Project 3: Density dependence in San Juan Island Harbor Seals

# Introduction

I wish to judge the weight of evidence for density dependence in harbor seals in the San Juan Islands of Washington State.  These populations were hunted to very low levels until the passage of the Marine Mammal Protection Act in 1972.  Since then, counts of Harbor Seals have increased dramatically.

I wish to know whether the data support density dependence for two reasons. **One**, conservation scientists wish to know whether we might expect continued growth of harbor seals, and if so, how much.  A population with density dependence will exhibit smaller population growth in the future than one without.  **Two**, I know that models with density dependent regulation have the potential to exhibit complex dynamic behaviors (dampened oscillations, limit cycles, deterministic chaos).  I wish to evaluate whether there is evidence for parameter values that give rise to those dynamic behaviors.

I also know that there are two ways to fit dynamic models: by assuming either that all error is in the population dynamic process (**Process Error Model**), or all error is in the observation process (**Observation Error Model**).  A priori, I do not know which of these is better suited to these data i.e., we do not know whether process error is more important than observation error or vice versa.  The process Error model says that external influences on the population are important (that is, the population is stochastic), while the observation Error model says that internal feedbacks described by the model equation are more important.

# Methods

## Model descriptions

Four models were fitted to harbor seal abundance data to assess whether a) the harbor seal population is experiencing density dependent growth and b) whether there was randomness in the population process or in our observations (process error vs. observation error). We chose to use discrete time models for ease of analysis and parameter estimation.

To address part a), we fit density independent and density dependent models to the data. Our discrete time density independent model is described by the following difference equation:

[1]

where is harbor seal abundance in year , is harbor seal abundance in year , and is the population growth rate. Our discrete time density independent model was based off the discrete time logistic growth model:

[2]

where is the carrying capacity of the population.

To address part b), we fit both above density independent and density independent models through either process error or observation error methods. For process error models, we assumed ’s are random variables drawn from a Poisson distribution (as the abundances are discrete counts) whose mean is , and that ’s are observations that were measured without any statistical error. The following is our density independent process error model:

[3]

where is the estimated starting population size, and is the previous year’s observed population abundance. The density dependent model is structured similarly:

[4]

where is the carrying capacity.

For our observation error models, we assumed our observed abundances were random variables drawn from a Poisson distribution whose mean equals . Our density independent model is as follows:

[5]

where is the estimated starting population size. Our density dependent model is below:

[6]

All estimated parameters (, , , ) were estimated using maximum likelihood.

## Methods for model comparison

Models were compared for best fit by using the Akaike information criterion (AIC) to evaluate the degree of support for density dependent growth in the population, and whether there was more support for observation or process error. The model that had the best fit based on this criterion then had confidence intervals for its calculated to evaluate the degree of support for complex population dynamics.

## Methods for confidence intervals

Confidence intervals for were calculated by creating negative log likelihood profiles for and while holding (or ) to its maximum likelihood estimate. We then found the intervals by adding 1.92 to the negative log likelihood of our maximum likelihood estimate of , and seeing which likelihoods for which values of in the profile fell under that likelihood value.

# Results

## Process Error

**Describe fits to the data, parameter estimates.**

A graph with a red and blue line

Description automatically generated The density independent process error model does not appear to fit as well as the density dependent process error model. The density dependent model still doesn’t fit tightly with the data, it just fits better than the density independent model. The parameter estimates for r and N0 for the density independent model were 0.0347 and 3127, respectively. The parameter estimates for r, N0, and k for the density dependent model were 0.275, 3375, and 8124, respectively.

**Figure 1.** Density independent and dependent process error models plotted against harbor seal abundances, with previous year abundances (Nt-1) on the x axis and its projected abundance counterpart (Nt) on the y axis. The density independent model is shown with the blue line, density dependent model shown with the red line.

**Briefly explain and evaluate goodness of fit**

While the density independent model estimates fewer parameters (and would make it more likely to have a lower AIC/better goodness of fit), it fits the data much worse than the density dependent model does, making the density dependent model a better fit (despite having more parameters) as it more consistently over and underestimates the data. The abundances also appear to taper off as Nt-1 gets larger, providing evidence for density dependence.

## Observation Error

**Describe fits to the data, parameter estimates**

A graph with a red and blue line

Description automatically generatedNeither of the models seems to fit the data that well, neither do either of them appear to consistently over or underestimate the data given a certain time step. The parameter estimates for r and N1 for the density independent model were 0.0473 and 4565, respectively. The parameter estimates for r, N1, and k for the density dependent model were 0.184, 3848, and 9377, respectively.

**Figure 2.** Density independent and dependent observation error models plotted over time against observed harbor seal abundances (Nt). The density independent model is shown with the blue line, density dependent model shown with the red line.

**Briefly Explain and evaluate goodness of fit**

Similarly to the process error model, the density dependent model (with more parameters) seems to fit the data better than the density independent model, especially as Nt appears to taper off over time, providing evidence for density dependence. However, the density dependent observation error model doesn’t look to fit better than the process error model, and has the same number of parameters, likely meaning the observation error models will be ruled out via AIC.

## Model Selection

**Describe results from AIC table.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Number of estimated parameters | Negative log likelihood | AIC | AIC |
| Process error: density independent | 2 | 964.195 | 1932.389 | 500.707 |
| Process error: density dependent | 3 | 712.841 | 1431.682 | 0.0 |
| Observation error: density independent | 2 | 1086.089 | 2176.177 | 744.496 |
| Observation error: density dependent | 3 | 758.071 | 1522.142 | 90.460 |

**Table 1.** AIC results for each of the four models.

The density dependent process error model had the lowest AIC of the four models. The other three models have AIC’s over 10, effectively ruling them out of further consideration.

**Explain (from data and model fits) why the data and models led to this result**

As detailed above, the density dependent process error model, while having the most estimated parameters, and while not providing the tightest fit to the data, most consistently over and underestimated the abundance of harbor seals from year to year, giving it the lowest AIC. While the density dependent observation error model also had a decently low likelihood, the fit was visibly worse than its process error counterpart and that showed up in the AIC and AIC. So even though the density independent models are nested within the density dependent models, they still clearly underperformed by comparison (visually and with AIC).

## Likelihood of complex behavior?

**Describe the estimated confidence interval for the parameter that governs complex behavior**

The estimated confidence interval for , the parameter that governs complex behavior in logistic models, is between 0.255 and 0.295, with maximum likelihood estimating it at 0.275.

**Explain (from the data and model fits) why the data do or do not support the possibility of dynamic behavior**

When gets above 1, that’s when complex behavior and deterministic chaos emerges in density dependent models. Given that the confidence interval of falls well below that, the data do not support the possibility of dynamic behavior in the population. Rather, it suggests that the population will smoothly move towards equilibrium/carrying capacity. This makes sense because over time, the harbor seal population appears to reach carrying capacity and only dip a tiny bit, signifying a pretty smooth transition into equilibrium.

# Discussion

**Use your description and explanation above to serve as the foundation to address interpretation to the real world:**

* **The strength of evidence for / against density dependence**
* **Concerns about the model fits and their implications for making inference.**
* **The prospects for further increases of Harbor Seals in the San Juan Islands**
* **The likelihood that populations such as Harbor Seals will exhibit complex population dynamics.**

The evidence for density dependent growth in the San Juan Islands harbor seal population is strong. Both density dependent models outperformed the density independent models, and no other model besides our chosen density dependent process error model had a AIC even close to 10, eliminating them from contention immediately. The density dependent models also appeared to track population abundance the best out of all the models. However, the density dependent process error model doesn’t fit the data exceedingly well, suggesting that more complex density dependent models should be considered for future analysis. Our model may describe the population the best out of the four models we looked at, but the models we used were fairly simple.

The lack of a tight fit between the model and the data also suggests that our model is poised to make very general inferences about the harbor seal population, but nothing specific. For example, we now know that the population is likely governed by density dependence, but the specific trajectory of population growth is something that we likely cannot infer from this model.

Given that I am confident in the population exhibiting density dependence, but less confident in its specific trajectory, I would say that harbor seal populations are likely to have limited growth in the coming years. Density dependence inherently limits growth, and harbor seal abundance definitely exhibits density dependent characteristics. Even outside of the data fitting a density dependent model the best, abundances themselves have been tapering off/been stable over the past few years (Figure 2). Thus, even despite the model not fitting perfectly, I would say the harbor seal population is not likely to experience dramatic growth in the coming years.

As for complex population dynamics, r values less than 1 generally don’t lead to complex population dynamics in density dependent systems. As the confidence interval for r for the harbor seals is between 0.255 and 0.295, even despite the weak model fit, I can confidently say that the harbor seal population is unlikely to exhibit complex dynamic behaviors. The data reflects a fairly smooth approach to equilibrium that characterizes density dependent systems with r-values below 1.