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Abstract

During the last decade, oyster aquaculture has rebounded in Virginia and has been associated with an increase in subaqueous leased area. Production levels remain historically low, however, and many leases are thought to be underutilized. This study uses a novel approach leveraging high-resolution environmental data to evaluate lease utilization and identify constraints on aquaculture development. Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) were used to define environmentally-determined production frontiers, i.e production possibilities based on empirical observations of aquaculture production, available space, and environmental conditions. Both methods estimated Lease Capacity Utilization (LCU, from 0 to 1) for leases producing oysters with intensive culture methods from 2007 to 2016. Models revealed significant heterogeneity in lease utilization and mean LCU scores of 0.25 (DEA) and 0.27 (SFA), which suggests many leases could scale up production or reduce the size of their lease to more efficiently utilize ambient environmental conditions (i.e., achieve scores closer to 1). Capacity underutilization arising from characteristics of the leaseholder and surrounding spatial environment were quantified and indicated efficiency gains for horizontally integrated leaseholders, though also suggested leases in more populated areas were less efficiently used, possibly due to increased use conflicts. These results highlight potential externalities and tradeoffs associated with aquaculture development and can inform the design of more efficient aquaculture leasing systems.

Keywords: Oyster aquaculture; Chesapeake Bay; Stochastic Frontier Analysis; Data Envelopment Analysis; Capacity Utilization; Marine Spatial Management.

Highlights:

- Production frontiers were constructed leveraging high-resolution environmental data.
- Two different methods used to construct production frontiers yielded similar results.
- Lease underutilization was found in oyster intensive aquaculture in Virginia.
- Production levels could grow considerably without increasing leased area.
- Lease underutilization was related to leaseholder attributes and spatial context.

Abbreviations

DEA: Data Envelopment Analysis
SFA: Stochastic Frontier Analysis
LCU: Lease Capacity Utilization

1. Introduction

Oyster aquaculture is a globally important and increasing part of the blue economy that provides economic benefits as well as multiple ecosystem services, including water filtration and habitat creation (Duarte et al., 2009; Alleway et al., 2019; Theuerkauf et al., 2019). Oysters were the highest volume and value marine shellfish produced via aquaculture in the United States in 2017, with over 36.5 million lbs harvested and an estimated value of US $186.3 million (NMFS, 2020). Continued growth of oyster aquaculture is anticipated given increasing populations, increasing seafood consumption per capita, and limited potential for increased exploitation of wild stocks (Duarte et al., 2009; SAPEA, 2017; Wijsman et al., 2019; FAO, 2020). Competition for space between oyster producers and other stakeholders, as well as social opposition, have been identified as key barriers for coastal aquaculture expansion in areas where different recreational, esthetic, residential, and commercial uses or activities occur (Knapp, 2012; Krause et al., 2015; Froehlich et al., 2017; Beckensteiner et al., 2020). Knapp and Rubino (2016) argue that U.S. marine aquaculture activity is well below its potential level and Gibbs (2009) suggests that social carrying capacity, which refers to the space dedicated to aquaculture that the local community is willing to accept (Inglis et al., 2000), may be the main constraint to aquaculture industry growth. This research evaluates oyster production potential on actively used privately leased grounds in Virginia, USA as related to the physical, biological and social environment, in order to identify factors that enhance or constrain oyster aquaculture development.

In Virginia, wild populations of eastern oyster (*Crassostrea virginica*) have experienced dramatic declines due to disease, water quality, habitat destruction and overfishing over the last two centuries (Rothschild et al., 1994; Schulte, 2017; Kennedy, 2018). The area once supported a dynamic public fishery (~ 3 million lbs/yr in the 1950's), where fishers harvested natural oyster beds (defined by the Baylor Survey in 1896; Schulte, 2017), as well as maintained a large "extensive aquaculture" industry, wherein fishers deposited oyster shells and potentially live seed oysters on the bottom of privately leased grounds for later harvest (~16 million lb./year in the 1950's; Haven et al., 1978). Though both of these fisheries continue, average annual aquaculture production levels from 1995 to 2005 were only 0.4 million lbs, 2.5% of the 1950's average. In recent years, oyster aquaculture has begun to rebound, reaching ~2.5 million lbs in 2016. Major contributors to this growth include the increasing cultivation of disease-resistant, hatchery-raised oyster strains, pioneering work on triploid oysters, and reliance on "intensive aquaculture" practices, i.e., the use of oyster cages or bags for production (also referred to as containerized aquaculture, Bosch et al., 2010; Hudson, 2018). Concurrent with the observed production rebound has been an increase in privately leased grounds. Today, the total amount of leased area is the largest it has ever been, with about 140,000 acres currently leased. Private leases have long been advocated as an effective tool for increasing oyster yields while also incentivizing sustainable practices (Alford, 1973; Agnello and Donnelley, 1975; Santopietro and Shabman, 1992; Beck et al., 2004). In Virginia, they provide the lessee exclusive and transferable rights to cultivate shellfish on state-owned submerged bottomland[1] for at least 10 years.

Despite recent growth in oyster landings and leased area in Virginia, production levels are still far below historical amounts, and Beckensteiner et al. (2020) found that, from 2006 to 2016, only 33% of leases were ever used for oyster production. Though in theory leases are for the “planting or propagating [of] oysters” (Virginia Code, Chapter 6, 28.2-603), in practice, minimal evidence is required to demonstrate use and enforcement mechanisms are limited, leading to leases potentially being obtained for a variety of non-aquaculture uses (Beckensteiner et al., 2020). Due to the low annual lease fees in Virginia (the lowest in the US, $1.50/acre/year), individuals may apply for a lease without the intention of using it for oyster culture in the immediate future (Mason, 2008). Some leaseholders are thought to be motivated by speculative leasing (with the intent of future resale at a profit; Mason, 2008) or may be driven by the desire to impede development of oyster farming “in their backyard” (“Not in my backyard” attitude; Dear, 1992). Previous research observed non-used leases in more populated, high-income regions, and also that non-used leases tended to be purchased later on by leaseholders possessing

[1] This includes areas from the mean low tide mark averaged over the past 20 years to three miles offshore (Virginia Code, Chapter 12, 28.2).

multiple leases, consistent with both speculative and exclusionary utilization (Beckensteiner et al., 2020).

Surrounding socioeconomic conditions that are correlated with the non-use of leases may also influence the degree of use and production efficiency, i.e., observed production as compared to maximum feasible production given available resources and assuming that aquaculturists aim to maximize profit. Though underutilization and non-use are two different phenomena, they may have similar underlying drivers and it is reasonable to expect that lease utilization could be affected by the surrounding socioeconomic environment and spatial context (e.g., reduced levels of utilization or increased inefficiency in higher density, higher income, or nearshore areas where user-conflicts might be more prevalent). Quantifying potential underutilization and its drivers as related to lease siting and the location of production is important for improving economic performance of the aquaculture sector, evaluating tradeoffs and barriers associated with aquaculture development, and furthering economically and socially efficient Marine Spatial Planning (MSP).

Empirical production frontier models have been widely used to examine the efficiency and capacity utilization of aquaculture industries. In general, these models use observations of actual commercial production together with associated inputs to construct the efficient production frontier - the maximum amount of output producible for a given input level (Farrell, 1957). Capacity utilization is the potential output producible given a set of fixed inputs (Kirkley, 2002). Two popular econometric approaches to evaluate production efficiency and capacity utilization include Stochastic Frontier Analysis (SFA; Aigner et al., 1977) and the non-stochastic Data Envelopment Analysis (DEA; Charnes et al., 1978). Production frontier analyses have been extensively used for estimating technical efficiency (TE, i.e., the difference between observed production and efficient production) in the aquaculture industry (see Iliyasu et al., 2016 and Sharma and Leung, 2003 for reviews of 41 aquaculture production frontier models), with most existing econometric studies examining aquaculture production considering discretionary, or controllable, inputs related to area used, feed, seed, labor (e.g., number of hours fished), technology (e.g. boat size, fuel), and effort intensity (crew number). Inefficiencies, meanwhile, have been investigated as related to farmers' skill, education, experience, or social network (Sharma and Leung, 2003; Chiang et al., 2004; Iliyasu et al., 2016; Scuderi and Chen, 2019). Schrobback et al. (2014) assessed capacity utilization for the Moreton Bay oyster aquaculture industry and considered size of the lease as a single fixed input.

Environmental inputs have rarely been explicitly incorporated into econometric models of aquaculture production (Schrobback et al. (2018), who included temperature and salinity in a revenue function for oyster production, is a notable exception). Clearly, environmental parameters determine the biological feasibility of aquaculture production, and environmental variables have been used extensively in biophysical production carrying-capacity models such as the Farm Aquaculture Resource Management (FARM) and *ShellGIS* (Ferreira et al., 2009; Silva et al., 2011; Newell et al., 2013). Though these models have been validated using empirical data, they do not construct production frontiers based upon observations of commercial farm production, nor are they able to assess interactions between contextual variables and farm output, efficiency, or lease use (McKindsey et al., 2006, Ferreira et al., 2009). In this study, we utilize non-discretionary environmental data to construct production frontiers for leases producing oysters with intensive culture methods in Virginia. These environmental production frontiers characterize potential production given the size of a lease and average environmental conditions experienced during grow out, and are based on observations of actual commercial production.

Efficient production observations are those producing the most among the set of leases with comparable sizes and environmental conditions. Inefficiency, or underutilization in this context, does not correspond to the technical production process (i.e., how farm-controlled inputs are transformed into outputs), but is instead related to the utilization of space given the underlying environment. Consequently, we use the term Lease Capacity Utilization (LCU) to describe lease performance in comparison to the empirical environmentally-determined production frontier.

The primary goal of this study was to assess how leaseholders used leased areas and the existing environment for oyster production. LCUs for oyster production were estimated from 2007 to 2016 using both SFA and DEA models. Capacity utilization rates were compared between the two methods and consistencies or inconsistencies identified. Model outputs were used to 1) estimate the extent of inefficiency in utilization of leased areas actively producing oysters with intensive culture methods, and 2) determine drivers of lease utilization related to leaseholder characteristics and the spatial context of production. The development and application of models that incorporate environmental and socioeconomic data in assessing aquaculture production potential is essential to improved MSP that promotes efficient utilization of space, reduces user-conflicts, and addresses tradeoffs inherent in aquaculture development.

2. Methods

2.1. Production frontier models

We developed and compared two common production frontier models that measure efficiency, the SFA (Aigner et al., 1977) and the non-stochastic DEA (Charnes et al., 1978). Both empirical methods consider observations of current production relative to the corresponding maximum output feasible, i.e., the efficient production frontier for a given set of inputs (Farrell, 1957).

Annual Lease Capacity Utilization (LCU) scores were computed from both SFA and DEA models for each lease during every year of oyster production. LCU could range from 0 to 1. If LCU is equal to one, the lease is on the frontier and its use is efficient, i.e., producing as much or more in comparison to other actively producing leases with similar sizes and environmental conditions. If LCU is less than one, the lease is not achieving maximum production and is therefore less efficient and underutilized for intensive oyster aquaculture.

2.1.1. Stochastic Frontier Analysis (SFA)

The SFA allows simultaneous estimation of inefficiencies and noise due to the inclusion of a composite error term (Aigner et al., 1977). The output-oriented log-linear translog stochastic production frontier model can be written as:

$$ln\, y_{i,t} = \beta_0 + \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}} \boldsymbol{\beta_k} ln\, x_{k,i,t} + \frac{1}{2}\sum_{\boldsymbol{j=1}}^{\boldsymbol{J}}\sum_{\boldsymbol{k=1}}^{\boldsymbol{K}} \boldsymbol{\beta_{jk}}\, ln\, x_{j,i,t}\, ln\, x_{k,i,t} + v_{i,t} - u_{i,t}. \qquad (1)$$

In (1), the response variable $ln(y_{i,t})$ is log-transformed output for the i^{th} observation at time *t*. $ln(x_{k,i,t})$ are the j^{th}/k^{th} log-transformed inputs of production associated with the i^{th} observation at time *t*. βs are unknown parameters to be estimated and β_0 is the intercept coefficient. $v_{i,t}$ are the random errors, independently and identically distributed with mean of zero and variance σ^2_v ($v_{i,t} \sim N(0, \sigma^2_v)$). $u_{i,t}$ are the non-negative random deviations associated with production inefficiencies, independently and identically distributed and assuming a normal distribution truncated at zero, with mean $\mu_{i,t}$ and variance σ^2_u ($u_{i,t} \sim N^+(\mu_{i,t}, \sigma^2_u)$, Aigner et al., 1977).

The lease capacity utilization model was specified following Battese and Coelli (1995) as:

$$u_{i,t} = \boldsymbol{Z_{i,t}}\, \boldsymbol{\delta_{SFA}} + \epsilon, \tag{2}$$

where $\boldsymbol{Z_{i,t}}$ is a (1 x m) vector of explanatory contextual variables possibly explaining lease utilization inefficiencies, some of which were log-transformed, and $\boldsymbol{\delta_{SFA}}$ is a (m x 1) vector of unknown parameters to be estimated. ϵ are the random errors with a half-normal distribution (i.e., to ensure u>0).

SFA lease capacity utilization for the i^{th} observation at the t^{th} time were calculated as:

$$LCU_{SFA\ i,t} = \frac{y_{i,t}}{y'_{i,t}} = \frac{e^{(\beta_0 + X_{i,t}\beta + v_{i,t} - u_{i,t})}}{e^{(\beta_0 + X_{i,t}\beta + v_{i,t})}} = e^{-u_{i,t}}, \tag{3}$$

which defines LCU as the ratio of observed output to the predicted maximum feasible output when it is affected by random variability alone.

Production frontier and inefficiency model parameters were estimated simultaneously by maximum likelihood in R (R Core Team, 2018) with the *frontier* package (Coelli and Henningsen, 2017). Marginal effects of inefficiency variables were calculated in the *frontier* package following the formula derived in Olsen and Henningsen (2011). We performed a likelihood ratio test to evaluate whether inclusion of the inefficiency term, $u_{i,t}$, significantly improved model fit (H_A: $\sigma^2_u \neq 0$), i.e., the null hypothesis was that variation in production simply reflects noise (H_0: $\sigma^2_u = 0$) and the model reduces to a simple ordinary least squares (OLS) regression. Relative importance of the inefficiency term was represented by γ, the ratio of σ^2_u/σ^2, where σ^2 is the sum of the noise and inefficiency variances.

In order to test for time-varying efficiency, an alternative SFA, the Error Component Frontier (ECF), was also developed based on Battese and Coelli (1992) in which LCUs may vary over time. Though as contextual inefficiency variables are ignored in this model, we focus here on the time invariant SFA (see Supplementary Table S1 for ECF results).

2.1.2. Data Envelopment Analysis (DEA)

DEA is a linear programing (LP) method first introduced by Charnes et al. (1978) and used to assess efficiency of a specific observation against the empirical efficient frontier defined by the most efficient observations of a group. Banker et al. (1984) extended the model to allow variable return to scale (VRS) to account for variability in the relationship between inputs and outputs across different levels of production. Given J_t leases at time t, each producing a single output with K different fixed inputs, the output-oriented VRS DEA model for the i^{th} lease in the t^{th} time can be formulated as:

$$\max_{\theta_{i,t},\lambda_{i,j,t}} \theta_{i,t} \tag{4.1}$$

such that:

$$\textstyle\sum_j \lambda_{i,j,t} y_{j,t} - \theta_{i,t} y_{i,t} \geq 0, \tag{4.2}$$

$$\textstyle\sum_j \lambda_{i,j,t} x_{j,k,t} - x_{i,k,t} \leq 0, \qquad \text{k=1,…, K} \tag{4.3}$$

$$\textstyle\sum_j \lambda_{i,j,t} = 1, \qquad \text{j=1,…, } J_t \tag{4.4}$$

$$\lambda_{i,j,t} \geq 0. \tag{4.5}$$

In (4.1-4.5), the i^{th} lease produces $y_{i,t}$ oysters at the t^{th} time with $x_{i,k,t}$ units of the k^{th} fixed input (i.e., lease size and environmental conditions). In this LP, the objective is to maximize $\theta_{i,t}$, the proportional increase (i.e., scalar multiplier) in output (i.e., oyster production) possible for the i^{th} lease at the t^{th} time (4.1) while remaining within the production possibility set. $1/\theta_{i,t}$ defines an efficiency score between 0 and 1. Each lease's utilization score in each year is calculated relative to an efficiency frontier where observations from the most efficient leases (largest production for a given input level) serve as benchmarks to inefficient leases. $\lambda_{i,j,t}$ is a non-negative scalar that places positive weight on observations that define the efficient frontier, which is constructed as a linear combination of efficient observations for each lease *i* at each time t. If $\theta_{i,t}$ equals 1 and $\lambda_{i,j,t}$ equals 0 for all $j \neq i$, then lease *i* is efficient and lies on the frontier. Four constraints have to be considered to ensure the projected point does not lie outside the feasible set. First, observations of outputs and inputs by leases on the production frontier described by $(\lambda_{i,j,t}x_{j,1,t}, \ldots, \lambda_{i,j,t}x_{j,K,t}; \lambda_{i,j,t}y_{j,t})$ have to be greater than or equal to (for output) or less than or equal to (for inputs) output and input levels for lease *i* at time *t* (4.2-4.3). Constraints (4.4) and (4.5) introduce restrictions related to returns to scale and ensure convexity. These constraints require that the sum of non-negative weights over all leases for a given lease *i* at time *t* equal one, such that lease *i* is only benchmarked against observations of similar scale. The LP problem needs to be solved $\sum_{t=1}^{T} J_t$ times, once for each lease *i* in each time period *t* (i.e., for each production observation). DEA lease capacity utilization for the i^{th} lease at the t^{th} time was calculated as:

$$LCU_{DEA\ i,t} = \frac{y_{i,t}}{\widehat{y_{i,t}}} = \frac{y_{i,t}}{y_{i,t}\theta_{i,t}} = \frac{1}{\theta_{i,t}}. \tag{5}$$

By construction, $LCU_{DEA\ i,t}$ are biased upward (Simar and Wilson 1998) and need to be corrected. This can be done through a smoothed bootstrap procedure[2] (Simar and Wilson, 2008; Bogetoft and Otto, 2011) that allows the construction of confidence intervals around efficiency scores and estimation of bias-corrected efficiency, i.e., $LCU^{*}_{DEA\ i,t}$.

Given bias-corrected estimates of utilization, $LCU^{*}_{DEA\ i,t}$, we used a linear regression model to explain potential drivers (Banker and Natarajan, 2008):

$$LCU^{*}_{DEA\ i,t} = \boldsymbol{Z_{i,t}}\ \boldsymbol{\delta_{DEA}} + \varepsilon, \tag{6}$$

[2] Repeated sampling from a smoothed version of the empirical (discrete) distribution of the efficient frontier, using kernel densities.

with $\boldsymbol{Z_{i,t}}$ a (1 x *m*) vector of explanatory contextual variables possibly explaining lease capacity utilization, some of which were log-transformed, $\boldsymbol{\delta_{DEA}}$ a (*m* x 1) vector of unknown parameters to be estimated, and ε a normally distributed random error. As DEA linear regression coefficients are in terms of efficiencies, when reporting coefficients estimated from (Eq. 6) we have reversed their sign to ease comparison with inefficiency parameter estimates from the SFA model.

DEA calculations (bootstrapped 2,000 times) were performed by minimal extrapolation[3] in R (R Core Team, 2018) with the *benchmarking* package (Bogetoft and Otto, 2018).

2.1.3. Conceptual and methodological differences between the two approaches

The SFA and DEA techniques differ in a number of ways (summarized in Table 1). First, while the DEA attributes all deviations from the frontier to inefficiencies, the SFA assumes two unobserved error terms related to inefficiency and statistical noise or measurement error. Although the deterministic nature of DEA can be argued to be a limitation, in that it does not account for random variations in output, it might also be viewed as a strength, in that no pre-defined functional relationship between inputs and output is required. Since SFA is a parametric approach, it requires an a priori functional form to be specified, such as the log-linear translog production function, and assumes specific distributions for the two error terms. When time effects were ignored in the SFA, one frontier was estimated for all observations, whereas DEA frontiers were calculated considering only observations from the same time period. An advantage of the SFA is that it simultaneously estimates parameters of the stochastic production frontier and parameters of the inefficiency model (Battese and Coelli, 1995), whereas DEA requires a

[3] The smallest production possibility set containing all observations and fulfilling model assumptions.

two-step procedure: first estimates of efficiency scores are produced, and then those estimates are regressed against variables thought to influence inefficiency. As the two methods are conceptually different and each has its own limitations, it is meaningful to apply and compare both approaches to evaluate LCU. Rank-based correlation between $LUE^{*}_{DEA\ i,t}$ and $LUE_{SFA\ i,t}$ scores was assessed with a Spearman test.

2.2. Data collection and processing

We analyzed leased grounds active during the period 2007-2016 in the Virginia waters of the Chesapeake Bay (Fig. 1). Data considered for the models defined above consisted of a set of lease, oyster harvest, environmental, management and socio-economic variables collected from the Virginia Institute of Marine Science (VIMS), the Virginia Marine Resource Commission (VMRC), the Virginia Department of Health (VDH), and the Internal Revenue Service (IRS). These data were combined together in a spatially-explicit PostgreSQL/PostGIS database (see Beckensteiner et al., 2020, for a complete description of data collection and processing).

2.2.1. Annual oyster production per lease

Lease polygons were available publicly through the VMRC's Chesapeake Bay Map[4], which also included leaseholder names and mailing addresses. We analyzed commercial leases with intensive oyster production reported between 2007 and 2016. Time series of annual oyster harvest per lease were provided by VMRC. Harvest data were separated by lease identification number, gear, and year. Intensive oyster production consists of production from bottom cages (81% of intensive oyster production data), rack and bags (8%), water column cages (2%), net

[4] https://webapps.mrc.virginia.gov/public/maps/chesapeakebay_map.php

pins (<1%), and other containerized gears including floats (8%). Leases in shellfish condemnation zones (provided by VDH) were not considered in our analyses since production is unlikely in upstream tidal waters (i.e., waters too fresh for optimal oyster growth) or polluted waters. Leased grounds on the Atlantic coast of the Eastern Shore (Fig. 1) were omitted because they are mostly used for hard clam (*Mercenaria mercenaria*) production and our environmental variables also did not adequately cover this region. Finally, since oysters may require two to three years to reach market size and leaseholders often need time to build financial capital and production infrastructure, efficient production might not be expected for leases two years old or younger. Leases under three years of age were therefore excluded from the analyses.

2.2.2. Non-discretionary environmental inputs

The production frontier models used lease size and environmental variables as fixed production inputs. Information about environmental conditions in the Chesapeake Bay were derived from an estuarine biogeochemical model, ChesROMS-ECB, which has an average grid resolution of 1.7 km (Feng et al., 2015). Values from the nearest ChesROMS grid cell within 1.7 km were extrapolated to leases not covered by the ChesROMS grid (i.e., in upstream areas of small tributaries; Fig. 1, darker gray cells). When several grid cells overlapped with a lease, the weighted sum of each environmental variable's value over those grid cells was assigned to the lease. Impacts of environmental factors on oyster growth and survival might be observed in production data for up to three years as oysters can require two to three years to reach market size (76 mm shell length; Harding, 2007). Therefore, we calculated spring averages (March to June, peak of growing season) over the two years preceding and up to the given year of an oyster production observation. Model results from ChesROMS-ECB were only available from 2003 to

2014, therefore, values for 2015 were based on the average between 2013 and 2014 observations, while values for 2016 were solely approximated by the 2014 value. It was thought this would not significantly impact production estimates since temporal variability was considerably smaller than spatial variability for all environmental variables and over the scales of this study. ChesROMS variables were all predicted at the base of the water column since about 80% of production observations were from bottom cages. The ChesROMS data include temperature, salinity, particulate organic carbon (POC), dissolved oxygen (O_2), chlorophyll *a* concentration, current velocity, and dissolved inorganic nitrogen (DIN). All can potentially reflect ambient water quality and influence oyster growth. Among these, we selected four environmental variables for inclusion in SFA and DEA models to reduce model collinearity (Supplementary Figure S1) and choose factors typically used in FARM models (Ferreira et al., 2009, Silva et al., 2011). Selected input variables were water temperature, salinity, dissolved oxygen (O_2), and particulate organic carbon (POC), each of which is thought to impact fundamental biological processes such as growth, disease, nutrition and respiration. Indeed, eastern oyster filtration capacity depends on water temperature and is optimal between 15 ºC and 25 ºC (Loosanoff, 1958). Eastern oysters can tolerate a broad range of salinity (5-40 psu, tolerance depending on life stage), but prefer upper mesohaline to polyhaline salinities (15-30 psu, Barnes et al., 2007). Although higher salinity could boost oyster growth, it is also associated with increased prevalence of the pathogens MSX (caused by *Haplosporidium nelsoni*) and Dermo (caused by *Perkinsus marinus*) (Haven et al., 1981; Shumway, 2011). POC was used as a proxy for food availability. O_2 level was a surrogate for anoxic and hypoxic conditions since oyster metabolism is significantly affected at O_2 concentrations lower than 3ppm (Wallace, 2001; Seitz et al., 2009).

Depth is more generally used in habitat suitability models for oyster production as a proxy for averaged environmental conditions (i.e., no temporal variability) and depth values shallower than 3m are usually more optimal for oyster production (Theuerkauf and Lipcius, 2016). Average depth per lease was included as an additional input characterizing the environment and was derived from a NOAA/NOS estuarine bathymetry digital elevation model, with a resolution of 10 m (National Centers for Environmental Information, 2017). Depth values, which were initially negative, were transformed to be strictly positive since SFA and DEA models require non-negative input values (the transformation preserved ordering of values with lower values corresponding to deeper areas). Summarized statistics of each input used in our analyses are given in Table 2.

2.2.3. Contextual variables

For analyses of factors influencing potential lease use inefficiencies, we included a set of variables related to the leaseholder, local spatial context, and socioeconomic conditions. The number of leases held per leaseholder per year was considered as potentially influencing lease capacity utilization (note that this number can comprise leases not included in this analysis, such as leases used with extensive gears, leases not used, or leases in polluted zones). Leaseholders owning several leases were thought to be larger, horizontally integrated operations and, therefore, potentially more efficient (e.g., due to economies of scale that reduce the average cost of production). Lease age was also included to account for experience level and temporal change, with older leases expected to have higher levels of utilization and be more efficient. This was reasonable because all leases in our dataset were continuously held by the same leaseholder during the study period 2007-2016 (i.e., no instances of lease turnover). A dummy variable "alternative gear" was set equal to one if any gears other than on-bottom cages were used on the lease and zero otherwise, indicating bottom cages were used. This variable was expected to increase efficiency since off-bottom systems could promote faster growth from a food-enriched water column and increased survival from lower predation exposure (Walton et al., 2013). Another dummy variable “both practices” was included to capture if a leaseholder was simultaneously producing oysters from both intensive and extensive practices from the same lease in a given year. Diversification of production methods was expected to decrease lease capacity utilization for intensive production as it may involve increased infrastructure and costs and reduce space available for intensive culture. Distance between a lease and its leaseholder’s home ZIP code centroid was also included (though leaseholder addresses were available, most were PO Boxes; Beckensteiner et al., 2020). Close proximity to a leaseholder’s home ZIP code was thought to enhance lease use via improved access and surveillance of grounds.

In prior research, actively used leases were also observed to be in close proximity to natural oyster beds, which are reserved for public use, as well as in congested areas with many other leases (Beckensteiner et al., 2020). A dummy variable “adjacent to Baylor” was included to assess if proximity to public Baylor grounds was a driver of lease utilization. Baylor grounds polygons were available publicly through the VMRC’s Chesapeake Bay Map. The fraction of leased acreage from different leaseholders within a 1 km buffer of a lease was used as a proxy for local congestion or agglomeration effects. Lease productivity was empirically observed to be higher in extremely shallow waters, potentially due to easier access (e.g., without a boat). The variable “deep area” was created as the ratio of leased area deeper than 0.5 m divided by the total leased area, with a larger fraction of a lease in waters deeper than 0.5m expected to reduce efficiency. Non-used leases were previously found to be in close proximity to Submerged Aquatic Vegetation (SAV) (Beckensteiner et al., 2020). SAV grounds compete for shallow space with cultured oysters as current management does not allow aquaculture in areas occupied by SAV (Wagner et al., 2012). The presence of SAV was therefore expected to have a negative impact on lease utilization for oyster production. A dummy variable “SAV present” was equal to one if the distance between a lease and a SAV ground was null during the t^{th} year, meaning that the lease was touching or partially covered by SAV grounds (annual SAV polygons provided by VIMS).

Finally, local socioeconomic conditions were represented by population density, approximated as the total number of personal and dependent tax exemptions for a ZIP code (i.e., number of exemptions is considered to be a proxy for number of people) divided by ZIP code area, and per household income, estimated as the total adjusted gross income for a ZIP code (adjusted for inflation) divided by the number of returns. These data were available annually from 2007 to 2016 from individual income tax statistics (IRS, 2019) and the values from the nearest ZIP code area were assigned to each lease. Lease utilization was expected to be lower in higher density and higher income regions, where user-conflicts might be more prevalent (Beckensteiner et al., 2020).

2.3. Model specifications summary

Annual oyster production per lease from intensive practices constituted outputs for the SFA and DEA models, with log-transformed production used in the SFA. Associated fixed inputs to construct efficient lease use frontiers in both approaches included lease size (discretionary) and temperature, salinity, O_2, POC, and mean depth (non-discretionary). All input variables were log-transformed for the SFA. Positive monotonic relationships between oyster production and input variables were expected, allowing their inclusion in the DEA under an assumption of free disposability (i.e., that increases in inputs should not decrease output). Factors potentially explaining lease capacity utilization included the number of leases held by the leaseholder, lease age, use of alternative gear, diversified production practices, distance to leaseholder ZIP code, adjacency to Baylor grounds, the fraction of nearby leased acreage from other leaseholders, the fraction of lease area deeper than 0.5m, SAV presence, population density, and average income (Table 3). There were 823 annual production observations from 297 leases and 200 leaseholders over 10 years (2007 to 2016). Mean annual oyster production per lease $y_{i,t}$ was 2,473 (±5,796) lbs (Table 2).

2.4. Oyster production forecasting

Oyster production forecasts were based strictly on environmental conditions using a simplified Cobb-Douglas SFA specification (equivalent to (1) where all $\beta_{jk} = 0$, i.e., interactions between inputs were not considered). Output, input and contextual variables were identical to those used in Eq.(1) (see Supplementary Table S2 for Cobb-Douglas results).

Predictions of maximum oyster production for an average size lease were calculated for each ChesROMS-ECB grid cell as:

$$\widehat{y_r} = e^{\beta_0 + X'_r \beta_k}. \tag{8}$$

$\widehat{y_r}$ is the predicted efficient production for the grid cell r. $\boldsymbol{\beta_k}$ is a (k x 1) vector of unknown parameters to be estimated from the Cobb-Douglas model and β_0 is the corresponding intercept coefficient. X'_r is a matrix of log-transformed inputs consisting of (constant) mean lease size, (spatially-varying) spring means of model outputs from ChesROMS and mean depth over the ChesROMS grid cell. ChesROMS model outputs were averaged over the period 2003 to 2014 for each grid cell. Estimates should be interpreted as maximum feasible oyster production for an average sized lease in a particular location based upon average environmental conditions and depth. Oyster production was forecast for the Virginia portion of the ChesROMS grid and restricted to leasable area as estimated in Beckensteiner et al. (2020) (i.e., legally leasable Chesapeake Bay area excluding Baylor grounds, clams grounds, shellfish condemnation zones, and waters deeper than 8m).

3. Results

3.1. SFA

3.1.1. SFA production frontier

We first specified a SFA with time-varying lease effects, ignoring contextual inefficiency variables (i.e., the ECF specification), in order to test for time-varying efficiency. Efficiencies were found to not change significantly over years (p-value = 0.3, Supplementary Table S2). We then ran the time-invariant SFA model including the $\boldsymbol{Z}_{i,t}$ vector of contextual variables to examine the drivers of inefficiencies. Lease size, temperature, POC and O_2 were found to significantly affect oyster production (Table 4). Lease size had a significant and positive influence on production of oysters: for every 1% increase in lease size, a 0.41% increase in oyster production was observed, suggesting decreasing returns to scale. There were significant interactions between temperature, POC and O_2 (Table 4). While temperature and food (i.e., POC) are drivers for oyster production, the negative effect of the interaction between O_2 and temperature on oyster production would suggest the potential importance of hypoxic conditions.

3.1.2. SFA lease capacity utilization

A likelihood ratio test was used to verify whether adding the inefficiency term $u_{i,t}$ significantly improved the fit of the model. The null hypothesis (H_0: σ^2_u=0, i.e., no inefficiency, only noise) was rejected (p-value <0.001), indicating that the fit of the SFA model was significantly better than the fit of the corresponding OLS model, and that significant lease use inefficiency existed. Relative importance (γ) of inefficiency in oyster production as compared to noise was equal to 0.83 (significant at 5% level, Table 4), indicating that inefficiency was the primary factor explaining deviations from the production frontier (γ>0.5). Predicted $LCU_{SFA\ i,t}$ across all observations from 2007 to 2016 ranged from ~0.0003 to 0.80, with a mean $LCU_{SFA\ i,t}$ of 0.27 (±0.21) (Figure 2A). This finding suggests that output from existing leases could scale up considerably or, alternatively, the area leased could be reduced.

3.1.3. Causes of inefficiency from the SFA

Since the dependent variable of the inefficiency model (Eq. 2) was defined in terms of inefficiency, a negative coefficient of a contextual variable in this model indicated that the variable reduced inefficiency, whereas a positive value indicated an increase in inefficiency. The number of leases per leaseholder was found to decrease lease use inefficiency (p-value <0.001), with every 1% increase in the number of leases per leaseholder producing an increase of 1.1% in $LCU_{SFA\ i,t}$ on average. Proximity to Baylor grounds was also found to increase lease use efficiency. On the other hand, distance to the leaseholder's home ZIP code, the fraction of lease area deeper than 0.5m, presence of SAV, population density and average income of the nearest ZIP code were all found to significantly increase inefficiency (p-values<0.05). For example, there were 2.7% and 1.8% decreases in $LCU_{SFA\ i,t}$ for every 1% increase in proportion of deep area and average income of the nearest ZIP code, respectively (Table 4 and Figure 3). The age of the lease had a positive effect on oyster production that was marginally significant (p-value<0.1), indicating that older leases were more efficiently used.

3.1.4. Predictions of oyster production

Predicted oyster production according to a Cobb-Douglas SFA specification was calculated for areas in the lower portion of the Chesapeake Bay (Figure 4A). Mouths of all major tributaries other than the Potomac river and the southeastern portion of the mainstem of the Chesapeake Bay were the most productive regions, likely driven by intermediate temperature levels and high concentrations of O_2 (Supplementary Figure S3). The upper range of maximum oyster production predictions (i.e., 4,500-7,000 lbs/average size lease, Figure 4 dark red) corresponds to the upper 85th percentile of observed production. When predictions were restricted to leasable area only (Figure 4B), east of the northern peninsula and southern and eastern portions of the mainstem of the Chesapeake Bay offered the highest production opportunities. The east of the mainstem also corresponds to areas with lower population density, whereas most other areas predicted to be highly productive abutted against high population densities (Figure 4C).

3.2. DEA

3.2.1. DEA lease capacity utilization

DEA estimated bias-corrected lease capacity utilization ($LCU^*_{DEA\ i,t}$) measures were produced for the same number of observations (lease-year combinations) using the same output and input variables as for the SFA. The estimated mean $LCU^*_{DEA\ i,t}$ was 0.25 (±0.24), while estimates ranged from 1.9e-5 to 0.74 (Figure 2B, Table 5). 29.53% of observations had non-bias-corrected $LCU_{DEA\ i,t}$ equal to 1 (Supplementary Figure S4), i.e., the efficient frontier observations. The frontier smoothing bootstrap placed most of these observations at an efficiency level near 0.6

(Figure 2B). Rank-based correlation between $LCU^{*}_{DEA\ i,t}$ and $LCU_{SFA\ i,t}$ scores was significantly positive (ρ= 0.65, p-value <0.05).

3.2.2. Causes of inefficiency from the DEA-OLS

Lease use inefficiency determinants identified by the DEA-OLS procedure were generally consistent with, though not identical to, those from SFA (Table 5). Coefficients of the number of leases per leaseholder and proximity to Baylor grounds were found to be negative and statistically significant (e.g., there was an increase of 3.6% in $LCU^{*}_{DEA\ i,t}$ for every 1% increase in the number of leases held by a leaseholder). This implies that lease use for oyster production by leaseholders with more leases (larger production scale), and from leases adjacent to public grounds, was more efficient (Figure 3B). Conversely, coefficients of the presence of SAV and population density had a positive sign and were statistically significant, indicating that leases with SAV grounds present or those in more populated areas were less efficiently used (Figure 3C; e.g., there was a decrease of 4.9% in $LCU^{*}_{DEA\ i,t}$ for every 1% increase in population density).

4. Discussion

We introduced the concept of "Lease Capacity Utilization", which considers the fixed inputs of available space and environmental conditions as defining production possibilities. This is a valuable utilization of traditional econometric production frontier methods for aquaculture performance assessment where environmental conditions are typically not well integrated in analyses (Sharma and Leung, 2003; Iliyasu et al., 2016). This analysis of Virginia lease use and inefficiency for intensive oyster production builds on and complements a prior analysis showing that many subaqueous leases in the Virginia part of the Chesapeake Bay are not used at all for oyster production, be that intensive or extensive (Beckensteiner et al. 2020). Similar factors driving non-use and correlated to surrounding socioeconomic conditions and leaseholder characteristics also lead to significant production inefficiency.

Although characterized by different underlying assumptions and constraints, both production frontier models revealed significant inefficiencies in intensive aquaculture practices in the Virginia waters of the Chesapeake Bay. A majority of LCU scores were less than 0.5, revealing substantial lease use inefficiency. On average, an active lease had an efficiency level of 0.27 ±0.21 (SFA result) or 0.25 ±0.24 (DEA result), meaning that the industry was operating on average 73% (75% with the DEA) below the maximum potential production, given the environment and size of leased area (note the large standard deviations however). To achieve a more efficient use of space and the existing environment, oyster production per lease could increase and/or the amount of space leased could be scaled down. It is believed that producers often only use a small fraction of their lease for oyster production (Beckensteiner et al., 2020; B. Stagg, VMRC, pers. comm.). Whether it is for the allocation of buffer zones against other aquaculturists or poachers, to allow for rotational harvesting[5] techniques, due to a lack of knowledge of where suitable grounds are when applying for a lease, or for other speculative or non-harvest-related reasons, producers tend to lease much more area than needed. Low ground rental costs provide little barrier to this behavior. This has probably contributed considerably to observed low levels of LCU. It is worth mentioning that fully efficient use may not be achievable, at least in the immediate future, due to constraints related to seed availability and oyster diseases (Schulte, 2017), potential triploid mortality events (Guévélou et al., 2019), and

[5] No evidence was found to suggest leases operating in a rotational manner were more efficient than others.

the presence of unsuitable substrate (sand and hard bottom are preferred for cages, B. Stagg, pers. comm., though floating gear could be used more widely). Other leaseholder-specific financial or technical factors may also constrain this expansion (e.g., available labor, capital, time, waterfront access). Nevertheless, the findings presented here strongly suggest that many leases are producing far under their maximum capacity. Overall, significant opportunity exists for improvement in lease use efficiency for oyster production in Virginia.

Though there were some contrasting results between the two different approaches (e.g., in terms of the relative impact of different explanatory variables on the magnitude of inefficiency), overall the models yielded similar conclusions and had four significant contextual variables in common. $LCU^{*}_{DEA\ i,t}$ and $LCU_{SFA\ i,t}$ scores were significantly correlated and mean scores were close (0.25 vs 0.27), however the median $LCU^{*}_{DEA\ i,t}$ was lower than $LCU_{SFA\ i,t}$ (0.12 vs 0.23, Figures 2 and 3). This is consistent since DEA does not accommodate any random noise, and other studies have found differences similar to those seen here (see Theodoridis and Anwar, 2011, for several comparisons of technical efficiency scores between the two approaches, and Odeck and Bråthen, 2012, for a meta-analysis of DEA and SFA studies). Odeck and Bråthen (2012) observed that TE scores were often higher for DEA and for panel data, however those studies used non-bias corrected scores. Differences in scores could also be due to whether the frontier was estimated yearly, such as the DEA, or estimated without a time effect such as our SFA (Hjalmarsson et al., 1996). Furthermore, the fact that a sizeable proportion of observations were found to be more efficient with DEA (peak near 0.6, due to 30% of observations having non-bias corrected $LUE_{DEA\ i,t}$ equal to 1) may be due to the inclusion of six inputs, which reduced the set of comparable leases for each production observation. Overall, despite considerable differences in functional form, assumptions, and constraints defining the translog

SFA and DEA models used in this study, LCU scores and underutilization drivers were similar and robust to these differences.

Potential increases in LCU depend on drivers of inefficiency. We found that the number of leases per leaseholder was a common factor influencing LCU between the two approaches. Larger producers (in terms of total production and number of leases, Figure 3 A and B) were the most efficient. The number of leases could be seen as a proxy for unobservable variables related to the scale of operation such as access to hatchery seed and organizational infrastructure. Leaseholders with several leases can also operate in a rotational manner to exploit different habitats. Although lease size had a positive effect on oyster production, this variable's coefficient indicated decreasing returns to scale at the individual lease level. These combined results indicating possible returns to scale at the organizational but not lease level, imply that more and smaller leases held by fewer leaseholders could bring efficiency gains in the utilization of space for intensive culture. This is not entirely surprising given prior research has frequently found scale efficiencies in aquaculture production (Chiang et al., 2004; Schrobback et al., 2014). Tradeoffs between industry consolidation, average lease size, and production efficiencies are important policy considerations for resource managers and stakeholders.

In areas where non-used leases are more prevalent, productive leases were also found to be less efficiently used. LCU was found to decrease significantly in more populated, high-income regions, as well as for leases adjacent or partially covered by SAV. These results are similar to those for differences between used and non-used leases in Virginia (Beckensteiner et al., 2020), suggesting that factors driving non-use may also lead to significant production inefficiencies and underutilization. In more populated, and potentially more heavily congested areas, leaseholders may tend to lease more area than needed to secure their activity, hence lowering their production per unit area. Growth of SAV and intensive aquaculture have been identified as mutually exclusive uses of the bottom grounds, generating concern and use conflict in many coastal areas of Virginia (Hershner and Woods, 1999). However, ecologically beneficial interactions between SAV and cultivated oysters is a growing research area and suggests the possibility of complementary use (M. Berman, pers. comm.). In contrast, leases closer to their leaseholder's ZIP code and in shallower waters were more efficiently used, plausibly due to better access. Finally, LCU increased for leases adjacent to the Baylor grounds. It is possible that leases in close proximity to natural oyster reefs are characterized by harder bottom or better water quality, improving production efficiency. It is also plausible that poaching from adjacent public grounds and reporting as production from nearby leases could artificially inflate output and make a lease appear more efficient.

Surprisingly, lease age, a proxy for experience, was only marginally significant in the SFA model (p-value=0.064) and did not have a significant effect on efficiency in the DEA model. Efficiency was also found to not change significantly over time in the SFA ECF specification. Our finding may suggest a potential need for enhanced training opportunities and knowledge transfer to ensure that leaseholders learn from their past experiences, or incorporate the newest available technology (e.g., improvement of seed quality, gear developments). It is worth reiterating that intensive aquaculture is relatively new and growing in Virginia, and it is possible that the period covered in this analysis (2007-2016) does not allow enough temporal variation to detect this effect. LCUs were marginally lower (p-values <0.1) for growers who had diversified their aquaculture practices (intensive and extensive gears), suggesting diversification may reduce efficiency, as has been observed in other studies (e.g., Asche and Roll, 2013; Scuderi and Chen, 2019). Note, however, diversification in those studies was in terms of harvested species and not culture methods. Finally, there was no difference in LCU according to the gear utilized. Cages, rack and bags, and floats led to similar use efficiencies. The gear effect may be confounded with that of other variables capturing access effects (i.e., distance to leaseholder's ZIP code, proportional deep area) as alternative off-bottom gears such as floats tend to be used in deeper waters.

Our approach included fine-scale environmental variables as non-discretionary inputs defining production possibilities. Oyster survival and growth depend on many variables, including water quality (e.g. salinity, temperature, turbidity, etc.) and algal bloom occurrences (Shumway, 2011). We observed significant increases in oyster production in the SFA model with increases in temperature. Oyster production was found to be higher in warmer waters, where growth and filtration rates are usually enhanced (Shumway, 1996). However, non-quadratic and quadratic terms were significant for temperature and POC, suggesting existence of thresholds for these variables. The SFA model also highlighted several significant interactions between environmental variables (temperature, O_2, and POC) and a few negative relationships between oyster production and environmental variables (O_2 and POC). Negative impacts from POC and from the interaction between O_2 and temperature on oyster production could suggest impacts from the presence of eutrophication and hypoxic conditions, common in shallow waters estuaries (Seitz et al., 2009). Due to the several significant interactions and complex environmental response, as well as potential collinearity among input factors (Supplementary Figure S1), production forecasts using the translog specification were unstable when predicting outside of leased areas in our dataset; therefore, a simplified Cobb-Douglas model without interaction terms was used for out-of-sample predictions. Efficiency scores and **Z** variable coefficients were not substantially affected but environmental input coefficients were different, likely due to multicollinearity (Supplementary Table S2). A model using orthogonal principal components for environmental variables was also developed to eliminate collinearity between inputs. Efficiency scores and drivers were robust to this formulation, but model interpretation was less intuitive. Further analysis of environmental production frontiers to determine key environmental drivers, their interactions, and production response is an important area for future research.

Although this research was able to discern lease use inefficiency and its potential drivers in Virginia, a few aspects of the data and models deserve further consideration. While we assumed positive monotonic relationships between inputs and output in the DEA model, results from the SFA specification show that these assumptions might not hold. Existence of complex interactions between environmental variables and oyster production suggests SFA may be a more appropriate approach when constructing environmentally determined production frontiers. On the other hand, approaches exist to include environmental variables with thresholds or to simultaneously incorporate desirable inputs and detrimental inputs (i.e., inputs that decrease production) by adding a fifth constraint to the DEA linear program (Eq. 4). For example, Reinhard et al. (2000) developed a DEA given conventional inputs and environmentally detrimental inputs to control for the effects of nitrogen surplus on dairy farms. Future work could use DEA formulations allowing for costly input disposal to incorporate environmental variables thought to decrease oyster production, or variables for which positive monotonic responses may not hold. Alternative approaches also exist that relax certain LP constraints for non-discretionary inputs and use multi-stage estimation procedures (Ruggiero 1998) or fuzzy set theory (Saati et al. 2011). While we used an output-oriented DEA model, these approaches should be considered when including environmental factors in input-oriented models.

5. Conclusion

With increased pressures and uses in coastal areas, it is important that commercial aquaculture activities are efficiently developed, managed, and operated. Results of this study suggest that to achieve an efficient use of leased grounds in Virginia, oyster production could be scaled up or the amount of leased area could be scaled down. It therefore appears that production levels could grow considerably in Virginia without increasing the area needed for cultivation. It may be possible to reduce inefficiencies through lease consolidation (i.e., more leases per leaseholder), better use of leased grounds in densely populated areas (e.g., reducing area not utilized), or expansion of production into regions with low conflict though higher operational costs (e.g., the mainstem of the Chesapeake Bay or areas along the Eastern Shore). This last option of increasing production in low conflict areas seems to provide large production opportunities based on our predictions (Figure 4B), while Beckensteiner et al. (2020) found that only about 10% of leasable area in the mainstem was occupied by leases. It should be noted that in many places with good environmental conditions oyster producers may need to use alternative gears such as floating cages, which can have more restrictive permitting requirements.

Stricter management tools, such as active-use and minimum planting requirements, could be implemented to provide incentives for more efficient use of leases. Research and management efforts could also be directed to assess causes and solutions for user-conflicts, such as activity zoning. The influence of lease-level and organizational production inputs that were not considered here, e.g., seed, number of cages/other gear, labor, could be assessed in future studies to evaluate technical efficiency. This would, however, require extensive leaseholder surveys and data collection. Some of this information is currently collected regularly, although it only covers a subset of the industry (voluntary survey with larger and/or well-established producers better represented and without lease-specific information, Hudson, 2018). Estimates of technical efficiency would inform and complement estimates of lease capacity utilization explored here, as the former relates to managerial skills and application of technology, which could further elucidate factors influencing efficient use of leased grounds and the existing environment.

Our results have significant value for industry, management and scientific research., Although this study concerns Virginia intensive oyster aquaculture, a number of other states in the U.S. using leased grounds for shellfish aquaculture may have similar issues; e.g., New Jersey and Connecticut also potentially have low levels of lease use (Beckensteiner et al., 2020). Applications of the approaches developed here to these regions are likely to be similarly informative for understanding and enhancing oyster aquaculture.

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Tables

Table 1. DEA and SFA characteristics. Adapted from Bogetoft and Otto (2011).

Approach	Data Envelopment Analysis (DEA)	Stochastic Frontier Analysis (SFA)
Data generation process	Deterministic	Parametric
Deviation source	Inefficiency, u	Noise v, and inefficiency, u
Multiplicative specification	$y=f(x, \beta).e^{(-u)}$	$y=f(x, \beta).e^{(-v)}.e^{(-u)}$
Estimation principle	Minimal extrapolation	Maximum likelihood
Time effect	Yes	Ignored*
Inefficiency factors estimation	Two-steps	One-step

*Time effects are currently not implemented within the *frontier* R package for SFA estimation with Z variables.

Table 2. Summary statistics of output and input variables estimated from active intensive leases and used in the frontier analyses. Spring averages (March to June from 2005 to 2014) of ChesROMS environmental variables were calculated for the two years preceding and up to the given year of the oyster production observation.

Variable	5^{th} percentile	Median	Mean	95^{th} percentile
Oyster production (lbs/lease)	23.52	736.43	2,473.34	10,984.55
Lease size (ha)	0.81	4.96	11.95	39.71
Temperature (ºC)	14.43	16.96	16.98	19.46
Salinity (psu)	8.10	16.98	16.62	22.56
POC (mmol-C / m^3)	93.35	156.10	152.91	208.09
O_2 (mmol-O_2 / m^3)	276.45	300.50	301.30	328.35
Depth (m)	-2.41	-0.66	-0.87	-0.043

Table 3. SFA and DEA specification summary.

Output, Y	Input, X	Contextual variables, Z
Oyster production (lbs)	Lease size (ha)	Number of leases
	Temperature (ºC)	Lease age (yr)
	Salinity (psu)	Alternative gear use (dummy)
	POC (mmol-C / m^3)	Both aquaculture (dummy)
	O_2 (mmol-O_2 / m^3)	Distance to leaseholder ZIP code (m)
	Depth (m)	Adjacent to Baylor (dummy)
		Leased area by others (proportion)
		Deep area (proportion)
		SAV present (dummy)
		Population density (ind./km^2)
		Average income ($1,000/household)

Table 4. SFA production frontier and inefficiency model. Significance is denoted by: $p<0.001$='***', $p<0.01$='**', $p<0.05$='*', $p<0.1$='.'. Lower values of the depth indicator correspond to deeper areas. Positive sign of a contextual variable coefficient indicates an increase in lease use inefficiency (i.e., a decrease in LCU).

Variables	Estimate	Std. Error	P-value	Signif.	Marg. Effect
Production frontier					
Intercept	1361.968	33.827	< 2.2e-16	***	
Ln lease size	0.413	0.049	< 2.2e-16	***	
Ln temperature	312.523	12.938	< 2.2e-16	***	
(Ln temperature)^2	-41.869	9.881	2.26E-05	***	
Ln temperature * Ln salinity	-0.504	3.132	0.872		
Ln temperature * Ln O_2	-52.328	8.211	1.85E-10	***	
Ln temperature * Ln POC	20.258	5.321	1.41E-04	***	
Ln temperature * Ln depth	1.138	5.564	0.838		
Ln salinity	-46.081	39.260	0.240		
(Ln salinity)^2	0.053	0.348	0.878		
Ln salinity * Ln O_2	6.469	5.700	0.256		
Ln salinity * Ln POC	1.990	0.577	0.001	***	
Ln salinity * Ln depth	0.447	0.733	0.542		
Ln O_2	-250.268	60.516	3.54E-05	***	
(Ln O_2)^2	8.560	19.815	0.666		
Ln O_2 * Ln POC	59.026	12.273	1.51E-06	***	
Ln O_2 * Ln depth	20.772	11.144	0.062	.	
Ln POC	-368.991	78.563	2.64E-06	***	
(Ln POC)^2	-5.382	1.607	0.001	***	
Ln POC * Ln depth	-2.120	1.516	0.162		
Ln depth	-109.300	74.924	0.145		
(Ln depth)^2	-2.140	1.622	0.187		
Inefficiency model					
Intercept	-15.560	5.761	0.007	**	
Ln number of leases	-0.775	0.136	1.34E-08	***	-1.128
Lease age	-0.224	0.119	0.059	.	-0.326
Alternative gear	0.188	0.274	0.493		0.273
Both aquaculture	0.025	0.362	0.944		0.037
Ln distance to leaseholder ZIP code	0.304	0.102	0.003	**	0.443

Adjacent to Baylor	-0.939	0.324	0.004	**	-1.367
Fraction leased area by others	0.525	0.904	0.561		0.765
Fraction deep area	1.877	0.499	1.70E-04	***	2.732
SAV present	0.508	0.253	0.045	*	0.740
Ln population density	0.309	0.112	0.006	**	0.450
Ln average income	1.228	0.503	0.015	*	1.787
Variance parameters					
σ^2 (= $\sigma^2_u + \sigma^2_v$)	4.007	0.541	1.26E-13	***	
γ (= σ^2_u / σ^2)	0.832	0.037	< 2.2e-16	***	
Log-likelihood	-1,507.559				
Mean efficiency	0.267				

Table 5. DEA-OLS regression results. Significance is denoted by: p<0.001='***', p<0.01='**', p<0.05='*', p<0.1='.'. Sign of the coefficients obtained from (Eq. 6) have been reversed so that reported signs of DEA coefficients are expected to be the same as those for SFA coefficients.

Variables	Estimate	Std. Error	P-value	Signif.
Inefficiency model				
Intercept	-0.457	0.332	0.169	
Ln number of leases	-0.036	0.007	9.81E-07	***
Lease age	-0.002	0.281	0.779	
Alternative gear	-0.014	0.020	0.474	
Both aquaculture	0.040	0.025	0.100	.
Ln distance to leaseholder ZIP code	-0.007	0.007	0.332	
Adjacent to Baylor	-0.122	0.019	1.83E-10	***
Fraction leased area by others	-0.110	0.063	0.081	.
Fraction deep area	-0.014	0.026	0.594	
SAV present	0.084	0.017	8.48E-07	***
Ln population density	0.049	0.008	1.70E-10	***
Ln average income	0.017	0.031	0.596	
Adjusted r^2	0.195			
Mean efficiency	0.247			

Figures

Fig. 1. Leases analyzed during the period 2007-2016 (in green). Other leases excluded from the dataset (in red) included leases with no intensive oyster production, riparian leases, leases not within 1.7 km from the nearest ChesROMS grid cell (lighter grey grids), leases on the Atlantic coast of the Eastern Shore, and those in condemned zones.

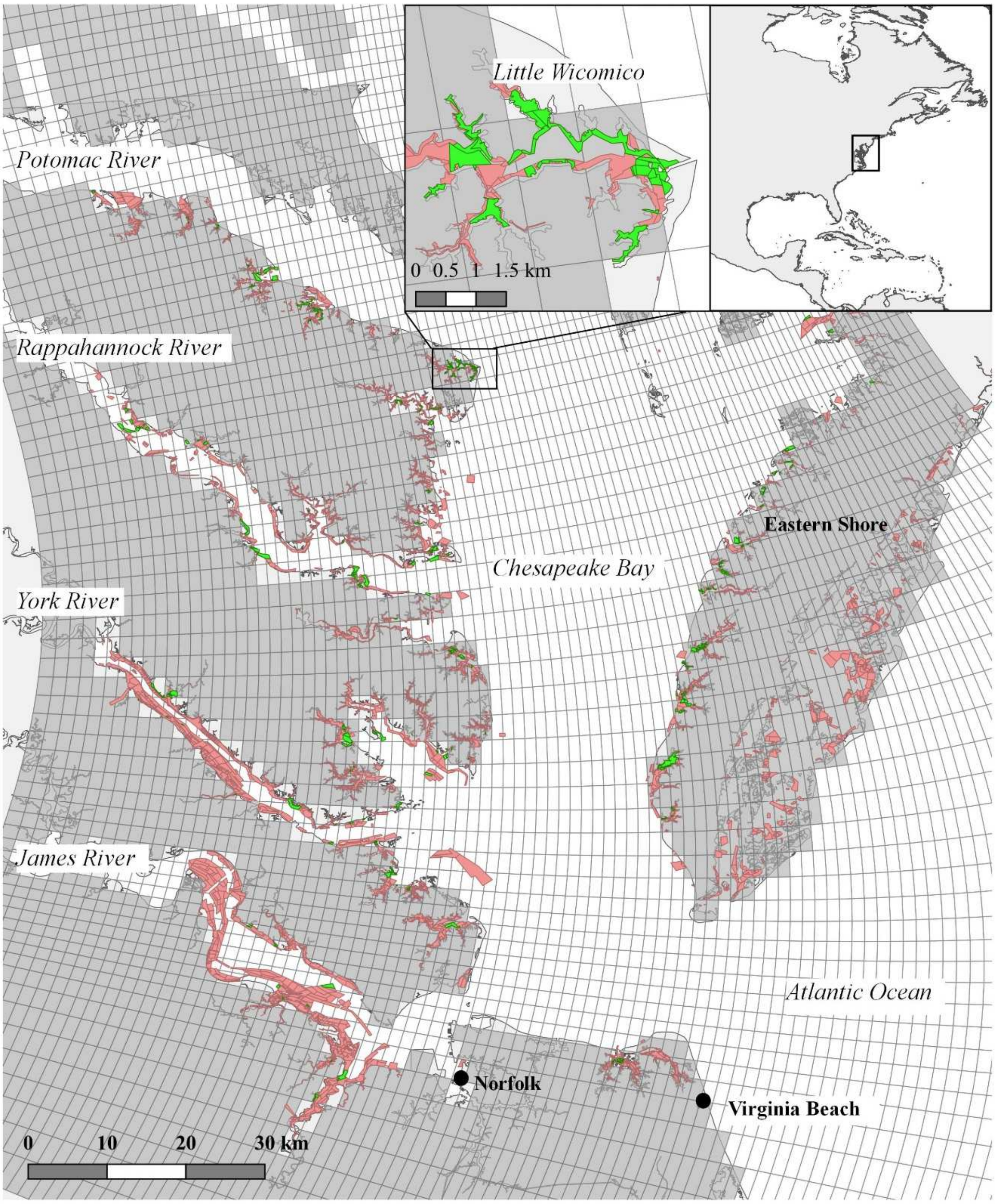


Fig. 2. Frequency distributions of lease capacity utilization estimates from SFA (A) and DEA (B) models. Dashed bold red lines represent mean LCUs, regular red lines represent median LCUs, and grey dashed lines represent standard deviations.

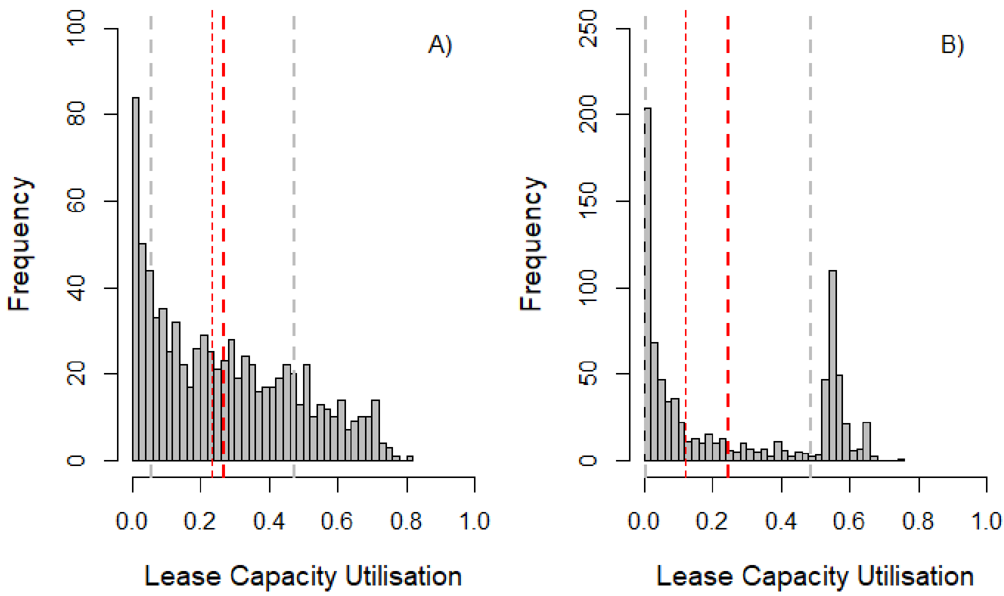


Fig. 3. Inefficiency estimates from SFA (A) and DEA (B) models for each contextual variable. Significance is denoted by: p<0.001='***', p<0.01='**', p<0.05='*', p<0.1='.', non-significant='NS'.

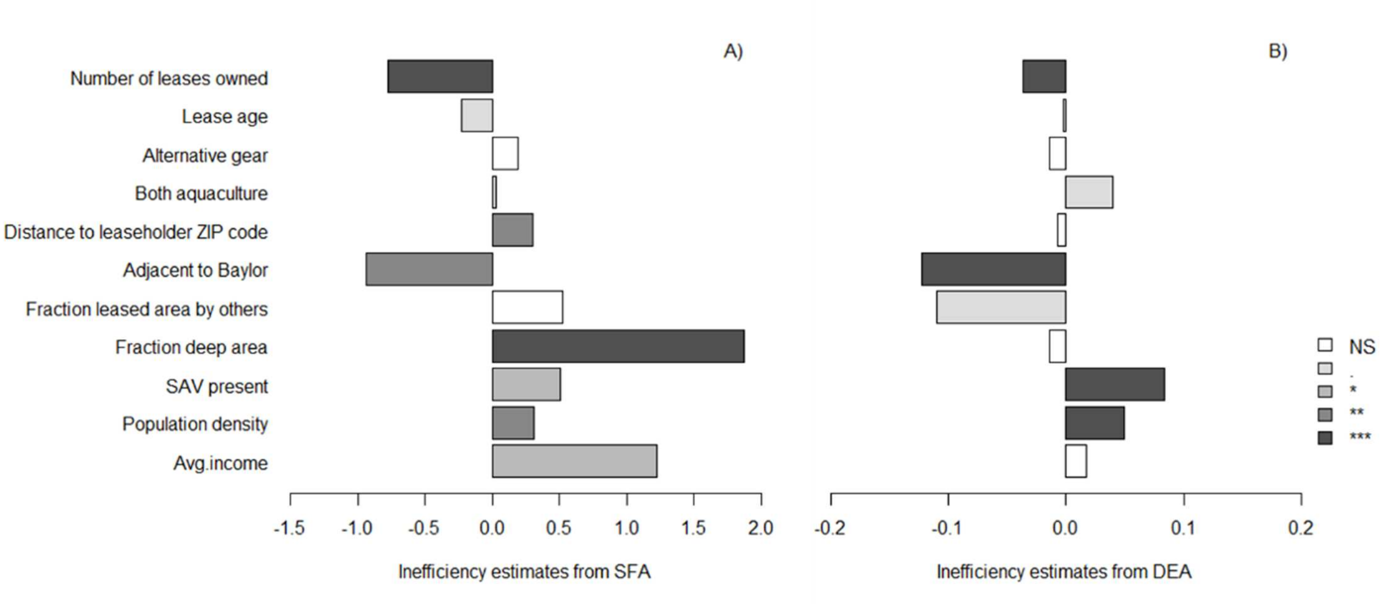
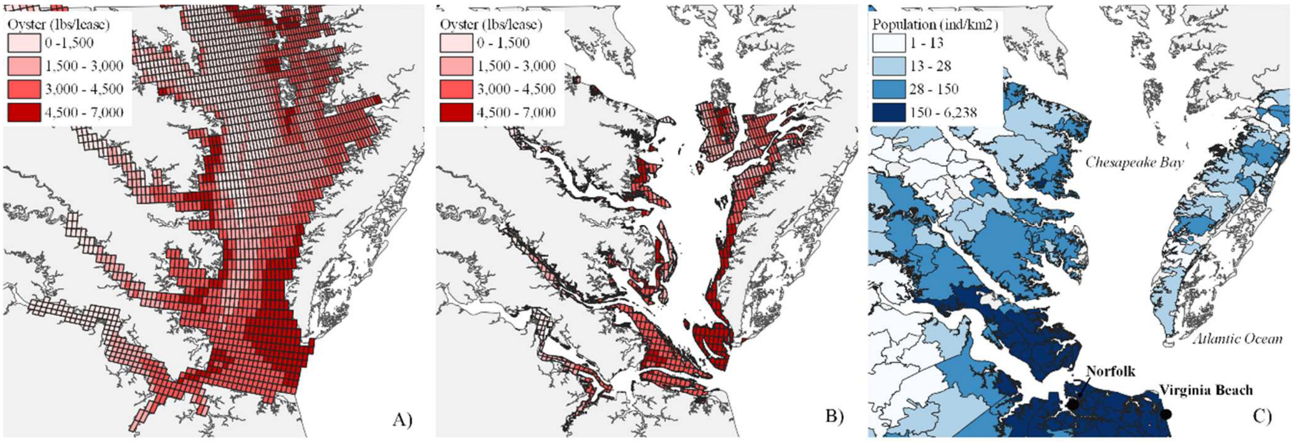
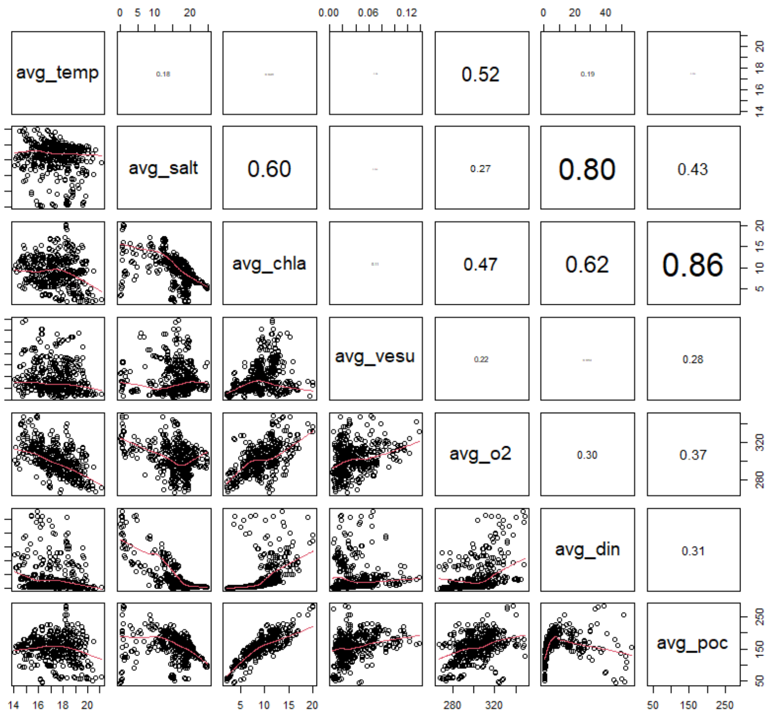


Fig. 4. Predictions of maximum oyster production based on Cobb-Douglas SFA estimates for the Virginia portion of the ChesROMS grid (A), for leasable areas only (B), and average population density per ZIP code for the 2006-2016 period (C). The area shown includes four major tributaries, which from north to south are: Potomac, Rappahannock, York, and James Rivers.

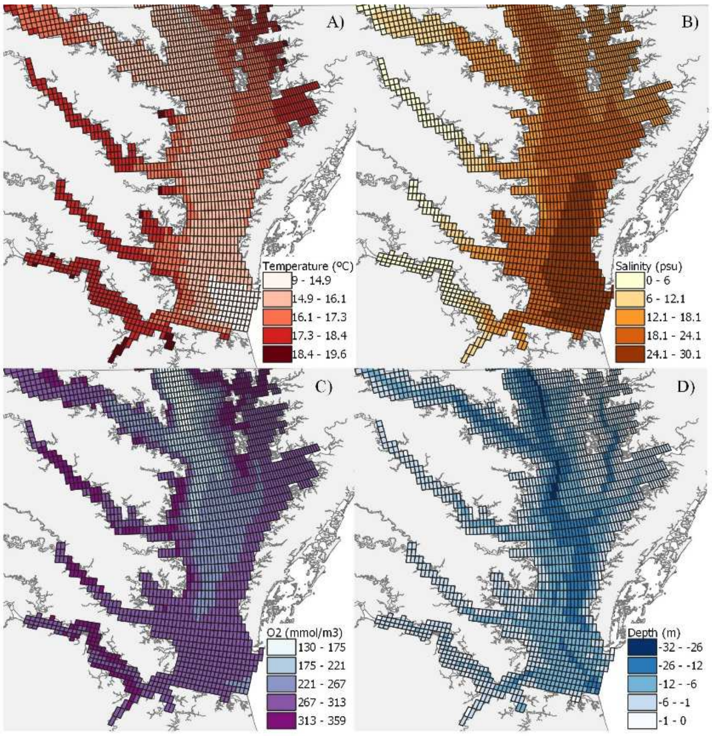


Supplementary Material

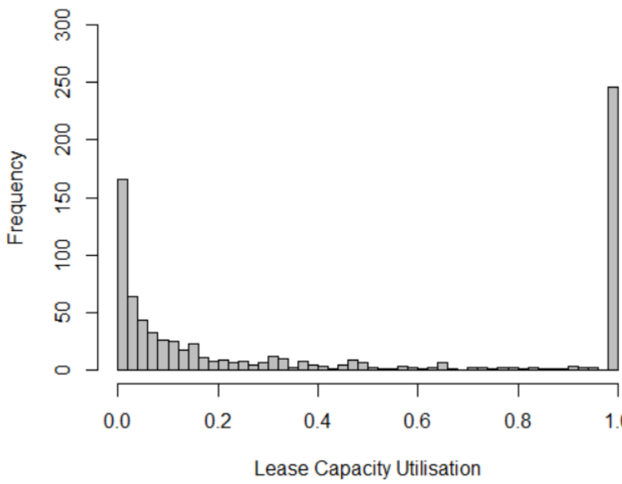
Supplementary Figure S1. ChesROMS environmental variables correlations.



Supplementary Figure S3. Average spring means of ChesROMS model output for bottom temperature (A), salinity (B), and O_2 (C) over the period 2003-2014, and average depth (D) for each corresponding grid cell.



Supplementary Figure S4. Frequency distributions of non-bias corrected lease use efficiency from the DEA model.



Supplementary Table S1. Translog SFA Error Components Frontier results (ignoring Z variables). Significance is denoted by: p<0.001='***', p<0.01='**', p<0.05='*', p<0.1='.'.

Variables	Estimate	Std. Error	P-value	Signif.
Production frontier				
Intercept	1374.422	1.457	<2.2e-16	***
Ln lease size	0.353	0.092	1.18E-04	***
Ln temperature	224.375	44.195	3.84E-07	***
(Ln temperature)^2	-29.807	9.982	0.003	**
Ln temperature * Ln salinity	6.765	3.651	0.064	.
Ln temperature * Ln O2	-50.946	7.231	1.84E-12	***
Ln temperature * Ln POC	21.506	2.648	<2.2e-16	***
Ln temperature * Ln depth	12.630	3.612	4.72E-04	***
Ln salinity	-112.821	41.760	0.007	**
(Ln salinity)^2	0.310	0.390	0.426	
Ln salinity * Ln O2	15.232	5.977	0.011	*
Ln salinity * Ln POC	0.596	0.624	0.339	
Ln salinity * Ln depth	1.389	0.749	0.064	.
Ln O_2	-180.510	19.444	<2.2e-16	***
(Ln O_2)^2	-5.429	6.717	0.419	
Ln O2 * Ln POC	47.628	3.227	<2.2e-16	***
Ln O2 * Ln depth	43.559	3.365	<2.2e-16	***
Ln POC	-310.553	18.826	<2.2e-16	***
(Ln POC)^2	-3.639	1.550	0.019	*
Ln POC * Ln depth	-3.606	2.151	0.094	.
Ln depth	-269.922	15.416	<2.2e-16	***
(Ln depth)^2	0.242	1.780	0.892	
Variance parameters				
σ^2 (= $\sigma^2_u + \sigma^2_v$)	3.113	0.494	3.01E-10	***
γ (= σ^2_u / σ^2)	0.607	0.065	<2.2e-16	***
Time	0.011	0.011	0.325	
Log-likelihood	-1463.536			
Mean efficiency	0.137			

Supplementary Table S2. SFA production frontier and inefficiency model according to a Cobb-Douglas production function. Significance is denoted by: p<0.001='***', p<0.01='**', p<0.05='*', p<0.1='.'. Lower values of the depth indicator correspond to deeper areas.

Variables	Estimate	Std. Error	P-value	Signif.	Marg. Effect
Production frontier					
Intercept	-27.584	10.978	0.012	*	
Ln lease size	0.415	0.052	2.03E-15	***	
Ln temperature	-0.089	0.878	0.919		
Ln salinity	0.653	0.114	9.85E-09	***	
Ln O_2	5.801	1.673	0.001	***	
Ln POC	-0.397	0.240	0.098	.	
Ln depth indicator	-0.513	0.491	0.296		
Inefficiency model					
Intercept	-11.780	5.271	0.025	*	
Ln number of leases	-0.730	0.131	2.44E-08	***	1.461
Lease age	-0.197	0.106	0.064	.	0.395
Alternative gear	0.259	0.238	0.278		-0.518
Both aquaculture	0.001	0.319	0.998		-0.002
Ln distance to leaseholder ZIP code	0.236	0.092	0.010	*	-0.472
Adjacent to Baylor	-0.907	0.253	3.46E-04	***	1.815
Fraction leased area by others	0.744	0.848	0.380		-1.490
Fraction deep area	1.754	0.426	0.000	***	-3.512
SAV present	0.315	0.213	0.141		-0.630
Ln population density	0.210	0.102	0.040	*	-0.420
Ln average income	1.017	0.472	0.031	*	-2.036
Variance parameters					
σ^2 (= $\sigma^2_u + \sigma^2_v$)	3.707	0.445	< 2.2e-16	***	
γ (= σ^2_u / σ^2)	0.808	0.048	< 2.2e-16	***	
Log-likelihood	-1,534.643				
Mean efficiency	0.228				