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Agriculture Performance and Inflation Dynamics in Rwanda: Application of Machine Learning.

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Abstract

This paper investigates the nexus between agricultural performance and inflation dynamics in Rwanda using machine learning techniques, particularly by applying elastic net regression on quarterly data spanning from 2008Q1 to 2023Q2. The study focuses on four key crops of Rwanda namely: maize, vegetables, Irish potatoes, and beans to assess the impact of dry spells and heavy rains during planting, growing, and harvesting periods on crop production. Results suggest that crops are more sensitive to heavy rains than dry spells. Additionally the study uses crop production, rainfall, and previous headline inflation(as proxy for other costs) to predict fresh food inflation. As expected, the findings indicate that an increase in crop production lowers fresh food inflation, while the deviation from mean rainfall increases fresh food inflation. It was also found that high cost of production leads to a rise in fresh food inflation.Furthermore, the study uses six different Machine learning models and Auto regressive moving average model(ARMA) to forecast fresh food inflation ,it was found that Decision tree and Gradient boosting models outperform other models.Finally, the study uses the average of the two best models to forecast in-sample fresh food inflation, and the results are consistent with the Actual fresh food inflation.

Keywords: Machine learning,Climatic conditions, Inflation, Forecasting, Crop production.

JEL Classification: C53,C63,E31

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1 Introduction

Agriculture plays a pivotal role in the economic and social fabric of many developing countries, and Rwanda is no exception, where the percentage of the population engaged in the agriculture sector accounts for 69 percent of private households NISR (2023).The interplay between agricultural performance and inflation dynamics in Rwanda presents a complex and dynamic relationship that warrants in-depth exploration. As Inflation dynamics have far-reaching implications for both macroeconomic stability and the welfare of households, With a predominantly agrarian economy, the performance of the agricultural sector is intricately linked to the overall economic stability and well-being of the Rwandan population. Specifically, agriculture affects inflation through food inflation, which distorts the welfare of citizens.The available evidence regarding the welfare effects of elevated food inflation on rural communities is not entirely conclusive. However, there is clear evidence pointing to a substantial adverse impact on the well-being of urban populations Malhotra & Maloo (2017) and it is also believed that high inflation harms the economic growth Rutayisire (2015).

Rwanda has made great strides in the last 30 years, with the economy growing and poverty rates falling significantly. With a share of 27% in GDP, of which 17% is from food crops, the performance of the agriculture sector in Rwanda has important implications for the standards of living for Rwandans and the country's economic development. From a socio-economic perspective, the overall poverty rate has seen a substantial decline, dropping from 60.4% in 2000 to 38.2% in 2017, with agriculture playing a pivotal role in this positive trend NISR (2023). Agriculture has also become a significant source of foreign exchange, given the increasing basket of exportable products, such as coffee, tea, pyrethrum, animal products, macadamia, flowers, fruits, vegetables, cereals, and grains.

However, Rwanda's agricultural performance is profoundly influenced by a range of weather-related factors, including floods, droughts, and delayed rainfall. These climatic challenges pose significant threats to crop production and food security, impacting the livelihoods of many farmers across the country Sebaziga (2014). One prominent issue is the occurrence of floods, often resulting from heavy rainfall. These floods damage crops, erode topsoil, and disrupt planting schedules. Addressing this challenge requires investments in proper drainage systems, the use of raised beds, and the cultivation of flood-resistant crop varieties. The recent flood was recorded in May 2022, where 139 lives were lost, live stocks died, and many crops were destroyed MINEMA (2022). Additionally, droughts present a substantial threat to agriculture in Rwanda as insufficient rainfall leads to water scarcity, adversely affecting crop growth and reducing yields.Rainfall distribution also matters as delayed or erratic rainfall disrupts planting schedules and affects overall crop growth.

The recent string of poor harvests, spanning about six quarters, has directly contributed to inflation spikes observed the Rwandan economy. In the second quarter of 2023, for instance, headline inflation surged to 15.2 percent, with fresh food inflation reaching a staggering 40.4 percent. These increases can be attributed to reduced agricultural output, leading to scarcities and subsequent price rises in essential food items. Such inflationary pressures have significant socio-economic implications, as they erode purchasing power, particularly among low-income households, exacerbating poverty levels. Understanding the relationship between agricultural performance and inflation dynamics is therefore important as this would guide policymakers on the implementable reforms to address food-driven inflationary pressures. To the central bank, such analysis is also useful in determining the appropriate monetary policy response.

Meanwhile, despite the anecdotal evidence of an existing relationship between the performance of food agricultural output and inflation dynamics, empirical research to quantify the contribution of shocks to food agricultural output on inflation dynamics in Rwanda has not gained much attention. The few available studies on inflation dynamics have focused on analyzing the impact of macroeconomic variables and policies include Hakizimana (2022) and Kimolo et al. (2023). At the same time, none of the existing analyses has researched on fresh food inflation, which is the most volatile component of the CPI basket in Rwanda.

The foregoing therefore forms the basis for the motivation of the current study. In particular, the objective of this research is to forecast fresh food inflation in Rwanda through examining the relationship between agricultural performance and inflation dynamics by addressing the following questions: What are the drivers of fresh food inflation in Rwanda?,How does the performance of agricultural output affect the dynamics of fresh food inflation in Rwanda? Do Machine learning models outperform the traditional models in forecasting fresh food inflation in Rwanda? In line with the above, the analysis focuses on the impact of four major crops, notably: Irish potatoes, maize, beans and vegetables. Selection of these crops is influenced by their large weights in the consumer basket as reflected in the CPI and their share in total crop production. Furthermore, these being weather-dependent crops, investigating the impact of climatic conditions on performance of these crops and, therefore, on inflation dynamics is part of the current analysis. Specifically, our interest is to assess the impact of deviations from normal rain on production performance for each of the selected crops and the resultant effect on headline inflation through fresh food prices.

Traditionally, researchers have modelled the dynamics of macroeconomic variables using a variety of models, ranging from the straightforward univariate time series models to structural macroeconomic models such as the dynamic stochastic general equilibrium (DSGE) models. Recently, the availability of big datasets and the progress made in computing technology have drawn attention to machine learning techniques, which are being explored as viable substitutes for the statistical forecasting models commonly used by monetary authorities. Among others, using machine learning techniques has the advantage that it offers the chance to create forecasting models with an ideal bias-variance trade-off Malhotra & Maloo (2017). Therefore, motivated by the foregoing, the analysis in this study has employed machine learning techniques to address the research questions raised earlier. As discussed in Section 5.3, details about the machine learning technique, including the procedure for obtaining estimates and the associated inference, are provided.

This study is a contribution to existing literature on inflation dynamics in several ways. Firstly, the focus on fresh food inflation and its key (supply-side) determinants like weather shocks and crop production is a contribution to the understanding of why inflation is more volatile in agrarian economies, particularly in developing economies, than their counterparts in the industrialized world. The application of machine learning techniques also provides a platform for assessing the relevance of this methodology in applied research. To policymakers in agrarian economies, the findings of this study are an important reference in the design of implementable reforms to enhance crop production and control weather-driven inflationary pressures.

This paper is organized as follows: In Section 2 and 3 we provide a comprehensive stylised factors and review of the relevant literature, highlighting the current state of research in the field respectively. Section 4 presents the methodology employed in our study, including details about the data collection process data pre-processing and the analytical techniques utilized. In Section 5, we present the results of our analysis, discussing key findings and implication as well as providing insights and interpretations. Finally, in Section 6, we conclude our paper with a summary of our findings, and policy recommendations.

2 Stylized Facts

2.1 The Effects of Weather Shocks on Agriculture and Inflation in Rwanda

Weather shocks in Rwanda have significantly impacted agriculture and inflation by damaging infrastructure and disrupting supply chains (see Table1). Notably, the loss of life, injuries, and damage to housing disrupt labor availability and productivity that affect agricultural production. Similarly, crop and forest destruction, livestock losses, and damaged roads and bridges impede agricultural production and distribution, which may induce supply-driven inflationary pressures.

Category	**2019**	**2020**	**2021**	**2022**
Death	134	298	116	205
Injury	271	414	248	401
Houses Damage	5691	8098	4808	4156
Damages Crop (Ha)	10610.45	4661.5	3802.3	1917.7
Forests (Ha)		458	167	73
Livestock Cattle	113	132	97	85
Other Livestock		3365	2043	116
Roads	30	154	48	72
Bridges	40	103	39	59
Markets	4	6	4	2
Factories	2	1	4	4

Table 1: Impact of flood in Rwanda
Source:MINEMA(2023)

The recent destructive flood occurred in May 2023, where in Rwanda heavy rains led to major damage across various areas of the nation, notably in the Western, Northern, and Southern provinces. Main lives were lost and crops valued at 5,752,687,938 Rwf were also damaged as shown in Table 2.

SN	Crops	Yield (T/ha)	Affected area (ha)	Production loss (MT)	Crop loss (Rwf)
1	Beans	0.80	1075.6	860.5	1 204 829 570
2	Maize	1.30	837.8	1089.1	364 936 302
3	Soybean	0.50	59.7	29.9	22 642 974
4	Irish potatoes	6.30	329.4	2075.3	949 123 091
5	Rice	4.10	149.8	614.3	281 054 490
6	Vegetables	11.10	48.3	536.1	423 857 852
7	Banana	12.20	162.9	1987.4	894 296 832
8	Sorghum	1.10	34.1	37.5	25 171 020
9	Sweet potatoes	7.50	123.0	922.5	461 270 223
10	Yams	7.40	94.4	698.6	348 624 032
11	Fruits	6.40	3.7	23.4	23 118 512
12	Sugar cane	78.30	50.9	3985.5	
13	Tea	8.00	61.6	492.8	147 840 000
14	Coffee	6.25	5.2	32.5	13 325 000
15	Cassava	15.20	63.2	960.6	576 517 426
18	Peas	0.80	0.4	0.3	641 737
19	Wheat	1.20	15.5	18.6	14 430 719
20	Pyrethrum	2.50	0.3	0.8	1 008 150
	Total		3115.9	14 365.7	5 752 687 938

Table 2: Impact of flood on crops
Source: MINAGRI (2023)

2.2 Agriculture Sector in Rwanda

Agriculture accounts for 27 percent of the total GDP in Rwanda, and around 69 percent of Rwandans are employed in the agriculture sector while 62.6 percent are engaged in crop farming, 50.4 percent in livestock husbandry, 50.8 percent in the horticulture sector, and 0.5 percent in Apiculture NISR (2023). Beans cultivation is the most prevalent agricultural activity in Rwanda, involving 80 percent of all households engaged in crop farming, followed by maize (56.3%), cassava (48.7%), sweet potatoes (44.3%), and banana (24.4%). Rwandans also cultivate different vegetables like amaranth, which comprise 10.6 percent of total household growing crops, with cabbage (3.0 percent), eggplant (2.5 percent), tomatoes (1.8 percent), onions percent, and carrots 1.4 percent.It is therefore not surprising that these crops also constitute a large share in the composition of the CPI basket in Rwanda.

2.3 Composition of Rwanda inflation

National bank of Rwanda(NBR) employs three primary classifications in its analysis of overall inflation. The initial categorization comprises twelve components,with food (constituting 27.4 percent of the CPI basket), housing (weighing 20.8 percent), and transport (holding 12.5 percent) playing significant roles in CPI inflation. These components include highly volatile items, such as fresh food products, and energy-related items like fuels, lubricants, firewood, and charcoal.Over the past decade, these three main components have consistently contributed to over 70 percent of variations in CPI inflation.

Two more important classifications are also applied: (i) imported vs domestic inflation and (ii) core versus Non-core inflation. Non-core inflation is made of fresh food and energy. Empirical studies on Rwanda found that there is a strong and significant co-movement between headline inflation,core and domestic inflation Mwenese & Kwizera (2018).The composition of Rwanda's CPI basket is presented in table 3.

	CPI Components	Weight (%)
01	Food and non-alcoholic beverages	27.4
02	Alcoholic beverages and tobacco	4.9
03	Clothing and footwear	5.3
04	Housing, water, electricity, gas and other fuels	20.8
05	Furnishing, household equipment and routine household maintenance	3.8
06	Health	1.3
07	Transport	12.5
08	Communication	3.1
09	Recreation and culture	3.1
10	Education	2.7
11	Restaurants and hotels	8.8
12	Miscellaneous goods and services	6.4
	General Index	100

Table 3: CPI 12 Components
Source:BNR (2023)

3 Related Literature

Different researchers have used different techniques to model inflation, ranging from the traditional time series models to machine learning techniques. However, studies linking agriculture and inflation dynamics using machine learning techniques are limited. Notably,Boescha & Ziegelmannb (2023) compares the time series forecasting accuracy of several machine learning techniques and conclude that the Weighted Lag Adaptive elastic net regression (WLadaENet) performs well in forecasting inflation dynamics in the USA. Similarly,Maehashi & Shintani (2020) utilised factor models and nine different machine learning methods to forecast various macroeconomic variables, including inflation, in Japan. They found that machine learning techniques perform better than the conventional auto-regressive models, particularly for the medium to long-term forecast horizons.

Chakraborty & Joseph (2017) present a literature summary with an application of the various machine learning techniques to economic and policy problems including inflation projection. The outcome shows that machine learning models generally outperform the traditional modelling approaches, such as VAR and AR models.In analysis of food inflation in India using the gradient boosted regression trees (BRT),Malhotra & Maloo (2017) find that all predictor variables are fairly important in explaining food inflation while international prices have limited influence.

Within the sub-Saharan Africa region, some studies have also modelled the effects of agriculture on the inflation process, notably:Diouf (2008) on Mali;Kinda (2011) on Chad; Durevall et al. (2013) on Ethiopia ; Adam (2016) on Tanzania and Mawejje & Lwanga (2016) on Uganda. However, unlike our study, none of these infer their conclusions from results of the working in machine learning techniques. They have also not allowed for the impact of the interaction between agricultural crop production and weather conditions in their analysis on the impact of inflation dynamics.

In the context of Rwanda,Ruzima & Veerachamy (2015),Nyoni (2019), Hakizimana (2022) and Kimolo et al. (2023) are also among the existing scholars for inflation dynamics in Rwanda using some other methodologies than the machine learning techniques. Their analyses focused on effects of macroeconomic variables and policies using ARMA and/or VAR models except for Hakizimana (2022) who, in addition to the above, also applied machine learning techniques of Random Forest, Ridge Regression, LASSO Regression and K Nearest Neighbor (KNN). The current study complements these studies by examining the impact of agricultural crop performance and weather conditions, particularly heavy rainfall and dry spells, on inflation dynamics.

There are limited studies on the context of Rwanda that deal with predicting specifically inflation using machine learning techniques. However, non-structural models such as Autoregressive Moving Average (ARMA), vector autoregressive (VARs and BVARs) are used for short-term forecasting while the Quarterly Projection Model (QPM) has been adopted as a tool for medium-term forecasting at the National Bank of Rwanda Mwenese & Kwizera (2018).

We note that, despite the importance of fresh food inflation in an agrarian economy such as Rwanda, none of the previous scholars has had interest in projecting this category of inflation while accounting for the effects of the different patterns associated with its key drivers such as weather conditions and crop production. It is against this background that this study seeks to cover this literature gap. Our aim is to provide the best model to forecast fresh food inflation, which is the most volatile component of Rwanda's CPI basket.

4 Methodology

4.1 Machine learning

Machine learning is a branch of artificial intelligence that focuses on creating methods and algorithms that let computers learn from data and become more efficient at certain activities without needing to be explicitly programmed. By seeing patterns and connections in datasets, these algorithms enable users to categorize information, forecast outcomes, and make the best choices possible based on historical data. supervised learning, in which the algorithm learns from labeled examples, unsupervised learning, which finds patterns in unlabeled data, and reinforcement learning, in which the algorithm learns by trial and error based on rewards or penalties, are just a few of the approaches that make up machine learning. The type of problem, the data at hand, and the intended result determine which algorithm to use and how to configure it Murphy (2012).

Machine learning originated in the mid-20th century with early concepts proposed by researchers like Turing (1950) and Samuel (1959). Progress was limited by computational constraints until the 1990s when advancements in computing power and the internet fueled a resurgence. In the early 21st century, machine learning saw rapid growth, driven by big data and breakthroughs in algorithms, particularly deep learning. Today, machine learning is pervasive across industries, driving innovations in areas such as recommendation systems, healthcare,banking sector and autonomous vehicles.

4.2 Estimation and forecasting procedure

This study uses secondary data obtained from the National Institute of Statistics of Rwanda and Rwanda Meteorology Agency, where Python programming language was used as a tool to investigate the dynamics between agricultural performance, inflation, and climatic conditions in Rwanda. The dataset encompasses information related to two harvesting periods (season A and season B) to capture the impact of crop production and rainfall, by focusing on four key crops: maize, vegetables, Irish potatoes, and beans. The selection of these crops was based on their share in total crop production, and sensitivity to weather shocks.

The study also used the feature importance technique of elastic net regression to assess the sensitivity of crop production on dry spells[1] and heavy rainfall [2] as rainfall distribution also matters Asadi et al. (2019).These climatic factors are identified as crucial variables affecting the yields of the selected crops Sebaziga (2014).

In the next step, the study estimates the impact of rainfall and crop production on inflation by using Elastic Net regression, on quarterly data starting from 2008Q1 to 2023Q2, a method utilized by Zou & Hastie (2005) and Boescha & Ziegelmannb (2023). With this method, multi-collinearity and feature selection are solved to provide better prediction accuracy and model interpretation.
Therefore, the minimization problem for net regression was formulated as follows:

$$\min_{\beta_0,\beta}\left\{\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\beta_0-\sum_{j=1}^{p}x_{ij}\beta_j\right)^2+\lambda\left(\alpha\sum_{j=1}^{p}|\beta_j|+\frac{1-\alpha}{2}\sum_{j=1}^{p}\beta_j^2\right)\right\} \tag{1}$$

Where:

- N is the number of samples.
- p is the number of features.
- y_i is the target variable for sample i.
- x_{ij} is the value of feature j for sample i.
- β_0 is the intercept term.
- β is the vector of coefficients.
- λ is the regularization parameter.
- α is the mixing parameter between L1 and L2 penalties.

[1]A dry spell is defined as 7 consecutive dry days. A dummy variable was created with value =1 for the dry day (if rainfall is less than 0.85mm)

[2]Heavy rainfall dummy was created with value =1 if the observed rainfall on that day is greater than the mean plus 4 times the standard deviation

The optimal values for the hyper-parameters in regularized regressions (λ and α) were typically achieved through a grid search combined with an iterative k-fold cross-validation[3] technique Zou & Hastie (2005). The features variables considered for the analysis are Rcrops_y-o-y (Year-On-Year Crop Production), Rainfall, Headline_infl-1 (lagged headline inflation), while Fresh_infl (Fresh Food Inflation), was used as the target variable.The lagged headline inflation has been included as a proxy for other costs that may affect fresh food inflation like fertilizers, seeds, shipment, labor, international commodity prices, speculations, while crop production is uses as a key item to influence fresh food inflation and rainfall to reflect weather-related challenges.The selection of these variables has been influenced by existing literature which attaches their high importance in explaining variations in fresh food inflation.

In conclusion, Six different machine learning 4 techniques were employed to forecast fresh food inflation,namely: Decision tree, Gradient boosting, Elastic net regression, Support vector regression, Random forest, and K-nearest neighbors. The selection of these models was based on their potential to address complex patterns in the data, and the results were compared with AutoRegressive Moving Average (ARMA(2,2)) as a traditional model for further comparison, while the best models selection was based on different evaluation metrics.5.

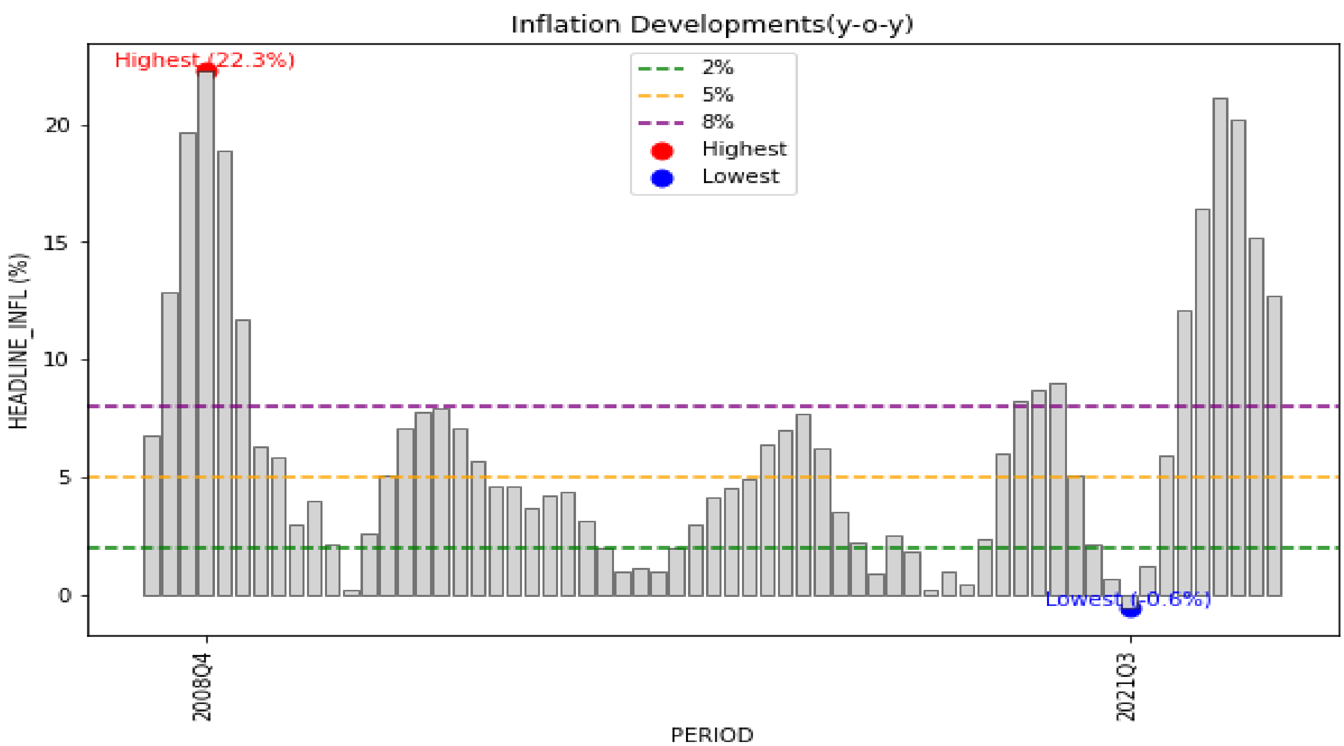
[3]Cross-validation (CV) is a technique used to evaluate the performance of a predictive model by repeatedly splitting the dataset into training and validation subsets. In our case, fold=3 was used based on the size of the dataset, and the desired trade-off between bias and variance in the estimated performance.This choice strikes a balance between computational efficiency and robust estimation of the model's performance

5 Discussion of findings

5.1 Inflation dynamics in Rwanda

Figure 1 shows the dynamics of headline inflation from 2008Q1 to 2023Q2. As reflected in that figure, inflation in Rwanda has been volatile and, at times, surpassed the NBR's 2-8 percent target range. External shocks, alongside weather-related challenges, have played a pivotal role in influencing this deviation. The country's susceptibility to global economic shifts underscores the complexity of maintaining stable inflation rates. Additionally, adverse weather conditions affecting agriculture, a cornerstone of the Rwandan economy, contribute to fluctuations in inflation.

Figure 1: Headline inflation dynamics overtime

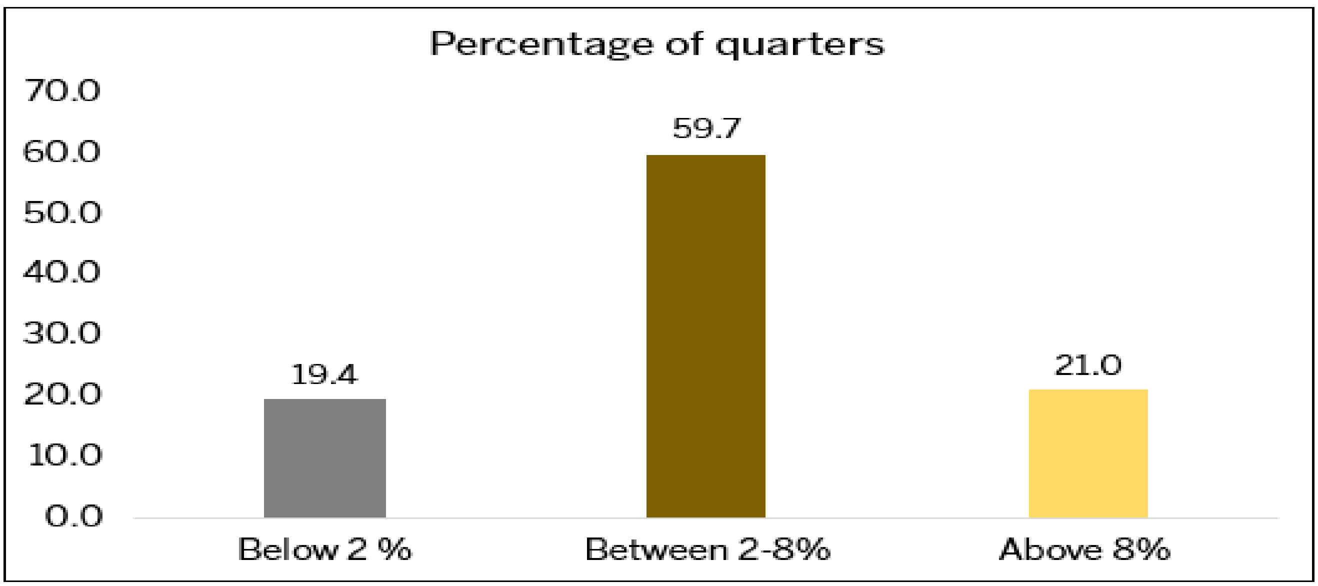


Source: Author's computation

As shown in figure 1, sometimes inflation went out of the band due to both domestic and external shocks.In 2008Q4, inflation surged due to scarcity in agricultural production coupled with a rise in global

commodity prices.In 2016 a combination of drought which affected crop production together with an increase in imported inflation contributed to the inflationary pressures.Moreover,during 2020 inflation surpassed the upper band reflecting the impact of COVID-19 on production, supply chains, and transport.
Conversely, the lowest inflation was recorded in 2021Q3, primarily attributed to a base effect of higher prices that was recorded in the previous year,while during the followed year of 2022, the Post-COVID-19 recovery period, adverse weather conditions, the impact of Russia-Ukraine war coupled with the depreciation of the Rwandan franc led to observed high inflation.

Figure 2: Inflation deviation from the band



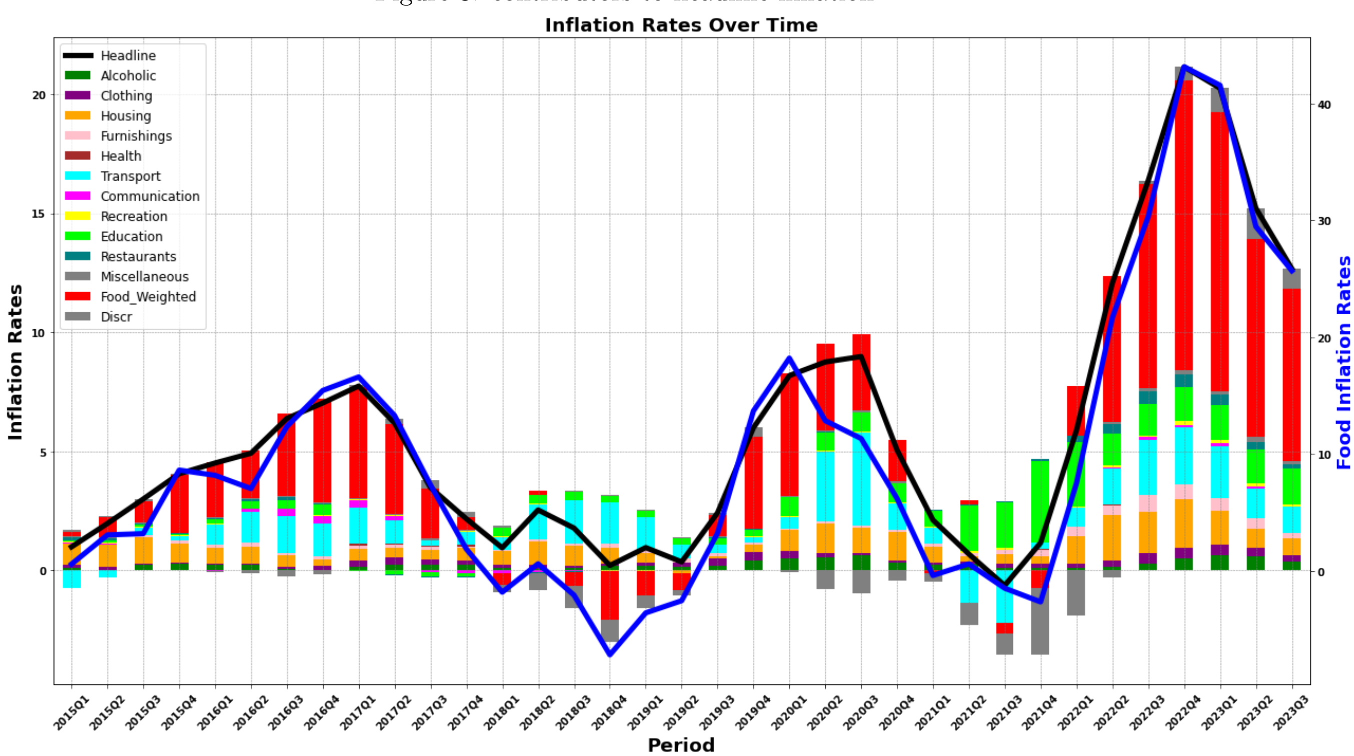
Source: Author's own computation

Despite these challenges, the analysis has found that the National Bank of Rwanda has proactively managed inflation by adopting an appropriate monetary stance, complemented by concurrent government policies to mitigate inflationary pressures,such as subsidies on fertilizers and seeds, coupled with the removal of VAT, exemplify strategic measures by the Government aimed at enhancing agricultural productivity and stabilizing the economy.This is as revealed in figure 2 which shows that for the sample period used in this study, inflation was contained within the 2-8 percent target range during 59.7 percent of that period.These concerted efforts reflect a multifaceted approach to addressing the factors contributing to inflation volatility in Rwanda.

5.2 Agriculture performance,food and headline inflation in Rwanda

Historically, food inflation has been co-moving with headline inflation (see figure 3).Moreover it has been observed that this increase in both inflation is associated with lower crop production which may explain the influence of agriculture sector performance on cost of living in Rwanda.

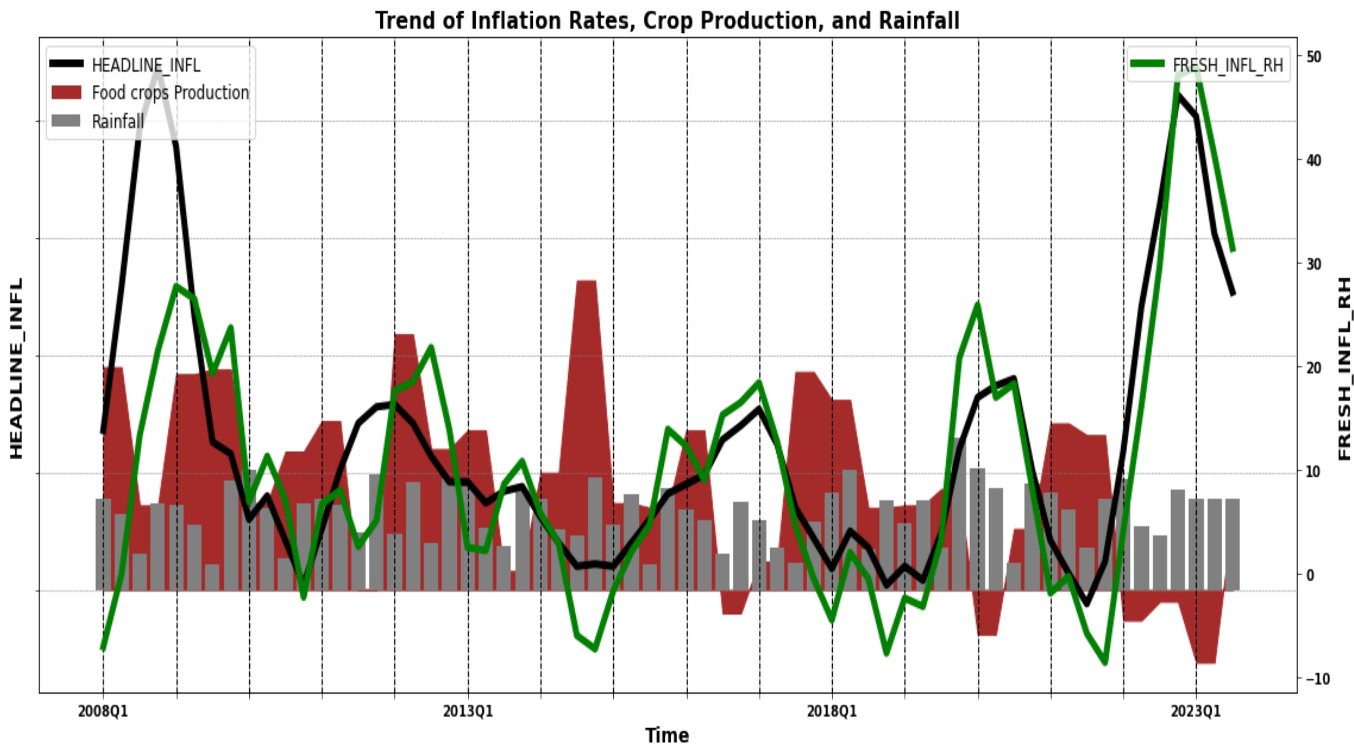
Figure 3: contributors to headline inflation



Source: Author's own computation

Confirming this observation, figure 4 reveals that lower agriculture performance lead to high food inflation which is associated with peaks in headline inflation. A notable example is in 2022Q4 when year-on-year food inflation peaked to 43.1 percent from 25.7 percent recorded in the previous quarter.

Figure 4: **Food inflation as the main contributor to headline Inflation**



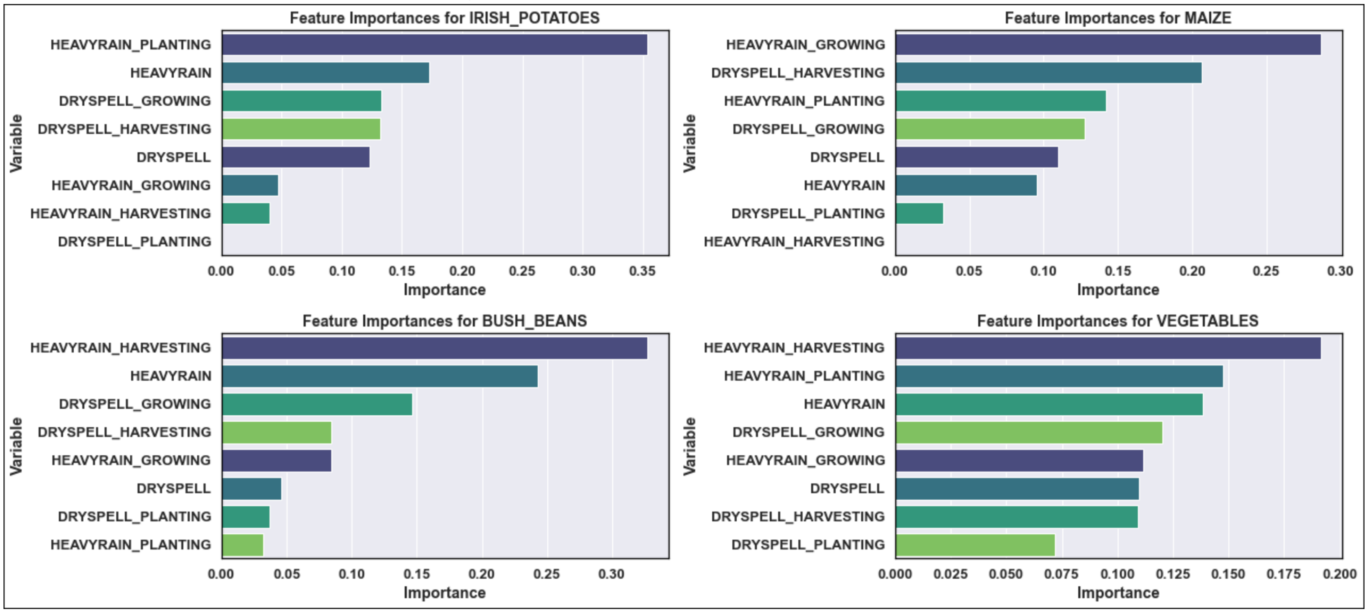
Source: Author's own computation

5.3 Machine Learning Estimation:Results from the Feature Importance Analysis

5.3.1 Sensitivity to Heavy Rainfall

The claim that heavy rainfall at certain stages of crop growth affects some crops aligns with the concept of required rainfall for optimal growth.The varying susceptibility of crops to specific weather patterns can be linked to their distinct moisture needs during critical phases of their life cycle. The study validated this by employing the Feature Importance tool in Machine Learning whose results are presented in figure 5.As noted from that figure, Irish potatoes exhibit sensitivity to heavy rainfall during the planting period while maize is sensitive to heavy rainfall during the growing period. On the other hand, vegetables and beans are predominantly affected by heavy rainfall during the harvesting period.

Figure 5: **Feature importance**



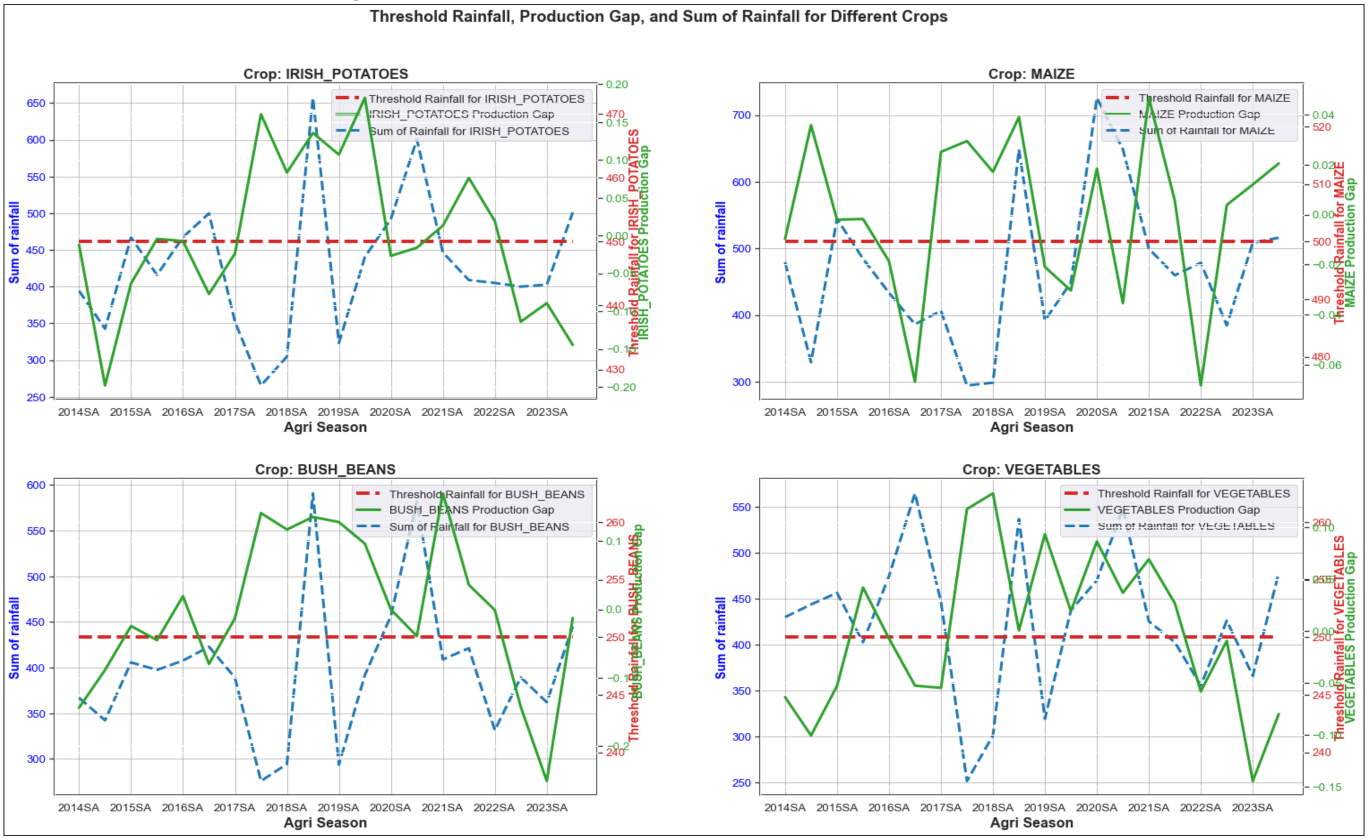
Source: Author's own computation

5.3.2 Required Rainfall analysis

In figure 6, the threshold rainfall necessary for optimal growth for the selected crops is presented. Based on the information used in this analysis, Irish potatoes have the threshold amount of required rainfall of 450 mm. As revealed in figure 6 and explained in section 5.3.1,this crop is sensitive to heavy rainfall during the planting phase. Heavy rainfall at this stage can affect soil structure, making it less conducive to tuber development. For maize, the threshold rainfall is 500 mm. Heavy rainfall during its growing phase can lead to waterlogging and affect root health as well as nutrient uptake. At the same time, insufficient rainfall might stunt growth. Meanwhile, beans and vegetables, characterized by the lowest threshold rainfall of 250 mm, thrive in well-drained conditions. Heavy rainfall during their growing phase might lead to water saturation in the soil, impacting root health and nutrient absorption. The feature importance of highlighting the impact of heavy rainfall aligns with these crops' vulnerability to excessive moisture.

The observed relationships between feature importance and required rainfall underscore the importance

Figure 6: **Required rainfall vs crop production**



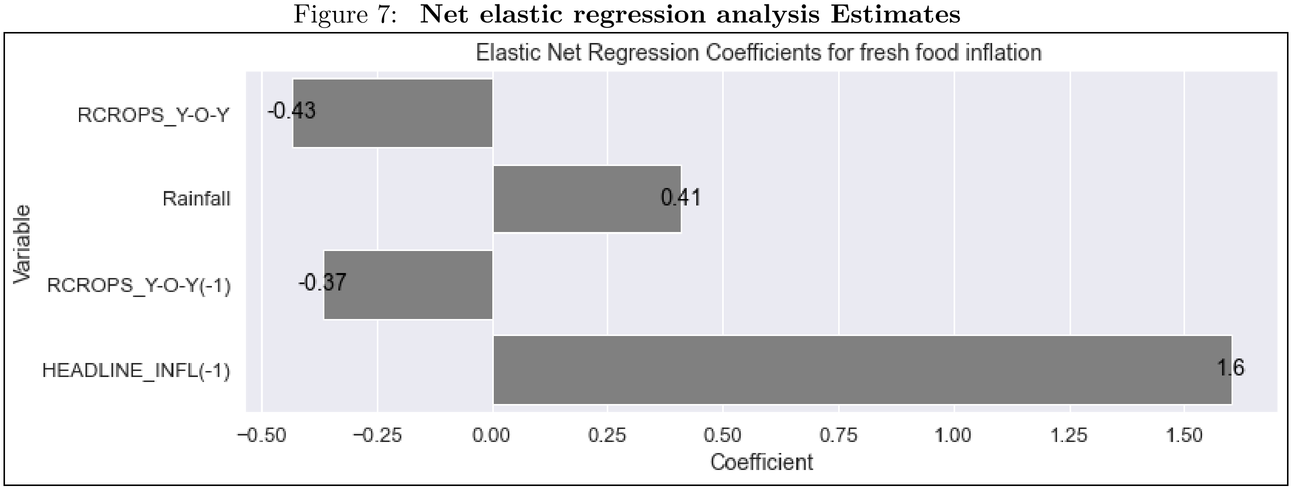
Source: Author's own computation

of aligning weather conditions with the specific needs of each crop. Tailoring agricultural practices based on these insights can enhance resilience, optimize resource use, and contribute to improved crop yields in the studied regions. This connection between feature importance and required rainfall provides valuable insights for farmers, policymakers, and agricultural practitioners to develop targeted strategies for crop management in response to varying climatic conditions NAEB (2023). However, when utilizing the necessary amount of rainfall (required rainfall) to assess the impact of deviations from normal rain on productivity and inflation, the results yielded inconclusive findings. Perhaps this points to the fact that rainfall amount alone is not sufficient to explain crop production but rather its distribution as well as other factors such as fertilizers, seeds quality, types of agriculture system, which are out of this study scope.

5.3.3 Relationship between Rainfall,agricultural production and inflation dynamics

A further analysis was conducted to understand the relationship between rainfall, agricultural production and inflation's dynamics with fresh food inflation. Net elastic regression was used to address this issue. Figure7 presents the outcome of the analysis. Moreover, the analysis indicates that an increase in crop production lower fresh food inflation,while An increase in rainfall increases fresh food inflation the result that aligns with expectations. Crops, being sensitive to heavy rainfall, experience a potential decline in yield, thereby contributing to an upward pressure on prices. The negative relationship between crop production and fresh food inflation reinforces the notion that climatic factors significantly influence agricultural output and, subsequently, impact on inflation dynamics. As anticipated, results in Figure7 also indicate a positive relationship between previous period's (lag 1) prices and current fresh food prices. This implies that if prices were higher during the previous period,affect farmer's cost of production,then current period's prices will likely to increase. This finding aligns with economic expectations, as past price levels serve as a significant factor in shaping current market dynamics.

Figure 7: **Net elastic regression analysis Estimates**



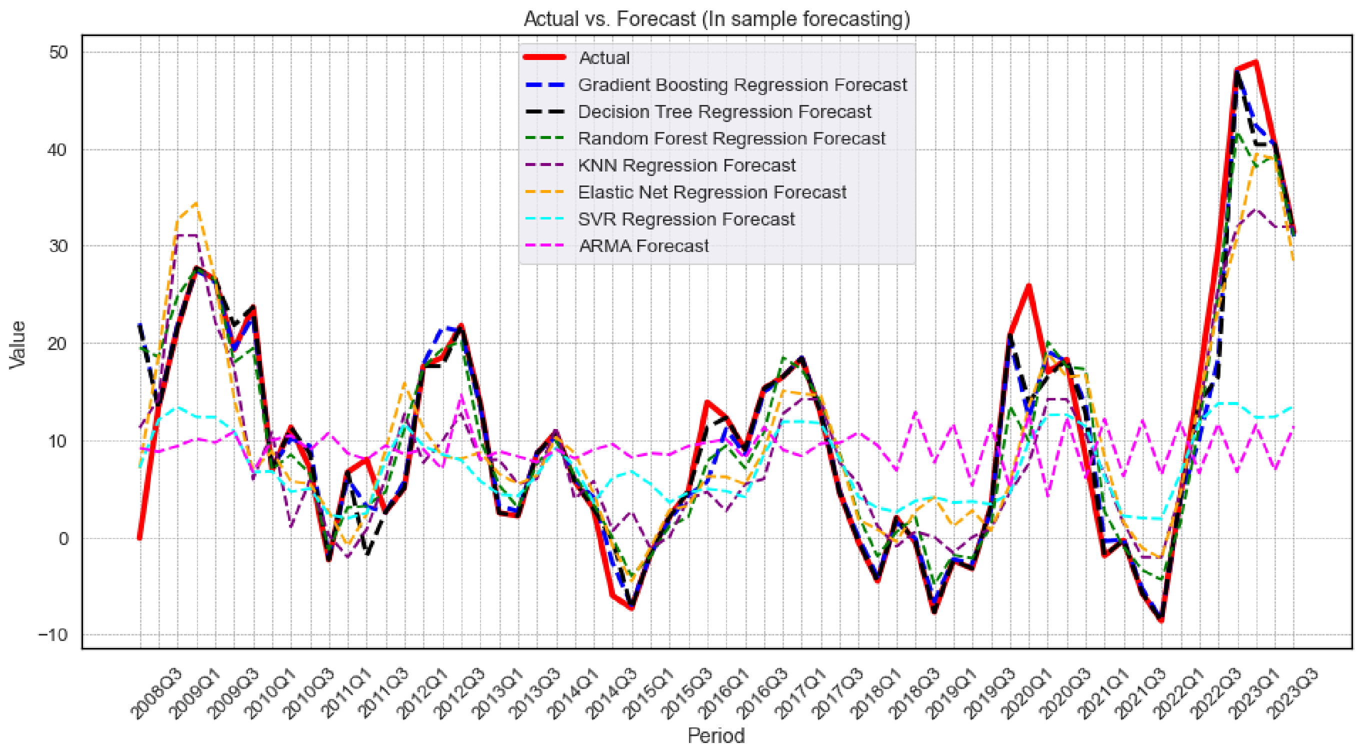
Source: Author's computation

The comprehensive analysis employing elastic net regression elucidates the intricate relationship between climatic conditions, crop production, and fresh food inflation in Rwanda. The nuanced understanding of these dynamics provides valuable insights to policymakers and stakeholders in the agricultural sector, thereby facilitating informed decision-making in the context of a changing climate and its impact on food prices.

5.3.4 Forecasting fresh food inflation

An in-sample forecasting exercise was conducted to predict fresh food inflation by using cost of production, crop production, and rainfall as feature importance with different models4. Based on different evaluation metrics13 the study confirms that decision tree and gradient boosting out perform other models in forecasting.

Figure 8: **Fresh food inflation projection**

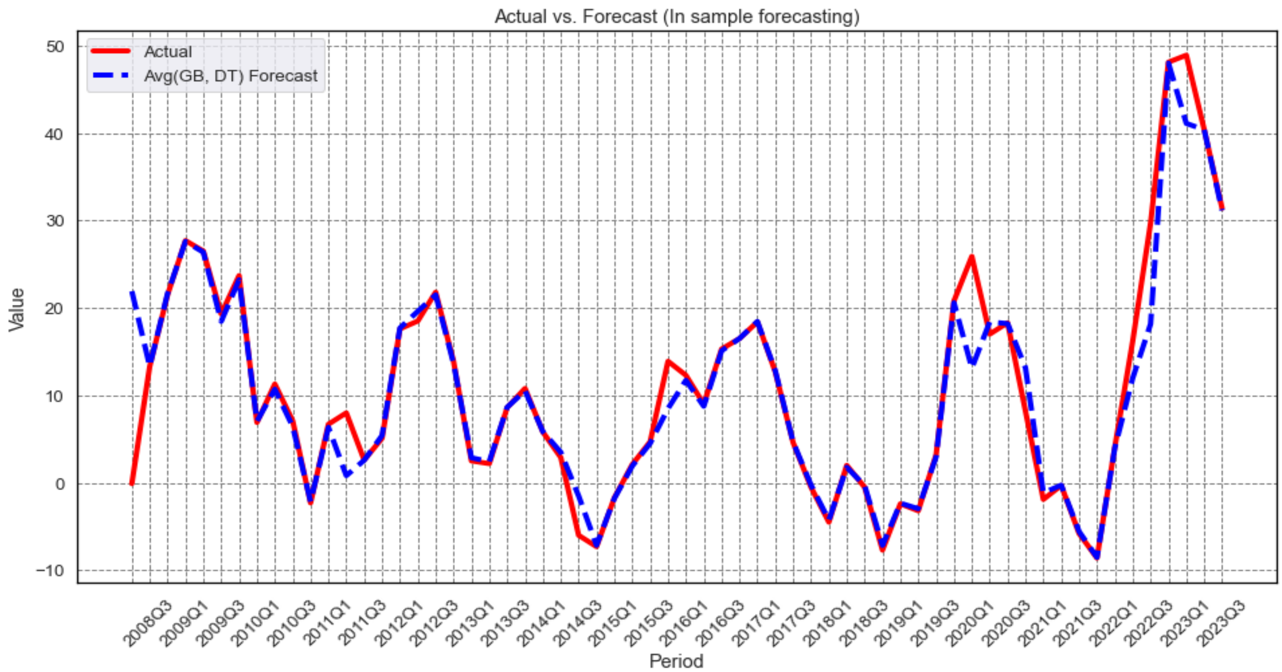


Source: Author's computation

To conclude,the average of two selected models namely: decision tree and gradient boosting models was considered as the best model to predict fresh food ,as the forecasts outcomes are consistent with realised inflation.

As way forward,despite being in-sample forecasts, these precision metrics suggest that obtaining forecasts for rainfall from meteorological data and crop production forecasts from the Ministry of Agriculture,

Figure 9: **Fresh food inflation projection**



Source: Author's computation

combined with available data on overall inflation, can enable accurate predictions of fresh food inflation in Rwanda. This in turn, has implications for forecasting trends in food and headline inflation.

6 Conclusion and Recommendations.

This study has examined the link between agricultural performance and inflation dynamics in Rwanda, with a specific emphasis on the "Application of Machine Learning." The study underscores a compelling correlation between weather-related challenges, particularly heavy rainfall, and their adverse effects on both agricultural production and price dynamics. The study generally concludes that there is a negative effect of heavy rainfall on Rwanda's agricultural landscape. In light of these insights, it would be imperative to shift the focus toward implementing best practices that mitigate the sector's dependency on unpredictable natural factors to bolster agricultural production while concurrently stabilizing commodity prices.

Policymakers should encourage and support the adoption of weather-resilient agricultural practices. This includes the promotion of drought-and heavy rains resistant crop varieties and water management strategies to mitigate the adverse effects of both heavy rainfall and drought on crop yields. The government should also invest in and improve irrigation infrastructure to reduce the dependence on rain-fed agriculture.
Additionally, concerned institutions should establish and strengthen early warning systems for extreme weather events by providing timely information about impending heavy rainfall or drought to enable farmers to make informed decisions, such as adjusting planting schedules or implementing water-saving measures. The government also should strengthen the availability of affordable and accessible agricultural insurance schemes which can provide a safety net for farmers by compensating for losses incurred due to adverse weather conditions, helping to stabilize income and mitigate the economic impact.

Furthermore, allocation of resources to agricultural research and extension services to continually assess and disseminate information on climate-resilient farming practices can mitigate weather-related challenges. This includes the development of improved crop varieties and the provision of extension services to educate farmers on best practices to deal with changing climatic conditions.Last but not least, developing cross-border cooperation can strengthen group efforts to address the common challenges posed by climate change. By executing educational campaigns to raise awareness among farmers about the potential impacts of climate change on agriculture can give them the tools they need to put adaptive measures into place and improve their ability to adapt to changing climate circumstances.

By implementing these recommendations, policymakers can contribute to building a more resilient agricultural sector. These measures can, in turn, help moderate the impact on crop production and contribute to more stable food prices in the face of climatic variability.

References

Adam, C. (2016). Food prices and inflation in Tanzania. *Journal of African Development*, *18*(2), 19–40.

Asadi, S., Bannayan, M., & Monti, A. (2019). The association of crop production and precipitation; a comparison of two methodologies. *Arid Land Research and Management*, *33*(2), 155–176.

Boescha, K., & Ziegelmannb, F. A. (2023). Machine learning methods and time series: a through comparison study via simulation and US Inflation Forecasting.

Chakraborty, C., & Joseph, A. (2017). Machine learning at central banks.

Diouf, M. A. (2008). Modeling inflation for Mali. *IMF Working Paper*.

Durevall, D., Loening, J. L., & Birru, Y. A. (2013). Inflation dynamics and food prices in Ethiopia. *Journal of development economics*, *104*, 89–106.

Hakizimana, C. (2022). Forecasting inflation of Rwanda using macroeconomics variables (2006q1-2019q4). *University of Rwanda*.

Kimolo, D. W., Odhiambo, N. M., & Nyasha, S. (2023). Inflation dynamics in post-independence rwanda. *Ovidius University Annals, Economic Sciences Series*, *23*(2), 105–116.

Kinda, M. T. (2011). *Modeling inflation in Chad.*

Maehashi, K., & Shintani, M. (2020). Macroeconomic forecasting using factor models and machine learning: an application to Japan. *Journal of the Japanese and International Economies*, *58*, 101104.

Malhotra, A., & Maloo, M. (2017). Understanding food inflation in India: A Machine Learning approach. *arXiv preprint arXiv:1701.08789*.

Mawejje, J., & Lwanga, M. M. (2016). Inflation dynamics and agricultural supply shocks in Uganda. *African Journal of Economic and Management Studies*, *7*(4), 547–567.

MINEMA. (2022). *The annual disaster effect report.*

Murphy, K. P. (2012). *Machine learning: A probabilistic perspective.* MIT Press.

Mwenese, B., & Kwizera, A. (2018). Modelling and forecasting inflation dynamics in Rwanda. *BNR Economic Review*, *13*, 45–71.

NAEB. (2023). *A study on price volatility in agriculture and livestock products.*

NISR. (2023). *The fifth rwanda population and housing census report.*

Nyoni, T. (2019). Demystifying inflation dynamics in Rwanda: an arma approach.

Rutayisire, M. J. (2015). *Threshold effects in the relationship between inflation and economic growth: Evidence from Rwanda.* African Economic Research consortium.

Ruzima, M., & Veerachamy, P. (2015). A study on determinants of inflation in Rwanda from 1970–2013. *International Journal of Management and Development Studies*, *4*(4), 390–401.

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development*, *3*(3), 210–229.

Sebaziga, J. N. (2014). Association between madden-julian oscillations and wet and dry spells over Rwanda. *Rwanda Meteo.*

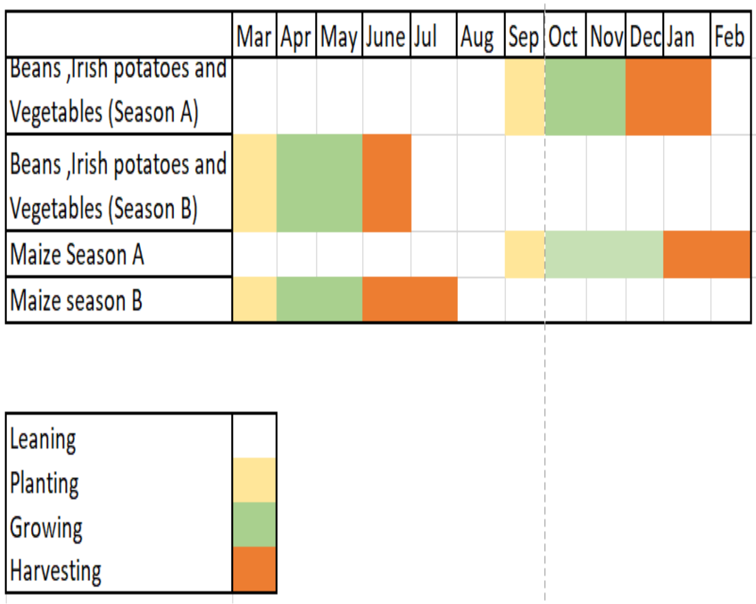
Turing, A. M. (1950). Computing machinery and intelligence. *Mind*, *59*(236), 433–460. doi: 10.1093/mind/LIX.236.433

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *67*(2), 301–320.

Appendices

1.Agriculture seasons in Rwanda

Figure 10: Crop cycles



source:MINAGRI(2023)

2.Considered weather station for rainfall data

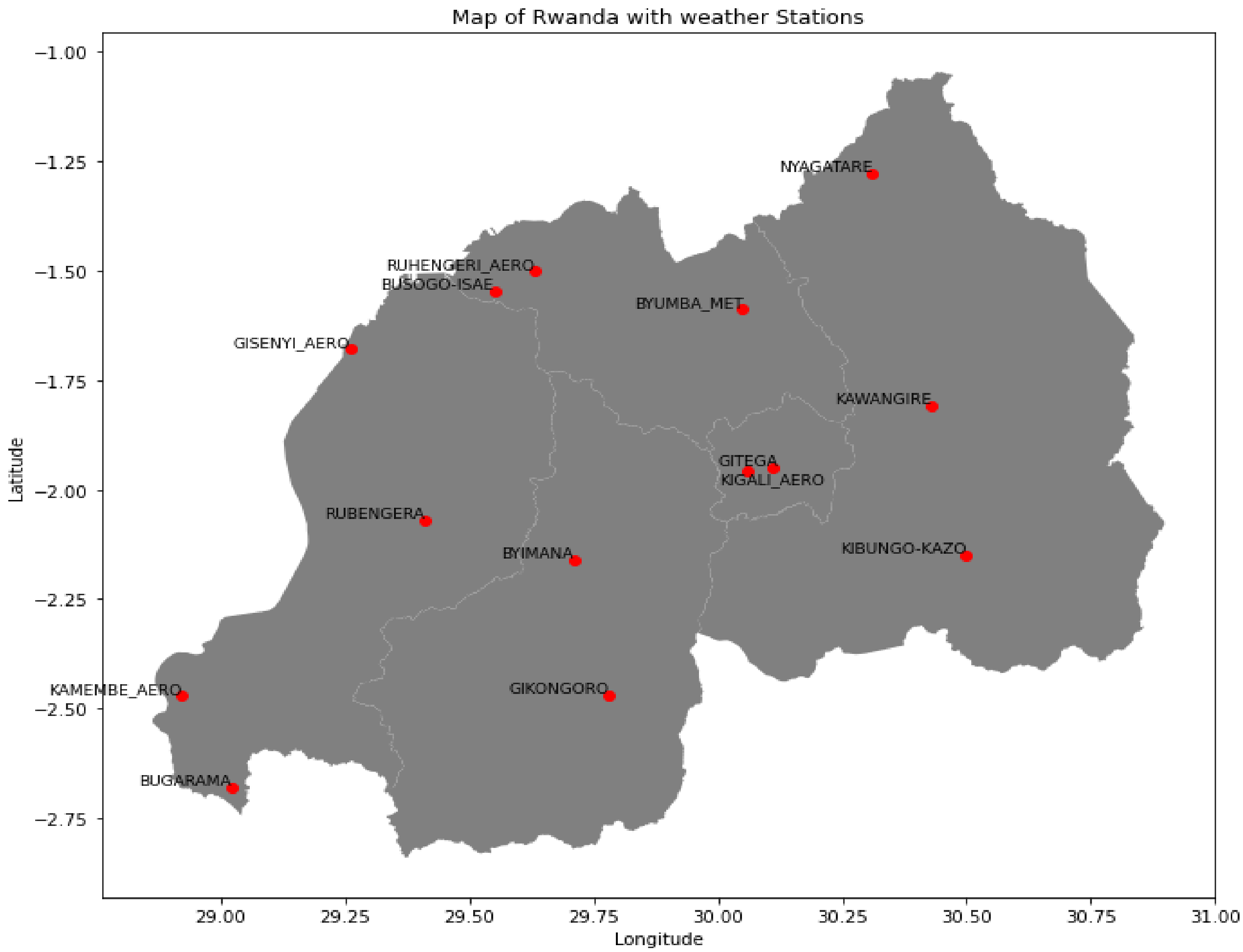
Figure 11: weather station

	STATION/CROPS	Irish potatoes	Beans	Maize	Cooking banana	vegetables
1	BUSOGO ISAE					
2	RUHENGERI AERO"					
3	BYUMBA MET					
4	GISENYI AERO					
5	GIKONGORO MET					
6	GISENYI AERO					
7	RUBENGERAMET					
8	KAMEMBE AERO					
9	KIBUNGO KAZO					
10	NYAGATARE					
11	BYIMANA					
12	BUGARAMA RIZ					
13	KIGALIAERO					
14	KAWANGIRE					

source:Author’s computation

3.Rwanda weather stations map

Figure 12: Rwanda weather stations map



source:Author's computation

4. **Used models for forecasting**

Model	**Main Goal**
ARMA	To capture and predict the future values of a time series by combining information from its own past values (autoregressive component) and the past forecast errors (moving average component).
Elastic net regression	To achieve a balance between feature selection and regularization (Ridge and LASSO) to minimize SSE.
Support Vector Regression (SVR)	To find a hyperplane that best fits the data within a specified margin of error while maximizing the margin and controlling margin violations.
Gradient boosting (GB)	To iteratively improve the predictive performance of a model by combining multiple weak learners (usually decision trees) into a strong learner.
K-nearest neighborhood	To identify the nearest neighbors of a given query point, so that we can assign a class label to that point.
Decision tree (DT)	To recursively partition the feature space to make binary decisions that maximize predictive accuracy, interpretability, and simplicity.
Random Forest (RF)	To create an ensemble of decision trees that collectively provide more accurate and robust predictions than any individual tree in the forest.

Table 4: List of Machine Learning Models and Their Main Goals

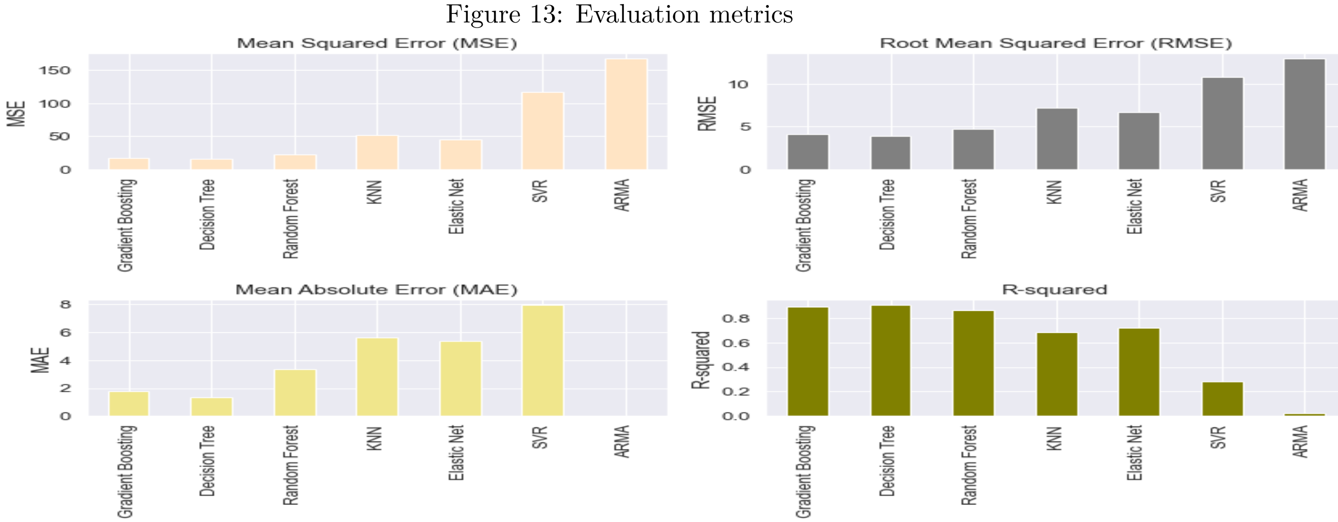
5. Used evaluation metrics

Metric	Goal
MSE	Mean Squared Error (MSE) measures the average squared difference between the predicted values and the actual values. Lower MSE indicates better model performance.
RMSE	Root Mean Squared Error (RMSE) is the square root of MSE, providing a measure of the average magnitude of the errors in the predicted values. Like MSE, lower RMSE values indicate better model performance.
MAE	Mean Absolute Error (MAE) is the square root of MAE, it provide a single, easy-to-interpret measure of the average prediction error, which can be useful for assessing the overall performance of a predictive model
R-squared	R-squared (Coefficient of Determination) measures the proportion of the variance in the dependent variable that is predictable from the independent variables in a regression model. The goal of R-squared is to maximize its value, with 1 indicating a perfect fit where all variations in the dependent variable are explained by the independent variables, and 0 indicating no explanatory power.

Table 5: Metrics and their Goals

6. Results of evaluation metrics

Figure 13: Evaluation metrics



source:Author's computation