**Spatiotemporal trends in salmon metapopulation contributions to portfolio effects in Western Alaska**

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**Introduction:**

Chinook salmon populations are experiencing unprecedented declines across much of their range. This trend is especially severe in Western Alaska watersheds, which contain some of the world's last pristine Chinook habitat but have seen steep declines in returning Chinook and Chum salmon in recent years. Salmon from this region support lucrative commercial fisheries, contribute billions of dollars to regional and global economies, and have historically supported subsistence harvests for dozens of communities in the region. As runs have collapsed, however, many upstream communities have voluntarily reduced or ceased subsistence fishing altogether, triggering a region-wide crisis of food insecurity, cultural loss, and the potential disappearance of a critical economic resource. As a result, resource managers face the difficult task of designing management strategies which balancing ongoing harvest opportunities with the urgent need to rebuild salmon populations and strengthen their resilience to future perturbations.

There is growing recognition of the critical role that intrapopulation variability plays in fostering resilience at the ecosystem scale in both terrestrial and aquatic ecosystems. In salmon populations, substantial variation in both return timing and spatial distribution of habitat use produces significant complexity in life history strategies within and among populations. Overall population performance in salmon ecosystems is shaped by the statistical averaging of multiple distinct, semi-independent sub-units distributed across space and time. Weak or negative covariance among these stocks helps buffer the broader population against the poor performance of any individual subunit, whose success may fluctuate in response to a dynamic mosaic of multi-dimensional environmental conditions. This “portfolio effect” dampens ecosystem variability by distributing risk across its components, much in the same way that financial diversification of a portfolio spreads investment risk across sectors to reduce overall volatility. Ecosystems composed of numerous negatively or weakly correlated “assets” are therefore better equipped to withstand both localized and system-wide disturbances, as such events may favor some components while disadvantaging others. In many salmon populations, particularly those at lower latitudes, this natural complexity has been eroded due to poor management and anthropogenic impacts on salmon ecosystems (Griffiths et al., \_). As a result, many systems now exhibit increased synchrony across subunits, leading to greater covariance in performance and generating “boom-or-bust” cycles in ecosystem productivity. This homogenization increases ecosystem vulnerability, even if aggregate return numbers appear stable or even more productive than more diversified ecosystems in the short term. Consequently, long-term resilience is better assessed by the health and viability of contributing subunits rather than by total run size alone.

Efforts to rebuild and conserve the long-term resilience of Western Alaska Chinook salmon must therefore account for this spatiotemporal complexity and design management strategies which maintain it in the long term. These include designing harvest methods which consider both overall exploitation rate as well as the timing of harvest throughout the season. Strategies that concentrate harvest in periods of peak abundance (e.g., highest CPUE per day), for example, may fail to account for whether this peak consists of a mix of vulnerable, weak stocks or a single, more robust stock that can sustain higher exploitation. Instead, management strategy should aim to allow harvest opportunities on healthy stocks while minimizing the risk of overexploitation for co-migrating weak stocks. In practice, however, implementing such stock-specific management approaches requires detailed data on the spatiotemporal ecology of salmon populations; information that has historically been limited at sufficiently fine spatial and temporal scales.

In the absence of fine-scale data on stock-specific spatial ecology in Western Alaska, management strategies have been implemented at relatively coarse spatial scales across large river basins. In the Yukon River Basin, for example, decisions are based on broad stock aggregates defined by the resolution of available genetic baselines. As a result, large portions of the watershed (e.g. Canadian-origin salmon) are managed as a single aggregate stock. This approach obscures the presence of multiple contributing sub-stocks, each of which may exhibit substantial variation in life history traits both within and across seasons (Connors et al., 2023). In contrast, the Kuskokwim River Basin employs front-end closure strategies aimed at allowing an estimated number of early-returning fish to escape before harvest begins. While this strategy supports basin-wide escapement goals, it does not account for the relative stock composition of fish protected by the closure versus those exposed to harvest afterward. Moreover, assessments of basin health are typically conducted on annual timescales and focus primarily on total returns over time. This overlooks the relative health of individual sub-stocks and shifts in their spatiotemporal distribution or contribution to the broader metapopulation portfolio. In both cases, managing based on aggregate spatial or temporal patterns risks obscuring underlying trends which may very independently from the aggregate and respond differently to environmental pressures or management actions. Here, we apply otolith-based methods to reconstruct spatiotemporal patterns of Chinook salmon natal origin distribution in the Kuskokwim River basins to: (1) identify the spatiotemporal structure of returning populations in Alaska’s most productive salmon-bearing watersheds; (2) assess how this structure varies with overall run dynamics; and (3) evaluate the potential impacts of harvest strategies, including front-end closures, on stocks across these systems.

**Methods:**

**Otolith Sample sets**

Otoliths were collected over multiple years from both the Yukon and Kuskokwim River basins. Sampling was conducted continuously at the Lower Yukon Test Fishery (LYTF) near Emmonak, Alaska, and at the Bethel Test Fishery (BTF) near Bethel, Alaska. Both fisheries are designed to monitor the stock composition of returning salmon throughout the duration of the run. Approximately 500 otoliths were collected over the full duration of the run from the Kuskokwim River between 2017 and 2021, and from the Yukon River in 2015, 2016, and 2021. From these, about 250 otoliths were selected for analysis to ensure coverage across the full sampling period and to provide proportional representation relative to catch per unit effort (CPUE) throughout the run.

**Sample Prep and LA-ICPMS**

Otoliths were sectioned along the transverse plane, mounted on microscope slides, and polished to expose internal growth structures (CITE). Prepared samples were analyzed at the University of Utah Strontium Isotope Laboratory using laser ablation inductively coupled plasma mass spectrometry (LA-ICP-MS). Laser ablation was conducted along a transect from the otolith core to just beyond the inferred onset of marine growth. The result is a continuous measurement of Sr87/86 from early development until movement to the marine environment. From these data, the Sr8786 value associated with the natal freshwater rearing period was manually extracted by examining changes in Sr8786 and Sr88 from the core region and morphological features of the otolith visible among the ablation path.

**Isoscape Development**

Isoscapes were constructed to model spatial variation in Sr87/86 ratios across the river basin, following the methodology described in Brennan et al. (2016) and Makhlouf et al. (2025). Briefly, Sr87/86 values were derived from water samples collected throughout both river basins (Supp. 1) and modeled using spatial stream network modeling, which considers several geologic and hydrological covariates as well as Euclidian distance and hydrological connectivity between sampling sites. The result is a spatially continuous estimate of Sr87/86 and associated uncertainty for all tributaries in the basin (Figure 2).

**Assignment framework and priors**

For each fish, a posterior probability of origin was calculated by comparing the extracted natal Sr8786 value to values predicted across the isoscape using a Bayesian probabilistic framework. This approach incorporates both spatial variation in isotopic ratios and associated error;

**[ Insert Model Here]**

**In which..**

**[ Describe the Model Here]**

**Presence and habitat priors**

Several priors were included to limit assignments to areas within the river basin suitable for spawning Chinook salmon. First, a stream order prior was applied to limit assignments to higher-order tributaries, reflecting Chinook Salmon’s known preference for spawning in larger streams. Only reaches with a stream order of 4 or greater were included in assignments (assigned a prior value of 1), while smaller tributaries were excluded (assigned a value of 0). Second, a habitat suitability prior was used to exclude regions below a threshold contributing slope value (threshold to be inserted from [source]), thereby preventing assignment to exceedingly slow or flat reaches determined to be unsuitable of spawning Chinook. Finally, data was included on observed locations of spawning chinook presence derived from USGS Arctic-Yukon-Kuskokwim (AYK) Chinook Salmon Intrinsic potential mapping. This dataset synthesizes several sources of data on observed Chinook salmon spawners (CITE, CITE, CITE) to provide a binary 0 or 1 value for locations with or without observations across the dataset. To avoid biasing regions without observations but with low sampling effort, this prior was only applied to mainstream tributaries and those with the second highest stream order. From these tributaries, reaches identified in the IP dataset as lacking observed Chinook spawning were assigned as a value of 0.

**Production estimates and time binning**

Basin-scale estimates of natal origin distribution were generated for each year by summing posterior probabilities across all individuals at each spatial location. To examine temporal patterns within the run, the dataset was divided into four temporal quartiles. The first quartile extended through June 11th, corresponding to the end of the front-end fishing closure on the Kuskokwim River. The second and third quartiles each spanned 10 days, while the final quartile included the remainder of the run. Minor variation in the duration of the fourth quartile occurred among years due to differences in run timing and length; however, these deviations were limited to a few days and represented a negligible portion of the overall CPUE. For each quartile, tributary-specific production estimates were normalized to sum to one. For each quartile, values were rescaled to range from 0-1, and figures were produced to display the relative concentration of natal origin distributions across the basin.

**Management units and timeseries construction**

Tributaries across the basin were grouped into management units based on regions of management concern identified by the Alaska Department of Fish and Game (ADFG). These included key tributaries such as [insert list of tributaries, e.g., the Salcha, Chena, Tanana, etc.]. For each of these systems, all upstream stream segments were grouped together and assigned a common management unit identifier. Additional tributaries not explicitly identified in ADFG’s management priorities were organized into units of comparable size or hydrological significance, including [insert remaining groupings here]. Rescaled production values were binned by management unit and rescaled to sum to one within each quartile. The resulting dataset are timeseries of proportional contribution for each region and for each quartile (Q0-Q4) from 2017-2021 (Figure X).

**Dynamic Factor Analysis**

To identify shared temporal patterns in salmon run timing across management units, we applied Dynamic Factor Analysis (DFA) to time series data of proportional contributions within each quartile. DFA is a multivariate time series technique that models observed series as linear combinations of a smaller set of latent trends, capturing underlying structure in the data while accounting for observation error. This approach is particularly well suited for dimensionality reduction across multiple correlated time series. It provides a systematic framework for identifying the number and shape of underlying trends, estimating their influence (loadings) on each time series, and exploring the effects of potential covariates.

**Model Selection**

We used a three-stage model selection approach. First, we compared models with one to four latent trends by calculating **partial R²**, defined as:

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where Rm2R^2\_{m}Rm2​ is the overall R2R^2R2 for the model with mmm trends and Rm−12R^2\_{m-1}Rm−12​ is the R2R^2R2 for the model with one fewer trend. This metric lets us see exactly how much extra variation each additional trend explains, rather than relying on information criteria alone. Second, using the number of latent trends that provided the best fit in the first stage, we selected the optimal structure for the observation error covariance matrix R\mathbf{R}R. We compared two common options: “**diagonal and equal**,” which assumes that all time series have the same observation error variance and are uncorrelated; and “**diagonal and unequal**,” which also assumes no correlation between series but allows each one to have its own error variance. Finally, we tested whether including covariates improved model performance by adding two variables: the relative CPUE for each management unit at each time step, and the total annual run size. We compared models with and without these covariates to evaluate whether they explained additional variation beyond the latent trends, helping to identify potential drivers of the observed temporal patterns

**Model Results and Spatial representation of feature loading**

From the best-fitting model, we extracted the underlying latent trends and the corresponding loadings for each time series on each trend. To improve interpretability, we applied varimax rotation, a common method that clarifies the loading patterns by making it easier to see which management units are most strongly associated with each trend. Factor loadings were mapped onto their corresponding management units within the watershed to provide a clearer, spatially explicit understanding of the spatiotemporal patterns.

**Results:**

Model comparison using partial R2R^2R2 values indicated that a two-trend model best explained the temporal patterns in management unit contributions. The first trend accounted for X% of the total variance, while the second explained an additional Y% (partial R2=ZR^2 = ZR2=Z). Adding a third trend resulted in minimal improvement (partial R2<0.05R^2 < 0.05R2<0.05), supporting the choice of two underlying trends. Comparison of observation error structures favored the diagonal and unequal model over the diagonal and equal alternative (ΔAICc = X), indicating that observation error variances differ among management units and supporting unit-specific error terms. Models including relative CPUE, combined CPUE, and annual run size as covariates showed no improvement in fit (ΔAICc > 2), suggesting that none of these covariates explain additional variation in timing patterns beyond the identified latent trends.

**Underlying Trends and spatial loadings**

**Trend 1** (Figure X) explained **X%** of the overall variance and was characterized by variable contributions to Q1, a relatively stable mean in Q2, and a clear increase in contributions to Q3 and Q4 (green and orange) beginning around 2019. This upward trend in the latter half of the dataset (2019–2021) suggests a shift in timing toward later portions of the run. Management units such as *[insert positively loading groups]* loaded strongly and positively on this trend, indicating they followed this pattern. In contrast, units like *[insert negatively loading groups]* exhibited negative loadings, suggesting the opposite temporal pattern—i.e., declining contributions to Q3 and Q4 in recent years.

**Trend 2** showed a more stable mean overall, but with a marked increase in contribution from Q1 over time. Throughout most of the dataset, contributions from Q1 and Q2 were relatively balanced; however, in the final year (2021), Q1 dominated, with greatly reduced contributions from later quartiles. This trend was primarily driven by strong positive loadings from management units in the upper Kuskokwim River, including *[insert units like X, X, X]*. Notably, these areas differ considerably in total production levels, indicating that despite these differences, they shared a common shift in run timing patterns over time

**Discussion:**

Our analysis identified two major underlying trends in the spatiotemporal ecology of Chinook salmon in the Kuskokwim River basin. Both trends reveal shifts in spatiotemporal patterns that have important implications for rebuilding Chinook salmon populations.

Trend 1 shows production shifting away from [X, Y, Z management units] toward [X, Y, Z management units], with particularly notable increases in late-season contributions (Q3-Q4) beginning around 2019. This redistribution may significantly impact both the timing and magnitude of fish available to upstream communities such as McGrath, Alaska, which relies on runs from tributaries near the confluence of [specific tributary] and the mainstem Kuskokwim River. [Add 1-2 sentences about specific implications - e.g., timing mismatch with traditional harvest windows, changes in stock availability, etc.]

Trend 2 reveals a steady increase in Q1 contributions throughout the dataset, with a notable decoupling from Q2 production patterns. Management units with strong positive loadings on this trend—primarily upper Kuskokwim tributary groups including [X, Y, Z]—showed dramatically higher Q1 contributions in 2021 compared to 2017. This shift suggests that the early portion of the run is becoming increasingly dominated by these upper basin stocks, with their peak contribution window moving earlier in the season.

This temporal concentration has important implications for both ecological resilience and management effectiveness. The growing dominance of upper Kuskokwim stocks in Q1 may reflect [environmental drivers/competitive release/habitat changes], while the decoupling from Q2 suggests a compression of run timing that could reduce overall temporal diversity. This trend is further supported by the decreasing contribution of the upper Kuskokwim region during the latter half of the run, as is evident by their negative loadings onto Trend 1. Taken together. Thes trends suggest that upper Kuskokwim stocks are increasingly dominant in the first quartile and absent towards the latter half of the run, where the proportional contribution is more rapidly coming from X,Y,Z.

**Implications for Management**

**Implications for ecosystem resilliance**