VINÍCIUS FELLYPE CAVALCANTI DE FRANÇA

BIOECONOMIA PESQUEIRA EM PERNAMBUCO: ANÁLISE ECONÔMICA DA PRODUÇÃO E COMERCIALIZAÇÃO DE PESCADO

Recife,

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UNIVERSIDADE FEDERAL RURAL DE PERNAMBUCO
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Vinícius Fellype Cavalcanti de França
Orientador: Dr. Humber Agrelli de Andrade

Dissertação apresentada ao Programa de Pós-graduação em Recursos Pesqueiros e Aquicultura da Universidade Federal Rural de Pernambuco como exigência para obtenção do título de Mestre.

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Prof. Dr. Humber Agrelli de Andrade
(Orientador)
[Departamento de Pesca e Aquicultura]
[Universidade Federal Rural de Pernambuco]

Prof. Dr. Luiz Flavio Arreguy Maia Filho
(Membro externo)
[Departamento de Economia]
[Universidade Federal Rural de Pernambuco]

Prof. Dr. Luis Otávio Brito da Silva
(Membro interno)
[Departamento de Pesca e Aquicultura]
[Universidade Federal Rural de Pernambuco]

Prof. Dr. Thierry Frédou
(Suplente)
[Departamento de Pesca e Aquicultura]
[Universidade Federal Rural de Pernambuco]

Prof. Dr[a]. Ruth Beatriz Mezzalira Pincinato
(Suplente)
[Department of Safety, Economics and Planning]
[University of Stavanger]

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“Words have power. Yet that power must be rooted in truth and justice. Words must never stand apart from those principles.”

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Resumo

A pesca e a aquicultura têm papel essencial na economia de diversas comunidades tradicionais do interior ao litoral. Estas atividades vêm sendo apontadas na literatura como relevantes para o enfrentamento de problemas globais associados à fome e má nutrição, seja por geração de renda direta ou pela oferta de proteína de qualidade a preços acessíveis para estratos sociais mais baixos. Entretanto, ainda que pesca e aquicultura desempenhem papeis socioeconômicos relevantes para países tropicais, estudos avaliando a dinâmica econômica destes setores são escassos, e no caso do Brasil geralmente limitados às regiões Sul e Sudeste do país. Diante disto, no presente trabalho foram analisados modelos lineares generalizados para avaliar aspectos econômicos relacionados a produção aquícola e ao mercado de pescados no estado de Pernambuco, com resultados divididos em dois trabalhos. Em um deles foi realizado um levantamento de dados censitário com os produtores aquícolas do município de Feira Nova (Agreste de Pernambuco), com a coleta de informações acerca de características de manejo, aspectos da propriedade, cultivo e variáveis econômicas, utilizadas para calcular índices de rentabilidade das fazendas. Em seguida, foram ajustados modelos lineares generalizados para compreender a relação das variáveis com os índices de rentabilidade calculados. Posteriormente, fez-se uso da base de dados do Centro de Abastecimento e Logística de Pernambuco (CEASA-PE) para analisar a volatilidade dos preços da sardinha comercializada no estado e avaliar o desempenho preditivo de dois algoritmos de *machine learning* na análise econômica de comercialização de pescado. No primeiro artigo, as variáveis relacionadas à manejo e economia apresentaram maior poder explicativo dos índices de rentabilidade da produção aquícola de Feira Nova. Entretanto houve diferenças importantes sobre como as variáveis estão relacionadas aos índices econômicos nos cultivos de camarão e de tilápia, evidenciando o potencial de aplicabilidade de modelos lineares generalizados neste contexto analítico. No segundo artigo, a volatilidade dos preços da sardinha variou ao longo do período avaliado, apresentando picos durante o período da pandemia do novo coronavírus (COVID-19). Ambos os algoritmos de *machine learning* avaliados demonstraram medidas de erro reduzidas, evidenciando a aplicabilidade destas ferramentas para predição de preços de pescado, mas a rede neural com memória de curto e longo prazo (Long Short-Term Memory [LSTM]) apresentou desempenho superior ao Fbprophet. Os resultados expostos ampliam o conhecimento acerca da economia aquícola e da dinâmica de preços do mercado de pescados no estado de Pernambuco.

Palavras-chave: Bioeconomia; Precificação; Desenvolvimento rural; Aquicultura em águas interiores; Pesca de pequenos pelágicos; Machine learning.

Abstract

Fisheries and aquaculture have an essential role in the economics of several traditional communities from inland to the coastal zones. These activities have been highlighted in literature as relevant for addressing global problems associated with hunger and malnutrition, whether by generating income or by offering quality protein at affordable prices to low-income households. However, even though fishing and aquaculture play important socioeconomic roles for tropical, studies evaluating the economic dynamics of these sectors are scarce, and in the Brazilian case, generally limited to South and Southeast regions of the country. Given this, in the present work generalized linear models were analyzed to evaluate the economic aspects related to aquaculture and the fish market in the state of Pernambuco, with results divided into two works. In one of them, a census data survey was carried out with the aquaculture producers from Feira Nova municipality (Pernambuco's Agreste), with the collection of information about management characteristics, aspects of the properties, cultures, and economic variables, used to calculate indices of farm's profitability. Generalized linear models were then adjusted to understand the relationship between the variables and the calculated profitability indices. Subsequently, the Pernambuco Supply and Logistics Center (CEASA-PE) database was used to analyze the volatility of sardine prices sold in the state and evaluate the forecasting performance of two machine learning algorithms in the analysis of trade and commercialization of seafood items. In the first article, variables related to management and economy presented higher explanatory power for the profitability indices of aquaculture production in Feira Nova. However, there were important differences in how the variables are related to economic indices in shrimp and tilapia farming, evidencing the potential applicability of genearalized linear models in this analytical context. In the second article, the volatility of sardine prices varied throughout the period evaluated, showing peaks during the period of the new coronavirus (COVID-19) pandemic. Both evaluated machine learning algorithms demonstrated reduced error measurements, highlighting the applicability of these tools to forecast seafood prices, but the long short-term memory (LSTM) neural network performed better than Fbprophet. The results presented expand knowledge about the aquaculture economy and the price dynamics of Pernambuco's fish market.

Key words: Bioeconomy; Pricing; Rural development; Inland aquaculture; Small pelagic fishery; Machine learning.

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SUMÁRIO

INTRODUÇÃO GERAL

Vêm-se discutindo em diversos ambientes, abrangendo campos políticos e acadêmicos, o conceito de bioeconomia, recebendo vasta notoriedade ainda que sua definição siga sendo discutida (Barañano et al., 2021). No centro deste debate, têm-se três linhas principais do pensamento bioeconômico, a linha que enfatiza a importância de estudos e aplicações de inovações biotecnológicas em diferentes setores da economia, a linha que foca no processamento e agregação de valor a recursos biológicos brutos e o estabelecimento de novos mercados buscando otimização de atividades que acompanham a humanidade a milênios à exemplo da agricultura, pecuária e pesca, e pôr fim a linha bioecológica com a busca de processos ecológicos que otimizem o uso de energia e nutrientes das atividades, evitando monoculturas e promovendo a biodiversidade (Bugge et al., 2016; Barañano et al., 2021).

Contemporaneamente, vêm-se chamando atenção para estudos visando agregar valor à subprodutos e resíduos advindos de setores produtivos, minimizando assim a emissão de dejetos em ambientes naturais e otimizando as operações econômicas das produções (Stevens et al., 2018). Entretanto, no contexto de países emergentes, estudos avaliando o desempenho econômico de alguns setores produtivos ainda são embrionários, trazendo relevância a análises de rentabilidade e da volatilidade de seus produtos.

Apesar do debate teórico acerca do significado e abrangência do conceito, o setor de produção de alimentos está intrinsecamente atrelado à estudos e inovações bioeconômicas, sendo alvo de modernizações, e incentivos fiscais em diversos países (Guillen et al., 2019; Wang et al., 2020). Este setor vem recebendo esta atenção no âmbito da bioeconomia devido à necessidade de suprir a crescente demanda por alimento e remediar problemas globais associados a insegurança alimentar intensificada após a pandemia do novo coronavírus [Sars-Cov 2] (Pawlak & Kolodziejczak, 2020; FAO et al., 2021). Além disto, a importância econômica da produção de alimento no produto interno bruto vem apresentando constante crescimento em diversas economias (Khan et al., 2019; Lemes et al., 2020; Shamsuzzaman et al., 2020), com as atividades pesqueira e aquícola sendo vertentes promissoras.

O Brasil é muitas vezes citado como o *celeiro do mundo* devido a sua volumosa produção agrícola (Simoes et al., 2020). Apesar do grande destaque no setor de produção de alimentos, a produção aquícola brasileira não atingiu sua capacidade plena, mesmo com os contantes crescimentos do setor a partir da década de 1980 (Marques et al., 2020). Estima-se que a aquicultura brasileira seja composta por cerca de 233,000 propriedades produtivas espalhadas ao longo do território nacional, gerando uma receita média anual de R$ 6,9 bilhões (IBGE, 2022), mas com evidente potencial de expansão do setor.

A produção aquícola brasileira, em sua maior parte é operada em pequena e média escala, popularizando-se com o desenvolvimento de cultivos em baixa salinidade que propiciaram a interiorização da aquicultura nacional, expandindo o horizonte produtivo do setor (Valenti et al., 2021). O avanço da aquicultura para o interior do Brasil, pode ser estratégico para promover avanços sociais e desenvolvimento rural para comunidades com acesso a água e condições climáticas adequadas, trazendo renda, gerando empregos e contribuindo para a segurança alimentar por meio da produção de alimento de alta qualidade (Fonseca et al., 2017). É, portanto, evidente a importância de se realizar o levantamento de dados produtivos e econômicos da atividade.

O interesse acerca do desempenho financeiro de sítios aquícolas vem apresentando crescimento. Ainda assim, análises econômicas relacionadas a aquicultura são escassas no Brasil e por vezes limitadas à região Sul (Castilho-Barros et al., 2020), o que contrasta com o fato de que a região Nordeste é responsável por 99,7% da produção da carcinicultura nacional, além de produzir volumes relevantes de peixes (IBGE, 2022). O Nordeste brasileiro apresenta características climatológicas ideais para o cultivo de camarões e tilápia, tendo seu desenvolvimento inicial sido estabelecido nas zonas estuarinas, com posteriores avanços para o interior com o uso de águas de barragens e poços artesianos (Guimaraes et al., 2016; Valenti et al., 2021). O estado de Pernambuco é produtor aquícola relevante na região, sendo apontado como o pioneiro da atividade no Brasil (Santos & Mattos, 2009; IBGE, 2022), com o município de Feira Nova se tornando um polo produtivo relevante, devido a vantagens logísticas por sua proximidade com a capital, e abundância de recursos hídricos.

A principal espécie cultivada em todas as regiões do Brasil, com exceção da região Norte, é a Tilápia, sendo responsável por 61% de toda produção piscícola do país (Valenti et al., 2021). A produção de tilápia é feita principalmente em tanques escavados, mas com alta relevância do cultivo em tanques-rede (Calixto et al., 2020). A produção camaroeira do Brasil é um setor concentrado majoritariamente na região Nordeste do país, com cerca de 95% de seus produtores sendo classificados como pequenos ou médios (Rocha, 2019), tendo uma produção ascendente desde 2003, com uma dinâmica econômica variável sendo influenciada por diversos fatores (Valenti et al., 2021), evidenciando a necessidade de compreensão acerca das principais influências econômicas nesta atividade.

Assim como a aquicultura, também a pesca brasileira desempenha um papel socioeconômico primordial para milhões de brasileiros, especialmente nas regiões Norte e Nordeste (Neto et al., 2021). A pesca como atividade extrativista está mais sujeita a oscilações com elevadas flutuações dos volumes de captura das principais espécie alvo. Uma das principais espécies capturadas no Brasil é a sardinha (*Sardinella brasiliensis*), que movimenta um importante polo pesqueiro nas regiões Sul e Sudeste, onde o estoque é mais abundante (Schroeder et al., 2014; Neto et al., 2021). Apesar das capturas serem concentradas no eixo Sul-Sudeste, a cadeia de comercialização da sardinha tem abrangência nacional.

A sardinha é a principal espécie dos pequenos pelágicos pescada em águas brasileiras, estando entre os pescados mais consumidos no país e sendo uma das principais fontes de proteínas das merendas escolares do sistema público de educação brasileiro (Bento et al., 2018). As flutuações de capturas deste pescado advindas de colapsos seguidos abriram as portas para sardinhas importadas no mercado doméstico nacional devido à crescente demanda por sardinhas no mercado interno devido à sua popularidade, especialmente, mas não exclusivamente, entre os estratos de menor poder aquisitivo (Pincinato & Asche, 2018).

Para além do suprimento de sardinhas no mercado interno, a entrada de sardinhas importadas no Brasil, auxiliou a minimizar a volatilidade dos preços para a indústria de enlatamento nacional, porém a variabilidade das capturas nacionais segue influenciando a dinâmica dos preços para os consumidores finais (Pincinato & Asche. 2018). Tal problemática, traz relevância a tentativas de predição dos preços das sardinhas comercializadas no Brasil, tanto para minimizar os riscos dos investidores e demais envolvidos na cadeia produtiva (Wang et al., 2020), quanto para consumidores, tendo em vista que os preços são os principais fatores analisados na escolha de pescados para alimentação (Supartini et al., 2018), e que este recurso tem grande importância para a segurança alimentar das populações de baixa renda do Brasil.

Modelos lineares generalizados são amplamente utilizados para um melhor entendimento acerca de quais fatores explicam uma determinada variável resposta, sendo utilizada em contextos de análise multivariados, podendo contribuir com o entendimento de diversos fenômenos da produção e comercialização aquícola (Tsuda et al., 2012). Com relação a predição de preços, algoritmos de *machine learning* figuram entre as principais ferramentas contemporâneas para análises preditivas, porém subutilizados nas ciências marinhas (Kamalov et al., 2021; Yang et al., 2022). Entre esses algoritmos, o Prophet e redes neurais com memória de curto e longo prazo [*Long Short-Term Memory* – (LSTM)] são dois dos mais utilizados no contexto de análise de séries temporais, porém ainda que tenham aplicabilidade similar, a diferenciação de suas estruturas pode resultar em resultados divergentes (Abbasimehr et al., 2020; Rathore et al., 2022).

Diante do exposto, com destaque para a interiorização da aquicultura no nordeste, e para a cadeia produtiva da sardinha, o presente trabalho de dissertação tem como objetivo a análise de rentabilidade e o entendimento da relação entre variáveis de cultivo e desempenho econômico de produções aquícolas de pequena escala localizadas no município de Feira Nova (Agreste de Pernambuco) e avaliar o desempenho de duas técnicas de predição dos preços da sardinha comercializada no Centro de Abastecimento e Logística de Pernambuco (CEASA-PE). Os resultados expostos ampliam o conhecimento acerca da produção aquícola realizada no interior de Pernambuco, e contribuem para minimização dos riscos comerciais atrelados a incertezas quanto a variação dos preços de pescado para investidores e demais envolvidos na cadeia produtiva da sardinha no Brasil. Os resultados de cada eixo de análise são apresentados de maneira individual no formato de dois artigos científicos.

Objetivos

Geral

Utilizar modelos matemáticos para analisar aspectos econômicos relacionados a produção e comercialização do pescado no estado de Pernambuco.

Específicos

- Avaliar a rentabilidade da produção aquícola em um município do Agreste pernambucano;
- Identificar a relação entre variáveis de cultivo e a rentabilidade das produções aquícolas em um município do Agreste pernambucano;
- Identificar períodos de volatilidade nos preços da sardinha comercializada no CEASA-PE;
- Avaliar a capacidade preditiva de algoritmos de machine learning para com os preços da sardinha comercializada no CEASA-PE.

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Bioeconomic modelling for small-scale aquaculture farms in Brazilian Northeastern semi-arid region.

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1. ARTIGO CIENTÍFICO I - Bioeconomic modelling for small-scale aquaculture farms in Brazilian Northeastern semi-arid region.

Abstract

Aquaculture has presented an outstanding growth, being a key component in the gross domestic production for several economies worldwide. However, despite its continuous innovations, most of aquaculture production comes from small scale farms indicating the relevance of economic analysis for such productions. In Brazil, aquaculture plays a relevant role in rural communities with water access, although the economic feasibility of these farms is scarce in literature. The present work aims to evaluate the influence of several variables related to aquaculture production, by using generalized linear models (GLM), and economic feasibility of small farms in a Northeastern Brazilian town. Data was collected by interviews encompassing all producers from Feira Nova city and modelled by using the software R. Results points that despite structural challenges, aquaculture production may be a profitable activity in Brazilian Northeastern small properties, with socioeconomic outputs in the region, although governance improvements directed to this sector are encouraged.

Key words: economic feasibility; rural development; bioeconomy.

Introduction

Aquaculture is currently the food production sector with the world's fastest growth (FAO, 2022), encompassing a wide range of management strategies, target species, and culture technologies resulting in a variety of social, economic, and environmental outcomes (Gephart et al., 2020). As the global consumption of fish and seafood items had presented significant growth in the last decades, its productive sector has been playing an important role as source of income to millions of people around the world, especially in Asia and Latin America (FAO, 2020; De Silva & Yuan, 2022).

The aquaculture industry presents frequent technological innovations in its management techniques aiming the improvement of its productivity (Khanjani & Sharifinia, 2020; Manoharan et al., 2020). However, most of its production comes from small-scale inland farms (Asche et al., 2009; FAO, 2022), which has not been receiving the proper attention in economic analysis and technical guidelines which may roughly impact the profitability of these firms (Asche et al., 2009; Filipski & Belton, 2018; Lima et al., 2020).

In Brazil, aquaculture industry has been gaining economic notoriety since the early 1980s with the number of aquaculture farms currently being estimated around 233,000, generating about R$ 6.9 billion of gross revenue in 2021 (US$ 1.23 billion [average exchange rate from the period]) being the second largest aquaculture producer in Latin America, behind Chile (IBGE, 2021; Valenti et al., 2021). Most of Brazilian production is destinated to the domestic market, although continuous increments in the exports volume indicate this sector potential to grow its importance in Brazilian economy (Marques et al., 2020; Peixe Br, 2023). Among the different culture modalities, inland aquaculture has been growing and being widely present in small country towns with favorable characteristics to the development of this activity, such as water access and adequate weather conditions (Flores & Filho 2019; Henry-Silva et al., 2019). Tilapia (*Oreochromis niloticus*.) and white shrimp (*Penaeus vannamei*) are the main representatives of fish and shrimp produced in the country, accounting for, respectively, 361.286 Tons, and 78.637 Tons harvested in 2021 (IBGE, 2022), with its production being a relevant income alternative to rural communities along Brazil.

Inland aquaculture can play a strategic role in the promotion of rural development and poverty alleviation in the country, producing high quality protein with processing alternatives to aggregate value to its residuals, generating income and ensuring food security to rural communities (Fonseca, et al., 2017; Marques, et al., 2020). The aquaculture contribution to the household income of the producers is downplayed without adequate technical guidance (Mulokozi et al, 2020), highlighting the importance of directed public policies to small-scale aquaculture to improve its social returns. However, the continuous changes in Brazilian federal agencies responsible for that sector had leaded to a lack of medium- or long-term programs to improve the sustainability of the national aquaculture, and an inconsistent statistical knowledge about the overall volume of aquatic organisms caught and farmed in the country (Neto et al., 2021; Valenti et al., 2021).

The Northeastern region of Brazil occupies a significant position within the country's shrimp aquaculture industry, cultivating around 99.71% of all shrimp farmed in the country (IBGE, 2022) since the region presents climatic characteristics which are ideal to shrimp farming (Guimarães et al., 2016; Carvalho et al., 2019). Despite various of northeastern aquaculture sites have developed in estuarine zones, the inland aquaculture has rapidly grown in the countryside of the region, due to the presence of dams as water sources (Valenti et al., 2021). In the northeastern region, Pernambuco state is pointed as the pioneer of aquaculture in Brazil (Santos & Mattos, 2009), it is the current fourth bigger aquacultural producer in Brazilian northeastern region, and tenth fish producer in Brazil with 31.960 Tons of fish and 3.248,5 Tons of shrimp, having potential to grow even more (Peixe BR, 2023; IBGE 2022).

Interest about financial and profitability performance of aquaculture firms have increased significantly, with a growing trend of the number of scientific articles regarding this theme since 2006 with a higher attention to developing countries farms, and to the sector's contribution as an employment driver (Campo & Zuniga-Jara, 2018; Fry et al., 2019). However, most of these studies did not use bioeconomic models to better understand the relationship between productive variables, which may aid aquaculture entrepreneurs in improving their management strategies and maximizing profits (Nobre et al., 2009; Byron et al., 2015), highlighting the importance of modelling to help decision making in small-scale aquaculture farms.

In this context, this study aims to analyse the economic feasibility of small aquaculture farms in a city in the countryside of the Brazilian state of Pernambuco, and fit models to key variables related to the economic earns and losses of the farms helping to identify structural arrangements and specific management strategies to enhance the Feira Nova producers' profit and respective social benefits. Productive and economic differences among different species are assessed. The results contribute to understanding the economical dynamics of the inland aquaculture in a relevant aquaculture region in Latin America.

Material and methods

Study area

Pernambuco state is divided into five mesoregions according to its climatic characteristics which are "Região metropolitana do Recife", "Zona da mata", "Agreste", "Sertão" and "Sertão do São Francisco" (SILVA-FILHO et al., 2020). The Agreste mesoregion is characterized for presenting semiarid climate with average annual precipitation smaller than 80mm/year but housing some water reservoirs such as Carpina dam which is one of the most important sources of water for the people from its nearby cities such as Limoeiro, Lagoa do Carro and Feira Nova (NOBREGA et al., 2015; BEZERRA et al., 2021; ALBUQUERQUE & CARVALHO, 2021). The study was carried out in the municipality of Feira Nova (Fig. 1), once it has become a relevant aquaculture hub in Pernambuco, cultivating especially *P. vannamei* and *O. niloticus*, over the cassava culture which had historically been its main economic activity (JÚNIOR et al., 2017).

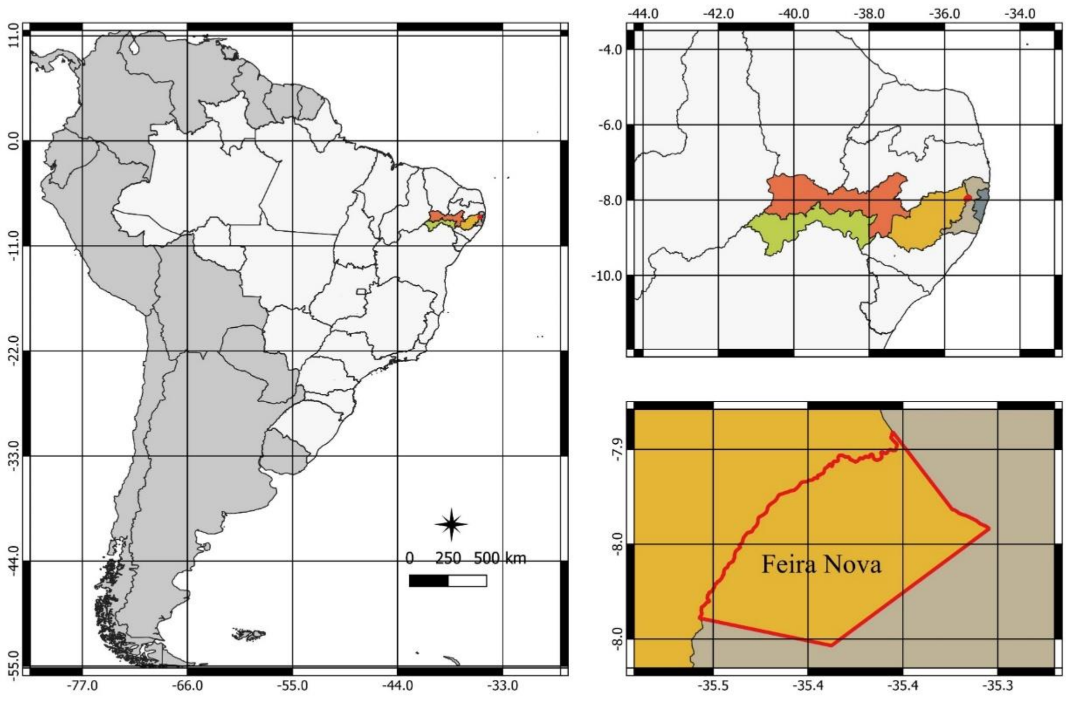

Figure 1 - Map of the study area. Pernambuco mesoregions on the upper-right plot, in red Sertão, green Sertão do São Francisco, yellow Agreste, grey the Zona da mata and in purple Região Metropolitana do Recife. Low-right plot indicate the municipality of Feira Nova (Pernambuco's Agreste).

Data acquisition and aquaculture characterization

Since inland aquaculture is gaining economic notoriety in Pernambuco's countryside, and Feira Nova become a relevant hub in Agreste mesoregion, a census questionnaire was applied in partnership with the Secretary of Agriculture from the municipality of Feira Nova to characterize the elements of the aquaculture production in the city. The questionnaire was divided into four sections to evaluate the characteristics of the farm, the culture aspects, producers' management ability, and the economic variables (Table 1). Questions about the farms characteristics encompass specially the size of the farms and their productive area in order to rank the properties; The culture aspects section evaluate productive variables such as the cultured species, yearly production, and level of humane intervention during the cultivation, such as the presence of aerators or thermic control in the pounds; The management ability section aimed to evaluate if the producers had some training before the beginning of their activities and how well they are handling their productions; And finally, the economic section aimed to gather information about the main costs of the aquaculture in Feira Nova.

The questionnaire was applied through face-to-face interviews in the producers' farms, and cell phone interviews were done when producers were not in the farm during the visitation. Interviews were made from September to November in 2022 covering all Feira Nova aquaculture producers by that time. The answers were deposited in an electronic spreadsheet and organized in four sections, according to the nature of the variable, for being used in further analysis. The data was pre-processed by using the Python interface (Version 3.8.5) with the aid of the Pandas library (The Pandas Development Team, 2020).

Table 1 - Questionnaire applied to the farmers divided into sections in the municipality of Feira Nova

Variables	Description
Farm Characteristics:	
Farm Area	Farm area in hectares
Pound Number	Number of pounds in the farm
Productive area	Water slide area in hectares
Nursery tank	Number of nursery tanks in the farm
Culture Aspects:	
Target Species	Specie cultivated in the farm
Stocking Density	Number of animals per area unity (m^2)
Yearly Yield	Total produced in a year interval (Kg)
Number of cycles	Number of productive cycles in a year interval
Aerator	Uses aerator in the culture (0 = No, 1 = Yes)
Thermic control	Makes the thermic control of the culture (0 = No, 1 = Yes)
Feed per month	Amount of feed used in a month interval (Kg)
Soil treatment	Clean the soil after a cultivation cycle (0 = No, 1 = Yes)
Probiotic	Kind of probiotic used
Marketing	Forms in which the product is commercialized
Juveniles	Number of juveniles bought per year
Water source	Mainly source of water for the cultivation
Average weight	Average weight commercialized
Management ability:	
Technical assistance	Have technical orientation from someone (0 = no, 1 = yes)
Technology	Try adopting new cultivation technologies for the farm (0 = no, 1 = yes)
Training	Had formal training before working with aquaculture (0 = no, 1 = yes)
Years of culture	How long has been working on aquaculture

Education	Degree of education
Economic variables:	
Price of the product	Price of the product by kilogram
Juveniles' Price	Price of a thousand juveniles
Price of feed	Price of the feed used in the cultivation (bag of 25kg)
Price of probiotic	Price of the probiotic used in the farm (1 Kg)
Consultancy price	Average fee paid to consultancy per month
Income	Importance of aquaculture in producer's monthly income (0 = only source of income, 1 = main source of income, 2 = complementary source of income)
Electricity	Electricity cost in a month interval
Daily workers	Count on daily workers in specific periods of the cultivation (0 = no, 1 = yes)
Number of daily workers	Number of daily workers
Dailly workers Payment	Average paid to each daily worker per day
Number of full-time workers	Number of full-time workers in the farm
Land remuneration	Lease price of the land hectare
Workers average salary	Average salary paid to each farmer worker

Economic Analysis

After the data collection, the farmer's productivity (Kg/Hc/Year) was calculated, the stocking densities for tilapia and shrimp were standardized in the number of organisms/m² of wet area scale. Economic variables were converted from BRL to the commercial US$ according to the exchange rate from August eighth, 2023. After this, an exploratory analysis was carried out to identify patterns and the productive general aspects of the aquaculture in Feira Nova. The variables related to economy and management were used to calculate the annual gross revenue (GR), and the following costs indicators of the firm, effective operating cost (EOC), non-disbursable operating cost (NOC), total operating cost (TOC), land opportunity cost (LOC) and total cost (TC). Calculations of these six main quantities denoted in capital letters are showed below.

GR was calculated as:

$$GR = Yy \cdot Pp \qquad (1)$$

in which Yy is the yearly yield in Kg and Pp is the price of each kilogram of the cultured organism sold to middlemen. EOC is calculated as:

$$EOC = Ds + Lp + Fs + Jus + Es \qquad (2)$$

in which Ds is the total spent with daily laborer, Lp is the total paid for the full-time workers, Fs is the total spent with feed, Jus is the total spent with fingerlings, for the fish farmers, or post-larvae for the shrimp farmers, and Es is the total spent with electricity. These five quantities are calculated in a yearly basis as showed below.

Total spent with day laborer (*Ds)* is calculated as:

$$Ds = Qc \cdot Qdc \cdot Dp \quad (3)$$

with Qc being defined as the number of productive cycles per year, Qdc the quantity of day labors per productive cycle, and Dp being the average price of one day of services from a day labor.

Total paid for the full-time labors (Lp) is calculated as:

$$Lp = (Nw \cdot Ws) \cdot 12 \quad (4)$$

In which Nw is the number of full-time workers in the farm per month, Ws is the monthly workers average salary, and this product is multiplied by twelve to convert the calculation to an annual basis.

The amount spent with feed in the farm during a year (Fs) is calculated as:

$$Fs = Fbn \cdot Fbp \quad (5)$$

with Fbn representing the number of feed bags used in a year in the farm and Fbp is the price of the feed bag. The net weight of each bag is 25 Kg.

The total spent with fingerlings, for the fish farmers, or post-larvae for shrimp farmers during a year is:

$$Jus = Nmi \cdot Pmi \quad (6)$$

with Nmi being the quantity of thousands of fingerlings (or post-larvae) bought in a year in the farm, and Pmi is the average price of a thousand of fingerlings (or post-larvae). Finally, the last term of equation 2 is the total spent with electricity in a year (Es) which was calculated by multiplying the average spending of the farm with electricity by 12 to put it in an annual scale of spend.

The third main quantity is the non-disbursable operational cost (NOC) which is calculated as:

$$NOC = Cons + Fas + Ivr \quad (7)$$

$Cons$ is the total spent with consultancy in a year by the farm. Fas is the total paid to family workers per year:

$$Fas = (Nfw \cdot Sfw) \cdot 12 \quad (8)$$

with Nfw representing the number of family members involved in the farm activities, Sfw being the average salary for the family workers and the product is multiplied by 12 to convert the calculation to an annual basis. Finally, the last term of equation 6 is Ivr, which is the investor's remuneration, which was assumed to be equivalent to 30% of EOC (Castilho-Barros, 2020).

The fourth main quantity is the total operational cost (TOC) which is the sum of the effective operational cost (EOC) and the non-disbursable cost (NOC) showed above. The land opportunity cost (LOC) is the product between the estimation of the income from the lease of one hectare for one year (Li) in Feira Nova, and the productive area of the farm in hectares (Pa):

$$LOC = Li \cdot Pa \quad (9)$$

Finally, the total cost of the aquaculture activity (TC) in Feira Nova is:

$$TC = TOC + LOC \quad (10)$$

All the calculations above were adapted from Matsunaga et al (1976) and Campos (2003).

Values of GR and TC were used to calculate indicators as gross margin (GM), liquid revenue (LR), and profitability index (P) as described by Martin et al. (2008) and Castillo-Barros et al. (2020). The cash immediately available to cover the current business expenses is the liquid revenue (LR):

$$LR = GR - TC \quad (11)$$

Gross margin (GM) is a ratio related to the economical sustainability of the activity in the short-term showing the financial and operational conditions of the activity. Gross margin calculation is:

$$GM = LR/TC \cdot 100 \quad (12)$$

Finally, the profitability index (P) is related to the production's attractiveness in the long-term. This indicator is calculated as:

$$P = LR/GR \cdot 100 \quad (13)$$

To access if there are significant differences among the mean scores of the costs and economic profitability indices depending on the cultured species, we used the non-parametric test of Mann-Whitney U.

Modelling

Feira Nova commercial aquaculture only produces two species, which differs their respective productive and economic outputs implying in differences among their profitability indicators. We purposed generalized linear models to investigate the different relations between the four sections from Tab. 1 and the rentability indicators for each culture.

In generalized linear models (GLM), we have:

$$E(Y) = \beta X \quad (14)$$

in which $E(Y)$ is the average expected answer to the response variable, X is the explanatory variables' matrix design, and β the estimated parameters vector. It was assumed that response variables approximately followed a normal distribution $Y \sim N(\mu, \sigma^2)$. Link functions considered were identity, inverse, and log. Explanatory models were fitted using exploratory variables in logarithmic and original scales.

Variance inflation factor (VIF) of the variables was assessed to identify strong redundancies among explanatory variables. Variables with highest scores were removed one by one to avoid redundancy until all the model's variables present VIF lower than 5 (Akinwande et al., 2015). Then, explanatory variables were selected by using *forward* or *backward* procedures based on Akaike information criterium (AIC) value (Akaike, 1974). This criterium allow to select models with balanced trade-off among bias and the variance of estimations. By the end of this process, all, some, or none of the variables may be kept in the model. In this last condition, it would indicate that none of the explanatory variables evaluated are relevant to the response variables comprehension.

Finally, we assessed diagnostics of selected models' residuals to evaluate normality, bias, homoscedasticity, and eventual presence of outliers. As the number of variables in models may differ, the model's adjusted squared R's (Adj. R^2) will be evaluated to a fair comparison. Comparisons between models fitted using response variables in logarithmic or original scales and the same number of explanatory variables relied on diagnostic of residuals. Groups of variables that explained all economic indices had their adjusted deviance accessed by an analysis of variance (ANOVA) to check which of the variables were more important for the models. All procedures were done with the software R (R core team, 2021).

Results

General characteristics

All Feira Nova producers (13) answered the questionnaire, among which 6 were tilapia producers and 7 shrimp producers. Aquaculture is the main income of 30.7% of the producers and being a complimentary income for the rest, with all producers selling their harvests fresh but one also selling it frozen. Only 15.3% of the farmers had formal training before beginning their cultures, and only 7.6% have thermic control in its culture by using a greenhouse. The aquaculture activity in Feira Nova is recent, with firms having around 2 years of activity in average, although the oldest farm has 6 years. Only 3 (23%) of Feira Nova producers counted with technical assistance in their cultures, among which two are shrimp farmers and one a fish farmer. Cultures are done in farms ranging from 0.5 to 14 ha with productive area ranging from 0.009 to 4 ha. Feira Nova's aquaculture presents only two cultured species, *O.niloticus* and *P.vannamei* with distinctions between their cultures (Table 2). Shrimp cultures had higher stocking densities, numbers of ponds and of post larvaes, although fish farming had greater productivity and yearly yield values, even though presented less cycles per year. The mean number of nursery tanks are higher for tilapia culture than for shrimp culture.

Table 2 - General and zootechnical characteristics of fish and shrimp farming in Feira Nova (PE).

		Fish farming, n=6		Shrimp farming, n=7	
Variable	Units	Mean (sd)	Min; Max	Mean (sd)	Min; Max
Farm area	ha	3.46 (3.92)	0.5; 9	7.17 (5.72)	1.2; 14
Productive area	ha	0.39 (0.42)	0.009; 0.9	0.99 (1.37)	0.04; 4
Pound number	units	4.66 (4.03)	1; 11	6.14 (3. 67)	3; 14

Nursery tanks	units	0.66 (0.81)	0; 2	0.57 (0.97)	0; 2
Years of culture	years	2.33 (1.16)	1; 3.5	2.71 (1.79)	1; 6
Stocking density	units/m²	11.1 (3.31)	6; 15	94.28 (32.58)	40; 150
Yearly yield	kg	64308 (81486)	850; 120001	16548 (15429)	2940; 48000
Average final weight	g	916.66 (278.68)	500; 1200	11.85 (2.47)	10; 17
Yearly productive cycles	units	1.9 (0.15)	1.7; 2	3 (0)	3; 3
Productivity	kg/ha/year	153540 (54579)	83335; 222222	26318 (12108)	11700; 41860
Feed per month	kg	7869.51 (10206.52)	92; 25000	1926.14 (1768.81)	313; 5600
Fingerlings or Post larvae per year	thousands	68.66 (83.34)	3; 207	1830.5 (1781.1)	368; 5555

Three different water sources were used by the producer, the Carpina's Dam, artesian wells, and exceeding water from the Pernambuco's Sanitation Company [Compania Pernambucana de Saneamento, (COMPESA)]. Most of shrimp farming use water from Carpina's Dam, but 28.7% of the producers also used artesian wells. Half of fish producers use artesian wells' waters, 33.7% used the Dam's water and 16.7% used COMPESA's water (Fig. 2).

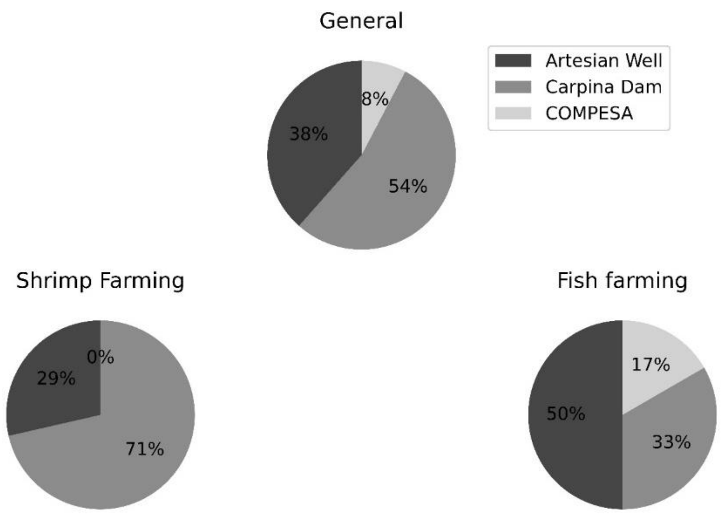

Figure 2 - . Percentage of producers that uses each water source per cultured species.

All fish producers treat the pound's soil after a productive cycle, while only 57.1% of the shrimp producers do it. The use of probiotics in Feira Nova presents distinct patterns depending on the cultured species, with its use being more widespread among the shrimp farmers which is not present in less than 15% of these farmers, while more than 30% of the fish farmers does not use probiotics (Fig. 3). For fish farming it was only reported the use of water and soil probiotics, with the application of probiotic in the water being the main utilization for the probiotic in this aquaculture modality. Shrimp farming also uses water probiotic, but the main probiotic for this modality is the application in the feed.

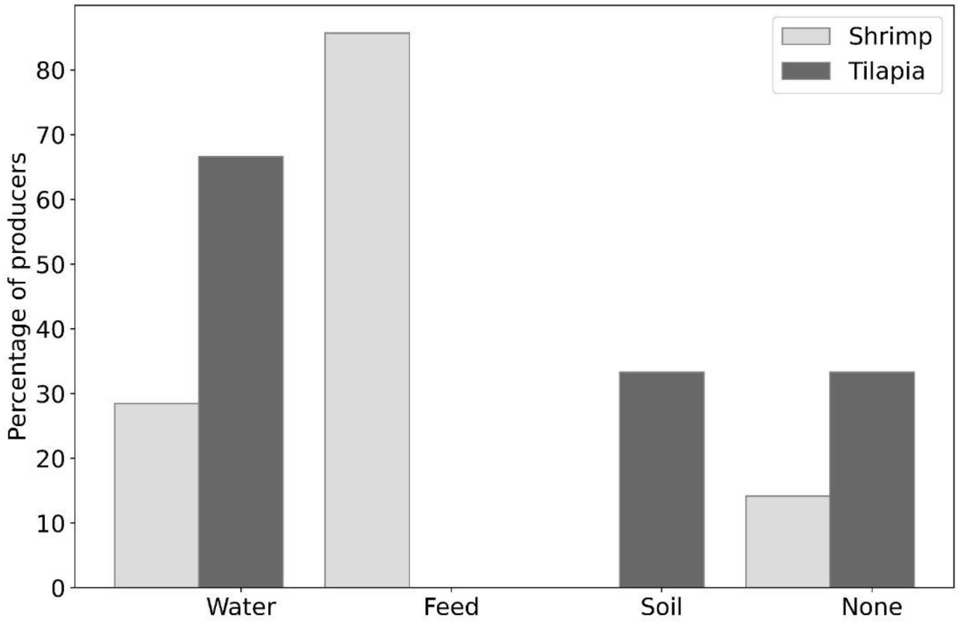

Figure 3 - . Percentual of probiotic use for the aquaculture modalities in Feira Nova (PE)

Economic aspects

Feira Nova's aquaculture employs 55 workers encompassing daily laborers, permanent workers, and family workers. The proportion of daily and permanent workers are similar, with the daily modality slightly suppressing the permanent modality and family workers being the smaller category overall (Fig. 4). However, when analyzed by culture, differences are notable, with fish farming having higher contribution of permanent and daily than family workers in its production. In opposition, in shrimp farming the participation of family labor has the most important contribution against all other modalities.

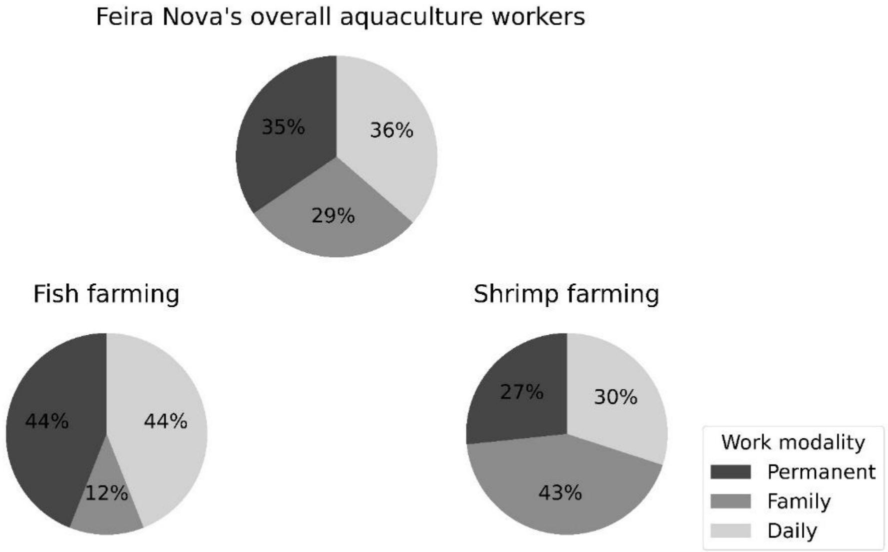

Figure 4 - Proportion of permanent, family, and daily workers in the general aquaculture and for each cultured species in Feira Nova (PE).

The effective operational, non-disbursable operational, total operational and land opportunity costs were compared (Table 3). The biggest costs in the production for both cultures were feeding and electricity, with fish culture presenting higher scores of these variables. The third highest cost for fish farming was the annual salary of the permanent labors, while for shrimp farming the costs with post larvae were higher than the labor costs. As shrimp culture is an activity with family nature in Feira Nova, their costs with family and temporary labors were greater than for tilapia farming. Overall fish cultures presented higher cost values (EOC, NOC, TOC, and TC) than shrimp cultures, except for the land opportunity cost (LOC). In spite of the means are different, no statistical significative difference was identified among fish and shrimp cultures, mostly because the variability among farms is high.

Table 3 - Mean scores and standard deviation of production costs and the cost indices of effective operational cost (EOC), non-disbursable operational cost (NOC), total operational cost (TOC), land opportunity cost (LOC), and total cost (TC) for fish and shrimp cultures in the municipality of Feira Nova and their Mann-Whitney's U Test p-value

		EOC	NOC	TOC	LOC	TC
Fish farming	Fulltime laborers	4800(4895.1)		4800(4895.1)		4800(4895.1)
	Daily laborers	35.8(38.3)		35.8(38.3)		35.8(38.3)

	Feed	62307.6(74367.7)		62307.6(74367.7)		62307.6(74367.7)
	Electricity	6588(6592.2)		6588(6592.2)		6588(6592.2)
	Fingerlings	3194(3508.1)		3194(3508.1)		3194(3508.1)
	Consultancy		160(357.7)	160(357.7)		160(357.7)
	Family workers		360(804.9)	360(804.9)		360(804.9)
	Investor return		23077.6(26250.1)	23082.4(28751.3)		23082.4(28751.3)
	Land opportunity cost				1571.5(1542.9)	1571.5(1542.9)
	Total (US$/Year)	**76925.4(87500.4)**	**23597.6(26088.1)**	**100523.1(113579.2)**	**1571.5(1542.9)**	**102094.6(114978.1)**
		EOC	NOC	TOC	LOC	TC
Shrimp farming	Permanent employees	3291.4(3239.5)		3291.4(3239.5)		3291.4(3239.5)
	Temporary employees	61.7(57.2)		61.7(57.2)		61.7(57.2)
	Feed	20522.1(18752.5)		20522.1(18752.5)		20522.1(18752.5)
	Electricity	5040(3903.7)		5040(3903.7)		5040(3903.7)
	Post larvae	4119(4014.1)		4119(4014.1)		4119(4014.1)
	Consultancy		274.2(433.2)	274.2(433.2)		274.2(433.2)
	Family workers		1337.1(1606.6)	1337.1(1606.6)		1337.1(1606.6)
	Investor return		9910.2(8626.9)	9910.27(9318.2)		9910.27(9318.2)
	Land opportunity cost				3961.7(5107.1)	3961.7(5107.1)
	Total (US$/Year)	**33034.2(28756.5)**	**11521.7(7803.7)**	**44555.9(36426.1)**	**3961.7(5107.1)**	**48517.6(41333.1)**
	p-value	0.95	0.94	0.94	0.22	0.94

The rentability indicators of Feira Nova aquaculture point to distinct economic performances according to the cultured species in the firms. Fish farming presented higher mean values of all rentability indicators, although no significative statistical differences were found (Table 4). Despite fish farming had presented the highest mean values, the maximum values for gross margin and profit, were scored by a shrimp farmer, and the negative values were exclusively from a fish farmer.

Table 4 - Mean, standard deviation, minimum, and maximum values of gross revenue (GR), liquid revenue (LR), gross margin (GM), and profit (P) from Feira Nova's producers and their respective Mann Whitney p-values

		GR (US$)	LR (US$)	GM (%)	P (%)
Fish farming	Mean (sd)	129035.9 (148425.1)	26941.2 (34067.4)	17.8 (12.4)	14.1 (9.8)

Price (Kg) = 2.23 (0.26) US$					
	Min; Max	2210.0; 400000.0	-288.3; 95015.7	-3.8; 31.1	-4.0; 23.7
Shrimp farming					
Price (Kg)= 3.45 (0.15) US$	Mean (sd)	56934.6 (48368.9)	8417.1 (7900.1)	15.1 (10.8)	12.4 (7.8)
	Min; Max	9996.0; 163200.0	56.2; 23143.9	0.5; 37.3	0.5; 27.1
	p-value	0.94	0.83	0.53	0.53

Generalized linear models

The variables were modelled according to their nature. A fish producer with negative values of liquid revenue, gross margin and profit due to much lower final weight and revenue price was not considered in this modelling section. Despite the proximity of their rentability indices, fish and shrimp cultures in Feira Nova presented substantially different characteristics, which were pointed out in the selected models (Table 5).

Table 5 - The best generalized linear models for gross revenue (GR), liquid revenue (LR), gross margin (GM), and profit (P) from Feira Nova's producers, and their respective scores of adjusted R squared (Adj. R^2) and Akaike information criterium (AIC).

		Fish farming		Shrimp farming	
Group of variables	Dependent Variable	Adj. R^2	Selected model	Adj. R^2	Selected model
Farm Characteristics	GR	0.99	$Log(GR)^a = 9.6 + 0.34\,log(At) + 2.87Wa$	0.88	$GR^a = 9.97 + 0.14Np$
	LR	0.99	$LR^a = 6.95 + 0.23log(At) + 4.45Wa$	0.80	$LR^b = -16062 + 14767log\,(Np)$
	GM	0	$GM = 22.2$	0	$GM = 2.86$
	P	0.39	$P^a = 12.52 + 1.007Np$	0	$P = 0.06$
Culture Aspects	GR	0.98	$Log(GR)^a = 2.42 - 0.34Ws + 5.23E^{-6}Fm$	0.99	$GR = 1.43 + 0.98log\,(Th)$
	LR	0.97	$LR^a = 6.05 + 0.01Tf + 3.12St$	0.81	$LR^a = 2.84 + 0.83log\,(Tf)$
	GM	0.99	$GM = -138.64 + 24.11log(Fw) + 11.61Ps - 12.36St$	0	$GM = 0.99$
	P	0.58	$P = -141.8 + 23.16log\,(Fw)$	0	$P = 0.93$
Management Ability	GR	0.88	$GR^b = 1.49E^{-4} - 1.51E^{-7}Ye - 4.12E^{-5}Yc$	0.69	$\log\,(GR)^b = 0.07 + 0.02Ta - 0.001Yc$
	LR	0.99	$LR = -1.5E^5 + 2.8E^4Yc + 6.4E^4Ntec + 4.8E^3Ye$	0.87	$LR^a = 11.12 + 0.53Yc - 4.1Ta$

	GM	0.81	$GM^b = -3.15 + 14\,log(Yc) + 1.07Ye$	0.95	$GM^b = 0.17 - 0.004Yc - 0.006Ye$
	P	0.81	$P = 0.15 + 10.36log(Yc) + 0.7Ye$	0.98	$P^a = 0.89 + 0.08Ye + 0.09Yc + 0.35Ntec$
Economic Variable	GR	0.99	$log\,(GR)^a = 4.72 - 1.69log(Pk) - 0.02Pf - 9.09E^{-5}Pp$	0.99	$log(GR) = 9.76 + 0.001El + 0.78Mi + 0.0005Pp$
	LR	0.99	$log\,(LR)^a = 2.3 + 0.002Sa - 0.07Mi - 0.01Pf$	0.91	$log(LR) = 3.67 + 1.28Mi + 0.78log\,(El)$
	GM	0.99	$GM = 25.35 - 0.03Pp + 0.06Sa - 1.27Mi$	0.77	$log(GM) = -4.96 + 1.29Mi - 0.06Dp + 2.28Pk$
	P	0.92	$log(P) = 2.95 - 0.001Pp + 0.21Nw$	0.67	$P^b = 0.03 - 0.15Mi + 0.01Pf + 0.008Dp$

Note: models marked with [a] were built with the log link, [b] with link inverse and without mark with the link identity. β is the model's intercept, At the total area of the farm in hectares, Wa the productive area of the farm in hectares, Np the number of pounds, Th the total harvested in a year,Np is the number of pounds, Tf the quantity of thousands of juveniles, Ws the water source of the farm, Fm the total weight of feed used in a month, St the soil treatment after a cultivation cycle, Fw the final weight of the product, Ps the use of probiotic in the soil, Ye the years of formal education, Yc the years of culture, $Ntec$ if the producer tries to adopt new technologies in their farm, Ta if the producer counts with technical assistance, E the total paid for electricity in a month, Pk the price of a kilogram of the product, Pp the price of the probiotic used,Pf the price of a thousand juveniles, Dp the price paid to daily labors, Sa the average salary paid to a full-time laborer in a month, Mi indicating if aquaculture is the producer main income and Nw the number of workers in the farm.

Fish culture had the economic group of variables as the ones with higher adjusted R^2 while shrimp culture did not exhibit a dominant group of variables, with management ability variables being the main variables for modelling GM and P while economic variables were more relevant for the models of GR and LR. Farm characteristics variables did not explain GM for tilapia, GM, and P for shrimp, while Culture aspects explained all economical indices for tilapia farming but did not explain GM and P for shrimp farming.

Economic variables had different importance among cultures. Fish farming presented significant residual deviance in the revenue price of the organism for GR model , the average salary paid for LR model, in probiotic prices and average salary paid for GM model, and no significant residual deviance for the P model, while shrimp farming had significant residual deviance in electricity spent and the main income condition for GR and LR models but no significance for GM and P models (Table 6). On the other hand, management ability only presented 10% significant deviance in GR and LR models for fish farming, while shrimp farming had higher significant deviance for the variables in GM and P models (Table 7).

Table 6 - Adjusted deviance of the economic group of variables models for fish and shrimp cultures in the municipality of Feira Nova (PE).

Fish culture				Shrimp culture			
Response	Explanatory variables	resid. Dev	Pr(>F)	Response	Explanatory variables	resid. Dev	Pr(>F)

GR	Null	22.59	-	GR	Null	2.92	-
	$\text{Log}(Pk)$	0.83	0.01*		El	0.61	0.002**
	Pf	0.17	0.10		Mi	0.11	0.01*
	Pp	0.01	0.20		Pp	0.01	0.06
LR	Null	28.90	-	LR	Null	6.15	-
	Sa	0.94	0.03*		Mi	2.48	0.02*
	Mi	0.16	0.18		$\text{Log}(El)$	0.55	0.04*
	Pf	0.07	0.45	GM	Null	1.91	-
GM	Null	360.39	-		Mi	1.16	0.20
	Pp	211.66	0.008**		Dp	0.98	0.46
	Sa	1.00	0.006**		Pk	0.42	0.24
	Mi	0.02	0.09	P	Null	1.43	-
P	Null	1.14	-		Mi	0.89	0.26
	Pp	0.71	0.08[a]		Pf	0.69	0.45
	Nw	0.08	0.06[a]		Dp	0.46	0.42

Note: [a],* and ** represent respectively significance at 10, 5, and 1%. El is the total paid for electricity in a month, Pk the revenue price of the cultured organism kilogram, Pp the price of the probiotic used, Pf the price of a thousand juveniles, Dp the price paid to daily labours, Sa the average salary paid to a full-time labourer in a month, Mi indicating if aquaculture is the producer main income and Nw the number of workers in the farm.

Table 7 - residual deviance and significance of the management ability group of variables from fish and shrimp culture in the municipality of Feira Nova (PE).

Fish culture				Shrimp culture			
Response	Explanatory variables	resid. Dev	Pr(>F)	Response	Explanatory variables	resid. Dev	Pr(>F)
GR	Null	$1.14E^{11}$	-	GR	Null	2.92	-
	Ye	$5.73E^{10}$	0.09[a]		Ta	1.94	0.27
	Yc	$1.25E^{10}$	0.11		Yc	1.32	0.35
LR	Null	$60.73E^{8}$	-	LR	Null	$35.53E^{8}$	-
	Yc	$36.92E^{8}$	0.07[a]		Yc	$18.35E^{8}$	0.10

	Ntec	$15.03E^{8}$	0.08[a]		Ta	$13.47E^{8}$	0.27
	Ye	$35.77E^{6}$	0.09[a]	GM	Null	580.60	-
GM	Null	360.39	-		Yc	158.22	0.006**
	log(Yc)	140.65	0.12		Ye	26.00	0.02*
	Ye	65.14	0.26	P	Null	267.27	-
P	Null	187.47	-		Ye	77.54	0.007**
	log(Yc)	67.03	0.11		Yc	17.00	0.02*
	Ye	94.92	0.30		Ntec	2.72	0.08[a]

Note: [a], * and ** represent respectively significance at 10, 5, and 1%. Ye is the years of formal education, Yc the years of culture, Ntec if the producer tries to adopt new technologies in their farm, Ta if the producer counts with technical assistance.

Discussion

Feira Nova’s aquaculture have been developing a relevant role in Pernambuco’s Agreste, contributing to the income of several families involved with the production, whether they are entrepreneurs or workers, by generating income and high-quality food products. Such positive outputs are in consonance with literature that pointed this sector as a key contributor for rural communities’ economic growth, with notable potential in hunger alleviation (Wang et al., 2020; Garlock et al., 2022). These aquaculture aspects related to rural development encourage the creation of governmental programs in Brazil to develop this activity in rural communities with water access, especially in northeastern region once poverty have been a historical concern in this region that hosts 59% of all Brazilian that live in extreme poverty condition (Nepomuceno et al., 2015; Marengo et al., 2021).

Despite the positive economic results, Feira Nova producer’s harvests supply exclusively middleman for the slaughter market, with a wide range of unexplored markets for being assessed. Castilho-Barros et al., (2020) showed that even though the slaughter market is the main destination for aquaculture products in Brazil, the economic outputs supplying recreational fishing farms were more attractive for small scale producers in Southern Brazil, drawing attention to market diversification for the aquaculture sector with the “fish and pay” farms being a potential market for small producers in Brazil (Freire et al., 2016).

Economic variables and management ability were the only group of variables that explained all indices for both cultures in the municipality of Feira Nova, which is aligned with literature that points the importance of such aquaculture aspects in their economic performance (Rahman et al., 2019; Suárez-Puerto et al., 2023). The management ability variables showed the high significance of years of culture and education for both shrimp and fish farming highlighting the importance of the producer's know-how for a better economic performance in the long-term for small-scale productions. Such relation among management and rentability had been pointed in Rahman et al., (2020) results which showed positive correlation of management ability and economic gains for small scale shrimp farms in Bangladesh and reinforced by our results in Brazilian semi-arid.

Among the variables related to management ability, technical assistance is only mentioned two models for shrimp farming, positively correlated for GR and negatively for LR. However, the total of producers that count with technical assistance in their cultures in Feira Nova is significantly low which may lead to biased conclusions for this variable. Extension programs focused on technical assistance for aquaculture production were key factors in the early development of remarkable cultures, such as the American catfish in U.S and the entire aquaculture sector in China (Wang et al., 2020; Engle et al., 2021), which encourages the creation of technical assistance program for small scale aquaculture producers in Brazil.

The economic group of variables was the main group to explain all fish farming rentability indices and for shrimp farming it explained well GR and LR. For fish farming the probiotic price was pointed as one of the main variables for explain the rentability indices, showing that despite the abundance of positive outcomes resulting from the probiotic application in aquaculture farms (Dias et al., 2020; Pimentel et al., in press), the costs associated to this practice may be a limiting factor in Feira Nova highlighting the need for establish specific protocols to make the use of probiotics more economically sustainable to small scale farms in Brazilian semi-arid.

Shrimp farming presented electricity expenditure and the main income status of aquaculture in the producers' income positively correlated for GR and LR. As shrimp farming is mainly carried in familiar scale, such results may indicate the need for professionalization of this activity as only high electricity spends in Feira Nova cultures are directly related to the use of aerators in their pounds, which leads to improvements in the cultured species' life quality although such aeration systems must be well balanced to pounds volumes to avoid unnecessary costs (Boyd et al., 2021).

The rentability indices of the cultures in Feira Nova suggests economic feasibility for the aquaculture sector in the town, whether it is a familiar of commercial activity. However, there is still a large margin for improvement with the need of better governance from federal agencies once participatory management and multifaceted programs focused on the small scale aquaculture production had been pointed as key issues to encourage the development of this activity (Diedrich et al., 2019; Henríquez-Antipa & Cárcamo, 2019). In addition, access to rural credit for small-scale aquaculture farmers is difficult and limited in Brazil owing to bureaucratic problems. (Valenti et al., 2021), which stickles both improvements to existing farms and entry of new producers in this market, evidencing the necessity for democratize rural credit to small aquaculture farmers in the country.

Conclusion

Small-scale inland aquaculture has been an expanding sector in the semi-arid region of Northeast Brazil, although this sector has presented shortcomings in public policies, with no working regulations and difficulties in accessing rural credit. However, our results show that, in addition to the associated challenges, Feira Nova's aquaculture is resilient with positive rentability indices on average, evidencing the potential of this activity for the construction of a rural development program for rural communities with water resources. The establishment of generalized linear models to explain the economic performance of small-scale farms improves the knowledge of farms' economic dynamics, thereby improving profitability. Our results encourage the creation of governmental aquaculture data collection programs in Brazil to assist in the creation of more robust models to explain aquaculture economic dynamism that may aid the establishment of management protocols and guidelines for structural investments to improve socio-economic outputs.

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Prices forecasting of a small pelagic species in a South American supply center: A machine learning approach.

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2. ARTIGO CIENTÍFICO II – Prices forecasting of a small pelagic species in a South American supply center: A machine learning approach.

Abstract

Small pelagic fishes have a key role in human nutrition, especially in emerging countries, as they are affordable protein sources and provide income for fishing communities. Despite their nutritional benefits for human health, prices are the main factor when choosing seafood as diet components, which highlights the relevance of an economic analysis, since changes in fish prices might alter the feeding patterns of populations worldwide. This study analyzed the price dynamics of the *Sardinella brasiliensis* in one of the main markets in northeast Brazil and employed machine learning techniques to forecast future prices. The dataset was obtained from the Pernambuco Supply and Logistics Center website, and it was modeled using the FbProphet library in addition to a long-short-term memory (LSTM) neural network in order forecast future prices. Both algorithms reached low error metrics, but LSTM performed significantly better, showing its usability in the economic context of marine products.

Key words: Bioeconomy, Deep learning, Food security, Machine learning, Price volatility.

Introduction

Small pelagic fish have an important environmental, cultural, and economic role around the world, in addition to being an affordable source of protein, contributing to the access to good quality feed items by low-income populations worldwide (Juliani et al., 2019; Asiedu et al., 2021; Hasselberg et al., 2021; Birge et al., 2021). This is extremely relevant in view of the intensified growing hunger in the world against the backdrop of the COVID-19 pandemic, which has had a negative impact on the income of millions of people, consequently increasing the global malnutrition index (Fao, 2021; Mandal et al., 2021).

Small pelagic fisheries are generally conducted by artisanal fleets in developing countries (Ba et al., 2017; Teh & Pauly, 2018; Asiedu et al., 2021), but present significant participation in industrial fishing in the world, being responsible for employing 23% of EU fishermen between 2012 and 2016 (Scientific, Technical, and Economic Committee for Fisheries [STECF], 2019; Rybicki et al., 2020). Despite the well-known nutritional composition and benefits of fish for human health (Tilami & Sampels, 2017; Pal et al., 2018), its price is one of the main factors for it to be chosen as a component of a diet in developed and developing countries (Supartini et al., 2018; Terin, 2019; Obiero et al., 2019; Ferrer et al., 2020), indicating that disturbances in fish prices might significantly alter the feeding pattern of several populations around the world.

In Brazil, the most representative fishery of small pelagic species is that of the Brazilian sardine (*Sardinella brasiliensis*) which happens in the southeast-south regions of the country, especially between the states of Rio de Janeiro (22°S) and Santa Catarina (29°S) (Schroeder et al., 2014; Schroeder et al., 2022), and supplies all of the other regions. The first commercial catches of the Brazilian sardine are dated in the late 50s, with rapid growth in the 60s and a historical peak of 228,000 tons in 1973 (Cergole et al., 2002), presenting large fluctuations, with a first collapse in 1990 (31,000 tons) which was determinant to establish fishing regulations such as the enlargement of the fishery closure period (IBAMA, 1991; IBAMA, 1992). Despite the landings increments in 1996 and 1997, when respectively 100,000 and 118,000 tons were obtained, a second collapse took place in 2000, with only 17,000 tons (Cergole et al., 2002), and a third one is currently ongoing (Schroeder et al., 2022).

Sardines are among the most consumed seafood in Brazil, especially considering but not limited to the low-income consumers, with growing demand in the domestic market in the last decades after the second collapse. This gives way to imported sardines in the Brazilian market, even though Brazilian ones are perceived as a higher quality product (Pincinato & Asche, 2018). Sardines, in general, are one of the main protein sources in Brazilian public school meals (Bento et al., 2018), and they are part of a variety of traditional dishes in different regions of the country (Ferreira-Araújo et al., 2021).

In the state of Pernambuco (Northeast region), the bigger supplier of food items and one of the main providers of fishing products is the Pernambuco Supply and Logistics Center [(Centro de Abastecimento e Logística de Pernambuco - CEASA-PE)], which receives fresh and frozen fish from all over Brazil and caters different vendors that uses the CEASA-PE physical installations to trade their products with consumers, retailers, wholesale markets, and food industries in northeast Brazil (Shinohara et al., 2020) having the sardines from Santa Catarina (Southern region) among its products.

Differently from internationally traded species, such as tilapia and salmon, the prices of domestic species such as the Brazilian Sardine present higher volatility in the national market (Pincinato et al., 2022). Uncertain prices of feeding items may increase the risks to stakeholders and people involved in the productive chain, consequently jeopardizing the feeding habits of millions of people in Brazil, so the application of forecasting techniques is of significant interest for those involved in this market (Wang et al., 2021).

Machine learning is one of the most widespread methods of forecasting contemporaneously and has been widely used to predict prices of electricity (Yang et al., 2022), stock values (Kamalov et al., 2021; Aker, 2022), and even COVID-19 spread (Chafiq et al., 2020; Gaur, 2020). It has the potential to bring a wide range of improvements to the cultivation of aquatic organisms by monitoring and predicting water quality parameters and feeding (Yang et al., 2020). Even though its use to forecast prices is widely spread, studies using this approach to predict seafood prices are scarce.

Among the several machine learning forecasting techniques, two of the most widely spread methods currently are the library FbProphet and the long short-term memory (LSTM) neural networks, which had been used in diverse ways, since they are able to give valuable insights and predictions in the analysis of time series (Abbahsimehr et al., 2020; Vischwas & Patel, 2020). Despite its common applicability in time series studies, FbProphet and LSTM networks present different structures, which may generate distinct answers to single problems, with one technique overcoming the other depending on the context (Chatuverdi et al., 2022; Rathore et al., 2022).

Therefore, the present research aims to analyze the available historical series of prices from the Brazilian sardines commercialized at the CEASA-PE, to point possible volatility drivers, to forecast future prices through two distinct univariate machine learning techniques, the FbProphet and an LSTM neural network, and, lastly, to compare their results. This will be helpful to understand the price dynamics of native species in the Brazilian domestic market, which is relevant to decision-making among stakeholders and public agents.

Material & Methods

Fish Market Data Acquisition and Preprocessing

The dataset used was obtained through the combination of daily updated reports on the CEASA-PE website (Ceasa, 2022), which has a quotation service that shows the daily minimum, maximum, and most common prices of all products commercialized in the location, as well as their origin, sales unit, kind of product and market situation. After obtaining data on all CEASA-PE products, we filtered the dataset in order to get specific information about the Brazilian sardine, resulting in a data-frame with 2.253 rows and 4 columns, for the prices at minimum, maximum, and most common, plus the date of collection from January 2nd, 2013, to June 2022.

The resulting dataset presented 107 missing values for minimum and maximum prices, and nineteen for most common prices, which were filled with the average value for each variable of the month that presented the missing value, a conventional method for handling missing data for continuous variables (Thakur et al., 2021). Following this, we examined the monthly data for each year, and values under or above the interquartile range were considered outliers and replaced by the average value of the month that presented that value, then the range between maximum and minimum prices (mm) was calculated. These initial analyses were conducted using software R (version 4.0.3) (R core team, 2021) and the package “pandas” (The Pandas Development Team, 2020) in the programming language Python (version 3.8.5).

Time Series Exploratory Analysis

The analysis was performed in the Python interface to visualize the time series of minimum (Min), most common (Mcom), maximum (Max), and range of min-max (Mm) prices. Then, the moving average and moving standard deviation of the economic time series were calculated, respectively using a 30-day window to smooth the series for better visualization and check their volatility over the years. Their stationarity was assessed through the Dickey-Fuller test to check if the series presented trends or seasonality (Dickey & Fuller, 1979) using the Akaike Information Criterion (AIC) (Akaike, 1974) to select the legs with a better tradeoff between bias and variance, and following this, the variables considered non-stationary were decomposed with the aid of the library Statsmodel (Seabold & Perktold, 2010) in order to visualize their trends. The variables also had their autocorrelation calculated with the aid of the Pandas library (The Pandas Development Team, 2020), using daily, monthly, and annual horizons to check how the past values of the variables were correlated with their current value in different time horizons.

Prices Forecasting

Several types of forecasting are globally widespread in the machine learning context, being tremendously dependent on the data available. In our context, univariate techniques were selected since the available dataset only included data about sardine prices through the years. Among these forecasting techniques, we chose to work with the FbProphet library (Taylor & Letham, 2017) and a long short-term memory (LSTM) neural network, which has successfully predicted economic variables, and has been widely used in a wide range of prediction contexts, from stock markets prices to changes in environmental variables (Zhou et al., 2019; Toharudin et al., 2021). To avoid biased forecasts, we choose to predict only the non-stationary variables.

FbProhet is an open-source library developed by the Facebook Data Science Team and uses a decomposable time series model with three components:

$$y(t) = g(t) + s(t) + h(t) + \in (t) \qquad (1)$$

where *g(t)* represents the stepwise growth curves (linear or logistic) for modeling the non-periodic changes in the time series, the trend component of the series; *s(t)* represents the seasonal changes; *h(t)* the effects of holidays in regular schedules, ε(*t)* the error term, and *t* the time value (Battineni et al., 2020; Vischwas & Patel, 2020).

With this forecasting technique, the predictions are made based on the seasonal effects in the data using a Fourier series, providing a flexible model, so *s(t)* is derived as:

$$s(t) = \sum_{n=1}^{N} (an \cos\left(\frac{2\pi nt}{P}\right) + bn \sin\left(\frac{2\pi nt}{P}\right)) \qquad (2)$$

where *P* is the parameter that needs to be estimated for a given "*n*" which is variable depending on the kind of available series (Battineni et al., 2020; Toharudin et al., 2021). The FbProphet library has three pre-established kinds of seasonality with specific "*n*" values for each kind: daily, weekly, and yearly, which can be applied to the models according to the kind of modeling that better fits the analysis. For the modeling, the dataset was divided into three subsets only containing data for Max, Mcom, and Min. Then, each of these subsets was split into the train, and test datasets with the train contained 95% of the total data, with the remaining 5% of data in the test set of data. The training dataset was used to fit the models and the test data frame to check the accuracy of the model's predictions.

LSTM is a recurrent neural network (RNN) with internal memory and multiplicative gates which are applied in several tasks such as prediction, classification, and diverse types of analysis (Smagulova & James, 2019). LSTM is suitable for time series forecasting, once it can fit data patterns in the long term, whereas in the short term its memory has lookback windows, which leads to accurate performances predicting in short time horizons (Budiharto, 2021). The LSTM structure differs from the conventional architectures of RNNs as it contains a cell and gates that controls the flow of information (Abbahsimehr et al., 2020) as illustrated in Fig. 1 with notations explained in Table 1.

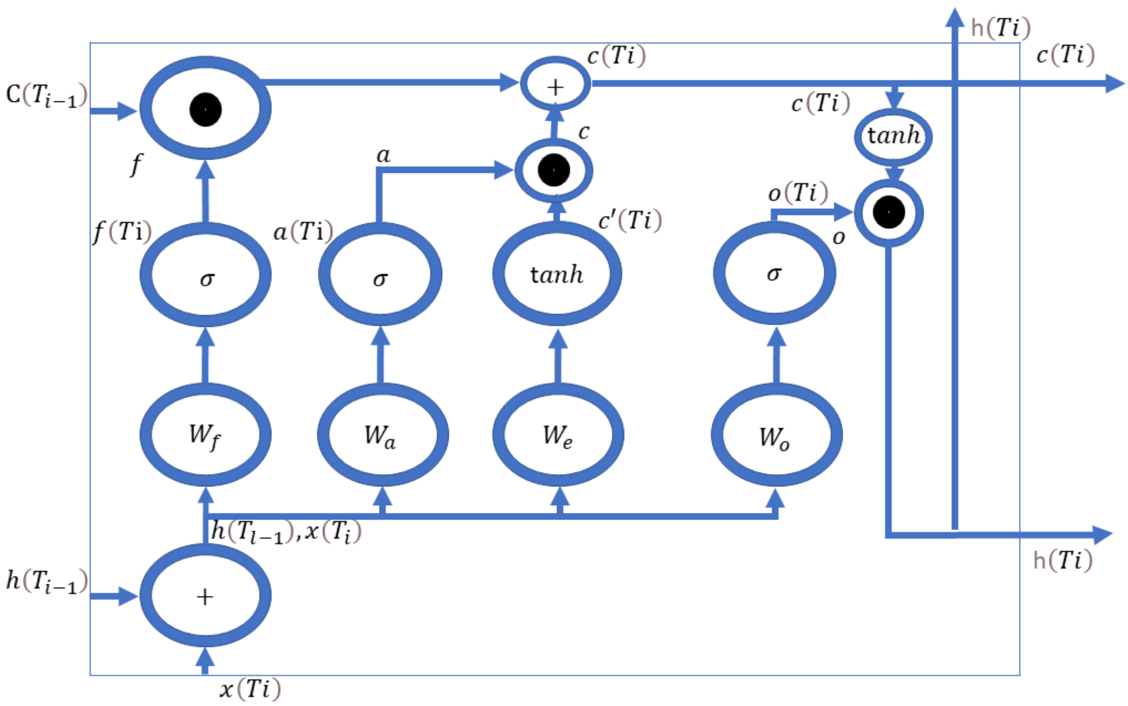

Figure 1 - The LSTM Layer Structure (adapted from Greff et al., 2017)

Table 1 - LSTM Notations and Respective Meanings

Notation	Meaning
X (Ti)	Input value
$\mathrm{H}(T_{l-1})$ and $\mathrm{H}(Ti)$	Output value at time points T_{l-1} and Ti
$\mathrm{C}(T_{l-1})$ and C (Ti)	Cell states at time points T_{l-1} and Ti
$\mathrm{B} = \{\mathrm{Ba}, \mathrm{B}f, \mathrm{Bc}, \mathrm{Bo}\}$	Biases of input gate, forget gate, internal state and output gate
$\mathrm{W1} = \{\mathrm{Wa}, \mathrm{W}f, \mathrm{Wc}, \mathrm{Wo}\}$	Weight matrices of input gate, forget gate, internal state and output gate

$W2 = \{Wha, Whf, Whc, Who\}$	The recurrent weights
$a = \{a(ti), f(ti), c(ti), o(ti)\}$	The output results of input gate, forget gate, internal state and output gate

The operation of LSTM consists of the forgetting gate $f(T\mathrm{i})$ using $x(T\mathrm{i})$ and $h(T_{i-1})$ as inputs to calculate the information preserved in $C(T_{i-1})$ using a sigmoid activation. The input gate $a(T\mathrm{i})$ computes the values of $c(Ti)$ by taking $x(T\mathrm{i})$ and $h(T_{i-1})$, while the output gate $o(Ti)$ regulates the output of the LSTM, considering $c(Ti)$ and applying both sigmoid and tanh layers. Distinctly from the FbProphet, LSTM networks fit the data seasonality without the need of specification for the kind of seasonality. The data for modeling was divided into two data frames for train and test, then converted into arrays for being applied to the model. To get a short-term prediction, the test dataset corresponded to the last six months of data (5% of the whole dataset), while the rest of the data was used to train.

RNNs present diverse hyper-parameters such as optimizer, learning rate, number of epochs to fit, and loss measure, that might be tuned differently according to the main core of the model (Goodfellow et al., 2016). Its performance is straightly dependent of its hyperparameters selections, which caused the development of several optimization techniques of these parameters in last decades, even though manual selection based on user experience is one of the most widely used selections techniques (Li et al., 2021; Chen et al., 2022). Since manual selection may compromise reproducibility and other tuning techniques may be highly computational costing, we chose to tune our hyperparameters using the random search method, due to its simplicity and relatively low computational demand (Andonie, 2019).

The random search has the assumption that the hyperparameters have different importance in the model, and works by iteration, testing a random set of possible scores for hyperparameters, instead of all possible combinations as the grid search, then training multiple neural networks and storing its metrics to select the model with better performance (Bergstra & Bengio, 2012). We used the aid of the Keras library (Gulli & Sujit, 2017) to apply the random search function, which returned us a neural network with three layers, one LSTM followed by two Dense, with 64, 4, and 1 neuron respectively, with a learning rate of 0.006 and an Adam optimizer trained for 128 epochs.

Model Evaluation

After obtaining models to predict the values of the variables, the models were evaluated according to the metrics of root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE), which are error measures extensively used for comparing time series forecasting methods (Reich et al., 2016; Koo et al., 2020; Qi et al., 2020). These metrics were taken from the scikit-learn library (Pedregosa et al., 2011). Temporal validation techniques were used to analyze the performance of the models using part of the training set of data as a validation set, before fitting the model with the whole training data frame, evaluating different prediction horizons of time, observing the variation in error metrics over a one-year horizon for each of the modeling techniques.

For the FbProphet we applied a temporal cross-validation using the cross-validation function available in its own package, which divided the train set into two parts, one for training and one to validate the model's prediction metrics before using the whole training set to predict the test dataset. LSTM was evaluated by a simple temporal validation, once a temporal cross validation has a high computational cost, dividing the train set of data into training and validation data frames, containing respectively 70% and 30% of the original training dataset. Then, the tuned model was fit with the splatted training set and evaluated in validation, after which, we fitted the model with the whole training data frame to predict the test portion of data.

Results

Minimum (Min), maximum (Max) and most common (Mcom) prices varied over the years, presenting falling periods in early 2013 and growth from late 2013 to early 2014. Max prices presented a relative stability from middle 2014 to 2016 with few variations during this time while Mcom, Min and Mm presented variation in their values. Despite great variation, growing periods were commonly found between 2020 and 2022 for all variables except Mm which presented a fall after middle 2021. The difference between maximum and minimum prices (Mm) also presented variations with highest values around 2020 and early 2021, and a fall from middle 2021 to 2022, due to an increase in Min prices that reached values close to Max prices (Fig. 2).

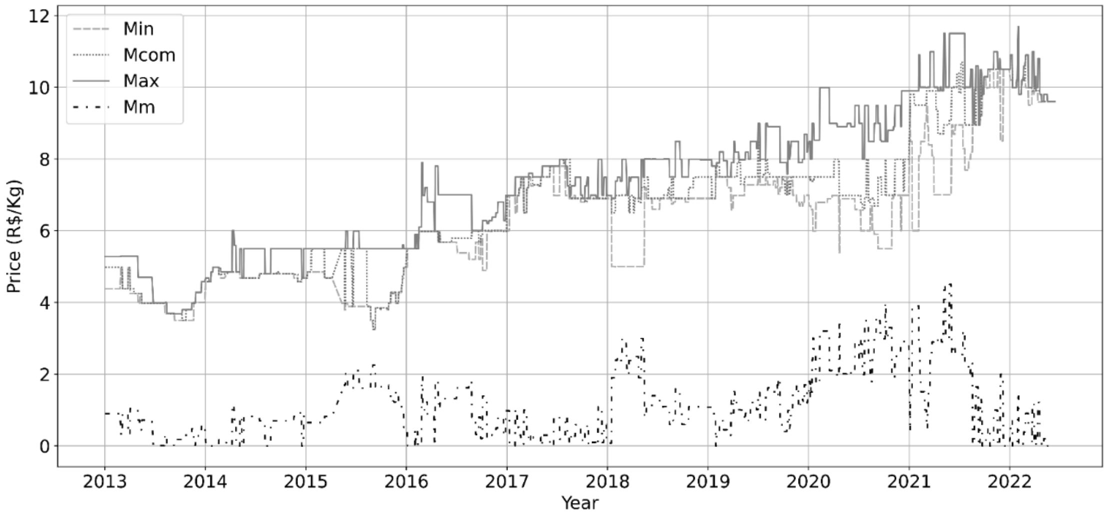

Figure 2 - Variation of Minimum (Min), Maximum (Max), Most Common (Mcom) and Range of Prices (Mm) Throughout the Analyzed Years in Pernambuco Supply and Logistics Center (CEASA-PE)

All variables were classified as non-stationary variables, except Mm, which presented a Dickey-Fuller p-value smaller than 0.05, indicating that Min, Max and Mcom have trend or seasonal effects on their variations (Table 2). Although the non-stationary variables presented growing trends, with Mcom and Max having continuous increments during the whole series, Min prices presented distinctions on their variation, with increasing values from 2014 to 2017, low variation among 2017 and 2020, and growing variation from 2020 to 2022 (Fig. 3).

Table 2 - Dickey Fuller Result of the Minimum (Min), Maximum (Max), Most Common (Mcom) and Range of Prices (Mm) Variables

Metrics	Min	Max	Mcom	Mm
p-value	0.7191	0.6375	0.7903	0.0033
No. of lags used	24.0000	10.0000	22.0000	10.0000

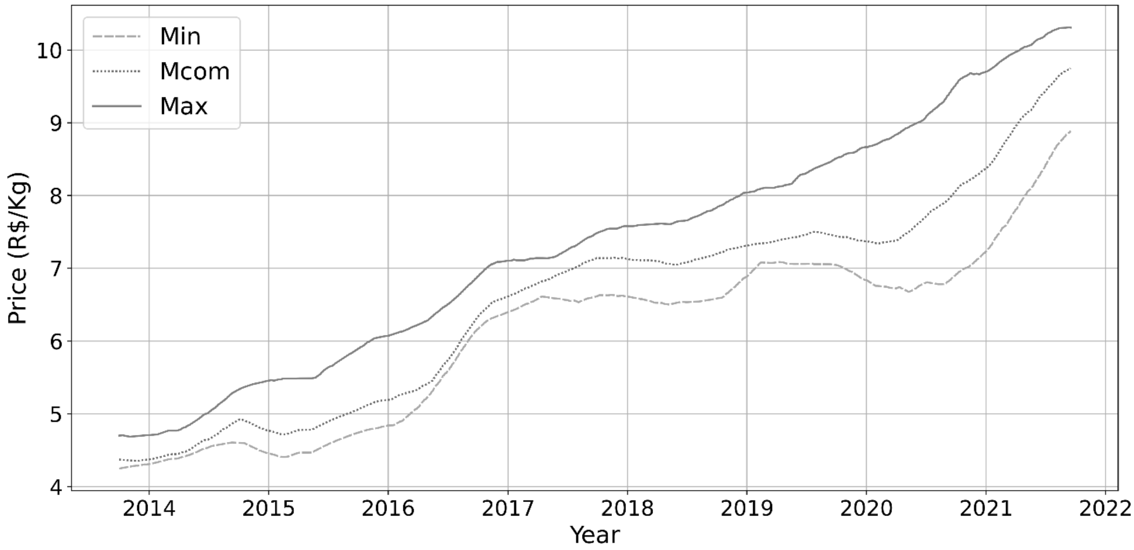

Figure 3 - Trends of Minimum (Min), Maximum (Max) and Most Common (Mcom) Prices Time Series Along the Years

The autocorrelation test showed distinct patterns of correlation from the variables past values and their most recent data, with the Max prices presenting autocorrelation of 0.97, 0.95 and 0.87, respectively, for one-week, one-month and one-year horizons. Mcom presented 0.98 and 0.95 for one-week and one-month; within a one-year interval, its scores dropped, reaching autocorrelation around 0.70. Min prices presented scores higher than 0.90 in one-week and one-month, however, in one year the presented autocorrelation was lower than 0.60, and Mm prices only showed autocorrelation higher than 0.70 in the time interval of one-week (Table 3).

Table 3 - Autocorrelation of the Minimum (Min), Maximum (Max), Most Common (Mcom) and Range of Prices (Mm) Variables Along the Intervals of One Week, One Month and One Year

Economic Variables	One Week	One Month	One Year
Min	0,9673	0,9154	0,5280
Max	0,9749	0,9540	0,8778
Mcom	0,9814	0,9502	0,7053
Mm	0,8126	0,6685	-0,1614

The Max and Mcom variables rolling means presented variability over the years, but with an increasing trend, although there was a slight decrease at the end of the series. Min also presented a growing trend in its rolling mean, but relative stabile periods were common in its series, especially in the periods of 2014 to 2015 and early 2018 to 2019, but with growing prices since late 2020, and Mm presented huge variability in its rolling mean during the whole series. Differences among the variation of their volatility (rolling standard deviation) were observed, with Mm being the most volatile variable, showing great variations since the first years of our analysis. Max and Mcom presented few peaks of volatility from 2013 to 2017, but huge variations after this period are notable, while Min prices showed volatility peaks in 2018, indicating distinct variation patterns among the variables, as well as after 2020, during the period of the COVID-19 pandemic (Fig. 4).

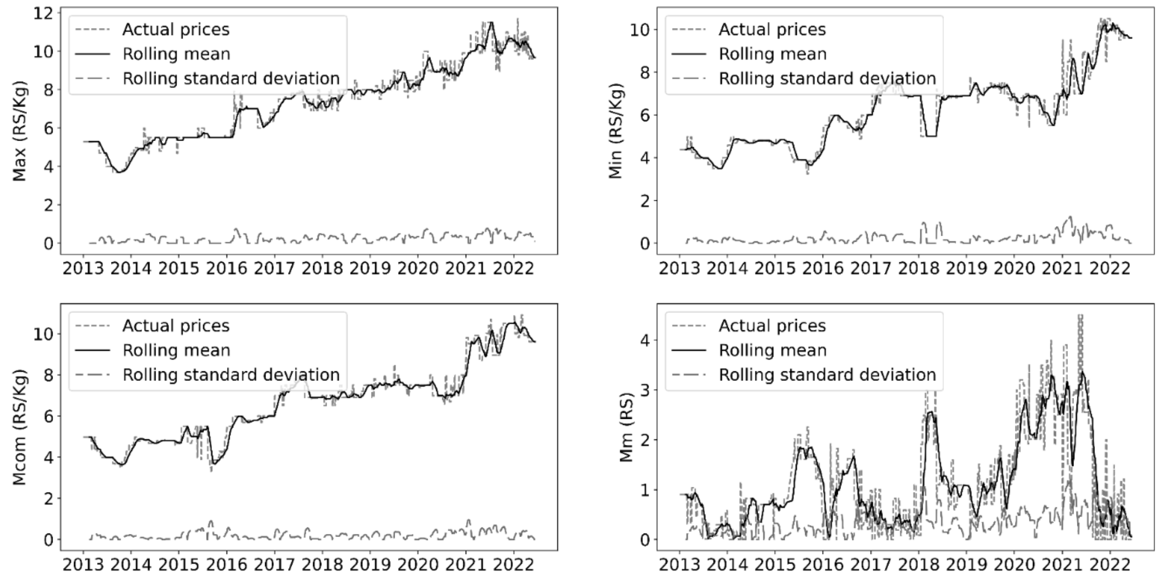

Figure 4 - Time Series of Minimum (Min), Maximum (Max), Most Common (Mcom) and Range of Prices (Mm), and Their Respective Rolling Means and Rolling Standard Deviation (Volatility)

The FbProphet modeling had daily, and annual seasonalities selected in all models for presenting a better fit. Models for Max and Mcom prices scored low error metrics in validation, with MAPE lower than 0.15 and test sets of data, with MAPE around 0.15 while Min prices had similar error metrics on validation and slightly higher errors in testing (Table 4). Cross-validation revealed that the prediction of the model presented low error metrics even at horizons of one-year for Max and Mcom prices, although Min prices presented higher error metrics in a smaller horizon for predictions (Fig. 5). Although the min prices model presented higher error metrics than the others, it was still capable to fit the data, showing predictability capacity (Fig. 6).

Table 4 - FbProphet Model Error Metrics in the Validation and Test Sets of the Original Dataset for Each Economic Variable

Economic Variables	Data Frame	RMSE	MAPE	MAE
Min	Validation	1.239	0.147	1.060
	test	1.639	0.164	1.612
Mcom	Validation	1.159	0.101	0.858
	test	1.462	0.135	1.335
Max	Validation	0.616	0.051	0.616
	test	1.287	0.114	1137

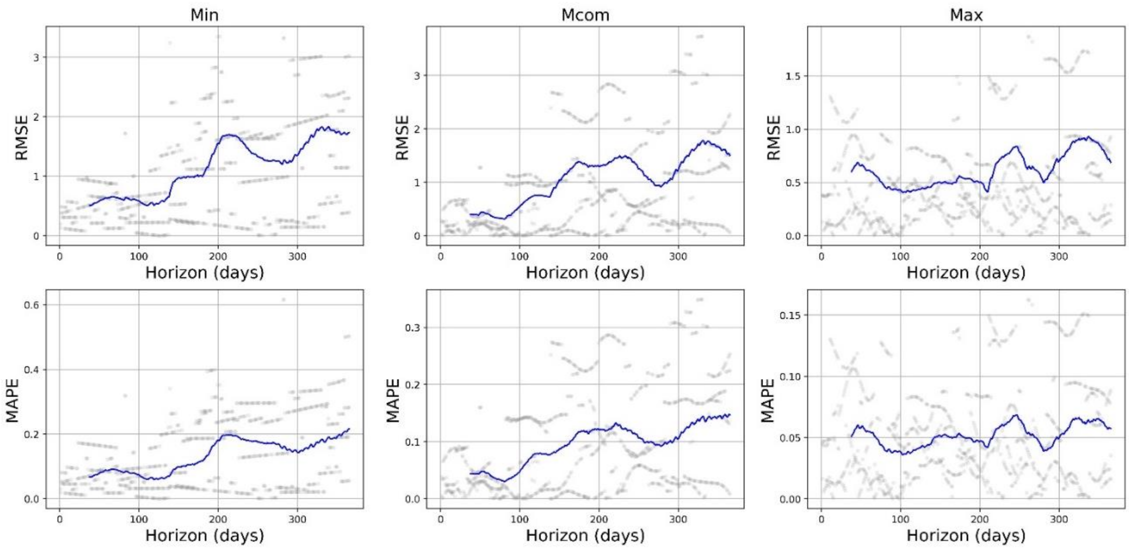

Figure 5 - Variation of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) of the FbProphet Models in the Price Variables in Different Time-Horizons of Forecasting. Grey points are the error metric for each day and the blue line is the moving average of the error metric in the cross-validation process

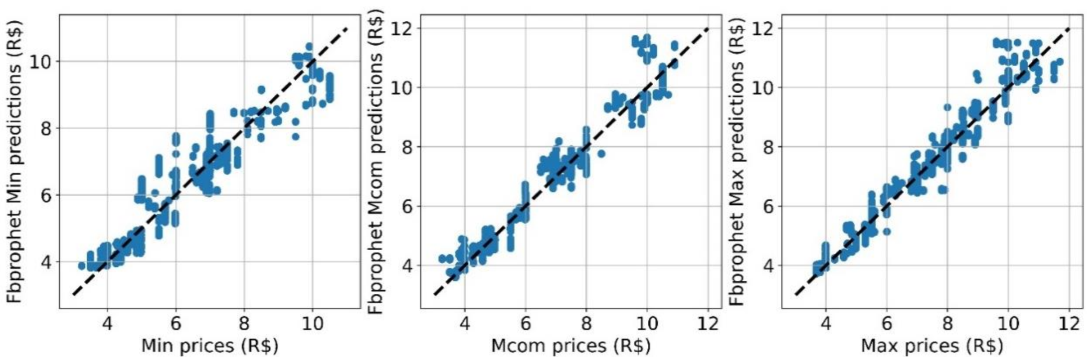

Figure 6 - Scatter Plot of the Real Minimum (Min), Maximum (Max) and Most Common (Mcom) Prices Against the Fbprophet Forecast for Each Variable

The LSTM network had low error metrics (MAPE < 0.03) on all predictable variables in validation, assuring us that we could apply it to the test data frame. In the test data frame, the highest error obtained was in the max variable (MAPE = 0.013), although test predictions presented smaller error metrics than validation forecasts (Table 5). The model presented general predictions close to the real prices of all variables (Fig. 7).

Table 58 - LSTM Network Error Metrics in the Validation and Test Sets of the Original Dataset for Each Economic Variable

Economic Variables	Data Frame	RMSE	MAPE	MAE
Min	Validation	0.326	0.018	2.027
	test	0.095	0.004	0.315
Mcom	Validation	0.337	0.022	0.207
	test	0.165	0.009	0.098
Max	Validation	0.598	0.051	0.503
	test	0.316	0.013	0.136

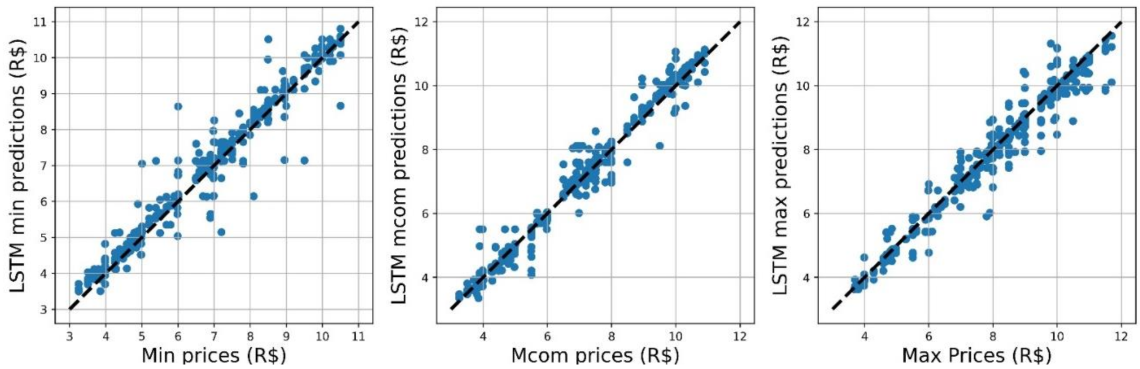

Figure 7 - Scatter Plot of the Real Minimum (Min), Maximum (Max) and Most Common (Mcom) Prices Against the LSTM Forecast for Each Variable

Discussion

Knowledge of food price variation plays a key role in the development of public policies on food security (Jacobi et al., 2021). Since fish are generally considered commodities, their prices may present high volatility due to diverse external factors (Taghizadeh-Hesary et al., 2019; Pincinato et al., 2020). To better understand these economic dynamics, the application of machine learning algorithms is a helpful tool to predict and bring valuable insights to researchers and decision makers (Sezer et al., 2020; Tang et al., 2020; Mele et al., 2021).

Imported sardines are important in the Brazilian market for being a more reliable supplier for processing industry, once national sardine fisheries present high fluctuation in catches (Pincinato & Asche, 2018). Nevertheless, all sardines traded in CEASA-PE and analyzed in this work were national catches originating from Santa Catarina and Rio Grande do Sul. Previous studies about Brazilian sardine prices noticed its volatility: Pincinato et al. (2022) studies in the Company of storehouses and general warehouses of São Paulo [Companhia de Entrepostos e Armazéns Gerais de São Paulo – CEAGESP] showed sardine prices as the most volatile in the market. Imported sardines are commonly traded in CEAGESP, which does not occur in CEASA-PE, which may be the reason for this difference, even though volatility was intensified during the COVID-19 pandemic in both places.

The pandemic scenario resulting from the spread of the new human coronavirus (SARS-CoV-2) has increased food prices globally and, consequently, influenced food security, especially in middle-income countries (Falkendal et al., 2021; Narayanan & Saha 2021). In Brazil, the COVID-19 pandemic changed the spending patterns of consumers, worsened nutrition indicators and advanced dietary inequalities (Mendes et al., 2021). Accordingly, Brazilian sardine prices showcased significant increments in standard deviation during pandemic years, which evidences the role of COVID-19 as a volatility driver in the Brazilian native fish species prices in the domestic market.

The relationship between the COVID-19 pandemic and food prices volatility may be explained by the social distancing policies. Although this strategy was efficient in avoiding the spread of the virus (Alfano & Ercolano, 2020), its varying levels of social restrictions impacted food prices, with falling prices during lighter restrictions periods and growing prices during more severe restriction periods (Akter, 2020). This pandemic scenario had a distinct nature from previous food crises, which were characterized by instantly growing prices and not by high volatility in food supply chain from producer to consumers (Clapp & Moseley, 2020; Aday & Aday, 2020). There is a need for specific food security policies in global and local spheres, as governments whose political agenda included food security as top priorities presented positive results avoiding food crises (Yu et al., 2020).

Diverse factors might influence the price dynamic of seafood products (Januchowski-Hartley et al., 2020; Castro-Gutiérrez et al., 2022), among which climate change, total capture, and fuel price are highlighted (Cheilari et al., 2013; Sala et al., 2018; Pincinato et al., 2020; Guerra et al., 2021). In this study, price variables presented distinct variations in their volatility since strong autocorrelation of economic variables show that univariate analyses could give us accurate predictions depending on the horizon. Most common

(Mcom) and maximum (Max) prices had high autocorrelation (> 0.7) in all the horizon scenarios proposed in this research, which resonates in the high accuracy of our model forecasts in these time horizons. Minimum (Min) prices presented low autocorrelation in the one-year interval, which suggests that different factors might have influenced its dynamics during this period. Volatility dissimilarities are reported to alter stock market prices autocorrelation (Faff & McKenzie, 2007), which may also occur with seafood prices and may be pointed as an relevant factor in the differentiation in the autocorrelation of Min from the other variables.

FbProphet modeling had good metrics predicting the variable prices using annual and daily seasonality, returning a mean absolute percentage error (MAPE) lower than 1.7 both in validation and test values. On the other hand, Min metrics were higher than the metrics obtained for Max and Mcom. This difference between the error metrics among the economic variables may be due to the change in trends between late 2020 and early 2021 in the Min variable, which may have not been properly caught by the FbProphet once its algorithm only tracks the data changes when there is trend modification (Rathore et al., 2022). The trend's change in Min prices occurred in the dataset's final part, so it may not have been part of the train dataset, which would have made the model not catch this trend variation, thus resulting in higher Min error metrics than in the other variables.

FbProphet has been used to predict prices of cryptocurrency and even energy demands (Chaturvedi et al., 2022; Rathore et al., 2022), but had not yet been applied to seafood products price prediction, and it performed well in the three economic variables evaluated. Max was the variable in which the FbProphet model performed better, giving us a horizon prediction of one year, having a root mean square error (RMSE) lower than one, an outstanding performance mainly due to the high autocorrelation of this variable. Mcom also had low error metrics, although significantly higher than Max, and Min forecasts are the ones with higher error metrics, despite presenting good metrics with horizons up to 150 days. These results indicate that Fbprophet may be used to predict seafood prices, but the use of the cross-validation is essential to avoid inaccurate predictions.

The long short-term memory (LSTM) neural network has proved to be a useful tool for predicting and understanding the dynamic of economic variables on different contexts, since this kind of network is able to store previous information about the variables and fit the data variations in the short-term while the historical trends and seasonality are caught in the long-term (Cao et al., 2019; Budiharto, 2021; Lin et al., 2021).

Previous studies proved that LSTM outperformed other modelling techniques, such as FbProphet and ARIMA models in economic contexts (Tang et al., 2021), although factors such as different forecast horizons may lead to distinct error metrics (Muzaffar & Afshari, 2019), which may explain the differences among our results in validation and test, once these data frame distinct data volumes imply in different forecast horizons. In marine sciences the application of this type of neural network is widespread in physical oceanographic studies (Liu et al., 2018; Kim et al., 2020; Jorges et al., 2021), but economic analyses of seafood products are scarce and the present study's results have shown that the application of LSTM in this context has a promising potential as it has the lowest error metrics on all economic variables.

Even though our results were obtained through a univariate analysis, its low error metrics showed that the utilization of LSTM neural networks and FbProphet algorithm may be applicable to the study of price variation of seafood items, opening the door to more complex analyses that include other features. Other variables were not evaluated in the modeling, so we have no direct evidence on what the main influence on the fluctuation of the price of the CEASA-PE sardine is. However, peaks of volatility after 2020 may be an indicator of the COVID-19 impact on seafood prices in the Brazilian market, as it has also impacted important seafood markets worldwide (Akter, 2020; Amos et al., 2022). For further studies, the acquisition and evaluation of more variables are indicated, since food prices may be influenced by factors such as oil prices, which in some market situations influence food items price volatility (Hau et al., 2020), helping create a more robust analysis and contribute to understanding the price dynamic of seafood items.

Conclusion

Sardine prices at the CEASA-PE have presented great variation over the years, with increasing trends since 2013 and differences among minimum, maximum and most common prices volatilities. Peaks after 2020 evidence the possible role of the COVID-19 pandemic as a volatility driver of fish prices in Brazilian domestic market, impacting the spending pattern of consumers and advancing food inequalities. The knowledge about the pricing dynamics of popular food items such as sardine may help improve public policies in order to avoid sudden price increments and consequently the unaffordability of these popular food items, minimizing the impact of food crises. Despite the infrequent utilization of machine learning algorithms in the context of economic analyses of seafood items, its application may be a powerful tool to study seafood price dynamics with forecasting potential.

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Considerações finais

Diante do exposto, é possível afirmar que a aquicultura em Pernambuco tem potencial para desempenhar um papel estratégico para promover desenvolvimento rural em áreas interiores do estado que contenham reservas hídricas suficiente para a realização desta atividade. Entretanto, estudos de impacto ambiental e análises de água prévias são essenciais para que a implementação de sítios aquícolas seja feita de maneira responsável, de modo a não comprometer o abastecimento de água em regiões que possam estar sujeitas à escassez deste recurso devido às mudanças climáticas. Além disto, evidenciou-se a capacidade preditiva de algoritmos de *machine learning* no contexto econômico do mercado de pescados, com a utilização desta ferramenta analítica sendo recomendada para minimizar incertezas dos envolvidos na cadeia de produção destes produtos. Porém, ressalta-se a necessidade de atualização dos dados e novos treinamentos dos algoritmos, tendo em vista o dinamismo do mercado de commodities e que perturbações nas tendências das séries de preços não capturadas pelos algoritmos utilizados podem comprometer seu desempenho no médio e longo prazo.