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1 Abstract

This paper forecasts monthly cocoa prices using data from the International Cocoa Organization and climate records from Ghana. After standardized the data, a series of time series models were applied to forecast the prices, including Exponential Smoothing (ETS), ARIMA, SARIMA, linear regression with climate covariates, and GARCH models. what was found, and why this matters

2 Introduction

Forecasting commodity prices is a challenge in economics and statistical modelling because of the multi-factorial drivers of price behaviour. However, forecasting commodity prices is important for producers, traders and policymakers to have more understanding about the market. Cocoa is a globally traded commodity with significant economic relevance, particularly in regions where it is both produced and consumed at scale such as Ghana. For stakeholders such as producers, traders, and policymakers, accurate forecasting is vital to design procurement strategies, manage supply chain risks, and stabilize income.

Some real-world examples also show the importance of forecasting the Cocoa price. In 2016–2017, global cocoa prices declined by over 30% (International Cocoa Organization 2016), leading to significant income losses for smallholder farmers in Ghana. However, cocoa exports constitute a major share of national revenue in Chana. This forced some farmers to abandon cocoa cultivation or turn to alternative livelihoods, including environmentally damaging activities such as illegal mining (Bryant and Mitchell 2021). In order to stabilize the price of cocoa, Ghana and Côte d'Ivoire jointly introduced the Living Income Differential (LID) in 2019, establishing a $400-per-ton premium on cocoa exports to support farmer incomes (Squicciarini, Vandeplas, and Barreiro-Hurle 2021). This real-world example shows how price instability can widely influence the economic and social consequences, and highlights the importance of forecasting models.

This paper aims to develop an accurate model for predicting cocoa prices. The paper investigates the monthly behaviour of cocoa prices by using two key datasets, including daily cocoa futures prices from the International Cocoa Organization and daily climate data from Ghana, the largest cocoa-producing country in the world. The analysis focuses on modelling the monthly change in log-transformed cocoa prices. The differencing method was use to address non-stationarity. A series of forecasting models was evaluated, including Exponential Smoothing (ETS), ARIMA, SARIMA, linear regression with climate covariates, and GARCH models. Each model was trained on a 70% subsample and assessed using the remaining 30% sample, which is a 70/30 train-test split. Forecast accuracy was assessed with root mean square error (RMSE), AIC, and BIC, with all predictions back-transformed to the original price scale.

3 Literature Review

Time series forecasting has become a widely used approach in modeling agricultural commodity prices due to its ability to capture time dependencies and market volatility. Novanda et al. (2018) compared different forecasting techniques for coffee prices, including Moving Average (MA), ARIMA, and decomposition methods. Their findings showed that ARIMA has reliable performance across both international and domestic markets. This shows that ARIMA may be a suitable model for this paper.

Building upon Novanda's research, Deina et al. (2022) conducted a advanced comparative analysis and emphasized data preprocessing in the research. They identified and removed nonstationary components such as seasonality and trend first and then use the Partial Autocorrelation Function (PACF) to make lag selection. They compared several forecasting techniques, including Exponential Smoothing (ES), Autoregressive (AR), ARIMA, Multilayer Perceptron (MLP), and Extreme Learning Machines (ELM), to find the most accurate prediction model. This study offers insights into model selection strategies for time series forecasting. Our study also emphasis the importance on preprocessing and model comparison.

Anusha, Kumar, and Deevi (2019) further demonstrated that combines ARIMA with artificial neural networks can have better forecasting performance when dealing with nonlinear patterns and volatility clustering in agricultural export prices. Motivated by these findings, our paper applies a hybrid ARIMA-GARCH model to capture both the trend and volatility structure in cocoa price.

Finally, Sampson Ankrah (2014) investigated the impact of world cocoa prices on cocoa production in Ghana using a regression model with ARIMA errors. While both their study and ours are about Ghanaian cocoa, the focus are different. Sampson Ankrah (2014) emphasized the effect of international prices on production, while our analysis aims to forecast cocoa prices with climate variables as potential predictors.

In summary, previous studies provided valuable insights into the strengths and limitations of various time series and hybrid models in price forecasting. With these insights, models including ARIMA, SARIMA, ETS, and GARCH were applied to forecast the cocoa prices.

4 Methodology

At the initial stage of this study, we primarily considered time series models to forecast trends in cocoa prices. The models employed included the ETS (Error, Trend, Seasonal) model, the ARIMA (AutoRegressive Integrated Moving Average) model, and the SARIMA (Seasonal ARIMA) model. During the training of these models, only historical cocoa price data were used.

Prior to model fitting, we conducted preprocessing on the raw data by aggregating the daily price data into monthly frequency. The representative value for each month was calculated as the average of all available daily prices in that month, ignoring any missing values during the calculation. This step was intended to reduce data noise and ease computational burden. We then split the data into a training set and a testing set in a 7:3 ratio.

For the ETS model, we built the model directly on the raw price data. Through initial visual analysis, we examined the data's trend, seasonality, and error volatility to determine the structure (additive or multiplicative) of the three ETS components. For uncertain configurations, we applied automatic model fitting and compared multiple candidate models. The model with the lowest corrected Akaike Information Criterion (AICc) was selected as the final ETS model.

Before fitting the ARIMA and SARIMA models, we first transformed the price data to achieve stationarity by applying logarithmic transformation and differencing. We then examined the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to preliminarily identify the orders of the models (p, d, q) and seasonal components (P, D, Q, s). When the cutoffs were unclear, we employed a grid search over different parameter combinations and selected the optimal model based on the lowest AICc value.

Once the ARIMA and SARIMA models were obtained, we conducted diagnostic analysis on their residuals, with a particular focus on autocorrelation. If the ACF plots of the residuals showed significant autocorrelation, it indicated that the model failed to capture all underlying volatility structures. In such cases, we further applied the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to account for heteroskedasticity in the residuals and improve forecasting performance.

In addition to time series models, we also developed a multiple linear regression model to incorporate external explanatory variables identified in our literature review, such as climate change. The training data for this model also consisted of the first 70% of the full dataset. Since linear regression models cannot inherently capture temporal dependencies among variables, we introduced several lagged variables to improve the model's ability to reflect dynamic changes over time. As a result, observations with missing lagged values were removed from the dataset.

After fitting the models, we conducted a systematic evaluation of all candidate models (ETS, ARIMA, SARIMA, GARCH, and linear regression). First, we used AICc as one of the main criteria for model selection to compare their in-sample fitting performance. Then, we performed residual diagnostics on the training set, including residual plots, ACF and PACF plots, and the Ljung-Box test to examine whether the residuals resembled white noise. For the linear regression model, we further tested residual normality and assessed multicollinearity using metrics such as the Variance Inflation Factor (VIF) to evaluate the model's robustness and explanatory power.

Following model validation on the training set, we evaluated the out-of-sample forecasting performance of each model using the testing set. Based on the parameters estimated from the training data, we generated forecasts for the testing set and calculated multiple forecast error metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Sum of Squared Errors (SSE). By comparing these evaluation results, we assessed the generalization capability and predictive stability of each model, and ultimately selected the best-performing model as the final forecasting model in this study.

5 Data

This study uses two sources of data: international cocoa price data from the International Cocoa Organization (ICCO) and local climate data from Ghana. The ICCO dataset provides daily cocoa futures prices (in USD per tonne), while the climate dataset includes daily measurements of precipitation and temperature from a major cocoa-producing region in Ghana. The observation is from October 1994 to November 2024, which allows both long-term trends and short-term seasonal effects analysis.

To prepare the data for time series analysis, several preprocessing steps were undertaken. After importing the dataset, prices were converted to numeric values and date formats were standardized. The climate data for each day was the average of existed multiple observations of that day. The two datasets were merged by date and the data was summarized on a monthly basis. The dependent variable, *Price*, represents the monthly average of daily cocoa prices.

Table 1 presents the summary statistics for the variables used in this study, including cocoa prices and daily climate indicators from 1994 to 2024. The cocoa price (USD) range from a minimum of 778.4 to a maximum of 10,690.7, with a median value of 2,330.7, which indicates significant variability over time. Daily Perception values are mostly zero with 75% of the data at or below 0.3, but the maximum is 10.28. Temperature data shows relative stability. The average of daily maximum temperature is 88.4°F and mean of minimum is 73.8°F. Overall, the dataset shows greater fluctuations in Price and Daily Perception compared to the more stable temperature records.

Table 1: Summary Statistics of Important Variables

Date	Price	Daily Perception	Average Temperature	Maximum Temperature	Minimum Temperature
Min. :1994-10-12	Min. : 778.4	Min. : 0.00000	Min. :73.60	Min. : 76.50	Min. :61.00
1st Qu.:2005-02-01	1st Qu.: 1689.4	1st Qu.: 0.00000	1st Qu.:78.56	1st Qu.: 85.50	1st Qu.:72.57
Median :2014-10-16	Median : 2330.7	Median : 0.07775	Median :80.50	Median : 88.67	Median :73.67
Mean :2012-09-06	Mean : 2589.3	Mean : 0.24756	Mean :80.62	Mean : 88.44	Mean :73.85
3rd Qu.:2020-09-16	3rd Qu.: 2931.2	3rd Qu.: 0.30042	3rd Qu.:82.60	3rd Qu.: 91.25	3rd Qu.:75.00
Max. :2024-11-28	Max. :10690.7	Max. :10.28000	Max. :88.00	Max. :101.00	Max. :82.00

In Figure 1, the top panel shows the trend of cocoa prices over time (in USD per tonne). From 1994 to around 2015, prices fluctuated modestly between USD 1500 and USD 3500. However, prices increase dramatically in recent years, which justifies the use of volatility-sensitive models such as GARCH. The left bottom temperature graph shows a seasonal cycle, fluctuating between roughly 76°C and 88°C, without strong long-term trend. The bottom-right graph presents daily precipitation levels. The majority of observations are close to zero, but there are some extreme outliers. This indicates there are some heavy rainfall days existing.

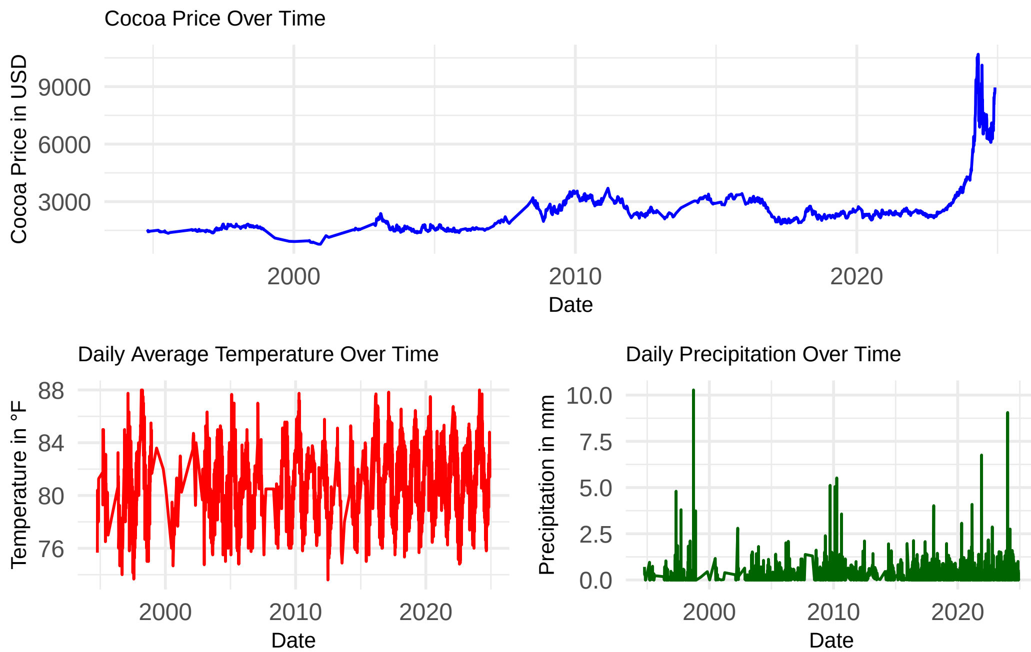

Figure 1: Time Series of Cocoa Price, Local Average Temperature, and Precipitation

Figure 2 presents the STL (Seasonal-Trend-Loess) decomposition of the cocoa price time series. The seasonal component captures strong seasonal components, showing yearly cycles likely related to cocoa harvesting seasons or international price trends. The trend component indicates an significant increase in prices starting around 2001. The remainder component highlights short-term fluctuations and irregularities not captured by the trend or seasonality.

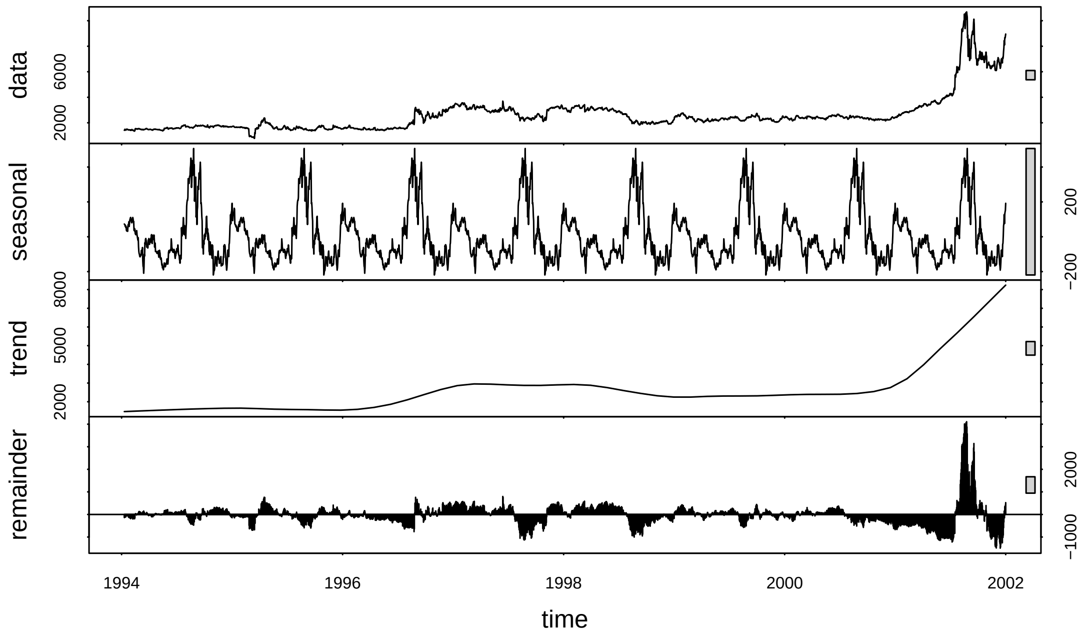

Figure 2: Decompose of Series of Prices

In summary, the datasets capture both economic and environmental determinants affecting cocoa pricing at a monthly base. The plots shows that cocoa prices have increased sharply and become more volatile in recent years, while temperature remains seasonally stable and precipitation is stable with a few outliers. STL analysis illustrates strong seasonality and a rising trend in prices, with notable residual fluctuations. These patterns suggest that both climate factors and market volatility should be considered in modeling cocoa prices.

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