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APPLIED RESEARCH

Determinants of inefficiency in shrimp aquaculture under environmental impacts: Comparing shrimp production systems in the Mekong, Vietnam

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Abstract

Shrimp aquaculture systems vary from primitive (extensive/improved extensive) to more industrialized (intensive/semi-intensive) farms, and the impacts of environmental shocks may differ between them. This article applies the Cobb–Douglas stochastic production frontier function to evaluate the determinants that impact the inefficiency of these intensive and extensive systems in Vietnam. Data is from a survey of 436 white-leg shrimp (*Litopenaeus vannamei*) farms in the Mekong Area. Our findings show that farmers with self-reported experiences of drought have higher production efficiency, while experiences of irregular weather reduce efficiency. In addition, education and feeding practice/stocking density adjustment measures increase extensive efficiency. Furthermore, longer crop duration impacts the two systems differently, increasing intensive farm efficiency but decreasing extensive farm efficiency. Interestingly the efficiency effects differ for the two technologies, with two exceptions; efficiency increases for both locations further from the sea and decreases with disease occurrence.

KEYWORDS
inefficiency, Mekong delta, shrimp farms, stochastic frontier analysis, technical efficiency, Vietnam

1 | INTRODUCTION

Asia is projected to contribute almost 90% of world aquaculture production by 2030, with shrimp being important exported species providing a vital source of foreign exchange earnings for several developing countries in the region (FAO, 2018, 2020). Vietnam was the world's third-largest seafood exporter in 2016, with the largest share of export revenue (USD 7.3 billion) coming from farmed catfishes and shrimp (FAO, 2018). White-leg shrimp production contributed substantially to Vietnamese total shrimp export value, which increased from 1.6 billion USD in 2008 to nearly 3.9 billion USD in 2017 (Le, 2018). White-leg shrimp production increased rapidly from 93,503 tons in 2000 to 683,000 tons in 2017 (Nhu, 2016), and approximately 1.6 million Vietnamese are involved in the shrimp value chain in the Mekong area of Vietnam (Phillips, Subasinghe, Tran, Kassam, & Chan, 2016). This rapid growth contributes significantly to employment and poverty alleviation in the region. However, the shrimp industry is also being challenged by the impacts of extreme climate events and climate variability (ADB, 2013). For example, in 2016, more than 81 thousand hectares of shrimp breeding ponds were damaged by the effects of the worst prolonged drought in 90 years and the subsequent saltwater intrusion (FAO, 2016).

Consequently, local shrimp communities in coastal provinces, especially those that rely heavily on aquaculture, have gradually become aware of erratic and increasingly unpredictable weather reducing crop output and household livelihoods (Van Quach, Murray, & Morrison-Saunders, 2017). With the Vietnamese government's USD 10 billion shrimp export target for 2025, there is, however, an emerging concern for the sustainability of shrimp production, given the impact of natural disaster risks (Nguyen, Nguyen, & Jolly, 2019). White-leg shrimp expansion dominates production to meet the government's targeted plans, motivating our focus. Its production systems are grouped into two central systems: extensive/improved extensive (hereafter extensive) farming and intensive/semi-intensive (hereafter intensive) farming. The extensive system is indicative of nonindustrialized, usually low budget, limited capital access, low-cost inputs, and limited management activities in large areas. Such systems use whatever is in the water, operate more naturally, and focus on local market demand. In contrast, intensive farms control the production factors with more inputs within limited farming areas, producing high yields, targeting export markets, and contracts with shrimp middlemen rather than small local markets.

Shrimp culture has been considered high-risk, high return, and heavily relies on the natural environment and shrimp ecosystem, which demands comprehensive management to maintain productivity. In the Mekong delta region, the shrimp farmers identified frequently occurring environmental risks, including extreme weather conditions (sea-level rise, drought, saline intrusion, and irregular weather) and environmental threats (water cross pollution and disease). The unexpected or even expected threats require new farmers or even experienced ones to raise their awareness of and preparedness for environmental and climate risks. From a management perspective, it is also urgent to ensure and coordinate incentive mechanisms and timely regulations to ensure productivity and efficiency during disasters. Thus, the farmers' perceptions, their climate-related coping mechanisms, and farming management practices in relation to efficiency have sparked increased research in recent years (Folorunso et al., 2021; Holsman et al., 2019; Kam, Badjeck, & Teh, 2012; Nagothu et al., 2012; Nguyen et al., 2018; Nguyen & Fisher, 2014; Nguyen, Nguyen, Jolly, & Nguelifack, 2020; Reid et al., 2019; RIA2, 2014; Tran et al., 2013; Van Quach et al., 2017).

Regarding farming efficiency measurement, stochastic frontier analysis (SFA) is a widely applied methodology in many aquaculture studies of developing countries in the last decade (Alam, Guttormsen, & Roll, 2019; Alam, Khan, & Anwaru Huq, 2012; Asamoah, Nunoo, Osei-Asare, Addo, & Sumaila, 2012; Folorunso et al., 2021; Begum, Hossain, Tsiouni, & Papanagiotou, 2015; Begum, Hossain, & Papanagiotou, 2013; Bimbao, Paraguas, Dey, & Eknath, 2000;

Bukenya, Hyuha, Molnar, & Twinamasiko, 2013; Dey, Paraguas, Bimbao, & Regaspi, 2000; Dey et al., 2005; Ghee-Thean, Islam, & Ismail, 2016; Hukom, Nielsen, Asmild, & Nielsen, 2020; Irz & Victoria, 2003; Islam, Tai, & Kusairi, 2016; Kareem, Aromolaran, & Dipeolu, 2009; Kumar, Birthal, & Badruddin, 2004; Kumaran et al., 2017; Le, Le, & Nguyen, 2020; Nagothu et al., 2012; Ogundari, 2014; Ogundari & Aklnbogun, 2010; Radhakrishnan, Sivaraman, & Krishnan, 2021; Sadika, Siegfried, Madan, Nazmul, & Puran, 2012; Sharma & Leung, 2000a, 2000b; Singh, 2008; Singh, Dey, Rabbani, Sudhakaran, & Thapa, 2009; Yuan, Yuan, Dai, Zhang, & Gong, 2019). There are some efficiency studies of Vietnamese aquaculture, such as Dey et al. (2000, 2005), Dey, Kamaruddin, Paraguas, and Bhatta (2006), Folorunso et al. (2021), Long, Van Thap, Hoai, and Thuy (2020), Nguyen et al. (2020), and Nguyen and Fisher (2014), but very few that include the impact of climate change (see however Folorunso et al. (2021) and Nguyen et al. (2018, 2020) for catfish and shrimp aquaculture). For example, Nguyen et al. (2018) assessed the impacts of flood and saline water intrusion in the Vietnamese catfish industry, while Nguyen et al. (2020) measure the impacts of natural disasters and disease on intensive shrimp farming in two provinces of Vietnam. The recent research of Folorunso et al .(2021) estimated the impact of environmental hazards (e.g., experienced drought, flood, and pollution events) on shrimp production in Khanh Hoa province. These three studies assess the effects of environmental threats based on farmers' perception data, which is also applied here. However, none of the earlier efficiency papers identified what extreme climate events and environmental threats are currently threatening Vietnamese white-leg shrimp production in the Mekong delta or measured how the effects of farmers' perception of these challenges combined with their adaptive measures impact on farming efficiency. This also adds to the literature by studying both extensive and intensive farm technologies in Vietnamese shrimp aquaculture. These expansions are developed in our analysis. Our dataset consists of 436 white-leg shrimp extensive and intensive farms in single production cycles (2016/17), situated in the Bac Lieu and the Ca Mau provinces of the Mekong, provided by a survey conducted via face-to-face interviews.

The contribution of this article is first to explore which determinants (e.g., socio-economic, farm site characteristics, and farming management activities), in Vietnamese white-leg shrimp farm level data, explain farming inefficiency in the different production systems in the Mekong region. We introduce new potential explanatory factors to further develop the shrimp efficiency knowhow, including farmers' perception of climate events and adaptive measures. Second, we identify significant results and management implications of relevance to policymakers and producers for improving the white-leg shrimp sector's efficiency and governance along sustainable lines.

2 | MATERIALS AND METHODS

2.1 | Model

According to efficiency studies from 2000 to 2021 (see Appendix A), three approaches are commonly applied in efficiency measurement of aquaculture: stochastic frontier analysis, data envelopment analysis, and meta frontier analysis. First, data envelopment analysis is a nonparametric technique that can accommodate multiple outputs. However, this technique is deterministic and attributes all deviations from the frontier to inefficiencies, making it less appropriate to case studies where uncontrollable factors (e.g., disease outbreaks) account for substantial variation in output (Sharma & Leung, 2003). In contrast, the SFA model utilizes parametric techniques, which support the identification of differences in farming efficiency, controlled by two components: farming technical inefficiency and stochastic noise (Sharma & Leung, 2003). This approach is appropriate for studying agri- and aquaculture in developing countries since, according to Gunaratne and Leung (1996). Farming data there is heavily influenced by measurement errors and other stochastic factors (e.g., weather conditions). Finally, meta-frontier analysis allows the measurement and comparison of farming efficiency for several individual countries or regions over separate production frontiers (Gunaratne & Leung, 1996; Sharma & Leung, 2000a, 2000b). This method applies either data envelopment (e.g., Nguyen & Fisher, 2014; Rahman, Nielsen, Khan, & Asmild, 2019; Ton Nu Hai, Van Meensel, & Speelman, 2020) or SFA approaches (e.g., Gunaratne & Leung, 1996; Onumah & Essilfie, 2020). Battese (2002) and Lau and Yotopoulos (1989) state that the lack of comparable data and the presence of inherent differences across countries are the two major limitations in using the meta-production function approach. Equivalent differences, and data limitations regarding the intensive and extensive systems challenge our study. Therefore, we apply the stochastic frontier technique separately for each technology, thus not comparing efficiency as such, but rather assessing the factors that influence efficiency in the two production systems.

Furthermore, Cobb–Douglas and other flexible form (translog) functions are most commonly applied in the SFA literature (Battese, 1997). Primarily, sample size and estimation convenience often dictate the choice of functional form in aquaculture production analyses, to provide interpretable research findings. Gunaratne and Leung (1996) and Irz and Victoria (2003) point out that the Cobb–Douglas function firmly supports analysis of relatively small sample sizes, while multicollinearity issues often occur in relation to the translog function. Even if the sample size was not a limiting factor in our study, the translog form may not be appropriate due to a large number of zero values for several input variables and their squared and interaction terms (Sharma, 1999). Based on this, the Cobb–Douglas stochastic frontier function seems functional and suitable for our dataset.[1]

Following Aigner, Knox Lovell, and Schmidt (1977), the Cobb–Douglas stochastic frontier function is described by $Y_i = f(X_i;\alpha)\exp(\varepsilon_i)$, where Y_i is the best practice production of the farm $i = 1,\ldots.N$, given the vector of inputs X_i and the technology represented by the function $f(X_i;\alpha)$. α is a vector of unknown coefficients associated with the input vectors (X_i) of the production function. The component error term, ε_i, splits into the error term, $v_i i\tilde{d}dN(0,\sigma_v^2)$, and the non-negative deviation between the frontier and the observed productivity of each farm, u_i, $\varepsilon_i = v_i - u_i$, where, u_i represents technical inefficiency, and is assumed to follow a truncated normal distribution suggested by Aigner et al. (1977) and Meeusen and Van Den Broeck (1977). In addition, we assume u_i is a function of exogenous variables ,$u_i = z_i\delta + \omega_i$, where z_i is a vector of explanatory variables which impact shrimp inefficiency. To assure that u_i is non-negative as stated above, the error term ω_i is assumed to have a truncated normal distribution where the point of truncation is $-z_i\delta$. Therefore, $\omega_i > -z_i\delta$ and $u_i\tilde{N}^+(-z_i\delta + \sigma_u^2)$, while δ is a vector of unknown parameters.

To overcome inconsistencies in the assumptions regarding the independence of inefficiency effects, Battese and Coelli (1995) suggested a single-stage SFA estimation procedure to examine the determinants of technical inefficiencies in terms of farm-specific characteristics, an approach we apply here. Maximum likelihood estimation provides the estimations for the α's and variance parameters. Aigner et al. (1977) suggest using a likelihood function to measure two variance parameters representing u and v, so that $\sigma^2 = \sigma_V^2 + \sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{\sigma^2} = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_V^2}$, where γ-values lie between 0 and 1, with $\gamma = 1$ implying that all the deviations from the frontier are explained by technical inefficiency (Coeil, Rao, & Battese, 2005). The estimated λ ($\lambda = \frac{\sigma_u}{\sigma_v}$) identifies the relationship between the standard deviation of the inefficiency term and the error term. SFA also allows different hypotheses to be tested to confirm the presence of technical inefficiency (see Table 4). The related null hypotheses tests use the generalized likelihood ratio (LR) statistics, given by: $LR = -2[\ln\{L(H_0)\} - \ln\{L(H_1)\}])\tilde{\chi}^2$, where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and alternative (H_1) hypotheses, respectively. The test result rejects the null hypotheses with LR values significantly higher than the critical values given by Kodde and Palm (1986). The technical efficiency (TE) index of shrimp farm i in the sample (TE_i) is defined as the ratio of observed output to the corresponding frontier output and is given by: $TE_i = \exp(-u_i) = \frac{Y_i}{f(X_i;\alpha)exp(v_i)}$.

2.1.1 | The empirical model

In this article, we measure the TE using the log-linear form of a Cobb–Douglas stochastic production frontier with output-oriented inefficiency, specified by

$$lnY_i = \alpha \ln X_i + v_i - u_i \quad (1)$$

Iinuma, Sharma, and Leung (1999) noted that using a geometric mean or quantity index based on revenue shares or prices for different fish species is more appropriate than using actual quantity (e.g., total fish production) in production frontier analysis when estimating multi-output production of a polyculture (extensive) system. However, most previous studies have insufficient data on the revenue and price of species. Thus, the harvested yield is used as output instead. In this study, physical units of output quantities are available, while quality per hectare of the different farms is not observed. Therefore, Y_i is a quality-adjusted output, measured using the log of normalized quality-adjusted quantity of harvested shrimp per crop, as suggested by Fernandez-Cornejo and Jans (1995) (see Appendix B), and X_i is a vector consisting of the inputs for shrimp farming.

The choice of input variables come from the surveyed shrimp practices and a literature review on SFA in aquaculture (see the details in Appendix A), for instance, carp (Sharma & Leung, 2000a, 2000b); salmon (Asche & Roll, 2013); tilapia (Alam et al., 2012; Bukenya et al., 2013); freshwater aquaculture (Dey et al., 2005); and white-leg shrimp (Kumaran et al., 2017; Nguyen et al., 2020). This resulted in the selection of six inputs included in the production function here:

1. Seed stocking density (seeds/m^2)
2. Feed use (kilos)
3. Labor (man-days)
4. Farm size (hectares)
5. Chemical and fuel cost (1,000 VND)
6. Other operating costs (1,000 VND)

Seed stocking density is represented as seed input per crop. The quantity of feed used in ponds is measured in kilos per production cycle. In our sample, only a small amount of feed is used in semi-extensive installations, while traditional extensive farming has no feed use. Labor input is measured in the number of man-hours in the crop since many farm-owners operate independently and do not include labor costs in their budgets. The number of man-hours is found by multiplying the number of days in the recent crop with 8 hr per day and the number of owners and workers laboring on the farm, as suggested by Alam et al. (2012). The physical farm size can be considered as a proxy of the capital invested. Farm size (measured in hectares) is the total area farmers use for shrimp culture in their most recent crop. Many empirical efficiency papers mention the weakness of the quality of inputs used (Battese, 1997), so inputs in a physical quantity or the corresponding monetary value are often employed (Dey et al., 2005). In this article, chemical and fuel costs and other operating costs are two of six inputs measured by monetary value (1,000 VND) per crop. Farmers use chemicals and energy, for example, probiotics, to increase shrimp appetite and aeration systems to balance the pond water quality and support better growth. Other operating costs may include interest payments, silt removal costs, and the like. According to Battese (1997), several extensive farms do not have feed use and other inputs, and the production function should therefore include the corresponding dummy variables of inputs to avoid bias from the obtained estimators of these inputs. Therefore, three dummy variables of the other operating costs, feed use, and region are included in estimating the extensive and intensive production inefficiency.

The Schumpeterian theory of development emphasizes that the efficiency of shrimp farmers depends on technological know-how and the socio-economic conditions under which they work. Hence, variables representing farmers' socio-economic characteristics, farming characteristics and farmers' perception of climate factors and their adaptive measures, are used to assess technical inefficiency.

2.2 | Shrimp farming in the Mekong region of Vietnam

Shrimp aquaculture in Vietnam started as traditional extensive farming with several local species in the 1980s. White-leg shrimp was introduced into Vietnam at the turn of the century and spread to the Mekong. This region is a low-level plain bordered by the South China Sea and the Gulf of Thailand, which is highly vulnerable to climate change. Since the mid-1980s, several intensified farming methods have entered shrimp cultivation, such as semi-intensive and intensive farming, followed by some super-intensive farming systems in recent years. Shrimp productivity differs over extensive farming with 300 kg/ha, semi-intensive farming providing 1,5–2 tons/ha, and intensive farms with 5–7 tons/ha per crop. Due to high-cost initial investments for intensive farms, the Mekong farmers are predominantly small-scale, applying improved extensive systems. These farmers have limited access to capital and are risk-averse, leading to the persistence of extensive culture.[2] Water exchange in extensive farms follows the tidal systems, leading water into ponds at high tide, while water is discharged at low tide. Extensive farms stock from 4 to 6 post larvae per square meter, use no aeration equipment, and frequently adopt partial harvesting when the new and full moon cycle occurs. The improved extensive systems also operate with low investment costs, mostly utilize natural food from the rice fields, with less chemical use than in intensive production systems. Local authorities encourage shrimp farmers to develop extensive farms, especially improved ones, due to sustainability perspectives and the high adaptability of this system to climate change and saltwater intrusion.

The study location of Bac Lieu and Ca Mau provinces provides natural advantages related to seawater exchange which is beneficial for culturing shrimp under controlled circumstances. However, both our studied provinces are exposed to dramatic changes in sea levels and frequently experience saltwater intrusions and other environmental threats (e.g., disease, water cross pollution). In 2016, more than half of all households were defined as low-income and greatly affected by the twin impacts of drought and saline intrusion (UNDP, 2016).

Data on weather conditions and water parameters (temperature, precipitation, pH, salinity, etc.) are limited in Vietnam, so we collected data on farmers' perceptions of extreme weather conditions. Both the intensive and extensive systems surveyed experienced similar extreme weather conditions and environmental threats during 2016–2017 (see Figure 1). Figure 1 illustrates the percentage of intensive and extensive shrimp farmers that experienced the different climate events prolonged drought, irregular weather, and saline water intrusion in their most recent crops. Saline water intrusion refers to conditions beyond white-leg shrimp salinity tolerance, while drought is defined as a long period of exceptionally high temperature and lack of precipitation in shrimp crops. Irregular weather, encompassing a sudden change in temperature and heavy rainfall, occurs unpredictably, leading to significant water temperature and quality variations, which may bring stress and a large chance of shrimp disease. The above concepts are similar to the study of NACA (2011). Water cross pollution represents one of the environmental issues that farmers perceived as a threat, including the spread of pollution into shared waterways, such as disease incurred from other farms or factory effluent into the same water intake sources as theirs.

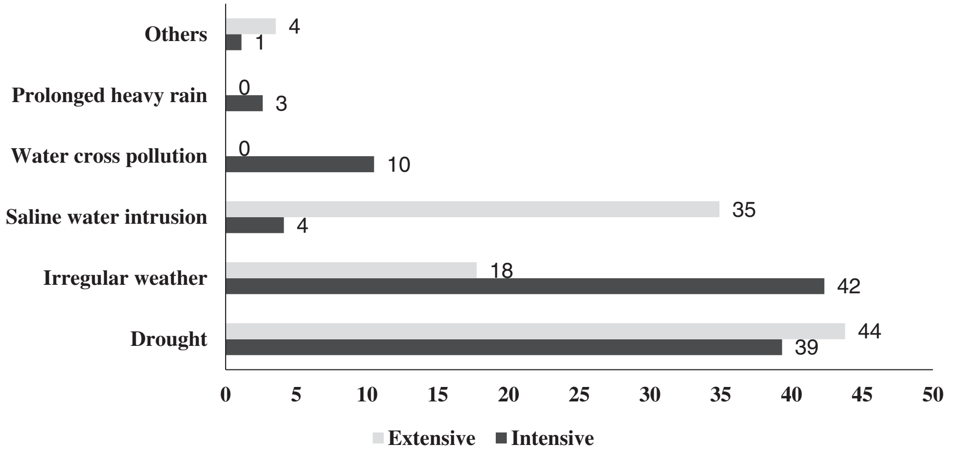

FIGURE 1 The percentage of intensive and extensive shrimp farms that experienced different climatic events occurring in their most recent crop

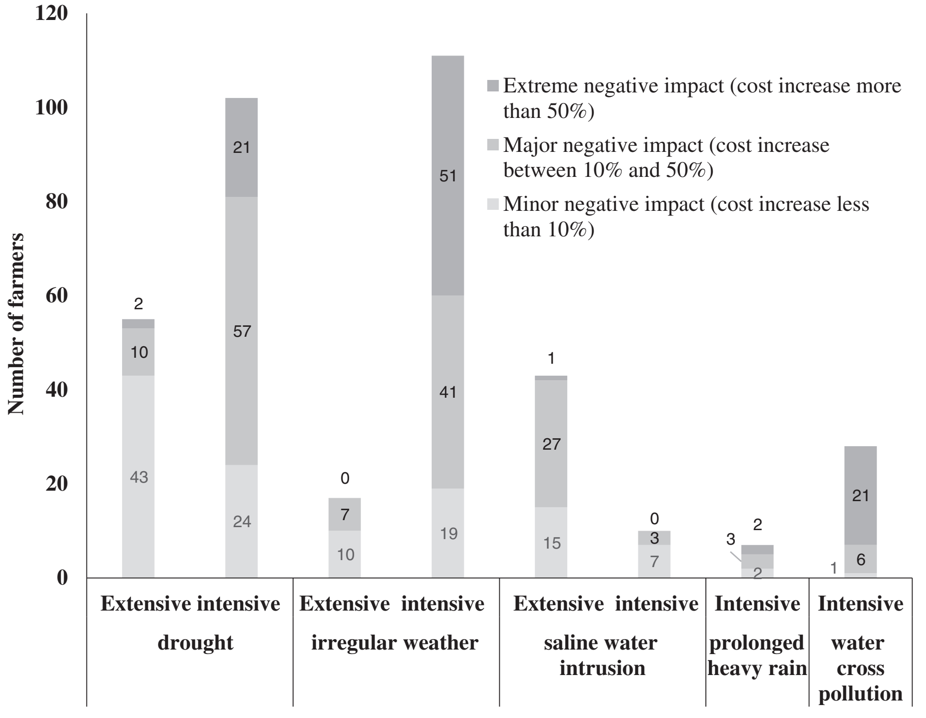

FIGURE 2 Extensive and intensive farmers' perception of economic impact of different environmental issues (total number of farmers in each group)

As can be seen from Figure 1, approximately 40% of both farming systems experienced drought. In addition, more than 40% of the intensive farms reported irregular weather, far exceeding that of extensive farms. Regarding saline water intrusion, 35% of extensive farms but only 4% of intensive households experienced this phenomenon occurring on the farm. Furthermore, only a small proportion of intensive (10%) and no extensive farms recorded cross-water pollution. Finally, less than 3% of intensive farms noted the experience of prolonged heavy rain in their previous crop, while 4% of extensive farms confirmed other climatic events (e.g., seawater, floods, storms, so on).

Next, extensive, and intensive shrimp farmers assessed the severity level given the abovementioned climatic events and environmental threats. Notably, we employ a severity assessment of the cost of these threats in the form of a seven-point Likert scale[3] set of questions for the listed climatic events occurring in the most recent crop, as presented in Figure 2.

In Figure 2, a substantial share of farmers in both extensive and intensive systems in our sample perceived irregular weather and water cross pollution, drought, and saline water intrusion as having environmental impacts on shrimp production. Prolonged heavy rain was excluded due to a very small number of intensive farmers and no extensive farmers provided assessment of severity.

In our sample, farmers' adaptations, collected from discussions in focus group meetings, are autonomous adaptive measures used by shrimp farmers. After a review and selection process following Alauddin and Sarker (2014) and factor analysis, we include five potential adaptive measures as follows: (i) *Change in feeding schedules/stocking densities*—Farmers can adjust the number of shrimp or feed amount in the pond. (ii) *Change water exchange schedules*—Farmers reorganize water exchange strategies to maintain the pond water level. (iii) *Water conservation*—This is displayed in many forms, for instance, low or zero water exchange or recirculation water systems to avoid water shortage and water cross pollution. (iv) *Water treatments*—Including applying lime or chemicals/medicines in grow-out ponds for stabilizing the growth stages of shrimp, or water pumping and filtering when pond water levels are insufficient during prolonged drought conditions. (v) *Pond renovation*—Upgrading bank/dyke height, deeper ponds, and farming site renovation purposes during natural disasters.

Irregular weather was the environmental issue that most farmers declared awareness of. However, most farmers only provided their adaptive responses in relation to drought. Drought is considered one of the almost regular extreme weather events that has caused serious damage to human lives in Vietnam over a longer period of time. Therefore, shrimp farmers are familiar with frequent drought occurrences annually, and are experienced, well-equipped and prepared for precautionary actions to cope with its impact. Although we also collected other measures for the remaining environmental events, we did not include these measures in the final model due to insufficient data.

2.3 | Data sampling

The data collection procedure consisted of focus group discussions, pretest surveys, and face-to-face interviews: First, group discussions included the participation of key local informants (management officials and technicians, and representatives of shrimp households) gathering in provincial aquaculture departments. These meetings aimed to identify shrimp aquaculture's current status and select communes and target groups of farmers to approach. Next, the registered shrimp farmer lists were provided by the officers of extension and the provincial Department of Aquaculture. Second, pretest surveys were implemented with the 10 shrimp farmers in each province to finalize the questionnaire. Third, face-to-face interviews were a randomized selection of individual shrimp farms from the obtained list. Local people were employed as guides to the farming areas and secured farmers' permission for carrying out the survey. However, when a selected farmer refused to be interviewed, the snowball sampling procedure, a non-probability sampling technique, was applied in our study. This technique provides referrals to recruit samples required for a research study. In other words, the interviewer asked refusers to recommend another person with similar farming characteristics as theirs. As a result, the total sample is 436 white-leg shrimp farms classified into two groups: 169 extensive farms and 267 intensive farms.

All shrimp farmers are landowners, and shrimp farming is their primary source of income. During the data collection period from March to July 2017, several shrimp farmers had temporarily halted their shrimp business due to financial constraints and losses that year and provided information on the most recent crop they cultured after September 2016. Thus, to assure a sufficient sample size, also observations from 2016 are counted in our sample. The consistency of the crop production cycle is therefore a limitation in our study, though we span less than a year of crop rotations, in a period with relatively similar conditions.

2.4 | Data description

Table 1 presents the data description and summary statistics for both intensive and extensive aquaculture technologies. Experience is measured in the years the farmer has worked in shrimp aquaculture production, while education is measured by years in school. Adaptive measures to drought effects are interaction terms generated between farmers' coping measures and perception of drought occurrence in shrimp crops.

The differences between extensive and intensive farming are stark; an average extensive farm is five times larger than an average intensive farm, while the average intensive farm yield is 7.7 tons per hectare, against extensive farms' average of 166 k per hectare. Seed stocking density (number of postlarvae released per square meter pond) on average is about six for extensive against sixty-nine for intensive farms. For most parameters, the variation within each group is also considerable. On average, the production cycle of intensive farms takes about 2.8 months, ranging from one to a maximum of four months, while the average production cycle of extensive farms is about 2.3 months,

TABLE 1 Data description

Variable	Unit	Extensive ($n = 169$)				Intensive ($n = 267$)			
		Mean	*SD*	Min	Max	Mean	*SD*	Min	Max
Output									
Total shrimp yield	kg/crop	348.43	297.5	40	2,000	3,069.2	3,041.6	10	25,000
Quality adjusted output	kg/crop	345.1	299.7	32.4	1,915.3	3,540.6	3,935.1	5.4	32,221.5
Input variables in the production frontier									
Feed use	kg/crop	10.18	39.98	0	350	3,743.90	3,725.4	250	30,000
Seed stocking density	No. post larvae/pond m^2	6.51	3.27	2	21	69.0	29.0	25	240
Farm size	Hectare	2.1	1.26	0.4	8	0.4	0.4	0.1	3
Labor use	Man-hours/crop	576.80	203.9	240	1,440	1,008.9	622.7	240	4,320
Chemicals and fuel/electricity costs	1,000 VND/crop	3,066.2	2,015.4	400	17,000	74,742.6	83,331.3	5,500	783,260
Other operating cost	1,000 VND/crop	978.89	917.01	0	8,000	3,916.4	7,847.3	0	85,000
Feed use dummy	Yes = 1; otherwise = 0	0.11	0.31	0	1	1	0	1	1
Other operating cost dummy	Yes = 1; otherwise = 0	0.85	0.36	0	1	0.6	0.5	0	1
Regional dummy	1 = Bac Lieu, otherwise = Ca Mau	0.47	0.50	0	1	0.5	0.5	0	1
Perception data of environmental factors									
Drought	Yes = 1; otherwise = 0	0.33	0.47	0	1	0.48	0.50	0	1
Saline water intrusion	Yes = 1; otherwise = 0	0.40	0.49	0	1	0.30	0.46	0	1
Irregular weather	Yes = 1; otherwise = 0	0.63	0.48	0	1	0.91	0.29	0	1
Water cross-pollution	Yes =1; otherwise = 0	0.34	0.47	0	1	0.64	0.48	0	1
Disease occurrence	Yes =1; otherwise = 0	0.11	0.31	0	1	0.2	0.4	0	1
Socioeconomic factors									
Experience	Years	21.7	7.98	4	53	9.6	7.1	1	30
Education	Years	6.18	2.87	1	16	8.1	4.2	1	22
Credit access	Yes = 1; otherwise = 0	0.25	0.44	0	1	0.3	0.4	0	1
Farm characteristics variables									
Adopting good management activities	Total number of activities	0.95	0.42	0	6	2.12	0.24	3	13

(Continues)

TABLE 1 (Continued)

		Extensive ($n = 169$)				Intensive ($n = 267$)			
Variable	**Unit**	**Mean**	***SD***	**Min**	**Max**	**Mean**	***SD***	**Min**	**Max**
Duration of crop	Number of months	2.3	0.7	1	6	2.8	0.8	1	4
Farming site description									
Planned area	Planned = 1; otherwise = 0	23.06	7.33	0	1	12.5	6.4	0	1
Distance from farm to sea	km	0.83	0.38	0	1	0.7	0.5	0	1
Adaptive measures to drought effect									
Change feeding practice/stocking density	Interaction term	0.19	0.39	0	1	0.15	0.36	0	1
Change water exchange schedules	Interaction term	0.37	0.48	0	1	0.11	0.32	0	1
Water conservation	Interaction term	0.02	0.15	0	1	0.06	0.24	0	1
Water quality management	Interaction term	0.04	0.19	0	1	0.16	0.37	0	1
Pond renovation	Interaction term	0.01	0.08	0	1	0.05	0.22	0	1

Note: The statistics are presented in frequencies and percentages for binary variables and the mean value for numeric variables. *SD* is the standard deviation. 1 USD = 22,765 VND. The number of extensive farmers adopting good management activities is 161. There are 266 observations with intensive sample's fuel/electricity, and chemicals costs are (missing values are removed from the sample). Thus, only 427 observations are used in the next stochastic frontier function estimation. See Appendix B for correlation tables (Tables B1 and B2). The variables regarding the extreme climatic events were generated from positive points (1–3), that is, perceived negative impacts, in the Likert scale, interacting with those events' occurrence. Planned area describes whether farming location belongs to a government-approved shrimp area, coded 1, otherwise 0. Planned area infrastructure (e.g., road improvement, electricity supply, dike, embankment, and dam construction) can support the reduction of environmental problems caused by farming systems threatening the stability of the whole Mekong region (e.g., erosion, land subsidence). The distance from the farm to the sea is measured by the Euclidian distance from the farming site (e.g., farms' villages or hamlets) to the closest coastal point to indicate the probability of saline water intrusion. Crop duration was measured as the number of months between the release of shrimp in the grow-out pond to harvesting.

TABLE 2 Percentage of Vietnamese white-leg shrimp extensive and intensive farms adoption of various management and monitoring practices, shrimp yield, harvested size, and sales price

	Extensive ($n = 169$)	Intensive ($n = 267$)
Feed and cost management practices		
Use of feeding tray/ siphon activity to check feed consumption	0	95.9
Regular feed conversion ratio calculations	0	34.5
Regular operating cost analysis	3.6	58.8
Other cost monitoring practices	0	2.3
Pond management and monitoring practices		
Daily monitoring of water quality parameters	85.8	98.5
Daily monitoring of sediment condition	0.6	67.8
Daily monitoring of influent and effluent waters	1.2	49.1
Daily monitoring of water quality parameters	28.4	84.6
Other practices	0	2.3
Farming management and monitoring practices		
Daily monitoring of stock survival	81.7	88.4
Daily monitoring of shrimp behavior	53.3	97.8
On and off-farm shrimp health check when disease occurred	0.6	56.6
Other water quality monitoring practices	1.8	24.3
Shrimp yield, harvested size, and sales price		
Shrimp yield (kg/ha)	166	7,700
Sales price of harvested shrimp (1,000 VND per kg)	106 (50–185)	120 (30–190)
No. of harvested shrimp per kg per crop	77 (30–200)	79 (30–320)

Note: Number in bracket is min and max figures.

ranging from one up to six months. Table 2 shows the percentage of good aquaculture management activities related to the pond, farm, and feeding in intensive and extensive farms. There are prominent distinctions between extensive and intensive farms regarding the adoption of management practices (e.g., monitoring practices in feed and cost, pond, and farming management practices[4]). Table 2 reveals a limited use of management activities related to pond, farm, and feed practices in the extensive production system, except for daily monitoring of water quality parameters, checking stocking survival (over 80% of farms), and daily monitoring of shrimp behavior (over 50% of farms). In contrast, most intensive farms performed several management and monitoring practices. This finding is similar to the findings of Sharma and Leung (2000a, 2000b). In our survey, however, only a few intensive farms recommended regular feed conversion ratio calculations and other water quality monitoring measures (34.5% and 24.3%, respectively).

On average, harvested shrimp is sold for 106,000 VND per kilo (approximately 4.6 USD) from extensive farms and 120,000 VND per kilo (around 5.3 USD) from intensive farms. Though the lowest price obtained by extensive and intensive farms is 50,000 VND (nearly 2.1 USD) and 30,000 VND (around 1.3 USD), respectively, on average, the highest prices are very similar, around 190,000 VND (nearly 8.3 USD) on average. In our survey, though the average size of shrimp is similar in both farming systems, the size distribution is skewed toward larger shrimp sizes in the intensive farms.

3 | RESULTS

Table 3 identifies the partial elasticities of the production coefficients, that is, the marginal change in output (shrimp yield) from a change in a single input while other inputs are held constant. Furthermore, we provide the sum of

TABLE 3 Output elasticities and elasticity of scale of intensive and extensive production systems

	Extensive				Intensive			
Inputs	Elasticity	*SE*	*t*-ratio	*p*-value	Elasticity	*SE*	*t*-ratio	*p*-value
Farm size	0.268***	0.091	2.940	.003	0.003	0.037	0.090	.925
Feed use	−0.104	0.171	−0.610	.544	0.807***	0.047	17.030	.000
Seed stocking density	0.152	0.098	1.550	.120	0.039	0.065	0.600	.550
Labor use	0.283	0.202	1.400	.162	0.145***	0.047	3.100	.002
Chemicals and fuel/ electricity costs	0.355***	0.083	4.260	.000	0.220***	0.045	4.870	.000
Other operating cost	0.226***	0.079	2.850	.004	−0.021	0.037	−0.580	.563
Other operating cost dummy	−1.513***	0.559	−2.710	.007	0.208	0.345	0.600	.547
Feed use dummy	0.302	0.719	0.420	.674				
Regional dummy (Bac Lieu province)	0.032	0.107	0.300	.764	−0.092	0.094	−0.970	.330
Elasticity of scale	1.181***	0.282	4.19	.000	1.179***	0.081	14.44	.000

Note: For the intensive frontier, the feed dummy is removed from the estimation since all intensive farmers used feed as their main input.
***Significant at 1%.
**Significant at 5%.
*Significant at 10%.

TABLE 4 Likelihood-ratio of hypothesis tests on model specifications

	Likelihood value		Likelihood-ratio test (LR)	DF	Critical value at 99%	Decision
Test of null hypotheses (H_0)	Restricted model	Unrestricted model				
Intensive						
No effects of technical inefficiency are present $H_0 : \delta = 0, \gamma = 0$	−198.39	−96.43	203.93	18	29.927	Reject H_0
Technical inefficiency effects have a half normal distribution with mean zero $H_0 : \delta = 0$	−172.57	−96.43	152.29	17	28.485	Reject H_0
Extensive						
No effects of technical inefficiency are present $H_0 : \delta = 0, \gamma = 0$	−144.39	−122.68	43.43	15	29.927	Reject H_0
Technical inefficiency effects have a half normal distribution with mean zero $H_0 : \delta = 0$	−144.49	−122.68	43.63	14	28.485	Reject H_0

Note: The corrected critical value for the null hypothesis is obtained from Table 1 of Kodde and Palm (1986).
Abbreviation: DF: degree of freedom.

TABLE 5 Maximum likelihood estimates of technical inefficiency coefficients of intensive and extensive production systems

	Extensive ($n = 161$)		Intensive ($n = 266$)	
	Estimates	*SE*	Estimates	*SE*
Perceived environmental factors				
Drought	−0.908***	0.214	−0.091	0.507
Saline water intrusion			−0.166	0.500
Irregular weather	0.736***	0.231	−0.054	0.973
Water cross pollution	0.079	0.147	0.694	0.596
Disease	0.788***	0.288	3.296**	1.356
Socioeconomic factors				
Experience	−0.143	0.168	−0.461	0.427
Education	−0.464***	0.145	0.361	0.321
Credit access	−0.145	0.160	−0.039	0.436
Farm characteristics variables				
Duration of crop	1.260***	0.303	−2.725***	0.765
Adopting management activities	0.248	0.209	1.371	0.913
Farming site				
Planned area	−0.350*	0.206	−0.538	0.511
Distance to sea by province	−0.170***	0.055	−1.115**	0.458
Adaptive measures to drought				
Change feeding practice/ stocking density	−0.350*	0.182	−1.001	0.883
Change water exchange schedules	0.053	0.154	−0.571	1.090
Water conservation	−0.127	0.326		
Water quality management	−1.425	1.438	−1.072	0.772
Pond renovation			−2.237**	0.963
Constant	0.243	0.637	−3.223	3.060
Variance parameters				
Λ	0.144**	0.057	3.441***	0.162
σ_u	0.075	0.049	0.899***	0.159
σ_v	0.518***	0.029	0.261***	0.018
Log-likelihood	−122.68		−98.33	
Mean TE score	0.83		0.78	

Note: *SE* is standard error. Robustness checks which underline the reliability of our estimations.
*Significant at 10% level.
**Significant at 5% level.
***Significant at 1% level.

partial elasticities of production to measure economies of scale. The percentage change in output relative to the percentage change in all inputs indicates how farmers can reallocate input resources and raise productivity through improvements in TE.

In Table 3, the total output elasticities of the extensive and intensive systems are all large, different from one, and at a 1% significance level. Both production functions exhibit increasing returns to scale; a simultaneous increase in all inputs by a certain percentage results in a greater increase in output. Thus, if inputs are increased by 10%, intensive and extensive output increases by 17.9% and 18.1%, respectively. Notably, coefficients of farm size and chemicals and fuel/electricity inputs are positive and statistically significant, contributing to the extensive shrimp yield. The larger extensive farms (here, larger grow-out pond size) provide higher yields, equivalent to the study of Bukenya et al. (2013), where they found similar results and argued that the expansion in shrimp area was necessary to ensure optimal stocking capacity. Chemicals and fuel/electricity inputs positively impact yields in both intensive and extensive farms, similar to the findings regarding the contribution of chemicals, fertilizer, and other costs in the extensive and semi-intensive systems studied by Sharma and Leung (2000a, 2000b) and Radhakrishnan et al. (2021). Output elasticity of other operating costs and its dummy is significant, pointing to the important role of other operating costs in extensive production, as expected. The slope coefficient of feed use, and a feed dummy are insignificant for extensive farms, indicating that extensive farmers are efficient in not using feed as it does not increase their yield, as extensive farms in our study area mainly rely on nature-based feed resources.

Different results appear for intensive farms, where the feed input has the highest elasticity. We do not find a statistically significant contribution to production from seed stocking in either system, as opposed to the findings of Sharma and Leung (2000a, 2000b). Labor contributed to white-leg shrimp yield in intensive farms, opposing results found in Kumaran et al. (2017).

Next, the generalized likelihood-ratio hypotheses tests for the model specification are presented for both technologies, intensive and extensive, in Table 4.

In Table 4, we test the presence and distribution of inefficiency. We observe that all null hypotheses tests are rejected at a 1% significance level for both systems. Thus, based on the first test, we can conclude a significant effect of the inefficiency term in the model. Similarly, the rejection of the second null hypothesis for both systems suggests that a half-normal distribution of the standard stochastic error component is not appropriate. Therefore, the observed inefficiency in both intensive and extensive farms can be attributed to the variables specified in the model.

Next, the maximum likelihood estimates of the Cobb–Douglas production estimations for intensive and extensive shrimp production systems with five adaptive measures to drought, described earlier are presented in Table 5.

Eight extensive and one intensive farm had incomplete production data and missing values and were therefore removed from the sample, making the number of observations in extensive and intensive systems 161 and 266, respectively. Due to the relatively high positive correlation between the perception of drought and saline water intrusion (see Table C1 in Appendix C), the perception of saline water intrusion is removed for the extensive farm estimation. Also, adaptive measures such as pond renovation and change in water exchange schedules are removed from the estimations due to insignificant effects for both farm systems. In Table 5, the values of λ, which describe the ratios of the standard deviation of the inefficiency components to the standard deviation of the error

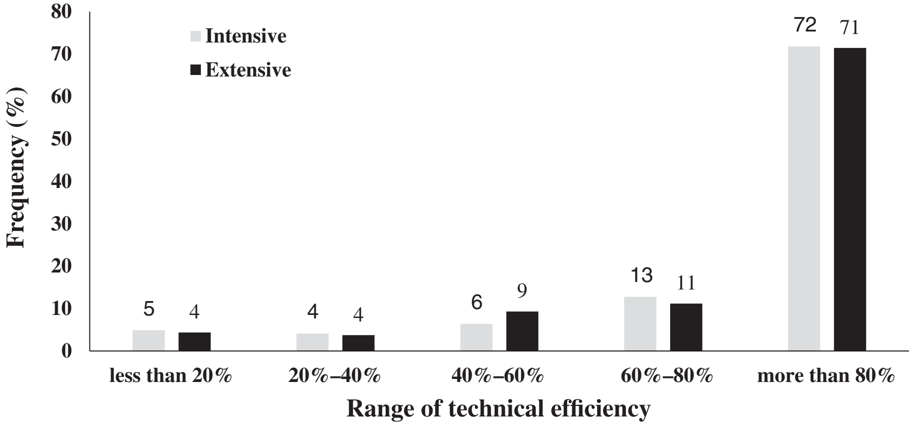

FIGURE 3 Frequency distributions of technical efficiency scores for intensive and extensive shrimp farms

components in all models, are significant at 5% level for extensive farms while at 1% level for intensive farms. Ogundari and Aklnbogun (2010) suggest that a value of λ larger than 1 supports that TE differences among farms are an important reason for the variation in fish production, which we show to be the case for the Vietnamese intensive shrimp farms.

There are several statistically significant impacts of explanatory variables on technical inefficiency for the intensive and extensive models. The main factor that increased intensive farming inefficiency was disease occurrence, while an increase in the duration of the crop period increased the extensive farm inefficiency. We found that crop duration strongly impacts farming inefficiency but in differing directions for intensive and extensive systems. A longer crop duration reduces the inefficiency of intensive shrimp farms while it increases inefficiency in extensive farms. None of the coefficients of variables related to the perception of climatic events and environmental issues such as drought and saline water intrusion, irregular weather, or water cross-pollution were statistically significant in the intensive farming system. In contrast, extensive farmers who perceived irregular weather had increased technical inefficiency at a 1% significance level, while perhaps more surprisingly, perception of drought is shown to reduce inefficiency at a 1% level. Education and belonging to planned areas reduce technical inefficiency as expected in extensive farms, but we fail to prove this relationship for the intensive farms. Finally, a greater distance from the sea is associated with less inefficiency in extensive and intensive farming systems.

We obtain positive efficiency impact from adaptive measures, such as for change in feeding practice/stocking density in extensive farms, while pond renovation reduces intensive farms' inefficiency. Adopting good aquaculture practices in the farm, feed, and pond management activities did not significantly impact TE in extensive or intensive farms.

For robustness checks we also estimated translog functional forms, and the SFA of both systems without including adaptive measures, largely providing robust results confirming the impact of farmers' perceptions regarding drought.

The TE values imply that, on average, intensive and extensive farmers produce 78% and 83% of maximum output, respectively. In Figure 3, the distribution of TE is graphically demonstrated for the intensive and extensive systems, and these scores show a similar pattern.

More than 80 % of all farms in both systems in our study have a TE above 60%. Most shrimp farms (more than 70% for both intensive and extensive) exhibited TE above 80%. Less than 20% of the extensive and intensive farmers were operating at TE levels below 40%. The strong right-side skewness in Figure 3 may be a result of the shrimp business being the household's main income source, and farmers have on average more than 20 years of operating making them well-practiced in allocating inputs to secure outputs gains.

4 | DISCUSSION

Our analysis highlighted a somewhat counterintuitive result that perception of drought enhances efficiency in extensive farms. Drought perception is inherent “a subjective judgment made about its characteristics and severity” (IPCC, 2019, p. 27) and is one of the key factors shaping farmers' choice of adaptation. Therefore, farmers who perceive high severity levels of drought occurring in their crops may have a greater active response to drought events. As learned anecdotally in the interviews, farmers shared their experiences of warning systems of climatic events by collecting and exchanging information among shrimp farmer groups or cooperatives and announcements from the local aquaculture department. From this, shrimp farmers may more vigorously apply proactive adaptation measures to deal with these kinds of climatic events. Nguyen et al. (2018) concluded that Vietnamese catfish farmers have higher TE under flood and salinity intrusion effects. The authors explained these results by the precautionary measures taken, resulting in a positive effect, similar to what may be argued here for drought. Furthermore, different degrees of drought is normal during the production year, making the farmers experienced in dealing with this challenge.

Furthermore, extensive farms may be less vulnerable to drought than intensive farms due to differences in accessing and conserving water. First, an advantage of the extensive farm is the water exchange from the tidal system, which supports the maintenance of water levels in extensive ponds. In contrast, frequent operation of water pumps/exchange and aeration are required in intensive systems. Second, according to the Mekong River Commission (2016), many farmers adapt to climate change by using water conservation and reservoirs or groundwater to overcome dry conditions, something extensive farms in our sample currently apply. In our estimation, including adaptive measures to drought, we found the adoption of water quality management provided reduced inefficiency in extensive and intensive farms. However, we failed to show these effects to be statistically significant. In contrast, applying adaptive measures involving changes in feeding schedules/stocking density for reducing the competition for oxygen in ponds when drought occurs decreased TE, with 10% statistical significance for extensive systems.

As mentioned above, extensive farms' efficiency decreased with increasing shrimp crop duration. A similar result regarding this relationship was also found by Ruiz-Velazco, Hernández-Llamas, and Gomez-Muñoz (2010), who suggested that increased crop duration involves higher input use and costs, as well as increased risk of disease, contributing in reducing efficiency. This result could also be the case for intensive systems, as Long et al. (2020) found. However, our results suggested that a longer duration of the shrimp crops increased farming efficiency in intensive systems. A possible explanation could be that intensive and extensive production serves different markets. The largest share of harvested shrimp from intensive farms is ordered by intermediaries (middlemen) in the shrimp supply chain, targeting export markets. Therefore, when intensive farmers receive purchasing orders from buyers requesting high-quality and large shrimp, they adjust the crop duration to achieve the required size. For example, Kumaran et al. (2017) suggested that the average crop duration for a white-leg shrimp crop was 112 days, while for producing the bigger sizes (25–30 g), the duration was approximately 120–140 days. Meanwhile, the extensive farms' yield usually consists of small quantities and mainly serves local markets and restaurants at lower prices. Therefore, when choosing longer crop rotation in intensive farms, the positive effect of the higher market price for larger-sized shrimp may be greater than the increased costs and risks of disease. Furthermore, thanks to more advanced technology, short rotations characterize the intensive system. Thus, intensive farmers are expected to control disease risk better than extensive farms. However, when disease does occur in intensive systems, the reduction in efficiency is very large. This result implies the importance of applying biosecurity measures in intensive farms to mitigate the spread of disease from crop to crop, especially when reducing crop duration to secure the maximum of 4 crops per year.

Our results showed that an increase in the years of extensive farmer schooling led to an increase in farming TE. Furthermore, increasing the number of farms belonging to a planned area enhances the extensive efficiency. Similarly, increasing the distance of both intensive and extensive farms from the sea seems to impact efficiency positively. These results point to how the local government can promote efficiency in extensive shrimp farming by encouraging education and the expansion in rearing planned areas. More public investment in such planned areas further from the coast also seems to be a recommendable practice.

Apart from disease and distance to the coast, intensive and extensive farm inefficiency and productivity seem to react very differently to the variables studied, as presented above. This finding identifies fundamental differences between the two production methods, such as how they experience various environmental challenges. The environmental challenges seem greater for extensive farms, while disease poses the main threat to intensive farms.

5 | CONCLUSIONS

This article utilized the Cobb–Douglas stochastic frontier approach for presenting an empirical analysis of environmental impacts on shrimp production and farming inefficiency in the Mekong Delta region. Our target is to provide information concerning the possibilities for improved production and mitigating environmental effects for extensive and intensive white-leg-shrimp farm systems. Interestingly, the two rearing technologies respond to externalities very differently. For example, even though they perceived the severity of climate events, extensive farms seem more vulnerable to environmental effects, such as irregular weather. Though extensive farms are impacted by disease occurrence, shrimp disease is shown to have the most detrimental effect on intensive farm efficiency. Furthermore, farmers' adaptive measures to increase efficiency vary for the two farming technologies. Finally, robustness checks underline the reliability of our estimations, especially regarding the perception of drought positively affecting extensive systems technical efficieny.

The results identify three potential actions that intensive farms can perform to reduce inefficiency: first, increasing crop duration may be a key factor, presumably due to the export targets and market demands for larger shrimp size. The benefits from a longer crop duration appear to outweigh the increased costs and disease risks. Second, given the dual effects of drought and saline water intrusion, a longer distance from farm location to the sea significantly reduces inefficiency for intensive farms. Third, intensive farms can advantageously increase their TE by adopting pond renovation, which may mitigate the climate effects.

For extensive farms, perception of irregular weather and disease occurrence and longer crop duration have the most detrimental impacts on efficiency. However, we found that this simple farming technology can be significantly resilient to other shocks, such as drought. In addition, an increased distance of extensive farms to the sea is identified as a protective factor in increasing farming efficiency. The results indicate three possible actions for extensive farmers to reduce inefficiency: The first one is reducing crop duration. The increased costs and disease risks in a longer crop duration appear to outweigh the benefits of producing larger shrimp for extensive farmers, as was also the case for intensive farmers. The second action is the implementation of adaptive measures such as changing feeding practices/stocking density as drought occurs. The third action is education; farmers with more education have a significantly lower inefficiency. These findings indicate that training programs providing knowledge of best practices, climate, and environmental risks in shrimp production could be a key factor in increasing efficiency for extensive farmers.

Results from our study showed that governmentally planned areas could increase efficiency for extensive farmers. Policymakers could devise regulatory schemes emphasizing developing planned areas restricting and reducing the risk of environmental degradation of natural ecosystems. Furthermore, our findings indicate that a diversified set of production methods may well be recommendable for a balanced, inclusive, and risk-adjusted portfolio of shrimp production. Today, there are global challenges related to shrimp farming's social, economic, and environmental problems (e.g., the COVID-19 pandemic, market barriers, climate change). Thus, the solutions to secure food security and poverty alleviation are essential priorities. Local governments of developing countries can beneficially target shrimp production systems using different policy schemes.

It is worth noting, however, that the results of this study are largely obtained by using perception data, which may be limited by unavoidable bias connected to the respondents. Therefore, collecting further data to expand temporally and increase the randomness in sample distribution would be advantageous.

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CONFLICT OF INTERESTS

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

This article is a part of the first author's PhD project. Co-authors are the first author's supervisors, contributing to the survey design, materials and method, data analysis and interpretation, and article development.

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ENDNOTES

[1] We do, however, also carry out robustness checks and likelihood ratio (LR) tests for Cobb–Douglas and Translog functions. The null hypothesis (square and interaction terms are different from zero) of the LR results showed the translog model could be reduced to the Cobb–Douglas specification.

[2] https://seafood-tip.com/sourcing-intelligence/countries/vietnam/shrimp/extensive/.

[3] The seven-point Likert scale consists of −3: Extremely positively impacted (cost reduction of more than 50%), −2: Major positively impacted (cost reduction between 10% and 50%), −1: Minor positive impact (cost reduction less than 10%), 0: No consequence, 1: Minor negative impact (cost increase less than 10%), 2: Major negative impact (cost increase between 10%–50%), 3: Catastrophic/extremely negative impact (cost increase above 50%).

[4] The questions used in the survey regarding adoption of various management and monitoring practices in Table 2 are inspired by Sharma and Leung (1998). All the questions are dummy variables (yes = 1, no = otherwise).

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