ABSTRACT

Title of Thesis: PREDICTING THE SALINITY HISTORY OF OYSTERS IN DELAWARE BAY USING OBSERVING SYSTEMS DATA AND NONLINEAR REGRESSION

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Salinity is a major environmental factor that influences the population dynamics of fish and shellfish along coasts and estuaries, yet methods for predicting the salinity history at specific sampling stations are not widely available. The specific aim of this research was to predict the history of salinity experienced by juvenile and adult oysters (*Crassostrea virginica*) collected at sampling stations in Delaware Bay as part of the Selection along Estuarine Gradients in Oysters (SEGO) project. To do so, empirical relationships were created to predict salinity at five oyster bed stations using observing systems data and then applied to construct indices of salinity exposure over an oyster's lifetime. The desired accuracy was +/- 2 psu. Three independent sources of salinity data were used in conjunction with observing systems data to construct and validate the predictive relationships. Observing systems data from the USGS station at Reedy Island Jetty and continuous near-bottom measurements taken by the U.S. Army Corps of Engineers (ACOE) from 2012-2015 and 2018 were employed to fit nonlinear empirical models at each station. Haskin Shellfish Research Laboratory (Haskin) data were used to evaluate model fit, then ACOE data from 2018 (withheld from model fitting in the validation analysis) and SEGO data from 2021 were used to validate models. The best-fitting models for predicting salinity at the oyster bed stations given the salinity at Reedy Island Jetty were logarithmic in form. The root mean square error (RMSE) of the models ranged from 1.3 to 1.6 psu when model predictions were compared with Haskin data, 0.5 to 1.5 when compared with ACOE data, and 0.6 to 0.8 when compared with SEGO data. All of these models were within the desired accuracy range. Results demonstrate that observing systems data can be used for predicting salinity within +/- 2 psu at oyster bed stations within 39 km in upper Delaware Bay. When these models were applied to estimate low salinity exposure of 2-year-old oysters via the metric of consecutive days below 5 psu, the indices suggested that there could be as much as a 42-day difference in low salinity exposure for oysters at stations 31 km apart. This study helps further our understanding of the salt distribution in Delaware Bay as well as the effect of low-salinity stress on the life cycle and genetic differentiation of oysters. In addition, the approach of using observing systems data to predict salinity could be applied to advance understanding of salt distribution and the effect of low salinity exposure on living resources in other estuaries.

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by

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(Table 3). Also depicted are the salinity data at the Reedy station used as the independent variable in the regression model (light blue line is 15-min data, dark blue line is the daily average) and the ACOE data at the Cohansey station used to validate the model (gray line is 15-min data, black point is the daily average).

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Introduction

Salinity is one of the main factors contributing to the health, physiological processes, and distribution of the ecologically, commercially, and culturally important eastern oyster *Crassostrea virginica* (Shumway 1996). In general, higher salinity (> 15 psu) favors greater oyster production and faster growth (Menzel et al. 1966, Fang et al. 2016) and also results in high mortality due to a greater prevalence of MSX and dermo diseases (Andrews and Ray 1988, Ford and Haskin 1988, Powell et al. 2003). Low salinity (< 5 psu) inhibits *C. virginica* growth (Rybovich et al. 2016) while providing a refuge from dermo and MSX diseases resulting in decreased mortality rates (Bushek et al. 2012). By closing their shells and ceasing to filter feed, eastern oysters can survive in very low salinities (< 7 psu) for as many as seven days (Ford 1985, Levinton et al. 2011). However, long-term exposure (more than a week) to low salinity (< 2 psu) when accompanied by high water temperatures can result in high mortality (Wasson et al. 2016., Southworth et al. 2017). Hence eastern oysters can be found in wide regions of estuaries where median salinities are higher than 5 psu (Galtsoff 1964, Castagna and Chanley 1973, Munroe et al. 2013). Although it is clear that salinity has a strong influence on the population dynamics of *C. virginica*, less is known about the direct influence of salinity on the natural selection of oysters.

Studies on the genetic architecture of eastern oysters provide evidence of the ability of *C. virginica* to locally adapt to the environmental conditions of their native habitat (Burford et al. 2014, Li et al. 2020). Genomic study on phenotypically differentiated populations based on their salinity tolerance shows genetic differentiation between different populations (She et al. 2018).

Recent studies show that oyster's tolerance of low salinity is a heritable trait that can be selectively induced (McCarty et al. 2020).

Another recent research program is the Selection along Estuarine Gradients in Oysters (SEGO) project (NSF OCE-1756712), the goal of which is to determine if the population genetics of eastern oysters can be structured by hyposalinity stress during the larval and/or early post-settlement stages. Previous research has shown that long durations of low salinity induce mortality that could influence population genetics of *C. virginica*. In Breton Sound, LA, low salinity (< 5 psu) for a long period of time coupled with high temperature (> 25^{o}C) caused starvation due to the failure of osmoregulation (La Peyre et al. 2013). In the James River, a tributary of Chesapeake Bay, *C. virginica* mortality increased when salinity was < 2 psu over a period of more than a week when temperatures were > 28 ^{o}C (Southworth et al. 2017). In Delaware Bay, *C. virginica* larval survival is higher at salinities that are closer to the parental source salinity (Eierman and Hare 2013). Building upon these findings, the SEGO program addresses the hypothesis that low salinity exposure results in within-generation selection. A salinity metric that estimates the duration of exposure low salinity is therefore crucial for the SEGO project. The aim of this study was to create empirical models that predict the history of salinity at five SEGO sampling sites in Delaware Bay. The methods developed in this study could be applied to any estuary with an observing system, not just within Delaware Bay.

Delaware Bay is a partially-mixed coastal plain estuary on the northeastern seaboard of the United States, characterized by a strong salinity gradient (Aristizabal 2013). The estuary has a mean depth of 7 m, a length of 215 km, and a maximum depth exceeding 30 m (Sharp 1984, Pareja Roman 2019). Although earlier studies classified Delaware Bay as a well-mixed estuary (Garvine et al. 1992), more recent investigations revealed that although the shallow flanks are well mixed, the deep main channel shows strong vertical stratification (Aristizabal 2013). Classical gravitational circulation exists in Delaware Bay with low salinity outflow on the flanks, high salinity bottom inflow in the main channel, and lateral shear over the flanks (Wong 1995, Wong and Moses-Hall 1998). More than half of Delaware Bay's freshwater comes from the Delaware River, 14% comes from the Schuylkill River, and no other source contributes more than 1% to the total discharge (Sharp 1984). Garvine et al. (1992) found that the salt field responded weakly to changes in discharge. Another recent study supports this finding: three-dimensional model simulations of Delaware Bay show that the salinity field is similarly insensitive to river discharge (Aristizabal 2012).

In Delaware Bay and other coastal plain estuaries, three mechanisms govern the time rate of change of salt content at locations along the axis of the estuary: freshwater flow, steady shear dispersion, and tidal oscillatory salt flux (MacCready 2004). Freshwater flow dilutes salt in the system and the other two mechanisms – tidal oscillatory salt flux and steady shear dispersion – add salt to the system (MacCready 2004). Delaware Bay is dominated by M2 tides, with a relatively large M2 tidal volume flux ratio to freshwater discharge (Wong 1995). Tides propagate from the shelf as progressive waves, and due to Delaware Bay’s funnel shape, the tidal energy is concentrated, increasing from lower to upper Bay (Galperin & Mellor 1990; Hall et al. 2013). Salt is added to the system by steady shear dispersion from estuarine exchange flow. As opposed to classical estuarine exchange flow, Delaware Bay has two oceanward branches in the shallow flanks and a landward branch in the deepest part of the channel (Wong 1994, 1995).

Several studies have been conducted on Delaware Bay to develop models for predicting the salinity field. Galperin and Mellor (1990) developed a three-dimensional time-dependent numerical model to investigate salinity intrusion in Delaware Bay. A two-dimensional analytical model was developed to investigate the residual circulation of Delaware Bay by McCarthy (1991). Previous studies in Delaware Bay have shown that freshwater discharge from the Delaware River correlates with long-term salinity variation in the Bay (Wong 1994, 1995). Whitney and Garvine (2006) implemented a three-dimensional hydrodynamic model using wind, tide, and freshwater discharge as the primary forcing agents. Later, Munroe et al. (2013) simulated the bottom salinity of six oyster beds in Delaware Bay using a three-dimensional hydrodynamic model and compared their results with field observations to understand the effects of extreme flooding on oyster mortality. Although salinity and discharge are weakly related in Delaware Bay, Wong (1995) showed a strong relationship between mean monthly observations of salinity at two stations on the shoals of Delaware Bay.

Although the studies reviewed above have been conducted to understand and predict the salinity regime in Delaware Bay, there are few widely available methods for predicting the salinity history at specific oyster sampling stations without invoking a fully three-dimensional hydrodynamic model and with an accuracy of +/- 2 psu, a requirement of the SEGO project. In this paper, we propose a method that builds on Wong (1995) to predict the daily salinity history of oysters using empirical regression models and observing system data. This paper describes (1) empirical model development, (2) validation of salinity predictions with field observations, and (3) application of the models to create indices of low salinity exposure for *C. virginica* at specific locations.

Methods

Empirical models were fit to historical data of salinity at each of five oyster beds in Delaware Bay and then validated with historical data sets and with field observations collected during the SEGO program. After validation, empirical models were used to calculate indices of low salinity exposure for *C. virginica*. The oyster bed stations- Hope Creek, Arnolds, Cohansey, Shell Rock, and New Beds were located on the New Jersey side of Delaware Bay on the shoals (Fig. 1).

2.1. Data sets

Two main data sets (Table 1) were used to construct the empirical models at the five oyster bed locations. The first data set was from a US Geological Survey observing system station (ID: 01482800) named "Delaware River at Reedy Island Jetty, New Castle County" (referred to as "Reedy dataset") (Fig. 1). It has a long record of near-surface data recorded every 15 minutes from 2007 to 2019, with 2018 being a wet year with frequent high discharge events (Fig. 2). The sonde was 1.4 meters below the water surface.

The second salinity dataset used to construct the empirical models came from the U.S. Army Corps of Engineers (referred to as "ACOE dataset"). This dataset was collected in response to the deepening of the Delaware River navigational channel. The dataset has continuous near-bottom (1 m off the bottom) measurements of temperature and specific conductivity taken every 30 minutes at the five oyster bed stations from July-December in 2012- 2015 and 2018 using a YSI series 6600EDS V2 data sondes (Bromilow & Wong 2018, Bushek et al. 2014, 2015, 2016). Data sondes were swapped once per month. The depths of the monitoring stations over the oyster beds were 5-8 meters (Bushek et al. 2014, 2015, 2016) and waters at these shoal stations were well mixed (ref) and in the upper layer of the Delaware Bay salinity structure, allowing comparison between Reedy and ACOE datasets despite the sensors being at different depths.

Additional data sets were used to evaluate model fit and validate model predictions. As part of Haskin Shellfish Research Laboratory's regular monitoring programs (I. Burt, pers comm.), discrete monthly bottom salinity observations were available at the five oyster bed stations from 1999-2018 (Table 1). This salinity dataset (referred to as "Haskin dataset") was used to select the best fitting empirical model.

Field measurements of salinity were collected during the SEGO program for model validation. HOBO Saltwater Conductivity Data Loggers (HOBO U24-002-C) were fixed to a frame and suspended in the water about 5-10 cm off the bottom from May to November 2021 at the Hope Creek, Cohansey, and New Beds stations (Manuel 2022). These data loggers stored measurements of conductivity and temperature every 15 minutes. Sensors were swapped out on a monthly basis during summer and a calibrated YSI sensor was used to take measurements near the sensor *in situ* to check sensor accuracy upon deployment and retrieval. Data loggers at the Cohansey station were lost halfway through the deployment period. Data were formatted for analysis and screened for instrument malfunctions and fouling problems. This field data was important for model validation because it was collected after the dredging was complete in the Delaware River navigational channel (conducted from 2012 and 2018) that could have affected the salinity regime.

2.2. Data curation

Data curation was conducted on the Reedy, ACOE, and SEGO datasets to prepare them for analysis. All of the null values were removed. In addition, salinity at Reedy station and in the SEGO field data was calculated from temperature and specific conductivity using the wql R package (Jassby and Cloern 2017). This code was also used in Hill et al. (1986). The time stamps in all datasets were converted to the same time zone (GMT).

Potential instrument malfunctions and fouling problems were investigated in the ACOE dataset. Graphs of daily average salinity at an oyster bed station versus daily average salinity at Reedy and were created and visually inspected to identify erroneous measurements caused by sensor malfunction or fouling. There was a strong relationship between these variables, although several hundred data points (0.8% of total data set) fell well below most data. To determine if these data points were the result of instrument malfunctions or fouling, these data points were plotted against time. Plots (not shown) showed sudden changes in salinity or gradual, linear increases in salinity measurements near the end of a deployment indicative of sensor fouling.

To ensure that the anomalous data were due to instrument malfunctions and sensor fouling and not the result of sudden changes in freshwater flow or wind, both freshwater and wind data were downloaded. Freshwater data was from station USGS 01463500 Delaware River at Trenton, NJ (Fig. 2). The data was formatted, null values were removed, and data was plotted on the same graph as salinity data, showing that there were no significant high discharge events at the same time as the anomalous data.

The next step was to investigate whether the abnormal data points occurred because of a sudden wind event. Wind data from Brandywine Shoal Light was used from the NOAA website. The hourly data was downloaded from June-December of 2012 2013, 2014, 2015, and 2018, matching the ACOE dataset record. Plots of the wind records showed that there were no strong wind events during the times of the anomalous data. Based on these analyses, it was concluded that the anomalies in the data were caused by sensor fouling. These data points were removed from the dataset, with a loss of less than 0.8% of data.

In the SEGO dataset, biofouling and sediment deposition on HOBO sensors influenced the accuracy of the salinity measurements, likely because sensors were deployed only 5-10 cm above the oyster beds. Inspection of time series plots, comparison of data with YSI sensors, and comparison of data with freshwater discharge records were conducted, similar to the quality assurance methods for the ACOE dataset. Sensor fouling was a more significant problem than in the ACOE dataset, with 35%, 8%, and 57% of data being discarded at Hope Creek, Cohansey, and New Beds stations, respectively.

After curation, salinity data from Reedy, ACOE, and Haskins datasets were plotted and compared at each oyster bed station during the years 2012, 2013, 2014, 2015, and 2018 (Fig. 3). The Haskins data fell within the measurements taken by ACOE, and the ACOE data had similar trends as the Reedy Point data, as expected, providing confidence that these data sets were robust, comparable, and suitable for further analyses.

2.3. Matching time series

Each of the ACOE and Haskin time series were shifted by the tidal phase lag and aligned in time to prepare the time series for analysis. Because the Reedy, Hope Creek, Arnolds, Cohansey, Shell Rock, and New Beds stations were located along a transect from upper to lower bay, and the tidal wave progresses from lower to upper bay, the peak in salinity during a tidal period occurred at different times at each station. Shifting the time series by the tidal phase lag corrected this difference. First, the “tide.info” function of the HelpersMG package in R was used to predict the tidal heights (m) at Reedy and the oyster bed stations. The time series of tidal heights were then graphed, and the time difference between peaks (i.e., the tidal phase lag) was calculated. This difference was used to adjust the time series of salinity at the oyster bed stations.

After shifting by the tidal phase lag, the time of the Reedy and oyster bed measurements needed to be aligned because the times of the measurements were not the same. To do this, an R-script was developed to find the measurements at Reedy Island Jetty that bracketed the time of measurement in the ACOE dataset, then linear interpolation was used to estimate the salinity at Reedy Island Jetty at the same time as the measurements over the oyster beds.

After time series were aligned, daily averages were calculated. Daily average values smoothed the variations in tides and were more applicable to the SEGO program's need of summarizing the salinity exposure of oysters over time. In addition, preliminary analysis (not reported here) showed that models based on daily average values had better fits than those based on data with 15-min resolution.

2.4. Model fitting

Once the data was matched in time, nonlinear regression models were fit to daily average Reedy and daily average ACOE data to predict salinity over an oyster bed (S_{ACOE}) given the salinity at Reedy Island Jetty (S_{Reedy}). All of the ACOE data (ACOE datasets from 2012-2015, 2018) were used in these models.

After an initial exploration of multiple model types, the following models were selected for analysis and fit to the ACOE data (2012-2015, 2018):

a) Cubic polynomial

$$S_{ACOE} = S_{Reedy} + a(S_{Reedy})^2 + a(S_{Reedy})^3 \quad (1)$$

b) Asymptotic model

$$S_{ACOE} = a + b(\frac{1}{S_{Reedy} - c)}) \quad (2)$$

c) Logarithmic model

$$S_{ACOE} = a + b(log(S_{Reedy} - c)) \quad (3)$$

where *a*, *b*, *c* are the parameters of the equations.

To determine which model best fit the data, 95% prediction intervals were constructed using the predFit function of R investr package (Greenwell et al. 2014). In addition, the root mean square error (RMSE) was calculated (Eq. 4) using the monthly observations of near-bottom salinity in the Haskins dataset and empirical model predictions at each of the five stations. The equation was:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{Obs,i} - X_{Model,i})^2}{n}} \tag{4}$$

where X was salinity from model results (*Model*) and from observations (*Obs*), and n = number of data points.

After comparative analysis, the logarithmic regression model was chosen as the final model based on 95% prediction intervals, root-mean-square error with Haskin observations, and visual inspection of plots of the model fits overlaid on the data.

Although the logarithmic regression models worked most effectively, plots of predictions compared to ACOE 2018 data showed that there were five low salinity events during which the predictions were not effective. The main issue was that salinities at the oyster bed stations were not predicted effectively when salinity at Reedy was below 0.3 psu. In other words, salinity could keep decreasing at the oyster bed stations when salinity at Reedy remained constant below 0.3 psu. To resolve this issue, a number of methods were attempted, including fitting a relationship between discharge and Reedy salinity, using an anomaly of discharge or lagged discharge to predict Reedy salinity, and employing changes in temperature to estimate changes in salinity, among others. However, the best resulting solution came from using a simple correction factor (CF):

$$CF = \sum_{i=1}^{n} \frac{|S_p - S_o|}{n} \tag{5}$$

where CF is the difference between predicted (S_p) and observed (S_o) salinity for each station when Reedy salinity was below 0.3 psu and n = number of data points. With the correction factor, the final model was:

$$S_{ACOE} = a + b(log(S_{Reedy} - c)) \text{ when } S_{Reedy} >= 0.3\,psu \quad (6)$$

and

$$S_{ACOE} = a + b(log(S_{Reedy} - c)) - CF \text{ when } S_{Reedy} < 0.3\,psu \quad (7)$$

where *a*, *b*, *c* are the parameters of the equations. In Equation 7, the correction factors (CF) were 0.76, 0.84, 1.13, 1.02 and 1.07 for the models at Hope Creek, Arnolds, Cohansey, Shell Rock, and New Beds stations, respectively.

The logarithmic model then was fit to the Haskin data from each oyster bed station without the 2018 data so that the 2018 data could be used in a validation analysis (the "partial" model). For the partial model, the correction factors were: 0.95, 1.20, 1.65, 1.45 and 1.76 at Hope Creek, Arnolds, Cohansey, Shell Rock, and New Beds stations, respectively.

2.5. Model Validation

Two sets of validation analyses were conducted. First, partial model predictions were compared with ACOE observations from July to December 2018 at the oyster bed stations. The root mean square error (RMSE) between model predictions and observations at each station was calculated using Eq. 4. Plots of model fit over time were created.

Second, the reliability of the full models (i.e., those based on all available ACOE data: 2012-2015 and 2018) was validated with the SEGO datasets. Daily averages of the SEGO salinity measurements and predictions of the empirical models at the three stations (Hope Creek, Cohansey and Shell Rock) were used to calculate RMSE. Plots of model fit over time were created.

2.6. Application: index of low salinity exposure

The intent for developing the regression models was to predict the history of daily salinities experienced by oysters in Delaware Bay for the SEGO program. As a case study to demonstrate the utility of the regression models, several indices were calculated to characterize the salinity that oysters experienced before they were collected: 1) the number of consecutive days with salinity below 5 psu at each station, 2) the cumulative number of days with salinity below 5, 7, 9, and 11 psu, and 3) the average salinity experienced over an oyster's lifetime. To compare indices and demonstrate their utility, the indices were calculated at each of the five oyster bed stations for 2-year-old oysters collected on April 23, 2019. Because the oysters were 2 years old when they were collected, model predictions were made from April 23, 2017 to April 23, 2019. Observations were used when available (5 months of the 2017-2019 time period) and empirical models were employed when observations were missing. The full model was used and the correction factor (Eq. 7) was applied whenever Reedy salinity was below 0.3 psu.

Results

3.1. Model Fitting

After data curation and shifting by the tidal phase lag, cubic polynomial, asymptotic and logarithmic models were fit to the Reedy and ACOE long-term data to predict salinity at oyster bed stations. All models fit reasonably well (Tables 2, 3), with the logarithmic models having best performance based on the widths of the 95% prediction intervals (Figs. 4 and 5). The width of the prediction intervals for the logarithmic model fits were either equal to or slightly smaller (by 0.10) than the intervals for the asymptotic fits and were consistently smaller (by 0.2 or 0.3) when compared to the intervals for the cubic polynomial fits (Tables 2 and 3).

In addition, the RMSE based on Haskins data indicated that the logarithmic models provided the best fit (Tables 2 and 3). The RMSE of the logarithmic models were either equal to or less than those for the asymptotic models, and the RMSE of the asymptotic models values were either equal to or less than those of the cubic polynomial models. When the logarithmic predictions were compared with the Haskin dataset, the RMSE varied between 1.3 and 1.5, with the lowest values at stations located closest to Reedy station and higher values down the estuary (Table 3, Fig. 5). The RMSE values for the Haskin dataset were the same with or without correction factors, most likely due to the sparse monthly data and the rarity of high discharge events that dropped salinity at Reedy station below 0.3.

Haskin observations were compared with logarithmic model predictions (Fig. 6) to evaluate model fit. The R^2 values of the linear trend lines that were fit to scatterplots of observations versus prediction were 0.89, 0.91, 0.88, 0.84 and 0.86 at Hope Creek, Arnolds, Cohansey, Shell Rock, and New Beds, respectively, indicating reasonable model fit.

3.2. Model Validation

Two independent datasets were used to assess the effectiveness of the logarithmic model predictions. First, the partial models (fit without the ACOE 2018 data) were compared with the ACOE observations from July-December 2018 (see plots of model predictions versus observations in Fig. 7-11). The RMSE values ranged from 0.5 to 1.5 (Table 4) with lowest values at the most upstream stations Hope Creek and Arnolds (Figs. 7, 8). Highest RMSE values occurred with the models fit to data at the Cohansey and New Beds stations which were further down-estuary (Table 4, Figs. 9, 11). During the high discharge event from August 15, 2018, to August 25, 2018, the model predictions of Arnolds and Cohansey deviated from observations despite the use of the correction factor when Reedy salinity was very close to zero (Figs. 8, 9).

The full models (including the ACOE 2018 data and correction factor) (Table 3) were compared with the SEGO dataset. The RMSE for the SEGO field observations increased as stations progressed down estuary (Table 3), increasing from 0.6 at Hope Creek to 0.8 at New Beds (Figs. 12-14). Similar to the validation analysis with the 'partial' ACOE data set, the empirical model for Hope Creek performed best and Cohansey and New Beds performed the worst. The models appear to be skilled at capturing the sub-tidal variability in salinity at the three oyster bed stations for these rather short time series (Tables 3, Figs. 12-14).

3.3. Index of low salinity history

A combination of observations and predictions were used to calculate different types of salinity indices to quantify the 2-year history of salinity exposure of oysters collected at each station on April 23, 2019. When calculating these indices, Arnolds and Shell Rock stations had the most salinity observations during these oysters' lifetime (25% observations versus 75% model predictions), whereas Cohansey and New Beds had the least amount of data available (~12% observations versus 88% model predictions) (Fig. 15). Note that oysters collected in 2019 in the SEGO program were alive during 2018, one of the wettest years in Delaware Bay (Fig. 2), during which large drops in the salinity at Reedy and oyster sampling stations occurred.

The first set of salinity indices that were calculated for the SEGO program were the number of consecutive days with salinity below 5, 10, and 15 psu (Table 5, Fig. 16). At Hope Creek station, oysters spent 42 consecutive days below salinity 5 psu, while at the Cohansey station, oysters were predicted to spend only one day below 5 psu. At the Shell Rock and New Beds stations, oysters spent zero days below 5 psu. Oysters at the Hope Creek station spent 55% of the 2 years in salinities below 10 psu, while oysters at the nearby station Arnolds (8.7 km away) spent only 13% of the time in waters with salinities less than 10 psu. At the Hope Creek station, oysters spent 100% of their life in salinities below 15 psu, while in the New Beds station (31.1 km away), oysters spent only 12% of their life in salinities below 15 psu.

The second set of salinity indices was the number of cumulative days with salinity below 5, 7, 9, and 11 psu. At Hope Creek station oysters spent 284 cumulative days below 5 psu, whereas predictions at the Cohansey station indicated that oysters had spent only 3 total days below 5 psu. Similar to the index of consecutive days below a given salinity, oysters spent zero days below 5 psu at the Shell Rock and New Beds stations. The cumulative salinity index suggested that oysters collected in April 2019 experienced salinities below 11 psu for 91% of their life at the Hope Creek station and 74% of their life at Arnolds station. In contrast, at stations down estuary, oysters collected at Shell Rock spent 33% days below 11 psu and oysters collected at New Beds station (just 9.1 km away from Shell Rock) spent only 9% days below 11 psu.

The average salinity experienced over an oyster's lifetime was also calculated. Using a combination of model predictions and observations, 2-year-old oysters sampled in April 2019 were predicted to have experienced average salinities in their lifetime of 6.4, 8.8, 12.0, 13.2, and 15.3 psu for Hope Creek, Arnolds, Cohansey, Shell Rock, New Beds stations, respectively. Based on these predictions, 2-year-old oysters sampled in April 2019 at New Beds, the furthest station down-estuary station, experienced 2.4 times higher salinity on average than those at Hope Creek, the station furthest up-estuary.

Discussion

Overall, results indicate that it is possible to use the salinity data at the Reedy station observing system to predict the salinity over oyster beds up to 39 km down-estuary with an accuracy of +/- 2 psu. The three independent data sets used with model fitting and validation analyses demonstrated that long-term observational data and empirical regression models can be used to predict the history of salinity experienced by juvenile and adult oysters collected at different sampling stations in Delaware Bay. Note that the models validated well despite the dredging that occurred from 2012 to 2018. The dredging deepened the Delaware River navigational channel from 40 feet to 45 feet, but apparently did not markedly change the RMSE of salinity predictions when compared to data from 2018 and 2021, lending confidence in this method.

This study builds on previous approaches that employed empirical and hydrodynamic models to predict salinity at specific stations in estuaries. Robust empirical relationships between salinity and freshwater flow have been developed for the San Francisco estuary (e.g., Jassby et al. 1995, Hutton et al. 2016) and Delaware Bay (Wong 1995). Hydrodynamic models also have been used to predict salinity at specific stations, including in Delaware Bay (Whitney and Garvine 2006, MacCready 2007, Hofmann et al. 2009, Aristizabal 2013). While these approaches are clearly useful for predicting salinity, the empirical models presented here are designed specifically to estimate salinity over oyster beds using salinity data that is currently available at a USGS-maintained long-term observation station.

There are several caveats to be considered when using empirical models to predict salinity at oyster bed sampling stations. First and foremost, access to the Reedy long-term observational dataset is required and the empirical models are limited to predicting salinity at the five oyster bed stations in upper Delaware Bay. In addition, the empirical models were based on ACOE data that were measured between May and December, so changes in salinity during winter and early spring models (January - April) are not captured within the model. Another caveat to note is that the accuracy of the empirical relationships is limited by the salinity at the Reedy station: when Reedy salinity was close to zero, the skill of the models was reduced, even after applying a correction factor. Finally, the empirical models might not give accurate predictions if salinity distributions change in Delaware Bay due to dredging and/or climate change. Over the current decade (2001-2011), 20% of very large discharges and 50% of extreme discharges occurred compared to the 100 years of discharge record (Voynova and Sharp 2012). Extreme storm events are predicted to occur more frequently in this area, causing long durations of low salinity of the water (Wetz and Yoskowitz 2013). It is projected that by 2080–2099, winter runoff will increase 15–43% due to increased precipitation and snowmelt in Delaware Bay (Hawkins et al. 2021). These studies likely indicate new empirical models would need to be fit with updated salinity observations to make accurate predictions in future decades.

Keeping these main caveats in mind, there are merits for using empirical models to predict salinity at specific oyster bed sampling stations. First, for fisheries management, empirical models are simple and easy to use and relatively inexpensive compared to hydrodynamic model development. In addition, these models can be based on well-maintained and openly accessible observing systems data. Furthermore, the empirical models are capable of capturing the shortterm effects of river discharge events as well as seasonal variation in salinity, both of which are critically important for the life cycles of oysters and other living marine resources.

The empirical models also improve understanding of the response of salinity to high discharge events on the shoals of Delaware Bay, a region that has not been studied as thoroughly as salinity along the main channel (but see Aristizabal 2013). From 2012-15, the mean discharge of the Delaware River at Trenton was 295 $m^3 s^{-1}$ but for 2018 alone the mean discharge was 593 $m^3 s^{-1}$. Effect of high discharge events of 2018 can be seen on salinity predictions (Fig. 7-14). For example, there was a high discharge event starting on July 23, 2018, that lasted for 10 days (Fig. 2). This 10-day event decreased salinity by 50% at Hope Creek (Fig. 7), 41% at Arnolds (Fig. 8), 33% at Cohansey (Fig. 9), 31% at Shell Rock (Fig. 10), and 25% at New Beds (Fig. 11), according to predictions based on empirical models. Combined, these predictions indicate that the effect of high discharge events on salinity decreased down-estuary.

Another new finding of this research was the logarithmic shape of the relationship between salinity at the Reedy station and the salinity at oyster bed stations down-estuary. While it was surprising that the shape was not linear, it likely resulted from the salinity field reacting to high discharge events in a funnel-shaped estuary. We propose that the logarithmic shape is caused by two types of situations: 1) when discharge was high (e.g., higher than 75th percentile in daily average discharges) and 2) when discharge is low (less than the 25th percentile) (Fig. 18). As depicted in the conceptual diagram, high discharge pushes the salt front (defined as the location where the 1 psu isohaline touches the bottom) past the Reedy station so the change in salinity at Reedy was low while further downstream the change in salinity at the oyster bed stations continued to decrease (Fig. 18a). During low discharge conditions (Fig 18b), the salt front would be further up-estuary than the Reedy station and salinity isohalines would be more evenly spaced resulting in change in salinity at Reedy that were similar, and linearly related, to changes in salinity at the oyster bed stations.

At first glance, one might conclude that the funnel-shape of the Delaware Bay could contribute to the logarithmic shape of the relationship. Monosmith et al. (2002) concluded that for San Francisco Bay, when river discharge increases, the salinity field is pushed downstream to sections of the bay where depth and channel cross-sectional area are greater and hence isohalines could be closer together in the wider section. In this study, the salinity at the oyster bed stations changed faster than the salinity at Reedy during high discharge conditions (Fig. 18a), However, numerical model predictions (not shown) do not indicate that isohalines were closer together in the region of the oyster beds. Hence, the funnel shape of the estuary may or may not be controlling the logarithmic shape, and additional investigations are needed to discern the influence of the shape of the estuary on the salinity response.

Application of the empirical relationships to develop metrics of the 2-year history of salinity exposure of oysters resulted in new understandings. One of the surprising findings of this research was the large difference in low salinity exposure between stations that were only 31 km apart. In addition, there was an agreement between all three indices that oyster mortality should be higher at upper bay stations due to low salinity exposure, which is similar to what has been found previously (Powell et al. 2012, Munroe et al. 2013). Nevertheless, the magnitude of the difference between low-salinity exposure between stations may not have been appreciated without these new metrics.

There are a variety of management applications that the empirical model predictions could support. These salinity estimates will used as part of the SEGO program to investigate the phenotypic and genomic consequences of selection in oysters at small spatial scales and identify if salinity stress could structure the population genetics of oysters during the larval and/or early post settlement stages. Furthermore, the predictive models could be used to project the influence of high and low discharge events on the salinity experienced by oysters and other sessile organisms and help identify which oyster populations may be more or less susceptible to salinity-related diseases and reduced growth. In addition, the empirical models could be used to identify which stations could be most negatively affected by factors related to climate change (such as salinity shifts due to sea level rise and increased precipitation) and take necessary measures to safeguard oyster populations there. Furthermore, empirical models to predict salinity could be applied for other applications including prediction of intake salinity for power plants or geochemical changes due to salt such as phosphorous flux from sediments (Scudlark et al., 1989).

Further research could be done to improve empirical models and prediction of salinity in Delaware Bay. New locations for observing system measurement could be explored to avoid very low salinity records during high discharge events. In addition, exploration of additional freshwater sources to the estuary would be beneficial. For example, the empirical model performed the worse at Cohansey and New Beds stations with all datasets (Tables 3 and 4), which may be due to the presence of two small tributaries near these stations (Maurice and Cohansey Rivers). This indicates that if more than one source of freshwater flow controls the salinity at a specific station, or if other factors like wind are prominent, then additional variables will be required in the regression models. Hence, for Delaware Bay, another step forward would be to incorporate the effects of small tributaries into the empirical model. Furthermore, a three-dimensional hydrodynamic model could be invoked to provide comparisons between empirical and hydrodynamic predictions (this work is ongoing). Finally, empirical models could also be applied to predict the salinity history of other organisms that have important contributions to fisheries or support fished species.

In summary, using empirical models based on long-term observing data appears to be useful for predicting the salinity history of oysters at specific stations in Delaware Bay, making the models a practical tool for management of natural resources and also in furthering knowledge about the salinity regime of the Bay. It was possible to calculate the salinity history of oysters in upper Delaware Bay in a simple yet robust manner and develop metrics of salinity exposure that allowed comparison between oyster populations. Applying this approach in other estuaries would expand our knowledge of both the influence of low salinity events on oysters as well as further our understanding of the influence of freshwater discharge and basin shape on salinity at locations important for living resources.

Funding and Data Sources

Sincere thanks to Dr. Larry Sanford and Dr. Salme Cook for their guidance. We are grateful to the Haskin Shellfish Research Laboratory and Horn Point Laboratory staff for their support. This research was funded by the National Science Foundation (OCE-1756712) and by a University of Maryland Center for Environmental Science Horn Point Laboratory Graduate Research Fellowship to Archi Howlader. Data sources for the salinity data from Haskin Shellfish Research Laboratory at Rutgers University and U.S Army Corps of Engineers (ACOE) are summarized in Table 1. The Reedy Island Jetty salinity and freshwater flow data was publicly available data from the United States Geological Survey (Table 1).

Tables

Table 1: Datasets obtained for this research along with the years of record, measured variables, and data sources.

Name	Time period	Sources	Measurements
Haskin data: Haskin Laboratory Oyster Bed Monitoring Program	1999-2018	Dr. Daphne Munroe, Haskin Shellfish Research Lab	Near-bottom salinity at monthly intervals
Reedy data: Delaware River at Reedy Island Jetty, New Castle County (USGS 01482800)	2007-2021	USGS website: https://waterdata.usgs.gov/nwis/uv?site_no=01482800	Near-surface temperature, specific conductivity at hourly (2007- June 2011) and 15-min (July 2011-2021) intervals
River discharge: Delaware River at Trenton, NJ (USGS 463500)	2007-2021	USGS website: https://waterdata.usgs.gov/usa/nwis/uv?01463500	Discharge
ACOE data: U.S. Army Corps of Engineers	July - Dec 2012 - 2015, 2018	David A. Wong, Versar	Salinity at 30-min intervals

Table 2: Model fit (95% prediction intervals, root mean square error) and parameter estimates (*a*, *b*, *c*) for asymptotic and cubic polynomial non-linear regression models based on daily average salinity data from Reedy Jetty and ACOE stations during 2012-2015 and 2018. An independent dataset (Haskin dataset) was used to calculate root mean square error.

	Asymptotic					Cubic Polynomial				
Stations	95% Prediction interval	*a*	*b*	*c*	Root mean square error	95% Prediction interval	*a*	*b*	*c*	Root mean square error
Hope Creek	2.5	26.9	-292.7	-11.4	1.3	2.7	-0.26	0.01	0	1.5
Arnolds	4.1	22.0	-113.6	-6.2	1.3	4.3	-0.32	0.02	0	1.3
Cohansey	3.9	29.1	-206.9	-9.3	1.4	4.0	-0.22	0.01	0	1.4
Shell Rock	3.9	32.0	-254.7	-10.7	1.4	4.0	-0.20	0.01	0	1.3
New Beds	5.2	30.9	-190.4	-9.4	1.6	5.4	-0.20	0.01	0	1.7

Table 3: Prediction intervals, parameter estimates (*a*, *b*, *c*), and validation statistics for the logarithmic regression models based on daily average salinities for each oyster bed station including 2012-2015 and 2018 ACOE data (i.e., the 'full' models). Two independent datasets were used to validate the full model. The distance from these stations to the Reedy Point observing system station is included. "With CF" indicates the predictions were corrected whenever Reedy salinity was below 0.3 using the correction factor (CF) (Eq.6 and 7) and "Without CF" indicates that the predictions were not modified using the correction factor (CF). 'Null' indicates no data was available.

Logarithmic - Full models

Stations	95% prediction interval	*a*	*b*	*c*	Distance from Reedy (km)	Root mean square error (Haskin Lab Dataset) (Without CF)	Root mean square error (Haskin Lab Dataset) (With CF)	Root mean square error (SEGO Dataset) (With CF)
Hope Creek	2.4	-9.9	8.9	-3.5	7.9	1.3	1.3	0.6
Arnolds	4.1	1.5	5.5	-1.3	16.6	1.3	1.3	Null
Cohansey	3.8	-0.6	7.5	-2.6	26.4	1.4	1.4	0.7
Shell Rock	3.8	-1.6	8.3	-3.2	29.9	1.3	1.3	Null
New Beds	5.1	4.3	6.6	-2.5	39.0	1.5	1.5	0.8

Table 4: Prediction intervals, parameter estimates (*a*, *b*, *c*), and root mean square errors for the logarithmic regression models based on daily average salinities for each oyster bed station excluding the 2018 ACOE data (i.e., the 'partial' models). ACOE daily average observations from 2018 were used to calculate the root mean square error. The distance from these stations to the Reedy Point observing system station is included. The predictions were corrected whenever Reedy salinity was below 0.3 using the correction factor (CF) (Eq. 7).

Logarithmic - Partial models						
Stations	95% prediction interval	*a*	*b*	*c*	Distance from Reedy (km)	Root mean square error (ACOE Dataset) (corrected)
Hope Creek	2.5	13.1	9.9	-4.4	7.9	0.5
Arnolds	4.4	1.5	5.5	-1.4	16.6	0.7
Cohansey	3.5	-0.2	7.4	-2.5	26.4	1.4
Shell Rock	3.8	-3.3	8.8	-3.8	29.9	0.9
New Beds	5.0	3.7	6.8	-2.9	39.0	1.5

Table 5: Maximum number of consecutive days with salinity below 5, 10, and 15 psu at each oyster bed station from April 23, 2017, to April 23, 2019, as predicted with the full logarithmic regression models in Table 3.

Stations	Days (below 5 psu)	Days (below 10 psu)	Days (below 15 psu)
Hope Creek	42	404	730
Arnolds	17	92	565
Cohansey	1	25	274
Shell Rock	0	18	130
New Beds	0	15	88

Table 6: Cumulative days with salinity below 5, 7, 9 and 11 psu at each oyster bed station from April 23, 2017- April 23, 2019 as predicted with the full logarithmic regression models in Table 3.

Stations	Days (below 5 psu)	Days (below 7 psu)	Days (below 9 psu)	Days (below 11 psu)
Hope Creek	284	449	574	666
Arnolds	103	235	387	537
Cohansey	3	50	172	335
Shell Rock	0	4	83	244
New Beds	0	0	1	63

Figures

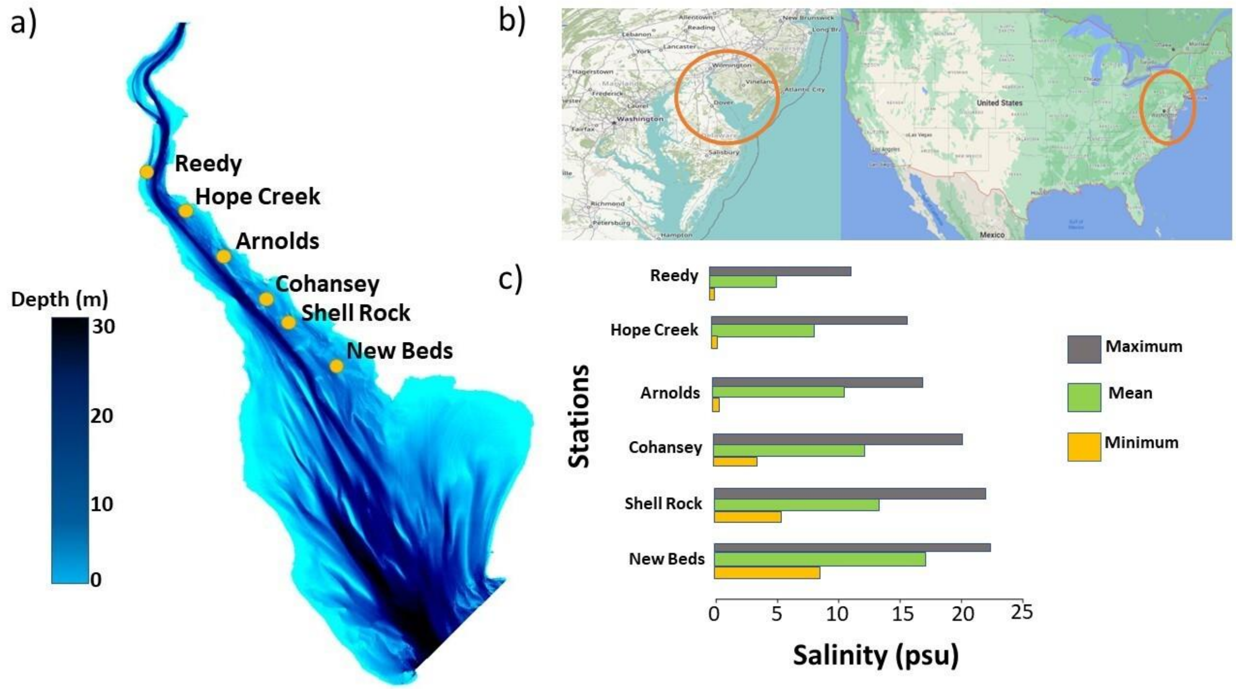

Fig. 1. a) Depth (m, color bar to left) of Delaware Bay with the locations of the Reedy Island observing system station and the five oyster bed stations for which empirical models were developed. Bathymetric data from NOAA (https://catalog.data.gov/dataset/delaware-bay-de-nj-m090-bathymetric-digital-elevation-model-30-meter-resolution-derived-from-so). b) The inset maps of North America with the location of Delaware Bay circled in orange. Maps made in QGis (https://www.qgis.org/) using data from Google Maps. c) The minimum (orange), mean (green), and maximum (dark gray) salinity at each oyster bed station based on observations (source: U.S. Army Corps of Engineers) during July - December 2012 - 2015, 2018 and also at Reedy station (source: USGS station 01482800) for the same time period. One standard deviation of the mean is 2.7, 3.2, 3.1, 3.3, 3.4, and 3.0 at Reedy, Hope Creek, Arnolds, Cohansey, Shell Rock, and New Beds, respectively.

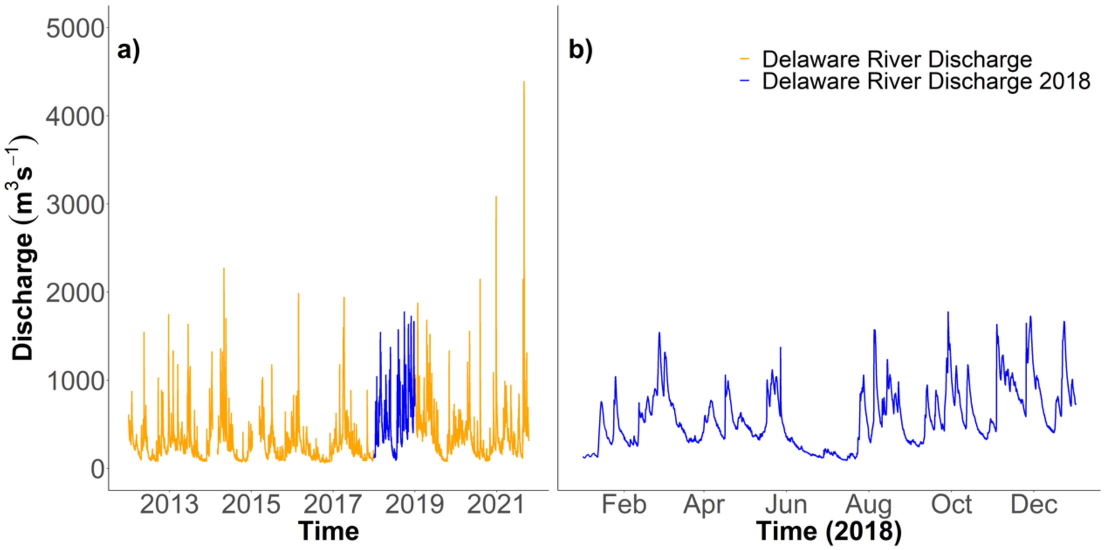

Fig. 2. Daily discharge of the Delaware River at Trenton (source: USGS station 1463500) a) during 2012-2022 (yellow line) and b) during 2018 (blue lines). During the year 2018, there were a large number of extreme storm events that resulted in extremely low salinity at the Reedy station.

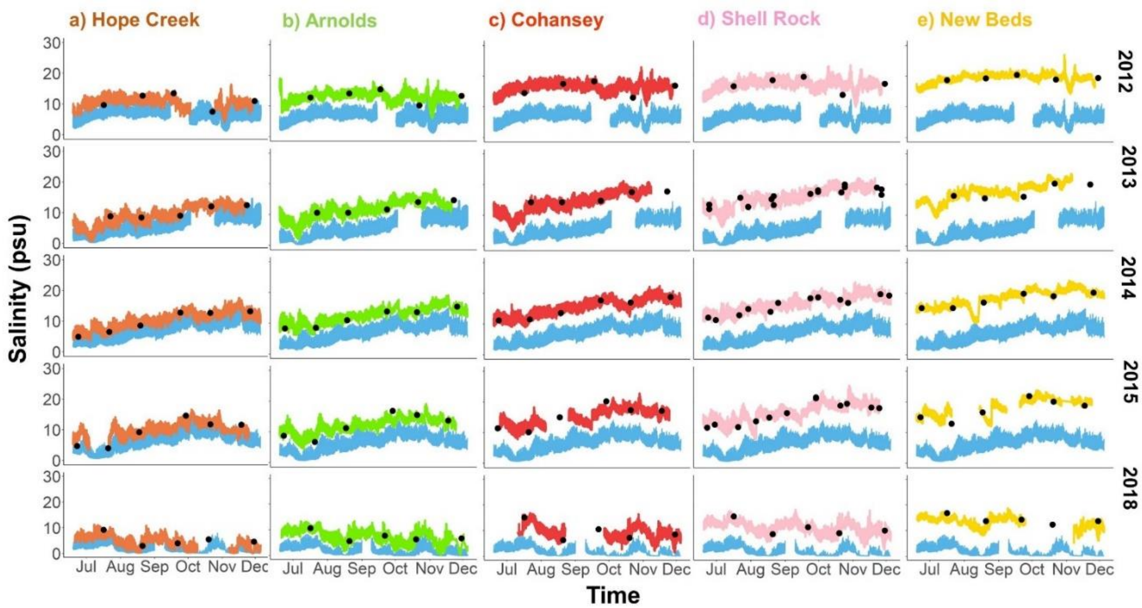

Fig. 3. Time series comparison between daily average salinity in the Reedy (blue lines), ACOE (colored lines), and Haskin (black dots) datasets for the oyster bed stations (columns) for different years (rows). According to the figure, the Haskins data is within the ACOE measurements, and the ACOE data shows similar trends in salinity as the Reedy data, especially for nearby stations.

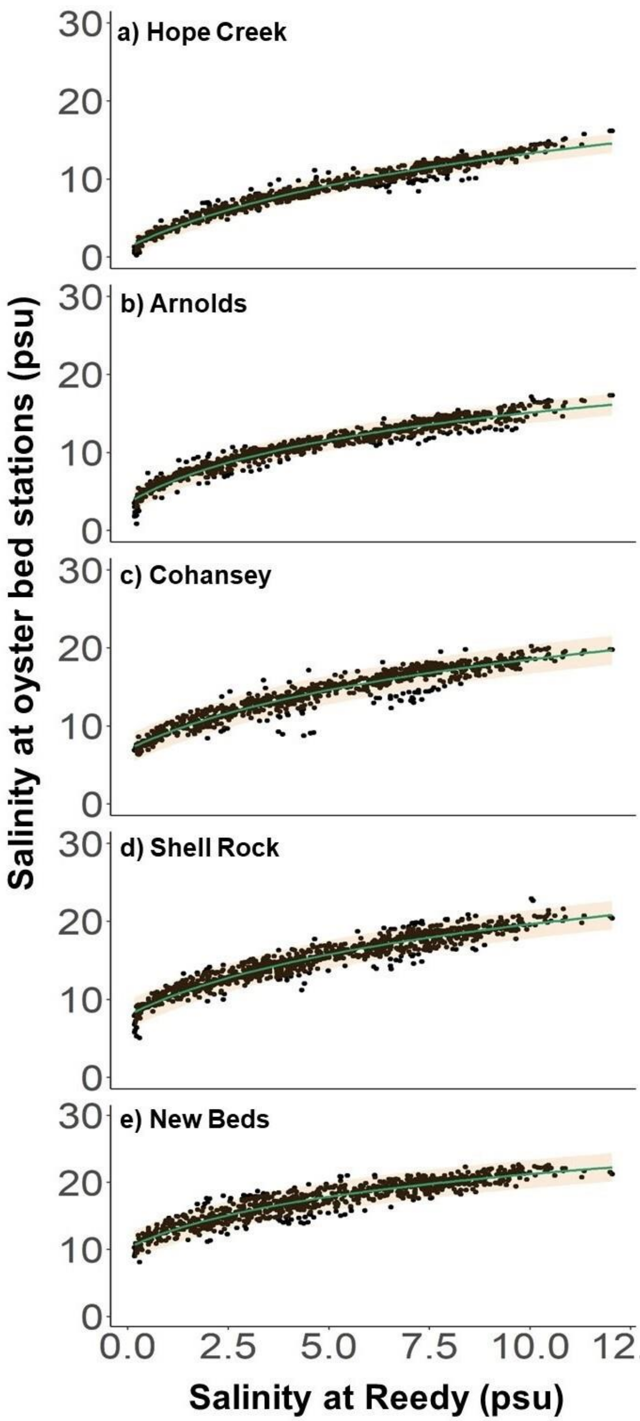

Fig. 4. The logarithmic regression fit (green line) fit to the daily-average salinity at Reedy station and the daily-average ACOE salinities (2012-2015, 2018) (black dots) at oyster bed stations a) Hope Creek, b) Arnolds c) Cohansey, d) Shell Rock and e) New Beds. The widths of the 95% prediction intervals (Table 3) for the nonlinear regressions are indicated by the orange shaded region.

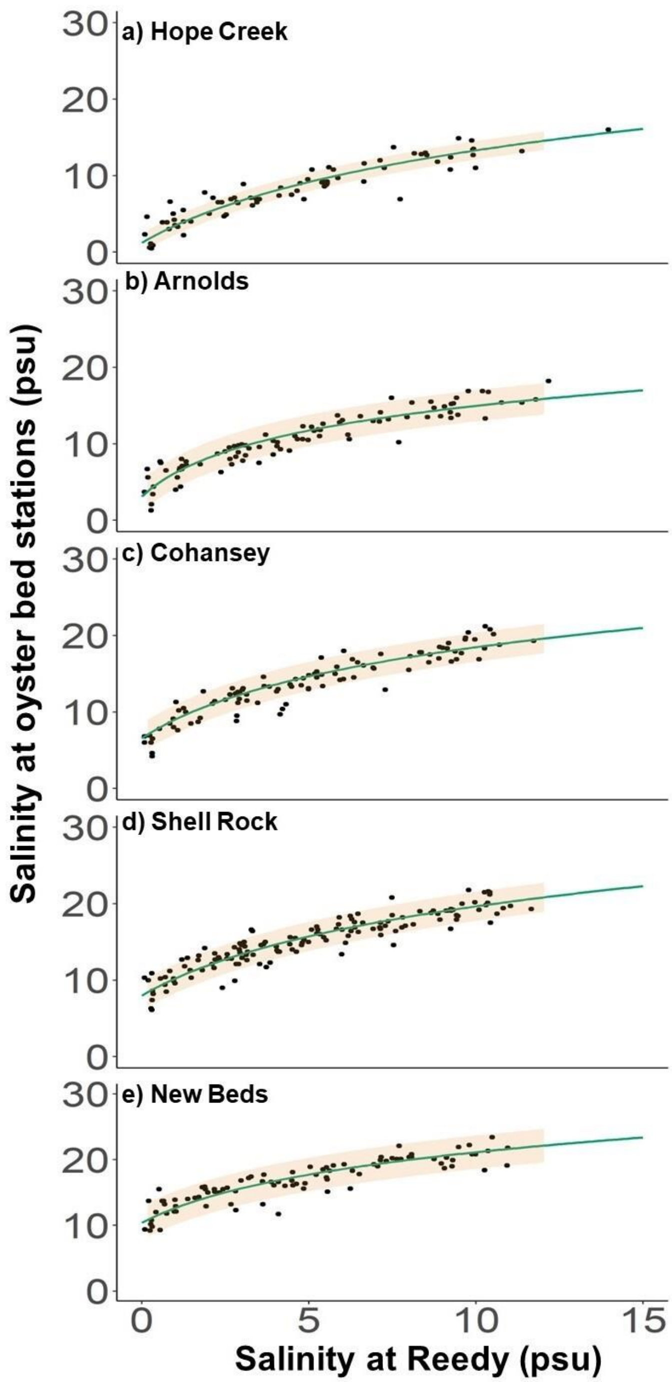

Fig. 5. Observations of salinity from the Reedy dataset versus observed salinity from Haskins data set (black dots) at oyster bed stations a) Hope Creek, b) Arnolds c) Cohansey, d) Shell Rock and e) New Beds. Also shown are the logarithmic regression models (green line) between of daily-average salinity at Reedy station versus daily-average ACOE salinities (2012-2015, 2018) at oyster bed stations. The widths of the 95% prediction intervals for the logarithmic regressions (Table 3) are indicated by the orange shaded region. Root-mean-square values are provided in Table 3.

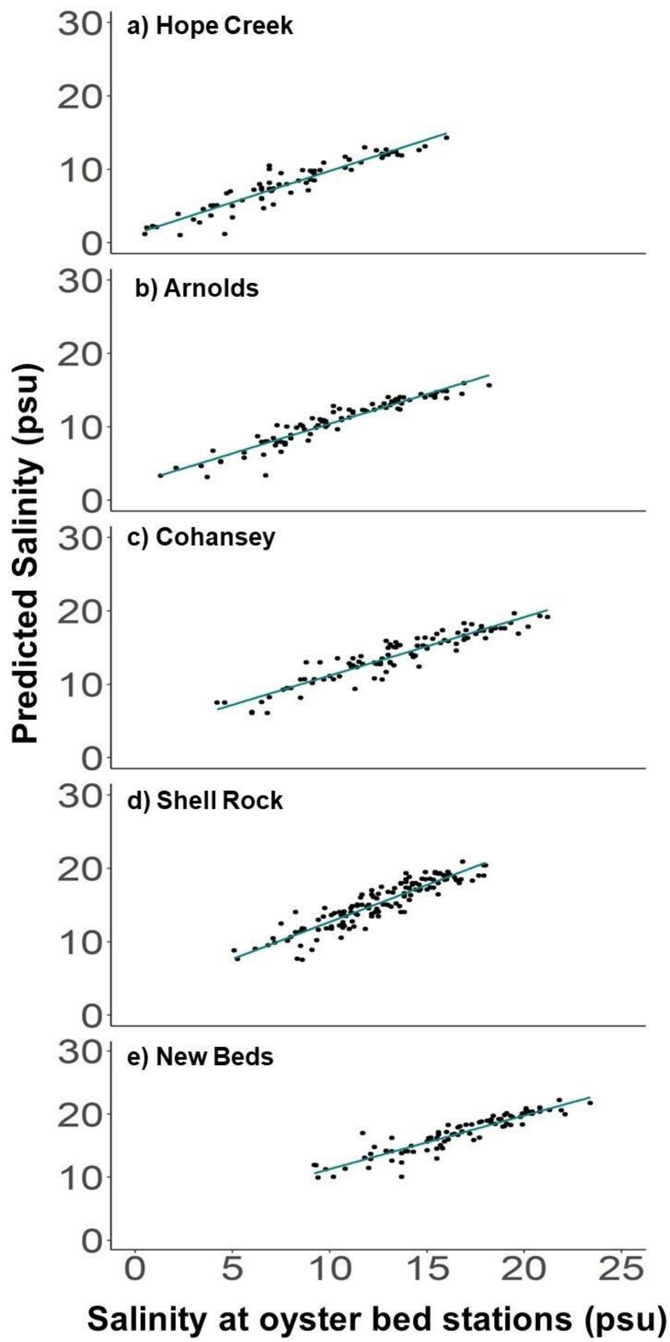

Fig. 6. Observations of salinity at oyster bed stations from the Haskin dataset versus predicted salinity from logarithmic models fit (Table 3). Also included are linear regression lines (green). R^2 values for the lines are 0.89, 0.91, 0.88, 0.84 and 0.86 at Hope Creek, Arnolds, Cohansey, Shell Rock, and New Beds, respectively.

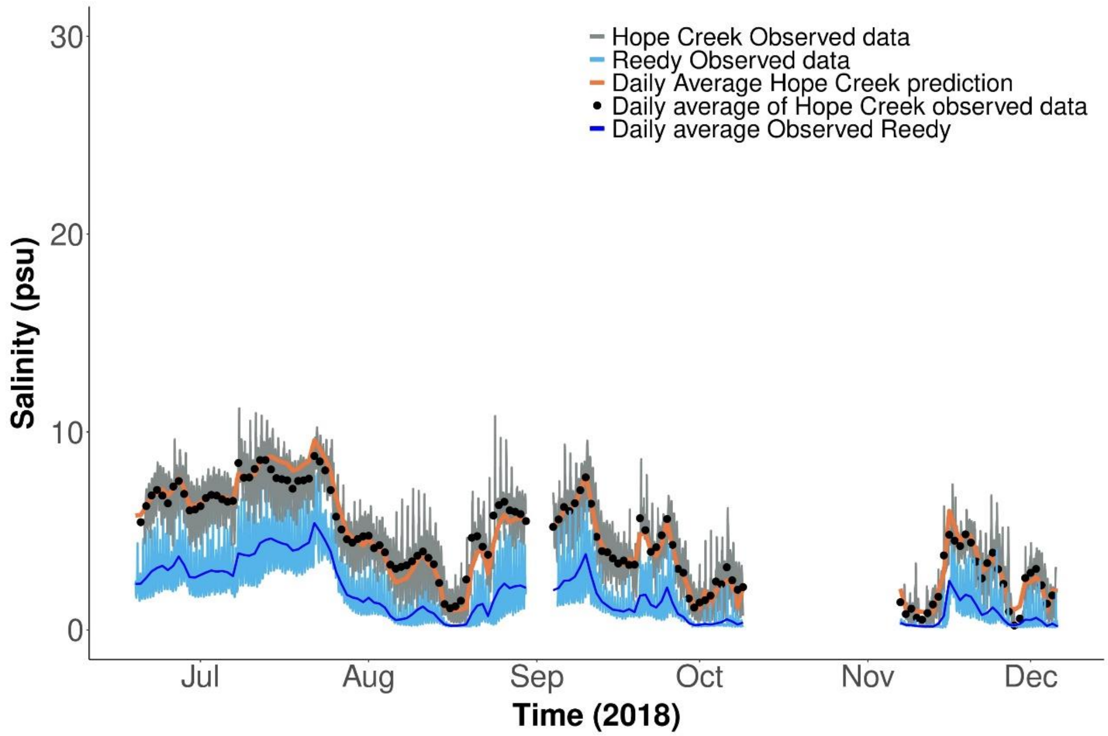

Fig. 7. Empirical model prediction of salinity at the Hope Creek oyster bed station in 2018 (orange line) as predicted with the partial logarithmic regression models (Table 4). Also depicted are the salinity data at the Reedy station used as the independent variable in the regression model (light blue line is 15-min data, dark blue line is the daily average) and the ACOE data at the Hope Creek station used to validate the model (gray line is 15-min data, black point is the daily average).

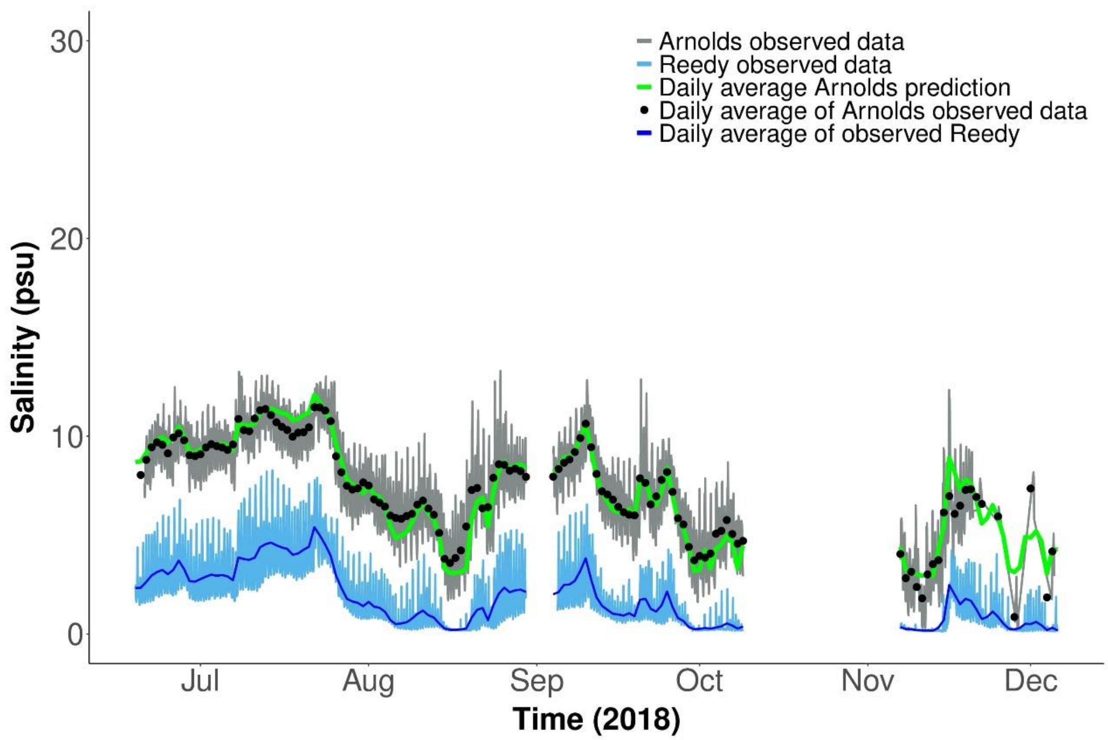

Fig. 8. Empirical model prediction of salinity at the Arnolds oyster bed station in 2018 (green line) as predicted with the partial logarithmic regression models (Table 4). Also depicted are the salinity data at the Reedy station used as the independent variable in the regression model (light blue line is 15-min data, dark blue line is the daily average) and the ACOE data at the Arnolds station used to validate the model (gray line is 15-min data, black point is the daily average).

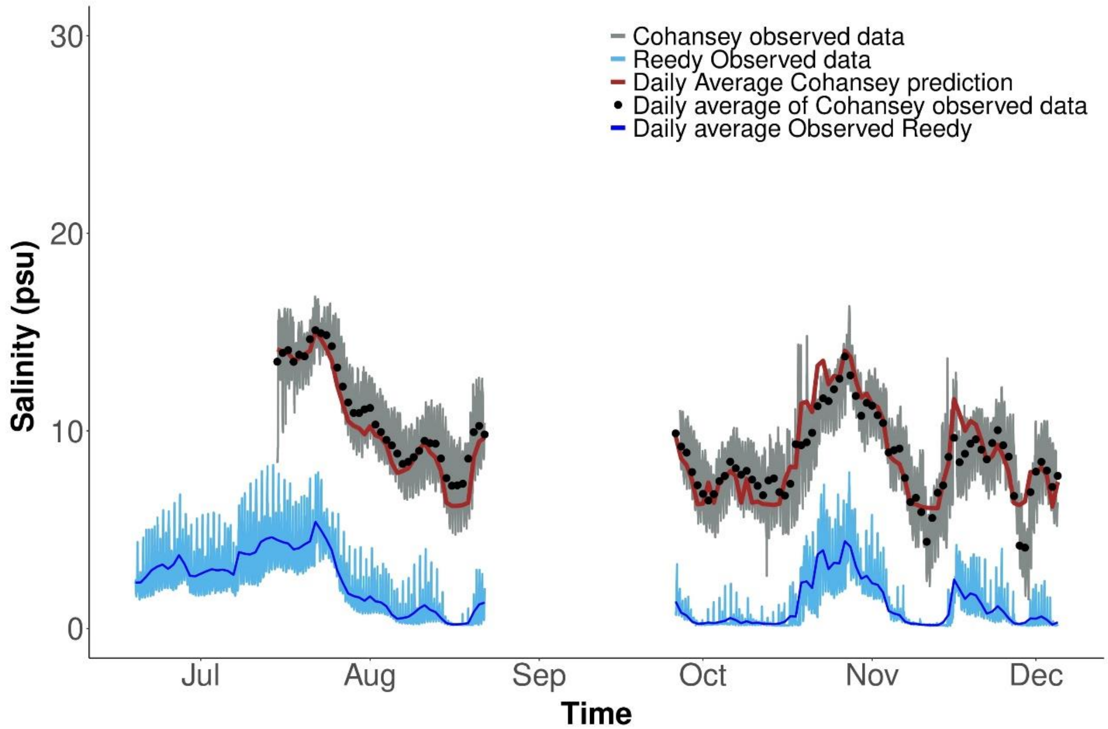

Fig. 9. Empirical model prediction of salinity at the Cohansey oyster bed station in 2018 (dark maroon line) as predicted with the partial logarithmic regression models (Table 4). Also depicted are the salinity data at the Reedy station used as the independent variable in the regression model (light blue line is 15-min data, dark blue line is the daily average) and the ACOE data at the Cohansey station used to validate the model (gray line is 15-min data, black point is the daily average).

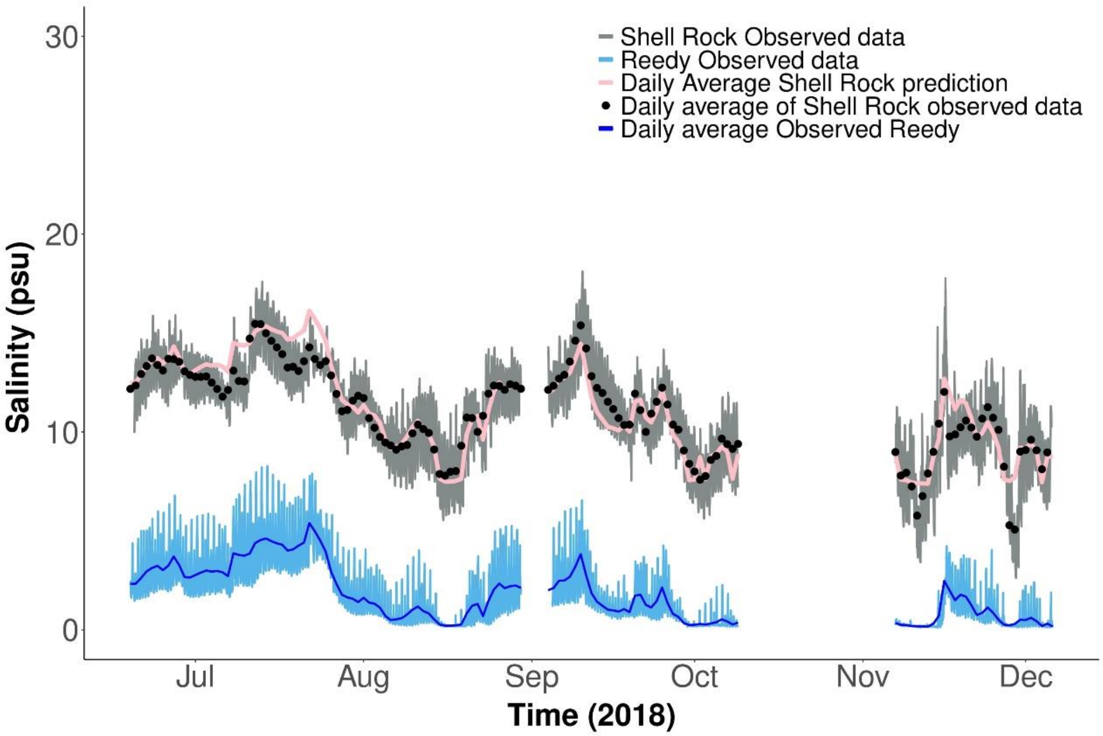

Fig. 10. Empirical model prediction of salinity at the Shell Rock oyster bed station in 2018 (pink line) as predicted with the partial logarithmic regression models (Table 4). Also depicted are the salinity data at the Reedy station used as the independent variable in the regression model (light blue line is 15-min data, dark blue line is the daily average) and the ACOE data at the Shell Rock station used to validate the model (gray line is 15-min data, black point is the daily average).

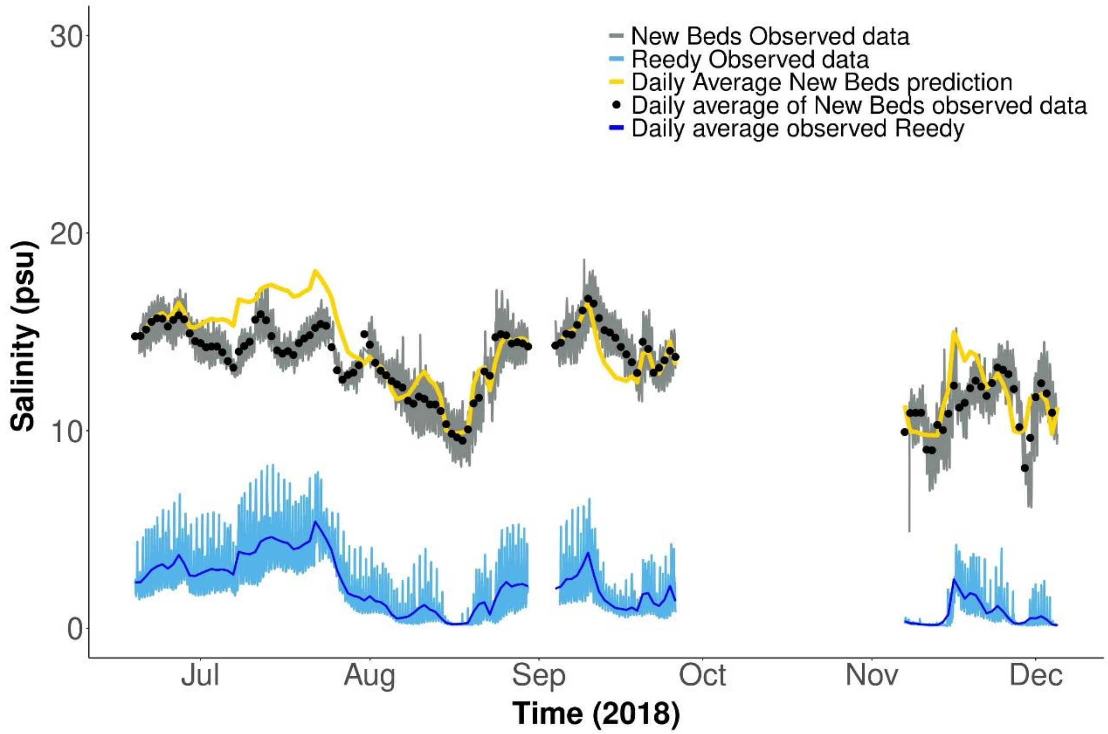

Fig. 11. Empirical model prediction of salinity at the New Beds oyster bed station in 2018 (Yellow line) as predicted with the partial logarithmic regression models (Table 4). Also depicted are the salinity data at the Reedy station used as the independent variable in the regression model (light blue line is 15-min data, dark blue line is the daily average) and the ACOE data at the New Beds station used to validate the model (gray line is 15-min data, black point is the daily average).

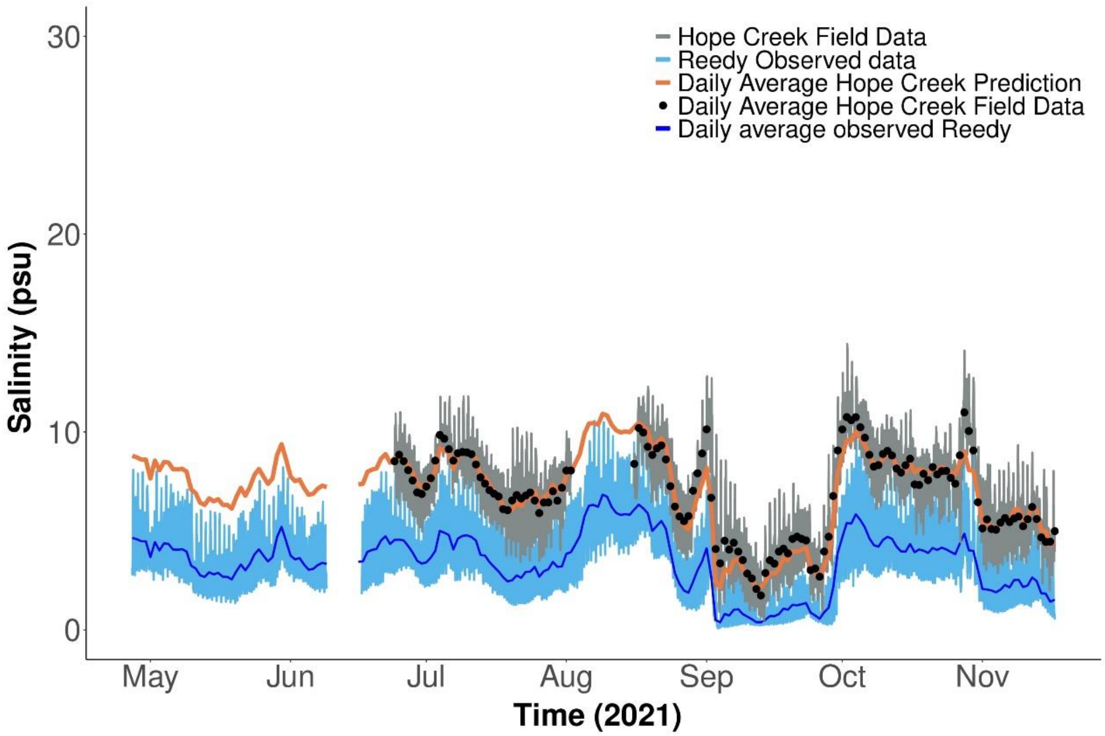

Fig. 12. Empirical model prediction of salinity at the Hope Creek oyster bed station in 2021 (orange line) as predicted with the full logarithmic regression models (Table 3). Also depicted are the salinity data at the Reedy station used as the independent variable in the regression model (light blue line is 15-min data, dark blue line is the daily average) and the ACOE data at the Hope Creek station used to validate the model (gray line is 15-min data, black point is the daily average).

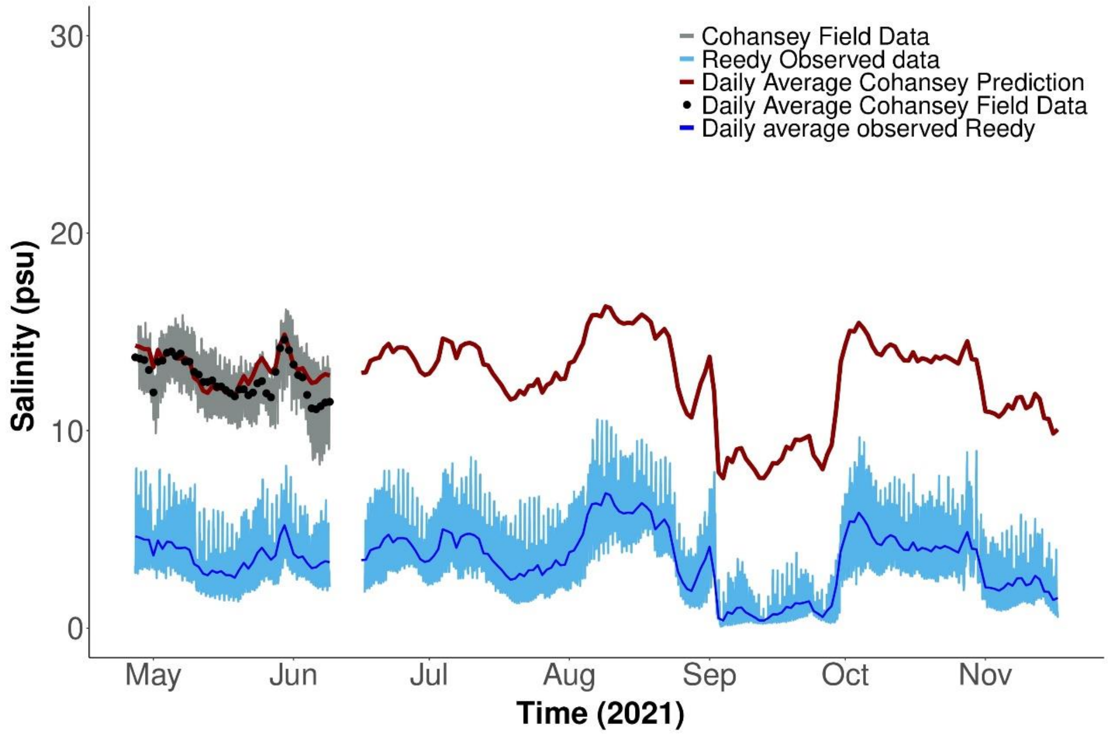

Fig. 13. Empirical model prediction of salinity at the Cohansey oyster bed station in 2021 (dark maroon line) as predicted with the full logarithmic regression models (Table 3). Also depicted are the salinity data at the Reedy station used as the independent variable in the regression model (light blue line is 15-min data, dark blue line is the daily average) and the ACOE data at the Cohansey station used to validate the model (gray line is 15-min data, black point is the daily average).

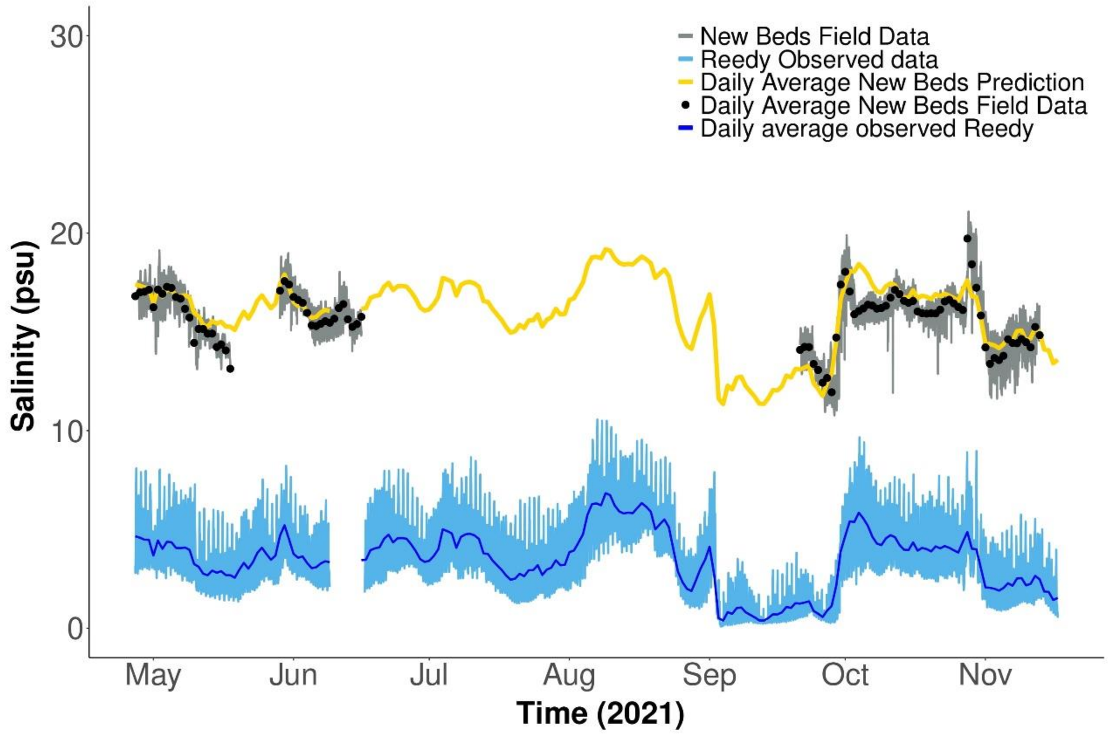

Fig. 14. Empirical model prediction of salinity at the New Beds oyster bed station in 2021 (Yellow line) as predicted with the partial logarithmic regression models (Table 3). Also depicted are the salinity data at the Reedy station used as the independent variable in the regression model (light blue line is 15-min data, dark blue line is the daily average) and the ACOE data at the New Beds station used to validate the model (gray line is 15-min data, black point is the daily average).

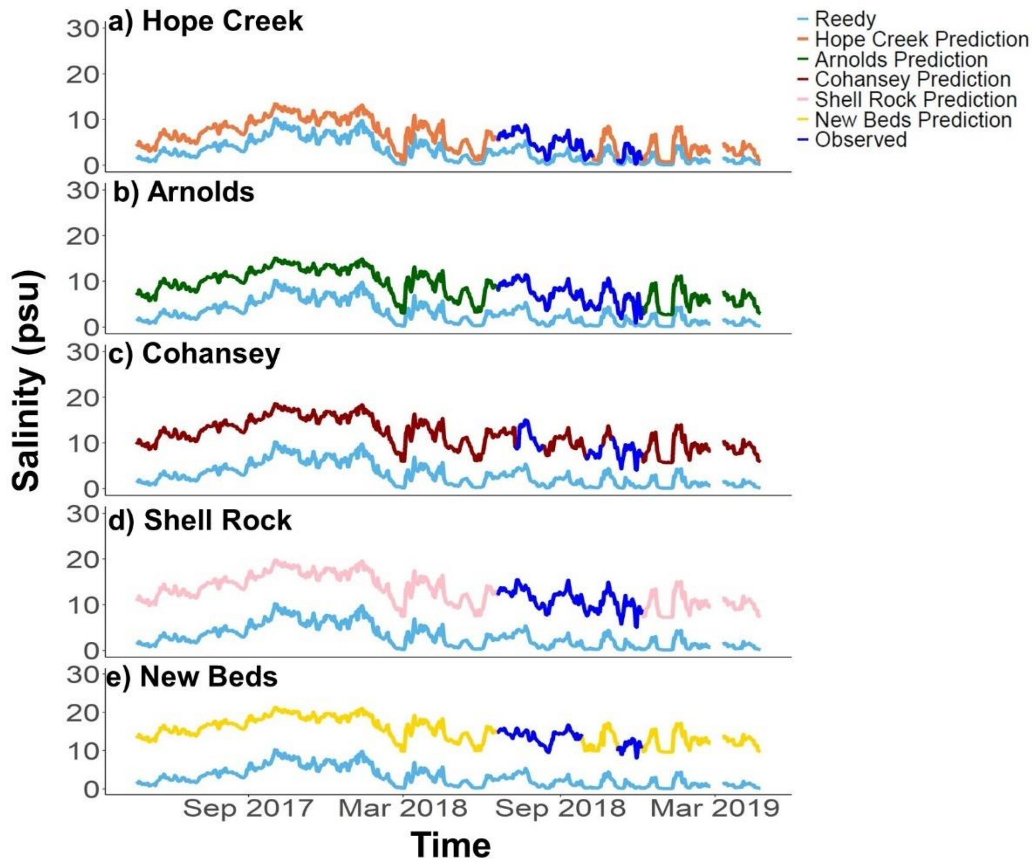

Fig. 15. Combination of observations (bright blue lines, ACOE datasets) and predictions used to calculate salinity indices. Predictions are indicated by colored lines at a) Hope Creek (orange), b) Arnolds (green), c) Cohansey (maroon), d) Shell Rock (pink), e) New Beds (yellow) and are based on the full logarithmic regression models (Table 3). The Reedy observing system data (light blue line) is also shown.

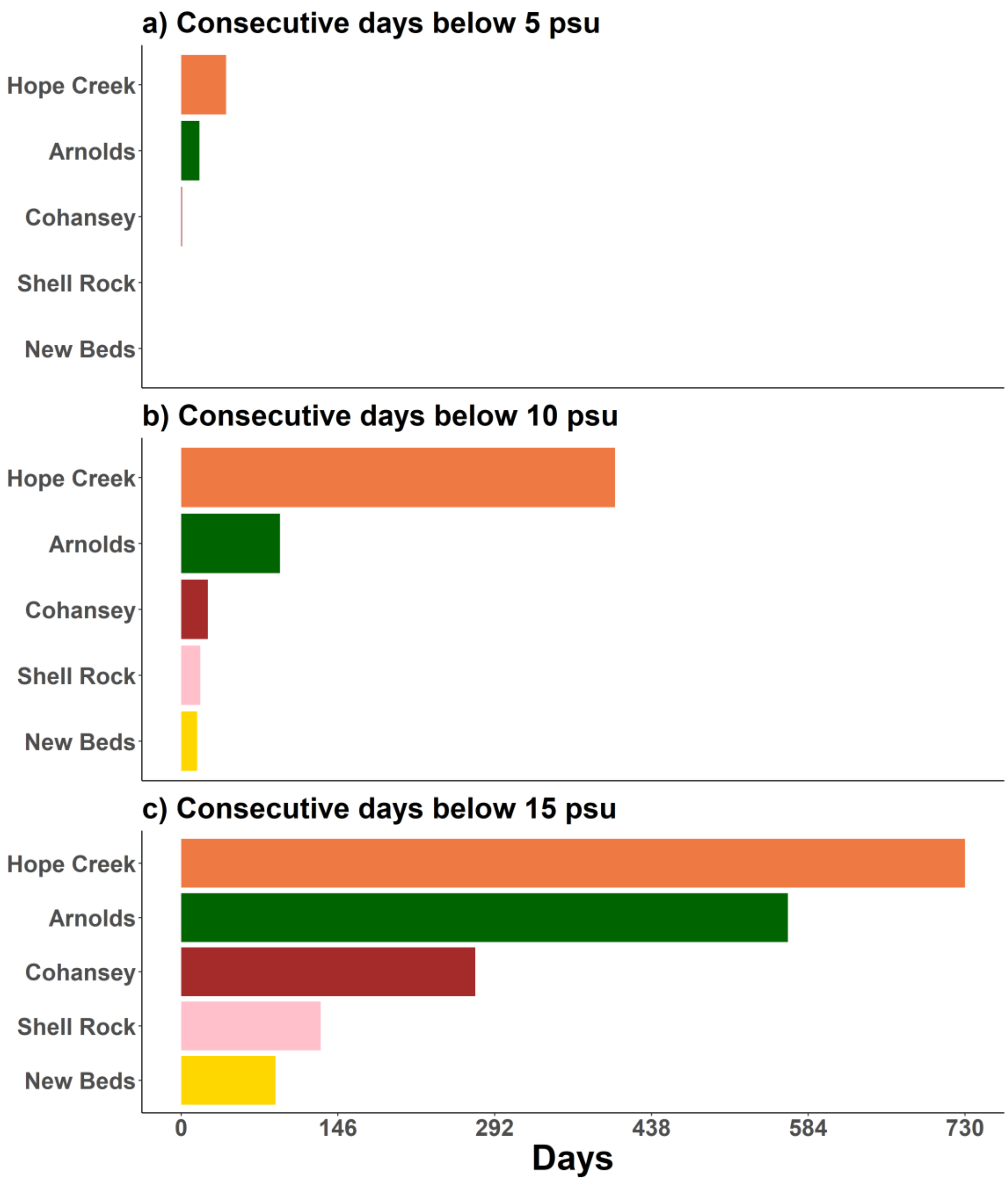

Fig. 16. Bar graph depicting index of the maximum number of consecutive days of salinity (April 23, 2017, to April 23, 2019) for each oyster bed: Hope Creek (orange), Arnolds (green), Cohansey (maroon), Shell Rock (pink), New Beds (yellow). Salinity is predicted with the full logarithmic regression models (Table 3).

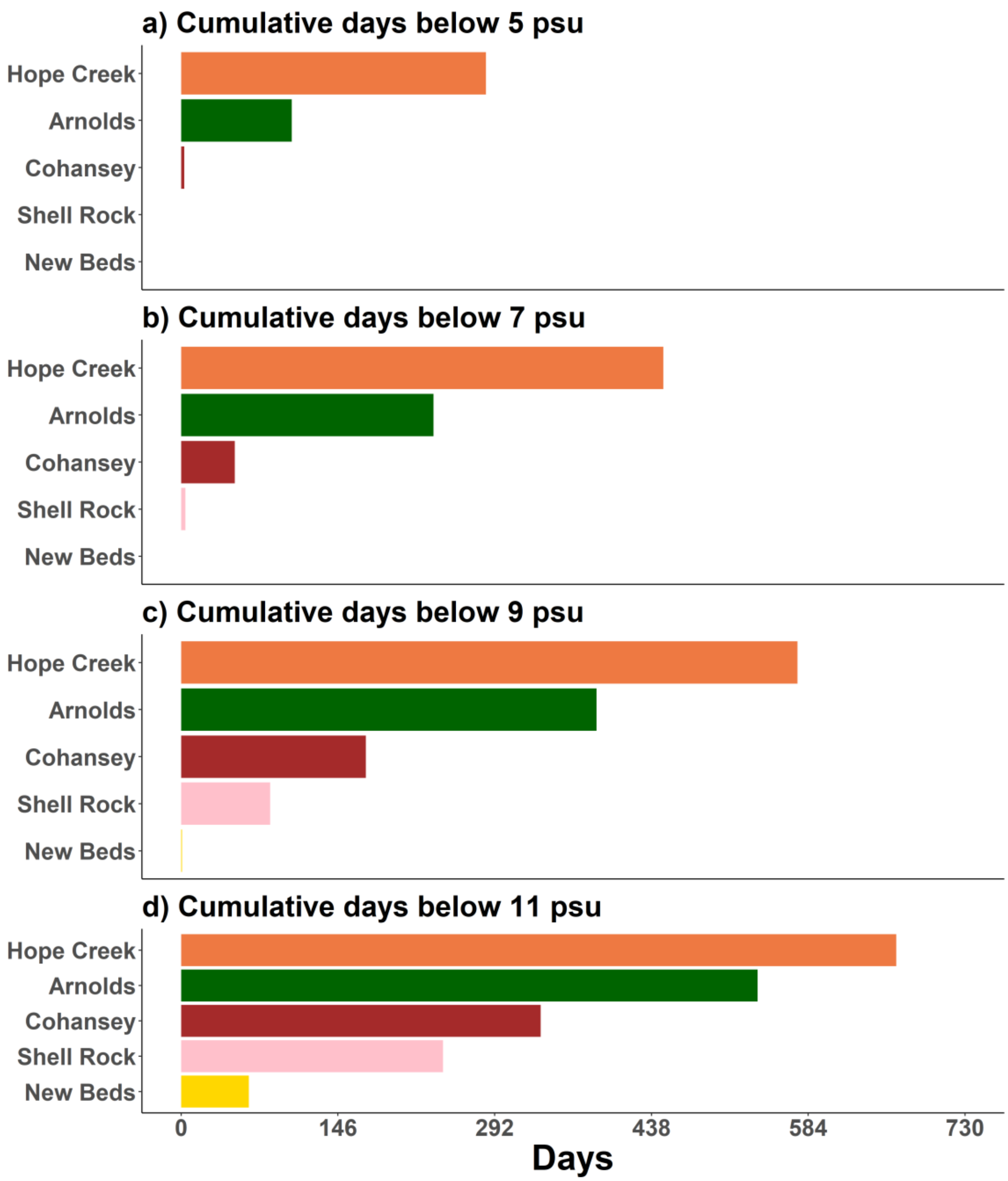

Fig. 17. Bar graph depicting index of the cumulative days of salinity (April 23, 2017, to April 23, 2019) for each oyster bed: Hope Creek (orange), Arnolds (green), Cohansey (maroon), Shell Rock (pink), New Beds (yellow). Salinity is predicted with the full logarithmic regression models (Table 3).

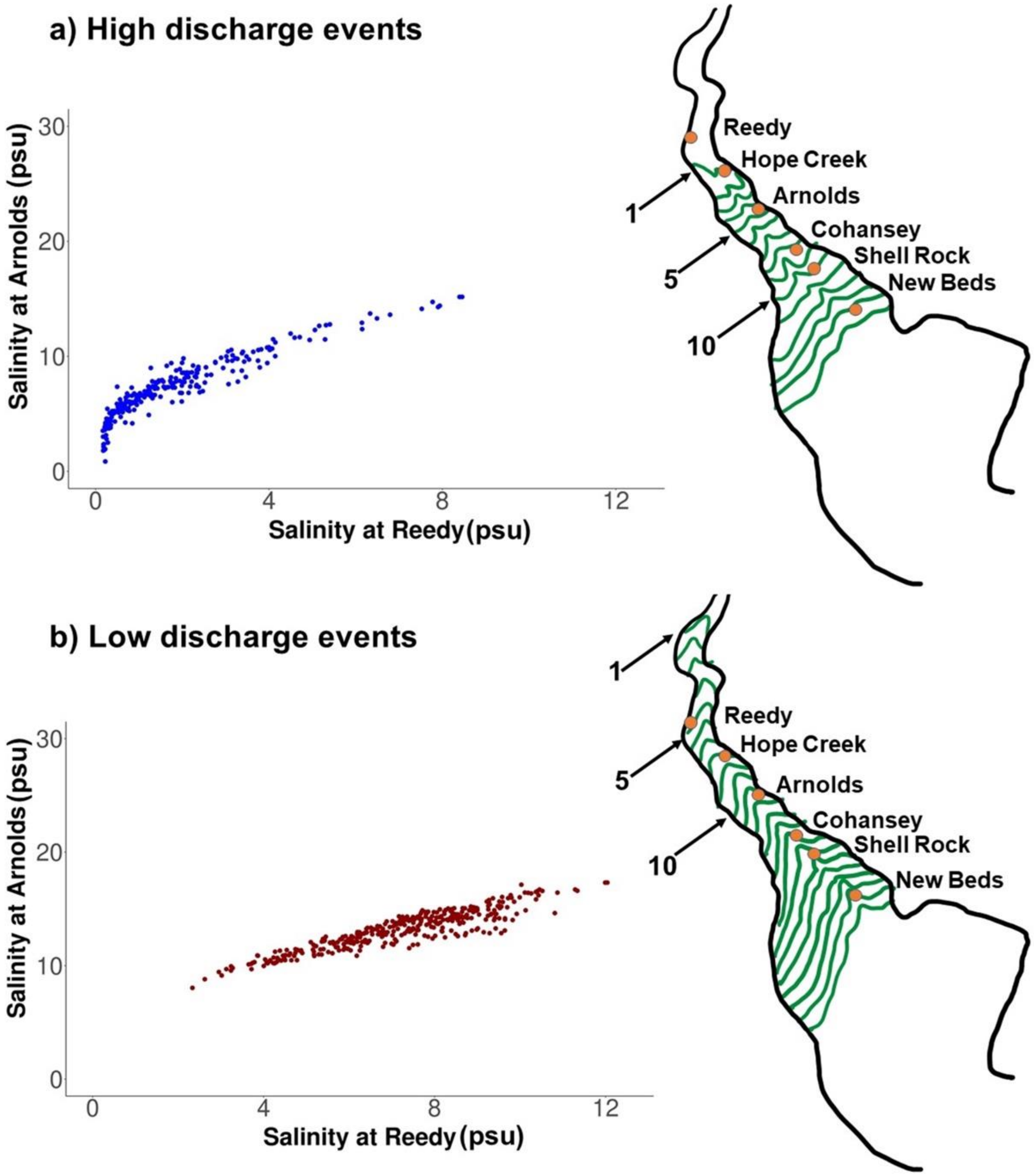

Fig. 18. Conceptual diagram explaining the logarithmic shape of the empirical models. a) High discharge events. The shape of the curve during high discharge events (left panel) and salinity isohalines of Delaware Bay during those events (right panel). Blue circles are the daily average salinity values that corresponded to greater than or equal to the 75th percentile of daily average discharge values from June to December 2012-2015 and 2018. b) Low discharge events. The shape of the curve during low discharge events (left panel) and salinity isohalines of Delaware Bay during those events (right panel). Maroon circles are the daily average salinity values that correspond to less than the 25th percentile of daily average discharge values from June to December 2012-2015 and 2018 Isohaline values of 1, 5, and 10 are indicated to the left of each diagram.

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