Machine Learning Forecasting of the Economic Impacts of Red Tides in the Southwest Florida Coast

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This is a non-peer-reviewed preprint submitted to EcoEvoArXiv.

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Abstract

Red tides, a form of Harmful Algal Bloom (HAB), pose a severe threat to Florida's wildlife, fisheries, and coastal communities. These blooms release harmful brevetoxins, which kill marine life and devastate fisheries, diminishing both yields and revenue. Approximately 16 million Florida residents live in counties bordering the coastline and are directly or indirectly affected by red tides through health risks, reduced quality of life, or employment instability. For example, the revenue of fishermen decreased 62.8% during red tide seasons and fisheries have experienced a 13.7% decrease in production for the past decade, with a 26.4% average increase for price per pound. With rising global temperatures, red tides are expected to become more frequent and severe, further damaging Florida's marine ecosystem and local economy. This paper leveraged advanced predictive modeling to analyze red tide patterns and assess its risks to inform future policy making. Using an LSTM model, this study predicts that *Karenia brevis* cell counts will increase by 4.5% annually, leading to substantial economic losses to the fishing industry. Using a SARIMAX model, by 2030, it is estimated that (1) the total pounds lost for all fish will be 71,318,313 pounds and (2) the total fish stock value to decrease by $282, 790, 208. After running a Monte Carlo simulation, the estimated value of fish stock lost by 2030 will be $2,545,123,304. This paper also used a burden ratio model to quantify how red tide-related impacts are distributed across income groups based on differences in exposure, vulnerability, and adaptive capacity. Using this model, it was found that by 2030, lower-income communities—who face higher job disruption, limited healthcare access, and greater dependence on affordable seafood—will bear 60% of the red tide-related economic losses, highlighting the need for targeted interventions.

Introduction

Harmful algae blooms (HABs) occur from the process of eutrophication, which is when nutrients (predominantly phosphorus, nitrogen, and carbon) flow from the runoff of farmlands or homes downriver to bodies of water, building up at a rate that 'overfeeds' algae that preexists in the environment [1]. HABs can produce toxins that poison and kill native marine life, posing a threat to many local fisheries. Due to prolonged buildup of nutrients, as well as increased precipitation and temperatures, HAB cases have been consistently prevalent along the coasts of Florida. This report isolates *Karenia brevis,* otherwise known as red tides, which is the most common HAB in Florida, and can be distinguished at >100,000 cells per liter as a red-brown coloring in the water [2].

In 2018, the incidence of red tides surged following Hurricane Irma, which redistributed nutrients from Lake Okeechobee. A similar pattern was observed during the 2004-2006 red tide event, which coincided with an especially active hurricane season [3]. Intense storms contribute to red tide formation by bringing heavy rainfall that cause excessive nutrient runoff into coastal waters—conditions that stimulate *K. brevis* growth.

Red tides release brevetoxins, or PbTx, a class of neurotoxins that disrupt nervous systems of marine organisms, significantly diminishing their health. PbTx accumulates in shellfish; if consumed, this can lead to Neurotoxic Shellfish Poisoning (NSP) in humans. Symptoms of NSP include nausea, vomiting, respiratory distress, paresthesias of the mouth, lips and tongue as well as distal paresthesias, ataxia, slurred speech and dizziness [4].

Importantly, *K. brevis* blooms primarily occur within 130 miles off the Florida coastline, an area where environmental conditions are particularly favorable for nutrient accumulation and *K. brevis* proliferation [5]. This proximity places coastal communities at high risk for both economic and health consequences, especially given Florida's heavy reliance on aquatic resources and tourism.

Despite the serious health and environmental implications associated with red tides, public awareness of their impacts has remained alarmingly limited. A survey revealed that 44.6% of coastal residents were unaware of the formation of red tides, and that 46.7% of residents feel that it is safe enough to stay at the beach during an active red tide event [6]. This lack of awareness results in fewer preventative actions being taken at the individual and local level: residents may continue behaviors that contribute to runoff, local governments may underinvest in mitigation strategies, and policymakers feel less pressure to enact stricter regulations.

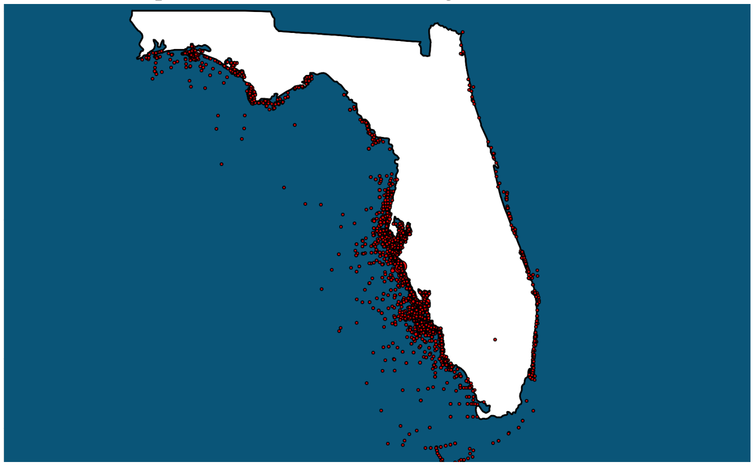

Figure 1: Karenia brevis blooms from 2014 through 2024 in Florida

However, the consistency of such events has become an increasing global concern. The economic damage of *K. brevis* exceeds millions due to fishery closures, reduced harvests, and decreased tourism. Florida's economy—largely dependent on coastal activities—suffers extensively during prolonged red tide events. Tourism alone, which brings in over $100 billion annually, sees sharp declines in affected regions [7]. Approximately 16 million Florida locals live in counties bordering the coastline [8] and are directly or indirectly affected by red tides through health risks, reduced quality of life, or employment instability. The revenue of fishermen decreased 62.8% during red tide seasons and fisheries have experienced a 13.7% decrease in production for the past decade, with a 26.4% average increase for price per pound, aligning with the increase in red tide cases [9, 10].

Methodology

Data Methodology

The data methodology for the mathematics model depends on identifying and collecting data sources to achieve the following goals: develop a model to project *K. brevis* bloom trends in the future, project the financial losses associated with K. *brevis* blooms, and identify its effects on groups of different income groups.

Data Identification and Categories

This study primarily draws from five datasets: (1) NOAA temperature data from 2015-2024; (2) Florida Fish and Wildlife Conservation Commission (FWC) reportings of Karenia brevis blooms and cell counts from 2015-2024; (3) National Water Quality Monitoring Council reportings of nutrients levels in the water; (4) the FWC fisheries landings summaries from 2014-2024; and (5) the American Community Survey median household income data from 2015-2025.

Data Cleaning

The datasets underwent numerous cleaning processes to ensure consistency across all data sources. The first step was to conjoin data from several sources. The Florida Fish and Wildlife Conservation Commission dataset, which included records of *K. brevis* cell counts, along with their associated sample dates, latitude, and longitude, was combined with NOAA temperature records and the National Water Quality Monitoring Council's nutrient data. The next step was to standardize the formats and units of measurement. For instance, all nutrient concentrations were converted to mg/L to maintain uniformity and temperature records were converted to Celsius. Next, missing or incomplete data was addressed. Rows with missing values such as *K. brevis* cell counts, sampling dates, or temperature were removed and excluded from analysis.

Additionally, ZIP code and median household income data from the American Community Survey were filtered to only retain those located along the Florida coastline. For the purpose of this report, "on or near the coast" was defined as ZIP codes situated within 3 miles of the shoreline or ZIP codes falling within counties that directly border the Gulf of Mexico. This definition aligns with the spatial range most heavily affected by red tide events, proven by previous research [11]. ZIP codes not situated on or near the coast were excluded from the analysis.

Florida's coast varies significantly in terms of temperature and nutrient inputs, which influence *K. brevis* bloom formation. Thus, Florida was partitioned geographically into 3 regions with similar environmental features based on latitude and longitude to create more targeted and accurate models (Table 1).

Table 1: Florida partitioned into 3 regions based on latitude and longitude (Figure 2)

Region	**Latitude**	**Longitude**
Region 1	24.51° N to 26.57° N	80.00° W to 87.42° W
Region 2	26.57° N to 28.64° N	80.00° W to 87.42° W
Region 3	28.64° N to 30.71° N	80.00° W to 87.42° W

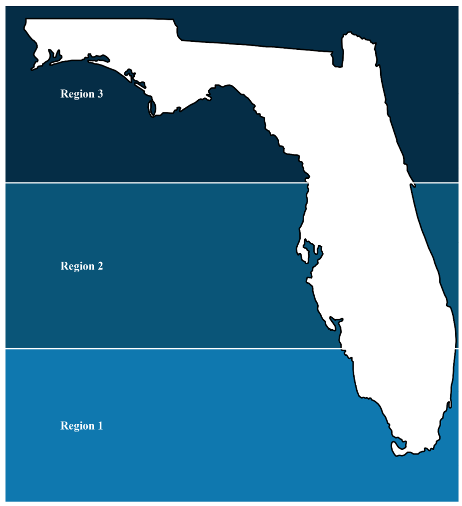

Figure 2: Florida partitioned into 3 regions based on latitude and longitude

Mathematics Methodology

The goal for the mathematics methodology is to develop a model to project the severity of red tides, forecast the financial losses associated with *K. brevis* blooms, and identify its effects on groups of different affluence.

Long-Short Term Memory

Long-Short Term Memory (LSTM) is a type of recurrent neural network designed to handle short-term and long-term dependencies in sequential data [12]. At the core of an LSTM is its memory cell, which is a component that acts as a repository for information across time steps. This cell state serves as a conveyor belt that carries relevant information throughout the processing of a sequence without significant loss. LSTMs also use three main gates to manage the flow of information: the input gate, forget gate, and output gate [12]. The input gate decides how much new information should be added to the memory cell. The forget gate determines what information in the cell should be discarded. The output gate controls what information is sent out of the cell for further processing or predictions.

The LSTM is set up with four sequential layers and is bidirectional, meaning it can learn from both past and future context within time steps. The bidirectional attribute is key to capturing the temporal dynamics that influence *K. brevis* bloom development. Each layer includes hidden units and builds on the previous one, which enables the model to learn complex time-based patterns that influence *K. brevis* behavior. Hidden units are the individual neurons in a layer that process information and help the model learn internal representations of the input data. Each layer of the LSTM contains a certain number of hidden units—50, 60, 80, and 120 respectively—to help the model capture both short-term fluctuations and longer-term trends in bloom activity.

Since the model takes into account extreme weather events, at the output stage, the model has two output heads which are each designated to a specific task and both build upon the previous four sequential layers. The primary prediction head focuses on forecasting the overall intensity of the bloom by estimating the log-transformed cell count. It uses a fully connected, 120 unit layer that maps the final LSTM output down to a single continuous value.

The second head is designed to classify whether a red tide event will escalate into an extreme level. Extreme events involve sudden spikes in cell counts that can lead to large-scale fish kills, beach closures, and potential health risks. This layered approach helps the model focus on the most relevant historical patterns that signal an incoming extreme event. A rectified linear unit activation function was applied to all the model's layers, which aids in understanding nonlinear relationships in the data that can capture previously missing context to assist in predicting extreme events. In the final step, a sigmoid activation is applied, which condenses the model's output into a single probability between 0 and 1 to indicate how likely an extreme event will occur, which is then factored into the final prediction output.

To prevent overfitting and improve generalization, a dropout layer is placed between LSTM layers—where deeper LSTM layers use progressively higher dropout rates. This dropout randomly deactivates a fraction of the neurons during training, decreasing the chance of over-reliance on specific paths through the network, leading to a more robust and generalizable model.

The model receives 5 features: latitude, longitude, *K. brevis* cell count, ambient temperature, nutrient levels and seasonality information encoded through sine and cosine transformations of the sampling data. The cyclical features capture the inherent seasonality of the calendar year that can affect algae bloom dynamics. This helps the LSTM to learn recurring seasonal effects that could potentially trigger or suppress blooms.

Model Training

After normalizing the features, the data is split into a 80/20 ratio, where 80% of the data is used for training the model, while the remaining 20% is held out for validating the model. Training is completed using the Adam optimization algorithm with a carefully tuned learning rate α to minimize the mean squared error (MSE) loss function.

Cross-Validation

After training the model for 100 epochs, the LSTM model achieved an $R^2 = 0.784$ for region 1, $R^2 = 0.813$ for region 2, and $R^2 = 0.691$ for region 3.

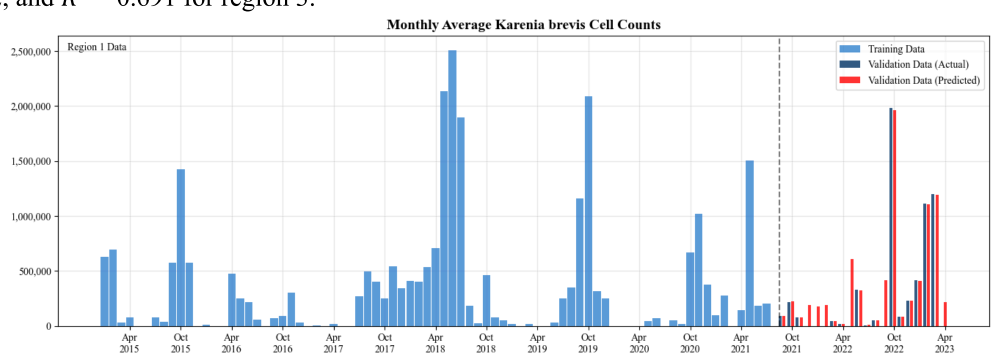

Figure 3: Cross-validation of the validation data for Region 1

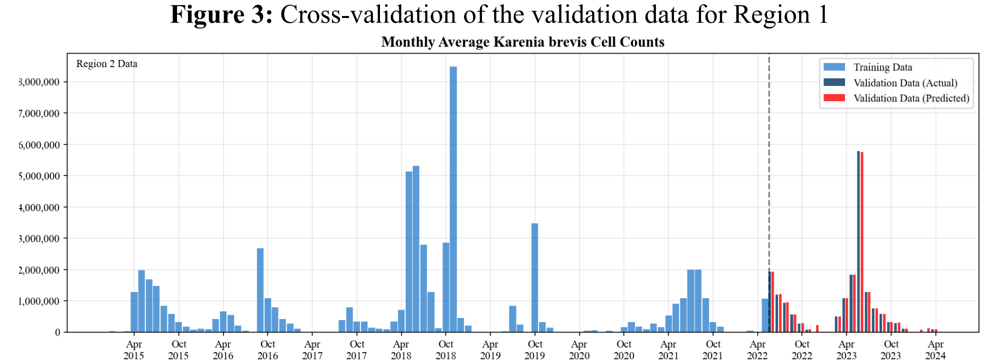

Figure 4: Cross-validation of the validation data for Region 2

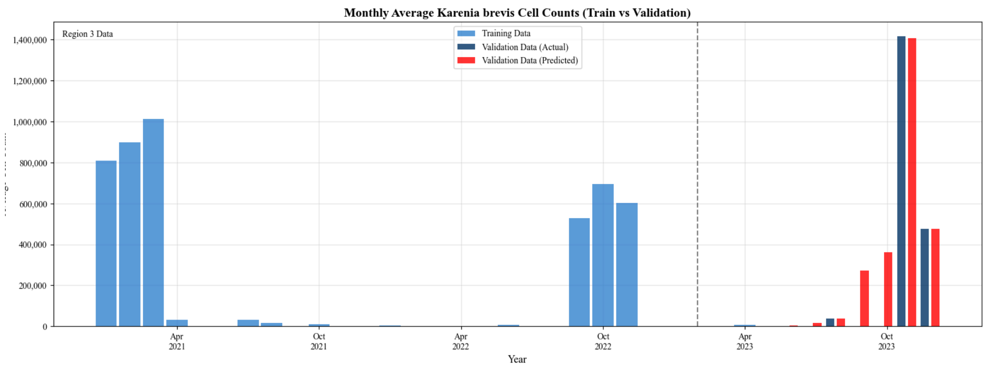

Figure 5: Cross validation of the validation data for Region 3

Financial Losses Attributed to K. brevis

The Florida-west, which is highly affected by *K. brevis* blooms, has shown a 9.59% increase in the cost of fish per pound (Figure 6). Conversely, in the Florida-east, where there is not as high of a *K. brevis* prevalence rate, the cost of fish per pound is seen to decrease in recent years.

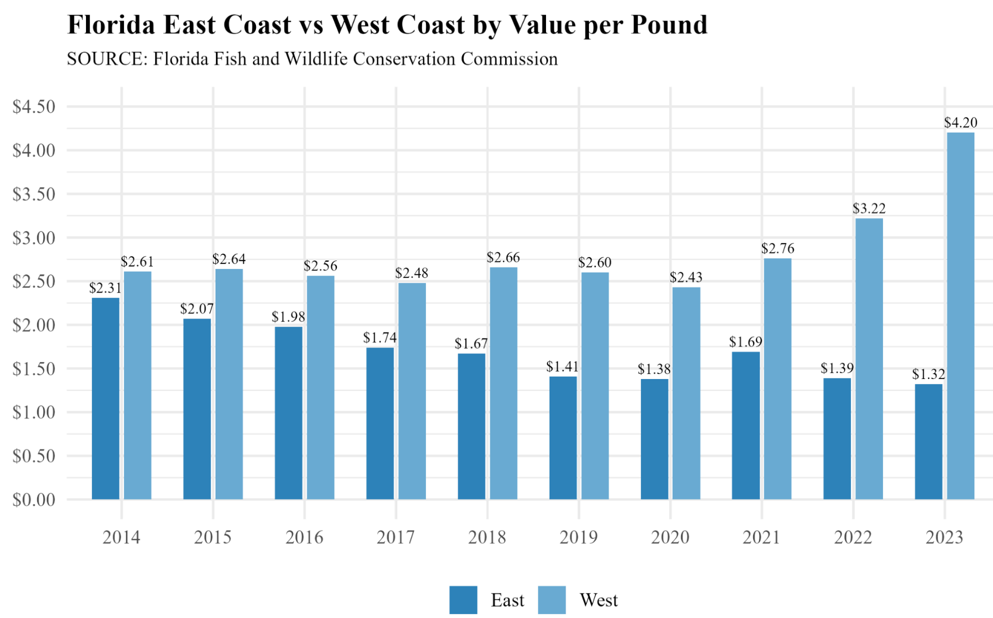

Figure 6: Comparison between Florida East and West coast: Value per pound

Thus, the goal of this section is to estimate and forecast the future financial losses attributed to *K. brevis* through a SARIMAX model and Monte Carlo simulation.

<u>SARIMAX</u>

A Seasonal AutoRegressive Integrated Moving Average with exogenous regressors (SARIMAX) model was used to estimate potential losses in seafood sector revenue due to *K. brevis* blooms. SARIMAX is a model that is specifically designed for time series forecasting where external factors influence the target variable. It works by using past values of variables to predict future values, taking the difference of series to remove trends to stabilize data over time, accounts for past forecasting errors to refine predictions, and incorporates exogenous variables—predictors that are not part of the target series but significantly affect it.

In this report, the results of the LSTM—which estimates red tide severity over time—is used as an exogenous input to the SARIMAX model. These external predictors allow the model to account for the impact of worsening red tide events on future fish stock losses.

Monte Carlo Simulation

A Monte Carlo simulation is a computational model that uses repeated random sampling to estimate the behavior of a system.

In this study, the Monte Carlo simulation was utilized to determine the distribution of possible outcomes of fish stock losses in Florida by 2030 as a result of *K. brevis* blooms. These blooms are known to cause significant ecological and economic damage, but the exact extent of fish stock losses in any given year remains uncertain due to the unpredictable nature of environmental factors. To model these uncertainties, the simulation was run n = 10,000 times.

All the simulated financial losses are calculated from the following equation:

Simulated Financial Losses = (Total Pounds Lost)(Average Price Per Pound) (equation 1)

Burden Ratio

The model examines the vulnerability of various socioeconomic groups to *K. brevis* events. Severe blooms, characterized by concentrations exceeding 100,000 cells/L, can lead to substantial fish stock losses, not just disrupting supply chains, but placing disproportionate burdens on groups of different affluence. Scarcity of catch raises market prices and strains coastal families that rely on affordable seafood; meanwhile, fishermen often must travel farther along the coast to find viable grounds, increasing transportation costs and, in turn, the prices at which they sell their catch [13]. Employment effects also compound these pressures: workers in fishing and tourism frequently face reduced hours or job losses during active events, with one University of Florida survey reporting a 61% decline in average sales revenue [1, 14]. Health impacts add another layer of vulnerability: airborne toxins associated with red tides can provoke chronic respiratory issues, and lower-income individuals—who often have less access to healthcare—are more likely to experience complications from exposure [4].

Depending on income levels, the severity of *K. brevis* cases can vary significantly from person to person. Thus, a burden ratio, represented as a percentage, was created for each income group, i, to reflect how *K. brevis* affects people of different affluence.

$$\text{Percentage Burden}_i = \frac{\delta_i \cdot C_i}{\sum_{j=1}^{n} \delta_i \cdot C_i} \times 100 \qquad \text{(equation 2)}$$

Where

$$C = \frac{\textit{Total Cost of a K. Brevis Bloom}}{\textit{Income}} \qquad \text{(equation 3)}$$

and

$$\delta_i = \frac{A_i}{\sum_{j=1}^{n} A_j} \qquad \text{(equation 4)}$$

Here, δ_i represents the group's share of vulnerability, calculated from the group's vulnerability divided by the total vulnerability to the economic impact of a red tide bloom. The value A_i is a measure of exposure, vulnerability, or consumption for group i, and the denominator is the sum of these measures over all n groups.

In this model, the exposure weight A_i is assigned based on the income group under the assumption that lower-income populations are more vulnerable to the effects of *K. brevis* blooms due to higher percentage of lost income, higher healthcare costs, and reduced adaptive capacity. This is to reflect the lower-affluence groups' increased sensitivity and reduced resilience to economic disruptions.

Results

LSTM Results

With the LSTM model architecture trained and validated, the model can now be used to forecast future red tide activity. By leveraging historical trends and projected environmental conditions, the model forecasts monthly average *K. brevis* cell counts from 2022–2030 (Figure 7-9).

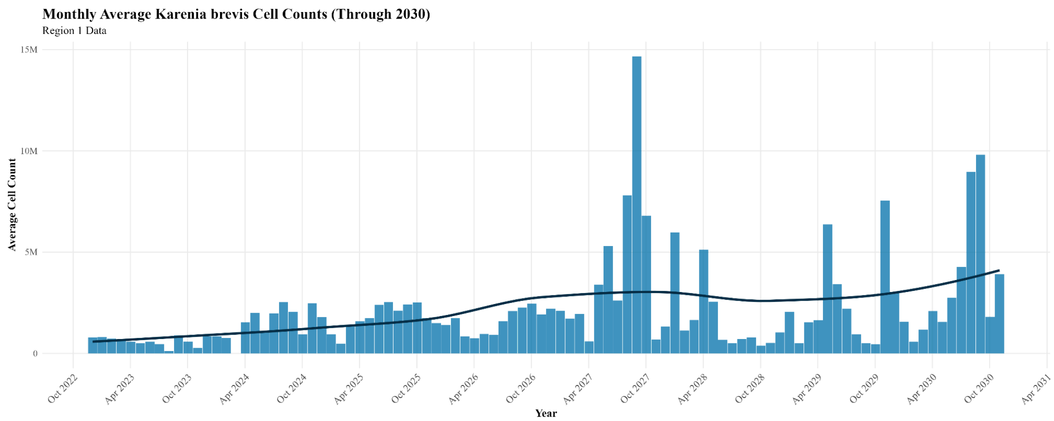

Figure 7: Forecasted red tide trends in Region 1. The smooth line represents the 1-month rolling average of *K. brevis* blooms over time.

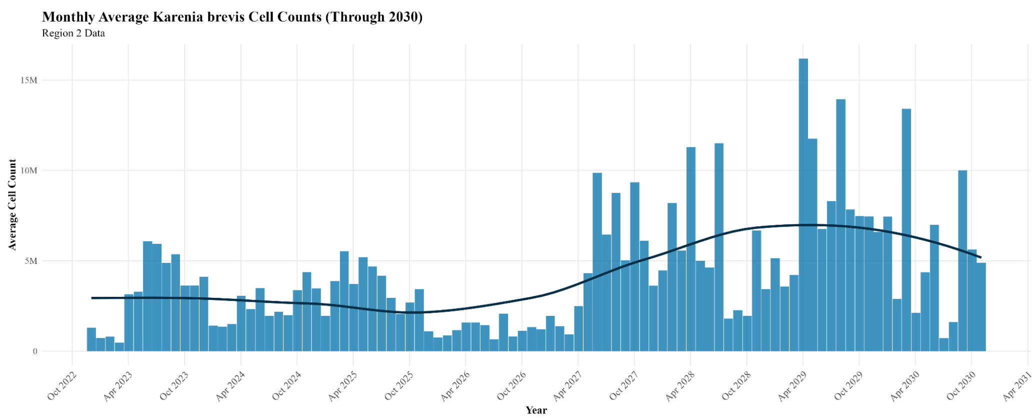

Figure 8: Forecasted red tide trends in Region 2. The smooth line represents the 1-month rolling average of *K. brevis* blooms over time.

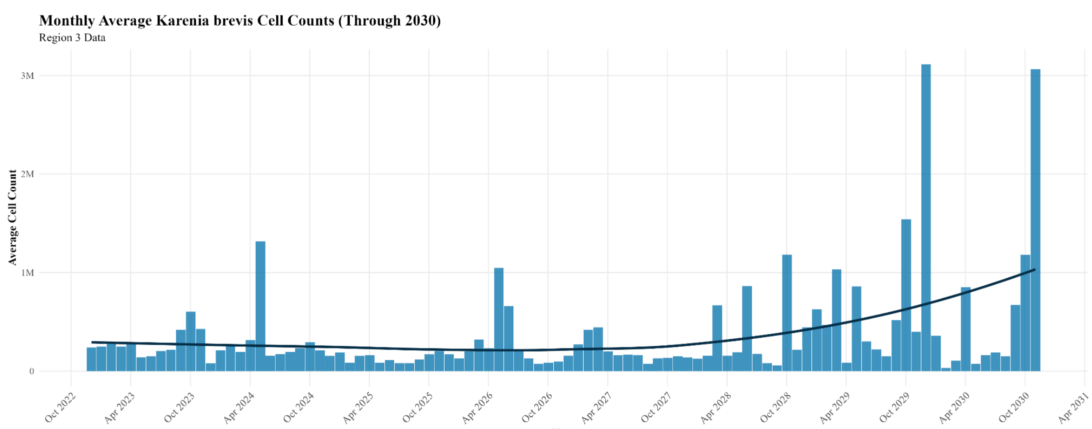

Figure 9: Forecasted red tide trends in Region 3. The smooth line represents the 1-month rolling average of *K. brevis* blooms over time.

SARIMAX Results

Using the SARIMAX model, future trends were forecasted based on historical catch data and market prices. By analyzing historical data on shifts in both fish populations and economic factors like stock value, the model provides insight into the expected changes in fishery values over the coming years. The following figures illustrate how fish stocks are projected to change based on past patterns, revealing the scale of potential financial losses for Florida's seafood sector by 2030.

Figure 10 indicates that the average annual pounds lost for all fish, projected, is 7.56%. Thus, the total pounds of fish lost by the year 2030 is 71,318,313 pounds.

Figure 11 indicates that the average annual value lost for all fish in Florida is projected to be 11.34%. Thus, the total fish stock value decrease by 2030 is $282, 790, 208.

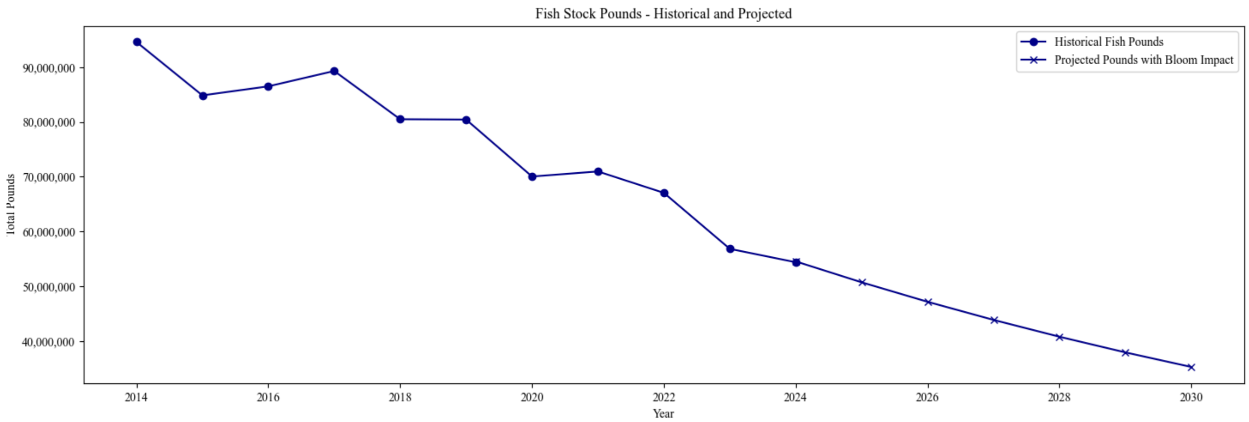

Figure 10: Historical and projected total pounds of fish stock fished in Florida.

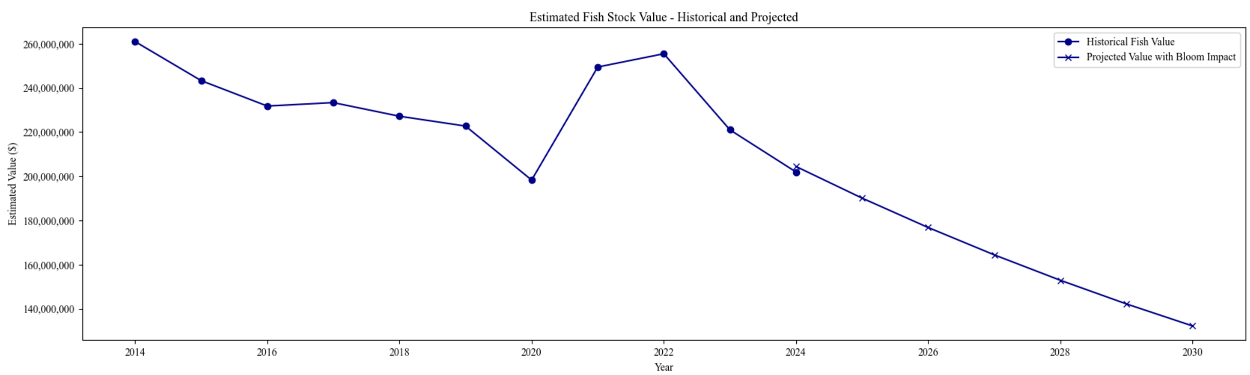

Figure 11: Historical and projected total fish stock value in Florida

While the overall pounds lost and total stock value decreases are calculated for all fish species combined, price per pound projections—both inflation-adjusted and non-inflation-adjusted—were modeled for snapper, grouper, and crab individually to reflect the different economic significance of these species

These three species were chosen for pricing analysis because they are the most valuable seafood species in Florida, with crab being the most valuable shellfish, and snapper being the most valuable fish, followed by grouper [15].

Table 4: Estimated annual price per pound increase for snapper, grouper, and crab by 2030

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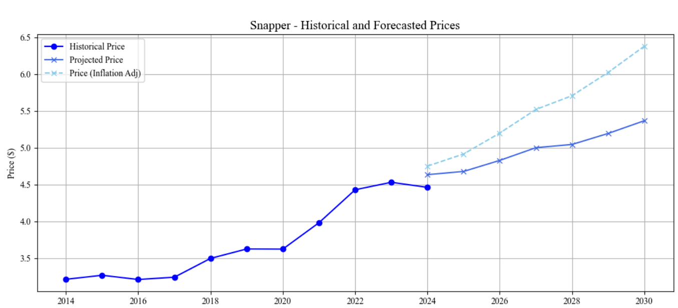
<td>
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<td>The average annual nominal increase for snapper is $0.12/lb.

The calculated inflation-adjusted annual increase for snapper is $0.27/lb

The total change over 6 years is $0.73/lb, while the total inflation-adjusted change over 6 years is $1.62/lb.</td>
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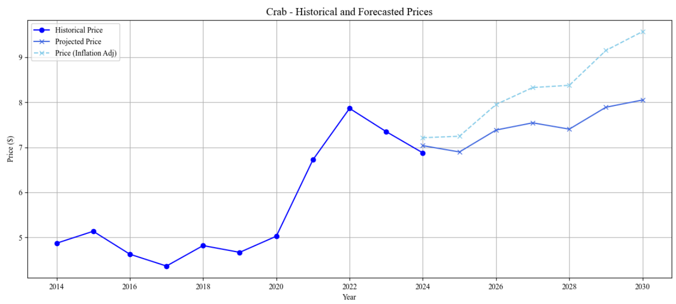
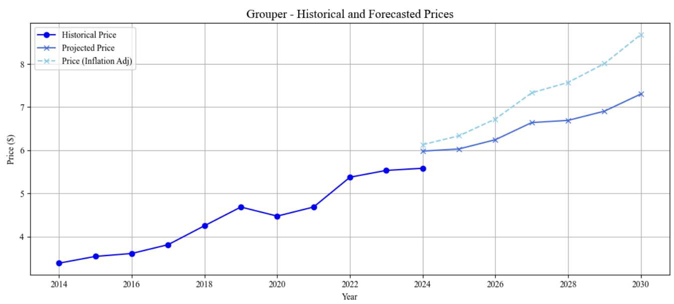
Figure 12: Historical and Projected Snapper Price Per Pound	
 **Figure 13:** Historical and Projected Grouper Price Per Pound	The annual nominal increase for grouper is $0.22/lb. The inflation-adjusted annual increase for grouper is $0.43/lb The calculated total change over 6 years is $1.32/lb, and the total inflation-adjusted change over 6 years is $2.58/lb.
 **Figure 14:** Historical and Projected Crab Price Per Pound	The annual nominal increase for crab is $0.17/lb. The inflation-adjusted annual increase for crab $0.39/lb. The total change over 6 years is $1.01/lb, while the total inflation-adjusted change over 6 years is calculated to be $2.34/lb.

Monte Carlo Simulation Results

The results of the Monte Carlo Simulation provide a probabilistic range of outcomes which can inform stakeholders and fisheries the potential financial risks posed by *K. brevis.*

The results of the Monte Carlo Simulation are as follows:

- **Mean Total Value:** $2,545,123,304
- **Median Total Value:** $2,544,692,758
- **5th Percentile Value:** $2,510,818,208
- **95th Percentile Value:** $2,580,754,335

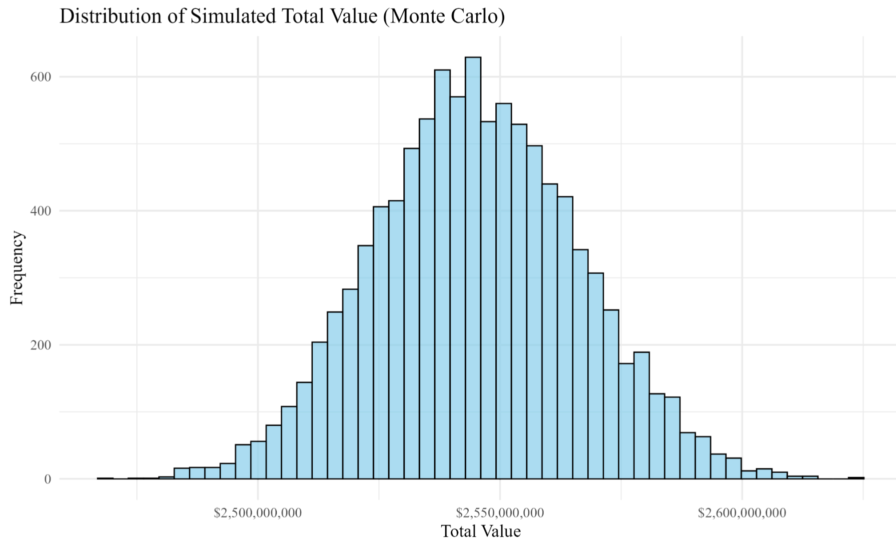


Figure 15: Statistical distribution of scenarios from the Monte Carlo Simulation

According to the Monte Carlo simulation, the scenario in the 5th percentile yielded $2,510,818,208 to be lost in fish stocks (Figure 15). In the scenario in the 95th percentile, the Monte Carlo simulation yielded $2,580,754,335 to be lost in fish stocks. The overall difference between the two estimates is $69,936,127.

Burden Ratio Results

By 2030, it was found that lower-income groups are projected to bear on average 58.97% of red tide-related economic losses despite earning less than a third of what higher-income groups make.

Table 5: Burden ratios associated with groups of different affluence

Group	Average Percent of Cost Borne by 2030 Across Regions 1, 2, 3	Average Annual Income
Low Affluence	58.97%	$30,000
Middle Affluence	29.5%	$60,000
High Affluence	11.53%	$120,000

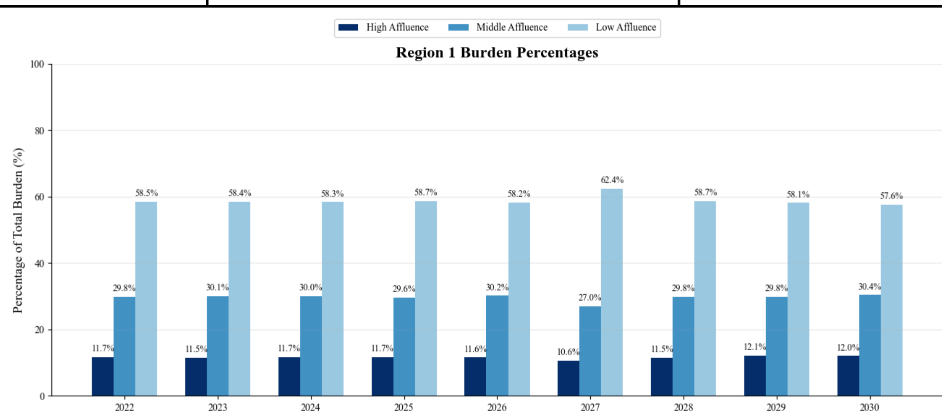


Figure 16: Region 1 Burden Ratio

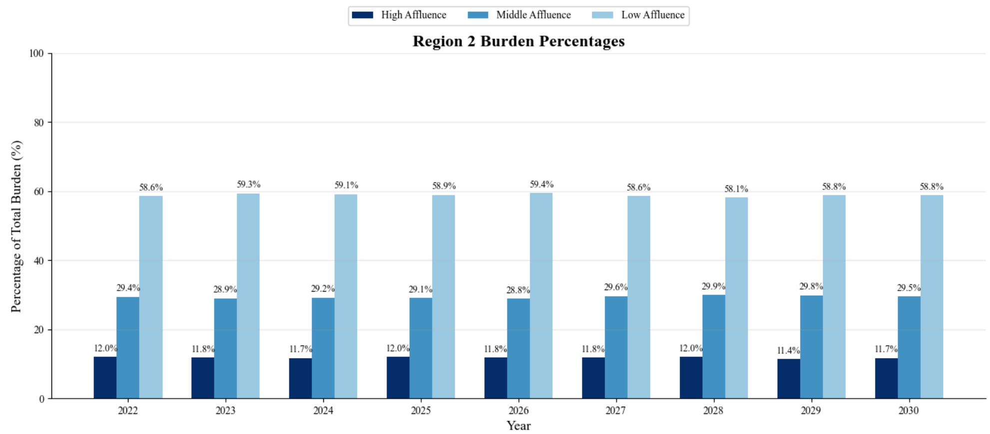


Figure 17: Region 2 Burden Ratio

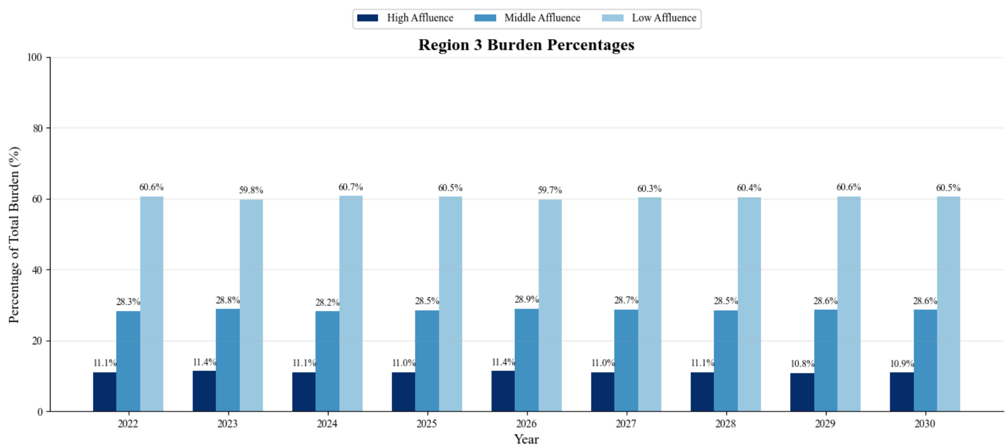


Figure 18: Region 3 Burden Ratio

Discussion

The findings of this study underscore a concerning trend: as *K. brevis* blooms become more frequent and intense, both ecological and economic systems along Florida's Gulf Coast face long-lasting consequences. The predictive outcomes of the Long Short-Term Memory (LSTM) model revealed an estimated 4.5% annual increase in *K. brevis* cell counts through 2030, with especially high bloom intensities in Regions 1 and 2—areas where nutrient concentrations and water temperatures are more favorable for algal proliferation (Figure 7-9). These forecasts are consistent with data indicating that warmer sea surface temperatures and intensified runoff events accelerate *K. brevis* growth cycles. The model's high validation scores (R^2 values ranging from 0.691 to 0.813 across regions) further indicates the model's robustness in capturing temporal dependencies such as seasonal peaks, storm impacts, and interannual variability.

The SARIMAX model's projections reveal that fish stock will decline by approximately 71 million pounds by 2030, while total stock value will fall by $282.8 million (Figure 10-11). These results indicate that increases in red tide events can have significant impacts on fish yield; as yield declines due to the toxic brevetoxins, market prices rise in response to diminished supply. This dynamic not only reflects the ecological consequences of *K. brevis* proliferation but also exposes economic volatility in coastal fish markets. This can be further correlated in the projections for the four seafoods that showed inflated prices with increased red tide events. Thus, red tide events can incur economic damage to local fisheries and the local communities that rely on seafood.

Monte Carlo simulation further quantified the financial impact of increasing red tide events. Running 10,000 stochastic iterations yielded a mean total loss of $2.54 billion in fish stock value, with a relatively narrow 5th–95th percentile range ($69,936,127). This constrained range indicates a high likelihood that economic losses will consistently reach multi-billion-dollar levels; the consistency of these outcomes reinforces the urgency of effective policy measures and environmental conservation.

When these financial trends are considered through the burden ratio model, distinct economic disparities are highlighted. By 2030, lower-income coastal communities are projected to shoulder nearly 59% of total red tide-related losses, despite earning less than one-third of the income of higher-affluence groups (Table 5). This disproportionate burden stems from various socioeconomic factors: dependence on fisheries and tourism for employment, reduced access to healthcare for red tide-related respiratory illnesses, and limited capacity to adapt to income volatility. From this, it can be deduced that red tides are not only harmful to the environment and the economy, but they are additional accelerators of socioeconomic disparity and environmental injustice.

The results across all aforementioned predictive models highlight the importance and urgency for targeted intervention. Implementing robust mitigation strategies, such as bioretention cells and bioswales, could reduce nutrient inflow and thus prevent overfeeding of *K. brevis*. Ultimately, robust red tide forecasting, environmental conservation policies, and community protection are vital to reducing the detrimental impacts of red tides.

Conclusion

This study quantifies how intensifying Karenia brevis blooms cause significant economic losses and translate to uneven social burdens along Florida's Southwest coast. Using a SARIMAX framework with exogenous bloom indicators and a Monte Carlo simulation, a cumulative loss of 71,318,813 pounds across all fish stocks is projected by 2030. These results are consistent with observed market dynamics during severe bloom years—higher operating costs and price volatility—and highlight the exposure of fishery- and tourism-dependent communities to recurrent red tide shocks.

Limitations

While this study provides valuable insights into the financial impacts of red tides in the Southwest Florida coast, a limitation of these models must be acknowledged. Specifically, the models are trained on historical datasets, so they cannot fully capture future, unprecedented shifts in environmental or socioeconomic conditions. Thus, the models are prone to forecasting an over- or under-estimation in face of unpredictable events.

Acknowledgements

We would like to thank our advisor, Mr. Gonzalez, for giving us invaluable advice and suggestions, we couldn't have done it without his help.

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