Technical Efficiency of Connecticut Long Island Sound Lobster Fishery: A Nonparametric Approach to Aggregate Frontier Analysis

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Abstract

In this paper, we address the question whether the technical efficiency of a fishing industry is affected by the determinants of ambient water quality of the aquatic ecosystem. Using zone specific data from 1998 – 2007 for the Connecticut Long Island Sound lobster fishery and an approach combining a bootstrapping technique with data envelopment analysis, we obtained the DEA estimates of technical efficiency for each fishing zone. We then used the bootstrapped-DEA results and Censored Quantile Regression to assess the impact of the environmental variables on different efficiency percentiles. A key result indicates when environmental conditionals are favorable (high dissolved oxygen levels) efficiency is low and when environmental conditionals are less favorable (high levels of nitrogen), efficiency is high. The results show that the intensity of significant impacts given the contextual variables may vary among high and low efficiency periods.

Keywords: technical efficiency, data envelopment analysis, censored quantile regression, lobster, harvest, Long Island Sound

JEL Classification: Q22, Q57

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1. Introduction

The returns to marine fishing are heavily dependent on the water quality of the aquatic system. At any given time, there are multiple ways in which water quality affects marine life. For example, changes is ambient water quality can impact the growth and mortality rate of different species in the ecosystem. Spatial differences in water quality can induce species to migrate from one area to another within the system. The impact is further complicated by the response of individual species, which depend not only on the direct impact of water quality on the species but also on its effect on other species that can indirectly affect a related species (for example, species that are related through the food chain).

The factors outlined above can all affect the economic return to fishing through direct and indirect effects on the catch per unit of fishing effort (CPUE). The CPUE indirectly reflects the abundance of the stock, the true size of it being unknown. In case of commercial fisheries, changes in ambient water quality can affect both firm level and industry level profit earnings through the impact on the marginal cost of harvesting. Given that ambient water quality is determined by factors outside fishers' control, it is a source of the randomness to aggregate harvest. Water quality that is conducive to proliferation of stock may be considered as a composite input that fishers do not have to pay for explicitly. However, fishers may end up paying an implicit price, either through an increase in cost and/or loss in profit, for any degradation in terms of ambient water quality.

An environmental problem that currently affects the ambient water quality in many aquatic systems worldwide is marine hypoxia, a condition of low dissolved oxygen in the water that makes it difficult for aquatic species to survive. Among other factors, hypoxic conditions can be generated as a result of increase in nutrients, such as nitrates and phosphates, in the water. When these nutrients get added to the water body, typically through fertilizers in agricultural runoff and sewage materials, it leads to a response by the ecosystem referred to as eutrophication.[5] Eutrophication can lead to rapid growth in phytoplankton such as algae. When these organisms die, dissolved oxygen is used up in the bacterial decomposition, thereby reducing the oxygen level in the water. The severity of the hypoxic conditions developed in the water system depends on a number of factors such as the volume of annual nutrient loadings, the specific nature of the aquatic system, the location of the water body, differences in surface and bottom level water temperature and oceanographic phenomenon such as upwelling and downwelling etc. The presence of hypoxic conditions has resulted in many dead zones in different parts of the world's oceans where marine life cannot be supported because of depleted oxygen levels (Breitburg, 2002). The presence of hypoxic water zones and in extreme cases dead zones highlight the need to better understand the impact of environmental variables on both marine life and commercial fisheries that depend on it. Ambient water quality can potentially affect the relative competitiveness of fishing industries through impact on stock and harvest.

In this paper, we focus on the relationship between ambient water quality and technical efficiency of a fishery. Our premise is that we view the optimal range of ambient water quality as an input in the production process. It depends on components such as dissolved oxygen, nitrogen, salinity, temperature etc. The optimal range of ambient water quality can be defined simply as the condition in which species in the ecosystem can grow

[5] For definitions of eutrophication, see http://toxics.usgs.gov/definitions/eutrophication.html.

at their natural growth rate consistent with ecological sustainability of the species. Any significant deviation from that range can result in an adverse impact on stock and possibly on harvest. For example, a significant drop in dissolved oxygen in the water body implies a shift away from the ideal water quality. Moderate to severe hypoxia exists when the dissolved oxygen level is between 4 mg/l and 2 mg/l while severe hypoxic conditions exist when the oxygen level drops below 2mg/l.

We focus on the Long Island Sound (LIS) ecosystem, which experiences hypoxic water conditions every year. The sound is home to a number of New England fisheries where fishers from New York, Connecticut and Rhode Island fish every year. The water quality of the sound is crucial for the viability of the economies that thrive on it. We focus on the Connecticut Long Island Sound lobster fishery. The industry has a license moratorium implying lobstermen who held a license between 1995 and 2003 can renew their licenses annually. However, new fishing licenses are not issued implying the industry sized is regulated by the state.[6] The lobster industry has long been one of the most commercially valuable fishing industries in the state. However, it has been struggling in recent years primarily because of a steep drop in total landings. Lobster is a bottom dwelling slow moving species known to be sensitive to hypoxic water conditions.

We use monthly industry level data from 1998 to 2007 for the lobster industry to estimate the technical efficiency of the fishery for the three contiguous fishing zones where the industry operates. Using data envelopment analysis (DEA) combined with a

[6] This information was obtained from personal communication with Matthew Gates at Connecticut Department of Energy and Environmental Protection.

bootstrapping technique, we obtained estimates of technical efficiency of three fishing zones where Connecticut lobstermen fish. The bootstrapped-DEA results were then combined with Censored Quantile Regression (CQR) to assess the impact of the environmental variables on different efficiency percentiles. The performance of the fishing zones is evaluated with respect to distinct efficiency percentiles assessing how the different contextual (environmental) impact high and low efficiency fishing zones and phases differently. This paper contributes to the fisheries economics literature on productivity analysis by adopting a two-stage bootstrapped DEA-CQR approach. To the best of our knowledge, it is the first paper to use an approach that combines bootstrapped DEA with CQR to evaluate zone specific efficiency level of any fishing industry and analyze the relationship between zone specific technical efficiency of the industry and the environmental variables that characterize the ambient water quality of the ecosystem. It is also the first study that focuses of an efficiency analysis on the Connecticut Long Island Sound lobster fishery using spatially differentiated data. The rest of the paper is organized as follows: Section provides the conceptual background and discussion of the related literature, while Section 3 presents the methodology. Section 4 discusses the data and the results. Finally, Section 5 concludes.

2. Conceptual Background and Related Literature

Technical efficiency (TE) may be defined as an indicator of the distance between actual production level and the maximum feasible production level, given available factors of input and technology. Alternatively, TE can be a measure of the minimum level of inputs needed to produce a given level of output. In other words, TE captures the extent of inefficiency in the production process. In the context of fisheries, TE indicates the maximum harvest level attainable by a production unit, given inputs and technology, or the minimum level of inputs that are necessary to attain a certain harvest level, given available fishing technology. Assessing technical efficiency of fisheries is essential for both sustainable management of the renewable resource and for understanding the scope of performance improvement of commercial industries. The process is complicated because of the stochastic nature of the production process. Also, lack of detailed input data often poses a challenge for accurate assessment. There are three primary approaches to measuring technical efficiency: (1) a nonparametric programming approach also known as data envelopment analysis (DEA), (2) a parametric programming approach, and (3) a parametric statistical approach commonly referred to as stochastic frontier analysis or SFA (Kirkley, Squires, and Strand, 1995). Both DEA and SFA, the more commonly used methods, are frequently used by economists for constructing best-practice frontiers for various production processes. However, they differ fundamentally in the way the best-practice frontiers are generated.

The DEA approach has its roots in mathematical programming whereas the SFA approach is much more directly linked to econometric theory. Given that, while the slack analysis of DEA provides insight for increasing or reducing input resources to improve efficiency scores, the SFA method focuses on the economic justification of a given production function and subjecting it to further hypothesis testing (Lin and Tseng, 2005). The SFA method being a parametric approach has some advantages and disadvantages over DEA, mainly related to the assumption of a stochastic relationship between the inputs used and the output produced. Data envelopment analysis developed over 30 years ago (Cook and Seiford, 2009). It is considered to be a powerful tool for measuring efficiency, above all for its capacity to simultaneously process multiple inputs and outputs, thereby aiding managers in decision-making. In conjunction with multivariate data analysis techniques, DEA enables the impact of contextual variables on efficiency levels to be measured (Cooper, Seiford, and Tone, 2007). On the other hand, although SFA handles only one output each time, it is possible to adapt the techniques developed for the estimation of a stochastic production frontier in the single-output case to the estimation of a stochastic output distance function in the multiple-output case. One possibility is to consider the dependent variable as the reciprocal of the norm of the output vector.

In the context of fisheries, the first technical efficiency study was by Hannesson (1983) who estimated a deterministic frontier using a single input. Since then both DEA and SFA have been used to assess technical efficiency of fisheries. In a seminal paper, Kirkley, Squires and Strand (1995) used stochastic frontier analysis to estimate technical efficiency for the period 1987 – 1990 for a sample of sea scallop vessels operating in the mid-Atlantic region. While many have relied on SFA on technical efficiency estimation in fisheries (for example, see Sharma and Leung, 1998; Vestergaard et al. 2002; Kompas et al., 2003; and Vinuya, 2010) primarily because of the inherent stochastic nature of the harvesting process, Felthoven (2002) and Walden (2006) have used DEA for estimation of technical efficiency. In fact, Walden (2006) addresses a key limitation of DEA as a method to estimate technical efficiency in fisheries. Because DEA is a deterministic approach, it is often criticized for its inability to account for the randomness in the fisheries data. Walden (2006) addresses this issue by presenting a bootstrapped DEA model as way of constructing a stochastic version of the traditional DEA model. In this paper, we estimate zone specific aggregate TE for CT LIS lobster fishery using data envelopment analysis using a similar approach. We extend the fisheries literature by using quantile regressions to study the impact of environmental variables on the efficiency scores. Traditional linear regression method illustrate the causal relationship between the dependent variable and a set of regressions based on the conditional mean of the dependent variable as a function of the exogenous variables. Quantile regression allows researchers to identify the relationship between the dependent variable and the regressors by using either the conditional median or other quantiles of the dependent variable. In our context, application of quantile regression helps to address the question whether environmental variables impact technical efficiency differently in high efficiency or low efficiency periods. Below we specify our model in detail.

3. Methodology:

Our decision to focus on zone level technical efficiency using industry level data is a result of both data limitation and choice. We have industry level zone specific data on harvest and inputs provided by Connecticut Department of Energy and Environmental Protection, the state department that oversees CT marine fishing. Fishermen level data were not available to us. In our case, given our interest lies in understanding the spatial impact of environmental variables such as dissolved oxygen and nitrogen on the technical efficiency of the industry as a whole, we are able to specify the DEA model treating each fishing zone as the decision making unit (DMU).

3.1 Data Envelopment Analysis (DEA)

In a DEA model, efficiency is defined as the ratio of the sum of weighted output to the sum of weighted inputs. For example, given k outputs and l inputs, the efficiency level for each zone i at time t (e_{it}) can be calculated as:

$$e_{it} = \frac{\sum_{p=1}^{r} \alpha_p h_p}{\sum_{j=1}^{l} s_j x_p} \tag{1}$$

where α_p and s_j are two sets of weights that will be obtained through a maximization process.

It is worth noting that nonparametric efficiency estimators such as DEA typically rely on linear programming techniques for computation of estimates, and are often characterized as deterministic, as if to suggest that the methods lack any statistical underpinnings (Simar and Wilson, 2004). Applied studies that have used these methods have typically presented point estimates of inefficiency, with no measure or even discussion of uncertainty surrounding these estimates (Cesaro et al., 2009). Indeed, many papers contain statements where efficiency is described as being computed or calculated as opposed to being estimated, and results are frequently referred to as efficiencies rather than efficiency estimates (Ray, 2010; Zarepisheh et al., 2010).

The choice of terminology in describing the nonparametric efficiency approaches and their results is perhaps understandable given (until very recently) the lack of a "tool box" with aids for diagnostics, inference etc, such as the one available to researches using parametric approaches (Simar and Wilson, 2004). To solve these problems, bootstrap techniques have been introduced into DEA analysis (Cesaro et al., 2009). The bootstrap technique permits the sensitivity of efficiency scores relative to the sampling variation of the frontier to be analyzed, avoiding problems of asymptotic sampling distributions. DEA results, in fact, may be affected by sampling variation in the sense that distances to the frontier are underestimated if the best performers in the population are not included in the sample. To account for this, Simar and Wilson (1998, 2000) originally proposed a bootstrapping method allowing the construction of confidence intervals for DEA efficiency scores which relies on smoothing the empirical distribution. This technique consists of a simulation of a true sampling distribution by mimicking a data generating process, using the outputs from DEA. In this way, a new dataset is created and DEA is re-estimated using this dataset. Repeating the process many times allows a good approximation to be achieved of the true distribution of the sampling (Cesaro et al, 2009).

The method used in this research departs from that presented by Simar and Wilson (2004), which adapted the bootstrap methodology to the case of DEA efficiency estimators and uses a Gaussian kernel density function for random data generation. All the computations were carried out with R codes developed by the authors; 1000 bootstrap replications were performed on model (1), following the discussion presented by Simar and Wilson (1998, 2004) and Curi et al. (2011) on deriving statistical properties for each fishing zone vis-à-vis bias estimation, and central tendency correction.

3.2. Censored Quantile Regression (CQR)

Traditional regression models cannot answer an important question: "do environmental variables influence high and low efficiency in fishing activity in different ways?". A more comprehensive picture of the effect of the contextual variables on the efficiency levels can be obtained via CQR. Quantile regression models the relation between a set of contextual variables and specific percentiles (or quantiles) of the response variable. It specifies changes in the quantiles of the efficiency. As a matter of fact, the quantile regression parameter estimates the change in a specified quantile of the response variable produced by a one unit change in the predictor variable. This allows comparing how some percentiles of the efficiency levels may be more affected by certain environmental or contextual variables than other percentiles. This is reflected in the change in the size of the regression coefficient.

According to Leng and Tong (2013), the quantile regression was introduced by Koenker and Bassett (1978) and has become an increasingly important tool in statistical analysis. They have actually introduced the general quantile regression (QR) estimation that became the most popular approach (Chernozhukov and Hong, 2002).Contrary to the usual model for the conditional mean, it provides distributional information on the dependence of T on Z. The Tth conditional quantile function of the dependent variable T given covariates Z, $Q_T\ (T|Z)$, is defined as $Q_T\ (T|Z) = \inf\{v\colon F_0(v|Z) \geq T\}$, where F_0 is the cumulative conditional distribution function of T given Z. Correspondingly, a quantile regression model for $Q_T\ (T|Z)$ with $T \in (0, 1)$ can be denoted as

$Q_T(T|Z) = \beta_{\tau}' Z.$ (2)

In our context, since our DEA efficiency scores between 0 and 1, the dependent variable is censored. When data are subject to censoring, statistical estimation and inference for quantile regression is more involved. Indeed, a naive procedure that completely ignores censoring may give highly biased estimates (Koenker, 1987). Equivariance to monotone transformations is an important property of quantile regression models (Powell, 1986).

Powell (1986, 1984) first studied Censored Quantile Regression (CQR) with fixed censoring. For random censoring, Ying et al. (1995) proposed a semiparametric median regression model. Despite the simplicity of their method, this procedure requires the unconditional independence of the survival time and censoring time. This assumption is often restrictive as conditional independence, given the covariates, is more natural (Kalbfleisch and Prentice, 2002). In addition, the estimating equation approach proposed in Ying et al., (1995) involves solving non-monotone discrete equations, creating difficulty for optimization. As a consequence, inferential procedures such as the resampling approach in Jin, Ying and Wei (2001), or the bootstrap method, can be prohibitive computationally.

Chernozhukov and Hong (2002) argue that the CQR models allow covariates to shift location, scale, and the entire shape of the distribution and permit distribution-free specifications. As such, CQR models compare favorably to the normal Amemiya-Tobin, Cox, Buckley-James, and other approaches. According to the authors, in this model, the latent variable Y_i^* is left censored by the observable, possibly random, censoring points *Ci*, and we observe

$$Yi = Y_i^* \vee C_i, \qquad X_i, \qquad C_i, \qquad \sigma_i = 1\ (Y_i = Ci) \qquad (3)$$

Y_i^* is assumed to be *conditionally independent of the censoring point Ci* ; that is, for all $y \in$ IR, where IR is the set of real numbers, X_i is the set of explanatory variables, C_i is the set of censored values, and σ_i is the right censoring for the efficiency scores (censoring at 1).

$$P\ (Y^* < y|Xi,\ Ci) = P(Y^* < y|Xi), \text{ so that } Q_{Y^*|Xi,Ci}\ (T|Z) = \beta_T^t\ Z \qquad (4)$$

Conditioning on *Ci,* equation (4) and the equivariance transformation yield the following CQR model (Powell, 1986):

$$Q_{Yi\ |Xi,\ Ci\ (T|Z)} = \beta_T^t\ Z \vee C_i \qquad (5)$$

4. Data and Results

Our dataset contains monthly observations from 1998 - 2007 for each of the three fishing zones – western LIS, central LIS and eastern LIS. The data for the aggregate monthly lobster harvest, price, inputs variables and all environmental variables used in the study have been collected and provided by the Connecticut Department of Energy and Environmental Protection (CT DEEP). The environmental data have been collected at various stations in the sound where monitoring stations are located. Data for the environmental variables are typically collected once every month. Sometimes during the summer months, data were collected twice with a gap of 15 days in the same month. For those months the average of the two observations was used. Each data point corresponds to a fishing zone (western, central or eastern LIS) and a particular month in the chosen time period. Because of missing data for some variables, we include 315 observation in our analysis. Table 1 shows the descriptive statistics for the inputs, outputs, and the contextual or environmental variables in the sample.

[Insert Table 1 here]

In table 1, the statistics for each variable are presented for the entire Long Island Sound. The variables, aggregate fishing days and number of fishermen, are our aggregate measures of inputs. They were used to obtain the technical efficiency estimates for the fishing zones. The variable aggregate fishing days refers to the total number of fishing days recorded for all the fishers fishing in that zone in any given month. Number of fishermen for each zone refers to total number of fishermen operating in that zone in a particular month. For the environmental variables, we use both surface level and bottom level estimates for each of the variables – oxygen and nitrogen levels, salinity, and temperature. The dissolved oxygen level is measured in mg/l. The nitrogen level includes both dissolved nitrogen in the water column and particulate nitrogen (for example, found algal cells). The temperature is measured in Celsius and the salinity level is measured in Practical Salinity Units, a standard measure for ocean salinity levels.

4.1. Discussion of results from bootstrapped DEA and CQR models

The efficiency levels calculated for 3 fishing zones from 1998 to 2007, using bootstrapped-DEA and considering different grouping criteria, are given in Figs. 1, 2a-c, and 3. More precisely, in Fig. 1, bootstrapped-DEA scores are grouped by year (top), month (middle), and fishing zone (bottom). Kruskal-Wallis tests for median differences revealed significant results within these grouping schemes, suggesting not only that there are significant differences in efficiency with respect to each fishing zone, but also that efficiency in fishing is seasonal. Although there are significant differences in efficiency among the years, it is not possible to affirm that there is a long run tendency towards higher efficiency levels.

A clear picture emerges when contextual variables are grouped by fishing zone and month (cf. Fig. 2a, 2b, and 2c). While Kruskal-Wallis tests reveal significant differences only in nitrogen and salinity levels within the three fishing zones (top), an analysis grouped per month reveal that dissolved oxygen, nitrogen and salinity levels, temperature, and harvest price are seasonal phenomena (middle and bottom), as long as they significantly differ over the course of the year. This suggests the eventual impact of these contextual variables that may be embedded within the grouping schemes: fishing zone and month. Fuel prices did not vary significantly within both grouping schemes.

Nevertheless, the correlogram presented in Fig 3. reveals several issues. First, surface and bottom measures for each one of the environmental variables dissolved oxygen, nitrogen, temperature, and salinity are strongly correlated. These measures should be, from now on, substituted by their averages, in order to avoid collinearity problems. Second, bootstrapped DEA scores are positively correlated to dissolved oxygen and nitrogen levels, and negatively correlated to temperature and salinity.

[Insert Fig. 1. here]

Results for the CQR of the efficiency scores on these averaged environmental variables for oxygen, nitrogen, temperature, and salinity are presented for selected efficiency percentiles in Table 1 (tau = 0.20, 0.40, 0.60, and 0.80). The full set of results for these percentiles is given in the Appendix and depicted in Fig. 4. Significances and bootstrapped lower and upper confidence intervals can also be found in the Appendix. The standard errors and confidence limits for the CQR coefficient estimates were obtained with asymptotic and bootstrapping methods. Both methods provide robust results (Koenecker and Hallock, 2001), with the bootstrap method preferred as more practical (Hao and Naiman, 2007). Therefore, the bootstrap results derived originally for the DEA scores were also used to bootstrap for the CQR coefficient estimates.

As one can easily note from Table 2, the signs of the relationships between the contextual/environmental variables and the efficiency levels do not change for different quantiles - although the same cannot be affirmed with respect to their significances as illustrated in Fig. 4. It is worth noting that the magnitudes of the coefficients vary from quantile to quantile. As a matter of fact, this effect happens because rather than predicting the mean of the dependent variable, CQR looks at the quantiles of the dependent variable. By choosing tau = 0.4 or 0.6, the 40th and 60th percentiles of the data are being used to compute the regression. Therefore, CQR allows answering the question: “For which type of fishery - high or low efficiency -the impact of a given contextual/environmental variable prevails?”

[Insert Fig. 2a. here]

[Insert Fig. 2b. here]

[Insert Fig. 2c. here]

[Insert Fig. 3. here]

[Insert Table 2 here]

The CQR results presented in Table 2 above indicate that temperature and salinity present a straightforward interpretation with respect to their impact on fishery efficiency: higher temperature and salinity, lower efficiency. On the other hand, however, the impacts of oxygen and nitrogen are counterintuitive. It appears that efficiency is low when oxygen is superabundant, and that the reverse is true in case of nitrogen. One possible explanation is that when environmental conditions are favorable for fishery (e.g. high oxygen levels), proportionally more inputs (fishing days and fishing men) are allocated for a given harvest that is generated. On the other hand, when environmental conditions are not so favorable (e.g. high nitrogen levels), proportionally less inputs are allocated for a given harvest or output generated. This dichotomous attitude towards risk-taking and parsimony in light of different environmental conditions may explain this unexpected behavior of efficiency levels.

More precisely, the effect of a higher oxygen levels and lower nitrogen levels has a larger negative impact on the higher quantiles of fishery efficiency in Long Island. The same occurs with the negative effects of temperature and salinity: larger in higher quantiles of fishery efficiency than in lower ones. It is important to note in Fig. 4 that the CQR coefficients for the environmental variables cross the horizontal "effect equals zero" axis in some quantiles. A rigorous interpretation of this effect would suggest that the effects of nitrogen and salinity, previously discussed, may not be significant to all range of quartiles.

The results presented here suggest a number of policy implication for the lobster fishery in Long Island and, more generally, any fishery. There are different possible courses of action both for fishing companies and the fishing regulatory agency. For example, decisions regarding rebalancing the workload - number of fisherman and fishing days - in light of environmental conditions, accurate assessment and analysis of water quality conditions, and establishing decision support systems for resource dimensioning. Since individual fishers may not often have a clear view on these environmental indicators and how they impact the productivity of fishing activity, we deem necessary the accurate measurement of these conditions at the sea level so that resource dimensioning in the case of the inputs would not be decided without an empirical basis.

[Insert Fig.4. here]

5. Conclusion

The performance and profitability of commercial fishing industries depend on the ambient water quality of the aquatic ecosystems in which the harvesting activities take place. This raises the question whether there exists any relationship between the efficiency levels at which an industry operates and the environmental factors that influence the ambient water quality. The technical efficiency of a fishing industry can vary both temporally and spatially across fishing zones. In this paper, we presented a novel two-stage approach based to estimate the zone specific technical efficiency of Connecticut Long Island Sound lobster industry and analyze the relationship between industry level efficiency and a range of environmental variables that affect the ambient water quality of Long Island Sound system. The technical efficiency levels calculated for the three contiguous fishing zones for the period 1998 to 2007, using bootstrapped-DEA and considering three different grouping criteria - by year, month, and by fishing zone. Quantile regressions were then used to analyze the impact of environmental variables such as bottom and surface level dissolved oxygen, nitrogen, water temperature and salinity on the efficiency scores. The results show that the effect of a higher oxygen levels and lower nitrogen levels has a larger negative impact on the higher quantiles of fishery efficiency indicating the complexity of the relationship between ambient water quality and the technical efficiency of a fishery. A better understanding of the relationship between technical efficiency and the determinants of ambient water quality has important policy implications. Specifically, our results emphasize the role of the government in accurate periodic assessment of water quality conditions and taking into account such information in the context of sustainable fisheries management. Specifically, the question that arises is how do environmental variables affect the cost of fishing across seasons and zones given the seasonal and spatial differences in their effects on technical efficiency. This is an area that warrants further research particularly because fishery managers worldwide are associated with using policy tools to reduce economic inefficiencies such as excess harvesting capacity and bycatch that often lead to unnecessarily higher production costs and ecological damage.

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Table 1. Descriptive Statistics

Variable Type			Min	Max	Mean	SD
Contextual and Environmental Variables	Trend	Year	1,998.00	2,007.00	2,002.50	2.88
		Month	1	12	6.5	3.46
		Time	1	120	60.5	34.69
	Location	Zone	1	3	2	0.82
	Prices and Costs	Price	2.98	8.95	4.63	0.92
		Average_Diesel_Price_NE	1.06	3.59	1.86	0.66
		Average_Diesel_Price_Eastern	0.97	3.39	1.77	0.65
	Environment	Dissolved_Oxygen_Bottom	2.53	13.01	8.43	2.23
		Dissolved_Oxygen_Surface	5.4	14.04	9.24	1.66
		Nitrogen_Bottom	0.1	0.61	0.28	0.09
		Nitrogen_Surface	0.1	0.99	0.31	0.1
		Temperature_Bottom	-0.82	22.1	11.29	6.75
		Temperature_Surface	-0.68	24.26	12.07	7.21
		Salinity_Bottom	13.49	32.11	28.48	1.98
		Salinity_Surface	12.73	31.73	25.58	4.32
Inputs and Outputs	Outputs	Harvest	98	512,439.00	34,347.17	57,892.16
	Inputs	Aggregate Fishing_Days	8	1,231.00	238.22	226.3
		Number of Fishermen	4	117	32.49	20.38

CQR results:

Table 2. Coefficients for the CQR for selected percentiles

	tau= 0.2	tau= 0.4	tau= 0.6	tau= 0.8
(Intercept)	0.507371207	0.640751569	0.611847706	0.797330829
Oxygen	-0.024614520	-0.028467184	-0.025659464	-0.034007465
Nitrogen	0.039804947	0.036306909	0.181778732	0.240886886
Temperature	-0.007656111	-0.008919842	-0.007914481	-0.010375697
Salinity	-0.003826074	-0.005664683	-0.006146372	-0.008348809

CQR results

tau: 0.2

Coefficients:

	Value	Lower Bd	Upper Bd	Std Error	T Value	Pr(>|t|)
(Intercept)	0.50737	0.19134	0.82341	0.16070	3.15733	0.00173
Average Dissolved Oxygen	-0.02461	-0.04341	-0.00582	0.00955	-2.57610	0.01040
Average Nitrogen	0.03980	-0.08864	0.16825	0.06531	0.60945	0.54262
Average Temperature	-0.00766	-0.01245	-0.00287	0.00244	-3.14292	0.00181
Average Salinity Interaction	-0.00383	-0.00837	0.00071	0.00231	-1.65757	0.09829

tau: 0.4

Coefficients:

	Value	Lower Bd	Upper Bd	Std Error	T Value	Pr(>|t|)
(Intercept)	0.64075	0.50101	0.78049	0.07105	9.01788	0.00000
Average Dissolved Oxygen	-0.02847	-0.03818	-0.01876	0.00494	-5.76545	0.00000
Average Nitrogen	0.03631	-0.04919	0.12181	0.04347	0.83512	0.40421
Average Temperature	-0.00892	-0.01166	-0.00618	0.00139	-6.40959	0.00000
Average Salinity Interaction	-0.00566	-0.00811	-0.00321	0.00125	-4.54693	0.00001

tau: 0.6

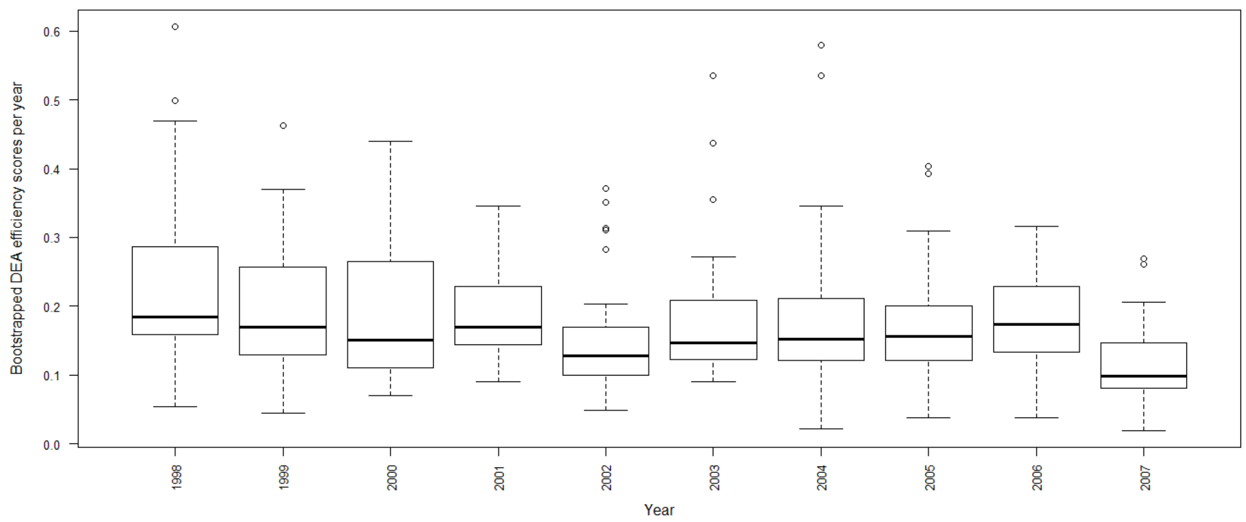
Coefficients:

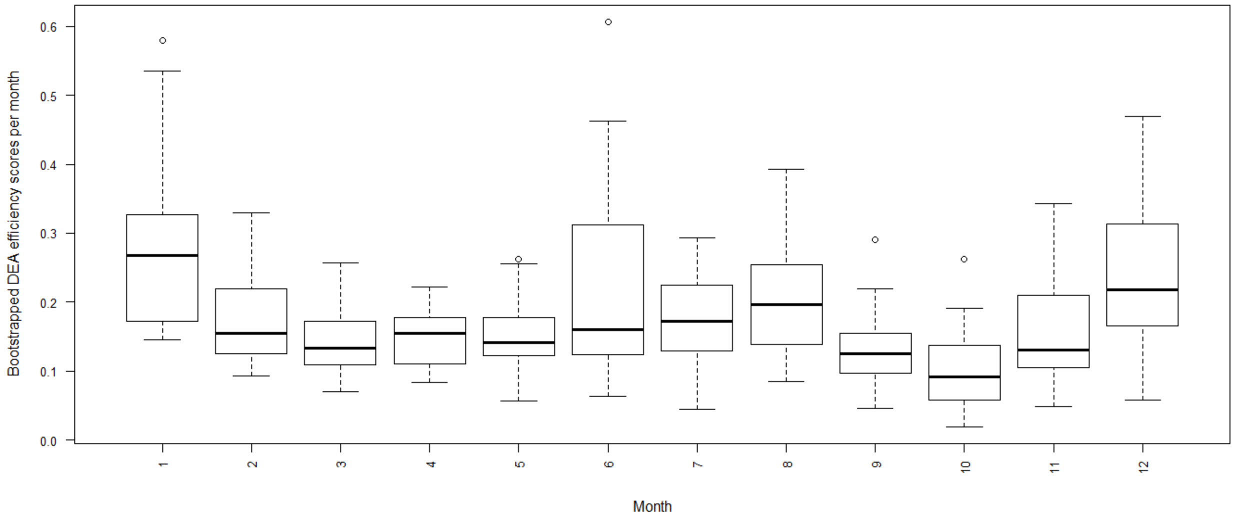
	Value	Lower Bd	Upper Bd	Std Error	T Value	Pr(>|t|)
(Intercept)	0.61185	0.32140	0.90229	0.14768	4.14298	0.00004
Average Dissolved Oxygen	-0.02566	-0.04289	-0.00843	0.00876	-2.92846	0.00363
Average Nitrogen	0.18178	0.00041	0.36315	0.09222	1.97108	0.04949
Average Temperature	-0.00791	-0.01249	-0.00334	0.00233	-3.39952	0.00075
Average Salinity Interaction	-0.00615	-0.01045	-0.00184	0.00219	-2.80896	0.00525

tau: 0.8

Coefficients:

	Value	Lower Bd	Upper Bd	Std Error	T Value	Pr(>|t|)
(Intercept)	0.79733	0.44625	1.14841	0.17851	4.46651	0.00001
Average Dissolved Oxygen	-0.03401	-0.05836	-0.00965	0.01239	-2.74585	0.00634
Average Nitrogen	0.24089	0.03059	0.45119	0.10693	2.25270	0.02489
Average Temperature	-0.01038	-0.01725	-0.00350	0.00350	-2.96716	0.00321
Average Salinity Interaction	-0.00835	-0.01771	0.00101	0.00476	-1.75484	0.08015


Bootstrapped DEA efficiency scores per year
0.0
0.1
0.2
0.3
0.4
0.5
0.6
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
Year


Bootstrapped DEA efficiency scores per month
0.0
0.1
0.2
0.3
0.4
0.5
0.6
1
2
3
4
5
6
7
8
9
10
11
12
Month

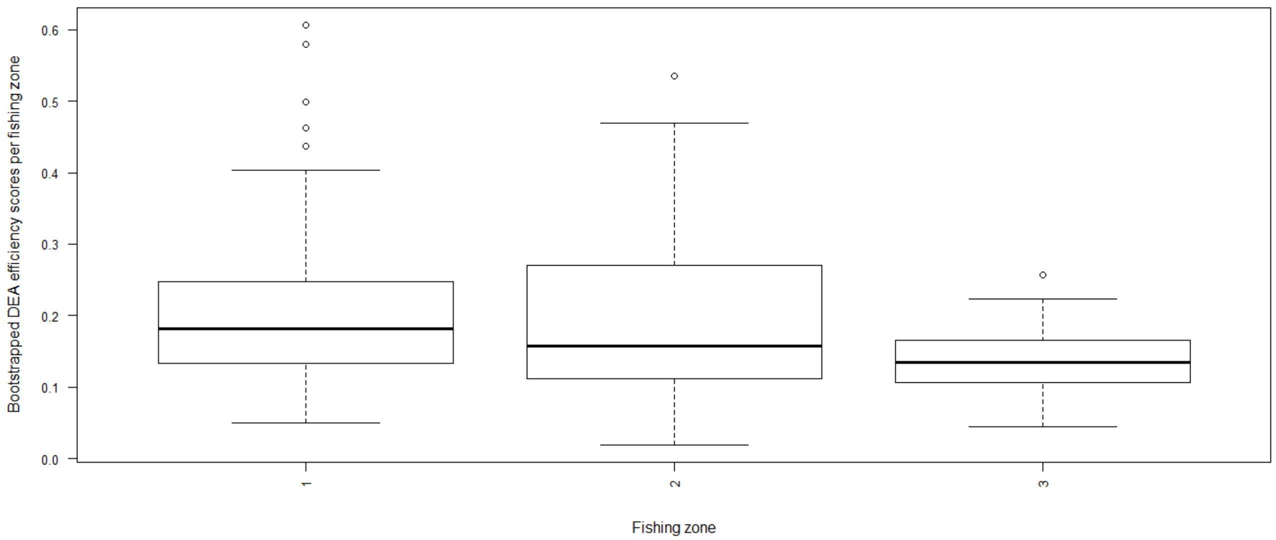


Fig. 1. Efficiency levels grouped by year, month, and fishing zone

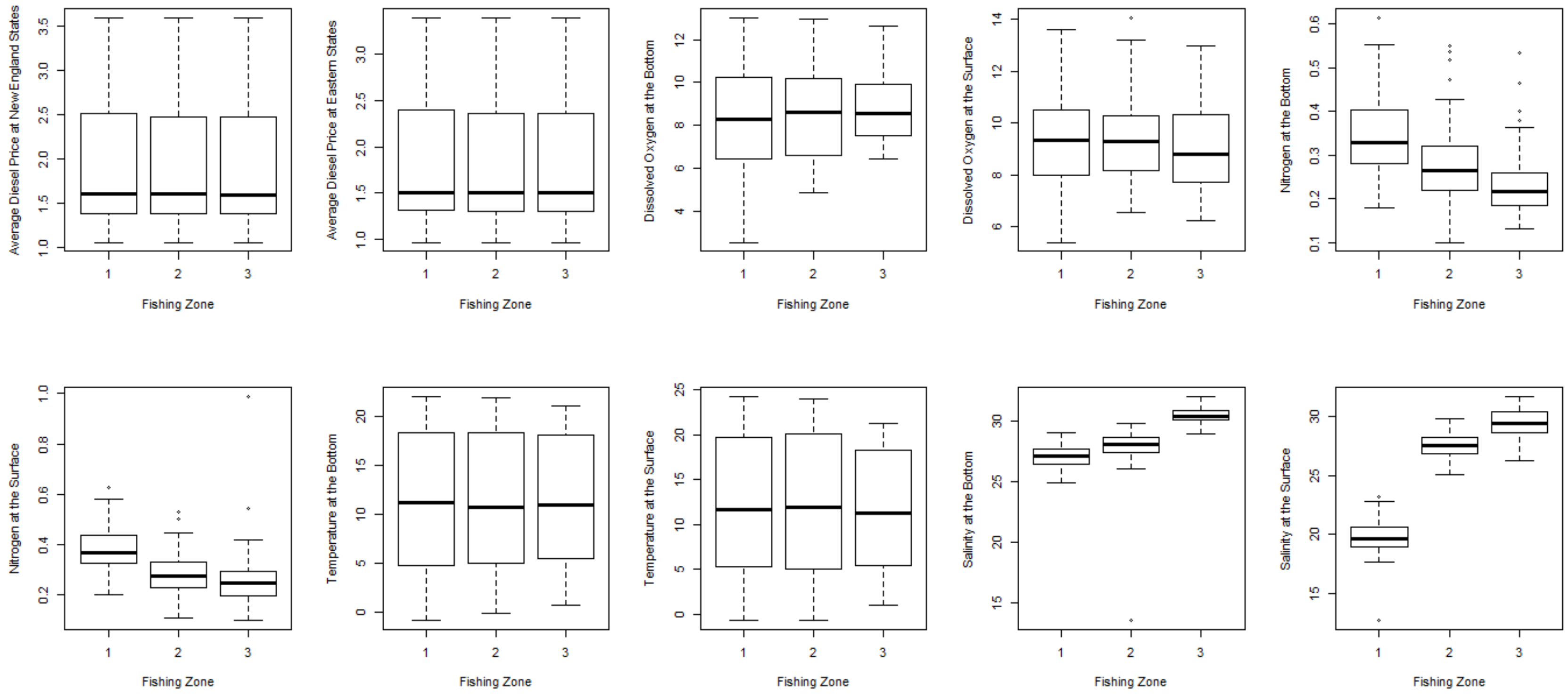


Fig. 2a. Contextual Variables grouped by fishing zone

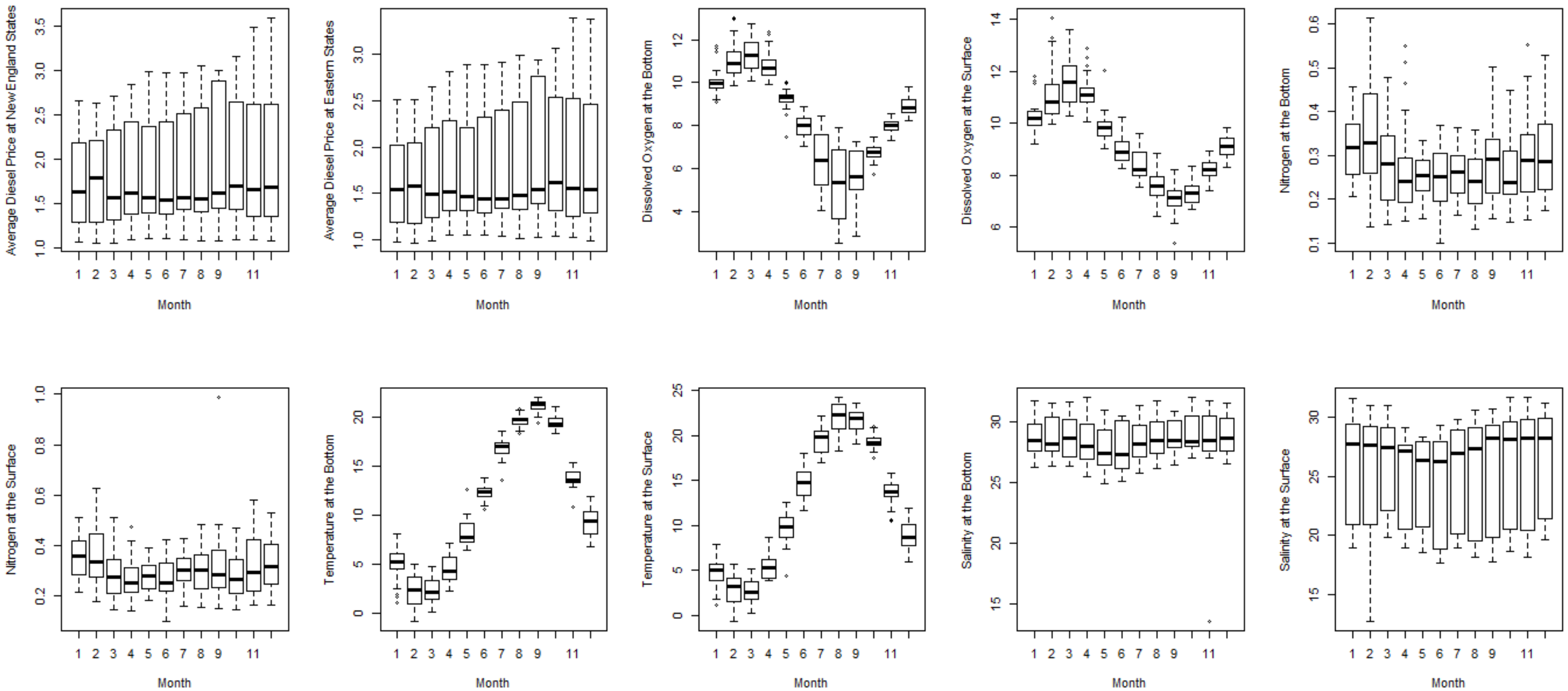


Fig. 2b. Contextual variables grouped by month

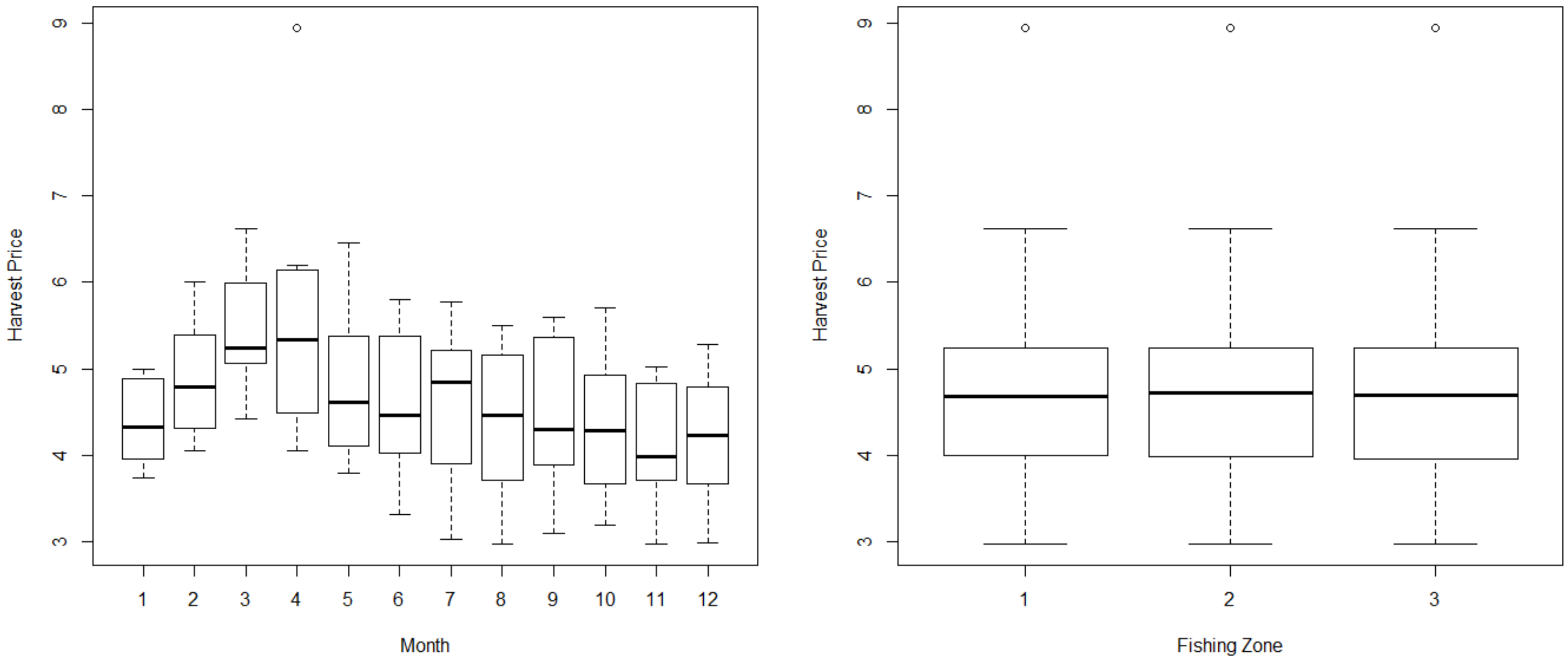


Fig. 2c. Contextual variables grouped by fishing zone and month.

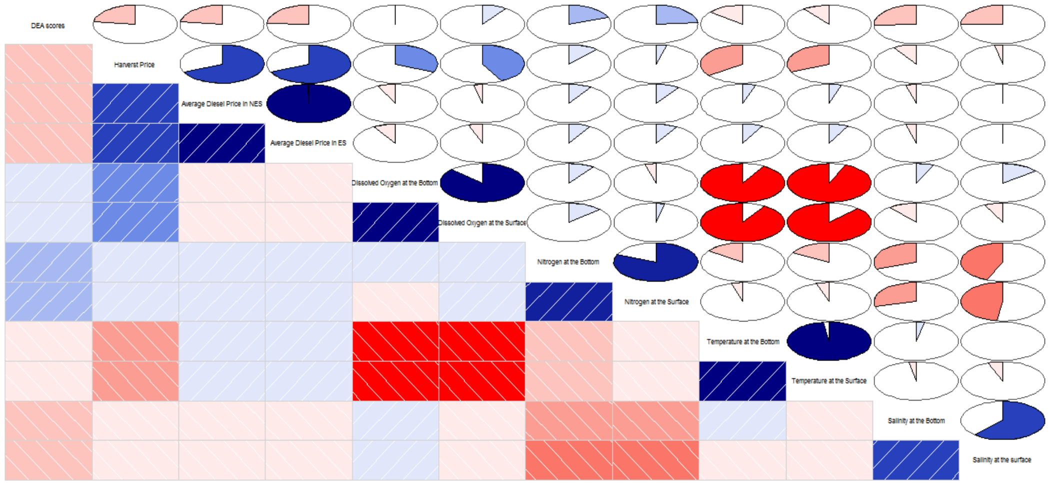


Fig. 3. Correlogram for the DEA boostrapped efficiency scores and the contextual variables

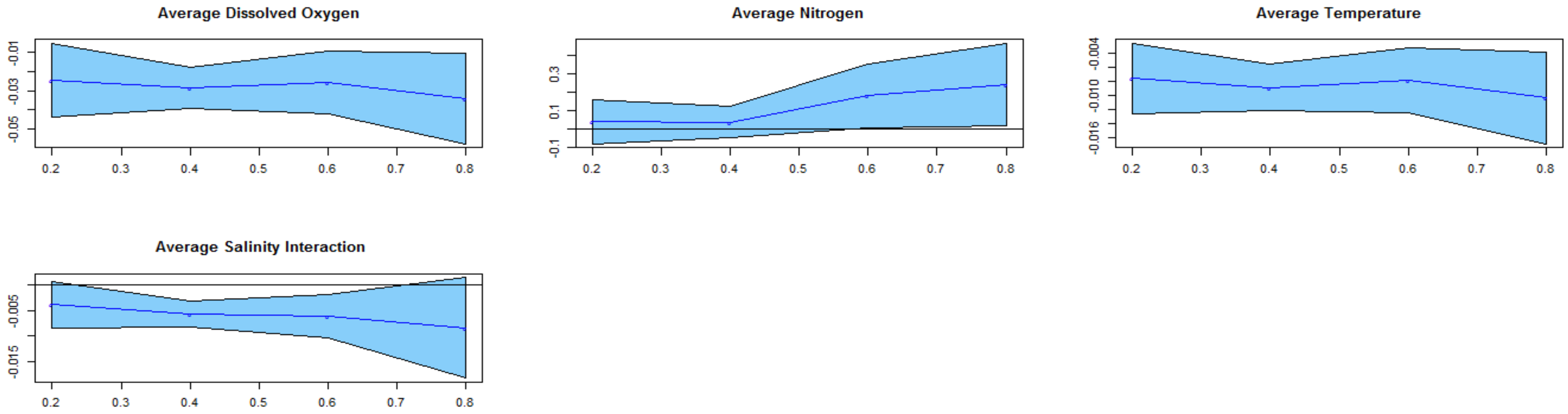


Fig 4. Censored Quantile Regression Coefficients Plots. The solid blue line indicates the quantile regression point estimates, the lighter blue region is a pointwise 95% confidence band. X-axis represents the quantiles and Y-axis represents the coefficients for each contextual variables.