Development and Evaluation of Assessment Tools and Management Strategies for Salmon Fisheries in Western Alaska

by

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Abstract

The management of natural resources is fraught with difficulties stemming from uncertainty and conflicting objectives, and fisheries for Pacific salmon *Oncorhynchus* spp. in western Alaska are no exception, but rather provide a fantastic example. This area of the world is tremendously remote, making resource monitoring and decision-making challenging. It has widely been proposed that quantitative tools can be useful in aiding decision-making by producing predictions of uncertain states of nature, system responses to harvest, and quantifying likely outcomes of candidate management actions. In this dissertation, a variety of such quantitative tools that seek to serve these purposes are developed and evaluated. Throughout, the Kuskokwim River salmon fishery is used as a case study to illustrate the development and evaluation of these tools.

Before investigating three primary research topics in Chapters **??**, **??**, and **??**, an overview of the difficulties faced by practitioners of salmon management is provided in Chapter 1. The management of salmon resources is presented as a three-tiered decision-making hierarchy made up of (1) guiding objectives stemming from societal values, (2) inter-annual management strategies which define how the objectives are to be attained in the long-term, and (3) finer-scale (e.g., in-season) tactics used to implement the strategy. The important considerations and key uncertainties at play at each level are discussed, as is the role of quantitative tools in this endeavor.

Chapter **??** focuses on salmon migration timing, the problems that its inter-annual variability inserts for salmon managers and assessments of run abundance, and the development and evaluation of a forecasting tool that attempts to predict the timing of the run before any fish arrive. Run timing variability is well-known and pervasive problem: in-season abundance

index data are often consistent with many different run scenarios ranging from small and early to large and late, making decisions about the magnitude of harvestable surplus difficult. Run timing has been widely shown to covary with environmental variables linked to temperature such that early run years tend to coincide with warm years, suggesting that useful predictive relationships may exist. A statistically-rigorous approach to forecasting the date of 50% run completion for Kuskokwim River Chinook salmon *O. tshawytscha* was developed based on relationships with air temperature, sea surface temperature, sea ice concentration, and the Pacific Decadal Oscillation Index. An objective and intuitive temporal variable selection approach (the sliding climate window algorithm) was employed to determine the time periods for each variable most likely to produce accurate forecasts and relied heavily on multi-model inference based on information criteria to combine multiple forecasts in the face of a high degree of model uncertainty. The rather complex forecasting framework was found to perform no better on average at forecasting the median run date than the most naïve model that used solely the historical average as the forecast. However, the environmental variable forecast did have value in terms of improving the accuracy and reducing the statistical uncertainties in interpretations of an in-season run abundance index. This chapter should serve as a useful example for researchers faced with high-dimensional spatio-temporal variable selection problems, particularly with respect to the formal evaluation of the performance of alternative forecasts using retrospective cross-validation techniques.

Chapter **??** takes a broader view of the in-season management problem by simulation-testing a set of four different harvest control strategies in a framework known as stochastic management strategy evaluation. A detailed mathematical caricature of the Kuskokwim River salmon system was constructed based on empirical data to serve as the operating model with which to test different decision rules for determining how many days the fishery should be open each week. Strategy performance was assessed relative to four pre-defined management objectives dealing with both conservation and exploitation such that key trade-offs could be identified as well as strategies that might serve to balance them. A key research question was regarding strategy complexity and performance: whether more involved and data-intensive feedback strategies should be favored over simpler fixed-schedule strategies. The primary finding revealed by this work was that several strategies ranging from simple to complex can perform essentially equally well at attaining the objectives of salmon management in the Kuskokwim River as defined by the utility functions used. This finding suggests that oftentimes in-season management is often made more difficult than needed, and that perhaps more focus should be placed on the transparency and defensibility of strategies.

Chapter **??** takes an even broader view still, and addresses the topic of assessment of salmon fisheries that harvest fish from multiple substocks as a mixed-stock. Different substocks within a larger salmon-producing drainage vary in their size and resilience to harvest pressure (i.e., intrinsic productivity), which suggests a trade-off between maximizing harvest and preserving substock biodiversity exists. To incorporate this trade-off into harvest policies, an assessment of the heterogeneity in substock size and productivity must be completed to gauge harvest potential and the expected level of erosion in biodiversity at a range of fishing intensities. Salmon populations are often assessed as single stock units using simple regression approaches, however, this chapter makes a compelling case for integrating data from multiple substocks into a single assessment model that represents population dynamics and observation processes at the substock-level using a state-space analytical framework. A range of assessment methods were constructed that varied in their assumptions about process variability and were applied to empirical data from Kuskokwim River Chinook salmon substocks and evaluated in a simulation-estimation context. All state-space models assessed performed substantially better than regression-based approaches at returning accurate and precise estimates of biological reference points at the substock- and mixed-stock level, and by capturing the sources of variability allowed for more rich ecological interpretations which may be useful in future policy analyses.

The dissertation concludes with Chapter 2 which presents further reflection on the utility, performance, and generality of the tools developed in these studies.

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Chapter 1

Introduction

Wild Pacific salmon *Oncorhynchus* spp. represent a fantastic natural resource, which results largely from their unique life history strategy. Pacific salmon exhibit a migratory strategy known as anadromy: adults spawn in freshwater where eggs hatch and juveniles rear for 0, 1, or 2 years. Juveniles then migrate to the ocean where they spend the majority of their lives feeding on abundant prey resources. Once reaching maturity, adults return to their natal streams to spawn and complete the life cycle. The result of this life history strategy is an incredibly productive resource that grows entirely on its own and all but delivers itself to harvesters when the time comes for exploitation.

There is a long history of salmon fishery resource development, exploitation, regulation, and dependence throughout Alaska (Cooley 1963). In many cases, the resource use is dictated by the locality of the system; for example, stocks located near urban areas are often primarily exploited by recreational fishers whereas more remote stocks often constitute commercial and/or subsistence uses. This dissertation discusses the challenges and explores quantitative tools for assessing and informing management of more remote stocks and the fisheries that rely heavily upon them, with particular relevance to the remote areas of western Alaska.

Like for all exploited natural resources, the management of Pacific salmon fisheries involves making decisions about how to exploit the resource in order to best attain a suite of biological, social, and economic objectives (Walters 1986). These decisions are inherently difficult due to conflicting objectives and uncertainties in system state, system response to management actions, and implementation (Walters and Holling 1990). Put another way, assuming a manager knows exactly what they wish to obtain, getting there is made difficult by not knowing (for example) how large the harvestable surplus is, how the stock will respond to harvesting, or that their management action will actually obtain what is desired. Despite these difficulties, a decision must be made (without decision-making there is no management; Hilborn and Walters 1992) and the consequences, whether favorable or undesirable, must be accepted. Thus, I would argue that the science of monitoring, assessment, and prediction in the context of Pacific salmon fisheries is tasked with informing the relative likelihood of different outcomes conditional on a candidate management action, such that they can be compared with the guiding objectives and trade-offs between competing objectives can be considered in making the decision.

The management of Pacific salmon fisheries can be thought of as a hierarchy of (1) guiding objectives, (2) management strategies to attain objectives, and (3) tactics to implement the management strategies (Table 1.1). At the upper level, long-term decisions are made about the objectives of the resource exploitation. These long-term objectives constitute what could be referred to as fundamental objectives: they are desired endpoints, but do not at all imply how they should be attained. These fundamental objectives often involve notions of sustainability and maintenance of biological diversity and often include social objectives such as maximization and stability of harvest or profit. Already, it is clear that these fundamental objectives are often conflicting. For example, consider the objective of maximizing harvest: in fisheries that harvest multiple stocks (i.e., distinct spawning units), oftentimes maximum harvest may only obtained by overexploiting weak stock components and possibly eroding diversity. As another example, consider the objective of long-term sustainability: in order to ensure that the stock is sustained, some level of harvest fluctuations must be accepted (lower harvests must be allowed when the stock is at low abundance). These conflicting objectives imply that trade-offs exist (all objectives cannot be maximized simultaneously). It is worth noting here that the decisions made at the uppermost level of the management hierarchy are based purely on societal values and salmon stock assessment scientists should play little-to-no advisory or advocacy roles in making these decisions, except to the extent that they are also members of society (Walters and Martell 2004). The Policy for the Management of Sustainable Salmon Fisheries[1] states that the objectives of salmon management in Alaska are

> "...to ensure conservation of salmon and salmon's required marine and aquatic habitats, protection of customary and traditional subsistence uses and other uses, and the sustained economic health of Alaska's fishing communities."

The policy goes on to say that managers should target "...to the extent possible, maximum sustained yield [MSY]."

The second level of the management hierarchy is made up of harvest strategies and policies that guide how the long term objectives are to be obtained. The State of Alaska has selected the fixed escapement policy as the management strategy to obtain the long-term objectives of sustainability and yields that are close to the maximum. These escapement goals are given as ranges that dictate the target number of spawning adults each year; any portion of the stock above the escapement goal is considered surplus (excess biological production) and should be harvested for the benefit of society. Uncertainty at this intermediate level of the management hierarchy (e.g., regarding the optimal escapement goal) is often a result of incomplete understanding of system status and function. For example, in order to determine what the optimal escapement goal should be to obtain MSY, knowledge of stock productivity and carrying capacity are required. These quantities are often derived using spawner-recruit analyses (see Walters and Martell 2004, Ch.7 for an overview), which are inherently uncertain: data are rarely informative about the shape of the true underlying population dynamics relationships (Walters and Hilborn 1976), but instead provide snapshot in time (e.g., 20+ years) of how the population has responded to its environment and harvesting, and are often fraught with measurement errors (Ludwig and Walters 1981). Traditionally, it has been

[1] 5 AAC 39.222; a peice of legislation that defines correct salmon management practices by the Alaska Department of Fish and Game. Available at: http://www.adfg.alaska.gov/static/regulations/regprocess/fisheriesboard/pdfs/2016-2017/jointcommittee/5aac39.pdf

thought that these uncertainties can be reduced by more monitoring and the development of rigorous assessment and prediction models to better understand system function. However, it has often been argued that while monitoring and assessment models are obviously important (performance relative to objectives must be measured after all), true understanding of system behavior comes only from experimentation in management (the concept of "active adaptive management"; Walters 1986). A classic example is to assess the maximum productivity of the stock (i.e., in the absence of density dependent mortality), the spawning stock must be forced to small sizes and the resulting distribution of recruitments must be observed (Walters and Hilborn 1976). However, management actions that ensure these observations are made may be undesirable to many managers and stakeholders, considering that exploiting a stock down to these low levels is risky (Walters 1986).

At the lowest level in the management hierarchy, intra-annual (or in-season) decisions are made regarding how to exploit the current year's run according to the rules of the strategy defined in the intermediate decision level. In other words, given a management strategy (i.e., fixed escapement), the manager is still tasked with deciding how to best implement the fishery within a year to ensure the strategy is followed. As is illustrated in this dissertation, these decisions at the intra-annual level of the management hierarchy are often poorly informed by data which can result in indecisiveness, subjectivity, non-transparency, frustration, and missed opportunities.

This dissertation is partitioned into three primary projects (Chapters **??**, **??**, and **??**), each which expands on the aforementioned difficulties in decision-making and develops and implements quantitative tools intended to help guide managers of Pacific salmon fisheries. Each chapter relies on the Kuskokwim River drainage in western Alaska as a case study, which is characterized by being a large drainage (>50,000 km^2), harvests are taken by primarily subsistence users who are nearly all native Alaskans, and the primary species of interest being Chinook salmon (*O. tshawytscha*). Although this dissertation is quite narrow in its geographical and biological focus, a wide range of management issues are addressed and the developed tools and assessment methods are evaluated thoroughly. Furthermore, the concepts and tools discussed, developed, and evaluated have broad generality and will be of interest to other systems with similar spatial structures, exploitation characteristics, and/or population dynamics.

Chapter **??** works at the intra-annual level of the hierarchy to develop and evaluate the performance of a run timing forecast model that can be used to aid in the interpretation of in-season data. I illustrate why uncertainty in run timing makes the interpretation of in-season abundance data difficult and review what is known about mechansims driving variability of Pacific salmon run timing. The overall objective of Chapter **??** is to develop and evaluate the reliability of a run timing forecast model for Kuskokwim River Chinook salmon. A secondary goal of Chapter **??** is to retrospectively assess the utility of having access to the run timing forecast model in terms of reducing uncertainty and bias in run size indices used in intra-annual harvest management decisions.

Chapter **??** again addresses the lowest level of the management hierarchy (i.e., intra-annual decision-making), but in this case in a more direct sense using an analysis framework known broadly as management strategy evaluation (MSE; e.g., Butterworth 2007; Punt et al. 2014). This analysis evaluates a set of harvest control decision rules to identify strategies that perform well at attaining pre-defined objectives (e.g., meeting the escapement goal, distributing harvest equally across villages and substock components, etc.) across a range of biological states (e.g., run size, stock composition, and run timing). The strategies assessed in this chapter fall along a continuum of complexity in their decision rules and the resulting increase in information requirements, and each has several substrategies representing alternative ways of implementing the same strategy. Analyses of this variety are useful because while the fixed escapement policy seems simple to execute, actually doing so is made difficult largely due to uncertainty regarding the size of the incoming run (i.e., the amount of harvestable surplus is not known). Additionally, there may be a set of decision rules that perform well at limiting harvest in low run size years but doing so in a “fair way”, where the burdens of shortages are not carried primarily by any particular subset of resource users, nor are the harvest burdens borne by a select subset of the substocks spawning within the larger drainage. If a consistent set of rules or triggers could be identified that perform reasonably well at meeting management objectives without precise knowledge of run size or harvestable surplus, it could prove useful to managers and decision-making within the region.

Chapter **??** moves up the hierarchy to the second level and attempts to extend the single stock assessment models currently used in many systems in Alaska to multi-stock assessments. When an aggregate stock is made up of several distinct components, each with their own productivity, it is likely that exploitation at some level (e.g., 50%) results in the more productive components being under-exploited while the weaker stocks may be over-exploited. This reality implies a trade-off: to preserve stock diversity, some harvest must be foregone. Before the shape and magnitude of these types of “harvest-biodiversity” trade-offs can be quantified, some understanding of the variation in substock productivity and carrying capacity is required. The multi-stock assessment framework developed in Chapter **??** will be tailored to provide this information for these sorts of trade-off analyses and others that require similar information sources. Multi-stock assessments may assume one of several different model structures (e.g., by fitting separate models to the data from each stock or by fitting a single model to all data simultaneously). In some cases, one approach may be preferable over the other, and a primary objective of Chapter **??** will be to evaluate the estimation performance of a range of assessment strategies.

Table 1.1: One way of viewing the structure of renewable natural resource (including salmon) management as described in the text, including examples of alternatives and sources of uncertainty at each level.

Examples	**Sources of Uncertainty**
Fundamental Objectives	
Ensure sustainability	Relative importance of objectives
Maximize harvest	Problem boundaries
Stabilize harvest	
Maximize economic value	
Inter-annual Strategies	
Constant escapement	Stock productivity
Constant exploitation rate	Stock status
Constant catch	Drivers of stock change
Adaptive exploitation	Shape/magnitude of trade-offs
Intra-annual Tactics	
Triggers and thresholds	Harvestable surplus
Time, area, gear restrictions	Uninformative data
Limited participation	Fisher behavior

Chapter 2

Conclusions

In writing this dissertation, I sought to develop, evaluate, and illustrate quantitative tools that may be used to address challenges in salmon management in western Alaska. Specifically, the tools sought to reduce uncertainty in decision-making (in the case of the run timing forecast in Chapter **??**) and inform policy analyses by identifying and measuring the shape and magnitude of trade-offs between competing objectives (for in-season management in Chapter **??** and long-term management in Chapter **??**). In a broad sense, I believe I have accomplished this objective. The work presented in this dissertation provides a detailed look at ways quantitative tools can be used in the management of salmon fisheries in western Alaska – some were novel to salmon management, all were novel with respect to the Kuskokwim River. This final chapter serves as my reflection on my doctoral work, including further insights on each of the three primary research projects I completed as well as my time working in Kuskokwim River management system at the Yukon Delta National Wildlife Refuge during the summers of 2016 – 2018.

2.1 Further insights on each project

2.1.1 Chapter 2: Run timing forecasts

My work on developing run timing forecasts for Kuskokwim River Chinook salmon has not proven as fruitful as I would have hoped. In each year since its inception following the 2016 season, the forecast model did not provide good forecasts of D_{50}: both 2017 and 2018 were moderately late runs yet the forecast model suggested the runs would be several days early.

Furthermore, a subsequent analysis (Staton and Catalano 2019) strongly suggested that using the forecast model provides no utility for improving perceptions of run size based on test fishery data. The cause for this finding is two-fold. First, although the environmental relationships were present for all evaluated variables (Figure **??**; Table **??**), the residual variability was too high to result in accurate and precise forecasts based on them. Second, inter-annual variability in the Bethel Test Fishery catchability (i.e., the fraction of total run captured; the inverse is commonly referred to as "run-per-index"; Flynn and Hilborn 2004) is the dominant cause of uncertainty in using this index for predicting run size for much of the season, not run timing. Staton and Catalano (2019) illustrated that the average CV of abundance predictions from a relationship between historical abundance and cumulative catch-per-effort each day was approximately 38% early in the season and 30% at the end of the season (Figure 4 therein). So even after the test fishery is done catching Chinook salmon, a large amount of uncertainty still remains in the actual run size (this finding was the same for methods that included and excluded the run timing forecast). Based on the variability of errors made by these predictions, it seems this level of uncertainty is appropriate (also shown in Figure 4 of Staton and Catalano 2019). These findings illustrate that the Bethel Test Fishery is a poor index of run size, and that the run timing forecast did not improve this situation.

Still, the forecasting framework I developed was a statistically-rigorous approach to dealing with high-dimensional variable selection over time and space. To my knowledge, the sliding climate window algorithm I employed has not widely been used in ecological problems. This must either be due to the computational costs or because it is not well-known, given it is an intuitive and objective approach to select temporal periods for prediction. After giving a talk on the forecasting approach I developed, a prominent ecologist in my field asked whether I thought this constituted a "data dredge" analysis, with the implication that it was a bad thing if so. In my view, data dredging is the practice of searching for all possible relationships that significantly support some hypothesis and discarding those that do not, or otherwise developing and confirming ad-hoc hypotheses based on such a search. First, the notion of statistical significance was never used in my analysis: all decisions were made based on actual out-of-sample predictive performance (through forecast cross-validation) or an index of predictive performance (Akaike's Information Criterion). Second, no biological hypotheses were tested in this analysis. Instead, the search was conducted to find the variables most appropriate for forecasting run timing. In these cases, I think it is completely rational to perform as exhaustive of a search as possible, and the approach I developed served as an intuitive and objective means to do this.

It has been brought to my attention that methods exist that may provide better forecasts than the approach I used, which was simple/multiple regression at its core. Specifically, machine learning tools like random forests could show promise. Additionally, upon further reflection it is possible that having a continuous forecast of D_{50} could be less useful than a discrete forecast of an early, average, or late run. Such a forecast could be obtained using a multinomial logistic regression (Agresti 2002, Ch. 7), which would provide predicted probabilities that the run will be early, average, or late. In my experience, uncertainty is more appropriately interpreted by managers when presented as the probability of outcomes rather than using uncertainty intervals. There would surely be some loss of resolution (e.g., not all early runs are equally so), but the categories could be selected based on how the D_{50} within each would influence the management inference. For example, there should exist some thresholds of early/late timing that would drastically change the inference from if it was an average run; I would propose that these thresholds be used to delineate the categories.

2.1.2 Chapter 3: In-season MSE analyses

In this stochastic MSE analysis of a large salmon-producing river system in western Alaska, I found several important implications, some that were known *a priori* and some that were not. For example, the finding that more conservative substrategies should be favored in small runs as opposed to large runs makes intuitive sense and could have been determined without conducting this analysis. However, the findings that management performance was generally most sensitive to run timing in large runs rather than small runs was not necessarily known *a priori*, nor was the finding that good performance can be attained with a wide range of management strategies. This analysis was useful in that it provided an objective basis for strategy comparisons and necessitated critical thinking about the important drivers of system dynamics (e.g., effort responses to fishery conditions) as well as the direct ways in which information influences a particular decision. It is my hope that when presented to fisheries managers and stakeholders in the region, perhaps a more-informed dialog may be had regarding the merits and detriments of candidate management strategies.

The most complex assessed management strategy (Strategy #4; explicit harvest target, selected probabilistically, updated with in-season information) is a computer-based representation of the strategy implemented by the U.S. Fish and Wildlife and the Kuskokwim River Inter-Tribal Fisheries Commission for the portion of the fishery within the Yukon Delta National Wildlife Refuge in the years 2015 – 2018. Each year has differed in the method and rigor used to (1) initially select the season-wide harvest target (H_T), (2) utilize in-season information to update H_T and the weekly target ($H_{T,w}$), and (3) determine how much fishing opportunity should be allowed conditional on $H_{T,w}$. The overarching structure (e.g., the use of H_T based on an escapement limit threshold; S_L), however, is the same as the simulated strategy and the probabilistic selection of H_T based on risk tolerance ($P*$) and S_L was conducted for the first time in 2018.

With the current amount of information available for in-season management, this is among the most complex management strategies that could be used for the Kuskokwim Chinook salmon harvest control situation, and a key finding of the MSE analysis was that it did not perform overwhelmingly better than far simpler strategies. In the very smallest runs (50,000 – 80,000), it did provide substantially better escapement performance than other policies, but only because the fishery was all but shut down completely. If this is desirable, the schedules used by Strategies #2 and #3 (Figure **??**) could be altered to be more conservative for forecasts falling in this bin. Additionally, uncertainty in the forecast could be included by weighting schedules by the probability that the run will be in each run size bin according to the pre-season forecast. In the next smallest category (80,000 – 130,000), the gains in escapement utility by using Strategy #4 were negligible in comparison to other simpler strategies, and came at the cost of reducing the harvest utility by approximately half (Figure **??**). Likewise, it showed no real gains in harvest equity or even substock exploitation utilities, though no assessed strategies strongly influenced these metrics. As a result of these findings, I suggest that salmon fisheries managers in the Kuskokwim River and similar systems consider applying simpler schedule-based strategies based solely on a pre-season forecast (as in Strategy #2) or conditioned on in-river species composition (as in Strategy #3). Given the finding that many strategies perform similarly, however, perhaps the more important question now becomes which strategy could meet other objectives not included in this analysis (e.g., fishers' desire to know when to expect fishing opportunities far in advance, desire to fish early in the season, etc.) and is transparent to the parties involved.

2.1.3 Chapter 4: Multi-stock spawner-recruit analyses

For my last project, I evaluated spawner-recruit methods for mixed-stock salmon fisheries. I developed a novel state-space framework for simultaneously estimating spawner-recruit parameters from the substocks within a larger drainage basin when they are all harvested as a mixed-stock – the method was shown to perform substantially better than simpler regression-based approaches that, though they have long been known for their problems (Ludwig and Walters 1981; Walters 1985; Walters and Martell 2004), they are still applied to estimate salmon population dynamics parameters and to provide management recommendations (Clark et al. 2009; Korman and English 2013).

An alternative assessment approach would be to attempt to fit separate state-space models to the individual substocks as opposed to the more integrated approach I developed. This approach should retain the benefits of (1) not needing to exclude some observations because they do not constitute fully observed brood year pairs and (2) separately modeling the population dynamics and observation processes to (at least partially) handle the time-series and errors-in-variables biases. However, given that not all substock have age composition data, the individual models would require auxiliary information that was never observed for that substock and the degree of synchrony between subtocks would only be available as part of an ad-hoc analysis of patterns from individual substocks. The more integrated state-space approach I took did not require such auxiliary age-composition data: only substocks with observed data were fitted for age composition, and they informed the maturity model parameters to be used for other substocks. Additionally, by incorporating a covariance matrix for recruitment variability, the degree of synchrony in substock dynamics could be informed by years with data on multiple data on substocks, which could be then used to inform the latent recruitment states in cases where there were fewer observations to inform them. Further, as computationally-intensive as the model I developed was, this approach would be even more so given independent MCMC sampling would need to be conducted for each substock, which is a primary reason why it was not evaluated here.

Although the state-space model was applied only to the Kuskokwim River data and the simulation was designed to mimic the data collection and substock heterogeneity for that system, the model potentially has wide applicability to other systems. Many salmon populations are harvested in mixed stocks; good examples include: the Columbia River in the northwestern contiguous United States, the Fraser and Skeena River drainages in British Columbia, Canada, the Bristol Bay stocks in southwestern Alaska, and the Yukon River in western Alaska and Canada. All of these systems are composed of several distinct spawning units, some portion of the harvest occurs as a mixed-stock, and should have data time series at least as rich as the Kuskokwim River Chinook salmon data set I used. Granted, in some situations modifications would be necessary for each specific case. For example, in the Bristol Bay fishery for sockeye salmon, some harvest occurs by “intercept fleets”, where fishers in one district may also harvest fish from other stocks that are migrating through that area but some harvest also occurs in-river. This kind of situation would require more detailed information harvest separated by mixed- and non-mixed sources, but I believe this would be within the abilites of the state-space model given the data are available.

2.2 Reflections on working for USFWS

In 2016 – 2018, I took on a more-involved role in the management of Kuskokwim River salmon fisheries by working as a Pathways Student[1] with the U.S. Fish at Wildlife Service at the Yukon Delta National Wildlife Refuge based out of Bethel. Between May and August of these years, I abandoned my graduate work[2] and focused on in-season salmon assessment. In this role, I lead several efforts dealing with providing information to managers: (1) compiling, analyzing, and presenting run assessment information in consistent formats[3], (2) developing and applying statistically-rigorous approaches to estimating harvest and effort arising from short-duration block-openers[4] and presenting this information to managers, and (3) presenting risk assessments of seeing undesirable escapement outcomes conditional on different harvest levels[5]. I have enjoyed this role enormously, and it was highly rewarding to apply my

[1] Unofficial title: Quantitative Ecologist

[2] And my loving and understanding girlfriend (as of 2016), fiancé (as of 2017), and wife (as of 2018)

[3] Referred to as the “Daily Assessment Updates”, over 250 documents were produced using `{rmarkdown}`; examples available upon request.

[4] Documented in Staton and Coggins (2016), Staton and Coggins (2017), Staton (2018), plus a synthesis manuscript currently in preparation

[5] 2018 only; with the aid of a Shiny application I wrote, which has become commonly known as the “P* model” (https://bstaton.shinyapps.io/BayesTool/).

quantitative skills to real world applied management problems, and to see the inferences be used in decision-making. There were several instances where I frustratingly saw the tools be used in ways in which they were not designed to be used, but hopefully these are "growing pains" with being exposed to something new and with more experience they will become used more appropriately (i.e., as intended). Though there was a distinct boundary between the topics I worked on in-season in this role and my more academic work (i.e., presented in Chapters **??**, **??**, **??** herein), I certainly used what I learned in each aspect to inform the other. I have no doubt my summers spent in Bethel resulted in better dissertation research, particularly with respect to developing the operating model and candidate management strategies used in Chapter **??**, and that I would have been less valuable to the management system without the quantitative training I have received in my graduate program.

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