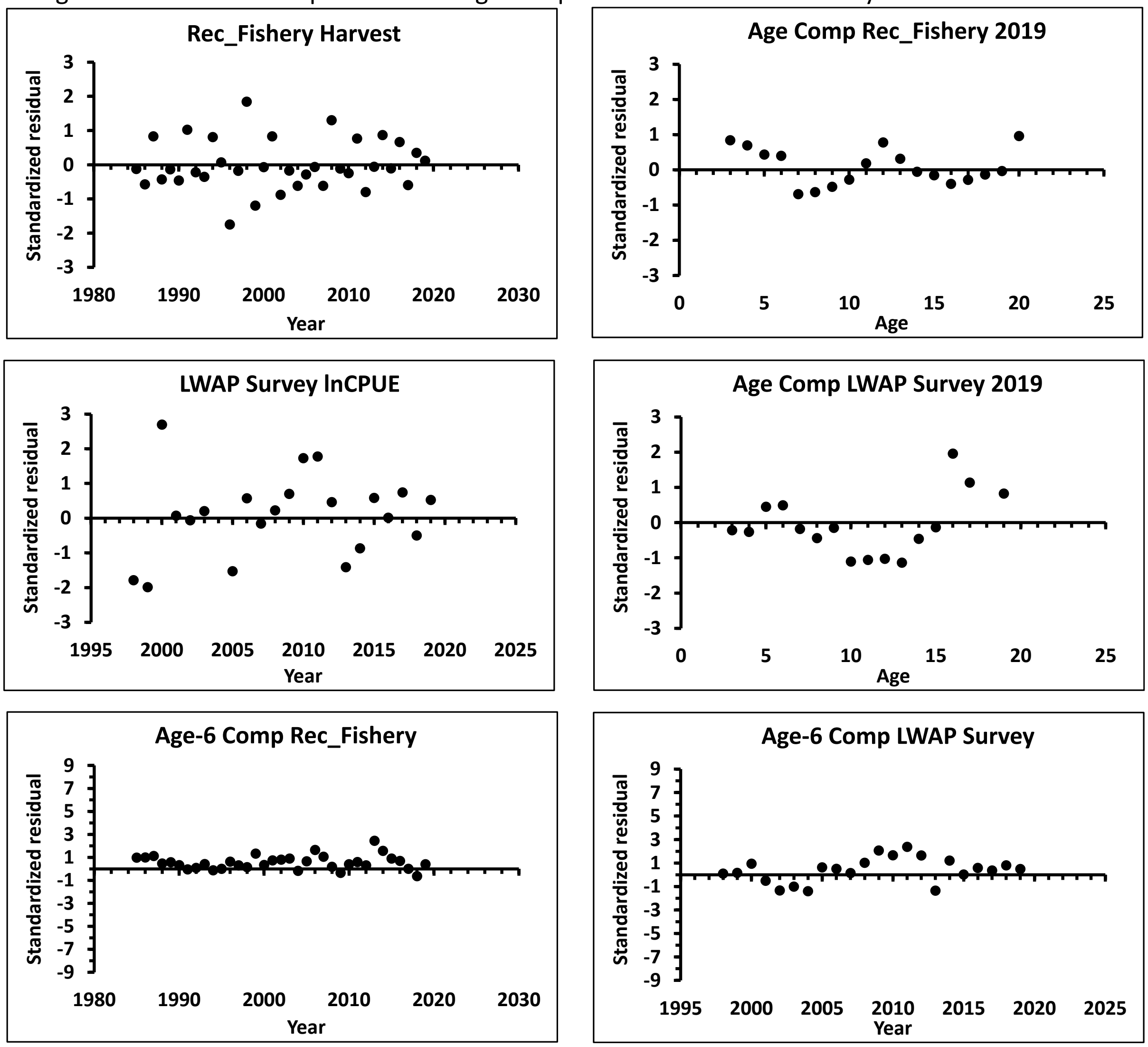
4.3 Residual plots WIIM-03-04-20. There was one outlier (SDRES=4.9) outside the range of plotted values for age 20 and older in the panel for the age composition of the LWAP survey in 2017.



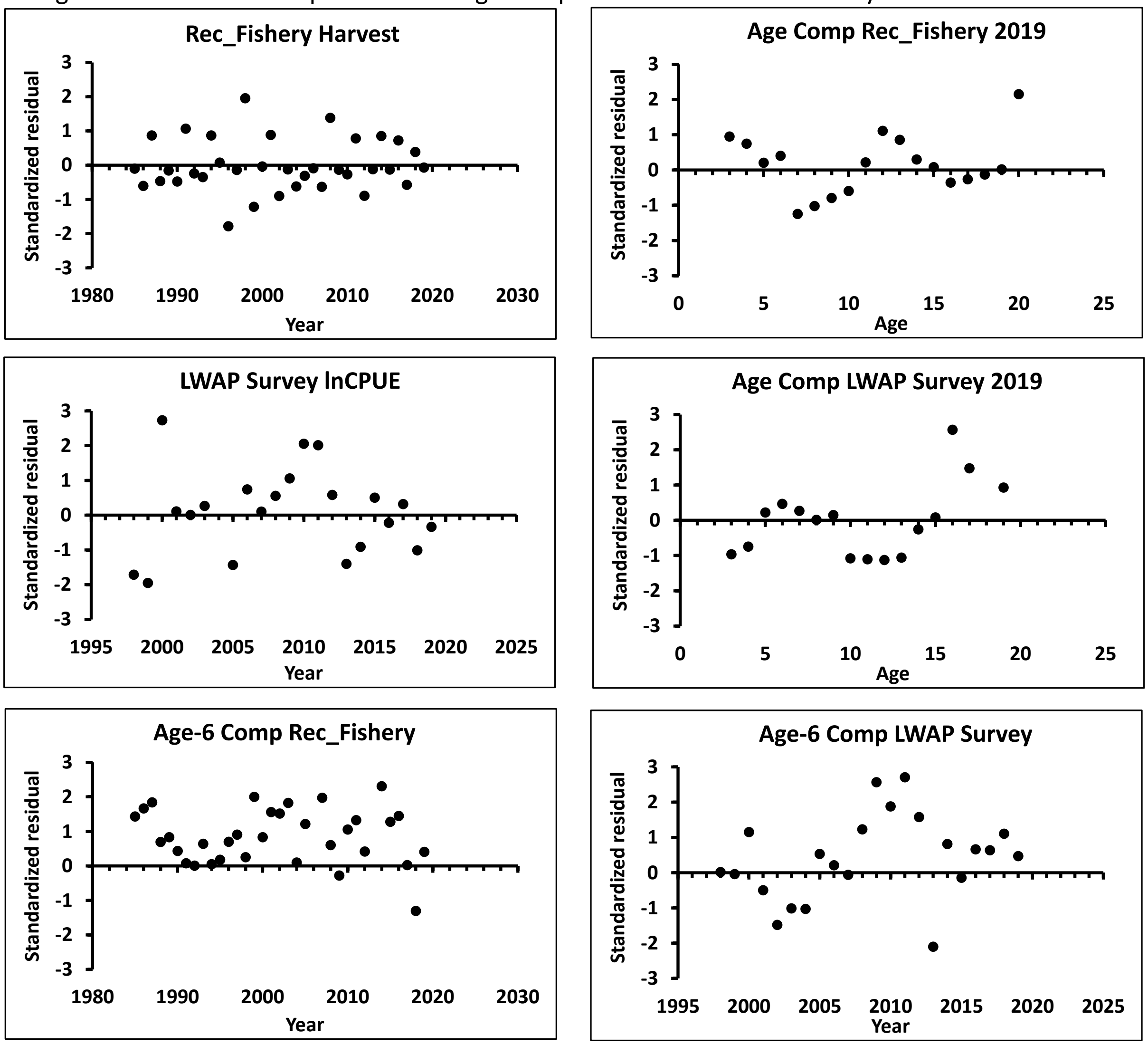
4.4 Residual plots WIIM-04-02-20. There was one outlier (SDRES=4.95) outside the range of plotted values for age 20 and older in the panel for the age composition of the LWAP survey in 2017.



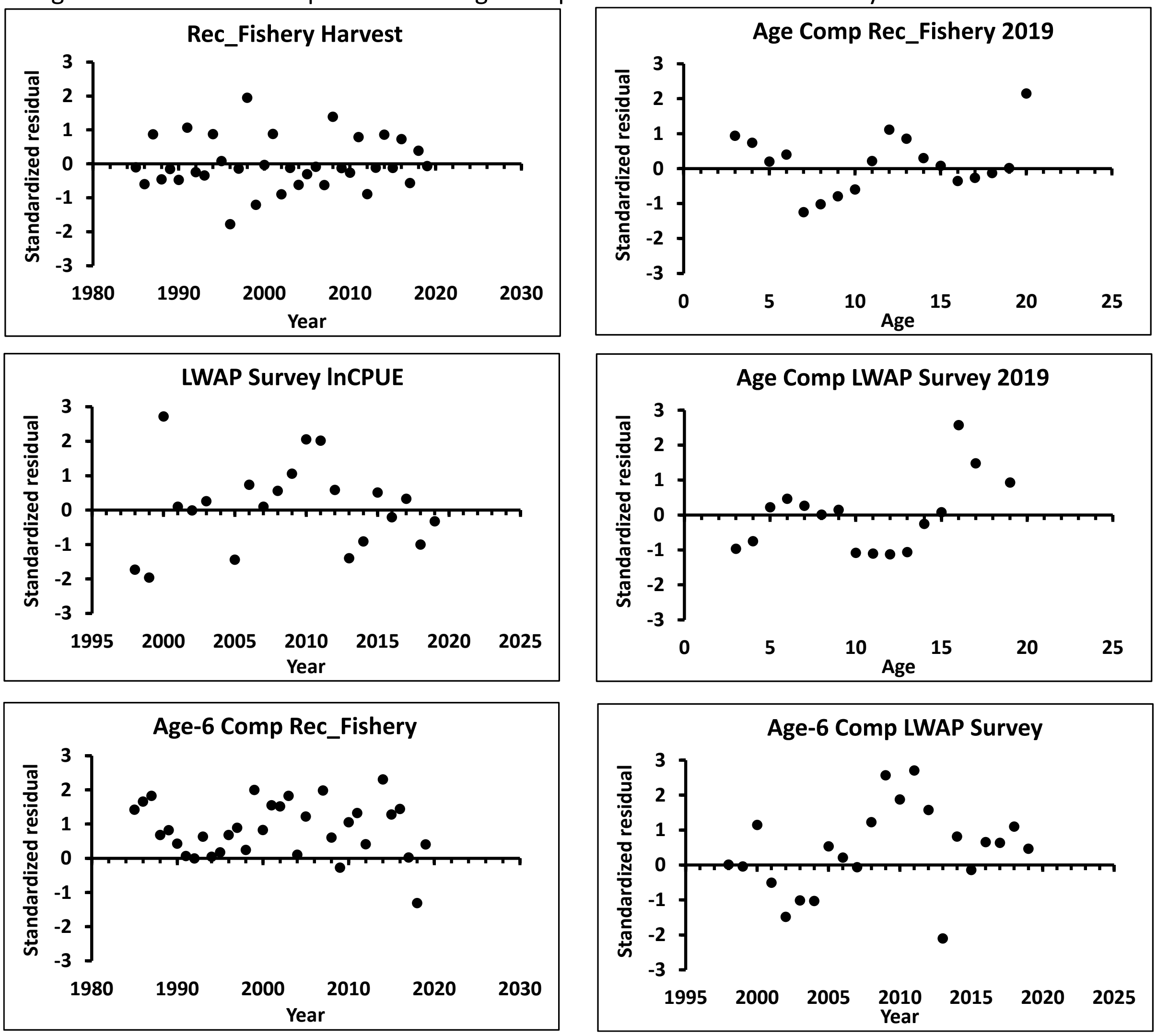
4.5 Residual plots WIIM-09-21-20. There was one outlier (SDRES=8.09) outside the range of plotted values for age 20 and older in the panel for the age composition of the LWAP survey in 2019.



4.6 Residual plots WIIM-10-09-20. There was one outlier (SDRES=8.95) outside the range of plotted values for age 20 and older in the panel for the age composition of the LWAP survey in 2019.



4.6 Residual plots WIIM-11-11-20. There was one outlier (SDRES=8.94) outside the range of plotted values for age 20 and older in the panel for the age composition of the LWAP survey in 2019.



5.0 Selectivity and Catchability

Selectivity of 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 of the LWAP survey (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 02-18-20 version, there was little difference in selectivity of the recreational fishery among versions of the stock assessment, whereas modification of commercial selectivity for the 11-11-20 version did substantially increase selectivity for ages 5-15 (Figure 5.1). Annual differences in selectivity of ages 3-9 in the LWAP survey were larger for the 10-09-20 and 11-11-20 versions than previous versions (Figure 5.2).

Figure 5.1. Age-specific proportional selectivity of the recreational and commercial fisheries for six versions of the WIIM Lake Trout stock assessment, 1985-2019.

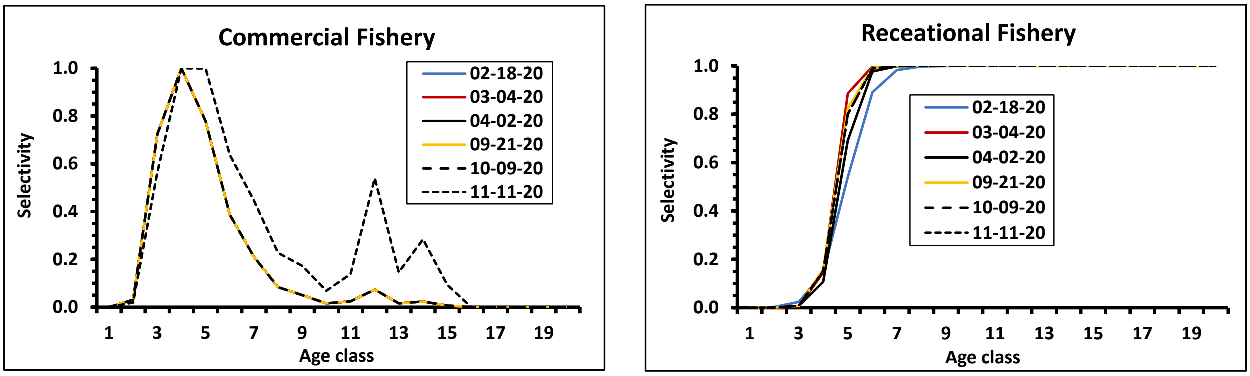
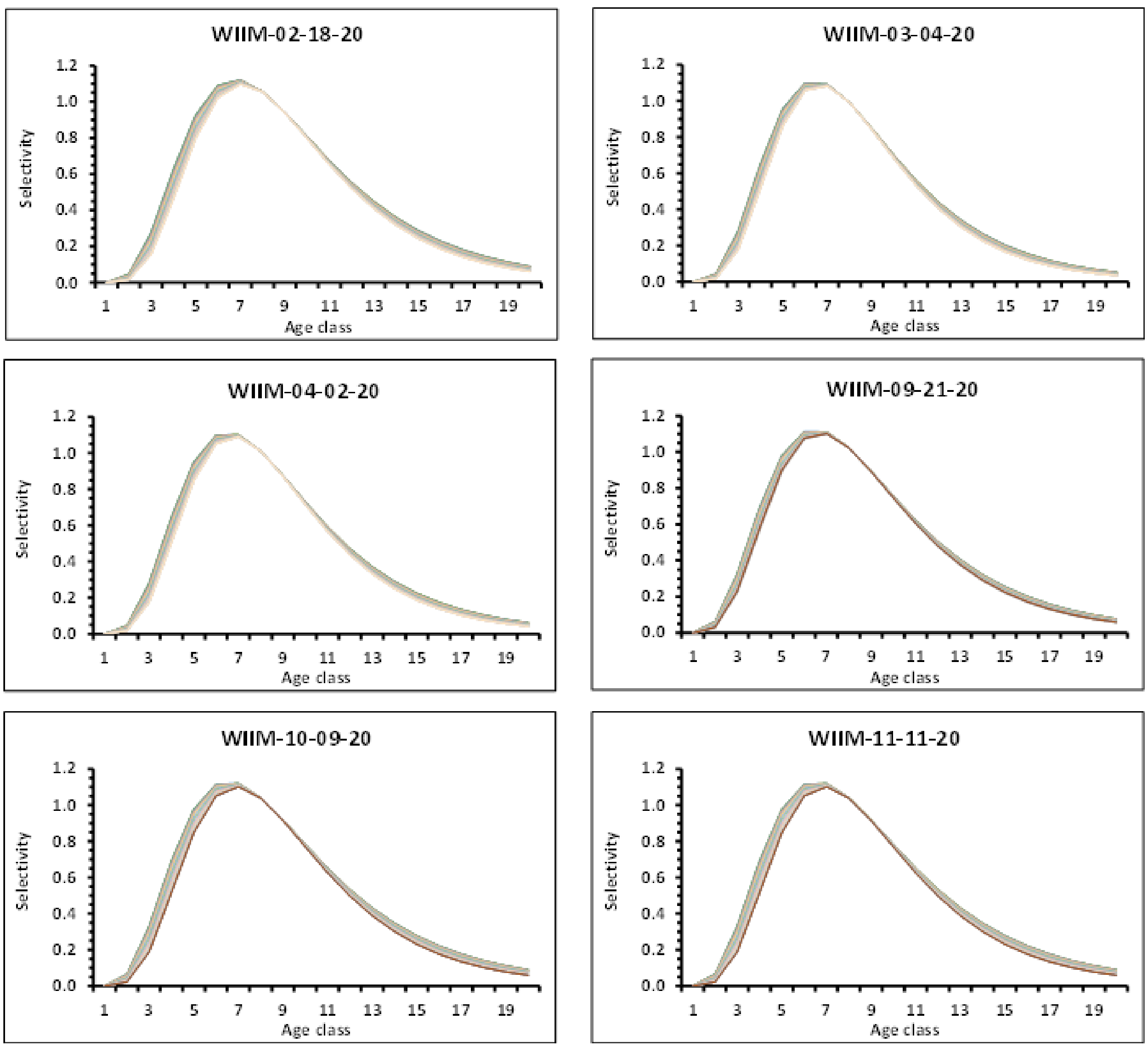
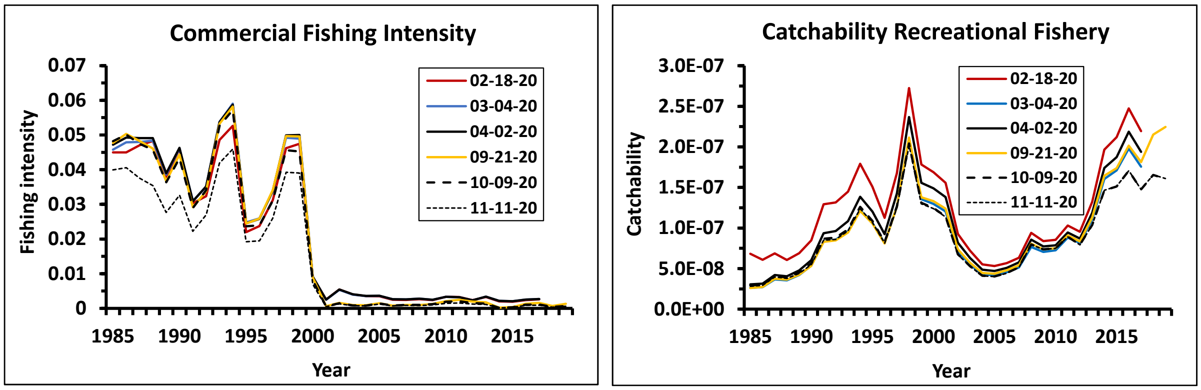


Figure 5.2. Age-specific proportional selectivity of the Lakewide Assessment Plan survey for six versions of the WIIM Lake Trout stock assessment, 1985-2019. Each line represents selectivity for a given year.



We estimated time varying catchability for the recreational fishery and commercial fishing intensity 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 but was lowest for the 11-11-20 version after we corrected selectivity (Figure 5.3). Differences in catchability of the recreational fishery among the different versions of the stock assessment were most pronounced during 1985-1996 and 2015-2019 (Figure 5.3).

Figure 5.3. Annual commercial fishing intensity and catchability of the recreational fishery for six versions of the WIIM Lake Trout stock assessment, 1985-2019.



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 all but the commercial 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 below in Table 6.0.

Table 6.0. Starting values for selectivity and catchability parameters of the commercial and recreational fisheries and LWAP survey that were varied to test stability of the WIIM Lake Trout stock assessments. The middle starting value is the original for each version of the stock assessment.

Parameter	SCAA variable & (starting values)	Description
Commercial fishing 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 (-1.5,1.5,3.0)	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.

Our WIIM models always arrived at the same final annual estimates of population biomass given our range of starting values for selectivity and catchability, thus, there was no effect of starting values on the estimated biomass trajectory. Consequently, we considered all versions of the WIIM 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. Interestingly, the 11-11-20 version could not achieve convergence when the starting value for the ***p2***-value of the LWAP survey selectivity was 1.6, but it could reach convergence at 1.5.

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 WIIM Lake Trout stock assessments.

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:

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

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).

Retrospective patterns for most estimated quantities were small but were most pronounced for the last three versions of the WIIM stock assessment (Figure 7.1). Mohn's rho values for all quantities ranged from -7% to +6% for the 02-18-20, 03-04-20, and 04-02-20 versions, whereas for the 09-21-20, 10-09-20, and 11-11-20 versions ***ρ-***values ranged from -29% to +13% (Figure 7.1). The largest retrospective patterns occurred for population abundance in the 10-09-20 and 11-11-20 versions where a negative pattern was evident, i.e., as years were peeled off abundance declined. For the last two versions of the WIIM stock assessment there was a -29% bias in population abundance and a -11% bias in population biomass. Retrospective patterns for individual quantities for each version of the stock assessment are shown in Figures 7.2 to 7.7.

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

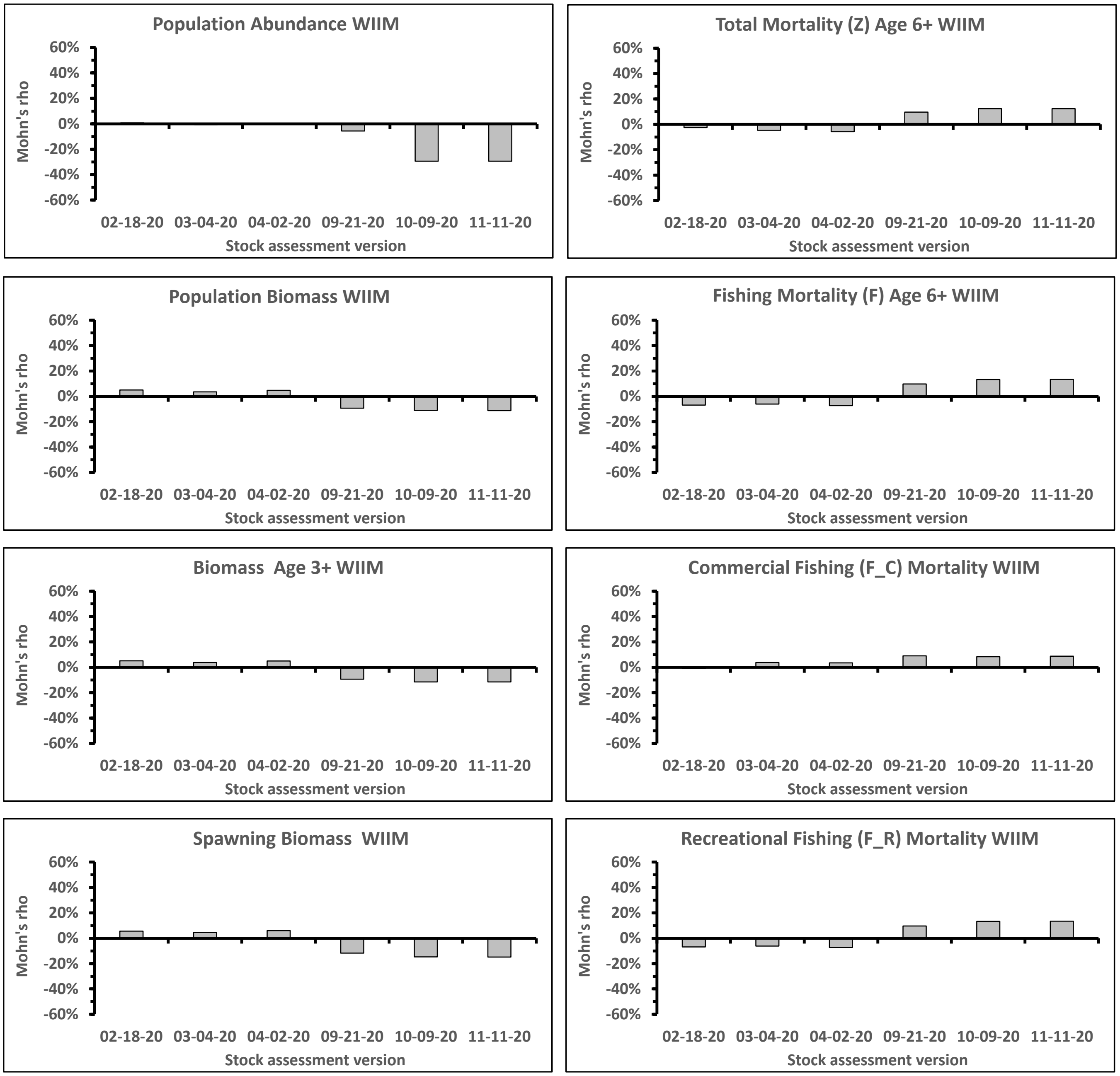


Figure 7.2. Retrospective plots WIIM-02-18-20.

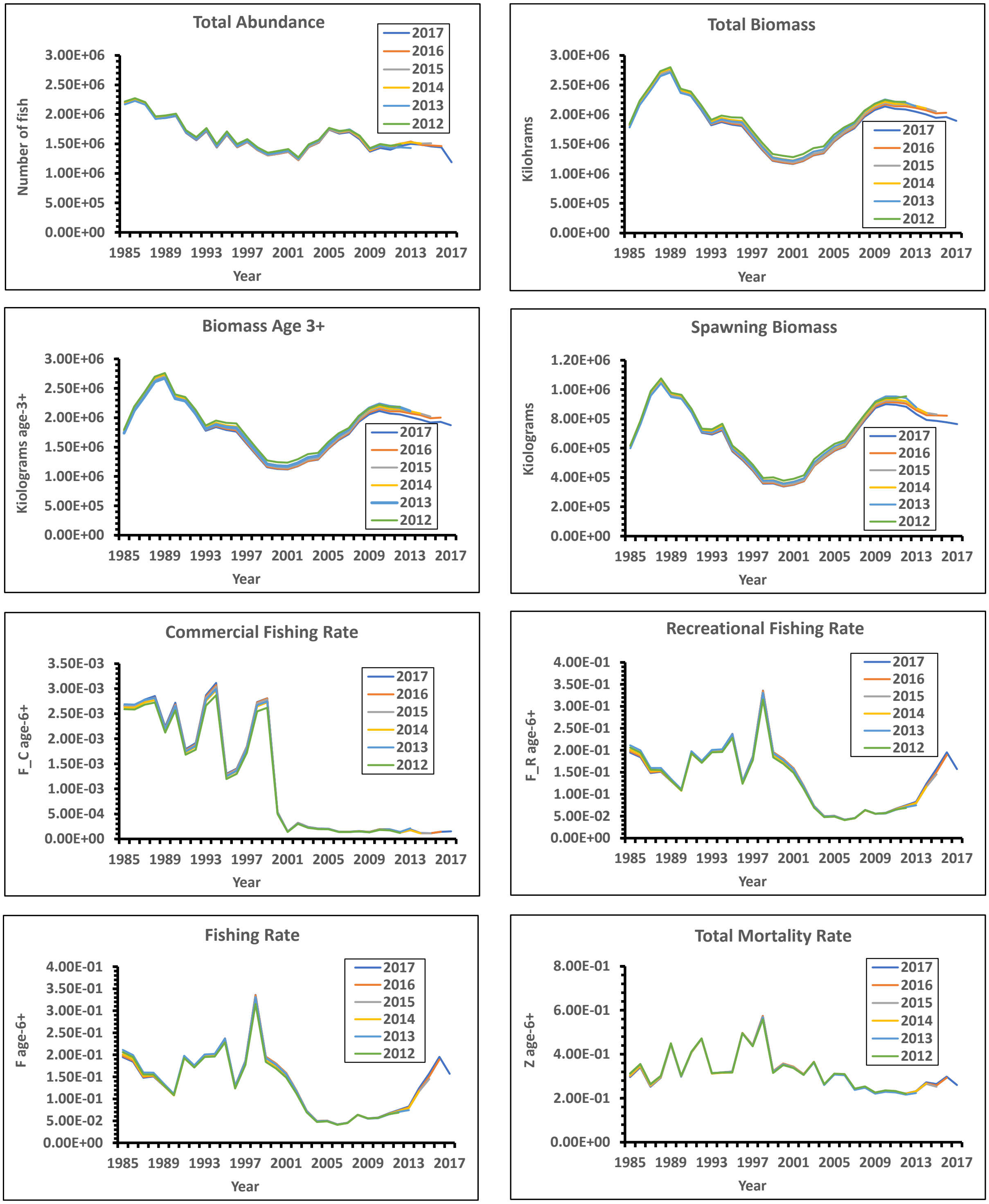


Figure 7.3. Retrospective plots WIIM-03-04-20.

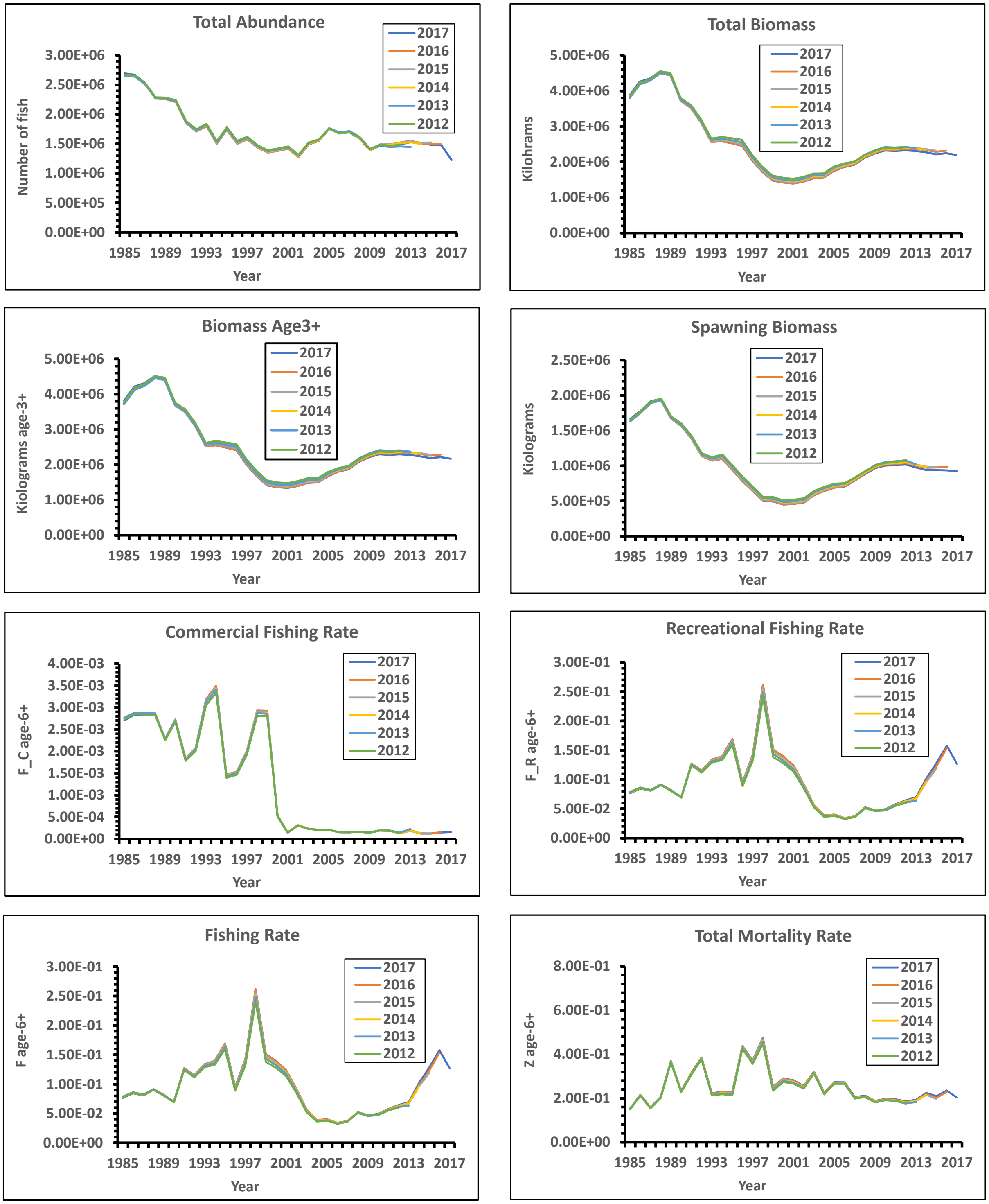


Figure 7.4. Retrospective plots WIIM-04-02-20.

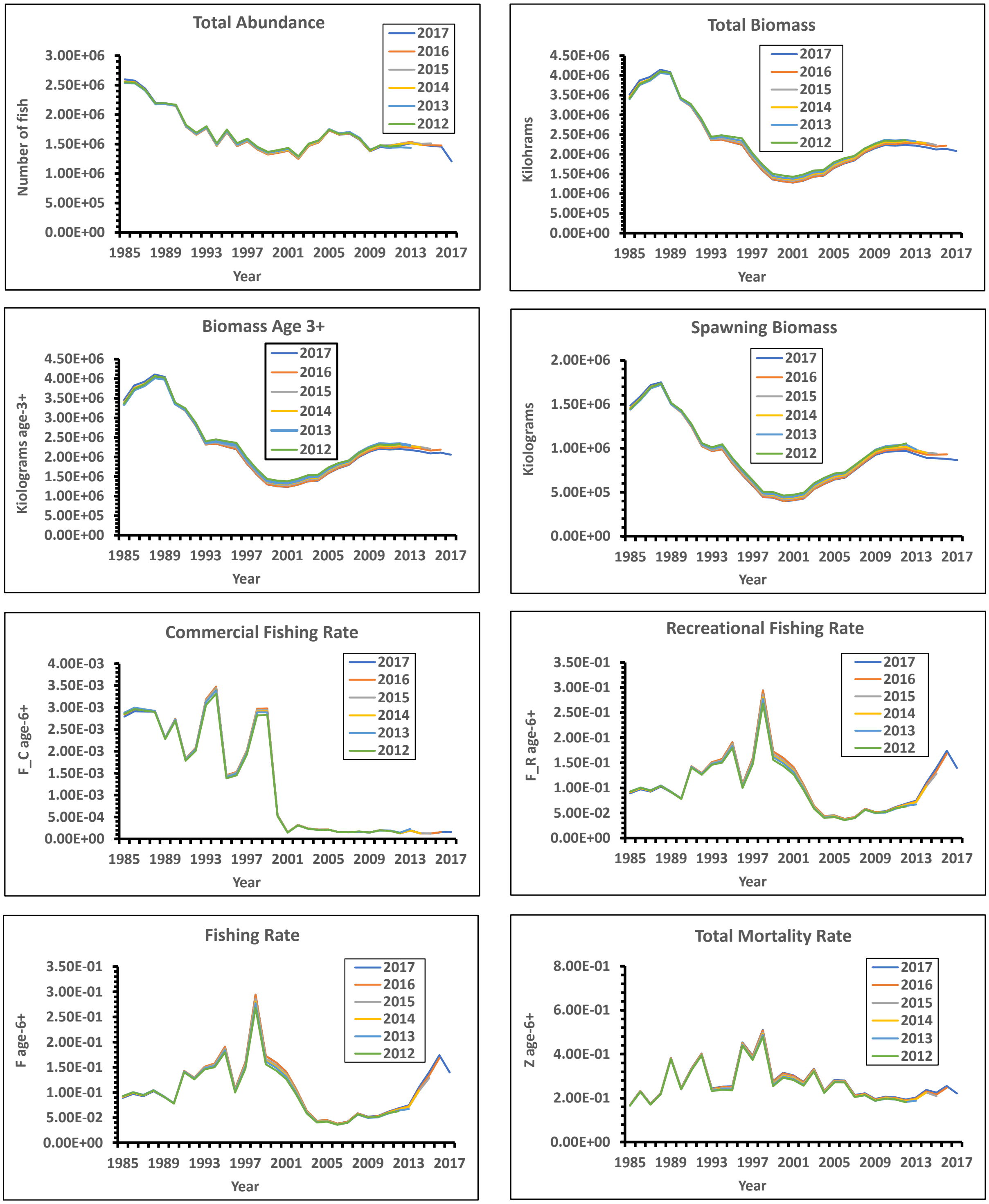


Figure 7.5. Retrospective plots WIIM-09-21-20.

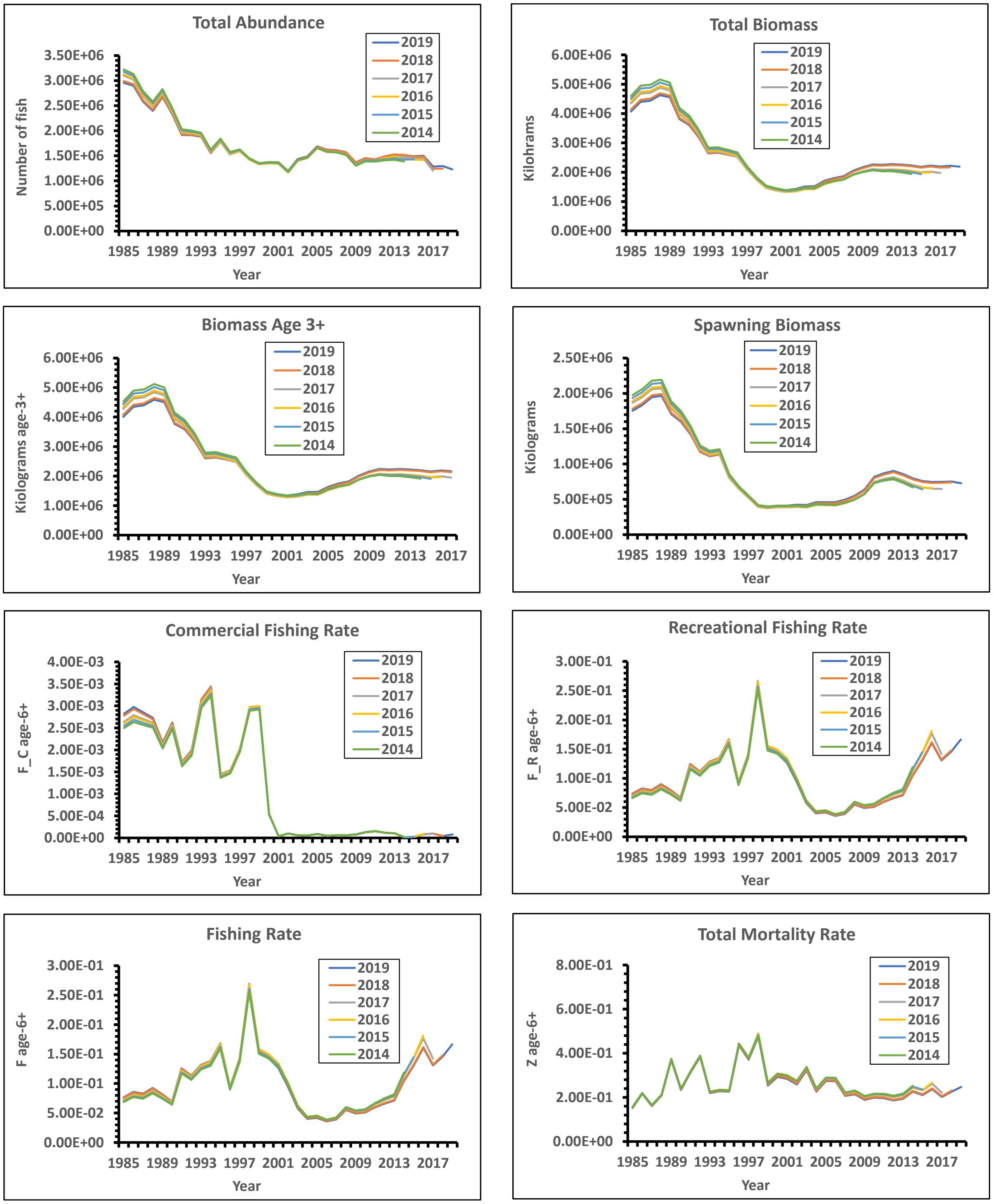


Figure 7.6. Retrospective plots WIIM-10-09-20.

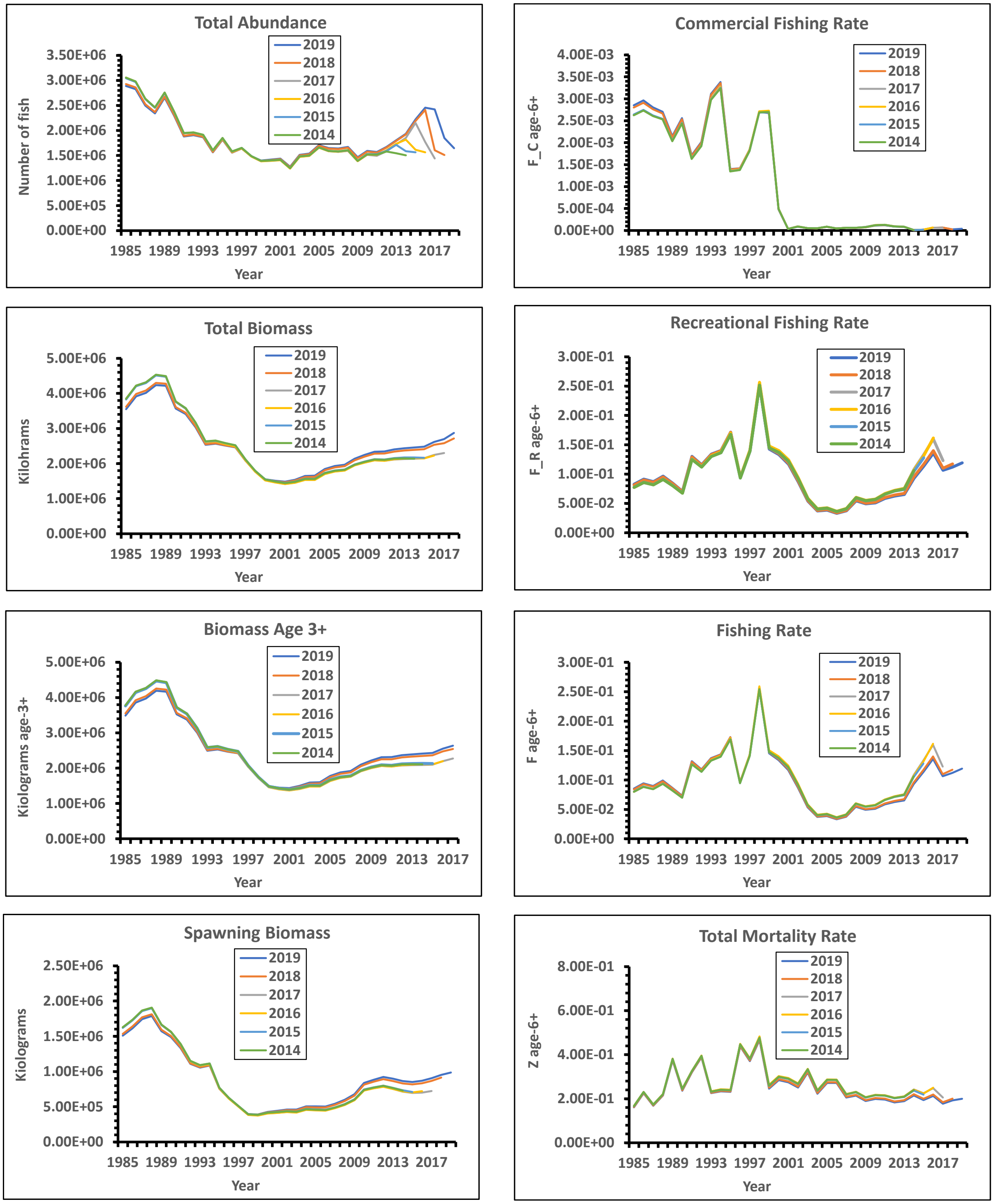
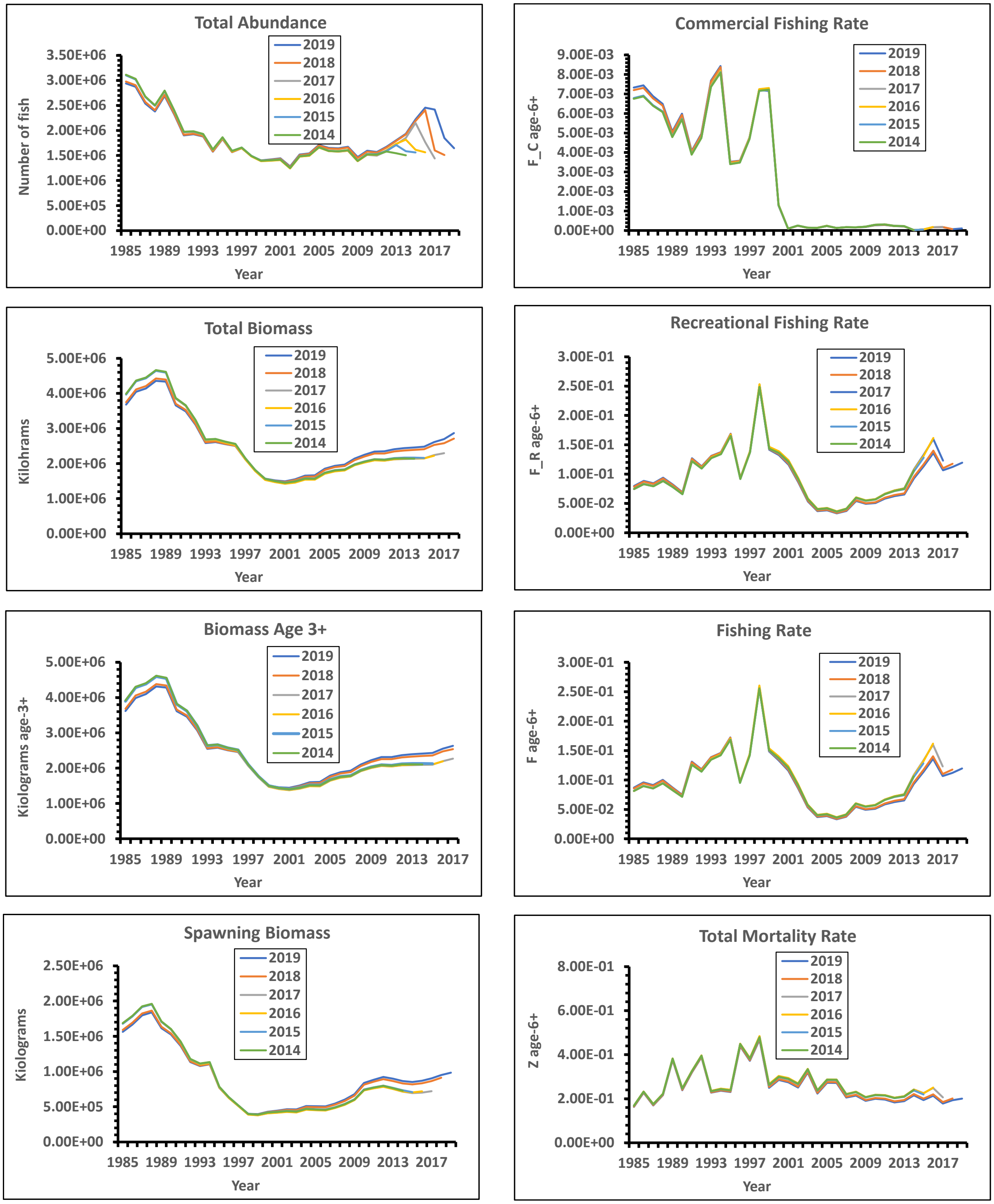


Figure 7.7. Retrospective plots WIIM-11-11-20.



8.0 MCMC Simulations

We conducted Markov chain Monte Carlo (MCMC) simulations to obtain estimates of the full posterior distribution for quantities estimated in the WIIM stock assessment and to diagnose potential issues in the validity of the estimated posterior distributions. Although management of Lake Michigan lake trout has largely been based on point estimates, the MSC has used MCMC diagnostics because issues with the posterior distribution could also indicate that the highest posterior density point estimates (penalized likelihood estimates) could be compromised. 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 WIIM Lake Trout stock assessments.

Quantity (figure title)	Description
Negative Log Likelihood (NLL)	sum of likelihood catch, survey CPUE, & age composition
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 WIIM 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	small pattern, some stickiness, uneven	small skew, several 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 WIIM stock assessment (Figures 8.1 to 8.11). The Objf and NLL trace plots consistently scored lower than other quantities (12 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 and total biomass (14 points) were generally good and scored higher for the 03-04-20 and 04-02-20 versions than for other 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 likelihoods profiles were very similar among all versions of the stock assessment scoring between 12 and 14 of 18 possible points. Total abundance scored 13 of 18 points and total biomass scored 14 of 18 points.

Autocorrelation plots did decline with lag and were generally 10% or less at the final lag (Figures 8.2 to 18.12). The Objf and NLL scored only 12 and 13 point, respectively, of 18 points, whereas all population demographic quantities scored either 17 or 18 of 18 possible points. Autocorrelation was four points less for the 02-18-20 version (24 of 30 points) than all other versions that scored 28 of 30 points (Table 8.1).

Overall, the 03-04-20 and 04-02-20 versions ranked the highest based on our scoring system, accumulating 79 and 74 points, respectively, of 90 possible points. The 02-18-20 version scored the lowest (66 of 90 points) of all versions of the WIIM stock assessment. The 11-11-20 version with the corrected commercial fishery selectivity had an intermediate score of 70 out of 90 points.

Table 8.1. Ranking scores of the Markov chain Monte Carlo trace plots (trace), posterior distributions (den.), and autocorrelation (corr.) for six version of the WIIM Lake Trout stock assessments.

WIIM	MCMC	Population quantity										
version	plot	Objf	NLL	AvgN	AvgtotB	AvgB3	AvgSSB	F_R	F_C	AvgF	AvgZ	Total
02-18-20	trace	2	2	2	2	2	2	2	2	2	3	21
	dens.	3	2	2	2	2	2	2	2	2	2	21
	corr.	2	3	2	2	2	2	3	2	3	3	24
03-04-20	trace	2	2	3	3	3	3	3	3	3	3	28
	dens.	2	3	3	3	2	2	2	2	2	2	23
	corr.	2	2	3	3	3	3	3	3	3	3	28
04-02-20	trace	2	2	3	3	3	3	2	2	2	2	24
	dens.	2	3	2	3	2	2	2	2	2	2	22
	corr.	2	2	3	3	3	3	3	3	3	3	28
09-21-20	trace	2	2	2	2	2	2	2	2	2	2	20
	dens.	2	2	2	2	2	2	2	2	2	2	20
	corr.	2	2	3	3	3	3	3	3	3	3	28
10-09-20	trace	2	2	2	2	2	2	2	2	2	2	20
	dens.	2	2	2	2	2	2	2	2	2	2	20
	corr.	2	2	3	3	3	3	3	3	3	3	28
11-11-20	trace	2	2	2	2	2	2	2	2	2	3	21
	dens.	2	2	2	2	2	2	2	2	2	3	21
	corr.	2	2	3	3	3	3	3	3	3	3	28

8.1 Trace plots and posterior distributions WIIM-02-18-20.

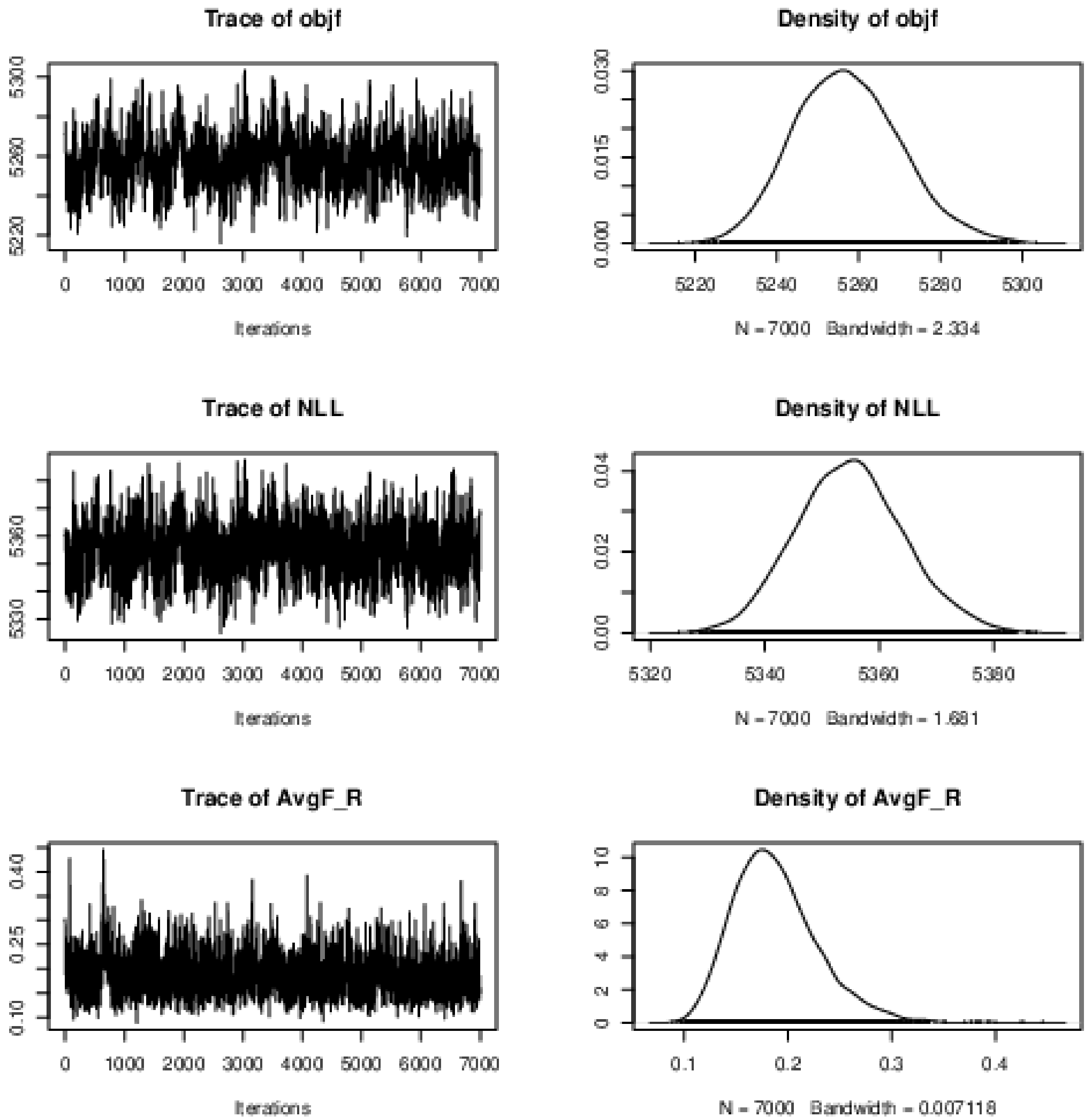


Figure 8.1 cont'd.

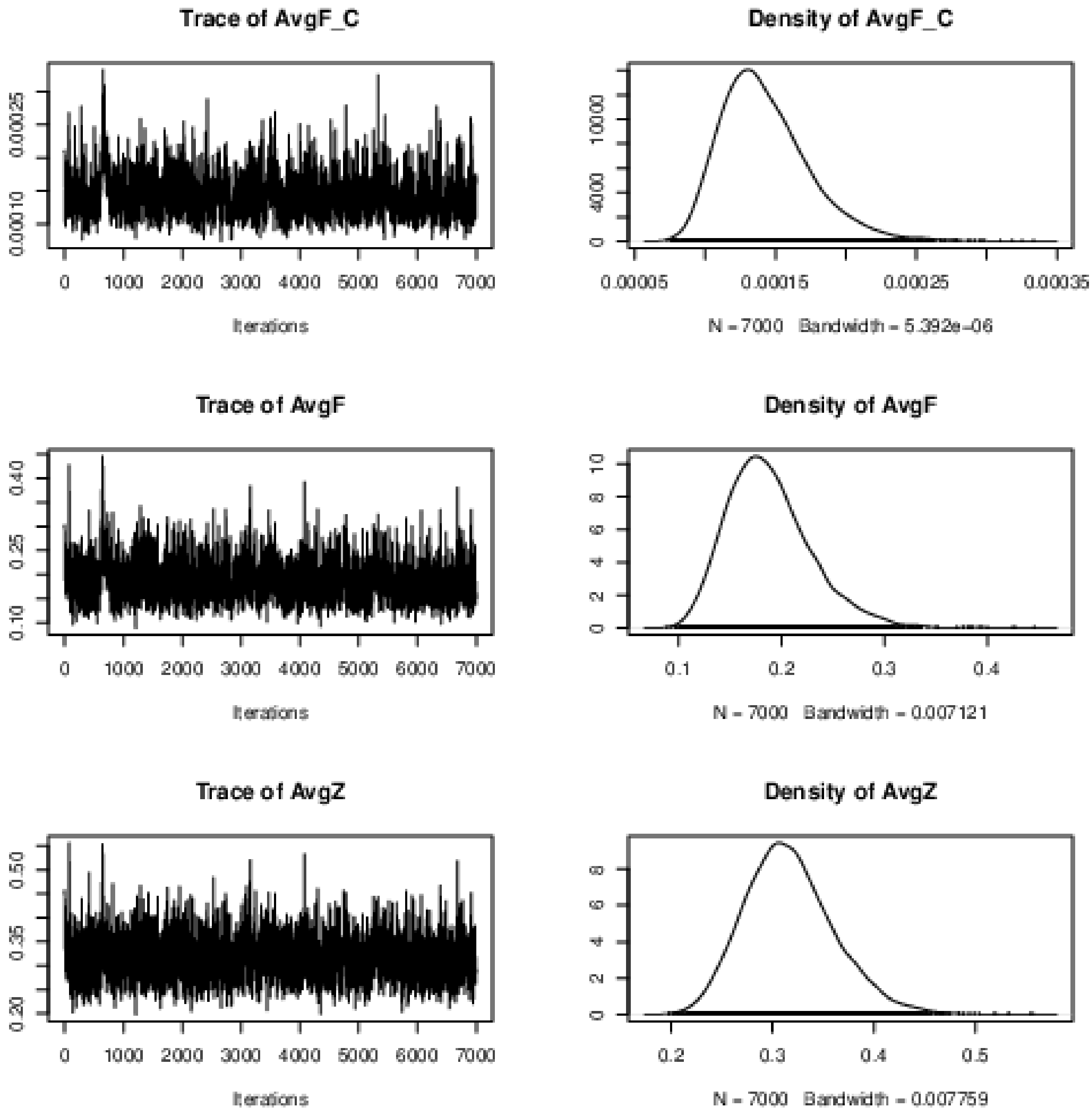


Figure 8.1 cont'd.

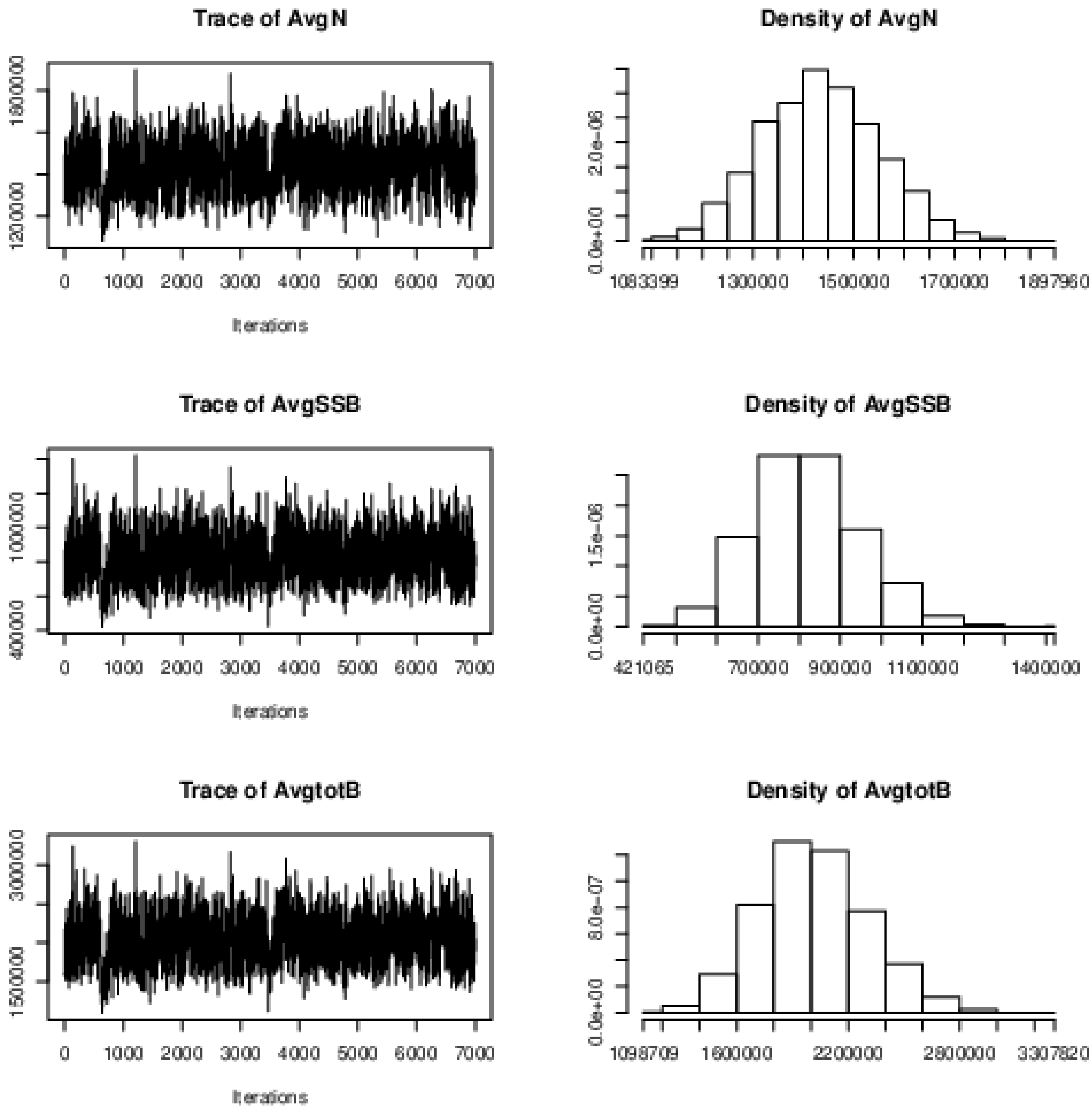
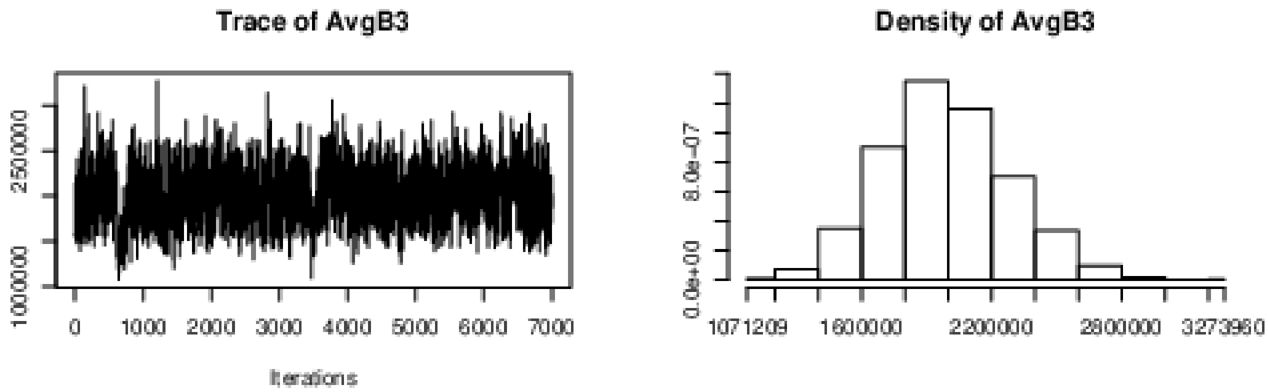


Figure 8.1 cont'd.



8.2 MCMC autocorrelations WIIM-02-18-20.

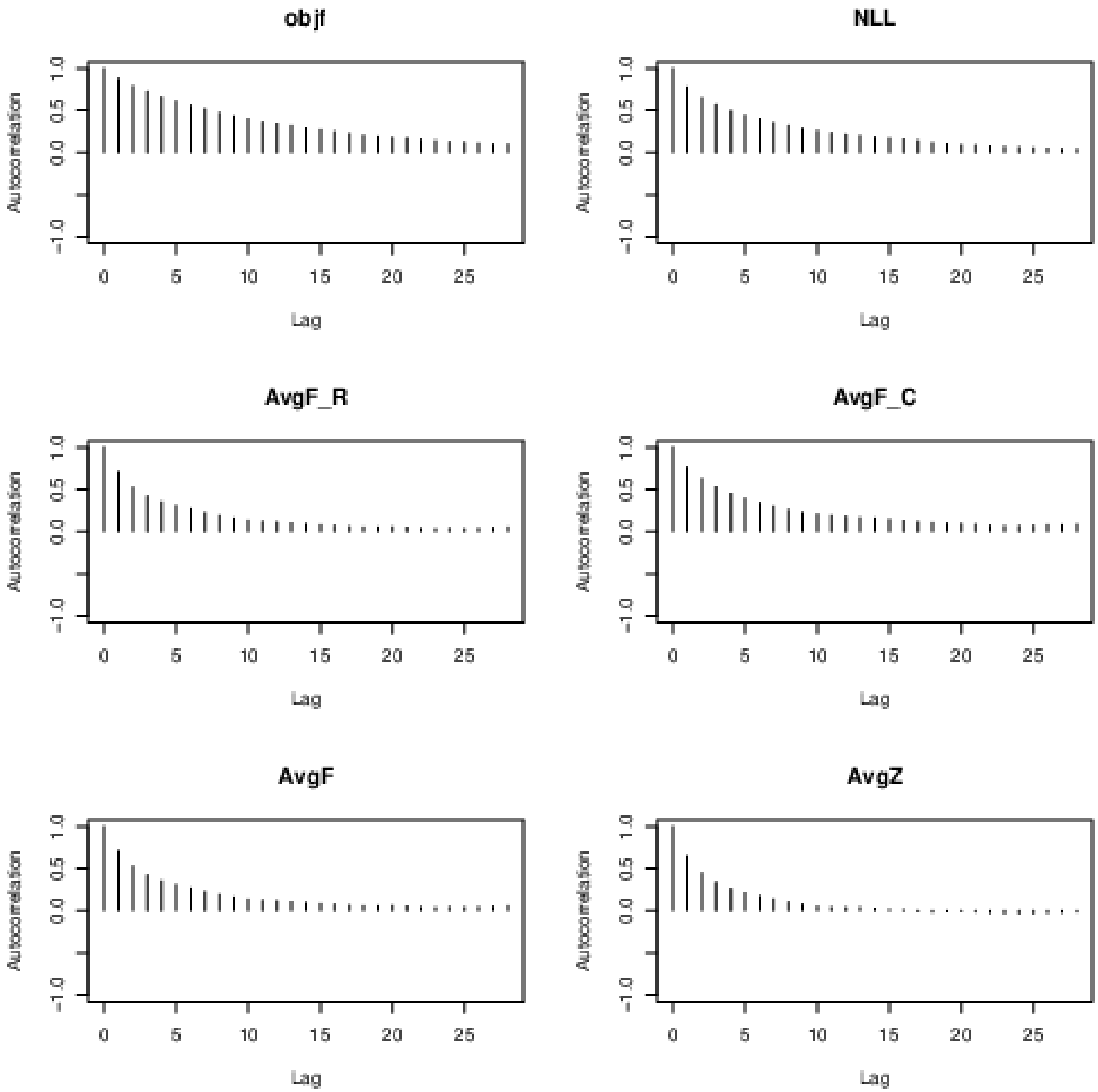


Figure 8.2 cont'd.

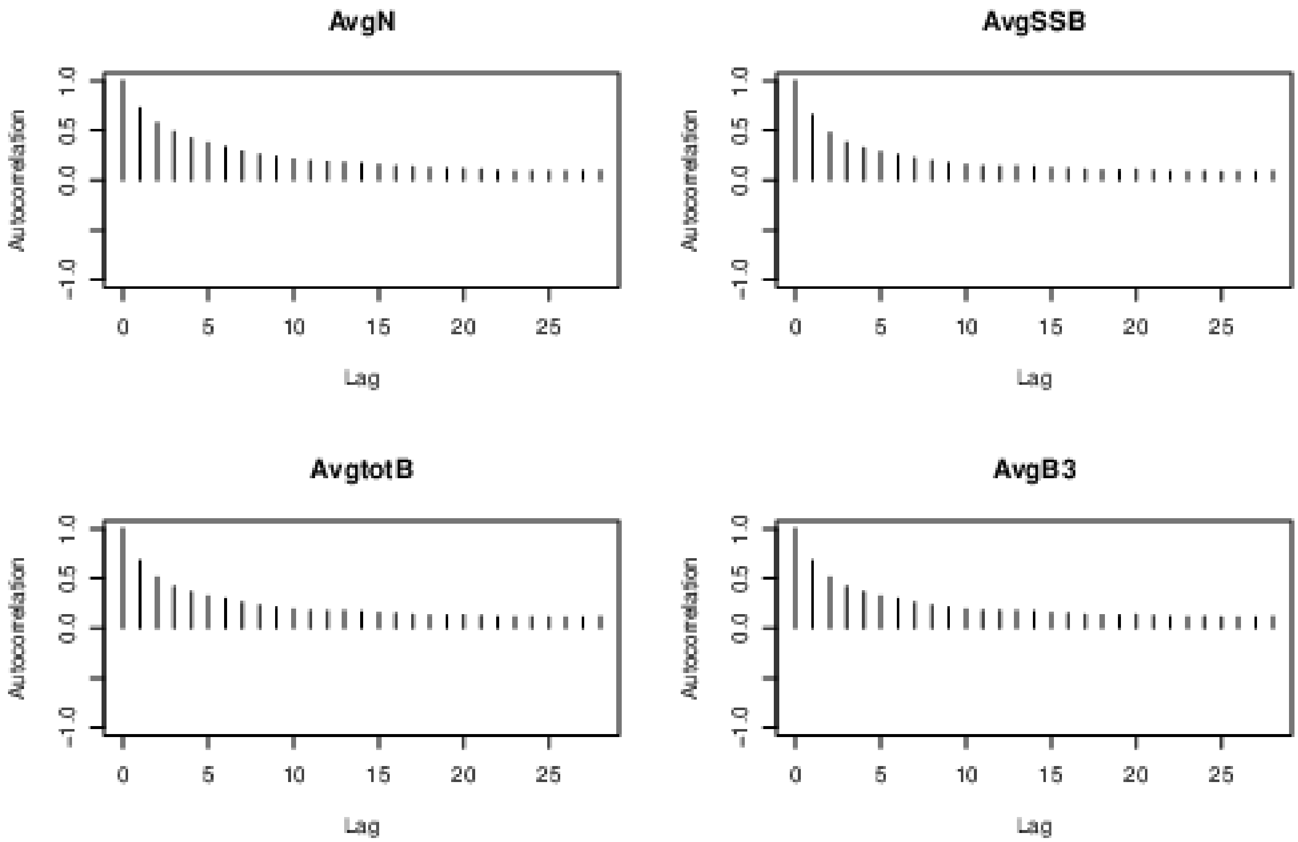


Figure 8.3. MCMC trace plots and posterior distributions WIIM-03-04-20.

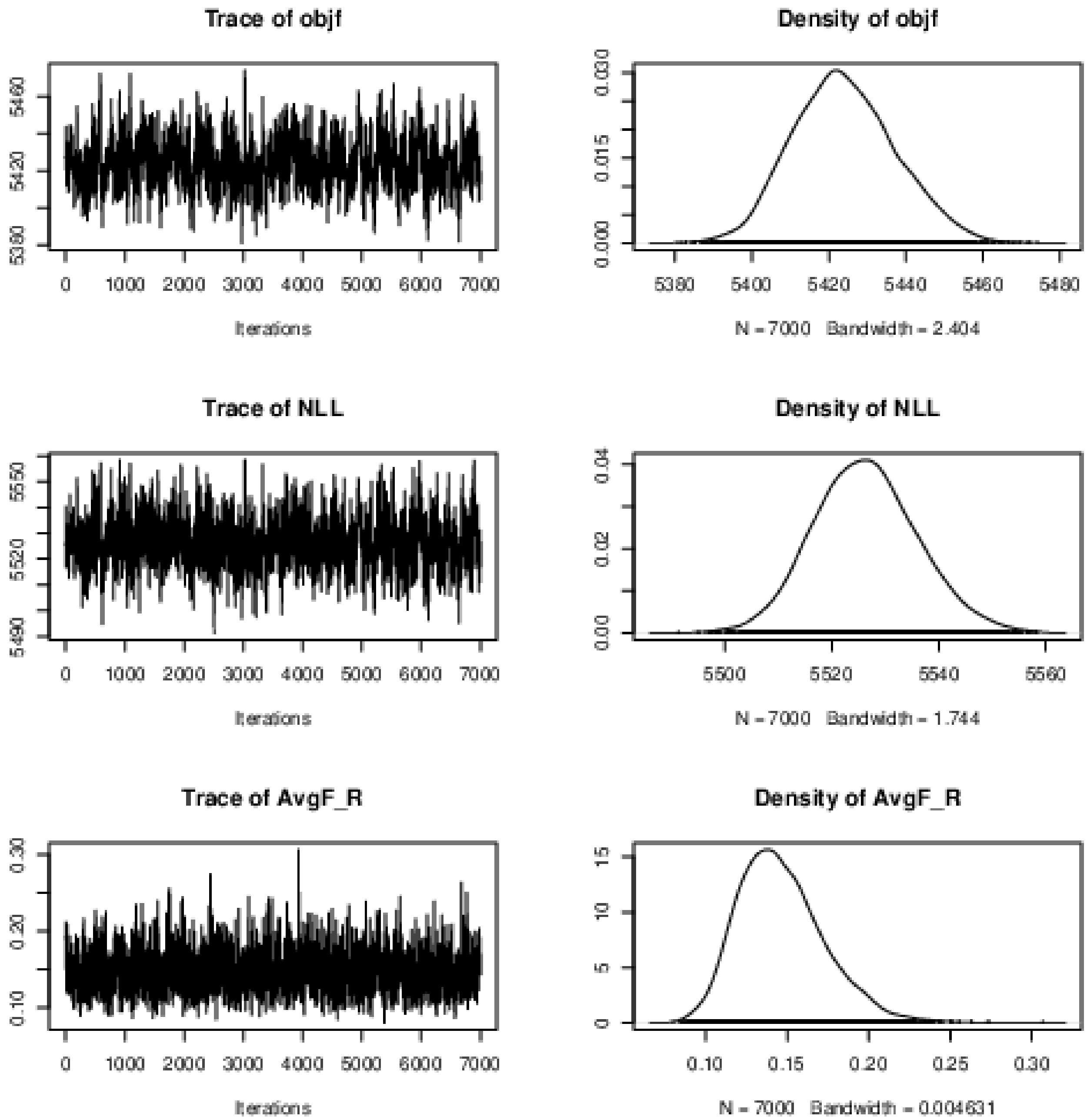


Figure 8.3 cont'd.

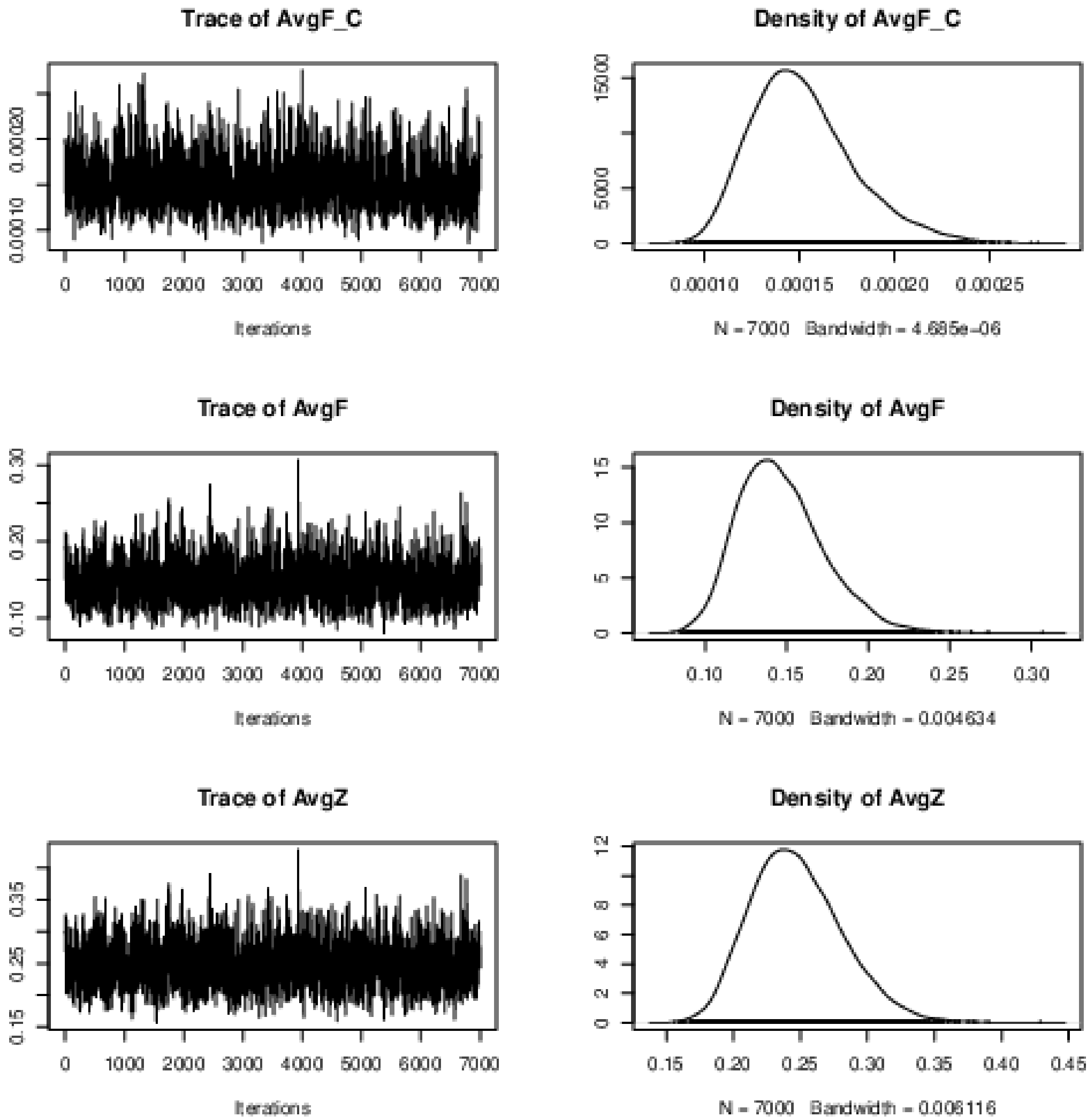


Figure 8.3 cont'd.

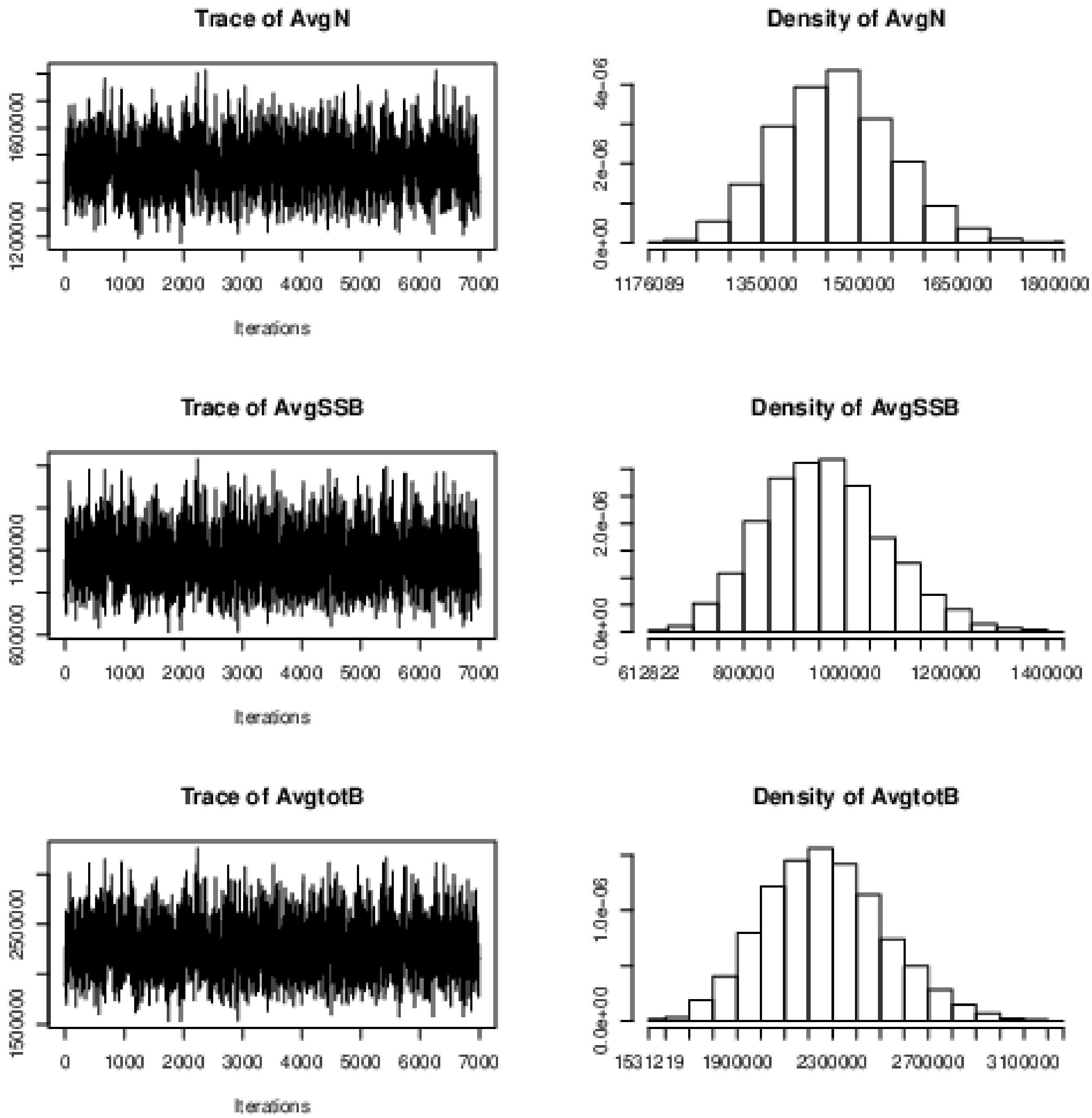


Figure 8.3 cont'd.

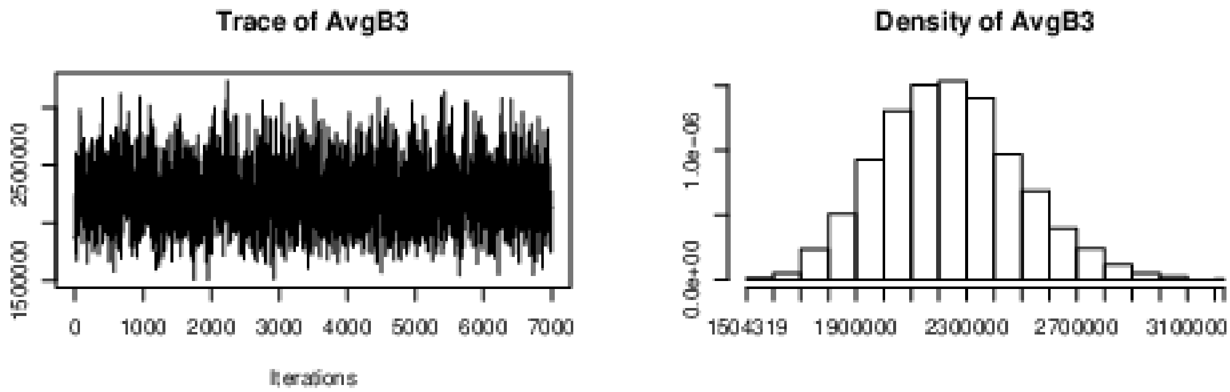


Figure 8.4. MCMC autocorrelations WIIM-03-04-20.

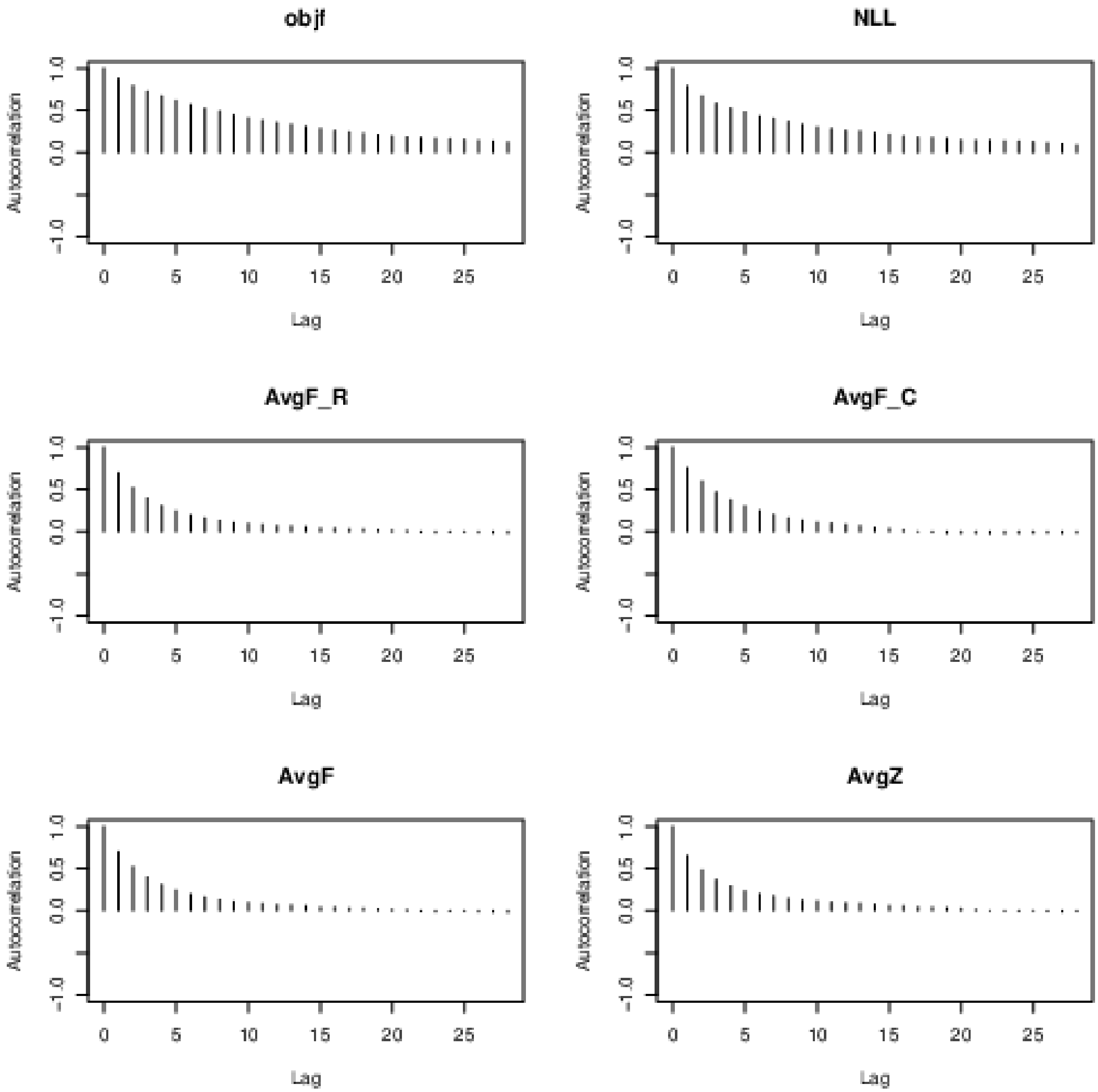


Figure 8.4 cont'd.

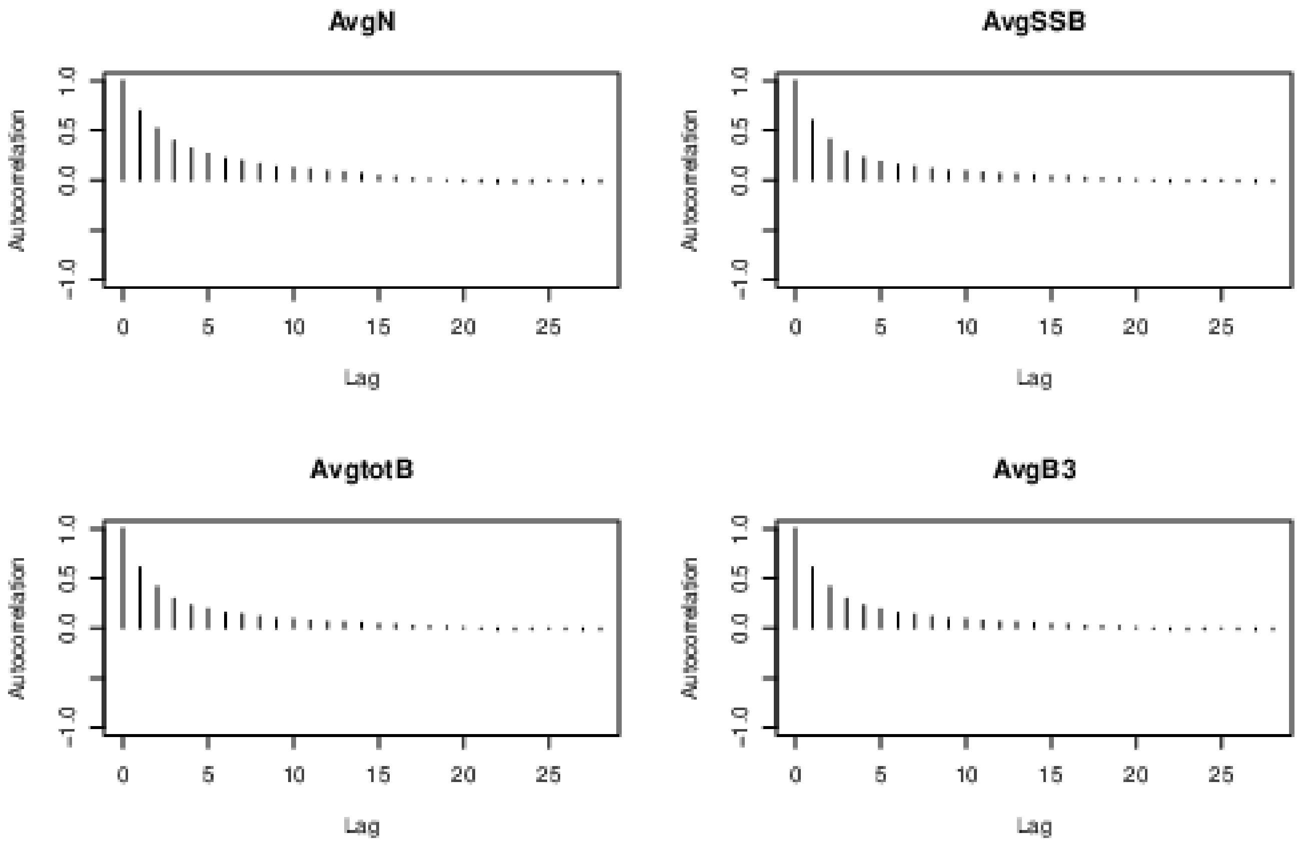


Figure 8.5. MCMC trace plots and posterior distributions WIIM-04-02-20.

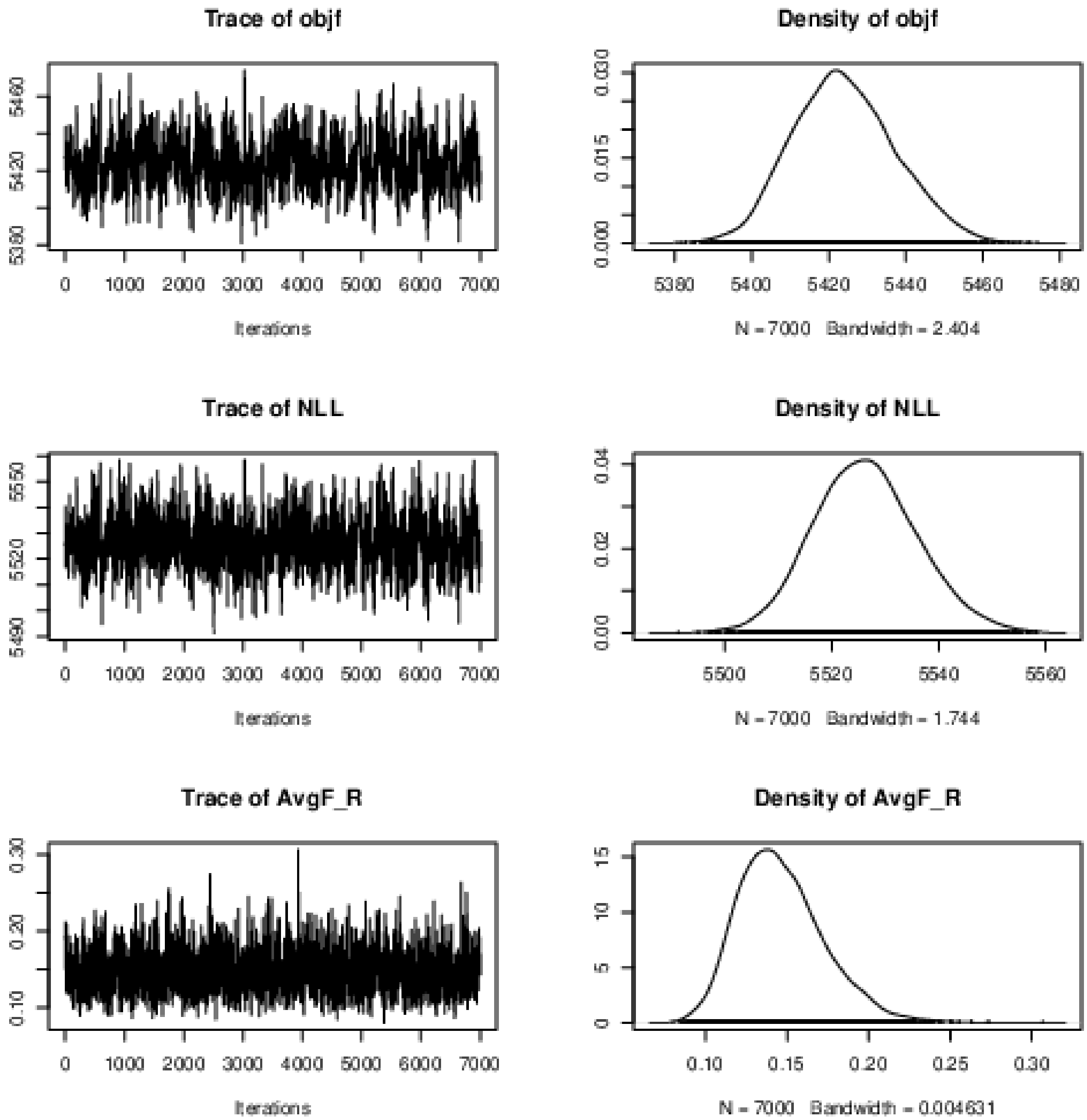


Figure 8.5 cont'd.

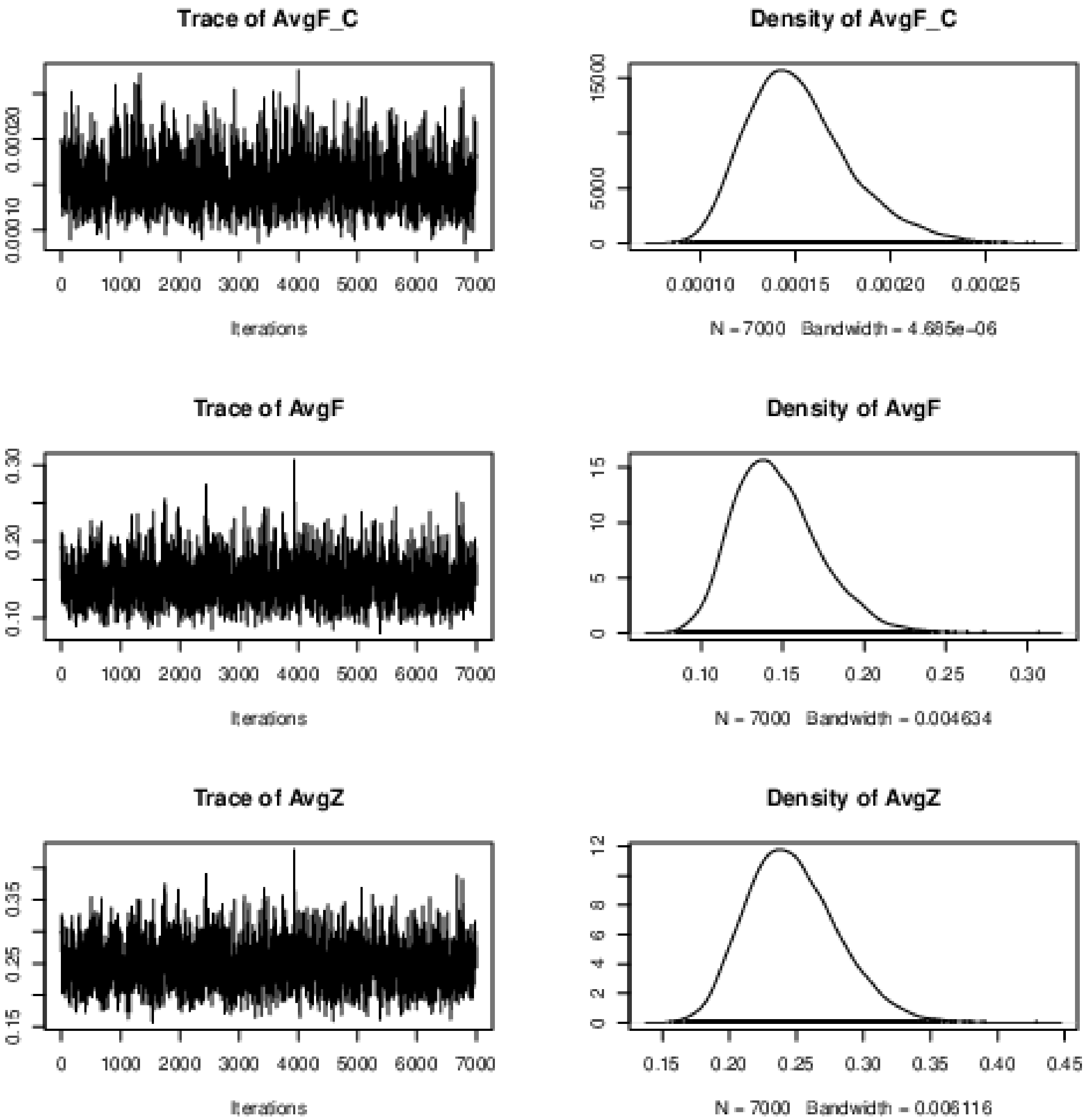


Figure 8.5 cont'd.

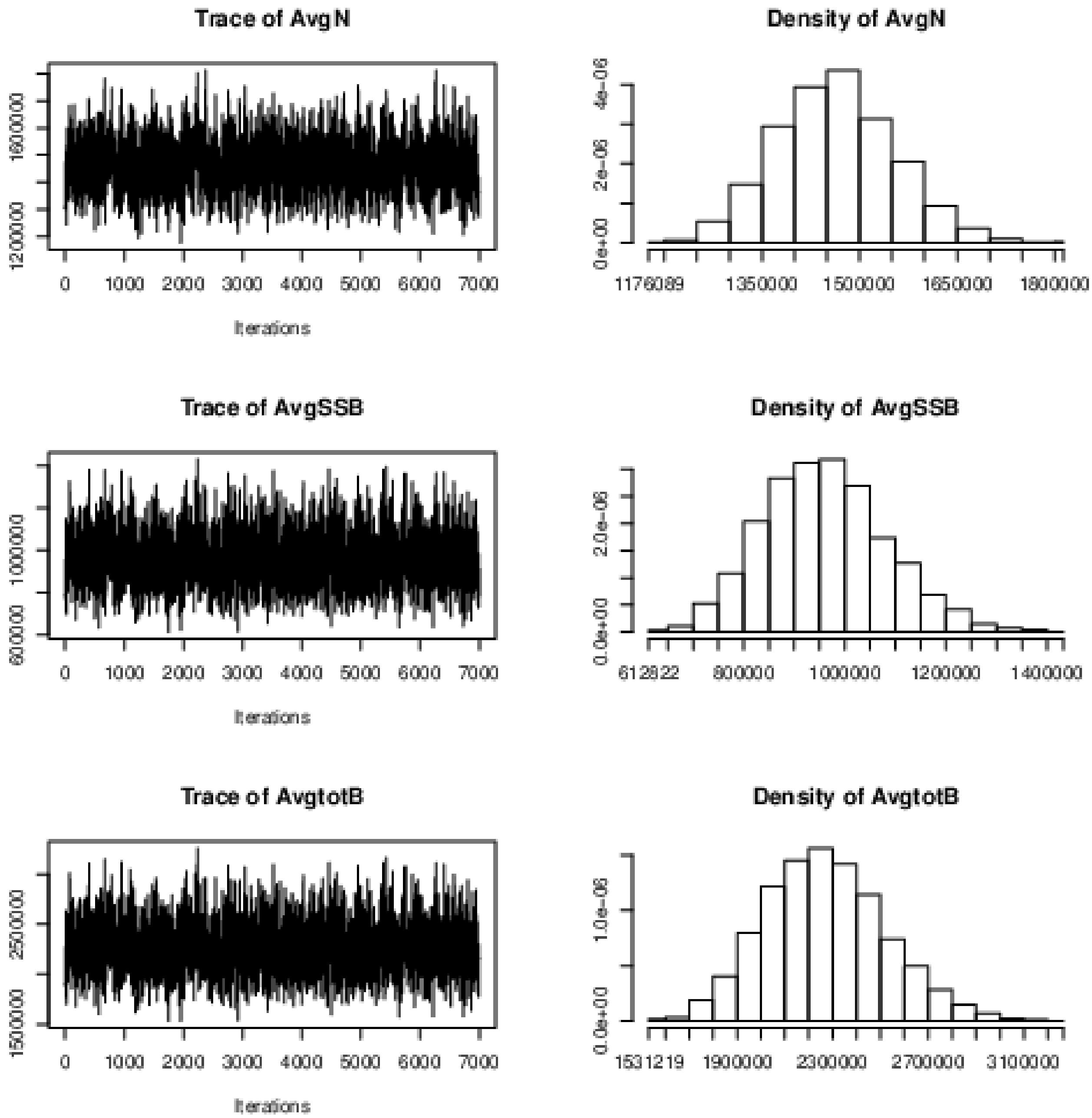


Figure 8.5 cont’d.

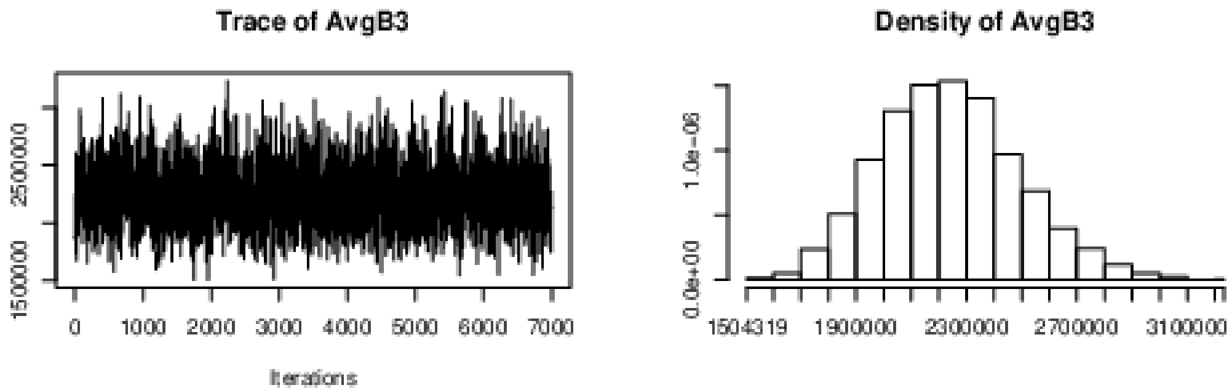


Figure 8.6. MCMC autocorrelations WIIM-04-02-20.

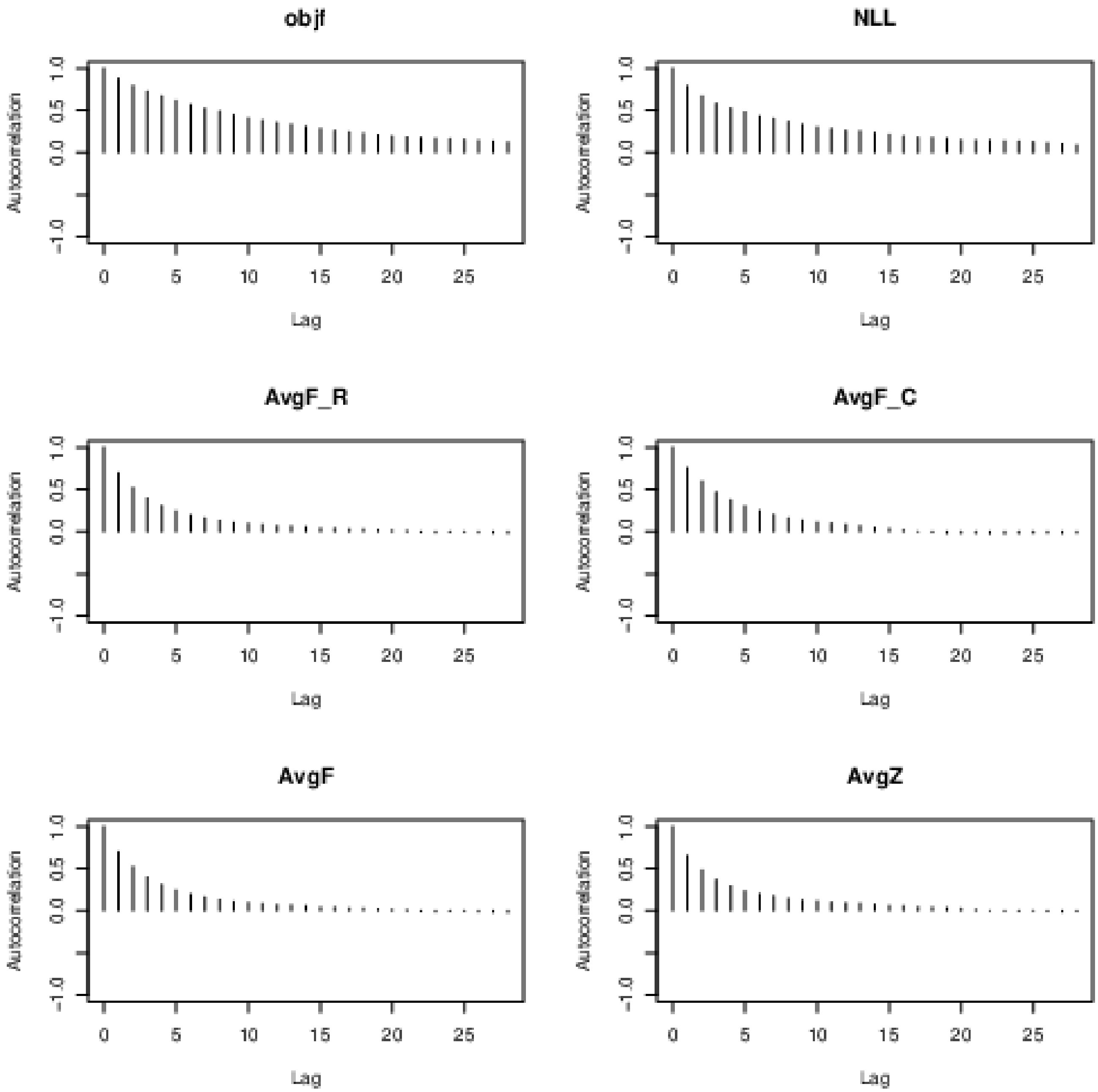


Figure 8.6 cont'd.

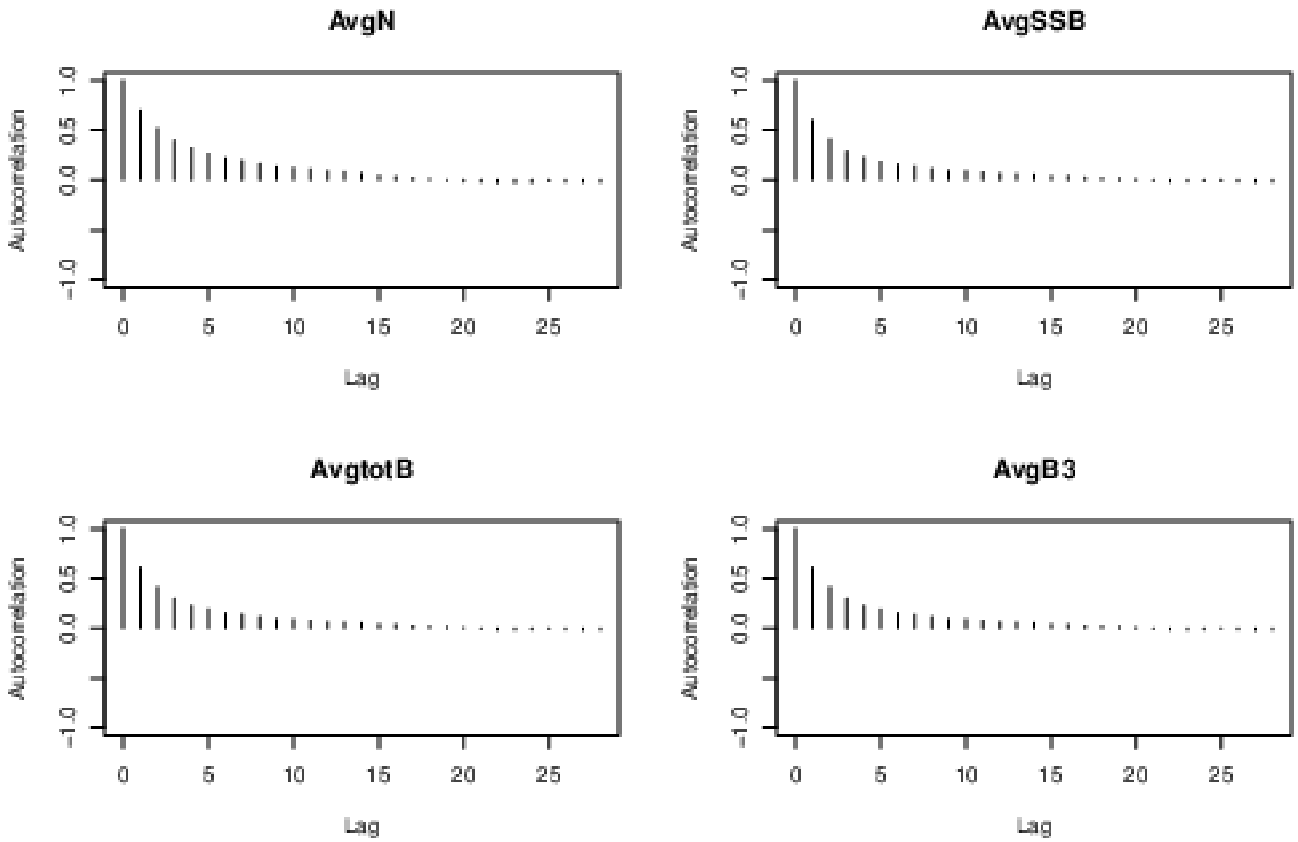


Figure 8.7. MCMC trace plots and posterior distributions WIIM-09-21-20.

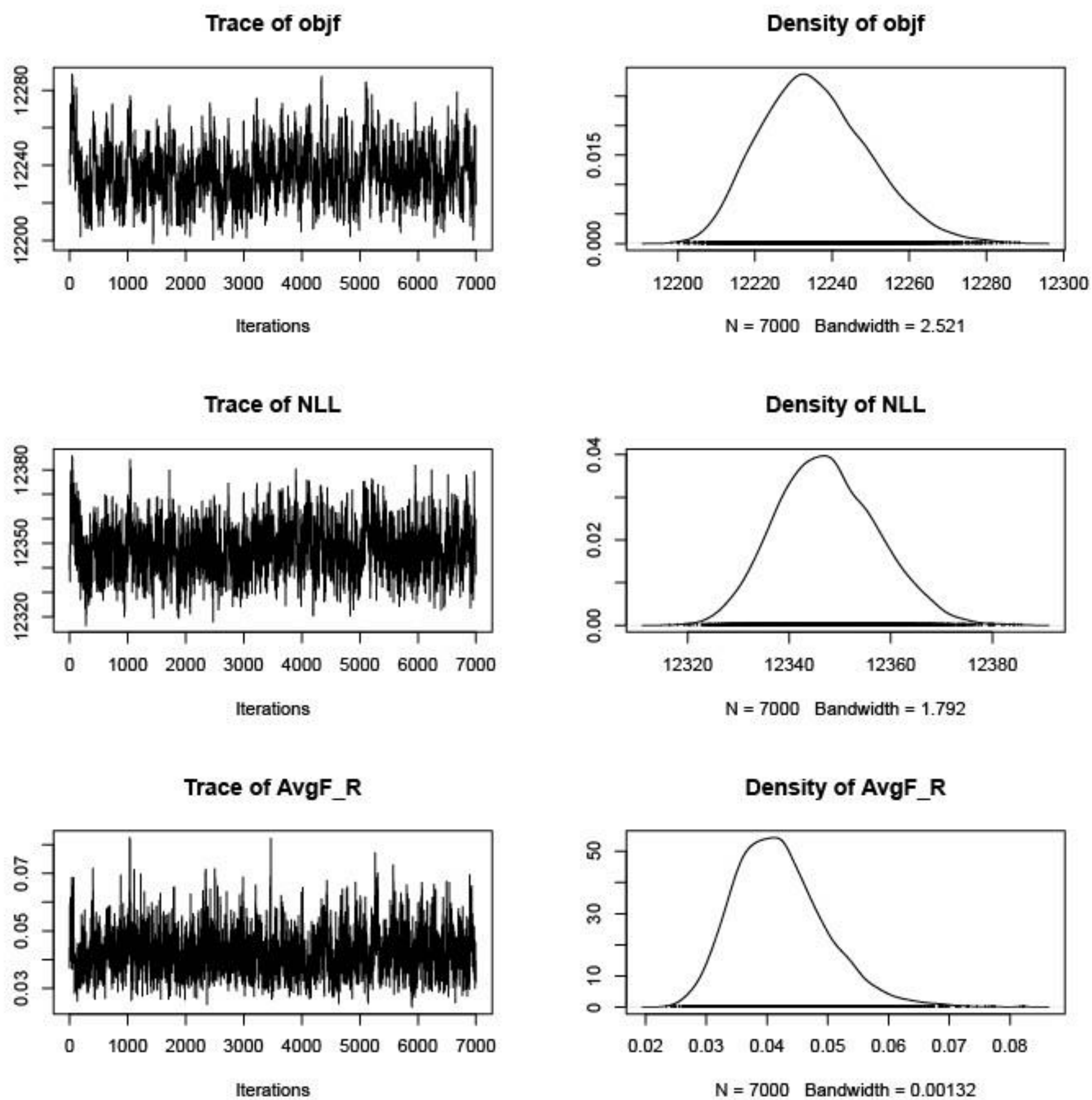


Figure 8.7 cont'd

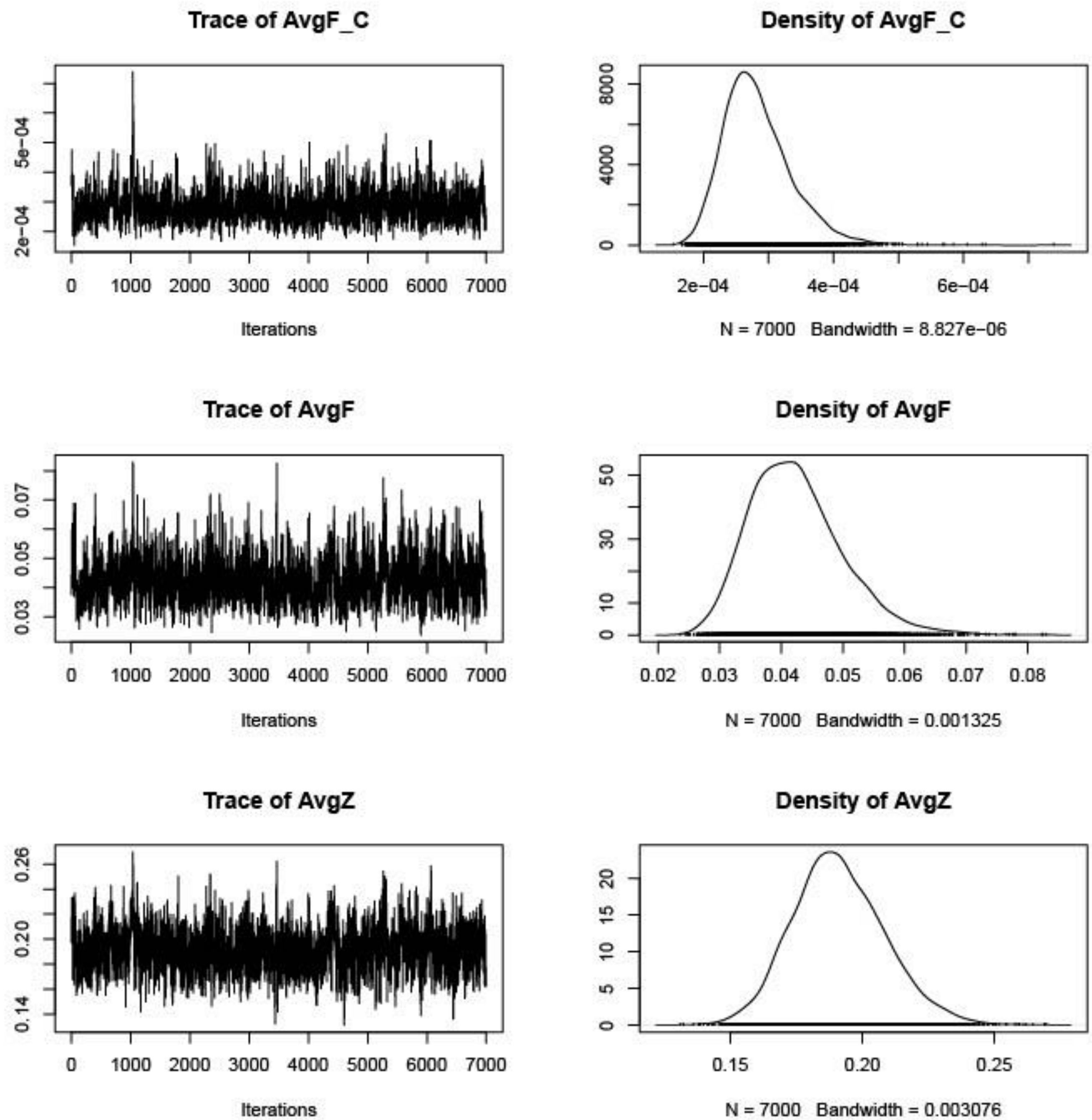


Figure 8.7 con'd

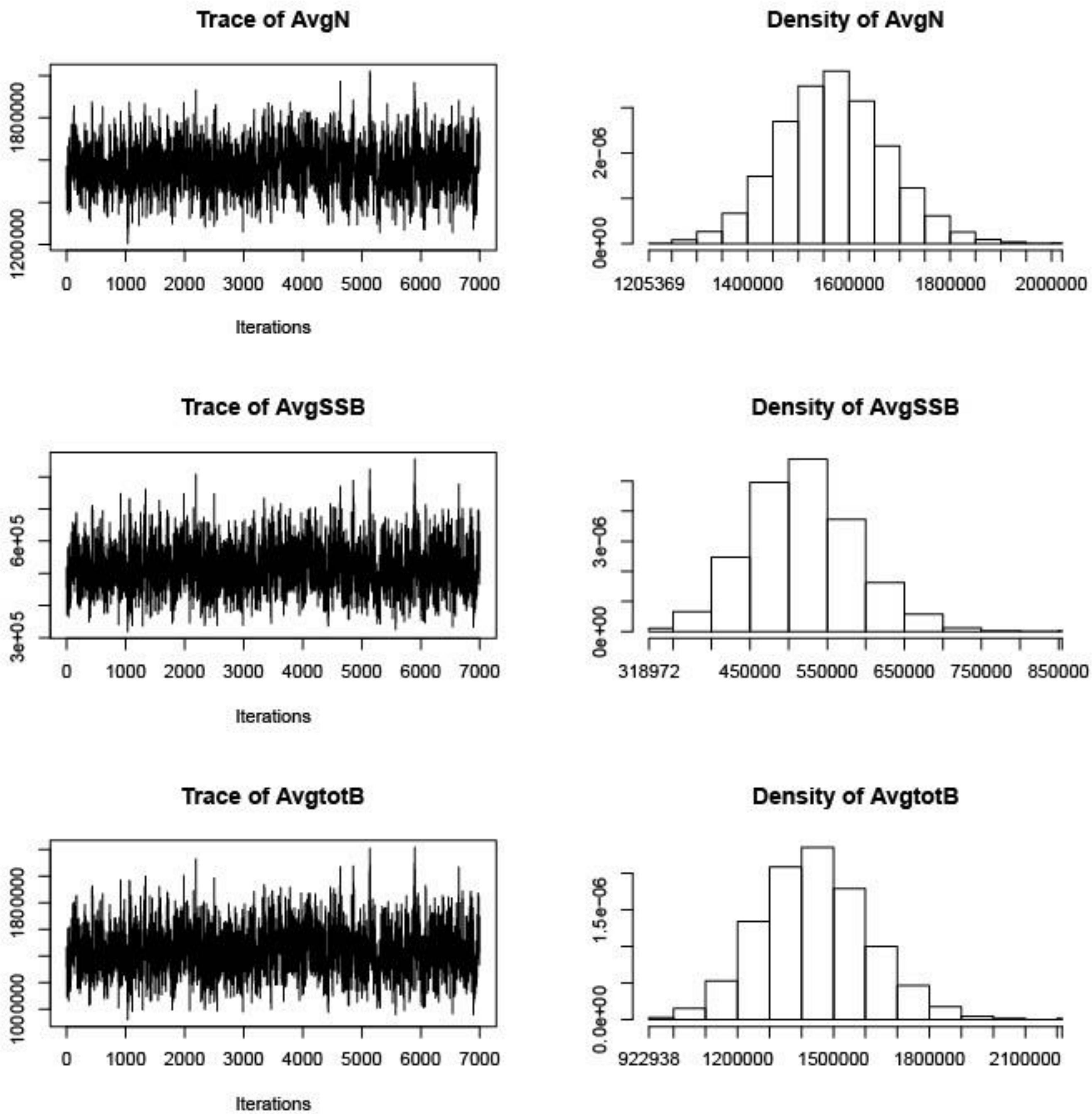


Figure 8.7 cont'd

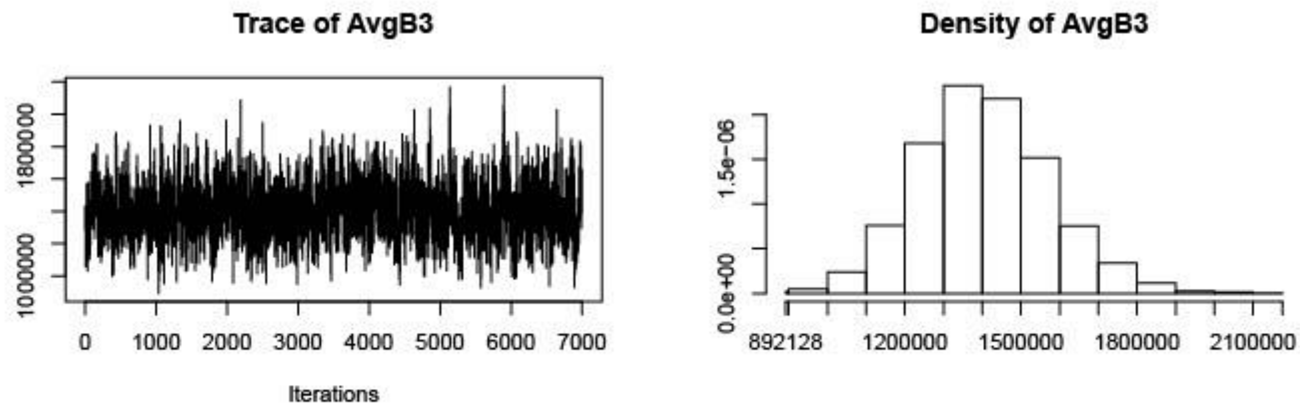


Figure 8.8. MCMC autocorrelations WIIM-09-21-20.

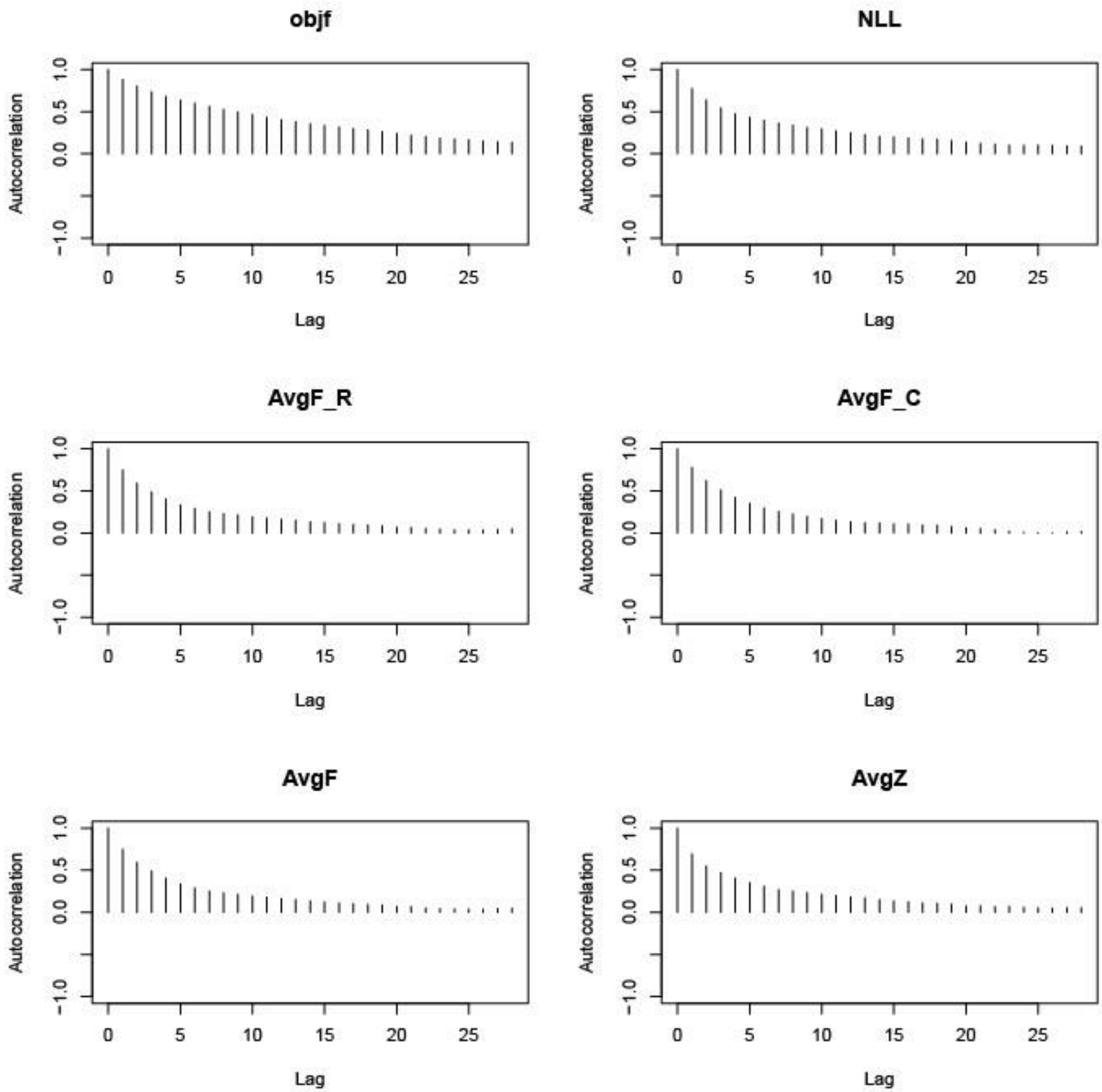


Figure 8.8 cont'd

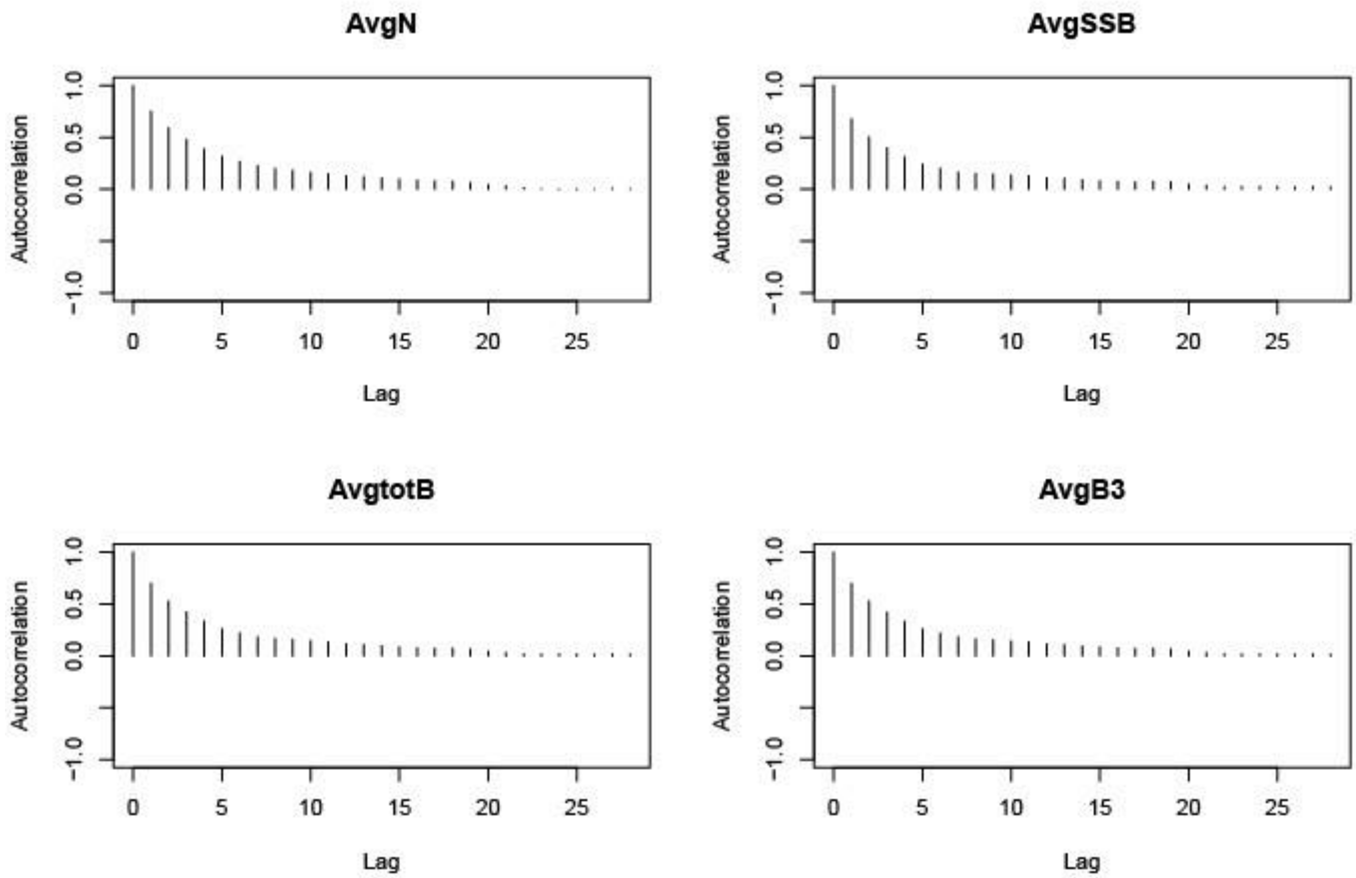


Figure 8.9. MCMC trace plots and posterior distributions WIIM-10-09-20.

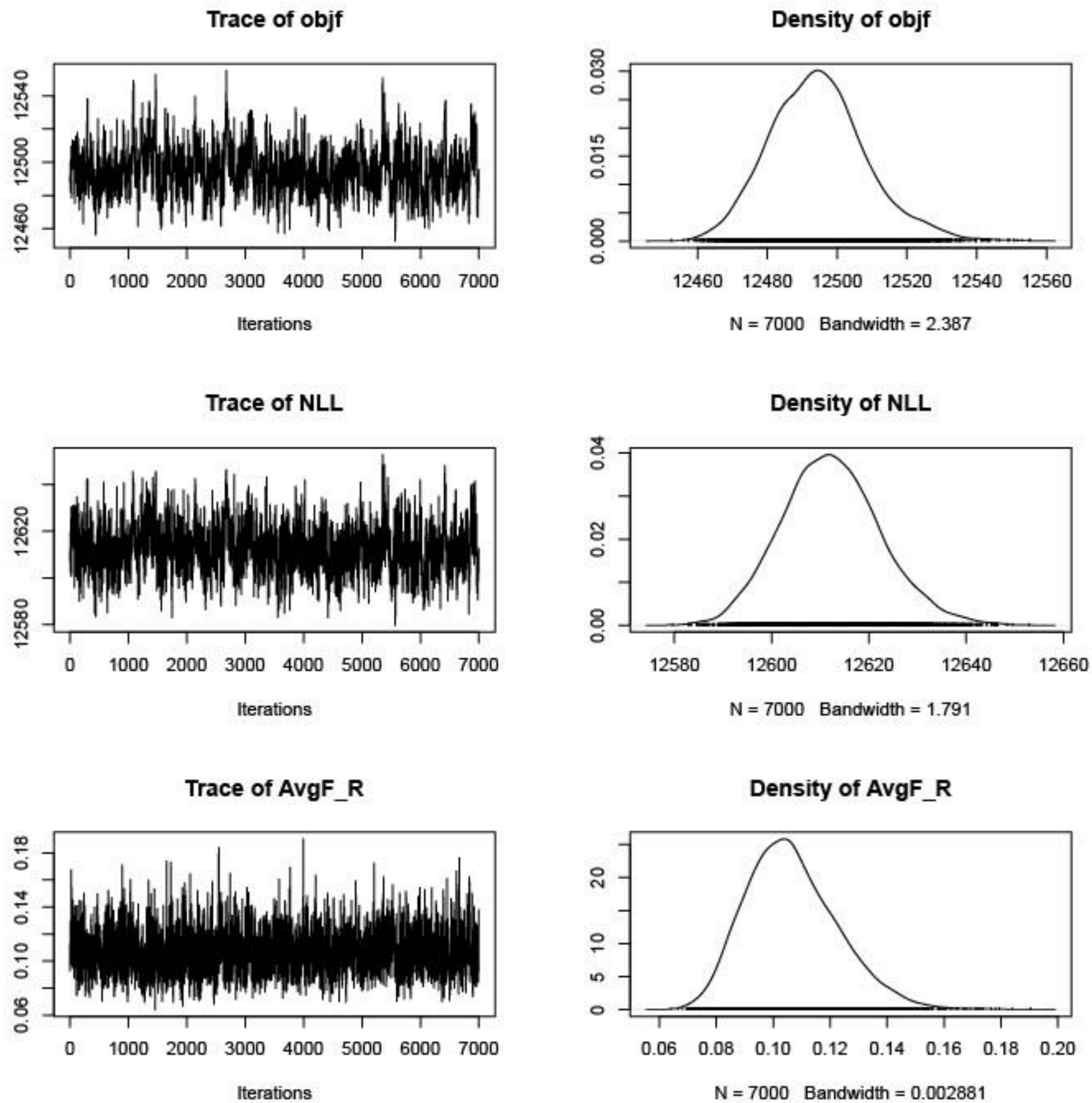


Figure 8.9 cont'd

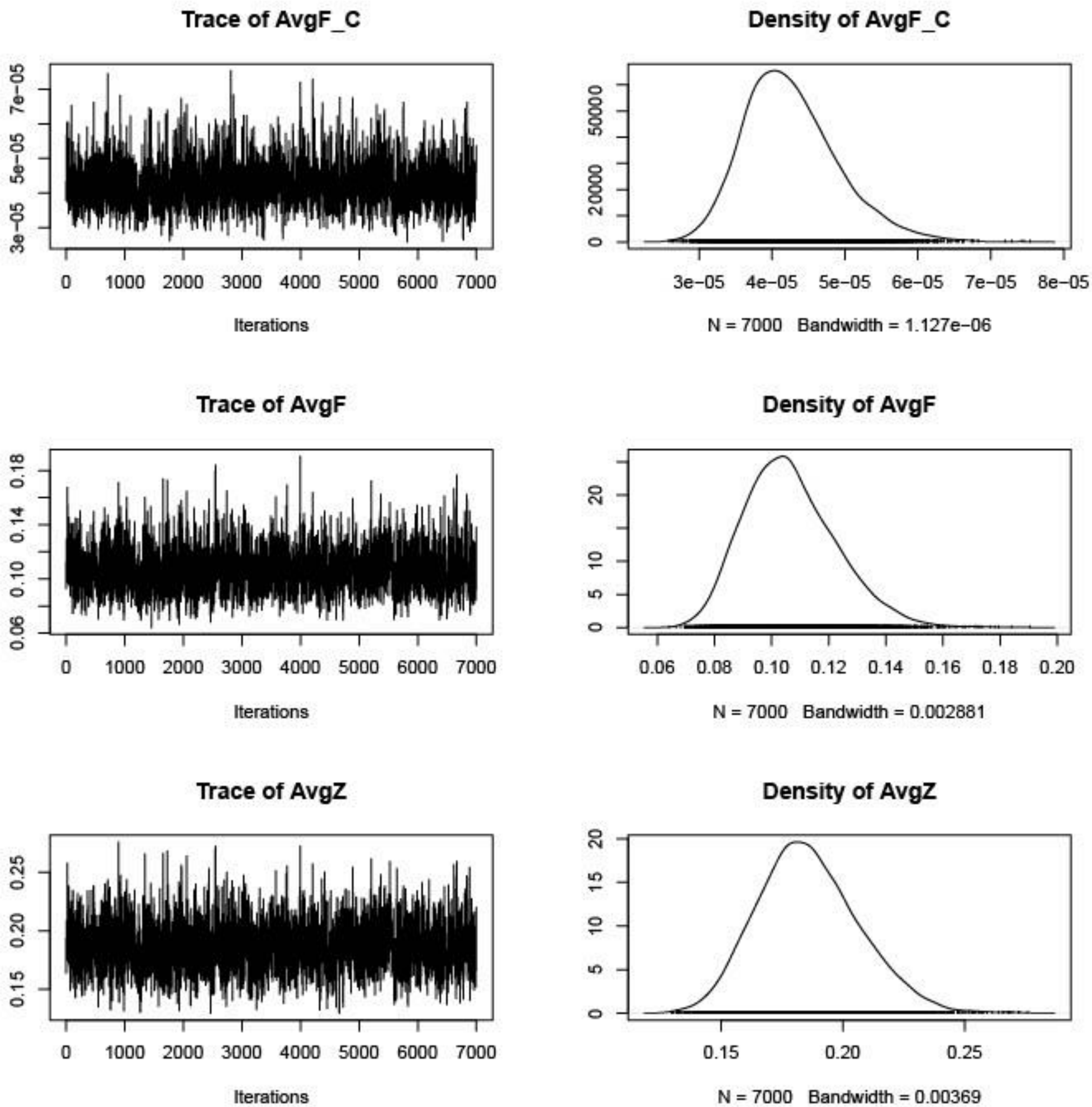


Figure 8.9 cont'd

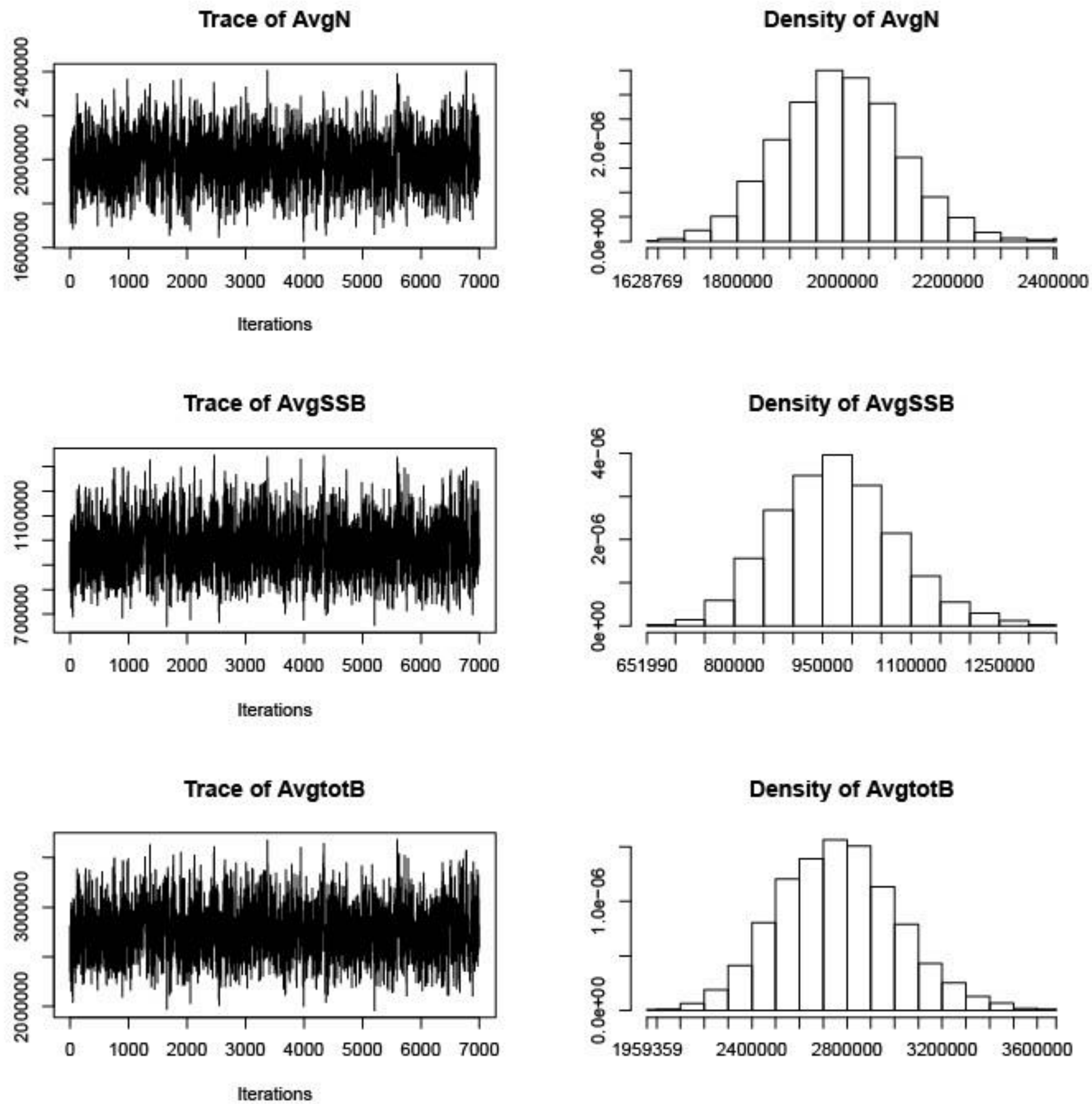


Figure 8.9 cont'd

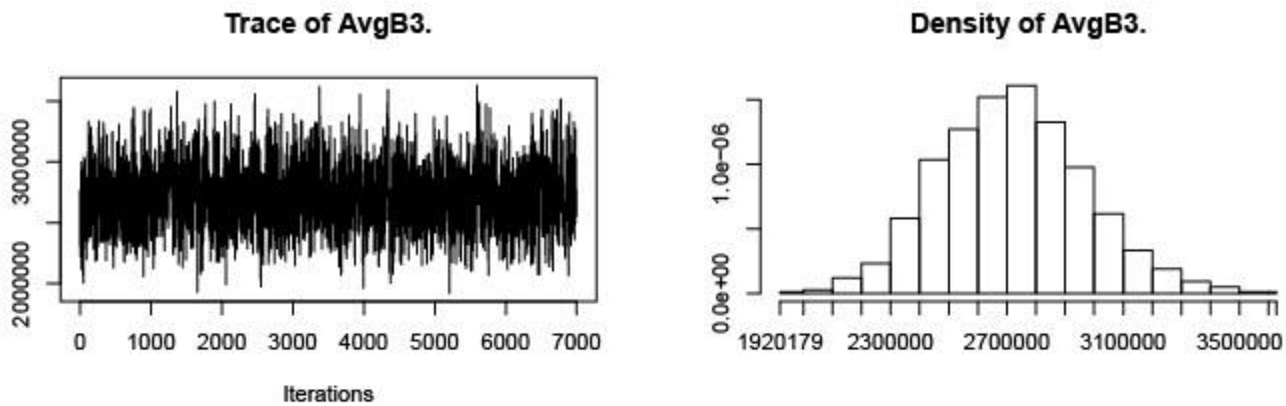


Figure 8.10. MCMC autocorrelations WIIM-10-09-20.

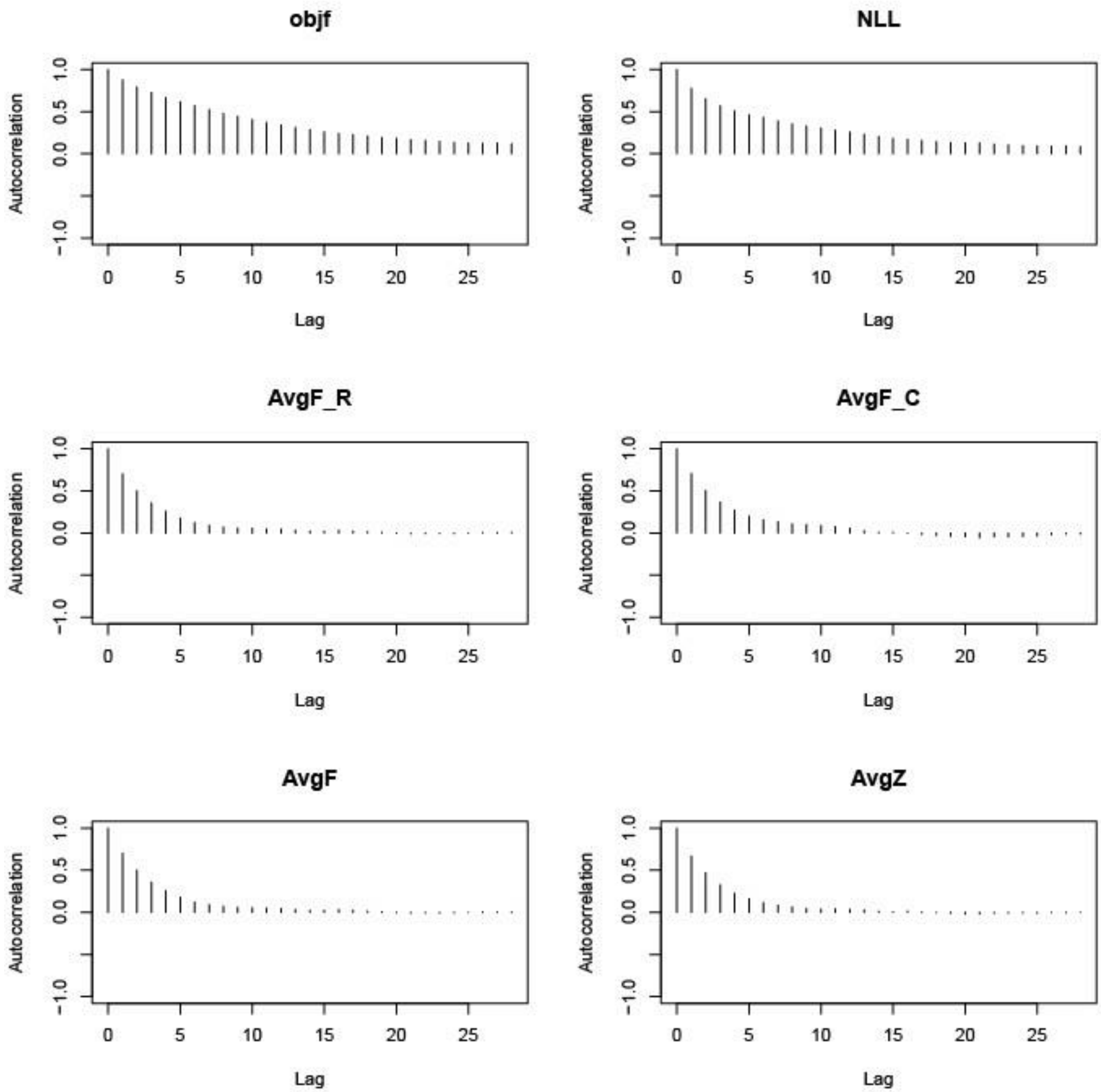


Figure 8.10 cont'd.

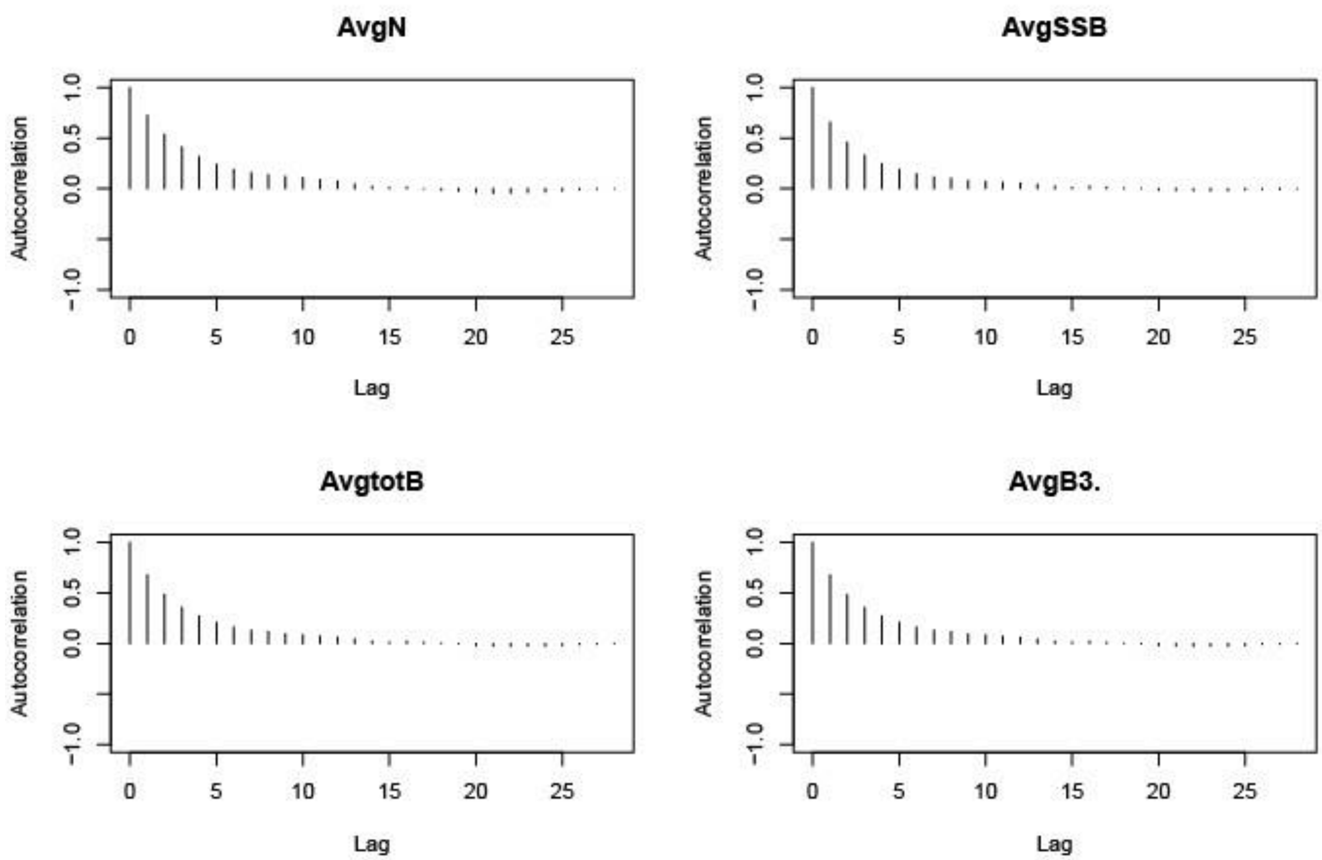


Figure 8.11. MCMC trace plots and posterior distributions WIIM-11-11-20.

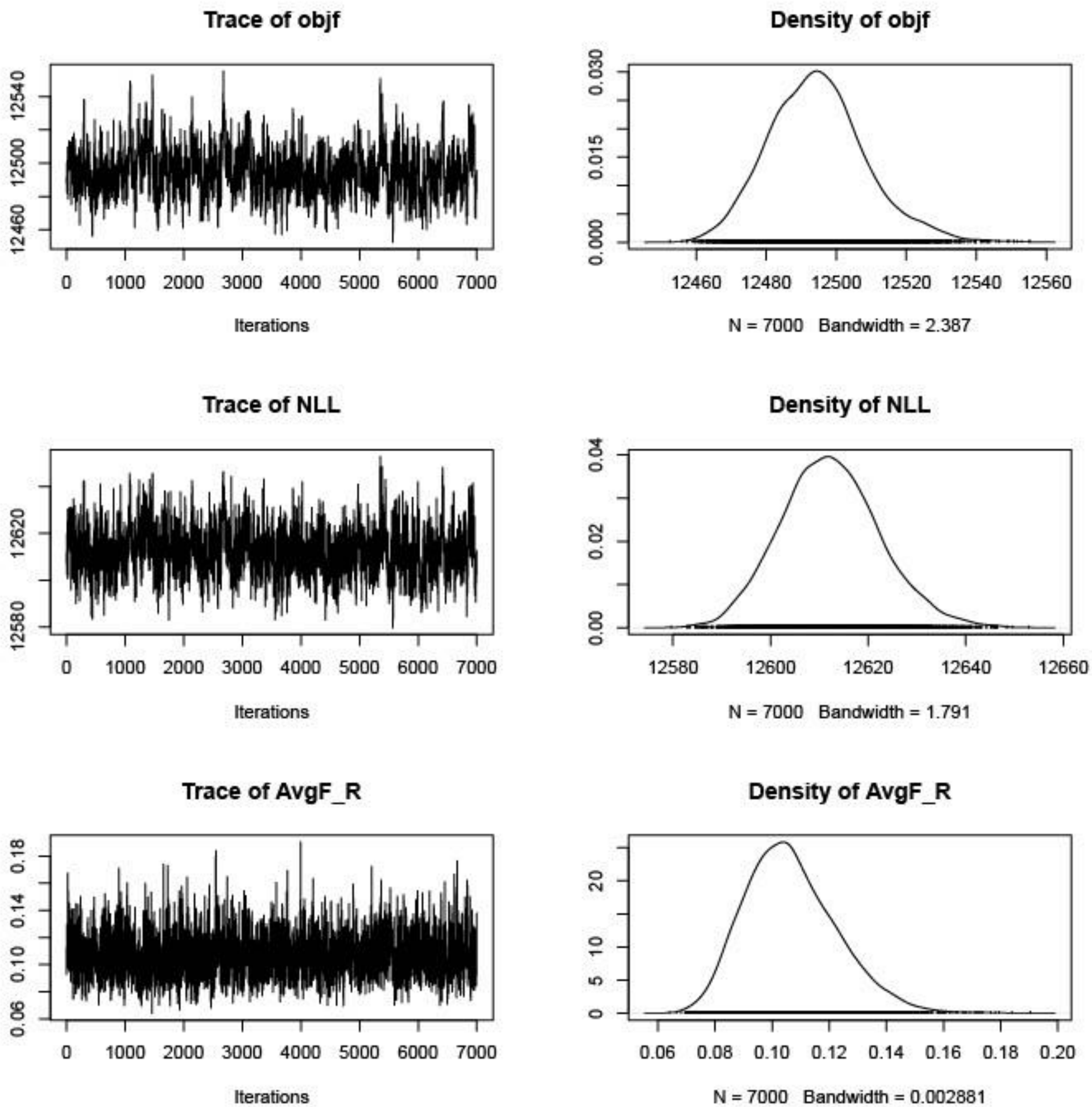


Figure 8.11 cont'd.

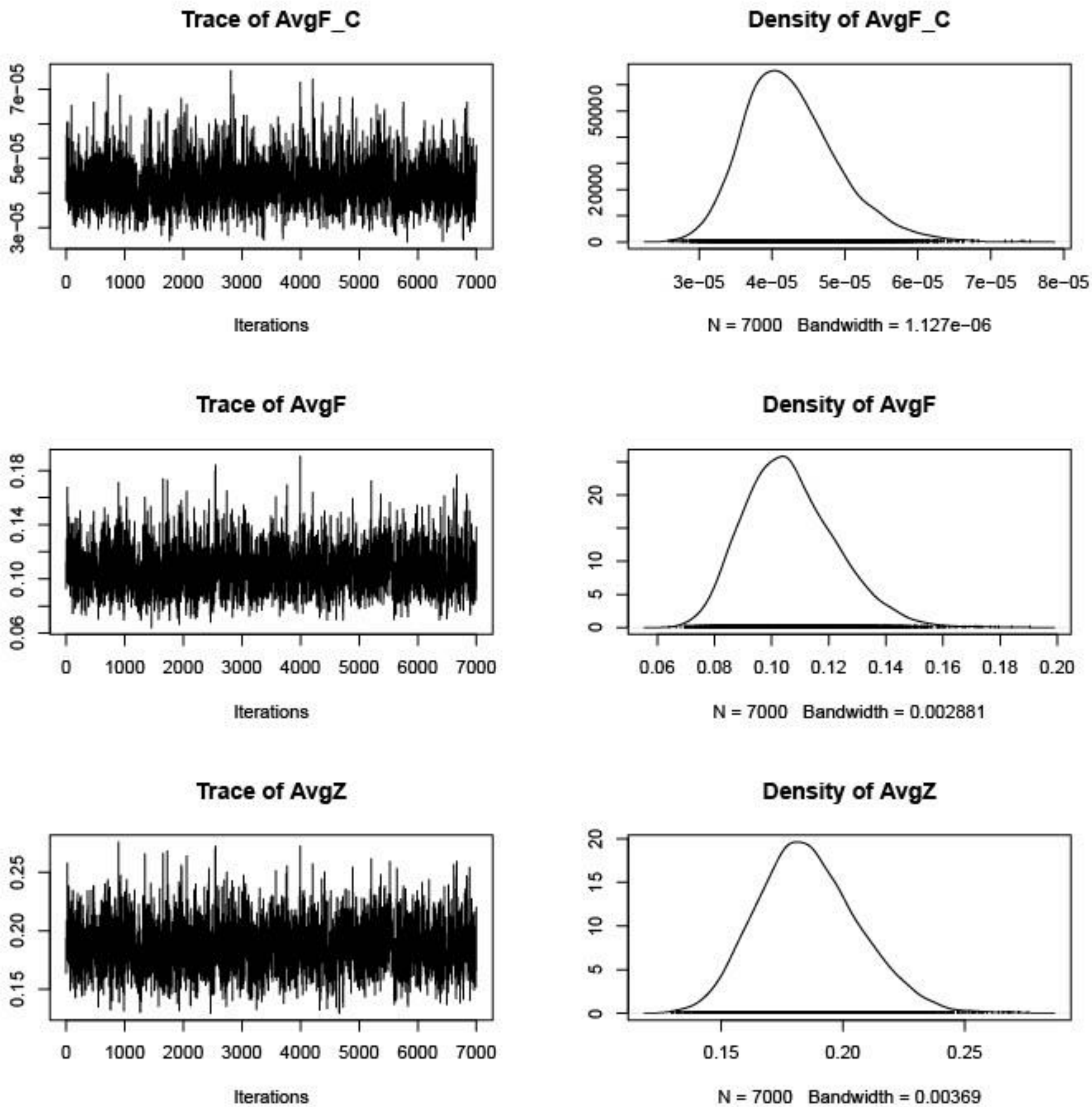


Figure 8.11 cont'd.

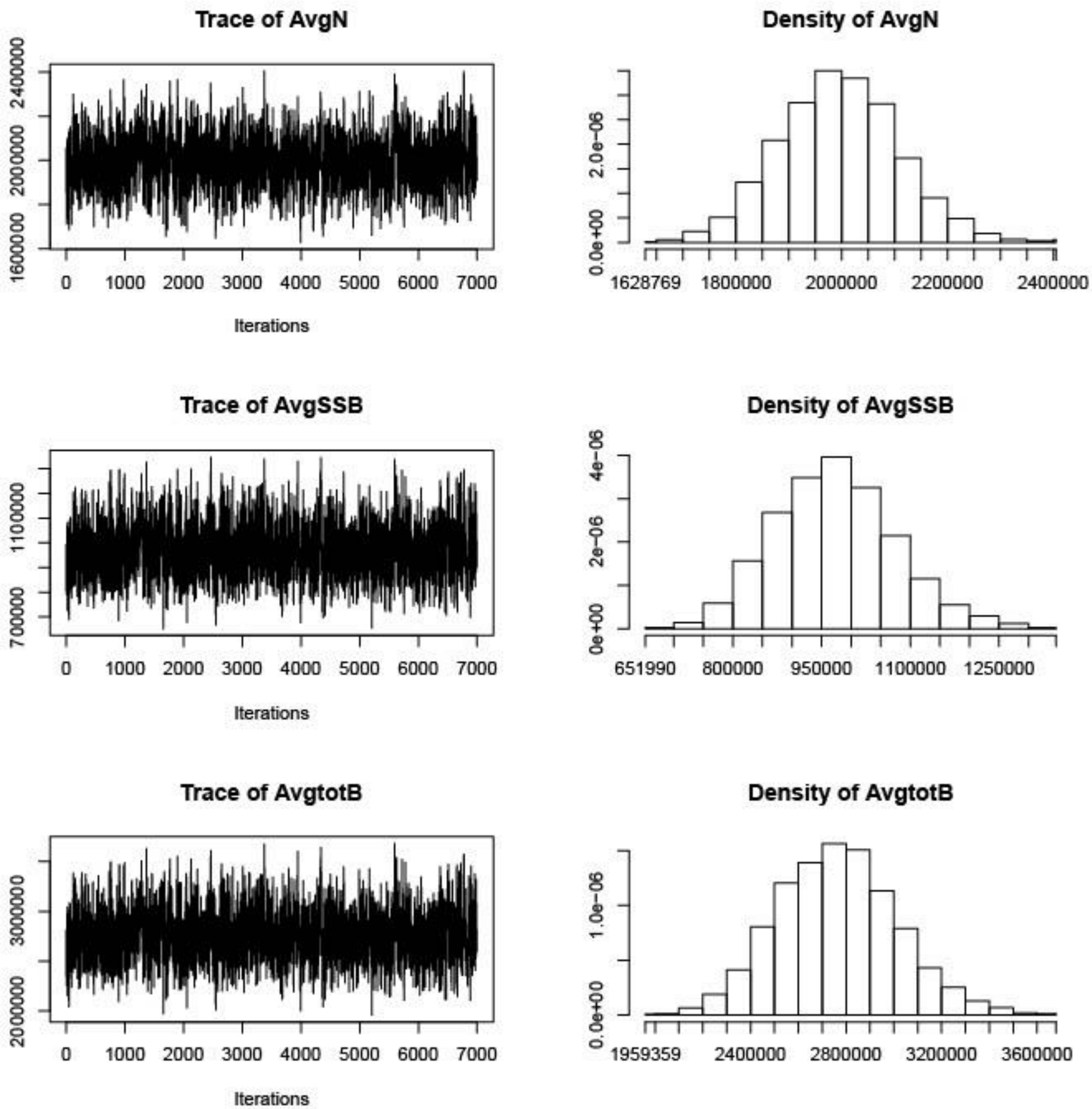
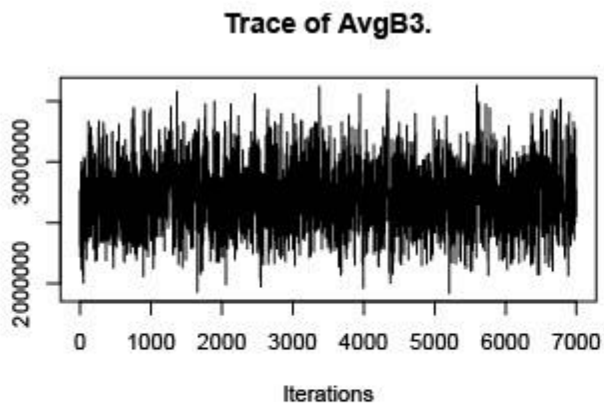


Figure 8.11 cont'd.



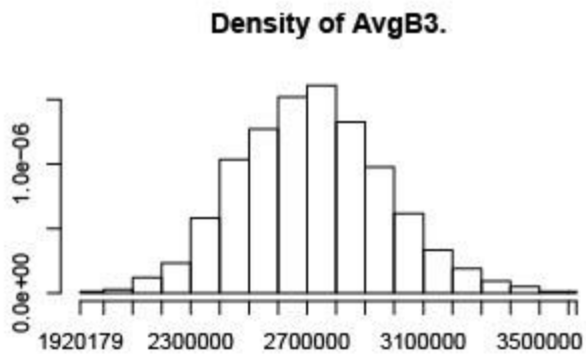


Figure 8.12. MCMC autocorrelations WIIM-11-11-20.

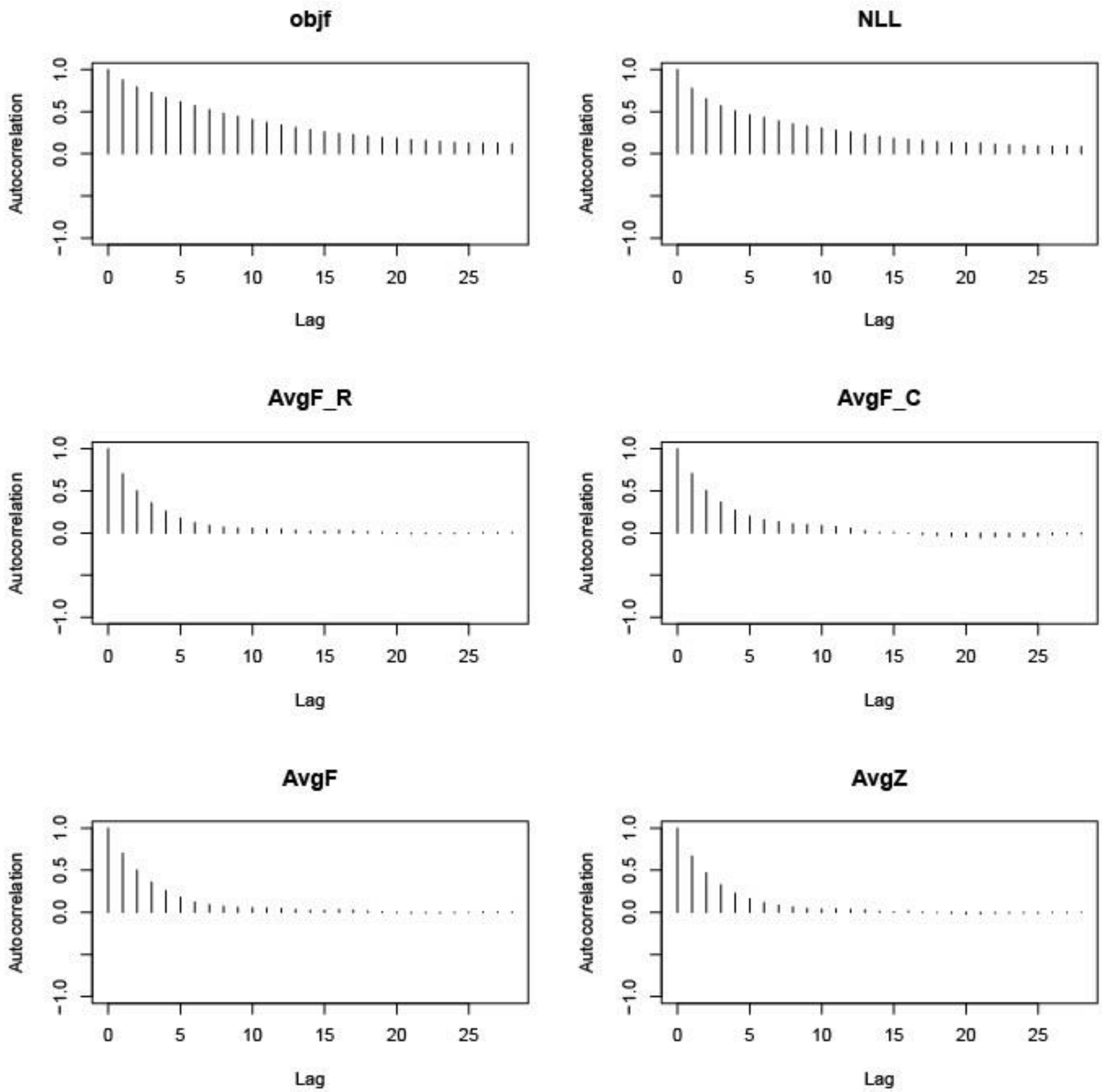
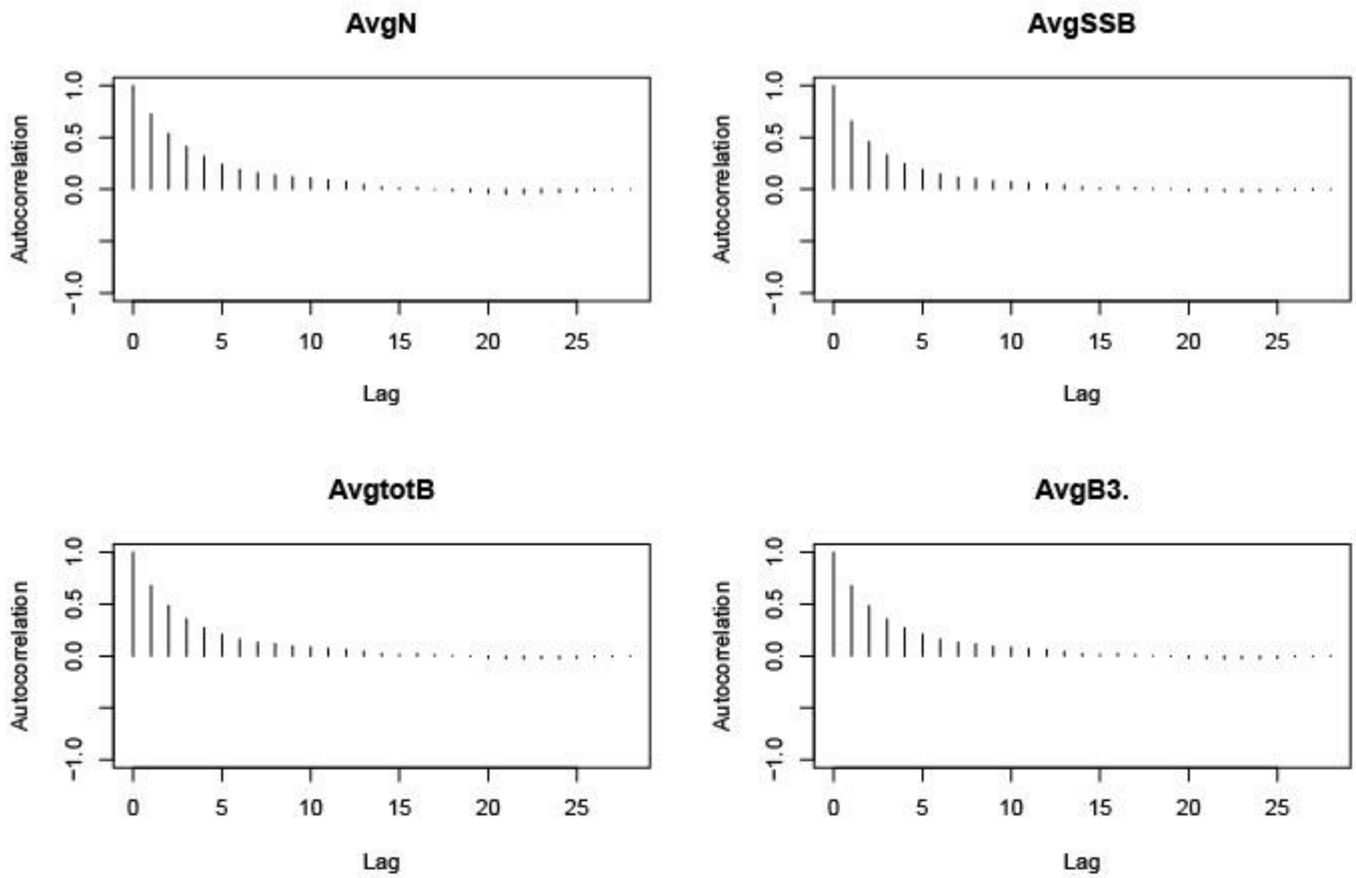


Figure 8.12 cont'd.

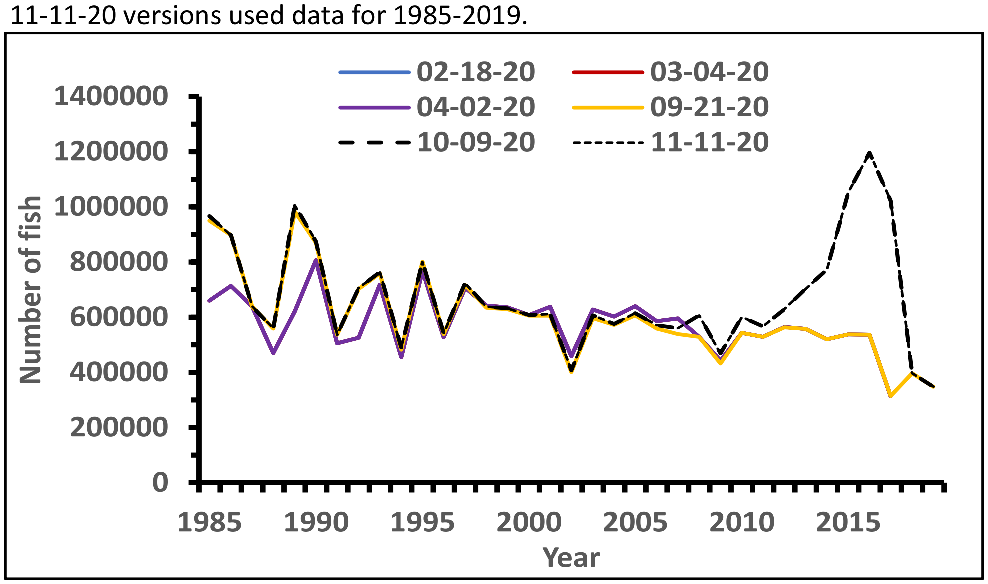


9.0 Summary

The structure of all six versions of the WIIM 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 MSC. 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. The proportion of age-6 trout in the recreational fishery harvest for the 10-09-20 and 11-11-20 versions tended to be overpredicted relative to observed values and exhibited larger SDRES than other versions.

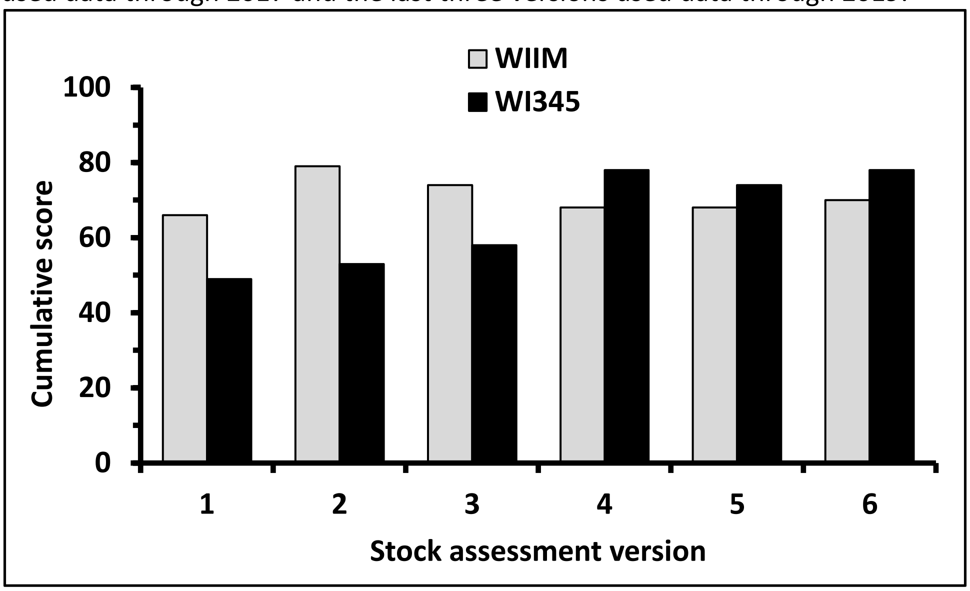
Retrospective patterns were smaller for the first three versions of the WIIM stock assessment than for the last three versions, and the 10-09-20 and 11-11-20 versions had the largest retrospective patterns for abundance and biomass (Figure 7.1). The retrospective patterns in abundance of the last two versions were likely caused by how we estimated abundance at age-1 and the nearly exponential increase in proportion wild Lake Trout at the end of the time series. In versions prior to 10-09-20, we estimated the number of hatchery yearling-equivalents based on stocking rates and survival of fingerlings before fitting the model, and after fitting the model we estimated abundance of wild year classes based on estimates of age-1 abundance and the proportion wild information (Ebener et al. 2020). In the 10-09-20 and 11-11-20 versions, we used proportion wild to expand the number of hatchery yearling-equivalents (equation 3) to represent the total abundance of wild plus hatchery fish for each year classes, then we fit the model. Thereafter, we used proportion wild for each year class to allocate the number of age-1 recruits into hatchery and wild fish. This increased abundance at age 1 three-fold for the 2012-to 2016-year classes over that in earlier versions (Figure 9.1) because the proportion wild was so high (21% to 69%) for these year classes (Ebener et al. 2020).

Figure 9.1 . Annual number of age-1 recruits estimated for six versions of the WIIM Lake Trout stock assessment during 1985-2019. The 02-18-20, 03-04-20, and 04-02-20 versions used data for 1985-2017, while the 09-21-20, 10-09-20, and 11-11-20 versions used data for 1985-2019.



While the 03-04-20 version of the WIIM stock assessment scored highest in our ranking of MCMC output (Table 8.1), the differences in scores among versions was not substantial, particularly when compared to differences among scores for the WI345 stock assessment. The changes we made to data analysis and model structure in the WIIM stock assessment were nearly identical to the changes we made in the six versions of the WI345 stock assessment (Ebener et al. 2021). The only difference between the changes we made to the WI345 and WIIM stock assessments was that in the WI345 stock assessment we had to use a generic age-length key to estimate age composition of the LWAP survey, whereas for WIIM we estimated age composition of the LWAP survey using age data from the catch. The scores for the first three versions of the WI345 stock assessment ranged from 49 to 58 compared to 74 to 78 for the last three versions, whereas scores for the WIIM stock assessment ranged from 66 to 79 for the first three versions and 68 to 70 for the last three versions (Figure 9.2). It is obvious based on the ranked scores that the different versions of the WIIM stock assessment were all reasonable, whereas that was not true for the WI345 stock assessment. However, because commercial selectivity was estimated incorrectly for all but the 11-11-20 and 01-02-21 versions of the WIIM and WI345 stock assessments, these last two versions of both stock assessment should be viewed as the most reliable.

Figure 9.2. Markov chain Monte Carlo ranking scores for six versions of the WIIM and WI345 stock assessments. The first three versions of both stock assessments used data through 2017 and the last three versions used data through 2019.



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11.0 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 WIIM/read.mcmc.R")

#set location of your MCMC file
```

```
my.mcmc.file <- "C:/Users/tflwc/Desktop/datafiles/LAT Model Lake Michigan/Model evaluations WIIM/WIIM-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 <- "WIIM-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()
```