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

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Abstract

As recurrent disease outbreaks impart economic adversity across the global shrimp farming sector in general, and in Asia in particular, clarifying determinants of outbreak susceptibility carries significance for sustainability in economic growth and social and environmental prospects. 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 shrimp farming industry has emerged as a vital player in meeting the increasing demand for seafood, with an estimated trade value of USD 28 billion annually (FAO, 2020). This growth is notably outpacing that of other aquaculture species, with the intensification of shrimp farming playing a pivotal role since the 1980s. Technological breakthroughs, large expected profits, and a rise in domestic and international demand have driven this intensification (Leung et al., 2000). Small-scale intensive culture characterized by high stocking density involving less than 0.5 hectares of farmland, has provided substantial production volumes (Nguyen, 2017). The participation of a large number of small-scale farmers in the shrimp value chain has led to the rapid expansion of intensive systems, contributing significantly to job creation in Asian rural regions (Phillips et al., 2016). Industrial production systems such as semi-intensive and intensive practices, introduced since the start of this millennium, have provided benefits in reducing horizontal transmission of shrimp disease and improving seed and biosecurity regimes. (Hoa et al., 2011; Hasan et al., 2020)

In 2018, Vietnam, the world's third largest producer of farmed shrimp, had a total shrimp production of 745,000 tons, with the Mekong Delta (MKD) accounting for 90% of this production (Nguyen et al., 2021). The Vietnamese government, aligning with the 2020 Master Plan for shrimp aquaculture has approved a further 190,000 hectares for industrial shrimp farming (Nguyen, 2017), aiming to achieve an aquatic product export value of about 10 billion USD by 2025. This ambitious goal and export target involves a planned transition towards more technologically advanced and intensified shrimp farm systems, which the government views as a strategy to increase output potential while strengthening adaptive capacity to increasing climate variability and extreme weather events that have become steadily more prevalent in recent decades (FAO, 2016). Nonetheless, the highest risk of loss in the shrimp industry appeared to be associated with more intensive farming practices (FAO, 2013). In addition, FAO (2020) pointed 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 is susceptible to various viral diseases[1]. Notable examples include Red body disease caused by *Taura syndrome virus*, (TSV); *White spot disease* attributed to *White spot syndrome virus* (WSD); *White feces syndrome* associated with *Hepatopancreatic parvovirus* (HPV); and *Yellow head disease* caused by *Yellow head virus* (YHV) (Thitamadee et al., 2016; Chi 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). Notably, WSD infection occurs via horizontal and vertical transmission, i.e., within or between generations (Walker & Mohan, 2009; Hoa et al., 2011). 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 Hepatopancreatic Necrosis Disease* (AHPND), or what used to be called Early Mortality Syndrome (EMS) (Tang et al., 2020). This disease initially surfaced in Asia in 2009 (FAO, 2013). AHPND results in mass mortalities (more

[1] the observed effects of *Taura syndrome virus* (TSV) and *infectious hypodermal and hematopoietic necrosis virus* (IHHNV) on WLS have markedly diminished, primarily attributed to the introduction of resilient shrimp stocks and the adoption of effective biosecurity measures (Flegel, 2012). *Decapod iridescent virus 1 (iDIV1) and IHHNV* also impact Asian shrimp but were not observed or recorded at our research sites (Flegel, 2012).

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

The Vietnamese government's 2020 Master plan for shrimp aquaculture involves a number of trade-offs that require consideration, 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). Particularly noteworthy were the large disease outbreaks in 2010, which recurred in 2015. The impact of AHPND was profound, leading to a significant 50% reduction in shrimp production from 2010 to 2011, with estimated losses surpassing $60 million (FAO, 2013; Huong et al., 2016; NACA, 2012). The estimated losses due to WSD exceeded US$ 26 and US$ 11 million in 2010 and 2015, respectively (Shinn et al., 2018). By 2015, the impact of AHPND had expanded to 23 provinces, with estimated losses reaching $97.96 million. Although production recovered by 2017 due to disease control efforts, sporadic, localized outbreaks still affect shrimp farms in specific areas (Tang et al., 2019). 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 exist connected to tracing the origins of shrimp broodstock with disease due to thousands of unregistered traders serving small-scale shrimp farmers (Tran et al., 2013).

Despite shrimp aquaculture serving as the primary income provider in the Mekong coastal areas, there has been a limited focus on Vietnamese shrimp studies that explore the critical factors influencing disease outbreaks related to farming practices and cultural techniques (Leung & Tran, 2000; Duc et al., 2015; Khiem et al., 2020; Nguyen et al., 2021). Hoa et al. (2011) reported the past spread of WSD infection in Vietnam through interviewing farmers about infected ponds across different farming systems. They found infection in enhanced extensive shrimp farms primarily resulted from the continual recurrence of WSD within the same pond across the cycle, possibly from remaining pathogens where disinfection was incomplete. In contrast, semi-intensive shrimp farms reported more cases from nearby ponds, maybe as greater water links enabled transmission (Hoa et al., 2011). Identifying infection sources and transmission pathways is central to reducing disease risk, but the reliability of such identification using farmer surveys, as applied here and in most of the literature, is questionable, and rather requires effective tracking or reporting information seldom available in developing countries. The focus of much of the disease literature has therefore been on identifying critical factors of disease outbreaks, to provide information for farmers and managers concerning relevant disease-reducing behavior and policy. Li et al. (2016) highlighted a scarcity of information concerning aquaculture farmers' knowledge and practices in disease management control measures, including their capacity to accurately diagnose shrimp disease. Researchers have emphasized the need for practical guidance for shrimp farmers that consists of improvements in production conditions, such as facility upgrades and the implementation of biosecurity measures to reduce the occurrence of diseases (Emerenciano et al., 2022; Le et al., 2022; Le & Armstrong, 2023; NACA, 2011; Subasinghe et al., 2023; Subasinghe et al., 2000).

Leung et al. (2000) posed that the risk and protective factors affecting disease outbreaks vary across different production systems and farm-specific aspects. For instance, larger pond areas and farms that discharge waste into channels of water supply were associated with higher disease occurrence in shrimp-intensive farms. In contrast, extensive farms that extracted water from the sea through canals had lower disease occurrence. However, Corsin et al. (2001) argued that closeness to estuaries or the sea can result in widely fluctuating salinity levels, often leading to an increased risk of disease risk in farmed WLS. FAO (2013) points out that southern Vietnam's colocation of semi-intensive and intensive farming systems increases the likelihood 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 WSD risk when stocking density increased. Stocking density in intensive farms is significantly higher than in extensive farms, which has been identified as an explanatory factor for disease occurrence as Tendencia et al. (2011) discovered an increased risk of WSD when stocking density was elevated. 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, such as pond drying and the practice of polyculture, decreased the likelihood of disease. Nguyen et al. (2021) argued that a combination of control measures is essential to prevent the spread of infectious diseases, with biosecurity measures playing a protective role in reducing disease occurrence. Le et al. (2022) indicated that in the context of disease management in MKD, most intensive farms take proactive measures to implement effective biosecurity. These measures adhere to recognized good aquaculture practices and are instrumental in mitigating disease risks. Farmers daily monitor disease-related parameters, such as water quality, shrimp health, and overall farm management activities.

The impact of environmental conditions on the likelihood of disease outbreaks is widely uncontested, although data in this regard is limited. These considerations have driven our study, which aims to analyze and predict disease occurrence using farm-level data from shrimp farming. Predicting disease occurrence at the farm level is crucial for effective management and intervention in the intensive shrimp farming system.

In this study, we collected primary data through a survey of 267 intensive white-leg shrimp farms conducted from Sep 2016 to August 2017 in two Vietnamese provinces, Bac Lieu and Ca Mau, located in the Mekong region, which are significant hubs for WLS shrimp production in Vietnam (Le et al., 2022; Le & Armstrong, 2023). This study had received ethics approval from the Institutional Review Board (IRB) of Nha Trang University, Vietnam. The IRB approval ensured that the research design, methods, and procedures adhere to ethical guidelines and standards, safeguarding the rights, privacy, and well-being of all survey participants involved in this study. Furthermore, the requirements given by SIKT (then the Norwegian Centre for Research Data) for data collection and storage were followed.

We employed recommended logistic regression techniques (Leung & Tran, 2000; Devi & Prasad, 2006; Tendencia et al., 2011; Duc et al., 2015; Boonyawiwat et al., 2017; Hasan et al., 2020) and extended the set of explanatory variables by incorporating farmers' perceptions of extreme climate events, such as drought, saline water intrusion, prolonged heavy rain, and water cross pollution, and their adaptive measures, which impact the probability of disease occurrence.

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, this study also seeks to provide policy input for shrimp industry management and disease control under the impacts of extreme climate events and environmental risks, supporting 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 occurrence in farms, as provided by surveyed farmers. These factors include (i) farmers’ perceptions of climatic events, (ii) adaptation measures, (iii) farmer biodata, (iv) farm site characteristics, (v) biosecurity measures, and (vi) culture method.

(2) Provide disease control policy recommendations for Vietnamese policymakers and other developing country governments aiming to boost WLS intensification growth under the effects of extreme climate events.

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). 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.

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 related 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 site 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[2] 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

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

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 was a randomized selection of individual intensive farms from the list. In addition, a "snowball" sampling method was applied (Quyen et al., 2020). Once a randomly selected farmer refused to be interviewed, we asked them to recommend another person with a similar farm. We implemented 267 shrimp farmer interviews of approximately 30–45 minutes each.

2.2 Variable selection and research hypotheses

The presence of disease was the dependent variable in this study, which was binary and recorded as farmers who experienced disease occurrence in their previous crop. Table 1 provides an overview of the independent variables categorized into the six groups of factors. Most of the collected data were in the form of (yes/no), with exceptions in the case of 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), as well as culture method variables (months of stocking, stocking density). Additional factors, including specific water parameters discussed in the literature (Corsin et al., 2005; Ruiz-Velazco et al., 2010; Tendencia et al., 2010; Yu et al., 2006) may be relevant but fell outside the scope of this study.

< INSERT TABLE 1 HERE >

Table 1 presents the six groups of explanatory variables along with the expected signs based on relevant literature findings on disease occurrence prediction (see Appendix A). We present our expectations regarding the impact of adaptive measures adopted by shrimp farmers and their perceptions of extreme climate events, such as irregular weather and drought, during their farming crop. We aim to uncover valuable insights and policy implications for climate adaptation and disease prevention in the context of shrimp farmers cultivating WLS in the face of extreme climate conditions.

2.3 Data description

Table 2 presents the 47 potential predictors selected for this study, which are categorized into six groups as shown in the table. Farmers were asked to document the presence of shrimp diseases in their most recent farming crop, which extended from September 2016 to May 2017, and this accounted for 50.2% of the sample. Regarding climate events that impacted significantly shrimp crops, most farmers identified irregular weather (41.6%) and drought (38.2%) as the most problematic. In contrast, prolonged heavy rain, saline water intrusion, and water pollution had lower reported occurrences, all below 10%. When respondents were asked about adaptive measures that they take to adapt to extreme weather events, their responses predominantly centered around dealing with drought. Therefore, this study focused on the adaptive measures that farmers employ in response to drought. The most selected measures were changes in the schedule of feeding practices, water exchange, and other treatments (e.g., use of probiotic/chemical treatment, lime application to ponds). These measures were also recognized in the findings of a study by Le et al. (2022).

The farmers' biodata offered insight into shrimp farm owners' backgrounds. On average, these farm owners had nine years of experience in shrimp farming. Their experience ranged from a minimum of one year for the youngest farmer to a maximum of thirty years for the oldest. 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 was 43, with the youngest being 21 and the oldest 76 years old.

In the Mekong area, the tradition of shrimp aquaculture is typically handed down from father to son, from one generation to the next, serving as the primary source of the family's income. A shrimp farmer often assumes the role of the family head and employs family members as workers. Among our sample, only about 54% of farmers had participated in training programs related to farming knowledge, organized by local authorities and shrimp processing companies. In contrast, 30% of farmers had benefited from extension services and were actively involved in farmer associations. Approximately 25% of the sample relied on bank credit for financial support, while most farmers invested their own capital in their shrimp business.

The number of operating years of shrimp farming ranged from one to thirty years, with an average of eight years. Seventy percent of the farms were located within the provincial planning area. The primary water source was directly from the sea, accounting for 81% of farmers. Only about 31% of farmers apply fry analysis (fry quarantine certificate of seed). Furthermore, only 40% of farmers reported cases of disease outbreak symptoms to the local authorities, as most preferred to address such situations independently, relying on their own experience and knowledge. About 50% of farming households had separate water supply and drainage systems, while more than 80% of these households had sedimentation ponds in place for water treatment before releasing shrimp seeds to grow-out ponds. The average stocking density was 68 individuals per square meter with a range from 25 to 240 shrimp per square meter. The average crop duration was 2.8 months, with variations between one to four months. In our interviews in MKD, we learned that the cultivation period of WLS was typically less than 30 days when the disease was discovered, which aligned with the observations of Nguyen et al. (2021).

< INSERT TABLE 2 HERE>

2.4. Methods

This section outlines our methodology for predicting the key factors influencing disease occurrence during climate events. We will also provide in-depth explanations of our logistic regression approach and the robustness checks we employed to ensure the accuracy and reliability of our models and estimations. An overview of the approach is depicted in Figure 1.

<INSERT FIGURE 1 HERE>

In Figure 1, we began with a total of 47 predictors extracted from aquaculture literature related to disease occurrence in shrimp farming, our research objectives, and typical shrimp farming practices in the Mekong region. A comprehensive list of these 47 predictors can be reviewed in Table 1, marking the initiation of our data management process. The second step involved variable selection in Figure 1, where we randomly divided the entire sample of 267 observations into two subsets: a training set (80% - 215 observations) and a testing set (20% - 52 observations). We employed the training set to identify potential predictors associated with planning disease occurrence, while the testing set served to validate the model's performance.

Working with as many as 47 predictors can lead to complex predictive models that may introduce redundancies concerning disease occurrence. Redundant variables will provide lower predictive power and model reliability (Hall & Holmes, 2003). Therefore, we applied techniques aimed at constraining the coefficients, such as stepwise procedure and regularization in the logistic regression model. This was done to enhance prediction accuracy and model interpretability, ensuring the best fit for our dataset. The next subsections, including logistic regression, logistic regression with subset selection, and Regularization, provide brief introductions to each approach with the objective of variable selection (step 2). We aim to underscore the main differences and the computational advantages among the employed techniques for identifying the best predictors explaining the likelihood of disease occurrence.

Logistic regression

Logistic regression is an often-used method to assess critical factors affecting disease in shrimp farming, often complemented by other models for robustness checks (see Table A1- Appendix).

P is the probability that the outcome will occur. We predict the log odds of disease occurrence as follows:

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

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). Taking the exponentiation of the coefficients gives the odds ratio. A value greater than 1 signifies that a factor increases the odds of disease, while a value less than 1 indicates that a factor reduces the odds. We then use the maximum-likelihood method from the Hosmer and Lemeshow goodness-of-fit test to estimate the coefficients $\beta_1\ldots\beta_n$(Hosmer et al., 2013). 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).

The backward stepwise procedure is usually preferred as the forward stepwise approach could potentially eliminate important variables (Leung & Tran, 2000; Alapide-Tendencia, 2012). 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 selection of the single best model for predicting disease occurrence, whether through forward or backward stepwise regression, involves evaluating cross-validated prediction error, negative log-likelihood value, equivalently largest adjusted R squared[3] as well as AIC, and BIC values.

We applied the Ridge, Elastic Net, and Lasso logistic regression on the testing set to compare predicted outcomes and actual outcomes (see Table A3 – Appendix). The accuracy of these predictions, indicating whether disease occurred or not, measures the model's performance. Once potential variables were identified via subsection and regularization, we further examined the results of the fitted logistic regression model. Statistically significant variables were selected if the p-value was less than 10%.

In general, this variable selection step contributes to determining the signs and degree of possible variables' association with disease occurrence. In addition, as part of our 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).

3. RESULTS

3.1 Results of backward logistic regression

Our analysis, as detailed in Table 3, reveals that the Lasso regression gives the best-fit model with the lowest value of the AIC (82.04) and the highest accuracy classification in testing data (75%) compared to other logistic regressions with subset selection approaches. In contrast, the backward logistic regression had the same level of prediction accuracy (75%) but a higher AIC value (237.11) compared to the Lasso regression. While both models performed well on predictive accuracy, backward logistic regression identified a subset of predictors generating accuracy on par with the more complex Lasso specification. This balance between explanatory

[3] 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.

power and simplicity justified emphasis on the backward logistic regression method, even with slightly weaker fit statistics. We therefore opted for backward logistic regression, prioritizing its superior balance between prediction accuracy and model simplicity.

<INSERT TABLE 3 HERE>

Table 3 displays the model performance measure for the full set of logistic regression methods utilized, including the backward stepwise logistic approach ultimately selected. As depicted in Figure 1, backward regression identified an optimal subset of 13 key variables with p-values lower than a 10% significance level. Table 4 presents the detailed output for disease predictors selected through the backward logistic regression. Out of those thirteen variables, nine exhibited p-values below 5% significance, confirming a robust association with disease occurrence likelihood. The odds ratio serves as a measure of the expected shift in the odds of farms experiencing disease for each one-unit change in an independent variable, holding other variables constant. An odds ratio above one indicates an increase in disease odds, while below one signifies reduced odds.

There were notable risk-increasing factors associated with shrimp disease probability. They were longer crop duration, increased years in operation, higher levels of farmer education, and application of other measures related to pond management. For example, regarding years in operation, the odds ratio is 1.581. This means for each additional year of operation; the disease probability increases by 58.11%.

In addition, prominent protective factors, leading to reduced disease odds, include changes in feeding practices, training participation, extension services, regular feed conversion ratio calculations, and stocking. For example, regarding training participation, the odds ratio is 0.345. This means that for one unit increase in training participation (going from 0 training to 1 training), the probability of disease occurrence is expected to decrease by 34.55%. These patterns help us understand the conditions and practices that either reduce or increase the disease probability.

< INSERT TABLE 4 HERE>

3.2 Robustness checks

Several additional logistic regression models were run to evaluate the robustness of the results from the backward stepwise method. Comparing key predictors across models provides a check on whether the findings are sensitive or consistent (Leung & Tran 2000). We found general agreement regarding the direction of effects for important variables like extension services and regular feed conversion ratio calculations, education, training participation, crop duration, and stocking density.

In addition, in the Bayesian and BIC stepwise models (Table A2 in Appendix), two factors - years in operation and changes in feeding schedules - were no longer significantly associated with disease occurrence, unlike in the backward logistic regression. This indicates a slight variability between models regarding which indicators retain statistical significance. However, the signs of the coefficients for the most relevant variables persisted across specifications, underscoring robustness.

The Lasso model (Table A3 in Appendix) retained most of the mentioned predictors (e.g., training participation, extension service, education, crop duration, stocking density) but not changes in the schedule of feeding practices, as prominent. Adaptive measures were still negative, suggesting a protective tendency. The appearance of years in operation instead of separate water supply/drainage systems and other adaptive measures rather than a change in feeding schedules demonstrated slight variability in retained variables. While the magnitude and precision of estimates shifted, the signs of the coefficients for the most significant variables persisted across Ridge, Lasso, and Elastic Net approaches. This indicates a degree of parameter estimate stability and generalizability of the backward logistic regression results regarding the direction of effects, indicating robustness in estimation. However, continued expansion and sensitivity testing of disease predictor models are demanded to account for additional farm-level complexities. For instance, future data collection could assess interactive effects between stocking density, adaptive behaviors, and local climate fluctuations. Such model refinements would strengthen causal attribution and strategic precision regarding influential disease drivers across diverse shrimp operating contexts.

4. DISCUSSION

Our backward logistic regression model demonstrated 75% accuracy in correctly classifying disease outcomes on the testing data. This signals that it can differentiate well between disease presence and absence.

The research findings revealed the determinants that reduce and increase the chance of shrimp disease occurrence. Hence, we identified several protective factors that significantly negatively impact the likelihood of disease occurrence. Training participation, extension services, regular FCR calculations, and stocking density contributed 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 crop duration (number of stocking months), applying other measures for daily pond management, years in operation, and education. These will be discussed in the following subsections.

4.1 Protective factors

In the following, we listed seven factors that influenced disease occurrence in Vietnamese WLS farming. First, regarding self-adaptive measures taken by shrimp farmers, we found that changing the feeding practices schedule, which includes feeding amounts, input, and timing, was significantly associated with a lower chance of disease outbreaks. This finding aligns with Abdelrahman et al. (2019) who pointed out that prolonged drought can impact pond water temperature, resulting in reduced survival and shrimp weight. Adjusting feeding schedules including reducing feed inputs, can help mitigate the effects of pond water pollution and the potential for shrimp disease.

In the case of shrimp mortality caused by extreme drought, prompt measures such as reducing or stopping feeding[4] the shrimp in grow-out ponds, supplementing shrimp feed with vitamin C and minerals, and adhering to prescribed feeding guidelines, can increase shrimp recovery and health. It is essential to note that the adjustment of feed input aims at managing the impact of water conditions while supplementing shrimp feed with essential nutrients is crucial for supporting shrimp health during extreme drought. Furthermore, Mekong farmers were legally required to report disease status and seek technical guidance from local authorities or farmers' groups to effectively address and prevent potential issues.

Though we failed to obtain statistically significant results for other adaptive measures in backward logistic analysis, it is worth noting that their direction was negative, as expected. The other adaptation measures involved using chemicals (i.e., chlorine, lime application) for pond treatment and reducing algal growth[5]. In addition, farmers employed techniques such as pumping microbial products from sediment ponds to stabilize pH and prevent algal blooms, and aeration to ensure sufficient oxygen amounts at the pond bottom. These responses were essential for coping with drought and reducing the likelihood of disease outbreaks in Mekong shrimp farming.

Second, we identified that carrying out feed conversion ratio calculations (biosecurity measures) significantly lowered the chance of shrimp disease. The feed conversion ratio is a measure of how efficiently the shrimp converts the feed they consume into biomass. This suggests that careful and efficient feed calculation, which reduces feed redundancy in grow-out ponds, can contribute to disease occurrence control. It helps to reduce feed waste in the surrounding environment of intensive farms, contributing to better biosecurity practices. The

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

[5] 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.

significance of this finding was supported by Corsin et al. (2001), indicating that higher feed amounts were associated with an increased risk of introducing WSD into Vietnamese shrimp ponds. Therefore, engaging in feed calculations is a proactive measure that contributes to maintaining healthier pond conditions with lower pollution levels, resulting in reduced shrimp disease occurrence.

Third, farmers' participation in training courses (e.g., lectures, workshops, field trips) organized by local government, non-profit organizations, and processing companies significantly lowered the likelihood of shrimp disease. Such training courses can enhance farmers' awareness of environmental impacts on their farms and surrounding communities. Nguyen (2017) emphasized that training should focus on disease prevention and aquaculture production. When shrimp disease outbreaks occur, the costs incurred by farmers, local governments, and even communities for disease management and control may be substantial. Suitable training programs can empower shrimp farmers with knowledge and skills to cope effectively with climate and environmental impacts. They can promote responsible actions concerning protecting shared water sources, thereby mitigating severe environmental impacts.

Fourth, increasing extension services through technical support including visits from local government, input suppliers, and processing companies, had a significant impact on reducing the likelihood of shrimp disease. For instance, when farmers report shrimp disease to the local government, they receive free supplies of chemicals for water treatment. In addition, the local governments' extension service can provide water sample analysis at local laboratories, enabling the identification of disease risks and specific disease types that farmers may face. Technical visits as part of extension services can include guidance on designing farming infrastructure and providing support for the operation of intensive production systems. This information related to shrimp farming technology can help improve the biosecurity system and farming environment, resulting in more effective disease prevention and ultimately reducing the chance of shrimp disease outbreaks.

Lastly, we found that the stocking density had a noteworthy impact on the likelihood of disease. It is important to note that we observed that the higher the stocking density, above the average of 68 individuals per square meter, the lower the chance of disease, which may appear counterintuitive. Though Tendencia et al. (2011) also found that stocking density was negatively correlated with shrimp disease, these findings require a more detailed explanation. One possible explanation is the management practices adopted by intensive farms in our sample. These farmers may employ advanced technology such as multi-phasic integrated intensive shrimp production systems and recirculation aquaculture systems. Technological innovations, e.g., the implementation of biofloc systems, have become increasingly prevalent. In our sample, we observed farms implementing robust biosecurity measures and sustained high stocking density without a significantly increased disease risk. Though intensified density can exacerbate or boost waste accumulation challenges (Tendencia et al., 2011), our findings imply that certain advanced practices may mitigate these disease issues. Farms utilizing super-intensive technology and expertise may represent the subset applying higher density. Therefore, advanced methods providing resilience, or lower disease likelihood, may also stem from broader operational capabilities allowing farmers to intensify responsibly. Further research controlling for farm complexity should consider separating the true impact of production intensity on health parameters.

4.2 Risk factors

Several risk factors increase the chance of shrimp disease outbreaks. These factors include crop duration, other pond management activities, education level, and years in operation. Extensive use of land for shrimp farming as found in intensive farms, combined with longer crop duration, can lead to soil deterioration, reduced nutrient levels, and pollutant contamination, all contributing to increased disease risk. More surprisingly, adopting other pond management activities and higher levels of schooling, significantly increase the likelihood of disease while individuals with an average of only 8 years of education tend to have a relatively low risk of disease. We found that experience and education are negatively correlated in our data, suggesting that less educated farmers tend to have a lower likelihood of disease. Mekong farmers have traditionally carried out their business based on experience passed on from father to son (Le et al., 2022). Most farmers have developed their management skills through a 'learning by doing' approach (Duy et al., 2021). Shrimp farmers concerned with disease risk to their farm profitability have a history of undertaking more disease risk management (Lebel et al 2021), seemingly taking proactive measures based on hands-on experience in disease prevention.

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 aimed at growth enhancement might inadvertently increase the susceptibility to diseases. Pond management strategies include various aspects, such as implementing pond preparation, creating a secure rearing environment through chemical treatment to prevent infections, or implementing pond renovation. Furthermore, disease control in shrimp farming necessitates attention to diverse aspects, from selecting seed sources for nursery ponds to executing harvesting processes. In the study of Nguyen et al. (2021), several risk factors associated with shrimp farming disease were identified, such as the ownership of settling ponds, sun-drying ponds exceeding 62 days, and the introduction of stock from multiple suppliers into grow-out ponds.

5. CONCLUSIONS AND FUTURE RESEARCH

This study identified key protective and risk factors that significantly impact the probability of disease occurrence in intensive shrimp farms. Key focal points for reducing the probability of disease occurrence included increasing farmers' adaptive measures (e.g., adjustment of feeding schedules) on their farms, increasing farmers' participation in training programs, and the provision of extension services. Such approaches help control the carrying capacity in ponds or manage the usage of feed inputs.

Our findings can inform regulatory and policymaking efforts in shrimp disease management for intensive farms, further boosting shrimp production with intensification in the Mekong area. By collecting information/data from farmers in the region, local authorities can develop a toolbox that integrates the various approaches and model testing, potentially providing more comprehensive forecasts than the farmers can carry out independently.

Last but not least, our results underscore the critical management roles of farm owners and workers on each farm. They play a key role in managing and identifying the likelihood of disease occurrence. Therefore, collecting farm-level input data is invaluable, 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. These actions can provide early warnings and alerts to farms, timely preventing or mitigating disease outbreaks.

Future research could be enriched by exploring further infection sources and transmission pathway elements combined with risk factors and preventive behaviors. Although the current study faced limitations due to data constraints and relied solely on available survey data, we acknowledge the value of a more comprehensive investigation that integrates these variables with water quality and climate change indicators over time. Such insight could significantly enhance our understanding of disease management strategies in the WLS shrimp business. A larger data sample would also improve model performance and enable advanced analysis using other advanced machine-learning techniques.

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	267 respondents analyzed	

Data management:		Result:
Step 1: Data description	The expected sign in specific sets of explanatory factors	Table 1
	47 Potential predictors were grouped into six groups	Table 2

Step 2: Variable selection and Data analysis[1]	(1) Splitting the dataset into two subsets	Results:
- Logistic regression with:	(Training set: 80% of observations, testing set: 20% of observations)	Table A2 (Appendix)
(1) Subset selection	(2) Applying backward and forward logistic regression.	
(2) Regularized approaches	Remove predictors > 10% significance level.	Table A3
	(3) Applying Ridge, Elastic Net, and Lasso logistic regressions	(Appendix)

Step 3: Results		Result:
Model performance:	13 predictors were selected from Shrinkage estimation.	Table A3
- AIC/BIC values		(Appendix)
- Model prediction accuracy in testing data - Robustness checks	Bayesian logistic regression, and stepwise regression using BIC for the robustness check, confirmed the 9 suggested predictors.	Table 3 Table A2 (Appendix)
- Backward Logistic regression	9 predictors were found from backward Logistic regression.	Table 4

FIGURE 1: Overview of research methods

Notes: AIC: Akaike information criterion. R Studio was employed for the analysis in this study.

[1] Subset selection and regularization approaches were utilized to prevent overfitting and underfitting in model estimation. Backward stepwise logistic regression with a likelihood ratio test removed the least contributing factors sequentially to obtain the minimum Log-likelihood. Forward stepwise regression incrementally added significant predictors. Ridge, Elastic Net, and Lasso regressions on the testing data compared predicted to actual outcomes (see Table A3). Bayesian logistic regression and BIC stepwise regression provided robustness checks (see Table A2).

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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.

TABLE 2: Characteristics of Survey Respondents and Potential Explanatory Variables for Disease Occurrence (Observations: 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	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					
	Use of feeding tray/ siphon activity to check feed consumption	Yes =1, no = 0	0.959	0.199	0	1
	Regular Feed Conversion Ratio calculations	Yes =1, no = 0	0.345	0.476	0	1
	Regular operating cost analysis	Yes =1, no = 0	0.588	0.493	0	1
	Other feed monitoring measures	Yes =1, no = 0	0.022	0.148	0	1
	Daily monitoring of water quality parameters	Yes =1, no = 0	0.985	0.122	0	1
	Daily monitoring of checking sediment condition	Yes =1, no = 0	0.678	0.468	0	1
	Daily monitoring of checking water of influent and effluent waters	Yes =1, no = 0	0.491	0.501	0	1
	Daily monitoring of water quality parameters	Yes =1, no = 0	0.846	0.361	0	1
	Daily monitoring of stock survival	Yes =1, no = 0	0.884	0.321	0	1
	Daily monitoring of shrimp behavior	Yes =1, no = 0	0.978	0.148	0	1
	On-farm and off-farm shrimp health check when disease occurred	Yes =1, no = 0	0.566	0.497	0	1
	Other pond management activities	Yes =1, no = 0	0.243	0.430	0	1
	Seed sourced from a well-known seed company	Yes =1, no = 0	0.914	0.281	0	1
	Pond renovation and other costs	Yes =1, no = 0	0.607	0.489	0	1
	Break for minimum 30 days between crops	Yes =1, no = 0	0.828	0.378	0	1
	Fry analysis (quarantine certificate of seed following regulations)	Yes =1, no = 0	0.311	0.464	0	1
	Report disease outbreak to the nearest aquaculture or veterinary authority	Yes =1, no = 0	0.408	0.492	0	1
	Separate water supply/drainage system	Yes =1, no = 0	0.502	0.501	0	1
	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.

TABLE 3: The model accuracy and AIC indicators for various logistic regression.

	Forward stepwise regression	Backward stepwise regression	Lasso logistic regression	Ridge logistic regression	Elastic Net logistic regression	Stepwise regression using BIC	Bayesian logistic regression, stepwise
Corrected accuracy (%)	0.75	0.75	0.75	0.69	0.73	0.73	0.75
AIC	285.74	237.11	82.04	147.57	87.39	241.12	238.17

TABLE 4: Results of fitted backward logistic regression model for intensive shrimp farms (N=215 observations)

	Odds ratio	Estimate (log-odds)	S.E.	P-value
(Intercept)	0.012	-4.368	4.293	0.309
Adaptive measures to drought				
Change in the schedule of feeding practices	0.370	-0.995*	0.569	0.080
Other adaptive measures	0.448	-0.804	0.557	0.149
Farmer biodata				
The farmer's age	3.885	1.357	0.860	0.115
Education	2.075	0.730**	0.363	0.044
Training participation	0.345	-1.065**	0.420	0.011
Extension services	0.319	-1.143**	0.447	0.011
Farm site characteristics				
Years in operation	1.581	0.458*	0.252	0.069
Biosecurity measures				
Regular Feed Conversion Ratio calculations	0.378	-0.973**	0.438	0.026
Other cost-monitoring measures	0.000	-15.368	831.032	0.985
Other pond management activities	2.651	0.975*	0.497	0.050
Report disease outbreak to the nearest aquaculture or veterinary authority	1.978	0.682	0.449	0.129
Culture method				
Duration of crop	18.029	2.892***	0.633	0.000
Stocking density	0.260	-1.346**	0.560	0.016
AIC		237.11		
Corrected accuracy (%) in the testing set		0.75		

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

Notes: Odds ratio = exp(log-odds). The odds ratio shows the change in odds of disease occurrence for a 1-unit increase in that predictor variable. The further below 1 the odds ratio is, the more protective the factor is against disease. The further above 1 it is, the more the factor increases disease risk. Factors that exhibit a statistically significant negative association reduce disease risk, i.e., the odds ratio is less than 1, while a statistically significant positive association increases disease risk, i.e. the odds ratio is greater than 1 (Leung et al., 2000).