FORECASTING AGRICULTURAL OUTPUT USING MACHINE LEARNING APPROACH BASED ON RANDOM FOREST ALGORITHM: HOW IMPORTANT ARE ENVIRONMENTAL AND CLIMATE VARIABLES?

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ABSTRACT

Many researchers have worked on the nexus between agricultural output, climate and environmental variables in recent times due to the high importance of food security. However, many of the traditional econometric models used are unable to forecast agricultural output with high accuracy. In this study, we examine the forecasting performance of the random forest machine learning algorithm and compare its predictive performance with other machine learning algorithms like K Nearest Neighbourhood (KNN), Support Vector Machine (SVM), Decision Tree (DT), Robust Linear Model (RLM), Random Forest (RF), and Least Angle Regression (LARS) using data from Africa's largest economy, Nigeria. The result shows that the random forest machine learning algorithm outperforms other machine learning algorithms because it has the lowest Root Mean Square Error (RMSE) of 3500.989, followed by LARS with RMSE of 3524.157, SVM with RMSE of 3756.603, DT with RMSE of 3863.969, RLM with RMSE of 4032.575, and the KNN algorithm with RMSE of 5524.410. Variable importance results show that temperature is the best predictor of agricultural output in Nigeria, followed by CO_2 emissions, while rainfall does not affect agricultural output. Therefore, the government and policymakers should adopt climate-smart farming practices, climate and environmental education, especially for farmers, and carbon neutrality or reduction policies, together with research and development, to ensure agricultural sustainability and food security in Nigeria and other developing countries.

OUTLINE

- **MOTIVATION**
- **OBJECTIVES**
- **LITERATURE**
- **DATA & METHODOLOGY**
- **FINDINGS AND DISCUSSION**
- **CONCLUSION AND POLICY RECOMMENDATION**

MOTIVATION

- The world is faced with a great food insecurity crisis, and the worst hit is countries in Sub-Saharan Africa (of which Nigeria is part), which are also among the worst affected by the adverse effects of climate change. The world food crisis is caused by the impact of the COVID-19 pandemic, climate change, and the recent Ukraine invasion by the Russian Federation.
- Agricultural output in Nigeria has been volatile as supported by statistics from Central Bank of Nigeria (Falola and Heaton, 2008).
- Climate change affects all agriculture sectors, including crop production, livestock production, fishing, and forestry (Ozor, 2009; Akinbobola, Adedokun & Nwosa, 2015).
- The prediction of agricultural output is growing into a significant challenge faced by agricultural organisations and institutions. (Gbadamosi et al., 2019). Many of the traditional econometric models used are unable to forecast agricultural output with high accuracy.

OBJECTIVES

- To determine the best machine learning model for predicting agricultural output using climate and environmental variables.
- Evaluating the impact of climate and environmental variables on agricultural output and food security.

CONCEPTUAL FRAMEWORK

- **Climate change refers to changes in the climate's mean variability properties that continue over a prolonged period, typically within decades or more. The impact of climate change is immense, and both food security and climate change are now major issues and catastrophes on a global scale.**

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- **Food security exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life." - 1996 World Food Summit in FAO (2008). When such is not the case, we experience food insecurity.**

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- **Machine learning involves building mathematical models to help understand data (VanderPlas, 2016). It is a sub-domain of artificial intelligence that allows a computer to learn from data without being initially programmed (Cedric, 2022).**

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THEORETICAL LITEREATURE

- **Anthropogenic Climate Change Theory:**

Anthropogenic (or "man-made") global warming (AGW) is the most popular climate change theory that most people know. According to the theory, greenhouse gas emissions from humans, primarily nitrous oxide, carbon dioxide (CO_2), and methane, are responsible for the world's steady rise in temperature. According to proponents of the AGW theory, famines, species extinction, crop failure, extreme weather, famines, and hundreds of other calamities are caused by human-made CO_2.

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- **Ricardian Cross-Sectional theory:**

The cross-sectional Ricardian method is used to examine agricultural production. David Ricardo (1772–1823), who made the original insight that the value of land would reflect its net productivity, is the one who inspired the name. The Ricardian model (RM) analyzes how variations in the local climate affect net income or land value. The model's main strength is its capacity to incorporate adjustments made by farmers and adapt their operations to climate change (Adeosun, Asare-Nuamah, & Mabe, 2021).

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- **Production Function theory:**

This theory outlines the production function and guarantees that the outputs of several types of Crops are examined in various climates (Reinsborough, 2003; Adeosun, Asare-Nuamah, & Mabe, 2021). The model presupposes that different crop kinds cannot adjust to the changing climate. The model's weakness in this hypothesis is that it undervalues agriculture's benefits of climate change.

LITERATURE

WORLD SUSTAINABILITY CONFERENCE 3.0

EMPIRICAL LITERATURE

Nigeria's current food insecurity is escalating due to climatic conditions that have reduced agricultural productivity (Ani, Anyika & Mutambara, 2022).

Tirado et al. (2022) concluded that food security and nutrition, as well as adaptation to climate change, are not distinct objectives but frequently fall under various sectors.

Ayinde, Muchie and Olatunji (2011), Enete (2014),Nwaiwu et al. (2014), Atedhor (2015), Agba et al. (2017), Wang et al. (2018), Muhammad et al. (2022), established relationships between climate change and agricultural productivity.

Jacques et al. (2018) found that climate change, on a global scale, will lead to about a 2%–15% decrease in agricultural productivity by the year 2050, culminating in a 1.3%–56% surge in the prices of food and between 1 and 4% expansion of the area under cultivation.

LITERATURE

EMPIRICAL LITERATURE

Rajesh (2011), Ramesh and Vardhan (2013), Everingham et al. (2016), Babatunde et al. (2019), Rezapour et al. (2021), Cedric et al. (2022), Aworka et al. (2022) employed different data mining/machine learning models to predict agricultural yield.

Joshi et al.(2015); Olaiya & Adeyemo (2012); Shikonun, El-Bolok & Ismail (2005); Auroop & Karsten (2008) applied data mining techniques to weather forecasting and prediction of climate change.

Ojo & Baiyegunhi (2020) showed the importance of climate adaptation of methods by farmers as Ikhuoso et al. (2020) advocate for collaborative efforts to address climate change in the face of geometric population growth and rapidly diminishing scarce resources.

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DATA

The variables used in this study are agricultural output as the dependent variable and temperature, rainfall, and CO2 emissions per capita as the explanatory variables.

Annual rainfall and temperature data are sourced from the Climate Change Knowledge Portal were used in this study from 1980 to 2020. The annual data for CO2 emissions was sourced from World Bank Development Indicators for the years 1980 to 2018 and from countryeconomy.com for the years 2019 and 2020. The annual data for the agricultural output was sourced from the Central Bank of Nigeria's statistical bulletin for the years 1980 to 2020.

DATA & METHODOLOGY

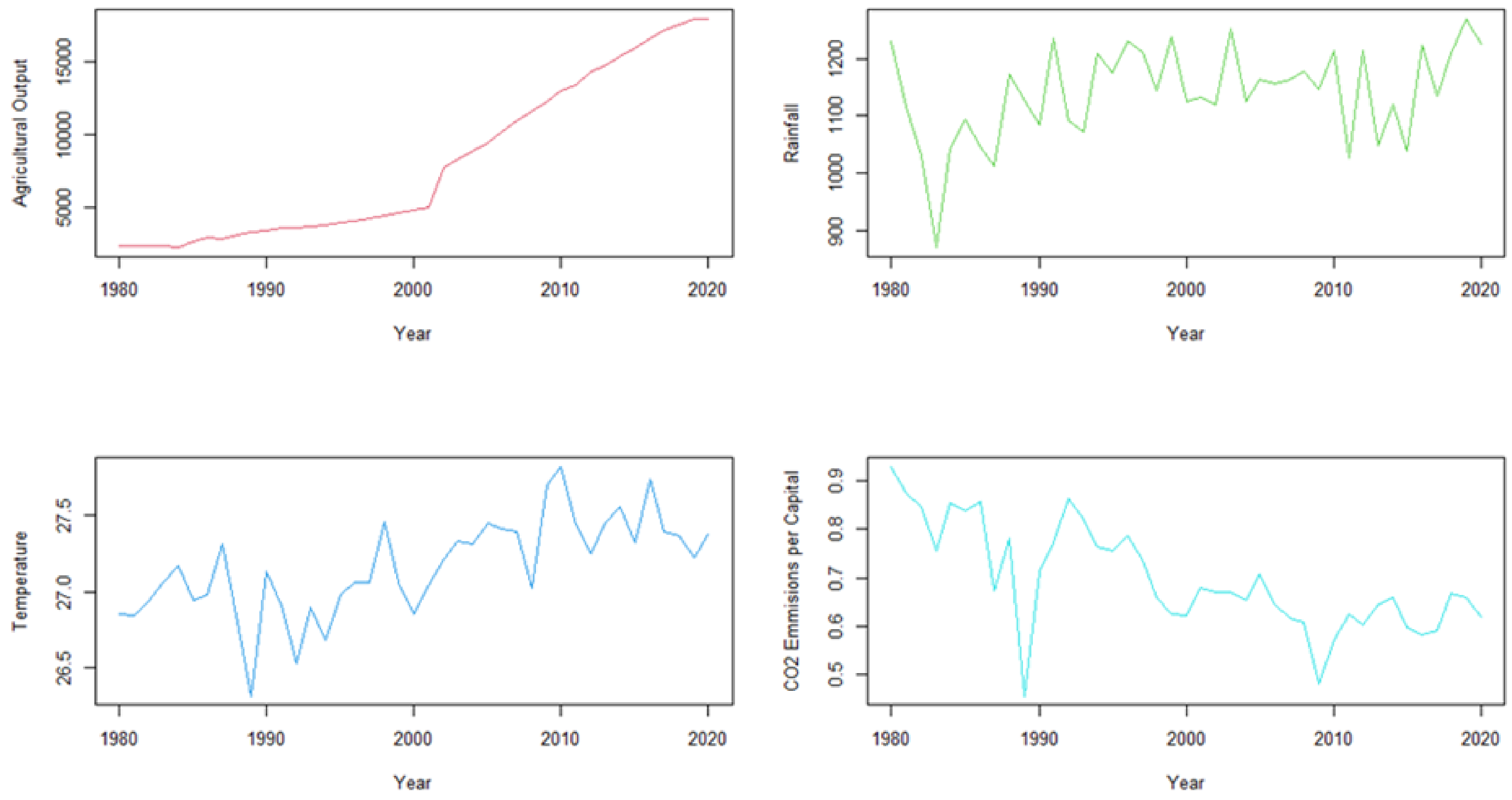

Figure 1: Trend of each variable under consideration.

DATA & METHODOLOGY

The machine learning models considered in this study include the KNN algorithm, Decision Tree, Support Vector Machine, Robust Linear Model (RLM), Random Forest, and Least Angle Regression.

Random Forest: An ensemble learning method in which several decision trees are trained, each with a bootstrapped sample of data known as out-of-bag observations. This learning technique calculates the total score for each observation by comparing the actual value of the observation with the prediction from a subset of trees not trained using that observation. This total score is used to evaluate the random forest's performance. (Umarani, Juliana & Deepab, 2021).

The random forest can be used for regression and classification purposes. In regression problems, the Mean square error (MSE) is used to decide how data branches from each node.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(fi - yi)^2$$

where N is the number of data points,

fi is the value returned by the model and

yi is the actual value for data point i.

DATA & METHODOLOGY

In classification problems, we could use the Gini index or Entropy to determine how nodes are on a decision tree branch. However, the Entropy is more mathematically intense than the Gini index due to the logarithmic function used in calculating it.

The formulas are as follows;

$$Gini = 1 - \sum_{i=1}^{c} (p_i)^2$$

,

where p_i represents the relative frequency of the class you observe in the dataset, and c represents the number of classes.

$$Entopy = \sum_{i=1}^{c} -p_i * log_2(p_i)$$

Entropy uses the probability of a given outcome to decide how the node should branch.

FINDINGS AND DISCUSSION

S/N	MODEL	RMSE	MAE	R SQUARED	RANKING
1.	KNN	5524.410	5037.368	0.369	CO2>T>R
2.	DT	3863.969	2910.529	0.664	CO2>T>R
3.	SVM	3756.603	2883.367	0.701	CO2>T>R
4.	RLM	4032.575	3328.131	0.682	T>CO2>R
5.	**RF**	**3500.989**	**2732.087**	**0.659**	**T>CO2>R**
6.	LARS	3524.157	2976.324	0.746	CO2>T>R

TABLE 1: Model Performance Metrics Before Feature Selection

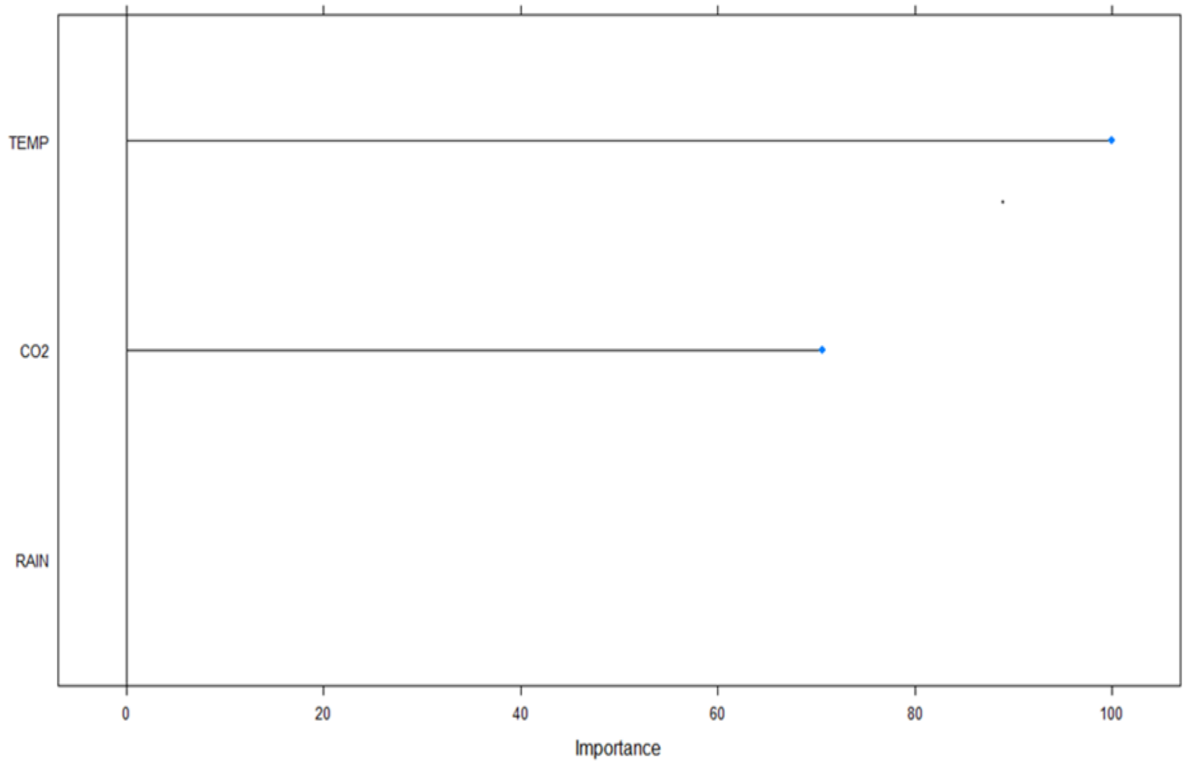

Fig. 2: Feature Importance Plot of Random Forest

Variable importance results show that temperature is the best predictor of agricultural output in Nigeria, being at 100 mark. It is followed by CO2 emissions per capita which is well beyond the 60 mark. From the plot, rainfall does not predict agricultural output in Nigeria.

FINDINGS AND DISCUSSION

The predominance of agriculture in the northern part of Nigeria can explain the positive relationship between temperature and agricultural output, i.e. the northern part of Nigeria contributes a larger percentage to agricultural output. Most crops cultivated in the northern part of Nigeria need high temperature.

Rainfall's relationship with agricultural output could be explained by the less contribution of temperature-susceptible crops to the nation's total agricultural output.

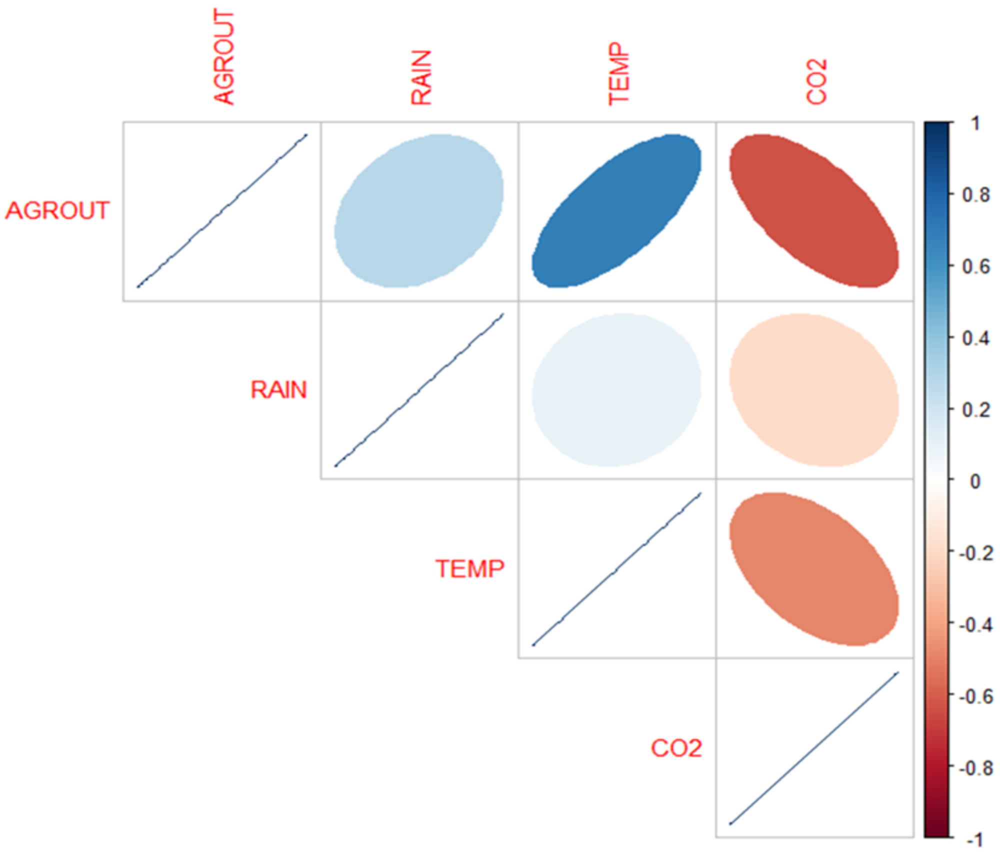

Fig. 3. Correlation Matrix for Random Forest

FINDINGS AND DISCUSSION

CO_2 emissions' relationship with agricultural output could be through the channel of economic growth. By this, we mean that economic growth, according to the environmental Kuznets curve, contributes to CO_2 emissions. This means that the more economic growth, the more shift from agriculture to more manufacturing.

The experience of global warming due to CO_2 emissions leads to rising sea levels and flooding, affecting crops negatively and reducing agricultural output. Also, global warming, resulting from CO_2 emissions, negatively affects aquaculture (fishery).

CO_2 emissions also lead to ocean acidification and an increase in ocean surface temperature, which affects the marine ecosystems negatively; thus, it leads to a fall in agricultural output (fishery).

DATA & METHODOLOGY

The study investigated the impact of climate change on agricultural output using a machine-learning approach. Six machine learning models were used to determine the best model that explains the relationship between climate change and agricultural output in Nigeria. The best model was the Random Forest, which had the lowest Root Mean Square Errors (RMSE) and MAE. Variable importance results show that temperature is the best predictor of agricultural output in Nigeria, followed by CO_2 emissions, while rainfall does not predict the agricultural output. We also discovered from the correlation matrix that there is; a very strong positive relationship between temperature and agricultural output; a weak positive relationship between rainfall and agricultural output; and a strong negative relationship between CO_2 emissions and agricultural output.

Therefore, the government and policymakers should adopt climate-smart agricultural practices, climate and environmental education, especially for farmers, and carbon neutrality or reduction policies, together with research and development, to ensure agricultural sustainability and food security in Nigeria and other developing countries.

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