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# Scenario Modelling of the Seasonality of Food Availability in Kenya

**Mbugua Margaret Wambui - 097982**

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*Strathmore Institute of Mathematical Sciences*
**Strathmore University**
**Nairobi, Kenya**

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**DECLARATION**

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.



MARGARET W. MBUGUA ............ [*Name of Candidate*]

................................................ [*Signature*]

09/02/2021 ................................... [*Date*]

This Research Project has been submitted for examination with my approval as the Supervisor.

MELEAH OLECHE ............ [*Name of Supervisor*]

................................................ [*Signature*]

09/02/2021 ................................... [*Date*]

Strathmore Institute of Mathematical Sciences

Strathmore University

## Abstract

The Agriculture sector is the backbone of the Kenya's economy; it contributes 25% of the Kenya's GDP. However, over the years there has been a gap between the food consumption and the food requirement needed by the people. This has emerged from the effects of a rapid increase in the population growth and climate changes in the country. The small-scale farmers who contribute 75% of the total agricultural market are from time to time faced with various risks like climate changes and have less resources to curb these difficulties. Previous research has been done on how to improve the technology efficiency among the farmers and assist them in making better decisions and working in conducive environment. Various models have been introduced to access the various risks and shed light on the prediction of the agricultural productivity in the country. In this paper, we used the GLOBE model where we collected Kenya's baseline diets and population projections data from World Bank, FAO and United Nations. We analysed the dependency of these variables to the expected agricultural productivity in the future. The data was used to get the estimates of the average capita food consumption over various scenarios in the year 2030. In conclusion, we estimated three scenarios of the future food consumption and food requirement using the Economic (GLOBE) Sub-Model. This allowed us to isolate the effects of population growth and climate changes to the food system in Kenya and ultimately estimate food security gap.

## Abbreviations

| | |
|---|---|
| **GLOBE** | Economic Sub-model |
| **ESG** | Economic Scenarios Generators |
| **FAO** | Food and Agriculture Organization of the United Nations |
| **GDP** | Gross Domestic Product |
| **USAID** | United States Agency for International Development |
| **UN** | United Nations |

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# Chapter 1: Introduction

## 1.1 Background Information

According to (Kenya Agricultural Research Institute, 2019) agriculture is a key contributor to the Kenya's GDP since it accounts for 25%. The agriculture sector also provides 65% of the total Kenya's exports and gives 18% formal employment to the Kenyan population. The sector mostly consists of the small and medium farmers who own an average land of 0.2 to 3 ha. The small-scale production contributes 75% of the total agricultural market production.

According to the United Nations Food and Agriculture Organization, approximately 14% of the world's food is lost after harvest and before reaching shops and markets. Moreover, a one-third of the world's total food is wasted. We realize that minimizing this food loss and waste is critical. This will enable us to end hunger in the world where approximately 821 million people are already suffering. The use of Food Inventories has been applied to reduce food wastage since the food inventory systems are better in matching food demand and supply and thus reduce shelf losses.

In all businesses there is a risk and the agriculture sector is no exemption. Thus, it is crucial to model the various risks farmers are exposed to; political, economic and production risks, so that they can make better decisions. Climate change which includes extreme weather events and economic developments have proven to be among the major contributors to the supply and demand of the agricultural productivity and food security. Based on (Meonghun Lee et al., 2013), an IoT system was introduced in the agricultural production where it was discovered we can quantitatively predict the demand by consumption of agricultural products. However, the variation of production and harvest by the change of farm's cultivated region, disease, weather change and insect damage could not be predicted. This shows that the demand and supply of agricultural products has not yet been controlled properly.

From a study done on assessing the utility of rainfall observations and seasonal forecasts to anticipate food insecurity in East Africa (Samwel, Abutto et al., 2019)

East Africa region is observed to experience persistent food insecurity and the levels vary from year to year across the region. A quantitative analysis is used to capture the rainfall information in anticipating agricultural productivity and the food security outcomes across households in the East Africa region.

There is a growing need to model the climatic conditions and population growth that affect the food security in Kenya and try to balance the agriculture sustainability and food wastage. Given that much can be done before it happens, my study aims to model the future outcomes using the relevant variables by taking into account population factors when adapting to climate change.

## 1.2 Problem Statement

According to the (Kenya National Bureau of Statistics, 2019) data, we see that country's population has risen by 26% from 2009 (37.7 million) to 2019 (47.6 million). This translates to an addition of 9.9 million people and the rapid growth is set to continue in the coming years. Based on (USAID Kenya: Agriculture and Food Security, 2020) the agricultural productivity has been observed to gradually stagnate in the recent years, despite the continuous population growth in the country.

According to (Pretty, Toulmin et al., 2011) In sustainability of the agriculture we currently experience the challenge of how to spread the effectiveness of processes to millions of small-scale farmers across Africa. The study emphasizes on the use of science and technologies in the farmer's inputs and how to improve the farmer's knowledge. The agricultural production system based on IoT (Meonghun Lee et al., 2013) introduces a system that supports the decision making process by using IoT sensors to forecast agricultural production. This system was also used as a unified system to support the processes of sowing seeds through selling agricultural products to consumers. The IoT system through correlation analysis between the crop statistical information and agricultural environment information has enhanced the ability of farmers, researchers and government officials to analyze current conditions and predict future harvest.

Based on (Vergara, Wang et al., 2014) currently there are no market information systems operating in developing countries that also incorporate weather modelling for risk management. We observe that a successful market information system can be combined with weather information, agricultural market intelligence, crop yield modelling, commodity pricing and agricultural finance and insurance. Another approach is used where (V.P., V.V. et al., 2018) a stochastic model is introduced in estimating the probability of productivity losses in crop production in the conditions of various climatic scenarios, including the bad and abnormally seasons.

It is important to incorporate risk in production as a variable when coming up with a model as farmers are exposed to economic, production and political risks. As observed in the study of (Thorne and Hennessy, 2007) a stochastic is used as an approach for farm planning, where it assists the farmers given the specific risk aversion of individual farmers.

From the numerous studies that have been conducted, my study majors on using the Economic (GLOBE) Sub-Model to forecast future food consumption and food requirement. The model used produces three set of scenarios that allow us to isolate the effects of population growth and climate change on the food system and food security. The scenarios produced by the Economic model are meant to best mirror what might actually happen in the years to come. The set of scenarios in the model include climate change and high population growth, no climate change and high population growth and finally climate change and low population growth.

## 1.3 Research Objectives

1. To analyze the impacts of the climatic changes and population growth on the country's food security.
2. To estimate Kenya's future food security gap using the Economic GLOBE model.

## 1.4 Significance of the research

The aim of my study is to shed some light on the impacts of climatic changes which include increase of temperature and changes in rainfall amounts and the impact of a rapid population growth of Kenya. The research allows us to isolate the various impacts of the two variables.

We are finally able to get an estimate of the food security gap from the three scenarios and will encourage more conversations on how we can reduce Kenya's rapid population growth, for example by use of family planning. The government, knowing what to expect, they can adequately plan for its citizens by taking the necessary actions to reduce food insecurity and food wastage in the country. This approach will assist in curbing the problem on food sustainability for the growing population of Kenya.

# Chapter 2: Literature Review

## 2.1 Introduction

This chapter was organized using the thematic approach where we examined the studies previously done to identify the common themes of the ideas and patterns related to the study.

For over years, small-scale farmers who contribute 75% of the total agricultural market in Kenya have been vulnerable to the uncertain environmental conditions, exposure to risks and work without the basic agricultural inputs or updated technology and information. There has also been an imbalance in the Kenya's population accelerating growth rate and the agricultural sustainability.

The agricultural sector has been affected by the climatic changes and population growth. These two variables have resulted in a mismatch between the food consumption and food requirement.

## 2.2 Theoretic Framework

According to (Ochieng et al., 2016) we observe that climate variability has had a significant impact over years on the rain fed agricultural production mostly in the developing countries. The small-scale farmers have been the most vulnerable to risks and must make production decisions in a high risk and uncertain environment with regard to rainfall and temperature.

Evidence obtained from (Hohl, 2018) suggests that there are other major contributors to the supply and demand of the agricultural products and food security which include the extreme weather events and economic developments. A previous study by (Gill et al., 2012) shows the that natural agricultural production resources, particularly water and land have shrunk and degraded. The problem has further been aggravated by the global climate change and extreme weather variations widely affecting the agricultural yields, increasing production instability and degrading natural resources. Following a research by (Bhat, 2017) we see that the sustainability challenges in the agriculture sector, mostly affect the low- and medium- income countries.

In relation to food security, (Surampalli et al., 2020) shows the dual pressures of population growth and the adverse impacts of climate changes on agricultural sustainability and productivity. A study carried out in Botswana discovered that the decline in productivity has been contributed by technological regression and the low growth in technical efficiency and scale efficiency.

### 2.3 Empirical Framework

In this section we observe the various approaches used by different researchers to improve the agricultural productivity across the different countries around the world.

From (Thorne and Hennessy, 2007) we see the deliberation on the use of risk in production as a variable when coming up with a model since the farmers are exposed to political, economic and production risks. They further showed that a stochastic approach to farm planning could assist farmers given the specific risk aversion of individual farmers.

In response to the food insecurity and agricultural sustainability, (Meonghun Lee et al., 2013) introduced an IoT monitoring system which was designed to analyze the crop environment conditions, and improve the efficiency of the decision-making process by analyzing the harvest statistics. In this study, the IoT system worked using correlation analysis between the information's of the crop statistical and the agricultural environment. This has enhanced the expertise of farmers to analyze the current conditions and predict future harvest.

In India, a randomized experiment was used to show that improved technology enhances the agricultural productivity by incorporating modern inputs and the cultivation practices. Improved technologies that reduce risk by protecting production in the bad years, have the capability of increasing the agricultural productivity in the normal years (Emerick et al., 2016).

A quantitative analysis was used in East Africa to show how isolation of the values of rainfall information can be used in forecasting food security outcomes across the households in the region. Following this study, we can quantify a positive correlation between food insecurity and when the rainfall experienced is low using the comparison between the observed rainfall and temperature with food security classifications (Perez et al., 2019).

Recent work has been done on the use of a software tool that simulates future paths of the economies and financials in the market, and enhances the nature of risk elements within the economy (Hal Pedersen et al., 2016). The applications of the Economic Scenario Generators are that they can extend to broad analyses from the limited tasks. The Economic Scenario Generators are different from other types of economic models, however they often utilize the same mathematical concepts and model equations. The aim of an Economic Scenario Generator is to provide a reasonable depiction of the full range of future dynamics and distributions of economic. This is to enable risk to be appropriately assessed and the risk mitigation strategies can be evaluated. The key objective of an Economic Scenario Generator is to produce a set of scenarios that represent the type of economic conditions of what might actually happen in the future. Thus, Economic Scenarios Generators are often parameterized to reflect a real world behavior.

A pilot testing model in Ethiopia (Moreland and Smith, 2012) was done to try and combine the impact of climate changes and the population growth on the food security of Ethiopia. The model used consisted of 3 sub-models where a population model was used to project the country's population, a food requirement model was used to project the food energy requirements for a healthy population and an economic model for the projections of food consumption. The study was able to isolate the impacts of the climate change and population growth to predict Ethiopia's food security gap in 2050.

## 2.4 Research Gap

However, the models approach sometimes have led to some limitations in terms of using complex models which are not reliable and valid when transferring to different conditions (Paola et al., 2015). According to (Vergara et al., 2014) we noticed that currently we do not have any market information system operating in a developing country that also includes weather modelling for risk management. An example of a successful market information system would be that that combines weather information, crop-yield modelling, agricultural market intelligence and agricultural finance and insurance.

The model used by (Moreland and Smith, 2012) uses averages of the national's data which do not necessary give the full picture of the country's food security and may introduce errors.

## 2.5 Conclusion

This chapter covers the several studies carried out to try and improve the agricultural productivity for the population and assist the farmers in incorporating technology in their production. It gives an opportunity to expand on the reviewed work by incorporating other risk variables that affect the crop yield and the agriculture sustainability into a model that predicts and produces the scenarios expected to reflect the future outcomes. This is in line with the (Meonghun Lee et al., 2013) where an IoT monitoring system helps to predict future harvest by incorporating various variables.

By trying to combine various variables for example climate changes and population growth rates may be useful in predicting the food security since the two variables have significant impacts on the agricultural productivity of various countries in Africa.

# Chapter 3: Research Methodology

## 3.1 Research Design and Justification

The model used in this research study is the GLOBE model which is maintained at the Institute of development studies of Sussex University. The model is a global (CGE model) computable general equilibrium model that contains the country level data. This model takes account of the climate change variables, population growth and also covers a variety of agricultural commodities.

The Economic GLOBE model not only solves the within country models but also the country trade relationships simultaneously. For this study however, we used the results of the country of interest; Kenya. The GLOBE model was used to forecast the future food consumption of a region and thus was very effective in estimating the food security of our country.

The model allowed us to combine the projections of Kenya's population over the years with the climate changes. For instance, from Famine Early Warning Systems Network (FEWS NET, 2021) the rural food security in Kenya has been deteriorating due to climatic changes; increase in temperature and low rainfall amounts. From World Bank Group we see that the temperature levels have been rising and are expected to increase by 1 Celsius between the years 2020-2030.

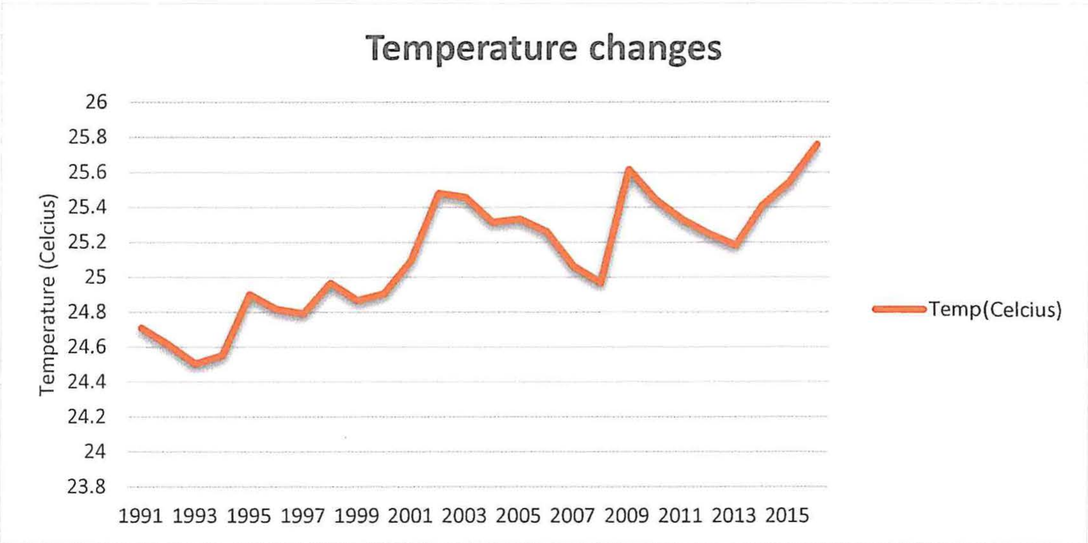


*Figure 1: Mean temperature, Kenya 1991-2016*

By taking on this methodology, we were aware that population growth rates and climate changes are not the only factors affecting the agricultural productivity. We however, believe that the two variables significantly impact the food security in Kenya and they rapidly change over the years.

### 3.2 Population and Sampling

The climate projections; temperature and rainfall were collected from the World Bank Group and the population projections were attained from the United Nations (Our World in Data). The climatic changes were from year 1991 to 2016 while the population projections were from 1991 to 2100. The population data used was for our country Kenya as a whole. We sampled out the years 2010 to 2030 to make an estimate of the food consumption using credible historic data.

The baseline diets used for the country were cereals, meat, fish and seafood, eggs milk, vegetables and vegetable oil, starchy roots, sugar crops and fruits were obtained from the World Data Atlas. These diets provided the energy (kcal) requirements used to estimate the food security and the baseline year was 2018.

The indices for the food consumption per capita were collected from the GLOBE Model at Sussex University, as predicted from 2010 to 2030. These indices in the GLOBE model allowed us to estimate the annual growth rates. The sample years used in the model to represent the country's estimated food security, ran from 2010, 2015, 2020, 2025 to 2030.

### 3.3 Data Collection

The data of the study was obtained from the Food and Agriculture Organization of the United Nations (FAO), World Bank Group, United Nations, GLOBE model at Sussex University and World Data Atlas.

The type of data used was quantitative data, where the variables included; climate and weather changes, population growth rates, food consumption indices and baseline diets were discrete and in ratio form, so that they were modelled to provide the future scenarios.

The data used was an example of a panel data, which was collected for the several variables over a period of 20 years. The variables' data were simulated across the selected period of time (2010-2030) using Microsoft Excel software that allowed the construction of the scenarios.

### 3.4 Data Analysis

The indices from the GLOBE model were used to calculate the annual growth rates from 2010 to 2030. These growth rates were applied to the baseline diets according to the food categories in consideration of the effects of population and climate changes to get the three scenarios. The scenarios displayed the various per capita household consumption growth rates of Kenya from year 2010 to 2030.

The scenarios included; no climate change with high population growth, climate change with high population growth and climate change with low population growth. The Food consumption growth rate under no climate change used a negligible one per cent (1%) since zero per cent (0%) gave zero results and this was not credible to be compared with the other two scenarios.

The food requirement was calculated as an of the average energy (kcal) required daily by a person in consideration to the climate changes; temperature and rainfall changes under the three scenarios.

Both the food consumption average and food requirement were calculated on the basis of year 2030 which is a good estimate to what to expect in the future. The food security gap was finally calculated as the difference between the food requirement and food consumption under the scenarios. This method allowed us to isolate the impacts of climate change and population growth rates in Kenya in relation to the food security.

# Chapter 4: Results and Analysis

## 4.1 Food Consumption

The per capita household consumption growth rates in Kenya from year 2010 and 2030 under the three scenarios are shown below in table 1, 2 and 3.

*Table 1: The capita Household Consumption Growth Rates, Kenya 2010-2030: No climate change and High Population Growth*

| Food | 2010 | 2015 | 2020 | 2025 | 2030 |
|---|---|---|---|---|---|
| Cereals | 0% | 2% | 2% | -1% | -2% |
| Meat | 0% | 0% | 0% | 0% | 0% |
| Fish and Seafood | 0% | 0% | 0% | 0% | 0% |
| Eggs | 0% | 0% | 0% | 0% | 0% |
| Milk | 0% | 1% | 1% | -1% | -1% |
| Vegetables | 0% | 1% | 1% | -1% | -1% |
| Starchy roots | 0% | 1% | 1% | -1% | -1% |
| Sugar crops | 0% | 0% | 0% | 0% | 0% |
| Fruits | 0% | 1% | 1% | -1% | -1% |

*Table 2: The capita Household Consumption Growth Rates, Kenya 2010-2030: Climate change and High Population Growth*

| Food | 2010 | 2015 | 2020 | 2025 | 2030 |
|---|---|---|---|---|---|
| Cereals | 0% | -37% | -15% | 8% | 7% |
| Meat | 0% | -4% | -2% | 1% | 1% |
| Fish and Seafood | 0% | -1% | 0% | 0% | 0% |
| Eggs | 0% | 0% | 0% | 0% | 0% |
| Milk | 0% | -20% | -8% | 4% | 4% |
| Vegetables | 0% | -15% | -6% | 3% | 3% |
| Starchy roots | 0% | -17% | -7% | 4% | 3% |
| Sugar crops | 0% | -4% | -2% | 1% | 1% |
| Fruits | 0% | -15% | -6% | 3% | 3% |

*Table 3: The capita Household Consumption Growth Rates, Kenya 2010-2030: Climate change and Low Population Growth*

| Food | 2010 | 2015 | 2020 | 2025 | 2030 |
|---|---|---|---|---|---|
| Cereals | 0% | -15% | -6% | 3% | 3% |
| Meat | 0% | -2% | -1% | 0% | 0% |
| Fish and Seafood | 0% | 0% | 0% | 0% | 0% |
| Eggs | 0% | 0% | 0% | 0% | 0% |
| Milk | 0% | -8% | -3% | 2% | 2% |
| Vegetables | 0% | -6% | -2% | 1% | 1% |
| Starchy roots | 0% | -7% | -3% | 2% | 1% |
| Sugar crops | 0% | -2% | -1% | 0% | 0% |
| Fruits | 0% | -6% | -2% | 1% | 1% |

The GLOBE model was appropriate for modelling the impact of the climate changes and population growth rates as shown above. The scenarios represented the varying per capita household consumption growth rates over the period.

The growth rates calculated from the GLOBE model indices were applied to the various food categories to get the three scenarios. The two population projections used here included one for a high population growth rate and another for a low population growth rate as shown in figure 2.

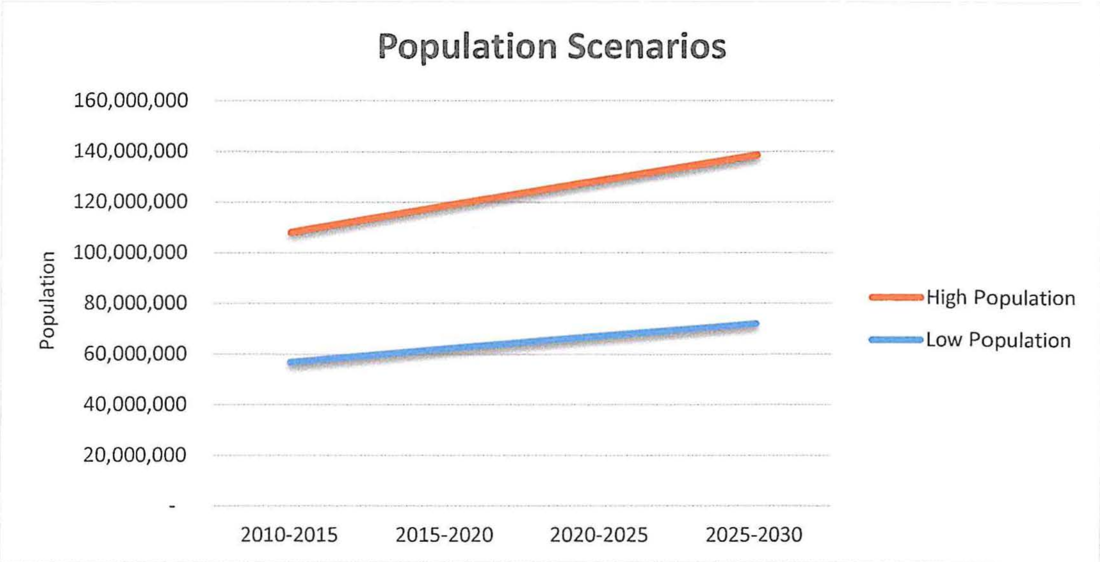


*Figure 2: Population Scenarios*

## 4.2 Food Requirement

The baseline diets were obtained from World Data Atlas in 2018 which each food category represented its energy (kcal) and the average Kenya's diet being 2,197 kcal per capita per day.

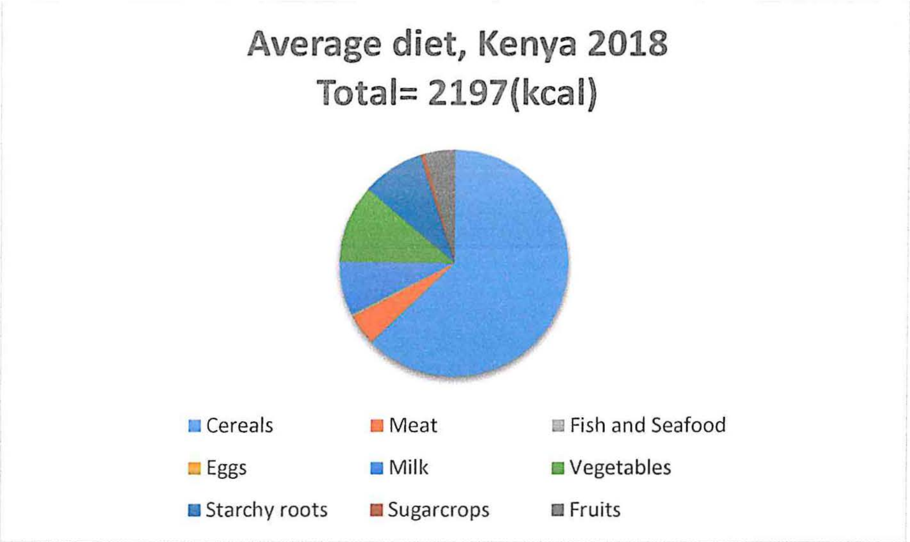


*Figure 3: Baseline Diet, Kenya*

Using the growth rates calculated from the GLOBE model, we calculated the food requirement by the Kenya's population under the three scenarios.

*Table 4: The Food requirement under the 3 scenarios*

| Column1 | Effects of climate and population growth | Requirement kcal (2197) |
|---|---|---|
| Scenario 1 | 0.46% | 10.08 |
| Scenario 2 | -1.72% | (37.72) |
| Scenario 3 | -0.69% | (15.09) |

## 4.3 Food Security Gap

The Food security Gap in Kenya was calculated as the difference between the food requirement by the population and the amount of food being consumed in the year 2030. This is shown in table 5 where the food availability shortfall is displayed under the 3 scenarios.

*Table 5: Food Security Gap in Kenya 2030*

| Requirement | Consumption | Gap |
|---|---|---|
| **Scenario 1** | | |
| No climate change and high population growth | | |
| 10.08 | 2.73 | **7.35** |
| **Scenario 2** | | |
| Climate change and high population growth | | |
| (37.72) | -10.23 | **(27.49)** |
| **Scenario 3** | | |
| Climate change and low population growth | | |
| (15.09) | -4.09 | **(10.99)** |

# Chapter 5: Discussions

## 5.1 The Model

The GLOBE model allowed the combination of the climate change and population growth rates, which we have observed from the above tables and figures that they make big differences in the scenarios.

In table 1 and table 2, we can isolate the impact of climate change which we see it has a significant impact across the food categories. A lower consumption rate is observed in table 2 than in table 1 for it has a climate change. In table 2 and table 3, the impact of population growth is isolated to calculate the per capita food consumption growth rates. Table 2 shows the lowest per capita consumption growth rates across the years for it is affected by both the climate changes and population growth rates.

In table 5, under food security there a huge shortfall in the food security under the scenario 2; climate change and high population growth.

This model is effective in estimating the food availability or food security in relation to the climate changes and rapid population growth rates in Kenya. This reduces agricultural risks to the stakeholders for they are able to estimate the food security and adapt the necessary actions to curb this problem. This will also allow the government in planning for the future. They can be involved by encouraging the local farmers, by selling to them quality seeds and other resources to increase their agricultural produce.

This study is in relation to the quantitative analysis that was used in East Africa to show how isolation of the values of rainfall information can be used in forecasting food security outcomes across the households in the region. In the study, we see how we can quantify a positive correlation between food insecurity and when the rainfall experienced is low using the comparison between the observed rainfall and temperature with food security classifications (Perez et al., 2019).

## 5.2 Conclusions

Kenya has been experiencing a stagnated agricultural sustainability and food security despite the growing population. The country's population has risen by 26% from 2009 (37.7 million) to 2019 (47.6 million). This translates to an addition of 9.9 million people and the rapid growth is set to continue in the coming years (Kenya National Bureau of Statistics, 2019).

*Table 6: Population Projections*

| Year | Population |
|---|---|
| 2010 | 40,512,680 |
| 2015 | 45,667,320 |
| 2020 | 50,905,190 |
| 2025 | 56,101,390 |
| 2030 | 61,249,070 |

The population of Kenya is observed to increase rapidly in the years to come as shown above in table 6. The climate changes are no less expected to change as seen in the World Bank Group data. The projections show an increase of temperatures by 1 degree Celsius and weather conditions in a range of (7%-10%) during the short rainfall season between the years 2020 and 2030.

The research study has been able to estimate the food security gap of Kenya in 2030 as shown in table 5, by incorporating climate changes and population growth rates. The results provide a good estimate and a good comparison for the expected population number to the food consumption. It is clear that there will be an imbalance on the population (61,249,070) and the food shortfall (27.49).

The study has also shown the impacts of the two variables separately. In scenario 2 the food security is higher (27.49) as compared to when there are no climatic effects where the food shortfall is 7.35. Comparing scenario 2 and scenario 3, we see that a low population growth rate has a smaller food security gap as compared to when the population growth is high when climatic conditions are constant.

Based on the two research objectives, it was clear that the model not only allowed us to assess the impacts of climatic changes and population growth but also estimate the food security gap of Kenya. The research study would also be useful to the various stakeholders in the agricultural sector for example the government, where it can prepare for its citizen in advance to the adverse effects of climatic changes and an accelerated population growth.

The GLOBE model was a useful model in estimating food security gap for a country and will provide a platform for more research and discussions on how more variables can be incorporated to estimate the food availability and technology advancement in the agricultural sector.

### 5.3 Limitations

Nonetheless, my model has some limitations to it which include; use of wrong assumptions for example the fertility rates used 4 (high fertility rate) and 2 (low fertility rate). This may not always be the reason for the accelerated population growth and may arise from other issues such as improved healthcare facility and decrease in mortality rates.

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