Report Submission to

STATE WATER RESOURCES CONTROL BOARD

By

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

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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 FWMT 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 signficance 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 (occuring 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 FWMT'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 strengthes 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 resouces):

1) <u>Derivation of indices</u>. 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) <u>Sampling intensity of the FMWT survey</u>. 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) <u>Deeper investigation of fish abundance in relation to turbidity.</u> The emergence of *Secchi Depth* as an important variable indicates that more refined analyses should be conducted to analyze how turbidity structures biotic communites 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) <u>Spatiotemporal analyses of habitat utilization</u>. 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 FWMT 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 FWMT 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 occurences 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.

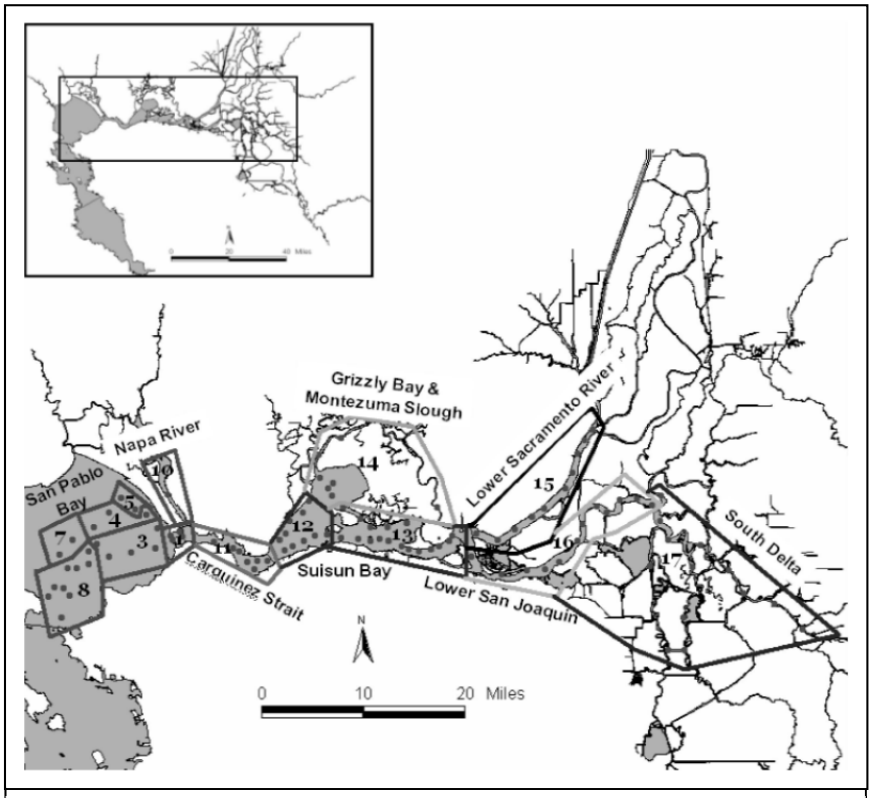

Figure 1. Areal stratification of the Fall Midwater Trawl Survey (numbered polygons) and fixed sampling locations within each stratum (dots). Strata 2, 6, and 9, have not been sampled since 1973 and are thus omitted from the map. The above image was taken from Newman (2008).

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 3.7m^2) 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:

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

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:

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

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

[2]The 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 produced 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 symetrical 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). Equiping 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 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 in 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:

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

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, $\boldsymbol{x}_i$ is the vector of covariates for the ith value of the response variable, β is a vector of parameters to be estimated, and Y_i is the ith 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 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:

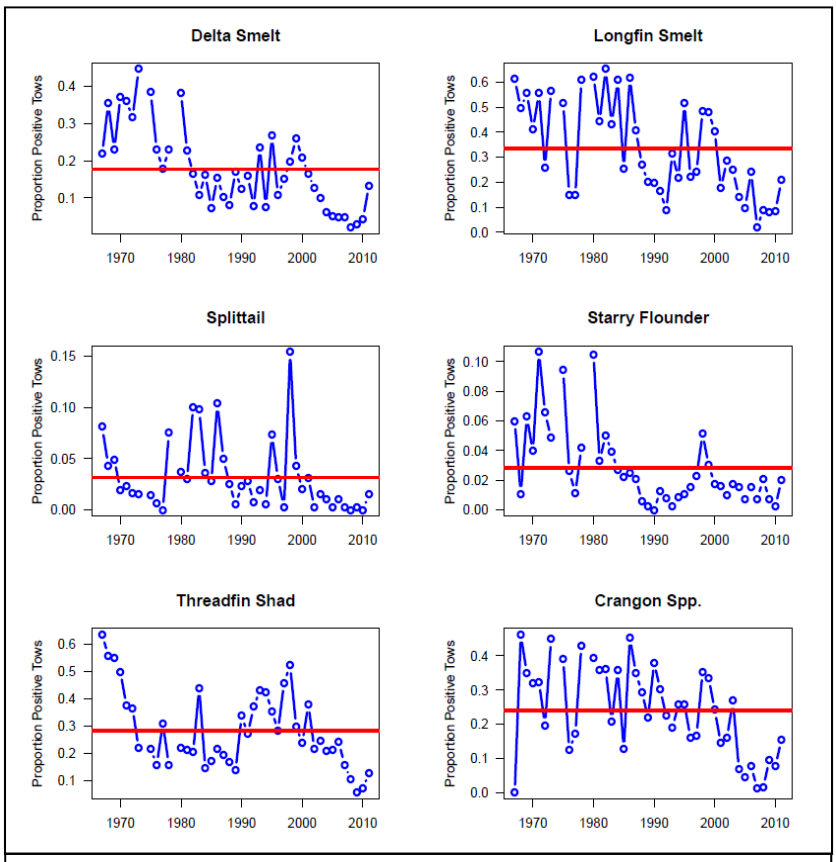

Figure 2. Annual proportion of FMWT survey tows conducted in September-December where at least one target specimen (Delta Smelt, Longfin Smelt, Splittail, Starry Flounder, Threadfin Shad, and Crangon Spp) was encountered (blue line) and mean value (red line) from 1967-2011. No sampling occurred in 1974,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

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

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 symetrical 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 D_1 contained covariates *Year* and *Month*; model D_2 contained *Year*, *Month*, and *Region*; model D_3 contained *Year*, *Month*, and *Secchi Depth*, which was standardized to have a mean of zero and a standard deviation of one; and model D_4 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 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 A_1-A_{16} 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

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[3]The 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:

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

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:

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

Naturally, it follows then that the 'best' fitting model within a candidate set is the one with ΔAIC = 0, however, it should be noted that models with 0< ΔAIC < 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:

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

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 ith 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 estiamte 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 ($\widehat{\sigma}_y$) 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:

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

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:

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

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 ΔAIC=0.0 for model D_4, for all species except starry flounder (Appendix A, Tables A1A-A6A; for starry flounder, ΔAIC = 0.0 for model D_2 and ΔAIC = 0.21 for model D_4). However, a ΔAIC=0.21 is virtually indistinguishable from ΔAIC = 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 a 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.

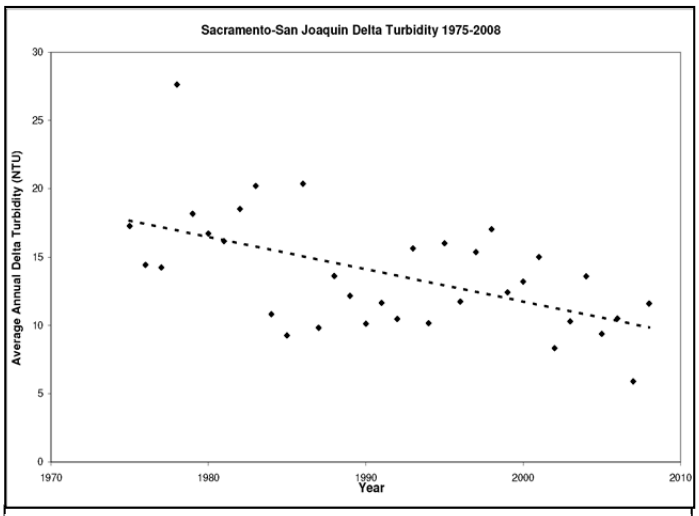

Figure 3. Mean annual turbidity, declining throughout the Sacramento-San Joaquin Delta from 1975–2008. From monthly data provided by California Department of Water Resources, Environmental Monitoring Program, and published by Cloern et al. (2011).

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 turbitity 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.

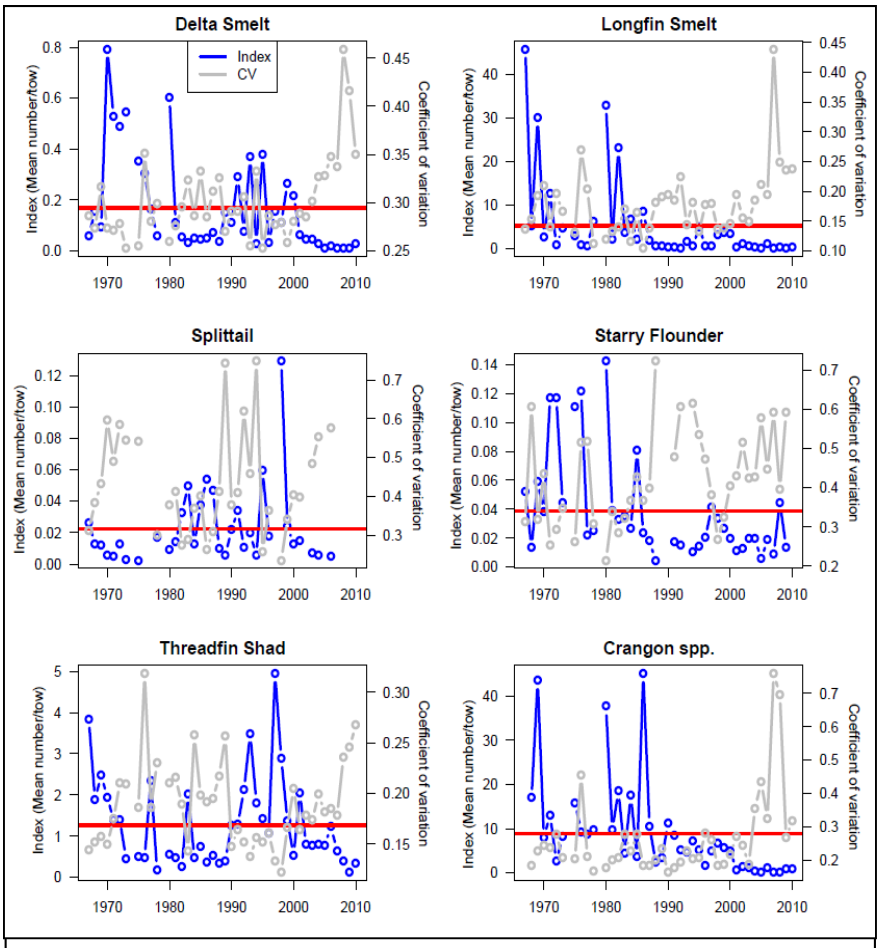

Figure 4A. Estimated indices of relative abundance (mean number/tow, blue line) and associated coefficients of variation (CV, gray line) for delta smelt, longfin smelt, Sacramento splittail, starry flounder, threadfin shad, and crangon spp. based on a delta-lognormal GLM applied the FMWT survey data 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.

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

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.

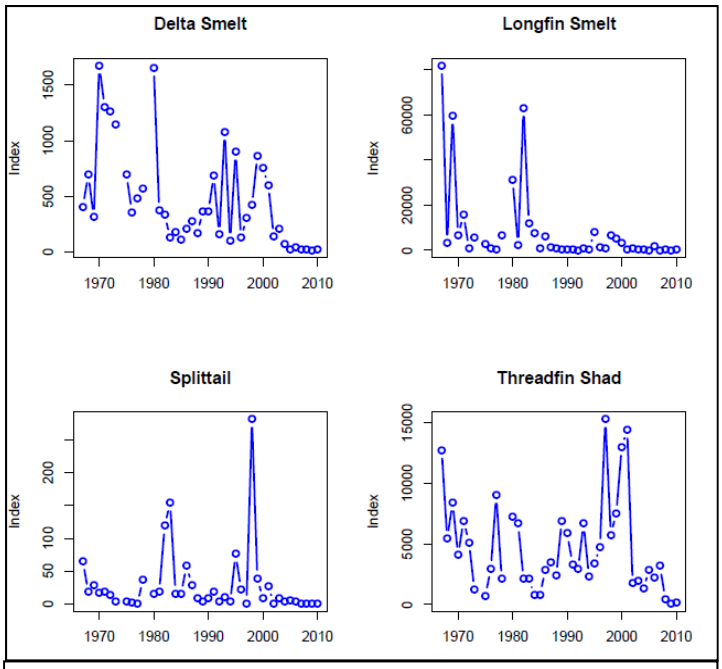

Figure 4B. Estimated indices of relative abundance for delta smelt, longfin smelt, Sacramento splittail, and threadfin shad published by DFG, 1967-2010.

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

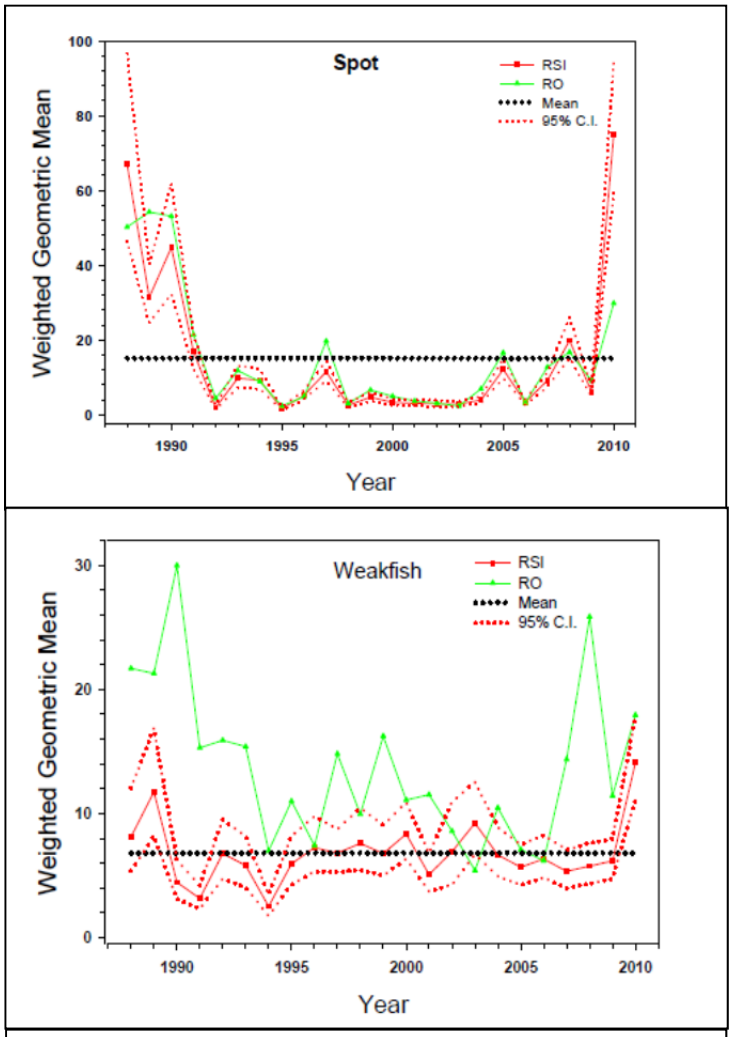

Figure 5. Indices of abundance of juvenile spot and weakfish in lower Chesapeake Bay from 1988-2010 derived from the VIMS Juvenile Finfish Trawl Survey. The black dotted line represents the long-term average catch-per-tow.

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 D_4 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*

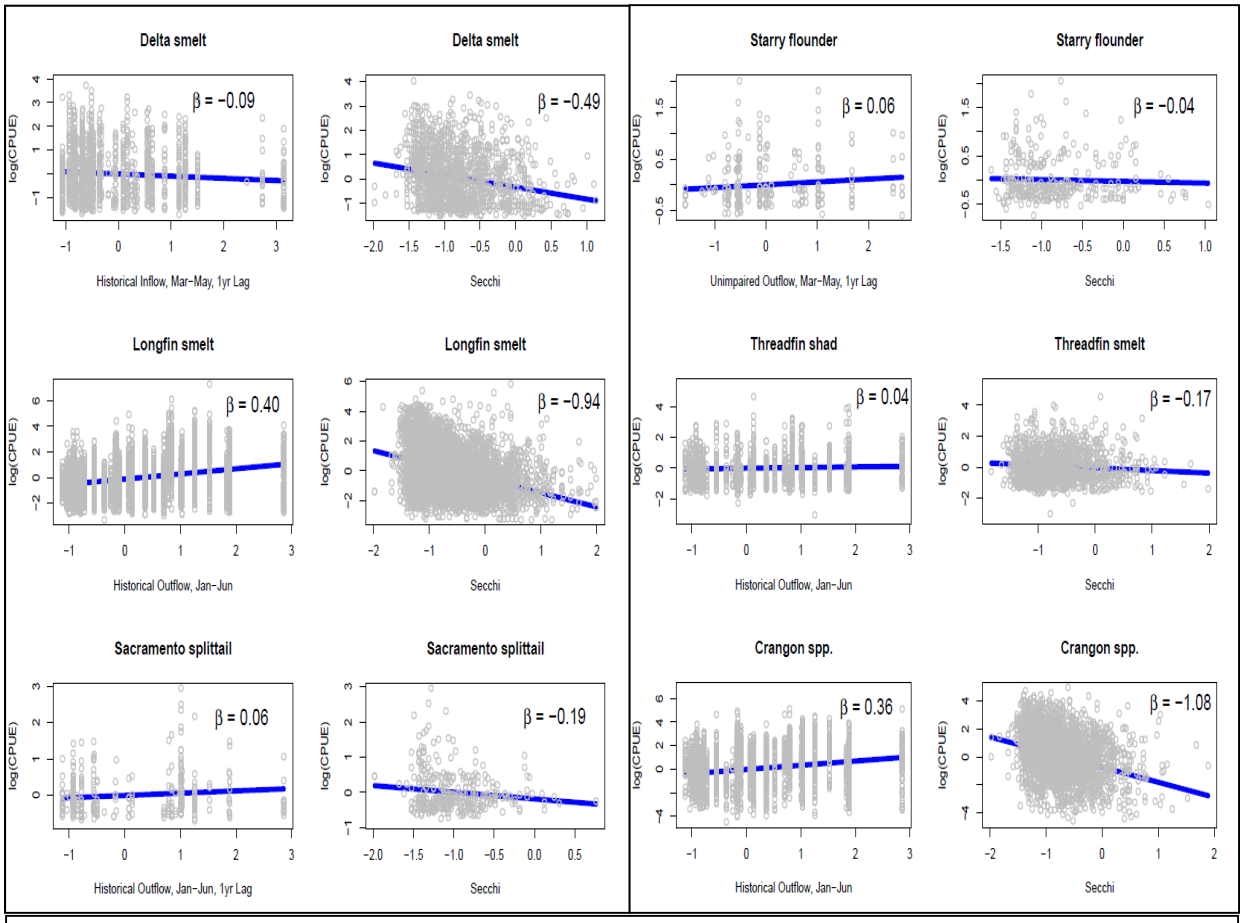

Figure 6. Partial residuals plots showing fits of the estimated coefficients (blue lines) associated with the 'best' flow variable and *Secchi Depth* for delta smelt, longfin smelt, Sacramento splittail, starry flounder, threadfin shad, and Crangon spp. from the lognormal models fitted to the FMWT survey 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 (ΔAIC = 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, Mar-May, 1yr Lag* is the 'best' fitting lognormal model (model A_{14} has ΔAIC =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 ΔAIC = 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(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.

Species	Presence/Absence (Binomial ΔAIC=0)	Abundance (Lognormal ΔAIC=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 (β = -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*, β = 0.40; Sacramento splittail: *Historical Outflow, Jan-June, 1yr Lag*, β = 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 prediced 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*.

Species	Estimated coefficient of 'best' fitting flow covariate	Estimated coefficient of *Secchi Depth*
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 ΔAIC	Lognormal AIC	Lognormal ΔAIC
D_1	*Year*, *Month*	11138.0	2436.4	7076.9	237.0
D_2	*Year*, *Month*, *Region*	9149.2	447.6	6918.6	78.7
D_3	*Year*, *Month*, *Secchi*	10183.8	1482.3	6965.0	125.0
D_4	*Year*, *Month*, *Region*, *Secchi*	8701.6	0.0	6840.0	0.0

Model D_4: Binomial null deviance = 12170.5 with 29% explained, lognormal null deviance = 2815.9 with 19% explained.

(B) Delta smelt: Binomial component

Parameter	Estimate	SE	*p*-value		Parameter	Estimate	SE	*p*-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		$\beta_{Region3}$	n/a	n/a	n/a
β_{1984}	0.14	0.23	0.55		$\beta_{Region4}$	-0.56	0.57	0.33
β_{1985}	-0.32	0.27	0.24		$\beta_{Region5}$	-0.38	0.61	0.54
β_{1986}	-0.05	0.22	0.82		$\beta_{Region7}$	n/a	n/a	n/a
β_{1987}	-0.04	0.24	0.86		$\beta_{Region8}$	n/a	n/a	n/a
β_{1988}	-0.62	0.26	0.02		$\beta_{Region10}$	0.33	0.58	0.57
β_{1989}	0.72	0.22	0.001		$\beta_{Region11}$	0.88	0.38	0.02
β_{1990}	0.42	0.24	0.07		$\beta_{Region12}$	1.61	0.35	<0.0001

β_{1991}	0.95	0.23	<0.0001		$\beta_{Region13}$	3.24	0.35	<0.0001
β_{1992}	0.07	0.26	0.78		$\beta_{Region14}$	3.05	0.35	<0.0001
β_{1993}	1.50	0.22	<0.0001		$\beta_{Region15}$	3.97	0.35	<0.0001
β_{1994}	-0.27	0.27	0.31		$\beta_{Region16}$	3.00	0.35	<0.0001
β_{1995}	1.54	0.21	<0.0001		$\beta_{Region17}$	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		$\beta_{Region3}$	n/a	n/a	n/a
β_{1984}	-0.32	0.18	0.08		$\beta_{Region4}$	0.68	0.55	0.22
β_{1985}	0.06	0.23	0.80		$\beta_{Region5}$	0.27	0.59	0.64
β_{1986}	-0.14	0.18	0.45		$\beta_{Region7}$	n/a	n/a	n/a
β_{1987}	0.28	0.20	0.17		$\beta_{Region8}$	n/a	n/a	n/a
β_{1988}	0.15	0.22	0.50		$\beta_{Region10}$	0.91	0.55	0.10
β_{1989}	0.26	0.18	0.14		$\beta_{Region11}$	0.47	0.36	0.19
β_{1990}	0.27	0.19	0.17		$\beta_{Region12}$	0.78	0.34	0.02
β_{1991}	0.73	0.18	<0.0001		$\beta_{Region13}$	1.18	0.33	0.0004
β_{1992}	0.24	0.22	0.27		$\beta_{Region14}$	1.14	0.33	0.001
β_{1993}	0.44	0.17	0.01		$\beta_{Region15}$	1.44	0.33	<0.0001
β_{1994}	-0.40	0.23	0.08		$\beta_{Region16}$	0.86	0.34	0.01
β_{1995}	0.43	0.16	0.01		$\beta_{Region17}$	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 ΔAIC	Lognormal AIC	Lognormal ΔAIC
D_1	*Year, Month*	14963.0	3521.7	16417.3	715.5
D_2	*Year, Month, Region*	12113.0	671.7	15944.3	242.5
D_3	*Year, Month, Secchi*	12969.3	1528.0	16104.4	402.6
D_4	*Year, Month, Region, Secchi*	11441.3	0.0	15701.8	0.0

Model D_4: Binomial null deviance = 17971.0 with 37% explained, lognormal null deviance = 13277.7 with 44% explained.

(B) Longfin smelt: Binomial component

Parameter	Estimate	SE	*p*-value		Parameter	Estimate	SE	*p*-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		$\beta_{Region3}$	-0.88	0.15	<0.0001
β_{1984}	-0.12	0.23	0.60		$\beta_{Region4}$	-0.80	0.17	<0.0001
β_{1985}	-1.31	0.23	<0.0001		$\beta_{Region5}$	-0.78	0.19	<0.0001
β_{1986}	-0.18	0.22	0.39		$\beta_{Region7}$	-1.24	0.21	<0.0001
β_{1987}	-1.11	0.21	<0.0001		$\beta_{Region8}$	-0.39	0.15	0.01
β_{1988}	-2.18	0.22	<0.0001		$\beta_{Region10}$	-0.76	0.24	0.002
β_{1989}	-2.33	0.23	<0.0001		$\beta_{Region11}$	0.14	0.13	0.31
β_{1990}	-2.32	0.23	<0.0001		$\beta_{Region12}$	0.68	0.13	<0.0001
β_{1991}	-2.39	0.23	<0.0001		$\beta_{Region13}$	0.17	0.12	0.16
β_{1992}	-3.10	0.26	<0.0001		$\beta_{Region14}$	-0.38	0.13	0.005
β_{1993}	-1.20	0.22	<0.0001		$\beta_{Region15}$	-0.50	0.13	<0.0001
β_{1994}	-2.21	0.23	<0.0001		$\beta_{Region16}$	-1.98	0.14	<0.0001
β_{1995}	-0.34	0.22	0.12		$\beta_{Region17}$	-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		$\beta_{Region3}$	-0.09	0.13	0.51
β_{1984}	-1.83	0.13	<0.0001		$\beta_{Region4}$	-0.50	0.14	0.0005
β_{1985}	-2.24	0.17	<0.0001		$\beta_{Region5}$	-0.73	0.17	<0.0001
β_{1986}	-1.59	0.13	<0.0001		$\beta_{Region7}$	-0.46	0.20	0.02
β_{1987}	-2.51	0.14	<0.0001		$\beta_{Region8}$	0.32	0.13	0.01
β_{1988}	-2.89	0.16	<0.0001		$\beta_{Region10}$	-0.54	0.20	0.01
β_{1989}	-2.94	0.18	<0.0001		$\beta_{Region11}$	-0.11	0.11	0.30
β_{1990}	-3.23	0.18	<0.0001		$\beta_{Region12}$	0.35	0.10	0.00
β_{1991}	-3.34	0.19	<0.0001		$\beta_{Region13}$	0.05	0.10	0.59
β_{1992}	-3.41	0.24	<0.0001		$\beta_{Region14}$	-0.30	0.11	0.01
β_{1993}	-2.67	0.15	<0.0001		$\beta_{Region15}$	-0.36	0.11	0.001
β_{1994}	-2.99	0.18	<0.0001		$\beta_{Region16}$	-1.31	0.12	<0.0001
β_{1995}	-2.04	0.13	<0.0001		$\beta_{Region17}$	-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 ΔAIC	Lognormal AIC	Lognormal ΔAIC
D_1	*Year, Month*	3396.7	624.0	861.9	21.4
D_2	*Year, Month, Region*	2960.0	187.3	843.1	2.7
D_3	*Year, Month, Secchi*	2914.8	142.1	851.6	11.1
D_4	*Year, Month, Region, Secchi*	2772.7	0.0	840.4	0.0

Model D_4: Binomial null deviance = 3944.0 with 30% explained, lognormal null deviance = 173.5 with 21% explained.

(B) Sacramento splittail: Binomial component

Parameter	Estimate	SE	*p*-value		Parameter	Estimate	SE	*p*-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		$\beta_{Region3}$	n/a	n/a	n/a
β_{1984}	-0.39	0.39	0.32		$\beta_{Region4}$	0.86	0.71	0.22
β_{1985}	0.45	0.43	0.29		$\beta_{Region5}$	0.77	0.75	0.31
β_{1986}	0.93	0.31	0.002		$\beta_{Region7}$	n/a	n/a	n/a
β_{1987}	0.63	0.36	0.08		$\beta_{Region8}$	n/a	n/a	n/a
β_{1988}	-0.53	0.43	0.22		$\beta_{Region10}$	2.42	0.70	0.001
β_{1989}	-1.76	0.76	0.02		$\beta_{Region11}$	1.47	0.63	0.02
β_{1990}	0.21	0.44	0.63		$\beta_{Region12}$	1.65	0.60	0.01
β_{1991}	0.43	0.43	0.32		$\beta_{Region13}$	1.66	0.60	0.01
β_{1992}	-0.63	0.65	0.34		$\beta_{Region14}$	2.91	0.60	<0.0001
β_{1993}	-0.14	0.47	0.76		$\beta_{Region15}$	1.53	0.61	0.01
β_{1994}	-1.44	0.76	0.06		$\beta_{Region16}$	1.33	0.63	0.04
β_{1995}	0.98	0.33	0.003		$\beta_{Region17}$	-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		$\beta_{Region3}$	n/a	n/a	n/a
β_{1984}	-0.33	0.21	0.11		$\beta_{Region4}$	0.35	0.41	0.39
β_{1985}	-0.08	0.23	0.72		$\beta_{Region5}$	0.63	0.42	0.14
β_{1986}	-0.18	0.16	0.24		$\beta_{Region7}$	n/a	n/a	n/a
β_{1987}	-0.04	0.19	0.85		$\beta_{Region8}$	n/a	n/a	n/a
β_{1988}	-0.41	0.24	0.08		$\beta_{Region10}$	0.62	0.40	0.13
β_{1989}	0.24	0.43	0.58		$\beta_{Region11}$	0.29	0.36	0.43
β_{1990}	-0.40	0.24	0.09		$\beta_{Region12}$	0.12	0.35	0.72
β_{1991}	-0.15	0.23	0.51		$\beta_{Region13}$	0.07	0.35	0.85
β_{1992}	-0.30	0.38	0.42		$\beta_{Region14}$	0.37	0.35	0.29
β_{1993}	-0.16	0.26	0.54		$\beta_{Region15}$	0.04	0.36	0.91
β_{1994}	-0.17	0.44	0.70		$\beta_{Region16}$	0.05	0.37	0.90
β_{1995}	-0.14	0.17	0.41		$\beta_{Region17}$	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 ΔAIC	Lognormal AIC	Lognormal ΔAIC
D_1	*Year, Month*	3162.3	289.0	528.8	13.1
D_2	*Year, Month, Region*	2964.0	92.0	514.1	0.0
D_3	*Year, Month, Secchi*	3029.9	143.6	527.9	13.9
D_4	*Year, Month, Region, Secchi*	2881.0	0.0	513.5	0.21

Model D_4: Binomial null deviance = 3395.7 with 18% explained, lognormal null deviance = 84.1 with 23% explained.

(B) Starry flounder: Binomial component

Parameter	Estimate	SE	*p*-value		Parameter	Estimate	SE	*p*-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		$\beta_{Region3}$	1.06	0.43	0.01
β_{1984}	-0.81	0.43	0.06		$\beta_{Region4}$	1.38	0.42	0.001
β_{1985}	0.20	0.46	0.66		$\beta_{Region5}$	1.91	0.42	<0.0001
β_{1986}	-0.89	0.43	0.04		$\beta_{Region7}$	0.21	0.63	0.73
β_{1987}	-0.92	0.45	0.04		$\beta_{Region8}$	0.30	0.51	0.56
β_{1988}	-2.43	0.76	0.001		$\beta_{Region10}$	0.96	0.52	0.07
β_{1989}	-2.81	1.04	0.007		$\beta_{Region11}$	0.74	0.40	0.07
β_{1990}	n/a	n/a	n/a		$\beta_{Region12}$	0.80	0.38	0.04
β_{1991}	-0.98	0.53	0.07		$\beta_{Region13}$	0.27	0.38	0.48
β_{1992}	-1.38	0.65	0.03		$\beta_{Region14}$	0.07	0.41	0.87
β_{1993}	-2.61	1.04	0.01		$\beta_{Region15}$	-0.77	0.45	0.09
β_{1994}	-1.56	0.65	0.02		$\beta_{Region16}$	-2.22	0.68	0.001

β_{1995}	-1.60	0.57	0.01		$\beta_{Region17}$	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		$\beta_{Region3}$	0.39	0.20	0.05
β_{1984}	0.16	0.19	0.42		$\beta_{Region4}$	0.61	0.20	0.003
β_{1985}	0.39	0.20	0.048		$\beta_{Region5}$	0.61	0.20	0.003
β_{1986}	0.09	0.19	0.62		$\beta_{Region7}$	0.24	0.29	0.40
β_{1987}	-0.12	0.20	0.55		$\beta_{Region8}$	0.26	0.24	0.28
β_{1988}	-0.02	0.34	0.96		$\beta_{Region10}$	0.45	0.24	0.07
β_{1989}	-0.01	0.46	0.98		$\beta_{Region11}$	0.26	0.19	0.17
β_{1990}	n/a	n/a	n/a		$\beta_{Region12}$	0.42	0.18	0.03
β_{1991}	-0.03	0.24	0.91		$\beta_{Region13}$	0.27	0.18	0.15
β_{1992}	0.24	0.28	0.39		$\beta_{Region14}$	0.13	0.20	0.49
β_{1993}	0.02	0.47	0.96		$\beta_{Region15}$	0.25	0.22	0.26
β_{1994}	0.001	0.31	1.00		$\beta_{Region16}$	0.72	0.32	0.03
β_{1995}	0.31	0.27	0.24		$\beta_{Region17}$	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 ΔAIC	Lognormal AIC	Lognormal ΔAIC
D_1	*Year, Month*	15405.4	2736.5	14770.0	1241.6
D_2	*Year, Month, Region*	13067.7	398.8	13548.0	19.7
D_3	*Year, Month, Secchi*	15321.4	2652.4	14629.1	1100.7
D_4	*Year, Month, Region, Secchi*	12669.0	0.0	13528.3	0.0

Model D_4: Binomial null deviance = 16877.0 with 26% explained, lognormal null deviance = 9796.9 with 34% explained.

(B) Threadfin shad: Binomial component

Parameter	Estimate	SE	*p*-value		Parameter	Estimate	SE	*p*-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		$\beta_{Region3}$	-0.52	0.20	0.01
β_{1984}	-1.92	0.22	<0.0001		$\beta_{Region4}$	-0.02	0.19	0.91
β_{1985}	-1.32	0.22	<0.0001		$\beta_{Region5}$	-0.17	0.22	0.46
β_{1986}	-1.71	0.20	<0.0001		$\beta_{Region7}$	0.06	0.23	0.79
β_{1987}	-1.69	0.21	<0.0001		$\beta_{Region8}$	-0.86	0.21	0.00
β_{1988}	-1.84	0.21	<0.0001		$\beta_{Region10}$	-0.19	0.28	0.49
β_{1989}	-2.06	0.22	<0.0001		$\beta_{Region11}$	-0.11	0.16	0.51
β_{1990}	-0.55	0.19	0.004		$\beta_{Region12}$	-0.43	0.15	0.005
β_{1991}	-0.76	0.19	<0.0001		$\beta_{Region13}$	0.12	0.14	0.39
β_{1992}	-0.25	0.19	0.19		$\beta_{Region14}$	0.94	0.15	<0.0001
β_{1993}	-0.06	0.19	0.77		$\beta_{Region15}$	1.70	0.14	<0.0001
β_{1994}	-0.33	0.19	0.09		$\beta_{Region16}$	2.17	0.14	<0.0001
β_{1995}	-0.57	0.19	0.002		$\beta_{Region17}$	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		$\beta_{Region3}$	0.14	0.22	0.51
β_{1984}	-0.54	0.21	0.010		$\beta_{Region4}$	0.06	0.21	0.78
β_{1985}	-0.66	0.19	0.001		$\beta_{Region5}$	0.15	0.24	0.54
β_{1986}	-0.99	0.17	<0.0001		$\beta_{Region7}$	-0.14	0.25	0.57
β_{1987}	-0.67	0.18	0.0002		$\beta_{Region8}$	0.02	0.24	0.95
β_{1988}	-0.98	0.20	<0.0001		$\beta_{Region10}$	-0.38	0.30	0.21
β_{1989}	-0.62	0.20	0.002		$\beta_{Region11}$	-0.18	0.18	0.31
β_{1990}	-0.80	0.15	<0.0001		$\beta_{Region12}$	-0.37	0.17	0.03
β_{1991}	-0.51	0.16	0.002		$\beta_{Region13}$	-0.17	0.15	0.27
β_{1992}	-0.49	0.15	0.001		$\beta_{Region14}$	0.29	0.16	0.07
β_{1993}	-0.13	0.14	0.375		$\beta_{Region15}$	0.39	0.15	0.01
β_{1994}	-0.58	0.15	<0.0001		$\beta_{Region16}$	0.69	0.15	<0.0001
β_{1995}	-0.64	0.15	<0.0001		$\beta_{Region17}$	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 ΔAIC	Lognormal AIC	Lognormal ΔAIC
D_1	*Year, Month*	13403.6	3325.5	13021.6	340.7
D_2	*Year, Month, Region*	11302.6	1224.5	12821.0	140.1
D_3	*Year, Month, Secchi*	11368.1	1290.0	12952.7	271.7
D_4	*Year, Month, Region, Secchi*	10078.1	0.0	12681.0	0.0

Model D_4: Binomial null deviance = 14730.9 with 32% explained, lognormal null deviance = 12128.9 with 37% explained.

(B) Crangon spp.: Binomial component

Parameter	Estimate	SE	*p*-value		Parameter	Estimate	SE	*p*-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		$\beta_{Region3}$	-1.34	0.18	<0.0001
β_{1985}	-0.88	0.25	0.0003		$\beta_{Region4}$	-1.73	0.19	<0.0001
β_{1986}	0.05	0.21	0.82		$\beta_{Region5}$	-2.02	0.23	<0.0001
β_{1987}	-0.17	0.21	0.41		$\beta_{Region7}$	-2.84	0.34	<0.0001
β_{1988}	-1.00	0.21	<0.0001		$\beta_{Region8}$	-0.71	0.17	<0.0001
β_{1989}	-0.89	0.22	<0.0001		$\beta_{Region10}$	-1.25	0.25	<0.0001
β_{1990}	0.43	0.21	0.04		$\beta_{Region11}$	0.33	0.13	0.012
β_{1991}	0.096	0.21	0.65		$\beta_{Region12}$	0.54	0.13	<0.0001
β_{1992}	-0.21	0.22	0.33		$\beta_{Region13}$	-0.34	0.12	0.005
β_{1993}	-0.75	0.22	0.001		$\beta_{Region14}$	-1.11	0.14	<0.0001
β_{1994}	-0.41	0.22	0.056		$\beta_{Region15}$	-1.34	0.13	<0.0001
β_{1995}	-0.78	0.22	0.0003		$\beta_{Region16}$	-2.45	0.16	<0.0001
β_{1996}	-1.81	0.22	<0.0001		$\beta_{Region17}$	n/a	n/a	n/a

β_{1997}	-0.96	0.22	<0.0001		β_{Secchi}	-1.86	0.05	<0.0001

(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		$\beta_{Region3}$	-0.08	0.22	0.72
β_{1985}	-0.84	0.26	0.001		$\beta_{Region4}$	-0.84	0.23	0.0003
β_{1986}	0.94	0.18	<0.0001		$\beta_{Region5}$	-1.54	0.29	<0.0001
β_{1987}	-0.35	0.19	0.06		$\beta_{Region7}$	-1.04	0.47	0.03
β_{1988}	-1.14	0.20	<0.0001		$\beta_{Region8}$	0.39	0.21	0.06
β_{1989}	-0.92	0.22	<0.0001		$\beta_{Region10}$	-0.92	0.30	0.00
β_{1990}	-0.71	0.19	0.0001		$\beta_{Region11}$	-0.07	0.14	0.60
β_{1991}	-0.76	0.20	0.0001		$\beta_{Region12}$	0.02	0.13	0.86
β_{1992}	-1.02	0.22	<0.0001		$\beta_{Region13}$	-0.38	0.13	0.003
β_{1993}	-0.71	0.23	0.002		$\beta_{Region14}$	-1.02	0.15	<0.0001
β_{1994}	-0.53	0.21	0.01		$\beta_{Region15}$	-0.22	0.15	0.16
β_{1995}	-0.60	0.20	0.003		$\beta_{Region16}$	-2.14	0.20	<0.0001
β_{1996}	-0.78	0.23	0.001		$\beta_{Region17}$	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
$\beta_{Unimp.Inflow.Jan-Jun}$	0.11	0.03	<0.0001		$\beta_{Hist.Inflow.MM.1yrLag}$	-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
$\beta_{Region3}$	n/a	n/a	n/a		$\beta_{Region3}$	n/a	n/a	n/a
$\beta_{Region4}$	-0.56	0.57	0.32		$\beta_{Region4}$	0.73	0.57	0.20
$\beta_{Region5}$	-0.46	0.61	0.45		$\beta_{Region5}$	0.29	0.62	0.64
$\beta_{Region7}$	n/a	n/a	n/a		$\beta_{Region7}$	n/a	n/a	n/a
$\beta_{Region8}$	n/a	n/a	n/a		$\beta_{Region8}$	n/a	n/a	n/a
$\beta_{Region10}$	0.36	0.57	0.53		$\beta_{Region10}$	0.89	0.57	0.12
$\beta_{Region11}$	0.89	0.37	0.02		$\beta_{Region11}$	0.64	0.38	0.09
$\beta_{Region12}$	1.51	0.35	<0.0001		$\beta_{Region12}$	0.86	0.35	0.015
$\beta_{Region13}$	3.02	0.34	<0.0001		$\beta_{Region13}$	1.22	0.34	0.0004
$\beta_{Region14}$	2.77	0.35	<0.0001		$\beta_{Region14}$	1.14	0.35	0.001
$\beta_{Region15}$	3.67	0.34	<0.0001		$\beta_{Region15}$	1.45	0.36	<0.0001
$\beta_{Region16}$	2.99	0.35	<0.0001		$\beta_{Region16}$	1.01	0.35	0.004
$\beta_{Region17}$	1.41	0.37	0.0001		$\beta_{Region17}$	0.76	0.37	0.042
β_{Secchi}	-1.42	0.05	<0.0001		β_{Secchi}	-0.49	0.05	<0.0001

Model A_7: Binomial null deviance = 12170.5 with 22% explained. Model A_{14}: 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
$\beta_{Unimp.Inflow.Jan-Jun}$	0.48	0.02	<0.0001		$\beta_{Hist.Outflow.Jan-Jun}$	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
$\beta_{Region3}$	-0.69	0.15	<0.0001		$\beta_{Region3}$	0.08	0.16	0.59
$\beta_{Region4}$	-0.76	0.16	<0.0001		$\beta_{Region4}$	-0.47	0.17	0.004
$\beta_{Region5}$	-0.85	0.18	<0.0001		$\beta_{Region5}$	-0.87	0.19	<0.0001
$\beta_{Region7}$	-1.15	0.20	<0.0001		$\beta_{Region7}$	-0.46	0.23	0.047
$\beta_{Region8}$	-0.17	0.14	0.22		$\beta_{Region8}$	0.50	0.15	0.001
$\beta_{Region10}$	-0.79	0.23	0.001		$\beta_{Region10}$	-0.37	0.23	0.11
$\beta_{Region11}$	0.06	0.13	0.66		$\beta_{Region11}$	-0.17	0.12	0.18
$\beta_{Region12}$	0.46	0.12	0.0001		$\beta_{Region12}$	0.30	0.11	0.01
$\beta_{Region13}$	0.03	0.11	0.79		$\beta_{Region13}$	0.08	0.11	0.45
$\beta_{Region14}$	-0.54	0.13	<0.0001		$\beta_{Region14}$	-0.29	0.12	0.02
$\beta_{Region15}$	-0.48	0.12	<0.0001		$\beta_{Region15}$	-0.38	0.12	0.002
$\beta_{Region16}$	-1.56	0.13	<0.0001		$\beta_{Region16}$	-0.92	0.14	<0.0001
$\beta_{Region17}$	-3.64	0.25	<0.0001		$\beta_{Region17}$	-1.11	0.34	<0.0001
β_{Secchi}	-1.38	0.04	<0.0001		β_{Secchi}	-0.94	0.04	<0.0001

Model A_7: Binomial null deviance = 17971.0 with 29% explained. Model A_1: 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
$\beta_{Unimp.Inflow.Jan-Jun}$	0.56	0.05	<0.0001		$\beta_{Hist.Outflow.Jan-Jun.1yrLag}$	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
$\beta_{Region3}$	n/s	n/s	n/s		$\beta_{Region3}$	n/s	n/s	n/s
$\beta_{Region4}$	0.83	0.70	0.24		$\beta_{Region4}$	0.41	0.40	0.31
$\beta_{Region5}$	0.77	0.74	0.30		$\beta_{Region5}$	0.63	0.43	0.14
$\beta_{Region7}$	n/s	n/s	n/s		$\beta_{Region7}$	n/s	n/s	n/s
$\beta_{Region8}$	n/s	n/s	n/s		$\beta_{Region8}$	n/s	n/s	n/s
$\beta_{Region10}$	2.15	0.69	0.002		$\beta_{Region10}$	0.69	0.39	0.08
$\beta_{Region11}$	1.39	0.62	0.02		$\beta_{Region11}$	0.48	0.36	0.18
$\beta_{Region12}$	1.52	0.60	0.01		$\beta_{Region12}$	0.26	0.35	0.45
$\beta_{Region13}$	1.56	0.59	0.01		$\beta_{Region13}$	0.20	0.34	0.57
$\beta_{Region14}$	2.68	0.59	<0.0001		$\beta_{Region14}$	0.46	0.34	0.18
$\beta_{Region15}$	1.46	0.61	0.02		$\beta_{Region15}$	0.16	0.35	0.66
$\beta_{Region16}$	1.27	0.63	0.04		$\beta_{Region16}$	0.13	0.36	0.71
$\beta_{Region17}$	-0.25	0.82	0.76		$\beta_{Region17}$	0.06	0.48	0.91
β_{Secchi}	-1.90	0.13	<0.0001		β_{Secchi}	-0.19	0.08	0.01

Model A_7: Binomial null deviance = 3944.0 with 25% explained. Model A_9: 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**	***p*-value**		**Parameter**	**Estimate**	**SE**	***p*-value**
β_0	-4.48	0.37	<0.0001		β_0	-0.01	0.17	0.97
$\beta_{Hist.Outflow.Jan-Jun}$	0.14	0.05	0.01		$\beta_{Unimp.Outflow.Mar-May.1yrLag}$	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
$\beta_{Region3}$	1.06	0.43	0.01		$\beta_{Region3}$	0.30	0.19	0.11
$\beta_{Region4}$	1.33	0.41	0.001		$\beta_{Region4}$	0.54	0.19	0.004
$\beta_{Region5}$	1.74	0.41	<0.0001		$\beta_{Region5}$	0.39	0.19	0.03
$\beta_{Region7}$	0.09	0.62	0.88		$\beta_{Region7}$	-0.03	0.28	0.92
$\beta_{Region8}$	0.33	0.51	0.52		$\beta_{Region8}$	0.11	0.23	0.62
$\beta_{Region10}$	1.00	0.51	0.05		$\beta_{Region10}$	0.35	0.23	0.13
$\beta_{Region11}$	0.76	0.40	0.06		$\beta_{Region11}$	0.18	0.18	0.31
$\beta_{Region12}$	0.89	0.38	0.02		$\beta_{Region12}$	0.36	0.17	0.04
$\beta_{Region13}$	0.41	0.38	0.28		$\beta_{Region13}$	0.18	0.17	0.29
$\beta_{Region14}$	0.15	0.40	0.70		$\beta_{Region14}$	0.03	0.18	0.85
$\beta_{Region15}$	-0.70	0.45	0.12		$\beta_{Region15}$	0.12	0.21	0.58
$\beta_{Region16}$	-1.96	0.68	0.004		$\beta_{Region16}$	0.58	0.31	0.07
$\beta_{Region17}$	n/a	n/a	n/a		$\beta_{Region17}$	n/a	n/a	n/a
β_{Secchi}	-1.30	0.12	<0.0001		β_{Secchi}	-0.04	0.05	0.44

Model A_1: Binomial null deviance = 3395.7 with 13% explained. Model A_{12}: 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**	***p*-value**		**Parameter**	**Estimate**	**SE**	***p*-value**
β_0	-2.68	0.13	<0.0001		β_0	0.86	0.16	<0.0001
$\beta_{Hist.Outflow.Jan\text{-}Jun}$	0.23	0.02	<0.0001		$\beta_{Hist.Outflow.Jan\text{-}Jun}$	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
$\beta_{Region3}$	-0.47	0.19	0.01		$\beta_{Region3}$	0.17	0.22	0.46
$\beta_{Region4}$	0.02	0.19	0.90		$\beta_{Region4}$	0.02	0.21	0.92
$\beta_{Region5}$	-0.06	0.21	0.77		$\beta_{Region5}$	0.14	0.25	0.56
$\beta_{Region7}$	0.09	0.22	0.68		$\beta_{Region7}$	-0.06	0.25	0.82
$\beta_{Region8}$	-0.80	0.20	<0.0001		$\beta_{Region8}$	0.10	0.25	0.69
$\beta_{Region10}$	-0.17	0.27	0.54		$\beta_{Region10}$	-0.41	0.31	0.19
$\beta_{Region11}$	-0.09	0.16	0.56		$\beta_{Region11}$	-0.14	0.18	0.44
$\beta_{Region12}$	-0.36	0.15	0.01		$\beta_{Region12}$	-0.30	0.17	0.08
$\beta_{Region13}$	0.18	0.14	0.18		$\beta_{Region13}$	-0.11	0.16	0.47
$\beta_{Region14}$	0.94	0.14	<0.0001		$\beta_{Region14}$	0.32	0.16	0.04
$\beta_{Region15}$	1.66	0.14	<0.0001		$\beta_{Region15}$	0.46	0.15	0.003
$\beta_{Region16}$	2.12	0.14	<0.0001		$\beta_{Region16}$	0.78	0.15	<0.0001
$\beta_{Region17}$	2.97	0.14	<0.0001		$\beta_{Region17}$	2.29	0.16	<0.0001
β_{Secchi}	-0.74	0.04	<0.0001		β_{Secchi}	-0.17	0.04	<0.0001

Model A_1: Binomial null deviance = 16877.0 with 20% explained. Model A_1: 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
$\beta_{Unimp.Outflow.Mar-May}$	-0.19	0.02	<0.0001		$\beta_{Hist.Outflow.Jan-Jun}$	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
$\beta_{Region3}$	-1.21	0.17	<0.0001		$\beta_{Region3}$	0.04	0.24	0.85
$\beta_{Region4}$	-1.57	0.18	<0.0001		$\beta_{Region4}$	-0.99	0.25	<0.0001
$\beta_{Region5}$	-1.86	0.22	<0.0001		$\beta_{Region5}$	-1.69	0.31	<0.0001
$\beta_{Region7}$	-2.59	0.33	<0.0001		$\beta_{Region7}$	-1.45	0.51	0.005
$\beta_{Region8}$	-0.62	0.16	0.0001		$\beta_{Region8}$	0.50	0.22	0.02
$\beta_{Region10}$	-1.24	0.24	<0.0001		$\beta_{Region10}$	-1.06	0.33	0.001
$\beta_{Region11}$	0.31	0.13	0.01		$\beta_{Region11}$	-0.10	0.15	0.50
$\beta_{Region12}$	0.36	0.12	0.002		$\beta_{Region12}$	-0.04	0.14	0.76
$\beta_{Region13}$	-0.36	0.11	0.001		$\beta_{Region13}$	-0.38	0.14	0.01
$\beta_{Region14}$	-1.10	0.13	<0.0001		$\beta_{Region14}$	-1.08	0.16	<0.0001
$\beta_{Region15}$	-1.24	0.13	<0.0001		$\beta_{Region15}$	-0.37	0.16	0.02
$\beta_{Region16}$	-2.16	0.15	<0.0001		$\beta_{Region16}$	-1.99	0.21	<0.0001
$\beta_{Region17}$	n/a	n/a	n/a		$\beta_{Region17}$	n/a	n/a	n/a
β_{Secchi}	-1.78	0.05	<0.0001		β_{Secchi}	-1.08	0.06	<0.0001

Model A_4: Binomial null deviance = 14730.9 with 32% explained. Model A_1: lognormal null deviance = 12128.9 with 37% explained.