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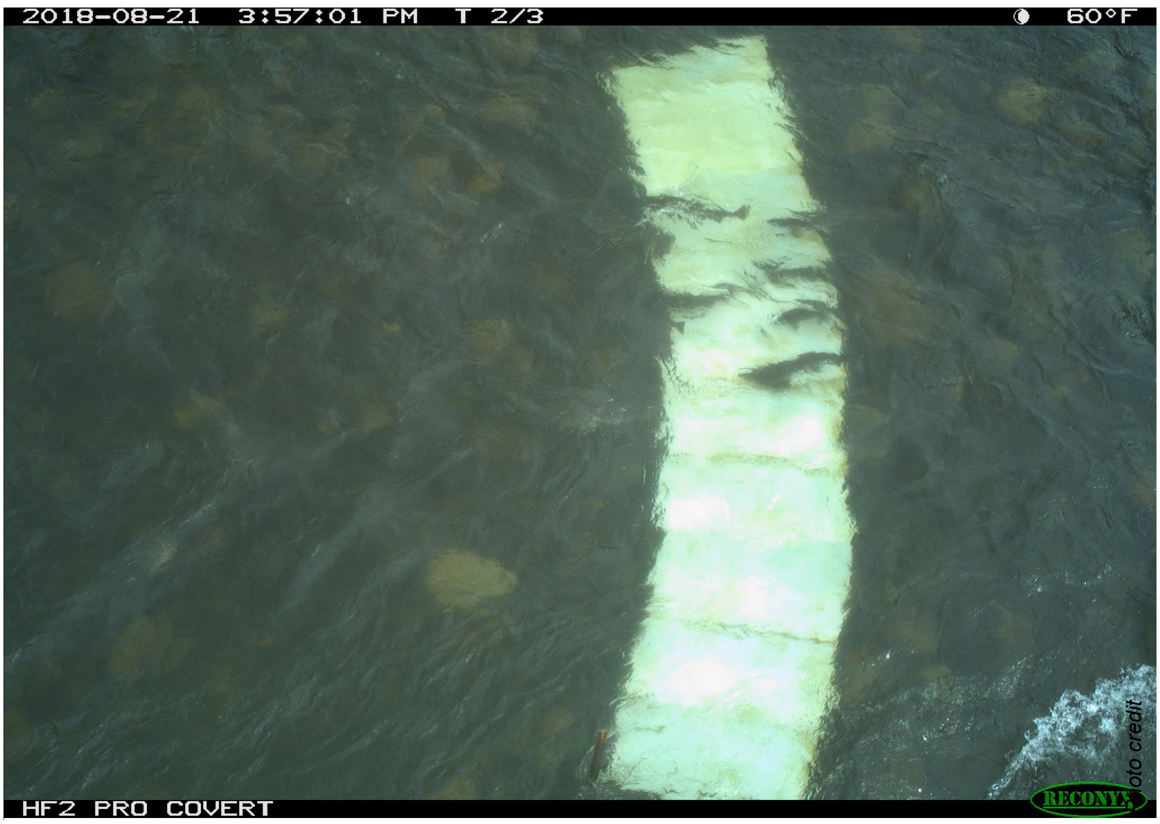
Estimating Sockeye Salmon Escapement into Akalura Lake 2022, Kodiak National Wildlife Refuge, Alaska

Gareth K. VanHatten



Kodiak National Wildlife Refuge
April, 2024

The mission of the National Wildlife Refuge System is to administer a national network of lands and waters for the conservation, management and where appropriate, restoration of the fish, wildlife, and plant resources and their habitats within the United States for the benefit of present and future generations of Americans.

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Keywords:

Akalura River, Alitak District, Kodiak Island, Sockeye salmon, *Oncorhynchus nerka*, , time-lapse cameras, ,

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Estimating Sockeye Salmon Escapement into Akalura Lake 2022, Kodiak National Wildlife Refuge, Alaska

Gareth K. VanHatten

Abstract

A time-lapse photography and video recording system was used to enumerate adult sockeye salmon (*Oncorhynchus nerka*) entering Akalura Lake. In 2022, the system was installed on 10 June 2022 and operated through 09 September 2022. The time-lapse photography camera recorded 3 sequential pictures at the start of each minute for the duration of the project. Following a double-sampling protocol, a polynomial model of the relationship between time-lapse and video counts was found to be the most parsimonious model to estimate salmon passage across the season. In 2022, estimated daily salmon passage peaked at 271 on September 01, 2022, and by the end of the season a total of 2287 (95% CI=1776–3049) sockeye were estimated to have migrated into Akalura Lake.

Introduction

Management of salmon within the Kodiak Management Area (KMA) is the responsibility of Alaska Department of Fish and Game (ADF&G) – Commercial Fisheries Division monitors salmon escapement on many systems within Kodiak Refuge. Escapement goals for KMA salmon stocks are based on the Policy for the Management of Sustainable Salmon Fisheries (SSFP; 5 AAC 39.222) and the Policy for Statewide Salmon Escapement Goals (EGP; 5 AAC 39.223). These policies were adopted by the Alaska Board of Fisheries in 2000 and 2001, respectively, to ensure the state's salmon stocks would be conserved, managed, and developed using the sustained yield principle. Escapement information provides the basis for ensuring biological integrity and is the foundation for in-season management actions that regulate commercial, sport, and subsistence harvest of salmon (Spalinger 2006). Historical studies have documented salmon utilizing over 800 systems within the KMA (Johnson and Keyse 2013), with only 49 of these systems supporting yearly sockeye salmon spawning populations (Johnson and Blanche 2010). Of these 49 systems, escapement is monitored on 10 systems. During the annual review of escapement goals in 2005 by ADF&G the Akalura, Uganik, and Little River escapement goals were eliminated. The elimination of these goals was based on reliable escapement estimates not being consistently collected due to budget constraints (Nelson et al. 2005).

Sockeye salmon data has been collected on Akalura Lake intermittently starting in 1923 (Edmundson et al. 1994), with the most recent study being conducted in 2021 (VanHatten 2023). Historical data (1992–2003) show that at one time the Akalura sockeye salmon run was a bi-modal population with a small early run occurring in June. This system has been monitored during 1944–1958, 1987–2002, and 2015–2022. Due to lack of funding, sockeye salmon abundance data were not collected between 2002 and 2015. The escapement estimates generated from the 2015–2021 field seasons are provided to ADF&G as an indicator for abundance and trend of sockeye salmon in Akalura drainage. The lack of recent escapement estimates hinders management decisions focused on sustainable yield and management decisions focused on maintaining the energy and nutrients that spawning salmon provide to riparian and terrestrial ecosystems (Wilson and Halupka 1995, Wipfi and Baxter 2010).

Thus, it is important for Kodiak National Wildlife Refuge managers to have accurate escapement data to assess whether escapement is sufficient to maintain historical ecosystem productivity and function as well as subsistence needs.

Study Area

Akalura Lake is located in southwestern Kodiak Island, 15.3 miles northwest of Ahkiok. Akalura Lake has a surface area of 4.9 km^2, a mean depth of 10 m, and a maximum depth of 22 m (Schrof et al. 2000). Four creeks feed into the lake: Mud Creek, Falls Creek, Eagle Creek, and Crooked Creek (Edmundson et al. 1994). The outlet stream, Akalura Creek, is 1.9-km long and drains into a saltwater lagoon before entering Cannery Cover in Olga Bay. Akalura Creek is a narrow, clear-water creek with a 2.8 km tributary,Humpy Creek (Figure 1).

Methods

Federal and State fisheries managers utilize several different methods, each with their own strengths and weaknesses, to monitor salmon escapement and passage, including fixed or floating weirs (federal and state), counting towers (private organizations), sonar (federal and state), and aerial surveys (state) (Cousens et al 1982). Although these methods can provide the desired information, they are expensive and relatively labor intensive. On small creeks (<15 m wide), remote video methods can collect comparable data and are less expensive and labor intensive in the field; however, the time required to manually process an entire season of raw video into estimates of salmon escapement can be prohibitively time consuming (Deacy et al 2016).

To address the challenges associated with quantifying the sockeye salmon from video in Akalura River, Deacy (2016) developed a double-sampling time-lapse photo and video camera system survey method. This method was first implemented in 2012 and then refined from 2013–2015 on 11 creeks in southwest Kodiak, Alaska. The method provides the benefits of a remote video system (e.g., low maintenance, noninvasive, inexpensive, and accurate counts), while reducinglabor costs associated with reviewing an entire season of videos.

To utilize a remote camera system without time-consuming video enumeration, we used the methods developed by Deacy (2016). For our study, the variable of interest is the number of sockeye salmon migrating upstream each hour, which we quantified with an above-water video camera. The more easily measured and related measurement is the number of salmon detected in time-lapse images each hour. Time-lapse photography is recorded for the entire study season, while the video recordings are only measured on a sample of time periods to provide an estimate of detection probability associated with hourly salmon counts using the time-lapse still images. The total time required to review footage in this double-sampling scheme is low relative to video-only approaches because we only enumerate sockeye salmon in a subset of the hour-long sample units. We determined the sockeye salmon passage for the remaining hours by modeling the relationship between the subsample of hourly video counts and photo counts and then used the model to predict sockeye salmon migration across the entire run. In addition, the time-lapse photo counts provide an understanding of general run timing over the field season. Using the statistical package R, we were able to combine data from 2015 to 2021 to calculate an estimator for the 2021 estimate.

Time-lapse camera system

The camera/video system was installed before the start of the sockeye salmon run, 13 June 2021 (Figure 2). It was imperative for the camera/video system to be installed early enough before the start of the sockeye salmon run, which according to historical data indicates this time to normally occur after late July to early August. In 2021, the site was visited every 10 days, except for one period lasting greater than 10 days. The purposes of site visits were to ensure all equipment was working, clean the panels, and change out SD memory cards. To record time lapse images of passing salmon, we used a ReconyxR Hyperfire PC800 camera (Reconynx Inc., Holmen, WI), programmed to take three photos in rapid succession (<1 sec between frames) each minute, 24 hrs./day. We followed the protocol of Deacy et al. (2016) for the use of time lapse and infrared lights to capture salmon movement.

To help detect salmon, we secured 50.8 cm–76.2 cm white High-Density Polyethylene (HDPE) contrast panels to the bottom of the stream below the cameras by attaching them to a heavy chain (Figure 3). See Deacy et al. (2016) for details.

At the end of the season, we counted salmon from the time-lapse photos for the previous season. We recorded the date, time, and photo number for photos that recorded salmon. This method allowed us to review video footage of those hours when salmon were present. Finally, we summed hourly upstream and downstream counts separately.

Statistical analysis

We used a model-based double-sampling approach to estimate salmon escapement (Deacy et al. 2016) to estimate annual salmon passage (total number of salmon that moved upstream from the camera system).

We selected hours that spanned the full range of hourly time-lapse salmon counts, including both periods with high numbers and periods with low numbers of salmon passing over the panels in both directions. Also, we selected hours where we were confident of nearly 100% detection (census) of salmon movements from video footage. We excluded hours with poor sight ability, such as bad glare or poor lighting.

Next, we modeled video counts as a function of time-lapse photo counts for the subsample. All statistical analyses were conducted using the escapement package (https://github.com/mccrea-cobb/escapement) in R (Team 2020). See "Session Information" for details. We compared four different models: first and second order linear regressions and first and second order segmented (or "split-point") linear regression models (Muggeo 2008). The segmented regression allowed the slope to differ across ranges of the predictor variable. This model makes ecological sense for salmon swimming in a creek because salmon swimming upstream (positive values) might move slower and thus have a greater chance of being detected in a time-lapse burst. In contrast, salmon swimming downstream (negative values) might move faster and have a lower likelihood of detection. To address this possibility, we set split-point (slope inflection point) at zero.

To assess relative model fit, we compared Akaike's Information Criterion values corrected for small sample sizes (ΔAIC_c; Akaike (1974)). We calculated 95% confidence intervals around escapement point estimates using bootstrap resampling methods. Using the most parsimonious model, we predicted hourly salmon passage over the monitoring period. We summed hourly salmon passage to estimate daily passage and annual escapement. Because we did not use random sampling to select our modeling subsample, it is inappropriate to use the model variance to calculate confidence intervals for total escapement. Instead, we bootstrapped our subsample (Canty and Ripley 2020) with replacement, refit our model using the top model structure, and re-predicted the total escapement (Efron and Tibshirani 1993). We repeated this 1,000 times and used the 2.5 and 97.5 percentile values as upper and lower 95% confidence intervals of total escapement.

Results

We quantified salmon from 168 hours of video to model the relationship between hourly up and downstream counts ofsalmon in the videos and salmon in time-lapse photos. We estimated the minimum escapement of Akalura sockeye salmon in 2022 was 2,287 (95% CI: lower CI =1,776, upper CI = 3,049, Table 1; Figure 4). We estimated that daily sockeye salmon passage peaked at 271 salmon on 1 September 2022. Based on ΔAIC_c, the most parsimonious model was the linear model (Tables 2 and 3, Figure 7). Using the coefficient estimates from the linear model, we were able to estimate the daily passage and total annual escapement.

Discussion

The 2022 estimate of sockeye salmon escapement was the fourth lowest estimate since the start of the project in 2015. Salmon escapement estimates have a downward trend since 2016 with the lowest estimate in 2020 (338 fish) and a slight increase in 2021 and 2022. Our minimum annual escapement estimate for 2022 is lower than the estimates for 2015 through 2019 (Figure 4 and 5), even though there was continuous data collected between June 24 and September 10 (Figure 5).

Unlike previous years, the 2022 estimate was the result of the project operating without incident, full recording of video and time-lapse photos since the onset of the project.

The downward trend of salmon escapement at Akalura could be the result of low salmon returns to the Alitak District. However, this trend was not observed at the Dog Salmon drainage (123,986 sockeye, below Akalura River) orUpper Station, Olga Lakes (244,519 sockeye, above Akalura River), which both had relatively strong returns in 2022 (ADFG personal communication) and have met their lower escapement goals for the past six years. A more thorough in-depth study should be conducted to gain a full understanding of the relationship between all the systems within the Alitak District.

The Akalura system has optimal characteristics (small, shallow and fast moving water) to monitor fish movements using the Deacy et al (2016) time-lapse and video method.The continued collection of data from the Akalura system shows how important both the time-lapse photos and video are to calculating annual estimates of salmon escapement. The 2028 field season was the 8th consecutive year sockeye salmon data were collected at Akalura Creek. We analyzed data from all years to reduce uncertainty in our estimates . .

Recommendations

Time-lapse and video system

It is recommended to continue collecting paired time lapse photo and video to assess whether the assumptions associated with this type of project is fully met. Continued data collection will allow us to determine whether there are differences in conditions across years, which would need to be accounted for in the modeling framework. For example, installing illumination lights for nighttime detection of fish movement.

Equipment specifications

In 2018, the video system was upgraded to record in color and at night. An infrared lighting system was added to the camera system so that we could monitor fish movement at night easier. Due to the limited power supply, we recommend that a solar-powered lighting system is added in future seasons to ensure migrating fish are recorded at night.

Acknowledgements

The work conducted and analysis of the data in this report are the results of previous work conducted by Kodiak National Wildlife Refuge volunteers and employees. We would like to thank McCrea Cobb for his input into the survey design. We would also like to thank those individuals who helped in the construction and maintenance of the camera system. We would like to thank the many volunteers and full-time employees with the Kodiak National Wildlife Refuge for their contribution to the collection and analysis of the data from this project.

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Tables

Table 1. Annual escapement estimates based on the top model, 2015 – 2019, Akalura River, Kodiak Island, Alaska, 2021.

Year	Escapement (CI)
2015	22,474 (19,094 – 26,837)
2016	32,914 (26,314 – 37,496
2017	6,281 (5,215 – 7,699)
2018	5,475 (4,773 – 6,375)
2019	2,088 (1,678 – 2,673)
2020	344 (270 – 467)
2021	1,312 (1,052 – 1,652)
2022	2,287 (1,776 – 3,049)

Table 2. AIC_c table of the candidate model set for estimating minimum annual salmon escapement, Akalura River, Kodiak Island, Alaska, 2021.

Models	K	AICc	Δ AICc	Model likelihood	AICCc weight
Polynomial	3	6081.11	0.00	0.6	0.6
Segmented polynomial	4	6081.92	0.80	0.4	1.0
Segmented	3	6212.86	131.74	0.0	1.0
Linear	2	6213.04	131.92	0.0	1.0

Table 3. Summary of the most parsimonious model (polynomial) using the minimum annual sockeye salmon escapement, Akalura River, Kodiak Island, Alaska, 2021

Predictor	B	SE	t	p
Photo	8.30	0.468	17.76	<0.001
I (photo^2)	0.15	0.012	12.22	<0.001

Figures

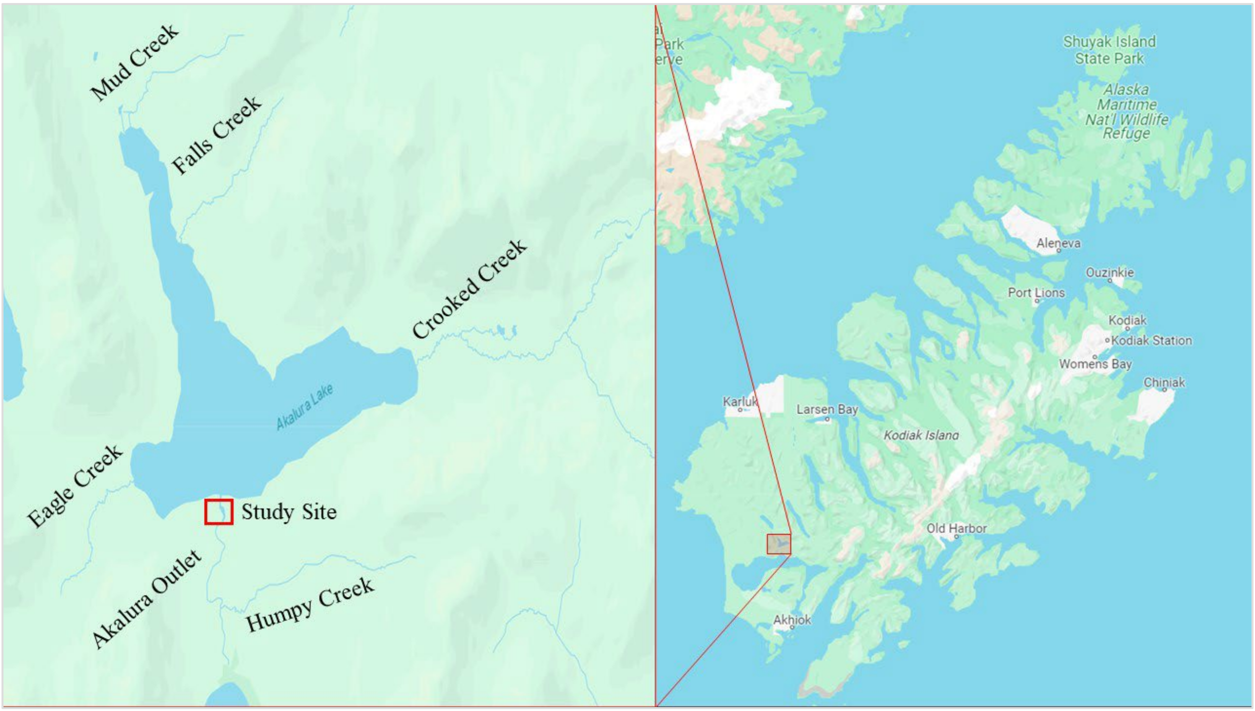

Figure 1. Location of Akalura Lake and the associated weir, Kodiak Island, Alaska, 2022.

Figure 2. Sockeye salmon counting system showing time-lapse camera, infrared light, and video camera locations, Akalura River, Kodiak Island, Alaska.

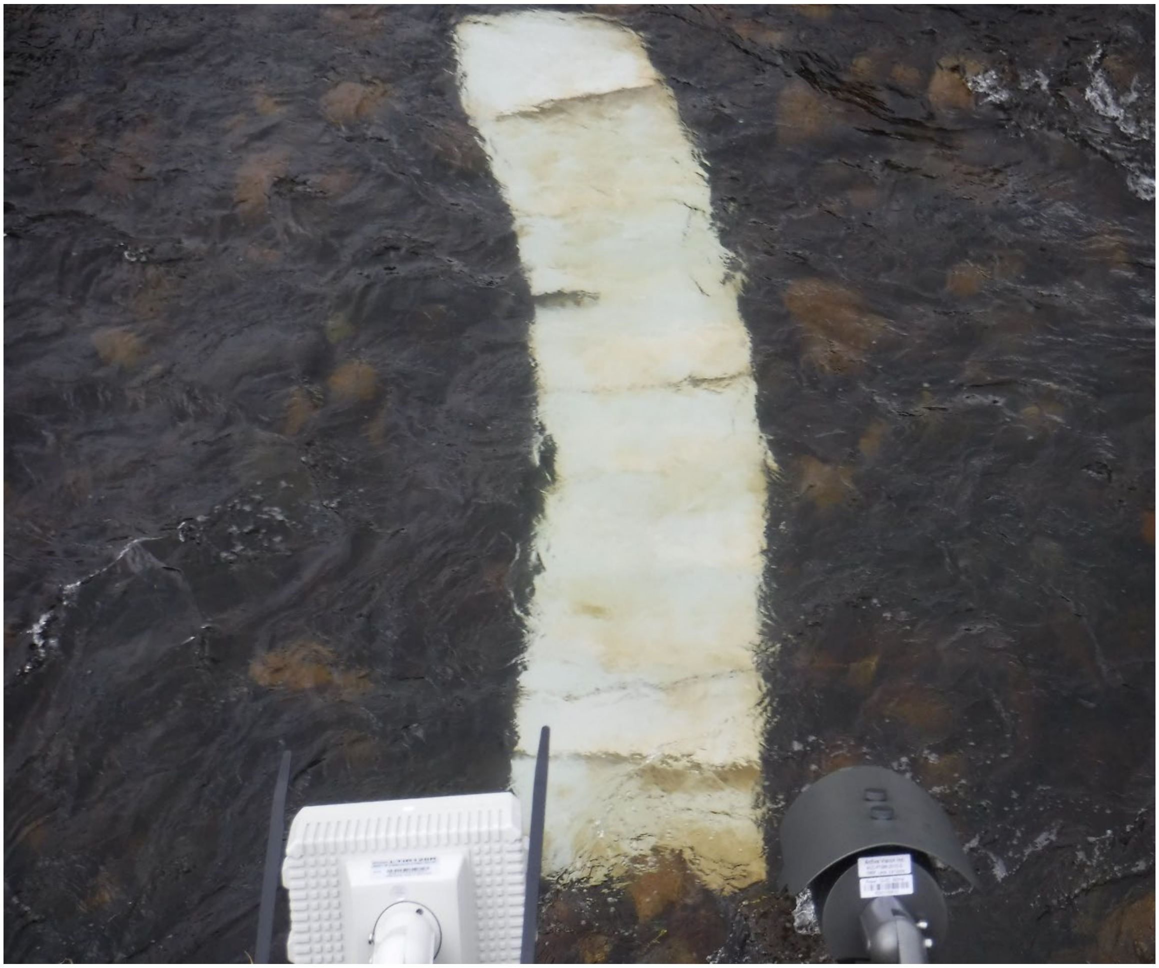

Figure 3. Time-lapse photograph of fish moving upstream across HDPE contrast panels, Akalura River,Kodiak Island, Alaska.

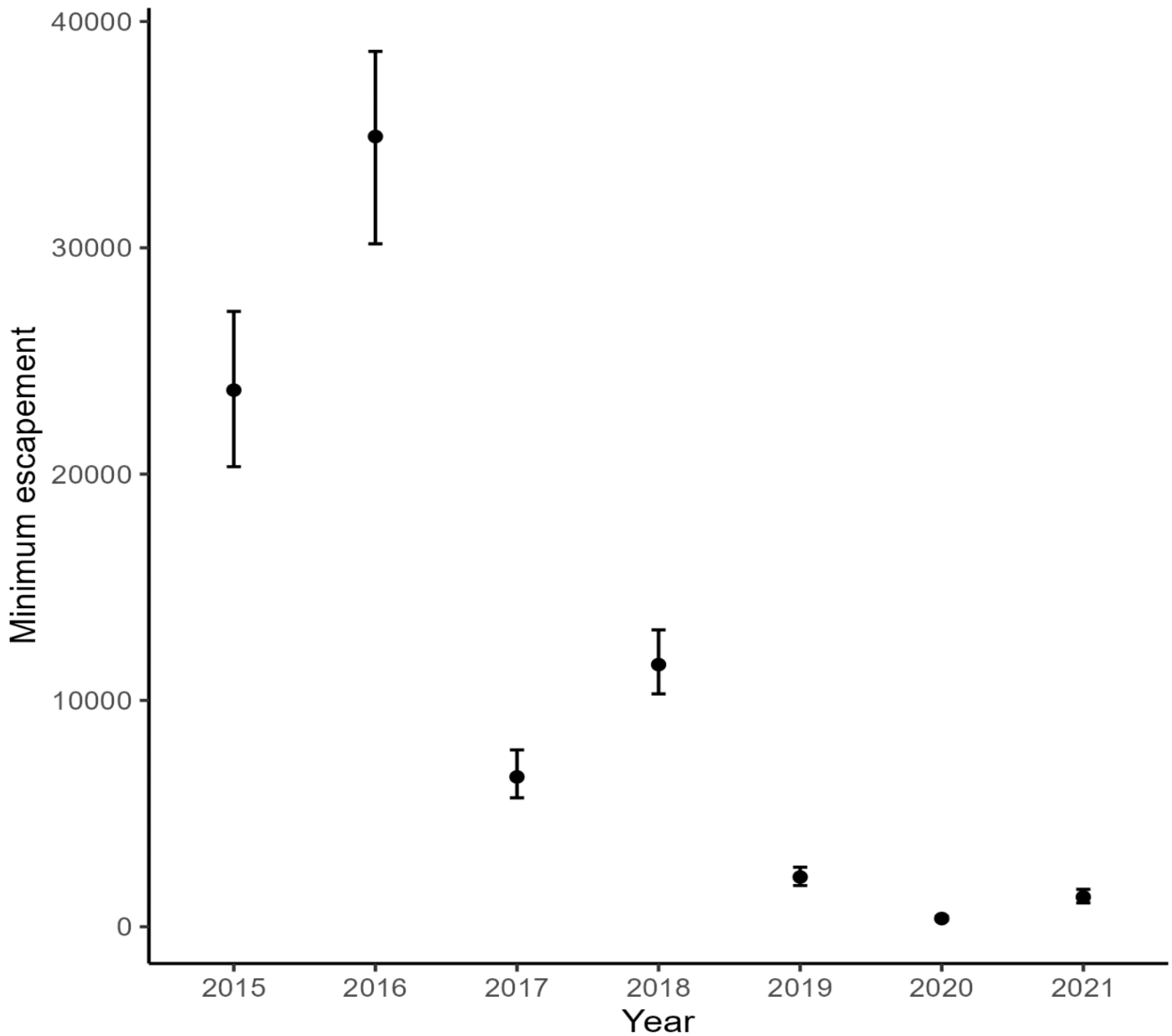

Figure 4. Mean estimate of annual minimum sockeye salmon escapement from 2015 to 2021, Akalura River, Kodiak Island, Alaska. Error bars represent 95% CIs.

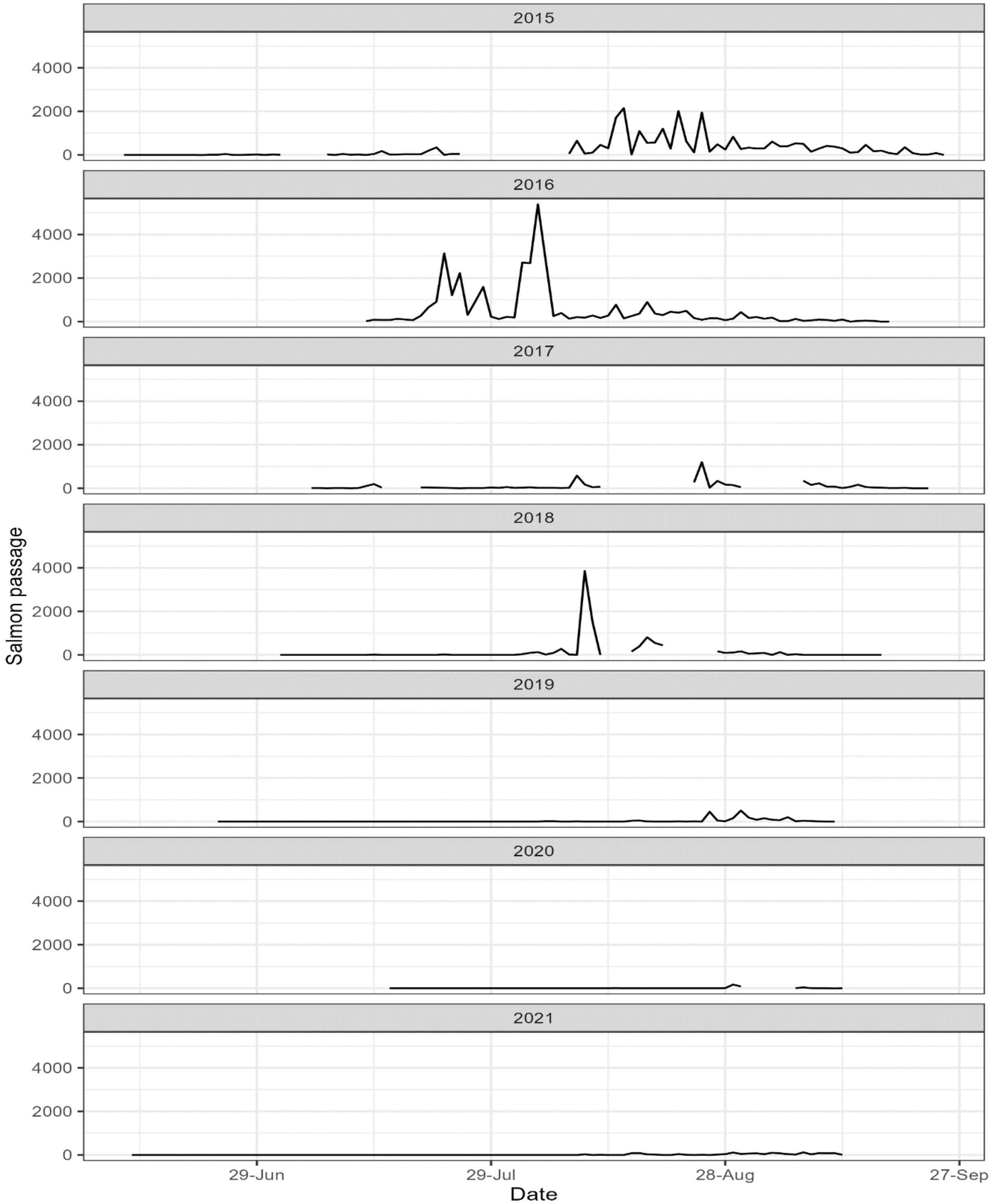

Figure 5. Daily salmon escapement estimates, 2015–2021, Akalura River, Kodiak Island, Alaska, 2021.

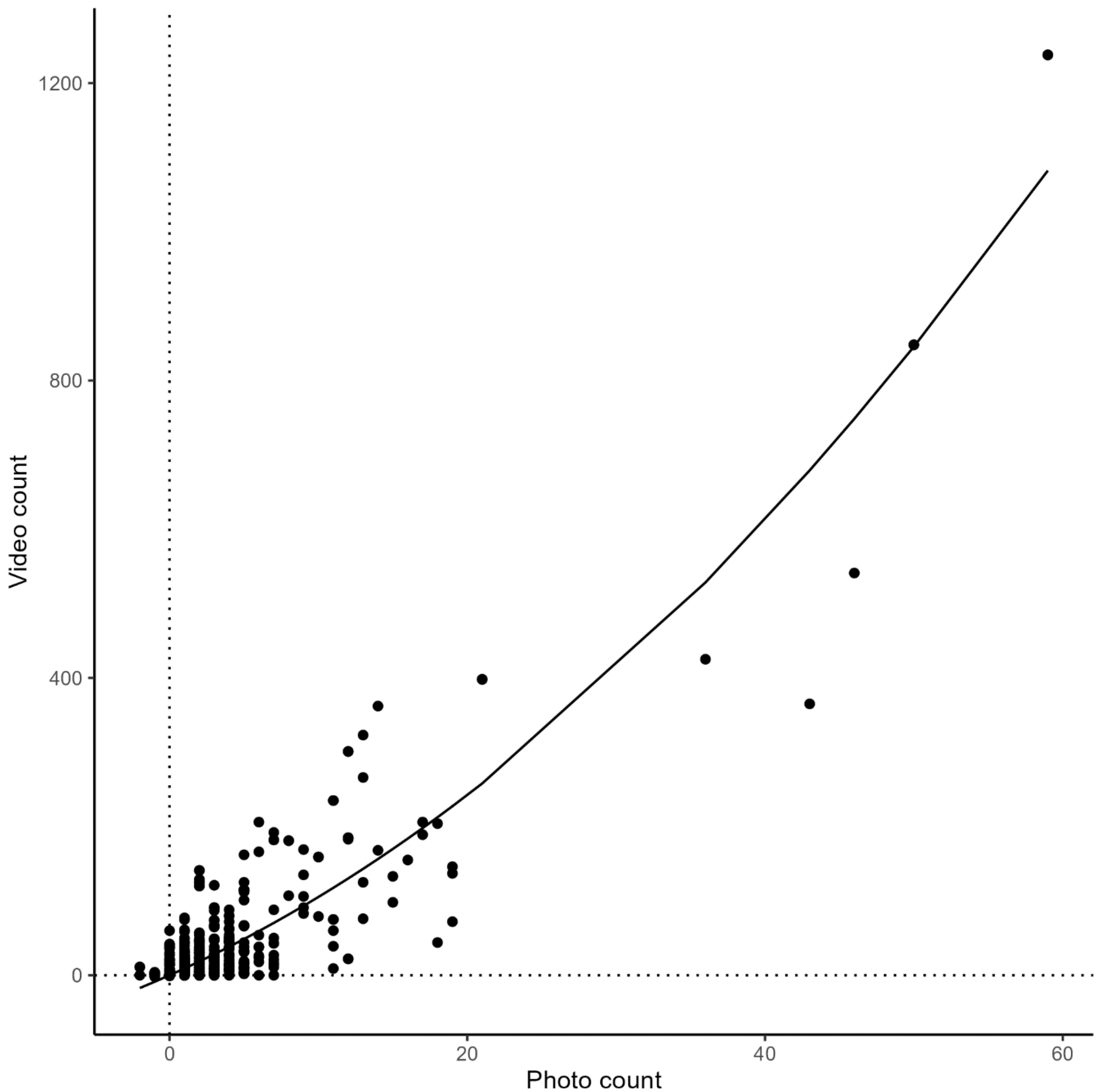

Figure 6. The relationship between paired hourly video and time-lapse camera salmon counts (points), Akalura River, Kodiak Island, Alaska. The line shows the fit of the most parsimonious model (polynomial), 2021.

Appendix A

R Session InformationR version 4.0.3 (2020-10-10) Platform: x86_64-w64-mingw32/x64 (64-bit) Running under: Windows 10 x64 (build 18363)

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