Simulating Future Escapements for the Late-Run Kenai River Chinook Salmon

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Abstract

The late-run Kenai River chinook salmon *Oncorhynchus tshawytscha*, which are managed under the principle of maximum sustained yield (MSY) have experienced declines in run size in recent years. Several runs in the past ten years have not met the lower end of escapement goals. Alaska Department of Fish and Game sets escapement goals that use the Ricker stock-recruitment model as their basis. The historical vital rate parameters deduced from records form the basis for these calculations. In this paper, I create a model that uses historical variation in vital rates to simulate late-run chinook runs for 20-year periods in the future using recorded average harvest rates, and a theoretical lower harvest scenario. From the simulations, the median number of lower escapement failures is 2 per 20 year period for both a normal and reduced harvest scenario. No significant differences were found between the mean escapements of both harvest scenarios. The results of this model suggest that manipulating harvest levels alone will not significantly improve escapement, and that other factors in chinook life history will need to be improved to achieve that goal.

Introduction

Alaska's Kenai River supports multiple fisheries for four different salmon species, each with their own run timing and seasonality. One of the most important fisheries is that of the Chinook Salmon *Oncorhynchus tshawytscha.* The chinook salmon is the basis for a popular and economically important sport fishery in the area. The Alaska Department of Fish and Game (ADF&G) manages the fishery under the principle of maximum sustained yield using models based on historical data (Sechrist and Rutz 2014). Ensuring these models achieve the desired results in harvest and escapement is paramount to the long term sustainability of the fishery. This is poignant since 4 of the runs in the last 10 years did not meet lower end of the escapement goal range.

The chinook salmon fishery in the Kenai has two distinct runs, the first run being defined as occurring before July 1st, and the late run occurring after July 1st and extending into mid August. The early run has a smaller average escapement than the late run. The two distinct runs spawn in different parts of the river, and are generally thought of as distinct sub-populations (Fleischman and Reimer 2017).

Chinook salmon migrate simultaneously with other salmon species. When counting by ARIS sonar, the length of the fish is able to be measured, however the species is not discernable. Fleischman and Reimer (2017) found that sockeye salmon, one other most prevalent species in the Kenai, is not likely to be over 75cm from mid eye to tail fork (METF). Therefore, in measurements, only salmon over 75cm METF are counted as chinook salmon.

In addition to the sonar counts, ADF&G counts salmon through records of commercially caught salmon, personal-use, and sport caught salmon. These statistics contribute to the sonar data to give escapement and harvest numbers.

Projection of the yearly run size and escapement is a goal which ADF&G works toward in order to manage the fishery sustainably. Fleischman and Reimer (2017) constructed a state-space model to determine vital rates and historical run re-construction for the Kenai river fishery. They determined lower and upper bounds for the vital rates based on the Ricker stock recruit model.

The Ricker model is as follows:

$$R = S\alpha e^{-\beta S}$$

R: Number of recruits

S: Number of spawners

α: Recruits per spawner

β: A term for density dependence.

Re-constructed vital rates for the fishery is based on varied sources of data from ADF&G extending back to 1986. From this data set, the vital rates of the fishery can be extracted and fitted to a stock recruitment model. The median value for α derived from their model for late run chinook was α=3.5. The .05 and .95 percentiles were 1.6 and 8.7 respectively. The median value for beta was $\beta = 3.03 \cdot 10^{-5}$ with .05 and .95 percentiles from $1.56 \cdot 10^{-5}$ to $4.89 \cdot 10^{-5}$ (Fleischman and Reimer 2017).

Maximum sustained yield occurs in this model at the number of spawners where the difference between recruits and spawners is the greatest. This is given by the following approximation: $S_{MSY} = \frac{ln\,\alpha}{\beta}[0.5 - 0.07 \ln \alpha]$ (Hilborn 1985). This corresponds to the peak of the graph of per-generation increase in Figure 2 and is the mean escapement goal.

With the parameters given, this calculates the mean for escapement goal at 17,046 spawners. In Fleischman and Reimer (2017), their range given for escapement is 13,500–27,000 spawners for their 2017 escapement goals including variation in the parameters according to their state-space model. Figure 1 shows the number of recruits as a function of the number of spawners using median vital rates. Figure 2 shows the per-generation increase in population as a function of the number of spawners referred to here as ‘Delta R’.

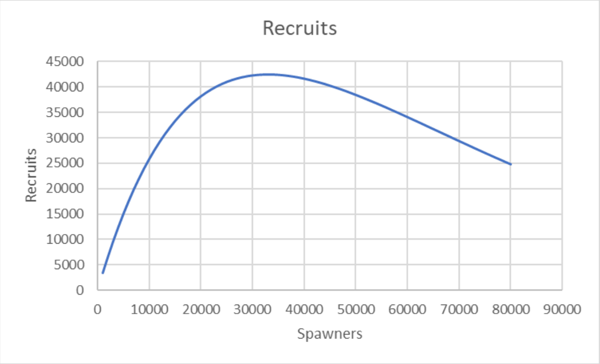

Figure 1: Recruits plotted as a function of number of spawners.

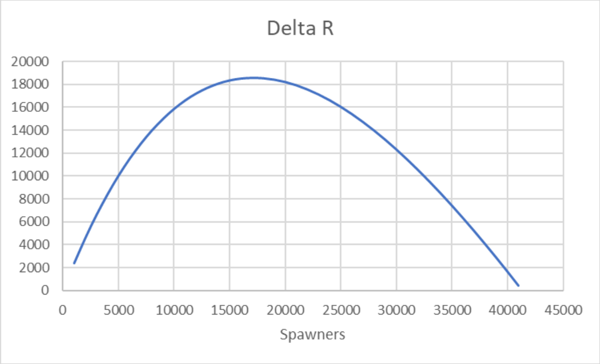

Figure 2: Delta-R, The per-generation increase in recruits plotted as a function of spawners.

Figure 3 shows the ratio of the number of recruits to spawners as a function of the number of spawners using spawner-recruit data from 1986 through 2012 in the Kenai River. The trend-line function of this allows a simplified way of observing the fit of the model to recorded data.

$$R/S = \alpha e^{-\beta S}$$

The fit explains a portion of the variation in data (R^2, 0.373).

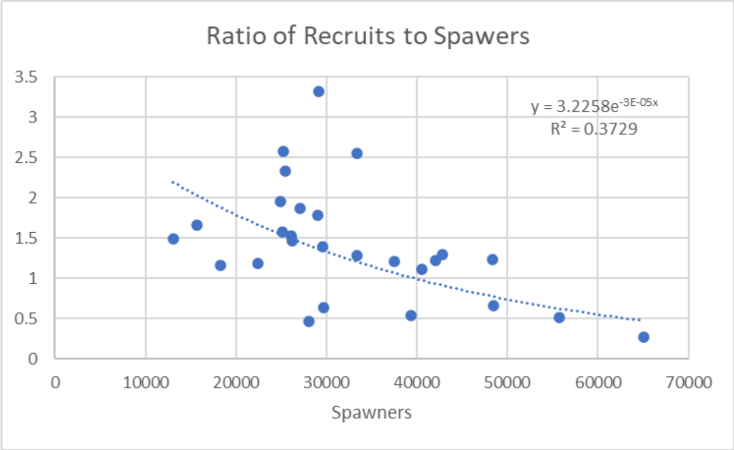

Figure 3: Ratio of recruits to spawners plotted as a function of the number of spawners.

Simulating Future Runs Based on Historical Data

ADF&G publishes measured and re-constructed run and harvest data for the late run Kenai River chinook salmon (Begich 2019). From this data, the measured parameter α (recruits per spawner) can be calculated for each brood year. The natural measured variation in α over years 1986-2012 is what will be used to simulate environmental stochasticity for 20 year periods starting from the last measured total run count. This forward simulation can be used to predict what the Chinook salmon run and harvest may look like in the near future, and importantly, predict the frequency of runs that don't achieve escapement goals using measured harvest rates. Knowing the frequency of simulated runs that don't achieve escapement goals will help to fine-tune the allowable harvest to the vital rate variation and minimize the likelihood of an over-harvest. Ensuring that escapements remain within a margin of ideal levels will help ensure the long term sustainability of the fishery.

Methods

I tabulated run data from 1986 through to 2012 by brood year. This data includes the number of parent fish that spawned in a given year, and the number of spawned fish from that year that returned to spawn. A brood year is considered all of the fish that were spawned in the river during the same season. This is determined by ADF&G by measuring a sample of chinook scales of fish caught in their in-river netting project, through sport fishing, and commercially caught fish. The scale ring patterns can give an estimate of fish age. Salmon return from the ocean to migrate up-river at a variety of ages, meaning that a brood year of chinook returns over the course of several years. Data on runs 2013 through 2019 has been collected, however not all fish of those brood years have returned and been counted. See Appendix 1 for the run data on chinook salmon >75cm.

Using the equation $\alpha = \frac{R}{Se^{-\beta S}}$, the value of α for each brood year can be calculated (Figure 4). The geometric mean of α for all measured brood years is (mean, 3.22; SD, 1.57). A close examination of how this value has changed over time appears to indicate two distinct modes, separated by a large 'bump' from 1996 to 2002. For this simulation, the values beginning in 2003 through 2012 will be used (mean, 2.07; SD, 0.547). This drop in the mean in recent years may reflect a change in the life history of chinook salmon. I considered the density dependency term β constant in the model.

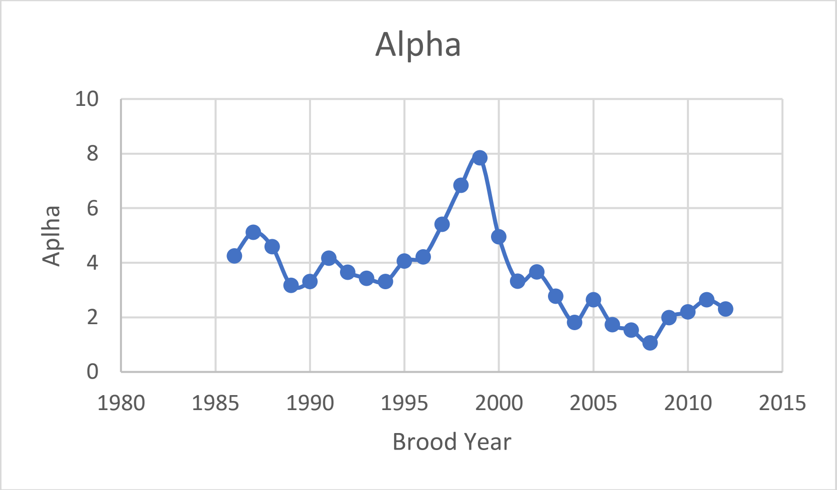

Figure 4: the value of alpha (recruits per spawner), plotted over years 1986 through 2012

I used statistics software R to simulate the salmon population for 20 generation periods based on the stock-recruit model. The value of α was randomized and fitted to a normal distribution by the 'rnorm' function, which takes a mean and standard distribution to generate a normal distribution. All values below 1 were removed to reflect the same observation in the data-set that there were no measured values of α below 1 in the data, possibly representing a slight skew in the distribution of measured α values.

I simulated the normal yearly harvest rates by looking at historical rate of harvest and simulating the mean and standard deviation (mean, 0.347; SD, 0.0667). The rate of harvest is a proportion of the total run. I also will simulate a lower harvest rate scenario with a lower mean of 0.247 and the same standard deviation. If the projected escapement was less than the escapement goal, I simulated the rate of harvest at 0.08 to reflect that a small harvest occurs before ADF&G restricts the fishery when the in-season migration rate is too low. The escapement value to start the simulation was the latest recorded escapement in 2019 of 11555.

After a simulation was completed, I then counted the number of occurrences that the mean and lower escapement goal (17046 and 13500) was not reached over the 20 year period. If an escapement did not meet the mean or lower threshold, I labeled it as an escapement failure. This process was repeated 50 times, each simulation representing a different possible 20 year period for a total of 1000 chinook run simulations. A second set of 1000 generation simulations was done to calculate the number of escapement failures using the lower harvest rate scenario. See Appendix 2 for the model's R code.

Results

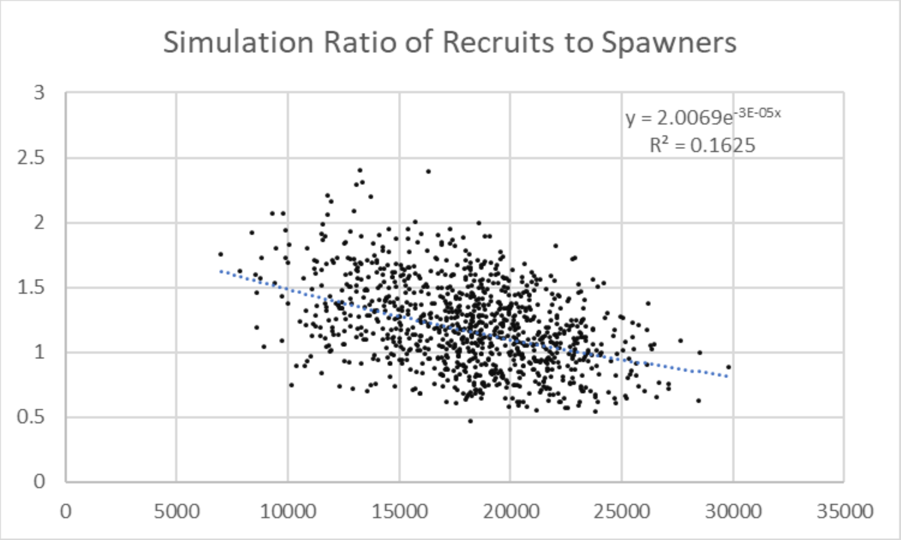

Figure 5: The simulated data points showing the fit of the generated data points to the stock-recruit model.

Fit of Simulated Data to Model Predictions

When the simulated data points are fit to the stock-recruit model (Figure 5), 16% of the variation can be explained by the model. This is lower than the 37% fit of the measured data, and may be explained by an excessive amount of variation programmed into the simulated parameter α.

Normal Harvest Scenario

For the normal harvest scenario, the mean of the lower escapement goal failures is 2.5 failures, median 2, over 20 years, and the mean of the mean escapement goal failures is 6.72, median 6.5 over 20 years (Figure 6). The mean escapement for the total of 1000 simulated runs is 18142.

Lower Harvest Scenario

In the lower harvest scenario, the mean of the lower escapement failures is 2.56 failures, median 2 over 20 years, and the mean of the mean escapement failures is 6.92, median 6, over 20 years. (Figure 7). The mean escapement for the total of 1000 simulated runs is 18078 spawners.

Comparison of Means

There is not a significant difference in mean escapement between the two harvest scenarios (T-Test: P>0.05). In comparing the count of lower escapement failures between the two harvest scenarios, no significant differences were found using a Poisson distribution GLM.

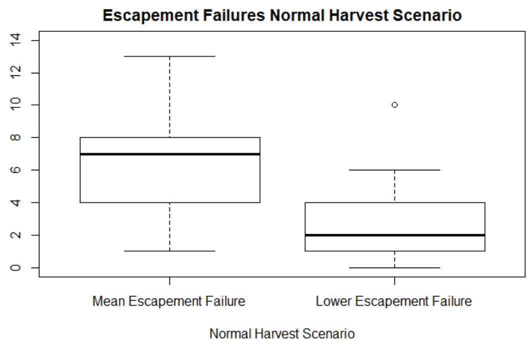

Figure 6: Number of escapement failures in the ‘normal harvest scenario.’

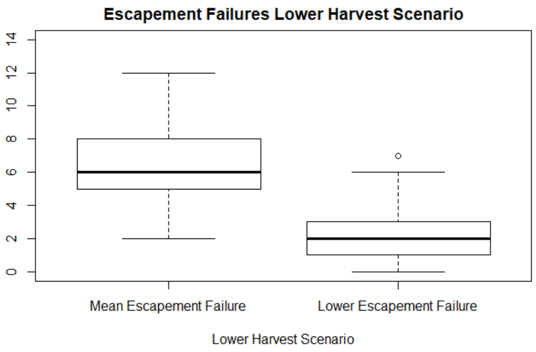

Figure 7: Number of escapement failures in the ‘lower harvest scenario.’

Discussion

Managing the health of the Kenai river chinook is of importance for the economy, culture, and ecological integrity of the local area. The lack of difference between mean escapement and number of escapement failures in the normal and reduced harvest scenarios suggest that modest reductions in harvest are not likely to substantially improve escapement numbers in the chinook fishery. What may be deduced is that improving escapement will require improving survivorship at some life stage before spawning, or spawning success once the fish migrate up-river.

The excessive variation from the spawner-recruit model in the simulation is caused by excessive variation in α. Even though the mean and standard deviation were taken from the real data, these descriptive statistics may not capture the distribution accurately. The ‘rnorm’ function in R may also contribute to excessive variation.

The lower number of recruits per spawners occurring from years 2003-2012 could be indicative of a change in survival for chinook salmon at some stage in their life history. Ohlberger et al. (2018) proposes that increased predation at sea from marine mammals, fishing pressures and climate change as possible explanations for demographic changes. Spawning habitat degradation or some other kind of disruption in the spawning process could also explain the reduction in recent years. This would require a focus away from pure spawning and recruitment style management, and a shift toward looking at habitat improvement. I only focus on the late run chinook salmon in this paper, which is known to spawn in the main-stem river, whereas the early run spawns in the tributaries (Fleischman and Reimer 2017). These two populations could be experiencing different trends based on their different timing and spawning locations.

The value for β was held constant arbitrarily, a better study design would include variations in both of these model parameters, which would better reflect the real population. The value of β determines the effective carrying capacity taking into account intra-species competition, and also the rate of growth for each escapement size, and therefore realistically will fluctuate. Assuming that β remains constant is assuming that the carrying capacity does not change.

Chinook migrate at ages commonly from 2 to 7 years old (Hankin et al. 1993). This model did not take into account the age proportions of chinook salmon, namely that they will not all spawn at the same age. The effect of this is that any effect on the numbers and spawning effectiveness of a brood year of fish will be distributed over runs occurring in a 3 to 4 year span. I suspect this would have a dampening effect on the results of any single escapement failure on future populations due to it being distributed over multiple years.

In this model, any change in a group of spawners affects the immediate next run of fish. This is a simplification of the model that reduces its realism. Future models building off of this one should take the age proportions and age distributed runs into account to enable a more accurate model of this population.

References

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Appendix 1: Kenai River Late-Run Chinook Salmon >75cm counted by run year

Run Year	4 Year	5 Year	6 Year	7 Year	Total Run	Escapement	Harvest	Exploitation
1986		28843	28643	2881	60367	42101	18266	0.303
1987		20049	53373	1315	74737	48393	26344	0.352
1988		5929	55173	9289	70391	42815	27576	0.392
1989		6559	29895	5161	41615	26253	15362	0.369
1990		4818	26277	1884	32979	25139	7840	0.238
1991		8331	26933	2381	37645	27133	10512	0.279
1992		9550	39956	1610	51116	37469	13647	0.267
1993		9510	46669	3341	59520	33432	26088	0.438
1994		7332	42680	3149	53161	26145	27016	0.508
1995		10074	30070	3353	43497	24874	18623	0.428
1996		14613	28372	968	43953	29056	14897	0.339
1997		9872	34222	1251	45345	25221	20124	0.444
1998		8100	33132	1898	43130	33385	9745	0.226
1999		10198	33151	2308	45657	29100	16557	0.363
2000		12019	28189	1511	41719	25502	16217	0.389
2001		9976	34200	1578	45754	29531	16223	0.355
2002		13123	40530	2257	55910	40514	15396	0.275
2003		17229	49350	1405	67984	48461	19523	0.287
2004		24465	64462	2385	91312	65112	26200	0.287
2005		15010	65599	3580	84189	55688	28501	0.339
2006		10299	40112	6711	57122	39305	17817	0.312
2007		12498	27552	4371	44421	29664	14757	0.332
2008		8869	30653	3158	42680	28094	14586	0.342
2009		4703	21594	1747	28044	18251	9793	0.349
2010		8760	11719	1701	22180	13037	9143	0.412
2011		6843	18636	902	26381	15731	10650	0.404
2012		8470	13681	1055	23206	22453	753	0.032
2013		3622	9994	766	14382	12305	2077	0.144
2014		4684	8225	494	13403	11980	1423	0.106
2015		6302	15302	1192	22796	16825	5971	0.262
2016		12114	12091	1213	25418	14754	10664	0.420
2017	102	15116	13643	1053	29914	19948	9965	0.333
2018		6016	11206	349	17571	16813	758	0.043
2019	6	4664	7839	272	12780	11555	1225	0.096

Appendix 2: Model to simulate potential escapements for 20 year periods

~~~~
```{r}
# A method to simulate the population of Kenai River Chinook salmon over time


LWR_Escapement_Goal <- 13500
Escapement_Goal  <- 17046

mean_alpha <- 2.06
sd_alpha <- 0.547

beta <- 3.03e-05

Mean_Harvest_Rate <- 0.347
SD_Harvest_Rate <- 0.0667

year <- 1
sim <- 1

Table <- (c())
Results <- (c())
Simulation2 <- c()

```

```{r while loop}
while (sim<=50) { # Runs selected number of simulations
  Parent_Escapement <- 11555  #Sets initial escapement for the 20 year period
  Harvest_Rate <- rnorm(30,Mean_Harvest_Rate, SD_Harvest_Rate)
  alpha <- rnorm(30,mean_alpha,sd_alpha)
  alpha <- alpha[ alpha > 1 ] # Removes alpha values less than 1. Helps to skew the distribution to match the real one
  Harvest_Rate <- Harvest_Rate[Harvest_Rate > 0.1]

  while (year<=20) { # 20 year period simulation loop

    Total_Run <- Parent_Escapement*alpha[year]*exp(-beta*Parent_Escapement) #1 The Ricker model
    Escapement_Projection <- Total_Run-(Total_Run*Harvest_Rate[year]) #What the Escapement is projected to be
with normal harvest rates.

    if (Escapement_Projection >= Escapement_Goal) { #2 Determine the harvest rate if  slow year or normal year

      Harvest <- Harvest_Rate[year]*Total_Run

    } else {

      Harvest <- 0.08 * Total_Run # Harvest isn't exactly zero in slow run years even after fishery shut-down.

    }


    Parent_Escapement <- Total_Run-Harvest # 3  Compute this last so that it is programmed for the next loop
    Table <- rbind(Table, c(year,sim,Total_Run,Harvest,Parent_Escapement,alpha[year]))
~~~~

~~~
    year <- year+1 #Increase year number by 1
  }


  year <- 1 # Reset year number

  Simulation <- as.data.frame(Table)
  names(Simulation) <- c('Year','sim','TotalRun','Harvest','Escapement','Alpha')


  a <- any(Simulation$TotalRun <= 2000) #Checks for any 'crash' in the population.

  b <- length(which(Simulation$Escapement < Escapement_Goal))

  c <- length(which(Simulation$Escapement < LWR_Escapement_Goal ))

  Results <- rbind(Results, c(sim,a,b,c))
  Simulation2 <- rbind(Simulation2,Simulation) # Diverts the data into separate data frame so we can look at it.
  Simulation <- (c()) #Erases the data frame with yearly information so that the counts of escapement failures remain
accurate

  Table <- (c()) #Erases the table so that only one  simulation is contained in it at a time.
  sim <- sim+1 # Increases the simulation number by 1
  rm(a,b,Harvest_Rate,alpha)
}

Results <- as.data.frame(Results)
names(Results) <- c('Simulation','RunFailures','Mean Escapement Failure', 'Lower Escapement Failure')
sim <- 1 #resets sim number
```

```{r}
write.csv(Simulation2,"NORM_SIM.csv", row.names = FALSE)
write.csv(Results,"NORM_Results.csv", row.names = FALSE)
```
~~~