Feasibility report for:

Landscape-scale analysis of the relationship between juvenile Chinook size and growth and stream temperature in western Alaska

A research funding proposal to the Western Alaska Landscape Conservation Cooperative under the "Changes in freshwater temperatures and its impacts" request for proposals.

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Juvenile Chinook salmon, *Oncorhynchus tshawytscha* .

Introduction

Chinook salmon, *Oncorhynchus tshawytscha*, are a critical component of commercial, sport, and subsistence fisheries in western Alaska. Recently, Chinook salmon abundance has synchronously declined across many Alaskan stocks, resulting in cultural and socioeconomic hardship for user groups, and emphasizing the need for deeper understanding of Chinook salmon biology. In response to the Western Alaska Landscape Conservation Cooperatives (WALCC) call for proposals to examine "*Changes in freshwater temperatures and its impacts*", we submitted a project proposal to examine associations between landscape-level patterns in freshwater temperature and juvenile Chinook salmon populations during their juvenile freshwater life stage.

Water temperature plays a critical role in the health of pre-smolt salmon life stages (hereafter "juvenile"), and changes in water temperature may be a strong driving factor of growth and survival of juvenile Chinook salmon (Margolis et al. 1995; Quinn 2004). Furthermore, climate is expected to warm substantially in the coming decades in western Alaska, potentially affecting juvenile salmon condition in freshwater habitats (Griffiths and Schindler 2012). In brief, our project proposes to implement a landscape-scale meta analysis using statistical modeling to infer juvenile salmon size at age and annual growth from extant forklength data, which is available with substantial spatial and temporal coverage. We investigate whether there is a discernible relationship between climate and juvenile salmon condition by examining the association between juvenile salmon size or growth and patterns in stream temperature.

After initial review of our project proposal in 2013, questions were raised by the proposal review committee as to the availability of temperature and fish data at sufficient coverage to be able to successfully implement the proposed methods. In response to those questions, we requested and were successfully awarded seed money to examine the feasibility of the project. The objective of this feasibility report is to demonstrate whether sufficient juvenile salmon and temperature data exist to successfully implement the proposed data analysis.

Specifically we:

1. Provide an update on analytical methods to infer juvenile salmon size and growth from forklength data.
2. Summarize spatial and temporal coverage of juvenile Chinook salmon forklength data and the temperature data
3. Summarize spatiotemporal overlap in fish and temperature data

In the subsequent section, we provide a brief update on development of analytical methods to handle juvenile fish forklength data. Then we summarize juvenile Chinook salmon forklength data available through the State of Alaska Freshwater Fish Inventory database (http://www.adfg.alaska.gov/index.cfm?adfg=ffinventory.main). Following this, we discuss the availability of landscape-scale temperature products that we propose to use as a proxy for freshwater temperatures. A beneficial outcome of this feasibility effort is that we identified Landsat-based temperature products which present an improvement over the previously proposed “skin temperature” product. For example, Landsat-based temperature layers are available throughout the entire state at a spatial resolution of 60m or better. Finally, we conclude with an assessment of the feasibility of the project given data identified during this initial effort.

Given the substantial fish and temperature data overlap revealed in this assessment, we are confident that our proposed project is feasible and will provide novel insight into landscape scale patterns in Chinook salmon biology.

Update on forklength model developments

As part of the feasibility effort funded by WALCC, we have continued to refine methodology to implement finite Gaussian mixture models on juvenile salmon forklength data, with working models cast in a Bayesian statistical framework. Bayesian implementation provides a framework for incorporating a priori biological information into the fitting of the finite mixture models to juvenile salmon forklength data, such as knowledge that young of year cohorts of juvenile salmon have a smaller mean size than age 1+ cohorts, or beliefs about the size range for young of year or age 1+ cohorts. Furthermore, we intend to use model estimates from finite mixture models to characterize populations sampled at many different locations as the “dependent” variable in subsequent regression modeling to examine the association between temperature and either size at age of juvenile salmon, or when available, annual growth as measured by comparing size at age between successive cohorts within a given sample of forklengths from a population, across the Alaskan landscape.

Importantly, the Bayesian framework allows for an elegant process to accommodate the fact that these regression data are model output and thus contain “observation error” of known form. Ultimately, we will conduct a form of weighted regression analyses implemented in the Bayesian framework whereby statistical weights for size at age data can be specified by using posterior distributions for estimates of size at age as subsequent priors on regression data—in other words, a posteriori information from mixture model fits is incorporated directly as a priori information on data for regressions to examine the landscape ecology of juvenile salmon. At the time of this writing, we have developed preliminary R (RDCT 2013) and JAGS (Plummer 2003) code with working models to conduct both finite Gaussian mixture modeling and weighted regression analyses on size at age data (i.e. model output from mixture model analyses). Example JAGS model code are provided in Appendices 1 and 2.

Pacific salmon forklength data

Fish forklength data are sourced from the publicly available Alaska Freshwater Fish Inventory database managed by the Alaska Department of Fish and Game. In addition to being regularly maintained by dedicated database staff, data flow into the Freshwater Fish Inventory database continues annually (albeit with some lag between time of collection and time of data entry). At present, data are current through 2012, with data from the 2013 collection season partially available, and data from 2014 pending. Juvenile Chinook salmon data are available with strong spatial (Figure 1) and temporal coverage (Table 1), providing samples from populations spanning over a range of 1,000 kms and spanning more than 20 years.

While not directly incorporated into our WALCC proposal, the Freshwater Fish Inventory database also includes significant information on juvenile Chum salmon, *O. keta*, Coho salmon, *O. kisutch*, Pink salmon, *O. gorbushca*, and Sockeye salmon, *O. nerka*. For example, approximately 66,802 forklengths are available for Coho salmon from 1988-2012, with expansive state-wide coverage (Appendix 3). The existence of forklength data on other Pacific salmon of comparable spatial and temporal coverage to that of Chinook provides opportunity to examine landscape-scale patterns across related taxa and test for possible generalities in any identified relationships between juvenile salmon biology and the environment across species.

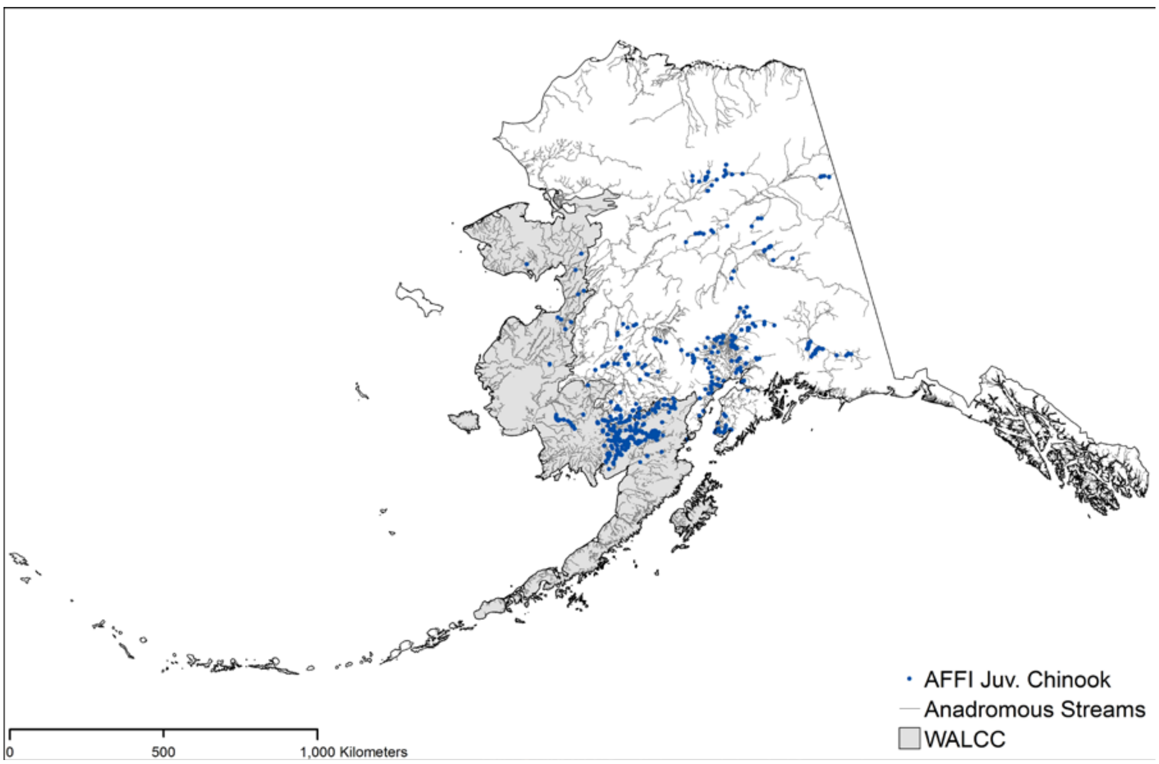

Figure 1. Distribution of juvenile Chinook salmon forklength datasets (blue dots) across the Alaskan landscape. Datasets are defined as a collection of fish lengths from the same site and time (see Table 1). Data are from the Alaska Freshwater Fish Inventory Database and incorporate 20,788 individual juvenile Chinook salmon fish lengths from 1988 – 2012 (data entry by Alaska Department of Fish and Game still in progress for 2013-2014); approximately 17,306 juvenile Chinook salmon fish lengths are within the WALCC boundary (gray shaded area).

Table 1. Summary of juvenile Chinook salmon forklength data contained in the Alaska Freshwater Fish Inventory database 1988 – 2012.

	WALCC		All Alaska	
Years	Datasets[a]	Total lengths	Datasets[a]	Total lengths
1988	.	.	3	5
1991	16	149	16	149
1994	.	.	7	22
1999	.	.	3	7
2000	.	.	2	11
2002	.	.	28	86
2003	31	273	48	374
2004	10	48	21	166
2005	52	501	60	738
2006	247	2959	276	3231
2007	21	337	37	430
2008	83	1145	128	6894
2009	6	41	74	8087
2010	8	53	24	201
2011	3	25	33	329
2012	3	10	12	58
Total	480	5541	772	20788

[a] A dataset represent a collection of forklengths at a specific site location (i.e. siteID in the Alaska Freshwater Fish Inventory database).

Temperature Data

We originally proposed to utilize the "skin temperature" climate product available from the National Center for Environmental Prediction (NCEP). In investigating skin temperature data further and consulting with remote sensing experts versant in Alaska climate products (personal communication with Jason Geck, Alaska Pacific University), we identified a well-vetted method for generating radiometric surface temperatures using NASA Landsat thermal imagery. This approach provides a higher resolution and more widely implemented temperature data product compared to NCEP skin temperature. Whereas skin temperature information are available with up to 2km spatial resolution, Landsat provides state-wide temperature data at a spatial resolution of 60m to 30m with 16-day frequency (Table 2).

The Landsat-7 and -8 Enhanced Thermal Mapper (ETM) senses a wide range of electromagnetic wavelength bands including visible, infrared, and thermal bands. The thermal bands indicate thermal radiation released from the earth surface and are used to derive land and water surface temperatures. These Landsat ETM sensors are very stable and provide accurate and precise measures of local radiometric land and water surface temperature. Methods for deriving temperature from these remotely sensed thermal images have been the subject of extensive research and calibration (see Schotta et al. 2012). Several studies have validated the accuracy of Landsat-derived surface temperatures using in situ water temperature measurements. For example Mustard et al. (1999) validated estuarine temperatures generated from Landsat 4 with in situ water temperatures finding < 1°C discrepancy between the two temperature values. In the context of our study in Alaska, the WALCC funded AK-OATS project (http://aknhp.uaa.alaska.edu/aquatic-ecology/akoats/; WALCC 2013) has organized an information clearinghouse to identify in-stream freshwater datasets. While the in situ freshwater temperature data sets as identified in AK-OATS are not available with sufficient spatial and temporal regularity to incorporate them directly into our proposed landscape-scale meta analysis on juvenile salmon ecology, they do provide opportunity to examine the consistency between in situ data and Landsat temperature data and validate and/or adjust satellite-derived temperature products.

The application of remote thermal imaging to stratified aquatic systems presents challenges (Hook et al. 2004a,b), but shallow, lentic systems such as Alaskan anadromous streams that mix continuously are ideal candidates for remote thermal sensing techniques (e.g. Faux et al. 2001; Torgerson et al. 2001; Cohen and Goward 2004). Landsat thermal imagery has been used in numerous ecological studies to assess marine, lake and river surface temperatures in Alaska (e.g. study of the Yukon River plume by Dean et al. 1989) and abroad (e.g. Schneider et al. 1996; Simon et al. 2014; Wawrzyniak et al. 2012), including landscape-scale studies examining the interaction between water temperature and aquatic/marine organism biology (Chinook ecology: Torgerson et al. 1999; resident freshwater fish growth: Budy et al. 2011; marine benthic fauna: Calabretta and Oviatt 2008).

The Landsat imagery spanning our study period (1988 – present) is publically accessible through the U.S. Geological Survey Explorer (Table 2). Temperature data derivation algorithms outlined in NASA's Landsat Science Data Users Handbook (http://Landsathandbook.gsfc.nasa.gov/pdfs/Landsat7_Handbook.pdf) will be used to calculate local effective surface temperature (°C) in the study area (Figure 2).

The spatial grain of Landsat derived products is very fine, providing good opportunity to assess landscape scale associations between juvenile salmon biology and (a proxy) for freshwater temperature at any point in Alaska (Figure 2). The combination of landscape-wide coverage and fine spatial resolution provides the opportunity to extract temperatures along stream corridors in close proximity (e.g. ± 1km) to juvenile salmon forklength collection locations. This level of spatial grain provides opportunities for examining second-order properties of surface temperature regimes such as local temperature variability or extremes. Finally, cloud cover can obscure the study area resulting in unusable temperature readings at a specific location and time. In these cases the high spatial resolution allows us to implement standard nearest-neighbor averaging methods to interpolate missing data.

The temporal grain of Landsat thermal imagery provides between 22 to 23 temperature records for each grid cell (except in 2013 when combined Landsat-7 and -8 provide 45 records; Table 2) in the study region per year. This level of temporal grain somewhat limits options for examining second-order properties of surface temperature regimes (e.g. variability or extremes). In order to interpolate temperature data between Landsat image dates such that we can generate localized surface temperature values that match the spatial location and sample date for juvenile forklength data in the Alaska Freshwater Fish Inventory database, we will use time-series smoothers such as Generalized Additive Models with generalized cross validation for "optimal smoothing" (Wood 2006). Such methods allow for efficient interpolation of data, as well as construction of values of interest along fitted time series such as rates of change (e.g. Fewster et al. 2000; Sethi et al. 2014). Furthermore, we will examine an index of cumulative temperature in order to provide a metric that integrates temperature regimes experienced by juvenile salmon over a given time period.

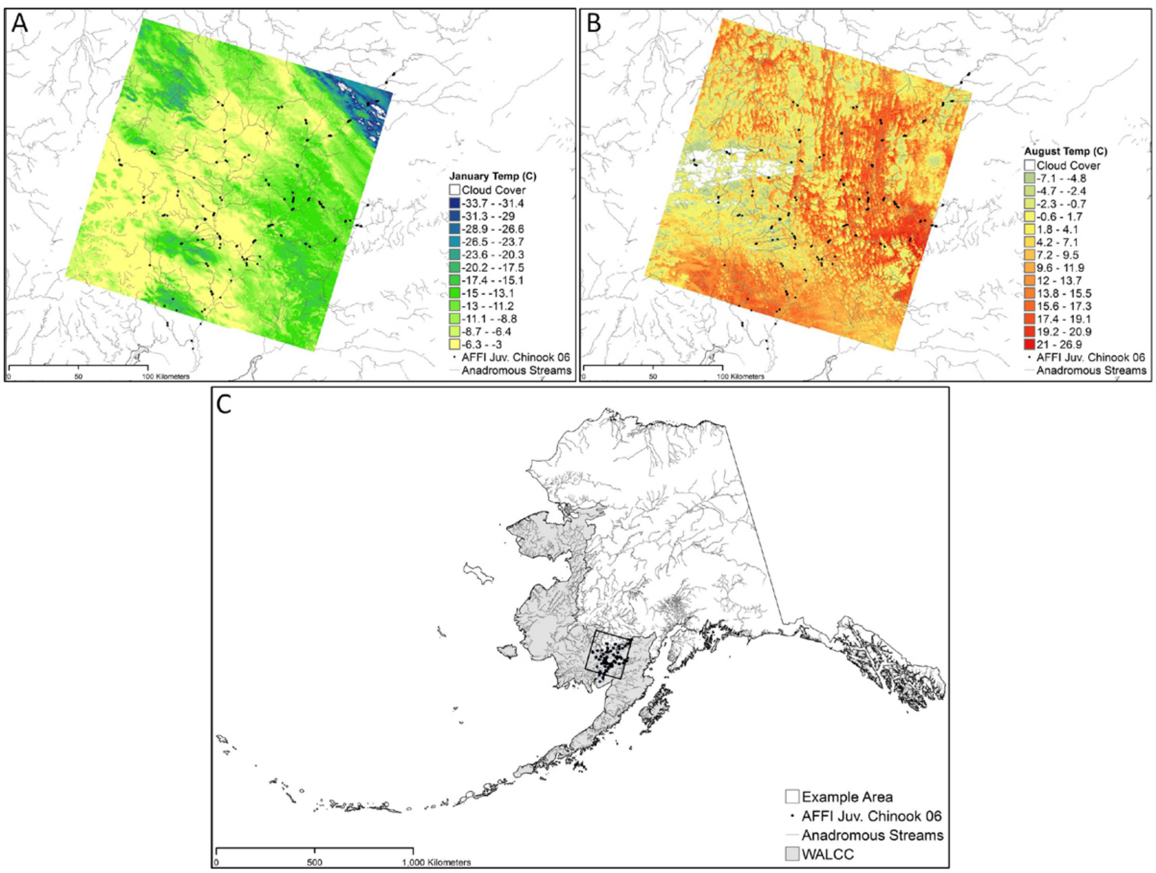

Figure 2. Example Landsat-7 Enhanced Thermal Mapper temperature data demonstrating spatial resolution (60m) and overlap with juvenile Chinook salmon forklength data (black dots) in January (A) and August (B) 2006. The example study area is indicated in panel C.

Table 2. Landsat surface temperature data sources, temporal grain, and spatial grain for statewide Alaska coverage 1990-2014.

Years	Source	Temporal grain (days)	Spatial grain (m)
1990-1998	Landsat 4/5	16	60
1999-2012	Landsat 7	16	30
2013	Landsat 7/8	8[a]	30
2014	Landsat 8	16	30

[a] In 2013, Landsat 7 and 8 earth orbits were staggered such that this year has in effect an 8-day temporal grain from two separate instruments each with 16-day sampling frequency (approximately 45 sampling dates for the year).

Concluding feasibility assessment

In closely examining the juvenile salmon forklength and temperature products as part of this feasibility project, we are confident the necessary ingredients are available to conduct landscape-scale examination of the interaction between juvenile Chinook salmon ecology and freshwater temperatures in Alaska.

Broadly speaking, there are two degrees of data burden necessary to implement our proposed project. At the finest scale, analytical methods in the project require spatiotemporally explicit samples on juvenile salmon populations with associated freshwater temperature information. Examination of juvenile Chinook salmon forklength data contained in the Alaska Freshwater Fish Inventory demonstrates a large number of sampled populations with good spatial and temporal coverage, and with adequate samples sizes to implement forklength modeling. Data of similar coverage are also available for other Pacific salmon species such as Coho salmon which often overlap in geographic distribution with Chinook salmon. Furthermore, implementation of forklength modeling in a Bayesian framework provides the opportunity to incorporate a priori information about juvenile salmon biology into the data analysis and appropriately account for uncertainty throughout the analytical framework in the project proposal. Similarly, by adopting Landsat-based temperature products in lieu of skin temperature, we greatly increase the spatial resolution of the temperature data and leverage methods proven successful by many previous freshwater studies.

Secondly, at a broader scale, landscape-level inference about the relationship between juvenile salmonid biology and the freshwater environment is strongest with good spatial and temporal range of sampled fish populations. In this respect the Alaska Freshwater Fish Inventory database is quite rich, providing samples on juvenile Chinook populations spread throughout the WALCC landscape, and more broadly across central and interior Alaska. Similarly, state-wide and fine scale coverage of Landsat-based surface temperature data are available to match sampled fish locations.

The freshwater life stage of juvenile Chinook salmon has been demonstrated to be an important period where populations experience several survival bottlenecks from egg deposition through to smoltification, ultimately setting the stage for adult-return productivity. By providing insight into the association between juvenile salmon condition and stream environment, this work moves beyond description of environmental patterns and makes a useful connection to the biology of key fish species, thus improving our understanding of potential impacts from future changes in the western Alaska landscape associated with ongoing climate change.

This feasibility assessment reinforced for us the unique opportunity for a broad-scale landscape meta analysis--on the oder of 10^4 to 10^5 km^2--provided by the spatial and temporal extent of both the juvenile salmon and surface temperature data. Further, comparing information generated from populations of juvenile salmon within WALCC to populations throughout the State will provide insight into the spatial scale at which associations (or lack thereof) between juvenile salmon biology and freshwater temperatures play out. Finally, the methods and modeling framework developed here will support analyses of other Pacific salmon species (e.g. the Alaska Freshwater Fish Inventory database contains over 60,000 juvenile Coho forklengths), revealing associations between stream environment and juvenile biology across taxa and ultimately contributing important information regarding whether climate change may differentially impact Pacific salmon species.

Acknowledgments

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Appendix 1. Example JAGS model code for finite Gaussian mixture models fit to juvenile salmon fork length data.

```
# JAGS model to estimate a 2-component finite Gaussian mixture model
model {
  # data passed to JAGS and variables definitions
    # fork length mixture modeling
      # K number of component Normal distributions, here defined as K=2
      # y[] vectors of univariate forklength data for years 2011,2012
      # N.v number of fork length datapoints
      # a[K] vector of 1's of length K for K component distributions, used in prior for pi[]
  # parameter to be estimated, and thus necessitating priors (and initial values)
    # fork length mixture modeling
      # mu1 location of smallest-mean component
      # mu2shift shift parameter to define ordered larger-mean component
      # tau[] vector of component distribution precision parameters = 1 / sigma^2
      # pi[]vector of K component distribution proportions present

  # internal variables
    # S[] vector of N group membership labels

  # derived parameters
    # sigma[] vector of K component distribution spread parameters
    # mu[] vector of K component distribution means

  # priors
    # Dirichlet prior on component distribution proportions
      pi.mix[1:2] ~ ddirch(a[])
    # component normal spread priors (i.e. precision, 1/sigma^2 = tau)
      for(k in 1:2){tau.mix[k] ~ dgamma(1,.1)} # should lead to diffuse prior for sd about
uniform on 0 to 5+
    # location parameter prior, with implicit natural ordering of cohorts
      mu1.mix ~ dunif(25,100) # can input informed values here if desired
      mu2shift ~ dunif(10,100)  # can input informed values here if desired
    # reconstruct locations for component distributions
      mu.mix[1] <- mu1.mix
      mu.mix[2] <- mu1.mix+mu2shift
  # fork length mixture model likelihoods
    for(i in 1:N.v[1]){
      S[i] ~ dcat(pi.mix[])
      y[i] ~ dnorm(mu.mix[S[i]],tau.mix[S[i]])
      }
  # derived parameter to track
    for (m in 1:2){sigma.mix[m] <- pow(1/tau.mix[m],.5)}

  } # end JAGS model
```

Appendix 2. Example JAGS code for weighted regression

The below JAGS code fits a simple weighted regression model of the following form:

$y_i = \alpha + \beta x_i + \gamma_i + \varepsilon_i$,

$\gamma \sim Normal(0, \sigma_\gamma^2)$ known observation error,
$\varepsilon \sim Normal(0, \sigma_\varepsilon^2)$ residual error,

where "observation error" is accommodated in the model by imposing an observation level zero mean Normal random deviate (γ) specified with a priori known variance as generated from external modeling output (e.g. output from finite mixture modeling). In this form, dependent variable data which are observed with higher error have less influence on regression parameter estimates as compared to those dependent variable data observed with less observation error. In addition, regression models of this form appropriately propagate uncertainty about regression input data.

```
# Example JAGS model for Bayesian weighted regression
model {
  # passed to JAGS
    # y[] vector of dependent variable mu (e.g. posterior mean from posterior from external
modeling effort)
    # obs.tau posterior distributions for regression "dependent data" from external
modeling, here
    # input as observation error priors on regression data.
    # x[] independent variable observations
    # n total number data points

  # priors for regression depednent variable input values passed to JAGS
    for(j in 1:n){gamma.obs[j] ~ dnorm(0,obs.tau[j])}
  # priors for regression estimating linear change in size over time
    alpha ~ dnorm(0,.001)
    beta ~ dnorm(0,.001)
    tau.reg ~ dgamma(.1,.1)
  # likelihood
    for(i in 1:n){
      pred[i] <- alpha+beta*x[i]) + gamma.obs[i] # add on observation variance of known form
(informed prior)
      y[i] ~ dnorm(pred[i],tau.reg) # now residual variance
      }
  # derived parameters
    sigma.reg <- pow(1/tau.reg,.5)
} # end JAGS model block
```

Appendix 3. Juvenile Coho salmon forklength data coverage.

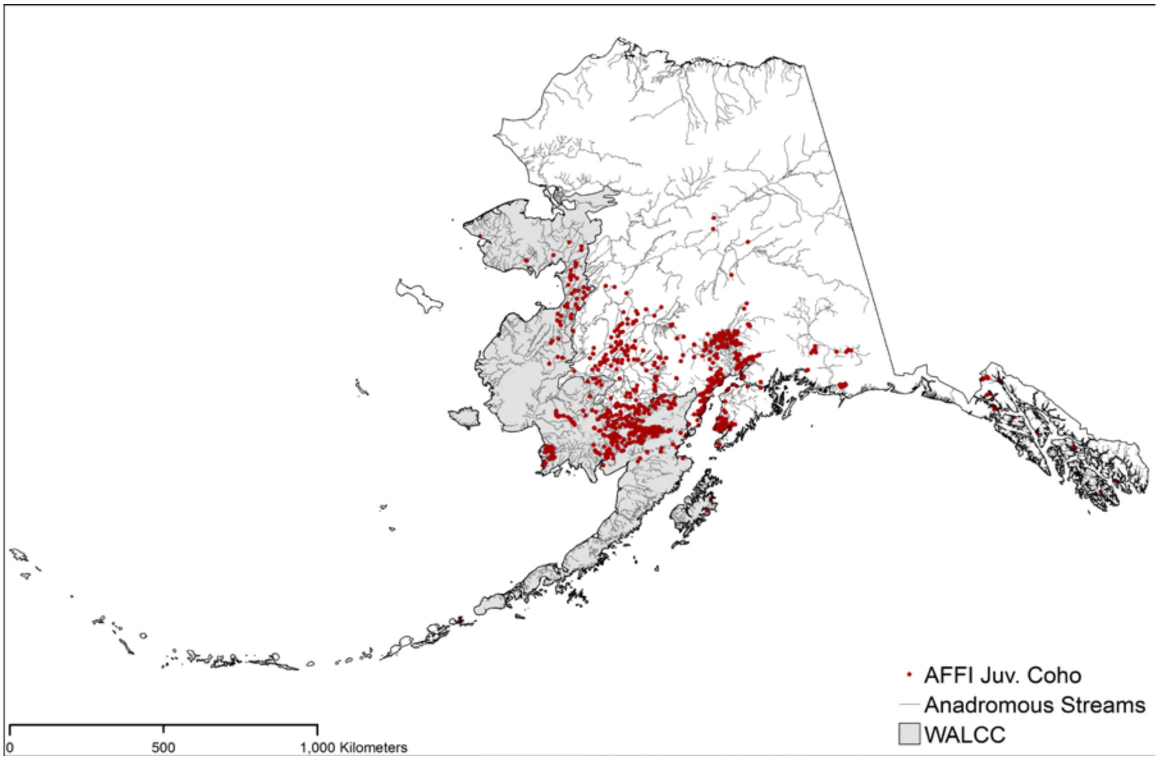

Figure A3.1. Distribution of juvenile Coho salmon forklength data sets (red dots) across the Alaskan landscape. Data sets are defined as a collection of fish lengths from the same site (see Table A.1). Data are from the Alaska Freshwater Fish Inventory Database and incorporate 66,858 individual juvenile Coho salmon fish lengths from 1988 – 2012 (data entry by Alaska Department of Fish and Game still in progress for 2013); approximately 17,306 juvenile Chinook salmon fish lengths are within the WALCC boundary (gray shaded area).

Table A3.1. Summary of juvenile Coho salmon forklength data contained in the Alaska Freshwater Fish Inventory database 1988 – 2012.

	WALCC		All Alaska	
Year	Datasets[a]	Total lengths	Datasets[a]	Total lengths
1988	.	.	16	60
1991	36	605	36	605
1993	.	.	5	17
1994	.	.	6	67
1995	.	.	6	18
1996	.	.	7	20
1998	.	.	27	82
1999	.	.	8	44
2000	.	.	12	57
2002	.	.	123	642
2003	81	1572	120	2226
2004	99	1075	102	1098
2005	90	2771	99	2952
2006	143	1113	159	1192
2007	61	1421	156	1946
2008	260	12028	406	39983
2009	30	389	154	14428
2010	15	185	16	308
2011	25	536	48	698
2012	14	88	35	359
Total	854	21783	1541	66802

[a] A dataset represent a collection of forklengths at a specific site location (i.e. siteID in the Alaska Freshwater Fish Inventory database).