I. AYKSSI TITLE PAGE

Arctic-Yukon-Kuskokwim Sustainable Salmon Initiative
Project Final Product*

IN-SEASON MANAGEMENT POLICIES FOR KUSKOKWIM CHINOOK

by:

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II. ABSTRACT

Management of salmon fisheries to simultaneously achieve both conservation (e.g., ensuring adequate escapement) and fishery performance (e.g., meeting subsistence harvest needs) objectives is challenging because of uncertainty and annual variability in run size and timing. Uncertainty in run size is problematic because it is the largest determinant as to whether competing fishery and conservation objectives will be achieved. Uncertainty in run timing is challenging because it confounds interpretation of in-river abundance indices such that run size is highly uncertain until a large fraction of the run has been observed. Alaskan Chinook salmon stocks have experienced low returns in recent years particularly in western Alaska. The mechanisms producing these low returns are not fully understood, but the declines have clearly strained local communities that use these resources. Managers of these stocks are faced with a balancing act of preventing recruitment overfishing while allowing fishers as much opportunity as possible to utilize these limited resources. In some systems, including the Kuskokwim River, the decline in Chinook stocks has not been accompanied by similar declines in other species such as chum and sockeye salmon. The mixed species nature of these fisheries further complicates in-season management decision-making if harvest of an abundant stock must be curtailed to prevent incidental harvest of a stock that is at low abundance. However, such mixed stock fisheries also provide opportunities to meet the needs of subsistence fishers by compensating for reduced harvest on weak runs by increasing harvest on more abundant runs of other salmon species.

In salmon fisheries that simultaneously harvest a mixture of stocks (e.g., tributary stocks, different species), selective harvest can be achieved by implementing harvest control rules that manipulate the timing of fishing to target one species while the other is at relatively low abundance. Harvest control rules are formal management decision rules that dictate the allowable amount (and/or spatiotemporal distribution) of harvest or fishing mortality as a function of an estimate of the current state of the stock (usually abundance or fishing mortality) relative to pre-defined thresholds. It is not uncommon for fisheries managers to use control rules that limit the time and place of harvest to minimize incidental harvest of non-target species. Control rules can range from simple pre-defined schedules, schedules that changes in response to perceived fish abundance, or yet more complicated probabilistic control rules that set harvest limits consistent with acceptable risk of failing to meet escapement goals. Probabilistic harvest control rules have been proposed as one approach to implementing precautionary management by incorporating uncertainty into management decisions and may serve to protect stocks that are at low abundance, yet few examples exist of these control rules in salmon fisheries. When considering multi-species fisheries, harvest control rules could even consider the abundance ratio of species as an indicator to assist with scheduling the selective harvest of a particular stock while protecting the others. For example, a ratio indicator could facilitate selective harvest of a less abundance species if fishing opportunities are limited to those times in which the abundance of an alternative species is high thereby saturating the fishery and limiting harvest of the species to be protected.

Science-based salmon management involves choosing from among a set of competing harvest strategies the strategy that is anticipated to provide the best balance among competing objectives after explicitly considering trade-offs. Given the recent declines in Alaskan Chinook salmon stocks, particularly along the Kuskokwim River, it is imperative that management strategies be developed and tested for performance relative to a broad suite of objectives that include conservation (escapement) and subsistence fishery objectives. In particular, the evaluation of management strategies for multi-species subsistence fisheries in the face of low Chinook salmon run abundance is especially relevant given the mixed species runs in the Kuskokwim River. Moreover, formalizing the in-season tactical management decision process via the implementation of harvest control rules that have been tested via simulation could (1) increase transparency in the management process, (2) force more structured thinking about the process and the uncertainties involved, (3) foster improved communication with

stakeholders, and (4) improve continuity of decision-making following management staff changes. This project addressed these needs via the completion of four objectives:

Objective 1: Reconstruct historical in-season run and fishery dynamics of Kuskokwim River Chinook, chum, and sockeye salmon stocks
Objective 2. Evaluate trade-offs when choosing among candidate in-season harvest control rules.
Objective 3. Elicit agency and stakeholder input on objectives and options, and facilitate technology transfer of in-season modeling tools
Objective 4. Develop a probabilistic Bayesian in-season run forecasting tool

We met these objectives through the development of two manuscripts, one of which has been published in the Canadian Journal of Fisheries and Aquatic Sciences (CJFAS), and one that is in preparation. In Appendix A we present a manuscript that describes and management strategy evaluation (MSE) of in-season harvest management for the Kuskokwim River Chinook salmon subsistence fishery in western Alaska. The MSE tested four primary management strategies that ranged in their complexity and information needs. Our findings showed that all assessed strategies can perform well, but that the more complex strategies tended to perform better when the incoming run was small. Additionally, the optimal settings (i.e., aggressive or conservative with respect to fishing opportunity) of each strategy depended on run size, with conservative settings favored in smaller runs. This analysis necessitated the construction of an operating model that attempted to realistically depict an annual run and fishery for Chinook and Chum/Sockeye Salmon in the Kuskokwim River. The model was parameterized based on the best available scientific information as well as stakeholder input (Appendix B), and was tested via simulation to assess the degree to which it was able to recreate historical patterns in subsistence harvest (Appendix C). In Appendix D we present a manuscript that will be published in CJFAS in 2019 that assesses the performance of two Bayesian information-updating procedures to predict the run size during the season. The Bayesian updating approach we developed provided a probabilistic expression of run size beliefs, which was used as the basis for the development of an online run prediction and risk assessment tool that was disseminated to Kuskokwim salmon managers prior to the 2018 salmon run. The tool was used to assist with the structuring of harvest management deliberations during the 2018 run.

In addition to model development and analysis, we participated in four NFWF-funded Capacity Building Workshops that were arranged by AYKSSI and facilitated by the Quantitative Fisheries Center at Michigan State University. We attended four of these stakeholder meetings at which we gave presentations on in-season management and other related topics. The technical workshops also provided an opportunity for information transfer among workshop participants and allowed further refinement of models and precise consideration of stakeholder objectives used to evaluate the performance of alternative management policies.

III. PRESS RELEASE

Salmon return each year to their natal rivers to spawn, putting them within reach of people who rely on the runs for food, income, and cultural enrichment. Responsible management of the harvest of these salmon is an ever-present goal for these fisheries. Management of salmon harvest during the run is difficult because managers are never quite sure how many salmon will return to the river to spawn. In the face of this uncertainty, managers are tasked with allowing as much fishing opportunity as possible without reducing the number of spawning fish so much that future salmon runs are reduced. Having clear and transparent decision rules regarding when, where, and how fishing will be allowed are critical to responsible management. Understanding which decision rules perform the best over the long term is critical to choosing which decision rules to adopt. A team of researchers from Auburn University, Michigan State University, and the US Fish and Wildlife Service has been using computer simulation models to assess the relative performance of a candidate set of decision rules for Kuskokwim River Chinook Salmon subsistence fisheries. They look at a range of different types of rules from simple closed-until-open strategies that don't require much data, to complex strategies that account for the risk of overfishing but that require a lot of data inputs. The results of their simulations suggest that a wide range of strategies can perform well, but that the more complex policies that consider risk and those that are more conservative tend to perform better in smaller runs. Ultimately, the Auburn team hopes to provide fishery managers and stakeholders with better tools to help them move forward with decisions on when, where, and how many Chinook salmon to harvest in the Kuskokwim and beyond.

IV. PROJECT EVALUATION

The proposed project had four objectives as follows:

Objective 1: Reconstruct historical in-season run and fishery dynamics of Kuskokwim River Chinook, chum, and sockeye salmon stocks. We completed this objective as planned although data were insufficient to reliably and independently estimate all of the parameters that control in-season run and harvest dynamics for the Kuskokwim River. Thus we were unable to fit a traditional maximum likelihood or Bayesian reconstruction model to meet this objective. Instead we gathered all of the necessary information from published sources, and where appropriate constructed estimation models. Ultimately we were able to obtain estimates of run timing distributions, spatial and temporal distribution of fishing effort and harvest, and escapement. Obtaining estimates of catchability, fishing effort dynamics, and chum/sockeye abundance were more challenging due to the lack of data from which to estimate these components. Thus we proposed models for each and conducted a tuning exercise to assess the degree to which the in-season operating model could reproduce historical spatial and temporal patterns in harvest. The final operating model structure is described in Appendix A. Our efforts to parameterize the model are described in Appendix B, and the model tuning/validation exercise is described in Appendix C.

Objective 2. Evaluate trade-offs when choosing among candidate in-season harvest control rules. We developed an operating model that predicted the behavior of the Kuskokwim River Chinook Salmon and Chum/Sockeye Salmon run and fishery. We developed four major classes of harvest control rules that represent a range of complexity, ease of implementation, and data requirements and evaluated the relative performance of the control rules relative to a set of performance indicators that represented objectives related to escapement, harvest, spatial evenness in exploitation, and upstream/downstream harvest equity. The harvest control rules that we developed are not meant to represent our recommendation for those that *should* be used, but are rather examples of those that *could* be used. In developing the control rules, we attempted to capture the essence of some of the management approaches that have at times been employed previously for Kuskokwim Chinook, while also exploring some new approaches. This analysis thus represents a starting point and a framework that could be used to explore and quantitatively evaluate in-season harvest control rules in the future. This model and the subsequent analysis is described in a draft manuscript in Appendix A. Supporting documentation for the operating model is presented in Appendix B and C. The operating model was used as the basis for a value of information analysis (manuscript in preparation; see Manuscripts under V. Deliverables, below) that was an important component of a project funded by the National Center for Ecological Analysis and Synthesis (NCEAS) and led by M. L. Jones.

Objective 3. Elicit agency and stakeholder input on objectives and options, and facilitate technology transfer of in-season modeling tools. We shared our findings with area stakeholders and biologists at six management meetings from 2015-2018. At these meetings we shared our progress on the development of the in-season operating model, and explored the dynamics of the model in a series of interactive sessions involving meeting participants. For example, at the November 2016 Capacity Building Workshop we presented an Excel version of the operating model and engaged with meeting participants to demonstrate the model and have them suggest management scenarios that could be run in real time at the meeting. We also solicited their input on model realism and gained valuable information on their objectives, desirable management options, and fisher behavior. We conducted a similar exercise with a revised version of the model at the May 2017 Capacity Building Workshop. Early on in the study, we participated in the 2015 Capacity Building Workshop in Aniak, which focused heavily on stakeholder perspectives and objectives, as well as management options. This meeting was extremely important in helping us identify the four major classes of performance indicators: escapement, harvest, exploitation evenness, and harvest equity.

Objective 4. Develop a probabilistic Bayesian in-season run forecasting tool. We successfully developed, tested, and published a probabilistic Bayesian run size forecasting tool. The tool uses test fishery catch rate data and in-season harvest estimates to iteratively update estimates of the expected size (and uncertainty) of the Kuskokwim River Chinook Salmon run. Then the model takes a user specified declaration of tolerance for the risk of failing to meet escapement goals and estimates the additional harvest that can be taken without exceeding this risk tolerance level. The model can also take any candidate harvest level, and estimate the probability that escapement goals would not be met under that amount of proposed harvest, and it can do this each day of the run as it iteratively updates our understanding of the size of the run as data accumulate during the season. The model is also able to incorporate any prior knowledge that may exist on expected run timing as informed by environmental covariates. The run prediction tool was made available via an online application that we developed, which allowed stakeholders and managers to access and use the tool throughout the run via a user-friendly interface. The tool was used in 2018 to enhance and clarify the deliberations of the Kuskokwim River salmon managers. We provided training to the managers on how to use the tool at a workshop in March 2018. We described the tool in a manuscript that has been accepted for publication. In the paper we evaluated the performance of the tool at run prediction with and without the use of indices of run timing. The accepted manuscript is attached in Appendix D. The tool can be accessed at https://bstaton.shinyapps.io/BayesTool/. The user manual can be accessed at https://bstaton.shinyapps.io/BayesTool_UserMan/. Technical documentation can be accessed at: https://bstaton.shinyapps.io/BayesTool_TechDoc/.

V. DELIVERABLES

The findings of our project have been and will continue to be disseminated via conference and management meeting presentations and peer-reviewed manuscripts. We have completed eleven presentations, attended six management meetings, attended three professional conferences, and submitted two manuscripts for peer review publication with one having been published. We currently have two manuscripts in preparation. We have also developed an online computer application to allow stakeholders and managers to make probabilistic in-season run size predictions and consider risk tolerance in the setting of harvest targets.

Reports:
Semiannual progress reports January 2016, July 2017, January 2018, and July 2018

Presentations:

Staton*, B.A., M.L. Jones, M.J. Catalano, L. G. Coggins Jr., B.M. Connors, and S.B. Truesdell. 2018. The expected value of information for intra-annual harvest management in Pacific salmon fisheries. American Fisheries Society Conference. Atlantic City, NJ.

Staton, B. A. and M. J. Catalano. 2018. A decision support tool for considering Kuskokwim Chinook Salmon harvest targets during the run. A presentation to Kuskokwim River Salmon Managers. Bethel and Anchorage, AK.

Staton, B. A. and M. J. Catalano. 2018. Evaluation of several approaches to Bayesian updating of pre-season indicators of run strength in Pacific Salmon fisheries. Western Division of the American Fisheries Society Conference. Anchorage, Alaska.

Staton, B. A. and M. J. Catalano. 2017. Evaluation of several approaches to Bayesian updating of pre-season indicators of run strength in Pacific Salmon fisheries. American Fisheries Society Annual Conference. Tampa, Florida.

Catalano, M. J., B. A. Staton, T. Farmer, D. Gwinn, L. G. Coggins, Jr., M. L. Jones, Z. Liller. 2017. Project Update: Kuskokwim Chinook In-Season Modelling. AYKSSI Capacity Building Workshop. Bethel Alaska.

Staton*, B. A. and M. J. Catalano. 2017. An introduction to in-season models for salmon management. National Center for Ecological Analysis and Synthesis (NCEAS) Meeting: Using participatory modeling to empower community engagement in salmon science. Bethel, Alaska.

Staton*, B. A. and M. J. Catalano. 2017. Simulation of in-season harvest management strategies for Kuskokwim River Chinook salmon. AYKSSI Capacity Building Workshop. Bethel, Alaska.

Staton*, B. A. and M. J. Catalano. 2016. Update on simulation of in-season harvest management strategies for Kuskokwim River Chinook salmon. AYKSSI Capacity Building Workshop. Bethel, Alaska.

Staton*, B. A. and M. J. Catalano. 2016. Simulation of in-season harvest management strategies for Kuskokwim River Chinook salmon. AYKSSI Capacity Building Workshop. Anchorage, Alaska.

Catalano, M. J. 2015. Simulation of in-season harvest management strategies for Kuskokwim River Chinook salmon. AYKSSI Capacity Building Workshop. Aniak, Alaska.

Catalano, M. J. 2015. Simulation approaches to evaluating in-season management strategies for AYK salmon stocks. Kuskokwim River Interagency Meeting. Bethel, Alaska.

Manuscripts:

Staton, B. A. and Catalano, M. J. *In press*. Bayesian information updating procedures for Pacific salmon run size indicators: evaluation in the presence and absence of auxiliary migration timing information. Canadian Journal of Fisheries and Aquatic Sciences.

Staton, B. A., M. J. Catalano, and L. Coggins. *In preparation*. Evaluation of In-Season Harvest Management Strategies for Kuskokwim River Chinook Salmon using a Stochastic Simulation Model.

Staton, B. A., M. L. Jones, M. J. Catalano, L. G. Coggins, Jr., B. M. Connors, S. B. Truesdell, W. R. Bechtol. *In preparation*. Assessing the Value of Information for In-Season Management of Subsistence Salmon Fisheries in Large River Basins.

Computer Applications Developed

Staton, B. A. and M. J. Catalano. A Bayesian risk assessment tool for in-season management of Kuskokwim River Chinook Salmon: a shiny app in program R. https://bstaton.shinyapps.io/BayesTool/.

Meetings Participated:

Kuskokwim River Salmon Managers Meeting. March 2018. Anchorage and Bethel, Alaska

Kuskokwim River Chinook Salmon In-season Management Procedure Workshop. February 2018, Anchorage, Alaska

AYKSSI Capacity Building Workshop. May 2017. Bethel and Anchorage, Alaska.

AYKSSI Capacity Building Workshop. November 2016. Bethel, Alaska.

AYKSSI Capacity Building Workshop. May 2016. Bethel, Alaska.

AYKSSI Capacity Building Workshop. November 2015. Aniak, Alaska.

VI. PROJECT DATA SUMMARY

Our analysis produced simulated data sets and parameter estimates from Bayesian and maximum likelihood assessment models. All model outputs are available upon request from the PI.

VII. APPENDIX: SUBMITTED OR DRAFT MANUSCRIPTS

Appendix A:

Staton, B. A., Catalano, M. J., M. L. Jones, and L. Coggins. *In preparation*. Evaluation of Iin-Season harvest management strategies for Kuskokwim River Chinook Salmon using a stochastic simulation model. Draft Manuscript.

Appendix B:

Staton, B. A. and M. J. Catalano. Validation of the in-season operating model for Kuskokwim River Chinook Salmon. Supporting documentation for Appendix A draft manuscript.

Appendix C:

Staton, B. A. and M. J. Catalano. Parameterization of the in-season operating model for Kuskokwim River Chinook Salmon. Supporting documentation for Appendix A draft manuscript.

Appendix D:

Staton, B. A. and Catalano, M. J. *In press – expected 2019 publication*. Bayesian information updating procedures for Pacific salmon run size indicators: evaluation in the presence and absence of auxiliary migration timing information. Canadian Journal of Fisheries and Aquatic Sciences. *Published online December 2018.*

APPENDIX A

Evaluation of In-Season Harvest Management Strategies For Kuskokwim River Chinook Salmon using a Stochastic Simulation Model

Abstract

In-season management of Chinook salmon subsistence fisheries in large river basins is conducted in the presence of much uncertainty, primarily with respect to run size and timing. Managers must manipulate the amount of time in which fishing is allowed to ensure adequate escapement to sustain future harvests while simultaneously providing as much opportunity in the current year as possible. In doing so, they may use a set of decision rules to open or close the fishery based on either intuition or assessment information. Inferences about which strategies may perform better in certain circumstances can be informed using management strategy evaluation, an analytical method in which decision rules and information sources are tested against simulated conditions to measure likely management performance. We conducted a management strategy evaluation for in-season harvest management for the Kuskokwim River Chinook salmon subsistence fishery in western Alaska to test four primary management strategies that ranged in their complexity and information needs. Findings showed that all assessed strategies can perform well, but that the more complex strategies tended to perform better when the incoming run was small. Additionally, the optimal settings (i.e., aggressive or conservative with respect to fishing opportunity) of each strategy depended on run size, with conservative settings favored in smaller runs. The findings of this chapter extend the knowledge about in-season salmon harvest management strategies, which is mostly regarding commercial fisheries, to include subsistence fisheries as well and should be informative to fishery managers in the region.

1 Introduction

In-season harvest management of Pacific salmon (*Oncorhynchus* spp.) fisheries in large river systems is undertaken in the presence of a large amount of uncertainty about how to schedule fishing opportunities. In order to manage in a fully-informed way, a manager would require continuous and accurate information on arrival timing, run size, fleet dynamics, and harvest. With knowledge on these components, it would be theoretically possible to perfectly harvest the available surplus each year (Adkison and Cunningham 2015). In reality, these quantities (when available) are often highly uncertain (Adkison and Peterman 2000; Flynn and Hilborn 2004; Hyun et al. 2012) which results in difficulties in decision-making about how to best implement the fishery in order to meet a set of pre-defined objectives dealing with both conservation and exploitation.

In addition to the substantial uncertainty in decision-making, there are often sharp trade-offs between competing objectives, such as the desire to provide adequate and equitable harvest opportunity *versus* the desire to ensure adequate escapement (Catalano and Jones 2014). Oftentimes, managers are also concerned with spreading exploitation evenly among stock subcomponents (Schindler et al. 2010), but this may conflict with aspects dealing with the ideal time to harvest salmon as a result of weather or fish quality conditions (Carney and Adkison 2014b; Adkison and Cunningham 2015). When given the task of balancing trade-offs such as these, the manager has the ability to manipulate the fishing gear used as well as the spatiotemporal distribution of fishing effort by opening or closing the fishery for various amounts of time, though it is rarely clear as to how to manipulate these management "levers" to achieve the desired outcomes. Presumably, different strategies to performing these manipulations (termed "management strategies") will exhibit differential performance at meeting the objectives and balancing trade-offs.

Management strategy evaluation (MSE) has been proposed as a powerful tool for determining how to manage exploited natural resource systems with competing management objectives (Cooke 1999; Butterworth 2007). MSE is a stochastic simulation-based analytical technique whereby management strategies are evaluated by comparing their relative performance at meeting pre-defined objectives under simulated (though realistic) conditions. A management strategy can be thought of as all of the steps that encompass the collection of data, subsequent analyses, and resulting decision-making surrounding the exploitation of a resource. The MSE approach tests a range of such strategies to find the one(s) that are likely to be most robust to uncertainty and balance trade-offs. This approach is powerful as it can provide general insights without having to test strategies on the real system, which would be incredibly time-intensive (each year is one sample) and costly given that some candidate strategies can be risky (Walters and Martell 2004). Punt et al. (2014) outlined a set of 7 steps to an MSE that must be conducted in order for the analysis to be meaningful:

(1) identification of management objectives and performance measures for each; preferably under the direction of stakeholders and managers,
(2) identification of the key uncertainties present in the system (biological, assessment, implementation, etc.),
(3) identification of candidate management strategies for evaluation,
(4) development of one or more models that serve as the representation of the real system including reasonably realistic representations of biological and fishery components (termed the "operating model"),
(5) selection of parameters to drive the operating model in accordance with the real system,
(6) simulation of executing each strategy using the operating model(s), and
(7) summary of performance measures, and presentation to managers and stakeholders.

Two broad classes of strategies could be conceived for in-season salmon management: effort control using either (1) a fixed schedule set at the start of the season or (2) a feedback strategy where the fishery is opened or closed in response to in-season data (i.e., management by emergency order, Adkison and Cunningham 2015). There exist many substrategies that fall into these two broad categories based on (1) the level of risk aversion on the part of the manager (i.e., aggressive *versus* conservative) and (2) the timeliness and reliability of information available to the manager. In general, more complex strategies will require more data to inform their implementation (Carney and Adkison 2014b). Given the wide range of strategy complexity, it is worthwhile investigating if more complex (and data-intensive) strategies provide better management performance than simpler strategies that use less information. Carney and Adkison (2014a) and Carney and Adkison (2014b) evaluated feedback *versus* fixed schedule strategies for sockeye salmon (*O. nerka*) stocks in Bristol Bay, Alaska, and found trade-offs between maximizing harvest and reducing inter-annual variability in harvest magnitude as well as spreading harvest pressure among substock components. Su and Adkison (2002) evaluated a set of schedule-based strategies that ranged in their aggressiveness and found differences in strategy performance based on which objective carried most weight in utility functions, which implies that trade-offs exist.

An MSE analysis for subsistence salmon fisheries in large drainages (such as the Yukon and Kuskokwim systems in western Alaska) necessitates different considerations than these two examples which focused on commercial fisheries. While the types of strategies considered and conservation-based objectives (adequate escapement and temporally-distributed harvest) are broadly consistent, the fleet dynamics and harvest-based objectives may be different. Subsistence fishers are less concerned with maximizing harvest as they are with maintaining consistent harvests that meet their needs and that harvest opportunities allow exploitation consistent with cultural practices (e.g., time of season and frequency of opportunities). The fleet dynamics of subsistence fisheries are quite different than commercial fisheries in that they are limited by processing capacity and have a fixed targeted harvest for the season. Due to this processing capacity, harvest of targeted species (such as Chinook salmon *O. tshawytscha*) in subsistence fisheries is limited by the species composition, sometimes expressed as a ratio of chum (*O. keta*) + sockeye:Chinook salmon. Subsistence fishers must stop fishing when they reach their processing capacity, and when this ratio is high (e.g., > 20), the catch will be dominated by chum/sockeye salmon. In-season harvest management strategies have that acknowledge these characteristics have not been evaluated for subsistence salmon fisheries, highlighting a clear need for work that focuses on this topic.

In this study, we investigate the performance of a variety of in-season harvest control rules for subsistence salmon fisheries in large drainage systems using a MSE approach. Though the analysis will be tailored to the Kuskokwim River Chinook salmon subsistence fishery, the framework developed will be general enough for application to other in-river salmon fisheries in large drainages in which the primary users are subsistence fishers. The objectives of the analysis will be to:

(1) develop a stochastic simulation model of the Kuskokwim River fishery system that allows simulation of a wide range of biological conditions,

(2) assess the performance of several realistic in-season harvest management strategies that capture a range of complexity in their management dexterity and need for information, and

(3) highlight the strength of trade-offs between competing objectives, and find management strategies that might balance them better than others.

2 Methods

The analysis was carried out by developing a stochastic simulation model of a subsistence salmon fishery system and imposing several management strategies separately. The operating model, which simulated the system dynamics, was tailored to the Kuskokwim River subsistence salmon fishery and had a spatiotemporal structure (see Section 2.3). Four primary strategies were identified (see Section 2.2) based on input from managers, biologists, and stakeholders from the Kuskokwim River drainage, as well as from academic experts in the field of Pacific salmon management. These strategies were explicitly selected to explore a range of complexity, with more complex strategies requiring more information for their implementation. Each primary strategy had several substrategies varied in the degree of aggressiveness in allowing fishing opportunities according to the rules of the primary strategy. Each management strategy was tested by simulating many hypothetical and independent salmon seasons in a Monte Carlo framework such that performance was tested at many different run scenarios including run size size, run timing, and species composition. Performance of each strategy and substrategy was assessed relative to the attainment of four objectives (Section 2.1) using a set of utility functions (Section 2.5).

2.1 Identification of management objectives

As indicated by Punt et al. (2014), the objectives selected for evaluation in an MSE analysis should be informed by communications with stakeholders and managers to determine what outcomes are deemed desirable. As part of a complementary project intended to build capacity in the engaged representatives from the local stakeholder group, four multi-day workshops were held in Alaska over the period spanning autumn 2015 – 2017. The workshops were led by by experts in meeting facilitation and salmon biology and management and were highly interactive. Presentations were given about the difficulties in salmon management, the basics of their biology, the ways information can be used in decision-making, and ways that simulation models can be used to evaluate management strategies. In the first of these workshops, stakeholders and managers were solicited for input regarding which outcomes are important to their view. Based on the themes that emerged, four main objectives for Chinook salmon management at the in-season level were identified. This is a critical component of this study, because the objectives define the necessary complexity of the operating model and they provide the context for measuring which strategies might perform better than others. They can be grouped as follows:

Sustainability-based

(1) Ensure adequate drainage-wide Chinook salmon escapement to the spawning grounds to support sustained subsistence yields into the future,

(2) Ensure that the Chinook salmon substocks have even exploitation rates within a given year,

Exploitation-based

(3) Ensure that Chinook salmon subsistence harvest needs are met at the basin-scale,

(4) Ensure that when Chinook salmon harvest restrictions are necessary, the burdens are spread evenly among the various villages.

This list is provided here to set the context for the rest of the methods, see Section 2.5 for a description of the utility functions used to measure the attainment of each objective. In this analysis, it was assumed that the abundance of chum/sockeye salmon was high enough to meet both harvest and escapement needs, so no objectives were developed regarding their management.

3.2.2 Assessed management strategies

A set of four primary in-season harvest management strategies were evaluated for this analysis. Managers in large salmon-producing river basins have the tools of time, area, and gear restrictions at their disposal for managing harvest. Strategies assessed here focused primarily on the time (i.e., when in the season fishing is allowed) aspect of these tools. Each of the four strategies represented a different way of determining if the fishery should be open on a given day of the season. Given the historical season for Chinook salmon (the species of interest in this analysis) management in the Kuskokwim River, each strategy focused on a five week period between June 1 and early July. Based on Chinook salmon run timing through the lower Kuskokwim River (50% complete on June 22 in an average year) and the timing that chum and sockeye salmon become vastly dominant in the species composition of the run (Figure 2 Appendix B), it is only during this time that management actions affecting subsistence harvest can have any meaningful impact on the attainment of Chinook salmon objectives (both those based in conservation and exploitation).

2.2.1 Strategy #1: "Closed until open"

Under this first and most naïve management strategy, the simulated manager selected a single day on which to open the entire fishery, before which it remained completely restricted (closed) and after which it remained unrestricted (open) for the rest of the season. The decision of which day to open was not explicitly informed by any "previous data" on the part of the manager, or changed based on in-season information. We evaluated three reasonable dates to start the fishery: June 1, June 12, and June 23. These dates represent the historical average 1%, 12%, and 55% percentage points of the Chinook salmon run as indexed by the Bethel Test Fishery (Bue and Lipka 2016).

3.2.2.2 Strategy #2: "Forecast-based fixed schedule"

Under this strategy, the manager used a pre-season run size forecast (described in Section 2.4.1) with which to inform the decision about how often fishing opportunities should be provided. This was conducted by developing categories (hereafter "bins") of run sizes that triggered a decision regarding how many days to allow fishing in each week: e.g., if the run was forecast to be less than 80,000 Chinook salmon, the number of days of fishing allowed per week would be less than if the the run was forecast to be between 130,000 and 180,000. Substrategies were represented by three different sets of schedules conditional on the pre-season forecast, ranging from conservative (fewer fishing days per week) to aggressive (more days per week).

In developing these schedules that dictated how many days (D) the fishery would be open during week w conditional on a forecast falling in bin b, three main qualities were desired. First, for any week $w \geqslant 0$ and forecast bin $b \geqslant 0$, $D_{w,b}$ for conservative schedules should be less than the neutral and aggressive schedules, and aggressive schedules should have the highest $D_{w,b}$ in the same w and b. Second, $D_{w,b}$ should generally increase as the forecast bin increases – i.e., years with larger anticipated runs can allow fewer restrictions to the fisher. Finally, $D_{w,b}$ should generally increase as the season progresses (increasing w), because the species composition shifts towards chum/sockeye salmon later in the season lessening the concern for high catches of Chinook salmon that may endanger the ability to meet escapement needs.

We developed a linear model that would return $D_{w,b}$ depending on the week w, forecast bin b, and schedule type (i.e., aggressive *versus* conservative; Figure 1). The model took the form:

$$D_{w,b} = \delta_0 + \delta_1 C + \delta_2 A + \delta_3 w + \delta_4 Cw + \delta_5 Aw + \delta_6 b^2 + \delta_7 bw, \tag{1}$$

where C and A are dummy variables indicating either conservative or aggressive schedules, respectively, w is the week index (five weeks: $0 \leqslant w \leqslant 4$), b is the forecast bin index (five bins: $0 \leqslant b \leqslant 4$). A and C are mutually exclusive and $A = C = 0$ for the neutral schedule. The vector δ contains coefficients for how $D_{w,b}$ depends on the values of the covariates (C, A, w, and b):

$$\delta = \begin{bmatrix} 0.25 & -0.25 & 0.25 & 0.25 & -0.50 & 0.50 & 0.50 & 0.50 \end{bmatrix}$$

For example, in the first week ($w = 0$), first bin ($b = 0$), and the neutral schedule ($A = C = 0$), $D_{w,b} = \delta_0 = 0.25$. For the same b and w, $D_{w,b} = \delta_0 + \delta_1 = 0$ for the conservative schedule ($C = 1$) and $D_{w,b} = \delta_0 + \delta_2 = 0.5$ for the aggressive schedule. The slope of conservative and aggressive schedules differ from the neutral schedule by -0.5 and 0.5 days/week in all bins, respectively, and all slopes increase by 0.5 days/week for each increase in bin. The intercept of all schedules increases by $0.5b^2$ days for each increase in the bin. Cases in which $D_{w,b}$ would exceed 7 days were rescaled such that $D_{w,b} = 7$, the same was done to prevent $D_{w,b} < 0$.

2.2.3 Strategy #3: "Forecast/ratio-based variable schedule"

This strategy was similar to Strategy #2 in that it used a pre-season forecast to set a schedule for each week, though rather than treating the different possible schedules as conservative or aggressive substrategies, the manager treated them as tactics to be employed selectively based on additional information. The manager made this selection based on in-season species composition information collected at a simulated test fishery site (described in Section 2.4.2). The species composition (expressed as a ratio in terms of chum+sockeye:Chinook salmon) is an important aspect of the fishery, because subsistence fishers are self-limited in the number of fish they can successfully process per fishing trip, and Chinook salmon harvest can be limited during times when the species ratio is high. Based on the historical percentile of the ratios in the previous week ($\phi_{p,w-1}$), the manager selected either the conservative, neutral, or aggressive schedule for the appropriate forecast bin b for use in week w as indicated in Figure 1.

Three substrategies were assessed, dealing with how the trigger percentiles were selected, as shown in Table 1. The "neutral" set of ratio trigger points specified that the manager would employ conservative schedules in accordance with the forecast bin until $\phi_{p,w-1}$ exceeded the 33% percentile of all historical ratios, at which point they would use the appropriate neutral schedule (from Figure 1). If at any w, $\phi_{p,w-1}$ exceeded the 66% percentile, the manager would switch to the aggressive schedule. The rationale here is that the more chum and sockeye there are relative to each Chinook salmon, the fewer Chinook will be caught and the more opportunity can be allowed for species of non-conservation concern. The "conservative" substrategy used cut-offs of 66% and 85% to make these transitions, and the "aggressive" substrategy used cut-offs at 15% and 33% (Table 1). The resulting ratio trigger points are shown in Table 2.

2.2.4 Strategy #4: "Explicit harvest target"

Under this strategy, the manager took on a much more active decision-making process wherein they decided how many days to allow fishing in each week of the season based on an explicit harvest target (H_T) selected probabilistically to ensure some escapement threshold (S_L) would be exceeded that season. This was the most complex management strategy, as the manager needed to know how much harvest had been taken to date and how long they should allow fishing each week based on how many fish they wish to allow to be caught. H_T was apportioned among weeks ($H_{T,w}$) according to historical Chinook salmon run timing and represented the number of Chinook salmon the manager wishes to see harvested in week w. $H_{T,w}$ could be updated in response to (1) whether in-season abundance index data suggest the Chinook salmon run is either smaller or larger than forecast or (2) whether harvest data suggest the fishery is either ahead of or behind schedule in meeting H_T.

This strategy had two main phases as shown in Figure 2. In the pre-season phase, managers used a forecast, management target, and risk tolerance to set a value for H_T and $H_{T,w}$ to start the season. Then, the in-season phase proceeded as a weekly cycle of Bayesian abundance estimation (described in Section 2.4.3), re-evaluation of H_T in accordance with updated knowledge and S_L, determination of remaining harvest, a decision of the number of days to fish based on an updated $H_{T,w}$, and estimation of harvest outcomes.

Three substrategies were formulated by building three different "harvest tables" which dictated how many days the fishery should be open in week w based on the value of $H_{T,w}$ and differed in how aggressive or conservative they were (Figure 3). The neutral table started with 0.5 days for the case of $0 < H_{T,w} \leqslant 5,000$ and increased by 1 day for each additional 5,000 Chinook salmon in $H_{T,w}$. The aggressive harvest table resulted in fishing 1.5 times as many day as the neutral table for all $H_{T,w} > 0$. If this rule would result in greater than 7 days it was capped at 7 days. The conservative table was constructed the same way except with 0.5 times as many days as the neutral table.

The probabilistic approach to selecting and updating the season-wide harvest target (H_T) in this fourth and most complex assessed management strategy is a relatively novel approach to the management of Pacific salmon fisheries (but see Catalano and Jones 2014, for another application using simulation techniques). The problem is to select some value for H_T that will ensure the drainage-wide total escapement (S) will exceed some critical escapement limit threshold (S_L) with probability equal to $1 - P^*$. The quantity P^* represents a manager's tolerance for risk of seeing the undesirable outcome of $S < S_L$ occur. $\Pr(S < S_L|H_T)$ can be calculated from a cumulative probability density function expressing beliefs about total run size. If F_N is this expression of beliefs, then $F_N(S_L + H_T) = \Pr(N < S_L + H_T) = \Pr(S < S_L|H_T)$. The value H_T can be manipulated to ensure the condition $\Pr(S < S_L) < P^*$ is satisfied. When new information accumulates in F_N (through Bayesian updating; Section 2.4.3), H_T can be updated as well to ensure the condition is still satisfied. For this analysis, $S_L = 65,000$ (the lower bound of the current drainage-wide escapement goal for Chinook salmon; Hamazaki et al. 2012) and $P^* = 0.1$. This probabilistic harvest control rule is similar to those used in marine fisheries when setting sustainable fishing mortality targets, and explicitly accounts for uncertainty and risk when determining allowable fishing activity based on limit management reference points (Prager et al. 2003; Shertzer et al. 2010).

2.3 Description of the operating model

The role of the operating model was to simulate the true dynamics of the fishery system, which included the important dynamics of the biological (i.e., the salmon) and social (i.e., the fishers) components of the fishery. The operating model was structured such that important spatial and temporal dynamics of fish and fishers in the Kuskokwim River subsistence salmon fishery could be captured. The biological and fishery components of the operating model were informed using as much empirical information as possible (see Appendix B for a description of data sources and preparation for use in these contexts). Furthermore, simulated outcomes of the fishery components (i.e., magnitude and spatiotemporal distributions of Chinook salmon harvests) under a "no management" scenario were compared to those observed in historical data in years the subsistence fishery was unrestricted (Appendix C). This was an important validation of the behavior of the operating model to ensure it adequately reproduced the patterns and variability of inter-annual observations from the real system according to the best available scientific information.

The operating model tracked in-river salmon abundance, fishing effort, harvest, and escapement in each of in each of 26 discrete river reaches (hereafter indexed by r) along the main stem Kuskokwim River over the span of approximately 130 days (late-May to the start of October; hereafter indexed by d). Although the month of June and early July are the primary salmon harvest periods in the Kuskokwim River subsistence fishery, this long temporal scale was needed to allow all simulated fish to migrate completely through the entire Kuskokwim River model. The operating model was written in Program R (R Core Team 2018).

2.3.1 Biological components

The biological submodel was made up of two aggregate salmon populations: one Chinook salmon population and one of chum and sockeye salmon together. Chinook salmon are the species of primary management interest in this analysis; the other species were included because harvest dynamics for Chinook salmon are influenced by the relative abundance of all three species in the harvesting gear. The Chinook salmon population was subdivided into three spatially-explicit substocks representing spawning aggregations in the lower, middle, and upper reaches of the drainage, which was necessary to assess the equal exploitation rate objective and enforce the realities of in-river sequential (i.e., “gauntlet”) fisheries. River entry timing and relative abundance of each Chinook substock was informed by Kuskokwim River telemetry studies (Stuby 2007; Smith and Liller 2017a,b). These studies indicate that the middle river substock is the largest (~60% of the total abundance) and enters the river mixed with the tail-end of the upper river substock (~20% of the total abundance). The lower river substock enters mixed with the middle river substock and is approximately the same size as the upper river substock.

To initialize the model, the size of the total abundance of Chinook salmon (N_{tot}) that would return to the system in the simulated year was obtained as a random sample from a distribution with density equal to that fitted to the historical distribution of run sizes over the period (1976 – 2017; as presented in Liller et al. 2018, and further described in Appendix B.1.1). The total annual abundance of each Chinook salmon substock (N_s) was then obtained:

$$N_s = N_{tot}\pi_s, \tag{2}$$

where π_s is a Dirichlet random vector representing the proportion of the total run made up of fish returning to each of the three Chinook salmon substocks with hyperparameters informed by the distribution of radio telemetry tagged fish (see Appendix B.1.2 for details). The number of fish from each Chinook salmon substock that entered the first reach each day of the season was then populated:

$$A_{d,1,s} = N_s p_{d,s}, \tag{3}$$

where $A_{d,1,s}$ is in-river abundance on day d in reach r for substock s and $p_{d,s}$ is a run timing variable representing the fraction of the run from that substock entering on that day of the season. $p_{d,s}$ was modeled using a logistic density function, standardized to sum to one within each substock over the season:

$$p'_{d,s} = \frac{e^{\frac{d-D_{50,s}}{h_s}}}{h_s\left(1+e^{\frac{d-D_{50,s}}{h_s}}\right)^2}, \tag{4}$$

$$p_{d,s} = \frac{p'_{d,s}}{\sum_d p'_{d,s}}, \tag{5}$$

where $p'_{d,s}$ are elements of the unstandardized timing curve as given by the substock-specific location ($D_{50,s}$) and scale (h_s) parameters, also informed using the telemetry data (Appendix B.1.3.2). Detailed information regarding total abundance or spatial differences in run timing of various substocks of Kuskokwim River chum and sockeye salmon is not available. Accordingly, the aggregate population representing these species was modeled using historical estimates of daily relative abundance from a long time series of a standardized catch-per-effort (CPE) index (the Bethel Test Fishery – BTF; Bue and Lipka 2016). Daily relative abundance was represented by ϕ_d, calculated as the observed ratio of the CPE of chum + sockeye salmon to Chinook salmon (Appendix B.1.5). Simulated entry timing and abundance of the chum/sockeye aggregate stock was obtained from the total daily entering abundance of Chinook salmon and a randomly drawn annual vector of ϕ from the historical data set:

$$A_{d,1,4} = \phi_d \sum_{s=1}^{3} A_{d,1,s} \tag{6}$$

The movement of fish through the main stem of the river was modeled using a "boxcar" approach (Walters and Martell 2004), in which each reach had associated rates of in-river "mortality" (i.e., the removal of fish from the main stem due to fishery harvest and escapement). The main stem mortality rate resulting from fish escaping to spawning tributaries for reach r for substock s ($\psi_{r,s}$) was obtained using the historical telemetry studies (Appendix B.1.4) and represented the fraction of all fish from substock s that survived all harvesters prior to and including reach r that would spawn in a tributary with a main stem confluence in reach r. As telemetry information was only available for Chinook salmon (s = 1, 2, or 3), $\psi_{r,s}$ for the chum/sockeye stock (s = 4) was assumed to be the same as for Chinook salmon, though with the removal of the spatial substock structure (Table 2 Appendix B). Many factors contributed to the simulated fishing mortality rate in reach r on day d, as described in Section 2.3.2, though it was assumed that fishing mortality o ccurred b efore escapement mortality:

$$S_{d,r,s} = \psi_{r,s} \left(A_{d,r,s} - H_{d,r,s}\right), \tag{7}$$

where $S_{d,r,s}$ is escapement and $H_{d,r,s}$ is harvest. Any fish that survived these sources of main stem mortality remained in the main stem, but would transition to the next reach on the next day with probability equal to one:

$$A_{d+1,r+1,s} = A_{d,r,s} - H_{d,r,s} - S_{d,r,s} \tag{8}$$

All reaches were assigned a length of 35 km, which is the approximate mean estimated travel distance per day for Chinook salmon in the main stem Kuskokwim River (Smith and Liller 2017a,b).

2.3.2 Fishery components

There were five primary factors used to model the subsistence fishery dynamics in each reach: (1) maximum daily effort ($E_{\mathrm{MAX},r}$; effort expressed in boat trips per day), total maximal salmon need by species, maximum daily salmon catch per boat per day (abbreviated by CPB; maximum is denoted CPB_{MAX}), (4) effort responses to fishery conditions, and (5) a measure of fishery selection for different species. Since 1990, the Alaska Department of Fish and Game (ADF&G) has conducted rigorous post-season sampling from the 26 villages in the Kuskokwim River documenting the number of fishing households and salmon harvest by species (these estimates are presented in Hamazaki 2011; Carroll and Hamazaki 2012; Shelden et al. 2014; Shelden et al. 2015; Shelden et al. 2016a; and Shelden et al. 2016b). This wealth of information was used to inform maximal salmon need and effort (described in Appendices B.2.1 and B.2.2, respectively) for villages in each reach r. CPB_{MAX} and effort responses were informed by recent studies of the in-season subsistence fishery dynamics in the lower Kuskokwim River (Staton and Coggins 2016, 2017; Staton 2018d) and fishery selection was obtained by comparing these data with the catches at the BTF on the same day in the same years.

An effort response model was needed to replicate observed patterns in effort dynamics in recent years, namely that effort declines as the season progresses (Staton and Coggins 2016, 2017; Staton 2018d). This decline is thought to be a result of two primary factors: attainment of harvest needs and in-river species composition, but finer-scale factors are certainly at play as well. A logit-linear model was constructed to specify the fraction of maximum fishing effort that would fish in each reach each day if the fishery were open ($p_{E,d,r}$):

$$\text{logit}(p_{E,d,r}) = \beta_0 + \beta_1 full_{d,r} + \beta_2 stop_{d,r} + \beta_3 \delta_{d-1,r,CH} + \beta_4 \delta_{d-1,r,CS} + \beta_5 \phi_{d,r} \tag{9}$$

The effort response model operated on a reach-specific basis, and had five terms in addition to the intercept (β_0):

<u>Time of season effects: β_1 and β_2</u>

β_1 was an effect used to increase effort to near-full capacity after a critical date. The indicator $full_{d,r}$ took on a 0 value prior to this date and a 1 after it; the critical date was in early June for the first reach and increased by one-quarter day for each upstream reach. This effect was intended to capture the behavior that few fishers will participate early in the season before many fish have arrived in their area. Additionally, it is reasonable to expect that essentially all lower-river fishers will be done fishing for Chinook, chum, and sockeye salmon by mid-July (Hamazaki 2008), so the B_2 coefficient was included to force effort to drop to near 0 around this time for lower-river villages, where $stop_{d,r}$ had the same one-quarter day lag for upstream villages as done for $full_{d,r}$.

Attainment of subsistence needs effects: β_3 and β_4

The covariates $\delta_{d-1,r,CH}$ and $\delta_{d-1,r,CS}$ represented the cumulative fraction of met needs by villages in reach r as of the previous day for Chinook and chum/sockeye salmon, respectively. β_3 and β_4 had negative values, which reflected the nature of a subsistence fishery that more fishers will exit the fishery as the season progresses and more harvest needs are met.

Species composition effect: β_3 and β_4

β_5 was a response to the local in-river species ratio of chum+sockeye:Chinook salmon. It has been observed in recent years that effort declines as the season progresses (and chum/sockeye become more abundant in-river) even when Chinook, chum, and sockeye salmon needs are far from being met (as defined by the Amounts Reasonably Necessary for Subsistence Needs as determined by the Alaska Board of Fisheries; ANS; Table 4 Appendix B). The important mechanism captured here is that the species composition and abundance of chum and sockeye salmon becomes so high in late June (Figure 2 Appendix B) that it is not uncommon to catch several dozen fish of these species in a single gill net drift, which may b e undesirable to some fishers given limited processing and storage capacity.

The general pattern that arises from this model is low effort early in the season due to low in-river abundance and catch rates, a peak when most harvesting activity occurs due to favorable catch rates, and a rapid decline as salmon needs are met. The coefficients were selected to generally reproduce recent observations of effort dynamics (Staton and Coggins 2016, 2017; Staton 2018d) and historical harvest timing data (Hamazaki 2008, 2011, and see Appendix B for a validation). Coefficient values were $\beta_0 = 0$; $\beta_1 = 3$; $\beta_2 = -100$; $\beta_3 = -4$;

$\beta_4 = -5.5$, and $\beta_5 = -0.05$ – note that the effect for attainment of Chinook salmon needs was weaker than that of chum/sockeye. This indicates that effort should decline more quickly with the attainment of chum/sockeye needs rather than for Chinook salmon, which was intended to reflect the desirability of the latter species to subsistence fishers in the Kuskokwim drainage.

Subsistence fishers are limited by processing time and space, and thus have a self-imposed catch limit. CPB_{MAX} was needed to prevent CPB from being proportional to in-river abundance at high salmon densities. A value of 60 total salmon per day was used, and came from a mixture of recent observations (Staton and Coggins 2016, 2017; Staton 2018d) and from speaking with stakeholders about their harvest and processing behavior.

It has been observed that fishers in the Kuskokwim River do not target all salmon species in proportion to their relative abundance as indexed by the BTF (Staton and Coggins 2016, 2017; Staton 2018d). Whether due to a size-selective bias of the gear or due to fisher preference, the observed species ratio in the fishery is typically skewed more towards Chinook salmon than is the BTF on the same days, by a factor of approximately 0.6. That is, if the BTF (which is assumed to sample the vulnerable relative abundance representatively) exhibits a species ratio of 15:1 (chum+sockeye:Chinook), the fishery would be expected to exhibit a species ratio of 9:1. This selectivity correction was included into the fishery model when apportioning harvest to species.

Realized effort on day d in reach r ($E_{d,r}$) was calculated by combining $E_{\text{MAX},r}$, $p_{E,d,r}$, and the fraction of a 24-hour day the fishery was open ($F_{d,r}$):

$$E_{d,r} = p_{E,d,r} E_{\text{MAX},d,r} F_{d,r} \tag{10}$$

$F_{d,r}$ was manipulated by the management strategies presented in Section 2.2. Total salmon harvest ($H_{d,r,tot}$) was obtained as:

$$H_{d,r,tot} = \min\left(1 - e^{-E_{d,r}q} \sum_{s=1}^{4} A_{d,r,s}, E_{d,r}CPB_{\text{MAX}}\right) \tag{11}$$

The term $1 - e^{-E_{d,r}q}$ is equivalent to a daily exploitation rate in the absence of processing capacity, and includes effort and catch efficiency (i.e., catchability; q). The minimum statement in (11) enforces the maximum daily harvest per boat trip. This total salmon harvest was apportioned to each Chinook salmon substock based on (1) the known level of selectivity towards Chinook salmon and (2) the relative abundance of each substock s. That is, the species ratio of $H_{d,r,tot}$ was reduced from the true species ratio $\phi_{d,r}$ by a factor of 0.6 to obtain Chinook and chum/sockeye salmon harvest, then the Chinook salmon harvest was apportioned by the substock relative abundance. The maximum daily exploitation rate of any $A_{d,r,s}$ was capped at 0.9.

2.4 Simulated assessment data collection

The simulated assessment structure differed based on the management strategy used based on the richness of information required for each management strategy: e.g., Strategy #1 (closed until open) required no information whatsoever whereas Strategy #4 (explicit harvest target) required a pre-season forecast, in-season abundance data, a method to update abundance perceptions, and weekly in-season harvest estimates. Only data sources that could be useful for in-season management were simulated, e.g., because weir projects that assess escapement to specific tributaries are located so far from the bulk of the fishery they are not useful to determining in-season harvest opportunities.

2.4.1 Pre-season run size forecast

Pre-season forecasts of Chinook salmon total abundance were obtained as a bias-corrected lognormal random deviate from the true run:

$$\log\left(N_{tot,fcst}\right) \sim \mathrm{N}(-\frac{\sigma_F^2}{2}, \sigma_F) \tag{12}$$

where $\sigma_F = 0.27$ which is the estimated standard deviation of historical forecast errors using the current forecast method (presented in Staton and Catalano *In Press*[1]). When used in Strategies #2 and #3, only the point estimate of $N_{tot,fcst}$ was used to categorize the run as being a member of one of five discrete run size "bins", as displayed in Figure 1. When used in Strategy #4, the uncertainty in the forecast method was incorporated by treating the forecast as a bias-corrected lognormal probability density function (PDF), with standard deviation equal to σ_F.

2.4.2 Test fishery index

A test fishery that produced daily catch-per-effort ($CPE_{TF,d,j}$) for each salmon stock j ($n_j = 2$; one aggregate Chinook salmon stock and one aggregate chum/sockeye stock) was simulated in the first river reach and was assumed to index the run prior to any fishery harvest. The test fishery had an expected daily catchability (q_{TF}) and two sources of sampling variability: a catchability deviation representing annual fluctuations in river conditions and age/size composition of the incoming run (Flynn and Hilborn 2004) and daily fluctuations in fish vulnerability:

$$CPE_{TF,d,j} = A_{d,1,j} \frac{e^{q_{TF}+\varepsilon_{TF,y}+\gamma_{TF,d}}}{1+e^{q_{TF}+\varepsilon_{TF,y}+\gamma_{TF,d}}} \tag{13}$$

where $A_{d,1,j}$ is the total abundance of fish from species j each day in the first reach, and $\varepsilon_{TF,y}$ and $\gamma_{TF,d}$ are logit-scale sampling errors operating on the annual and daily time scales, respectively. These sampling errors were normally-distributed with standard deviations equal to $\sigma_\varepsilon = 0.15$ and $\sigma_\gamma = 0.2$ and q_{TF} was set to 0.004 – these settings resulted in simulated test

[1]DOI: https://doi.org/10.1139/cjfas-2018-0176

fishery with similar properties as the Bethel Test Fishery. Daily species compositions were expressed as the ratio of chum+sockeye:Chinook salmon:

$$\phi_{TF,d} = \frac{CPE_{TF,d,CS}}{CPE_{TF,d,CH}} \tag{14}$$

where $j = CH$ for Chinook salmon and $j = CS$ for chum/sockeye salmon.

2.4.3 Bayesian updates of perceived run abundance

In assessed Strategy #4, the manager used in-season information regarding run abundance contained in the sampled values of $CPE_{TF,d,CH}$ to update the PDF provided by the pre-season forecast in a Bayesian framework. The analytical methods to perform this Bayesian update were identical to those presented in Staton and Catalano (*In Press*), however, a brief description will be provided here. Based on a regression relationship fitted to historical data of the form:

$$\log(N_{tot,y}) = \hat{\beta}_{0,d} + \hat{\beta}_{1,d} \sum_{k=1}^{d} CPE_{TF,k,CH,y} + \hat{\varepsilon}_{N,y,d}, \tag{3.15}$$

it is possible to predict total annual abundance on any day d of the season from the sum of all observed $CPE_{TF,CH}$ data through day d. Thirty historical years were simulated for fitting this historical relationship, which is highly variable for low values of d as a result of run timing and sampling variability, though becomes more informative as d increases and the run approaches completion. Uncertainty was propagated to predictions of abundance *via* Monte Carlo simulation of the regression parameters and residuals from their respective estimated sampling distributions as described in Staton and Catalano (*In Press*). This process yields a daily distribution of likely run size outcomes according to the in-season data alone, and can be viewed as new evidence with which to update prior information. The prior distribution each day was the PDF of the pre-season run forecast, and the PDF of abundance predictions from (15) was used as the likelihood to obtain the posterior PDF, denoted by $\Pr(N_{tot}|CPE_{TF,d})$.

2.4.4 Weekly harvest estimates

In assessed Strategy #4, the manager had the ability to track in-season Chinook salmon harvest, such that progress toward attainment of the season-wide harvest target (H_T) could be monitored. Weekly harvest estimates were produced as random deviates from a symmetric truncated normal distribution with mean equal to the true weekly harvest, coefficient of variation (CV) equal to 15%, and lower and upper boundaries at 0 and 2 $\times$ true weekly harvest, respectively – these boundaries ensured unbiased and all positive harvest estimates. A CV of 15% was used because this is the approximate CV obtained using the in-season harvest estimation method developed and employed by Staton and Coggins (2016), Staton and Coggins (2017), and Staton (2018d). Cumulative estimated harvest was obtained by summing weekly estimates; uncertainty in harvest estimation was not considered. Estimates were created only for the villages within the Yukon Delta National Wildlife Refuge (YDNWR; reaches 1 – 9; Table 4 Appendix B); this is a small enough area to be surveyed feasibly and it accounts for approximately 95% of all historical subsistence Chinook salmon harvest in the Kuskokwim River drainage (Hamazaki 2011).

2.5 Utility functions

Due to the lack of a common scale to the various objectives (Section 2.1), it was important to devise metrics than can be compared between objectives. These metrics are termed "utility functions", and here they are on the scale of [0,1], where 0 indicates complete failure to meet an objective and 1 indicates complete success. Objectives can then be weighted based on their importance to different managers and an aggregate score can be obtained as a weighted sum across the different utilities. Each objective received a unique utility function, as described below.

2.5.1 Attainment of aggregate escapement needs

Adequate escapement is the primary conservation objective, and is necessary to ensure the Chinook salmon stock can continue to produce adequate subsistence yields in the future. Thus, a rational metric to use is one based on the ability of the escaping spawning abundance to produce enough adult recruits to allow for attainment of subsistence harvest needs. The best scientific understanding of this ability is based in population dynamics of the stock, specifically the spawner-recruit dynamics. If the Ricker (1954) spawner-recruit model is to believed (as is often done in salmon population analyses, Fleischman et al. 2013, see Chapter 4, this dissertation as well), then there is a theoretical spawner abundance, termed S_{MAX}, that is most likely to produce maximum recruitment, termed R_{MAX}. R_{MAX} may be a more important metric for subsistence salmon fisheries than maximum sustained yield, given subsistence fishers tend to value consistently high abundance and catch rates over simply maximizing their long-term catch (Hamazaki et al. 2012). We generated the utility function using a curve that represented the probability that a given escapement will produce 90% of R_{MAX} under equilibrium conditions, which would ensure high future catch rates and enough surplus of Chinook salmon to meet subsistence needs in the long-term.

To obtain this curve, termed a probability profile (Fleischman et al. 2013), We fitted the Bayesian state-space model presented in Hamazaki et al. (2012) to the Kuskokwim River aggregate population data over the period 1976 – 2017 using JAGS (Plummer 2017). This utility function assigned high utility (> 0.9) to escapements between approximately 70,000 –125,000, with lower utility on either end outside of this range (Figure 4). One important consideration, however, is that if the Chinook salmon run is larger than approximately 230,000 fish, the subsistence fishery alone, which has historically harvested a maximum of approximately 110,000 fish (Hamazaki 2011), cannot harvest enough fish to place escapement within that range. This fact is important when considering the value of this metric in very large runs.

2.5.2 Even substock exploitation rates

In the absence of any information regarding the productivity of the different Chinook salmon substocks within the Kuskokwim River drainage, the default preference would be that all substocks should receive the same exploitation rate ($U_s = \frac{H_s}{N_s}$). Thus we attempted to find a metric that would have a high value (near 1) if all Chinook salmon substocks had relatively equal U_s and that would provide a low value (near 0) if the U_s were vastly uneven. One such metric is the Schutz coefficient (Schutz 1951; Habib 2012), which is often used in econometrics to measure income inequality (e.g., Kennedy et al. 1996). The Schutz coefficient takes the form:

$$z = \frac{\sum_i^n |x_i - \bar{x}|}{2\sum_i^n x_i}, \tag{16}$$

where x_i is the income of earner i, $\bar{x}$ is the average income among all n earners, and z is the Schutz coefficient. Technically speaking, this index represents the fraction of the total income that would need to be redistributed reach perfect equity ($z = 0$), which has earned it an alternate name: the "Robin Hood Index." Here it is viewed simply as an index of evenness among substock-specific exploitation rates within a given year.

Several modifications were made to the Schutz coefficient in (16) for use in this utility metric. First, U_s was substituted for x_i and $n = 3$ to represent the three simulated Chinook salmon substocks. Second, given perfect equity (or evenness) of exploitation rates would be deemed a success, the complement of the Schutz coefficient was obtained for the utility function: $z' = 1 - z$. Third, the smallest value attainable for z' is n^{-1} but a complete failure needed to be represented by 0 to be consistent with the other utility functions. Thus, z' was normalized to be on the [0,1] scale:

$$z'' = \frac{z' - n^{-1}}{1 - n^{-1}} \tag{17}$$

Finally, if all x_i elements are 0, z'' is undefined. In these cases, z'' was assigned the utility of 1, given the U_s are even. Several examples of this utility function are presented in Table 3.

2.5.3 Attainment of aggregate subsistence needs

The Alaska Board of Fisheries has produced ANS ranges, which represent the range of salmon harvests by species that would reasonably be expected to meet subsistence salmon needs of fishers in the Kuskokwim River drainage (Appendix B.2.1). This range is 67,200 – 109,800, with a midpoint of 88,500. A "hockey-stick" utility function for drainage-wide Chinook salmon harvest was used that reached its maximum at 1 if harvest was above the midpoint of the ANS range, and a fraction of it (H_{CH}/88,500) otherwise.

2.5.4 Evenness of subsistence harvests

In addition to meeting the needs of the aggregate population of subsistence fishers, it is also generally desirable that Chinook salmon harvest be distributed evenly among the villages in each region (relative to their salmon needs). Thus, we used the same modified Schutz coefficient (z'') shown in Section 2.5.2 to quantify evenness of need-adjusted harvests (harvest/need) for villages located in the lower, middle, and upper regions of the Kuskokwim Drainage (Table 4 Appendix B). In this case, high utility would be placed on outcomes in which a relatively equal fraction of Chinook salmon needs were harvested by villages in these regions.

2.5.5 Total Utility

The four objectives and utility metrics described above were collapsed into one measure that allowed quantification of overall performance and simple comparisons between strategies. This metric, termed total utility (V_T) was calculated as the weighted sum across each of the four objective-specific metrics:

$$V_T = V_S \omega_S + V_U \omega_U + V_H \omega_H + V_E \omega_E \tag{18}$$

where V_x and ω_x represent the utility measure and weighting factor for objective x, respectively (S = aggregate escapement, U = even U_s, H = aggregate harvest, E = equitable harvest). The default case assigned equal weight to each objective, but three alternate weighting schemes were assessed as well to determine the sensitivity of conclusions to this choice (Section 2.7.3).

2.6 Monte Carlo simulation

For each assessed strategy, M = 5,000 hypothetical runs were simulated with different total Chinook salmon run size, aggregate and substock-specific entry timings, substock compositions, and species compositions. Assessment errors were introduced randomly as well and each substrategy was tested on the Monte Carlo sample. The utility for each objective was calculated for each simulated year and strategy and was saved for summarization.

2.7 Summarization of management performance

Two levels of post-stratification of run types was conducted to facilitate inference. First, runs were stratified into 5 categories based on total Chinook salmon abundance (N_{tot}): [50K,80K], (80K,130K], (130K,180K], (180K,230K], and (230K,450K], and were the same as the bins used to categorize pre-season run size forecasts for Strategies #2 and #3. These were selected roughly based on the level of needed management restrictions to ensure the subsistence fishery would not harvest too many fish to damage escapement utility. Runs in the first two strata may require substantial restrictions, those in the third and fourth may require light or no restrictions, and the majority of runs in the fifth strata should require no management whatsoever to ensure near full attainment of the escapement and harvest objectives. Second, run timing was stratified into 3 categories: >3 days early, >3 days late, and all runs. The average utility value across Monte Carlo samples for each strategy/substrategy was calculated for each objective in each run size/timing stratum.

2.7.1 Within-strategy comparisons

Substrategies within each of the four primary strategies were compared at each run size stratum for each utility metric. The effect of run timing variability was assessed by qualitatively assessing which strategies had largely different outcomes for either the “early” or “late” strata than the “all” stratum.

2.7.2 Between-strategy comparisons

The best-performing substrategy in each run size stratum across all run timing strata according to the total utility measure was extracted and its performance was compared to that of other strategies. In selecting the best substrategy, it often occurred that negligible differences were found between substrategies according to the total utility metric (V_T): in these cases of a “tie” (defined as a case where the second best substrategy was within 5% of the best) the substrategy that performed best with respect to escapement utility was selected for comparison, if that was again a tie, then utility measures from all substrategies included in the tie were averaged and noted as a “hybrid” substrategy.

2.7.3 Evaluation of sensitivity to weighting schemes

The default case was to weight all four metrics equally when obtaining total value ($\omega_S = \omega_H = \omega_E = \omega_U = 1$), but three other weighting schemes were used for sensitivity analyses:

- *Simple-view*: $\omega_S = 1$; $\omega_H = 1$; $\omega_E = 0$; $\omega_U = 0$
- *Escapement-oriented*: $\omega_S = 1; \omega_H = 0.5$; $\omega_E = 0.25$; $\omega_U = 0.75$
- *Harvest-oriented*: $\omega_S = 0.5; \omega_H = 1$; $\omega_E = 0.75$; $\omega_U = 0.25$

The "simple-view" is intended to focus only on the two primary objectives of salmon management, and the escapement- *versus* harvest-oriented scenarios are opposites of one another, with the aggregate objective (V_S or V_H) in each case carrying the most weight followed by the spatial distribution objectives (V_U or V_E).

In calculating the total utility (V_T; the only basis for comparison here), it was important to restandardize it for comparisons between weighting schemes (ω_x). This is because these different combinations have differing maximally-attainable V_T. For example, the maximum attainable V_T for the "simple-view" case is 2, but it is 4 for the default case. For this comparison, the different V_T values for each weighting scheme were rescaled to be a fraction of the maximally-attainable V_T for that weighting scheme ($\sum_x \omega_x$).

3 Results

3.1 Operating model realism

The operating model was found to adequately capture the important dynamics of the fishery when left unrestricted with respect to total harvest magnitude as well as spatiotemporal patterns in the distribution of Chinook salmon harvest at a range of all simulated run sizes, timings, and species/stock compositions (Appendix C). Some amount of fine-tuning was required of the catchability parameter (q) and the effort response model coefficients (β_n) to reproduce these patterns, however no behaviors arose that seemed highly questionable. In general, the level of simulated inter-annual variability was similar to that observed in the historical data (Appendix C). Based on these findings, inference regarding policy performance proceeded under the assumption that the operating model reasonably captured the system dynamics.

3.2 Within-strategy comparisons

3.2.1 Strategy #1: "Closed until open"

Strong patterns were found in the relative performance of the different substrategies of assessed Strategy #1 (Figure 5), particularly with regards to the expected utility for the aggregate harvest (V_H) and escapement (V_S) objectives. In the "smallest" simulated runs ($<$ 80,000), only the June 23 substrategy resulted in any measurable amount of escapement utility ($V_S \approx 0.2$), the other two assessed earlier dates resulted in V_S near 0. This finding in the smallest runs was not at all sensitive to the timing with which simulated Chinook salmon entered the river (as indicated by the overlap in the three lines, Figure 5). In "small" simulated runs (80,000 – 130,000), more escapement utility was attained for each substrategy, but the declining pattern remained. In these runs, however, run timing variability did greatly impact the ability to meet escapement needs: late runs had the tendency to result in higher V_S even when the river was opened completely beginning on June 1. Escapement utility was generally highest in the "medium-sized" runs (130,000 – 180,000), with all three substrategies resulting in $V_S \geqslant 0.8$ and little sensitivity to run timing. The June 23 substrategy resulted in the lowest V_S in "large" runs between 180,000 – 230,000, as a result of allowing many Chinook salmon to escape; the case was the same for all substrategies of the "largest" runs ($>$ 230,000), but in these runs there is no management action that could allow the subsistence fishery to harvest enough fish to obtain high escapement utility according to the function used (Figure 4). Greater harvest utility was obtained with earlier opening dates, as would be expected given Chinook salmon abundance becomes overwhelmed by chum and sockeye salmon in the later part of June. These results highlight a trade-off between harvest and escapement in runs smaller than 130,000: earlier fishing resulted in more harvest, but less escapement utility.

Harvest equity (V_E) was maximized at the intermediate substrategy (June 12) for small runs, but reached its maximum with the earliest date with larger runs. The utility resulting from equal exploitation rates (V_U) was flat over the continuum of assessed start dates, however there was a slight trend for later fishing dates to have higher values of V_U. Run timing influenced the value of V_U as well, with earlier runs generally having greater utility. The default total utility metric (V_T; obtained with all weights $\omega_x = 1$) was roughly equal between substrategies in small runs (indicating that each balanced the trade-offs differently), whereas V_T was greatest for the intermediate and earliest start dates in larger runs (i.e., more aggressive start dates).

Given the relatively small changes in the V_E and V_U metrics between substrategies, we thought it important to look more closely at patterns with the raw output of exploitation rate by substock (U_S; Figure 6) and the fraction of salmon needs that were met (Figure 7). With respect to U_S, the most noticeable di˙erence between substrategies was that the exploitation rate for all substocks was lower for the late opening dates than for early opening dates (Figure 6). Due to the limiting nature of the subsistence fishery, t he exploitation rates declined with increasing run sizes. In all substrategies, the exploitation rate of the upper river substock was greater than for the lower and middle river substocks, however this di˙erence declined as the opening date was delayed. Regarding the evenness of attainment of harvest needs between villages in di˙erent regions of the drainage, the greatest unevenness was found for large runs combined with the June 23 substrategy, in which upper river fishers often exceeded their minimal needs but lower river fishers obtained less than half of theirs. Overall, the changes in these raw output values seemed more substantial than what was indicated by the use of the modified Schutz coefficient, as shown in Figure 5.

3.2.2 Strategy #2: "Forecast-based fixed schedule"

Just as in assessed Strategy #1, the expected utilities for the aggregate harvest (V_H) and escapement (V_S) objectives were those most influenced by the choice of substrategy of assessed Strategy #2. The conservative substrategy resulted in higher V_S in small runs, but at the cost of lower V_H (Figure 8). In large runs, however, there was much less contrast in substrategy performance. Run timing variability again played a key role in determining management success: small runs tended to have higher V_S when the run was late (but lower V_H), whereas late runs were a detriment to the success of both objectives in larger runs. It was only in small runs that harvest equity (V_E) or harvest rate evenness (V_U) were sensitive to the selection of substrategy – in medium and the large run scenarios these metrics were essentially equal along the continuum of conservative to aggressive fishing schedules. In general, Strategy #2 was also influenced by run timing variability (though less so than Strategy #1), and particularly in larger run sizes. V_T was largely the same between substrategies, with a slight tendency to favor more aggressive schedules in nearly all run size categories.

3.2.3 Strategy #3: "Forecast/ratio-based variable schedule"

Substrategies of assessed Strategy #3 (Figure 9) showed high similarity to the patterns in Strategy #2. The only difference of note between these two strategies was the difference in utility between substrategies was smaller for Strategy #3 than for Strategy #2 (i.e., overall shallower slopes in Figure 9) than in Figure 8.

3.2.4 Strategy #4: "Explicit harvest target"

The choice of the particular substrategy used for Strategy #4 had less of an impact on escapement or harvest utility than substrategies of Strategies #1-3 (Figure 10) in small runs. This indicates that the performance of this strategy in small runs was insensitive to the particular harvest table used (i.e., the linkage between the weekly harvest target and number of fishing days, Figure 3). This is likely a result of the probabilistic choice of a harvest target – because this method accounted for uncertainty in run abundance and risk in failing to meet the escapement limit, the harvest target was probably low enough in these small runs to where it did not matter which substrategy was used, they would all suggest very few fishing days per week. In larger runs, where the harvest target was larger, more contrast was found between substrategy performance with respect to harvest and escapement. Run timing variability affected the performance of this strategy, and as in other strategies the effect was strongest at large run sizes. V_E and V_U were generally unaffected by the choice of substrategy, but there was a slight tendency for the aggressive harvest table to exhibit lower values than the conservative one.

3.3 Between-strategy comparisons

After extracting the best substrategy from each of the four primary strategies at each run size (across all run timing scenarios), it was clear that conservative/neutral substrategies were favored in small runs and aggressive substrategies in large runs (Figure 11; note the predominance of light grey in left panels and darker grey in the right panels). Ties between substrategies were more common in larger runs, indicating the details of strategy implementation had less influence in larger runs. The largest differences in management performance between strategies were with respect to aggregate escapement and harvest in small and intermediate sized runs – the harvest equity and evenness of exploitation rate metrics were largely insensitive to the selection of strategy at all run sizes. In the smallest runs, Strategy #4 was strongly favored over other strategies with respect to escapement, likely as a result of its inherent risk aversion built into the probabilistic selection of the harvest target. However, Strategy #4 tended to result in less harvest utility in nearly all run sizes than the other strategies, indicating that more complexity in the decision rules still leaves room for management mistakes, but that they err on the side caution. Within a run size category, there was a high degree of similarity in total utility among strategies at all run sizes, though a weak pattern emerged that favored more complex strategies (#4) in small runs and simpler strategies (#1-3) in larger run scenarios.

3.4 Sensitivity to weighting schemes

It is important to consider how these findings regarding total utility might depend on how the various utility functions were weighted. The major pattern that arose was that when the weights were adjusted to the simple-view or escapement-oriented scenarios, the tendency to favor conservative substrategies in small runs was more apparent – the "harvest-oriented" weighting scenario favored either neutral or aggressive substrategies in even the smallest run sizes (Figure 12). The pattern of high similarity in overall performance between strategies remained, but there was a tendency to favor Strategy #4 (the most complex) more in the escapement-oriented weighting scenario than in the harvest-oriented weighting scenario (Figure 12). According to the "simple-view" weighting scenario, relative performance in the smallest runs was much lower in comparison to other run sizes than using other weighting schemes (Figure 12). This is because only the aggregate harvest and escapement objectives were considered in the simple view case (and both objectives score low in these smallest runs), whereas other weighting scenarios included the spatial distribution of these quantities in measuring management performance.

4 Discussion

The dominant trade-off we found, not surprisingly, was between harvest and escapement in small runs ($<$ 130,000). These runs do not have enough fish to allow for both high escapement and harvest utility, and given every fish that is harvested cannot also escape, it is clear as to why this is the case. The trade-off was identified because for most strategies, the more conservative substrategies tended to have higher escapement utility and lower harvest utility, and *vice versa*. In larger runs, this trade-off was not present, given enough fish were available for both objectives.

One of the more surprising findings in our view was the high degree of similarity in total utility (V_T) between management strategies (after filtering the best-performing substrategy). As an example, we expected that the explicit harvest target approach in Strategy #4 would strongly outperform the fixed schedule strategy (Strategy #2) because of its timely response to information. We see two plausible explanations for why the more complex strategies did not perform overwhelmingly-better in most cases. First, it is possible that the harvest table approach was too simple in Strategy #4. It is likely that managers may adapt the table based on run abundance or species composition. A more involved approach still would be to select fishing duration each week (D_w) based on an explicit prediction of how many fish would be captured conditional on each value of D_w under consideration. The candidate that results in predicted weekly harvest nearest to the desired weekly harvest ($H_{T,w}$) would then be selected. Understanding of the fishery dynamics at various run sizes would be required to trust these predictions strongly, but recent studies (Staton and Coggins 2016, 2017; Staton 2018d) have gone a long way towards providing this understanding for runs in the small category. These predictions can be made very simply as the product of three anticipated quantities and one policy variable: total boats/day $\times$ salmon catch/boat/day $\times$ % Chinook in catch $\times$ D_w. A second explanation is that the additional dexterity gained by a more complex strategy is only as good as the information informing it, and it is possible that it was too weak to implement Strategy #4 well. We attempted to mimic the properties of the data sources collected for in-season management in the Kuskokwim River; it is possible that more precise run assessment methods (e.g., sonar) would provide better information to implement this policy.

There are relatively few studies in the literature similar to the one presented here to allow comparison. Carney and Adkison (2014a) and Carney and Adkison (2014b) conducted analyses comparing fixed schedules and feedback strategies (referred to as "daily management" or "management by emergency order" therein). In both cases, they found the more complex feedback strategy did increase average annual catch without putting escapement at risk, but also resulted in more inter-annual variability in catch than the fixed schedule strategy. Inter-annual variability was not investigated in the analysis, but we found that the feedback strategies (those that used information collected in-season; Strategies #3-4) tended to result in the same or less harvest in most run sizes compared to the simpler fixed-schedule strategies (those that used no or only pre-season information; Strategies #1-2; Figure 11). Additionally, Carney and Adkison (2014a) state that a fixed schedule should perform better at spreading exploitation among stock components, but the analysis did not support this claim: we found that all strategies had highly similar performance with respect to evenness of exploitation rates. This was probably a result of the complexity of the operating model we constructed, which captured the behavior that fishers fish most intensively early in the season if allowed and incorporated a limiting effect of chum/sockeye salmon on Chinook salmon harvest through the processing capacity of subsistence fishers.

Examination of substrategy performance revealed that often the choice regarding the best depended on run size: more neutral or conservative substrategies were selected in small runs (< 130,000) and more aggressive substrategies in larger runs (> 180,000). This finding simply suggests that, regardless of the particular strategy being employed, it should not be implemented the exact same each year. Fishing schedules must be updated to adequately target which outcomes are likely to influence success that year. For example, in the smallest runs, it is possible to obtain moderate escapement utility (V_S = 0.7 with Strategy #4) with very little fishing activity. However, the most harvest utility possible in these runs is low (V_H = 0.4 with Strategy #1, June 1) and if this were enacted V_S would be 0. Clearly the more important objective in small runs such as these is escapement, so managers should adapt the strategy to behave in a more conservative way. The situation reverses in intermediate and large sized runs, where it is possible that both V_H and V_S benefit from more aggressive fishing (within reason). This finding makes intuitive sense, and to most salmon managers it was almost certainly known *a priori* to this analysis. However, this analysis (and ones like it) are useful in helping define these transition points and defining what a set of conservative *versus* aggressive schedules might look like.

In terms of robustness to variability in run timing, we found that all strategies were sensitive in large runs, but that only Strategy #1 was sensitive in small runs. This makes intuitive sense given Strategy #1 used only one "decision", and that was the day to open the fishery completely. As a result, an early opening date coupled with an early run is likely to produce more Chinook salmon harvest than the same opening and a late run because of the timing with which chum and sockeye salmon begin to dominate the species composition. If the Chinook salmon run shows up early, then a larger fraction of their run is vulnerable to lower river fishers before chum and sockeye salmon enter in large numbers and trigger the processing capacity limit, coupled with an early opening would result in high harvest. Conversely, if the Chinook run is early but coupled with a late opening, then Chinook harvest is likely to be low because much of the run has passed the lower river fishery. These dynamics can be easily understood because of the simple nature of Strategy #1. In the more complex strategies, more factors influenced the number of fishing days per week than simply the time of the season. For example, schedules for Strategies #2-3 were explicitly chosen to have fewer days early in the season than later in the season to prevent catching too many Chinook salmon when the abundance is high relative to other species. Furthermore, sampling variability was introduced into the decision-making process that could also serve to swamp the influence of run timing variability. Increased sensitivity at large run sizes was likely a result of the fact that more is at stake in large runs from a harvest perspective: there is more surplus in these years, and a proportional reduction in a large harvest affects the V_H utility function more than the same proportional reduction in a small harvest.

The final primary finding was that the weighting of objectives in the total utility function did influence the inference, but only regarding which substrategies (not strategies) were best and only in small runs. The escapement-oriented weighting scheme suggested that conservative substrategies performed better in these small runs. Weighting did not, however, change the inference that the different strategies performed similarly within a run size category. This indicates that perhaps managers with different inherent weights on their objectives should not necessarily change their decision rules entirely from other managers, but instead that they may just fine-tune the details of their implementation (e.g., specific trigger points).

The approach we used did have some weaknesses. First, inference regarding strategy performance conditioned on the particular objectives selected for this purpose, and more specifically, on the utility functions used to measure the degree of their attainment for each hypothetical salmon run. Each manager/stakeholder may have different objectives (or different ways to weight them), but the performance metrics were built around the four dominant themes discussed in management and stakeholder meetings regarding management objectives and the sensitivity to different weighting schemes (which might represent different managers or stakeholders) was assessed. Second, this simulation analysis required that the management strategy be expressed as a rigorous control rule, where the decision would be made the same way each time the same information was available. In reality, managers do not operate this way – one control rule cannot simultaneously consider all sources of information in such a programmatic way. This fact limits the realism of the analysis, but is not unique to these kinds of MSE analyses.

A population dynamics submodel was not incorporated into the operating model because we were primarily interested in the performance of in-season management strategies. Incorporation of a population dynamics submodel would move the analysis away from its focus on in-season strategies to long-term harvest control rules and the optimal level and spatial distribution of escapement. While these issues are important, we wanted this analysis to focus on the different ways a manager could behave in-season to meet a set of objectives they care about meeting in any given year (irrespective of population dynamics). This focus assumes that attainment of objectives specified here is indicative of good long-term performance. In contrast, if the focus of the analysis was on the long term performance of the objectives themselves (e.g., finding the best escapement goal), then a multi-year simulation approach with embedded population dynamics would be necessary. This type of approach would allow for management mistakes or successes in any given year to propagate to future years which, while potentially interesting, was beyond the scope of our study.

The primary characteristic that sets our analysis apart from other salmon MSE analyses is that it focused on in-season decision rules for subsistence fisheries, which behave quite differently than commercial fisheries such as the ones modeled by Carney and Adkison (2014a) and Carney and Adkison (2014b). As a result, we were able to assess strategies that exploit the characteristics of subsistence fisheries: namely declining effort with attainment of harvest needs and the self-limiting nature resulting from processing capacity. To our knowledge, strategies that acknowledge these characteristics have not been assessed using stochastic methods such as the one we used, making this work a novel contribution to the body of knowledge regarding in-season salmon management. Managers and stakeholders in the region may find the results informative as an objective evaluation of management strategy performance – a key point of interest here will be that there are several suitable strategies that could be implemented. At the very least it should serve to illustrate the concepts of how the in-season component could be modeled should a more-engaged participatory strategy evaluation process aimed at long-term performance is desired in the future.

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Table 1: Species ratio trigger point cut-offs used in Strategy #3. $\phi_{p,w-1}$ is the percentile of the average daily species ratio detected in the previous week at the simulated test fishery site when taken in context of all historical species ratios for week $w - 1$. Different substrategies are shown in the three columns: different thresholds that indicate when the manager should switch from using different schedules (as shown in Figure 1). For example, the neutral version of Strategy #3 would employ the conservative schedules following the pre-season forecast as shown in Figure 1 until the species ratio exceeds the 33% percentile of all historically observed ratios.

	Species Ratio Thresholds for Substrategies of #3		
Schedule	**Conservative**	**Neutral**	**Aggressive**
Conservative	$\phi_{p,w-1} \leqslant 66\%$	$\phi_{p,w-1} \leqslant 33\%$	$\phi_{p,w-1} \leqslant 15\%$
Neutral	$66\% < \phi_{p,w-1} \leqslant 85\%$	$33\% < \phi_{p,w-1} \leqslant 66\%$	$15\% < \phi_{p,w-1} \leqslant 33\%$
Aggressive	$\phi_{p,w-1} > 85\%$	$\phi_{p,w-1} > 66\%$	$\phi_{p,w-1} > 33\%$

Table 2: Specific species ratio trigger points used in assessed Strategy #3 when selecting which schedule type (Figure 1) to employ. For example, a manager in week 3 using the conservative substrategy would use the conservative schedule unless the average species ratio last week was above 1.4, at which point they would switch to the neutral schedule. Date ranges belonging to each week are shown in Figure 1. These trigger points were obtained from the cut-off rules shown in Table 1.

	Week				
Ratio Trigger Substrategy	**1**	**2**	**3**	**4**	**5**
Trigger Switch from Conservative to Neutral Schedules					
Conservative	0.7	2.4	1.4	4.6	17.1
Neutral	0.2	0.7	0.4	2.6	11
Aggressive	0.1	0.1	0	1.3	9.1
Trigger Switch from Neutral to Aggressive Schedules					
Conservative	1.2	3.1	1.8	6.5	26.2
Neutral	0.7	2.4	1.4	4.6	17.1
Aggressive	0.2	0.7	0.4	2.6	11

Table 3: Example values of the modified Schutz coefficient (z''; Section 2.5.2) used as the utility function for the objectives dealing with evenness of exploitation rates and harvest equity. Examples are in decreasing order of equity, with the top rows representing more equitable/even cases than those at the bottom of the table. When used for evenness of exploitation rates, the x_{Region} represent substock-specific exploitation rates (U_s). When used to measure equity, the x_{Region} represent the fraction of needed Chinook salmon harvested by villages within reaches located in each region.

x_{Lower}	x_{Middle}	x_{Upper}	z''
100%	100%	100%	**1**
10%	10%	10%	**1**
40%	40%	50%	**0.92**
40%	40%	70%	**0.8**
30%	30%	90%	**0.6**
15%	30%	90%	**0.5**
0%	10%	90%	**0.15**
0%	0%	10%	**0**

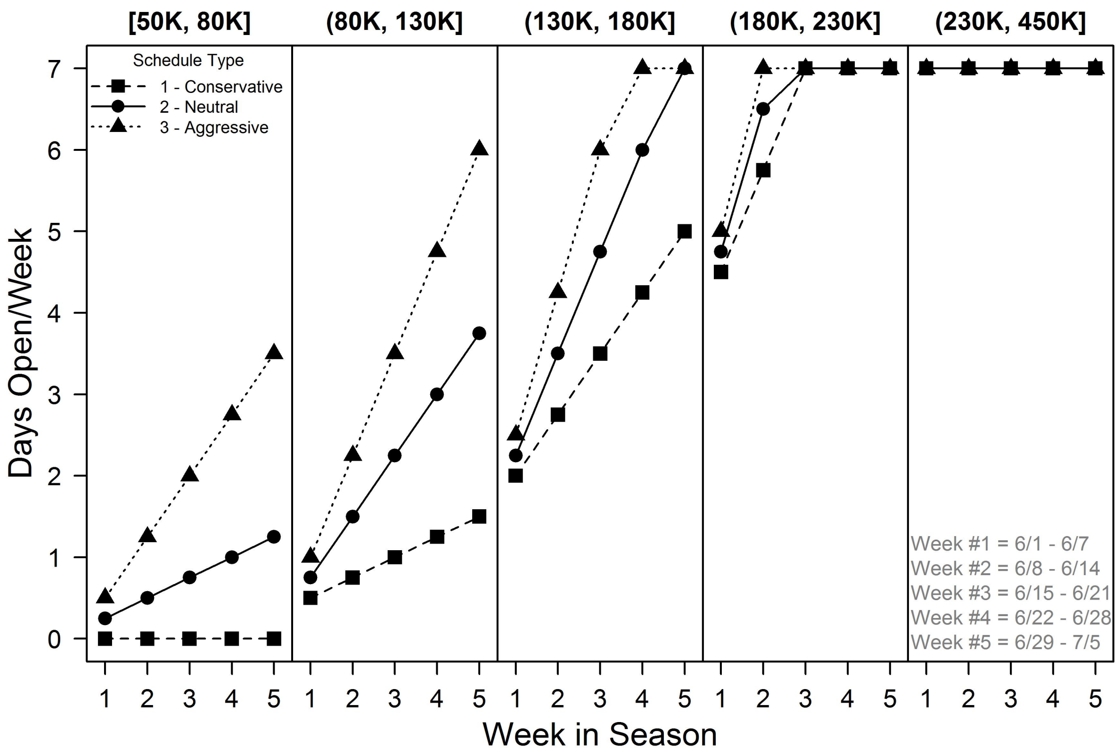

Figure 1: Representation of the harvest control rule in assessed Strategies #2 and #3. The number of days the fishery is to be opened per week is a function of the pre-season forecast, as shown by each of the five panels. The three lines in each panel represent the different substrategies of Strategy #2 or schedule types for Strategy #3. In Strategy #3, the manager would select to be conservative, neutral, or aggressive based on the percentile of recently-observed species ratios, as indicated in Table 1. In other words, the manager using Strategy #3 could adapt fishing schedules to in-season conditions, where as the #2 manager could not.

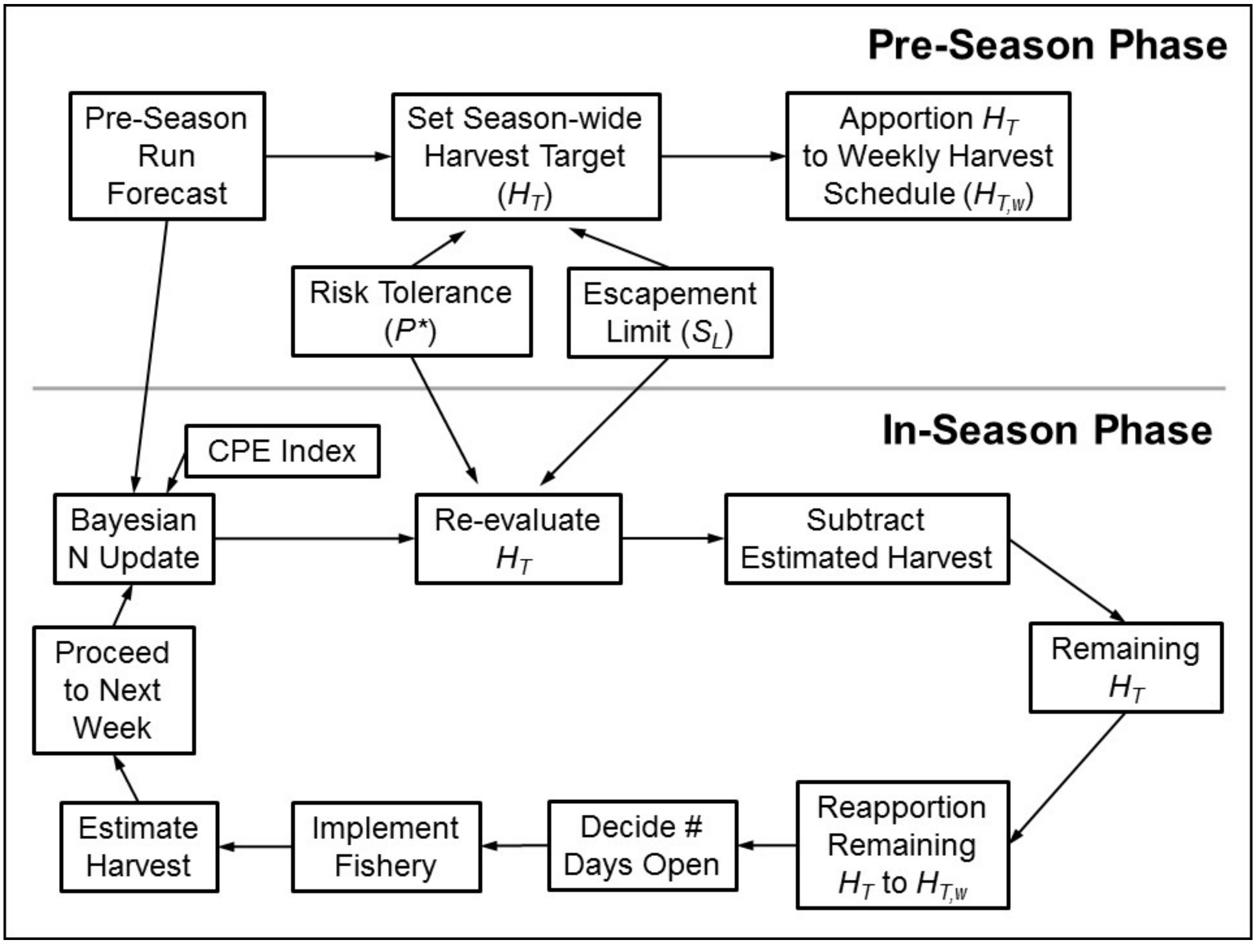

Figure 2: Depiction of the use of information to guide decision-making in assessed Strategy #4, partitioned into pre-season and in-season phases. All actions are taken with regards to Chinook salmon. **Pre-season actions** occur only once per season, and involve producing a pre-season forecast (with error) and using it to set a season-wide harvest target (H_T) based on (a) the probability distribution representing uncertainty in the pre-season forecast, (b) a limit point that escapement cannot fall below (S_L), and (c) the maximal acceptable probability for seeing the outcome $S < S_L$ (P^*). Targeted harvest by week ($H_{T,w}$) is initially set by apportioning the total among weeks according to a fixed schedule based on historical run timing data. **In-season actions** are represented by a weekly cycle that involves updating perceptions of abundance and adapting the season-wide harvest target H_T as appropriate to ensure the current posterior probability of attaining at least S_L given H_T still conforms with P^*, and the remaining allowable harvest for the season is obtained *via* subtracting cumulative estimated harvest already taken. Remaining harvest is then apportioned to the remaining weeks, and based on the value of $H_{T,w}$, the fishery will be opened for between 0 and 7 days for the week according to the harvest tables displayed in Figure 3. Harvest outcomes are monitored such that a weekly harvest estimate is available for use in the next week, which begins with obtaining a new posterior understanding of total run abundance.

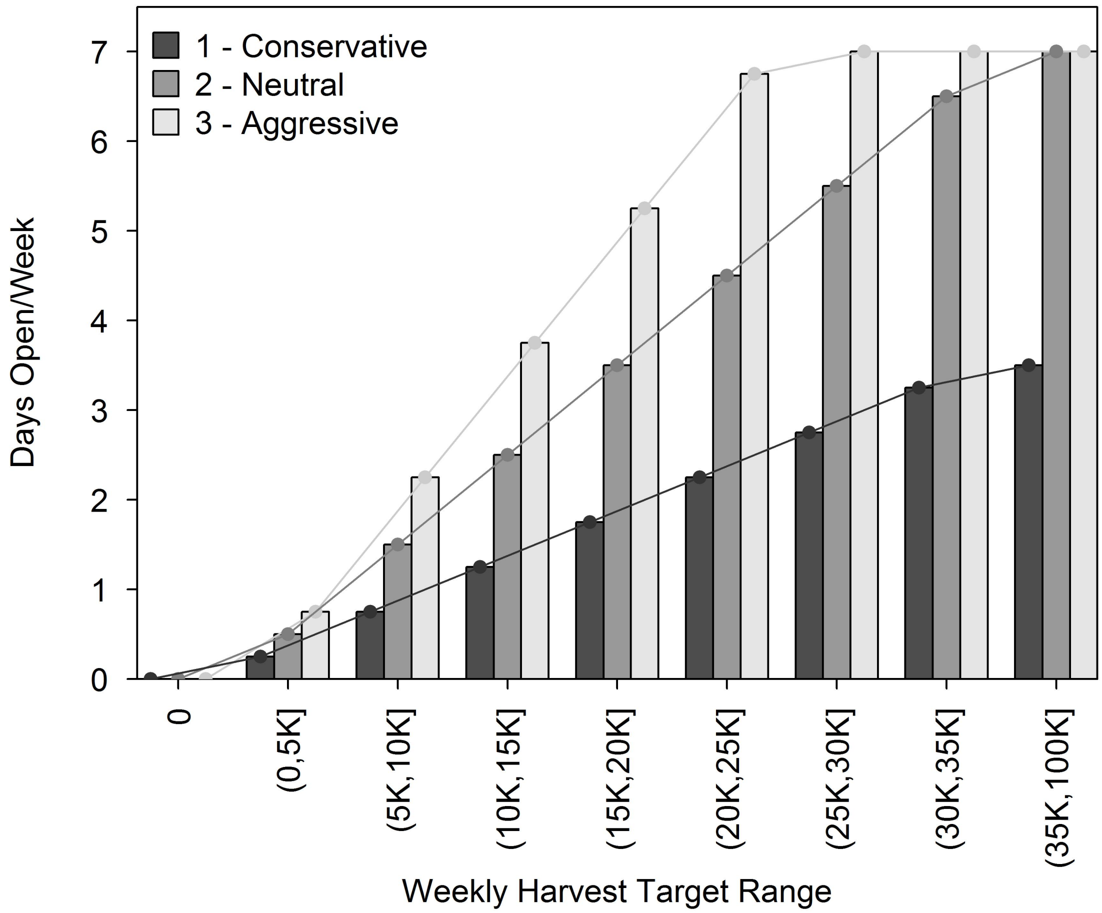

Figure 3: Representation of the "harvest tables" used in assessed Strategy #4. Based on how many fish are targeted each particular week ($H_{T,w}$), the manager would select the number of days to open the fishery. The process to obtain $H_{T,w}$ was rather involved, requiring pre-season forecasts, in-season abundance index data, and in-season harvest data to inform its value, as shown in Figure 2.

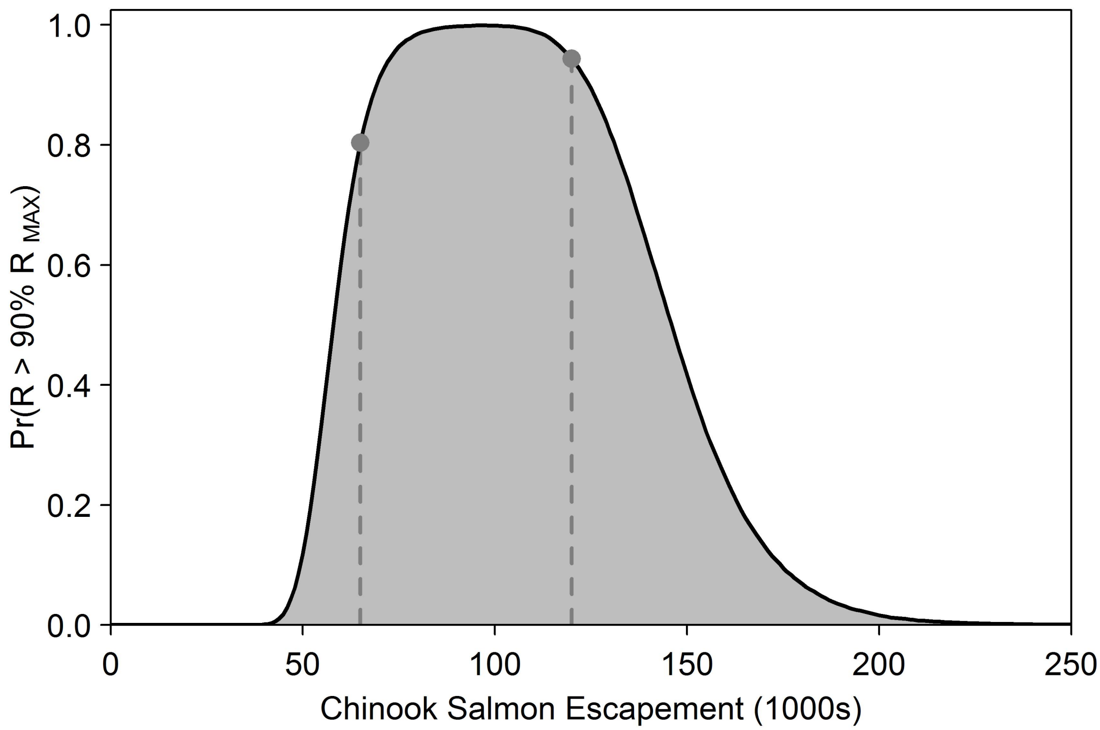

Figure 4: Estimated probability profile for Kuskokwim River Chinook salmon used as the utility function for drainage-wide escapement in this analysis. The height of the curve represents the currently understood probability that expected recruitment produced by a given escapement level will exceed 90% of R_{MAX}, and was obtained for the aggregate Chinook salmon stock using the Bayesian state-space estimation model presented in Hamazaki et al. (2012) updated with abundance, harvest, and age composition data through 2017. The vertical dashed lines are the endpoints of the current escapement goal range: 65,000 – 120,000.

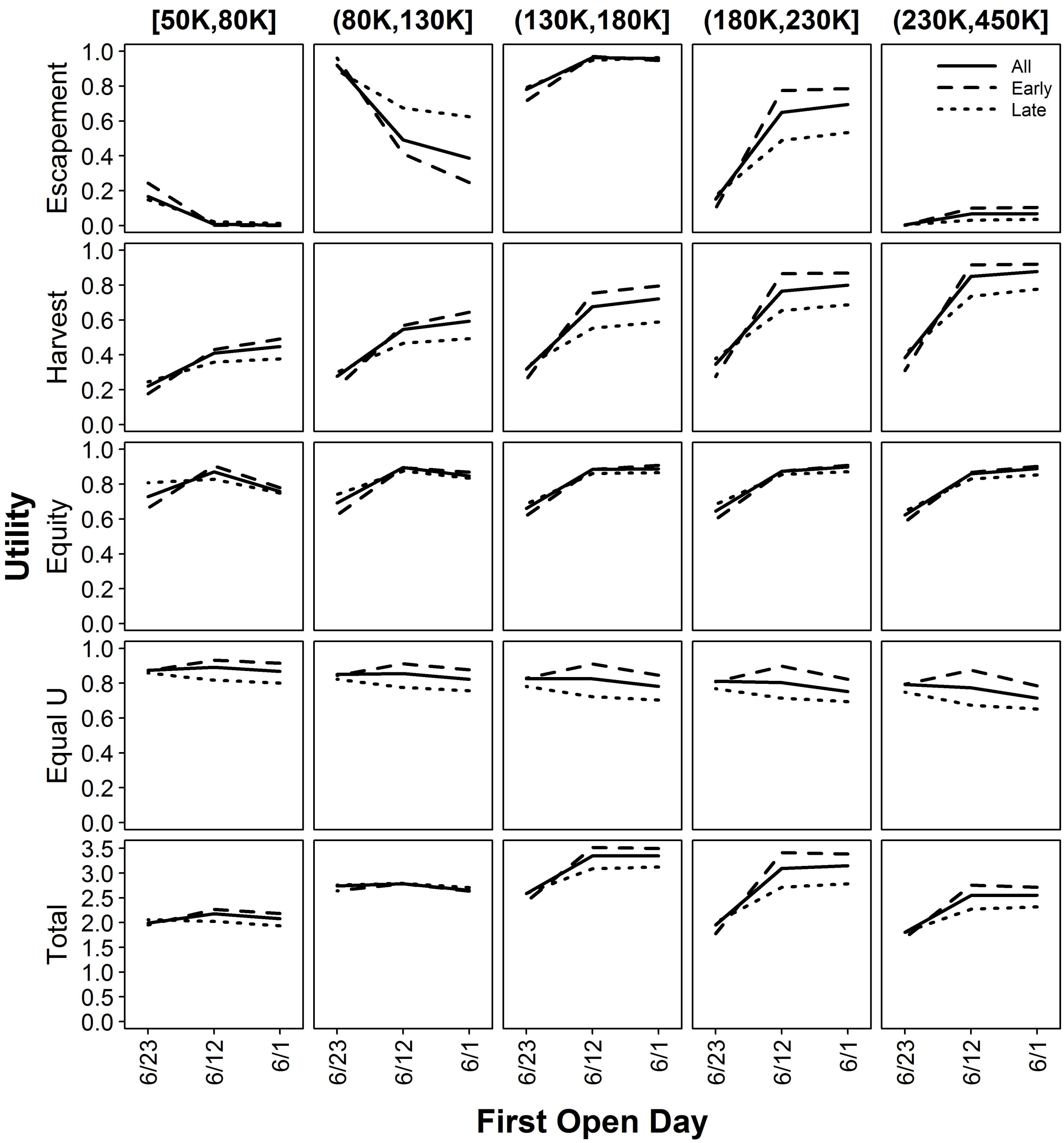

Figure 5: Detailed performance of assessed Strategy #1. Values of the utility functions (rows) separated by run size category (horizontal panels), run timing category (line type), and substrategy (x-axis, ordered from most conservative to aggressive). Substrategies of this policy differ in the date at which the fishery is opened completely. The form of each utility function is described in Section 2.5, and the total metric shown uses the default weighting scheme (all objective weights equal to 1).

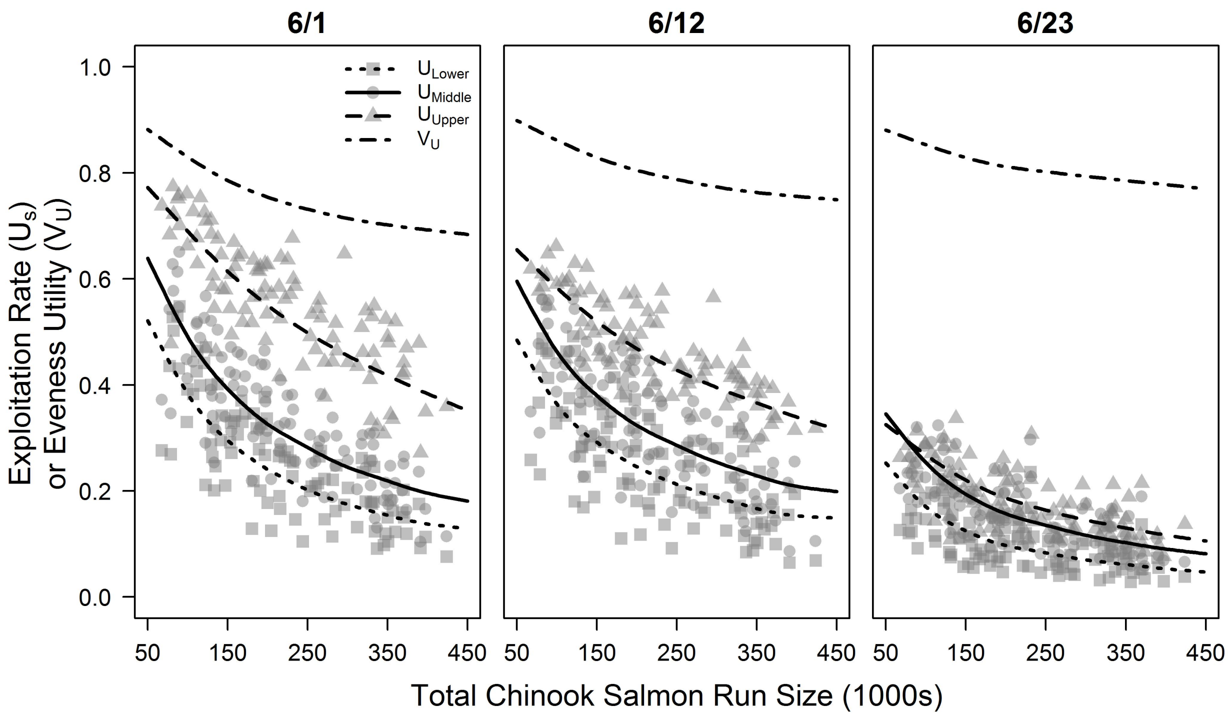

Figure 6: Chinook salmon substock-specific exploitation rates as a function of run size from 500 Monte Carlo trials, separated by different substrategies (i.e., opening dates) of assessed Strategy #1. Lines are fitted generalized additive models. The line denoted by V_U represents the model fitted to the utility metric as defined by the modified Schutz coefficient used (points not shown).

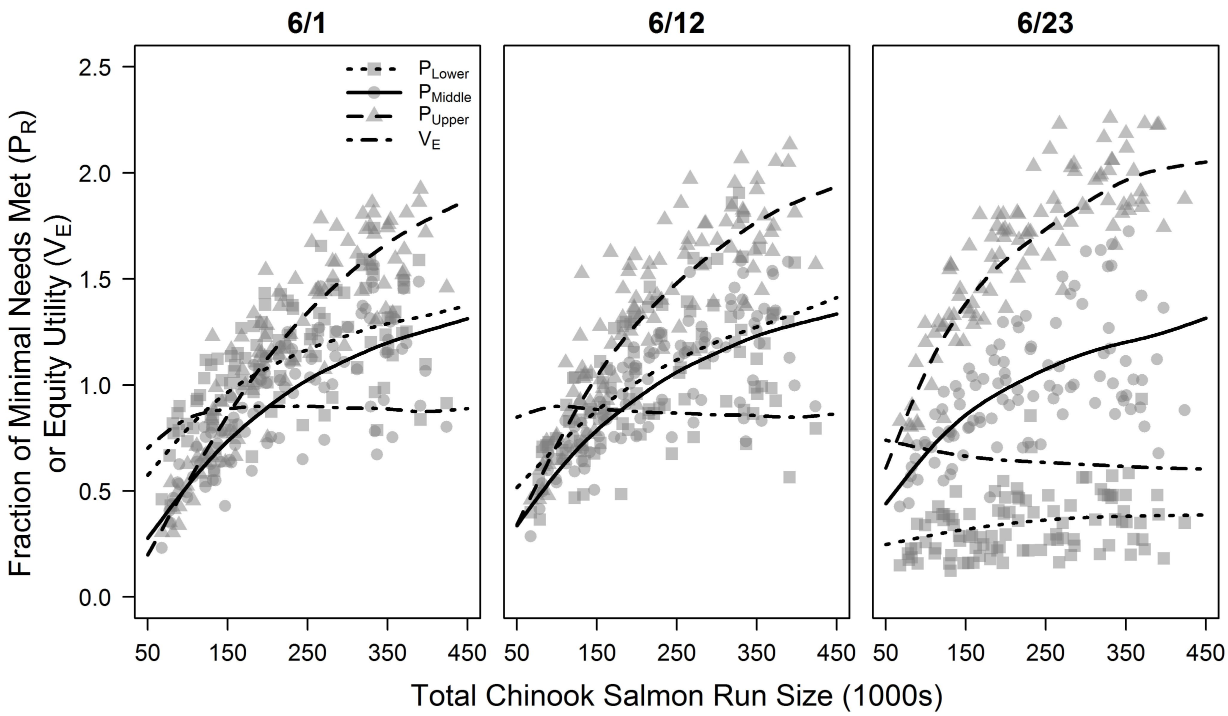

Figure 7: The fraction of minimal Chinook salmon harvest attained by villages in the lower, middle, and upper regions of the simulated Kuskokwim River as a function of run size from 500 Monte Carlo trials, separated by different substrategies (i.e., opening dates) of assessed Strategy #1. Lines are fitted generalized additive models. The line denoted by V_E represents the model fitted to the utility metric as defined by the modified Schutz coefficient used (points not shown).

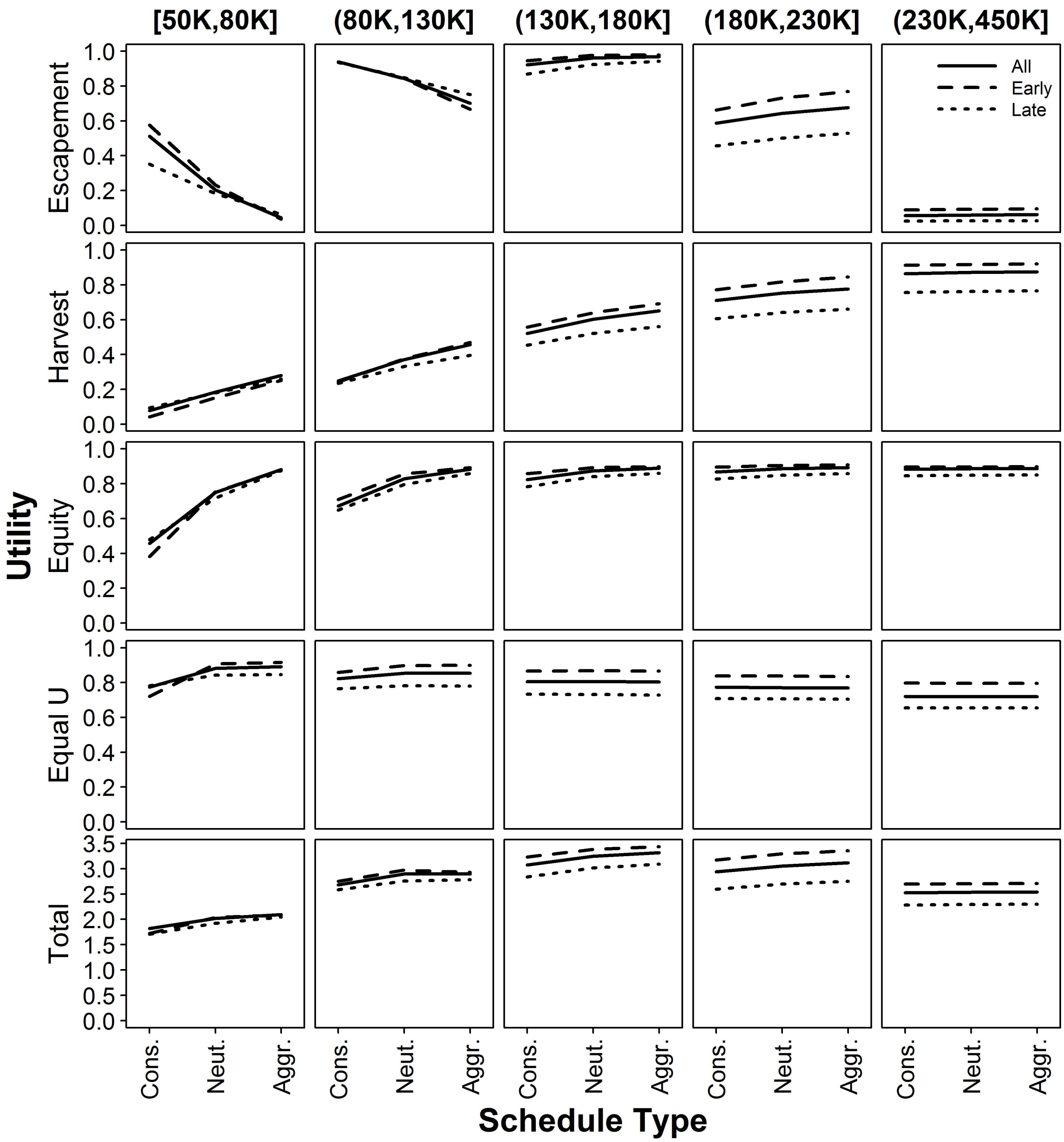

Figure 8: Detailed performance of assessed Strategy #2. The layout of panels in this figure is the same as in Figure 5, only substrategies represent di˙erent schedules conditional on a pre-season run size forecast (schedules shown in Figure 1).

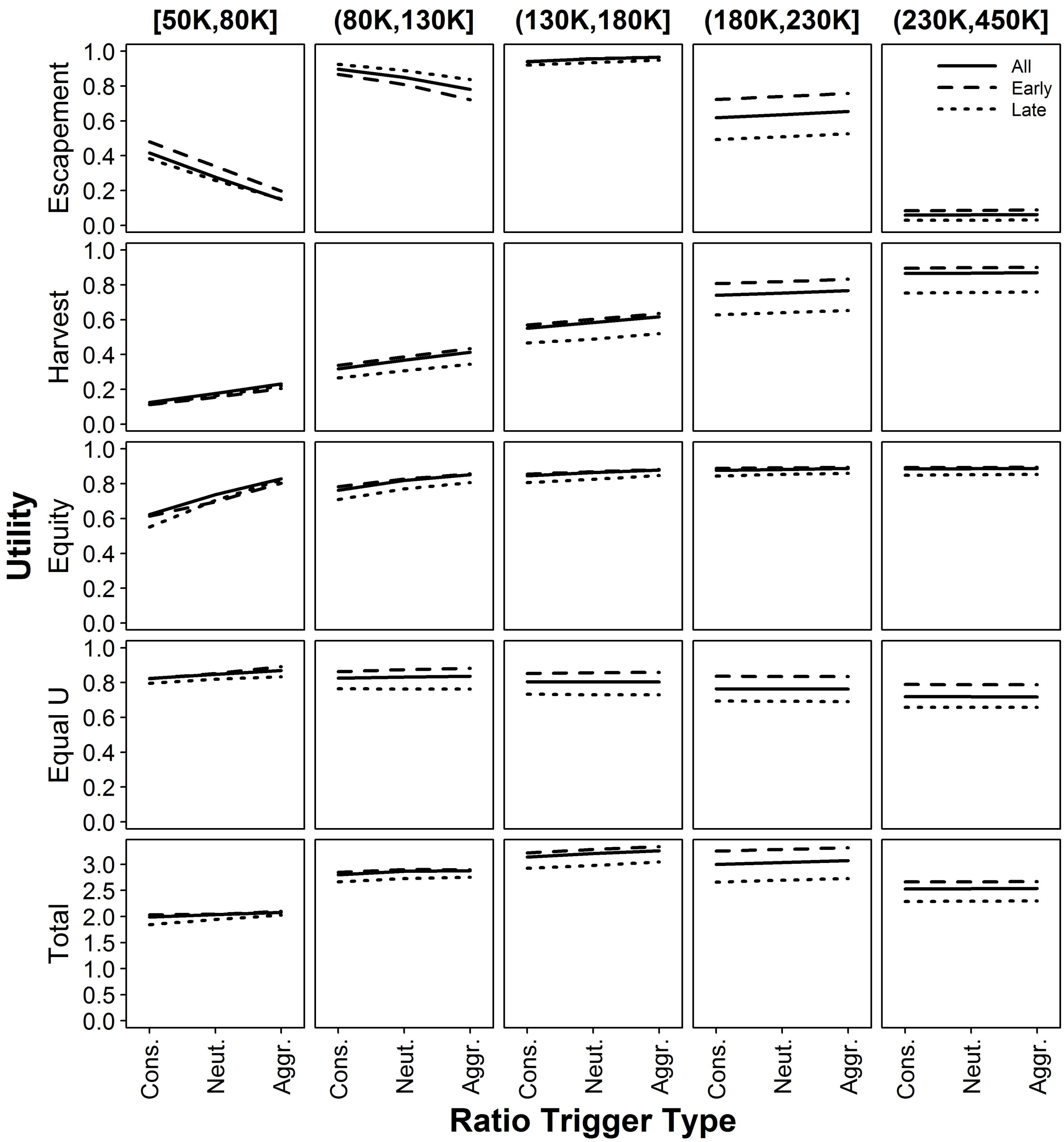

Figure 9: Detailed performance of assessed Strategy #3. The layout of panels in this figure is the same as in Figure 5, only substrategies represent di˙erent species ratios cut-o˙s used to pick fishing schedules conditional on a pre-season run size forecast (schedules shown in Figure 1, ratio thresholds shown in Table 2).

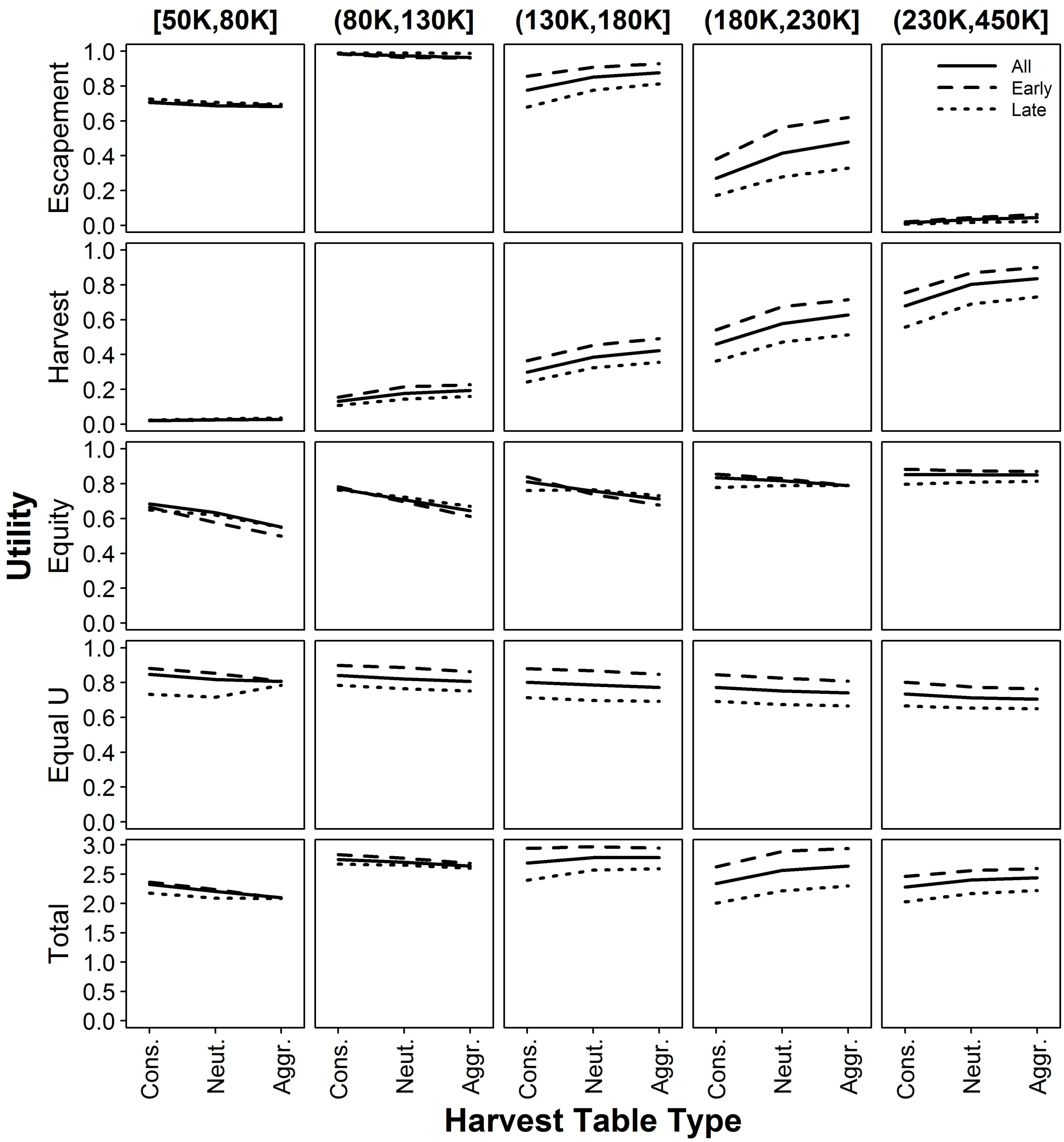

Figure 10: Detailed performance of assessed Strategy #4. The layout of panels in this figure is the same as in Figure 5, only substrategies represent di˙erent harvest tables used to set the number of days of open fishing per week based on how many fish are targeted to be harvested that week (harvest tables shown in Figure 3).

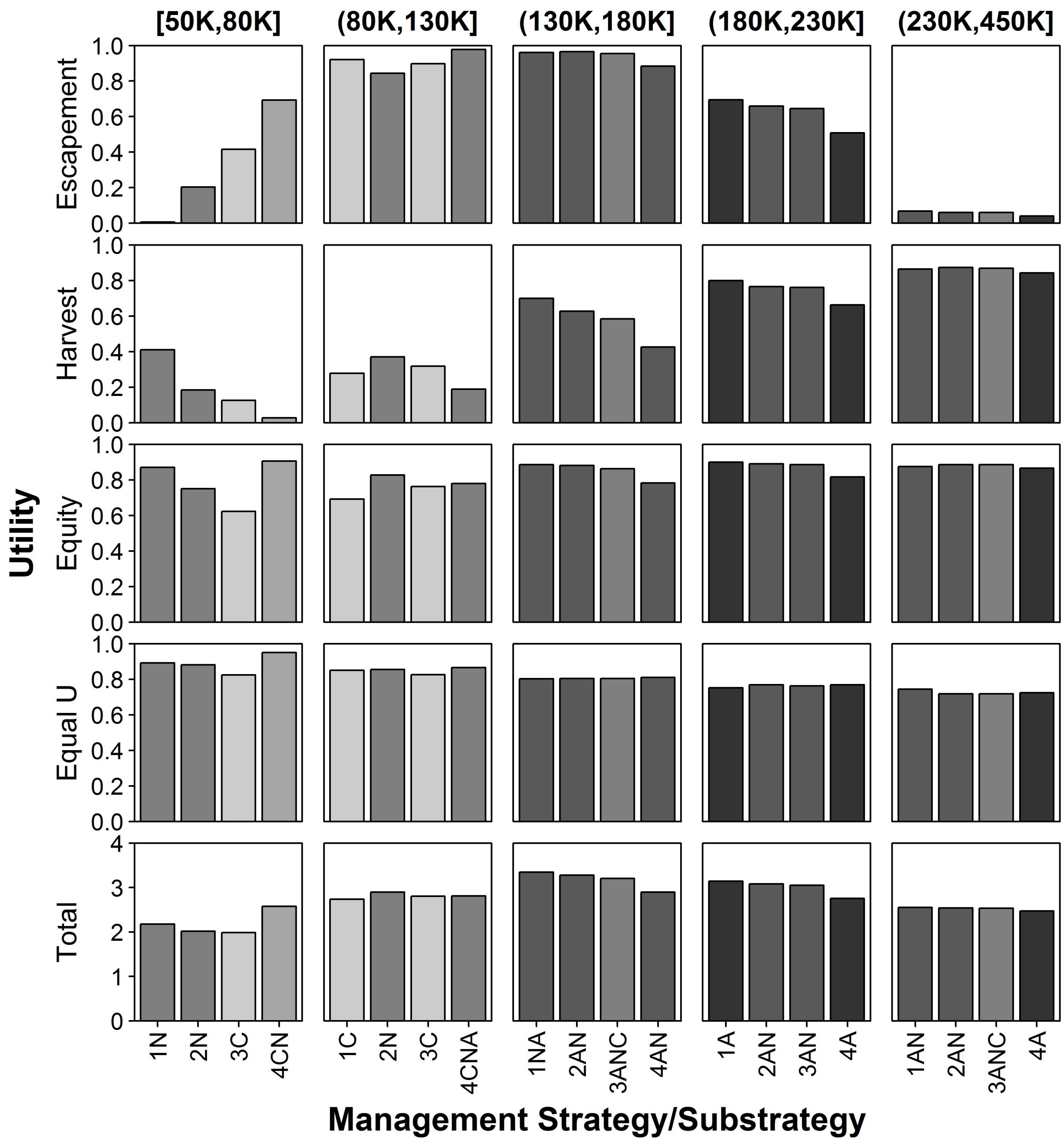

Figure 11: Comparison of utility according to the different metrics between strategies (with the best substrategy selected for comparison) and run sizes. Numbers represent the strategy, letters and colors indicate the selected substrategy (darker colors represent more aggressive substrategies; C = conservative, N = neutral, A = aggressive; multiple letters indicate a tie). Total utility was calculated according to the default weighting scheme, where all objectives received equal weight.

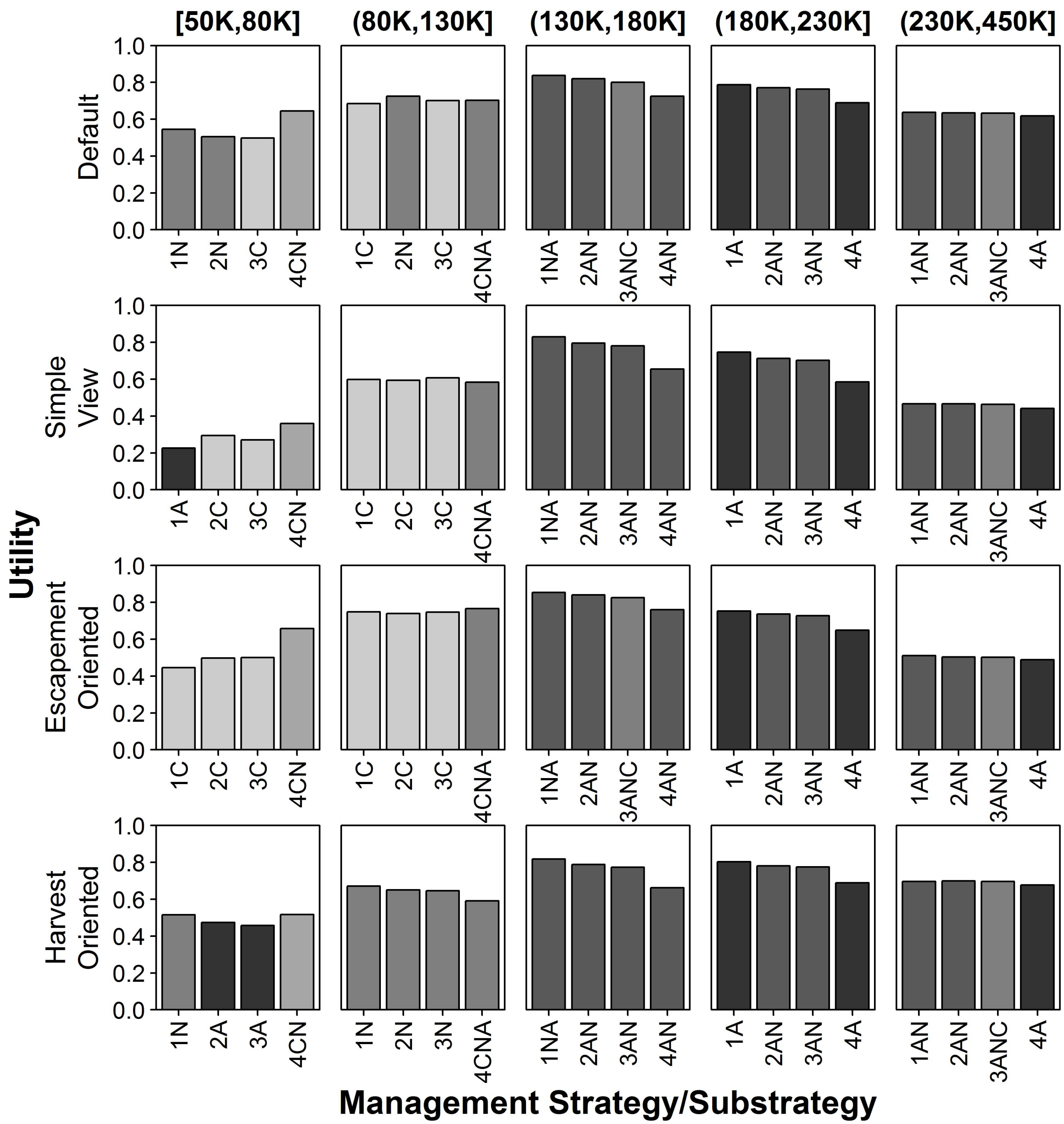

Figure 12: The total utility metric of the best-performing substrategy (letters/colors) for each strategy (numbers), when considering different weighting schemes (schemes described in Section 2.7.3). Bars are shaded based on the best substrategy, with darker greys representing more aggressive substrategies (C = conservative, N = neutral, A = aggressive; multiple letters indicate a tie). Total utility was scaled to the maximum attainable total utility for each weighting scheme, which is equal to the sum of the weights.

APPENDIX B

Parameterization of the In-season Operating Model for Kuskokwim River Chinook Salmon

There were two main components of the operating model that needed to be parameterized based on observed information for it to adequately represent the dynamics of the real Kuskokwim River subsistence salmon fishery: biological (abundance, timing, spatial characteristics of the salmon populations, etc.) and sociological (spatial distribution of effort and desired/needed harvest and temporal aspects of the effort dynamics). This appendix describes how empirical information collected in the Kuskokwim River drainage was used to parameterize the in-season operating model described in Appendix A.

1 Biological quantities

1.1 Chinook salmon total abundance

Drainage-wide total Chinook salmon run abundance was informed by Liller et al. (2018), which reported estimates in the years 1976 – 2017 from a maximum likelihood run reconstruction model. The model was fitted to 20 escapement indices, commercial fishery catch-per-unit-e˙ort, and nine years of drainage-wide estimates of total abundance obtained *via* large-scale mark-recapture experiments. Based on Liller et al. (2018), drainage-wide Chinook salmon abundance has varied between 79,238 (in 2012) and 411,724 (in 1994), with a mean of 216,929 and standard deviation of 87,556. A kernel density estimator was fitted to this distribution, and the cumulative density function was obtained to allow sampling of continuous run sizes in accordance with the historical frequency of run sizes (Figure 1). The distribution was truncated at the smallest and largest runs on record as of 2017 $\pm$ 30,000 fish.

1.2 Chinook salmon substock composition

Substock composition, or the fraction of the aggregate Chinook salmon run that was made up of fish from each substock, was informed by the proportions of telemetry fish that spawned in each region in the years 2015 and 2016 (Smith and Liller 2017a,b). Although telemetry data from 2003 – 2007 were also available, only these years were used because: (1) they allowed the incorporation of information from lower river fish (as a result of the tagging location; see Section 1.3.2) and (2) the management of the fishery resulted in less selection of upper river substocks in the harvest because fishing was pushed later in the season than in the 2003 – 2007 block of years.

In each run of the operating model, a random Dirichlet vector was drawn with parameter vector equal to [lower = 19, middle = 61, upper = 20], which results in an expectation roughly equal to the average contribution in 2015 and 2016. The use of a Dirichlet distribution with these parameters generated a modest amount of variability around the expected substock composition.

1.3 Chinook salmon run timing

1.3.1 Aggregate timing

Run timing information for the aggregate Chinook salmon stock was available from the Bethel Test Fishery (Bue and Lipka 2016), which has produced a daily value of catch-per-unit-effort for each day between June 1 and August 24 for the years 1984 – 2018. The estimates of location (D_{50}) and inverse scale (h) of a logistic function shown in Table 1 were used to quantify the timing with which the simulated aggregate Chinook salmon stock runs through the lower river.

1.3.2 Substock-specific timing

The timing of the specific Chinook salmon substocks (i.e., those spawning in lower, middle, and upper river tributaries) were informed by radio telemetry studies (Stuby 2007; Smith and Liller 2017a,b). The tag date and final tributary of each fish was available for the years 2003 – 2007 and 2015 – 2016. In the first block of years, the tagging site was located near Kalskag, which excluded any fish spawning in lower river tributaries. In the second block of years, the tag site was moved near the Johnson River, which allowed the inclusion of fish spawning in the lower river tributaries. Logistic models (2.1) were fitted to the data from each substock and year separately to obtain estimates of the D_{50} for each substock in each year data were available, and differences in D_{50} for the middle river substocks and each of the other substocks were calculated (Table 1). For parameterizing the run timing of middle river substocks, random values drawn from the aggregate population estimates were used, and random uniform deviations for the lower river and upper river D_{50} were used in accordance with the deviations shown in Table 1 (i.e., lower river substocks had a D_{50} value that was anywhere between 0 and 3 days later than that of the middle river, and upper river substocks had a value that was between 5 and 10 days earlier than middle river substocks.

1.4 Spatial distribution of escapement

Due to the spatial nature of the operating model, it was important to capture the behavior of fish becoming invulnerable to harvest by swimming up a spawning tributary. This aspect was informed using data from the telemetry studies: it was possible to quantify the fraction of all tagged fish that made it to a particular reach that ultimately spawned in a tributary with a confluence in that reach in each year. These fractions were averaged across years and the average was used to dictate how many fish from each substock s in reach r on day d would "peel off" from the mainstem into a tributary in that reach on that day. For the aggregate chum/sockeye stock, which does not have this kind of information, the substock structure was removed. These estimates are shown in Table 2.

1.5 Species ratios

Because chum and sockeye salmon lack the abundance data available for Chinook salmon, their daily entry dynamics were modeled using observed species ratios from the Bethel Test Fishery. These data were prepared by taking the catch-per-unit-effort of chum salmon plus sockeye salmon, and dividing it by the catch-per-unit-effort of Chinook salmon on each day of each year for which data were available. This represents how many vulnerable chum/sockeye salmon were available for harvest relative to Chinook salmon. Daily values that could not be calculated (i.e., when zero Chinook salmon were caught) were populated with the average value for all years for which a species ratio could be calculated on that same day. These annual time series were highly variable from day to day, likely as a result of sampling variability, so a cubic spline smoother was fitted to remove this variability. The time series of smoothed ratios from all years is shown in Figure 2.

In each simulated year, one randomly sampled annual time series was selected to generate the daily species composition for that year. To avoid anomalous outcomes, i.e., unlikely combinations of Chinook run timing and abundance matched with very high or low species ratios in the simulation. We investigated two historical variables for covariance with the species ratio: D_{50} and total Chinook salmon run size using a χ^2 test for independence. For each historical year, run timing, run size, and the first date at which a species ratio of 15:1 was observed were categorized into three bins, with endpoints delineated by the 33% and 66%

percentiles of each variable. We were interested in whether Chinook salmon runs with different run timing or size tended to coincide with attaining high species ratios earlier or later in the season. If these sorts of patterns were present, they would need to be accounted for in the simulation.

The first date of 15:1 ratios and Chinook salmon run timing had more non-independence ($\chi^2 = 11, df = 4, p = 0.027$) than Chinook salmon run size ($\chi^2 = 1.84, df = 4, p = 0.765$). This indicated that species ratios could be drawn independently with regards to the simulated Chinook salmon run size, but not the simulated run timing. As shown in Table 3, the probability of having early high ratios has been historically highest in early Chinook runs. Late Chinook salmon runs tended to occur in years that had later dates of 15:1. We incorporated these patterns in the simulation by first sampling the run timing for that simulated year, then assigning it to a category, then sampling a ratio category with probability equal to the appropriate column in Table 3. Finally, a year was randomly selected from the approximately 10 years in that same category, and the daily species ratios that year were used to drive the species composition time series in that simulated year.

2 Sociological quantities

2.1 Needed salmon harvest by river reach

The term "minimally needed salmon harvest" salmon harvest refers to the amount of salmon that would satisfy the very basics of the subsistence needs of fishers in the drainage – without meeting this level it is reasonable to assume the fishing population is experiencing hardship. "Maximally needed salmon harvest" represents the salmon harvest that would completely meet subsistence needs (i.e., if as many fish could be harvested as desired). The Alaska Board of Fisheries has produced ranges for each species, termed the "Amounts Reasonably Necessary for Subsistence" (ANS) and represents the drainage-wide range of harvest by species needed to sustain subsistence fishers each year. These ANS ranges are 67,200 – 109,800 for Chinook salmon and 73,400 – 175,100 for chum+sockeye salmon. In this analysis, the lower bound of the ANS range was used to specify minimally needed salmon harvest by species, and the upper bound of the range was used to specify maximally needed salmon harvests. Maximally needed amounts were used to drive the dynamics of the effort model and the midpoint between the minimal and maximal needs was used to measure the attainment of management objectives.

However, these values are only available for the entire drainage – they are not partitioned to individual villages. For this analysis, a minimal and maximal value was needed for the villages located within each reach. The drainage-wide totals were thus partitioned by calculating the average fraction that villages in each reach have harvested of the drainage-wide. Hamazaki (2011) present year-, species- and village-specific salmon harvests for the period (1990 – 2009), and data through 2015 can be found in Carroll and Hamazaki (2012), Shelden et al. (2014), Shelden et al. (2015), Shelden et al. (2016a), and Shelden et al. (2016b). Only years 1990 – 2000 were included for the spatial distribution of salmon need because stakeholders provided input during meetings that indicated the restrictions in recent years make the harvest proportions non-representative and that the earlier years are more reflective of how harvest should be distributed. The partitioned values by species are shown in Table 4.

2.2 Maximum daily effort by river reach

A key aspect of the sociological component to the operating model was the spatial distribution of maximum fishing effort, i.e., the greatest number of boat days that can be exerted by villages in each reach when the fishery is open. This maximum effort was altered as the simulated salmon season progressed based on the effort response submodel. The important characteristic to capture is the proportion of all effort that is attributable to each reach, i.e., the scale is not important as the efficiency of any one unit can be adjusted by altering the q parameter. To determine how effort should be apportioned to each reach, a simple index of effort for each village and year was devised based on the number of reported fishing households. The Alaska Department of Fish and Game has collected this information since 1990, and it is presented in the same studies that quantified subsistence harvest patterns: Hamazaki (2011), Carroll and Hamazaki (2012), Shelden et al. (2014), Shelden et al. (2015), Shelden et al. (2016a), and Shelden et al. (2016b). The data were reported as the number of households that "usually fish" and the number of households that "do not usually fish" as surveyed each year (as well as the number of "unknown" fishing status households). First, any unknown households were apportioned to the other two categories by assuming the information was missing at random: if 60% of the fishing households belonged to the "usually fishes" category in a village in a year, then 60% of the unknown households were apportioned to "usually fishes" and 40% to "does not usually fish". The effort index was calculated for each village as $1 \times \#$ usually $+ 0.5 \times \#$ not usually, summed the values across villages within each reach and year, calculated the annual proportion belonging in each reach, and averaged these values across years.

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Table 1: Difference between D_{50} for tagged fish destined for lower or upper river tributaries and those destined for middle river tributaries. These estimates were used to inform Chinook salmon substock-specific run timing.

Year	Lower	Upper
2003		-2.0
2004		-9.5
2005		-4.9
2006		-7.8
2007		-2.5
2015	-0.7	-10.7
2016	2	-9.8

Table 2: Spatial distribution of escapement in the operating model. The number in each cell represents$\psi_{r,s}$: the fraction of fish from a stock that make it to a reach and survive the fishery that ultimately escape and spawn in a tributary with a confluence with the main stem Kuskokwim located in that reach. These estimates were obtained from radio telemetry studies as described in Section 1.4, and the chum/sockeye salmon estimates were obtained by removing the substock structure from the Chinook salmon data.

		Chinook Salmon			
Reach #	**Tributaries in Reach**	**Lower**	**Middle**	**Upper**	**Chum/Sockeye**
Lower River					
4	Kwethluk	65.3%	0%	0%	12.4%
5	Kasigluk, Kisaralik	80.1%	0%	0%	6%
6	Tuluksak	100%	0%	0%	1.7%
Middle River					
9	Aniak	0%	28.1%	0%	24.6%
10	Owhat	0%	0.5%	0%	0.4%
11	Holokuk, Sue Creek, Veahna	0%	3.7%	0%	3.4%
12	Oskawalik	0%	2.7%	0%	2.4%
13	Crooked Creek, George	0%	6%	0%	4.8%
15	Vreeland, Holitna	0%	77.3%	0%	64.6%
16	Stony	0%	32.8%	0%	25.8%
17	Swift, Tatlawiksuk	0%	100%	0%	55.9%
Upper River					
20	Selatna, Black	0%	0%	6%	6%
22	Takotna	0%	0%	17.5%	17.5%
24	Middle Fork	0%	0%	94%	94%
26	South Fork, East Fork	0%	0%	100%	100%

Table 3: Non-independence of historically-observed Chinook salmon run timing and the date at which the species ratio of 15:1 chum+sockeye:Chinook was obtained. Columns sum to 1 and represent the empirical probability of observing a ratio type in each of the three categories along the rows. Independence would have all cells equal to 33.3% – note that early high ratios tend to occur in years with early Chinook salmon runs, and *vice versa*.

	Chinook Salmon Run Timing		
Ratio Category	**Earliest 33%**	**Middle 33%**	**Latest 33%**
Earliest 33%	66.7%	11.1%	20%
Middle 33%	33.3%	44.4%	20%
Latest 33%	0%	44.4%	60%

Table 4: Key sociological quantities used in the operating model, broken down by spatial area (reach). Each reach is 35 km in main stem river length. Effort ($E_{\mathrm{MAX},r}$) is expressed as the maximum number of boats fishing per day in reach r. The % columns represent the average fraction of the total harvest by species that was harvested by villages within each reach over the period 1990 – 2000. Harvest values have been rounded to the nearest 100 for ease of presentation, but the total column represents the sum of non-rounded quantities. Although these data were available through 2015, region stakeholders indicated that the recent years have been contaminated by harvest restrictions, and that these earlier years would be more representative.

			Chinook Salmon			**Chum/Sockeye Salmon**		
Reach #	**Villages in Reach**	**Effort**	**%**	**Min.**	**Max.**	**%**	**Min.**	**Max.**
Lower River								
1	Tuntutuliak, Eek	42	7.6%	5,100	8,300	6.2%	4,600	10,900
2	Atmautluak, Kasigluk, Nunapitchuk	74	11%	7,400	12,000	13.6%	10,000	23,900
3	Napakiak, Napaskiak, Oscarville, Bethel	415	40.5%	27,200	44,500	34.1%	25,000	59,600
4	Kwethluk, Akiachak	74	17.2%	11,600	18,900	15.2%	11,200	26,600
5	Akiak	18	4.3%	2,900	4,800	4.9%	3,600	8,600
6	Tuluksak	21	3.9%	2,600	4,300	4.4%	3,300	7,800
Middle River								
8	Lower Kalskag, Upper Kalskag	33	5.1%	3,400	5,600	4.2%	3,100	7,400
9	Aniak	46	4.2%	2,800	4,600	4.6%	3,400	8,100
10	Chuathbaluk	9	1.3%	900	1,400	2.1%	1,600	3,700
13	Crooked Creek	9	1%	600	1,100	1.5%	1,100	2,600
14	Red Devil	6	0.3%	200	400	1.1%	800	2,000
15	Sleetmute	12	1.1%	800	1,200	2.1%	1,500	3,600
16	Lime Village, Stony River	10	0.7%	500	700	4%	3,000	7,000
Upper River								
22	McGrath, Nikolai, Takotna, Telida	42	1.7%	1,100	1,800	1.9%	1,400	3,300
Total		**800**	**100%**	**67,200**	**109,800**	**100%**	**73,400**	**175,100**

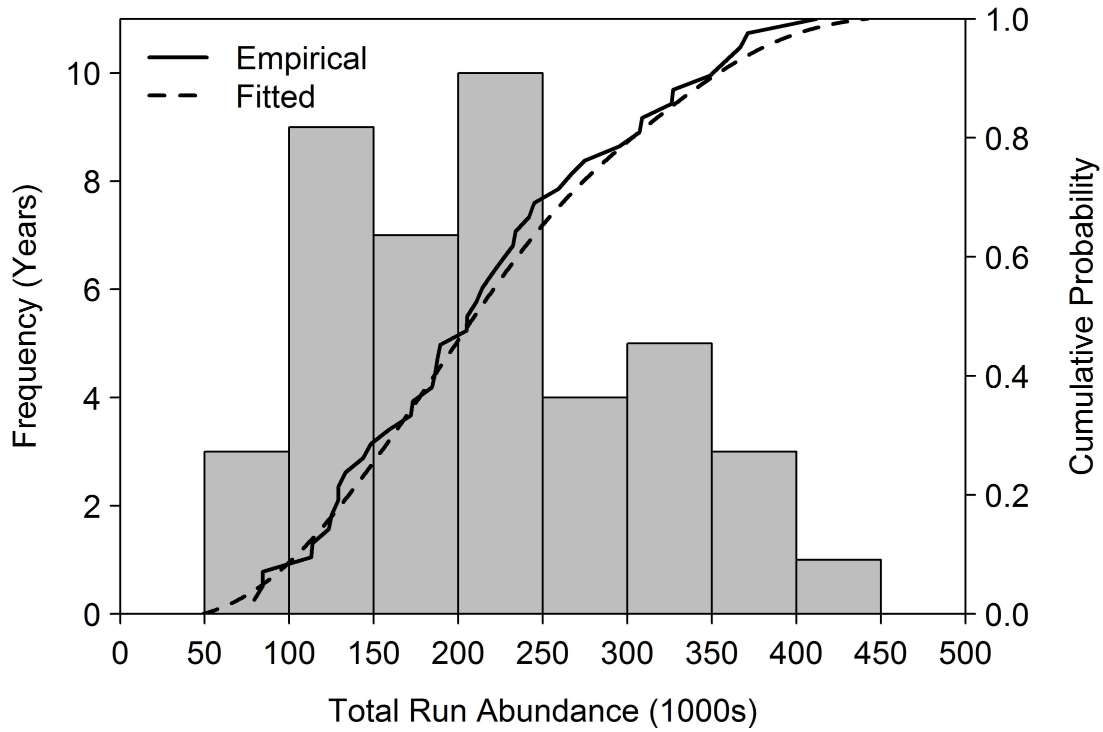

Figure 1: Distribution of total drainage-wide run size for Kuskokwim River Chinook salmon, as presented in Liller et al. (2018). This distribution was used to generate the run size of the aggregate Chinook salmon populations entering the fishery system in a simulated year. The secondary y-axis represents the probability of a run falling below a given run size according to the historical frequency of run sizes; where the solid line shows the empirical cumulative distribution function and the dashed line shows one obtained by fitting a kernel density smoother to the empirical data. The fitted distribution was used for simulation to prevent the same 42 run size values from being replicated in the analysis.

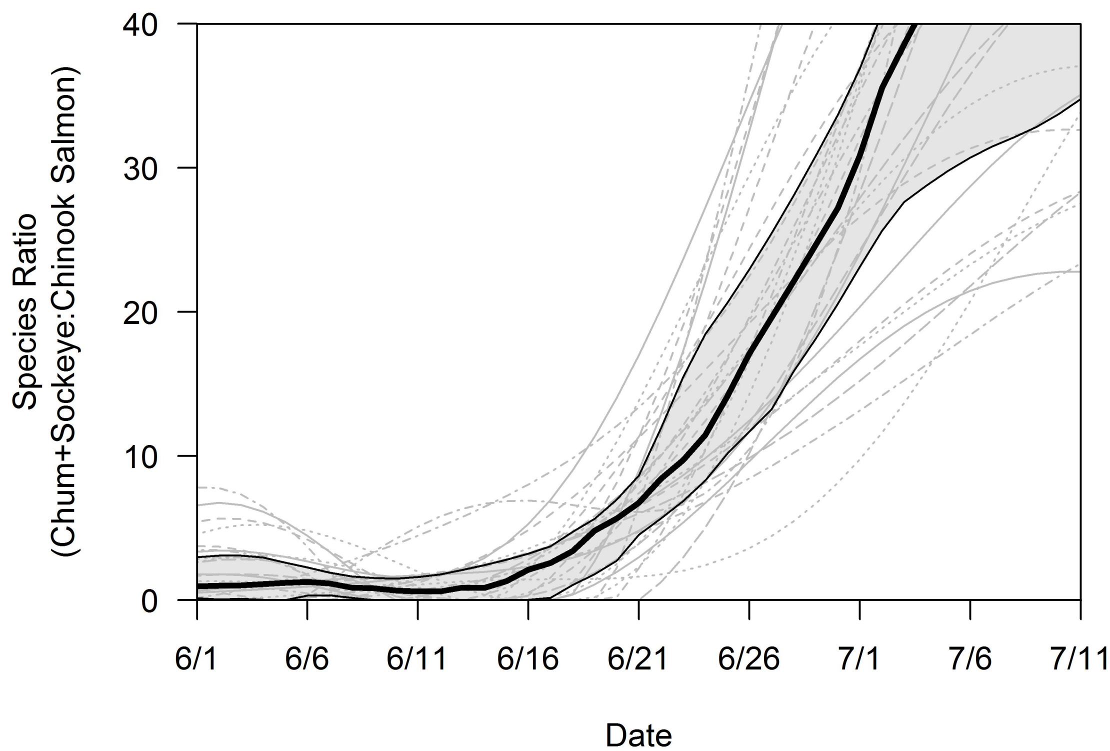

Figure 2: Smoothed species ratios of chum+sockeye:Chinook salmon as detected by the Bethel Test Fishery. Individual grey lines represent separate years from 1984 – 2017, the grey region represents the central 50% of all smoothed ratios on each day and the thick black line represents the daily median. Only this time period is shown because at ratios larger than 20, the differences in the influence of chum/sockeye salmon on Chinook salmon harvest by the subsistence fishery are negligable.

APPENDIX C

Validation of the In-season Operating Model for Kuskokwim River Chinook Salmon

For any simulation model used in the context of management strategy evaluation, the reliability of inferences drawn will be conditional on the ability of the model components to capture the important behavioral properties of the real system. Here, a brief validation is provided that the fishery component of the operating model did in fact provide a reasonable model of the real system when the fishery was unrestricted.

First, it is important that the model be able to replicate the relationship between total Chinook salmon run size and total subsistence salmon harvest. Capturing this pattern was important to ensure that the fishery would not inadvertently harvest an unrealistically large or small amount of fish in different run sizes than would typically occur, which would confound the inference regarding strategy performance. As shown in Figure 1, this historical relationship has been quite noisy for the observed historical time series, though an increasing pattern has emerged: in general, more fish have been harvested in years with large runs than years with small runs. It was found that by tuning the catchability (q) and effort response coeÿcients, this pattern could be reproduced quite well. Additionally, the scale and variability of modeled chum/sockeye harvests were also similar to the historically-observed distribution (Figure 2) – this was not key given chum/sockeye harvests did not inform any objectives, but the agreement contributes more evidence that the effort response model was adequately calibrated.

The next behavior of interest was the spatiotemporal distribution of harvest. Because in-river salmon fisheries are sequential, fish harvested in one area are invulnerable to harvest (and escapement) in upriver areas. It also means that communities in downriver communities may finish fishing earlier in the season because they are the first to experience favorable fishing conditions (i.e., high in-river abundance and resulting catch rates; in the Kuskokwim River drying weather also plays an important role). If the timing of harvest was not captured adequately, this would be an indication that the effort response coefficients were improperly tuned and could result in unrealistic conclusions. The patterns and variability in the day of the year at which various percentiles of Chinook salmon harvest was attained by reach compared between observed data and the modeled outcomes are shown in Figure 3. It seems that the patterns and variability in harvest timing were reasonably well-captured, particularly for downriver reaches. Reaches 14, 15, 16 and 22 seemed to have had the largest deviations between observed and modeled patterns, but given communities in these reaches harvest a negligible amount of Chinook salmon in comparison to the downriver villages (Figure 4), this finding is not concerning.

The final important characteristic was the spatial distribution of end-of-season harvest. Accurately representing this component of the system would further indicate model adequacy. Figure 4) shows a comparison of the proportion of total drainage-wide Chinook salmon subsistence harvest attributable to communities in each reach between observed and modeled outcomes. While the overall pattern was fully captured, there were moderate deviations between the model and observations in reaches 2, 3, and 4.

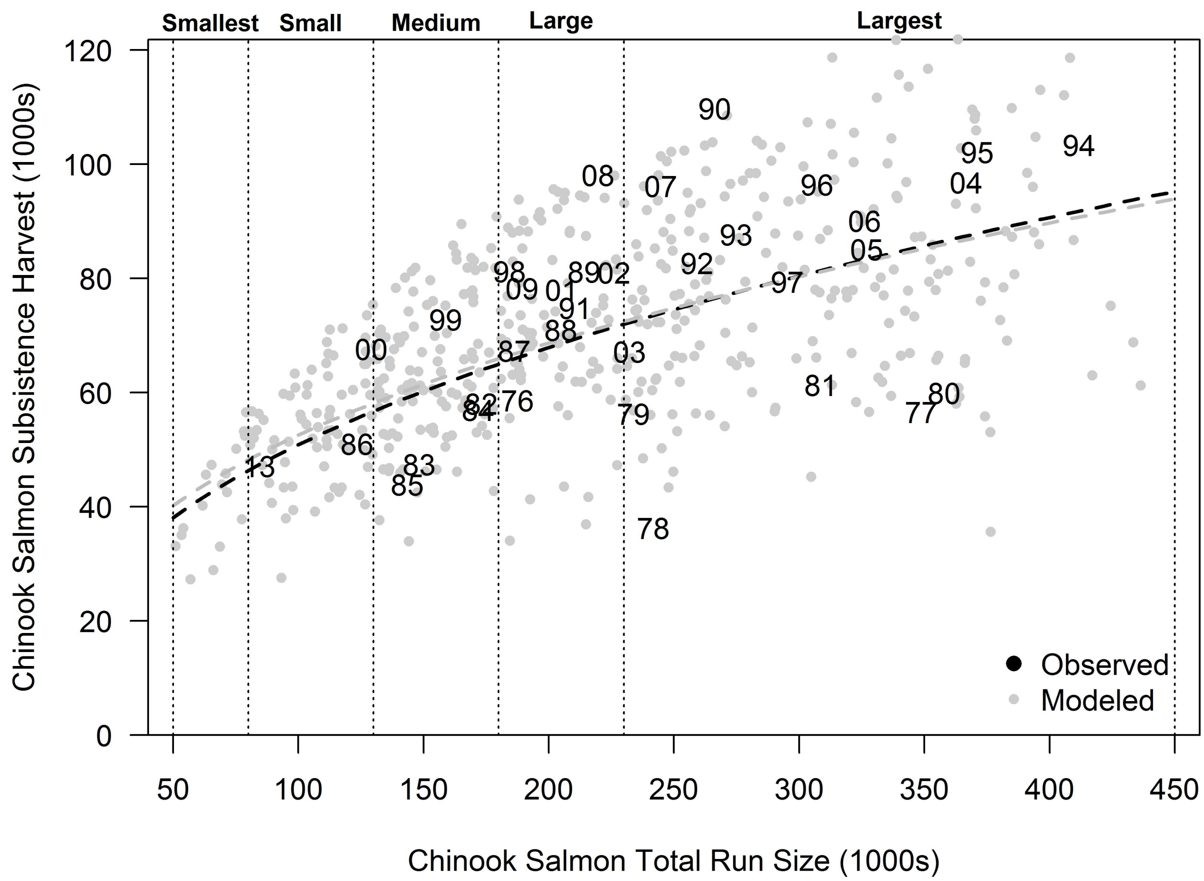

Figure 1: Observed and modeled Chinook salmon subsistence harvest as a function of total Chinook salmon run size. Individual black numbers are historical realizations in years with no harvest restrictions on the subsistence salmon fishery. Individual grey dots are modeled outcomes, each representing a hypothetical salmon run with different random subpopulation compositions, run timing, and species ratios. Fitted models display close agreement between the average simulated and observed harvest outcomes across the range of run sizes. Vertical dotted lines show the important run size strata used in this analysis.

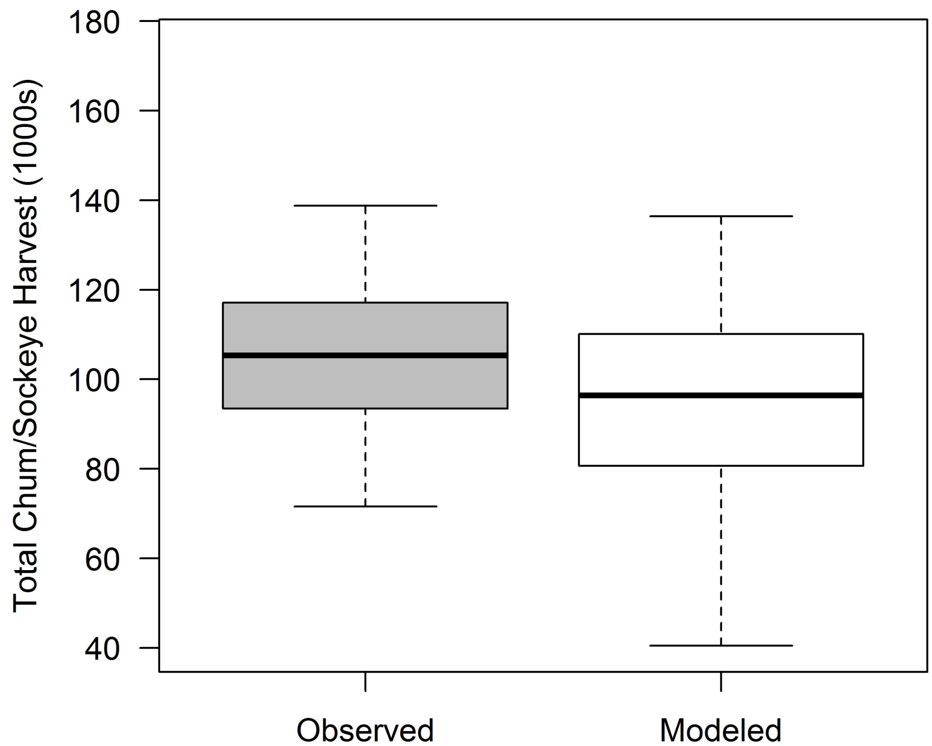

Figure 2: Comparison of the inter-annual distribution of observed and modeled chum/sockeye salmon harvests by villages located in the Kuskokwim River.

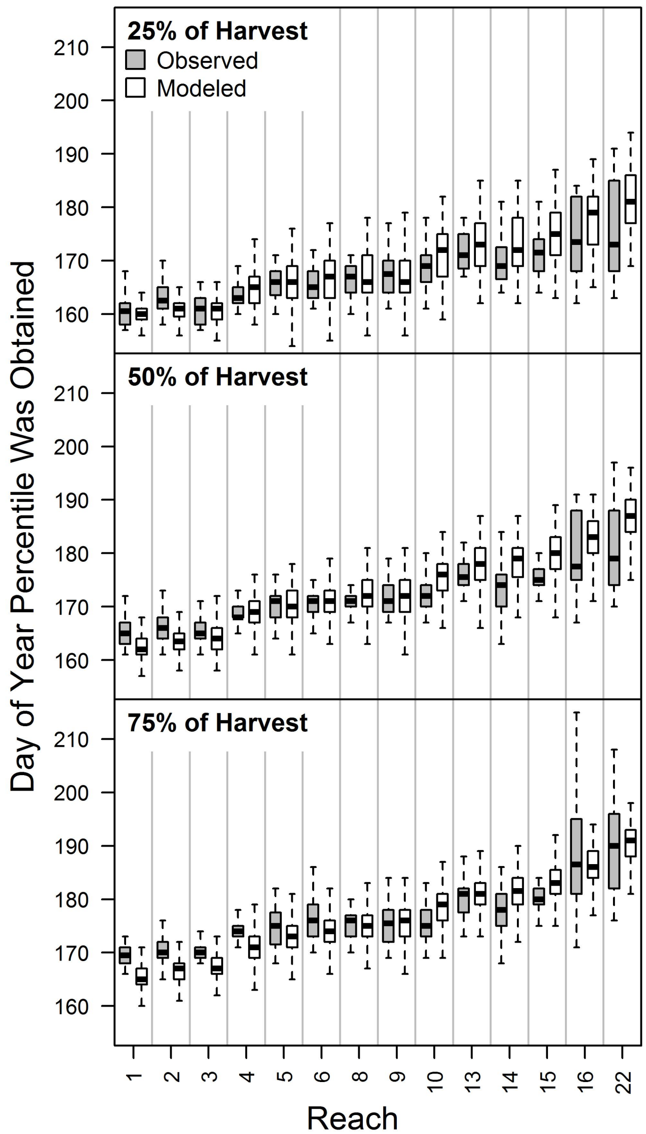

Figure 3: Comparison of the day of the year at which various percentiles of Chinook salmon harvest was attained by reach between observed and modeled outcomes. Variability in the observed boxplots is due to inter-annual variability in run size and timing and represents between-simulation variability for the modeled outcomes. Reach numbers are ordered from downriver to upriver. Note that not all reaches contain communities that harvest salmon.

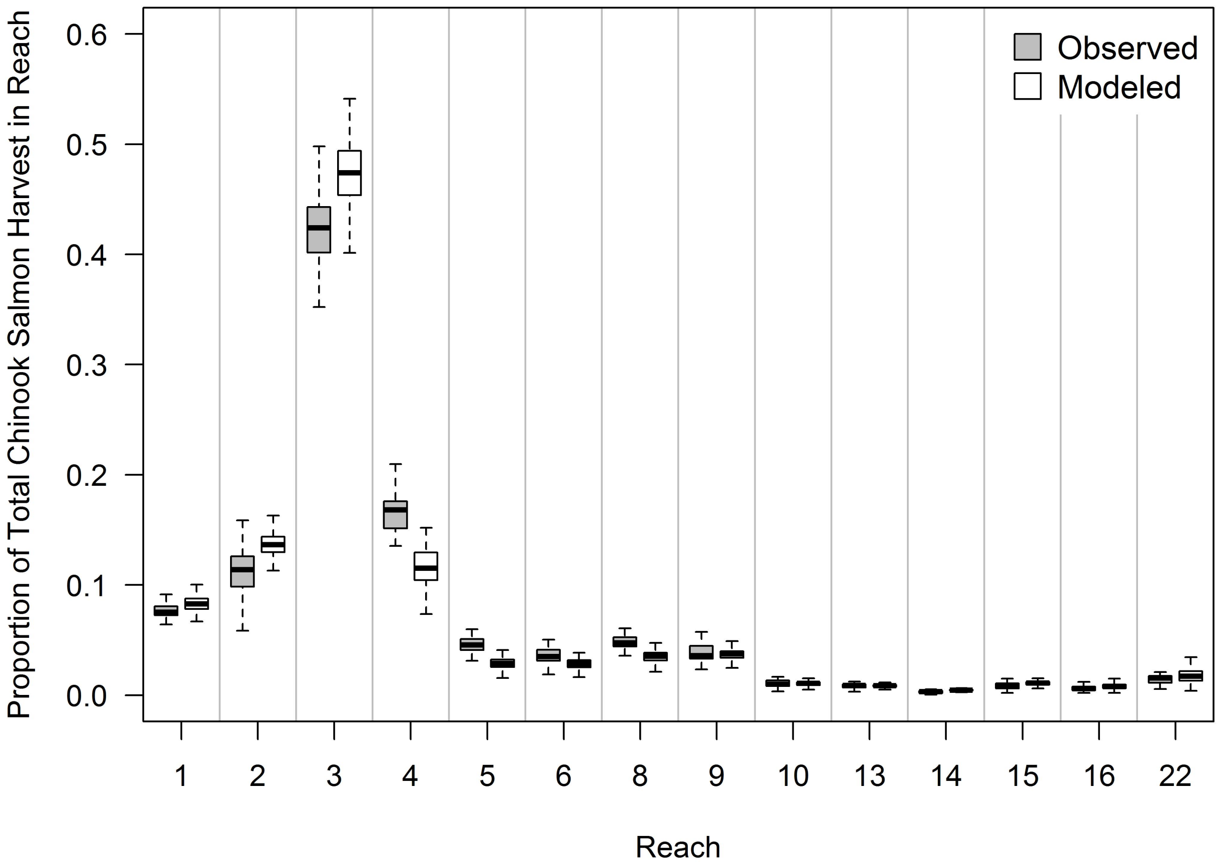

Figure 4: Comparison of the proportion of total drainage-wide Chinook salmon subsistence harvest attributable to communities in each reach between observed and modeled outcomes. Variability in the observed boxplots is due to inter-annual variability, and represents between-simulation variability for the modeled outcomes. Reach numbers are ordered from downriver to upriver. Note that not all reaches contain communities that harvest salmon.

APPENDIX D

Bayesian information updating procedures for Pacific salmon run size indicators: Evaluation in the presence and absence of auxiliary migration timing information

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Abstract

Pre-season forecasts of Pacific salmon run size are notoriously uncertain, and are thus often updated using various abundance indices collected during the run. However, interpretation of these in-season indices is confounded by uncertainty in migration timing. We assessed the performance of two Bayesian information-updating procedures for Kuskokwim River Chinook salmon: one that uses auxiliary run timing information and one that does not, and compared the performance to methods that did not involve updating. We found that in-season Bayesian updating provided more accurate run size estimates during the time when harvest decisions needed to be made, but that the incorporation of run timing forecasts had little utility in terms of providing more accurate run size estimates. The latter finding is conditional on the performance of the run timing forecast model we used; a more accurate timing forecast model may yield a different conclusion. The Bayesian approach we developed provided a probabilistic expression of run size beliefs, which could be useful in a transparent risk-assessment framework for setting and altering harvest targets in-season.

1 Introduction

Management strategies for in-river Pacific salmon (*Oncorhynchus* spp.) fisheries involve limiting harvest in-season such that some management reference point is likely to be achieved. These reference points are typically expressed as either a target escapement abundance or a target exploitation rate, or as ranges of these two quantities. Regardless of which way the management strategy is framed, a reliable measurement of the harvestable surplus is required to successfully implement the strategy on an annual basis. The harvestable surplus varies annually based on the total incoming run size, thus information regarding the total annual run size is often required for management of these fisheries. Run size information can be categorized into two broad classes: pre-season forecasts (i.e., before fish have arrived in fishery areas) and in-season estimates (i.e., once fish can be indexed). Though these terms are often used interchangeably (as are "predictions" and "projections"), for clarity we will refer to methods of the former class as "forecasts" and methods in the latter class as "estimates".

Methods to produce pre-season forecasts range from simple models based only on time series patterns (Haeseker et al. 2005) to complex models that incorporate spawner-recruit relationships (Adkison and Peterman 2000), sibling relationships (Peterman 1982), and/or environmental variables intended to explain variability in survival rates (Adkison and Peterman 2000). Murphy et al. (2017) presented pre-season forecast methodology for Yukon River Chinook salmon (*O. tshawytscha*) based on trawl surveys targeting juveniles shortly after marine entry, and this model has recently shown promise (K. Howard, pers. comm.). Not surprisingly, it has commonly been found that simpler models that do not require hypotheses about mechanisms driving recruitment variability perform as well or better than more complex forecast models that require such assumptions (Haeseker et al. 2005, 2008; Winship et al. 2015). Still, pre-season forecast models generally perform poorly and have wide uncertainty regions, resulting from incomplete understanding of drivers of survival and recruitment rates (Adkison et al. 1996; Adkison and Peterman 2000). Inaccurate annual forecasts have socioeconomic consequences for the fisheries that rely on them: Bocking and

Peterman (1988) found correlations between forecast errors and management performance and Costello et al. (1998) found a high expected value of information for better forecasts resulting from improved knowledge of the El Niño phase. These findings highlight the need for improved methods to produce pre-season forecasts or otherwise update them with in-season estimates as those data accumulate.

In-season estimators of run size also show quite a range of model complexity. Simple methods may be based purely on catch-per-effort (CPE) indices whereas more complex methods may incorporate observations of size/age structure (Flynn and Hilborn 2004) and substock structure (Hyun et al. 2005). Each of these methods attempt to expand some partially-observed component of the run to the total run size, and thus their predictive performance is tightly linked to uncertainty regarding run timing (i.e., the fraction of the run is complete on any given day of the season). For example, large/late runs and early/small runs have a tendency to create similar CPE indications of an average run early in the season (Adkison and Cunningham 2015), though neither run scenario would likely have the same harvestable surplus as an average run. Put another way, with the observation of indications of an average-sized run, the manager can rarely exclude these other extreme scenarios from consideration, resulting in uncertainty about how to prosecute the fishery to ensure the management strategy is implemented and annual fishery objectives are achieved. For this reason, many efforts have been made at forecasting the run timing pre-season as well as the run size (Staton et al. 2017; Mundy and Evenson 2011; Keefer et al. 2008; Anderson and Beer 2009). However, it is often unclear as to precisely how these run timing forecasts are to be included into run size estimators, or whether it is preferable to do so at all.

In the presence of multiple run size indicators (i.e., pre-season and in-season sources), it is often difficult to decide which information sources to trust at various points in the season for making management decisions when they inevitably disagree. One extreme would be to manage harvests based on the pre-season forecast all season and entirely ignore any indications provided by in-season estimates. The other extreme would be to do the opposite: abandon the pre-season forecast the day the first fish is detected by the in-season index project(s). It is our sense that few managers would feel comfortable taking either of these extremes, which implies that some method of transitioning from a pre-season forecast to in-season estimates is warranted. While some managers may prefer transitional approaches based on experience and intuition, a logical method to perform such a transition is based on the variance of each information source: sources with less uncertainty should drive management decisions more than those that are more uncertain. The calculations to conduct a formal variance-based transition can be framed in a classical inferential framework (Walters and Buckingham 1975) or as a Bayesian inferential problem (Fried and Hilborn 1988; Hyun et al. 2005). The Bayesian approach has a certain appeal as it provides a full probability model representing uncertainty regarding the truth of all possible run size outcomes (i.e., hypotheses), which can be seamlessly updated as new (i.e., in-season) information is made available. Such a probability model could be useful in formal risk assessments in the context of probabilistic control rules (Catalano and Jones 2014; Prager et al. 2003) used to set harvest targets.

The Kuskokwim River, located in Western Alaska, is a large drainage system that supports large subsistence fisheries for Chinook salmon. Being the species of greatest subsistence interest for this region and coupled with recent low abundances, Chinook salmon have been of primary management concern and is hereafter the focus of this paper. Although the river system is quite large (main stem $>$ 800 km, drainage area $>$ 50,000 km^2), the majority of the fishery is (in relation) spatially-constricted: 95% of the drainage-wide Chinook salmon harvest is attributable to the 16 villages located in the first 300 km of the main stem and 70% of the total Chinook salmon harvest is attributable to the 10 villages in the first 125 km (Hamazaki 2011). The fishery is managed with time, area, and gear restrictions implemented by short-notice in-season management actions intended to limit harvest to ensure a drainage-wide fixed escapement goal range is met each year. Information sources for in-season management include a pre-season run size forecast and an in-season CPE index of in-river abundance and species composition (the Bethel Test Fishery, BTF, operated annually from June 1 August 24 1984 2017; Bue and Lipka 2016). In recent years, in-season harvest estimates have also been produced (Staton and Coggins 2016, 2017) and have been used to track progress toward the attainment of total allowable harvest. Currently, no formal attempts at producing in-season estimates/updates of run size have been made. Decisions about limiting harvest opportunity have instead been made by qualitatively determining if the BTF index indicates a different run size than that suggested by the pre-season forecast by comparing the accumulation of daily CPE against those observed in previous years. This approach obviously has substantial pitfalls that include:

(1) the aforementioned confounding effect of annual variability in run timing,
(2) no accounting of annual variability in BTF catchability (i.e., run-per-index; Flynn and Hilborn 2004),
(3) no formal consideration of which source provides more information about the true run size at varying points in the season, and
(4) no explicit expression of how disagreements between the BTF index and the pre-season forecast should result in alterations to the in-season harvest management strategy (i.e., total allowable harvest).

In this paper, we seek to address these issues by developing a framework to formally update pre-season run size forecasts with in-season estimates of the total run size using Bayesian inference. Using data from the Kuskokwim River Chinook salmon fishery, we evaluated the assessment framework by applying it to previous years as well as determined the potential utility of incorporating auxiliary information from a recently-developed run timing forecast model for this fishery (Staton et al. 2017). Our objectives were to:

(1) develop two Bayesian updating tools: one that ignores auxiliary run timing information and one that includes it,
(2) determine if Bayesian updating provides better (more accurate/precise) inference than using either the forecast or in-season estimates alone, and

(3) determine if incorporating the run timing forecast information improves inferential performance.

2 Methods

We developed a Bayesian approach to updating the pre-season perception of run size with in-season data, both in the presence and absence of auxiliary run timing information. The approach proceeds by (1) determining the pre-season run size forecast for each year to serve as the prior distribution, (2) obtaining a likelihood function based on historical relationships and current information, and (3) the formal combination of the information derived in steps (1) and (2) using Bayes' Theorem to obtain a posterior probability function for total run size. The presence or absence of auxiliary run timing information was incorporated into step (2) when interpreting the consistency of the in-season CPE data with any one run size hypothesis. The reliability of inferences and quality of hypothetical management outcomes informed by the prior, likelihood, and posterior density functions were then compared between cases including and ignoring the auxiliary run timing information.

We used leave-one-out cross-validation scores to compare inferential performance between the different components of the Bayesian approach and the use/non-use of auxiliary run timing information. This approach was not retrospective, as it did not use only information available at the time the approach would have been used in previous years. Our chosen analysis framework emphasizes that we were not interested in how the approach would have performed in the past, but rather how they may perform in the future when presented with runs similar to those that have occurred in the past. By definition, the leave-one-out method necessitated that the training data set excluded the year that was being estimated. The years 1995 2017 were evaluated by producing weekly estimates on June 10, June 17, June 24, July 1, July 8, and July 15, which represent the approximate 10%, 30%, 60%, 80%, 90%, and 95% points of the historical average run timing through the lower river fishery, respectively

(Bue and Lipka 2016).

2.1 Pre-season run size forecast

Pre-season run size forecasts for Kuskokwim River Chinook salmon are made by assuming the current year's run will be similar in size to the previous year's run (Smith and Liller 2018), which stems from the observation of high serial auto-correlation in the run abundance time series (Figure 1a). The total run size each year is estimated post-season using a maximum likelihood drainage-wide run reconstruction model that integrates information from 20 escapement indices, fishery CPE data, mark-recapture-based estimates of drainage-wide abundance, and total fishery harvest over the time period of 1976-2017 (Bue et al. 2012; Liller et al. 2018). The most recent estimates provided in Liller et al. (2018) were used in this analysis and we assumed the point estimates represented the true run size in these years. Although the "last-year" rule for producing forecasts has only been used since 2014, we can hindcast its performance over the entire time series to obtain the precision of the forecast rule as though it had been used in the past. Errors in the forecast were assumed to be multiplicative:

$$\varepsilon_{F,t} = \log\left(\frac{N_{t-1}}{N_t}\right) \quad (1)$$

where N_t and N_{t-1} are the run sizes corresponding to year t and $t-1$, respectively, and $\varepsilon_{F,t}$ is the natural logarithm of the multiplicative error term in the forecast (values < 0 are underestimates and values > 0 are overestimates). The time series of all such $\varepsilon_{F,t}$ is presented in Figure 1b, and their distribution is shown in Figure 1c. The standard deviation of $\varepsilon_{F,t}$, hereafter denoted σ_F, was used to represent the uncertainty in the forecast in any given year in the analysis, expressed as a bias-corrected lognormal distribution. This lognormal distribution was assumed to represent the prior uncertainty regarding the size of the run in the absence of in-season assessment data.

2.2 Pre-season run timing forecast

Run timing forecasts for the Kuskokwim River Chinook salmon stock were produced using the methodology presented in Staton et al. (2017). Briefly, the forecast model predicts the day of the year at which 50% of the total annual cumulative CPE will be observed in the BTF (hereafter $D_{50,t}$) by exploiting linear regression relationships between $D_{50,t}$ and sea surface temperature, sea ice concentration, air temperature in Bethel, AK, and the Pacific Decadal Oscillation index. The forecast model was developed using variable selection criteria to determine the best time periods of these variables to include and model-averaging to handle forecast model uncertainty. We used the Staton et al. (2017) timing forecast model to produce forecasts of $D_{50,t}$ for the years 1995-2017, as well as their associated standard errors of prediction (Figure 2).

2.3 Likelihood function construction

2.3.1 Historical relationships

Information about run size is contained in the cumulative BTF CPE values observed each day of the run $\left(\text{CCPE}_{d,t} = \sum_{j=1}^{d} \text{CPE}_{j,t}\right)$, and thus these data formed the foundation for linking in-season abundance index data to different run size hypotheses in a likelihood framework. The total end-of-season abundance each year was related to $\text{CCPE}_{d,t}$ at various points in the season using multiple linear regression:

$$\log(N_t) = \beta_0 + \beta_{1,d} q_t + \beta_{2,d} \text{CCPE}_{d,t} + \beta_{3,d} \text{CCPE}_{d,t} q_t + \varepsilon_{d,t} \tag{2}$$

where $\beta_{j,d}$ are coefficients explaining the relationship on each day, q_t is a binary indicator based on the catchability period, and $\varepsilon_{d,t}$ are normally distributed errors with mean zero and variance equal to σ^2. The catchability period term was added because the efficiency of the BTF gear increased substantially beginning in 2008 as a result of a change in net-makers (Bue and Lipka 2016). Regression relationships like those in Eq. (2) are commonly used to estimate run size based on in-season data (Fried and Hilborn 1988; Flynn and Hilborn 2004; Hyun et al. 2005; Michielsens and Cave 2018). To allow incorporation of information from auxiliary run timing, we fitted an additional regression model:

$$\log(N_t) = \alpha_0 + \alpha_{1,d} q_t + \alpha_{2,d}\mathrm{CCPE}_{d,t} + \alpha_{3,d}\mathrm{CCPE}_{d,t} q_t + \alpha_{4,d} D_{50,t} + \gamma_{d,t} \tag{3}$$

where $\alpha_{j,d}$ and $\gamma_{j,d}$ are analogous to the $\beta_{j,d}$ coefficients $\varepsilon_{j,d}$ error terms in Eq. (2), respectively, and $D_{50,t}$ is the observed median run date in year t. The incorporation of $D_{50,t}$ is intended to explain additional variability in the relationship between N_t and $\mathrm{CCPE}_{d,t}$: in the absence of sampling variability, residuals from the fitted regression model in Eq. (2) should be mostly negative in years with early $D_{50,t}$ and should be mostly positive in years with later run timing. The relationships from Eq. (3) fitted to all years (1984 2017) at three points in the season are shown in Figure 3.

2.3.2 Leave-one-out predictions

To evaluate the performance of the relationships in Eqs. (2) and (3), one year was left out of the fitting procedure (i.e., the one being predicted), then the appropriate covariates on each day in the left-out year were inserted and predictions were made for N_t. With 23 years [only those with run timing forecasts from the Staton et al. (2017) model; 1995 2017], six dates each year, and two approaches (with and without run timing information), 276 leave-one-out predictions were made. Because a likelihood function that could be used to update the prior (i.e., the pre-season run forecast) was desired, uncertainty from the fitted regression model in Eq. (2) was propagated to predictions of N_t using a Monte Carlo procedure. First, random values of the regression coefficients for the model with year t left out were sampled from a multivariate normal distribution with mean vector and covariance matrix equal to the estimated values. These Monte Carlo values are denoted by $\dot{\beta}_{j,d,-t,b}$, for coefficient j, day d, left out year t, and Monte Carlo sample b. Then, random residuals ($\dot{\varepsilon}_{d,-t,b}$) were sampled from a bias-corrected lognormal distribution, with mean equal to $-0.5\hat{\sigma}^2_{-t}$ and variance equal to $\hat{\sigma}^2_{-t}$. These Monte Carlo samples were used to obtain a distribution of predicted values of the run size according to the in-season data through day d of the run $\dot{N}_{d,t,b,\mathrm{NULL}}$:

$$(4) \quad \log(\dot{N}_{d,t,b,\mathrm{NULL}}) = \dot{\beta}_{0,d,-t,b} + \dot{\beta}_{1,d,-t,b} q_t + \dot{\beta}_{2,d,-t,b}\mathrm{CCPE}_{d,t} + \dot{\beta}_{3,d,-t,b} q_t \mathrm{CCPE}_{d,t} + \dot{\varepsilon}_{d,-t,b}$$

To obtain the same quantity but in the presence of the run timing forecast ($\dot{N}_{d,t,b,\mathrm{FCST}}$), predictions were made by performing the same calculation as in Eq. (4), but using the corresponding quantities $\dot{\alpha}_{j,d,-t,b}$ and $\dot{\gamma}_{d,-t,b}$. We thought it important to include uncertainty in the forecast of $D_{50,-t}$, so Monte Carlo samples were made from a normal distribution with mean and variance equal to the prediction obtained for year t using the Staton et al. (2017) forecast model.

Once the Monte Carlo samples of $\dot{N}_{d,t,b,\mathrm{NULL}}$ and $\dot{N}_{d,t,b,\mathrm{FCST}}$ were obtained (which represented random draws from the likelihood function), the form of the likelihood probability density function (PDF) was estimated using a one-dimensional kernel density estimator fitted to 1×10^6 Monte Carlo samples. The resulting function is hereafter denoted by $\Pr(\dot{N}_{d,t,m}|N_{t,i})$, where m is a model index representing either the null or run timing forecast models and i is a continuous run size hypothesis.

2.4 Posterior estimation

To obtain Bayesian in-season updates of the perceived run size, the lognormal distribution representing uncertainty in the pre-season forecast was used as the prior information each day [denoted $\Pr(N_{t,i})$]. Although this was a simple one parameter Bayesian estimation problem, the likelihood PDF $\Pr(\dot{N}_{d,t,m}|N_{t,i})$ did not have a well-defined parametric form which could have allowed direct analytical calculation of the posterior PDF [$\Pr(N_{t,i}|\dot{N}_{d,t,m})$] using Bayes' Theorem. Instead, a custom random walk Metropolis-Hastings Markov Chain Monte Carlo (MCMC) algorithm (Chib and Greenberg 1995) was written using a lognormal proposal distribution. The lognormal proposal distribution was used as opposed to a symmetrical distribution (like the normal distribution) to prevent negative proposals. The standard deviation of this proposal distribution was tuned such that the acceptance rate of proposals was between 0.2 0.4 (Bédard 2007). Posterior convergence was assessed using two chains with over-dispersed initial values and the Potential Scale Reduction Factor (Brooks and Gelman 1998), and the Raftery-Lewis diagnostic was used to ensure enough effective samples were drawn to make adequate inference (Raftery and Lewis 1992). On each evaluated day and year, 1×10^5 posterior samples were drawn from each chain with a burn-in period of 1×10^4. These specifications resulted in more than enough samples to meet the criteria for convergence and adequate inference in all cases. All analyses were conducted in Program R (R Core Team 2018) and all code and data are archived in (Staton 2018).

2.5 Metrics of estimator performance

Inferential performance was evaluated using four criteria for each evaluated day d and year t: (1) mean absolute proportional error (MAPE) to quantify the magnitude of estimation errors, (2) mean proportional error (MPE) to measure bias, (3) the standard deviation of log-scale multiplicative errors (σ) to measure variability in estimation errors, and (4) the coverage of the 50%, 80%, and 95% confidence/credible regions. For calculation of MAPE, MPE, and σ, the median of the distributions $\Pr(N_{t,i})$, $\Pr(N_{t,i}|\dot{N}_{d,t,m})$, and $\Pr(\dot{N}_{d,t,m}|N_{t,i})$ were used as point estimates and the reconstructed values of N_t (Liller et al. 2018) were interpreted as the true run sizes. The purpose of evaluating the performance of inferences from the prior, likelihood, and posterior PDFs was to determine whether Bayesian updating provided better performance than not updating and utilizing either pre-season or in-season indicators all season long.

3 Results

3.1 Mean absolute proportional error

Errors in inference from median of the likelihood distribution function alone (i.e., BTF data only) were somewhat large early in the season (MAPE approximately 0.3), but steadily declined in size as the run approached completion (Figure 4a). At no point in the season did the in-season data alone produce smaller errors than the prior, but starting on June 17 the posterior showed slight improvements for the rest of the season in MAPE values. Likelihood and posterior inference was nearly identical between the null and run timing forecast models, which was found across all four descriptive statistics.

3.2 Mean proportional error

In terms of biases, all information sources remained within ± 0.05 units of no bias (Figure 4b) for the whole season. The prior and likelihoods were slightly positively biased (MPE = 0.01 0.04), but the posterior had a consistent and slightly negative bias. Because the posterior is an average of the prior and the likelihood, one would expect the posterior MPE to fall between those of the prior and likelihood. Figure 5 shows that for any given year, this was the case: the error from the posterior median fell between the errors made by the prior and the likelihood on each day in each year. Presumably, a combination of skewness to the PDFs and small sample size led to this somewhat counterintuitive finding.

3.3 Variability of errors and CV

As would be expected from Figure 4a, the variability in errors was greater for inference from the likelihood PDF than for the posterior PDF early in the season, and did not become lower than the variability of the prior errors for the entire season. As was found for MAPE, the variability of errors from posterior inference were smaller than the pre-season forecast for the entire season, and was always smaller than inference from the likelihood alone. As in the other statistics, there were only negligible differences between the approaches that included/excluded auxiliary run timing information. One key aspect that emerges from comparing Figures 4c and 4d is that they align closely for the same PDF types. The value of σ is calculated as $\mathrm{SD}\left(\log(N_{t,est}) - \log(N_{t,true})\right)$, which is the lognormal standard deviation. At relatively low values in the 0.2 0.3 range, these should be approximately equal to the coefficient of variation, which is supported by Figures 4c and 4d.

3.4 Credible region coverage

With the exception of the 50% region, the pre-season forecast (prior) had appropriate coverage levels (Table 1; appropriate defined here as coverage being within ± 5 percentage points of optimal coverage). 70% of the years fell within what was supposed to be a 50% interval, indicating that too much uncertainy was expressed at that confidence level for the prior. Other indicators tended to have less coverage than appropriate on June 10 for the 50% region, particularly the posterior. Regions at the 80% and 95% levels were typically more appropriately estimated than those for the 50% level. In general, likelihood coverage was more appropriate than posterior coverage on June 24 and July 8. Coverage values on July 15 are not presented as results were the same as for July 8.

4 Discussion

The findings of our analysis suggest that using the Bayesian in-season updating procedure described here would provide approximately the same (if not more) accuracy as the two aforementioned extremes: utilizing either the pre-season forecast or the in-season estimates all season. We found improvement in the average magnitude of out-of-sample prediction errors, variability in these errors, and confidence in run assessments when the Bayesian posterior was used rather than the in-season data alone (Figure 4). Some of these improvements were present when comparing the prior to the posterior, but were smaller in magnitude. In terms of bias, all information sources had small enough directionality that these estimators seem to be largely unbiased.

We expect that the finding that updating is preferable to utilizing in-season data alone is general to systems like the Kuskokwim River (e.g., the Nushagak and Yukon Rivers located in Western Alaska). These systems have similar in-season run size indicators (both systems have a sonar and the Yukon River has a lower-river test fishery) that suffer from the same problems as the data for the Kuskokwim, namely variability in index catchability and the confounding effect of run timing uncertainty. These two problems, particularly the latter, can lead to the in-season data providing inaccurate and highly uncertain run size for at least the first half of the season (Flynn and Hilborn 2004; Adkison and Cunningham 2015; Walters and Buckingham 1975). Thus, it is logical to expect that the desirability of updating pre-season forecasts rather than utilizing solely in-season estimates alone would be a general finding. The example of the Kuskokwim River assessment tool we developed is a generalization of previously-developed updating methods (e.g., Fried and Hilborn 1988) and could be generalized to other systems for the purpose of arbitrating between the relative information content of pre-season and in-season run size indicators, including those involving mixed stocks if timely data on the substock contribution to the total indicator were available.

We found that posterior inference gave smaller errors and less variability in errors than the pre-season forecast starting on June 17, but by a small margin. Chinook salmon migrate through the lower river fishery areas for much of the month of June in the Kuskokwim and harvest decisions regarding fishing opportunity are made on an approximately weekly-basis during this time. More accurate estimates early in the season are especially desirable, but it seems that there were often not strong updates to the posterior over the prior during this time. In many cases (e.g., 1995, 1997, 2008, 2009, 2014; Figure 5), the primary update occurred on June 10 and it continued to have approximately the same error for the whole season.

A key finding of our analysis was that incorporating auxiliary run timing information in the assessment provided no gain (or meaningful difference) in performance. This is not overly surprising given that Staton et al. (2017) reported that using the mean of all the $D_{50,t}$ values shown in Figure 2 provided slightly more accurate run timing forecasts than the environmental variable forecast. This is likely a result of the large number of years with close-to-average timing: although $D_{50,t}$ has exhibited a range of 17 days, 35% of past years have been within ± 1 day of the mean and 53% of past years have been within ± 2 days of the mean (Figure 2; Staton et al. 2017). The conclusion of no gain in performance in the presence of the run timing forecast was conditional on the accuracy and precision of the Staton et al. (2017) forecast model; because we did not evaluate performance for other systems, this finding may not be general. For systems that show greater (and more predictable) annual variability in run timing, it very well may be preferable to incorporate the auxiliary timing information. It is also possible that a better timing forecast model for the Kuskokwim River may become available in the future, in which case this study should be replicated to determine whether and to what degree increased predictive performance regarding run timing is reflected in the performance of in-season run assessments. To our knowledge, our work is the first to formally compare the performance of in-season abundance estimators in the presence and absence of auxiliary run timing information, and it suggests that one should not always *a priori* expect the use of outside information to aid in assessment performance proposed changes should always be evaluated to measure how well they perform against other approaches.

We found that in many cases the prior did well in comparison to the in-season data, especially towards the end of the season (e.g., Figure 4a). This similarity is almost certainly a result of two factors:

(1) the relatively-predictable nature of the Kuskokwim River Chinook salmon population dynamics based on its recent history which provided decent pre-season run size forecasts (Figure 1) and

(2) a high degree of annual sampling variability led to uninformative in-season data (note the spread of CCPE that can be observed at approximately the same run size in Figure 3).

Cause (1) is relatively rare for Pacific salmon in general and oftentimes attempts to obtain a useful forecast are incredibly resource-intensive (Murphy et al. 2017) or fruitless (Adkison et al. 1996; Adkison and Peterman 2000; Haeseker et al. 2005, 2008). Cause (2) affects the performance of all methods that obtain in-season run abundance estimates from partial CPE observations, and is known commonly as variability in the "run-per-index" (Flynn and Hilborn 2004). It seems that the large amount of sampling variability in run-per-index made the in-season data less informative than they would be with less noise.

Our approach used the only available index of abundance for Kuskokwim River Chinook salmon to provide the information on which to perform the updates: the BTF. Although extensive monitoring activities occur in this drainage, they are used primarily for indexing escapement and given the size of the system, they are not useful for in-season assessment. There are eight weirs operated with some consistency in the system, but fish do not typically arrive to these locations until mid-July when much of the run has passed the majority of the harvest area. However, in systems for which this time lag is not so great (like Bristol Bay sockeye salmon in which escapement counting towers are often only several days of travel upstream of the fishery districts), it is possible to include other information into the likelihood component of the Bayesian calculations which may provide better inference. For example, Fried and Hilborn (1988) used multiple indicies of abundance to build the likelihood used in their Bayesian framework. Recently, a lower-river sonar project has been operated in the Kuskokwim River, which could provide such additional information regarding run size. However, given this project is still very much in its infancy, we suggest waiting until it can be shown that it provides a reliable index of the run. If it is proven to be reliable, a decision of how to incorporate sonar data will need to be made. Two methods are immediately obvious: (1) incorporate it as an additional likelihood term the calculation of the posterior (as done by Fried and Hilborn 1988) or (2) calculate two posteriors (one using the BTF data and using the sonar data) and perform Bayesian model averaging. The latter of the two options would be preferable if placing unequal prior probabilities on the two models is desired.

There is some thought that in-season fishery-dependent indices of abundance could also prove useful for informing updates in some circumstances, so long as the catchability relationship is stationary. We assessed including the cumulative harvest downstream of the BTF site as an additional covariate in the regression models (not shown), and found essentially the same results. More variance in the relationships was explained, but the out-of-sample predictive performance (Figure 4) was the same.

We sought to address the four previously-identified issues with qualitative salmon run size assessment, which we believe our Bayesian approach does. The first issue was inadequate treatment of run timing uncertainty: our approach attempted to explain some additional variability in run-per-index values based on if the run was early or late. The second issue was the lack of accounting for annual variability in BTF catchability: our approach accounts for this in the full propagation of the uncertainty in the regression relationships in Figure 3. The third issue was a lack of the consideration of how much weight to place on pre-season versus in-season run size indicators, which our method handles intuitively using the laws of probability and Bayesian inference. The final issue was the lack of a formal expression for how disagreements in pre-season and in-season indicators should result in alterations to the harvestable surplus. While this last issue is much more about management than assessment, it is not difficult to see that our method provides the information necessary to inform such a decision. On any day of the season, the probability of an escapement outcome of interest [e.g., Pr(escapement<lower bound of the escapement goal)] conditional on a candidate harvest target can be calculated from the posterior. If this probability is deemed unacceptable, additional candidates can be proposed until the probability of the escapement outcome is deemed suitable. A similar approach could be extended to salmon fisheries managed with limit exploitation rates, by calculating the posterior exploitation rate if the candidate harvest target were to be taken (proposed harvest divided by posterior samples of total run size) and determining if the associated probability of falling above the limit rate is acceptable. This type of approach aligns closely with the probabilistic treatment of limit reference points in precautionary fisheries management, which has been gaining popularity in framing sustainable harvest policies for U.S. marine fisheries (Prager et al. 2003; Shertzer et al. 2010). Herein lies what we see as the greatest contribution of this work: it provides an assessment framework that can be used to provide greater transparency for harvest management decisions that are framed in terms of uncertainty and risk.

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Table 1. Estimated coverage of various regions in the prior, likelihood, and posterior distributions.

		June 10			June 24			July 8		
Info. Source	Timing Type	50%	80%	95%	50%	80%	95%	50%	80%	95%
Prior	-	70	78	100	70	78	100	70	78	100
Likelihood	NULL	48	74	96	52	83	91	57	83	91
Likelihood	FCST	48	70	96	43	83	87	57	83	91
Posterior	NULL	39	74	96	43	74	100	39	74	96
Posterior	FCST	43	78	96	43	78	96	43	74	96

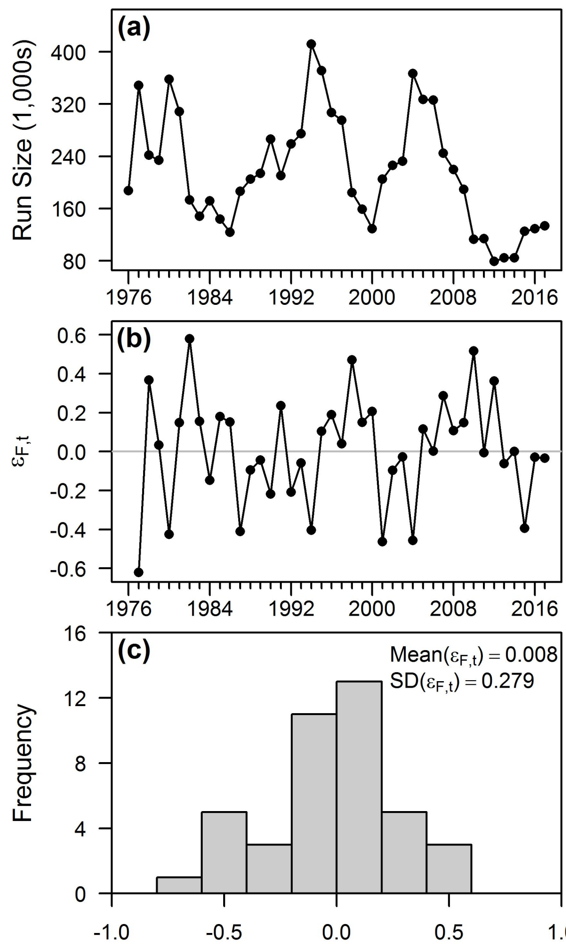

Figure 1. (a) Estimated run size time series from 1976-2017, (b) time series of log scale multiplicative pre-season forecast errors $\varepsilon_{F,t}$, and (c) distribution of the $\varepsilon_{F,t}$ values.

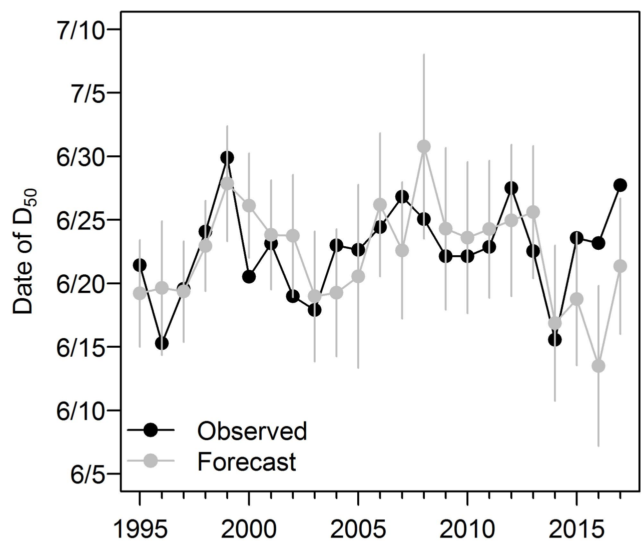

Figure 2. The time series of the observed median run date ($D_{50,t}$) with pre-season run timing forecasts and 95% prediction limits shown.

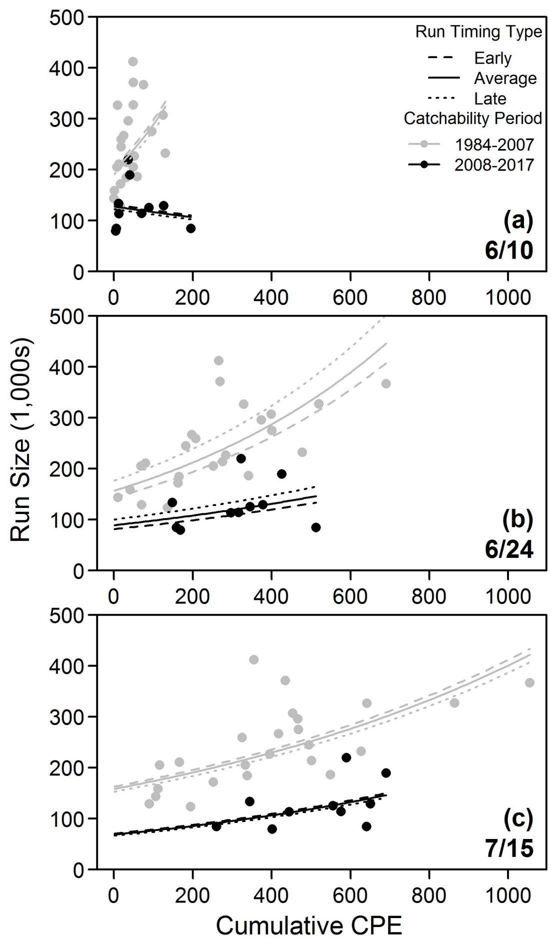

Figure 3. The fitted regression relationships from Eq. 3 at three points in the season. Different run timing scenarios are shown: dashed lines represent the prediction at a given $CCPE_d$ for the earliest run on record, dotted lines correspond to the latest run on record. Solid lines represent the prediction for a run with average timing, and is analogous to the estimates given by fitting Eq. 2.

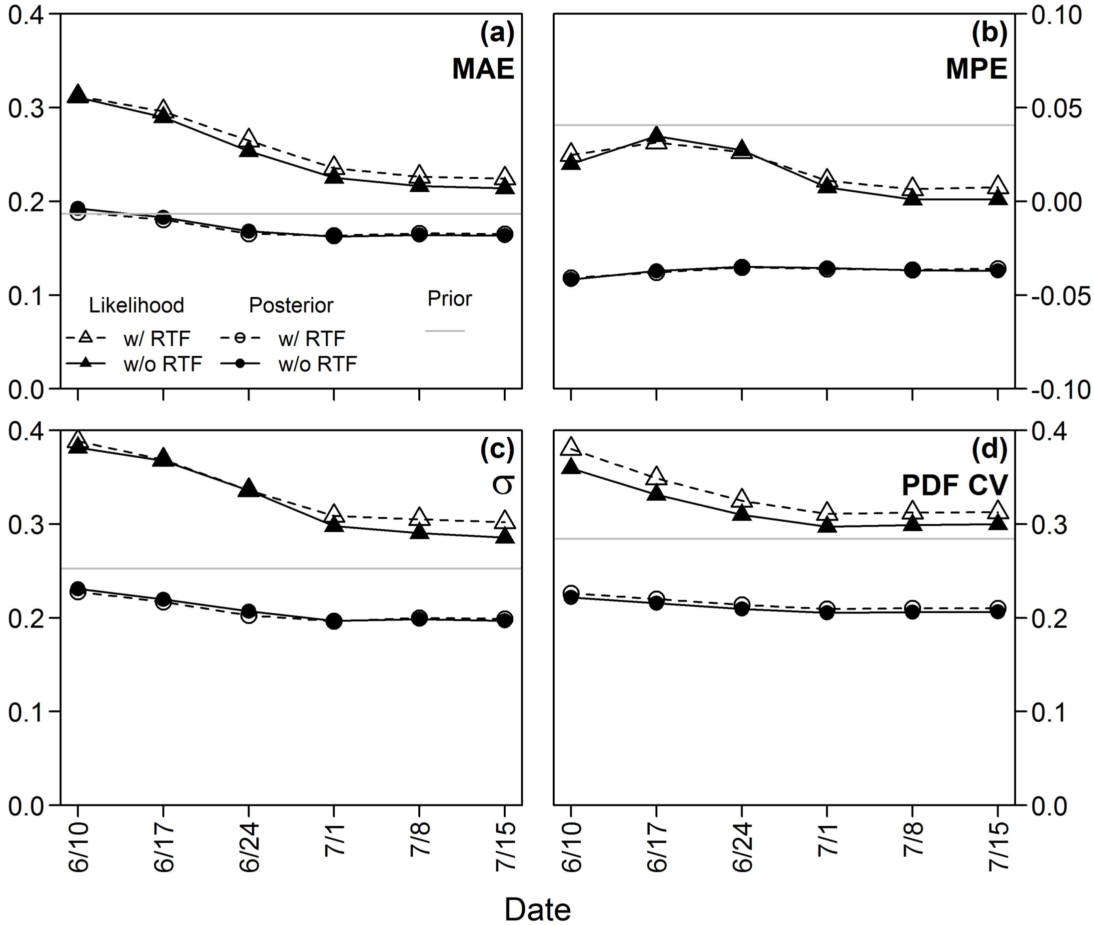

Figure 4. Summary of inferential performance of the prior (grey lines) likelihood (triangles) and posterior (circles) PDFs at various points in the season and in the presence (FCST) and absence (NULL) of the run timing forecast for $D_{50,t}$. (a) mean absolute proportional error in the median of each PDF, (b) mean proportional error in the median of each PDF (positive values are over-estimates), (c) the standard deviation of log-scale multiplicative errors), and (d) the coefficient of variation of each PDF. Note that the coefficient of variation and the variability of lognormal errors match well, indicating the appropriate level of uncertainty in the various PDFs.

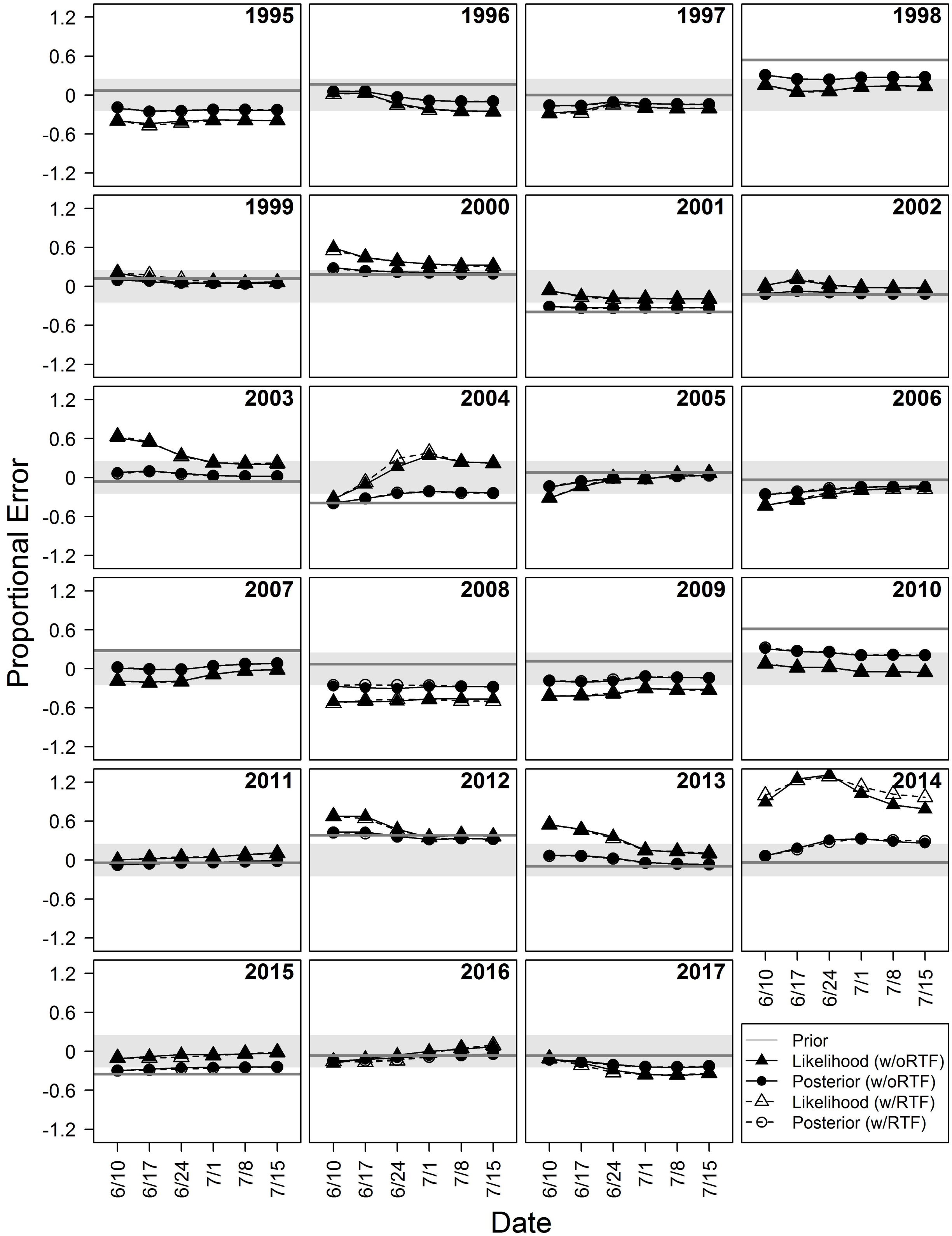

Figure 5. Annual break down of the proportional error presented in Figure 4. All lines and symbols have the same interpretation as in Figure 4. The light grey shaded area represents ±0.25. Note that in each year, the posterior error was between those of the prior and the likelihood functions.