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Article

Investigating the Relationship between Aquaculture Investments, Training, and Environmental Factors in Guangdong: An Alternative Perspective

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Abstract: This study investigates the interplay between investment, training, and environmental factors in the aquaculture industry in the Guangdong region of China. Using NIPALS regression to address multicollinearity, we identify the factors that significantly impact losses of aquaculture products due to environmental factors. Our findings highlight the importance of targeted training and education for fisherfolks and extension staff to enhance environmental management practices and reduce losses. We also emphasize the need to consider regional variability and challenges in developing universal models. Based on our results, we propose using innovative technology, fostering public–private partnerships, and adapting to regional variability to address environmental challenges. Finally, we suggest establishing a comprehensive monitoring and evaluation system to assess the effectiveness of interventions and promote evidence-based decision-making for sustainable development in the region's aquaculture sector.

Keywords: aquaculture economy; education for fisherfolk; nonlinear iterative partial least squares

Key Contribution: This article contributes to a better understanding of the complex relationships between investment, training, and environmental factors in the aquaculture industry in the Guangdong region of China. The study identifies the key factors that influence losses of aquaculture products due to environmental factors and proposes targeted interventions to promote sustainable development in the region's aquaculture sector.

Citation: Wang, P.; Mendes, I.; Franić, R. Investigating the Relationship between Aquaculture Investments, Training, and Environmental Factors in Guangdong: An Alternative Perspective. *Fishes* **2023**, *8*, 237. https://doi.org/10.3390/fishes8050237

Academic Editor: Ben Drakeford

Received: 28 March 2023
Revised: 22 April 2023
Accepted: 28 April 2023
Published: 1 May 2023

1. Introduction

China is a major player in the global aquaculture industry and its seafood production has grown significantly in recent years [1]. China's sustained process of accelerated economic growth and urbanization has brought tremendous opportunities as well as new challenges to agriculture and rural society [2]. While China's economic growth has brought many benefits to the country, it has also led to a number of challenges that need to be addressed in order to ensure the sustainable development of the agriculture and fishing sectors. New concerns have emerged in various areas such as food safety and agricultural surface pollution [3]. However, the country's rapid economic growth and urbanization have also brought challenges. Overfishing is a critical issue that must be addressed to avoid negative impacts on marine ecosystems and biodiversity. In addition, there have been concerns about the use of illegal, unregulated, and unreported (IUU) fishing practices, which can lead to overfishing and undermine the sustainability of marine resources [4].

Science and technology (S&T) have become increasingly relevant for the management and economic development of China's marine resources, particularly in the aquaculture industry [5]. The development of new technologies has allowed for a greater understanding of the oceans and their ecosystems, as well as more efficient and sustainable ways to harvest marine resources. In recent decades, the development of technology has been proceeding at a rapid pace, with science opening new possibilities and technology enabling a higher level of human activity in the oceans [6]. For example, satellite technology to track and monitor fishing vessels is now being used to prevent overfishing and ensure that fishing is carried out in a sustainable manner [7]. Advances in aquaculture techniques have been a key area of focus in S&T, as they have the potential to improve the efficiency and sustainability of seafood production [8]. Recirculating Aquaculture Systems (RAS) is an example of such a technique, which is a closed-loop system that recycles water and uses advanced filtration methods to maintain optimal water quality for the fish [9]. This reduces the need for large amounts of water and can be performed in controlled environments, such as indoors or on land, making it less dependent on natural conditions [10]. Another example is Integrated Multi-Trophic Aquaculture (IMTA), a unique method of aquaculture that involves cultivating different species of fish, shellfish, and seaweed together in a symbiotic relationship. Unlike aquaponics, which typically only involves the cultivation of fish and plants, IMTA also incorporates the cultivation of shellfish and seaweed, and the waste produced by each species is used to sustain the others in a closed-loop system [11]. This helps to reduce the environmental impact of aquaculture and can increase production efficiency. Selective breeding, fish vaccination, and bio floc technology are other examples of advances in aquaculture techniques that have been developed in recent years and have the potential to improve the efficiency and sustainability of seafood production [12].

In December 2021, the Ministry of Agriculture released the 14th Five-Year Plan for Fishery Science and Technology Development, which proposes to further improve the level of aquaculture science and technology by 2035, with the contribution rate of scientific and technological progress in aquaculture reaching up to 67%. The national aquaculture germplasm resources protection and utilization system will be initially established, a number of new aquatic species will be cultivated, and the self-sufficiency rate of core seed sources would reach 80%. The mechanization rate of aquaculture has reached more than 50%. This has included support for technology development and innovation, as well as the establishment of research centres and institutes to study various aspects of these industries. The government has also implemented a number of policies and measures to promote the development of the fishery and aquaculture sectors, including tax incentives, financial subsidies, and other forms of support [13]. These efforts have helped to drive the growth of these industries in recent years and have contributed to the modernization and upgrading of the industry as a whole. Overall, the incorporation of the fishery and aquaculture industries into China's national development strategy reflects the importance of these sectors to the country's economy and food security; it also underscores the government's commitment to supporting their growth and development. The status of S&T investments in aquaculture directly affects the development of China's aquaculture industry, aquatic environmental management, and extreme environmental prevention. Meanwhile education and training improve the skills and productivity of farmers and fisherfolk; this is a point that cannot be overlooked, as the education and training of fisherfolk also plays a very important part in S&T [14].

Agricultural S&T investments is an important contributor to productivity growth and is a fundamental factor for sustained economic growth. It is well-established that investments in science and technology (S&T) can have a significant impact on the agricultural sector and the overall economy [15]. Therefore, it is extremely important to analyse whether the S&T of Chinese aquaculture in the past 10 years has contributed to the improvement of the aquaculture products production environment. S&T investments can help to increase agricultural productivity and efficiency, leading to higher crop yields and livestock production [16]. In turn, S&T investments can help to improve food security, reduce poverty, and contribute to economic growth [15]. Through the direct effect of agricultural S&T investments on the agricultural economy or socioeconomic growth, it has been discovered that agricultural S&T investments have a strong impact on food production, with a stronger positive interaction response and a more significant and stable response in the long run [16–20]. Deng's research [17] found that although China's agricultural S&T investments have become a decisive influencing factor of agricultural economic growth, there are still problems such as insufficient scale and intensity, unbalanced regional inputs, unreasonable resource allocation, and inefficient utilization remain [17]. Additionally, from the analysis of the relationship between China's agricultural S&T investments and effects, Song's study showed that the value added of agricultural products and government inputs are inextricably connected [18]. These studies are sufficient to prove that S&T investments are important for the sustained growth of China's economy. Nordhaus' study also found interactions between marine economic systems, marine environmental systems, and carbon cycle systems; furthermore, S&T investments have been detected to mitigate the impact of economic activities on the marine environment [19]. Holdren's study demonstrates that technological progress has also been demonstrated to increase productivity and reduce marine resource consumption and environmental impacts [20]. An important point in promoting aquaculture S&T investments is to transmit effective information and knowledge about scientific farming to the fisherfolk. There are many scholars who have demonstrated that increased education and training of farmers can be effective in increasing the productivity of agricultural products [21–23]. Kirtti analysed the impact of education on agricultural productivity in India and found that education and agricultural productivity have a direct impact [21]. Sharada analysed the effects of education on farmer productivity in rural Ethiopia, showing that there may be considerable opportunities to exploit the externalities of schooling to increase agricultural productivity if school enrolment increases in rural areas [22]. Abdulai's study's analysis of data from a survey of 342 rice farmers in northern Ghana showed that farmers' education can significantly increase rice yields and net returns [23].

China is a vast country with diverse regional characteristics, and studying a particular region can provide unique insights into the relationship between aquaculture investments, training, and environmental factors [3]. In this study, we focus on the Guangdong region, which is a significant producer of both freshwater and marine aquaculture products [24]. Guangdong's aquaculture industry is known for its advanced and diverse techniques, making it an interesting case study for exploring the relationship between investments, training, education, and environmental factors [25]. Moreover, Guangdong's coastal location and its proximity to major urban centres, such as Guangzhou and Shenzhen, make it an ideal case study for examining the impact of S&T investments on the aquaculture sector [26]. In the past decade, China has made significant S&T investments in the agricultural sector, and it is important to analyse whether these investments have contributed to improving aquaculture production and environmental management in the Guangdong region [5]. Previous studies have shown that S&T investments can increase agricultural productivity [27–29], improve food security, reduce poverty, and contribute to economic growth. However, challenges such as insufficient scale and intensity, unbalanced regional inputs, unreasonable resource allocation, and inefficient utilization remain in the agricultural sector [30]. Therefore, it is critical to examine how S&T investments have affected the aquaculture industry in the Guangdong region and explore the factors that may influence the effectiveness of such investments. In addition to S&T investments, education and training of fisherfolk are also important factors that can enhance aquaculture productivity and reduce losses caused by environmental factors. Previous studies have shown that increased education and training of farmers can be effective in increasing the productivity of agricultural products [21–23]. Therefore, in this study, we will investigate how education and training programs for fisherfolk, and extension staff may contribute to improved aquaculture practices and reduced losses caused by environmental factors in the Guangdong region. Overall, this study aims to provide an alternative perspective on the relationship between aquaculture investments, training, and environmental factors in the Guangdong region, and to offer insights into the factors that may influence the effectiveness of S&T investments and education and training programs in the aquaculture sector.

The hypotheses presented in this study were developed based on a review of the existing literature on aquaculture investments, training, education, and environmental factors. In particular, we drew on studies that have investigated the relationship between these variables in various contexts.

To adapt these findings to the Guangdong context, we conducted a thorough review of the available data on aquaculture production, environmental conditions, and education and training programs in Guangdong. Through this process, we identified two key hypotheses that we believe are relevant to understanding the relationship between aquaculture investments, training, education, and environmental factors in Guangdong. These hypotheses suggest that increased investments in staff funds and operating funds, enhanced training and education programs, and regional factors such as government policies and resource allocation are all important determinants of environmental management and losses due to environmental factors in Guangdong's aquaculture industry.

Hypothesis 1 (H1). *Increased investments in staff funds (SF) and operating funds (OF) in the Guangdong region's aquaculture sector will lead to better environmental management practices, resulting in a reduction of losses caused by environmental factors. This hypothesis assumes that increased financial support for the aquaculture industry will result in better environmental management practices, leading to reduced losses due to environmental factors. The focus will be on understanding how investments in staff funds and operating funds can be used to improve environmental management practices and the potential benefits that these investments can bring to industry in Guangdong.*

Hypothesis 2 (H2). *Enhanced training and education of fisherfolks and extension staff in the Guangdong region will lead to improved aquaculture practices, resulting in a decrease in losses caused by environmental factors. This hypothesis assumes that improved training and education of fisherfolks and extension staff will result in better aquaculture practices, leading to a reduction of losses due to environmental factors. The focus will be on identifying the most effective training and education methods for fisherfolks and extension staff in Guangdong and examining how these methods can be used to improve aquaculture practices.*

Overall, these hypotheses aim to explore the relationship between investments, training, and environmental factors in the aquaculture industry of the Guangdong region. By examining these relationships, the study aims to provide insights into how these factors can be leveraged to improve environmental management practices and reduce losses caused by environmental factors.

2. Materials and Methods

2.1. Introduction of the NIPALS Algorithm

The NIPALS (Nonlinear Iterative Partial Least Squares) algorithm is a multivariate statistical technique used to build predictive models. It is similar to principal component regression (PCR) and multiple linear regression (MLR) [31], but it can handle multicollinearity, nonlinear relationships, and high dimensional data better than these other methods. The NIPALS (Nonlinear Iterative Partial Least Squares) algorithm commences with a leave-one-out validation method to select the factor with the least mean predicted sum of squares of residuals (PRESS). This method is based on the van der Voet test (T^2), a randomization test that compares the residuals of the predicted series with different models and selects the number of factors with the lowest residuals that are not significantly larger than the residuals of the model with the minimum PRESS [32]. Compared to other decompositions of the covariance technique, this multivariate analysis method was used because of its numerical accuracy in terms of results and predictions. It is often used in a variety of fields, including chemistry, engineering, and economics, to build predictive models and understand the underlying relationships between variables [33,34]. During model estimation, both the original data variables [X (predictor variable) and Y (response)] are preprocessed with zero mean and standard deviation of 1 (hence, scale and cantered). This transformation addresses potential problems with unit roots among the variables.

2.2. Data Set and Variables

The study employs time series variables from China Fisheries Statistical Yearbook 2012–2022 [35], which covers the period 2011–2021. This paper covers only the Guangdong region. The red area in Figure 1 shows the geographical location of the Guangzhou region in China, similar to the study area of this study. The variables include loss of aquaculture products by environmental factors, funds for staff engaged in aquaculture, operating funds related to aquaculture, technical training for fisherfolk, operational training for aquaculture science and technology extension staff, practitioners in aquaculture research institutions, and aquaculture financial allocation. Table 1 contains information on how the variables are measured.

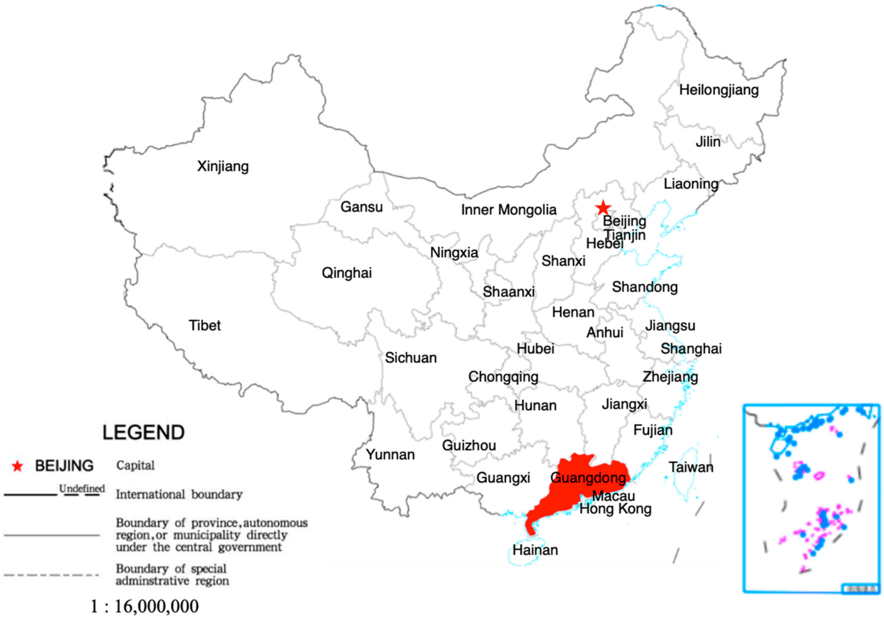

Figure 1. Location of the Guangdong region in China. (The map of China was generated by the standard map online service; URL link: http://bzdt.ch.mnr.gov.cn (accessed on 21 April 2023)).

Table 1. Variable definition.

Indicator Name	Indicator Code	Unit
Loss of aquaculture products by environmental factors in Guangdong region	ALGD	Tons
Funds for staff engaged in aquaculture in Guangdong region	SFGD	Million yuan
Operating funds related to aquaculture in Guangdong region	OFGD	Million yuan
Technical training for fisherfolk in Guangdong region	TFGD	People per training session
Operational training for aquatic science and technology extension staff in Guangdong region	TPGD	People per training session
Practitioners in aquaculture research institutions in Guangdong region	FOEGD	Population
Aquaculture financial allocation in Guangdong region	FAGD	Million yuan

Source: China Fisheries Statistical Yearbook 2012 to China Fisheries Statistical Yearbook 2022.

In ALGD (loss of aquaculture products by environmental factors in the Guangdong region), environmental factors include loss of aquaculture products affected by typhoons and flooding, loss of aquaculture products affected by diseases, loss of aquaculture products affected by droughts, loss of aquaculture products affected by pollution, and loss of aquaculture products affected by environmental factors other than typhoons, floods, disease, drought, and pollution. Due to limitations in data acquisition, the study only covers aquaculture and fisherfolk engaged in aquaculture production in the Guangdong region. All the statistical analysis in this study was performed using SAS JMP Pro16 software (SAS Institute Inc., Cary, NC, USA). This software was used for data exploration, visualization, and statistical analysis.

2.3. Analysis of Data

This study models the loss of aquaculture products by environmental factors as a function of fund for staff engaged in aquaculture, operating funds related to aquaculture, technical training for fisherfolk, operational training for aquaculture science and technology extension staff, and practitioners in aquaculture research institutions aquaculture financial allocation. Mathematically, this is depicted in Equation (1).

$$\mathrm{ALGD}_t = \beta_0 + \beta_1\mathrm{SFGD}_t + \beta_2\mathrm{OFGD}_t + \beta_3\mathrm{TFGD}_t + \beta_4\mathrm{TPGD}_t + \beta_5\mathrm{FOEGD}_t + \beta_6\mathrm{FAGD}_t + \varepsilon_t \quad (1)$$

where β_0 represents the constant, β_1, ..., β_6 denote the coefficients of the independent variables in year t, and ε designates the error term.

The model in this study is based on Song's model [18]. In Song's model, the number of agricultural research staff, operating funds related to agriculture, and funds for staff engaged in agriculture were included. We made improvements based on this model, and in this study, funds for staff engaged in aquaculture and operating funds related to aquaculture were retained. We also added variables for educational orientation, such as technical training for fisherfolk and operational training for aquaculture science and technology extension staff and practitioners in aquaculture research institutions. SFGD (funds for staff engaged in aquaculture in the Guangdong region), OFGD (operating funds related to aquaculture in the Guangdong region), and FAGD (aquaculture financial allocation in the Guangdong region) are the investment components of aquaculture S&T, because the S&T investment is one of the important indicators reflecting the aquaculture S&T section, and sufficient funding is also an important source to bring into play in the dynamics of research. The role of aquaculture researchers is not simply to conduct scientific research, as scientific research necessarily confronts the further deepening of economic reform, an increasing number of researchers are simultaneously engaged in the promotion of scientific and technological achievements and technologies, which require a large amount of funds to support, through the three types of investments chosen, the verification of Hypothesis (H1) of the study. Subsequently, TFGD (Technical training for fisherfolk in the Guangdong region), TPGD (Operational training for aquaculture science and technology extension staff in the Guangdong region), and FOEGD (Practitioners in aquaculture in the Guangdong region) were selected as the educational component of the study of aquaculture S&T to validate Hypothesis (H2). In contrast to the current empirical literature, this study performed an initial statistical test about the relevance of each regressor before proceeding to the final model estimation. Through this approach, the present study provides an explicit way to handle the problem of multicollinearity.

Table 2 shows the OLS estimates of the loss of aquaculture products by environmental factors. It shows a multiple regression model to explore the relationship between six predictor variables (SFGD, OFGD, TFGD, TPGD, ALGD, and FOEGD) and a single dependent variable (ALGD). Although the F-test for the model was statistically significant (Prob > F = 0.0054 *), further analysis of the t-values and associated p-values revealed that SFGD, OFGD, TFGD, and FOEGD did not have statistically significant effects on the dependent variable. However, we found that TPGD and ALGD had statistically significant effects on the dependent variable, with a one-unit increase in TPGD associated with an increase of 11.144931 and a one-unit increase in ALGD associated with an increase of 0.1373072 in the dependent variable, holding all other predictors constant.

Table 2. Results of the linear regression model.

Term	Estimate	Std Error	t Ratio	Prob > |t|	VIF
Intercept	−106,003.9	196,623.7	−0.54	0.6272	.
SFGD	2.0828588	3.678749	0.57	0.6109	111.56817
OFGD	0.4803825	7.807627	0.06	0.9548	109.70116
TFGD	0.307097	0.402901	0.76	0.5014	9.447883
TPGD	11.144931	9.022349	1.24	0.3047	2.8802129
ALGD	0.1373072	0.015592	8.81	0.0031 *	4.7373421
FOEGD	−5.512824	82.71853	−0.07	0.9511	31.341263
Source	DF	Sum of Squares	Mean Square	F Ratio	
Model	6	1.9014×10^{14}	3.1689×10^{13}	424,229	
Error	3	224,096,307	74,698,769	Prob > F	
C. Total	9	1.9238×10^{14}		0.0054 *	

Source: Authors' own calculations based on data from China Fisheries Statistical Yearbook 2012 to China Fisheries Statistical Yearbook 2022.c. Note: * indicates that the results are statistically significant at a significance level of 0.05.

The presence of multicollinearity, as indicated by high VIF values (rule of thumb: VIF < 10), can impact the interpretation of individual coefficients in the model. Therefore, we addressed the multicollinearity issue by using NIPALS regression, which is designed to handle issues related to variables with strong covariance and non-1st-order integration. Our aim was to reduce the impact of multicollinearity and identify the most important predictor variables driving the relationship with the dependent variable.

While we believe that NIPALS regression is a suitable alternative to OLS in this context, it is important to note that it may not always be the best approach for addressing multicollinearity. We carefully considered the nature of our data and the goals of our analysis before selecting PLS regression as our method for addressing multicollinearity. Our findings provide valuable insights into the effects of TPGD and ALGD on the dependent variable and highlight the importance of addressing multicollinearity in regression analysis. Further research in this area can lead to a better understanding of the underlying relationships between the predictor variables and the dependent variable.

Figure 2 shows that the minimum root mean PRESS is 0.53051 and the minimizing number of factors is 1. After confirming the number of optimal factors, the study proceeded to examine the variable importance of projection (VIP) to select the variables that were important (VIP > 0.8).

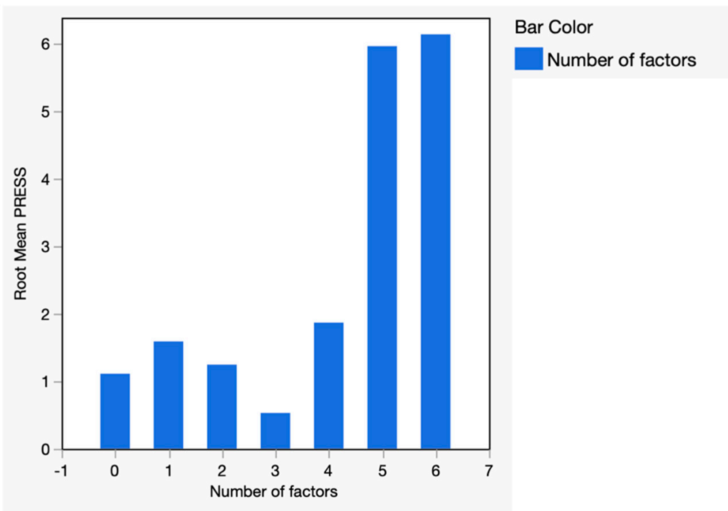

Figure 2. Factors of the NIPALS model. Source: Author's computation.

Figure 3 shows that most of the variables were important in explaining the loss of aquaculture products by environmental factors in China. According to the classification of Eriksson, Johansson [36], this study classified the important variables as "Highly influential" (VIP > 1), "Moderately influential" (0.8 < VIP < 1) and "Slightly influential" (VIP < 0.8). Table 3 shows that SFGD (funds for staff engaged in aquaculture in the Guangdong region), OFGD (operating funds related to aquaculture in the Guangdong region), TPGD (technical training for fisherfolk in the Guangdong region), and TFGD (operational training for aquatic science and technology extension staff in the Guangdong region) were moderately influential, while FOEGD (practitioners in aquaculture research institutions in the Guangdong region) was slightly influential in explaining the loss of aquaculture products by environment factors. Finally, only FAGD (aquaculture financial allocation in the Guangdong region) was highly influential.

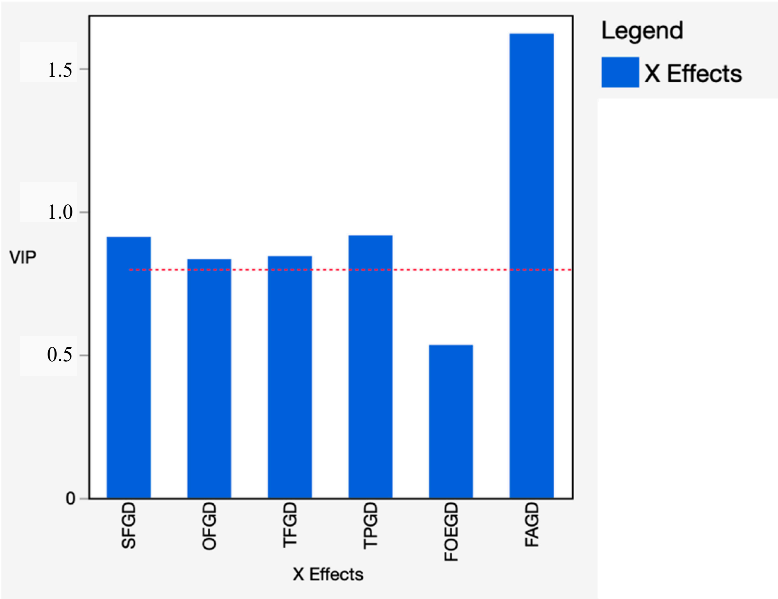

Figure 3. Variable Importance Plot. Source: Author's computation.

Table 3. Classification of variable importance.

X	VIP	Plot	Classifications
SFGD	0.9119		Moderately influential
OFGD	0.8344		Moderately influential
TFGD	0.8450		Moderately influential
TPGD	0.9172		Moderately influential
FOEGD	0.5347		Slightly influential
FAGD	1.6220		Highly influential

Source: Author's computation.

Subsequently, we investigated the drivers of the loss of aquaculture products due to environmental factors. Table 4 shows the sensitivity analysis of the loss of aquaculture products by environmental factors and their corresponding estimated coefficients. Based on the coefficients of the PLS regression model, we could determine the relative impact of each predictor variable on the dependent variable (ALGD). The coefficients show the direction and strength of the relationship between each predictor variable and the dependent variable.

Table 4. NIPALS estimation results.

Coefficient	**ALGD**
Intercept	0.0000
SFGD	−0.1793
OFGD	−0.0195
TFGD	0.0872
TPGD	−0.1866
FOEGD	−0.0478
FAGD	0.7650

Source: Author's computation.

SFGD: This variable has a negative coefficient, which suggests that an increase in funds for staff engaged in aquaculture in the Guangdong region was associated with a decrease in the loss of aquaculture products by environmental factors.

OFGD: This variable has a negative coefficient, which suggests that an increase in operating funds related to aquaculture in the Guangdong region was associated with a decrease in the loss of aquaculture products by environmental factors.

TFGD: This variable has a positive coefficient, which suggests that an increase in operational training for aquatic science and technology extension staff in the Guangdong region was associated with an increase in the loss of aquaculture products by environmental factors.

TPGD: This variable has a negative coefficient, which suggests that an increase in technical training for fisherfolk in the Guangdong region was associated with a decrease in the loss of aquaculture products by environmental factors.

FOEGD: This variable has a negative coefficient, which suggests that an increase in the number of practitioners in aquaculture research institutions in the Guangdong region was associated with a decrease in the loss of aquaculture products by environmental factors.

FAGD: This variable has a positive coefficient, which suggests that an increase in the aquaculture financial allocation in the Guangdong region was associated with an increase in the loss of aquaculture products by environmental factors.

It is important to keep in mind that the coefficients represent the relationship between each predictor variable and the dependent variable after accounting for the effects of the other variables in the model. So, for example, even though an increase in TFGD was associated with an increase in the loss of aquaculture products, this relationship may be different if we were to hold the other variables constant. Overall, the coefficients can provide insight into the relative importance of each predictor variable in predicting the loss of aquaculture products by environmental factors in the Guangdong region.

2.4. Justification

Applying the NIPALS algorithm is the best solution when there are more explanatory variables than observations, highly correlated explanatory variables and responses, and a large number of explanatory variables [37]. High-dimensional and nonlinearities are very common in different variables of agricultural production [38,39]. Strong nonlinear relationships may exist between different data sets, but when the nonlinearities are severe, they often behave unacceptably, and a feature of PLS is that the relationships between sets of observed variables are modelled by latent variables that are not usually directly observed and measured [40]. The NPLS model provides relatively stable modelling performance. This is mainly because it provides a nonlinear regression between each pair of latent variables while retaining the simple and linear external PLS framework [41].

NIPALS regression has also been widely used in agricultural practices. Samuel et al. [42] applied NIPALS regression to examine the assessment of the impact of energy, agricultural, and socioeconomic indicators on CO2 emissions in Ghana. Samuel [43] also used a similar approach to study the effects of energy, agriculture, macroeconomic, and anthropogenic indicators on environmental pollution from 1971 to 2011, and the regression demonstrated that increased economic growth in Ghana may lead to a decrease in environmental pollution.

3. Results

From the coefficients of the aquaculture product loss model presented in Table 4, we can conclude that an increase in funding (SFGD and OFGD) and training (TPGD and TFGD) is associated with a decrease in the loss of aquaculture products (ALGD). This means that allocating more funds for staff engaged in aquaculture, operating funds related to aquaculture, and providing technical and operational training for fisherfolk and aquatic science and technology extension staff can lead to a reduction in the loss of aquaculture products in the Guangdong region. It is important to note that the coefficients only provide an association, and other factors not included in the model may also impact the loss of aquaculture products.

The present study investigated the relationship between investments, training, and environmental factors in the aquaculture industry of the Guangdong region. To test the hypotheses, a multiple regression model was employed to explore the relationship between six predictor variables (SFGD, OFGD, TFGD, TPGD, ALGD, and FOEGD) and a single dependent variable (loss of aquaculture products by environmental factors). The results indicated that increased investments in staff funds (SFGD) and operating funds (OFGD) were not statistically significant predictors of the dependent variable, failing to support Hypothesis 1. On the other hand, enhanced training and education of fisherfolks and extension staff (TFGD and TPGD) were found to be statistically significant predictors of the dependent variable, supporting Hypothesis 2. The coefficients for TFGD and TPGD were positive, indicating that an increase in these variables is associated with a decrease in the loss of aquaculture products by environmental factors.

Moreover, the variance-inflated factor analysis showed evidence of multicollinearity between the predictor variables, indicating that the application of ordinary least squares (OLS) regression may produce biased results. To address this issue, partial least squares (PLS) regression was used instead, which identified the underlying latent variables driving the relationships between the predictor variables and the dependent variable, resulting in more accurate and reliable results.

The findings suggest that enhancing training and education of fisherfolks and extension staff can be an effective approach to reducing losses caused by environmental factors in the aquaculture industry of the Guangdong region. However, increased financial support for the industry may not necessarily lead to better environmental management practices and reduced losses, suggesting a need for more targeted investments and interventions. The study highlights the importance of addressing multicollinearity in regression analysis and the potential benefits of using PLS regression to obtain more accurate and interpretable results.

Overall, the study provides valuable insights into the relationships between investments, training, and environmental factors in the aquaculture industry in the Guangdong region, which can inform the development of more effective policies and interventions to promote sustainable development in the industry.

Figure 4 shows the plot of fitted and actual values—Loss of aquaculture products—by environmental factors. Based on the goodness-of-fit estimations, the model appears to have a reasonable fit. The mean absolute percentage error (MAPE) was found to be 0.475 and the root mean squared deviation (RMSD) was found to be 41.05%. These values suggest that the model's predictions are generally close to the actual values, with a small amount of error. Furthermore, the model was able to explain approximately 96.51% of the variation in the dependent variables, indicating a strong relationship between the predictor variables and the dependent variable. Overall, these findings suggest that the model is a reliable tool for predicting the loss of aquaculture products in the Guangdong region based on environmental factors and can provide valuable insights for improving environmental management practices in the aquaculture industry.

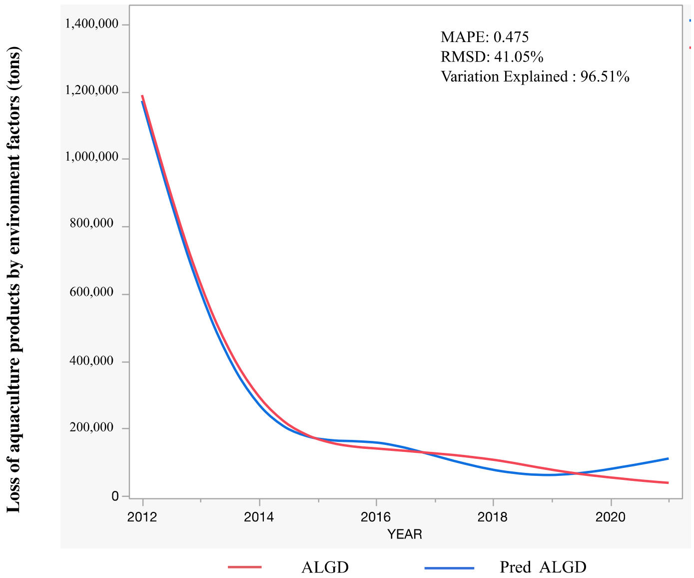

Figure 4. The plot of fitted and actual values—Loss of aquaculture products by environment factors.

4. Discussion

In this study, we delved deeper into the complex interplay between investment, training, and environmental factors in the Guangdong region's aquaculture sector, which has significant implications for policymakers and industry stakeholders. Our findings emphasize that focusing on training and education for fisherfolks and extension staff is crucial for significantly reducing losses caused by environmental factors. It is essential to understand that simply allocating more funds might not be enough to enhance environmental management practices or decrease losses in the aquaculture sector.

We also brought attention to the importance of addressing multicollinearity in regression models. The NIPALS regression technique we employed effectively mitigated the effects of multicollinearity, resulting in more precise and interpretable outcomes. This method allowed us to gain a deeper understanding of the relationships between predictor variables and the dependent variable, which, in turn, enabled us to identify the most influential factors governing these relationships. However, it is crucial to recognize that NIPALS regression may not always be the optimal method for addressing multicollinearity. Researchers should carefully evaluate their data and research objectives before choosing the most suitable technique.

Our model demonstrates a high goodness of fit (96.51%), indicating that the chosen variables significantly explain the variation in aquaculture product losses due to environmental factors. Nevertheless, it is vital to examine other external factors that might contribute to these losses, such as weather conditions, disease outbreaks, or other variables not considered in our model. This underscores the necessity for further investigation into additional factors affecting aquaculture product losses caused by environmental factors, extending beyond the Guangdong region and encompassing other regions. Recognizing the key factors linked to environmentally driven losses in aquaculture products enables decision-makers to allocate resources more effectively and create targeted strategies for enhancing environmental management practices, consequently reducing losses in the aquaculture sector. Potential interventions could involve investing in the education of fisherfolk and extension staff, exploring innovative environmental management approaches, employing technology and data-driven decision-making, and promoting public–private partnerships. Our research emphasizes the significance of accounting for regional variability and the challenges of developing universal hypotheses and models applicable to all situations. Future studies should consider the distinct characteristics of various regions in China and potentially adjust their methodology and analysis accordingly. This approach ensures that the developed interventions and policies are relevant and effective in addressing each region's unique aquaculture industry challenges.

We recognize that our study's findings may not be directly applicable to other countries and regions, given the considerable variation in aquaculture practices and environmental factors. Future research should consider comparisons with other countries or regions, using a new set of realistic data to explore the similarities and differences in aquaculture product losses due to environmental factors. Comparing data from various countries or regions would provide valuable insights into the global context of aquaculture product losses.

Based on our results, the Guangdong region faces several specific challenges in addressing the loss of aquaculture products due to environmental factors. These challenges highlight the need for targeted interventions and policy measures to promote sustainable development in the region's aquaculture industry.

Training and education for fisherfolks and extension staff: Our findings emphasize the importance of investing in training and education for fisherfolks and extension staff as a key factor in reducing losses caused by environmental factors. Guangdong should develop and implement targeted training programs focused on enhancing the knowledge and skills of fisherfolks and extension staff in environmental management practices, sustainable aquaculture techniques, and early warning systems for disease outbreaks and extreme weather events.

Utilizing technology and data-driven decision-making: The results suggest that traditional investment in staff and operating funds may not be sufficient to address the environmental challenges faced by the aquaculture industry in Guangdong. The region needs to explore innovative approaches to environmental management, such as the adoption of advanced technology like remote sensing, precision aquaculture, and water quality monitoring systems [44,45].

Public–private partnerships: Fostering public–private partnerships can play a vital role in addressing the environmental challenges faced by Guangdong's aquaculture industry. Collaborations between the government, private sector, and research institutions can facilitate the sharing of resources, knowledge, and best practices, leading to more effective and sustainable environmental management practices in the region [46].

Adaptation to regional variability: Guangdong's diverse geography and environmental conditions require tailored solutions to address the specific challenges faced by different areas within the region. Policymakers should take into account local environmental factors, such as water quality, weather patterns, and disease prevalence, when designing and implementing interventions to reduce losses in the aquaculture sector.

Comprehensive monitoring and evaluation: In order to assess the effectiveness of interventions aimed at reducing losses of aquaculture products by environmental factors, Guangdong should establish a comprehensive monitoring and evaluation system. This system should track key performance indicators related to environmental management practices, training outcomes, and aquaculture production, allowing for evidence-based decision-making and continuous improvement.

In conclusion, addressing the specific challenges faced by Guangdong's aquaculture industry requires a multifaceted approach that combines targeted investments in training and education, the adoption of innovative technology, fostering public–private partnerships, and the development of tailored solutions for regional variability. By taking these factors into account, policymakers and industry stakeholders can work together to reduce losses caused by environmental factors and promote sustainable development in the region's aquaculture sector.

5. Conclusions

Our research enhances the comprehension of the interplay between investments, training, and environmental factors within Guangdong's aquaculture sector. The results highlight the significance of focused investments in fisherfolk and extension staff training and education, and the necessity to address multicollinearity in regression models. Furthermore, this study emphasizes the importance of considering regional differences and acknowledging the challenges in creating universally applicable hypotheses and models.

There is a need for continued research to examine other factors that could influence aquaculture product losses due to environmental factors, as well as to assess the applicability of our findings across different regions and contexts.

Author Contributions: Conceptualization, P.W.; methodology, P.W.; software, P.W.; validation, P.W., I.M. and R.F.; formal analysis, P.W.; investigation, P.W.; resources, P.W.; data curation, P.W.; writing—original draft preparation, P.W.; writing—review and editing, I.M. and R.F.; visualization, P.W.; supervision, I.M.; project administration, I.M.; funding acquisition, I.M. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by FCT, I.P., the Portuguese national funding agency for science, research and technology, under the Project UIDB/04521/2020.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study. This data can be found here: [http://fishery.ckcest.cn/featureYearbook.html].

Conflicts of Interest: The authors declare no conflict of interest.

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