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1 **Environmentally-determined production frontiers and lease utilization in Virginia's**
2 **eastern oyster aquaculture industry**

3
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14

15 **Abstract**

16 During the last decade, oyster aquaculture has rebounded in Virginia and has been associated
17 with an increase in subaqueous leased area. Production levels remain historically low, however,
18 and many leases are thought to be underutilized. This study uses a novel approach leveraging
19 high-resolution environmental data to evaluate lease utilization and identify constraints on
20 aquaculture development. Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis
21 (DEA) were used to define environmentally-determined production frontiers, i.e production
22 possibilities based on empirical observations of aquaculture production, available space, and
23 environmental conditions. Both methods estimated Lease Capacity Utilization (LCU, from 0 to
24 1) for leases producing oysters with intensive culture methods from 2007 to 2016. Models
25 revealed significant heterogeneity in lease utilization and mean LCU scores of 0.25 (DEA) and
26 0.27 (SFA), which suggests many leases could scale up production or reduce the size of their
27 lease to more efficiently utilize ambient environmental conditions (i.e., achieve scores closer to
28 1). Capacity underutilization arising from characteristics of the leaseholder and surrounding
29 spatial environment were quantified and indicated efficiency gains for horizontally integrated
30 leaseholders, though also suggested leases in more populated areas were less efficiently used,

31 possibly due to increased use conflicts. These results highlight potential externalities and
32 tradeoffs associated with aquaculture development and can inform the design of more efficient
33 aquaculture leasing systems.

34

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

37

38 **Highlights:**

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

44

45 **Abbreviations**

46 DEA: Data Envelopment Analysis

47 SFA: Stochastic Frontier Analysis

48 LCU: Lease Capacity Utilization

49

50 **1. Introduction**

51 Oyster aquaculture is a globally important and increasing part of the blue economy that provides
52 economic benefits as well as multiple ecosystem services, including water filtration and habitat
53 creation (Duarte et al., 2009; Alleway et al., 2019; Theuerkauf et al., 2019). Oysters were the
54 highest volume and value marine shellfish produced via aquaculture in the United States in 2017,
55 with over 36.5 million lbs harvested and an estimated value of US \$186.3 million (NMFS, 2020).
56 Continued growth of oyster aquaculture is anticipated given increasing populations, increasing
57 seafood consumption per capita, and limited potential for increased exploitation of wild stocks
58 (Duarte et al., 2009; SAPEA, 2017; Wijsman et al., 2019; FAO, 2020). Competition for space

59 between oyster producers and other stakeholders, as well as social opposition, have been
60 identified as key barriers for coastal aquaculture expansion in areas where different recreational,
61 esthetic, residential, and commercial uses or activities occur (Knapp, 2012; Krause et al., 2015;
62 Froehlich et al., 2017; Beckensteiner et al., 2020). Knapp and Rubino (2016) argue that U.S.
63 marine aquaculture activity is well below its potential level and Gibbs (2009) suggests that social
64 carrying capacity, which refers to the space dedicated to aquaculture that the local community is
65 willing to accept (Inglis et al., 2000), may be the main constraint to aquaculture industry growth.
66 This research evaluates oyster production potential on actively used privately leased grounds in
67 Virginia, USA as related to the physical, biological and social environment, in order to identify
68 factors that enhance or constrain oyster aquaculture development.

69 In Virginia, wild populations of eastern oyster (*Crassostrea virginica*) have experienced
70 dramatic declines due to disease, water quality, habitat destruction and overfishing over the last
71 two centuries (Rothschild et al., 1994; Schulte, 2017; Kennedy, 2018). The area once supported a
72 dynamic public fishery (~ 3 million lbs/yr in the 1950's), where fishers harvested natural oyster
73 beds (defined by the Baylor Survey in 1896; Schulte, 2017), as well as maintained a large
74 "extensive aquaculture" industry, wherein fishers deposited oyster shells and potentially live
75 seed oysters on the bottom of privately leased grounds for later harvest (~16 million lb./year in
76 the 1950's; Haven et al., 1978). Though both of these fisheries continue, average annual
77 aquaculture production levels from 1995 to 2005 were only 0.4 million lbs, 2.5% of the 1950's
78 average. In recent years, oyster aquaculture has begun to rebound, reaching ~2.5 million lbs in
79 2016. Major contributors to this growth include the increasing cultivation of disease-resistant,
80 hatchery-raised oyster strains, pioneering work on triploid oysters, and reliance on "intensive
81 aquaculture" practices, i.e., the use of oyster cages or bags for production (also referred to as

82 containerized aquaculture, Bosch et al., 2010; Hudson, 2018). Concurrent with the observed
83 production rebound has been an increase in privately leased grounds. Today, the total amount of
84 leased area is the largest it has ever been, with about 140,000 acres currently leased. Private
85 leases have long been advocated as an effective tool for increasing oyster yields while also
86 incentivizing sustainable practices (Alford, 1973; Agnello and Donnelley, 1975; Santopietro and
87 Shabman, 1992; Beck et al., 2004). In Virginia, they provide the lessee exclusive and
88 transferable rights to cultivate shellfish on state-owned submerged bottomland¹ for at least 10
89 years.

90 Despite recent growth in oyster landings and leased area in Virginia, production levels
91 are still far below historical amounts, and Beckensteiner et al. (2020) found that, from 2006 to
92 2016, only 33% of leases were ever used for oyster production. Though in theory leases are for
93 the “planting or propagating [of] oysters” (Virginia Code, Chapter 6, 28.2-603), in practice,
94 minimal evidence is required to demonstrate use and enforcement mechanisms are limited,
95 leading to leases potentially being obtained for a variety of non-aquaculture uses (Beckensteiner
96 et al., 2020). Due to the low annual lease fees in Virginia (the lowest in the US, \$1.50/acre/year),
97 individuals may apply for a lease without the intention of using it for oyster culture in the
98 immediate future (Mason, 2008). Some leaseholders are thought to be motivated by speculative
99 leasing (with the intent of future resale at a profit; Mason, 2008) or may be driven by the desire
100 to impede development of oyster farming “in their backyard” (“Not in my backyard” attitude;
101 Dear, 1992). Previous research observed non-used leases in more populated, high-income
102 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).

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

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

117 Empirical production frontier models have been widely used to examine the efficiency
118 and capacity utilization of aquaculture industries. In general, these models use observations of
119 actual commercial production together with associated inputs to construct the efficient
120 production frontier - the maximum amount of output producible for a given input level (Farrell,
121 1957). Capacity utilization is the potential output producible given a set of fixed inputs (Kirkley,
122 2002). Two popular econometric approaches to evaluate production efficiency and capacity
123 utilization include Stochastic Frontier Analysis (SFA; Aigner et al., 1977) and the non-stochastic
124 Data Envelopment Analysis (DEA; Charnes et al., 1978). Production frontier analyses have been
125 extensively used for estimating technical efficiency (TE, i.e., the difference between observed

126 production and efficient production) in the aquaculture industry (see Iliyasu et al., 2016 and
127 Sharma and Leung, 2003 for reviews of 41 aquaculture production frontier models), with most
128 existing econometric studies examining aquaculture production considering discretionary, or
129 controllable, inputs related to area used, feed, seed, labor (e.g., number of hours fished),
130 technology (e.g. boat size, fuel), and effort intensity (crew number). Inefficiencies, meanwhile,
131 have been investigated as related to farmers' skill, education, experience, or social network
132 (Sharma and Leung, 2003; Chiang et al., 2004; Iliyasu et al., 2016; Scuderi and Chen, 2019).
133 Schrobback et al. (2014) assessed capacity utilization for the Moreton Bay oyster aquaculture
134 industry and considered size of the lease as a single fixed input.

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

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

155 The primary goal of this study was to assess how leaseholders used leased areas and the
156 existing environment for oyster production. LCUs for oyster production were estimated from
157 2007 to 2016 using both SFA and DEA models. Capacity utilization rates were compared
158 between the two methods and consistencies or inconsistencies identified. Model outputs were
159 used to 1) estimate the extent of inefficiency in utilization of leased areas actively producing
160 oysters with intensive culture methods, and 2) determine drivers of lease utilization related to
161 leaseholder characteristics and the spatial context of production. The development and
162 application of models that incorporate environmental and socioeconomic data in assessing
163 aquaculture production potential is essential to improved MSP that promotes efficient utilization
164 of space, reduces user-conflicts, and addresses tradeoffs inherent in aquaculture development.

165

166 **2. Methods**

167 ***2.1. Production frontier models***

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

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

178

179 2.1.1. Stochastic Frontier Analysis (SFA)

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

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

183 In (1), the response variable $\ln(y_{i,t})$ is log-transformed output for the i^{th} observation at time t .
 184 $\ln(x_{k,i,t})$ are the $j^{\text{th}}/k^{\text{th}}$ log-transformed inputs of production associated with the i^{th} observation at
 185 time t . β s are unknown parameters to be estimated and β_0 is the intercept coefficient. $v_{i,t}$ are the
 186 random errors, independently and identically distributed with mean of zero and variance σ_v^2
 187 ($v_{i,t} \sim N(0, \sigma_v^2)$). $u_{i,t}$ are the non-negative random deviations associated with production
 188 inefficiencies, independently and identically distributed and assuming a normal distribution
 189 truncated at zero, with mean $\mu_{i,t}$ and variance σ_u^2 ($u_{i,t} \sim N^+(\mu_{i,t}, \sigma_u^2)$, Aigner et al., 1977).

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

$$u_{i,t} = \mathbf{Z}_{i,t} \boldsymbol{\delta}_{SFA} + \epsilon, \quad (2)$$

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

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

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

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

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

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

212

213 2.1.2. Data Envelopment Analysis (DEA)

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

$$\max_{\theta_{i,t}, \lambda_{i,j,t}} \theta_{i,t} \quad (4.1)$$

221 such that:

$$\sum_j \lambda_{i,j,t} y_{j,t} - \theta_{i,t} y_{i,t} \geq 0, \quad (4.2)$$

$$\sum_j \lambda_{i,j,t} x_{j,k,t} - x_{i,k,t} \leq 0, \quad k=1, \dots, K \quad (4.3)$$

$$\sum_j \lambda_{i,j,t} = 1, \quad j=1, \dots, J_t \quad (4.4)$$

$$\lambda_{i,j,t} \geq 0. \quad (4.5)$$

222 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
 223 (i.e., lease size and environmental conditions). In this LP, the objective is to maximize $\theta_{i,t}$, the
 224 proportional increase (i.e., scalar multiplier) in output (i.e., oyster production) possible for the i^{th}
 225 lease at the t^{th} time (4.1) while remaining within the production possibility set. $1/\theta_{i,t}$ defines an
 226 efficiency score between 0 and 1. Each lease's utilization score in each year is calculated relative
 227 to an efficiency frontier where observations from the most efficient leases (largest production for
 228 a given input level) serve as benchmarks to inefficient leases. $\lambda_{i,j,t}$ is a non-negative scalar that
 229 places positive weight on observations that define the efficient frontier, which is constructed as a

230 linear combination of efficient observations for each lease i at each time t . If $\theta_{i,t}$ equals 1 and
 231 $\lambda_{i,j,t}$ equals 0 for all $j \neq i$, then lease i is efficient and lies on the frontier. Four constraints have to
 232 be considered to ensure the projected point does not lie outside the feasible set. First,
 233 observations of outputs and inputs by leases on the production frontier described by
 234 $(\lambda_{i,j,t}x_{j,1,t}, \dots, \lambda_{i,j,t}x_{j,K,t}; \lambda_{i,j,t}y_{j,t})$ have to be greater than or equal to (for output) or less than or
 235 equal to (for inputs) output and input levels for lease i at time t (4.2-4.3). Constraints (4.4) and
 236 (4.5) introduce restrictions related to returns to scale and ensure convexity. These constraints
 237 require that the sum of non-negative weights over all leases for a given lease i at time t equal
 238 one, such that lease i is only benchmarked against observations of similar scale. The LP problem
 239 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
 240 production observation). DEA lease capacity utilization for the i^{th} lease at the t^{th} time was
 241 calculated as:

$$LCU_{DEA\ i,t} = \frac{y_{i,t}}{\widehat{y}_{i,t}} = \frac{y_{i,t}}{y_{i,t}\theta_{i,t}} = \frac{1}{\theta_{i,t}}. \quad (5)$$

242 By construction, $LCU_{DEA\ i,t}$ are biased upward (Simar and Wilson 1998) and need to be
 243 corrected. This can be done through a smoothed bootstrap procedure² (Simar and Wilson, 2008;
 244 Bogetoft and Otto, 2011) that allows the construction of confidence intervals around efficiency
 245 scores and estimation of bias-corrected efficiency, i.e., $LCU_{DEA\ i,t}^*$.

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

$$LCU_{DEA\ i,t}^* = \mathbf{Z}_{i,t} \boldsymbol{\delta}_{DEA} + \varepsilon, \quad (6)$$

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

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

254 DEA calculations (bootstrapped 2,000 times) were performed by minimal extrapolation³
255 in R (R Core Team, 2018) with the *benchmarking* package (Bogetoft and Otto, 2018).

256

257 *2.1.3. Conceptual and methodological differences between the two approaches*

258 The SFA and DEA techniques differ in a number of ways (summarized in Table 1). First, while
259 the DEA attributes all deviations from the frontier to inefficiencies, the SFA assumes two
260 unobserved error terms related to inefficiency and statistical noise or measurement error.

261 Although the deterministic nature of DEA can be argued to be a limitation, in that it does not
262 account for random variations in output, it might also be viewed as a strength, in that no pre-
263 defined functional relationship between inputs and output is required. Since SFA is a parametric
264 approach, it requires an a priori functional form to be specified, such as the log-linear translog
265 production function, and assumes specific distributions for the two error terms. When time
266 effects were ignored in the SFA, one frontier was estimated for all observations, whereas DEA
267 frontiers were calculated considering only observations from the same time period. An advantage
268 of the SFA is that it simultaneously estimates parameters of the stochastic production frontier
269 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.

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

275

276 ***2.2. Data collection and processing***

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

284

285 *2.2.1. Annual oyster production per lease*

286 Lease polygons were available publicly through the VMRC's Chesapeake Bay Map⁴, which also
287 included leaseholder names and mailing addresses. We analyzed commercial leases with
288 intensive oyster production reported between 2007 and 2016. Time series of annual oyster
289 harvest per lease were provided by VMRC. Harvest data were separated by lease identification
290 number, gear, and year. Intensive oyster production consists of production from bottom cages
291 (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

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

301

302 2.2.2. *Non-discretionary environmental inputs*

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

315 2014, therefore, values for 2015 were based on the average between 2013 and 2014 observations,
316 while values for 2016 were solely approximated by the 2014 value. It was thought this would not
317 significantly impact production estimates since temporal variability was considerably smaller
318 than spatial variability for all environmental variables and over the scales of this study.

319 ChesROMS variables were all predicted at the base of the water column since about 80% of
320 production observations were from bottom cages. The ChesROMS data include temperature,
321 salinity, particulate organic carbon (POC), dissolved oxygen (O₂), chlorophyll *a* concentration,
322 current velocity, and dissolved inorganic nitrogen (DIN). All can potentially reflect ambient
323 water quality and influence oyster growth. Among these, we selected four environmental
324 variables for inclusion in SFA and DEA models to reduce model collinearity (Supplementary
325 Figure S1) and choose factors typically used in FARM models (Ferreira et al., 2009, Silva et al.,
326 2011). Selected input variables were water temperature, salinity, dissolved oxygen (O₂), and
327 particulate organic carbon (POC), each of which is thought to impact fundamental biological
328 processes such as growth, disease, nutrition and respiration. Indeed, eastern oyster filtration
329 capacity depends on water temperature and is optimal between 15 °C and 25 °C (Loosanoff,
330 1958). Eastern oysters can tolerate a broad range of salinity (5-40 psu, tolerance depending on
331 life stage), but prefer upper mesohaline to polyhaline salinities (15-30 psu, Barnes et al., 2007).
332 Although higher salinity could boost oyster growth, it is also associated with increased
333 prevalence of the pathogens MSX (caused by *Haplosporidium nelsoni*) and Dermo (caused by
334 *Perkinsus marinus*) (Haven et al., 1981; Shumway, 2011). POC was used as a proxy for food
335 availability. O₂ level was a surrogate for anoxic and hypoxic conditions since oyster metabolism
336 is significantly affected at O₂ concentrations lower than 3ppm (Wallace, 2001; Seitz et al., 2009).

337 Depth is more generally used in habitat suitability models for oyster production as a

338 proxy for averaged environmental conditions (i.e., no temporal variability) and depth values
339 shallower than 3m are usually more optimal for oyster production (Theuerkauf and Lipcius,
340 2016). Average depth per lease was included as an additional input characterizing the
341 environment and was derived from a NOAA/NOS estuarine bathymetry digital elevation model,
342 with a resolution of 10 m (National Centers for Environmental Information, 2017). Depth values,
343 which were initially negative, were transformed to be strictly positive since SFA and DEA
344 models require non-negative input values (the transformation preserved ordering of values with
345 lower values corresponding to deeper areas). Summarized statistics of each input used in our
346 analyses are given in Table 2.

347

348 *2.2.3. Contextual variables*

349 For analyses of factors influencing potential lease use inefficiencies, we included a set of
350 variables related to the leaseholder, local spatial context, and socioeconomic conditions. The
351 number of leases held per leaseholder per year was considered as potentially influencing lease
352 capacity utilization (note that this number can comprise leases not included in this analysis, such
353 as leases used with extensive gears, leases not used, or leases in polluted zones). Leaseholders
354 owning several leases were thought to be larger, horizontally integrated operations and,
355 therefore, potentially more efficient (e.g., due to economies of scale that reduce the average cost
356 of production). Lease age was also included to account for experience level and temporal change,
357 with older leases expected to have higher levels of utilization and be more efficient. This was
358 reasonable because all leases in our dataset were continuously held by the same leaseholder
359 during the study period 2007-2016 (i.e., no instances of lease turnover). A dummy variable
360 “alternative gear” was set equal to one if any gears other than on-bottom cages were used on the

361 lease and zero otherwise, indicating bottom cages were used. This variable was expected to
362 increase efficiency since off-bottom systems could promote faster growth from a food-enriched
363 water column and increased survival from lower predation exposure (Walton et al., 2013).
364 Another dummy variable “both practices” was included to capture if a leaseholder was
365 simultaneously producing oysters from both intensive and extensive practices from the same
366 lease in a given year. Diversification of production methods was expected to decrease lease
367 capacity utilization for intensive production as it may involve increased infrastructure and costs
368 and reduce space available for intensive culture. Distance between a lease and its leaseholder’s
369 home ZIP code centroid was also included (though leaseholder addresses were available, most
370 were PO Boxes; Beckensteiner et al., 2020). Close proximity to a leaseholder’s home ZIP code
371 was thought to enhance lease use via improved access and surveillance of grounds.

372 In prior research, actively used leases were also observed to be in close proximity to
373 natural oyster beds, which are reserved for public use, as well as in congested areas with many
374 other leases (Beckensteiner et al., 2020). A dummy variable “adjacent to Baylor” was included to
375 assess if proximity to public Baylor grounds was a driver of lease utilization. Baylor grounds
376 polygons were available publicly through the VMRC’s Chesapeake Bay Map. The fraction of
377 leased acreage from different leaseholders within a 1 km buffer of a lease was used as a proxy
378 for local congestion or agglomeration effects. Lease productivity was empirically observed to be
379 higher in extremely shallow waters, potentially due to easier access (e.g., without a boat). The
380 variable “deep area” was created as the ratio of leased area deeper than 0.5 m divided by the total
381 leased area, with a larger fraction of a lease in waters deeper than 0.5m expected to reduce
382 efficiency. Non-used leases were previously found to be in close proximity to Submerged
383 Aquatic Vegetation (SAV) (Beckensteiner et al., 2020). SAV grounds compete for shallow space

384 with cultured oysters as current management does not allow aquaculture in areas occupied by
385 SAV (Wagner et al., 2012). The presence of SAV was therefore expected to have a negative
386 impact on lease utilization for oyster production. A dummy variable “SAV present” was equal to
387 one if the distance between a lease and a SAV ground was null during the t^{th} year, meaning that
388 the lease was touching or partially covered by SAV grounds (annual SAV polygons provided by
389 VIMS).

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

399

400 ***2.3. Model specifications summary***

401 Annual oyster production per lease from intensive practices constituted outputs for the SFA and
402 DEA models, with log-transformed production used in the SFA. Associated fixed inputs to
403 construct efficient lease use frontiers in both approaches included lease size (discretionary) and
404 temperature, salinity, O₂, POC, and mean depth (non-discretionary). All input variables were
405 log-transformed for the SFA. Positive monotonic relationships between oyster production and
406 input variables were expected, allowing their inclusion in the DEA under an assumption of free

407 disposability (i.e., that increases in inputs should not decrease output). Factors potentially
408 explaining lease capacity utilization included the number of leases held by the leaseholder, lease
409 age, use of alternative gear, diversified production practices, distance to leaseholder ZIP code,
410 adjacency to Baylor grounds, the fraction of nearby leased acreage from other leaseholders, the
411 fraction of lease area deeper than 0.5m, SAV presence, population density, and average income
412 (Table 3). There were 823 annual production observations from 297 leases and 200 leaseholders
413 over 10 years (2007 to 2016). Mean annual oyster production per lease $y_{i,t}$ was 2,473 ($\pm 5,796$)
414 lbs (Table 2).

415

416 **2.4. Oyster production forecasting**

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

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

$$\hat{y}_r = e^{\beta_0 + X'_r \beta_k}. \quad (8)$$

423 \hat{y}_r is the predicted efficient production for the grid cell r . β_k is a ($k \times 1$) vector of unknown
424 parameters to be estimated from the Cobb-Douglas model and β_0 is the corresponding intercept
425 coefficient. X'_r is a matrix of log-transformed inputs consisting of (constant) mean lease size,
426 (spatially-varying) spring means of model outputs from ChesROMS and mean depth over the
427 ChesROMS grid cell. ChesROMS model outputs were averaged over the period 2003 to 2014 for
428 each grid cell. Estimates should be interpreted as maximum feasible oyster production for an

429 average sized lease in a particular location based upon average environmental conditions and
430 depth. Oyster production was forecast for the Virginia portion of the ChesROMS grid and
431 restricted to leasable area as estimated in Beckensteiner et al. (2020) (i.e., legally leasable
432 Chesapeake Bay area excluding Baylor grounds, clams grounds, shellfish condemnation zones,
433 and waters deeper than 8m).

434

435 **3. Results**

436 **3.1. SFA**

437 *3.1.1. SFA production frontier*

438 We first specified a SFA with time-varying lease effects, ignoring contextual inefficiency
439 variables (i.e., the ECF specification), in order to test for time-varying efficiency. Efficiencies
440 were found to not change significantly over years (p-value = 0.3, Supplementary Table S2). We
441 then ran the time-invariant SFA model including the $\mathbf{Z}_{i,t}$ vector of contextual variables to
442 examine the drivers of inefficiencies. Lease size, temperature, POC and O₂ were found to
443 significantly affect oyster production (Table 4). Lease size had a significant and positive
444 influence on production of oysters: for every 1% increase in lease size, a 0.41% increase in
445 oyster production was observed, suggesting decreasing returns to scale. There were significant
446 interactions between temperature, POC and O₂ (Table 4). While temperature and food (i.e., POC)
447 are drivers for oyster production, the negative effect of the interaction between O₂ and
448 temperature on oyster production would suggest the potential importance of hypoxic conditions.

449

450 *3.1.2. SFA lease capacity utilization*

451 A likelihood ratio test was used to verify whether adding the inefficiency term $u_{i,t}$ significantly

452 improved the fit of the model. The null hypothesis ($H_0: \sigma_u^2=0$, i.e., no inefficiency, only noise)
453 was rejected (p-value <0.001), indicating that the fit of the SFA model was significantly better
454 than the fit of the corresponding OLS model, and that significant lease use inefficiency existed.
455 Relative importance (γ) of inefficiency in oyster production as compared to noise was equal to
456 0.83 (significant at 5% level, Table 4), indicating that inefficiency was the primary factor
457 explaining deviations from the production frontier ($\gamma>0.5$). Predicted $LCU_{SFA\ i,t}$ across all
458 observations from 2007 to 2016 ranged from ~0.0003 to 0.80, with a mean $LCU_{SFA\ i,t}$ of 0.27
459 (± 0.21) (Figure 2A). This finding suggests that output from existing leases could scale up
460 considerably or, alternatively, the area leased could be reduced.

461

462 3.1.3. Causes of inefficiency from the SFA

463 Since the dependent variable of the inefficiency model (Eq. 2) was defined in terms of
464 inefficiency, a negative coefficient of a contextual variable in this model indicated that the
465 variable reduced inefficiency, whereas a positive value indicated an increase in inefficiency. The
466 number of leases per leaseholder was found to decrease lease use inefficiency (p-value <0.001),
467 with every 1% increase in the number of leases per leaseholder producing an increase of 1.1% in
468 $LCU_{SFA\ i,t}$ on average. Proximity to Baylor grounds was also found to increase lease use
469 efficiency. On the other hand, distance to the leaseholder's home ZIP code, the fraction of lease
470 area deeper than 0.5m, presence of SAV, population density and average income of the nearest
471 ZIP code were all found to significantly increase inefficiency (p-values <0.05). For example,
472 there were 2.7% and 1.8% decreases in $LCU_{SFA\ i,t}$ for every 1% increase in proportion of deep
473 area and average income of the nearest ZIP code, respectively (Table 4 and Figure 3). The age of
474 the lease had a positive effect on oyster production that was marginally significant (p-value <0.1),

475 indicating that older leases were more efficiently used.

476

477 *3.1.4. Predictions of oyster production*

478 Predicted oyster production according to a Cobb-Douglas SFA specification was calculated for
479 areas in the lower portion of the Chesapeake Bay (Figure 4A). Mouths of all major tributaries
480 other than the Potomac river and the southeastern portion of the mainstem of the Chesapeake
481 Bay were the most productive regions, likely driven by intermediate temperature levels and high
482 concentrations of O₂ (Supplementary Figure S3). The upper range of maximum oyster
483 production predictions (i.e., 4,500-7,000 lbs/average size lease, Figure 4 dark red) corresponds to
484 the upper 85th percentile of observed production. When predictions were restricted to leasable
485 area only (Figure 4B), east of the northern peninsula and southern and eastern portions of the
486 mainstem of the Chesapeake Bay offered the highest production opportunities. The east of the
487 mainstem also corresponds to areas with lower population density, whereas most other areas
488 predicted to be highly productive abutted against high population densities (Figure 4C).

489

490 **3.2. DEA**

491 *3.2.1. DEA lease capacity utilization*

492 DEA estimated bias-corrected lease capacity utilization ($LCU_{DEA}^*_{i,t}$) measures were produced for
493 the same number of observations (lease-year combinations) using the same output and input
494 variables as for the SFA. The estimated mean $LCU_{DEA}^*_{i,t}$ was 0.25 (± 0.24), while estimates
495 ranged from 1.9e-5 to 0.74 (Figure 2B, Table 5). 29.53% of observations had non-bias-corrected
496 $LCU_{DEA}^*_{i,t}$ equal to 1 (Supplementary Figure S4), i.e., the efficient frontier observations. The
497 frontier smoothing bootstrap placed most of these observations at an efficiency level near 0.6

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

500

501 3.2.2. Causes of inefficiency from the DEA-OLS

502 Lease use inefficiency determinants identified by the DEA-OLS procedure were generally
503 consistent with, though not identical to, those from SFA (Table 5). Coefficients of the number of
504 leases per leaseholder and proximity to Baylor grounds were found to be negative and
505 statistically significant (e.g., there was an increase of 3.6% in $LCU_{DEA}^*_{i,t}$ for every 1% increase
506 in the number of leases held by a leaseholder). This implies that lease use for oyster production
507 by leaseholders with more leases (larger production scale), and from leases adjacent to public
508 grounds, was more efficient (Figure 3B). Conversely, coefficients of the presence of SAV and
509 population density had a positive sign and were statistically significant, indicating that leases
510 with SAV grounds present or those in more populated areas were less efficiently used (Figure
511 3C; e.g., there was a decrease of 4.9% in $LCU_{DEA}^*_{i,t}$ for every 1% increase in population
512 density).

513

514 4. Discussion

515 We introduced the concept of “Lease Capacity Utilization”, which considers the fixed inputs of
516 available space and environmental conditions as defining production possibilities. This is a
517 valuable utilization of traditional econometric production frontier methods for aquaculture
518 performance assessment where environmental conditions are typically not well integrated in
519 analyses (Sharma and Leung, 2003; Iliyasa et al., 2016). This analysis of Virginia lease use and
520 inefficiency for intensive oyster production builds on and complements a prior analysis showing

521 that many subaqueous leases in the Virginia part of the Chesapeake Bay are not used at all for
522 oyster production, be that intensive or extensive (Beckensteiner et al. 2020). Similar factors
523 driving non-use and correlated to surrounding socioeconomic conditions and leaseholder
524 characteristics also lead to significant production inefficiency.

525 Although characterized by different underlying assumptions and constraints, both
526 production frontier models revealed significant inefficiencies in intensive aquaculture practices
527 in the Virginia waters of the Chesapeake Bay. A majority of LCU scores were less than 0.5,
528 revealing substantial lease use inefficiency. On average, an active lease had an efficiency level of
529 0.27 ± 0.21 (SFA result) or 0.25 ± 0.24 (DEA result), meaning that the industry was operating on
530 average 73% (75% with the DEA) below the maximum potential production, given the
531 environment and size of leased area (note the large standard deviations however). To achieve a
532 more efficient use of space and the existing environment, oyster production per lease could
533 increase and/or the amount of space leased could be scaled down. It is believed that producers
534 often only use a small fraction of their lease for oyster production (Beckensteiner et al., 2020; B.
535 Stagg, VMRC, pers. comm.). Whether it is for the allocation of buffer zones against other
536 aquaculturists or poachers, to allow for rotational harvesting⁵ techniques, due to a lack of
537 knowledge of where suitable grounds are when applying for a lease, or for other speculative or
538 non-harvest-related reasons, producers tend to lease much more area than needed. Low ground
539 rental costs provide little barrier to this behavior. This has probably contributed considerably to
540 observed low levels of LCU. It is worth mentioning that fully efficient use may not be
541 achievable, at least in the immediate future, due to constraints related to seed availability and
542 oyster diseases (Schulte, 2017), potential triploid mortality events (Guévelou et al., 2019), and

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

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

549 Though there were some contrasting results between the two different approaches (e.g.,
550 in terms of the relative impact of different explanatory variables on the magnitude of
551 inefficiency), overall the models yielded similar conclusions and had four significant contextual
552 variables in common. $LCU_{DEA}^*_{i,t}$ and $LCU_{SFA}_{i,t}$ scores were significantly correlated and mean
553 scores were close (0.25 vs 0.27), however the median $LCU_{DEA}^*_{i,t}$ was lower than $LCU_{SFA}_{i,t}$ (0.12
554 vs 0.23, Figures 2 and 3). This is consistent since DEA does not accommodate any random noise,
555 and other studies have found differences similar to those seen here (see Theodoridis and Anwar,
556 2011, for several comparisons of technical efficiency scores between the two approaches, and
557 Odeck and Bråthen, 2012, for a meta-analysis of DEA and SFA studies). Odeck and Bråthen
558 (2012) observed that TE scores were often higher for DEA and for panel data, however those
559 studies used non-bias corrected scores. Differences in scores could also be due to whether the
560 frontier was estimated yearly, such as the DEA, or estimated without a time effect such as our
561 SFA (Hjalmarsson et al., 1996). Furthermore, the fact that a sizeable proportion of observations
562 were found to be more efficient with DEA (peak near 0.6, due to 30% of observations having
563 non-bias corrected $LUE_{DEA}_{i,t}$ equal to 1) may be due to the inclusion of six inputs, which
564 reduced the set of comparable leases for each production observation. Overall, despite
565 considerable differences in functional form, assumptions, and constraints defining the translog

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

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

582 In areas where non-used leases are more prevalent, productive leases were also found to
583 be less efficiently used. LCU was found to decrease significantly in more populated, high-
584 income regions, as well as for leases adjacent or partially covered by SAV. These results are
585 similar to those for differences between used and non-used leases in Virginia (Beckensteiner et
586 al., 2020), suggesting that factors driving non-use may also lead to significant production
587 inefficiencies and underutilization. In more populated, and potentially more heavily congested
588 areas, leaseholders may tend to lease more area than needed to secure their activity, hence

589 lowering their production per unit area. Growth of SAV and intensive aquaculture have been
590 identified as mutually exclusive uses of the bottom grounds, generating concern and use conflict
591 in many coastal areas of Virginia (Hershner and Woods, 1999). However, ecologically beneficial
592 interactions between SAV and cultivated oysters is a growing research area and suggests the
593 possibility of complementary use (M. Berman, pers. comm.). In contrast, leases closer to their
594 leaseholder's ZIP code and in shallower waters were more efficiently used, plausibly due to
595 better access. Finally, LCU increased for leases adjacent to the Baylor grounds. It is possible that
596 leases in close proximity to natural oyster reefs are characterized by harder bottom or better
597 water quality, improving production efficiency. It is also plausible that poaching from adjacent
598 public grounds and reporting as production from nearby leases could artificially inflate output
599 and make a lease appear more efficient.

600 Surprisingly, lease age, a proxy for experience, was only marginally significant in the
601 SFA model (p -value=0.064) and did not have a significant effect on efficiency in the DEA
602 model. Efficiency was also found to not change significantly over time in the SFA ECF
603 specification. Our finding may suggest a potential need for enhanced training opportunities and
604 knowledge transfer to ensure that leaseholders learn from their past experiences, or incorporate
605 the newest available technology (e.g., improvement of seed quality, gear developments). It is
606 worth reiterating that intensive aquaculture is relatively new and growing in Virginia, and it is
607 possible that the period covered in this analysis (2007-2016) does not allow enough temporal
608 variation to detect this effect. LCUs were marginally lower (p -values <0.1) for growers who had
609 diversified their aquaculture practices (intensive and extensive gears), suggesting diversification
610 may reduce efficiency, as has been observed in other studies (e.g., Asche and Roll, 2013; Scuderi
611 and Chen, 2019). Note, however, diversification in those studies was in terms of harvested

612 species and not culture methods. Finally, there was no difference in LCU according to the gear
613 utilized. Cages, rack and bags, and floats led to similar use efficiencies. The gear effect may be
614 confounded with that of other variables capturing access effects (i.e., distance to leaseholder's
615 ZIP code, proportional deep area) as alternative off-bottom gears such as floats tend to be used in
616 deeper waters.

617 Our approach included fine-scale environmental variables as non-discretionary inputs
618 defining production possibilities. Oyster survival and growth depend on many variables,
619 including water quality (e.g. salinity, temperature, turbidity, etc.) and algal bloom occurrences
620 (Shumway, 2011). We observed significant increases in oyster production in the SFA model with
621 increases in temperature. Oyster production was found to be higher in warmer waters, where
622 growth and filtration rates are usually enhanced (Shumway, 1996). However, non-quadratic and
623 quadratic terms were significant for temperature and POC, suggesting existence of thresholds for
624 these variables. The SFA model also highlighted several significant interactions between
625 environmental variables (temperature, O₂, and POC) and a few negative relationships between
626 oyster production and environmental variables (O₂ and POC). Negative impacts from POC and
627 from the interaction between O₂ and temperature on oyster production could suggest impacts
628 from the presence of eutrophication and hypoxic conditions, common in shallow waters estuaries
629 (Seitz et al., 2009). Due to the several significant interactions and complex environmental
630 response, as well as potential collinearity among input factors (Supplementary Figure S1),
631 production forecasts using the translog specification were unstable when predicting outside of
632 leased areas in our dataset; therefore, a simplified Cobb-Douglas model without interaction terms
633 was used for out-of-sample predictions. Efficiency scores and Z variable coefficients were not
634 substantially affected but environmental input coefficients were different, likely due to

635 multicollinearity (Supplementary Table S2). A model using orthogonal principal components for
636 environmental variables was also developed to eliminate collinearity between inputs. Efficiency
637 scores and drivers were robust to this formulation, but model interpretation was less intuitive.
638 Further analysis of environmental production frontiers to determine key environmental drivers,
639 their interactions, and production response is an important area for future research.

640 Although this research was able to discern lease use inefficiency and its potential drivers
641 in Virginia, a few aspects of the data and models deserve further consideration. While we
642 assumed positive monotonic relationships between inputs and output in the DEA model, results
643 from the SFA specification show that these assumptions might not hold. Existence of complex
644 interactions between environmental variables and oyster production suggests SFA may be a more
645 appropriate approach when constructing environmentally determined production frontiers. On
646 the other hand, approaches exist to include environmental variables with thresholds or to
647 simultaneously incorporate desirable inputs and detrimental inputs (i.e., inputs that decrease
648 production) by adding a fifth constraint to the DEA linear program (Eq. 4). For example,
649 Reinhard et al. (2000) developed a DEA given conventional inputs and environmentally
650 detrimental inputs to control for the effects of nitrogen surplus on dairy farms. Future work could
651 use DEA formulations allowing for costly input disposal to incorporate environmental variables
652 thought to decrease oyster production, or variables for which positive monotonic responses may
653 not hold. Alternative approaches also exist that relax certain LP constraints for non-discretionary
654 inputs and use multi-stage estimation procedures (Ruggiero 1998) or fuzzy set theory (Saati et al.
655 2011). While we used an output-oriented DEA model, these approaches should be considered
656 when including environmental factors in input-oriented models.

657

658 **5. Conclusion**

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

673 Stricter management tools, such as active-use and minimum planting requirements, could
674 be implemented to provide incentives for more efficient use of leases. Research and management
675 efforts could also be directed to assess causes and solutions for user-conflicts, such as activity
676 zoning. The influence of lease-level and organizational production inputs that were not
677 considered here, e.g., seed, number of cages/other gear, labor, could be assessed in future studies
678 to evaluate technical efficiency. This would, however, require extensive leaseholder surveys and
679 data collection. Some of this information is currently collected regularly, although it only covers
680 a subset of the industry (voluntary survey with larger and/or well-established producers better

681 represented and without lease-specific information, Hudson, 2018). Estimates of technical
682 efficiency would inform and complement estimates of lease capacity utilization explored here, as
683 the former relates to managerial skills and application of technology, which could further
684 elucidate factors influencing efficient use of leased grounds and the existing environment.

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

691

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701

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907

908 **Tables**

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

910

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.

911

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

916

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 (°C)	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

917

918 **Table 3.** SFA and DEA specification summary.

919

Output, Y	Input, X	Contextual variables, Z
Oyster production (lbs)	Lease size (ha)	Number of leases
	Temperature (°C)	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)	

920

921 **Table 4.** SFA production frontier and inefficiency model. Significance is denoted by:
 922 $p < 0.001 = '***'$, $p < 0.01 = '**'$, $p < 0.05 = '*'$, $p < 0.1 = '.'$. Lower values of the depth indicator
 923 correspond to deeper areas. Positive sign of a contextual variable coefficient indicates an
 924 increase in lease use inefficiency (i.e., a decrease in LCU).

Variables	Estimate	Std. Error	P-value	Signif.	Marg. Effect
<i>Production frontier</i>					
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		
<i>Inefficiency model</i>					
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
<i>Variance parameters</i>					
$\sigma^2 (= \sigma_u^2 + \sigma_v^2)$	4.007	0.541	1.26E-13	***	
$\gamma (= \sigma_u^2 / \sigma^2)$	0.832	0.037	< 2.2e-16	***	
Log-likelihood	-1,507.559				
Mean efficiency	0.267				

925

926 **Table 5.** DEA-OLS regression results. Significance is denoted by: $p < 0.001 = \text{'***'}$, $p < 0.01 = \text{'**'}$,
927 $p < 0.05 = \text{'*'}$, $p < 0.1 = \text{'.'}$. Sign of the coefficients obtained from (Eq. 6) have been reversed so that
928 reported signs of DEA coefficients are expected to be the same as those for SFA coefficients.

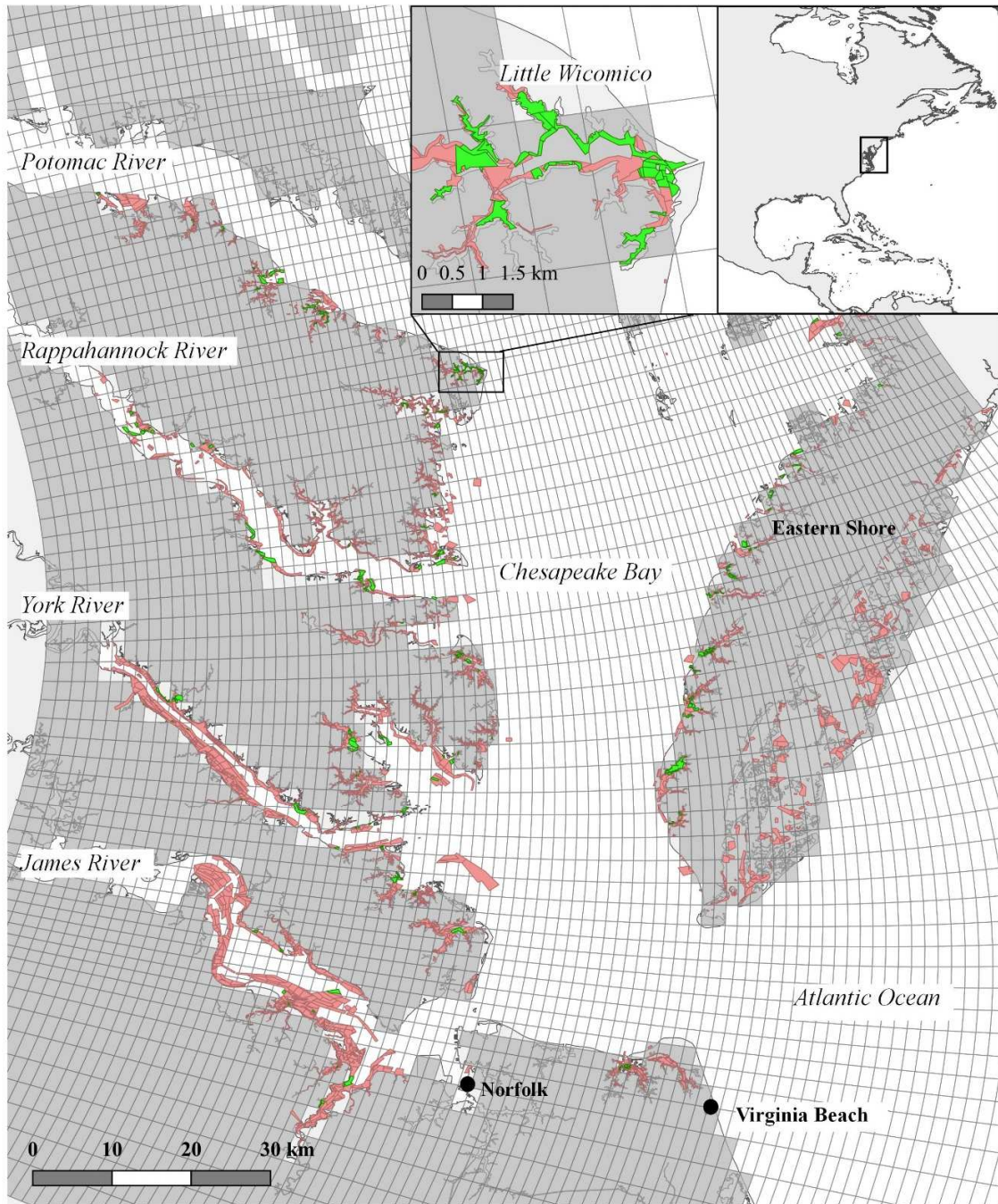
929

Variables	Estimate	Std. Error	P-value	Signif.
<i>Inefficiency model</i>				
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			

930

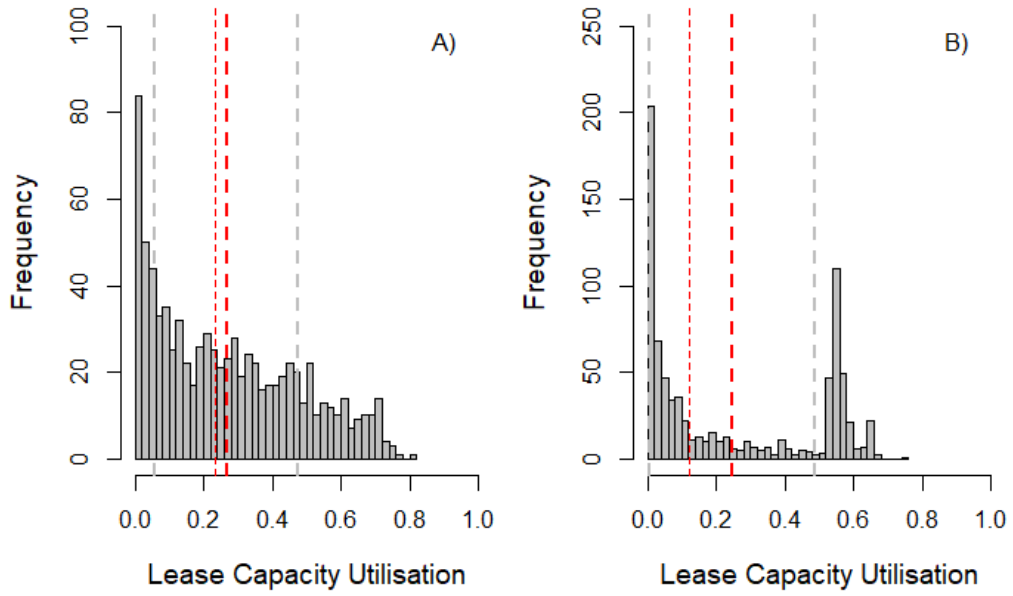
931 **Figures**

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



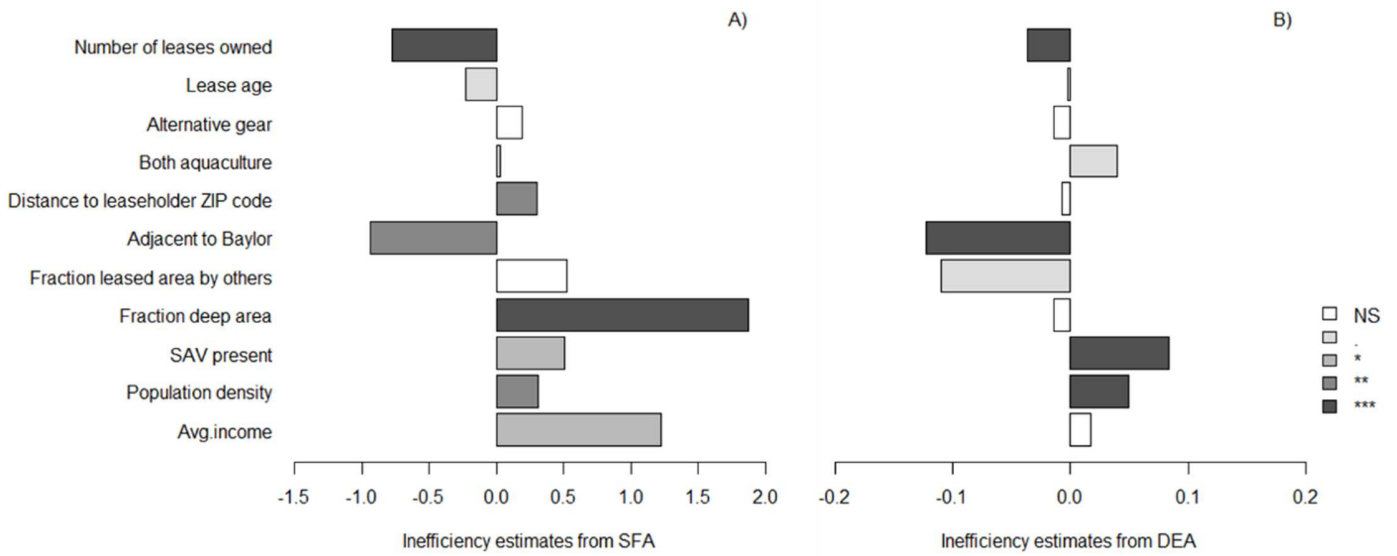
936

937 **Fig. 2.** Frequency distributions of lease capacity utilization estimates from SFA (A) and DEA
938 (B) models. Dashed bold red lines represent mean LCUs, regular red lines represent median
939 LCUs, and grey dashed lines represent standard deviations.
940



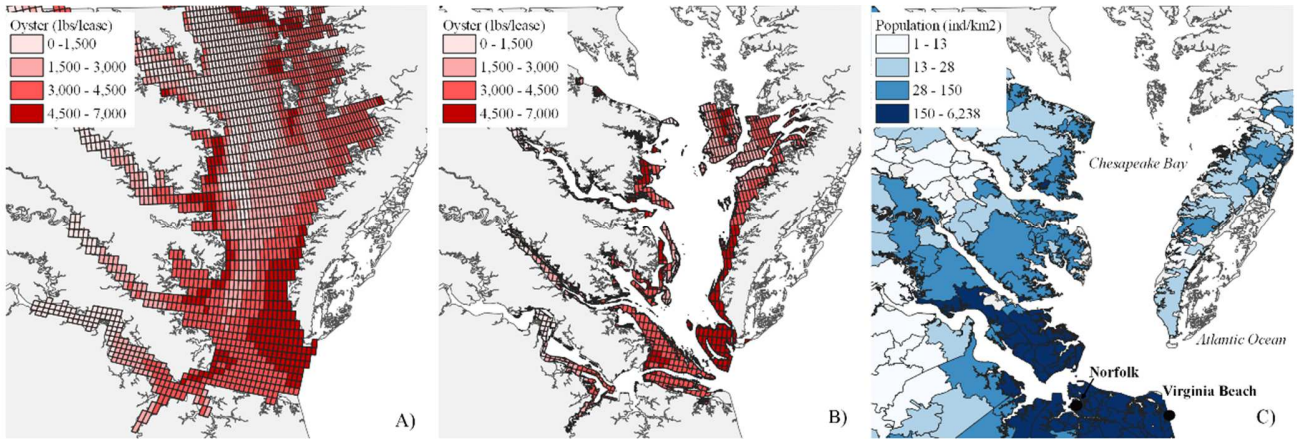
941

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



946

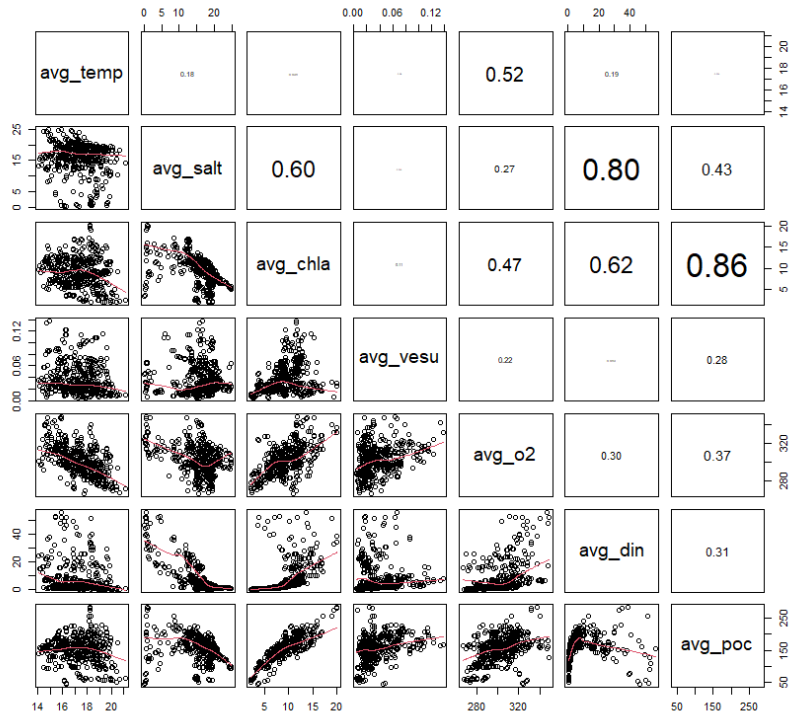
947 **Fig. 4.** Predictions of maximum oyster production based on Cobb-Douglas SFA estimates for the
948 Virginia portion of the ChesROMS grid (A), for leasable areas only (B), and average population
949 density per ZIP code for the 2006-2016 period (C). The area shown includes four major
950 tributaries,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

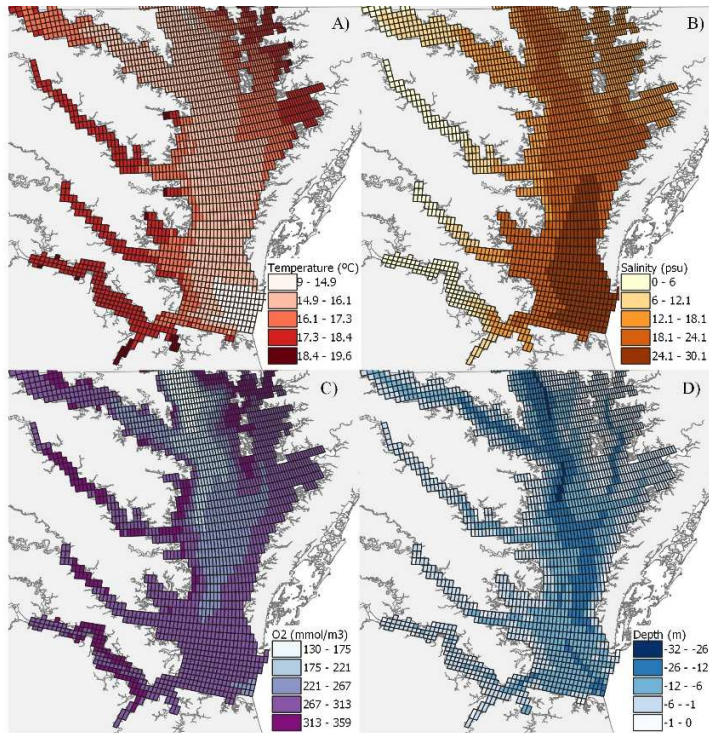
955 **Supplementary Figure S1. ChesROMS environmental variables correlations.**



956

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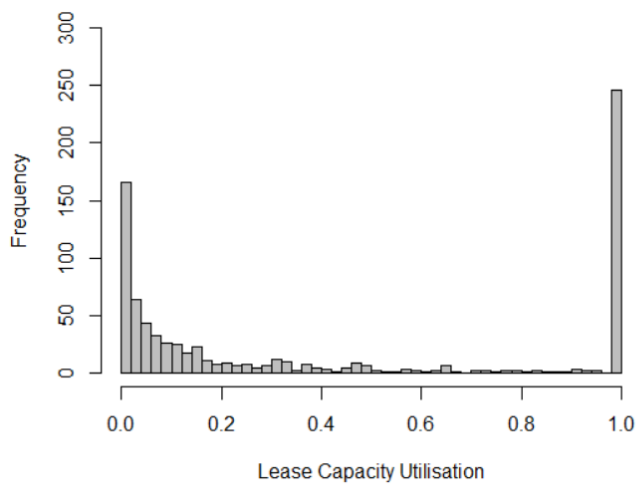
958 **Supplementary Figure S3.** Average spring means of ChesROMS model output for bottom
959 temperature (A), salinity (B), and O₂ (C) over the period 2003-2014, and average depth (D) for
960 each corresponding grid cell.
961



962

963

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



966

967 **Supplementary Table S1.** Translog SFA Error Components Frontier results (ignoring Z
 968 variables). Significance is denoted by: p<0.001='***', p<0.01='**', p<0.05='*', p<0.1='.'.
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Variables	Estimate	Std. Error	P-value	Signif.
<i>Production frontier</i>				
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 O ₂	-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 O ₂	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 O ₂ * Ln POC	47.628	3.227	<2.2e-16	***
Ln O ₂ * 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	
<i>Variance parameters</i>				
$\sigma^2 (= \sigma_u^2 + \sigma_v^2)$	3.113	0.494	3.01E-10	***
$\gamma (= \sigma_u^2 / \sigma^2)$	0.607	0.065	<2.2e-16	***
Time	0.011	0.011	0.325	
Log-likelihood	-1463.536			
Mean efficiency	0.137			

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971 **Supplementary Table S2.** SFA production frontier and inefficiency model according to a Cobb-
 972 Douglas production function. Significance is denoted by: p<0.001='***', p<0.01='**',
 973 p<0.05='*', p<0.1='.'. Lower values of the depth indicator correspond to deeper areas.
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Variables	Estimate	Std. Error	P-value	Signif.	Marg. Effect
<i>Production frontier</i>					
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		
<i>Inefficiency model</i>					
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
<i>Variance parameters</i>					
$\sigma^2 (= \sigma_u^2 + \sigma_v^2)$	3.707	0.445	< 2.2e-16	***	
$\gamma (= \sigma_u^2 / \sigma^2)$	0.808	0.048	< 2.2e-16	***	
Log-likelihood	-1,534.643				
Mean efficiency	0.228				

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