TECHNICAL ASSISTANCE REPORT

RWANDA

FURTHER STRENGTHENING THE NOWCASTING FRAMEWORK AT THE NATIONAL BANK OF RWANDA

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Glossary

AFE	IMF's Regional Technical Assistance Center for Eastern Africa—AFRITAC East
CPI	Consumer Price Index
COICOP	Classification of Individual Consumption by Purpose
DFM	Dynamic Factor Model
EA	External Assumption
GDP	Gross Domestic Product
FPAS	Forecasting and Policy Analysis System
MCM	IMF Monetary and Capital Markets Department
MPF	Monetary Policy Framework
MPR	Monetary Policy Report
MPRD	Monetary Policy and Research Directorate
NBR	National Bank of Rwanda
NTF	Near-Term Forecast
QPM	Quarterly Projection Model
TA	Technical Assistance

Preface

In accordance with the IMF Monetary and Capital Markets Department (MCM) and AFRITAC East (AFE) technical assistance (TA) project on Forecasting and Policy Analysis System (FPAS), an on-site TA mission on "*Further strengthening the nowcasting framework at the National Bank of Rwanda*" (NBR) took place during October 9–18, 2023. The mission team comprised Messrs. Eilert Husabø and Pål Bergset Ulvedal Short-Term Experts (STXs), the Norges Bank). Jianping Zhou (Senior Economist, MCM) provided support from the IMF HQ.

The daily technical sessions were attended by staff from the forecasting teams of the Monetary Policy & Research Directorate. Mr. Thierry Mihigo Kalisa (Chief Economist of the NBR) joined a concluding session.

The mission would like to thank the NBR staff and management for the engaging and productive discussions.

Executive Summary

In response to a request from the NBR, a TA mission on FPAS took place during October 9–18, 2023. The mission followed up on the recommendations from the December 2022 FPAS mission, with the objectives of (i) further strengthening the understanding and use of nowcasting frameworks for Gross Domestic Product (GDP) and Consumer Price Index (CPI) inflation at the NBR, and (ii) analyzing the effects of weather shocks on food crop production and fresh food prices. The mission built on the progress made during the earlier mission, which focused on improving the nowcasting framework for the key domestic variables (including CPI and GDP) and building tools for analyzing new data releases and assessing the nowcasting systems.[1]

The mission completed the following tasks: (1) improved forecast evaluation by fixing the problems with using different Core CPI definitions for the medium-term Quarterly Projection Model (QPM) and the nowcasting models; (2) provided hands-on training to the NBR staff on using CPI nowcasting tools for monitoring monthly inflation outcomes and on creating and interpreting uncertainty fan charts for GDP and CPI projections; (3) enhanced the NBR staff's understanding of how high-frequency real sector indicators are constructed in the GDP nowcasting models; and (4) established a system for analyzing weather shocks (in particular rainfall) on food crop production and fresh food prices.

Going forward, the GDP and CPI nowcasting frameworks need to be refined further to support deeper analysis at a disaggregated level. Doing so would enable a better understanding of current developments in the economy and storytelling. The nowcasting model systems will also need to be integrated with the new in-house database currently under construction at the NBR. NBR staff plan to create one or more diffusion indexes using the Food Price Expectations Survey. Further technical support in constructing these indexes and understanding their use in the FPAS may be needed.

[1] In this report, nowcasting and near-term forecasting are used interchangeably. Strictly speaking, nowcasting GDP refers to the process of predicting the current state and near-term forecasting (NTF) refers to the process of predicting future GDP using real-time economic data.

Recommendations

Table 1. Key Recommendations

Recommendations	Priority	Timeframe 1/
Forecasting and Policy Analysis System		
NBR should organize the data from the Food Price Expectations Survey as time series, develop diffusion indexes and start to use them systematically in the FPAS.	High	Medium-term
NBR should adapt the Quarterly Projection Model and Near-Term Forecasting systems to collect input data from the new in-house database system that is currently being established.	High	Medium-term
NBR should continue refining the models in the nowcasting system for the twelve main CPI Classification of Individual Consumption by Purpose (COICOP) groups. This should be done with a view to increase understanding of inflation dynamics, and with a goal to move from forecasting core, energy, and food inflation directly, to forecasting these three groups bottom-up.	Medium	Medium-term

1/ Near term: < 12 months; Medium term: 12 to 24 months.

Introduction

1. The NBR started implementing a price-based monetary policy framework (MPF)[2] in January 2019 and has since made good progress in developing a model-based FPAS framework to support its operation. The FPAS framework generates model-based forecasts, which are presented to the Monetary Policy Committee (MPC) as an input for the monetary policy decision and published in the quarterly monetary policy reports (MPRs). Since 2020, AFE has supported the development of this framework through a mix of regular TA missions and bilateral and multilateral workshops.

2. While the NBR's QPM is relatively well developed, this has not been the case for the nowcasting framework. An FPAS framework includes three technical elements: the frameworks for analyzing and forecasting foreign developments, the nowcasting framework, and the QPM. At the start of the TA project, the former two were relatively less developed than the latter at the NBR and yet their results provide crucial inputs—external assumptions (EAs) and initial conditions (IC)—to the QPM that produces medium-term inflation forecasts and the model-based policy responses.

3. Therefore, the last four TA missions all focused on developing the NBR's nowcasting framework. The nowcasting frameworks at central banks are the responsibility of the sector experts and the nowcasting team. Their expert contribution to the forecast is essential for storytelling. Their deep knowledge of key sectors/variables and their understanding of economic developments and drivers are crucial additions to the results of tools and models. Hence, a sophisticated nowcasting framework requires a dedicated team of experts equipped with a large set of analytical tools and models.

4. These missions have brought considerable improvements to the nowcasting framework, though further enhancements remain needed. The NBR's nowcasting systems for GDP and CPI have been performing well in many respects; however, they lack relevant indicators and mechanisms for agricultural production and food prices. The NBR therefore expressed a need for TA in developing a framework for analyzing effects of weather shocks on agricultural production and food prices. This was the main focus of this mission.

[2] In EAC countries, it is common to refer "inflation-based MPF" as "price-based MPF".

I. The Nowcasting Framework

5. **The NBR's nowcasting framework is managed by a team of sector experts.** The team includes one to three staff who are responsible for each key variable or sector, such as inflation, real sector activity/GDP, fiscal performance, the labor market, and other primary sectors in the domestic economy. The nowcasting team is responsible for monitoring these variables/sectors, and developing and running analytical tools and models in both aggregate and disaggregate form. The experts perform forecast error analysis, provide judgements (often also on the longer horizon), help interpret the near and medium-term forecast, provide input text for the NBR's MPRs, and draft internal memos of new data releases. Their expertise, tools, models, and tasks differ from those of the core model team, and therefore they often belong to separate divisions within the Research department[3] or may even come from different departments within the NBR, but mostly from the Monetary Policy and Research Directorate (MPRD).[4]

A. The Nowcasting System for CPI

6. **The three previous FPAS missions focused on developing tools for analyzing inflation outcomes and on building a system of models for nowcasting inflation:**

a) **During the September 2021 mission, several tools were developed to facilitate deeper disaggregate analysis of inflation to facilitate a better understanding of inflation dynamics and underlying inflationary pressures.** Such tools provide up-to-date, high frequency data to inform judgment in the inflation forecasting process and improve narrative of inflation developments. Moreover, it is often in the details on the disaggregate level that sources to forecast errors are found. Understanding the errors made in the previous forecast is crucial for the current forecast. NBR staff regularly use the tools developed during that mission. Output from the tools, such as charts and measures of underlying inflation, are also now used for communicating inflation developments in the NBR's MPRs.

b) **During the March 2022 mission a system of nowcasting models based on different indicators/explanatory variables was developed.** The system was built on out-of-sample forecast error calculations and model averaging. It covered headline, core, food, and energy inflation. The refined system outperformed a benchmark Autoregressive–Moving-Average (ARMA) and the existing Vector Auto Regressive system (VAR) on all relevant horizons for nowcasting e.g., up to six months.

c) **The December 2022 mission expanded the nowcasting system for CPI.** More specifically, the mission extended the system to forecast headline and core CPI from the 12 main COICOP groups, trained NBR staff further on how to use the tools and developed a framework for bridging the gap between the nowcasting-system and the policy model (the Inflation Dashboard). This framework directly addressed requests made by the inflation forecast team (FT) at the NBR. The December 2022 mission

[3] The Research department has two divisions: (1) Economic Research, and (2) Modeling and Forecasting.

[4] The MPRD has three departments: (1) Research; (2) Monetary policy, and (3) Statistics.

also focused on the importance of conducting regular forecast error analysis and developed a framework to this end.

7. **This mission revisited the nowcasting system to strengthen the understanding of how the forecasts are constructed.** Particular attention was given to how the system produces forecasts on a monthly frequency, and subsequently transforms those forecasts to a quarterly frequency. This set up also allows for comparing forecasts to actual outcomes on a monthly basis. The mission recommended that the inflation team update inflation nowcasting and the Inflation Dashboard with every new inflation outcome. Furthermore, the mission assisted NBR staff in unifying the definition of Core CPI used in the QPM and nowcasting systems. Lastly, the mission provided hands-on training on creating and interpreting uncertainty fan charts for CPI.

B. The Nowcasting System for GDP

8. **The original nowcasting framework at the NBR included some bridge equations based on domestic explanatory variables and a Dynamic Factor Model (DFM).** These elements were used to "backcast" (forecast of the previous quarter outcome) an estimated monthly GDP variable (quarterly GDP divided by 3). The framework did not include out-of-sample evaluations of the forecast and were all based on annual changes. Hence, this framework displayed some inherent shortcomings.

9. **The March 2022 mission started to build an EViews-based system for GDP nowcasting, similar to the one developed for CPI.** The new system aims to be more transparent to provide support for judgement and storytelling. It consists of simple bivariate bridge equations with indicators that have proven to perform well in out-of-sample forecasting. The system makes both a backcast and a nowcast for the previous and current quarter, based on a model averaging. This system outperforms a simple benchmark auto regressive model for both the one- and two-quarter horizons.

10. **The mission in December 2022 focused on refining the nowcasting system and on establishing a good understanding of the system in the GDP nowcasting team.** It extended the nowcasting system by providing disaggregate forecasts for the main sectors (Agriculture, Industry, Services and Net Taxes). The disaggregate GDP nowcasts complements the aggregate nowcasts developed in March 2022 and helps provide a story behind the nowcast.

11. **This mission revisited the different parts of the nowcasting system to further strengthen the process for which the final nowcasts are constructed.** The system now can produce updated nowcasts for GDP at any point in time, even when high-frequency indicators are not available for the full quarter. The mission demonstrated the process of, using forecasts from autoregressive models to fill in the missing monthly indicators. The mission also revisited the construction of uncertainty bands around the nowcasts, discussed how to visualize the forecast with uncertainty bands, and how to use the bands to understand the range of potential outcomes and to communicate the level of confidence in forecasts.

II. Analysis of the Effects of Rainfall

12. **Previous missions identified shortcomings in the existing system for forecasting agricultural production and fresh food price inflation.** The nowcasting systems for inflation and GDP have been successful in nowcasting most of its sub-components. However, recent weather shocks have contributed to a shortfall in agricultural production and an increase in fresh food prices that the system has not been able to capture.

13. **This mission established a framework for analyzing weather shocks on food crop production and food price inflation.** The model uses daily rainfall data from weather stations across Rwanda to identify dry-spells and periods of heavy rainfall and estimates their effects on crop production. A separate model estimates the effects of changes in crop production on fresh food prices.

14. **Considerable time was spent on collecting and transforming data to be used in the analysis, including data on daily rainfall, gap variables for agricultural production, aggregate price of imported fertilizer and back-casting of CPI based on data for actual price levels.** Untransformed data are stored in Excel-files, and EViews-programs are used for transforming data and aggregating across groups and time where necessary. The EViews-programs are flexible in the sense that all definitions of groups, relevant time periods and threshold values may be easily changed. An overview of the system is shown in chart 1, and a manual for how to update and make changes to the system is included in appendix 3.

15. **Semi-annual data on food crop production was collected from the Seasonal Agricultural Survey.** The Seasonal Agricultural Survey from the National Institute of Statistics Rwanda provides data on crop production in seasons A, B and C from 2013 to 2023. As season C accounts for a negligible share of total production, the mission decided to focus on seasons A and B exclusively. Due to some extreme outliers in 2013, data from that year were not included in the estimation sample. As a result, only 20 data points of crop production for each single crop on a semi-annual frequency were available for estimation.

16. **Food crop production data were seasonally adjusted and transformed to gaps to account for increasing trends.** The models for crop production were set up to explain the level of production, rather than growth rates. In order to account for trends in the production levels that are unrelated to the weather, log-deviations from a linear trend were used to construct a production gap for each crop. Descriptive statistics of the data used in the model estimations is provided in Appendix III.

17. **In the crop production model, rainfall in the relevant areas in the relevant months was linked to crop production in the following growing season.** For example, for sweet potatoes, rainfall in all stations excluding Kigali station in the period from September through December will be relevant for crop production output in Season A; see tables 2 and 3.

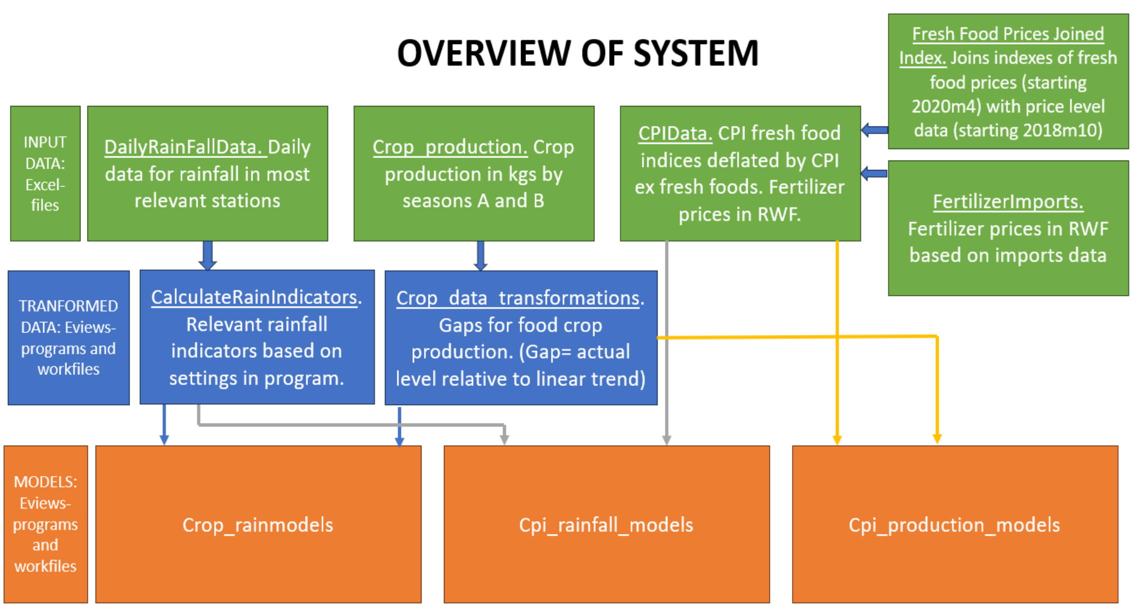
18. **A specialist in Agricultural Meteorology from the Rwanda Meteorology Service joined the mission for several days to help establish a framework linking rainfall to crop production.** In general, for fresh food production, rainfall during the growing season will help to increase output, while too much rainfall in the planting or harvesting season will reduce output. The Agricultural Meteorologist

together with NBR staff identified which weather stations were relevant for each single food crop, and also identified the planting, growing and harvesting months for the crops.

19. **Data on rainfall was provided by the Rwanda Meteorology Service.** The dataset comprises daily rainfall data from fourteen weather stations across Rwanda. Rainfall is measured in millimeters per day. Rainfall data for each single crop was aggregated by taking the average of rainfall in all relevant stations on a daily basis. The NBR-team and the Agricultural Meteorologist identified some threshold levels that were used to identify episodes of heavy rain or dry spells. For example, a day where it rains more than 4 standard deviations above average, is counted as a heavy rainfall. While a period of 7 days with no rainfall is counted as a dry spell. [5]

20. **This framework is only meant as a starting point for looking into the effects of rainfall on crop production.** It was for example outside the scope of this mission to do a thorough analysis of what might be the true threshold values for different food crops when it comes to rainfall. The framework, however, allows NBR-staff to test different values when looking further into the issues.

Figure 1. Overview of Rainfall Models Framework



Source: IMF TA mission team and NBR staff.

[5] A day with less than 0.85 mm rain counts as a day with no rainfall, as the rain will not reach the roots of the plants.

A. Agricultural Production

21. **Finding a straightforward relationship between rainfall and agricultural production is challenging due to the complexity of their interaction.** For example, different crops have different needs for water in different growing stages. They also differ in the maximum amount of rainfall they can withstand. Moreover, agricultural production also depends on other important factors.

22. **The analysis focused solely on the effect of rainfall, as data for other important explanatory variables is not available.**[6] Many other factors besides rainfall are likely important in explaining variations in the level of agricultural production, in particular, the availability and cost of fertilizers in different parts of the country, the availability, cost, and quality of seeds, weather conditions during crop storage, and the access to market.

23. **Short data series on crop production also pose empirical challenges.** As mentioned above, only 20 data points of crop production were available for estimation.

24. **Nonetheless, a system for estimating the effects of rainfall on crop production of the most important crops was established.** Panel data methods were used to take advantage of cross sectional variations in addition to time variation. Table 2 and 3 summarize the relevant weather stations and the relevant months that are used in the rain indicators for different crops.

25. **More specifically, the panel data model developed to investigate the effects of rainfall on crop production consists of different crops, with corresponding rain indicators for each crop, depending on where they are primarily grown.** An advantage of this approach is the use of cross-sectional variations in addition to time variations. A drawback is that we have to assume that all crops are affected equally by rainfall, which might not necessarily be the case. As more data is made available, this assumption should therefore be relaxed.[7]

26. **The model is described by the following equation:**

$$y_{i,t} = C + \beta_0 y_{i,t-1} + \beta_1 DS_{i,t}^{P} + \beta_2 HR_{i,t}^{P} + \beta_3 HR_{i,t}^{H} + \beta_4 TR_{i,t} + \varepsilon_{i,t}$$

Where $y_{i,t}$ (*productiongap*) is a gap measure of crop production for the different crops, $DS_{i,t}^{P}$ (*dryspell_planting*) is a dummy variable indicating whether there was a dry-spell during the planting period in the relevant areas for each crop, $HR_{i,t}^{P}$ (*heavyrain_planting*) and $HR_{i,t}^{H}$ (*heavyrain_harvesting*) are dummy variables indicating whether there was heavy rainfall during the planting and harvesting periods, respectively, and $TR_{i,t}$ (*sum*) is the average amount of rainfall during the growing and harvesting periods. Subscript *i* denotes different crops and rainfall in the relevant geographical area for the crop. Here we are

[6] The mission initially considered additional variables to control for weather shocks, such as temperature and broader aspects of climate variability like changes in precipitation patterns and frequency of extreme weather events (e.g., floods, droughts), which could provide a more comprehensive understanding of the impact of weather shocks on crop production. The mission discussed with the agricultural expert from the meteorological services about whether to include data on temperature variations. In his view temperature is never a concern for agricultural production in Rwanda, where the rainfall is the single most important factor. The mission nevertheless looked at data on temperature and found that many observations were missing.

[7] This assumption could be relaxed by estimating individual time series regression models for each singe crop.

using parsimonious notations. The relevant geographical area for each crop is shown in Table 2. Rainfall data for each single crop is aggregated by taking the average of rainfall in all relevant stations on a daily basis. The crop production gap $y_{i,t}$ is defined as the crop production in volume, measured as the log deviation from a linear trend. A level measure of crop production seems relevant as rainfall is expected to affect the level of crop production rather than the growth rate. As there is an increasing trend in production of many crops which is unrelated to weather effects, it is necessary to detrend the data. A dry spell (DS) is defined as seven consecutive days without rainfall, while heavy rainfall (HR) is defined as a day when it rained more than four standard deviations above average level for the relevant region.

27. The equation is estimated using the Pooled Least Square regression model, noting that in EViews the properties of pooled data analysis are identical to panel data analysis. In pooled data sets, time series data is structured as panel data using the names of the series as a cross-sectional identifier. The "?" in Table 4 denotes that the cross-section identifiers that have been used, including fresh food crops and rainfall in relevant geographical areas as summarized in the table (see EViews 12 User's Guide II page 1062).

Table 2. List of Food Crops and Relevant Weather Stations

Product	Relevant Stations
Irish potatoes	BUSOGO ISAE, RUHENGERI AERO, GIKONGORO MET, GISENYI AERO, BYUMBA MET
Sweet potatoes	ALL excluding Gitega and Kigali Aero
Bush beans	ALL excluding Gitega and Kigali Aero
Climbing beans	
Soya beans	
Green peas	
Maize	NYAGATARE, KIBUNGOKAZO, RUHENGERI AERO, BUSOGO ISAE, BYIMANA, BYUMBA MET, GIKONGORO MET, KIGALI AERO
Vegetables	BUGARAMA RIZ, BUSOGO ISAE, RUHENGERI AERO, GISENYI AERO, BYUMBA MET, KAMEMBE AERO

Source: NBR staff.

Table 3. List of Food Crops and Relevant Months for Different Production Stages

	Season A			Season B		
Crop	Planting	Growing	Harvesting	Planting	Growing	Harvesting
Irish potatoes Sweet potatoes Bush beans Climbing beans Soya beans Green peas	Sep	Oct–Early Nov	Late Nov–Dec	Mar	April–Early May	Late May–June
Maize	Sep	Oct–Early Dec	Late Dec–Jan	Mar	April–May	June
Vegetables	Sep	Oct–Early Nov	Late Nov–Dec	Mar	April–Early May	Late May–June

Source: NBR staff.

28. The system identified two rules of thumb with respect to the effects on crop production of dry spells during the planting season and heavy rainfall during the harvesting season. A wide range of rain indicators during the different stages (planting, growing, and harvesting) were tested. Two strongly significant results, that also are in line with theory, seem to be stable across different specifications of the models. The first is that dry spells during the planting season are expected to lower crop production by around 7 percent. The second is that heavy rainfall during the harvesting season is expected to lower crop production by around 5 percent (Table 4).[8,9] According to the estimated models, the total amount of rainfall (i.e., rainfall from start to end of the growing season) does not have a significant effect on crop production, after controlling for unusual weather events.

29. The newly developed framework should be used to inform judgement in the nowcasting process. While the estimated model identifies effects of rainfall on crop production, it is not set up to be a part of the nowcasting system. While rainfall influences crop production, other sources of information such as news and surveys may also provide important and timely information about the outlook for crop production. The NBR should start monitoring daily rainfall data, and use the rules of thumb to inform judgement, together with other sources of information. The estimated model should be updated bi-annually when new crop production data is available.

[8] There results also indicate a significant negative effect of heavy rainfall during the planting season on crop production. However, this result is less robust across different model specifications.

[9] It is important to stress that these estimates might not be robust because of the short sample size. The estimates should be cross-checked against other relevant studies if available.

Table 4. Estimation Results: The Effects of Rainfall on Crop Production

Dependent Variable: PRODUCTIONGAP_?
Method: Pooled Least Squares
Date: 10/19/23 Time: 12:14
Sample: 2014S1 2023S2
Included observations: 20
Cross-sections included: 8
Total pool (balanced) observations: 160

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019950	0.033848	0.589396	0.5565
PRODUCTIONGAP_?(-1)	0.093938	0.060936	1.541582	0.1252
DRYSPELL_PLANTING_?	-0.067300	0.028058	-2.398578	0.0177
HEAVYRAIN_PLANTING_?	-0.046950	0.018974	-2.474400	0.0144
HEAVYRAIN_HARVESTING_?	-0.050053	0.019083	-2.622992	0.0096
SUM_?	1.31E-05	7.99E-05	0.163530	0.8703

R-squared	0.122267	Mean dependent var	1.28E-15
Adjusted R-squared	0.093769	S.D. dependent var	0.094330
S.E. of regression	0.089798	Akaike info criterion	-1.945727
Sum squared resid	1.241810	Schwarz criterion	-1.830408
Log likelihood	161.6582	Hannan-Quinn criter.	-1.898900
F-statistic	4.290380	Durbin-Watson stat	2.035795
Prob(F-statistic)	0.001109		

Source: IMF and NBR staff.

B. Fresh Food Prices

30. **Similarly, a system for estimating the effects of variations in crop production on food prices was established.** Disaggregate data for fresh food prices starts in January 2019. The short data series makes it difficult to identify highly robust results. Panel data models were used to take advantage of cross sectional variation in food prices. A total of eleven food groups were included (see Table 5). These foods are considered staples and account for a significant portion of fresh food price variation in Rwanda. The food groups were linked to the crops considered most relevant. Crop production for growing seasons A and B was added to the model as deviation from a normal level.[10] The panel model also included the effect of variations in the price of imported fertilizer.

31. **The following model was estimated to identify the relationship between variations in crop production and fresh food prices**:

$$\Delta p_{i,t} = C + \beta_0 \Delta p_{i,t-1} + \beta_1 \Delta p_{i,t-2} + \beta_2 \Delta p_{i,t-3} + \beta_3 y_{i,t} + \beta_3 \Delta f_{t-2} + \varepsilon_{i,t}$$

[10] The CPI models assume that variations in crop output will affect CPI food prices in the first month following the growing season. For example, higher-than-normal output (a positive production gap) in the fall season (Season A) will lead to a decline in prices in January. Season B crop output is assumed to affect CPI food prices in June. Crop output is thus assumed not to affect the monthly changes in prices in the intermittent months, but the level effect from price growth in January and June will be fully captured.

Where $p_{i,t}$ (*cpi*) is the log level of CPI for fresh food crop *i* in period *t* and Δ denotes the first difference, $y_{i,t}$ (*production*) is the gap measure for crop production as explained above, and f_{t-2} (*bnr_fertilizer_rwf*) is the log level of fertilizer prices in Rwandan Francs in period *t-2*. As explained previously in paragraph 26, the "?" in Table 5 denotes that the cross-section identifiers have been used. In this case the cross-section identifiers are fresh food prices and corresponding crop production data as shown in Table 5.

32. The analysis identified a simple rule of thumb for effect of crop production on fresh food prices. The analysis suggests that a 10 percent decline in crop production relative to its normal level is associated with a 5 percent increase in fresh food prices, and vice versa, see Table 6.[11] Here a normal level of crop production is defined as the linear trend of crop production over time. The model therefore assumes that that crop production is increasing over time for most foods. Furthermore, the analysis indicates that a 10 percent increase in the RWF price of imported fertilizer is associated with a 1 percent increase in fresh food prices.

33. The rule of thumb should be used to inform judgement in the nowcasting process. In particular, it could be used in conjunction with results from the crop production models and other information regarding development in agricultural output. The estimated model should be updated bi-annually when new crop production data is available.

Table 5. List of Fresh Food Prices and Corresponding Crop Production Data Used in Estimations

Product	CPI Code	Crop Production Data
Irish Potatoes	01.1.7.7.01	Irish Potato
Sweet Potatoes	01.1.7.8.01	Sweet Potato
Dry Beans	01.1.7.5.01	Bush beans / Climb beans
Fresh Beans	01.1.7.3.02	
Green peas (dry)	01.1.7.5.02	Peas
Green peas (fresh)	01.1.7.3.03	
Maize (dry)	01.1.1.6.02	Maize
Maize (fresh)	01.1.1.6.01	
Tomatoes	01.1.7.3.04	Vegetables
Carrots	01.1.7.4.03	
Onion	01.1.7.4.01	

Source: NBR staff.

[11] It is important to stress that these estimates might not be robust because of the small sample size. The estimates should be cross-checked against other relevant studies if available.

Table 6. Estimation Results: Effects of Variations in Crop Production on Fresh Food Prices

Dependent Variable: DLOG(CPI?)
Method: Pooled Least Squares
Date: 13/10/23 Time: 10:01
Sample (adjusted): 2019M02 2023M09
Included observations: 56 after adjustments
Cross-sections included: 11
Total pool (balanced) observations: 616

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012957	0.004457	2.907046	0.0038
DLOG(CPI?(-1))	0.042451	0.040253	1.054604	0.2920
DLOG(CPI?(-2))	-0.247794	0.038866	-6.375563	0.0000
DLOG(CPI?(-3))	0.080673	0.040365	1.998588	0.0461
PRODUCTION?	-0.482844	0.115149	-4.193190	0.0000
DLOG(BNR_FERTILIZER_RWF(-2))	0.081804	0.032874	2.488387	0.0131

R-squared	0.103197	Mean dependent var	0.013088
Adjusted R-squared	0.095846	S.D. dependent var	0.113016
S.E. of regression	0.107463	Akaike info criterion	-1.613646
Sum squared resid	7.044477	Schwarz criterion	-1.570562
Log likelihood	503.0028	Hannan-Quinn criter.	-1.596894
F-statistic	14.03882	Durbin-Watson stat	2.024918
Prob(F-statistic)	0.000000		

Source: IMF and NBR staff.

III. Next Steps

34. The NBR should start monitoring data on rainfall in order to detect weather events that could affect crop production. Procedures for obtaining and analyzing daily rainfall data from the relevant weather stations should be established. The framework developed during this mission could be used for this purpose. The identified rules of thumb should be used to inform judgement in the nowcasting process.

35. The Food Price Expectations Survey should be used actively in the nowcasting process. During the mission, staff presented results from the quarterly NBR Food Price Expectation Survey. In the survey, farmers across the country are asked about their expectations for food prices and crop production, as well as how relevant factors such as rainfall, and fertilizer and seed availability have impacted agricultural output. The NBR has used this survey as a qualitative input to the forecast process.

36. The mission recommended that the historical results from the survey should be organized as time series data, and that a diffusion index should be created from the data. This could potentially be a great source of information for variations in fresh food production and prices. Experience from other countries suggests that such surveys are often very useful indicators and highly valuable in nowcasting systems.

37. The nowcasting framework should continue to be refined and improved to support deeper monetary policy analysis. The framework based on a disaggregated level will help facilitate a better understanding of economic developments and more effective policy communication with better storytelling.

38. The CPI and GDP NTF tools should be used on a monthly basis as part of the forecasting process and FPAS work at the NBR going forward. The CPI NTF system includes monthly forecasts of ten subgroups of the core CPI inflation as well as two subgroups of food inflation, thus enabling the assessment of the key drivers of the inflation as well as the nature of inflation shocks. It also allows for the "real time" monitoring of monthly inflation outcomes relative to the forecast. Similarly, the GDP NTF-system focuses on forecasting production in the different sectors and significantly improves the forecasting results. It should replace the current DFM. The analysis based on these NTF systems provides crucial input for the nowcast and the nowcast meeting during the forecast process.

39. The QPM and NTF systems should be integrated in the in-house database currently being constructed. Currently, input data for the NBR forecasting framework is stored in Excel files. During the mission NBR staff presented plans for moving data to a more robust database system. When the new database system is finalized, NBR staff should make necessary changes to existing forecasting systems to make them compatible with the revamped database. The NBR may benefit from technical assistance in this process. The December 2022 mission recommended that the NBR should continue work on the system for EAs for QPM. The specifics of this recommendation will have to be revised when the setup of the new database system is finalized.

Appendix I. Presentation for the Concluding Session

Slide 1

Effects of weather shocks in Rwanda

Results from IMF TA Mission

October 2023

Slide 2

Main findings

- The impact from weather to crop production is complex, and varies across crops and regions
- Hard to estimate complex models based on only 11 years (22 seasons) of data
  - Crop production data starts in 2013
  - Price data is only available since 2019 (5 years)
- We rely on both cross section and time variation (panel regression)
- No simple stable relationship between rainfall and crop production
  - Other factors (diseases, fertilizer availability, acerage …)
  - Current data may not be granular enough
- We find effects negative effects of dry spells during the planting season, and heavy rain during the harvesting season
- Clear effect of crop production on food prices

Slide 3

Panel Data Model for capturing effects of rainfall on crop production and prices

Slide 4

PRODUCTS

Product	CPI Code	Crop Production Data
Irish Potatoes	01.1.7.7.01	Irish Potato
Sweet Potatoes	01.1.7.8.01	Sweet Potato
Dry Beans	01.1.7.5.01	Bush beans / Climb beans
Fresh Beans	01.1.7.3.02	
Green peas (dry)	01.1.7.5.02	Peas
Green peas (fresh)	01.1.7.3.03	
Maize (dry)	01.1.1.6.02	Maize
Maize (fresh)	01.1.1.6.01	
Tomatoes	01.1.7.3.04	Vegetables
Carrots	01.1.7.4.03	
Onion	01.1.7.4.01	

Slide 5

RELEVANT MONTHS FOR RAINFALL DATA

Product	Plant A	Growing A	Harvest A	Plant B	Growing B	Harvest B
Irish Potatoes	Sep	Oct – Early Nov	Late Nov - Dec	Mar	April – Early May	Late May – June
Sweet Potatoes						
Dry Beans						
Fresh Beans						
Green peas (dry)						
Green peas (fresh)						
Maize (dry)	Sep	Oct – Early Dec	Late Dec - Jan	Mar	April – May	June
Maize (fresh)						
Tomatoes	Sep	Oct – Early Nov	Late Nov - Dec	Mar	April – Early May	Late May – June
Carrots						
Onion						

Slide 6

RELEVANT STATIONS

Product	Relevant Stations
Irish Potatoes	BUSOGOISAE, RUHENGERIAERO, GIKONGOROMET, GISENYIAERO, BYUMBAMET
Sweet Potatoes	ALL excluding Gitega and Kigaliaero
Dry Beans	ALL excluding Gitega and Kigaliaero
Fresh Beans	
Green peas (dry)	
Green peas (fresh)	
Maize (dry)	EAST/SOUTH: NYAGATARE, KIBUNGOKAZO, RUHENGERIAERO, BUSOGOISAE, BYIMANA, BYUMBAMET, GIKONGOROMET, KIBUNGOKAZO, KIGALIAERO
Maize (fresh)	
Tomatoes	BUGARAMARIZ, BUSOGOISAE, RUHENGERIAERO, GISENYIAERO, BYUMBAMET, KAMEMBEAERO
Carrots	
Onion	

Slide 7

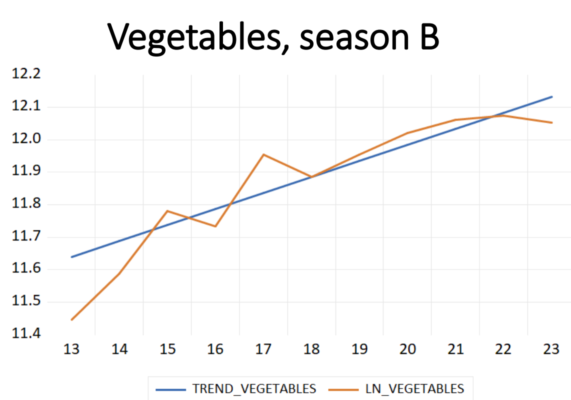
Rain indicators

- Rain indicators:
  - Sum of precipitation each season
  - Precipitation in deviation from average (squared)
  - Precipitation in deviation from required level (squared)
- Dummy for dry spell
  - 7 consecutive days without rain (no rain = less than 0.85 mm)
- Dummy for heavy rainfall
  - Rainfall of more than 3 standard deviations above mean

Slide 8

Transformation of crop production data

- Focus only on season A and B
- Some crops are grown more in one season than the other
- We look at the level of crop production relative to the trend for that season
  - Log linear trend
  - Ignoring 2013 when computing the trend (outlier)



Slide 9

Models for crop production

Slide 10

Simple model with sum of rainfall

$$gap_{j,t} = c + \beta_1 gap_{j,t-1} + \beta_2 sumRain_{j,t}$$

Dependent Variable: PRODUCTIONGAP_?
Method: Pooled Least Squares
Date: 10/19/23 Time: 12:14
Sample: 2014S1 2023S2
Included observations: 20
Cross-sections included: 8
Total pool (balanced) observations: 160

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.050357	0.032289	1.559592	0.1209
PRODUCTIONGAP_?(-1)	0.109717	0.060473	1.814332	0.0715
SUM_?	-0.000115	7.00E-05	-1.639638	0.1031

R-squared	0.036994	Mean dependent var	1.28E-15
Adjusted R-squared	0.024727	S.D. dependent var	0.094330
S.E. of regression	0.093156	Akaike info criterion	-1.890511
Sum squared resid	1.362452	Schwarz criterion	-1.832851
Log likelihood	154.2409	Hannan-Quinn criter.	-1.867097
F-statistic	3.015616	Durbin-Watson stat	1.916721
Prob(F-statistic)	0.051864		

Slide 11

Model with squarred deviation from requirement

$$gap_{j,t} = c + \beta_1 gap_{j,t-1} + \beta_2 (sumRain_{j,t} - requirement_j)^2$$

Dependent Variable: PRODUCTIONGAP_?
Method: Pooled Least Squares
Date: 10/19/23 Time: 12:14
Sample: 2014S1 2023S2
Included observations: 20
Cross-sections included: 8
Total pool (balanced) observations: 160

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003100	0.010099	0.306960	0.7593
PRODUCTIONGAP_?(-1)	0.109049	0.060957	1.788947	0.0756
(SUM_?-REQUIREMENT_?)^2	-1.17E-07	1.86E-07	-0.627149	0.5315

R-squared	0.022952	Mean dependent var	1.28E-15
Adjusted R-squared	0.010505	S.D. dependent var	0.094330
S.E. of regression	0.093833	Akaike info criterion	-1.876034
Sum squared resid	1.382319	Schwarz criterion	-1.818375
Log likelihood	153.0827	Hannan-Quinn criter.	-1.852621
F-statistic	1.844046	Durbin-Watson stat	1.909598
Prob(F-statistic)	0.161586		

Slide 12

Model with flood and dry spell indicators in different periods

Dependent Variable: PRODUCTIONGAP_?
Method: Pooled Least Squares
Date: 10/19/23 Time: 12:14
Sample: 2014S1 2023S2
Included observations: 20
Cross-sections included: 8
Total pool (balanced) observations: 160

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019950	0.033848	0.589396	0.5565
PRODUCTIONGAP_?(-1)	0.093938	0.060936	1.541582	0.1252
DRYSPELL_PLANTING_?	-0.067300	0.028058	-2.398578	0.0177
HEAVYRAIN_PLANTING_?	-0.046950	0.018974	-2.474400	0.0144
HEAVYRAIN_HARVESTING_?	-0.050053	0.019083	-2.622992	0.0096
SUM_?	1.31E-05	7.99E-05	0.163530	0.8703

R-squared	0.122267	Mean dependent var	1.28E-15
Adjusted R-squared	0.093769	S.D. dependent var	0.094330
S.E. of regression	0.089798	Akaike info criterion	-1.945727
Sum squared resid	1.241810	Schwarz criterion	-1.830408
Log likelihood	161.6582	Hannan-Quinn criter.	-1.898900
F-statistic	4.290380	Durbin-Watson stat	2.035795
Prob(F-statistic)	0.001109		

Slide 13

Models for food prices

Slide 14

Model linking real food prices to rainfall

Dependent Variable: DLOG(CPI?)
Method: Pooled Least Squares
Date: 19/10/23 Time: 12:41
Sample (adjusted): 2019M01 2023M09
Included observations: 57 after adjustments
Cross-sections included: 12
Total pool (balanced) observations: 684

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.013546	0.004287	3.159980	0.0016
DLOG(CPI?(-1))	0.060124	0.037202	1.616155	0.1065
DLOG(CPI?(-2))	-0.236615	0.037142	-6.370500	0.0000
DLOG(BNR_FERTILIZER_RWF(-2))	0.073426	0.029405	2.497059	0.0128
SUM?	-1.86E-05	2.61E-05	-0.713473	0.4758
HEAVYRAIN_HARVESTING?	0.038999	0.021457	1.817542	0.0696

R-squared	0.069958	Mean dependent var	0.012695
Adjusted R-squared	0.063100	S.D. dependent var	0.104262
S.E. of regression	0.100919	Akaike info criterion	-1.740273
Sum squared resid	6.905127	Schwarz criterion	-1.700554
Log likelihood	601.1733	Hannan-Quinn criter.	-1.724903
F-statistic	10.19993	Durbin-Watson stat	2.012863
Prob(F-statistic)	0.000000		

Slide 15

- Crop production 10 per cent below its *normal level* is associated with a 5 per cent increase in fresh food prices, and vice versa.
- *Normal level* of crop production is defined as linear trend (i.e. *normal level* is increasing over time for most crops)
- Additionally: a 10 per cent incrase in RWF price of fertilizer is associated with 1 per cent increase in fresh food prices

Dependent Variable: DLOG(CPI?)
Method: Pooled Least Squares
Date: 13/10/23 Time: 10:01
Sample (adjusted): 2019M02 2023M09
Included observations: 56 after adjustments
Cross-sections included: 11
Total pool (balanced) observations: 616

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012957	0.004457	2.907046	0.0038
DLOG(CPI?(-1))	0.042451	0.040253	1.054604	0.2920
DLOG(CPI?(-2))	-0.247794	0.038866	-6.375563	0.0000
DLOG(CPI?(-3))	0.080673	0.040365	1.998588	0.0461
PRODUCTION?	-0.482844	0.115149	-4.193190	0.0000
DLOG(BNR FERTILIZER RWF(-2))	0.081804	0.032874	2.488387	0.0131

R-squared	0.103197	Mean dependent var	0.013088
Adjusted R-squared	0.095846	S.D. dependent var	0.113016
S.E. of regression	0.107463	Akaike info criterion	-1.613646
Sum squared resid	7.044477	Schwarz criterion	-1.570562
Log likelihood	503.0028	Hannan-Quinn criter.	-1.596894
F-statistic	14.03882	Durbin-Watson stat	2.024918
Prob(F-statistic)	0.000000		

Slide 16

Quantitative findings

- A reduction (increase) in production of a crop by 10% is expected to give an increase (reduction) of the price of that crop by 5%
- A dry spell during planting season is expected to reduce crop production by 6.5%
- Heavy rainfall during harvesting season is expected to reduce crop production by 5%
- These estimates are based on a short sample, and are uncertain
- Other sources should be used to inform judgement about crop production and prices

Slide 17

Survey on food price expectations

- Potentially a useful source to nowcast crop production and prices
- Answers from farmers incorporate more information than rainfall data alone
- Data must be organized as time series
- Diffusion indices should be constructed for different crops
- Could be very useful to forecast both production and prices

Slide 18

Conclusion

- We find effects negative effects of dry spells during the planting season, and heavy rain during the harvesting season on crop production
  - Positive effects on food prices
- Clear effect of crop production on food prices
- The effect of rainfall on crop production is complex, and varies across different crops and regions
  - Using crop production across districts from the Seasonal Agricultural Survey could improve the results
- Results from the Survey on food price expectations should be used for nowcasts of agricultural production and food prices

Appendix II. User Guide for the Rainfall Models

HOW TO DO A NORMAL UPDATE

A: UPDATE EXCEL FILES

1. Fresh Food Prices Joined Index.xlsx: Joines indexes of fresh food prices (starting in 2020m4) with price level data (starting in 2018M10). The data is used as input in CPIData.xlsx.

    a. Copy data for **indexes** of fresh food prices (from excel file from NISR) to sheet named "PasteIndicesHere". Make sure that the dates in row 1 do not change compared to what they were before pasting the new data.

    Output data can be found in sheet "JoinedIndex".

    PS: If the historical **price level data** changes, the values in sheet "PriceData" should be updated.

2. FertilizerImports.xlsx: Creates fertilizer prices in RWF based on imports data (imports in KGs and USDs) and USDRWF exchange rate. The data is used as input in CPIData.xlsx.

    a. Add data for value (in USD) and volume (in KGs) to columns B and C, respectively, in sheet "Fertilizers".

    b. Add USDRWF (monthly average) in column E.

    Output is found in column F

3. CPIData.xlsx: Calculates relative prices for CPI fresh food prices. Prices are calculated relative to CPI excluding food prices. The data is used as input in 3_cpi_production_models.prg and 3_cpi_rainfall_models.prg.

    a. Copy data for the relevant CPI series from sheet "JoinedIndex" in Fresh Food Prices Joined Index.xlsx and paste them in sheet called "PasteDataHere" in columns B to L.

    b. Copy cpi_core_qpm_su and cpi_xcore_energy_su from Database_domestic_variables.xlsx and paste them in sheet called "PasteDataHere" in columns M and N. Also paste weights if they have changed. (These data are used for computing CPI excluding food.)

    c. Copy data for BNR_fertilizer_rwf from FertilizerImports.xlsx and paste it to column O in "PasteDataHere".

    Output is found in sheet "DataToEviews" and is loaded by the eviews programs.

4. Crop_production.xlsx: Organizes crop production data for season A and B. The data is used as input in 2_runsecond_crop_data_transformations.prg.

    a. Copy data from the excel file containing crop production data and paste data to sheets "Season A" and Season B", respectively. Notice that the data has to be transposed. (Sheet "Season C" is not being used as this is not an important growing season.)

    Data is loaded by 2_runsecond_crop_data_transformations.

5. DailyRainFallData.xlsx: Contains daily rainfall data for most relevant stations. The data is used as input in 1_runfirst_calculaterainindicators.prg.

a. Data is received from the meteorological services. Paste data into sheet “Daily_rain”.

Output is loaded by 1_runfirst_calculaterainindicators.prg

B: RUN EVIEWS PROGRAMS

HOW TO: ADD A NEW PRICE SERIES TO THE CPI RAINFALL MODEL:

1. Add new price series to CPIData.xlsx.

   a. Find the price series in Fresh food prices joined index.xlsx in the way described above and paste them in the column directly to the right of the final column in “PasteDataHere” starting in row 2
      i. COICOP code in row 2.
      ii. Name in row 3
      iii. Paste the data from row 4 and onwards

   b. In sheet “RebaseIndices”:
      i. Copy formulas in rows 1, 2 and from row for onwards from the final column to the column directly to its right
      ii. Make a name for the new series in row 3, using the same structure as before (for example *cpi_banana_cooking)*

   c. In sheet “DataToEviews”
      i. Copy formulas in final column to the column directly to its right

2. Make changes to 3_cpi_rainfall_models.prg:

   a. Add the new name (that you used in 1.b.ii) to string % allCPIs, for example:

      %allCPIs=”cpi_banaba_cooking cpi_maize-fresh”

   b. Link the new crop to a station:

```
' Link crops to stations
%north = "irish_potato"
%allexkigali = "bean_fresh pea_fresh bean_dry pea_dry sweet_potato"
%eastsouth = "maize_fresh maize_dry banana_cooking"
%westnorth = "tomato onion carrot"
%regions = "north allexkigali eastsouth westnorth"
```

   c. Add required rainfall:

```
smpl @all
series requirement_maize_fresh=500
series requirement_irish_potato=450
series requirement_bean_fresh=250
series requirement_pea_fresh=requirement_bean_fresh
series requirement_bean_dry=requirement_bean_fresh
series requirement_pea_dry=requirement_bean_fresh
series requirement_sweet_potato=requirement_bean_fresh
series requirement_tomato=requirement_bean_fresh
series requirement_onion=requirement_bean_fresh
series requirement_carrot=requirement_bean_fresh
series requirement_banana_cooking=requirement_bean_fresh
series requirement_maize_dry=requirement_maize_fresh
```

d. Update import function to correspond to the new final column in “DataToEviews” in CPIData.xlsx.

```
import %locationNameDataFile range="DataToEviews"!$B$3:$M$81 colhead=1 na="NA" @freq M 2018M10 @smpl @all
```

HOW TO ADD A NEW CROP SERIES TO THE CROP RAINFALL MODEL:

1. Update 2_runsecond_crop_data_transformation

   a. Add the name of the crop in string %Groups. You HAVE TO use the same name as is used in crop_production.xlsx

```
%pages="Season_a Season_b"
%Groups="cooking_banana irish_potatoes maize BUSH_E
```

2. Update 3_crop_rainmodels.prg

   a. Add the new name to string %groups

```
%groups="cooking_banana irish_potatoes m
```

   b. Link crop to station

```
' Link crops to stations
%north = "irish_potatoes"
%allexkigali = "bush_beans climbing_beans soya_beans peas sweet_potatoes"
%eastsouth = "cooking_banana maize"
%westnorth = "vegetables"
%regions = "north allexkigali eastsouth westnorth"
```

   c. Add requirement:

```
'smpl @all
series requirement_irish_potatoes=450
series requirement_climbing_beans=250
series requirement_bush_beans=250
series requirement_soya_beans=250
series requirement_peas=250
series requirement_sweet_potatoes=250
series requirement_maize=500
series requirement_vegetables=250
series requirement_cooking_banana=250
```

HOW TO ADD A NEW CROP SERIES TO THE CPI CROP PRODUCTION MODEL:

1. If the new CPI series is not in CPIdata, do the steps mentioned above to include it

2. If the new production series is not in the 2_runsecond_crop_data_transformation, add it like indicated above.
3. Add name of new cpi series to string %allCPIs, link crop to cpi (meaning link the name in this program to the name in 2_runsecond_crop_data_transformation) and add crop_gap name to string %productioncrops

```
!lastYear=@datestr(@now,"yyyy")+0
%locationNameDataFile="C:\RwandaOctober23\Final_rain_program\CpiData.xlsx"
%allCPIs="cpi_banana_cooking cpi_maize_fresh cpi_maize_dry  cpi_bean_fresh

   ' Link crops to prices
   %irish_potatoes = "irish_potato"
   %beans = "bean_fresh pea_fresh bean_dry pea_dry sweet_potato"
   %maize = "maize_fresh maize_dry"
   %vegetables = "tomato onion carrot"
   %cooking_banana ="banana_cooking"

   %productioncrops = "irish_potatoes beans maize vegetables cooking_banana"
```

4. Update the import function to correspond to number of columns in CPIData:

```
import %locationNameDataFile range="DataToEviews"!$B$3:$M$81 colhead=1 na="NA" @freq M
```

HOW TO ADD A NEW STATION TO DAILYRAINFALLDATA.XLSX:

1. Add name of new station and data to the immediate right of the existing final column:

P8

	A	E	F	G	H	I	J	K	L	M	N	O	P
1		BYUMBAMET	GIKONGOROMET	GISENYIAERO	GITEGA	KAMEMBEAERO	KAWANGIRE	KIBUNGOKAZO	KIGALIAERO	NYAGATARE	RUBENGERAMET	RUHENGERIAERO	NAME_NEW_STATION
2	01.01.2006	0	8	0	0	0	0	0	0	0	10	0	x
3	02.01.2006	0	2	4.5	0	10.8	0	0	0	0	0	0	x
4	03.01.2006	0	0	1.1	0	1.4	0	0	0.8	0	0	0	x
5	04.01.2006	0	3	8	0	0	0	0	0	0	0	0	x
6	05.01.2006	0	0	1.5	0	0.1	0	0	0	0	0	9	x
7	06.01.2006	0	14	0	0	0	0	0	0	0	0	0	x
8	07.01.2006	0	7	2.4	0	2.1	0	0	0.2	0	15	0	
9	08.01.2006	0	0	17.8	0	3.6	0	0	0	0	0	4	
10	09.01.2006	0	0	1	0	0	0	0	4.3	0	0	0	
11	10.01.2006	0	3	4.7	0	3.5	0	0	0	29	5	3	

2. In 1_runfirst_caculaterainindicators: add the name of the new station to %allStations and designate it to a stationgroup

```
'STATIONS --> ADD OR REMOVE NAMES TO CALCULATE NEW GROUPS
'creates four groups of rainfall data
%Groups="allExKigali north WestNorth EastSouth"

%allStations = "NAME_NEW_STATION BUGARAMARIZ BUSOGOISAE BYIMANA BYUMBAMET GIKON
%allExKigaliStations="BUGARAMARIZ BUSOGOISAE BYIMANA BYUMBAMET GIKONGOROMET GISEN
%northStations="BUSOGOISAE RUHENGERIAERO GIKONGOROMET GISENYIAERO BYUMBAMET" 'F
%WestNorthStations="BUGARAMARIZ BUSOGOISAE RUHENGERIAERO GISENYIAERO BYUMBAMET
%EastSouthStations="NAME_NEW_STATION NYAGATARE KIBUNGOKAZO RUHENGERIAERO BUSO

'SEASONS
```

3. You can of course also move an existing station from one group to another.

HOW TO MAKE A NEW STATION GROUP IN 1_runfirst_calculaterainindicators:

1. Add name of new group in %groups and make new string for group name. Add station names to the new group.

```
'STATIONS --> ADD OR REMOVE NAMES TO CALCULATE NEW GROUPS
'creates four groups of rainfall data
%Groups="allExKigali north WestNorth EastSouth south"

%allStations = "BUGARAMARIZ BUSOGOISAE BYIMANA BYUMBAMET GIK(
%allExKigaliStations="BUGARAMARIZ BUSOGOISAE BYIMANA BYUMBAME
%northStations="BUSOGOISAE RUHENGERIAERO GIKONGOROMET GISE
%WestNorthStations="BUGARAMARIZ BUSOGOISAE RUHENGERIAERO GI
%EastSouthStations="NYAGATARE KIBUNGOKAZO RUHENGERIAERO BUS
%southStations="nameofstationX nameofstationY"

'SEASONS
```

2. The group also needs to be specified in 3_crop_rainmodels.prg (And in the same way in cpi_rainfall_models):

```
%south="cassava"
%regions = "south north allexkigali eastsouth westnorth"
```

HOW TO REMOVE CROPS FROM PANEL MODELS:

1. In 3_cpi_rainfall_models.prg and 3_cpi_production_models: remove the name of the crop from %allCPIs string:

```
!lastYear=@datestr(@now,"yyyy")+0
%locationNameDataFile="C:\RwandaOctober23\Final_rain_program\CpiDat
%allCPIs="cpi_banana_cooking cpi_maize_fresh    cpi_maize_dry  cpi_bea
```

2. In 3_crop_rainfall_models.prg: remove the name of the crop from %groups string

```
%groups="cooking_banana irish_potatoes
```

HOW TO CHANGE MONTHS FOR SEASONS:

1. This is done in 1_runfirst_calculaterainindicators. It is quite self-explanatory:
   a. %allExKigali_plantingSeasonA=”9” means that rainfall and all rain indicators related to season A are calculated using values for September. If it is changed to 10, then values for October will be used. MONTHS SHOULD NOT OVERLAP BETWEEN SEASONS

Appendix III. Data – Descriptive Statistics

Data series	Frequency and sample	Transformation	Mean	Standard deviation
Prices				
CPI Irish Potatoes	Monthly. 2018M10 – 2023M9	First difference of log-level.	0.013	0.098
CPI Sweet Potatoes			0.012	0.041
CPI Dry Beans			0.016	0.099
CPI Fresh Beans			0.013	0.15
CPI Green peas (dry)			0.021	0.072
CPI Green peas (fresh)			0.005	0.242
CPI Maize (dry)			0.016	0.113
CPI Maize (fresh)			-0.005	0.13
CPI Tomatoes			0.013	0.198
CPI Carrots			0.013	0.104
CPI Onion			0.016	0.165
Fertilizer prices	Monthly. 2018M10 – 2023M8		0.007	0.134
Crop production				
Irish potatoes	Semi-annual. 2014 Season A – 2023 Season A	Log-deviation from linear trend	(Mean will by definition be equal to zero)	0.101
Sweet potatoes				0.063
Bush beans				0.110
Climbing beans				0.062
Soya beans				0.124
Green peas				0.148
Maize				0.032
Vegetables				0.076
Rainfall				
BSOGO ISAE	Daily. 2014M01D01 - 2023M07D31	Level (mm)	3.85	7.78
BYIMANA			3.43	8.58
BYUMBA MET			3.41	7.76
GIKONGORO MET			4.11	8.50
GISENYI AERO			3.22	7.20
KAMEMBE AERO			3.59	7.25
KIBUNGOKAZO			2.87	7.12
KIGALI AERO			2.48	6.44
RUHENGERI AERO			3.26	6.51
BUGARAMA RIZ			4.13	9.28
NYAGATARE			2.29	6.47