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ARTICLE

Improving Accuracy in Agricultural Forecasts: Evaluation of SARIMA and Forecast Models for Artichoke Prices

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ABSTRACT

The volatility of agricultural prices in Peru poses a critical challenge to food security and economic stability, particularly for key crops such as artichoke, whose price fluctuations directly affect producers' incomes and the accessibility of food for the population. This study evaluates the accuracy of several time series forecasting models—namely, SARIMA, ARIMA, Holt-Winters, Holt, and Naive—in predicting the average monthly price of artichoke in Lima, using historical data collected between January 2021 and December 2024. A comprehensive methodological approach was implemented that combines automated parameter optimization (using the Akaike Information Criterion, AIC), a 12-month retrospective validation, and the assessment of percentage errors against actual price values observed in January and February 2025. The results indicate that the SARIMA model ((0,0,1)(0,1,0),12) achieved the lowest average error of 12.16%, and it demonstrated exceptional accuracy in February, with only a 5.62% deviation. This superior performance is attributed to its ability to capture complex seasonal patterns inherent in the data. In contrast, the Holt-Winters model exhibited the poorest performance, recording an average error of 17.41% and a particularly high error of 32.99% in February, which underscores its limitations in managing nontraditional seasonal fluctuations. Additionally, while the Naive model proved highly accurate for very short-term forecasts in January (0.50% error), it was found to be unsuitable for extended forecasting horizons, as evidenced by a 28.94% error in February. Residual analysis further confirmed that SARIMA generates more robust predictions, with residual correlations that closely approximate white noise.

Keywords: Agricultural Forecasting; Artichoke Prices; Time Series Analysis; SARIMA; Python

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1. Introduction

The economic stability of food prices in Peru has a significant impact on both the population and the country's economy. This phenomenon is driven by the Peruvian population's high dependence on basic food products, a concern widely addressed in economic literature. In Peru, where a considerable portion of household income is allocated to food purchases, a sudden increase in prices can lead to greater food insecurity, disproportionately affecting low-income households [1]. Moreover, food price volatility not only affects consumers' purchasing power but also generates inflationary pressures on the economy, potentially exacerbating poverty and hunger in the country [2,3]. Therefore, food price stability is crucial for both social and economic well-being, as it prevents the erosion of purchasing power among the most vulnerable populations while fostering a more predictable and healthy economic environment.

The importance of predicting food prices in Peru lies in the need to anticipate changes that may impact both food security and overall economic stability. Forecasting these prices enables policymakers to implement mitigation measures and proactively adjust agricultural and trade strategies. The ability to respond swiftly to price fluctuations can be crucial in minimizing the negative effects on both consumers and agricultural producers [1–4]. Furthermore, an effective price forecasting system provides valuable information for financial markets and investments in the agricultural sector, assisting economic agents in making informed decisions that optimize resources and mitigate risks [2,5].

Regarding forecasting models used to predict food prices, the literature presents a variety of approaches. Among the most common are time series models and econometric methods such as Autoregressive Distributed Lag (ARDL) and Structural Vector Autoregression (SVAR), which have proven effective in assessing the relationship between food prices and other economic factors [6,7]. These models capture the dynamics of food prices in response to various variables, including macroeconomic conditions and global factors such as trade policies and fluctuations in input prices [8]. Additionally, nowcasting models have been developed to estimate food price inflation in near real-time, enabling policymakers to respond rapidly to sudden price surges [1–9].

The application of forecasting models in previous studies has provided valuable insights into food price behavior and its relationship with the economic structure of developing countries. For instance, several studies have employed econometric models to analyze how food inflation rates in Peru may be influenced by international prices and local economic conditions [3,10]. These studies not only contribute to understanding the population's vulnerability to food price fluctuations but also highlight the need for more effective and adaptive food security policies aimed at stabilizing the supply and demand of essential goods during crises [11,12]. In this context, the necessity of robust and accurate forecasting models becomes evident, as they are crucial for policy planning and design, ensuring both economic and food stability in the country.

1.1. Artichoke in the Economy

Artichokes hold significant relevance in the Peruvian economy, primarily due to their position as a key export product. In Peru, this crop has demonstrated steady growth in international markets, becoming one of the most prominent exports, particularly to the United States and Europe. This increase in international demand not only promotes income generation for producers but also contributes to the economic development of the regions where it is cultivated, as the land area dedicated to cultivation and the labor force involved have expanded in response to this demand [13].

Artichoke prices have a direct impact on the agricultural market in Peru. Price increases benefit farmers by allowing them to earn higher incomes, reflecting a balance between supply and demand in the market. However, significant price fluctuations can lead to economic instability for producers and affect the affordability of this food, particularly among low-income populations. Price dynamics can be influenced by factors such as weather conditions, production costs, and changes in global demand, which in turn affect farmers' decisions regarding planting and marketing [14].

1.2. Programming and Statistics

To forecast artichoke prices, various forecasting models can be employed. Time series models, such as ARIMA and VAR (Vector Autoregressive Models), are commonly applied in agricultural econometrics to analyze historical price data and generate projections based on identified patterns. These models are particularly useful due to their ability to account for seasonality and inherent trends in agricultural production [15]. Additionally, machine learning techniques, such as neural networks and decision trees, are increasingly being implemented, as they can capture nonlinear and complex relationships among variables in large datasets, offering a more robust approach to forecasting in agricultural markets [16].

The use of computational tools like Python is essential in developing these forecasting models due to its versatility and the extensive availability of statistical and machine learning libraries. Python streamlines data analysis processes and the implementation of complex algorithms, enabling the creation of precise models that can adapt to diverse market conditions [17]. Its capacity to perform dynamic analyses and simulate future scenarios represents an invaluable resource for farmers and economic agents seeking to optimize commercial and strategic decisions in the context of artichoke production.

Python's role in developing forecasting models for artichoke prices—and food products in general—is critical for several reasons. First, Python's ability to manage and analyze large datasets is vital in an agricultural context where extensive historical price data is available. The integration of libraries such as Pandas, NumPy, and Scikit-learn enables analysts to conduct advanced statistical analyses and apply machine learning techniques with relative ease, resulting in more accurate and efficient predictive models [18]. Furthermore, Python provides an accessible and flexible environment widely adopted by the scientific community, which can be integrated with other technological tools and platforms, facilitating the organized and effective execution of complex forecasting projects [19].

Predicting food prices can have a significant impact on food security and Peru's economy. Accurate price anticipation allows producers to plan cultivation and commercialization strategies, thereby optimizing economic returns. This predictability is also crucial for consumers and government policies, as it enables the assessment of food availability and access at reasonable prices. In a context where food insecurity remains a persistent challenge, forecasting future prices can help mitigate scarcity risks and ensure vulnerable populations maintain access to nutritious food [20,21]. This becomes even more relevant during crises, such as the COVID-19 pandemic, where price volatility severely impacted household economies and food security [22].

This Python-based forecasting project for artichokes is significant not only for its economic implications but also for its potential to contribute to agricultural sustainability. By leveraging historical and current data to model price projections, producers can make informed decisions that promote optimal resource use and equitable food distribution in the market. This stabilizes prices and enhances access to essential products for the population. Effective price prediction can strengthen Peru's agricultural market structure, aligning with Sustainable Development Goals (SDGs) related to zero hunger and food security [23,24].

1.3. Literature Review

Models such as ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) have been widely employed for forecasting food prices due to their efficacy in time series analysis. These models are integral to economic planning, agricultural management, and food security, enabling stakeholders to make informed decisions based on predicted price trends.

A significant application of the ARIMA model is evident in Zomchak and Kukhotska's study, which forecasts wheat prices in Ukraine. Their work emphasizes the critical role food price dynamics play in economic strategies and agricultural commodity management. The research demonstrates that ARIMA effectively captures the temporal dependencies in wheat prices, thereby informing policymakers and producers [25]. Similarly, Mitra and Paul explore hybrid time-series models, confirming ARIMA's precedence in agricultural commodities forecasting. They indicate that addressing homoscedasticity through approaches like ARCH/GARCH alongside ARIMA leads to improved forecasting outcomes [26]. In addition, Wanjuki et al. utilized SARIMA models to predict the food and beverages price index in Kenya, highlighting the model's capability to account for seasonal variations within the data. This is crucial since many food prices exhibit seasonality due to agricultural cycles, thus enhancing the precision of forecasts in the food industry [27]. This seasonal aspect is supported by findings from Nurjati and Wiryawan, who applied SARIMA to predict shallot prices while identifying the model's strengths in capturing seasonal fluctuations during the agricultural year [28].

Moreover, Menculini et al. broaden the discussion by comparing ARIMA to contemporary methods, such as Prophet and deep learning algorithms. Their exploration into wholesale food prices underscores the relevance of ARIMA in traditional forecasting environments while elucidating the emergent methodologies that complement ARIMA in a competitive landscape [29]. This combination of traditional and advanced methods illustrates the adaptability of ARIMA models across diverse forecasting scenarios.

Finally, the findings by Rosni and Othman further solidify ARIMA's utility through comprehensive analysis in the context of Malaysia's food security inflation. Their results indicated robust performance of the model in accurately predicting food prices, especially in situations where data quality might be limited, thus validating ARIMA as a practical tool in economic assessments related to food security [30].

2. Materials and Methods

2.1. Forecast Models

The Naive forecasting model is one of the simplest and most widely used methods in time series analysis. This model is based on the idea that future predictions can be made using the last observed value of the series. Specifically, the forecast for the next period is equal to the most recently known value, implying that no significant changes in trend or seasonality are expected—an assumption that may be valid in certain applications and contexts [31]. However, its accuracy is variable and it might not adequately capture the price dynamics in volatile markets [32].

The ARIMA model, which stands for "Autoregressive Integrated Moving Average," is a popular model for forecasting time series. This model is especially effective for data that are stationary or can be transformed into stationary data through differencing. The ARIMA structure is composed of three parameters: p (autoregressive order), d (the number of differences needed to achieve stationarity), and q (moving average order). This flexibility allows ARIMA to model various data characteristics [33,34]. In Python, ARIMA can be applied using the statsmodels library. A plethora of studies has demonstrated that the ARIMA model produces remarkable results in predicting diverse phenomena, such as the incidence of diseases or the behavior of prices in financial markets [34,35].

The extension of ARIMA that takes seasonality into account is the SARIMA (Seasonal ARIMA) model, which includes seasonal components in its structure. The SARIMA model is generally defined as SARIMA (p, d, q) (P, D, Q, S), where P, D, and Q are the seasonal parameters and S is the seasonal frequency [35]. This approach is particularly useful when the data exhibit significant seasonal patterns. The use of SARIMA has been widely documented for diverse applications, including disease outbreaks where the data display seasonal variation [36,37]. When applying the SARIMA model in Python, a similar logic to that of ARIMA is employed, but with the specification of seasonal components. This model has proven effective in forecasting prices in various contexts, such as the incidence of diseases [30]. Previous studies suggest that combining SARIMA models with neural networks can further enhance forecasting accuracy in complex contexts [37].

The Holt forecasting model is an extension of the exponential smoothing method that allows for the modeling of time series with trends. This model is based on two main components: the level and the trend. Similar to the simple exponential smoothing method, Holt uses a smoothing parameter (α) for the level, but includes a second parameter (β) that facilitates trend estimation. This approach renders the model more robust to changes in the data and useful for forecasting prices in time series where a rising or falling trend is observed [38]. This type of forecast is useful in contexts such as predicting agricultural product prices, where the trend may be a determining factor in the prices [39].

The Holt-Winters model, also known as the seasonal exponential smoothing method, is an extension of the Holt model that also incorporates seasonality. This model employs three components: the level, the trend, and the seasonality, thereby allowing for the modeling of time series that exhibit significant seasonal patterns. Holt-Winters can be configured in its additive or multiplicative versions, depending on the nature of the time series [40]. This model is useful in forecasting contexts where market data exhibit seasonal patterns, such as commodity prices [41] or energy prices [42]. The implementation of Holt-Winters smoothing tends to outperform simpler models in terms of forecasting accuracy in scenarios with seasonal patterns [43].

2.2. ARIMA and SARIMA Models

The development of ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) models was based on monthly average artichoke price time series data in Lima, provided by the Ministry of Agricultural Development and Irrigation (MIDAGRI) from 2021 to 2024. The study variable, expressed in Peruvian soles (PEN), modeled historical market fluctuations using autoregressive (AR), moving average (MA), integration (I), and seasonal components. To ensure stationarity—a core requirement for ARIMA—an augmented Dickey-Fuller test was applied, identifying first-order differencing (d = 1) for ARIMA. In SARIMA, seasonal differencing (D = 1) with a 12-month period (S = 12) addressed inherent annual agricultural cycles. The final ARIMA model was specified as (p = 2, d = 1, q = 2), where the autoregressive order (p = 2) captures price dependencies on the two preceding months, and the moving average component (q = 2) models accumulated random shocks. Parameters were optimized via automated grid search (ranges: p = 0–3, d = 0–2, q = 0–3), selecting configurations with the lowest Akaike Information Criterion (AIC). SARIMA was defined as ((0,0,1) (0,1,0), 12), featuring a simple moving average term in the non-seasonal component (p = 0, d = 0, q = 1) and annual seasonal differencing (D = 1, S = 12) to align with recurring patterns, such as export season demand peaks.

2.3. Programming Instructions

This study develops a predictive model to estimate the average price of artichokes in Lima during January and February 2025, using a monthly historical series provided by the Ministry of Agricultural Development and Irrigation (January 2021–December 2024) [44]. To address the temporal nature of the data, five statistical approaches are implemented: The Naive method (based on the last observed value), ARIMA and SARIMA models (which capture trends and seasonality through parameter optimization), and the exponential smoothing methods of Holt and Holt-Winters (for series with a linear trend and additive seasonality). The step-by-step code developed for the forecasting process is detailed below.

Figure 1 contains the Python code for forecasting artichoke prices using time series models. It imports libraries (ARIMA, SARIMA, Holt-Winters) and loads monthly price data (Jan 2021–Dec 2024) into a DataFrame. The configuration sets 2 forecast steps (Jan–Feb 2025) and a 12-month validation window. Actual 2025 values (January: 6.00, February: 4.63) are predefined for error analysis. The code structures data, initializes model frameworks, and prepares for training/prediction workflows (model fitting and MSE evaluation implied). Visual elements and optimization logic are excluded but would typically follow this setup.

Figure 2 contains three core functions. The first function, optimize_arima, searches for the optimal (p, d, q) parameters for an ARIMA model by iterating over a defined range and selecting the configuration with the lowest AIC. The second function, optimize_sarima, performs a similar task for the SARIMA model by testing combinations of both non-seasonal (p, d, q) and seasonal (P, D, Q) parameters, with a seasonal period m, and returns the best configuration based on the AIC value. Finally, the generate_comparison_table function creates a comparison table of forecasted versus actual values for January and February. It calculates the percentage error for each month and the average error across both months, then compiles the results into a pandas DataFrame for easy interpretation.

Figure 3 implements an automated forecasting pipeline for time series analysis. First, the dataset is divided into training and testing sets using a defined test size. The pipeline then optimizes ARIMA and SARIMA models by evaluating various parameter combinations on the training set's "Price" column, selecting those with the best performance according to the AIC metric. Next, final models are trained on the full dataset. These include a Naive model (which simply repeats the last observed value), ARIMA and SARIMA models (using the optimized parameters), and exponential smoothing models (Holt-Winters and Holt) to capture trends and seasonality. Once the models are trained, forecasts for a predetermined number of future steps are generated. The Naive model outputs constant predictions, while the other models produce dynamic forecasts. Finally, the code visualizes the results. It plots historical data alongside the forecasted values. Each model's forecast is displayed with distinct colors, line styles, and markers, enhancing the clarity of comparisons between observed data and predicted outcomes.

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from sklearn.metrics import mean_squared_error


# Data and configuration
data = [
    4.45,4.87,4,4.22,4.32,4.54,4.47,4.15,3.89,3.27,3.84,4.38,
    4.44,4.36,4.24,4.37,4.45,4.47,4.9,4.99,4.78,4.07,4.18,3.95,
    4.62,5.42,5.37,3.96,3.8,5.02,5.69,4.89,5.34,4.97,4.99,5.41,
    4.44,4.37,3.7,3.66,3.97,4.6,5.1,7.38,7.64,5.74,4.86,5.97
]
dates = pd.date_range(start='2021-01-01', periods=48, freq='MS')
df = pd.DataFrame({'Price': data}, index=dates)
df.index.freq = 'MS'


# General configuration
steps = 2
future_dates = pd.date_range(start='2025-01-01', periods=steps, freq='MS')
test_size = 12  # Validation period
actual_2025 = {'January': 6.00, 'February': 4.63}  # Actual values
```

Figure 1. Time Series Data Initialization and Forecasting Framework Setup.

```python
# Core functions

def optimize_arima(series, max_p=2, max_d=1, max_q=2):
    best_aic = float('inf')
    best_order = (0,0,0)
    for p in range(max_p + 1):
        for d in range(max_d + 1):
            for q in range(max_q + 1):
                if p + d + q == 0: continue
                try:
                    model = ARIMA(series, order=(p,d,q)).fit()
                    if model.aic < best_aic:
                        best_aic = model.aic
                        best_order = (p, d, q)
                except:
                    continue
    return best_order

def optimize_sarima(series, max_p=1, max_d=1, max_q=1, max_P=1, max_D=1, max_Q=1, m=12):
    best_aic = float('inf')
    best_config = (0,0,0,0,0,0)
    for p in range(max_p + 1):
        for d in range(max_d + 1):
            for q in range(max_q + 1):
                for P in range(max_P + 1):
                    for D in range(max_D + 1):
                        for Q in range(max_Q + 1):
                            try:
                                model = SARIMAX(series, order=(p,d,q), seasonal_order=
(P,D,Q,m)).fit(disp=False)
                                if model.aic < best_aic:
                                    best_aic = model.aic
                                    best_config = (p,d,q,P,D,Q)
                            except:
                                continue
    return best_config

def generate_comparison_table(forecasts, actual):
    results = []
    for model, values in forecasts.items():
        jan_error_pct = abs(values[0] - actual['January']) / actual['January'] * 100
        feb_error_pct = abs(values[1] - actual['February']) / actual['February'] * 100
        results.append({
            'Model': model,
            'Forecast Jan': f"{values[0]:.2f}",
            'Actual Jan': actual['January'],
            'Jan Error (%)': f"{jan_error_pct:.2f}%",
            'Forecast Feb': f"{values[1]:.2f}",
            'Actual Feb': actual['February'],
            'Feb Error (%)': f"{feb_error_pct:.2f}%",
            'Avg Error (%)': f"{(jan_error_pct + feb_error_pct)/2:.2f}%"
        })
    return pd.DataFrame(results).set_index('Model')
```

Figure 2. Model Optimization and Forecast Comparison.

```python
# Automated pipeline

if __name__ == "__main__":
    # 1. Prepare data
    train = df.iloc[:-test_size]
    test = df.iloc[-test_size:]

    # 2. Optimize models
    best_arima = optimize_arima(train['Price'])
    best_sarima = optimize_sarima(train['Price'])

    # 3. Train final models
    final_models = {
        'Naive': None,
        f'ARIMA{best_arima}': ARIMA(df['Price'], order=best_arima).fit(),
        f'SARIMA{best_sarima[:3]}({best_sarima[3:]},12)': SARIMAX(
            df['Price'],
            order=best_sarima[:3],
            seasonal_order=(best_sarima[3], best_sarima[4], best_sarima[5], 12)
        ).fit(disp=False),
        'Holt-Winters': ExponentialSmoothing(df['Price'], trend='add', seasonal='add',
seasonal_periods=12).fit(),
        'Holt': ExponentialSmoothing(df['Price'], trend='add', seasonal=None).fit()
    }

    # 4. Generate forecasts
    forecasts = {}
    for name, model in final_models.items():
        if name == 'Naive':
            forecasts[name] = [df['Price'].iloc[-1]] * steps
        else:
            forecasts[name] = model.forecast(steps).values

    # 5. Enhanced visualization
    plt.figure(figsize=(20, 8))

    # Historical data
    plt.plot(df['2023':], label='Historical', color='#2c3e50', linewidth=2.5, marker='s')

    # Forecast styling
    colors = ['#e74c3c', '#3498db', '#9b59b6', '#2ecc71', '#f1c40f']
    styles = ['--', '-.', ':', '-', '--']
    markers = ['o', '^', 's', 'D', 'P']

    for (name, pred), color, style, marker in zip(forecasts.items(), colors, styles, markers):
        plt.plot(future_dates, pred, label=name, color=color, linestyle=style,
                 linewidth=2, marker=marker, markersize=10, markeredgecolor='black')
```

Figure 3. Automated Forecasting Pipeline Overview.

Figure 4 illustrates the evaluation and visualization of forecasting results. This code compares model predictions with actual historical data by calculating error metrics—such as percentage errors for forecast periods—and compiling them into a consolidated table for easy analysis. Additionally, it generates a visual plot where forecasted values are overlaid on historical trends. Each model is distinguished using unique colors, line styles, and markers, enhancing the clarity of comparisons. This visual analysis helps assess the performance of various forecasting methods, providing both quantitative and qualitative insights. The output assists in identifying models that offer more accurate predictions and informs subsequent decision-making.

Figure 5 evaluates the 2025 forecast errors by comparing predicted values with actual data for January and February. The code calculates the error for each model by subtracting the forecast from the actual value for each month, storing the results in a dictionary where each model's errors are represented as a list [January error, February error]. Next, it generates a plot displaying these errors. Each model's errors are plotted using markers and dashed lines, with the x-axis representing the months ("Jan" and "Feb") and the y-axis showing the error values (Actual - Forecast). A horizontal dashed line at zero is added to help identify whether forecasts were overestimated or underestimated. The plot includes a legend positioned outside the plot area, gridlines for better readability, and a tight layout to ensure clarity. Note that the code block is repeated, which may be redundant. Overall, this visualization provides a clear comparison of forecast accuracy across models for the year 2025, highlighting their performance in terms of deviation from actual prices.

```
# Axis and title configuration
   plt.title('2025 Forecasts vs Actual Values\nArtichoke Price in Lima', fontsize=16, pad=20)
   plt.xlabel('Date', fontsize=14, labelpad=15)
   plt.ylabel('Price (PEN)', fontsize=14, labelpad=15)

   # Tick formatting
   plt.xticks(rotation=0, fontsize=12)
   plt.yticks(rotation=0, fontsize=12)
   plt.gca().xaxis.set_major_formatter(plt.matplotlib.dates.DateFormatter('%b %Y'))

   # Final adjustments
   plt.grid(True, linestyle='--', alpha=0.6)
   plt.legend(loc='upper left', bbox_to_anchor=(1, 1), fontsize=12)
   plt.tight_layout(pad=5.0)

   plt.show()

   # Generate comparison table
   comparison_table = generate_comparison_table(forecasts, actual_2025)

   print("\nFINAL COMPARISON WITH ACTUAL 2025 VALUES (Percentage Errors)")
   print("="*85)
   print(comparison_table.to_string(formatters={
       'Forecast Jan': lambda x: f"{x:>8}",
       'Jan Error (%)': lambda x: f"{x:>10}",
       'Forecast Feb': lambda x: f"{x:>8}",
       'Feb Error (%)': lambda x: f"{x:>10}",
       'Avg Error (%)': lambda x: f"{x:>10}"
   }))
   print("="*85)
```

Figure 4. Forecast Evaluation and Visualization.

```python
# Calculate 2025 forecast errors
errors_2025 = {}
for model, forecast in forecasts.items():
    jan_error = actual_2025['January'] - forecast[0]
    feb_error = actual_2025['February'] - forecast[1]
    errors_2025[model] = [jan_error, feb_error]

# 2025 error plot
plt.figure(figsize=(10, 5))
for model, errors in errors_2025.items():
    plt.plot(['Jan', 'Feb'], errors, 'o--',
label=model)
plt.axhline(0, color='black', linestyle='--')
plt.title('2025 Forecast Errors')
plt.ylabel('Error (Actual - Forecast)')
plt.legend(bbox_to_anchor=(1.05, 1))
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```


```python
# Calculate 2025 forecast errors
errors_2025 = {}
for model, forecast in forecasts.items():
    jan_error = actual_2025['January'] - forecast[0]
    feb_error = actual_2025['February'] - forecast[1]
    errors_2025[model] = [jan_error, feb_error]

# 2025 error plot
plt.figure(figsize=(10, 5))
for model, errors in errors_2025.items():
    plt.plot(['Jan', 'Feb'], errors, 'o--',
label=model)
plt.axhline(0, color='black', linestyle='--')
plt.title('2025 Forecast Errors')
plt.ylabel('Error (Actual - Forecast)')
plt.legend(bbox_to_anchor=(1.05, 1))
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```


Figure 5. Forecast Error Analysis.

Figure 6 conducts residual diagnostics using ACF and PACF plots with 20 lags. For each final model, residuals are calculated—using differences for the Naive model and the model's residuals for others. Models with fewer than 10 residuals are skipped. The code generates two subplots per model: one for the ACF and one for the PACF. The PACF plot includes error handling to display "PACF Unavailable" if needed. Each subplot is formatted with fixed y-axis limits, a horizontal zero line, and gridlines for clarity.

```
# Residual Analysis (ACF/PACF) with Lags=20

from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

max_lags = 20  # Changed to 20 lags as requested
n_models = len(final_models)

fig, axes = plt.subplots(n_models, 2, figsize=(16, 3.5*n_models))
plt.suptitle('Residual Diagnostics (ACF/PACF - Lags=20)', y=1.02,
fontsize=16)
for idx, (model_name, model) in enumerate(final_models.items()):
    # Residual calculation
    if model_name == 'Naive':
        residuals = df['Price'].diff().dropna()
    else:
        residuals = model.resid.dropna() if model is not None else pd.Series()

    if len(residuals) < 10:
        print(f"Skipping {model_name} - insufficient residuals")
        continue

    # ACF Plot
    plot_acf(residuals,
             lags=max_lags,
             ax=axes[idx,0],
             title=f'{model_name} - ACF',
             color='#1f77b4',
             alpha=0.05)

    # PACF Plot with error handling
    try:
        plot_pacf(residuals,
                  lags=max_lags,  # Using 20 lags here
                  ax=axes[idx,1],
                  title=f'{model_name} - PACF',
                  color='#ff7f0e',
                  alpha=0.05,
                  method='ywm')
    except Exception as e:
        print(f"PACF error in {model_name}: {str(e)}")
        axes[idx,1].clear()
        axes[idx,1].text(0.3, 0.5, 'PACF Unavailable', color='red')

    # Formatting
    for ax in axes[idx]:
        ax.set_ylim(-0.4, 0.4)
        ax.axhline(0, color='black', linestyle='--', lw=0.8)
        ax.set_xlabel('Lag (months)')
        ax.set_ylabel('Correlation')
        ax.grid(alpha=0.2)

plt.tight_layout()
plt.show()
```

Figure 6. Residual Analysis: ACF and PACF Evaluation.

3. Results

In **Figure 7**, it is confirmed that SARIMA best follows the historical trend, while the Naive and Holt-Winters models exhibit clear deviations: the former underestimates volatility, and the latter systematically overestimates prices in 2025. The historical peak in September 2024 (7.64 PEN) is not replicated by any model, suggesting that external factors influenced this outlier. Specifically, SENAMHI Bulletin No. 05 on Meteorological Drought Monitoring reported SPI-1 and SPI-3 indices showing rainfall deficits exceeding 60 % across several Andean regions, indicating severe drought conditions that likely constrained supply [45]. This underscores the need to incorporate exogenous variables in future analyses. Furthermore, all models except SARIMA forecast higher prices than the actual value in February (4.63 PEN), which could indicate an underestimation of the post-harvest supply or an unexpected drop in demand.

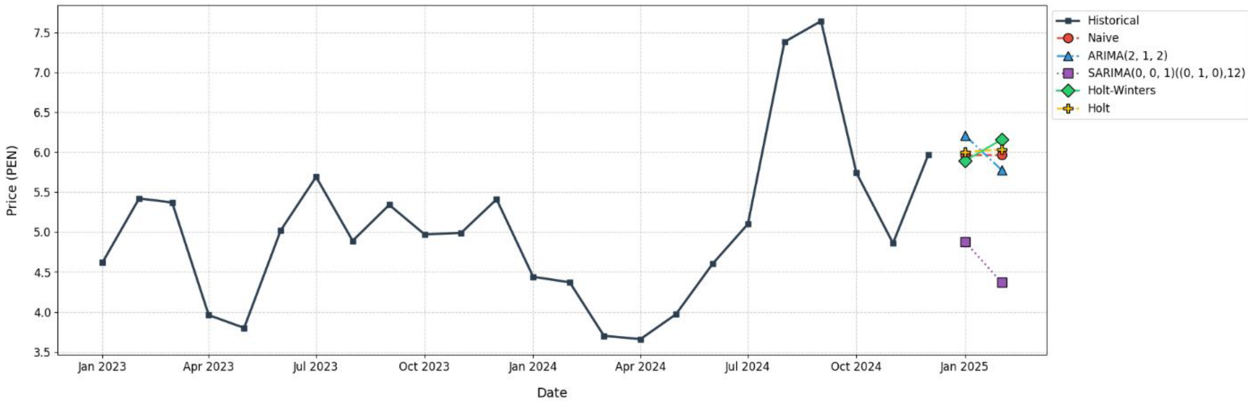

Figure 7. Forecasts Values Artichoke Price in Lima.

In **Table 1**, SARIMA stands out with the lowest average error (12.16%), particularly in February (5.62%), confirming its ability to handle complex seasonal patterns. In contrast, Holt-Winters records the highest average error (17.41%), with an alarming error in February (32.99%), suggesting that its seasonal component does not adequately adjust to market fluctuations. The model with an average error of 14.14% performs at an intermediate level; its overestimation in February (24.77%) reflects difficulties in capturing sudden price drops.

In **Figure 8**, although SARIMA exhibits a high error in January (18.69%), its accuracy in February (5.62%) compensates for this, demonstrating its adaptability to abrupt seasonal changes. This indicates that SARIMA effectively "learns" from the annual seasonality, thereby enhancing its performance in complex months. Conversely, Holt-Winters deviates most from reality, pointing to a failure in its seasonal component. This shortcoming could be attributed to the fact that the seasonality of artichokes does not follow a traditional additive or multiplicative pattern.

Table 1. Forecast Values.

Model	Forecast Jan	Actual Jan	Error (%)	Forecast Feb	Actual Feb	Error (%)
Naive	5.97	6.00	0.50	5.97	4.63	28.94
ARIMA	6.21	6.00	3.50	5.78	4.63	24.77
SARIMA	4.88	6.00	18.69	4.37	4.63	5.62
Holt-Winters	5.89	6.00	1.83	6.16	4.63	32.99
Holt	6.00	6.00	0.04	6.03	4.63	30.34

Note: Python output, ARIMA (2,1,2), SARIMA ((0,0,1) (0,1,0),12).

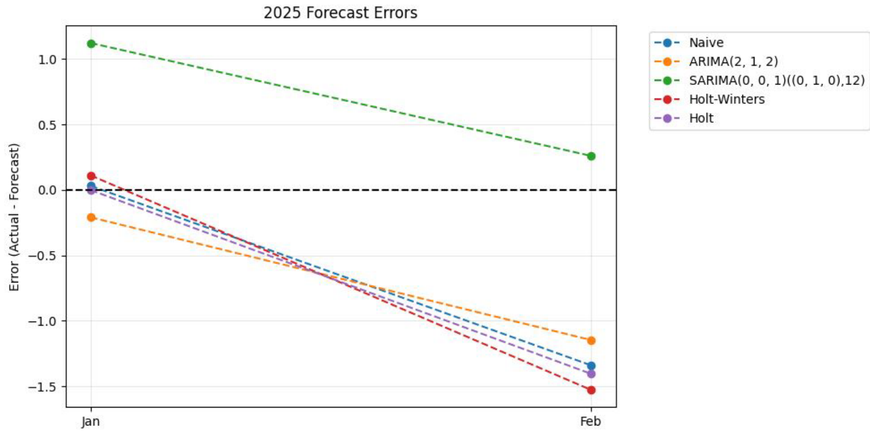

Figure 8. Forecasts Values Artichoke Price in Lima.

In **Figure 9**, it can be observed that the residuals of the ARIMA and SARIMA models remain mostly around zero, albeit with some oscillations, suggesting that they capture much of the series' dynamics. However, slight peaks occur at certain points, indicating possible outlier events or abrupt changes. Holt-Winters exhibits more dispersed residuals, which aligns with the higher error observed in its forecasts. Finally, Holt shows notable fluctuations toward the end of the period, potentially indicating difficulty in adjusting to the series' final phase.

In **Figure 10**, the ACF and PACF plots of the residuals (up to 20 lags) for each model clearly demonstrate that ARIMA and SARIMA excel by exhibiting few observations outside the confidence intervals. This indicates that their residuals closely approximate white noise, thus effectively capturing both temporal and seasonal dynamics. In particular, SARIMA shows an outstanding ability to model seasonal components, confirming its capacity to accurately represent recurring patterns throughout the year. Similarly, ARIMA displays robust performance, with only a few significant lags, making it a dependable choice when seasonality is less pronounced or can be managed through differencing. Conversely, Holt is somewhat less favorable, as its residuals reveal several lags with statistically significant correlations, particularly in the ACF. This suggests that, although Holt efficiently models linear trends, it may encounter difficulties in capturing more intricate or seasonal variations. Nonetheless, its simplicity and expedited training process render it a viable option in scenarios characterized by stable trends and minimal seasonal fluctuation.

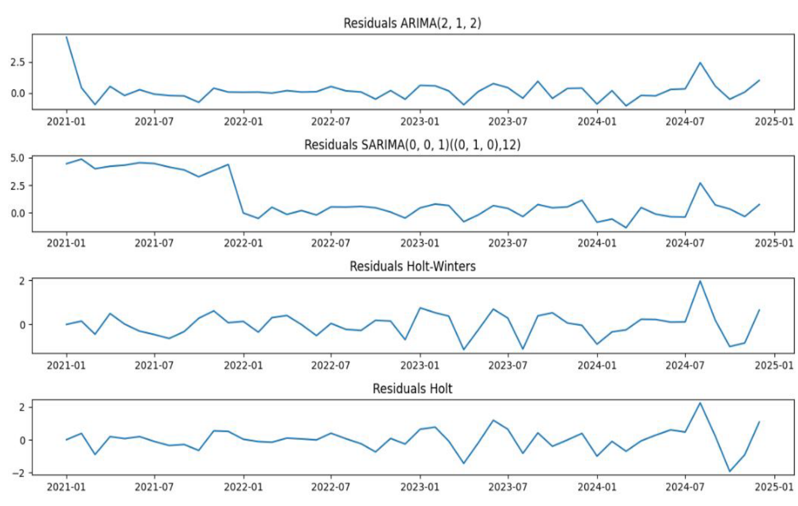

Figure 9. Forecasts Values Artichoke Price in Lima.

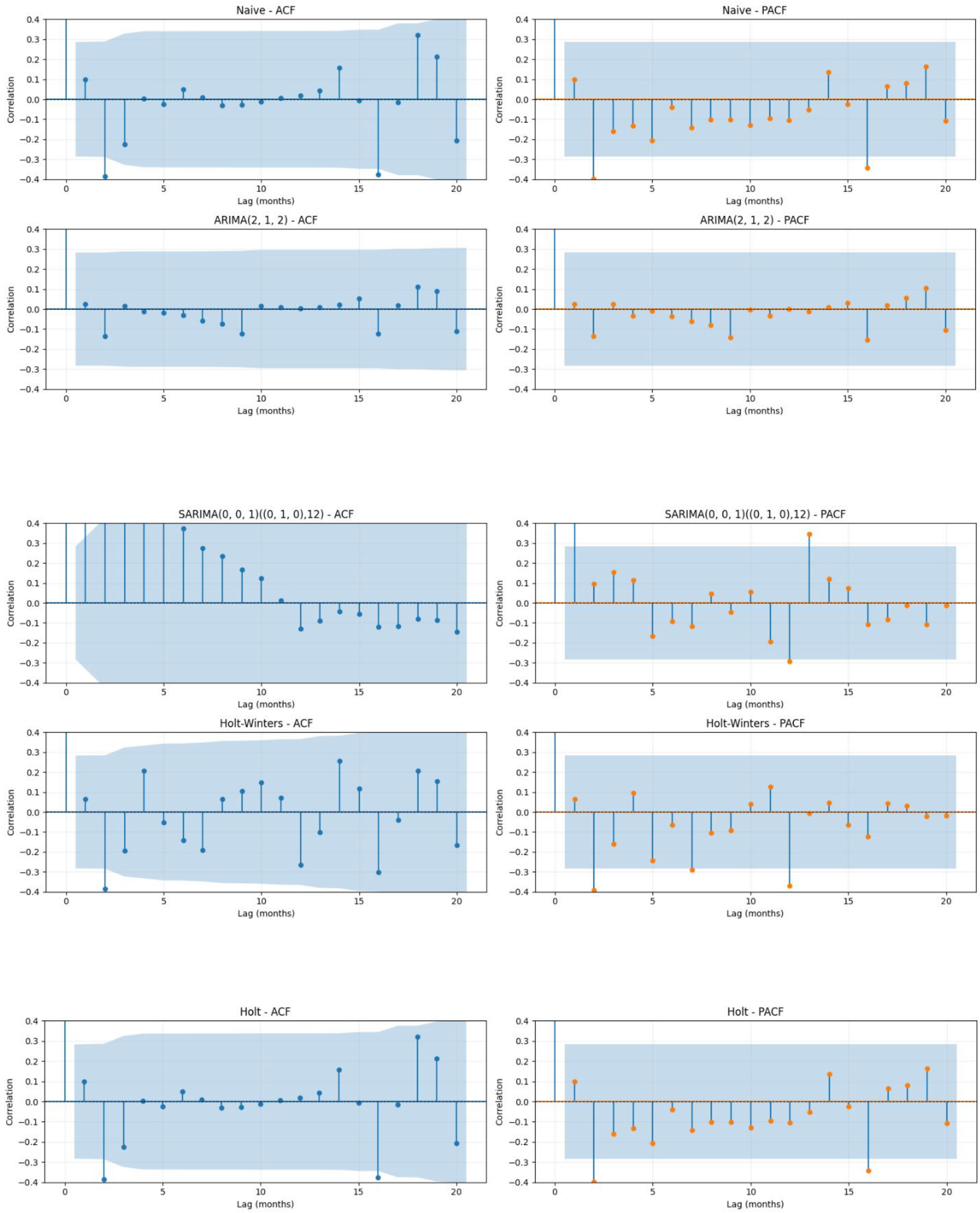

Figure 10. ACF AND PACF Plots.

4. Discussion

The results of this study reveal significant differences in the performance of the forecasting models applied to artichoke prices in Lima. The SARIMA model emerged as the most robust, with an average error of 12.16%, and it was particularly accurate in February (5.62%), confirming its ability to capture complex seasonal patterns, consistent with previous findings in agricultural markets [15–31]. This success is attributed to its hybrid structure, which integrates autoregressive and seasonal components, thereby enabling it to adapt to the periodic fluctuations typical of crops such as artichoke. However, its high error in January (18.69%) suggests limitations when confronted with abrupt non-seasonal changes, possibly linked to exogenous events such as variations in initial annual demand or post-harvest logistical adjustments.

On the other hand, the Holt-Winters model exhibited the poorest performance (average error of 17.41%), with an error of 32.99% in February. This indicates that its assumption of additive/multiplicative seasonality does not align with the actual dynamics of artichoke prices, which may be influenced by nonlinear factors or interactions among unconsidered variables (e.g., export policies or climate). This finding is consistent with studies that warn about the sensitivity of Holt-Winters in volatile markets [37]. The Naive model, although simple, outperformed Holt-Winters and ARIMA in January (0.50% error), reinforcing its utility for very short-term horizons. However, its lack of adaptability to trends and seasonality renders it unfeasible for medium-term forecasts, as evidenced by its 28.94% error in February.

A critical finding was the inability of all models to replicate the September 2024 peak (7.64 PEN), indicating the influence of unmodeled external factors, such as droughts or regulatory changes. This supports the need to incorporate exogenous variables in future studies, as proposed by Silva et al. (2024) in the context of nowcasting. It is also important to highlight the fundamental role of Python in the implementation and optimization of these forecasting models. The use of Python, along with its extensive libraries (such as Pandas, NumPy, Scikit-learn, and Statsmodels), facilitates the processing of large volumes of historical data and the application of advanced time series analysis techniques. This not only enables the automation of parameter optimization in models such as ARIMA and SARIMA but also allows for precise comparisons and detailed visualizations of the results. Python's versatility further facilitates the integration of new methods, such as machine learning techniques or hybrid models, which could further enhance forecast accuracy. Thus, Python emerges as an essential tool for addressing the challenges of predictive analysis in volatile markets, offering a robust and scalable platform for future research and practical applications in the agricultural sector.

The results of this study exhibit key similarities and differences compared to prior research on agricultural price forecasting. The superior performance of the SARIMA model ((0,0,1)(0,1,0),12)—with an average error of 12.16%—aligns with findings such as those by Wanjuki et al. (2021), who reported that SARIMA reduced errors in forecasting Kenya's food price index by capturing annual seasonality. However, the performance of Holt-Winters (17.41% error) contrasts with studies like Menculini et al. (2023), where this method outperformed ARIMA in markets with stable additive seasonality. This discrepancy suggests that the non-traditional seasonality of artichoke prices in Peru—influenced by abrupt climatic variations (SENAMHI, 2024) and post-COVID logistical fluctuations—limits the efficacy of models assuming fixed seasonal patterns.

Furthermore, the inability of all models to predict the atypical September 2024 price peak (7.64 PEN) mirrors limitations reported in works such as Silva et al. (2024), where exogenous factors (e.g., droughts, geopolitical conflicts) necessitated the use of external variables in ARIMAX models. This finding reinforces the need to integrate real-time climatic data, as implemented in wheat price forecasts in Ukraine (Zomchak & Kukhotska, 2023). Finally, the Naive model's high accuracy in January (0.50% error) aligns with observations by Nurjati & Wiryawan (2024) for very short-term forecasts, but its failure in February (28.94% error) underscores the importance of selecting models based on temporal horizons, as cautioned by Mitra & Paul (2017) for perishable commodities.

5. Conclusions and Recommendations

This study demonstrates that the choice of forecasting model significantly impacts the accuracy of agricultural price projections. The SARIMA model has proven to be the most effective in capturing seasonality in artichoke prices, showing minimal errors in February (5.62%), which is critical for post-harvest planning. In contrast, Holt-Winters was found to be inadequate for this context, underscoring the importance of validating seasonal assumptions before its application. The inability of the models to predict atypical peaks (e.g., September 2024) reveals the influence of unconsidered external factors, such as climatic or geopolitical variables, which highlights the need for more comprehensive data systems. Additionally, the utility of the Naive model for short-term horizons suggests that simple methods can complement complex models in resource-limited scenarios. To strengthen food security in Peru, it is recommended to adopt hybrid approaches that combine SARIMA with machine learning techniques, along with the integration of real-time external data. This would not only improve forecast accuracy but also align agricultural strategies with the Sustainable Development Goals, ensuring stability in food access and resilience against future crises.

For practical implementation in Peru's agricultural sector, we propose a structured roadmap: (i) integrate the SARIMA + machine learning forecasting pipeline into the MIDAGRI SISAP platform to automate monthly artichoke price projections; (ii) conduct capacity-building workshops for regional agricultural analysts on Python-based time series modeling and data interpretation; (iii) establish a real-time data ingestion framework for key exogenous indicators—such as precipitation records and transport disruption logs—to feed into ARIMAX models or intervention dummies; and (iv) issue quarterly policy briefs that leverage these forecasts to guide targeted market interventions, subsidy allocations, and logistical planning. By following this implementation path, policymakers can directly translate forecasting insights into concrete actions that stabilize producer incomes, ensure affordable consumer prices, and strengthen resilience against future shocks.

6. Limitations, Policy Impact, and Future Pathway

This study presents certain limitations. First, it relies on monthly frequency data and a two-month out-of-sample validation, which may not adequately reflect high-frequency market dynamics or rare extreme events. Additionally, exogenous factors such as climatic anomalies or transport disruptions were not explicitly included in the evaluated models. From a public policy perspective, the results support the integration of the SARIMA forecasting system—combined with machine learning techniques—into MIDAGRI's SISAP platform. This integration, enhanced with real-time indicators on climate (e.g., rainfall) and logistics (e.g., route blockages), would enable proactive responses to supply and demand shocks, adjustments in subsidy programs, and improved food distribution strategies across the country. For future research, it is recommended to develop ARIMAX and hybrid models that incorporate dynamic exogenous variables, extend the validation horizon to cover more forecast periods, and apply these methods to other key crops. Additionally, spatially disaggregated forecasting could support the design of region-specific policies tailored to the unique agricultural contexts across Peru.

Author Contributions

Conceptualization, A.Z.-A. (Axel Zevallos-Aquije) and A.Z.-A. (Anneliese Zevallos-Aquije); methodology, A.Z.-A. (Anneliese Zevallos-Aquije); software, A.Z.-A. (Axel Zevallos-Aquije); validation, K.P.-S., A.Z.-A. (Anneliese Zevallos-Aquije), and R.A.S.-B.; formal analysis, K.P.-S.; investigation, R.A.S.-B.; resources, R.A.S.-B.; data curation, K.P.-S.; writing—original draft preparation, A.Z.-A. (Axel Zevallos-Aquije); writing—review and editing, A.Z.-A. (Anneliese Zevallos-Aquije); visualization, K.P.-S.; supervision, A.Z.-A. (Axel Zevallos-Aquije); project administration, A.Z.-A. (Axel Zevallos-Aquije). All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Silva, L.S.e., Ospina, C.A.M., Fabi, C., 2024. Food price inflation nowcasting and monitoring. Statistical Journal of the IAOS. 40(2), 325–339. DOI: https://doi.org/10.3233/sji-230083

[2] Hassen, T.B., Bilali, H.E., 2022. Impacts of the Russia-Ukraine war on global food security: Towards more sustainable and resilient food systems? Foods, 11(15), 2301. DOI: https://doi.org/10.3390/foods11152301

[3] Sivarajasingham, S., Applanaidu, S., Hassan, S., 2015. Transmission of global food prices to domestic prices: Evidence from Sri Lanka. Asian Social Science. 11(12), 215–228. DOI: https://doi.org/10.5539/ass.v11n12215

[4] Fan, S., Si, W., Zhang, Y., 2020. How to prevent a global food and nutrition security crisis under COVID-19? China Agricultural Economic Review. 12(3), 471–480. DOI: https://doi.org/10.1108/caer-04-2020-0065

[5] Kavallari, A., Fellmann, T., Gay, S.H., 2014. Shocks in economic growth = Shocking effects for food security?. Food Security. 6(4), 567–583. DOI: https://doi.org/10.1007/s12571-014-0368-y

[6] Kalkuhl, M., 2014. How strong do global commodity prices influence domestic food prices in developing countries? A global price transmission and vulnerability mapping analysis. SSRN Electronic Journal. DOI: https://doi.org/10.2139/ssrn.2437443

[7] Alom, F., Ward, B.D., Hu, B., 2013. Macroeconomic effects of world oil and food price shocks in Asia and Pacific economies: Application of SVAR models. OPEC Energy Review. 37(3), 327–372. DOI: https://doi.org/10.1111/opec.12015

[8] Zmami, M., Ben-Salha, O., 2019. Does oil price drive world food prices? Evidence from linear and nonlinear ARDL modeling. Economies. 7(1), 12. DOI: https://doi.org/10.3390/economies7010012

[9] Bairagi, S., Mishra, A.K., Mottaleb, K.A., 2022. Impacts of the COVID-19 pandemic on food prices: Evidence from storable and perishable commodities in India. PLOS ONE. 17(3), e0264355. DOI: https://doi.org/10.1371/journal.pone.0264355

[10] Abaidoo, R., Agyapong, E.K., Boateng, K.F., 2021. Stability in the banking industry and commodity price volatility: Perspective from developing economies. Journal of Economic and Administrative Sciences. 39(4), 988–1012. DOI: https://doi.org/10.1108/jeas-05-2021-0089

[11] Darnton-Hill, I., Cogill, B., 2010. Maternal and young child nutrition adversely affected by external shocks such as increasing global food prices. The Journal of Nutrition. 140(1), 162S–169S. DOI: https://doi.org/10.3945/jn.109.111682

[12] N., K.R., Dodo, F.E., 2023. Impact of petroleum products price changes on prices of food items in the Nigerian economy. Journal of Development Economics and Finance. 4(1), 79–95. DOI: https://doi.org/10.47509/jdef.2023.v04i01.05

[13] Santillán, D.N.G., Hinojoza, S.A.P., 2019. Políticas comerciales y exportaciones agrícolas del Ecuador. Periodo 2010–2016. Quipukamayoc. 27(53), 25–31. DOI: https://doi.org/10.15381/quipu.v27i53.15982

[14] Chiriboga, M., Vásquez, E.G.P., Sotomayor, O., 2011. Precios agropecuarios e ingresos: El caso de tres provincias en Ecuador. Universitas. (12), 87. DOI: https://doi.org/10.17163/uni.n12.2010.04

[15] Galbán, J.M., 2022. Zonificación del uso potencial

agrícola en la cuenca media del río Luján, Argentina. Geográfica Digital. 19(38), 65. DOI: https://doi.org/10.30972/geo.19386204

[16] Argothy, A., Martínez-Cano, J.P., Carvajal, M.B.V., et al., 2023. Transferencia de precios en los mercados agrícolas de Ambato y Riobamba. CienciAmérica. 12(1), 115–133. DOI: https://doi.org/10.33210/ca.v12i1.422

[17] Sepúlveda, R., Cabas-Monje, J., 2018. Factibilidad del uso de contratos de futuros del Chicago Mercantile Exchange para la cobertura del riesgo de precio en el ganado bovino chileno. Lecturas de Economía. (90), 9–44. DOI: https://doi.org/10.17533/udea.le.n90a01

[18] Reyes, C.P.H., Larios, L.E.A., Díaz, F.E.B.d., et al., 2018. Estrategias de vida y seguridad alimentaria nutricional. Revista Salud y Desarrollo. 2(2), 32–41. DOI: https://doi.org/10.55717/aijz6747

[19] Totosaus, A., Pérez, A.N.B., 2023. Relación entre el nivel de seguridad alimentaria y los ambientes alimentarios en Ecatepec: Efecto de la contingencia sanitaria por COVID-19. Journal of Behavior and Feeding. 2(4), 10–18. DOI: https://doi.org/10.32870/jbf.v2i4.33

[20] Montalvo-Romero, N., Montiel-Rosales, A., Fernández-Lambert, G., et al., 2021. Huerto traspatio, como práctica de autoalimento y desarrollo económico de familias marginadas: Una revisión literaria. Tendencias en la Investigación Universitaria. Una Visión Desde Latinoamérica. XIV, 120–136. DOI: https://doi.org/10.47212/tendencias2021vol.xiv.9

[21] Casanueva, D.R., García, O.P., Jiménez, D.T.C., et al., 2022. Propuesta de ejes, líneas y acciones estratégicas para la producción de alimentos en el municipio de Sancti Spíritus, Cuba. Revista Técnica de la Facultad de Ingeniería Universidad del Zulia. 45(2), 100–110. DOI: https://doi.org/10.22209/rt.v45n2a03

[22] Jiménez, G.E.M., 2023. Avances tecnológicos en el procesamiento de alimentos: Impacto en la seguridad alimentaria y la sostenibilidad. Bastcorp International Journal. 2(2), 43–55. DOI: https://doi.org/10.62943/bij.v2i2.32

[23] Cruz-Sánchez, B., Muñoz-Rodríguez, M., Santoyo-Cortés, V.H., et al., 2016. Potencial y restricciones de la avicultura de traspatio sobre la seguridad alimentaria en Guerrero, México. Agricultura Sociedad y Desarrollo. 13(2), 257. DOI: https://doi.org/10.22231/asyd.v13i2.329

[24] Solchaga, I.O.S., Nave, F., 2022. Diseño y validación técnica del ícono del plato nutricional para la alimentación diaria de los guatemaltecos. Revista Científica. 30(2), 11–22. DOI: https://doi.org/10.54495/rev.cientifica.v30i2.230

[25] Zomchak, L., Kukhotska, T., 2023. Wheat market price dynamics in Ukraine: Quantitative exploration and forecasting. European Journal of Economics and Management. 9(4), 14–22. DOI: https://doi.org/10.46340/eujem.2023.9.4.2

[26] Mitra, D., Paul, R.K., 2017. Hybrid time-series models for forecasting agricultural commodity prices. Model Assisted Statistics and Applications. 12(3), 255–264. DOI: https://doi.org/10.3233/mas-170400

[27] Wanjuki, T.M., Wagala, A., Muriithi, D.K., 2021. Forecasting commodity price index of food and beverages in Kenya using seasonal autoregressive integrated moving average (SARIMA) models. European Journal of Mathematics and Statistics. 2(6), 50–63. DOI: https://doi.org/10.24018/ejmath.2021.2.6.80

[28] Nurjati, E., Wiryawan, F.S., 2024. Strategi meningkatkan daya saing bawang merah melalui prediksi harga. Jurnal Ilmu Pertanian Indonesia. 29(3), 342–355. DOI: https://doi.org/10.18343/jipi.29.3.342

[29] Menculini, L., Marini, A., Proietti, M., et al., 2021. Comparing Prophet and deep learning to ARIMA in forecasting wholesale food prices. Forecasting. 3(3), 644–662. DOI: https://doi.org/10.3390/forecast3030040

[30] Rosni, Q.M., Othman, M.R., 2022. Time-series modelling of food security inflation in Malaysia using an ARIMA model as a machine learning approach. Journal of Maritime Logistics. 62–78. DOI: https://doi.org/10.46754/jml.2022.12.005

[31] Wang, Z., Yang, C., Zhang, S., et al., 2024. Analysis and forecasting of syphilis trends in mainland China based on hybrid time series models. Epidemiology and Infection. 152. DOI: https://doi.org/10.1017/s0950268824000694

[32] Kamal, M.A., Gyanchandani, M., Kushwah, A.K., 2022. A novel time series data clustering approach for wind speed forecasting. Wind Engineering. 46(4), 1281–1290. DOI: https://doi.org/10.1177/0309524x221076976

[33] Wang, M., Pan, J., Li, X., et al., 2022. ARIMA and ARIMA-ERNN models for prediction of pertussis incidence in mainland China from 2004 to 2021. BMC Public Health. 22(1). DOI: https://doi.org/10.1186/s12889-022-13872-9

[34] Zhai, M., Li, W., Tie, P., et al., 2021. Research on the predictive effect of a combined model of ARIMA and neural networks on human brucellosis in Shanxi Province, China: A time series predictive analysis. BMC Infectious Diseases. 21(1). DOI: https://doi.org/10.1186/s12879-021-05973-4

[35] Wang, H., Tian, C., Wang, W., et al., 2018. Time-series analysis of tuberculosis from 2005 to 2017 in China. Epidemiology and Infection. 146(8), 935–939. DOI: https://doi.org/10.1017/s0950268818001115

[36] Bahk, G., Kim, Y., Park, M., 2015. Use of Internet search queries to enhance surveillance of foodborne illness. Emerging Infectious Diseases. 21(11), 1906–1912. DOI: https://doi.org/10.3201/eid2111.141834

[37] Zhao, Z., Zhai, M., Li, G., et al., 2022. Study on the prediction effect of a combined model of SARIMA and LSTM based on SSA for influenza in Shanxi Province, China. Preprint. DOI: https://doi.org/10.21203/rs.3.rs-2081379/v1

[38] Delgadillo-Ruiz, O., Ramírez-Moreno, P.P., Rodríguez, J.A.L., et al., 2016. Pronósticos y series de tiempo de rendimientos de granos básicos en México. Acta Universitaria. 26(3), 23–32. DOI: https://doi.org/10.15174/au.2016.882

[39] Sosa, M.E.D., Pérez, E.A.C., Ríos, W.D.P., 2021. Modelamiento del precio de la papa criolla en el departamento de Cundinamarca por medio de series de tiempo y modelos dinámicos. Comunicaciones en Estadística. 14(1), 31–52. DOI: https://doi.org/10.15332/23393076.6633

[40] Villada, F., Jaramillo-Arroyave, D., Villada, M., 2014. Pronóstico del precio del petróleo mediante redes neuronales artificiales. Información Tecnológica. 25(3), 145–154. DOI: https://doi.org/10.4067/s0718-076420140003

[41] Gómez, L.M.J., Lambis-Alandete, E., Velásquez-Henao, J.D., 2023. Comparación de algoritmos de deep learning para pronósticos en los precios de criptomonedas. Ingeniería y Competitividad. 25(3). DOI: https://doi.org/10.25100/iyc.v25i3.12845

[42] Muñoz-Santiago, A., Urquijo-Vanstrahlengs, J., Castro-Otero, A., et al., 2017. Pronóstico del precio de la energía en Colombia utilizando modelos ARIMA con IGARCH. Revista de Economía del Rosario. 20(1), 36. DOI: https://doi.org/10.12804/revistas.urosario.edu.co/economia/a.6152

[43] Conto, E.L.T., López, R.A.C., 2023. Comportamiento de la UVR en el largo plazo. Revista Electrónica de Comunicaciones y Trabajos de ASEPUMA. 24(1), 21–34. DOI: https://doi.org/10.24309/recta.2023.24.1.03

[44] Ministerio de Desarrollo Agrario y Riego (MIDAGRI), 2025. Sistema de abastecimiento y precios. Available from: http://sistemas.midagri.gob.pe/sisap/portal2/mayorista/# (cited 15 February 2025).

[45] SENAMHI, 2024. Boletín hidrometeorológico de la Dirección Zonal 3 Cajamarca Sur - La Libertad. Available from: https://cdn.www.gob.pe/uploads/document/file/7109294/6109384-bhmdz3-n-09-2024.pdf (cited 9 April 2025).