***Dissertation Proposal***

**Evaluating salmonid population dynamics and survey methodology using integrated pre-existing data**

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**Introduction**

The conservation of salmon and trout for environmental, tribal, commercial, and recreational use is of tremendous importance to fish and wildlife agencies in the Pacific Northwest. Additionally, multiple Evolutionarily Significant Units comprising many salmonid populations are protected under the US Endangered Species Act of 1973 (National Oceanic and Atmospheric Administration 2025a). Since 1980, the state of Oregon alone has spent over $9 billion in the effort to protect and restore populations of steelhead trout (*Oncorhynchus mykiss*) and Pacific salmon (*Oncorhynchus spp.*) in the Columbia River Basin. However, the impacts of these restoration efforts remain difficult to quantify (Jaeger and Scheuerell 2023). To determine the value of investments like these, policymakers and fisheries managers need accurate assessments of the salmonid populations in question.

To assess the impact of conservation policy and interventions, various survey methods are employed to estimate the abundance of target species over time. Each method is accompanied by some cost and presumably characterized both by an inherent level of precision and potentially some inherent directional bias. Past studies have shown a positive relationship between the intensity of sampling efforts and the precision of abundance estimates in both aquatic and terrestrial species (Walsh et al. 2001, Nuno et al. 2013, Annear et al. 2024). This makes intuitive sense, and managers must balance the cost of more intensive sampling efforts against the level of precision they hope to achieve. While low levels of precision in survey methods lead to low confidence in point estimates of population abundance or forecasts, directional bias presents a more pernicious problem as it may lead to the mismanagement of imperiled species, invasive species, and commercially valuable populations, due to over- or under-estimation of their numbers (Tracey and Fleming 2022, Satterthwaite and Shelton 2023). Indeed, in the United States, decisions of whether to list or de-list species as endangered under the Endangered Species Act are based on abundance estimates that may be influenced by such bias (National Oceanic and Atmospheric Administration 2025b). It has been shown that when directional bias can be assessed, it may be corrected by combining multiple datasets using bias parameters to achieve more accurate measures of central tendency in abundance estimates (Polansky et al. 2023).

Spawning salmon and trout are surveyed in freshwater using a variety of methods. Methods may vary from visual inspection of known spawning grounds to counts of salmon migrating up stream at fixed points to inferential methods estimating total escapement in a stream system based on periodic counts of spawners. Survey methods conducted at terminal spawning grounds include foot surveys of live fish, carcass counts, and visual inspection of salmonid nests known as redds (Johnson et al. 2007, Oregon Department of Fish and Wildlife 2024). Within streams, adult fish may be captured and counted at weirs before being released to continue their upstream migration (Anderson et al. 2015). A different survey approach involves capturing salmonid as juveniles and fitting them with small passive integrated transponders or PIT-tags. This enables tagged fish to be electronically counted as adults years later, as the return to their natal spawning grounds takes them past sensor arrays (Lamb et al. 2024). In more remote localities, aerial surveys are favored with fish being counted from fixed-wing aircraft, trading precision for the ability to survey sites which are otherwise very difficult to access (Walker 2015). Finally, these methods and more may be included in the estimation of total escapement through a variety of area-under-the-curve and peak spawner count estimation methods (English et al. 1992, Parken et al. 2003, Millar and Jordan 2013). Given this variety of survey methods dependent on various technology and statistical techniques, each method will be characterized by some degree of imprecision, and perhaps some intrinsic tendency to over- or under-estimate spawning salmonids.

My research seeks to measure the levels of precision and relative bias accompanying various survey methods by comparing observations from 68 populations of Chinook (*O. tshawytscha*) and coho salmon (*O. kisutch*) and steelhead trout throughout Oregon. These surveys were conducted by biologists from the Oregon Department of Fish and Wildlife (ODFW) from 1980 to 2022, using 31 distinct survey methods. The precision inherent to a survey method (and the associated variance of estimates derived from these surveys) directly impacts the ability to detect changes throughout time, as large confidence intervals may obscure shifting abundance regimes (Vallecillo et al. 2021). This work will also seek to determine whether directional bias exists in some survey methods, although bias estimates will necessarily be defined relative to other survey methods, as “true” censuses of the underlying salmonid populations do not exist.

**Methods**

Data include annual observations of “natural-origin salmon and steelhead abundance” or NOSA, covering 68 populations of Chinook and coho salmon and steelhead trout throughout

Oregon from 1980 to 2022. Crucially, each observation also includes the method by which the abundance survey was conducted. Data have been collected through 31 unique survey methods (fully enumerated in the attached appendix). The data contain 2,924 individual observations, of which 848 are missing NOSA values almost entirely related to years in

which no survey was conducted (15 observations confoundingly include a survey method along with a null value). While trends are difficult to observe visually, as seen in Figure 1, simple linear regressions evaluating the effect of time on the natural log of abundance describe 34 (half) of the surveyed salmonid populations as having no statistically significant change across the study period. Of the remaining 34 populations, 23 exhibit a statistically significant increase in abundance, while the other 11 show evidence of decline.

The accuracy of the linear regression estimates of trends in abundance described above are dependent on the precision of the observed data. The frequency with which survey methods are employed is not uniform across the study period, as described in Figure 2. While some methods such as redd counts have been widely used throughout the study period, other methods have seen drastic changes in usage. If different survey methods indeed exhibit varying levels of precision and/or inherent directional bias, the statistical significance estimated by simple regression models must be questioned.

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AI-generated content may be incorrect.*Figure 1: Changes in abundance of individual salmonid populations from 1980 to 2022. Note that not all populations are represented throughout the entirety of the study period.*

Being that the goal of this analysis is to isolate variance and bias in different survey

methods, it is vital to distinguish variability in observations due to survey method from variation in the natural state of salmonid populations. Multivariate autoregressive state space (MARSS) models are well suited for this purpose, as they can mathematically distinguish observation error from process/state error and assign separate variance parameters to each (Holmes et al. 20120. Recall the generic MARSS model formulation from chapter 1:

Observation equation: **yt** = **Zxt** + **a** + **Ddt**, + **vt**, where **vt**∼MVN(0,**R**)

Process/state equation: **xt** = **Bxt−1** + **u** + **Cct** + **wt**, where **wt**∼MVN(0,**Q**)

Critical to these models is **Z**, which assigns each of *n* observations in the vector **yt**to one of *m* states in the vector **xt**. **Z** may be specified such that every observation in **yt**is representative of its own underlying state (in which case *n* = *m* and **Z** is an identity matrix), such that every observation in **yt**is representative of one underlying state (in which case *m* = 1 and **Z** is a column vector of 1s), or specified to assign observations to any number of states in between (crucially *m* must always be less than or equal to *n*).

I model each salmonid species separately, leading to three data subsets respectively

containing 18 Chinook populations, 27 coho populations, and 23 steelhead populations. I drop observations with no recorded survey method or NOSA value prior to analysis. I also drop any observation related to a survey method that appears fewer than ten times throughout a given dataset. While this is unfortunate, 7 methods relate to three or fewer observations, meaning estimates of these methods’ variance and bias would be very unreliable. These dropped methods are highlighted in the attached appendix. With data already sorted by species, each observation contains four crucial pieces of information: 1) an estimate of natural-origin spawner abundance (denoted mathematically from here on as *y*), 2) the population of interest (denoted with the subscript *p*), 3) the survey method used (denoted with the subscript *s*), and 4) the year of observation (denoted with the subscript *t*).

Applying the MARSS model structure to the analysis described above involves determining how best to structure spawner abundance data (*yp,s,t*) and specify model parameters to isolate precision and bias in salmonid survey methods. Particular attention is paid to the inputs and parameterization of the observation equation. **yt**is arranged such that each row relates to observations of population *p* by survey method *s*. **Z** is specified such that each

population as identified in the data will correspond to a distinct underlying natural state. By specifying each population as an underlying state, the model will be able to assess variation in the natural state of the population as separate from variation in counts arising due to the survey method employed. The vector **a**contains a unique bias term for each survey method, irrespective of population. One method will be selected as a reference against

*Figure 2: Groups of survey methods and the frequency of their employment from 1980 to 2022. The nine groups displayed in the figure are bins containing each of the 31 survey methods described in the data.*

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AI-generated content may be incorrect. which other methods will be measured, meaning that for this method **a**is set equal to zero. **R** is specified in a similar manner, with a unique *r* term for each method placed in the corresponding places along **R**‘s diagonal. Again, this is irrespective of population to capture the variation inherent in each survey method.

Below is an example of the observation equation written out in matrix form. In this example, two populations of salmonid have been surveyed with a total of five survey methods. As indicated by the *y* term subscripts, population one has been surveyed with methods one through four and population two with methods one, four, and five. **Z** is specified with two columns relating to the two populations which here are considered underlying states (*x1* and *x2*). Survey method one has been selected as the reference method against which other methods’ directional bias will be measured. Therefore, in **a**, those rows which correspond to an observation taken with method one are set equal to zero, while all other methods are represented by an *a* parameter which repeats as often as the method appears. Finally, **R** is specified so that each survey method is represented by an *r* parameter which again repeats as often as the method appears, in order to capture the variance inherent to each.

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The process/state equation is more straightforward. It is constructed to be as parsimonious as possible, in that in this analysis it essentially acts as a receptacle for the natural variance in annual salmonid spawner returns. **B**is specified as an identity matrix, meaning the whole equation becomes a random walk. Whether the vector **u**is set to zero or allowed to estimate a trend in each population’s growth will depend on model fit. One method for evaluating the impact of allowing a trend in population growth would be to estimate **u** without including an observation equation in the modeling approach and evaluate how these estimates differ from those returned by the full MARSS specification. Finally, the terms along the diagonal of **Q**will be set equal to each other in initial model specifications, although the inclusion of other specifications (unequal population variances and allowing for equal variance and equal covariance terms) will also depend on model fit. Below is an example of the process/state equation written out in matrix form.



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*Figure 3: Chinook salmon survey method variance and directional bias, bias relative to reference method ‘Mark-recapture estimate at weir’.*

**Results**

The following figures display the variance and relative directional bias of survey methods for all three salmonid species of interest. I selected those survey methods the literature suggests would be least biased as the reference methods for bias estimation (Johnson et al. 2007). Other approaches for choosing a reference method could be applied here (i.e., selecting the method most employed in each dataset, selecting the method with the lowest variance in each dataset, etc.). Trends in survey method behavior are discernable both within and across species.

Figure 3 displays variance and bias related to Chinook salmon surveys. Nine survey methods are evaluated, with ‘Mark-recapture estimate at weir’ serving as the reference method.

A graph of a method

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*Figure 4: Coho salmon survey method variance and directional bias, bias relative to reference method ‘Dam counts (video)’.*

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*Figure 5: Steelhead trout survey method variance and directional bias, bias relative to reference method ‘In-river weir count’.*

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*Figure 6: Chinook, coho and steelhead trout survey method variance and directional bias, bias relative to reference method ‘Dam counts + Expansion below dam’ – the only method employed across all three species.*

**Discussion**

Understanding levels of precision in salmonid survey methods will enable fisheries managers to better understand the reliability of abundance estimates upon which they must make decisions. Understanding directional bias in these survey methods will help policymakers to more accurately determine the long-term cost-effectiveness of conservation efforts. Recall once again that decisions to list and de-list species under the US Endangered Species Act are made based on population surveys of the sort this work is interrogating. Low precision in survey methods may lead to shifts in population regimes going undetected, while consistent directional bias could lead to over- or under-estimation of target populations. Understanding these survey methods’ levels of precision and directional bias relative to each method’s cost of implementation will further help fisheries managers in programming future salmonid survey efforts.

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Method dropped due to insufficient data

Method dropped for steelhead due to insufficient data, retained for Chinook

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