Evaluating satellite data products and state monitoring data as substitutes for on-farm data for oyster aquaculture modeling

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Short Title: Data substitution for aquaculture model inputs

ABSTRACT

Chesapeake Bay has experienced nutrient related water quality impairment for decades due to discharge of nutrients (nitrogen, phosphorus) from human related activities in the watershed.

Water quality monitoring indicates a need for additional nutrient management. Oyster aquaculture has become a focus as an additional management strategy because oysters remove nutrients as they feed. Models can estimate oyster harvest and related nutrient removal, helping to develop comprehensive management plans that include oyster aquaculture. Water quality measures for at least one year are required as model inputs. Field sampling and laboratory analyses are time and resource intensive. There is interest in finding less costly methods of data collection, or in using data already being collected for other purposes as model inputs.

Satellite data products, and water quality data collected by Maryland Department of Natural Resources (MD DNR) were compared with *in situ* data collected at two oyster farms in MD Chesapeake Bay (Chester River and North Tangier Sound) for the same timeframe. Statistically there are no differences between on-farm and MD DNR data, nor differences between on-farm and satellite Chlorophyll a (Chl) data at either site, but variability is high and satellite Chl means are lower. Model estimated oyster harvest using on-farm and MD DNR data as model inputs, and using satellite Chl data as inputs, are not significantly different at either site but satellite modeled harvest results are lower at both sites. Mean Average Percent Error (MAPE) analysis shows all model results are Reasonably accurate despite differences in Chl sources and variability among sites. Modeled oyster harvest based on a sensitivity test of ±10% satellite Chl substituted for on-farm Chl showed minimal change (<5%) and no change of MAPE rating. Results suggest that MD DNR data and satellite Chl can be substituted for on-farm measurements. This strategy maximizes efficiency of resource use and adds value to existing monitoring and satellite data programs while providing needed information for resource managers and the shellfish industry.

INTRODUCTION AND BACKGROUND

Eutrophication, or nutrient pollution, is a continuing problem in many waterbodies within the United States (US) and globally. Nutrient discharges (i.e., nitrogen (N), phosphorus (P)) to coastal waters have increased to levels far above natural levels due to human activities (US CWA 1972). High nutrient loads cause disruption to proper functioning of a waterbody's ecological system and can disrupt the economic and social health of the surrounding population if, for example, fisheries lose production, or coastal tourism declines (NRC 2000, Cloern 2001, Bricker et al. 2003, 2014). Eutrophication challenges in coastal waters led to national and regional legislation, such as the US Clean Water Act (US CWA 1972), the Chesapeake Bay Action Plan (2008), Executive Order 13508 for Chesapeake Bay Protection and Restoration (2009), and the Chesapeake Bay Watershed Agreement (2014) that were designed to protect healthy waters and remediate degraded coastal water quality.

The Chesapeake Bay and its tributaries were among the US estuaries that showed more severe nutrient related impacts in two national assessments (Bricker et al. 2003, 2008). The Chester River and North Tangier Sound, two Maryland (MD) Chesapeake Bay tributaries and the locations of the study sites, have historically had Chl concentrations above, and dissolved oxygen (DO) concentrations below, median values reported among US estuaries (Table 1, Bricker et al. 2007). A Total Maximum Daily Load (TMDL) analysis identifies the maximum amount of a pollutant (e.g. nutrients) a waterway can receive and still be able to meet water quality standards. It is a regulatory tool that assists in development of plans to restore pollutant impaired waters to acceptable quality. A nutrient TMDL was established in the Chester River in 2006 because of observed nutrient impairment (US EPA 2008, MDE 1998). Because of continuing nutrient-related degradation, the US Environmental Protection Agency (EPA) established the Chesapeake Bay-wide TMDL for nutrients in 2010 that continues today (US EPA 2010). Continuing nutrient-related water quality issues suggest that additional nutrient management is needed.

TABLE 1 NEAR HERE

FIGURE 1 NEAR HERE

Bioextractive nutrient removal by oysters, clams, mussels and other bivalve shellfish aquaculture has gained momentum during the last 20 years as research has shown potential nutrient removal capabilities in addition to the provision of seafood (e.g. Lindahl et al. 2005, Cornwell et al. 2016, 2023, Bricker et al. 2018, 2020, Rose et al. 2014, Reitsma et al 2017, Holbach et al. 2020). Bivalve shellfish aquaculture is a promising strategy for nutrient management, that can be used in combination with traditional land-based interventions. Models have been used to estimate nutrient removal associated with bivalve shellfish aquaculture harvest because simulations can provide results in less time than the typical 1 to 3 year production cycle (e.g. Ferreira et al. 2007, 2009, Filgueira et al 2014, Rose et al. 2015, Parker and Bricker 2020). However, data input records for at least a year are needed to run model simulations and can be labor and resource intensive to collect for a single study at a farm site. There are other data sources that might be used that are being collected for other purposes that could save time and resources.

The objective of this study was to evaluate whether state monitoring data and satellite Chl data might be substituted for on-farm Chl and other needed water quality data model input measurements. This study was conducted in two parts; 1) to test if data already being collected by other agencies were representative of on-farm measurements and thus could be used as model inputs, and 2) whether model results using those data were comparable to results using project-specific data measured on oyster farms.

STUDY SITES – CHESTER RIVER & NORTH TANGIER SOUND, MARYLAND CHESAPEAKE BAY

Eight Maryland Chesapeake Bay oyster farm sites that were sampled in Parker and Bricker (2020) were evaluated for possible inclusion in this study. Two farms, one in Chester River and one located at the boundary of Honga River and Tangier Sound, were selected because these were the only farm sites where a 3x3 pixel grid box of satellite data around the study site did not contain land interference (Figure 1). The oyster growers, both using bottom cage operations and both cultivating triploid Eastern oyster (*Crassostrea virginica*), provided detailed information about cultivation practices used during the typical cultivation cycle (Parker and Bricker 2020).

The Chester River has a total area of 196 km^2 (Bricker et al. 2007). The oyster farm used for this study is located in mid-Chester River, which is mostly brackish, with a long-term average salinity of 12 (Bricker et al. 2007) and an average 9 from 2016 to 2018 (Parker and Bricker 2020; Figure 1, Tables 1, 2). Salinity is within the range of tolerable salinities for *C. virginica* (5–40, with an optimum of 15–25; Shumway 1996), though the Chester River is known to experience low salinities (<4) at times of heavy rainfall. The average tidal height is 0.48 m.

Residence time is 27 days, greater than the median value for US estuaries (~5 days, Bricker et al. 2007). High residence times (> 10 days) suggest susceptibility to eutrophication; slower water replacement has been associated with higher level nutrient-related degradation (Bricker et al. 2014).

The North Tangier Sound has an area of 1057 km^2 which includes a large sound with smaller tributary bays and tidal rivers including the Nanticoke, Wicomico, Manokin, Big Annemessex and Pocomoke Rivers (Figure 1). The oyster farm is located at the southern end of Honga River where it meets Tangier Sound. The long-term average salinity of the Sound is 13 (Bricker et al. 2007) and average salinity from 2016 to 2018 was also 13 (Parker and Bricker 2020). The average tidal height for Tangier/Pocomoke Sound is 0.67 m, and residence time is 12 days (Bricker et al. 2007), greater than the median for US estuaries (~5 days) but less than the Chester River.

Dissolved oxygen and Chl are used as indicators of nutrient enrichment and eutrophication impacts (Bricker et al. 2003). Surface Chl concentrations, representing algal biomass, above 20 μg/L are indicative of nutrient enrichment (Bricker et al. 2003) causing declines in submerged aquatic vegetation (US EPA 2000, Stevenson et al. 1993) and community shifts in phytoplankton from a diverse mixture to monoculture (Twilley et al. 1985). Highest annual (90^{th} percentile) Chl concentrations in both the Chester River and Tangier Sound systems are higher than the median of 90^{th} percentile Chl concentrations of US estuaries (Table 1) indicating nutrient related impacts.

Dissolved oxygen concentrations less than 5 mg/L are considered stressful to water column dwelling organisms such as American shad, white perch and other fish; bottom-dwelling organisms such as crabs and oysters are less sensitive, requiring only 3 mg/L to thrive (US EPA 2003). Concentrations between 2 and 5 mg DO/L are considered 'Biologically Stressful' and mobile organisms flee areas where these concentrations are observed (Bricker et al. 2003). Lowest annual (10^{th} percentile) DO concentrations are lower than the median of 10^{th} percentile values of US estuaries and lower than thresholds indicative of impairment (Bricker et al. 2003) in Chester River, but not in North Tangier Sound.

Successive Eco Health Report Cards (UMD 2015-2020) showed that Chester River and North Tangier Sound, had failing grades for overall water quality health and for Chl concentrations, and best or better grades for DO conditions. Maryland DNR assessments for the same regions (MD DNR 2015, 2015a) show failure to meet N standards at both sites, and failure to meet summer DO standards in Chester River.

METHODS AND MATERIALS

The dataset from a one-time study of two Chesapeake Bay oyster farms (Parker and Bricker, 2020) was compared to two alternate data sources, satellite Chl data products from the Copernicus Sentinel – 3 Ocean and Land Color Instrument (OLCI) using an algorithm for optically complex waters (Gilerson et al. 2010) and data from the long-term MD DNR monitoring program (MD DNR 2016-2018). The on-farm dataset was considered the 'true' dataset. Satellite and MD DNR data were selected to match the 2016 to 2018 timeframe of the on-farm data set. Model outputs from simulations using the on-farm datasets from Parker and

Bricker (2020) deemed the 'true' model output, were compared to model results using the alternate datasets as inputs.

On-farm *In situ* Monitoring Data

The on-farm dataset includes temperature, salinity, Chl, DO, total suspended solids (TSS) and total volatile solids (TVS), the minimum data inputs needed to run the Farm Aquaculture Resource Model (FARM; Ferreira et al. 2007), the model used in this study. *In situ* samples were collected monthly at the Chester River (N = 23) and North Tangier Sound (N = 24) oyster farm locations in a two-year study from May 2016 to August 2018, with exceptions due to boat operation and ice condition issues (missing data at Chester River for September 2016, January, March, April, September 2017; missing data for North Tangier Sound for September 2016, September, December 2017, January 2018). Samples were analyzed at the University of Maryland (UMD) Chesapeake Biological Laboratory (CBL) Nutrient Analytical Services Laboratory (NASL) with a typical overall percent error of <5% (J. Frank, personal communication, UMD CBL NASL, September 19, 2024, UMD CBL NASL 2019a, b, c, d, Parker and Bricker 2020). Surface data are used to represent farm conditions, despite the use of bottom oyster cages, because the sites are shallow (<2.5 m) with well-mixed water columns with no expected nor observed difference between surface and bottom water quality due to tidal and wind mixing.

Satellite Data

Satellite products cannot provide all needed model input parameters. Only Chl, TSS and sea surface temperature (SST) are available from satellites in this area. For the purpose of this study the focus was Chl, so only Chl satellite data products were used. Daily Ocean and Land Color Instrument (OLCI) images with a native spatial resolution of 0.3 km from Copernicus Sentinel-3 satellites of the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) were used. The OLCI sensor operates on two separate spacecraft: Sentinel-3A (launched February 2016) and Sentinel-3B (launched April 2018) that pass over the Chesapeake Region twice per day, i.e. one instrument each on two Sentinel-3 satellites. Daily imagery from both Sentinel-3A and Sentinel-3B from May 2016 through August 2018, the timeframe to match the timeframe of sampling on the farm, were used in this study. The map in Figure 1 gives an example of features that are visible in imagery from the 300 m spatial resolution of the OLCI sensor.

The satellite images were processed with a Chl algorithm that uses the red-edge band, referred to as Red Edge 2010 (RE10 Chl, Gilerson et al. 2010), by NOAA National Centers for Coastal Ocean Science (including invalid pixel flags), as outlined by Wolny et al. (2020) for Chesapeake Bay, and validated in Wynne et al. (2022). Specifically, the RE10 algorithm uses the relative amount of red and near-infrared light fluoresced by phytoplankton and was calibrated with Chesapeake Bay *in situ* Chl data (Gilerson et al. 2010, Wynne et al. 2022), reducing the high Chl bias in coastal regions of NASA standard Chl algorithms which compare the relative absorption of blue to green light. This algorithm was selected based on a comparison of the efficacy of five satellite-based Chl algorithms in Chesapeake Bay where it performed best for Chesapeake Bay, with a 36% Median Absolute Error (Wynne et al. 2022), and improved spatial resolution to 300 m, compared to other operational Chl products. Higher spatial resolution is critical when applying to on-farm models, given their location in narrow tributaries and close to land.

Phytoplankton biomass (estimated from Chl concentrations), is the primary food source for oysters and was the focus of satellite data estimates.

The satellite overpasses were gridded on a 0.3 km Universal Transverse Mercator (UTM) grid daily and Chl data were extracted for a 3x3 box (9 grid cells) around the two oyster farm locations in the Chester River and North Tangier Sound (Figure 1). The Chester River farm site is very close to the coastline, so the number of values in the 3x3 box (9 pixels) was quite low due to effects of coastal turbidity, tides, and shallowness (N = 66). The North Tangier Sound farm site contained more values (N = 255) in the 3x3 box. Cloud cover reduces the number of values for both sites as well. The median Chl value was used, for comparison to the on-farm dataset, as long as at least 5 of the 9 measurements of the 3x3 grid-cell box were present.

Maryland Department of Natural Resources Long-term *In situ* Monitoring Data

Monthly measures from MD DNR Chesapeake Bay long-term monitoring program for salinity, temperature, Chl, DO, TSS, and TVS (MD DNR 1984 – present) were compared to on-farm *in situ* water quality measurements. The MD DNR data for the period May 2016 to August 2018 were selected to match the on-farm sampling timeframe, having been sampled in the same month and, on average, sampled within 3 days of the on-farm samples. Data were acquired for two of the MD DNR long-term sample stations that were closest to the oyster farm locations (Figure 1, Table 2). The station closest to the Chester River farm is MD DNR station ET4.2 (N = 28) in the Lower Chester River. The station closest to the North Tangier Sound oyster farm site was station EE3.1 (N = 27) in North Tangier Sound. In both cases, the sampling stations were ~8 km from the farm site and only surface data were used for the analysis. Sampling, analytical, and quality control / quality assurance protocols are described in MD DNR Quality Assurance Project Plans (MD DNR 2020, 2023). MD DNR monitoring program samples are analyzed at the UMD CBL NASL and overall error is typically <5% (J. Frank, personal communication, September 19, 2024, UMD CBL NASL).

TABLE 2 NEAR HERE

Since the MD DNR long-term monitoring stations (ET4.2, EE3.1) are at deeper water sites, it was important to be certain that those data were representative of water characteristics at the shallower farm sites. To confirm this, MD DNR long-term monitoring data were compared to MD DNR shallow water monitoring data at the locations closest to the on-farm locations (Appendix I). The shallow water monitoring program collects data at a station for three-year periods; the shallow water monitoring at the closest shallow water stations differed from the on-farm study period (2016-2018), so data from the shallow water monitoring program were compared to data from the long-term monitoring stations for the matching periods: 2008-2010 for North Tangier Sound and for 2004–2006 for the Chester River. The results of the comparative analysis indicated there was no significant difference between the long-term monitoring station surface sample data and shallow water monitoring station data during the overlapping period at either location, suggesting that the long-term station data could adequately represent the shallow water areas. Thus, data from the two long-term monitoring stations (ET4.2, EE3.1) were used with confidence to represent the shallow water areas of the oyster farms.

Statistical Methods

On-farm, MD DNR, and satellite Chl data were analyzed for mean differences in concentrations among sites (Chester and North Tangier), among years (2016-2018), and among months (Jan. - Dec.). Monthly MD DNR and satellite mean Chl concentrations were used to evaluate the representativeness of monthly on-farm mean Chl concentrations. Levene tests of Chl data found that variances among groups were not homogeneous, therefore Kruskal-Wallis tests were used to determine mean differences in Chl concentrations among data types, sites, and years. Subsequently, multiple comparison tests were performed using the Wilcoxon rank sum exact test. Base R statistical packages (https://cran.r-project.org/) were used for analysis. The Levene Test, Kruskal.test and pairwise Wilcox.test functions were used for Chl data analysis. Probability values (p-values) less than 0.05 indicated violations of the null hypothesis.

On-farm and MD DNR mean water quality parameters (Chl, DO, TSS, TVS, temperature, salinity) were compared for differences among sites. Levene test for water quality data found that variances among groups were homogeneous. Linear models were used to calculate the mean estimates for water quality parameters and determine significant differences in mean concentrations among sites (Gotelli 2004). The mean estimates were calculated using the linear model (lm) function. The 95% confidence intervals were calculated using the predict function. Significant differences among sites for water quality data mean estimates were determined based on the overlap among sites. Overlapping 95% confidence intervals indicate no significant difference and non-overlapping 95% confidence intervals indicate a significant difference.

A Mean Absolute Percentage Error (MAPE) analysis was used to compare relative accuracy of oyster model simulations when MD DNR and satellite Chl data were substituted for the on-farm data (Moreno et al. 2013). Mean Absolute Percentage Error is the average difference between the predicted value and the observed value. In this study, since the observed harvest data were unavailable, comparison was made of average differences among Chl data sources by using each data source as input for running the oyster production model. The modeled harvest results from the on-farm input dataset are considered the observed and the estimated harvest using the MD DNR dataset and the satellite Chl substituted for the on-farm Chl are considered the predicted values. The MAPE function from the MLmetrics R software package was used to calculate the MAPE. The equations for calculating each MAPE are:

On-Farm vs. DNR = mean(abs(sum((On-Farm-DNR)/On-Farm))) * 100

On-Farm vs. Satellite = mean(abs(sum((On-Farm-Satellite)/On-Farm))) * 100

Interpretation of the MAPE results is based on Lewis (1982), where:

MAPE <10% - Highly accurate

MAPE 10-20% - Good accuracy

MAPE 20-50% - Reasonable Accuracy

MAPE >50% - Inaccurate

Farm Aquaculture Resource Management (FARM) model

Data were applied to the Farm Aquaculture Resource Management (FARM, Ferreira et al. 2007) model to evaluate differences in model output using the three different datasets. The model combines physical and biogeochemical models, bivalve growth models, and water quality screening models to determine shellfish production (harvest) and for eutrophication assessment at the farm scale (Ferreira et al. 2007). Water properties are transported both horizontally and vertically in the model, but the vertical component only applies to suspended culture; the oyster farm sites in this study use bottom cage culture. The model is driven by peak (i.e., mid-tide) current speeds measured *in situ* for both spring and neap tides, which are interpolated to generate the full semi-diurnal cycle for both height and velocity, and the change of amplitude through the lunar cycle. Velocities are not residuals, and the tidal height and velocity are calculated explicitly for each model timestep (Ferreira et al. 2007). A sensitivity analysis of model outputs from various inputs from different locations showed the model to be robust and a useful tool for analysis of farm production, profit maximization, and potential nutrient removal (Ferreira et al. 2007). The model has been validated for oysters and several other species with results showing good agreement with reported shellfish harvest (Ferreira et al. 2009).

The Chesapeake Bay calibration of the model (Cubillo et al. 2018), used in Parker and Bricker (2020), was used in this study. The model has also been calibrated and used successfully in Long Island Sound and Great Bay Piscataqua (Dvarskas et al. 2020, Bricker et al. 2018, 2020) where modeled harvest results were in agreement with reported harvest, in several European waterbodies (Ferreira et al. 2009), in China (Ferreira et al. 2008), and in Chile (Silva et al. 2011).

Environmental data required for simulations are temperature, salinity, Chl, TSS, and TVS. The model can accommodate samples that are taken on different dates. Interviews with oyster growers provided additional model inputs needed including information about farm operations such as size of farm, oyster seeding density, size of oyster seed and harvestable oysters, and typical mortality over the cultivation cycle (Cubillo et al. 2018, Parker and Bricker 2020). Current speeds were taken from the NOAA buoy closest to each study site (Parker and Bricker 2020). Eight model simulations for each data set at each farm location were made using different mortalities (20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%) to represent the range of potential modeled harvest given the range of mortalities reported by MD oyster growers (20%–90%). The output of interest was the modeled estimates of oyster harvest amount (hereafter 'modeled harvest') because this is what is used to determine the potential nutrient credits an oyster grower can receive within the Chesapeake Bay Nutrient Credit Trading Program (MD NTP n.d., MDE n.d., Cornwell et al. 2016, Wheeler 2020, MD CG 2023).

Comparison was made of the modeled oyster harvest output from simulations using the on-farm and MD DNR datasets as inputs at the two farm study sites. In the simulation to compare results using on-farm and satellite Chl, only the Chl data were substituted with satellite Chl while all other variables remained the same. Additional modeling was done with these satellite data to test the model sensitivity to the use of satellite Chl. For both sites, sensitivity simulations were made for all mortalities using satellite Chl both increased and decreased by 10%.

Modeled estimates can be validated by comparison to reported harvest as was done in a validation study (Ferreira et al. 200). In this study, because of industry privacy considerations harvest data were not available for individual farms. A single harvest number provided by the grower for 2016 oyster harvest at the Chester River farm was 13.6 m tons (at 70% mortality due to low salinity excursions CBF 2019; Parker and Bricker 2020). Annual variability for 2016-2018 for combined harvest from all MD cage grown oysters was 12%, which provides additional insight (UME n.d.).

RESULTS

Comparative analysis of on-farm, MD DNR and satellite datasets

Statistical comparison of the three datasets for Chl was made by a Kruskal-Wallis test, results are shown in Figure 2a. The on-farm Chl data are not significantly different from satellite and MD DNR Chl concentrations at either site, but results are variable. The satellite Chl means at both sites are lower, particularly at the North Tangier site.

Figure 2b shows that there is no significant difference in Chl concentrations among the three years at either site for any dataset. There are also no significant differences between the on-farm and satellite data among the different years, nor between on-farm and MD DNR data among the three years of data.

The combined years of data were also evaluated to see if there were differences in monthly data at the two study sites (Figure 2c). There were no statistically significant differences in data between the on-farm and satellite data, nor between the on-farm and MD DNR data at either location. The maximum and minimum concentrations at the on-farm locations are reflected in maximum and minimum concentrations in both MD DNR data and satellite datasets. For example, the Chester River Chl data shows highest concentrations in month 8 that are also observed in the MD DNR and satellite datasets at month 8, but the relative difference in concentration is greater in on-farm and DNR datasets than the relative difference in the satellite dataset. The North Tangier site also shows consistency in data among the three sources, particularly in the minimum concentrations which all datasets show at month five, though satellite Chl concentrations were lower overall.

FIGURE 2 NEAR HERE

The comparisons of on-farm and MD DNR measures of additional water quality parameters (salinity, temperature, DO, TSS, TVS) are shown in Figure 3a-e. These results show that data from MD DNR and on-farm measurements are not significantly different for any parameter at either site, but the data are variable. Salinity, temperature, and DO show the greatest concurrence. Total suspended solids and TVS concentrations are higher in the on-farm datasets at both sites, though statistically there is no significant difference for either parameter at either site.

FIGURE 3 NEAR HERE

FARM Model Results

Results of the FARM model application to all three datasets are shown in Table 3. The modeled harvest results using the MD DNR data are higher than results using on-farm data at the Chester River, and the results using the satellite Chl are lower at both sites. The overlap of 95% confidence intervals of model results from the three different datasets indicates no significant differences between FARM modeled harvest based on the on-farm and MD DNR datasets at

TABLE 3 NEAR HERE

either location, nor between results using the on-farm and satellite Chl data at either location (Table 3). Variability, however, is high with average standard deviations of 17% (MD DNR dataset), 24% (on-farm dataset), 32% (satellite Chl dataset) among the Chester River model results, and 37% (on-farm and MD DNR datasets) and 50% (satellite Chl dataset) among the North Tangier Sound model results. Satellite Chl showed lower modeled harvest at both sites, lower than both on-farm and MD DNR results. At both sites, there is an increasing difference in model estimated harvest as modeled oyster mortality increases, reaching 50% lower harvest at 90% mortality at the North Tangier site.

Results of the sensitivity test showed that 10% increases and 10% decreases in satellite Chl model inputs, with all other variables the same, led to increases and decreases in model estimated harvest at both sites. Modeled harvest results at the Chester River site were an average of 17.0 and 15.7 metric tons for the increased and decreased satellite Chl, respectively. At the North Tangier site model estimated harvest results were 28.3 and 18.7 metric tons for increased and decreased satellite Chl, respectively. The variability in harvest results on average (32% at Chester River, 47% at North Tangier) was similar to variability of results using the original satellite Chl dataset (32% at Chester River, 50% at North Tangier).

Mean Average Percent Error analysis results

The MAPE analysis indicates that all sources of Chl data input at both sites provide Reasonable accuracy (MAPE < 30%; Figure 4). More accurate results were achieved when MD DNR data were substituted for on-farm data, where North Tangier (1.9%, Highly accurate) was more accurate than Chester River (12%, Good accuracy). Substituting satellite for on-farm Chl data at both sites resulted in less accurate results; the MAPE at Chester was 13% (Good accuracy) and at North Tangier was 29% (Reasonable accuracy). The combined MAPE results at each site show that overall accuracy, combined results for on-farm vs MD DNR and on-farm vs satellite, was greater at the Chester River site (25%, Reasonable accuracy) than at the North Tangier Sound site (30.9%, Reasonable accuracy).

The MAPE for the satellite sensitivity results using ±10% satellite Chl show a change of 1% (greater) accuracy at the Chester River site and 4% (lesser) accuracy at the North Tangier site. Neither change results in a change in the overall MAPE outcome, results indicate Good relative accuracy for Chester River and Reasonable relative accuracy at the North Tangier site.

FIGURE 4 NEAR HERE

DISCUSSION

Negative impacts of nutrient discharges to Chesapeake Bay waters continues to be a challenge. A large body of work suggests that oyster aquaculture can partially address the need for additional nutrient management (e.g., Cornwell et al. 2016, 2023 and citations within, Town of Mashpee Sewer Commission 2015, Reitsma et al. 2017, Rose et al. 2015, Lindahl et al. 2005, Parker and Bricker 2020, Bricker et al. 2018, 2020). Oyster aquaculture has shown similar N removal rates and implementation costs as some traditional approved nutrient Best Management Practices (BMPs; Rose et al. 2014). In 2016 the Chesapeake Bay Program approved harvested aquaculture oyster tissue as an additional nutrient Best Management Practice (BMP, Cornwell et al. 2016, 2023) to help achieve water quality goals.

While the amount of nutrients removed by oyster aquaculture can be estimated by the number of oysters that are harvested and the per oyster nutrient content (Cornwell et al. 2016), this can also be achieved by model-determined mass balance of assimilated and excreted phytoplankton and detrital material that is filtered (eaten) by the oyster farm population (Ferreira et al. 2007). Model scenarios can also be used to estimate expected changes in farm harvest due to changes in aquaculture practices or changes in environmental conditions, without the cost and time to install actual farms (Parker and Bricker 2020, Bricker et al. 2018, 2020). This can be helpful in the development and success of comprehensive nutrient management plans that include installations of oyster farms (e.g. Lindahl et al. 2005, Cornwell et al. 2016 and citations within, Reitsma et al. 2017). Model simulations require water quality parameters as inputs, which can be costly to obtain at the temporal scales needed. This study aimed to determine whether other sources of data being collected for other purposes, by MD DNR and by satellite, could substitute for project specific data as model inputs.

On-farm, MD DNR, and Satellite data comparisons at the farm study sites

The MD DNR monitoring dataset included Chl and all other parameters needed for the FARM model simulations. There were no significant differences between the on-farm and MD DNR datasets for any parameter (Fig. 3a-e) and the MD DNR data were deemed suitable as substitutes for on-farm data. Comparative results show that, while variable, the on-farm, MD DNR and satellite Chl datasets are consistent in annual patterns of maximum and minimum values and lend confidence that alternate data sources can be used as substitutes for on-farm Chl, though satellite Chl is lower at both sites (Figure 2).

The satellite Chl means are lower for several possible reasons including spatial and temporal differences in sampling compared to *in situ* sampling. Spatial differences occur because satellite Chl data represent an average of data within a 3x3 grid (or 900 m^2 area) around the site location; subpixel variability within that area of water is expected when compared to a single water sample. Temporal differences occur because there is only one monthly *in situ* sample taken while an assessment of the Chl concentration using satellite data may be more indicative of the sub-daily variability (including tidal fluctuations) and daily changes (including changes in phytoplankton biomass), which is more indicative of what the oyster bed is experiencing. Errors in satellite Chl using the RE10 algorithm were identified to be 36% Mean Absolute Error, which is typical of satellite derived chlorophyll (Wynne et al. 2022). This variability is not captured with one time per month sampling. While it introduces more variability in the dataset, it provides more frequent sampling than monthly sampling can provide.

Previous studies have found correspondence between satellite and *in situ* monitoring for parameters (e.g., Chl, TSS, SST) when algorithms are calibrated with local *in situ* data (Werdell et al. 2009, Keith 2014, Gohin et al. 2020 - MODIS/AQUA, VIIRS/NPP and OLCI-A/Sentinel-3, Palmer et al. 2020 and Giardino et al. 2010 - MERIS). As an example, satellite Chl data derived from MERIS images and *in situ* data for the Neuse and Tar–Pamlico River estuaries and adjoining Pamlico Sound showed a 1:1 correspondence after calibration (Keith 2014). The Keith (2014) study showed that satellite data were also better able than *in situ* monitoring data to capture the spatial extent and timing of higher Chl concentrations that are used to inform nutrient management.

Locally calibrated algorithms, however, may not necessarily produce data that are reflective of every location in the region nor of all time periods of interest. These algorithms rely on *in situ* data to fit them, and the distribution of these data may be different from the distribution of the on-farm or MD DNR data used in this analysis. Other studies have similarly shown mixed success, and estuarine waters with high organic matter content can make it difficult for Chl to be accurately retrieved from satellite measurements (e.g., Gohin et al. 2020, Boudaghpour et al. 2020). The satellite data in this study are reflective of the range of *in situ* Chl concentrations and are representative of monthly patterns. By comparing monthly *in situ* sampling with monthly means of daily Chl, it is difficult to say whether the monthly sampling overestimates the overall Chl for a month or if the satellite Chl algorithm truly underestimates the monthly Chl concentration an oyster bed experiences. All that can definitively be said is that monthly averaged daily satellite data were lower than a single monthly on-farm sample, particularly at the North Tangier site (Figs. 2a-c).

This study used a 300 m satellite Chl product as a replacement for monthly *in situ* Chl monitoring. It is difficult to assess whether the errors in the satellite imagery are responsible for decreased modeled harvest numbers, or if the frequency of *in situ* monitoring causes an overestimate of the results; future efforts could address this. Higher resolution spatial data are available from newer satellites (e.g., Sentinel-2, Landsat-8) and might better capture water mass conditions closer to the farm, as has been demonstrated successfully for aquaculture site selection by Snyder et al. (2017). However, the tradeoff with these satellite missions is lower temporal frequency (approximately a 5-day repeat). Commercial satellites, as provided by

PlanetScope SuperDove satellites, could provide daily 3 m pixel imagery, however, it is not currently available for operational environmental use. The higher spatial resolution OLCI Chl data products in this study did show greater concurrence with *in situ* observations than a preliminary comparison made with lower resolution data from MODIS at the 1 km scale, but may benefit from the even higher resolution data.

While this study indicates that satellite Chl may not be as suitable as the MD DNR data as model inputs to estimate aquaculture harvest, other relevant studies have used satellite data specifically for issues related to aquaculture. In one case, satellite data that replicated *in situ* data for model inputs were used to inform spatial planning and improved risk management of harmful algal blooms for successful aquaculture siting and operation (Snyder et al., 2017, Palmer et al. 2020, Smith and Bernard, 2020). Another study used satellite temperature data to understand the rate of larval development of mussels to help advise farmers about the ideal time for collecting seed for aquaculture (Filgueira et al. 2015). A promising study used satellite-derived Chl and TSS concentrations at the scale of an oyster farm, coupled with eco-physiological models, to estimate oyster clearance and Chl consumption rates (Gernez et al. 2017). In each of these studies, it was anticipated that satellite data might be used in place of the time and resource-intensive one-time study sampling schemes as model inputs, though additional parameters are needed to complete the suite of needed model inputs. It is noteworthy that the satellite Chl data alone could potentially be used to determine locations where food availability would support successful oyster growth, as shown in Bricker et al. (2016) and Filgueira et al. (2014), thus supporting successful siting and potential industry expansion, though the concurrence of satellite and on-farm Chl data in this study is not as strong as that noted in previous studies. Continuing improvements in satellite capabilities are expected to improve the concurrence with *in situ* data.

Model results using the alternate datasets

Model simulations using satellite Chl substituted for on-farm Chl were conducted despite the seeming underestimate of on-farm Chl so that a full comparison could be made of model results using both alternate datasets. The lower model estimated harvest at both sites is the result of the lower Chl values of the satellite dataset because all other input variables were the same (Table 3). The average variability among the range of modeled harvest results using different mortalities is highest for the satellite Chl dataset, 32% at the Chester River site and 50% at the North Tangier site. The reason for the increase in magnitude of the underestimation of harvest with increasing mortality of the satellite Chl results in Chester River is unknown. It is likely a function of the model operations because this pattern is also observed in Chester River MD DNR results. A possible explanation is that as mortality increases the impact of the difference in Chl concentration between the datasets is enhanced which may be why the differences are more apparent in the Chester River site where satellite Chl concentrations (and modeled harvest) are lower, and MD DNR Chl concentrations (and modeled harvest) are higher, than the on-farm modeled harvest values.

Sensitivity was tested at the time of the FARM model development which found the model to be a robust tool suitable for this type of modeling (Ferreira et al. 2007). A sensitivity test was done in this study to evaluate the potential magnitude of bias in model results from the use of the satellite Chl data that underestimated on-farm Chl data. A full sensitivity test of all variables would be more revealing and future efforts could address this. The sensitivity test results for ±10% satellite Chl concentrations show the model is working properly, increasing and decreasing harvest results with increases and decreases in Chl model inputs, respectively. The variability in sensitivity analysis results agrees well with variability of results using the original satellite Chl dataset (32% at Chester River, 50% at North Tangier) with an average of 32% among results at the Chester River site and 47% at the North Tangier site.

MAPE analysis

Variability among model results using on-farm and MD DNR data was higher at North Tangier (37% for both on-farm and MD DNR results) than Chester River (24% for on-farm, 17% for MD DNR results). A MAPE analysis was conducted to evaluate the relative accuracy of model results using the alternate datasets compared to results using on-farm data. Accuracy for all results for all datasets are at least Reasonably accurate (<30% error; Figure 4). The satellite Chl model results show 13% error at Chester River, deemed Good relative accuracy, compared to 12% error of the MD DNR dataset results (Lewis 1982). There is a greater difference in accuracy at the North Tangier site with the accuracy of the satellite data set results showing Reasonable accuracy (29% error) and MD DNR results High accuracy (1.9% error). The MAPE analysis of the sensitivity test results shows that error decreased at the Chester River site by 1% and increased at the North Tangier site by 4% with changes in Chl model inputs, but this did not change the accuracy at either site. The greater difference at the North Tangier site is likely a location effect, potentially related to error in the satellite data from more clouds or reflectance at that site than at Chester River or from the greater amount of data points at that site. The small changes in the MAPE results confirm the robustness of the model to the use of different data sources and suggest that satellite Chl data can be used as a substitute for on-farm Chl, recognizing that there may be greater error in remotely sensed data than *in situ* data and that there may also be location differences.

Model results and reported oyster harvest

The MAPE analysis suggests that the alternate datasets can be used to provide Reasonably accurate predictions of on-farm model results, however, the question about validity and representativeness of actual oyster harvest remains. Comparison of model results to reported harvest is the best way to validate models as has been shown for the FARM model in several European estuaries (Ferreira et al. 2007, 2009). Due to privacy issues surrounding the MD aquaculture industry, there was only one harvest value available for the Chester River farm (2016 harvest of 13.6 metric tons at 70% mortality; Parker and Bricker 2020) but annual variability was not known. Variability among all MD cage grown harvests for 2016 – 2018 was 12% (UME n.d.), which could be used to inform potential annual variability at the Chester River site. The uncertainty about how the overall MD variability relates to the Chester River farm prevents a robust comparison and true validation of results. Speculatively, a comparison of the range of harvest amounts using that variability shows overlap with on-farm, satellite Chl, and MD DNR modeled harvest results for mortalities from 70 – 90%. The variability within the datasets, the uncertainty of harvest and of variability of harvest makes it difficult to know how well model results represent oyster harvest. Additional harvest numbers would benefit these results.

Substitutability of alternate data sources

Results of the MAPE analysis for MD DNR stations showing High (1.9%, North Tangier Sound) and Good (12%, Chester River) accuracy suggest that the MD DNR datasets can be substituted for on-farm *in situ* sampling data (Figure 4). This analysis suggests that satellite Chl data can also be substituted for on-farm Chl but with lower relative accuracy, particularly in North Tangier (13% in Chester River, 29% in North Tangier). While satellite Chl can be used, it is important to recognize the greater error in satellite data due to sampling spatial coverage, frequency, and location as discussed, though here the MAPE shows error less than Mean Absolute Error of 36% that is typical of satellite data (Wynne et al. 2022). The substitution of on-farm data with alternate data sources will save time and resources while providing similar results. The use of MD DNR data adds value to that dataset and highlights the value of the MD DNR monitoring program to researchers and by extension to the expanding aquaculture industry and the agencies that manage lease permits.

Potential costs reduction using alternate datasets

The costs for a project specific study for sample collection and analysis estimated here at ~$7700 / sampling station^{-1} year^{-1} from costs associated with labor, travel, supplies, and lab analysis, could be reduced or eliminated by using existing datasets such as those from the MD DNR long-term monitoring program (MD DNR 1984 – present). Fortunately, the MD DNR makes available their data from a network of 83 Chesapeake Bay and tidal tributary monitoring stations, sampled since 1984 in support of Maryland's bi-annual assessment of state waters that is required under the Clean Water Act. To benefit from use of an alternate dataset, the comparability must be true between the target study site and the alternate data site; some verification sampling, as done in this study, would be needed to confirm the assumption. The potential use of MD DNR data as a substitute for on-farm data with no significant difference to model results highlights the value of the existing long-term MD DNR monitoring program to researchers.

CONCLUSIONS

Nutrient related water quality impairments are a continuing challenge to Chesapeake Bay coastal waters. Oyster aquaculture bioextraction has been suggested as a nutrient management strategy. Modeling can help resource managers to develop comprehensive nutrient management plans that include oyster farms (e.g. (e.g. Town of Mashpee Sewer Commission 2015; Cornwell et al. 2016), but acquisition of data required to run models is costly. Maryland DNR and satellite data sources were tested to see if they could substitute for on-farm data as model inputs thereby reducing costs of time and resources.

Comparisons of Chl and other parameters used as model inputs showed that although variable, there was no significant difference in concentrations between on-farm and MD DNR, nor between on-farm and satellite Chl at either of the farm study sites; satellite Chl was lower at both sites. Modeled oyster harvest showed the same; there was no significant difference between on-farm and MD DNR modeled harvest, nor between on-farm and satellite Chl modeled harvest at either site though satellite results were lower at both sites. A sensitivity test of the satellite Chl data ($\pm$10%) showed increased and decreased harvest results with the increased and decreased Chl concentrations confirming the robustness of the model. Additional reported harvest numbers would put these results into clearer perspective.

These results suggest that both MD DNR and satellite Chl data can be substituted for on-farm project specific data. The higher variability and seeming underestimate of Chl concentrations and modeled oyster harvest results using the satellite Chl dataset indicate that they may be considered less suitable for this modeling purpose than MD DNR data, however, MAPE analysis showed that all model results were of at least Reasonable relative accuracy. Accuracy of model results using MD DNR data were Good in Chester River and High in North Tangier, and model results using satellite Chl data were Good and Reasonable in Chester River and North Tangier Sound, respectively. Model sensitivity results using $\pm$10% satellite Chl showed minimal change in associated error (i.e. 1% decrease error at Chester, 4% increase error at North Tangier), showing the model is robust to deviations using different data sources. Optimistically, future advances in marine optics and satellite engineering may show better and more useful results in these Chesapeake Bay tributaries as have been observed in other places described in previous work such as in North Carolina, and European and Mediterranean coastal areas (Keith 2014, Gohin et al. 2020).

This study benefited from access to data from MD DNR’s long-term monitoring program and from satellite Chl data products, showing substitutability of those data that are already being collected for other purposes that could save funds, time, and resources. The use of these data for oyster modeling represents a potential value added to the monitoring programs and highlights the value of these programs to researchers, resource managers, and to the aquaculture community.

This analytical approach is transferrable to other locations where oyster aquaculture is supported, there is an existing state or local monitoring program, and the water quality at the farm and monitoring program sites is not significantly different. To be fully operational a calibrated model would also be required, as would an initial comparison of alternate data sources.

Looking more broadly, this study is an example of the potential value of long-term monitoring data for a variety of situations, for example, where needed data were lost or were never collected. Although the MD DNR data are regional in scale, and the (potentially global) satellite data were processed using regional algorithms, the access to environmental data collected on different spatial and temporal scales by different methods that were designed to address different science questions was useful for this study. This is consistent with and illustrative of the objectives of 'The Framework for Integrated Monitoring and Related Research' (Bricker and Ruggiero 1998, Murdoch et al. 2014) that sought to make data collected by various science disciplines, by various methods and scales, accessible so that the data could be used synergistically to help solve multi-disciplinary multi-scale environmental questions. While this study was small in scale, it illustrates the value of existing data collection programs and the integrated use of seemingly unrelated data sources to address pressing environmental issues.

REFERENCES

Boudaghpour, S., H. Sadat A. Moghadam, M. Hajbabaie, and S. H. Toliati. 2020. Estimating chlorophyll-A concentration in the Caspian Sea from MODIS images using artificial neural networks. *Environ. Eng. Res*. 25(4): 515-521.

Bricker, S.B., J. G. Ferreira, and T. Simas. 2003. An integrated methodology for assessment of estuarine trophic status. *Ecol. Modell*. 169: 39–60.

Bricker, S.B., J.G. Ferreira, C. Zhu, J.M. Rose, E. Galimany, G.H. Wikfors, C. Saurel, R. Landeck Miller, J. Wands, P. Trowbridge, R.E. Grizzle, K. Wellman, R. Rheault, J. Steinberg, A.P. Jacob, E.D. Davenport, S. Ayvazian, M. Chintala, and M.A. Tedesco. 2018. The role of shellfish aquaculture in reduction of eutrophication in an urban estuary. *Environmental Science & Technology* 52: 173-183.

Bricker, S.B., R.E. Grizzle, P. Trowbridge, J.M. Rose, J.G. Ferreira, K. Wellman, C. Zhu, E. Galimany, G.H. Wikfors, C. Saurel, R. Landeck Miller, J. Wands, R. Rheault, J. Steinberg, A.P. Jacob, E.D. Davenport, S. Ayvazian, M. Chintala, and M.A. Tedesco. 2020. Bioextractive removal of nitrogen by oysters in Great Bay Piscataqua River Estuary, New Hampshire, USA. *Estuaries and Coasts* 43:23–38.

Bricker, S.B., T.L. Getchis, C.B. Chadwick, C.M. Rose, and J.M. Rose. 2016. Integration of ecosystem-based models into an existing interactive web-based tool for improved aquaculture decision-making. *Aquaculture* 453:135–146.

Bricker, S.B., K.C. Rice, and O.P. Bricker III. 2014. From Headwaters to Coast: Influence of Human Activities on Water Quality of the Potomac River Estuary. *Aquat Geochem* 20: 291-324.

Bricker, S.B., B. Longstaff, W. Dennison, A. Jones, K. Boicourt, C. Wicks, and J. Woerner. 2008. Effects of Nutrient Enrichment in the Nation's Estuaries: A Decade of Change. Special issue of *Harmful Algae* 8: 21-32.

Bricker, S., B. Longstaff, W. Dennison, A. Jones, K. Boicourt, C. Wicks, and J. Woerner. 2007. Effects of Nutrient Enrichment in the Nation's Estuaries: A Decade of Change, National Estuarine Eutrophication Assessment Update. NOAA Coastal Ocean Program Decision Analysis Series No.26. National Centers for Coastal Ocean Science, Silver Spring, MD. 322pp.

Bricker O.P. and M.A. Ruggiero. 1998. Toward A National Program For Monitoring Environmental Resources. *Ecological Applications* 8(2): 326-329.

Chesapeake Bay Action Plan. 2008. https://bayactionplan.com/

Chesapeake Bay Foundation (CBF). 2019. 2018 State of the Bay: A Stiff Reality Check https://www.cbf.org/blogs/sa70%ve-the-bay/2019/01/2018-state-of-the-bay-a-stiff-reality-check.html#:~:text=Instead%20of%20the%20average%2041,in%20ten%20of%20twelve%20months.

Chesapeake Bay Watershed Agreement. 2014. https://d18lev1ok5leia.cloudfront.net/chesapeakebay/documents/FINAL_Ches_Bay_Watershed_Agreement.withsignatures-HIres.pdf

Cloern, J.E., 2001. Our evolving conceptual model of the coastal eutrophication problem. *Mar. Ecol. Prog. Ser.* 210: 223–253.

Cornwell, J., J. Rose, L.Kellogg, M. Luckenbach, S. Bricker, K. Paynter, C. Moore, M. Parker, L. Sanford, B. Wolinski, A. Lacatell, L. Fegley, and K. Hudson. 2016. Panel recommendations on the oyster BMP nutrient and suspended sediment reduction effectiveness determination decision framework and nitrogen and phosphorus assimilation in oyster tissue reduction effectiveness for oyster aquaculture practices. Chesapeake Bay Program (CBP) Partnership, Annapolis, MD.

Cornwell, J., S. Bricker, A. Lacatell, M. Luckenbach, F. Marenghi, C. Moore, M. Parker, K. Paynter, J. Rose, L. Sanford, W. Wolinski, O.N. Caretti, J. Reichert-Nguyen, and H.W. Slacum. 2023. Nitrogen and phosphorus reduction associated with harvest of hatchery-produced oysters and reef restoration: Assimilation and enhanced denitrification: Panel recommendations. Report submitted to the Chesapeake Bay Program Partnership Water Quality Goal Implementation Team. January 27, 2023.

Cubillo, A. M., S. B. Bricker, M. Parker, and J.G. Ferreira. 2018. NCCOS Ecological Assessment to support NOAA's Choptank Complex Habitat Focus Area: eutrophication and shellfish aquaculture/ restoration ecosystem services modeling: final report. Submitted to NOAA NCCOS, Cooperative Oxford Laboratory by Longline Environmental, Ltd., National Oceanic and Atmospheric Administration, National Ocean Service, National Centers for Coastal Ocean Science, Silver Spring, MD.

Dvarskas, A., S.B. Bricker, G.H. Wikfors, J.J. Bohorquez, M.S. Dixon, and J.M. Rose. 2020. Quantification and Valuation of Nitrogen Removal Services Provided by Commercial Shellfish Aquaculture at the Subwatershed Scale. Environmental Science & Technology 54:, 16156-16165.

Executive Order 13508. 2009. Chesapeake Bay Protection and Restoration https://obamawhitehouse.archives.gov/realitycheck/the_press_office/Executive-Order-Chesapeake-Bay-Protection-and-Restoration

Ferreira, J. G., A. J. S. Hawkins, and S. B. Bricker. 2007. Management of productivity, environmental effects and profitability of shellfish aquaculture - the Farm Aquaculture Resource Management (FARM) model. *Aquaculture* 264:160–174.

Ferreira, J.G., A. Sequeira, A.J.S. Hawkins, A. Newton, T.D. Nickell, R. Pastres, J. Forte, A. Bodoy, and S.B. Bricker. 2009. Analysis of coastal and offshore aquaculture: Application of the FARM model to multiple systems and shellfish species. *Aquaculture* 292: 129–138.

Ferreira, J.G., H.C. Andersson, R.A. Corner, X. Desmit, Q. Fang, E.D. de Goede, S.B. Groom, H. Gu, B.G. Gustafsson, A.J.S. Hawkins, R. Hutson, H. Jiao, D. Lan, J. Lencart-Silva, R. Li,

X. Liu, Q. Luo, J.K. Musango, A.M. Nobre, J.P. Nunes, P.L. Pascoe, J.G.C. Smits, A. Stigebrandt, T.C. Telfer, M.P. de Wit, X. Yan, X.L. Zhang, Z. Zhang, M.Y. Zhu, C.B. Zhu, S.B. Bricker, Y. Xiao, S. Xu, C.E. Nauen, and M. Scalet. 2008. SPEAR. Sustainable Options for People, Catchment and Aquatic Resources. IMAR-Institute of Marine Research, ISBN 978-972-99923-2-2, 184 pp.

Filgueira, R., T. Guyondet, L.A. Comeau, and J. Grant. 2014. A fully-spatial ecosystem-DEB model of oyster (*Crassostrea virginica*) carrying capacity in the Richibucto Estuary, Eastern Canada. *J. Mar. Syst*. 136: 42–54.

Filgueira, R., M.S. Brown, L.A. Comeau, and J. Grant. 2015. Predicting the timing of the pediveliger stage of Mytilus edulis based on ocean temperature. *Journal of Molluscan Studies* 81: 269– 273.

Gernez P., D. Doxaran, and L. Barillé. 2017. Shellfish Aquaculture from Space: Potential of Sentinel2 to Monitor Tide-Driven Changes in Turbidity, Chlorophyll Concentration and Oyster Physiological Response at the Scale of an Oyster Farm. *Front. Mar. Sci*. 4:137.

Giardino, C., M. Bresciani, R. Pilkaityte, M. Bartoli, and A. Razinkovas. 2010. *In situ* measurements and satellite remote sensing of case 2 waters: first results from the Curonian Lagoon. *Oceanologia* 52 (2): 197–210.

Gilerson, A., A.A. Gitelson, J. Zhou, D. Gurlin, W. Moses, I. Ioannou, and S.A. Ahmed. 2010. Algorithms for remote estimation of chlorophyll-a in coastal and inland waters using red and near infrared bands. *Optics Express* 18(23): 24109-24125.

Gohin, F, P. Bryère, A. Lefebvre, P.-G. Sauriau, N. Savoye, V. Vantrepotte, Y. Bozec, T. Cariou, P. Conan, S. Coudray, G. Courtay, S. Françoise, Anne Goffart, T. Hernández Fariñas, M. Lemoine, A. Piraud, P. Raimbault, and M. Rétho. 2020. Satellite and *In situ* Monitoring of

Chl-*a*, Turbidity, and Total Suspended Matter in Coastal Waters: Experience of the Year 2017 along the French Coasts. *J. Mar. Sci. Eng. 8*: 665 doi:10.3390/jmse8090665

Gotelli, N. J., and A.M. Ellison. 2004. *A primer of ecological statistics*. Sunderland, Mass: Sinauer Associates Publishers. Keith, D. 2014. Satellite remote sensing of chlorophyll a in support of nutrient management in the Neuse and Tar–Pamlico River (North Carolina) estuaries. *Remote Sensing of Environment* 153: 61–78**.**

Holbach, A., M. Maar, K. Timmermann, D. Taylor. 2020. A spatial model for nutrient mitigation potential of blue mussel farms in the western Baltic Sea. Science of the Total Environment 736: 139624 https://doi.org/10.1016/j.scitotenv.2020.139624

Keith, D. 2014. Satellite remote sensing of chlorophyll *a* in support of nutrient management in the Neuse and Tar–Pamlico River (North Carolina) estuaries. *Remote Sensing of environment* 153: 61-78.

Lewis, C.D. 1982. *Industrial and business forecasting methods*. London: Butterworths.

Lindahl, O., R. Hart, B. Hernroth, S. Kollberg, L. O. Loo, L. Olrog, A. S. Rehnstam-Holm, J. Svensson, S. Svensson, and U. Syversen. 2005. Improving marine water quality by mussel farming: a profitable solution for Swedish society. *Ambio* 34:131–138.

Maryland Nutrient Trading Program (MD NTP). No date. http://mdnutrienttrading.org/

Maryland Credit Generation FAQ: Oyster Aquaculture (MD CG). 2023. Credit Generation for Oyster Aquaculture. https://mde.maryland.gov/programs/Water/WQT/Documents/Guidance%20PDFs/Oyster%20Aquaculture_FAQ.pdf

Maryland Department of the Environment (MDE). 1998. 1996 and 1998 303(d) lists of impaired waters.

https://mde.maryland.gov/programs/Water/TMDL/Integrated303dReports/Documents/Integrated_Report_Section_PDFs/303d_1996-1998/1996_1998list.pdf

Maryland Department of the Environment (MDE). No date. Water Quality Trading Registry and Market place. https://mde.maryland.gov/programs/water/WQT_Registry_Market.aspx

Maryland Department of Natural Resources (MD DNR). 2023. Quality Assurance Project Plan for the Maryland Department of Natural Resources Chesapeake Bay Mainstem and Tributary Water Quality Monitoring Program- Chemical and Physical Properties Component.

Maryland Department of Natural Resources (MD DNR). 2020. Section 106 Ambient Water Quality Monitoring (CORE/Trend Monitoring) Quality Assurance Project Plan.

Maryland Department of Natural Resources (MD DNR). 2015a. Tidewater Ecosystem Assessment. Water Quality and Habitat Assessment Overall Condition 2012-2014 – Upper Eastern Shore. https://eyesonthebay.dnr.maryland.gov/eyesonthebay/documents/UpperEasternShoreupdatesummary2015.pdf

Maryland Department of Natural Resources (MD DNR). 2015. Tidewater Ecosystem Assessment. Water Quality and Habitat Assessment Overall Condition 2012-2014 – Lower Eastern Shore. https://eyesonthebay.dnr.maryland.gov/eyesonthebay/documents/LowerEasternShoreupdatesummary2015.pdf

Maryland Department of Natural Resources (MD DNR) 2016 – 2018. Eyes on the Bay Fixed Station Monthly Monitoring. http://eyesonthebay.dnr.maryland.gov/bay_cond/bay_cond.cfm?param=bdo&station=ET42 https://eyesonthebay.dnr.maryland.gov/bay_cond/bay_cond.cfm?station=EE31&param=bdo

Maryland Department of Natural Resources (MD DNR). 1984 – present. Eyes on the Bay. https://eyesonthebay.dnr.maryland.gov/

Moreno, J.J.M., A.P. Pol, A.S. Abad, and B.C. Blasco. 2013. Using the R-MAPE index as a resistant measure of forecast accuracy. *Psicothema* 25 (4): 500-506.

Murdoch, P.S., M. McHale, and J. Baron. 2014. Reflections on a Vision for Integrated Research and Monitoring After 15 Years. *Aquat Geochem* 20, 363–380.

National Research Council (NRC). 2000. Clean Coastal Waters: Understanding and reducing the effects of Nutrient Pollution. National Academy Press, Washington, DC, 405 pp.

Palmer, S. C. J., P. M. Gernez, Y. Thomas, S. Simis, P. I. Miller, P. Glize, and L. Barillé. 2020. Remote Sensing-Driven Pacific Oyster (Crassostrea gigas) Growth Modeling to Inform Offshore Aquaculture Site Selection. *Frontiers in Marine Science* Vol. 6: Article 802. doi: 10.3389/fmars.2019.00802

Parker, M. and S. Bricker. 2020. Sustainable Oyster Aquaculture, Water Quality Improvement and Ecosystem Service Value Potential in Maryland, Chesapeake Bay. *Journal of Shellfish Research.* 39(2): 1–13.

Reitsma, J., D.C. Murphy, A.F. Archer, and R.H. York. 2017. Nitrogen extraction potential of wild and cultured bivalves harvested from nearshore waters of Cape Cod, USA. *Mar. Pollut. Bull.* 116:175–181.

Rose, J.M., S.B. Bricker, M.A. Tedesco, and G.H. Wikfors. 2014. A role for shellfish aquaculture in coastal nitrogen management. *Env. Sci. & Tech.* 48 (5): 2519–2525.

Rose, J.M., S.B. Bricker, and J.G. Ferreira. 2015. Modeling shellfish farms to predict harvest-based nitrogen removal. *Mar. Poll. Bull.* 453: 135–146.

Shumway, S. 1996. Natural environmental factors. In: Kennedy, V.S., R.I.E.Newell, and A.F. Eble, editors. The eastern oyster *Crassostrea virginica*. College Park, MD: Maryland Sea Grant College. pp. 467–513.

Silva, C., J.G. Ferreira and S.B. Bricker, T.A. DelValls, M.L. Martín-Díaz, and E. Yáñez. 2011. Site selection for shellfish aquaculture by means of GIS and farm-scale models, with an emphasis on data-poor environments. *Aquaculture* 318: 444–457.

Smith, M.E. and S. Bernard. 2020. Satellite Ocean Color Based Harmful Algal Bloom Indicators for Aquaculture Decision Support in the Southern Benguela. *Frontiers in Marine Science* Vol. 7: Article 61. doi: 10.3389/fmars.2020.00061

Stevenson, J.C., L.W. Staver, and K.W. Staver. 1993. Water quality associated with survival of submersed aquatic vegetation along an estuarine gradient. *Estuaries* 16(2): 346–361.

Snyder, J., E. Boss, R. Weatherbee, A.C. Thomas, D. Brady, and C. Newell. 2017. Oyster aquaculture site selection using Landsat-8-derived sea surface temperature, turbidity and chlorophyll-a. *Frontiers in Marine Science* Vol 4: article 190. doi:10.3389/fmars.2017.00190

Town of Mashpee Sewer Commission. 2015. Final Recommended Plan/ Final Environmental Impact Report. Comprehensive Wastewater Management Plan, Town of Mashpee; GHD Inc.: Hyannis, MA.

Twilley, R.R., W.M. Kemp, K.W. Staver, J.C. Stevenson, W.R. Boynton. 1985. Nutrient enrichment of estuarine submersed vascular plant communities. I. Algal growth and effects on production of plants and associated communities. *Mar. Ecol. Prog. Ser*. 23, 179–191.

United States Clean Water Act (US CWA). 1972. https://www.boem.gov/sites/default/files/documents//The%20Clean%20Water%20Act%20of%201972.pdf

United States Environmental Protection Agency (US EPA). 2003. *Ambient Water Quality Criteria for Dissolved Oxygen, Water Clarity and Chlorophyll a for the Chesapeake Bay and Its Tidal Tributaries.* EPA 903-R-02-002. Page xv. Open water 30-day criteria used.

United States Environmental Protection Agency (US EPA). 2008. Decision Rationale Total Maximum Daily Loads of Fecal Coliform for the Restricted Shellfish Harvesting Area of the Chester River in the Lower Chester River Basin, Southeast Creek Basin, and Middle Chester River Basin, Kent and Queen Anne's Counties, Maryland.

United States Environmental Protection Agency (US EPA). 2010. Chesapeake Bay Total Maximum Daily Load for Nitrogen, Phosphorus and Sediment. Established by the U.S. Environmental Protection Agency Region 3, Philadephia, PA and Region 2, Washington, D.C. and in collaboration with Delaware, the District of Columbia, Maryland, New York, Pennsylvania, Virginia, and West Virginia. https://www.epa.gov/chesapeake-bay-tmdl/chesapeake-bay-tmdl-document

United States Environmental Protection Agency for the Chesapeake Bay Program. 2000. *Chesapeake Bay Submerged Aquatic Vegetation Water Quality and Habitat-Based Requirements and Restoration Targets: A Second Technical Synthesis.* Printed by the United States Environmental Protection Agency for the Chesapeake Bay Program. United States Environmental Protection Agency Region 3, Philadelphia, PA. 233pp.

University of Maryland (UMD) Eco Report Card. 2015-2020. Chesapeake Bay. https://ecoreportcard.org/report-cards/chesapeake-bay/watershed-regions/lower-eastern-shore/ ; https://ecoreportcard.org/report-cards/chesapeake-bay/watershed-regions/upper-eastern-shore/

University of Maryland Center for Environmental Science Chesapeake Biological Laboratory Nutrient Analytical Services (UMD CBL NASL). 2019a. Standard operating procedure for determination of dissolved inorganic ammonium (NH4) in fresh/estuarine/coastal waters.

University of Maryland Center for Environmental Science Chesapeake Biological Laboratory Nutrient Analytical Services (UMD CBL NASL). 2019b. Standard operating procedure for determination of dissolved inorganic nitrate plus nitrite (NO3+NO2) in fresh/estuarine/coastal waters using cadmium reduction.

University of Maryland Center for Environmental Science Chesapeake Biological Laboratory Nutrient Analytical Services (UMD CBL NASL). 2019c. Determination of total suspended solids (TSS) and total volatile solids (TVS) in fresh/estuarine/coastal waters. (Reference Method: EPA Method 160.2 and Standard Methods 208 E.) Available at: https://www.umces.edu/sites/default/files/ Total Suspended Solids and Total Volatile Solids Method 2019- 1.pdf.

University of Maryland Center for Environmental Science Chesapeake Biological Laboratory Nutrient Analytical Services (UMD CBL NASL). 2019d. Standard operating procedures for fluorometric determination of chlorophyll a in waters and sediments of Fresh/Estuarine/Coastal Areas. doi:1037//0033-2909.I26.1.78

University of Maryland Extension (UME) Oyster Aquaculture Dashboard. No date. https://go.umd.edu/OysterAquacultureDashboard

Werdell, P.J., S.W. Bailey, B.A. Franz, L.W. Harding Jr., G.C. Feldman, C.R. McClain. 2009. Regional and seasonal variability of chlorophyll-a in Chesapeake Bay as observed by SeaWiFS and MODIS-Aqua, Remote Sensing of Environment 113, pp. 1319–1330.

Wheeler, T. 2020. Oyster growers hope polluters will shell out for nutrient credits. *Bay Journal* 30(3):14–16.

Wolny JL, M.C. Tomlinson, S.S. Uz, T.A. Egerton, J.R. McKay, A. Meredith, K.S. Reece, G.P. Scott, and R.P. Stumpf. 2020. Current and Future Remote Sensing of Harmful Algal Blooms in the Chesapeake Bay to Support the Shellfish Industry. *Front. Mar. Sci*. Vol.7: Article 337. doi: 10.3389/fmars.2020.00337

Wynne, T.T. , M.C. Tomlinson, T.O. Briggs, S. Mishra, A. Meredith, R.L. Vogel and R.P. Stumpf. 2022. Evaluating the Efficacy of Five Chlorophyll-*a* Algorithms in Chesapeake Bay (USA) for Operational Monitoring and Assessment. *Mar. Sci. Eng.* 10(8):1104 doi: 10.3390/jmse10081104

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APPENDIX 1: Comparison of shallow water station to long-term station water quality data for the Chester River and Honga River.

Renee Karrh, Maryland Department of Natural Resources (DNR)

Summary:

This project tested the available shallow water data (SWM) for the Chester and Honga rivers compared to the long-term (LTRM) DNR stations in Chester River and Upper Tangier Sound, respectively, for the 3-year periods of the shallow water monitoring in those rivers. The objective was to test if there was a significant difference between the two DNR sample program datasets. Surface layer sample data were used in the comparisons.

DNR Shallow water monitoring in the Honga (2008-2010) and Chester rivers (2004-2006) was not completed during the time period of the NOAA study (2018-2020). Long-term DNR stations in Chester River (ET4.2) and Upper Tangier Sound (EE3.1) were the closest available to the NOAA on-farm locations; these LTRM stations were available for the same time period as the NOAA data collected on-farm.

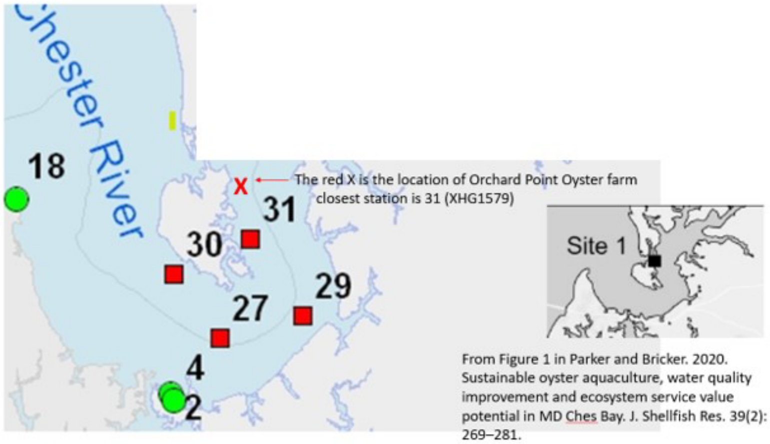
Because of the differences in time periods, only the DNR sampling at LTRM stations could be used to compare directly to the NOAA collected data. DNR LTRM data may be useful for oyster

harvest modeling by NOAA if the data collected from DNR LTRM was not significantly different from the data collected at SWM stations closest to the NOAA on-farm locations.

No significant difference was found between the DNR LTRM and SWM stations closest to the NOAA on-farm stations for the earlier time periods. This provides confidence that using the DNR LTRM data for the time period that matches the NOAA sampling represents the conditions in shallow waters near the on-farm locations for the time period of the NOAA study.

Methods:

Data from the closest SWM station location to the NOAA on-farm location and the LTRM station were tested in pairs (shallow water monitoring station compared to the long-term station). For Chester River, station ET4.2 was sampled in both DNR programs for the years of shallow water monitoring (2004-2006); the data for this station was treated as separate for the SWM program (ET4.2**s**) and the LTRM program (ET4.2). The Honga River SWM station data were compared to the Upper Tangier Sound LTRM station (EE3.1) because there is no LTRM station in the Honga River. Stations were compared using a one-way non-parametric Kruskal-Wallis test, followed by a Tukey test of each pair. Kruskal Wallis and Tukey results for all testing pairs are summarized in Tables 1 and 2. Figures 3 and 4 provide boxplots for the Chester and Honga stations, respectively.



Station	map#
XGG8458	2
XGG8359	4
ET4.2	27
XGG9992	29
XHG0859	30
XHG1579	31

Figure 1. Subset of shallow water calibration stations in the Chester River**.** Green circles show the continuous monitoring locations. Red squares show water quality mapping calibration stations. Inset table shows the station name corresponding to the number on the map. Station XHG1579 (map #31) was the closest to the NOAA on-farm location.

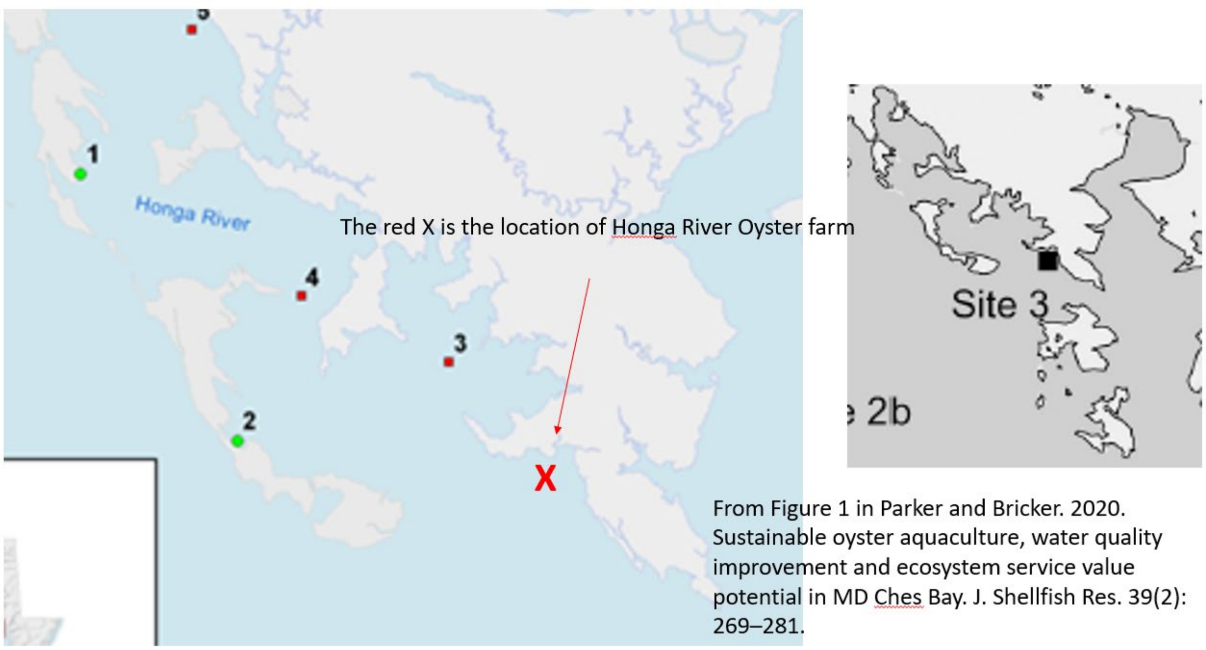


Figure 2. Shallow water calibration stations in the Honga River**.** Green circles show the continuous monitoring locations: 1. XCG9168, 2. XCG5495. Red squares show water quality mapping calibration stations: 3. XCH6533, 4. XCH7507. Station XCH6533 (map #3) was the closest to the NOAA on-farm location.

Table 1. Results of the pairwise comparison of the DNR shallow-water monitoring (SWM) station (XHG1579) and the DNR long-term monitoring (LTRM) station (ET4.2) for the Chester River. Also shown is the comparison between the SWM sampling (ET4.2**s**) and LTRM sampling (ET4.2) at the long-term station. Significance was determined at $p < 0.05$. Parameters are dissolved oxygen (do), salinity, water temperature (wtemp), Secchi depth (secchi), chlorophyll *a* (chla), total suspended solids (tss) and volatile suspended solids (vss). Note that volatile suspended solids samples are not collected at the Chester River LTRM station but were collected during the SWM sampling at the same station.

2004-2006

		ET4.2**s** (SWM)			ET4.2 (LTRM)		
Station	Parameter	KW statistic	p value KW	p value Tukey	KW statistic	p value KW	p value Tukey
XHG1579 (SWM)	do	0.0838	0.7722	0.7669	2.0217	0.1551	0.1655
	salinity	0.0014	0.9699	0.8976	0.1331	0.7152	0.5977
	wtemp	0.0040	0.9498	0.9502	0.3496	0.5544	0.5108
	secchi	4.9955	**0.0254**	0.0675	1.9394	0.1637	0.1577
	chla	2.8425	0.0918	**0.0399**	0.4280	0.5130	0.1588
	tss	3.6305	0.0567	0.0939	0.6688	0.4135	0.3133
	vss	0.1439	0.7044	0.6416			
ET4.2 (LTRM)	do	1.3112	0.2522	0.2772			
	salinity	0.3351	0.5627	0.5228			
	wtemp	0.1241	0.7246	0.5486			
	secchi	0.0838	0.7723	0.8655			
	chla	1.1705	0.2793	0.6008			
	tss	0.7871	0.3750	0.2268			
	vss						

Table 2. Results of the pairwise comparison of the DNR shallow-water monitoring (SWM) station (XCH533) in the Honga River and the DNR long-term monitoring (LTRM) station (EE3.1) in the North Tangier Sound. Significance was determined at $p < 0.05$. Parameters are dissolved oxygen (do), salinity, water temperature (wtemp), Secchi depth (secchi), chlorophyll *a* (chla), total suspended solids (tss) and volatile suspended solids (vss).

2008-2010

		EE3.1 (LTRM)		
station	Parameter	KW statistic	p value KW	p value Tukey
XCH6533 (SWM)	do	0.2054	0.6504	0.5393
	salinity	0.1521	0.6965	0.7338
	wtemp	0.3646	0.5460	0.5546
	secchi	0.0007	0.9791	0.8914
	chla	1.8293	0.1762	0.3796
	tss	0.0839	0.7721	0.9007
	vss	0.4563	0.4993	0.2953

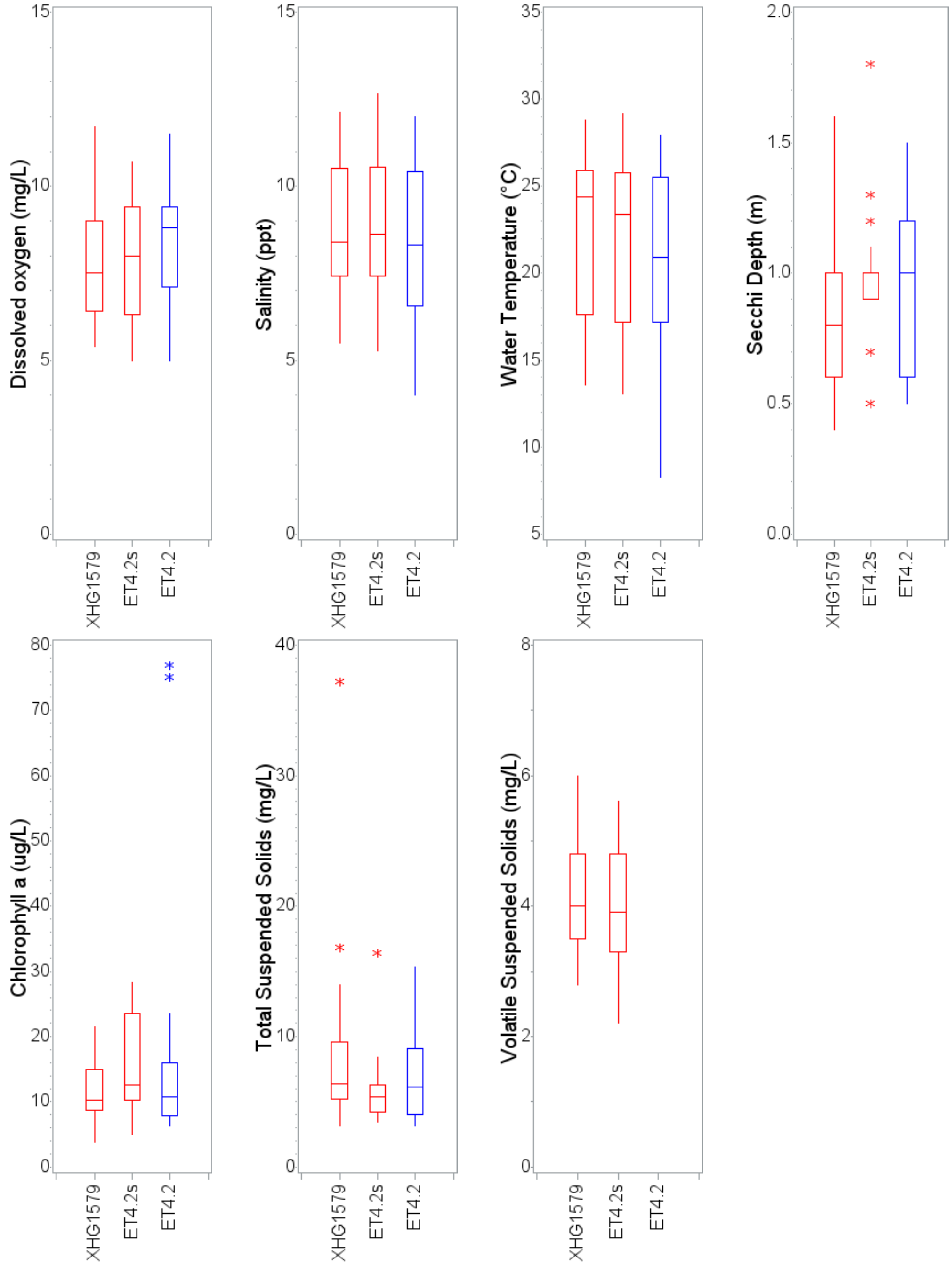


Figure 3. Box plots of each parameter for the Chester River SWM station (XHG1579) and LTRM station (ET4.2). Data is also shown for the SWM sampling at the long-term station (ET4.2**s**). Data is from April-October for 2004-2006. Volatile suspended solid samples are not collected at the LTRM station but were collected during the SWM sampling at the sample location.

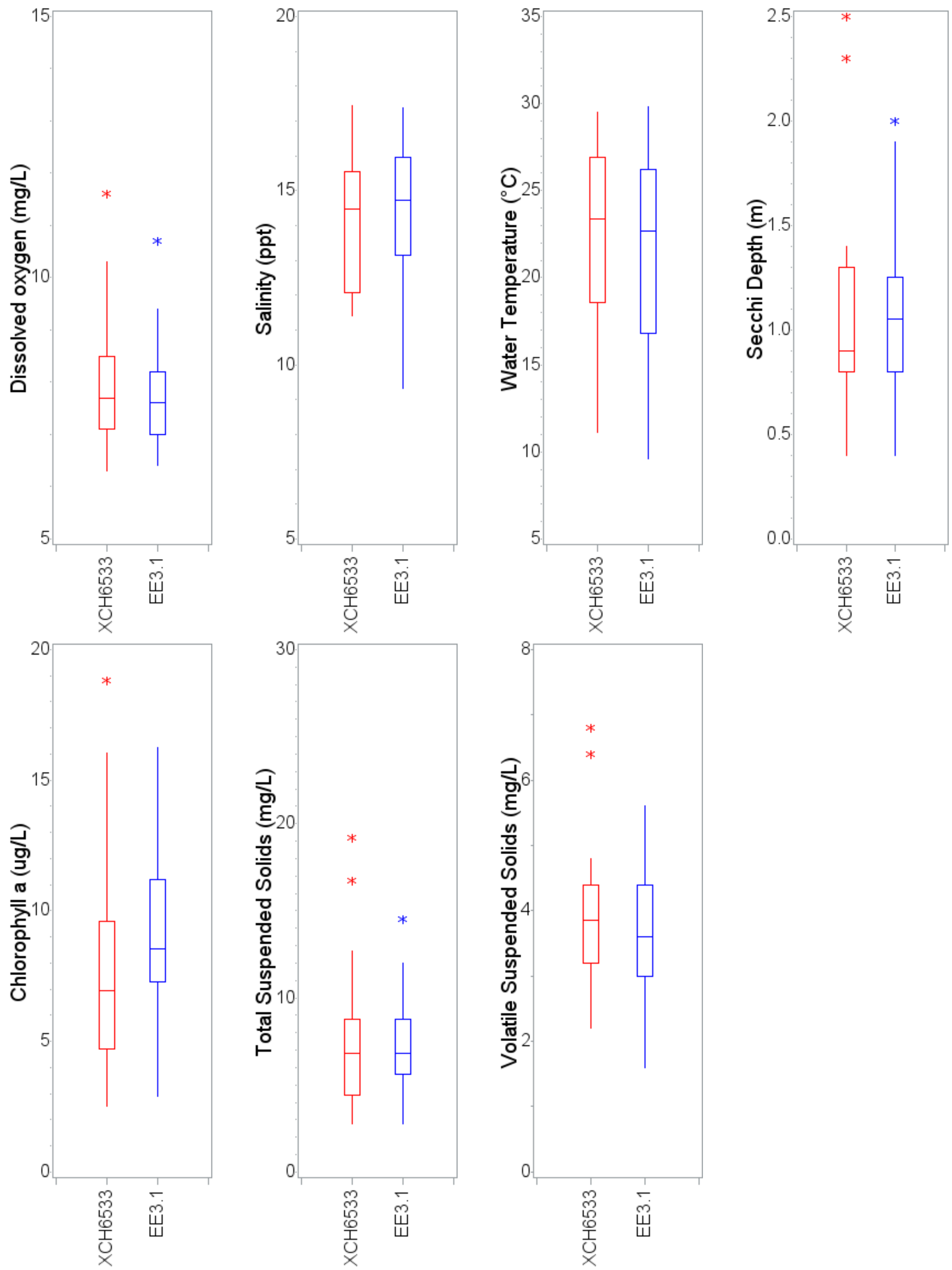


Figure 4. Box plots of each parameter for the Honga River SWM station (XCH6533) and Upper Tangier Sound LTRM station (EE3.1). Data is from April-October for 2008-2010.

Results:

Chester River station XHG1579 is not significantly different from long term data for ET4.2 for any parameter for the years measured 2004-2006 April-October (shallow water monitoring is only done in those months). However, there is some slight indication that there are differences with the shallow water data at ET4.2**s** for chlorophyll *a* (chla) and Secchi (but only one of the tests indicated a difference and not a very strong significance (p value not less than 0.01). The comparison between ET4.2**s** and ET4.2 did not indicate significant differences. This is an indication of the variability in sampling on different days even at the same station (usually about a week apart between the programs), the variability in those parameters in general. Some dates also had two field replicates collected in both programs, so that could be an additional source of difference.

Honga River station XCH6533 was not significantly different from EE3.1 (Upper Tangier Sound) for any of the parameters tested for the years 2008-2010.

Conclusion:

The two long-term stations are a good surrogate for water quality in the areas of the NOAA on-farm stations based on the years for which there was shallow water data collected. With only the long-term stations currently being monitored, this is the best available data without having a separate monitoring program and the associated costs.

Additional information on the DNR SWM and LTRM monitoring programs and access to all data is available at Eyesonthebay.dnr.maryland.gov.

Tables and Figures for Bricker et al.

Table 1: Data for US estuaries included in the National Estuarine Eutrophication Assessment (Bricker et al. 2007) showing the range and median values and the number of estuaries evaluated for Chlorophyll, Dissolved Oxygen, Salinity, and Residence time for the early 2000s. The median values for Chl are the median of 90th percentile or highest observed values, and the median for DO is the median of 10th percentile or lowest values, that are observed over an annual cycle.

Parameter	National*			Study Sites	
	Range	Median	Number estuaries	Chester River	Tangier / Pocomoke Sound
Chlorophyll *a* concentration (μg/L) 90th percentile of monthly measures	1 - 60	7.37	70	23.4	23.0
Dissolved oxygen (mg/L) 10th percentile of monthly measures	0 – 9.5	5.43	69	0.511	5.1
Average Salinity	4 - 29	21	138	12	13
Residence time (days)	1 - 3841	5	112	27	12

*from: Bricker et al. 2007, data represent conditions in the early 2000s

Table 2: Months and values of maximum and minimum concentrations of water quality variables in Lower Chester River and North Tangier Sound. (From the MD DNR monitoring program, climatological maximum and minimum are long-term mean values from 1985 to 2019)

	Upper Eastern Shore/Lower Chester River (MD DNR station ET4.2)		Lower Eastern Shore - North Tangier Sound (MD DNR station EE3.1)	
	Month of climatological maximum (value)	Month of climatological minimum (value)	Month of climatological maximum (value)	Month of climatological minimum (value)
Bottom Dissolved Oxygen (mg/L)	February (9.97)	July (1.80)	February (11.8)	August (5.06)
Surface Water Temperature (°C)	July (29.4)	January (2.62)	July (29.1)	February (3.32)
Secchi depth (m)	November (1.47)	July (0.89)	November (1.28)	February (0.74)
Surface Salinity	October (11.8)	May (7.22)	November (16.3)	April (13.0)
Surface Chlorophyll (µg/L)	February (13.0)	March (8.12)	March (15.0)	May (4.78)

Table 3: FARM model harvest results using on-farm, MD DNR, and Satellite Chl* and on-farm data at each farm site. The mean, standard deviation, standard error, and upper and lower confidence limits of the sample mean (CL) are shown ( ).

	CHESTER			NO. TANGIER		
	on-farm data	MD DNR data	Satellite Chl	on-farm data	MD DNR data	Satellite Chl
mortality	Harvest (metric tons/cycle)			Harvest (metric tons/cycle)		
20	24.1	24.7	23.4	52.1	51.9	44.4
30	22.9	23.9	21.8	47.8	47.6	39.7
40	21.6	23.0	20.1	43.6	43.2	34.4
50	20.3	21.9	18.2	39.2	38.3	29.3
60	18.6	20.6	16.2	34.1	33.4	24.2
70	16.7	19.2	14.2+	28.3	27.8	17.9
80	14.3	17.3	11.4	22.5	21.8	13.5
90	11.0	14.4	8.0	14.6	14.0	7.0
Mean	18.7	20.6	16.7	35.3	34.8	26.3
Standard Deviation	4.5	3.5	5.3	12.9	13.0	13.1
Standard Error	1.6	1.2	1.9	4.6	4.6	4.6
Upper 95% CL	22.4	23.6	21.1	46.1	45.7	37.2
Lower 95% CL	14.9	17.7	12.2	24.5	23.8	15.4

*Satellite Chl data were substituted for on-farm Chl but all other variables used for the simulation were the on-farm data.

+The only reported oyster harvest is from the Chester River farm for 2016: 13.6 metric tons at 70% mortality.

Figure captions

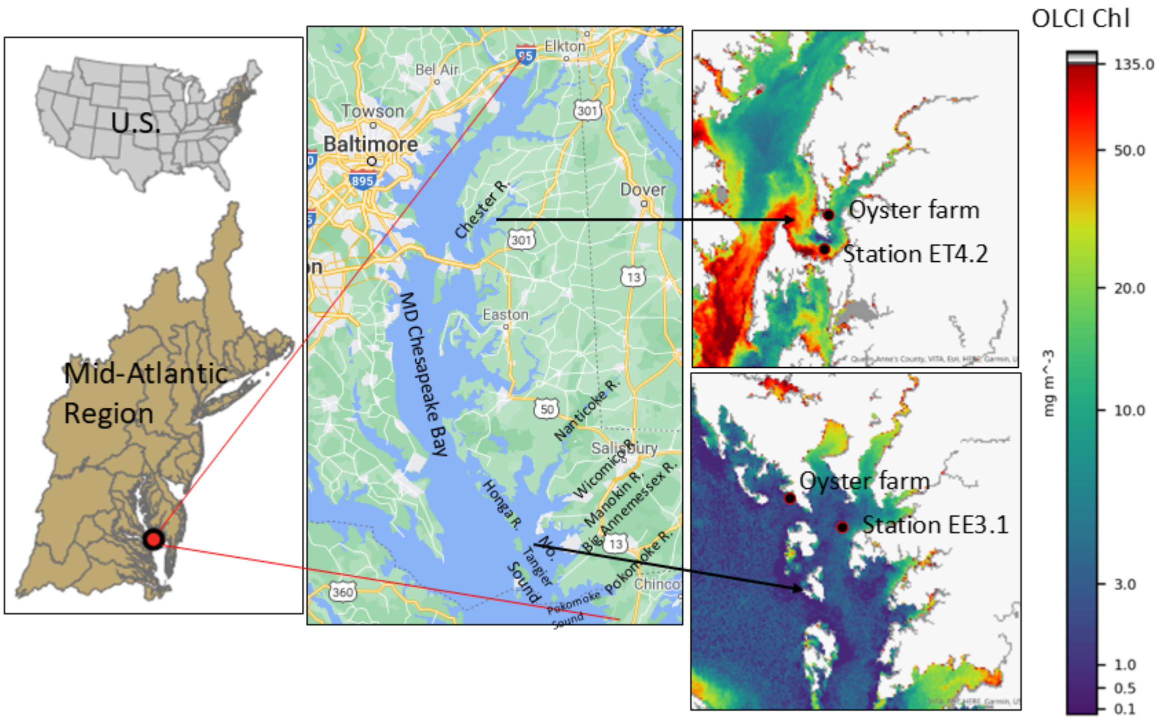
Figure 1: Study site locations – Chester River and North Tangier Sound oyster farms in MD Chesapeake Bay within the Mid-Atlantic Region of the United States. The distance between farm location and nearest MD DNR monitoring program sampling location is ~8 km for both. The Ocean Land Color Instrument (OLCI) chlorophyll data product imagery is shown in the right hand panel illustrating the features that are visible from the 300m spatial resolution of the OLCI sensor.

Figure 2: Comparison of satellite, MD DNR and on-farm datasets for Chl for all data (a), for separate years of data (b), and for combined years of data by month (c). Boxes represent median, 75^{th} and 25^{th} quantiles of all data, where the black dots indicate outliers. Note that on-farm data are missing for some months: at Chester River for September 2016, January, March, April, September 2017; missing data for North Tangier Sound for September 2016, September, December 2017, January 2018. Kruskal-Wallis tests were used to determine mean differences in Chl concentrations among data types, sites, and years. Subsequently, multiple comparison tests were performed using the Wilcoxon rank sum exact test.

Figure 3(a – e): Comparative analysis of MD DNR and on-farm data sets for: a) temperature, b) salinity, c) dissolved oxygen, d) total suspended solids (TSS), e) total volatile solids (TVS) for Chester River and North Tangier Sound study sites. Boxes represent the median, 25^{th} and 75^{th} quantiles of all data, large dots represent the mean and upper and lower 95% confidence interval of the indicated dataset. Levene test for water quality data found that variances among groups were homogeneous. Linear models were used to calculate the mean estimates for water quality parameters and determine significant differences in mean concentrations among sites. Overlapping 95% confidence intervals indicate no significant difference and non-overlapping 95% confidence intervals indicate a significant difference.

Figure 4: Results of Mean Average Percentage Error (MAPE) analysis of model results where percentage error <10 indicates Highly accurate forecasting, 10 – 20 indicates Good forecasting, 20-50 indicates Reasonable forecasting and >50 indicates Inaccurate forecasting (Moreno et al. 2013). The values in the middle of the boxes are the MAPE values for each comparison at each site; the overall prediction accuracy (combined results for on-farm vs MD DNR and on-farm vs satellite) is greater at Chester (25% - Reasonable) than No. Tangier Sound (30.9% - Reasonable accuracy). Results of the sensitivity analysis to changes in satellite Chl ($\pm$ 10%) show +1% accuracy at Chester River and -4% accuracy at North Tangier.

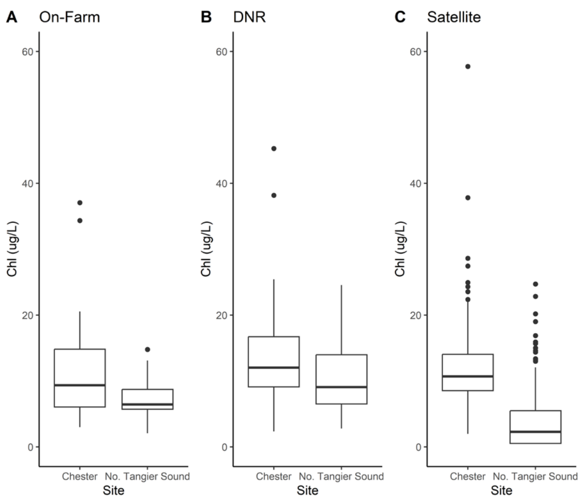
Figure 1



U.S.
Mid-Atlantic
Region
Elkton
Bel Air
Towson
Baltimore
Dover
Chester R.
Easton
MD Chesapeake Bay
Nanticoke R.
Salisbury
Wicomico R.
Manokin R.
Big Annemessex R.
Honga R.
Tangier
Sound
Pokomoke R.
Pokomoke
Sound
Chinco
Oyster farm
Station ET4.2
Oyster farm
Station EE3.1
OLCI Chl
mg m^-3
135.0
50.0
20.0
10.0
3.0
1.0
0.5
0.1

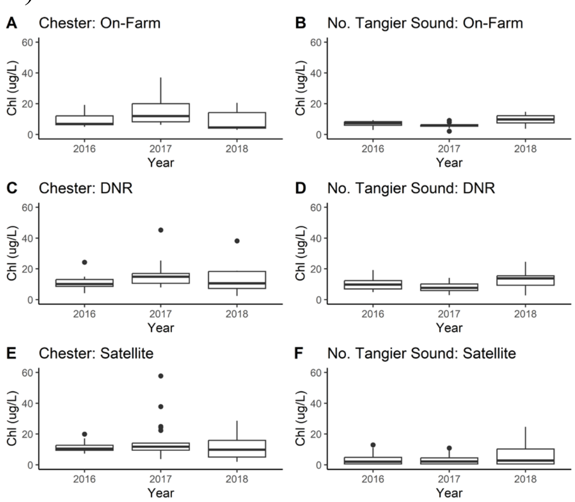
Figure 2

a.)



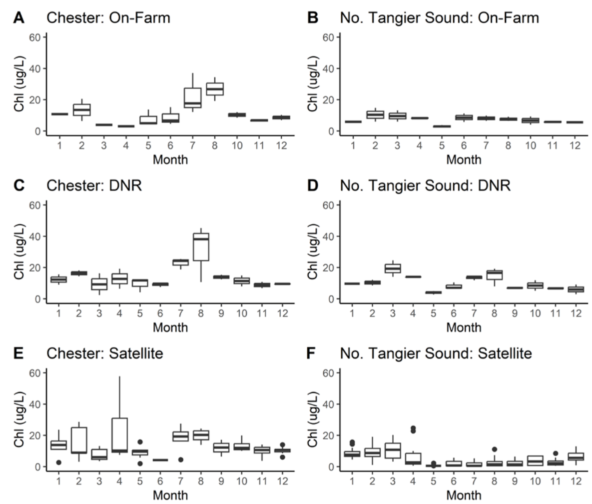
A On-Farm
B DNR
C Satellite
Chl (ug/L)
0
20
40
60
Chester
No. Tangier Sound
Site

b.)



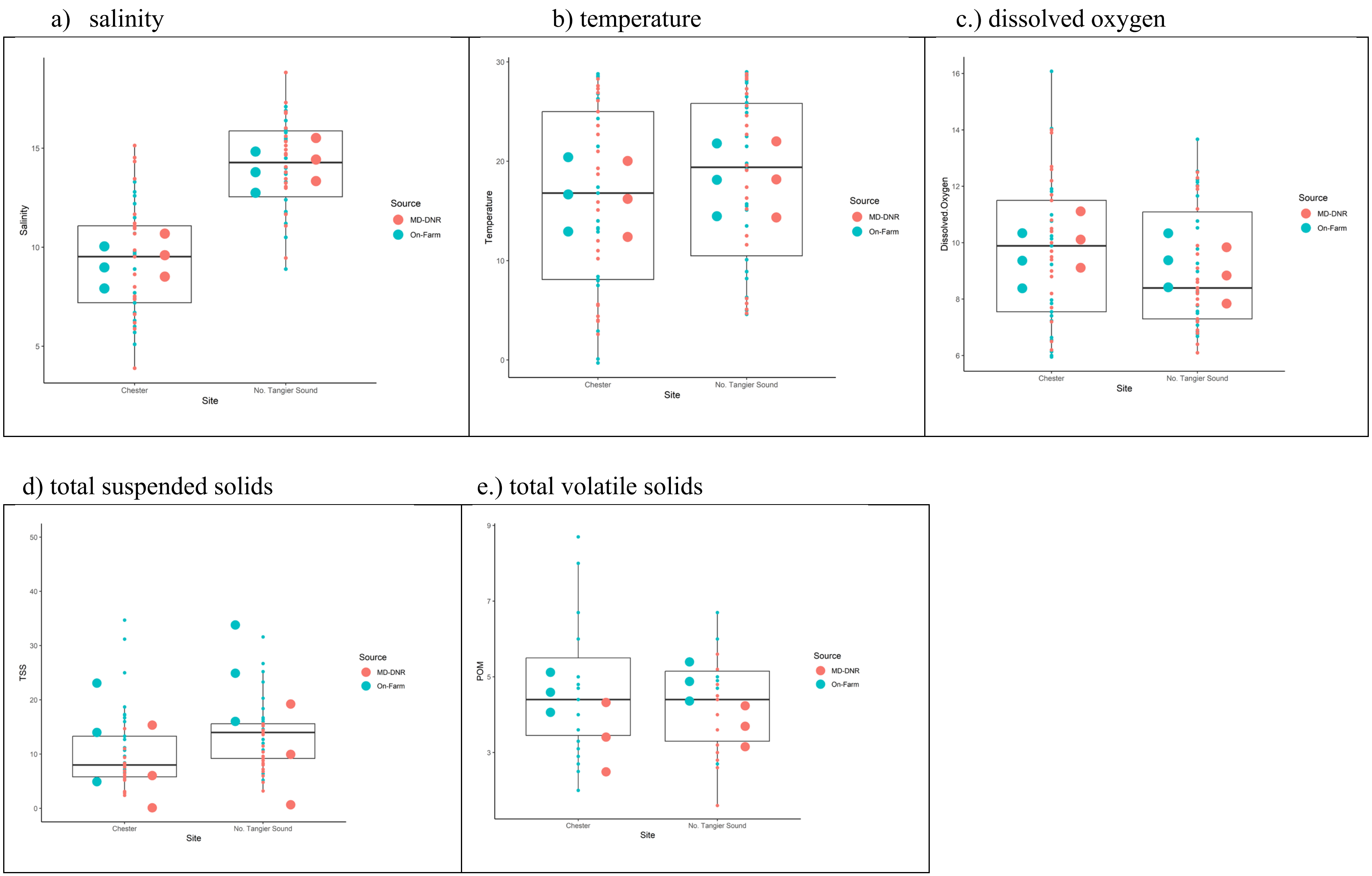
A Chester: On-Farm
B No. Tangier Sound: On-Farm
C Chester: DNR
D No. Tangier Sound: DNR
E Chester: Satellite
F No. Tangier Sound: Satellite
Chl (ug/L)
0
20
40
60
2016
2017
2018
Year

c.)



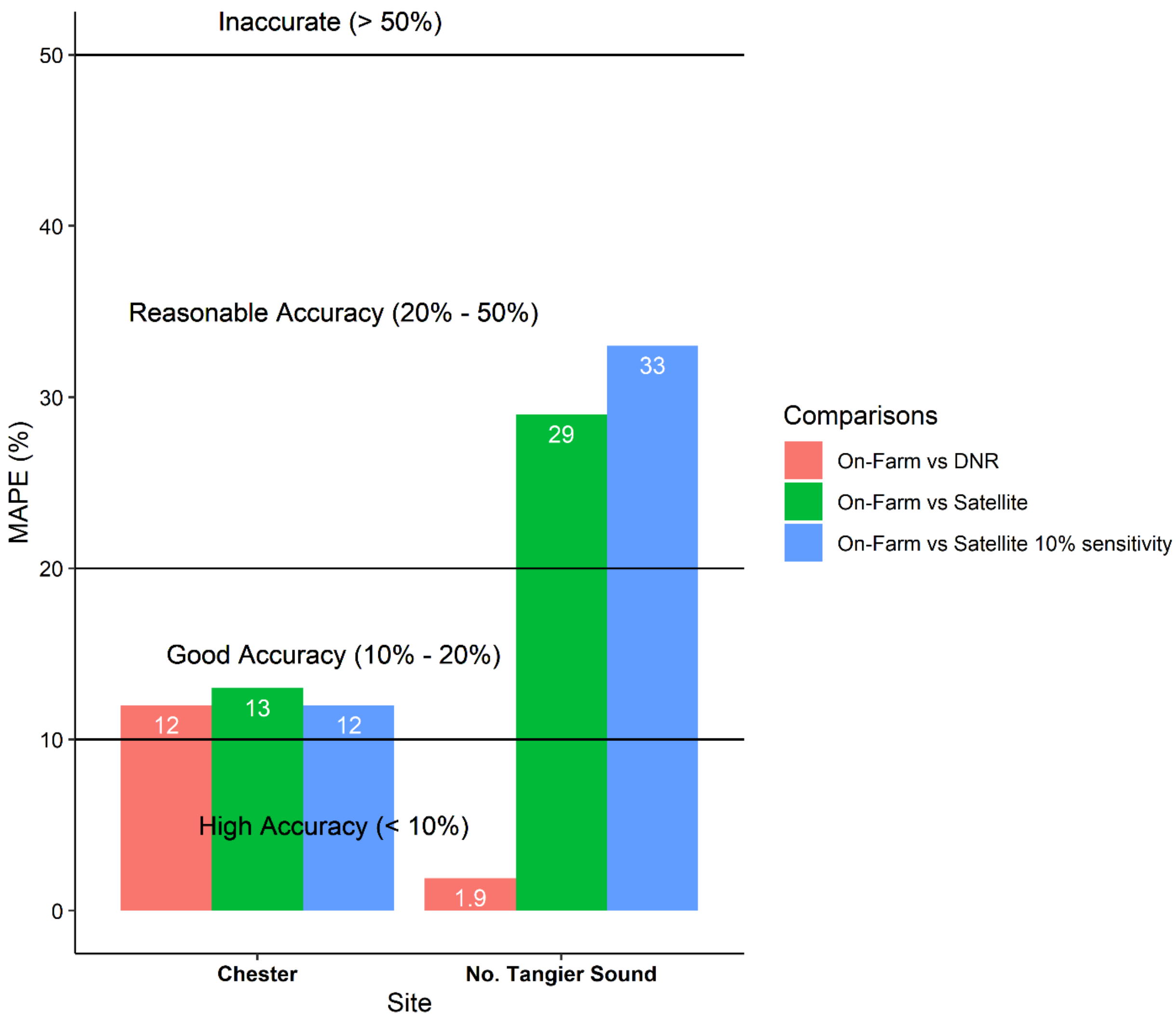
A Chester: On-Farm
B No. Tangier Sound: On-Farm
C Chester: DNR
D No. Tangier Sound: DNR
E Chester: Satellite
F No. Tangier Sound: Satellite
Chl (ug/L)
0
20
40
60
1 2 3 4 5 6 7 8 9 10 11 12
Month

Figure 3



a) salinity
b) temperature
c.) dissolved oxygen
d) total suspended solids
e.) total volatile solids
Salinity
Temperature
Dissolved Oxygen
TSS
POM
Site
Chester
No. Tangier Sound
Source
MD-DNR
On-Farm

Figure 4


Inaccurate (> 50%)
Reasonable Accuracy (20% - 50%)
Good Accuracy (10% - 20%)
High Accuracy (< 10%)
MAPE (%)
50
40
30
20
10
0
12
13
12
1.9
29
33
Chester
No. Tangier Sound
Site
Comparisons
On-Farm vs DNR
On-Farm vs Satellite
On-Farm vs Satellite 10% sensitivity