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Toward Fish Silage Emulsion from Barbados: A Mixture of Experts Analysis

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Abstract: Fish silage emulsion is a sustainable alternative to synthetic fertilizers. Fish silage emulsion offers several benefits, including fertilizing crops, reducing methane emissions, and helping reduce dependence on nitrogenous fertilizers. To assess the market for fish silage emulsion in Barbados, one needs to consider the fertilizer market. This assessment should consider market demand, price, supply, and the potential for export to neighboring countries. This study uses the mixture of experts (MoE) model to forecast fertilizer prices, measured by the Fertilizer Price Index (FPI). The MoE model is a machine learning framework intended to optimize model parameters efficiently while minimizing the corresponding processing requirements. It accomplishes this by utilizing a set of specialized submodels, known as "experts," along with a gating system that dynamically identifies the most pertinent experts for each input. Using monthly FPI data from January 2021 to February 2025, forecasts were generated. The model projects the index to rise from 133.47 in February 2025 to 153.1040 in the 5-step ahead forecast and further to 200 in the 10-step ahead forecast.

Keywords: mixture of experts model, fertilizer prices, fish silage emulsion, Barbados

1. Introduction

Barbados, as a small open economy, is heavily reliant on trade to meet its domestic needs, particularly for agricultural goods and inputs. In the agricultural sector, the country depends significantly on imports such as synthetic nitrogenous fertilizers. As a minor participant in global value chains, Barbados is highly vulnerable to supply disruptions, which pose significant economic risks. Geopolitical tensions, natural disasters, or logistical bottlenecks can severely impact the availability of these inputs. Such disruptions not only threaten timely access to fertilizers but are also likely to be accompanied by price increases, further straining the country's agricultural productivity and food security.

In addition to supply chain vulnerabilities, the environmental consequences of synthetic nitrogenous fertilizers add another layer of concern for Barbados. While these fertilizers are required for enhancing soil fertility and boosting crop yields, their overuse can result in ecological damage. Excessive application contributes to soil degradation, water pollution through nitrogen runoff, and increased greenhouse gas (GHG) emissions, all of which exacerbate environmental challenges. For Barbados, a small island developing state already susceptible to the impacts of climate change due to its geographic location, addressing these issues is an important priority. Exploring sustainable alternatives is required to mitigate environmental harm while reducing dependency on imported fertilizers.

One sustainable solution is the production of fish silage emulsion. Fish silage is a liquid product derived from fish waste, which can be directly used as a fertilizer. Fish silage can be processed into fish emulsion, which is an organic fertilizer that improves soil fertility and crop yields. The fish emulsion contains key elements like nitrogen, phosphorus, potassium, calcium, and magnesium, all of which are vital for plant growth [1, 2].

The production of fish silage emulsion is also an attractive project in Barbados as it can help address a fish waste problem in the country. Barbadians consume between 5,000 and 6,000 tons of fish each year, with around 3,000 tons coming from local fishing vessels [3]. As fish plays a key role in the national diet, a substantial amount of waste is produced during processing and consumption. This waste is often discarded in landfills, where it decomposes anaerobically, releasing methane (CH_4), a GHG that contributes to global temperature rise and the corresponding climate change. Given the environmental and public health risks posed by landfill disposal, it is important for Barbados to adopt more sustainable solutions for managing fish waste.

The price of fertilizer is critically important for Barbados, as it directly impacts agricultural productivity, food security, and the cost of living in the country. As such, the outlook or forecast of fertilizer prices is important as it provides insight into the expected "business as usual" scenario for stakeholders in Barbados if no alternative solutions are pursued. Additionally, such forecasts offer a clear justification for exploring locally produced fish silage emulsion as a sustainable and cost-effective alternative to imported fertilizers.

The corresponding research question is "What is the market potential for fish silage emulsion in Barbados and neighboring Caribbean countries?"

As such, the objective of this study is to perform a market assessment for fish silage emulsion in Barbados. Since fish silage emulsion is not a commonly traded product in markets, the assessment will focus on evaluating the fertilizer market. This evaluation should include (1) an assessment of fertilizer import demand in

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Barbados, (2) a forecast of fertilizer prices, (3) an analysis of the supply of fertilizers in Barbados, and (4) an exploration of the prospects for exporting fish silage emulsion to neighboring Caribbean countries.

The rest of this study is structured as follows. Section 2 provides a literature review. Section 3 considers the imports of fertilizer in the Caribbean Community (CARICOM) region. Section 4 outlines the data and the methodology for the forecasting of fertilizer prices. Section 5 presents the results. Section 6 furnishes a discussion. Section 7 concludes this study.

2. Literature Review on Fish Silage Industry in Barbados

Barbados has the highest population density among CARICOM countries, with 659 individuals per square kilometer (km²) and a total population of 280,693 as of 2020 [3]. To satisfy its food requirements, the country relies heavily on imports, with approximately 90% of consumed food being sourced from abroad. This dependency not only classifies Barbados as a net food importer but also makes it highly vulnerable in terms of food security.

The Barbados Fisheries Policy 2023–2033 highlights that the country's fisheries production has fluctuated between 1,300 and 3,500 metric tons annually from 2005 to 2016, with average production reaching approximately 2,300 tons in 2018 [3]. According to the World Integrated Trade Solution (WITS) database, Barbados imported fish and seafood products, including fish, crustaceans, mollusks, and other aquatic invertebrates, valued at US$36,193,329 in 2023. This represented about 9% of the nation's total food imports. The primary imported species include dolphinfish, billfish/marlin, swordfish, tuna, and kingfish [3].

There has been limited research on the fish waste industry in Barbados.

Drakes et al. [4] conducted a study on fish silage in Barbados. The analysis was not econometric in nature but relied instead on a series of assumptions to construct a financial assessment. The study assumed that there was no existing infrastructure for fish silage production in Barbados and that public markets would be the responsible agents for producing silage at an off-site facility. Additionally, the volume of fish waste available was estimated at 5 tons per day. The cost estimates were limited to the first year of operation and excluded ongoing expenditures such as asset depreciation. Furthermore, the study assumed that the final product, fish silage, would be sold directly to local animal feed producers.

The capital expenditure required to establish the facility was estimated at US$153,400.00 and included costs for land, building, machinery (such as a grinder, pump, mixing tank, and storage tank), testing equipment, and a vacuum truck. Operating expenditures, which accounted for waste collection services and labor, were estimated at US$112,520.00. This brought the total estimated cost of setting up and running the facility in the first year to US$265,920.00. The proposed facility would process 1,521 tons of fish waste annually, yielding approximately 1,368 tons of fish silage.

The study did not account for the cost of formic acid, a key input in the silage production process, which costs US$1,500 for a minimum quantity of 35 kg. As an alternative, the study identified molasses, available at US$1 per 3.78 liters, as an organic substitute. Based on international market prices for fish meal and soymeal, the authors projected that fish silage could be competitively priced for sale to local feed producers. Revenue from the annual production of fish silage was estimated to range between US$528,485 and US$2,044,900, depending on the market price. At a benchmark price equivalent to soybean meal (US$386.32 per ton), the operation would generate an annual operating surplus of US$262,573.92. However, once the cost of formic acid was factored in, the model reflected a significant loss of approximately US$1.69 million, highlighting the sensitivity of financial viability to input costs.

King et al. [5] study was a follow-up to the earlier work conducted by Drakes et al. [4], focusing on the generation and utilization of fish waste in Barbados. Their primary aim was to provide updated estimates and an overview of fish waste sources generated across the country. The study was mainly qualitative and descriptive in nature, relying on stakeholder perspectives rather than any econometric modeling. The authors conducted 18 interviews with stakeholders involved in fish processing and fisheries management. Interviews were conducted with representatives from all 6 fish processing plants in the country and with 12 out of the 13 landing sites under the oversight of the Barbados Fisheries Division.

King et al. [5] found that the fish offal generated in Barbados is approximately 3,140 tons annually. The lion's share of this waste—2,566 tons—originates from fish landing sites, while the residual 574 tons come from fish processing plants. Notably, King et al. [5] found that 94.5% (2,958 tons) of the waste is disposed of in the Mangrove Landfill in Vaucluse, St. Thomas. Additionally, 4.3% (144 tons) of the waste is lost at sea, resulting in approximately 1.2% (38 tons) currently being utilized via small-scale projects. These findings highlight a substantial underutilization of fish waste resources in Barbados, reflecting an untapped economic opportunity.

Two major landing sites, namely, the Bridgetown Fisheries Complex and Oistins, were identified as the primary contributors to fish waste in the country. The mentioned landing sites account for 60.3% and 34.0% of the waste generated, respectively. The most common fish species contributing to the waste include flying fish, dolphinfish, yellowfin tuna, and marlin, among others. These species are significant not only for their volume but also for their potential to provide useful by-products if processed.

King et al. [5] also noted a range of innovative projects currently being explored in Barbados for fish waste. These projects include the production of minced fish products, burgers, wieners, and other value-added foods by Morgan's Fish House and Ocean Fisheries. Furthermore, Morgan's Fish House has developed products such as fish leather and dog treats from fish skins and is innovating with the conversion of fish offal into fish silage for use in animal feed. While these projects represent important early steps in valorizing fish waste, they remain limited in scale relative to the total volume of waste generated.

King et al. [5] study concluded with three recommendations from stakeholders. They are as follows. First, there is a need for efficient sorting and collection systems at the fish markets and processing facilities to consolidate waste for further processing. Second, there should be an establishment of best practices for the timely freezing and storage of waste to preserve quality and mitigate against spoilage. Third, stakeholders lobbied for the establishment of a centralized plant in the country, which could process the entirety of the fish waste into value-added products for the agricultural sector.

Currently, the Caribbean Regional Fisheries Mechanism (CRFM) and the Food and Agriculture Organization (FAO) are collaborating with small-scale stakeholders in Barbados on a project focused on producing fish silage. Specifically, these stakeholders are looking into developing fish silage emulsion as a fertilizer. However, there is currently no market assessment for fish emulsion in Barbados. There is no assessment of the import demand of fertilizer and no assessment or forecast for the price of fertilizer. A market assessment of import demand would be useful as it would reflect the size of the local demand. Similarly, a forecast of fertilizer prices would be valuable, as it could signal whether prices are likely to rise in the near future. Such information is important, as increasing fertilizer prices would lead to higher crop production costs for farmers, further highlighting the need for cost-effective and sustainable alternatives like fish silage emulsion.

This study aims to address that gap by evaluating the demand for fish silage-based fertilizers. This study will also assess and forecast fertilizer prices. Furthermore, this study will consider the supply of fertilizers in Barbados and explore the prospects for exporting fish silage emulsion to neighboring Caribbean countries.

The next section examines the imports of fertilizer in CARICOM.

3. Imports of Fertilizer in CARICOM

Data on fertilizer imports within the CARICOM region were collected from the WITS database. Two SITC classifications were used: SITC 272 (fertilizers, crude, other than those of division 56) and SITC 56 (fertilizers [other than those of group 272]). To provide a comprehensive assessment of fertilizer imports in the CARICOM region, the study first presents the imports under SITC 272 and SITC 56 separately. Subsequently, the total fertilizer imports were calculated by combining the data from both SITC 272 and SITC 56.

As can be seen in Table 1, Barbados imported approximately US$77,000 worth of SITC 272 in 2019. By 2023, imports had decreased to around US$62,000. This data indicates that Barbados is among the lower importers of SITC 272 within CARICOM.

Note, Figures A1–A4 in the Appendix correspond with Tables 1–4.

As illustrated in Table 2, Barbados imported approximately US$2.7 million worth of SITC 56 in 2019. By 2023, this figure had increased to around US$3 million. The data highlights that imports of SITC 56 surpassed those of SITC 272, a trend observed not only in Barbados but also across many other CARICOM member states.

As outlined in Table 3, Barbados imported approximately US$2.8 million worth of fertilizer, including SITC 272 and SITC 56, in 2019. By 2023, fertilizer imports had risen to around US$3.1 million. The data indicates that Barbados remains one of the smaller importers of fertilizer within CARICOM, with countries such as Guyana, Suriname, and Belize leading in fertilizer imports across the region. In 2020, CARICOM's total fertilizer imports amounted to US$83.072 million. This year was chosen for analysis due to comprehensive data availability across most member states, except for St. Kitts and Nevis, for which estimates were derived by substituting the last year of available data.

As highlighted in Table 4, fertilizer imports accounted for 0.18% of Barbados' total imports in 2019 but decreased to 0.15% by 2023. This demonstrates that fertilizer imports make up a very small portion of the country's overall imports. This trend is not unique to Barbados, as other CARICOM member states also exhibit similarly low import shares for fertilizers. However, countries like Guyana, Suriname, and Belize, while leading the region in fertilizer imports, maintain comparably low percentages relative to their total imports.

Despite the small import shares, the total value of fertilizer imports across CARICOM member states ranges from approximately US$1 million to US$40 million.

Table 1
Imports of SITC 272 (fertilizers, crude, other than those of division 56) in CARICOM in USD 1,000 (2014–2023)

Year	Antigua and Barbuda	The Bahamas	Barbados	Belize	Dominica	Grenada	Guyana	Jamaica	St Kitts and Nevis	St Lucia	St Vincent and the Grenadines	Suriname	T&T
2014	$49.45	$412.90		$317.33		$22.97	$48.71	$10.11	$93.05	$13.47	$0.83	$299.43	$35.90
2015	$47.75	$607.37		$169.85		$14.08	$81.46	$221.15	$95.68	$7.93	$1.11	$132.25	$84.80
2016	$51.00	$701.82		$111.92	$36.07	$24.83	$36.09	$98.09	$94.09	$1.60	$0.40	$106.59	$60.06
2017	$34.17	$631.62		$28.07	$32.72	$28.45	$48.60	$249.27	$105.66	$2.08	$5.04	$112.12	$83.60
2018	$50.67	$645.33		$53.19	$55.85	$56.09	$811.35	$28.59		$6.39	$9.66	$120.27	$146.02
2019	$107.45	$727.24	$77.64	$62.47	$517.91	$58.81	$212.16	$26.99		$8.29	$9.27	$114.24	$193.92
2020	$121.34	$509.78	$57.63	$104.44	$212.18	$43.27	$637.29	$16.82		$6.09	$13.51	$147.63	$418.80
2021	$373.08	$1,172.91	$16.74	$52.37	$99.68	$26.99	$23.99	$34.14			$10.73	$107.09	$297.21
2022	$409.07	$968.92	$59.94	$121.02	$84.54	$90.47	$1,167.23	$68.58			$23.83	$107.98	$260.67
2023	$364.04	$1,061.10	$62.58	$253.83	$136.06	$13.66	$1,505.44	$266.06			$0.79	$70.16	

Table 2
Imports of SITC 56 (fertilizers [other than those of group 272]) in CARICOM in USD 1,000 (2014–2023)

year	Antigua and Barbuda	The Bahamas	Barbados	Belize	Dominica	Grenada	Guyana	Jamaica	St Kitts and Nevis	St Lucia	St Vincent and the Grenadines	Suriname	T&T
2014	$350.37	$3,064.52		$18,576.93		$396.85	$32,581.71	$16,785.51	$176.31	$1,650.26	$1,598.47	$17,356.06	$5,789.25
2015	$449.77	$2,899.90		$18,766.32		$571.50	$33,235.13	$9,284.04	$231.10	$1,883.68	$990.97	$11,367.27	$6,251.65
2016	$488.03	$3,104.73		$17,211.07	$749.95	$228.31	$28,284.31	$7,864.90	$228.74	$935.37	$1,257.54	$7,070.94	$5,883.51
2017	$368.52	$2,982.17		$15,616.74	$572.26	$356.00	$14,200.33	$7,675.89	$175.55	$1,164.88	$927.38	$14,763.62	$5,474.58
2018	$496.91	$3,389.68		$18,499.20	$972.84	$465.12	$31,429.21	$15,945.28		$1,479.67	$999.66	$8,060.75	$5,673.79
2019	$482.58	$1,947.50	$2,779.57	$17,663.88	$990.26	$583.34	$28,074.34	$10,079.03		$1,398.50	$993.73	$9,334.46	$6,378.42
2020	$421.63	$1,257.21	$2,645.67	$16,495.88	$839.42	$509.08	$24,336.55	$9,026.71		$1,043.14	$1,110.42	$16,735.63	$6,081.32
2021	$519.56	$2,294.90	$2,510.73	$22,453.67	$1,267.90	$457.54	$34,814.60	$13,427.33			$1,242.44	$14,158.72	$7,250.40
2022	$465.35	$2,513.22	$3,691.64	$32,655.48	$978.26	$1,025.01	$45,029.72	$18,026.34			$2,910.89	$32,675.00	$9,046.16
2023	$721.75	$2,489.06	$3,054.34	$26,688.01	$1,050.26	$1,293.03	$39,743.02	$12,185.67			$1.064.47	$40,022.35	

Table 3
Imports of fertilizer (SITC 272+56) in CARICOM in USD 1,000 (2014–2023)

Year	Antigua and Barbuda	The Bahamas	Barbados	Belize	Dominica	Grenada	Guyana	Jamaica	St Kitts and Nevis	St Lucia	St Vincent and the Grenadines	Suriname	T&T
2014	$399.82	$3,477.42		$18,894.25		$419.81	$32,630.42	$16,795.62	$269.36	$1,663.73	$1,599.30	$17,655.48	$5,825.14
2015	$497.52	$3,507.27		$18,936.16		$585.58	$33,316.59	$9,505.19	$326.78	$1,891.61	$992.08	$11,499.52	$6,336.46
2016	$539.03	$3,806.55		$17,322.99	$786.02	$253.14	$28,320.39	$7,962.99	$322.83	$936.97	$1,257.93	$7,177.53	$5,943.58
2017	$402.69	$3,613.79		$15,644.81	$604.98	$384.44	$14,248.93	$7,925.17	$281.21	$1,166.96	$932.42	$14,875.74	$5,558.18
2018	$547.57	$4,035.01		$18,502.39	$1,028.69	$521.21	$32,240.57	$15,973.87		$1,486.05	$1,004.31	$8,181.03	$5,819.80
2019	$590.02	$2,674.74	$2,857.21	$17,726.35	$1,508.17	$642.15	$28,286.50	$10,106.02		$1,406.78	$1,003.00	$9,448.70	$6,572.34
2020	$542.97	$1,766.99	$2,703.30	$16,600.32	$1,051.60	$552.35	$24,973.84	$9,043.52		$1,049.23	$1,123.93	$16,883.26	$6,500.12
2021	$892.64	$3,467.81	$2,527.47	$22,506.04	$1,367.58	$484.53	$34,838.59	$13,461.46			$1,253.18	$14,265.81	$7,547.61
2022	$874.43	$3,482.14	$3,751.58	$32,776.50	$1,062.79	$1,115.48	$46,196.95	$18,094.92			$2,934.72	$32,782.98	$9,306.84
2023	$1,085.79	$3,550.16	$3,116.92	$26,941.84	$1,186.33	$1,306.69	$41,248.46	$12,451.73			$1,065.26	$40,092.51	

Table 4
Import shares ((SITC 272+56)/Total Imports) in CARICOM (2014–2023)

Year	Antigua and Barbuda	The Bahamas	Barbados	Belize	Dominica	Grenada	Guyana	Jamaica	St Kitts and Nevis	St Lucia	St Vincent and the Grenadines	Suriname	T&T
2014	0.07%	0.09%		1.96%		0.13%	1.83%	0.29%	0.10%	0.26%	0.44%	0.97%	0.05%
2015	0.11%	0.11%		1.90%		0.17%	2.24%	0.19%	0.11%	0.32%	0.30%	0.60%	0.07%
2016	0.11%	0.13%		1.82%	0.37%	0.07%	1.74%	0.17%	0.10%	0.14%	0.38%	0.61%	0.07%
2017	0.06%	0.10%		1.71%	0.31%	0.09%	0.81%	0.14%	0.09%	0.18%	0.28%	1.23%	0.08%
2018	0.10%	0.11%		1.93%	0.34%	0.10%	1.34%	0.26%		0.22%	0.28%	0.54%	0.08%
2019	0.10%	0.08%	0.18%	1.80%	0.52%	0.13%	0.70%	0.16%		0.23%	0.30%	0.55%	0.10%
2020	0.11%	0.08%	0.18%	2.11%	0.58%	0.14%	1.07%	0.19%		0.20%	0.35%	1.10%	0.13%
2021	0.15%	0.10%	0.15%	2.12%	0.72%	0.11%	0.79%	0.23%			0.34%	1.03%	0.13%
2022	0.14%	0.09%	0.17%	2.38%	0.40%	0.19%	1.24%	0.23%			0.67%	1.82%	0.15%
2023	0.16%	0.08%	0.15%	2.01%	0.39%	0.21%	0.79%	0.16%			0.23%	2.36%	

Notably, the data for the years 2024 and 2025 are not available. Additionally, there is no forecast of market demand for up to 2030, a key target year for the nationally determined contributions of Barbados, as well as many other Parties to the Paris Agreement.

The next section outlines the data and methodology for the forecasting of fertilizer prices.

4. Data and Methodology for Forecasting

Nitrogenous fertilizers come in various forms, brands, and compositions, with differences in their nitrogen (N), phosphorus (P), and potassium (K) content, commonly referred to as NPK ratios, which cater to diverse agricultural needs. Given this variability, assessing the price of a single type or brand of fertilizer would not reflect a true representation of all fertilizer prices. Instead, a more holistic approach would involve considering an index that aggregates prices across different fertilizer types and brands, reflecting broader market dynamics. In this context, the Fertilizer Price Index (FPI) emerges as a sensible tool for evaluating fertilizer prices, as it captures the average price movements of a basket of nitrogenous fertilizers, accounting for variations in composition and brand.

The data used for forecasting is the FPI, identified by the ticker I:FPINH3XX. This data originates from the World Bank but was collected via YCharts [6]. The dataset is available at a monthly frequency, spanning from January 2021 to February 2025, and consists of 50 observations.

4.1. Consideration of traditional univariate methods

The Autoregressive Integrated Moving Average (ARIMA) model is a commonly used statistical technique for predicting univariate time series. It comprises three aspects, namely: the autoregressive (AR) component, which captures the relationship between the present and past value of a variable; the integrated (I) part, which accounts for non-stationarity in data for a variable; and the moving average (MA) aspect, which models the dependence in the error term to help improve predictive accuracy. The ARIMA model is appropriate for forecasting time series that are linear and follow the normal distribution [7].

Unfortunately, in many practical econometric applications, time series data on variables may be nonlinear and do not follow the normal distribution. Many time series on economic variables may exhibit nonlinearity, structural breaks, and other complexities. As such, when the ARIMA model is applied to such data, the model cannot forecast when there would be a turning point in a trend. In other words, if a time series has been steadily increasing, ARIMA is unable to predict when or at what level the time series will reverse and begin to decline. Consequently, more advanced models capable of capturing nonlinear dynamics are required for better forecasting.

The Long Short-Term Memory (LSTM) model emerges as one model that is stronger than the traditional ARIMA model. The LSTM is a type of artificial neural network, which is a machine learning model that is specifically designed to learn long-term dependencies in sequential data [8].

While the LSTM is a good model, the mixture of experts (MoE) model is a stronger modeling framework than the standard LSTM as it uses a collection of specialized submodules, referred to as experts, along with a gating mechanism that selects the most relevant expert or combination of experts for each input. Notably, LSTM itself can be included as one of the expert models within the MoE framework to handle various aspects of analyzing time series data. This approach allows the MoE to better manage nonlinear time series data as it assigns different modeling tasks to different experts, rather than an LSTM model, which undertakes all the tasks for itself.

4.2. Introduction to mixture of experts models

The MoE model is a machine learning paradigm designed to scale model parameters efficiently without proportionally increasing computational demands. It achieves this by leveraging a collection of specialized submodels, referred to as "experts," and a gating mechanism that dynamically selects the most relevant experts for each input. This conditional computation approach allows MoE models to handle complex tasks while maintaining computational efficiency, making them particularly well-suited for large-scale applications such as natural language processing, computer vision, and multimodal tasks [9–11].

4.3. Using mixture of experts (MoE) for univariate forecasting

The MoE model can be adapted for univariate forecasting tasks. This can be done by using specialized submodels (experts) and dynamic routing mechanisms to capture diverse temporal patterns in time series data [12, 13].

4.3.1. MoE layer in Transformer-based models

In Transformer-based models, an MoE layer performs conditional computation by dynamically assigning input data to experts based on a gating mechanism [14]. For each input X, the gating function determines which experts are activated:

1) Dense MoE

In dense MoE, all experts are activated for every input. The output is computed as:

$$y = \sum_{i=1}^{n} g_i(x) \cdot f_i(x) \tag{1}$$

where:

$g_i(x)$ is the softmax output of the gating function for the i-th expert.

$f_i(x)$ is the output of the i-th expert.

Dense MoE ensures full utilization of all experts but may incur higher computational costs compared to sparse MoE [15–17].

2) Sparse MoE

In sparse MoE, only the top-k experts with the highest gating scores are selected for each input. The output is given by:

$$y = \sum_{i \in top-k} g_i(x) \cdot f_i(x) \tag{2}$$

Sparse MoE reduces computational overhead by activating only a subset of experts, making it suitable for large-scale forecasting tasks.

The expert layer returns the weighted sum of the selected experts' outputs, where the weights are determined by the softmax of the gating function's output decoders [18, 19]. This approach enables the model to focus computational resources on the most relevant experts for each input. The MoE layer in Transformer-based models is displayed in Figure 1.

4.3.2. Various gating functions employed in MoE models

The gating mechanism plays a critical role in MoE models by determining how inputs are routed to experts. Several gating functions have been proposed:

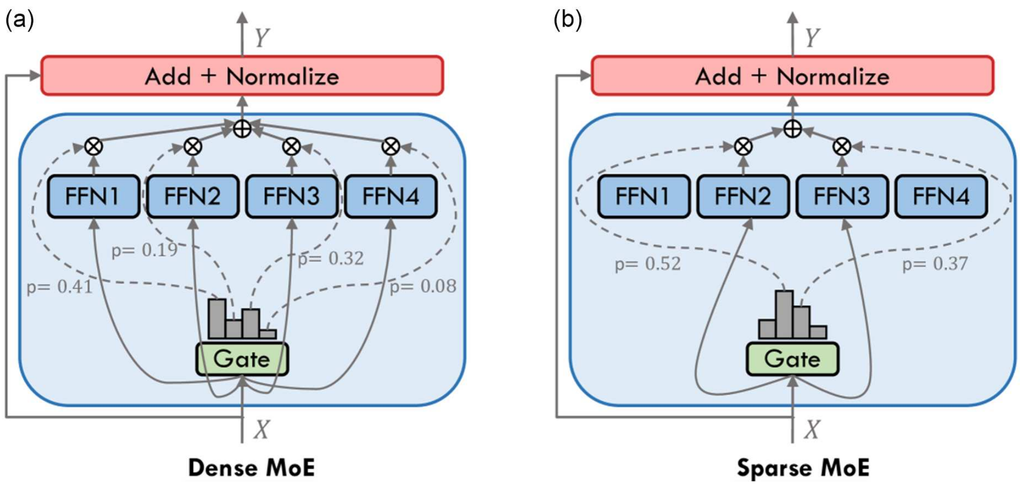
1) Sparse MoE with top 1 gating

Top 1 gating activates only the highest-scoring expert for each input. While computationally efficient, this approach may lead to load imbalance if certain experts are overutilized.

2) BASE layers

BASE layers combine trainable and non-trainable gating mechanisms, enabling flexible expert selection while maintaining stability.

Figure 1
An illustration of an MoE layer in Transformer-based models



Source: Cai et al. [20]

3) Grouped domain mapping and random gating

As seen in PanGu-∑ [21], tokens are first routed to domain-specific expert groups, followed by random selection within the group. This approach balances domain-specific expertise with randomness.

4) Expert-choice gating

In expert-choice gating, each expert selects the top-k tokens it will process. This inversion of the token-choice paradigm ensures uniform token distribution but may result in uneven token coverage [22].

5) Attention router

Attention routers use attention mechanisms to determine expert activation, allowing for context-aware expert selection.

6) Soft MoE with expert merging

Soft MoE avoids discrete expert selection by merging all experts' parameters through a weighted average. This approach maintains full differentiability and enhances training stability.

Each gating function has unique advantages and trade-offs, making them suitable for different forecasting scenarios. Figure 2 displays the gating functions employed in MoE models.

4.3.3. Mixture of attention heads and shared expert architectures

1) Mixture of attention heads (MoA)

MoA combines multi-head attention with MoE to enhance performance while reducing computational costs. It employs two sets of experts: one for query projection and one for output projection, selected using a common gating network. To reduce complexity, MoA shares key (*Wk*) and value (*Wv*) projection weights across attention experts, allowing shared pre-computation of key and value sequences.

2) Shared expert

In shared expert architectures, each token is processed by a fixed expert (dense FFN) and a gating-selected expert [23]. This approach achieves two-expert engagement per layer without increasing communication costs beyond top-1 gating. Shared expert designs have gained traction in recent models like DeepSeekMoE and Qwen1.5-MoE [16].

These architectures enable efficient integration of MoE into Transformer-based models, enhancing their scalability and performance. Figure 3 shows the mixture of attention heads and shared expert architectures.

4.3.4. Taxonomy of MoPEs based on placement within the transformer model architecture

The taxonomy of mixture of parameter-efficient experts (MoPE) is based on their placement within the Transformer architecture:

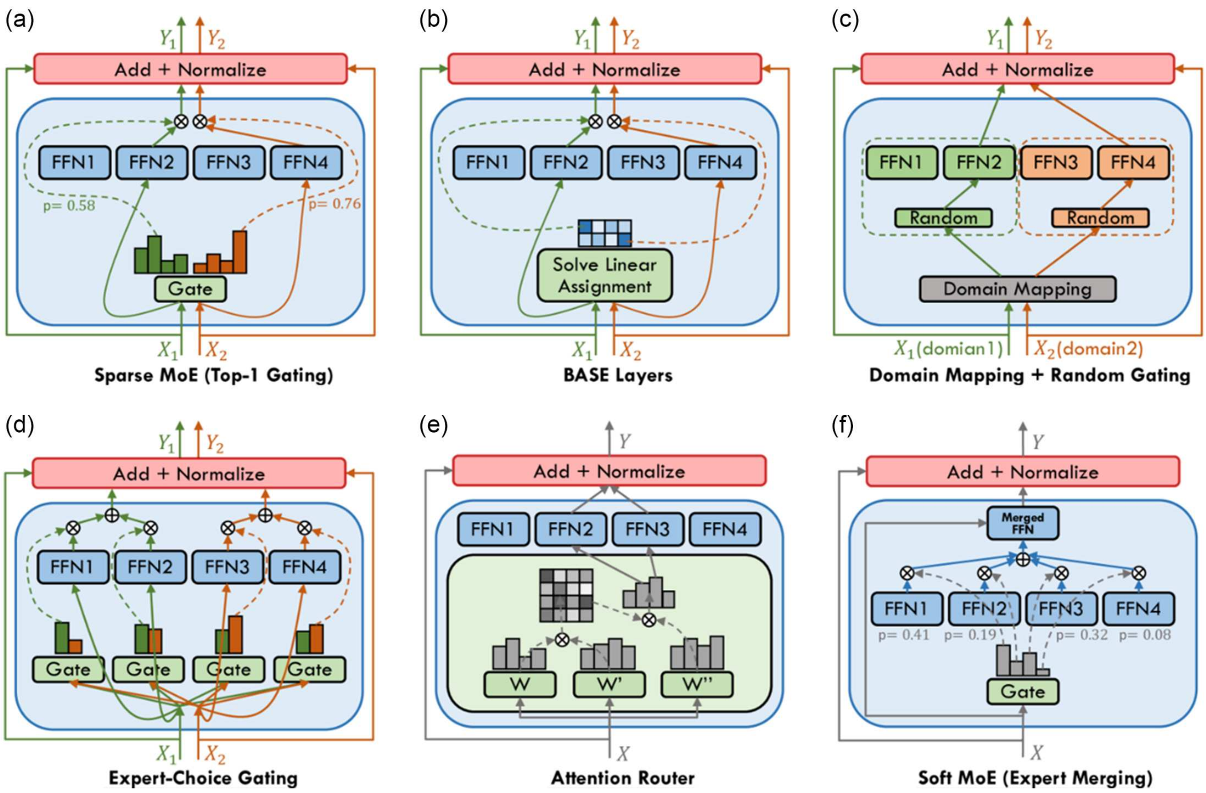
1) Integration with key and value modules

MoPE can be integrated into the key and value modules of the attention mechanism, with applicability extending to the query and output projection modules. This allows for fine-grained control over attention computations.

2) Application to FFN

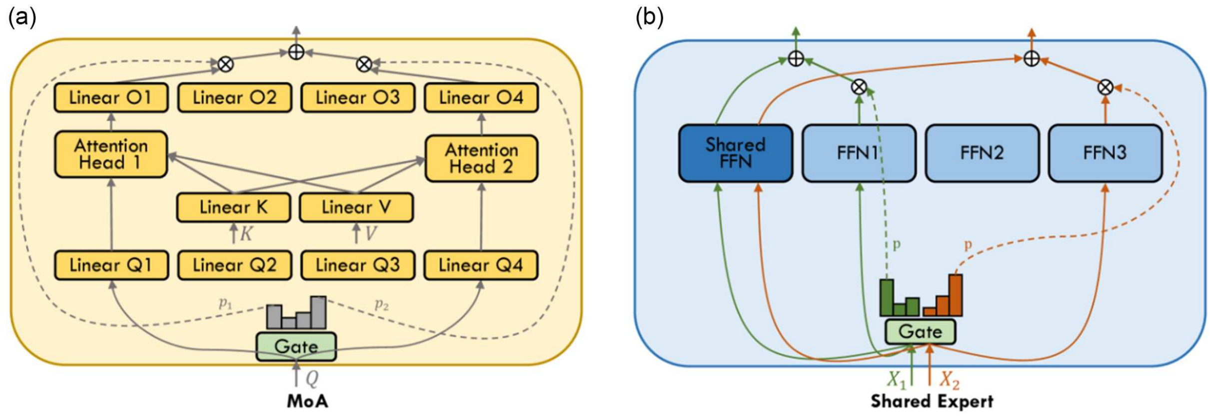
MoPE can be applied to the feed-forward network (FFN) layers, replacing traditional FFNs with parameter-efficient experts.

Figure 2
Various gating functions employed in MoE models



Source: Cai et al. [20]

Figure 3
Mixture of attention heads [24] and shared expert [25] architectures



Source: Cai et al. [20]

This approach reduces computational demands while preserving model capacity.

3) MoPE integration at the transformer block level

At the Transformer block level, MoPE applies two distinct groups of experts—one for attention and one for FFN—each regulated by its own gating mechanism. This modular design enables specialized handling of different components within the block.

4) Layer-wise integration of MoPE

In layer-wise integration, each Transformer layer is treated as a unified entity, with a single gating mechanism orchestrating the interplay among experts. This holistic approach captures the combined dynamics of attention and FFN within a unified framework.

This taxonomy highlights the flexibility of MoPE in adapting to various architectural placements, enabling efficient scaling and specialization. Figure 4 shows the taxonomy of MoPEs based on placement within the Transformer model architecture.

4.3.5. Schematic representation of training and inference schemes related to MoE

The schematic representation of MoE training and inference schemes provides an abstracted view of model transitions:

1) Original scheme without architectural transformation

The original scheme involves training and inference without architectural changes, maintaining the dense or sparse MoE configuration throughout.

2) Merging of distinct expert models

Exemplified by Branch-Train-Mix [26], this approach merges multiple pretrained dense expert models into a unified MoE model. The merged model undergoes fine-tuning to optimize expert collaboration.

3) Transition from dense to sparse model

This scheme starts with dense model training and progressively transitions to a sparse MoE configuration, balancing computational efficiency and performance.

4) Conversion from sparse to dense Model

Inverse to the previous scheme, this approach converts a sparse MoE model into a dense model for hardware-friendly inference.

These schemes demonstrate the adaptability of MoE models across different stages of training and deployment. Figure 5 shows the training and inference schemes related to MoE.

4.3.6. Diverse parallel strategies for MoE

Efficient scaling of MoE models in distributed environments relies on diverse parallel strategies:

1) Expert parallelism

Each expert is assigned to a distinct device, while non-expert layers are duplicated across devices. This approach minimizes communication overhead and maximizes computational efficiency.

2) Hybrid parallelism

Hybrid strategies combine expert parallelism with other parallel techniques, such as tensor parallelism, pipeline parallelism, and sequence parallelism. Examples include:

Data + Expert + Tensor Parallelism [10, 25].
Data + Expert + Pipeline Parallelism [27].
Expert + Tensor Parallelism [28].

3) Hierarchical all-to-all communication

Hierarchical communication strategies enhance intra-node processing while reducing inter-node data exchanges, improving scalability [29].

4) Pipelining

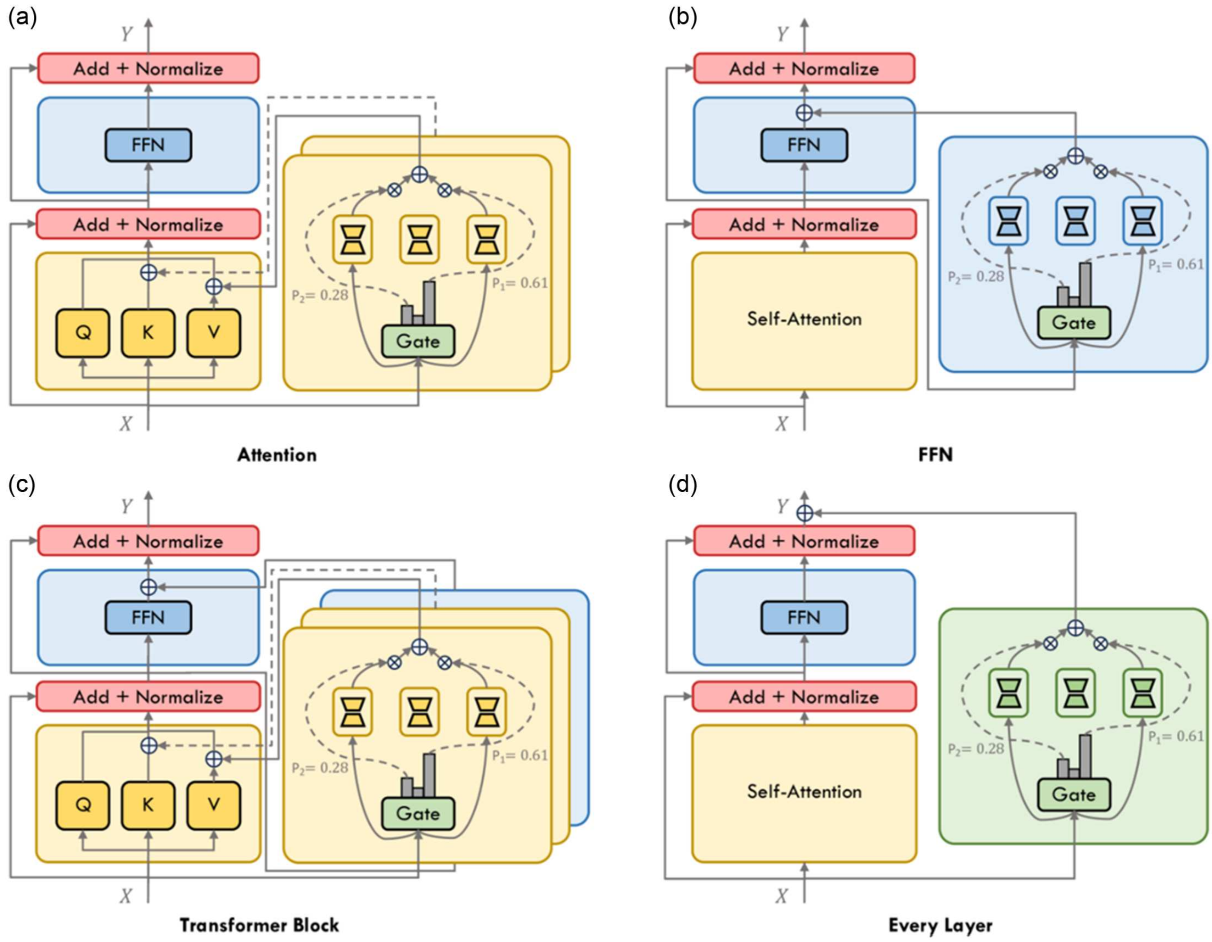
Pipelining overlaps communication and computation, reducing total time costs. Systems like Tutel [30] and FasterMoE [27] employ pipelining to optimize performance.

These strategies ensure efficient resource utilization and scalability in large-scale MoE deployment. Figure 6 shows the parallel strategies for MoE.

4.4. How the MoE model was implemented regarding expert selection and gating mechanisms

The study's MoE architecture served as a cooperative group of specialized forecasters, and the model's capacity to adapt depended heavily on the interactions between the experts and the gating network. Fundamentally, the MoE depended on a self-organizing mechanism that permitted such roles to develop naturally through learning rather than operating under a strict pre-programmed

Figure 4
The taxonomy of MoPEs based on placement within the transformer model architecture



Source: Cai et al. [20]

framework where each expert was allocated a specific duty (e.g., trend detection, cycle recognition, noise filtering). This independence, which is an inherent characteristic of the MoE model, was important to the model's ability to forecast time series with ever-increasing efficiency and specialization.

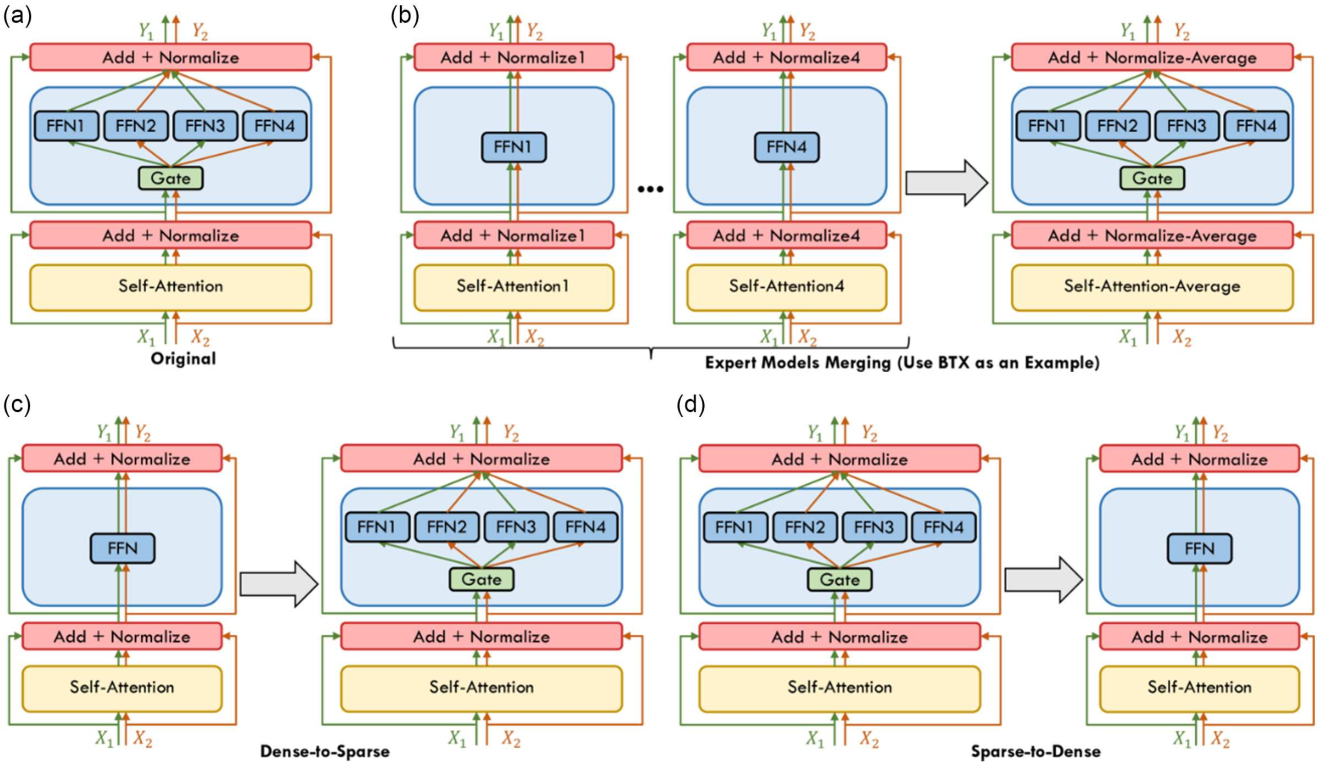
The same input sequences, which were windows of previous input values, were presented to all three LSTM-based experts. Due to the influence of the gating network and the feedback loop produced by the backpropagation of prediction error, each expert developed unique internal representations and behavioral inclinations even though they were given identical data. Each expert was able to discover distinct dynamic patterns in the time series due to this approach. The training dynamics, in which each expert is gently encouraged to contribute where they perform best, minimize the overall loss across all inputs and produce specialties rather than imposing them from the outside.

As the decision layer, the gating network learned to give the experts dynamic, context-dependent weights for every input sequence. After passing the flattened input sequence through a fully connected linear layer, it produced a three-dimensional vector that represented each expert's pre-softmax ratings. The model's confidence in each expert's suitability for the current sequence was expressed by the output, which, after applying the softmax function, generated a valid probability distribution over the three experts. As the model learned which expert's output was the best predictive under various circumstances, these gating weights changed over time, molded by the model's loss function, and improved over time.

Due to this dynamic weighting system, a convex combination of all expert outputs, weighted by the gate, rather than just one expert, determined the final forecast for any given input. This made it possible for the model to adaptively consult the most pertinent expert or experts for each sequence, ensuring that no single expert dominated the predictions across all input types. The stacked expert outputs (shape: batch size × 1 × num_experts) and the reshaped gate weights (shape: batch size × num_experts × 1) were technically multiplied by a batch matrix (bmm) to produce a single scalar prediction for each batch sample. With the help of the gate's learned preferences, this process made sure that expert forecasts interpolated smoothly.

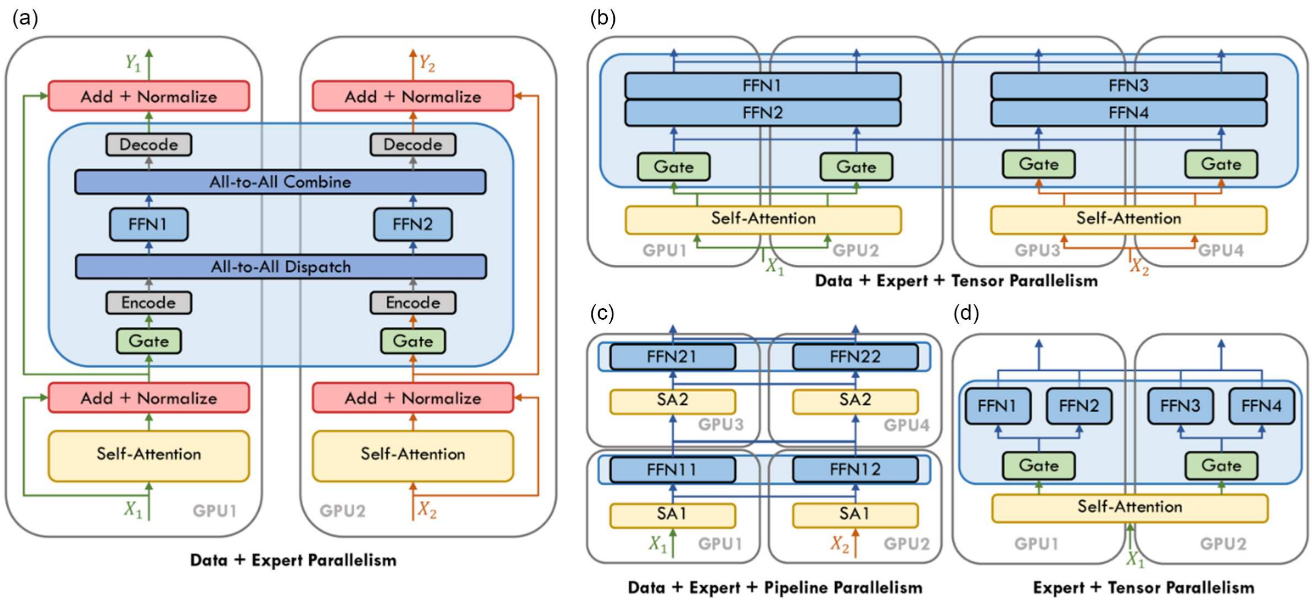
From the standpoint of learning, the gate and the experts were trained end-to-end using the same loss function, which is usually the mean squared error (MSE) between the actual next value in the sequence and the model's final output. Importantly, the gating network learned to favor the experts that consistently increased prediction accuracy for specific input patterns by

Figure 5
Schematic representation of training and inference schemes related to MoE



Source: Cai et al. [20]

Figure 6
Diverse parallel strategies for MoE



Source: Cai et al. [20]

receiving gradient signals from the final loss. A natural division of work resulted from the experts' simultaneous training to reduce inaccuracy in the sequences to which they were most commonly assigned. This prompted each expert to improve their internal depiction of a particular type of temporal behavior in the data throughout epochs.

The code and data for the model are available at https://github.com/doncharles005/MoE.

The next section presents the results.

5. Results

Before applying any model, basic pretests should be performed to determine whether the data is normally distributed and exhibits linearity. These pretests are important because if the data is not normally distributed or is nonlinear, regression models that rely on assumptions of linearity and normality, such as those based on ordinary least squares (OLS), would produce inaccurate coefficients and unreliable results. Consequently, traditional OLS-based regression models may not be suitable for modeling such data. In these cases, alternative methods that do not depend on assumptions of linearity and normality, such as machine learning models, would be more appropriate for achieving accurate modeling outcomes.

Table 5
Descriptive statistics on FPI

	FPI
Mean	163.1950
Median	154.5050
Maximum	293.7300
Minimum	82.96000
Std. Dev.	52.66601
Skewness	0.719083
Kurtosis	2.349528
Jarque-Bera	5.190487
Probability	0.074628
Sum	8159.750
Sum Sq. Dev.	135911.7
Observations	50

The null hypothesis of the Jarque-Bera (JB) test is a joint hypothesis of the skewness being zero and the excess kurtosis being zero. In other words, the null hypothesis is that the data comes from a normal distribution, and the alternative hypothesis is that the data does not come from a normal distribution.

In Table 5, the probability of the JB test statistic was 0.07, which would lead to the rejection of the null hypothesis at the 10% level of significance. This suggests that the data is not normally distributed at the 10% significance level.

The Bai-Perron test for L+1 vs. L sequentially determined breaks is a method used to identify the presence of multiple structural breaks in a dataset. It begins by testing the null hypothesis of no breaks against the alternative hypothesis of at least one break. If the null hypothesis is rejected, the test continues, sequentially evaluating the number of structural breaks until the null hypothesis can no longer be rejected. In Table 6, the Bai-Perron test proceeded until the null hypothesis of four breaks was not rejected, indicating that there were four structural breaks in the FPI data and suggesting that the data is nonlinear.

Table 6
Bai-Perron tests of L+1 vs. L sequentially determined breaks

Sequential F-statistic determined breaks:			4
		Scaled	Critical
Break Test	F-statistic	F-statistic	Value**
0 vs. 1 *	23.20746	23.20746	8.58
1 vs. 2 *	90.85355	90.85355	10.13
2 vs. 3 *	15.63005	15.63005	11.14
3 vs. 4 *	18.24949	18.24949	11.83
4 vs. 5	0.473288	0.473288	12.25
* Significant at the 0.05 level.			
** Bai-Perron (*Econometric Journal*, 2003) critical values.			
Break dates:			
	Sequential	Repartition	
1	2023M03	2021M10	
2	2021M10	2022M08	
3	2022M08	2023M03	
4	2023M12	2023M12	

Given the findings that the FPI data is not normally distributed and exhibits nonlinearity, there is clear justification for using a machine learning method to model the data. Consequently, this study proceeds with the application of the MoE methodology.

5.1. Forecasting results

The MoE is applied, and the results of the actual, fitted, and residuals for the FPI Index are displayed in Figure 7.

The actual, fitted, and residuals are key components used to evaluate the performance and accuracy of the model. The actual values represent the observed or true data points from the dataset. The fitted values, also known as predicted or estimated values, are the outputs generated by the model based on its learned parameters. The residuals are the differences between the actual and fitted values. A good model will have fitted values that closely align with the actual values, indicating accurate predictions.

In Figure 7, since the fitted values are close to the actual values, it suggests that the model has a good fit.

Diagnostic Results:

Test Mean Squared Error (MSE): 0.0170

Test Mean Absolute Error (MAE): 0.1073

The training error loss and validation error loss are metrics used during the model development process to evaluate how well a neural network is learning from the data and generalizing to unseen data. The training error measures the model's performance on the data it was trained on, while the validation error assesses its performance on a separate dataset that the model has not seen during training. In Figure 8, the training loss declines but is higher than the validation loss. This is a good result since if the training error is low, but the validation error is significantly higher, it indicates that the model may be overfitting. Conversely, if both the training and validation errors are high, the model may be underfitting. Additionally, as the training and validation loss plots are declining, it shows that the loss is decreasing over epochs, indicating the model is learning.

A low MSE value of 0.0170 and an MAE of 0.1073 suggest that the model's predictions are generally close to the actual values.

Figure 7
The actual, fitted, and residual results for the FPI index

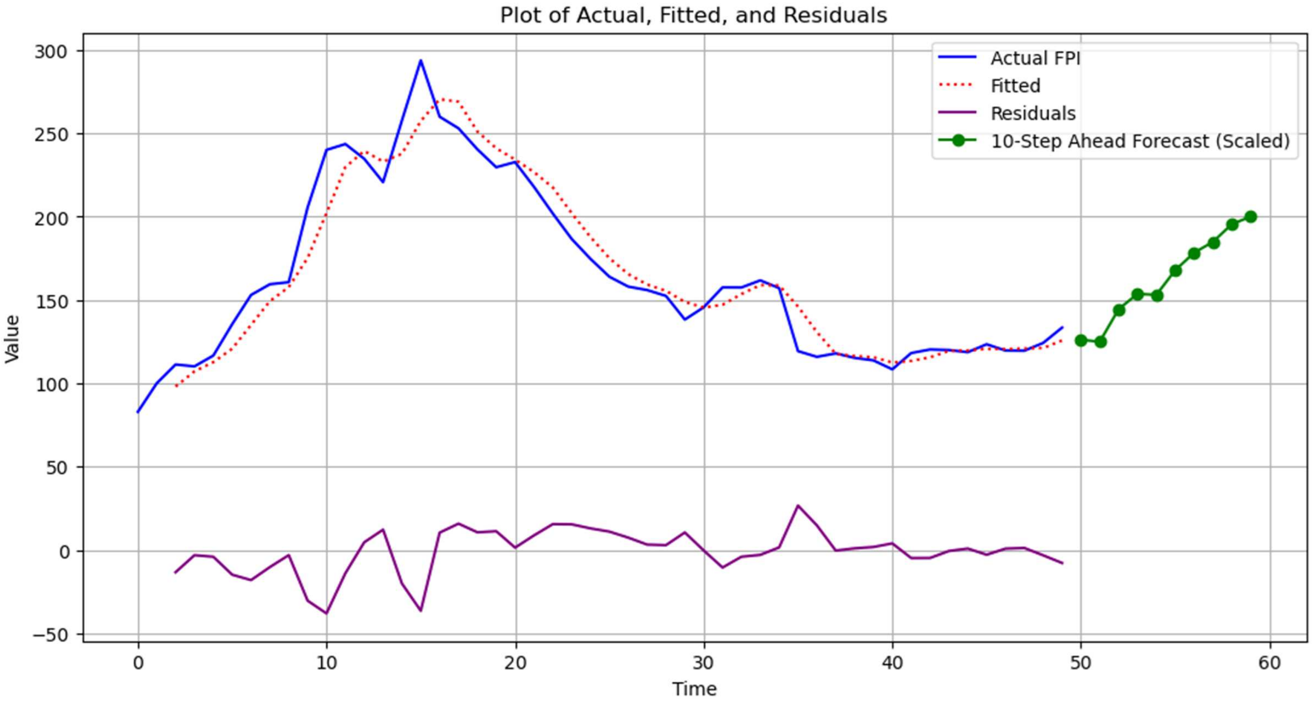
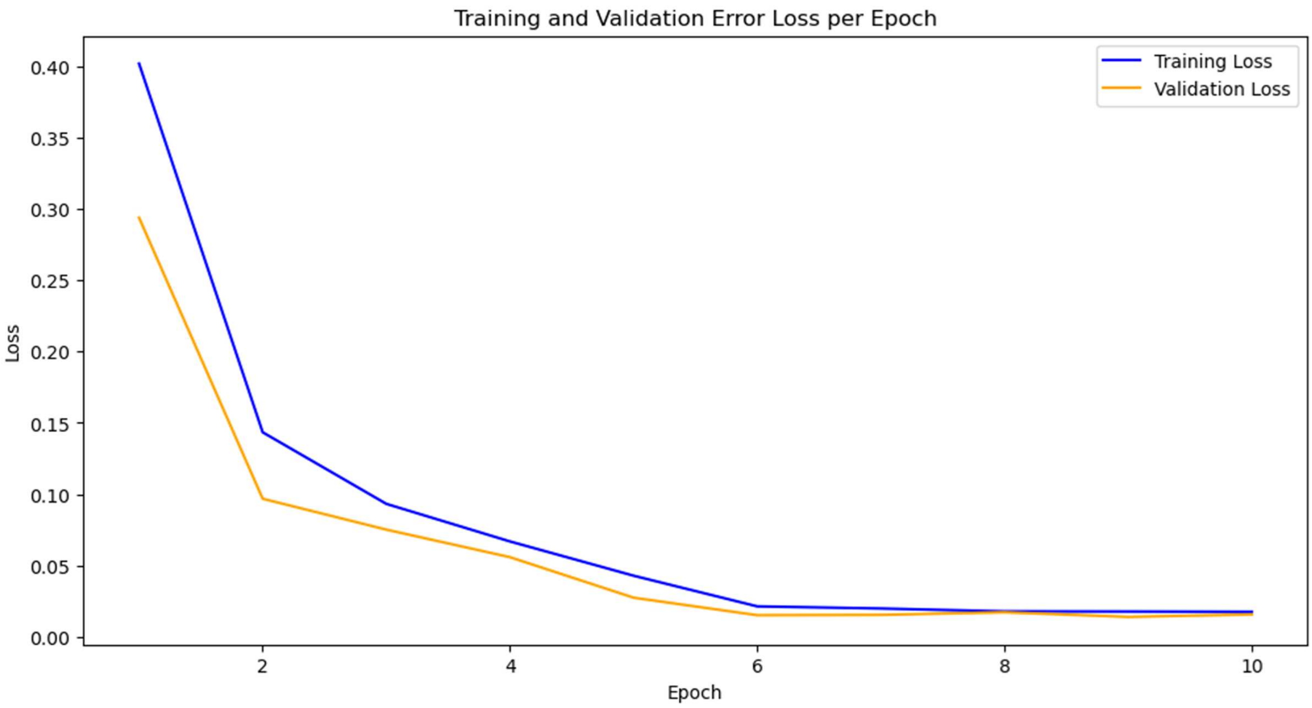


Figure 8
Training and validation error loss results



N-Step Ahead Out-of-Sample Forecasts:
Time Point 50: 126.1912
Time Point 51: 125.0000
Time Point 52: 144.5483
Time Point 53: 153.7257
Time Point 54: 153.1040
Time Point 55: 167.9146
Time Point 56: 178.3505
Time Point 57: 184.8863
Time Point 58: 195.5121
Time Point 59: 200.0000

The n-step ahead out-of-sample forecasts indicate that fertilizer prices are likely to increase. According to the model, the index is projected to rise from 133.47 in February 2025 to 153.1040 in the

Table 7
Results of ARIMA (111) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	–0.338339	0.220282	–1.535937	0.1314
MA(1)	0.815420	0.177442	4.595422	0.0000
SIGMASQ	193.6617	28.34783	6.831624	0.0000
R-squared	0.204321	Mean dependent var		1.030816
Adjusted R-squared	0.169727	S.D. dependent var		15.76270
S.E. of regression	14.36286	Akaike info criterion		8.238058
Sum squared resid	9489.425	Schwarz criterion		8.353883
Log likelihood	–198.8324	Hannan-Quinn criter.		8.282002
Durbin–Watson stat	1.952714			

5-step ahead forecast and further to 200 in the 10-step ahead forecast. This implies a 14.71% increase in fertilizer prices between February 2025 and five months in the future, based on the FPI. Similarly, there would be a 49.85% increase in fertilizer prices from February 2025 to ten months in the future.

To verify the superiority of the MoE forecast results over the traditional univariate linear regression model and the ARIMA model, the results of the ARIMA model are considered. These results are displayed in Table 7.

As seen from Table 7, the coefficient of the AR term is −0.338339, but it has a probability of 0.1314, suggesting that it is statistically insignificant. This statistical insignificance is a bad aspect of the result because it suggests that the AR term has no effect on the model. The MA term has a coefficient of 0.815420, but its probability of 0.0000 makes it statistically significant.

The Coefficient of Determination is 0.2043, suggesting a bad fit for the model. The Durbin–Watson statistic of 1.952714 is not between the dU (Upper critical value) of 1.65 and the dL (Lower critical value) of 1.78. Therefore, it is not in the inconclusive region. However, the statistic is greater than dU, suggesting that there is no evidence of positive first-order autocorrelation. This absence of autocorrelation is a good result.

However, the root mean squared error from the ARIMA model was 80.411785. Therefore, the MSE was 6466.050. This MSE of the ARIMA was significantly higher than the MSE of the MoE, which was 0.0170. Thus, the MoE was the better model.

The next section furnishes a discussion.

6. Discussion

As mentioned in the literature review, there is limited research on the fish waste industry in Barbados.

Both the Drakes et al. [4] and King et al. [5] studies provide useful qualitative insights into the generation and management of fish waste in Barbados. However, neither study undertakes any form of econometric market analysis. Their methodologies are predominantly descriptive, relying on stakeholder interviews to inform waste sources and highlight current usage practices. While these descriptive approaches are useful for establishing baseline knowledge and stakeholder perspectives, they do not provide the quantitative evidence necessary to assess the market potential of fish silage emulsion, particularly as a fertilizer substitute.

This represents a major gap in the literature. There is currently no econometric assessment of fertilizer prices for Barbados. Without a good model to forecast fertilizer prices, the outlook for fertilizer prices would be speculative. Entrepreneurs in Barbados venturing into the fish silage emulation industry would be relying on guesswork. A good model is required to forecast fertilizer prices especially one that can forecast turning points and changes in trends before they occur. This gap can only be bridged through the econometric modeling and forecasting of time series, which was addressed in Section 5.

6.1. Market segments

The fertilizer market can be classified into nitrogenous fertilizers for leafy crop growth, phosphorus fertilizers for root and flower development, potassic fertilizers to enhance plant resilience, NPK fertilizers that blend nitrogen, phosphorus, and potassium in specific ratios, and micronutrient fertilizers that provide important secondary nutrients and trace elements to rectify soil deficiencies.

Fertilizer demand varies based on the type of crop being cultivated. Therefore, it can be categorized based on the crops for its intended use, for instance: nitrogen and phosphorus fertilizers for grains and cereals, NPK fertilizers for fruits and vegetables, phosphorus fertilizers for oilseeds, and specialty fertilizers for ornamental plants.

Fertilizers are also segmented based on how they are applied to crops. For instance, there are solid, liquid, and organic fertilizers, all of which are applied differently.

Crop farming in Barbados is dominated by approximately 8,199 small agricultural holdings operated by farmers working on land sizes ranging from 0.2 to 10 hectares, collectively covering 6,074 hectares, or about 14% of the island's total land area. These farmers cultivate a variety of crops, including vegetables, root crops, and fruit crops, each with unique nutrient requirements. The fertilizer market in Barbados is influenced by variations in farming practices, as some farmers rely on rain-fed agriculture, while around 10% use irrigation systems supported by the Barbados Agricultural Development and Marketing Corporation. Annually, approximately 16,000 tons of vegetables and root crops are produced across roughly 5,000 acres.

Given these factors, Barbadian farmers need fertilizers specifically adapted to their soil conditions and crop nutrient demands. The local fertilizer market includes nitrogenous fertilizers, phosphatic fertilizers, potassic fertilizers, NPK fertilizers, and micronutrient fertilizers. Retail outlets in Barbados offer both solid and liquid fertilizer options to meet the diverse needs of farmers.

6.2. Supply of fertilizers

The supply of fertilizers in Barbados is primarily managed by distributors, as there is no significant fertilizer manufacturing within the country. Several companies play a key role in distributing fertilizer products to meet agricultural needs.

One prominent distributor is Massy Distribution (Barbados) Ltd., located on the Mighty Grynner Highway in St. Michael, Barbados. As the leading food and agricultural input supplier, the company provides farmers with a wide array of products, including fertilizers, seeds, chemicals, and farming equipment.

Another key player is the Eastern Caribbean Fertilizer Co. (Barbados) Ltd., based at Uplands Factory in St. John. This company specializes in the distribution of fertilizers and also serves as the authorized distributor for Brandt products in Barbados. These products include fertilizers, insecticides, pesticides, and bio-stimulants, catering to the diverse needs of the agricultural sector.

6.2.1. Supply of fertilizer in CARICOM

Within the CARICOM region, Trinidad and Tobago (T&T) stands out as a significant player in the fertilizer industry due to its ammonia production capabilities. T&T operates 11 world-scale ammonia production plants, with a combined annual capacity of 5.2 million metric tons (MT). This substantial output positions T&T as one of the largest ammonia exporters globally.

Despite its strong ammonia production, T&T does not manufacture fertilizers domestically. Instead, ammonia and urea are produced for export, while finished fertilizer products are imported to meet local demand. These imports are managed by multiple distributors operating within T&T.

A key distributor in the Caribbean fertilizer market is Caribbean Chemicals & Agencies Ltd (CCAL). CCAL is a major supplier of agricultural inputs across the English-speaking Caribbean, offering a wide range of products such as insecticides, fungicides, herbicides, adjuvants, seeds, and equipment like knapsack sprayers and irrigation hoses. The company sources its products from leading international brands and distributes them to farmers and agricultural businesses throughout the region. However, it is important to note that CCAL operates solely as a distributor and does not engage in fertilizer manufacturing.

6.2.2. Alternative fertilizer projects

In the CARICOM region, alternative fertilizer initiatives are gaining attention as part of efforts to address agricultural and environmental challenges. One notable project focuses on manufacturing fertilizers from sargassum, a marine biomass that has been causing significant inundation issues across the Caribbean. The CRFM, in collaboration with Plant & Food Research of New Zealand, is leading this effort under the Sargassum Products for Climate Resilience in the Caribbean Project. This project aims to transform sargassum into sustainable products, including liquid fertilizers and compost, thereby addressing the recurring problem of sargassum influx.

6.3. Prospects for export

The review of the import demand revealed that in 2020, CARICOM's total fertilizer imports amounted to US$83.072 million. This suggests that there is a demand for fertilizer in the CARICOM region. There is little to no fertilizer production in the CARICOM region. Therefore, there is an opportunity for entrepreneurs in Barbados to produce fish silage emulsion, which in turn can be exported to other CARICOM member states.

However, several factors should be considered when attempting to export. They include the expected standards for the fertilizer industry, CARICOM export standards, and the trade procedures for countries.

6.3.1. Standards for the fertilizer industry

To safeguard workers, customers, and the environment, fertilizer handling and production must follow stringent safety regulations. To ensure quality, environmental preservation, and consumer safety, standards are set by national regulatory agencies as well as international groups such as the International Fertilizer Association (IFA). These requirements cover critical aspects such as quality control testing, assured analysis, appropriate labeling, and environmental impact considerations. The sole international fertilizer association, the IFA, has over 500 members in 80 different nations. Sustainable agriculture systems are encouraged in the European Union (EU) by the Common Agriculture Policy, while standards are established by the European Committee for Standardization (CEN). The industry is governed in the United States by the Department of Agriculture and the Environmental Protection Agency (EPA).

Since Barbados is not a member of the IFA, there are no guidelines for the manufacturing of fertilizer or fish silage emulsion in the country. Testing is not a mandatory requirement. Nevertheless, it should be a part of fertilizer production for:

Nutrient content standards: To avoid deficiencies and toxicities, fertilizers should specify N-P-K ratios, macronutrients (Ca, Mg, S), and micronutrients (Fe, Zn, Mn, Cu, B, Mo).

Contaminant limits: According to EU and EPA regulations, heavy metals (As, Cd, Pb, Hg, and Cr) must reach certain criteria, such as 20 mg/kg of cadmium in phosphate fertilizers. Controlling organic contaminants, such as microbiological risks and persistent organic pollutants, is also necessary.

Particle size distribution: Powdered fertilizers ought to reduce particles for safety, whereas granular fertilizers should have particles between 2 and 4 mm for consistent application.

Moisture content: In order to avoid deterioration, fertilizers need to keep their moisture content between 5 and 10%.

Requirements for packaging: Sturdy, airtight materials like polyethylene or polypropylene ought to safeguard against deterioration and contamination.

Labeling: N-P-K content, usage guidelines, risks, and expiration dates should all be included on labels.

6.3.2. Standards required for exporting

To ensure quality, safety, and environmental sustainability, a number of regional standards and guidelines have been created especially to govern agricultural inputs within the CARICOM region. Regional organizations like the Caribbean Regional Organization for Standards and Quality (CROSQ) and the Caribbean Agricultural Health and Food Safety Agency create these standards and guidelines. A producer's products must adhere to these set criteria in order to be cleared at ports when exporting agricultural inputs to other CARICOM nations.

CARICOM regional biotechnology biosafety policy and strategy: A framework for standardizing biotechnology and biosafety procedures throughout the region is provided by the CARICOM Regional Biotechnology Biosafety Policy and Strategy.

CARICOM regional standard code of practice for fish and fishery products: The CARICOM Regional Standard, which was created by the CARICOM Regional Organization for Standards and Quality (CROSQ), provides recommendations for the sanitary production, handling, and storage of fish and fisheries products. It highlights the Hazard Analysis Critical Control Point

(HACCP) methodology to guarantee that goods fulfill safety and health requirements.

CARICOM regional organization for standards and quality for labeling of foods – pre-packaged foods – specification: "FCRS 5:202x, Labelling of Foods – Pre-packaged foods – Specification," the final draft standard, was made available for vote by the CARICOM Regional Organization for Standards and Quality in 2024.

The labeling specifications for pre-packaged goods meant for consumer and catering use are the main emphasis of the draft CARICOM Regional Standard FCRS 5:202x. It contains recommendations for nutritional labeling, which call for unambiguous statements of calorie levels, protein, carbs, lipids, vitamins, minerals, and other nutrients. In order to promote public health programs and encourage informed decision-making, this standard seeks to guarantee that consumers have access to clear and accurate information regarding the nutritional value of food products.

In 2024, the CARICOM Regional Organization for Standards and Quality issued the final draft standard, "FCRS 5:202x, Labelling of Foods – Pre-packaged foods – Specification," for voting.

The draft CARICOM Regional Standard FCRS 5:202x focuses on the labeling requirements for pre-packaged foods intended for consumer and catering use. It includes detailed guidelines for nutritional labeling, requiring clear declarations of nutrients, energy values, protein, carbohydrates, fats, vitamins, and minerals. This standard aims to ensure consumers have access to accurate and transparent information about the nutritional content of food products, promoting informed decision-making and supporting public health initiatives.

Good agricultural practices standards: Good Agricultural Practices (GAP) guidelines, which establish minimal standards for good agricultural practices throughout the fresh produce supply chain, have also been adopted by several Caribbean nations. These guidelines cover production, harvesting, post-harvest handling, packaging, storage, and transportation, and they are applicable to fruits, vegetables, herbs, spices, and root crops. Regardless of size or complexity, they are intended to be universal and applicable to all farms and packing operations. The goal of GAP standards is to ensure that fresh produce satisfies quality requirements, is safe to eat, and conforms to laws in both domestic and foreign markets.

To guarantee that their agricultural products meet the expected standards of importing nations, exporters must adhere to GAP guidelines. Customs clearance may be refused if certain requirements are not met. Consequently, conformity facilitates easy access to markets.

For the fish silage emulsion production, this would include the following.

1) Inspection of raw materials to ensure the production of a high-quality product.

To guarantee the end product's safety, nutritional content, and general quality, quality assurance and control should be implemented during the production process. For instance, there should be monitoring for heavy metals like lead, cadmium, and mercury, which can build up in fish waste from polluted marine environments.

2) Proper record keeping should be implemented to assist in product and process traceability.
3) The product's traceability and marketability are further improved by appropriate labeling and documentation.
4) To avoid cross-contamination during production, stringent cleaning and sanitization procedures should be used.
5) Processing equipment should receive routine maintenance to guarantee reliable operation and high-quality output.
6) To prevent rodents, insects, or other pests from contaminating the fish silage emulsion manufacturing operations, a pest control program should be implemented.
7) To avoid contamination during production, the people involved in production should maintain good personal hygiene.
8) Monitoring the fish silage emulsion's storage conditions is part of post-production quality control. To avoid contamination and moisture intrusion, the product should be kept in sturdy, sealed containers.

6.3.3. Procedures for exporting

To place fish emulsion on retail shelves across various CARICOM markets, Barbados producing stakeholders must first establish partnerships with distributors who have access to key retail outlets. These outlets may include agricultural supply stores, hardware shops, and, in some cases, supermarket chains, as certain supermarkets also stock agricultural inputs.

If a producer in Barbados is exporting fish silage emulsion to CARICOM member states, the importer (distributor) must ensure the following documents are prepared:

1) A CARICOM area invoice, which is issued by the supplier and is required for all goods entering the CARICOM region.
2) The supplier's invoice, which specifies the product, quantity, and value.
3) A copy of the Airway Bill (for air transport) or Bill of Lading (for sea transport).
4) A customs declaration form.
5) A certificate of origin, which is provided by the supplier to verify the product's country of origin.

For goods listed on a country's negative list, an import license is mandatory. Although fish silage emulsion is not explicitly included on the negative list for CARICOM countries, fish itself is classified as such. Since fish silage emulsion currently lacks a specific classification, it could potentially be misclassified as fish. While the tariff for fish imported from within CARICOM is 0%, customs officers might still request an import license as a precautionary measure.

Given that several issues have been identified, the next subsection considers some solutions.

6.4. Recommended solutions to address market readiness challenges

To address the regulatory and market readiness challenges associated with developing a fish silage emulsion industry in Barbados, a multifaceted strategy should be adopted. This strategy includes several elements. They are as follows.

6.4.1. Develop national standards for fish silage fertilizers

Barbados should work through its national standards body, the Barbados National Standards Institution, in collaboration with the CROSQ to develop national standards for fish silage and fish silage-based fertilizers. It would be logical to align these standards with international benchmarks such as those of the IFA and the CEN. This helps ensure that critical features of fertilizers such as nutrient content, contaminant limits, pH ranges, and safety protocols are clearly defined and addressed. Developing such standards should facilitate a structured regulatory framework to guide production, labeling, and quality assurance.

6.4.2. Introduce mandatory testing and certification protocols

Given the absence of mandatory testing within the country, as well as the risks associated with no testing, it would be rational for the country to introduce mandatory testing requirements. However, to do this, local capacity has to be developed. As such, there is scope to develop testing capacity locally in Barbados through partnering with extra-regional accredited regional labs. After the capacity for testing has been developed, the government can proceed to implement mandatory testing requirements. There can be requirements to test microbial load, heavy metals, and nutrient content, all of which should inform labeling. This testing can be complemented with the implementation of a mandatory certification system. This ensures that whatever fish silage emulsion product hits retail outlets would be of an acceptable quality.

6.4.3. Align product labeling and packaging with emerging CARICOM standards

Labeling complements testing. The technical information of the fish silage emulsion product, which was verified through testing, should be placed on the product's labels.

Importantly, while the draft CARICOM standard "FCRS 5:202x" focuses on food labeling, it offers a framework for labeling requirements that can be adapted for fertilizers. The Government of Barbados can lobby CARICOM for the expansion of the FCRS standards to cover agricultural inputs and adopt similar labeling practices for fish silage fertilizers. This includes specifying nutrient composition, instructions for use, warnings, shelf life, and contact details for traceability.

Apart from labeling, there should be a requirement for producers to adopt proper and durable packaging to ensure the minimization of leakage, spoilage, and contamination.

6.4.4. Capacity building and technical training

Certainly, capacity-building activities targeting producers, as well as regulators, are important. As such, the enabling environment for fish silage emulsion in Barbados can be enhanced through several initiatives. This includes training in safe handling and processing of fish silage, good manufacturing practices, and adherence to environmental guidelines. Public authorities such as the Ministry of Agriculture could facilitate these training programs in collaboration with donor agencies operating in the country, such as the FAO or the CRFM, to build capacity within the country.

6.4.5. Trade missions

The Government of Barbados can actively support regional market access for fish silage emulsion products by organizing trade missions to other Caribbean countries. Coordinated delegations made up of policy experts from the Ministry of Affairs and Foreign Trade and the Ministry of Agriculture and Food and Nutritional Security, as well as representatives of the stakeholders that make fish silage emulsion, can travel on these trips. The Barbados delegation can interact with trade ministries, private sector players, and agricultural organizations in target markets during these excursions, demonstrating the advantages and caliber of Barbados' fish silage emulsion product. In addition to increasing awareness and fostering consumer confidence in the product, product demonstrations and sample distribution can spark discussions about import regulations, standard alignment, and potential collaborations.

6.4.6. B2B meetings with distributors

Business-to-business (B2B) meetings between regional distributors and local producers of fish silage emulsion can also be facilitated by the Barbados government. Through the establishment of connections with distributors in various Caribbean nations, the government can facilitate the development of a well-organized trade channel in which Barbados producers focus on production, while distributors oversee logistics, marketing, and retail distribution within their respective markets.

6.5. Fish silage projects in other countries

The idea of transforming fish waste into a useful product is not far-fetched as there are similar projects in other countries.

6.5.1. The Philippines

The Community Fish Landing Centers (CFLC) project, a component of the Bureau of Fisheries and Aquatic Resources' Targeted Actions to Reduce Poverty and Generate Economic Transformation (TARGET) program, was implemented in the Philippines. The project offered multipurpose infrastructure in partnership with the National Anti-Poverty Commission and local governments. The first floor was utilized for fish trading, while the second floor was utilized for the manufacture of fish silage and drying. Commercial marine fish waste, specifically from Bali sardines, a highly commercialized species in the Philippines, was the main source of fish waste used in the experiment. The CFLC experiment produced silage by processing fish waste. Additionally, by turning tuna canning waste into fish meal, fish skin into leather, and fish and shrimp processing waste into protein concentrates for animal feed, the project also implemented a circular economy for fish waste.

6.5.2. Bangladesh

Aquaculture has allowed Bangladesh to become self-sufficient in the production of fish, with a total production of about 4.76 million metric tons. Seafood processing facilities in the country produce more than 43,000 tons of seafood waste annually. Fish feed accounts for roughly 50–60% of total production costs, making it a substantial component of aquaculture costs. Fish silage was made from seafood waste produced during the processing of key aquaculture species in Bangladesh in order to lower feeding costs and support sustainable resource management.

The next section concludes this study.

7. Conclusion

Recall, the research question for this study is "What is the market potential for fish silage emulsion in Barbados and neighboring Caribbean countries?"

Barbados imported approximately US$3.1 million worth of fertilizers in 2023, which includes products classified under SITC 272 and SITC 56. This marks an increase from the US$2.8 million imported in 2019. Across the wider CARICOM region, fertilizer imports amounted to around US$83.072 million in 2023, with individual member states importing between US$1 million and US$40 million annually. These figures highlight the significant demand for fertilizers in Barbados and the broader CARICOM market, underscoring the potential for alternative fertilizer solutions.

The Fertilizer Price Index serves as a useful tool for assessing fertilizer price trends, capturing the average price movements of a basket of nitrogenous fertilizers. Using the MoE model on monthly FPI data from January 2021 to February 2025, forecasts were generated. The model projects the index to rise from 133.47 in February 2025 to 153.1040 in the 5-step ahead forecast and further to 200 in the 10-step ahead forecast. This indicates a 14.71%

increase in fertilizer prices over five months and a 49.85% increase over ten months. These projected price hikes provide strong justification for exploring sustainable alternatives like fish silage emulsion in Barbados.

The supply of fertilizers in Barbados is predominantly managed by distributors, as there is no significant domestic fertilizer manufacturing. Massy Distribution (Barbados) Ltd., a leading distributor, supplies farmers with a wide range of agricultural inputs, including fertilizers, seeds, chemicals, and farming equipment. Another key player is the Eastern Caribbean Fertilizer Co. (Barbados) Ltd., which specializes in fertilizer distribution and serves as the authorized distributor for Brandt products in Barbados. Regionally, Caribbean Chemicals & Agencies Ltd. stands out as a major supplier of agricultural inputs, offering fertilizers, insecticides, fungicides, herbicides, adjuvants, seeds, and equipment across the English-speaking Caribbean.

T&T plays a notable role in the global fertilizer industry due to its ammonia production capabilities, operating 11 world-scale ammonia plants with a combined annual capacity of 5.2 million metric tons. However, T&T does not manufacture finished fertilizers domestically; instead, it exports ammonia and urea while importing finished fertilizer products. Additionally, innovative projects, such as the CRFM-led initiative to produce fertilizers from sargassum, are gaining traction as sustainable alternatives. Despite these efforts, fertilizer production remains limited within the CARICOM region, presenting opportunities for entrepreneurs in Barbados to fill this gap.

There is significant potential for Barbadian entrepreneurs to export fish silage emulsion to neighboring CARICOM member states. To succeed, they must first establish partnerships with distributors who have access to key retail outlets, such as agricultural supply stores, hardware shops, and supermarkets. When exporting, ensuring product quality and compliance with regional standards is important. The product should be properly packaged, labeled, and tested to confirm nutrient content. Labels must include essential information such as the expiration date, usage instructions, and safety guidelines. Consistency in quality and adherence to export requirements will enhance market acceptance and competitiveness.

The fish silage project represents a promising and sustainable initiative. Environmentally, it aligns with the principles of a circular economy by transforming fish waste into a valuable resource. If left unutilized, fish waste would end up in landfills, where its decomposition releases methane, a potent greenhouse gas contributing to climate change. Through repurposing this waste, the project mitigates environmental harm while creating economic value.

Furthermore, the project advances multiple Sustainable Development Goals (SDGs) in Barbados. They include:

SDG 12 (Responsible Consumption and Production): Promoting resource efficiency and reducing waste by utilizing fish by-products.

SDG 13 (Climate Action): Cutting methane emissions from landfills and lowering the agricultural sector's carbon footprint through organic fertilization.

SDG 14 (Life Below Water): Supporting sustainable fisheries and reducing marine pollution by addressing fish waste disposal.

SDG 15 (Life on Land): Enhancing soil health and promoting sustainable agricultural practices through the use of organic fertilizers.

This multifaceted approach not only addresses environmental and economic challenges but also positions Barbados as a leader in sustainable agricultural innovation within the CARICOM region.

Future work can involve the modification of the MoE framework with a simulation/sensitivity framework like the Monte Carlo simulation. Monte Carlo also produces the probability associated with each outcome. Therefore, future work can build on the MoE by integrating it with a Monte Carlo simulation.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in https://github.com/doncharles005/MoE and https://wits.worldbank.org/.

Author Contribution Statement

Don Charles: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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