Essays on Forecasting and International Trade in Grain Markets

by

Walter Oliver Ac Pangan

B.S., Zamorano University, 2017
M.S., Kansas State University, 2021

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

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College of Agriculture

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Manhattan, Kansas

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Abstract

Essay 1 – Forecasting Long-term Grain Supply of Low- and Middle-Income Countries. Forecasting models are powerful tools for predicting food supply trajectories, helping policymakers design strategies to improve food security. This study aims to enhance the accuracy of long-term grain supply forecasts by incorporating country-specific characteristics and evaluating alternative modeling techniques. Using a dataset spanning 1980 to 2021 for 78 countries, we evaluate various models to forecast aggregate grain production in each country. To assess model forecast accuracy, we employed a time-series cross-validation approach. Our analysis reveals that Autoregressive Integrated Moving Average models with exogenous variables, country-specific coefficients, linear trends, and weather variables significantly improve forecast accuracy. Our preferred model achieved a mean absolute error of approximately 10% of average production. While there is room for further improvement, our approach represents a substantial advancement over existing methods used by USDA reports.

Essay 2 – In-Season US Corn Acreage Forecasting Using Machine Learning. Estimates of US corn acreage planted estimation are released in two reports. First is the “Prospective Plantings Report,” released in March, and the “Acreage Report,” published in June. The acreage values from these two surveys are later incorporated into the WASDE monthly reports. Most of these reports rely on statistical survey methods to gather data directly from the farmers, with information released on established dates throughout the year. Our study aims to develop machine learning models to deliver accurate and timely updates for in-season corn acreage forecasts. Our methodology employs a dataset from 1995 to 2020 with 92 variables on markets, weather, and field conditions to assess if publicly available data up to May can provide

additional information to predict acreage allocation. The results reveal that we improve the accuracy level to forecast acreage planted. The RF model yields a Mean Absolute Error (MAE) of 33,440 acres, which is lower than the 88,744-acre MAE generated from USDA's Acreage Report estimates. Also, our findings demonstrate the significant predictive value added by incorporating the information of USDA's *Prospective Plantings Report* estimates into models. This indicates modeling complexity alone cannot compensate for the unique insights embedded in farmer survey data. Our study offers a valuable tool to generate a forecast of acreage planted that complements the information provided by the WASDE reports.

Essay 3- Effects of Non-Tariff Trade Barriers in Rice Markets: The Case of Rice Export Bans Imposed by India. In 2024, as a consequence of export market restrictions imposed by major rice exporters, the FAO's price index of rice reached its highest nominal level in 16 years. When international grain market prices surge, national governments frequently intervene to minimize the impact on their domestic food markets. India, the world's major rice exporter, implemented an export ban on broken rice in 2022 and on non-basmati rice in 2023. This paper investigates the effects of the rice export bans imposed by India on the trade flows in the international market. We exploit the differences in export quantities and values on the two major types of rice . Our results indicate that the broken rice export ban had a larger impact on the international broken rice markets since India had a major market share of exports, and the increased exports from other countries were not statistically significant. Also, the results showed that the milled rice export ban had a smaller negative impact because the increase in exports from other countries was larger and statistically significant.

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Nathan Hendricks

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Chapter 1 - Forecasting Long-term Grain Supply of Low- and Middle-Income Countries

1.1.Introduction

The world population is expected to reach 9.8 billion by 2050, with the demand for food expected to increase by 50% by 2050 (FAO, 2023; WRI, 2019). The food supply is subject to several sources of uncertainty, such as climate change, technological advancements, and resource depletion. Such uncertainty can lead to price volatility and food insecurity, as the world experienced during the COVID-19 pandemic with food supply chain disruptions.

Forecasting models are powerful tools for understanding the future trajectories of the food supply and policymakers use these forecasts to design strategies to mitigate food security. Previous studies have demonstrated that official forecasting released by government agencies has a significant impact on the markets and decisions on supply chains (Adjemian, 2012; S. H. Irwin et al., 1994; Isengildina-Massa et al., 2006, 2021). Global supply forecasts also have international trade implications, since they can be used to discover potential trade opportunities for agricultural commodities. However, forecasting grain production is a challenge since a model must capture and incorporate the variables and dynamics that affect agricultural production, and the complexity increases for longer term forecasts.

This study evaluates alternative methods to provide reliable international grain supply forecasts 10 years into the future. The approach of this study is to assess the accuracy of regression, a time series model, and machine learning models. The regression models are constructed considering several specifications such as pooled or country-specific coefficients, linear or non-linear trends, alternative predictors, and different types of fixed effects. The Autoregressive Integrated Moving Average incorporating exogenous variables (ARIMAX) models are estimated using different combinations of ARIMA orders (*p, d, q*) and differ predictor variables. Random Forest (RF) and Xtreme Gradient Boosting (XGBoost) machine learning models are fitted using a wider set of predictor variables and a grid of values was used to tune the hyperparameters. Lastly, we select the best model specification using an out-of-sample validation methodology that accounts for the time-series nature of the data and the goal of long-term forecasting (10-years into the future).

Our work informs the International Food Security Assessment (IFSA) that is released annually by the U.S. Department of Agriculture (USDA). This report provides a one-year and ten-year projection of food security indicators for 83 low- and middle-income countries. The IFSA report forecasts demand for grains (food and non-food), grain production, and the implied additional grain supply requirement. The implied additional grain supply requirement is the gap between the demand and supply of food from a region, which is important for assessing food security and potential areas of food aid needs and international trade opportunities. Previous work by Zereyesus et al. (2022) evaluates the IFSA supply forecasting model using a cross-validation approach to select the best model specification, showing that disaggregating yield models to the subregional level improved yield prediction. We build on their work by (i) developing a time-series out-of-sample validation approach specifically designed for long-term forecasting, (ii) forecasting harvested area and not just yield, and (iii) considering a broader set of potential model specifications.

There are four major strands of literature related to our work on modeling international grain supply. First, climate change is likely to affect global production. Climate change, including temperature and precipitation changes, can potentially reduce not only the grain production and yield but the global agricultural Total Factor Productivity (TFP) (Ceglar et al., 2018; Lobell et al., 2011; Ortiz-Bobea et al., 2021).

For example, the concurrent heat stress and droughts influence on average 53 percent of the inter-annual maize yield variability (Ceglar et al., 2018). Climate change has reduced global agricultural TFP by about 21 percent since 1961 (Ortiz-Bobea et al., 2021). However, crop production to climate change can be mitigated by using improved information forecasting systems for seasonal climatic conditions (Hansen, 2012; Jones et al., 2000; Mase & Prokopy, 2014).

Second, prior studies utilize heterogeneous and potentially non-linear yield trends across countries to forecast future global supply of food (Grassini et al., 2013; Ray et al., 2012). Understanding these trends and conditions provides insights about the potential for grain production to increase in the future, and the rate at which the growth might occur becomes relevant in terms of policy and food security. Hafner's (2003) analysis reveals yield trends across 188 nations, demonstrating that the growth in yield is not constrained by overarching physiological limitations on crop productivity. Third, several studies estimate how global supply responds to prices (Haile et al., 2014; Hendricks et al., 2015; M. J. Roberts & Schlenker, 2013).

Haile et al. (2016) observe that higher futures prices stimulate an expansion in global crop supply, as anticipated. However, they note that grain price volatility acts as a deterrent. In a related study, Haile et al. (2014) report that global acreage adjusts in response to international crop prices, price risks, input costs, and temporal trends. However, the purpose of these studies is to estimate a supply elasticity that is relevant for policy analysis rather than forecasting supply in the future.

Recently, more studies have employed machine learning models to forecast final yields during the growing season. Cai et al. (2019) forecasted wheat yield by employing climate and satellite data and comparing regression-based methods (LASSO) with machine learning methods such as Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Networks (ANN). Their results show that machine learning is more accurate when modeling crop yield and that employing climate and satellite data provides better estimates than using one of them alone. Feng et al. (2020) employs a hybrid yield forecasting approach to predict wheat yield, showing that the accuracy of the predictions is higher for the Random Forest model than for the process-based crop model and multiple linear regression models. Fillipi et al. (2019) forecasted grain crop yield using a multi-layered, multi-farm data set and Random Forest models, and their findings show that as more information about within-season data becomes available, the forecast accuracy increases.

Johnson et al. (2016) developed crop yield forecasting models for barley, canola, and wheat using Multiple Linear Regression (MLR), Bayesian Neural Networks (BNN), and model-based recursive partitioning (MOB). Employing remote sensed vegetation indices such as NDVI and EVI as predictors. Their results showed that BNN and MOB models have significantly higher forecasting accuracy than MLR for the case of barley. Similar results by Li et al.(2007) find that ANN models have higher prediction accuracy than MLR models. Roznik et al. (2023) estimated corn yield forecasts using satellite and weather data employing XGBoost, and their results indicate that XGBoost models have a similar accuracy forecast to the current World Agricultural Supply and Demand Estimates (WASDE) corn yield forecasts, which are based on survey methodology.

Some studies have focused on forecasting only one aspect of production, whether yield or area. As mentioned earlier, Zereyesus et al. (2022) forecast global yields. Haile et al. (2016) develop an acreage response model as a function of its own and competing crop prices, input prices, and other exogenous variables to forecast harvested area 3 months prior to planting.

While the studies mentioned above provide evidence of climate change impacts, heterogeneous yield trends, supply elasticities, or forecast one aspect of production, there is less work that incorporates all three factors and forecasts both area and yield simultaneously in an international context. We address this gap in the literature by developing long-term (10-year) forecasts of both acreage and yield for low- and middle-income countries. In terms of Mean Absolute Errors, our selected model reduces 10-year forecast errors by more than half compared to the model currently used in the USDA IFSA (International Food Security Assessment) report.

1.2.Methods

Our modeling methodology aims to find the best specification at out-of-sample forecasting of grain production. We establish a general model specification and evaluate several variations to accomplish this objective. Note that for our analysis, we aggregate the production of six grains (barley, corn, rice, millet, sorghum, and wheat) using caloric equivalents, rather than modeling the production of individual crops. The following part of this section provides a general description of the four models estimated in this study which are Regression, Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX), Random Forest (RF), and Xtreme Gradient Boosting (XGBoost) models. Lastly, we describe our out-of-sample validation methodology to assess the models.

1.2.1 Decomposition of Production Forecasts

Our approach to forecast grain production employs the decomposition of production into two components: harvested area and yield (i.e., production per unit of area). This is written as

$$Prod_{i,t} = Area_{i,t} * Yield_{i,t}, \qquad (1.1)$$

where $Prod_{it}$ is the production in country (i) and year (t), $Area_{it}$ is the harvested area, and $Yield_{it}$ is the yield. We estimate separate models to forecast $Area_{it}$ and $Yield_{it}$. Then we generate a forecast of production by multiplying the forecast of $Area_{it}$ times the forecast of $Yield_{it}$.

1.2.2 Regression Models

The general econometric specification to forecast production is written as:

$$Y_{i,t} = f(t, \theta_i) + \beta_i X_{i,t} + \alpha_i + \varepsilon_{i,t}, \qquad (1.2)$$

where Y_{it} denotes the dependent variable: either Area (Millions of Hectares) or Yield (Millions of kcal per Hectare) for country *(i)* and year *(t)* ; $f(t, \theta_i)$ denotes a trend that could either be linear or non-linear; β_i are the coefficients for each predictor variable; X_{it} are the predictor variables (i.e., futures prices, spot prices, temperature, and precipitation); α_i are country-fixed effects; and ε_{it} are the residuals. In the most general specification, we allow country-specific trends and country-specific coefficients on predictors so that the coefficients have an i subscript θ_i and β_i. The OLS model is estimated using the "fixest" package in R (version 0.12.0.)

Note that our objective is to forecast production into the future and not to provide causal estimates of how different factors affect production. Therefore, we do not impose economic theory on the specification. Instead, we keep the specification as flexible as possible and allow out-of-sample prediction errors to guide the model selection. Next, we summarize each of the variations on the general model specification in Equation 1.2 that we considered and assess the forecast accuracy of each specification.

Predictor Variables: We consider specifications with different predictors included in X_{it}. One option that we consider is to have no additional controls and model production simply according to trends. We also consider different combinations of prices, precipitation, and temperature as predictors.

Pooled versus Country-Specific Coefficients: We estimate a single coefficient for each of the predictors (i.e., pooled) or we allow the coefficients to differ across countries.

Fixed Effects: The specifications also include some that have a common intercept across countries and others with country-specific intercepts (i.e., country fixed effects), sub-regional intercepts, or regional intercepts.

All 3,444 combinations of predictors, pooled versus country-specific coefficients, and fixed effects that we considered in this study are illustrated in Tables A1 and A2 in the Supplementary Appendix A. All model specifications result from evaluating multiple combinations of variables and model structures considered during the estimation process.

Linear versus Poisson: We also estimate all 3,444 regressions using ordinary least squares (OLS) and a Poisson regression to allow different functional forms for how the predictors impact production. Poisson models the functional form $Y_{it} = \exp(\cdot)$, which is similar to an OLS model where the dependent variable is a natural logarithm (i.e., $\ln(Y_{it})$). While the linear specification assumes that a change in the predictor affects the dependent variable by a certain number of units, the Poisson specification assumes that a change in the predictor affects the dependent variable by a certain proportion.

Linear versus Non-linear Trends: The trend is either assumed to be linear or a flexible non-linear function. When a non-linear relationship is allowed, we use a natural cubic spline with three knots. Natural cubic splines have several advantages over polynomials in that they allow non-symmetric, non-linear trends with relatively few parameters estimated (James et al., 2013).

To summarize, all 3,444 model specifications were fitted with area as the dependent variable and again with yield as the dependent variable. Then these models were fitted using both OLS and Poisson models and with linear and nonlinear trends.

1.2.3 Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) models

We also estimate Autoregressive Integrated Moving Average models with exogenous variables (ARIMAX). ARIMAX models account for the historical information of a series using autoregression, moving averages, and differentiating (Box & Jenkins, 1970). Also, we include the effect that one or more exogenous variables have on the stationary variable Y_t. According to Hyndman and Athanasopoulos (2018), the ARIMAX model is written as:

$$Y'_{i,t} = \sum_{\tau=1}^{p} \phi_i Y'_{i,t-\tau} + \sum_{\tau=1}^{q} \varphi_i \varepsilon_{i,t-\tau} + \beta_i X_{i,t} + \alpha_i + \varepsilon_{i,t}, \quad (1.3)$$

where $Y'_{i,t}$ is the differentiated time series variable predicted (i.e., Area or Yield). The predictors on the right-hand side include lagged values of $Y'_{i,t}$, lagged errors (ϵ_{t-q}), and exogenous variables (X_{it}). This is defined as an ARIMAX model where the orders (p, d, q) are defined as p is the order of the autoregressive component, d is the degree of time series differencing, and q is the order of the moving average component. Further, this model incorporates exogenous variables (X_{it}), and α_i is the intercept. The ARIMAX models are estimated using the "forecast" package in R (version 8.22.0).

Autoregressive Component: This component of the model assumes the current observation has a relation with past observations. The Autoregressive order is denoted as p and indicates the number of lagged observations of the dependent variable used to estimate the model.

Differencing Component: This component of the model is used to make the time series stationary if needed. The differencing removes seasonality and a linear trend if present. The Differencing order is denoted as d.

Moving Average Component: This component of the model assumes the current observation has a relation with a linear combination of past error terms.

Predictor Variables (X_{it})*:* This component of the model helps to incorporate changes or shocks to the model faster than only considering and relying on lag values as a source of information. Exogenous variables considered in the model include prices and weather variables. Several combinations of orders and exogenous variables were assessed as described below.

The non-stationary nature of the production, area, and yield series across countries is confirmed by Augmented Dickey-Fuller (ADF) test. We difference the time series to address the non-stationary nature of the data. We used Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to look for appropriate ARIMA orders (p, d, q). We employed the R-function "*auto.arima*" to look for potential ARIMA orders (p, d, q) . According to Hyndman & Athanasopoulos (2014) the "*auto.arima*" function from the forecast R-package selects the best model using AICc criterion.

To keep the potential specifications more concise, we limit the possible order combinations to only four sets of orders (*p, d, q*) based on ACF, PACF, and the "*auto.arima"* function selections. We identified that the most common orders selected across the 78 countries are (1,1,1), (1,1,0), (0,1,1), and (0,1,0). The ARIMA models are estimated using Maximum Likelihood (ML). The combinations of ARIMA orders and predictors are shown in Table A3 of the Supplementary Appendix. In total, 328 different ARIMAX specifications were considered.

1.2.4 Random Forest (RF) models

An advantage of using machine learning algorithms to forecast is that we can use several variables and let the algorithm select among the variables depending on which variables provide more predictive power. According to Breiman (2001), the Random Forest algorithm is an ensemble learning method that aggregates a large set of predictions of decision trees to improve accuracy and robustness. The major strength of the model is its ability to avoid overfitting and enhance predictive performance by averaging the results of multiple trees. For more details about the RF algorithm refer to Breiman (2001).

RF models have hyperparameters that must be tuned to provide the best forecast. To generate the RF models, we employ the R-package '*randomForest* 'version (4.7.1.1), and tune three hyperparameters: the Number of Trees (N_{tree}), the Number of Features to Consider for each Split (m_{try}), and the Node size or Minimum Samples per Leaf (N_{node}). Following the recommendation of James et al. (2013), we use the default values for $N_{tree} = 500$, and $m_{try} = p/3,$. where p is the number of predictor variables used to estimate the RF model (e.g., we tuned the parameter $N_{node},$ first using as reference the default value 5, and considering a range of values to assess how the MAE increases or decreases as we change the node size).

1.2.5 Xtreme Gradient Boosting (XGBoost) models

We employ the XGBoost model to generate forecasts. According to Friedman , this algorithm is based on the principles of gradient boosting, iteratively combining simple decision tree models to optimize the accuracy of the predictions. As it moves forward at each step, it identifies the errors made by the current model and generates a new model that focuses on correcting the errors made by the previous model, so gradually the prediction performance improves. This approach enables XGBoost to handle large and complex datasets efficiently, while at the same time minimizing the prediction errors by optimizing a predefined objective function. For more details about the XGBoost algorithm refer to Friedman (2002).

The XGBoost model has 5 hyperparameters to tune. To tune the hyperparameters, we follow a methodology similar to that employed by Roznik et al. (2023). Initially, we explore a range of values around the default settings for each hyperparameter of the R-package '*xgboost*' version (1.7.10.1). Based on preliminary insights from these values, where we assess each parameter separately, we identify a range of values where MAE of each model tends to be the lowest. After determining this range, we create a grid encompassing all the hyperparameters, including the identified value ranges that are likely to produce a lower MAE. Finally, we iterate through all potential combinations within this grid to select the hyperparameter values that yield the lowest MAE. After completing the tuning process previously described, the selected values are as follows: Maximum Depth (*max_depth* = 3), Learning Rate or eta ($\boldsymbol{\eta}$ = 0.05), Subsample (*subsample* = 0.8), Minimum Sum of Instance weights (*min_child_weight* = 3), Number of Boosting Rounds (*nrounds* = 500), and Objective Function to Minimize (*objective* = reg:squarederror). After tuning the hyperparameters, we generate the rolling forecasts to perform the out-of-sample validation to assess the forecast accuracy of the ML models as described in the following section.

1.2.6 Time Series Out-of-Sample Validation

We employ out-of-sample validation on our time series data to evaluate the forecast accuracy of each model specifications. Out-of-sample validation assesses forecast performance by comparing predicted values with actual values, a standard procedure widely used for model evaluation in classification and regression (Bergmeir et al., 2018). First, the model is estimated (i.e., training the model) with a portion of the data referred to as the training data. Then, the fitted model is used to predict the outcome of a different portion of the data, referred to as the testing data. We use an out-of-sample validation exercise that accounts for the time-series nature of the forecast. For example, the model is trained with data up to a certain year, and then the model is used to predict production for some year in the future (Hyndman & Athanasopoulos, 2014).

We perform out-of-sample validation using point rolling forecasts 10 years into the future with the following procedure. First, we train the model with data from 1980 to 2002 and predict the outcome for 2012. Second, the model is trained with data from 1980 to 2003 and the outcome for 2013 is predicted. We continue this process, each time extending the training period by one year and forecasting the next year until we reach the most recent available data in 2021. This results in ten different models, each providing a 10-year-ahead forecast. The complete data set spans from 1980 until 2021. Figure 1.1 illustrates the out-of-sample validation procedure.

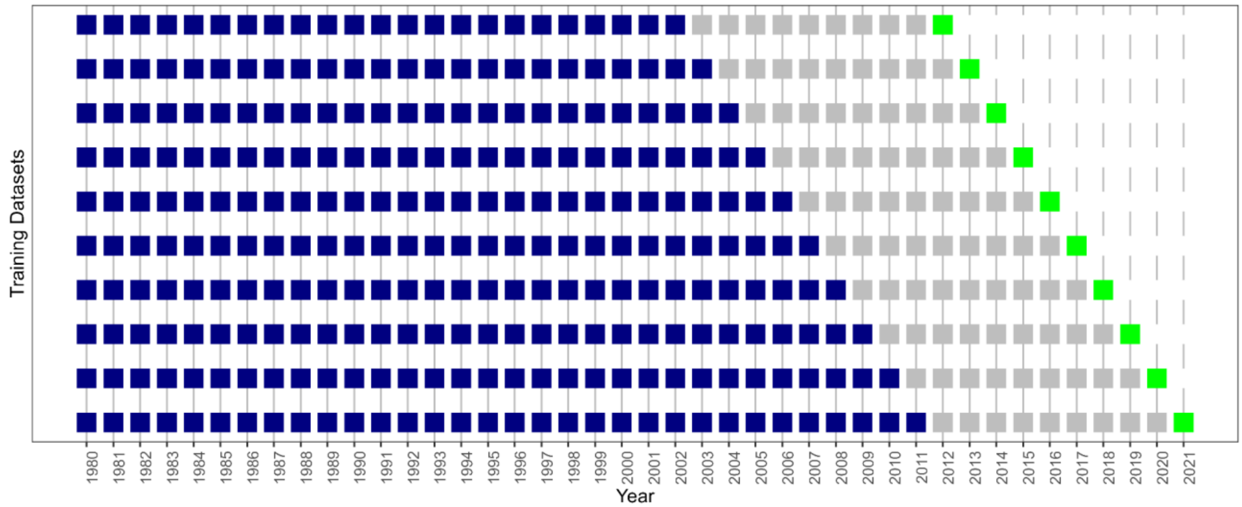


Figure 1. Out of Sample Validation

Note: Blue boxes represent train data, gray boxes indicate unused data, and green boxes show predicted outcome

Figure 1.1 Out-of-sample Validation

1.2.7 Accuracy Metrics

Estimating the model for yield and area separately leads us to several combinations of specifications to estimate production using the forecasted values. We select the top ten models for predicting area and yield (for regression and ARIMAX models). Subsequently, we calculate production using all possible combinations of the top ten models for area and yield predictions, resulting in 100 forecasts of production for regression and 100 forecasts for ARIMAX specifications. For RF and XGBoost, there is only one selected specification for area and one specification for yield, so each model only has one forecast for production.

The prediction errors, the difference between the out-of-sample forecasted production values and the real production values in the test dataset, are used to calculate the Mean Absolute Error (MAE) in Equation 1.4, Mean Absolute Percentage Error (MAPE) in Equation 1.5, and Root Mean Square Error (RMSE) in Equation 1.6.

$$MAE = \frac{\frac{1}{N}\sum_{i=1}^{N}(\frac{1}{10}\sum_{t=1}^{N}|\hat{Y}_{i,t} - Y_{i,t}|)}{\frac{1}{N}\sum_{i=1}^{N}(\frac{1}{10}\sum_{t=1}^{10} Y_{i,t})} \tag{1.4}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left\{\frac{1}{10}\sum_{t=1}^{10}\left[\frac{|\hat{Y}_{i,t} - Y_{i,t}|}{Y_{i,t}} * 100\right]\right\} \tag{1.5}$$

$$RMSE = \frac{1}{N}\sum_{i=1}^{N}\left\{\left[\frac{1}{10}\sum_{t=1}^{10}(\hat{Y}_{i,t} - Y_{i,t})^2\right]^{1/2}\right\}, \tag{1.6}$$

where $\hat{Y}_{it}$ is the forecasted value and Y_{it} is the real value of the predicted variable. To create a single accuracy measure across countries, we average the accuracy measures across the 10 years and across all countries, where N is the total number of countries. We do not calculate a weighted average MAE or RMSE across countries because these metrics already implicitly include weighting—countries with larger production will tend to have larger errors and effectively receive more influence in the aggregate metric. We divide the MAE by average production so that the MAE is interpreted as the error relative to average production.

Our preferred accuracy metric is MAE, so the preferred specification has the smallest MAE. These metrics are commonly used to evaluate forecasting models, but there is no clearly dominant metric since all have advantages and limitations. While we use MAE as the criteria to select the preferred model specification, we also show results for MAPE and RMSE. Our main results—that ARIMAX provides the best forecast and that our forecast is a significant improvement compared to the current IFSA model—are not affected by the selected accuracy metric.

Using the selected model specification, we forecast production for one year and ten years into the future (i.e., 2023 and 2033) as would be the practice of the USDA IFSA report. To create a production forecast in 2023 and 2033, we do not attempt to forecast prices or weather in the future, so we use the most recent five-year average for each predictor as the assumed value for future years.

1.3.Data

We collect production, area, prices and weather data across 78 countries from 1980 to 2021 for six major crops: corn, sorghum, millet, barley, wheat and rice. The IFSA report that USDA assembles each year includes 83 countries; however, we use 78 countries in our analysis due to data limitations of some countries that are discussed in more detail in Supplementary Appendix A.

Production, Area, and Yield: We obtain production and harvested area from the USDA Foreign Agricultural Service Production, Supply and Distribution (PSD). The unit for production is millions of kilocalories (kcal), area is in hectares, and yield is in millions of kilocalories per hectare. While PSD has production data in metric tons, we convert to calories using the caloric equivalents from FAOSTAT (2023), allowing us to aggregate production across crops. Yield is calculated as total grain production divided by total area.

Prices: Our model specifications consider two different measures of crop prices as predictors variables in the model specifications: futures prices from the Chicago Board of Trade and local spot prices from the World Bank commodity price database. We use futures and spot prices a month before planting for each crop since it is the most relevant prices as farmers make most production decisions before planting a crop and it avoids endogeneity concerns (Haile et al., 2016; Hendricks et al., 2015). We construct crop prices relevant to the crop season of each country using the United Nations Food and Agriculture Organization Global Information and Early Warning System (GIEWS), which provides planting months for different countries and crops. However, some countries do not have specified planting months, so we spatially interpolate these missing planting months using nearest neighbor interpolation. Then, we aggregate prices across crops using a simple and weighted average to derive an average annual grain price for each country. The weights used to estimate the weighted average represent a share of grain production for the specific crop between 1990 and 1999. Futures and spot prices are in USD per million kilocalories.

Weather: Annual and monthly weather data at the country level are obtained from the Climatic Research Unit (CRU) at the University of East Anglia. CRU creates monthly country-level data by averaging monthly gridded weather data within each country. We use the cumulative precipitation (mm) and the average temperature (°C) for each month and year.

The summary statistics in Table 1.1 are from the final data set used to forecast production that spans from 1980 to 2021 for 78 countries. It is important to highlight that not all countries produce the same crops, so even if some crop price measures are global, they will differ across countries due to different crops being produced and different planting seasons. The average production in our data set is 1885.5 million kilocalories, with an average harvested area of 3.31 million hectares and an average yield of 4.8 million kcal per hectare.

Table 1.1 Summary Statistics, data from 1980 until 2021.

Variable	Units	N	Mean	St_Dev	Min	Max
Production	Million kcal	3179	1,885.5	823251,375.2	19075,836.2	65069,188.4
Area	Million Hectare	3179	3310,023.1	10275,109.6	8,000.0	93417,000.0
Yield	Million kcal per Hectare	3179	4.8	2.9	0.5	20.9
Future Prices (Simple Average)	USD per Million kcal	3179	1,182.9	537.1	426.4	3,587.8
Future Prices (Weighted Average)	USD per Million kcal	3179	2656	3,369.3	0	16,766.9
Spot Prices (Simple Average)	USD per Million kcal	3179	796.4	305.3	345.7	2,917.4
Simple Average (Weighted Average)	USD per Million kcal	3179	28,235.7	31,631.0	371.8	319,695.0
Annual Precipitation	mm/Year	3179	1,101.1	723	13	3274.5
January Precipitation	mm/Month	3179	64.7	80.6	0	435.8
February Precipitation	mm/Month	3179	60.8	72.3	0	479.7
March Precipitation	mm/Month	3179	70.4	69.5	0	409.5
April Precipitation	mm/Month	3179	74.6	64.5	0	399.5
May Precipitation	mm/Month	3179	92.6	85.6	0	565.4
June Precipitation	mm/Month	3179	104.4	112.4	0	595
July Precipitation	mm/Month	3179	122.8	133.5	0	961.4
August Precipitation	mm/Month	3179	135.8	146.5	0	1442.6
September Precipitation	mm/Month	3179	122.5	121.9	0	610
October Precipitation	mm/Month	3179	103.7	97	0.1	562.5
November Precipitation	mm/Month	3179	76	76.1	0	522.8
December Precipitation	mm/Month	3179	68	77.8	0	495.4
Annual Temperature	°C	3179	22	6.5	-1.5	30.1
January Temperature	°C	3179	18.1	10.9	-25.5	29
February Temperature	°C	3179	19.4	10.4	-23.9	30.9
March Temperature	°C	3179	21.4	8.9	-12.4	33.5
April Temperature	°C	3179	23.1	7.1	-1.5	34.8
May Temperature	°C	3179	23.9	6.1	4.3	35.2
June Temperature	°C	3179	24.2	5.6	4.7	35
July Temperature	°C	3179	24.2	5.2	4.2	34.8
August Temperature	°C	3179	24.2	4.7	6.3	33.8
September Temperature	°C	3179	23.8	4.8	7.2	33.9
October Temperature	°C	3179	22.6	6.3	-2.6	31.5
November Temperature	°C	3179	20.6	8.4	-14.2	30.2
December Temperature	°C	3179	18.7	10	-21.3	28.6

1.4. Results and Discussion

The discussion of the results is composed of five sections. First, we discuss the forecast accuracy of the alternative models. Second, we describe the preferred model specification that provides the best forecast accuracy. Third, we illustrate the out-of-sample validation technique with the preferred specification. Fourth, we discuss the forecasts of future production in 2023 and 2033 using the preferred specification. Finally, we compare our forecast accuracy with the current IFSA model. It is important to highlight that our main objective is to evaluate alternative methods to provide reliable grain supply forecasts for the long term and improve forecast accuracy. Therefore, we do not examine any causal inference relations between the predictor variables and production.

The information generated in this study contributes to assessing the food security status of the low- and middle-income countries. Forecasting food production is essential to identify potential supply shortages since we can determine which countries are more likely to have demand outpace supply. Also, this can be interpreted from an international trade angle since major grain exporter countries, like the U.S., can identify future demand for grain in the global markets.

1.4.1 Forecast Accuracy of Alternative Models

Figure 1.2 depicts the best models to predict production, specifically showing the Top 50 ARIMAX models, the Top 50 OLS models, the best RF Model, and the best XGBoost model. OLS models performed better than Poisson model and linear trends performed better than natural cubic splines, so we only show results using OLS with linear trends. Using the difference between the forecast and the real production values, we estimate the accuracy measures MAE, MAPE, and RMSE. A lower MAE, MAPE, and RMSE indicates better model forecast performance. We rank the models based on MAE, where the model with the lowest MAE is ranked first. The MAPE and RMSE are plotted using the MAE ranking (see Figure 1.2).

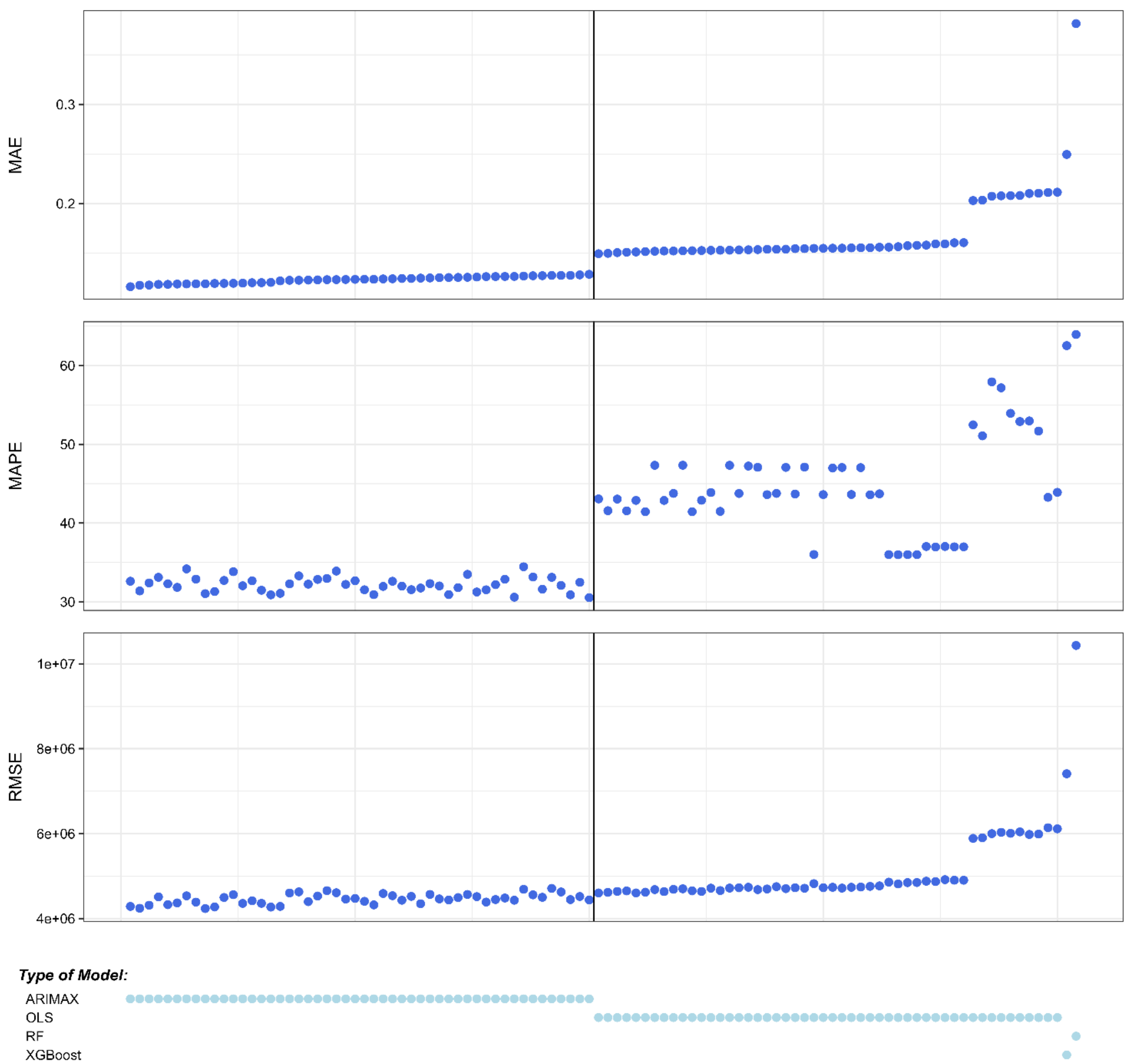


Figure 2. Accuracy Comparison: Top 50 Regression, Top 50 ARIMAX and Top 2 Machine Learning Models

Figure 1.2 Accuracy Comparison: Top 50 Regression, Top 50 ARIMAX and Top 2 Machine Learning Models

Three key observations stand out from Figure 1.2. First, the ranking reveals that the Top 50 ARIMAX models span MAE values representing between 10-13% of average production, while the MAPE values range is 20-35%, and RMSE values range is 4,000,000-4,700,000. Second, although the model with the lowest MAE is not the model with the lowest MAPE and RMSE, the metrics give relatively similar conclusions. For example, all three metrics indicate that ARIMAX models are preferred to OLS, RF, or XGBoost. The ARIMAX model with the lowest MAE also has one of the lowest RMSE. Third, Trends and temperature are common predictors among the top 50 best models for yield and area, either in OLS or ARIMAX, for both area and yield models (See Figure A1 in Supplementary Appendix A).

Additionally, the orders (*p, d, q*) of ARIMAX models having lower error results for area models are (0,1,0). Whereas, for yield models, it is unclear which orders perform best since we find all the orders considered in the top 10 ranking. While these figures cannot show what aspects of the model specification improve prediction the most, the results indicate that models with country-specific trends and country-fixed effects are especially important for prediction accuracy (See Figure A1 in Supplementary Appendix A).

Another important observation from Figure 1.2 is that machine learning models perform substantially worse than linear ARIMAX and OLS regression models. For example, XGBoost has errors that are about 30% the size of average production, while ARIMAX has errors that are only about 10% the size of average production. Although machine learning models did about as well predicting yield, machine learning models were much worse at predicting area. Machine learning excels in applications with large data with lots of predictors that have nonlinearities and interaction effects—often highly disaggregated data. Our setting has relatively limited aggregate data and there is not a large set of predictors, so simple models like linear trends tend to perform relatively well. Machine learning also performs well in settings with predictions of outcomes in similar settings as the training data. In our context, we are forecasting 10 years beyond the training sample, so simple prediction methods perform better for such long-term forecasts.

1.4.2 Preferred Model Specification

There are two preferred ARIMAX model specifications, one for Yield and one for Area. These models are used together to provide the lowest MAE of the forecast for production. The model specifications are:

$$\Delta Yield_{i,t} = \beta_i Temperature_{i,t} + \varphi_i \varepsilon_{i,t-1} + \alpha_i + \varepsilon_{i,t}, \quad (1.7)$$

$$\Delta Area_{i,t} = \beta_i Temperature_{i,t} + \beta_i SpotPriceSA_{i,t} + \alpha_i + \varepsilon_{i,t}, \quad (1.8)$$

where $Yield_{it}$ and $Area_{it}$ represent Yield and Area predicted, $Temperature_{it}$ is average annual temperature, and $SpotPriceSA_{it}$ is the Spot Price using a Simple Average. Both model include country-specific coefficients and intercepts since the ARIMAX models are estimated separately for each country. The yield ARIMAX model has orders (0, 1, 1) which indicates the model is estimated using times series (Yield) differenced, with a Moving Average component of the yield. The area ARIMAX model has orders (0, 1, 0), implying differencing but no Autoregressive or Moving Average components. Note that the two preferred specifications both include differencing with an intercept, this indicates that the models implicitly include country-specific linear trends for area and yield.

1.4.3 Out-of-sample Validation

Figure 1.3 depicts an example of ten-year rolling forecasts generated for 2012 and 2021 that were used in the out-of-sample validation. The vertical lines indicate the end of the training data sets used to create the prediction. For example, when predicting production for 2012, we use a training dataset from 1980 to 2002 to fit the model, then we predict area and yield in 2012. Finally, we calculate production in 2012 using the area and yield predictions as shown in green in Figure 1.3.

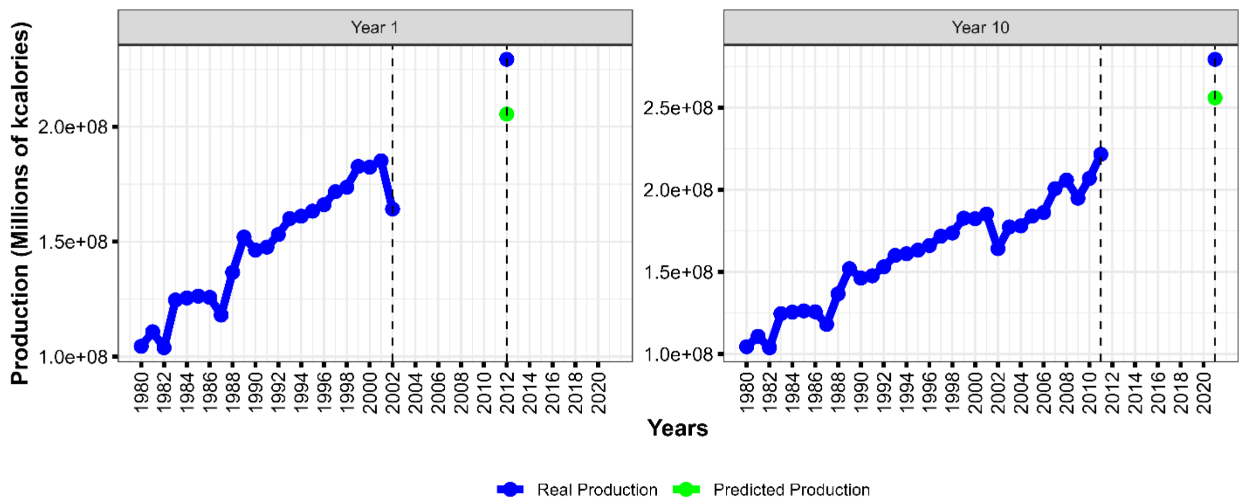


Figure 3. Time-series validation preferred specification

Figure 1.3 Time-series validation preferred specification

Out-of-sample prediction accuracy is shown by comparing the green point to the blue point. The graphs illustrate the challenge of forecasting production for 10 years in the future. For some countries, the trend in production in the training data up to 10 years prior to the prediction is leading in a different direction than actual production after the training period leading to an increase in forecasting errors. This reflects the importance of utilizing out-of-sample validation to select the preferred model specification since unforeseen events can change the production trend at the country level and the out-of-sample validation avoids selecting a model that overfits the data. The model predicts well, especially in countries with large production, such as Cambodia, India, Indonesia, Malawi, Nigeria, and Pakistan. Countries that are less politically stable or where data quality may be a concern generally have poorer prediction accuracy.

1.4.4 Forecasting with Preferred Model Specification

Figure 1.4 shows the forecasts for 2023 and 2033 production based on the preferred model specification to predict production for two example countries, Benin and India. We train the models with all data from 1980 to 2021 to create the forecasts. Note that production is predicted for 2023 since 2023 production data were unavailable at the time when the analysis was conducted. Actual production in the historical data is indicated in blue, and the point forecasts for 2023 and 2033 are indicated in red in Figure 1.4. The forecasts for 2023 and 2033 assume average prices and weather from the most recent five-year observed period. The 2023 forecast values shown in Figure 1.4 are only shown for the purpose of demonstrating how a model trained for long-term forecasting performs in a short-term context; no additional assessment was conducted on these forecasted points.

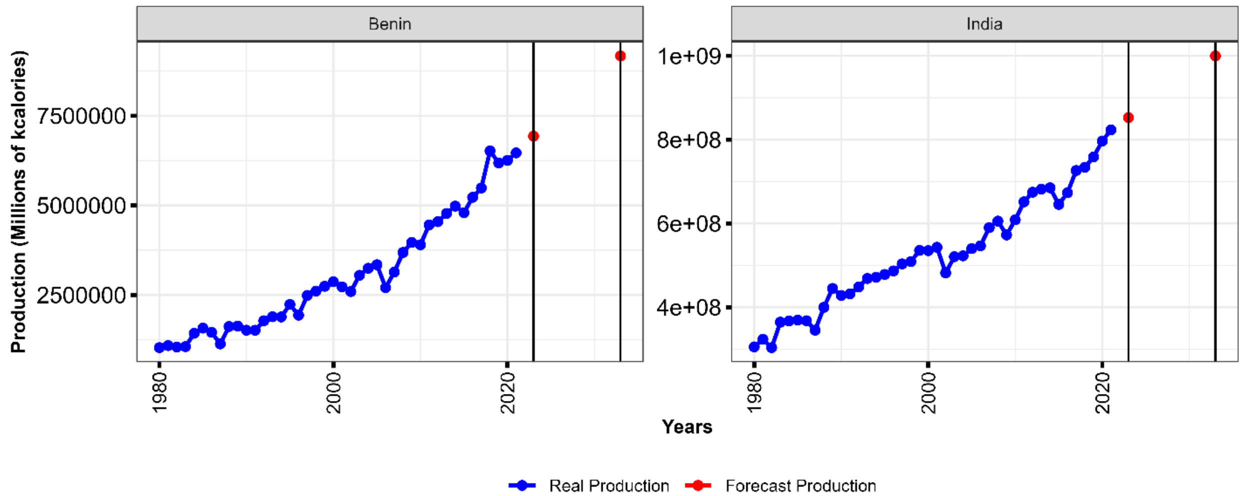


Figure 4. Forecast of 2023 and 2033

Figure 1.4 Forecast Production for 2023 and 2033

Additionally, Figure A2 in the Supplementary Appendix A shows the 2023 and 2033 forecasts for all 78 IFSA countries included in this study. There are a few noteworthy observations. First, production is expected to increase by 2033 for all countries except Armenia, Eswatini, Gambia, Georgia, Honduras, Lesotho, Somalia, and Yemen. Second, smaller developing countries tend to have more erratic production trends, so it is difficult to make reliable long-term forecasts of production. This could be a consequence of poorer quality production data due to the lack of infrastructure or entities that produce the data. Alternatively, it is possible that the lack of knowledge or access to technology makes production more volatile across years. Additionally, political instability is an external factor that can impact the quality and access of high-quality crop production data and create more volatility in production.

1.4.5 Comparison with the current IFSA model

There are some data and modeling differences when comparing the performance of the current IFSA model and our preferred model specification. First, the current IFSA model does not forecast harvested area using an econometric model like in our preferred specification. Instead, the current IFSA model's area equation is calibrated using the rolling average of the prior 3-years of data. Second, the current IFSA model uses subregional-specific trends, subregional-specific coefficients and country-specific intercepts. Third, the IFSA model uses a lagged moving-average grain yield ratio, which incorporates domestic grain and fertilizer prices. Fourth, the current IFSA model does not include weather variables as predictors. Additionally, the current IFSA model is an Ordinary Least Squares (OLS) model, while our preferred specification is estimated using ARIMAX. The methodology to estimate the current IFSA model employs the following econometric regression:

$$Yield_{i,t} = \beta_{1,r}t + \beta_{2,r}MA2Rev\_Fert_{i,t} + \beta_{3,r}MA5Rev\_Fert_{i,t} + \alpha_i + \varepsilon_{i,t}, \quad (1.9)$$

where $Yield_{it}$ denotes the current Yield (millions of kcal per Hectare), α_i are country fixed effects, and $\varepsilon_{i,t}$ are residuals. The subscript i denotes each country, t denotes a year, and r denotes the subregion. Note that the coefficients on the trend and variables are specific to each subregion rather than each country. The variable $MA2Rev\_Fert_{i,t}$ denotes a lagged moving average of the grain yield ratio over the previous two years as shown in the following equation:

$$MA2Rev\_Fert_{i,t} = \frac{1}{2}\sum_{\tau=1}^{2}\left(\frac{DGrainP_{i,t-\tau}}{DFertP_{i,t-\tau}} * Yield_{i,t-\tau}\right) \quad (1.10)$$

where *DGrainP* is the domestic grain price and *DFertP* is the domestic fertilizer price. The variable $MA5Rev\_Fert_{i,t}$ is calculated in a similar way, but using a lagged 5-year moving average. For more information about the current IFSA model, see Zereyesus et al. (2022b).

To compare the current IFSA model and our preferred model specification to forecast yield, we employ our out-of-sample validation to assess the forecast accuracy of both models. There are some limitations to being able to compare the models. For example, the IFSA model includes a 2-year and 5-year moving average, so the training data can only start from 1985 and not 1980 as used to validate our selected model. Another limitation is related to data availability; we can only use data from 65 countries and not 78 countries because the current IFSA model uses additional variables that are not available across all the countries.[1]

Using a data set with the same time frame and countries to estimate the models, we estimate the models using the current IFSA model specification and our preferred model specification. We forecast yield using our out-of-sample validation to get the accuracy metrics (MAE, MAPE, and RMSE) for each model. Table 1.2 shows our selected model specification shows substantially better MAE, MAPE, and RMSE values than the current IFSA model specification. In terms of MAE, our preferred model specification reduces the 10-year forecast errors by more than half.

[1] To compare the methods, we use the same set of countries by dropping the following 13 countries: Burma, Congo, Cote d'Ivoire, Democratic Peoples Republic of Korea, Namibia, Buinea-Bissau, Somalia, South Africa, Democratic Republic of the Congo, Sudan (Former), Eritrea, Laos, and Yemen

Table 1.2 Accuracy measures of current IFSA model and selected model (65 Countries from 1985 to 2021)

Model	MAE	MAPE	RMSE
Preferred Yield Model	0.20	24.35%	1.43
Current USDA Yield Model	0.45	63.05%	2.86

In addition to improved forecast accuracy, there are two other major benefits of our preferred specification. First, our revised methodology to forecast production allows us to forecast harvested area, which offers more insights into grain supply projections. Second, our revised methodology allows us to cover a larger number of countries and include a longer period in the training data. As shown in Table A5 in the Supplementary Appendix, the accuracy metrics of our selected model are better when using all countries and the longer training data period.

1.4.6 Limitations and Future Research

This section highlights the limitations of our empirical study. First, the selected model specification will vary according to which accuracy measure is used as a criteria selection since the decision depends on the specific objectives of the forecast. Second, our models do not include any variable to capture policy changes affecting each country's supply. Third, we assume the climate in 10 years will be similar to the recent climate, but future work could incorporate climate change projections in the forecasts.

Adjemian et al. (2020) highlight the value of probabilistic forecasting methods. While our current study solely focuses on point forecasts, aligning with USDA IFSA's current practice, it is important to acknowledge the potential benefits of exploring alternative approaches. Distributional, interval and probabilistic forecasts are believed to offer valuable insights into the uncertainty surrounding predictions, providing more comprehensive understanding of potential outcomes.

Additionally, several studies have highlighted the importance of forecast combinations and how relying on a single forecast can lead to larger errors due to potential model misspecification (G. M. Martin et al., 2022; Wang et al., 2023). Ramsey et al. (2024) demonstrated how forecast combinations can substantially improve accuracy of short-run projections of crop acreage in the United States. Currently, the USDA does not engage in any form of forecast combination, but future research could assess different approaches to show the value of this methodology when forecasting.

We combined forecasts by averaging point predictions from the OLS, ARIMAX, Random Forest, and XGBoost models (e.g., using combinations of two, three, or all four models). However, this approach did not improve performance compared to the ARIMAX model alone. Consistent with the weak performance of machine learning models, forecast combinations are unlikely to yield significant improvements in our context of limited data and long-term forecasting.

1.5.Conclusions

This study evaluates alternative methods to provide reliable long-term forecasts of grain supply. Our study uses aggregated data at the country level and includes variables to capture and incorporate the heterogeneous conditions of each country and, consequently, to increase the forecast accuracy of grain supply models. The data set to train the models spans from 1980 until 2021 and includes 78 countries. We assess the accuracy of all models in this study using an out-of-sample validation methodology that accounts for the time-series nature of the data and the challenges of long-term forecasting. The preferred model specification is selected based on the Mean Absolute Error (MAE).

The results reveal four ways to improve forecast accuracy. First, the country-specific coefficients can increase the forecast accuracy. Pooled coefficients reduce the number of parameters that must be estimated, while country-specific coefficients allow the model to capture more heterogeneity. Second, linear trends provide higher forecast accuracy than non-linear trends. Third, the best model specifications include weather variables such as temperature. Fourth, ARIMAX models with exogenous variables show higher accuracy than OLS, RF and XGBoost models.

ARIMAX models, including fewer variables as predictors, show lower MAE values, implying that simpler models have higher accuracy. The lowest MAE achieved across all the models developed is approximately around 10%, which can be interpreted as an indicator of potential for further improvement of these types of long-term forecasting models. We consider this percentage acceptable given our study's context, which focuses on long-term projections and high level of data aggregation. To draw more precise conclusions, it would be necessary to fit forecasting models using higher-frequency data. This would allow for capturing, controlling, and incorporating local conditions within each country, enabling more detailed and specific insights.

While there are limitations of our work, we also show that our approach makes significant improvements in the accuracy of the 10-year forecast compared to existing methods. Combining our grain supply forecasts with grain demand forecasts will allow a transparent assessment of the future landscape of food security and international trade. In countries where demand growth is expected to outpace supply growth, there will be an increase in grain demand leading to an increase of imports or food aid. Countries with a greater supply increase than demand are expected to increase their grain exports to international markets.

Chapter 2 - In-Season US Corn Acreage Forecasting Using Machine Learning

2.1. Introduction

The US Department of Agriculture (USDA) publishes a variety of report series to provide agricultural stakeholders (i.e., farmers, traders, and data analysts) with up-to-date and projected market conditions, annual acreage, annual prospective plantings, weekly crop progress and condition, monthly grain stocks, and monthly crop production reports. All this information helps reduce market price uncertainties that are used for crop decision planning. The Monthly World Agricultural Supply and Demand Estimates (WASDE) report is a well-known report and is widely used by stakeholders. Most of these reports rely on statistical survey methods to gather data on production and usage, with information released on established dates throughout the year.

USDA acreage estimation before harvest is mainly released in two reports. First is the "*Prospective Plantings Report*," which is released in late March. Second, is the "*Acreage Report*," which is published in late June. The acreage values from the surveys are incorporated into the WASDE monthly report. Note that adjustments in acreage estimates are made throughout the season, anytime the planted acreage estimates are reviewed, or new information becomes available. Planted acreage estimates reported in June are subject to change in August, September, October, and November when the yield survey data is collected and released in other production and yield reports. Also, other sources such as the Farm Service Agency (FSA) certified acreage data released in October, the December Agricultural Survey, and the Census Data collected every five years are sources of information that can potentially adjust the acreage estimates (Good & Irwin, 2011).

The WASDE report is released monthly, but their acreage estimates mainly use information from the *Prospective Plantings Report* and the *Acreage Report*. May WASDE is the first to include supply and demand estimates for the new marketing year. The acreage allocation in the reports for May and June is typically adopted from the *Prospective Plantings Report* and is adjusted according to major events happening in the states, e.g., major weather disruption, strong market signals that would reasonably affect intentions, policy changes or shocks, sometimes remain unchanged (USDA-ERS, 2025). USDA National Agricultural Statistics Services (NASS) mainly update their predictions until the *Acreage Report* is available in late June. In the 2023 marketing year, the USDA-projected corn-planted acreage at the end of the season increased by just over 4% relative to estimates produced back in February (Janzen & Franken, 2023).

Currently, the USDA is the primary source of public information in agriculture, and stakeholders (e.g., traders, farmers, and market analysts) adjust their expectations accordingly to USDA reports since it has been generally regarded as accurate and trustworthy (CME Group, 2025; Isengildina-Massa et al., 2024; Karali et al., 2019). The other option that stakeholders have is to rely on private forecasts. Advanced corn acreage forecasting models are likely in use within the private sector, but these tools are not disclosed or made publicly available. USDA acreage forecast relies on survey data, which gives USDA a relative accuracy advantage, as shown by (Isengildina-Massa et al., 2020)

Our study aims to develop and evaluate machine learning (ML) models to deliver accurate and timely updates for in-season crop acreage forecasts using data on planting conditions and markets. Employing an out-of-sample prediction approach, we assess whether our models can improve the predictions compared to the values reported by USDA in late June. Our primary question is straightforward yet crucial: Can publicly available data on planting conditions and markets up to May provide additional information to what was released in the Prospective Plantings Reports? This research aims to offer an additional tool to enhance the information provided by the May WASDE report regarding corn acreage estimates.

The decision to construct an ML model to forecast acreage allocation for late May has been made for two major reasons. First, we consider that a model to forecast acreage allocation during the gap between March and June (which are the months when USDA conducts the surveys) is valuable due to the uncertainty and expectations of the ongoing season situation. The second reason is that we can construct a model using the information publicly available up to May, so the model can incorporate information about weather and market conditions from March until late May, see Figure 2.1. This information was obtained after the survey was conducted in early March. We assume that weather and market conditions could have changed farmers' planting intentions.

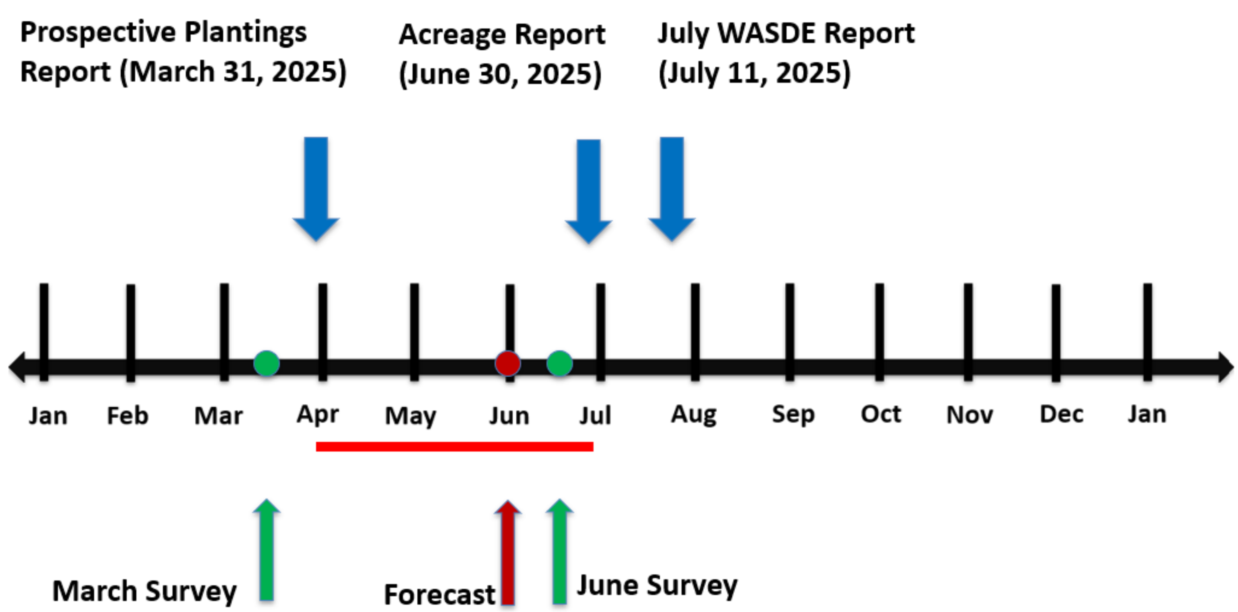


Figure 2.1 Crop Calendar and Report Released Timeline

The purpose is to give a forecast when the uncertainty starts to increase since the next official report with acreage estimates will be available until late June (that is, the *Acreage Report,* which releases acreage estimates using survey-based data), so there is a 3-month window where there is no official information about acreage allocation in the US.

An important goal of machine learning is making predictions, and when those predictions are about future events, the process is known as forecasting. Recently, there has been an increasing trend of literature looking at yield forecasts using machine learning (ML) algorithms. Three key areas where machine learning has made major advances are cross-validation, dimension reduction, and handling complex, non-linear patterns.

For example, a study by Roznik et al. (2023) employed an XGBoost model to assess the accuracy of corn yield forecast using ML. Their results show that the XGBoost model can generate predictions similar to the WASDE August forecast but using near real-time forecasts using open-source data. Kang et al. (2020) assessed county-level maize yield prediction in the US Midwest using machine learning techniques (Lasso, Support Vector Regressor, Random Forest, XGBoost, Long-Short Term Memory (LSTM), and Convolutional Neural Network (CNN)). Their results show that crop yield forecasting benefits from advanced algorithms and large amounts of data, and their forecast outperformed the predictions from the June and July WASDE reports. Peng et al. (2018) demonstrate that incorporating a satellite-based enhanced vegetation index (EVI) significantly improves the yield forecasting performance at the county level.

Crane-Droesch (2018), using corn yield data in the US Midwest, shows that semi and non-parametric models (such as CNN) outperform in predicting yields than parametric models. Roznik et al. (2022) demonstrate that using higher resolution NDVI with cropland mask can lead to more accurate crop yield estimations compared to lower resolution NDVI. Khaki et al. (2020) assessed the forecasts of corn and soybean yields across the U.S. Corn Belt. Using environmental and management data from 2016 to 2018, the authors compare the CNN-RNN, Random Forest (RF), deep fully connected neural networks (DFNN), and LASSO. The CNN-RNN approach achieved the lowest RMSE. While there is a large body of literature focused on yield forecasting in the US, the literature on in-season acreage planted forecasting is less developed. The purpose of most studies that model corn acreage is to focus on policy applications rather than forecasting approaches. We acknowledge there are studies (e.g., Yang et al. (2021); Young (2019), Zhou et al. (2024)) that use remote sensing and machine learning to estimate the yield, production, and crop progress during the growing season, but this is beyond our objective since we are interested in forecasting acreage planted in May, which is early in the season.

Another literature strand focuses on how USDA constructs its forecast and how accurate its estimates are. Studies by Irwin and Good (2011) and Young (2019) approach how corn acreage is estimated in USDA reports and how it is mainly constructed by survey data. Irwin and Hubbs (2020) showed the correlation, ratio, and differences between the USDA NASS final planted acreage estimates for corn and the USDA Farm Service Agency (FSA) final estimates. Both agencies reported their final estimates by January following the planting year in analysis. On average, for the period of 2011 to 2019, the final FSA estimate represents 96.7% of the final USDA NASS planted acreage estimates. The difference in estimated acres planted averages about 3.006 million acres. A few studies have focused on how to improve the acreage forecast, such as Ramsey and Adjemian (2024), who analyzed traditional and machine learning-based forecast combination methods and demonstrated their potential to enhance USDA projections for nationwide corn and soybean acreage.

Lastly, previous studies have also covered the assessment of factors such as prices (Haile et al., 2014; Hausman et al., 2012; Hendricks et al., 2014; Pates & Hendricks, 2021), weather and climate shocks (Miao et al., 2016; S. M. Ramsey et al., 2021) that influence acreage allocation decisions.

The first major contribution of this study is the development of a model to forecast planted acreage in the early stages of the growing season in late May. Most of the literature published has been done to improve the yield forecasts rather than acreage. The results show that using our methodology, the forecast errors are smaller than the forecasting errors of the June *Acreage Report* estimates. Since the MAE generated by the Random Forest model only represent 56% of the errors when compared to the USDA estimates from the June survey.

In summary, our model is more accurate than USDA estimates used in the July WASDE report, and it has the advantage that it is available one month earlier. These projections offer essential insights into the potential size of the crop and carry significant implications for corn and soybean prices (S. Irwin, 2021; Janzen, 2024).

The second major contribution of our analysis shows the importance of the *Prospective Plantings Report*. We develop models using planting intentions values and models without them in order to see how the predicting power that variable brings to the models and assess the accuracy of their forecasts. The fact that our results show that we can forecast more accurately than the June *Acreage Report* does not imply that the USDA reports have no value. The forecast errors without planting intentions are twice as large as our preferred forecasts. Our findings provide insights into the value of the secondary public data available, which can be used together with the USDA information to make forecasting more accurate. The results reveal that by incorporating the conditions and events that happened from March to May (3 months), it is possible to increase the accuracy of the acreage planted forecasts.

2.2. Data

The data analysis approach of this study is predictive, which is one of the primary advantages of machine learning in terms of using extensive datasets. Therefore, the explanatory data set included a large set of variables. These variables fit into the broader categories of weather, prices, historical production, location, and trend. For all the variables, we collect annual time series spanning from 1995 to 2020. Our dataset includes 35 states that produce the most corn and represent 98% of the corn planted in the US. The decision to filter out the lowest production states is to avoid noise and missing values since there are some states where their acreage planted is small, increasing the variance and increasing the complexity of the predictions.

To estimate our model, we use panel data comprising 92 variables aggregated at the state level on an annual basis. See Table B1 in Appendix B for the complete list of the variables included in this study. In the following section, we describe each variable and explain the data processing steps applied. All variables are grouped into broader categories: *Acreage, Production, Yield, Fertilizer Prices, Futures Prices, Suitable Days for Field Work, Temperature, Precipitation, Soil Moisture Exposure, and Technological Innovation*. To capture the effects of factors such as prices, weather, and field conditions from February through May, we construct separate variables for each month to allow for month-specific coefficients. This data structure enables us to identify which months contribute more significantly to improving the model's predictive power.

Prospective Plantings Report, *Acreage Report*, and Actual Corn Acreage Planted values are obtained from USDA NASS. These variables are reported each year at the state level but are differentiated by the month in which the estimates are published. For example, planting intentions are reported each year in March, representing farmers' intended acreage for corn. The acreage planted data is collected by early June and is released in late June in the *Acreage Report*. The final acres planted are reported at the end of the season, typically the following calendar year. These reports together provide a timeline of producer intentions and actual planting outcomes, which are essential for modeling production expectations and adjustments throughout the season. Some of these monthly time series data can be retrieved through the USDA Quick Stats tool up to a certain year. However, when data for later years is unavailable, we extract the missing values from USDA report PDF documents to complete the dataset. For instance, the planting intentions values from the *Prospective Planting Report* can be retrieved from 2013 until 2024 using the USDA Quick Stats Tool. However, to complete the dataset from 1995 until 2012, we scraped PDF and txt files using R code.

The Futures Prices variable is a daily time series collected from the Commodity Research Bureau (CRB). It reflects market expectations about future commodity prices, particularly corn, and serves as a forward-looking indicator of economic incentives faced by producers. We focus on the futures contract expiring in December, which aligns with the typical corn harvest and sale period. We assume that farmers consider the December contract price when making acreage allocation decisions at the beginning of the planting season. These variables capture market signals that influence production decisions, as higher futures prices generally incentivize increased corn acreage. We aggregate future prices from daily to monthly time series using a simple average.

The fertilizer price index is a monthly time series at the national level from USDA NASS, which uses the price in 2011 as a baseline to construct the index, capturing trends in cost over time. This index serves to reflect the average prices farmers pay for key fertilizer types. Since we are forecasting corn acres, nitrogen (e.g., Anhydrous ammonia) is highly relevant because this nutrient plays a key role in corn production and is highly correlated with corn output (Ibendahl, 2025).

Days Suitable for Field Work is a weekly time series at the state level collected from USDA NASS. This variable is derived from the USDA Crop Progress and Conditions reports, which measure the average number of days per week during which field conditions are suitable for agricultural operations in activities such as planting, fertilizing, and harvesting. *Days Suitable for Field Work* reflect a composite assessment of soil moisture, weather conditions, and field accessibility. For our modeling purposes, we aggregate the weekly values into annual and state levels in order to align with the spatial-temporal structure of our panel dataset. This variable serves as a proxy for agronomic feasibility and operational timing at the state level.

Temperature and precipitation are collected from the PRISM climate group maintained by Oregon State University (PRISM Climate Group, 2025). The data from PRISM are processed in four steps. Step 1: Download the bulk historic weather data from the PRISM database. Step 2. Aggregate the daily grid data to county-level values by taking an average of all the grid values located within the county boundaries. Step 3. Aggregate the county-level data to the state level using a weighted average, where the weights are the historical corn acreage planted in each county. In this way, the counties that produce more corn have higher weight values and will be properly represented in the state-level data. Step 4. To estimate the degree days using the maximum and minimum temperature values from PRISM, we followed the methodology employed by Schlenker and Roberts (2009) to estimate the temperature exposure for each threshold. The thresholds represent *Degree Days* exposure from 0 to 10C, 11C to 20C, 21 to 30C, 31 to 40C, 41 to 50C, and below zero. Lastly, we aggregated the data by adding the number of days per month at the state level.

Soil moisture data is collected from MODIS, a satellite instrument NASA developed**.** The data employs volumetric soil moisture measurements derived from the Short-term Prediction Research and Transition-Land Information System (SPoRT-LIS) provided by NASA (NASA, 2025). We employ the SPoRT-LIS outputs daily volumetric soil moisture for the soil layer from 0 to 10 cm. at the spatial resolution of approximately 1 km^2. Data processing for the Soil Moisture data includes the following steps. Step 1. Aggregate gridded data to the county level. Step 2. Aggregate data from the county level to the state level using a weighted average by historical county-level planted acreage. Step 3. Like the degree day exposure estimation, soil moisture exposure to a certain level in volumetric terms per day is estimated using the same methodology employed by Schlenker and Roberts (2009) to estimate degree days exposure and aggregated to the monthly level by adding the number of days per month.

2.3. Methods

This study focuses on constructing a machine learning model to forecast change in planting intentions with the objective of improving the forecast of the actual corn acreage planted at the end of the season. Our study follows and adapts a similar methodology employed by Roznik et al. (2023), who use an ML model named the XGBoost model to forecast yields by employing spatial-temporal datasets. Our model to forecast corn acreage is formulated as a function of variables from the supply and demand side, weather, field conditions, location, and trend. We develop ML models to forecast acreage allocation in late May, using all the information available up to that date.

Using a machine-learning model, we can build non-parametric models to create forecasts; some advantages are that those models can make estimations without explicit parameters and capture complex relationships that parametric models may be missing. They are also more flexible and can handle big data when the functional form is unknown.

2.3.1 In-Season Acreage Forecast Model

Acreage allocation is determined weeks before the planting season, and the farmer's decision is influenced by many factors that shape their expectations. The planting intentions released in the March Report by USDA provide information about how much acreage the farmers plan to allocate for corn at the beginning of the season. However, it is expected that at the end of the season, the actual acreage planted changes due to several factors (e.g., weather, prices). These factors influence corn acreage allocation and may have linear or non-linear effects. The US crop calendar for corn indicates that planting starts in April and ends in June, while harvest starts in September and ends in December (USDA-NASS, 2010).

The conceptual model outlined in Equation (2.1) is developed to generate forecasting of variable *Change in Planting Intentions* for corn using state-level data. In our modeling approach, we first forecast the $Change\_in\_Planting\_Intentions_{i,t}$. The variable $Change\_in\_Planting\_Intentions_{i,t}$ is modeled as a function of several factors, as shown in Equation (2.1),

$$Change\_in\_Planting\_Intentions_{i,t} = f\left(Weather_{(i,t)}, Prices_{(i,t)}, PriorProduction_{(i,t)}, Location_{(i,t)}, Trend_{(i,t)}\right) \quad (2.1)$$

where $Change\_in\_Planting\_Intentions_{i,t}$ is the difference (or change) between the $PlantingIntentions_{i,t}$ and the variable $Acres_{i,t}$ (which denotes the actual corn acreage planted at the end of the season), at state (i), and year (t). We can classify the predictors into five broad categories: weather, prices, prior production, location, and trends. $Weather_{(i,t)}$ includes all the variables related to weather conditions, precipitation (monthly and annual), temperature (max, min, average, Degree Days), Days Suitable For Fieldwork, and soil moisture data. $Prices_{(i,t)}$ denotes all the variables influencing acreage values from the demand side and related to the market conditions (i.e., futures prices and fertilize price index). $PriorProduction_{(i,t)}$ are the variables influencing acreage values from the supply side (i.e., acreage planting intentions and historical crop yields). $Location_{(i,t)}$ denotes a variable to indicate the state. This variable intends to capture the state-specific conditions. $Trend_{(i,t)}$ denotes a variable to indicate the trend due to technology improvements over time.

All the variables included aim to incorporate into the model factors the influence of crop planting decisions and enhance the model's ability to forecast acreage allocation. By incorporating factors that represent market and field conditions, weather variability, spatial heterogeneity, and temporal trends, these variables serve as proxies to predict, capture, and reflect the complex decision-making process farmers undertake when allocating acreage. We expect the inclusion of all these variables to enable the model to identify relevant patterns and nonlinear interactions between environmental and economic conditions. Consequently, the model is expected to become more responsive to real-world signals, improving both the precision and reliability of in-season acreage forecasts. For more details about each variable, see the Data Section.

Second, we subtract the $\widehat{Change\_in\_Planting\_Intentions}_{i,t}$ forecasted to the planting intentions values from USDA's *Prospective Plantings Report*, see Equation 2.2. Once we have the $Predicted\_Acres_{i,t}$ values, we compare our predictions with the acres estimates published in the

USDA *Acreage Report*, which are incorporated in the July WASDE report. To assess which predicted values are more accurate, we estimate the accuracy measures MAE, RMSE, and MAPE.

$$Predicted\_Acres_{i,t} = PlantingIntentions_{i,t} - Change\_in\_Planting\_Intentions_{i,t} \quad (2.2)$$

In the case of in-season forecasts, such as the model constructed in this study, the variables included in the model must already be publicly available up to the forecast date. Consequently, the model includes only the information available up to late May to generate the acreage forecast. Our modeling approach takes into consideration that there is a lag between the day that the data is recorded and the day the data is released to the public. Our modeling also considers the non-linearity assumption, which implies there is no parametric functional form such as a linear quadratic or logistic relationship. We employed an exposure-based approach for variables such as temperature and soil moisture, which allows a flexible estimation of the coefficient at different degree days and soil moisture thresholds. The approach has been employed previously by (Ortiz-Bobea et al., 2021; Schlenker & Roberts, 2009)

We assume the ML models can identify and exploit non-linear relationships with high complexity. The models are estimated and tuned using the following algorithms: Random Forest (RF) and Extreme Gradient Boosting (XGBoost). The ML models employed in this study have been described in the Methods section from Chapter 1 of this dissertation. The hyperparameters are tuned using a cross-validation procedure, which is described in the following section. Furthermore, we estimate OLS with Fixed Effects (FEOLS) models, which will serve to compare the ML models with a traditional regression model approach.

2.3.2 Leave One Year Out Cross Validation (LOYOCV)

The LOYOCV is a variant of the cross-validation standard procedure, which involves splitting the dataset into training datasets and a validation (one out) set. The model fits using the training datasets, and the estimated model is used to make predictions that are compared with the values in the validation dataset. Our cross-validation uses a variation of the leave-one-out-cross-validation (LOOCV) approach. In our case, we group the one-out observation by year, which can be designated as LOYOCV. The LOYOCV procedure consists of first creating folds grouped by year of data. Then, the model is fitted using the training folds, leaving one (year) group out. This portion can be referred to as the validation fold (D. R. Roberts et al., 2017).

Machine learning models have hyperparameters that must be tuned to provide the best forecast. In this study, we employ the LOYOCV to tune the hyperparameter of the models, while the FEOLS models use it to make the variable selection given the number of years in our dataset. This is a standard procedure employed for model evaluation (Bergmeir et al., 2018). To tune to the hyperparameters of the RF and XGB models, we employ a grid approach. For each parameter, we first start with a wide range of values, and once a value that outperforms others in accuracy is identified, we create a matrix with a set of values that we identified can provide higher accuracy and test combinations of similar values in order to identify and select the hyperparameter combination that provides the highest accuracy measures.

For the RF model, we tune the hyperparameters, the Number of Features to Consider for each Split (m_{try}) and the Number of Trees (N_{tree}). Following the recommendation of James et al. (2013), we use the default values for $m_{try} = p/3$, where p is the number of predictor variables used to estimate the RF model (e.g., we tuned the parameter N_{tree}=375, first using as reference the default value for $m_{try} = 32$, and considering a range of values to assess how the MAE increases or decreases as we change the node size). For the XGBoost model, we iterate through all potential combinations using the grid approach to select the hyperparameter values that yield the lowest MAE. After completing the tuning process previously described, the selected values are as follows: Maximum Depth (*max_depth* = 3), Learning Rate or eta ($\boldsymbol{\eta}$ = 0.1), Subsample (*subsample* = 1), Minimum Sum of Instance weights (*min_child_weight* = 1), Number of Boosting Rounds (*nrounds* = 25). After tuning the hyperparameters, we generate the forecasts to perform the LOYOCV to assess the forecast accuracy of the models.

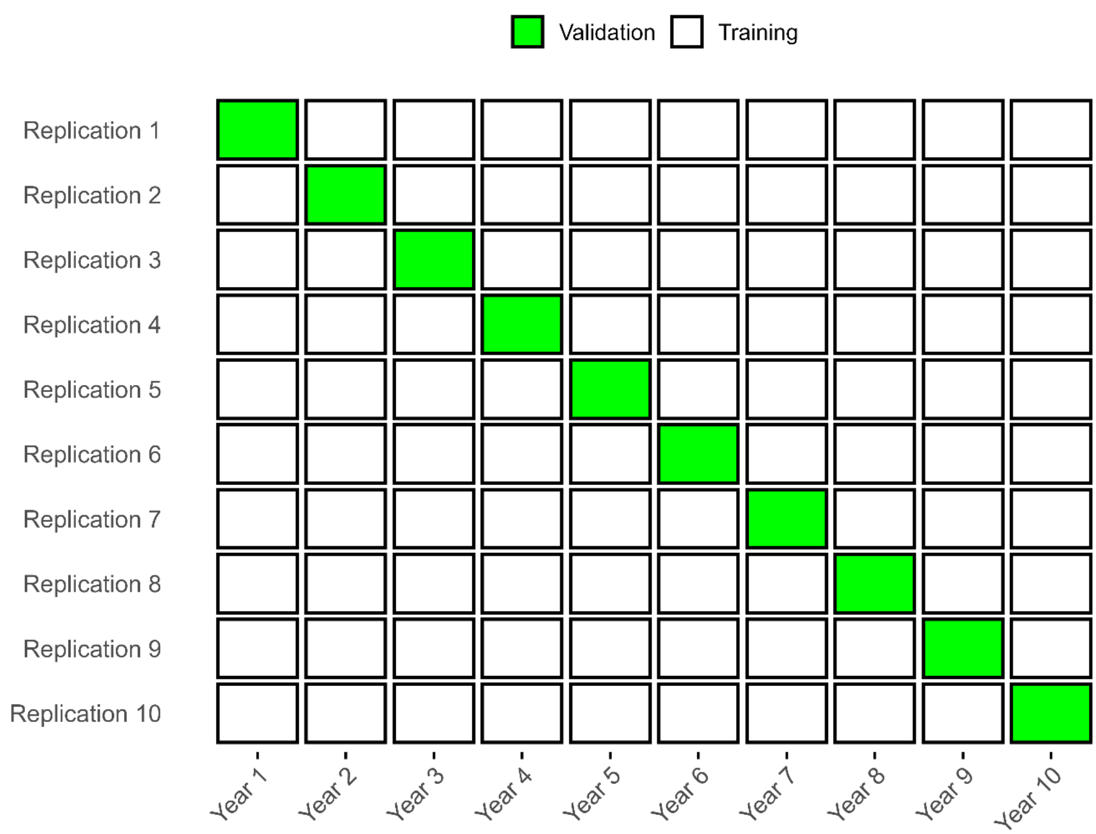


Figure 2.2 Leave One Year Out Cross-Validation (LOYOCV)

Figure 2.2 depicts an example of the LOYOCV. The white squares reflect the years that will be in the training dataset, while the green squares reflect the year of data left out and will serve as a validation dataset. For instance, if we have 10 years of data, as in Figure 2.2, and if we perform the LOYOCV procedure, we could have 1fold for validation and nine training datasets, which are grouped by year, for each replication.

In our case, when using a dataset from 1995 until 2020, we have 25 training datasets (or 25 folds grouped by years) and one validation fold (or one year of data holdout) for each replication. Using the fitted model to predict the outcome, the value predicted is compared with the values of the validation fold (the one-year holdout). The LOYOCV procedure helps to use the available data to train and validate our model, unlike other approaches, such as the walk-forward cross-validation. Given that our model predicts the variable $Change\_in\_Planting\_Intentions_{i,t}$, and by making the folds grouped by year of data,. Also, by employing this setup, we assume no autocorrelation but allow dependence within years of data (Hyndman & Athanasopoulos, 2014).

2.3.3 Accuracy Measures

We estimate several model specifications to estimate acreage planted and the change in planting intentions based on the planting intentions values. The prediction errors, the difference between the out-of-sample forecasted acreage values and the real production values in the validation fold (the year of data hold out), are used to calculate the Mean Absolute Error (MAE) in Equation 2.3, Mean Absolute Percentage Error (MAPE) in Equation 2.4, and Root Mean Square Error (RMSE) in Equation 2.5.

$$MAE = \frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\left|\hat{Y}_{i,t} - Y_{i,t}\right| \qquad (2.3)$$

$$MAPE = \frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\left[\frac{\left|\hat{Y}_{i,t} - Y_{i,t}\right|}{Y_{i,t}} * 100\right] \qquad (2.4)$$

$$RMSE = \frac{1}{NT}\sum_{t=1}^{T}\left[\sum_{i=1}^{N}(\hat{Y}_{i,t} - Y_{i,t})^2\right]^{1/2} \qquad (2.5)$$

where $\hat{Y}_{it}$ is the forecasted value, and Y_{it} is the real value of the predicted variable. The "T" denotes the total number of datasets used to perform the LOYOCV process. To create a single accuracy measure across states, we average the accuracy measures across 26 years and across all states, where N is the total number of states in the data set. Our dataset includes 35 states. We use MAE as the criteria to select the preferred model specification, and we also report the results for MAPE and RMSE. MAE allows us an easier and direct interpretation of the error when predicting acreage planted. In our case, we ended up with 25 validation datasets (folds grouped by year) when estimating the models from 1995 to 2020.

2.4. Results and Discussion

The discussion of the results is composed of the following sections. In the first section, we discuss the forecast accuracy of the acreage models. In the second section, we analyze the variables of importance of the models. In the third section, we compare the models that Forecast Final Acreage Planted Rather than the Change in Planting Intentions. In the last section, we assess the predictive value of the *Prospective Plantings Report* estimates.

2.4.1 Assessing Forecast Accuracy of the Acreage Models

Our results reveal that by using secondary data sources available up to May and incorporating the USDA planting intentions values, we can forecast acreage planted by late May with higher accuracy than the USDA acreage planted estimates published in late June. The value and relevance of these results is that the forecast of acreage planted can potentially be available a month before USDA posts its official forecast in *Acreage Report,* which is released in late June and incorporated into the WASDE July report.

To compare our model's performance in forecasting, we estimated the accuracy measures of the survey values provided by USDA (see the third and fourth rows in Table 2.1). The accuracy measures of the survey conducted in early March (and released in the *Prospective Plantings Report*) are MAE of 88,744 acres, which implies, on average, across years and states, the Planting Intentions differ from final acreage by 88,744 acres for corn. Further, the RMSE is 168,429 acres, and MAPE is 6.16%. The accuracy of the values from the survey conducted in early June (and released in the Acreage Report and incorporated into the July WASDE report) has, on average, an accuracy measure of MAE 59,379, RMSE 163,310, and a MAPE of 4.32. As expected, the error value of the June Report is smaller since this is after the end of the typical planting season.

Table 2.1 shows the predicted values using machine learning with data available in late May are more accurate than the survey values released by USDA on the *Prospective Plantings Report* (released in March) and the Acreage Report (released in June). The RF model achieves an average MAE of 33,440 acres across years and states when forecasting actual acreage planted.

Compared to the USDA's Acreage Report estimates, which have an MAE of 59,379 acres, the RF generates a MAE which only represents 56% of the error produced by the USDA estimates. While if we compared to the USDA's Prospective Planting estimates, which have an MAE of 88,744 acres, the RF generates an MAE which only represents 37% of the error produced by the USDA estimates. As expected, the acreage estimates from the June survey are more accurate since it incorporates more information later in the season.

Using the acreage planted by state shown in Table B2 in the Appendix B, we estimate how much this error would represent depending on the state in which you are making the prediction. For example, in 2024, on average across states, 25,735,571 acres of corn were planted. The forecasting error of 33,440 acres would represent an error of 0.13%. Table 2.1 also shows that the values of RMSE are similar for RF and XGBoost models, but accuracy metrics are different when comparing MAE and MAPE, showing how each metric behaves with respect to error size and distribution. MAE values reveal that, on average, both models deviate from the actual values by a similar margin. RMSE penalizes larger errors more heavily due to squaring. This suggests RF may have a few very large errors when forecasting that increases exponentially in the RMSE. MAPE measures the relative error compared to the actual value. RF performs better in terms of relative accuracy.

Table 2.1 Accuracy of Acreage Predictions when Forecasting Change in Planting Intentions, using Leave One Year Out Cross Validation

Rank	Model	RMSE	MAE	MAPE
1	RF	62,498	33,440	2.60
2	XGBoost	62,824	41,988	4.93
3	Survey June	163,310	59,379	4.32
4	Survey March	168,429	88,744	6.16
5	FEOLS	192,987	114,702	11.86

Overall, the FEOLS model performed worse when predicting planted acres. The MAE values for the FEOLS are twice those of the Survey June values. To estimate the FEOLS model, we use a parsimonious approach, so instead of including all the variables used in the ML model, we include only 14 independent variables and state fixed effects. These variables were chosen based on their importance in the ML models to identify which factors can bring more predicting power to directly predict the acres planted. The FEOLS model includes: *Acreage Planted (Actual, 1-Year-Lag), Yield (1-Year-Lag), Planting Intentions, Fertilize Price Index March (Base 2011), Corn Futures Price (Dec Contract – March Quote), Suitable Days For Field Work (April), Precipitation (March), Precipitation (April), Soil Moisture Exposure February (Bins 9–16, 33–40, and 41–50), Degree Days (February 11°C to 20°C), Trend, and State fixed effects.*

2.4.2 Variable Importance Across Models

In this section, we focus on discussing the variable importance of the RF since this was the model that showed higher accuracy. The variable importance matrix from an ML model reveals how the algorithm weighs the importance among the variables that are considered for estimating the model and how that importance varies, depending on the way that each algorithm works. In Random Forest (RF) models, the variable importance matrix shows how much each predictor contributes to the model's predictive performance (Breman, 2001). Specifically, we use the Gini Index (also called Mean Decrease in Impurity). To facilitate the interpretation of variable importance, we rescale and show the variable importance in terms of percentage (0 - 100%), where 100% indicates the highest relative importance.

Figure 2.3 depicts the variable importance matrix for the top 20 predictors from the RF model when forecasting the change in planting intentions. The variable with higher variable importance is the Trend, which is a proxy for agricultural production innovation improvements over time. Figure 2.3 shows that this variable, as a predictor, contributes 4.7% to the model's overall predictive performance. Overall, and as expected, the variables capturing weather and field conditions appear to help predict how the change in planting intentions is influenced by these factors. The variable *Days Suitable For Fieldwork* in April and *Precipitation* levels during April and May appear to play a significant role in determining planted acreage. The variable *Suitable Days For Field Work* is composed of a variable that serves as a proxy of weather and field conditions that indicate the feasibility of operational work in the fields. The matrix shows that this variable has a 4% variable importance, which implies this predictor contributes 4% to the model's predictive performance.

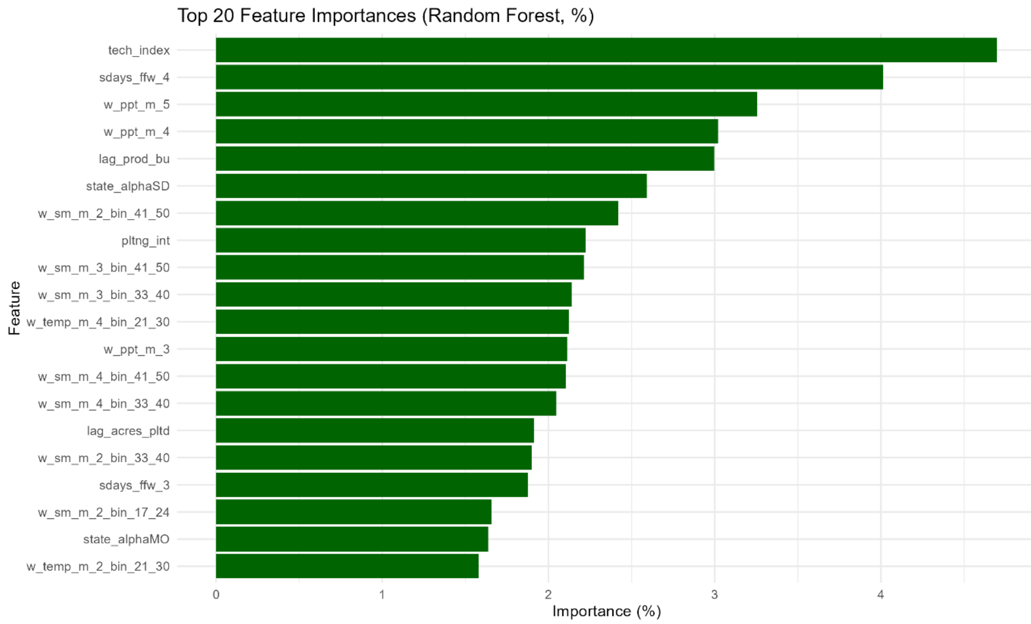


Figure 2.3 Variable Importance of Random Forecast model when forecasting Change in Planting Intentions Random Forest

Another variable among the most influential predictors is the *Soil Moisture Exposure* at different levels of exposure during February, March, and April. This aligns with the fact that planting dates across US states happen during these months. These variables support the idea that acreage planted and changes in intentions are highly correlated with all these variables. The planting intentions variable ranks 8th among the most important variables in our most accurate RF model, contributing 2.2% to the model's predictive power.

2.4.3 Comparison to a Model that Forecasts Final Acreage Planted Rather than the Change in Plating Intentions

We also constructed a model to predict planted acreage directly without having to estimate the change in planting intentions. Like the previous *Change in Planting Intentions* model, this model assumes Acres as a function of several factors, as shown in the following Equation 2.6.

$$Acres_{i,t} = f\big(Weather_{(i,t)}\,, Prices_{(i,t)}, PriorProduction_{(i,t)}, Location_{(i,t)}, Trend_{(i,t)}\,\big) \quad (2.6),$$

where $Acres_{i,t}$ denotes crop acreage planted (corn) at location (i) at time (t)

Table 2.2 shows that when predicting the acreage planted directly, the OLS with fixed effects and simpler specifications have higher accuracy of forecasting but do not reach the accuracy level of the Survey values.

Table 2.2 Acreage Forecast Accuracy Measures when Predicting Acreage Planted Directly

Rank	Model	RMSE	MAE	MAPE
1	Survey June	163,310	59,379	4.32
2	March Survey	168,429	88,744	6.16
3	FEOLS	169,928	101,558	10.99
4	XGB	175,328	103,464	7.38
5	RF	212,191	125,987	11.11

Some of the reasons why the forecasting model using the *Change in Planting Intentions* can achieve higher forecasting accuracy are as follows. The estimation of change in planting intentions helps to normalize observations across time and states (see Figure 2.4 and Figure 2.5). This variable captures and incorporates imbalances and reveals state-level nuances not evident when predicting acreage directly, such as state-specific weather and farmland size. Standardizing observations stabilizes the variability of the dependent variable, improving model accuracy in short-term horizons. Conceptually, the change in planting intentions acts as a bridge between March conditions and the factors influencing final planted acreage. On the other hand, forecasting planted acreage directly is challenging due to the various dynamics affecting farmers' decisions.

Additionally, the non-normal distribution of planted acreage increases modeling complexity, reducing predictability.

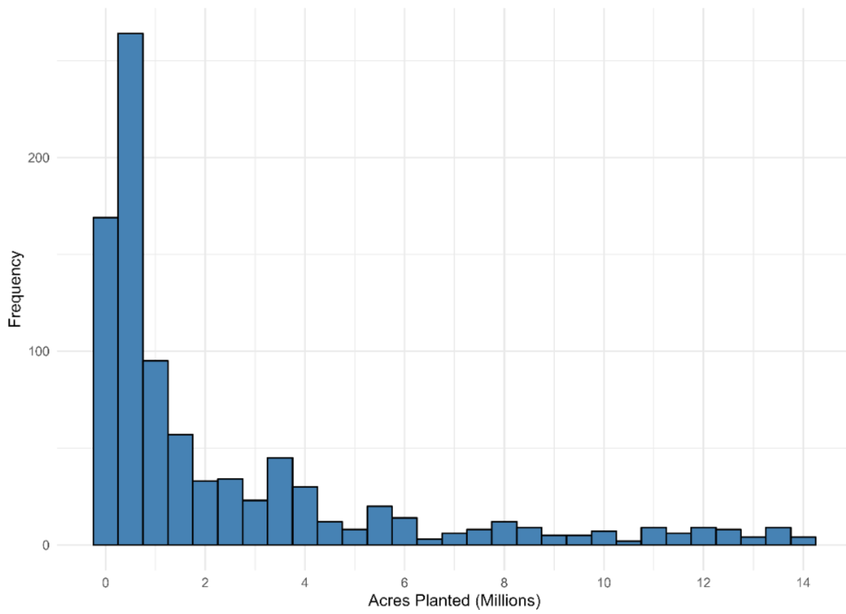


Figure 2.4 Histogram of Acreage Planted Observations across States from 1995 to 2020

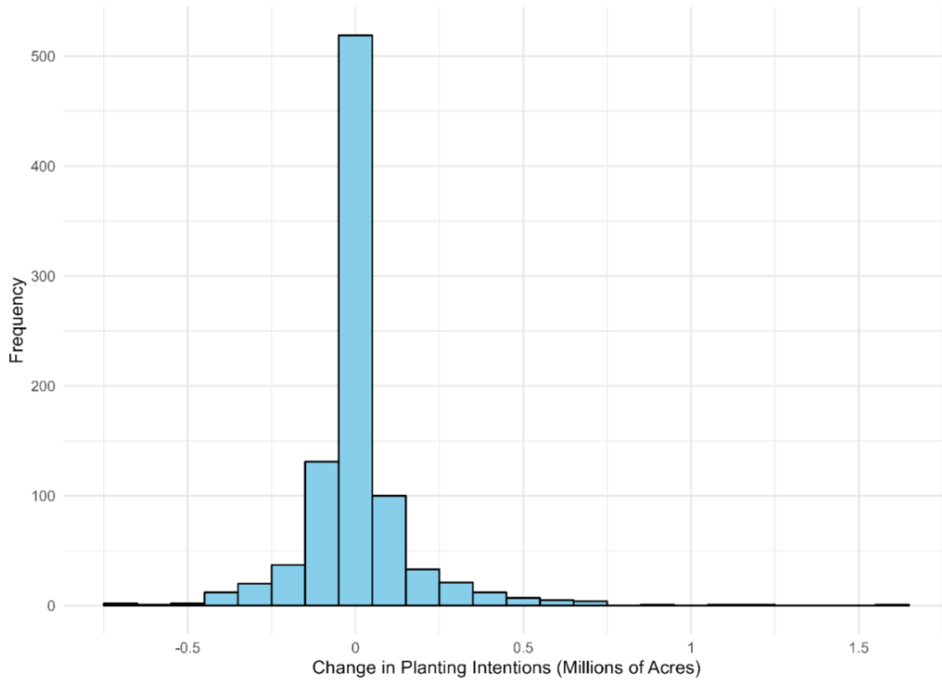


Figure 2.5 Histogram of Change in Planting Intentions Observations Across States from 1995 to 2020

Overall, across models that predict acres planted directly, the results show that planting intentions rank as the most important variable in both the RF and XGBoost models, highlighting the relevance of USDA planting intentions survey input across methods. It is followed in importance by the 1-year lag of acreage planted and the 1-year lag of corn production. Also, when comparing variable importance across ML models, the results indicate that the XGBoost model places greater emphasis on planting intentions, whereas the RF model distributes importance among the top three other variables.

Additionally, the state variable (used as categorical variables) emerges as a key predictor, suggesting the existence of state-level differences that can be used to improve forecasting accuracy. This implies that each state has unique conditions that influence the amount of acreage planted. This indicates the acreage planted variable has a cross-sectional component of the dataset since there are states that allocate large amounts of acreage for corn that are mainly located in the northern Midwest. For that reason, it will have a strong influence on when planting and how much, for example, on average in the last ten years, for the case of Iowa, which is the largest corn producer (14.16%, 132,700,000 acres), followed by Illinois (12.23%, 111,100,000 acres), and Nebraska (10.81, 98,000,000 acres). For more details about the acreage planted by state, see Table B2 in Appendix B.

2.4.4 Predictive Value of the Planting Intentions Report

Our results underscore the predictive value of the USDA's *Prospective Plantings Report*. To quantitatively assess the marginal contribution of planting intentions data to model performance, we estimate models using the best specification with and without the planting intentions variable. Then, we estimate the accuracy measures for the two models and the planting intentions values with respect to the final acreage planted released by USDA at the end of the season, see Table 2.3.

When estimating the acreage planted directly, our ML and regression models show the variable planting intentions as the most important variable in predicting acreage planted directly. However, these models cannot outpace the accuracy of the values provided for the *Prospective Plantings Report* and the Acreage Report. This highlights the prediction value of the survey input and its relevance as a primary data source since they are collecting data directly from farmers.

Table 2.3 Accuracy measures of models when including and omitting the planting intentions variable

Model	Accuracy Measure	NPI Value	PI Value	% Improvement
FEOLS	RMSE	256,693	169,928	33.80%
	MAE	161,773	101,558	37.20%
	MAPE	21.32	10.99	48.50%
XGB	RMSE	265,627	175,328	34.00%
	MAE	163,396	103,464	36.70%
	MAPE	12.69	7.38	41.80%
RF	RMSE	287,959	212,191	26.30%
	MAE	180,934	125,987	30.40%
	MAPE	20.68	11.11	46.30%

Note: NPI denotes models that do not include planting intentions.

The MAE of the Prospective Planting Reports values are 88,744.. Table 2.3 shows that the error of our most accurate FEOLS model without including the information on the *Planting Intentions* is 161,773 acres, which is twice as large as the USDA estimates. That means that the Prospective Planting Reports estimate is twice as good as our model, which only includes publicly available data. When comparing the FEOLS model, including the planting intentions information, the MAE is 101,558, which is 14.3% greater than the USDA estimates. This means the *Prospective Plantings Report*s estimates are 14.3% better than our model estimates, using only publicly available data. This implies our predictive models incorporating only the secondary data sources are not a reasonable substitute for the *Prospective Plantings Report* predictions.

The results show that the inclusion of planting intention values can improve model accuracy across all models. OLS with fixed effects models perform best among model-based approaches, outperforming both RF and XGBoost when predicting end-of-season planted acreage.

We calculate the percentage improvement of model performance when including the planting intentions variable vs. excluding it. Using the following Equation 2.7.

$$Improvement(\%) \quad = \frac{Error_{NPI} - Error_{PI}}{Error_{NPI}} \qquad (2.7),$$

Including planting intentions reduces forecasting error by 30% to 48%, with the largest gains in MAPE. This reinforces the predictive and economic value of USDA's survey data. These results show that planting intention values can substantially increase the accuracy across models. These show that surveys conducted by USDA can provide high value for all stakeholders.

Our empirical results demonstrate the significant predictive value added by incorporating the USDA's *Prospective Plantings Report* into models that forecast acreage planted. While machine learning (ML) and regression models can approximate seasonal changes in acreage using secondary public data. Our results indicate that a model without planting intentions is not as accurate as the planting intentions report. This indicates modeling complexity alone cannot compensate for the unique insights embedded in farmer survey data.

2.5. Conclusion

This analysis assesses machine learning and regression models to provide accurate corn acreage planted. We employed an annual time series aggregated at the state level and included variables that incorporate the heterogeneous conditions of each state. We also allowed monthly coefficients to capture the condition up to May in order to increase the in-season forecast accuracy of corn acreage planted models. Our results focus on answering our primary question: Can we create a reliable ML model using publicly accessible data to generate accurate and timely forecasts?

Our results reveal that with our current dataset using secondary data sources and incorporating the Planting Intentions Report information from USDA, we can generate acreage forecast that can outperform the accuracy level of the survey results released by USDA's *Acreage Report*, which are published on late June. The most accurate RF model achieves an average MAE of 33,440 acres across years and states when forecasting actual acreage planted. The RF model yields a Mean Absolute Error (MAE) of 33,440 acres, significantly lower than the 88,744-acre MAE from the USDA's June survey-based Acreage Report. This indicates that our model produces a smaller forecasting error, this error is just 56% of the error associated with the USDA estimates. Forecasting changes in planting intentions gives the advantage of forecasting a variable normally distributed, which helps to improve the accuracy of the models. Also, our methodology to construct models has the advantage of generating the acreage planted forecast one month earlier than the values coming from the survey conducted in early June and posted in late June in the USDA's *Acreage Report* and incorporated in the July WASDE Report.

The Random Forest model (which is the model most accurately identified in this study) shows that the most important variables for forecasting change in planting intentions are the *Trend, Suitable Days for Fieldwork* in April, Precipitation in May, and Precipitation in April. The variable *Trend* can reflect the time component of the panel data. The *Suitable Days For Field Work* is a composed variable that serves as a proxy of the interaction of other variables such as temperature, soil moisture, and precipitation. That influences the operational feasibility of fieldwork.

When assessing the value of the planting intentions survey, the results demonstrate the significant predictive value added by incorporating the USDA's *Prospective Plantings Report* into models that forecast acreage planted. While machine learning (ML) and regression models can approximate seasonal changes in acreage using secondary public data. Our results indicate that a model without planting intentions is not as accurate as the USDA's Acreage report estimates. The results show that when modeling the actual acres planted directly, both ML and regression models identify the planting intentions variable as the most important predictor. Across models, the accuracy measures suggest that a model that does not incorporate the planting intentions information can decrease their accuracy. This indicates modeling complexity alone cannot compensate for the unique insights embedded in farmer survey data. This outcome highlights the unique value of survey-based data as a primary source of information and reinforces the importance of farmer-reported intentions in enhancing predictive accuracy.

Overall, this study offers a methodology to estimate models to improve the predictive ability for acreage planted estimations. Specifically, it provides a tool to generate timely in-season updates of acre forecasts of corn in the US. Our study contributes to the ongoing analysis of these forecasting models and can complement the acreage predictions released in periodic reports from government agencies. We consider that having another reliable source of information during the months when USDA does not provide updates on acreage allocation is highly valuable for the corn market stakeholders and policymakers. Lastly, this study will contribute to filling the gap in the literature about the assessment and development of acreage forecasting models to generate in-season estimates, which are less common and developed than the forecasting models for yield or production in the US.

Chapter 3 - Effects of Non-Tariff Trade Barriers in Rice Markets: The Case of Rice Export Bans Imposed by India

3.1. Introduction

Rice is a staple consumed by half of the global population, providing around 21% of the world's calorie intake (Bin Rahman & Zhang, 2023) and employing around 11% of global cropland (Yuan et al., 2021). Asia accounts for approximately 90% of the rice cultivation and production area worldwide, and nearly 90% of global rice is consumed in Asia (Adjao & Staatz, 2015). As a consequence of export market restrictions imposed by major rice exporters, in 2024, the FAO's price of rice reached its highest nominal level in 16 years following a set of export bans imposed by India (FAO, 2025).

The rice supply chain (such as other food supply chains) is frequently exposed to significant local and international disruptions. The growing integration and interconnection of global food systems have demonstrated that events such as climate shocks (IPPC, 2012; Tack et al., 2025; Varma, 2025) and geopolitical conflicts (Boyko et al., 2024; Steinbach, 2023) can exert pressure on the food systems. These disruptions often lead to price volatility and trade flow changes, which negatively impact food security (Headey & Martin, 2016).

When international grain market prices surge, national governments frequently intervene to minimize the impact on their domestic food markets. However, such actions often amplify the price spike and intensify the associated international welfare transfer resulting from the terms of trade shift (K. Anderson et al., 2013; K. Anderson & Nelgen, 2012; W. Martin & Anderson, 2012).

Recently, the Indian government implemented an export ban and tariffs on various types of rice. In September 2022, they banned exports of broken rice (Global Trade Alert, 2024). In July 2023, the Indian government banned the export of non-basmati white rice, representing a large shrinking in rice supply in global markets (USDA-FAS, 2023b). India is the world's largest rice exporter, accounting for roughly 40 percent of global rice trade in 2022. India exported 31% of broken rice and 27% of milled rice in 2021 (COMTRADE, 2024). As a major rice exporter, any trade barriers enacted by India are expected to influence the international grain markets.

Our study aims to measure the effects of India's export bans on rice on international rice markets. With this objective, this study first quantifies the export ban's impacts on how trade flows changed in India and across major rice exporters. Second, we aim to identify the redistribution effects on trade flows at the country level because of an export ban imposed by India. We seek these objectives, and we need to understand and provide some insights about how the export restriction implemented by a major exporter country can influence the trade patterns in international markets.

The first strand of the literature that our study contributes is the study that explores the assessment of the effect of a non-tariff barrier, which is less common in international trade literature published since most of the studies assess tariff barriers. The Global Trade Alert database collects information on protectionist trade policies that are imposed unilaterally. These policies likely change the treatment of domestic commercial interest relative to foreign commercial interest. India's ban on exports is driven by domestic supply concerns, and this implies there is no retaliatory reason against any country, so it is expected that it will affect all the countries, with major effects on the countries that depend on rice exports from India. The set of export restrictions imposed on rice aims to procure low domestic prices (Glauber & Mamun, 2024).

Since 1980, the use of Non-Tariff Barriers (NTBs) as international trade instruments has increased (Coughlin & Wood, 1989), while the tariffs have decreased between 1997 and 2015 (Niu et al., 2018). A study by Kinzius et al. (2019) showed that between 2009 and 2014, the implementation of NTBs reduced the imports of products by 12%; this trade-dampening effect is thus comparable to other trade defense instruments. On average, NTBs can have similar trade restrictions effects as tariffs (Bratt, 2017; Hoekman & Nicita, 2011; Looi Kee et al., 2009).

An export restriction imposed by a major producer and exporter (e.g., India) will likely have economic impacts globally and domestically. Studies focusing on the previous literature measure the economic impact of export restrictions on the world (Headey & Martin, 2016; Jensen & Anderson, 2017; W. Martin & Anderson, 2012). Other studies have also focused on evaluating the impact of export restrictions on domestic markets (Götz et al., 2013; Groom & Tak, 2015; Porteous, 2017).

A recent study showed that it is estimated that the India rice-export ban imposed on non-basmati rice represented an annualized consumer surplus loss of $365 million among all global rice consumers (Nes et al., 2025). Fathelrahman et al. (2024) using a Global Partial Equilibrium Simulation Model (GSIM), estimated that the export ban on non-basmati rice would have a negative impact on global welfare of $1.7 billion. As these studies have shown, export restrictions imposed by a country with a high international market share as an exporter are expected to have a large impact on the international rice markets and potentially other grain markets. A study by Jensen and Anderson (2017) supports the conclusions of previous literature on the need for control of export restrictions.

The second area of the literature that our study contributes is the analysis that explores changes in the trade flows of the international markets when a trade barrier is imposed by a major exporter of that product. Trade policy changes likely have non-linear effects, but their implementation can create significant disparities across products, affecting trade flow dynamics between countries with different patterns of comparative advantage and specialization and producing shifts in trade flows and production (Baqaee & Farhi, 2024; Fajgelbaum et al., 2020).

Tariffs are price-based barriers and their effects on trade flows are commonly studied. Some studies, such as Carter and Steinbach (2020), have used a gravity model using an event study framework to estimate the four potential tariff effects classified as trade destruction, trade diversion, trade deflection, and trade effects. These four effects are more predictable since they are price-induced substitution patterns (J. E. Anderson & Van Wincoop, 2003; Magee, 2008).

However, the trade redistribution effects of non-tariff barriers remain less explored. NTB's (e.g., export bans, quotas, technical or sanitary standards) do not directly alter prices but instead restrict access, increase compliance costs and uncertainty. NTB's often result in asymmetric trade responses and policy chain reactions (similar to the tariffs) from other countries, which can redirect trade flows in less predictable ways (Beestermöller et al., 2018; Disdier & Fontagné, 2010; Looi Kee et al., 2009).

Furthermore, our study analyzes the non-tariff redistribution effects at the country level and uses disaggregated HS-6 product level data of the general category of Rice (HS1006). While this study is focused on the rice markets, our analysis is relevant to the grain markets since rice is one of the major staples globally.

This study contributes to addressing the literature gap in the analysis of the effects of non-tariff barriers in international rice markets. Specifically, it provides a more detailed estimation of the effects of export bans on broken and non-basmati rice markets, highlighting trade redistribution effects that have been relatively underexplored in the existing literature, which has primarily focused on welfare implications. Moreover, this study offers recent insights into how export bans influence trade flow patterns, using data from one year after the implementation of the ban on non-basmati rice and two years for broken rice.

This paper is composed of the following sections. Section 2 explains a conceptual economic framework of the potential effects of the export bans. Section 3 describes the data employed in our study and lists the trade barriers that were implemented by India's policy. Section 4 describes our econometric modeling approach and its rationale. Section 5 provides the results and discussion of our findings and limitations of our study. Section 6 is the conclusion of our analysis.

3.2. Methods

3.2.1 Conceptual Framework

In this paper, we quantify the impact of the export ban imposed by India on its partners. The export ban is a non-tariff barrier instrument. The effects of trade redistribution remain less explored in the literature than tariff effects. Adapting the same analogy of theoretical models to identify the tariff's potential effects, we adapted the four propositions used by previous literature e.g., (Bown & Crowley, 2007; Carter & Steinbach, 2020; Park, 2009), where we expect a reduction in trade of the targeted rice from India (trade destruction effect). Other countries may increase exports when the export ban is implemented (trade deflection effect) or decrease exports (trade depression).

Assume that Country A imposes an export ban. An export ban theoretically implies zero trade from Country A with all partner countries on a specific product. For our case, we will not consider the adaptation of the definition of the trade diversion effects since, in the tariff scenario, trade diversion implies that when a tariff is implemented by country A against export B, it will cause an increase in imports to country A from country C. The analogy for the export ban would be if India imposed an export ban on only one country and their exports to other countries increased. However, India imposed the export ban on all countries, so I do not expect trade diversion in this case. We define our three propositions regarding the potential effects of the export ban actions as follows.

- First, an export ban imposed by country A causes exports from country A to all other countries C to decline (Trade destruction).
- Second, an export ban imposed by country A causes exports from country B to country C to increase (Trade deflection). This effect could occur as a consequence of Country B being able to offset the supply gap left by Country A's export ban, so Country B would increase its exports to other countries that previously traded with India.
- Third, an export ban imposed by country A causes exports from country B to country C to decrease (Trade depression). This effect could occur because of the following. First, one possibility is that the other countries (Country B) may have tried to protect their own consumers from the higher prices in the international markets, so they could have implemented an export restriction trying to insulate themselves from the effects of the India export bans. Second, a possible scenario is that if there are higher rice prices, then the importer countries (Country C) cannot import the same amount of rice as before the export ban was implemented;

this would be reflected as a decrease in the quantity exporter from the major exporter country to that specific country.

This section describes a simple conceptual framework that describes the market equilibrium conditions and the changes that an export ban causes in the supply and demand curve. Specifically, Figure 3.1 shows the effects of the export ban on the domestic market of a major rice exporter and how that affects the global market. Theoretically, when an export ban is implemented, the trade flow from the exporter to its partners must be zero; for this reason, the data employed in this analysis are the trade flows reported by the importers, since they will reflect more accurately the changes in the rice exports as a consequence of the India export bans.

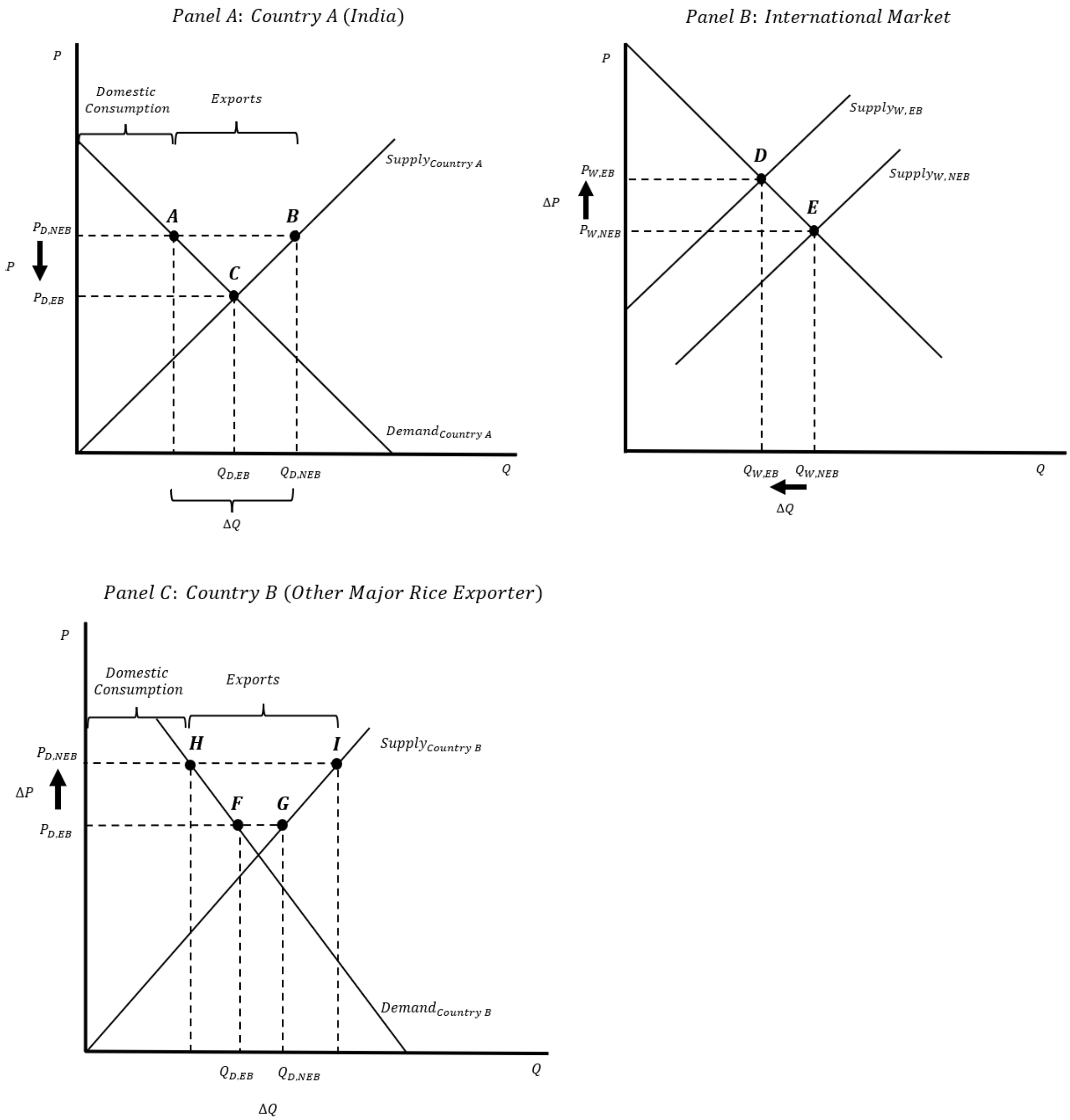


Figure 3.1 Market Equilibrium Changes when India Rice Export Ban is Imposed

Note: Domestic rice price (P_D), Domestic quantity (Q_D), International rice price (Q_W), and the International Quantity (P_W). The reduction of exports from India, is depicted in Panel A as the difference between point A and B. We assume one year after the export ban implementation the domestic quantity produced equals the domestic quantity consumed (point C). While in Panel B the change in International Quantity (ΔQ) represent the Indian exports to the rest of the world that change after the export ban was imposed. These economic outcomes are depicted in equilibrium under two scenarios: first, when the export ban was not imposed (NEB), and second, when the export ban was imposed (EB).

Figure 3.1 is focused on showing the potential trade flow changes that the export ban can trigger. Equilibrium occurs when the excess supply of rice from India is equal to the excess demand for Indian rice from the rest of the world. Panel A depicts equilibrium outcomes in the Indian domestic markets and shows how the trade destruction effects represent a decline in exports. Panel B depicts outcomes in the international market, where the supply is reduced as a consequence of the export ban from a major rice exporter, which increases the price of rice.

Panel C depicts the outcomes in Country B, which represents another major rice exporter. When the rice prices increase in the international markets, the exports from Country B tend to increase. The difference between the quantity from point F to G and the quantity H to I shows the total amount of exports the increased from Country B, which could be described as a trade deflection effect. Figure 3.1 does not depict the potential trade depression effects that the ban could trigger, but those are explained previously in this section.

We are using data from one year after the export ban on non-basmati rice was imposed and two years after the export ban on broken rice was imposed. We assume that countries can adjust their supply during this period. We assume no cross-commodity impacts, which implies that the changes in the trade instruments imposed in another type of rice that are not in the model will not affect our rice of interest.

3.2.2 Empirical Approach

3.2.2.1 Reduced Form Analysis

Adapting a similar framework used to measure the effects of trade barriers (tariff and non-tariff instruments) in the trade flows Carter & Steinbach (2020), we employ a gravity model with fixed effects, which is considered a workhorse of international trade analysis and is commonly used to quantify the effects of trade policy (Yotov et al., 2016). To estimate the three model specifications described in this section, we employ a monthly data series at the HS-6 product level. We are interested in analyzing the effects of two export bans imposed by India. First, the broken rice (100640) export ban was imposed at the HS-6 level in September 2022, and the rice export ban imposed on non-basmati rice (10063090) was imposed at the HS-8 in July 2023. To estimate the export ban effects of non-basmati rice, due to data availability, our study uses product level data of milled rice (100630) at the HS-6 category, which includes non-basmati rice as a subcategory at the HS8 level. So, from this point on, we will use the term milled rice to refer to the non-basmati category.

3.2.2.2 Effects of the Export Bans on the trade flows

To measure the impact of the export bans imposed by India on the trade flows of major rice exporters, we adopt the following regression specifications as shown in Equations 3.1 and 3.2.

For Broken Rice (100640):

$$Y_{i,j,m,y} = exp\big[\, \beta_1 EB\_BrokenRice_{m,y} * 1[i = India] + \beta_2 EB\_BrokenRice_{m,y} * 1[i \neq India] \;+\; \alpha_{i,j} + \alpha_{j,m} + \alpha_{i,y} \,\big] + \epsilon_{i,j,m,y} \qquad (3.1)$$

For Milled Rice (100630):

$$Y_{i,j,m,y} = exp\big[\, \beta_1 EB\_MilledRice_{m,y} * 1[i = India] + \beta_2 EB\_MilledRice_{m,y} * 1[i \neq India,] \;+\; \alpha_{i,j} + \alpha_{j,m} + \alpha_{i,y} \,\big] + \epsilon_{i,j,m,y} \qquad (3.2)$$

where, exp denotes the exponential function, $Y_{i,j,m,y}$ is the value of exports in millions of USD (or in millions of Kg) from exporting country *(i)* to importing country *(j),* at month *(m)* and year *(y).* The variable $EB\_MilledRice_{m,y} * 1[i = India]$ is equal to 1 if the export ban imposed by India is in effect and the exporter country *(i)* is India, and zero otherwise. The variable

$EB\_MilledRice_{m,y} * 1[i \neq India,]$ is equal to 1 if the export ban imposed by India is in effect and the exporter country *(i)* is another major rice exporter but India, and zero otherwise.

The models include a series of controls to isolate and identify the effects of the export ban. The model includes the fixed effect, $\alpha_{i,j}$ are exporter-importer, and $\alpha_{j,m}$ are importer-month, $\alpha_{i,y}$ are exporter-year fixed effects. The exporter-importer fixed effects ($\alpha_{i,j}$) controls for all the time-invariant bilateral variables between the country pair countries (e.g., trade costs, distance). The importer-month ($\alpha_{j,m}$) fixed effects control for the cyclical conditions that the importer country encounters with all the trade partners each month. The exporter-year ($\alpha_{i,y}$) fixed effects control for the annual conditions that the exporter countries face on international rice trade. To identify the parameter of interest in all regression models, we employ the Poisson pseudo-maximum likelihood (PPML). The use of this parameter allows us to use zero trade flows in our regressions (Gong and Samaniego, 1981; Sylva and Tenreyro, 2006). This parameter is suitable for our analysis since we are analyzing an export ban, and zero trade flow values are highly expected among countries' trade partners.

3.2.2.3 Effects of the Export Bans by Country

To properly identify and show the trade diversion and trade deflection effects as a consequence of the export ban on major rice exporters, we estimated models where, instead of grouping the other countries in just one binary variable, we disaggregated the binary variable in order to estimate country-specific coefficients. Model 2 specification is an extended version of model 1, where we employ the following model specification shown in Equations 3.3 and 3.4. For Broken Rice (100640):

$$Y_{i,j,m,y} = exp\left[\ \beta_1 EB\_BrokenRice_{m,y} * 1[i = India]\ + \sum_{c \neq India} \beta_{2,i} EB\_BrokenRice_{m,y} * 1[i = c]\ \ +\ \alpha_{i,j} + \alpha_{j,m} +\ \alpha_{i,y}\ \right] + \epsilon_{i,j,m,y} \qquad (3.3)$$

For Milled Rice (100630):

$$Y_{i,j,m,y} = exp\left[\ \beta_1 EB\_MilledRice_{m,y} * 1[i = India]\ + \sum_{c \neq India} \beta_{2,i} EB\_MilledRice_{m,y} * 1[i = c]\ \ +\ \alpha_{i,j} + \alpha_{j,m} +\ \alpha_{i,y}\ \right] + \epsilon_{i,j,m,y} \qquad (3.4)$$

where the subscript c denotes a list of countries that are considered major rice exporters, as explained previously in the Data section, the list of countries included in our study are those countries considered major rice exporters, which includes all the countries that contributed to 90% of the trade flows of the international rice markets (depending on which type of rice the export ban was imposed) 12 months prior to the implementation of the export ban. As explained in the Conceptual model section, the coefficients of these variables aim to measure the effects of trade destruction when the coefficient is negative, indicating a decline in exports from India to its partners. Trade deflection effects if the coefficient is positive, indicating an increase in exports from Country B to Country C. Also, if the coefficient is negative, indicating the exports from major exports decline and can be described as trade depression effects as a consequence of export bans.

3.2.2.4 Effect of the Export Bans by Region and Income Category

The third model specification focuses on the changes in trade patterns from the perspective of the importing countries. Complementary to model 1 and model 2, where we identify how the trade flow among major rice exporters changed. Model 3 reveals what group of countries may be more affected by the changes in the international markets as a consequence of the export bans imposed by India.

This third model specification is an extended version of models 1 and 2 previously described, with the key difference being that we use an interaction of the Export Ban binary variable grouping the importing rice countries depending on their region and by income category. The income and region groups based on the classification are published by the World Bank (2025). Since broken rice and milled rice have different types of markets, different countries import this type of rice. For model 3, we estimate how the trade flow by groups (by region and by country income category) changes when the export bans are in effect, meaning we estimate a specific coefficients group, and the countries are grouped.

By Income Category:

For Broken Rice (100640):

$$Y_{i,j,m,y} = exp\left[\beta_1 EB\_BrokenRice_{m,y} * 1[i = India] + \sum_k \beta_{2,k} EB\_BrokenRice_{m,y} * 1[i \neq India \,\&\, j \in k] + \alpha_{i,j} + \alpha_{j,m} + \alpha_{i,y} \right] + \epsilon_{i,j,m,y} \qquad (3.5)$$

For Milled Rice (100630):

$$Y_{i,j,m,y} = exp\left[\beta_1 EB\_MilledRice_{m,y} * 1[i = India] + \sum_k \beta_{2,k} EB\_MilledRice_{m,y} * 1[i \neq India \,\&\, j \in k] + \alpha_{i,j} + \alpha_{j,m} + \alpha_{i,y} \right] + \epsilon_{i,j,m,y} \qquad (3.6)$$

where the subscript k denotes a list of groups of countries classified by their income, using the World Bank classification, we group the countries into low-income, low-middle-income, upper-middle-income, and high-income groups. The $\beta_{2,k}$ denotes the coefficient of the country-specific variable $EB\_MilledRice_{m,y}$, it will show the change in quantity imported from countries when

India is not an exporter. As in the previous model 1 and 2, β_1 denotes the coefficient of the variable that captures the loss in exports from India.

By Region:

For Broken Rice (100640):

$$Y_{i,j,m,y} = exp\left[\, \beta_1 EB\_BrokenRice\_Region_{m,y} * 1[i = India] \quad + \sum_r \beta_{2,r} EB\_BrokenRice\_Region_{m,y} * 1[i \neq India\ \&\ j \in r] + \alpha_{i,j} + \alpha_{j,m} + \alpha_{i,y} \,\right] + \epsilon_{i,j,m,y} \tag{3.7}$$

For Milled Rice (100630):

$$Y_{i,j,m,y} = exp\left[\, \beta_1 EB\_MilledRice\_Region_{m,y} * 1[i = India] \quad + \sum_r \beta_{2,r} EB\_MilledRice\_Region_{m,y} * 1[i \neq India\ \&\ j \in r] + \alpha_{i,j} + \alpha_{j,m} + \alpha_{i,y} \,\right] + \epsilon_{i,j,m,y} \tag{3.8}$$

where the subscript r is a vector that contains a list of groups of countries classified by their income, this list of groups is based on the region in which this country is located: East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia, Sub-Saharan Africa. The list of countries included in this analysis is only those that contribute to 90% of the trade of the international rice markets and are aggregated according to their income classification based on the World Bank criteria.

3.3. Data

The Harmonized System (HS) codes are a standardized numerical method system used to classify traded products (International Trade Administration, 2024). At the HS-4, the major category for rice has the code HS 1006, which includes the HS-6 level four major rice categories, which are Husk Rice (100610), Husked Rice (100620), Milled Rice (100630), and Broken Rice (100640). This study will focus on the Milled and Broken Rice categories.

Table 3.1 shows the description of the products, and the timeline of the trade instruments India has been implementing in the rice markets. This study focuses on the export ban imposed on broken rice (100640) in the HS-6 category in September 2022 and the rice export ban imposed on non-basmati rice (10063090) imposed at the HS-8. To estimate the export ban effects of non-basmati rice, due to data availability, our study uses product level data of Milled Rice (100630) at the HS-6 category, which includes non-basmati rice as a subcategory at the HS-8 level. So, from this point on, we will use the term milled rice to refer to the non-basmati category.

To focus our study on major exporters and importers in the international markets, we limit our dataset to the following criteria. We selected the countries that contributed 90% of the international rice market of each type (broken and milled rice) a year prior to the export ban being imposed. For instance, for the export ban for broken rice that was imposed in September 2022, we consider all the countries that traded broken rice from September 2021 until August 2022 and contributed 90% of the trade flows of broken rice. With this, we ensure that we focus on the major players of the rice market, depending on the type of rice, and avoid noise and missing values in the econometric analysis since we want to assess how countries reacted to the export ban.

We employ a monthly time series of bilateral trade flows at the HS-6 product level code from January 2021 until September 2024. For the rice category broken rice (100640), the dataset includes 24 exporters and 34 importer countries. The dataset includes 64,128 observations. For the rice category milled rice (100630), the dataset includes 24 exporters and 58 importer countries. This dataset includes 124,992 observations. The product-level export data is collected from UN COMTRADE. To construct our dataset and estimate the models, we use the data reported by the importer countries.

Table 3.1 Timeline summary of trade barriers imposed by India

No	HS-4	HS-6	Description	HS-8	Description	Export Restrictions	Date Implemented	Date Removed
1	1006							
2		100610	Rice with Husk			20% Export Duty (Tariff)	9/9/2022	10/23/2024
3		100620	Rice Husked			20% Export Duty (Tariff)	9/9/2022	10/23/2024
4		100630	Milled Rice	10063010	Parboiled Rice	20% Export Duty (Tariff)	8/25/2023	9/28/2024
5						10% Export Duty (Tariff)	9/28/2024	10/23/2024
6				10063020	Basmati Rice	Minimum Export Price (MEP)	8/27/2023	10/14/2024
7				10063090	Non-Basmati Rice	20% Export Duty (Tariff)	9/9/2022	
						Export Ban	7/27/2023	9/28/2024
						Minimum Export Price (MEP)	9/28/2024	10/14/2024
8		100640	Rice, Broken			Export Ban	9/9/2022	Still in place

3.4. Results and Discussion

This section is composed of two parts. First, we present a descriptive analysis about the export ban effects. In the second part, we present the empirical approach, in which we discuss the estimates of our econometric models.

3.4.1 Descriptive Analysis:

This section focuses on analyzing the trade flow percentage changes one year before and one year after the implementation of the export bans. First, we show some descriptive evidence of how imports of rice change on average across countries and by regional location and depending on their income category using the World Bank Classification.

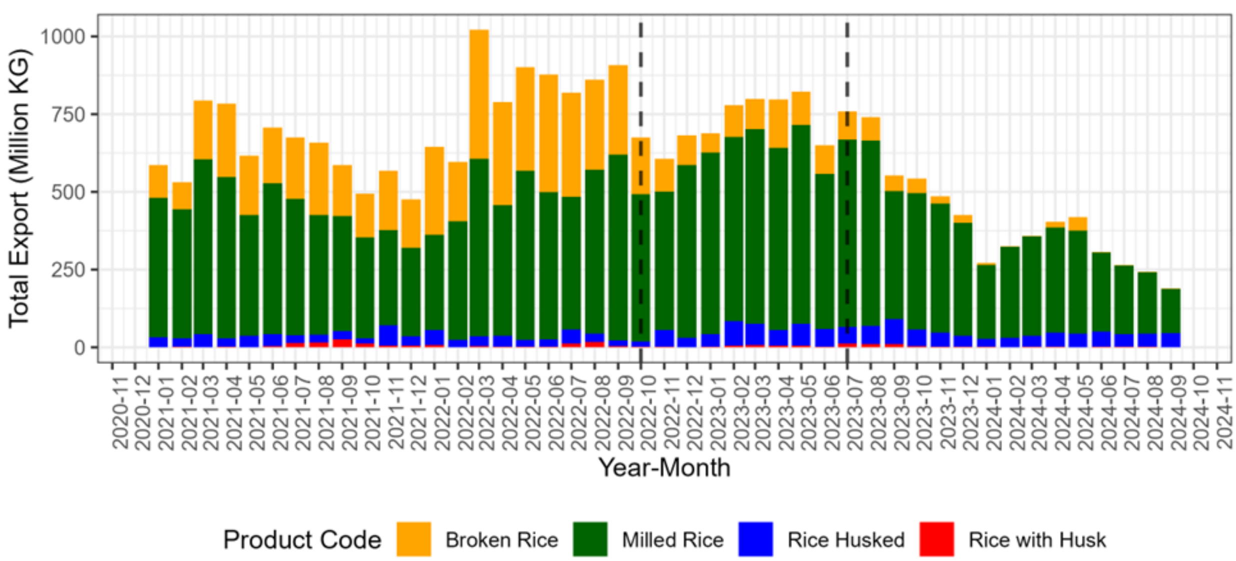


Figure 3.2 India Rice Exports to the World by Rice Type at the HS-6 product level.

Figure 3.2 shows how the exports of rice in India decreased after the two export bans were imposed. The dotted black lines indicate the broken rice export ban imposed in September 2022 and the non-basmati rice export ban implemented in July 2023. Global rice exports and imports are expected to decrease as a consequence of the impact of India's export bans. It is expected that Sub-Saharan African countries change their trade flows substantially since they are the countries that import most of the rice exported by India. On the other hand, the increasing demand for rice in the global market will put pressure on other major rice exporters such as US, Brazil, Thailand, Vietnam, and Pakistan (USDA-FAS, 2023a).

It is important to remember that the broken rice category depends on the production of the subcategories from milled rice. However, in this analysis, we assume no cross-commodity effects, so we treat the category broken rice as non-dependent on the other rice subcategories.

3.4.2 Comparing the effects of the two exports bans

When comparing the effects of the two export bans, Figure 3.2 shows that the effects of the export ban on broken rice (100640) are substantial and have a major dimension, while those effects from the export ban on milled rice (100630). Broken rice exports decline immediately but do not go to zero until approximately 24 months after the export ban was implemented. Although milled rice exports declined, it is important to note that this category includes three subcategories, and the export ban of interest was imposed only on non-basmati rice (10063090). We can see that India is still exporting parboiled and basmati rice, so milled rice exports do not go to zero.

In the case of broken rice, the other major broken rice exporting countries did not increase their exports significantly, which would indicate that they were not able to offset the supply gap left by India. In the broken rice market, India had a global rice market share of 38% before the ban. We can see the market share of Myanmar (10%), Vietnam (11%), and Pakistan (14%). However, 12 months after the export ban was imposed, it increased to 16% and 14%. However, Pakistan decreased to 6%. Adding the market share of the other three major broken rice exporters, which is 35%, we can see that India has a higher dominance as an exporter in the broken rice international market than on milled rice where we add the market share of the two other major milled rice export account for 32%.

The results show that while other countries increased their export significantly to offset the supply of milled rice, where India had a market share of 30% of the global rice market. Before the export ban, Thailand and Vietnam were the major milled rice exporters, with a market share of 17% and 15%, respectively. While 12 months after the export ban was imposed, we can see that Thailand's and Vietnam's market share increased to 23% and 18%.

The results of this comparison of export quantities by country reveal that in the case of broken rice market countries with higher increase in their exports are Spain (622%), Singapore (237%), Togo (119%), Brazil (106%), Mozambique (73%), and Paraguay (40%) while the countries with large decrease change in their exports during that period of time are Pakistan (-78%), China (-77%), United Arab Emirates (-53%), South Africa (-28%) and USA (-25%).

In the case of the milled rice market, we see that rice exporters such as Pakistan (55%), Thailand (70%), Thailand (53%), Japan (49.6%) and Singapore (48%) increase their exports while other countries such Tanzania (-97%), Peru (-72%), Belgium (-29%), Argentina (-27%), Laos (-26.1), and United Arab Emirates (-21%) decrease their exports.

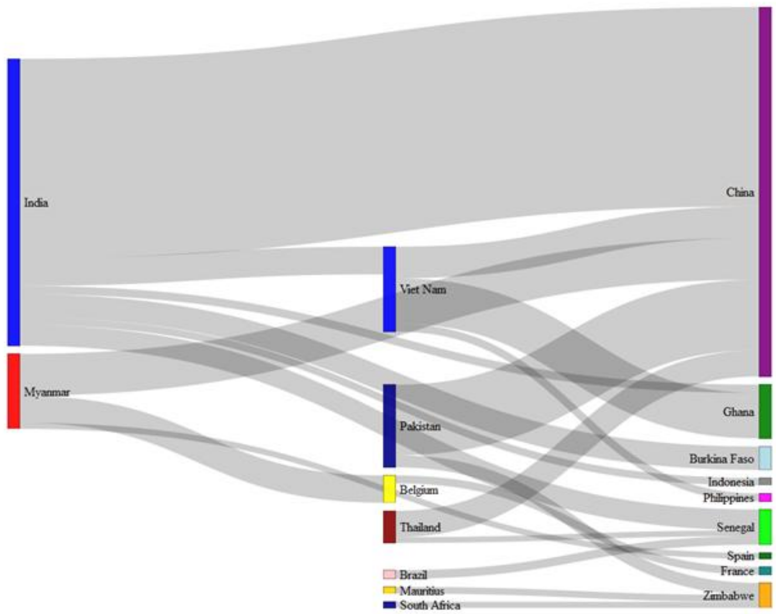
In the following sections, Figure 3.3 and Figure 3.4 show how India lost its presence in the rice markets after imposing the export bans. Specifically, Figure 3.3 shows how trade flows among major broken rice exporters change over time, comparing the average of the trade flows 12 months before and 12 months after the export ban was enacted by India. Figure 3.4 shows how India lost its position as a major rice exporter in the broken rice international market.

Countries such as Myanmar, Vietnam, and Thailand increase their presence in the international rice market. India almost completely lost its presence in the broken rice markets after 24 months. In the case of Pakistan, we can see how it reduced its exports during the 12 months after the export ban was imposed but increased its exports and increase its market share after 12 months.

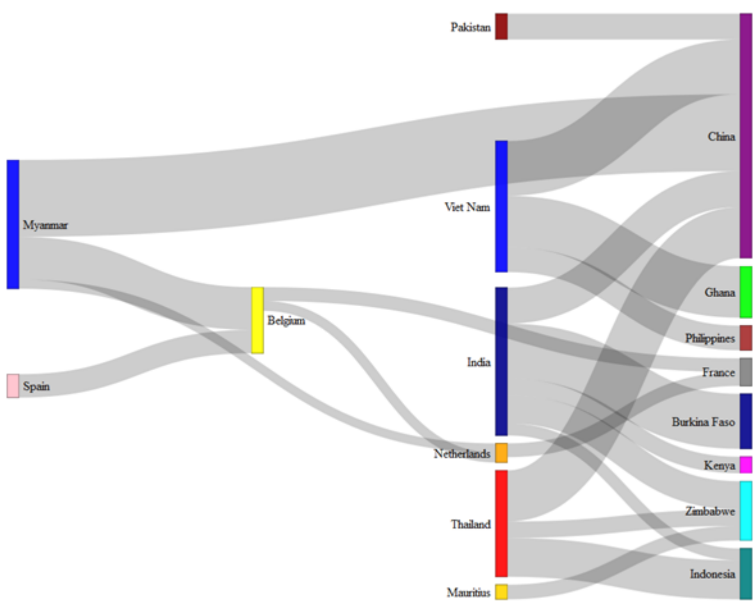
Complementary, we estimated the import quantities and the percentage change in the major rice importer one year before and after the export bans were imposed, in each type of rice. It is important to highlight that the percentage changes present in this section are estimates based on the following process: we added the quantity exported by each country in exports 12 months before and 12 months after the export ban was implemented. Then we calculated the percentage change using as a denominator the total exports one year before and as a numerator the total exports 12 months after the export restriction was imposed. Further, percentage changes could represent different quantities based on the size of the quantity exported by each country. See Table C1, Table C2, Table C3, and Table C4 in Appendix C.

Figure 3.3 Trade flow patterns of broken rice at the HS-6 level (100640) before and after the export ban imposed by India in October 2022.

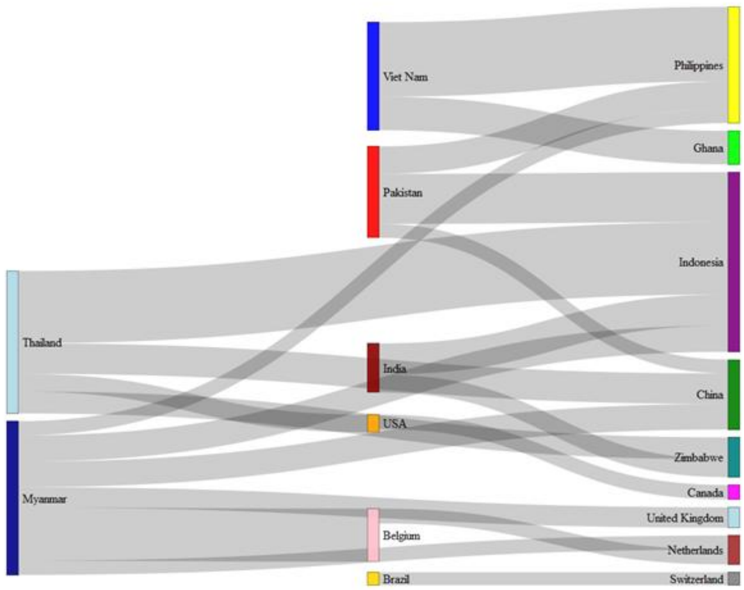
1 Year before the export ban (October 2021 until September 2022):



1 Year after the export ban (October 2022 until September 2023):



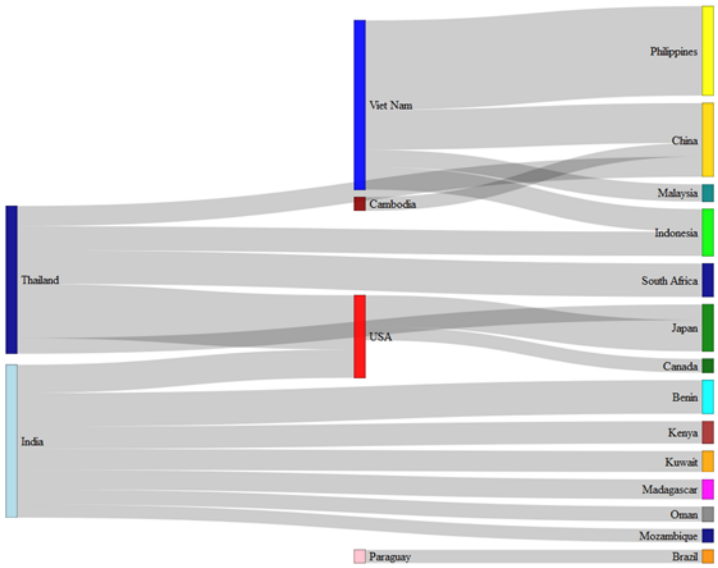
2 Years after the export ban (October 2023 until September 2024):



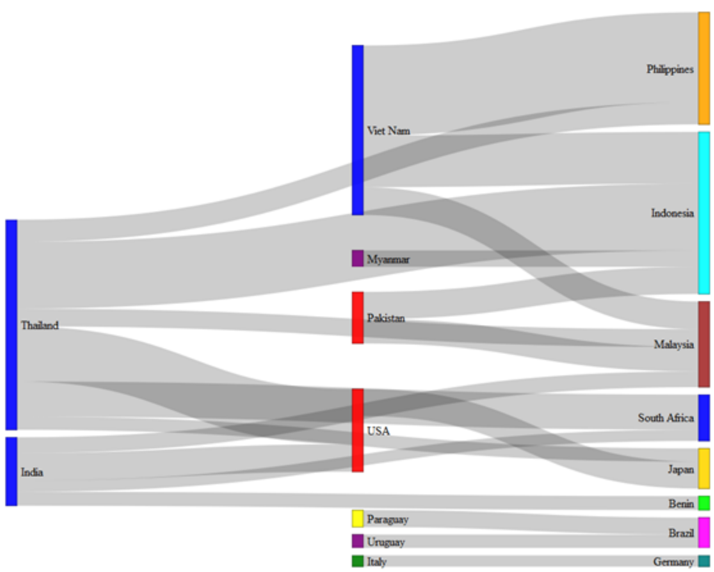
The following Figure 3.3 shows how India lost its position as a major milled rice exporter in the international markets after the export ban imposed on non-basmati rice (10063090). We can see how countries such as Thailand and Vietnam increase their presence in the international rice market.

Figure 3.4 Trade flows patterns of milled rice at the HS-6 level (100630) after the export ban on non-basmati rice (10063090) imposed by India in July 2023

1 Year before the export ban (August 2022 until July 2023):



1 Year after the export ban (August 2023 until July 2024):



Note: The export ban imposed by India on July 2023 is at the HS-8 category level for rice (10063090), while the graph reflects data at the HS-6 level of milled rice (100630) exports.

3.4.3 Empirical Approach: Trade Flow Effects

In this section, we present the estimates of the econometric models described previously. We empirically assess how exports of rice change on average (across countries and by country) when an export ban is implemented. We exploit differences in trade flows (exports/imports) in the rice markets among major grain exporting/importing countries. As expected, our results show that the export ban (which is a non-tariff trade barrier) imposed by India has a significant impact on the trade patterns among the major rice exporters and importers, triggering trade destruction effects, trade deflation effects, and trade depression effects.

The main results of the specification for Model 1 are shown in Table 3.2 and Table 3.3. To estimate the effects of the India rice export bans on bilateral trade flows between India and its existing network of imports, we employ a gravity model with fixed effects. Table 3.2 and Table 3.3 shows the results of model 1, which aims to measure the changes in exports from India to other countries and changes in exports from other countries considered major rice exporters. As expected, the export ban on broken rice had a destructive effect, significantly decreasing exports from India to its current trading network partners.

Theoretically, when an export ban is implemented, the trade flow from the exporter to its partners must be zero. However, our data reveal that even after the export ban took effect, India continued exporting broken rice the following year. This explains why the coefficient is not closer to -1, which would indicate full implementation of the export ban, reducing exports to zero. India’s exports to its trade partners after the ban was enacted may reflect previously signed contracts that still had to be fulfilled. Figure 3.3 and Figure 3.4 show that after twelve months, the broken rice exports from India declined closer to zero values.

Table 3.2 Effects of Export Ban on Broken Rice (100640) imposed on September 2022. Dataset from January 2021 to September 2024.

Units	USD			KG		
Variable	Coefficient	Std. Error	Sig.	Coefficient	Std. Error	Sig.
EB_BrokenRice *1[i=India]	-0.693	0.233	***	-0.716	0.179	***
EB_BrokenRice*1[i≠India]	0.124	0.140		0.135	0.168	
Fixed Effects						
Exporter(i)-Importer(j)	Yes			Yes		
Exporter(i)-Year(y)	Yes			Yes		
Importer(i)-Month(m)	Yes			Yes		
Pseud R2	0.844			0.882		
Observations	14748			14748		

Our results indicate there was an increase in exports from other countries as a consequence of the export ban, but the increase was not statistically significant. India was the major broken rice exporter in 2022, having a market share of 38%, and the results suggest that other countries cannot easily offset that market share left by India. Another potential reason is that this type of rice or market is not of interest to other countries since the profit margin is probably lower than that of other types of rice markets.

It is important to highlight that while the export ban on broken rice (100640) was imposed at the HS-6 level code, the export ban imposed on non-basmati rice (10063090) was at the HS-8 level product code. Table 3.3 shows the models' results, which aim to quantify the effects of the export ban at the HS8 level on non-basmati rice (10063090), which falls under the HS-6 category of milled rice (100630).

Table 3.3 Effects of Export Ban on Milled Rice (100630), imposed on July 2023. Dataset from January 2021 to September 2024.

Units	USD			KG		
Variable	Coefficient	Std. Error	Sig.	Coefficient	Std. Error	Sig.
EB_MilledRice*1[i=India]	-0.097	0.109		-0.232	0.170	
EB_MilledRice*1[i≠India]	0.295	0.000	.	0.295	0.098	***
Fixed Effects						
Exporter(i)-Importer(j)	Yes			Yes		
Exporter(i)-Year(y)	Yes			Yes		
Importer(i)-Month(m)	Yes			Yes		
Pseud R2	0.904			0.882		
Observations	43836			43692		

The coefficient on the variable EB_MilledRice*1[i=India], as expected, shows the export ban has a negative effect on exports from India; however, it is not significant. The variable EB_MilledRice*1[i≠India] shows an increase in exports from other major rice exporters when the export ban is in effect and is statistically significant. The results suggest that the other countries increased and were highly interested in offsetting the market share left by India.

When comparing the estimates of the model's value or quantities to quantify the export ban effects, the findings reflect that when using rice value (USD) data to quantify the effects of the export ban, the estimates show a lower negative effect than the model using quantities (KG). This also reminds us not only to look at product values but also quantities since it is important to have deeper insights into the effects of the export ban. In this case, the prices of rice exports can increase as a result of the shortage of rice in international markets, which could hide the potential effects of the export ban because even though the exports in quantity decline, the value of those exports can be increasing.

It is important to highlight that exports in value (USD) and quantity (KG) react in opposite directions as a consequence of the change in supply. When the export ban is implemented, there is less supply, which will trigger higher prices, and the opposite would happen if the quantity supply increased and the prices decreased. The upward estimates when using the value of trade flows to estimate gravity models has been previously shown by (Dall'Erba, Chen, and Nava, 2021). As stated in our objective, we are focusing on analyzing the trade flow changes rather than the price or welfare impacts. Given the context of our analysis, the use of quantities exported (KG) as a dependent variable is more appropriate. Using this criterion in the following section, we focus on discussing the estimates from the models that use trade flows data in quantities (KG), however, we still report the estimates of the models using value (USD).

The identification of the effects of the export ban on non-basmati could be affected by three reasons. First, the price of rice increases as a consequence of the export ban. Second, the model has been estimating using HS-6 level data when the export ban was imposed at HS-8, which leads to diffuse the identification of the effects of the export ban since there are two other categories of rice (basmati and parboiled) that are still exported by India under the category milled rice while the export ban on non-basmati is already in place. Finally, it is possible to have a substitution effect among types of rice as a consequence of other trade barriers imposed previously, such as the export ban on broken rice, the minimum export price (MEP) on basmati rice, or the tariff on parboiled rice.

To analyze at the country level, the redistribution trade effects, we estimate model 2, and to analyze by group of countries based on their region or income category, we estimated model 3. While the results of model 1 show how the export ban, on average, had a positive impact on the trade flows of the other major rice exporters.

3.4.4 Trade Flow Changes Effects by Country (Major Exporters):

In this section, we focus on analyzing the effects of trade redistribution effects at the country level. The model 2 specification allows us to properly identify how the exports among major rice exporters change, considering the export bans imposed by India. Table 3.4 and Table 3.5 reveal in more detail the effects of trade deflection and trade depression as a consequence of the export ban at the country's level. As explained in our conceptual model, if an export ban imposed by country A causes exports from country B to country C to increase, this change can be described as a trade deflection effect. This effect could occur as a consequence of Country B being able to offset the supply gap left by Country A's export ban, so Country B would increase its exports to other countries that previously traded with India.

Trade depression can be described as the case when an export ban imposed by country A causes exports from country B to country C to decrease. This effect could occur because of the following. First, one possibility is that the other countries (Country B) may have tried to protect their own consumers from the higher prices in the international markets, so they could have implemented an export restriction trying to isolate the effects of the India export bans. Second, a possible scenario is that if there are higher rice prices, then the importer countries (Country C) cannot import the same amount of rice as before the export ban was implemented. This would be reflected as a decrease in the quantity of exports from the major exporter country to that specific country.

Also, as expected, these disaggregated models show the trade destruction effect of the rice exports from India, which is similar to the results shown in Table 3.2 and Table 3.3. Complementary to this analysis, the effects of changes in the trade flows at the country level are displayed on the Sankey graph in Figure 3.1 and Figure 3.2, showing that countries change their trade patterns and market shares following the implementation of the export bans.

For the case of the export ban imposed on broken rice. Table 3.4 shows the results of model 2, where we can identify statistically significant increases in their exports in countries such as Spain (2.043), Paraguay (0.797), Laos (0.842), Mozambique (0.161), and Italy (0.254). Also, we can identify a statistically significant decrease in the exports of countries such as Pakistan (-0.914), China (-0.517), and United Arab Emirates (-1.880).

For the case of the export ban imposed on milled rice. Table 3.5 shows the results of model 2, and the estimates reveal that there are countries that increase their exports significantly during the timeframe the export ban is in effect. Table 3.5 reveals the primary beneficiaries of the export ban imposed on broken rice are the countries Thailand (0.337), USA (0.262), Pakistan (0.687), China (0.566), Uruguay (0.606), Laos (2.377), and Tanzania (1.546). Also, we can identify a statistically significant decrease in the exports of countries such as Belgium (-2.444), Australia (-0.450), and Peru (-0.821).

It is interesting to see how the export ban can have opposite trade redistribution in the same country. We can see the case of China, where the export ban on broken rice causes a reduction (-0.517) of that product from China to their partners, whereas the export ban on milled rice causes an increase (0.566) in their exports of that product. A similar case is seen in Pakistan's exports, where the broken rice exports declined their exports (-0.858), whereas the milled rice export ban increased their export (0.687). This behavior reflects the difference in the rice markets. The type of rice that is grouped under the category milled rice, specifically non-basmati, is considered to have more value than broken rice, which is considered a low-value type of rice. Further, these changes in trade patterns are depicted in Figure 3.3 and Figure 3.4

Based on our conceptual model, we could describe the increase in exports from a country as a trade deflection effect and a decrease in exports from a country as a trade depression effect. However, we acknowledge that further analysis must be done to clearly identify and confirm whether the increase/decline in exports is related to causes other than the export bans imposed by India. Or if this was a consequence of trade barriers implemented by other major exporters intending to protect their domestic rice markets.

Table 3.4 Effects of Broken Rice Export Ban, when using country specific dummy variables, from January 2021 to September 2024.

Units	USD			KG		
Term	Coefficient	Std. Error	Sig.	Coefficient	Std. Error	Sig.
EB_BrokenRice*1[i=India]	-0.738	0.218	***	-0.757	0.170	***
EB_BrokenRice_MMR	-0.028	0.317		-0.007	0.357	
EB_BrokenRice_THA	0.306	0.342		0.347	0.349	
EB_BrokenRice_VNM	-0.066	0.205		-0.107	0.171	
EB_BrokenRice_PAK	-0.858	0.239	***	-0.914	0.248	***
EB_BrokenRice_ESP	1.751	0.820	*	2.043	0.845	*
EB_BrokenRice_MUS	-0.024	0.164		0.014	0.164	
EB_BrokenRice_BEL	0.183	0.184		0.206	0.189	
EB_BrokenRice_NLD	-0.027	0.125		0.098	0.138	
EB_BrokenRice_USA	-0.003	0.159		0.223	0.238	
EB_BrokenRice_PRY	0.758	0.240	**	0.797	0.205	***
EB_BrokenRice_BRA	1.092	0.763		1.519	0.753	*
EB_BrokenRice_KHM	-0.217	0.075	**	-0.073	0.094	
EB_BrokenRice_ZAF	-0.506	0.624		-0.526	0.615	
EB_BrokenRice_SGP	0.121	0.207		0.046	0.219	
EB_BrokenRice_TGO	-0.848	0.559		0.150	0.413	
EB_BrokenRice_ITA	0.158	0.094	.	0.250	0.124	*
EB_BrokenRice_ARE	-2.109	0.416	***	-1.880	0.452	***
EB_BrokenRice_TUR	-0.311	0.771		-0.017	0.664	
EB_BrokenRice_LAO	0.647	0.183	***	0.842	0.203	***
EB_BrokenRice_ARG	0.623	0.949		0.666	0.974	
EB_BrokenRice_CRI	0.463	0.277	.	0.399	0.258	
EB_BrokenRice_CHN	-0.199	0.283		-0.517	0.306	.
EB_BrokenRice_MOZ	0.180	0.249		0.349	0.161	*
Fixed Effects						
Exporter(i)-Importer(j)	Yes			Yes		
Exporter(i)-Year(y)	Yes			Yes		
Importer(i)-Month(m)	Yes			Yes		
Pseudo R2	0.846			0.860		
Observations	14748			14658		

Table 3.5 Effects of Milled Rice Export Ban, when using country specific dummy variables, from January 2021 to September 2024.

Units	USD			KG		
Term	Coefficient	Std. Error	Sig.	Coefficient	Std. Error	Sig.
EB_MilledRice*1[i=India]	-0.090	0.108		-0.223	0.170	
EB_MilledRice_VNM	0.208	0.170		0.211	0.207	
EB_MilledRice_THA	0.429	0.128	***	0.337	0.134	*
EB_MilledRice_USA	0.227	0.082	**	0.262	0.112	*
EB_MilledRice_KHM	0.176	0.187		0.159	0.223	
EB_MilledRice_PRY	0.134	0.139		-0.031	0.124	
EB_MilledRice_ITA	-0.055	0.048		-0.021	0.050	
EB_MilledRice_MMR	0.414	0.447		0.245	0.467	
EB_MilledRice_PAK	0.665	0.256	**	0.687	0.317	*
EB_MilledRice_CHN	0.392	0.227	.	0.566	0.310	.
EB_MilledRice_URY	0.606	0.174	***	0.600	0.117	***
EB_MilledRice_BEL	-0.244	0.074	**	-0.289	0.078	***
EB_MilledRice_NLD	0.031	0.062		-0.016	0.068	
EB_MilledRice_AUS	-0.450	0.212	*	-0.276	0.187	
EB_MilledRice_ARE	-0.237	0.373		-0.065	0.255	
EB_MilledRice_ESP	0.058	0.180		0.018	0.210	
EB_MilledRice_ARG	-0.183	0.417		-0.511	0.356	
EB_MilledRice_ZAF	0.536	0.682		0.648	0.721	
EB_MilledRice_SGP	0.348	0.182	.	0.277	0.218	
EB_MilledRice_GRC	-0.628	0.519		-0.516	0.526	
EB_MilledRice_LAO	2.377	0.297	***	2.217	0.270	***
EB_MilledRice_BGR	-0.422	0.460		-0.511	0.409	
EB_MilledRice_CAN	0.191	0.101	.	0.196	0.113	.
EB_MilledRice_TZA	1.546	0.096	***	1.156	0.075	***
EB_MilledRice_PER	-0.821	0.421	.	-1.191	0.403	**
EB_MilledRice_BRA	0.216	0.195		0.278	0.195	
EB_MilledRice_JPN	0.068	0.061		0.518	0.240	*
EB_MilledRice_DEU	-0.530	0.170	**	-0.4329	0.2872	
Fixed Effects						
Exporter(i)-Importer(j)	Yes			Yes		
Exporter(i)-Year(y)	Yes			Yes		
Importer(i)-Month(m)	Yes			Yes		
Pseudo R2	0.904			0.893		
Observations	43836			43692		

3.4.5 Trade Flow Changes in Major Importers, Model 3:

So far, we have focused on how trade flows change from the perspective of major exporters. However, a bilateral trade flow would represent an export from a country and imports from another country. An export ban theoretically reduces the exports to zero if fully implemented. In this section, we focus on the changes in the import trade flows of broken rice and milled rice in order to complement our analysis. To do that, we estimate model 3. We seek to identify which region and group of importer countries were more affected by the export bans and also will bring some insights about food security implications and how the two different rice markets react to export restrictions from a major exporter such as India.

3.4.6 Trade Flows Changes by Region

Table 3.6 shows the results of model 3 and reveals that the countries in the Latin America Region significantly increased their total imports of broken rice by 74.1%, from other major exporters. If these countries were importing a majority of their rice from India, then total imports would have still decreased as a consequence of the export ban on milled rice but the increase in imports from other regions allowed a substantial offset of the impacts of India's ban. The results also show that the region of North America, Sub-Saharan Africa, and East Central Africa declined their imports, but those changes were not significant. Table 3.6 and Table 3.7 shows the results of model 3 and reveals that East Asia & Pacific Region and Latinoamerica Region significantly increased their imports of milled rice by 0.527 and 0.656.

Table 3.6 Effects of Broken Rice Export Ban, by region, from January 2021 to September 2024

	USD				KG			
Term	Coefficient	Std. Error	P-Value	Sig.	Coefficient	Std. Error	P-Value	Sig.
EB_BrokenRice*1[i=India]	-1.109	0.418	0.008	**	-0.834	0.615	0.176	
EB_BrokenRice_RegionEAP	0.232	0.325	0.476		0.151	0.381	0.692	
EB_BrokenRice_RegionNAM	-0.072	0.327	0.824		-0.203	0.387	0.599	
EB_BrokenRice_RegionSSA	-0.127	0.204	0.533		-0.119	0.225	0.596	
EB_BrokenRice_RegionLAC	0.709	0.195	0.000	***	0.741	0.180	0.000	***
EB_BrokenRice_RegionECA	-0.197	0.258	0.444		-0.186	0.305	0.543	
Fixed Effects								
Exporter(i)-Importer(j)	Yes				Yes			
Exporter(i)-Year(y)	Yes				Yes			
Importer(i)-Month(m)	Yes				Yes			
Pseudo R2	0.851				0.862			
Observations	12823				12756			

Table 3.7 Effects of Milled Rice Export Ban, by region, from January 2021 to September 2024

	USD				KG			
Term	Coefficient	Std. Error	P-Value	Sig.	Coefficient	Std. Error	P-Value	Sig.
EB_MilledRice*1[i=India]	-0.157	0.114	0.167		-0.306	0.177	0.083	.
EB_MilledRice_RegionEAP	0.527	0.182	0.004	**	0.518	0.194	0.008	**
EB_MilledRice_RegionNAM	-0.138	0.139	0.319		-0.119	0.165	0.473	
EB_MilledRice_RegionSSA	-0.026	0.151	0.866		-0.154	0.210	0.464	
EB_MilledRice_RegionMENA	0.121	0.125	0.330		-0.042	0.158	0.791	
EB_MilledRice_RegionLAC	0.656	0.306	0.032	*	0.628	0.341	0.066	.
EB_MilledRice_RegionECA	-0.061	0.091	0.506		-0.157	0.131	0.230	
Fixed Effects								
Exporter(i)-Importer(j)	Yes				Yes			
Exporter(i)-Year(y)	Yes				Yes			
Importer(i)-Month(m)	Yes				Yes			
Pseudo R2	0.911699				0.9002			
Observations	38254				38130			

3.4.7 Trade Flow Changes by Income Category

Table 3.8 shows the results of model 3, revealing that the countries classified under the category Low Income and High Income decreased their imports of broken rice from countries other than India; however, those changes were not significant. Also, the results show countries under the category Low-Middle Income and upper-middle-income category increased their imports from countries other than India but not significantly.

Table 3.9 shows the results of model 3 and reveals that countries classified as upper-middle income increased their imports of milled rice from countries other than India statistically when the export ban on non-basmati rice was imposed by India. In contrast, countries classified as Upper Middle-Income Countries increase their imports by 42.1 % from countries other than India significatively.

This analysis is relevant since low- and middle-income countries or developed countries have different purchasing power, which implies that they tend to consume different types of rice. While the milled rice category includes rice as basmati is considered a luxury rice type, markets with high purchasing power will be the ones interested in buying this variety, while low- and middle-income countries will be more interested in buying broken rice at a lower price.

Table 3.8 Effects of Broken Rice Export Ban, by Income Category, from January 2021 to September 2024.

Term	USD				KG			
	Coefficient	**Std. Error**	**P-Value**	**Sig.**	**Coefficient**	**Std. Error**	**P-Value**	**Sig.**
EB_BrokenRice*1[i=India]	-1.123	0.427	0.008	**	-0.843	0.623	0.176	
EB_BrokenRice_LowI	-0.032	0.494	0.948		0.038	0.547	0.944	
EB_BrokenRice_LowMidI	0.202	0.234	0.389		0.243	0.246	0.324	
EB_BrokenRice_UppMidI	0.048	0.306	0.874		-0.013	0.357	0.970	
EB_BrokenRice_HighI	-0.185	0.228	0.416		-0.169	0.264	0.523	
Fixed Effects								
Exporter(i)-Importer(j)	Yes				Yes			
Exporter(i)-Year(y)	Yes				Yes			
Importer(i)-Month(m)	Yes				Yes			
Pseudo R2	0.851				0.862			
Observations	12823				12756			

Table 3.9 Effects of Milled Rice Export Ban, by Income Category, from January 2021 to September 2024.

Term	USD				KG			
	Coefficient	Std. Error	P-Value	Sig.	Coefficient	Std. Error	P-Value	Sig.
EB_MilledRice*1[i=India]	-0.154	0.113	0.173		-0.272	0.173	0.117	
EB_MilledRice_LowI	0.256	0.163	0.117		1.621	0.469	0.001	***
EB_MilledRice_LowMidI	0.102	0.179	0.570		0.283	0.185	0.126	
EB_MilledRice_UppMidI	0.724	0.215	0.001	***	0.421	0.208	0.043	*
EB_MilledRice_HighI	-0.071	0.084	0.397		-0.192	0.121	0.112	
Fixed Effects								
Exporter(i)-Importer(j)	Yes				Yes			
Exporter(i)-Year(y)	Yes				Yes			
Importer(i)-Month(m)	Yes				Yes			
Pseudo R2	0.913				0.900			
Observations	38254				38130			

3.4.8 Robustness Checks

The purpose of the robustness check is to evaluate the validity of our estimates with different fixed effects. We estimate a gravity model using an alternative set of fixed effects and expect that the outcome should not affect the significance of, and sign, dimension of our results for potential model misspecification. See Table C5 in Appendix C for more information.

3.4.9 Limitations of the Study

We recognized that a limitation of our model is not being able to control for all the factors commonly implemented for the multilateral resistance in the gravity model since it is a structural model. In our model, we are able to only control exporter-importer fixed effects ($\alpha_{i,j}$), importer-month ($\alpha_{j,m}$) and exporter-year (α_{y}) fixed effects controls; with this set of fixed effects, we are only partially controlling for the multilateral resistance of the gravity model framework. In order to control completely the multilateral resistance, we would need to include the controls for exporter-month-year ($\alpha_{i,m,y}$), however, our variable of interest in identifying the effects of the export ban imposed by India aligns with this control, so implementing it will not allow us to identify and estimate the parameters of our interest.

We acknowledge there are other trade barriers that may affect the identification of the effects of the export ban. Table 3.1shows the case of milled rice (100630), which has three rice subcategories at the HS-8 level: parboiled rice, basmati rice, and non-basmati rice. Also, Table 3.1 Timeline summary of trade barriers imposed by India

shows that there are other trade barriers implemented by the Indian government, such as the minimum export price (MEP) on basmati rice and export duties on parboiled rice. Moreover, there was an Export Duty on non-basmati rice before the export ban was enacted. These trade barriers may lead to misunderstandings about the effects of the export bans on our interests. We assume the effects of the export ban are more abrupt, and our model would be able to measure that since the export ban theoretically implies zero trade with country partners. Further, we assume there are no cross-commodity effects among rice types. Since this study seeks to identify the effects of the export bans in the rice markets and, using a set of fixed effects, we assume that the effects of these other trade barrier policies are being controlled in our model.

3.5. Conclusions

This paper investigates the effects of the export ban imposed by India, the export ban implemented on broken rice since September 2022, and the export ban on non-basmati rice in place since July 2023. The export ban is a non-tariff trade barrier that threatens the other countries' partners equally. We exploit the differences in export quantities and values on the two major types of rice under the HS-4 rice category, which includes all the uncooked and unprocessed rice types. First, our results indicate that the impact of the broken rice export ban had a larger impact on the international broken rice markets since India had a major market share of exports, and the exports from other countries increased but were not statistically significant. Second, the results showed that the milled rice export ban had a lower negative impact. However, the increase in exports from other countries was statistically significant.

Probably, the impact of the rice export bans on grain markets will depend largely on the ability of the major rice importers to find another source of rice and the ability of the major exporting rice countries to increase supply to gain market share. This research contributes to the strand of literature about how to identify and measure the effect of non-tariff barriers, which influence all trading partners equally. This provides some insights into how the changes in restrictions on trade in staple foods can change trade flow patterns. Rice export bans in India are suitable cases for this type of study. Overall, we identified the substantial trade flow changes in the global rice markets as a consequence of India's policy implementations. We consider the adjustment of the rice supply chain among countries varies depending on the infrastructure, policy, and technology of each country.

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Appendix A - Chapter 1

List of Countries Analyzed

The Supplementary Appendix A includes a forecast for 78 low and middle-income countries. The IFSA report that USDA assembles each year includes 83 countries, but we only include 78 countries in our analysis due to data limitations. The countries excluded from our analysis are the following:

- Cabo Verde, Jamaica, Djibouti, and Syria are excluded from the analysis due to data quality concerns. Jamaica production has very similar values for 12 years, between 2009 and 2021. Cabo Verde and Djibouti production data are erratic and very small quantities. Syria harvested area data show the same value for 20 years from 1980 until 2000.
- Sudan and South Sudan are combined into one country and labeled as Sudan (Former). Until 2011, Sudan and South Sudan were one country. Since the data before 2011 were combined, we aggregated the two countries to create a continuous time series.

Our study includes the following 78 countries; Afghanistan, Algeria, Angola, Armenia, Azerbaijan, Bangladesh, Benin, Bolivia, Buinea-Bissau, Burkina Faso, Burma, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Colombia, Congo, Cote d'Ivoire, Democratic People's Republic of Korea, Democratic Republic of the Congo, Dominican Republic, Ecuador, Egypt, El Salvador, Eritrea, Eswatini, Ethiopia, Gambia, Georgia, Ghana, Guatemala, Guinea, Haiti, Honduras, India, Indonesia, Iran, Kenya, Kyrgyzstan, Laos, Lebanon, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Moldova, Mongolia, Morocco, Mozambique, Namibia, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Peru, Philippines, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sri Lanka, Sudan (Former), Tajikistan, Tanzania, Togo, Tunisia, Turkmenistan, Uganda, Uzbekistan, Vietnam, Yemen, Zambia, Zimbabwe.

Econometric Models Tables:

Table A1 and A2, show the model specifications considered for estimating the econometric forecasting models in this study. Table A1 shows the variable combinations with pooled coefficients (i.e., estimating a single coefficient for all countries). Table A2 shows the variables with country-specific coefficients or different levels of fixed effects. We considered all combinations of models with pooled coefficients from Table A1 and country-specific variables or fixed effects from Table A2, so the total number of model specifications considered was 41x84=3,444. All 3,444s models were fitted with area as the dependent variable and again with yield as the dependent variable. All models were fitted using both OLS and Poisson models and with linear and nonlinear trends. Even though all the model specifications listed in this tables were considered, there are some cases where model fitting failed to converge, leading us to discard those model specifications. A model failing to converge is a consequence of the complexity of the model, data characteristics or numerical instability involving a large number of parameters.

Table A1: Combinations of pooled variables considered in econometric models. Part 1.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Year (Trend)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Simple Average Futuress Price		x	x	x	x	x	x	x	x	x	x	x	x	x							
Weighted Average Futuress Price															x	x	x	x	x	x	x
Simple Average Spot Price			x	x	x	x										x	x	x	x		
Weighted Average Spot Price							x	x	x	x										x	x
Precipitation (Annual)				x	x			x	x		x	x					x	x			x
Temperature (Annual)					x	x			x	x		x	x					x	x		

Table A1: Combinations of pooled variables considered in econometric models. Part 2.

Variable	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41
Year (Trend)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Simple Average Futuress Price																				
Weighted Average Futuress Price	x	x	x	x	x															
Simple Average Spot Price						x	x	x	x	x	x	x	x							
Weighted Average Spot Price	x	x					x	x	x	x				x	x	x	x			
Precipitation (Annual)	x		x	x				x	x		x	x			x	x		x	x	
Temperature (Annual)	x	x		x	x				x	x		x	x			x	x		x	x

Table A2. List of Country-Specific Variables and Fixed Effects Variables. Part 1.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Country*Year					x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futuress Price							x	x	x	x	x	x	x	x	x	x						
Country*Weighted Average Futuress Price								x	x	x	x		x	x	x	x	x	x	x	x		
Country*Simple Average Spot Price									x	x	x			x	x	x		x	x	x	x	x
Country*Simple Average Spot Price										x	x				x	x			x	x		x
Country*Precipitation					x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Temperature						x	x	x	x	x	x											
No Fixed Effect	x				x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country Fixed Effects		x																				
Subregional Fixed Effects			x																			
Regional Fixed Effects				x																		

Table A2. List of Country-Specific Variables and Fixed Effects Variables. Part 2.

Variable	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futuress Price					x	x	x	x	x	x	x	x	x	x								
Country*Weighted Average Futuress Price						x	x	x	x		x	x	x	x	x	x	x	x				
Country*Simple Average Spot Price	x						x	x	x			x	x	x		x	x	x	x	x	x	
Country*Simple Average Spot Price	x	x						x	x				x	x			x	x		x	x	x
Country*Precipitation	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Temperature				x	x	x	x	x	x													
No Fixed Effect	x	x																				
Country Fixed Effects			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Subregional Fixed Effects																						
Regional Fixed Effects																						

Table A2. List of Country-Specific Variables and Fixed Effects Variables. Part 3.

Variable	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futuress Price			x	x	x	x	x	x	x	x	x	x										
Country*Weighted Average Futuress Price				x	x	x	x		x	x	x	x	x	x	x	x						
Country*Simple Average Spot Price					x	x	x			x	x	x		x	x	x	x	x	x			
Country*Simple Average Spot Price						x	x				x	x			x	x		x	x	x		
Country*Precipitation	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Temperature		x	x	x	x	x	x															x
No Fixed Effect																						
Country Fixed Effects																						
Subregional Fixed Effects	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		
Regional Fixed Effects																					x	x

Table A2. List of Country-Specific Variables and Fixed Effects Variables. Part 4.

Variable	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futuress Price	x	x	x	x	x	x	x	x	x	x								
Country*Weighted Average Futuress Price		x	x	x	x		x	x	x	x	x	x	x	x				
Country*Simple Average Spot Price			x	x	x			x	x	x		x	x	x	x	x	x	
Country*Simple Average Spot Price				x	x				x	x			x	x		x	x	x
Country*Precipitation	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Temperature	x	x	x	x	x													
No Fixed Effect																		
Country Fixed Effects																		
Subregional Fixed Effects																		
Regional Fixed Effects	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

ARIMAX Models Table:

Table A3 shows all of the variable combinations considered to estimate the ARIMAX models in this study. Note that we estimate separate ARIMAX models for every country since it is a time series model. To make the comparison with tables A1 and A2 clearer, we have noted that they are country-specific coefficients in Table A3. Table A3 also lists the different ARIMA order (p, d, q) specifications that were considered. The total number of model specifications considered for ARIMAX was 328. All 328 models were fitted with area as the dependent variable and again with yield as the dependent variable. Even though all the model specifications listed in this table were considered there are some cases where model fitting failed to converge, leading us to discard those model specifications. Failing to converge a model is a consequence of the complexity of the model, data characteristics or numerical instability involving a large number of parameters.

Table A3: Variable combinations considered to estimate the ARIMAX models. Part 1.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price		x	x	x	x	x	x	x	x	x	x	x	x	x										
Country*Weighted Average Futures Price															x	x	x	x	x	x	x	x	x	x
Country*Simple Average Spot Price			x	x	x	x										x	x	x	x					
Country*Weighted Average Spot Price							x	x	x	x										x	x	x	x	
Country*Precipitation				x	x			x	x		x	x					x	x			x	x		x
Country*Temperature					x	x			x	x		x	x					x	x			x	x	
ARIMA Order (0-1-0)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
ARIMA Order (0-1-1)																								
ARIMA Order (1-1-0)																								
ARIMA Order (1-1-1)																								
No Intercept	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Intercept Country Specific																								

Table A3: Variable Combination considered to estimate the ARIMA models. Part 2.

Variables	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price																			x	x	x	x	x	x
Country*Weighted Average Futures Price	x	x																						
Country*Simple Average Spot Price			x	x	x	x	x	x	x	x										x	x	x	x	
Country*Weighted Average Spot Price				x	x	x	x				x	x	x	x										x
Country*Precipitation	x				x	x		x	x			x	x		x	x					x	x		
Country*Temperature	x	x				x	x		x	x			x	x		x	x					x	x	
ARIMA Order (0-1-0)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x							
ARIMA Order (0-1-1)																		x	x	x	x	x	x	x
ARIMA Order (1-1-0)																								
ARIMA Order (1-1-1)																								
No Intercept	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Intercept Country Specific																								

Table A3: Variable Combination considered to estimate the ARIMA models. Part 3.

Variables	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price	x	x	x	x	x	x	x																	
Country*Weighted Average Futures Price								x	x	x	x	x	x	x	x	x	x	x	x					
Country*Simple Average Spot Price									x	x	x	x								x	x	x	x	x
Country*Weighted Average Spot Price	x	x	x										x	x	x	x					x	x	x	x
Country*Precipitation	x	x		x	x					x	x			x	x		x	x				x	x	
Country*Temperature		x	x		x	x					x	x			x	x		x	x				x	x
ARIMA Order (0-1-0)																								
ARIMA Order (0-1-1)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
ARIMA Order (1-1-0)																								
ARIMA Order (1-1-1)																								
No Intercept	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Intercept Country Specific																								

Table A3: Variable Combination considered to estimate the ARIMA models. Part 4.

Variables	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price												x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Weighted Average Futures Price																								
Country*Simple Average Spot Price	x	x	x										x	x	x	x								
Country*Weighted Average Spot Price				x	x	x	x										x	x	x	x				
Country*Precipitation	x	x			x	x		x	x					x	x			x	x		x	x		
Country*Temperature		x	x			x	x		x	x					x	x			x	x		x	x	
ARIMA Order (0-1-0)																								
ARIMA Order (0-1-1)	x	x	x	x	x	x	x	x	x	x														
ARIMA Order (1-1-0)											x	x	x	x	x	x	x	x	x	x	x	x	x	x
ARIMA Order (1-1-1)																								
No Intercept	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Intercept Country Specific																								

Table A3: Variable Combination considered to estimate the ARIMA models. Part 5.

Variables	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price																				
Country*Weighted Average Futures Price	x	x	x	x	x	x	x	x	x	x	x	x								
Country*Simple Average Spot Price		x	x	x	x								x	x	x	x	x	x	x	x
Country*Weighted Average Spot Price						x	x	x	x					x	x	x	x			
Country*Precipitation			x	x			x	x		x	x				x	x		x	x	
Country*Temperature				x	x			x	x		x	x				x	x		x	x
ARIMA Order (0-1-0)																				
ARIMA Order (0-1-1)																				
ARIMA Order (1-1-0)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
ARIMA Order (1-1-1)																				
No Intercept	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Intercept Country Specific																				

Table A3: Variable Combination considered to estimate the ARIMA models. Part 6.

Variables	117	118	119	120	121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price									x	x	x	x	x	x	x	x	x	x	x	x
Country*Weighted Average Futures Price																				
Country*Simple Average Spot Price										x	x	x	x							
Country*Weighted Average Spot Price	x	x	x	x										x	x	x	x			
Country*Precipitation		x	x		x	x					x	x			x	x		x	x	
Country*Temperature			x	x		x	x					x	x			x	x		x	x
ARIMA Order (0-1-0)																				
ARIMA Order (0-1-1)																				
ARIMA Order (1-1-0)	x	x	x	x	x	x	x													
ARIMA Order (1-1-1)								x	x	x	x	x	x	x	x	x	x	x	x	x
No Intercept	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Intercept Country Specific																				

Table A3: Variable Combination considered to estimate the ARIMA models. Part 7.

Variables	157	158	159	160	161	162	163	164	165	166	167	168	169	170	171	172	173	174	175	176
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price										x	x	x	x	x	x	x	x	x	x	x
Country*Weighted Average Futures Price																				
Country*Simple Average Spot Price	x										x	x	x	x						
Country*Weighted Average Spot Price		x	x	x	x										x	x	x	x		
Country*Precipitation			x	x		x	x					x	x			x	x		x	x
Country*Temperature	x			x	x		x	x					x	x			x	x		x
ARIMA Order (0-1-0)									x	x	x	x	x	x	x	x	x	x	x	x
ARIMA Order (0-1-1)																				
ARIMA Order (1-1-0)																				
ARIMA Order (1-1-1)	x	x	x	x	x	x	x	x												
No Intercept	x	x	x	x	x	x	x	x												
Intercept Country Specific									x	x	x	x	x	x	x	x	x	x	x	x

Table A3: Variable Combination considered to estimate the ARIMA models. Part 8.

Variables	177	178	179	180	181	182	183	184	185	186	187	188	189	190	191	192	193	194	195	196
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price	x	x																		
Country*Weighted Average Futures Price			x	x	x	x	x	x	x	x	x	x	x	x						
Country*Simple Average Spot Price				x	x	x	x								x	x	x	x	x	x
Country*Weighted Average Spot Price								x	x	x	x					x	x	x	x	
Country*Precipitation					x	x			x	x		x	x				x	x		x
Country*Temperature	x					x	x			x	x		x	x				x	x	
ARIMA Order (0-1-0)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
ARIMA Order (0-1-1)																				
ARIMA Order (1-1-0)																				
ARIMA Order (1-1-1)																				
No Intercept																				
Intercept Country Specific	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Table A3: Variable Combination considered to estimate the ARIMA models. Part 9.

Variables	**197**	**198**	**199**	**200**	**201**	**202**	**203**	**204**	**205**	**206**	**207**	**208**	**209**	**210**	**211**	**212**	**213**	**214**	**215**	**216**
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price											x	x	x	x	x	x	x	x	x	x
Country*Weighted Average Futures Price																				
Country*Simple Average Spot Price	x	x										x	x	x	x					
Country*Weighted Average Spot Price			x	x	x	x										x	x	x	x	
Country*Precipitation	x			x	x		x	x					x	x			x	x		x
Country*Temperature	x	x			x	x		x	x					x	x			x	x	
ARIMA Order (0-1-0)	x	x	x	x	x	x	x	x	x											
ARIMA Order (0-1-1)										x	x	x	x	x	x	x	x	x	x	x
ARIMA Order (1-1-0)																				
ARIMA Order (1-1-1)																				
No Intercept																				
Intercept Country Specific	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Table A3: Variable Combination considered to estimate the ARIMA models. Part 10.

Variables	**217**	**218**	**219**	**220**	**221**	**222**	**223**	**224**	**225**	**226**	**227**	**228**	**229**	**230**	**231**	**232**	**233**	**234**	**235**	**236**
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price	x	x	x																	
Country*Weighted Average Futures Price				x	x	x	x	x	x	x	x	x	x	x	x					
Country*Simple Average Spot Price					x	x	x	x								x	x	x	x	x
Country*Weighted Average Spot Price									x	x	x	x					x	x	x	x
Country*Precipitation	x					x	x			x	x		x	x				x	x	
Country*Temperature	x	x					x	x			x	x		x	x				x	x
ARIMA Order (0-1-0)																				
ARIMA Order (0-1-1)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
ARIMA Order (1-1-0)																				
ARIMA Order (1-1-1)																				
No Intercept																				
Intercept Country Specific	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Table A3: Variable Combination considered to estimate the ARIMA models. Part 11.

Variables	**237**	**238**	**239**	**240**	**241**	**242**	**243**	**244**	**245**	**246**	**247**	**248**	**249**	**250**	**251**	**252**	**253**	**254**	**255**	**256**
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price												x	x	x	x	x	x	x	x	x
Country*Weighted Average Futures Price																				
Country*Simple Average Spot Price	x	x	x										x	x	x	x				
Country*Weighted Average Spot Price				x	x	x	x										x	x	x	x
Country*Precipitation	x	x			x	x		x	x					x	x			x	x	
Country*Temperature		x	x			x	x		x	x					x	x			x	x
ARIMA Order (0-1-0)																				
ARIMA Order (0-1-1)	x	x	x	x	x	x	x	x	x	x										
ARIMA Order (1-1-0)											x	x	x	x	x	x	x	x	x	x
ARIMA Order (1-1-1)																				
No Intercept																				
Intercept Country Specific	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Table A3: Variable Combination considered to estimate the ARIMA models. Part 12.

Variables	**257**	**258**	**259**	**260**	**261**	**262**	**263**	**264**	**265**	**266**	**267**	**268**	**269**	**270**	**271**	**272**	**273**	**274**	**275**	**276**
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price	x	x	x	x																
Country*Weighted Average Futures Price					x	x	x	x	x	x	x	x	x	x	x	x				
Country*Simple Average Spot Price						x	x	x	x								x	x	x	x
Country*Weighted Average Spot Price										x	x	x	x					x	x	x
Country*Precipitation	x	x					x	x			x	x		x	x				x	x
Country*Temperature		x	x					x	x			x	x		x	x				x
ARIMA Order (0-1-0)																				
ARIMA Order (0-1-1)																				
ARIMA Order (1-1-0)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
ARIMA Order (1-1-1)																				
No Intercept																				
Intercept Country Specific	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Table A3: Variable Combination considered to estimate the ARIMA models. Part 13.

Variables	277	278	279	280	281	282	283	284	285	286	287	288	289	290	291	292	293	294	295	296
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price													x	x	x	x	x	x	x	x
Country*Weighted Average Futures Price																				
Country*Simple Average Spot Price	x	x	x	x										x	x	x	x			
Country*Weighted Average Spot Price	x				x	x	x	x										x	x	x
Country*Precipitation		x	x			x	x		x	x					x	x			x	x
Country*Temperature	x		x	x			x	x		x	x					x	x			x
ARIMA Order (0-1-0)																				
ARIMA Order (0-1-1)																				
ARIMA Order (1-1-0)	x	x	x	x	x	x	x	x	x	x	x									
ARIMA Order (1-1-1)												x	x	x	x	x	x	x	x	x
No Intercept																				
Intercept Country Specific	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Table A3: Variable Combination considered to estimate the ARIMA models. Part 14.

Variables	**297**	**298**	**299**	**300**	**301**	**302**	**303**	**304**	**305**	**306**	**307**	**308**	**309**	**310**	**311**	**312**	**313**	**314**	**315**	**316**
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price	x	x	x	x	x															
Country*Weighted Average Futures Price						x	x	x	x	x	x	x	x	x	x	x	x			
Country*Simple Average Spot Price							x	x	x	x								x	x	x
Country*Weighted Average Spot Price	x										x	x	x	x					x	x
Country*Precipitation		x	x					x	x			x	x		x	x				x
Country*Temperature	x		x	x					x	x			x	x		x	x			
ARIMA Order (0-1-0)																				
ARIMA Order (0-1-1)																				
ARIMA Order (1-1-0)																				
ARIMA Order (1-1-1)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
No Intercept																				
Intercept Country Specific	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Table A3: Variable Combination considered to estimate the ARIMA models. Part 15.

Variables	**317**	**318**	**319**	**320**	**321**	**322**	**323**	**324**	**325**	**326**	**327**	**328**
Country*Year	x	x	x	x	x	x	x	x	x	x	x	x
Country*Simple Average Futures Price												
Country*Weighted Average Futures Price												
Country*Simple Average Spot Price	x	x	x	x	x							
Country*Weighted Average Spot Price	x	x				x	x	x	x			
Country*Precipitation	x		x	x			x	x		x	x	
Country*Temperature	x	x		x	x			x	x		x	x
ARIMA Order (0-1-0)												
ARIMA Order (0-1-1)												
ARIMA Order (1-1-0)												
ARIMA Order (1-1-1)	x	x	x	x	x	x	x	x	x	x	x	x
No Intercept												
Intercept Country Specific	x	x	x	x	x	x	x	x	x	x	x	x

Machine Learning Models:

The RF and XGBoost models are estimated using all the variables listed in the Table 1. The algorithm selects which variables provide the most predictive power to make the forecasts.

Table A4: Accuracy measures of selected model using different training datasets

Model	MAE	MAPE	RMSE
Selected Yield Model (65 Countries from 1985 to 2021)	0.20	24.35%	1.43
Selected Yield Model (75 Countries from 1980 to 2021)	0.14	23.02%	1.29

Note: The accuracy metrics of our selected model are better when using all countries and the longer training data period as shown in Table A4.

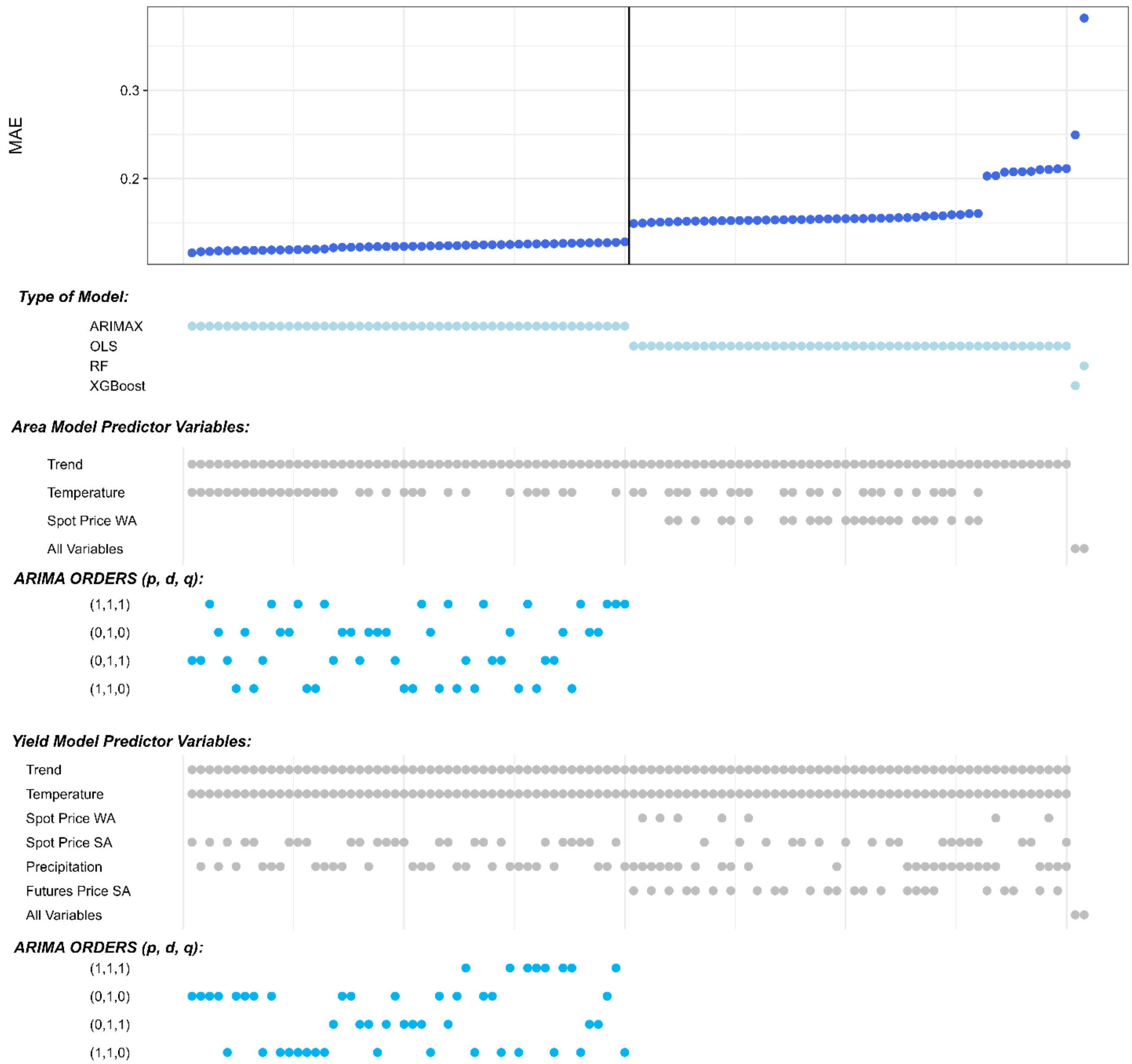

Figure A1. Model Specification of top model with lower MAE.

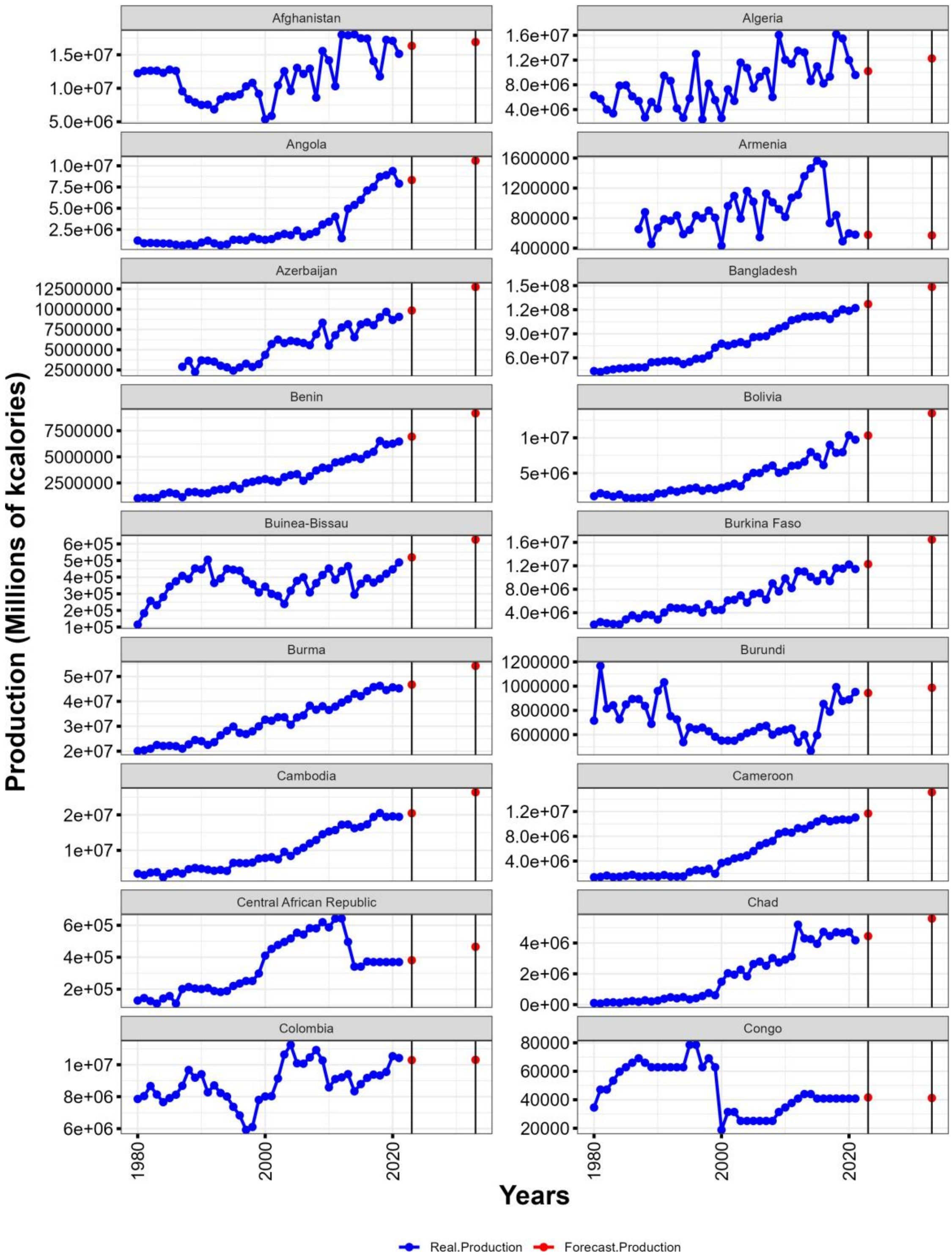

Figure A2: Forecasting with the preferred specification, Part 1.

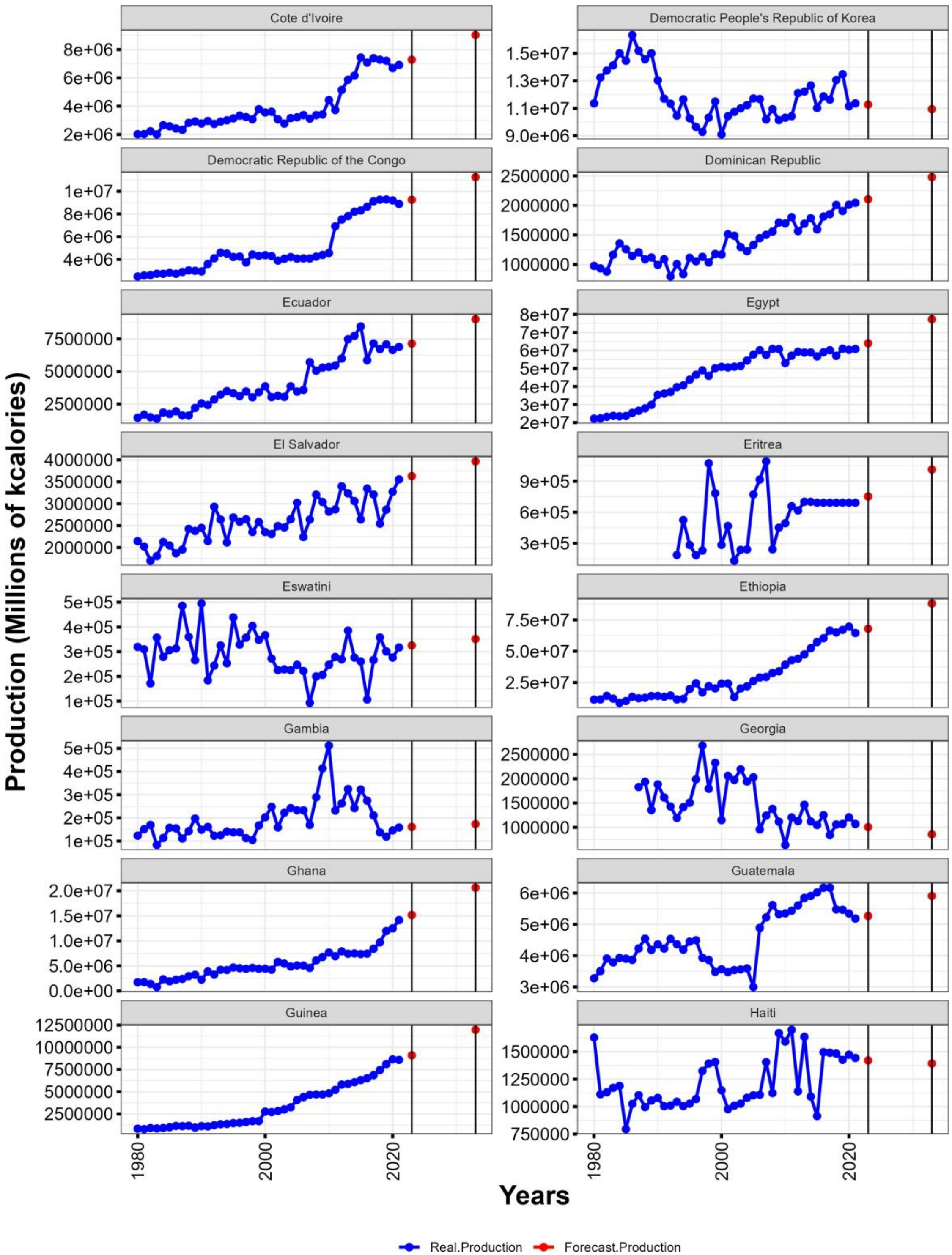

Figure A2: Forecasting with the preferred specification, Part 2.

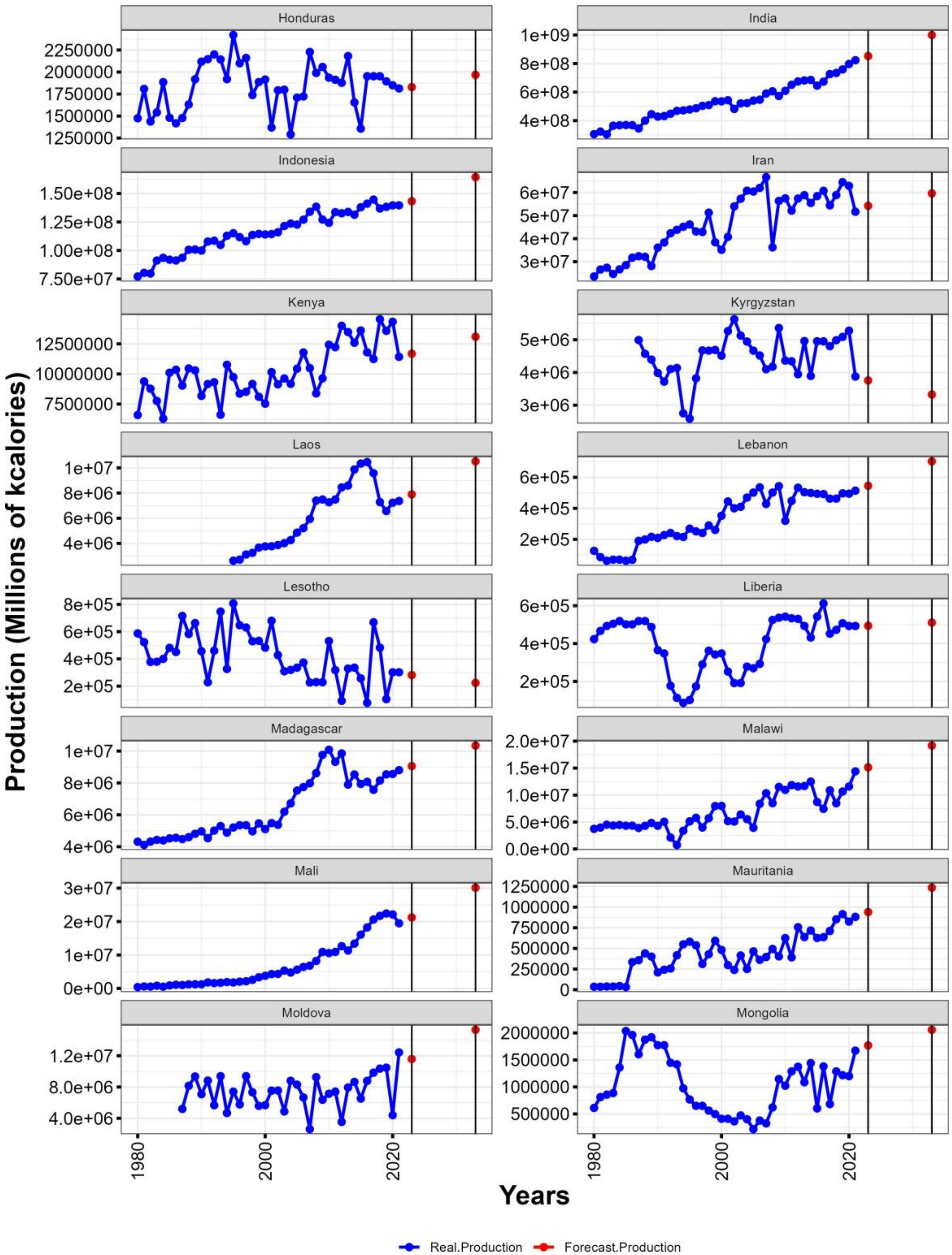

Figure A2: Forecasting with the preferred specification, Part 3.

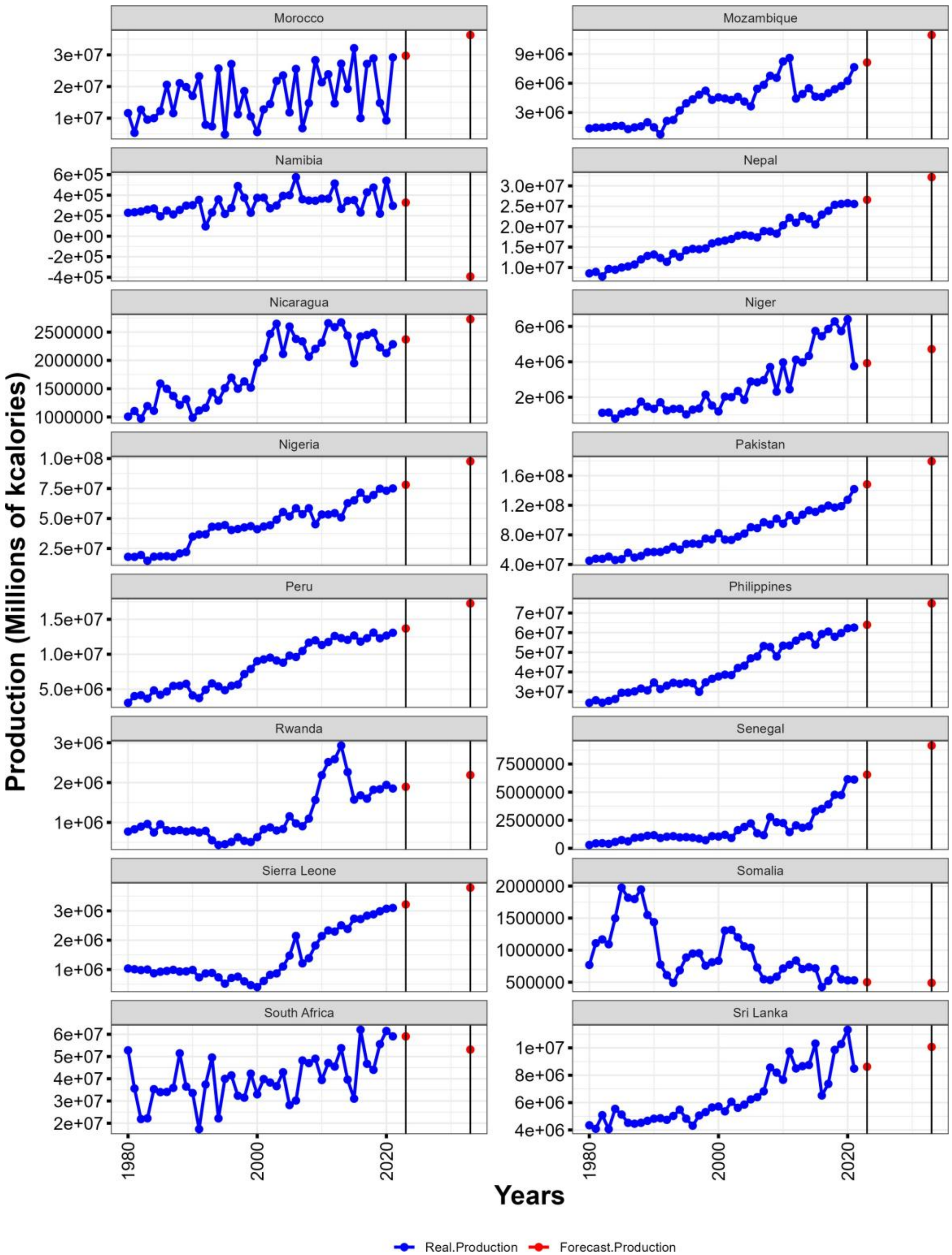

Figure A2: Forecasting with the preferred specification, Part 4.

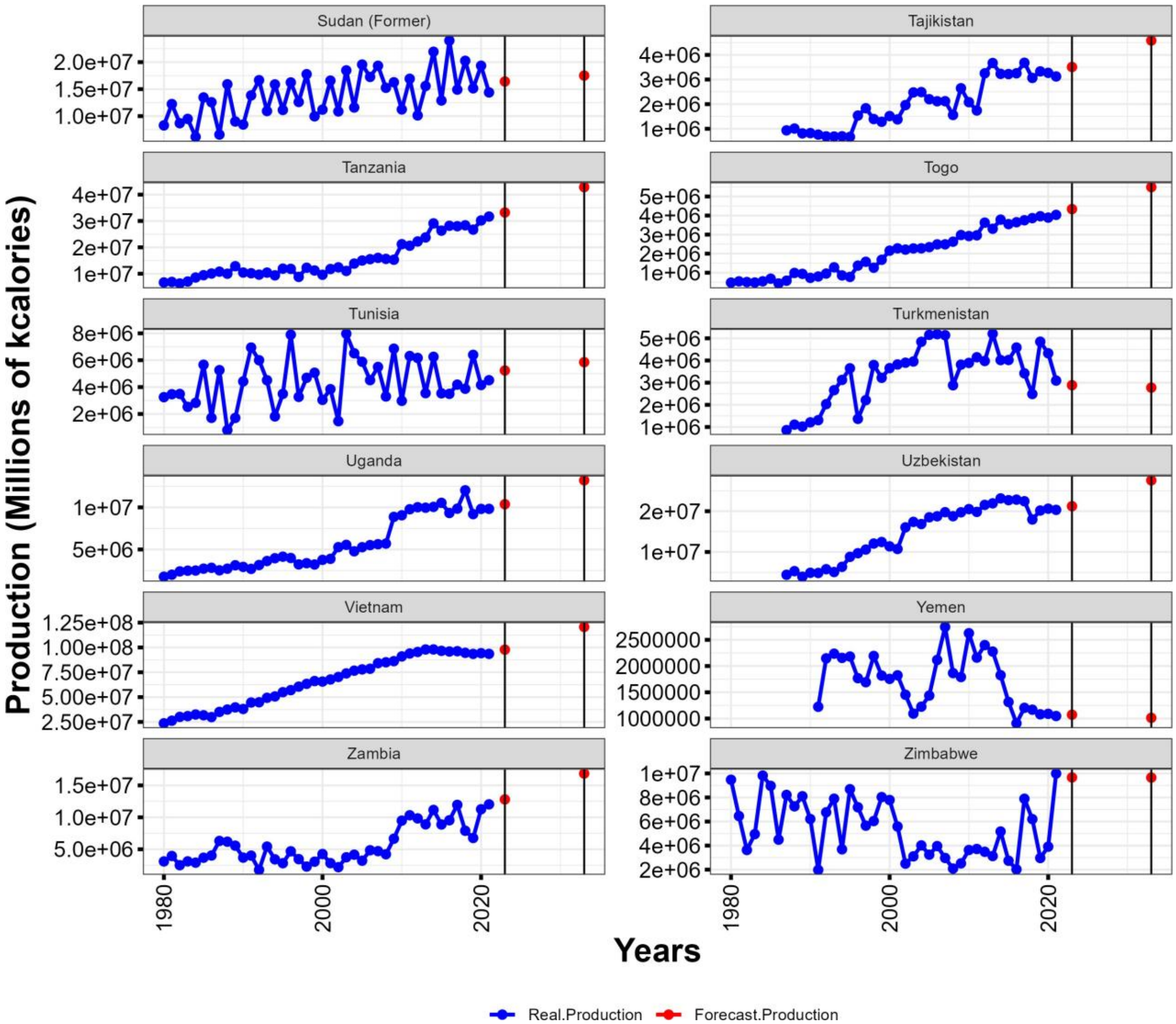

Figure A2: Forecasting with the preferred specification, Part 5.

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Appendix B - Chapter 2

Table B1. Summary Statistics of Variables

No	Variable	Units	Mean	Std.Dev.	Min	Max
1	Year		2007.5	7.5	1995	2020
2	Acreage Planted (June)	Acres	2423532.97	3297009.96	50000	14300000
3	Acreage Planted (Actual)	Acres	2412846.15	3279725.78	55000	14200000
4	Acreage Planted (Actual, 1-Year-Lag)	Acres	2400212.09	3271899.96	55000	14200000
5	Planting Intentions	Acres	2428807.69	3296165	53000	14600000
6	Production	Bushels	333067929.7	530631284.7	1820000	2740500000
7	Production (1-Year-Lag)	Bushels	328656170.3	525516558.8	1820000	2740500000
8	Yield	Bushels/Acrea	140.72	31.2	40	237
9	Yield (1-Year-Lag)	Bushels/Acrea	139.35	30.85	40	237
10	March Report Error	Acres	15961.54	167764.08	-700000	1650000
11	June Report Error	Acres	10686.81	136971.78	-2250000	550000
12	Fertilize Price Index , Annual (Base 2011)	Index	63.01	25.68	31.9	119.2
13	Fertilize Price Index , January (Base 2011)	Index	61.8	24.67	31.9	105.5
14	Fertilize Price Index , February (Base 2011)	Index	62.1	24.26	32.2	101.3
15	Fertilize Price Index , March (Base 2011)	Index	63.15	24.84	32.2	102.3
16	Fertilize Price Index , April (Base 2011)	Index	64.12	25.82	32.4	104.7
17	Fertilize Price Index , May (Base 2011)	Index	64.28	26.38	32.3	110.7
18	Nitrogen Price Index, Annual (Base 2011)	Index	65.15	25.38	28.1	113.1
19	Nitrogen Price Index, January (Base 2011)	Index	64.52	24.67	28.7	107.6
20	Nitrogen Price Index, February (Base 2011)	Index	64.52	23.61	28.7	107.8
21	Nitrogen Price Index, March (Base 2011)	Index	66.02	24.43	29	108.9
22	Nitrogen Price Index, April (Base 2011)	Index	67.3	25.81	29.3	114
23	Nitrogen Price Index, May (Base 2011)	Index	67.63	27.22	28.4	117.1
24	Corn Futures Price (Dec Contract – January Quote)	USD/Bushel	3.59	1.11	2.31	5.86
25	Corn Futures Price (Dec Contract – February Quote)	USD/Bushel	3.63	1.13	2.32	6.01
26	Corn Futures Price (Dec Contract – March Quote)	USD/Bushel	3.65	1.13	2.28	5.98
27	Corn Futures Price (Dec Contract – April Quote)	USD/Bushel	3.65	1.2	2.2	6.56

28	Corn Futures Price (Dec Contract – May Quote)	USD/Bushel	3.65	1.21	2.19	6.57
29	Corn Futures Price (Nearby Contract - January Quote)	USD/Bushel	3.54	1.37	2	7.15
30	Corn Futures Price (Nearby Contract - February Quote)	USD/Bushel	3.58	1.42	2	7.07
31	Corn Futures Price (Nearby Contract - March Quote)	USD/Bushel	3.65	1.45	2.04	7.26
32	Corn Futures Price (Nearby Contract - April Quote)	USD/Bushel	3.66	1.48	1.99	7.53
33	Corn Futures Price (Nearby Contract - May Quote)	USD/Bushel	3.69	1.47	1.97	7.22
34	Suitable Days For Field Work (January)	Days/Month	7.19	7.39	0.5	29.3
35	Suitable Days For Field Work (February)	Days/Month	7.87	7.76	0.3	27.2
36	Suitable Days For Field Work (March)	Days/Month	9.34	7.41	0	34.3
37	Suitable Days For Field Work (April)	Days/Month	17.21	6.7	0	33.7
38	Suitable Days For Field Work (May)	Days/Month	20.34	5.64	2.5	35
39	Precipitation (January)	mm/Month	60.33	50.64	0	320
40	Precipitation (February)	mm/Month	57.92	53.3	0	325
41	Precipitation (March)	mm/Month	69.74	50.02	0.7	381.6
42	Precipitation (April)	mm/Month	81.74	48.68	0.62	346.89
43	Precipitation (May)	mm	96.01	51.91	0.01	283.34
44	Degree Days (February, Below Zero °C)	Days/Month	14.28	8.46	0	30.92
45	Degree Days (February, 1°C - 10°C)	Days/Month	11.37	4.83	0.03	24.36
46	Degree Days (February, 11°C - 20°C)	Days/Month	4.5	4.63	0	19.35
47	Degree Days (February, 21°C - 30°C)	Days/Month	0.43	0.99	0	6.9
48	Degree Days (February, 31°C - 40°C)	Days/Month	0	0	0	0.03
49	Degree Days (February, 41°C - 50°C)	Days/Month	0	0	0	0
50	Degree Days (March, Below Zero °C)	Days/Month	14.28	8.46	0	30.92
51	Degree Days (March, 1°C - 10°C)	Days/Month	11.37	4.83	0.03	24.36
52	Degree Days (March, 11°C - 20°C)	Days/Month	4.5	4.63	0	19.35
53	Degree Days (March, 21°C - 30°C)	Days/Month	0.43	0.99	0	6.9
54	Degree Days (March, 31°C - 40°C)	Days/Month	0	0	0	0.03
55	Degree Days (March, 41°C - 50°C)	Days/Month	0	0	0	0
56	Degree Days (April, Below Zero °C)	Days/Month	14.28	8.46	0	30.92
57	Degree Days (April, 1°C - 10°C)	Days/Month	11.37	4.83	0.03	24.36
58	Degree Days (April, 11°C - 20°C	Days/Month	4.5	4.63	0	19.35
59	Degree Days (April, 21°C - 30°C)	Days/Month	0.43	0.99	0	6.9

60	Degree Days (April, 31°C - 40°C)	Days/Month	0	0	0	0.03
61	Degree Days (April, 41°C - 50°C)	Days/Month	0	0	0	0
62	Degree Days (May, Below Zero °C)	Days/Month	14.28	8.46	0	30.92
63	Degree Days (May, 1°C - 10°C)	Days/Month	11.37	4.83	0.03	24.36
64	Degree Days (May, 11°C - 20°C)	Days/Month	4.5	4.63	0	19.35
65	Degree Days (May, 21°C - 30°C)	Days/Month	0.43	0.99	0	6.9
66	Degree Days (May, 31°C - 40°C)	Days/Month	0	0	0	0.03
67	Degree Days (May, 41°C - 50°C)	Days/Month	0	0	0	0
68	Soil Moisture Exposure (February, 1 - 8)	Days/Month	0	0.04	0	0.87
69	Soil Moisture Exposure (February, 9 – 16)	Days/Month	1.42	4.4	0	31
70	Soil Moisture Exposure (February, 17 – 24)	Days/Month	7.66	8.86	0	30.91
71	Soil Moisture Exposure (February, 25 – 32)	Days/Month	12.19	7.34	0	29.82
72	Soil Moisture Exposure (February, 33 – 40)	Days/Month	7.38	7.3	0	28.36
73	Soil Moisture Exposure (February, 41 – 50)	Days/Month	1.92	4.04	0	28.61
74	Soil Moisture Exposure (March, 1 – 8)	Days/Month	0	0.04	0	0.87
75	Soil Moisture Exposure (March, 9 – 16)	Days/Month	1.42	4.4	0	31
76	Soil Moisture Exposure (March, 17 – 24)	Days/Month	7.66	8.86	0	30.91
77	Soil Moisture Exposure (March, 25 – 32)	Days/Month	12.19	7.34	0	29.82
78	Soil Moisture Exposure (March, 33 – 40)	Days/Month	7.38	7.3	0	28.36
79	Soil Moisture Exposure (March, 41 – 50)	Days/Month	1.92	4.04	0	28.61
80	Soil Moisture Exposure (April, 1 – 8)	Days/Month	0	0.04	0	0.87
81	Soil Moisture Exposure (April, 9 – 16)	Days/Month	1.42	4.4	0	31
82	Soil Moisture Exposure (April, 17 – 24)	Days/Month	7.66	8.86	0	30.91
83	Soil Moisture Exposure (April, 25 – 32)	Days/Month	12.19	7.34	0	29.82
84	Soil Moisture Exposure (April, 33 – 40)	Days/Month	7.38	7.3	0	28.36
85	Soil Moisture Exposure (April, 41 – 50)	Days/Month	1.92	4.04	0	28.61
86	Soil Moisture Exposure (May, 1 – 8)	Days/Month	0	0.04	0	0.87
87	Soil Moisture Exposure (May, 9 – 16)	Days/Month	1.42	4.4	0	31
88	Soil Moisture Exposure (May, 17 – 24)	Days/Month	7.66	8.86	0	30.91
89	Soil Moisture Exposure (May, 25 – 32)	Days/Month	12.19	7.34	0	29.82
90	Soil Moisture Exposure (May, 33 – 40)	Days/Month	7.38	7.3	0	28.36
91	Technology Index (Trend)	Index	13.5	7.5	1	26

Table B2. Average Corn Acreage Planted by State (From 2014 to 2024)

No.	State	Acreage	Percentage	Cumulative Percentage
1	Iowa	132,700,000	14.629	14.629
2	Illinois	111,100,000	12.248	26.877
3	Nebraska	98,200,000	10.826	37.702
4	Minnesota	81,450,000	8.979	46.681
5	Kansas	55,950,000	6.168	52.849
6	South Dakota	55,350,000	6.102	58.951
7	Indiana	53,550,000	5.903	64.854
8	Wisconsin	39,200,000	4.321	69.176
9	Missouri	34,700,000	3.825	73.001
10	Ohio	34,300,000	3.781	76.782
11	North Dakota	33,270,000	3.668	80.45
12	Texas	23,550,000	2.596	83.046
13	Michigan	22,900,000	2.524	85.571
14	Kentucky	14,490,000	1.597	87.168
15	Colorado	13,830,000	1.525	88.693
16	Pennsylvania	12,190,000	1.344	90.036
17	New York	10,350,000	1.141	91.177
18	North Carolina	9,190,000	1.013	92.19
19	Tennessee	8,420,000	0.928	93.119
20	Arkansas	6,800,000	0.75	93.868
21	Mississippi	6,020,000	0.664	94.532
22	Louisiana	5,250,000	0.579	95.111
23	Virginia	4,880,000	0.538	95.649
24	Maryland	4,605,000	0.508	96.156
25	California	4,210,000	0.464	96.62
26	Georgia	3,915,000	0.432	97.052
27	Oklahoma	3,630,000	0.4	97.452
28	South Carolina	3,535,000	0.39	97.842
29	Idaho	3,520,000	0.388	98.23
30	Alabama	2,945,000	0.325	98.555
31	Delaware	1,725,000	0.19	98.745
32	Washington	1,675,000	0.185	98.929
33	New Mexico	1,225,000	0.135	99.065
34	Montana	1,195,000	0.132	99.196
35	Wyoming	925,000	0.102	99.298
36	Florida	880,000	0.097	99.395
37	Vermont	873,000	0.096	99.491
38	Oregon	860,000	0.095	99.586

39	Arizona	840,000	0.093	99.679
40	New Jersey	753,000	0.083	99.762
41	Utah	735,000	0.081	99.843
42	West Virginia	463,000	0.051	99.894
43	Maine	299,000	0.033	99.927
44	Connecticut	241,000	0.027	99.953
45	Massachusetts	145,000	0.016	99.969
46	New Hampshire	133,000	0.015	99.984
47	Nevada	124,000	0.014	99.998
48	Rhode Island	20,000	0.002	100

Table B3. Accuracy of Acreage Predictions when Forecasting Change in Planting Intentions, using Walk Forward Validation

Rank	Model	RMSE	MAE	MAPE
1	Survey June	119,862	68,693	4.35
2	RF	184,317	98,338	6.23
3	XGBoost	190,479	100,722	6.49
4	Survey March	197,808	101,324	5.88
5	FEOLS (Top 15 Variables)	198,805	117,474	11.91
5	FEOLS_(All Variables)	269,849	191,987	29.46

Note: Using the Walk Forward Validation procedure and Mean Absolute Error (MAE) as the evaluation metric, we find that the Random Forest model does not achieve greater accuracy than the June survey-based estimates published in the USDA Acreage Report. Furthermore, a comparison of the results presented in Table 2.1 and Table B3 indicates that the accuracy measures obtained through Walk Forward Validation are consistently higher for each model than those reported under the Leave-One-Year-Out Cross-Validation procedure.

Appendix C - Chapter 3

Table C1. Import Quantities by Region: One Year Before and After the Broken Rice Export Ban

Income Group	Imports Before Milled Rice Export Ban	Imports After Milled Rice Export Ban		Imports Before Milled Rice Export Ban	Imports After Milled Rice Export Ban	
Units	USD	USD	Percentage (%)	KG	KG	Percentage (%)
East Asia & Pacific	920,155,104	479,751,802	-47.9	2,255,222,851	926,672,451	-58.9
Europe & Central Asia	436,062,556	367,214,509	-15.8	840,344,020	664,791,596	-20.9
Latin America & Caribbean	40,880,501	38,765,084	-5.2	105,402,059	88,852,750	-15.7
North America	41,489,350	62,406,997	50.4	77,988,037	133,935,536	71.7
Sub-Saharan Africa	472,832,705	262,162,043	-44.6	1,385,392,591	719,138,606	-48.1

Table C2. Import Quantities by Income Group: One Year Before and After the Broken Rice Export Ban

Income Group	Import Before Milled Rice Export Ban	Import After Milled Rice Export Ban		Import Before Milled Rice Export Ban	Import After Milled Rice Export Ban	
Units	USD	USD	Percentage (%)	KG	KG	Percentage (%)
High income	502,536,473	445,558,053	-11.3	977,027,356	833,680,601	-14.7
Low income	125,586,613	56,304,544	-55.2	764,329,729	364,572,699	-52.3
Lower middle income	383,121,104	329,604,756	-14.0	695,516,987	606,361,971	-12.8
Upper middle income	900,176,026	378,833,082	-57.9	2,227,475,487	728,775,668	-67.3

Table C3. Import Quantities by Region: One Year Before and After the Milled Rice Export Ban

Income Group	Imports Before Milled Rice Export Ban	Imports After Milled Rice Export Ban		Imports Before Milled Rice Export Ban	Imports After Milled Rice Export Ban	
Units	USD	USD	Percentage (%)	KG	KG	Percentage (%)
East Asia & Pacific	4,962,428,224	7,465,785,203	50.4	6,928,519,778	10,921,577,654	57.6
Europe & Central Asia	2,766,274,088	2,729,945,269	-1.3	2,759,511,570	2,458,755,006	-10.9
Latin America & Caribbean	579,932,818	859,909,175	48.3	951,823,642	1,211,005,672	27.2
Middle East & North Africa	2,839,125,764	2,690,735,127	-5.2	2,590,728,768	2,394,620,476	-7.6
North America	1,644,375,986	2,012,343,902	22.4	1,618,247,043	2,067,764,561	27.8
Sub-Saharan Africa	2,749,283,866	1,939,970,848	-29.4	5,379,831,692	3,454,584,845	-35.8

Table C4. Import Quantities by Income Group: One Year Before and After the Milled Rice Export Ban

Income Group	Import Before Milled Rice Export Ban	Import After Milled Rice Export Ban		Import Before Milled Rice Export Ban	Import After Milled Rice Export Ban	
Units	USD	USD	Percentage (%)	KG	KG	Percentage (%)
High income	7,720,894,678	8,256,005,330	6.9	7,391,582,032	7,728,408,126	4.6
Low income	693,319,900	265,624,571	-61.7	1,034,575,506	427,543,682	-58.7
Lower middle income	3,178,655,916	3,014,552,693	-5.2	4,643,852,149	4,833,459,063	4.1
Upper middle income	3,948,550,253	6,162,506,931	56.1	7,158,652,806	9,518,897,343	33.0

Table C5. Gravity Models Robustness Checks, Export Ban in Milled Rice (100630)

Model No.	Model 1			Model 2			Model 3			Model 4		
Units	KG			KG			KG			KG		
Variable	Coef.	Std. Error	Sig.	Coef.	Std. Error	Sig.	Coef.	Std. Error	Sig.	Coef.	Std. Error	Sig.
EB_Milled	-0.232	0.170		-0.175	0.110		-0.162	0.143		-0.175	0.172	
EB_Milled_OC	0.295	0.098	***	0.265	0.097	**	0.231	0.089	**	0.262	0.094	**
Fixed Effects												
Exporter(i)-Importer(j)	Yes			No			No			No		
Exporter(i)-Year(y)	Yes			Yes			No			No		
Importer(i)-Month(m)	Yes			No			Yes			No		
Exporter(i)-Importer(j)-Month(m)	No			Yes			No			No		
Exporter(i)-Importer(j)-Year(m)	No			No			Yes			Yes		
Exporter(i)-Month(m)	No			No			Yes			Yes		
Pseud R2	0.882			0.911			0.932			0.924		
Observations	43692			31441			35808			35808		