A Tool to Assist the Bluefish Technical and Monitoring Committees with Estimating Management Uncertainty

[Based heavily on K Drew & J McNamee (2020) ASMFC Risk and Uncertainty Policy]

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Introduction

The purpose of a management uncertainty buffer is to prevent a fishery from exceeding its catch limit. A buffer results in a catch target lower than the catch limit, making it less likely the limit is exceeded; when catch limits are surpassed it can both impact the population and result in future penalties to a fishery. For bluefish, buffers are applied separately to the recreational and commercial sectors and each buffer is determined while setting specifications. The Atlantic States Marine Fisheries Commission (Commission) Bluefish Technical Committee (TC) and Mid-Atlantic Fishery Management Council (Council) Bluefish Monitoring Committee (MC) debated at length during the 2022 specifications setting process whether and how to accommodate management uncertainty. The Bluefish TC/MC agreed to hold a meeting in advance of the 2023 specifications setting process to discuss potential methods related to objectively determining a management uncertainty buffer. A March 10, 2023 staff memo offered several potential methods. When the TC/MC met in March 2023, the groups thought the concept of an uncertainty matrix that could be scored could be useful in assessing management uncertainty. The candidate matrix included enforceability of management measures, monitoring adequacy, data precision, latent effort, and bluefish catch in other fisheries.

Council and Commission staff developed an uncertainty matrix, and a subgroup of the Bluefish TC/MC formed to further develop the tool for TC/MC consideration. After meeting to discuss the matrix, the subgroup thought the matrix lent itself to the Commission's risk and uncertainty policy tool framework (see pages 47-58 of August 2020 ASMFC Policy Board meeting materials), and worked to modify the tool for the MC/TC. The risk and uncertainty policy tool converts a combination of quantitative and qualitative scores into a quantitative representation of uncertainty; this tool could be used on an annual basis to assist the TC/MC in the determination of a management uncertainty buffer, should one be necessary. The original ASMFC risk and uncertainty tool has been pilot tested with Tautog, but because no management action was necessary, there was no need to implement the final results (see pages 5-14 of fall ASMFC Tautog Management Board meeting materials).

Methods

As noted in ASMFC's risk and uncertainty TC guidance document (Drew & McNamee 2020), the decision tool consists of a number of questions (qualitative or quantitative) converted to the same numerical scale for entry in the decision tree tool. The response scores are then weighted based on the relative importance of the information for the species; the decision tool then combines this information into a single value, through a sigmoid function (Drew & McNamee 2020).

The logistic function for calculating the management buffer is:

$$p(Z) = \frac{1}{1 + e^{-Z}}$$

Where $Z = a + b_1x_1 + b_2x_2 + \cdots$, denoting a list of inputs (x_n) times their weighting coefficients (b_n). The intercept, a, sets the initial scale of the Z score. An a of 0, corresponds to a default value of 50% when all risk or uncertainty factors are considered to be 0. While the intercept can be adjusted, the subgroup found it more convenient to simply rescale the output to range from -1 to +1 (buffers of -100% to +100%). While the MC is not currently permitted to liberalize an ACL, the subgroup thought it was important to allow for the possibility of positive buffers to offset some negatives elsewhere in the matrix to reach a net score, that could subsequently be set to zero to prevent ACL liberalizations. Default weightings are an important component of this decision tool and should be arrived at by TC/MC consensus. The subgroup has some suggested starting values pre-entered (and see below).

The decision tool, as currently structured for the Bluefish TC/MC, consists of 7 questions for the recreational and commercial sectors (Tables 1-2). The questions are applied to the recreational and commercial sectors separately as they each have their own buffer. The qualitative categories are scored on a scale of -5 to 5 and the lone quantitative category, removal prediction performance, uses historical observations.

Table 1. Template decision tool inputs, candidate weightings, and scoring metrics.

	Candidate Weighting		Scoring
Decision Tool Input	**Recreational**	**Commercial**	**Scale**
Compliance	**0.10**	**0.06**	-5 to 5
Enforceability	**0.10**	**0.06**	-5 to 5
Reporting	**0.10**	**0.06**	-5 to 5
Removals	**0.70**	**0.70**	Observed level
Bycatch	0.00	**0.06**	-5 to 5
Latent effort	0.00	**0.06**	-5 to 5
Adjustment	0.00	0.00	-5 to 5

Table 2. Template decision tool scoring question descriptions

Decision Tool Input	Description
How has compliance been in the past year?	How would you rate compliance with regulation(s) in the most recent year? This can be informed by ASMFC compliance reports and/or discussions with ASMFC Law Enforcement Committee (LEC).
How enforceable are the current/proposed regulations?	How enforceable are the current/proposed regulations?
How difficult is it to quantify catch?	How difficult is it to quantify catch (e.g., late reporting, underreporting, misreporting)?
Total removal prediction performance?	What is the total removal prediction performance (i.e., harvest plus dead discards)?
Bycatch.	Is there notable bycatch of bluefish from other fisheries?
Latent effort.	Is there notable latent effort?
Adjustment factor.	Is there anything else that ought to be considered (e.g., change in assessment methodology, permitting, assessment schedule, etc.)?

<u>*Weighting Factors*</u>

Each scored question has an associated weighting; this way the more important factors contribute more to the uncertainty buffer calculation. Proposed weightings for the commercial and recreational fisheries are given below and in Table 1. It is important to note the contribution of each of the components is a combination of both the score and the weighting; in other words, a component may have high weight but if the score is near zero it would not contribute much to the buffer.

One difference between the commercial and recreational weightings is bycatch and latent effort are ignored in the recreational fishery. The subgroup felt bycatch does not apply to the recreational fishery because all catch is accounted for through the Marine Recreational Information Program (MRIP). The group also assigned a zero weighting to recreational latent effort because while the number of license holders fluctuates it seems unlikely there would be a dramatic change in fishing effort over a one- or two-year period. A weight > 0 would simply reduce the relevancy of more important recreational items for bluefish. Both of these components are reasonable to include in the commercial uncertainty buffer calculation.

The adjustment factor was assigned a weight of 0 given the somewhat intangible and presently unspecified nature of the category; this category exists so if there is something important to consider in the future, not already captured by an existing category, the TC/MC could accommodate the consideration into the buffer.

Removals accounted for 70% of the weighting in both cases. This amounts to a relative importance of about 11.6 times any of the other factors in the commercial fishery and 7 times the importance relative to any other factor in the recreational fishery. The difference in relative importance is a function of the number of categories included; the subgroup felt a similar weighting for the quantitative component of both the commercial and recreational metrics would be a good starting point.

Compliance, enforceability, and reporting were set to 0.06 in the commercial fishery and 0.1 in the recreational fishery. The group arrived at these values by dividing the remaining weight exclusive of the removals category by the number of remaining categories. These weights reflect a belief that even if there are issues with any three of the factors, any impact is probably small relative to the removal overage or underage we are able to calculate quantitatively.

Several example figures are included in the appendices that explore the performance of the management uncertainty tool as a function of question weights and decision tool input questions (Appendix 1). Additional examples are pre-entered into the spreadsheet tool in cells B13:F19 of worksheets “Explore – rec” and “Explore – comm.”

Predicted Removals

The lone quantitative category in the uncertainty matrix reflects the capacity to accurately predict fishery removals. Historically, such predictions have been approached using the assumption recent dead catch is a good predictor of dead catch in the near future. The Recreation Demand Model (RDM), currently used to set regulations for summer flounder, scup, and black sea bass has not been developed for bluefish. The subgroup discussed three options for determining the under- or over-prediction of dead catch assuming the decision-making year is year t: (M1) use the most recent available dead catch in year t-2 relative to the final dead catch in year t-1, (M2) use the average dead catch in years t-4 through t-2 relative to the final dead catch in year t-1, or (M3) use the average percentage difference in years t-3 through t-1 as calculated using method (M1; Table 3). The subgroup decided to use method (M3) as it dampens the inter-annual variability by using three years of data and weights the annual underage/overages equally.

The subgroup suggests the difference between predictions and performance could be evaluated with confidence intervals in a substantially similar way as used with the Harvest Control Rule’s Percent Change Approach, except explicitly accounting for dead releases (Appendix 2). That is, if prediction performance of total removals falls within an 80% confidence interval, difference = 0%, otherwise, enter actual percent difference in the spreadsheet tool. This approach uses MRIP queries for AB1 and associated percent standard errors (PSEs) directly, as well as spring and fall dead B2 weight estimates (and associated 80% confidence intervals) generated from the Northeast Fisheries Science Center (NEFSC).

Table 3. Three methods explored to arrive at the percent difference between projected dead catch and observed dead catch. Note, the “Year” column refers to the year in which the decision is made for the next coming year (e.g., decision-making in 2022 for the 2023 fishery). The subgroup recommended M3 for use in the decision tool.

Year	*Dead Catch (mt)*	*1-yr pred*	*M1 %*	*3-yr pred*	*M2 %*	*M3 %*
2014	16,306	x	x	x	x	x
2015	18,632	x	x	x	x	x
2016	13,794	18,632	-12.5%	x	x	x
2017	17,809	13,794	35.1%	x	x	x
2018	8,149	17,809	-22.5%	16,745	-8.8%	14.2%
2019	9,398	8,149	118.6%	13,251	105.5%	0.0%
2020	7,970	9,398	-13.3%	11,785	41.0%	43.7%
2021	7,513	7,970	17.9%	8,505	47.9%	27.6%
2022	7,020	7,513	6.1%	8,293	13.2%	41.1%

Table 4. Example calculations for 2022 using each of the three methods in Table 3.

Model	Equation	Result
M1	$\frac{(7{,}970 - 7{,}513)}{7{,}513} \times 100$	6.08%
M2	$\frac{(8{,}505 - 7{,}513)}{7{,}513} \times 100$	13.2%
M3	$\frac{[118.6\% + (-13.3\%) + 17.9\%]}{3}$	41.1%

Compliance, Enforceability, and Reporting

Given their more subjective nature, items related to compliance, enforceability, and ability to quantify catch (reporting) were given less weight in both the commercial and recreational sectors in deference to fishery performance. The Commission's Law Enforcement Committee (LEC) and/or review of state compliance reports could help inform scoring related to compliance. Discussions with the LEC, Council and Commission Advisory Panels (APs), and/or the Coast Guard can help inform scoring for enforceability of regulations.

Species Specific Decision Tools

This tool can be adapted to other species, where question weights can be changed, and questions can be changed, added or subtracted using the very flexible weighted sum of scores and logistic equation. When applied to assessing management uncertainty, we recommend the core elements of the matrix include compliance, enforceability, quantification of catch, and fishery performance.

Appendix 1. Example scenarios to explore the performance of the decision tool and aid the TC/MC understanding of the influence of question weights

Figure 1. Exploration of the influence of recreational weights and decision tool inputs on management uncertainty buffers. For each figure below, weights for byctach, latent effort, and adjustment were all assumed to be zero, and all other non-quantitative factors were assumed to be equal to each other. The first two figures show the influence of weighting associated with removals prediction performance, assuming all other factor scores = 0. Note, the two figures represent the same information, but plot on the left is cropped to show just negative buffer values as the resulting positive buffer recommendations are not consistent with the TC/MC process.

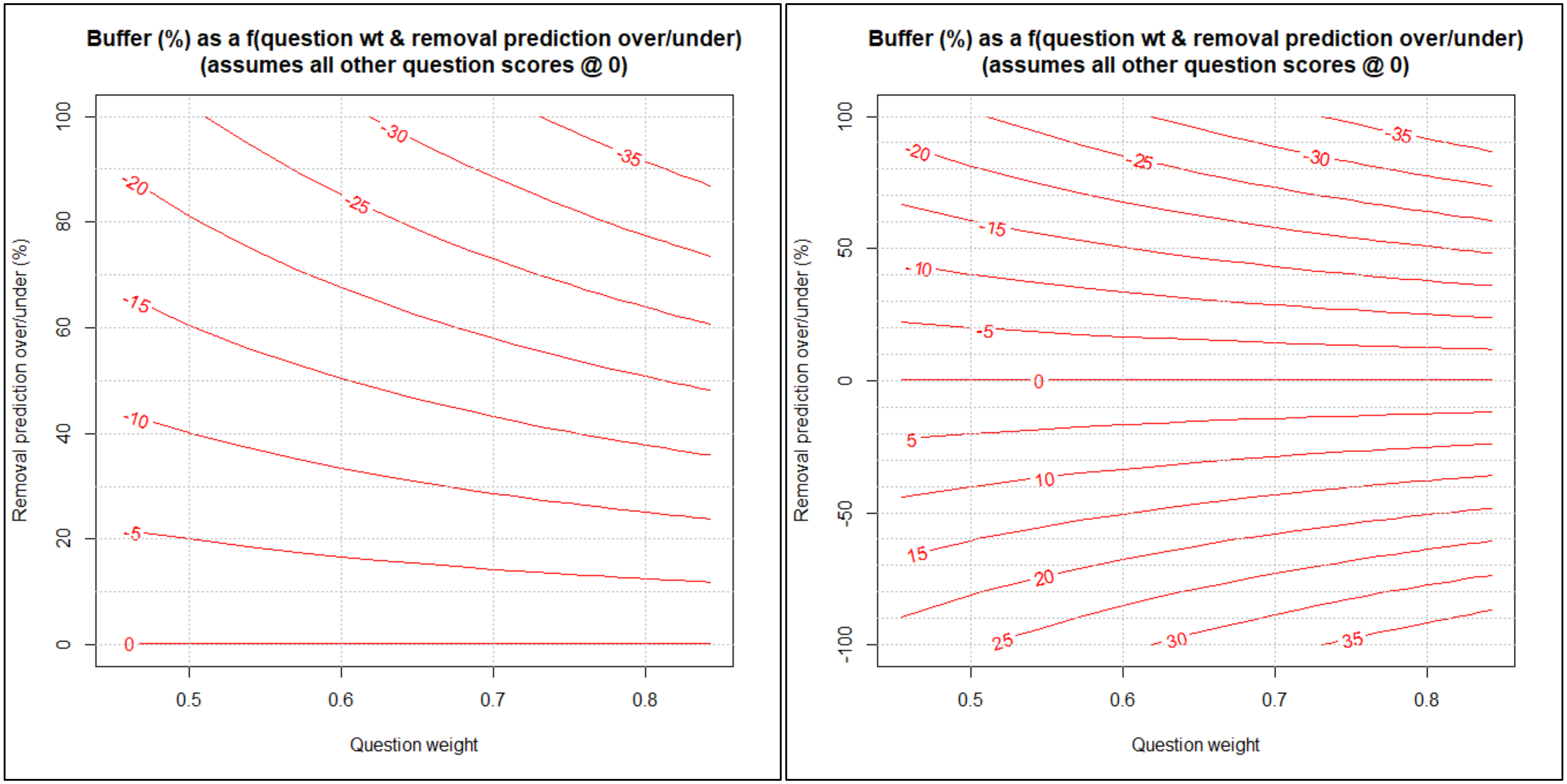


Figure 2. Further exploration of the influence of recreational weights and decision tool inputs on management uncertainty buffers. In the examples below, the weight associated with removals prediction performance is fixed at either 0.7 or 0.4, while the removals prediction performance varies between +/-100%, and one other question factor (e.g., compliance, enforceability, reporting), varies between +/-5. Figures below reflect weightings from the recreational fishery; performance from the commercial fishery weightings was similar.

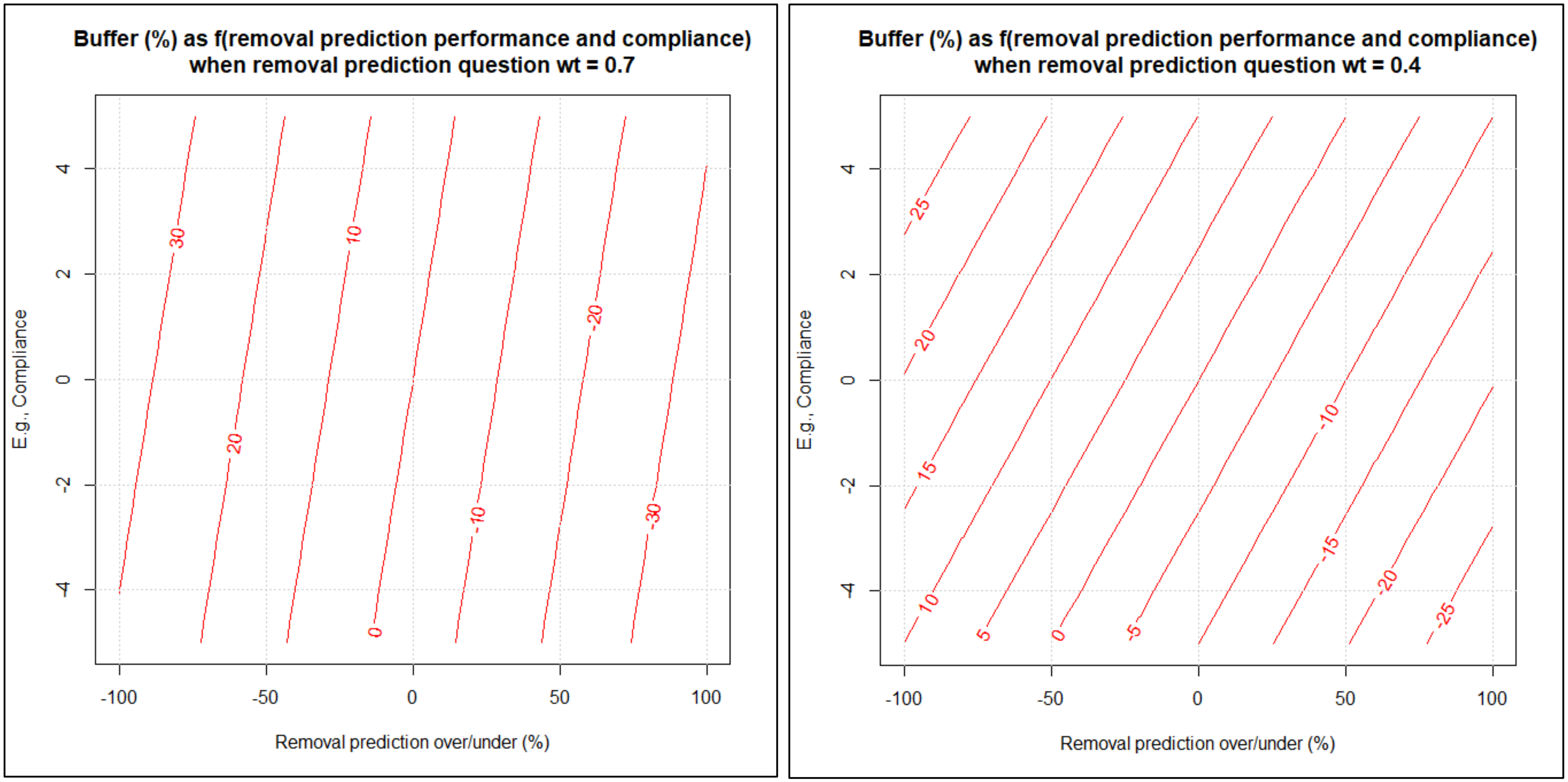
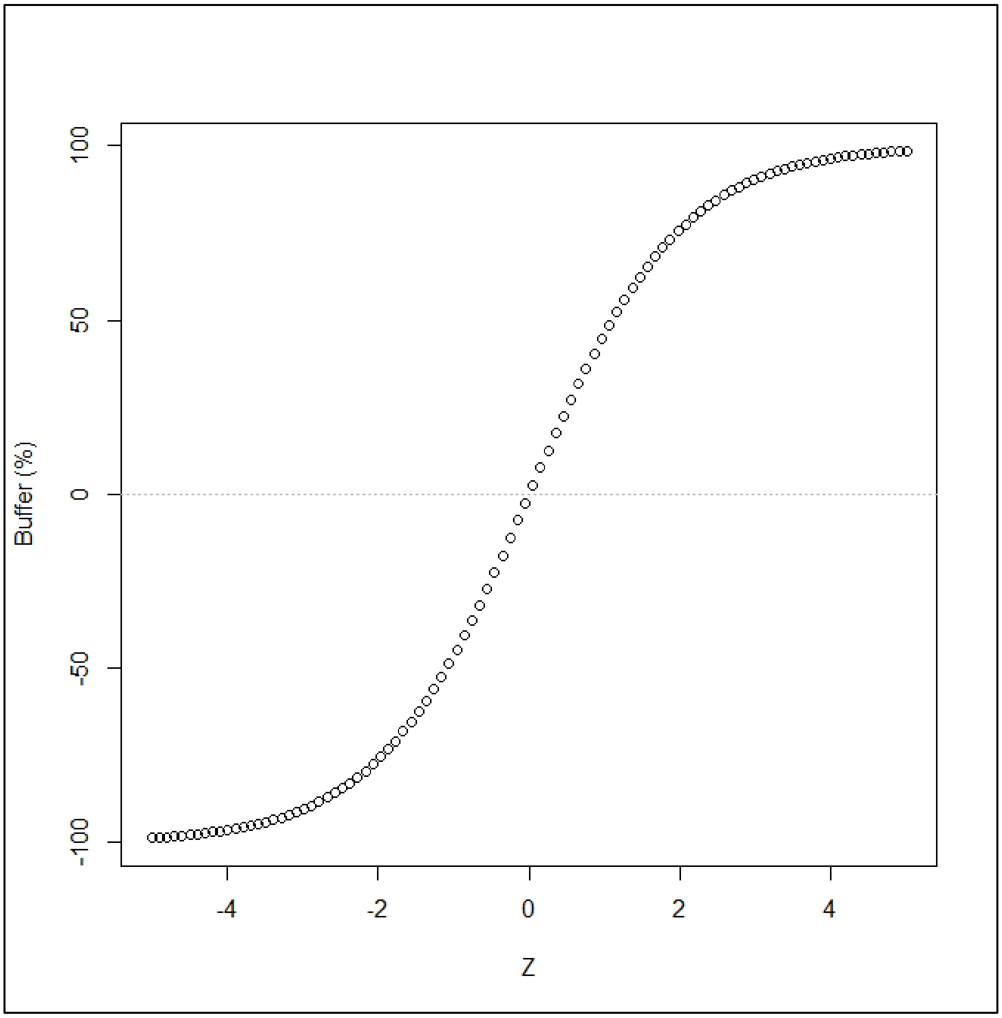


Figure 3. Illustration of the non-linear nature of the equation dynamics with respect to the buffer calculation.



Appendix 2. Confidence intervals around recreational dead catch estimates

Introduction

The contribution of dead catch prediction error to the decision score is expressed as the percent difference between predicted dead catch (i.e., using methods M1, M2, or M3 in §Predicted Removals above) and observed dead catch. Recreational removals, however, may have considerable associated uncertainty; as a result, it is possible the calculated percent difference that contributes to the score could be more of a function of this uncertainty than a deficiency in the dead catch prediction method. Here, a method is proposed to incorporate confidence bounds around the dead catch point estimate as a means of identifying a difference that is likely to be a true deficiency in dead catch prediction as opposed to a difference that is the result of random variation associated with the dead catch estimate.

Note, this method applies to recreational dead removals only. Both recreational harvest and dead releases are estimates; as a result, there is more concern over the precision of predicting recreational dead catch than for commercial fisheries, where the landings component is a census.

The method employed here suggests an 80% confidence interval is used to determine whether the dead catch prediction is statistically consistent with a point observation. This confidence level was chosen for consistency with the Harvest Control Rule's Percent Change Approach; another value could be used instead.

Method / Algorithm

1. Compile the annual dead catch point estimate variances[1]. These quantities include harvest (annual) and spring and fall dead releases (spring and fall dead releases were calculated separately for use in the assessment model to account for seasonal growth patterns; in the proposed method these were treated separately and then combined with harvest).
2. The confidence intervals around the dead catch point estimate components (i.e., harvest and spring/fall dead releases) are constructed via bootstrapping, and the proposed method used 10,000 random draws for each quantity. Using the mean and variance of each annual AB1 and seasonal dead B2 estimate, 10,000 random draws were made from a truncated normal distribution with a minimum at zero to avoid negative dead catch.
3. Compile 10,000 instances of point estimate dead catch by adding together the harvest (AB1) and spring and fall dead releases (dead B2). This distribution represents the uncertainty surrounding annual point estimates of dead catch. The 10th and 90th percentiles of the distribution represent the 80% confidence interval bounds.
4. If the dead catch estimate for the year in question falls within the 80% confidence interval bounds of the point estimate, the score for recreational removals would be zero; otherwise the percent difference between the dead catch prediction and point estimate would be used for the score.

[1] Standard deviations for dead recreational releases were calculated by estimating 80% confidence intervals for seasonal B2 numbers (LCL & UCL), generating total weight estimates of those dead releases using methods outlined in NOAA (2022; e.g., use of length-weight coefficients), and then back calculating the standard error that would be required to generate a confidence interval of the observed width.

Example Tables

		Total removals (wt)										
		Actual	Prediction			Performance						Prediction
Management year	Year	AB1+B2(dead)	1-yr pred	2-yr pred	3-yr pred	1-yr	2-yr	3-yr	method 3	LCL2yr	UCL2yr	w/in 80% CI?
2006	2005	19,266										
2007	2006	19,220										
2008	2007	20,694										
2009	2008	18,167	20,694	19,957	19,727							
2010	2009	20,395	18,167	19,431	19,360	13.9%	9.9%	8.6%		16,911	22,033	
2011	2010	22,533	20,395	19,281	19,752	-10.9%	-4.7%	-5.1%		18,649	24,276	TRUE
2012	2011	16,519	22,533	21,464	20,365	-9.5%	-14.4%	-12.3%	-2.2%	15,381	24,063	TRUE
2013	2012	16,656	16,519	19,526	19,816	36.4%	29.9%	23.3%	5.3%	14,939	18,222	TRUE
2014	2013	17,234	16,656	16,587	18,569	-0.8%	17.2%	19.0%	8.7%	15,283	18,601	FALSE
2015	2014	19,884	17,234	16,945	16,803	-3.4%	-3.8%	7.7%	10.7%	16,165	21,035	TRUE
2016	2015	22,043	19,884	18,559	17,925	-13.3%	-14.8%	-15.5%	-5.8%	18,696	23,114	TRUE
2017	2016	19,665	22,043	20,963	19,720	-9.8%	-15.8%	-18.7%	-8.8%	18,419	23,128	FALSE
2018	2017	19,433	19,665	20,854	20,531	12.1%	6.6%	0.3%	-3.7%	16,989	22,040	TRUE
2019	2018	9,461	19,433	19,549	20,380	1.2%	7.3%	5.6%	1.2%	8,690	21,568	TRUE
2020	2019	11,060	9,461	14,447	16,187	105.4%	106.6%	115.4%	39.6%	8,675	11,749	TRUE
2021	2020	8,535	11,060	10,261	13,318	-14.5%	30.6%	46.3%	30.7%	7,638	11,708	FALSE
2022	2021	6,662	8,535	9,798	9,686	29.6%	20.2%	56.0%	40.2%	6,021	9,379	TRUE
2023	2022	6,297	6,662	7,599	8,753	28.1%	47.1%	45.4%	14.4%	5,570	7,406	FALSE
2024	2023		6,297	6,480	7,165	5.8%	20.7%	39.0%	21.2%			FALSE

Not lagged; this is the output from R script:

	From MRIP		From A. Wood		From A. Wood		Joint dist	Joint dist
year	AB1.mt	AB1.CV	B2_MT.1	CV.1	B2_MT.2	CV.2	LCL80.2yr	UCL80.2yr
2005	17,120	0.10	1,253	0.21	894	0.19	NA	NA
2006	16,367	0.10	1,842	0.14	1,011	0.12	NA	NA
2007	18,252	0.09	769	0.12	1,673	0.18	17,619	22,324
2008	16,405	0.08	797	0.13	965	0.16	17,020	22,143
2009	18,476	0.10	1,265	0.34	654	0.16	16,911	22,033
2010	21,003	0.09	878	0.09	653	0.14	18,649	24,276
2011	15,522	0.09	539	0.17	458	0.17	15,381	24,063
2012	14,756	0.08	1,186	0.12	714	0.16	14,939	18,222
2013	15,603	0.08	995	0.47	637	0.12	15,283	18,601
2014	12,267	0.11	2,802	0.08	4,814	0.09	16,165	21,035
2015	13,653	0.09	3,973	0.07	4,417	0.07	18,696	23,114
2016	10,957	0.12	3,998	0.11	4,711	0.08	18,419	23,128
2017	14,548	0.17	3,018	0.14	1,868	0.10	16,989	22,040
2018	6,020	0.15	1,208	0.08	2,233	0.12	8,690	21,568
2019	7,056	0.09	2,820	0.15	1,185	0.17	8,675	11,749
2020	6,160	0.16	1,254	0.18	1,121	0.11	7,638	11,708
2021	5,607	0.13	516	0.09	539	0.13	6,021	9,379
2022	5,150	0.12	396	0.12	751	0.15	5,570	7,406

Example R Code

Load functions & libraries

```
library(readxl, quietly = TRUE, verbose=FALSE)
library(rmarkdown, quietly = TRUE, verbose=FALSE)
library(knitr, quietly = TRUE, verbose=FALSE)
```

Read in and combine data

```
b2 <- as.data.frame(read_xlsx(path="seasonalB2s.xlsx",range="K4:R40",sheet="B2")) # dead B2s

tail(b2)

##    season year     B2_MT   LCL_MT    UCL_MT    SE_LCL    SE_UCL         CV
## 31      1 2020 1254.4201 969.4387 1539.4015 222.37218 222.37218 0.17727090
## 32      2 2020 1120.5617 957.8012 1283.3222 127.00267 127.00267 0.11333840
## 33      1 2021  516.2453 457.3995  575.0911  45.91763  45.91763 0.08894536
## 34      2 2021  538.8222 448.7872  628.8572  70.25471  70.25471 0.13038570
## 35      1 2022  396.4003 337.7162  455.0843  45.79141  45.79141 0.11551810
## 36      2 2022  750.5497 606.2158  894.8835 112.62433 112.62433 0.15005580

ab1 <- as.data.frame(read_xlsx(path="seasonalB2s.xlsx",range="I16:K34",sheet="AB1"))
ab1$AB1.CV <-  ab1$AB1.PSE/100
ab1$AB1.mt <- ab1$AB1.kg/1000 # convert kg to mt

tail(ab1)

##    year   AB1.kg AB1.PSE AB1.CV    AB1.mt
## 13 2017 14547506    16.9  0.169 14547.506
## 14 2018  6019624    14.7  0.147  6019.624
## 15 2019  7056105     8.7  0.087  7056.105
## 16 2020  6160400    16.4  0.164  6160.400
## 17 2021  5607358    13.2  0.132  5607.358
## 18 2022  5150383    11.9  0.119  5150.383

# removals = rmvs
# Combine AB1 and B2 into a single data.frame
rmvs <- stats::reshape(b2[,c("season","year","B2_MT","CV")],timevar="season",idvar="year",direction="wide")
rmvs <- cbind(ab1[,c("year","AB1.mt","AB1.CV")],rmvs[,-1])
tail(rmvs)
```

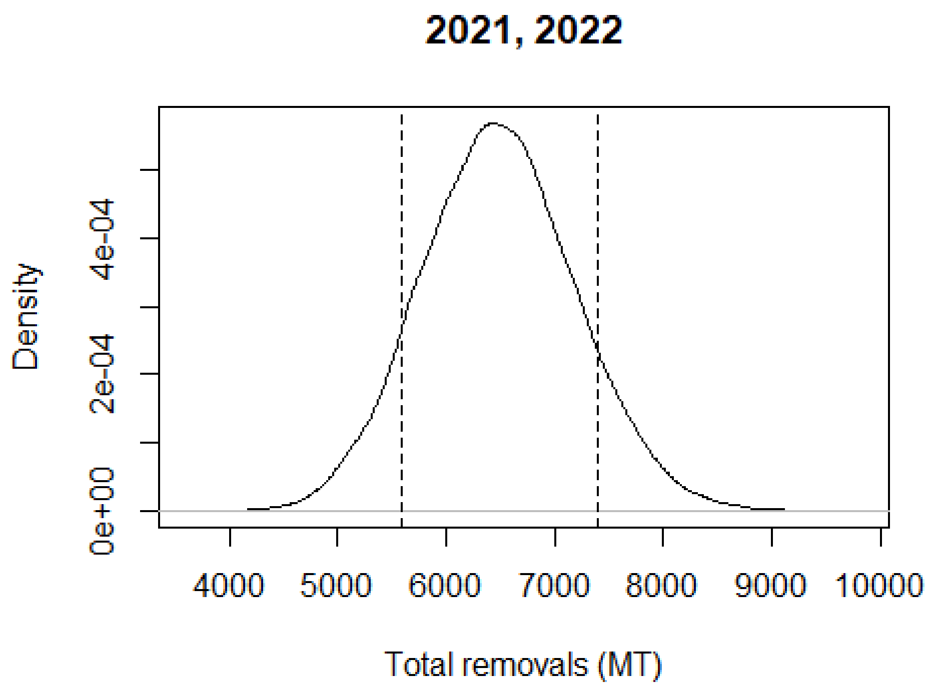
```
##    year    AB1.mt AB1.CV   B2_MT.1       CV.1   B2_MT.2      CV.2
## 25 2017 14547.506  0.169 3018.0328 0.13983800 1867.8090 0.1006084
## 27 2018  6019.624  0.147 1208.2634 0.08488466 2233.4355 0.1151319
## 29 2019  7056.105  0.087 2819.5446 0.15439540 1184.6757 0.1663490
## 31 2020  6160.400  0.164 1254.4201 0.17727090 1120.5617 0.1133384
## 33 2021  5607.358  0.132  516.2453 0.08894536  538.8222 0.1303857
## 35 2022  5150.383  0.119  396.4003 0.11551810  750.5497 0.1500558

# Keep track of negative randomly generated removals (crudely)
tracker <- as.data.frame(matrix(data=0,nr=nrow(rmvs),ncol=11))
tracker[,1] <- rmvs$year
colnames(tracker) <- c("Yr t","AB1 t","AB1 t-1","AB1 t-2","B2(1) t","B2(1) t-1",
   "B2(1) t-2","B2(2) t","B2(2) t-1","B2(2) t-2","check") # check -> add an asterisk if you have looked at this year
```

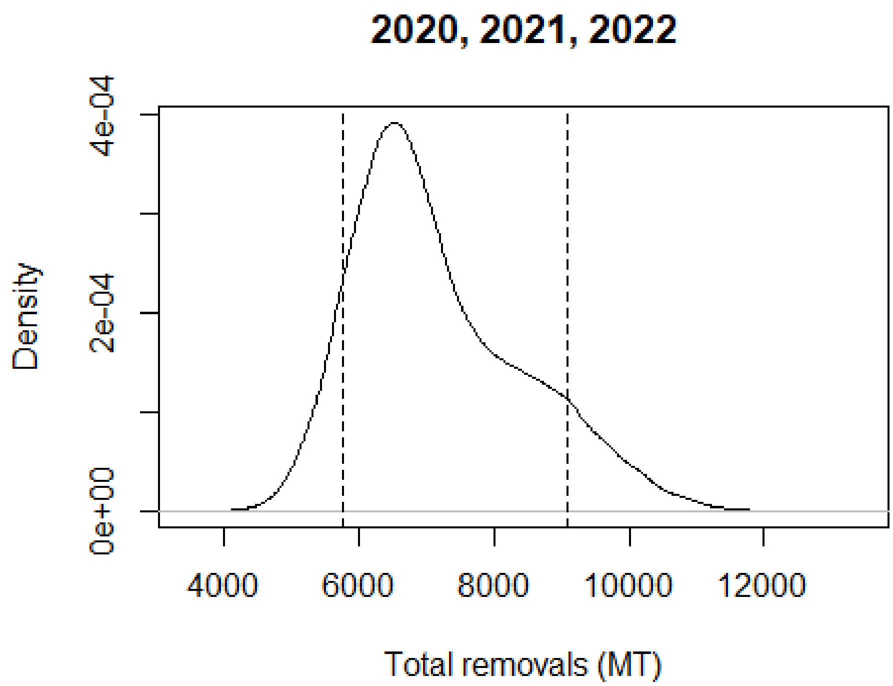
Calculations

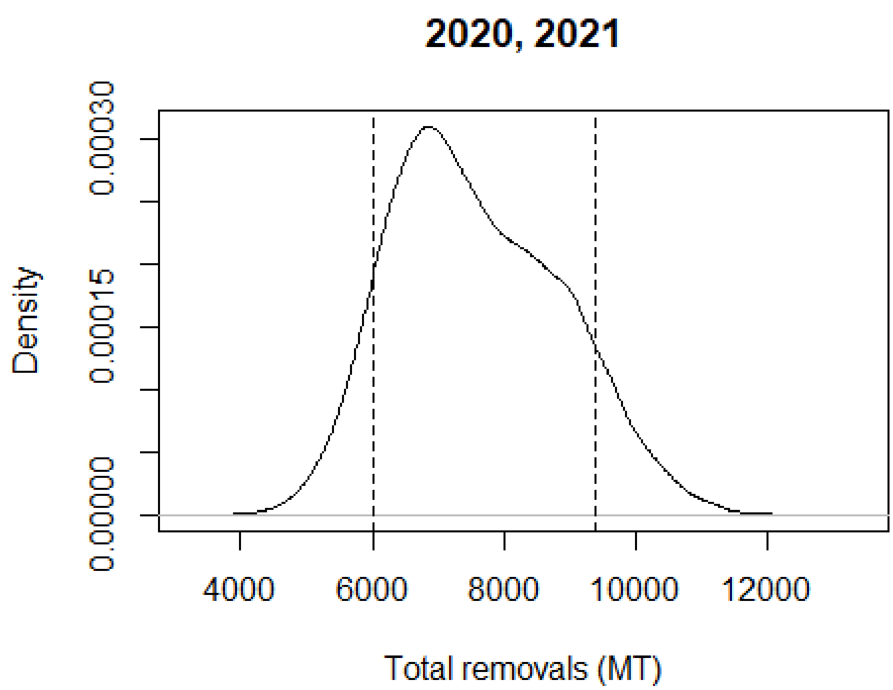
```
n <- 10000 # Enter the number of random draws you would like
tol <- 0.001 # Use this value to test whether removals are different from zero.


for(yr in 2022:2007) { # Note that code is indexed to count years backwards in time so that if yr=2022 then 2022, 2021
and 2020 are included
#yr <- 2022

   # AB1 for year t, t-1, and t-2
   x <- rnorm(n, mean=rmvs[rmvs$year==yr,"AB1.mt"], sd=rmvs[rmvs$year==yr,"AB1.CV"]*rmvs[rmvs$year==yr,"AB1.mt"])
   y <- rnorm(n, mean=rmvs[rmvs$year==(yr-1),"AB1.mt"], sd=rmvs[rmvs$year==(yr-1),"AB1.CV"]*rmvs[rmvs$year==(yr-
1),"AB1.mt"])
   z <- rnorm(n, mean=rmvs[rmvs$year==(yr-2),"AB1.mt"], sd=rmvs[rmvs$year==(yr-2),"AB1.CV"]*rmvs[rmvs$year==(yr-
2),"AB1.mt"])

      # Set any negative values due to high PSEs to zero (we'll keep track of these):
      x[x<0] <- 0
      y[y<0] <- 0
      z[z<0] <- 0


   # B2s for year t, t-1, and t-2, spring and fall
   e.1 <- rnorm(n, mean=rmvs[rmvs$year==yr,"B2_MT.1"], sd=rmvs[rmvs$year==yr,"CV.1"]*rmvs[rmvs$year==yr,"B2_MT.1"])
   e.2 <- rnorm(n, mean=rmvs[rmvs$year==yr,"B2_MT.2"], sd=rmvs[rmvs$year==yr,"CV.2"]*rmvs[rmvs$year==yr,"B2_MT.2"])
```

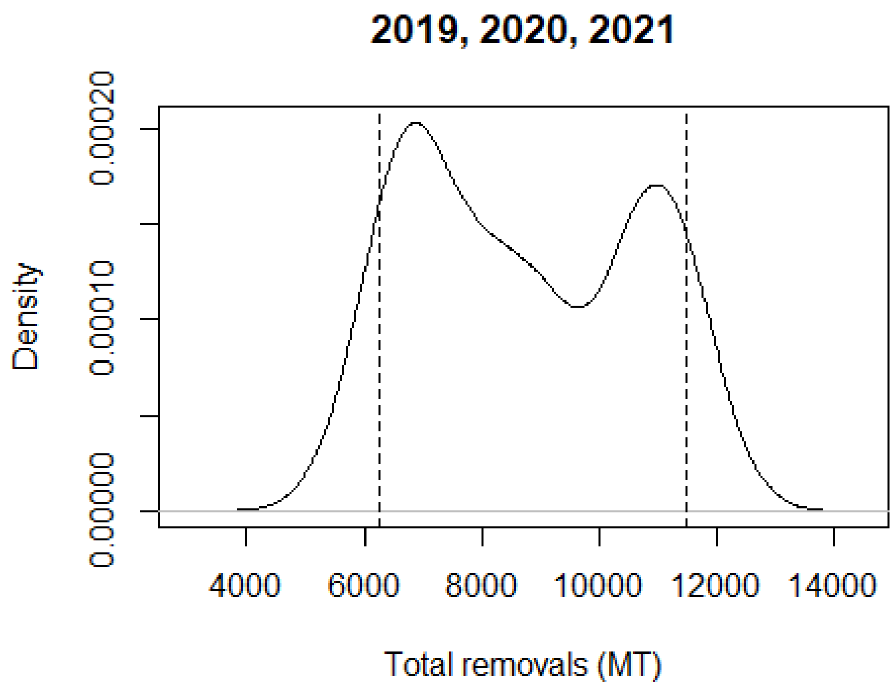
```
  f.1 <- rnorm(n, mean=rmvs[rmvs$year==(yr-1),"B2_MT.1"], sd=rmvs[rmvs$year==(yr-1),"CV.1"]*rmvs[rmvs$year==(yr-
1),"B2_MT.1"])
  f.2 <- rnorm(n, mean=rmvs[rmvs$year==(yr-1),"B2_MT.2"], sd=rmvs[rmvs$year==(yr-1),"CV.2"]*rmvs[rmvs$year==(yr-
1),"B2_MT.2"])

  g.1 <- rnorm(n, mean=rmvs[rmvs$year==(yr-2),"B2_MT.1"], sd=rmvs[rmvs$year==(yr-2),"CV.1"]*rmvs[rmvs$year==(yr-
2),"B2_MT.1"])
  g.2 <- rnorm(n, mean=rmvs[rmvs$year==(yr-2),"B2_MT.2"], sd=rmvs[rmvs$year==(yr-2),"CV.2"]*rmvs[rmvs$year==(yr-
2),"B2_MT.2"])

    # Set any negative values due to high PSEs to zero (we'll keep track of these too):
    e.1[e.1<0] <- 0
    e.2[e.2<0] <- 0

    f.1[f.1<0] <- 0
    f.2[f.2<0] <- 0

    g.1[g.1<0] <- 0
    g.2[g.2<0] <- 0

  # Tally up negative values
  tracker[tracker$Yr==yr,-c(1,11)] <-

sapply(list(x[x<tol],y[y<tol],z[z<tol],e.1[e.1<tol],f.1[f.1<tol],g.1[g.1<tol],e.2[e.2<tol],f.2[f.2<tol],g.2[g.2<tol]),l
ength)
    tracker[tracker$Yr==yr,11] <- "*"



  ########################
  # 2 yr CI
  CI.2yr <- data.frame("yr1"=x + e.1 + e.2,"yr2"=y + f.1 + f.2)
  plot(density(unlist(CI.2yr)),xlab="Total removals (MT)",main=paste(c(yr-1,yr),collapse=", "))
  abline(v=quantile(unlist(CI.2yr),c(0.10,0.90)),lty=2)
  rmvs[rmvs$year==yr,c("LCL80.2yr","UCL80.2yr")] <- quantile(unlist(CI.2yr),c(0.10,0.90))

  ########################
```

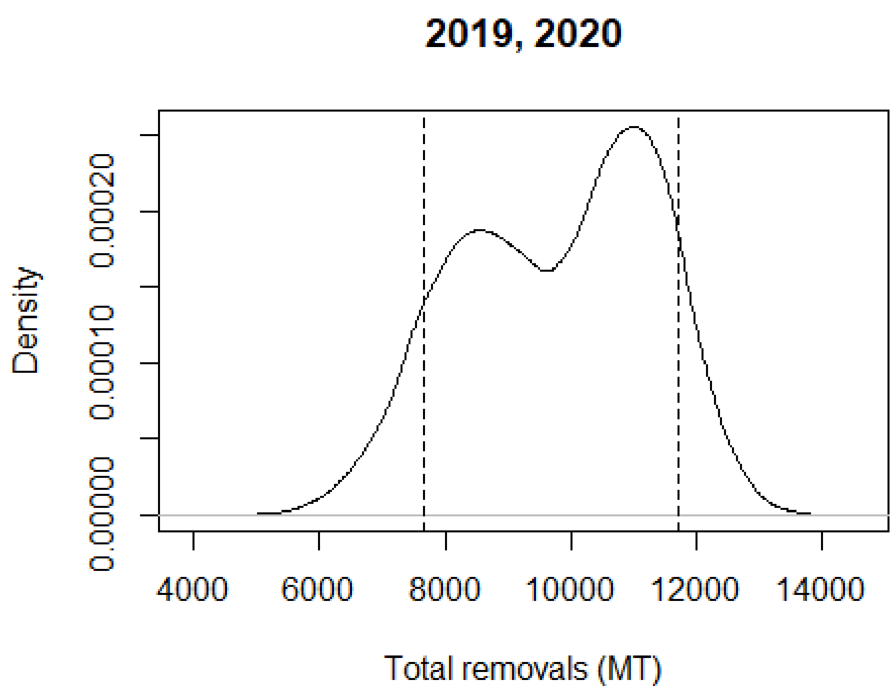
```
  # 3 yr CI
  CI.3yr <- data.frame(CI.2yr, "yr3"=z + g.1 + g.2)
  plot(density(unlist(CI.3yr)),xlab="Total removals (MT)",main=paste(c(yr-2,yr-1,yr),collapse=", "))
  abline(v=quantile(unlist(CI.3yr),c(0.10,0.90)),lty=2)
  rmvs[rmvs$year==yr,c("LCL80.3yr","UCL80.3yr")] <- quantile(unlist(CI.3yr),c(0.10,0.90))
}
```

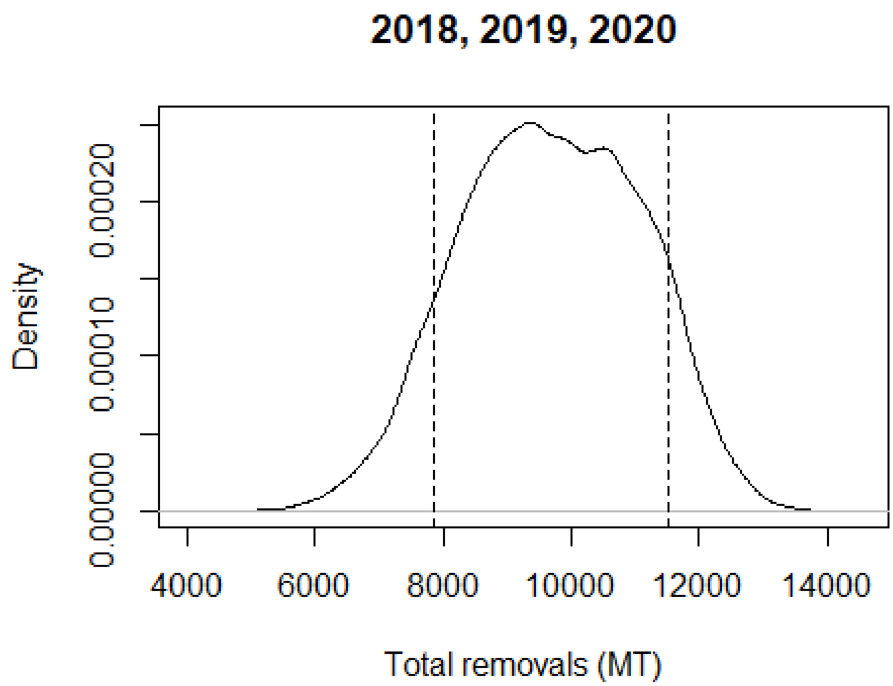

2021, 2022
Density
0e+00
2e-04
4e-04
4000
5000
6000
7000
8000
9000
10000
Total removals (MT)

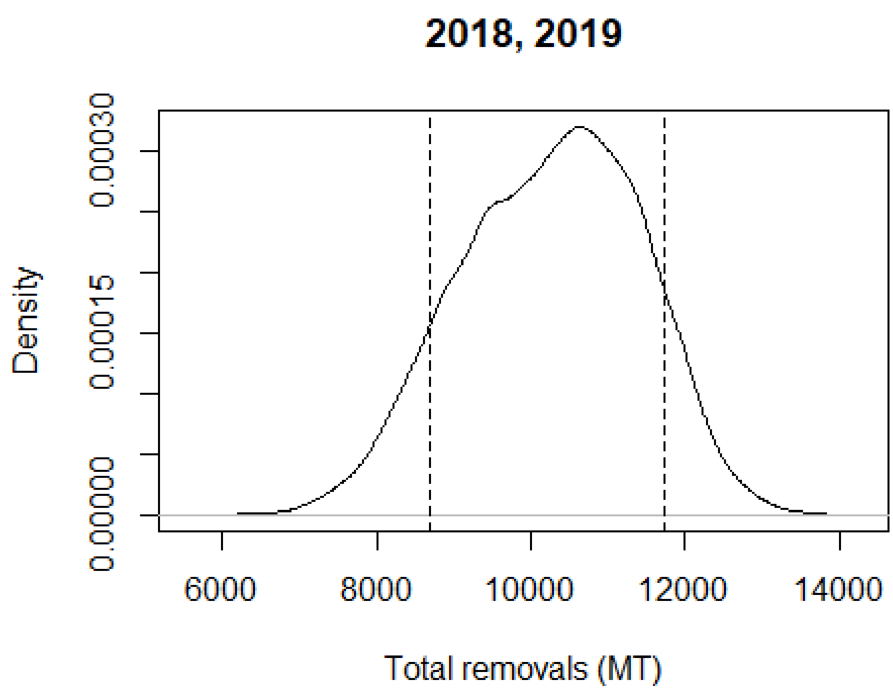

2020, 2021, 2022
Density
0e+00
2e-04
4e-04
4000
6000
8000
10000
12000
Total removals (MT)

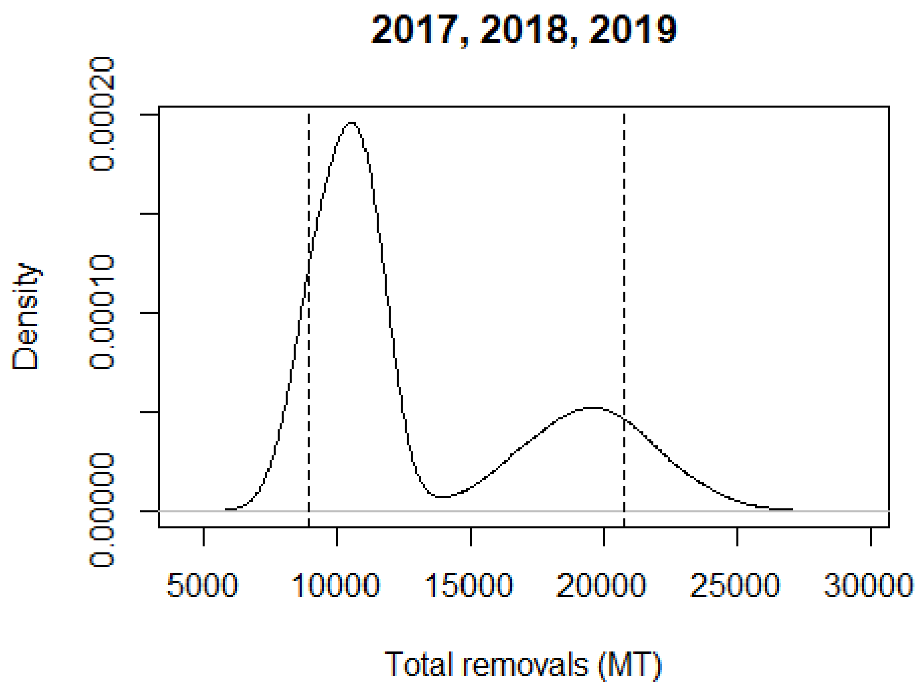

2020, 2021
Density
0.00000
0.00015
0.00030
4000
6000
8000
10000
12000
Total removals (MT)

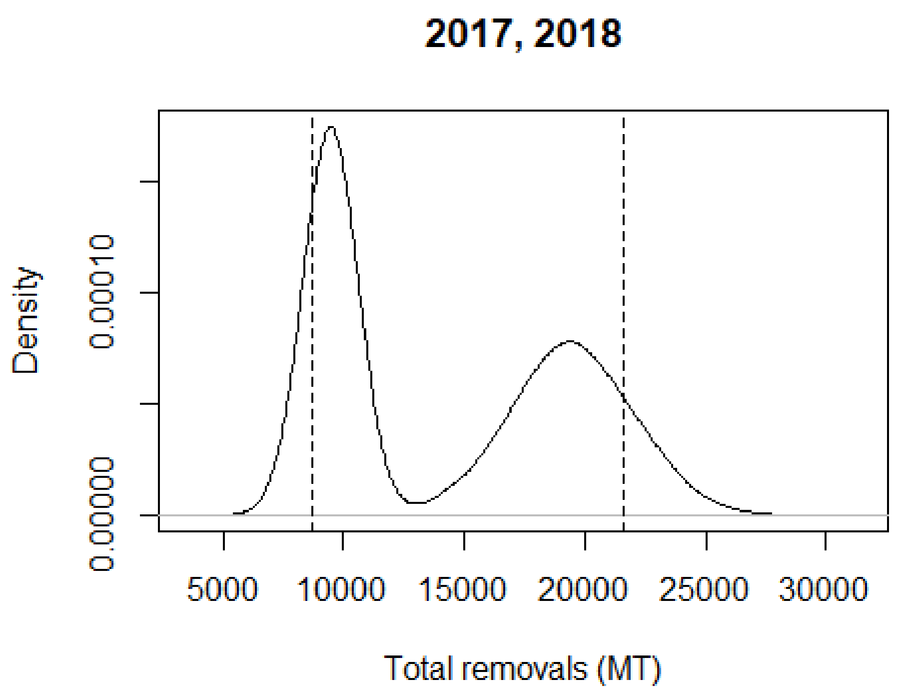

2019, 2020, 2021
Density
0.00000
0.00010
0.00020
4000
6000
8000
10000
12000
14000
Total removals (MT)

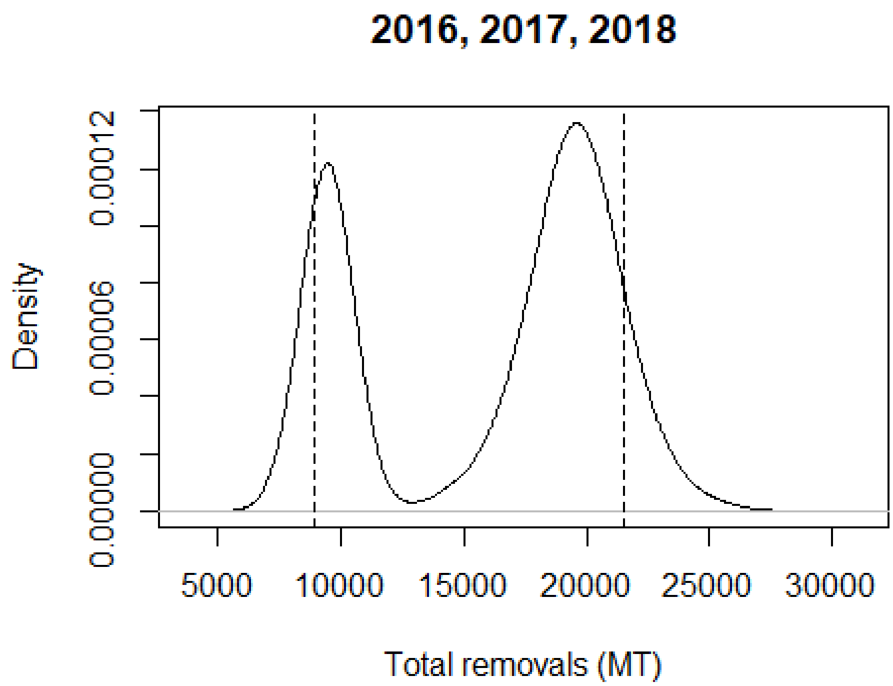

2019, 2020
Density
0.00000
0.00010
0.00020
4000
6000
8000
10000
12000
14000
Total removals (MT)

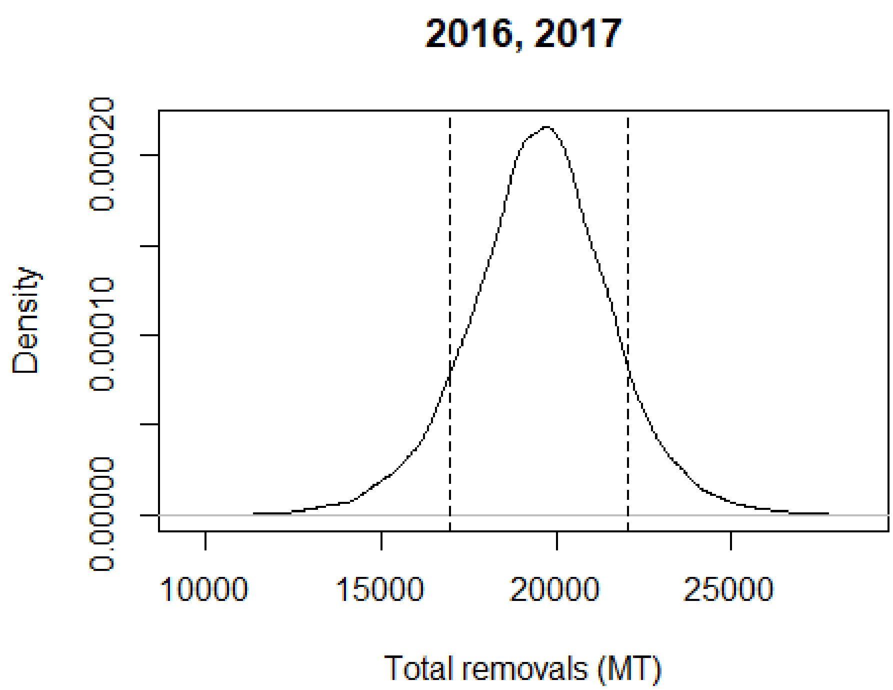

2018, 2019, 2020
Density
0.00000
0.00010
0.00020
4000
6000
8000
10000
12000
14000
Total removals (MT)

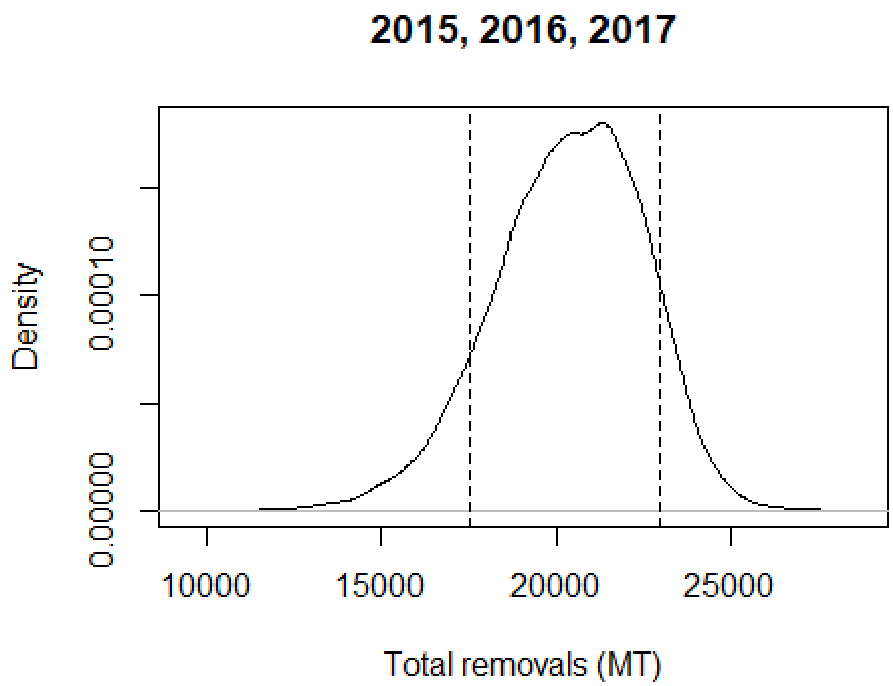

2018, 2019
Density
0.00000
0.00015
0.00030
6000
8000
10000
12000
14000
Total removals (MT)

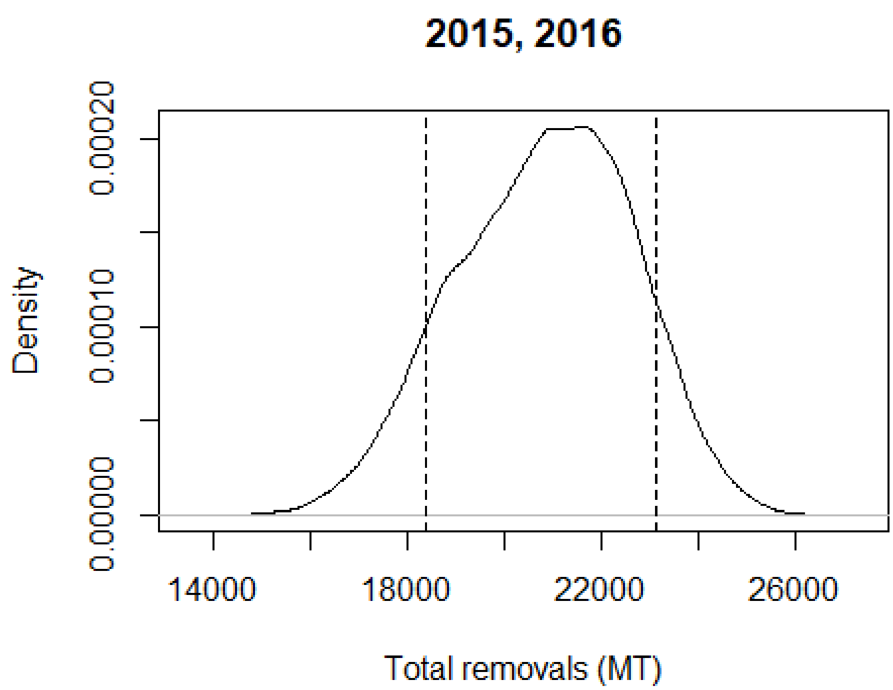

2017, 2018, 2019
Density
0.00000
0.00010
0.00020
5000
10000
15000
20000
25000
30000
Total removals (MT)


2017, 2018
Density
0.00000
0.00010
5000
10000
15000
20000
25000
30000
Total removals (MT)

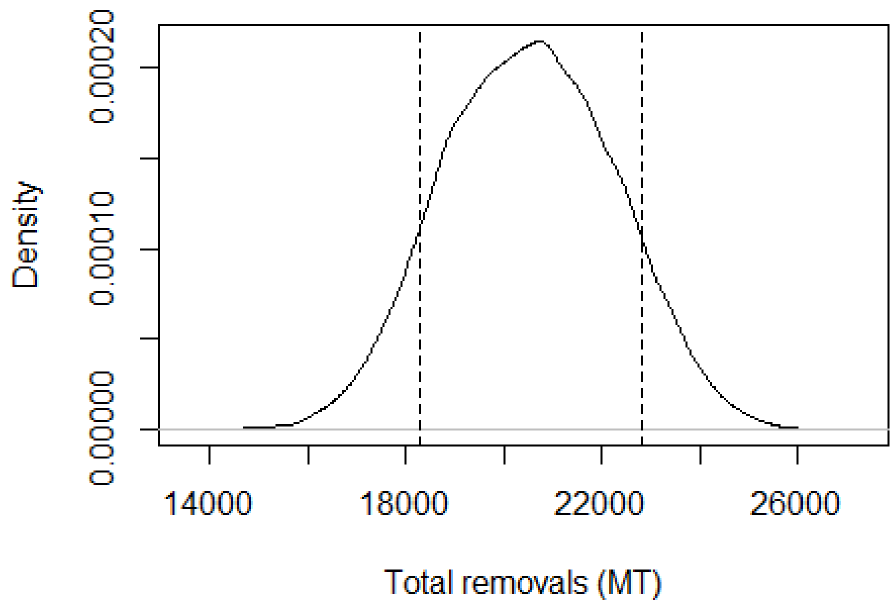

2016, 2017, 2018
Density
0.00000
0.00006
0.00012
5000
10000
15000
20000
25000
30000
Total removals (MT)


2016, 2017
Density
0.00000
0.00010
0.00020
10000
15000
20000
25000
Total removals (MT)

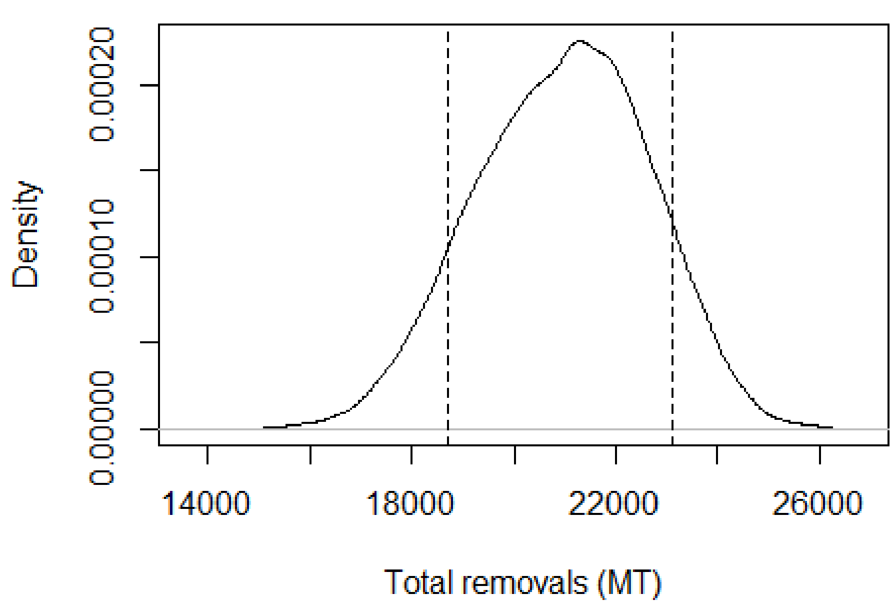

2015, 2016, 2017
Density
0.00000
0.00010
10000
15000
20000
25000
Total removals (MT)

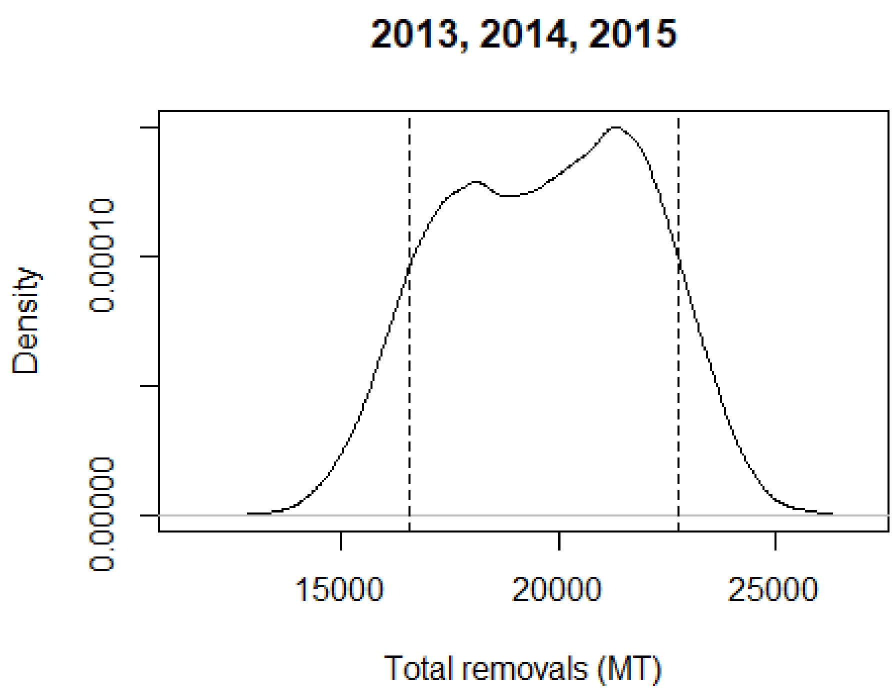

2015, 2016
Density
0.00000
0.00010
0.00020
14000
18000
22000
26000
Total removals (MT)

2014, 2015, 2016

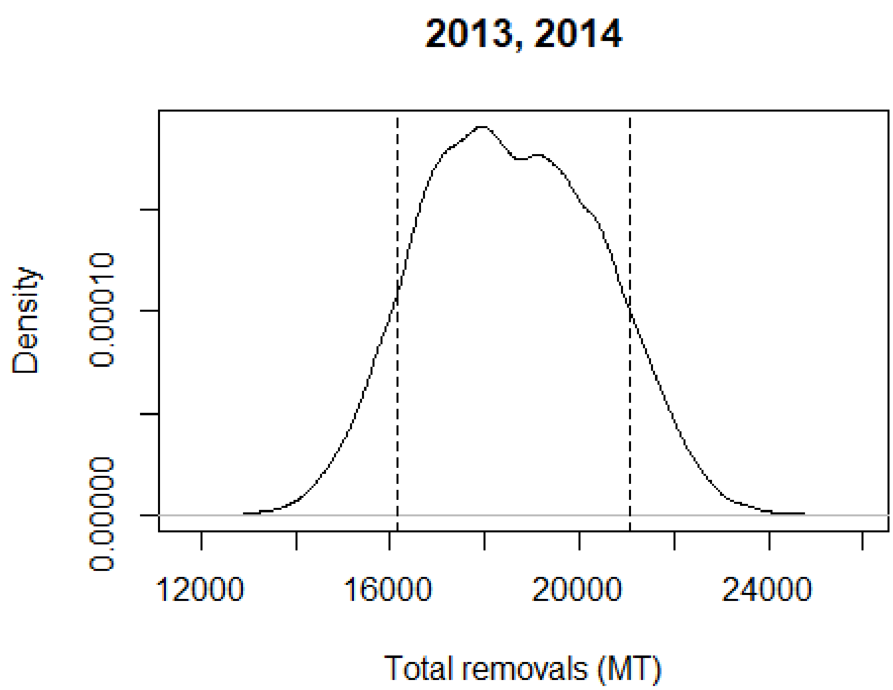


2014, 2015

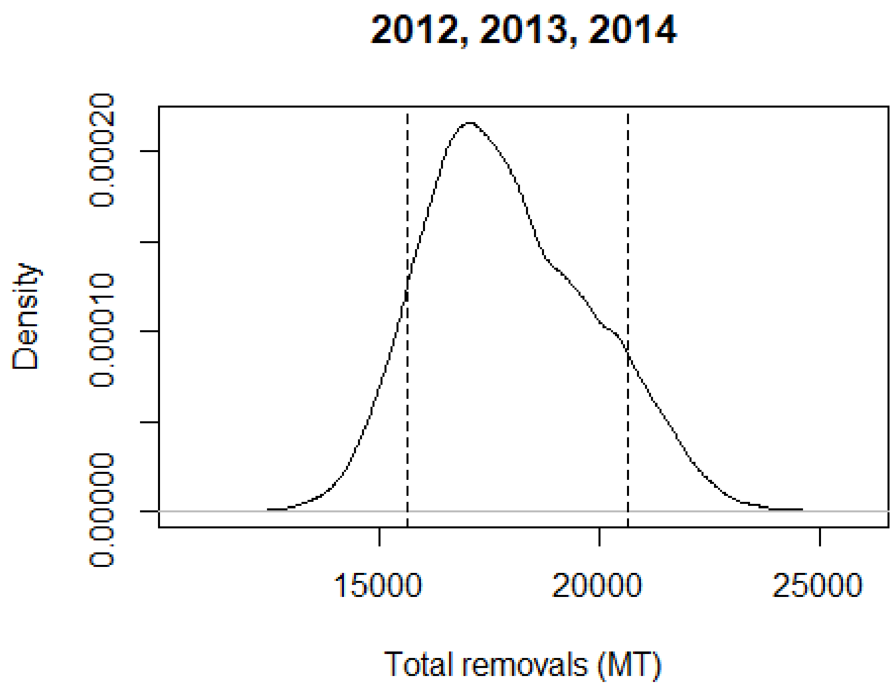




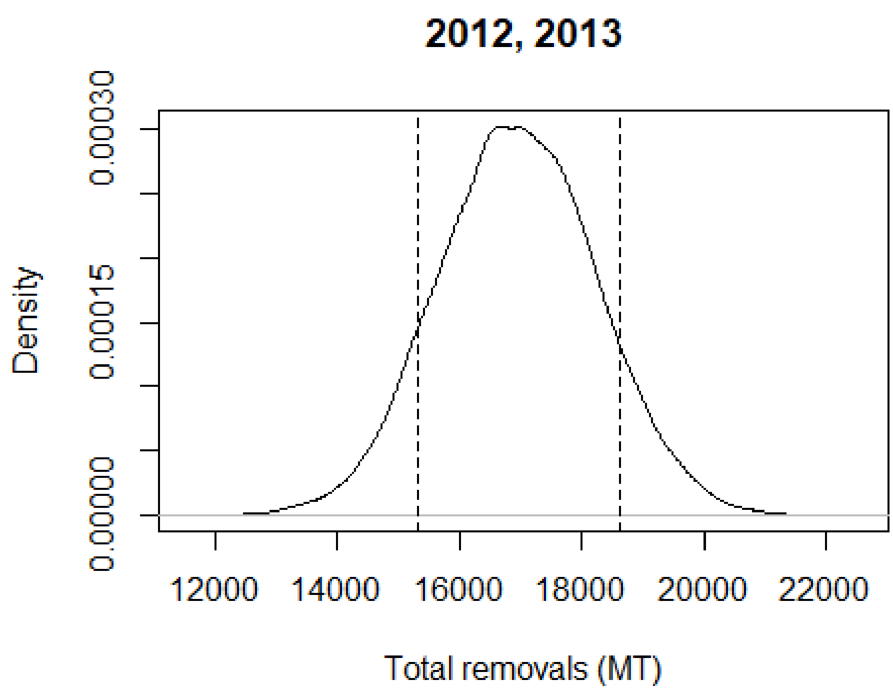
2013, 2014, 2015
Density
0.00000
0.00010
15000
20000
25000
Total removals (MT)



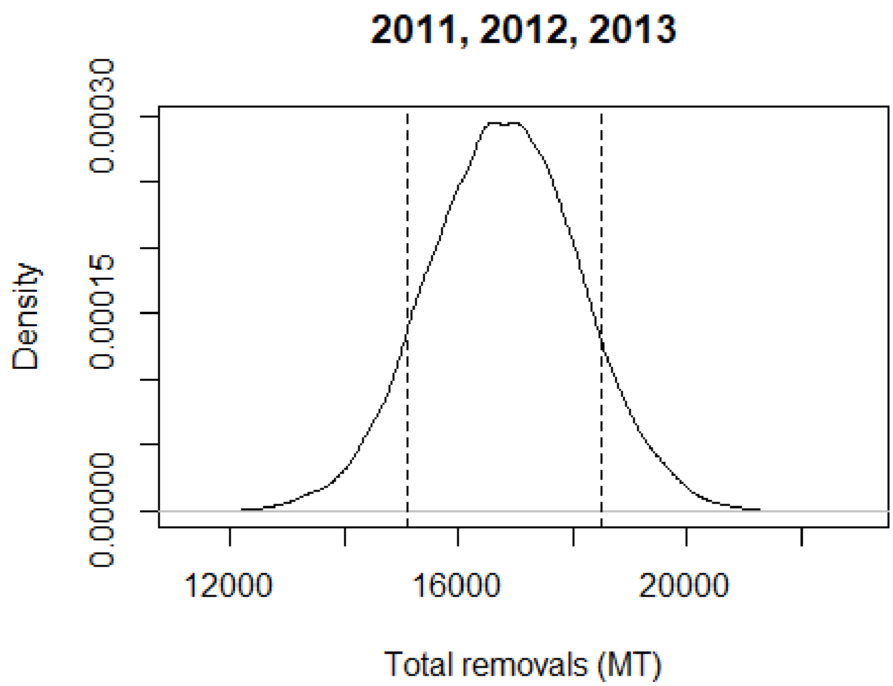
2013, 2014
Density
0.00000
0.00010
12000
16000
20000
24000
Total removals (MT)



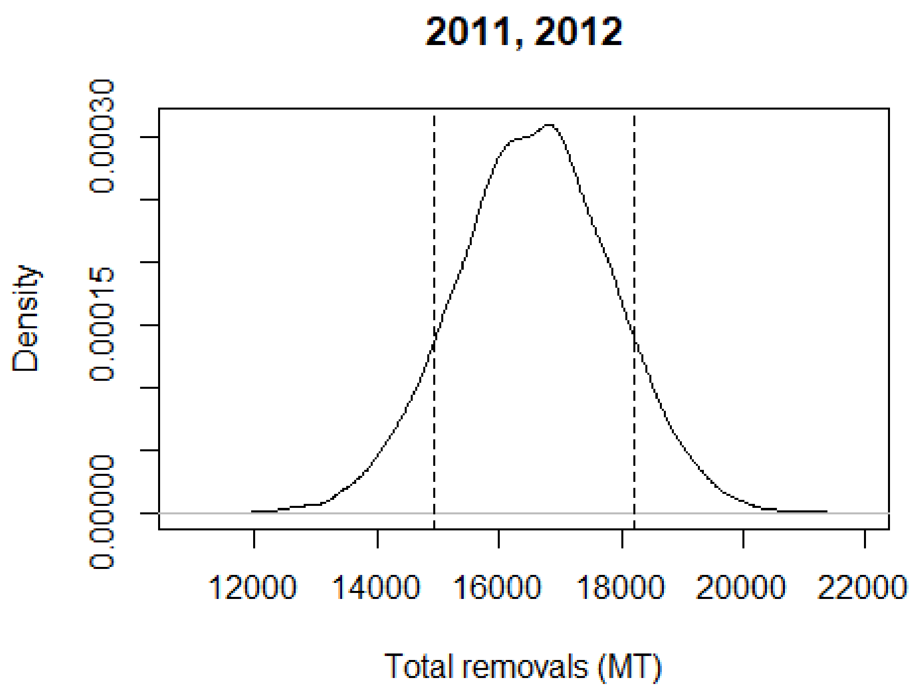
2012, 2013, 2014
Density
0.00000
0.00010
0.00020
15000
20000
25000
Total removals (MT)



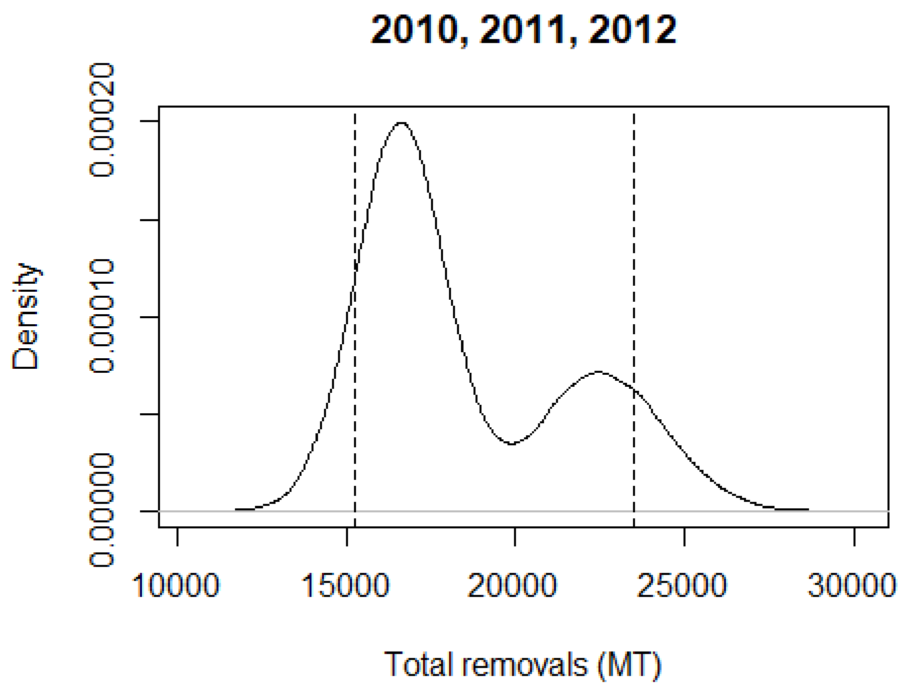
2012, 2013
Density
0.00000
0.00015
0.00030
12000
14000
16000
18000
20000
22000
Total removals (MT)

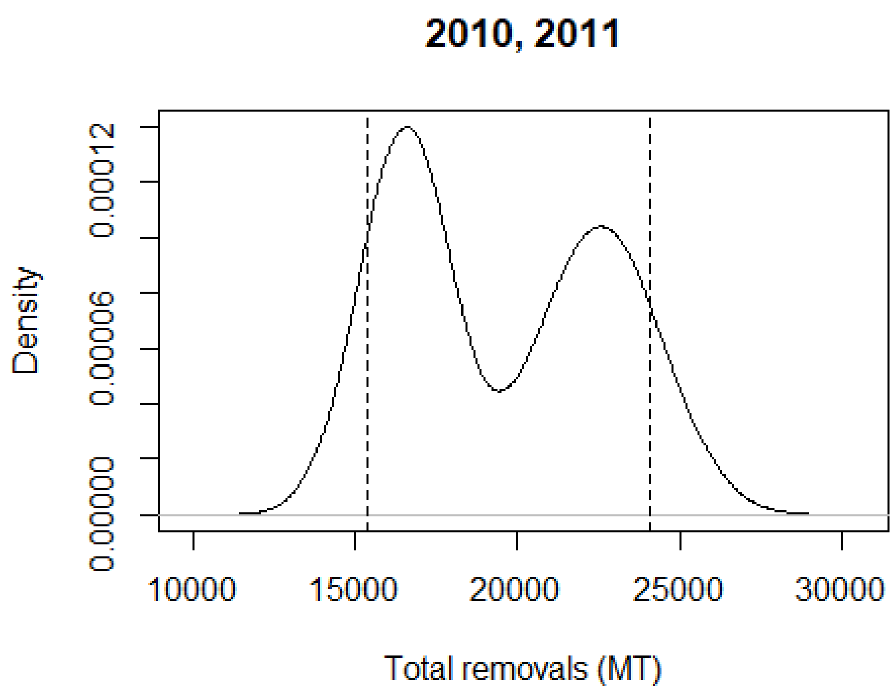


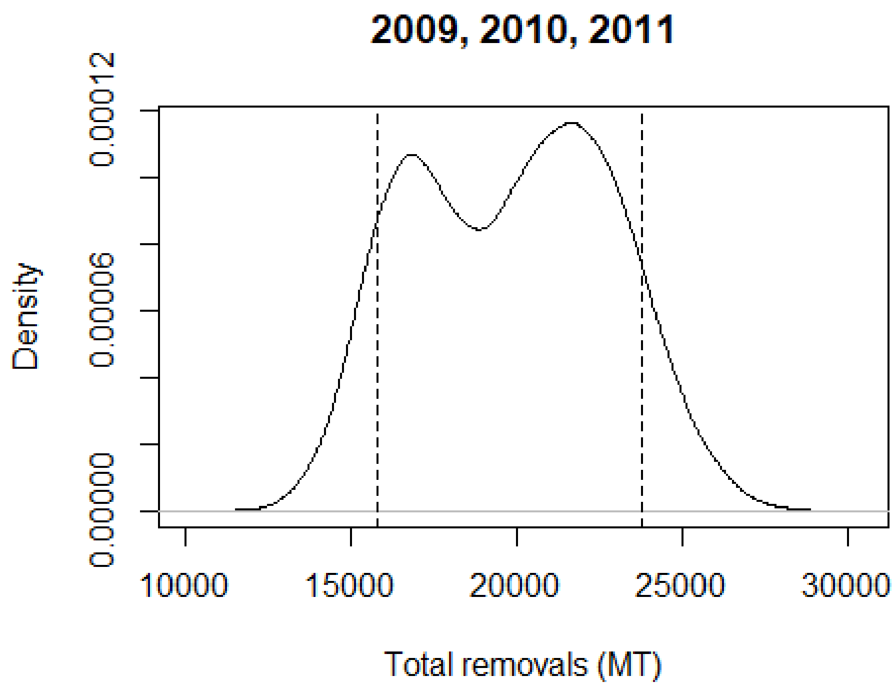
2011, 2012, 2013
Density
0.00000
0.00015
0.00030
12000
16000
20000
Total removals (MT)

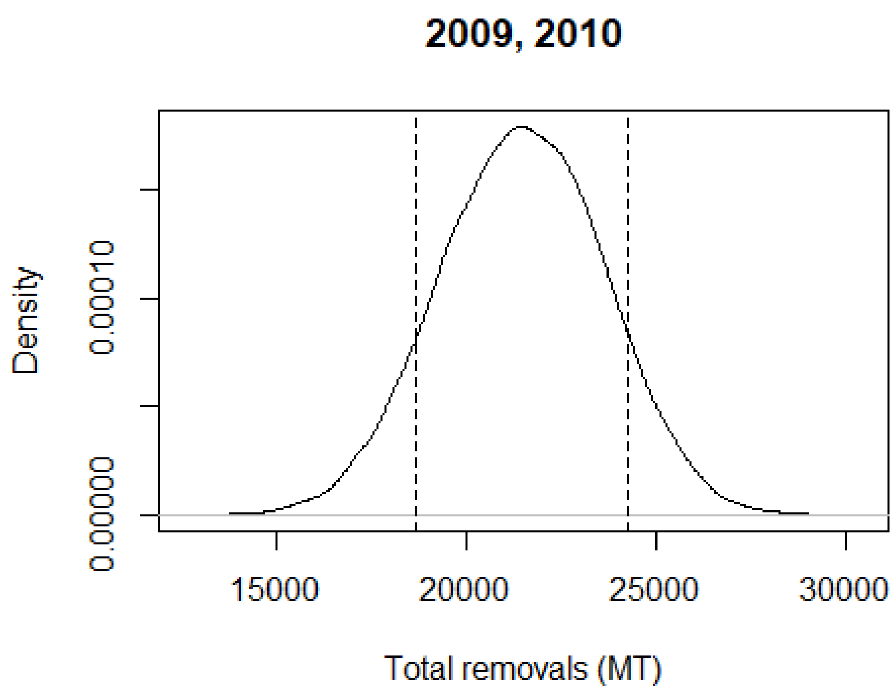


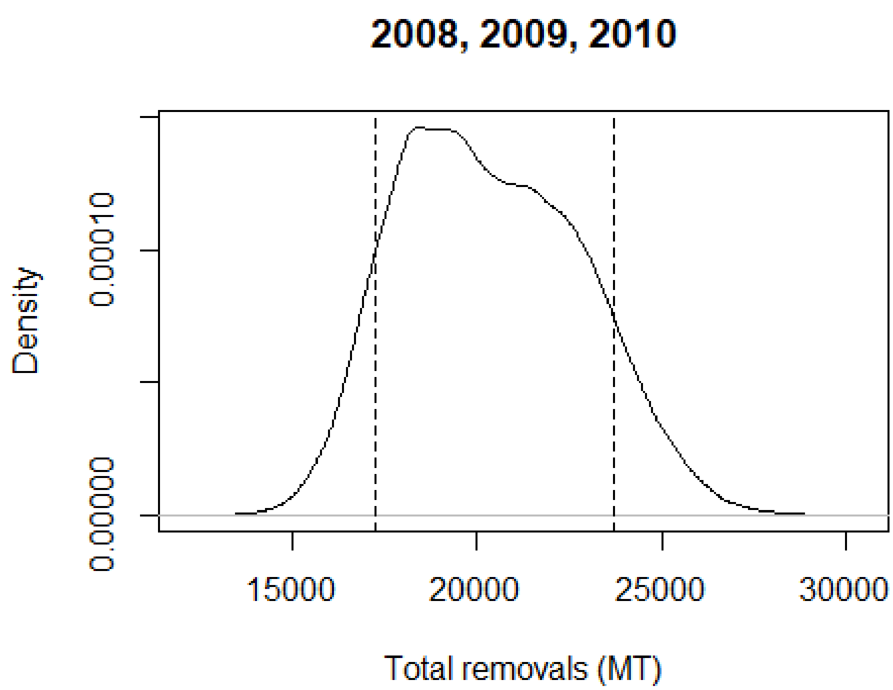
2011, 2012
Density
0.00000
0.00015
0.00030
12000
14000
16000
18000
20000
22000
Total removals (MT)

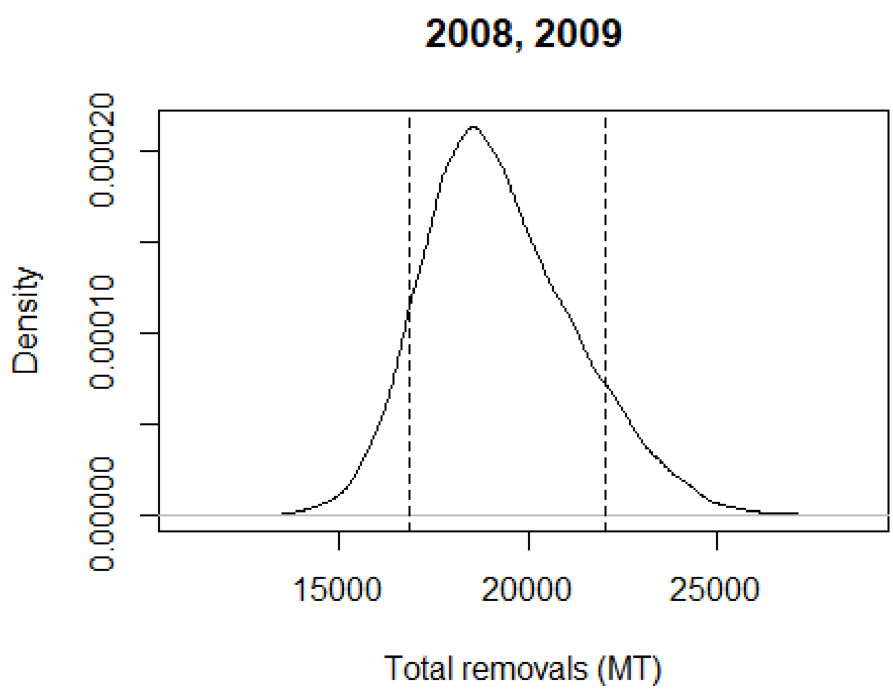

2010, 2011, 2012
Density
0.00000
0.00010
0.00020
10000
15000
20000
25000
30000
Total removals (MT)

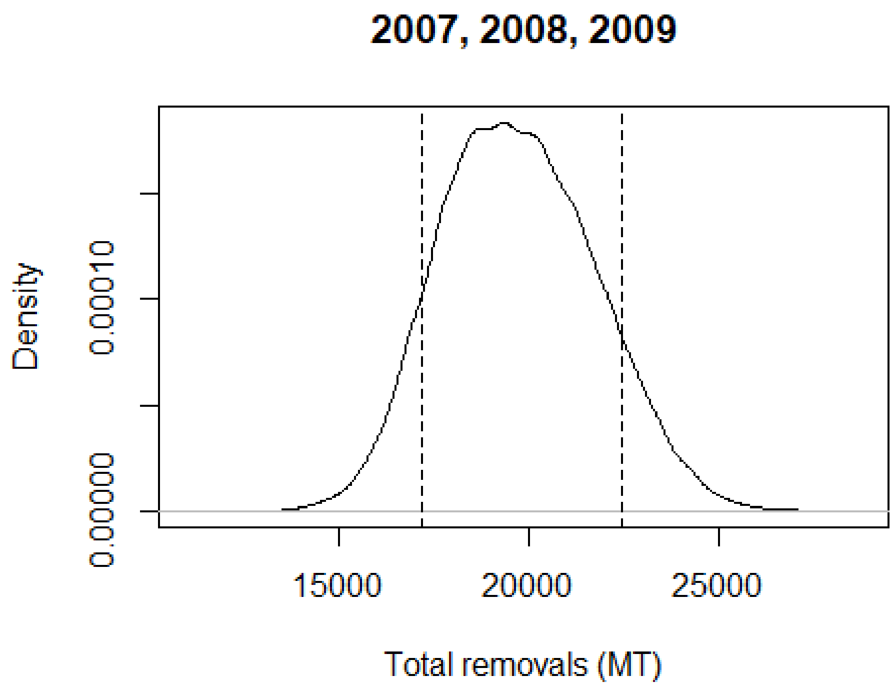

2010, 2011
Density
0.00000
0.00006
0.00012
10000
15000
20000
25000
30000
Total removals (MT)

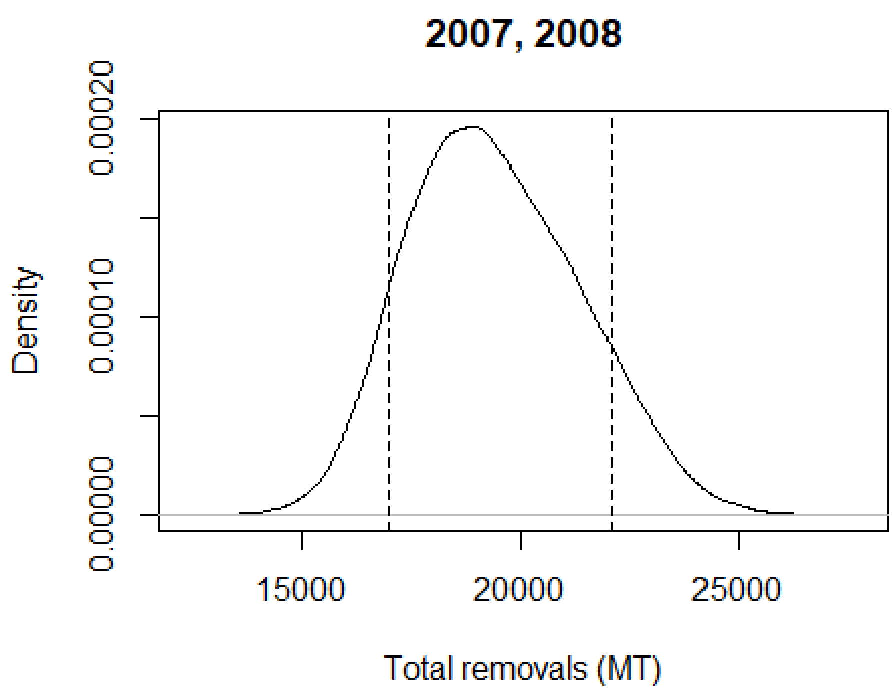

2009, 2010, 2011
Density
0.00000
0.00006
0.00012
10000
15000
20000
25000
30000
Total removals (MT)

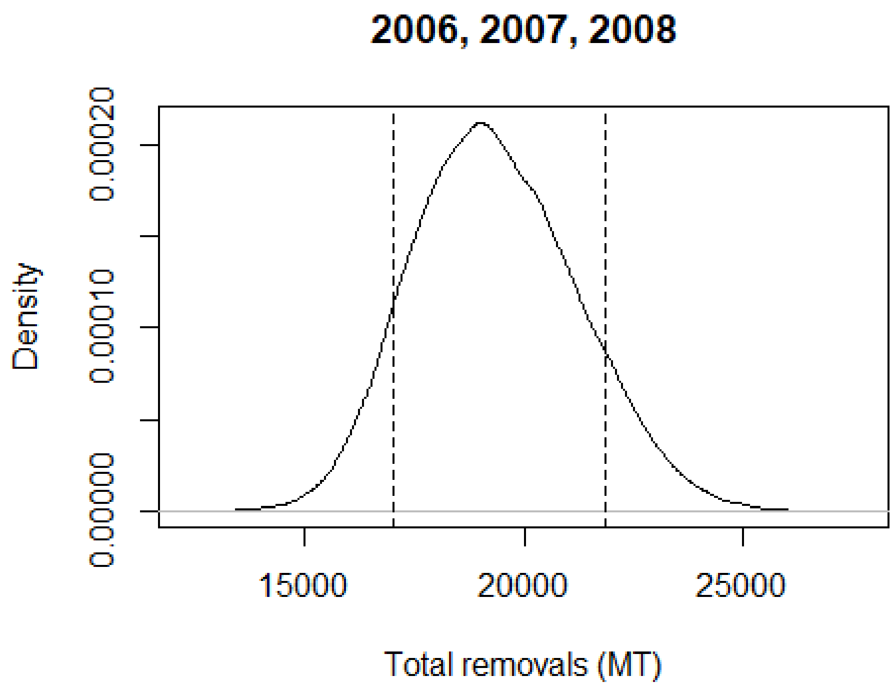

2009, 2010
Density
0.00000
0.00010
15000
20000
25000
30000
Total removals (MT)

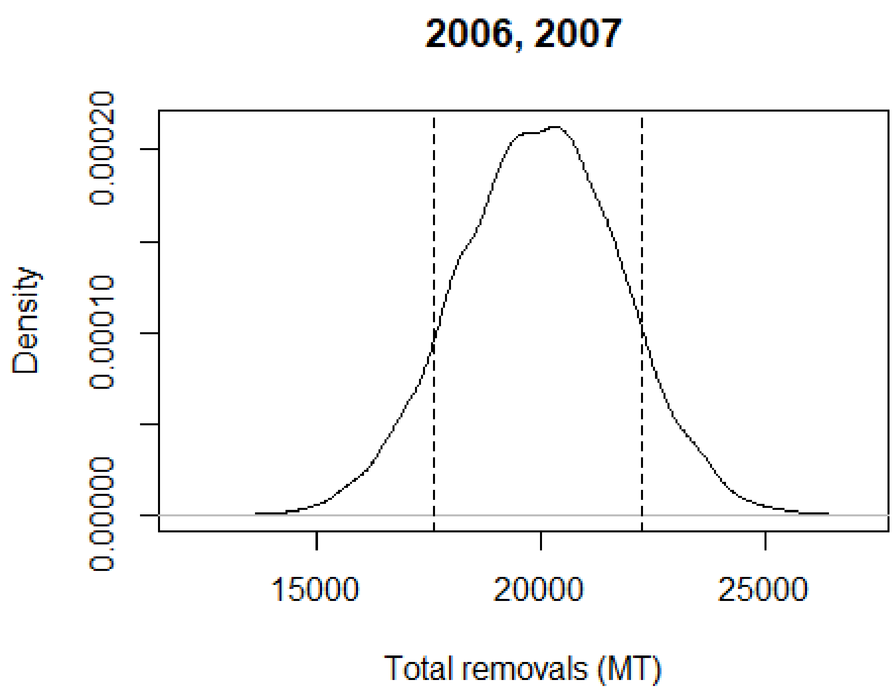

2008, 2009, 2010
Density
0.00000
0.00010
15000
20000
25000
30000
Total removals (MT)

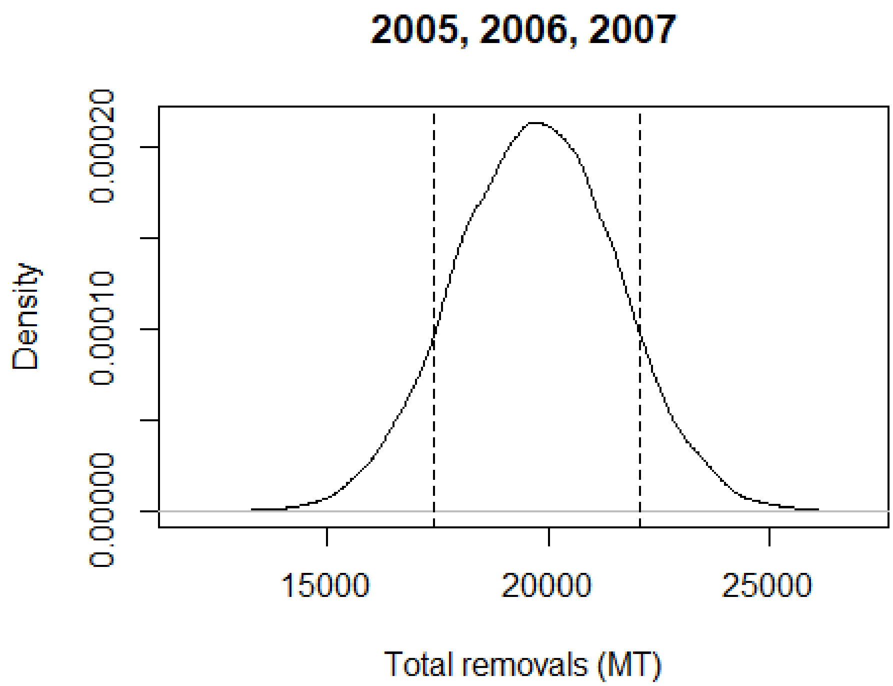

2008, 2009
Density
0.00000
0.00010
0.00020
15000
20000
25000
Total removals (MT)


2007, 2008, 2009
Density
0.00000
0.00010
15000
20000
25000
Total removals (MT)


2007, 2008
Density
0.00000
0.00010
0.00020
15000
20000
25000
Total removals (MT)


2006, 2007, 2008
Density
0.00000
0.00010
0.00020
15000
20000
25000
Total removals (MT)


2006, 2007
Density
0.00000
0.00010
0.00020
15000
20000
25000
Total removals (MT)



2005, 2006, 2007
Density
0.00000
0.00010
0.00020
15000
20000
25000
Total removals (MT)

Outputs

```
# How many negative removals did we generate (that were set equal to 0):
tracker

##      Yr t AB1 t AB1 t-1 AB1 t-2 B2(1) t B2(1) t-1 B2(1) t-2 B2(2) t B2(2) t-1
## 1   2005     0       0       0       0         0         0       0         0
## 2   2006     0       0       0       0         0         0       0         0
## 3   2007     0       0       0       0         0         0       0         0
## 4   2008     0       0       0       0         0         0       0         0
## 5   2009     0       0       0      16         0         0       0         0
## 6   2010     0       0       0       0        17         0       0         0
## 7   2011     0       0       0       0         0        16       0         0
## 8   2012     0       0       0       0         0         0       0         0
## 9   2013     0       0       0     175         0         0       0         0
## 10  2014     0       0       0       0       174         0       0         0
## 11  2015     0       0       0       0         0       184       0         0
## 12  2016     0       0       0       0         0         0       0         0
## 13  2017     0       0       0       0         0         0       0         0
## 14  2018     0       0       0       0         0         0       0         0
## 15  2019     0       0       0       0         0         0       0         0
## 16  2020     0       0       0       0         0         0       0         0
## 17  2021     0       0       0       0         0         0       0         0
## 18  2022     0       0       0       0         0         0       0         0
##      B2(2) t-2 check
## 1            0     0
## 2            0     0
## 3            0     *
## 4            0     *
## 5            0     *
## 6            0     *
## 7            0     *
## 8            0     *
## 9            0     *
## 10           0     *
## 11           0     *
## 12           0     *
```

```
## 13         0     *
## 14         0     *
## 15         0     *
## 16         0     *
## 17         0     *
## 18         0     *
```

```r
# Output all of the inputs (AB1, seasonal B2s, and associated CVs), as well as confidence intervals on removals
rmvs
```

```
##    year    AB1.mt AB1.CV   B2_MT.1       CV.1   B2_MT.2       CV.2 LCL80.2yr
## 1  2005 17120.025  0.101 1252.7219 0.20519210  893.5520 0.19041020        NA
## 3  2006 16366.669  0.101 1842.1177 0.13620020 1011.1503 0.11777040        NA
## 5  2007 18252.337  0.090  769.1757 0.12023410 1672.9162 0.18464870 17616.855
## 7  2008 16405.168  0.078  796.8515 0.12535580  964.9403 0.16234430 17009.255
## 9  2009 18475.659  0.103 1264.9786 0.34204570  654.1202 0.15522260 16878.471
## 11 2010 21002.809  0.088  877.5922 0.08903725  652.8570 0.13715000 18657.098
## 13 2011 15521.522  0.087  539.0502 0.16902770  457.9493 0.16904100 15379.426
## 15 2012 14755.927  0.083 1185.9839 0.12347280  713.9902 0.16156860 14920.933
## 17 2013 15602.979  0.076  994.6207 0.46998020  636.8346 0.12281610 15301.353
## 19 2014 12267.203  0.105 2802.3199 0.07727293 4814.2172 0.09166761 16148.865
## 21 2015 13652.658  0.085 3972.7974 0.06763120 4417.2656 0.07206018 18713.524
## 23 2016 10956.774  0.123 3997.6110 0.11223610 4710.8810 0.08449960 18392.285
## 25 2017 14547.506  0.169 3018.0328 0.13983800 1867.8090 0.10060840 16981.606
## 27 2018  6019.624  0.147 1208.2634 0.08488466 2233.4355 0.11513190  8684.417
## 29 2019  7056.105  0.087 2819.5446 0.15439540 1184.6757 0.16634900  8679.351
## 31 2020  6160.400  0.164 1254.4201 0.17727090 1120.5617 0.11333840  7652.242
## 33 2021  5607.358  0.132  516.2453 0.08894536  538.8222 0.13038570  6013.329
## 35 2022  5150.383  0.119  396.4003 0.11551810  750.5497 0.15005580  5594.275
##    UCL80.2yr LCL80.3yr UCL80.3yr
## 1         NA        NA        NA
## 3         NA        NA        NA
## 5  22275.010 17400.778 22074.942
## 7  22114.215 17027.050 21868.867
## 9  22063.313 17197.035 22442.127
```

```
## 11 24234.430 17264.315 23723.937
## 13 24112.090 15754.077 23756.444
## 15 18224.475 15238.858 23513.599
## 17 18604.743 15115.419 18497.408
## 19 21054.497 15612.075 20620.922
## 21 23125.375 16548.614 22757.250
## 23 23124.722 18273.938 22801.048
## 25 22021.511 17519.336 23001.435
## 27 21558.725  8974.338 21552.930
## 29 11731.645  8956.278 20747.910
## 31 11723.754  7852.860 11512.278
## 33  9384.314  6244.976 11478.434
## 35  7403.334  5749.086  9068.521
```