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Impact of Climate Change on the Technical Efficiency of Striped Catfish, *Pangasianodon hypophthalmus*, Farming in the Mekong Delta, Vietnam

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Abstract

The technical efficiency of randomly sampled pangasius farms in the Mekong Delta of Vietnam was estimated using data envelopment analysis, and factors affecting technical and scale efficiency were examined with bootstrap truncated regression. The mean technical efficiency score assuming variable returns to scale was 0.84. The technical efficiency of downstream farmers was higher due to lower energy costs and stocking once a year. Most of the up- and midstream farms needed to pump water and stocked at least three times in 2 yr. Regression analysis showed a positive effect on technical efficiency of the farmers’ education level and having experienced climate change impact through flooding or salinity intrusion in the past. Farms affected by salinity intrusion had a lower scale efficiency as they reduce stocking frequency and rate. In general, reducing fish mortality and the cost of inputs, increasing scale of operation, and being trained, using appropriate methods, in management strategies may improve technical efficiency.

KEYWORDS
climate change, efficiency, flooding, pangasius, salinity

The Mekong Delta (8°33′–10°55′N; 104°30′–106°50′E), often referred to as the food basket of Vietnam, is home for the striped catfish or pangasius, *Pangasianodon hypophthalmus*, Sauvage, farming sector. This sector is heralded as one of the most successful aquaculture developments in the world (De Silva and Phuong 2011). According to De Silva and Phuong (2011), this farming sector
started with cage culture in the upstream and midstream parts of the main branches of the Mekong river that runs through An Giang, Dong Thap, and Can Tho provinces. The industry expanded downstream to the Vinh Long, Tra Vinh, Soc Trang, and Ben Tre provinces after the successes of artificial seed stock supplies and the development of land-based pond culture of pangasius (De Silva and Phuong 2011; Bui et al. 2013). Currently, the sector on average produces in excess of 1 million m.t. of fish per year in a pond area of less than 7000 ha and generates an export income of about US$1.4 billion. Its input and processing components employ over 180,000 persons directly, often women. Its development over the last two decades, as well as the associated controversies, such as environmental, social, and safety issues, have been well documented (e.g., Bosma et al. 2009; Phan et al. 2009; Bui et al. 2010; De Silva et al. 2010; Nguyen 2010; Bosma et al. 2011; De Silva and Phuong 2011; Little et al. 2012).

The economic efficiency of farm operation divides into technical and allocative efficiency. Kaliba and Engle (2006) explained that the technical efficiency (TE) reflects the ability of farms to produce a maximum level of output from a given set of inputs, whereas allocative efficiency refers to the ability of farms to use inputs in optimal proportions, given their prices. In the case of pangasius farms in the Mekong Delta, information regarding farm-specific input prices and the possibility of farmers to minimize costs by adjusting input proportions are lacking or limited. Therefore, the appropriate model to assess the economic efficiency of pangasius farms is the TE. Studies investigating TEs of aquaculture farming systems, particularly for tropical systems, are sparse. For instance, Sharma and Leung (1998, 2000) investigated TE of carp production in Nepal and India, respectively, using a stochastic frontier production function, and analyzed factors influencing the TE by the maximum likelihood estimation approach. Using the same method, Dey et al. (2000) examined the TE and the effect elements of tilapia growout operations in ponds in the Philippines, and Ogundari and Akinbogun (2010) assessed the factors affecting the TE of 64 tilapia, carp, and catfish farms in Nigeria. Kaliba and Engle (2006) estimated technical and allocative efficiency of catfish farms in Arkansas, USA, using data envelopment analysis (DEA), and identified factors determining inefficiency using a Tobit regression approach, and Binh et al. (2010) used the same method to assess the historical improvement of economic productivity in pangasius culture. In the before-mentioned studies, the authors focused on the explanatory variables based on socioeconomic factors only because such variables probably directly influence production efficiency (Dey et al. 2000). The climatic change impacts on the TE of aquaculture farming systems are poorly understood. We will explore this knowledge gap as this contributes to developing mitigation and adaptation measures (De Silva and Soto 2009; De Silva 2012) for this food production sector.

Vietnam, especially the Mekong Delta, is susceptible to climate change impacts (Dasgupta et al. 2007). Due to expected climate change impacts on hydrological regimes and on sea-level rise, the pangasius farms located in upstream and midstream regions will encounter longer flood periods and larger inundation areas, while downstream, larger areas (potentially more farmers) will be affected and farmers may experience higher salinity levels during a longer period (Anh et al. 2014). De Silva and Soto (2009) noted that impacts of climate change on capture fisheries have received more attention in the scientific literature and policy making compared to those on aquaculture. They stressed the need to address vulnerabilities of major aquaculture farming systems and proposed appropriate mitigation and/or adaptation measures to maintain the viability of these systems. Recently, the impacts of climate change on TE have been investigated in various agricultural systems. Oyekale (2012) analyzed the impact of climate change on cocoa agriculture in Nigeria and found the effects of changes in both temperature and rainfall were statistically significant. Makki et al. (2012) pointed out the significant effect of climate factors on TE of paddy farm operations in Kalimantan Province, Indonesia. Examining the effects of rainfall, temperature, and humidity factors on efficiency of three types
of rice production (AUS, AMAN, and BORO) in Bangladesh, Hossain et al. (2013) found humidity has a significant positive effect on all types, temperature has a negative impact on production efficiency, and rainfall has a positive impact only on BORO rice production.

This study aims to identify the major factors that affect the TE of pangasius farms and explores the relationships between those factors and the impacts climate change has or would have on pangasius farming. According to Anh et al. (2015), the pangasius farmers’ perception of and adaptation to climate change impacts differed between the three regions that can be distinguished in the Mekong Delta regarding pangasius farming. The pangasius culture was developed in the upstream and midstream regions by traditional fish farmers. Once the success was imminent, investors mainly expanded the culture in the downstream region using the same technical package (Phan et al. 2009; De Silva and Phuong 2011). This study compares and analyzes TE and influencing factors by regions. The results of this study are expected to provide policy insights to enhance the use of adaptation measures in the pangasius farming sector in particular and in aquaculture in general.

Materials and Methods

Study Area and Data Collection

The study area for this study was similar to that in our previous study (Anh et al. 2014). Briefly, in the delta, striped catfish farming occurs along two main branches, Tien River (upper) and Hau River (lower) and the associated canals of the Mekong River. Accordingly, the study was conducted in the six provinces where pangasius farming is most prevalent (Fig. 1). Along the Mekong branches these can be categorized into three production regions, namely upstream (An Giang and Dong Thap provinces), midstream (Vinh Long and Can Tho provinces), and downstream (Tra Vinh and Soc Trang provinces). For the primary study, 4% of the pangasius farms were randomly selected based on the frequency of distribution in the provinces and the lists of farms registered with the provincial authorities.

A draft questionnaire covering general information of the farmer household, cost of different inputs, production and income, as well as the owner perceptions and strategies to climate-change-induced impacts was developed by experienced socioeconomists and climate-change scientists. The draft questionnaire was a modified version of that used in an earlier study by Phan et al. (2009). The survey was conducted through face-to-face interviews, mostly with owners, in 2010 for five of the covered provinces and done for An Giang in 2011. Each interview was conducted by two interviewers trained and with past experience on conducting such surveys.

In addition to questions on the farm characteristics (size and labor use), revenues and expenses (cost of inputs such as fuel, electricity, chemicals, seed, and feed), the survey also included a set of questions related to the experience of farmers relating to the effects of climate change. Flooding and salinity intrusion were, for example, addressed as follows: “Climate change impact – flood (Y/N),” and “Climate change impact – salinity (Y/N),” for both seasons as well as by an open question.

The survey data were entered into a database developed for the purpose in MS Excel. The database was checked on consistency by calculating the feed conversion ratio (FCR). Data of farms with a FCR below 0.7 and above 3.9 were verified; the lower threshold is hard to reach even for farms using sophisticated recirculating aquaculture, and the farms with an
FCR of 4 and higher would have experienced an extreme event, or given erroneous information. When FCR remained outside these limits after the correction, these farms were excluded from the database. The final database contained 184 farms: 35, 43, 16, 63, 13, and 14 farms from each An Giang, Dong Thap, Vinh Long, Can Tho, Tra Vinh, and Soc Trang provinces, respectively. The data were analyzed in two steps. To examine the efficiency of striped catfish farm operations in the Mekong Delta, the TE of individual farms was assessed by using DEA (Simar and Wilson 2000). To identify whether there are significant relationships between a farm’s TE and impact from climate change factors and other farm characteristics, a regression model was employed.

Efficiency Measurements

The DEA technique, introduced by Charnes et al. (1978), was employed to estimate the TE of a decision-making unit (DMU) that employs multiple inputs to produce multiple outputs. This technique uses linear programming to measure TE of a DMU relative to a set of referenced DMUs. The TE is considered in terms of the optimal level of inputs to achieve a given level of output (an input orientation) or the optimal level of output that can be produced from a given set of inputs (an output orientation). The TE value varies between 0 and 1. If the TE value is equal to 1, the DMU gets TE and if TE is less than 1, DMU gets technical inefficiency. The envelopment surface of the oriented models can be either constant returns to scale (CRS) or variable returns to scale (VRS).

The present study applied the input-oriented model because in agriculture farmers have more control over the inputs rather than the outputs. In the case of the catfish farming sector in the Mekong Delta also, under certain constraints of high costs of inputs, especially of feed (Phan et al. 2009), the choice of a DEA input-oriented model seems the most appropriate.

Banker et al. (1984) developed the input-oriented model of Charnes et al. (1978) to allow farms to operate at increasing, constant, or decreasing returns to scale. Suppose we have \( n \) DMUs (DMU\(_o\); \( o = 1, 2, \ldots, n \)), which produce \( s \) outputs \( y_{ro} \) \( (r = 1, 2, \ldots, s) \) by utilizing \( m \) inputs, \( x_{io} \) \( (i = 1, 2, \ldots, m) \). An input-oriented model can be written as Equation 1. In Equation (1), \( x_{io} \) and \( y_{ro} \) are, respectively, the \( i \)th input and \( r \)th output for a DMU\(_o\) under evaluation, respectively. Solving that model \( n \) times results in optimal values of the objective function and the elements of intensity variables vector \( \lambda \) for each farm. For the DMU\(_o\) the optimal value \( \theta^*_o \) measures the maximal proportional input reduction without altering the level of outputs. The vector \( \lambda_j \) indicates participation of each considered farm in the construction of the virtual reference farm that the DMU\(_o\) is compared with

\[
\begin{align*}
\text{Min} \quad & \theta^*_o \\
\text{subject to} & \\
\sum_{j=1}^{n} \lambda_j x_{io} \leq \theta^*_o x_{io} & i = 1, 2, \ldots, m, \\
\sum_{j=1}^{n} \lambda_j y_{ro} \geq y_{ro} & r = 1, 2, \ldots, s, \\
\sum_{j=1}^{n} \lambda_j &= 1 & \lambda_j \geq 0 & j = 1, \ldots, n, \quad (1)
\end{align*}
\]

The scale efficiency (SE) measures were computed as the ratio of the measure of TE calculated under the assumption of CRS to the TE measure calculated under the assumption of VRS (Banker et al. 1984; Fare et al. 1985). If the value of SE is equal to 1, then DMU\(_o\) is considered as a scale-efficient unit and this unit shows the CRS property, and if SE\(_j\) is less than 1, then the production mix of DMU\(_o\) is not scale efficient.

Although the application of this method is straightforward, it overestimates TE because the empirical sample is usually a fraction of the entire population of DMUs. This problem can be solved by a bootstrapping method (Simar and Wilson 2000, 2007). Therefore, in this study, we used the DEA-bootstrap running in the R environment to estimate TE and confidence intervals to allow for statistical inference (Bogetoft and Otto 2011).
The Factors Influencing Farm Technical Efficiency

To estimate the relationship between the efficiencies, different farm characteristics, and impacts due to climate change, we applied the bootstrap procedure to improve statistical efficiency in the truncated regression model (Simar and Wilson 2007):

$$D_i \approx \beta_0 + \sum_{m=1}^{k} \beta_m Z_{mi} + \sigma_i$$ (2)

As the model of Simar and Wilson (2007) assumed that 1 was the left-hand-side limit, whereas the TE value was bounded by 0 and 1, the term of $D_i$ was defined as $D = 1/TE$. $D$ can be seen as the distance from TE point of farm $i$ to the efficiency frontier and gets the value greater or equal to 1 (in case of farm gets TE). The $D_i$ is inverse to TE so that positive influence on $D$ means negative influence on TE, or inversely. $Z$’s are explanatory variables that affect farm operation efficiency, $k$ is the number of explanatory variables, $\beta_m$ are parameters of the model, and $\epsilon_i$ are random error terms.

Due to the tendency to increase scale of operations of downstream pangasius farms, the relationship among farm characteristics, climate change impacts, and SE was investigated.

$$SE_i \approx \alpha_0 + \sum_{m=1}^{k} \alpha_m Z_{mi} + \epsilon_i$$ (3)

where $SE_i$ is the SE for farm $i$, $Z$’s are explanatory variables that affect farm SE, $k$ is the number of explanatory variables, $\alpha_m$ are parameters of the model, and $\epsilon_i$ are random error terms.

The explanatory variables in Equations (2) and (3) included age of farmer (years), aquaculture experience of farmer (years of aquaculture performance), education level of farmer (1 = higher than elementary school; 0 = elementary school or lower), access to extension training (1 = yes; 0 = no), flood effects (1 = yes, 0 = no), salinity intrusion effects (1 = yes, 0 = no), upstream location (dummy with 1 = yes, 0 = no), and midstream location (dummy with 1 = yes, 0 = no). The dummies were included to separate the farm-level impacts of flooding and salinity from the general regional impact. Effects of flood and salinity were used as proxies for the effect of past experience with climate change.

The bootstrap truncated regression model was employed using STATA software.

Data Description

The variables used to estimate TE of farms were calculated per pond unit for 1 yr (Table 1). The input data included the pond area; the number of workers; the cost of energy (US$) consisting of fuel and electricity; the cost of chemicals (US$), including drugs, antibiotics, and others; the cost of feed (US$), including vitamins and industrial and farm-made pellets; and the number of seed (fingerlings) stocked. The output data consisted of pangasius production volumes (metric tons). The surveyed factors affecting TE included age of farmers, aquaculture experience, education level, aquaculture training participation of farmers, impact of flooding and salinity intrusion, and the regions (Table 1).

The surveyed farms had a pond area from 0.08 to 1.20 ha and produced 10–1000 m.t. of striped catfish per year (Table 1). The use of inputs was comparable for seed, labor, and feed.
but the use of chemicals (including veterinary drugs) varied much more between farms. The use of energy also varied a lot, partly due to the fact that some downstream farms, benefiting from gravity flow, did not use fuel or electricity for pumping water. Energy and chemicals were aggregated inputs. They were measured in monetary value because farmers usually do not remember or keep records of exact quantities of these inputs. In practice, the cost of feed and seed were the highest cost factors in pangasius farming.

On a per-hectare basis (Table 2), farm operational cost was highest upstream and lowest downstream. Conversely, the production (yield) of farms was highest upstream and lowest downstream. Farmers downstream also stocked less fish and mostly stocked once a year instead of three times in 2yr as is the practice in mid- and upstream farms. The average age of the household’s heads was 44yr, both overall and in the upstream and midstream regions. Farmers in the downstream regions were on average 4yr older. Aquaculture experience in pangasius farming varied from 1 to 20yr. Farmers in the upstream and midstream regions, where striped catfish culture originated, had more experience than those in the downstream regions. Most of the farmers (80%) had an education level higher than elementary school; education level was lowest in the downstream and highest in the upstream area. More than half of the farmers had attended training courses for striped catfish aquaculture offered by local fisheries extension services, universities, and/or private companies.

All farmers in the upstream and most in the midstream regions felt the effect of flooding in the past 7yr but none downstream, whereas salinity intrusion was felt in the downstream provinces only. Farmers in the upstream and midstream regions estimated the economic losses due to hazardous flooding either as a 10 to 100% decrease of production or as a 5 to 300% increase of cost for fish disease treatment. Farmers experiencing salinity could not attribute specific losses as they adjusted the farming system to accommodate the seasonally recurring event.

Results

**TE Scores**

The DEA-bootstrap program calculated TE under CRS and VRS with the assumption that TE under CRS is not significantly different from TE under VRS (the null hypothesis). The calculated results rejected the null hypothesis. The TE scores under VRS of farms varied from 0.45 to 1.00, with a mean value of 0.84. SE ranged from 0.13 to 1.00, with a mean value of 0.80 (Table 3).

The mean TE for all farms was 0.84 under VRS. This implies that farmers produced pangasius at an average 84% of the potential efficiency of current technology and input levels. This also means that farms can reduce their inputs by 16% and keep the same production level. One third of the farms has a TE below 0.6 and thus have a large opportunity to improve their profits. Under CRS, the majority of the farms had a TE below 0.80, with slightly more than half in the range of 0.60–0.80. Vice versa, under VRS, more than 55% of the farms had a TE higher than 0.80 (Table 3). The SE of 56% of the farms was above 80%, and thus at least 44% of the farms were producing at suboptimal scale in the present market context.

**Comparison of TE among Upstream, Midstream, and Downstream Regions**

Under VRS, farm TE in the downstream area scored significantly higher compared to the other regions \((P < 0.05; Table 4)\). The SE was lowest in the downstream region \((P < 0.05)\), which aligned with the lower stocking density and frequency.

**Factors Affecting Farm’s TE**

The bootstrap truncated regression of distance \((D)\) demonstrated that farmer’s age, farmer’s aquaculture experience, and having received training by extension services affected the distance to the TE frontier positively. This means that these factors reduced the TE. Inversely, the impacts of education, flooding, and salinity intrusion on distance were negative and improved the TE. The level of the factor for salinity was double that of flooding; the latter
Table 2. Summary statistics of input and output variables of the sampled striped catfish farms of the Mekong delta, Vietnam, according to production region (ha/yr).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Upstream (n = 78)</th>
<th>Midstream (n = 79)</th>
<th>Downstream (n = 27)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Avg.</td>
<td>SD</td>
<td>Range</td>
</tr>
<tr>
<td>Pond area (ha)</td>
<td>0.42</td>
<td>0.27</td>
<td>0.1–1.2</td>
</tr>
<tr>
<td>Labor (persons)</td>
<td>6.8</td>
<td>5.6</td>
<td>2–33</td>
</tr>
<tr>
<td>Energy cost (US$)</td>
<td>1409</td>
<td>2587</td>
<td>0–11,906</td>
</tr>
<tr>
<td>Chemical cost (x1000 US$)</td>
<td>26.2</td>
<td>50</td>
<td>0.45–300</td>
</tr>
<tr>
<td>Seed (x1000 pieces)</td>
<td>641</td>
<td>236</td>
<td>100–1400</td>
</tr>
<tr>
<td>Feed (x1000 US$)</td>
<td>511</td>
<td>447</td>
<td>67–2204</td>
</tr>
<tr>
<td>Striped catfish production (tons)</td>
<td>580</td>
<td>373</td>
<td>80–2500</td>
</tr>
<tr>
<td>Farmers’ age (yr)</td>
<td>44</td>
<td>8.7</td>
<td>27–68</td>
</tr>
<tr>
<td>Farmers’ aquaculture experience</td>
<td>5.4</td>
<td>3.1</td>
<td>1–20</td>
</tr>
<tr>
<td>Farmers’ education</td>
<td>1</td>
<td>0.2</td>
<td>0–1</td>
</tr>
<tr>
<td>Farms’ access to extension training</td>
<td>0.6</td>
<td>0.5</td>
<td>0–1</td>
</tr>
<tr>
<td>Flood effect</td>
<td>1</td>
<td>0.2</td>
<td>0–1</td>
</tr>
<tr>
<td>Salinity intrusion effect</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

Table 3. Distribution of farm technical and scale efficiency scores using data envelopment analysis input orientation.

<table>
<thead>
<tr>
<th>Five classes of TE</th>
<th>TE scores under CRS</th>
<th>TE scores under VRS</th>
<th>SE scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number</td>
<td>Frequency (%)</td>
<td>Number</td>
</tr>
<tr>
<td>≤0.2</td>
<td>1</td>
<td>0.5</td>
<td>1</td>
</tr>
<tr>
<td>0.2–0.4</td>
<td>8</td>
<td>4.6</td>
<td>3</td>
</tr>
<tr>
<td>0.4–0.6</td>
<td>49</td>
<td>26.6</td>
<td>24</td>
</tr>
<tr>
<td>0.6–0.8</td>
<td>96</td>
<td>52.2</td>
<td>53</td>
</tr>
<tr>
<td>0.8–1</td>
<td>30</td>
<td>16.3</td>
<td>103</td>
</tr>
<tr>
<td>Mean</td>
<td>0.66</td>
<td>0.84</td>
<td>0.80</td>
</tr>
<tr>
<td>SD</td>
<td>0.15</td>
<td>0.17</td>
<td>0.17</td>
</tr>
<tr>
<td>2.5% Value</td>
<td>0.64</td>
<td>0.82</td>
<td>0.78</td>
</tr>
<tr>
<td>97.5% Value</td>
<td>0.68</td>
<td>0.87</td>
<td>0.83</td>
</tr>
</tbody>
</table>

CRS = constant returns to scale; SE = scale efficiency; TE = technical efficiency; VRS = variable returns to scale.

was higher than the effect for education. The effects of age, aquaculture experience, flood, and salinity intrusion were statistically significant at the 5% level (Table 5).

The bootstrap truncated regression model demonstrated that age, education, training, and flood affected the farm’s SE positively. Inversely, the impact of experience and salinity intrusion on SE was negative. These effects were statistically significant at a 5% level (Table 6). The factor for the effect of salinity is about double to 50-fold larger than other factors.

**Discussion**

Our study used interview data. Both the one-time survey on economic data and the farmers’ responses to questions regarding their appreciation could cause a degree of uncertainty. The farmers might have estimated their cost and production, and thus made mistakes, or they may have missed bills while accounting if answers were based on written documentation. All surveys were conducted in a year with normal weather, and the farmers appreciated the influence of climate change and resulting impacts on their pangasius farming operation based on past experience.

**Comparing the TE**

Under the assumption of VRS the TE score of the pangasius farms was 0.84. This score is identical to the TE under VRS of the Vietnamese pangasius sector found for 2006 (0.85) by Binh et al. (2010), but higher than the one for
Table 4. Farm efficiency scores using data envelopment analysis input orientation in the three regions.

<table>
<thead>
<tr>
<th>Regions</th>
<th>TE scores under CRS</th>
<th>TE scores under VRS</th>
<th>SE scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>95% CI</td>
</tr>
<tr>
<td>Upstream</td>
<td>0.64</td>
<td>0.17</td>
<td>0.61–0.68</td>
</tr>
<tr>
<td>Midstream</td>
<td>0.68</td>
<td>0.14</td>
<td>0.65–0.71</td>
</tr>
<tr>
<td>Downstream</td>
<td>0.66</td>
<td>0.08</td>
<td>0.62–0.69</td>
</tr>
</tbody>
</table>

CI = confidence interval; CRS = constant returns to scale; TE = technical efficiency; VRS = variable returns to scale.

Table 5. Bootstrap truncated regression estimates of the model using distance to the technical efficiency frontier as outcome.a

<table>
<thead>
<tr>
<th></th>
<th>95% Confidence intervals</th>
<th>Mean</th>
<th>SD</th>
<th>95% Confidence intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_0 )</td>
<td></td>
<td>1.257</td>
<td>1.099</td>
<td>1.412</td>
</tr>
<tr>
<td>Age of farmer</td>
<td></td>
<td>0.003*</td>
<td>0.001</td>
<td>0.005</td>
</tr>
<tr>
<td>Aquaculture experience</td>
<td></td>
<td>0.023*</td>
<td>0.016</td>
<td>0.029</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td>-0.047*</td>
<td>-0.112</td>
<td>0.015</td>
</tr>
<tr>
<td>Access to extension training</td>
<td></td>
<td>0.026*</td>
<td>-0.015</td>
<td>0.067</td>
</tr>
<tr>
<td>Flooding effect</td>
<td></td>
<td>-0.074*</td>
<td>-0.137</td>
<td>-0.009</td>
</tr>
<tr>
<td>Salinity intrusion effect</td>
<td></td>
<td>-0.159*</td>
<td>-0.289</td>
<td>-0.034</td>
</tr>
<tr>
<td>Upstream region (dummy)</td>
<td></td>
<td>0.089*</td>
<td>-0.048</td>
<td>0.217</td>
</tr>
<tr>
<td>Midstream (dummy)</td>
<td></td>
<td>-0.100*</td>
<td>-0.237</td>
<td>0.021</td>
</tr>
</tbody>
</table>

aValues marked with asterisks indicate that factor is significant at a 5% confidence level.

Table 6. Bootstrap truncated regression estimates of the influence of the explanatory variables on the scale efficiency.a

<table>
<thead>
<tr>
<th></th>
<th>95% Confidence intervals</th>
<th>Mean</th>
<th>SD</th>
<th>95% Confidence intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_0 )</td>
<td></td>
<td>0.964*</td>
<td>0.787</td>
<td>1.142</td>
</tr>
<tr>
<td>Age of farmer</td>
<td></td>
<td>0.005*</td>
<td>0.002</td>
<td>0.007</td>
</tr>
<tr>
<td>Aquaculture experience</td>
<td></td>
<td>-0.018*</td>
<td>-0.027</td>
<td>-0.009</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td>0.133*</td>
<td>0.052</td>
<td>0.221</td>
</tr>
<tr>
<td>Access to extension training</td>
<td></td>
<td>0.145*</td>
<td>0.092</td>
<td>0.199</td>
</tr>
<tr>
<td>Flooding effect</td>
<td></td>
<td>0.093*</td>
<td>0.013</td>
<td>0.175</td>
</tr>
<tr>
<td>Salinity intrusion effect</td>
<td></td>
<td>-0.281*</td>
<td>-0.486</td>
<td>-0.117</td>
</tr>
<tr>
<td>Upstream region (dummy)</td>
<td></td>
<td>-0.215*</td>
<td>-0.370</td>
<td>-0.066</td>
</tr>
<tr>
<td>Midstream region (dummy)</td>
<td></td>
<td>-0.022*</td>
<td>-0.169</td>
<td>0.113</td>
</tr>
</tbody>
</table>

aValues marked with asterisks indicate that factor is significant at a 5% confidence level.

2002 (0.69) by those authors, as well as the 0.75 found by Pham et al. (forthcoming). The latter authors considered the capital cost of short-term loans and investment; our database did not include information to do this. TE was also higher (0.73) than the catfish farms in Arkansas (Kaliba and Engle 2006) and the fish farms in Nigeria (0.79; Ogundari and Akinbogun, 2010). This score is comparable also to those of the aquaculture sector in other countries, such as trout pond farming in the Black Sea Region, Turkey (0.82; Cinemre et al. 2006), tilapia pond operations in the Philippines (0.83; Dey et al. 2000), semi-intensive/intensive carp farming in India (0.80; Sharma and Leung 2000), Chinese fish farms polyculture (0.83; Sharma et al. 1999), and carp farming in Bangladesh (0.85; Ferdous and Murshed-e-Jahan 2008). However, except for the target species, the recommendations resulting from these TE could not really be compared because the farming technologies, input and output variables, and the scale of operation may be very different.

A TE under VRS of 0.84 would imply that average fish yield could increase by 16% while decreasing inputs. According to Pham et al. (forthcoming), considering also the cost of capital (see below), the fish yield could simultaneously increase by 30% relative to the VRS frontier. The gap with the attainable yield is in both cases probably related to a high mortality.

The Impact of Scale on TE

The TE under VRS being nearly 20% higher than the TE under CRS is indicative for the fluctuation of the scale of the farm operations. A higher TE under VRS of farms located downstream (0.96) compared to those upstream and midstream (0.82) regions can be explained by the lower cost of operation related to a smaller pond area, and lower costs for energy from fuel and electricity. The latter is due to the need for pumping to exchange the water being on average lower because of the larger possibility to use the tidal regime. In all three regions, the need to use a pump to refresh water depends on the location,
inside or outside the flood protection dyke, and the quantity of water required, being low in the first month of culture. However, the SE of farms downstream is lowest, which may be due to the fact that some of these farms stock only once per year. In agreement with Binh et al. (2010), these arguments imply that measures to increase TE of pangasius farms include the reduction of input cost as well as the increase of the scale of operation of smaller farms. The latter is in agreement with Kumar and Engle (2017), stating that the key to profitability appears to be related more to the proportionality of input and that investments in technology, such as aerators in channel catfish culture, need to go along with increased densities.

**Farmer Characteristics and Strategies**

The range of calculated TEs is large, which might indicate that the input–output market of pangasius is very volatile, which is in agreement with the observation of De Silva and Phuong (2011). When prices offered are below production cost, traditional farmers tend to wait for better market prices, however sometimes without success; although their feeding cost increases, the weight of the fish hardly increases, and they accumulate losses due to higher feeding cost. According to Pham et al. (forthcoming), the contribution of feed to inefficiency was only 3%, while capital cost contributed 42%; labor and pond area were other large contributors with shares of 23 and 16%, respectively. Thus technical inefficiency is driven by fish mortality and a high capital cost; the latter is mainly due to delayed payment by the processing companies after delivery of fish by the farmers. At least one progressive fish farmer had a coping strategy, but better access of farmers to legal institutions in case of delayed payment might be needed.

Production and market strategy of Nguyen Thanh Son, An Lac Tay Commune, Ke Sach District, Soc Trang Province (collected during open interviews by the main and corresponding authors held in 2012):

“I plan my production and sell as scheduled: some harvests I lose, others I gain, and on average I make good money.”

“I sell to the company having the best price and I check at forehand with the bank if the company is capable of paying me as fast as possible, to reduce my cost of interest.”

The age and training of farmers decreased the TE but significantly increased the SE. Meanwhile higher education increased both TE and SE. Our nonpublished survey data show that the farmer’s participation in training remained below 65%, even in the biased sample, but was higher in the downstream area, which might explain the relationship of training on SE (being lower in downstream). However, older farmers may gradually have acquired larger farms, and the farmers having larger ponds might have been invited more frequently for training related to the new technology of pangasius aquaculture. However, longer aquaculture experience in traditional practices may also become an obstacle to improve performance and scale. Anh et al. (2015) revealed that pangasius farmers in the downstream region, where this study found the lowest SE score and the higher TE scores under VRS, had low confidence in the effectiveness of technical training by government agencies. The latter might be due to the general top-down lecturing approach of the trainers instead of a more effective participatory approach (Brown and Fadillah 2013) Although these farmers had the shortest experience, they also were the oldest and had the lower education level. The awareness on climate change was also better among higher educated farmers (Anh et al. 2015). Thus education is a factor making a difference, while awareness is essential for adaptation and both higher TE and SE will increase the capacity to adapt. However, a fish farmer has not just a single way to achieve economic efficiency, which remains an act of balancing the use of inputs, their associated costs, and the yield (Johnson et al. 2014).
Impact of Salinity and Flooding on TE

Both salinity and flooding apparently increased the TE. This might be due either to precautionary measures having a positive effect or to the subjective measurements of the effects of flooding and salinity by farmer self-reporting. The self-reporting may introduce a bias in the sense that the more efficient farmers may be the ones that are more likely to report flooding and salinity. Farmers culturing pangasius in a location with risk of flooding might have taken measures to reduce the risk of heavy losses, thus becoming the most efficient upstream farmers. The number of farmers suffering from salinity is much smaller than those suffering from flooding, while the factor in the regression function for salinity is doubled. Indeed the salinity effect is strongly correlated with the downstream region. Most farmers downstream also have lower cost and therefore higher TE; preventing impact from salinity by reducing stocking density or frequency of stocking might have strengthened the efficiency.

Farmers in upstream and midstream areas having to deal with increased and prolonged periods of high water levels may have built larger ponds with higher dykes and larger pumping systems. To recover their investments they also stock more seed. These factors explain the positive effect of flooding on SE. Inversely, salinity intrusion occurs seasonally every year and forces the farmers in the downstream region to adjust their cropping plan and avoid stocking young fish in the seasons at high salinity levels. Therefore salinity intrusion reduces the capacity of the farmer to increase scale through, for example, stocking more frequently or stocking more fish. An alternative option for upscaling might be to organize themselves in input/output cooperatives to reduce cost and improve margins, respectively.

Mitigation of Climate Change Impacts

In the future, climate change impact may cause prolonged and more frequent flooding and expand the area of salinity intrusion in the dry season (De Silva and Phuong 2011; Anh et al. 2014). To mitigate these effects of climate change, the upstream and midstream farms will have to invest in dyke enforcement, while the downstream farms might opt for stocking fingerlings at a more advanced age after nursing them on higher ground (Anh et al. 2014). The government might support the design of adaptation strategies, including studies on the cost efficiency of these strategies. In particular, the cost efficiency of strategies proposed for climate-change adaptation in downstream areas, such as producing a salinity-tolerant strain of pangasius (De Silva and Phuong 2011; Nguyen et al 2016) needs in-depth studies.

Conclusions

The TE of pangasius farms in the Mekong Delta of Vietnam observed in this study is on par with fish farms operated in other countries. The higher educated farmers and the more efficient farmers perceived impact of climate change and knew how to deal with these influences. Pangasius farmers in the flood-prone areas of the upstream and midstream regions had larger scales of operation, whereas salinity intrusion reduced the scale of farms located in the downstream regions. The TE of the farmers lagging behind can be improved by reducing the delay between delivery of fish to the processing industries and payments to farmers, thus decreasing farmers’ capital cost. Further gains can come from more efficient use of inputs, such as feed, seed, labor, and an increased scale of operation, as well as an improved approach of training institutions. Having a higher education resulted in higher TE, but training by extension services did not, and farmers’ opinion on the effectiveness of these trainings reflected this. The overall adaptation strategy (e.g., better dykes) requires a one-time investment, while the increased salinity level downstream will require increased recurrent operational costs either at the sector level (e.g., breeding salinity tolerant pangasius) or at the farm level (e.g., a prolonged nursery phase).

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