Towards improving farmers livelihood in Nigeria using food price forecasting

Divinefavour Odion[1], Joaquin Gajardo[2], Thijs Defraeye[2,4], Thomas Motmans[3], Kanaha Shoji[2], Roberta Evangelista[3], Daniel Onwude[2*]

[1]Constructor University Bremen, Campus Ring 1, 28759 Bremen, Germany

[2]Empa, Swiss Federal Laboratories for Materials Science and Technology, Laboratory for Biomimetic Membranes and Textiles, Lerchenfeldstrasse 5, CH-9014 St. Gallen, Switzerland

[3]BASE, Basel Agency for Sustainable Energy Elisabethenstrasse 22, 4051 Basel,

[4] Food Quality and Design, Wageningen University & Research, P.O. Box 17, 6700 AA Wageningen, the Netherlands

Nigeria's agricultural sector represents approximately 25% of the country's overall GDP and is a major source of employment for its population. This sector is largely driven by smallholder farmers who grow fruits and vegetables on farms under 4 hectares. Despite their significant contribution to food production in Nigeria, most smallholder farmers, approximately 70%, live in poverty, earning less than $1.9 per day. One of the key factors contributing to this situation is a lack of access to market price information. Farmers currently rely only on historical prices to decide on when, what, where and the price to sell their produce. This can lead to suboptimal decisions, resulting in food loss and loss of potential income. To address this challenge, we developed a machine learning pipeline. It utilizes a Random Forest model trained on historical monthly fresh produce prices for Nigeria that are regularly scraped from the internet. We deployed our trained model through an open-access mobile application, Coldtivate. Our model accurately predicted market prices for crops such as tomatoes, onions, potatoes, and plantains in various Nigerian states. The prediction success rate of our model varied across the various states in Nigeria. It ranged from 1% to 20% in Mean Absolute Percentage Error (MAPE) for predictions up to 8 months ahead. When evaluated on a hold-out test set, it yielded an RMSE of 45.16. The average MAPE of our model, when considering state-time-commodity averages, is up to 5% lower than other baseline models, including the benchmark rolling-average, CatBoost, XGBoost, and SARIMA. By detecting patterns and trends in food prices, farmers can use our tool to make more informed decisions about when and what to sell to optimize profit, thereby improving revenue. Furthermore, our model provides a foundation for future machine learning model development in food price forecasting in agrarian countries.

Keywords: Food price forecasting; market intelligence; online machine learning; smallholders; farmer's income; food waste; food loss

* Corresponding author: daniel.onwude@empa.ch (D. Onwude) Empa, Swiss Federal Laboratories for Materials Science and Technology, Laboratory for Biomimetic Membranes and Textiles, Lerchenfeldstrasse 5, CH-9014 St. Gallen, Switzerland

1 Introduction

In Nigeria, agriculture is a vital sector, contributing to over 24% of the country's total GDP and employing two-thirds of its labor force comprising mostly of farmers [1]. Most of these farmers are smallholders, estimated to be around 38 million, who grow crops on farms that are less than 4 hectares in size [2]. Despite their contribution to food production in the country, over 72% of these smallholder farmers live below the poverty line of $1.9 per day [3]. One of the key reasons contributing to this situation is the lack of market price intelligence among these farmers. The majority of fruits and vegetables produced by this category of farmers are from the Northern regions and largely sold in the Southern regions where a significant number of food markets are located [4]. At these markets, participants such as smallholders, traders, and food vendors sell fresh produce. These include tomatoes, onions, bell peppers, etc. They sell directly to consumers at diverse price ranges. Prices vary across the country, influenced by farm-market proximity and seasonality. As an example, prices for fresh produce are generally lower in markets closer to farming regions. This is a result of the cost of transporting goods from the farms to the market. Additionally, there's lower demand in these areas compared to larger cities in the south. In these cities, higher demand drives up prices (See Figure S5). Notwithstanding, currently, there are no standard methods or defined approaches for estimating the future market prices of commodities produced by smallholder farmers in Nigeria. Smallholders often resort to reviewing the historical prices of a food in the recent past. This method is equivalent to having a naive model that predicts the future prices of fresh produce using only the prices from the immediate previous time steps without consideration of other external factors and anomalies such as fuel prices, foreign exchange rates, and inflation that may influence the changes in the prices of certain goods. All this makes that smallholder famers would sell their produce at unfavorable prices, leading to loss in revenue due to lack of adequate market price intelligence (access to existing and future market price) [5]. This highlights the need for a more accurate and holistic approach that considers relevant economic influences such as foreign exchange rates. It also needs to include variables such as domestic fuel prices and inflation rates. These considerations will lead to more accurate price predictions.

Several researchers have developed machine learning models with algorithms such as Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Support Vector regressor (SVR), Tree based algorithms, and Neural networks. These models aim to predict the market prices of avocado, rice, wheat, corn, etc. However, the models did not consider external predictors in the form of economical influencers such as domestic fuel prices, inflation levels, and foreign exchange rates. To our best knowledge, rarely did these machine learning models accurately predict the markets prices of fresh produce considering the economic features mentioned above. These predictors are indispensable in having a robust machine learning model as they capture the true variance in the data with respect to time. Besides, there is no known online machine learning model that accurately predicts the markets prices of tomato, potato, onion, and plantain produced in Nigeria up to 8 months into the future. Ma et al.[6] presented a commodity price forecasting system to aid small and marginal farmers in India make informed decisions on when to sell their harvest. The system integrated data from the Indian Ministry of Agriculture and Farmers Welfare's website Agmarket with machine learning algorithms to generate accurate price forecasts. The forecasts were presented in an easy-to-understand format that highlights the key historical pricing data that informs each forecasted trend and seasonal components. [7] also presented a software-application led solution to help farmers optimize profits. The study compared various machine learning and deep learning solutions, including Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Support Vector Regression (SVR), Prophet, and Extreme Gradient Boosting (XGBoost) to identify the most suitable algorithm for the forecasting engine of the software application. The study showed the LSTM model as the best with the lowest average mean squared error (MSE) of 0.304. However, these models did not consider other economic factors such as inflation and foreign exchange rates. Besides, the systems proposed did not consider the deployment and regular retraining of the models in an online learning approach for model improvement. More research is also needed to help understand the full impact of these technologies on smallholders and the economy, and to identify the most effective strategies for integrating them into agricultural development programs. As such, our research endeavors culminated in the development of a robust forecasting tool, which we subsequently deployed via a publicly accessible mobile application. This app serves to track and monitor vital metrics pertaining to the improvement of smallholders' livelihoods over time. Our approach represents a valuable contribution to the existing literature and offers a promising means of addressing the complex challenges faced by smallholder farmers.

Supply chain firms often struggle to reduce forecast errors despite sharing information and maintaining integration. Real et al. [8] applied a nonlinear Machine Learning algorithm to forecast distorted demand signals at the upstream end of an extended supply chain. RNN, SVM, NN, and MLR demonstrated significantly better performance than naïve, moving average, and trend methods in predicting these signals. Avocado, a popular breakfast staple, has seen inconsistent pricing due to increased demand. Juan et al. [9] developed an approach to estimate avocado sales in the United States using historical sales records and weather data. Linear Regression, Multilayer Perceptron, Support Vector Machine for Regression, and Multivariate Regression Prediction Model were applied, with the latter two yielding the best results, showing a correlation coefficient of 0.995 and 0.996, and an RMSE of 7.971 and 7.812, respectively. Zuriani et al. [10] proposed an Enhanced Artificial Bee Colony (eABC) to predict daily food prices in time series data using three different configurations. A Swarm Intelligence approach, Artificial Bee Colony (ABC), was utilized to optimize the parameters of the Least Square Support Vector Machine, addressing the critical issue of overfitting. The method was compared with Back Propagation Neural Network and Genetic Algorithm, and empirical results showed higher prediction accuracy due to the model's effective learning of time series data patterns. Sidra et al. [11] introduced a trade-oriented forecasting framework comprising machine learning and deep learning models to predict stock prices and short-term movement. Eight regression models were built to predict stock prices, and classification models were designed for predicting price movement using Logistic Regression, Decision Tree, K-Nearest Neighbor, Artificial Neural Networks, Random Forest, Bagging, Boosting, Support Vector Machines, and Long and Short-Term Memory Networks. The best regression model result was achieved by LSTM, with an RMSE of 2.36 and a correlation of 0.99. Yuehjen et al. [12] proposed an integrated model using ARIMA-ANN, ARIMA-SVR, and ARIMA-MARS to predict the prices of major crops such as rice, wheat, and corn. The primary contribution of this model is its ability to predict without the need for extensive effort in obtaining future values of explanatory variables. The integrated ARIMA-SVR significantly outperformed individual ARIMA and SVR models in terms of MSE, RMSE, and MAPE. However, the model's limitation lies in its computational expense and intuitive nature when identifying the correct ARIMA model among numerous possibilities.

Building upon these diverse approaches and the challenges they present; our study takes a distinct route. We recognize the limitations of data availability and historical records, as we lack market-level data and have only limited historical data beyond 2017. Therefore, some of the methods applied in the cited papers may not be applicable or effective for our specific use case. However, despite these challenges we aim to address these limitations by developing an online machine learning system based on the Random Forest model. Our system accurately predicts market prices for tomato, onion, plantain, irish potato (potato), and sweet potato in each state of Nigeria, up to 8 months into the future. There are 36 states and a Federal Capital Territory in the federal republic of Nigeria. These states are divided into six geopolitical regions: the North-East, North-West, North-Central, South-East, South-West, and South-South. Each of these regions is determined by a combination of geographical, historical, and cultural elements. The North-East region, for example, includes states such as Borno, Adamawa, and Yobe, while the North-West region encompasses states such as Kano, Kaduna, and Sokoto. The North-Central region includes states such as the Federal Capital Territory, Niger, and Kwara, while the South-East region is home to states such as Abia, Anambra, and Enugu. The South-West region comprises of Lagos, Oyo, and Ogun states, while the South-South region is made up of states such as Rivers, Delta, and Akwa Ibom.

We benchmark our model against a simple rolling-average baseline, SARIMA, and other tree-based algorithms including Catboost, and XGboost. Our model will be made accessible via an open-access data science mobile application called Coldtivate [13] with an intuitive user interface, providing small-holder farmers with the real-time insights of market prices and trends to make informed decisions and improve their business returns. This research paper elucidates the advantages of a unified, consolidated model capable of discriminating between the 37 states, and precisely predicting forthcoming food prices for a diverse assortment of fresh produce vended in each state.

1.1 The state of the art of food price forecasting in low- and medium-income countries

We question the status quo of estimating the future market prices of fresh produce. The question is whether relying solely on past historical prices and information about harvest seasons is sufficient to accurately predict future prices of fresh produce. Several studies have been conducted on food price prediction using historical price data. In [14] the authors conducted two experiments to evaluate the performance of five novel machine learning models in predicting the future prices of chicken, chili, and tomato in Malaysia. The first experiment evaluated the models trained solely on historical price data, while the second experiment involved incorporating additional predictors, such as temperature, humidity, precipitation, and crude oil price, into the training of the models. The results showed that Long Short-Term Memory (LSTM) was the best suited of the five models. Additionally, the results indicated a significant improvement in the model performance when external predictors were utilized in the training process. Also recently, Guo et al. [15] developed a framework for predicting the daily prices of corn in China using a univariate time series forecasting approach. In their analysis, they discovered that an ensemble method, combining 4 algorithms which include an Attention Mechanism algorithm, Long Short-term Memory (LSTM), Autoregressive Integrated Moving Average (ARIMA), and Back Propagation (BP) Neural Network was the most accurate model for forecasting the daily corn prices. Nonetheless, the literature research findings indicate that this approach of univariate time-series modeling is inadequate for addressing the complexities of our problem domain, which encompasses price estimation for smallholder farmers in low-and medium-income countries within the agricultural sector. This limitation may arise from the model's inability to account for other crucial economic factors, such as fuel prices, consumer price indexes, and exchange rates, which also significantly impact food prices. Additionally, this method is unable to account for unusual price fluctuations. This leads to a methodology that is likely to give less accurate food market price predictions. To address these limitations, we present a new model in this paper that can be used to make more accurate future price predictions.

1.2 The proposed methodology

A Random Forest model trained on the average monthly prices of the 5 selected commodities for the period of 2017 – 2022 was used to predict the market prices of tomato, onion, plantain, potato (Irish potato) and sweet potato. We have selected these commodities because they are some of the more popular fresh produce sold by smallholders in Nigeria. In addition, there are lots of historical open-source data for these fresh produce relative to others. This model includes 6 other predictors namely, Last Month Price, Last 5 Month Price, Consumer Price Indexes, USD to Naira exchange rates, Crude oil prices and State price roll-ups. A web-scraping pipeline was designed to obtain the food price data and external predictors. It fetches data from the official e-library site of the National Bureau of Statistics (NBS) [16], the official website of the Central Bank of Nigeria (CBN) [17], and the Yahoo finances website [18]. The model is retrained monthly using this data. An open-access data science based mobile application called Coldtivate [13], will host the model. It will allow users to choose from a list of fresh produce and states. Users can then view the 8-month price forecasts for the chosen food in their selected state.

2 Data and methods

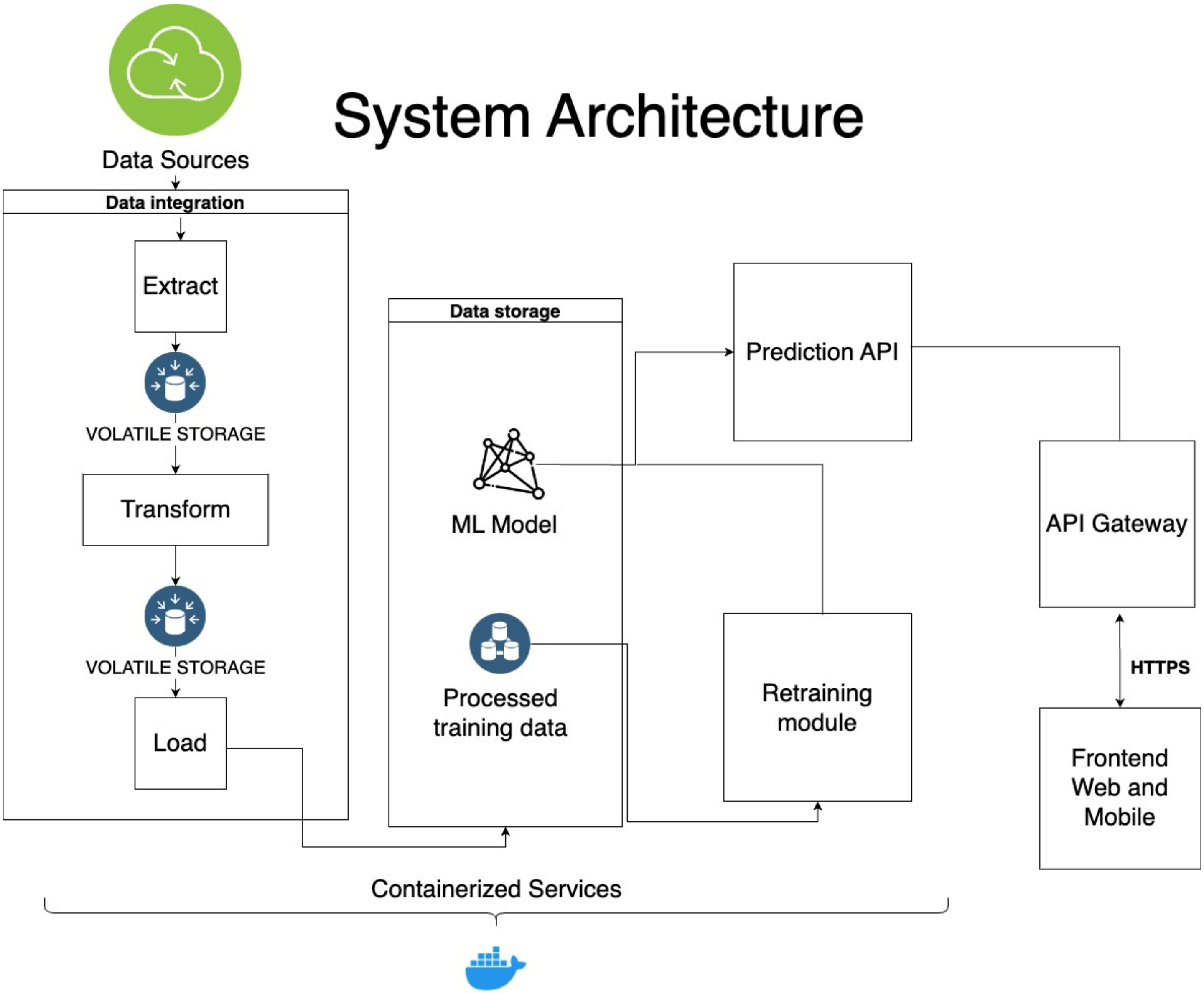
This section discusses details about the characteristics of the training data, findings from the exploratory data analysis carried out on the data, the preprocessing steps to train machine learning models, and feature selection processes. A retraining module is connected to the scraping module and is used to regularly retrain the machine learning model on the most recently scraped data. A flowchart representation of the described methodology is given in Figure 1.

The data for this study was obtained by scraping three online repositories and processed with the pipeline depicted in Figure 1. An Extract Transform Load (ETL) architecture was utilized to gather and process the data into a suitable format for machine learning model (re)training. The processed data was subsequently loaded into the Data storage, along with the serialized machine learning model, thus completing the ETL process. The model is retrained on updated data at monthly intervals. A prediction Application Programming Interface (API) was developed to facilitate the querying of the model with prompts containing the target state and food names in JSON format. The model, in turn, provides 8-month forecast related to the query prompts to the mobile application's front-end via the interface. The proposed architecture and API have the potential to enhance the efficiency and timeliness of food price predictions, to the benefit of users.

Figure 1 Flowchart detailing the System Architecture of the food price forecasting tool

2.1 Training data and features

The training data covered historical food prices (monthly average) from January 2017 until October 2022. A consolidated label encoded dataset with monthly averaged prices for all 5 commodities in all 37 states is used for training the machine learning models. The processed dataset consists of 9 features which are, Date, State labels, Food labels, Last Month Lagged prices, Last 5



months lagged prices, Consumer Price Indexes, USD to Naira Conversion rates, Crude oil prices and State roll-ups. The features used for training the models are grouped into three categories which are:

1. Label features ('st_label', 'comm_label'): The label features consisting of state and food labels are categorical features that represent the 37 states and 5 commodities which have been label encoded.
2. Lagged features (Last_Month_Price', 'Last_5M_Price'): The lagged features consist of 'Last_Month_Price' and 'Last_5M_Price' which represent the food prices shifted one and five times respectively (i.e for a given datapoint in the market price timeseries, the 'Last_Month_Price' feature represents the price of one food commodity in one state in the previous month and the 'Last_5M_Price' represents the price 5 months ago).

3. Exogenous features ('CPI', 'USDtoNaira', 'Crude_prices'): The Exogenous features include the 'Crude_price', 'USDtoNaira', and 'CPI' features. The Consumer price Index ('CPI') feature consists of the monthly Consumer price indexes for all items classified under "Goods and services" at the country level. The CPIs are calculated with reference to a 2009 base period. The 'USDtoNaira' feature contains the monthly averaged USD to Naira exchange rates consistent with the timespan of the food prices. The 'Crude_prices' feature consists of official monthly Crude oil domestic prices in Naira per barrel.
4. Roll-up features ('state_roll'): The 'state_roll' feature represents the aggregated mean of the prices of all 5 commodities per month for each state.

2.2 Methods

We conducted an Exploratory Data Analysis (EDA) on the training data to determine useful statistical properties for modeling, such as autocorrelation tests, location-based analysis, and multicollinearity tests on the food price time series. This preliminary step was essential for informing our approach to developing an accurate forecasting model. Furthermore, we conducted correlation tests for the exogenous variables to determine those that were worth including in the model to improve prediction accuracy. After concluding the EDA on the data and features, we trained various machine learning models and a statistical model which include CatBoost, Random Forest, XGBoost, and SARIMA. Finally, we compared the 4 models against a naïve rolling-average benchmark model to measure the advantages of machine learning in this problem. To ensure a fair comparison, each model was trained on the same dataset. We performed Grid Search cross-validation to tune each model's hyperparameters for the best fit. Subsequently, the models were evaluated on the hold-out test set using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) as the key metrics for determining the most suitable approach. The Random Forest model had the lowest overall Mean Absolute Percentage Error (MAPE) results (See Figure 6) with an average of approximately 11% MAPE and 45.16 RMSE for all commodities and states.

2.2.1 Data preprocessing

The data preprocessing consisted of two steps. First, the categorical columns containing the state and food names were converted into numerical features using the LabelEncoder class from the scikit-learn (sklearn) Python library [19]. This was necessary to ensure that the algorithms could effectively process the state names and food names. Then, missing values in the lagged feature columns (consisting of Last_Month_Price and Last_5M_Price) were filled in using linear interpolation. In the training dataset, the first five rows of the lagged price columns for each state-food combination contained missing values due to the absence of data from prior months, as the dataset started from January 2017. For example, 'Last_Month_Price' had one missing value because of a lack of data from December 2016, and 'Last_2M_Price' had two missing values due to the unavailability of data for November and December 2016. To address this issue, the food prices for each state in January 2017 were reverse linearly interpolated and inserted into the missing value columns.

The present study reports on two distinct experimental setups designed to train and evaluate machine learning models for the given task. In the first experiment, a fixed train-test split ratio was utilized to hold out a portion of the data as a single test set. The models were trained on the remaining data and evaluated on the held-out test set. In the second experiment, we employed a temporal cross-validation framework to evaluate the models on multiple test sets. Specifically, the data was split into several non-overlapping temporal folds, and the models were trained and evaluated on each fold iteratively. The final results were obtained by averaging the performance of the models across all folds and presented as a consolidated single metric for easy comparison between models.

2.2.1.1 Train and Test Split

In the first experiment (single test-set evaluation), the processed dataset was split into two parts for model training. Utilizing the date column of the dataframe and the Python libraries 'pandas' [20] and 'datetime', we partitioned the dataframe into two disjoint subsets. The first subset comprised a training set encompassing the time interval spanning from '2017-01' to '2022-02,' and the second subset consisted of a test set containing the period between '2022-03' to '2022-10'. The training set represented approximately 88% of the entire dataset and the test set represented the remaining 12% of the latest historical data in the dataframe. The standard practice in conventional machine learning approaches involves dividing the available dataset into train and test sets, where the test set comprises a larger proportion. However, for our forecasting objective, we faced a scarcity of open-source historical food prices. To overcome this limitation, we have adjusted the ratio of test data in our study to a lower percentage than what is commonly used in conventional approaches. This split allows for a robust evaluation of the machine learning algorithms, where the model is trained on a significant portion of the data, and the remaining portion is used to test the model's generalization performance. All models were trained and fine-tuned on the training dataset, and then evaluated using MAPE and RMSE on the test dataset.

In the second experiment, we employed a temporal cross-validation methodology to evaluate the generalization performance of the machine learning models over time. To do this, we initially created a training set with monthly averaged food prices from January 2017 to December 2020 and designated the following eight months (January 2021 to August 2021) as the initial test set. We then performed temporal cross-validation by iteratively training all five models on the expanding training set and assessing their predictive accuracy on each successive test set. The Mean Absolute Percentage Error (MAPE) was used as the performance metric throughout this process. To account for the temporal dynamics of the data, we conducted sequential iterations of the experiment by increasing the size of the training set by 1 month per iteration and shifting the test set one month forward per iteration. This process was repeated for 26 train-test splits, resulting in 26 MAPE score sets for each model. To obtain a comprehensive evaluation metric, we computed the final MAPE score for each model as the average of the MAPE across all train-test splits. By leveraging the temporal cross-validation framework, our study provides a rigorous assessment of the models' predictive power over time, which is crucial for practical applications in the food market.

2.2.2 Machine learning modeling

In order to compare different machine learning algorithms for the specific task, we trained a set of 5 models. This included a benchmark 5-month rolling-average model, a SARIMA model, and three machine learning models which include Random Forest, XGboost and CatBoost. The performance of these models was then evaluated on a separate test set to determine which one was the best performing. In this evaluation, we used the Mean absolute percentage error (MAPE) and Root mean square error (RMSE) as the primary metrics to compare the accuracy of the different models. The 5 models included in the evaluation phase are briefly described below.

2.2.2.1 Naive model (Benchmark)

The naive model approximates the current approach employed by smallholders in Nigerian markets which stems down to utilizing historical price data from recent months as the foundation for their food price forecasts. We use a simple rolling-average algorithm. A single forecast from this model is calculated as the arithmetic average of the last 5 months of prices.

2.2.2.2 Random Forest model

The Random Forest model is a popular tree-based model that implements gradient bagging (Figure S3), a modeling approach of training several weak estimators in which a model forecast is computed as the arithmetic average of the predictions of all the weak estimators/trees in the model. We implemented the Random forest model with Python's 'sklearn.ensemble' library [21]. See Figure S2 in Supplementary materials for the schematic diagram of gradient bagging algorithms.

2.2.2.3 CatBoost model

Catboost is a novel gradient boosting tree-based algorithm developed by Yandex researchers [22]. Gradient boosting is an ensemble modeling technique that utilizes several weak learners/models in a sequential manner. Gradient boosting starts by fitting a weak learner to the data, then a second learner is fit to the same data with the aim of accurately predicting the cases where the previous learner performed poorly, and this process is repeated for as many learners as specified in the ensemble. The combination of the predictions of all the models in the ensemble is expected to be better than a single model. See Figure S4 in Supplementary materials for the schematic diagram of gradient boosting algorithms.

2.2.2.4 XGBoost model

XGBoost is a tree-based model that implements gradient boosting (See Figure S4 in Supplementary materials) designed to optimize computation speeds and machine learning performance. In contrast, CatBoost, another gradient boosting algorithm, focuses on handling categorical features effectively and reducing overfitting through a unique boosting strategy. While both models offer valuable advantages, it is essential to evaluate their performance in the specific context of our study. XGBoost was developed by [23].

2.2.2.5 SARIMA model

SARIMA stands for Seasonal Auto-Regressive Integrated Moving Average. SARIMA is an extension of ARIMA for forecasting univariate time series with a seasonal component. The statistical model consists of 2 components which are trend and seasonality. We utilized Python's 'statsmodel' api library [24] to implement the SARIMA model.

2.2.3 Feature selection

We conducted linear correlation analysis on various covariates that could improve the prediction accuracy of the models. Research showed that some economic factors influence the market price of food items in Nigeria such as the domestic fuel prices, foreign exchange rates, and inflation [25]. The NBS [16], Yahoo Finances [18] and CBN [17] maintain online repositories where historical data on such economic variables can be sourced from in the same manner as the food prices. The data for the monthly Crude oil domestic rates, monthly consumer price indexes for all items, and monthly conversion rates of the United States Dollar to Nigerian Naira were obtained from these sources. The time granularity and historical timespan for each of these features are the same as that of the food prices, however, their spatial granularity is different. The spatial granularity for the Crude oil prices, consumer price indexes, and USD to Naira conversion rates is set at the country level. To select the most relevant economic variables, we examined the correlations between these factors and the food prices and chose the ones with the strongest relationships.

From the results of the autocorrelation tests on the market price time series, we determined that the historical look-back range of prices with the greatest effect on the current price was 3 to 5 months. In a trial-and-error-based approach, we computed 1 and 5 months lagged prices features, 3 and 5 months lagged prices averages and standard deviations. We then passed them as features for the forecasting models eliminating the features in the set that didn't improve the MAPE of the models when evaluated on the test set. Our results proved the 'Last_Month_ price' and 'Last_5_Month' to be the features giving the best entropy gain results from the set of Lagged features. The state labels feature groups the price data into 37 categories corresponding to the states in Nigeria, the food label feature column describes the 5 food commodity names. Furthermore, we included the state roll-up feature column where each row contains the aggregated mean of the prices of all 5 commodities per month for each state

2.2.4 Model (re)training

We aim to make our model publicly available[13]. Users can call for future forecasts of the selected commodities in real-time. In order to achieve this, we have implemented an online-learning pipeline that is divided into (1) Scraping pipeline, and (2) Retraining module.

2.2.4.1 Scraping pipeline

The scraping pipeline involves python scripts that gather the most recent food prices, consumer price indexes, crude oil export prices and conversion rates from various sources. The data is extracted from the e-library portal of the National Bureau of Statistics [16], Yahoo Finances website [18], and the official repository of the Central Bank of Nigeria (CBN) [17]. After the data is collected, it is incorporated into a 'master' dataframe (a single consolidated dataset containing historical food prices for the 5 commodities across all 37 states), which is then transformed and encoded as described in Section 2.2.1. Additionally, the scraping module includes a prediction API that allows for making predictions by calling the Random Forest model through the command line interface. The model generates predictions by processing a subset of relevant independent variables. The first month's forecast serves as the basis for the subsequent predictions, which are achieved by shifting the lagged features of the subset one step to the right. This process is repeated for all eight forecasting steps, with each forecast replacing the corresponding feature in the sequence. A visual representation of this process can be seen in Figure 2, which depicts a flowchart of the prediction procedure.

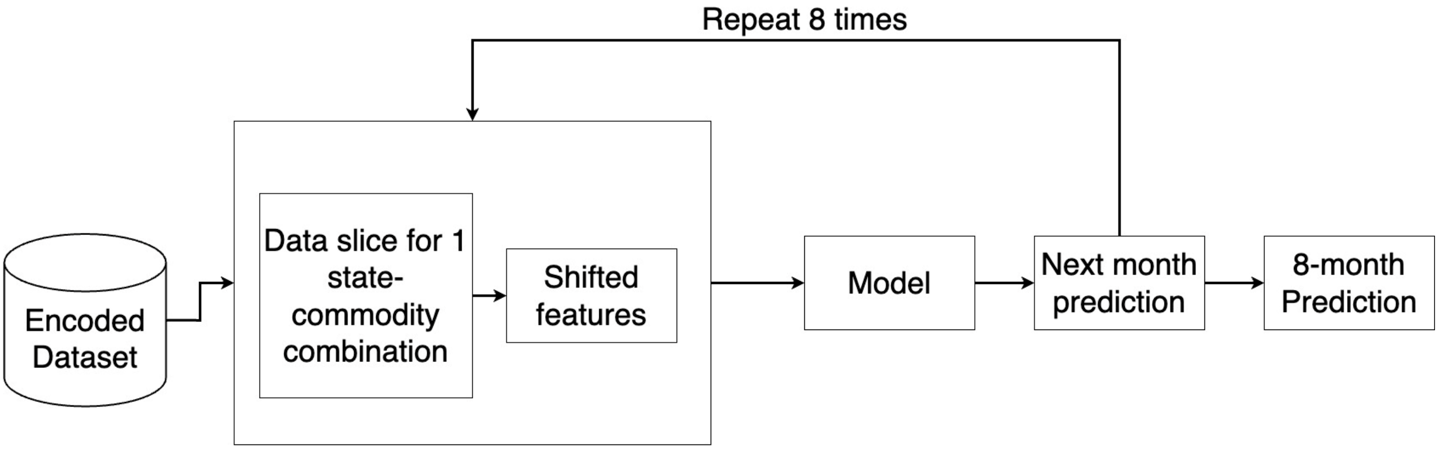


Figure 2 Flowchart representation of a single prediction call via the prediction module

2.2.4.2 Retraining module

The model is retrained periodically (monthly) using the updated and preprocessed training dataset from the scraping pipeline. The retraining is executed in three consecutive steps:

1. A new model is trained using the updated and consolidated encoded data from the latest scraping attempt.
2. The new and current saved models are evaluated on a single hold-out test set consisting of the latest scraped prices using MAPE.
3. If the new model performs better, the old model is replaced in the backend by the new model, and if the old model has a better result, it overwrites the older model and is re-evaluated in the next retraining iteration. To visualize the order of execution of the scraping and retraining modules, see Figure 3.

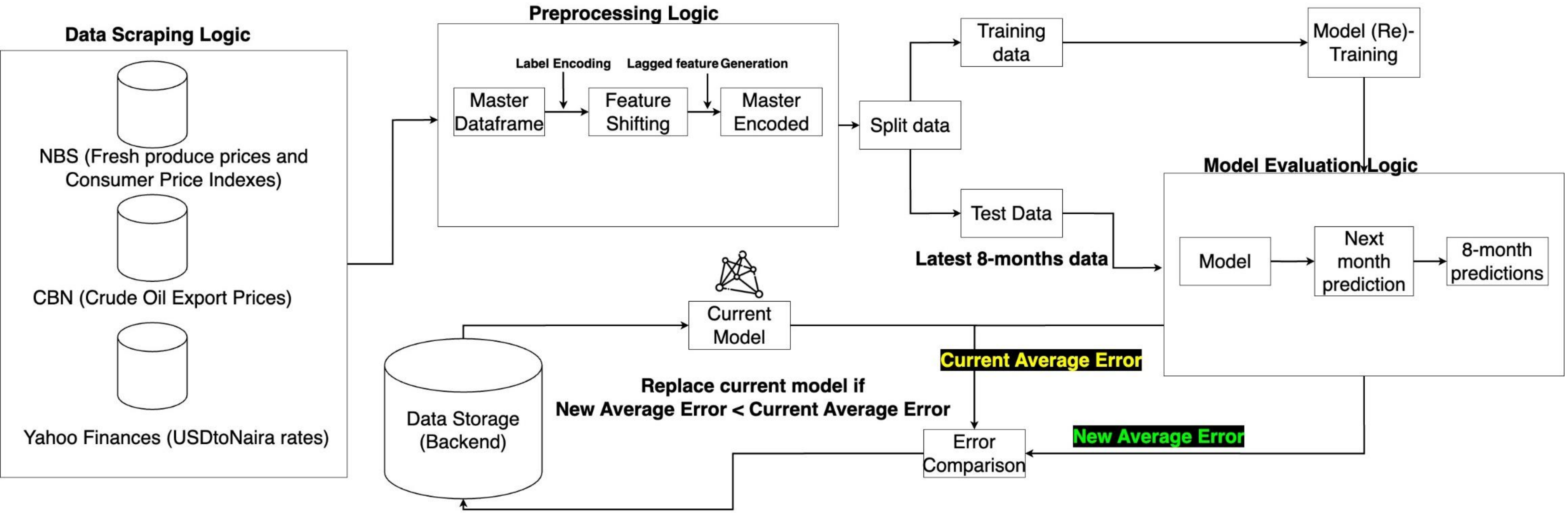


Figure 3 Flowchart Representation of (Re)Training Process

2.2.5 Key performance metrics

We have chosen two key performance metrics to assess our model's performance on the test set: the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE). MAPE is one of the most popular metrics for assessing the performance of machine learning forecasting models. This is the case in [26] where MAPE is proven to be quite suitable for this application. RMSE measures the average difference between the predicted and actual values. When compared to the MAPE metric, RMSE is less sensitive to extreme values or outliers in the data but on the other hand is also harder to interpret. Therefore, in this paper we use MAPE as the primary metric for evaluation of the models and RMSE as a secondary metric.

The formulas are illustrated as follows:

$$MAPE = 1/n \times \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \times 100 \tag{1}$$

$$RMSE = \sqrt{\left[\frac{\Sigma(F_t - A_t)2}{n}\right]} \tag{2}$$

Where:

n = The number of times the summation occurred

A_t = Actual value

F_t = Forecast value

3 Results and discussion

3.1 Historical food prices

Here, we present line plots depicting the food prices for selected states, namely Lagos, Kano, and Plateau in Figure 4. Kano and Plateau are two of the largest producers of fresh produce in Nigeria while Lagos has the largest consumer market for fresh produce in Nigeria. This analytical approach enabled us to ascertain the historical trends and seasonal attributes of the food prices. Through this preliminary analysis, we could evaluate the necessity of employing machine learning techniques to tackle the problem at hand. In the event that the food prices exhibit minimal fluctuations over time, there may be no pressing need to utilize sophisticated forecasting methodologies to predict future prices. Conversely, if the observations demonstrate considerable temporal variance in the historical prices, it would justify the implementation of more complex forecasting models.

Figure 4 reveals a considerable variability in the prices of the commodities within this time frame. For instance, the price of tomato in Lagos state increased from slightly above ₦100 ($0.22) per kg in January 2017 to approximately ₦400 ($0.86) per kg in October 2022. While a discernible positive trend is observed in the time series, seasonality components are less evident in the line plots, as is typical of such visualizations. All the historical food price plots exhibit similar patterns of large variances and standard deviations from the mean price within the timeframe (2017-01 until 2022-10) that are far greater than 100%. In contrast, the case of plantain prices in Plateau state is notable for an indeterminate trend component, featuring several positive and negative peaks within the given timeframe. Given the substantial temporal fluctuations in the historical food prices, using a non-linear model such as the machine learning model proposed in this research paper is justified for accurate forecasting of future prices.

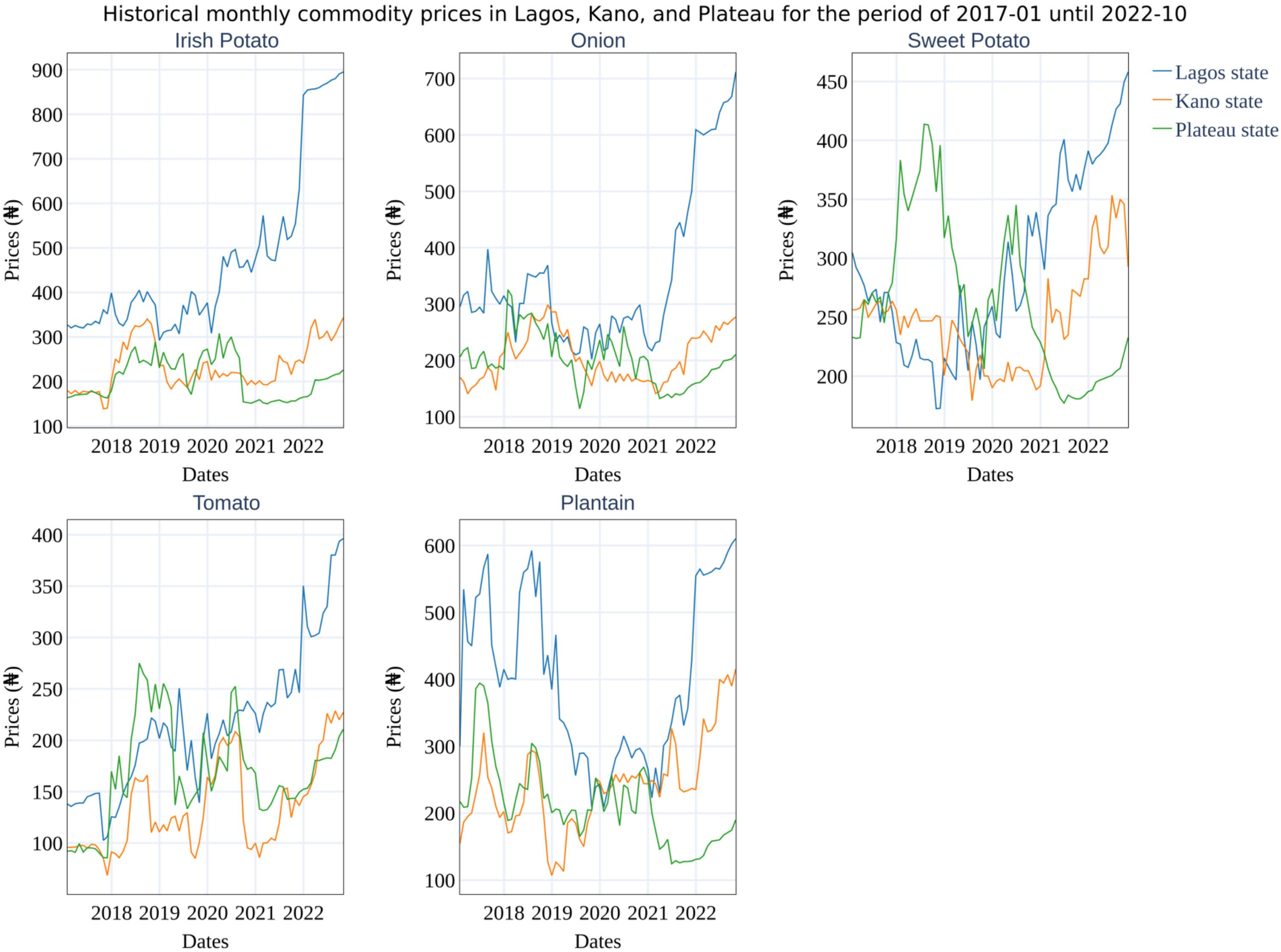


Figure 4. Line plots of the historical monthly prices of potato, onion, sweet potato, tomato, and plantain in Lagos, Kano, and Plateau states within the timeframe of January 2017 until October 2022.

3.2 Model comparison

This section provides an overview of the results obtained from training various algorithms on the dataset and evaluating their performance using a hold-out test set. As outlined in Section 2.2.2, we experimented with 5 different models, each with its own set of hyper-parameters. In this section, we compare the results of each model when evaluated on the same hold-out test sets. We present the results of evaluating the models on a single test set and those from temporal cross-validation (multiple test sets).

3.2.1 Single hold-out test set evaluation using MAPE

Figure 5 shows the consolidated Mean Absolute Percentage Error (MAPE) for the 5 models, averaged over all 5 commodities and all 37 states. We utilized monthly averaged food price data, spanning January 2017 to February 2022, for model training. The models were then evaluated on a hold-out test set, consisting of March to October 2022 data. This set encompassed five commodities across 37 states, assessing predictive efficacy for price movements. From the aggregated MAPE line plot (Figure 5), it is evident that the best performer is the Random Forest model, with XGBoost and Catboost close behind. One possible explanation for this performance is that Random Forest models tend to handle noisy and small datasets better [27]. Unsurprisingly, the SARIMA model performs worse on average than the basic benchmark model, which predicts the last 5-month rolling average prices. This inferior performance of SARIMA may be attributed to its inability to effectively capture the statistical properties of the different time series within the single training set, consisting of various time series with diverse characteristics. The benchmark model, on the other hand, achieves a MAPE below 20% for most forecast steps (excluding the 6^{th} and 8^{th} months). This observation does not undermine the importance of machine learning in this problem but emphasizes the need for further analysis. The results are considered myopic because they are based on a single test set at a certain time and does not account for the entire time range of data. To really visualize the advantage of machine learning over the baseline we explore temporal cross validation as discussed in section 3.2.3.

We visualized the distribution of the 8-month average forecast Mean Absolute Percentage Error (MAPE) for each model using box plots (Figure 6). As shown in Figure 6, the box plots clearly illustrate the distribution of the average forecast MAPE for each model. The box in the plot represents the interquartile range (IQR) of the errors, with the line inside the box representing the median MAPE. The whiskers extending from the box show the range of the MAPE, excluding any outliers. The results indicate a superior accuracy of the Random Forest model in predicting the target variable. This was particularly notable in the early time steps, specifically months 1 and 2, as illustrated by the line plot in Figure 5. However, it demonstrated less consistency than the XGBoost model. We prioritize the forecast accuracy for the earlier months because these are the most important for driving informed decision-making, especially time-constrained ones.

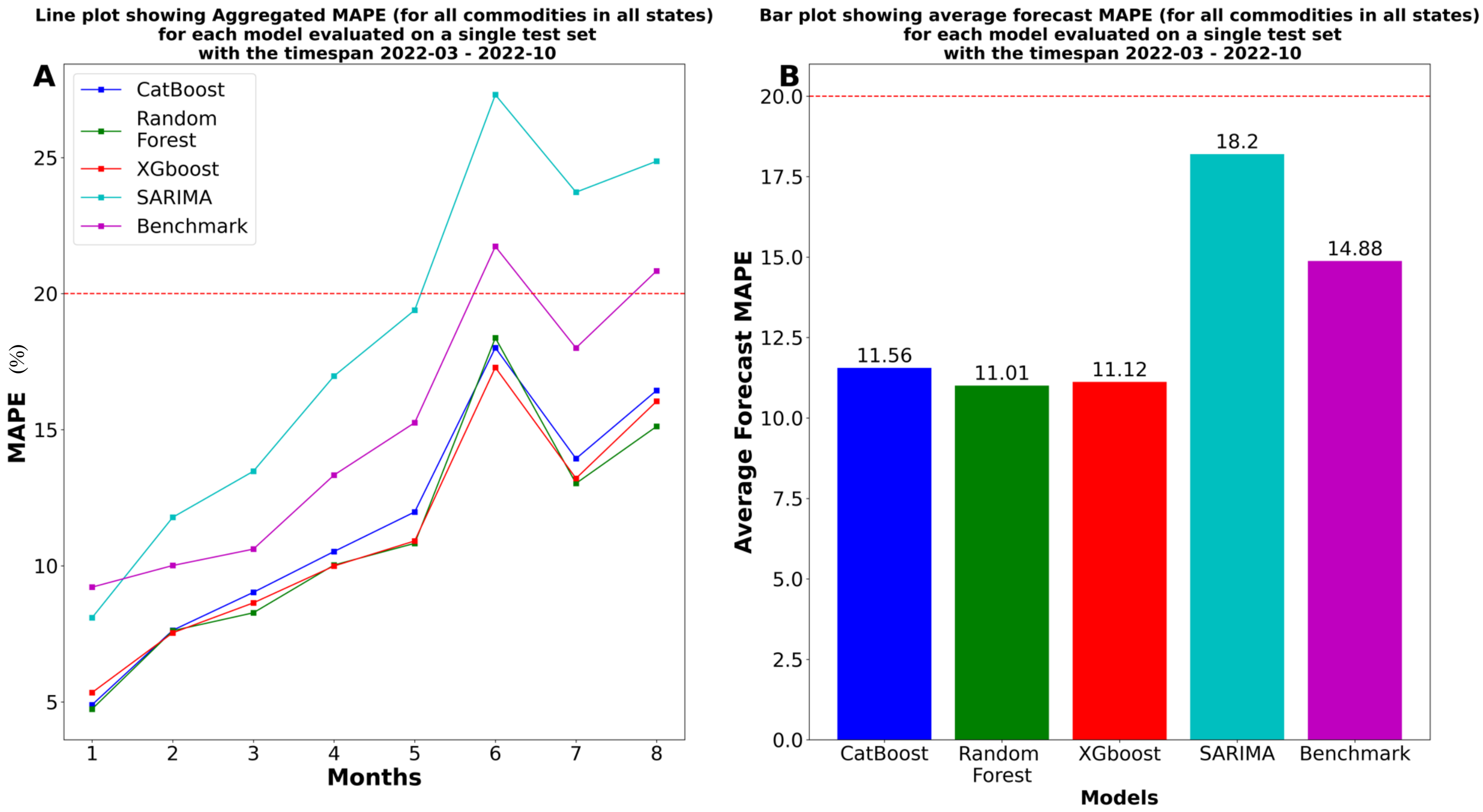


Figure 5. (A) Line plot showing Aggregated MAPE (for all 5 commodities in all 37 states) for each model evaluated on a single test set with the timespan 2022-03 - 2022-10 (B) Bar plot showing the average forecast MAPE for each model evaluated on a single test set with the timespan 2022-03 - 2022-10. The red dotted line represents the 20% acceptable error limit. The bars from left to right, correspond to the CatBoost, Random Forest, SARIMA, XGBoost, and Benchmark rolling-average models, respectively.

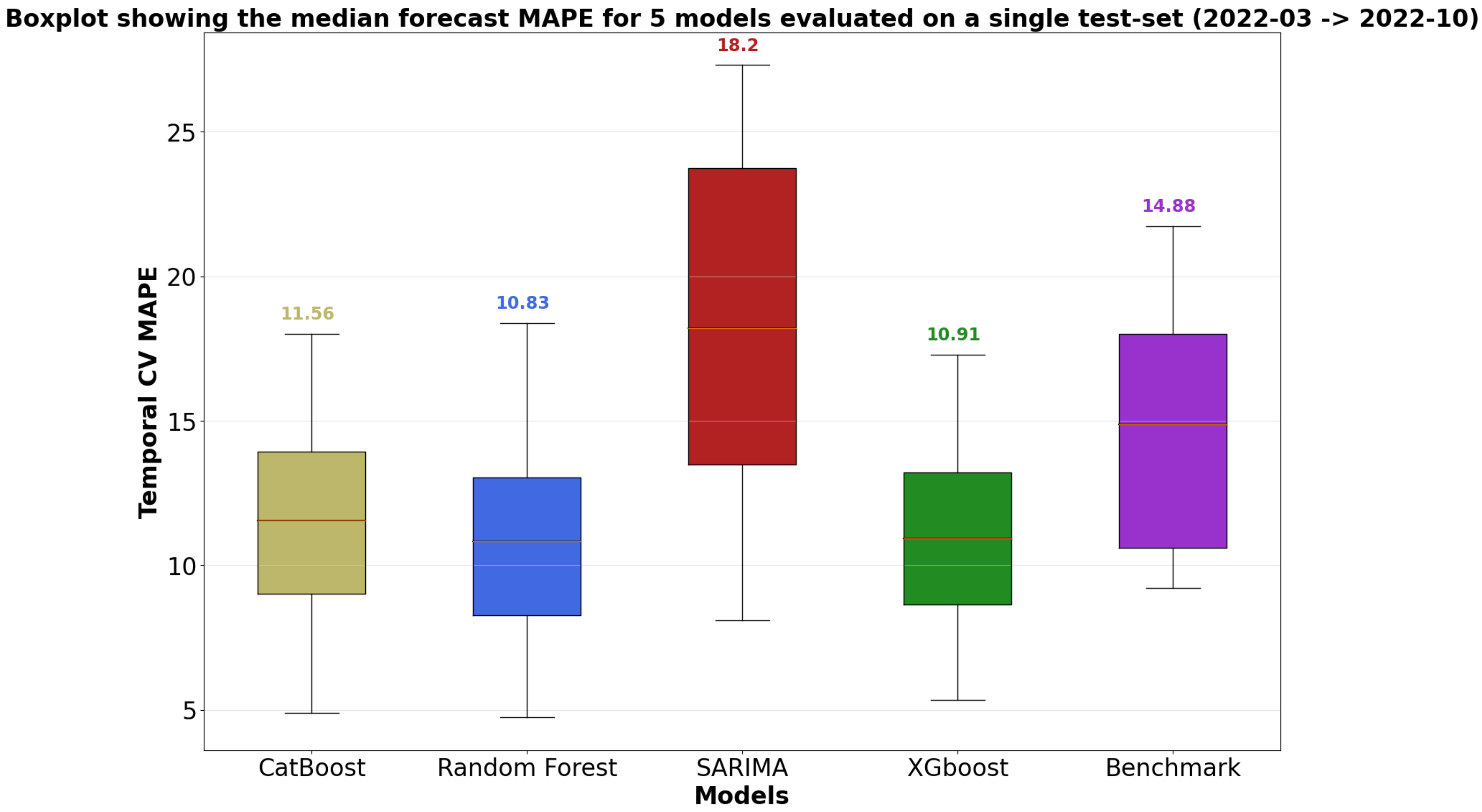


Figure 6. Box-plot illustrating the aggregated MAPE (for all commodities in all states) for each model evaluated on a single test set spanning from 2022-03 to 2022-10. Each box represents the interquartile range (IQR) with whiskers as quantiles, and the middle line denoting the median average forecast MAPE. The numbers at the top correspond to the median values of the boxes. The boxes, from left to right, correspond to the CatBoost, Random Forest, SARIMA, XGBoost, and Benchmark rolling-average models, respectively.

3.2.2 Single hold-out test set evaluation using RMSE

The Root Mean Squared Errors (RMSEs) of the five models were computed in a single test-set evaluation and presented in Table 1. RMSE represents the square root of the average of the squared differences between predicted and actual values. The average RMSE values displayed in Table 1 were computed by averaging the RMSEs of model forecasts for all commodities in all states, as done for the MAPE metric. The results indicate that decision tree-based algorithms performed similarly, with the Random Forest model having the lowest RMSE value of ₦45.16. The Catboost model had an average RMSE of ₦45.48, making it a close second, while XGBoost performed relatively worse with an average RMSE of ₦50.17. In contrast, the SARIMA and the rolling-average benchmark models produced less promising results. The SARIMA model had an average RMSE of ₦70.96, while the rolling-average benchmark had an RMSE of ₦60.84. The results further indicate that Random Forest outperformed other models such as XGBoost, SARIMA, and the rolling-average benchmark suggesting a more predictive power when it comes to predicting food values for smallholder farmers in Nigeria. By accurately predicting food values, farmers can anticipate market trends, adjust their production strategies, and make informed decisions regarding when to sell their produce. This information can aid in optimizing crop selection, timing of harvest, pricing strategies, and resource allocation.

Table 1 Performance Evaluation of 5 Models evaluated on a single test set with the timespan 2022-03 - 2022-10 – Mean Absolute Percentage Error (MAPE) and Average Root Mean Squared Error (RMSE) Values For All Commodities Across All States

MODELS	MAPE (%)	RMSE (Naira)
Benchmark	14.88	60.84
SARIMA	18.20	70.96
Random Forest	11.01	45.16
XGBoost	11.12	50.17
CatBoost	11.56	45.48

3.2.3 Temporal cross-validation

Prior to evaluating the performance of the five proposed models using Temporal Cross-Validation (CV), it is imperative to conduct a thorough analysis of the historical food prices time series. This would enable us to visually inspect the price variances within the CV duration and establish a reasonable threshold for assessing the efficacy of the models. To this end, Figure 7 illustrates the line plots of the food prices averaged across all states (37) for the duration spanning from January 2020 to September 2022. Additionally, the corresponding standard deviations from the mean price during this period are depicted. Notably, for the Irish potato, onion, and plantain commodities, the standard deviation ranges approximately ±70%. Conversely, the sweet potato and tomato commodities exhibit lower standard deviations at approximately ±40%. Aside from the inherent unpredictability of price fluctuations, substantial variances can also be attributed to the considerable differences between states in the Northern regions, where the majority of food is produced, and states in the Southern regions, where most of the food is consumed. Further details on this topic can be found in Section 5 of the Supplementary material.

The flowchart of the temporal/time-series cross-validation performed in this study is shown in Figure 8. The results of the cross-validation experiment for the 5 models are presented in the supplementary material (Tables S1 to S10). The total number of test sets used in the cross-validation is 26, and the consolidated results for each food class were averaged over 26. In simple terms, the temporal CV aims to showcase how well the models perform over time by utilizing rolling test sets. Instead of focusing on a single 8-month window, the evaluation expands to 33 months, concurrently increasing the training data. For smallholders, the model exhibiting the least average forecast MAPE from temporal CV which in our case is the Random Forest (See tables S2 and S6 in supplementary materials) will likely be the most adaptive. It would best accommodate the price data's temporal variance. Consequently, it would demonstrate the greatest predictive capability, remaining robust as new data are integrated via the pipeline (section 2.2.4.1). Maintaining a model that efficiently generalizes to new data ensures the continuous provision of quality market intelligence. This means that smallholders are empowered with information to make informed decisions even in the future to come.

Leveraging the insights garnered from the aforementioned plots and recent research in the field of time series forecasting, we established a threshold of 20% Mean Absolute Percentage Error (MAPE) for the evaluation of the five models under consideration. Furthermore, we considered this 20% threshold acceptable for our specific use case, targeting the improvement of smallholder farmer income in Nigeria through food price forecasting.

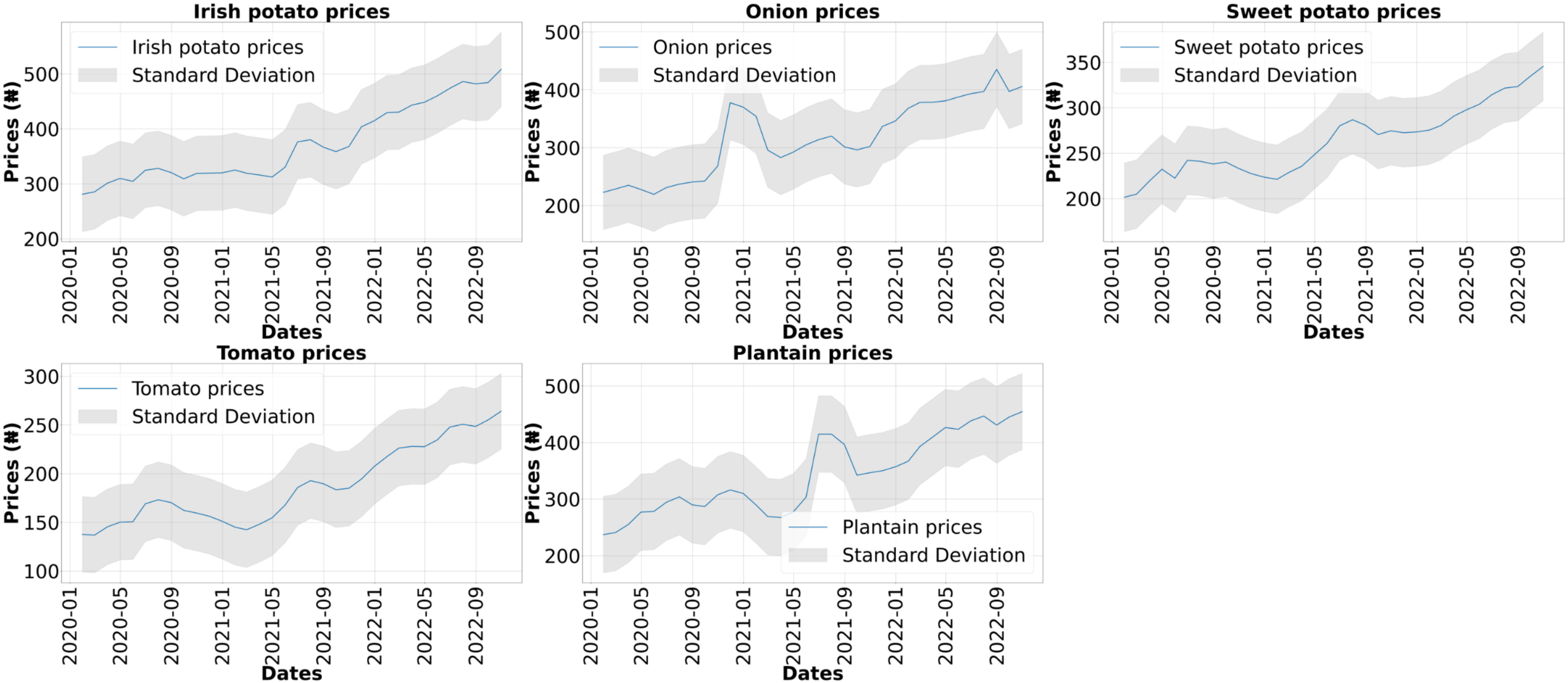


Figure 7. Line plot showing the monthly historical food prices and the standard deviations from the mean (per food) within the time frame of 2020-01 until 2022-09. The data is averaged over all 37 states

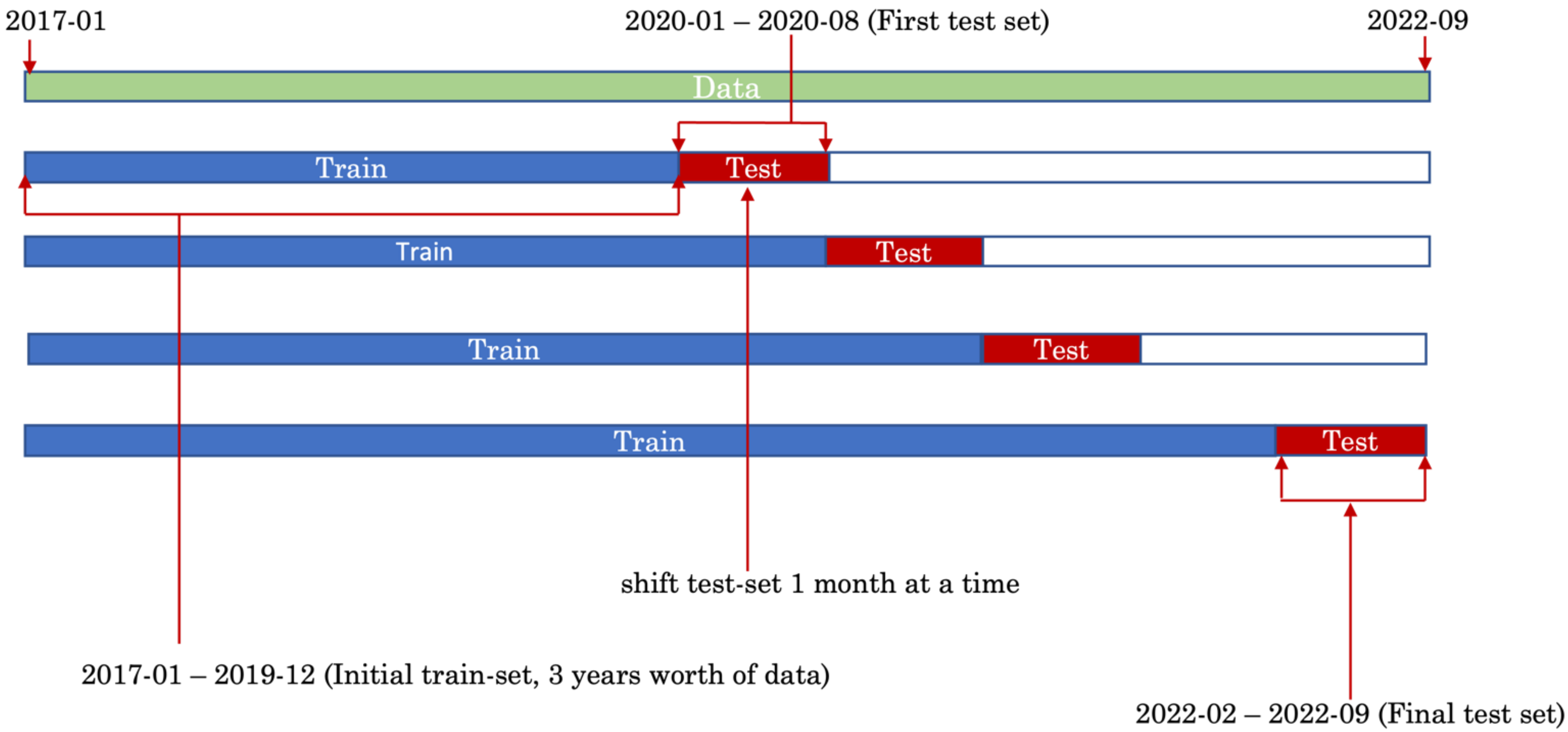


Figure 8. Graphical representation of temporal cross-validation

3.2.3.1 State-wise Temporal Cross Validation

In this section, the results of temporal cross-validation Mean Absolute Percentage Error (MAPE) for the Random Forest model are presented on a state-by-state basis. Figure 9 displays the 8-month average forecast MAPE computed across the CV test-sets (26) for all commodities in the form of bar plots. In addition to the consolidated results (see tables S1-S10 in the supplementary materials), our finding further indicates that the random forest model outperforms the benchmark and the other models on average across all states. However, it is also evident that the simpler 5-month rolling average model performs similarly well to the machine learning models, as seen in the consolidated results tables (S1 – S10). This result could be due to two main reasons: first, the training data might not be sufficient for the machine learning models to reach their maximum potential, leading to similar performance as simpler models such as the Benchmark. Second, the forecasting problem at hand could be highly linear, making it easier for linear models to achieve comparable performance. We noted that these are not the only possible explanations for these results, and further analysis may reveal other factors. By leveraging online machine learning and model retraining techniques, we assert that the advantages of machine learning models will become increasingly apparent as the training dataset grows larger. The analysis further reveals that the model performs poorly in 5 states, namely Kaduna, Nasarawa, Ebonyi, Kogi, and Ogun, where the 8-month average forecast MAPE exceeds 20%. This represents 13.5% of the total states in Nigeria and provides an opportunity for model optimization. Nonetheless, the performance of our model gave satisfactory results and can therefore be a useful tool for smallholder farmers to increase income due to better market intelligence. The table S1 of the supplementary materials also contain details of the performance of the random forest model in different states

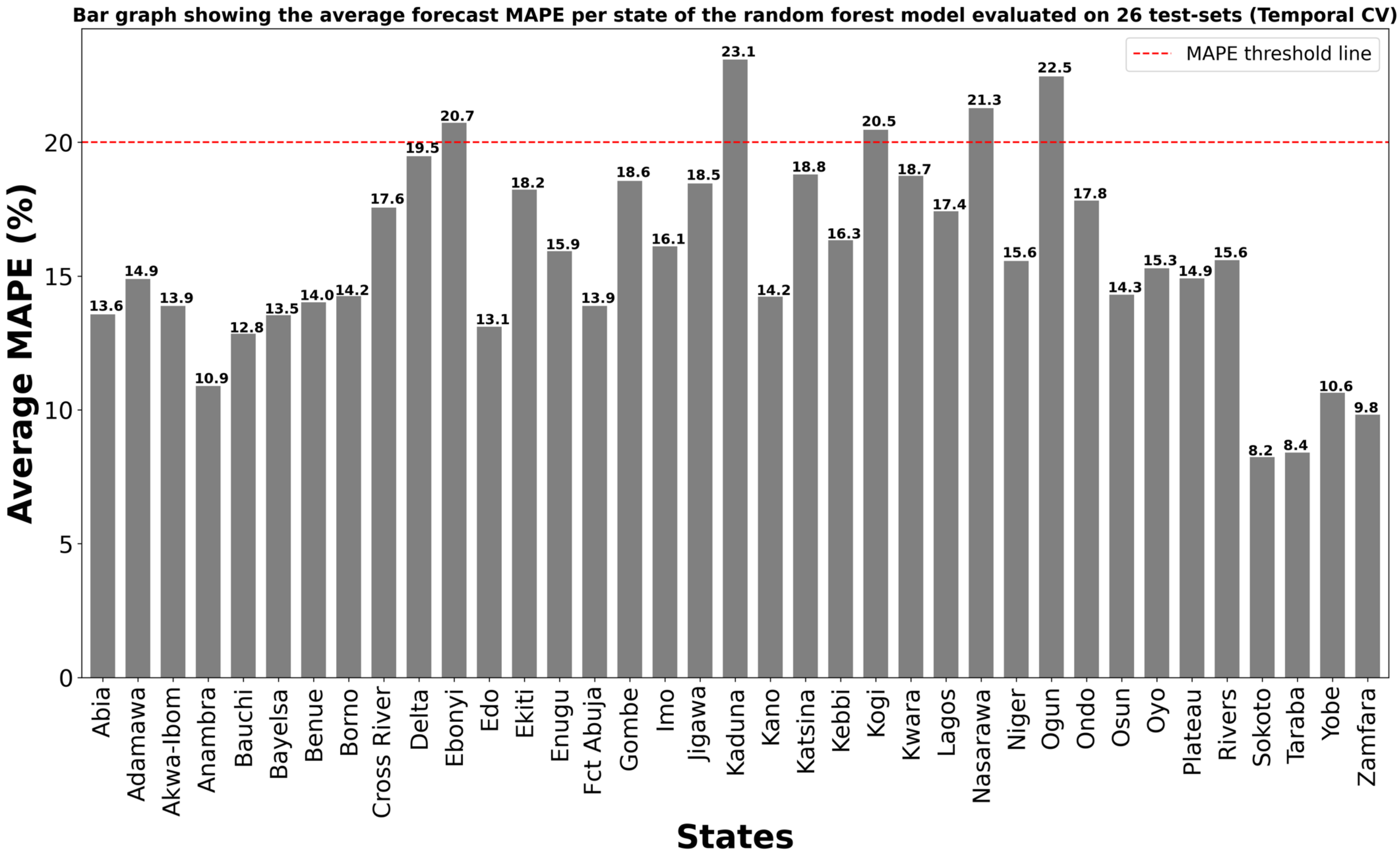


***Figure 9** Bar graph depicting the mean forecast MAPE per state, averaged over 26 test sets, for the random forest model using a temporal cross-validation approach. The red dotted line represents the 20% acceptable error limit. States with a MAPE exceeding this threshold include Kaduna, Nasarawa, Ebonyi, Kogi, and Ogun.*

3.2.3.2 Commodity-wise Temporal Cross Validation

Figure 10 shows the cross-validation MAPE results for the Random Forest model, displayed per food commodity. The 8-month average forecast MAPE, computed from the CV test-sets across all states, is represented by each bar. The result based on the commodity-based cross-validation indicate that the Random Forest model performs well for all commodities, with the highest accuracy in Irish potato and Plantain. All food commodity classes have an average MAPE below 20%, which is considered good performance. This demonstrates that the model's forecasts typically deviate from actual prices by an average of 20%. This performance metric, superior to methods heavily dependent on historical prices, offers smallholders substantial market intelligence. As a result, they are empowered to make decisions about their fresh produce that are more grounded in data.

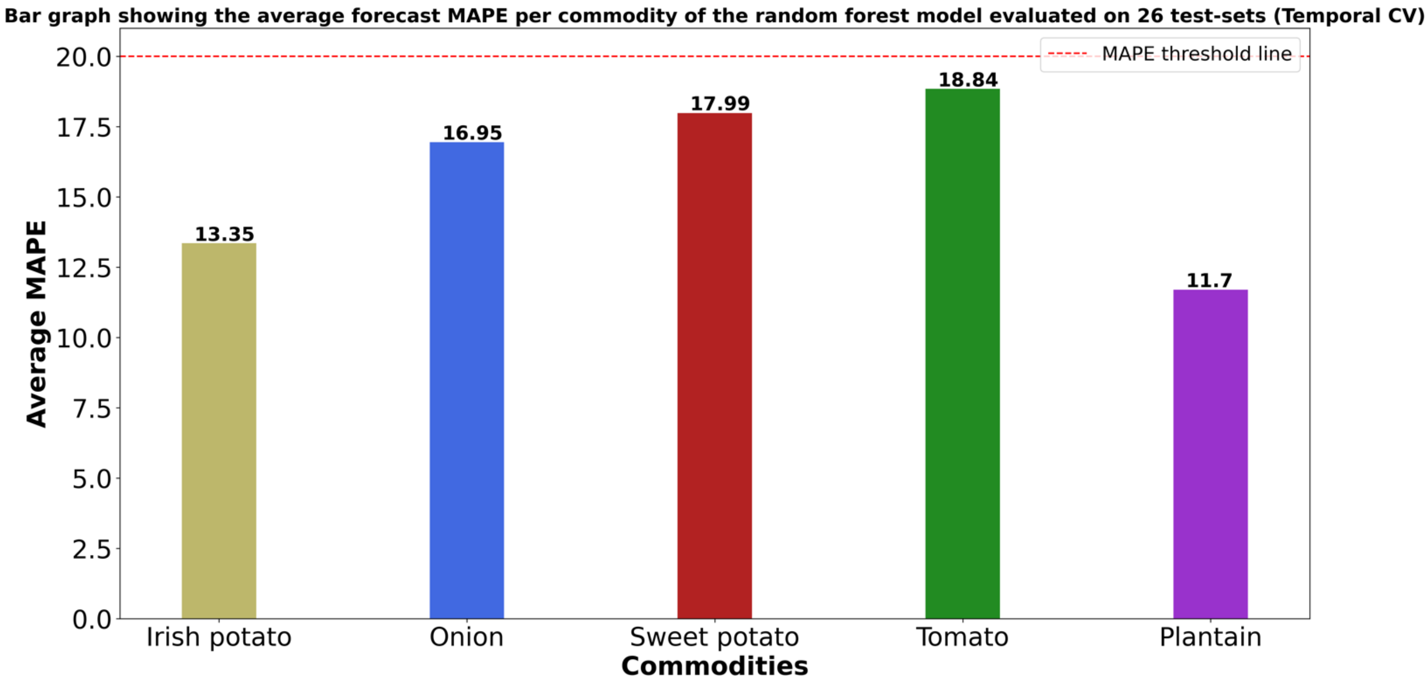


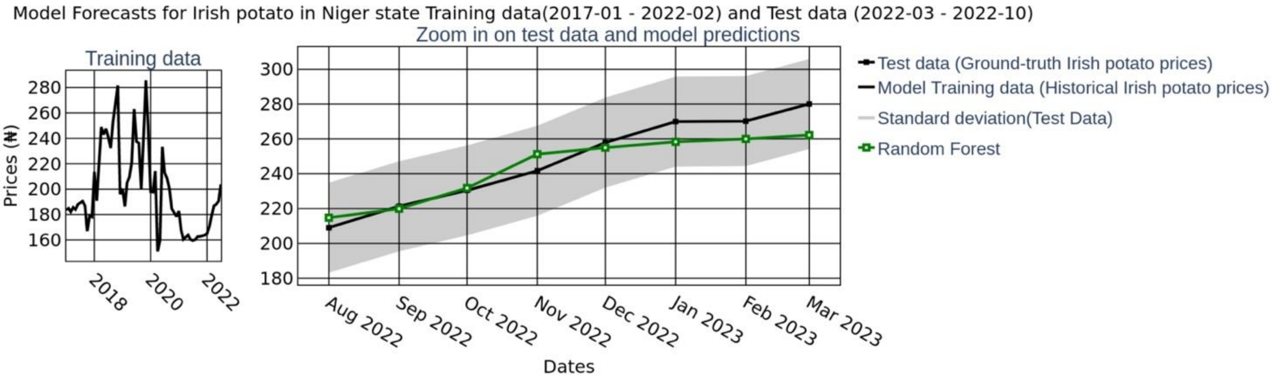
Figure 10. Bar graph showing the 8-month average forecast MAPE per food commodity for the random forest model evaluated over 26 test-sets in a temporal cross-validation approach. The red dotted line signifies the acceptable error limit. Average forecast MAPE for all food commodity classes are below the desired threshold of 20%

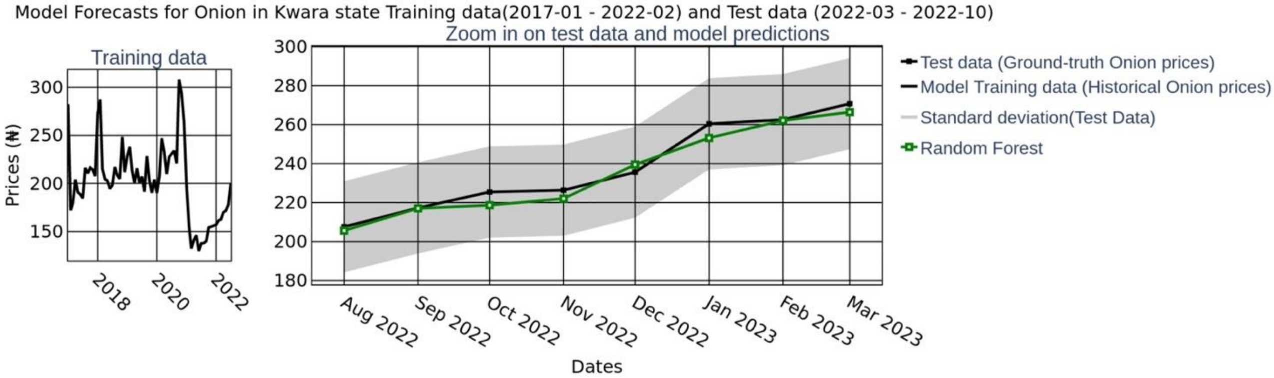
3.2.4 Validation of Random Forest model

Here, we compare the Random Forest model's real-time price predictions with actual data from August 2023 to March 2023. A specific state is chosen for each commodity to demonstrate the model's effectiveness.

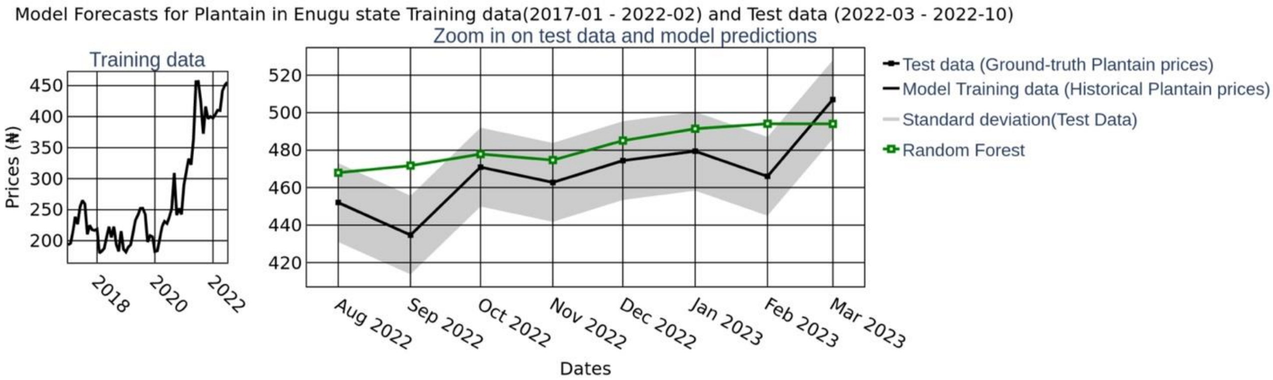
Figure 11 presents line plots depicting the price trends of irish potato, onion, sweet potato, tomato, and plantain in various Nigerian states. Our analysis reveals the superiority of the random forest model in forecasting the price trends of these commodities as seen in Figures 5 and 6. In the case of Irish potato prices in Niger state, the RF model offers highly accurate price predictions with minor deviations. The model exhibits an overestimation bias in the initial four months, while later predictions slightly underestimate the actual prices. Notwithstanding these deviations, it's notable that the average forecast error remains within the standard deviation of the observed prices, demonstrating the model's reliability. Analogously, the model demonstrates a comparable performance when forecasting Onion prices in Kwara state. Under-confidence is detected in the predictions for the third and fourth months but the model accurately adapts to the rising trend seen in the final months. Regarding the Sweet potatoes market in Taraba state, the RF model demonstrates commendable accuracy, with a notable exception in the final two months where it tends to overestimate prices. This indicates a potential limitation of the model in accounting for sudden market changes or rare events. A similar limitation is observed in predicting Plantain prices in Enugu state, where the model fails to account for a sudden drop in prices towards the beginning of September. The model, nevertheless, manages to reconcile this forecast error over the subsequent six months, achieving accurate predictions. Finally, when forecasting Tomato prices in Plateau state, the model accurately captures the overall positive trend, albeit with a slight underestimation bias during the fourth, fifth, and sixth months. A slight overestimation is noticed for the last two months, reinforcing the need for constant monitoring and adjustment of the model parameters to optimize its performance.

In summary, the current model boasts of a great forecasting accuracy for a majority of the states in Nigeria. This means that smallholder farmers can be confident of the forecast provided by this tool and by leveraging this technology, make smart decisions to reduce loss and scale their profit margins.


Model Forecasts for Irish potato in Niger state Training data(2017-01 - 2022-02) and Test data (2022-03 - 2022-10)
Training data
Prices (₦)
Zoom in on test data and model predictions
Test data (Ground-truth Irish potato prices)
Model Training data (Historical Irish potato prices)
Standard deviation(Test Data)
Random Forest
Dates


Model Forecasts for Onion in Kwara state Training data(2017-01 - 2022-02) and Test data (2022-03 - 2022-10)
Training data
Prices (₦)
Zoom in on test data and model predictions
Test data (Ground-truth Onion prices)
Model Training data (Historical Onion prices)
Standard deviation(Test Data)
Random Forest
Dates


Model Forecasts for Sweet potato in Taraba state Training data(2017-01 - 2022-02) and Test data (2022-03 - 2022-10)
Training data
Prices (₦)
Zoom in on test data and model predictions
Test data (Ground-truth Sweet potato prices)
Model Training data (Historical Sweet potato prices)
Standard deviation(Test Data)
Random Forest
Dates


Model Forecasts for Plantain in Enugu state Training data(2017-01 - 2022-02) and Test data (2022-03 - 2022-10)
Training data
Prices (₦)
Zoom in on test data and model predictions
Test data (Ground-truth Plantain prices)
Model Training data (Historical Plantain prices)
Standard deviation(Test Data)
Random Forest
Dates

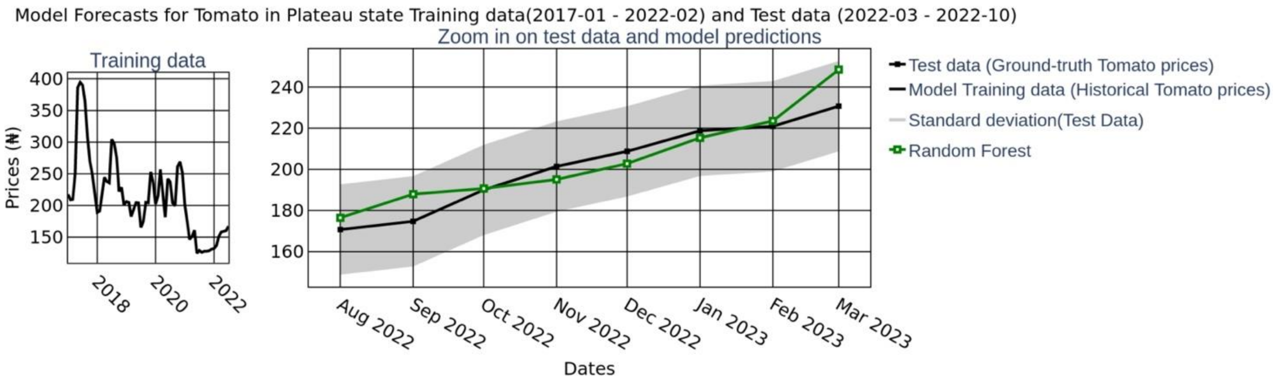

Model Forecasts for Tomato in Plateau state Training data(2017-01 - 2022-02) and Test data (2022-03 - 2022-10)
Training data
Prices (₦)
Zoom in on test data and model predictions
Test data (Ground-truth Tomato prices)
Model Training data (Historical Tomato prices)
Standard deviation(Test Data)
Random Forest
Dates

Figure 11. Verification of Model's Forecasts for Irish Potato, Onion, Sweet Potato, Tomato, and Plantain Prices in Various Nigerian States.

4 Model implementation in open-access mobile app

The deployment of our machine learning (ML) model presents a compelling use case for supporting smallholder farmers in making informed decisions. Specifically, the model can help farmers identify the optimal regions to sell their harvest, plan planting and harvest seasons to maximize profits during sales, and make other crucial decisions related to crop management. These benefits extend beyond smallholders to encompass larger organizations such as government bodies, NGOs, and research institutions. The model leverages historical food price data and provides accurate forecasts of future prices several months ahead. This information is invaluable to larger organizations when making decisions and policies that impact smallholders positively.

To provide users with access to the model's insights, we have developed a data science-based mobile application called Coldtivate [13] . The app is open-access and available on both Android and iOS. Within the Coldtivate app, users will be able to select fresh produce and states (See Figure 12) within Nigeria to generate monthly forecasts of average fresh produce prices up to eight months in advance. Note that the app is also available for stakeholders in India. The app's interface includes a graph that displays both historical and forecasted prices, allowing users to visualize recent price trends and make informed decisions accordingly. As an example Figure 12B show the market price of tomato in Lagos state from April 2023 to August 2023. Similarly, the farmer could decide from Figure 12C what state and month they would target to sell their produce and make the most profit. With such a powerful tool at their disposal, they can optimize their revenue and at the same time reduce food loss by knowing when and where to sell even before harvest, which is one of the main drivers of food loss at the farm.

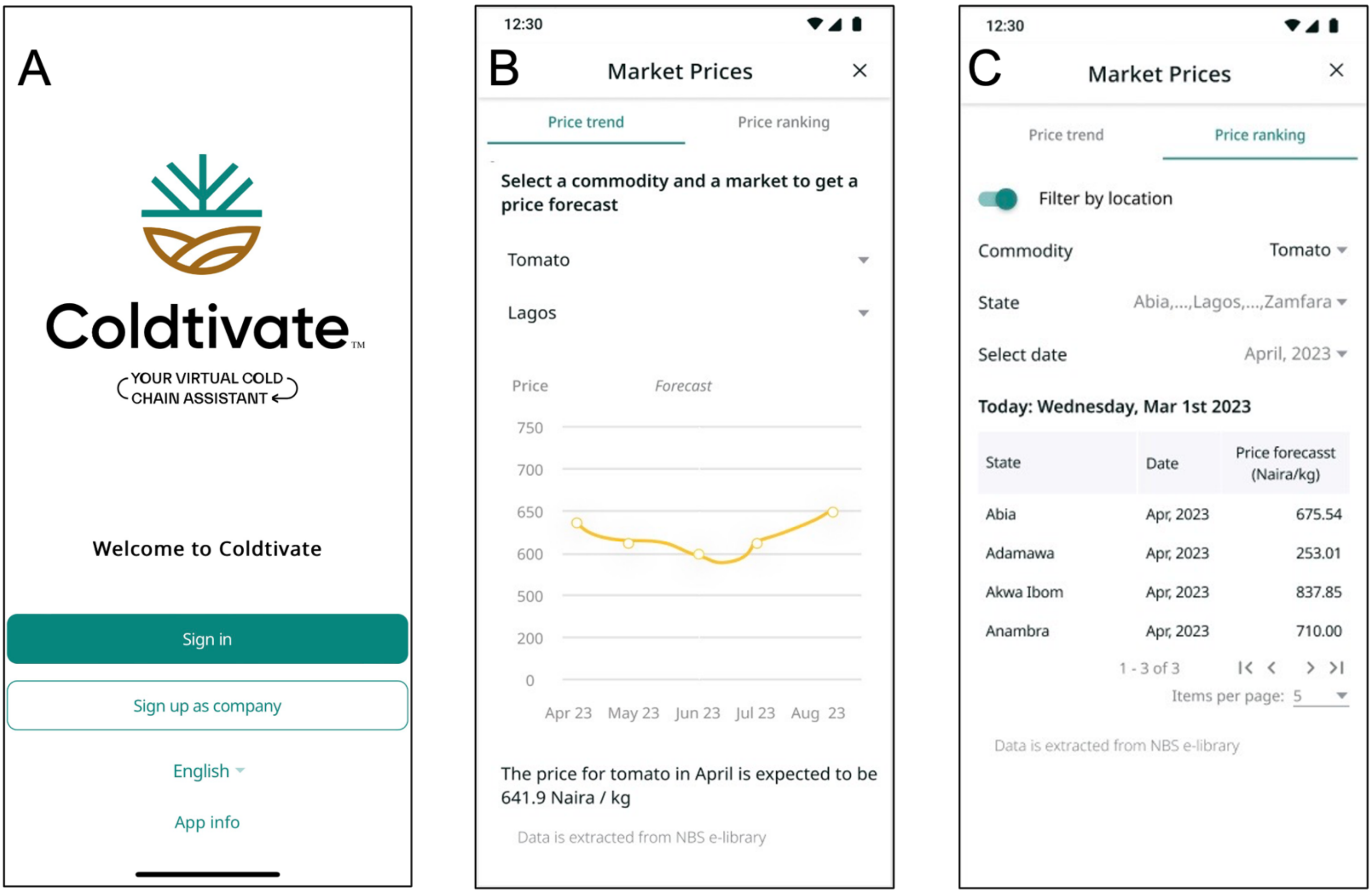


Figure 12 Initially designed sketches for machine learning model prediction graph in Coldtivate. The Price trend section displays the historical prices and forecasts for a user selected food and state. The price ranking section displays the prices of a user selected food for all states per month arranged in ascending or descending order based on user preference.

Challenges

In this section we discuss the challenges faced during the development of the fresh produce market price forecasting tool. We also provide recommendations on how to resolve them for further development or applications of the price forecasting tool.

1. Inadequate Training Data: The available open-source data for training the machine learning algorithms is limited. Currently, only monthly averaged prices from January 2017 to March 2023 are available, which results in a mere 75 data points per food commodity per state. To address this challenge, it is necessary to have more historical food commodity prices available, with a higher frequency (e.g., daily or weekly). This can be done through private-public partnership of government organizations, NGOs, policy makers, and research organizations in Nigeria to gather relevant and trustworthy statistical data and make it open-source. By doing so, the methodology outlined in this paper can be successfully reproduced with improved results. The positive implications of gathering relevant data is not limited to fresh produce price forecasting, they can be converted to other data driven solutions for smallholders such as interactive web

maps hosting relevant geospatial insights [28], smart supply-chains with decentralized cooling and refrigerated transport solutions, etc., as recommended in [4].

2. Poorly Structured Open-source Repositories: Another challenge faced in the development of the food price forecasting tool was the poor structure of the NBS e-library site [16]. The food price and Consumer Price Index (CPI) data is uploaded on the e-library site as Microsoft Excel sheets, which presents a challenge for the web scraping module to efficiently and accurately update the training data. Changes to the structure of the Excel sheets, such as dimensions, column names, sheet numbers, or indexes, can result in incorrect data being scraped. To mitigate this risk, the scraping module has been tested to remain robust in the event of some changes. However, it is not possible to anticipate all possible modifications to the Excel sheets, leaving the possibility of future failures if the scraping module is not regularly maintained and updated in tandem with the website. A solution to this challenge would be for the National Bureau of Statistics (NBS) to improve the web-scraping friendliness of their website by using dynamic HTML tables instead of traditional Microsoft Excel worksheets to store open-source data.

3. Inconsistent Data Quality: While developing our food price forecasting tool, we recognized areas for improvement related to data quality within the NBS dataset. Occasionally, inconsistencies and gaps were present in the food prices, which can potentially influence the accuracy of model predictions. We view these inconsistencies not as flaws, but as opportunities for enhancement. By advocating for stringent data quality control processes, we aim to ensure the usage of only high-quality, complete data for training and testing our model, thus bolstering the model's reliability. We were able to make significant strides in reducing this challenge using data imputation techniques, such as linear interpolation.

4. Limited Features for Model Training: The lack of availability of additional features, such as geopolitical events and demand and supply levels, limits the ability of the model to capture all the factors affecting food prices. This could be a reason for the less accurate predictions and lower overall model performance in some Nigerian states. To address this challenge, additional variables/ features that capture the economical influencers of food prices in Nigerian markets should be made openly available, collected and incorporated into the model training, as long as they are relevant and have a significant impact on food prices.

While the challenges discussed may affect the potential impact of the ML forecasting tool in Coldtivate, it's important to underscore the tool's existing value. Our methodology, even at its current stage, provides adequate prediction accuracy, offering valuable market price insights and trends for 85% of states (see Figure 9) and all major produced commodities in Nigeria. This translates to substantial support for smallholder farmers in their decision-making process. Furthermore, by providing high-quality historical price data with a higher frequency at weekly or daily levels, the methodology presented in this paper can be scaled and applied to achieve better results. As a result, the overall impact of ML forecasting tools on the lives of smallholder farmers can be increased significantly.

5 Conclusions

This paper presents a new application of machine learning in the field of agriculture and the food supply chain, specifically for fresh produce price forecasting in Nigeria. A robust system has been implemented to accurately predict real-time food prices across different states, using an online-learning approach. This approach periodically scrapes open-source repositories for historical food prices and external factors such as inflation, foreign exchange rates, and domestic fuel prices. It also retrains a machine learning model with the latest data to enhance forecast accuracy. Several machine learning and statistical models were evaluated using the MAPE and RMSE performance metrics, and the best performing model, Random Forest, was selected. The analysis showed that a non-linear model trained on historical prices of fresh produce, supported by economic influencers as predictors, can accurately forecast future fresh produce prices. Our key findings are:

- Compared to SARIMA, CatBoost, XGboost, and a 5-month rolling average benchmark, Random Forest model accurately predicts 8 month average market prices of tomato, onion, plantain, and potato across 37 states in Nigeria. The model achieved an average Mean Absolute Percentage Error (MAPE) of <20%. This error is much less than the typical price variation throughout the year and between different years.
- The criteria with the largest influence on the model performance is the historical market prices followed by USD to Naira exchange rates. The historical market prices accounted for approximately 92% of the model performance while exchange rates coupled with other exogenous factors contributed to the model accuracy by 7 to 8%.
- Non-linear, tree-based machine learning algorithms are better suited for fresh produce market price prediction for a volatile value chain like Nigeria and provide forecasts that are at least 5-7 % more accurate when compared to linear models such as SARIMA and rolling-average (benchmark). Tree-based models combined with external economical variables also ensure a model more robust to outliers.
- Our model performed better in fresh produce producing states like Kano, Plateau, and Sokoto with less volatility compared to states where they are largely consumed like Lagos.

We have integrated this model into a mobile application called Coldtivate [13].The purpose of Coldtivate is to reduce postharvest losses in the food supply chain and increase smallholder farmer's income. Smallholders can use Coldtivate to access valuable insights on maximizing the shelf life of their fresh produce and market intelligence, including historical food prices and price forecasts. Policy makers, government organizations, NGOs, and other stakeholders can also use the features offered by Coldtivate including the fresh produce knowledge hub, fruit and vegetable digital twins and price forecasting models to make informed decisions to mitigate postharvest losses and increase smallholder income.

References

[1] "Nigeria at a glance | FAO in Nigeria | Food and Agriculture Organization of the United Nations." https://www.fao.org/nigeria/fao-in-nigeria/nigeria-at-a-glance/en/ (accessed Feb. 08, 2023).

[2] V. Ricciardi, N. Ramankutty, Z. Mehrabi, L. Jarvis, and B. Chookolingo, "How much of the world's food do smallholders produce?," *Glob Food Sec*, vol. 17, pp. 64–72, Jun. 2018, doi: 10.1016/J.GFS.2018.05.002.

[3] Doris Dokua Sasu, "Nigeria: share of global poverty 2016-2023 | Statista," *Share of global population living in extreme poverty in Nigeria 2016-2023*, Feb. 08, 2023. https://www.statista.com/statistics/1287840/share-of-global-population-living-in-extreme-poverty-in-nigeria/ (accessed Feb. 13, 2023).

[4] D. Onwude *et al.*, "Bottlenecks in Nigeria's fresh food supply chain: What is the way forward?," *Trends Food Sci Technol*, vol. 137, pp. 55–62, Jul. 2023, doi: 10.1016/J.TIFS.2023.04.022.

[5] N. F.N., C. J., E. H.A., E. J.A., and A. C.N., "Ict for Agriculture Knowledge Management in Nigeria: Lessons and Strategies for Improvement," *Science Journal of Agricultural Research and Management*, vol. 2012, 2012, doi: 10.7237/SJARM/192.

[6] W. Ma, K. Nowocin, N. Marathe, and G. H. Chen, "An interpretable produce price forecasting system for small and marginal farmers in India using collaborative filtering and adaptive nearest neighbors," in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Jan. 2019. doi: 10.1145/3287098.3287100.

[7] C. Z. Yuan and S. K. Ling, "Long Short-Term Memory Model Based Agriculture Commodity Price Prediction Application," in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Aug. 2020, pp. 43–49. doi: 10.1145/3417473.3417481.

[8] R. Carbonneau, K. Laframboise, and R. Vahidov, "Application of machine learning techniques for supply chain demand forecasting," *Eur J Oper Res*, vol. 184, no. 3, pp. 1140–1154, Feb. 2008, doi: 10.1016/J.EJOR.2006.12.004.

[9] J. Rincon-Patino, E. Lasso, and J. C. Corrales, "Estimating Avocado Sales Using Machine Learning Algorithms and Weather Data," *Sustainability 2018, Vol. 10, Page 3498*, vol. 10, no. 10, p. 3498, Sep. 2018, doi: 10.3390/SU10103498.

[10] Z. Mustaffa, Y. Yusof, and S. S. Kamaruddin, "Enhanced artificial bee colony for training least squares support vector machines in commodity price forecasting," *J Comput Sci*, vol. 5, no. 2, pp. 196–205, Mar. 2014, doi: 10.1016/J.JOCS.2013.11.004.

[11] S. Mehtab and J. Sen, "A Time Series Analysis-Based Stock Price Prediction Using Machine Learning and Deep Learning Models," *International Journal of Business Forecasting and Marketing Intelligence*, vol. 6, no. 4, p. 272, Apr. 2020, doi: 10.1504/IJBFMI.2020.115691.

[12] Y. E. Shao and J. T. Dai, "Integrated feature selection of ARIMA with computational intelligence approaches for food crop price prediction," *Complexity*, vol. 2018, 2018, doi: 10.1155/2018/1910520.

[13] "Coldtivate App – Your VCCA Nigeria," 2022. https://yourvcca.org/nigeria/the-app/ (accessed Feb. 13, 2023).

[14] Z. Chen, H. S. Goh, K. L. Sin, K. Lim, N. K. H. Chung, and X. Y. Liew, "Automated Agriculture Commodity Price Prediction System with Machine Learning Techniques," *Advances in Science, Technology and Engineering Systems Journal*, vol. 6, no. 4, pp. 376–384, Aug. 2021, doi: 10.25046/AJ060442.

[15] Y. Guo *et al.*, "Agricultural Price Prediction Based on Combined Forecasting Model under Spatial-Temporal Influencing Factors," *Sustainability 2022, Vol. 14, Page 10483*, vol. 14, no. 17, p. 10483, Aug. 2022, doi: 10.3390/SU141710483.

[16] "Home | National Bureau of Statistics." https://nigerianstat.gov.ng/ (accessed Dec. 29, 2022).

[17] "Central Bank of Nigeria :: Crude Oil Price." https://www.cbn.gov.ng/rates/crudeoil.asp (accessed Dec. 29, 2022).

[18] "USD/NGN (NGN=X) Live Rate, Chart & News - Yahoo Finance." https://finance.yahoo.com/quote/NGN%3DX/history?period1=1632164022&period2=1663700022&interval=1mo&filter=history&frequency=1mo&includeAdjustedClose=true&guccounter=2 (accessed Dec. 29, 2022).

[19] F. Pedregosa FABIANPEDREGOSA *et al.*, "Scikit-learn: Machine Learning in Python Gaël Varoquaux Bertrand Thirion Vincent Dubourg Alexandre Passos PEDREGOSA, VAROQUAUX, GRAMFORT ET AL. Matthieu Perrot," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011, Accessed: Mar. 03, 2023. [Online]. Available: http://scikit-learn.sourceforge.net.

[20] J. Reback *et al.*, "pandas-dev/pandas: Pandas 1.2.2," Feb. 2021, doi: 10.5281/ZENODO.4524629.

[21] "sklearn.ensemble.RandomForestClassifier — scikit-learn 1.2.1 documentation." https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html (accessed Feb. 16, 2023).

[22] A. V. Dorogush, V. Ershov, and A. Gulin, "CatBoost: gradient boosting with categorical features support," Oct. 2018, doi: 10.48550/arxiv.1810.11363.

[23] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System", Accessed: Feb. 16, 2023. [Online]. Available: https://github.com/dmlc/xgboost

[24] "Introduction — statsmodels." https://www.statsmodels.org/stable/index.html (accessed Feb. 16, 2023).

[25] I. O. Fasanya and F. Olawepo, “Determinants of food price volatility in Nigeria,” *Agricultura Tropica et Subtropica*, vol. 51, no. 4, pp. 165–174, Dec. 2018, doi: 10.2478/ats-2018-0019.

[26] H. Hewamalage, K. Ackermann, and C. Bergmeir, “Forecast Evaluation for Data Scientists: Common Pitfalls and Best Practices,” Mar. 2022, [Online]. Available: http://arxiv.org/abs/2203.10716

[27] R. Díaz-Uriarte and S. Alvarez de Andrés, “Gene selection and classification of microarray data using random forest,” *BMC Bioinformatics*, vol. 7, no. 1, pp. 1–13, Jan. 2006, doi: 10.1186/1471-2105-7-3/FIGURES/1.

[28] D. Odion *et al.*, “A GIS-based interactive map enabling data-driven decision-making in Nigeria’s food supply chain,” *MethodsX*, vol. 10, p. 102047, Jan. 2023, doi: 10.1016/J.MEX.2023.102047.

SUPPLEMENTARY MATERIAL

1. Descriptive Statistics

The table below shows the summary statistics of the master data set for training. Each row corresponds to a single feature and each column a statistical measure.

Table S1 Summary statistics of model training features/variables

S/N	Variable	count	mean	Standard Deviation	min	25%	50%	75%	Max
1	st_label	12950	18	10.677491	0	9	18	27	36
2	comm_label	12950	2.8	2.135498	0	1	3	4	6
3	Price	12950	260.619192	136.387363	50.745599	177.15884	226.00047	303.544623	1733.333333
4	Last_Month_Price	12950	258.294068	133.957026	50.745599	176.185597	225	301.211402	1733.333333
5	Last_2 M_Price	12950	256.113953	131.740086	50.745599	175.006232	223.754374	300	1733.333333
6	Last_3 M_Price	12950	253.890157	128.759596	56.825851	174.361775	222.990274	296.896162	1103.72
7	Last_4 M_Price	12950	251.71337	126.231933	56.825851	173.05	222.222222	294.371667	1103.72
8	Last_5 M_Price	12950	249.614021	123.676883	56.825851	172.181465	221.626071	292.029182	1103.72
9	USDto Naira	12950	347.683477	47.976806	305.202381	306.057143	306.957045	410.017	437.5
10	CPI	12950	314.063937	63.569037	215.721235	260.474592	306.170969	361.230543	455.354112
11	State_roll	12950	260.619192	101.970929	107.516245	189.922232	230.502781	310.31068	547.008807
12	Crude_price	12950	67.593286	21.416584	14.28	54.87	65.93	74.72	130.1

2. Correlation matrix

The relationship between the variables in the training dataset can be represented graphically using a correlation matrix. This can be implemented with the Pandas library in Python. The Pearson's correlation coefficient between all the variables in the data is displayed in a correlation matrix (Figure S1), showing the linear correlation between the features. The matrix reveals that the features with the highest correlation to the target variable (Price) are the lagged features, with 'Last_Month_Price' having the highest correlation coefficient of 0.95. This indicates that these lagged Price features will likely be the best predictors for future Prices. After the lagged features, the 'state_roll' feature has the next highest correlation with Price, with a correlation coefficient of 0.75. This makes sense because these features are generated from the Price variable through a shift or aggregation operation, resulting in a high linear correlation. The exogenous variables, including 'USDtoNaira', 'CPI', and 'Crude_price', have a relatively low linear correlation with the commodity Price. However, this does not necessarily mean that they are not significant in determining the accuracy of the model. Further investigation is necessary to examine the potential non-linear relationships between these variables and the target variable. Therefore, decision tree-based machine learning models have been used in this study, as they are capable of capturing non-linear relationships, overcoming the limitations of linear dependencies between features.

Another aspect of the correlation matrix is multicollinearity between features, where two or more independent variables are highly correlated, which can undermine the statistical significance of an independent variable in regression. The correlation matrix shows high correlation between the lagged features, as well as between the 'CPI' and 'USDtoNaira' features with a value of 0.88. However, since the chosen model is a tree-based model (random forest), this is not a concern. The random forest implements bootstrapping with replacement and gradient bagging to address issues of multicollinearity. By training multiple weak learners on random sub-samples of the features, the likelihood of two highly correlated features being used in the same learner is reduced, and even if that happens, the gradient bagging process ensures that it does not impact the overall model performance.

The incorporation of categorical features, such as 'st_label' and 'comm_label' facilitates the introduction of additional contextual information into a time series forecasting model. In our study, these features aim to capture the differences in states and commodities that may affect the fluctuations in commodity prices. However, the linear correlation analysis between these categorical features and the target variable 'Price' reveals low negative correlations of '-0.16' and '-0.12', respectively. While linear correlation is an important factor in model performance, it is not the sole determinant. In particular, the incorporation of categorical features can enhance the model's ability to capture the underlying dynamics and patterns in the time series data, even when the correlation with the target variable is low or non-linear.

Therefore, in the present study, we do not perform any further analysis of the low correlation values between the categorical features and the target variable. We acknowledge that these features can still provide valuable contextual information for the model and may contribute to its overall forecasting accuracy, despite their low correlation with the target variable. The effectiveness of these features in improving the model's performance will be evaluated through experimentation and evaluation in subsequent analyses.

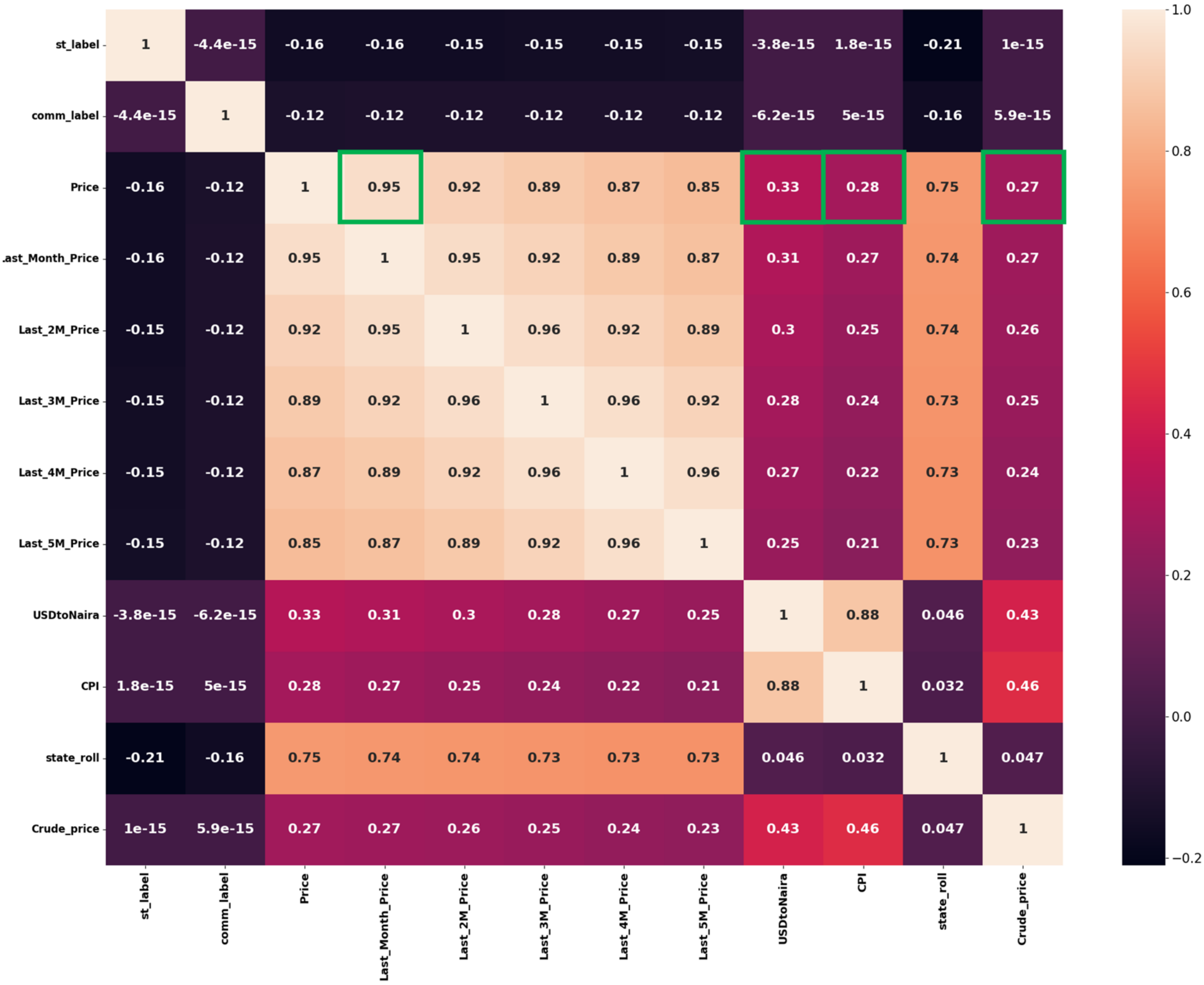


Figure S1 Feature/Variable Correlation matrix. The highlighted green boxes indicate the linear correlation coefficients between the 'Last_Month_Price' and commodity prices, as well as the correlation between exogenous features ('USDtoNaira', 'CPI', 'Crude_price') and the commodity prices.

3. Ranking of the model features

In this section, we explore the feature importance as determined by our Random Forest model. We employ the built-in 'feature_importance' method of Scikit-learn's Random Forest regressor to identify the variables that most profoundly impact the model's predictive ability. As depicted in Figure S2, the 'Last_Month_Price' feature emerges as the most significant influencer. This strong influence of 'Last_Month_Price' is a double-edged sword. On the positive side, it reflects the strong correlation of 0.95 between the last month's price and the current price, contributing significantly to the model's impressive Mean Absolute Percentage Error (MAPE) of 11.01%. This means that, under stable market conditions, our model can make highly accurate predictions based largely on the price from the previous month.

However, this heavy reliance on a single feature raises potential concerns about the model's robustness to unpredictable market events, where the past month's price may not be a reliable indicator of the current price. In such scenarios, a model overly dependent on this feature may struggle to make accurate predictions. To balance performance and robustness, we have chosen to maintain our current model due to its high accuracy under regular conditions. However, we are also setting up a close monitoring system. This system will alert us to any significant deviations between the actual prices and the model's predictions, enabling us to respond swiftly to changes in market conditions. This approach allows us to leverage the predictive power of 'Last_Month_Price' while remaining vigilant to potential market shifts that could impact model performance.

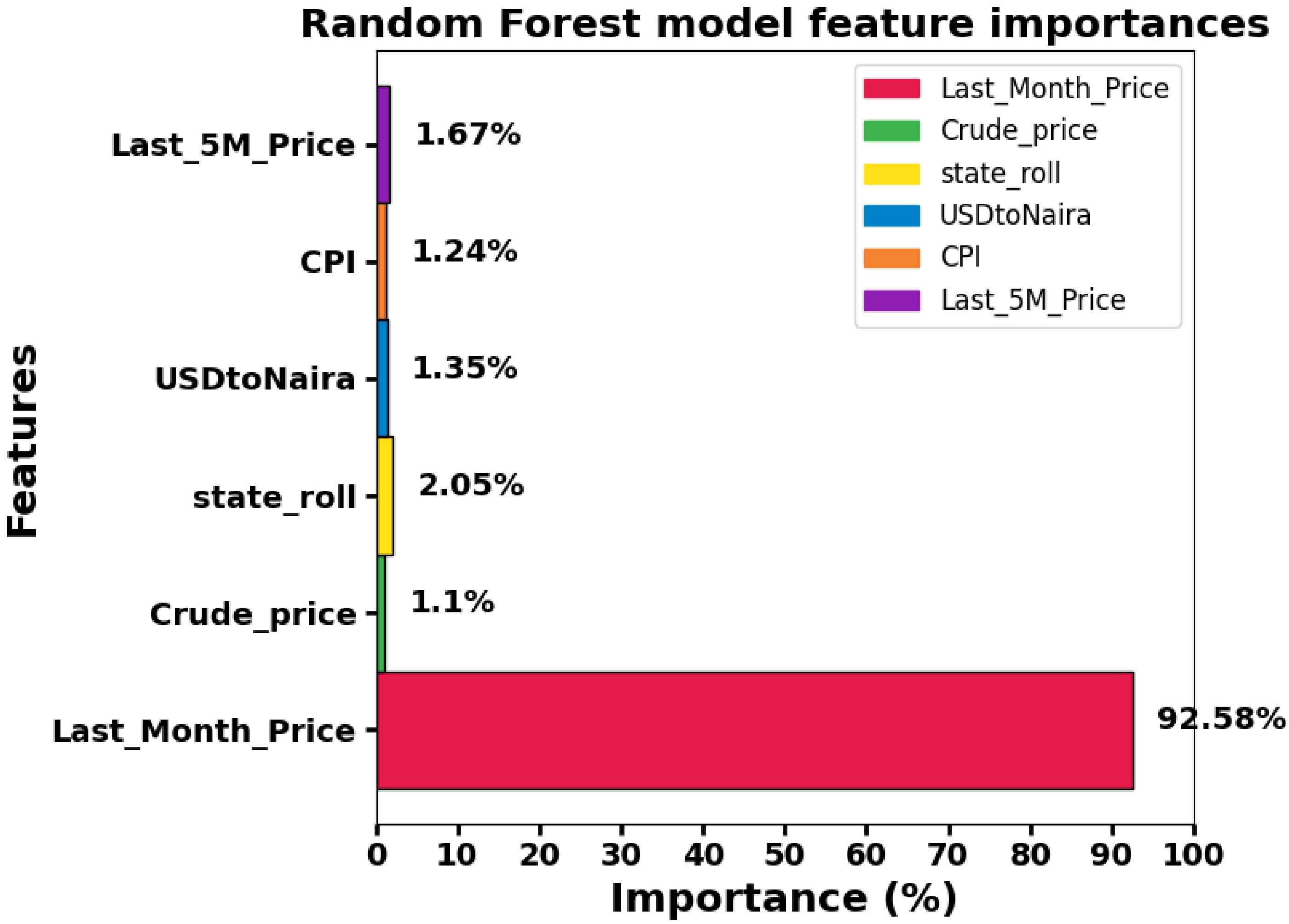


Figure S2 Visualization of the Random Forest (RF) model's feature importances expressed in percentages.

4. Machine learning model parameters

The tuned hyper-parameters of each model are enumerated and briefly explained in this section. These are a set of adjustable configuration options that influence the performance and accuracy of a machine learning model. To tune/adjust the hyper-parameters of each ml model we utilized a grid search cross validation approach and for the SARIMA we utilized a step-wise cross validation approach with Akaike Information Criterion (AIC) as the key metric for deciding the model parameters with the best-fit to the training data.

a. Naive Model (Benchmark)

The naive model approximates the current approach used by smallholders to forecast commodity prices in Nigerian markets using a simple rolling-average algorithm. A single forecast from this model is calculated as the arithmetic average of the last 5 months of prices. Smallholders and the likes currently do not have access to historical commodity prices for different states presented in such a synergized manner and because of this are unable to make accurate predictions of the commodity prices and often just predict that the prices of commodities remain more or less the same for the immediate next month. In order to model this methodology, a framework has been created to forecast commodity prices in this manner. This model is a baseline for evaluating the advantages of the statistical and machine learning models.

b. CatBoost Model

CatBoost is a novel gradient boosting tree-based algorithm developed by Yandex researchers. Gradient boosting is an ensemble modeling technique that utilizes several weak learners/models in a sequential manner. Gradient boosting starts by fitting a weak learner to the data, then a second learner is fit to the same data with the aim of accurately predicting the cases where the previous learner performed poorly, and this process is repeated for as many learners as specified in the ensemble. The combination of the predictions of all the models in the ensemble is expected to be better than a single model. CatBoost is popular for the algorithm's ability to train at fast speeds and relatively high accuracy in fitting to small amounts of data when compared to other tree-based models. The 'CatboostRegressor' class from the official 'catboost' python package was used to train a regressor on the commodity price data. First a Grid search cross validation method was applied on the dataset with the model object as the estimator and passing integer ranges as values for tuning the hyper parameters to attain the model with the best fit. The four hyper parameters tuned for the model include the 'depth', 'learning_rate', 'n_estimators', and 'l2_leaf_reg'. The depth' parameter adjusts the tree depth of each tree in the model, the 'learning_rate' parameter is used to adjust the gradient step size of the model to attain model convergence on the training data. The 'n_estimators' parameter tunes the number of trees or estimators used in the model and the 'l2_leaf_reg' parameter is used to penalize the loss function of the model. The results of running cross validation on the training data yielded a model with a 'depth' value of 16, 'learning_rate' of 0.1, n_estimators value of 500, and 'l2_leaf_reg" value of 16. The model with best fit was then evaluated on the test set.

c. XGBoost Model

XGBoost is a tree-based model that implements gradient boosting, developed by Tianqi Chen as part of the Distributed (Deep) Machine Learning Community (DMLC) group. The XGBoost algorithm is specially designed for optimizing computation speeds and machine learning performance. The hyper parameters tuned in the Grid search cross validation process were 'n_estimators' (Number of trees/estimators in the model), the 'max_depth' (the maximum depth of each tree), 'nthread' (the number of parallel processor threads to use for model training), 'learning_rate' (to adjust step size for reducing model overfitting), 'reg_lambda' (L2 regularization parameter). The cross validation yielded a model with 'n_estimators' value of 500, 'max_depth' of 16, 'learning_rate' value of 0.1, 'reg_lambda' value of 16, with the 'nthread' parameter value set to -1 to indicate utilization of all available parallel processor threads during training. The best fit model was selected for evaluation on the test dataset.

d. SARIMA (PDQ, pdq)m

SARIMA stands for Seasonal Auto-Regressive Integrated Moving Average. SARIMA is an extension of ARIMA for forecasting univariate time series with a seasonal component. The statistical model consists of 2 components which are trend and seasonality. These components are specified by 7 adjusted hyper parameters of the SARIMA model. These are:

p: Trend autoregression order.

d: Trend difference order.

q: Trend moving average order

P: Seasonal autoregression order.

D: Seasonal difference order.

Q: Seasonal moving average order

M: Number of timesteps for a single seasonal period

Without the differencing operations the SARIMA model can be written formally using the concise formula below:

$\Phi p(Bs)\ \phi(B)\ \nabla Ds\ \nabla dxt = \Theta Q(Bs)\theta(B)wt$

Where:

Wt : the nonstationary time series

s: represents the period of the time series

$\phi(B)$ and θ (B): The ordinary autoregressive and moving average components represented by polynomials of orders p and q respectively.

Φp (Bs) and ΘQ (Bs): The seasonal autoregressive and moving average components of orders P and Q.

∇d and ∇Ds: are the ordinary and seasonal difference components.

B: Backshift operator

The SARIMA model is fit to the data by estimating the values of the parameters p, d, q, P, D, Q, and s that minimize the error between the predicted values and the observed values in the data. Once the model is fit, it can be used to forecast future values of the time series. Utilizing a stepwise cross-validation approach to tune the above hyper-parameters and Akaike information criterion (AIC) as the key metric our results describe a SARIMA model with the following hyper-parameters specified as the best fit:

SARIMA(1,0,0)(2,1,0)12

e. Random Forest Model

The Random Forest model is a popular tree-based model that implements gradient bagging, a modeling approach of training several weak estimators in which a model forecast is computed as the arithmetic average of the predictions of all the weak estimators/trees in the model. The Random Forest estimator was fine-tuned using a grid search cross validation approach resulting in a best-fit model with hyper parameters 'n_estimators' and 'max_depth' tuned to 500 and 16 respectively. The ' n_jobs' parameter was set to a value of -1 to allow full utilization of available CPU threads. The model was fit to the training data and evaluated on the test set

Schematic Representation of Gradient Bagging and Gradient Boosting Algorithms

The diagrams below depict the schematic of the internal architecture of Gradient bagging implemented in Random Forest and Gradient boosting implemented in CatBoost and XGBoost algorithms. See section 2.2.2 above for explanations of the concepts.

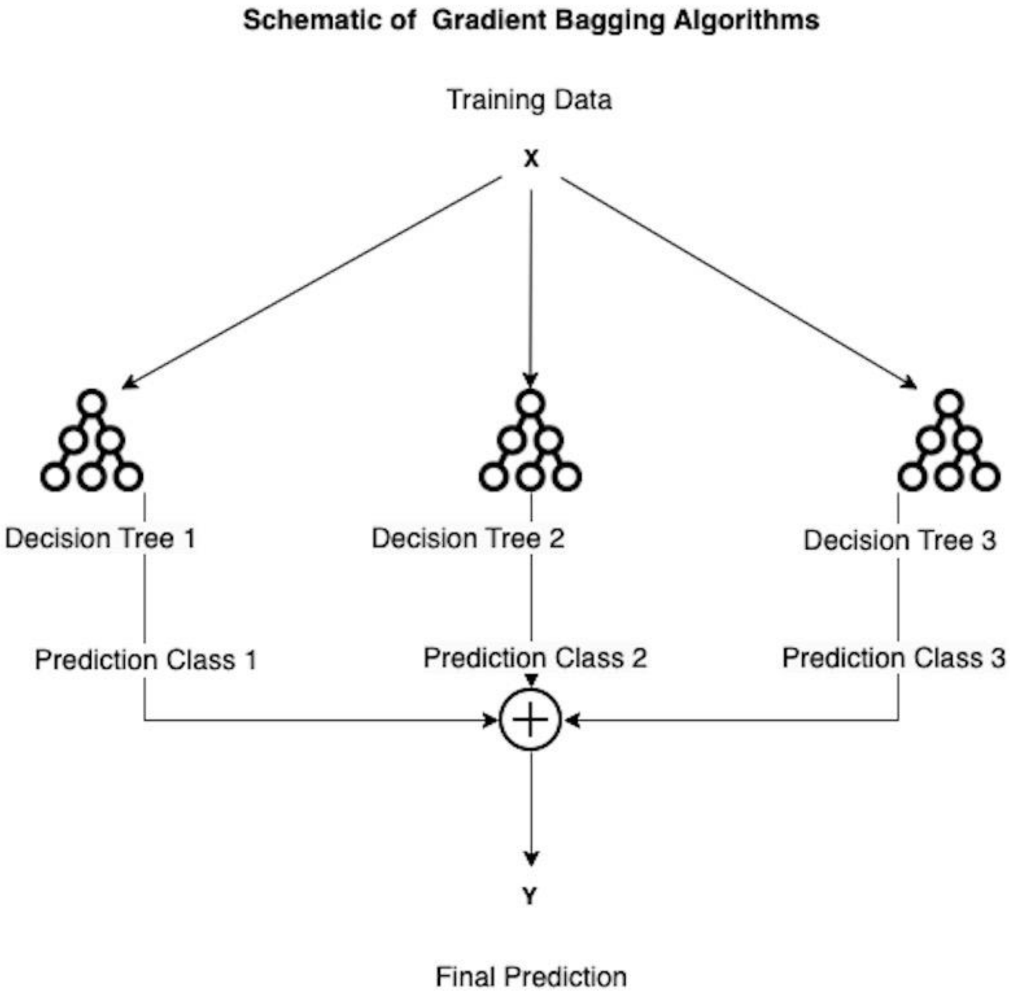


Figure S3. Schematic representation of Gradient Bagging algorithm

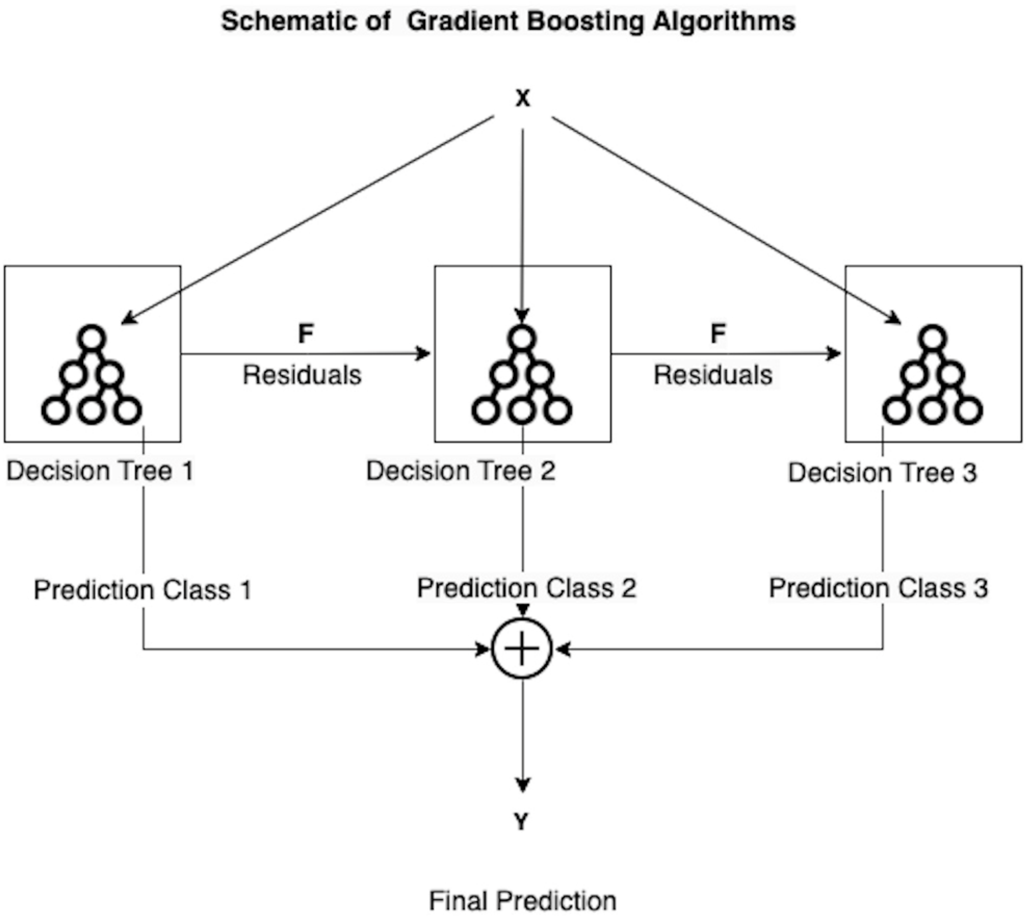


Figure S4. Schematic representation of Gradient Boosting algorithm

5. Location-based analysis

We demonstrate the variations in prices between the states in Nigeria for the five commodities using map visualizations, the figures are color-coded for clarity (Figure S5). The data within each state boundary represents the average yearly price of the commodity from 2017 to 2022 for that state. From the figures, we can see a regional variation in prices of Irish potato (A), onion (B), plantain (C), tomato (D), and sweet potato (E).

As previously noted in the introduction, the majority of Nigeria's fresh produce is produced in the Northern regions and transported to the southern markets where they are sold to consumers. To compensate for expenses associated with transportation, preservation, and logistics, smallholders in the southern states tend to charge higher prices than those in the Northern states. For example, in Figure S5 (D), it can be seen that prices of tomato ranged from an average of ₦158 to ₦520 across the different states over the period of 2017 to the present. Additionally, it is clearly visible that prices are highest in the southern states of Rivers, Bayelsa, Akwa-Ibom, and Edo, while they are lowest in the Northern states of Bauchi, Borno, Gombe, and Kano, where the majority of tomatoes sold in Nigeria are farmed. Figures S3(A) and S3(B) for potato and onion, respectively, both exhibit a similar pattern, however, the market price of plantain in Figure S5(C) provides a contrasting example. Plantain is primarily grown in the southeast, southwest, and south-south regions of Nigeria and as seen in Figure S5(C), the most expensive plantain food is found in Abuja, Anambra, Akwa-Ibom, Lagos and Rivers states, while the cheapest can be found in Kwara, Cross River, Taraba, Gombe, and Osun. According to a recent analysis of the banana and plantain value chain in West Africa, some of the primary factors contributing to the high cost of plantain is the poor state of the transportation network within states, demand and supply, etc. These disparities may account for the higher cost of plantain in a state, where it is produced, as compared to other states where it is only mostly sold.

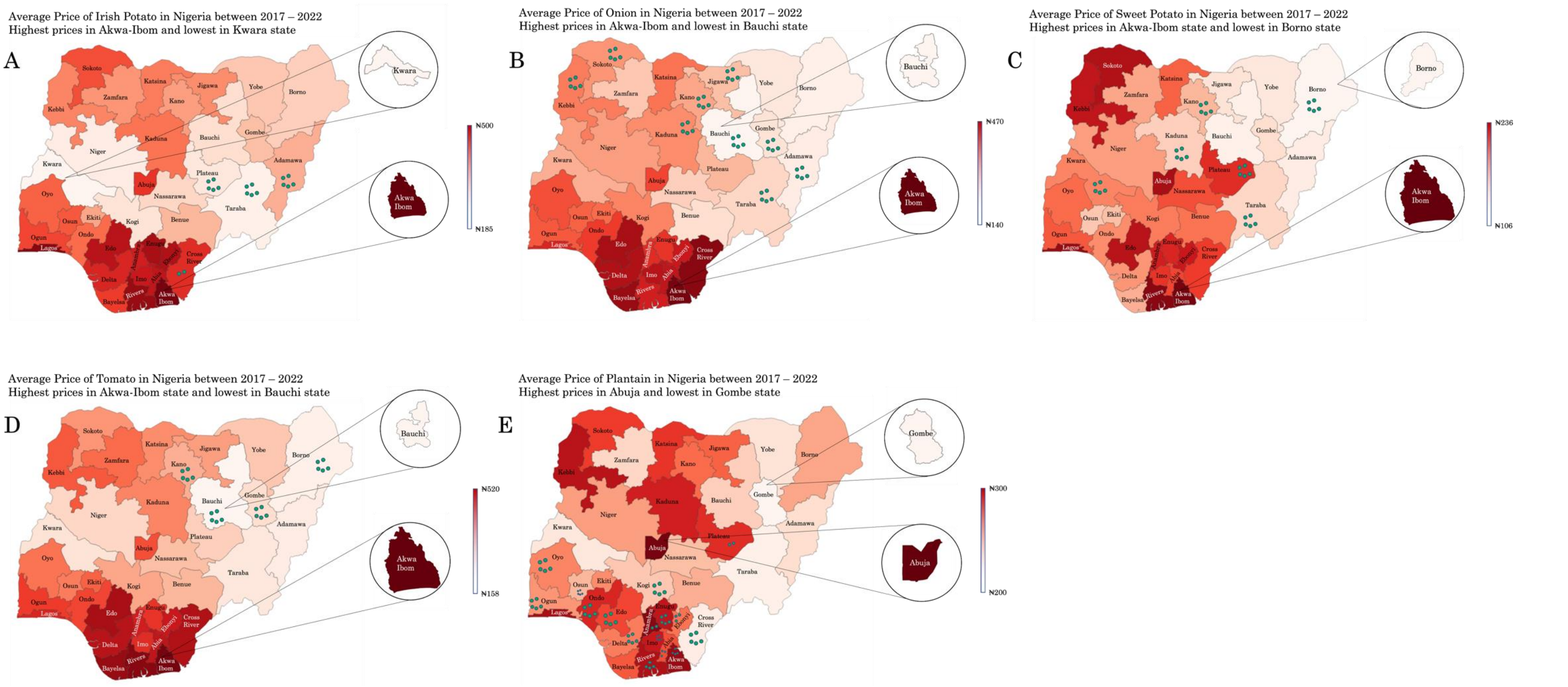


Figure S5. Maps showing the average monthly price of irish potato, onion, sweet potato, tomato, and plantain across states in Nigeria between 2017 and 2022 including the states with the highest and lowest recorded average monthly averaged prices. Green dots indicate states where the respective commodity was majorly produced in Nigeria during (timeline 2017 - 2022).

6. State-wise Temporal Cross validation

This section displays the temporal cross-validation MAPE results per state for the 5 models which include Random forest, CatBoost, XGBoost, SARIMA, and the Rolling-average (Benchmark) model. Each row represents the average MAPE computed across the CV test-sets for all commodities.

1. Random Forest:

Table S2 MAPE results per state for Random forest model evaluated over 26 test sets in Temporal CV approach

States	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Abia	7.143815162	10.77360775	13.27521944	14.53367178	14.54989792	14.7955477	16.12190902	17.34393403	13.56720035
Adamawa	8.689779961	11.43858699	14.04438173	15.08362846	15.64061754	16.44452107	17.88685993	19.88809852	14.88955927
Akwa-Ibom	8.538599199	11.20385063	12.23254124	13.62953346	14.79704331	16.15184295	17.04118077	17.50209821	13.88708622
Anambra	6.82993599	8.719062004	9.789963366	10.20288484	11.35657238	12.31536071	13.33350843	14.60155985	10.89360595
Bauchi	7.687794084	10.30683791	10.42004628	12.4115691	13.78793025	14.85143524	16.03794394	17.24989751	12.84418179
Bayelsa	7.716811977	11.05626703	12.23945454	13.99546238	14.91315405	15.23311321	15.98620075	17.13374282	13.53427585
Benue	7.319506005	10.88506437	12.65731873	14.32457836	15.14575876	16.17044364	17.47939058	18.1846995	14.02084499
Borno	9.190751291	13.01618151	14.16395436	14.03184013	14.04517454	14.35617852	16.90906116	18.28601414	14.24989446
Cross River	9.654941319	14.84659802	17.7867642	18.57727456	18.76820289	19.61935643	19.93127434	21.30020879	17.56057757
Delta	11.15706288	15.70257692	19.07412556	20.48886291	20.81445578	21.27903612	22.33826301	24.94970782	19.47551138
Ebonyi	12.06521527	18.55571369	20.66791118	21.8572932	21.58264064	22.2654593	23.97097717	24.8421433	20.72591922
Edo	7.101755224	9.538816158	11.05260182	12.65411124	14.74002634	15.58589382	16.38209212	17.78550329	13.1051
Ekiti	9.889253655	13.81018269	16.37989447	18.59408077	20.55824471	21.09642037	22.16882366	23.35349302	18.23129917
Enugu	9.657988597	12.23203682	14.46264951	15.28595052	17.39511093	18.35469902	19.33993823	20.68603638	15.92680125
Fct Abuja	8.243341059	11.39996899	13.15126254	13.7319007	14.9501874	15.69117887	16.62110746	17.32080109	13.88871851
Gombe	9.158029417	13.03578075	16.23607951	18.94418227	20.74213267	22.47808507	23.4652008	24.37184356	18.55391675
Imo	9.883369746	13.15270498	14.93689917	15.5691958	16.84563491	18.28870049	19.9280214	20.28045902	16.11062319
Jigawa	9.519757438	14.0993991	16.82933059	18.08304923	20.60282227	21.77911502	23.03231092	23.78739745	18.46664775

Kaduna	11.43399804	16.53596858	20.57390274	23.47346584	26.77797029	27.72720571	28.73577856	29.48398334	23.09278414
Kano	8.86165544	11.69353338	12.49670136	14.54558454	15.90357369	16.77418165	16.61788	16.9826861	14.23447452
Katsina	11.24406485	14.4307925	16.52916988	19.16015229	21.20410756	22.34131265	22.79495866	22.68606888	18.79882841
Kebbi	8.989640933	12.74796376	14.81874335	16.1499685	17.94391152	19.36441077	20.54158581	20.17317534	16.341175
Kogi	10.94635003	16.3836831	20.23593197	21.57473211	22.41410306	23.52563536	24.07312377	24.58057951	20.46676736
Kwara	9.963559628	15.22553518	18.63542069	20.50535264	21.24093362	21.14275669	21.28197654	21.96746745	18.7453753
Lagos	9.703832106	14.06778255	16.91305479	18.19597483	19.62289212	20.57968289	20.10953424	20.22639043	17.42739299
Nasarawa	10.95167676	15.7548519	19.69969651	19.95591801	22.12363212	21.94800292	30.27005568	29.53304254	21.27960956
Niger	8.094819149	11.44943827	13.53465366	15.39930735	16.99850491	18.29135358	19.09098098	21.67900882	15.56725834
Ogun	11.25639639	16.7758674	20.56994163	23.85938141	26.21606813	26.33964885	26.53855458	28.11189884	22.45846965
Ondo	9.936374664	13.66912542	15.91331037	17.88954624	19.39098393	20.73800956	21.85364076	23.17297439	17.82049567
Osun	6.133118214	10.09939061	12.70460943	14.45525628	15.91340641	17.64714904	18.41218034	19.05000191	14.30188903
Oyo	4.861953002	10.88440617	14.05563894	16.27287997	18.19217884	18.92638316	19.64284128	19.48898352	15.29065811
Plateau	3.41989337	9.497195146	12.5756311	15.40132048	17.62437835	19.52257796	20.09042421	21.13614319	14.90844548
Rivers	4.725313107	10.58093903	14.22340514	16.09372092	17.80317215	19.44862787	20.33045529	21.56928055	15.59686426
Sokoto	1.30273488	5.679944163	7.104798455	8.495140627	9.318879342	10.34827251	11.38174049	12.24492978	8.234555032
Taraba	2.34687742	6.176812274	7.732834213	8.330052101	9.304518741	9.71838109	10.99343807	12.67180001	8.409339239
Yobe	2.097672123	7.74444685	10.08215013	10.71303432	11.81635755	13.26579296	13.9894879	15.39914715	10.63851112
Zamfara	2.483597109	6.452282796	8.714609086	10.17823187	11.29964206	12.5757279	13.38936468	13.48079026	9.821780721
Average	8.059492851	12.15197825	14.50039464	16.01751595	17.36067086	18.29679732	19.4084342	20.33799974	15.76666048

2. CatBoost:

Table S2 MAPE results per state for CatBoost model evaluated over 26 test sets in Temporal CV approach

States	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Abia	8.599801349	12.16160556	14.8869358	17.09159432	17.94109978	19.0726863	20.29744207	20.77321862	16.35304797
Adamawa	10.30177036	14.24162929	16.61713179	17.98776091	18.45286987	20.05894966	21.85135944	23.39659097	17.86350779
Akwa-Ibom	10.62493447	14.4469714	16.25866567	18.24647919	19.69267461	20.47903522	21.33439655	22.25269813	17.9169819
Anambra	7.98999087	10.47893799	11.78945342	12.71896932	13.22395083	14.14749467	15.22581135	16.36795623	12.74282059
Bauchi	8.138231163	10.82960489	12.39740657	14.08829316	15.3330513	16.69887463	17.53526306	18.94349978	14.24552807
Bayelsa	7.474147492	11.56642509	12.86726647	14.56456561	15.09172853	15.37837995	16.71929322	17.7035447	13.92066888
Benue	8.997116808	13.0518778	15.73376155	17.10326131	17.78971128	18.71281023	19.58209481	20.33058424	16.41265225
Borno	10.99077755	15.35088158	16.90904084	18.0324447	18.93404366	19.94788941	21.84404067	22.64146197	18.08132255
Cross River	11.8060735	18.63139982	22.94999198	25.27676327	27.12489287	28.21376104	29.68976345	29.88576022	24.19730077
Delta	12.95166591	17.61390442	21.50062781	22.76986424	23.63939121	24.2890596	25.56867813	27.42335564	21.96956837
Ebonyi	11.95009787	16.77406843	19.73577623	20.85729166	21.430249	22.95324354	24.19840715	23.87656617	20.22196251
Edo	7.852908201	10.82070138	12.94243808	14.57804917	15.44913312	17.12795723	18.41614784	20.06058839	14.65599043
Ekiti	10.73129945	15.64423757	18.62058332	22.52140465	24.27741473	25.97138937	26.90602325	27.97745039	21.58122534
Enugu	9.685115789	13.1672625	15.00912939	16.99559805	18.67601956	19.53847076	20.58094383	22.20152023	16.98175751
Fct Abuja	10.46763306	15.28937843	18.56025507	19.6796289	20.80109626	21.76122225	22.04494887	22.71016931	18.91429152
Gombe	13.9986279	19.08003087	24.52689391	27.17420749	29.47361545	31.36807838	33.04736583	33.00074036	26.45869502
Imo	12.82409258	17.75277049	20.45059427	21.66825519	22.64394174	23.98193989	24.60448186	25.58501523	21.18888641
Jigawa	12.63104275	16.99004132	20.48809999	21.71701926	23.07074759	23.83077965	24.89230615	25.77606821	21.17451312
Kaduna	15.5519529	22.20668576	26.8239897	29.97645585	32.67106157	31.69097778	30.77293514	31.49614371	27.6487753
Kano	9.507251293	13.6743307	15.3878206	16.08803061	17.27826943	18.27425498	17.94271557	17.5877316	15.7175506
Katsina	14.33723217	18.65214698	22.12187948	24.89688345	25.74231497	25.56724265	25.78129753	25.81084218	22.86372993

Kebbi	10.27126337	16.11761133	19.58069753	20.87543645	22.38229642	24.61092299	25.54679644	26.10980942	20.68685425
Kogi	13.82887542	20.22641426	24.76210953	25.89790704	26.22333976	27.13796276	27.04307756	27.18365042	24.03791709
Kwara	12.43478374	19.08135176	24.34020468	27.24929971	29.49662788	30.84680525	31.72144562	32.62936312	25.97498522
Lagos	10.27274318	14.83903058	18.45670047	20.63764065	21.80257938	22.62112305	22.77617164	23.64728134	19.38165879
Nasarawa	11.44385856	16.58330421	19.58957015	22.58565191	24.27638864	24.96970969	33.65615054	30.47449334	22.94739088
Niger	8.983035163	13.56831229	16.37972555	19.11672402	21.38075829	23.24672026	24.51321409	26.07409671	19.1578233
Ogun	11.95428072	19.28279692	23.29118048	26.64389029	29.57058259	30.49190873	32.25556035	33.44799986	25.86727499
Ondo	11.42938137	15.6184655	19.04752367	20.79679416	22.50929612	24.12114235	25.71357649	27.02095229	20.7821415
Osun	8.112357343	12.5347577	16.09550113	18.94139006	20.91283348	23.27080655	24.43481132	25.87868917	18.77264334
Oyo	6.447963392	11.53629983	16.09210466	19.58843736	21.23444496	22.15478287	22.63944849	22.04085203	17.7167917
Plateau	7.421701308	11.37551755	14.18968431	15.94689399	18.82087631	21.13688341	21.9039144	21.99029812	16.59822118
Rivers	7.79866342	12.96815275	17.46153112	19.51756331	21.91897801	24.08107122	24.47681472	24.80734196	19.12876456
Sokoto	4.490325279	7.183803491	8.628541829	9.66634104	10.07819116	11.09922151	12.20639266	12.73853574	9.51141909
Taraba	6.188141959	9.760771819	11.45445623	12.69404524	14.03100746	14.19836866	15.38266512	16.68068103	12.54876719
Yobe	5.525812934	7.993206384	9.842172436	10.87999418	12.28514755	13.98374861	15.31866893	16.6657113	11.56180779
Zamfara	4.84405101	7.906040206	10.10491819	11.3358773	13.17382483	14.13562977	15.02571684	15.10119977	11.45340724
Average	9.969162206	14.45947916	17.45660443	19.36234343	20.77930947	21.92354878	23.06622003	23.73763411	18.8442877

3. XGBoost:

Table S3 MAPE results per state for XGBoost model evaluated over 26 test sets in Temporal CV approach

States	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Abia	7.342176638	11.1719872	13.48713609	14.78608099	14.97495941	15.54301884	16.55890976	17.72592634	13.94877441
Adamawa	10.05264403	12.94621827	15.65351734	17.23662136	18.59319587	18.61885789	20.85215232	23.11980178	17.13412611

Akwa-Ibom	9.059678933	12.00074682	13.51287937	14.89739328	16.2490992	16.65769623	17.95872734	18.27740807	14.82670365
Anambra	7.851350957	10.1556917	11.09826662	11.67628314	12.60524488	13.38787729	13.48286222	14.36241972	11.82749957
Bauchi	7.920920635	10.52649217	11.62885176	13.65885358	15.29950642	16.03624889	17.27444572	18.52616589	13.85893563
Bayelsa	7.890264649	12.48090649	14.43207075	16.87526867	17.52420229	17.54227506	18.48211142	19.26387363	15.56137162
Benue	8.115486351	11.42537663	13.29143005	14.99171813	15.84034752	16.45746437	17.67876396	18.25390732	14.50681179
Borno	9.706214777	14.38133599	16.54912241	15.76519481	15.95559366	17.20342389	18.67998024	20.02262363	16.03293618
Cross River	10.17889445	14.78633974	18.09729622	19.67075928	20.76601623	22.06952096	22.78594678	24.70001334	19.13184838
Delta	11.76321423	16.92061221	20.84308789	21.84955404	22.60404091	24.20875571	25.49943291	27.29969545	21.37354917
Ebonyi	11.4125817	17.9454905	21.15673161	22.22413816	21.7551954	22.10533327	24.40071045	25.13815968	20.7672926
Edo	7.392361561	9.592850875	11.88584335	13.08566841	14.99600018	16.52782784	17.34399054	19.00531006	13.7287316
Ekiti	9.90671592	14.26062054	16.35252284	19.24138175	22.35669282	23.53080306	26.10260767	27.74056052	19.93648814
Enugu	9.740006415	12.96479668	14.86128137	16.71526251	18.91849433	20.31414196	21.59499093	22.41137098	17.19004315
Fct Abuja	8.629938418	13.01528078	16.32782271	17.04628667	18.01968745	18.64700606	19.79223846	20.51548614	16.49921834
Gombe	9.72195246	15.36934586	18.66201432	22.0273836	24.03372947	26.32649683	27.35396851	28.094769	21.44870751
Imo	10.22917818	15.16312193	17.12156707	17.30191842	19.06193682	19.83532225	20.51684525	21.57565193	17.60069273
Jigawa	11.0016732	15.46875333	19.37897726	20.11667307	21.90879904	23.17951196	25.32047731	25.93418806	20.28863165
Kaduna	11.87851953	18.25793927	22.51758606	25.93005612	28.8038502	30.80276552	30.44147464	31.25351811	24.98571368
Kano	9.82604393	13.34870712	15.36275721	16.89669755	18.23028198	19.16966641	19.36472048	19.0486727	16.40594342
Katsina	10.66733632	15.70880214	19.07082799	21.65552911	23.58257495	25.1159702	26.14609136	25.07902154	20.8782692
Kebbi	9.2264955	13.90340281	16.23912469	17.59088793	18.95155354	20.50121626	21.47043823	21.53275619	17.42698439
Kogi	10.65319626	16.18414243	20.25641172	23.32798849	23.07865347	24.78984328	24.63955326	25.34021105	21.03375
Kwara	9.349386487	13.97125985	17.59861741	19.05187082	20.52603891	22.69291647	24.51624172	25.54261791	19.1561187

Lagos	10.02757979	15.57879673	18.63693249	19.58217184	20.79382979	21.2107206	21.34018919	21.67882427	18.60613059
Nasarawa	10.94131043	16.26986507	20.72756434	22.56868144	24.95910642	24.75153836	33.68106727	31.52336032	23.17781171
Niger	8.206655404	11.3854434	14.09600958	16.03261677	17.93210866	19.76373889	20.72532493	23.08715293	16.40363132
Ogun	11.39294685	18.3798116	21.91018773	25.67415402	27.17291179	26.0943203	27.22492319	29.25976279	23.38862728
Ondo	10.23448472	14.10627497	16.7016876	19.39712678	20.89751648	22.72284299	24.79670551	25.87246568	19.34113809
Osun	6.940089197	10.24088946	13.01844167	15.85662577	17.8649022	20.29726526	21.46865505	22.0724205	15.96991114
Oyo	7.2025012	12.51934202	17.08639645	19.71686405	22.70346623	23.07983073	23.54871381	23.04339434	18.6125636
Plateau	7.090813799	12.72108731	16.35442784	20.40438653	22.47884288	24.33158694	24.05219828	24.83485864	19.03352528
Rivers	8.163447039	13.52717943	17.95641612	20.34266673	22.4561589	24.76633792	25.49210509	25.90311165	19.82592786
Sokoto	4.857375504	8.275058149	9.320175824	10.32245148	10.49886832	11.43849817	12.05007468	12.7594499	9.940244004
Taraba	6.246680059	9.640037721	11.46405855	12.87910153	14.8876226	15.31149109	16.41731223	18.88235043	13.21608177
Yobe	5.604036368	9.589834274	12.28395012	13.50253986	15.6674605	18.11631559	18.59192813	18.93191756	14.0359978
Zamfara	5.083394432	8.309686111	10.57116201	11.98531083	13.70447617	15.24065263	16.83438824	16.8208665	12.31874211
Average	8.959663414	13.31063588	16.09495012	17.88876128	19.36899908	20.4970027	21.74273695	22.55227202	17.55187768

4. SARIMA

Table S4 MAPE results per state for SARIMA model evaluated over 26 test sets in Temporal CV approach

States	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Abia	15.66287284	68.21127945	889.5930683	18857.19234	431812.0932	9739678.049	234449463.5	5423432199	708509122.9
Adamawa	21.24742874	39.63107839	79.0446004	178.8479984	497.5868792	1617.305944	5302.56609	17264.20307	3125.054136
Akwa-Ibom	12.21738322	17.64927533	36.45930093	154.437261	840.2457397	6013.277894	47939.02649	342905.5968	49739.86376
Anambra	18.77952078	29.67319043	48.42258186	114.5463882	449.0842756	2091.23081	9996.148337	48765.48556	7689.171333
Bauchi	41.60617704	124.6882439	1808.798177	39850.89225	865200.3347	18399174.76	431769040.5	8912115488	1170398841

Bayelsa	18.858358	27.79691776	38.05818868	65.94996408	169.4207663	670.5008801	3240.60233	19544.85754	2972.005618
Benue	18.52087995	27.36673334	35.86807749	61.47046061	134.9727212	466.5277367	1384.914829	4336.969694	808.3263916
Borno	21.9335267	49.90684356	199.2839101	1201.968247	8206.057416	53786.06624	354790.7793	2386133.505	350548.6875
Cross River	73.44096177	118.1681065	669.1667525	11124.14855	223620.1635	3284865.997	59044294.68	1116185586	147343794
Delta	21.20941436	48.97317028	188.2460586	1094.518013	7527.684068	49169.66632	171464.8778	1336730.724	195780.7374
Ebonyi	23.7162489	36.08587895	48.3728394	62.12137818	83.6602742	108.6738457	212.0531422	338.1912305	114.1093548
Edo	20.92054333	50.54392838	157.5948389	915.6524995	6419.451523	51028.83053	409295.3753	3226302.262	461773.8288
Ekiti	25.27933672	38.3515913	50.53211285	77.69941224	128.6441246	254.1546152	572.310981	1421.315375	321.0359436
Enugu	22.82042995	44.58337494	101.9831587	367.5890169	1617.101341	7254.337097	35422.94812	166907.2332	26467.32447
Fct Abuja	25.14030138	33.28631634	38.03562752	47.03233297	46.07149017	52.58577936	63.07625414	75.26497569	47.5616347
Gombe	15.85405417	24.09372744	79.11770453	475.7509022	4040.276169	35765.38461	444072.6955	4372321.528	607099.3376
Imo	24.89847316	86.68475052	722.4368849	8791.210897	123938.117	1011464.556	16449891.15	201542626	27392193.13
Jigawa	19.37655258	27.21042788	30.39878978	34.38224242	51.10126804	88.79594338	200.2384192	537.47916	123.6228504
Kaduna	22.90490137	39.76960198	118.6756604	744.1140571	6482.762592	53094.09341	397947.2451	3461520.998	489996.3204
Kano	24.75920474	43.30331641	114.3709778	391.2836811	1669.700626	7447.588908	32920.49649	150471.1846	24135.33598
Katsina	22.31182931	80.81794934	847.8590826	12230.96814	185631.4331	2990483.246	49383271.84	738041184.2	98826719.09
Kebbi	22.94436131	34.23971261	52.90846902	96.46189246	271.8546467	1139.371702	5426.972131	28663.95728	4463.588774
Kogi	19.69759225	57.7564127	991.2605433	33046.50573	1298014.188	56604656.32	2161812854	81043330656	10407885037
Kwara	23.25939607	54.65220397	208.5405233	2063.354517	19939.21559	204794.6529	1959494.687	19498468.62	2710630.873
Lagos	19.01053729	42.29197953	142.3781791	625.4721503	3708.876813	19429.32016	112034.6213	645751.8482	97719.22742
Nasarawa	25.39837588	48.58677396	362.4045307	8132.851636	209147.2529	5861082.258	165430402.5	4826214476	624715459.7
Niger	23.32045062	35.58703763	77.14735438	259.4209102	1353.485846	8514.913818	55337.70339	347355.6684	51619.65591

Ogun	80.81652575	253.3054702	6066.315005	235611.7651	9145510.226	367264040	14316528182	543314199283	69750922378
Ondo	21.03039785	39.36834771	126.9683316	919.7372134	11495.43008	138461.5017	2017554.854	28238716.43	3800916.915
Osun	26.96513107	55.92343401	292.7184596	2770.79783	31903.91714	401032.9671	4876506.802	64457884.22	8721309.289
Oyo	16.70705462	58.44948304	570.9131791	7431.691703	102312.4178	1433181.368	20498141.78	273151113.9	36899103.4
Plateau	14.28864581	19.54952878	29.04155116	45.63190681	88.11105434	182.9701261	561.7334246	1579.364827	315.086383
Rivers	14.00522617	20.01470055	28.70324943	46.84945632	106.4687346	311.114155	1044.621324	3871.229312	680.3757699
Sokoto	17.19876565	25.3428026	48.60636469	114.5484174	410.4583691	1836.449362	9140.091312	45066.1885	7082.360486
Taraba	21.91516224	218.4792718	7533.827958	343560.4095	15919457.96	694875139	29651806723	1322190483437	169069179511
Yobe	15.62283293	22.6083684	33.39587823	53.47115635	94.35426217	213.2871792	567.5040136	1604.971658	325.6519186
Zamfara	13.84556881	21.81759669	52.08195493	169.6013142	833.3042445	3985.532679	27365.64573	146101.1689	22317.87475
Average	23.9860655	55.80456288	619.4467547	19778.11747	773330.0941	31419258.83	1273463571	53193720181	6812424602

5. Benchmark (rolling-average) model

Table S5 MAPE results per state for Benchmark model evaluated over 26 test sets in Temporal CV approach

States	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Abia	9.682455429	11.12036114	12.41003561	13.33680345	14.32237291	15.92235634	16.87978314	17.82078792	13.93686949
Adamawa	10.31093719	12.26062444	14.17773882	15.57737469	17.22358415	18.83459486	20.37996952	21.70683737	16.30895763
Akwa-Ibom	9.524844772	10.82684512	12.0232637	13.30822841	14.4637071	16.30702078	17.56208329	18.91678788	14.11659763
Anambra	6.953893773	8.036803347	8.786629265	9.441114363	10.97264226	12.56076021	13.83578123	15.03790321	10.70319096
Bauchi	9.609235689	10.8147349	12.23881233	13.89763909	15.27904995	17.18433964	18.40192622	19.72195693	14.64346184
Bayelsa	9.287803281	10.38172664	11.43476542	12.38335943	12.94995328	14.24835159	15.8399031	17.52617673	13.00650493
Benue	9.991445567	11.44107218	12.84159469	13.99028335	15.53597307	17.31318116	18.217521	19.20328536	14.81679455
Borno	10.81813765	12.14963545	13.28601082	14.12323247	15.21056007	16.83702602	19.23545751	20.67662456	15.29208557

Cross River	11.43534723	13.19213617	14.59245537	15.85610624	16.89991361	18.57840988	19.63837042	20.84360587	16.3795431
Delta	15.51712452	17.96300743	19.83933659	21.23557747	22.40682325	25.06477718	26.98238696	28.32374663	22.1665975
Ebonyi	16.17481192	18.36576269	19.94610057	21.49263765	22.67689573	24.49305582	25.81841637	27.12108799	22.01109609
Edo	8.991419125	10.2537786	11.48816039	12.92773629	14.79349157	16.75112489	18.02077999	19.33227648	14.06984592
Ekiti	13.05564828	15.12059168	16.8843623	18.64728522	21.02223548	23.48645842	25.28488959	27.50328951	20.12559506
Enugu	11.45600331	13.11528492	14.11993423	15.37263107	16.6510265	18.31834485	19.65774234	21.14558826	16.22956944
Fct Abuja	10.43800594	11.69199678	13.07131029	13.95602445	14.89051689	16.20386957	17.19593734	18.50902141	14.49458533
Gombe	12.95526897	14.92123619	16.8244074	18.69967692	20.32770808	22.02549396	22.75167633	23.06943231	18.94686252
Imo	12.80921977	14.17228056	14.96867048	15.45799569	16.60129529	18.20834959	18.94811041	19.41079063	16.32208905
Jigawa	13.01080471	14.77175093	16.48536146	17.63613293	19.14317553	20.38858587	20.87239361	21.33541591	17.95545262
Kaduna	15.51505995	18.08702479	19.69271023	21.84688983	24.25352808	26.3075542	28.18929117	29.76563805	22.95721204
Kano	11.71952447	13.16165589	14.53361942	15.77247328	16.26304323	17.36232607	17.77009274	18.44269283	15.62817849
Katsina	13.74091728	15.82151238	16.96032371	18.0988922	18.78069504	19.72224428	19.95556094	20.08966916	17.89622687
Kebbi	11.00532349	12.78471285	14.33815961	15.81051918	17.25180076	19.10626094	19.73609851	20.04940009	16.26028443
Kogi	15.38439577	17.61398505	19.71225984	20.81532352	21.86941282	22.98147029	24.11100844	25.5578567	21.00571405
Kwara	13.46898434	15.68795975	16.7373696	17.35085571	18.28114506	18.70105869	19.16676863	19.85676303	17.4063631
Lagos	13.55226227	15.59400866	17.01146343	18.02646634	18.32141842	19.20093611	19.69010267	19.95216926	17.6686034
Nasarawa	14.12806131	16.11395155	17.70208444	18.71045139	19.76924623	20.86775874	29.80516282	30.85984124	20.99456972
Niger	11.05660434	12.68421812	14.12181261	15.33592257	16.87233796	19.04664602	20.59303059	22.39511199	16.51321052
Ogun	11.78320993	13.41366382	15.46916713	17.31330079	19.58015916	22.07473111	23.66576782	25.0905026	18.54881279
Ondo	12.33052599	14.03960574	15.83688842	17.67229372	19.74118161	21.80194102	23.06221756	24.73155306	18.65202589
Osun	8.877831186	10.2327081	11.41906691	12.71908527	13.87683215	15.68075175	16.56508664	17.83567527	13.40087966

Oyo	10.58466836	11.96669404	13.3465545	14.55676025	15.18189882	15.14947142	14.84865272	14.64828094	13.78537263
Plateau	11.32600375	13.01061254	14.40379396	15.37478917	16.10592713	16.55939113	16.8620299	17.12981379	15.09654517
Rivers	11.12504091	12.44518124	13.85189738	15.27342069	16.34178789	17.34678127	18.07887719	19.34102271	15.47550116
Sokoto	7.161137877	8.387872763	9.150334049	9.994176916	10.94550184	12.36951236	13.36674674	14.47177337	10.73088199
Taraba	6.881194866	7.795400993	8.422579676	9.341634874	10.57913082	12.08539519	13.34479084	14.7667047	10.40210399
Yobe	9.620655939	10.76742388	11.6907577	12.69147976	13.50617656	14.7402438	15.52855338	16.65060405	13.14948689
Zamfara	7.248977625	8.171619383	9.175191668	10.21296484	11.03370106	11.99602356	12.64904968	13.1861804	10.45921353
Average	11.31169694	12.92917407	14.29716173	15.52047404	16.75475269	18.26558375	19.52735182	20.59529374	16.1501861

6. Commodity-wise Temporal Cross validation

In this section, the cross-validation MAPE results for each of the remaining 4 models is displayed per commodity. Each row represents the average MAPE computed across the CV test-sets for all states.

1. Random Forest

Table S6 MAPE results per commodity for Random forest model evaluated over 26 test sets in Temporal CV approach

Commodities	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Irish potato	7.679865816	10.57556874	11.97099628	13.33898235	14.30759467	15.13467123	16.3325522	17.49966032	13.35498645
Onion	9.771946779	13.95560244	16.31850507	17.35301026	18.18419997	18.81508513	19.90883705	21.278357	16.94819296
Sweet potato	9.918296727	13.74802144	16.11146935	18.00542905	19.91775472	21.23495635	22.26893059	22.68985766	17.98683949
Tomato	9.938182092	14.49133445	17.6457042	19.3690664	20.92104215	21.6082218	22.98855518	23.7899041	18.8440013
Plantain	2.98917284	7.989364207	10.4552983	12.02109168	13.47276278	14.69105206	15.54329601	16.43221961	11.69928219
Average	8.059492851	12.15197825	14.50039464	16.01751595	17.36067086	18.29679732	19.4084342	20.33799974	15.76666048

2. CatBoost:

Table S7 MAPE results per commodity for CatBoost model evaluated over 26 test sets in Temporal CV approach

Commodities	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Irish potato	8.836550216	12.29234325	14.21486759	15.83132568	16.6891316	17.74013315	18.85537308	19.87299126	15.54158948
Onion	11.00075436	15.83189363	18.81140704	20.63119053	21.75414308	22.8948401	24.10877875	25.08386371	20.0146089
Sweet potato	12.78553109	17.80061581	21.36773296	23.22455054	24.78350644	25.64939035	26.07907005	26.42372911	22.26426579
Tomato	11.21700549	16.70193663	20.50760516	23.01628472	24.86077842	26.17595373	28.23793663	28.78542808	22.43786611
Plantain	6.005969867	9.670606463	12.38140941	14.1083657	15.80898779	17.15742657	18.04994162	18.52215837	13.96310822
Average	9.969162206	14.45947916	17.45660443	19.36234343	20.77930947	21.92354878	23.06622003	23.73763411	18.8442877

3. XGBoost:

Table S8 MAPE results per commodity for XGBoost model evaluated over 26 test sets in Temporal CV approach

Commodities	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Irish potato	8.274571575	11.46118877	13.18282188	14.73290631	15.75905641	16.32982558	17.46565211	18.46587915	14.45898772
Onion	10.01500645	14.52627379	17.39094334	18.60639322	19.76297952	20.82800808	22.28281778	23.71002715	18.39030617
Sweet potato	10.36478601	15.27805273	18.31447574	20.24590511	22.0745367	23.60474233	24.45759856	24.81332224	19.89417743
Tomato	9.901251144	14.79559537	18.1884056	20.42366902	21.90906041	22.9297117	25.07230413	25.76568868	19.87321076
Plantain	6.242701891	10.49206873	13.39810404	15.43493277	17.33936236	18.79272581	19.43531216	20.00644286	15.14270633
Average	8.959663414	13.31063588	16.09495012	17.88876128	19.36899908	20.4970027	21.74273695	22.55227202	17.55187768

4. SARIMA

Table S9 MAPE results per commodity for SARIMA model evaluated over 26 test sets in Temporal CV approach

Commodities	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Irish potato	21.46695915	49.64637906	417.5220567	8138.341263	176402.8739	3809860.285	90077532.87	1937539170	253951449.2
Onion	29.37078848	51.82458041	174.6979601	1883.841589	32616.60283	459899.9566	8071449.764	151553261.3	20014920.92
Sweet potato	22.27613354	47.00944244	268.3345722	3079.413532	43530.36273	553993.6927	9015388.638	128053736.6	17208758.29

Tomato	30.77787845	76.93595656	1110.426741	38266.49683	1448531.98	58173760.98	2250359003	85039978728	10918749939
Plantain	16.03856785	53.60645593	1126.252443	47522.49416	2165568.651	94098779.23	4009794480	178711476008	22852197944
Average	23.98606 55	55.80456288	619.4467547	19778.11747	773330.0941	31419258.83	1273463571	53193720181	6812424602

5. Benchmark (rolling-average)

Table S10 MAPE results per commodity for Benchmark model evaluated over 26 test sets in Temporal CV approach

Commodities	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Average
Irish potato	9.228347059	10.56280578	11.82566191	12.98812236	14.29266349	15.97380171	17.27019712	18.57392476	13.83944053
Onion	12.58714832	14.40127588	15.87350639	17.16046833	18.49398547	20.37774703	21.85503097	23.27105971	18.00252776
Sweet potato	12.85710803	14.67539499	16.10486535	17.42966725	18.72794914	20.25191305	21.05315393	21.70175875	17.85022631
Tomato	12.8279627	14.70341788	16.28682092	17.55055211	18.86464109	20.35923673	22.45151717	23.62046186	18.33307631
Plantain	9.057918593	10.30297584	11.39495407	12.47356014	13.39452423	14.36522021	15.00685991	15.80926359	12.72565957
Average	11.31169694	12.92917407	14.29716173	15.52047404	16.75475269	18.26558375	19.52735182	20.59529374	16.1501861