

Delta Outflows and Related Stressors Workshop February 10 and 11, 2014

PWA Supporting Documentation

SURVEY INEFFICIENCIES

SmeltCam: Underwater Video Codend for Trawled Nets with an Application to the Distribution of the Imperiled Delta Smelt

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Competing Interests: DO is employed by SureWorks LLC. SureWorks LLC intends to market the device, the SmeltCam. There are no patents, or further products in development or marketed products to declare. This does not alter the authors' adherence to all the PLOS ONE policies on sharing data and materials, as detailed online in the guide for authors.

Conceived and designed the experiments: FF DP KBN TS DC RB SBS EVN. Performed the experiments: FF DP DO DC SBS. Analyzed the data: FF DP DO KBN DS. Contributed reagents/materials/analysis tools: DO DS. Wrote the paper: FF DP DO KBN TS DC RB SBS DS EVN.

Received March 22, 2013; Accepted May 20, 2013.

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This article has been corrected. See [PLoS One. 2013 December 13; 8\(12\): 10.1371/annotation/0c42ea0f-6d99-44a7-84ff-aeec57133f13](#).

Abstract

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Studying rare and sensitive species is a challenge in conservation biology. The problem is exemplified by the case of the imperiled delta smelt *Hypomesus transpacificus*, a small delicate fish species endemic to the San Francisco Estuary, California. Persistent record-low levels of abundance and relatively high sensitivity to handling stress pose considerable challenges to studying delta smelt in the wild. To attempt to overcome these and other challenges we have developed the SmeltCam, an underwater video camera codend for trawled nets. The SmeltCam functions as an open-ended codend that automatically collects information on the number and species of fishes that pass freely through a trawled net without handling. We applied the SmeltCam to study the fine-scale distribution of juvenile delta smelt in the water column in the upper San Francisco Estuary. We learned that during flood tides delta smelt were relatively abundant throughout the water column and that during ebb tides delta smelt were significantly less abundant and occurred only in the lower half and sides of the water column. The results suggest that delta smelt manipulate their position in the water column to facilitate retention in favorable habitats. With the application of the SmeltCam we increased the survival of individual delta smelt by 72% compared to using a traditional codend, where all of the fish would have likely died due to handling stress. The SmeltCam improves upon similar previously developed silhouette photography or video recording devices and demonstrates how new technology can be developed to address important questions in conservation biology as well as lessen the negative effects associated with traditional

Conservation of endangered species faces many challenges. A key difficulty is studying and monitoring populations in which individuals are by definition low in abundance and rarely observed. Solutions to this problem often address sampling design and fitting appropriate models to data [1], [2]. Potential solutions could also involve alternative methods and new technology. For example, remote photography or video methods are commonly used in ecology to address a variety of research questions [3], [4], [5], [6] and could be applied to the study of imperiled species. In particular, underwater video systems are becoming increasingly popular for studying fishes in marine [7], [8], estuarine [9], [10], [11] and freshwater habitats [12], [13]. They are especially desirable when a key objective is to minimize or avoid the adverse effects of handling stress associated with traditional sampling methods [14], [15].

The need for alternative methods to study imperiled species is exemplified by the case of the delta smelt *Hypomesus transpacificus* in the upper San Francisco Estuary. The delta smelt is a formerly abundant euryhaline pelagic fish endemic to the upper San Francisco Estuary that has experienced substantial declines in abundance (Fig. 1) [16], [17]. Abundance declines have been attributed to multiple interacting factors including foodweb alterations, physical habitat loss, contaminants and water diversions [16], [17], [18], [19]. To complicate matters further, the delta smelt is a small (maximum fork length ~ 90 mm) fish that typically dies with minimal handling stress (20); it is assumed that most individuals collected in routine monitoring surveys do not survive. Because of their small size and delicate nature, wild delta smelt have not been tagged for remote tracking or for mark-recapture studies with presently available tools or technology (but see [21] for a study on cultured delta smelt). Delta smelt live in turbid pelagic habitats [22], [23] and therefore cannot be directly observed in their natural environment. Currently available hydroacoustic methods are of limited utility because three other fish species (longfin smelt *Spirinchus thaleichthys*, wakasagi *H. nipponensis*, and Mississippi silversides *Menidia audens*) co-occur with delta smelt and have a nearly identical body size and shape, which complicates species differentiation. Because of these challenges, sampling with trawled nets has been the only feasible method of studying delta smelt ecology in the wild.

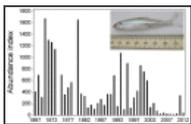


Figure 1

Time series of delta smelt abundance indices (unitless) from the California Department of Fish and Wildlife's Fall Midwater Trawl Survey.

Due to their extremely low abundance and delicate nature, continued study and monitoring of delta smelt poses a considerable challenge for scientists and managers. To overcome such challenges, resource agencies have invested in developing the SmeltCam, an underwater video camera codend for trawled nets (Fig. 2). Here, we describe the SmeltCam and its first application to advancing the understanding of delta smelt ecology. The purpose of our study was to better understand the fine-scale distribution of delta smelt. Our study question was: does the vertical and horizontal distribution of delta smelt vary by tide stage? The answer to this question is relevant for many reasons, including the opportunity to generate more precise population estimates of delta smelt [24]. Long-term fish monitoring in the upper San Francisco Estuary is not designed to generate actual population estimates of fishes. Rather, it generates dimensionless interannual indices of relative abundance. Sample design-based population estimates for delta smelt have been generated from the available monitoring data but are necessarily subject to its biases and limitations [24]. Three of the key issues are that sampling takes place (1) generally at center channel, (2) irrespective of tide stage, and (3) with the net towed obliquely through the water column. These issues present problems in extrapolating the trawl catches volumetrically to generate sample design-based population estimates because it is not known how delta smelt are distributed across tides vertically or horizontally in the water column. Another immediate application of our study is that the knowledge obtained on fine-scale habitat use can be used to inform

behavior models examining the distribution and movements of delta smelt.



[Figure 2](#)

The SmeltCam.

Methods

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SmeltCam

The SmeltCam functions as an open-ended codend that automatically collects information on the number and species of fishes that pass freely through a trawled net. Key components of the SmeltCam include a bridle system that connects to a trawled net, a water-tight electrical housing and a ballast hull ([Fig. 2](#)).

The SmeltCam body is a combination of welded sheet aluminum and machined plate aluminum. The overall dimensions of the unit are 93 cm (length)×56 cm (width)×38 cm (height). In the configuration used in our study, a 4-point bridle system with turnbuckles and shackles was used to attach the SmeltCam to the four load-bearing lines of the trawled net. The unit weighs 48.5 kg dry and valves are used to adjust and maintain water levels in portions of the hollow ballast hull in order to achieve neutral buoyancy. The addition of ballast water adds considerably to the unit's weight and necessitated a davit to lift it from and to the deck during and after deployment. The interior chamber of the SmeltCam where fish and other objects pass is 76.2 cm (length)×18.9 cm (width)×18.9 cm (height).

The starboard side of the unit contains the sealed electrical housing chamber. Within the electrical housing chamber are components and sensors that control and/or monitor positioning, physical conditions, lighting, and video functions. A global positioning system (GPS; uBlox-6 chipset, U-blox America Inc, San Jose California, USA) records position coordinates with an approximate 3 meter level of accuracy. A pressure gauge within the unit records depth with a vertical resolution of approximately 8 cm. Accelerometers measure the tilt, roll, and pitch of the device in the water. Sensors measure the interior computer and air temperature. Relative humidity is also measured to detect failure of the chamber seal and exposure of electronics to water.

The internal wall of the sealed electrical housing chamber is a 43 cm (length) × 25 cm (height) acrylic window that serves as the viewing area for the video system. The viewing area is essentially the interior chamber of the unit and thus has the same dimensions. Custom 8,000 lumen white LED is used to cast a wide swath of light to blanket the entire viewing window with even, wide angle of incidence lighting that reduces backscatter and specular reflection off of passing fish and other objects. A grayscale camera (Genie HM1400; Teledyne Dalsa, Billerica, Massachusetts, USA) mounted on the inside of the sealed electrical housing chamber captures 1600 ×1200 megapixel resolution images at a rate of sixty frames per second. The system is powered by 120 V AC 60 Hz, supplied by a 3000 W Honda portable generator, however on-board ship power is also suitable. Internal power supplies converted the 120 V AC power to 24 V DC and 12 V DC power. Power and communications to components in the sealed electrical housing chamber are provided by a simple, flexible, 3-conductor 14AWG waterproof cable, 180 m in length. Communications are sent up and down the same cable via powerline communications, in which TCP/IP packets are encoded on top of the 120 V AC power. The communications link over the 180 m distance is approximately 20 mbits/second.

Custom software has been developed to operate the system and to record data, which is operated with a standard laptop computer. A series of algorithms control object detection, tracking and identification. Object detection and tracking algorithms utilize gradient contour methods from raw image information obtained from the camera. Species identification is accomplished through algorithms in a support vector machine

(SVM). The system uses several feature vectors to uniquely describe each species. The feature list includes object size, size and shape-independent list of shape moments (Hu moments), aspect ratio, defect from pure ellipse, RMS error (or deviation from) normalized species image, and radial local pattern. The SVM takes in all of the features and generates species identifications with an associated level of confidence for each object passing through the field of vision.

Training the SVM algorithm to identify fish species is an ongoing exercise and involves using positively identified images and metadata. Two separate cross-validation efforts were completed prior to conducting to this field study. The initial effort involved a training sample of human-identified images of delta smelt, threadfin shad *Dorosoma petenense* and American shad *Alosa sapidissima* acquired from the field in September 2011 to classify 306 images acquired in October 2011. Classification success was 88% for delta smelt, 56% for American shad and 37% for threadfin shad. We also conducted a k-fold cross validation using all fifty of the field-collected images of delta smelt obtained over the lifetime of the SmeltCam. The library of images was divided into 10 subsets ($k = 10$) where for each subset 10% of the images was used as a training set to identify the remaining 90% of the images. The average success rate over the 10 subsets was 91%, meaning that the algorithm could positively identify 91% of the images that a human could positively identify. Online training is planned for the next phase of development, in which every positively identified object that passes through the device helps to improve the SVM algorithm. Algorithms are available upon request (inquiries should be sent to darren.odom@sureworkslc.com). While the algorithm works relatively well, it is continually being improved. Hence for this study we reviewed each image obtained during sampling and provided a relatively subjective human-assigned level of confidence for each species identification.

All system components and live video from the camera can be monitored in real time on board the research vessel and simultaneously written to file. Ultimately, each fish passing through the field of vision is given a species identification with an associated level of confidence, and all other sensor data is also recorded including date, time, GPS coordinates and depth. All images are also recorded and, as in the case of our study, can be reviewed for accuracy.

Delta Smelt Ecology

The delta smelt was listed as a threatened species under both the California and Federal Endangered Species Acts in 1993. The listing status was changed to endangered by California in 2009. In 2010, a Federal status review determined endangered status was warranted but precluded by other higher priority listing actions.

Delta smelt abundance has been variable but has exhibited a substantial long-term decline ([Fig. 1](#)) [[16](#)], [[24](#)], [[25](#)]. The delta smelt is one of four fish species in the estuary which have exhibited further step-declines in about 2002 and have remained near all time record lows for the last decade, defining an era in the ecosystem known as the pelagic organism decline [[18](#)]. Long-term trends in abundance of delta smelt and other fishes are generated from data collected by the California Department of Fish and Wildlife's (CDFW) Fall Midwater Trawl Survey (FMT), which has been conducted each year since 1967, with the exception of 1974 and 1979.

The delta smelt is an opportunistic carnivore that feeds primarily on planktonic copepods, cladocerans, mysids, and amphipods. It is primarily an annual species with very few individuals living and spawning a second year. Spawning takes place during spring in freshwater tidal habitats [[17](#)], [[26](#)]. Young delta smelt move downstream with the tides until they reach favorable rearing habitats in the low salinity zone (~1–6) of the estuary [[27](#)], although some apparently remain in upstream reaches year-round [[26](#)]. During the summer and fall, juvenile delta smelt live primarily in the upper San Francisco Estuary associated with the low salinity zone [[17](#)], [[23](#)]. In winter delta smelt migrate upstream to freshwater habitats where spawning occurs during spring.

Study Area and Design

Our study focused on the fine scale distribution of juvenile delta smelt in the upper estuary during fall. Field sampling for delta smelt was conducted under a permit granted to the Interagency Ecological Program by the

U.S. Fish and Wildlife Service. We conducted our study November 27–30, 2012 in the Sacramento River adjacent to Sherman Island, approximately between routine FMT stations 704 and 705 (Fig. 3). We chose this region because: (1) long-term FMT monitoring data indicate delta smelt remain relatively abundant in this area due to suitable habitat conditions [23], (2) two other studies, one examining movements of delta smelt (J. Burau, U.S. Geological Survey, Sacramento, California, personal communication) and another examining sampling efficiency of several different trawled nets (R. Baxter, unpublished data), effectively sampled delta smelt in this area in the two months preceding our study, September-October 2012, and (3) routine FMT sampling in the three months preceding our study also detected delta smelt in the area.

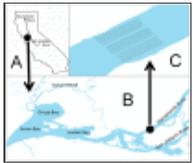


Figure 3
Map of the study area showing the (A) location of the upper San Francisco Estuary in California, (B) location of the study site in the upper estuary, and (C) orientation of trawling lane transects in the tidal Sacramento River channel.

Physical conditions during our study were typical for the region during the fall but dramatically changed shortly thereafter (Fig. 4). During the study a storm moved across California and produced a moderate amount of intermittent rain and south winds in the immediate study area. The storm persisted after our study and within two weeks produced what is colloquially termed “first flush” conditions, which refers to the initial onset of substantially elevated river flows and turbidity entering the estuary (Fig. 4; data obtained from the California Data Exchange Center <http://cdec.water.ca.gov/>). These conditions are associated with the upstream migration of delta smelt to areas where spawning ultimately occurs during spring [26], [28]. Our study, therefore, observed fine-scale delta smelt distribution patterns during typical fall conditions prior to the “first flush” and the upstream migration of delta smelt.

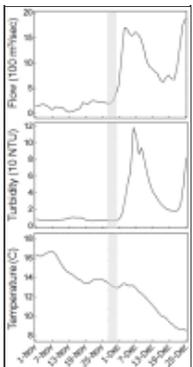


Figure 4
Seasonal time series of flow, turbidity and water temperature with the study period shaded in gray.

We conducted our study using the same equipment (e.g., research vessel, net, and crew) as is normally used for the FMT. The only exception was that the SmeltCam was affixed to a slightly modified codend of the net rather than the codend being tied closed. Descriptions of the standard FMT protocol and sampling sites are readily available [23], [29]. The net itself is 17.6 m long with a square mouth opening of 3.66 m in width and height. It has nine tapered panels of stretch mesh from 14.7 cm near the mouth to 1.3 cm in the codend. To generate the data used to calculate the interannual indices of relative abundance, the FMT collects samples via a 12-minute oblique trawl conducted at 100 sites distributed across the tidal freshwater to mesohaline regions of the estuary each month from September to December. To attach the SmeltCam, the codend of the net was modified by slightly adjusting the lengths of the last two mesh panels and attaching an additional panel of 0.64 cm knotless mesh measuring 74.9 cm in length sewn to a 7.6 cm-diameter vinyl collar attached to the SmeltCam housing. These modifications increased the total length of the net from 17.6 m to 17.8 m.

As mentioned above, long-term FMT data and recent research efforts helped guide our study design. The aforementioned study examining delta smelt movements influenced our experimental design with its observation that delta smelt were collected during flood tides but rarely during ebb tides in surface samples

taken with a Kodiak Trawl in both 2010 and 2012. Expanding upon that observation and to more closely examine the position of delta smelt in the water column, we set up a factorial study design with three factors and two levels for each factor, thus $2^3 = 8$ possible treatments. The three factors and their corresponding levels were: (1) horizontal position in the water column (H: center of the channel versus side of the channel), (2) vertical position in the water column (V: upper half versus lower half) and (3) tidal phase (T: flood versus ebb). The response variable, fish counts, was defined as the number of delta smelt collected in a 10-minute trawl. Since counts are functions of density and volume sampled, and our interest was in how density varied by treatment combination, the volume of water filtered by the trawl was estimated using a mechanical flowmeter (model 2030R, General Oceanics, Inc.) deployed off the side of the research vessel during each trawl.

Available time and resources facilitated the day-time collection of fifty-six samples over a four day period, thereby allowing seven replicates per treatment combination. To determine the adequacy of these sample sizes, we estimated, given seven replicates and a standard deviation for fish counts of 2.1 (based on thirty-five FMT samples taken during the previously mentioned net efficiency study), that there was a 95% probability of rejecting a test of the null hypothesis of no factorial effects, i.e., the expected fish counts are the same for all treatment combinations, when at least one of the combinations had an expected catch that was three fish above (or below) that for other combinations. Further, pairwise differences in fish counts as small as three would be detected with 79% probability and as large as four would be detected with 95% probability.

We used a combination of GIS (geographic information system) and GPS to select and occupy sampling locations in the Sacramento River channel in order to achieve our study objective. GIS (ArcGIS 9.3.1, ESRI, Redlands, California, USA) was used to generate a total of twenty-one possible equidistant trawling lanes oriented longitudinally in the channel; the first and last seven lanes represented the sides of the channel while the middle seven lanes represented the center of the channel ([Fig. 3](#)). Sides of the channel were treated as a single unit and the specific side sampled was determined randomly. The number of lanes and their spacing were generated so that trawling in one lane would have no effect on adjacent lanes. The lanes were loaded into a GPS unit and tracked by the research vessel during sampling. Water depth averaged 10.5 m during ebb tides and 10.1 m during flood tides. Sampling depth (upper half versus lower half of the water column) was achieved by maintaining the net either above or below mid-depth during a trawl, targeting $\frac{1}{4}$ or $\frac{3}{4}$ depth (~ 2.6 or 7.9 m), respectively. Water depth was determined by a boat-mounted sonar unit. Net depth was adjusted with the length of cable between the net and the boat and determined by the SmeltCam's depth sensor, which was monitored in real-time during trawls.

A ten-minute sample was recorded for each trawl once the net and SmeltCam were positioned at the appropriate depth. The water filtered by the net during the time it took to go from the surface to the appropriate depth at deployment and then back again at retrieval was not considered part of the sample and was not recorded. For consistency, trawls were done so that the net was towed longitudinally in the channel against the current (i.e., upstream during ebb tides and downstream during flood tides). The order in which lanes and depths were sampled was randomly generated. Sampling necessarily had to follow the order of the tides. We examined forecasted tidal velocities generated from the CALSIM Hydrologic Model [\[30\]](#) to appropriately arrange sample collection around the tides. Sampling took place only during daylight hours, consistent with FMT protocol.

We measured water temperature ($^{\circ}\text{C}$), salinity, turbidity (NTU), Chl *a* concentration ($\mu\text{g/L}$), pH and dissolved oxygen concentration (mg/L) immediately preceding and following each trawl in both the upper and lower half of the water column. Spot measurements were taken with a handheld YSI multiparameter sonde rigged with a communication cable long enough to reach the appropriate depth (YSI Inc, Yellow Springs, Ohio).

To statistically evaluate the effects of the three main factors (tide, horizontal and vertical position in the water column) on delta smelt density and the water quality variables, we fit several models commonly used for

count data. In particular, we fit log linear Poisson models, models allowing for overdispersion (the quasi-Poisson and negative binomial), and models allowing for excess zeros (the zero inflated negative binomial), where overdispersion and excess zeros are with reference to the Poisson distribution [31]. Model fitting was done using the statistical computing environment R, version 2.15.1 [32], along with the R package ‘pscl’ [33], [34]. To make between model comparisons, we calculated AIC values, $AIC = 2*k - 2*\log(\text{Likelihood})$, where k = the number of parameters. AIC simultaneously quantifies goodness of fit, as defined by the likelihood of the data, and model complexity (as measured by k), and models with the smallest AIC values are considered preferable [35]. For each model, P-values for factors and factor combination were also calculated to assess the significance of particular factors.

Results

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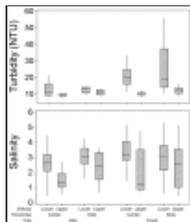
We collected 52 samples during the four days of field study; mechanical problems with the research vessel prohibited us from completing our intended number of replicates for each treatment ([Table 1](#)). In total we collected 30 samples during flood tides and 22 samples during ebb tides. Due to variations in tidal velocities the volume of water sampled per 10-minute trawl varied from 4,388 m³ to 8,057 m³, but on average was comparable across the eight treatments ([Table 1](#)).

Treatment	Mean (m³)	SD (m³)
1	4388	1000
2	4500	1100
3	4600	1200
4	4700	1300
5	4800	1400
6	4900	1500
7	5000	1600
8	5100	1700

[Table 1](#)

Average±one standard deviation of the water volume (m³) sampled across the eight study treatments.

Water temperature averaged 13.8°C and varied by less than 1°C during the entire study (minimum = 13.5°C, maximum = 14.2°C). Dissolved oxygen concentration ranged from 8.4 mg/L to 8.9 mg/L, pH ranged from 7.4 to 7.8 and chlorophyll *a* concentration ranged from 1.2 µg/L to 3.5 µg/L. Given their low variability, these water quality variables were not included in subsequent analyses. Salinity averaged 2.6 and ranged from 0.4 to 5.3. As determined by a standard generalized linear model, salinity differed significantly ($P < 0.05$) with horizontal position across the channel and vertical position in the water column. Salinity averaged about one unit higher in the center of the channel versus the side of the channel, and also on the bottom half of the water column versus the upper half of the water column ([Fig. 5](#)). Salinity did not differ across tides because we sampled the full tidal cycle. Consequently, salinity values expectedly overlapped during ebb and flood tides. Turbidity averaged 15.7 NTU and ranged from 7.6 NTU to 80 NTU. Turbidity exhibited statistically significant differences ($P < 0.05$) among all combinations of factors and their interactions except for the tide:horizontal position, horizontal position:vertical position and tide:horizontal position:vertical position interactions. The most striking pattern with turbidity was that it was higher in the lower half of the water column, and substantially higher during flood tides ([Fig. 5](#)). Both salinity and turbidity were lowest during ebb tides in the center of the channel in the upper half of the water column.



[Figure 5](#)

Box plots of turbidity and salinity by tide and position in the water column.

We collected 352 individual fish comprised of 6 different species during our study: green sturgeon *Acipenser medirostris* (1), starry flounder *Platichthys stellatus* (1), American shad (23), striped bass *Morone saxatilis* (43), threadfin shad (87), and delta smelt (197). Count data on all of the species except for delta smelt were insufficient for further analysis. Of the 197 delta smelt collected, 142 individuals swam through the SmeltCam ([Fig. 6](#)) while 55 were entangled in the mesh of the net. We measured the fork lengths of 29 of the 55 individuals that were found in the net; they ranged from 51 mm to 75 mm (average = 64.5 mm and

standard deviation = 5.2 mm). Subsequent summaries and analyses focus on individual delta smelt observed by the SmeltCam. The level of confidence in the identifications (human-assigned) ranged from 4%–100%, with 100% comprising the majority of the values (Fig. 7). Because there was 100% confidence in most of the identifications, the sample distribution (count of individual delta smelt per sample) did not change when examined across varying levels of confidence in species identification (Fig. 8). Nonetheless, to err on the side of caution we focus our analyses hereafter on individual delta smelt that were identified to species with 100% confidence.

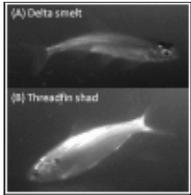


Figure 6
Examples of raw images of (A) delta smelt and (B) threadfin shad obtained by the SmeltCam during our field study.

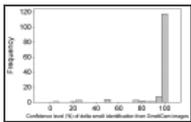


Figure 7
Frequency histogram of the confidence level (%) that delta smelt were correctly identified to species.

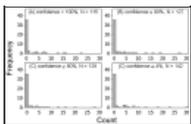


Figure 8
Frequency histograms of the count of delta smelt collected per sample for individuals that were correctly identified to species on SmeltCam images with (A) 100%, (B) $\geq 90\%$, (C) $\geq 80\%$, and (D) $\geq 4\%$ confidence.

Delta smelt were observed in 16 of 52 samples, thus zero counts were observed in 69% of the samples. The number of delta smelt per sample ranged from 0 to 22 (average = 2.2, standard deviation = 4.7), while density ranged from 0 to 37/10,000 m³ (average = 3.8/10,000 m³, standard deviation = 8.3/10,000 m³). The average and standard deviation were more than two times higher than expected based on the aforementioned net efficiency study, which observed a mean of 0.9 delta smelt per sample and a standard deviation of 2.1.

The mean delta smelt density was 5.9/10,000 m³ for flood tides versus 0.8/10,000 m³ for ebb tides. For positive samples only (excluding the zero counts), the mean density was 14.9/10,000 m³ for flood tides versus 5.0/10,000 m³ for ebb tides. Delta smelt were observed throughout the water column on flood tides but only at the lower half and side of the channel on ebb tides (Fig. 9).

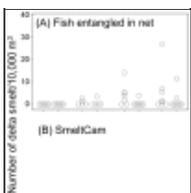


Figure 9
Individual values of delta smelt density (number/10,000 m³) by tide and position in the water column for fish that were (A) found entangled in the mesh of the net when it was retrieved and (B) observed by the SmeltCam.

We fit the following families of models: Poisson (Po), quasi-Poisson (q-Po), negative binomial (NB), and zero-inflated negative binomial (ZINB). In each case the response variable was the observed number of delta smelt caught. We used a log link function to model the expected number of delta smelt caught. The expected number is the density times the volume sampled, and since the log of the volume sampled was handled as an offset, the factors were thus modeling expected delta smelt density. For each of the four model families, expected fish density was modeled using the following set of nested models (and the R syntax for the model formula):

1. Main effects only (H+V+T)
2. Main effects with 2-way interactions (H*V+H*T+V*T)

3. Main effects, 2-way and 3-way interactions (H*V*T)

The results are summarized in [Table 2](#). The Poisson models found many more statistically significant factors and factor combinations than the other three families of models. However, this is due to relatively small, and likely too small, estimated variances (based on results for the other families of distributions and the fact that the Poisson models had the highest AIC values).



[Table 2](#)

Summary of model fitting results for the nested set of factors and four different families of distributions.

The quasi-Poisson model provides estimates of the inflation of the variances relative to the Poisson, e.g., overdispersion multipliers of 6.0 to 7.6. AIC values are not calculated for quasi-Poisson models because there is no likelihood. Quasi-AIC values have been developed [\[35\]](#) but they are of use only for comparing different quasi-Poisson models, not for comparing differences between families of distributions. Restricting attention to just the quasi-Poisson combinations, with the enlarged variance only the main effect of tide was found statistically significant for all three factorial combinations.

Amongst the negative binomial models, the main effects model has the smallest AIC value. The AIC value for the two-way interaction model is quite similar and negligible based on a rule of thumb [\[35\]](#), i.e., a difference of 2 units or less is not important. Given two models with negligibly different AIC values, the simpler model is preferable. Like the quasi-Poisson, the negative binomial model also increases the variance relative to the Poisson. Ver Hoef and Boveng [\[36\]](#) address the question of choosing between quasi-Poisson and negative binomial models and note that the key distinction is the nature of the variance function. The negative binomial variance is $\mu(1 + \mu/\theta)$, the multipliers shown in [Table 2](#) are $1/\theta$, in contrast to the quasi-Poisson $\mu \cdot \phi$, where ϕ is the overdispersion parameter. Ver Hoef and Boveng [\[36\]](#) suggest plotting $(y - \mu)^2$ against μ to select between the two families. Such plots were produced and the relationships were quite similar for quasi-Poisson and negative binomial and failed to indicate a preference for one family over the other. We note that the estimated coefficients for the tide effect were quite similar for quasi-Poisson (1.8) and negative binomial (2.0), so choosing between the two families does not seem critical.

Based on AIC values, the zero inflated binomial models are the best of the three families for which AIC can be calculated, with the main effects model our preference (based on the above argument on comparing AIC values). Zero inflated models are mixture models of the following general form: $\pi f(0) + (1 - \pi) f(\text{non-negative})$, where π is the probability that the data come from the degenerate distribution, $f(0)$, where 0 is the only possible outcome and $f(\text{non-negative})$ is the probability distribution allowing 0's and positive outcomes. The probability π was modeled according to a simple logistic model, $\log(\pi/(1 - \pi)) = \beta$, while the negative binomial distribution was used for $f(\text{non-negative})$ with the expected counts modeled as functions of the factor levels. For all three sets of factorial combinations, π , was 0.61, i.e., there was at least a 61% probability of failing to catch any delta smelt (the probability of no delta smelt also includes the case where the negative binomial model yields a zero). This value seems reasonable given the observed 69% of zeros in the catches. Like the quasi-Poisson and negative binomial models, the sole significant factor was the main effect of the tide, with a similar coefficient of 1.7 for the flood level effect.

Discussion

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Our results suggest that the distribution of juvenile delta smelt in the water column varied across tides. We found that delta smelt were relatively common and abundant throughout the water column during flood tides. However, during ebb tides delta smelt were less abundant, and were observed only in the lower half of the water column and sides of the channel. This pattern emerged from both the fish observed by the SmeltCam and those that were found entangled in the mesh of the net after it was retrieved. With regard to this specific pattern, there is no bias associated with not knowing the exact depth at which the fish entangled

in the mesh of the net were captured because none were captured during ebb tides in the center of the channel (Fig. 9). Interestingly, variability in salinity and turbidity exhibited the same general pattern as did delta smelt, and may be the proximal reason for the distributions observed. The performance of the SmeltCam degrades when turbidity exceeds approximately 80 NTU. Turbidity reached 80 NTU in one of fifty-two samples we collected; a flood tide treatment from the lower half of the water column and side of the channel. Seven delta smelt were observed in this sample. It is possible that more delta smelt were actually present but were missed by the SmeltCam because of the elevated turbidity. If this were true, it would be consistent with the overall pattern of delta smelt distribution and would not have changed the results. Salinity and turbidity are both important components of delta smelt physical habitat [22], [23]. We hypothesize that delta smelt, by simply remaining within preferred turbidity and salinity conditions across tides, could have produced much of the pattern observed. However, it appeared that delta smelt manipulate their position in the water column either through keying in on these water quality conditions or the physics underlying them.

Our results were consistent with other studies in 2010 and 2012 that found delta smelt to be abundant on flood tides but not on ebb tides (J. Burau, U.S. Geological Survey, Sacramento, California, unpublished data), although the studies were conducted under very different net flow conditions. The general consistency in results across studies in multiple years and the observation that physical habitat is a likely underlying mechanism, together provide strong evidence that delta smelt were not randomly distributed in the water column across tides. However, the extent to which the pattern observed at this location holds true at night or at other locations is uncertain. Although we did not sample at night, the delta smelt movements study did and found no difference in catch patterns compared to the day.

There is sufficient evidence to suggest that the patterns of delta smelt distribution observed in this particular location are not applicable across the entire system. Our unpublished analyses (separate independent analyses by FF, KBN and DS) of the FMT data set demonstrate a high degree of variability in delta smelt catches across tides among sampling sites. It therefore seems likely that localized physical as well as biological components of habitat influence delta smelt distribution across the system. The likelihood that delta smelt distribution in the water column across tides varies spatially in the system has important implications for the original motivation for our study. We generated information relevant to informing methods that could be developed to extrapolate survey data to generate more precise population estimates of delta smelt. However, it is clear that additional study is needed to characterize variability at other locations in order to successfully revise present methods of estimating delta smelt population size. Areas of particular interest are the broad expansive shallow water shoals located in Suisun, Grizzly and Honker bays (Fig. 3).

There is also sufficient data to suggest that the patterns of distribution we observed do not hold true for other life stages of delta smelt. A previous study of delta smelt larvae found no effect of tide on vertical distribution [37]. Similar to above, our unpublished analyses (separate independent analyses by KBN and DS) of post-larval and juvenile delta smelt long term monitoring data sets (CDFW's 20 mm and Summer Towntnet Surveys) demonstrate a high degree of variability in delta smelt catches across tides among sampling sites. Interestingly, previous studies demonstrated that the larvae of several native and exotic fishes (other than delta smelt) in San Francisco Estuary appeared to be behaviorally flexible in maintaining vertical position under different environmental conditions to maximize retention [38]. Together, these observations suggest that fish distribution in the water column varies according to localized habitat conditions.

Tidal movements, migrations and transport are well documented in systems worldwide and are usually associated with exploiting favorable habitats [39], [40]. Invertebrates such as penaeid shrimp are well known to selectively move or migrate with tides [41] as are fish. For example, flounder larvae *P. flesus* entered the water column on flood tides to move upstream into the Elbe River Estuary, Germany [42]. Similarly, plaice larvae *Pleuronectes platessa* accomplish passive but selective horizontal transport by entering the water column during flood tides and remaining on the bottom during ebb tides [43]. Studies in a tropical tidal mangrove have also shown that fish were distributed on the bottom during ebb tides and entered the water column during flood tides to exploit intertidal habitats [44]. For delta smelt, it appears that individuals

manipulate their position in the water column to facilitate either movement or retention at different life stages. As alluded to above, we believe that the patterns we observed for juvenile delta smelt facilitate retention in favorable habitats. However, upstream migration of adults and downstream migration of larvae is undoubtedly facilitated by tidal transport and net flows. As mentioned, a previous study found no effect of tide on the vertical distribution of delta smelt larvae [37], suggesting they may be passively transported downstream by net flows until reaching favorable habitats near the low salinity zone where they effectively maintain position [27], potentially by manipulating their position in the water column. As a case in point, anadromous rainbow smelt *Osmerus mordax* larvae are known to vertically migrate to maintain position in regions of high prey density [45], [46]. The ability of young fishes to change their vertical distribution ontogenetically [47], [48] or in response to varying net flow conditions [38] appears to be a common strategy for retention in favorable habitats.

There are several advantages and disadvantages of the SmeltCam versus similar camera systems that have been used previously to photograph objects passing through the codend of nets. Silhouette photography or video recording devices have been developed for examining plankton distributions at various scales [3], [6], [9], [49], [50]. Perhaps the biggest limitation of the present generation SmeltCam is that it has been designed for a particular size range of fish. Modifications to the system could be made for sampling large-bodied fishes with larger nets or for sampling smaller organisms such as fish larvae or other planktonic organisms. An advantage of the SmeltCam is the incorporation of new technology enabling rapid digital photography, automatic object recognition, automatic data collection, and real time observation. We are actively working on improving the system in several ways including redesigning the frame and hull to make the unit lighter and easier to handle by a single individual, enhancing software to improve and expand automatic image recognition and adding size measurements, incorporating tools to record water quality parameters in real time during sampling, and matching the unit with trawled nets with dimensions that will decrease the entanglement of fishes and improve survival.

One potential concern associated with the SmeltCam is the possibility of predation occurring inside the unit given its dimensions and light emission, both of which could potentially attract and congregate predators such as striped bass. Although we did not conduct an exhaustive investigation on the topic, we found no evidence of predation attributed to the SmeltCam during our study. Immediately upon collection we sacrificed and examined the stomach contents of 5 striped bass (that were either entangled in the net or couldn't fit through the opening of the SmeltCam) that were large enough to consume fish. None of the stomachs contained any fish remains; one stomach contained one isopod and the other four stomachs were empty.

Our study demonstrates how new technology can be developed to address key questions and uncertainties in conservation biology, and that imperiled species can be studied with relatively little harm. During our study we observed a total of 197 individual delta smelt. Of this total, 142 individuals passed through the SmeltCam alive while 55 died as a result of getting entangled in the mesh of the net. Thus, with the application of the SmeltCam in this study we increased the survival of individual delta smelt by 72% compared to using a traditional codend where all of the fish would have likely died due to handling stress. Survival is likely to increase in future studies as the SmeltCam is matched with nets with dimensions that will decrease entanglement. The SmeltCam can be affixed to virtually any type of trawled net or other fish congregating device facilitating a broad array of potential applications. The development and application of new technology such as the SmeltCam provides many new opportunities to studying imperiled species such as delta smelt and can be readily applied to other species and systems.

Acknowledgments

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This study was conducted under the auspices of the Interagency Ecological Program for the San Francisco Estuary (IEP). It was made possible by the efforts of many individuals from many organizations and truly exemplified the collaborative mission of the IEP. We thank the members of the IEP Management Team,

especially IEP Lead Scientist Anke Mueller-Solger and IEP Program Manager Kelly Souza, for their support. Ted Swift of the California Department of Water Resources (DWR) was instrumental in the early stages of developing the concept for the SmeltCam. Gina Benigno and Nick Van Ark of DWR provided invaluable laboratory and field support during the development of the SmeltCam. David Fullerton of the Metropolitan Water District of Southern California contributed to the development of the study design. The field work was successful because of the skills and dedication of Dave Hull, Ken Flowers and Katie Osborn from the CDFW. Karen Gerhts of DWR graciously provided the YSI sonde for the field study. Discussions with Wim Kimmerer of San Francisco State University and Pete Smith of the US Geological Survey (USGS) assisted with model fitting and interpretation. We thank Larry Brown of USGS, Peter Moyle of UC Davis, Brendan Ebner of James Cook University, and two anonymous reviewers for comments that improved the manuscript. The views and opinions expressed in this paper are those of the authors and do not necessarily reflect the official policy or position of their respective agencies.

Funding Statement

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Funding for the research and development of the SmeltCam has been provided by the Bureau of Reclamation and the California Department of Water Resources. The California Department of Fish and Wildlife provided funding in the form of in-kind services. The State and Federal Contractors Water Agency (SFWCA) provided some additional funding to conduct the field study. SFWCA had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

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Working Draft

8/12/2013

Supplemental monitoring and quantitative approaches for improving the assessment of Delta Smelt abundance and distribution

Purpose

The proposed study concepts are primarily intended to complement currently implemented methods of quantifying gear selectivity, at least in relative terms, and to determine the degree that samples from IEP surveys are representative of the Delta Smelt population. Therefore, these studies are expected to improve accuracy of the survey data and to quantify bias associated with making inferences from current survey and monitoring data regarding the abundance and distribution of Delta Smelt in the San Francisco Estuary. The field study concepts articulated in this proposal are coupled to a commitment to intensive analysis and the development of appropriate changes to monitoring methods that may improve management of Delta Smelt protections while minimizing the impacts of protective measures on water operations.

Background

While many of the IEP surveys were designed and initiated several decades ago with the intent of catching juvenile Striped Bass and Chinook Salmon, the existing surveys including those that target Delta Smelt (e.g., 20mm and Spring Kodiak Trawl) are collecting individuals at nearly all life stages (except eggs) throughout much of the spatial territory likely occupied by Delta Smelt. Because these surveys collect data on many other fish species and because of the lengthy historical time series generated by these surveys, they should be kept in operation. These surveys have the potential to provide much of the data necessary to inform our decisions and predict the effects of management actions. However there are concerns over potential and known biases due to a variety of factors. What is most needed to improve our understanding are special studies and investigations which can provide additional information regarding these potential biases to (a) increase the value of historical and currently collected data and (b) guide potential changes and additions to the survey programs. Below are concepts for special studies and investigations we have identified as important for estimating the abundance and distribution of Delta Smelt, for the ongoing development of the life cycle model, and for future biological opinions and the BDFWO monitoring survey review. Please note that all increases in sampling will result in an increase in Delta Smelt take. Therefore, study implementation will likely be phased to maximize new information and minimize take. All budget figures provided are approximate yearly costs. Total cost will depend on development of specific study plans and implementation planning during the 3–5 year study period.

Objectives

The proposed concepts address the following objectives:

1. Quantify factors affecting the relative gear selectivity for IEP surveys that provide abundance and distribution data for Delta Smelt. Important correlates include ontogenetic stage (size and growth), net dimensions, deployment methods, and environmental variables such as turbidity, temperature, flow, and tide.
2. Determine the vertical and lateral distribution of pelagic life stages of Delta Smelt over a range of potential environmental drivers, including tidal effects.
3. As appropriate, develop potential adjustments to current monitoring strategies to account for findings in #1 and #2 above, as well as other recent studies in this area, in order to support more efficient protective measures for Delta Smelt. This objective includes development of reliable population size estimation, and any adjustments that might be needed to ongoing monitoring to reduce sources of bias and ensure appropriate spatial and temporal coverage.
4. Quantify pre-salvage entrainment losses in the vicinity of the south Delta export facilities.

Methods

Gear Selectivity Studies (Objective 1)

Gear selectivity evaluations are needed to integrate catch data from multiple surveys to estimate abundance and ultimately to model population dynamics for Delta Smelt and other species of management concern. Data from simultaneous, adjacent deployment of IEP survey gears during the tidal cycle will permit the estimation of selection curves relating the relative capture probability of Delta Smelt of a given size across gears. The selection curves will be modeled statistically following Millar and Fryer (1999). The sampling design and analytical approaches for the single location and multiple gear evaluations (described below) was approved by IEP in 2012. Sampling efforts in the fall (juvenile to sub-adult) and spring (larvae to juveniles) were successful and data collection and model development are ongoing.

Multiple Gears (Single Location): Field sampling will be repeated seasonally to collect information for different Delta Smelt life stages and to estimate selectivity for different IEP fish monitoring gears (Table 1). Each field sampling effort will use the gear types currently targeting the particular life stage present and those gear types that target earlier and later life stages. The goal will be to seasonally sample as Delta Smelt transition from being effectively sampled by one gear (or set of gears) to another gear (or another set) to capture how relative selectivity changes with fish size (and ontogeny). For each gear and tow, we will identify and measure all fishes to the nearest mm fork length for juveniles through mature adults. Larvae will be identified and measured in the lab to the nearest 0.1 mm total length. Within each sampling period, proposed monthly effort will entail two days of field work. Sampling will stop when take is exceeded or if sufficient data are obtained for robust modeling.

Gear deployment will follow the protocols used by the respective agencies, except that tow durations will be 10 min (see Honey et al. 2004 for survey and gear descriptions). During each field day, we will deploy gears with the following frequency by tide: 6 flood tows, 6 ebb tow and 1-2 tows on each slack water (14 replicate tows per day). Field work will be planned for daylight hours over a three-day period (sampling on days 1 and 3) when flood and ebb tides occur primarily during daylight hours. Data will be checked, processed and evaluated for sufficiency prior to further sampling.

Table 1. Target Delta Smelt life stages and the gears, time period, and sampling effort proposed to determine relative efficiencies of standard fish monitoring survey gears. Note: TNS = Summer Townet Survey, FMWT = Fall Midwater Trawl, OT = Bay Study Otter Trawl, SKT = Spring Kodiak Trawl, CMWT = Chipps Island Midwater Trawl, SLS = Smelt Larva Survey, 20mm = 20mm Survey.

Life stage(s)	Gears deployed	Months sampled	Sampling effort
Juvenile to Sub-Adult	TNS, FMWT, OT, SKT, CMWT, Beach seine	August through October	2 days / month
Pre-Spawning Adults	FMWT, SKT, OT, CMWT, Beach seine	December through January	2 days / month
Spawning Adults	FMWT, SKT, OT, CMWT, Beach seine	March through April	2 days / month
Larvae to Juveniles	SLS, 20mm, TNS, Beach seine	April through June	2 days / month

We will select sampling locations based on relatively high local densities of Delta Smelt detected during routine fish monitoring. The most likely sampling range for juveniles to sub-adults will be in the lower Sacramento River between Chipps Island and Decker Island; sampling for spawning adults and larvae and juveniles may take place in the Sacramento Deep Water Ship Channel; however, the channel width may be insufficient to simultaneously deploy all gears targeting adults. Depending on the number of gears, GPS coordinates for 3–5 trawl lanes will be established and provided to boat operators. For each tow, vessels towing each gear type will be randomly assigned to a trawl lane. We will deploy beach seines in the vicinity of the trawl lanes if suitable shallow habitat is available.

Shadow Trawling (Multiple Locations): Additional side-by-side trawling will be conducted monthly with the FMWT and SKT in conjunction with the regular surveys. Ten long-term sites will be randomly selected from each of four regions (40 sites total). The SKT will be co-deployed simultaneously during the FMWT survey on four days monthly (10 sites per day) from September through December. Similarly, the FMWT will be co-deployed during the SKT survey on four days monthly from January through March. Although the selectivity curves will be similar to the gear evaluations described above, this experiment will be conducted under identical conditions to the regular surveys. Therefore, we will be able to estimate the relative selectivity and probability of zero catch regionally at the survey sites. Moreover, this design ensures that sampling will take place over a broad range of environmental conditions that may affect gear selectivity.

We will collect environmental measurements following survey protocols. Repeated sampling over a range of environmental variables will permit the assessment of how Delta Smelt interact with the environment and how these interactions influence catch by the survey gears. In order to be sampled by the net, Delta Smelt must first be available (present) and subsequently retained after contact with the net. For example, the vertical distribution of Delta Smelt may change during the tidal cycle affecting the relative availability of individuals to oblique tows compared to surface tows. Similarly, turbidity may influence the relative ability of Delta Smelt to detect and avoid trawled gears. To improve our understanding of these interactions, models representing *a priori* hypotheses regarding the impact of environmental variables on catch will be developed and assessed in an information-theoretic framework (Burnham and Anderson 2002).

Vertical and Lateral Distribution Studies (Objective 2)

Understanding how environmental variables influence the vertical and lateral distribution of Delta Smelt is critical to ensure that samples from IEP surveys are comparable and representative of the Delta Smelt population. In addition, IEP surveys sample the water column and channel habitats in different ways and provide a depth- (for oblique tows) and time-integrated (tow duration) snapshot of catch. Although the gear selectivity evaluation described previously will provide some insight into the vertical and lateral distributions of Delta Smelt, availability (presence) and avoidance (present but not captured) are confounded and difficult to separate in the study design. In contrast, SmeltCam technology replaces the cod-end of towed gears with video cameras and thus provides instantaneous depth- and channel-specific catch data with reduced lethal take. Pilot efforts have successfully deployed the SmeltCam in conjunction with the FMWT and suggest that adult Delta Smelt are accurately identified. However, the lower size limit for accurate identification remains speculative. We suggest continued pilot efforts of one week per month during the summer and fall (August through October) with the modified FMWT or other modified gears such as the TNS to investigate the vertical and lateral distribution of Delta Smelt. The proposed tests are needed to establish the minimum size range and effectiveness of the SmeltCam under various conditions for consistent and unambiguous identification and to standardize the quality assurance and quality control procedures for data processing.

Develop Appropriate Adjustments to Monitoring Programs (Objective 3)

New information developed by us and others may indicate that current monitoring efforts could be improved. Objectives #1 and #2 are intended to explore whether existing sampling gears and strategies are still appropriate to address management information needs. If monitoring shortcomings are established, translating those findings into improved monitoring protocols will require careful assessment of the specific issues that need to be addressed, modeling and testing of potential solutions, and implementation of study design modifications. This work will also require careful assessment of the data needs of the delta smelt life cycle modeling efforts that are underway, especially the Newman et al. effort. Close collaboration with life cycle modelers will help ensure that any monitoring adjustments that are developed are crafted to reduce prediction error and in other ways improve the usefulness of the life cycle models. The financial support summarized in Task 3.1 in the attached budget is intended to

provide a strong and direct link between the monitoring investigations described in this proposal and the ongoing life cycle modeling. The following sampling elements describe some of the issues that may be investigated.

Random Sampling (FMWT): Inferential statistics generally assume that samples are obtained randomly from the target population. The bias resulting from sampling non-random fixed stations during the IEP survey remains unknown. If the bias is not negligible, survey data may not adequately reflect true population trends that are needed for managing the recovery of Delta Smelt. Therefore, it is critical to determine the degree that samples from non-random sites are representative of the Delta Smelt population. We will conduct stratified random sampling at 80 sites within three regions monthly from September through December coincident with the FMWT survey. Although we will initially partition strata by region, post-stratification by environmental variables such as salinity and temperature may be attempted to increase precision. Monthly sampling will occur over an eight-day period (10 sites per day) on days that do not conflict with the gear selectivity evaluations or shadow trawling.

Increased Survey Effort: Infrequent sampling and sparse data may also result in increased variability and reduced precision. Catch data are often highly variable and patchy in space and time and repeated sampling is critical for obtaining a representative sample of the population. Currently, the FMWT and SKT are conducted monthly over an eight- and five-day sampling period, respectively. Doubling these efforts to sampling twice per month will be attempted from December through May targeting regions of high importance to Delta Smelt and regions with high uncertainty of catch data. The additional sampling may be conducted at the long-term fixed sites or by stratified random sampling depending on preliminary results. Adjusting sampling regimes or gears to reduce detection limits may also be important, and will be considered in this work.

Spatial Coverage: Geographically appropriate sampling is important for making inferences regarding habitat use, overall abundance, and population dynamics. Bias may result if regions or habitat types that could be important for Delta Smelt are not surveyed or are inadequately surveyed. Currently, IEP surveys have limited coverage in several regions, including the Cache Slough Complex and the Sacramento Deep Water Ship Channel. Increasing the frequency of the USFWS beach seine (year round) and larval trawl survey (February through July) at Liberty Island will facilitate the parameterization of Delta Smelt occupancy models. Sampling other shallow-water habitats in the Cache Slough Complex may require the deployment of alternative gears if depths are not sufficient for surface trawling. In addition, more sites are needed in the Sacramento Deep Water Ship Channel to improve spatial resolution of the IEP surveys for all life stages of Delta Smelt.

Quantify Pre-Salvage Entrainment Losses (Objective 4)

Previous pilot studies generated useful information about the relationship between marked Delta Smelt present in the Clifton Court Forebay (CCF) and their resulting salvage at the Skinner Fish Facility (SFF). It is important to conduct further studies to improve our understanding of unaccounted entrainment losses on the different life stages of Delta Smelt. These results should be useful to inform modeling

efforts to assess population-level impacts of entrainment losses. A percentage of the fish entrained into CCF is lost and unable to reach the screens of the SFF. Such loss is referred to as pre-screen loss, and it excludes the loss due to partial collection of fish entering the fish facility, which is termed fish facility efficiency. The proposed objectives are to obtain mark-recapture estimates for the: 1) fish facility efficiency for larva, juvenile and adult Delta Smelt at the SFF, 2) percent of marked larva, juvenile and adult Delta Smelt released at the entrance of CCF and recaptured at the SFF, and 3) pre-screen loss for larva, juvenile and adult Delta Smelt.

Delta Smelt to be used in the mark-recapture experiments will be produced at the UC Davis Fish Conservation and Culture Lab, which is a short distance from the release locations at the SFF and the entrance of CCF. Mark-releases for each life stage will be timed to coincide with the historical corresponding occurrence of larva, juvenile and adult wild Delta Smelt in the south Delta. Larva, juvenile, and adult Delta Smelt will be marked with SE-MARK™ Calcein. In addition, each adult Delta Smelt will have a unique photonic mark per test (POW'R-Ject System, New West Technologies) to differentiate days and/or location of fish releases. Based on the results of a previous marking study by James Hobbs (UC Davis), it is not deemed necessary to trans-generationally mark adult Delta Smelt considered in the proposed study. However, this option will be considered if required.

Each experiment will include one mark-recapture test releasing marked Delta Smelt just up current from the louvers at the SFF and one at the entrance of CCF. The anticipated numbers of fish to be used in each test and the timing between tests and experiments is based on previous studies. Year 1 will include two experimental releases of larva Delta Smelt, each conducted at least one month apart. Approximate numbers of larvae for each experimental release are: SFF (n = 1,000), entrance of CCF (n = 40,000). Year 2 will include two experiments on juvenile Delta Smelt, each conducted at least one month apart. Approximate numbers of juveniles for each test are: SFF (n = 400), entrance of CCF (n = 20,000). Year 3 will include eight experiments on adult Delta Smelt, four of which will be conducted at least one day apart. The other four adult experiments will be conducted as described, at least one month apart, from the first four experiments. Approximate numbers of adults for each test are: SFF (n = 100), entrance of CCF (n = 1,500).

Budget (yearly)

See attached pdf.

References

- Burnham, K.P., and Anderson, D.R. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Springer-Verlag, New York.
- Honey, K., R. Baxter, Z. Hymanson, T. Sommer, M. Gingras, and P. Cadrett. 2004. IEP long-term fish monitoring program element review. Interagency Ecological Program for the San Francisco Bay/Delta Estuary, Technical Report 78.
- Millar, R. B., and Fryer, R. J. 1999. Estimating the size-selection curves of towed gears, traps, nets and hooks. *Rev. Fish Biol. Fish.* 9: 89-116.

Project title: Delta smelt monitoring
 Bio-Day Rate: 9950

Objective 1 (Gear Selectivity Studies)

Task 1.1: Continue side-by-side fishing gear comparison studies

Gear	# of Crew	Days per shift	Day Rate	Cost per shift	Shift per month ¹	Cost per month	Months sampled	Month per year	Cost per year
CHWT (2 techs., 1 boat op.)	3	1.5	\$950	\$4,275	2	\$8,550	Aug-Oct., Dec-Jan., Mar-Apr	7	\$59,850
FMWT (2 techs., 1 boat op.)	3	1.5	\$950	\$4,275	2	\$8,550	Aug-Oct., Dec-Jan., Mar-Apr	7	\$59,850
OT (3 techs., 1 boat op.)	4	1.5	\$950	\$5,700	2	\$11,400	Aug-Oct., Dec-Jan., Mar-Apr	7	\$79,800
SKT (2 techs., 2 boat ops.)	4	1.5	\$950	\$5,700	2	\$11,400	Aug-Oct., Dec-Jan., Mar-Apr	7	\$79,800
SLS (2 techs., 1 boat op.)	3	1.5	\$950	\$4,275	2	\$8,550	Apr-Jun	3	\$24,650
TNS (2 techs., 1 boat op.)	3	1.5	\$950	\$4,275	2	\$8,550	Apr-Jun	3	\$24,650
20mm (2 techs., 1 boat op.)	3	1.5	\$950	\$4,275	2	\$8,550	Apr-Jun	3	\$24,650
Beach Seine (2 techs.)	2	1.5	\$950	\$2,850	2	\$5,700	Aug-Oct., Dec-Jan., Mar-Apr., Apr-Jun	10	\$57,000
Data Entry and Lab (4 techs.)	4	J	\$950	\$3,800	2	\$7,600	Aug-Oct., Dec-Jan., Mar-Apr., Apr-Jun	10	\$76,000
Data Analysis (Statistician)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000
Data Analysis (Modeler)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000

¹Assumes 2 sites (or repeat sampling at 1 site) and 1 site per day = 2 x 12-hr shifts

Subtotal: \$629,200

Task 1.2: Co-deployment of SKT and FMWT during both surveys (shadow trawling)

Gear	# of Crew	Days per shift	Day Rate	Cost per shift	Shift per month ¹	Cost per month	Months sampled	Month per year	Cost per year
FMWT (2 techs., 1 boat op.)	3	1	\$950	\$2,850	4	\$11,400	Sept-Mar	7	\$79,800
SKT (2 techs., 2 boat ops.)	4	1	\$950	\$3,800	4	\$15,200	Sept-Mar	7	\$106,400
Data Entry and Lab (2 tech.)	2	J	\$950	\$1,900	4	\$7,600	Sept-Mar	7	\$51,200
Data Analysis (Statistician)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000
Data Analysis (Modeler)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000

¹Assumes 40 sites (10 sites per region) and 10 sites per day = 4 x 8-hr shifts

Subtotal: \$207,600

Objective 2 (Vertical and Lateral Distribution Studies)

Task 2.1: Continue SmeltCam studies

Gear	# of Crew	Days per shift	Day Rate	Cost per shift	Shift per month ¹	Cost per month	Months sampled	Month per year	Cost per year
FMWT/TNS (2 techs., 1 boat op.)	3	1	\$950	\$2,850	5	\$14,250	Aug-Oct	3	\$41,750
Engineer	NA	NA	NA	NA	NA	\$40,000	Aug-Oct	3	\$120,000
Data Processing	NA	NA	NA	NA	NA	\$10,000	Aug-Oct	3	\$30,000
Data Analysis (Statistician)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000
Data Analysis (Modeler)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000

¹Assumes 5-day sampling period = 5 x 8-hr shift

Subtotal: \$221,750

Objective 3 (Develop Adjustments to Monitoring Programs)

Task 3.1: Development of monitoring strategies and support for life cycle model

Category	#	Days per shift	Day Rate	Cost per shift	Shift per month ¹	Cost per month	Months sampled	Month per year	Cost per year
Statistician/modelers	1	1	\$935	\$935	15	\$14,025	NA	12	\$168,300
Biologist	1	1	\$935	\$935	15	\$14,025	NA	12	\$168,300
Technical support	1	1	\$935	\$935	6	\$5,610	NA	12	\$67,320

Subtotal: \$403,920

Task 3.2: Conduct stratified random sampling during FMWT

Gear	# of Crew	Days per shift	Day Rate	Cost per shift	Shift per month ¹	Cost per month	Months sampled	Month per year	Cost per year
FMWT (2 techs., 1 boat op.)	3	1	\$950	\$2,850	8	\$22,800	Sept-Dec	4	\$91,200
Data Entry and Lab (1 tech.)	1	1	\$950	\$950	2	\$3,800	Sept-Dec	4	\$15,200
Data Analysis (Statistician)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000
Data Analysis (Modeler)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000

¹Assumes 40 sites (allocated by region) and 10 sites per day = 8 x 8-hr shifts

Subtotal: \$156,400

Task 3.3: Increase FMWT and SKT sampling frequency during late winter and early spring

Gear	# of Crew	Days per shift	Day Rate	Cost per shift	Shift per month ¹	Cost per month	Months sampled	Month per year	Cost per year
FMWT (2 techs., 1 boat op.)	3	1	\$950	\$2,850	3	\$8,550	Dec	1	\$8,550
SKT (2 techs., 2 boat ops.)	4	1	\$950	\$3,800	3	\$11,400	Jan-May	5	\$57,000
Data Entry and Lab (1 tech.)	1	1	\$950	\$950	3	\$2,850	Dec-May	6	\$17,100
Data Analysis (Statistician)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000
Data Analysis (Modeler)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000

¹Assumes 30 sites (10 sites per region or strata) and 10 sites per day = 3 x 8-hr shift

Subtotal: \$117,650

Task 3.4: Survey potential Delta smelt habitat under sampled by existing surveys

Gear	# of Crew	Days per shift	Day Rate	Cost per shift	Shift per month ¹	Cost per month	Months sampled	Month per year	Cost per year
LVT ² (2 techs., 1 boat op.)	3	1	\$950	\$2,850	6	\$17,100	Apr-Jun	3	\$51,300
SKT (2 techs., 2 boat ops.)	4	1	\$950	\$3,800	6	\$22,800	Aug-Oct., Dec-Jan., Mar-Apr	7	\$159,600
Data Entry and Lab (1 tech.)	1	1	\$950	\$950	6	\$5,700	Aug-Oct., Dec-Jan., Mar-Apr., Apr-Jun	10	\$57,000
Data Analysis (Statistician)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000
Data Analysis (Modeler)	NA	NA	NA	NA	NA	NA	NA	NA	\$25,000

¹Larval trawl from USFWS Liberty Island survey (suitable for shallow habitat)

²Assumes 6 regions (Cache Slough Complex, Sacramento Deep Water Ship Channel etc.) and 1 region per day = 6 x 8-hr shifts

Subtotal: \$272,900

Objective 4 (Mark-Recapture Studies)

Task 4.1: Mark-recapture studies at the Clifton Court Forebay and Skinner Fish Facility

Gear	# of Crew	Days per shift	Day Rate	Cost per shift	Shift per month	Cost per month	Months sampled	Month per year	Cost per year ¹
Project Management	NA	NA	NA	NA	NA	NA	NA	NA	\$12,000
Risk Culture	NA	NA	NA	NA	NA	NA	NA	NA	\$38,000
Delta smelt Marking	NA	NA	NA	NA	NA	NA	NA	NA	\$30,000
Mark-Recapture Experiments	NA	NA	NA	NA	NA	NA	NA	NA	\$33,000
Data Processing and Reporting	NA	NA	NA	NA	NA	NA	NA	NA	\$67,000

¹Average yearly cost for three-year study (yearly costs range from \$170,000 in year 1 to \$80,000 in year 3)

Grand total: \$1,474,670

Report Submission to
STATE WATER RESOURCES CONTROL BOARD

By

Robert J. Latour, Ph.D
Consultant to Sacramento Valley Water Users Group and
Northern California Water Association



Data Analyses in Relation to Water Flow for Fishes in the Sacramento-San Joaquin Delta
Ecosystem

Robert J. Latour, Ph.D
Consultant

September 14, 2012

I. Introduction

The State Water Resources Control Board's (SWRCB) August 16, 2012 Revised Notice of Public Workshops and Request for Information states the following as questions to be addressed in the October 1-2, 2012 workshop:

1. What additional scientific information should the State Water Board consider to inform potential changes to the Bay-Delta Plan relating to Bay-Delta fish resources, and specifically pelagic fishes and salmonids, that was not addressed in the 2009 Staff Report and the 2010 Delta Flow Criteria Report? . . . What is the level of scientific certainty or uncertainty regarding the foregoing information?
2. How should the State Water Board address scientific uncertainty and changing circumstances, including climate change, invasive species and other issues? Specifically, what kind of adaptive management and collaboration (short, medium, and long-term), monitoring, and special studies programs should the State Water Board consider related to Bay-Delta fisheries as part of this update to the Bay-Delta Plan?

This report addresses these questions by reviewing the results of the California Department of Fish and Game's (DFG) Fall Midwater Trawl (FMWT) survey. Examining the FMWT data set represented a logical first step since the indices of abundance derived from this sampling program have been central to recent state and federal protection efforts for various fish species inhabiting the Delta. A number of peer-reviewed manuscripts contain analyses that statistically relate the FMWT survey's abundance indices to environmental variables (e.g., X_2 ; Jassby et al. 1995, Kimmerer 2002, and others). These studies have generally concluded that there are statistically significant relationships between species relative abundance and Delta flows.

It is important to recognize, however, that any index of abundance is a synthesis of many raw field observations (often hundreds), so the reasonability of any derived statistical relationships involving the FMWT indices depends on the assumption that the indices truly reflect species' total abundance. Upon careful review of the FMWT survey design and DFG's analytical protocol for analyzing the FMWT survey data, several limitations were identified that created questions regarding the representativeness of the indices.

Accordingly, this report contains a new analysis of the FMWT survey data for six selected species in an effort to: (i) provide indices of relative abundance with estimates of precision that were derived from statistically defensible methods, and (ii) investigate the statistical relationships of key covariates such as flow (*Historical* and *Unimpaired Inflow* and *Outflow*) and turbidity (coarsely represented as *Secchi Depth*) with the underlying FMWT survey data. Because the analysis in this study was designed to investigate the raw FMWT survey data, it directly addresses the foundational strength of the previously documented statistical relationships between environmental covariates and species relative abundance. It also characterizes the underlying uncertainty surrounding those relationships. Given that statistical analyses of relationships between FMWT survey results and Delta flows

were central to the SWRCB's 2010 Delta Flow Criteria Report, revisiting the data from a 'first principles' perspective was appropriate.

The primary conclusions of this report are:

- A. The FMWT survey employs a fixed station design, which implies that monthly trawl samples are collected at roughly the same locations each year. This type of design limits the ability of the FMWT survey to detect systematic changes in the habitat utilization of Delta species. Shifts in habitat preferences by Delta species, possibly to areas not sampled by the FMWT, are plausible given the physical and environmental changes experienced by the Delta over the 1967-2010 FMWT survey period. Changes in relevant species' habitat use away from areas routinely sampled by the FMWT survey would necessarily manifest themselves in decreased indices of relative abundance.
- B. The methods used by DFG to calculate indices of abundance for Delta species do not follow a statistically defensible protocol. DFG's atypical estimation procedure results in indices with units of (water volume) times (fish counts), which are difficult to interpret. For example, what does a change in the longfin smelt index from 11864 to 7408 (volume) times (fish) units really mean for relative or total population abundance? Also missing from DFG's analysis protocol are estimates of uncertainty for the indices. Collectively, the calculation methods and lack of estimates of precision raise questions about how representative the indices are of true abundance, and about the degree of confidence associated with temporal patterns that they indicate, respectively.
- C. While DFG's data and methodology exhibit certain problems as described above, given the importance of DFG's abundance indices to investigations of the Delta species' status and related regulatory proceedings, this report contains a statistical analysis of the relationships between the FMWT survey data and a number of environmental covariates. Application of generalized linear models (GLMs) to the FMWT survey data for analysis of 'Daily' covariates (those measured at the same time as sampling), model selection statistics favored the model with *Year*, *Month*, *Region*, and *Secchi Depth*. All covariates were statistically significant for all models and species, with the exception of one species/model combination. The significance of the *Year*, *Month*, and *Region* are not overly surprising, but the importance of *Secchi Depth* suggests that turbidity may be an important structuring variable for species in the Delta. All estimated coefficients of *Secchi Depth* were negative, which indicates that Delta species' relative abundance is higher under conditions of greater turbidity and lower under conditions of lower turbidity. Over recent decades, turbidity in the Delta has decreased, markedly so in the late 1990s, so this conclusion is consistent with documented water quality changes in the Delta.
- D. The temporal patterns of the indices estimated in this study using peer-reviewed statistical methods showed some degree of qualitative agreement to those

provided by DFG. However, consistent with those peer-reviewed methods, this study's alternative estimation method was designed to provide statistically appropriate estimates of annual average-catch-per-tow. The scales of the indices are noteworthy. For delta smelt, the highest index achieved from 1967-2010 was 0.79 average-catch-per-tow (occurring in 1970), and the full time-series average was 0.17. For Sacramento splittail and starry flounder, the highest index values were 0.13 and 0.14, with corresponding time-series averages of 0.02 and 0.04, respectively. This indicates that the catch rate for these species has been less than 1.0 fish-per-tow (on average) over the life of the FMWT survey. Relative to other similar fish-sampling trawls in the United States that are believed to provide reliable measure of relative abundance, several of the FMWT's catch rates are quite low. Low encounter rates (frequency of tows that capture target species) combined with generally low overall numbers of fish collected following successful encounters underpin the low estimated index values. Such consistently low index values raise legitimate questions about the efficacy of the FMWT program in providing measures of relative abundance that track patterns in true abundance.

- E. In contrast to DFG's abundance indices, the newly-derived species abundance indices in this report are associated with statistically-derived estimates of precision. The estimated coefficients of variation (CV) for all species were generally acceptable, with most values ranging between 0.2-0.45. Higher CVs were estimated for periods within the time-series for Sacramento splittail, starry flounder, and Crangon spp. The CVs for starry flounder were consistently higher than those of the other species, which is likely related to the unreliability of a midwater trawl for sampling a predominately bottom-dwelling flatfish species.
- F. This study analyzed the statistical relationships between the species' abundance and 16 different variations of Delta streamflow measures (technically, "covariates").¹ GLMs were fitted to the FMWT survey data and model selection statistics indicated that the flow covariate within the 'best' fitting model varied by model type and species. The flow covariate that 'best' explained variation in species' relative abundance often was the *Unimpaired Inflow* (defined as Sacramento River plus Yolo Bypass) covariate, which is largely an unmanageable flow variable. Within the 'best' fitting models, all flow covariates and *Secchi Depth* were statistically significant (with an exception of *Secchi Depth* for one species/model combination). The statistical analysis, however, produced the following conclusions:

¹ The four base measures of those flow variables are *Unimpaired Inflow*, *Unimpaired Outflow*, *Historical Inflow* and *Historical Outflow*. (Inflow used in this study is defined as Sacramento River plus Yolo Bypass.) Each of those variables then was analyzed using four different averaging periods, specifically January-June, March-May, January-June with a one-year lag and March-May with a one-year lag, producing 16 different flow covariates used in the statistical analysis. The averaging periods are based on the use of similar averaging periods for Category A criteria in the SWRCB's 2010 Delta Flow Criteria Report.

- a. *Turbidity has a stronger statistical relationship with species abundance than flow.* The strengths of the statistical relationships of the FMWT survey data with *Secchi Depth* were greater than those with flow (again with the aforementioned species/model exception). This result suggests that turbidity may have a stronger structuring influence on the FMWT survey data than flow.
- b. *Small and variable statistical relationship between abundance and flow*
The coefficients between flow covariates and species relative abundance are small and, at times, inverse. In particular, delta smelt abundance showed a small, but statistically significant, inverse relationship with the 'best' fitting flow covariate, meaning that the species' relative abundance declined as that flow covariate increased.
- c. *Uncertain effect of manageable flow variables.* Although flow covariates and *Secchi Depth* showed statistically significant relationships with species relative abundance, the amount of underlying variation in the data is substantial and suggests that it is highly uncertain whether changes in manageable flow variables will generate any statistically-predictable increases in the relative abundances of Delta species. In particular, given the wide variations in species relative abundance over the 1967-2010 FWMT survey period, the small statistical relationships between flow covariates and abundance suggest that other environmental factors have more of an effect on abundance.

Recommendations for Further Analysis, Monitoring and Special Studies

The above conclusions suggest that the SWRCB's consideration of updates to the Bay-Delta Plan would be benefited by implementation of the following additional analyses, monitoring and special studies programs (many of which could be conducted with existing resources):

- 1) Derivation of indices. Despite the historic lineage of the methods used by DFG to calculate indices of relative abundance from the FMWT survey data, the lack of use of well established statistical methods that can also provide estimates of precision limits the interpretation of population status of Delta species. In contrast, the results stated in this report demonstrate a statistical model-based approach that could be used routinely without additional fieldwork. There are other defensible approaches as well. In short, consistently applying to the FMWT data peer-reviewed analytical techniques for evaluating survey data would significantly increase the understanding of fish abundance patterns that are important for policy decision making. Applying such techniques to the FWMT data in the SWRCB's present proceeding would be possible without significant new investments in staffing or equipment.
- 2) Sampling intensity of the FMWT survey. It is unclear how it was determined to use the current number of sampling stations for the FMWT survey. Field work is

expensive, so it would seem important to know if the current level of sampling intensity is needed to achieve desired levels of precision. It is possible that it can be shown statistically that less sampling effort can lead to indices with acceptable associated estimates of error. Such a finding then could free up valuable time, staff, and money that could be redirected to improve understanding of Delta species in several ways:

- a. Pilot studies directed at sampling locations/depths/habitats besides those traditionally sampled by the FMWT survey. In effect, such pilot studies would explore through field observations whether or not Delta species have undergone systematic shifts in habitat utilization over time and space.
 - b. Pilot studies to investigate through field observations how the diel movements of Delta species (if at all) affect availability to the trawl survey net.
 - c. Pilot studies designed to evaluate trawl net performance and consistency under different tidal and flow conditions. Side scan sonar and flume testing are untapped technologies that could be used to investigate the consistency of gear geometry and thus the catchability of species across various typical tidal and flow conditions within the Delta.
- 3) Deeper investigation of fish abundance in relation to turbidity. The emergence of *Secchi Depth* as an important variable indicates that more refined analyses should be conducted to analyze how turbidity structures biotic communities within the Delta. By definition *Secchi Depth* is a coarse measurement of turbidity, so investigating the effects of more direct measures of turbidity on Delta species relative abundance is a natural next step. Such an analysis could be statistical and could be conducted within the SWRCB's existing process by comparing species abundance data with more robust measures of Delta turbidity. For example, if available, monitoring data on suspended sediment concentrations in the Delta could be used as statistical covariates of Delta species abundance.
- 4) Spatiotemporal analyses of habitat utilization. Following from 2a above, exploration through focused statistical analyses of existing FMWT survey data of whether or not Delta species have undergone systematic shifts in habitat utilization over time and space. For example, as discussed later in this report, the FMWT survey is based on trawl tows within 14 regions of the Delta and an associated *Region* factor is recorded for each such tow. A statistical analysis could be conducted within the SWRCB's existing process to determine, based on the relationship of this *Region* factor to species abundance over the 1967-2010 FMWT survey period, whether there are meaningful trends in the locations within the Delta's regions where species of interest have been caught. Such an analysis could be based on existing data and would not require additional field work.

- 5) Process oriented studies. Consider ‘simultaneous’ deployment of different sampling methods, such as fish trawl nets and plankton nets, to synoptically understand how predators and key prey are collectively distributed in the environment. Ongoing fish diet studies would benefit from such synthetic data since prey selectivity could be inferred, which would aid the understanding of food web dynamics in the Delta. As discussed in recommendation 2) above, if additional resources would be necessary to conduct such studies, those resources potentially could be acquired by changing existing sampling methods while still maintaining statistically acceptable rates of precision in the resulting abundance data.

The real costs of monitoring programs are vessel time, fuel, gear, and personnel. Getting out in the field with a competent crew is no easy task. Once such a task has been achieved, it is important to implement sampling and statistical protocols that maximize not only the data collected in both types and amounts, but also the understanding of fish population dynamics that can be derived from the data.

II. Methods and Background

In the present study, analyses designed to investigate the relationships of fish abundance and Delta flows, along with other biological, environmental, and sampling covariates were based on data collected by DFG’s FMWT survey. Examining the FMWT data set represented a logical first step since the indices of abundance derived from this sampling program have been central to recent state and federal protection efforts for various fish species inhabiting the Delta. The focal species of this report are: delta smelt (*Hypomesus transpacificus*), longfin smelt (*Spirinchus thaleichthys*), starry flounder (*Platichthys stellatus*), Sacramento splittail (*Pogonichthys macrolepidotus*), threadfin shad (*Dorosoma petenense*), and a combined shrimp group (*Crangon spp.*).

All FMWT survey data and associated program protocol documents were graciously provided via an ftp site by Dave Contreras, DFG. This data set contains the CPUE information for all target species along with the associated sampling metadata (e.g., *Year*, *Month*, and *Region* of sampling) and several environmental covariates (e.g., *Temperature*, *Salinity*, and *Secchi Depth*). Monthly flow values for four flow variables were provided via email by Walter Bourez, MBK Engineers, following personal communication.

A. Brief life history review of relevant species

Delta smelt: This species is one of six along the Pacific Rim currently associated with the genus *Hypomesus*. Delta smelt are relatively small and attain a maximum size of approximately 80 mm total length (TL). These fish have a fairly restricted home range and are most abundant in the lower salinity portions of estuaries. Delta smelt are primarily an annual species, with some individuals surviving two years. This life history strategy implies that persistence of the population is driven by maximizing growth, survival, and reproductive success on an annual basis. Loss of just one year-class can be very detrimental, since an annual life cycle is not inherently designed to overcome failed year-classes. Delta smelt are semi-anadromous meaning that they migrate to freshwater for

spawning, but do not spend some portion of their life in oceanic waters. Transitioning from estuarine to fresh waters for the purposes of spawning is sufficient to be semi-anadromous. Delta smelt larvae are most prevalent from mid-April through May, which suggests that spawning begins in late February to March. In general, delta smelt are considered to be planktivorous and rely on various copepod prey throughout life.

Longfin smelt: This species is a small pelagic fish that also has a relatively short life span. Most longfin smelt live only two years, although some three-year-old individuals have been observed. Longfin smelt inhabit estuaries, bays, and near coastal habitats, and their spatial distribution within the estuary varies seasonally. Typically, longfin smelt are found down estuary during summer and farther upstream during cooler months. This species is fully anadromous implying that it spends part of its life in oceanic waters and migrates to into freshwater rivers to spawn. Maturity is reached at two years of age and spawning occurs primarily at night during the months of February through April. Longfin smelt engage in daily migrations within the water column such that during daylight hours these fish inhabit deeper habitats while during night they can be found near the surface. This diel migration coincides with feeding as most longfin smelt prey on various types of zooplankton, which are more ubiquitous in the water column during night. Longfin smelt reach sizes of 6-7 cm standard length (SL) by 9-10 months of age, and maximum size is generally 15 cm SL.

Starry flounder: This species is typically found in oceanic and estuarine waters with rare occurrences in freshwater. Starry flounder are commercially and recreationally valuable, prosecuted primarily by bottom trawls offshore and anglers from piers and boats in estuarine habitats. In California, starry flounder peak spawning occurs from November to February and larvae are advected into nursery habitats within estuaries. As with many flatfishes, starry flounder exhibit sexual dimorphic growth and maturation, with males maturing earlier than females (ages 2-3 vs 4-6) and attaining generally smaller maximum sizes than females. Maximum age has been reported to be 21 years. Starry flounder feed on a variety of prey types throughout their life cycle, ranging from plankton at younger ages to shrimp, crabs, and small fishes at older ages.

Sacramento splittail: This species is a cyprinid and the Sacramento-San Joaquin Delta serves as the center point of its home range. Splittail can live up to 8-10 years, but longevity is typically not longer than 5 years of age. Maturity is generally reached in two years and peak spawning occurs from March through April. The distribution of splittail fluctuates seasonally and annually, however, the general distributional pattern of this species suggests that fish reside in the estuary proper during summer and early fall with adults migrating upstream for spawning during late fall and early spring. Splittail forage primarily on benthic organisms during daylight. Key prey types include copepods, opossum shrimp, and amphipods, although detritus is often a large portion of what has been observed in the stomachs of this species. Splittail are targeted by recreational anglers but the scale of removals and fishing mortality is largely unknown.

Threadfin shad: This species is a schooling pelagic forage fish and a member of the family Clupeidae. Threadfin shad rarely exceed 100 mm in length and can be found in brackish and freshwater habitats. Maximum age has been reported to be four years, but longevity of

most fish is 2-3 years. Although threadfin shad inhabit lower salinity habitats, freshwater is necessary to support successful spawning. In California, threadfin shad typically spawn from April to August in and around areas with structure, usually submerged aquatic vegetation. During all life stages, threadfin shad are planktivorous and feed on primarily on crustacean zooplankton. This species was intentionally introduced into several California aquatic ecosystems in the early 1950s primarily to provide forage for key sportfishes.

Crangon spp.: This shrimp group is considered to provide a key role in ecosystem functioning primarily as prey for higher trophic levels, but also as predators of various planktonic organisms, particularly ichthyoplankton.

B. FMWT Survey Design and Sampling Protocol

The FMWT survey has operated annually in the San Francisco Estuary (referred to herein as Delta) since 1967, with the exception of 1974, portions of 1976 and 1979. The ‘index period’ for many targeted fishes in the Delta, which is defined to be the ‘temporal window’ where sampling activities are believed to provide representative abundance information, has historically been designated as the autumn months. Consequently, the data germane to the present study were those derived from sampling activities occurring in the months of September through December each year.

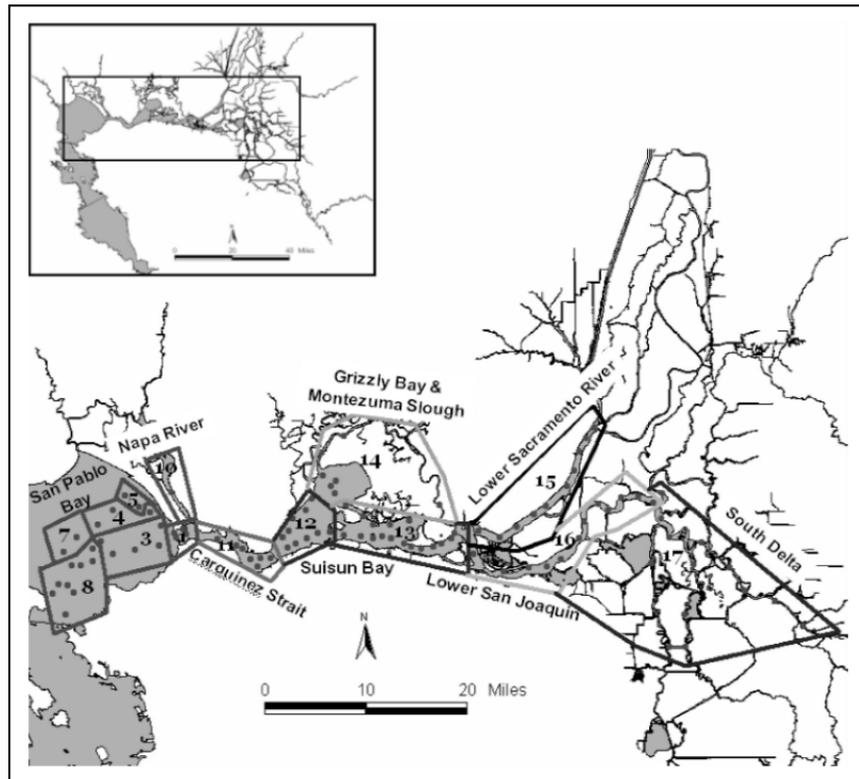


Figure 1. Areal stratification of the Fall Midwater Trawl Survey (numbered polygons) and fixed sampling locations within each stratum (dots). Strata 2, 6, and 9, have not been sampled since 1973 and are thus omitted from the map. The above image was taken from Newman (2008).

The survey follows a stratified fixed station design such that sampling occurs at approximately the same locations each month within predefined strata (Figure 1). At each sampling location, a ten minute oblique tow is made from near bottom to the surface using a square midwater trawl (mouth opening 3.7m²) with variable mesh in the body of the trawl net (20.3 to 2.5cm) and a 1.3cm stretch mesh cod end. Each catch is sorted,

enumerated by species, and growth information (length, weight) is recorded for all fish captured or species-specific subsamples in the case of large catches. Over the course of the survey, the number of stations sampled per month during autumn has ranged from approximately 70-80 during the 1960s-1970s to 95-100 from the late 1990s to the present.

C. Calculation of Abundance Indices from the FMWT survey

DFG calculates the annual FMWT survey index for any given species as the sum of four monthly indices. The calculation of each monthly index is based on the arithmetic mean catch-per-tow for stations within each of the 14 areas or strata delineated in Figure 1. Formally, the mean catch in month m and area a , denoted as $\bar{c}_{a,m}$, is given by:

$$\bar{c}_{m,a} = \frac{1}{n_a} \sum_{s=1}^{n_a} c_{m,a,s} \quad \text{eq (1)}$$

where n_a is the number of stations in area a and $c_{m,a,s}$ is the number of fish captured during month m in area a at station s . The overall monthly index, I_m , is a weighted sum of the mean catches by month and area, which can be expressed as:

$$I_m = \sum_{a=1}^{14} w_a \bar{c}_{m,a} \quad \text{eq (2)}$$

where w_a is the weight for area a defined to be an estimate of the water volume in each area in ten thousands of acre feet. In summary, the monthly abundance index calculated by DFG from the FMWT data is the average number of fish caught in a given area multiplied by the estimated water volume of that area, summed up over the 14 areas sampled by the survey.

III. Analysis

A. Notable Limitations of the FMWT Survey

A reasonable guiding principle that can be used to evaluate any fish monitoring program is as follows: if the consistency of survey practices is subject to appreciable error over any measurable axis, then automatically we must question the representativeness of data derived from that sampling program.

Bennett (2005) and Newman (2008)² both articulated several important concerns regarding the methods (both field and analytical) DFG has used to derive indices of abundance from the FMWT survey data. Bennett's study is more of a general review

²The institutions of employment for W. Bennett and K. Newman are the John Muir Institute of the Environment, Bodega Marine Laboratory, University of California, Davis and the U.S. Fish and Wildlife Service, respectively.

whereas Newman's manuscript is a technical summary with analytical advancements. Many of the criticisms noted by these authors also are conclusions of this, which I initially arrived at independently and later confirmed following review of Bennett (2005) and Newman (2008). Below is a summary of the concerns surrounding the FMWT survey (purposely relying on those articulated by Newman (2008)) along with some additional commentary brought out by this study. Woven into the summary of each point are comments regarding the interpretability of the published FMWT survey indices as true measures of target species abundance.

1. Survey Design and Analytical Methods for Calculating Indices

Following from eq (2), the units of the annual FMWT indices are sums of water volumes of each area times average fish counts for each area, rather than a measure of fish counts alone. The units of any survey program are a direct function of how the indices themselves are derived, so in effect, criticism of the units of the FMWT survey indices amounts to criticism of the methods used for calculation. In general, the purpose of analyzing survey data is to produce an index value defined to be an unbiased estimate of the average catch-per-unit-effort (CPUE). DFG's indices are not average CPUEs, which renders it very difficult to interpret the meaning of the values they take on in the context of relative or total abundance of Delta species. Additional details regarding how DFG's calculation methods of abundance indices do not conform with standard treatments of survey data are discussed below.

First, in the case of the FMWT survey, the standard unit of sampling effort is defined to be a single trawl tow, although it is possible to express effort as water volume sampled since these measurements have been recorded via flowmeters since 1985. The FMWT indices are quasi-averages meaning that a weighted mean CPUE is calculated. However, those weighted means are not divided by the sum of the weighting factors, which is necessary when deriving an estimate of a mean from a stratified sampling design (Cochran 1977). DFG's use of the arithmetic mean estimator inherently assumes that the underlying observations follow a normal distribution (the familiar symmetrical bell curve), which is not generally the case with fish survey data. By definition, surveys should sample locations without pre-existing knowledge of the abundances of the target species at these locations in an effort to maintain an unbiased approach to measuring abundance. Consequently, CPUE data tend to be positively skewed, which means that over the course of a sampling month or year, the survey program accumulates high frequencies of low catches and low frequencies of high catches, largely because the core habitat area of most fishes is far smaller than the total survey area. The bell curve of a normal probability distribution is not a good match for these data since there are not symmetric frequencies of CPUE observations around some type of central value. The arithmetic mean of samples is only an unbiased estimator of the population mean if the underlying data follow the normal distribution, and inspection of simple annual histograms of the FMWT CPUE data from 1967-2010 suggest that the normality assumption is not met. Thus, the use of the arithmetic mean by the DFG in its calculation of abundance indices from the FMWT data is questionable.

Second, DFG's use of a fixed station design is problematic since changes in the distribution and habitat utilization of target species are inherently confounded with changes in the measured abundances at sampling locations. For example, suppose that the abundance of a particular fish species is constant over two consecutive years, but that in the second year there is a shift in habitat utilization such that an appreciable fraction of fish move to areas not sampled by the FMWT survey. Modest shifts in annual habitat use by fishes are plausible and often driven by year-to-year variability in environmental conditions. As a result, in the above example, a habitat shift in year two away from locations routinely sampled by the FMWT would lead to a lower index of abundance even though total abundance has remained constant over the two-year time frame.

Lastly, although the core function of surveys is to provide indices of relative abundance, equally important are estimates of precision for those indices, and such estimates are absent from the analytical procedures used by the DFG in its treatment of the FMWT survey data. Newman (2008) used a design-based estimation procedure to provide variance estimates of total delta smelt abundance estimates, so some progress has been made. However, more progress is needed and the efforts of this study to rework the derivation of indices from the FMWT survey data with associated estimates of coefficients of variation (CVs) can be viewed as an additional advancement.

2. Consistency of Trawl Gear Performance

It has been documented by Newman (2008) and acknowledged by DFG staff (via FMWT survey protocol document reviewed by R.J. Latour) that the volume of water sampled by the trawl can vary considerably between tows. Consistency of gear performance in the field across time and space is paramount to any survey program, since changes in survey indices are assumed to reflect changes in the underlying abundance of target species. If tow volumes between stations by area, month, and/or year change substantially, then the area weights should also change (Newman 2008). DFG's analytical protocol for the FMWT survey data does not reflect this idea.

For illustration of this point, Newman (2008) provided the following simple example. If the true abundance of a particular fish species is the same in a given area and month for two consecutive years, but the volume filtered in each tow during the second year was twice the volume filtered in the first year, then application of constant weighting factors would yield an index for year two that is approximately twice that of year one, even though true abundance remained constant over time. Although Newman (2008) suggested that the scale of changes in delta smelt population over time have been large enough to mitigate the effects of inaccuracies due to variation in volume sampled, the issue itself speaks to the concept of tow standardization.

Along those lines, my review of protocol documents associated with the FMWT program did not reveal any summaries of attempts by DFG staff to investigate consistency of gear geometry during tows. Over the past decade, fish sampling programs and commercial fishers in North America have made significant efforts to use various technologies to understand net behavior under different tidal conditions and over different substrate types

(R.J. Latour, personal observations). Equipping trawl nets with hydroacoustic sensors that provide real-time measurements of door spread, headline height, bottom contact, wing spread, and many other parameters has been by far the most popular method. Examples of programs that routinely use hydroacoustic mensuration gear include: fish trawl surveys operated in the U.S. by the National Marine Fisheries Services and the Virginia Institute of Marine Science (VIMS), trawl surveys under the direction of the Department of Fisheries and Oceans in Canadian waters, and the majority of the commercial trawling fleet that targeting groundfishes, herring, and squid stocks off the New England coast and within the mid-Atlantic Bight.

The relatively small size of the net used by the FMWT survey may make the use of hydroacoustic net mensuration gear logistically challenging. Nevertheless, side scan sonar and flume testing represent seemingly untapped viable alternatives to gain insight about the FMWT net geometry. Note that the Centre for Sustainable Aquatic Resources at Memorial University, Newfoundland, Canada has the largest flume tank in the world and routinely tests trawl net performance for both standardized survey programs and commercial fishers. The absence of some type of independent verification of gear performance should raise legitimate questions regarding the FMWT's ability to maintain consistent towing over time and space, and therefore the representativeness of the abundance indices derived from FMWT survey data.

3. Size Selectivity of FMWT Survey Gear

Another criticism of the FMWT survey is that the trawl gear is size-selective and that index calculation methods do not account for this issue. Size-selectivity refers to the idea that the sampling net systematically collects animals of a particular size range that is different than the actual size range of the target species in the environment. If all sizes of a particular species are not equally vulnerable to the sampling gear, then the numbers of fish caught at any given location may not be representative of the true total abundance at that location (e.g., many 'large' or many 'small' fish are not captured by the gear). In fairness, all sampling gear is size-selective to some degree, so this concern is not unique to the FMWT program. And on positive note, a covered cod-end experiment was conducted to investigate selectivity for the FMWT net and selectivity estimates for delta smelt derived from modern statistical techniques were provided by Newman (2008), so good progress in this area has been made.

4. Use of a Four Month 'Index Period'

The final criticism of the FMWT survey involves questioning the utility of an annual index derived from monthly sampling over a protracted time period (four months), since doing so relies on the assumption that the month-to-month survival pattern of target species is constant over years. This issue can be mitigated by either providing monthly estimates of abundance (as done so by Newman (2008)) or by reducing the 'index period' (i.e., number of months for which data are used to estimate indices) to be reflective of a perceived optimal time window for which the FMWT survey is believed to provide the best measure of abundance for the species under consideration. It should be noted that while it may be

desirable to reduce the ‘index period’ to fewer than four months as a means of addressing the between year variation in monthly survival problem, doing so should be based on a rigorous temporal analysis of existing data. Moreover, a similar argument can be made to consider modifying the spatial domain used to derive indices of abundance. The current analytical protocol assumes that spatial patterns of survival within months are constant over years, which may not be plausible given the alterations that the Delta has experienced over the course of the past decades. Particular areas within the Delta that were once key habitat for target species may no longer be, and vice versa, so a rigorous spatial examination of existing data may also be warranted.

B. Alternative Approach to Estimation of Indices and Testing of Covariates

Given the aforementioned analytical limitations of the DFG’s protocol for deriving indices of abundance for fishes in the Delta, the results of review of several reports and peer-reviewed manuscripts, and the interest in investigating the role of various environmental covariates (particularly flow) on abundance of key fish species in the Delta expressed in the SWRCB’s 2010 Delta Flow Criteria Report an independent analysis of the FMWT survey data was warranted. Specifically, while that FMWT survey data has certain limitations that demonstrate uncertainty about trends in the abundance of Delta fish species, those data have been the primary basis for management decisions concerning those species. An analysis of the relationships between trends in that survey data and relevant environmental factors therefore may be important for the SWRCB’s consideration of new Delta flow objectives.

The analysis of fish survey data can typically take one of two paths: (i) if the field operations of the program follow a known and defensible sampling design (e.g., stratified random sampling approach), then design-based estimation methods can be utilized, or (ii) if the field procedures do not closely align with a theoretically established design and/or there is interest in standardizing the index for the influence of covariates, then a model-based approach can be utilized. The analyses conducted by Newman (2008) are an effort to overcome some of the analytical limitations of DFG’s protocol through the use of design-based methods. In the discussion section of that manuscript, the author also noted that model-based inference is a viable alternative and fruitful area of further research. The analyses in this study can therefore be viewed as complementary to those of Newman (2008) and in the spirit of fulfilling the need for future research identified by Newman (2008).

Generalized linear models (GLMs; McCullagh and Nelder 1989) are commonly applied to survey for the purpose of standardizing catch and effort data (Maunder and Punt 2004), and are therefore the focal methodology of this study. GLMs are defined by the statistical distribution of the response variable, which in this case is CPUE, and how a linear combination of explanatory variables relates to the mean of the response variable. Formally, GLMs are defined as:

$$g(\mu_i) = \mathbf{x}_i^T \boldsymbol{\beta} \quad \text{eq (3)}$$

where g is the differentiable monotonic link function that brings together the response variable (random model component) and explanatory variables (systematic model component), $\mu_i = E(Y_i)$ which is the expected value or mean of the response variable, \mathbf{x}_i is the vector of covariates for the i^{th} value of the response variable, β is a vector of parameters to be estimated, and Y_i is the i^{th} value of the response variable (Maunder and Punt 2004).

Inspection of the raw FMWT CPUE data from 1967-2011 for delta smelt, longfin smelt, Sacramento splittail, starry flounder, threadfin shad, and Crangon spp. (shrimp) revealed that in many years the proportion of tows where at least one target specimen was captured was quite low (denoted positive tows, Figure 2). For all species examined, there has been a general decline in the proportion of positive tows, particularly since the late 1990s and to values often below 0.10. Given approximately 100 tows per monthly cruise, this suggests that target species are encountered only 10% of the time. If not dealt with properly, the presence of many zero catches in the data set can invalidate the underlying assumptions of GLMs and thus jeopardize statistical inference. Although a variety of accepted statistical

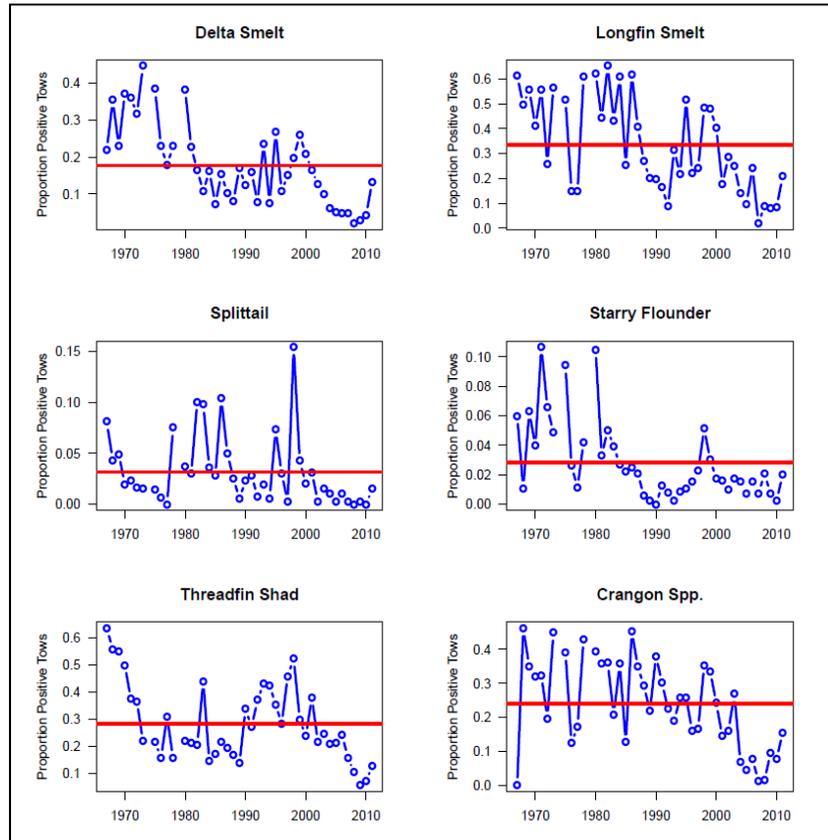


Figure 2. Annual proportion of FMWT survey tows conducted in September-December where at least one target specimen (Delta Smelt, Longfin Smelt, Splittail, Starry Flounder, Threadfin Shad, and Crangon Spp) was encountered (blue line) and mean value (red line) from 1967-2011. No sampling occurred in 1974, September 1976, December 1976, and 1979.

techniques can be used to deal with zero catches, I decided to formulate a delta-GLM where the probability of obtaining a zero catch and the catch rate based on tows that encountered at least one target specimen are modeled separately (Aitchison 1955, Lo et al, 1992, Stefansson 1996, Dick 2004). The general form of a delta-GLM model is:

$$\Pr(Y = y) = \begin{cases} p & y = 0 \\ (1 - p)f(y) & \text{otherwise} \end{cases} \quad \text{eq (4)}$$

where p is a generic parameter that represents the probability of obtaining a zero catch and $f(y)$ is probability distribution for tows where the target species was encountered. The

parameter p was modeled with the binomial distribution since this component of the model handles the presence/absence of the target species in the FMWT trawl tows. Visual examination of raw CPUE data from tows where the target species was encountered (i.e., actually caught) along with diagnostics plots of model fits assuming various probability distributions for $f(y)$ suggested that a lognormal distribution was reasonable for modeling mean CPUE from the positive catches (i.e., number of fish caught per tow).

1. Analysis of 'Daily' Covariates

Given a finalized specification for the delta-GLM, a two pronged approach was taken to investigating the role of covariates on the FMWT survey data. First, a total of four delta-lognormal GLM parameterizations involving various combinations of covariates associated with the daily FMWT sampling activities were fitted to the CPUE data. The purpose of this analysis was to identify the 'best' fitting model containing covariates synoptic with sampling. From this model, the statistical significance of those covariates was documented and an index of abundance was derived for each species considered.

The covariates considered in the analysis are defined as follows: *Year*, which was a categorical variable denoting the year of sampling, *Month*, which was a categorical variable denoting the month of sampling, *Region*, which was defined to be area of the Delta following the Area designations of the FMWT stratification scheme, and *Secchi Depth*, which is the depth at which a symmetrical black and white pattern on a small disk attached to a line is no longer visible. *Secchi Depth* is a measure of transparency of the water and is related to water turbidity.

From those covariates, a total of four model parameterizations were fitted to the data for each species: model D₁ contained covariates *Year* and *Month*; model D₂ contained *Year*, *Month*, and *Region*; model D₃ contained *Year*, *Month*, and *Secchi Depth*, which was standardized to have a mean of zero and a standard deviation of one; and model D₄ contained *Year*, *Month*, *Region* and *Secchi Depth* (D labels denote 'daily' analysis).

The variables *Temperature* and *Salinity* are absent from all models considered. Various plots of raw data revealed a somewhat expected appreciable degree of inverse correlation among *Salinity* and *Region* (i.e., *Salinity* goes down as one moves up the estuary) and among *Temperature* and *Month* (i.e., as autumn progresses toward winter, e.g., *Month* goes from 9 to 12, *Temperature* of surface waters goes down). Correlation among covariates amounts to collinearity and this phenomenon should be avoided when fitting GLMs as it can cause numerical instability and biased parameter estimates (Fox 2008). Hence, a single covariate was chosen from each pair (*Salinity* vs *Region* and *Temperature* vs *Month*) and it was decided to include *Region* and *Month* since these variables are by definition more general than *Salinity* and *Temperature*. Lastly, interaction terms were also not explicitly considered in the delta-GLMs largely because for several species (notably starry flounder), there are many combinations of *Month* and *Region* where all tows resulted in zero catches. Inclusion of covariates with many 'null' levels would compromise interpretation of results.

2. Analysis of ‘Annual’ Covariates

In the analysis described above, each model contained a *Year* factor, which is simply a proxy for the annual status of the Delta ecosystem (synthesis of environmental, climatological, physical, etc. effects and the resultant relative fish abundance as measured by the FMWT survey). Statistical significance of the *Year* factor implies that CPUE changes appreciably over an annual time scale for at least some of the years in the analysis, but it does not provide direct identification of the annual process(es) responsible for those changes. Therefore, a second step in the analysis was initiated where the *Year* factor within the ‘best’ fitting model was replaced with specific flow covariates tabulated on annual time scales. Those ‘annual’ flow covariates were *Historical* and *Unimpaired Outflow* and *Historical* and *Unimpaired Inflow*.³ All inflow covariates were defined to include flow from the Sacramento River plus Yolo Bypass. For each of these variables, a single ‘annual’ flow value was calculated by averaging monthly flow values four different ways: (i) from Jan-Jun within the year of sampling, (ii) from Mar-May within the year of sampling, (iii) from Jan-Jun of the preceding sampling year, and (iv) from Mar-May of the preceding sampling year (denoted as models A₁-A₁₆ to symbolize ‘annual’ analysis). Mechanically, for each of the 16 models, a single flow value was replicated for each tow within each year of the FMWT data set. To illustrate this point, suppose the monthly average *Historical Outflow* from January to June in 1967 is given by F_{1967} . Then the *Historical Outflow, Jan-Jun* covariate for 1967 would take on the F_{1967} value replicated according to the number tows made during that year. This concept was carried forward for all years in the time-series such that the 43 unique flow averages (1967-2010) of the 16 different flow variables were each replicated based on the year-specific number of tows made by the FMWT survey.

Lagged flow variables were considered because several of the target fish species do not reach sexual maturity until at least two years of age, so it is reasonable to hypothesize that there could be delayed effects of flow on the relative abundance of species sampled by the FMWT survey. All ‘annual’ flow values were based on calculations derived from water monitoring observations (Walter Bourez, MBK Engineers, personal communication). Lastly, the ‘annual’ flow values and the aforementioned daily *Secchi Depth* measurements were standardized to have a mean of zero and a standard deviation of one to improve the numerics underlying the model fitting process and to facilitate comparisons of the relative effects of these variables on the probability of capture (referred to as binomial model)⁴ and mean CPUE based on positive catches (referred to as lognormal model).

Postulation of multiple models implies that some type of model selection criterion was needed to objectively discriminate among competing parameterizations. Akaike’s Information Criterion (AIC; Akaike 1973, Burnham and Anderson 2002) was used to compare among the models in both the ‘daily and ‘annual’ analyses. AIC is a commonly used model selection statistic that is designed to achieve the most parsimonious

³The base flow data that I used were provided by Walter Bourez of MBK Engineers and are based on DAYFLOW and the Department of Water Resources publication *California Central Valley Unimpaired Flow Data*.

⁴ “Probability of capture” also is referenced as “presence/absence.”

description of the underlying data. Models with lots of parameters by definition are expected to provide better fits to data, however, the inclusion of many parameters leads to estimated coefficients (the β 's from eq (3)) with lower precision than simpler models, which affects the quality of inferences about the significance of the covariates being considered. So there is a natural tradeoff between model complexity and precision of estimated parameters, and AIC can help with identifying the appropriate balance. Formally, AIC is defined as:

$$\text{AIC} = -2 \log(\hat{L}) + 2k \quad \text{eq (5)}$$

where \hat{L} is the estimated maximum likelihood value and k is the number of estimated parameters. The first term of the AIC equation pertains to model fit and it will tend toward smaller values for better fitting models. The second term is an added adjustment that is a function of the number of model parameters and designed to balance the improved fit of models with many parameters. Therefore the most parsimonious description of the data is the model with the lowest total AIC value. The absolute magnitude of an AIC value is not overly useful given that is intended as a relative measure of model parsimony among the parameterizations considered in the analysis. Accordingly, it is helpful to examine ΔAIC for each fitted model, which is the difference between the AIC value for a particular model and the smallest AIC value of all models considered:

$$\Delta\text{AIC} = \text{AIC} - \text{AIC}_{\min}. \quad \text{eq (6)}$$

Naturally, it follows then that the 'best' fitting model within a candidate set is the one with $\Delta\text{AIC} = 0$, however, it should be noted that models with $0 < \Delta\text{AIC} < 2$ can also be viewed as having received notable empirical support (Burnham and Anderson 2002).

This report's derivation of indices of abundance from 1967-2010 alternative to those provided by DFG was based on the 'best' fitting model from the four considered in the 'daily' analysis. The unbiased estimated index of abundance in year y (I_y) was calculated as:

$$\hat{I}_y = \hat{p}_y \hat{\mu}_y \quad \text{eq (7)}$$

where $\hat{p}_y = \frac{\exp(\hat{\beta}_0 + \hat{\beta}_y + \sum_{i=1}^q \hat{\beta}_i x_{i,y})}{1 + \exp(\hat{\beta}_0 + \hat{\beta}_y + \sum_{i=1}^q \hat{\beta}_i x_{i,y})}$ is the probability of a non-zero catch (modeled via logistic regression) and the mean CPUE based on positive catches is $\hat{\mu}_y = \exp\left(\hat{\gamma}_0 + \hat{\gamma}_y + \sum_{i=1}^q \hat{\gamma}_i x_{i,y} + \frac{1}{2} \hat{\sigma}^2\right)$, such that $\hat{\beta}_0$ and $\hat{\gamma}_0$ are the estimated intercepts, $\hat{\beta}_y$ and $\hat{\gamma}_y$ are the estimated coefficients for year y , $\hat{\beta}_i$ and $\hat{\gamma}_i$ the estimated coefficients for $x_{i,y}$ which is the i^{th} covariate in year y (total of q covariates beyond the intercepts and year factors), and $\hat{\sigma}^2$ is the estimate of the dispersion parameter and necessary for bias-correction of the back transformed lognormal component of the delta-GLM.

In general terms, the indices of relative abundance in this report were calculated by multiplying an estimate of the probability that the FMWT survey encounters a given

species by an estimate of the average CPUE from tows when that species is actually captured by FMWT. This approach is one of a few standard options for deriving indices of relative abundance from survey information when there are a large number of zero catches in the data set (again, see Figure 2 and associated discussion).

When extracting the annual predicted index values from any GLM, it is necessary to account for the multiple levels (in the case of categorical covariates) and values (with continuous variables) during year y by specifying single values for $x_{i,y}$ (so called marginal means, Searle et al. 1980). In the case of continuous variables, the contribution to the annual predicted indices was given by the product of the estimated coefficients and the mean values of the observations of $x_{i,y}$. For categorical variables, the contribution was taken to be the mean value of the estimated coefficients for all levels. Lastly, to stabilize the jackknife routine (see next paragraph) used to derive standard errors, a data filter was imposed where levels of the categorical variables were removed if there was less than two trawls tows where the target species/group was captured.

Standard errors of the annual indices ($\hat{\sigma}_y$) were derived from a jackknife routine (Efron 1981), which is a nonparametric procedure that consists of fitting the delta-lognormal GLM to repeated subsamples of the original data set by omitting a single observation at a time. If the original underlying data set consists of n observations, then each subsample is comprised of $n-1$ observations, and fitting the delta-lognormal model to each subsample leads to n estimated indices for each year in the time-series. The jackknife estimate of the standard error for each annual index is then calculated from the n estimated indices obtained from the model fits to the data subsamples. The formal expression for the estimated standard error of each index value is as follows:

$$\hat{\sigma}_y = \left[\frac{n-1}{n} \sum_{i=1}^n (\hat{I}_i - \hat{I}_y)^2 \right]^{1/2} \quad \text{eq (8)}$$

where \hat{I}_i are the estimated indices from the subsamples, \hat{I}_y is the index value for year y derived from fitting the delta-lognormal GLM to the full data set, and n is the total number of observations. The coefficients of variation (CV) is the ratio of the standard error to the mean:

$$\widehat{CV}_y = \frac{\hat{\sigma}_y}{\hat{I}_y} \quad \text{eq (9)}$$

which is the inverse of the signal to noise ratio and helpful in demonstrating the extent of variability in relation to the estimated CPUE index value for each year.

IV. Results

Over the course of Sept-Dec during the years 1967-2010, a total of 14,658 tows were conducted by the FMWT survey. The data from these tows generally formed the basis for examining the significance of covariates and for developing indices of abundance for

selected species alternative to the abundance indices provided by DFG. However, as noted above, a data filter was applied to ensure that there were at least two trawl tows with positive catches within each level of each covariate for each year in the analysis. This additional but necessary restriction implied that the actual number of tows underlying derivation of the indices was less than 14,658 tows for some species (data losses most often resulted from removal of specific areas within the *Region* covariate, but some years were also removed; maximum number of tows ignored was 4,861 for Sacramento splittail followed by 2,988 for starry flounder). Also, uncharacteristically high *Secchi Depth* values were noted for 607 tows (measurements considerably larger than for the other ~14,000), so those were also eliminated to mitigate against the effects of outliers on the modeling results.

A. 'Daily' Analysis

Of the four delta-lognormal GLM parameterizations fitted to the FMWT survey CPUE data for analysis of 'Daily' covariates, AIC-based model selection for both the binomial and lognormal models suggested that models containing *Year*, *Month*, *Region*, and *Secchi* provided the acceptable explanations of the observed data. Supporting this conclusion is the fact that $\Delta\text{AIC}=0.0$ for model D_4 , for all species except starry flounder (Appendix A, Tables A1A-A6A; for starry flounder, $\Delta\text{AIC} = 0.0$ for model D_2 and $\Delta\text{AIC} = 0.21$ for model D_4). However, a $\Delta\text{AIC}=0.21$ is virtually indistinguishable from $\Delta\text{AIC} = 0.0$, so model D_4 was applied for all species to maintain modeling consistency.

These results suggest that, beyond the expected *Year* effect, some degree of appreciable variation in FMWT survey CPUE data was also explained by *Month* of sampling, *Region* of sampling, and *Secchi Depth*. However, simply because a suite of covariates is found to improve model fit, the overall amount of additional variation explained by inclusion of those covariates relative to the model with no covariates must be examined. For the binomial model, the percent of the total variation in the data explained by the covariates ranged from 18-37%, while for the lognormal model, the range was 19-44%. The maximum percentages both were for the longfin smelt CPUE analysis and the minimum percentages for the binomial and lognormal models were for starry flounder and delta smelt, respectively. For all species, the 'best' fitting model explained less than half of the total variation in the observed data, which strongly suggests that there are other key covariates that play a role in structuring the FMWT survey CPUE information.

After identifying which model provided the 'best' fit for each species, the next step involved examining the estimated coefficients (relative magnitude and sign, i.e., positive/negative), associated standard errors, and *p*-values which underpin the statistical significance of each covariate level (in the case of categorical variables) and covariate itself (in the case of continuous variables). The intercept of each model, denoted by β_0 , sets the reference point for interpretation of the categorical covariates.

For all models except those fitted to the Crangon spp. data, the binomial and lognormal intercepts were set to be September, 1967, in Region 1. For Crangon spp., no data were

collected in 1967 so the reference year was set to 1968. Given these reference points, the coefficients of all other levels of *Month* should be viewed directional deviations from September, the coefficients of all other levels of *Year* should be viewed directional deviations from 1967 (or 1968 for Crangon spp.), and the coefficients of all other levels of *Region* should be viewed directional deviations from Region 1.

The *p*-values provide information regarding the statistical significance of each of those directional deviations when tested against zero. The cutoff *p*-value for inferring significance is usually taken to be $\alpha = 0.05$, so any *Month*, *Year*, and *Region* level coefficient with a *p*-value less than α implies that there is either a significant increase (positive value) or decrease (negative value) from the reference point associated with the binomial or lognormal models. Conversely, *p*-values greater than α suggest that coefficients associated with levels of *Month*, *Year*, and *Region* are not statistically different from zero, and thus are not statistically different from the reference point. For a continuous covariate, such as *Secchi Depth*, interpretation of the modeling results is a bit simpler. By definition there are no levels associated with a continuous variable, and as such, a single coefficient is estimated and the related *p*-value provides guidance for statistical significance of that coefficient when tested against zero. If the estimated coefficient is negative, with a *p*-value less α , then the effect of *Secchi Depth* on either the binomial and lognormal models will be higher for lower *Secchi* measurements and lower for higher *Secchi* measurements. This follows because *Secchi Depth* was standardized to have a mean of zero such that low *Secchi* observations were negative, which when multiplied by the negative estimated coefficient leads to a positive effect.

Similarly, high *Secchi Depth* observations were positive, which when multiplied by the negative estimated coefficient leads to a negative effect.

Admittedly, there are a lot of estimated coefficients for each species, so it is a bit cumbersome to interpret the estimation results and, perhaps more importantly, to draw general conclusions regarding the effects of the modeled covariates from the binomial and lognormal models. Some general guidance is provided below.

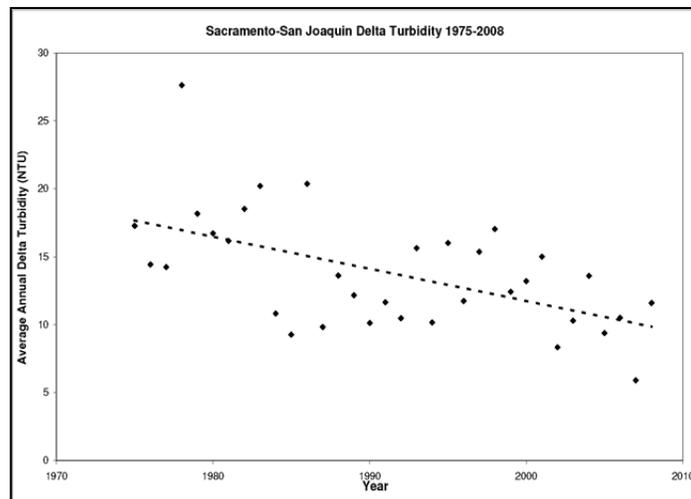


Figure 3. Mean annual turbidity, declining throughout the Sacramento-San Joaquin Delta from 1975–2008. From monthly data provided by California Department of Water Resources, Environmental Monitoring Program, and published by Cloern et al. (2011).

The statistical significance of many of the *Year* levels is not surprising as it reasonable to conclude based on known changes to the Delta ecosystem that the presence/absence and relative abundance of species has changed notably during 1967-2010. The estimated *Year* effects allow for detection of regimes of significantly higher or lower than reference year

presence/absence (Appendix A, Tables A1B-A6B) and relative abundance (Appendix A, Tables A1C-A6C). Accordingly, the *Year* levels drive the patterns associated with model predicted indices of relative abundance over the time-series. The levels of *Year* are simply proxies for the annual state of the Delta ecosystem, so identifying a specific variable or set of variables responsible for the predicted annual trends in species relative abundance beyond a 'generic' *Year* effect requires additional investigation (see a first attempt in the 'annual' analysis section below).

Statistical significance or lack thereof for the levels of *Month* provides some insight into the degree of seasonal patterns in presence/absence and relative abundance, but as with the *Year* covariate, levels of *Month* are also proxies for time-periods, albeit more refined than annual. Significance of *Month* effects do not provide direct evidence of any causative seasonal mechanism or variable, although a plausible hypothesis might be within year movements where species undergo localized migrations in response to the seasonal physical and environmental dynamics present within the Delta.

The levels of the *Region* covariate are proxies for location within the Delta, and arguably habitat type, so it is not overly surprising that many of these estimated coefficients were significant given that most fishes have preferred habitat types and specific home ranges. But again, the levels of *Region* are proxies for other more causative mechanisms responsible for structuring the distribution of species. A deeper investigation of the importance of *Region* might involve incorporating specifically defined habitats such as submerged aquatic vegetation (SAV), sandy, or muddy bottom assuming such habitat characterizations have been made for the locations sampled by the FMWT survey.

The statistical significance of *Secchi Depth* for all binomial models and all but one lognormal model (starry flounder) brings to the forefront the idea that water turbidity influences the presence/absence and relative abundance of species within the Delta. By definition, *Secchi Depth* is a coarse measurement of turbidity, so future investigations should evaluate the impacts of more robust metrics of turbidity on FMWT survey CPUE. All estimated coefficients of the *Secchi Depth* covariate were negative regardless of model type or species, and because this variable was standardized, low *Secchi Depth* values correspond to increases in presence/absence and relative abundance, and high *Secchi Depth* values imply corresponding decreases in those metrics. Since the general patterns of relative abundance for various species derived from the FMWT survey data show declines over the time-series (DFG's published indices and those presented below), consistency of this *Secchi Depth* interpretation with the evolving understanding of how the Delta has changed over recent decades could only be maintained if turbidity in the Delta has decreased over time. Such a finding has recently been published in the primary literature (Figure 3). Hypothesized mechanisms for increased presence/absence and relative abundance with higher Delta turbidity include: (i) decreased gear avoidance due to compromised sensory based detection of the FMWT net by species (a sampling based explanation which amounts to a temporal change in catchability), (ii) populations thrive under turbid conditions perhaps because more planktonic prey are present (true higher species relative abundances from a bottom-up perspective), and (iii) decreased predation mortality possibly because higher turbidity reduces the success of predators (true higher species

relative abundances from a top-down perspective). Clearly, each of these hypotheses warrants further investigation.

B. Derivation of Alternative Indices

The final step in the ‘Daily’ Analysis was to derive indices of abundance for species alternative to those published by DFG and with associated estimates of precision from the ‘best’ fitting model. In general, the patterns of the indices from this analysis do not differ qualitatively from those offered by DFG (Figures 4A,B). Prior to the mid-1980s, the indices show mostly variable patterns in relative abundance for the target species, and near the late 1990s, the indices generally decline up to 2010. In terms of precision, the estimated CVs for all species were generally acceptable, with most values ranging between 0.2-0.45. There are exceptions though with higher values corresponding to periods within the time-series for Sacramento splittail, starry flounder, and Crangon spp.

As mentioned previously, the units of DFG’s indices are water volume times average fish counts summed over all areas sampled. This calculation method is not overly intuitive, which renders it difficult to interpret the actual catch rate values and the scale of changes in relative abundance. For example, the DFG index of relative abundance for longfin smelt went from 11864 volume*fish in 1983 to 7408 volume*fish in 1984. Clearly, the relative abundance went down over the two-year period, but what does a reduction of 4456 volume*fish units

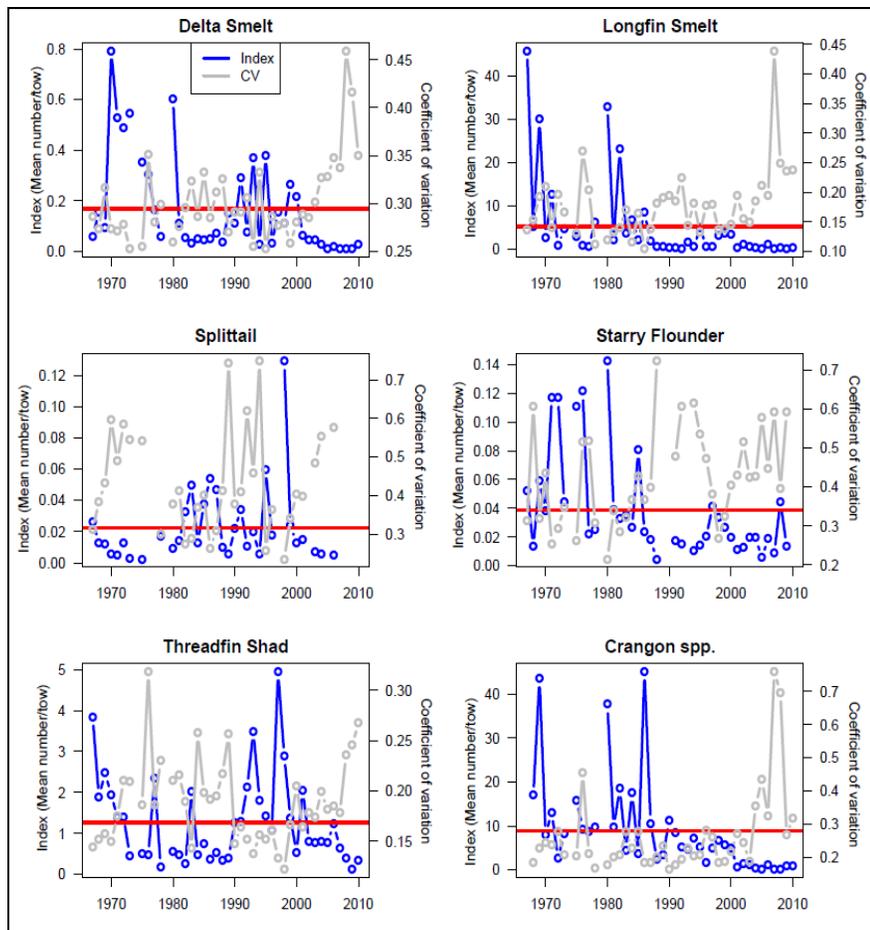


Figure 4A. Estimated indices of relative abundance (mean number/tow, blue line) and associated coefficients of variation (CV, gray line) for delta smelt, longfin smelt, Sacramento splittail, starry flounder, threadfin shad, and crangon spp. based on a delta-lognormal GLM applied the FMWT survey data from 1967-2010. The red lines are the average index value across the time-series. No sampling occurred in 1974, September 1976, December 1976, and 1979. Other years with missing index values are due to insufficient catches to warrant estimation of a relative abundance measure.

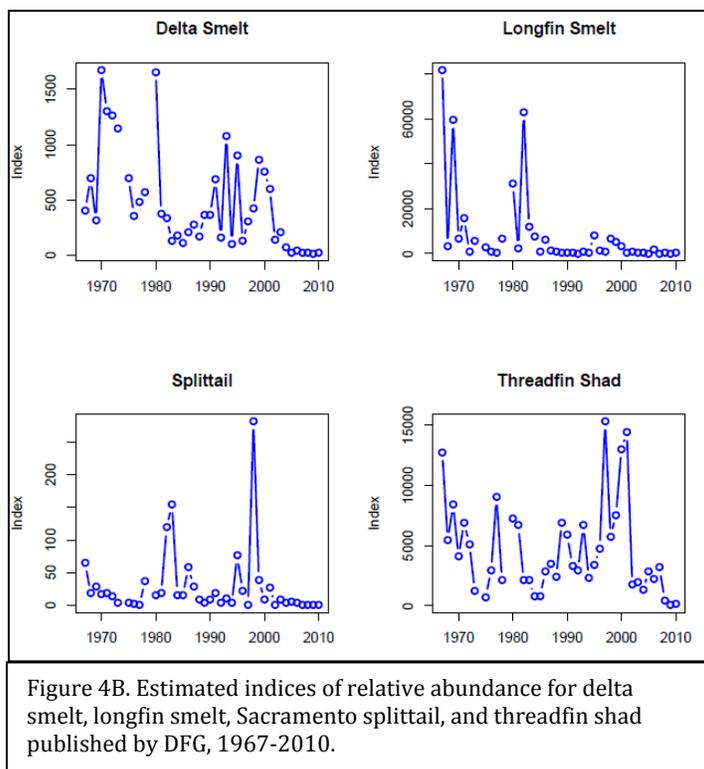
really mean for the population status of longfin smelt? It is hard to say because the numerical values do not relate to any relative or total population level parameter. In contrast to the methods used by DFG, the estimation approach taken in this study was designed to yield indices as unbiased estimates of average-catch-per-tow. From 1983-1984, the longfin smelt indices went from an average of 3.54 fish-per-tow to an average of 6.76 fish-per-tow. Not only do the methods used in this study provide a different pattern of relative abundance for longfin smelt over the two-year period (increasing instead of decreasing), the magnitude of the change is interpretable. The FMWT survey captured, on average, approximately twice as many longfin smelt per-tow in 1984 as it did in 1983.

From this study, the highest index for delta smelt from 1967-2010 was 0.79 fish-per-tow (1970), and the full time-series mean relative abundance was 0.17 fish-per-tow (Figure 4A). For Sacramento splittail and starry flounder, the highest relative abundance values were

0.13 and 0.14 fish-per-tow and the time-series averages were 0.02 and 0.04 fish-per-tow, respectively. Collectively, never achieving an annual mean catch-per-tow greater than say 1.0 fish-per-tow implies that not many animals are routinely captured by the FMWT survey, which raises legitimate questions about the efficacy of the program in providing measures of relative abundance that track patterns in true abundance.

For comparison, the Virginia Institute of Marine Science (VIMS) Juvenile Finfish Trawl Survey is a fisheries-independent sampling program that has operated in Chesapeake Bay continuously since the 1950s. As indicated by its name, the survey is designed to provide indices of abundance for juvenile fishes. Although there are differences between the VIMS and FMWT surveys (e.g., differences in overall net size, mesh sizes, deployment procedures, etc.) the indices for two sciaenid species (spot and weakfish), the VIMS program is believed to provide reliable measures of juvenile abundance are included here (Figure 5). Note that the long term average catch-per-tow for spot and weakfish is slightly less than 20 and 10 fish, respectively. These catches-per-tow are orders of magnitudes higher than the FMWT's catches-per-tow for delta smelt, Sacramento splittail and starry flounder.

For longfin smelt, threadfin shad, and Crangon spp., the highest FMWT index values were 45.7, 4.9, and 45.1 individuals-per-tow and the long-term averages were 5.1, 1.3, and 8.8,



respectively. In general, the scale of these indices are more reasonable and suggestive that the FMWT more routinely encounters these species and that catches are occasionally high. The 'spiked' nature of the longfin smelt indices in the early 1960s and 1980s does give pause, but inspection of the raw data for those years showed frequent catches of several hundred fish-per-tow in specific years. This suggests that the high index values for those years were not functions of a small number of very large catches resulting from unusually high localized relative abundance at a few stations, which would otherwise be cause for concern.

By definition, trawl surveys are multispecies sampling platforms, and as such, some species will be sampled well while others will not be sampled well. These differences in sampling effectiveness are because the life history and habitat utilization of some species are more closely aligned with the gear configuration and deployment methods than for other species. A somewhat obvious example of mismatch for the FMWT survey is starry flounder. Should the use of a midwater trawl (even with an oblique tow such that there is some attempt for bottom contact) be expected to reliably sample a largely bottom dwelling species? Probably not, and the consistently low mean CPUE of this species provided by the FMWT likely confirms this idea. In the case of a more pelagic oriented species such as delta smelt, there may be more conceptual consistency between survey design and target species life history. Yet, mean CPUE has still remained quite low over the time-series, which warrants asking more refined questions. As noted previously, a key limitation of the FMWT survey is the use of a fixed station sampling design such that roughly the same locations are sampled each month. It follows then that if delta smelt (or any other species for that matter) have exhibited any type of directed habitat shift over time, which could be expected given the physical and environmental changes experienced

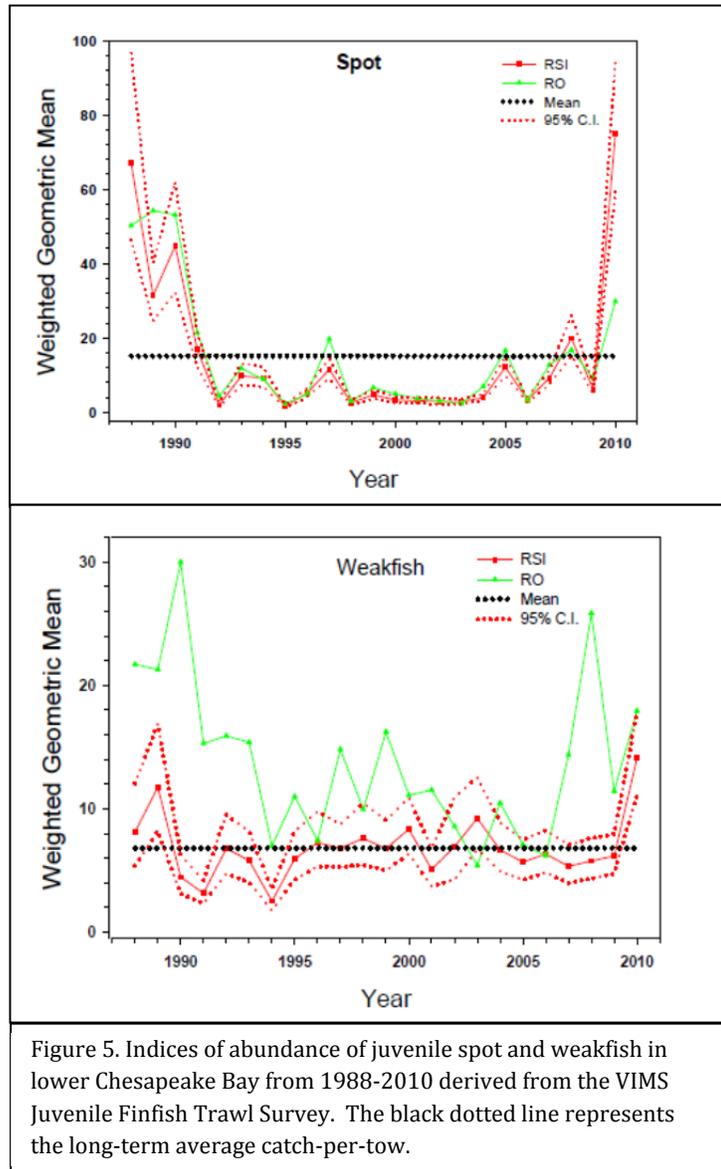


Figure 5. Indices of abundance of juvenile spot and weakfish in lower Chesapeake Bay from 1988-2010 derived from the VIMS Juvenile Finfish Trawl Survey. The black dotted line represents the long-term average catch-per-tow.

by the Delta over recent decades, then temporal patterns in the FMWT indices of relative abundance would be confounded with changes in species distribution. Independent corroboration of species relative abundance patterns are needed, perhaps through index validation studies involving other data sources.

C. 'Annual' Analysis

From the 16 delta-lognormal GLM parameterizations fitted to the FMWT survey CPUE data where the *Year* covariate in model D₄ from the 'daily' analysis was replaced by an 'annual' flow metric, AIC-based model selection showed that the particular flow covariate that had the most empirical support varied by model type and species. For delta smelt, longfin smelt, and Sacramento splittail, the binomial (presence/absence) model with *Unimpaired*

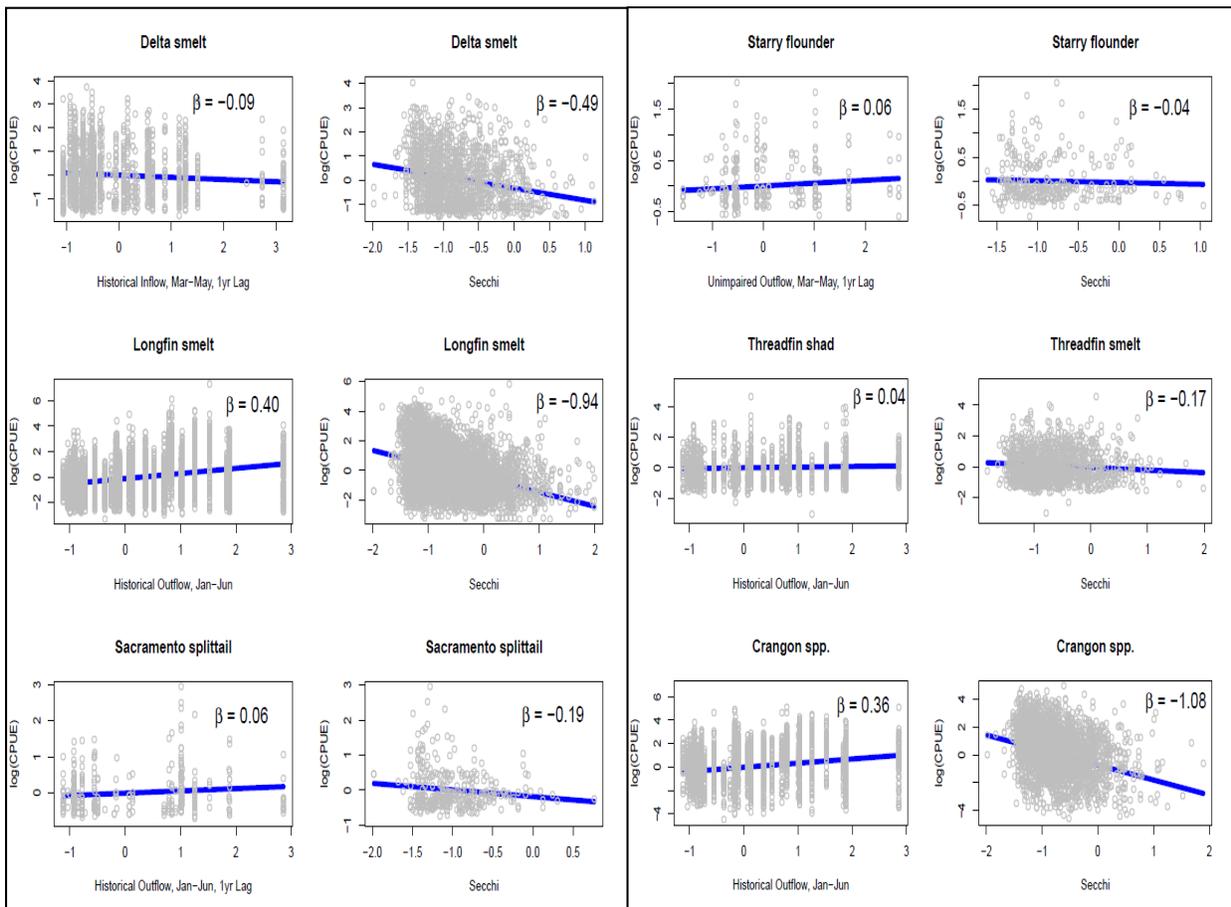


Figure 6. Partial residuals plots showing fits of the estimated coefficients (blue lines) associated with the 'best' flow variable and *Secchi Depth* for delta smelt, longfin smelt, Sacramento splittail, starry flounder, threadfin shad, and Crangon spp. from the lognormal models fitted to the FMWT survey CPUE data (positive tows), 1967-2010. In the upper right portion of each plot is the estimated coefficient for each covariate (the β values), which represent the magnitude and direction of the statistical relationship. An inclining line indicates a positive relationship between the covariate and the species' relative abundance, with a more steeply inclined line representing a more positive relationship. A declining line indicates a negative relationship between the covariate and the species' relative abundance, with a more steeply declining line representing a more negative relationship.

Inflow, Jan-Jun received the most empirical support ($\Delta\text{AIC} = 0.0$), while various forms of the *Historical Outflow* covariate corresponded to the 'best' fitting lognormal (average catch-per-tow) model (Appendix B, Tables B1A-B3A). Table B1A shows *Historical Inflow, March-May, 1yr Lag* is the 'best' fitting lognormal model (model A₁₄ has $\Delta\text{AIC} = 0.0$) for delta smelt. *Historical Outflow, Jan-Jan* was important for the respective binomial models of starry flounder and threadfin shad along with the respective lognormal models of threadfin shad and Crangon spp. (Appendix B, Table B4A-B6A). Although $\Delta\text{AIC} = 0.0$ does signify the 'best' fitting model, situations when ΔAIC values differ by only a few units suggest that the empirical evidence supports multiple models. This is particularly the case for the lognormal models of Sacramento splittail, starry flounder, and threadfin shad, which collectively indicate there is not necessarily a dominate flow covariate influencing the CPUE when those species are captured by the FMWT.

Regardless of model type or species, coefficients of the flow covariates from the 'best' fitting models were mostly positive and all statistically significant (Appendix B, Tables B1B-B6B). An exception is delta smelt, for which the coefficient of the 'best' fitting flow covariate, was statistically significant and negative. Positive coefficients combined with the standardized flow covariates implies that low flow values correspond to reductions in the presence/absence and mean relative abundance of species, while high flow values yield increases in those metrics. The opposite effect occurs in the case of a negative estimated coefficient. For example, because the coefficient of the 'best' fitting flow covariate for delta smelt was negative, delta smelt relative abundance decreased as that flow covariate increased. Since the flow and *Secchi Depth* variables were all standardized, it is appropriate to compare the estimated coefficients as a means of inferring the relative impact of those variables on CPUE.

A helpful way to visualize the variability in the underlying data and the relationship of the covariates on observed CPUE (the estimated coefficients derived from the GLMs) is by constructing partial residuals plots. Such plots depict fits of specific covariates to the data while accounting for the presence of all other covariates in the model. For the present analysis, examination of partial residuals plots for the flow variables and *Secchi Depth* from the lognormal model (positive tows) yielded several interesting results (Figure 6).

1. *Significant Variation and Uncertainty in Relationship of Abundance to Flow.* As demonstrated in the results depicted in Figure 6, there is significant variation in the underlying CPUE data in relation to flow and among the relationship between the relative abundance of relevant species and the 'best' fitting flow covariate.⁵ Figure 6's graphs for delta smelt and longfin smelt depict this variation with widely-ranging catches occurring at vastly different levels of the best-fitting flow covariate (*Historical Inflow, March-May, with 1yr Lag* for delta smelt and *Historical Outflow, Jan-Jun* for longfin smelt). Note that the y-axes of the plots in Figure 6 are $\log(\text{CPUE})$ because of fitting a lognormal GLM, so the

⁵ As discussed above (see page 23), the 'best' fitting model is the one with a ΔAIC value of 0.0. Please see Appendix B, Tables B1(A), B2(A), B3(A), B4(A), B5(A), B6(A) and B7(A) for the analysis of which variables fit each species' CPUE data best.

variance in the actual data concerning the relationship of CPUE to flow covariates is considerably greater than shown in plots.

2. *Significant Variation in Which Flow Covariates Provided the Best Fit to the FMWT Survey Data.* The "(A)" tables in Appendix B indicate that there is a wide range in which flow covariate provided the 'best' fit to the binomial (presence/absence) and lognormal (mean CPUE from positive tows) models for the species considered in this study. The following Table 1 summarizes which flow covariates were associated with the 'best' fitting binomial and lognormal models.

Table 1. Summary of which flow covariates provided the 'best' fit of the binomial and lognormal models fitted to the FMWT survey data, 1967-2010.

<u>Species</u>	<u>Presence/Absence</u> (Binomial $\Delta AIC=0$)	<u>Abundance</u> (Lognormal $\Delta AIC=0$)
Delta smelt	Unimpaired inflow, Jan-Jun	Historical Inflow, Mar- May, 1yr Lag
Longfin smelt	Unimpaired inflow, Jan-Jun	Historical Outflow, Jan-Jun
Sacramento splittail	Unimpaired inflow, Jan-Jun	Historical Outflow, Jan-Jun, 1yr Lag
Starry flounder	Historical outflow, Jan-Jun	Unimpaired Outflow, Mar-May
Threadfin shad	Historical Outflow, Jan-Jun	Historical Outflow, Jan-Jun
Crangon spp.	Unimpaired Outflow, Mar-May	Historical Outflow, Jan-Jun

The lack of a single dominate flow covariate underscores the uncertainty in identifying which flow covariate might be adjusted to produce statistically-probable increases in relative abundance. In particular, the fact that *Unimpaired Outflow* is the 'best' fitting covariate for presence/absence for several species, but is the 'best' fitting covariate for mean CPUE based on positive tows for only starry flounder (which itself is not the 'best' fitting covariate for presence/absence for starry flounder) indicates that it is particularly uncertain whether managed flow covariates would generate statistically-probable increases in species relative abundance.

3. *Species' Variable Relationships to Best-Fit Flow Covariates.* The lines and estimated coefficients for each covariate (the β values)⁶ in the graphs in columns 1 and 3 of Figure 6 depict the strength of the statistical relationship between the 'best' fitting flow covariate and CPUE for each species, based on the the positive

⁶ The higher the β value is for a covariate, the more that covariate explains changes in the relevant species' abundance, with a positive β value indicating a positive relationship and a negative relationship indicating a negative relationship.

tows in the FMWT survey data. Instances where the slope of the line is positive indicate that the relationship is positive, with a more steeply sloped line representing a stronger effect of the flow covariate on CPUE. In cases where the slope of the line is negative, the relationship is inverse.

As the lines and β estimates in Figure 6 indicate, different species have different relationships with even the best-fit flow covariates. For example, delta smelt have a small, but significantly inverse relationship ($\beta = -0.09$) with *Historical Inflow, Mar-May, 1yr Lag*. This implies that CPUE actually decreases slightly as that flow covariate increases. The CPUE of longfin smelt and Sacramento splittail slight positiverelationships with their respective best-fit flow variables (longfin: *Historical Outflow, Jan-Jun*, $\beta = 0.40$; Sacramento splittail: *Historical Outflow, Jan-June, 1yr Lag*, $\beta = 0.06$). Similarly interpreted positive increases in CPUE with flow are also evident with the other species examined.

In particular, the disparity between the variable and relatively small statistical effects of flow covariates on species relative abundance and very significant variations in the FMWT survey's results over the 1967-2010 period demonstrates that it is highly uncertain whether changes in manageable flow parameters would generate any statistically-predictable increases in the relative abundances of those species. This disparity underscores the very likely idea that covariates other than flow play a key role in structuring species' relative abundance in the Delta.

4. *More Significant Relationships of Species Relative Abundance to Other Environmental Factors.* Comparisons of other environmental covariates to the CPUE generated by the FWMT also indicates that such other factors may have a more significant effect on the relative abundance of species than any flow parameter. As depicted in Figure 6, this point is supported most strongly by the statistical relationships between CPUE and *Secchi Depth*, which is a coarse indicator of turbidity in the Delta. Figure 6's lines and β estimates in columns 2 and 4 indicate that *Secchi Depth* has a stronger statistical effect on CPUE than any of the flow covariates, with the exception of *Unimpaired Flow* for starry flounder. For all species, there is an inverse relationship between *Secchi Depth* and CPUE, indicating that higher turbidity (lower *Secchi Depth* values because the Secchi disk cannot be seen as far below the surface) corresponds to higher predicted CPUE, and vice-versa for lower turbidity (higher *Secchi Depth* values associated with seeing the disk at deeper depths). Table 2 summarizes a comparison of the estimated effects on CPUE modeled with the lognormal GLM for the 'best' fitting flow covariate and *Secchi Depth*, and in each case except for starry flounder, the β coefficient of *Secchi Depth* is larger in magnitude than the β coefficient of flow.

Table 2. Summary of estimated coefficients from the flow covariate that provided the 'best' fit within the lognormal GLM model and *Secchi Depth*.

<u>Species</u>	<u>Estimated coefficient of 'best' fitting flow covariate</u>	<u>Estimated coefficient of <i>Secchi Depth</i></u>
delta smelt	-0.09	-0.49
longfin smelt	0.40	-0.94
Sacramento splittail	0.06	-0.19
starry flounder	0.06	-0.04
threadfin shad	0.04	-0.17
Crangon spp.	0.36	-1.08

These results are consistent with two points made in the literature. First, there are numerous environmental factors affecting species in the Delta and adjusting controllable flow parameters would be unlikely to provide notable benefits for the species examined in this study. Second, and more specifically, these results are consistent with the suggestion in the literature that recent reductions in the Delta's turbidity have been a significant factor in the decline of the Delta's fish species. As indicated in Cloern et al. (2011) and depicted in Figure 3 above, average annual Delta turbidity declined approximately 40% during the 1975-2008 period when many of the Delta's fish species are believed to have declined. Schoellhamer (2011) has further suggested that a step-decrease in Delta turbidity in the late 1990s, possibly as a result of the depletion of the Delta's erodible sediment pool, may have contributed to the noted decline in relative abundance during the early 2000s.

Each of these conclusions must be understood in the context of the FMWT's limitations since all are based on statistical analyses that rely on the FWMT survey CPUE data. Most importantly, the fixed-station design of the FWMT cannot document changes in the distribution and habitat utilization of species within the Delta that very likely have occurred during 1967-2010. Accordingly, consideration of management decisions that could be based on FWMT data should be done so with a cognizant understanding of biases associated with limitations of the FMWT program.

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Appendix A. Tables showing the ‘daily’ analysis model fit statistics (A), parameter estimates, standard errors, and *p*-values for the binomial model (B), and parameter estimates, standard errors, and *p*-values for the lognormal model (C) fitted to FMWT survey CPUE data for delta smelt, longfin smelt, Sacramento splittail, starry flounder, threadfin shad, and Crangon spp.

Table A1. Delta smelt
(A)

Model	Covariates	Binomial AIC	Binomial Δ AIC	Lognormal AIC	Lognormal Δ AIC
D ₁	<i>Year, Month</i>	11138.0	2436.4	7076.9	237.0
D ₂	<i>Year, Month, Region</i>	9149.2	447.6	6918.6	78.7
D ₃	<i>Year, Month, Secchi</i>	10183.8	1482.3	6965.0	125.0
D ₄	<i>Year, Month, Region, Secchi</i>	8701.6	0.0	6840.0	0.0

Model D₄: Binomial null deviance = 12170.5 with 29% explained, lognormal null deviance = 2815.9 with 19% explained.

(B) Delta smelt: Binomial component

Parameter	Estimate	SE	<i>p</i> -value	Parameter	Estimate	SE	<i>p</i> -value
β_0	-5.25	0.39	<0.0001	β_{1998}	0.55	0.22	0.01
β_{1968}	0.78	0.21	0.000238	β_{1999}	1.27	0.21	<0.0001
β_{1969}	0.34	0.24	0.16	β_{2000}	0.87	0.22	<0.0001
β_{1970}	1.91	0.24	<0.0001	β_{2001}	0.16	0.22	0.48
β_{1971}	1.83	0.23	<0.0001	β_{2002}	0.15	0.23	0.52
β_{1972}	1.51	0.24	<0.0001	β_{2003}	-0.18	0.24	0.45
β_{1973}	1.75	0.22	<0.0001	β_{2004}	-0.52	0.28	0.06
β_{1974}	n/a	n/a	n/a	β_{2005}	-0.86	0.29	0.003
β_{1975}	1.57	0.22	<0.0001	β_{2006}	-0.58	0.30	0.05
β_{1976}	1.50	0.28	<0.0001	β_{2007}	-0.85	0.29	0.004
β_{1977}	0.80	0.23	0.001	β_{2008}	-1.41	0.40	0.0005
β_{1978}	0.23	0.22	0.28	β_{2009}	-1.19	0.36	0.001
β_{1979}	n/a	n/a	n/a	β_{2010}	-0.34	0.31	0.27
β_{1980}	1.72	0.22	<0.0001	β_{Oct}	0.12	0.08	0.11
β_{1981}	0.62	0.22	0.004	β_{Nov}	0.08	0.08	0.33
β_{1982}	0.00	0.22	1.00	β_{Dec}	0.21	0.08	0.01
β_{1983}	-0.33	0.25	0.18	β_{Region3}	n/a	n/a	n/a
β_{1984}	0.14	0.23	0.55	β_{Region4}	-0.56	0.57	0.33
β_{1985}	-0.32	0.27	0.24	β_{Region5}	-0.38	0.61	0.54
β_{1986}	-0.05	0.22	0.82	β_{Region7}	n/a	n/a	n/a
β_{1987}	-0.04	0.24	0.86	β_{Region8}	n/a	n/a	n/a
β_{1988}	-0.62	0.26	0.02	β_{Region10}	0.33	0.58	0.57
β_{1989}	0.72	0.22	0.001	β_{Region11}	0.88	0.38	0.02
β_{1990}	0.42	0.24	0.07	β_{Region12}	1.61	0.35	<0.0001

β_{1991}	0.95	0.23	<0.0001		β_{Region13}	3.24	0.35	<0.0001
β_{1992}	0.07	0.26	0.78		β_{Region14}	3.05	0.35	<0.0001
β_{1993}	1.50	0.22	<0.0001		β_{Region15}	3.97	0.35	<0.0001
β_{1994}	-0.27	0.27	0.31		β_{Region16}	3.00	0.35	<0.0001
β_{1995}	1.54	0.21	<0.0001		β_{Region17}	1.23	0.38	0.001
β_{1996}	-0.19	0.24	0.43		β_{Secchi}	-1.28	0.06	<0.0001
β_{1997}	0.85	0.23	0.0002					

(C) Delta smelt: Lognormal component

Parameter	Estimate	SE	p-value	Parameter	Estimate	SE	p-value
β_0	-0.51	0.36	0.16	β_{1998}	0.07	0.17	0.66
β_{1968}	0.18	0.16	0.27	β_{1999}	0.30	0.16	0.06
β_{1969}	0.06	0.19	0.74	β_{2000}	0.49	0.17	0.004
β_{1970}	0.77	0.16	<0.0001	β_{2001}	-0.08	0.18	0.66
β_{1971}	0.46	0.16	0.004	β_{2002}	-0.38	0.19	0.04
β_{1972}	0.67	0.17	<0.0001	β_{2003}	-0.07	0.20	0.74
β_{1973}	0.54	0.15	0.0005	β_{2004}	-0.19	0.24	0.43
β_{1974}	n/a	n/a	n/a	β_{2005}	-0.72	0.25	0.005
β_{1975}	0.29	0.16	0.06	β_{2006}	-0.48	0.26	0.06
β_{1976}	0.17	0.21	0.42	β_{2007}	-0.68	0.26	0.01
β_{1977}	0.26	0.18	0.14	β_{2008}	-0.30	0.37	0.42
β_{1978}	-0.23	0.17	0.17	β_{2009}	-0.43	0.32	0.19
β_{1979}	n/a	n/a	n/a	β_{2010}	-0.42	0.27	0.12
β_{1980}	0.69	0.15	<0.0001	β_{Oct}	0.00	0.06	0.99
β_{1981}	0.001	0.17	0.99	β_{Nov}	-0.09	0.06	0.15
β_{1982}	-0.06	0.18	0.73	β_{Dec}	-0.13	0.06	0.02
β_{1983}	-0.23	0.21	0.26	β_{Region3}	n/a	n/a	n/a
β_{1984}	-0.32	0.18	0.08	β_{Region4}	0.68	0.55	0.22
β_{1985}	0.06	0.23	0.80	β_{Region5}	0.27	0.59	0.64
β_{1986}	-0.14	0.18	0.45	β_{Region7}	n/a	n/a	n/a
β_{1987}	0.28	0.20	0.17	β_{Region8}	n/a	n/a	n/a
β_{1988}	0.15	0.22	0.50	β_{Region10}	0.91	0.55	0.10
β_{1989}	0.26	0.18	0.14	β_{Region11}	0.47	0.36	0.19
β_{1990}	0.27	0.19	0.17	β_{Region12}	0.78	0.34	0.02
β_{1991}	0.73	0.18	<0.0001	β_{Region13}	1.18	0.33	0.0004
β_{1992}	0.24	0.22	0.27	β_{Region14}	1.14	0.33	0.001
β_{1993}	0.44	0.17	0.01	β_{Region15}	1.44	0.33	<0.0001
β_{1994}	-0.40	0.23	0.08	β_{Region16}	0.86	0.34	0.01
β_{1995}	0.43	0.16	0.01	β_{Region17}	0.46	0.36	0.20
β_{1996}	-0.42	0.20	0.03	β_{Secchi}	-0.48	0.05	<0.0001
β_{1997}	0.20	0.18	0.27				

Table A2. Longfin smelt
(A)

Model	Covariates	Binomial AIC	Binomial Δ AIC	Lognormal AIC	Lognormal Δ AIC
D ₁	<i>Year, Month</i>	14963.0	3521.7	16417.3	715.5
D ₂	<i>Year, Month, Region</i>	12113.0	671.7	15944.3	242.5
D ₃	<i>Year, Month, Secchi</i>	12969.3	1528.0	16104.4	402.6
D ₄	<i>Year, Month, Region, Secchi</i>	11441.3	0.0	15701.8	0.0

Model D₄: Binomial null deviance = 17971.0 with 37% explained, lognormal null deviance = 13277.7 with 44% explained.

(B) Longfin smelt: Binomial component

Parameter	Estimate	SE	<i>p</i> -value	Parameter	Estimate	SE	<i>p</i> -value
β_0	0.11	0.21	0.60	β_{1998}	-1.02	0.22	<0.0001
β_{1968}	-0.84	0.23	0.0003	β_{1999}	-0.55	0.21	0.01
β_{1969}	-0.12	0.25	0.62	β_{2000}	-1.05	0.22	<0.0001
β_{1970}	-1.29	0.25	<0.0001	β_{2001}	-2.88	0.23	<0.0001
β_{1971}	-0.42	0.23	0.07	β_{2002}	-1.62	0.22	<0.0001
β_{1972}	-1.95	0.25	<0.0001	β_{2003}	-2.15	0.22	<0.0001
β_{1973}	-0.91	0.23	<0.0001	β_{2004}	-2.59	0.24	<0.0001
β_{1974}	n/a	n/a	n/a	β_{2005}	-3.37	0.25	<0.0001
β_{1975}	-0.97	0.23	<0.0001	β_{2006}	-1.87	0.22	<0.0001
β_{1976}	-1.88	0.31	<0.0001	β_{2007}	-5.15	0.41	<0.0001
β_{1977}	-2.24	0.24	<0.0001	β_{2008}	-2.93	0.26	<0.0001
β_{1978}	-0.51	0.22	0.02	β_{2009}	-3.28	0.27	<0.0001
β_{1979}	n/a	n/a	n/a	β_{2010}	-3.13	0.26	<0.0001
β_{1980}	0.06	0.23	0.80	β_{Oct}	0.30	0.07	<0.0001
β_{1981}	-1.06	0.22	<0.0001	β_{Nov}	1.09	0.07	<0.0001
β_{1982}	-0.08	0.22	0.710423	β_{Dec}	1.93	0.07	<0.0001
β_{1983}	-1.26	0.22	<0.0001	β_{Region3}	-0.88	0.15	<0.0001
β_{1984}	-0.12	0.23	0.60	β_{Region4}	-0.80	0.17	<0.0001
β_{1985}	-1.31	0.23	<0.0001	β_{Region5}	-0.78	0.19	<0.0001
β_{1986}	-0.18	0.22	0.39	β_{Region7}	-1.24	0.21	<0.0001
β_{1987}	-1.11	0.21	<0.0001	β_{Region8}	-0.39	0.15	0.01
β_{1988}	-2.18	0.22	<0.0001	β_{Region10}	-0.76	0.24	0.002
β_{1989}	-2.33	0.23	<0.0001	β_{Region11}	0.14	0.13	0.31
β_{1990}	-2.32	0.23	<0.0001	β_{Region12}	0.68	0.13	<0.0001
β_{1991}	-2.39	0.23	<0.0001	β_{Region13}	0.17	0.12	0.16
β_{1992}	-3.10	0.26	<0.0001	β_{Region14}	-0.38	0.13	0.005
β_{1993}	-1.20	0.22	<0.0001	β_{Region15}	-0.50	0.13	<0.0001
β_{1994}	-2.21	0.23	<0.0001	β_{Region16}	-1.98	0.14	<0.0001
β_{1995}	-0.34	0.22	0.12	β_{Region17}	-4.19	0.26	<0.0001

β_{1996}	-2.46	0.23	<0.0001		β_{Secchi}	-1.16	0.05	<0.0001
β_{1997}	-1.86	0.22	<0.0001					

(C) Longfin smelt: Lognormal component

Parameter	Estimate	SE	p-value	Parameter	Estimate	SE	p-value
β_0	3.42	0.14	<0.0001	β_{1998}	-2.08	0.13	<0.0001
β_{1968}	-1.73	0.14	<0.0001	β_{1999}	-2.26	0.13	<0.0001
β_{1969}	-0.39	0.15	0.01	β_{2000}	-2.03	0.14	<0.0001
β_{1970}	-2.21	0.16	<0.0001	β_{2001}	-3.55	0.18	<0.0001
β_{1971}	-1.07	0.14	<0.0001	β_{2002}	-2.78	0.15	<0.0001
β_{1972}	-2.80	0.19	<0.0001	β_{2003}	-3.09	0.16	<0.0001
β_{1973}	-1.82	0.14	<0.0001	β_{2004}	-3.18	0.20	<0.0001
β_{1974}	n/a	n/a	n/a	β_{2005}	-3.54	0.22	<0.0001
β_{1975}	-2.23	0.14	<0.0001	β_{2006}	-2.60	0.16	<0.0001
β_{1976}	-2.89	0.28	<0.0001	β_{2007}	-3.69	0.46	<0.0001
β_{1977}	-2.64	0.20	<0.0001	β_{2008}	-3.18	0.24	<0.0001
β_{1978}	-1.76	0.13	<0.0001	β_{2009}	-3.51	0.24	<0.0001
β_{1979}	n/a	n/a	n/a	β_{2010}	-3.12	0.24	<0.0001
β_{1980}	-0.34	0.13	0.01	β_{Oct}	0.30	0.06	<0.0001
β_{1981}	-2.50	0.14	<0.0001	β_{Nov}	0.349	0.06	<0.0001
β_{1982}	-0.65	0.13	<0.0001	β_{Dec}	0.28	0.06	<0.0001
β_{1983}	-1.80	0.14	<0.0001	β_{Region3}	-0.09	0.13	0.51
β_{1984}	-1.83	0.13	<0.0001	β_{Region4}	-0.50	0.14	0.0005
β_{1985}	-2.24	0.17	<0.0001	β_{Region5}	-0.73	0.17	<0.0001
β_{1986}	-1.59	0.13	<0.0001	β_{Region7}	-0.46	0.20	0.02
β_{1987}	-2.51	0.14	<0.0001	β_{Region8}	0.32	0.13	0.01
β_{1988}	-2.89	0.16	<0.0001	β_{Region10}	-0.54	0.20	0.01
β_{1989}	-2.94	0.18	<0.0001	β_{Region11}	-0.11	0.11	0.30
β_{1990}	-3.23	0.18	<0.0001	β_{Region12}	0.35	0.10	0.00
β_{1991}	-3.34	0.19	<0.0001	β_{Region13}	0.05	0.10	0.59
β_{1992}	-3.41	0.24	<0.0001	β_{Region14}	-0.30	0.11	0.01
β_{1993}	-2.67	0.15	<0.0001	β_{Region15}	-0.36	0.11	0.001
β_{1994}	-2.99	0.18	<0.0001	β_{Region16}	-1.31	0.12	<0.0001
β_{1995}	-2.04	0.13	<0.0001	β_{Region17}	-1.90	0.30	<0.0001
β_{1996}	-2.78	0.17	<0.0001	β_{Secchi}	-0.64	0.04	<0.0001
β_{1997}	-2.97	0.16	<0.0001				

Table A3. Sacramento splittail
(A)

Model	Covariates	Binomial AIC	Binomial Δ AIC	Lognormal AIC	Lognormal Δ AIC
D ₁	<i>Year, Month</i>	3396.7	624.0	861.9	21.4
D ₂	<i>Year, Month, Region</i>	2960.0	187.3	843.1	2.7
D ₃	<i>Year, Month, Secchi</i>	2914.8	142.1	851.6	11.1
D ₄	<i>Year, Month, Region, Secchi</i>	2772.7	0.0	840.4	0.0

Model D₄: Binomial null deviance = 3944.0 with 30% explained, lognormal null deviance = 173.5 with 21% explained.

(B) Sacramento splittail: Binomial component

Parameter	Estimate	SE	<i>p</i> -value	Parameter	Estimate	SE	<i>p</i> -value
β_0	-5.79	0.67	<0.0001	β_{1998}	1.45	0.29	<0.0001
β_{1968}	-0.54	0.39	0.17	β_{1999}	-0.13	0.37	0.72
β_{1969}	-0.43	0.41	0.30	β_{2000}	-0.38	0.44	0.39
β_{1970}	-1.32	0.53	0.01	β_{2001}	-0.42	0.39	0.28
β_{1971}	-1.07	0.49	0.03	β_{2002}	-2.71	1.04	0.01
β_{1972}	-0.91	0.57	0.11	β_{2003}	-1.02	0.49	0.04
β_{1973}	-1.78	0.56	0.002	β_{2004}	-0.97	0.58	0.09
β_{1974}	n/a	n/a	n/a	β_{2005}	-2.56	1.04	0.01
β_{1975}	-1.90	0.57	0.001	β_{2006}	-1.18	0.58	0.04
β_{1976}	-0.57	1.05	0.59	β_{2007}	-2.53	1.04	0.01
β_{1977}	n/a	n/a	n/a	β_{2008}	n/a	n/a	n/a
β_{1978}	-0.10	0.33	0.77	β_{2009}	-1.83	1.04	0.08
β_{1979}	n/a	n/a	n/a	β_{2010}	n/a	n/a	n/a
β_{1980}	-0.62	0.40	0.12	β_{Oct}	-0.31	0.14	0.03
β_{1981}	-0.50	0.41	0.23	β_{Nov}	-0.49	0.16	0.002
β_{1982}	0.50	0.31	0.10	β_{Dec}	-0.57	0.15	0.0001
β_{1983}	0.87	0.31	0.01	β_{Region3}	n/a	n/a	n/a
β_{1984}	-0.39	0.39	0.32	β_{Region4}	0.86	0.71	0.22
β_{1985}	0.45	0.43	0.29	β_{Region5}	0.77	0.75	0.31
β_{1986}	0.93	0.31	0.002	β_{Region7}	n/a	n/a	n/a
β_{1987}	0.63	0.36	0.08	β_{Region8}	n/a	n/a	n/a
β_{1988}	-0.53	0.43	0.22	β_{Region10}	2.42	0.70	0.001
β_{1989}	-1.76	0.76	0.02	β_{Region11}	1.47	0.63	0.02
β_{1990}	0.21	0.44	0.63	β_{Region12}	1.65	0.60	0.01
β_{1991}	0.43	0.43	0.32	β_{Region13}	1.66	0.60	0.01
β_{1992}	-0.63	0.65	0.34	β_{Region14}	2.91	0.60	<0.0001
β_{1993}	-0.14	0.47	0.76	β_{Region15}	1.53	0.61	0.01
β_{1994}	-1.44	0.76	0.06	β_{Region16}	1.33	0.63	0.04
β_{1995}	0.98	0.33	0.003	β_{Region17}	-0.18	0.83	0.83

β_{1996}	-0.18	0.39	0.65		β_{Secchi}	-2.02	0.16	<0.0001
β_{1997}	-2.09	1.04	0.04					

(C) Sacramento splittail: Lognormal component

Parameter	Estimate	SE	p-value		Parameter	Estimate	SE	p-value
β_0	0.18	0.38	0.63		β_{1998}	0.19	0.14	0.18
β_{1968}	-0.17	0.21	0.40		β_{1999}	0.04	0.19	0.84
β_{1969}	-0.36	0.21	0.09		β_{2000}	-0.34	0.24	0.16
β_{1970}	-0.19	0.31	0.55		β_{2001}	-0.15	0.21	0.49
β_{1971}	-0.59	0.27	0.03		β_{2002}	-0.30	0.61	0.62
β_{1972}	0.16	0.32	0.61		β_{2003}	-0.28	0.27	0.30
β_{1973}	-0.59	0.32	0.06		β_{2004}	-0.52	0.32	0.10
β_{1974}	n/a	n/a	n/a		β_{2005}	-0.99	0.63	0.12
β_{1975}	-0.56	0.31	0.08		β_{2006}	-0.45	0.32	0.16
β_{1976}	-0.63	0.60	0.29		β_{2007}	-0.71	0.59	0.23
β_{1977}	n/a	n/a	n/a		β_{2008}	n/a	n/a	n/a
β_{1978}	-0.34	0.17	0.04		β_{2009}	-0.46	0.60	0.44
β_{1979}	n/a	n/a	n/a		β_{2010}	n/a	n/a	n/a
β_{1980}	-0.43	0.21	0.04		β_{Oct}	-0.09	0.07	0.24
β_{1981}	-0.13	0.22	0.56		β_{Nov}	-0.01	0.09	0.87
β_{1982}	-0.27	0.16	0.08		β_{Dec}	-0.19	0.09	0.02
β_{1983}	-0.21	0.17	0.21		β_{Region3}	n/a	n/a	n/a
β_{1984}	-0.33	0.21	0.11		β_{Region4}	0.35	0.41	0.39
β_{1985}	-0.08	0.23	0.72		β_{Region5}	0.63	0.42	0.14
β_{1986}	-0.18	0.16	0.24		β_{Region7}	n/a	n/a	n/a
β_{1987}	-0.04	0.19	0.85		β_{Region8}	n/a	n/a	n/a
β_{1988}	-0.41	0.24	0.08		β_{Region10}	0.62	0.40	0.13
β_{1989}	0.24	0.43	0.58		β_{Region11}	0.29	0.36	0.43
β_{1990}	-0.40	0.24	0.09		β_{Region12}	0.12	0.35	0.72
β_{1991}	-0.15	0.23	0.51		β_{Region13}	0.07	0.35	0.85
β_{1992}	-0.30	0.38	0.42		β_{Region14}	0.37	0.35	0.29
β_{1993}	-0.16	0.26	0.54		β_{Region15}	0.04	0.36	0.91
β_{1994}	-0.17	0.44	0.70		β_{Region16}	0.05	0.37	0.90
β_{1995}	-0.14	0.17	0.41		β_{Region17}	0.05	0.49	0.92
β_{1996}	-0.21	0.21	0.33		β_{Secchi}	-0.18	0.09	0.04
β_{1997}	-0.28	0.60	0.64					

Table A4. Starry flounder
(A)

Model	Covariates	Binomial AIC	Binomial Δ AIC	Lognormal AIC	Lognormal Δ AIC
D ₁	<i>Year, Month</i>	3162.3	289.0	528.8	13.1
D ₂	<i>Year, Month, Region</i>	2964.0	92.0	514.1	0.0
D ₃	<i>Year, Month, Secchi</i>	3029.9	143.6	527.9	13.9
D ₄	<i>Year, Month, Region, Secchi</i>	2881.0	0.0	513.5	0.21

Model D₄: Binomial null deviance = 3395.7 with 18% explained, lognormal null deviance = 84.1 with 23% explained.

(B) Starry flounder: Binomial component

Parameter	Estimate	SE	<i>p</i> -value	Parameter	Estimate	SE	<i>p</i> -value
β_0	-3.62	0.47	<0.0001	β_{1998}	-0.32	0.35	0.37
β_{1968}	-1.47	0.64	0.02	β_{1999}	-0.62	0.40	0.12
β_{1969}	0.17	0.39	0.66	β_{2000}	-0.89	0.47	0.06
β_{1970}	-0.71	0.45	0.12	β_{2001}	-1.32	0.49	0.01
β_{1971}	0.57	0.34	0.09	β_{2002}	-1.37	0.57	0.02
β_{1972}	0.66	0.39	0.09	β_{2003}	-1.13	0.47	0.02
β_{1973}	-0.38	0.39	0.33	β_{2004}	-0.77	0.50	0.13
β_{1974}	n/a	n/a	n/a	β_{2005}	-1.83	0.64	0.004
β_{1975}	0.44	0.34	0.19	β_{2006}	-1.12	0.50	0.02
β_{1976}	0.17	0.66	0.80	β_{2007}	-1.65	0.64	0.01
β_{1977}	-0.62	0.58	0.29	β_{2008}	-0.15	0.46	0.75
β_{1978}	-0.67	0.38	0.08	β_{2009}	-1.28	0.65	0.05
β_{1979}	n/a	n/a	n/a	β_{2010}	-2.75	1.04	0.01
β_{1980}	0.71	0.33	0.03	β_{Oct}	0.01	0.15	0.96
β_{1981}	-0.39	0.41	0.34	β_{Nov}	-0.26	0.16	0.10
β_{1982}	-0.44	0.36	0.22	β_{Dec}	-0.47	0.16	0.003
β_{1983}	-0.53	0.39	0.17	β_{Region3}	1.06	0.43	0.01
β_{1984}	-0.81	0.43	0.06	β_{Region4}	1.38	0.42	0.001
β_{1985}	0.20	0.46	0.66	β_{Region5}	1.91	0.42	<0.0001
β_{1986}	-0.89	0.43	0.04	β_{Region7}	0.21	0.63	0.73
β_{1987}	-0.92	0.45	0.04	β_{Region8}	0.30	0.51	0.56
β_{1988}	-2.43	0.76	0.001	β_{Region10}	0.96	0.52	0.07
β_{1989}	-2.81	1.04	0.007	β_{Region11}	0.74	0.40	0.07
β_{1990}	n/a	n/a	n/a	β_{Region12}	0.80	0.38	0.04
β_{1991}	-0.98	0.53	0.07	β_{Region13}	0.27	0.38	0.48
β_{1992}	-1.38	0.65	0.03	β_{Region14}	0.07	0.41	0.87
β_{1993}	-2.61	1.04	0.01	β_{Region15}	-0.77	0.45	0.09
β_{1994}	-1.56	0.65	0.02	β_{Region16}	-2.22	0.68	0.001

β_{1995}	-1.60	0.57	0.01		β_{Region17}	n/a	n/a	n/a
β_{1996}	-1.24	0.49	0.01		β_{Secchi}	-1.15	0.13	<0.0001
β_{1997}	-0.46	0.44	0.29					

(C) Starry flounder: Lognormal component

Parameter	Estimate	SE	p-value		Parameter	Estimate	SE	p-value
β_0	-0.26	0.21	0.23		β_{1998}	-0.11	0.15	0.46
β_{1968}	0.08	0.28	0.77		β_{1999}	-0.02	0.17	0.89
β_{1969}	-0.01	0.17	0.96		β_{2000}	-0.05	0.21	0.81
β_{1970}	0.14	0.18	0.48		β_{2001}	-0.22	0.22	0.33
β_{1971}	0.30	0.14	0.04		β_{2002}	0.01	0.26	0.97
β_{1972}	0.19	0.16	0.25		β_{2003}	0.18	0.21	0.38
β_{1973}	0.23	0.17	0.18		β_{2004}	-0.14	0.22	0.52
β_{1974}	n/a	n/a	n/a		β_{2005}	-0.39	0.29	0.18
β_{1975}	0.36	0.14	0.01		β_{2006}	0.15	0.22	0.49
β_{1976}	0.57	0.28	0.05		β_{2007}	-0.08	0.29	0.79
β_{1977}	-0.10	0.25	0.70		β_{2008}	0.13	0.21	0.54
β_{1978}	-0.07	0.17	0.67		β_{2009}	0.05	0.29	0.85
β_{1979}	n/a	n/a	n/a		β_{2010}	0.11	0.47	0.82
β_{1980}	0.37	0.14	0.01		β_{Oct}	-0.04	0.07	0.53
β_{1981}	0.13	0.18	0.47		β_{Nov}	0.02	0.07	0.82
β_{1982}	-0.04	0.15	0.81		β_{Dec}	-0.01	0.07	0.87
β_{1983}	0.15	0.17	0.38		β_{Region3}	0.39	0.20	0.05
β_{1984}	0.16	0.19	0.42		β_{Region4}	0.61	0.20	0.003
β_{1985}	0.39	0.20	0.048		β_{Region5}	0.61	0.20	0.003
β_{1986}	0.09	0.19	0.62		β_{Region7}	0.24	0.29	0.40
β_{1987}	-0.12	0.20	0.55		β_{Region8}	0.26	0.24	0.28
β_{1988}	-0.02	0.34	0.96		β_{Region10}	0.45	0.24	0.07
β_{1989}	-0.01	0.46	0.98		β_{Region11}	0.26	0.19	0.17
β_{1990}	n/a	n/a	n/a		β_{Region12}	0.42	0.18	0.03
β_{1991}	-0.03	0.24	0.91		β_{Region13}	0.27	0.18	0.15
β_{1992}	0.24	0.28	0.39		β_{Region14}	0.13	0.20	0.49
β_{1993}	0.02	0.47	0.96		β_{Region15}	0.25	0.22	0.26
β_{1994}	0.001	0.31	1.00		β_{Region16}	0.72	0.32	0.03
β_{1995}	0.31	0.27	0.24		β_{Region17}	n/a	n/a	n/a
β_{1996}	0.32	0.22	0.15		β_{Secchi}	-0.07	0.06	0.22
β_{1997}	0.31	0.19	0.11					

Table A5. Threadfin shad
(A)

Model	Covariates	Binomial AIC	Binomial Δ AIC	Lognormal AIC	Lognormal Δ AIC
D ₁	<i>Year, Month</i>	15405.4	2736.5	14770.0	1241.6
D ₂	<i>Year, Month, Region</i>	13067.7	398.8	13548.0	19.7
D ₃	<i>Year, Month, Secchi</i>	15321.4	2652.4	14629.1	1100.7
D ₄	<i>Year, Month, Region, Secchi</i>	12669.0	0.0	13528.3	0.0

Model D₄: Binomial null deviance = 16877.0 with 26% explained, lognormal null deviance = 9796.9 with 34% explained.

(B) Threadfin shad: Binomial component

Parameter	Estimate	SE	<i>p</i> -value	Parameter	Estimate	SE	<i>p</i> -value
β_0	-1.73	0.20	<0.0001	β_{1998}	0.02	0.18	0.91
β_{1968}	-0.26	0.20	0.20	β_{1999}	-0.93	0.19	<0.0001
β_{1969}	-0.06	0.21	0.79	β_{2000}	-1.41	0.20	<0.0001
β_{1970}	0.02	0.21	0.94	β_{2001}	-0.72	0.19	0.0001
β_{1971}	-0.73	0.21	0.0004	β_{2002}	-1.25	0.20	<0.0001
β_{1972}	-0.63	0.22	0.004	β_{2003}	-1.23	0.19	<0.0001
β_{1973}	-1.52	0.22	<0.0001	β_{2004}	-1.26	0.21	<0.0001
β_{1974}	n/a	n/a	n/a	β_{2005}	-1.23	0.20	<0.0001
β_{1975}	-1.43	0.21	<0.0001	β_{2006}	-0.81	0.20	<0.0001
β_{1976}	-1.65	0.29	<0.0001	β_{2007}	-1.40	0.21	<0.0001
β_{1977}	-0.75	0.21	0.0003	β_{2008}	-1.72	0.23	<0.0001
β_{1978}	-2.30	0.22	<0.0001	β_{2009}	-2.55	0.28	<0.0001
β_{1979}	n/a	n/a	n/a	β_{2010}	-1.98	0.26	<0.0001
β_{1980}	-1.73	0.21	<0.0001	β_{Oct}	0.46	0.07	<0.0001
β_{1981}	-1.73	0.21	<0.0001	β_{Nov}	1.07	0.07	<0.0001
β_{1982}	-1.90	0.20	<0.0001	β_{Dec}	1.41	0.07	<0.0001
β_{1983}	-0.21	0.19	0.26	β_{Region3}	-0.52	0.20	0.01
β_{1984}	-1.92	0.22	<0.0001	β_{Region4}	-0.02	0.19	0.91
β_{1985}	-1.32	0.22	<0.0001	β_{Region5}	-0.17	0.22	0.46
β_{1986}	-1.71	0.20	<0.0001	β_{Region7}	0.06	0.23	0.79
β_{1987}	-1.69	0.21	<0.0001	β_{Region8}	-0.86	0.21	0.00
β_{1988}	-1.84	0.21	<0.0001	β_{Region10}	-0.19	0.28	0.49
β_{1989}	-2.06	0.22	<0.0001	β_{Region11}	-0.11	0.16	0.51
β_{1990}	-0.55	0.19	0.004	β_{Region12}	-0.43	0.15	0.005
β_{1991}	-0.76	0.19	<0.0001	β_{Region13}	0.12	0.14	0.39
β_{1992}	-0.25	0.19	0.19	β_{Region14}	0.94	0.15	<0.0001
β_{1993}	-0.06	0.19	0.77	β_{Region15}	1.70	0.14	<0.0001
β_{1994}	-0.33	0.19	0.09	β_{Region16}	2.17	0.14	<0.0001
β_{1995}	-0.57	0.19	0.002	β_{Region17}	2.99	0.15	<0.0001

β_{1996}	-1.03	0.19	<0.0001		β_{Secchi}	-0.83	0.04	<0.0001
β_{1997}	0.11	0.19	0.57					

(C) Threadfin shad: Lognormal component

Parameter	Estimate	SE	p-value		Parameter	Estimate	SE	p-value
β_0	1.44	0.19	<0.0001		β_{1998}	-0.32	0.13	0.02
β_{1968}	-0.53	0.14	0.0002		β_{1999}	-0.39	0.15	0.01
β_{1969}	-0.45	0.15	0.003		β_{2000}	-0.93	0.16	<0.0001
β_{1970}	-0.72	0.15	<0.0001		β_{2001}	-0.12	0.14	0.39
β_{1971}	-0.49	0.16	0.002		β_{2002}	-0.59	0.17	0.001
β_{1972}	-0.58	0.17	0.001		β_{2003}	-0.66	0.16	<0.0001
β_{1973}	-0.91	0.19	<0.0001		β_{2004}	-0.58	0.18	0.001
β_{1974}	n/a	n/a	n/a		β_{2005}	-0.65	0.17	0.0001
β_{1975}	-0.95	0.19	<0.0001		β_{2006}	-0.55	0.17	0.001
β_{1976}	-0.84	0.28	0.003		β_{2007}	-0.71	0.19	0.0002
β_{1977}	-0.05	0.16	0.75		β_{2008}	-0.90	0.23	<0.0001
β_{1978}	-1.11	0.20	<0.0001		β_{2009}	-1.33	0.30	<0.0001
β_{1979}	n/a	n/a	n/a		β_{2010}	-0.90	0.27	0.001
β_{1980}	-0.57	0.18	0.002		β_{Oct}	0.00	0.06	0.97
β_{1981}	-0.71	0.18	<0.0001		β_{Nov}	-0.04	0.06	0.50
β_{1982}	-1.13	0.18	<0.0001		β_{Dec}	-0.22	0.06	0.0005
β_{1983}	-0.51	0.14	0.0002		β_{Region3}	0.14	0.22	0.51
β_{1984}	-0.54	0.21	0.010		β_{Region4}	0.06	0.21	0.78
β_{1985}	-0.66	0.19	0.001		β_{Region5}	0.15	0.24	0.54
β_{1986}	-0.99	0.17	<0.0001		β_{Region7}	-0.14	0.25	0.57
β_{1987}	-0.67	0.18	0.0002		β_{Region8}	0.02	0.24	0.95
β_{1988}	-0.98	0.20	<0.0001		β_{Region10}	-0.38	0.30	0.21
β_{1989}	-0.62	0.20	0.002		β_{Region11}	-0.18	0.18	0.31
β_{1990}	-0.80	0.15	<0.0001		β_{Region12}	-0.37	0.17	0.03
β_{1991}	-0.51	0.16	0.002		β_{Region13}	-0.17	0.15	0.27
β_{1992}	-0.49	0.15	0.001		β_{Region14}	0.29	0.16	0.07
β_{1993}	-0.13	0.14	0.375		β_{Region15}	0.39	0.15	0.01
β_{1994}	-0.58	0.15	<0.0001		β_{Region16}	0.69	0.15	<0.0001
β_{1995}	-0.64	0.15	<0.0001		β_{Region17}	2.24	0.15	<0.0001
β_{1996}	-0.49	0.16	0.002		β_{Secchi}	-0.18	0.04	<0.0001
β_{1997}	0.12	0.14	0.38					

Table A6. Crangon spp.

(A)

Model	Covariates	Binomial AIC	Binomial Δ AIC	Lognormal AIC	Lognormal Δ AIC
D ₁	<i>Year, Month</i>	13403.6	3325.5	13021.6	340.7
D ₂	<i>Year, Month, Region</i>	11302.6	1224.5	12821.0	140.1
D ₃	<i>Year, Month, Secchi</i>	11368.1	1290.0	12952.7	271.7
D ₄	<i>Year, Month, Region, Secchi</i>	10078.1	0.0	12681.0	0.0

Model D₄: Binomial null deviance = 14730.9 with 32% explained, lognormal null deviance = 12128.9 with 37% explained.

(B) Crangon spp.: Binomial component

Parameter	Estimate	SE	<i>p</i> -value	Parameter	Estimate	SE	<i>p</i> -value
β_0	0.02	0.20	0.91	β_{1998}	-0.85	0.21	<0.0001
β_{1969}	-0.50	0.25	0.045	β_{1999}	-0.52	0.21	0.014
β_{1970}	-0.85	0.26	0.001	β_{2000}	-0.86	0.21	<0.0001
β_{1971}	-0.96	0.23	<0.0001	β_{2001}	-2.10	0.23	<0.0001
β_{1972}	-1.22	0.35	<0.0001	β_{2002}	-1.38	0.22	<0.0001
β_{1973}	-0.71	0.22	0.001	β_{2003}	-0.85	0.21	<0.0001
β_{1974}	n/a	n/a	n/a	β_{2004}	-2.28	0.27	<0.0001
β_{1975}	-0.73	0.22	0.001	β_{2005}	-3.10	0.30	<0.0001
β_{1976}	-0.70	0.32	0.027	β_{2006}	-2.40	0.26	<0.0001
β_{1977}	-0.42	0.23	0.069	β_{2007}	-4.48	0.49	<0.0001
β_{1978}	-0.74	0.21	0.001	β_{2008}	-3.59	0.46	<0.0001
β_{1979}	n/a	n/a	n/a	β_{2009}	-1.40	0.25	<0.0001
β_{1980}	-0.31	0.22	0.16	β_{2010}	-1.94	0.26	<0.0001
β_{1981}	-0.49	0.21	0.022	β_{Oct}	-0.12	0.07	0.10
β_{1982}	-1.11	0.21	<0.0001	β_{Nov}	-0.02	0.07	0.75
β_{1983}	-1.82	0.22	<0.0001	β_{Dec}	-0.35	0.07	<0.0001
β_{1984}	-0.62	0.22	0.004	β_{Region3}	-1.34	0.18	<0.0001
β_{1985}	-0.88	0.25	0.0003	β_{Region4}	-1.73	0.19	<0.0001
β_{1986}	0.05	0.21	0.82	β_{Region5}	-2.02	0.23	<0.0001
β_{1987}	-0.17	0.21	0.41	β_{Region7}	-2.84	0.34	<0.0001
β_{1988}	-1.00	0.21	<0.0001	β_{Region8}	-0.71	0.17	<0.0001
β_{1989}	-0.89	0.22	<0.0001	β_{Region10}	-1.25	0.25	<0.0001
β_{1990}	0.43	0.21	0.04	β_{Region11}	0.33	0.13	0.012
β_{1991}	0.096	0.21	0.65	β_{Region12}	0.54	0.13	<0.0001
β_{1992}	-0.21	0.22	0.33	β_{Region13}	-0.34	0.12	0.005
β_{1993}	-0.75	0.22	0.001	β_{Region14}	-1.11	0.14	<0.0001
β_{1994}	-0.41	0.22	0.056	β_{Region15}	-1.34	0.13	<0.0001
β_{1995}	-0.78	0.22	0.0003	β_{Region16}	-2.45	0.16	<0.0001
β_{1996}	-1.81	0.22	<0.0001	β_{Region17}	n/a	n/a	n/a

β_{1997}	-0.96	0.22	<0.0001	β_{Secchi}	-1.86	0.05	<0.0001
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(C) Crangon spp.: Lognormal component

Parameter	Estimate	SE	p-value	Parameter	Estimate	SE	p-value
β_0	3.49	0.19	<0.0001	β_{1998}	-0.24	0.19	0.20
β_{1969}	1.33	0.22	<0.0001	β_{1999}	-0.70	0.19	0.0002
β_{1970}	-0.07	0.22	0.75	β_{2000}	-0.54	0.20	0.01
β_{1971}	0.52	0.21	0.01	β_{2001}	-1.42	0.24	<0.0001
β_{1972}	-0.88	0.26	0.00	β_{2002}	-1.29	0.23	<0.0001
β_{1973}	-0.17	0.19	0.38	β_{2003}	-1.96	0.20	<0.0001
β_{1974}	n/a	n/a	n/a	β_{2004}	-2.12	0.33	<0.0001
β_{1975}	0.52	0.20	0.01	β_{2005}	-2.32	0.38	<0.0001
β_{1976}	-0.05	0.37	0.90	β_{2006}	-0.67	0.31	0.028
β_{1977}	-0.35	0.24	0.14	β_{2007}	-2.62	0.69	0.0001
β_{1978}	0.04	0.18	0.82	β_{2008}	-2.00	0.63	0.001
β_{1979}	n/a	n/a	n/a	β_{2009}	-1.83	0.28	<0.0001
β_{1980}	1.03	0.19	<0.0001	β_{2010}	-1.18	0.31	0.0001
β_{1981}	-0.19	0.19	0.32	β_{Oct}	-0.14	0.07	0.046
β_{1982}	1.00	0.19	<0.0001	β_{Nov}	-0.57	0.08	<0.0001
β_{1983}	0.22	0.22	0.32	β_{Dec}	-0.93	0.07	<0.0001
β_{1984}	0.51	0.19	0.01	β_{Region3}	-0.08	0.22	0.72
β_{1985}	-0.84	0.26	0.001	β_{Region4}	-0.84	0.23	0.0003
β_{1986}	0.94	0.18	<0.0001	β_{Region5}	-1.54	0.29	<0.0001
β_{1987}	-0.35	0.19	0.06	β_{Region7}	-1.04	0.47	0.03
β_{1988}	-1.14	0.20	<0.0001	β_{Region8}	0.39	0.21	0.06
β_{1989}	-0.92	0.22	<0.0001	β_{Region10}	-0.92	0.30	0.00
β_{1990}	-0.71	0.19	0.0001	β_{Region11}	-0.07	0.14	0.60
β_{1991}	-0.76	0.20	0.0001	β_{Region12}	0.02	0.13	0.86
β_{1992}	-1.02	0.22	<0.0001	β_{Region13}	-0.38	0.13	0.003
β_{1993}	-0.71	0.23	0.002	β_{Region14}	-1.02	0.15	<0.0001
β_{1994}	-0.53	0.21	0.01	β_{Region15}	-0.22	0.15	0.16
β_{1995}	-0.60	0.20	0.003	β_{Region16}	-2.14	0.20	<0.0001
β_{1996}	-0.78	0.23	0.001	β_{Region17}	n/a	n/a	n/a
β_{1997}	-0.47	0.23	0.045	β_{Secchi}	-0.80	0.07	<0.0001

Appendix B. Tables showing ‘annual’ analysis model fit statistics (A), parameter estimates, standard errors, and *p*-values for the ‘best’ fitting binomial and lognormal models (B) fitted to FMWT survey CPUE data for delta smelt, longfin smelt, Sacramento splittail, starry flounder, threadfin shad, and Crangon spp.

Table B1. Delta smelt
(A)

Model	Flow variable	Binomial AIC	Binomial ΔAIC	Lognormal AIC	Lognormal ΔAIC
A ₁	Historical Outflow, Jan- Jun	9500.7	12.0	7048.6	17.3
A ₂	Historical Outflow, Mar-May	9505.4	16.7	7044.8	13.5
A ₃	Unimpaired Outflow, Jan-Jun	9497.0	8.3	7048.6	17.3
A ₄	Unimpaired Outflow, Mar-May	9505.9	17.2	7045.8	14.5
A ₅	Historical Inflow, Jan- Jun	9495.0	6.3	7048.1	16.8
A ₆	Historical Inflow, Mar- May	9505.8	17.1	7047.1	15.7
A ₇	Unimpaired Inflow, Jan-Jun	9488.7	0.0	7048.2	16.9
A ₈	Unimpaired Inflow, Mar-May	9503.6	14.9	7047.4	16.1
A ₉	Historical Outflow, Jan-Jun, 1yr Lag	9504.6	16.0	7044.5	13.2
A ₁₀	Historical Outflow, Mar-May, 1yr Lag	9500.5	11.8	7034.0	2.7
A ₁₁	Unimpaired Outflow, Jan-Jun, 1yr Lag	9505.4	16.8	7045.9	14.6
A ₁₂	Unimpaired Outflow, Mar-May	9501.7	13.0	7041.2	9.8
A ₁₃	Historical Inflow, Jan- Jun, 1yr Lag	9505.6	16.9	7042.6	11.2
A ₁₄	Historical Inflow, Mar- May, 1yr Lag	9498.6	9.9	7031.3	0.0
A ₁₅	Unimpaired Inflow, Jan-Jun, 1yr Lag	9504.7	16.0	7045.9	14.6
A ₁₆	Unimpaired Inflow, Mar-May, 1yr Lag	9501.5	12.8	7040.0	8.6

(B) Delta smelt

Binomial Component				Lognormal Component			
Parameter	Estimate	SE	p-value	Parameter	Estimate	SE	p-value
β_0	-4.71	0.34	<0.0001	β_0	-0.38	0.34	0.27
$\beta_{\text{Unimp.Inflow.Jan-Jun}}$	0.11	0.03	<0.0001	$\beta_{\text{Hist.Inflow.MM.1yrLag}}$	-0.09	0.02	<0.0001
β_{Oct}	0.16	0.07	0.02	β_{Oct}	0.007	0.06	0.90
β_{Nov}	0.20	0.07	0.007	β_{Nov}	-0.05	0.06	0.40
β_{Dec}	0.22	0.07	0.002	β_{Dec}	-0.13	0.06	0.03
β_{Region3}	n/a	n/a	n/a	β_{Region3}	n/a	n/a	n/a
β_{Region4}	-0.56	0.57	0.32	β_{Region4}	0.73	0.57	0.20
β_{Region5}	-0.46	0.61	0.45	β_{Region5}	0.29	0.62	0.64
β_{Region7}	n/a	n/a	n/a	β_{Region7}	n/a	n/a	n/a
β_{Region8}	n/a	n/a	n/a	β_{Region8}	n/a	n/a	n/a
β_{Region10}	0.36	0.57	0.53	β_{Region10}	0.89	0.57	0.12
β_{Region11}	0.89	0.37	0.02	β_{Region11}	0.64	0.38	0.09
β_{Region12}	1.51	0.35	<0.0001	β_{Region12}	0.86	0.35	0.015
β_{Region13}	3.02	0.34	<0.0001	β_{Region13}	1.22	0.34	0.0004
β_{Region14}	2.77	0.35	<0.0001	β_{Region14}	1.14	0.35	0.001
β_{Region15}	3.67	0.34	<0.0001	β_{Region15}	1.45	0.36	<0.0001
β_{Region16}	2.99	0.35	<0.0001	β_{Region16}	1.01	0.35	0.004
β_{Region17}	1.41	0.37	0.0001	β_{Region17}	0.76	0.37	0.042
β_{Secchi}	-1.42	0.05	<0.0001	β_{Secchi}	-0.49	0.05	<0.0001

Model A₇: Binomial null deviance = 12170.5 with 22% explained. Model A₁₄: lognormal null deviance = 2816.0 with 10% explained.

Table B2. Longfin smelt

(A)

Model	Flow variable	Binomial AIC	Binomial ΔAIC	Lognormal AIC	Lognormal ΔAIC
A ₁	Historical Outflow, Jan- Jun	12826.3	20.3	17091.1	0.0
A ₂	Historical Outflow, Mar-May	12936.1	130.1	17193.3	102.2
A ₃	Unimpaired Outflow, Jan-Jun	12808.4	2.3	17099.7	8.6
A ₄	Unimpaired Outflow, Mar-May	12968.8	162.7	17208.3	117.3
A ₅	Historical Inflow, Jan- Jun	12838.6	32.6	17154.0	63.0
A ₆	Historical Inflow, Mar- May	12950.7	144.7	17253.0	162.0
A ₇	Unimpaired Inflow, Jan-Jun	12806.1	0.0	17154.7	63.7
A ₈	Unimpaired Inflow, Mar-May	12996.2	190.1	17266.5	175.4
A ₉	Historical Outflow, Jan-Jun, 1yr Lag	13253.9	447.9	17401.3	310.2
A ₁₀	Historical Outflow, Mar-May, 1yr Lag	13272.7	466.7	17393.1	302.1
A ₁₁	Unimpaired Outflow, Jan-Jun, 1yr Lag	13269.3	463.3	17383.8	292.7
A ₁₂	Unimpaired Outflow, Mar-May	13265.4	459.3	17389.0	297.9
A ₁₃	Historical Inflow, Jan- Jun, 1yr Lag	13268.9	462.8	17389.5	298.4
A ₁₄	Historical Inflow, Mar- May, 1yr Lag	13267.6	461.5	17388.6	297.6
A ₁₅	Unimpaired Inflow, Jan-Jun, 1yr Lag	13271.8	465.7	17379.6	288.5
A ₁₆	Unimpaired Inflow, Mar-May, 1yr Lag	13263.0	457.0	17397.2	306.1

(B) Longfin smelt

Binomial Component				Lognormal Component			
Parameter	Estimate	SE	p-value	Parameter	Estimate	SE	p-value
β_0	-1.47	0.11	<0.0001	β_0	1.09	0.11	<0.0001
$\beta_{\text{Unimp.Inflow.Jan-Jun}}$	0.48	0.02	<0.0001	$\beta_{\text{Hist.Outflow.Jan-Jun}}$	0.40	0.02	<0.0001
β_{Oct}	0.36	0.06	<0.0001	β_{Oct}	0.37	0.07	<0.0001
β_{Nov}	1.09	0.06	<0.0001	β_{Nov}	0.35	0.07	<0.0001
β_{Dec}	1.70	0.06	<0.0001	β_{Dec}	0.18	0.06	0.003
β_{Region3}	-0.69	0.15	<0.0001	β_{Region3}	0.08	0.16	0.59
β_{Region4}	-0.76	0.16	<0.0001	β_{Region4}	-0.47	0.17	0.004
β_{Region5}	-0.85	0.18	<0.0001	β_{Region5}	-0.87	0.19	<0.0001
β_{Region7}	-1.15	0.20	<0.0001	β_{Region7}	-0.46	0.23	0.047
β_{Region8}	-0.17	0.14	0.22	β_{Region8}	0.50	0.15	0.001
β_{Region10}	-0.79	0.23	0.001	β_{Region10}	-0.37	0.23	0.11
β_{Region11}	0.06	0.13	0.66	β_{Region11}	-0.17	0.12	0.18
β_{Region12}	0.46	0.12	0.0001	β_{Region12}	0.30	0.11	0.01
β_{Region13}	0.03	0.11	0.79	β_{Region13}	0.08	0.11	0.45
β_{Region14}	-0.54	0.13	<0.0001	β_{Region14}	-0.29	0.12	0.02
β_{Region15}	-0.48	0.12	<0.0001	β_{Region15}	-0.38	0.12	0.002
β_{Region16}	-1.56	0.13	<0.0001	β_{Region16}	-0.92	0.14	<0.0001
β_{Region17}	-3.64	0.25	<0.0001	β_{Region17}	-1.11	0.34	<0.0001
β_{Secchi}	-1.38	0.04	<0.0001	β_{Secchi}	-0.94	0.04	<0.0001

Model A₇: Binomial null deviance = 17971.0 with 29% explained. Model A₁: lognormal null deviance = 13278.0 with 24% explained.

Table B3. Sacramento splittail
(A)

Model	Flow variable	Binomial AIC	Binomial ΔAIC	Lognormal AIC	Lognormal ΔAIC
A ₁	Historical Outflow, Jan- Jun	3008.9	4.2	837.3	2.4
A ₂	Historical Outflow, Mar-May	3008.0	3.4	840.0	5.2
A ₃	Unimpaired Outflow, Jan-Jun	3009.7	5.1	838.6	3.7
A ₄	Unimpaired Outflow, Mar-May	3034.1	29.5	840.7	5.8
A ₅	Historical Inflow, Jan- Jun	3008.2	3.5	837.2	2.3
A ₆	Historical Inflow, Mar- May	3014.0	9.4	840.3	5.4
A ₇	Unimpaired Inflow, Jan-Jun	3004.6	0.0	837.2	2.3
A ₈	Unimpaired Inflow, Mar-May	3036.5	31.8	840.2	5.3
A ₉	Historical Outflow, Jan-Jun, 1yr Lag	3123.2	118.5	834.9	0.0
A ₁₀	Historical Outflow, Mar-May, 1yr Lag	3121.1	116.5	841.0	6.1
A ₁₁	Unimpaired Outflow, Jan-Jun, 1yr Lag	3123.8	119.1	837.4	2.5
A ₁₂	Unimpaired Outflow, Mar-May	3119.3	114.7	840.9	6.0
A ₁₃	Historical Inflow, Jan- Jun, 1yr Lag	3123.7	119.1	836.0	1.1
A ₁₄	Historical Inflow, Mar- May, 1yr Lag	3118.8	114.2	840.6	5.7
A ₁₅	Unimpaired Inflow, Jan-Jun, 1yr Lag	3122.9	118.2	838.5	3.6
A ₁₆	Unimpaired Inflow, Mar-May, 1yr Lag	3115.8	111.2	840.6	5.7

(B) Sacramento splittail

Binomial Component				Lognormal Component			
Parameter	Estimate	SE	p-value	Parameter	Estimate	SE	p-value
β_0	-6.01	0.60	<0.0001	β_0	-0.12	0.35	0.74
$\beta_{\text{Unimp.Inflow.Jan-Jun}}$	0.56	0.05	<0.0001	$\beta_{\text{Hist.Outflow.Jan-Jun.1yrLag}}$	0.06	0.02	0.01
β_{Oct}	-0.25	0.13	0.06	β_{Oct}	-0.06	0.07	0.39
β_{Nov}	-0.47	0.15	0.002	β_{Nov}	-0.04	0.08	0.60
β_{Dec}	-0.56	0.14	<0.0001	β_{Dec}	-0.16	0.08	0.04
β_{Region3}	n/s	n/s	n/s	β_{Region3}	n/s	n/s	n/s
β_{Region4}	0.83	0.70	0.24	β_{Region4}	0.41	0.40	0.31
β_{Region5}	0.77	0.74	0.30	β_{Region5}	0.63	0.43	0.14
β_{Region7}	n/s	n/s	n/s	β_{Region7}	n/s	n/s	n/s
β_{Region8}	n/s	n/s	n/s	β_{Region8}	n/s	n/s	n/s
β_{Region10}	2.15	0.69	0.002	β_{Region10}	0.69	0.39	0.08
β_{Region11}	1.39	0.62	0.02	β_{Region11}	0.48	0.36	0.18
β_{Region12}	1.52	0.60	0.01	β_{Region12}	0.26	0.35	0.45
β_{Region13}	1.56	0.59	0.01	β_{Region13}	0.20	0.34	0.57
β_{Region14}	2.68	0.59	<0.0001	β_{Region14}	0.46	0.34	0.18
β_{Region15}	1.46	0.61	0.02	β_{Region15}	0.16	0.35	0.66
β_{Region16}	1.27	0.63	0.04	β_{Region16}	0.13	0.36	0.71
β_{Region17}	-0.25	0.82	0.76	β_{Region17}	0.06	0.48	0.91
β_{Secchi}	-1.90	0.13	<0.0001	β_{Secchi}	-0.19	0.08	0.01

Model A₇: Binomial null deviance = 3944.0 with 25% explained. Model A₉: lognormal null deviance = 173.5 with 12% explained.

Table B4. Starry flounder
(A)

Model	Flow variable	Binomial AIC	Binomial ΔAIC	Lognormal AIC	Lognormal ΔAIC
A ₁	Historical Outflow, Jan- Jun	3000.1	0.0	503.8	4.5
A ₂	Historical Outflow, Mar-May	3006.4	6.2	503.1	3.8
A ₃	Unimpaired Outflow, Jan-Jun	3001.8	1.7	503.7	4.5
A ₄	Unimpaired Outflow, Mar-May	3006.6	6.5	503.1	3.9
A ₅	Historical Inflow, Jan- Jun	3002.3	2.1	503.9	4.6
A ₆	Historical Inflow, Mar- May	3007.1	7.0	503.5	4.2
A ₇	Unimpaired Inflow, Jan-Jun	3002.4	2.3	503.8	4.5
A ₈	Unimpaired Inflow, Mar-May	3006.6	6.5	503.6	4.4
A ₉	Historical Outflow, Jan-Jun, 1yr Lag	3005.4	5.3	503.2	4.0
A ₁₀	Historical Outflow, Mar-May, 1yr Lag	3007.4	7.3	502.7	3.4
A ₁₁	Unimpaired Outflow, Jan-Jun, 1yr Lag	3006.3	6.2	502.3	3.0
A ₁₂	Unimpaired Outflow, Mar-May	3007.7	7.6	499.3	0.0
A ₁₃	Historical Inflow, Jan- Jun, 1yr Lag	3004.9	4.7	502.9	3.2
A ₁₄	Historical Inflow, Mar- May, 1yr Lag	3007.6	7.5	501.8	2.2
A ₁₅	Unimpaired Inflow, Jan-Jun, 1yr Lag	3005.6	5.5	502.0	2.4
A ₁₆	Unimpaired Inflow, Mar-May, 1yr Lag	3007.8	7.6	499.6	0.0

(B) Starry flounder

Binomial Component				Lognormal Component			
Parameter	Estimate	SE	<i>p</i> -value	Parameter	Estimate	SE	<i>p</i> -value
β_0	-4.48	0.37	<0.0001	β_0	-0.01	0.17	0.97
$\beta_{\text{Hist.Outflow.Jan-Jun}}$	0.14	0.05	0.01	$\beta_{\text{Unimp.Outflow.Mar-May.1yrLag}}$	0.06	0.03	0.03
β_{Oct}	0.07	0.14	0.59	β_{Oct}	-0.01	0.06	0.85
β_{Nov}	-0.16	0.16	0.30	β_{Nov}	-0.02	0.07	0.82
β_{Dec}	-0.40	0.15	0.01	β_{Dec}	-0.01	0.07	0.83
β_{Region3}	1.06	0.43	0.01	β_{Region3}	0.30	0.19	0.11
β_{Region4}	1.33	0.41	0.001	β_{Region4}	0.54	0.19	0.004
β_{Region5}	1.74	0.41	<0.0001	β_{Region5}	0.39	0.19	0.03
β_{Region7}	0.09	0.62	0.88	β_{Region7}	-0.03	0.28	0.92
β_{Region8}	0.33	0.51	0.52	β_{Region8}	0.11	0.23	0.62
β_{Region10}	1.00	0.51	0.05	β_{Region10}	0.35	0.23	0.13
β_{Region11}	0.76	0.40	0.06	β_{Region11}	0.18	0.18	0.31
β_{Region12}	0.89	0.38	0.02	β_{Region12}	0.36	0.17	0.04
β_{Region13}	0.41	0.38	0.28	β_{Region13}	0.18	0.17	0.29
β_{Region14}	0.15	0.40	0.70	β_{Region14}	0.03	0.18	0.85
β_{Region15}	-0.70	0.45	0.12	β_{Region15}	0.12	0.21	0.58
β_{Region16}	-1.96	0.68	0.004	β_{Region16}	0.58	0.31	0.07
β_{Region17}	n/a	n/a	n/a	β_{Region17}	n/a	n/a	n/a
β_{Secchi}	-1.30	0.12	<0.0001	β_{Secchi}	-0.04	0.05	0.44

Model A₁: Binomial null deviance = 3395.7 with 13% explained. Model A₁₂: lognormal null deviance = 84.1 with 11% explained.

Table B5. Threadfin shad
(A)

Model	Flow variable	Binomial AIC	Binomial ΔAIC	Lognormal AIC	Lognormal ΔAIC
A ₁	Historical Outflow, Jan-Jun	13486.8	0.0	13666.3	0.0
A ₂	Historical Outflow, Mar-May	13561.7	74.9	13671.2	4.9
A ₃	Unimpaired Outflow, Jan-Jun	13542.8	56.0	13670.0	3.7
A ₄	Unimpaired Outflow, Mar-May	13586.1	99.3	13671.1	4.8
A ₅	Historical Inflow, Jan- Jun	13500.9	14.0	13668.4	2.1
A ₆	Historical Inflow, Mar- May	13569.5	82.7	13670.8	4.5
A ₇	Unimpaired Inflow, Jan-Jun	13539.2	52.4	13670.7	4.4
A ₈	Unimpaired Inflow, Mar-May	13585.4	98.6	13670.89	4.6
A ₉	Historical Outflow, Jan-Jun, 1yr Lag	13582.9	96.0	13669.04	2.7
A ₁₀	Historical Outflow, Mar-May, 1yr Lag	13602.3	115.4	13670.93	4.6
A ₁₁	Unimpaired Outflow, Jan-Jun, 1yr Lag	13578.2	91.4	13670.28	4.0
A ₁₂	Unimpaired Outflow, Mar-May	13590.0	103.1	13671.27	5.0
A ₁₃	Historical Inflow, Jan- Jun, 1yr Lag	13583.7	96.9	13668.7	2.4
A ₁₄	Historical Inflow, Mar- May, 1yr Lag	13602.4	115.6	13670.94	4.6
A ₁₅	Unimpaired Inflow, Jan-Jun, 1yr Lag	13581.1	94.2	13670.1	3.8
A ₁₆	Unimpaired Inflow, Mar-May, 1yr Lag	13589.3	102.5	13671.01	4.7

(B) Threadfin shad

Binomial Component				Lognormal Component			
Parameter	Estimate	SE	<i>p</i> -value	Parameter	Estimate	SE	<i>p</i> -value
β_0	-2.68	0.13	<0.0001	β_0	0.86	0.16	<0.0001
$\beta_{\text{Hist.Outflow.Jan-Jun}}$	0.23	0.02	<0.0001	$\beta_{\text{Hist.Outflow.Jan-Jun}}$	0.04	0.02	0.03
β_{Oct}	0.41	0.06	<0.0001	β_{Oct}	0.01	0.06	0.87
β_{Nov}	0.98	0.06	<0.0001	β_{Nov}	-0.07	0.06	0.26
β_{Dec}	1.34	0.06	<0.0001	β_{Dec}	-0.21	0.06	0.00
β_{Region3}	-0.47	0.19	0.01	β_{Region3}	0.17	0.22	0.46
β_{Region4}	0.02	0.19	0.90	β_{Region4}	0.02	0.21	0.92
β_{Region5}	-0.06	0.21	0.77	β_{Region5}	0.14	0.25	0.56
β_{Region7}	0.09	0.22	0.68	β_{Region7}	-0.06	0.25	0.82
β_{Region8}	-0.80	0.20	<0.0001	β_{Region8}	0.10	0.25	0.69
β_{Region10}	-0.17	0.27	0.54	β_{Region10}	-0.41	0.31	0.19
β_{Region11}	-0.09	0.16	0.56	β_{Region11}	-0.14	0.18	0.44
β_{Region12}	-0.36	0.15	0.01	β_{Region12}	-0.30	0.17	0.08
β_{Region13}	0.18	0.14	0.18	β_{Region13}	-0.11	0.16	0.47
β_{Region14}	0.94	0.14	<0.0001	β_{Region14}	0.32	0.16	0.04
β_{Region15}	1.66	0.14	<0.0001	β_{Region15}	0.46	0.15	0.003
β_{Region16}	2.12	0.14	<0.0001	β_{Region16}	0.78	0.15	<0.0001
β_{Region17}	2.97	0.14	<0.0001	β_{Region17}	2.29	0.16	<0.0001
β_{Secchi}	-0.74	0.04	<0.0001	β_{Secchi}	-0.17	0.04	<0.0001

Model A₁: Binomial null deviance = 16877.0 with 20% explained. Model A₁: lognormal null deviance = 9796.9 with 30% explained.

Table B6. Crangon spp.
(A)

Model	Flow variable	Binomial AIC	Binomial ΔAIC	Lognormal AIC	Lognormal ΔAIC
A ₁	Historical Outflow, Jan- Jun	11347.2	35.4	13259.4	0.0
A ₂	Historical Outflow, Mar-May	11327.7	16.0	13306.6	47.3
A ₃	Unimpaired Outflow, Jan-Jun	11350.9	39.2	13276.3	16.9
A ₄	Unimpaired Outflow, Mar-May	11311.7	0.0	13335.9	76.5
A ₅	Historical Inflow, Jan- Jun	11349.0	37.2	13292.3	32.9
A ₆	Historical Inflow, Mar- May	11332.9	21.1	13335.0	75.6
A ₇	Unimpaired Inflow, Jan-Jun	11355.6	43.8	13301.4	42.1
A ₈	Unimpaired Inflow, Mar-May	11317.8	6.1	13359.4	100.0
A ₉	Historical Outflow, Jan-Jun, 1yr Lag	11365.1	53.3	13390.4	131.0
A ₁₀	Historical Outflow, Mar-May, 1yr Lag	11350.3	38.6	13390.3	131.0
A ₁₁	Unimpaired Outflow, Jan-Jun, 1yr Lag	11366.5	54.8	13394.0	134.6
A ₁₂	Unimpaired Outflow, Mar-May	11347.5	35.8	13392.5	133.1
A ₁₃	Historical Inflow, Jan- Jun, 1yr Lag	11357.8	46.1	13392.7	133.3
A ₁₄	Historical Inflow, Mar- May, 1yr Lag	11341.3	29.6	13390.5	131.2
A ₁₅	Unimpaired Inflow, Jan-Jun, 1yr Lag	11364.2	52.4	13395.4	136.0
A ₁₆	Unimpaired Inflow, Mar-May, 1yr Lag	11337.4	25.6	13394.4	135.0

(B) Crangon spp.

Binomial Component				Lognormal Component			
Parameter	Estimate	SE	p-value	Parameter	Estimate	SE	p-value
β_0	-0.96	0.11	<0.0001	β_0	2.95	0.14	<0.0001
$\beta_{\text{Unimp.Outflow.Mar-May}}$	-0.19	0.02	<0.0001	$\beta_{\text{Hist.Outflow.Jan-Jun}}$	0.36	0.03	<0.0001
β_{Oct}	-0.08	0.07	0.22	β_{Oct}	-0.01	0.08	0.85
β_{Nov}	0.04	0.07	0.52	β_{Nov}	-0.47	0.08	<0.0001
β_{Dec}	-0.29	0.06	<0.0001	β_{Dec}	-0.90	0.08	<0.0001
β_{Region3}	-1.21	0.17	<0.0001	β_{Region3}	0.04	0.24	0.85
β_{Region4}	-1.57	0.18	<0.0001	β_{Region4}	-0.99	0.25	<0.0001
β_{Region5}	-1.86	0.22	<0.0001	β_{Region5}	-1.69	0.31	<0.0001
β_{Region7}	-2.59	0.33	<0.0001	β_{Region7}	-1.45	0.51	0.005
β_{Region8}	-0.62	0.16	0.0001	β_{Region8}	0.50	0.22	0.02
β_{Region10}	-1.24	0.24	<0.0001	β_{Region10}	-1.06	0.33	0.001
β_{Region11}	0.31	0.13	0.01	β_{Region11}	-0.10	0.15	0.50
β_{Region12}	0.36	0.12	0.002	β_{Region12}	-0.04	0.14	0.76
β_{Region13}	-0.36	0.11	0.001	β_{Region13}	-0.38	0.14	0.01
β_{Region14}	-1.10	0.13	<0.0001	β_{Region14}	-1.08	0.16	<0.0001
β_{Region15}	-1.24	0.13	<0.0001	β_{Region15}	-0.37	0.16	0.02
β_{Region16}	-2.16	0.15	<0.0001	β_{Region16}	-1.99	0.21	<0.0001
β_{Region17}	n/a	n/a	n/a	β_{Region17}	n/a	n/a	n/a
β_{Secchi}	-1.78	0.05	<0.0001	β_{Secchi}	-1.08	0.06	<0.0001

Model A₄: Binomial null deviance = 14730.9 with 32% explained. Model A₁: lognormal null deviance = 12128.9 with 37% explained.

Robert J. Latour

Institute Address

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Education

May 2000 Ph.D., Biomathematics, North Carolina State University
Dec 1996 M.B.A., Biomathematics, North Carolina State University
May 1994 B.A., Mathematics, Western New England College

Experience

Jul 2008 - present Associate Professor, Virginia Institute of Marine Science, School of Marine Science, College of William & Mary
Jul 2008 - Jun 2011 Moses D. Nunnally Distinguished Associate Professor, Virginia Institute of Marine Science, School of Marine Science, College of William & Mary
Jul 2004 - Jun 2008 Assistant Professor, Virginia Institute of Marine Science, School of Marine Science, College of William & Mary
Jul 2001 - Jun 2003 Research Assistant Professor, Department of Fisheries Science, Virginia Institute of Marine Science, College of William & Mary
Jan 2000 - Jun 2001 Postdoctoral Research Associate, Department of Fisheries Science, Virginia Institute of Marine Science, College of William & Mary
Jan 1998 - May 1999 Mathematics Instructor, Durham CAPE Program, Shaw University

Research interests

Quantitative fisheries ecology with particular emphasis on predator-prey interactions and ecosystem-based approaches to fisheries management. Population dynamics modeling and stock assessment of exploited marine resources.

Honors and awards

2010 Plumeri Award for Faculty Excellence, College of William & Mary

Publications

* Indicates my graduate student; † Indicates graduate student collaboration

1. Gauthier, D.T., **R.J. Latour**, H.D. Gaff, W.K. Vogelbein. In press. Mycobacteriosis in striped bass (*Morone saxatilis*). For: Northeast Atlantic Coast Striped Bass Fisheries Management. M. Armstrong and P. Perra, eds.
2. †Balazik, M.T., S.P. McIninch, G.C. Garman, and **R.J. Latour**. 2012. Age and growth of Atlantic sturgeon (*Acipenser oxyrinchus oxyrinchus*) in the James River, Virginia, 1997-2011. Transactions of the American Fisheries Society 141:1074-1080.
3. **Latour, R.J.**, E.J. Hilton, *P.D. Lynch, T.D. Tuckey, B.E. Watkins, and J.E. Olney. 2012. Evaluating the current status of American shad (*Alosa sapidissima*) stocks in three Virginia rivers. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science 4:302-311.
4. *Lynch, P.D., K.W. Shertzer, and **R.J. Latour**. 2012. Estimating relative abundance of highly migratory bycatch species. Fisheries Research 125-126:27-39.
5. **Latour, R.J.**, D.T. Gauthier, J. Gartland, C.F. Bonzek, *K.A. McNamee, and W.K. Vogelbein. 2012. Impacts of mycobacteriosis on the growth of striped bass (*Morone saxatilis*) in Chesapeake Bay. Canadian Journal of Fisheries and Aquatic Sciences 69:247-258.
6. *Buchheister, A. and **R.J. Latour**. 2011. Trophic ecology of summer flounder in Chesapeake Bay inferred from stomach content and stable isotope analyses. Transactions of the American Fisheries Society 140:1240-1254.
7. †Schloesser, R.W., M.C. Fabrizio, **R.J. Latour**, G.C. Garman, B. Greenlee, M. Groves, and J. Gartland. 2011. Ecological Role of Blue Catfish in Chesapeake Bay Communities and Implications for Management. In P. Michaletz and V. Travnicek, eds., Conservation, ecology, and management of worldwide catfish populations and habitats. American Fisheries Society, Bethesda, MD.
8. *Horodysky, A.Z., R.W. Brill, P.G. Bushnell, J.A. Musick, and **R.J. Latour**. 2011. Comparative metabolic rates of common western Atlantic Ocean sciaenid fishes. Journal of Fish Biology 79:235-255.
9. *Lynch, P.D., J.E. Graves, and **R.J. Latour**. 2011. Challenges in the assessment and management of highly migratory bycatch species: a case study of the Atlantic marlins. Pages 197-226 in W.W. Taylor, A.J. Lynch, and M.G. Schechter, editors. Sustainable fisheries: multi-level approaches to a global problem. American Fisheries Society, Bethesda, Maryland.
10. *Lynch, P.D., M.J. Brush, and **R.J. Latour**. 2011. Simulated short-term impacts of the Atlantic menhaden reduction fishery on Chesapeake Bay water quality. North American Journal of Fisheries Management 31:70-78.
11. Frisk, M.G., T.J. Miller, **R.J. Latour**, and S.J.D. Martell. 2011. Assessing biomass gains from marsh restoration in Delaware Bay using Ecopath with Ecosim. Ecological Modeling 222:190-200.

12. Gauthier, D.T., K.S. Reece, J. Xiao, M.W. Rhodes, H.I. Kator, **R.J. Latour**, C.F. Bonzek, J.M. Hoenig, and W.K. Vogelbein. 2010. Quantitative PCR assay for *Mycobacterium pseudoshottsii* and *Mycobacterium shottsii* and application to environmental samples and fishes from Chesapeake Bay, USA. *Applied and Environmental Microbiology* 76:6171-6179.
13. Garrison, L.P., J.S. Link, D.P. Kilduff, M.D. Cieri, B. Muffley, D. Vaughan, A. Sharov, B. Mahmoudi, and **R.J. Latour**. 2010. An expansion of the MSVPA approach for quantifying predator-prey interactions in exploited fish communities. *ICES Journal of Marine Science* 67:856-870.
14. *Horodysky, A.Z., R.W. Brill, E.J. Warrent, J.A. Musick, and **R.J. Latour**. 2010. Comparative visual function in four piscivorous fishes inhabiting Chesapeake Bay. *Journal of Experimental Biology* 213:1751-1761.
15. *Buchheister, A. and **R.J. Latour**. 2010. Turnover rates and fractionations of $\delta^{13}\text{C}$ and $\delta^{15}\text{N}$ in tissues of a migratory coastal predator, summer flounder (*Paralichthys dentatus*). *Canadian Journal of Fisheries and Aquatic Sciences* 67:445-461.
16. *Lynch, P.D., M.J. Brush, E.D. Condon, and **R.J. Latour**. 2010. Net removal of nitrogen through ingestion of phytoplankton by Atlantic menhaden (*Brevoortia tyrannus*) in Chesapeake Bay. *Marine Ecological Progress Series* 401:195-209.
17. Graves, J.E., *A.Z. Horodysky, and **R.J. Latour**. 2009. Use of pop-up satellite archival tag technology to study postrelease survival of and habitat utilization by estuarine and coastal fishes: an application to striped bass (*Morone saxatilis*). *Fishery Bulletin* 107:373-383.
18. †Hoffman, J.C., C.F. Bonzek, and **R.J. Latour**. 2009. Estimation of bottom trawl catch efficiency for two demersal fishes, the Atlantic croaker and white perch, in Chesapeake Bay. *Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science* 1:255-269.
19. *Horodysky, A.Z., R.W. Brill, E.J. Warrent, J.A. Musick, and **R.J. Latour**. 2008. Comparative visual function in five sciaenid fishes inhabiting Chesapeake Bay. *Journal of Experimental Biology* 211:3601-3612.
20. Gauthier, D.T., **R.J. Latour**, D. Heisey, C.F. Bonzek, J. Gartland, E.J. Burge, W.K. Vogelbein. 2008. Mycobacteriosis is associated with mortality in wild striped bass (*Morone saxatilis*) from Chesapeake Bay, USA. *Ecological Applications* 18:1718-1727.
21. *Horodysky, A.Z., R.W. Brill, M.L. Fine, J.A. Musick, and **R.J. Latour**. 2008. Acoustic pressure and particle motion thresholds in six sciaenid fishes. *Journal of Experimental Biology* 211:1504-1511.
22. Hoenig, J.M., **R.J. Latour**, and J.E. Olney. 2008. Estimating stock composition of American shad in Virginia using mark-recovery data. *North American Journal of Fisheries Management* 28:507-515.
23. **Latour, R.J.**, J. Gartland, C.F. Bonzek, and R.A. Johnson. 2008. The trophic dynamics of summer flounder (*Paralichthys dentatus*) in Chesapeake Bay. *Fishery Bulletin* 106:47-57.

24. †Horodysky, A.Z., D.W. Kerstetter, **R.J. Latour**, and J.E. Graves. 2007. Habitat utilization and vertical movements of white marlin (*Tetrapturus albidus*) released from commercial and recreational fishing gears in the western North Atlantic Ocean: inferences from short-duration pop-up archival satellite tags (PSATs). *Fisheries Oceanography* 16:240-256.
25. †Jiang, H., K.H. Pollock, C. Brownie, J.M. Hoenig, **R.J. Latour**, B.K. Wells, and J.E. Hightower. 2007. Tag return models for catch-and-release fisheries: striped bass natural mortality estimates change with age and calendar year. *North American Journal of Fisheries Management* 27:387-396.
26. Olney, J.E., **R.J. Latour**, B.E. Watkins, and D.G. Clarke. 2006. Migratory behavior of American shad (*Alosa sapidissima*) in the York River, Virginia with implications for estimating in-river exploitation from tag-recovery data. *Transactions of the American Fisheries Society* 135:889-896.
27. Gartland, J., **R.J. Latour**, A.D. Halvorson, and H.M. Austin. 2006. Diet composition of young-of-the-year bluefish (*Pomatomus saltatrix*) in the lower Chesapeake Bay and the coastal ocean of Virginia. *Transactions of the American Fisheries Society* 135:371-378.
28. Lipcius, R.M. and **R.J. Latour**. 2006. Food web interactions and modeling. Pages 103-144 in Chesapeake Bay Fisheries Ecosystem Advisory Panel (National Oceanic and Atmospheric Administration Chesapeake Bay Office). *Fisheries ecosystem planning for Chesapeake Bay*. American Fisheries Society, Trends in Fisheries Science and Management 3, Bethesda, Maryland.
29. †Goldman, K.J., S.D. Anderson, **R.J. Latour**, and J.A. Musick. 2004. Homeothermy in adult salmon sharks, *Lamna ditropis*. *Environmental Biology of Fishes* 71:403-411.
30. Simpfendorfer, C.A., R. Bonfil, and **R.J. Latour**. 2004. Mortality estimation. *In* Elasmobranch Fisheries Management Techniques. J.A Musick and R. Bonfil (eds.). Joint publication between the Asia-Pacific Economic Cooperation (APEC), International Union for the Protection of Nature (IUCN), and the Virginia Institute of Marine Science (VIMS).
31. **Latour, R.J.** 2004. Tagging methods and associated data analysis. *In* Elasmobranch Fisheries Management Techniques. J.A Musick and R. Bonfil (eds.). Joint publication between the Asia-Pacific Economic Cooperation (APEC), International Union for the Protection of Nature (IUCN), and the Virginia Institute of Marine Science (VIMS).
32. **Latour, R.J.**, J.M. Hoenig, D.A. Hepworth, and S.D Frusher. 2003. A novel tag-recovery model with two size classes for estimating fishing and natural mortality, with implications for the southern rock lobster (*Jasus edwardsii*) in Tasmania, Australia. *ICES Journal of Marine Science* 60:1075-1085.
33. **Latour, R.J.**, M.J. Brush, and C.F. Bonzek. 2003. Toward ecosystem-based fisheries management: strategies for multispecies modeling and associated data requirements. *Fisheries* 28:10-22.
34. Welsh, S.A., A. Kahnle, B. Versak, and **R.J. Latour**. 2003. Use of tag data to

- compare growth rates of Atlantic Coast striped bass. *Fisheries Management and Ecology* 10:289-294.
35. **Latour, R.J.**, J.M. Hoenig, and K.H. Pollock. 2002. Properties of the residuals from two tag-recovery models. *Fishery Bulletin* 100:856-860.
 36. **Latour, R.J.**, K.H. Pollock, C.A. Wenner, and J.M. Hoenig. 2001. Estimates of instantaneous rates of fishing and natural mortality for red drum in South Carolina waters. *North American Journal of Fisheries Management* 21:733-744.
 37. **Latour, R.J.**, J.M. Hoenig, J.E. Olney, and K.H. Pollock. 2001. Diagnostics for multiyear tagging models with application to Atlantic striped bass (*Morone saxatilis*). *Canadian Journal of Fisheries and Aquatic Sciences* 58:1716-1726.
 38. **Latour, R.J.**, J.M. Hoenig, J.E. Olney, and K.H. Pollock. 2001. A simple test for nonmixing in multiyear tagging studies: application to striped bass tagged in the Rappahannock River, Virginia. *Transactions of the American Fisheries Society* 130:848-856.

Work in progress

* Indicates my graduate student; † Indicates graduate student collaboration

1. *Sweetman, C.J., T.T. Sutton, M. Vecchione, and **R.J. Latour**. In review. Distribution of *Bathylagus euryops* (Teleostei: Bathylagidae) along the Northern Mid-Atlantic Ridge. *Deep-Sea Research I*.
2. *Sobocinski, K.L., J.J. Orth, M.C. Fabrizio, and **R.J. Latour**. In review. Historical comparison of fish community structure in lower Chesapeake Bay seagrass habitats. *Estuaries and Coasts*.
3. *Buchheister, A, C.F. Bonzek, J. Gartland, and **R.J. Latour**. In review. Patterns and drivers of the demersal fish community of Chesapeake Bay. *Marine Ecological Progress Series*.
4. *Sweetman, C.J., T.T. Sutton, M. Vecchione, and **R.J. Latour**. Feeding ecology of *Bathylagus euryops* (Teleostei: Bathylagidae) along the Northern Mid-Atlantic Ridge. Target journal: *Marine Ecological Progress Series*.
5. *Wor, C., E.N. Brooks, and **R.J. Latour**. Evaluating the impact of stock structure uncertainty in stock assessments of sailfish in the Atlantic Ocean. Target journal: *Fisheries Research*.
6. †Funkey, C.P., **R.J. Latour**, and D.A. Bronk. Abiotic Release of low molecular weight nitrogen from wastewater treatment plant effluent organic nitrogen. Target journal: *Environmental Science & Technology*.

Other publications

- Hilton, E.J., G.D. Johnson, E.D. Houde, and **R.J. Latour**. 2011. Obituary, John Edward Olney, Sr. (1947-2010). *Copeia* 2011:332-341.

- Vaughan, D., J. Brust, M. Cieri, **R.J. Latour**, B. Mahmoudi, J. McNamee, G. Nesslage, A. Sharov, J. Smith, and E. Williams. 2011. The 2011 Atlantic Menhaden Stock Assessment for Peer Review. Atlantic States Marine Fisheries Commission Stock Assessment Report No. 10-02.
- Christensen, V., A. Beattie, C. Buchanan, H. Ma, S.J.D. Martell, **R.J. Latour**, D. Preikshot, M.B. Sigrist, J.H. Uphoff, C.J. Walters, R.J. Wood, and H. Townsend. 2009. Fisheries Ecosystem Model of the Chesapeake Bay: Methodology, Parameterization and Model Explanation. U.S. Dep. Commerce, NOAA Tech. Memo. NMFS-F/SPO-106, 146 p.
- Kilduff, P., J. Carmichael, and **R.J. Latour**. 2009. Guide to Fisheries Science and Stock Assessment. Publication of the Atlantic States Marine Fisheries Commission.
- Bonzek, C.F., E.D. Houde, S. Giordano, **R.J. Latour**, T.J. Miller, and K.G. Sellner. 2007. Baywide and Coordinated Chesapeake Bay Fish Stock Monitoring. CRC Publication 07-163, Edgewater, MD. 70 p.

Grants

- Jun 2012 - May 2014. Virginia Sea Grant. Ecosystem analysis of nearshore U.S. east coast fisheries \$99,974. Co-PI two-investigator project (student fellowship).
- Jan 2012 - Dec 2013. Virginia Environmental Endowment. Climate change and the fisheries food web in the Chesapeake Bay and coastal Atlantic Ocean. \$87,000. Lead PI on multi-investigator project.
- Jan 2012 - Dec 2012. Recreational and Commercial Fisheries Advisory Board of the Virginia Marine Resources Commission. Survey design for adult Atlantic menhaden along the U.S. east coast. \$55,373. Lead PI on multi-investigator project.
- Sep 2011 - Aug 2014. Estimating population size and survival rates of blue catfish in Chesapeake Bay tributaries. \$176,223. Co-PI on multi-investigator project.
- Aug 2011 - Jul 2012. Characterizing the growth dynamics of blue catfish in the Chesapeake Bay watershed. \$45,649. Lead PI on multi-investigator project.
- Aug 2005 - Dec 2012. NOAA through the MAFMC Research Set-Aside Program, Southern New England Collaborative Research Initiative, Atlantic States Marine Fisheries Commission. Data collection and analysis in support of multispecies stock assessments in the mid-Atlantic: Northeast Area Monitoring and Assessment Program Nearshore Trawl Program (NEAMAP). \$6,290,776. Joint lead PI on three-investigator project.
- Jun 2010 - May 2013. NOAA/NMFS. VIMS Shark Research Program. \$300,000. Co-PI on two-investigator project.
- Feb 2010 - Jan 2013. U.S. Fish and Wildlife Service, Virginia Marine Resources Commission. Monitoring relative abundance and bycatch of American shad in Virginia's rivers. \$1,029,594. Co-PI on two investigator project.

- Apr 2005 - Mar 2013. U.S. Fish and Wildlife Service, Virginia Marine Resources Commission. Data collection and analysis in support of single and multispecies stock assessments in Chesapeake Bay: the Chesapeake Bay multispecies monitoring and assessment program (ChesMMAP). \$3,326,474. Joint lead PI on two-investigator project.
- Aug 2010 - Jul 2011. Virginia Sea Grant. Food web structure in Chesapeake Bay and environmental effects on fish diets: supporting ecosystem-based approaches to fisheries management. \$40,508. Co-PI on two-investigator project (student fellowship).
- Aug 2010 - Jul 2013. National Science Foundation. CAMEO: Collaborative Research: Patterns of connectivity in northwest Atlantic fishery ecosystem. \$117,612 VIMS portion. Co-PI on multi-investigator project.
- Jan 2010 - Dec 2011. Recreational and Commercial Fisheries Advisory Board of the Virginia Marine Resources Commission. Connecting productivity in eelgrass beds to recreationally important finfishes in Chesapeake Bay: forage fishes as trophic conduits. \$58,329. Co-PI on multi-investigator project (student lead PI).
- Jun 2009 - May 2012. National Marine Fisheries Service and Sea Grant Population Dynamics Graduate Fellowship Program. Expanding quantitative approaches to assessing the population status and dynamics of large pelagic fishes. \$96,249. Co-PI on two-investigator project (student fellowship).
- Jan 2008 - Dec 2008. Recreational and Commercial Fisheries Advisory Board of the Virginia Marine Resources Commission. Pilot study: Application of Pop-Up Satellite Archival tags (PSATs) to assess the postrelease survival, habitat utilization and short term movement of striped bass in Virginia's winter recreational fishery. \$71,371. Co-PI on multi-investigator project.
- Jan 2007 - Dec 2007. Recreational and Commercial Fisheries Advisory Board of the Virginia Marine Resources Commission. A genetic assessment of the potential for local depletion of Atlantic menhaden (*Brevoortia tyrannus*) within Chesapeake Bay. \$48,620. Co-PI on multi-investigator project.
- Jul 2006 - Jun 2008. Recreational and Commercial Fisheries Advisory Board of the Virginia Marine Resources Commission. Visual function in Chesapeake Bay sport and prey fishes: summer flounder, bluefish, cobia, and Atlantic menhaden. \$94,568. Co-PI on multi-investigator project (student lead PI).
- Jul 2006 - Dec 2007. Recreational and Commercial Fisheries Advisory Board of the Virginia Marine Resources Commission. Towards validation of juvenile indices of abundance for several fish species in Chesapeake Bay. \$60,916. Lead PI on multi-investigator project.
- Jul 2005 - Jun 2008. U.S. Environmental Protection Agency Chesapeake Bay Program. Modeling Atlantic menhaden in support of nutrient and multispecies management. \$256,699. Co-PI on multi-investigator project.

- Jul 2005 - Jun 2006. Recreational Fisheries Advisory Board of the Virginia Marine Resources Commission. Visual function in Chesapeake Bay sportfishes: striped bass, weakfish, spotted seatrout, Atlantic croaker, spot, and red drum. \$54,818. Co-PI on multi-investigator project (student lead PI).
- Oct 2005 - Sep 2007. Atlantic States Marine Fisheries Commission. Evaluating the use of airborne Light Detection and Ranging (LIDAR) and hydroacoustics for estimating the abundance and distribution of Atlantic menhaden in Chesapeake Bay. \$312,570. Co-PI on multi-investigator project.
- Oct 2005 - Sep 2006. Virginia Cooperative Marine Education and Research Program. Energy density of common prey species of recreationally and commercially important marine fishes in Chesapeake Bay. \$33,625. Co-PI on multi-investigator project (student lead PI).
- May 2005 - Apr 2006. National Marine Fisheries Service. Age- and time-specific estimates of fishing and natural mortality for striped bass. \$34,635 Co-PI on multi-investigator project.
- Jan 2005 - Dec 2005. Recreational Fisheries Advisory Board of the Virginia Marine Resources Commission. The value of seagrass habitats to the ecosystem in Chesapeake Bay. \$58,221. Lead PI on multi-investigator project.
- Jul 2004 - Jun 2006. Virginia Environmental Endowment. Multispecies data collection and modeling in support of ecosystem-based fisheries management in Chesapeake Bay. \$195,000. Lead PI on multi-investigator project.
- Dec 2003 - Nov 2004. Multispecies based approaches to fisheries management: the ecological role of Atlantic menhaden in Chesapeake Bay. The Keith Campbell Foundation for the Environment, Inc. \$25,000. Lead PI on multi-investigator project.
- Oct 2003 - Sep 2005. NOAA Chesapeake Bay Stock Assessment Committee. Natural mortality of juvenile blue crabs: quantifying predation impacts by finfish in lower Chesapeake Bay seagrass beds. \$165,381. Co-PI on multi-investigator project.
- Jun 2003 - Aug 2006. Recreational Fisheries Advisory Board of the Virginia Marine Resources Commission. Establishment of a Chesapeake Bay trophic interaction laboratory services program. \$277,475. Co-PI on multi-investigator project.
- Oct 2002 - Dec 2006. NOAA Chesapeake Bay Office. Design and implementation of a Chesapeake Bay multispecies monitoring and assessment program (ChesMMAP). \$1,129,000. Joint lead PI on two-investigator project.
- Oct 2002 - Sep 2003. NOAA/NMFS Institute of Marine and Coastal Sciences at Rutgers University. Age-specific trophic interactions of bluefish (*Pomatomus saltatrix*) in the mainstem Chesapeake Bay. \$10,000. Lead PI on multi-investigator project.

Jul 2001 - Jun 2003. Virginia Environmental Endowment. Development of a multispecies tropho-dynamic model in support of sustainable fisheries management in Chesapeake Bay \$639,092. Lead PI on multi-investigator project.

Jun 2000 - Aug 2001. Recreational Fisheries Advisory Board of the Virginia Marine Resources Commission. Using tag-recovery data to estimate migration rates of striped bass (*Morone saxatilis*) spawned on the Chesapeake Bay. \$25,638. Lead PI on multi-investigator project.

Program staff

Current staff members:

James Gartland, Marine Scientist III, Co-PI, 2002-present

Debra Gauthier, Marine Scientist I, 2003-present

Melanie Chattin, Laboratory & Research Specialist II, 2005-present

Evan McOmber, Laboratory & Research Specialist II, 2007-present

Jameson Gregg, Laboratory & Research Specialist II, 2008-present

Kevin Spanik, Laboratory & Research Specialist II, 2008-present

Gregg Mears, Laboratory & Research Specialist II, 2011-present

Past staff members:

Adam Boddicker, Laboratory & Research Specialist II, 2011

David Lange, Marine Scientist II, 2007-2011

Stefanie Dukes, Laboratory & Research Specialist II, 2007-2009

RaeMarie Johnson, Marine Scientist II, 2004-2010

Patrick Lynch, Laboratory & Research Specialist I, 2003-2004

Aimee Halvorson, Laboratory & Research Specialist I, 2002-2003

Eric Brasseur, Laboratory & Research Specialist II, 2001-2008

Teaching summary

Spring 2009 - 2012, MSCI 504. Fundamentals of Statistical Methods and Data Analysis, SMS/VIMS, Instructor

Fall 2005 - 2009, 2011, MSCI 671. Fisheries Population Dynamics, SMS/VIMS, Instructor.

Spring 2008, MSCI 698. Advanced Fisheries Population Dynamics, Independent study, SMS/VIMS, Instructor.

Fall 2004 - 2007. MSCI 528. Marine Fisheries Science, SMS/VIMS, Co-Instructor.

Spring 2003, 2007, 2008, 2010. MSCI 649. Modeling Biological and Ecological Systems, SMS/VIMS, Co-Instructor.

Aug 2006. Fisheries Tagging Studies: Theory, Design and Applications, ASMFC workshop, Co-Instructor.

Fall 2000, 2002 - 2003. MSCI 528. Marine Fisheries Science, SMS/VIMS, Lecturer.

Jun 2003. MSCI 548. Marine Fisheries Science and Management: A Professional Development Course for Secondary Science Teachers, Lecturer.

Jun 2000. FIS4104. Tag Return Models for Fisheries Research, U.S. Fish Wildlife Service National Conservation Training Center, Co-Instructor.

Spring 2000. MSCI 698. Modeling Biological Systems, SMS/VIMS, Instructor.

Spring, Fall 1998, Spring 1999. MA 112. A Survey of Mathematics, Durham CAPE Program, Shaw University, Instructor.

Student advising*Current students:*

Patrick D. Lynch, Ph.D program, VIMS

Andre Buchheister, Ph.D program, VIMS

Kathryn L. Sobocinski, Ph.D program, VIMS, co-advisor with J. Emmett Duffy

Mark Stratton, Ph.D program, VIMS

Kristene Parsons, Ph.D program, VIMS

Christopher J. Sweetman, Ph.D program, VIMS

Carissa L. Gervasi, M.S. program, VIMS

Past students:

- Christopher J. Sweetman, M.S., 2012, VIMS, co-advisor with Mike Vecchione. Thesis: Distribution and feeding ecology of *Bathylagus euryops* (Teleostei: Microstomatidae) along the northern mid-Atlantic ridge, from Iceland to the Azores. Current position: Ph.D. program, VIMS, R.J. Latour advisor.
- Catarina Wor Lima, M.S., 2012, VIMS, co-advisor with John E. Graves. Thesis: Impacts of stock structure uncertainty in stock assessment derived management benchmarks. Current position: Ph.D. program, UBC, S.J.D. Martell advisor.
- Andrij Horodysky, Ph.D, 2009, VIMS, co-advisor with John A. Musick. Dissertation: Comparative sensory and energetic ecology of sciaenid fishes and their competitors in Chesapeake Bay, VA. Current position: Assistant Professor, Hampton University.
- Justine Woodward, M.S., 2009, VIMS, co-advisor with Mary C. Fabrizio. Thesis: Investigating the relationships between recruitment indices and estimates of adult abundance for striped bass, weakfish, and Atlantic croaker. Current position: Virginia Marine Resources Commission.
- Andre Buchheister, M.S., 2008, VIMS. Thesis: Stable isotope dynamics in summer flounder tissues, with application to dietary assessments in Chesapeake Bay. Current position: Ph.D. program, VIMS, R.J. Latour advisor.
- Patrick D. Lynch, M.S., 2007, VIMS. Thesis: Feeding ecology of Atlantic menhaden (*Brevoortia tyrannus*) in Chesapeake Bay. Current position: Ph.D. program, VIMS, R.J. Latour advisor.
- Kathleen A. McNamee, M.S., 2007, VIMS. Thesis: The growth and trophic ecology of striped bass (*Morone saxatilis*) in Chesapeake Bay, with reference to mycobacteriosis. Current position: science teacher, Washington-Lee High School, Arlington, VA.

Student committees

Current Ph.D: Lela Schlenker (VIMS), Allison Colden (VIMS); Alison Deary (VIMS); Jonathan Lefcheck (VIMS); Ryan Schloesser (VIMS); Matthew Balazik (Virginia Commonwealth University)

Current M.S.: Jeanna Hudson (VIMS)

Past Ph.D: Mark Henderson (2012, VIMS); William Connelly (2011, Chesapeake Biological Laboratory, University of Maryland); Chris Prosser (2011, VIMS); Michael Larkin (2011, RSMAS, University of Miami); Patrick McGrath (2010, VIMS); Jason Romine (2008, VIMS); Daniel Ha (2006, VIMS); Christian Hager (2004, VIMS)

Past M.S.: Carolina Funkey (2011, VIMS); Matthew Wahlan (2011, VIMS); Heather Wiseman (2010, VIMS); Daniel Dutton (2010, VIMS); Branson Williams (2010, VIMS); William Tarantino (2008, VIMS); Sally Upton (2008, VIMS); Abigail Lynch (2008,

VIMS); Aaron Aunins (2006, VIMS); Debra Lambert (2005, VIMS); Patrick McGrath (2005, VIMS); Jason Romine (2004, VIMS); Reid Hyle (2004, VIMS)

Manuscript peer review

Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science; Journal of Fish Biology; Estuaries and Coasts; Transactions of the American Fisheries Society; North American Journal of Fisheries Management; Marine Ecological Progress Series; Journal of Northwest Atlantic Fishery Science; Canadian Journal of Fisheries and Aquatic Sciences; Journal of Environmental Management; Fishery Bulletin; New Zealand Journal of Marine and Freshwater Research

Proposal peer review

National Science Foundation; Texas Sea Grant; North Carolina Sea Grant; Florida Sea Grant; NOAA Fisheries and Rutgers Bluefish Along the Atlantic Coast Research Program; Virginia Marine Resources Commission; Virginia Environmental Endowment

Advisory service

Member, MAFMC, Scientific and Statistical Committee, 2008 - present
Scientific Uncertainty Subcommittee, 2009 - present

Member, ASMFC Atlantic Menhaden Technical Committee, 2006 - present
Stock Assessment Subcommittee May 2007 - present
Chairman, May 2009 - May 2011
Vice-chairman, May 2008 - May 2009

Chairman, 49th Northeast Regional Stock Assessment Review Committee (SARC 49), Dec 2009, Woods Hole, MA

Member, external panel to review the NEFSC Foodweb Dynamics Program, Jul 2009, Woods Hole, MA

Member, ASMFC Multispecies Technical Committee, 2002 - present
MSVPA Subcommittee, 2005 - present

Invited Expert, ASMFC American Shad Technical Committee, Jun 2006

Invited Expert, Meeting of the Virginia Senate Committee on Agriculture, Conservation and Natural Resources, Nov 2006

Member, VIMS panel to advise Virginia Marine Resources Commission on permitting for King William Reservoir, 2004

Member, ASMFC Assessment Science Committee, 2003 - 2008

Member, Chesapeake Bay Ecosystem Modeling Advisory Panel, 2001 - 2007

Invited Expert, ASMFC Striped Bass Tagging Subcommittee, 2000 - 2004, 2012

Poster presentations

* indicates my graduate student

*Lynch, P.D., M.J. Brush and **R.J. Latour**. Simulated short-term impacts of the Atlantic menhaden reduction fishery on Chesapeake Bay water quality. 25th Annual Meeting of the Tidewater Chapter of the American Fisheries Society, Gloucester Point, VA, March 2011.

*Lynch, P.D., M.J. Brush and **R.J. Latour**. Simulated short-term impacts of the Atlantic menhaden reduction fishery on Chesapeake Bay water quality. Virginia Council of Graduate Schools, Sixth Annual Graduate Research Forum, Richmond, VA, February 2011.

*Buchheister, A. and **R.J. Latour**. Examining assumptions often made in stable isotope analyses: an example using a migratory estuarine fish. 137th Annual Meeting of the American Fisheries Society in San Francisco, CA. September 2007.

Parthre, D.J., C.F. Bonzek, J. Gartland, *A.Z. Horodysky, and **R.J. Latour**. Factors affecting the diet of Atlantic croaker (*Micropogonias undulatus*) in Chesapeake Bay, USA, 2004-2005. 136th Annual Meeting of the American Fisheries Society in Lake Placid, NY. September 2006.

*Lynch, P.D., E.D. Condon, M.J. Brush, and **R.J. Latour**. Filtration rates of phytoplankton by juvenile Atlantic menhaden, *Brevoortia tyrannus*, in Chesapeake Bay. 136th American Fisheries Society Annual Meeting in Lake Placid, NY. September 2006.

*Lynch, P.D., J. Gartland, R.A. Johnson, E.A. Brasseur, *K.A. McNamee, C.F. Bonzek, and **R.J. Latour**. Age-specific diet composition of summer flounder (*Paralichthys dentatus*) in Chesapeake Bay. 7th Annual Chesapeake Bay Integrated Research Symposium, Laurel, MD. April 2005.

Gartland, J., E.A. Brasseur, R.A. Johnson, *P.D. Lynch, and **R.J. Latour**. Age-specific diet composition of weakfish (*Cynoscion regalis*) in the Chesapeake Bay. 6th Annual Chesapeake Bay Integrated Research Symposium, Laurel, MD. February 2004.

Oral presentations

Speaker is first author; * indicates my graduate student; † Indicates graduate student collaboration

*Buchheister, A., C.F. Bonzek, J. Gartland, and **R.J. Latour**. Patterns and drivers of the demersal fish community in Chesapeake Bay. Talk at the 142nd American Fisheries Society Annual Meeting in St. Paul, MN. August 2012.

Gamble, R.J., J.S. Link, *A. Buchheister, C.M. Martinez, J.S. Collie, M.G. Frisk, T.J. Miller, H.W. Townsend, and **R.J. Latour**. Features and patterns within and across northeast U.S. estuarine, coastal, and oceanic ecosystems: An empirical analysis. Talk

at the 142nd American Fisheries Society Annual Meeting in St. Paul, MN. August 2012.

Bonzek, C.F., **R.J. Latour**, and J. Gartland. Development of surveys and databases in support of ecosystem based fisheries management. Talk at the 142nd American Fisheries Society Annual Meeting in St. Paul, MN. August 2012.

Wilberg, M., *A. Buchheister, **R.J. Latour**, and T. Miller. Effects of predation refugia on the sustainability of linked predator-prey fisheries. Talk at the 142nd American Fisheries Society Annual Meeting in St. Paul, MN. August 2012.

Wilberg, M., *A. Buchheister, **R.J. Latour**, and T. Miller. Effects of predation refugia on the sustainability of linked predator-prey fisheries. Talk at the 6th World Fisheries Conference, Edinburgh, Scotland. May 2012.

*Sobocinski, K., R.J. Orth, K.L. Heck, Jr., and **R.J. Latour**. Fishes in eelgrass beds in lower Chesapeake Bay: Community description and historical comparison. Talk at the 21st Biennial Conference of the Coastal and Estuarine Research Federation in Daytona Beach, FA. November 2011.

*Lynch, P.D., K.W. Shertzer, and **R.J. Latour**. Estimating the relative abundance of highly migratory bycatch species. Talk at the 141st American Fisheries Society Annual Meeting in Seattle, WA. September 2011.

*Buchheister, C.F. Bonzek, J. Gartland, and **R.J. Latour**. Coherent annual trends in diets of Chesapeake Bay fishes. Talk at the 141st American Fisheries Society Annual Meeting in Seattle, WA. September 2011.

*Sobocinski, K., R.J. Orth, K.L. Heck, Jr., and **R.J. Latour**. Fishes in eelgrass beds in lower Chesapeake Bay: Community description and historical comparison. Talk at the 141st American Fisheries Society Annual Meeting in Seattle, WA. September 2011.

*Wor, C., J. Graves, and **R.J. Latour**. Evaluating the impacts of stock structure uncertainty on sailfish stock assessment in the Atlantic Ocean. Talk at the 141st American Fisheries Society Annual Meeting in Seattle, WA. September 2011.

Horodysky, A.Z., R.W. Brill, P.G. Bushnell, J.A. Musick, and **R.J. Latour**. Comparative metabolic rates of common western north Atlantic sciaenid fishes. Talk at the 141st American Fisheries Society Annual Meeting in Seattle, WA. September 2011.

Vogelbein, W.K., D.T. Gauthier, **R.J. Latour**, H.D. Gaff, and J.M. Hoenig. Mycobacteriosis in Chesapeake Bay striped bass. Talk at the 141st American Fisheries Society Annual Meeting in Seattle, WA. September 2011.

*Lynch, P.D., K.W. Shertzer, and **R.J. Latour**. Estimating the relative abundance of highly migratory bycatch species. Talk at the 25th Annual Meeting of the Tidewater Chapter of the American Fisheries Society, Gloucester Point, VA, March 2011.

- Latour, R.J.**, D.T. Gauthier, J. Gartland, C.F. Bonzek, H.D. Gaff, K.A. McNamee, and W.K. Vogelbein. Impacts of mycobacteriosis on the growth of striped bass (*Morone saxatilis*) in Chesapeake Bay. Talk at the 25th Annual Meeting of the Tidewater Chapter of the American Fisheries Society, Gloucester Point, VA, March 2011.
- Gauthier, D.T., J. Xiao, **R.J. Latour**, H.D. Gaff, K.A. Reece, and W.K. Vogelbein. Ecology of fish-pathogenic mycobacteria in Chesapeake Bay. Talk at the 25th Annual Meeting of the Tidewater Chapter of the American Fisheries Society, Gloucester Point, VA, March 2011.
- Gauthier, D.T., J. Xiao, **R.J. Latour**, H.D. Gaff, K.A. Reece, and W.K. Vogelbein. Ecology of fish-pathogenic mycobacteria in Chesapeake Bay. Talk at the 36th Eastern Fish Health Workshop in Mt. Pleasant, SC. March 2011.
- †Funkey, C.P., **R.J. Latour**, D.A. Bronk. Abiotic release of labile nitrogen from effluent organic nitrogen. Talk at the Advancing Science of Limnology and Oceanography Aquatic Sciences Winter Meeting in San Juan, PR. February 2011.
- Latour, R.J.**, E.J. Hilton, B.E. Watkins, T.D. Tuckey, *P.D. Lynch, and J.E. Olney. Evaluating restoration efforts of American shad in Virginia. Talk at the 140th American Fisheries Society Annual Meeting in Pittsburgh, PA. August 2010.
- Horodysky, A.Z., R.W. Brill, E.J. Warrant, J.A. Musick, **R.J. Latour**. Visual ecology of benthic and pelagic piscivores in coastal mid-Atlantic waters: implications for predator-prey dynamics. Talk at the 140th American Fisheries Society Annual Meeting in Pittsburgh, PA. August 2010.
- Horodysky, A.Z., R.W. Brill, M.L. Fine, J.A. Musick, and **R.J. Latour**. Acoustic pressure and particle motion thresholds in six sciaenid fishes. Talk at the Joint Meeting of Ichthyologists and Herpetologists, Providence, RI. July 2010.
- †Schloesser, R., M.C. Fabrizio, **R.J. Latour**, G.C. Garman, B. Greenlee, M. Groves, and J. Gartland. Ecological role of blue catfish in Chesapeake Bay communities and implications for management. Talk at the 2nd International Catfish Symposium, St. Louis, MO, June 2010.
- *Lynch, P.D., J.E. Graves, **R.J. Latour**. Quantitative challenges in the assessment of highly migratory bycatch species: a case study of the Atlantic marlins. Talk at the 139th American Fisheries Society Annual Meeting in Nashville, TN. August 2009.
- *Buchheister, A., and **R.J. Latour**. Assessing summer flounder diets with stable isotopes using multiple tissues. Talk at the 138th American Fisheries Society Annual Meeting in Ottawa, ON, Canada. August 2008.
- Latour, R.J.**, J. Gartland, and C.F. Bonzek. An analysis of current and alternate management strategies for summer flounder (*Paralichthys dentatus*) recreational fishery in Virginia. Talk at the 138th American Fisheries Society Annual Meeting in Ottawa, ON, Canada. August 2008.

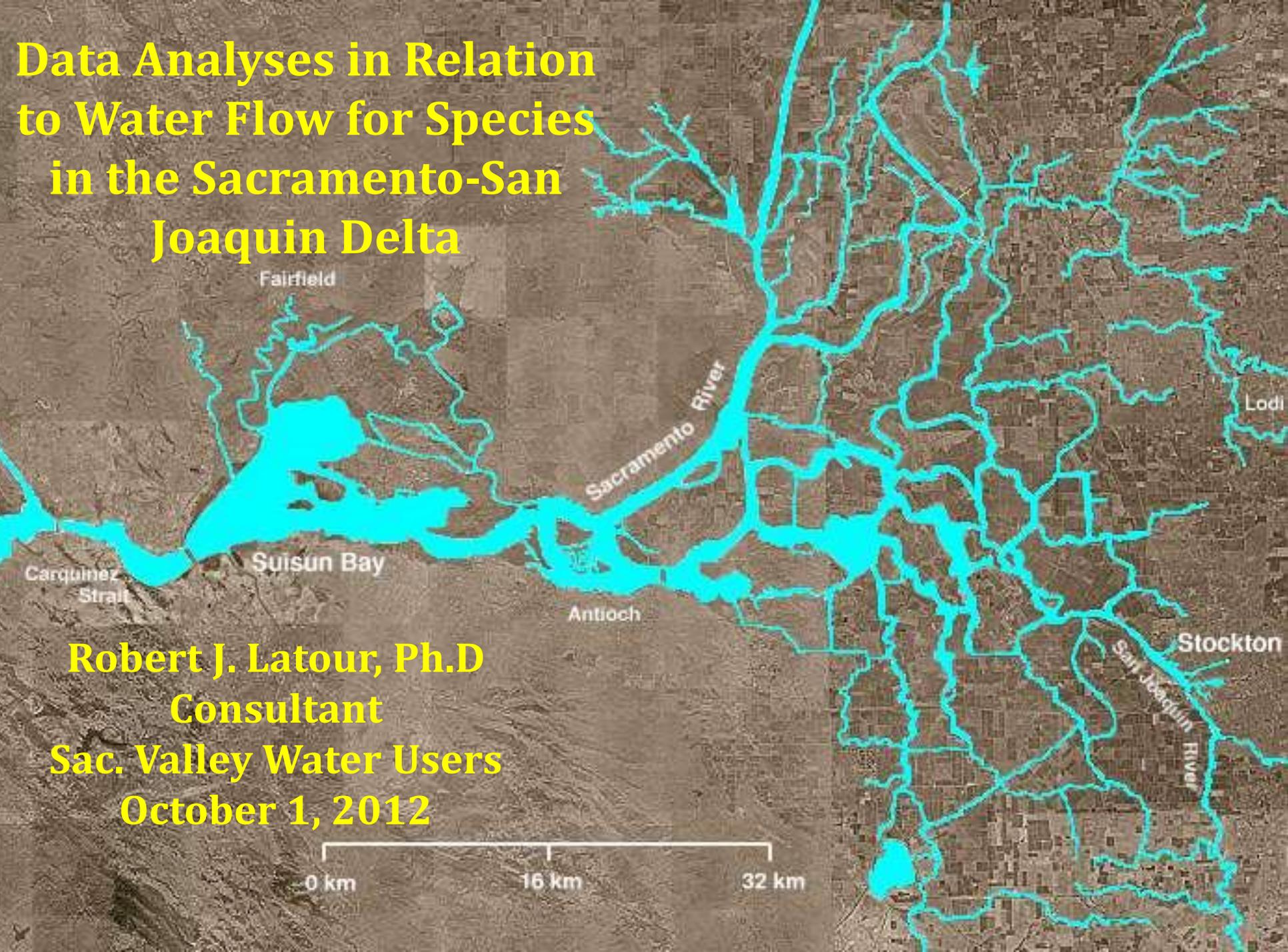
- *Horodysky, A.Z., R.W. Brill, E.J. Warrant, J.A. Musick, and **R.J. Latour**. Visual function in Chesapeake Bay's predatory fishes. VIIIth International Congress Biology of Fish, Portland, OR. July, 2008.
- *Lynch, P.D., M.J. Brush, E.D. Condon, and **R.J. Latour**. Modeling the feeding ecology of Atlantic menhaden to address water quality concerns in Chesapeake Bay. Talk at the 138th American Fisheries Society Annual Meeting in Ottawa, ON, Canada. August 2008.
- *Woodward, J., **R.J. Latour**, M.C. Fabrizio, and C.F. Bonzek. Using linear models to validate recruitment indices. Talk at the 138th American Fisheries Society Annual Meeting in Ottawa, ON, Canada. August 2008.
- van Montfrans, J., **R.J. Latour**, and D. Combs. Predation impacts by striped bass and croaker on juvenile blue crabs in seagrass beds, Chesapeake Bay, VA. Talk at the 37th Benthic Ecology Meeting in Providence, RI. April 2008.
- Bonzek, C.F., **R.J. Latour**, and J. Gartland. Are piscivores in Chesapeake Bay forage limited? Talk at the 137th American Fisheries Society Annual Meeting in San Francisco, CA. September 2007.
- *Horodysky, A.Z., R.W. Brill, J.A. Musick, and **R.J. Latour**. Seeing the forage through the trees: visual function in Chesapeake Bays predatory fishes. Talk at the 137th American Fisheries Society Annual Meeting in San Francisco, CA. September 2007.
- Latour, R.J.**, J. Gartland, C.F. Bonzek. The [mis]calculation of diet indices. Talk at the 137th American Fisheries Society Annual Meeting in San Francisco, CA. September 2007.
- *Lynch, P.J., M.J. Brush, E.D. Condon, and **R.J. Latour**. Ingestion rates of phytoplankton by Atlantic Menhaden (*Brevoortia tyrannus*) in Chesapeake Bay. Talk at the 137th American Fisheries Society Annual Meeting in San Francisco, CA. September 2007.
- Parthre, D.J., C.F. Bonzek, J. Gartland, and **R.J. Latour**. Feeding ecology of summer flounder in Chesapeake Bay, USA, 2004-2006. Talk at the 137th American Fisheries Society Annual Meeting in San Francisco, CA. September 2007.
- Latour, R.J.**, K.A. McNamee, D.T. Gauthier, J. Gartland, C.F. Bonzek, and W.F. Vogelbein. Impacts of mycobacteriosis on the biology and ecology of striped bass (*Morone saxatilis*) in Chesapeake Bay. Invited seminar at the Center for Marine Science Technology, North Carolina State University, Morehead City, NC. March 2007.
- Latour, R.J.** Small fish, big controversy: Menhaden in Chesapeake Bay. Invited talk in the Virginia Institute of Marine Science After Hours Lecture Series, VIMS, Gloucester Point, VA. February 2007.
- Latour, R.J.**, D.T. Gauthier, C.F. Bonzek, and W.K. Vogelbein. Epizootiology of mycobacteriosis in Chesapeake Bay striped bass (*Morone saxatilis*). Invited seminar at Stony Brook University, Stony Brook, NY. September 2006.

- Bonzek, C.F., **R.J. Latour**, and M.C. Fabrizio. Judging the effectiveness of a new fishery-independent survey in Chesapeake Bay: A cross-validation approach. Talk at the 136th American Fisheries Society Annual Meeting in Lake Placid, NY. September 2006.
- Fabrizio, M.C., **R.J. Latour**, and C.F. Bonzek. Patterns in abundance of juvenile fishes in Chesapeake Bay. Talk at the 136th American Fisheries Society Annual Meeting in Lake Placid, NY. September 2006.
- [†]Hoffman, J.C., C.F. Bonzek, **R.J. Latour**. A novel approach to abundance estimation of fishes in Chesapeake Bay: application to Atlantic croaker. Talk at the 136th American Fisheries Society Annual Meeting in Lake Placid, NY. September 2006.
- *Horodysky, A.Z., R.W. Brill, J.A. Musick, and **R.J. Latour**. Electroretinographic assessment of visual function in six commercially and recreationally important estuarine fishes. Talk at the 136th American Fisheries Society Annual Meeting in Lake Placid, NY. September 2006.
- Latour, R.J.**, D.T. Gauthier, C.F. Bonzek, and W.F. Vogelbein. Epizootiology of mycobacteriosis in Chesapeake Bay striped bass (*Morone saxatilis*). Talk at the 136th American Fisheries Society Annual Meeting in Lake Placid, NY. September 2006.
- *McNamee, K.A., C.F. Bonzek, J. Gartland, and **R.J. Latour**. Estimating caloric intake by diseased and non-diseased striped bass (*Morone saxatilis*) in Chesapeake Bay. Talk at the 136th American Fisheries Society Annual Meeting in Lake Placid, NY. September 2006.
- Gauthier, D.T., **R.J. Latour**, C.F. Bonzek, and W.F. Vogelbein. Mycobacteriosis in Chesapeake Bay striped bass (*Morone saxatilis*): Large-scale field survey. Talk at the 5th International Symposium on Aquatic Animal Health in San Francisco, CA. September 2006.
- *Horodysky, A.Z., R.W. Brill, J.A. Musick, and **R.J. Latour**. Electroretinographic assessment of visual function in six commercially and recreationally important estuarine fishes. Talk at the VIIth International Congress on the Biology of Fish in St. Johns, Newfoundland, CAN. July 2006.
- Latour, R.J.**, C.F. Bonzek, and J. Gartland. Tropic ecology of fishes in Chesapeake Bay. Invited seminar at Chesapeake Biological Laboratory, Solomons, MD. April 2006.
- *Horodysky, A.Z., D.W. Kerstetter, **R.J. Latour**, and J.E. Graves. Habitat utilization of white marlin released from commercial and recreational fishing gears. Talk at the 4th International Billfish Symposium in Avalon, Santa Catalina Island, CA. November 2005.
- Latour, R.J.**, J.F. Walter III, A.Z. Horodysky, J.E. Graves and D.W. Kerstetter. A simulation of sampling frequency and transmission percentage for PSATs: application to white marlin. Talk at the 4th International Billfish Symposium in Avalon, Santa Catalina Island, CA. November 2005.

- Brush, M.J. and **R.J. Latour**. Coupling top-down, multispecies fisheries models to simplified nutrient-plankton models in support of nutrient and multispecies management in Chesapeake Bay. Talk at the 18th Biennial Conference of the Estuarine Research Federation in Norfolk, VA. October 2005.
- Latour, R.J.**, J. Gartland, and C.F. Bonzek. Do the stomach contents of striped bass and weakfish suggest localized depletion of Atlantic menhaden in Chesapeake Bay? Talk at the 18th Biennial Conference of the Estuarine Research Federation in Norfolk, VA. October 2005.
- van Montfrans, J., D.M. Combs, and **R.J. Latour**. Fish predation impacts on juvenile blue crabs in Chesapeake Bay seagrass beds. Talk at the 18th Biennial Conference of the Estuarine Research Federation in Norfolk, VA. October 2005.
- Bonzek, C.F., **R.J. Latour**, and J. Gartland. Examining the influence of spatial and temporal diet variability on estimates of predator consumption in a dynamic estuary. Talk at the 135th American Fisheries Society Annual Meeting in Anchorage, AK. September 2005.
- Goldman, K.J., S.D. Anderson, **R.J. Latour**, and J.A. Musick. Endothermy and thermoregulation in the salmon shark, *Lamna ditropis*. Talk at the 135th American Fisheries Society Annual Meeting in Anchorage, AK. September 2005.
- *Horodysky, A.Z., D.J. Parthre, J.A. Musick, and **R.J. Latour**. Trophic interactions of Atlantic croaker and spot in Chesapeake Bay. Talk at the 135th American Fisheries Society Annual Meeting in Anchorage, AK. September 2005.
- Latour, R.J.**, J. Gartland, and C.F. Bonzek. Do the stomach contents of striped bass and weakfish suggest localized depletion of Atlantic menhaden in Chesapeake Bay? Talk at the 135th American Fisheries Society Annual Meeting in Anchorage, AK. September 2005.
- *Horodysky, A.Z., **R.J. Latour**, J.A. Musick, B. Deffenbaugh, and R.W. Brill. Hearing abilities of sciaenid fishes determined via auditory brainstem response using a novel echo-cancellation algorithm. Talk at the Joint Meeting of Ichthyologists and Herpetologists in Tampa, FL. July 2005.
- Latour, R.J.**, J.M. Hoenig, W.S. Hearn, and K.H. Pollock. A framework for estimating natural mortality. Talk at the ASMFC Natural Mortality Workshop in Baltimore, MD. April 2005.
- Hoenig, J.M., **R.J. Latour**, and P.W. Sadler. What's wrong with my tagging study? An investigation of heterogeneity. Talk at the 134th American Fisheries Society Annual Meeting in Madison, WI. August 2004.
- Latour, R.J.**, J. Gartland, and C.F. Bonzek. Abundance, distribution, age-structure, and diet composition of weakfish (*Cynoscion regalis*) in Chesapeake Bay. Talk at the 134th American Fisheries Society Annual Meeting in Madison, WI. August 2004.

- Pollock, K.H., J. Honghua, J.M. Hoenig, and **R.J. Latour**. Incorporating catch and release fishing into age-dependent tag return models. Talk at the 134th American Fisheries Society Annual Meeting in Madison, WI. August 2004.
- Brush, M.J. and **R.J. Latour**. Multispecies modeling of Atlantic menhaden and its predators in Chesapeake Bay II: coupling species-specific bioenergetics models. Talk at the 133rd American Fisheries Society Annual Meeting in Quebec City, PQ, Canada. August 2003.
- Latour, R.J.**, M.J. Brush, and A. Beattie. Multispecies modeling of Atlantic menhaden and its predators in Chesapeake Bay I: An Ecopath with Ecosim (EwE) approach. Talk at the 133rd American Fisheries Society Annual Meeting in Quebec City, PQ, Canada. August 2003.
- Latour, R.J.**, J.E. Olney, B.A. Versak, S.A. Welsh, H. T. Hornick, and R.E. Harris, Jr. Mortality estimates of coastally migrating striped bass of Chesapeake Bay origin. Talk at the 132nd American Fisheries Society Annual Meeting in Baltimore, MD. August 2002.
- Latour, R.J.**, J.E. Olney, B.A. Versak, H. T. Hornick, and R.E. Harris, Jr. Estimates of fishing mortality for striped bass resident to Chesapeake Bay. Talk at the 132nd American Fisheries Society Annual Meeting in Baltimore, MD. August 2002.
- Latour, R.J.**, J.M. Hoenig, J.E. Olney, and K.H. Pollock. Diagnostics for multiyear tagging models - tests for lack of complete mixing and examination of patterns in residuals. Talk at the 131st American Fisheries Society Annual Meeting in Phoenix, AZ. August 2001.
- Latour, R.J.**, K.H. Pollock, C.A. Wenner, and J.M. Hoenig. Estimates of fishing and natural mortality rates for South Carolina red drum. Talk at the 129nd American Fisheries Society Annual Meeting in Phoenix, AZ. August 1999.

Data Analyses in Relation to Water Flow for Species in the Sacramento-San Joaquin Delta



Fairfield
Carquinez Strait
Suisun Bay

Sacramento River
Antioch

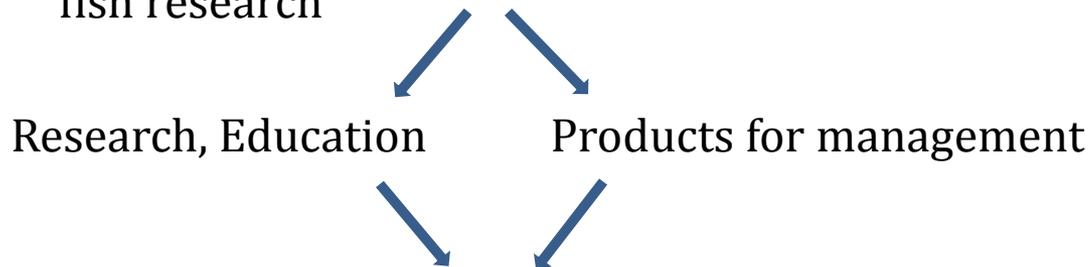
Lodi
Stockton
San Joaquin River

Robert J. Latour, Ph.D
Consultant
Sac. Valley Water Users
October 1, 2012

0 km 16 km 32 km

Professional Background

- Ph.D., Biomathematics, North Carolina State University
- Associate Professor, Department of Fisheries Science, Virginia Institute of Marine Science (VIMS)
- VIMS' mission: research, education, advisory service
 - School of Marine Science, College of William & Mary
 - Virginia state agency – Dep't of Fisheries Science
 - Implement fish monitoring
 - Provide scientific support to regulatory agencies
- VIMS uses surveys as platforms for state and regional fish research



- ChesMMAP – mainstem Chesapeake Bay
- NEAMAP – coastal Atlantic, NC to New England



Chesapeake Bay

Methods to Improve Understanding of Fish Populations

- *Apply standard catch-per-trawl-tow analysis to DFG raw fall mid-water trawl (FMWT) data*



Delta smelt

- Existing FMWT abundance index is based on (average fish caught) x (water volume), so index values are difficult to interpret
- No documented understanding of how the number of fish caught per individual trawl tow relates to different environmental variables
- None of the variables considered, including spring flows, explain much of the overall variation in trawl data for pelagic fishes
- *Year* is a ‘better’ predictor of pelagic abundance than spring flow – *Year* is a composite of environmental conditions in a given year
- *Different fish species have varying relationships with different flow variables*
 - Wide range of trawl catches at different levels of flow
 - Delta smelt abundance has an inverse relationship with the “best” fitting spring flow variable
- *Turbidity has a stronger relationship with pelagic fish abundance than flow does*
 - Turbidity coefficient is twice as large as ‘best’ fitting flow variable for longfin³

Methods to Improve Understanding of Fish Populations **(cont)**

- ***Further catch-per-tow analyses could:***

- *Identify broad temporal/spatial shifts in habitat use over 1967-2010 FMWT period*

- *Analyze turbidity-abundance relationship with more robust turbidity data: literature indicates significant reductions in Delta turbidity occurred concurrent with pelagic fish population declines*



Longfin smelt

- ***Reallocate existing resources to maximize information gathered by FMWT***

- *FMWT catches very few of target species per tow: 1967-2010 average = 0.17 delta smelt per tow*

- *Similar trawls in Chesapeake Bay catch 10-20 of target species per tow*

- *It may be possible to reduce number of tows without increasing error of indices and reallocate resources to pilot trawl projects:*

- *Sample more locations and more depths to identify changes in habitat use*

- *Investigate diel movements*

- *Investigate trawl net performance*

Scope of Analysis

- Address workshop notice's questions about uncertainty in 2010 Delta flow criteria report analysis and new information
- Articles suggest a positive relationship between flow and abundance:
 - Jassby et al. 1995; Kimmerer 2002: X2 ↑ leads to a ↓ in species relative abundance
 - Sommer et al. 2007: ↑ flow leads to ↑ species relative abundance



Threadfin shad

- Prior analyses based on abundance indices or coarse metrics of catch-per-trawl based on DFG FMWT survey data
- Issues analyzed:
 - Uncertainties in FMWT survey methodology and DFG abundance indices
 - Analysis of FMWT survey data to provide standardized abundance estimates and error margins (estimates of precision)
 - Application of standard statistical methods to analyze relationships between raw of catch-per-trawl data and spring flow variables
- Develop recommendations for further analysis with existing resources

Initial Impressions & Analytical Direction

- **Uncertainty in FMWT abundance indices**
 - FMWT abundance index difficult to interpret because it is based on (fish caught) x (water volume) – What does change from 11864 to 7408 (fish caught) x (water volume) mean?
 - Index has no estimate of error range
- **Apply statistical models to raw data to address FMWT issues**
 - Reliance on USFWS work, paper by USFWS biologist (Newman 2008) similarly identified constraints with FMWT
 - Newman (2008) suggested statistical models with additional covariates for better understanding of FMWT data

SAN FRANCISCO ESTUARY & WATERSHED SCIENCE
Sponsored by the Estuarine Program and the UC Davis Affiliate Institute of the Environment

 **Peer Reviewed**

Title:
Sample design-based methodology for estimating delta smelt abundance

Journal Issue:
[San Francisco Estuary and Watershed Science, 6\(3\)](#)

Author:
[Newman, Ken B.](#), U.S. Fish and Wildlife Service

Publication Date:
2008

Publication Info:
San Francisco Estuary and Watershed Science, John Muir Institute of the Environment, UC Davis

Permalink:
<http://escholarship.org/uc/item/99p428z6>

Keywords:
gear selectivity, Horvitz-Thompson, Hypomesus transpacificus, ratio estimators, stratified random sampling

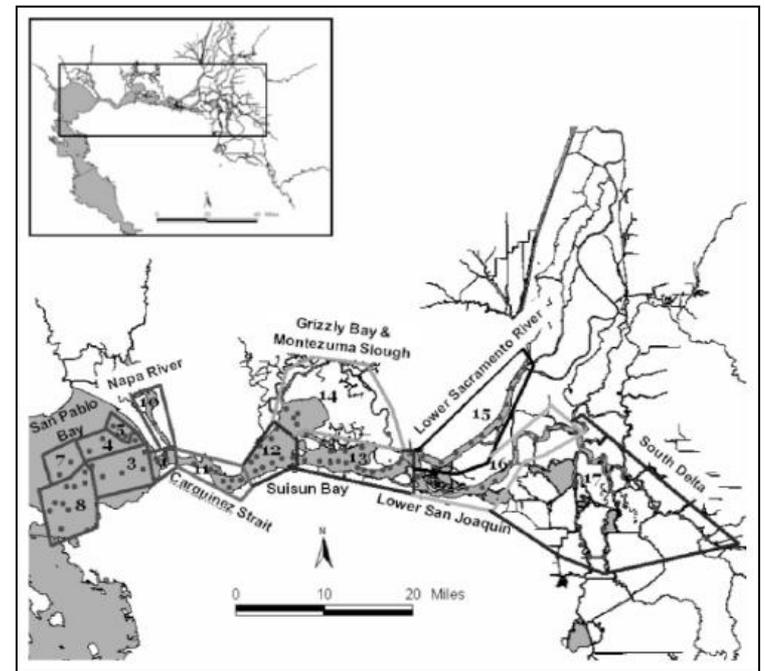
Abstract:
A sample design-based procedure for estimating pre-adult and adult delta smelt abundance is described. Using data from midwater trawl surveys taken during the months of September, October, November, and December for the years 1990 through 2006 and estimates of size selectivity of the gear from a covered codend experiment, stratified random sample ratio estimates of delta smelt abundance were made per month. The estimation procedure is arguably an improvement over the dimensionless delta smelt indices that have been used historically in that (1) the volume sampled is used in a manner that leads to directly interpretable numbers and (2) standard errors are easily calculated. The estimates are quite imprecise, i.e., coefficients of variation in the range of 100% occurred. The point estimates are highly correlated with the monthly indices, and conclusions on abundance declines are quite similar. However, both the estimates and indices may suffer from selection biases if the trawl samples are not representative of the true densities. Future work is needed in at least three areas: (1) gathering additional information to determine the validity of assumptions made, in particular determining the possible degree of selection bias; (2) developing procedures that utilize survey data gathered from earlier life history stages, such as larval surveys; (3) embedding a life-history model into the population estimation procedure.

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Initial Impressions

- **Uncertainties in FMWT data**
 - **Low catch rates of target species. 1967-2010 averages:**
 - Delta smelt: 0.17 fish-per-tow
 - Splittail: 0.02 fish-per-tow
 - Starry flounder: 0.04 fish-per-tow
 - *Compare:* VIMS Juvenile Finfish Trawl Survey – since 1950s, 20 and 10 fish-per-tow of targeted species
- **FMWT does not account for habitat changes**
 - fixed sampling stations that would not identify changes in habitat use
- **Submissions to SWRCB show changes in habitat use**
 - Independent science panel, p. 8



Newman 2008

Independent Science Panel:

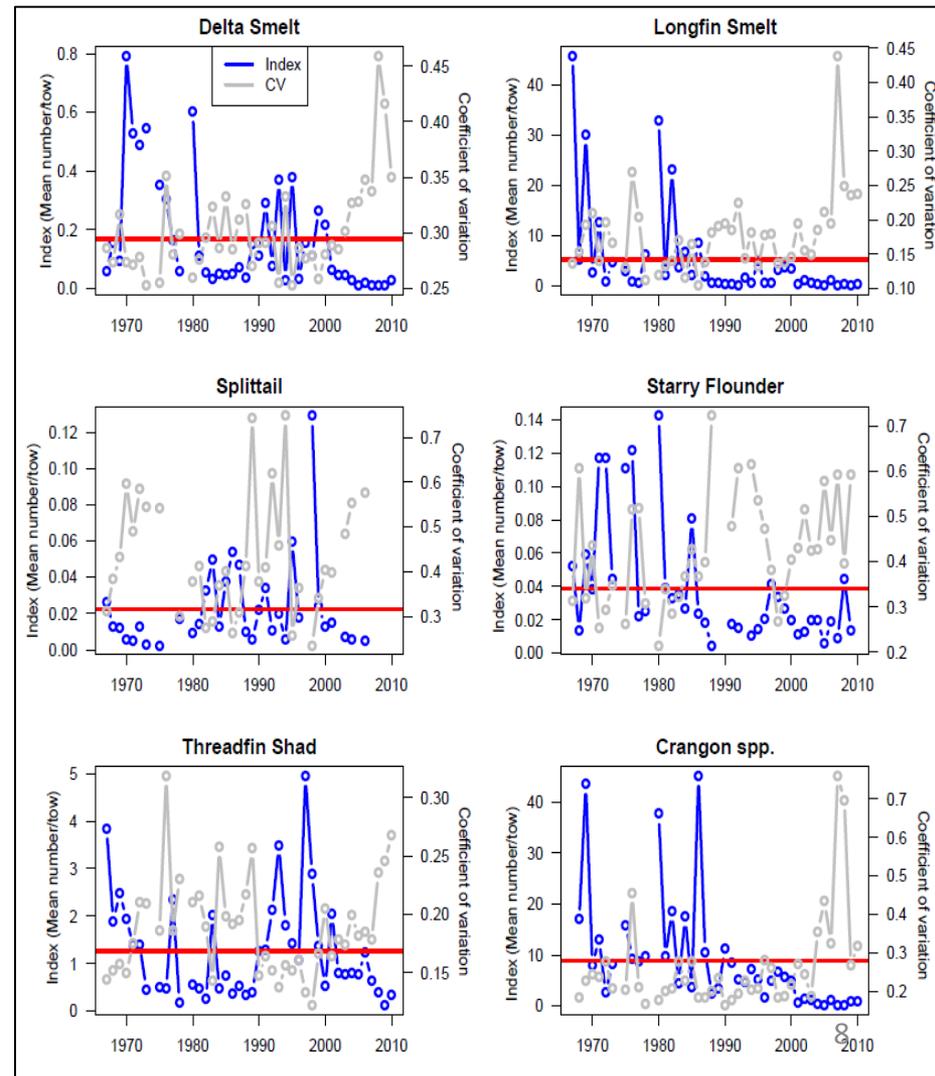
“[L]ongfin smelt distribution has shifted to downstream bays and into deeper waters”

“While the center of distribution of delta smelt is still in the low-salinity zone, the species has shown evidence of increasing use of Cache Slough Complex in the north Delta.”

“Threadfin shad center of distribution used to be in the south Delta . . . , but the species has recently been concentrated in the Sacramento Deep Water Ship Channel”

Statistical Analysis – Initial Steps

- Applied generalized linear model (GLM) to FMWT data
 - GLMs commonly are used to derive abundance indices (mean catch-per-tow) and to examine significance of covariates like flow and turbidity
- Due to low encounter-per-tow, I analyzed raw FMWT data in two categories:
 - *Likelihood of catching at least one fish of a species* (presence/absence – binomial)
 - *No. of fish caught on successful tows* (relative abundance – lognormal)
- The following covariates all were statistically significant
 - *Year*: discernible trends in catch-per-tow over years
 - *Month*: differing catch-per-tow results in different months
 - *Area*: differing catch-per-tow results due to location of tow within Delta
 - *Secchi*: ↑ catch-per-tow with ↑ turbidity
- Coefficients of variation (CV) are acceptable to support analyses



Statistical Analysis – ‘Best’ Fitting Flow Covariates

- Substituted 16 different ‘spring’ flow variables for *Year* in statistical analysis

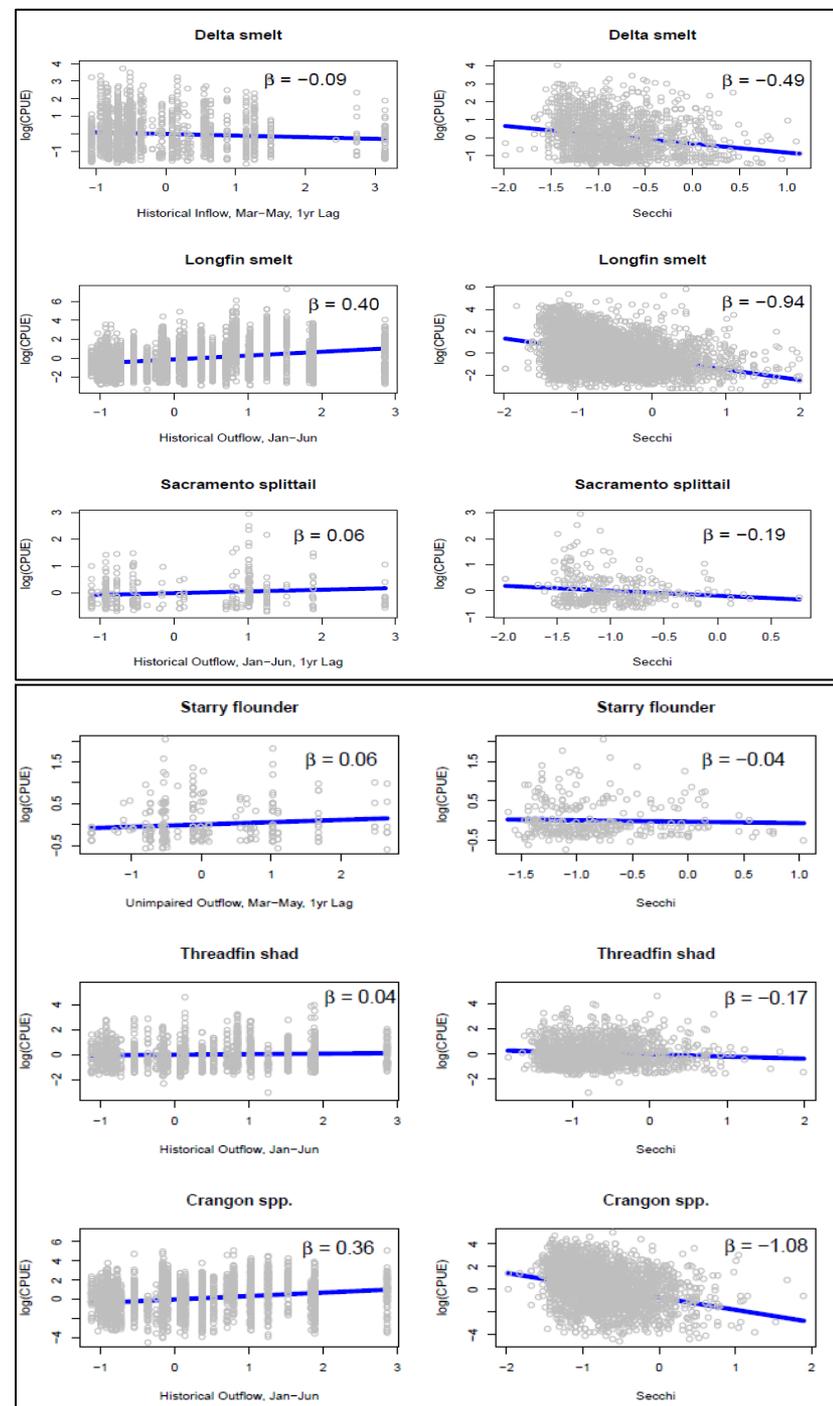
<u>Species</u>	<u>Presence/Absence</u> (Binomial $\Delta AIC=0$)	<u>Abundance</u> (Lognormal $\Delta AIC=0$)
Delta smelt	Unimpaired Inflow, Jan-Jun	Historical Inflow, Mar-May, 1yr Lag
Longfin smelt	Unimpaired Inflow, Jan-Jun	Historical Outflow, Jan-Jun
Sacramento splittail	Unimpaired Inflow, Jan-Jun	Historical Outflow, Jan-Jun, 1yr Lag
Starry flounder	Historical Outflow, Jan-Jun	Unimpaired Outflow, Mar-May
Threadfin shad	Historical Outflow, Jan-Jun	Historical Outflow, Jan-Jun
Crangon spp.	Unimpaired Outflow, Mar-May	Historical Outflow, Jan-Jun

- Different ‘spring’ flow covariates were the ‘best’ fit for different species and for presence/absence and abundance

- *Unimpaired flow* covariates were most common ‘best’ fitting covariate
 - *Unimpaired flow* is calculated, not actual, flow
 - ‘Best’ fit does not guarantee any particular level of biological response

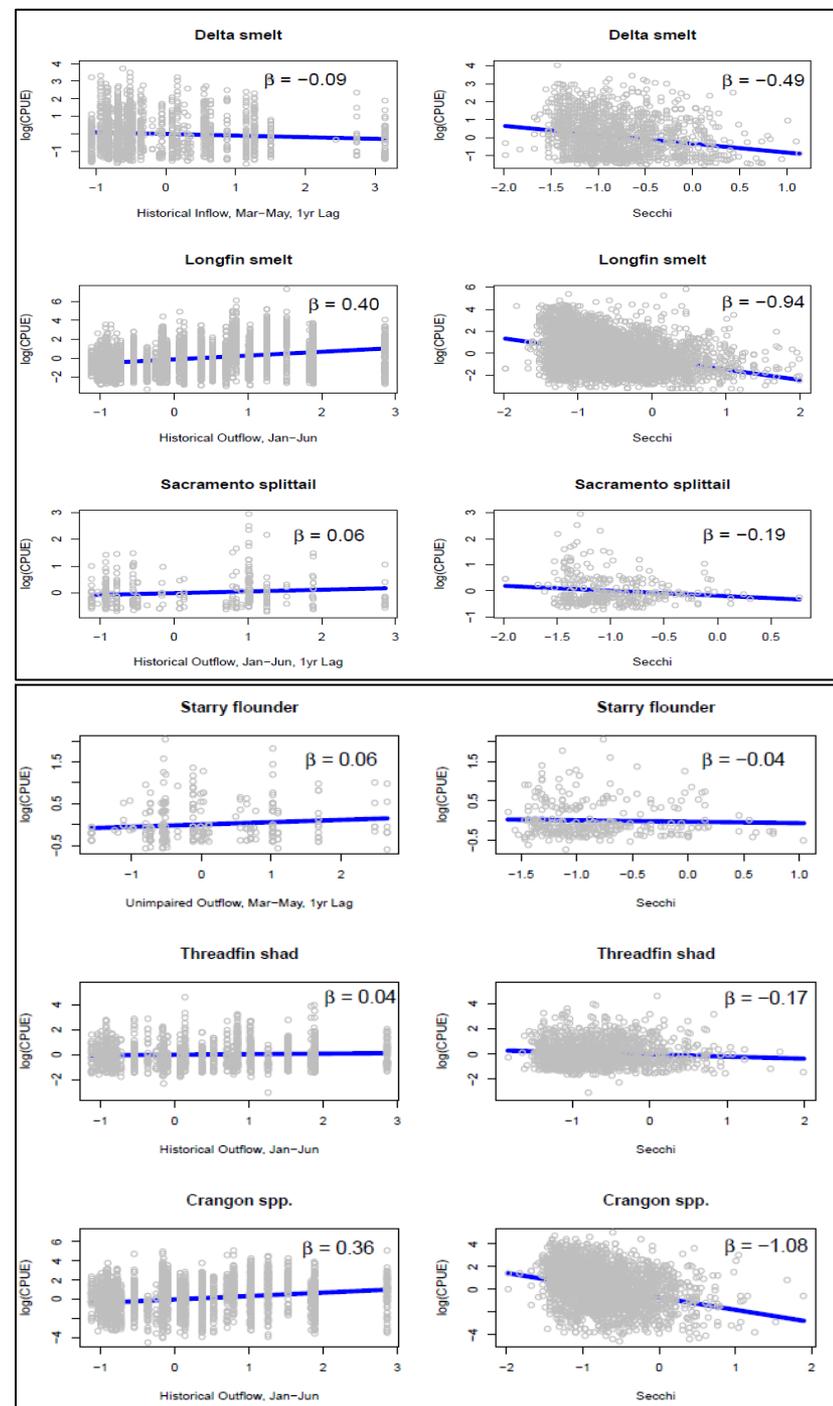
Statistical Analysis – Flows

- ***CPUE analysis shows widely variable flow-abundance relationships, with turbidity relating more strongly to relative abundance***
- Flow relationships based only the small portion of tows that actually caught the target species
- ‘Best’ fitting spring flow variables show widely varying relationships with trawl catches
- ‘Best’ fitting flow variable was different for different species



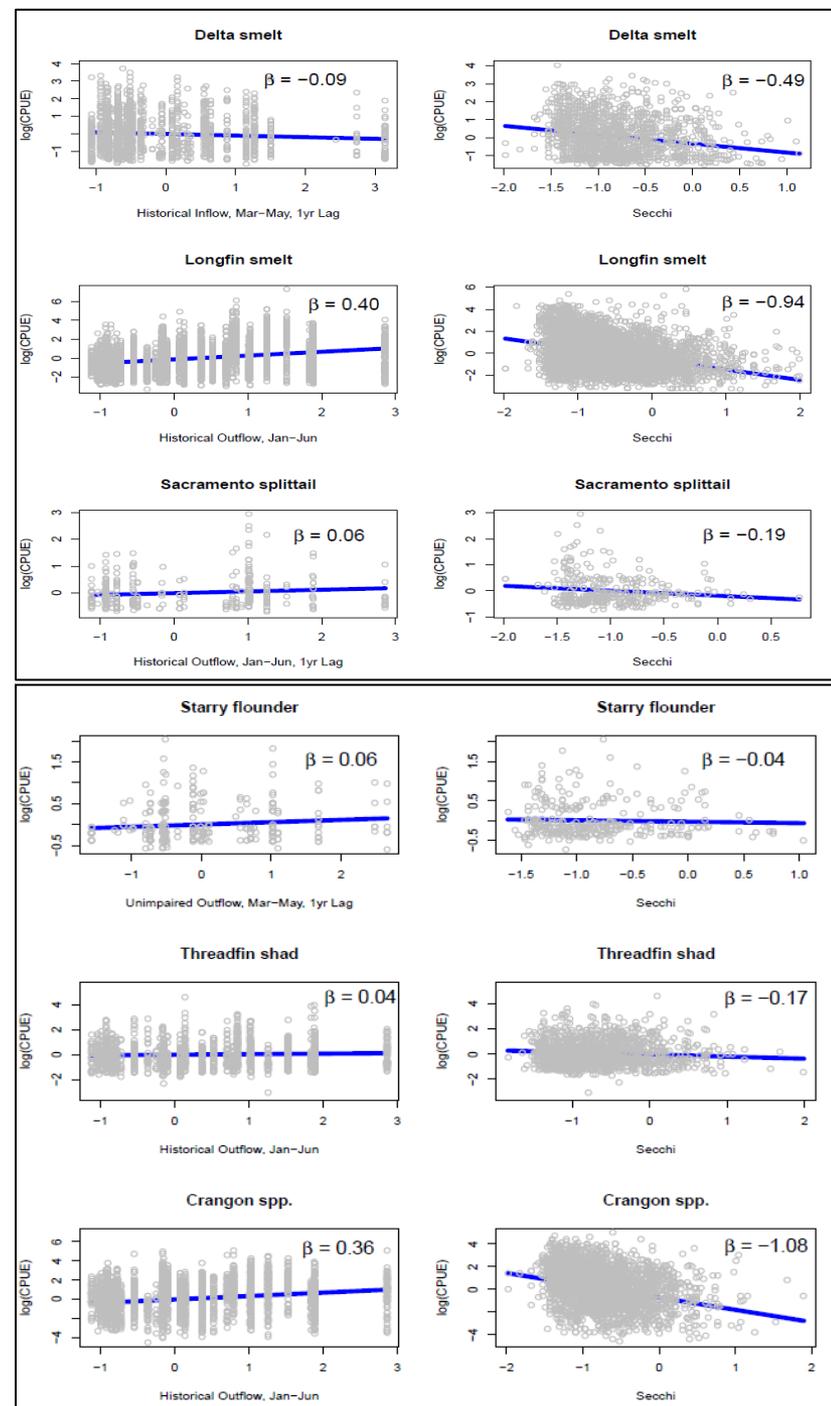
Statistical Analysis – Flows (cont)

- **No flow variable explains much of the variation in pelagic fish catch data**
 - Statistically significant relationships exist, i.e., coefficients are different than 0. Statistical significance does not always equal biological significance
 - The high degree of variability at each flow level means that flow levels, by themselves, do not have much biological significance
 - Specifically, flow variables' very small coefficients indicate that spring flow does not strongly relate to fish catch



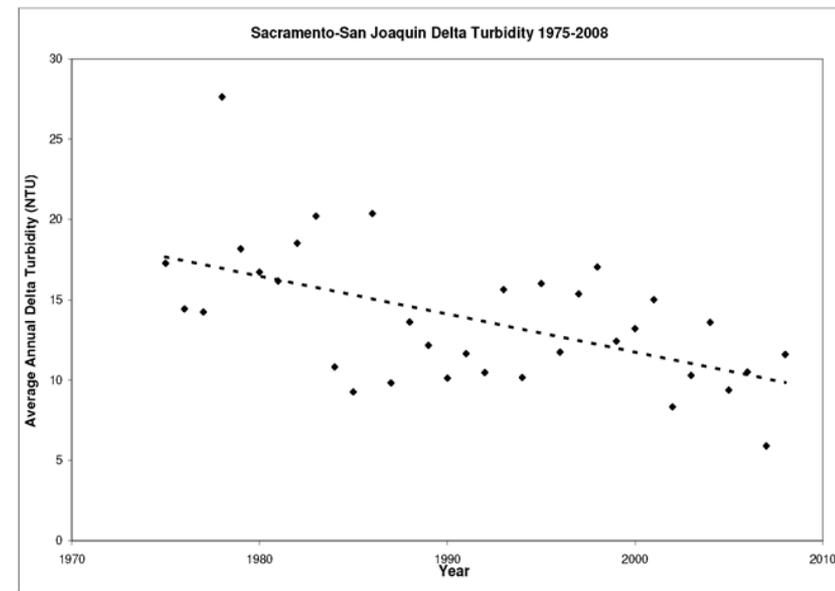
Statistical Analysis – Flows (cont)

- **Different species have different relationships with ‘best’ fit spring flow variable**
 - Delta smelt’s abundance has an inverse relationship with ‘best’ fit flow variable
 - Longfin smelt’s abundance relationship with turbidity is double its relationship with the ‘best’ fit flow variable
- **Turbidity consistently has a stronger relationship (i.e., higher β) with abundance than flow does**
 - Lower Secchi depth means higher turbidity
 - Turbidity has a positive relationship with abundance



Statistical Analysis – Turbidity

- ***Turbidity has stronger relationship with abundance than flow does***
 - Turbidity-abundance relationship is at least twice as strong as flow-abundance relationship
- ***Delta turbidity has declined significantly as pelagic fish populations have declined***
 - 40% turbidity decline 1975-2008
 - Step-decline in Delta turbidity in late 1990s
- ***Turbidity may affect pelagic fish abundance and surveys in many ways – higher turbidity means:***
 - Decreased predation
 - Higher primary productivity
 - Decreased gear avoidance



Cloern et al. 2011

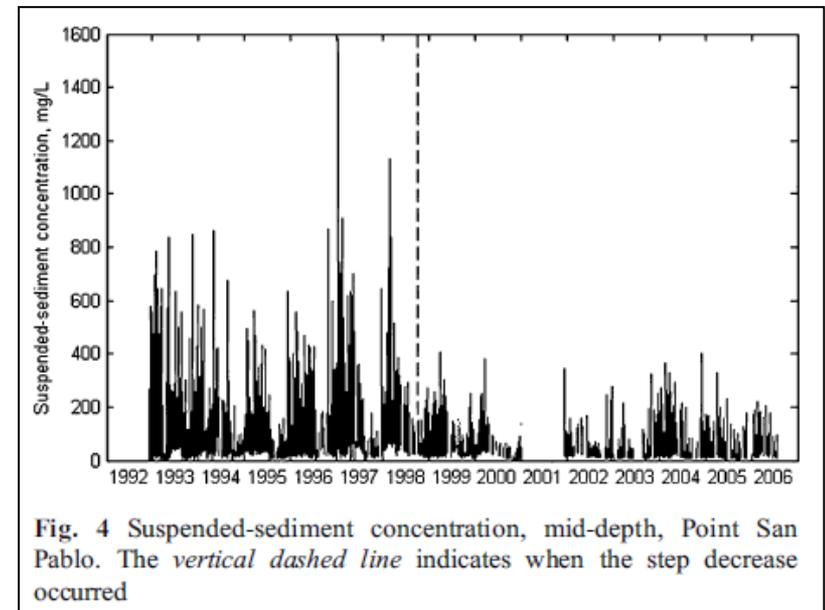


Fig. 4 Suspended-sediment concentration, mid-depth, Point San Pablo. The vertical dashed line indicates when the step decrease occurred

Schoellhamer 2011

Recommendations – Existing Data

- **SWRCB could further analyze existing data to identify trends and most important habitat and implementation measures**
- **Turbidity – SWRCB should investigate with more robust turbidity data**
 - *Secchi* is a coarse measure of turbidity
 - More robust data is available – Schoellhamer (2011) uses total suspended solids data
- **Habitat use – trends in FMWT catch data**
 - Analyzing trends in *Region* factor in FMWT data could identify changing habitat use and subregions for specific attention
 - Changes in distribution noted by science panel

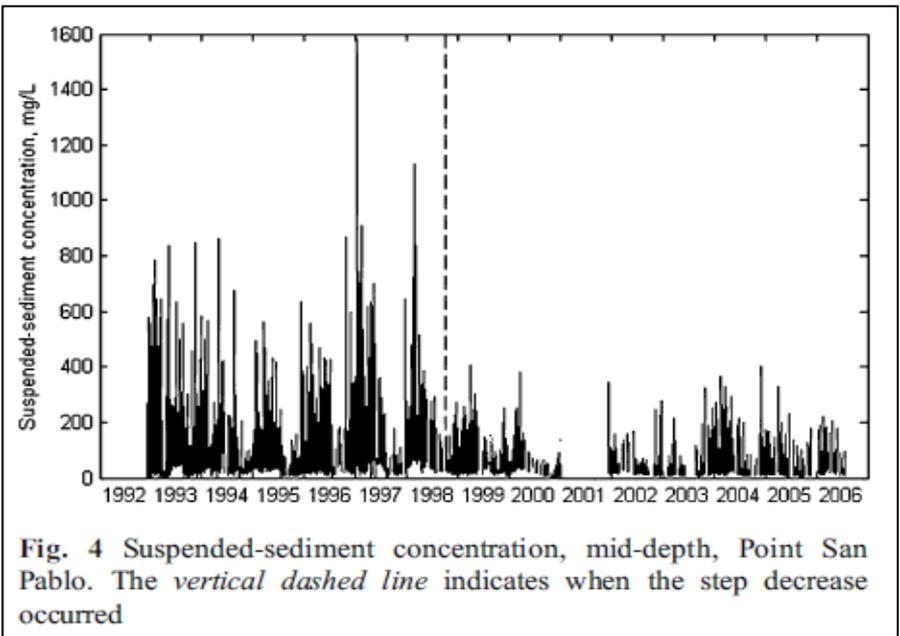


Fig. 4 Suspended-sediment concentration, mid-depth, Point San Pablo. The vertical dashed line indicates when the step decrease occurred

Schoellhamer 2011

Independent Science Panel (p 8):

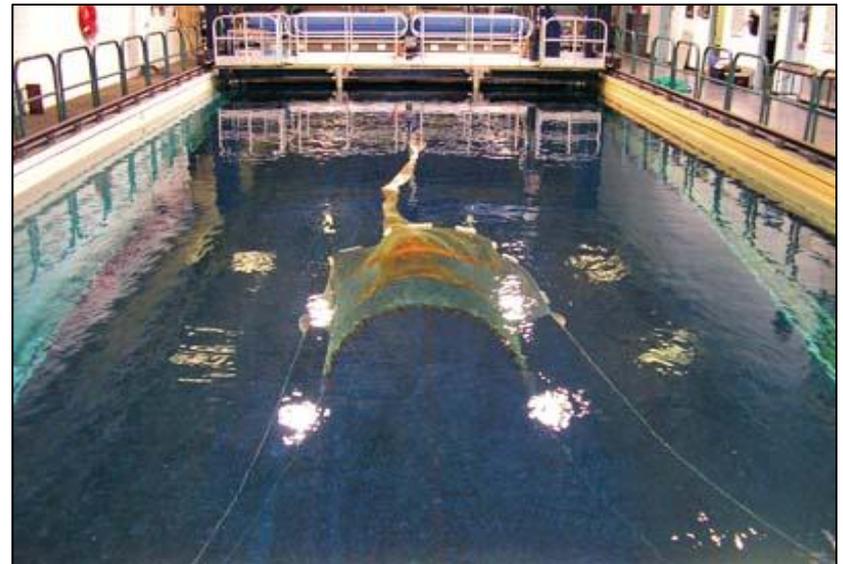
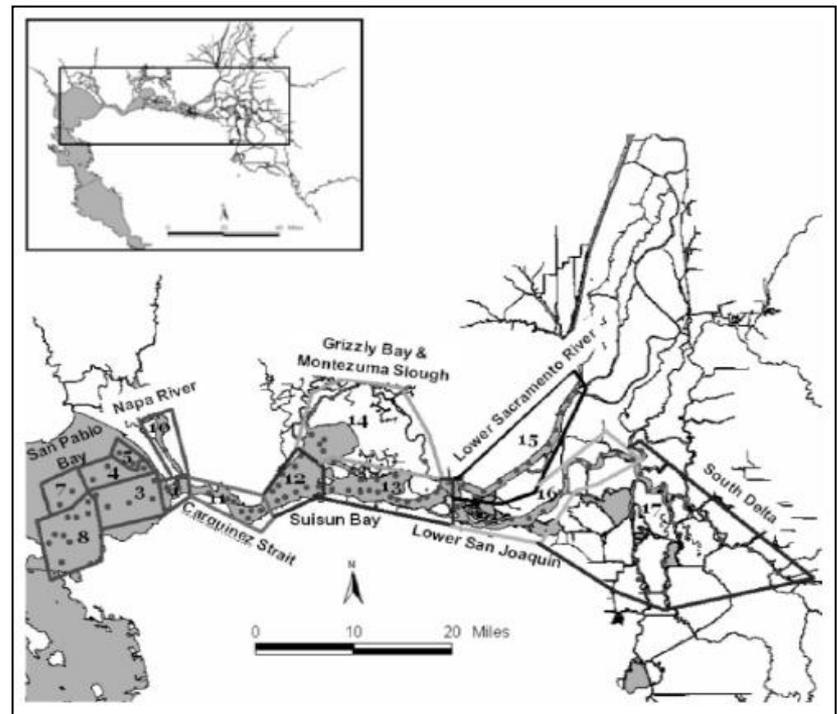
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Recommendations – Existing Resources

- *DFG may be able to reduce FMWT tows without increasing sampling error and reallocate resources to pilot and additional studies*
- *Pilot studies*
 - Additional locations/depths/habitats to assess any changes in habitat use
 - Trawl net performance in variable conditions (flume tank tests)
- *Changes to FWMT trawls*
 - Expand trawl hours to assess diel movements and differential tow success
 - For example, add plankton sampling



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Conclusions

- ***Uncertainties in FMWT Abundance Index***
 - FMWT does not capture changes in habitat use – independent science panel shows changes in habitat use by several species
 - FMWT abundance index difficult to understand. What does change from 11864 to 7408 (fish caught) x (water sampled) mean?
 - No estimate of error range in abundance index
 - FMWT catches very few of target species per tow
- ***Statistical CPUE analysis based on FMWT raw data indicates widely variable flow-abundance relationships and that turbidity has better relationship with abundance than flow does***
 - No flow variable explains much of the variation in pelagic fish abundance
 - ‘Best’ fit flow variable is different for different species
 - Small and variable relationships between catch and flow covariates – A small, but inverse, relationship exists between delta smelt and ‘best’ fit spring flow variable
 - Turbidity consistently has a stronger relationship to abundance than flow does