Evaluation of key assumptions underlying analyses of delta smelt survey data

Robert J. Latour, Ph.D.
Virginia Institute of Marine Science
College of William & Mary
Gloucester Point, VA 23062

Introduction

Aquatic fish and invertebrate populations are routinely surveyed by scientists using a variety of sampling techniques such as trawls, dredges, gillnets, and traps. With all of these sampling methods, the primary goal of a survey is to obtain representative data that allows estimation of key population quantities that can be used to support management. When available, survey data are often considered vital components of analytical investigations into the biology, ecology, and population status of natural aquatic populations.

Survey data are often analyzed to derive estimates of relative abundance indices, and temporal patterns in these indices are assumed to proportionally reflect changes in the true underlying total abundance or density of target populations. The link between abundance indices and true population size is given by the proportionality constant, q, which is referred to as the catchability coefficient in the equation $C = qEN$, where C is survey catch, E is survey effort, and N is total population abundance. In many sampling situations, the parameter q can be viewed as the product of target species' availability, defined as the proportion of the population present within the survey area (or subarea), and gear efficiency, which is the proportion of the animals encountered by the sampling gear that are successfully captured (Kimura and Somerton 2006). Therefore, $q = q_a q_e$, where the subscripts a and e denote availability and efficiency respectively (Kotwicki et al. 2014). Availability is related to the underlying population dynamics of target species while gear efficiency can be affected by environmental conditions, physical morphology of the survey locations, changes in survey vessel, or modifications to sampling gear and/or deployment protocols. Despite the possible influence of these variables on the components of q, time-series of relative abundance indices are often derived from estimation techniques assuming constant catchability.

Estimation of relative abundance indices, which are typically expressed as the mean catch-per-unit-effort (CPUE) of a survey over a defined spatiotemporal period (e.g., yearly across full sampling area), generally relies on one of two statistical methods; use of either design-based estimators or model-based procedures. For design-based methods, the mean CPUE value is estimated using an analytical equation consistent with the underlying statistical design of the survey such as random stratified sampling. If samples are taken in accordance with the assumptions of the statistical design, particularly with respect to independence of samples (uncorrelated CPUE observations vs. temporally/spatially correlated CPUEs), then design-based estimators will yield an unbiased estimate of the mean CPUE. Model-based methods such as generalized linear models (GLMs, McCullagh and Nelder 1989, Maunder and Punt 2003) are often used in situations where a formally defined sampling design has not been used to collect samples, and/or if there is interest in evaluating the statistical significance of hypothesized covariates on CPUE. An unbiased estimate of the mean CPUE can again be derived provided the properties of the survey data are consistent with model assumptions, particularly those pertaining to the underlying distribution of CPUE measures, variance structure (heteroscedascity, overdispersion), model specification (linearity, vs. nonlinearity), and again, independence of CPUE observations.

San Francisco Bay is the largest estuary on the west coast of the United States. Freshwater is supplied to the bay primarily from the Sacramento and San Joaquin rivers, which converge to form a complex mosaic of tidal freshwater areas known collectively as the Sacramento-San Joaquin Delta (referred herein as the Delta). Over the past century, the Delta has experienced considerable anthropogenic changes in the form of lost wetlands (Atwater et al. 1979), sediment loading (Schoellhamer 2011), invasive species (Cohen and Carlton 1998), and input of contaminants (Connor et al. 2007). Analyses of survey data by the California Department of Fish and Wildlife (CDFW) have shown long-term declining patterns in abundance indices for several fish species, particularly since the early 2000s (Sommer et al. 2007). These patterns along with complementary analyses of other Delta fish and ecosystem attributes have collectively supported the conclusion that overall abundance of several pelagic fishes is currently quite low. Specific to the available survey data, however, temporal patterns in CPUE only represent changes in overall population abundance when gear catchability has remained constant over time and throughout the survey area. If survey catchability has systematically changed temporally or spatially, perhaps in response to specific changes in ecosystem attributes or biological requirements of target fish populations, then trends in CPUE indices trends may no longer adequately reflect true changes in total fish population abundance.

In addition to the assumption of constant catchability over time and space, analyses of survey data using either design- and model-based procedures often assume statistical independence among survey collections. Failure to meet this assumption implies that survey CPUE measures are temporally and/or spatially autocorrelated. Since the distribution of many aquatic species can follow temporal and/or spatial gradients or clusters (schools), it is possible for autocorrelated field observations of CPUE to manifest within survey datasets. Despite the intuitive likelihood that routinely operated fish monitoring programs sample clusters of individuals, contemporary analyses of survey data are often based on methods that do not formally account for autocorrelated samples.

Meeting the assumptions of methods used to analyze survey data is critical to developing confidence in derived population quantities. Also valuable is knowing if particular assumptions have been violated, since such information is key to understanding sources of scientific uncertainty. At present, it does not appear that the assumptions of constant catchability and independence among CPUE samples have been comprehensively evaluated for fish surveys in the Delta. Therefore, this proposal is designed to formally assessing these assumptions for two important surveys targeting delta smelt (*Hypomesus transpacificus*).

Relevance/Rationale

When the catchability of survey gear used to sample fish populations changes systematically in response to biological, environmental, physical, or sampling covariates, CPUE measures may not maintain a consistent proportional relationship with overall abundance. Additionally, CPUE samples taken ‘close’ in time or space have the potential to be correlated, which implies CPUE observations are not statistically independent and overall survey sample sizes are effectively lower than the actual number of collections completed in a given time period. Quantifying the effects of factors hypothesized to influence survey catchability and investigating the presence and potential impacts of autocorrelation among samples will aid in developing more comprehensive and robust interpretations of existing delta smelt survey data.

Additionally, the results of this project can directly inform ongoing mechanistic modeling efforts such as those focused on developing a delta smelt life cycle model and evaluating population level consequences of entrainment. Developing a more informed understanding of spatiotemporal patterns in delta smelt relative abundance, relationships with ecosystem attributes, and potential biases inherent to survey data can aid in the refinement of more complex modeling activities that utilize survey data for calibration and of validation. The results of this project can also be used to potentially refine future field investigations of delta smelt. In particular, if temporal/spatial autocorrelation is notable within the Delta fish survey programs, then effective sample sizes are less than perceived sample sizes and oversampling may be occurring. Thus, efforts could be directed at modifying future survey activities to gain efficiencies and potentially redistribute valuable resources toward hypothesis driven studies that are otherwise not possible given the current budget climate.

Applications of findings to management

Survey data for delta smelt are a key information source for inferring population status and supporting advanced population level modeling activities. Accordingly, estimated quantities from survey datasets are important foundational components of the science underpinning management. In general, development of robust management strategies should simultaneously balance the varied perspectives of stakeholders and the scientific uncertainty in basal data and subsequent analyses of those data. This project is therefore designed aid management efforts by evaluating potential sources of scientific uncertainty through quantitative evaluation of two important analytical assumptions inherent to analyses of delta smelt survey data. If catchability is deemed to not significantly vary across a myriad of covariates, then confidence that surveys maintain a constant proportional relationship among CPUE and overall abundance of delta smelt can grow. Similarly, if temporal and/or spatial autocorrelation of CPUE measures is negligible, then effective survey sample sizes will be on par with those currently part of Delta fish survey programs, and confidence that sampling intensity is adequate can be maintained. However, if either or both of these analytical assumptions are appreciably violated, then such information will aid efforts to understand sources of scientific uncertainty which can, in turn, be directly incorporated into the management process.

Key Questions

The Interagency Ecological Program (IEP) is a consortium of three state, six federal, and one non-governmental organization designed to provide ecological information in support of science-based management of San Francisco Bay and the Delta. The CDFW, which is one of the state organizations within the IEP consortium, oversees several longstanding survey data collection programs in support of IEP and related scientific activities. Germane to the present proposal are the Fall Midwater Trawl Survey (FMWT[1]) and the Spring Kodiak Trawl Survey (SKT[2]), which provide stage-specific abundance

[1] See https://www.dfg.ca.gov/delta/projects.asp?ProjectID=FMWT for more information on the FMWT survey.
[2] See https://www.dfg.ca.gov/delta/projects.asp?ProjectID=SKT for more information on the SKT survey.

indices that are used to infer population status of pelagic fishes in the Delta. Accordingly, the following research questions are posed:

1) Catchability.
   a) Are there specific covariates that significantly affect catchability of delta smelt by the FMWT and SKT survey programs?

   b) How do predicted CPUE and probabilities of false zeros[3] vary over the domains of covariates deemed to significantly affect catchability?

2) Independence of survey samples.
   a) Is there evidence of temporal/spatial autocorrelation among survey samples of delta smelt collected by the FMWT and SKT survey programs?

   b) If notable temporal/spatial autocorrelation is detected, can delta smelt abundance indices be re-estimated by taking into account the inherent correlation structure of the FMWT and SKT survey samples?

Methods/Investigative Approach

A variety of statistical models will be fitted to the raw FMWT and SKT delta smelt survey data to address the objectives of this proposal. For the FMWT survey, Latour (*in press*) recently demonstrated that delta smelt CPUE data (count-per-tow) were zero-inflated (Fig. 1) and effectively modeled with a zero-inflated negative binomial generalized linear model (GLM; Zuur et al. 2012). Therefore, this modeling framework will serve as the starting point for analyses of the FMWT survey data. The PI is less familiar with the SKT delta smelt survey data, although these data also appear to be zero-inflated (Fig. 1). Accordingly, standard and zero-inflated GLMs will serve as a starting point for the SKT analysis, however, if diagnostics of preliminary model fits do not support these model types, then various generalized additive model (GAM; Wood 2006) formulations will be considered. Once final model structures are identified for both data sets, a suite of covariates hypothesized to influence catchability will be examined. Diagnostics associated with fits of those models and other parameterizations will then be evaluated for the presence of temporal/spatial correlation among survey samples. Statistical analyses for question (1) will be conducted using the software package R (R Core Development Team 2014) and analyses addressing question (2) will be implemented using the 'rjags' package within R and/or R interfaced with WinBUGS (Lunn et al. 2000).

Catchability: The covariates of the FMWT and SKT sampling programs that will be investigated for effects on catchability include, but are not limited to: sampling time of day (*ToD*), *Secchi depth*, *Tidal cycle*, and *Depth* of sampling locations. As mentioned previously, FMWT delta smelt CPUE data were effectively modeled with a zero-inflated negative binomial GLM (Latour *in press*), which can be described generally as:

---

[3] Probabilities of false zeros arise from zero-inflated data, which has been shown to be characteristic of the FMWT survey data (Latour *in* press) and is likely an issue with the SKT survey data (more on this below).

$$\Pr(Y=y)=\begin{cases}\pi+(1-\pi)\cdot\left(\dfrac{k}{\mu_i+k}\right)^k & y=0\\[2ex] (1-\pi)\cdot\dfrac{\Gamma(y+k)}{\Gamma(k)\cdot\Gamma(y+1)}\cdot\left(\dfrac{k}{\mu+k}\right)^k\cdot\left(\dfrac{\mu_i}{\mu+k}\right)^y & \text{otherwise}\end{cases} \tag{1}$$

where y is the value of the response variable and π and μ are the means of the binomial and negative binomial distributions, respectively. Here the binomial distribution is used to model probability of a false zero, which is the result of excess zeros in the data, and the negative binomial model is used to describe the probability of observing a specific CPUE value of y (defined as count-per-tow), including true zeros. A GLM is achieved when the means of the distributions are modeled as linear combinations of specific covariates:

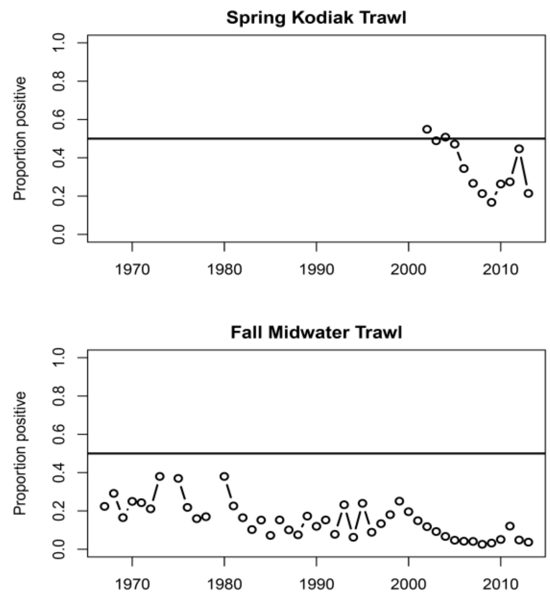

Fig.1. Proportion of tows where at least one delta smelt was captured, Spring Kodiak Trawl (2002-2013) and Fall Midwater Trawl (1967-2013). Reference line corresponds to 0.5.

$$\begin{aligned} f(\pi) &= \beta_0+\sum_{i=1}^{m}\beta_i X_i \\ g(\mu) &= \gamma_0+\sum_{i=1}^{m}\gamma_i X_i \end{aligned} \tag{2}$$

where the X_i' s are the values of the m covariates, the f and g terms are the link functions which relate each linear combination to the distribution mean (logit for the binomial, log for the negative binomial), and the β_i's and γ_i's are the estimated parameters that quantify the effects of those covariates on the response variable.

For a generic covariate Z that is hypothesized to influence catchability (specifically q_e), equation (2) could take the form:

$$\begin{aligned} f(\pi) &= \beta_0+\sum_{i=1}^{m-1}\beta_i X_i+\beta_m Z_m \\ g(\mu) &= \gamma_0+\sum_{i=1}^{m-1}\gamma_i X_i+\gamma_m Z_m \end{aligned} \tag{3}$$

where the X_i's are covariates that statistically control for 'other' covariates (e.g., spatiotemporal) affecting the probability of a false zero and q_e that, in turn, allow the effects of covariate Z to be more directly isolated. If Z is a dichotomous categorical covariate, such as ToD (Z =0 for morning tows, Z=1 for afternoon tows; Casey and Myers 1998, Benoit and Swain 2003), then the quantity e^{β_m} is the odds ratio of obtaining a false zero observation in the afternoon compared to the morning. For the count model component, e^{γ_m} represents an estimate of afternoon sampling power relative to morning sampling power, or more specifically, the relative change in q_e. These interpretations can easily be extended to accommodate polychotomous categorical covariates such as *Tidal cycle* (flood, ebb, slack). If Z is a continuous covariate such as *Secchi depth* or *Temperature*, then $e^{c\beta_m}$ and $e^{c\gamma_m}$ represent the change in the odds ratio and q_e, respectively, for a change of c units in Z.

For each survey dataset, several combinations of covariates will be considered and model diagnostics along with selection criteria (e.g., AIC, BIC) will be used to discriminate among competing parameterizations. Model selection statistics will provide insight about the relative impacts of hypothesized covariates on probabilities of false zeros and q_e. From the model(s) receiving strong empirical support, effects of covariates on odds ratios and q_e will be derived and used to broadly address question 1a.

To address question 1b, predictions from strongly supported model(s) across the domains of all covariates included will be generated to express the relative effects (for categorical covariates) and functional relationships (continuous covariates) of covariates on probabilities of false zeros and CPUE. The intent of these model predictions is to provide detailed insight into how false zero probabilities and CPUE vary temporally (e.g., *Year*, *Month*, *ToD*), spatially (e.g., *Area*, *Latitude*, *Longitude*), and in response to physical (e.g., *Tidal cycle*) and environmental conditions (e.g., *Temperature*, *Salinity*, *Secchi depth*) within the Delta. For CPUE, model derived predictions can be used to complement previous and ongoing investigations regarding spatiotemporal patterns of delta smelt and relationships of relative abundance with Delta ecosystem characteristics. Since application of zero-inflated models to delta smelt survey data is relatively new, the intent of these predictions is to complement those provided by Latour (*in press*) and to more comprehensively understand false negatives. In general, classifying false zeros is important but difficult to accomplish. False zeros are observations recorded in a dataset that are not really or should not be zeros. These can manifest as a result of misidentification of target organisms, poor experimental protocols (e.g., sampling time at locations is too short, suboptimal gear types or configurations), or because of 'animal errors' (e.g., behavioral aspects of organisms present at sampling locations prevent their collection; Zuur et al. 2012). For delta smelt, species misidentification is not likely an issue and the FMWT and SKT surveys utilize experimental protocols general similar to trawl surveys that target small fishes operating outside of the Delta. False zero probabilities could be tied to delta smelt behavioral when interacting with sampling gear, and patterns in these quantities across the domains of covariates could prove useful in understanding sampling dynamics.

Although the methods outlined above have the potential to yield information about factors affecting probabilities of false zeros and q_e, as configured they require temporal and spatial independence among survey samples. If either type of correlation is present within the survey data, then the modeling approach will need to be modified, and methods to do so are described below.

Temporal, Spatial Correlation: As mentioned previously, application of design-based estimators or model-based procedures for deriving abundance indices from survey data requires temporal and spatial independence. If survey samples close in time/space are more similar to one another than those more separated in time/space, then effective samples sizes are lower than realized, sample data may not be representative, and estimated indices of abundance can be biased (Dormann et al. 2007, Zuur et al. 2009, Zuur et al. 2012). To assess the degree of temporal and spatial correlation within delta smelt FMWT and SKT survey data (question 2a), various model parameterizations will be fitted under the assumption of independence among samples (as described above). From those models, detailed analyses of the residuals will be conducted. Pearson residuals will be plotted over time/space and LOESS smoothers will be fitted. A notably curved, systematically increasing, or systematically decreasing LOESS smoother would suggest an appreciable degree of temporal/spatial correlation. Sample variograms, which characterize the variance of the difference among residuals between sampling dates/locations across all sampling dates/locations can also be used to detect the presence of correlation. Both the classic method of moments and the robust Cressie estimation approaches will be used to derive variograms, and if either type exhibits notable patterns across time/distance, then temporal/spatial correlation is likely present within the survey data. If temporal/spatial correlation is detected, then models will be extended to formally incorporate temporally/spatially correlated residuals. This amounts to fitting models of the form:

$$CPUE = f\,(covariates) + temporally/spatially\ correlated\ residuals \tag{4}$$

where the covariates represent the large-scale patterns in the CPUE data and the residuals capture the small-scale temporally/spatially correlated patterns. Although various approaches can be used to model data with non-independent residuals, conditional auto-regressive correlation (CAR) represents a commonly used method (Zuur et al. 2012). Therefore, CAR models will be developed in a Bayesian framework, fitted to delta smelt CPUE data, and used to generate the aforementioned estimated quantities and model predictions (question 2b).

Application of CAR models to large datasets such as the FMWT and SKT surveys can be computationally intensive. Because of the Bayesian estimation framework and implementation of Markov Chain Monte Carlo (MCMC) approximation of the posterior distribution, the large number of CPUE measurements (several thousand tows), and the potentially high number of estimated parameters (> 75 for zero inflated GLMs), fitting CAR models will likely require extensive computing time. Therefore, test models will be explored. For abbreviated datasets of 3-4 years, both Bayesian formulations of standard and CAR models will be fitted and the results will be compared to identify optimal MCMC configurations (number of chains, draws, burn-in) and to evaluate effects of temporal/spatial correlation on estimated abundance indices. If the effects of temporal/spatial correlation on estimated indices from abbreviated datasets are not significant, then CAR treatment of the full datasets may not be warranted. However, if estimated abundance indices from the two model types are appreciably different, then CAR analysis of all available data will likely be necessary.

Interfacing with broader CAMT activities

It is important to emphasize that this project is intended to complement previous and ongoing investigations into the status of delta smelt. Although a sole PI is listed on this project, the proposed research will not be conducted in isolation. Formal efforts will be made to engage with other investigators associated with CAMT supported activities (e.g., Fall Outflow and Entrainment Teams) to ensure utility of research results and to serve as an additional analytical resource for activities beyond those outlined in this proposal. Interactions will be facilitated by periodic conference calls, webinars, and in-person meetings.

Investigative Challenges

General Limitation: This project is based on utilizing existing survey data to quantify the effects of various covariates on catchability and temporal/spatial correlation among samples. While evaluation of these issues is important to understanding sources of uncertainty in available delta smelt survey data, this project cannot overcome potential limitation inherent to survey design. Both the FMWT and SKT surveys are based on fixed station sampling designs, which implies that systematic changes in the population-level availability of delta smelt at sampling locations and subsequent survey-derived population quantities confounded. Mechanistically, population-level changes in availability to surveys can occur if the overall distribution and habitat preferences of delta smelt have appreciably changed over time. Additional exploratory field studies represent the only viable approach to addressing this concern.

Catchability: The primary weakness in addressing question (1) again relates to the reliance on existing survey data that has been collected in accordance to a specific sampling design not specifically configured to investigate changes in survey catchability. Using the aforementioned $Z{=}ToD$ example, it would be best to systematically replicate trawl tows at randomly selected sampling locations throughout the Delta during morning and afternoon (and also during night to fully characterize diel migrations), which would more effectively ensure that the localized delta smelt abundance being sampled throughout the day is constant. As mentioned above, application of GLM-type models requires making the assumption that delta smelt relative abundance is constant within combinations of other covariates included in the analysis. If those other covariates represent spatiotemporal factors such as *Year-Month-Area*, then the proposed approach requires the assumption that delta smelt abundance is constant during morning and afternoon for any given *Year-Month-Area* combination. Perhaps this assumption is reasonable since survey areas are typically sampled within a few days. Despite potential limitations like the one described here, the proposed analyses remain valuable since they are based on the foundational information currently used to infer the population status of delta smelt, and also because they can be used comparatively once field studies specifically designed to assess impacts of covariates on relative catchability can be conducted.

Temporal, Spatial Correlation: Modern advancements in computing power have undoubtedly facilitated the application of sophisticated statistical methods in recent years. Despite these advancements, complex statistical models fitted to very large datasets can require significant amounts of computing time. The FMWT and SKT surveys are both longstanding and thousands of trawl tows have been conducted over the lifetimes of each sampling program. While not insurmountable, a primary challenge in addressing question (2) is the reality that application of CAR models to the rich FMWT and SKT survey datasets using a Bayesian estimation framework will be time consuming (of course, this concern is only germane if temporal/spatial correlation among samples is detected).

Technology Transfer

A written report that provides a detailed summary of the study's need/rationale, analytical methods, results, and conclusions will be submitted no later than 30 days after the end date of the project.

Findings will also be presented orally as needed/requested. From the written report, at least one manuscript will be developed for publication in the peer-reviewed scientific literature. All data utilized in the project are publically available and computer code developed specifically for this project will be made available upon request.

Schedule

The overall timeline for the project is expected to encompass 12 weeks, broken down as follows:

- Weeks 1-4: Acquire FMWT and SKT survey data from the CDFW; basic QA/QC of data; exploratory analyses of delta smelt CPUE; determination of optimal model structure(s); estimation of abundance indices and covariate effects on survey catchability; application of data correction factors and estimation of alternative abundance indices; preliminary evaluation of temporal/spatial correlation among samples.
- Weeks 5-10: Create test datasets; fit standard and Bayesian models to test data to ensure reproducibility of results estimation approaches; refine MCMC configuration; augment Bayesian models with CAR structure for test data; compare CAR and standard modeling results and abundance indices from test data; implement CAR model for full datasets.
- Weeks 11-12: Report preparation and presentation of findings to CAMT.

Budget

Total project cost is $89,400 broken down as follows: $72,000 for completion of analyses and report preparation (60 working days at $1200/day [$150/hr]) and $17,400 for time and travel expenses for interfacing with investigators broadly associated with CAMT activities (assumed two trips to CA [$1,500/trip = $3,000; 3 days/trip = $7,200] and 6 days [$7,200]).

Literature Cited

Atwater, B.F., S.G. Conrad, J.N. Dowden, C.W. Hedel, R.L. MacDonald, and W. Savage. 1979. History, landforms and vegetation of the estuary's tidal marshes. In San Francisco Bay: The Urbanized Estuary, ed. T.J. Conomos, 347-385. San Francisco: Pacific Division American Association for the Advancement of Science.

Benoit, H. and D.P. Swain. 2003. Accounting for length- and depth-dependent diel variation in catchability of fish and invertebrates in an annual bottom-trawl survey. ICES Journal of Marine Science 60:1298-1317.

Casey, J.M. and R.A. Myers. 1998. Diel variation in trawl catchability: is it clear as day and night? Canadian Journal of Fisheries and Aquatic Sciences 55:2329-2340.

Cohen, A.N., and J.T. Carlton. 1998. Accelerating invasion rate in a highly invaded estuary. Science 279:555-558.

Connor, M.S., J.A. Davis, J. Leatherbarrow, B.K. Greenfield, A. Gunther, D. Hardin, T. Mumley, J.J. Oram, and C. Werme. 2007. The slow recovery of San Francisco Bay from the legacy of organochlorine pesticides. Environmental Research 105:87-100.

Dormann, C.F. and 16 co-authors. 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. Ecography 30:609-628.

Kimura, D.K. and D.A. Somerton. 2006. Review of statistical aspects of survey sampling for marine fisheries. Reviews in Fisheries Science 14:245-283.

Kotwicki, S., J.N. Ianelli, and A.E. Punt. 2014. Correcting density-dependent effects in abundance estimates from bottom-trawl surveys. ICES Journal of Marine Science 71:1107-1116.

Latour, R.J. In press. Explaining patterns of pelagic fish abundance in the Sacramento-San Joaquin Delta. Estuaries & Coasts.

Lunn, D.J., A. Thomas, N. Best, and D. Spiegelhalter. 2000. WinBUGS – a Bayesian modeling framework: concepts, structure, and extensibility. Statistics and Computing 10:325-337.

Maunder, M.N. and A.E. Punt. 2003. Standardizing catch and effort data: a review of recent approaches. Fisheries Research 70:141-159.

McCullagh, P. and J.A. Nelder. 1989. *Generalized linear models*, 2nd ed. London: Chapman and Hall.

Schoellhamer, D.H. 2011. Sudden clearing of estuarine waters upon crossing the threshold from transport to supply regulation of sediment transport as an erodible sediment pool is depleted: San Francisco Bay, 1999. Estuaries and Coasts 34:885-899.

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.

Wood, S.N. 2006. *Generalized Additive Models*. Chapman and Hall/CRC.

Zuur, A.F., E.N. Ieno, N.J. Walker, A.A. Saveliev, and G.M. Smith. 2009. *Mixed effects models and extensions in ecology with R*. New York: Springer.

Zuur, A.F., A.A. Saveliev, and E.N. Ieno. 2012. *Zero inflated models and generalized linear mixed models with R*. Newburgh: Highland Statistics Ltd.

ROBERT J. LATOUR

Virginia Institute of Marine Science
College of William & Mary
P.O. Box 1346, Gloucester Point, VA, 23062

Phone: (804) 684-7312
Fax (804) 684-7327
Email: latour@vims.edu

A. PROFESSIONAL PREPARATION:

2000	Ph.D.	Biomathematics, North Carolina State University
1996	M.BMA	Biomathematics, North Carolina State University
1994	B.A.	Mathematics (*magna cum laude*), Western New England College

B. PROFESSIONAL HISTORY:

2013 – present	Professor, Virginia Institute of Marine Science, College of William & Mary
2008 – 2013	Associate Professor, Virginia Institute of Marine Science, College of William & Mary
2008 – 2011	Moses D. Nunnally Distinguished Associate Professor, Virginia Institute of Marine Science, College of William & Mary
2004 – 2008	Assistant Professor, Virginia Institute of Marine Science, College of William & Mary
2001 – 2004	Research Assistant Professor, Virginia Institute of Marine Science, College of William & Mary
2000 – 2001	Postdoctoral Researcher, Virginia Institute of Marine Science, College of William & Mary

C. FIVE RECENT PUBLICATIONS (*my graduate student, **graduate student collaboration):

Latour, R.J. In press. Explaining patterns of pelagic fish abundance in the Sacramento-San Joaquin Delta. Estuaries & Coasts.

*Sobocinski, K.L. and bf R.J. Latour. 2015. Trophic transfer in seagrass systems: Estimating seasonal production of an abundant seagrass fish, *Bairdiella chrysoura*, in lower Chesapeake Bay. Marine Ecology Progress Series 523:157-174.

*Buchheister, A. and R.J. Latour. 2015. Diets and trophic guild structure of a diverse fish assemblage in Chesapeake Bay, USA. Journal of Fish Biology 86:967-992.

**Lefcheck, J.S.,*A. Buchheister, **K.M. Laumann,*M. Stratton, *K.L. Sobocinski, **S. Chak, **T.R. Clardy, P.L. Reynolds, R.J. Latour, J.E. Duffy. 2014. Dimensions of biodiversity in Chesapeake Bay demersal fishes: patterns and drivers through space and time. Ecosphere 5:art14.

*Sweetman, C.J., T.T. Sutton, M. Vecchione, and R.J. Latour. 2013. Distribution of the biomass dominant pelagic fish, *Bathylagus euryops* (Argentiniformes: Microstomatidae), along the northern Mid-Atlantic Ridge. Deep-Sea Research I 78:16-23.

FIVE ADDITIONAL PUBLICATIONS (* my graduate student, ** graduate student collaborator):

Hudson, J., D.K. Steinberg, T.T. Sutton, J.E. Graves, and R.J. Latour. 2014. Myctophid feeding ecology and carbon transport along the Northern Mid-Atlantic Ridge. Deep Sea Research I 93:104-116.

*Sobocinski, K.L., J.J. Orth, M.C. Fabrizio, and R.J. Latour. 2013. Historical comparison of fish community structure in lower Chesapeake Bay seagrass habitats. Estuaries & Coasts 36:775-794.

*Buchheister, A, C.F. Bonzek, J. Gartland, and R.J. Latour. 2013. Patterns and drivers of the demersal fish community of Chesapeake Bay. Marine Ecological Progress Series 481:161-180.

*Lynch, P.D., K.W. Shertzer, and R.J. Latour. 2012. Estimating relative abundance of highly migratory bycatch species. Fisheries Research 125-126:27-39.

Latour, R.J., E.J. Hilton, *P.D. Lynch, T.D. Tuckey, B.E. Watkins, and J.E. Olney. 2012. Evaluating the current status of American shad (*Alosa sapidissima*) stocks in three Virginia rivers. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science 4:302-311.

D. SYNERGISTIC ACTIVITIES:

NMFS Advisory Panel for Atlantic Highly Migratory Species (SEDAR Pool)
Atlantic Menhaden Technical Committee, Atlantic States Marine Fisheries Commission
Science and Statistics Committee, Mid Atlantic Fishery Management Council

E. CO-AUTHORS AND COLLABORATORS (last four years):

Balazik, M. (VCU); Bonzek, C. (VIMS); Bronk, D. (VIMS); Brill, R. (NOAA/VIMS); Brush, M. (VIMS); Buchheister, A. (CBL); Bushnell, P. (IU); Chak, S. (VIMS); Collie, J. (URI); Clardy, T. (VIMS); Duffy, E. (VIMS, Smithsonian); Fine, M. (VCU); Fabrizio, M. (VIMS); Frisk, M. (Stony Brook); Funkey, C. (Lund U.); Garman, G. (VCU); Garrison, L. (NMFS); Gartland, J. (VIMS); Gauthier, D. (ODU); Graves, J. (VIMS); Greenlee, R. (VDGIF); Groves, M. (MDDNR); Hilton, E. (VIMS); Horodysky, A. (Hampton U.); Hudson, J. (VIMS); Langford, B. (VCU); Laumann, K. (VIMS); Lefcheck, J. (VIMS); Link, J. (NMFS); Lynch, P. (NMFS); Martell, S. (Pacific Halibut Commission/UBC); McIninch, S. (VCU); Miller, T. (CBL); Musick, J. (VIMS); Orth, J. (VIMS); Reese, K. (VIMS); Rhodes, M. (VIMS); Reynolds, P. (UC Davis); Schloesser, R. (VIMS); Sharov, A. (MDDNR); Shertzer, K. (NMFS); Sobocinski, K. (Oregon State); Stewart, J. (VCU); Stratton, M. (VIMS); Steinberg, D. (VIMS); Sutton, T. (NOVA Southeastern); Sweetman, C. (VIMS); Tuckey, T. (VIMS); Watkins, B. (VIMS); Wilberg, M. (CBL); Vecchione, M. (NMFS); Vogelbein, W. (VIMS)

F. ADVISORS:

Graduate advisor (M.BMA, Ph.D.): Kenneth H. Pollock, North Carolina State University
Post-doctoral advisor: John E. Olney, VIMS, College of William & Mary

G. ADVISEES:

Graduate students (13 students, 16 degree programs): Zoemma Warshafsky (co-advisor, M.S., current); Christopher Sweetman (Ph.D., current); Kristene Parsons (Ph.D., current); Mark Stratton (Ph.D., current); Cassidy Peterson (M.S., current); Carissa Gervasi (M.S., 2015); Kathryn Sobocinski (co-advisor, Ph.D., 2014); Andre Buchheister (Ph.D., 2013); Patrick D. Lynch (Ph.D., 2012); Christopher Sweetman (co-advisor, M.S., 2012); Catarina Wor Lima (M.S., 2012); Andrij Z. Horodysky (co-advisor, Ph.D., 2009); Justine Woodward (co-advisor, M.S., 2009); Andre Buchheister (M.S., 2008); Patrick D. Lynch (M.S., 2007); Kathleen A. McNamee (M.S., 2007)