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A study of economic efficiency, adaptive measures to extreme climatic events, and drivers of disease in Vietnamese white leg shrimp aquaculture

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Table of Acronyms

ADB	Asian Development Bank
ASC	Aquaculture Stepwardship Council
FAO	Food And Agriculture Organization of the United Nations
FCR	Feed conversion ratio
FishStatJ	Database (Software for Fishery and Aquaculture Statistical Time Series)
GAP	Global Aquaculture Practices
GOAL	Global aquaculture alliance
GSO	General Statistics Office of Vietnam
IUCN	International Union for Conservation of Nature
MNL	Multinomial logistic regression
MKD	Mekong Delta
NACA	Network of Aquaculture Centers in Asia Pacific
RAS	Recirculating aquaculture systems
UN	United Nations
VASEP	Vietnam Association of Seafood Exporters and Producers
WLS	White-leg shrimp

List of papers

Paper I:

Le, N. T. T., Hestvik, E. B., Armstrong, C. W., & Eide, A. (2022). Determinants of inefficiency in shrimp aquaculture under environmental impacts: Comparing shrimp production systems in the Mekong, Vietnam. *Journal of the World Aquaculture Society*, 1–21. https://doi.org/10.1111/jwas.12874

Paper II:

Le, N. T. T., Armstrong, C. W., Brækkan, E. H., & Eide, A. Climatic events and disease occurrence in intensive *Litopenaeus vannamei* shrimp farming in the Mekong area of Vietnam. (Under review)

Paper III:

Le, N. T. T. & Armstrong, C. W. Choice of climate risk adaptation measures in shrimp farming – A case study from the Mekong, Vietnam. (Under review)

Summary

This thesis covers three primary focal research areas: estimating efficiency in shrimp farming, assessing farmers' choices of adaptive measures, and predicting disease occurrence in shrimp farms under the impact of perceived climate and environmental issues. The research methods were selected from relevant literature and applied to the surveyed data, combined with robustness checks, providing statistically significant results responding to various research questions related to the economics of shrimp farming under the influence of extreme weather. *Vannamei* shrimp farming in Bac Lieu and Ca Mau provinces in the Mekong Delta of South Vietnam was used as the applied context. These two provinces have a variety of shrimp farming systems, producing a major share of shrimp production in Vietnam. In addition, these two provinces' locations are prone to diverse impacts of climate change, satisfying the focal issue studied.

The first research objective targets farming efficiency regarding shrimp yield for both intensive and extensive farming systems. Our findings provide empirical evidence that shrimp farmers' perceptions of extreme climate events, education level, climate adaptation, farm's distance to the sea, disease factors in the crop, and shrimp crop duration affect the efficiency of the farming systems. Furthermore, we demonstrate that identifying determinants that increase or decrease crop inefficiencies in well-managed inland farms can provide important economic benefits given severe weather.

The second research objective was to identify the drivers of farmers' choices in different cultivation systems (intensive and extensive) using five adaptation measures to extreme weather and environmental issues in the Mekong region. Socioeconomic factors, knowledge sharing, service accessibility, farm characteristics, and farmer perceptions significantly influence farmers' adaptation choices, providing policy implications for developing adaptive capacity to climate change in shrimp farming.

The final research objective deals with disease occurrence detection in intensive shrimp farming – a rapidly emerging shrimp farming system in the Mekong due to high stocking densities and the adoption of various production inputs. This study is done to identify risk and protective factors associated with farmers and farming characteristics, as well as other aspects impacting disease outbreaks. Our findings highlight the importance of developing training activities and extension services and applying meaningful protective measures (regular feed conversion ratio calculations, feeding practice schedule changes) to minimize disease occurrence. In addition, an increase in shrimp crop length and the number of years of operation greatly affect the likelihood of disease risk. The results provide information for managing shrimp production and controlling disease.

PART 1. INTRODUCTION

1. Background and motivation

1.1 Overview of White leg shrimp *(Litopenaeus vannamei)* culture in Mekong, Vietnam.

Global aquaculture production reached 122.6 million tonnes with a 281.5 billion USD value in 2020 (FAO, 2022). FAO (2022) emphasized the aquaculture sector's current and potential role in feeding the world's growing population, supporting fisheries communities, securing livelihoods, and contributing to global food security, especially in developing and least-developed countries. Inland-farmed shrimp growth also supports solving the challenges of increasingly depleted wild marine resources.

Asian nations dominate the global aquaculture industry, producing 91.6% of world production (FAO, 2022). China, Indonesia, Vietnam, India, and Thailand are Asia's top five leading shrimp producers. White leg shrimp (WLS) (*Litopenaeus vannamei*), the world's most widely cultured crustacean (Nguyen, 2017), is the target species in this thesis. In Figure 1, we observe that Vietnam has grown rapidly to be placed among the top three largest shrimp producers after China and India since 2018 (FAO, 2022), and this is where this thesis has its focus.

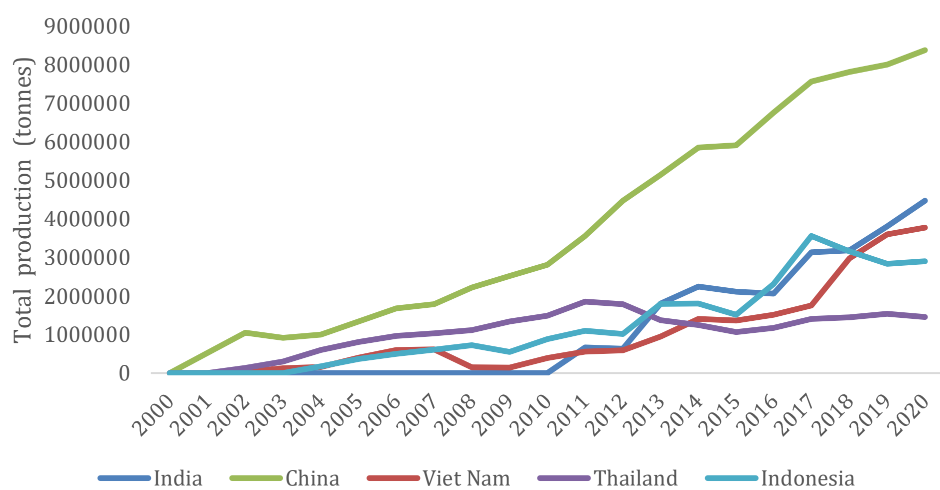

Figure 1: The top five producers of WLS aquaculture production (2000-2020).
Data source: FAO (2021) FishStatJ

The Vietnamese government introduced significant policies (e.g., Resolution 09/2000/NQ-CP on June 15, 2000) to promote the shrimp industry's development, which has led to the conversion of low-yield rice/salt fields and wild areas into shrimp ponds (Tran et al., 2013). These policies supported WLS farming which is largely concentrated in 13 provinces in the Mekong River Delta (MKD), producing over 84 percent of the national shrimp volume in brackish and freshwater in 2020 (GSO, 2020). Shrimp farming in Vietnam has experienced significant growth in both production quantity and land area coverage since 2011 (figure 2). The land area of shrimp farming has increased by, on average, 1.4% per year since 2020 (GSO, 2021), and increased by 5.7 % per year since 2022, while the production in 2021 increase 4.3% compared to 2020 (VASEPb, 2022). Thanks to the growht of land and production, the increase in export value is positve obtaining over 3.78 billion USD in export value in 2020 (GSO, 2021), increasing 11% compared in 2020, and reached about 4.3 billion USD in 2022 (VASEPa,b, 2022) (figure 3)

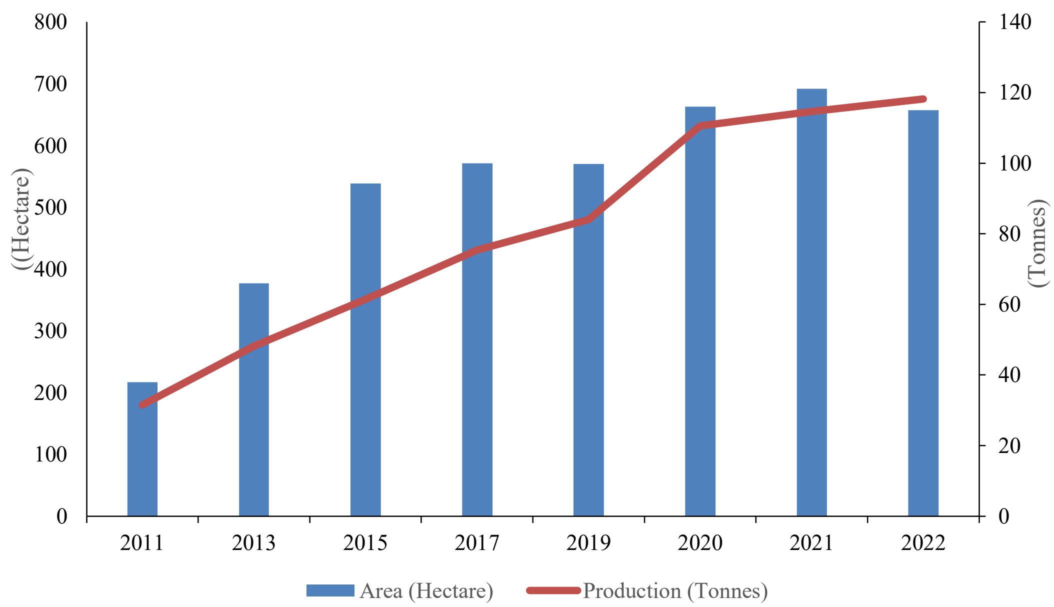

Figure 2:The farming area and production value of Vietnamese WLS from 2011 to 2022

Data source: FishStat - FAO Fishery and Aquaculture Global Statistics, GSO (2021), VASEPa,b (2022)

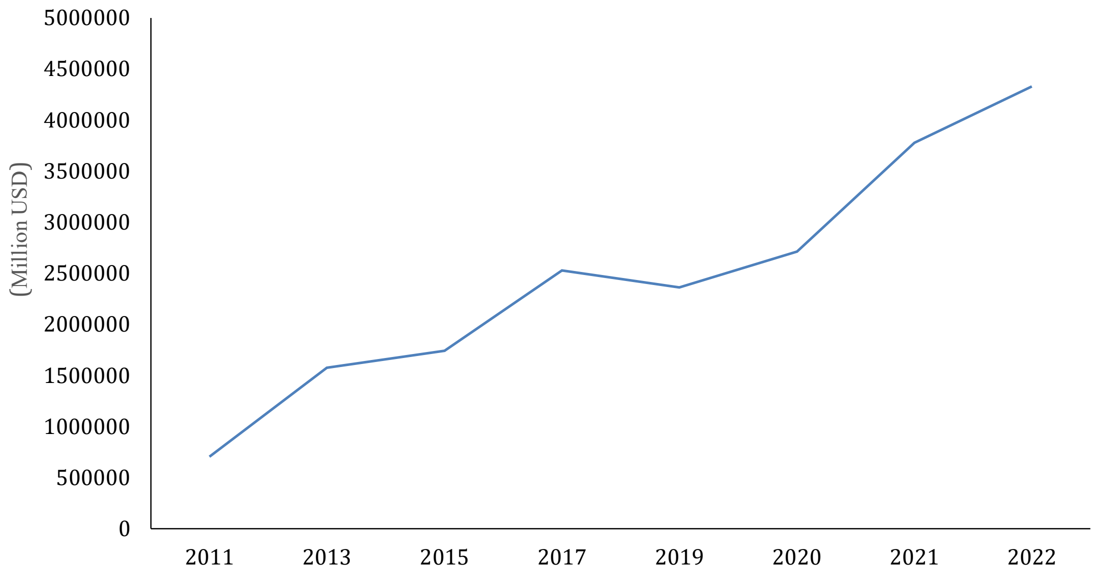

Figure 3:The export value of Vietnamese WLS from 2011 to 2022

Data source: FishStat - FAO Fishery and Aquaculture Global Statistics, GSO (2021), VASEPa,b (2022)

The Vietnamese government aims for a shrimp export value of 10 billion USD in 2025 by promulgating Decision No. 79/QD-TTg dated 18/01/2018 (Government of Vietnam, 2018), with WLS representing 60% of the Vietnamese shrimp production. However, the recent growth in shrimp industry land area use, indirectly leading to competition for natural resources, raises concern for the sustainable use of resources (e.g., the need for selecting appropriate areas and different production systems for culturing shrimp aquaculture), and its impact on the ability to achieve the export target.

In addition, several factors challenge the growth of the Vietnamese shrimp industry. Climate change effects may hinder sustainable industry growth and export targets (Nguyen et al. 2021; Tran et al., 2022). With a long coastline, diverse topography, and climate variability, Vietnam has been among the five most affected by climate change (Bangalore et al., 2019; World Bank Group & Asian Development Bank, 2021). FAO (2018) emphasized that Vietnam is one of the two most vulnerable countries (besides Egypt) regarding brackish water aquaculture. The Mekong Delta faces serious challenges from climate change events, such as the twin effects of drought and saltwater intrusion, which affected shrimp production in 2016 (FAO, 2016). National income in Vietnam is projected to decline by up to 3.5% by 2050, due to climate change (World Bank Group & Asian Development Bank, 2021). FAO (2022) alerted that aquatic animal diseases and climate variability are serious constraints to the expansion and development of sustainable aquaculture. Furthermore, VASEP (2021) identified that Vietnamese shrimp aquaculture had experienced other challenges, such as fragmented and weak value chains, production-induced environmental impacts, food safety issues, and a lack of traceability and quality control. FAO, furthermore, calls for accelerating transformative changes in national policy, management, and innovation, together with equitable investment, to achieve sustainable growth in the aquaculture sector after it experienced a decline in 2020 due to the COVID-19 outbreak (FAO, 2022)

Taking on board these concerns, the roles of climate resilience and sustainable development of the Mekong Delta were focal points in Resolution No. 120/NQ-CP (issued by the Vietnamese Government) and highly recommended the role of shrimp culture as a key component in the fisheries sector's development (GSO, 2021).

Given the above facts, sustainable shrimp expansion seems to require improved industrial management and planning. All levels of shrimp operations (local, national, regional, and international) require development that addresses social, economic, and environmental problems, as this determines the foundation for proper aquaculture management strategies (Md Noor & Harun, 2022).

Hence, this thesis aims to discuss key recommendations for achieving a sustainable production in the WLS aquaculture industry and farming adaptation to climate events in the Mekong region. This includes farming efficiency measurement, issues of disease occurrence control, and assessment of shrimp farmers' adaptation choices to climate events, which may provide evidence and policy recommendations for local authorities. The next section will discuss the sustainable development of WLS production in the Mekong region of Vietnam, covering economic, social, and environmental dimensions.

1.2 The development of the shrimp industry toward sustainable production

Many countries with large shrimp production, including Vietnam, have faced environmental, economic, and social challenges in shrimp farming. As a result, there is a growing interest in developing more sustainable shrimp farming practices that balance economic benefits with environmental protection and social equity.

Sustainable development is defined as the "*use of the environment and resources that meet the needs of the present without compromising the ability of future generations to meet their own needs*" (UN World Commission on Environment and Development, 1987, p16). According to FAO (1997, p7), "*such sustainable development (in the agriculture, forestry, and fisheries sectors) conserves land, water, plant, and animal genetic resources, is environmentally non-degrading, technically appropriate, economically viable and socially acceptable"*. This thesis discusses the development of sustainable aquaculture, with a focus on the shrimp sector, not only based on maximizing benefits, but also reducing accumulation of detriments from negative impacts on the natural and social environment. Economic sustainability implies that humans can support themselves through an activity over time. Social sustainability, however, focuses more on overall societal or individual welfare, and distribution (Brown et al., 1987). Environmental sustainability involves conducting an activity without harming the environment and compromising the resources needed for future use, i.e. the *"continued productivity and functioning of ecosystems and the protection of genetic resources and the conservation of biological diversity''* (Brown et al., 1987, p717). Sustainable development requires the incorporation of all three pillars, environmental, economic and social sustainability, into human activities.

The interactions between the three pillars depend on government policies' impacts on maintaining production sustainability. The UN World Commission of Environment and Development (1987) stated that economic growth was no longer perceived as the central sustainability problem, but rather, it was considered part of the solution to environmental and social problems. Sustainable development emphasizes the need for economic development to consider conservation by acknowledging resource limitations and ecosystem-carrying capacity and advocates for integrating conservation objectives into policy to address the current focus on the economic objective (IUCN, 1980). It has become increasingly clear that sustainable development also involves balancing trade-offs between different desirable objectives (Purvis et al., 2019).

In this thesis, the central element is the economic pillar. However, the study's focus is the overlap of economics with the social and environmental pillars (see Figure 3), given several external forces (e.g., climate change, socioeconomic change, and policy change). The thesis includes studies of efficiency, farmers' choice of adaptation, and disease control involving economic, social, and environmental aspects, respectively, as illustrated in Figure 4.

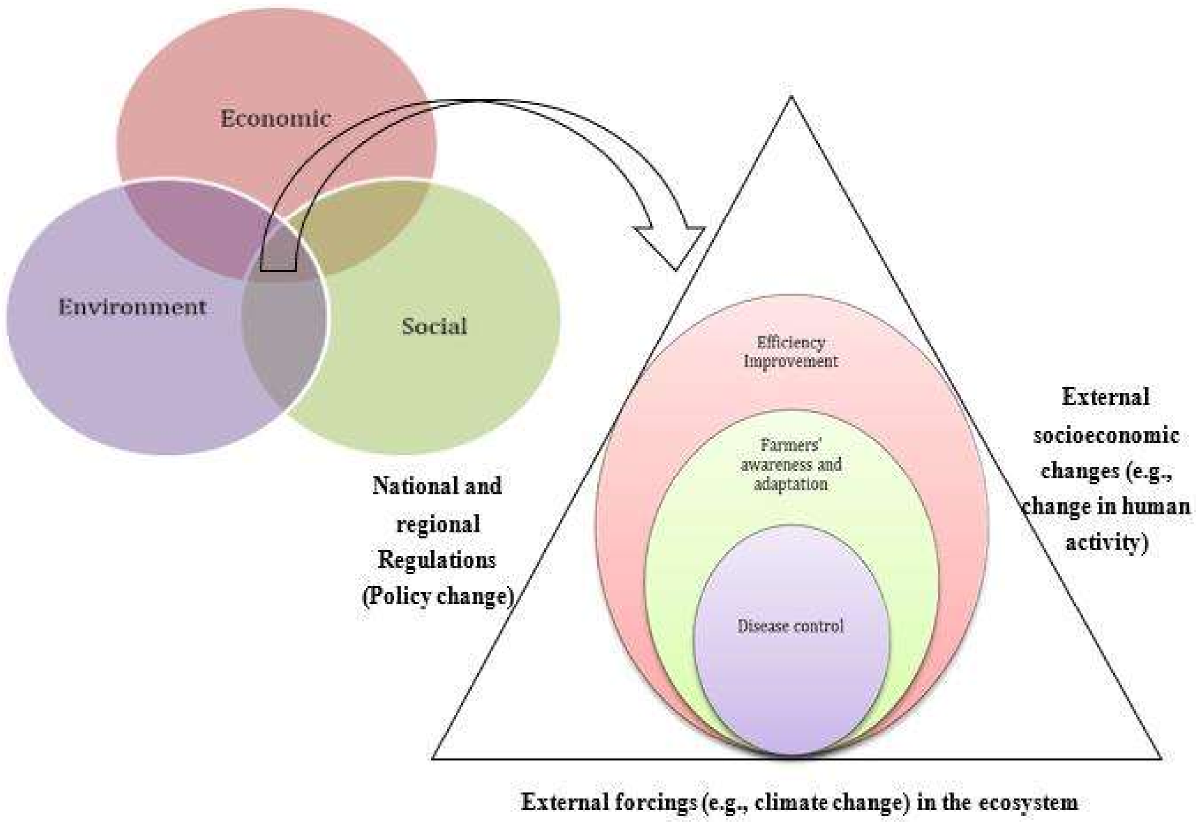

Figure 4: The suggested sustainable development framework for WLS shrimp under climate change impacts

Figure 4 demonstrates the three focus areas within the economic pillar of sustainable management in shrimp farming under the impacts of extreme climate events, that this thesis studies. The thesis empirically assesses the efficiency and farmers' adaptation choices for intensive and extensive WLS farming in Mekong, Vietnam. The assessment of disease prediction focuses primarily on intensive farms. Three central challenges within the sustainable development of Vietnamese WLS aquaculture will be introduced briefly in the next subsections.

1.3 Three primary potential challenges for sustainable development in shrimp farming under the impact of climate change.

1.3.1 Production efficiency improvement in the economic dimension

Pursuing profit is the industry’s foremost goal, as profitable operations are necessary for continued farming. However, it can be hard to reconcile economic and environmental goals. Diverse production systems and management practices have been developed for responsible aquaculture operations to generate greater revenue and environmental protection. From an economic perspective, there are several ways to improve production efficiency in shrimp farming, including mitigating disease risks through effective management of all aspects of the farm, as well as standardizing, automating, and optimizing practices. Efficiency analysis in shrimp farming is important because it can help identify areas where improvements can be made to increase production efficiency. By analyzing the efficiency of different aspects of shrimp farming, such as feed management and operating expenses, farmers can make informed decisions about optimizing their operations, leading to productivity and profitability improvement for the farm. Improving efficiency can also have environmental benefits by reducing resource use and waste generation. Farmers can reduce their environmental impact and contribute to the goal of responsible consumption and production. Additionally, increasing efficiency can also help improve the economic viability of shrimp farming, which can contribute to the goal of decent work and economic growth. Therefore, the efficient utilization of input resources is essential for sustainable aquaculture and is one aspect studied in this thesis.

1.3.2 Shrimp disease prevention in the Environmental Dimension.

Shrimp disease has become one of the top challenges facing the shrimp industry in recent years, especially in Asia (FAO, 2020). There are several hurdles associated with shrimp disease prevention in the environmental dimension. Even when farming at higher levels of know-how and technology, farmers are still at risk of crop failure if shrimp disease occurs. Bacteria or viruses mainly cause shrimp diseases through pollutants in water sources, poor aquaculture practices management, and poor-quality shrimp post larvae. Acute hepatopancreatic necrosis syndrome (AHPND), white spot syndrome virus, yellow head virus diseases, and white feces syndrome are all common shrimp diseases impacting shrimp aquaculture (Lightner, 2011; Thitamadee et al., 2016; Worranut et al., 2018) It is critical to explore drivers affecting disease occurrence in the shrimp industry in the Mekong region, as disease outbreaks can have devastating consequences on the industry's productivity and sustainability.

1.3.3 Farmers' climate perceptions and choices of adaptation in the social dimension

The study of social sustainability is critical for achieving an equitable society. This involves addressing the root causes of social inequality, poverty, and other unethical practices that continue to exist in various regions of the world. The rapid growth of shrimp aquaculture has appropriated natural resources and disrupted existing production, distribution, and social relations systems. This can lead to new inequalities, and questions arise as to who benefits and who loses. Market volatility makes commercial shrimp producers prioritize short-term profits over environmental and social sustainability. Little data is available concerning the social composition, employment conditions and organizational structure of processing and marketing elements in the shrimp production chain (Barraclough et al., 1996).

This thesis covers social sustainability issues by examining the impact of various factors on farmers' ability to adapt to climate risks. This study highlights the social aspects of promoting sustainable shrimp farming practices by investigating farmers' climate perceptions, socioeconomic knowledge sharing, service accessibility, and choices of adaptation strategies. In the thesis, a literature review from 2000-2022 revealed that previous studies focused on farm management, characteristics, and practices, while limited research was aimed at farmers' perceptions of climate risks and coping strategies (see Part 2- Papers). In addition, we found that literature is scarce regarding the analysis of WLS farmers' choices concerning practical adaptive measures, farming efficiency enhancement, and drivers of disease occurrence under climate change impacts. This knowledge gap underscores the necessity for further investigation and documentation of these research topics. Such documentation could focus on farmer data, including farmers' involvement, farmers' awareness and their responses, management activities, and other farming characteristics, to gain valuable insights into the most effective strategies to mitigate the effects of extreme climate change and other environmental stressors on shrimp farming practices. This could ultimately benefit the farmers and the industry by promoting sustainable and resilient practices that can mitigate the impacts of climate change.

The three papers in this thesis study different aspects of the three pillars to achieve sustainable shrimp aquaculture production, sustain local livelihoods, reduce poverty, ensure social security, and preserve the environment. Key differences in the three studies of each dimension will briefly be presented in the research objectives in section 1.4.

1.4 Research objectives

This thesis comprises three studies examining different aspects of sustainable development for the WLS industry in the two most severely climate change-prone provinces, Bac Lieu and Ca Mau, in the Mekong region of Vietnam, under the context of emerging challenges of increasing climate-related vulnerability in the sector.

There are several research questions in this thesis:

(1) What are the key factors of production inefficiency in extensive and intensive WLS farming?

[paper 1]

(2) What are the major risk and protective factors influencing disease occurrence in WLS intensive farms in the Mekong region as severe climate events occur? [paper 2]

(3) What are the adaptive measures implemented by WLS farmers at the farm level to address climate risks in the Mekong region, and what are the key drivers of farmers' adaptation choices, including socioeconomic factors, farm characteristics, knowledge sharing, service accessibility, and farmers' perceptions of climate risks in both intensive and extensive farming production systems? [paper 3]

The contribution of this thesis relates to sustainable development for the WLS industry, potentially providing lessons for less developed countries regarding the promotion of the shrimp sector incorporating economic, social, and environmental aspects. It may help farmers and policymakers in planning to maintain a sustainable shrimp farming industry, livelihoods, and social stability. Furthermore, there is a great lack of relevant climate change data in developing countries; hence, this thesis provides primary source data collection based at the shrimp farm level to assess these sustainability issues under the climate change context. The thesis includes a face-to-face interview with 437 farmers to collect quantitative socio-economic assessments of two production systems – extensive and intensive farming in Bac Lieu and Ca Mau provinces, MKD. The common denominator in all three studies is the analysis of surveyed Vietnamese WLS farmers' perceptions and their behavior related to extreme climate events.

2. Methods and models

A brief outline of methods and models employed in the three studies is given in this section, including stochastic frontier analysis to assess technical efficiency, generalized linear models, multinomial logit regression to measure farmers' choice of adaptive measures, and binary logistic regression to measure disease occurrence.

2.1 Stochastic frontier analysis for measuring technical efficiency.

The ability of a firm to achieve maximum output from a given set of inputs under an output-oriented approach, known as technical efficiency (TE), is a fundamental concept in production analysis (Coeil et al., 2005). In shrimp farming, the technical efficiency of a farm is the ratio of the observed harvested output to the corresponding frontier output (Le et al., 2022; Sharma & Leung, 2003). TE ranges between 0 and 1, where one implies that a farm operates on the frontier, i.e., it is fully efficient as it obtains its maximum feasible output. Otherwise, the farm operates beneath the frontier, implying it works within its potential capability. Three approaches are commonly applied in the efficiency measurement of aquaculture: stochastic frontier analysis, data envelopment analysis, and meta-frontier (Folorunso et al., 2021; Gunaratne & Leung, 1996; Hai et al., 2020; Le et al., 2022; Nguyen & Fisher, 2014; Onumah and Essilfie, 2020; Sharma & Leung, 2000). Meta-frontier analysis allows for measuring and comparing farming efficiency for several countries or regions over separate production frontiers

(Gunaratne & Leung, 1996; Sharma & Leung, 2003). Battese (2002) and Lau & Yotopoulos (1989) state that the two major limitations of using the meta-frontier approach are the need for comparable data and inherent differences across countries. Data envelopment analysis (DEA) is a non-parametric method that can accommodate multiple outputs; it is deterministic and assigns all deviations from the frontier to inefficiencies, making it less appropriate to case studies in shrimp aquaculture where uncontrollable factors (e.g., disease outbreaks) account for substantial variation in output (Sharma & Leung, 2000).

In contrast, the stochastic frontier analysis 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, 2000). This approach is appropriate for studying agricultural and aquaculture production in developing countries since, according to Gunaratne and Leung (1996), farming data is heavily influenced by measurement errors and other stochastic factors (e.g., weather conditions). Stochastic production frontiers, derived from production theory, represent the highest expected output for a given input level and the producer's efficiency in utilizing those inputs. Furthermore, Cobb-Douglas and other flexible (translog) functions are most applied in the stochastic frontier analysis literature (Battese, 2002 ; Sharma & Leung, 2000). The Cobb-Douglas stochastic frontier function is functional and suitable when dealing with relatively small sample sizes and other data limitations often prevalent when working on intensive and extensive systems in aquaculture (Sharma, 1999; Gunaratne & Leung, 1996; Irz, X., & Mckenzie, V. 2003), as is the case also in our study. Therefore, we apply the stochastic frontier technique separately for each technology, thus not comparing efficiency but assessing the factors influencing efficiency in the two production systems.

We apply a single-stage stochastic frontier analysis estimation procedure to examine the determinants of technical inefficiencies, with maximum likelihood estimation providing the estimates for the parameters (Le et al., 2022). In the following, we describe the Cobb Douglas production function:

$$lnY_i \ = \alpha lnX_i + v_i \ - \ u_i \tag{1}$$

and $u_i = z_i\delta + \omega_i$, α, δ are vectors of unknown coefficients associated with the input and potential explanatory factors, and ω_i is an error term. In the following, we describe the Cobb-Douglas stochastic frontier function which represents the farms' technological relationship between the main inputs X_i (seed, feed, land, labor, chemicals, and other operating costs) and Y_i, which is the quality-adjusted output, as Fernandez-Cornejo and Jans (1995) suggested. The input variables are chosen based on surveyed shrimp practices and relevant papers on stochastic frontier analysis in aquaculture (Alam et al., 2012; Asche & Roll, 2013; Bukenya et al., 2013; Kumaran et al., 2017; Mohan Dey et al., 2005; Sharma & Leung, 2000). In addition, the inefficiency of shrimp farmers, u_i, is a function of a vector z_i of potential explanatory variables such as farmers' perception of environmental events, farmers' socio-economic characteristics, farming characteristics, farming site description, farmers' knowledge, and adaptive measures to drought effects.

2.2 Generalized linear models.

Generalized linear models (GLMs), including logistic regression and multinomial logit regression, are applied in this thesis to assess the determinants of disease occurrence and farmers' choice of climate change adaptation in shrimp farming, respectively. The primary difference between logistic regression and the multinomial logit model lies in the number of categories of the dependent variable they model. For example, logistic regression models are used for binary outcomes, while multinomial logit models are used for more than two categories. The detailed methodology of each study will be presented in the following subsections.

2.2.1 Logistic regression for measuring disease occurrence prediction.

We employ the recommended logistic regression approach (Duc et al., 2015; Hasan et al., 2020; Leung & Tran, 2000; Tendencia et al., 2011) and randomly divide the total dataset into training and testing datasets. In the training set, potential predictors are analyzed to determine their ability to explain disease occurrence. The model's performance is evaluated with the testing set. This study applied logistic regression using a stepwise procedure and regularization techniques to select potential primary explanatory variables. Each approach employed in the variable selection step highlights the main differences and computational advantages of each technique used to identify the best predictors to explain the likelihood of disease occurrence. The logistic regression model predicts the odds of disease occurrence, specified as follows:

$$Log\left(\frac{P(x)}{1-P(x)}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \qquad (2)$$

where $\left(\frac{P(x)}{1-P(x)}\right)$ is the 'odds' of the outcome of the shrimp disease outbreak, which is binary, with yes coded as farm recorded to have disease in the crop, otherwise no.

The logarithm of the odds is a linear function of the potential variables. In logistic regression analysis, the coefficients indicate the anticipated change in the odds of disease occurrence with each unit change in the explanatory variable. A positive coefficient indicates that an increase in the corresponding factor will increase the chance of disease occurrence. Conversely, a negative coefficient suggests that increasing the factor will reduce the likelihood of disease occurrence.

In the stepwise procedure, there are backward and forward logistic regressions. The backward stepwise logistic regression method with a likelihood ratio test eliminates the explanatory factor contributing the least to explaining the model at each consecutive step until the smallest possible log-likelihood ratio is obtained. In contrast, forward stepwise logistic regression begins with a model containing no predictors and then adds one after another until all relevant predictors are in the model. The backward stepwise procedure is usually preferred as the forward stepwise approach could eliminate important variables.

Second, this study also employed logistic regression via the regularization approach, including Lasso, Ridge, and Elastic Net, which was employed to exclude irrelevant variables and reduce the variance in the estimation. Finally, after identifying the possible variables via subset selection and regularization, the fitted logistic regression model results are explained by statistically significant variables. Notably, the final model selection for predicting disease occurrence should consider the cross-validated prediction error, negative log-likelihood value, equivalently largest adjusted R squared or AIC, and BIC values. We emphasize estimating the impact of farmers' perceptions of extreme climate events (drought and irregular weather) and farmers' adaptive measures, acting as crucial potential variables in predicting the probability of disease emergence.

2.2.2 Multinomial logit regression for measuring the farmers' adaptation choices.

The Multinomial logit (MNL) is a widely used method for evaluating the factors that influence agricultural farmers' choices of adaptation to climate risks (Abdur Rashid Sarker et al., 2013; Addisu et al., 2016; Alam, 2015; Alauddin & Sarker, 2014; Arunrat et al., 2017; Chu et al., 2010; Deressa et al., 2009; Gbetibouo, 2009; Gbetibouo et al., 2010). However, to our knowledge, it has yet to be applied to Vietnamese WLS aquaculture studies. While some studies have quantitatively analyzed shrimp aquaculture to discuss the adaptation strategies (Do & Ho. 2022; Joffre et al., 2019), our study aims to employ the MNL to assess the drivers that affect farmer adaptation choices, using Vietnamese shrimp farm-level data.

The Multinomial Logit Model (MNL) estimates the preferred adaptation measure of shrimp farmers among multiple options. A particular adaptive measure's choice is determined by its utility compared to other decisions. The MNL model estimates the probability of choosing each option from the explanatory variables and is formulated as follows:

$$Prob\left(y = j|X_j\right) = \frac{exp\ (\beta_j X_j)}{1 + \sum_{k=1}^{J} exp\left(\beta_j X_j\right)}, \qquad j = 1, \ldots. J \tag{3}$$

Equation (3) formulates the likelihood of observing the *j*th outcome, where the exponential coefficient (β_j) is associated with one unit change in the corresponding independent variable (X_j), at fixed levels of all other independent variables (X_k, where $k \neq j$), and y represents the categories of adaptive measures. Prob(y) is the response probability. The sum of probabilities equals one, and it determines the influence of explanatory variables on adaptation choices. The study also evaluates the marginal probabilities or effects, which indicate the expected change in the likelihood of a given choice for a unit change in the explanatory variables. Equation (4) provides the marginal effects of explanatory variables, which are given as

$$\frac{\partial Prob_j}{\partial X_k} = Prob_j\left(\beta_{jk} - \sum_{k=1}^{J-1} Prob_j \beta_{jk}\right) \tag{4}$$

The MNL model estimates the probability of choosing each option and evaluates the marginal effects of explanatory variables on adaptation choices.

3. Data and data collection

WLS is cultured in many production systems, such as extensive, intensive, and super-intensive. This expanse of production systems provides diverse possible rearing locations for WLS, depending on the local economy, shrimp farmers' financial status, and the application of various operating criteria for securing shrimp growth. A current trend in the culture of WLS is low-salinity inland production. Over the last forty years, South-East Asia[1] and China have emerged as suitable culturing areas. The first introduction of WLS in Asia, from South America, occurred in 1980 in the Philippines, followed by Taiwan in 1981 and China in 1988. In 1996, WLS aquaculture production spread rapidly to other Asian nations, including Thailand, Indonesia, Vietnam, Malaysia, and India (Briggs et al., 2004).

Vietnam is a developing country with limited public secondary data availability. Hence assessment of the economic, social, and environmental aspects within the economic sustainability pillar requires data collection. The choice of research site, survey design, and approach to data collection are presented in the following.

3.1 Research sites

In the sample at the research sites, the group of respondents encompasses both intensive and extensive scale farming systems, where the latter features low stocking densities and relies primarily on natural feeding methods. In the research sample, the extensive systems also include improved extensive, which are well-suited for low-income farmers with ample land resources. The improved extensive operates similarly to the extensive system, with the only difference being slighly higher production cost due to applying some modifications such as the use of certain inputs (i.e., supplementary feed, fertilizers, lime) In constrast, intensive farming encompasses multiple levels, including super-intensive, intensive,

[1] South-East Asia includes Thailand, Vietnam, Indonesia, Bangladesh, Malaysia, Philippines, Myanmar, and Taiwan.

and semi-intensive, characterized by their industrial nature and dependence on supplementary feed. This type of farming requires substantial investment in farming infrastructure, such as irrigation systems, transportation, electricity, water, and mechanics. In our research areas, the extensive and intensive farming systems vary in inputs, including water exchange methods, farming practices, capital, labor, feed, chemical use, stocking density, and land area. Furthermore, the market target of these two systems also differs. Intensive farmers harvest shrimp to meet the demand for large yields and specific shrimp size requirements of processing companies or intermediaries (middlemen). Conversely, extensive farmers harvest shrimp according to the monthly tide schedule, largely serving domestic market demand and supporting family businesses.

3.2 Survey design and data collection

The survey design includes three parts. The first part consists of the production and biodata of the interviewed shrimp farmers. It comprises education, age, experience, training, association participation, regional placement, extension services, and credit access. Information on shrimp inputs at stocking time, and yields at harvesting time, are targeted to measure technical efficiency. The second part covered farmers' perception of extreme weather and farmers' adaptive and biosecurity measure choices. Farmers' perceptions of climate risks and environmental issues are based on their experience of the negative impacts of climatic events. Extreme climate events in shrimp farming include drought, saline water intrusion, irregular weather, prolonged heavy rains, and water cross pollution. The last part of the survey asked for disease status and culture methods in farming (stocking density and shrimp crop duration). The survey procedure also allowed farmers and other relevant persons to participate in local focus-group discussions (FGDs) and validate preliminary study results from our field trials. Hence, the study has benefited from about 16 key informants in both provinces who have discussed the general information related to climate change in shrimp farming, how farmers implement the adaptation to mitigate climate change, farming practice management, biosecurity applications, farming characteristics, disease issues in each system, and market information. The results of the FGDs were used to construct the additional potential explanatory variables in the survey design.

Next, a structured questionnaire was developed based on the study of Leung & Tran (2000), with modifications applied from the inputs of the FGDs. The provincial agricultural extension center and the Department of Aquaculture provided a list of registered shrimp farmers. Ten pre-test surveys were conducted to assess the farmers' understanding of the questionnaire. The final survey was modified based on the results of the pre-tests, with local terms applied, and the interviewer team trained to collect data through face-to-face interviews. Finally, the interview process was completed at the farms, in the offices of the Department of Aquaculture or the shrimp farmers' cooperatives in Bac Lieu and Ca Mau provinces. The sample consisted of a randomized selection of individual farms from the provided list, with a "snowball" sampling method applied in case a randomly selected farmer refused to be interviewed. Snowball sampling involves asking the farmer to recommend another person with a similar farm. A sample of 437 shrimp farmer interviews was collected, each taking approximately 30-45 minutes.

The summary of the three papers in this thesis which all analyze different elements of the above survey data, will be presented in the next section.

4. Summary of the papers

4.1 Paper 1: Identifying the determinants of farming inefficiency in two different production systems (extensive and intensive) under the impacts of extreme climate events.

This study employed the stochastic frontier approach to identify key factors affecting the farming efficiency of WLS shrimp production systems as extreme climate events occur in Mekong, Vietnam. Farm-level data was obtained from 437 intensive and extensive farmers in the shrimp crop of 2016 - 2017. This study provides insight into WLS production inefficiency, including the need for farming management practices and adaptation, as well as suggestions for improving the sustainability and profitability of shrimp aquaculture operations. With the current aquaculture practice, farmers achieved an average efficiency of around 83% for extensive and 78% for intensive farms. Our study also identified that feed, labor, chemicals and fuels/electricity costs significantly impacted intensive production.

In contrast, factors such as farmland size, other operating costs, and chemicals and fuels/electricity costs also played a substantial role in extensive farming, particularly improved extensive systems. Our findings reveal that the two farming technologies react differently to climate change. Adaptive measures taken by farmers can increase the efficiency differences between these two farming technologies. The study found that intensive shrimp farms can reduce production inefficiency by increasing the length of crop duration, being further from the sea to avoid drought and saline water intrusion and adopting pond renovation to mitigate the effects of climate events. The most detrimental impacts on efficiency in extensive farms are farmers' perception of extreme weather events, disease occurrence, and longer crop duration. The study recommends increasing the efficiency of extensive farmers by reducing the crop duration, implementing changing feeding practices as an adaptation strategy, and securing individual educational attainment. The results also suggest that locating in government-planned areas could increase efficiency for extensive farmers.

4.2 Paper 2: Identifying the protective and risk factors affecting disease detection.

This research delves into the crucial factors influencing the likelihood of disease outbreaks in the severely climate-risk-prone provinces of the Mekong region. Data from 267 intensive shrimp farms on climate and environmental issues, adaptive measures, biosecurity applications, farming characteristics, and disease issues created a list of 52 potential explanatory variables. Logistic regressions with subset and regularization approaches were utilized to assess the positive and negative effects of farming characteristics, management activities, perceived extreme climate events, and the surrounding environment.

The research results highlight enhancing farmer engagement in training programs and offering extension services, such as technical support and disease treatment advice, in addition to raising awareness among farmers regarding the severity of weather events, particularly droughts, and encouraging farmers to take proactive or adaptive measures such as adjusting feeding schedules. Moreover, our findings emphasize the importance of information sharing within the shrimp industry and concerning climate events. Additionally, utilizing measures for changing feeding practices and regular

FCR ratio calculations in intensive farms helps reduce disease risk and mitigate water pollution, thereby sustaining the production system.

The findings indicate several risk factors as the primary challenges to WLS shrimp farming in the Mekong Delta. For instance, increasing the years in operation and crop duration can lead to grow-out ponds potentially contaminating pollutants in the culturing environment and surrounding water resources if farmers ignore chemicals and microbial communities in the water source treatment during culturing and after harvesting.

4.3 Paper 3: Identifying the shrimp farmer choices of adaptive measures to climate events.

The research analyzes farm-level survey data from 437 intensive and extensive shrimp farmers in Bac Lieu and Ca Mau provinces, Mekong, Vietnam, to identify their adaptation choices when faced with extreme climate events. An MNL model was employed to assess the determinants of adaptation strategies adopted by farmers in response to drought and irregular climate. Based on the literature review, fourteen explanatory variables regarding socioeconomic factors, farm characteristics, service accessibility, knowledge sharing, and farmers' perception of climate risks were suggested as driving forces behind farmers' decisions to adopt adaptive measures.

The findings showed five adaptation options most farmers selected in response to severe drought and irregular weather (water treatment, change in water exchange schedules, water conservation, early harvesting, and change in feeding schedules/ stocking density). Our research identified crucial factors behind farmers' decision-making processes. Specifically, we found that the availability of credit access and a larger farm area, coupled with fewer ponds, were significant motivators for farmers to alter their water exchange schedules. In contrast, perceiving the occurrence and severity of droughts and irregular weather patterns encouraged farmers to choose water treatment options. Furthermore, farmers with access to extension services, having more years of schooling, and those with limited shrimp land adopted water conservation practices.

The significant differences in the choice of adaptive measures across production systems are impacted by explanatory variables, which could have important implications for policymakers. Change in water exchange schedules was the extensive farmers' preferred choice when they perceived climate risks. The local and provincial governments could motivate intensive farmers to apply water conservation by promoting knowledge sharing (training program attendance) and increasing access to extension services and credit. In the next section, Table 1 briefly presents the key findings of the three studies. Based on these results, several key messages are highlighted for policy implications, potentially providing input for sustainable shrimp development in relation to the different production farming systems.

5. Conclusions and policy implications

The three papers of this thesis answered research questions related to promoting the sustainable development of Vietnamese WLS shrimp production. Mostly, the studies of efficiency and farmers' adaptation choices for the two production systems react to different inputs, both as regards what actions the individual farmers could take to improve efficiency and the actions recommended for the managers. This diversity underlines the complexities of managing the shrimp sector and individual farmer attempts to move from one technology to another.

Table 1 shows the differences in objectives of intensive and extensive farmers when operating farms and coping with extreme events, especially the prolonged impact of drought and irregular weather. The first and third papers indicate the economic and social impacts via determinants of inefficiency reduction and farmers' adaptation choices in both production systems, with messages regarding adopting recommended management practices and self-adaptation strategies to mitigate the pressure of environmental concerns and increase economic gains. The most important suggestion is that shrimp farmers should focus on managing disease control in both production systems, though it seems more urgent for intensive farmers. Next, the government should focus on planning shrimp areas by considering increasing the distance from farms to the sea and encouraging employment of significant adaptive measures (e.g., water treatment, and stocking density, change in water exchange schedule, pond renovation for intensive farms, and change in feeding practice for the extensive system).

In addition, key inputs related to farmers' perception of climate change issues (drought and irregular weather), knowledge sharing (farmers' training participation), and service accessibility (bank credit access) may considerably support livelihood improvements for shrimp farmers. For example, shrimp farmers that perceive drought and irregular weather tend to choose changes in feeding practices/stocking density and water treatment during these climate events.

In the study of shrimp disease occurrence prediction at high stocking density farms, intensive farmers could beneficially focus on management activities in farming, such as adopting biosecurity and adaptive measures, gaining knowledge, and service accessibility. The important alerting message is the shrimp crop culturing duration in both production systems. Long culturing time in shrimp crops under severe irregular weather increases inefficiency for extensive farmers, while intensive farmers may have increased shrimp disease outbreaks in their farms. Years in operation may reflect environmental degradation, but more surprisingly, selecting other pond management activities and having higher education attainment are also factors that increase shrimp disease occurrence. However, the variable of other pond management activities may reflect different issues that do not necessarily apply to disease, and furthermore higher education is negatively correlated with experience, which may contribute to explaining this result. Though there are potential explanations for the more counterintuitive results, as mentioned above, these results underline the complexities of the shrimp farming systems, pointing to the need for further research.

Table 1: *The key factors in the thesis research affecting farming efficiency, disease occurrence prediction, and farmers' adaptation choices in intensive and extensive production systems.*

Group of factors	Intensive production systems			Extensive production systems	
	Farming efficiency	*Disease occurrence*	*Farmers' adaptation choices*	*Farming efficiency*	*Farmers' adaptation choices*
Perception of environmental issues			Severe Irregular weather	Severe Drought Severe Irregular weather	Severe Drought
Socioeconomics		Education	Education	Education	Experience
Farm characteristics	Disease			Disease	
Farming site		Years in operation		Planned area	Planned area
	Distance to sea			Distance to sea	
Adaptive measure	Pond renovation	Change in the schedule of feeding practices	Water Conservation Water treatment Feed schedules and stocking density	Change feeding practice/stocking density.	Change in water exchange schedule
Biosecurity measures		Regular FCR Ratio calculations Other pond management activities			
Knowledge sharing		Training participation			Training participation
Culture methods	Duration of crop	Stocking density Duration of crop		Duration of crop	
Service Accessibility		Extension services			Credit access

Notes: Factors that increase efficiency or reduce disease are in black, while ones that reduce efficiency or increase disease are in red. The blue color are factors positively affects the farmers' adaptation choices.

6. Future research

In this section, I propose future research directions related to improving some of the limitations of the studies carried out in this thesis. One clear limitation of this thesis is the limited number of samples collected, mainly due to the lack of willingness of farmers to participate in the interviews and financial constraints for extending the dataset size. This limitation hinders a greater disaggregation of production systems, opening for different degrees of intensive and extensive culture. Therefore, the study could not provide a detailed analysis of the economic efficiency, disease occurrence, or adaptive measure choice among a broader set of production systems than solely intensive versus extensive in *vannamei* culture. Future shrimp research may beneficially identify differences within intensive (intensive - semi-intensive - super-intensive) and extensive farming (traditional extensive; improved extensive) and even extend to integrated production systems (shrimp-rice, shrimp-fish, and shrimp mangrove). Researchers may consider three ways of expanding data collection. First, data collection could beneficially be expanded over the years, incorporating time-series data to document and analyze the facts and changes in shrimp farming characteristics and management of different production systems. Second, the data could be extended spatially from inland farms to coastal farms or farms that obtained best practice certifications in shrimp farming (e.g., ASC and Global GAP) versus those that did not. Third, the incorporation of qualitative data, such as interviews or focus groups, could contribute to a better understanding of the factors influencing the relationship between independent variables and the outcome of interest.

Another issue is research method improvement; once we build up a sufficiently large dataset of shrimp farming, state-of-the-art data science applications such as advanced machine learning techniques (e.g., neural networks, random forest) can be employed. Using these new methods may provide potential benefits for shrimp farm management in predicting disease occurrence and reducing feed costs with real-time alerts (FAO, 2020). This enables local government and shrimp farmers to build powerful predictive toolboxes that allow for the control of disease, management of production costs, and application of preventive measures for climate change impacts.

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PART 2. PAPERS

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APPLIED STUDIES

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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 $Y_i = \mathrm{f}(X_i;\alpha)\exp(\varepsilon_i)$, where Y_i is the best practice production of the farm $i = 1,....N$, given the vector of inputs X_i and the technology represented by the function $\mathrm{f}(X_i;\alpha)$. 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

$$lnY_i = \alpha \ln X_i + v_i - u_i \tag{1}$$

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.

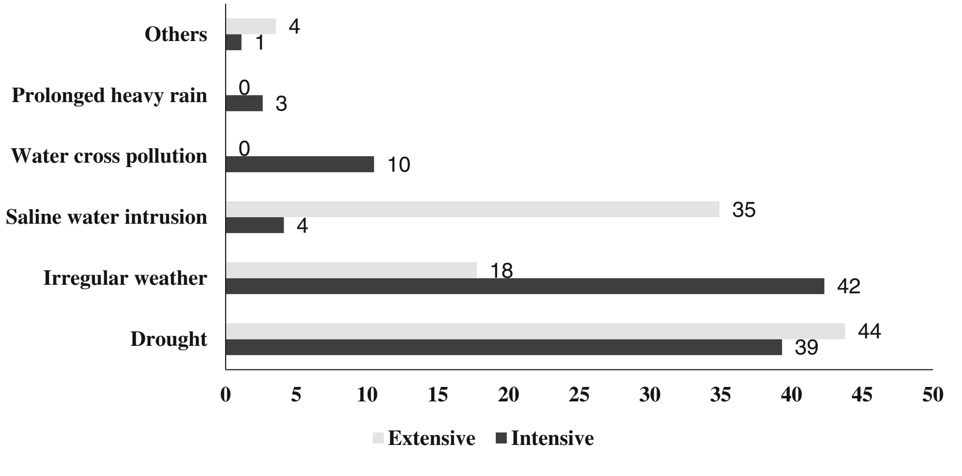

FIGURE 1 The percentage of intensive and extensive shrimp farms that experienced different climatic events occurring in their most recent crop

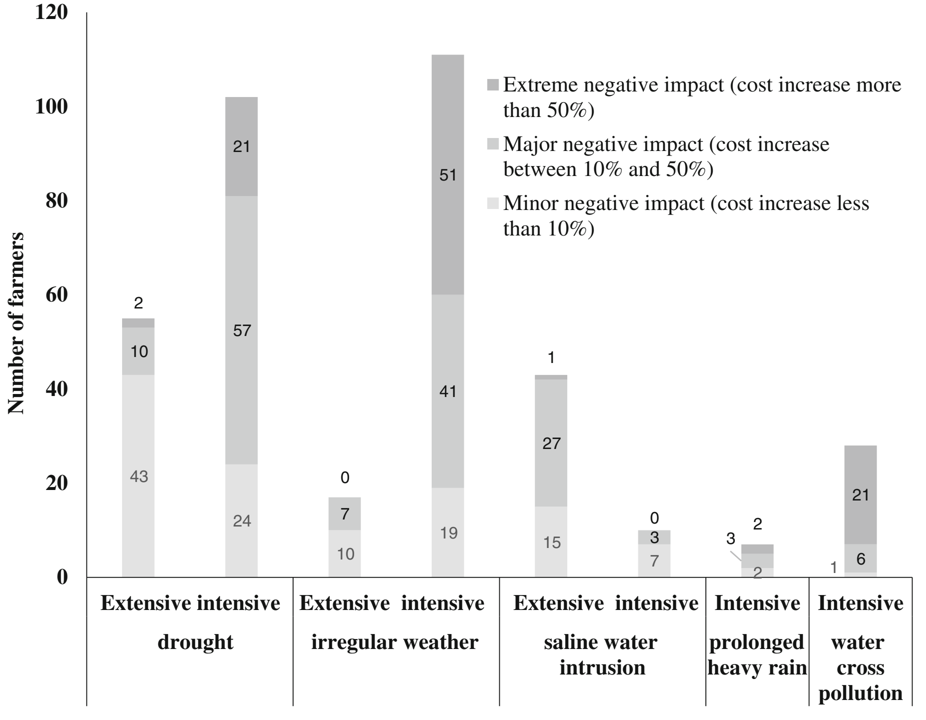

FIGURE 2 Extensive and intensive farmers' perception of economic impact of different environmental issues (total number of farmers in each group)

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)

Variable	Unit	Extensive ($n = 169$)				Intensive ($n = 267$)			
		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

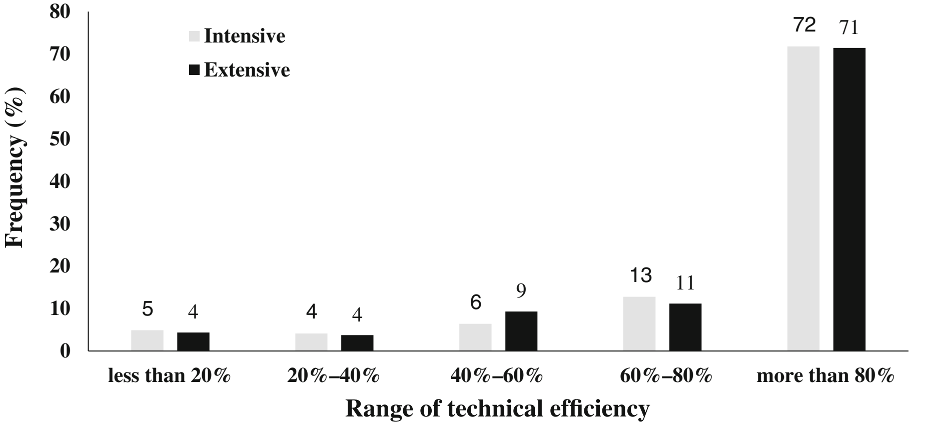

FIGURE 3 Frequency distributions of technical efficiency scores for intensive and extensive shrimp farms

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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SUPPORTING INFORMATION

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APPENDICES

Appendix A

The quality adjusted output (Yi: output quantity) in equation (3) is calculated as follows:

Step 1:

In practice, the number of shrimps per kilo harvested from a pond affects price and quality. Shrimp size captures almost everything related to the quality of shrimp. So, in step 1, we run an OLS regression between size (the number of shrimps per kilo at harvesting time) and price P.

P = _b[_cons] + _b[size] * size

Step 2: Calculating the predicted price for each farm.

We calculate the predicted price for each observation, and the predicted price measured at the mean of all independent variables. Then we take the ratio of these two. If the ratio is above 1, this indicates a higher quality of shrimp.

Step 3: We multiply the price ratio by the quantities, and thereby get quality-adjusted quantities

Appendix B: Literature reviews of stochastic frontier technical efficiency papers in aquaculture industries

No	Authors	Species	Methodology	Obs	Countries	System/Mean TE			Factors influencing inefficiency terms
						Extensive	Semi-intensive	Intensive	
1	Gunaratne & Leung (1996)	Shrimp (Black tiger)	Stochastic metaproduction frontier	1895	Bangladesh	0.42	0.55	-	Farm size (+)
					India	0.61	0.64		Farm size (+), Owner land (+), feed management (-)
					Indonesia	0.48	0.67	0.51	Farm size (+), Owner land (-), pond management (-)
					Malaysia	-	0.78	0.76	Experience (+), Owner land (+), feed management (-)
					Philippines	0.47	0.47	0.70	Experience (-), shrimp management (-)
					Sri Lanka	-	0.69	0.79	Farm size (-), Owner land (-), feed management (-)
					Taiwan	-	-	0.47	Pond management (-)
					Thailand	-	-	0.59	Farm size (-), Experience (-), feed management (-)
					Vietnam	0.35	0.37	-	Shrimp management (-), pond management (-)
2	Gunaratne & Leung (1997)	Shrimp (Black tiger)	SFA and DEA	83	Malaysia		0.78 (SFA) 0.80 (DEA)	0.76 (SFA) 0.79 (DEA)	-
3	Sharma & Leung, (1998)	Carp	SFA	286	Nepal	0.69	0.8		Pond area, Fish management index (-), Water management index (-), Feed management index (-),
4	Sharma (1999)	Carp	SFA	602	Pakistan	0.56	067		Extensive: Fish managment index, Water management index (-), Feed management index (-), Pond area (+), Experience (-) Semi-intensive/Intensive: Fish managment index (-), water management index(-), Feed management index(-), Experience (+), Pond area (+)
5	Iinuma et al. (1999)	Carp	SFA	94	Malaysia	0.42			intensive culture dummy (-), ownership (+), pond age (+)
6	Sharma & Leung (2000a)	Carp	Stochastic meta production frontier	2329	Nepal	0.60	0.68		Extensive: Fish managment index, water management index (-), Feed management index (-), Pond area (+), Primary activity (-) Semi-intensive/Intensive: Fish managment index(-), water management index(-) Feed management index (-), Experience (+), Pond area (-)
					India	0.50	0.79		
					Bangladesh	0.48	0.74		
					Pakistan	0.62	0.74		
7	Sharma & Leung (2000b)	Carp	SFA	906	India	0.67	0.81		Primary activities (-), Fish management index (-), Water management index (-), Feed management index (-), State dummy (Andra Pradesh) (-)

					India	0.59	0.81		
					Nepal	0.62	0.78		
					Pakistan	0.56	0.73		
8	Dey et al. (2000)	Tilapia	SFA	78	Philippines	0.83			Farm area (-), Education (-), Age (-)
9	Bimbao et al. (2000)	Tilapia hatchery operators	SFA	78	Philippines	0.48			Cost production by unit of fry/fingerling (-)
10	Karagiannis et al. (2002)	Seabass, Seabream	SFA	30	Greece	0.79			Farm size (-), specialization in seabass and seabream (-), scientists (-)
11	Irz & Victoria (2003)	Tilapia, Shrimp, Fish	SFA	95	Philippines	0.53 (brackish water); 0.83 (fresh water)			Fresh water: Cycle (-), pond quality (-), farm size (+) Brackish water: Experience (-), manager's visits
12	Kumar et al. (2004)	Shrimp	SFA	105	India	0.69			Education (-); Experience (-); Farm size (-); Leased in farm (+); source of water to farm; source of seed; capital investment (-); distance from market; State dummies (Andra Pradesh, Karnataka) (-)
13	Chiang et al. (2004)	Milkfish	SFA	433	Taiwan	0.84			Year dummies (98, 99) (-); Monoculture (-); freshwater (+); Education (not able to read) (-); Education (above senior high school) (+); Experience (+); Labor (+); states dummies (Chiayi, Tainan) (+)
14	Dey et al. (2005)	Carp and another freshwater species	SFA	1000	China	0.77	0.84	0.93	Extensive: Regional dummy (-) Semi-intensive: Farm size (-), Distance from seed supplier (+), regional dummy (+) Intensive: Farm size (-)
					India	0.65	0.86		Extensive: Education (-), Farm area (+), Own dummy (-) Semi-intensive/intensive: Education (-), Farm area (+)
					Thailand	0.72	0.91		Extensive: Farm area (-), Own dummy (-), Distance from seed supplier/market (+) Semi-intensive/intensive: Farm area (-), Distance from seed supplier/market (+)
					Vietnam	0.42	0.48		Extensive: Age (-), Education (-). Semi-intensive/intensive: Farm area (-), Distance to nearest market (+)
15	Dey et al.(2007)	Shrimp	SFA	30	India	0.61	0.62		Pond size (+), Tenure status (company-based) (-), distance from water source (+), (number of years since pond was constructed (-)
					Indonesia	0.48	0.67	0.51	
					Malaysia	-	0.78	0.76	
					Philippines	0.47	0.47	0.7	
					Sri Lanka	-	0.69	0.79	
					Thailand	-		0.47	
					Vietnam	0.95	0.37		

16	Kareem et al. (2009)	Fish	SFA	100	Nigeria	Concrete pond (TE: 0.55) Earther pond (TE: 0.84)		Experience (-)
17	Ogundari & Aklnbogun (2010)	Fish	SFA	64	Nigeria	Without risk (TE: 0.92) With risk (TE: 0.79)		Labor (-), experience (-), education (-), access to market (-)
18	Alam et al. (2012)	Tilapia	SFA	50	Bangladesh	0.78		Age (-), Income (+), Culture length (-), Water color (-)
19	Nagothu et al. (2012)	Shrimp	SFA	300	India	0.54		Stocking density (-), Experience (-), Number of society (-), Cyclone storm – level of success (-) and flood from rain (-)
20	Sadika et al. (2012)	Shrimp	SFA	185	Bangladesh	0.71		Education (+), Training (-), share of non-farm income (-), (non-farm income)^2(+), family labor (-), ownership (-), water quality (+), Distance from pond to water source (+), farm size (-), (farm size)^2(+), local dummy (-)
21	Asche & Roll (2013)	Salmon	SFA	4901	Norway	0.82		Disease (+), Insurance disbursement (+), Trout producer (+), Age (+), Achieved salmon price (+), Utilized production capacity (-), Lack of smolt (+), Salmon and trout producer (+)
22	Bukenya et al. (2013)	Fish	SFA	200	Uganda	Allocative efficiency: Pond size (1.15), feed resource (1.64), fingerlings usage (3.71), labor (-0.94)		Extension services (-), Record keeping (-), credit (-)
23	Begum et al. (2013)	Shrimp	SFA	90	Bangladesh	0.82		Education (-), Age (-), Non-farm income (-), Distance of the shrimp farm from water canal (-)
24	Ghee-Thean et al. (2016)	Shrimp (White-leg)	SFA	100	Malaysian	0.81		Seminar conducted by extension agents (-), Land ownership (-), shrimp seed size (-)
25	Sandvold (2016)	Salmon	SFA cost function	2011	Norway	0.79		hatcheries will probably be able to increase their productivity and reduce costs, Technical efficiency explained by variation in farm costs
26	Islam et al. (2016)	Fin fish	SFA	78	Malaysia	0.38 (fish cage)		Production cycle (-)
27	Kumaran et al. (2017)	Shrimp (White-leg)	SFA	604	India	0.90		Duration of the crop (days) (+), Consultant -availability (+), No. of crops – one (-)
28	Nguyen et al. (2018)	Striped catfish	DEA	184	Vietnam	0.84		Age of farmer (+), experience (-), education (+), assess to extension training (+), flooding effect (+), salinity intrusion effect (-) upstream (-)
29	Alam et al. (2019)	Tilapia	SFA	399	Bangladesh	0.92		Education (+), Extension service (-), Training (-), regional dummies (-) (e.g., Mymensingh compared to Noakhali, Feni compared to Noakhali)
30	Yuan et al. (2019)	Tilapia	SFA	300	China	0.79	0.78	Less than 1 hectare: Association (-) More than 1 hectare: Area (-), Arear squared (+), Experience (>15 years) (-), Association (-).
31	Nguyen et al. (2020)	Shrimp (White-leg)	Profit efficiency	279	Vietnam	0.90		Average size of pond (-), Education (-), Experience (-), Impact of natural disaster (+), number of pond (-), age (-), integration pump for the reduction of energy (-)

32	Onumah & Essilfie (2020)	Fish	Stochastic meta production frontier	320	Great Accra Region	0.72			Age (-), Gender (-), Education (-), Household size (-), Major occupation (-), Pond type (-), Ownership (-), FFA (+), Extension (-)
					Ashati Region	0.61			Age (-), Education (-), Household size (-), Major occupation (-), Pond type (-), Ownership (-), FFA (-), Extension (-), Market access (-)
					Western Region	0.68			Major occupation (+), Ownership (+), FFA (+), Extension (-), Market access (-)
					Volta Region	0.82			Age (-), Education (-), Major occupation (-), Pond type (-), Ownership (-), FFA (-), Extension (-)
33	Radhakrishnan et al. (2021)	Shrimp (White-leg)	SFA	150	India			0.95	Age (-), Experience (-), Education (-), Occupation (+), Technology adoption (-)
34	Folorunso et al. (2021)	Shrimp (White-leg)	SFA	80	Vietnam		0.65	0.76	Semi-intensive: Education (-), Pollution (+) Intensive: Education (-), Pollution (+)

Notes: DEA: Data envelopment analysis; SFA: stochastic frontier analysis. Included here despite being a DEA paper as Nguyen et al. (2018) are one of few Vietnamese technical efficiency studies, employing the perception of climatic events affecting the inefficiency.

Appendix C: Correlation analysis among explanatory variables

TABLE C1 Correlation analysis among explanatory variables in the extensive farm sample

	Farmer's perception of drought	Farmer's perception of saline water intrusion	Farmer's perception of irregular weather	Farmer's perception of water cross pollution	Disease	Duration of crop	Experience	Education	Credit access	Adopt farming management activities	Planned area	Distance to sea by province	Change feeding practice / stocking density	Change water exchange schedules	Water conservation	Water treatments	Pond renovation
Farmer's perception of drought	1																
Farmer's perception of saline water intrusion	0.64	1															
Farmer's perception of irregular weather	0.27	0.37	1														
Farmer's perception of severe water cross pollution	0.11	0.22	0.37	1													
Disease	-0.09	-0.09	-0.24	-0.04	1												
Duration of crop	0.02	0.27	0.10	0.30	-0.03	1											
Experience	-0.05	-0.14	0.00	-0.09	-0.01	-0.23	1										
Education	0.12	-0.02	-0.09	-0.03	0.07	-0.05	-0.41	1									
Credit access	-0.29	-0.31	-0.26	-0.19	0.01	-0.11	0.16	0.01	1								
Adopt farming management activities	0.12	0.16	0.13	-0.13	-0.21	0.00	0.16	-0.12	-0.08	1							
Planned area	-0.13	-0.26	-0.22	-0.45	0.03	-0.47	0.17	0.03	0.23	0.18	1						
Distance to sea by province	-0.33	-0.34	-0.28	-0.11	0.07	-0.12	0.10	-0.10	0.14	-0.11	0.23	1					
Change feeding practice / stocking density	-0.14	-0.11	0.05	0.00	0.06	-0.04	0.12	-0.09	0.00	0.11	0.18	0.06	1				
Change water exchange schedules	-0.05	-0.24	-0.05	0.10	0.08	0.06	0.01	0.10	0.04	-0.07	0.07	0.23	0.36	1			
Water conservation	0.23	0.19	0.12	0.23	0.09	0.12	-0.15	0.01	-0.09	-0.13	-0.24	-0.15	-0.08	0.05	1		
Water treatments	0.21	-0.03	0.02	0.00	0.16	-0.16	0.02	0.04	-0.12	-0.05	-0.08	-0.05	-0.01	0.13	-0.03	1	
Pond renovation	0.11	0.10	0.06	0.11	-0.03	0.19	-0.03	-0.04	-0.05	0.03	-0.17	-0.07	-0.04	0.11	0.50	-0.02	1

TABLE C2 Correlation analysis among explanatory variables in the intensive farm sample

	Farmer's perception of drought	Farmer's perception of saline water intrusion	Farmer's perception of irregular weather	Farmer's perception of water cross pollution	Disease	Duration of crop	Experience	Education	Credit access	Adopt farming management activities	Planned area	Distance to sea by province	Change feeding practice / stocking density	Change water exchange schedules	Water conservation	Water treatments	Pond renovation
Farmer's perception of drought	1																
Farmer's perception of saline water intrusion	0.03	1															
Farmer's perception of irregular weather	0.02	-0.21	1														
Farmer's perception of severe water cross pollution	0.00	-0.06	0.14	1													
Disease	0.11	-0.05	0.09	0.17	1												
Duration of crop	-0.03	0.14	-0.14	-0.11	-0.54	1											
Experience	-0.05	0.12	-0.18	-0.27	-0.35	0.19	1										
Education	0.01	-0.14	0.08	0.05	-0.04	-0.02	-0.10	1									
Credit access	0.01	0.05	0.01	-0.09	0.16	-0.14	-0.10	0.05	1								
Adopt farming management activities	0.13	-0.31	0.02	-0.08	-0.02	0.03	0.03	0.02	-0.15	1							
Planned area	-0.16	-0.37	-0.01	-0.05	-0.01	-0.03	-0.12	0.16	0.04	0.19	1						
Distance to sea by province	-0.24	-0.34	-0.04	-0.14	-0.27	-0.06	0.31	0.13	-0.15	0.10	0.62	1					
Change feeding practice / stocking density	0.11	-0.07	-0.04	-0.14	0.07	0.00	-0.01	-0.06	0.11	0.09	0.09	0.03	1				
Change water exchange schedules	0.04	0.03	-0.09	-0.06	0.07	0.04	-0.05	-0.04	0.12	0.03	-0.06	-0.15	0.54	1			
Water conservation	0.23	-0.10	-0.03	0.06	-0.07	0.08	0.08	0.08	0.00	0.04	-0.01	0.08	-0.02	0.16	1		
Water treatments	0.17	-0.15	0.00	-0.25	-0.04	0.01	0.05	-0.11	0.09	0.21	0.21	0.19	0.12	0.01	-0.11	1	
Pond renovation	0.15	0.03	-0.04	-0.04	0.06	-0.07	0.05	0.03	0.02	0.03	-0.22	-0.10	-0.05	0.18	0.29	-0.01	1

CLIMATIC EVENTS AND DISEASE OCCURRENCE IN INTENSIVE *LITOPENAEUS VANNAMEI* SHRIMP FARMING IN THE MEKONG AREA OF VIETNAM.

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Abstract

This study employs logistic regression to assess the probability of disease occurrence in intensive white leg shrimp (WLS) (*Litopenaeus vannamei*) aquaculture under the impact of explanatory factors grouped in (1) farmers' perceptions of climatic events, (2) adaptation measures (3) farmer biodata, (4) farm site characteristics, (5) biosecurity measures, and (6) culture method. The analysis was performed using a survey of 267 Vietnamese small-scale intensive shrimp farms in the Mekong region. Significant contributors to lowering the chance of shrimp disease occurrence include (1) regularly carrying out feed conversion ratio calculations, (2) increasing participation in training programs and extension services, (3) implementing adaptive measures related to changes in feeding schedules, and (4) increasing stocking density. The main risk factors increasing the chance of shrimp disease are the duration of the crop and more years in operation. This quantitative evidence contributes to identifying important focal points for policymakers and intensive shrimp farmers in monitoring and managing the shrimp industry under the potential impacts of climate change.

KEYWORDS: Disease occurrence, climatic events, logistic regression, white leg shrimp, Vietnam

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1. INTRODUCTION

The global market of farmed shrimp products is growing faster than other species (FAO, 2020). Since the 1980s, the intensification process in the shrimp industry has increased thanks to technological breakthroughs, large expected profits, and a rise in domestic and international demand (Leung et al., 2000). Small-scale intensive culture generally uses less than 0.5 hectares of farmland with high stocking density and can provide large production volumes (Nguyen, 2017). Compared to the extensive system, the expansion in intensive shrimp farming is based on adopting new technology, enhanced feed formulation, and pathogen-free post-larvae (Vaiyapuri et al., 2021). The participation of many small-scale farmers in the shrimp value chain contributes to the rapid expansion of intensive systems and substantial job creation in Asian rural regions. Hasan et al. (2020) state that the several industrial production systems (semi-intensive and intensive) introduced in Asia since the start of this millennium have provided benefits of reduced horizontal transmission of shrimp disease via commercial feed and improved seed and biosecurity regimes.

Nonetheless, the highest risk of loss in the shrimp industry appears to be associated with more intensive farming practices (FAO, 2013). In addition, FAO (2020) points out that disease is already the main problem for shrimp aquaculture, especially in Asia and Latin America. Adverse changes in water quality due to increased stocking densities and rates of feeding lead to a rising incidence of disease with the subsequent application of chemicals and antibiotics (Li et al., 2016).

1.1 Disease issues in shrimp farming

White-leg shrimp (WLS) aquaculture experiences many kinds of viral diseases, including red body disease (Taura syndrome virus, TSV); white spot disease (white spot syndrome virus, WSD); white feces syndrome (WFS), and yellow head virus (YHV)

(Thitamadee et al., 2016; Thi et al., 2017; Worranut et al., 2018). WSD has accounted for the largest share of economic loss due to disease in Asia, exceeding $20 billion in 2016 (Shinn et al., 2018). WSD infection occurs via horizontal and vertical transmission, i.e., within or between generations (Walker & Mohan, 2009). Horizontal transmission is impacted by numerous factors connected to the shrimp culture environment (Corsin et al., 2005). In addition to water quality and waste management, Hasan et al. (2020) underline the reduction in disease transmission facilitated by farm clusters. Vertical disease transmission is primarily connected to shrimp broodstock in early life stages (Corsin et al., 2005; Walker & Mohan, 2009). Another such common disease in WLS aquaculture is Acute Hepatol Pancreatic Necrosis Syndrome (AHPND), or what used to be called Early Mortality Syndrome (EMS). This disease initially surfaced in Asia in 2009 (FAO, 2013). AHPND results in mass mortalities (more than 70 %, and sometimes up to 100%) during the first 35 days post-stocking in newly prepared ponds (FAO, 2013).

1.2 Motivation for this study

Vietnam is an interesting case for study due to the immense growth in intensification in the shrimp industry and the increasing risk of drought and other extreme weather in recent decades (FAO, 2016). Total shrimp production in Vietnam was 745,000 tons in 2018, and the Mekong Delta is the largest area, where approximately 90% of the nation's shrimp production occurs (Nguyen et al., 2021). Following the 2020 Master Plan of the Vietnamese government, a further 190,000 hectares was approved for industrial shrimp farming (Nguyen, 2017). The government aims to achieve an aquatic product export value of about 10 billion USD by 2025. This goal involves moving towards more intensified technology in shrimp farms.

However, trade-offs concerning achieving the country's master plan should be considered, as intensification growth is often paired with disease emergence, causing stress on aquatic animals and resulting in unexpected complex interactions (host, pathogen, and environment) (Millard et al., 2020). Vietnam has experienced dramatic short-term declines in shrimp production due to natural disasters and disease in recent decades (Nguyen et al., 2021). Large disease outbreaks occurred in Vietnam in 2010 and were repeated in 2015. The estimated losses due to AHPND and WSD were more than US$ 26 and US$ 11 million in 2015, respectively (Shinn et al., 2018). Local authorities encourage planned intensification of shrimp aquaculture but face challenges due to the substantial unmanaged expansion of largely unregistered intensive shrimp farms. In addition, problems are connected to tracing the origins of shrimp broodstock with the disease due to thousands of unregistered traders serving small-scale shrimp farmers (Tran et al., 2013).

Farm-level disease occurrence prediction plays a vital role in management intervention in the intensive system. Despite shrimp aquaculture being the primary income provider in the Mekong coastal areas, few Vietnamese shrimp studies assess the key factors amongst farming practices and cultural techniques affecting disease outbreaks (Duc et al., 2015; Khiem et al., 2020; Leung & Tran, 2000, Nguyen et al., 2021). According to Li et al. (2016), there is little information about aquaculture farmers' knowledge and practices concerning disease management control measures, including their capacity to diagnose shrimp disease correctly. Therefore, the impact of existing environmental conditions on the chance of disease outbreaks is largely uncontested, but data is limited. The above-outlined facts motivate our study in analyzing and predicting disease occurrence using shrimp farm-level data.

The primary data was collected from a survey of 267 intensive white leg shrimp farms conducted from March to August 2017 in two Vietnamese provinces (Bac Lieu and Ca

Mau) in the Mekong region, leading areas for WLS shrimp production in the country (Le et al., 2022). In this study, we apply recommended logistic regression (Leung & Tran, 2000; Tendencia et al., 2011; Duc et al., 2015; Hasan et al., 2020) and expand upon the explanatory variable set applied in earlier studies by including farmers' perceptions regarding extreme climate events (drought, saline water intrusion, prolonged heavy rain, and water cross pollution) and their adaptive measures, impacting the probability of disease emergence.

1.3 Objective of the study

Using logistic regression, the paper contributes to updating and expanding the shrimp literature with key factors predicting the likelihood of shrimp disease status (disease/no disease). Furthermore, we aim to deliver policy input for shrimp industry management and disease control under the effects of extreme climate events and environmental risks. The findings can support shrimp industry growth to achieve national export targets while maintaining sustainability under intensification targets.

The specific objectives of this research include the following:

(1) Identify major risk and protective factors influencing the chance of disease in farms, as provided by surveyed farmers. There are six diverse groups of factors, including (i) farmers' perceptions of climatic events, (ii) adaptation measures, (iii) farmer biodata, (iv) farm site characteristics, (v) biosecurity measures, and (vi) culture method. This analysis contributes to the shrimp disease prediction literature and supports disease control and protection against environmental deterioration in the growth path of sustainable intensification of the WLS shrimp business.

(2) Provide disease control policy input to Vietnamese policymakers and other developing country governments who are boosting WLS intensification growth under the effects of extreme climate events.

The material and methods are presented in section 2, with subsections on literature review, study design, variable selection, methodology, and research hypotheses. Section 3 presents the results regarding shrimp disease prediction. Then follows the discussion in section 4, concluding remarks as the final part.

2. MATERIAL AND METHODS

2.1 Study framework

Previous findings linked to farm management, farm characteristics and practices, and other elements impacting the chance of shrimp disease occurrence were identified from the literature since 2000, as shown in Table A1 (see Appendix A). In addition, farmers' perceptions of high-risk weather events and farmers' adaptive measures have yet to be addressed in previous studies of Vietnamese WLS shrimp farms. This knowledge gap is therefore attempted to be remedied in this paper.

First, we organized focus group discussions (FGD) with 6-8 participants in each province, with the participation of aquaculture technicians, shrimp farm owners, and local officials in the provincial aquaculture extension services department. We opened the discussion by obtaining detailed information relating to the following:

1. The climate and environmental issues and their assessed severity.
2. Adaptive measures to these climate risks in shrimp practices.
3. Biosecurity applications.
4. Information on farming characteristics (land uses, water sources, culture periods, and production systems).

5. Disease issues in shrimp farming in MKD.

The FGDs contributed to the list of potential explanatory variables.

Second, the structured questionnaire[1] is a modified version of previous surveys (Leung & Tran, 2000; Nagothu et al., 2012; Tendencia et al., 2011), combined with input from the FGDs. The list of registered shrimp farmers was received from the provincial Agricultural Extension Center and the Department of Aquaculture. Ten pre-test surveys were performed in each province to check the understanding of the farmers regarding the structured questionnaire. The interview process took place at the farms or offices of the Department of Aquaculture and shrimp farmers' Cooperatives. Third, we modified the final survey from the pre-test results by applying local terms and trained the interviewer team to collect data through face-to-face interviews. Our sample is a randomized selection of individual intensive farms from the list. In addition, a "snowball" sampling method was applied by Kim et al. (2020). Once a randomly selected farmer refused to be interviewed, we asked them to recommend another person with a similar farm. We collected 267 shrimp farmer interviews for approximately 30–45 minutes each.

2.2 Variable selection and research hypotheses

The presence of disease is the dependent variable in this study is binary, recorded by farmers who had disease occurrence in their previous crop. Table 1 describes the independent variables within the six groups of factors. Most of the data collected are dummies (yes/no) except other factors related to the farmer's biodata (experience, education, and farmer's age), farm site characteristics (number of years farmers cultured shrimp, distance from farms to the nearest sea point, shrimp area), and culture method (months of stocking, stocking density). Additional factors, such as specific water parameters discussed in the literature (Corsin et al.,

[1] The structured questionnaire can be provided upon request from the first author.

2005; Ruiz-Velazco et al., 2010; Tendencia et al., 2010; Yu et al., 2006) may be relevant but are outside the scope of this study.

TABLE 1: The expected sign in specific sets of explanatory factors

No	The group name of potential predictors	Total variables	Expected sign
1	Farmer’s perception of extreme climate and environmental risks	5	+
2	Adaptive measures to extreme climatic events	6	-
3	Farmer biodata	7	-
4	Farm site characteristics	8	+/-
5	Biosecurity measures	19	-
6	Culture method	2	+
	Total number of potential predictors	47	

Notes: More detail on the possible explanatory variables in each group can be found in Table 2.

We hypothesize that farmers' perceptions of negatively impacting extreme climate and environmental factors can reduce shrimp disease occurrences. Shrimp farmers experienced the prevalence of climatic events in the past and assessed the severity levels of these risks via increased farm operating costs. Thus, they may adapt by selecting appropriate adaptive measures. We expect that these adaptive measure variables will contribute to mitigating the effects of extreme climate events on shrimp farms, reducing disease occurrence.

Adopting biosecurity measures is in adherence to good aquaculture practices in farming, such as farm health management strategies with daily monitoring of feed, pond, and farm management activities. Such approaches help control the carrying capacity in ponds or monitor the usage of feed inputs. Farm health management strategies may include ensuring biosecurity in ponds through, for instance, shrimp seed purchase from well-known seed sources with certificates stating appropriate screening of post-larvae. In intensive farms, biosecurity measures may include creating a secure rearing environment. Regarding chemical usage, responsible and safe use of drugs and chemicals is essential where treatments are required. Tendencia et al. (2011), perhaps somewhat surprisingly, found that the pre-stocking health analysis of fry was positively correlated to WSD infection in polyculture. In contrast, Leung et al. (2000) found that adopting good shrimp farming practices (drying ponds and the practice of polyculture) resulted in a lower chance of disease. Therefore, we expect biosecurity measures adopted by shrimp farmers will reduce disease occurrence in shrimp ponds.

We expect that elements in farmers' biodata can reduce disease occurrence since shrimp culture knowledge is provided from diverse sources, such as more years in school, more experience in culturing shrimp, and participation in training programs. Furthermore, having credit access via bank loans may improve farming management activities, leading to a lower chance of disease occurrence.

Regarding farm site characteristics, Leung et al. (2000) posed that risk and protective factors affecting disease outbreaks vary over production systems and other specific aspects of the farms. For instance, larger pond areas and the presence of farms emitting refuse into channels of water supply were characteristics that resulted in greater disease occurrence. In contrast, extensive farms that extracted water from the sea through canals had lower disease occurrence. In opposition to this, Corsin et al. (2001) state that closeness to estuaries or the sea provides widely fluctuating salinity levels, often associated with increased disease risk in farmed WLS. FAO (2013) points out that southern Vietnam's co-location of semi-intensive and intensive farming systems increases the probability of AHPND mortalities in intensive systems. Therefore, farm site characteristics may work in both directions regarding the likelihood of disease. Lastly, Tendencia et al. (2011) found increased WDS risk when stocking density increased. Stocking density in intensive farms is much higher than in extensive farms. We also expect factors connected to the culture method may impact disease occurrence.

2.3. Methods

Including 47 predictors leads to complex predictive models, which may cause redundancies concerning disease occurrence. Furthermore, redundant variables will provide lower predictive power and model reliability (Hall & Holmes, 2003). Hence, underfitting and overfitting challenge model accuracy. Therefore, we apply techniques constraining the coefficients (e.g., stepwise procedure, regularization) in the logistic regression model to obtain better prediction accuracy and model interpretability with the best fit to our dataset. An overview of the approach applied is illustrated in Figure 1.

	267 respondents analyzed	
Data management: Step 1: Data description for 47 variables	Potential predictors were divided into six groups	Result: Table 1
Step 2: Variable selection - Logistic regression with: (1) Subset selection (2) Regularized approaches - Robustness checks	Splitting the dataset into two subsets (training data 80%, test data: 20%) Remove predictors > 10% significance level → 13 predictors were selected from Shrinkage estimation.	Results: Table 2
Step 3: Results interpretation and discussions - Backward Logistic regression	Model performance: - Model prediction accuracy in testing data	Result: Table 3

FIGURE 1: Overview of research methods

Notes: AIC: Akaike information criterion. R Studio was employed for the analysis in this study. We employed subset selection and regularization approaches to reduce overfitting/underfitting.

In Figure 1, step 1 describes 47 variables in the dataset to illustrate the typical shrimp farming operation in the Mekong area, labeling six groups (see Table 1). Next, in step 2, the variables or variable selection takes place, and we randomly split the total sample into two subsets: training (80% - 215 observations) and testing (20% - 52 observations). Finally, we analyzed the training set for obtaining potential predictors connected to explaining disease occurrence, while the testing set was used for checking the corrected model performance.

The next subsections briefly introduce the main concepts of each approach to gain variable selection (step 2), aiming to highlight the main differences and the computational advantages among the employed techniques for seeking the best predictors explaining the likelihood of disease occurrence.

2.3.1 Logistic regression

Logistic regression is an often-used method to assess critical actors affecting disease in shrimp farming, often complemented by other models for robustness checks (see Table A1- Appendix A). P is the probability that the outcome occurs. We predict the odds of disease occurrence as follows:

$$Log\left(\frac{P(x)}{1-P(x)}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (1)$$

where $\left(\frac{P(x)}{1-P(x)}\right)$ is the 'odds' of the outcome and has two classes, farms that experience disease and farms that do not (Leung & Tran, 2000). According to equation (1), the logarithm of the odds (so-called logit) is a linear function of the potential variables $X(x_1, \ldots, x_n)$ (see table 3).

We then use the maximum-likelihood method from Hosmer and Lemeshow goodness-of-fit test (Hosmer & Lemeshow, 2000) to estimate the coefficients $\beta_1 \ldots \beta_n$. The exponential of the regressors (β) represents the expected change in the odds of disease occurrence versus no disease per unit change in the explanatory variable, other things being equal. A positive coefficient implies that an increase in the corresponding factor will increase the chance of disease occurrence. In contrast, a negative coefficient indicates that an increase in that factor will reduce the likelihood of disease occurrence (Tendencia et al., 2011).

2.3.1.1 Logistic regression with subset selection (stepwise procedure)

The backward stepwise logistic regression method with a likelihood ratio test was applied to the reduced variables. The process begins with eliminating the explanatory factor contributing the least to explaining the model at each consecutive step until the smallest possible log-likelihood ratio is obtained. In contrast, forward stepwise logistic regression begins with a model containing no predictors and then adds one after another until all relevant predictors are in the model. Notably, the variable added in the final model must provide the greatest improvement to model fit. The backward stepwise procedure is usually preferred as the forward stepwise approach could potentially eliminate important variables (Leung & Tran, 2000). As multicollinearity was found, the stepwise procedure was repeated, replacing a specific predictor that highly correlated with another independent factor of the same class of equal importance, to check the contribution to the variability. The single best model selection (forward and backward stepwise) for predicting disease occurrence uses cross-validated prediction error, negative log-likelihood value, equivalently largest adjusted R squared[2] or AIC, and BIC values.

2.3.1.2 Logistic regression with Regularization

Another approach to excluding irrelevant variables and reducing the variance in the estimation is regularization (e.g., Lasso, Ridge, and Elastic Net) to shrink the estimated coefficient toward zero to obtain variance reduction. Shrinkage models mainly use a shrinkage

[2] The log-likelihood (LL) ratio is an attained indicator from a stepwise logistic regression that reflects the statistical fit of the model and measures the relationship between the dependent and independent variables. The smaller the deviance, the better the fit. The adjusted R-squared (R2) value indicates the strength of the relationship between the outcome and predictor.

penalty ($\lambda \sum_j \ \beta_j{}^2$), where $\lambda \geq 0$ is the tuning or shrinkage parameter, assuring a small shrinkage penalty to obtain the best model fit. We also can use cross-validation to estimate the error rate on test data (for each λ value). We choose the λ value that gives the smallest error rate. The final model is refit by using all variables and selecting the λ value.

Ridge logistic regression is defined as $\log L(\beta) - \lambda \sum_{j=1}^{p} \beta_j{}^2$, searching for the coefficients of predictors that fit the data best, with the condition that the shrinkage penalty is small when $\beta_1 \ldots . \beta_p$ go towards 0, ahere p is the total number of predictors. Unlike the Ridge, the Lasso logistic regression is described by $\log L(\beta) - \lambda \sum_{j=1}^{p} |\beta_j|$. In this equation, the penalty term forces irrelevant coefficients to be zero when λ is sufficiently large. This technique has a major advantage over Ridge regression in making the model simpler, more interpretable, and provides a more accurate prediction than Ridge regression. Similar to Ridge, λ increases, the variance decreases, and the bias increases. However, Lasso selects only a relevant subset of predictors explaining the outcome.

Elastic Net is the combination of Ridge and Lasso penalty: $\log L(\beta) - \lambda \left[(1 - \alpha) \frac{1}{2} \sum_{j=1}^{p} \beta_j{}^2 + \sum_{j=1}^{p} |\beta_j| \right]$ where α, the mixing proportion, toggles between Lasso and Ridge. In this function, α works to control the total amount of penalization. For instance, for the pure Lasso penalty, α=1, while the pure Ridge has α =0; otherwise, Elastic Net operates with alpha ranges between 0 and 1. We apply the Ridge, Elastic Net, and Lasso logistic regression on test data to compare predicted and actual outcomes (see Table A3 – Appendix A). The proportion of correctly predicted outcomes (disease or no disease) measures how the model's performance. After identifying the possible variables via subsection and regularization, the fitted logistic regression model results are explained by statistically significant variables if the p-value is less than 10%. This variable selection step contributes to determining the signs and degree of possible variables' association with disease occurrence. In addition, implementing the robustness check for logistic regression with subset selection and regularization, we employed Bayesian logistic regression, and stepwise regression using BIC as the performance evaluator (see Table A2 – Appendix A).

3. RESULTS

3.1 Data description

Table 2 provides the 47 selected potential predictors, organized into the six groups in Table 2. Farmers recorded the presence of shrimp disease in their most recent farming crop from September 2016 to May 2017, accounting for 50.2% of the sample. Regarding weather and environmental events that seriously negatively affect shrimp crops, farmers voted for irregular weather and drought, 41,6% and 38,2 %, respectively. In contrast, prolonged heavy rain, saline water intrusion, and water pollution had a lower prevalence (all less than 10%). In group 2, when interviewers asked for adaptive measures to cope with extreme weather events, most farmers responded with measures in relation to drought. Therefore, this study employed farmers' adaptive responses related to drought. We found that the most selected measures were changes in the schedule of feeding practice, water exchange, and other treatments (e.g., use of probiotic/chemical treatment, lime application to ponds). These measures are also recognized in the study of Le et al. (2022).

Group 3 covered farmers' biodata, presenting shrimp farm owners' information. On average, the farm owners had nine years of experience in shrimp farming. The youngest had one year of experience, while the oldest farmer had 30. The education level of shrimp farmers in the sample ranged from about eight years (primary level) to the highest of 22 years (post-graduate). The average farmer's age is 43, with the youngest being 21 and the oldest 76. Aquaculture in the Mekong, especially in the shrimp industry, is usually handed down from father to son and is the family's main income. A shrimp farmer is usually the head of the family and employs family members as workers. In our sample, only about 54% of farmers had participated in training on farming knowledge organized by local authorities and shrimp companies. On the other hand, 30% of farmers received agricultural extension services and participated in fisheries associations. Approximately 25% of the sample borrows money from banks, while most farmers spend personal capital on their shrimp business.

In group 4, the number of operating years of shrimp farming ranges from one to thirty years, the average being eight years. Seventy percent of farms belonged to the planning area of the province. The main water source is directly from the sea (81% of farmers). Regarding group 5, biosecurity measures, Le et al. (2022) showed that most intensive farms applied the best aquaculture management activities connected to feed and relevant operating costs, ponds, and farm conditions (approximately 90% of the total). However, only about 31% of farmers apply fry analysis (fry quarantine certificate of seed). Only 40% of farmers reported to the local government when there were disease or disease outbreak symptoms, as most decided to handle the situation by themselves based on their own experience and knowledge. Fifty percent of farming households have separate water supply/drainage systems. More than 80% of farm households have sedimentation ponds for water treatment before releasing shrimp seeds to grow-out ponds. In group 6, The stocking density is 68 individuals per square meter on average, ranging from 25 to 240 shrimp per square meter. The average crop period was 2.8 months, ranging from one to four months. From the farmer interviews in MKD, we learned that WLS was cultured for less than 30 days: the signs of disease were identified by high shrimp mortality rate in the pond. In this case, farmers were forced to carefully destroy and apply disease treatment to avoid the disease spreading to other shrimp ponds and farms.

TABLE 2: Data Description (N=267)

No	Factors	Data type	Data description			
			Mean	S. D	Min	Max
	Disease		0.502	0.500	0	1
	Group 1: Farmers' perception of negatively impacting extreme climatic and environmental events					
1	Drought	Yes =1, no = 0	0.382	0.487	0	1
2	Irregular weather	Yes =1, no = 0	0.416	0.494	0	1
3	Saline water intrusion	Yes =1, no = 0	0.037	0.190	0	1
4	Prolonged heavy rain	Yes =1, no = 0	0.026	0.160	0	1
5	Water Cross pollution	Yes =1, no = 0	0.105	0.307	0	1
	Group 2: Adopted adaptive measures to the climatic event(drought)					
6	Change in the schedule of feeding practices	Yes =1, no = 0	0.139	0.346	0	1
7	Adjust stocking densities	Yes =1, no = 0	0.037	0.190	0	1
8	Change another type of production system (e.g., extensive, shrimp mangrove)	Yes =1, no = 0	0.060	0.238	0	1
9	Change in the schedule of water exchange	Yes =1, no = 0	0.112	0.316	0	1
10	Water conservation	Yes =1, no = 0	0.015	0.122	0	1
11	Other measures	Yes =1, no = 0	0.109	0.312	0	1
	Group 3: Farmer's biodata					
12	Experience year	Yes =1, no = 0	9.637	7.129	1	30
13	Schooling year	Yes =1, no = 0	8.075	4.227	1	22
14	The farmer's age	Yes =1, no = 0	43.633	10.011	21	76

15	Farmer participated in a training course in a recent year	Yes =1, no = 0	0.547	0.499	0	1
16	Member of farmer group or shrimp association	in number of years	0.300	0.459	0	1
17	Extension services	in number	0.300	0.459	0	1
18	Access the bank loan	Yes =1, no = 0	0.255	0.437	0	1
	Group 4: Farm sites characteristics					
19	Years in operation	in number of years	8.972	6.626	1	30
20	The distance from farms to the primary water source	in number (meter)	133.408	239.104	0	3000
21	The distance from the farming area to the sea (estimated from Google maps)	in number (meter)	12.477	6.353	4.46	28.33
22	Belonged to planned areas for shrimp aquaculture	Yes =1, no = 0	0.708	0.456	0	1
23	Total farm area per hectare	in number (1000 m2)	0.402	0.399	0.1	3
24	Water source (estuary/river)	Yes =1, no = 0	0.094	0.292	0	1
25	Water source (direct from sea)	Yes =1, no = 0	0.831	0.375	0	1
26	Water source (canal from sea)	Yes =1, no = 0	0.064	0.245	0	1
	Group 5: Biosecurity measures					
27	Use of feeding tray/ siphon activity to check feed consumption	Yes =1, no = 0	0.959	0.199	0	1
28	Regular Feed Conversion Ratio calculations	Yes =1, no = 0	0.345	0.476	0	1
29	Regular operating cost analysis	Yes =1, no = 0	0.588	0.493	0	1
30	Other feed monitoring measures	Yes =1, no = 0	0.022	0.148	0	1
31	Daily monitoring of water quality parameters	Yes =1, no = 0	0.985	0.122	0	1
32	Daily monitoring of checking sediment condition	Yes =1, no = 0	0.678	0.468	0	1
33	Daily monitoring of checking water of influent and effluent waters	Yes =1, no = 0	0.491	0.501	0	1
34	Daily monitoring of water quality parameters	Yes =1, no = 0	0.846	0.361	0	1
35	Daily monitoring of stock survival	Yes =1, no = 0	0.884	0.321	0	1

36	Daily monitoring of shrimp behavior	Yes =1, no = 0	0.978	0.148	0	1
37	On-farm and off-farm shrimp health check when disease occurred	Yes =1, no = 0	0.566	0.497	0	1
38	Other pond management activities	Yes =1, no = 0	0.243	0.430	0	1
39	Seed sourced from a well-known seed company	Yes =1, no = 0	0.914	0.281	0	1
40	Pond renovation and other costs	Yes =1, no = 0	0.607	0.489	0	1
41	Break for minimum 30 days between crops	Yes =1, no = 0	0.828	0.378	0	1
42	Fry analysis (quarantine certificate of seed following regulations)	Yes =1, no = 0	0.311	0.464	0	1
43	Report disease outbreak to the nearest aquaculture or veterinary authority	Yes =1, no = 0	0.408	0.492	0	1
44	Separate water supply/drainage system	Yes =1, no = 0	0.502	0.501	0	1
45	Sedimentation pond	Yes =1, no = 0	0.824	0.382	0	1
	Group 6: Culture methods					
46	The Duration period of the most recent crop (no. of months)	In number	2.805	0.813	1	4
47	Stocking density – the number of shrimps per m^2 in a grow-out pond	In number	68.981	28.955	25	240

Notes: Other feed monitoring measures and other pond management activities include own practices related to biosecurity measures that shrimp farmers undertake in their ponds.

3.2 Results of logistic regression

We found that the backward logistic regression gives the best fit model with the lowest value of AIC (237.11) and the highest accuracy classification in testing data (75%) compared to other logistic regressions with subset selection approaches. Regarding logistic regression results with regularization, Lasso regression had the highest prediction rate in the testing data (75%) but did not achieve as low an AIC as the backward logistic model. Otherwise, the prediction of the Ridge model has the lowest prediction accuracy (69%).

A set of 13 variables from the backward logistic regression with p-values lower than a 10% significance level was kept. Therefore, Table 3 only shows the results of the backward logistic regression, with nine out of thirteen predictors statistically significantly capturing the disease status. The variables positively correlated to disease occurrence are the duration of crop, years in operation, education, and other measures related to pond management. In addition, we found that several factors lower the chance of disease in shrimp farming, including changes in the schedule of water exchange, training participation, extension services, regular feed conversion ratio calculations, and stocking density.

TABLE 3: Results of fitted backward logistic regression model for intensive shrimp farms (N=215 observations)

	Estimate	S.E.	P-value
(Intercept)	-4.368	4.293	0.309
Adaptive measures to drought			
Change in the schedule of feeding practices	**-0.995***	0.569	0.080
Other adaptive measures	-0.804	0.557	0.149
Farmer biodata			
The farmer's age	1.357	0.860	0.115
Education	**0.730****	0.363	0.044
Training participation	**-1.065****	0.420	0.011
Extension services	**-1.143****	0.447	0.011
Farm sites characteristics			
Years in operation	**0.458***	0.252	0.069
Biosecurity measures			
Regular Feed Conversion Ratio calculations	**-0.973****	0.438	0.026
Other cost-monitoring measures	-15.368	831.032	0.985
Other pond management activities	**0.975***	0.497	0.050
Report disease outbreak to the nearest aquaculture or veterinary authority	0.682	0.449	0.129
Culture method			
Duration of crop	**2.892*****	0.633	0.000
Stocking density	**-1.346****	0.560	0.016
AIC	**237.11**		
Corrected accuracy (%) in the testing set	0.75		

Notes: The dataset split was 80% for the training and 20% for the test sets.

Significance level '***' 0.001 '**';0.01 '*' 0.05 '.'

3.3 Robustness checks

We found that the sign of key variables in all logistic models (see Appendix A - Table A2) are similar to those found in backward logistic regression, indicating robustness in estimation. For example, in Table A2, the results of the Bayesian logistic model and the stepwise regression using BIC point out only five main predictors explaining shrimp disease occurrence at 1% and 5%, namely extension services, regular FCR calculation, other measures of pond water management, crop duration, and stocking density. In addition, years in operation and adaptive measures related to the change in feeding schedules fail to be statistically significantly correlated to disease. Regarding regularization, we found that Lasso regression (Table A3 in Appendix A) highlights similar key predictors as the backward logistic model (e.g., training participation, extensive service, education, crop duration, stocking density). However, several variables were changed, such as other adaptive measures rather than a change in feeding schedules, and years in operation instead of separate water supply/drainage systems. To sum up, the signs of these coefficients were the same in the Ridge, Lasso, and Elastic Net reflecting robustness.

4. DISCUSSION

Our model performance fit of the backward logistic regression is about 75%, slightly higher than that of Tendencia et al. (2011) for WSD disease incidence in monoculture or intensive WLS farming. The research findings reveal the determinants that reduce and increase the chance of shrimp disease occurrence. Hence, we identified several protective factors that significantly negatively impact on the likelihood of disease occurrence. Training participation, extension services, regular FCR calculations, and stocking density contribute to a lower chance of shrimp disease occurrence. In addition, we found risk variables that have a positive relationship with shrimp disease, such as the length of the growth period (number of stocking months), applying other measures for daily pond management, and education. These will be discussed in the following subsections.

4.1 Protective factors

In the following, we list seven factors that influence the disease prevalence in Vietnamese WLS farming. First, regarding self-adaptive measures taken by shrimp farmers, we found that changing the feeding schedule was significantly associated with a lower chance of disease outbreaks. Prolonged drought affects the pond water temperature, reducing survival and shrimp weight (Abdelrahman et al., 2019). Changing feeding schedule measures include adjusting feeding amount, feeding input, and feeding schedules to contribute to feeding reduction in ponds. This measure may reduce pond water pollution and shrimp disease.

Farmers observed that once shrimp start to die due to extreme drought, it is necessary to reduce feed or stop feeding immediately since diseased shrimp will eat less or even not eat at all[3]. In addition, it is necessary to enhance the shrimp's health by adding vitamin C and minerals to shrimp feed to help shrimp recover and get healthy quickly, according to the prescribed feeding guidelines.

Furthermore, Mekong farmers have to report disease status and receive technical guidance from local staff or farmers' groups to advise timely handling, avoiding disease spread in the farming area. Though we failed to obtain a statistically significant impact of other adaptive measures in backward logistic regression, the sign of this variable was negative, as expected. Other adaptation measures of shrimp farming involve using chemicals (Chlorine,

[3] When the temperature is more than 32 degrees Celius, WLS will stop eating and hide in the pond bottom, cover themselves in the mud, leading to the high risk of toxic contamination (e.g., H_2S, NO_2, CO_2, NH_3), pathogenic bacteria and lack of oxygen in the pond bottom. As the temperature increases, the respiration process of shrimp increases along with a rise in biochemical reactions in the pond water. Hence, shrimp are prone to disease due to a lack of oxygen.

lime application) for pond treatment and reducing algal growth[4]. In addition, farmers can pump water from sediment ponds and use microbial products to stabilize pH and prevent algal blooms. Last but n ot least, aeration ensures sufficient oxygen amounts at the pond bottom. These responses are being applied by Mekong farmers and may mitigate the impact of drought and lower the chance of disease outbreaks.

Second, in addition to a change in feeding schedules, we identify that feed conversion ratio calculations (biosecurity measures) significantly lower the chance of shrimp disease. Higher amounts of feed were associated with a higher probability of introducing WSD into ponds in Vietnamese shrimp farming (Corsin et al., 2001). Therefore, the feed calculation activity could help control feed redundancy in grow-out ponds and reduce feed waste in the environment in the vicinity of intensive farms. Furthermore, it is usually a significant improvement when the pond water is less polluted, making disease occurrences on farms less frequent.

Third, farmers' participation in training courses (e.g., lectures, workshops, field trips) organized by local government, non-profit organizations, and processing companies lower the chance of disease. Such training courses can enhance farmers' awareness of environmental impacts on their farms and communities. According to Nguyen (2017), training should be conducted on disease prevention and aquaculture production. Once shrimp disease appears, farmers, local governments, and even communities must pay high costs to handle the disease and control the damage spread. Hence, suitable training programs may enhance the shrimp farmer's capacity to cope with climate and environmental impacts and increase farmers' responsible actions concerning protecting shared water sources, thereby restricting severe environmental impacts.

[4] Algal blooms cause a lack of oxygen in the water, pH fluctuations, and accumulation of toxins in pond water, resulting in mass mortality of shrimp.

Fourth, increasing extension services through technical support via technical visits from local government, input agencies, and processing companies can reduce the chance of shrimp disease. For instance, when farmers report shrimp disease to the local government, they can receive free supplies of chemicals for water treatment. In addition, the local governments' extension service can provide a water sample analysis at local laboratories and identify the risk of disease spread and which type of disease the farmer faces. What is more, technical visits can include guidance for farming infrastructure design and services for the operation of intensive production systems. Thus, information related to shrimp farming technology can help improve the biosecurity system and farming environment, reducing the chance of shrimp disease.

Lastly, we found that the higher the stocking density, the lower the chance of disease. Tendencia et al. (2011) also found that stocking density was negatively correlated with shrimp disease. However, these authors need a clear explanation and mention that feces and uneaten feed accumulate at the ponds' bottom. Hence, higher stocking density causes more organic matter, making our finding a surprising result. However, in our sample, intensive farmers may employ advanced technology (multi-phasic integrated intensive shrimp production systems and recirculation aquaculture systems), technological innovations (e.g., commercial implementation of biofloc systems), and biosecurity infrastructure establishment to allow high stocking density without increased disease emergence.

4.2 Risk factors

Several risk factors increase the chance of shrimp disease outbreaks. They include longer crop duration, adoption of other pond management activities, having more years of schooling, and longer time in operation. The first and last variables showed that longer crop duration and longer time in operation can increase the likelihood of shrimp disease. This makes sense for intensive farms as a longer crop duration increases the risk of catching a disease. In addition, a larger number of years of operating shrimp culture leads to soil deterioration, fewer nutrients, and pollutant contamination.

However, perhaps more surprisingly, the other two variables, adopting other pond management activities and more years of schooling, also increase disease occurrence. Assuring disease control in shrimp farming includes care concerning various aspects, not solely based on pond management. There may be trade-offs between the goals of different pond management decisions. For instance, decisions to increase growth may inadvertently increase the susceptibility to diseases. Alternatively, this result may also point to ineffective management decisions. Pond management strategies may include creating a secure rearing environment by applying a chemical treatment to avoid infections or implementing pond renovation. Furthermore, disease control in shrimp farming requires attention to various aspects, ranging from selecting seed sources for nursery ponds to executing harvesting processes. In the study of Nguyen et al. (2021), they mentioned several risk factors associated with shrimp farming disease, specifically the ownership of settling ponds, sun-drying ponds exceeding a duration of 62 days, and the introduction of stock from multiple suppliers into grow-out ponds.

Regarding education, our sample has a large variation in age, education, and experience. Farmers have traditionally carried out their business based on experience passed on from father to son. They maintain their shrimp business based on their understanding of the industry and hands-on experience. We found that experience and education are negatively correlated in our data, which may explain why less educated farmers have a lower chance of disease.

5. CONCLUSIONS AND FUTURE RESEARCH

This study identifies key protective and risk factors that significantly impact the probability of disease occurrence in intensive shrimp farms. Focal points for reducing the probability of disease occurrence are shown to be (1) Increasing farmers' adaptive measures (e.g., adjustment of feeding schedules) in their farms, and (2) increasing farmers’ participation in training programs and provision of extension services (e.g., increasing technical support regarding farming practices, techniques, and disease treatment). Such approaches help control the carrying capacity in ponds or manage the usage of feed inputs.

Our findings can support action by regulators and policymakers in shrimp disease management in intensive farms, further boosting shrimp production with intensification in the Mekong area. For instance, by gathering information/data from farmers in the region, local authorities can build a toolbox, integrating the various approaches and model testing, which may provide more comprehensive forecasts than the farmers can carry out.

Last but not least, from the results outlined above, we recognize the important management roles of farm owners and workers operating on each farm. Farm owners and workers can manage and give the first status identification of the likelihood of disease. Therefore, input data at the farm level is considered valuable information, especially regarding factors such as feed data, crop duration, adaptive measures, and regularly estimated feed ratios, which could be mandatory requirements and recorded more regularly. Such actions can provide early warnings and alerts to farms, timely preventing or mitigating disease outbreaks.

Future research should beneficially include water quality and climate change indicators over time. In addition, a larger data sample would improve model performance, allowing for more advanced analysis using statistical tools developed in recent years, such as other advanced machine learning techniques and artificial intelligence approaches.

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DATA AVAILABILITY STATEMENT

Research data are not shared. Data sharing does not apply to this article as no new data were created or analyzed in this study

APPENDIX A:

TABLE A1: Factors affecting the probability of disease in shrimp farming

Authors	Species	Country	Method	Observations	Factors affecting the probability of disease
Leung & Tran (2000)	*Shrimp (P.monodon)*	13 Asian countries*	Stepwise procedures, Logistic regression	3951 (779 intensive, 910 semi-intensive, 2262 extensive)	*Intensive:* No. of years of shrimp farming at site (+), Inter-tidal zone (+), canal from sea (-), no. of farms within 3 km (-). *Semi-intensive:* Inter-tidal zone (+), soil type (+), farm operator (-); canal from sea (-), no. of farms share water supply (-), no. of farms discharge effluent into water supply canal (+), measures taken to reduce environmental impacts (-) *Extensive:* No. of years of shrimp farming at the site (-), Inter-tidal zone (-), supra-tidal zone (-), loam soil (-), other soil types (+), farm operators (+), salt/brackish water (-), no. of farms discharge effluent into water supply canal (+).
Leung et al. (2000)	Shrimp *(P.monodon)*	Vietnam	Logistic regression, stepwise procedures, and artificial neural networks.	480 (86 semi-intensive, 394 extensive)	Discharge water into the intake and drainage canal (+), silt deposit (-), polyculture (-), dry pond (-), site selection (-), and water source (-).
Corsin et al. (2001)	Rice-shrimp *(P. monodon)*	Vietnam	Univariate and multivariate analysis, stepwise forward logistic regression	24 ponds	Average weight at 1 month (-), total dead shrimp detected (+), location (+), number shrimp with bacteria in antennal scales at harvest (-)
Devi & Prasad (2006)	Prawn	India	Logistic regression	180	*Semi-intensive:* Prior land use (-), farm area (+), number of farms discharge effluent into water supply canal (+), environmental impacts (-), silt removal (+), apply chemical (-), frequency of water exchange (+), discharge (+), Feed (+) *Extensive:* Prior land use (+), Farm operator (-), farm area (+), number of farms discharge effluent into water supply canal (+), stocking density (-), silt removal (+), frequency of water exchange (+), number of water monitoring measures (-), number of feed and cost measures (-).

Nagesh et al. (2009)	Shrimp *(P.monodon)*	India	Chi-square test	60	No provision for inlet/outlet (+), number of ploughs (+) desilting depth (+), preparation (+), source of seeds-feral seeds (-), acclimatization (+), stocking density (+), no. water exchange per day (+), type of aeration (+), number of crops per year (-)
Tendencia et al. (2010)	Shrimp *(P.monodon)*	Philippines	Binary logistic regression (Backward stepwise)	75 ponds (semi-extensive)	*WSD infection:* Temperature fluctuation (+), temperature (-), water transparency (-), yellow vibrio colonies (-) *WSD outbreak:* pH fluctuation (-), temperature (+), Salinity (+).
Tendencia et al. (2011)	Shrimp *(P.monodon)*	Philippines	Binary logistic regression, stepwise procedure	174 (Poly and mono)	*Monoculture:* Stocking density (-), plankton (-), mangrove to pond area ratio (-), pond size (+), share water (+), same receiving and source (+), *Polyculture:* Climate (+), sludge removal (+), live mollusks (+), commercial pellet (+)
Karim et al. (2012)	*Shrimp (P.monodon)*	Bangladesh	Binomial probit regression analysis	350	Constructed pond age (+), constructed pond area (+), sludge removal (-), aquatic weed control using chemical (-), weed control manually (+), reservoir (-)
Duc et al. (2015)	Rice-shrimp *(P.monodon)*	Vietnam	Logistic regression	191 (127 intensive, 64 rice-shrimp	*Intensive:* Pond area (+), period of pond dry (+), stocking density second (+) *Rice-Shrimp:* Pond area (+), water level (-), fry test (-), stocking density first (+), stocking density second (+)
Piamsomboon et al. (2015)	Shrimp *(P.vannamei)*	Thailand	Binary logistic regression, univariate and multivariate analysis	157 (intensive farms)	Water source (Canal) (-), lime application to pond bottom (-), probiotic used in feed (-), owner of multiple farms (+), year-round continuous culture (+), distance from nearest national highway (-)
Boonyawiwat et al. (2017)	Shrimp *(P.vannamei P.monodon,* Multispecies)	Thailand	Logistic regression	478	Polyculture (-), use of predator fish in water preparation (+), delay the first day of feeding (-), Post-larvae (PL) stocking density (+), source of PL (+), reservoir availability (+), chlorine treatment (+), water ageing prior to use (-), multiple shrimp species (+)
Yaemkasem et al. (2017)	*Marine shrimp*	Thailand	Binary logistic regression	165	Farm with WSD in previous crop (+), source of water from the sea (+), staff visited during the culture (-), stocking density (+), water added without treatment during the cultivation period (+)
Worranut et al. (2018)	Shrimp *(P.vannamei P.monodon)*	Thailand	Network analysis, Univariate analysis, tested by Conditional logistic regression	165	Regular farm visits (+), reliable post-larvae provider (-)

Hasan et al. (2020)	*Shrimp*	Bangladesh	Logistic regression	233	Farm operated by tenant worker (+), use of fertilizer (-), water source – direct natural (+), reservoir (-), frequency of water exchange (-)
Khiem et al. (2020)	*Shrimp*	Vietnam	Logistic regression, artificial neural network, decision tree, and K-nearest neighbor analyses	763 samples from 80 ponds of 50 farms	Opaque muscle (-), poor growth (-), poor appetite (-), dirty gills (+), empty gut (+) hepatopancreatic atrophy (+), tough hepatopancreas (+), discontinuous gut (+), soft shell (+), shrimp age (-), timing of symptom detection (-), fresh smear test result (+), NH4 level (-), pond area (+), water pH (-), province (-)
Hien et al. (2021)	*Shrimp*	Vietnam	Logistic regression	134	The presence of fish-eating birds (+)

* Including Bangladesh, Cambodia, China, India, Indonesia, Korea, Malaysia, Myanmar, Philippines, Siri Lanka, Taiwan, Thailand, and Vietnam

TABLE A2: Results of logistic regression with stepwise procedures, BIC and Bayesin in intensive farms (N=215) – Robustness check

	Forward Logistic regression			Backward Logistic regression			Stepwise regression using BIC as a performance evaluator			Bayesian logistic regression,		
	Estimate	S.E.	P-value	Estimate	S.E.	P-value	Estimate	S.E.	P-value	Estimate	S.E.	P-value
(Intercept)	-8.813	6.081	0.147	-4.368	4.293	0.309	2.630	2.139	0.219	-4.041	4.031	0.316
Group 1: Farmers' perception of negatively impacting extreme climatic and environmental events												
Drought	-0.028	1.690	0.987									
Irregular weather	0.307	1.366	0.822									
Saline water intrusion	0.253	1.633	0.877									
Prolonged heavy rain	1.186	1.823	0.515									
Water Cross pollution	0.244	1.487	0.870									
Group 2: Adopted adaptive measures to the climatic event(drought)												
Change in the schedule of feeding practices	-0.629	0.929	0.499	**-0.995***	0.569	0.080				-0.811	0.513	0.114
Adjust stocking densities	-0.776	1.271	0.542									
Change to another type of production systems	-0.286	1.585	0.857									

Change in the schedule of water exchange	0.194	0.927	0.834									
Water conservation	-0.599	1.133	0.597									
Other measures	-0.930	1.010	0.357	-0.804	0.557	0.149						
Group 3: Farmer's biodata												
Experience year	0.168	0.369	0.649									
The farmer's age	1.868*	1.057	0.077	1.357	0.860	0.115				1.271	0.808	0.116
Education	**0.844****	0.413	0.041	**0.730****	0.363	0.044				**0.723****	0.332	0.029
Farmer participated in a training course in a recent year	**-1.052***	0.546	0.054	**-1.065****	0.420	0.011				**-0.827****	0.379	0.029
Member of farmer group or any shrimp association	-1.076	0.735	0.143									
Extension services	-0.741	0.613	0.227	**-1.143****	0.447	0.011	-1.369***	0.376	0.000	**-1.151*****	0.421	0.006
Access the bank loan	0.276	0.560	0.622									
Group 4: Farm sites characteristics												
Years in operation	0.397	0.361	0.271	**0.458***	0.252	0.069				0.376	0.236	0.111
The distance from farms to the primary water source	0.298	0.199	0.134									
The distance from the farming area to the sea	-0.657	0.581	0.258									
Belonged to planned areas for shrimp aquaculture	-0.067	0.801	0.933									
Total farm area per hectare	-0.295	0.302	0.329									

Group 5: Biosecurity measures												
Use of feeding tray/ siphon activity to check feed consumption	1.615	1.358	0.234									
Regular Feed Conversion Ratio calculations	-1.480**	0.668	0.027	**-0.973****	0.438	0.026	-0.925**	0.358	0.010	**-1.092*****	0.400	0.006
Regular operating cost analysis	0.384	0.637	0.547									
Other cost-monitoring measures	-14.813	834.298	0.986	-15.368	831.032	0.985				-2.035	1.551	0.190
Daily monitoring of water quality parameters	2.708	2.604	0.298									
Daily monitoring of checking sediment condition	0.310	0.551	0.574									
Daily monitoring of checking water of influent and effluent waters	0.148	0.610	0.808									
Other pond management activities	0.642	0.749	0.392	**0.975***	0.497	0.050	**1.275*****	0.477	0.007	**0.966****	0.469	0.039
Daily monitoring of stock survival	0.071	0.880	0.936									
Daily monitoring of shrimp behavior	-1.968	2.044	0.336									
On-farm and off-farm shrimp health check when disease occurred	0.682	0.718	0.343									
Other water quality monitoring measure	-0.119	0.645	0.854									

Seed sourced from well-known seed company	-0.440	0.851	0.605									
Spending money on pond renovation and other costs	0.158	0.615	0.797									
Break for a minimum of 30 days between crops	-0.267	0.795	0.737									
Fry analysis	0.226	0.554	0.684									
Report disease outbreaks to the neatest aquaculture or veterinary authority	0.609	0.536	0.256	0.682	0.449	0.129				0.424	0.405	0.295
Separate water supply/drainage system	0.657	0.518	0.205									
Sedimentation pond	0.308	0.610	0.614									
Group 6: Culture methods												
The duration period of the most recent crop	**3.220*** **	0.735	0.000	**2.892*** **	0.633	0.000	**2.635*** **	0.552	0.000	**2.761*** **	0.598	0.000
Stocking density	**-1.478** **	0.702	0.035	**-1.346** **	0.560	0.016	**-1.353*** **	0.511	0.008	**-1.306** **	0.530	0.014
AIC:	285.74			237.11			241.12			238.17		
Corrected accuracy (%)	0.75			0.75			0.73			0.75		

TABLE A3: Coefficients of Logistic regressions with regularization in the training dataset.

Factors	Ridge logistic regression (a)	Lasso logistic regression (b)	Elastic Net logistic regression (c)
	Coef.	Coef.	Coef.
(Intercept)	-0.5	0.83	0.76
Group 1: Farmers' perception of negatively impacted extreme climatic and environmental events			
Drought	-0.25	-0.39	-0.34
Irregular weather	0.12		
Saline water intrusion	0.24		
Prolonged heavy rain	0.21		
Water Cross pollution	0.06		
Group 2: Adopted adaptive measures to the climatic event(drought)			
Change in the schedule of feeding practices	-0.25		-0.11
Adjust stocking densities	-0.2		
Change to other type of production systems	-0.31		
Change in schedule of water exchange	-0.06		
Water conservation	-0.01		
Other measures	-0.31	-0.06	-0.17
Group 3: Farmers' biodata			
Experience year	0.16	0.13	0.15
The farmer's age	0.22		

Education	0.19	0.1	0.12
Farmer participated in a training course in a recent year	-0.29	-0.24	-0.26
Member of farmer group or any shrimp association	-0.17		
Extension services	-0.45	-0.62	-0.6
Access the bank loan	-0.12		
Group 4: Farming sites characteristics			
Years in operation	0.12		0.03
The distance from farms to the primary water source	0.05		
The distance from the farming area to the sea	-0.08		
Belonged to planned areas for shrimp aquaculture	-0.09		
Total farm area per hectare	-0.06		
Group 5: Biosecurity measures			
Use of feeding tray/ siphon activity to check feed consumption	0.47		
Regular Feed Conversion Ratio calculations	-0.39	-0.51	-0.47
Regular operating cost analysis	0.02		
Other cost-monitoring measures	-1.01	-0.01	-0.33
Daily monitoring of water quality parameters	0.47		
Daily monitoring of checking sediment condition	0.15		0.06
Daily monitoring of checking water of influent and effluent waters	0.11		
Daily monitoring of water quality parameters	0.33	0.51	0.46
Daily monitoring of stock survival	-0.17		
Daily monitoring of shrimp behavior	-0.48		
On-farm and off-farm shrimp health check when disease occurred	0.09		

Other pond management activities	0.04		
Seed sourced from a well-known seed company	-0.07		
Spending money on pond renovation and other costs	0.05		
Break for minimum of 30 days between crops	-0.17		
Fry analysis	-0.03		
Report disease outbreaks to the neatest aquaculture or veterinary authority	0.05		
Separate water supply/drainage system	0.19	0.07	0.1
Sedimentation pond	0.18		
Group 6: Culture methods			
The duration period of the most recent crop	1	1.69	1.51
Stocking density	-0.57	-0.67	-0.64
Corrected accuracy (%) in testing data	**0.69**	**0.75**	**0.73**

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CHOICE OF CLIMATE RISK ADAPTIVE MEASURES IN SHRIMP FARMING – A CASE STUDY FROM THE MEKONG, VIETNAM

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ABSTRACT

Extreme climate events challenge the livelihoods of shrimp farmers worldwide. A comprehensive analysis of farmers' choices of adaptive measures is essential for developing approaches that can lessen the effects of these climate risks. This study presents the determinants that influence the choice of adaptive measures in response to two climate risks: drought and irregular weather, using a survey of 437 shrimp farmers in the Vietnamese Mekong region and applying a multinomial logit model. Five adaptation choices identified include changing feeding schedules/ stocking densities, changing water exchange schedules, water conservation, water treatments, and early harvesting. The results revealed that education, training, extension services, credit access, farm size, pond numbers, and the farmers' perception of drought and irregular weather are the main factors influencing farmers' choices of adaptive measures. Intensive and extensive farmers chose different adaptations to climate risks, with the former applying various measures while the latter chose to change water exchange schedules. The conclusions bring policy implications concerning how to cope with climate risks.

Keywords: climate risks, adaptation, shrimp aquaculture, multinomial logit model, Vietnam.

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1. Introduction

There has been rapid growth in Vietnamese white-leg shrimp (*Litopenaeus vannamei*) farming in recent years (Nguyen et al., 2019; Shinji et al., 2019). The broader importance of shrimp aquaculture development is underlined by the considerable inclusion in the shrimp value chain of rural, household-based extensive and intensive production. This significant trend contributes to employment and income, alleviating poverty while securing national exports and foreign exchange (Phillips et al., 2007). However, increasing climate variability and complexity seriously challenge shrimp culture growth, severely impacting production yields and threatening seafood supply (FAO, 2016).

1.1 Climate issues threatening Vietnamese shrimp aquaculture in the Mekong region.

Vietnam is one of three nations (including Egypt and Thailand) with the highest vulnerabilities regarding brackish water production in the face of climate-driven change (FAO, 2020). In addition, the Mekong Delta (MKD) region of Vietnam, which produces 60-75% of the total national shrimp production (Nguyen, 2017), suffered in 2016 its worst drought in 90 years (FAO, 2016). Due to natural disasters and unstable weather, there have been substantial losses in Vietnamese shrimp production in recent years (Nguyen et al., 2021). Drought and saline intrusion are frequent critical issues for the Mekong aquaculture and require appropriate response measures (Sebastian et al., 2016).

In shrimp culture, NACA (2012) and Quach et al. (2015) reported that drought and irregular weather are prominent climate risks, leading to massive losses for shrimp production in the Mekong region. NACA (2012) and Quach et al. (2015) stated that drought implies high temperatures and lack of precipitation for a long per, seriously affecting shrimp aquaculture. Irregular weather (e.g., sudden changes in temperature and heavy rainfall) occurs unpredictably, leading to substantial water temperature and quality variations, bringing stress and a greater chance of shrimp disease.

1.2 Motivation for this study

Increasingly, local agricultural and shrimp-producing communities in coastal regions have become aware of climate impacts and the severity of climate events (e.g., increasing temperature, sea-level rise, salinity intrusion) (Halder et al., 2012; Hasan & Kumar, 2020; Quach et al., 2017). Consequently, shrimp farmers' risk perception is one of the critical drivers for their risk management responses or adaptation (Shameem et al., 2015). Such adaptation is an actual adjustment in practices, processes, capital, or decision changes in response to observed or expected climate risks to reduce vulnerability or enhance resilience (Adger et al., 2007).

However, significant barriers hinder the implementation of adaptation strategies and perceptions (Adger et al., 2007), and adaptation strategy choices contributing to mitigating climate risks vary amongst farmers (Arunrat et al., 2017). Furthermore, a lack of understanding regarding farm households' perceptions of weather conditions may lead to ineffective policies incentivizing individual and group adaptation measures (Alam et al., 2017). Arunrat et al. (2017) stated that policy support is crucial for enhancing agricultural farmers' adaptive capacity and adequate preparation concerning expected climate change, which can also be claimed to be the case for the aquaculture sector.

There are a large number of studies on climate adaptation in terrestrial farming worldwide, including in Asia. For instance, Dang et al. (2019) and Singh (2020) synthesize a substantial number of papers regarding factors influencing agricultural farmers' climate change adaptation globally, while Shaffril et al. (2018) focus on similar practices and strategies in Asian countries. Galappaththi et al. (2020) discussed three adaptation strategies for applying water quality management and changing farming practices in aquaculture. In addition, several international climate adaptation projects (Abery et al., 2009; Muralidhar et al., 2012; Joffre et al., 2019; NACA, 2011, 2012; Shelton, 2014) provide general recommendations regarding adaptation to climate risks in shrimp farming in Vietnam and India. However, equivalent academic studies identifying the determinants of farmers' adaptation choices to climate risks are limited in WLS culture (see Shameem et al., 2015; Seekao & Pharino, 2016, and Do & Ho (2022) for studies of Bangladeshi, Thai, and Vietnamese shrimp farming). Therefore, our study collected farm-level data to investigate these choices and provide quantitative input to support Vietnamese shrimp sector policymaking. We surveyed 437 *Litopenaeus vannamei* shrimp farms from March to August 2017 in two provinces (Bac Lieu and Ca Mau) of Vietnam's Mekong region.

Climate risk perception is inherently a "*subjective judgment that people make about the characteristics and severity of a risk*" (Shukla et al., 2019, p.822). Farmers' perceptions are "*subjective judgments which inform appropriate reactions, based on explicit and tacit knowledge about the characteristics and severity of risk*" (Soubry et al., 2020, p.211). Based on subjective perceptions after experiencing extreme climate occurrences in recent years and assessing the climate risk severity levels concerning cost increases, interviewed shrimp farmers selected their preferred adaptive choices for coping. Amongst the reported ten identified adaptive measures, we focus on the most common five choices: (1) change in feeding schedules/ stocking densities, (2) change in water exchange schedules, (3) water conservation, (4) water treatments, and (5) early harvesting. These adaptive measures are autonomous adaptations adopted by shrimp farmers.

Multinomial logit (MNL) is a common method employed for assessing factors influencing agricultural farmer adaptation choices to climate risks (Addisu et al., 2016; Alam, 2015; Alauddin & Sarker, 2014; Arunrat et al., 2017; Chu et al., 2010; Deressa et al., 2009; Gbetibouo, 2009; Gbetibouo et al., 2010; Gebrehiwot & Van Der Veen, 2013; Sarker et al., 2013), but has to our knowledge hardly been applied for similar studies in aquaculture. Though there exists quantitative analysis of shrimp aquaculture (Do & Ho, 2022; Joffre et al., 2019), ours aim to employ MNL for assessing drivers affecting farmer adaptation choices using Vietnamese shrimp farm-level data.

1.3 Objective of the study

The research objectives include the following:

1) Identify shrimp farm-level adaptive measures to climate risks in the Mekong,

2) Analyze potential crucial explanatory variables (socio-economic factors; farm characteristics, knowledge sharing, service accessibility, and farmer's perception of climate risks that drive farmers' adaptation choices in different farming production systems, i.e., intensive and extensive shrimp farming, and

3) Provide knowledge emanating from our results to assist Vietnamese and other countries' shrimp farmers and policymakers in understanding shrimp practices and adaptation choices better.

Section 2 presents Materials and Methods with subsections on the formulation of the MNL model, the study design, farmers' choice of adaptive measures in shrimp farming, and potential explanatory factors driving the adaptation choices. Section 3 highlights results evaluating determinants affecting farmers' adaptation choices. Finally, sections 4 and 5 include discussions and concluding remarks.

2. Material and Methods

This section elaborates on the study design, the MNL model, adaptive measure choices, and key determinants affecting farmers' adaptation.

2.1 Study design

Data collection started with reviewing the adaptation choice literature in agri- and aquacultural sectors, followed by field trips to aquaculture farms, focus group discussions (FDG), and the implementation of a pre-test survey. The final step was face-to-face interviews with shrimp farmers. Farm visits provided a better understanding of shrimp practices. FGD, with 6-8 participants in each province, was used to generate detailed information on farmers' coping strategies for climate risks and develop the final questionnaire before implementing the survey. FGD participants were staff members who worked at provincial aquaculture departments, local shrimp farmers, technicians, and staff from the extension services department. In addition, members of the FGDs provided lists of shrimp farmers representing a cross-section of shrimp farming communities. Thus, we apply an extensive survey that captures many responses. The twenty pre-test samples in each province were useful for improving the questionnaire design. The final survey collected data from face-to-face interviews with 437 shrimp farmers using a structured questionnaire[1], identifying farmers' perceptions regarding the severity level of CR occurrences in shrimp farming, socio-economic factors, farming characteristics, and farmers' adaptive measures when perceiving their impacts.

2.2 Method

The multinomial logit model (MNL) allows us to estimate the shrimp farmer's selection of the most preferred adaptation across more than two choices. The *i*th farmer will choose the *j*th adaptive measure that gives him/her a greater utility U_{ij} than other *k* options, described as:

$$U_{ij}\left(\beta_j X_i + \epsilon_j\right) > U_{ik}(\beta_k X_i + \epsilon_k), \qquad k \neq j \tag{1}$$

where X_i describes a vector of explanatory variables influencing adaptation choices, β_j and β_k are estimated parameters, with ϵ_j and ϵ_k being the error terms. MNL also allows the estimation of the probability of choosing each choice option in the set of explanatory variables (Greene, 2003).

The MNL includes the assumption of independence of irrelevant alternatives (IIA), with the basis of this assumption being that independent and homoscedastic disturbance terms of eq. (1) are required to obtain unbiased and consistent parameter estimates.

[1] The survey consists of (1) the information of climate factors that shrimp farmers perceived in their most recent crop, (2) farmer's adaptive measures to these climate risks in shrimp practices, (3) biosecurity applications, (4) information on farming characteristics (e.g., land uses, culture period), and (5) disease issues in shrimp farming.

The probability of observing the jth outcome for a given X is formulated as:

$$\text{Prob}(y = j|X) = \frac{\exp(\beta_j X)}{1 + \sum_{k=1}^{J} \exp(\beta_j X)}, \qquad j = 1, \dots . J \tag{2}$$

Where y denotes adaptive measure categories. $\text{P}(y = \text{j}|x)$ defines the response probability, which we know once the probabilities for j = 1, . . ., J are determined. The sum of the probabilities equals one.

As Gebrehiwot & Van Der Veen (2013) state, the estimated parameters from equation (2) only provide information on how the explanatory variables influence the adaptation choices but do not determine the magnitude of each choice. Therefore, we also assess the marginal effects or marginal probabilities, providing the expected change in probability of a given a choice to a unit change in the explanatory variables. (Greene, 2003). Marginal effects of the explanatory variables are shown as:

$$\frac{\partial \text{P}_\text{j}}{\partial \text{X}_\text{k}} = \text{P}_\text{j} \left(\beta_{\text{jk}} - \sum_{\text{k}=1}^{\text{J}-1} \text{P}_\text{j} \beta_{\text{jk}} \right) \tag{3}$$

In this paper, farmers' adaptations are autonomous in the sense that the farmers cover the costs of adaptive measures, though we do not assess the actual costs here. Instead, we employ the concept of farmers' perception of climate risks as a critical factor shaping farmers' choice of adaptation. Individual adaptation strategies are considered potential solutions to mitigate the negative impacts of environmental issues. The next part briefly elaborates on the classification of adaptation strategies.

2.3 Farmer's Choices of adaptive measures in shrimp farming

In the literature, many agricultural studies identify farmer intention, perception, and choice of adaptation strategies supplying measurement of several specified adaptive choices to climate change (Abidoye et al., 2017; Arunrat et al., 2017; Deressa et al., 2009; Gebrehiwot & Van Der Veen, 2013; Maya et al., 2019; Sarker et al., 2013), Within the shrimp aquaculture field, Ahmed & Diana (2015) and Shameem et al. (2015) suggested several adaptive measures to protect Bangladeshi shrimp cultures such as the construction of earthen dams, higher dikes, increased embankment height, deeper ponds, as well as fencing and netting around shrimp farms for flood management, use of medical resources and the application of liming. Seekao & Pharino (2016) mentioned nets surrounding ponds and dykes enclosing ponds when flooding occurs in Thailand. In addition, these authors focus on farmers operating in vulnerable areas with challenging financial circumstances, suggesting low-cost options such as alternative crop patterns and harvest seasons. In Vietnamese shrimp farming, Abery et al. (2009) identify adaptations to climate change such as securing better water quality through maintaining pond water levels, planting trees on pond dykes to provide shade or stability, listening to radio weather warnings, harvesting shrimp prior to the arrival of severe storms, developing better crop calendars for storm impacts, reducing stocking density, culturing new species, practicing polyculture, and using smaller ponds for minimizing the impacts related to irregular seasonal changes. Do & Ho (2022) found that three adaptation strategies (dikes upgrade, lining plastic sheets, and settling ponds) contribute to higher productivity in shrimp farming. In addition, NACA (2012) indicates several adaptation measures practiced by shrimp farmers to mitigate climate change, such as changing the surface water, making ponds deeper and ditches wider, and increasing dike height. Shelton (2014) presents the Lower Mekong Basin project, which provided recommendations to increase cooperation and communicate lessons learned as relevant adaptive measures. Furthermore, these authors suggested training related to improving culturing techniques. Pilot shrimp farming models have been developed to enhance management capacity for upgrading production, accessing the market, mitigating disease-related risks, and improving water quality (Dung, 2017). Joffre et al. (2019) studied various disease, market, and climate risk perceptions. These authors found that such risk perceptions, farmer clustering, and network interactions positively influenced Vietnamese shrimp culture adaptive practices, particularly regarding water quality management, disease, and feed input controls.

Reviewing the shrimp culture literature, we collated lists of climate occurrences and relevant adaptive measures from the farm to government policy levels. However, to date, few aquaculture studies assess determinants driving farmers' adaptation choices to climate risks at the farm level in Vietnam (see however (Nguyen, 2017), especially for *vannamei* shrimp, something we attempt to remedy here.

The specific adaptation choices in shrimp farming are employed from the reviewed literature and focus group discussions in the study of Le et al. (2022). Based on this, many different adaptive measures were listed in the survey as possible responses to climate risks. The farmers ticked all measures they had applied and added alternative measures used. Based on this, we chose the ten most relevant adaptation options in Table 2. Shrimp farmers apply adaptation actions based on different aquaculture technologies for managing pond water quality, as presented in Table 1. These measures contribute to maintaining shrimp health and coping with potential climate, production, and environmental risks.

Table 1 Farmers' adaptive measures to perceived climate risks.

No	Adaptive measures	Interpretation of measures
1	Change feeding practice schedules	This measure includes a change in feeding schedules and the amount of feed used in a shrimp crop. This option provides cost savings and adjusts timely and appropriately the amount of feed during extreme climatic events (e.g., drought or heavy rain).
2	Change distribution strategies	This option involves flexibility in distributing farm output in the shrimp supply chain. Seeking alternative markets to sell shrimp is an option for farmers when harvested shrimp size cannot meet the purchasers' demands or contracts. This option helps to attain cost compensation when extreme climatic events occur.
3	Early harvesting	Harvesting early aims to save the shrimp crop when faced with expected severe climatic events or water cross pollution, thereby reducing

		vulnerability to disease. Farmers adjust the stocking period to protect sensitive growth stages impacted by climate variability.
4	Adjust stocking densities	Farmers can adjust the number of shrimps in the pond in the current or next crop depending on their production system and the kind of extreme climate event (e.g., drought, irregular weather, prolonged rain). The reduction in stocking density can help manage water quality during climate occurrences.
5	Culturing new species	This measure includes the choice of changing to new species of aquatic animal culture. For example, farmers may consider the gain and loss of continuing to culture white leg shrimp during prolonged climate occurrences, or switching to another species (e.g., giant tiger shrimp) that is more robust to the climate occurrence.
6	Switch to another type of production system	A possibility here is to change from monoculture to polyculture. For example, the combination of different species such as shrimp – fish, shrimp – crab, rice – shrimp, or mangrove- shrimp are production systems that farmers use to adapt to climate change.
7	Change water exchange scheduling	This strategy of planning and reorganizing water exchange in order to make appropriate decisions on timing for water exchange to manage the pond water level.
8	Water conservation	Water conservation is displayed in many forms, for instance, low or zero water exchange, or recirculation water systems. In addition, using reservoir or sediment ponds for water stocking allows farmers to avoid or reduce water shortage and cross pollution.
9	Water treatment	This measure includes the application of lime or chemicals in ponds to maintain the water conditions needed for stabilizing the growth stages of shrimp and/or water pumping and filtering when pond water levels are insufficient during prolonged drought conditions.
10	Pond renovation	This option includes upgrading bank/dyke height, deeper ponds, etc., for pond renovation purposes. Such upgrading may contribute to better biosecurity systems for pond management.

Sarker et al. (2013) and Alauddin & Sarker (2014) suggested that an MNL model with more than ten choice options could be expected to fail to produce statistically significant results, recommending a lumping together of several options. We found this to be the case when including all options in Table 2 in the MNL model. We, therefore, adopted a reduction in choice options by merging closely related measures into single groups. For example, we combined two choices, a change in feeding schedules and stocking density adjustment. We renamed a change in feeding schedules/ stocking density since farmers simultaneously practiced these two measures. In addition, due to a meager selection by farmers (less than 10%), we excluded five choices from our adaptation choice categories: switching to another production system, culturing new species, changing the distribution channel, and pond renovation. The final five-choice options are specified as follows:

$$y = \begin{cases} 1 = \text{Change in feeding schedules/ stocking density} \\ 2 = \text{Change in water exchange schedules} \\ 3 = \text{Water conservation} \\ 4 = \text{Water treatment} \\ 5 = \text{Early harvesting} \end{cases}$$

Figure 1 shows the farmers' most preferred adaptation choices: change in water exchange schedules (33% of farmers), followed by water treatment (27%). Water conservation and early harvesting are both chosen by 14 % of the farmers, while the lowest percentage of farmers (12%) applied change in feeding schedules/ stocking density.

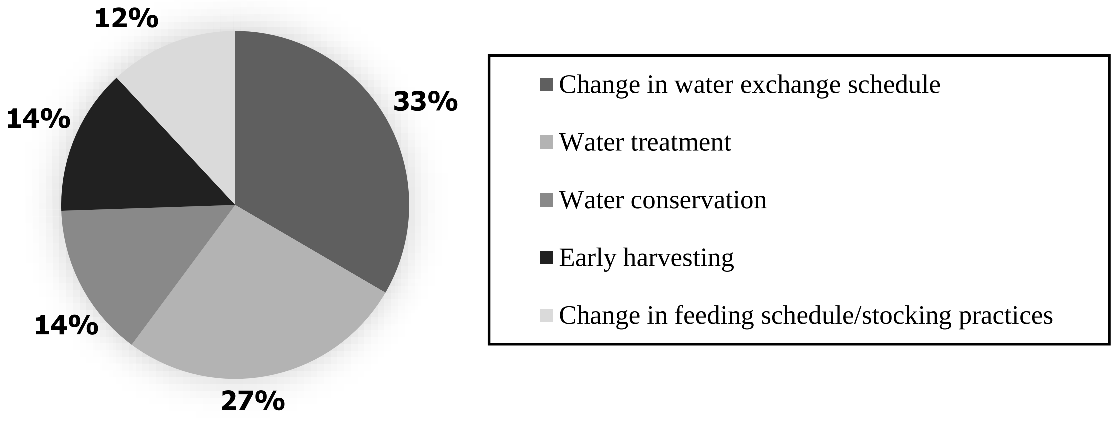

Fig.1. Farmer's choice of adaptive measures (%)

2.4 Explanatory variables explaining adaptation choices to climate risks.

The agricultural studies applying MNL assessments of adaptation measures draw attention to many internal and external factors affecting farmers' choices. This study extracts explanatory variables from an extensive literature review (see Table A1 - appendix A) and FGD. Therefore, we grouped potential explanatory variables into five classes: socio-economic factors; farm characteristics; knowledge sharing; service accessibility; and farmers' perception of climate risks. Socioeconomic factors include experience, education, number of family members, and farmers' income. Based on the literature, we hypothesize that these factors may positively or negatively impact farmers' choices.

Regarding farm characteristics, we include two factors related to disease and governmentally planned areas in the list of explanatory variables suggested in the literature. These were mentioned FGD as some of the main factors determining farmers' responses. Shrimp farms that experienced disease earlier can be expected to actively select farming measures for managing the impact of climate risks to limit the spread of disease. Planned area defines who belongs to governmentally accepted planned areas for shrimp aquaculture. Those who belong to governmentally planned areas gain from the advantages of irrigation systems (dyke and dam construction) and other development (electricity, roads) provided by the local government, creating more efficient preparation for taking active measures to adapt to climate risks. Based on the literature, we expected factors related to farm characteristics might work both ways affecting farmer adaptation choices.

This study suggests that farm area and pond numbers can be used to classify extensive and intensive shrimp farming production systems. Farms with large areas and few ponds represent extensive farming, i.e., more low-technology farming, while intensive farmers operate high-tech small farming areas with many ponds. Extensive shrimp farming often involves larger areas with low-technology operations, including feed provided by the natural environment. Intensive farming favors smaller areas and compounds using many inputs, such as capital, labor, feed, chemicals, seed, and high stocking density. Intensive farms of less than 0.5 hectares can harvest large yields with a short crop (2-3 crops/year), bringing substantial income to shrimp farmers. The production system is represented by a dummy variable (intensive equals one and extensive production system equals zero), highly correlated with farm area and pond numbers. The different degrees of extensive and intensive farming are expected to co-exist also into the future.

We assess the role of knowledge-sharing via farmer clusters and training program attendance and expect them to shape farmers' adaptation regarding climate risks positively. Farm clusters define membership of small farmer groups (neighbors in the same areas) or shrimp associations (e.g., Association of Seafood Exporters and Producers - VASEP) and cooperatives (e.g., at the commune level). Joffre et al. (2019) identify farmer clusters as playing a significant role in adaptive behavior by providing shrimp business networks and information sharing. They indicated that social interactions could shape risk perception. We expected social interaction through participation in farmers' clusters to increase awareness of climate risks, improving the chance of farmers choosing adaptive measures. Though training programs have failed to significantly impact farmers' adaptation choices in the literature (Arunrat et al., 2017), we keep this variable in our estimation due to suggestions from FGD and reviewed projects presented in section 2. We expected participation in training programs could increase the sharing of climate-related information and lessons learned from success stories of adopting adaptive measures and provide up-to-date technological know-how in shrimp farms, potentially encouraging further adaptation.

Regarding service accessibility, extension services are understood as providing technical visits offered by provincial or local aquaculture departments and private companies, guiding shrimp farmers with water treatment, disease control, and farming management activities. Via such technical visits, farmers can receive information regarding CR warnings, water sample testing when climate risks and disease appear, or specific advice for constructing farm infrastructure, pond design, and water treatment systems, should farmers wish to convert to intensive/super-intensive systems. Therefore, we expect extension services to enhance the farmers' response to climate risks. In addition, credit access is a dummy coded for those who receive a credit via official bank loans, potentially contributing to farmers' adaptation to climate risks.

Our analysis regarding farmers' perception of climate risks includes drought and irregular weather. We found these to be the two most identified climate risks in our Mekong shrimp farmer sample (see Figure 2).

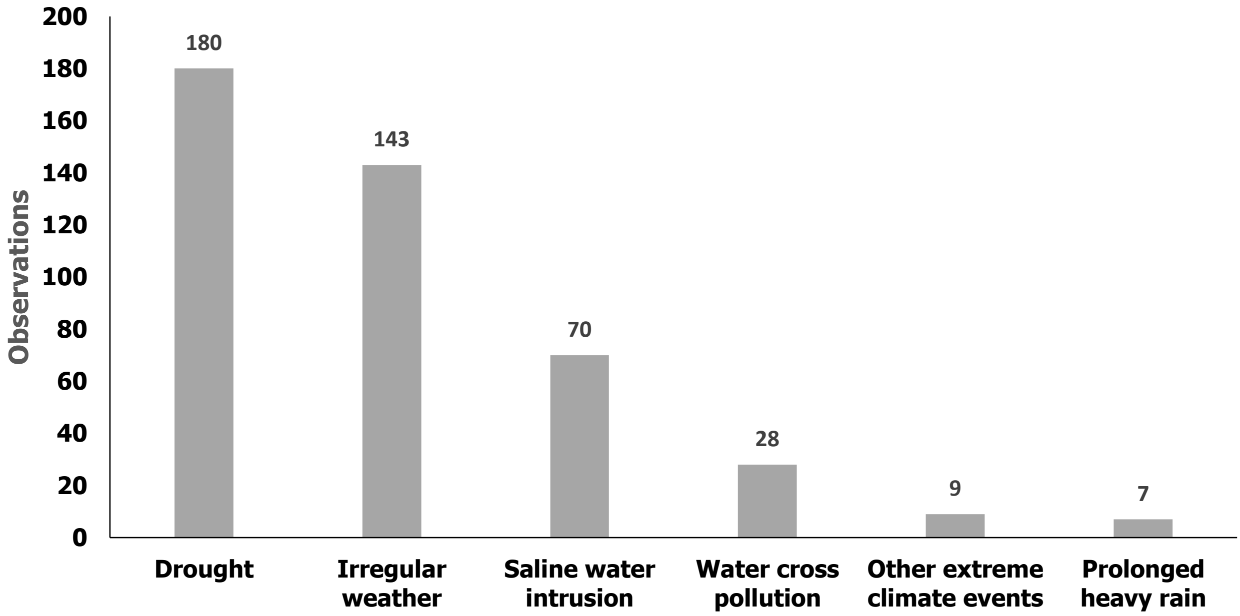

Fig. 2. Farmer's perception of different kinds of extreme climate events occurring in shrimp farming

In addition, we also asked the shrimp farmers to assess the severity of these two climate risks using a seven-point Likert scale[2]. The degree of severity is defined in relation to an

[2] We define a seven-point Likert scale consisting of -3: Extremely positively impacted (cost reduction of more than 50%), -2: Major positively impacted (cost decline between 10%-50%), -1: Minor positive impact (costs decline by less than 10%), 0: No consequence, 1: Minor negative impact (costs rise by less than 10%), 2: Major negative impact (costs rise between 10%-50%), 3: Catastrophic/ extremely negative impact (costs rise by more than 50%).

increase in farm cost. Farmers' perceptions of climate risk factors are dummies in our analysis, generated from climatic risks interacting with the different degrees of increased costs. We expected farmers’ perceptions of climate risks to affect adaptation choices positively, i.e., the expectation of higher costs would increase adaptation but found that adaptative measures were mainly carried out in relation to drought and irregular weather. Therefore, we employed farmers’ perceptions of drought and irregular weather in the final model estimation.

Table 2 describes the fourteen explanatory variables, organized into five classes for testing the influence on farmers’ adaptation choices. Most are dummy variables (yes/no), while others are continuous variables related to socioeconomic factors and farm characteristics (farm size in hectares and pond numbers).

The average working experience of farmers in the shrimp business was 14 years, and the average education level was a primary school. In our sample, only 21% are members of farmer clusters, while nearly 50% of the farmers participated in training courses held by provincial or local governments. In addition, 76% of farmers belonged to a planned area, and 19% experienced shrimp disease in their crops. We found that a small proportion of the sample of farmers have access to extension services and official bank loan credit (20% and 26%, respectively). In the sample, 36% and 29%, respectively, perceived that drought and irregular weather phenomena were severe. In the following, we employ the MNL model to determine how the effects of farmers’ perceptions of drought and irregular weather, and other explanatory factors impact farmers’ adaptive measure choices.

Table 2 Data description

	Factors	Description	Expected sign	Var. type	Mean	S. E	Min	Max
	Socio-economic factors							
1	Experience of farm owner	Number of years in shrimp business	+/-	In number	14.29	9.49	1	53
2	Education of farm owner	Number of schooling years	+/-	In number	7.32	3.92	0	22
3	Owner household size	Number of family member	+/-	In number	4.27	1.20	1	13
4	Farm income	Total shrimp farm income (million VND/crop)	+/-	In number	10.97	1.48	5	15
	Farm characteristics							
5	Farm area	Total shrimp area per hectare	+/-	In number	1.05	1.18	0.1	8.0
6	Pond numbers	The number of ponds used for culturing shrimp	+	In number	1.42	0.88	1	7
7	Planned areas	Dummy variable	+	1: Yes; 0: No	0.76	0.43	0	1
8	Disease risk	Dummy variable	+	1: Yes; 0: No	0.19	0.40	0	1
	Knowledge sharing							
9	Training attendance	Dummy variable	+	1: Yes; 0: No	0.47	0.50	0	1
10	Farmer cluster	Dummy variable	+	1: Yes; 0: No	0.21	0.41	0	1
	Service accessibility							
11	Extension services	Dummy variable	+/-	1: Yes; 0: No	0.21	0.41	0	1
12	Credit access	Dummy variable	+/-	1: Yes; 0: No	0.26	0.44	0	1
	Farmer's perception regarding climate risks							
13	Drought	Dummy variable	+/-	1: Yes; 0: No	0.36	0.48	0	1
14	Irregular weather	Dummy variable	+/-	1: Yes; 0: No	0.29	0.46	0	1

Notes: *Number of observations is 437 but only 383 farmers reported income.*

3. Results

In this section, we present the results of the MNL models, but first, we describe the farmers' chosen adaptation options[3].

3.1 Multinomial logit model for choice of adaptive measures

Table 3 presents the Hausman test for the IIA assumptions. The null hypothesis (H_o) implies that the odds ratio for each specific pair of outcomes is independent of other alternatives or that deleting outcomes should not affect the odds among the remaining outcomes.

Table 3 Hausman test of IIA assumption in the MNL model for shrimp farmer's adaptation choices.

Omitted variables	$\chi 2$	DF	$p > \chi 2$	Decision
Change in feeding schedules /stocking density	-161.291	45	1.000	Accept Ho
Change in water exchange schedules	27.195	45	0.983	Accept Ho
Water conservation	2.636	45	1.000	Accept Ho
Water treatment	-4.168	45	1.000	Accept Ho
Early harvesting	-0.694	45	1.000	Accept Ho

Note: DF is degree of freedom

[3] Bivariate Probit models were also applied for robustness checks, and the results do not differ to any significant degree. The choice of change in water exchange schedules is used as the base in this modeling. No multicollinearity among the explanatory variables was found in the estimation.

The omitted variables achieved p-values of 1.000, indicating that the MNL satisfies the asymptotic assumptions of the Hausman test (Sarker et al., 2013), and we can accept the null hypotheses. We conclude, therefore, that the IIA assumptions are not violated, and the MNL model specification is appropriate for modeling shrimp farmers' adaptation choices to climate risks (Hausman & McFadden, 1984). Table 4 illustrates the empirical results of the MNL model with the base adaptation outcome (reference category) being a change in the water exchange schedules, the most chosen adaptation option (33 % of total surveyed farmers), simile ar to the study of Alam (2015).

Table 4 Parameter estimates of MNL adaptation choices.

Factors	Base outcome: Change in water exchange schedules							
	Feed schedules and stocking density		Water treatment		Water Conservation		Early Harvesting	
	Coef	p level	Coef	p level	Coef	p level	Coef	p level
Socio-economics factors								
Experience	0.022	0.413	-0.063*	0.081	0.020	0.375	-0.054*	0.098
Education	-0.023	0.696	0.152**	0.015	0.105**	0.027	0.018	0.779
Family size	-0.039	0.812	0.113	0.563	-0.199	0.188	-0.138	0.474
Income	-0.108	0.550	-0.172	0.409	0.128	0.429	-0.184	0.336
Farm characteristics								
Farm area	-1.041***	0.000	-1.362***	0.000	-1.109***	0.000	-0.569	0.044
Pond numbers	0.820	0.015	0.856**	0.019	0.754**	0.013	0.530	0.155
Planned area	0.404	0.528	-1.058*	0.083	-0.243	0.618	-1.472**	0.013
Disease occurrence	-1.120	0.119	-0.974	0.193	-0.480	0.361	-0.468	0.508
Knowledge sharing								
Training program attendance	-0.560	0.228	-1.702***	0.006	-0.683*	0.089	-0.008	0.989
Farmer cluster	-0.874	0.228	-1.222	0.154	-0.434	0.454	0.635	0.377
Service Accessibility								
Extension services	0.420	0.587	1.218	0.118	1.802***	0.003	0.040	0.962
Credit access	-0.474	0.288	-2.206***	0.002	-0.778*	0.051	-0.094	0.861
Farmer's perception to climate risks								
Drought	0.024	0.956	0.816	0.225	-0.322	0.410	-3.178***	0.004
Irregular weather	1.664**	0.013	2.806***	0.000	0.969	0.110	1.500**	0.021
Constant	-1.206	0.569	-0.791	0.747	-2.673	0.153	2.656	0.235
Log likelihood	-399.225							
Pseudo R2	0.2885							
LR chi2	323.71							
Observations	372							

Note: ***, **, and * imply statistical significance at 1, 5, and 10 % probability level, respectively.

The coefficients and p-values in Table 4 indicate the likelihood and statistical significance of farmers selecting one of the remaining adaptation choices compared to the base. Sixty-five farms contained insufficient data and were removed from the MNL adaptation choice estimation, resulting in 372 observations. Positive coefficients imply that a unit increase in explanatory variables will increase the likelihood of farmers choosing the appropriate adaptation compared to the reference adaptation. More specifically, education, extension services, pond numbers, planned area, and perception of climate risks (irregular weather and drought) are all statistically significant predictors driving the choice of other adaptation alternatives compared to the reference option. An increase in extension service accessibility is a factor that influences the choice of water conservation ahead of changes in the water exchange schedules. An increase in one year of schooling increases the likelihood of choosing water treatment and water conservation.

Regarding shrimp farm characteristics, all coefficients of farm area in the MNL model are negative and highly significant (1%), while the pond number coefficients are significant (from 5 to 10%) positive. Large pond numbers are a potential marker for intensive farms, while extensive farms have large land areas; these results imply that intensive farmers seem to adopt a broader set of adaptive measures relative to the base adaptation. In contrast, extensive farmers tend to stick to the base adaptation of water exchange schedule changes. The farmers who perceived irregular weather are more likely to adopt adaptations related to a change in feeding schedules/ stocking practices, water treatment, and early harvesting than the reference choice. Compared to the base, we failed to show a statistically significant relationship between disease occurrence, family size, income, farmer clusters, and farmer adaptation choices.

In contrast, statistically significant negative coefficients appear for experience, training program attendance, credit, and planned area, implying an increase in these variables reduces the likelihood of farmers choosing other adaptations than a change in water exchange schedules (the base category). More specifically, farmers who have more years of experience or training program attendance are more likely to choose the base adaption choice than selecting water treatment. Similarly, credit access negatively impacts the choice of reference option compared to water treatment or water conservation. A striking finding was the highly statistically significant probability of choosing the reference option ahead of pond renovation amongst farms in planned areas.

We present marginal effect values of the MNL model in Table 5 to interpret the expected change in probability of each adaptation choice for a unit change in the explanatory variable.

Table 5 Marginal effects from MNL adaptation choices

	Feed schedules and stocking density		Water exchange Schedules		Water Treatment		Water Conservation		Early harvesting	
Factors	dy/dx	P level	dy/dx	P level	dy/dx	P level	dy/dx	P level	dy/dx	P level
Socio-economic factors										
Experience	0.003	0.342	-0.001	0.825	-0.005**	0.034	0.006	0.165	-0.004*	0.065
Education	-0.012*	0.087	-0.015	0.114	0.008**	0.038	0.021**	0.013	-0.002	0.603
Family size	0.007	0.738	0.026	0.336	0.014	0.234	-0.043	0.155	-0.004	0.729
Income	-0.019	0.410	-0.001	0.977	-0.012	0.300	0.046	0.145	-0.013	0.250
Farm characteristics										
Farm area	-0.056	0.101	0.231***	0.000	-0.045**	0.017	-0.141***	0.002	0.011	0.522
Pond numbers	0.053	0.136	-0.165***	0.007	0.024	0.176	0.087*	0.074	0.001	0.958
Planned area	0.105	0.194	0.063	0.497	-0.061*	0.083	-0.016	0.862	-0.090**	0.033
Disease occurrence	-0.113	0.230	0.151	0.131	-0.036	0.421	-0.003	0.978	0.000	0.995
Knowledge sharing										
Training program attendance	-0.016	0.786	0.150**	0.047	-0.088**	0.027	-0.078	0.321	0.033	0.346
Farmer cluster	-0.091	0.293	0.113	0.339	-0.062	0.207	-0.030	0.766	0.070	0.106
Service accessibility										
Extension services	-0.069	0.436	-0.262**	0.035	0.028	0.480	0.358***	0.000	-0.055	0.235
Credit access	0.009	0.870	0.169**	0.023	-0.119***	0.007	-0.091	0.258	0.031	0.357
Farmer's perception to climate risks										
Drought	0.053	0.382	0.090	0.205	0.078*	0.061	-0.015	0.854	-0.206***	0.000
Irregular weather	0.124*	0.095	-0.303**	0.008	0.132***	0.007	0.008	0.938	0.039	0.253

Notes: ***, **, and * are significant at 1, 5, and 10 % probability levels, respectively.

As shown in Table 5, we found that more than four different input factors explain some adaptive measures. For example, the adaptation choices of water exchange schedules, water treatment, and water conservation respond to many factors (e.g., education, training program attendance, extension services, having credit access, farm area, and pond numbers, and perception of irregular weather) and are highly statistically significant. In contrast, farmers' education and irregular weather determine the choice of change in feeding schedules/ stocking density. The choice of early harvesting and change in feeding schedules/ stocking density is not impacted by the farming production system – extensive and intensive - captured by the two variables related to farm area and pond numbers. Water conservation and water treatment are, for the most part, similarly driven by the predictors. For instance, education plays a positive role, motivating the probability of choosing these adaptation options, while farm area plays a negative role, reducing the likelihood of selecting these choices.

Most explanatory factors have positive and negative effects, varying across the adaptation options. For example, service accessibility and knowledge sharing significantly impact two choices of methods. More specifically, farmers with access to extension services have a higher probability of conserving water and a lower probability of changing water exchange schedules. However, those participating in training programs are likelier to adopt water exchange schedules and less likely to apply water treatment.

Several factors have surprisingly different impacts on the same adaptation option. For example, socio-economic factors, such as experience and education, affect water treatment adaptation negatively and positively at 5% statistical significance, respectively. Similarly, within service accessibility, extension services and credit access have opposite effects on the change in water exchange schedules, at 5 % statistical significance.

Four factors, farmer clusters, family sizes, income, and disease occurrence, have no significant effect on adaptation choices. Thus, no factors have purely positive effects, but perhaps surprisingly, two factors have purely adverse significant effects: Experience and planned areas, each negatively influencing the same two adaptation options, water treatment and early harvesting. In contrast, several factors (extension services, credit access, farm area, pond numbers, and perception of climate risks - irregular weather and drought) are statistically strong predictors that positively drive farmer choice regarding several adaptive measures at a 1% or 5% significance level.

Table 5 reveals that there may be a significant difference in the choice of adaptation methods between intensive and extensive farms. As stated earlier, based on the typical differences between intensive and extensive farms regarding pond numbers and farmland, the results indicate that extensive farmers tend to adopt changing water exchange schedules. In contrast, intensive farmers are more likely to select water conservation. In the following section, we discuss factors that significantly increase the farmers' choice of adaptation methods and provide policy implications for developing appropriate approaches to lessen the effects of climate risks in shrimp farming.

4. Discussion

In the following, we assess the different factors that impact on adaptation choices for the intensive and extensive farmers.

4.1 Socio economics factors

Educational attainment and experience are socio-economic factors that play important roles in affecting positive adaptation choices, a result also noted by Do & Ho (2022). Education potentially enhances the farmers' desire and ability to select relevant adaptive water treatment and conservation measures. Water treatment and conservation require sound theoretical and practical knowledge and technical prowess, which can be conveyed via more years of schooling. Hence, encouraging farmers to go to school can increase knowledge and awareness for coping with climate risks. In contrast, farmers with less experience tend to choose early harvesting and water treatment when perceiving climate risks.

4.2 Farm Characteristics

We found that increased farm size increased the probability of changing water exchange schedules. In contrast, a unit decrease in farmland increases the probability of adopting water treatments and conservation. In addition, an increase in the number of ponds increased the likelihood of choosing water conservation, while a decrease in pond numbers increased the probability of changing water exchange schedules. Our findings are different from the suggestions of Joffre et al. (2019). Their results indicated that having more shrimp ponds affected farmers' adoption of water treatment measures and mentioned that smaller shrimp farms tended to adopt feed-input practices. As noted earlier, land area and pond numbers are in this study assumed to imply differences in production systems, extensive and intensive, respectively, and our findings indicate significant differences in farmer adaptation choice across these two technologies. We found that intensification made water conservation more likely, while extensive farms with greater farm size and fewer ponds have a higher probability of changing water exchange schedules. In our research sites, water conservation and water exchange are preferred since Bac Lieu and Ca Mau are coastal provinces with the advantage of a large density of river branches, providing irrigation for shrimp aquaculture. In the Mekong region, extensive farms have proximity to the coast or Mekong estuaries/rivers, allowing the employment of water exchange following the tidal system.

In contrast, intensive farms primarily operating further inland may face greater water pumping costs. Therefore, water conservation is a good option for intensive farmers to cope with climate risks. In addition, we found that farmers whose farms do not belong to planned areas assigned by local authorities are more likely to choose adaptive measures regarding early harvesting and water treatment when they perceive the severity of climate risks.

4.3 Knowledge sharing

We found a significant contribution of training program attendance influencing farmers' adaptation choices to climate risks, as previously suggested in development projects in Vietnam (NACA, 2011). For example, farmers with such attendance are more likely to choose water exchange schedule adaptation and have a low probability of choosing water treatments. In addition, recommended crop calendars, CR information, and environmental issues can easily be transferred to shrimp farmers via training programs.

4.4 Service accessibility

Gebrehiwot & Van Der Veen (2013) suggested that farmers who interacted with extension agents to a greater degree carried out adaptation responses to climate change. In this study, extension services or technical visits positively influence farmers' choice of water conservation rather than water exchange schedules. Furthermore, via technical assistance, farmers may consider the appropriate form of water conservation (restoring water or installing water circulation systems) based on their farming infrastructure and budget for coping with climate risks.

We found that an increase in farmers' official credit bank access resulted in an increase in the likelihood of choosing a change in water exchange schedules and reduced the probability of choosing water treatment. Thus, credit improved low-income farmers' chances of affording extra farm costs (e.g., water pumping, chemical/antibiotics) to increase the frequency of water exchange when climate risks appear. However, farmers who fail to borrow from banks may access other credit sources, such as loans from family members or other stakeholders (input agents/processing shrimp companies). For instance, farmers who access loans given by input agents often have to commit to purchasing these agents' shrimp inputs (e.g., seed, feed, chemicals) or have to establish pond structures or irrigation systems following guidance from seed companies. Hence, these forms of credit availability often come with strings attached that require choices that may not be optimal in isolation.

4.5 Farmer Perception of climate risks

Muralidhar et al. (2012) illustrated how high temperatures and irregular weather affect shrimp pond water quality via changes in salinity, pH, and oxygen levels, leading to higher disease occurrence, slower shrimp growth, and high development of algal blooms. Our study found that farmers' perceptions of irregular weather and drought significantly positively impacted farmers' behavior in choosing measures related to water treatment. Irregular weather also increased changes in feed schedules/stocking density. These two adaptation approaches seem to work appropriately as shrimp farmers put more effort into balancing water quality in grow-out ponds during irregular weather. In contrast, farmers who perceived the impacts of drought were less likely to choose early harvesting. Drought is a clear CR for shrimp aquaculture, but it is also an integral part of farmers' operations, as Mekong shrimp farmers must deal with drought in some form or another every year. In practice, early harvesting seems to be adopted to mitigate the loss when warnings of coming crises occur, for instance, notification of disease outbreaks following cross pollution in neighboring farms or forecasted natural disasters (e.g., heavy storms, typhoons). Mekong farmers may implement a partial harvest or harvest the entire crop in such cases, depending upon the situation.

5. Conclusion and Policy Implications

This study explores the key determinants of shrimp farmers' adaptive measures to cope with climate risks using the MNL model on farm-level survey data. Results display the vital role of farmers' perceptions regarding irregular weather and drought in motivating the selection of adaptation. Other primary factors shown to influence farmer adaptation choices to climate risks are socio-economic factors (experience, education); farm characteristics (farm size, pond numbers); knowledge sharing (training attendance), and service accessibility (extension services, credit access). Contributing to the literature on shrimp aquaculture and policy implications, we provide quantitative evidence of the explanatory variables that positively encouraged farmers' responses regarding adaptive measure selection.

This study has limited the adaptations to five major choices made by shrimp farmers for coping with climate risks. Our results indicate that most measures shrimp farmers take in response to climate risks are related to balancing the quality of water (e.g., changing the water exchange schedules, water treatment, and conservation), like Galappaththi et al. (2020)'s suggestions. Our study identified that change in water exchange schedules was the most preferred adaptation when farmers perceived climate risks. The results reveal substantial differences in the choice of adaptive measures across production systems. These findings may provide input to policymakers about which adaptive measures could be encouraged for intensive versus extensive farms, involving water conservation for the former and changing water exchange schedules for the latter. In addition, the provincial government may encourage water conservation by supporting the shrimp farmers' education attainment and increasing their access to extension services. Local government can boost the application of adjusted feeding schedules/stocking density and/or water treatment by providing alert messages regarding the severity of climate occurrences (e.g., irregular weather and drought) to increase awareness of the CR impact level. The target is to improve the coping capacity related to a change in water exchange schedules in extensive farming. In that case, the government may put more funding and effort into training programs and increase the accessibility of bank credit to farmers. Our findings highlight that intensive farms apply all adaptive measures barring change in water exchange schedules, more than extensive farms. Quach et al. (2017) suggest that policymakers should encourage more intensive shrimp farming to increase the resilience of shrimp farmers concerning climate change and its effects. In our analysis, we cannot make this link explicitly; intensive farms chose various adaptive measures regarding water quality when they perceived climate risks, while extensive farmers focus on one measure, namely change in water exchange schedules. It should be noted that Shelton (2014) finds that improved extensive shrimp farming is more sustainable for small-scale farmers, both environmentally and economically, despite it providing lower profitability than intensive shrimp farms. Therefore, from our results, the government can further motivate extensive farmers to carry out their favored adaptation choice by encouraging knowledge sharing (training program attendance) and increasing service accessibility (credit access).

As mentioned, high-tech intensive farming, also known as super-intensive shrimp farming, is increasingly desired in Vietnam to bolster further production. Super-intensive farming requires technological improvements such as bio-floc waste-water treatment and closed systems for assuring biosecurity and water quality, resulting in less pollution and lower impact of irregular weather. This system allows increased stocking density and more crops per year. However, super-intensive farming requires investment in capital, knowledge, and improved technology. In our survey, we have yet to include super-intensive farms. Though this may be the trend in the future, such investment is still a challenge for low-income shrimp farmers in less developed countries. Extensive and intensive/semi-intensive farming may be expected to continue in parallel with super-intensification. Furthermore, different market niches based on preferences for small-scale, sustainable products may allow for the coexistence of different types of farming in the future.

Finally, assessing how efficient and successful each adaptation measure is, while interesting and relevant, nevertheless lies beyond the scope of this paper and is left for future research.

Author contributions

The first author develops the survey and data collection, organizes, analyzes, and interprets the data, and develops the paper. The second author contributes to data analysis and interpretation and development the paper. Both authors have reviewed the final document and agree with its contents.

Declaration of Competing Interest

The authors declare no conflict of interest.

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Appendix A:

Table A1 Literature reviews on farmer choices in argi-aquaculture industries

Authors	Country	Method used	Data	Findings/ key factors affecting the farmer. adaptation choices	Adaptive measures
Do & Ho. (2022)	Vietnam	Endogenous swtiching regression	374 shrimp farmers	Education of farmers (+), Farmers' belief on changes in climatic conditions (+)	Upgrading pond dikes, Lining ponds with plastic sheets Having settling ponds
Ali et al. (2021)	Pakistan	BLR	400 smallholder farmers	Household size (+), assets (+), distance from the market (-), market access (-), food aid (-), food price (+) floods (-), disease (-), district dummy (-)	Tree planting Early sowing Terracing Irrigation Water Harvesting Non-farm activities Crop diversification
Thompson et al. (2021)	Nigeria	MNL	480 fish farmers	Experience (+), Income (+), access to credit (+), pond size (+)	Use of concrete/plastic pond Flood control/provision of the water outlet Provision of alternative water supply
Aftab et al. (2021)	Pakistan	MVP	500 households	Wealth (+), off-farm work (-), market distance (-), no. of tribes (+), agriculture extension (+), farming experience (+/-), farm to reiver distance (-). flood duration (+/-), past adaption (+)	Plinth elevation Communal flood preparation Shelterbelt Grain storage
Khan et al. (2021)	Pakistan	MVP, ordered probit model	480 rice growers	Farmer's age (+), Farm size (+), farm ownership (+/-), tube well (+/-), canal irrigated land (+), livestock holding (+/-), active farm labor (+/-), active farm labor (+), off-farm income (+/-), farm advisory (+/-), credit services (+/-), climate information access (+/-)	Supplementary irrigation Irrigation time changes Climate-smart variety Cultivation dates changes Fertilizer management Farm resizes. Short duration rice
Oparinde (2021)	Nigeria	MNL, Multinomial Endogenous Switching Regression	288 fish farmers	Gender (+), membership of cooperative (+), level of education (+), experience (+/-), non-farm income (+), no. of pond (+), awareness (+), perceived temperature (+), perceived rainfall (+)	Bore-hole construction. Stocking time adjustment Embankment creation

Wang et al. (2021)	China	BLR Multiple logistic regression	539 households	Informal social network (-), formal social network (+), interpersonal trust (+), institutional trust (+), social norms (+), no. of household labors (-), education level (-), income (-), no. of livestock (+), farmland (+), location condition (-), policy accessibility (+), perception of temperature change (-), perception of precipitation change (-)	Expansion strategy Adjust strategy. Contraction strategy
Khong et al. (2020)	Vietnam	Censored generalized, Poisson regress, Negative Binomial regression. Ordered logit model	441 rice farmers	Farmers are aware of the causes and impacts of salinity intrusion and have adopted autonomous strategies to cope. Drivers of preferences for long-term public adaptation strategy (sea dikes construction): farmers' willingness to pay for construction (+), impact on farm housing value (-), impact on water supply for agricultural activities (+), impact on habitation environment (+), impact on regional economics (-)	22 effectiveness of salinity adaptation strategies adopted by farmers (such as: constructing the dykes, changing planting time, etc.) 24 intended future salinity adaptation strategies (migrating to other places, getting information from TV, radio, etc.)
Kamba (2020)	Nigeria	MNL	150 arable crop farmers	Experiences (-), education (+), household size (-), years of residence (+), extension contact frequency (+), credit access (+)	Good soil conservation techniques Irrigation/Drainage/ Wetland farming Targeting rains to plant Multiple strategies
Esfandiari et al. (2020)	Iran	MNL	360 rice famers	Cultivated land area (+), Seed (+), Fertilizer (+), Pesticide (+), Water (+), Age (-), Education (+), Family income (+), land size (-),	Adjusting crop sowing and harvesting day Modifying crop varieties Changing the area of land under cultivation Irrigation control mechanism Mix cropping
Singh (2020)	India	Multi-criteria analysis (BLR)	200 agriculture farmers	Rainfall (+), temperature (+), Education (+), Land size (+), Income (+/-), above poverty line (+/-), Irrigated area (-), Agriculture credit (+/-), Information of climate (+), crop insurance (+/-),	Cropping pattern change Switch to non-farm Improve irrigation. Early maturing varieties Less water requiring crops
Joffre et al. (2019)	Vietnam	Hierarchical regression Mediation analysis	251 shrimp farmers	Water quality management: stocking density WLS (+), stocking density P. monodon (+), public/ private sector interactions (+), susceptibility climate (-), severity of market risk (+)	Water quality management Feed input practices Disease control input practices

				Feed input practices: stocking density WLS (+), public/ private sector interactions (+), neighbor interactions (-), susceptibility climate (-), severity of market risk (+) Disease control input practices: stocking density WLS (+), cluster (+), public sector interactions (+)	
Usman et al. (2019)	Malawi	BLR MVP	220 fishers	Age (-), education level (+), access to land (-), fishing experience (+), household size (+), fishing income (-), total income (-), social capital (+), access to extension service (+)	Increasing fishing effort Migration of fishing effort Investing in improved gear Livelihood diversification
Moroda et al. (2018)	Ethiopia	MNL	397 agricultural households	Gender (+/-), farmland size (+/), total annual income (+/-), access to weather forecast (+/-), access to credit service (+/-), distance to input/output market (+/-)	Crop management-related strategy Land management-related strategy Diversification into non-farm activities
Thoai et al. (2018)	Vietnam	BLR MVP	400 farmers (agri-forestry)	Farm size (+), Farming experience (+), Damage level (+), Access to credit (+), Attendance to training (+), Farm size (+)	Change crop variety. Switch to new cultivar types. Adjust farming calendar. Follow-up weather forecasts Intercropping
Arunrat et al.(2017)	Thailand	MNL	661 rice farmers	Gender (+), experience (+), Schooling (+), household size (+), farmer income (+), land ownership (+), credit access (+), distance to input/output markets (-), training attendance (+), communicating adaptation to climate change (+)	Changing rice varieties Practicing crop rotation Changing from old production site to another site Increased use of water sources and irrigation system Farming calendar adjustment
Abidoye et al. (2017)	South-East Asian*	MVP	1615 smallholder farmers	Perceived more drought (+/-), perceived more flood (-), household size(+/-), perceived more pets(+), education (-), experience (+/-), use past (+/-), expert time use past (+/-), Perceived warning (+), perceived more pets (+), primary job (-),	Crop date Crop variety Irrigation Crop type
Dubey et al. (2017)	Indian Sundarbans delta	Descriptive statistics, qualitative information	451 fish farming	73% of surveyed farmers were affected by cyclonic events. The common coping measure against cyclonic was to repair of pond dyke through earthwork (37%)	Repair pond dyke Increase pond dyke height. Plantations on pond dyke Pumping of saline water Application of lime Addition of fresh water Application of fertilizer

					Application of cow dung
Addisu et al. (2016)	Ethiopia	Heckman probit MNL	300 household	Hecman probit: Sex (-), education (-), wealth status (-), distance to the nearest health center (+), extension (-) MNL: Agro-ecology (+/-), Education (+), transport to market (-), income from crop sale (+)	Use of climate change resilient variety (both crop and livestock) Crop diversification Change planting date. Irrigation Other measures
Seekao & Pharino (2016)	Thailand	Descriptive analysis Social vulnerability index Descriptive analysis	100 shrimp farmers experienced flood vulnerability	Main adaptive practices: Placing nets around shrimp ponds (12.6%), constructing dykes (28.1%) Early harvesting prior to a flood occurring (9.7%)	Placing nets around shrimp ponds Increasing the height of dikes Early harvesting prior Changing the calendar for culturing shrimp.
Ahmed & Diana (2015)	Bangladesh	Field survey	100 shrimp farmers (Penaeus monodon)	Adaptation and management strategies to climate change for shrimp culture: Community-based adaptation and integrated coastal zone management	Community-based adaptation (6 adaptation strategies such as the construction of dams, and development of water irrigation) Integrated coastal zone management (6 adaptation strategies such as mangrove plantation and conservation, etc.)
Alam (2015)	Bangladesh	MNL	546 rice farmers	Education (+), tenure status (-), experience (+), electricity (+), Moderate institutional access (+), climate awareness – adversely affected (+), slightly affected (-)	Increased use of surface water Crop diversification Land use change
Shameem et al. (2015)	Bangladesh	Descriptive analysis	30 shrimp farmers	Main adaptive practices: 47% of the sample adopted the measure of increased embankment height.	Increased embankment height Digging pond inside the fish farm Liming Use medicine. Placing net around shrimp field
Alauddin & Sarker (2014)	Bangladesh	BLR MNL	1800 rice farmers	perceived severe drought (+/-), severe groundwater depletion (+/-), farm size (+), livestock ownership (+),	Direct-seeded rice More irrigation water. Supplementary irrigation

				access to climate information (-), access to subsidy (+), access to electricity for irrigation (-)	Short-duration and drought-tolerant rice varieties Changing planting dates and others Water-savings non-rice and horticultural crops
Gebrehiwot & Van Der Veen (2013)	Ethiopia	MNL	400 rural households	Sex (+), age (+), Education (+), Farm size (+), Farm income (+), information on climate change (+), temperature (+), precipitation (+/-), Argo-ecology (+)	Crop diversification Soil conservation Application of irrigation Planting trees Change in planting date.
Sarker et al. (2013)	Bangladesh	BLR MNL	550 rice farmers	Gender (+), age (+), education of household heads (+), experience (-), household assets, annual farm income (+), farm size (+), tenure status (+), farmer-to-farmer extension (+), access to credit (+), access to subsidy (-), access to electricity (+),	More irrigation Growing short-duration rice Greater emphasis on supplementary irrigation Changing planting trees Agro-forestry Use of different crop varieties Non-rice crops
Sofoluwe et al. (2011)	Nigeria	MNL	100 crop farmers	Off-farm (+), livestock (-), access loan (+)	Soil conservation Planting trees Planting variety Early and late planting
Gbetibouo et al. (2010)	South Africa	MNL	794 households	Household size (-), Experience (+), wealth (+), highly fertile soil (+), extension (+), farm size (+), credit (+), tenure (+) Latitude (+/-, longitude (+/-), temperature (+)	Portfolio diversification Irrigation Changed planting dates. Changed amount of land Livestock feed supplements Other
Abery et al.(2009)	Vietnam	Participatory approach	Stakeholders	Climate changes: hot weather, too much rain, canal/river level rise, storm, irregular seasonal change Impacts ranked: water quality, disease, slow growth, dike management, tidal flood leads to shrimp escape, sluice gate damage,	List of solutions/ adaptive measures with responsible agents and timing among farmers, scientists, and government.
Deressa et al. (2009)	Ethiopia	MNL	1000 households	Gender (+), education (+), age (+), income (+/-), non-farm income (+), extension (+), information on climate change (+), farmer – to- farmer extension (+), credit	Soil conservation Crop varieties Planting trees

	availability (+), local agroecology (+), temperature (+), precipitation (-)	Changing planting date Irrigation

Notes: BLR: Binary logistic regression, MVP: Multivariate probit regression, MNL: Multinomial logit model.
* including Bangladesh, Indonesia, Sri Lanka, Thailand, and Vietnam
Shelton, (2014) suggested the list of potential adaptation measures in fisheries and aquaculture from several countries (Bangladesh, Nepal, Vietnam, China, Fiji, Palau, Peru, Mexico, Egypt, Guinea, Senegal, Benin, Kenya, United Republic of Tanzania, Mozambique, Lake Malawi, and mitigating the different climate change impacts (reduced yields, increased variability, reduced profitability, increased risk, and increased vulnerability for those living near rivers and coasts)

Appendix B: The correlation matrix among choice options

	Change in feeding schedule/stocking practices	Change in water exchange schedule	Water treatment	Water conservation	Early harvesting
Change in feeding schedule/stocking practices	1				
Change in water exchange schedule	-0.2608	1			
Water treatment	-0.1505	-0.2896	1		
Water conservation	-0.2223	-0.4279	-0.2469	1	
Early harvesting	-0.1461	-0.2811	-0.1622	-0.2397	1

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