ADULT DELTA SMELT ENTRAINMENT

Study 1 - Factors Associated with Salvage

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Prepared for:

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Preface for Entrainment Study 1
Prepared by CAMT Delta Smelt Scoping Team

This Preface was prepared by the CAMT Delta Smelt Scoping Team (DSST) to provide context for the study presented herein (Entrainment Study 1) which was commissioned by the Collaborative Science and Adaptive Management Program (CSAMP) and overseen by the Collaborative Adaptive Management Team (CAMT) and the CAMT DSST from March 2015 to October 2017. The scope of work for the study was developed in collaboration with the DSST and subjected to an independent peer review organized by the Delta Science Program in 2014. The DSST was provided regular updates during the conduct of the study and provided feedback on modeling inputs and initial results. The DSST also provided written comments on draft versions of various study deliverables.

This study is one in a series of four separate but related studies intended to examine factors affecting the entrainment of adult Delta Smelt at the Central Valley Project (CVP) and State Water Project (SWP) water export facilities in the south Delta, and the consequences of that entrainment on the Delta Smelt population. The studies' respective subjects are as follows:

- Study 1 – determined factors predicting salvage;
- Study 2 – developed a behavior model that best explains Delta Smelt movements and entrainment into the interior Delta and SWP and CVP facilities; determined behavior-based proportional entrainment losses;
- Study 3 – estimated historical (1981-2016) adult Delta Smelt proportional entrainment loss; and
- Study 4 – intended to assess the population effects of various levels of adult Delta Smelt proportional entrainment loss.

The study yielded two reports: *Review and Basic Exploratory Statistical Analysis of Adult Delta Smelt Salvage at the State Water Project and Central Valley Project Fish Facilities* produced in July 2015 and *Re-examining Delta Smelt (Hypomesus transpacificus) Entrainment Dynamics at the Hub of California's Water Supply in the Upper San Francisco Estuary* produced in December 2016, as summarized in the attached executive summary. The study also resulted in a manuscript entitled "*After the Storm: Re-Examining Factors that Affect Delta Smelt (Hypomesus transpacificus) Entrainment in the Sacramento and San Joaquin Delta"*. The July 2015 report relied on statistical models to explore different factors potentially influencing entrainment. The December 2016 report responded to comments and suggestions from the DSST and employed more sophisticated statistical modeling techniques to further explain variability associated with various factors and combinations of factors.

Results from Study 1 were presented to CAMT and the CSAMP Policy Group, with assistance from the Delta Science Program in July 2018. The information presented herein represents the work of the independent investigators and does not necessarily reflect the positions of CSAMP member entities.

Executive Summary
CAMT Entrainment Study 1
Prepared by Lenny Grimaldo – Principal Investigator

In response to federal litigation from the 2008 USFWS Delta Smelt Biological Opinion on SWP and CVP operations, the Collaborative Adaptive Management Team (CAMT) solicited proposals from our investigator team to address two key uncertainties (See CAMT Progress Report and Entrainment Workplan) underlying salvage and entrainment: 1) Factors affecting salvage and entrainment; and 2) Population consequences of entrainment. In collaboration with the Delta Smelt Scoping Team (DSST), we reviewed conceptual models and hypotheses underlying these uncertainties and held several discussions to recommend priorities to most effectively meet management objectives. The ultimate goal of these recommendations is to support a more confident assessment of Delta Smelt entrainment in order to better evaluate the efficacy of management actions used to operate the water projects in a manner that is consistent with the Endangered Species Act (ESA).

Our investigator team developed the following studies: 1) An examination of factors affecting salvage at the SWP and CVP; 2) An individual-based modeling (IBM) study examining behavior and movement of adult Delta Smelt in the south Delta to better understand entrainment timing and population losses; 3) A re-examination of the historical time series of annual proportional loss estimates; and 4) A re-examination of factors affecting population growth rate using updated environmental covariates and proportional loss estimates in a published Delta Smelt life cycle model. The last study was not completed by the investigator team due to competing professional commitments of key investigators.

In Study 1, our investigator team explored a number of statistical models and covariates (many not considered by previous peer-review publications or by the 2008 Biological Opinion) to examine what factors affect salvage of Delta Smelt at SWP and CVP. The team developed three reports that evolved hand-in-hand with DSST input and feedback. Initially, the team focused on annual patterns of regression (Report 1) but moved to an approach that sought to explain what happens during the onset of first flush conditions (Reports 2 and 3). Ultimately, a Boosted Regression Tree (BRT) model was applied to SWP and CVP salvage data and showed that salvage at each facility was largely explained by the same factors identified in the previous reports, but with differences in the order of importance (Report 3). The BRT model explained 85% and 90% of the of the variance in salvage data during first flush at CVP and SWP facilities. These are appreciable improvements in fit compared to models used for the 2008 USFWS Biological Opinion (and references cited within). Therefore, this study contributed to improved understanding of factors that are important to Delta Smelt during first flush periods and can be applied to help management of Delta Smelt entrainment risk at SWP and CVP.

Policy Science Forum Summary
Factors Associated with Salvage of Adult Delta Smelt
Prepared by the Delta Science Program

Background

Published research that led to the 2008 FWS BiOp relied on Old and Middle River flows (OMR) as the primary factor affecting adult Delta Smelt entrainment and salvage. Although turbidity was also recognized in the BiOp as an important factor influencing adult Delta Smelt salvage, even the best models including OMR and turbidity explained less than 40% of the observed variability* in salvage.

Delta Smelt salvage models were updated by adding the most recent eight years of data (now spanning 1993-2016), testing alternative conceptual models, and including a new type of analysis (Boosted Regression Tree) to assess the conditions associated with salvage of adult Delta Smelt. Statistical approaches developed for this study explained over 85% of the observed variation in salvage and explored a greater range of hydrodynamic conditions.

Results

What did we learn about the factors that affect entrainment?

Several different models were tested, included some that treated SWP and CVP separately, as well as some that associated factors with entrainment based on the conditions during first flush, rather than the entire season (Dec 1 to March 30). Here, first flush is defines as Dec 1 to the day 50% of the salvage for the year had been reached.

- Factors affecting salvage at SWP and CVP differ, suggesting slightly different mechanisms at play. See the relative influence of each factor in the box.
- The models show small differences in the importance of factors affecting salvage during first flush versus factors affecting salvage for the entire time series—suggesting that management during first flush is critical for affecting salvage during the entire season.

	PROJECT	
TIME FRAME	CVP whole season FMWT index – 18 OMR flow – 10 CCF turbidity – 10 CVP exports – 8 Cumulative precip – 8 Gross channel depletion – 8 Yolo bypass flow – 7 Cosumnes River flow – 6 SWP export – 6	SWP whole season SWP exports – 29 Yolo bypass flow – 18 FMWT index – 11 OMR flow – 10 CCF turbidity – 9 Cumulative precip – 5
	CVP first flush* FMWT index - 25 Cumulative precip – 14 Days since December 1 – 10 OMR flow – 10 Yolo bypass flow – 10 CCF turbidity – 6 SWP exports – 5	SWP first flush* SWP exports – 23 Cumulative precip – 20 Yolo bypass flow – 18 OMR flow – 14 FMWT index – 11
	*Includes data from Dec 1 to the day 50% of the salvage for the year had been reached.	

What did we learn that could help us manage entrainment better? Information generated from this study reinforces and builds upon results of previous work suggesting adult Delta Smelt entrainment risk can be assessed and managed using a combination of factors. Consistent with prior analyses, exports and/or OMR (i.e., hydrodynamics) have high explanatory power, as does turbidity, but so does previous Fall Midwater Trawl index (abundance), precipitation, and river flows. Small differences were observed when comparing factors associated with entrainment at each facility as well as modeling based on first flush or the whole entrainment season.

Does the new analysis allow us to establish new standards for periods of higher and lower entrainment risk, different from those set in the BiOp? Thresholds for high and low entrainment risk are difficult to define, though model output from this study could assist in developing thresholds. The subjective nature of the question of appropriate thresholds is beyond the scope of the researchers, and would have to be the product of a dialogue between scientists and decision makers.

Can a model that predicts salvage based on conditions be made? To make a "near real-time" prediction tool, daily monitoring data would have to be used as input. Models to predict entrainment risk in near real-time did not perform adequately. It is hard to predict salvage when only a few daily observations are recorded in a year (using the post-POD years). So initial efforts using the models to predict salvage were not successful.

Even though the models did not have predictive power, conditions associated with historic salvage were still identified. The single most important predictor of salvage is the population size (FMWT index). Also, a look-up table was developed identifying the relative entrainment risk of various combinations of the levels of key system conditions.

What tool was expected to be the result of the investigation?

A highly desirable out come this investigation would have been a model for forecasting salvage in "near real-time." Although, initial attempts to apply the boosted regression tree model to forecast Delta Smelt salvage were not fruitful, a look-up table to assist in identifying times of increased and decreased entrainment risk under different conditions were created from BRT results.

How can this information be used? The entrainment risk look-up table could be useful to the Smelt Working Group, by providing a risk assessment of entrainment under current and projected conditions, which will be useful in developing their water operations and related fish monitoring recommendations.

Future work

Factors associated with Salvage. These studies could provide the Delta Smelt science community with a framework for developing AM experiments to test hypotheses about DS entrainment. For example, releasing tagged adult smelt during varying first flush conditions could be used to determine the rate and direction of fish move in the south Delta. These studies could also help further quantify pre-screen loss rates for fish entrained into Clifton Court Forebay, and further understand how those rates are influenced by export levels and other factors. The tagging studies might also better quantify loss rates in the channels leading to the SWP and CVP during first flush periods (relative to other areas of the delta) akin to research that has been done for salmonids in the estuary.

Early Product # 1 to the Collaborative Adaptive Management Team: Review and Basic Exploratory Statistical Analysis of Adult Delta Smelt Salvage at the State Water Project and Central Valley Project Fish Facilities

Authors: Entrainment Investigator Team

Date: 6/16/2015

Executive Summary: This memo presents an exploratory analysis of the adult Delta Smelt salvage data conducted in four steps. In *Step 1*, we qualitatively examined daily salvage and concurrent environmental/operational conditions in the South Delta to search for general patterns of interest. In *Step 2*, we considered appropriate time scales for exploratory statistical analysis and documented the covariation between covariates (predictors of salvage) averaged across different time periods, and the covariation among candidate predictor and response variables. In *Step 3*, we tested numerous alternative ways of explaining adult Delta Smelt salvage using the covariates from *Step 2*. In *Step 4*, we demonstrated why currently available data cannot robustly address the hypothesis that entrainment of adult Delta Smelt has impaired population viability – at least since 2003. Regarding this last point, we note that (*i*) it has never been a stated goal of the U.S. Fish and Wildlife Service (FWS) that its Incidential Take Statements (ITS) represent a level of entrainment beyond which population viability would be impaired, and (*ii*) ongoing work by Ken Newman (FWS) and this Investigative Team should provide additional scientific insight into the issue of whether the entrainment of adult Delta Smelt measurably affects the species' viability.

Introduction

The CAMT Delta Smelt Entrainment Study Proposal for Study Element 1, *Examining the factors that affect the magnitude, timing, and duration of adult delta smelt salvage at the SWP and CVP Fish Facilities: identifying thresholds that define low and high risk entrainment conditions* proposed to address four study questions posed to the Investigator Team by the Delta Smelt Subteam (DSST).

- Is there a relationship between Delta Smelt distribution and habitat conditions (e.g., turbidity, X2, temperature, food) during fall and subsequent distribution and associated entrainment risk in winter?

- What factors affect Delta Smelt entrainment during and after winter movements to spawning areas?

- How should winter “first flush” be defined for the purposes of identifying entrainment risk and managing take of Delta Smelt at the south Delta facilities?

- What habitat conditions (e.g., first flush, turbidity, water source, food, time of year) lead to adult Delta Smelt entering and occupying the central and south Delta?

This memo presents an exploratory analysis of the adult Delta Smelt salvage data that addresses some of all four questions above, but is unlikely to represent a “final answer” for any of them. Our analysis was conducted in four steps. In *Step 1*, we qualitatively examined daily salvage and concurrent environmental/operational conditions in the South Delta to search for general patterns of interest. In *Step 2*, we considered appropriate time scales for exploratory statistical analysis and documented the covariation between covariates (predictors of salvage) averaged across different time periods, and the covariation among our different predictor and response variables. In *Step 3*, we tested numerous alternative ways of explaining adult Delta Smelt salvage using the covariates from *Step 2*. In *Step 4*, we demonstrated why currently available data cannot robustly address the hypothesis that entrainment of adult Delta Smelt has impaired population viability – at least since 2003. Regarding this last point, we note that (*i*) it has never been a stated goal of the U.S. Fish and Wildlife Service (FWS) that its Incidential Take Statements (ITS) represent a level of entrainment beyond which population viability would be impaired, and (*ii*) ongoing work by Ken Newman (FWS) and this Investigative Team should provide additional insight into the issue of whether the entrainment of *adult* Delta Smelt measurably affects the species’ viability.

Overarching conceptual model of how and why adult Delta Smelt become entrained

Some aspects of the study questions provided to us can be addressed using available published information because the scientific specificity regarding several details of Delta Smelt habitat use has grown considerably during the past ten years. This section summarizes that newer understanding in a defensible conceptual model of how and why adult Delta Smelt end up salvaged at the State Water Project (SWP) and Central Valley Project (CVP) fish facilities. Both maturing juvenile and adult Delta Smelt are strongly affiliated with turbid water (Feyrer et al. 2007; 2013; Bennett and Burau 2014). Delta Smelt’s winter movements are facilitated by tidal surfing; specifically, Delta Smelt use behaviors that keep them associated with the tidal and advective movements of turbid water (Feyrer et al. 2013; Bennett and Burau 2014). Delta Smelt move in response to winter freshets[1] that increase turbidity and decrease salinity in the upper estuary; specifically, Delta Smelt habitat expands and so the fishes’ distribution expands with it. The details of Delta Smelt’s movements are the subject of a current scientific debate in the peer-reviewed literature, i.e., during these winter freshets are Delta Smelt “migrating,” or not

[1] Increases in freshwater flow caused by storms

(Sommer et al. 2011; Murphy and Hamilton 2013)? Thus, there has been a recent effort to understand how Delta Smelt move at tidal time scales (Feyrer et al. 2013; Bennett and Burau 2014). However, all of the authors listed above recognize that Delta Smelt expand their spatial distribution in response to winter flows and do so by tracking the spatial expansion of turbid fresh water in the system. Thus, Delta Smelt can move quickly in any compass direction that the fish find suitable at the time they decide to move. The primary difference between newer publications and older papers is that older papers suggested that Delta Smelt had a very gradual "diffuse" migration starting in fall (Bennett 2005) or spring (Moyle et al. 1992) that was not explicitly associated with changing water quality conditions.

Adult Delta Smelt can get entrained when they expand their distribution into the southern portion of the Delta when they follow the tidal and advective movements of turbid water into this region (Grimaldo et al. 2009). Exports have little effect on the tidal dispersion of turbidity in most of the estuary (Schoellhamer 2002; McKee et al. 2006); however, the operation of the Delta Cross Channel gates, and the magnitude of water exports relative to seasonal river inflows, exert some influence on the dispersion of turbid water (and Delta Smelt that happen to surf with it) into the southern Delta because these water project operations affect the flow of Sacramento and San Joaquin river water into and through the southern Delta (e.g., Arthur et al. 1996; Monsen et al. 2007; Kimmerer and Nobriga 2008). This is the basis of any conceptual model that assumes there is a mechanistic reason why adult Delta Smelt salvage increases when Old and Middle River (OMR) flows are negative and turbidity is high (e.g., Kimmerer 2008; Grimaldo et al. 2009).

The questions posed to our Investigator Team also expressed interest in how factors like water temperature and predator-prey dynamics involving Delta Smelt might also affect their vulnerability to entrainment. Peak Delta Smelt spawning occurs in association with water temperatures that most frequently occur during the spring (Bennett 2005; Rose et al. 2013a). However, most of the salvage of adult Delta Smelt happens during the winter (Grimaldo et al. 2009). Therefore, the majority of adult Delta Smelt salvage cannot be related to spawning *per se*. Exploratory analyses (not shown) found no indication that water temperatures have any influence on adult Delta Smelt salvage, which is consistent with previous studies (Grimaldo et al. 2009), so there is no further mention of water temperature in this memo.

The low-salinity zone rearing habitats often used by maturing juvenile Delta Smelt were once a productive fish nursery – particularly in the vicinity of Suisun Bay and Marsh. However, the productivity of this area has been substantially degraded by overbite clam grazing (Alpine and Cloern 1992; Feyrer et al. 2003; Kimmerer and Thompson 2014) and likely other limiting factors like chemical inhibition of diatom growth rates (Dugdale et al. 2013) and water diversions (Jassby and Powell 1994; Jassby et al. 2002). These ecological changes have left only a few (comparatively) productive habitats in the upper estuary: Napa River marshes (Cohen and

Bollens 2008), Suisun Marsh (Mueller-Solger et al. 2002; Hobbs et al. 2006), the Yolo Bypass (when it drains floodwaters; Mueller-Solger et al. 2002; Sommer et al. 2004), and parts of the southern half of the Delta (Lucas et al. 2002; Nobriga et al. 2005). The ability of Delta Smelt to use these few remaining comparatively productive habitats is often limited by physical and water quality conditions; e.g., the Yolo Bypass dries up, salinity is often too high in Napa River (Hobbs et al. 2007), and can be too high in parts of Suisun Marsh, and water temperature and transparency are often too high in the southern Delta (Feyrer et al. 2007; Nobriga et al. 2008).

During fall through the subsequent spring, Delta Smelt eat a wider variety of prey types than younger life stages (Lott 1998; Slater and Baxter 2014). These include planktonic crustaceans and larval fishes, and noteworthy proportions of benthic or epibenthic crustaceans as well. It is unknown whether the latter are eaten by Delta Smelt foraging near the bottom of the water column or taken incidentally when they are displaced (or migrate; Kimmerer et al. 2002) up into the water column. Regardless, available monitoring information cannot be used to fully characterize prey availability to adult Delta Smelt because no single survey method can capture all of the major prey categories consumed, and data on the potential prey field are not available at time scales relevant to winter dispersal of Delta Smelt. However, a recent life cycle model did use predator-prey theory and bioenergetics modeling to develop a food availability model that the authors applied to adult Delta Smelt (Rose et al. 2013a).

Parts of the southern Delta have high phytoplankton production (Lucas et al. 2002; Jassby 2008) and comparatively high fish biomass (Grimaldo et al. 2004; Nobriga et al. 2005). Thus, it is possible that Delta Smelt dispersing into the San Joaquin River during winter freshets are able to take advantage of elevated prey availability; however, this hypothesis has not been tested. In other words, it is not known whether Delta Smelt using the San Joaquin River or its distributary channels prior to spawning receive an energetic benefit that is not realized by fish rearing elsewhere in the estuary. Because this hypothesis has not been tested, we cannot evaluate it at this time. As a result, this initial product for the CAMT follows several other prior analyses of salvage data in that it focuses on a few environmental/operational covariates for the South Delta that are known to be mechanistically associated with the salvage of adult Delta Smelt.

Overview of factors that decouple salvage from entrainment

The salvage of Delta Smelt at the CVP and SWP fish facilities in the southern Delta is the most apparent form of incidental take involving the operations of these water projects because it is the only Project take that is observed and recorded. People naturally focus on salvage because they can "see" it. Therefore, it is not surprising that water management strategies designed to protect Delta Smelt have long focused on understanding this particular source of loss by experimenting with water operations to learn how to minimize Delta Smelt salvage in a manner that minimizes water supply disruption (Nobriga et al. 1999; 2000; Poage 2004; Hymanson and Brown 2006; Brown et al. 2009).

The CVP and SWP fish facilities attempt to separate fish from water diverted out of the Delta before the water gets pumped into these systems' aqueducts (Brown et al. 1996). Louver systems guide fish into the fish facilities where they are collected on smaller-meshed fish screens, placed into trucks and released back into the Delta at release sites along the Sherman Island levees. The salvage of fish is imperfect - particularly for small-bodied fishes. Thus, fish salvage represents a variable and unquantified fraction of the fish that were actually *entrained* in the diverted water (Brown et al. 1996; Kimmerer 2008; Castillo et al. 2012). The fish facilities staff record subsamples of the fish they collect and the counts are expanded into estimates of the daily salvage of each fish species. For Delta Smelt, these daily expanded salvage counts are available dating back to 1980 but the counts are considered more accurate since QA/QC procedures were standardized in 1993 (Grimaldo et al. 2009). Therefore, this memo only uses data for water years 1993-2014.

All three FWS Biological Opinions for the Coordinated Operations of the CVP and SWP (issued in 1995, 2005, and 2008, respectively), have developed an ITS based on summaries of daily expanded Delta Smelt *salvage*. By doing so, FWS made the explicit assumption that salvage is a reasonable proxy for entrainment. Delta Smelt embryos hatch into circa 5-mm larvae and the minimum fish size recorded at the fish facilities is 20 mm, so there cannot be any relationship at all between salvage and entrainment of larval Delta Smelt (Kimmerer 2008). The number of Delta Smelt salvaged at the fish facilities peaks at a length of about 30 mm, so there must still be considerable decoupling between the entrainment and salvage of Delta Smelt between 20–30 mm in size. However, most adult Delta Smelt are salvaged during the winter (between mid-December and March), and are greater than 50 mm long (Figure 1). Therefore, adult Delta Smelt are large enough to be screened and counted. The primary factors that might decouple entrainment and salvage of adult Delta Smelt are: predation in front of the fish facilities, and louver efficiencies that vary with pumping operations. Regarding the former, there is a commonly held belief that mortality rates of fish are higher in front of the SWP than the CVP fish facilities due to differences in "pre-screen loss[2]" because entrained fish have to traverse Clifton Court Forebay to reach the State's fish facility. Castillo et al. (2012) estimated that the pre-screen mortality rates for several experimental groups of Delta Smelt released into Clifton Court Forebay were circa 90-100 percent. This suggests that over a time scale of about 1 day to 1 week, even the salvage of Delta Smelt greater than 30 mm long may be highly decoupled from their actual entrainment. However, we provide evidence in this memo that over longer time

[2] Pre-screen loss is used as a catch-all phrase for mortality of fishes that occurs prior to the attempts to collect them at the fish facility screens. It is generally assumed that predation – particularly predation by striped bass residing in the forebay, and to lesser extent in front of the CVP fish screens, is the major source of pre-screen loss.

scales, the salvage of adult Delta Smelt is correlated with their relative abundance, and as such, salvage must also be a proxy for entrainment.

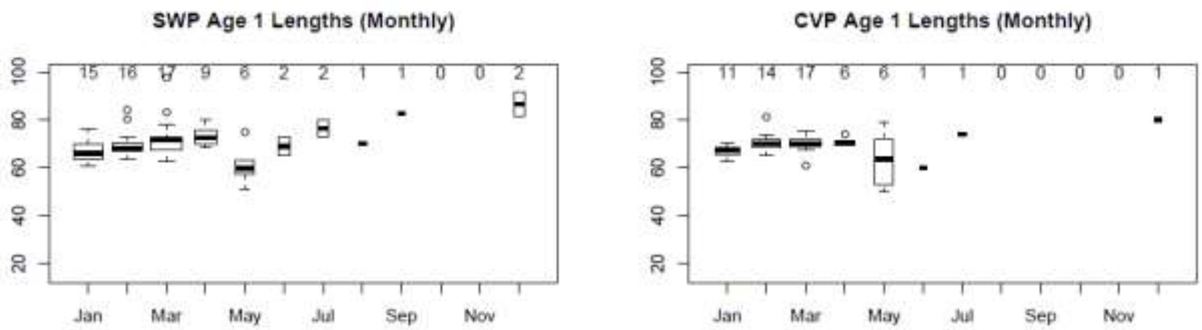

Figure 1. Boxplots summarizing monthly length measurements in millimeters of adult Delta Smelt taken at the State Water Project (SWP) and Central Valley Project (CVP) fish facilities (Skinner and TFCF respectively). Panels extracted from a Figure made by Ken Newman, USFWS. The numbers along the upper borders of each panel are the numbers of fish measured for fork length.

Methods

Step1 – Visual analysis of adult Delta Smelt salvage time series plots: We generated time series plots of adult Delta Smelt salvage and a concurrent index of south Delta conditions for each of the 22 water years 1993-2014. We used the plots to get a 'big picture' view of trends in the data, quantity of missing data, etc. In particular, we were evaluating how closely increases in salvage tracked changes in the conditions index described below (which directly addresses the third question posed to our Team) and we looked closely for situations where the conditions index changed enough to appear to change the rate of salvage so that we could describe the magnitude of those changes. The vast majority of adult Delta Smelt salvage has occurred between December 1 and March 31 in most years; after March, the salvage data begin to include and then become dominated by Age-0 Delta Smelt (Grimaldo et al. 2009). Based on this fairly consistent seasonal timing, we plotted data for December 1 (day 1) through March 31 (day 121 or 122 depending on leap years) of each water year, which is consistent with the time period analyzed by FWS in its 2008 BiOp.

The CVP and SWP fish facilities are located only about two miles from each other, but they sample water that differs in its fractional contributions from the Sacramento and San Joaquin rivers (Arthur et al. 1996). Each fish facility can be thought of as a large pump sampler, i.e., a type of fish sampling "gear". It is standard in fisheries science to correct fish catches for the amount of effort expended. In other words, to convert catch into catch per unit effort

(CPUE), which for the fish facilities is two-factored: (*i*) the amount of water exported, and (*ii*) the number and duration of salvage counts each day. The salvage data come corrected for the latter as expanded salvage. We corrected for the former by dividing daily salvage by daily exports at each facility. In *Step 1*, we plotted daily adult Delta Smelt salvaged · 10,000 m^{-3} of water exported, as an estimate of CPUE. We generated separate CPUEs for the SWP and CVP fish facilities. This conversion put Delta Smelt salvage into the same units that CDFW uses in its Spring Kodiak Trawl Survey (SKT) (https://www.wildlife.ca.gov/Regions/3).

We plotted daily salvage density separately for each fish facility as an accumulating total.

$$SD_{cum} = SD_i + \Sigma SD_{1 \ldots i-1} \quad (1)$$

In equation 1, SD_{cum} is the cumulative salvage density through day i, SD_i is the salvage density on day i, and $\Sigma SD_{1 \ldots i-1}$ is the sum of daily salvage densities for the water year on all days prior to day i; SD_{cum} reaches its final value for the year by day 121 or 122 (if not sooner). Note that these accumulated salvage densities are mathematical analogs to the trawl-based abundance indices calculated by CDFW. Therefore the March 31 value for each water year can be taken as an 'abundance index' of Delta Smelt based on 'sampling' conducted by the fish facilities.

Ken Newman (USFWS Mathematical Statistician) also recommended that instead of SD_{cum}, we use a salvage CPUE calculated as the December 1 – March 31 salvage total divided by the December 1 – March 31 export total. However, we did not do that because (*i*) raw salvage (S) and SD_{cum} are very highly correlated (see *Step 2* Results), and (*ii*) the SD_{cum} and the alternative version suggested by Newman are likewise highly correlated, though the slopes of the relationships differ dramatically between the two fish facilities (Figure 2). The very high correlations among these alternatives led us to believe that the use of SD_{cum} was a sufficient contrast to analyses based on raw salvage.

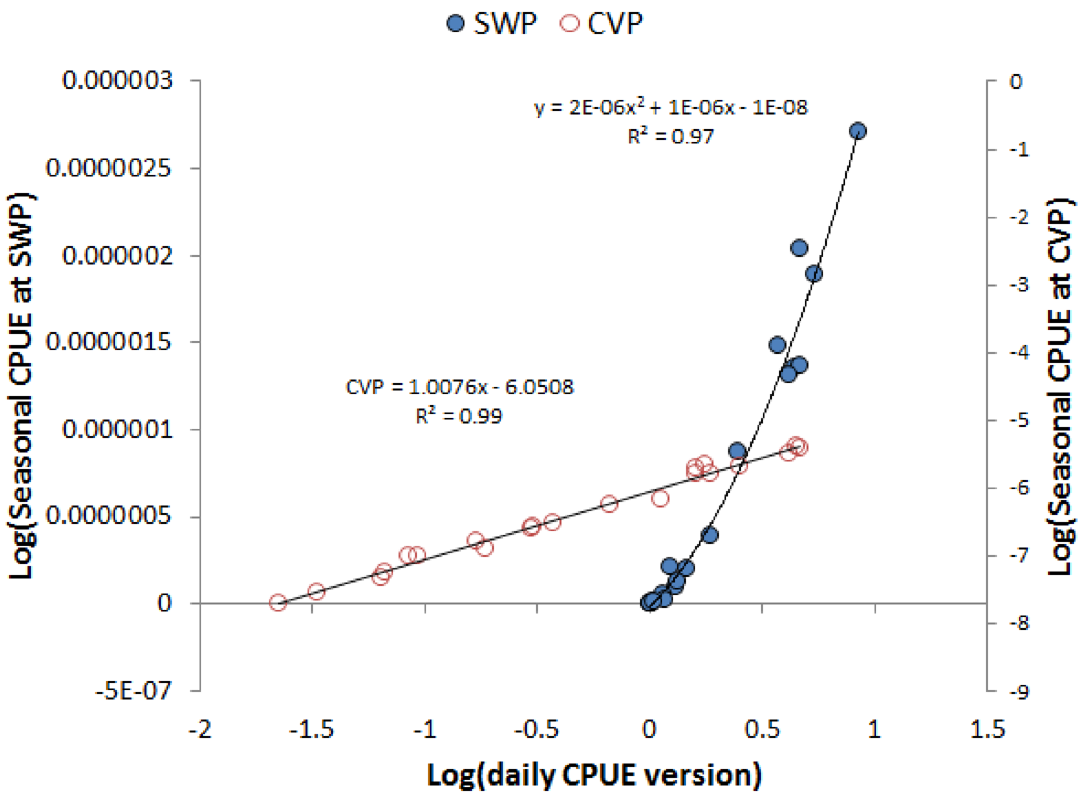

Figure 2. Scatterplots of two alternative versions of $\log_{10}$-transformed SWP and CVP salvage "abundance indices" for adult Delta Smelt. The constant 1 was added to the SWP indices before log-transformation because SWP salvage of adult Delta Smelt was zero in 2007 and 2011. The values of the x-axis are daily salvage per 10,000 m^3 summed for the period December 1 – March 31 of water years 1993-2013. The values for the y-axes are the sum of December 1 – March 31 salvage divided by the sum of December 1 – March 31 exports (in units of 10,000 m^3), for the SWP and CVP fish facilities, respectively.

As reported previously (e.g., Grimaldo et al. 2009; Deriso 2011), adult Delta Smelt salvage is often associated with a combination of negative OMR flows and the dispersal of turbid water into the southern Delta during a "first flush[3]" generated by increased runoff during winter storms.

$$FF_d = OMR_d \cdot NTU_d \qquad (2)$$

In equation 2, FF_d represents the South Delta conditions index alluded to above. It is the product of OMR_d, the sum of daily tidally-filtered flows in Old and Middle rivers, and NTU_d, the daily average turbidity measured at Clifton Court Forebay in nephelometric turbidity units (NTU). It was easy to see missing data using this construct because equation 2 is a product of two data sets, thus any day that is missing data from either data set has a value of zero. We received a

3The term "first flush" describes high river flow that follows the first major storm of the year, which often transports a large fraction of suspended sediment delivered to the Delta in any given year (Bergamaschi et al. 2001).

complete estimated daily OMR data set from Pete Smith in February 2015, so any missing values in FF_d are due to missing turbidity data. For the sake of argument, and to create a common set of graphical axes, we considered FF_d lower than negative 100,000 to be a general indicator of 'first flush' conditions dispersing into the southern Delta . This chosen threshold is arbitrary, but based on visual examination of all 22 plots.

We used graphical summaries to compare the CPUEs at the two fish facilities (SD_{cum}) and to compare CPUEs between the fish facilities and the SKT. We plotted the cumulative distribution of non-zero CPUEs at each fish facility and compared these qualitatively to the non-zero and mean south Delta CPUEs from the SKT.

Step 2 – Analysis to support choosing explanatory variables for Step 3: The hydrodynamic influences of water project operational decisions and natural inflow events on conditions in the estuary are time-dependent (Kimmerer and Nobriga 2008; Sommer et al. 2011). Previous evaluations of the adult Delta Smelt salvage data have been plotted and/or statistically analyzed at daily to seasonal time steps (Kimmerer 2008; Grimaldo et al. 2009; Deriso 2011; Manly unpublished; MWD 2014). Note that in the case of adult Delta Smelt, analysis of the data at a seasonal time scale is approximately equivalent to an annual time scale analysis because the vast majority of adult Delta Smelt salvage now occurs during a few months of the year in the winter (Grimaldo et al. 2009) because the southern Delta has become seasonally uninhabitable over time (Feyrer et al. 2007; Nobriga et al. 2008).

Management applications, including the potential for operational flexibility, are a key desired outcome of this investigation so new approaches might be best informed by short time scale analyses. Plots of the data on a daily time step are useful for visualizing general patterns. However, valid *statistical* analysis of the data at a daily time step is extremely problematic and therefore, we have not attempted such an analysis at this time. We may do so later pending the outcomes of the other elements of this investigation. The biggest problem with trying to statistically analyze the salvage data at a daily time step is that salvage (or lack of salvage) of Delta Smelt on any given day (n) is correlated with the salvage (or lack of salvage) on the prior day ($n – 1$) and likely to be correlated at multiple time lags (e.g., $n – 2$, $n – 3$, etc.) because daily salvage is also mechanistically linked to environmental/operational conditions occurring both during and prior to the observed salvage – again, likely at multiple lagging time steps. This multifaceted temporal autocorrelation in the data is apparent in the 'contrails' made by certain groups of data points in plots of daily salvage vs OMR (Figure 3). Therefore, if an investigator wanted to link daily salvage to environmental/operational conditions in a statistically defensible manner, they would first need to account for the daily and longer time scale autocorrelation in the salvage data and then find an objective way to link the left over variation in daily salvage to environmental/operational conditions potentially over yet another different time scale(s). Of itself this would be exceedingly difficult. The fact that a lot of key daily environmental and salvage data are missing, renders this approach inadvisable without assistance from validated particle tracking models that we will develop as part of this project.

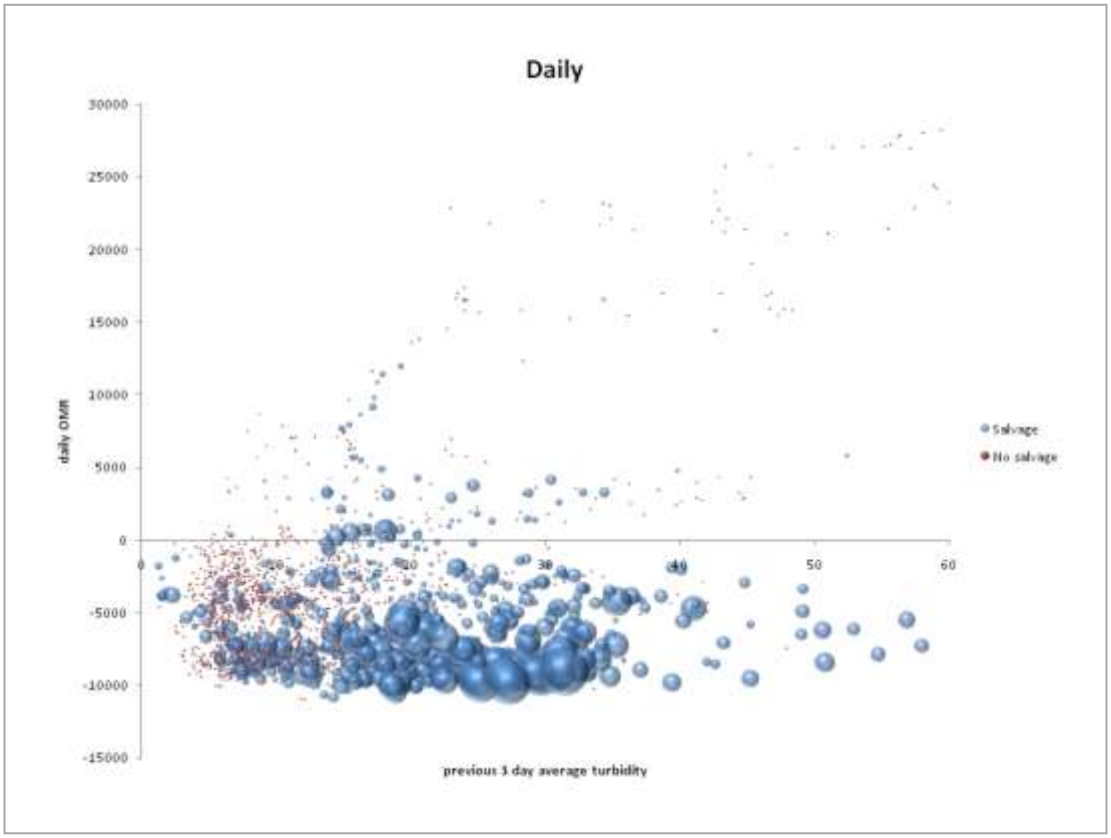

Figure 3. Recreation of Figure 3 from Deriso (2011; January 28, 2011 Declaration in support of Plaintiffs' request for injunctive relief in the delta smelt consolidated cases; court document # 772); however, unlike in the cited document, days with positive OMR flow were also included. The x-axis is average turbidity (NTU at Clifton Court Forebay) for three days prior to the daily salvage and the y-axis is the daily net flow in Old and Middle rivers (OMR) on the day of salvage. The blue datapoints are daily salvage of adult Delta Smelt normalized to the Fall Midwater Trawl abundance index; the larger the data point, the higher the salvage relative to population size. Red data = no salvage on that day. Time period plotted is December 1 – March 31, 1988-2009.

We did not summarize or analyze the salvage data at a monthly time step because many salvage events have straddled two or more calendar months. Thus, breaking these events into separate monthly averages could misrepresent the event both by parsing it and by including environmental data in calculations of monthly average conditions that had nothing to do with the salvage event. Thus, in *Step 2*, we compare seasonally-averaged covariates to alternative event-averaged covariates in an attempt to generate a maximum amount of contrast between short- and long time scale summaries of environmental/operational conditions in the southern Delta. In other words, our intent was to see whether we could generate statistically independent versions of some of our covariates by using event (5-day average) versus long (121-122 day average) versions. We compared the covariation among alternative covariates (e.g., OMR versus turbidity), covariates across time scales (e.g., event OMR versus seasonally-averaged OMR), and among different versions of response variables (e.g., raw salvage (S) versus salvage CPUE (SD_{cum})).

The rationale for developing and exploring event-averaged covariates was that it seems likely that environmental/operational conditions occurring during the *accelerating* part of the seasonally accumulating salvage are the conditions that best represent what actually *caused* the fish to occupy nearby channels in the south Delta from where they could be entrained (e.g., question 4). During the *decelerating* part of seasonally accumulating salvage, it seems likely that salvage is less connected to concurrent operations than with whether Delta Smelt had *already occupied* habitats near the SWP and CVP facilities. The event-averaged covariates are the lowest 5-day average OMR, the lowest 5-day average FF_d, and the highest 5-day average turbidity at Clifton Court Forebay that occurred in the 31 days prior to and including the day that adult Delta Smelt salvage exceeded its 50th percentile for each water year (Table 1). The choice of 31 days was arbitrary in that it represented one full calendar month, which may have no biological meaning. However, it was long enough to encompass the range of migration (dispersal) estimates generated by Sommer et al. (2011), which are the only available estimates. After SD_{cum} reaches its 50th percentile for the water year, the rate of salvage is slowing or decelerating. Thus, the event-averaging periods are very short time scale averages that differ among facilities and water years because they reflect differences in the timing of salvage among facilities and water years. In contrast, the seasonally averaged covariates reflect the same time period every year (conditions averaged for December 1 – March 31) and therefore the same values are applied to predict salvage at both fish facilities. Like the analysis for *Step 1*, the analysis for *Step 2* was qualitative – we generated scatterplots of candidate covariates and response variables so that we could assess whether they were correlated. This step helped us properly set up and interpret the quantitative results in *Step 3*.

Table 1. Summary of covariate values used in Steps 2 and 3 of this memo. N/A = not applicable because event averages cannot be generated when no salvage of adult Delta Smelt occurred. The season averages of the first flush index can be derived by multiplying season average OMR flow by season average turbidity; the event first flush indices do not necessarily correspond to the same day as minimum OMR flow or maximum turbidity and so their values are provided in the table.

			State Water Project			Central Valley Project		
Water Year	Season average OMR	Season average turbidity	Event average OMR	Event average turbidity	Event average first flush index (in thousands)	Event average OMR	Event average turbidity	Event average first flush index (in thousands)
1993	-5369	11.6	-8498	33.6	-276	-9300	25.7	-204
1994	-4742	12.8	-5343	15	-75	-5343	15	-71
1995	-3145	7.55	-8894	21.1	-169	-8894	21.1	-169
1996	-1281	9.57	-8446	8.2	-65	-8446	8.2	-65
1997	10376	28.1	7210	48.4	+40	3999	48.4	+40
1998	2103	22.1	-8992	19.9	-179	6188	44.6	+97
1999	-760	14.5	-731	31.3	-13	-3855	31.3	-62
2000	-5282	19.7	-8892	49.4	-331	-8892	49.4	-331
2001	-5681	13.8	-6894	33.3	-161	-7660	33.3	-161
2002	-7731	14.3	-10362	32.5	-232	-10362	33.3	-232
2003	-8185	17.0	-9546	30.5	-265	-9236	30.5	-265
2004	-8080	15.0	-10118	22.9	-198	-10118	22.9	-198
2005	-5525	23.0	-9462	55.1	-343	-9462	55.1	-343
2006	-2954	14.8	-9302	25.8	-175	-6742	15.3	-80
2007	-5462	8.50	N/A	N/A	N/A	-4734	10.5	-46
2008	-3728	21.6	-5062	57.8	-203	-5062	57.8	-203
2009	-2991	9.24	-5296	11.8	-62	-3734	9.9	-31
2010	-4382	13.6	-5566	18.9	-102	-5566	28.5	-103
2011	-4130	23.2	N/A	N/A	N/A	-5010	28.9	-124
2012	-4525	9.47	-5066	12.5	-40	-5162	10	-44
2013	-3575	13.8	-3524	32.5	-66	-6208	32.5	-101
2014	-2172	9.93	N/A	N/A	N/A	N/A	N/A	N/A

Step 3 – Basic statistical analysis of factors influencing adult Delta Smelt salvage: We wanted to keep things simple for this initial product so we used linear regression analyses in an information-theoretic approach to test numerous alternative hypothesized relationships between adult Delta Smelt salvage, abundance indices, and environmental/operational covariates. We used linear regression because it is a statistical tool that most people are familiar with, and we performed a lot of individual tests to evaluate whether this line of inquiry is sufficient to increase the understanding of adult Delta Smelt salvage (and by extension, entrainment) beyond the currently published state of science (i.e., Grimaldo et al. 2009).

The basic approach was to start with several alternative base models (equations 3-4 below), then add covariates (predictor variables) to the base models to see whether the covariates made for a better model. The base models represent alternative ways to test the assumption that the relative abundance of adult Delta Smelt in the ecosystem predicts adult Delta Smelt salvage. All hypothesis tests were performed separately for the SWP and CVP data to see whether the same models provided the best predictions of salvage at both fish facilities. We did this because all authors cited above have analyzed combined salvage (SWP + CVP) and in so doing have assumed *a priori* that the same factors affect the salvage of Delta Smelt at both locations. We wanted to determine whether that assumption was supported by the data. The variables in equations 3 and 4 were $\log_{10}$-transformed before the analysis. The constant 1 was added to the SD_{cum} and S data before log-transformation because the log of zero is mathematically undefined.

$$SD_{cum} \sim FMWT + \varepsilon \qquad (3)$$

$$S \sim FMWT + \varepsilon \qquad (4)$$

In equation 3, SD_{cum} is defined as it was in equation 1. In equation 4, S is the sum of December 1 – March 31 expanded salvage. In equations 3 and 4, $FMWT$ is the Fall Midwater Trawl index for the same water year (sometimes called "prior FMWT index" because it is recorded for the calendar year prior to the water year in which it is mostly encompassed), and ε is the standard least squares error estimates in the regression parameters. In all, there were four base models: two equations * two fish facilities.

We performed each of the following linear regression tests for each fish facility. For equations that include the terms *OMR*, *NTU*, or *FF*, these were also tested separately using seasonally-averaged and event-averaged versions of those covariates.

$$SD_{cum} \sim FMWT + NDOI + \varepsilon \qquad (5)$$

$$SD_{cum} \sim FMWT + OMR + \varepsilon \tag{6}$$

$$SD_{cum} \sim FMWT + NTU + \varepsilon \tag{7}$$

$$SD_{cum} \sim FMWT + FF + \varepsilon \tag{8}$$

$$SD_{cum} \sim FMWT + OMR + NTU + \varepsilon \tag{9}$$

$$SD_{cum} \sim FMWT + NDOI + OMR + NTU + \varepsilon \tag{10}$$

$$S \sim FMWT + NDOI + \varepsilon \tag{11}$$

$$S \sim FMWT + E + \varepsilon \tag{12}$$

$$S \sim FMWT + OMR + \varepsilon \tag{13}$$

$$S \sim FMWT + NTU + \varepsilon \tag{14}$$

$$S \sim FMWT + FF + \varepsilon \tag{15}$$

$$S \sim FMWT + OMR + NTU + \varepsilon \tag{16}$$

$$S \sim FMWT + NDOI + OMR + NTU + \varepsilon \tag{17}$$

$$S \sim FMWT + E + NTU + \varepsilon \tag{18}$$

$$S \sim FMWT + NDOI + E + NTU + \varepsilon \tag{19}$$

NDOI is a variable inspired by Grimaldo et al. (2009) based on DAYFLOW's Net Delta Outflow Index (NDOI); specifically it is $\log_{10}$(absolute value(mean December $NDOI_i$ – the water year 1993-2014 median of mean December *NDOI*)). This variable has minimum values when December Delta outflow in year *i* was near the long-term median and higher values when it was higher or lower than the long-term median. The variable was intended to test the hypothesis that adult Delta Smelt salvage has a spatial influence that is affected by Delta outflow or X2 in the period right before winter dispersal (question 1). Specifically, the conceptual model is that Delta Smelt salvage has been highest when flows prior to dispersal were of intermediate magnitude because very high flows largely disperse the population seaward of the Delta, limiting entrainment, and very low flows are associated with low turbidity so the population tends to not enter the southern half of the Delta where water clarity and entrainment risk are highest. Thus, we expected to see an inverse correlation between *NDOI* and *S* (or SD_{cum}).

OMR is the seasonal or event-averaged OMR flow (expected relationship = inverse), *NTU* is the seasonal or event-averaged turbidity at Clifton Court Forebay (expected relationship

= positive), and *FF* is the seasonal or event averaged conditions index defined as it was in equation 2 (expected relationship = inverse). *E* is the sum of exports for December 1 – March 31 of each water year (in m^3), calculated separately for the SWP and CVP. Project exports were only used as a covariate of raw salvage (*S*) because exports were 'built into' SD_{cum}. We did not include any analyses that included *E* and *OMR* in the same regression because these variables are correlated (see Results for *Step 2*).

Often in linear regression, the more covariates (predictor variables) that are used, the more total variation in a relationship is explained. In an attempt to account for this, statistical software often outputs an adjusted R^2 that penalizes the model for having increasing numbers of terms. However, this is not considered an adequate penalty anymore. As mentioned above, we used the information-theoretic approach originally proposed by Burnham and Anderson (1998) to guide our analysis in *Step 3* because it provides a more robust way to determine whether an additional covariate or covariates are legitimately explaining enough additional variance to warrant keeping them as predictors. The information-theoretic approach is a fancy way of saying that we used AIC_c[4] in addition to *P*-values and adjusted R^2 as indicators of whether one linear regression model was 'really' better than an alternative one. This process is straightforward. You start with a base model and calculate its AIC_c. Then you add a covariate or covariates plural, and recalculate the AIC_c. The general guideline is that if the AIC_c of the second model is more than 2.0 units lower than the base model, there is evidence that it is better, but not simply because it has more predictor variables in it. This process is repeated as necessary. In practice, -2.0 AIC units is just a guideline – in some cases an AIC_c should be expected to drop more than that, but we used it as a screening criterion, and in many cases AIC_c did drop more than 2.0 units when covariates were added. The main thing to keep in mind is that the AIC_c can only be compared for sets of covariates used to predict the same series of the response variable. Therefore, the AIC_c from SWP analyses cannot be compared to those from the CVP analyses (though the adjusted R^2 can be), nor can the season-average analyses for either fish facility be compared to their event-averaged analogs because the event-averaged data sets are subsets of the water year 1993-2014 data (Table 1).

We started by testing the two alternative base models per fish facility. Then we tested equations 5 through 19 for each fish facility using both seasonal average (full data set) versions and event-average (data subset per Table 1) versions. All told, we conducted 64 different hypothesis tests; the R code for all of the regression analyses that we tried is provided in an appendix to this document. All of the 64 linear regressions reported in the Results were statistically significant at the standard $\alpha < 0.05$, but for reference, a Bonferroni-corrected *P*-value for $n = 64$ hypothesis tests would be 0.0008. Thirty-nine of the models met even this highly conservative Bonferroni-corrected *P*-value and each result was checked for correct signs of

4 AIC is the Akaike Information Criterion which imposes a penalty on models for adding variables. The AICc is a 'corrected' version that adds yet another penalty when additional variables are added, making for very conservative results.

expected relationships (see Appendix). Thus, we are not particularly concerned about the number of hypothesis tests that were performed.

Several members of CAMT's Delta Smelt SubTeam (DSST) have also expressed an interest in searching for water management thresholds that may aid in limiting Delta Smelt salvage while allowing for flexibility in water diversion rates. To explore this possibility, we used generalized additive modeling (GAM) for several of the regression models to determine whether our linear regression analyses might be missing useful or previously unrecognized threshold relationships (i.e., nonlinear relationships) between environmental/operational predictors and the salvage of adult Delta Smelt. For now, we have limited this analysis to the SWP data because the results were not promising (see Results). Specifically, we generated GAM versions of the following equations which were described in linear form above.

$$S \sim FMWT + \mathrm{s}(E) + \varepsilon \quad (12)$$

$$S \sim FMWT + \mathrm{s}(OMR) + \varepsilon \quad (13)$$

$$S \sim FMWT + \mathrm{s}(NTU) + \varepsilon \quad (14)$$

$$S \sim FMWT + \mathrm{s}(FF) + \varepsilon \quad (15)$$

The letter 's' in front of the environmental/operational covariates indicates that we allowed the GAM analysis to make a nonlinear prediction of the relationship between that variable and Delta Smelt salvage. The basic logic in this analysis is that if the GAM predicts a nonlinear relationship, then there is support for a threshold. If it returns a linear relationship, then there is not. The mgcv package in R decides whether the relationship is best described as linear or nonlinear by comparing the extra degrees of freedom needed to generate a nonlinear prediction against the gain in explanatory power that is generated by doing so. Thus, the software may return a linear or a nonlinear prediction even when the smoothing term 's' is specified. We did not allow the software to return a nonlinear relationship between the FMWT index and salvage because (*i*) we did not have a reason to expect it should (i.e., higher abundance should predict higher abundance), and (*ii*) having all terms be nonlinear could (and would – not shown) generate highly confounded but conceptually unsupported relationships. We performed GAMs on the season average versions of equations 12 and 13 as well as the event average versions of equations 13-15. We present plots showing the GAM predictions. We also compared the linear and nonlinear versions of equation 13 to observed salvage in a separate plot. We used the same assumptions of normal distribution of error that are assumed in linear regression to keep these two analyses as comparable as possible.

<u>Step 4 – Simple assessment of why available data cannot robustly test the population impact of adult entrainment</u>: To our knowledge, FWS has never attempted to quantitatively link an ITS to Delta Smelt population increase or decrease, and we remind the reader that doing so has not been a stated goal of any previous ITS. That said, we developed a basic data summary to evaluate whether available data support the hypothesis that adult salvage (and by extension, entrainment) measurably affected Delta Smelt survival during water years 2003-2014. The analysis relied on three basic assumptions. First, salvage of adult Delta Smelt is correlated with abundance indices *because* both are samples of the same population, i.e., the correlation *is* explicitly assumed to be causation in this case. Second, years when salvage of delta smelt was higher than expected based on the FMWT, entrainment was "high" and in years when salvage was lower than expected based on the FMWT, entrainment was "low". Of course some of the variation in such a relationship is also due to imperfect sampling or 'observation error' – and state-space models could be employed to try to separate this observation error from the variability that was actually caused by environmental/operational conditions (e.g., Newman and Lindley 2006). Ken Newman is working on a method to do that and our team will be as well in the near future. Third, there is a fairly strong linear relationship between the FMWT and subsequent Spring Kodiak Trawl (SKT) indices with noteworthy variation only at low index values (see *Step 4* Results). One very parsimonious explanation for variation only at low index values is that the only substantial "noise" is observation error that we would expect at low abundance given imperfect sampling methods. We employed a simple visual analysis using a color-coded scatterplot to show that years with assumed "high" versus "low" entrainment produce no pattern on the FMWT v. SKT scatterplot.

Results

Step 1: Sudden increases in adult Delta Smelt salvage have often, but not always occurred coincident with FF_d decreasing below negative 100,000 (Figures 4-6). Extended periods of these 'first flush' conditions were apparent in water years 1993 (~ 45 days), 1998 (~ 45 days) 2000-2005 (~ 33 to 104 days), 2008 (~ 45 days), and 2011 (~ 60 days), though missing data during 2002 distort the pattern somewhat in that panel when FF_d may have been lower than negative 100,000 for most of a 104-day period. Accelerating salvage was associated with each of these water years except in 2011 when it lagged behind the event and was only observed at the CVP. Comparatively brief first flush conditions occurred in water years 1994 (~ 5 days) 1995 (~ 22 days), 2006 (~ 14 days), and 2013 (~ 17 days). Accelerating salvage was also frequently observed coincident with the comparatively brief first flush conditions in these years. No (or virtually no) first flush conditions occurred in water years 1996, 1999, 2007, 2009-2010, 2012, and 2014; however salvage was reported in most of these years as well.

A strong influence of Delta Smelt abundance on the seasonal salvage total is also apparent in Figures 4-6. In particular, salvage densities have gotten so low compared to historical that they had to be plotted on a different scale starting in water year 2006 and then again starting in water year 2009. This was partly because Delta Smelt abundance has gotten so low, but it likely also reflects the impact of the Service and NMFS' current OMR flow limits which started to be implemented in water year 2009 when the y-axis scale had to be lowered a second time.

In Figures 5 and 6, the numbers of Delta Smelt collected by the CDFW's SKT during January–March at stations in the southern Delta upstream of Jersey Point (trawl stations 812–915) are included to show just how infrequent detections of Delta Smelt have gotten in routine monitoring of the southern Delta in recent years. Note that the SKT only collected three Delta Smelt between January and March 2008, so catches were not any higher in the southern Delta in 2008 than in several other recent years despite the extended period of first flush conditions and comparatively high 'normalized' salvage that year.

The SKT trawls at stations 812 – 919 sampled a range of about 4,778 to 9,153 m^3 of water per tow (data not shown). This means that if a Delta Smelt is collected, the measured density 'automatically' exceeds 1 fish · 10,000 m^{-3} sampled. The cumulative distribution of adult Delta Smelt salvage densities is very similar at both the SWP and the CVP, but the CVP has slightly higher frequencies of low salvage densities in its upper quartile than the SWP. The SWP and CVP fish facilities both have a minimum detection limit for adult Delta Smelt near 0.001 fish · 10,000 m^3, or a detection limit about 1,000 times lower than a single pass of an SKT trawl (Figure 7). Since water year 1993, maximum salvage densities of adult Delta Smelt have never exceeded 0.322 and 0.393 fish · 10,000 m^{-3}, at the CVP and SWP fish facilities, respectively. Thus, the densities of fish observed in the fish facilities are far too low to be detected with single pass trawling (see Discussion).

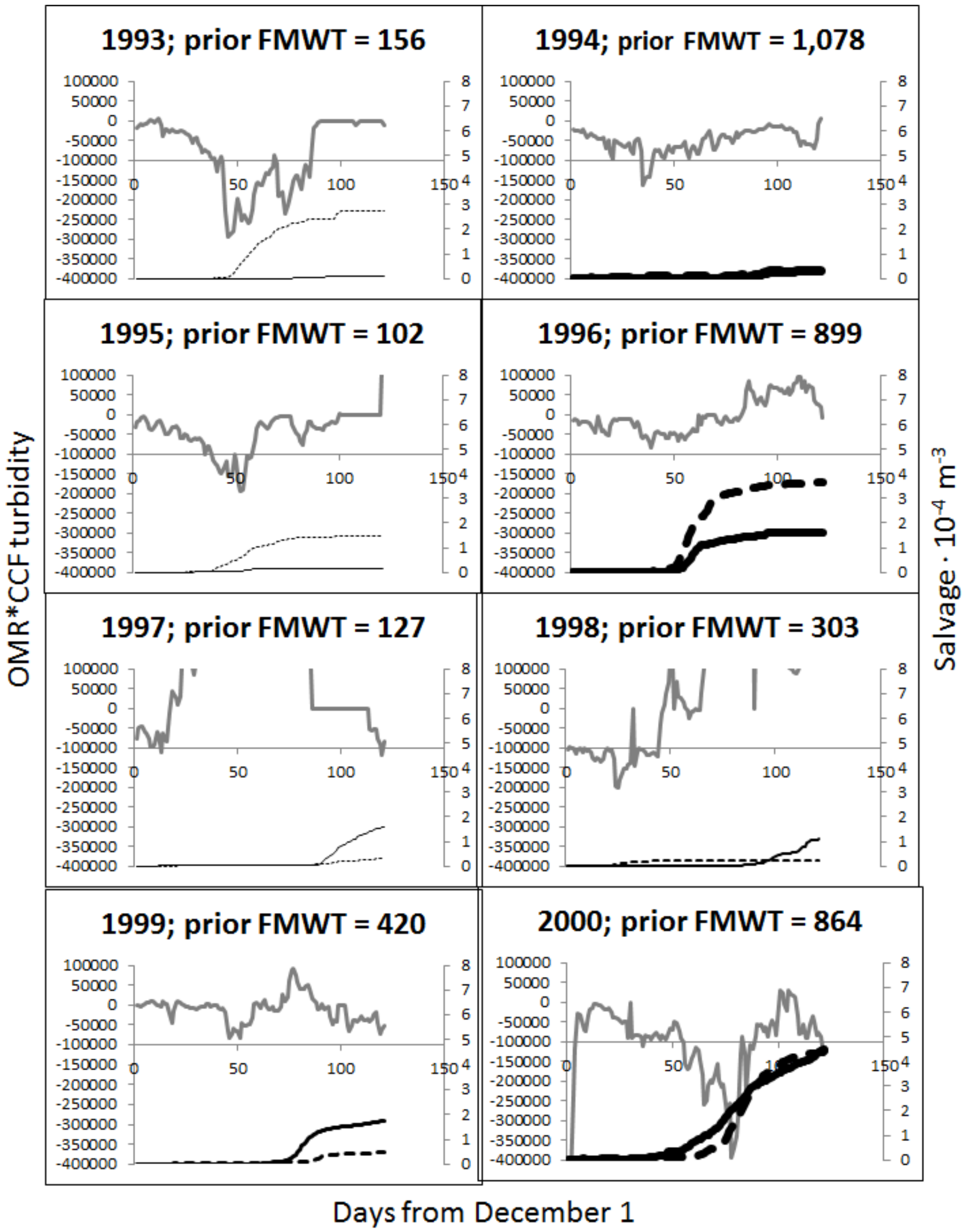

Figure 4. Time series of adult Delta Smelt salvage at the SWP (dashed lines) and CVP (solid black lines) fish facilities, water years 1993-2000 (left side y-axis = daily Old and Middle River (OMR) flow multiplied by daily turbidity at Clifton Court Forebay, CCF). The time series of the index of first flush conditions is shown as the solid gray line in each plot; missing data have a value of zero. Values of the first flush index less than -100,000 (i.e., where the x-axis crosses the y-axis) are considered indicative of first flush conditions. The thickness of the salvage lines reflects the magnitude of the prior Fall Midwater Trawl (FMWT) index, which is also reported at the top of each panel.

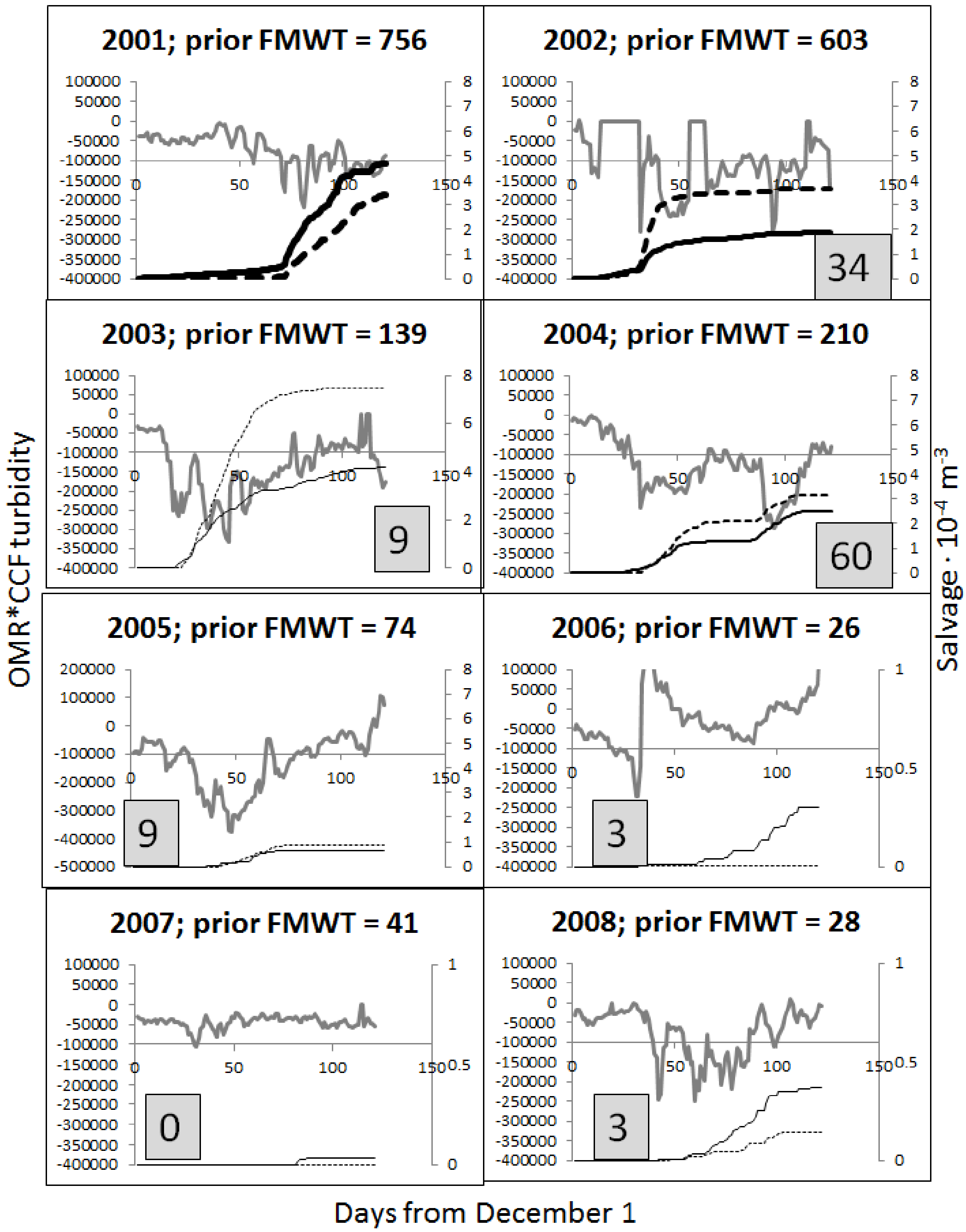

Figure 5. Time series of adult Delta Smelt salvage at the SWP (dashed lines) and CVP (solid black lines) fish facilities during water years 2001-2008 (left side y-axis = daily Old and Middle River (OMR) flow, multiplied by daily turbidity at Clifton Court Forebay, CCF). The time series of the index of first flush conditions is shown as the solid gray line in each plot; missing data have a value of zero. Values of the first flush index less than -100,000 (i.e., where the x-axis crosses the y-axis) are considered indicative of first flush conditions. The thickness of the salvage lines reflects the magnitude of the prior Fall Midwater Trawl (FMWT) index, which is also reported at the top of each panel. Note that the y-axis scale changes starting in water year 2006. The total number of Delta Smelt collected by the Spring Kodiak Trawl (SKT) surveys during January–March at all southern Delta stations upstream of Jersey Point (stations 812–915) is shown in the inset gray-shaded boxes. For reference, there were about 21 trawls taken in the inclusive region each year.

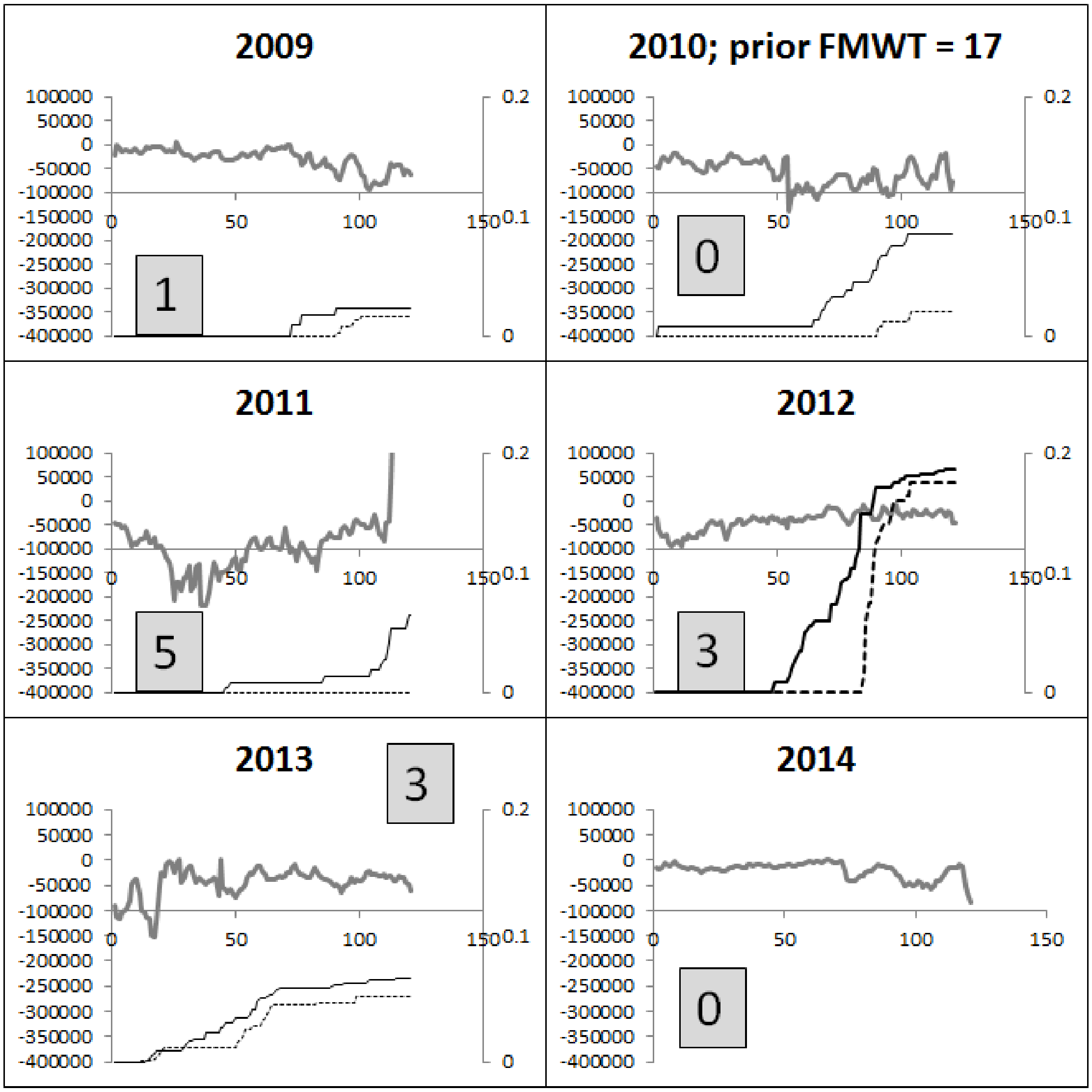

Figure 6. Time series of adult Delta Smelt salvage at the SWP (dashed lines) and CVP (solid black lines) fish facilities during water years 2009-2014. These years are those in which the current Service and NMFS Biological Opinions influenced conditions in the southern Delta (left side y-axis = daily Old and Middle River (OMR) flow, multiplied by daily turbidity at Clifton Court Forebay, CCF). The total number of Delta Smelt collected by the Spring Kodiak Trawl (SKT) surveys during January–March at all southern Delta stations upstream of Jersey Point (stations 812–915) is shown in the inset gray-shaded boxes. For reference, there were about 21 trawls taken in the inclusive region each year. Note that the y-axis scale is 1/40th of the value used for water years 1993-2005 and 1/5th of the scale used for water years 2006-2008.

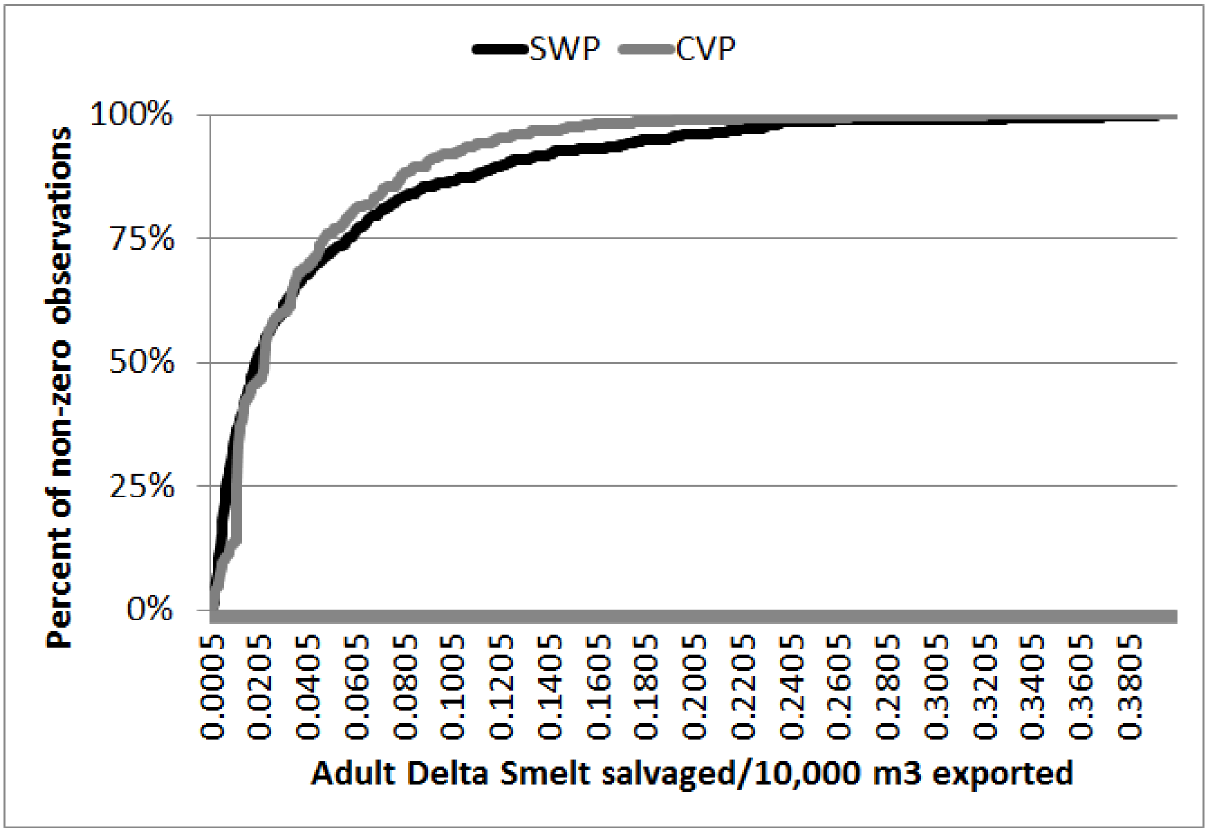

Figure 7. Cumulative frequency distributions of adult Delta Smelt daily salvage densities (fish · 10,000 m-3 of water exported) at the State Water Project and Central Valley Project fish facilities, water years 1993-2014. Note that most daily salvage densities in many years have been zero and thus are not shown in this plot which is limited to non-zero estimates.

Step 2: We had two sources of adult Delta Smelt salvage data to choose from. One was provided to us by Bob Fujimura (CDFW, during 2014) and the other was a length-corrected data set provided by Ken Newman (FWS) during 2015. The two datasets are very similar, but not identical (Figure 8). We chose to use the CDFW data set because there should have been no need for length correction of the data. During the months of December-March, most young of the year Delta Smelt have not even been spawned yet, much less grown to a salvageable size (≥ 20 mm). This extra step of 'correcting' the data for length may remove some misidentified fish (e.g., larvae of other species) from the counts, but it seems unnecessary given that the correlation between the two datasets is very high (Pearson R ~ 0.99).

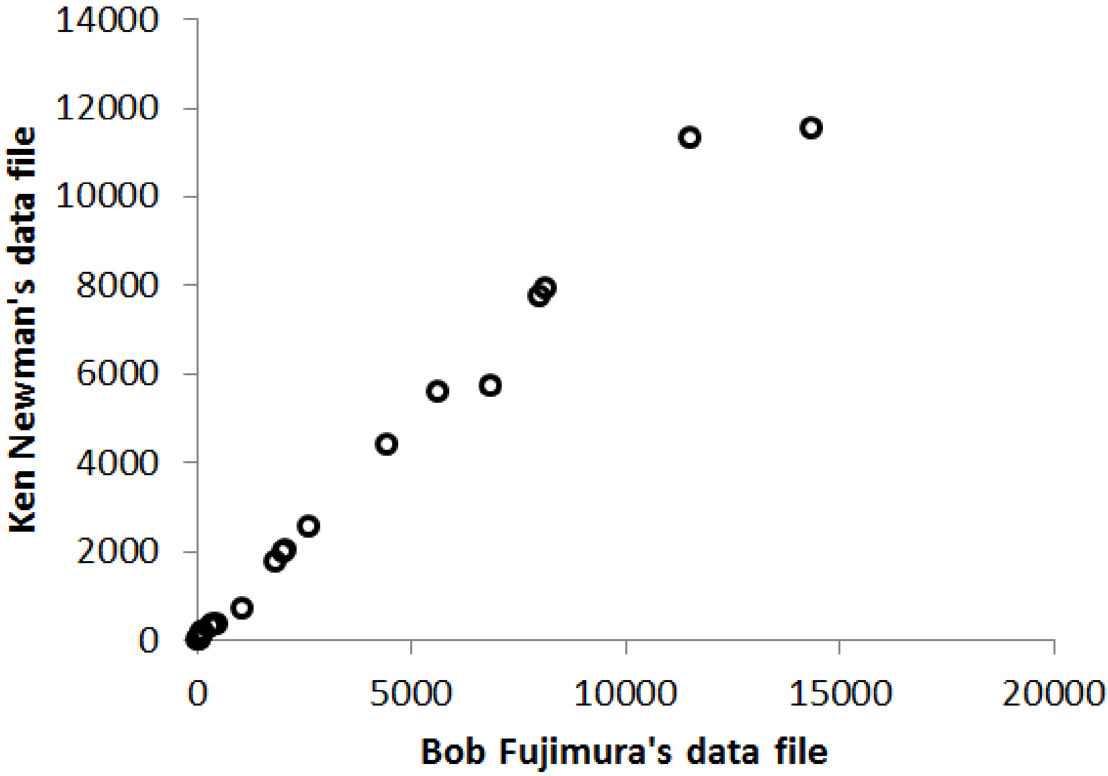

Figure 8. Scatterplot showing the relationship between the length-uncorrected adult Delta Smelt salvage numbers provided to us by Bob Fujimura (CDFW) and the length-corrected data set provided to us by Ken Newman (FWS). Both data sets are sum of salvage for December 1 – March 31 of water years 1993-2014. Note that neither data set had data for 2014, but adult Delta Smelt salvage was zero in water year 2014 so we have included that data point as zero in both data sets.

We compared results based on two versions of response variables derived from CDFW's adult Delta Smelt salvage data, the sum of December 1 – March 31 salvage (*S*), and SD_{cum}. At each fish facility, raw salvage totals and their SD_{cum} analogs are very highly correlated, essentially redundant variables (Figure 9a,b). However, SWP and CVP salvage (or SD_{cum}) are much more loosely correlated with each other (Figure 9c,d). We note the low CVP salvage compared to SWP in 1993 and 1995, and question whether the CVP adopted CDFW's QA/QC protocols as swiftly or completely as the SWP following the ESA-listing of Delta Smelt, particularly because salvage at the two facilities has been more concordant since.

There may be an interacting influence of exports and relative abundance on adult Delta Smelt salvage at both fish facilities because all four panels of Figure 10 imply positive associations of these predictor variables and salvage. The quantity of water exported is correlated with OMR flow, particularly SWP exports, which have shown a greater range over the past 22 winters (Figure 11). Note that even seasonal total exports are correlated with event averaged OMR flow which is a single 5-day average OMR flow extracted from each 121-122 day season.

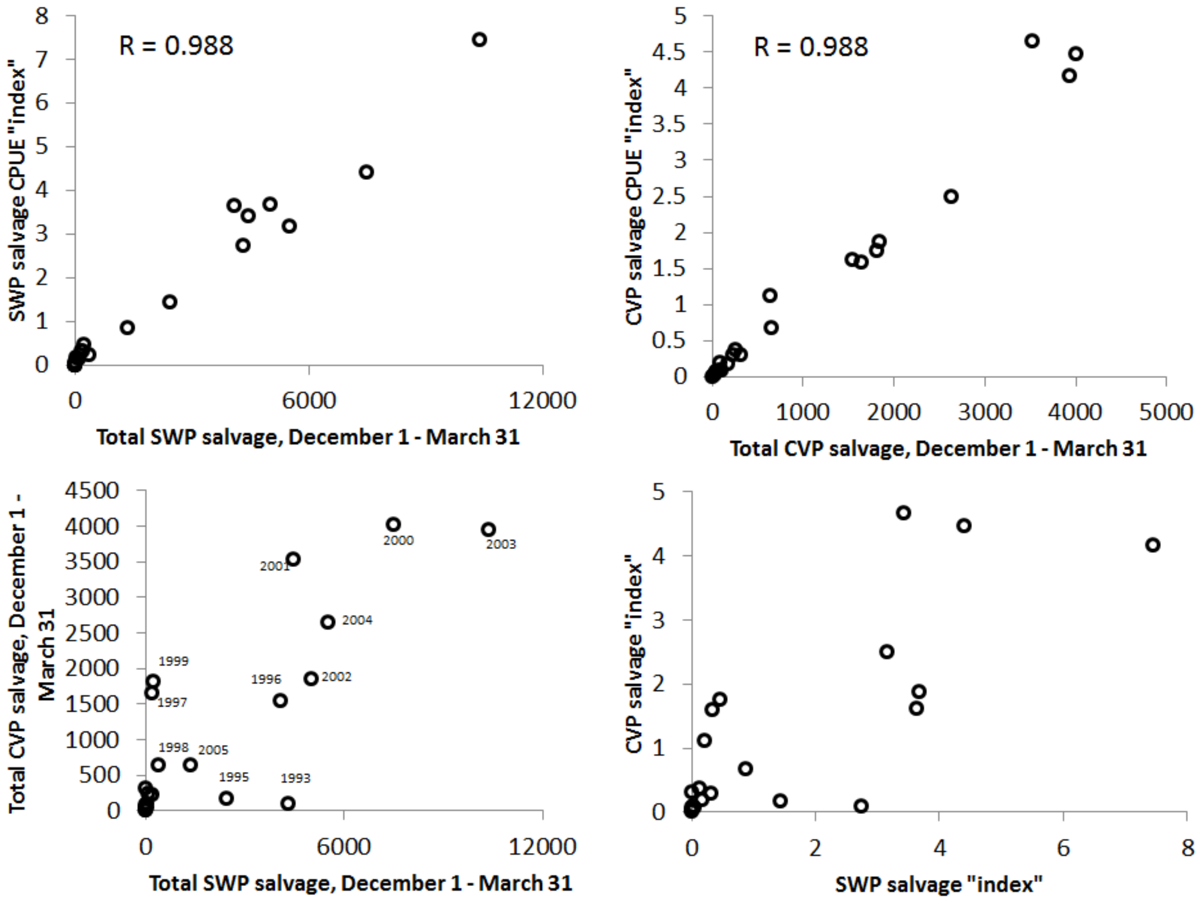

Figure 9. Scatterplots of relationships among dependent variables used in *Step 3*.

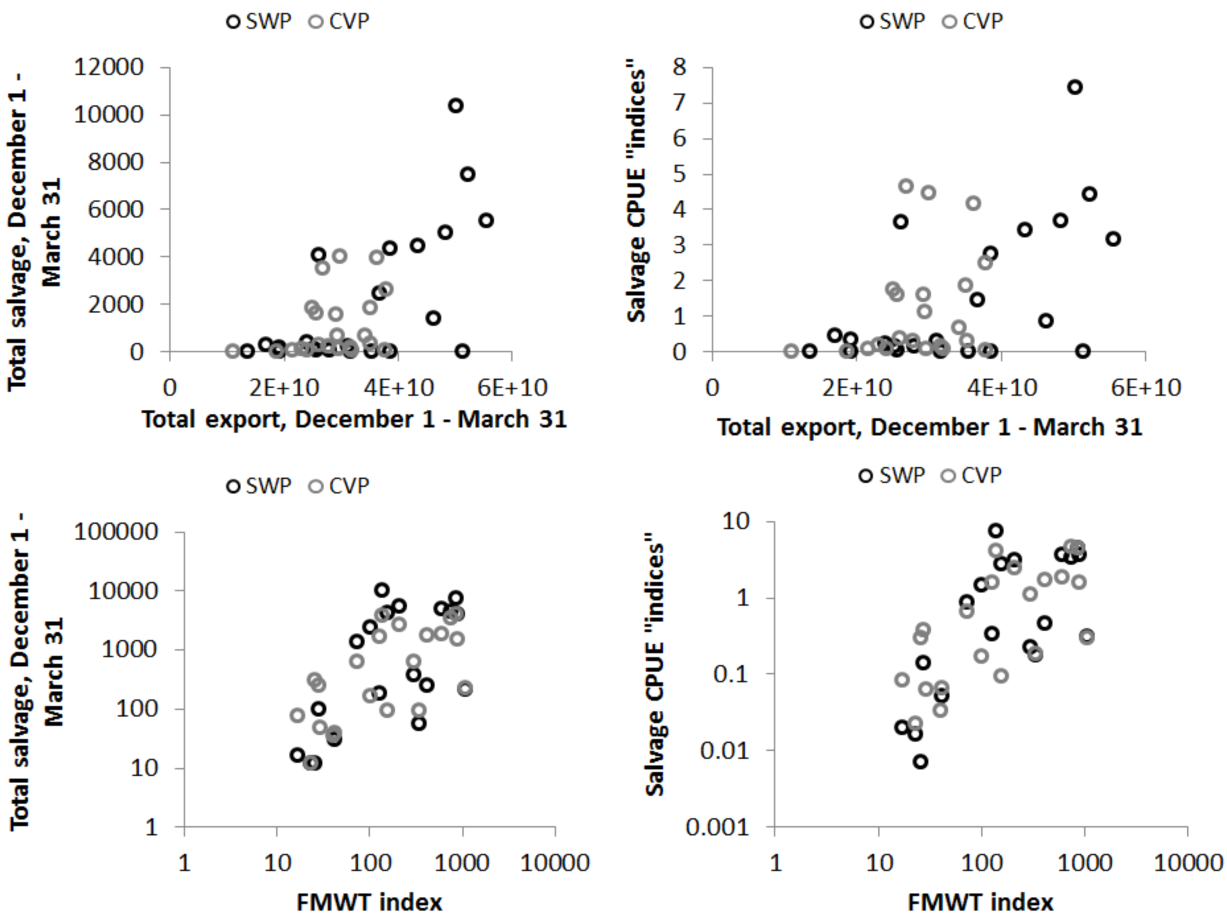

Figure 10. Scatterplots of water exports and the FMWT index versus dependent variables used in *Step 3*.

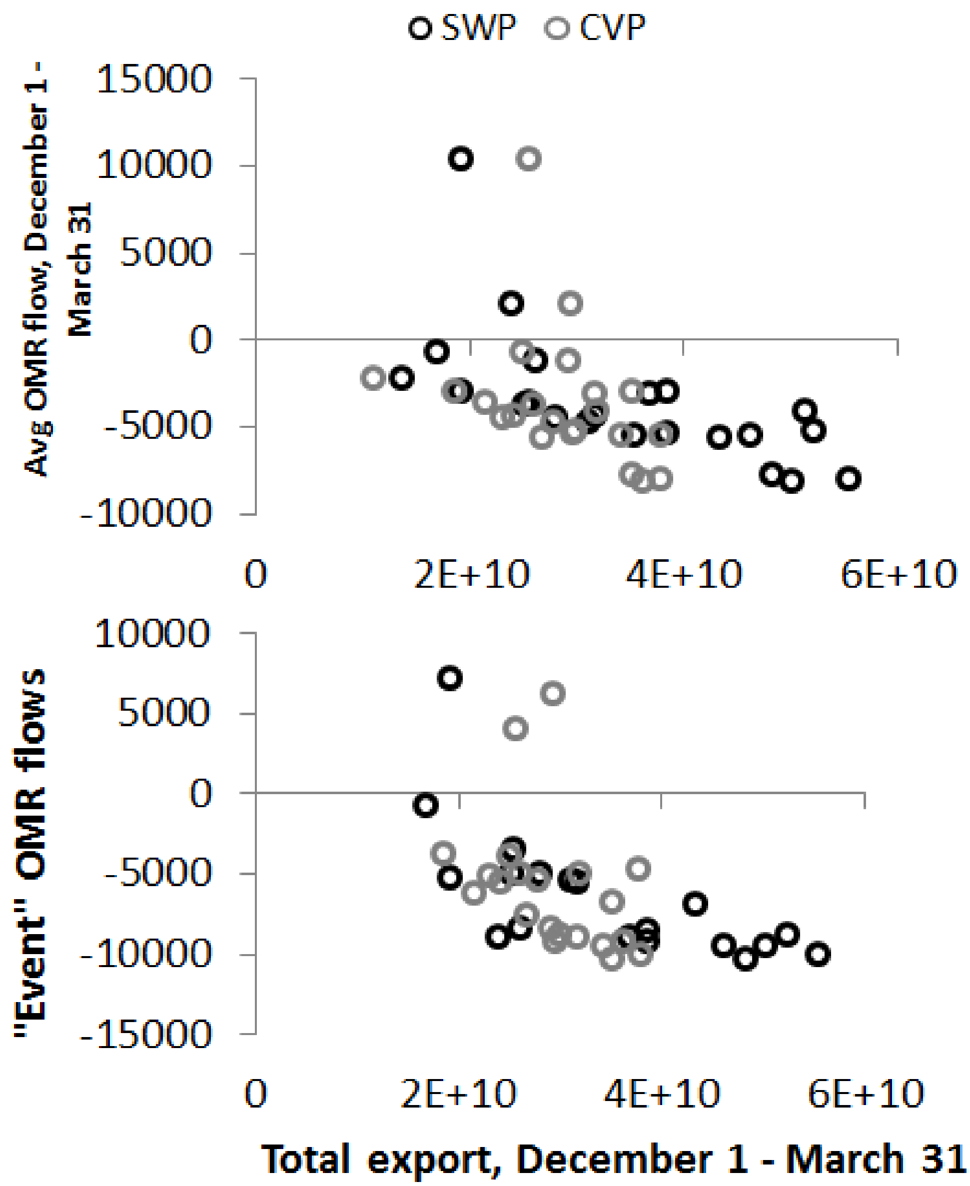

Figure 11. Scatterplots showing the relationships between water exported from the south Delta by the State Water Project (SWP) and Central Valley Project (CVP) versus seasonal and event averaged OMR flow.

The December 1 – March 31 exports at the SWP and CVP are correlated, but as mentioned above, CVP exports tend to be lower (Figure 12a). The primary south Delta environmental/operational covariates that we explored in this early product are OMR flow and turbidity at Clifton Court Forebay. These potential predictor variables of adult Delta Smelt salvage are not correlated, though the 1997 data point can make them appear to be at first glance (Figure 12b). The seasonal average versus "event" versions of OMR and turbidity are correlated (Figure 12c,d), though event OMR flows are often lower, and event turbidities often higher, than their seasonally-averaged analogs. Due to their inherent correlation, we did not use both versions in the same regression analyses in *Step 3*. Their underlying correlation can call into question whether our use of these alternatives actually represents two alternative hypotheses at all. We evaluate this more carefully based on the Results in *Step 3* and revisit this topic in the Discussion.

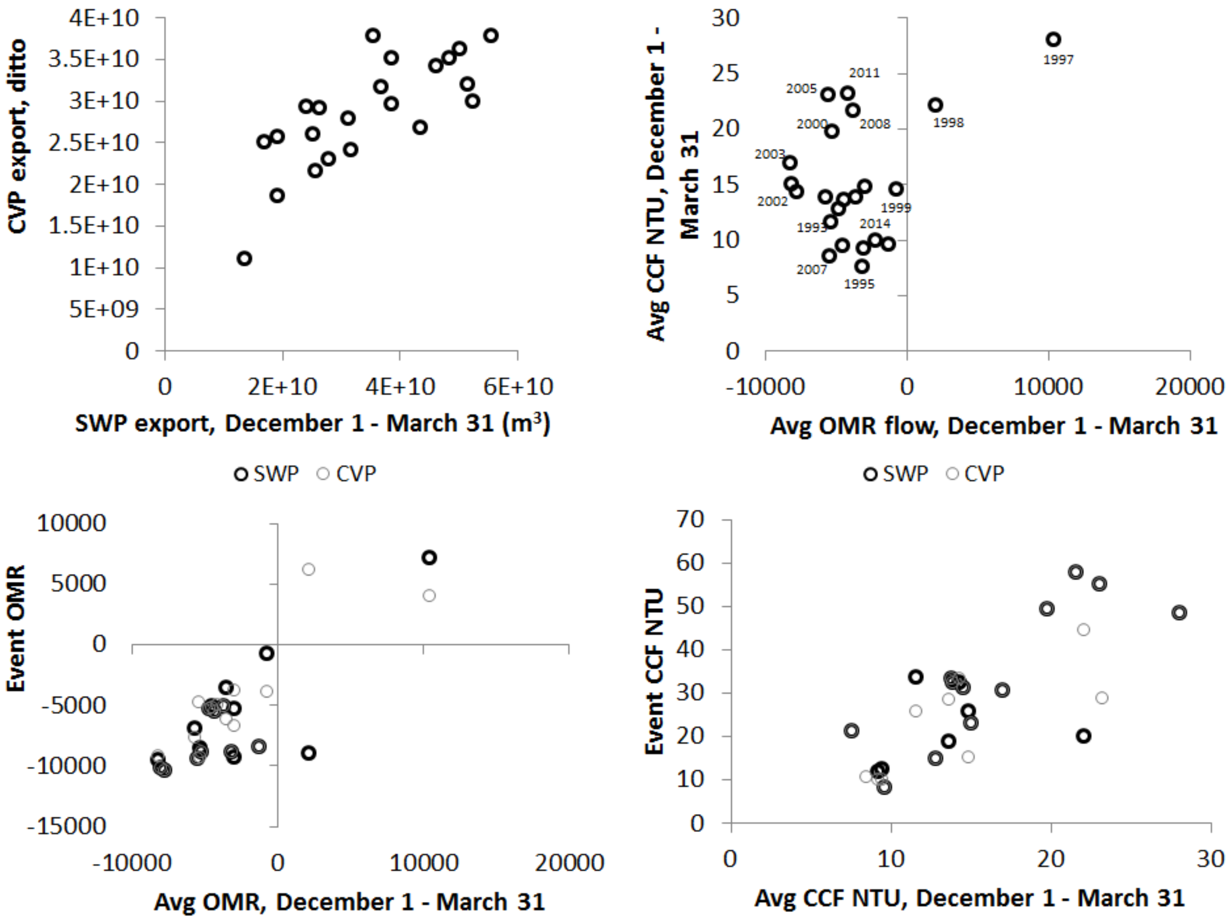

Figure 12. Scatterplots of the relationships among covariates (predictor or explanatory variables) used in *Step 3*.

Step 3: The proportion of variance explained by the SWP base models ranged from 0.26 – 0.49, and for the CVP base models it ranged from 0.38 – 0.45 (Table 2). All SWP and CVP base models were statistically significant despite their comparatively poor explanatory power (P = 0.0002 to 0.01 for SWP, and 0.0003 to 0.002 for CVP). The use of event-averaged covariates produced better fitting models for the SWP than the use of seasonally averaged covariates, but the same was not true of CVP salvage where both forms of covariates produced similar results (Table 2). In general, the best-fitting SWP salvage models included OMR flow or the *FF* covariate which had *OMR* in it. In contrast, the best-fitting CVP models were usually those that included the Clifton Court Forebay turbidity term (*NTU*). Despite the heavy penalty of the

AICc, the best-fitting models were often those that included three or four covariates. However, the sign of the NDOI term was always positive when it was part of a model that outperformed its base model (see Appendix). This was opposite of our hypothesis and suggests that the December outflow covariate is unreliable. It had relatively little explanatory power in the raw salvage models in which it was retained, but had an important albeit conceptually incorrect influence on several versions of equation 10. The signs of all other covariates retained in best-fitting models were consistent with our expectations (see Appendix). Equation 18 most consistently provided best statistical fits to the data that were most consistent with our *a priori* expectations. Several diagnostic plots of model fit are provided in the Appendix.

Table 2. Summary of linear regression results for exploratory analysis of factors influencing the salvage of adult Delta Smelt at the State Water Project (SWP) and Central Valley Project (CVP) fish facilities. Season and event base equations use only the California Department of Fish and Wildlife's Fall Midwater Trawl (FMWT) abundance index as a predictor variable or "covariate". The other model variations also include the FMWT index, but include the additional listed covariates as well. The numbers listed in each cell are adjusted R-squareds. They are in bold font if the adjusted R-squared exceeded 0.50, i.e., if the model explained more than half of the variation in adult Delta Smelt salvage. The numbers are reported in large bold font if the adjusted R-squared equalled or exceeded 0.75, i.e., if the model explained three-quarters or more of the variation in adult Delta Smelt salvage. Cells highlighted in light green had a corrected Akaike Information Criterion (AIC_c) more than 2.0 units lower than their base model; cells highlighted in dark green had an AIC_c more than 5.0 units lower than their base model.

	SWP		CVP	
Equation	Season	Event	Season	Event
3 (season base)	0.35		0.41	
3 (event base)		0.26		0.38
5: *NDOI*	0.33	0.23	0.48	0.45
6: *OMR*	0.47	0.41	0.38	0.35
7: *NTU*	0.32	0.25	0.49	0.48
8: *FF*	0.42	**0.53**	0.38	0.44
9: *OMR* + *NTU*	0.46	0.45	**0.51**	0.48
10: *NDOI* + *OMR* + *NTU*	0.49	**0.55**	**0.63**	**0.63**
4 (season base)	0.49		0.45	
4 (event base)		0.38		0.41
11: *NDOI*	0.47	0.35	0.47	0.44
12: *E*	**0.56**	**0.66**	**0.64**	0.49
13: *OMR*	**0.50**	0.49	0.43	0.39
14: *NTU*	0.48	0.44	**0.62**	**0.57**
15: *FF*	0.49	**0.68**	0.43	0.47
16: *OMR* + *NTU*	**0.51**	**0.62**	**0.63**	**0.58**
17: *NDOI* + *OMR* + *NTU*	0.48	**0.62**	**0.68**	**0.68**
18: *E* + *NTU*	**0.54**	**0.67**	**0.75**	**0.67**
19 *NDOI* + *E* + *NTU*	**0.51**	**0.65**	**0.78**	**0.77**

The GAMs returned nonlinear predictions of the season- and event-averaged relationships between OMR flow and adult Delta Smelt salvage, but linear predictions for the other environmental/operational covariates (Figure 13). This likely explains why linear regression models using exports to predict Delta Smelt salvage at SWP outperformed the linear regressions that used OMR flow (Table 2; Figure 14). In both the season- and event-averaged versions, the predicted OMR flow threshold for increasing adult Delta Smelt salvage was very near the -5,000 cfs limit prescribed in the FWS and NMFS BiOps. Thus, this analysis does not support an alternative OMR management threshold to the one currently in use. The linear predictions for the other event-averaged variables do not support the hypothesis that there are threshold values of turbidity or its interaction with OMR that can be used to manage the entrainment of adult Delta Smelt.

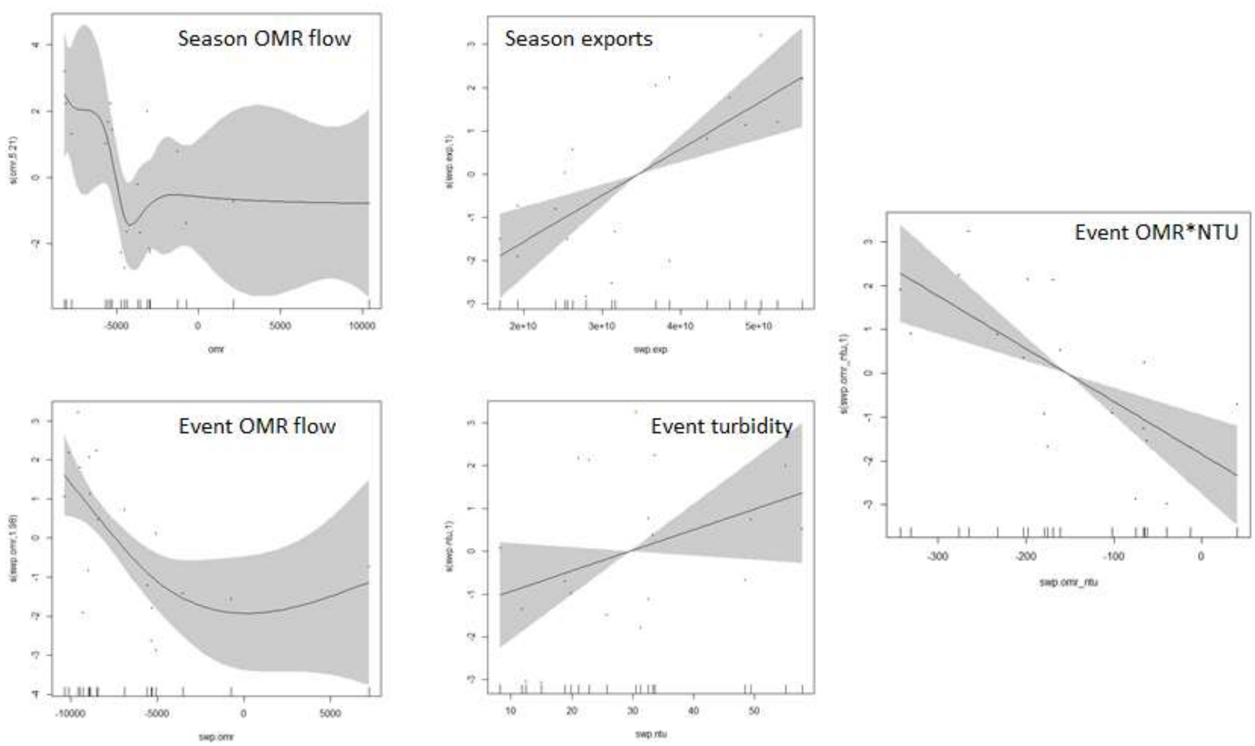

Figure 13. Plots showing the predicted 'shape' of relationships between several environmental/operational covariates and adult Delta Smelt salvage while controlling for a linear influence of relative abundance on salvage. Data points (barely visible) are observed data, the solid lines show the mean GAM prediction and the gray shading shows the predicted (parametric) 95% confidence interval.

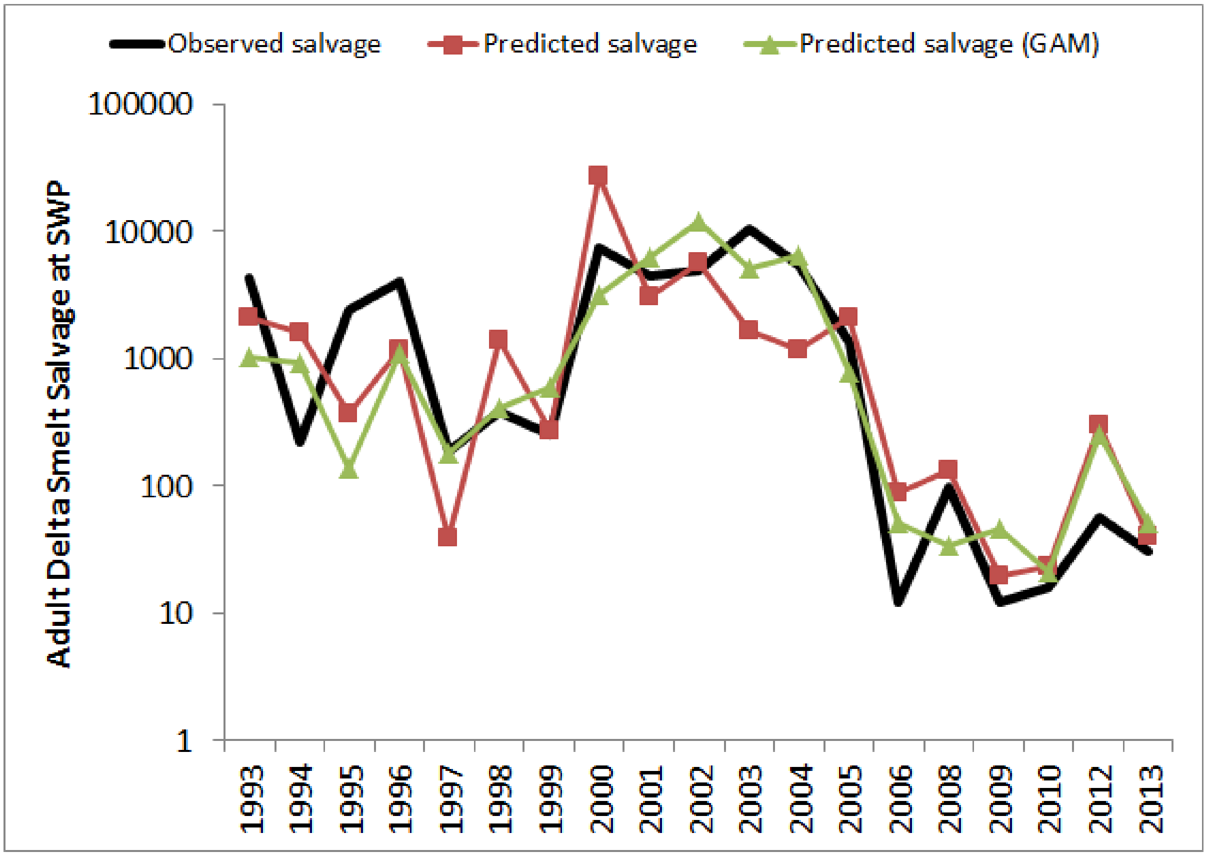

Figure 14. Time series of adult Delta Smelt salvage at the SWP fish facility (black line) and linear regression (red line) and GAM predictions (green line) of that salvage using the FMWT index and season-average OMR flow as predictors.

Step 4: As explained in *Step 3*, the FMWT is a statistically significant predictor of salvage at each fish facility. It is also a statistically significant predictor of the combined salvage at both fish facilities (for water years 1993-2013, the sum of the SWP and CVP SD_{cum}; N = 21; $r^2 = 0.54$; $P = 0.0002$). Recall that the raw salvage of adult Delta Smelt and the SD_{cum} are very closely correlated; Pearson r ~ 0.99 for both fish facilities, so there is no need to try alternative versions of this analysis.

In Figure 15, we plotted the 2002-2013 FMWT indices against the subsequent SKT indices (2003-2014). DFW produced the first version of this plot we had seen, but Nobriga et al. (2013) reproduced it to make the point that over-winter mortality of Delta Smelt was so consistent from year to year that looking for a predation impact on adults would not likely be productive. We think this logic also applies to entrainment, which can be conceptualized as a form of 'predation'. The FMWT surveys are almost always finished by the time adult salvage begins, and the SKT surveys are being conducted during, and often after, the major salvage events have occurred. However, the relationship between these two indices has almost no variation except at low index values. One very parsimonious explanation for variation only at low index values is that the only substantial "noise" is observation error that we would expect at low FMWT index values because the FMWT sampling is known to be less effective at capturing Delta Smelt than the SKT.

Thus, we posit that the low variance in the relationship between these successive abundance indices is evidence that over-winter mortality is relatively constant from year to year; no other pairs of Delta Smelt abundance indices show such a strong, linear relationship (Bennett 2005; Maunder and Deriso 2011; Nobriga et al. 2013). If over-winter mortality of adults is fairly constant, then year to year variation in entrainment cannot be causing measurable (using current survey techniques) variation in adult mortality. To add additional evidence for this conclusion, we color-coded the data points in Figure 15. The green data points were years with negative residuals in the combined SWP + CVP $SD_{cum} \sim FMWT$ relationship, i.e., years of lower than expected salvage. The red data points were the positive residuals or years of higher than expected salvage. The red data points and green data points are intermingled showing that the substantial variation in Delta Smelt densities at the fish facilities observed since winter 2003 does not explain variation in over-winter mortality.

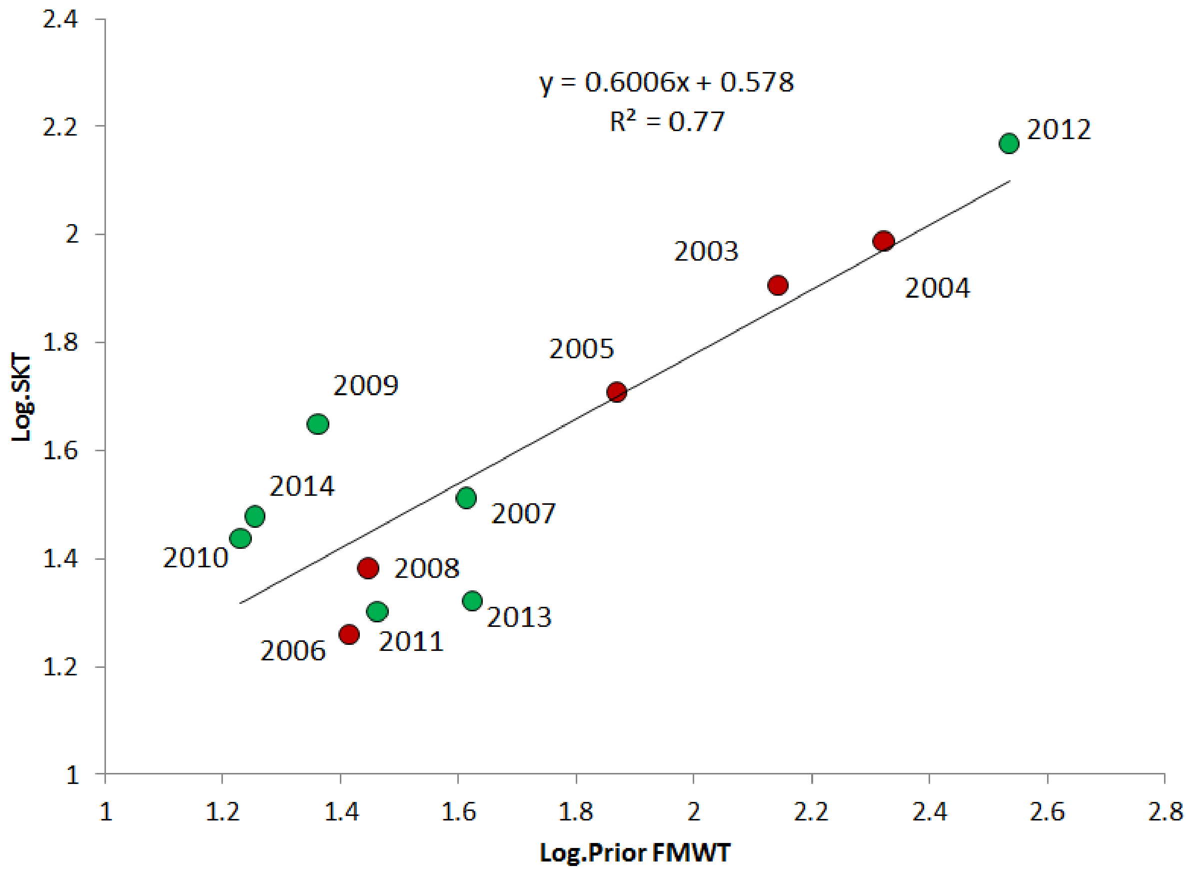

Figure 15. Scatterplot of the log-transformed Fall Midwater Trawl index (FMWT) versus the log-transformed adult Delta Smelt salvage index from the Central Valley Project (CVP) Tracy Fish Facility. Years of higher than expected salvage based on the residuals from a separate linear regression of SWP + CVP $SD_{cum} \sim FMWT$ are colored red; years of lower than expected salvage are colored green.

Discussion

On page 18 of its review of this element of the Entrainment Proposal, the Delta Science Program's Independent Review Panel noted:

> The products may not greatly advance knowledge, and there is some possibility the products may be misleading. The examination of factors relies heavily on aggregated data (e.g., the FMWT index for Delta Smelt is a sum of monthly CPUEs, and CVP and SWP abundance indices are analogs to the FMWT index created by summing the daily adult Delta Smelt salvage CPUEs for the period December 1 through March 31 of each water year from 1993 through 2013). The process of aggregation in itself may obscure real relationships or introduce spurious relationships. The results should be interpreted with caution.

The analyses we have presented in this memo largely confirm the concerns expressed by the Panel; seasonal averages of OMR and turbidity are correlated (and therefore, confounded) with their extremely short time-scale ‘event’ alternatives, and both can produce statistically significant explanations of the adult Delta Smelt salvage data (Table 2). This means that appropriate time scales for the management of environmental/operational conditions in the south Delta cannot be conclusively determined using the field data. Further, our GAM analyses did not support the hypothesis of threshold (nonlinear) relationships between environmental/operational variables other than OMR flow and in the case of OMR flow, did not support the hypothesis that there is a threshold different from the one currently specified in FWS’ and NMFS’ Biological Opinions. Thus, these preliminary results seem to reinforce the need for behavior-based PTM evaluations to better understand whether there are more effective management strategies for controlling the entrainment of adult Delta Smelt than the ones that are currently in use and on what time scales those strategies need to be applied.

We have shown some potentially interesting differences in which covariates best predict salvage at each fish facility (Table 2). Most SWP models that outperformed their base models included event-averaged *OMR* or *FF*, suggesting the possibility of managing short time scale events, but this will need to be confirmed using non-statistical methods. In contrast, the best-fitting CVP salvage models tended to include seasonally-averaged turbidity – a term that was never retained in the best SWP models (Table 2). This means that previous analyses, which were based on combined SWP and CVP salvage, may have confounded important differences that affect the detection of Delta Smelt at each fish facility. It will be very interesting to see if this pattern is predicted using our behavior-based PTM models.

Figure 15 suggests that interannual variation in the mortality of adult Delta Smelt is not high enough to be detected using current survey techniques (see also Rose et al. 2013a who estimated adult mortality rates averaged about 0.6% per day). Is it possible to reconcile what appear to be major year to year differences in entrainment with relatively constant over-winter mortality? During water years 2003-2014, the combined SWP and CVP salvage of adult Delta Smelt has ranged from zero in 2014 to more than 14,000 in 2003. The ability to reconcile these seemingly contrasting pieces of information relies on several key observations and hypotheses. First, we now have enough data to confirm that salvage is reflecting relative abundance and is therefore a proxy for entrainment – at least at a seasonal time scale. Second, we need to recognize that “population estimates” derived by expanding trawl densities are *minimum* estimates of population size because there is no way that net avoidance is zero, and there is no way that the established trawl lanes always sample through the center of Delta Smelt’s lateral and vertical distribution in each sampled channel or embayment (Feyrer et al. 2013; Bennett and Burau 2015). Third, it is also possible that available pre-screen loss (PSL) estimates are too high.

It can be risky to conclude that a source of mortality is not important based on statistical rather than explicitly mechanistic methods. Kimmerer (2011) developed an entrainment impact analysis for Delta Smelt generated using an empirical 26-year time series of the index ratio *FWMT/FMWT*$_{t-1}$ as an analytical baseline. Then, he used a statistical relationship with OMR in a resampling simulation to test the consequences of an explicit entrainment rate on the index ratio. The relationship with OMR flow that he used was similar or identical to the one in FWS' 2008 BiOp Effects Analysis for larval/juvenile entrainment. Kimmerer did not provide the equation so we don't know if it is precisely the same, but his conceptual description is consistent with FWS' analysis. In the simulations, Kimmerer tested the effect of an average entrainment loss of 10 percent per year (up to a maximum of 20 percent in any given year). In his simulation, this loss rate caused a substantial fish decline. He also showed through additional simulations that unless the loss rate was reaching levels of 60 percent to 80 percent in some years, a linear regression analysis would be highly unlikely to detect the impact. It is important to note that Kimmerer (2011) modeled "entrainment" as a total entrainment loss rate of an adult cohort and its progeny, whereas the analysis in *Step 4* and the conclusions drawn from it focus explicitly on adult salvage as a proxy for entrainment mortality in the winter months.

It has often been assumed that PSL is higher at the SWP than the CVP (Brown et al. 1996, but see Kimmerer 2008). We found that CVP salvage models had better total explanatory power than the SWP models (Table 2), a finding which is consistent with the hypothesis that PSL decouples entrainment and salvage to a greater degree at the SWP. However, we also found that the non-zero salvage densities are very similar at both fish facilities and the SWP has a higher frequency of comparatively high salvage densities (Figure 7), both of which argue against higher PSL at the SWP. The SWP fish facility may sometimes have comparatively high CPUE for adult Delta Smelt because it samples the water in Old River first, possibly depleting Delta Smelt density before the fish reach the CVP fish facility. The SWP also exports a higher fraction of Sacramento River water than the CVP (Arthur et al. 1996); Sacramento River water is likely to have much higher densities of Delta Smelt in it than San Joaquin River water exported into the CVP via the head of Old River. It will also be very interesting to see if this pattern is predicted using our behavior-based PTM models.

Castillo et al. (2012) estimated that PSL of adult Delta Smelt ranged from 90 percent to 100 percent in the SWP's Clifton Court Forebay (CCF). If the circa 14,000 adult Delta Smelt salvaged in 2003 had suffered an average PSL of 90 percent, the actual entrainment loss would have been on the order of 140,000 fish or about 10 percent of the population, which was estimated to have been between one and two million fish[5]. If we were to assume higher PSLs, the proportional entrainment estimates would quickly increase and become irreconcilable with the FMWT-SKT relationship shown in Figure 13 unless the expansions of SKT catch data into 'population estimates' are way too low. We suspect that PSL of wild Delta Smelt must be lower

[5] The 2003 adult Delta Smelt population size has been estimated to be between 1 and 2 million fish (Kimmerer 2008; Rose et al. 2013a). This number was not supported by Newman (2008), but the latter are based on FMWT rather than SKT so they are almost certainly too low because of the lower capture efficiency of the FMWT.

than Castillo et al.'s (2012) estimates, and that Delta Smelt population estimates must also be too low, in order for the salvage data to reconcile with the index data.

We note that the basic experimental design employed by Castillo et al. (2012), which was based on earlier experiments using Chinook Salmon (e.g., Gingras 1997), has two potential flaws that leave the interpretation of the results essentially unconstrained. First, the experiments involved captive-reared Delta Smelt that had never encountered a threat of predation before their release into the CCF. In other fish species, rearing in captivity has been shown to elicit behavioral changes that are maladaptive in the wild (Berejikian 1995; Stunz and Minello 2001), so the use of captive-raised fish in predation experiments likely leads to overestimates of predation rates on wild fish. Second, the experimental design lacked a control to deal with the potential lack of appropriate predator avoidance behavior of captive-raised Delta Smelt. In order to unambiguously quantify the relative vulnerability to predation of the test fish, there would ideally be an equivalent release of fish conducted somewhere else in the Delta where hypothesized predation vulnerability is lower; the "real" influence of pre-screen loss would be the difference between the loss rate in the Delta-proper and the loss rate in CCF. Unfortunately, such a study design is not currently feasible because there is no available way to reliably recapture Delta Smelt from within the open estuary with an equal probability to the fish facilities. Thus, for the time being, both "true" PSL, and our assumptions about it, are untestable.

Several recent studies have used a variety of statistical and simulation modeling approaches to test for water operations effects on Delta Smelt population dynamics (Brown et al. 2009; Mac Nally et al. 2010; Thomson et al. 2010; Kimmerer 2011; Maunder and Deriso 2011; Miller et al. 2012; Rose et al. 2013b). This emerging research focus on population impairment implicitly reflects an expectation that optimally, any BiOp covering water export operations in the Delta should only limit exports when they will limit the *viability* of the Delta Smelt population. The FWS' 2008 BiOp was clear that the goals of the OMR flow elements of the RPA were to reduce entrainment because doing so would increase spawning habitat—in other words, it was more of a *habitat* argument than a population dynamic or viability argument. There is little doubt that OMR flow limits achieve the goals stated in the 2008 BiOp (Kimmerer 2008; Grimaldo et al. 2009; this memo) because the winter distributions of Delta Smelt and the causes of their entrainment are much more certain than the population-dynamic effects of entrainment. Thus, it is the population-dynamic consequences of water operations alternatives that are of greatest scientific and resource management interest. In the past, the inability to link salvage to entrainment was considered a major obstacle to quantifying the impact of entrainment on Delta Smelt population dynamics and viability (Hymanson and Brown 2006). However, there may be ways to statistically bypass this problem (e.g., Kimmerer 2008; 2011) and behavior-based particle tracking models should help improve estimates of proportional entrainment.

The current state of science on Delta Smelt population dynamics has conceptual and analytical shortcomings. In the biggest picture conceptual sense, the opinions of the authors cited in the previous paragraph are that entrainment loss would impair population viability if

Delta Smelt population dynamics are density-independent (Kimmerer 2011; Rose et al. 2013b), but would not if Delta Smelt population dynamics are density-dependent, presumably because compensation for the loss would occur later in the life cycle, or because the dynamics are driven almost entirely by the prey and predators of Delta Smelt (Maunder and Deriso 2011; Miller et al. 2012).

Statistically speaking, Delta Smelt population dynamics are “density-dependent” (Bennett 2005; Maunder and Deriso 2011; Figure 16), but that does not mean that changes in Delta Smelt vital rates are actually resulting from changes in their density. The local research community has spent too much time asking if it is possible for “density-dependence” to occur in a rare and declining fish population such as Delta Smelt. The answer is yes in as much as abundance patterns that look like density dependence can arise even when fish populations are not self-limiting their own resource base (Walters and Korman 1999). The other critical piece of an argument for or against density dependence in Delta Smelt is compensation[6] and this dialogue has usually focused on whether Delta Smelt are exceeding a “carrying capacity”. It is not the possibility of a carrying capacity that provides the resilience in density-dependent population dynamics models, but the accelerating slope of the commonly used nonlinear models near the origin (meaning the population is predicted to grow faster and faster as abundance gets lower and lower) that generates their resilient predictions (Barrowman and Myers 2000). The papers that have used density-dependent (non-linear) equations to describe the relationships between successive Delta Smelt abundance indices have used the Ricker and Beverton-Holt models (Maunder and Deriso 2011; Miller et al. 2012) and so they have adopted statistical frameworks that are hyper-resilient to predicting extinction.

What is actually happening with Delta Smelt survival at its current very low abundance? Could we expect one statistical model or another to show us the “true” survival relationships among life stages given the limited confidence in the ability of current abundance indices to generate reliable year-to-year (or season to season) relative abundance estimates? During the period of FMWT monitoring, the Delta Smelt population has on several occasions appeared to compensate very strongly for low abundance, but only four times in almost 50 years of monitoring, and only when the recruits were born during wet years (Figure 16). Lierman and Hilborn (2001) showed that in some cases the real relationship between the abundance of successive fish life stages can be the opposite of what is predicted by Ricker and Beverton-Holt models, i.e., that the density-dependence can become *depensatory*, a situation in which abundance rebounds very slowly once it reaches low levels. Depensatory density-dependence can trap fishes into low abundance stanzas from which they may not recover. If Delta Smelt abundance has gotten low enough that depensatory factors are influencing their survival, then the

6 There are two basic types of theoretical density-dependence: compensatory and depensatory. In the former, populations are stabilized over time because their important vital rates like growth and survival increase as their abundance decreases and decrease as their abundance increases. In the latter, populations can be destablized and spiral toward extinction because important vital rates decrease once the population declines below a certain abundance level.

papers that have assumed compensatory density-dependent dynamics (Maunder and Deriso 2011; Miller et al. 2012) may be far too optimistic about Delta Smelt resilience to actual sources of mortality. Ironically, even the authors that assume density-*independence* (Kimmerer 2011; Rose et al. 2013a) may be too optimistic because they too might predict too much survival or reproduction at low abundance.

Depensation *M Liermann & R Hilborn*

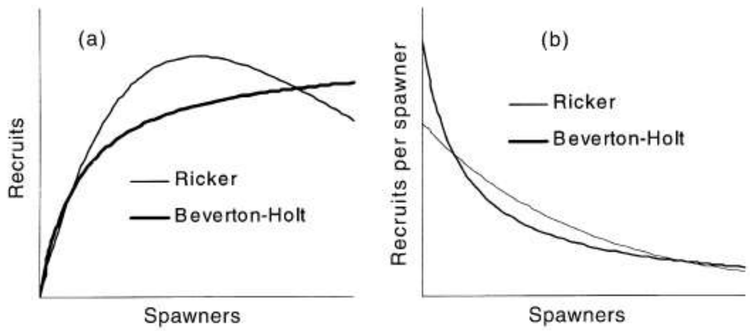

Figure 6 The Beverton–Holt and Ricker spawner-recruitment functions plotted as (a) recruits vs. spawners, and (b) recruits per spawner vs. spawners.

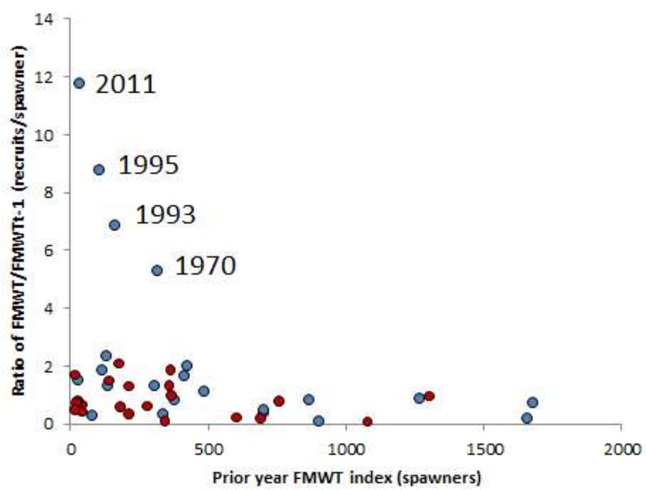

Figure 16. Figure 6 from Liermann and Hilborn (2001) showing hypothetical examples of density-dependent relationships among fish life stages and Delta Smelt Fall Midwater Trawl (FMWT) data plotted per Liermann and Hilborn's panel (b). The Delta Smelt data are colored blue if DWR classified their birth year as wet or above-normal, and red otherwise. The Delta Smelt data are consistent with density-dependent theory—particularly due to the strong compensatory responses observed in 1970, 1993, 1995, and 2011. Note also that the average recruits/spawner has generally been higher when the prior generation index was < 500, than when it was higher, suggesting that the evidence for density-dependence may not be due only to the four most visually obvious years.

References Cited

[Unpublished Declaration for District Court] Deriso, Dr. R. B. 2011. Declaration of Dr. Richard B. Deriso in support of Plaintiff's motion for injunctive relief. Case 1-09-cv-00407-OWW-DLB Document 772 Filed 1/28/2011.

[Unpublished Technical Report] Gingras, M. (1997). Mark/Recapture Experiments at Clifton Court Forebay to Estimate Pre-Screening Loss to Juvenile Fishes: 1976-1993.

http://www.water.ca.gov/iep/docs/tech_rpts/TR55.Mark-Recapture%20Experiments%20at%20Clifton%20Court%20Forebay%20to%20Estimate%20Pre-Screening%20Loss%20to%20Juvenile%20Fishes%201976-1993%20-%20Final%20Version.pdf

[Unpublished Technical Report] Hymanson, Z. P., and L. R. Brown. 2006. Fulfilling a paradoxical mandate: can the Environmental Water Account ensure the reliability of freshwater exports from the Sacramento-San Joaquin Delta and simultaneously protect Delta Smelt (*Hypomesus transpacificus*) from excessive entrainment? Interagency Ecological Program Newsletter 19(1):28-49. http://www.water.ca.gov/iep/newsletters/2006/IEPNewsletter_Winter2006final6.pdf

[Unpublished Technical Report] Lott, J. 1998. Feeding habits of juvenile and adult delta smelt from the Sacramento-San Joaquin River estuary. Interagency Ecological Program Newsletter 11(1):14-19. http://www.water.ca.gov/iep/newsletters/1998/winter/Feeding%20Habits%20of%20Juvenile%20and%20Adult%20Delta%20Smelt%20from%20the%20Sacramento-San%20Joaquin%20River%20Estuary.pdf

[Unpublished white paper] MWD (Metropolitan Water District). 2014. Proposal for a revised ITL and expected take for adult delta smelt [draft], dated 7/29/2014.

[Unpublished Technical Report] Nobriga, M., Z. Hymanson, K. Fleming, and C. Ruhl. 2001. Spring 2000 Delta Smelt salvage and Delta hydrodynamics and an introduction to the Delta Smelt Working Group's decision tree. Interagency Ecological Program Newsletter 14(2):42-46. http://www.water.ca.gov/iep/newsletters/2001/IEPNewsletterSpring2001.pdf

[Unpublished Technical Report] Nobriga, M., Z. Hymanson, and R. Oltmann. 2000. Environmental factors influencing the distribution and salvage of young Delta Smelt: a comparison of factors occurring in 1996 and 1999. Interagency Ecological Program Newsletter 13(2):55-65. http://www.water.ca.gov/iep/newsletters/2000/IEPNewsletter_Spring2000.pdf

[Unpublished Technical Report] Nobriga, M., T. Veldhuizen, and Z. Hymanson. 1999. Delta Smelt concerns result in changes in SWP and CVP operations. Interagency Ecological Program Newsletter 12(3):33-34. http://www.water.ca.gov/iep/newsletters/1999/summer/Delta%20Smelt%20concerns%20Result%20in%20Changes%20in%20SWP%20and%20CVP%20Operations.pdf

[Unpublished Technical Report] Poage, V. 2004. Why we do a "Post-VAMP Shoulder" for Delta Smelt. Interagency Ecological Program Newsletter 17(2):44-48. http://www.water.ca.gov/iep/newsletters/2004/IEPNewsletter_spring_2004.pdf

Alpine, A. E., & Cloern, J. E. (1992). Trophic interactions and direct physical effects control phytoplankton biomass and production in an estuary. *Limnology and Oceanography*, *37*(5), 946-955.

Arthur, J. F., Ball, M. D., & Baughman, S. Y. (1996). *Summary of federal and state water project environmental impacts in the San Francisco Bay-Delta Estuary, California*. San Francisco State University.

Barrowman, N. J., & Myers, R. A. (2000). Still more spawner-recruitment curves: the hockey stick and its generalizations. *Canadian Journal of Fisheries and Aquatic Sciences*, *57*(4), 665-676.

Bennett, W. A. (2005). Critical assessment of the Delta Smelt population in the San Francisco Estuary, California. *San Francisco Estuary and Watershed Science*, *3*(2).

Bennett, W. A., & Burau, J. R. (2015). Riders on the Storm: Selective Tidal Movements Facilitate the Spawning Migration of Threatened Delta Smelt in the San Francisco Estuary. *Estuaries and Coasts*, 38, 826-835.

Berejikian, B. A. (1995). The effects of hatchery and wild ancestry and experience on the relative ability of steelhead trout fry (*Oncorhynchus mykiss*) to avoid a benthic predator. *Canadian Journal of Fisheries and Aquatic Sciences*, *52*(11), 2476-2482.

Brown, L. R., Kimmerer, W., & Brown, R. (2009). Managing water to protect fish: a review of California's environmental water account, 2001–2005.*Environmental management*, *43*(2), 357-368.

Brown, R., Greene, S., Coulston, P., & Barrow, S. (1996). An evaluation of the effectiveness of fish salvage operations at the intake to the California Aqueduct, 1979-1993. San Francisco Bay: the ecosystem, AAAS, San Francisco, CA.

Castillo, G., Morinaka, J., Lindberg, J., Fujimura, R., Baskerville-Bridges, B., Hobbs, J., ... & Ellison, L. (2012). Pre-screen loss and fish facility efficiency for Delta Smelt at the south Delta's State Water Project, California. *San Francisco Estuary and Watershed Science*, *10*(4).

Dugdale, R., Wilkerson, F., Parker, A. E., Marchi, A., & Taberski, K. (2012). River flow and ammonium discharge determine spring phytoplankton blooms in an urbanized estuary. *Estuarine, Coastal and Shelf Science*, *115*, 187-199.

Dugdale, R. C., Wilkerson, F. P., & Parker, A. E. (2013). A biogeochemical model of phytoplankton productivity in an urban estuary: the importance of ammonium and freshwater flow. *Ecological Modelling*, *263*, 291-307.

Feyrer, F., Nobriga, M. L., & Sommer, T. R. (2007). Multidecadal trends for three declining fish species: habitat patterns and mechanisms in the San Francisco Estuary, California, USA. *Canadian Journal of Fisheries and Aquatic Sciences*, *64*(4), 723-734.

Feyrer, F., Portz, D., Odum, D., Newman, K. B., Sommer, T., Contreras, D., ... & Van Nieuwenhuyse, E. (2013). SmeltCam: Underwater Video Codend for Trawled Nets with an Application to the Distribution of the Imperiled Delta Smelt. *PloS one*, *8*(7), e67829.

Grimaldo, L. F., Sommer, T., Van Ark, N., Jones, G., Holland, E., Moyle, P. B., ... & Smith, P. (2009). Factors affecting fish entrainment into massive water diversions in a tidal freshwater estuary: can fish losses be managed?. *North American Journal of Fisheries Management*, *29*(5), 1253-1270.

Hobbs, J. A., Bennett, W. A., & Burton, J. E. (2006). Assessing nursery habitat quality for native smelts (Osmeridae) in the low-salinity zone of the San Francisco estuary. *Journal of Fish Biology*, *69*(3), 907-922.

Hobbs, J. A., Bennett, W. A., Burton, J., & Gras, M. (2007). Classification of larval and adult Delta Smelt to nursery areas by use of trace elemental fingerprinting. *Transactions of the American Fisheries Society*, *136*(2), 518-527.

Jassby, A. (2008). Phytoplankton in the upper San Francisco Estuary: recent biomass trends, their causes and their trophic significance. *San Francisco Estuary and Watershed Science*, *6*(1).

Jassby, A. D., Cloern, J. E., & Cole, B. E. (2002). Annual primary production: Patterns and mechanisms of change in a nutrient-rich tidal ecosystem.*Limnology and Oceanography*, *47*(3), 698-712.

Jassby, A. D., & Powell, T. M. (1994). Hydrodynamic influences on interannual chlorophyll variability in an estuary: upper San Francisco Bay-Delta (California, USA). *Estuarine, Coastal and Shelf Science*, *39*(6), 595-618.

Kimmerer, W. J. (2008). Losses of Sacramento River Chinook salmon and Delta Smelt to entrainment in water diversions in the Sacramento-San Joaquin Delta.*San Francisco Estuary and Watershed Science*, *6*(2).

Kimmerer, W. J. (2011). Modeling Delta Smelt losses at the south Delta export facilities. *San Francisco Estuary and Watershed Science*, *9*(1).

Kimmerer, W. J., Burau, J. R., & Bennett, W. A. (2002). Persistence of tidally-oriented vertical migration by zooplankton in a temperate estuary. *Estuaries*,*25*(3), 359-371.

Kimmerer, W. J., & Nobriga, M. L. (2008). Investigating particle transport and fate in the Sacramento-San Joaquin Delta using a particle tracking model. *San Francisco Estuary and Watershed Science*, *6*(1).

Kimmerer, W. J., & Thompson, J. K. (2014). Phytoplankton growth balanced by clam and zooplankton grazing and net transport into the low-salinity zone of the San Francisco Estuary. *Estuaries and Coasts*, *37*(5), 1202-1218.

Liermann, M., & Hilborn, R. (2001). Depensation: evidence, models and implications. *Fish and Fisheries*, *2*(1), 33-58.

Lucas, L. V., Cloern, J. E., Thompson, J. K., & Monsen, N. E. (2002). Functional variability of habitats within the Sacramento-San Joaquin Delta: Restoration implications. *Ecological Applications*, *12*(5), 1528-1547.

Mac Nally, R., Thomson, J. R., Kimmerer, W. J., Feyrer, F., Newman, K. B., Sih, A., ... & Castillo, G. (2010). Analysis of pelagic species decline in the upper San Francisco Estuary using multivariate autoregressive modeling (MAR).*Ecological Applications*, *20*(5), 1417-1430.

Maunder, M. N., & Deriso, R. B. (2011). A state–space multistage life cycle model to evaluate population impacts in the presence of density dependence: illustrated with application to Delta Smelt (Hyposmesus transpacificus).*Canadian Journal of Fisheries and Aquatic Sciences*, *68*(7), 1285-1306.

McKee, L. J., Ganju, N. K., & Schoellhamer, D. H. (2006). Estimates of suspended sediment entering San Francisco Bay from the Sacramento and San Joaquin Delta, San Francisco Bay, California. *Journal of Hydrology*,*323*(1), 335-352.

Miller, W. J. (2011). Revisiting assumptions that underlie estimates of proportional entrainment of Delta Smelt by state and federal water diversions from the Sacramento-San Joaquin Delta. *San Francisco Estuary and Watershed Science*, *9*(1).

Miller, W. J., Manly, B. F., Murphy, D. D., Fullerton, D., & Ramey, R. R. (2012). An investigation of factors affecting the decline of Delta Smelt (*Hypomesus transpacificus*) in the Sacramento-San Joaquin Estuary. *Reviews in Fisheries Science*, *20*(1), 1-19.

Monsen, N. E., Cloern, J. E., & Burau, J. R. (2007). Effects of flow diversions on water and habitat quality: Examples from California's highly manipulated Sacramento-San Joaquin Delta. *San Francisco Estuary and Watershed Science*, *5*(3).

Moyle, P. B., Herbold, B., Stevens, D. E., & Miller, L. W. (1992). Life history and status of Delta Smelt in the Sacramento-San Joaquin Estuary, California.*Transactions of the American Fisheries Society*, *121*(1), 67-77.

Müller-Solger, A. B., Jassby, A. D., & Müller-Navarra, D. C. (2002). Nutritional quality of food resources for zooplankton (Daphnia) in a tidal freshwater system (Sacramento-San Joaquin River Delta). *Limnology and Oceanography*, *47*(5), 1468-1476.

Murphy, D. D., & Hamilton, S. A. (2013). Eastward Migration or Marshward Dispersal: Exercising Survey Data to Elicit an Understanding of Seasonal Movement of Delta Smelt. *San Francisco Estuary and Watershed Science*,*11*(3).

Newman, K. B. (2008). Sample design-based methodology for estimating Delta Smelt abundance. *San Francisco Estuary and Watershed Science*, *6*(3).

Newman, K. B., & Lindley, S. T. (2006). Accounting for demographic and environmental stochasticity, observation error, and parameter uncertainty in fish population dynamics models. *North American Journal of Fisheries Management*, *26*(3), 685-701.

Nobriga, M. L., Feyrer, F., Baxter, R. D., & Chotkowski, M. (2005). Fish community ecology in an altered river delta: spatial patterns in species composition, life history strategies, and biomass. *Estuaries*, *28*(5), 776-785.

Nobriga, M. L., Loboschefsky, E., & Feyrer, F. (2013). Common Predator, Rare Prey: Exploring Juvenile Striped Bass Predation on Delta Smelt in California's San Francisco Estuary. *Transactions of the American Fisheries Society*,*142*(6), 1563-1575.

Rose, K. A., Kimmerer, W. J., Edwards, K. P., & Bennett, W. A. (2013a). Individual-based modeling of Delta Smelt population dynamics in the upper San Francisco estuary: I. Model description and baseline results. *Transactions of the American Fisheries Society*, *142*(5), 1238-1259.

Rose, K. A., Kimmerer, W. J., Edwards, K. P., & Bennett, W. A. (2013b). Individual-based modeling of Delta Smelt population dynamics in the upper San Francisco Estuary: II. Alternative baselines and good versus bad years.*Transactions of the American Fisheries Society*, *142*(5), 1260-1272.

Schoellhamer, D. H. (2002). Variability of suspended-sediment concentration at tidal to annual time scales in San Francisco Bay, USA. *Continental Shelf Research*, *22*(11), 1857-1866.

Slater, S. B.,& R. D. Baxter. (2014). Diet, prey selection, and body condition of Age-0 Delta Smelt, *Hypomesus transpacificus*, in the upper San Francisco Estuary. *San Francisco Estuary and Watershed Science* 12(3).

Sommer, T., Baxter, R., & Herbold, B. (1997). Resilience of splittail in the Sacramento–San Joaquin estuary. *Transactions of the American Fisheries Society*, *126*(6), 961-976.

Sommer, T. R., Harrell, W. C., Mueller-Solger, A., Tom, B., & Kimmerer, W. (2004). Effects of flow variation on channel and floodplain biota and habitats of the Sacramento River, California, USA. *Aquatic Conservation: Marine and Freshwater Ecosystems*, *14*(3), 247-261.

Sommer, T., Mejia, F. H., Nobriga, M. L., Feyrer, F., & Grimaldo, L. (2011). The spawning migration of Delta Smelt in the upper San Francisco Estuary. *San Francisco Estuary and Watershed Science*, *9*(2).

Stunz, G. W., & Minello, T. J. (2001). Habitat-related predation on juvenile wild-caught and hatchery-reared red drum< i> Sciaenops ocellatus</i>(Linnaeus).*Journal of Experimental Marine Biology and Ecology*, *260*(1), 13-25.

Thomson, J. R., Kimmerer, W. J., Brown, L. R., Newman, K. B., Nally, R. M., Bennett, W. A., ... & Fleishman, E. (2010). Bayesian change point analysis of abundance trends for pelagic fishes in the upper San Francisco Estuary.*Ecological Applications*, *20*(5), 1431-1448.

Walters, C., & Korman, J. (1999). Linking recruitment to trophic factors: revisiting the Beverton--Holt recruitment model from a life history and multispecies perspective. *Reviews in Fish Biology and Fisheries*, *9*(2), 187-202.

Appendix: R code and outputs for the linear regression analyses described in Step 3

The following text was pasted from R. We added red highlights to show where a predicted parameter had a sign that was opposite of its hypothesized relationship to Delta Smelt salvage and blue highlights where a model *P*-value was lower than the Bonferroni-adjusted *P*-value for the number of individual analyses performed.

```
R version 3.1.0 (2014-04-10) -- "Spring Dance"
Copyright (C) 2014 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)

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'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> ##4/22/2015##
>
> ##This is the R file for adult salvage regressions as they appear in Table 2 of the draft CAMT early product##
>
> ##The set up and summary of this analysis is in MS Excel file "Data double check.xls"##
>
>
> salvage <- read.csv(file.choose("AdultSalvageR_MasterMarch2015.csv"),header=TRUE)
>
> ##SWP cpue, seasonal average base model##
>
> swp.base.cpue <- lm(log(swp.cpue + 1) ~ log(fmwt), data = salvage)
>
> summary(swp.base.cpue)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt), data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
```

```
-1.03723 -0.28274 -0.03915  0.31000  1.46046

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.86310    0.44461  -1.941  0.06645 .
log(fmwt)    0.31141    0.08831   3.527  0.00212 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5707 on 20 degrees of freedom
Multiple R-squared:  0.3834,    Adjusted R-squared:  0.3526
F-statistic: 12.44 on 1 and 20 DF,  p-value: 0.002121

>
> AIC(swp.base.cpue)
[1] 41.65984
> correct.base.cpue <- (AIC(swp.base.cpue) + (12/19))
> correct.base.cpue
[1] 42.29142
>
> ##SWP equation 5##
>
> swp5.season <- lm(log(swp.cpue + 1) ~ log(fmwt) + ndoi, data = salvage)
>
> summary(swp5.season)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + ndoi, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-0.89012 -0.29625 -0.02687  0.33858  1.42020

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.21464    0.81748  -1.486  0.15373
log(fmwt)    0.32145    0.09205   3.492  0.00244 **
ndoi         0.08116    0.15711   0.517  0.61140
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5815 on 19 degrees of freedom
Multiple R-squared:  0.3919,    Adjusted R-squared:  0.3279
F-statistic: 6.124 on 2 and 19 DF,  p-value: 0.00886

> AIC(swp5.season)
[1] 43.35297
> correct25 <- (AIC(swp5.season) + (24/18))
> correct25
[1] 44.68631
>
> ##SWP equation 6##
>
> swp6.season <- lm(log(swp.cpue + 1) ~ log(fmwt) + omr, data = salvage)
>
> summary(swp6.season)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + omr, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-1.09886 -0.26010 -0.03151  0.33622  1.14709

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.051e+00  4.100e-01  -2.564  0.01900 *
log(fmwt)    3.015e-01  7.996e-02   3.771  0.00129 **
omr         -6.722e-05  2.876e-05  -2.337  0.03053 *
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5161 on 19 degrees of freedom
Multiple R-squared:  0.5211,    Adjusted R-squared:  0.4707
F-statistic: 10.34 on 2 and 19 DF,  p-value: 0.0009171

> AIC(swp6.season)
[1] 38.1006
> correct21 <- (AIC(swp6.season) + (24/18))
> correct21
[1] 39.43393
>
> ##SWP equation 7##
>
> swp7.season <- lm(log(swp.cpue + 1) ~ log(fmwt) + ntu, data = salvage)
>
> summary(swp7.season)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + ntu, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-1.04389 -0.29939 -0.03767  0.29145  1.46607

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.815268   0.576798  -1.413  0.17370
log(fmwt)    0.311185   0.090571   3.436  0.00277 **
ntu         -0.003084   0.022781  -0.135  0.89374
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5853 on 19 degrees of freedom
Multiple R-squared:  0.384,     Adjusted R-squared:  0.3192
F-statistic: 5.922 on 2 and 19 DF,  p-value: 0.01002

> AIC(swp7.season)
[1] 43.63863
> correct22 <- (AIC(swp7.season) + (24/18))
> correct22
[1] 44.97196
>
> ##SWP equation 8##
>
> swp8.season <- lm(log(swp.cpue + 1) ~ log(fmwt) + omr_ntu, data = salvage)
>
> summary(swp8.season)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + omr_ntu, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-1.07084 -0.26984 -0.03385  0.31811  1.27325

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.9165881  0.4205125  -2.180   0.0421 *
log(fmwt)    0.3114183  0.0833233   3.737   0.0014 **
omr_ntu     -0.0017069  0.0009172  -1.861   0.0783 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5385 on 19 degrees of freedom
Multiple R-squared:  0.4785,    Adjusted R-squared:  0.4236
F-statistic: 8.716 on 2 and 19 DF,  p-value: 0.002061

> AIC(swp8.season)
[1] 39.97623
```

```
> correct24 <- (AIC(swp8.season) + (24/18))
> correct24
[1] 41.30957
>
> ##SWP equation 9##
>
> swp9.season <- lm(log(swp.cpue + 1) ~ log(fmwt) + omr + ntu, data = salvage)
>
> summary(swp9.season)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + omr + ntu, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-1.06753 -0.30768 -0.00884  0.26460  1.05934

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.382e+00  5.607e-01  -2.465  0.02398 *
log(fmwt)    3.013e-01  8.047e-02   3.744  0.00149 **
omr         -7.852e-05  3.171e-05  -2.476  0.02345 *
ntu          1.931e-02  2.215e-02   0.872  0.39467
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5193 on 18 degrees of freedom
Multiple R-squared:  0.5405,    Adjusted R-squared:  0.4639
F-statistic: 7.058 on 3 and 18 DF,  p-value: 0.002463

> AIC(swp9.season)
[1] 39.19023
> correct23 <- (AIC(swp9.season) + (40/17))
> correct23
[1] 41.54317
>
> ##SWP equation 10##
>
> swp10.season <- lm(log(swp.cpue + 1) ~ log(fmwt) + ndoi + omr + ntu, data = salvage)
>
> summary(swp10.season)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + ndoi + omr + ntu,
    data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-0.8020 -0.2747  0.0224  0.2435  0.8885

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.346e+00  8.647e-01  -2.713 0.014771 *
log(fmwt)    3.248e-01  7.990e-02   4.065 0.000805 ***
ndoi         2.055e-01  1.432e-01   1.435 0.169365
omr         -9.241e-05  3.230e-05  -2.861 0.010821 *
ntu          2.154e-02  2.158e-02   0.998 0.332062
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5047 on 17 degrees of freedom
Multiple R-squared:  0.5902,    Adjusted R-squared:  0.4937
F-statistic:  6.12 on 4 and 17 DF,  p-value: 0.003066

> AIC(swp10.season)
[1] 38.67404
> correct26 <- (AIC(swp10.season) + (60/16))
> correct26
[1] 42.42404
>
```

```
> ##SWP raw salvage, seasonal average base model##
>
> swp1 <- lm(log(swp.salv + 1) ~ log(fmwt), data = salvage)
>
> summary(swp1)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt), data = salvage)

Residuals:
   Min     1Q Median     3Q    Max
-3.574 -1.452 -0.102  1.397  3.759

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -2.2501     1.7124  -1.314 0.203700
log(fmwt)     1.5684     0.3401   4.612 0.000169 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.198 on 20 degrees of freedom
Multiple R-squared:  0.5154,    Adjusted R-squared:  0.4911
F-statistic: 21.27 on 1 and 20 DF,  p-value: 0.0001687

>
> AIC(swp1)
[1] 100.9905
> correct1 <- (AIC(swp1) + (12/19))
> correct1
[1] 101.6221
>
> ##SWP equation 11##
>
> swp11.season <- lm(log(swp.salv + 1) ~ log(fmwt) + ndoi, data = salvage)
>
> summary(swp11.season)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + ndoi, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-3.7274 -1.3017  0.0963  1.3938  3.8741

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.2481     3.1584  -0.395 0.697112
log(fmwt)     1.5398     0.3556   4.330 0.000361 ***
ndoi         -0.2313     0.6070  -0.381 0.707345
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.247 on 19 degrees of freedom
Multiple R-squared:  0.519,     Adjusted R-squared:  0.4684
F-statistic: 10.25 on 2 and 19 DF,  p-value: 0.0009553

> AIC(swp11.season)
[1] 102.823
> correct6 <- (AIC(swp11.season) + (24/18))
> correct6
[1] 104.1563
>
>
> ##SWP equation 12##
>
> swp12.season <- lm(log(swp.salv + 1) ~ log(fmwt) + swp.exp, data = salvage)
>
> summary(swp12.season)

Call:
```

```
lm(formula = log(swp.salv + 1) ~ log(fmwt) + swp.exp, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.4669 -0.7258  0.2260  1.0145  2.6321 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -4.056e+00  1.837e+00  -2.207 0.039777 *  
log(fmwt)    1.427e+00  3.252e-01   4.388 0.000316 ***
swp.exp      7.231e-11  3.631e-11   1.991 0.061010 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.051 on 19 degrees of freedom
Multiple R-squared:  0.599,	Adjusted R-squared:  0.5568 
F-statistic: 14.19 on 2 and 19 DF,  p-value: 0.0001696

> AIC(swp12.season)
[1] 98.82014
> correct2 <- (AIC(swp12.season) + (24/18))
> correct2
[1] 100.1535
> 
> 
> ##SWP equation 13##
> 
> swp13.season <- lm(log(swp.salv + 1) ~ log(fmwt) + omr, data = salvage)
> 
> summary(swp13.season)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + omr, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.8523 -1.0365  0.1073  1.6621  3.1474 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -2.6172838  1.7394844  -1.505 0.148861    
log(fmwt)    1.5490545  0.3392430   4.566 0.000211 ***
omr         -0.0001313  0.0001220  -1.076 0.295523    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.19 on 19 degrees of freedom
Multiple R-squared:  0.5432,	Adjusted R-squared:  0.4951 
F-statistic:  11.3 on 2 and 19 DF,  p-value: 0.0005856

> AIC(swp13.season)
[1] 101.6899
> correct3 <- (AIC(swp13.season) + (24/18))
> correct3
[1] 103.0232
> 
> 
> ##SWP equation 14##
> 
> swp14.season <- lm(log(swp.salv + 1) ~ log(fmwt) + ntu, data = salvage)
> 
> summary(swp14.season)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + ntu, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.5005 -1.5318  0.2368  1.1277  3.6521 
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.16516    2.19594  -1.441 0.165760
log(fmwt)    1.57272    0.34482   4.561 0.000213 ***
ntu          0.05900    0.08673   0.680 0.504516
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.228 on 19 degrees of freedom
Multiple R-squared:  0.5269,    Adjusted R-squared:  0.4771
F-statistic: 10.58 on 2 and 19 DF,  p-value: 0.0008171

> AIC(swp14.season)
[1] 102.4611
> correct4 <- (AIC(swp14.season) + (24/18))
> correct4
[1] 103.7944
>
>
> ##SWP equation 15##
>
> swp15.season <- lm(log(swp.salv + 1) ~ log(fmwt) + omr_ntu, data = salvage)
>
> summary(swp15.season)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + omr_ntu, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-3.6201 -1.2734  0.0526  1.6882  3.3620

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.363680   1.719246  -1.375 0.185180
log(fmwt)    1.568405   0.340663   4.604 0.000194 ***
omr_ntu     -0.003623   0.003750  -0.966 0.346139
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.202 on 19 degrees of freedom
Multiple R-squared:  0.538,     Adjusted R-squared:  0.4894
F-statistic: 11.06 on 2 and 19 DF,  p-value: 0.0006512

> AIC(swp15.season)
[1] 101.9356
> correct5 <- (AIC(swp15.season) + (24/18))
> correct5
[1] 103.2689
>
>
> ##SWP equation 16##
>
> swp16.season <- lm(log(swp.salv + 1) ~ log(fmwt) + omr + ntu, data = salvage)
>
> summary(swp16.season)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + omr + ntu, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-4.1186 -0.8865  0.0196  1.1139  3.7442

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.6018292  2.3283237  -1.976 0.063631 .
log(fmwt)    1.5475760  0.3341443   4.631 0.000207 ***
omr         -0.0001990  0.0001317  -1.511 0.148139
ntu          0.1157583  0.0919614   1.259 0.224195
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.157 on 18 degrees of freedom
Multiple R-squared:  0.5801,    Adjusted R-squared:  0.5102
F-statistic:  8.29 on 3 and 18 DF,  p-value: 0.001127

> AIC(swp16.season)
[1] 101.8338
> correct4.5 <- (AIC(swp16.season) + (40/17))
> correct4.5
[1] 104.1868
>
>
> ##SWP equation 17##
>
> swp17.season <- lm(log(swp.salv + 1) ~ log(fmwt) + ndoi + omr + ntu, data = salvage)
>
> summary(swp17.season)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + ndoi + omr + ntu,
    data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-4.1256 -0.8903  0.0141  1.1107  3.7480

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.6440825  3.8017889  -1.222 0.238547
log(fmwt)    1.5486083  0.3513118   4.408 0.000384 ***
ndoi         0.0090113  0.6295458   0.014 0.988746
omr         -0.0001996  0.0001420  -1.405 0.177968
ntu          0.1158561  0.0948736   1.221 0.238691
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.219 on 17 degrees of freedom
Multiple R-squared:  0.5801,    Adjusted R-squared:  0.4813
F-statistic: 5.872 on 4 and 17 DF,  p-value: 0.003711

> AIC(swp17.season)
[1] 103.8335
> correct6.5 <- (AIC(swp17.season) + (60/16))
> correct6.5
[1] 107.5835
>
>
> ##SWP equation 18##
>
> swp18.season <- lm(log(swp.salv + 1) ~ log(fmwt) + swp.exp + ntu, data = salvage)
>
> summary(swp18.season)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + swp.exp + ntu, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-4.6605 -0.7292  0.1813  1.0398  2.8337

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.469e+00  2.186e+00  -2.044 0.055896 .
log(fmwt)    1.434e+00  3.334e-01   4.302 0.000429 ***
swp.exp      6.974e-11  3.781e-11   1.844 0.081673 .
ntu          3.076e-02  8.314e-02   0.370 0.715685
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 2.1 on 18 degrees of freedom
Multiple R-squared:  0.6021,    Adjusted R-squared:  0.5357
F-statistic: 9.078 on 3 and 18 DF,  p-value: 0.0007061

> AIC(swp18.season)
[1] 100.6534
> correct99 <- (AIC(swp18.season) + (40/17))
> correct99
[1] 103.0064
>
>
> ##SWP equation 19##
>
> swp19.season <- lm(log(swp.salv + 1) ~ log(fmwt) + ndoi + swp.exp + ntu, data = salvage)
>
> summary(swp19.season)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + ndoi + swp.exp +
    ntu, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-4.5734 -0.6767  0.2603  1.1091  2.8093

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.938e+00  3.413e+00  -1.154 0.264646
log(fmwt)    1.422e+00  3.483e-01   4.081 0.000778 ***
ndoi        -1.217e-01  5.890e-01  -0.207 0.838756
swp.exp      6.868e-11  3.919e-11   1.752 0.097739 .
ntu          3.222e-02  8.573e-02   0.376 0.711724
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.158 on 17 degrees of freedom
Multiple R-squared:  0.6031,    Adjusted R-squared:  0.5097
F-statistic: 6.457 on 4 and 17 DF,  p-value: 0.002378

> AIC(swp19.season)
[1] 102.5983
> correct100 <- (AIC(swp19.season) + (60/16))
> correct100
[1] 106.3483
>
>
> ##Start CVP seasonal CPUE models##
>
> ##base model##
>
> cvp.base.cpue <- lm(log(cvp.cpue + 1) ~ log(fmwt), data = salvage)
>
> summary(cvp.base.cpue)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt), data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-0.93063 -0.21147 -0.01207  0.13516  1.02228

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.75780    0.35737  -2.120 0.046663 *
log(fmwt)    0.27929    0.07098   3.935 0.000819 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4587 on 20 degrees of freedom
```

```
Multiple R-squared:  0.4364,    Adjusted R-squared:  0.4082
F-statistic: 15.48 on 1 and 20 DF,  p-value: 0.0008192

>
> AIC(cvp.base.cpue)
[1] 32.04892
> correct20.1 <- (AIC(cvp.base.cpue) + (12/19))
> correct20.1
[1] 32.6805
>
> ##CVP equation 5##
>
> cvp5.season <- lm(log(cvp.cpue + 1) ~ log(fmwt) + ndoi, data = salvage)
>
> summary(cvp5.season)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + ndoi, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-0.75375 -0.29647 -0.03715  0.16784  0.91280

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.71366    0.60697  -2.823 0.010858 *
log(fmwt)    0.30659    0.06834   4.486 0.000253 ***
ndoi         0.22068    0.11665   1.892 0.073857 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4318 on 19 degrees of freedom
Multiple R-squared:  0.5257,    Adjusted R-squared:  0.4758
F-statistic: 10.53 on 2 and 19 DF,  p-value: 0.0008366

> AIC(cvp5.season)
[1] 30.25213
> correct24.1 <- (AIC(cvp5.season) + (24/18))
> correct24.1
[1] 31.58546
>
> ##CVP equation 6##
>
> cvp6.season <- lm(log(cvp.cpue + 1) ~ log(fmwt) + omr, data = salvage)
>
> summary(cvp6.season)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + omr, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-0.9371 -0.2082 -0.0225  0.1334  0.9892

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -7.776e-01  3.732e-01  -2.084  0.05094 .
log(fmwt)    2.782e-01  7.278e-02   3.823  0.00115 **
omr         -7.088e-06  2.618e-05  -0.271  0.78952
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4698 on 19 degrees of freedom
Multiple R-squared:  0.4385,    Adjusted R-squared:  0.3794
F-statistic:  7.42 on 2 and 19 DF,  p-value: 0.004156

> AIC(cvp6.season)
[1] 33.96421
> correct21.1 <- (AIC(cvp6.season) + (24/18))
> correct21.1
```

```
[1] 35.29755
>
> ##CVP equation 7##
>
> cvp7.season <- lm(log(cvp.cpue + 1) ~ log(fmwt) + ntu, data = salvage)
>
> summary(cvp7.season)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + ntu, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-0.85672 -0.19446 -0.00549  0.12206  0.96003

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.28895    0.41901  -3.076 0.006216 **
log(fmwt)    0.28180    0.06579   4.283 0.000402 ***
ntu          0.03425    0.01655   2.070 0.052364 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4252 on 19 degrees of freedom
Multiple R-squared:   0.54,     Adjusted R-squared:  0.4916
F-statistic: 11.15 on 2 and 19 DF,  p-value: 0.0006249

> AIC(cvp7.season)
[1] 29.57636
> correct22.1 <- (AIC(cvp7.season) + (24/18))
> correct22.1
[1] 30.90969
>
> ##CVP equation 8##
>
> cvp8.season <- lm(log(cvp.cpue + 1) ~ log(fmwt) + omr_ntu, data = salvage)
>
> summary(cvp8.season)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + omr_ntu, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-0.93104 -0.21153 -0.01271  0.13446  1.02004

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -7.584e-01  3.675e-01  -2.064  0.05297 .
log(fmwt)    2.793e-01  7.282e-02   3.835  0.00112 **
omr_ntu     -2.041e-05  8.016e-04  -0.025  0.97995
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4707 on 19 degrees of freedom
Multiple R-squared:  0.4364,    Adjusted R-squared:  0.377
F-statistic: 7.355 on 2 and 19 DF,  p-value: 0.00431

> AIC(cvp8.season)
[1] 34.04817
> correct23.1 <- (AIC(cvp8.season) + (24/18))
> correct23.1
[1] 35.3815
>
>
> ##CVP equation 9##
>
> cvp9.season <- lm(log(cvp.cpue + 1) ~ log(fmwt) + omr + ntu, data = salvage)
>
> summary(cvp9.season)
```

```
Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + omr + ntu, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-0.86652 -0.19668  0.03104  0.21364  0.79142

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.524e+00  4.517e-01  -3.374 0.003380 **
log(fmwt)    2.777e-01  6.482e-02   4.284 0.000447 ***
omr         -3.255e-05  2.554e-05  -1.274 0.218799
ntu          4.353e-02  1.784e-02   2.440 0.025244 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4184 on 18 degrees of freedom
Multiple R-squared:  0.5781,    Adjusted R-squared:  0.5078
F-statistic: 8.221 on 3 and 18 DF,  p-value: 0.001175

> AIC(cvp9.season)
[1] 29.67643
> correct25.1 <- (AIC(cvp9.season) + (24/18))
> correct25.1
[1] 31.00976
>
> ##CVP equation 10##
>
> cvp10.season <- lm(log(cvp.cpue + 1) ~ log(fmwt) + ndoi + omr + ntu, data = salvage)
>
> summary(cvp10.season)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + ndoi + omr + ntu,
    data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-0.70952 -0.23286  0.03088  0.18483  0.56246

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.816e+00  6.174e-01  -4.561 0.000277 ***
log(fmwt)    3.092e-01  5.705e-02   5.421 4.59e-05 ***
ndoi         2.755e-01  1.022e-01   2.695 0.015340 *
omr         -5.118e-05  2.306e-05  -2.219 0.040373 *
ntu          4.653e-02  1.541e-02   3.020 0.007719 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3603 on 17 degrees of freedom
Multiple R-squared:  0.7044,    Adjusted R-squared:  0.6348
F-statistic: 10.13 on 4 and 17 DF,  p-value: 0.0002216

> AIC(cvp10.season)
[1] 23.85105
> correct26.1 <- (AIC(cvp10.season) + (60/16))
> correct26.1
[1] 27.60105
>
> ##CVP raw salvage, seasonal average base model##
>
> cvp1 <- lm(log(cvp.salv + 1) ~ log(fmwt), data = salvage)
>
> summary(cvp1)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt), data = salvage)
```

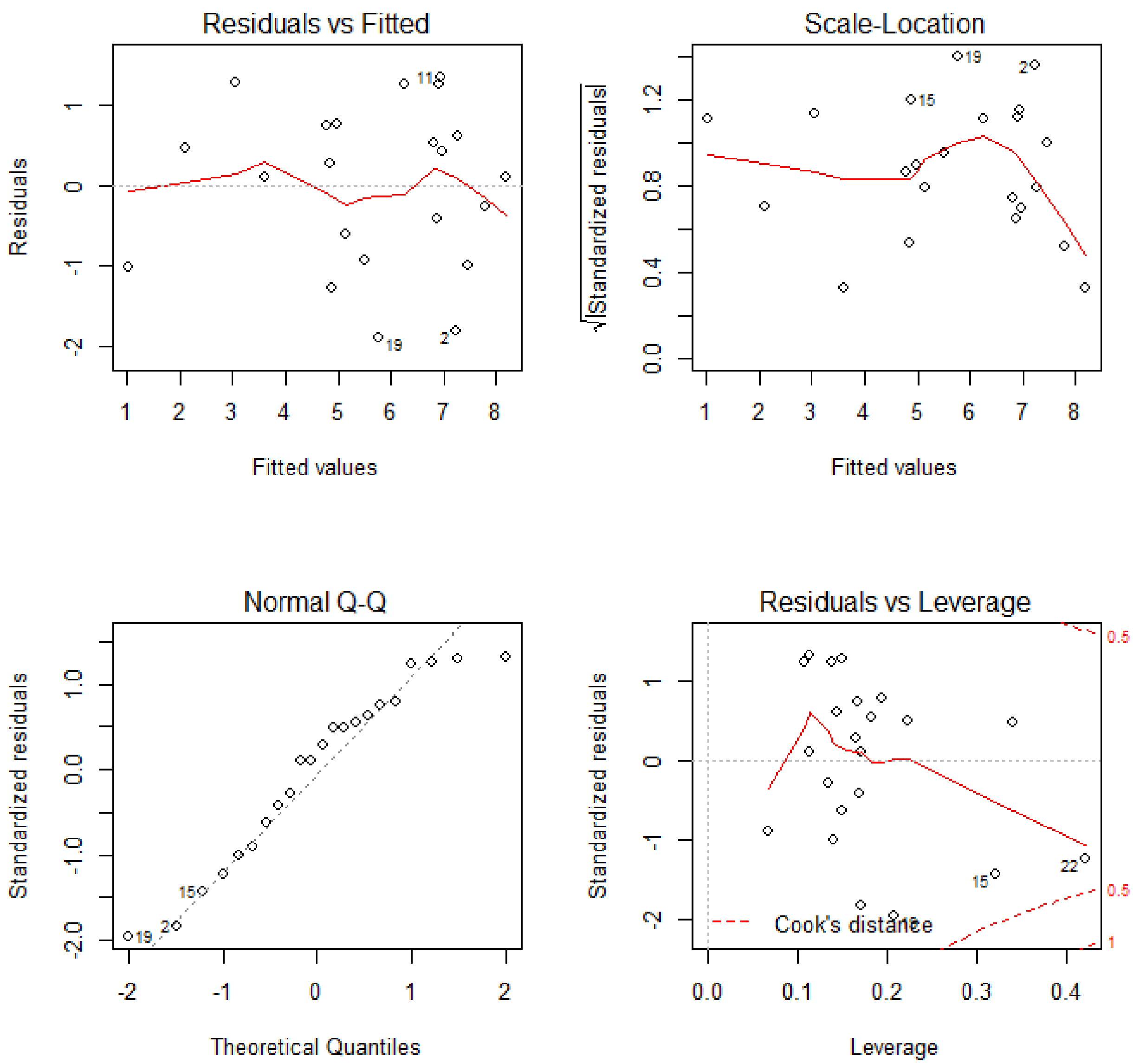
```
Residuals:
    Min      1Q  Median      3Q     Max 
-3.6004 -0.8369  0.0603  1.2408  2.5255 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   0.5569     1.2322   0.452 0.656145    
log(fmwt)     1.0529     0.2447   4.302 0.000347 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.582 on 20 degrees of freedom
Multiple R-squared:  0.4807,    Adjusted R-squared:  0.4547 
F-statistic: 18.51 on 1 and 20 DF,  p-value: 0.0003469

> 
> AIC(cvp1)
[1] 86.51215
> correct1.1 <- (AIC(cvp1) + (12/19))
> correct1.1
[1] 87.14373
> 
> 
> ##CVP equation 11##
> 
> cvp11.season <- lm(log(cvp.salv + 1) ~ log(fmwt) + ndoi, data = salvage)
> 
> summary(cvp11.season)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + ndoi, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.5462 -0.8392 -0.0122  1.0872  2.5331 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  -1.7595     2.1903  -0.803 0.431747    
log(fmwt)     1.1191     0.2466   4.538 0.000225 ***
ndoi          0.5348     0.4210   1.270 0.219263    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.558 on 19 degrees of freedom
Multiple R-squared:  0.5213,    Adjusted R-squared:  0.4709 
F-statistic: 10.35 on 2 and 19 DF,  p-value: 0.0009128

> AIC(cvp11.season)
[1] 86.71842
> correct6.1 <- (AIC(cvp11.season) + (24/18))
> correct6.1
[1] 88.05176
> 
> 
> ##CVP equation 12##
> 
> cvp12.season <- lm(log(cvp.salv + 1) ~ log(fmwt) + cvp.exp, data = salvage)
> 
> summary(cvp12.season)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + cvp.exp, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.39606 -0.92071 -0.01001  1.01927  2.17506 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept) -2.806e+00  1.430e+00  -1.963 0.064496 .
log(fmwt)    8.856e-01  2.062e-01   4.295 0.000391 ***
cvp.exp      1.462e-10  4.414e-11   3.312 0.003663 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.292 on 19 degrees of freedom
Multiple R-squared:  0.6708,    Adjusted R-squared:  0.6361
F-statistic: 19.35 on 2 and 19 DF,  p-value: 2.608e-05

> AIC(cvp12.season)
[1] 78.48501
> correct2.1 <- (AIC(cvp12.season) + (24/18))
> correct2.1
[1] 79.81834
>
>
> ##CVP equation 13##
>
> cvp13.season <- lm(log(cvp.salv + 1) ~ log(fmwt) + omr, data = salvage)
>
> summary(cvp13.season)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + omr, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-3.6088 -0.8236  0.0532  1.2558  2.5631

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 5.795e-01  1.289e+00   0.450 0.658101
log(fmwt)   1.054e+00  2.514e-01   4.193 0.000493 ***
omr         8.071e-06  9.043e-05   0.089 0.929816
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.623 on 19 degrees of freedom
Multiple R-squared:  0.4809,    Adjusted R-squared:  0.4262
F-statistic:   8.8 on 2 and 19 DF,  p-value: 0.001972

> AIC(cvp13.season)
[1] 88.50293
> correct3.1 <- (AIC(cvp13.season) + (24/18))
> correct3.1
[1] 89.83627
>
> ##CVP equation 14##
>
> cvp14.season <- lm(log(cvp.salv + 1) ~ log(fmwt) + ntu, data = salvage)
>
> summary(cvp14.season)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + ntu, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-2.7498 -0.6932  0.1781  0.7868  2.2373

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.90226    1.30745  -1.455  0.16201
log(fmwt)    1.06458    0.20530   5.185 5.26e-05 ***
ntu          0.15857    0.05164   3.071  0.00629 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.327 on 19 degrees of freedom
```

```
Multiple R-squared:  0.6529,    Adjusted R-squared:  0.6164
F-statistic: 17.87 on 2 and 19 DF,  p-value: 4.305e-05

> AIC(cvp14.season)
[1] 79.64575
> correct4.1 <- (AIC(cvp14.season) + (24/18))
> correct4.1
[1] 80.97908
>
>
> ##CVP equation 15##
>
> cvp15.season <- lm(log(cvp.salv + 1) ~ log(fmwt) + omr_ntu, data = salvage)
>
> summary(cvp15.season)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + omr_ntu, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-3.6088 -0.8263  0.0538  1.1960  2.6154

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.5826281  1.2642627   0.461 0.650142
log(fmwt)   1.0529454  0.2505098   4.203 0.000482 ***
omr_ntu     0.0008196  0.0027577   0.297 0.769538
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.619 on 19 degrees of freedom
Multiple R-squared:  0.4831,    Adjusted R-squared:  0.4287
F-statistic: 8.878 on 2 and 19 DF,  p-value: 0.001895

> AIC(cvp15.season)
[1] 88.41012
> correct5.1 <- (AIC(cvp15.season) + (24/18))
> correct5.1
[1] 89.74345
>
>
> ##CVP equation 16##
>
> cvp16.season <- lm(log(cvp.salv + 1) ~ log(fmwt) + omr + ntu, data = salvage)
>
> summary(cvp16.season)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + omr + ntu, data = salvage)

Residuals:
     Min       1Q   Median       3Q      Max
-2.48757 -0.75125  0.07355  0.96504  1.87247

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.6360419  1.4093014  -1.870  0.07777 .
log(fmwt)    1.0517420  0.2022528   5.200 6.03e-05 ***
omr         -0.0001016  0.0000797  -1.275  0.21851
ntu          0.1875631  0.0556630   3.370  0.00341 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.305 on 18 degrees of freedom
Multiple R-squared:  0.6817,    Adjusted R-squared:  0.6286
F-statistic: 12.85 on 3 and 18 DF,  p-value: 9.987e-05

> AIC(cvp16.season)
[1] 79.74342
```

```
> correct5.6 <- (AIC(cvp16.season) + (40/17))
> correct5.6
[1] 82.09636
>
>
> ##CVP equation 17##
>
> cvp17.season <- lm(log(cvp.salv + 1) ~ log(fmwt) + ndoi + omr + ntu, data = salvage)
>
> summary(cvp17.season)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + ndoi + omr + ntu,
    data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-2.3338 -0.5503  0.3395  0.7380  1.5200

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -5.763e+00  2.084e+00  -2.766  0.01321 *
log(fmwt)    1.128e+00  1.925e-01   5.859 1.89e-05 ***
ndoi         6.670e-01  3.450e-01   1.933  0.07005 .
omr         -1.467e-04  7.784e-05  -1.885  0.07663 .
ntu          1.948e-01  5.199e-02   3.747  0.00161 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.216 on 17 degrees of freedom
Multiple R-squared:  0.739,     Adjusted R-squared:  0.6776
F-statistic: 12.04 on 4 and 17 DF,  p-value: 8e-05

> AIC(cvp17.season)
[1] 77.37191
> correct5.7 <- (AIC(cvp17.season) + (60/16))
> correct5.7
[1] 81.12191
>
>
> ##CVP equation 18##
>
> cvp18.season <- lm(log(cvp.salv + 1) ~ log(fmwt) + cvp.exp + ntu, data = salvage)
>
> summary(cvp18.season)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + cvp.exp + ntu, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-1.8843 -0.8562  0.1940  0.7089  1.3478

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.306e+00  1.290e+00  -3.337  0.00367 **
log(fmwt)    9.213e-01  1.724e-01   5.343 4.45e-05 ***
cvp.exp      1.234e-10  3.758e-11   3.283  0.00414 **
ntu          1.306e-01  4.282e-02   3.049  0.00690 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.078 on 18 degrees of freedom
Multiple R-squared:  0.7829,    Adjusted R-squared:  0.7467
F-statistic: 21.64 on 3 and 18 DF,  p-value: 3.385e-06

> AIC(cvp18.season)
[1] 71.32337
> correct5.5 <- (AIC(cvp18.season) + (40/17))
> correct5.5
```

```
[1] 73.67631
>
> layout(matrix(c(1,2,3,4),2,2))
> plot(cvp18.season)
```




```
>
> ##CVP equation 19##
>
> cvp19.season <- lm(log(cvp.salv + 1) ~ log(fmwt) + ndoi + cvp.exp + ntu, data = salvage)
>
> summary(cvp19.season)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + ndoi + cvp.exp +
    ntu, data = salvage)

Residuals:
    Min      1Q  Median      3Q     Max
-2.2158 -0.7084  0.1908  0.7214  1.3972
```

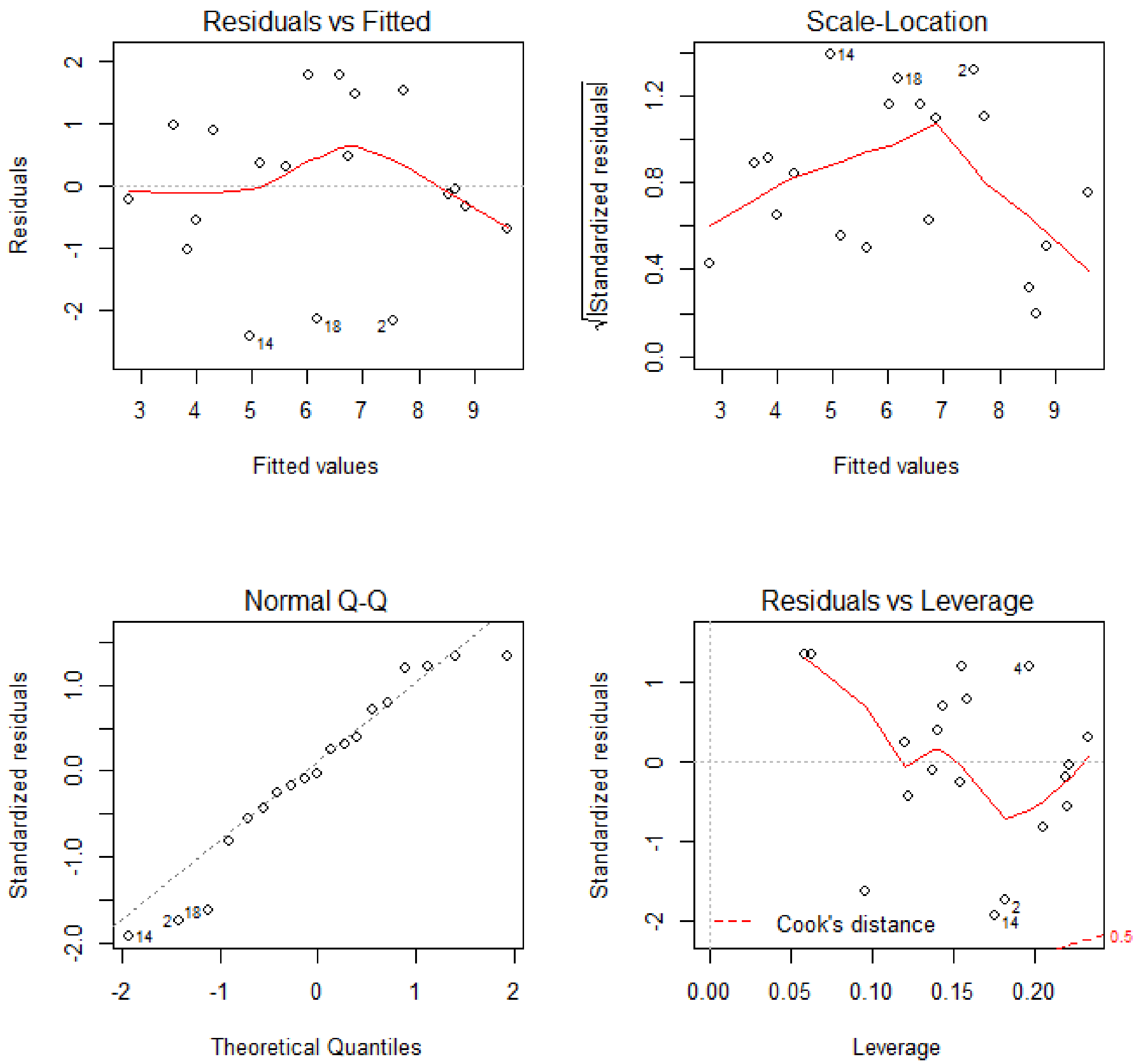
```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -6.716e+00  1.681e+00  -3.995 0.000937 ***
log(fmwt)    9.826e-01  1.620e-01   6.066 1.26e-05 ***
ndoi         5.487e-01  2.701e-01   2.032 0.058122 .
cvp.exp      1.288e-10  3.479e-11   3.702 0.001770 **
ntu          1.247e-01  3.963e-02   3.147 0.005881 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.995 on 17 degrees of freedom
Multiple R-squared:  0.8253,    Adjusted R-squared:  0.7842
F-statistic: 20.08 on 4 and 17 DF,  p-value: 2.904e-06

> AIC(cvp19.season)
[1] 68.54128
> correct5.8 <- (AIC(cvp19.season) + (60/16))
> correct5.8
[1] 72.29128
>
##The next section is the SWP CPUE event models##
>
> ##Next, I'm opening a new file for SWP event data comparisons.  This file excluded years of 0 SWP salvage == 2007, 2011, 2014##
>
> event.swp <- read.csv(file.choose("AdultSalvageR_March2015_SWPEvent.csv"),header=TRUE)
>
> ##Base model##
>
> swp30 <- lm(log(swp.cpue + 1) ~ log(fmwt), data = event.swp)
>
> summary(swp30)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt), data = event.swp)

Residuals:
     Min       1Q   Median       3Q      Max
-1.01884 -0.35099 -0.08044  0.35513  1.42976

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.7141     0.5558  -1.285   0.2161
log(fmwt)     0.2874     0.1058   2.717   0.0147 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6116 on 17 degrees of freedom
Multiple R-squared:  0.3027,    Adjusted R-squared:  0.2617
F-statistic:  7.38 on 1 and 17 DF,  p-value: 0.01466

>
> AIC(swp30)
[1] 39.12495
> correct30 <- (AIC(swp30) + (12/16))
> correct30
[1] 39.87495
>
> ##SWP equation 5 - event version##
>
> swp5.event <- lm(log(swp.cpue + 1) ~ log(fmwt) + ndoi, data = event.swp)
>
> summary(swp5.event)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + ndoi, data = event.swp)

Residuals:
     Min       1Q   Median       3Q      Max
-0.86053 -0.43121 -0.06633  0.33696  1.38569
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.08356    0.92881  -1.167   0.2605
log(fmwt)    0.29712    0.10991   2.703   0.0157 *
ndoi         0.08673    0.17245   0.503   0.6219
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6255 on 16 degrees of freedom
Multiple R-squared:  0.3136,    Adjusted R-squared:  0.2278
F-statistic: 3.654 on 2 and 16 DF,  p-value: 0.04929

> AIC(swp5.event)
[1] 40.82695
> correct301 <- (AIC(swp5.event) + (24/15))
> correct301
[1] 42.42695
>
>
> ##SWP equation 6 - event version##
>
>
> swp6.event <- lm(log(swp.cpue + 1) ~ log(fmwt) + swp.omr, data = event.swp)
>
> summary(swp6.event)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + swp.omr, data = event.swp)

Residuals:
     Min       1Q   Median       3Q      Max
-0.88979 -0.17155 -0.05509  0.31601  1.20503

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.046e+00  5.154e-01  -2.030   0.0593 .
log(fmwt)    2.617e-01  9.493e-02   2.757   0.0140 *
swp.omr     -7.164e-05  3.080e-05  -2.326   0.0335 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.545 on 16 degrees of freedom
Multiple R-squared:  0.4789,    Adjusted R-squared:  0.4138
F-statistic: 7.352 on 2 and 16 DF,  p-value: 0.005438

> AIC(swp6.event)
[1] 35.59153
> correct31 <- (AIC(swp6.event) + (24/15))
> correct31
[1] 37.19153
>
> ##SWP equation 7 - event version##
>
> swp7.event <- lm(log(swp.cpue + 1) ~ log(fmwt) + swp.ntu, data = event.swp)
>
> summary(swp7.event)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + swp.ntu, data = event.swp)

Residuals:
    Min      1Q  Median      3Q     Max
-0.9176 -0.4425  0.0069  0.3655  1.4230

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.03405    0.67133  -1.540   0.1430
log(fmwt)    0.30018    0.10762   2.789   0.0131 *
swp.ntu      0.00865    0.01001   0.864   0.4004
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6162 on 16 degrees of freedom
Multiple R-squared:  0.3338,    Adjusted R-squared:  0.2505
F-statistic: 4.008 on 2 and 16 DF,  p-value: 0.0388

> AIC(swp7.event)
[1] 40.25859
> correct32 <- (AIC(swp7.event) + (24/15))
> correct32
[1] 41.85859
>
>
> ##SWP equation 8 - event version##
>
> swp8.event <- lm(log(swp.cpue + 1) ~ log(fmwt) + swp.omr_ntu, data = event.swp)
>
> summary(swp8.event)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + swp.omr_ntu, data = event.swp)

Residuals:
     Min       1Q   Median       3Q      Max
-0.80828 -0.30064  0.08029  0.25024  1.04113

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.206586   0.469987  -2.567  0.02067 *
log(fmwt)    0.279514   0.084721   3.299  0.00453 **
swp.omr_ntu -0.003473   0.001070  -3.246  0.00506 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4895 on 16 degrees of freedom
Multiple R-squared:  0.5796,    Adjusted R-squared:  0.527
F-statistic: 11.03 on 2 and 16 DF,  p-value: 0.0009758

> AIC(swp8.event)
[1] 31.51148
> correct33 <- (AIC(swp8.event) + (24/15))
> correct33
[1] 33.11148
>
>
> ##SWP equation 9 - event version##
>
> swp9.event <- lm(log(swp.cpue + 1) ~ log(fmwt) + swp.omr + swp.ntu, data = event.swp)
>
> summary(swp9.event)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + swp.omr + swp.ntu,
    data = event.swp)

Residuals:
     Min       1Q   Median       3Q      Max
-0.79677 -0.39631  0.07757  0.29768  1.16898

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.562e+00  6.064e-01  -2.575  0.02111 *
log(fmwt)    2.778e-01  9.219e-02   3.013  0.00874 **
swp.omr     -7.992e-05  3.023e-05  -2.644  0.01841 *
swp.ntu      1.289e-02  8.689e-03   1.484  0.15862
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5257 on 15 degrees of freedom
```

```
Multiple R-squared:  0.5456,    Adjusted R-squared:  0.4547
F-statistic: 6.003 on 3 and 15 DF,  p-value: 0.006763

> AIC(swp9.event)
[1] 34.99005
> correct34 <- (AIC(swp9.event) + (40/14))
> correct34
[1] 37.84719
>
> ##SWP equation 10 - event version##
>
> swp10.event <- lm(log(swp.cpue + 1) ~ log(fmwt) + ndoi + swp.omr + swp.ntu, data = event.swp)
>
> summary(swp10.event)

Call:
lm(formula = log(swp.cpue + 1) ~ log(fmwt) + ndoi + swp.omr +
    swp.ntu, data = event.swp)

Residuals:
     Min       1Q   Median       3Q      Max
-0.74114 -0.31460 -0.00461  0.25055  0.94527

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.033e+00  9.055e-01  -3.350  0.00477 **
log(fmwt)    3.068e-01  8.491e-02   3.614  0.00282 **
ndoi         2.930e-01  1.431e-01   2.047  0.05989 .
swp.omr     -1.030e-04  2.967e-05  -3.471  0.00375 **
swp.ntu      1.604e-02  8.039e-03   1.995  0.06583 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4773 on 14 degrees of freedom
Multiple R-squared:  0.6503,    Adjusted R-squared:  0.5503
F-statistic: 6.508 on 4 and 14 DF,  p-value: 0.003553

> AIC(swp10.event)
[1] 32.01452
> correct35 <- (AIC(swp10.event) + (60/13))
> correct35
[1] 36.6299
>
> ##Raw salvage event base model##
>
> swp.raw.event.base <- lm(log(swp.salv + 1) ~ log(fmwt), data = event.swp)
>
> summary(swp.raw.event.base)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt), data = event.swp)

Residuals:
    Min      1Q  Median      3Q     Max
-2.9893 -1.3359  0.2073  1.3810  3.2247

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.5139     1.6853   0.305  0.76412
log(fmwt)     1.1166     0.3208   3.480  0.00286 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.855 on 17 degrees of freedom
Multiple R-squared:  0.416,     Adjusted R-squared:  0.3817
F-statistic: 12.11 on 1 and 17 DF,  p-value: 0.002865

>
> AIC(swp.raw.event.base)
[1] 81.28008
```

```
> correct77 <- (AIC(swp.raw.event.base) + (12/16))
> correct77
[1] 82.03008
>
> ##SWP equation 11 - event version##
>
> swp11.event <- lm(log(swp.salv + 1) ~ log(fmwt) + ndoi, data = event.swp)
>
> summary(swp11.event)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + ndoi, data = event.swp)

Residuals:
    Min      1Q  Median      3Q     Max
-3.2523 -1.2851  0.3293  1.2362  3.3179

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.2956     2.8279   0.458  0.65300
log(fmwt)     1.0961     0.3346   3.276  0.00476 **
ndoi         -0.1835     0.5251  -0.350  0.73125
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.905 on 16 degrees of freedom
Multiple R-squared:  0.4205,    Adjusted R-squared:  0.348
F-statistic: 5.804 on 2 and 16 DF,  p-value: 0.01272

> AIC(swp11.event)
[1] 83.13556
> correct80 <- (AIC(swp11.event) + (24/15))
> correct80
[1] 84.73556
>
>
> ##SWP equation 12 - event version##
>
> swp12.event <- lm(log(swp.salv + 1) ~ log(fmwt) + swp.exp, data = event.swp)
>
> summary(swp12.event)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + swp.exp, data = event.swp)

Residuals:
     Min       1Q   Median       3Q      Max
-2.39939 -0.61349 -0.04827  0.93844  1.78646

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.104e+00  1.411e+00  -1.490  0.15557
log(fmwt)    9.038e-01  2.427e-01   3.723  0.00185 **
swp.exp      1.070e-10  2.737e-11   3.909  0.00125 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.367 on 16 degrees of freedom
Multiple R-squared:  0.7013,    Adjusted R-squared:  0.6639
F-statistic: 18.78 on 2 and 16 DF,  p-value: 6.341e-05

> AIC(swp12.event)
[1] 70.54432
> correct8 <- (AIC(swp12.event) + (24/15))
> correct8
[1] 72.14432
>
> plot(swp12.event)
>
```

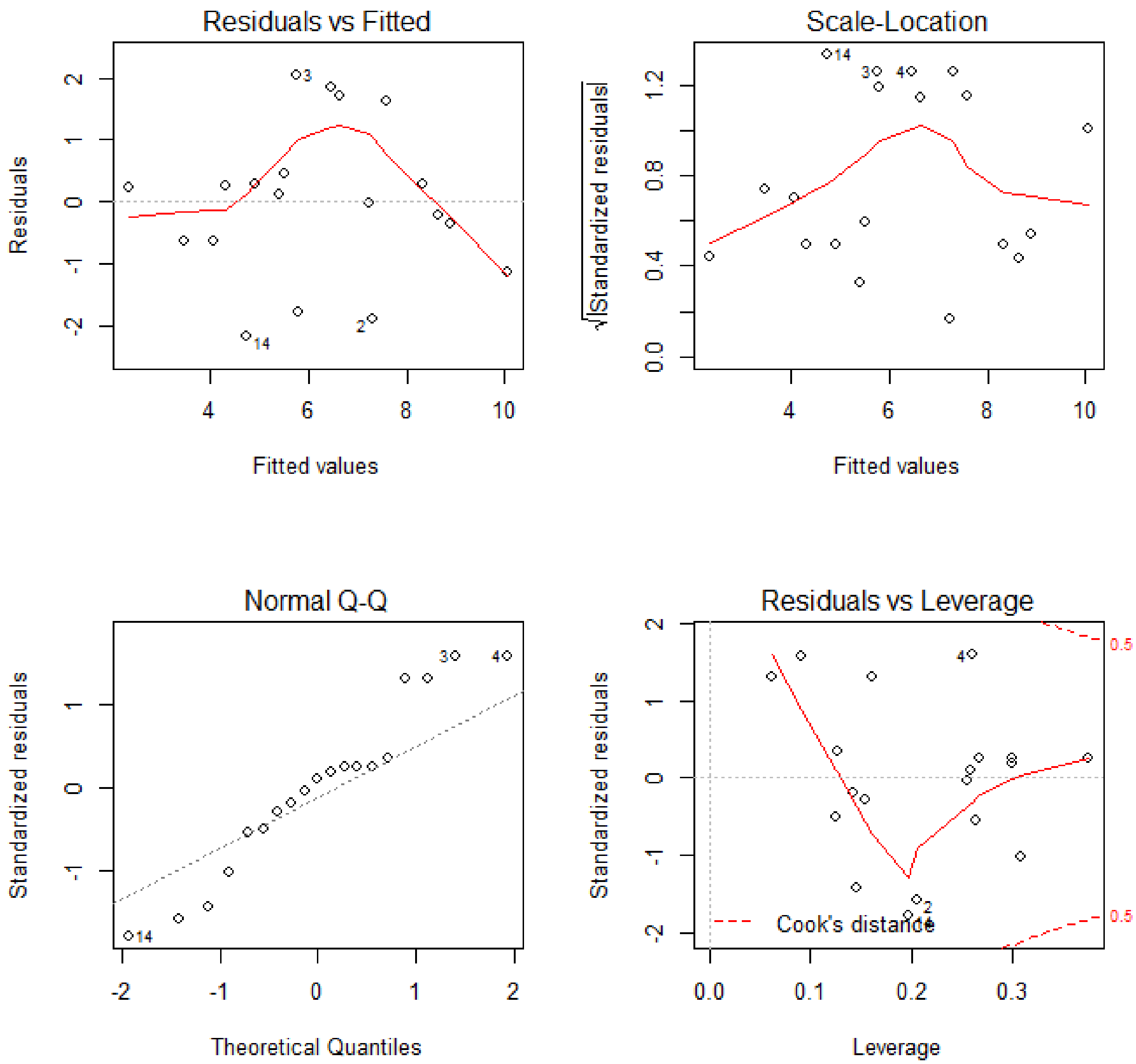



```
##SWP equation 13 - event version##
>
> swp13.event <- lm(log(swp.salv + 1) ~ log(fmwt) + swp.omr, data = event.swp)
>
> summary(swp13.event)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + swp.omr, data = event.swp)

Residuals:
    Min      1Q  Median      3Q     Max
-2.6447 -1.0896  0.1504  1.3097  2.5764

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.4446908  1.5879464  -0.280  0.78303
log(fmwt)    1.0424395  0.2924513   3.564  0.00259 **
swp.omr     -0.0002067  0.0000949  -2.178  0.04473 *
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.679 on 16 degrees of freedom
Multiple R-squared:  0.5496,    Adjusted R-squared:  0.4933
F-statistic:  9.76 on 2 and 16 DF,  p-value: 0.001695

> AIC(swp13.event)
[1] 78.3476
> correct9 <- (AIC(swp13.event) + (24/15))
> correct9
[1] 79.9476
>
>
> ##SWP equation 14 - event version##
>
> swp14.event <- lm(log(swp.salv + 1) ~ log(fmwt) + swp.ntu, data = event.swp)
>
> summary(swp14.event)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + swp.ntu, data = event.swp)

Residuals:
    Min      1Q  Median      3Q     Max
-2.3644 -1.2774 -0.2005  0.9211  3.1877

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.23418    1.92606  -0.641  0.53074
log(fmwt)    1.18622    0.30877   3.842  0.00144 **
swp.ntu      0.04726    0.02872   1.645  0.11938
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.768 on 16 degrees of freedom
Multiple R-squared:  0.5006,    Adjusted R-squared:  0.4381
F-statistic: 8.018 on 2 and 16 DF,  p-value: 0.003872

> AIC(swp14.event)
[1] 80.30972
> correct10 <- (AIC(swp14.event) + (24/15))
> correct10
[1] 81.90972
>
> ##SWP equation 15 - event version##
>
> swp15.event <- lm(log(swp.salv + 1) ~ log(fmwt) + swp.omr_ntu, data = event.swp)
>
> summary(swp15.event)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + swp.omr_ntu, data = event.swp)

Residuals:
    Min      1Q  Median      3Q     Max
-1.9243 -0.8172 -0.2095  1.0322  1.9225

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.187828   1.277371  -0.930 0.366241
log(fmwt)    1.089201   0.230261   4.730 0.000226 ***
swp.omr_ntu -0.012000   0.002907  -4.127 0.000790 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.331 on 16 degrees of freedom
Multiple R-squared:  0.7172,    Adjusted R-squared:  0.6818
F-statistic: 20.28 on 2 and 16 DF,  p-value: 4.096e-05

> AIC(swp15.event)
```

```
[1] 69.50593
> correct11 <- (AIC(swp15.event) + (24/15))
> correct11
[1] 71.10593
>
> ##SWP equation 16 - event version##
>
> swp16.event <- lm(log(swp.salv + 1) ~ log(fmwt) + swp.omr + swp.ntu, data = event.swp)
>
> summary(swp16.event)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + swp.omr + swp.ntu,
    data = event.swp)

Residuals:
    Min      1Q  Median      3Q     Max
-2.0593 -0.9630 -0.2803  1.2387  2.4078

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.854e+00  1.680e+00  -1.699 0.109972
log(fmwt)    1.117e+00  2.554e-01   4.375 0.000543 ***
swp.omr     -2.454e-04  8.374e-05  -2.930 0.010339 *
swp.ntu      6.028e-02  2.407e-02   2.504 0.024291 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.456 on 15 degrees of freedom
Multiple R-squared:  0.6824,    Adjusted R-squared:  0.6189
F-statistic: 10.74 on 3 and 15 DF,  p-value: 0.0005054

> AIC(swp16.event)
[1] 73.70979
> correct12 <- (AIC(swp16.event) + (40/14))
> correct12
[1] 76.56693
>
> ##SWP equation 17 - event version##
>
> swp17.event <- lm(log(swp.salv + 1) ~ log(fmwt) + ndoi + swp.omr + swp.ntu, data = event.swp)
>
> summary(swp17.event)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + ndoi + swp.omr +
    swp.ntu, data = event.swp)

Residuals:
     Min       1Q   Median       3Q      Max
-2.38781 -0.90550  0.01102  1.06845  2.11195

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.933e+00  2.773e+00  -1.779 0.096941 .
log(fmwt)    1.158e+00  2.600e-01   4.456 0.000543 ***
ndoi         4.139e-01  4.383e-01   0.944 0.361002
swp.omr     -2.780e-04  9.085e-05  -3.060 0.008486 **
swp.ntu      6.473e-02  2.461e-02   2.630 0.019785 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.461 on 14 degrees of freedom
Multiple R-squared:  0.7014,    Adjusted R-squared:  0.6161
F-statistic: 8.221 on 4 and 14 DF,  p-value: 0.001251

> AIC(swp17.event)
[1] 74.53647
> correct13 <- (AIC(swp17.event) + (60/13))
> correct13
```

```
[1] 79.15185
>
>
> ##SWP equation 18 - event version##
>
> swp18.event <- lm(log(swp.salv + 1) ~ log(fmwt) + swp.exp + swp.ntu, data = event.swp)
>
> summary(swp18.event)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + swp.exp + swp.ntu,
    data = event.swp)

Residuals:
    Min      1Q  Median      3Q     Max
-2.1681 -0.6291  0.1225  0.3663  2.0472

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.860e+00  1.547e+00  -1.849  0.08428 .
log(fmwt)    9.591e-01  2.453e-01   3.911  0.00139 **
swp.exp      9.846e-11  2.812e-11   3.502  0.00321 **
swp.ntu      2.608e-02  2.282e-02   1.143  0.27097
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.354 on 15 degrees of freedom
Multiple R-squared:  0.7252,    Adjusted R-squared:  0.6702
F-statistic:  13.2 on 3 and 15 DF,  p-value: 0.000175

> AIC(swp18.event)
[1] 70.95775
> correct14 <- (AIC(swp18.event) + (60/13))
> correct14
[1] 75.57314
>
> plot(swp18.event)
```




```
>
> ##SWP equation 19 - event version##
>
> swp19.event <- lm(log(swp.salv + 1) ~ log(fmwt) + ndoi + swp.exp + swp.ntu, data = event.swp)
>
> summary(swp19.event)

Call:
lm(formula = log(swp.salv + 1) ~ log(fmwt) + ndoi + swp.exp +
    swp.ntu, data = event.swp)

Residuals:
    Min      1Q  Median      3Q     Max
-2.2731 -0.6632  0.1240  0.4052  2.0922

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.601e+00  2.451e+00  -1.469  0.16397
log(fmwt)    9.731e-01  2.549e-01   3.818  0.00188 **
```

```
ndoi         1.565e-01  3.937e-01   0.397  0.69703
swp.exp      1.006e-10  2.946e-11   3.416  0.00417 **
swp.ntu      2.664e-02  2.353e-02   1.132  0.27661
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.394 on 14 degrees of freedom
Multiple R-squared:  0.7283,    Adjusted R-squared:  0.6506
F-statistic:  9.38 on 4 and 14 DF,  p-value: 0.000667

> AIC(swp19.event)
[1] 72.74458
> correct15 <- (AIC(swp19.event) + (60/13))
> correct15
[1] 77.35996
>
> ##Now the CVP event models##
>
> ##Next, I'm opening a new file for CVP event data comparisons.  This file excluded years of 0 CVP salvage == 2014##
>
> event.cvp <- read.csv(file.choose("AdultSalvageR_March2015_CVPEvent.csv"),header=TRUE)
>
> ##CVP CPUE event base model##
>
> cvp30 <- lm(log(cvp.cpue + 1) ~ log(fmwt), data = event.cvp)
>
> summary(cvp30)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt), data = event.cvp)

Residuals:
     Min       1Q   Median       3Q      Max
-0.92751 -0.22699  0.02687  0.13661  1.01992

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.74223    0.39152  -1.896  0.07331 .
log(fmwt)    0.27661    0.07655   3.614  0.00185 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4705 on 19 degrees of freedom
Multiple R-squared:  0.4073,    Adjusted R-squared:  0.3761
F-statistic: 13.06 on 1 and 19 DF,  p-value: 0.00185

>
> AIC(cvp30)
[1] 31.82766
> correct30.1 <- (AIC(cvp30) + (12/18))
> correct30.1
[1] 32.49432
>
> ##CVP equation 5 - event version##
>
> cvp5.event <- lm(log(cvp.cpue + 1) ~ log(fmwt) + ndoi, data = event.cvp)
>
> summary(cvp5.event)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + ndoi, data = event.cvp)

Residuals:
    Min      1Q  Median      3Q     Max
-0.7537 -0.3099 -0.0512  0.1840  0.9116

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.7041     0.6402  -2.662 0.015884 *
log(fmwt)     0.3051     0.0738   4.134 0.000623 ***
```

```
ndoi         0.2205     0.1199   1.839 0.082495 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4435 on 18 degrees of freedom
Multiple R-squared:  0.5011,    Adjusted R-squared:  0.4456
F-statistic: 9.038 on 2 and 18 DF,  p-value: 0.001916

> AIC(cvp5.event)
[1] 30.21255
> correct34.1 <- (AIC(cvp5.event) + (24/17))
> correct34.1
[1] 31.62431
>
> ##CVP equation 6 - event version##
>
> cvp6.event <- lm(log(cvp.cpue + 1) ~ log(fmwt) + cvp.omr, data = event.cvp)
>
> summary(cvp6.event)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + cvp.omr, data = event.cvp)

Residuals:
    Min       1Q   Median       3Q      Max
-0.91270 -0.23571  0.01808  0.13978  0.98030

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -7.916e-01  4.139e-01  -1.913  0.07183 .
log(fmwt)    2.725e-01  7.868e-02   3.463  0.00277 **
cvp.omr     -1.182e-05  2.555e-05  -0.463  0.64910
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4805 on 18 degrees of freedom
Multiple R-squared:  0.4143,    Adjusted R-squared:  0.3492
F-statistic: 6.366 on 2 and 18 DF,  p-value: 0.008112

> AIC(cvp6.event)
[1] 33.57931
> correct31.1 <- (AIC(cvp6.event) + (24/17))
> correct31.1
[1] 34.99108
>
> ##CVP equation 7 - event version##
>
> cvp7.event <- lm(log(cvp.cpue + 1) ~ log(fmwt) + cvp.ntu, data = event.cvp)
>
> summary(cvp7.event)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + cvp.ntu, data = event.cvp)

Residuals:
    Min       1Q   Median       3Q      Max
-0.73741 -0.27014  0.00848  0.16740  1.00133

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.157146   0.405594  -2.853 0.010564 *
log(fmwt)    0.279161   0.069993   3.988 0.000862 ***
cvp.ntu      0.013801   0.006345   2.175 0.043181 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4302 on 18 degrees of freedom
Multiple R-squared:  0.5307,    Adjusted R-squared:  0.4785
F-statistic: 10.18 on 2 and 18 DF,  p-value: 0.001104
```

```
> AIC(cvp7.event)
[1] 28.92643
> correct32.1 <- (AIC(cvp7.event) + (24/17))
> correct32.1
[1] 30.3382
>
> ##CVP equation 8 - event version##
>
> cvp8.event <- lm(log(cvp.cpue + 1) ~ log(fmwt) + cvp.omr_ntu, data = event.cvp)
>
> summary(cvp8.event)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + cvp.omr_ntu, data = event.cvp)

Residuals:
     Min       1Q   Median       3Q      Max
-0.81754 -0.19694  0.00452  0.26853  0.80832

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.8901813  0.3818831  -2.331  0.03158 *
log(fmwt)    0.2663033  0.0730243   3.647  0.00184 **
cvp.omr_ntu -0.0015488  0.0008917  -1.737  0.09949 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4474 on 18 degrees of freedom
Multiple R-squared:  0.4924,    Adjusted R-squared:  0.436
F-statistic:  8.73 on 2 and 18 DF,  p-value: 0.002237

> AIC(cvp8.event)
[1] 30.57378
> correct33.1 <- (AIC(cvp8.event) + (24/17))
> correct33.1
[1] 31.98554
>
>
> ##CVP equation 9 - event version##
>
> cvp9.event <- lm(log(cvp.cpue + 1) ~ log(fmwt) + cvp.omr + cvp.ntu, data = event.cvp)
>
> summary(cvp9.event)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + cvp.omr + cvp.ntu,
    data = event.cvp)

Residuals:
     Min       1Q   Median       3Q      Max
-0.69081 -0.29111  0.04633  0.22787  0.92272

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.292e+00  4.287e-01  -3.014  0.00782 **
log(fmwt)    2.715e-01  7.051e-02   3.850  0.00128 **
cvp.omr     -2.294e-05  2.339e-05  -0.981  0.34057
cvp.ntu      1.510e-02  6.488e-03   2.327  0.03256 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4306 on 17 degrees of freedom
Multiple R-squared:  0.5558,    Adjusted R-squared:  0.4774
F-statistic: 7.091 on 3 and 17 DF,  p-value: 0.002689

> AIC(cvp9.event)
[1] 29.77114
> correct303 <- (AIC(cvp9.event) + (5/2))
> correct303
[1] 32.27114
```

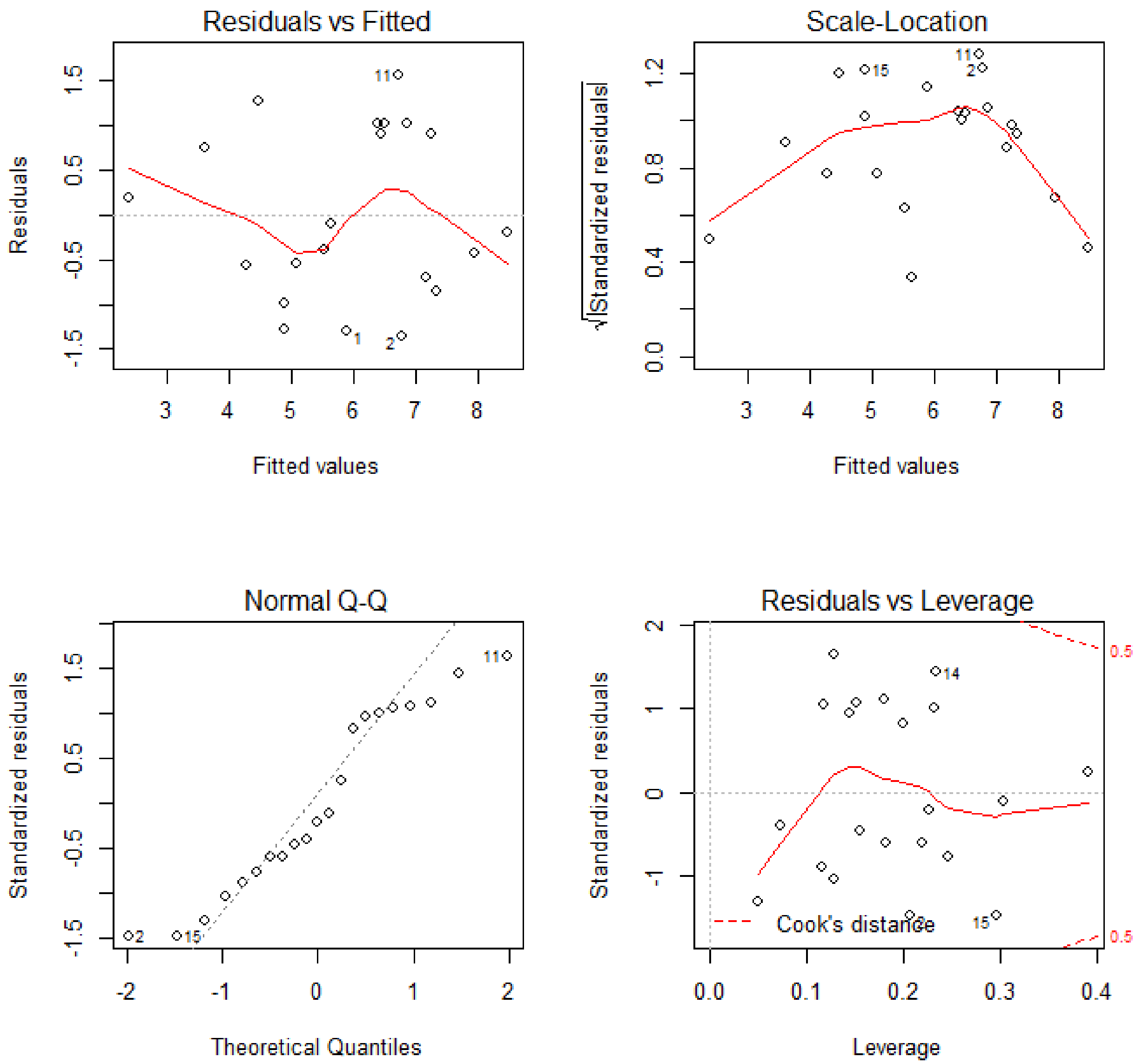
```
>
>
> ##CVP equation 10 - event version##
>
> cvp10.event <- lm(log(cvp.cpue + 1) ~ log(fmwt) + ndoi + cvp.omr + cvp.ntu, data = event.cvp)
>
> summary(cvp10.event)

Call:
lm(formula = log(cvp.cpue + 1) ~ log(fmwt) + ndoi + cvp.omr +
    cvp.ntu, data = event.cvp)

Residuals:
     Min       1Q   Median       3Q      Max
-0.49745 -0.28385  0.03476  0.18797  0.74372

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.645e+00  5.999e-01  -4.409 0.000439 ***
log(fmwt)    3.048e-01  6.054e-02   5.034 0.000122 ***
ndoi         2.837e-01  1.005e-01   2.823 0.012234 *
cvp.omr     -3.383e-05  2.007e-05  -1.685 0.111296
cvp.ntu      1.741e-02  5.525e-03   3.152 0.006174 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3626 on 16 degrees of freedom
Multiple R-squared:  0.7035,    Adjusted R-squared:  0.6294
F-statistic: 9.492 on 4 and 16 DF,  p-value: 0.0003956

> AIC(cvp10.event)
[1] 23.28092
> correct39 <- (AIC(cvp10.event) + (60/15))
> correct39
[1] 27.28092
>
> ##CVP raw salvage event base model##
>
> cvp.raw.event.base <- lm(log(cvp.salv + 1) ~ log(fmwt), data = event.cvp)
>
> summary(cvp.raw.event.base)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt), data = event.cvp)

Residuals:
    Min      1Q  Median      3Q     Max
-2.2482 -1.1839  0.2224  0.9838  2.3538

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.6904     1.1298   1.496 0.151017
log(fmwt)     0.8580     0.2209   3.884 0.000998 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.358 on 19 degrees of freedom
Multiple R-squared:  0.4426,    Adjusted R-squared:  0.4133
F-statistic: 15.09 on 1 and 19 DF,  p-value: 0.0009977

>
> AIC(cvp.raw.event.base)
[1] 76.33722
> correct7.1 <- (AIC(cvp.raw.event.base) + (12/18))
> correct7.1
[1] 77.00389
>
> ##CVP equation 11 - event version##
>
> cvp11.event <- lm(log(cvp.salv + 1) ~ log(fmwt) + ndoi, data = event.cvp)
```

```
>
> summary(cvp11.event)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + ndoi, data = event.cvp)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.27606 -1.04217  0.05901  0.98738  2.17752 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  -0.5103     1.9107  -0.267 0.792437    
log(fmwt)     0.9232     0.2203   4.191 0.000549 ***
ndoi          0.5044     0.3578   1.410 0.175690    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.324 on 18 degrees of freedom
Multiple R-squared:  0.498,	Adjusted R-squared:  0.4423 
F-statistic:  8.93 on 2 and 18 DF,  p-value: 0.002023

> AIC(cvp11.event)
[1] 76.13821
> correct98 <- (AIC(cvp11.event) + (24/17))
> correct98
[1] 77.54998
>
> ##CVP equation 12 - event version##
>
> cvp12.event <- lm(log(cvp.salv + 1) ~ log(fmwt) + cvp.exp, data = event.cvp)
>
> summary(cvp12.event)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + cvp.exp, data = event.cvp)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.18858 -0.78212 -0.09724  0.81038  1.94965 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1.229e+00  1.788e+00  -0.688 0.500474    
log(fmwt)    8.248e-01  2.056e-01   4.011 0.000819 ***
cvp.exp      1.050e-10  5.206e-11   2.016 0.058943 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.26 on 18 degrees of freedom
Multiple R-squared:  0.5453,	Adjusted R-squared:  0.4948 
F-statistic: 10.79 on 2 and 18 DF,  p-value: 0.0008305

> AIC(cvp12.event)
[1] 74.06078
> correct8.1 <- (AIC(cvp12.event) + (24/17))
> correct8.1
[1] 75.47255
>
>
> ##CVP equation 13 - event version##
>
> cvp13.event <- lm(log(cvp.salv + 1) ~ log(fmwt) + cvp.omr, data = event.cvp)
>
> summary(cvp13.event)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + cvp.omr, data = event.cvp)

Residuals:
```

```
   Min      1Q  Median      3Q     Max 
-2.2119 -1.2053  0.2237  0.9818  2.2565 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)   
(Intercept)  1.569e+00  1.196e+00   1.312  0.20608   
log(fmwt)    8.480e-01  2.274e-01   3.729  0.00154 **
cvp.omr     -2.904e-05  7.386e-05  -0.393  0.69881   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.389 on 18 degrees of freedom
Multiple R-squared:  0.4474,    Adjusted R-squared:  0.386 
F-statistic: 7.286 on 2 and 18 DF,  p-value: 0.004807

> AIC(cvp13.event)
[1] 78.15764
> correct9.1 <- (AIC(cvp13.event) + (24/17))
> correct9.1
[1] 79.56941
> 
> ##CVP equation 14 - event version##
> 
> cvp14.event <- lm(log(cvp.salv + 1) ~ log(fmwt) + cvp.ntu, data = event.cvp)
> 
> summary(cvp14.event)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + cvp.ntu, data = event.cvp)

Residuals:
   Min      1Q  Median      3Q     Max 
-1.5787 -0.8638 -0.1636  0.5745  2.2883 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.22905    1.09246   0.210 0.836286    
log(fmwt)    0.86701    0.18853   4.599 0.000223 ***
cvp.ntu      0.04861    0.01709   2.844 0.010759 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.159 on 18 degrees of freedom
Multiple R-squared:  0.6155,    Adjusted R-squared:  0.5727 
F-statistic: 14.41 on 2 and 18 DF,  p-value: 0.0001838

> AIC(cvp14.event)
[1] 70.5416
> correct10.1 <- (AIC(cvp14.event) + (24/17))
> correct10.1
[1] 71.95336
> 
> ##CVP equation 15 - event version##
> 
> cvp15.event <- lm(log(cvp.salv + 1) ~ log(fmwt) + cvp.omr_ntu, data = event.cvp)
> 
> summary(cvp15.event)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + cvp.omr_ntu, data = event.cvp)

Residuals:
   Min      1Q  Median      3Q     Max 
-1.9296 -0.9327  0.1101  0.9107  2.3114 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.261814   1.101250   1.146 0.266883    
log(fmwt)    0.828168   0.210583   3.933 0.000976 ***
cvp.omr_ntu -0.004487   0.002571  -1.745 0.098051 .  
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.29 on 18 degrees of freedom
Multiple R-squared:  0.5233,	Adjusted R-squared:  0.4703
F-statistic: 9.879 on 2 and 18 DF,  p-value: 0.001272

> AIC(cvp15.event)
[1] 75.05543
> correct11.1 <- (AIC(cvp15.event) + (24/17))
> correct11.1
[1] 76.4672
>
> ##CVP equation 16 - event version##
>
> cvp16.event <- lm(log(cvp.salv + 1) ~ log(fmwt) + cvp.omr + cvp.ntu, data = event.cvp)
>
> summary(cvp16.event)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + cvp.omr + cvp.ntu,
    data = event.cvp)

Residuals:
    Min      1Q  Median      3Q     Max
-1.4970 -0.6370 -0.2267  0.6739  2.0566

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.684e-01  1.148e+00  -0.147 0.885122
log(fmwt)    8.443e-01  1.888e-01   4.471 0.000336 ***
cvp.omr     -6.763e-05  6.265e-05  -1.079 0.295472
cvp.ntu      5.244e-02  1.738e-02   3.018 0.007757 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.153 on 17 degrees of freedom
Multiple R-squared:  0.6401,	Adjusted R-squared:  0.5766
F-statistic: 10.08 on 3 and 17 DF,  p-value: 0.0004767

> AIC(cvp16.event)
[1] 71.14944
> correct50 <- (AIC(cvp16.event) + (36/16))
> correct50
[1] 73.39944
>
> ##CVP equation 17 - event version##
>
> cvp17.event <- lm(log(cvp.salv + 1) ~ log(fmwt) + ndoi + cvp.omr + cvp.ntu, data = event.cvp)
>
> summary(cvp17.event)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + ndoi + cvp.omr +
    cvp.ntu, data = event.cvp)

Residuals:
     Min       1Q   Median       3Q      Max
-1.90695 -0.48876  0.05371  0.39582  1.61477

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.507e+00  1.666e+00  -2.105  0.05144 .
log(fmwt)    9.265e-01  1.681e-01   5.511 4.74e-05 ***
ndoi         7.002e-01  2.791e-01   2.509  0.02325 *
cvp.omr     -9.452e-05  5.575e-05  -1.695  0.10935
cvp.ntu      5.814e-02  1.534e-02   3.790  0.00161 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 1.007 on 16 degrees of freedom
Multiple R-squared:  0.7417,    Adjusted R-squared:  0.6772
F-statistic: 11.49 on 4 and 16 DF,  p-value: 0.0001372

> AIC(cvp17.event)
[1] 66.18202
> correct51 <- (AIC(cvp17.event) + (36/16))
> correct51
[1] 68.43202
>
##CVP equation 18 - event version##
>
> cvp18.event <- lm(log(cvp.salv + 1) ~ log(fmwt) + cvp.exp + cvp.ntu, data = event.cvp)
>
> summary(cvp18.event)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + cvp.exp + cvp.ntu,
    data = event.cvp)

Residuals:
    Min      1Q  Median      3Q     Max
-1.3496 -0.6902 -0.1895  0.9020  1.5659

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.686e+00  1.518e+00  -1.769 0.094757 .
log(fmwt)    8.338e-01  1.667e-01   5.002 0.000109 ***
cvp.exp      1.048e-10  4.219e-11   2.484 0.023698 *
cvp.ntu      4.857e-02  1.506e-02   3.225 0.004975 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.021 on 17 degrees of freedom
Multiple R-squared:  0.7179,    Adjusted R-squared:  0.6681
F-statistic: 14.42 on 3 and 17 DF,  p-value: 6.323e-05

> AIC(cvp18.event)
[1] 66.03758
> correct12.1 <- (AIC(cvp18.event) + (5/2))
> correct12.1
[1] 68.53758
>
> plot(cvp18.event)
```




```
>
> ##CVP equation 19 - event version##
>
> cvp19.event <- lm(log(cvp.salv + 1) ~ log(fmwt) + ndoi + cvp.exp + cvp.ntu, data = event.cvp)
>
> summary(cvp19.event)

Call:
lm(formula = log(cvp.salv + 1) ~ log(fmwt) + ndoi + cvp.exp +
    cvp.ntu, data = event.cvp)

Residuals:
     Min       1Q   Median       3Q      Max
-1.44428 -0.72364 -0.03602  0.62326  1.15539

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -6.068e+00  1.703e+00  -3.563 0.002594 **
log(fmwt)    9.196e-01  1.413e-01   6.508 7.22e-06 ***
```

```
ndoi        6.828e-01  2.315e-01   2.950 0.009414 **
cvp.exp      1.149e-10  3.517e-11   3.267 0.004841 **
cvp.ntu      5.265e-02  1.257e-02   4.188 0.000696 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8471 on 16 degrees of freedom
Multiple R-squared:  0.8173,    Adjusted R-squared:  0.7716
F-statistic: 17.89 on 4 and 16 DF,  p-value: 9.371e-06

> AIC(cvp19.event)
[1] 58.91782
> correct120 <- (AIC(cvp19.event) + (60/15))
> correct120
[1] 62.91782
```

```
GAM code
R version 3.1.0 (2014-04-10) -- "Spring Dance"
Copyright (C) 2014 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)

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'help.start()' for an HTML browser interface to help.
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> ##Here is GAM code that I tried on May 19, 2015 applied to the SWP event data file - to check for thresholds per Scott's email to Lenny##
>
> ##Not gonna lie - this is an example that was refined based on initial tooling around##
>
> ##I'm re-opening the file for SWP event data comparisons.  This file excluded years of 0 SWP salvage == 2007, 2011, 2014##
>
> ##I chose this to explore the exports vs OMR issue and the "why" the SWP models didn't explain as much variance as the CVP models##
>
> event.swp <- read.csv(file.choose("AdultSalvageR_March2015_SWPEvent.csv"),header=TRUE)
> library(mgcv)
Loading required package: nlme
This is mgcv 1.7-29. For overview type 'help("mgcv-package")'.
>
> ##mgcv does GAM##
>
>
> gam1 <- gam(formula = log(swp.salv) ~ log(fmwt) + s(omr, bs = "cr"), data = event.swp)
>
> summary(gam1)

Family: gaussian
Link function: identity

Formula:
log(swp.salv) ~ log(fmwt) + s(omr, bs = "cr")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.1814     1.7273   1.263   0.2310
log(fmwt)     0.7854     0.3334   2.356   0.0367 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Approximate significance of smooth terms:
        edf Ref.df     F p-value
s(omr) 5.21      6 2.261   0.109

R-sq.(adj) =  0.624   Deviance explained = 75.4%
GCV score = 3.4315  Scale est. = 2.1293    n = 19
>
> AIC(gam1)
[1] 75.63319
>
> plot(gam1, pages = 1, residuals = T, pch = 19, cex = 0.25, scheme = 1, color = "black", shade = T, shade.color = gray)
There were 18 warnings (use warnings() to see them)
>
> p1 <- predict(gam1)
>
> gam2 <- gam(formula = log(swp.salv) ~ log(fmwt) + s(swp.exp, bs = "cr"), data = event.swp)
>
> summary(gam2)

Family: gaussian
Link function: identity

Formula:
log(swp.salv) ~ log(fmwt) + s(swp.exp, bs = "cr")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.5113     1.2865   1.175  0.25727
log(fmwt)     0.9173     0.2453   3.739  0.00179 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
              edf Ref.df     F p-value
s(swp.exp) 0.9999      1 15.05 0.00122 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.663   Deviance explained = 70.1%
GCV score = 2.2677  Scale est. = 1.9096    n = 19
>
> AIC(gam2)
[1] 70.94578
>
> plot(gam2, pages = 1, residuals = T, pch = 19, cex = 0.25, scheme = 1, color = "black", shade = T, shade.color = gray)
There were 18 warnings (use warnings() to see them)
>
> p2 <- predict(gam2)
> plot(p1, p2, xlab = "GAM prediction of FMWT + OMR (Dec 1 - Mar 31)", ylab = "GAM prediction of FMWT + Exports (Dec 1 - Mar 31)")
> gam3 <- gam(formula = log(swp.salv) ~ log(fmwt) + s(swp.omr, bs = "cr"), data = event.swp)
>
> summary(gam3)

Family: gaussian
Link function: identity

Formula:
log(swp.salv) ~ log(fmwt) + s(swp.omr, bs = "cr")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.2345     1.3249   0.932  0.36619
log(fmwt)     0.9717     0.2525   3.848  0.00158 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
             edf Ref.df     F p-value
s(swp.omr) 1.979  2.341 5.229  0.0155 *
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.637   Deviance explained = 69.7%
GCV score = 2.6003  Scale est. = 2.0557    n = 19
>
> AIC(gam3)
[1] 73.10472
>
> plot(gam3, pages = 1, residuals = T, pch = 19, cex = 0.25, scheme = 1, color = "black", shade = T, shade.color = gray)
There were 18 warnings (use warnings() to see them)
>
> p3 <- predict(gam3)
> plot(p1, p3, xlab = "GAM prediction of FMWT + OMR (Dec 1 - Mar 31)", ylab = "GAM prediction of FMWT + SWP event OMR")
> gam4 <- gam(formula = log(swp.salv) ~ log(fmwt) + s(swp.ntu, bs = "cr"), data = event.swp)
>
> summary(gam4)

Family: gaussian
Link function: identity

Formula:
log(swp.salv) ~ log(fmwt) + s(swp.ntu, bs = "cr")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.0667     1.6296   0.041  0.96786
log(fmwt)     1.2015     0.3104   3.871  0.00136 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
           edf Ref.df     F p-value
s(swp.ntu)   1      1 2.767   0.115

R-sq.(adj) =  0.443   Deviance explained = 50.4%
GCV score = 3.7519  Scale est. = 3.1595    n = 19
>
> AIC(gam4)
[1] 80.5123
>
> plot(gam4, pages = 1, residuals = T, pch = 19, cex = 0.25, scheme = 1, color = "black", shade = T, shade.color = gray)
There were 18 warnings (use warnings() to see them)
>
> p4 <- predict(gam4)
> plot(p1, p4, xlab = "GAM prediction of FMWT + OMR (Dec 1 - Mar 31)", ylab = "GAM prediction of FMWT + SWP event turbidity")
> gam5 <- gam(formula = log(swp.salv) ~ log(fmwt) + s(swp.omr_ntu, bs = "cr"), data = event.swp)
>
> summary(gam5)

Family: gaussian
Link function: identity

Formula:
log(swp.salv) ~ log(fmwt) + s(swp.omr_ntu, bs = "cr")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.5661     1.2198   0.464 0.648819
log(fmwt)     1.1032     0.2322   4.751 0.000217 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                  edf Ref.df    F  p-value
s(swp.omr_ntu) 0.9982      1 16.9 0.000726 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.682   Deviance explained = 71.8%
GCV score =  2.138  Scale est. = 1.8006    n = 19
```

```
>
> AIC(gam5)
[1] 69.82761
>
> plot(gam5, pages = 1, residuals = T, pch = 19, cex = 0.25, scheme = 1, color = "black", shade = T, shade.color = gray)
There were 18 warnings (use warnings() to see them)
>
> p5 <- predict(gam5)
> plot(p1, p5, xlab = "GAM prediction of FMWT + OMR (Dec 1 - Mar 31)", ylab = "GAM prediction of FMWT + SWP first flush (event)")
> cor(p1, p2)
[1] 0.9237702
> cor(p1, p3)
[1] 0.8774454
> cor(p1, p4)
[1] 0.7844431
> cor(p1, p5)
[1] 0.8582036
> cor(p2, p3)
[1] 0.9124424
> cor(p2, p4)
[1] 0.7737601
> cor(p2, p5)
[1] 0.9209004
> cor(p3, p4)
[1] 0.7525294
> cor(p3, p5)
[1] 0.9040712
> cor(p4, p5)
[1] 0.8189081
>
```

Re-examining Delta Smelt (*Hypomesus transpacificus*) Entrainment Dynamics at the Hub of California's Water Supply in the Upper San Francisco Estuary

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Keywords San Francisco Estuary, Delta Smelt, entrainment, water diversion, boosted tree regression

Running page head: Delta Smelt salvage dynamics

Abstract

Managing endangered species presents many challenges when it becomes difficult to detect their presence in the wild. In the San Francisco Estuary, Delta Smelt (*Hypomesus transpacificus*) has declined to record low numbers in the long-term monitoring surveys which has elevated concern over their entrainment at the State Water Project (SWP) and Central Valley Project (CVP) water diversions. The objective of this paper was to revisit previous work on factors that affect adult Delta Smelt catches (salvage) at the SWP and CVP fish screens with updated conceptual models and new statistical approaches to determine factors that affect entrainment risk at time scales useful for resource managers. Analyses focused on describing salvage at an annual scale and during the onset of winter storms (first flush) that historically resulted in high salvage of adult Delta Smelt. Boosted Regression Tree (BRT) analysis was used to explore relationships between adult Delta Smelt salvage and a large suite of physical and biological predictor variables. Negative binomial models, Generalized Additive Models (GAM) and General Linear Models (GLMs) were than applied to the salvage data to test how a smaller set of variables identified from the BRT and revised conceptual models affected adult Delta Smelt salvage. Overall, the BRT found that exports, previous sub-adult abundance, and water temperature were important factors that described the onset of adult Delta Smelt salvage. Negative binomial and GAM models provided somewhat consistent results, showing an importance of SWP and CVP exports, previous sub-adult abundance, suspended sediment, and turbidity as important factors that affected Delta Smelt entrainment risk. Annual salvage was best explained by SWP and CVP exports and previous sub-adult abundance. Results from this study improve upon previous analyses of salvage data and provide a framework for understanding factors that best explain entrainment risk conditions during the onset of winter storms when they are most vulnerable to salvage. The results presented in this study can be applied by resource managers to develop strategies for reducing adult Delta Smelt entrainment risk, even when their population is low and it is difficult to detect their presence in the wild.

Introduction

Over the last couple of decades, fisheries management has redirected its focus from individual species to broader ecosystem objectives to address inherent complexities of aquatic environments (Link 2002, Hall and Mainprize 2004, Pikitch et al. 2004). For rare species, management objectives that focus on restoring ecosystem functions is considered desirable because it places an emphasis on the mechanisms that influence their survival and growth rather than on counts of individuals which may be difficult to detect as their population numbers decline. For species listed under the federal Endangered Species Act (ESA), the law does allow for recovery actions to be carried out through robust adaptive management plans that include consideration of habitat quality and quantity, reduced exposure to predators and contaminants, and improved access to rearing habitats but the law also requires that incidental take[1] of endangered species be reasonably minimized or avoided if they are likely to be encountered during an authorized activity or project. Recovery plans that can confidently predict when listed fish species are likely to be taken or impacted ultimately reduces management uncertainty and can help bolster conservation efforts if project activities are effectively timed (Pikitch et al. 2004).

In the upper San Francisco Estuary, (CA), national attention has been drawn to Delta Smelt (*Hypomesus transpacificus*), a small endangered fish whose numbers have declined to record low levels in regional monitoring programs (Sommer et al. 2007). Found nowhere else in the world, Delta Smelt seasonally reside within the hydrodynamic influence of two large water diversions that provide municipal water for over 23 million Californians (State Water Project, SWP) and support a multibillion dollar agricultural industry (Central Valley Project, CVP). When Delta Smelt are located near the SWP and CVP pumps, the United Fish and Wildlife Service (USFWS) imposes water diversion reductions to minimize entrainment losses (USFWS 2008) which can account for significant population losses in some years (Kimmerer 2008, Kimmerer 2011, Miller 2011). Entrainment losses, along with food supply and loss of habitat, have been shown to have adverse effects on Delta Smelt's population growth rate (Mac Nally et al. 2010, Kimmerer 2011, Maunder and Deriso 2011, Rose et al. 2013). An improved understanding of the mechanisms and factors that affect Delta Smelt entrainment is of high importance to managers, scientists and stakeholders charged with protecting the species while at the same time providing a reliable water supply to the people and agricultural communities of California.

Unlike traditional fisheries management where adult harvest can be determined through an estimate of stock size and spawner replacement rates (Deriso 1980), Delta Smelt are an annual species whose adult abundance estimates are measured by monthly trawl surveys during the late winter

[1] Federal ESA incidental take is defined as to harass, harm, pursue, hunt, shoot, wound, kill, trap, capture, or collect any threatened or endangered species (USFWS 1973)

(Interagency Ecological Program 2015) during the same time when they become lost to entrainment (Kimmerer 2008, Grimaldo et al. 2009). Therefore, concurrent assessments of water diversion impacts to the Delta Smelt population are difficult to estimate because their abundance is not confidently estimated until after the bulk of entrainment is likely to have occurred (e.g., see Fig. 11 in Kimmerer 2008). In addition, as the population continues to decline and the environment changes, the ability to detect Delta Smelt in the wild has also decreased over time (Latour 2015). As a result, managers and scientists cannot simply rely on the number of fish observed in surveys near the water diversions or those observed at the fish screen louvers (known as "salvage") in front of the SWP and CVP as the only evidence of entrainment risk. Managers and scientists most also consider conditions that are likely to produce higher entrainment risk based on historical relationships between salvage and physical-biological factors (Brown et al. 2009, Grimaldo et al. 2009).

In this paper, the conceptual model and factors known to affect Delta Smelt salvage at the SWP and CVP (Kimmerer 2008, Grimaldo et al. 2009, Miller 2011, Miller et al. 2012, Interagency Ecological Program 2015) are revisited and reexamined with new information and statistical approaches to produce an updated model of factors and conditions that most influence Delta Smelt entrainment risk. Note, the goal here is not to determine the effects of entrainment losses to the population which has been carried out previously and determined to have modest to substantial adverse effects on the Delta Smelt's population growth rate (Kimmerer 2008, Kimmerer 2011, Maunder and Deriso 2011, Miller 2011, Rose et al. 2013). The goal here is to determine how entrainment risk, calculated through the number fish salvaged, could be reduced in real-time through a more thorough understanding of conditions that produce adult Delta Smelt entrainment risk. Our specific study questions are the following: 1) What factors produce the onset of entrainment risk? and 2) What factors overall best predict entrainment risk conditions? The answers from this study can be used by resource managers to more confidently assign species protection rules while at the same time reduce management uncertainty of SWP and CVP water operations to help increase California's water supply reliability.

Conceptual models revisited

Previous research on adult Delta Smelt salvage dynamics emphasized that entrainment risk was seasonal and influenced by the behavior of fish during the onset of large precipitation events in the winter (Grimaldo et al. 2009, Sommer et al. 2011). Known as the "first flush" period, it is believed that increases in river inflows and turbidity trigger an upstream spawning migration of Delta Smelt from their low salinity (1-6 Practical Salinity Units; PSU) rearing habitats to upstream freshwater spawning habitats of the Sacramento-San Joaquin Delta; (herein referred to as the "Delta"; Grimaldo et al. 2009, Sommer et al. 2011). More recently, Murphy and Hamilton (2013) argue that adult Delta Smelt are not making unidirectional migration movements upstream during their spawning phase but rather making shorter dispersal movements from large embayments and channels toward adjacent shoals and marshes that may freshen up to support suitable spawning substrate. The migration model explicitly implies that Delta Smelt place themselves in entrainment risk through upstream migration movements that place them in front of the SWP and CVP pumping plants (Fig 1.). The dispersal model, as presented by Murphy and Hamilton (2013), does not offer a mechanism by which adult Delta Smelt get entrained because they are not found in channels near the SWP and CVP during the summer and fall prior to first flush periods (Nobriga et al. 2008, Sommer and Mejia 2013); during the summer and fall, they are found several kilometers downstream (Sommer and Mejia 2013). An extension of Murphy and Hamilton (2013), is that adult Delta Smelt expand their distribution upstream during first flush events as suitable habitat (i.e., turbidity, see Feyrer et al. 2007; Nobriga et al. 2008; Sommer and Mejia 2013) increases landward. In this case, expanding their range landward could result in an increased entrainment risk, especially if the channels leading to the SWP and CVP support suitable turbid waters that adult Delta Smelt are most associated with (Grimaldo et al. 2009).

Delta Smelt likely employ a number of behaviors, including short dispersal and longer migration movements, during first flush events depending on environmental conditions and their distribution prior to when the environment changes (Bennett and Burau 2015). For example, during years of high freshwater inflow, some adult Delta Smelt tend to remain in their seaward position as the environment freshens up around them which is consistent with the diffuse dispersion conceptual model presented by Murphy and Hamilton (2013). A small number of adults may even move *downstream* to the Napa River (tributary to San Pablo Bay) for spawning. However, even during periods of extreme freshwater inflow, a small number of Delta Smelt are also found in large numbers in the north Delta (Sommer and Mejia 2013) and some even get entrained at the SWP and CVP (Grimaldo et al. 2009), suggesting that some fish undertake active behaviors to move them upstream consistent with the spawning migration model described by Sommer et al. (2011).

Focused field studies of Delta Smelt during first flush periods show they aggregate near frontal zones at the shoal-channel interface, moving laterally into the shoals on ebb tides and back into the channel on flood tides (Bennett and Burau 2015). The results of this study suggest that adult Delta Smelt use active behaviors to minimize advection down-estuary during periods of increased inflow (i.e., maintain position), and in some cases, use tidal surfing and lateral movements nearshore to facilitate movements to upstream spawning habitats. Recognizing that not all Delta Smelt move upstream to spawn, the task of determining what behaviors some adult Delta Smelt may use to move to upstream spawning habitats is probably best approached using an individual-based model in 2d or 3d hydrodynamic flow field model environment (Goodwin et al. 2006, McElroy et al. 2012, Goodwin et al. 2014).

After review of recent research (Miller et al. 2012, Murphy and Hamilton 2013, Sommer and Mejia 2013, Interagency Ecological Program 2015), a revised conceptual model is presented here as a framework for implicitly testing hypotheses thought to influence adult Delta Smelt salvage and entrainment risk. The revised conceptual model recognizes a hierarchal importance of landscape attributes as mechanistic drivers of habitat attributes that potentially may affect Delta Smelt movement and ultimately their entrainment risk (Fig. 1). Some of the variables identified in the revised conceptual model presented here were overlooked in previous analyses of Delta Smelt salvage (Grimaldo et al. 2009). In some cases, some factors believed to be important were identified but the data remains insufficient (temporally and spatially) or unavailable for inclusion in the analyses presented here. For example, food may be an important factor that affects their survival and distribution during the first flush and subsequent staging period before spawning (IEP 2015) but collections of their key prey (e.g., zooplankton, macrocrustaceans, and amphipods) in the estuary are insufficient in time or space to allow inclusion in the analysis.

The revised conceptual model also places emphasis on first flush events as a key process that changes the environment *and* behavior responses of Delta Smelt (Fig. 1). Delta Smelt are salvaged in drier years when river inflows are low (i.e., weak or no significant first flush), but in these years, salvage levels are typically below that of management concern (USFWS 2008). Grimaldo et al. (2009) noted the importance of first flush events and examined intra-annual adult Delta Smelt salvage patterns at monthly (December to March) intervals, finding that monthly salvage was influenced by turbidity, X_2 (position of the 2 PSU bottom isohaline from the Golden Gate Bridge; see (Jassby et al. 1995), and SWP and CVP water diversions indexed by net Old and Middle River flow (OMR; see below). This work was important in illuminating the importance of turbidity and OMR flow as conditions that predicted within-season salvage but perhaps not at a response or temporal scale informative to resource managers who are mandated to reduce SWP and CVP water exports during the onset of first flush events (USFWS 2008). Where data are available, potential predictor variables identified in the conceptual model are tested here (see below).

Predator mortality in front of the fish louver screens may also play an important role in the number of adult Delta Smelt salvaged. Presumably, fish entering the Clifton Court Forebay, the reservoir leading to the SWP fish screens, suffer higher pre-screen loss than fish that enter the CVP directly from channels of the Delta. Castillo et al. (2012) estimated that the pre-screen mortality rates for several experimental groups of Delta Smelt released into Clifton Court Forebay were between 90 and 100 percent. It should be noted that this study was done under low SWP exports (93 $m^{3/}s$), which results in higher residence time of water in the Clifton Court Forebay, and presumably of fish before they show up at the screens. Higher residence times could lead to increased exposure to predators. Survival rates may be higher under higher SWP exports (i.e., > 200 m^3/s) when water, and presumably fish, moves much faster through Clifton Court Forebay.

Unfortunately, predator abundance data are sparse for the estuary. For this paper, data on the number of key predators salvaged at the fish screens were included in the analysis but it is recognized that large mobile predators are less susceptible to entrainment because they are able to freely swim away from the fish screens (Gingras and McGee 1997). Thus, predator salvage data is likely a poor indicator of their abundance in the area of the SWP and CVP. Nonetheless, salvage of predators and other fishes as community response variables were included in the BRT analysis to gleam any potential effects that might be important for explaining adult Delta Smelt salvage.

The revised conceptual model acknowledges the importance of operational drivers in affecting some habitat attributes. For example, combined SWP and CVP water exports may have little effect on the tidal dispersion of suspended sediment in the estuary (Schoellhamer 2002, McKee et al. 2006) but operations of large gates (Delta Cross Channel) on the Sacramento River that are opened to shunt water from the Sacramento towards the interior Delta to improve water quality for SWP and CVP exports could affect dispersion of turbid water (and Delta Smelt that happen to surf with it) towards the export pumps. (Arthur et al. 1996, Monsen et al. 2007, Kimmerer and Nobriga 2008). Also, the farther fish move landward to the interior Delta, the higher their entrainment risk given the volume of water pumped per day from the Delta by combined SWP and CVP exports (Arthur et al. 1996). This is the basis of any conceptual model that assumes there is a mechanistic reason why adult Delta Smelt salvage increases when OMR net flows are negative and turbidity is high (e.g., Grimaldo et al. 2009).

Finally, it is recognized that Delta Smelt distribution prior to the onset of winter storms could play a role in their entrainment risk, especially if it influences their movements into the south Delta once first flush events occur (Grimaldo et al. 2009). The number of Delta Smelt collected in the CDFW Fall Midwater Trawl Survey has decreased to just a handful of fish per year. Thus, this survey provides poor estimates of Delta Smelt distribution in the more recent years. Sommer and Mejia (2013) did find a positive relationship between X_2 and the center of the Delta Smelt distribution in the CDFW FMWT survey indicating that this is a reliable metric of their distribution useful for analyses. Note, the authors acknowledge that this relationship is not a perfect distribution metric for the entire Delta Smelt population because a small number of them are found in the freshwater region of north Delta year-around. (i.e., they do not show a relationship to X_2 or salinity itself). However, in the conceptual model presented here, it is unlikely that these fish move from the north Delta to the south Delta during first flush or any part of their life stage; therefore, December outflow was inferred as a surrogate for distribution of Delta Smelt that could be vulnerable to entrainment in the low salinity region of the estuary. As previously stated, questions about when and where fish move and how this influences their entrainment risk and daily salvage on equivalent time scales are probably best approached using IBM's

Methods

Study approach

The purpose of this paper was to determine the factors that affect salvage at relevant temporal scales informative for resource managers. Initial inspection of the daily salvage data (1993-2015) shows that the vast majority of adult Delta Smelt salvage occurs between December 1 and March 31, which is considered the annual salvage period for adult Delta Smelt since most only live one year (Fig. 3; Bennett 2005; Grimaldo et al. 2009). Within years, the salvage data exhibits considerable autocorrelation (5-12 days), suggesting that entrainment risk is not independent of day to day environmental and operational conditions. Grimaldo et al. (2009) examined intra-annual variation in the salvage dynamics by parsing the data arbitrarily into monthly intervals, but in retrospect, this approach likely mischaracterized the variation explained in the cases when salvage observations only occurred in a few days at the beginning or end of the month and were regressed against the monthly average of predictor variables.

Here, the salvage data was examined at the annual scale and aggregated into a response variable aimed at understanding factors that explain salvage during first flush dynamics. This was accomplished by only examining the period when daily cumulative salvage reached its 25th and 50th percentile for each "water year" starting from December 1st and ending on March 31st. This approach was taken because it is believed that environmental and operational conditions occurring during the accelerating part of the seasonally accumulating salvage are the conditions that best represent what actually caused the fish to occupy nearby channels in the south Delta from where they could be entrained. During the decelerating part of seasonally accumulating salvage, it seems likely that salvage is less connected to concurrent operations than with whether Delta Smelt had already occupied habitats near the SWP and CVP facilities. The 25th and 50th percentiles of cumulative salvage were selected to determine sensitivity of this approach for detecting differences in the explanatory variables which can vary dramatically during first flush events.

Adult Delta Smelt salvage data were first explored using Boosted Regression Tree (BRT) models. Boosting is an ensemble method considered ideal for examining large data sets with multiple parameters because it averages across many moderately fitting models to yield greater model performance than attempting to select a single or small group of perfectly fit models (Elith et al. 2008). While traditional model selection approaches seek to identify a parsimonious model with few parameters, boosting approaches seek to fit many parameters and shrink their contribution, similar to LASSO method (Hastie et al. 2001). At first iteration, the BRT is the best fitting regression tree. At second iteration, the regression tree that best fits the residuals of the first is added to the BRT. This sequence proceeds until deviance is minimized and adding more trees results in greater deviance. The contribution of each tree to the BRT is limited or shrunk by the learning rate, and up to several thousands of trees are commonly fit and added to produce the final BRT.

BRT models can generate more accurate predictions than Generalized Linear Models (GLMs) or General Additive Models (GAMs;(Leathwick et al. 2006) but results may lack the mechanistic interpretation of models that explicitly model the observation process, which is why negative binomial regression models were subsequently applied to the data. Negative binomial and GAM models were applied to salvage data at 25th and 50th cumulative salvage percentiles to handle the large number of zeros in the salvage observation that cause over-dispersion (Ver Hoef and Boveng 2007) and to handle the potential non-linear nature of the relationships between salvage and predictor variables respectively.

For the negative binomial regression models, a smaller subset of predictor variables identified from the BRT analysis were tested as potential factors that affect adult Delta Smelt salvage to provide meaningful interpretations useful for potential management implications and actions. For exploring annual salvage patterns, both GLM and GAM models were applied to determine best model fits to the data. GAM models were applied to the data to determine whether GLM analyses might be missing useful or previously unrecognized nonlinear relationships between environmental and operational predictors important for identifying thresholds useful for setting management rules (USFWS 2008). In both cases, models were applied to each fish facility separately and as a combined count to examine if patterns that underlie salvage were influence by different factors since the SWP export capacity (292 m^3/s) is almost two and half times greater than the CVP export capacity (130 m^3/s). The two projects have the potential to affect fish entrainment in different ways even though they are regulated as single entity (USFWS 2008).

Finally, it is worth noting that since the 2008 USFWS Biological Opinion was issued, exports have been constrained such that OMR flows are no more negative than -141 m3/s once entrainment risk conditions materialize for Delta Smelt (adults and juveniles) between December and June. In addition to this OMR flow cap, the USFWS can and has imposed more conservative export cutbacks when the fish monitoring data (CDFW surveys and fish salvage itself) and *in situ* turbidity gauges from the central Delta indicate elevated entrainment risk (USFWS 2008; https://www.fws.gov/sfbaydelta/cvp-swp/smelt_working_group.cfm). Additionally, export restrictions for protected salmonids are implemented during this timeframe depending on the rules provided in the National Marine Fisheries Service (NMFS) 2009 Biological Opinion. For the analyses presented here, the post 2008 years were not separated from the historical data that were largely unaffected by management operations during the winter period. However, it should be recognized that management actions since 2008 may have proactively reduced entrainment risk for Delta Smelt, which in turn, may affect interpretation of the results in the more recent years.

Data sources

The SWP and CVP water diversion intakes are located in the southern Sacramento-San Joaquin Delta (Fig. 2.). As previously mentioned, in front of the SWP and CVP water intakes are large fish facilities intended to reduce fish loss from the system due to entrainment. The state Skinner Fish Protective Facility (SFPF) and the federal Tracy Fish Collection Facility (TFCF) direct fish through a complex louver system into collecting screens where they are identified, measured, and eventually trucked and released back into the environment downstream from the SWP and CVP. A variable fraction of Delta Smelt may survive the capture, handling, trucking and release process (Miranda et al. 2010, Morinaka 2013). Despite whether they survive the handling and trucking process, any Delta Smelt observed at the fish facilities are considered as incidental take under the ESA. The SWP differs from the CVP in having a regulating reservoir known as the Clifton Court Forebay that temporarily stores water from Old River to improve operations of the SWP pumps.

Salvage operations have been operating almost daily for the last few decades at the TFCF (since 1958) and SPFF (since 1968)(Brown et al. 1996). Arguably, they are two of the largest fish sampling systems in the world. Up until the early 1990's, salvage counts and identification were focused on salmonids and striped bass. However, after Delta Smelt were listed in 1993, focus on proper identification and detections resulted in a change in count frequency of twice per day (1978 to 1992) to every two hours thereafter (Morinaka 2013). Daily salvage for each species per day for each facility are calculated by the following:

$$Sd = \sum_{i=0}^{n} si = Ci * (\frac{mpi}{ti})$$

where *Sd* is the total daily salvage, *si* is the salvage per sample, *Ci* is the number of fishes in a sample defined by the minutes of water pumped (*mpi*) per the counting time (*ti*). Typically, there are six sample periods per day and twenty individuals per species greater than 20 mm fork length (FL) are measured. Salvage data for Delta Smelt and other species used in the analysis were obtained from the California Department of Fish Wildlife (CDFW) ftp site (ftp://ftp.dfg.ca.gov/Delta%20Smelt/). Delta Smelt adult abundance estimates from the CDFW's FMWT monitoring survey were obtained from the same ftp site.

Physical and biological variables used in statistical models of Delta Smelt salvage included those used by Grimaldo et al. (2009) and new ones identified from the revised conceptual model (Fig. 1). Most of the physical and hydrodynamic data were obtained from the California Department of Water Resources (CDWR) long-term monitoring website portals (www.water.ca.gov/dayflow/; http://cdec.water.ca.gov) flow variables include those that are measured directly with gauges and those that are modeled. Combined net OMR flows were obtained from United States Geological Survey (USGS) acoustical velocity meters located near Bacon Island (Fig. 1; Arthur et al. 1996; http://waterdata.usgs.gov/ca/nwis/). OMR flows integrates a complex set of factors, including SWP and CVP exports, flows from the large and small tributaries into the interior Delta, daily and neap– spring tidal variation, local agricultural diversions, and wind (Monsen et al. 2007). Suspended-sediment concentration (mg/1) data were obtained from USGS (Personal Communication Tara Morgan-King).

Statistical analyses

The first step with the BRT analysis was to select a subset of predictor variables from over 50 candidate variables identified from the revised conceptual model. As bookends, the BRT analysis was performed on the 25th percentile and the annual data set. Available variables describing Delta-wide hydrodynamics, river flows, SWP and CVP exports, and metrics broadly describing Delta Smelt habitat attributes were considered (Table 1). Data on salvage of other species were grouped as variables describing the biological community which may have direct or indirect effects on Delta Smelt abundance and distribution. Overall, data were highly correlated, particularly among physical variables and among community variables (Table 2). In order to avoid misleading results associated with multicollinearity among variables, Principle Component Analysis (PCA) was used to reduce the dimensionality of the physical dataset and the community dataset to two smaller sets of uncorrelated (orthogonal) data. Only the set of principle components (PCs) explaining a large fraction of the variation in the data were desired; thus, only PCs with eigenvalues greater than one were retained for boosted regression tree analysis. Principle component rotations were inspected to determine which variables loaded on each PC and interpret the meaning of each PC. Prior to PCA, all physical and community variables were natural log transformed for normality. Correlation between physical and community PCs was quantified using Pearson's correlation coefficient. If physical and community variables were highly correlated, one variable was selected for removal from the predictor set. Physical PCs were preferentially retained over community PCs, because relationships between Delta Smelt salvage and physical variables could be interpreted mechanistically, while relationships with community variables were interpreted as merely correlational. PCA requires a complete dataset, so two physical variables with missing data were not included in the PCA but were included in the final set of physical variables, Clifton Court Forebay turbidity (Nephelometric Turbidity Unit, NTU) and water temperature (°C). These two variables were explored for correlations with physical PCs to assure that their inclusion in data used for boosted regression tree analysis did not introduce collinearity. If a variable was highly correlated with a PC, that variable was not retained for boosted regression tree analysis. High correlation with a PC suggested that the information contained within that variable's distribution was captured by a PC.

The boosted regression tree model was fit using R package dismo and the gbm.step function (R Development Core Team 2008). The gbm.step function used ten-fold cross validation to determine the optimal number of regression trees to fit. Trees were added until a deviance minima was reached. Learning rate was set to the lowest rate that reached a deviance minima with less than 3000 trees ($0.01 > l_r > 0.1$), and up to three-way interactions were modeled (tree complexity = 3). Half of the data was used as a training set while half was used as a test set.

Negative binomial models and GAM's were subsequently applied on a smaller subset of variables identified from the BRT analysis for the cumulative salvage percentiles (25^{th} and 50^{th}). Negative binomial models were done using the pscl package (Zeileis et al. 2008, Jackman et al. 2015) in the R statistical computing environment. GAMs were also applied to the cumulative salvage percentile data using a Poisson distribution with cubic regression spline smoothing functions (mgcv package in R). Only years where positive daily salvage observations (> 0 fish collected) were 5 or more days for the water year were included in the analyses. The annual data were analyzed use GLM and GAM models. Model comparisons were evaluated Akaike Information Criteria (AIC) values were calculated, AIC = 2*k – 2*log(Likelihood), where k = the number of parameters. AIC simultaneously quantifies goodness of fit, as defined by the likelihood of the data, and model complexity (as measured by k), and models with the smallest AIC values are considered preferable.

Results

Boosted Regression Trees

Principle component analysis reduced 11 highly correlated physical variables to 3 orthogonal PCs explaining 73% of all variation in physical data and 20 community variables to 7 PCs explaining 60% of all variation in community data (Tables 3 and 4). To aid in interpretation of Physical PCs, each Physical PC was plotted against one of the important variables loading on that PC (Fig. 3). Physical PC 2 and community PC 1 were highly correlated (Table 5), so community PC 1 was not retained for further analysis. Including previous year's FMWT, day in the spawning season, water temperature, and PCs, 12 variables were explored for associations with Delta Smelt salvage using BRT analysis. Clifton Court Forebay turbidity was not included in the final set of variables, because it was highly correlated with the first physical PC that loaded on outflow.

BRT analysis suggested that regardless of dataset, the most influential variable in the magnitude of Delta Smelt salvage was the second physical PC that loaded on daily export rate and OMR (Export PC). Higher salvage was associated with greater values of Export PC (Fig. 4). All three physical PCs had at least 5% influence in the fitted model (Table 6). Lower values of physical PC 3 that loaded on GCD and precipitation were associated with greater salvage. The most influential community variables were prior year's FMWT and the second community PC loading on Bullhead and Pike Minnow. Low salvage of Delta Smelt was associated with higher prior year's FMWT and higher values of the community PC 2. While it was not retained for the final analysis, preliminary analysis suggested that greater salvage of Delta Smelt was associated with higher values of the first community PC that loaded on anadromous fish and catfish.

The rank of influence varied slightly between models fit to the full dataset versus the 25th percentile dataset, but the list of influential physical and community variables was identical. In both models, interactive effects were apparent among the physical variables and prior year's FMWT (Fig. 3). Certain combinations of physical variables were more likely to be associated with salvage. Across temporal scales, the most consistent combinations with a high probability of salvage were a combination of water temperature between 8 and 10°C and high Export PC and a combination of prior year's FMWT greater than 100 and high Export PC.

All years were included in the negative binomial and GAM 25th and 50th percentile analyses except for water years (2007, 2009, 2011, 2014) when there were less than 5 daily salvage observations during the study period (121 days). During the eight highest salvage years, the 50th cumulative percentile was reached in as few as 40 days since December 1st (2001) to 57 days (1993). The fewest days it took for the onset of salvage (i.e., first daily salvage observation of the year) to the 50th percentile for any given water years was 14 days (2001). The fewest number of days between 25th and 50th percentiles within any given water year was 3 days.

Based on the BRT analysis, variables selected for the negative binomial analyses included combined SWP and CVP exports or OMR flow, December X_2, previous FMWT abundance, suspended sediment for San Joaquin river, Sacramento River flow, water temperature, and Clifton Court Forebay turbidity. Sacramento suspended sediment was considered but removed to do collinearity with Sacramento River flow. Although Clifton Court Forebay turbidity was not included in the BRT because of its collinearity with PC1, it was included in the cumulative salvage models because it is important compliance metric for the Delta Smelt entrainment management (USFWS 2008).

Overall, the GAM models explained a much higher percentage of the variance in the adult Delta Smelt salvage data than the negative binomial models (Tables 7 and 8). Nonetheless, both model approaches revealed an importance of SWP and CVP exports, Clifton Court Forebay turbidity, suspended sediment, water temperature, previous FMWT abundance, and prior fish distribution (indexed as December outflow) as significant predictor variables of Delta Smelt salvage (Figure 6). Models with SWP and CVP exports had lower AIC values than OMR flow for cumulative 25th and 50th percentile. Models with OMR are not further presented in this paper.

Overall, both GLM and GAM models show consistency with annual variance explained (Table 9). The GLM indicated an importance of SWP and CVP exports, Sacramento River flow, and previous FMWT abundance. The GAM model found that SWP and CVP exports and Vernalis suspended sediment were the most important variables that explained annual salvage patterns (Table 9). Delta Salvage response increased with higher exports and Vernalis suspended sediment (Figure 7).

Discussion

This study demonstrates that adult Delta Smelt salvage patterns are largely explained by hydrodynamics, some measure of water clarity (turbidity or suspended sediment), water temperature, and their adult abundance. These factors had explanatory significance for the onset of salvage and for overall annual salvage, suggesting that events that occur during the first flush period are important for influencing salvage at the annual level. Mechanistically, the results from this study offer little insights into what factors actually prompt Delta Smelt to disperse or migrate into the south Delta in the first place. These behaviors are likely related to their changing physiology as they begin staging and spawning (Sommer and Mejia 2013) and other environmental cues that alter their behavior once river inflow increases (Bennett 2005; Bennett and Burau 2015). Researchers in other estuaries have found that spawning behavior of other osmerids is often linked to changing lunar phases (Hirose and Kawaguchi 1998), semidiurnal tides (Middaugh et al. 1987) and water temperature (Nakashima and Wheeler 2002)

Although approached slightly differently in this study, combined SWP and CVP exports were found to be important predictors of adult Delta Smelt salvage in all the models explored. This result itself is not surprising given previous research on topic (Kimmerer 2008; Grimaldo et al. 2009) but it is worth noting that SWP and CVP exports slightly improved model performance from OMR flow, which integrates exports and San Joaquin River flow. The actual influence of SWP and CVP exports on Delta Smelt behavior is unknown. Recent research from Bennett and Burau (2015) suggests that Delta Smelt are not behaving passively during the onset of winter storms, even if they want to simply hold their longitudinal position. Except for wet years when river inflows are net seaward in south Delta channels (Arthur et al. 1996; Monsen et al. 2007), the relationship between higher exports and higher observed salvage is interpreted to represent two key processes that underlying entrainment rates and observed salvage. First, under higher exports, residence time of water in the south Delta channels is low and net flow is towards the SWP and CVP (Monsen et al. 2007; Kimmerer and Nobriga 2008). Therefore, for the Delta Smelt that do move into the south Delta during first flush, it is understandable that their entrainment would increase under higher exports and it would occur in rapid fashion (Kimmerer 2008). Second, it is likely that when residence time in the south Delta channels and Clifton Court Forebay is low, predator mortality is probably also lower (Cavallo et al. 2013), which could result in increased salvage observations at the fish facilities.

The importance of turbidity as a predictor of Delta Smelt salvage in most of the models examined is important because it has been overlooked in previous approaches (Kimmerer 2008) or not found significant in some previous models of Delta Smelt salvage (Grimaldo et al. 2009). As a habitat attribute, the relationship between turbidity and adult salvage confirms relationships that have been identified for Delta Smelt in a number of monitoring surveys for different life stages. Delta Smelt catches are higher when the water is more turbid, which is thought to reduce their predation risk (Feyrer et al. 2007; Nobriga et al. 2008; Sommer and Mejia 2013) and increase their catchability (Latour 2015).

It should be recognized that the Clifton Court Forebay turbidity monitoring station is the only gauge that has time series data going back to the early 1990's. Emerging hydrodynamic-turbidity modeling indicates that turbidity at this Clifton Court Forebay gauge is mostly influenced by wind events and turbidity/sediment that moves from the San Joaquin River via the eastern channel of Old River channel (Personal Communication, Michael MacWilliams, Anchor QEA) at shorter time intervals (i.e., hours and days). The eastern channel of Old River towards the San Joaquin River confluence is not region where Delta Smelt reside in any appreciable numbers or the direction they would enter the SWP and CVP. Therefore, the importance of Clifton Court Turbidity as a significant variable in the models presented here has limited interpretation as a variable likely to influence Delta Smelt entrainment risk at broader regional level. The USFWS recognizes the importance of Delta-wide turbidity and maintains a network of new in-river gauging stations installed with the purpose of helping guide real-time management decisions for Delta Smelt.

The inclusion of suspended sediment from the San Joaquin river sediment as a surrogate for water clarity is probably more informative for understanding the effect of landscape drivers on both Delta-wide turbidity and Delta Smelt salvage. Both the 25th and 50th GAM models include the two sediment sources as predictors of adult Delta Smelt salvage, showing that Delta Smelt linearly decreases with increasing San Joaquin River sediment. Because suspended sediment concentration is a reasonable proxy for turbidity and San Joaquin River flow, this relationship is consistent with the interpretation that as the Delta receives higher suspended sediment concentrations, Delta Smelt are likely to expand their distribution upstream except at the very high ends of freshwater inflow remain they remain downstream of the SWP and CVP.

An outstanding question is whether Delta Smelt will only move into the south Delta during first flush conditions or whether they would continually move in during subsequent storms. As stated previously, this question is probably best approached using an IBM coupled with a 2D or 3D model using first flush behaviors identified by Bennett and Burau (2015). Of the Delta Smelt that do migrate upstream to spawn, there is some evidence that Delta Smelt only make one large push to upstream habitats after the first flush. This can be gleamed from the salvage data itself which is highly unimodal in nature (see Figure 6 in Grimaldo et al. 2009) and from the CDFW SKT trawl data which shows very little movement of fish between regions from month to month (http://www.dfg.ca.gov/delta/projects.asp?ProjectID=SKT).

It is also important to note that once spawning commences in late February and early March, natural mortality must rapidly increase due to post-spawning senescence. This may explain why salvage of adult Delta Smelt is lower in March compared to December and January in most years and nearly zero by late April and May because, as we show here, abundance is a predictor of salvage. The model results presented here do indicate that entrainment risk increases when the center of the population, as indexed by December X_2, is landward. The mechanism underlying this relationship suggests that even small southward movements towards the SWP and CVP when the water in the south Delta is turbid could result in increased risk. In drier years, when river inflows are low and turbidity is low, entrainment risk is much lower, regardless of where the fish are located (e.g., see Figure 6).

The importance of biological interactions is difficult to extract from the data sources used in the analyses presented here. For example, the importance of stock size (previous FMWT) improving variance explained in most of the models presented here suggest that when abundance is higher, there is a greater chance of detecting them in the SWP and CVP if other habitat conditions are suitable. The only predator-prey interaction that could be gleamed from the BRT came from the positive response between brown bullhead and pike minnow PC variable and increased Delta Smelt salvage. It is unlikely that these fish are significant predators of Delta Smelt given their abundance is really low in the south Delta and at the SWP altogether. This is not to dismiss the importance of predatory effects but the lack of spatial and temporal predator data in the estuary prohibits confident assessment at this time.

Management Implications

Managing SWP and CVP during first flush periods creates conflict between resources managers who are required to reduce exports when Delta Smelt are vulnerable to entrainment versus operators who wish to improve the State's water storage and delivery by ramping up exports when freshwater inflows elevate in the Delta (Brown et al. 2009). Information generated from this study suggests that adult Delta Smelt salvage risk could be minimized through SWP and CVP export reductions during the onset of first flush conditions. Careful monitoring of Delta-wide turbidity, river inflow, suspended sediment inputs, fish distribution and water temperature could help determine when first flush conditions materialize. The extent and duration of potential management actions could vary depending on the strength of these conditions and the water supply tradeoffs. Note, this framework for management action alternative is currently built into the USFWS Biological Opinion for protecting Delta Smelt. The ability to test the efficacy of these rules under an adaptive management framework could provide some clarity on the real-time factors that could be manipulated by managers to optimize these rules in manner that enhances fish protection *and* water supply reliability.

The ability to develop coupled biological-hydrodynamic IBMs could also be helpful for testing hypotheses about finer scale movements of Delta Smelt under different exports and environmental conditions. This approach would be considered particularly desirable in light of recent CDFW surveys where only a handful of Delta Smelt caught annually. As the Delta Smelt becomes rarer, and it becomes increasingly difficult to track their movements from the surveys, IBM approaches applied to the historical data when Delta Smelt were more abundant could be useful for generating predictions about their real-time entrainment risk.

Emerging eDNA techniques for testing the presence or absence of Delta Smelt during first flush periods could also prove as a fruitful management tool (Schreier et al. 2016), if detection rates could be reasonably determined relative to their abundance and net southward flows to the water export facilities. New tagging techniques for cultured Delta Smelt (Wilder et al. 2016)could also be applied by releasing tagged fish during first flush periods to determine the rate and direction fish move in the south Delta. These studies could also help determine the effects of predation within the Clifton Court Forebay under high and low exports (Castillo et al. 2012) and in the channels that lead to the SWP and CVP during first flush periods akin to research that has been done for salmonids in the estuary (Cavallo et al. 2015).

Finally, it is worth noting that the ultimate objective for managing Delta Smelt entrainment should not focus on observed salvage. Rather, the management objective should be to target entrainment losses, in a traditional fisheries sense, to sustainable levels that do not compromise population growth rates (Maunder and Deriso 2011; Rose et al. 2013). The results presented in this study can help scientists and resource managers identify circumstances when those large entrainment losses are likely to occur, which can ultimately be used to develop risk assessment models, and real-studies (e.g., field and IBM's) of fish and their habitat attributes for improved Delta Smelt management. The question about whether the Delta Smelt population can rebound from record-low abundances, even with improved entrainment management during the winter, remains outstanding given the importance of other factors at play (i.e., poor food supply, growth, water temperatures; see Maunder and Deriso 2011; Rose et al 2013,) or other stage-specific dynamics that also appear limiting to the population (Bennett 2005, Maunder and Deriso 2011, Rose et al. 2013, Interagency Ecological Program 2015).

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Literature Cited

Arthur, J. F., M. D. Ball, and S. Y. Baughman. 1996. Summary of federal and state water project environmental impacts in the San Francisco Bay-Delta Estuary, California. San Francisco State University.

Bennett, W. A. 2005. Critical assessment of the delta smelt population in the San Francisco Estuary, California. San Francisco Estuary and Watershed Science **3**.

Bennett, W. A., and J. R. Burau. 2015. Riders on the Storm: Selective Tidal Movements Facilitate the Spawning Migration of Threatened Delta Smelt in the San Francisco Estuary. Estuaries and Coasts **38**:826-835.

Brown, L. R., W. Kimmerer, and R. Brown. 2009. Managing water to protect fish: a review of California's Environmental Water Account, 2001-2005. Environmental Management **43**:357-368.

Brown, R., S. Greene, P. Coulston, and S. Barrow. 1996. An evaluation of the effectiveness of fish salvage operations at the intake to the California Aqueduct, 1979-1993. Pages 497-518 *in* J. T. Hollibaugh, editor. San Francisco Bay The Ecosystem. Further Investigations into the Natural History of San Francisco Bay and Delta With Reference to the Influence of Man. Pacific Division of the American Association for the Advancement of Science, San Francisco, CA.

Castillo, G., J. Morinaka, J. Lindberg, R. Fujimura, B. Baskerville-Bridges, J. Hobbs, G. Tigan, and L. Ellison. 2012. Pre-Screen Loss and Fish Facility Efficiency for Delta Smelt at the South Delta's State Water Project, California. San Francisco Estuary and Watershed Science **10**.

Cavallo, B., P. Gaskill, J. Melgo, and S. C. Zeug. 2015. Predicting juvenile Chinook Salmon routing in riverine and tidal channels of a freshwater estuary. Environmental Biology of Fishes **98**:1571-1582.

Cavallo, B., J. Merz, and J. Setka. 2013. Effects of predator and flow manipulation on Chinook salmon (*Oncorhynchus tshawytscha*) survival in an imperiled estuary. Environmental Biology of Fishes **96**:393-403.

Deriso, R. B. 1980. Harvesting Strategies and Parameter Estimation for an Age-Structured Model. Canadian Journal of Fisheries and Aquatic Sciences **37**:268-282.

Elith, J., J. R. Leathwick, and T. Hastie. 2008. A working guide to boosted regression trees. Journal of Animal Ecology **77**:802-813.

Gingras, M., and M. McGee. 1997. A Telemetry Study of Striped Bass Emigration from Clifton Court Forebay: Implications for Predator Enumeration and Control. IEP Technical Report 54. January. Interagency Ecological Program for the San Francisco Bay/Delta Estuary.

Goodwin, R. A., J. M. Nestler, J. J. Anderson, L. J. Weber, and D. P. Loucks. 2006. Forecasting 3-D fish movement behavior using a Eulerian–Lagrangian–agent method (ELAM). Ecological Modelling **192**:197-223.

Goodwin, R. A., M. Politano, J. W. Garvin, J. M. Nestler, D. Hay, J. J. Anderson, L. J. Weber, E. Dimperio, D. L. Smith, and M. Timko. 2014. Fish navigation of large dams emerges from their modulation of flow field experience. Proceedings of the National Academy of Sciences of the United States of America **111**:5277-5282.

Grimaldo, L., T. Sommer, N. Van Ark, G. Jones, E. Holland, P. Moyle, P. Smith, and B. Herbold. 2009. Factors affecting fish entrainment into massive water diversions in a freshwater tidal estuary: can fish losses be managed? North American Journal of Fisheries Management **29**:1253-1270.

Hall, S. J., and B. Mainprize. 2004. Towards ecosystem-based fisheries management. Fish and Fisheries **5**:1-20.

Hastie, T., J. Friedman, and R. Tibshirani. 2001. Model Assessment and Selection. Pages 193-224 The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer New York, New York, NY.

Hirose, T., and K. Kawaguchi. 1998. Spawning ecology of Japanese surf smelt, Hypomesus pretiosus japonicus (Osmeridae), in Otsuchi Bay, northeastern Japan. Pages 213-223 *in* M. Yuma, I. Nakamura, and K. D. Fausch, editors. Fish biology in Japan: an anthology in honour of Hiroya Kawanabe. Springer Netherlands, Dordrecht.

Interagency Ecological Program, M., Analysis, and Synthesis Team. 2015. An updated conceptual model of Delta Smelt biology: our evolving understanding of an estuarine fish. Technical Report 90. January. Interagency Ecological Program for the San Francisco Bay/Delta Estuary, Sacramento, CA.

Jackman, S., A. Tahk, A. Zeileis, C. Maimone, J. Fearon, and M. S. Jackman. 2015. Package ‘pscl’.

Jassby, A. D., W. J. Kimmerer, S. G. Monismith, C. Armor, J. E. Cloern, T. M. Powell, J. R. Schubel, and T. J. Vendlinski. 1995. Isohaline position as a habitat indicator for estuarine populations. Ecological Applications **5**: 272-289.

Kimmerer, W. J. 2008. Losses of Sacramento River Chinook Salmon and Delta Smelt to Entrainment in Water Diversions in the Sacramento-San Joaquin Delta. San Francisco Estuary and Watershed Science **6**.

Kimmerer, W. J. 2011. Modeling Delta Smelt Losses at the South Delta Export Facilities. San Francisco Estuary and Watershed Science **9**.

Kimmerer, W. J., and M. L. Nobriga. 2008. Investigating Particle Transport and Fate in the Sacramento-San Joaquin Delta Using a Particle Tracking Model. San Francisco Estuary and Watershed Science **6**.

Latour, R. J. 2015. Explaining Patterns of Pelagic Fish Abundance in the Sacramento-San Joaquin Delta. Estuaries and Coasts.

Leathwick, J. R., J. Elith, and T. Hastie. 2006. Comparative performance of generalized additive models and multivariate adaptive regression splines for statistical modelling of species distributions. Ecological Modelling **199**:188-196.

Link, J. S. 2002. What does ecosystem-based fisheries management mean. Fisheries **27**:18-21.

Mac Nally, R., J.R. Thomson, W.J. Kimmerer, F. Feyrer, K.B. Newman, A. Sih, W. A. Bennett, L. Brown, E. Fleishman, S. D. Culberson, and G. Castillo. 2010. Analysis of pelagic species decline in the upper San Francisco Estuary using multivariate autoregressive modeling (MAR). Ecological Applications **20**:1417-1430.

Maunder, M. N., and R. B. Deriso. 2011. A state-space multistage life cycle model to evaluate population impacts in the presence of density dependence: illustrated with application to delta smelt (*Hypomesus transpacificus*). Canadian Journal of Fisheries and Aquatic Sciences **68**:1285-1306.

McElroy, B., A. DeLonay, and R. Jacobson. 2012. Optimum swimming pathways of fish spawning migrations in rivers. Ecology **93**:29-34.

McKee, L. J., N. K. Ganju, and D. H. Schoellhamer. 2006. Estimates of suspended sediment entering San Francisco Bay from the Sacramento and San Joaquin Delta, San Francisco Bay, California. Journal of Hydrology **323**:335-352.

Miller, W. J. 2011. Revisiting Assumptions that Underlie Estimates of Proportional Entrainment of Delta Smelt by State and Federal Water Diversions from the Sacramento-San Joaquin Delta. San Francisco Estuary and Watershed Science **9**.

Miller, W. J., B. F. J. Manly, D. D. Murphy, D. Fullerton, and R. R. Ramey. 2012. An Investigation of Factors Affecting the Decline of Delta Smelt (*Hypomesus transpacificus*) in the Sacramento-San Joaquin Estuary. Reviews in Fisheries Science **20**:1-19.

Miranda, J., R. Padilla, G. Aasen, B. Mefford, D. Sisneros, and J. Boutwell. 2010. Evaluation of mortality and injury in a fish release pipe. California Department of Water Resources, Sacramento, CA.

Monsen, N. E., J. E. Cloern, and J. R. Burau. 2007. Effects of Flow Diversions on Water and Habitat Quality: Examples from California's Highly Manipulated Sacramento-San Joaquin Delta. San Francisco Estuary and Watershed Science **5**.

Morinaka, J. 2013. Acute Mortality and Injury of Delta Smelt Associated With Collection, Handling, Transport, and Release at the State Water Project Fish Salvage Facility. Technical Report 89. November. Interagency Ecological Program, Sacramento.

Murphy, D. D., and S. A. Hamilton. 2013. Eastward Migration or Marshward Dispersal: Exercising Survey Data to Elicit an Understanding of Seasonal Movement of Delta Smelt. San Francisco Estuary and Watershed Science **11**.

Nobriga, M. L., T. R. Sommer, F. Feyrer, and K. Fleming. 2008. Long-Term Trends in Summertime Habitat Suitability for Delta Smelt (*Hypomesus transpacificus*). San Francisco Estuary and Watershed Science **6**.

Pikitch, E. K., C. Santora, E. A. Babcock, A. Bakun, R. Bonfil, D. O. Conover, P. Dayton, P. Doukakis, D. Fluharty, B. Heneman, E. D. Houde, J. Link, P. A. Livingston, M. Mangel, M. K. McAllister, J. Pope, and K. J. Sainsbury. 2004. Ecosystem-Based Fishery Management. Science **305**:346-347.

Rose, K. A., W. J. Kimmerer, K. P. Edwards, and W. A. Bennett. 2013. Individual-Based Modeling of Delta Smelt Population Dynamics in the Upper San Francisco Estuary: II. Alternative Baselines and Good versus Bad Years. Transactions of the American Fisheries Society **142**:1260-1272.

Schoellhamer, D. H. 2002. Variability of suspended-sediment concentration at tidal to annual time scales in San Francisco Bay, USA. Continental Shelf Research **22**:1857-1866.

Schreier, B. M., M. R. Baerwald, J. L. Conrad, G. Schumer, and B. May. 2016. Examination of Predation on Early Life Stage Delta Smelt in the San Francisco Estuary Using DNA Diet Analysis. Transactions of the American Fisheries Society **145**:723-733.

Sommer, T., C. Armor, R. Baxter, R. Breuer, L. Brown, M. Chotkowski, S. Culberson, F. Feyrer, M. Gingras, B. Herbold, W. Kimmerer, A. Mueller-Solger, M. Nobriga, and K. Souza. 2007. The Collapse of Pelagic Fishes in the Upper San Francisco Estuary. Fisheries **32**:270-277.

Sommer, T., and F. Mejia. 2013. A Place to Call Home: A Synthesis of Delta Smelt Habitat in the Upper San Francisco Estuary. San Francisco Estuary and Watershed Science **11**.

Sommer, T., F. H. Mejia, M. L. Nobriga, F. Feyrer, and L. Grimaldo. 2011. The Spawning Migration of Delta Smelt in the Upper San Francisco Estuary. San Francisco Estuary and Watershed Science **9**.

Ver Hoef, J. M., and P. L. Boveng. 2007. QUASI-POISSON VS. NEGATIVE BINOMIAL REGRESSION: HOW SHOULD WE MODEL OVERDISPERSED COUNT DATA? Ecology **88**:2766-2772.

Wilder, R. M., J. L. Hassrick, L. F. Grimaldo, M. F. D. Greenwood, S. Acuña, J. M. Burns, D. M. Maniscalco, P. K. Crain, and T.-C. Hung. 2016. Feasibility of Passive Integrated Transponder and Acoustic Tagging for Endangered Adult Delta Smelt. North American Journal of Fisheries Management **36**:1167-1177.

Zeileis, A., C. Kleiber, and S. Jackman. 2008. Regression models for count data in R. Journal of Statistical Software **27**:1-25.

Table 1. Predictor variables used to examine Delta Smelt salvage patterns.

Variable	Var Name	Data Source	Unit
1. Old and Middle River flow	OMR	Dayflow	m^3/s
2. Total SWP and CVP Exports	EXPORT	Dayflow	m^3/s
3. Previos Fall Midwater Trawl Index abundance index	FMWT	Dayflow	m^3/s
4. Clifton Court Forebay turbidity	CCFNTU	CDEC Station CLC	NTU
5.Freeport suspended sediment concentration	FSSC	USGS Station 11447650	mg/l
6. Vernalis suspended sediment concentration	Vernalis SSC	USGS Station 11303500	mg/l
7. Sacramento River Flow	SAC	Dayflow	m^3/s
8. Water Temperature at Mallard Island	Temp	CDEC Station MAL	^{0}C
9. Daily Delta precipitation at Stockton Fire Station No. 4	PREC	Dayflow	cm
10. Miscellaneous Water Diversions/Transfers	MISDV	Dayflow	m^3/s
11. San Joaquin River flow estimate past Jersey Point	WEST	Dayflow	m^3/s
12. Sacramento River flow estimate past Rio Vista	RIO	Dayflow	m^3/s
13. Net Delta outflow estimates at Chipps Island	OUT	Dayflow	m^3/s
14. Deltawide gross channel depletion estimate	GCD	Dayflow	m^3/s

15. Estimated distance from Golden Gate to 2 ppt Salinity	X_2	Dayflow	km

Table 2. Correlation matrix of physical variables used in statistical models to explore Detla Smelt salvage patterns

	VSSC	PRJEXP	PREC	MISDV	WEST	RIO	OUT	OMR	X2	GCD
FSSC	0.45	0.16	0.39	0.07	0.31	0.39	0.38	0.07	-0.26	-0.08
VSSC		0.23	0.50	0.02	0.33	0.45	0.44	0.00	-0.26	-0.15
PRJEXP			0.07	-0.02	-0.32	-0.02	-0.09	-0.66	0.00	0.04
PREC				0.01	0.44	0.42	0.44	0.08	-0.10	0.02
MISDV					0.09	0.20	0.18	0.19	-0.06	0.01
WEST						0.81	0.88	0.81	-0.69	-0.18
RIO							0.99	0.50	-0.63	-0.17
OUT								0.59	-0.67	-0.18
OMR									-0.51	-0.18
X2										0.42

Table 3. Principle component rotations used to interpret physical principle components. Only principle components with eigenvalues greater than one are shown. The tails of the distribution (5% highest and 5% lowest) of each PC's rotations are indicated in bright red, with progressively bluer shades indicating lower contributions to the principle component.

	PC1	PC2	PC3
interpretation	Outflow	Exports	GCD.Precipitation
λ	4.89	1.98	1.16
cumulative prop(var)	0.44	0.63	0.73
Freeport.SSC	0.32	0.25	0.04
Vernalis.SSC	0.33	0.28	0.07
Exports	-0.01	0.64	-0.22
PREC	0.24	0.19	0.57
MISDV	0.00	0.06	0.21
WEST	0.37	-0.26	0.20
RIO	0.42	0.12	-0.06
OUT	0.44	0.04	0.00
OMR	0.23	-0.56	0.07
X2	-0.37	0.10	0.36
GCD	-0.16	0.09	0.62

Table 4. Principle component rotations used to interpret biological community principle components. Only principle components with eigenvalues greater than one are shown. The tails of the distribution (5% highest and 5% lowest) of each PC's rotations are indicated in bright red, with progressively bluer shades indicating lower contributions to the principle component.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
interpretation	Anadromous .Catfish	CVPbullCHN. SWPbass	CVPLMBcrappie	Bull.Pminn	Blackbass. Pminn	CVPpminnSMB. SWPcrappie	SWPSMB. CVPcrappie
λ	4.53	1.72	1.42	1.21	1.06	1.02	1.01
cumulative prop(var)	0.23	0.31	0.38	0.44	0.50	0.55	0.60
ChinookSWP	0.35	-0.07	0.11	-0.14	0.11	-0.12	0.07
SthSWP	0.34	-0.03	0.21	-0.22	0.06	-0.15	0.30
StrBassSWP	0.20	-0.47	-0.18	-0.16	0.07	0.04	0.02
WhCatSWP	0.34	-0.18	0.12	0.10	0.05	0.12	-0.05
BrBullheadS	0.13	-0.20	0.06	0.44	0.00	0.20	0.16
ChanCatSWP	0.32	-0.22	0.11	0.06	0.06	0.14	-0.10
PikeMinnowS	0.08	-0.16	0.05	0.43	-0.25	-0.01	0.14
BlackCrappie	0.08	-0.29	-0.08	0.27	0.04	-0.41	0.16
LgMouthBass	0.02	-0.35	-0.23	-0.01	0.32	-0.10	-0.18
SmMouthBas	0.03	-0.05	0.02	-0.14	0.28	-0.29	-0.61
ChinookCVP	0.28	0.35	0.00	-0.04	0.12	-0.15	0.01
SthCVP	0.28	0.21	0.17	-0.30	-0.02	-0.19	0.28
StrBassCVP	0.34	0.06	-0.27	-0.08	-0.14	0.07	-0.13
WhCatCVP	0.32	0.21	-0.19	0.19	-0.16	0.14	-0.27
BrBullheadC	0.07	0.34	-0.19	0.34	0.25	0.00	0.00
ChanCatCVP	0.30	0.22	-0.10	0.09	-0.12	0.20	-0.18
PikeMinnow	0.00	0.19	-0.06	0.36	0.45	-0.38	0.12
BlackCrappie	0.02	0.04	-0.53	-0.12	-0.01	-0.04	0.42
LgMouthBass	-0.01	-0.05	-0.59	-0.15	-0.01	0.05	0.03
SmMouthBas	0.02	-0.03	-0.07	0.07	-0.62	-0.60	-0.18

Table 5. Correlation matrices of Principle Components.

	Phy.PC.Exports	Phy.PC.GCD.Precipitation	Bio.PC.Anadr.Catfish	Bio.PC.CVPbullCHN.SWPbass	Bio.PC.CVPLMBcrappie	Bio.PC.Bull.Pminn	Bio.PC.Blackbass.Pminn	Bio.PC.CVPpminnSMB.SWPcrappie	Bio.PC.SWPSMB.CVPcrappie
Phy.PC.Outflow	0.00	0.00	0.99	0.22	0.06	0.20	0.06	-0.03	0.03
Phy.PC.Exports		0.00	-0.08	-0.27	-0.27	-0.18	0.00	0.07	-0.05
Phy.PC.Precipitation			-0.01	-0.09	-0.11	0.12	-0.02	0.09	-0.19
Bio.PC.Anadr.Catfish				0.32	0.09	0.26	0.07	-0.04	0.03
Bio.PC.CVPbullCHN.SWPbass					0.00	0.00	0.00	0.00	0.00
Bio.PC.CVPLMBcrappie						0.00	0.00	0.00	0.00
Bio.PC.Bull.Pminn							0.00	0.00	0.00
Bio.PC.Blackbass.Pminn								0.00	0.00
Bio.PC.CVPpminnSMB.SWPcrappie									0.00

Table 6. Relative influence of all predictor variables in models fit to the full dataset or only "first flush" period data (25th percentile). Only variables with at least 5% of the influence were ranked; other variables were considered insignificant.

Variable	Relative influence (Rank) full dataset	Relative influence (Rank) 25th percentile
Phy.PC.Exports	0.25 (1)	0.24 (2)
PFMWT	0.20 (2)	0.19 (1)
Bio.PC.Bull.Pminn	0.11 (3)	0.19 (3)
Julian.day	0.10 (4)	0.05 (4)
Phy.PC.Outflow	0.07 (5)	0.05 (8)
Water.Temp	0.05 (6)	0.05 (5)
Phy.PC.GCD.Precipitation	0.05 (7)	0.06 (6)
Bio.PC.SWPSMPcrappie	-	-
Bio.PC.SWPbass	-	-
Bio.PC.Blackbass	-	-
Bio.PC.CVPpminnSMB.SWPcrappie	-	-
Bio.PC.CVPcrappieLMB	-	-

Table 7. Negative binomial (A) and GAM (B) output for statistical models exploring factors that explain cumulative 25th percentile Delta Smelt salvage patterns. Values in italics indicate best models based on AIC scores. Significant parameters (P< 0.05) within each model are indicated in bold.

A.

Model Parameters	Deviance Explained	AIC	ΔAIC
Exports	12.9	4363	404
Exports + log(PFMWT)	15.9	4343	384
Exports + log(PFMWT) + SAC	22.2	4296	337
Exports + log(PFMWT) + SAC + DecmeberX2	23.0	4045	86
Exports + log(PFMWT) + SAC + DecmeberX2 + CCFNTU	23.9	4041	82
Exports + log(PFMWT) + SAC + *DecmeberX2* ***+ CCFNTU +*** *WaterTemp*	***24.7***	***3959***	
Exports + log(PFMWT) + SAC *+ DecmeberX2* ***+ CCFNTU +*** *WaterTem**p +** VernalisSSC*	***25.0***	***3961***	***2***

B.

Model Parameters	Deviance Explained	AIC	ΔAIC
s(Exports)	23.5	54833	34027
s(Exports) + log(PFMWT)	28.8	51128	30322
s(Exports) + log(PFMWT) + s(SAC)	49.4	39820	19014
s(Exports) + log(PFMWT) + s(SAC)+ s(DecmeberX2)	59.9	30098	9292
s(Exports) + log(PFMWT) + s(SAC) + s(DecmeberX2) + s(CCFNTU)	60.7	27955	7149
s(Exports) + log(PFMWT) + s(SAC) + s(DecmeberX2) + s(CCFNTU) + s(WaterTemp)	69.9	21388	582
s(Exports) + log(PFMWT) + s(SAC) + s(DecmeberX2) + s(CCFNTU) + s(WaterTemp) + s(VernalisSSC)	***70.7***	***20806***	

Table 8. Negative binomial (A) and GAM (B) output for statistical models exploring factors that explain cumulative 50th percentile Delta Smelt salvage patterns. Values in italics indicate best models based on AIC scores. Significant parameters (P< 0.05) within each model are indicated in bold.

A.

Model Parameters	Deviance Explained	AIC	ΔAIC
Exports	26.0	6662	643
Exports + log(PFMWT)	27.0	6535	516
Exports + log(PFMWT) + SAC	27.0	6537	518
Exports + log(PFMWT) + SAC + DecmeberX2	31.3	6484	465
Exports + log(PFMWT) + SAC + DecmeberX2 + CCFNTU	32.9	6186	167
Exports + log(PFMWT) + SAC + DecmeberX2 + CCFNTU + WaterTemp	***33.5***	***6019***	
Exports + log(PFMWT) + SAC + DecmeberX2 + CCFNTU + WaterTemp + VernalisSSC	***33.5***	***6020***	***1***

B.

Model Parameters	Deviance Explained	AIC	ΔAIC
s(Exports)	30.4	10762 6	64706
s(Exports) + log(PFMWT)	42.0	90114	47194
s(Exports) + log(PFMWT) + s(SAC)	48.8	79803	36883
s(Exports) + log(PFMWT) + s(SAC)+ s(DecmeberX2)	63.2	58019	15099
s(Exports) + log(PFMWT) + s(SAC) + s(DecmeberX2) + s(CCFNTU)	65.6	53557	10637
s(Exports) + log(PFMWT) + s(SAC) + s(DecmeberX2) + s(CCFNTU) + s(WaterTemp)	71.2	44458	1538
s(Exports) + log(PFMWT) + s(SAC) + s(DecmeberX2) + s(CCFNTU) + s(WaterTemp) + s(VernalisSSC)	***72.1***	***42920***	

Table 9. GLM (A) and GAM (B) output for statistical models exploring factors that explain annual Delta Smelt salvage patterns. Values in italics indicate best models based on AIC scores. Significant parameters (P< 0.05) within each model are indicated in bold.

A.

Model Parameters	Adjusted r^2	AIC	ΔAIC
Exports	0.32	62.88	18.13
Exports + log(PFMWT)	0.65	48.57	3.82
Exports + log(PFMWT) + SAC	*0.71*	*44.75*	
Exports + log(PFMWT) + SAC + DecmeberX2	0.70	46.41	1.66
Exports + log(PFMWT) + SAC + DecmeberX2 + CCFNTU	0.69	48.22	3.47
Exports + log(PFMWT) + SAC + DecmeberX2 + CCFNTU + WaterTemp	0.70	47.66	2.91
Exports + log(PFMWT) + SAC + DecmeberX2 + CCFNTU + WaterTemp + VernalisSSC	0.72	46.85	2.1

B.

Model Parameters	Deviance explained	AIC	ΔAIC
Exports	42.75	61.443	13.76
Exports + log(PFMWT)	50.85	59.403	11.72
Exports + log(PFMWT) + SAC	71.17	53.616	5.933
Exports + log(PFMWT) + SAC + DecmeberX2	73.01	53.077	5.394
Exports + log(PFMWT) + SAC + DecmeberX2 + CCFNTU	74.07	50.763	3.08
Exports + log(PFMWT) + SAC + DecmeberX2 + CCFNTU + WaterTemp + **VernalisSSC**	83.31	47.683	

Figure 1. Revised conceptual model of factors and drivers influencing Delta Smelt salvage at the SWP and CVP.

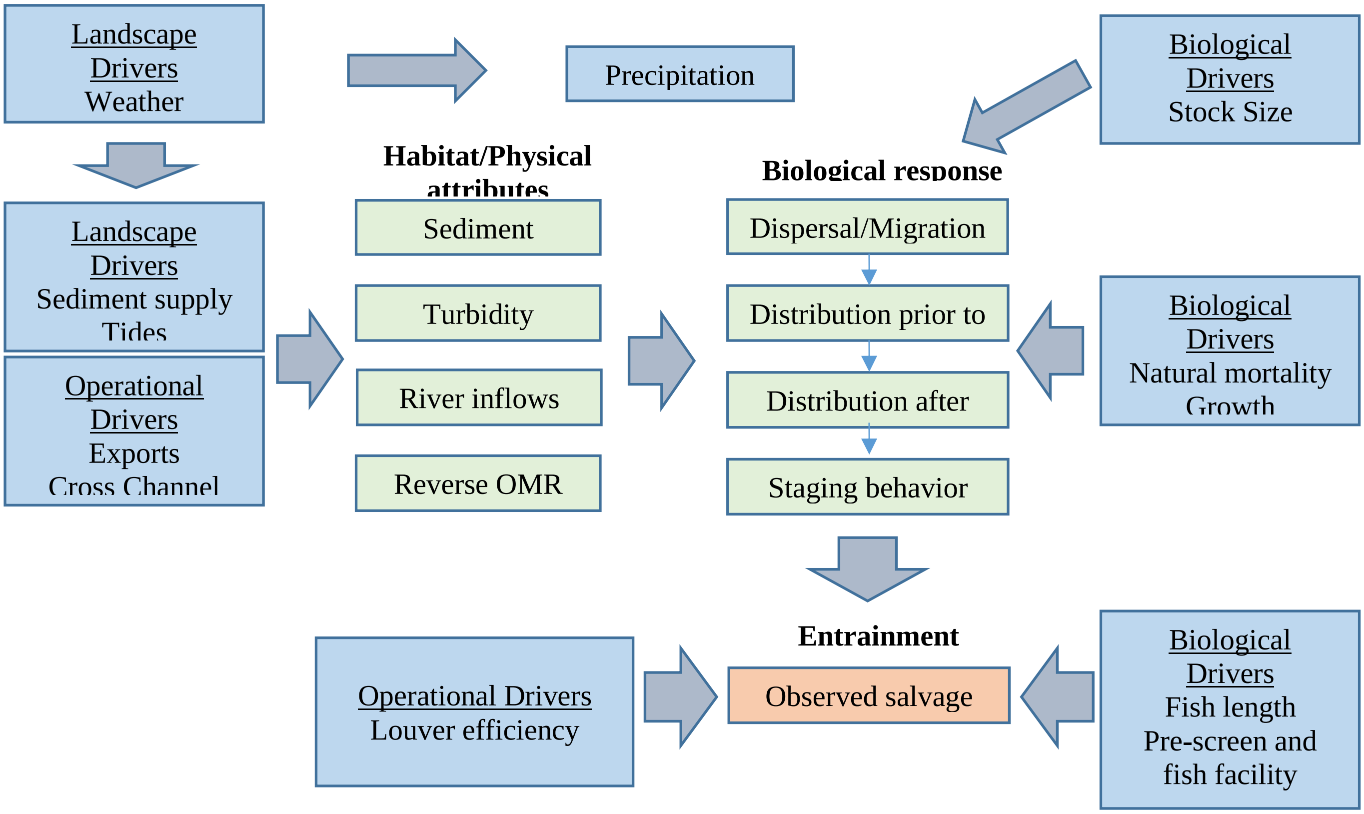

Figure 2. Map of the Upper San Francisco Estuary and Sacramento-San Joaquin Delta. Needs to be updated in revision.

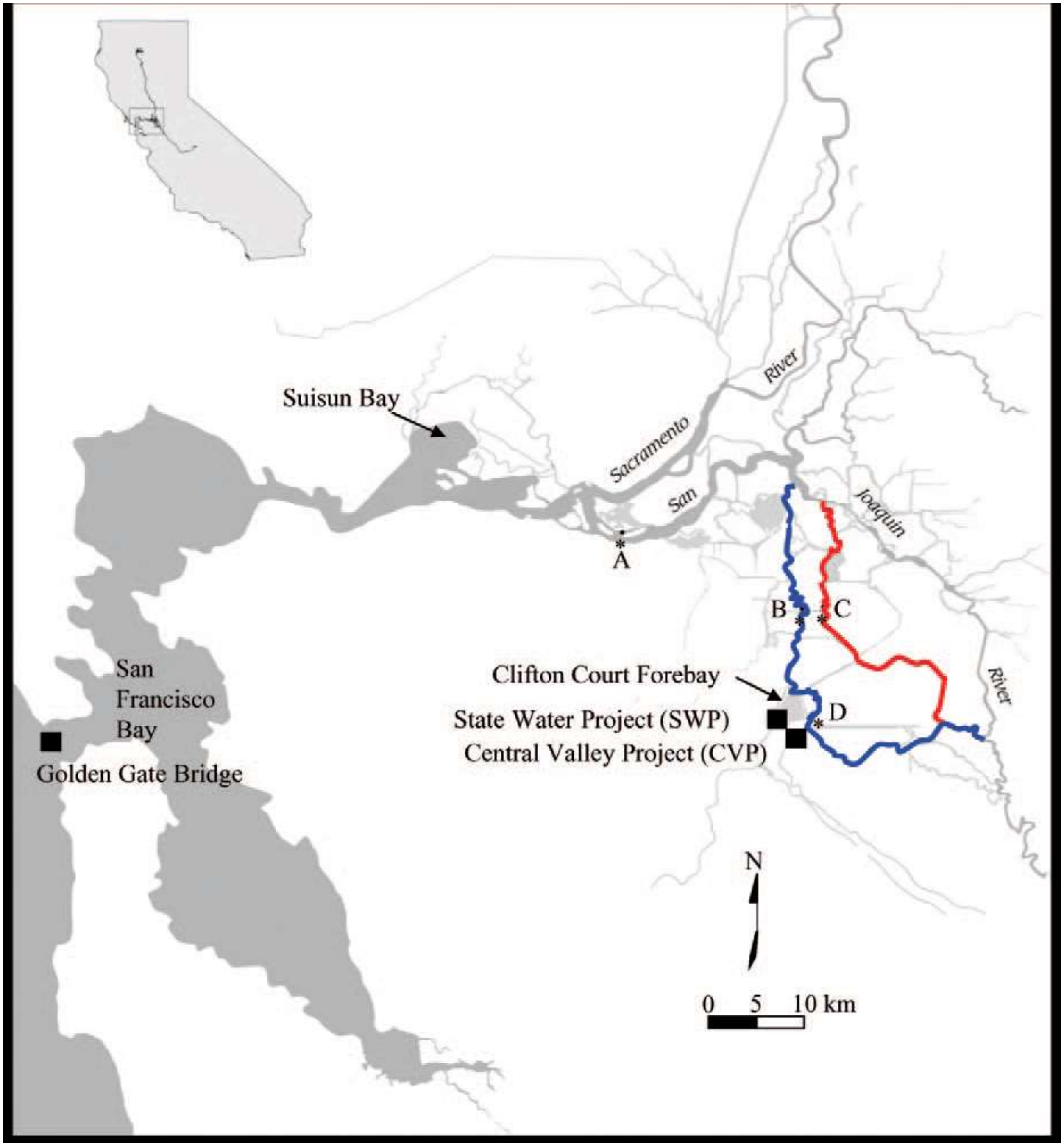

Figure 3. Relationship between the four physical PCs retained for BRT analysis and the primary physical variable loading on each PC. All variables were log transformed for normality.

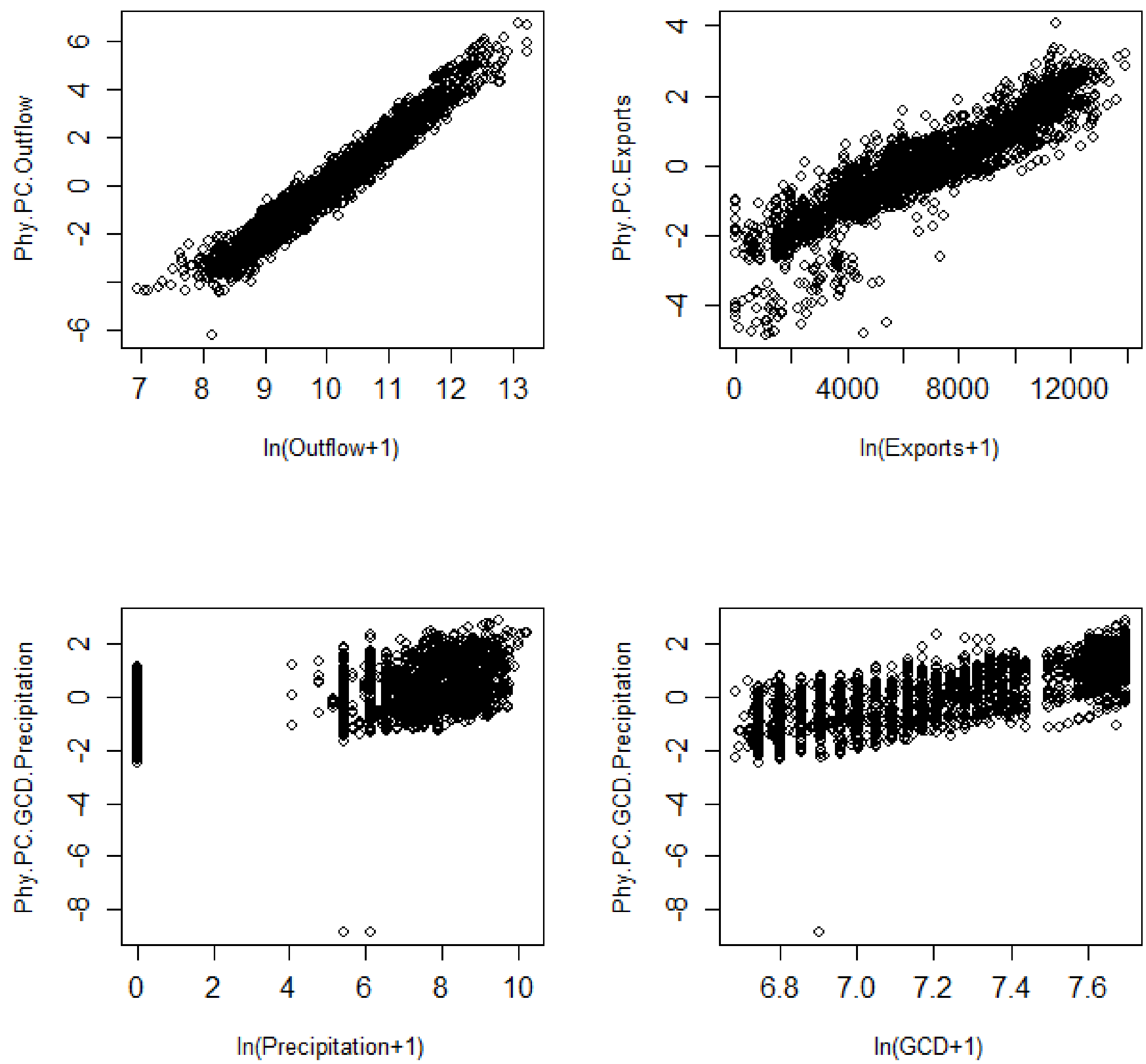

Figure 4. Boosted regression tree estimates of the magnitude of salvage at annual (A) and 25th percentile (B) annual response levels . Only the most influential variables are shown. Estimates represent expected salvage across the range of observed variable values, while holding all other variables at their means. Rug plots indicate observed variable values

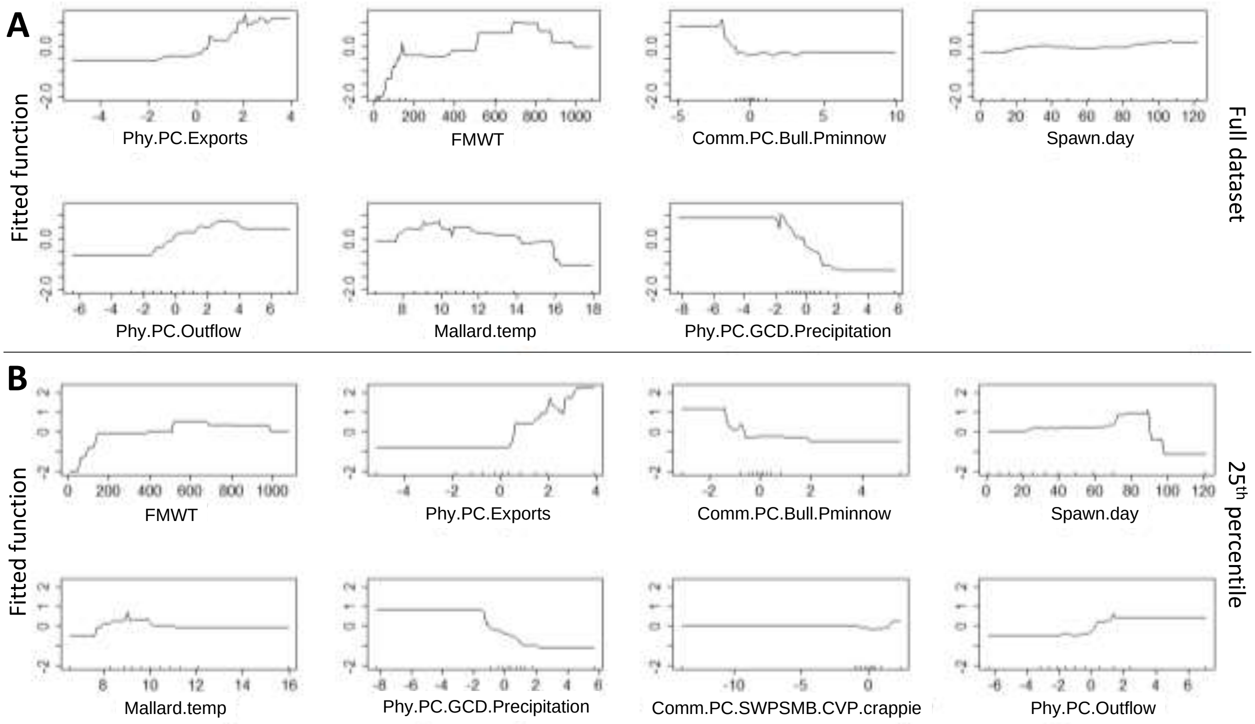

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Figure 5. The three most important two-way interactions between physical variables.

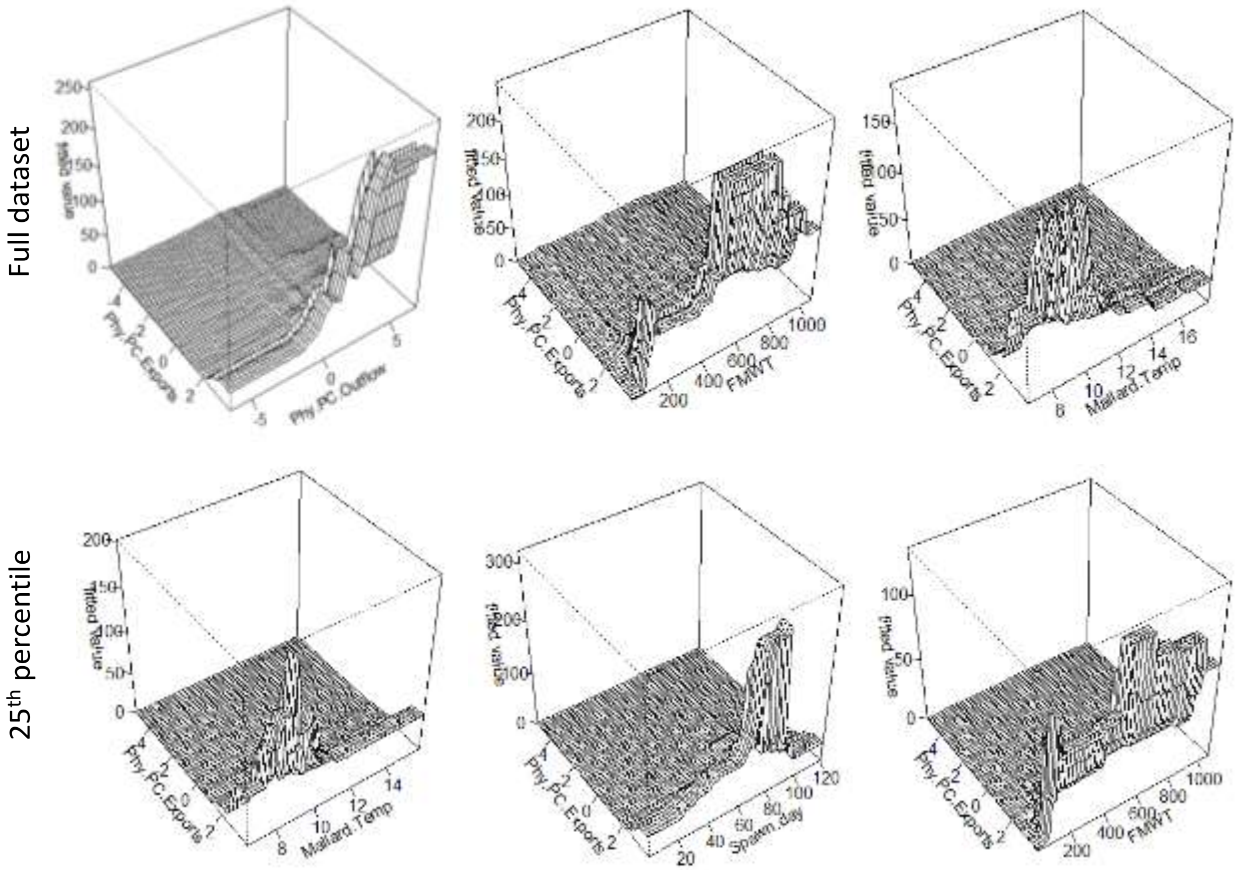


Figure 6. Plots showing the relationships between Delta Smelt salvage (cumulative 50th percentile, see text for details) and continuous predictor variables. Plots are fitted smooths and 95% confidence intervals for partial responses from generalized additive models. The y axis units are centered on zero and the number in the label is the estimated degrees of freedom of the smooth. Variables are explained in Table 1.

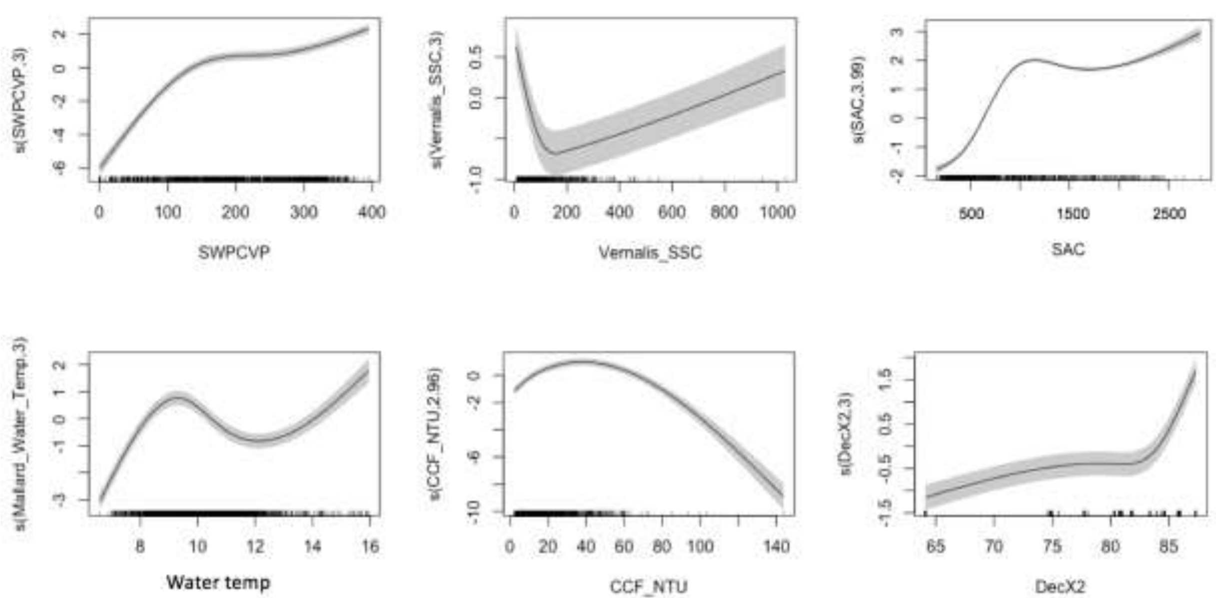
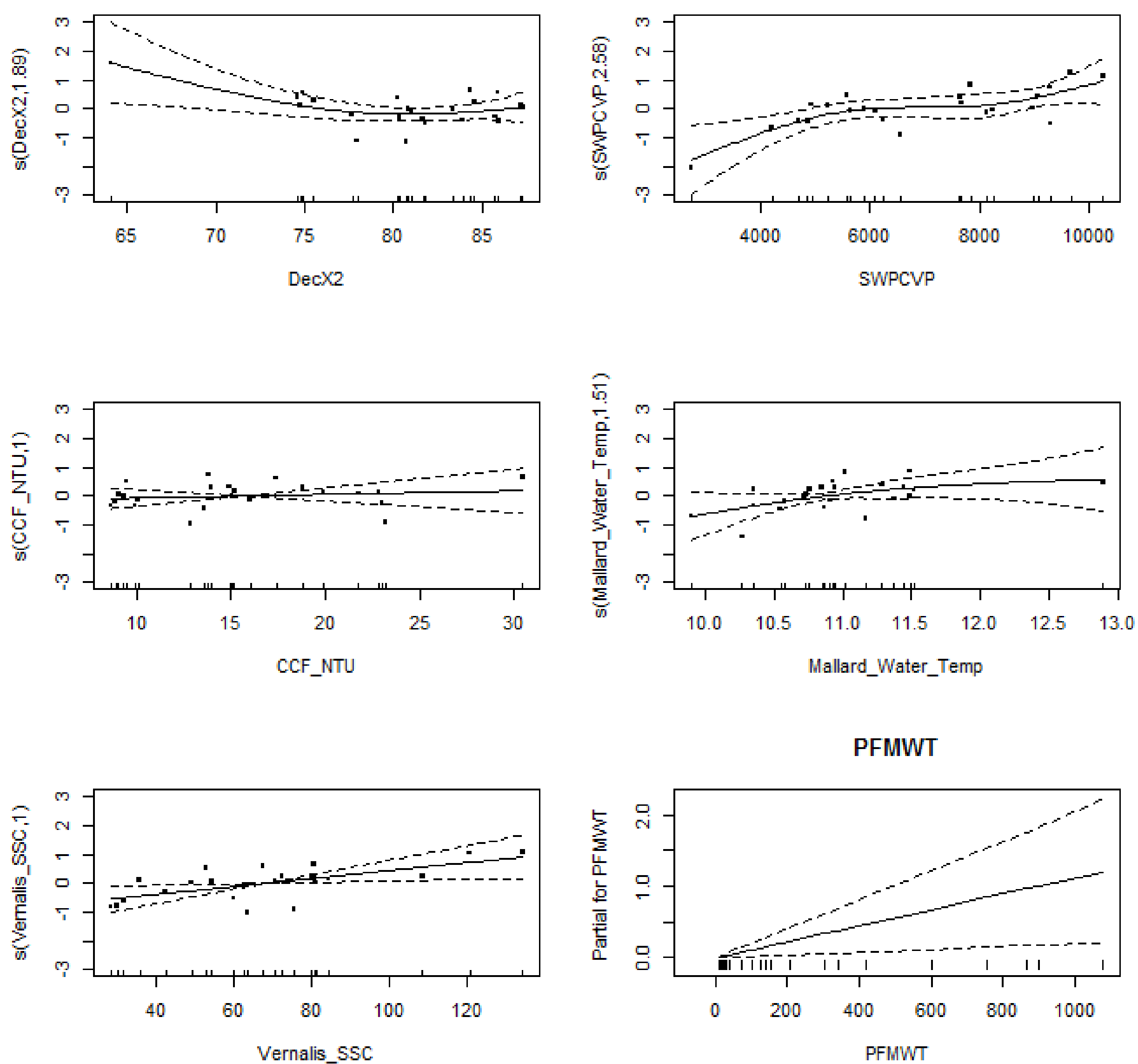


Figure 7. Plots showing the relationships between Delta Smelt annual salvage patterns and continuous predictor variables. Plots are fitted smooths and 95% confidence intervals for partial responses from generalized additive models. The y axis units are centered on zero and the number in the label is the estimated degrees of freedom of the smooth. Variables are explained in Table 1.



After the Storm: Re-Examining Factors that Affect Delta Smelt (*Hypomesus transpacificus*) Entrainment in the Sacramento and San Joaquin Delta

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Running page head: Delta Smelt salvage dynamics

Abstract

Managing endangered species presents many challenges when it becomes difficult to detect their presence in the wild. In the San Francisco Estuary, the state- and federally-listed Delta Smelt (*Hypomesus transpacificus*) has declined to record low numbers, which has elevated management concern over their entrainment at State Water Project (SWP) and Central Valley Project (CVP) water diversions. The objective of this paper was to: 1) revisit previous work on factors that affect the number of adult Delta Smelt collected (also known as "salvage) at the SWP and CVP fish screens with updated conceptual models and new statistical approaches; and 2) to determine factors that affect salvage risk at time scales useful for resource managers. Boosted Regression Tree (BRT) models were applied to the salvage data to determine if the factors that best explained salvage during the onset of winter storms ("first flush") differed from those that explained salvage over the season when adult Delta Smelt are vulnerable to salvage. Salvage from the SWP and CVP were examined separately because it was hypothesized that different factors could influence fish distribution and the collection efficiency of each facility. During first flush periods, salvage at each facility was best explained by water exports (sampling effort), precipitation (recently linked to movement and vulnerability to offshore trawling gear), abundance and Yolo Bypass flow. During the entire adult salvage season, SWP salvage was best explained by SWP exports, Yolo Bypass flow, and abundance whereas CVP salvage was best explained by abundance, Old and Middle River flows, and turbidity. This study suggests that adult Delta Smelt salvage is influenced by hydrodynamics, water quality, and population abundance The model approaches applied here offer an improvement from earlier approaches because they integrate and account for complex interactions between water exports and factors that operate independent of water exports. Forecast models that integrate real-time explanatory variables with fish distribution data may improve management strategies for minimizing salvage risk while maintaining operational flexibility.

Introduction

Over the last couple of decades, fisheries management has redirected its focus from individual species to broader ecosystem objectives to address inherent complexities of aquatic environments (Link 2002, Hall and Mainprize 2004, Pikitch et al. 2004). For rare species, management objectives that focus on restoring ecosystem functions are considered desirable because they emphasize mechanisms that influence species survival and growth rather than counts of individuals, which may be difficult to detect as population numbers decline. For species listed under the federal Endangered Species Act (ESA), the law allows for recovery actions to be carried out through robust adaptive management plans that include consideration of habitat quality and quantity, reduced exposure to predators and contaminants, and improved access to rearing habitats. However, the ESA also requires that incidental take[1] of endangered species be reasonably minimized or avoided where possible. Conservation plans that can confidently assess and predict when listed fish species are likely to be encountered may help speed species recovery (Pikitch et al. 2004).

In the upper San Francisco Estuary, (CA), national attention has been drawn to Delta Smelt (*Hypomesus transpacificus*), a small endangered fish whose numbers have declined to record low levels (Sommer et al. 2007; Moyle et. al. 2016). Found nowhere else in the world, Delta Smelt seasonally reside within the hydrodynamic influence of two large water diversions that provide municipal water for over 25 million Californians (State Water Project, SWP) and support a multibillion dollar agricultural industry (Central Valley Project, CVP). When Delta Smelt are located near the SWP and CVP pumps, the United Fish and Wildlife Service (USFWS) imposes flow limits that can result in water diversion reductions to minimize entrainment losses (USFWS 2008). Entrainment losses have accounted for significant population losses in some years (Kimmerer 2008, Kimmerer 2011). Statistical evaluations have indicated that entrainment losses, along with declining food supply and loss of habitat, have had adverse effects on Delta Smelt's population growth rate (Mac Nally et al. 2010, Kimmerer 2011, Maunder and Deriso 2011, Rose et al. 2013). An improved understanding of the mechanisms and factors that affect Delta Smelt entrainment is of high importance to natural resource managers, scientists and stakeholders who seek to both protect rare species and provide a reliable water supply to the people and agricultural communities of California.

Delta Smelt is an annual species whose adult relative abundance has historically been estimated by a multi-month trawl survey during the fall (Thomson et al. 2010). This survey has usually concluded shortly before adult Delta Smelt begin to become lost to entrainment (Kimmerer 2008, Grimaldo et al.

[1] Federal ESA incidental take is defined as to harass, harm, pursue, hunt, shoot, wound, kill, trap, capture, or collect any threatened or endangered species (USFWS 1973)

2009). However, major declines in the species have made it difficult to determine the abundance and distribution of this fish from this long-term survey (Latour 2015). Therefore, an assessment of water diversion impacts to the Delta Smelt population are difficult to estimate, particularly at time scales relevant to the co-management of the species' protection and water export. Thus, managers and scientists must also consider conditions that are likely to produce higher entrainment risk based on historical relationships between salvage and physical-biological factors (Brown et al. 2009, Grimaldo et al. 2009).

In this paper, the factors known to affect adult Delta Smelt salvage at the SWP and CVP (Kimmerer 2008, Grimaldo et al. 2009, Miller 2011, Miller et al. 2012, Interagency Ecological Program 2015) are revisited with new information to test the ability of several modern statistical approaches to predict the conditions that most influence Delta Smelt entrainment risk. Note, the goal here is not to determine proportional entrainment losses (i.e., fish entrained as a fraction of the population) or the effects of entrainment losses to the population - both of which have been examined previously (Kimmerer 2008, Kimmerer 2011, Maunder and Deriso 2011, Miller 2011, Rose et al. 2013). The goal here is to determine how well entrainment risk, as indexed by the number fish observed at the louver screens (known as "salvage"), could be quantified at time scales relevant to management. Our specific study questions were the following: 1) What subset of factors best predict salvage the SWP and CVP? 2) Does analysis at a seasonal time step similar to Grimaldo et al. 2009 produce qualitatively different results than an analysis that focuses on first flush? 3) Does accounting for autocorrelation in the salvage data improve model fit? 4) How well can SWP and CVP salvage be forecasted? Our hope was that addressing these questions would help resource managers improve real-time management actions to limit the entrainment of Delta Smelt, while also providing maximum operational flexibility for the SWP and CVP water projects (hereafter referred as the "Projects").

Methods

Study approach

Because one of the goals of this paper was to develop a model or set of models useful for understanding entrainment risk in real-time, only independent variables that are measured at daily or sub-daily increments *and* are readily accessible for download in real-time were used in the analysis (Table 1). Physical and biological variables used in statistical models of Delta Smelt salvage included those used by Grimaldo et al. (2009) and new ones identified in more recent conceptual models (Miller 2011; MAST 2015). Overall, the analysis was designed to test hypotheses about how Delta Smelt salvage is expected to responde to hydrodynamics, hydrology, distribution, adult stock size, and water quality. Food abundance and predator abundance have been identified has potentially important variables that influence adult Delta

Smelt salvage (Miller 2011) but data on these variables are not collected in sufficient temporal or spatial scales to make them useful for the analyses presented here.

Inspection of the daily adult Delta Smelt salvage data (1993-2016) shows that the vast majority of adult Delta Smelt salvage occurs between December 1st and March 31st. Thus, consistent with Grimaldo et al. (2009), daily cumulative salvage from December 1st and March 31st was aggregated into as seasonal response variable for the analysis. A first flush response variable was also created for this analysis from the seasonal data set. First flush events occur in association with the first major winter storm of the season (Bergamaschi et al. 2001); these events have been identified as triggers of high salvage in some years (Grimaldo et al. 2009). The first flush response variable was constructed by only including salvage from December 1st to the date that daily cumulative salvage reached its 50th percentile for the season (i.e., the seasonal midpoint of salvage). We reasoned the accelerating part of the seasonal salvage trends would best represent the environmental conditions that lead to entrainment events of high concern to managers. Finally, models were applied to each fish facility separately to examine if patterns that underlie salvage were influenced by different factors since the SWP export capacity (292 m^3/s) is almost two and half times greater than the CVP export capacity (130 m^3/s). Also, although the SWP and CVP intakes are located relatively close to each other (< 3 km), the SWP differs from the CVP in having a large regulating reservoir known as the Clifton Court Forebay (CCF) that temporarily stores water from Old River to improve operations of the SWP pumps. Pre-screen losses of entrained fish to milling predators are higher at the SWP compared to the CVP because the CCF supports high predator densities which can result in poor survival of fish through the shallow water leading up to the fish screens (Gingras 1997, Castillo et al. 2012). Thus, the two projects have the potential to observe different responses in salvage. Understanding the factors that affect salvage at each Project separately may shed light on finer scale dynamics useful for management applications.

Data sources

Project intakes are located in the southern Sacramento-San Joaquin Delta (Fig. 1). As previously mentioned, both the SWP and CVP have large fish screens at their intakes designed to save or “salvage” entrained fish. The SWP Skinner Fish Protective Facility (SFPF) and the CVP Tracy Fish Collection Facility (TFCF) direct fish through a complex louver system into collecting screens where they are eventually trucked and released back into the environment downstream from the SWP and CVP. A subsample of the salvaged fish are identified and measured. A variable fraction of Delta Smelt may survive the capture, handling, trucking and release process (Miranda et al. 2010, Morinaka 2013).

The fish salvage facilities have been operating almost daily for the last few decades at the TFCF (since 1958) and SPFF (since 1968; Brown et al. 1996). Arguably, they are two of the largest fish sampling systems in the world. Up until the early 1990’s, salvage counts and identification were focused on salmonids and striped bass (*Morone saxatilis*). However, after Delta Smelt were listed in 1993, focus on proper identification and detections resulted in a change in count frequency from twice per day (1978 to 1992) to every two hours thereafter (Morinaka 2013). Daily salvage for each species per day for each facility is calculated by the following equation:

$$Sd = \sum_{i=0}^{n} si = Ci * (\frac{mpi}{ti})$$

where *Sd* is the total daily salvage, *si* is the salvage per sample, *Ci* is the number of fishes in a sample defined by the minutes of water pumped (*mpi*) per the counting time (*ti*). Typically, there are six sample periods per day and twenty individuals per species greater than 20 mm fork length (FL) are measured. Salvage data for Delta Smelt and other species used in the analysis were obtained from the California Department of Fish Wildlife (CDFW) ftp site (ftp://ftp.dfg.ca.gov/Delta%20Smelt/). Delta Smelt adult abundance estimates from the CDFW's FMWT monitoring survey were obtained from the same ftp site.

Flow and water quality data were obtained from the California Department of Water Resources (CDWR) and United States Geological Survey website portals (www.water.ca.gov/dayflow/; http://cdec.water.ca.gov; http://waterdata.usgs.gov/ca/nwis/).

Statistical analyses

Adult Delta Smelt salvage data were first explored using Boosted Regression Tree (BRT) models. Regression trees seek to model a response variable using one or more predictor variables; data is recursively partitioned into a hierarchy of subsets, and the regression tree describes the structure of the hierarchy. The goal is to reduce multidimensional space into smaller subsets that can be described by very simple models. Regression trees split into branches at nodes, where nodes represent a value of a single predictor variable. Leaves on the branches represent a single value of predicted response over a range of the predictor variable, until the next node. To fit a regression tree, an algorithm identifies regions of greatest variance in the relationship of response and predictors as potential nodes. Between nodes, model predictions or leaves are simply the response that minimizes residual error (e.g. the mean), conditional on prior tree nodes and the path from the tree root. Regression trees can accommodate many distributions (binomial, normal, Poisson, etc.) and are generally insensitive to outliers (Elith et al. 2008), and they are suited to non-linearity in the response. Regression trees can be unstable with small datasets, because small changes in training data can result in large changes in tree splits (Hastie et al. 2001).

The boosting paradigm is that model performance is improved by averaging across many moderately fitting models rather than selecting a single or small group of perfectly fit models (Elith et al. 2008). While traditional model selection approaches seek to identify a parsimonious model with few parameters, boosting approaches seek to fit many parameters and shrink their contribution, similar to regularization methods (Hastie et al. 2001). Boosting is an ensemble method like model averaging, but the process is sequential and iteratively minimizes a loss function (deviance; analogous to sum of squared error). At first iteration, the boosted regression tree (BRT) is the best-fitting regression tree. At second iteration, the regression tree that best fits the residuals of the first is added to the BRT. This sequence proceeds until deviance is minimized and adding more trees results in greater deviance. The contribution of each tree to the BRT is limited or shrunk by the learning rate, and up to several thousands of trees are commonly fit and added to produce the final BRT.

Although the BRT allows for inclusion of multiple correlated variables, potential explanatory variables were screened for collinearity ($R^2 > 0.6$; Table 2) to reduce the number of predictors. If two variables were highly correlated, only the variable with the strongest conceptual link to salvage was selected for further inclusion. We reasoned that this would increase our ability to mechanistically interpret the results. SWP and CVP Project exports and Old and Middle River flows (OMR; see Grimaldo et al. 2009) were both examined in the BRT because both have potentially important applications for management targets. Four alternative combinations of data were explored to determine whether any combination improved model performance above other combinations: SWP and CVP exports as individual effects, combined SWP and CVP exports, OMR flow and San Joaquin River. The best combination of data, as indicated by percent of null deviance explained, was used for inference.

The boosted regression tree model was fit using R package dismo and the gbm.step function (R Development Core Team 2008). The gbm.step function used ten-fold cross validation to determine the optimal number of regression trees to fit. Trees were added until a deviance minimum was reached. Learning rate was set to the lowest rate that reached a deviance minimum with between 1,000 and 2,000 trees ($0.01 > l_r > 0.1$), and two-way interactions were modeled (tree complexity = 2). Half of the data were bagged as a training set at each iteration of the regression tree.

Diagnostics

The fit of models and residual error distributions were graphically checked with plots of observed versus predicted salvage and plots of model residuals versus observed salvage. In order to test the predictive capabilities of the model, an annual cross validation was performed by sequentially omitting five randomized years of data, refitting the model to the incomplete dataset, and predicting the missing salvage observations. Similarly, the fitted model was used to predict salvage using new, preliminary hydrodynamics data for Water Year 2017, including December 2016 through March 2017. If the model accurately predicted missing or new salvage observations, it was accepted as a predictive model of salvage; however, if the model did not accurately predict missing or new salvage observations, it could only provide an analysis of historical salvage.

Results

Salvage patterns and variable selection

In total, 2,911 days of observed salvage and corresponding explanatory variables, representing 24 years of adult Delta Smelt salvage were analyzed. Salvage at both Projects showed a marked decline after 2005 (Fig. 2). Correlation analysis of potential explanatory variables indicated that only OMR and San Joaquin River flow exceeded the threshold of $R^2 = 0.6$, so OMR and San Joaquin River flow were not included in the same dataset. Variables representing the day index and cumulative precipitation were somewhat correlated, and multicollinearity was apparent among all river flow variables (Table 2).

Boosted Regression Trees

Of the five alternative data combinations for deciding which Project export metrics to include (e.g., SWP plus CVP exports, SWP exports, CVP exports, OMR flow, and San Joaquin River flow), none explained a significantly greater percentage of observed salvage using either the data aggregated at the seasonal level or at the 50th percentile (Table 3). Therefore, separate SWP and CVP water exports data were used to fit the final model because they are more directly linked to our study questions for looking at the factors that affect salvage at each project separately. OMR was included because it has been used in previous examinations of adult Delta Smelt salvage (Grimaldo et al. 2009), is a management quantity (FWS 2008), and has a more direct effect on hydrodynamics experienced by Delta Smelt during entrainment.

BRT models of salvage indicated that regardless of time scale – first flush or entire adult salvage period – the best predictors of salvage at both Projects were prior FMWT, combined SWP and CVP exports, OMR, and South Delta turbidity (Table 4). Variation in Yolo Bypass flow, at the lower end of the Yolo flow distribution, was also a good predictor of salvage at both Projects (Fig. 3). In general, more variables appeared to influence CVP salvage, while only a few variables were influential predictors of SWP salvage. No individual predictor was associated with substantial variation in salvage, as indicated by the scale of predicted salvage (Fig. 4); however, substantial variation in predicted salvage resulted from various combinations of, or interactions between predictors (Fig. 5).

Comparison of influential predictors between the full dataset and the 50th percentile dataset indicated a difference in the first flush response observed in CVP salvage but little difference between SWP first flush salvage and salvage throughout the adult salvage season. Cumulative precipitation was a more influential predictor of SWP and CVP salvage during the first flush period, while turbidity was somewhat less influential during the first flush period than when considered across the entire season. Of less influence during the first flush period at the CVP were gross channel depletion, Cosumnes River flow, and CVP exports.

Although BRT models explained a large proportion of null deviance (94-86%), predictive performance was poor when entire years were removed and predicted from a model fit to other years. Of five sequentially omitted years, the highest R^2 values were for omitted year 2010 ($R^2 = 0.20 – 0.36$ for SWP and CVP models, respectively), and R^2 values for all other omitted years were less than 0.1 (Table 5).

Discussion

This study reinforces previous work that adult Delta Smelt salvage is largely explained by hydrodynamics (including Project exports and river inflows), water clarity (turbidity), precipitation, and adult abundance. However, the approach applied here provides an improved understanding of salvage risk for each Project separately and helped identify differences in the factors that influence salvage during first flush and over the season. Moreover, the statistical approach applied here is more robust than previous approaches (Grimaldo et al. 2009) which allows for stronger inference regarding the importance of factors that have led to salvage events during the previous 24 years. Key study findings are further discussed under key category of effects.

Hydrodynamic effects: It is not surprising that adult Delta Smelt salvage increases with SWP exports. SWP efforts are almost two and half times higher than the CVP, largely responsible for net reverse tidal flows in the south Delta during high Project exports (Arthur et al. 1996, Monsen et al. 2007). As previously mentioned, in some years, adult Delta Smelt move into the south Delta where they become more vulnerable to water exports because they become distributed within the hydrodynamic "footprint" of the Projects where the net movement of water is toward the pumping plants. Higher SWP exports contributes to proportionally lower residence time of south Delta water towards the Projects (Kimmerer and Nobriga 2008). Thus, any adult Delta Smelt that move into the channels during first flush periods become increasing vulnerable to salvage as Project exports increase, which may explain the sharp peaks (1-2 weeks duration) in adult Delta Smelt salvage in some years (Fig. 2). Delta Smelt may also experience reduced rates of predation during higher exports because of faster hydraulic residence time in the Old and Middle river channels that lowers exposure time as fish travel through channels toward the SWP and CVP fish facilities. Juvenile Chinook salmon incure lower mortality rates to predators in the south Delta when Project exports are high and hydraulic residence times are short (Cavallo et al. 2013).

What was surprising, was finding that CVP exports actually played a minor influence in directly affecting CVP salvage and that it had no detectable influence on SWP salvage. OMR flows had a higher influence on CVP salvage, moreso than even CVP exports, suggesting an indirect influence of SWP and CVP efforts as they both contribute to net reverse flows in the south Delta (Monsen et al. 2007). But the influence of OMR flow could also be related to San Joaquin River flow dynamics, especially for Delta Smelt that may take multiple routes to the salvage facilities. For example, it is generally assumed that

Delta Smelt largely move to the fish facilities via Old and Middle Rivers (Fig. 1). There are a number of routes that adult Delta Smelt can take to reach the fish facilities and even local dispersion around Project intakes themselves could influence which fish reach the CVP. OMR flows may have more of a mechanistic explanation for why adult Delta Smelt arrive at the CVP.

OMR flows have been used as metric for management of adult entrainment risk, because the magnitude of salvage observations was related to OMR in the US Fish and Wildlife's 2008 Biological Opinion (FWS 2008). Confirming those findings, BRT models of both CVP and SWP expected salvage increased at OMR < -5,000 cfs, when all other variables were held at their averages. Whle OMR flow was the second most important predictor of CVP salvage, more important than even CVP exports, the OMR threshold of -5,000 cfs was most notable in SWP salvage.

The importance of Yolo Bypass flow to SWP salvage may be less related to hydrodynamic effects and more related to changes in Delta-wide turbidity. The Yolo Bypass drains several smaller river tributaries and an inundated floodplain under high Sacramento River flow (Sommer et al. 2001). These sources of river and/or floodplain inputs could help increase turbidity that triggers movement upstream, though this likely affects movement of Delta Smelt into the northern Delta not the southern Delta. Because Yolo Bypass flow is correlated ($R^2 = .30$) with San Joaquin River flow (Table 2), the importance of Yolo Bypass flow may represent a system-wide increase in river flows that often lead to greater suspended sediment inputs and turbidity in the Delta.

Turbidity Effects: The importance of turbidity as a predictor of Delta Smelt salvage at the SWP and CVP is important because it has been overlooked in previous attempts to quantify entrainment losses (Kimmerer 2008, Kimmerer 2011, Miller 2011). Previous research examining adult Delta Smelt abundance and distribution in regional fish monitoring surveys shows that Delta Smelt are caught more frequently when the water is more turbid (Feyrer et al. 2007, Nobriga et al. 2008, Sommer and Mejia 2013). This may be an effect of gear catchability (Latour 2015) and/or habitat use that reduces predation risk. Because the Project facilities entrain massive volumes of water compared to the monitoring survey trawls and because water clarity in the south Delta is relatively high at other times of the year (Nobriga et al. 2008, Sommer and Mejia 2013), the association of Delta Smelt salvage and turbid water is unlikely a gear efficiency issue. Rather, it is more likely that the adult Delta Smelt are moving with and occupying turbid water consistent with their more general use of pelagic habitat, a hypothesis supported by one recent study conducted during first flush periods (Bennett and Burau 2015). Thus, when turbid water gets entrained, it has a higher probability of adult Delta Smelt occupancy, which may explain the patterns observed here and reported previously (Grimaldo et al. 2009).

Adult abundance: It is not surprising that estimated adult Delta Smelt stock size has a strong influence on SWP and CVP salvage. When there are more fish, there is a greater chance of detecting them at the SWP and CVP fish facilities, especially when a greater proportion of the population is overlapping the zone of influence, which is a function of exports. It should be recognized that natural mortality arising from spawning activity increases as the spring progresses. Thus, the stock size vulnerable to entrainment risk decreases substantially by the end of March. This may explain why salvage of adult Delta Smelt is lower in March, even after storms that increase turbidity, compared to December and January when most adult Delta Smelt are salvaged. Storms in April and May have not resulted in significant adult Delta Smelt salvage events over the time series examined here.

*Fish behaviors:*Results presented in this study cannot account for all behaviors that influence salvage risk. Adult Delta Smelt movement during the winter is likely linked to major change in their environment and pre-spawning activity (Bennett and Burau 2015). For both CVP and SWP 50th percentile data, precipitation (PREC) was found to be important relative to other variables. The underlying relationship between increasing precipitation and increased salvage is likely related to movements that some proportion of the population makes during first flush events (Grimaldo et al. 2009; Bennett and Burau 2015). How Delta Smelt respond to other environmental variables during first flush is unknown. Researchers in other estuaries have found osmerid spawning behavior to be influenced by lunar phasefda (Hirose and Kawaguchi 1998), semidiurnal tides (Middaugh et al. 1987) and water temperature (Nakashima and Wheeler 2002). Note that Delta Smelt show little movement after first flush events (Murphy and Hamilton 2013) (Polansky et al. 2017). This may explain the high year-to-year variation in observed salvage patterns (Grimaldo et al. 2009).

*Management Implications:*Managing Project exports during first flush periods creates conflict between resources managers responsible for the protection of Delta Smelt and water operators that want to maximize water exports during periods of increased river inflows (Brown et al. 2009). Information generated from this study reinforce previous work that suggested adult Delta Smelt salvage risk can be assessed (and managed) using a combination of factors that represent Delta Smelt habitat (e.g., turbidity), estimated adult stock size , and hydrodynamics (Project exports and river flows). Hence, real-time monitoring of Delta-wide turbidity, river inflow, and fish distribution remains a useful suite of tools for determining when first flush conditions materialize.

New tagging techniques for cultured Delta Smelt (Wilder et al. 2016) could also be applied by releasing tagged fish during first flush periods to determine the rate and direction fish move in the south Delta similar to approaches used with Chinook Salmon (*Oncorhyncus tschawytscha*; Perry et al. 2010; Buchanan et al. 2013). These studies could also help quantify predation rates within the Clifton Court Forebay under high and low exports (Castillo et al. 2012) and in the channels that lead to the SWP and

CVP during first flush periods akin to research that has been done for salmonids in the estuary (Cavallo et al. 2015).

A more relevant direct application of the BRT model is to use it as a forecasting tool for predicting salvage in real-time. However, our initial attempt to apply the BRT to forecast Delta Smelt salvage was not fruitful (Table 5). Nonetheless, because this study focused on identifying relationships between salvage and variables that are readily available for download in real-time, future efforts should seek to develop alternative forecast models that can be applied for management of adult Delta Smelt salvage. The development of coupled biological-hydrodynamic models could also prove useful as a management tool, especially if behavioral hypotheses can be reconciled with existing data on the species' distribution and historical salvage patterns (Bennett and Burau 2015).

It is worth noting that by analyzing SWP and CVP salvage independently, OMR flow was found to have smaller explanatory influence on salvage than some other variables. Currently, Project exports are managed through management of OMR flows. The basis for OMR flow management partially stems for earlier work showing that adult Delta Smelt salvage (Grimaldo et al. 2009) and proportional losses (Kimmerer 2008) increased as net OMR flow increased southward towards the Projects. The BRT model indicates that management must consider a number of factors to minimize salvage or entrainment risk. However, given the correlation of OMR and SWP and CVP models (Table 3), salvage and entrainment risk could be achieved through management of either indexes of the hydrodynamic influence from Project exports.

Finally, it is worth noting that the ultimate objective for managing Delta Smelt entrainment should not focus on observed salvage. Rather, the management objective should be to target entrainment losses, in a traditional fisheries sense, to sustainable levels that do not compromise population growth rates (Maunder and Deriso 2011; Rose et al. 2013). The results presented in this study can help scientists and resource managers identify circumstances when those large entrainment losses are likely to occur, which can ultimately be used to develop population risk assessment models. The question about whether the Delta Smelt population can rebound from record-low abundances, even with improved entrainment management during the winter, remains outstanding given the importance of other factors at play (i.e., poor food supply, growth, water temperatures; see Maunder and Deriso 2011; Rose et al 2013). Managers and scientists should focus on developing linked management actions that promote population growth within and between years (Bennett 2005, Maunder and Deriso 2011, Rose et al. 2013, Interagency Ecological Program 2015).

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Literature Cited

Arthur, J. F., M. D. Ball, and S. Y. Baughman. 1996. Summary of federal and state water project environmental impacts in the San Francisco Bay-Delta Estuary, California. San Francisco State University.

Bennett, W. A. 2005. Critical assessment of the delta smelt population in the San Francisco Estuary, California. San Francisco Estuary and Watershed Science **3**.

Bennett, W. A., and J. R. Burau. 2015. Riders on the Storm: Selective Tidal Movements Facilitate the Spawning Migration of Threatened Delta Smelt in the San Francisco Estuary. Estuaries and Coasts **38**:826-835.

Brown, L. R., W. Kimmerer, and R. Brown. 2009. Managing water to protect fish: a review of California's Environmental Water Account, 2001-2005. Environmental Management **43**:357-368.

Castillo, G., J. Morinaka, J. Lindberg, R. Fujimura, B. Baskerville-Bridges, J. Hobbs, G. Tigan, and L. Ellison. 2012. Pre-Screen Loss and Fish Facility Efficiency for Delta Smelt at the South Delta's State Water Project, California. San Francisco Estuary and Watershed Science **10**.

Cavallo, B., P. Gaskill, J. Melgo, and S. C. Zeug. 2015. Predicting juvenile Chinook Salmon routing in riverine and tidal channels of a freshwater estuary. Environmental Biology of Fishes **98**:1571-1582.

Cavallo, B., J. Merz, and J. Setka. 2013. Effects of predator and flow manipulation on Chinook salmon (*Oncorhynchus tshawytscha*) survival in an imperiled estuary. Environmental Biology of Fishes **96**:393-403.

Deriso, R. B. 1980. Harvesting Strategies and Parameter Estimation for an Age-Structured Model. Canadian Journal of Fisheries and Aquatic Sciences **37**:268-282.

Feyrer, F., M. L. Nobriga, and T. R. Sommer. 2007. Multidecadal trends for three declining fish species: habitat patterns and mechanisms in the San Francisco Estuary, California, USA. Canadian Journal of Fisheries and Aquatic Sciences **64**:723-734.

Gingras, M. 1997. Mark/Recapture Experiments at Clifton Court Forebay to Estimate Pre-Screening Loss to Juvenile Fishes: 1976-1993. Technical Report 55. Interagency Ecological Program for the San Francisco Bay/Delta Estuary, Sacramento, CA.

Grimaldo, L., T. Sommer, N. Van Ark, G. Jones, E. Holland, P. Moyle, P. Smith, and B. Herbold. 2009. Factors affecting fish entrainment into massive water diversions in a freshwater tidal estuary: can fish losses be managed? North American Journal of Fisheries Management **29**:1253-1270.

Hall, S. J., and B. Mainprize. 2004. Towards ecosystem-based fisheries management. Fish and Fisheries **5**:1-20.

Hirose, T., and K. Kawaguchi. 1998. Spawning ecology of Japanese surf smelt, Hypomesus pretiosus japonicus (Osmeridae), in Otsuchi Bay, northeastern Japan. Pages 213-223 *in* M. Yuma, I. Nakamura, and K. D. Fausch, editors. Fish biology in Japan: an anthology in honour of Hiroya Kawanabe. Springer Netherlands, Dordrecht.

Interagency Ecological Program, M., Analysis, and Synthesis Team. 2015. An updated conceptual model of Delta Smelt biology: our evolving understanding of an estuarine fish. Technical Report 90. January. Interagency Ecological Program for the San Francisco Bay/Delta Estuary, Sacramento, CA.

Jackman, S., A. Tahk, A. Zeileis, C. Maimone, J. Fearon, and M. S. Jackman. 2015. Package ‘pscl’.

Kimmerer, W. J. 2008. Losses of Sacramento River Chinook Salmon and Delta Smelt to Entrainment in Water Diversions in the Sacramento-San Joaquin Delta. San Francisco Estuary and Watershed Science **6**.

Kimmerer, W. J. 2011. Modeling Delta Smelt Losses at the South Delta Export Facilities. San Francisco Estuary and Watershed Science **9**.

Kimmerer, W. J., and M. L. Nobriga. 2008. Investigating Particle Transport and Fate in the Sacramento-San Joaquin Delta Using a Particle Tracking Model. San Francisco Estuary and Watershed Science **6**.

Latour, R. J. 2015. Explaining Patterns of Pelagic Fish Abundance in the Sacramento-San Joaquin Delta. Estuaries and Coasts.

Link, J. S. 2002. What does ecosystem-based fisheries management mean. Fisheries **27**:18-21.

Mac Nally, R., J.R. Thomson, W.J. Kimmerer, F. Feyrer, K.B. Newman, A. Sih, W. A. Bennett, L. Brown, E. Fleishman, S. D. Culberson, and G. Castillo. 2010. Analysis of pelagic species decline in the upper San Francisco Estuary using multivariate autoregressive modeling (MAR). Ecological Applications **20**:1417-1430.

Maunder, M. N., and R. B. Deriso. 2011. A state-space multistage life cycle model to evaluate population impacts in the presence of density dependence: illustrated with application to delta smelt (*Hypomesus transpacificus*). Canadian Journal of Fisheries and Aquatic Sciences **68**:1285-1306.

Miller, W. J. 2011. Revisiting Assumptions that Underlie Estimates of Proportional Entrainment of Delta Smelt by State and Federal Water Diversions from the Sacramento-San Joaquin Delta. San Francisco Estuary and Watershed Science **9**.

Miller, W. J., B. F. J. Manly, D. D. Murphy, D. Fullerton, and R. R. Ramey. 2012. An Investigation of Factors Affecting the Decline of Delta Smelt (*Hypomesus transpacificus*) in the Sacramento-San Joaquin Estuary. Reviews in Fisheries Science **20**:1-19.

Miranda, J., R. Padilla, G. Aasen, B. Mefford, D. Sisneros, and J. Boutwell. 2010. Evaluation of mortality and injury in a fish release pipe. California Department of Water Resources, Sacramento, CA.

Monsen, N. E., J. E. Cloern, and J. R. Burau. 2007. Effects of Flow Diversions on Water and Habitat Quality: Examples from California's Highly Manipulated Sacramento-San Joaquin Delta. San Francisco Estuary and Watershed Science **5**.

Morinaka, J. 2013. Acute Mortality and Injury of Delta Smelt Associated With Collection, Handling, Transport, and Release at the State Water Project Fish Salvage Facility. Technical Report 89. November. Interagency Ecological Program, Sacramento.

Murphy, D. D., and S. A. Hamilton. 2013. Eastward Migration or Marshward Dispersal: Exercising Survey Data to Elicit an Understanding of Seasonal Movement of Delta Smelt. San Francisco Estuary and Watershed Science **11**.

Nobriga, M. L., T. R. Sommer, F. Feyrer, and K. Fleming. 2008. Long-Term Trends in Summertime Habitat Suitability for Delta Smelt (*Hypomesus transpacificus*). San Francisco Estuary and Watershed Science **6**.

Pikitch, E. K., C. Santora, E. A. Babcock, A. Bakun, R. Bonfil, D. O. Conover, P. Dayton, P. Doukakis, D. Fluharty, B. Heneman, E. D. Houde, J. Link, P. A. Livingston, M. Mangel, M. K. McAllister, J. Pope, and K. J. Sainsbury. 2004. Ecosystem-Based Fishery Management. Science **305**:346-347.

Policansky, L. Add reference.

Rose, K. A., W. J. Kimmerer, K. P. Edwards, and W. A. Bennett. 2013. Individual-Based Modeling of Delta Smelt Population Dynamics in the Upper San Francisco Estuary: II. Alternative Baselines and Good versus Bad Years. Transactions of the American Fisheries Society **142**:1260-1272.

Schreier, B. M., M. R. Baerwald, J. L. Conrad, G. Schumer, and B. May. 2016. Examination of Predation on Early Life Stage Delta Smelt in the San Francisco Estuary Using DNA Diet Analysis. Transactions of the American Fisheries Society **145**:723-733.

Sommer, T., C. Armor, R. Baxter, R. Breuer, L. Brown, M. Chotkowski, S. Culberson, F. Feyrer, M. Gingras, B. Herbold, W. Kimmerer, A. Mueller-Solger, M. Nobriga, and K. Souza. 2007. The Collapse of Pelagic Fishes in the Upper San Francisco Estuary. Fisheries **32**:270-277.

Sommer, T., and F. Mejia. 2013. A Place to Call Home: A Synthesis of Delta Smelt Habitat in the Upper San Francisco Estuary. San Francisco Estuary and Watershed Science **11**.

Sommer, T. R., M. L. Nobriga, W. C. Harrel, W. Batham, and W. J. Kimmerer. 2001. Floodplain rearing of juvenile chinook salmon: evidence of enhanced growth and survival. Canadian Journal of Fisheries and Aquatic Sciences **58**:325-333.

Thomson, J. R., W.J.. Kimmerer, L.R. Brown, K.B. Newman, R. MacNally, W. A. Bennett, F. Feyrer, and E. Fleishman. 2010. Bayesian change point analysis of abundance trends for pelagic fishes in the upper San Francisco Estuary. Ecological Applications **20**:1431-1448.

Wilder, R. M., J. L. Hassrick, L. F. Grimaldo, M. F. D. Greenwood, S. Acuña, J. M. Burns, D. M. Maniscalco, P. K. Crain, and T.-C. Hung. 2016. Feasibility of Passive Integrated Transponder and Acoustic Tagging for Endangered Adult Delta Smelt. North American Journal of Fisheries Management **36**:1167-1177.

Zeileis, A., C. Kleiber, and S. Jackman. 2008. Regression models for count data in R. Journal of Statistical Software **27**:1-25.

Table 1. Variables used for examining adult Delta Smelt salvage dynamics at the SWP and CVP

Variable	Abbreviation	Source	
Sacramento River flow	SAC	Dayflow	http://www.water.ca.gov/dayflow/
Yolo Bypass flow	YOLO	Dayflow	
Cosumnes River flow	CSMR	Dayflow	
San Joaquin River flow	SJR	Dayflow	
Precipitation	PREC	Dayflow	
Cumulative precipitation since December 1	CPREC	Dayflow	
X2 on December 1	DecX2	Dayflow	
State Water Project exports	SWP	Dayflow	
Central Valley Project exports	CVP	Dayflow	
Contra Costa exports	OEXP	Dayflow	
North Bay Aqueduct exports	NBAQ	Dayflow	
Gross Channel Depletion	GCD	Dayflow	
Old and Middle River flows	OMR	United States Geological Survey	https://waterdata.usgs.gov/ca/nwis/rt
Mallard Island water temperature	Temp	California Data Exchange Center	https://cdec.water.ca.gov/
Clifton Court Forebay turbidity	CCF.NTU	California Data Exchange Center	
Day index beginning December 1	Day	-	
Fall Midwater Trawl index	FMWT	California Department of Fish and Wildlife	ftp://ftp.dfg.ca.gov/

Table 2. Coefficient of determination (R^2) matrix of physical variables. Variable combinations exceeding the threshold for acceptance as predictors to fit in the BRT model are highlighted in bold. Variables included the GAMs are italicized in the top row (see text for details).

	SAC	YOLO	CSMR	SJR	*SWP*	*CVP*	CCC	NBAQ	GCD	*PREC*	CPREC	*OMR*
Day	0.03	0.00	0.02	0.04	0.03	0.00	0.06	0.19	0.41	0.01	0.52	0.03
SAC		0.37	0.28	0.44	0.01	0.05	0.01	0.09	0.04	0.16	0.31	0.15
YOL			0.34	0.34	0.00	0.00	0.01	0.01	0.01	0.10	0.09	0.20
CSM				0.16	0.00	0.01	0.01	0.03	0.01	0.16	0.08	0.07
SJR					0.03	0.00	0.02	0.03	0.04	0.03	0.31	**0.65**
SWP						0.24	0.00	0.00	0.01	0.01	0.00	0.39
CVP							0.00	0.00	0.01	0.01	0.01	0.21
CCC								0.00	0.04	0.04	0.02	0.01
NBA									0.09	0.00	0.18	0.01
GCD										0.00	0.28	0.03
PREC											0.01	0.00
CPRE												0.15

	FMWT	*Temp*	*CCF. NTU*	*Dec X2*
Day	0.00	0.29	0.02	0.00
SAC	0.00	0.00	0.25	0.08
YOLO	0.00	0.00	0.19	0.01
CSMR	0.00	0.00	0.08	0.02
SJR	0.00	0.00	0.29	0.13
SWP	0.02	0.01	0.01	0.02
CVP	0.01	0.00	0.01	0.00
CCC	0.00	0.01	0.00	0.01
NBAQ	0.04	0.06	0.06	0.00
GCD	0.00	0.00	0.04	0.00
PREC	0.00	0.00	0.05	0.00
CPRE	0.01	0.12	0.14	0.00
OMR	0.00	0.00	0.14	0.09
FMWT		0.00	0.00	0.13
Temp			0.01	0.01
CCF. NTU				0.02

Table 3. Percent of null deviance explained by four alternative model Project export combinations using Boosted Regression Tree analysis. Values in parentheses represent 95% credible intervals over 500 bootstrapped models.

Full dataset	SWP salvage model		CVP salvage model	
	OMR	SJR	OMR	SJR
SWP Exports, CVP Exports	**94 (92-96)**	94 (92-96)	**85 (81-88)**	86 (83-88)
Combined SWP and CVP exports	94 (92-96)	94 (92-96)	86 (77-88)	86 (81-88)

50^{th} percentile dataset	SWP salvage model		CVP salvage model	
	OMR	SJR	OMR	SJR
SWP Exports, CVP Exports	**93 (90-94)**	94 (90-95)	**87 (84-90)**	87 (84-90)
Combined SWP and CVP exports	93 (90-95)	91 (93-95)	87 (83-90)	87 (84-90

Table 4. Relative influence of variables in models fit to the full dataset and data representing 50^{th} percentile (see text for details) using Boosted Regression Trees (BRTs). Only variables with at least 5% influence were ranked; other variables were considered insignificant.

Central Valley Project	Relative rank (influence)		State Water Project	Relative rank (influence)	
	Full dataset	50% dataset		Full dataset	50% dataset
FMWT	0.18 (1)	0.25 (1)	SWP	0.29 (1)	0.23 (1)
OMR	0.10 (2)	0.10 (4)	YOLO	0.18 (2)	0.18 (3)
CCF.NTU	0.10 (3)	0.06 (6)	FMWT	0.11 (3)	0.11 (5)
CVP	0.08 (4)	-	OMR	0.10 (4)	0.14 (4)
CPREC	0.08 (5)	0.14 (2)	CCF.NTU	0.09 (5)	-
GCD	0.08 (6)	-	CPREC	0.05 (6)	0.20 (2)
YOLO	0.07 (7)	0.10 (5)	CVP	-	-

CSMR	0.06 (8)	-	CSMR	-	-
SWP	0.06 (9)	0.05 (6)	SAC	-	-
CCC	-	-	CCC	-	-
Temp	-	-	Temp	-	-
PREC	-	-	NBAQ	-	-
SAC	-	-	Day	-	-
DecX2	-	-	GCD	-	-
NBAQ	-	-	PREC	-	-
Day	-	0.10 (3)	DecX2	-	-

Table 5. Coefficient of determination (R^2) between observed and predicted salvage when years of data were sequentially omitted. Values in parentheses represent 95% credible intervals over 500 bootstrapped models.

Predicted year	State Water Project	Central Valley Project
1998	0.006	0.01
1999	0.02	0.08
2004	0.20	0.36
2010	0.02	0.08
2013	0.02	0.05

Fig. 1. Map of the San Francisco Estuary and study region. State Water Project (SWP) and Central Valley Project (CVP) Project exports and fish facilities are located in the southern Sacramento-San Joaquin Delta. Old River and Middle River are indicated by blue and red lines respectively. Monitoring stations for water temperature (A) and turbidity (B) used in statistical models are shown on map.

Fig. 2. Annual combined SWP and CVP salvage from 1993 and 2016.

Fig. 3. Boosted regression tree (BRT) estimates of salvage at the CVP (A) and SWP (B). Only the most influential variables are shown. Estimates represent expected salvage across the range of observed variable values, while holding all other variables at their means. Blue lines indicate median model predictions; red lines indicate 95% credible intervals of predictions, and rug plots indicate observed variable values.

Fig. 4. The highest ranked two-way interactions between physical variables used in BRT models for the CVP (A) and SWP (B).

Fig. 5. Diagnostic plots for SWP salvage data examined using BRT models.

Fig. 6. Diagnostic plots for CVP salvage data examined using BRT models.

Fig. 1

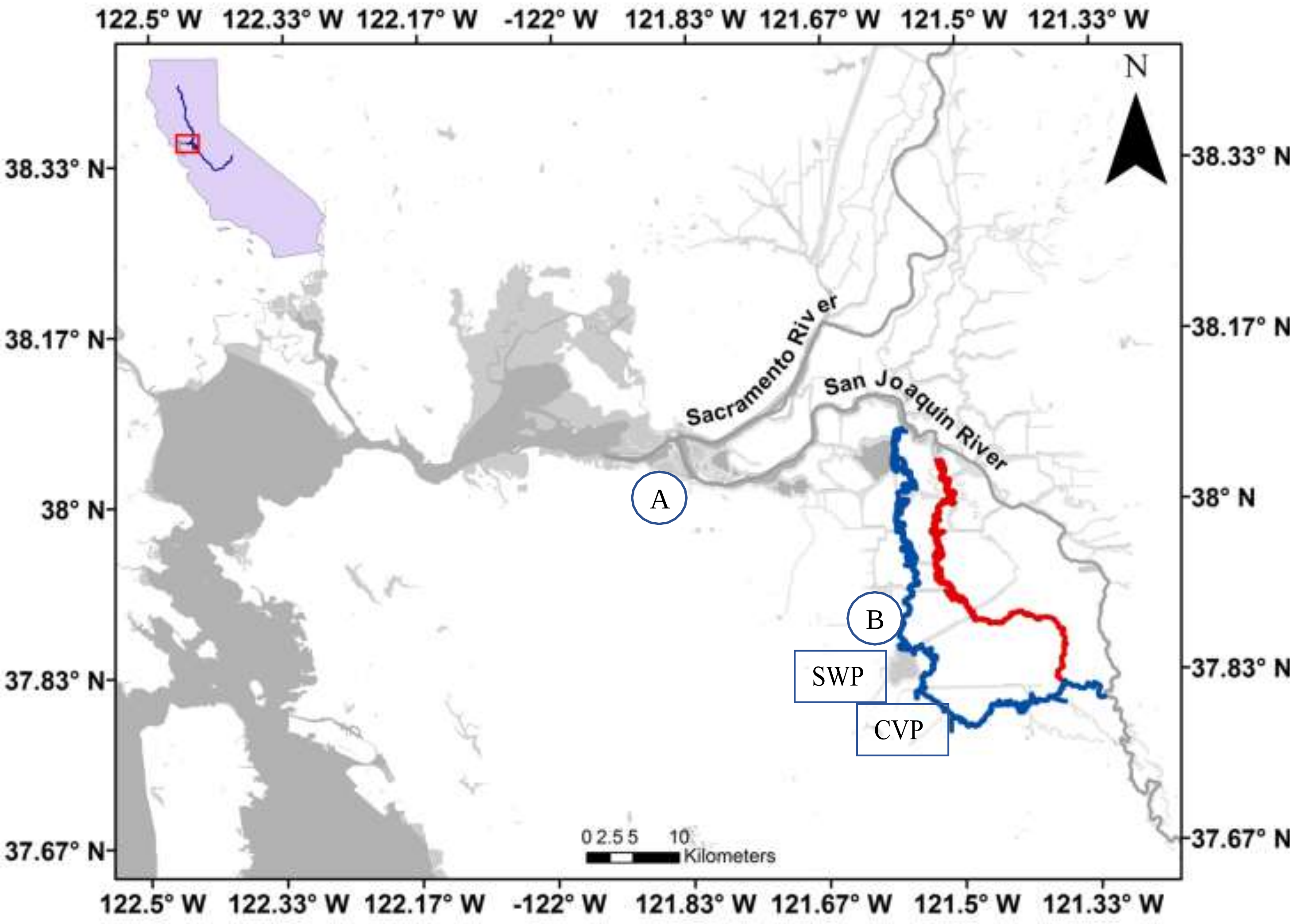
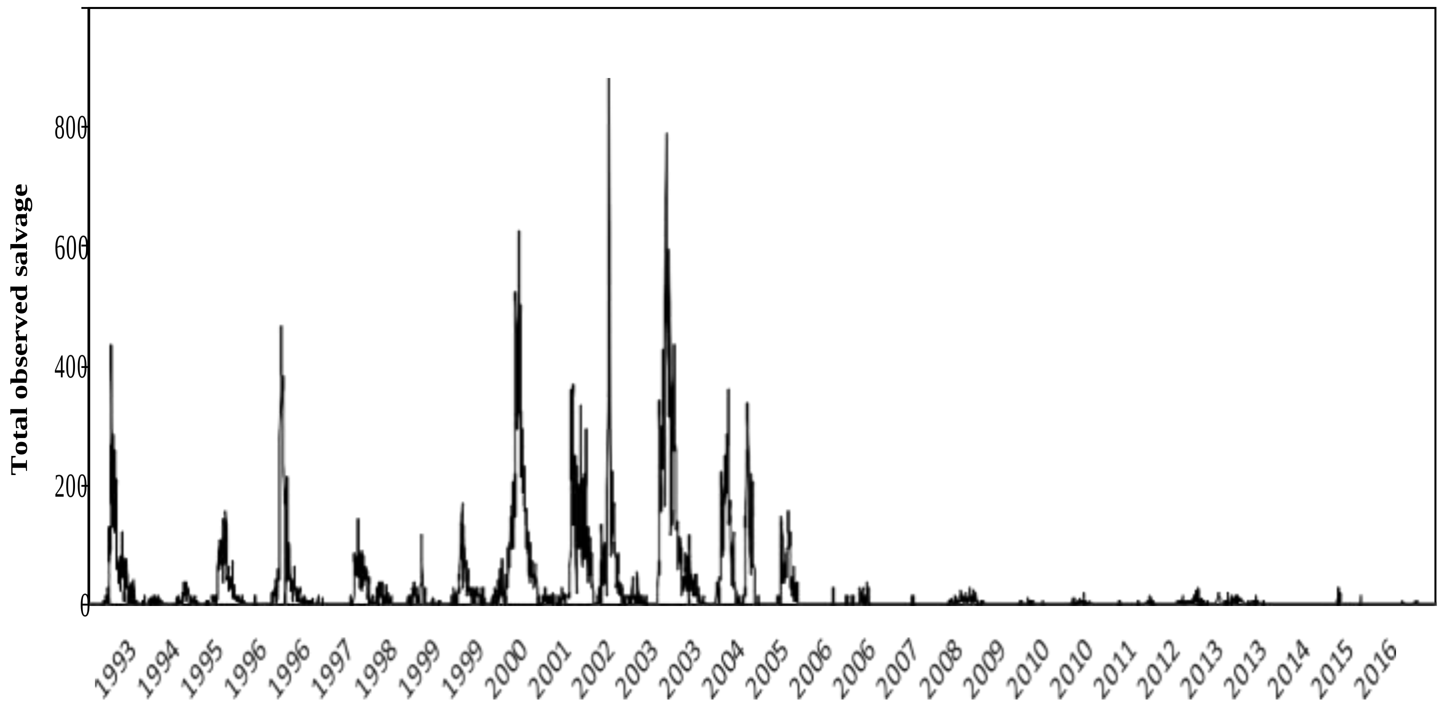

122.5° W
122.33° W
122.17° W
-122° W
121.83° W
121.67° W
121.5° W
121.33° W
38.33° N
38.17° N
38° N
37.83° N
37.67° N
N
Sacramento River
San Joaquin River
A
B
SWP
CVP
0 2.5 5 10
Kilometers

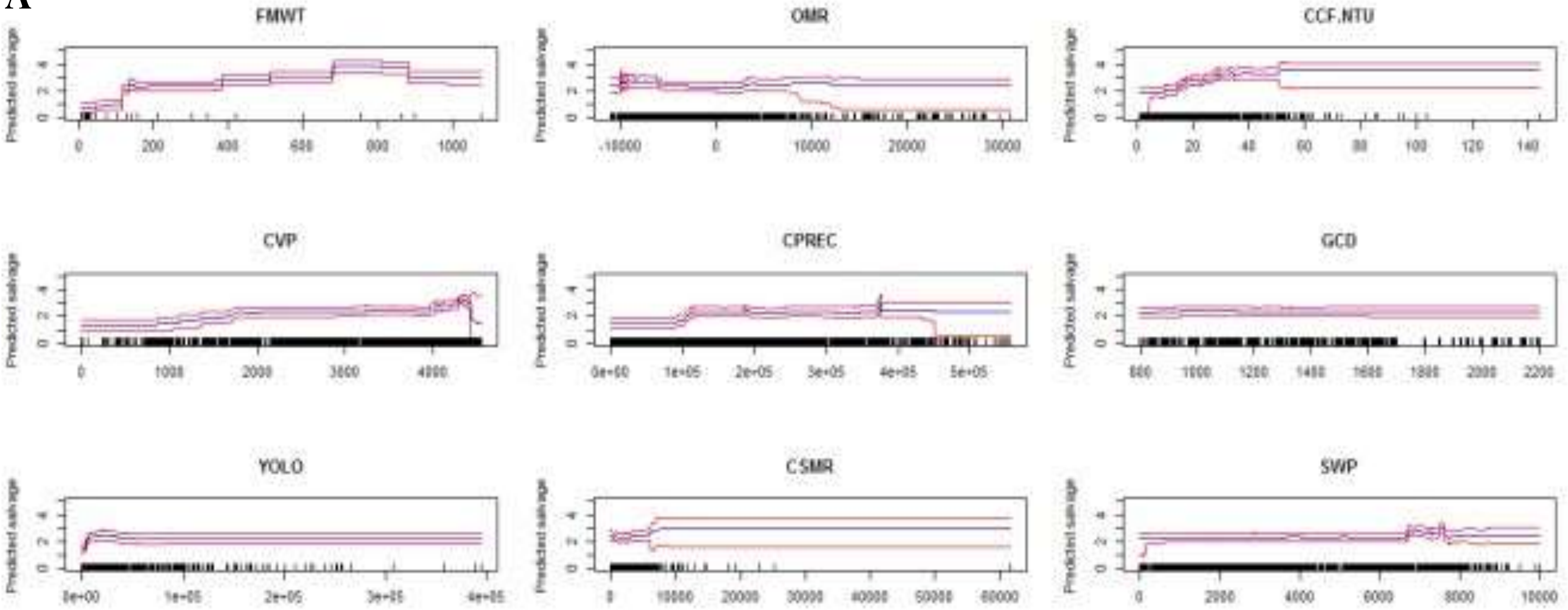
Fig. 2



Total observed salvage
0
200
400
600
800
1993
1994
1995
1996
1996
1997
1998
1999
1999
2000
2001
2002
2003
2003
2004
2005
2006
2006
2007
2008
2009
2010
2010
2011
2012
2013
2013
2014
2015
2016

Fig. 3

A


FMWT
OMR
CCF.NTU
CVP
CPREC
GCD
YOLO
CSMR
SWP
Predicted salvage

B

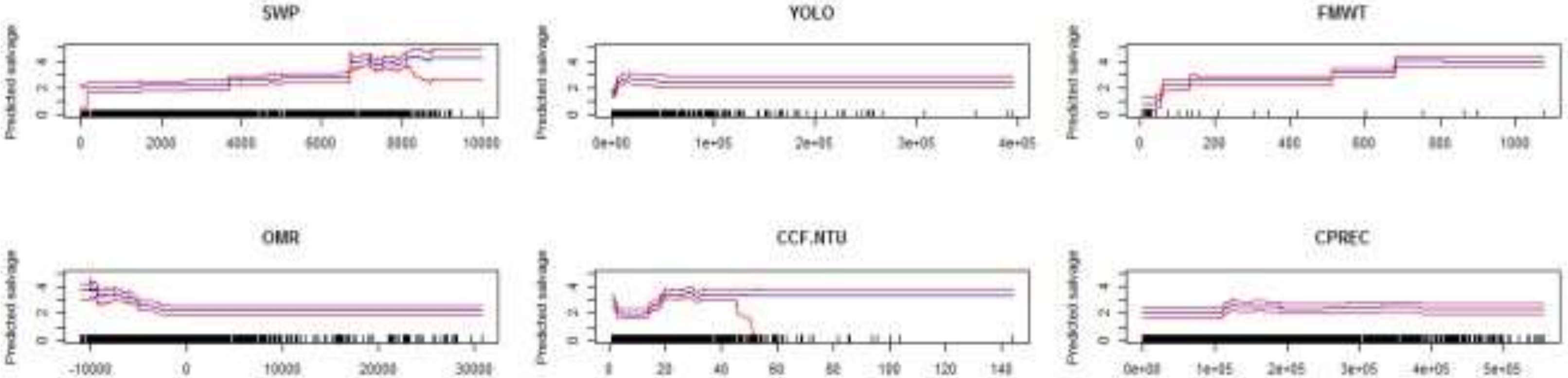


Fig. 4

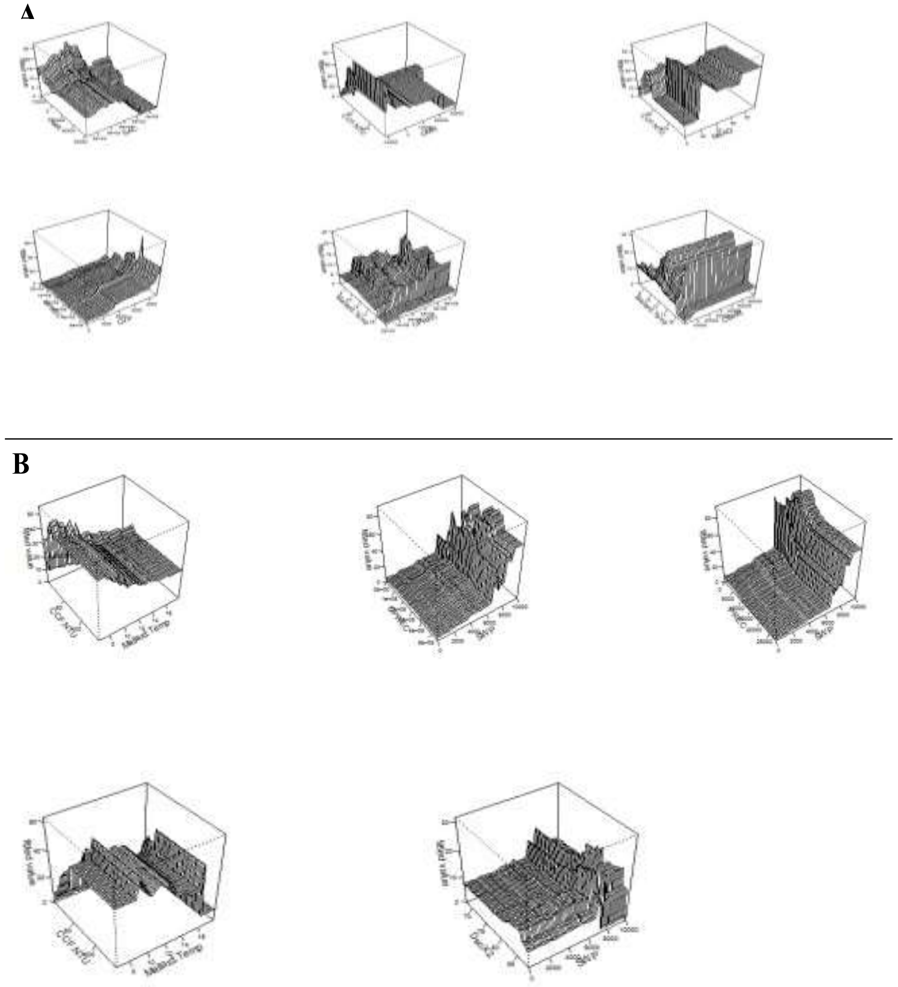
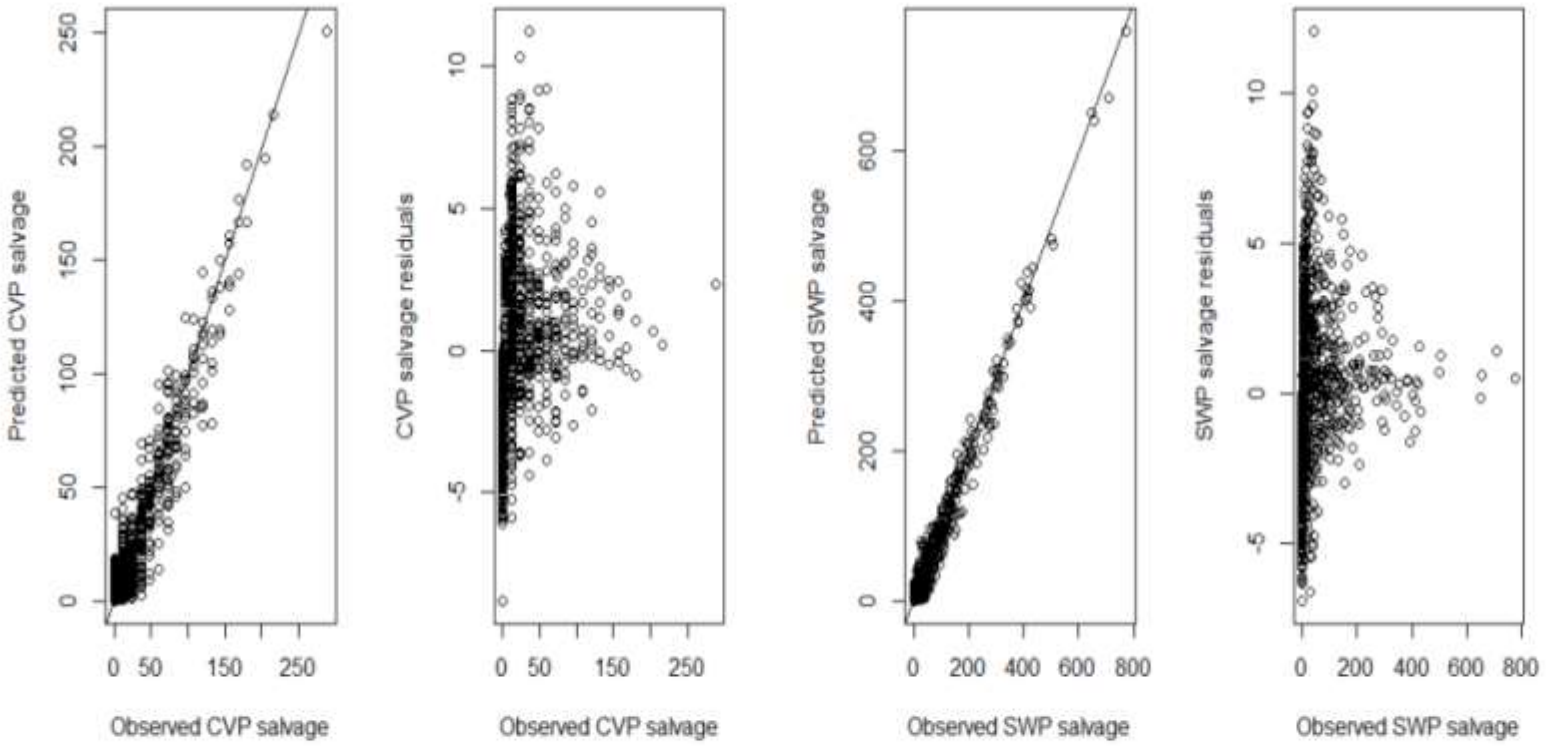
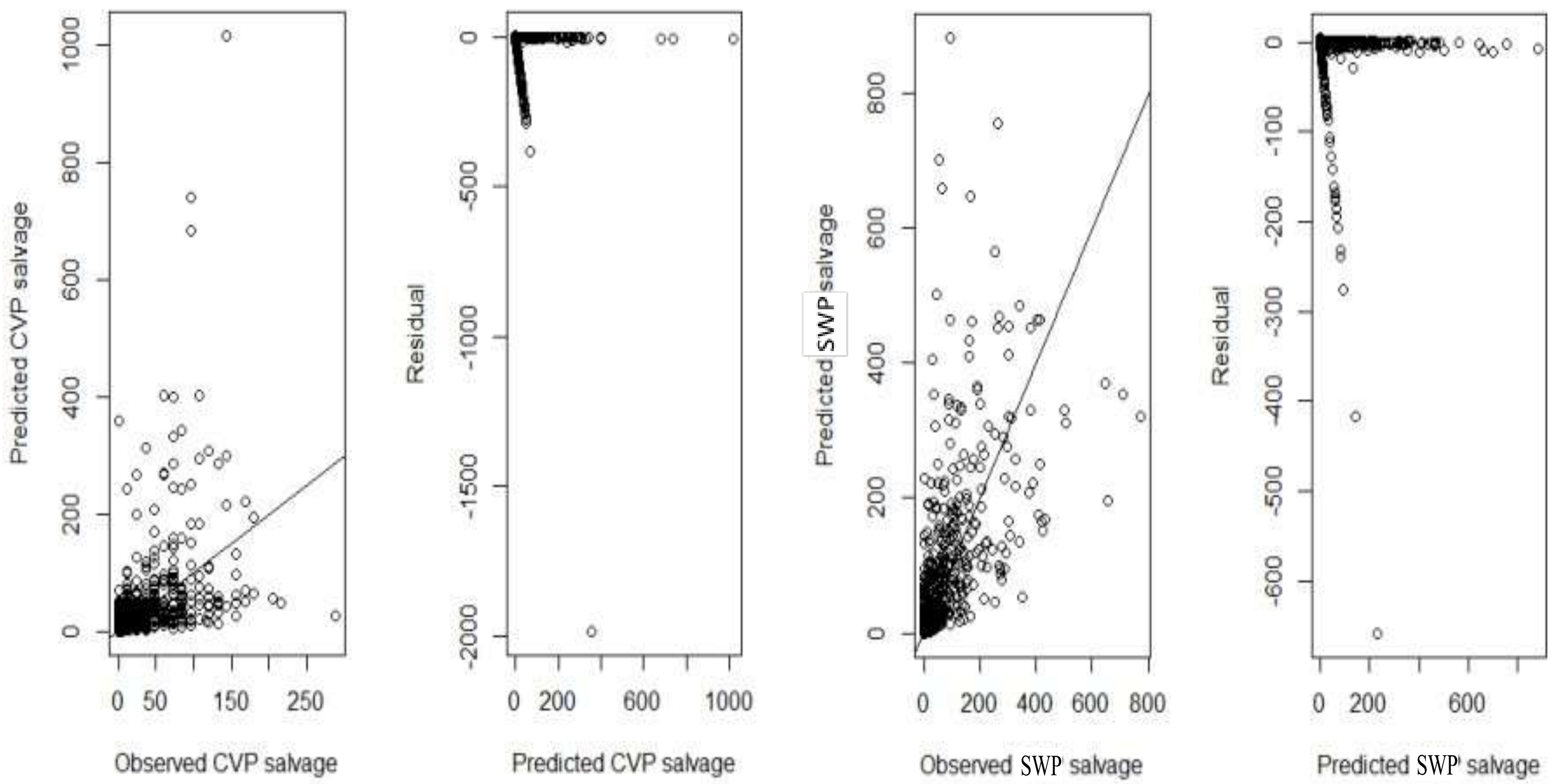


Fig. 5



Predicted CVP salvage
Observed CVP salvage
CVP salvage residuals
Observed CVP salvage
Predicted SWP salvage
Observed SWP salvage
SWP salvage residuals
Observed SWP salvage

1 Fig. 6



Predicted CVP salvage
Observed CVP salvage
Residual
Predicted CVP salvage
Predicted SWP salvage
Observed SWP salvage
Residual
Predicted SWP salvage