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RESEARCH

Machine Learning Forecasts to Reduce Risk of Entrainment Loss of Endangered Salmonids at Large-Scale Water Diversions in the Sacramento–San Joaquin Delta, California

Michael D. Tillotson*[1], Jason Hassrick[2], Alison L. Collins[3], Corey Phillis[3]

ABSTRACT

Incidental entrainment of fishes at large-scale state and federal water diversion facilities in the Sacramento-San Joaquin Delta, California, can trigger protective management actions when limits imposed by environmental regulations are approached or exceeded. These actions can result in substantial economic costs, and likewise they can affect the status of vulnerable species. Here, we examine data relevant to water management actions during January–June; the period when juvenile salmonids are present in the Delta. We use a quantile regression forest approach to create a risk forecasting tool, which can inform adjustments of diversions based on near real-time predictions. Models were trained using historical entrainment data (Water Years 1999–2019) for Sacramento River winter-run Chinook Salmon or Central Valley Steelhead and a suite of environmental and water operations metrics. A range of models was developed; their performance was evaluated by comparison of a quantile loss metric. The models were validated through examination of partial dependence plots, cross-validation procedures, and further evaluated through WY 2019 pilot testing, which integrated real-world uncertainty in environmental parameters into model predictions. For both species, the strongest predictor of loss was the previous week's entrainment loss. In addition, risk increased with higher water exports and more negative Old and Middle Rivers (OMR) flows. Point estimates of loss were modestly correlated with observations (R^2 0.4 to 0.6), but the use of a quantile regression approach provided reliable prediction intervals. For both species, the predicted 75th quantile appears to be a robust and conservative estimator of entrainment risk, with overprediction occurring in fewer than 20% of cases. This quantile balances the magnitude of over- and under-prediction and results in a low probability (< 5% of predictions) of unexpected high-take events. These models, and the web-based application through which they are made accessible to non-technical users, can provide a useful and complementary approach to the current system of managing entrainment risk.

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* Corresponding author: mike.tillotson@icf.com
1 ICF, Sacramento, CA 95814
2 ICF, San Francisco, CA 94105
3 The Metropolitan Water District of Southern California Sacramento, CA 95814

KEY WORDS

Sacramento–San Joaquin Delta, quantile regression forest, Chinook Salmon, Steelhead, machine learning, entrainment loss

INTRODUCTION

In California's increasingly arid climate, managing freshwater resources is a delicate balance between meeting the needs of fish and wildlife and the needs of agriculture and urban requirements to serve 25 million people (Service 2007). Ensuring a predictable water supply is increasingly constrained by effects on a growing list of species of concern. In the tidal Sacramento-San Joaquin River Delta (hereafter, the Delta), multiple vulnerable salmonid populations have the potential to interact with large-scale water-diversion projects, resulting in a wide range of operational limitations. Sacramento River winter-run Chinook Salmon (*Oncorhynchus tshawytscha*) are listed as endangered under the federal Endangered Species Act (ESA); Central Valley steelhead (*Oncorhynchus mykiss*) are listed as threatened. Minimizing the effects of water diversions on these and other fishes is critical for managing vulnerable populations, and for ensuring a reliable water supply. Clarifying the factors that influence risk of salmonid entrainment could help to inform more targeted and effective water management actions, but it has thus far proven difficult to untangle interactions of migratory species with complex hydrodynamics in the Delta (Bever et al. 2016).

Compared to current conditions, the historic Delta likely presented a relatively safe migration corridor for Chinook Salmon and Steelhead, with rich and ample floodplain habitat supporting additional growth before the stressful transition to marine waters (Sommer et al. 2001). In contrast, in the modern Delta, much of this floodplain habitat has been reclaimed as agricultural lands, and the remaining waterways are deeper, highly channelized, and inhabited by large populations of non-native predators, including Striped Bass, Black Bass and Catfish (Young et al. 2018; Lindley et al. 2019). In addition, water from the Delta is diverted and exported for irrigation and municipal water supplies, primarily from two large pumping facilities in the south Delta—the State Water Project (SWP) Harvey O. Banks Pumping Plant and the federal Central Valley Project (CVP) Jones Pumping Plant—which together commonly divert more than 25% the daily flow from the Sacramento and San Joaquin rivers (~ one-third of the days during the period when these salmonids are present in the Delta). Water exports of this magnitude are capable of altering natural flow regimes, and indeed, diversions commonly reverse the net direction of flow in portions of the Delta toward the pumping facilities, which may increase the potential to entrain out-migrating salmonids (Buchanan et al. 2013; Perry et al. 2018).

Chinook Salmon and Central Valley Steelhead must transit the Delta en route from their spawning grounds in the upper watersheds to oceanic feeding areas, and, despite reasonably targeted downstream movement (Buchanan et al. 2013; 2021), can spend days or weeks moving through complex network of channels, sloughs, and water diversions on their way to San Francisco Bay and the ocean beyond (Perry et al. 2013). Winter-run Chinook Salmon migrate downstream in their first year of life, shortly after emerging from the gravel, and so the period of downstream migration and residence in the Delta is critical for growth (Yoshiyama et al. 1998; Bellido–Leiva et al. 2021). The timing of downstream movement, and therefore the period of vulnerability to entrainment, depends on Sacramento River flows, and can thus vary markedly between years in response to hydrologic conditions (Michel et al. 2015; Notch et al. 2020). In contrast with the smaller winter-run Chinook Salmon juveniles, Central Valley Steelhead rear in upstream habitats for one or more years before out-migration (McEwan 2001), and transit through the Delta more rapidly and at a larger size, which should result in reduced entrainment risk (Williams 2006). However, unlike winter-run Chinook Salmon, which originate from a single population in the Sacramento River, Central Valley Steelhead are a stock complex, also spawning in the San Joaquin watershed, though in generally smaller numbers than Sacramento populations (Lindley et al. 2007). The body

Regardless of any life-history complexities or differences, juveniles from all anadromous species and populations must ultimately reach the ocean to complete their life cycle, and this is, at least in part, achieved by following river flow (Ramón et al. 2018). Although the pumping facilities are not located directly on primary migration corridors, the scale of diversions is often sufficient to alter flows through the Delta (Zeug and Cavallo 2014). Such flow alterations are likely to affect the migration routes of salmonids and may increase exposure to the pumping facilities, though the effect of entrainment risk is complex and continues to be an active area of research (Perry et al. 2016). In spite of this uncertainty, one of the primary management actions currently employed is to restrict the combined flows of the waterways located nearest the pumping facilities—the Old and Middle Rivers (OMR)—to no less than –5,000 cfs during months in which listed salmonids are most likely to be present in the Delta (NMFS 2019). Despite this management action, some proportion of the winter-run Chinook Salmon and Central Valley Steelhead populations nevertheless arrive in the vicinity of the pumping facilities, and the number of fish entrained tends to increase with higher exports (Kimmerer 2008; Newman and Brandes 2010). Thus, in addition to coarse, seasonal limitations such as OMR restrictions, forecasting near-term (i.e., weekly) risk of salmonid entrainment and modifying water operations accordingly is a critical component of the current management approach.

Following requirements of the ESA, the National Marine Fisheries Service (NMFS) issued a Biological Opinion (BO) in 2019, which requires a committee of natural resource agency fisheries biologists, water operators, and regulatory specialists to convene weekly to consult on demographic, environmental, and operational conditions at the pumping facilities that are anticipated to affect entrainment risk (Figure 1). The BO prescribes an Incidental Take Limit (ITL) based on entrainment loss, which the committee uses as a benchmark for recommending changes to operations, given trends in monitoring data from the rivers and in salvage at the water pumping facilities. Using a combination of rotary screw-trapping data in the main rivers that enter the Delta and routing probabilities (Perry et al.

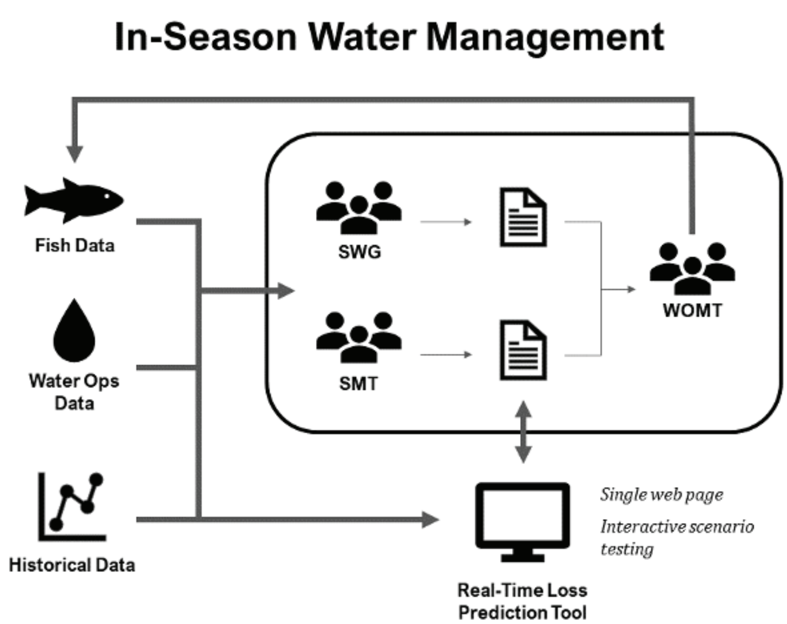

Figure 1 Schematic representation of the current approach to in-season management of entrainment risk—where the Smelt Working Group (SWG) and Salmon Management Team (SMT) jointly inform Water Operations Management Team (WOMT) decision-making—and the anticipated, complementary role of a quantitative prediction tool.

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2018), the Salmon Management Team (SMT) meets weekly to estimate the distribution of each run of salmonids approaching, within, or exiting the Delta to assess entrainment risk (Figure 1). Then, using expert judgement, the committee produces a rationale for changes in fish distribution relative to the diversion facilities in the South Delta, and posts its notes online with recommendations of exposure risk based on flows and export rates for water operations managers to consider, (*https://www.usbr.gov/mp/bdo/salmon-monitoring-team.html*). Weekly notes and the various sources of data taken into consideration for management recommendations can occupy 30 pages of text. Given these complexities, expert consultations are time- and resource-intensive to produce, and their recommendations are difficult to reproduce. Quantitative modeling approaches may provide useful, independent and complementary predictions of entrainment risk in a much more timely and reproducible fashion. Moreover, such tools could allow for sensitivity analyses and the comparison of environmental and operational scenarios, which would help focus protections for fish when necessary, and provide flexibility of exports from pumping facilities during periods of low risk. Ultimately, reliable forecasts of entrainment risk could inform an adaptive management approach where water exports are reduced in response to predictions of high entrainment in the coming week. To facilitate such an approach, forecasts of entrainment risk should be reliable enough to minimize unexpected high loss events (i.e., large under-predictions) while also avoiding consistently large over-predictions, which could lead to excessively conservative water management.

Incidental entrainment loss at the SWP and CVP pumping facilities is influenced by the interaction of environmental, behavioral, and water operation variables (Kimmerer 2008; Zeug and Cavallo 2014). Understanding the specific environmental and operational factors that influence entrainment risk has been the focus of previous studies (Grimaldo et al. 2009) and continues to be an important area of research. Forecasting risk to inform real-time operational decisions is a related, but distinct objective, and should be achievable even in the absence of a perfect understanding of the mechanisms that ultimately lead to the entrainment. Because the primary goal of a loss forecasting tool is prediction rather than description, machine learning methods—which have displayed superior predictive performance compared with traditional regression methods for many applications (Meinshausen and Ridgeway 2006; Elith et al. 2008)— may be appropriate. Ecological data commonly have characteristics such as multicollinearity among interacting variables, non-normal distributions, and uncertain interactions that may violate assumptions of parametric regression approaches (Zuur et al. 2009). To circumvent these issues in multi-dimensional situations, a range of machine-learning techniques are gaining favor in ecology and natural resource management (Olden et al. 2008).

While many methodological options exist, tree-based methods including random-forest (RF) and boosted regression trees (BRT) have been applied widely to ecological problems, are relatively interpretable, and can provide outputs well suited to evaluation of risk. These methods are based upon classification and regression trees, which iteratively split the response data based on a single predictor variable such that the between-group variance is maximized and the within group variance is minimized (Olden et al. 2008). The data are then continually split based on the next-best splitting rule, until each node has a single observation or other stopping criteria are met. Although intuitive, single regression trees typically are poor predictors and are very sensitive to the training data set. However, RF and BRT approaches add stochasticity to the selection of splitting rules, creating many individual trees, and resulting in more robust ensemble models that nevertheless retain the intuitive nature of a single tree (Olden et al. 2008; Brieuc et al. 2015). Apart from relatively strong predictive ability, tree-based regressions have several other beneficial characteristics. The tree structure inherently incorporates interactions, and unimportant variables need not be manually removed because they are rarely selected in the splitting process (Elith et al. 2008). Furthermore, the analysis requires no distributional assumptions, and inference is not biased by multicollinearity of predictors (though variable importance may not be appropriately resolved in the presence of highly correlated predictors).

Using a tree-based approach, our overall goal was to develop a predictive tool that could provide useful risk estimates of winter-run Chinook Salmon and Central Valley Steelhead being entraining at the CVP and SWP facilities. Specifically, we sought to develop and validate a model capable of (1) forecasting loss of juvenile Salmon and Steelhead at the pumping facilities based on environmental, operational, and biological variables that are either available in near-real time or are forecasted for at least 1 week, (2) providing an intuitive way to consider risk and uncertainty in loss predictions, and (3) facilitating the comparison of alternative operational scenarios. To achieve this goal, we identified potentially important predictors of entrainment, trained a series of models with varying levels of complexity using these data, evaluated predictive perfromance using multiple cross-validation approaches, developed a web-based prediction interface, and carried out real-world testing with the web tool during the 2019 salvage season.

METHODS

Data

We compiled all data for model training and testing from publicly available sources. The response variables included daily estimates of entrainment loss for winter-run Chinook Salmon and Central Valley Steelhead measured separately at the CVP and SWP pumping stations. Fish-collection facilities are located upstream of the pumps and use a series of louvers or screens to separate entrained fish from the flow of water. Fish captured in this way are deemed to have been salvaged. Collection and enumeration methods of the salvage process are explained in detail in Castillo et al. (2012). Briefly, fish are diverted into a holding tank where a sub-sample is counted over a given period—typically a 30-minute sub-sample over a 2-hour collection period—to estimate the total number of fish salvaged. After counting, salvaged fish are transported by trucks to the western Delta where they are released to continue migrating to sea. Fish that do not survive this process are counted as lost. Loss is estimated by applying various multipliers to salvage estimates to account for predation, screening efficiency, and handling/trucking mortality (Kimmerer 2008). Loss data were available for Water Years 1999–2020.

In a change from prior opinions, the 2019 BO specifies that the ITL for both winter-run and Chinook Salmon and Central Valley Steelhead is based on these loss estimates, and not raw salvage counts. In addition, the most recent BO includes two ITLs for each species based on single year loss and 3-year rolling average loss. Here, we evaluate models relative to the single-year values. For wild (naturally produced) winter-run Chinook Salmon, the maximum ITL in a single year is 2% loss of the estimated number of length-at-date juveniles entering the Delta, which is calculated annually based on estimates of adult spawning abundance in the prior year and assumptions of early life stage survival based on environmental conditions and survival data (NMFS 2009; O'Farrell et al. 2018). Seasonal runs of Chinook Salmon are identified in salvage —and counted against the ITL—using a length-at-date run estimation, which can result in misidentification with temporally overlapping runs (Harvey et al. 2014) but remains the best available method until rapid genetic identification becomes more widely available. Because less information is available on annual wild Central Valley Steelhead natal origin and abundance, the maximum ITL in a single year is fixed at a loss of 2,760 between December 1 and March 31, and a loss of 3,040 between April 1 and June 15 (NMFS 2019).

As noted in the Introduction, the Delta is a complex and heterogenous system, and so many environmental and operational variables are likely to influence the risk of entrainment while interacting in unknown ways (Zeug and Cavallo 2014; Grimaldo et al. 2009). Moreover, for fish to be salvaged, they must, of course, be present in the Delta, which is determined by many factors including species- and population-specific

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abundances, life histories, and phenologies. Given this environmental and biological complexity, the number of potentially relevant predictors of entrainment risk is almost infinitely large. As such, we did not undertake an exhaustive process of variable selection, but rather chose a set of predictor variables based primarily on those currently considered by the SMT (Table 1) that was intended to capture (1) environmental conditions that experts consult on that are thought to influence salmonid presence in the Delta (e.g., water temperature, precipitation, and inflow from the Sacramento and San Joaquin rivers); (2) operational conditions that might influence rates of entrainment (i.e., total diversions and OMR flow); and (3) indicators of relative abundance in the Delta (e.g., survey indices, recent salvage history, and date). We also limited predictor variables to those with data available for the entire salvage time-series (WY 1999–2020), and gave preference to variables with readily available forecasts. For model training, we aggregated all variables from daily observations to weekly means, except for precipitation and prior week salvage, which were summed, and Delta Cross Channel (DCC) gate status, which was listed as “opened” or “closed” based on a simple majority of daily statuses.

Modeling Approach

The basic objective of the predictive model was to provide an estimate of the range of plausible winter-run Chinook Salmon loss and Central Valley Steelhead and over the coming week, using a tree-based regression approach. A weekly time-step was chosen because it is compatible with the current format of risk evaluation (i.e., weekly meetings of resource managers), loss data are made publicly available at weekly intervals, and it reduces the effect of stochasticity in daily loss estimates. Because of a focus on interval rather than point predictions, we used a quantile regression forest (QRF) approach: a simple extension of the RF algorithm that retains the complete distribution of predictions from individual tress, rather than the mean prediction as in RF (Meinshausen and Ridgeway 2006). Each quantile should approximate the frequency with which the quantile prediction exceeds observed loss. For example, the 75th predicted quantile will be larger than observed loss in around 75% of cases. Thus, with the QRF output it is trivial to calculate any prediction interval of interest. The predictive model was initially developed as a single-step QRF model (hereafter the simple model), trained with data described above for water Years 1999-2020. For each species, three response variables were used: loss recorded at the CVP, at the SWP, and from the two facilities combined. The models were trained using the ‘quantregForest’ (Meinshausen 2017), in R (R Core Team 2019). A range of values for key algorithm parameters were tested, including the number of variables sampled at each tree split (mtry), the minimum number of terminal nodes (nodesize) and the number of trees in the forest (ntree), but the defaults were ultimately deemed sufficient aside from tree number, which was set to 300 for the sake of computational efficiency (Oshiro et al. 2012).

Feedback from potential model users included some concern regarding the reliance of the models on the prior week’s loss since it may lead to poor prediction early in the salvage season when few fish are observed. In an attempt to address this concern, we developed an alternative, two-step model formulation (hereafter referred to as the hurdle model). The hurdle model first trains a random forest classifier using the ‘randomForest’ package (Law and Wiener 2002). The response and predictor variables are the same as for the simple model, except that the responses are converted from continuous to binary (i.e., loss/no loss) and the prior week’s loss is excluded. A QRF model with the same formulation as the simple model is then fit to a censored data set containing only weeks with non-zero observed loss. The prediction from the classification model is then multiplied by the prediction in the simple model. Thus, the first step (RF classifier) predicts whether or not any loss will occur in the coming week based only on environmental and operational conditions, and when loss is predicted to occur, the second step (QRF regression) estimates the magnitude of loss using the complete set of predictors, (i.e., including the prior week’s loss). For each response

Table 1 Summary of predictor variables and data sources

Variable	Description	Category	Training source	Prediction source
temp.mal	Daily average water temperature at Mallard Island (°C)	Environment	CDEC[a]	NOAA San Francisco Bay Operational Forecast System[b]
precip	5-day precipitation runoff estimate for the Delta (cfs)	Environment	CDWR Dayflow[c]	Precipitation Forecast for Stockton Fire Station[d]
sac	Sacramento River Flow at Freeport (cfs)	Environment	CDWR Dayflow	Bay Delta Live[e]
sjr	San Joaquin River Flow at Vernalis (cfs)	Environment	CDWR Dayflow	Bay Delta Live
OMR	Sum of Old and Middle Rivers discharge; tide filtered in CFS at Middle River and Bacon Island from USGS (cfs)	Operations	Reclamation CVO Office[f]	Reclamation CVO Office
export	Sum of CVP and SWP discharge at HRO and TRP (cfs)	Operations	CDEC[g]	Bay Delta Live
dcc	Delta Cross Channel Gate status	Operations	CDWR Dayflow	Bay Delta Live
winter.pw	Previous week's CVP+SWP winter-run loss	Abundance	SacPAS Salvage and Loss Summary[h]	CDFW Salvage FTP[i]
steelhead.pw	Previous week's CVP+SWP Steelhead salvage	Abundance	SacPAS Salvage and Loss Summary	CDFW Salvage FTP
Winter_Seine	Chinook index in Sacramento Beach Seine survey, 6-week lag	Abundance	USFWS Delta Juvenile Fish Monitoring Program[i]	Bay Delta Live
Steelhead_Seine	*O. mykiss* index in Sacramento Beach Seine survey, 3-week lag	Abundance	USFWS Delta Juvenile Fish Monitoring Program	Bay Delta Live

a. *http://cdec.water.ca.gov/dynamicapp/staMeta?station_id=MAL*
b. *https://tidesandcurrents.noaa.gov/ofs/sfbofs/sfbofs_info.html#:~:text=The%20San%20Francisco%20Bay%20Operational,of%20the%20San%20Francisco%20Bay*
c. *https://data.ca.gov/dataset/dayflow*
d. *http://cdec.water.ca.gov/dynamicapp/staMeta?station_id=SFS*
e. *https://www.baydeltalive.com/ops/daily-operations-summary*
f. *https://waterdata.usgs.gov/usa/nwis/uv?site_no= 11312676, https://waterdata.usgs.gov/usa/nwis/uv?site_no=11313405*
g. *http://cdec.water.ca.gov/dynamicapp/staMeta?station_id=HRO http://cdec.water.ca.gov/dynamicapp/staMeta?station_id=TRP*
h. *http://www.cbr.washington.edu/sacramento/data/delta_loss_summary.html*
i. *https://dev.baydeltalive.com/fisheries/triggers-and-indices*

variable, both the simple and hurdle models were fit. The output of each model is the same: a predicted distribution of the response variable, which can be used to explore the range of potential outcomes, given a set of environmental and operational conditions.

Model Validation

Trained models were first qualitatively evaluated by examination of variable importance rankings—based on the percent change in mean squared error resulting from randomly permuting each predictor variable—and examination of partial dependence plots, which show the change in predicted loss in response to changing a single variable while holding all others at their means. For the hurdle model, variable importance and partial dependencies were examined separately for the classification and QRF components. We then evaluated the models' predictive performance using three separate approaches.

First, the 'quantregForest' functions use "bagging" (Liaw and Wiener 2002), which takes bootstrap samples from the training data set and then predicts the remaining cases while the forests are being constructed (Breiman 1996). A summary of this internal estimate of predictive performance is then reported in terms of percent of total variance explained. Second, we performed leave-one-out (LOO) and 10-fold cross-validation procedures where either a single year or random 10% of data were held back from the training set. Each model was then trained with the remaining data, and the resulting models used to predict the 1st,5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th quantiles. Because the QRF algorithm retains the complete response distribution, it is trivial to calculate a conditional mean identical to that produced by the random forest algorithm (Meinshausen and Ridgeway 2006), and so we also generated mean predictions. We compared the mean weekly predictions with observations using simple least-squares regression and the R^2 values taken as an indication of point-prediction performance. For the classification component of the hurdle models, we also calculated accuracy and the area under the receiver operating curve (AUC). For the quantile predictions, we calculated the prediction error of each weekly estimate using the quantile loss function suggested by Natekin and Knoll (2013) and then calculated the mean loss across all predictions.

While this quantile loss function allows performance between the model formulations to be compared, it does not provide an intuitive measure of model performance relative to the goals of resource managers. Assuming an adaptive management system where water exports would be reduced in response to predictions of high entrainment, two goals need to be balanced: minimizing large, unexpected loss events, and avoiding consistently large over-prediction, which could lead to unnecessarily conservative water management. To evaluate performance relative to these goals, for each model, cross-validation method, and a set of conservative quantiles (0.5, 0.75, 0.90 and 0.95), we calculated four metrics: the frequency of large, unexpected take events (defined as observed loss exceeding the relevant predicted quantile by 2% of the average ITL; 182 for winter-run Chinook Salmon and 116 for Central Valley Steelhead), the frequency of over-prediction by more than 1% of the average ITL, and the mean and median values of over- or under-prediction. We chose the asymmetrical definition of large under- and over-prediction events because the distribution of over-predictions is bounded by zero, while under-predictions are unbounded. For this portion of model validation, we were interested in the primary management-relevant outcome—total weekly loss, irrespective of salvage facility—and so focused on the final predictions of total winter-run Chinook Salmon and Central Valley Steelhead loss, and not the individual components of the hurdle model, or the independent predictions of models fit only to CVP or SWP data. Thus, results include four model formulations for each species. "Combined" models were trained with total loss data; CVP+SWP models represent the sum of predictions from models trained with only CVP or SWP loss data.

Finally, pilot-testing of the initially developed models (simple formulations trained with CVP and SWP combined) was conducted during the 2019 salvage season. Pilot testing was not only out-of-sample testing that exposed the model to new data, but also incorporated uncertainty inherent in the forecasts of environmental and operational predictor variables. The web-based application (described below) was used to create weekly predictions using the sources shown in the last column of Table 1 for forecasted values of predictor variables. Predictions of the median, 10th, and 90th quantiles were then graphically compared with observed loss.

Web-Based Application

To facilitate use of the predictive model by resource managers and other interested parties, we initially developed a web-based interface for the QRF models using the R package 'shiny' (Chang et al. 2015) that has since been incorporated into a suite of monitoring, evaluation, and web-based data products and services called SacPAS (Sacramento Prediction and Assessment of Salmon; *http://cbr.washington.edu/sacramento/lossandsalvage/*). The application provides a module that is used for in-season prediction of incidental entrainment loss and allows the user to manually set all forecasted predictor variables for sensitivity analyses and exploration of alternative water-operations scenarios. The web tool then provides graphical and tabular output of observed loss-to-date and predicted median and user-defined quantiles. The graphical output also compares cumulative observed and predicted loss relative to the average timing of loss observed in the training data set and scaled relative to the ITL or other value specified by the user.

RESULTS

Variable Importance and Conditional Effects of Predictors

Examination of variable importance rankings revealed that across all model formulations and for both species, the prior week's loss was by far the most important predictor, and the week of the Water Year (i.e., date) was the second most important variable in all cases but one: Steelhead loss at the SWP where OMR was the second most important variable (Figure 2; Table 2). For the presence/absence classification step of the hurdle model, week of Water Year and temperature were the first and second ranked variables. Examination of partial dependence plots revealed that the most important predictors (Figure 3), and the variables most directly responsive to water management actions (Figure 4) all had intuitive relationships with the risk of entrainment loss. The relationships between prior week and current week loss were positive, generally linear, and asymptotic (Figure 3). Seasonal patterns of loss were also well captured in the plots of partial dependence on week of Water Year; though the period of highest risk is more pronounced for Central Valley Steelhead. The influence of directly manageable variables (Figure 4) was modest when compared to the prior week's loss (Figure 3), but for both species, greater loss was predicted when OMR flows were negative, or exports increased.

Predictive Performance

Although both LOO and 10-fold cross validation were performed, the 10-fold approach produced consistently more optimistic results (i.e., suggested better predictive performance). This probably results from the fact that there is an unaccounted-for effect of year in determining the risk of entrainment and removing an entire year of data ensures that the model is trained completely naively to this annual effect. For the sake of clarity, we have chosen to report only the results from the more conservative LOO cross-validation. Based on these cross-validation results, the models for both species displayed modest, but potentially useful predictive ability. The Steelhead models provided more reliable point predictions with the overall R^2 between weekly observations and cross-validation predictions of ~0.60 compared with ~0.44 for winter-run Chinook Salmon (Table 3). The classification components of the hurdle models suggest a strong ability to predict whether any loss will occur based only on environmental and operational conditions. Model performance for both species is well balanced across accuracy, precision, and recall; and the AUC scores, which are generally greater than 0.8, indicate excellent discrimination (Table 4) (Hosmer and Lemeshow 2000).

Although the Central Valley Steelhead models produced more reliable point predictions of loss, the prediction intervals produced by winter-run Chinook Salmon models appear generally more useful based on the management-relevant validation metrics. Across the range of precautionary predicted quantiles, the winter-run Chinook Salmon models were less likely to produce a large under-prediction or a large over-prediction (Table 3). Selection of an appropriate quantile on which to base management responses

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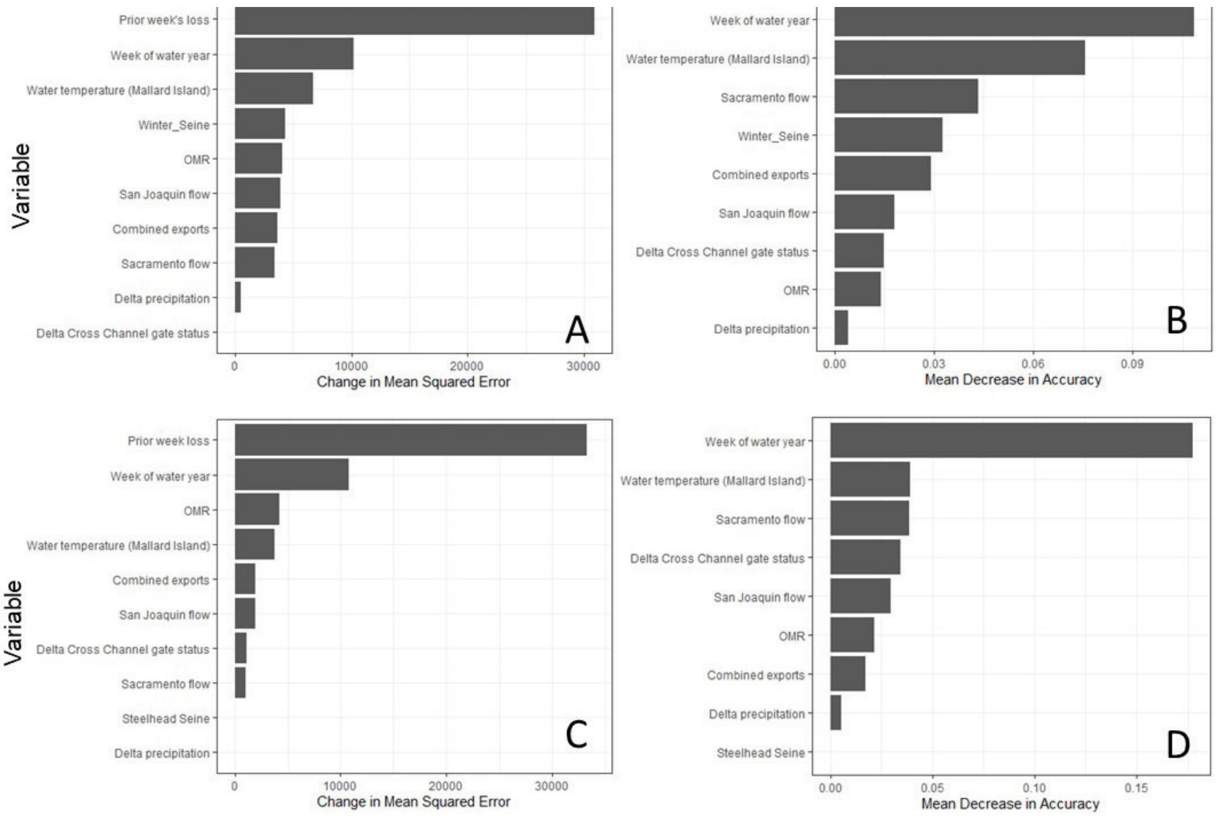

Figure 2 Variable importance rankings for each component of the hurdle model. Panels **A** and **C** show the change in mean squared error when each variable is excluded from the quantile regression forest (QRF) model for winter-run Chinook Salmon and Central Valley Steelhead, respectively. Panels **B** and **D** show the decrease in classification accuracy when each variable is excluded from the RF classifier model for winter-run Chinook Salmon and Central Valley Steelhead, respectively.

depends, ultimately, on the management community's risk tolerance. The winter-run Chinook Salmon median and 75th quantile predictions produce reasonably infrequent and balanced occurrences of large over- and under-prediction. For Central Valley Steelhead, there is a larger trade-off between frequent over- and under-prediction, and so avoidance of large, unexpected loss events comes at the cost of more frequent over-prediction (e.g., in >20% of cases for the 75th predicted quantile). Nevertheless, for both species the 75th predicted quantile appears to provide a reasonably precautionary management benchmark across all weeks of the salvage season, with modest over-prediction by far the most common outcome (Figure 5). Pilot testing in 2019 further supported the utility of the interval predictions indicated by these cross-validation results, where all loss observations between 1 January and 15 June (n=48) fell within the 10th-to-90th quantile prediction interval (Figure 7).

Model Comparison

As noted previously, the outsized influence of the prior week's loss on model predictions led to concern over poor predictive performance during the early weeks of a salvage season. The hurdle model formulation was intended to address this potential issue by first predicting whether any loss would occur using a classification model that excluded the prior week's loss from the predictors. Training models separately for the CVP and SWP pumping facilities was also considered as a potential method to increase the accuracy of loss predictions. However, across the range of model validation approaches, there was no clear evidence of a single, superior model formulation for either species. Point and interval prediction

Table 2 Summary of most important variables for each model formulation

Species	Model Structure	Type	Response	Variable importance rank: First	Second	Third
Winter run	Simple	QRF	Combined	Prior week loss	Week of WY	Temperature
			CVP	Prior week loss	Week of WY	Temperature
			SWP	Prior week loss	Week of WY	Temperature
	Hurdle	QRF	Combined	Prior week loss	Week of WY	Temperature
			CVP	Prior week loss	Week of WY	Temperature
			SWP	Prior week loss	Week of WY	Temperature
		RF (Binary)	Combined	Week of WY	Temperature	Sacramento flow
			CVP	Week of WY	Temperature	Sacramento flow
			SWP	Week of WY	Temperature	Sacramento flow
Steelhead	Simple	QRF	Combined	Prior week loss	Week of WY	Combined exports
			CVP	Prior week loss	Week of WY	OMR
			SWP	Prior week loss	OMR	Week of WY
	Hurdle	QRF	Combined	Prior week loss	Week of WY	Combined exports
			CVP	Prior week loss	Week of WY	OMR
			SWP	Prior week loss	Week of WY	OMR
		RF (Binary)	Combined	Week of WY	Temperature	Sacramento flow
			CVP	Week of WY	Temperature	Sacramento flow
			SWP	Week of WY	Temperature	San Joaquin flow

performance revealed no clear favored model formulation (Tables 3 through 5), and although the hurdle models appeared to avoid some level of prediction error during the earliest weeks when salvage typically occurs (Figure 5), these are not necessarily the weeks in which the first large pulses of entrainment occur in any given year. Examination of prediction errors during the first week of each salvage season in which greater than 5% of the annual loss occurred revealed poor predictive ability in these circumstances across all model formulations, with large under-predictions the norm (Figure 6A). In contrast, across all weeks in which greater than 5% of annual loss occurred, the 75th predicted quantiles for both species and all model formulations produced more balanced prediction errors (Figure 6B). In addition to indicating that the hurdle model formulation may be unnecessary, these results also suggest that use of a more precautionary management benchmark, such as the 90th quantile (Figure 6C and 6D), may be warranted early in the year when regular weekly loss is not yet occurring.

DISCUSSION

We developed a series of tree-based models to predict the risk of entraining juvenile winter-run Chinook Salmon and Central Valley Steelhead during large-scale water exports. Extensive cross-validation procedures revealed that, using a small and readily available set of predictor variables, this modeling approach can provide potentially useful point and interval estimates of salmonid loss 1 week into the future. Although the majority of the predictive power of the models derives from seasonality and the temporally autocorrelated nature of entrainment (i.e., the best predictor of loss is the prior week's loss), the model predictions are sensitive to water operations variables that management can directly influence. As such, these models provide managers the novel ability to consider the upcoming risk of salmonid entrainment loss

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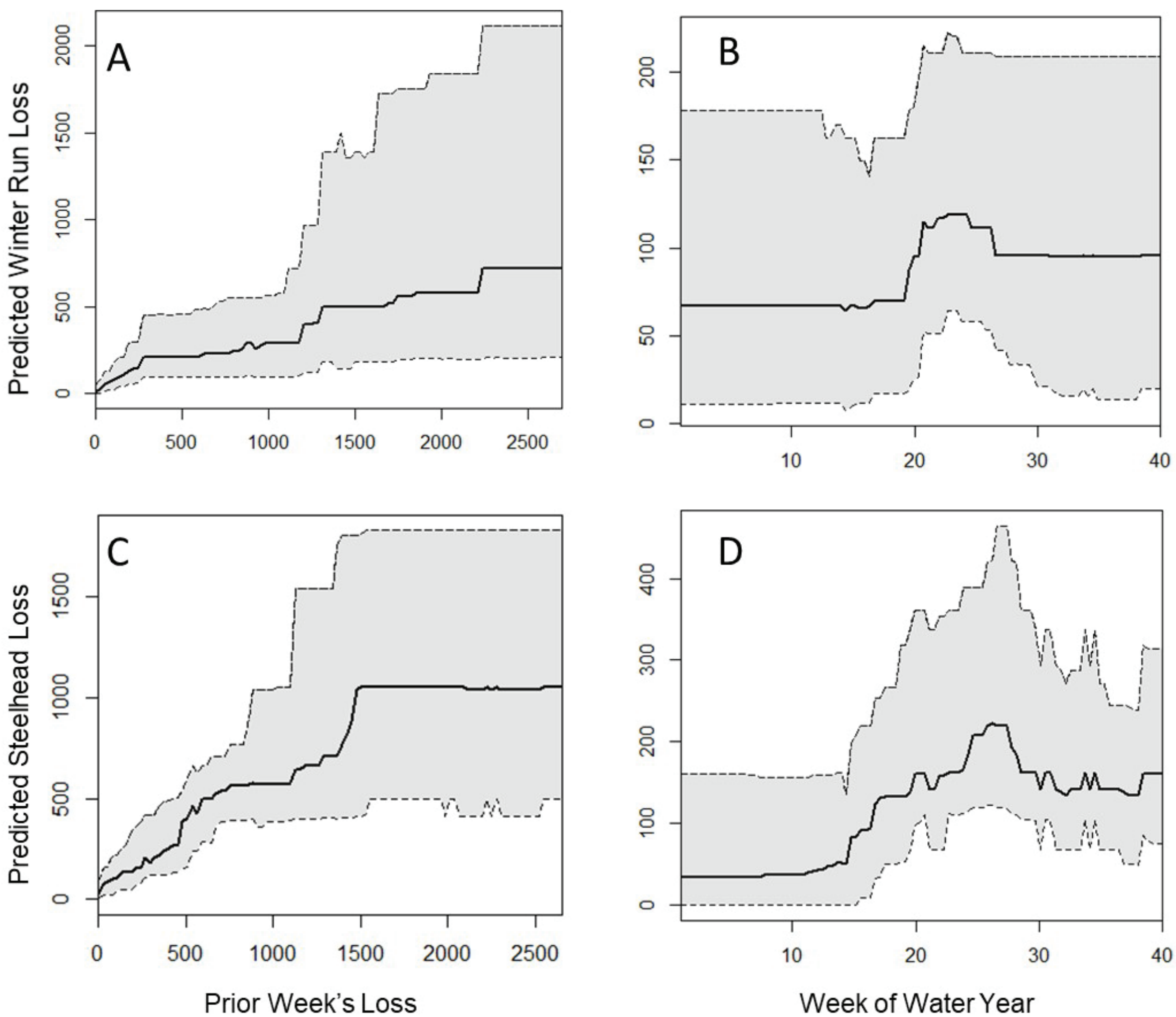

Figure 3 Partial dependence of model predictions on the two variables consistently ranked as the highest importance for both winter-run (**A-B**) and Central Valley Steelhead (**C-D**): the prior week's loss and the week of the Water Year. Predictions were made with all other variables held at their mean values. *Black lines* show predicted medians; the *shaded area* captures the interquartile range (25th–75th predicted quantiles).

Table 3 Summary of QRF model validation metrics

			Average quantile loss										
Species	**Model**	**Response**	**0.01**	**0.05**	**0.1**	**0.25**	**0.5**	**0.75**	**0.9**	**0.95**	**0.99**	**Sum**	R^2
Steelhead	Simple	Combined	**42**	41	39	33	**26**	**32**	64	95	196	566	**0.60**
		CVP+SWP	48	47	45	39	32	37	69	103	209	628	**0.60**
	Hurdle	Combined	**42**	**40**	**38**	**32**	**26**	34	**63**	**87**	167	**529**	0.59
		CVP+SWP	46	44	43	37	33	41	67	90	**163**	564	0.58
Winter run	Simple	Combined	**35**	35	**33**	**29**	**23**	**28**	**55**	88	216	542	0.43
		CVP+SWP	37	37	36	32	26	32	61	100	233	594	**0.44**
	Hurdle	Combined	**35**	**34**	**33**	**29**	24	30	57	**89**	196	**528**	**0.44**
		CVP+SWP	36	35	34	31	26	33	60	90	**187**	532	**0.44**

a. Bold values indicate the "best" model for each species; the lowest values for all quantile loss estimates and the highest R^2 value.

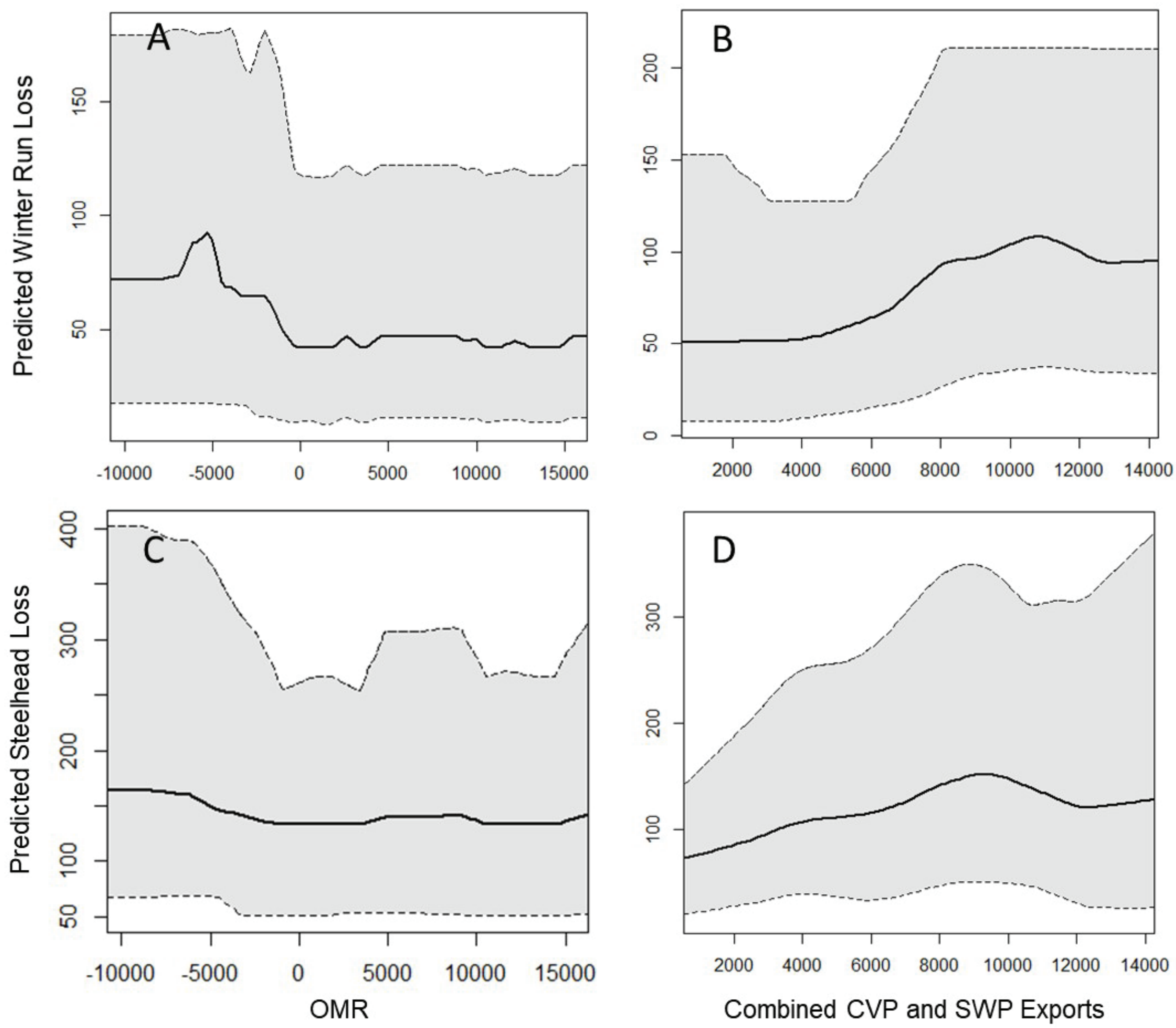

Figure 4 Partial dependence of model predictions on the two variables most responsive to management inputs for both winter run Chinook Salmon (**A-B**) and Central Valley Steelhead (**C-D**): combined water exports and OMR flow. Predictions were made with all other variables held at their mean values. *Black lines* show predicted medians; the *shaded area* captures the interquartile range (25th–75th predicted quantiles).

Table 4 Summary of validation metrics for RF classifier components of hurdle models

		Hurdle model classifier metrics			
Species	**Response**	**Accuracy**	**Precision**	**Recall**	**AUC**
Steelhead	Combined	0.83	0.83	0.83	0.83
	CVP	0.80	0.84	0.86	0.79
	SWP	0.83	0.85	0.86	0.82
Winter-run	Combined	0.86	0.89	0.89	0.84
	CVP	0.85	0.89	0.89	0.84
	SWP	0.86	0.86	0.89	0.83

under a range of possible operational scenarios. The combination of quantitative, reproducible estimates of risk with this scenario exploration capacity results in a potentially powerful and complementary tool to integrate with the existing, expert-based risk-management approach. Integration of these predictive models into a web-based application hosted on SacPAS—a familiar provider of fish monitoring data and tools in the Delta management community—allows the intended model users to generate risk forecasts and explore scenarios in a code-free manner (Figure 8).

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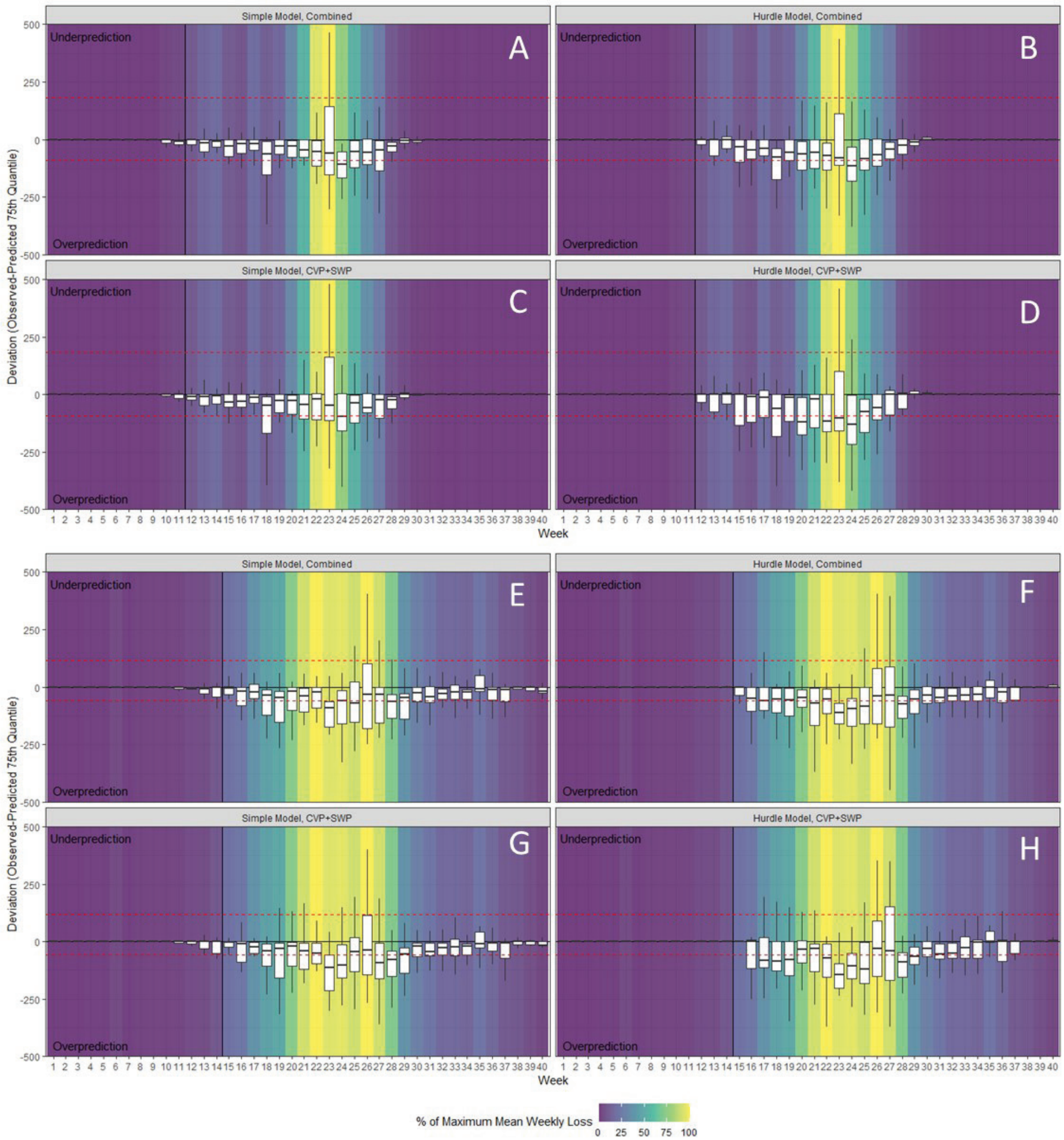

Figure 5 Boxplots of weekly prediction errors for four formulations of the winter-run Chinook Salmon (**A-D**) and Central Valley Steelhead (**E-H**) model. *Background shading* indicates the typical periods of maximum loss for each species. *Red dashed lines* show management-relevant over- and under-prediction thresholds of 1% and 2% of the average ITL, respectively. *Vertical black lines* show the first week with visible deviations for the hurdle models, and are intended to highlight increased predictive performance during the earliest weeks of the salvage season. Note that outliers are excluded to aid in visualization, but details on the frequency of occurrence of extreme values are provided in Table 4.

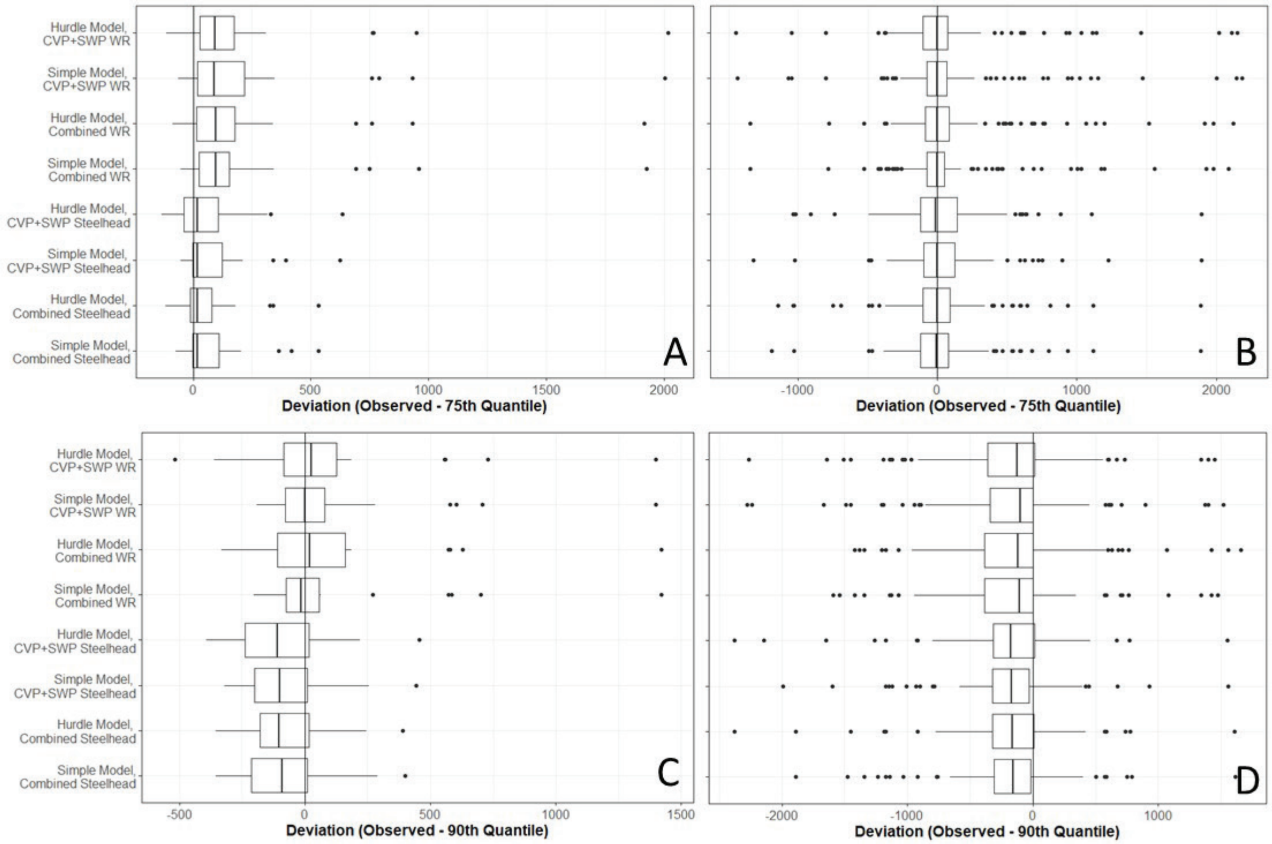

Figure 6 Boxplots of prediction errors for the 75th and 90th quantiles during weeks that loss exceeded 5% of the annual total. Panels A and C include only the first instance of loss above this threshold; panels B and D include all occurrences. Large under-predictions are far more common during the first high-loss occurrence, and performance does not appear to be improved in the hurdle model formulations.

Predictive Performance Relative to Management Needs

While we have reported a variety of standard validation metrics for predictive models for the application of these predictions to management, there remains the question of "how good is good enough?" The ecological processes that ultimately determine the rate of entrainment in the Delta are highly complex, and it is not surprising that the model's ability to provide a point estimate of loss is modest in absolute terms. However, for management purposes, the strength of the model is likely to be in the prediction intervals—especially the bounding by higher quantiles—rather than point estimates. The quantile regression framework allows for worst-case scenarios to be considered, and the range of potential outcomes to be examined, given a set of predictor variables (Cade and Noon 2003). Table 5 highlights the trade-offs between various predicted quantiles and shows that the models' 75th to 95th quantile predictions result in a very low probability of unexcepted large loss events (~ 1% to 5%). Use of increasingly precautionary quantiles does come at the expense of more frequent large over-predictions, especially for the Steelhead models. It is also important to note that these frequencies depend on the definition of large under- and over-prediction events. We selected values of 2% and 1% of the average ITLs for the large under- and over-prediction thresholds, assuming that water and fisheries managers would object to prediction errors greater than this magnitude. Overall, the predictive performance of the precautionary quantiles relative to the management targets that we have defined seems adequate. For purposes of risk forecasting and scenario evaluation. However, ultimately, the management process should determine what level of prediction error is tolerable, and therefore how much weight to place on model predictions.

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Table 5 Summary of predictive performance relative to management-relevant validation metrics

Model	Quantile	Species	Frequency of large under-prediction	Frequency of large over-prediction	Mean/Median under-prediction	Mean/Median over-prediction
Hurdle, combined	0.50	Steelhead	10%	6%	125/52	47/28
Hurlde, CVP+SWP			10%	5%	122/47	49/32
Simple, combined			10%	7%	124/51	44/23
Simple, CVP+SWP			10%	5%	123/46	45/24
Hurdle, combined	0.75		5%	22%	116/41	108/69
Hurlde, CVP+SWP			6%	21%	108/32	120/78
Simple, combined			5%	23%	127/47	83/46
Simple, CVP+SWP			6%	24%	131/45	85/49
Hurdle, combined	0.90		3%	40%	105/26	229/164
Hurlde, CVP+SWP			3%	35%	87/26	252/188
Simple, combined			2%	47%	174/83	153/83
Simple, CVP+SWP			2%	52%	185/77	166/95
Hurdle, combined	0.95		2%	46%	63/26	334/261
Hurlde, CVP+SWP			2%	40%	65/20	365/278
Simple, combined			1%	65%	124/87	223/121
Simple, CVP+SWP			1%	69%	175/90	243/146
Hurdle, combined	0.50	Winter run	5%	2%	168/42	44/23
Hurlde, CVP+SWP			6%	1%	163/43	48/27
Simple, combined			5%	2%	170/41	40/19
Simple, CVP+SWP			5%	1%	167/39	41/22
Hurdle, combined	0.75		3%	12%	177/31	124/71
Hurlde, CVP+SWP			3%	10%	159/31	135/79
Simple, combined			3%	12%	195/30	95/45
Simple, CVP+SWP			3%	11%	191/34	107/51
Hurdle, combined	0.90		2%	25%	173/24	303/203
Hurlde, CVP+SWP			2%	19%	127/27	339/227
Simple, combined			2%	27%	260/39	180/69
Simple, CVP+SWP			2%	28%	257/46	190/88
Hurdle, combined	0.95		1%	29%	144/24	498/344
Hurlde, CVP+SWP			1%	22%	97/26	525/391
Simple, combined			1%	36%	241/52	251/79
Simple, CVP+SWP			1%	38%	264/142	269/100

Implications for Water Management

The utility of these predictive models would be minimal if entrainment risk were totally independent of management inputs. Across species and model formulations, our results indicate that entrainment risk is influenced principally by variables beyond the control of any management action. The large influence of the prior week's loss and week of Water Year reflect the importance of seasonality, and the timing of salmonid presence in the Delta. However, despite the precedence of these essentially unmanageable variables (Figure 2), more responsive variables—including OMR flows and exports—have an appreciable influence on entrainment risk (Figure 4). Moreover, the

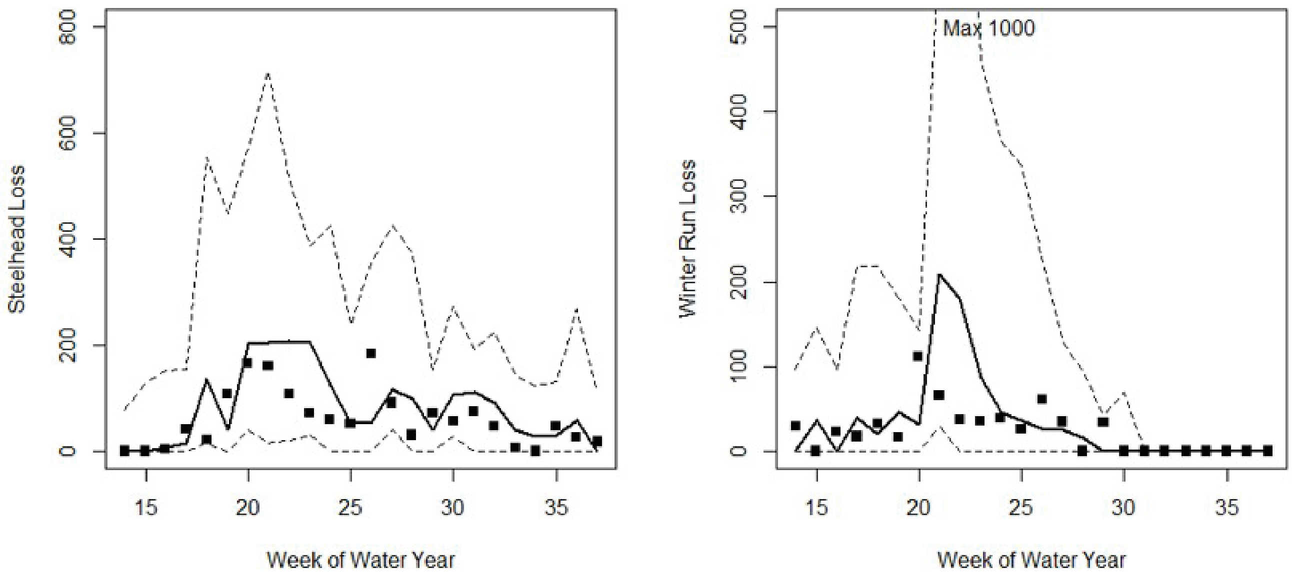

Figure 7 Results of pilot testing conducted during the 2019 salvage season. *Solid black lines* show median predictions; *dashed lines* enclose the 10th–90th quantile range. *Squares* show observed loss.

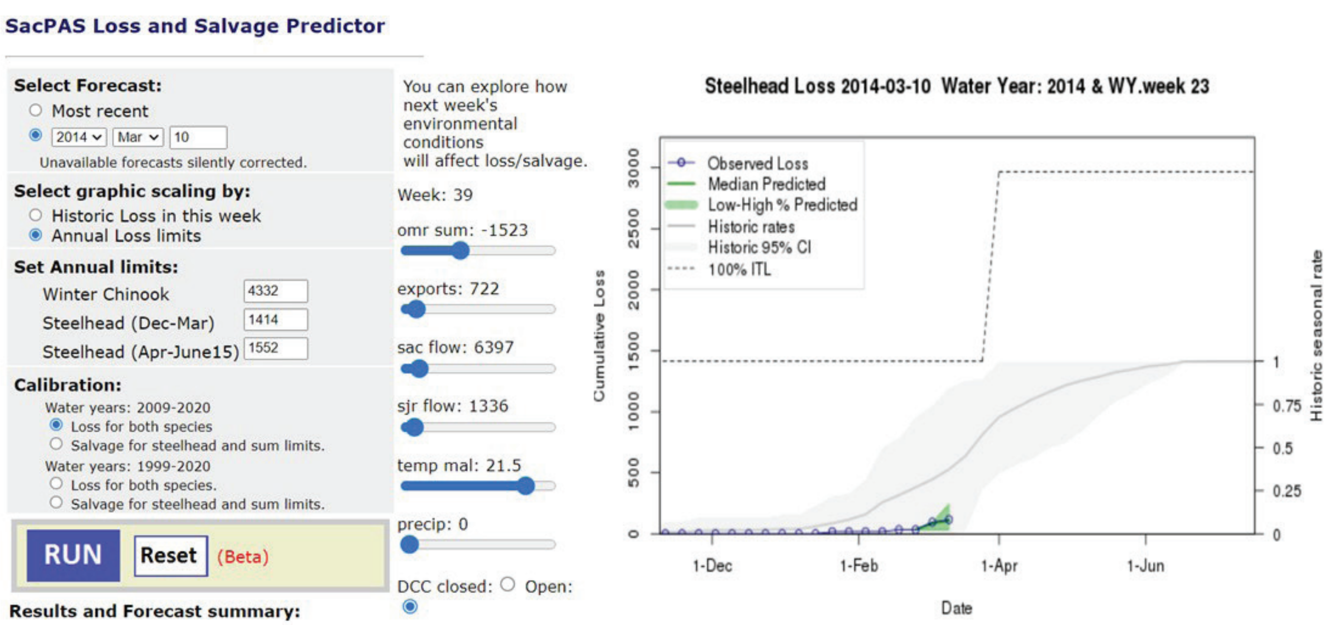

Figure 8 SacPAS user interface for prediction and scenario exploration using the loss-prediction models. User inputs and controls are shown on the *left*, and an example output of the graphical prediction report is shown on the *right*.

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relationships among loss, OMR, and exports are largely intuitive, with increased loss associated with higher exports and more negative OMR flows. These results are consistent with previous studies that have indicated a negative association between water exports and the survival of Chinook Salmon through the Delta. The influence of total exports on predicted loss of juvenile winter-run Chinook Salmon was qualitatively similar to the relationship reported by Kimmerer (2008), who reported that the proportion of out-migrating salmon entrained at the pumping facilities increased substantially when total exports increased above 6,000 to 7,000 cfs. Newman and Brandes (2010) similarly reported a negative association between water exports and juvenile Chinook Salmon survival, though as in our results, found the magnitude of this effect to be minor relative to stochastic or environmentally driven variation in entrainment. Our results are also consistent with the operating assumption that entrainment risk increases when OMR flow reverses toward the pumping facilities (NMFS 2019).

These results serve both to build confidence that the model is capturing important dynamics of the entrainment process and to show that the models can be useful for consideration of alternative operational scenarios. In theory, forecasts of low entrainment risk could offer the flexibility to increase water diversions. However, guidelines for the circumstances under which water diversions might be increased when salmonid entrainment risk is low would need to be established within the management process, and any flexibility could be further constrained by the BO criteria or other Delta management criteria, such as water quality control operations.

Limitations

As with all models, the entrainment risk prediction tools presented here are subject to limitations, and conditional on underlying assumptions. One potentially important limitation of these models is that much of their predictive power derives from the temporally autocorrelated nature of loss as evidenced by the high importance of the prior week's loss in all formulations of the models for both juvenile winter-run Chinook Salmon and Central Valley Steelhead. Because of this, when recent loss has not occurred, the model is more likely to produce a substantial under-prediction (Figure 6). The hurdle model formulation did not, as hoped, improve predictions under these circumstances, and, in the near term, use of a more precautionary quantile (e.g., 90th) seems warranted until loss is being regularly observed on a weekly basis. Longer term, exploration of upstream factors that influence the timing of entry into the Delta by Central Valley Steelhead and winter-run Chinook Salmon may offer a more informative forecast of when the period of increased entrainment risk is likely to begin. Another potential consequence of relying on temporal autocorrelation for prediction is that if Central Valley salmonid populations continue to decline, or if other management interventions effectively limit entrainment at the pumping facilities, model predictions may become less reliable. On the other hand, in either of these cases the chances of large entrainment events should also be reduced, which could serve to offset, in part, any reduction in predictive performance. Continued updating of the training data set, and exclusion of earlier years where salmonid populations were larger and high loss events were more common, may also help to improve model predictions under current conditions.

A critical limitation of the winter-run models is a reliance on phenotypic criteria; length of salmon at capture has been the primary way to assign runs, but this has been shown to be highly inaccurate. More than 50% of fish are classified as winter-run Chinook Salmon which actually belonging to spring, fall, or late-fall runs (Harvey et al. 2014). Genetic sampling that can rapidly distinguish runs with high reliability are being phased in to managing and monitoring of Central Valley Chinook Salmon (Meek et al. 2016). The accuracy of our model predictions for a given run can only be as good as the method of run assignment data being used, and for managers to be able to evaluate in-season entrainment risk, we have designed it to be consistent with methods prescribed by ITLs, which are still based on phenotypic, length-at-date identification. As currently implemented, the predictions produced by the winter-run Chinook Salmon model can be interpreted as particularly conservative (i.e., biased toward additional protection of winter-run Chinook Salmon), given this frequency of misclassification. However, this model can be easily adapted in the future if the ITL were changed to use genetic run assignments, assuming that rapid genetic run identification results can be returned within a few days.

CONCLUSION

In spite of these limitations, the models described here should provide useful information when used in concert with the current, expert-based approach to evaluating salmonid entrainment risk in the Delta. Although the predictions will be imperfect, through cross-validation we have quantified the expected frequency and magnitude of large and minor prediction errors. From our perspective, these patterns of prediction error seem tolerable, though those responsible for managing water and protecting these fishes must ultimately determine what is "good enough." Even if the predictive performance of these models is deemed insufficient, we believe this quantile-based risk forecast approach combined with the web application's in-season tracking provide a useful framework for exploring other predictive models. Given time and resource limitations, we focused on one promising method for prediction, rather than exploring an exhaustive range of modeling approaches. Inclusion of additional predictor variables, or integration of alternative modeling techniques into this framework could help to improve risk forecasts.

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