The effects of outdated data and outliers on Kenya's 2019 Global Food Security Index score and rank

by

Prisca Atieno

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Supervisor: Prof Sheryl L. Hendriks

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ABSTRACT

While composite indicators are considered robust in measuring food security, outdated data and outliers challenge their reliability. Outdated data can occur when national databases are not frequently updated while outliers are extremely small or large values in a study. Outdated data could be referred to as missing current data in composite indicators used for annual benchmarking exercises, where data must be frequently updated. Besides hindering useful information within an index, outdated data could also result in outliers in a database, especially when the outdated or missing current data are imputed by estimation. Studies that have assessed the robustness of composite indicators highlight that outdated data and outliers could bias results, thereby hindering an index's reliability. However, depending on the methods used when constructing a composite indicator, some methods can be considered robust even with the presence of outliers in a data point. Outdated national data could hinder countries from tracking the progress of international, national or regional commitments, such as the Sustainable Development Goals, while outliers could act as an unintended benchmark.

This study assessed the impacts of outdated data and outliers on Kenya's scores and rankings in the Global Food Security Index (GFSI). The study objective was achieved by assessing Kenya's performance in the 2019 GFSI result before and after removing outliers from the GFSI data points and updating Kenya's outdated indicators. Winsorisation was used to remove the outliers from the GFSI database, while the Spearman correlation and Paired t-tests were used to test for the statistical significance of the outdated data and outliers.

The study revealed that while Kenya's 2019 GFSI database did not have outliers, outliers in other countries' data points impacted Kenya's score and rank. For example, the winsorisation of outliers for other countries reduced Kenya's 2019 overall GFSI score by six points. Moreover, thirteen indicators in Kenya's 2019 GFSI database were found to be outdated. However, despite Kenya's score improving from updating the outdated data, the impact was minimal to increase the GFSI's mean score for all countries. That is, updating Kenya's outdated indicators was found not to differ significantly from zero.

The study concluded that Kenya's score and rank in the 2019 GFSI were affected by the outdated data in Kenya's database and outliers in other countries' data. The study, therefore, recommended that Kenya should update its national database and allow open access to the national data while the GFSI should identify and remove outliers from the data points.

DECLARATION

I, Prisca Atieno, declare that this dissertation, which I hereby submit in partial fulfilment of the requirement of the degree Master of Science in Agriculture (Agricultural Economics) at the University of Pretoria, is my own work and has not been submitted by me for any other degree at any other institution.

SIGNATURE: DATE: 20th April 2021

DEDICATION

I dedicate this dissertation to my son Dylan Sabato Ager and to my mum Pamela Atieno Ager, who was a mother to my son as I pursued this study.

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ASAL	Arid and semi-arid land
ASTGS	Agricultural Sector Growth and Transformation Strategy
CIDI	Composite I-distance Indicator
CFS	Committee on World Food Security
CAADP	Comprehensive Africa Agriculture Development Programme
CSI	Coping Strategy Index
DEA	Data Envelopment Analysis
DID	Difference-in-Difference
EIU	Economist Intelligence Unit
FAO	Food and Agriculture Organisation
GFSI	Global Food Security Index
GHI	Global Hunger Index
HAI	Human Asset Index
HRCI	Hunger Reduction Commitment Index
IFPRI	International Food Policy Research Institute
JRC	Joint Research Centre is the European Commission
KNFSNP	National Food and Nutrition Security Policy Framework
NNAP	National Nutrition Action Plan
KNBS	Kenya National Bureau of Statistics
PoU	Prevelence of undernourishment
PHI	Poverty and Hunger Index
PCA	Principal Component Analysis
UN-CDP	Nations Committee for Development Policy
USAID	United States Agency for International Development
WFP	World Food Programme
WHO	World Health Organisation
WTO	World Trade Organisation

CHAPTER 1: INTRODUCTION

1.1 Background

The availability of updated and complete data is one requirement for building a robust composite indicator (Freudenberg, 2003b). However, outdated data and the presence of outliers in databases challenge the process of building robust composite indicators (Nardo et al., 2005). Outdated data and outliers can occur when using data constructed from surveys or when data is obtained from national or international statistical sources (Giovanni, 2014). Outdated data are barriers to disclosing knowledge, while outliers can act as unintended benchmarks in composite indicators (Leys et al., 2013; Solaro et al., 2017). When not correctly handled, outdated data and outliers may affect findings and lead to biased results in benchmarking exercises (Santeramo, 2017; JRC-EC, 2008).

A composite indicator's ability to represent multidimensional concepts is mainly determined by the quality and accuracy of the indicators used in its construction (Nardo et al., 2005). The indicators for constructing a composite index should be specific, measurable, achievable, relevant and time-bound (Santeramo, 2015b). However, the selection of indicators is often affected by the lack of updated data due to missing current data values at the national or global level for specific countries (Thomas et al., 2017). Outdated indicators could be updated or replaced while outliers must be identified and removed statistically, for example, by winsorisation (JRC-EC, 2008; Santeramo, 2015a).

Over time, several indicators have been used to measure the concept of food security. Some indicators measure food security determinants, such as the sufficiency of supply. In contrast, other indicators measure food security outcomes such as an individuals' nutritional status or the mortality rate of children under five years of age (Jones et al., 2013; Coates, 2013). Significant variations exist among the food security indicators. Some indicators are used for monitoring or evaluation processes, while others are used in early warning systems (Carletto et al., 2013).

Moreover, some indicators only measure a single dimension of food security, such as access or food availability, as isolated contributing factors to food insecurity (Barrett, 2010). However, food security dimensions (access, availability, stability and utilisation) are hierarchal (Barrett, 2010). Food availability is necessary but not sufficient to guarantee access, while access to food (economically, physically or socially) is also necessary but does not guarantee food utilisation (Barrett, 2010). Overall, stability cuts across the access, availability and utilisation dimensions and is essential at all times to ensure food security in a country (Carletto et al., 2013; Thomas et al., 2017). The heterogeneity of the food security indicators raises the need for composite indicators to synthesise the information from different indicators (Santeramo, 2015b).

Composite indicators can summarise information from different indicators and give a comprehensive representation of a country's food security status. Composite indicators can also integrate large amounts of data into a summarised unique score, which is essential to rank countries in benchmarking exercises (Freudenberg, 2003b). Moreover, composite indicators are a useful tool in policy making processes and public communication due to their ease of interpretation (Nardo et al., 2005).

However, the robustness of a composite indicator can be affected by the subjectivity of methods used in its construction process, such as the weighting methods (JRC-EC, 2008). Some of the methods used when constructing composite indicators are easily manipulated to support desired policies (Freudenberg, 2003b; Mazziotta and Pareto, 2013). Therefore, a composite indicator's construction process must be transparent not to offer misleading information to its users (Freudenberg, 2003b). Research on how to improve the methodologies used in constructing a composite indicator and precise documentation of the steps is necessary to ensure transparency, especially the methods of handling outdated data, outliers, missing data and the weighting methods (Saisana and Saltelli, 2011). The Global Hunger Index (GHI), the Global Food Security Index (GFSI) and the Coping Strategy Index (CSI) are some examples of composite food security indicators (IFPRI, 2019; Pangaribowo et al., 2013; EIU, 2012).

1.2 Problem statement

The Global Food Security Index (GFSI) is a composite indicator measuring food security at the national level. The GFSI was developed by the Economist Intelligence Unit (EIU) in 2012. The index includes three dimensions, namely the affordability, availability and quality and safety dimensions for 34 indicators across 113 countries. The GFSI assesses how factors such as the change in the average cost of food and the sufficiency of food supply contribute to food-secure environments in a country (EIU, 2019).

Overall, the GFSI is considered robust due to its broad data coverage from sources such as the Food and Agricultural Organisation (FAO), World Bank and the World Food Programme (WFP) (Maricic et al., 2016; Chen et al., 2019). The GFSI also covers developed and developing countries, thereby giving a broad global representation of countries. Lastly, the GFSI uses qualitative and quantitative data for global ranking to include more indicators where quantitative data availability might be challenging (Maricic et al., 2016; Izraelov and Silber, 2019).

The GFSI, like other composite indicators, is affected by outdated data and outliers, which pose a challenge to disclosing reliable information and knowledge in the index (Caccavale and Giuffrida, 2020; JRC-EC, 2008). In its 2019 methodology, the GFSI does not clearly explain the methods used to deal with the outdated data or outliers in the index, even though some critical indicators such as micronutrient availability have consistently been reported based on outdated data (EIU, 2019). Using the same data consistently in a composite indicator without updating could considerably deteriorate a composite indicator's performance and reliability. Moreover, using the same data in an annual report for several years may not consider climatic, economic or social changes in a country over time (Abberger et al., 2018).

Thomas et al. (2017), researched the robustness of the GFSI assessment of countries' performances, while Maricic et al. (2016), assessed the robustness of the GFSI results based on the GFSI construction methods and the impact of using Composite I-distance Indicator (CIDI) weighting method. Thomas et al. (2017) and Maricic et al. (2019) concluded that the GFSI is robust and well correlated with existing food security indicators such as the FAO's prevalence of undernourishment (PoU) of the (FAO et al., 2019), making the GFSI reliable for measuring food security.

While the GFSI is considerably one of the reliable food security indicators, the GFSI has been criticised due to the subjectivity of its construction process (Maricic et al., 2016; Naftanaila et al., 2019). The indicators included in the GFSI and their weights in the final score are determined by the EIU panel of experts, which might lead to biased results (Thomas et al., 2017; Chen et al., 2019). Studies such as Maricic et al. (2019), Izraelov and Silber (2019) and Chen et al. (2019) have challenged this subjective weighting by the EIU panel of experts as being biased. However, these studies concluded that despite applying weights using statistical methods like the Principal Component Analysis, there was no significant variation from the results of the EIU panel of experts' assigned weights and the results obtained may be statistically more reliable.

However, no studies have challenged the use of outdated data and the lack of outliers removal in the GFSI. This study seeks to investigate the effect of outdated data and outliers on the GFSI country scores and ranks using Kenya as a case study.

1.3 Research questions

The study's overall objective was to determine how much-outdated data and outliers existed in the 2019 GFSI database and how correcting outliers and updating Kenya's database affected Kenya's score and ranking.

The specific research questions were:

i. Does the 2019 GFSI result contain outdated data and outliers?

ii. Does outdated data and outliers significantly affect the affordability, availability and quality and safety dimensions score and ranking for Kenya's 2019 GFSI result?

iii. Does updating Kenya's outdated data result in a statistically significant change in Kenya's overall 2019 GFSI score and rank relative to the 113 countries?

1.4 Research hypotheses

The study's first hypothesis was that the 2019 GFSI did not contain outdated data and outliers. The basis for this assumption was that the GFSI obtains data from international databases such as the FAO, World Bank and the World Trade Organisation (WTO), among other sources with broad data coverage (Maricic et al., 2016; Thomas et al., 2017). Like the GFSI, other food security composite indicators such as the PoU also use similar data sources when comparing countries' performances. For example, the GFSI, GHI and the PoU all measure the proportion of undernourished people in countries through a benchmarking process and relies on existing food security data sources. Therefore, it was assumed that the data used by the GFSI was relevant to rank countries as it was broad in data coverage and correlated well with other similar food security composite indicators.

The second hypothesis was that there was no statistically significant effect of the outdated data and outliers on Kenya's 2019 GFSI dimension scores and ranking. Kenya has consistently performed poorly in the GFSI dimensions (EIU, 2019). For example, Kenya has ranked among the bottom 30 countries since the GFSI was initiated in 2012 (EIU, 2019). Moreover, Kenya has never scored above 60 (out of 100) in any GFSI dimension since 2012 (EIU, 2019). Other factors could be contributing to the poor performance, such as, but not limited to, poor infrastructures (roads, storage facilities), limited investment in agriculture and volatility of agricultural production (Lolemtum et al., 2017; Benin et al., 2020). For example, Kenya relies on rain-fed agriculture with minimal irrigation infrastructure despite drought being a constant threat to Kenya's food security (Lolemtum et al., 2017). Due to these other factors contributing to Kenya's food insecurity, thereby poor GFSI scores and ranking, it could be assumed that outdated data and outliers have no significant statistical effect on Kenya's 2019 GFSI dimension scores and ranking.

The third hypothesis was that updating Kenya's data did not result in a statistically significant change in Kenya's overall 2019 GFSI score and rank relative to the 113 countries. Closset et al. (2014) noted that data availability is a challenge in most developing countries. Kenya also faces data availability challenges, as highlighted by Benin et al. (2020), when assessing how to improve data quality (accuracy, completeness, consistency, ease of update and timeliness) in the Comprehensive Africa Agriculture Development Programme (CAADP) Biennial Review. Benin et al. (2020) highlighted that data gaps (outdated and missing data) are a challenge, especially on critical indicators like ending hunger and halving poverty, which hinders the comprehensive assessment of the Malabo Declaration's achievement on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods. Therefore, updating Kenya's data might not change Kenya's 2019 GFSI score relative to the 113 countries due to data unavailability.

1.5 Research methodology

The study used secondary data from national and international databases. The data sources used include the Kenya National Bureau of Statistics (KNBS), Global Food Security Index (GFSI), Food and Agricultural Organisation of the United Nations (FAO), World Bank (WB), United Nations and the United States Agency for International Development (USAID).

Indicators with data from 2018 or older were considered outdated, while the skewness and kurtosis values were used to determine the outliers by examining the shape and the distribution of the GFSI indicators. Indicators with skewness and kurtosis absolute above two and 3.5 respectively were treated as outliers in line with the study's first objective.

A paired t-test and Spearman’s rank correlation tests were applied to test the outdated data and the outliers’ statistical significance on Kenya’s 2019 GFSI score and rank, respectively. The winsorisation method was used to remove the identified outliers. The winsorisation method involved replacing an indicator with extreme values such that the indicator value moves closer to the other sample values (Ghosh and Vogt, 2012; Kwak and Kim, 2017). The min-max normalisation method was applied to the winsorised indicators and updated Kenya’s 2019 GFSI indicators to render the indicators comparable with the GFSI 2019 indicators.

1.6 Limitations of the study

One limitation of this study is the data renormalisation. The study follows the GFSI min-max normalisation method to standardise data from different sources into a comparable unit. However, the data had to be renormalised after updating Kenya's outdated indicators. As a result, the renormalisation could affect the indicators’ weighting as it is linked to the GFSI countries scores and rank. This limitation, therefore, warrants further investigation on how best to improve the normalisation method.

1.7 Outline of the study

This dissertation is set as follows. In chapter two, a review of the related literature is presented, while Kenya's food security situation is presented in chapter three. The Global Food Security Index (GFSI) and its methodology is outlined in chapter four and chapter five the methods and procedures for achieving the research objectives, while the results and discussion of the findings are presented in chapter six. The conclusions and recommendations of the study chapter are presented in the last chapter.

CHAPTER 2: REVIEW OF RELATED LITERATURE

2.1 Introduction

Measuring food security is complicated by the multiple indicators used to measure its dimensions (Barrett, 2010). For example, to measure access to food, indicators such as infrastructural development like roads, political stability in a country or livelihood assets to draw from during shocks can be used. Similarly, infrastructural development and political stability indicators could also measure the food availability dimension of a country. The overlapping nature of food security indicators makes food security measurement complex and may hinder the results' reliability (Barrett, 2010). Using composite indicators is one way of overcoming food security measurement challenges. Composite indicators can aggregate the multiple indicators measuring food security dimensions into one index (Santeramo, 2015b). However, the challenges of outdated data and outliers could reduce the robustness of composite indicators and hinder the communication of useful information from the index. Moreover, outdated data and outliers in composite indicators could bias results when benchmarking countries in terms of food security.

The GFSI is reportedly a robust composite indicator for measuring food security (Chen et al., 2019). While this composite indicator has some advantages such as, including both developed and developing countries, some weaknesses limit its ability to effectively capture food security in those countries, such as outdated data and outliers. These challenges could affect the reliability and accuracy of the GFSI results (Giovanni, 2014; Closset et al., 2014). The GFSI's performance could be improved by continuously updating the databases, replacing outdated indicators and detecting and removing outliers (Kaufmann et al., 2011; JRC-EC, 2008).

2.2 An overview of global food security measurement

The concept of food security has evolved over the years, both in terms of its definition and measurement (Hendriks, 2015). Food availability globally and at the country level was the primary way of measuring food security in the 1970s. Increasing the production and supply of food was seen as the solution to achieving food security (Hendriks, 2015). Food balance sheets were used during this period (the 1970s) to estimate the sufficiency of supplied food in meeting the populations per capita energy needs (Jones et al., 2013; Hendriks, 2015). When measuring the psychological impact of food shortages, anthropometrics were used (Hendriks, 2015).

However, despite the increase in food production in the 1970s, food insecurity remained a problem of great concern (Hendriks, 2015).

Therefore, access to food became the main focus in the 1980s, following the publication of Sen's entitlement theory (Hendriks, 2015). Sen (1982) argued that people were not food insecure because the supply of food was limited, but because people lacked access to food. People's access to food was hindered by high food prices, low incomes and a lack of resources. Therefore, policies on poverty reduction, price stabilisation and social protection were implemented in the 1980s to improve food access (Hendriks, 2015).

In the 1990s, attention shifted to the nutrition aspect of food security (Coates, 2013). Despite improvements in the accessibility and the supply of food in the 1980s, the dietary quality remained a challenge (Coates, 2013). Micronutrient deficiency and stunting increased in the population, which lead to the inclusion of nutrition as part of food security in the World Food Summit of 1996 (Coates, 2013). Therefore, food security was defined at the World Food Summit of 1996 to exist when all people at all times have access to sufficient, safe and nutritious food to meet their dietary needs for active and healthy life (FAO, 1996). However, the Committee on World Food Security (CFS) in 2012 redefined the World Food Summit's definition of food security. The CFS added environmental, food preference and sanitation aspects of food security to the dimensions of accessibility, availability, stability and urtilisation as they also impact food security (CFS, 2012).

There is currently a lack of consensus on measuring food security's multiple dimensions due to its multidisciplinary nature (Jones et al., 2013). Food security affects different disciplines such as agriculture, economics or the environment (Hendriks, 2015). Each of these disciplines defines food security differently, which could hinder research - consequently affecting the implementation of essential policies, such as hunger reduction (Hendriks, 2015).

Data unavailability in both the national coverage (quantity) and quality also impede food security measurement (Cafiero, 2013; Yerramareddy and Babu, 2018). Data availability is a challenge, especially in most developing countries (Closset et al., 2014). A lack of financial resources to carry out frequent national surveys to update databases is one reason for the unavailability of quality data in these countries (Cafiero, 2013; Benin et al., 2020). As a result, these countries' missing data could hinder policy making toward achieving the SDGs or other global and regional agreements. Moreover, most developing countries are ranked using outdated data or low-quality data due to data unavailability, which may not reflect the actual food security situation (Benin et al., 2020). Data availability could be improved through frequent national household surveys using comprehensive data collection methods. Even though frequent national household surveys are costly. The data obtained could be useful in many different areas (De Haen et al., 2011; Yerramareddy and Babu, 2018).

Lack of open access to national data also hinders reliable measurement of food security. Yerramareddy and Babu (2018) state that open access to data is the starting point for making decisions. Open access to data is critical in enabling evidence-based policies by decision-makers in governments and private sectors. Benin et al. (2020) highlight that some African governments do not allow open access to data, especially in sensitive areas such as food security, which might expose poor policy choices or implementation. Therefore, the government prevents the release of such data for public use. This hinders the communication of valuable information and research to improve the different sectors of the economy. Publicising national data is one way of increasing food systems analysis towards achieving food security (Yerramareddy and Babu, 2018).

The use of existing secondary data sources could lead to inaccurate food security measurement, especially if the data is not adequately and sufficiently scrutinised to understand the real information that the data conveys (Cafiero, 2013). Some existing secondary data sources may be in differing formats or units or may be of low-quality (Benin et al., 2020). Standardisation of survey tools and formats is crucial when measuring food security to enable international comparisons and evidence-based monitoring and evaluation using the available secondary data (De Haen et al., 2011; Cafiero, 2013). Due to these global food security measurement challenges, composite indicators have been developed to overcome the shortcomings and improve the results' reliability.

2.3 Food security composite indicators

A composite indicator is an aggregated index often comprising individual indicators and weights representing the relative importance of each indicator based on a given underlying model (Nardo et al., 2005). The heterogeneity of existing indicators and the lack of consensus on how to compare and rank countries in terms of food security have driven international organisations to build composite indicators (Santeramo, 2015b). Composite indicators minimise the heterogeneity of the existing food security indicators by summarising the indicators into a single index to score and rank countries in different food security dimensions

(Santeramo, 2015b; Nardo et al., 2005). Moreover, composite indicators are essential, especially for public communication, due to ease of interpretation (JRC-EC, 2008). Policymakers also often rely on food security composite indicators as useful diagnostic tools for prioritising policies such as nutrition feeding or social safety net programmes (Turan et al., 2018). Poor performing countries could also learn from better-performing countries in such benchmarking exercises (Santeramo, 2017).

Although composite indicators help set policy priorities when benchmarking or monitoring country performances in terms of food security, environment, health or social aspects such as poverty, some factors may hinder their reliability (JRC-EC, 2008). Composite indicators may send misleading policy messages if poorly constructed or misinterpreted, thereby resulting in simplistic policy conclusions. Composite indicators may also lead to the implementation of inappropriate policies if the performance of dimensions that are difficult to measure are ignored. Furthermore, the choice of indicators to be included in the index and the weights could be the subject of political dispute (JRC-EC, 2008). Lastly, if a composite indicator's construction process is not transparent, it may disguise serious failings in some dimensions and increase the difficulty of identifying proper policy actions (JRC-EC, 2008). The construction process of a composite indicator is discussed in section 2.4.

The use of composite indicators when measuring food security has increased over time, as shown in

Table 2.**1**. Food security composite indicators are diverse. Some indicators can measure the global, household individual or national food security levels. By contrast, some composite indicators such as the Hunger Reduction Commitment Index (HRCI) measure governments' commitment to reducing hunger.

Table 2.1: Some of the existing food security indicators

Name of the indicator	**Developed by**
Global Food Security Index (GFSI)	Economist Intelligence Unit (EIU)
Global Hunger Index (GHI)	International Food Policy Research Institute (IFPRI)
Prevalence of Undernourishment (PoU)	Food and Agricultural Organisation of the United Nation (FAO)
Human Development Index	United Nations Development Programme (UNDP)
Human Development Index	United Nations Development Programme (UNDP)
The Coping Strategy Index (CSI)	Humanitarian Organisation CARE and the World Food Programme (WFP)

Source: (Pangaribowo et al., 2013; Izraelov and Silber, 2019).

Some food security composite indicators also measure factors contributing to food secure environments such as sufficiency of supply, such as the GFSI, while others composite indicators such as the GHI measure food security outcomes like the prevalence of undernourishment in a country (Pangaribowo et al., 2013).

2.4 The construction process of composite indicators

The main steps involved in the construction of a composite indicator is shown in Table 2.2. However, there is no single standard method for constructing composite indicators (Hudrliková, 2013). Opinions differ within studies on which of the seven steps for constructing a composite indicator are critical and subjective (Santeramo, 2017; Dialga and Thi Hang Giang, 2017; Hudrliková, 2013). Therefore, transparency in the methodology used is very critical, as every decision on the methods can impact the index's outcome (JRC-EC, 2008; Santeramo, 2015a).

Hudrliková (2013) states that when constructing a composite indicator, data aggregation, normalisation and weighting methods are the fundamental and subjective parts, while Santeramo (2017), stresses that normalisation and weighting approaches do not significantly affect the results. However, the aggregation and the imputation of missing data methods must be carefully selected in the construction process as they affect results (Santeramo, 2017). Caccavale and Giuffrida (2020) highlight that methods used for imputing missing data, normalisation, weighting and variable selection when constructing composite indicators cause variability in output, while the aggregation method has a minimal effect on the output. Regardless of the methods used when constructing a composite indicator, methods used for aggregation, normalisation, missing data imputation and weighting remain uncertain and lead to different results (Dialga and Thi Hang Giang, 2017). Overall, from the above studies, it could be concluded that the four main critical steps to construct a robust composite indicator after variable selection are the methods for missing data imputation, data normalisation, weighting and aggregation (Santeramo, 2017).

A composite indicator's construction process must, therefore, be transparent with sound statistical or conceptual principles for the results not to be misused to support desired policies (JRC-EC, 2008). Santeramo (2017) emphasises that attention must be paid to the method implemented when transforming raw data from different indicators into a single index as each method conveys different results. Nardo et al. (2005) have proposed a multivariate statistic approach to construct robust composite indicators. The multivariate statistic approach assesses the dataset's suitability, thereby understanding the implications of the methodological choices such as missing data imputation, normalisation, weighting and aggregation when constructing composite indicators.

Table 2.2: Steps for constructing a composite indicator

Steps	**Process**
Defining the phenomena	Defining the phenomena is essential for precisely identifying the specific indicators relevant to measuring the phenomena (JRC-EC, 2008).
Variable selection	When selecting variables, it is often common not to have complete international comparative quantitative data (JRC-EC, 2008). Qualitative data inclusion is encouraged to increase data coverage (JRC-EC, 2008). Where the desired data is not available proxy variables could also be used (Santeramo, 2017).
Missing data imputation	There is no definitive way of dealing with missing data when constructing composite indicators (JRC-EC, 2008). However, certain factors must be considered, such as the country's identity, indicators with missing data, the number of missing data for the given dimension and the type of dataset available (if continuous or ordinal) (JRC-EC, 2008).
Data Normalisation	Data normalisation is essential to render the selected variables comparable (JRC-EC, 2008). Examples of normalisation methods are min-max normalisation, standardisation and ranking, among others (Nardo et al., 2005). The normalisation method should consider the objectives of the composite indicator, data properties and outliers' presence (Nardo et al., 2005).
Weighting	When constructing composite indicators, the weighting method must be made explicit and transparent for reference by future studies on the index (Nardo et al., 2005). Examples of weighting methods are equal weighting, factor analysis and Principal Component Analysis (JRC-EC, 2008).
Aggregation	The aggregation methods imply for weights to reflect trade-offs between indicators such that high values of some indicators compensate for low values in other indicators (JRC-EC, 2008). Aggregation methods include geometric aggregation and linear aggregation.
Sensitivity and uncertainty analysis	Sensitivity and uncertainty tests are carried out to test the overall robustness of the methodologies used for constructing the composite indicator; data aggregation, normalisation, missing data imputation and the weighting methods (JRC-EC, 2008).

Source: Compiled by author.

2.5 An overview of outdated data in composite indicators

Outdated data in composite indicators occurs mainly due to a lack of frequent surveys to update databases (JRC-EC, 2008). Outdated data could be referred to as missing current data, especially for composite indicators reporting countries' performances in annual benchmarking exercises (Hudrliková, 2013; JRC-EC, 2008). The missing updated data from the previous year could be treated as outdated data because the current data is lacking to inform the phenomena under assessment (Abberger et al., 2018). In composite indicators, missing data (outdated data) can result in distorted findings on country performance, thereby incorrect policy prescriptions in benchmarking exercises (Freudenberg, 2003a).

Abberger et al. (2018) stress that, due to changes in economic relationships, social or even historical changes, data collected at a given point in time might not give a favourable reflection of the same situation in the future. For example, data used five years ago to report the food security may not be favourable in reporting the same country's food security situation five years into the future due to the changes (economic or social) in a country over time. Benin et al. (2020) have highlighted that data quality is critical for accurate and relevant measurement of a given phenomenon. Some factors affecting data quality include data inconsistency, cost of data collection, data's age, ease of update and the scope of information the data conveys of the measured phenomena. Constant update of databases is critical for keeping up with trends while improving the reliability of composite indicators such as the GFSI (Abberger et al., 2018).

Although it is critical to update composite indicators to improve their reliability frequently, composite indicators are often challenged by the unavailability of updated (outdated) data that hinders useful information (Santeramo, 2017). Data unavailability in quality, quantity and timeliness (current) pose a threat to composite indicators' reliability, as they generally require large amounts of data to measure a single phenomenon (JRC-EC, 2008). Using the same data in a composite indicator consistently without updating could considerably deteriorate the composite indicator's performance and reliability. Moreover, using the same data in an annual report for several years may not consider climatic, economic or social changes in a country over time (Abberger et al., 2018). Thomas et al. (2017) note that the use of outdated data in place of missing current data in composite indicators makes it impossible to consider recent changes in affecting a countries' food security situation, such as an El Nino occurrence.

While outdated data is a widespread problem when constructing composite indicators, several methods have been applied to handle this challenge (Cherchye et al., 2011). Some of these methods include; substituting the last data available for a country with outdated data, completely deleting or replacing indicators whose databases are no longer updated or estimating the missing current values based on the available outdated data (Cherchye et al., 2009). For example, the EIU uses estimated values for the missing quantitative (current) data in the GFSI to score and rank countries, while the outdated data are replaced with last available data for the given indicator for that country - which may not reflect actual food security situation in these countries (EIU, 2012). The use of inadequate methods for handling outdated data could hinder the robustness of composite indicators' up to date global benchmarking exercises (Cherchye et al., 2011). Therefore, updating outdated data or replacing outdated indicators is critical to improving the reliability of composite indicators' results (Kaufmann et al., 2011). This study attempts to improve the GFSI's reliability and robustness by updating outdated data (also referred to in this study as missing current data).

2.6 An overview of outliers in composite indicators

Outliers in research have been an issue of concern over time (Hawkins, 1980; Chambers, 1986). Outliers are extremely large or extremely small values contained in some variables in an observation (Thomas et al., 2017; Cousineau and Chartier, 2010). Chambers (1986) identifies two types of outliers, the representative outliers and non-representative outliers. The representative outliers are correctly measured values from sampled observations, which are outlying as a representative of the non-sampled part of the observations where similar values exist as believed. These representative outliers are handled during the survey estimation process (Chambers, 1986). By contrast, non-representative outliers occur due to errors resulting from incorrect values in the sample data, for example, through miscoding. The non-representative outliers are corrected during data editing when using outliers detection techniques such as the winsorisation method (Chambers, 1986).

It is essential to identify and remove outliers when building a composite indicator (Nardo et al., 2005). The detection of outliers is essential to identify if there are suspicious values in variables analysed and confirm that the variables' reported values are correct (Beaumont and Rivest, 2009). The identification of outliers allows a researcher to choose adequate and robust methods to remove the outliers (Beaumont and Rivest, 2009). Despite the importance of detecting outliers in research, many researchers do not report the method used to address outliers (Leys et al., 2013).

In composite indicators, outliers are problematic as they become unintended benchmarks in the composite indicator and may lead to a biased interpretation of the results (Dialga and Thi Hang Giang, 2017; Nardo et al., 2005). Skewness and kurtosis could be applied to detect outliers in composite indicators (Saisana and Saltelli, 2011; Nardo et al., 2005). Where an indicator with an absolute value greater than two and 3.5 for the skewness and kurtosis respectively indicates the presence of outliers (JRC-EC, 2008).

When dealing with normally distributed univariate data, the method to use for outlier detection and removal is z-score. By contrast, multiple regression more prefered for removing the outliers for data involving more than three variables (multivariate data) (Cousineau and Chartier, 2010). Other methods for removing outliers include Median Absolute Deviation (MAD), M-estimation, or the winsorisation method (Leys et al., 2013; Hawkins, 1980).

2.7 Conceptual framework

The conceptual framework for achieving robust and unbiased GFSI results for countries' scores and ranking is presented in Figure 2.1. The conceptual framework shows the relationship between outdated data, outliers and missing data and how they affect the GFSI scores and rank.

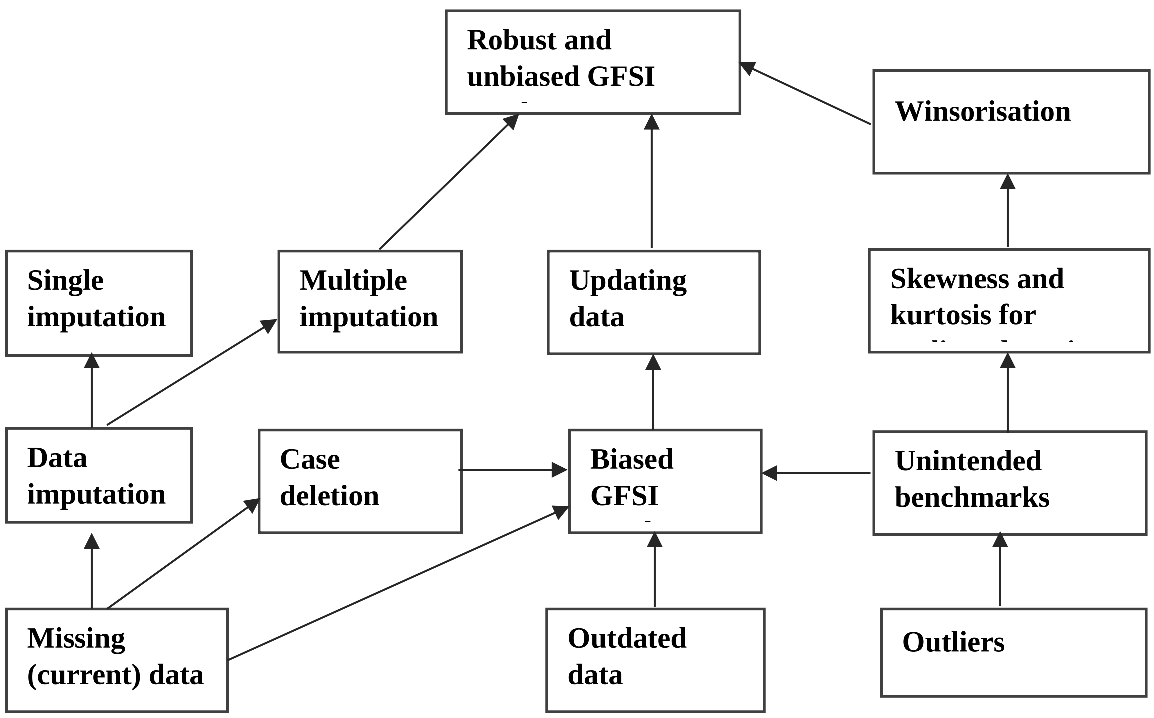

Figure 2.1: Conceptual framework for a robust and unbiased GFSI results
Source: Author**.**

The framework indicates that the outdated data, outliers and missing data result in biased scores and ranks in the GFSI. Outliers act as an unintended benchmark when not identified and removed from the GFSI (Thomas et al., 2017). For this study, the framework concentrates on updating outdated (missing current) data as defined in section 2.5. In the GFSI database, current data is missing, which could be imputed, replaced or updated (JRC-EC, 2008).

Due to missing updated data, the GFSI uses outdated from as old as 2013 to report the food security in 2019. In cases where a country completely lacks data from the previous years, the GFSI uses estimates to impute the missing data. Kaufmann et al. (2011) have frequently updated the composite governance indicators since 2003 to improve the performance of the Worldwide Governance Indicators (WGI) without imputing the data. Benin et al. (2020) highlighted that data timeliness is a critical factor in the policy environment to ensure mutual accountability to commitments and for taking actions to non-commitments to policies.

2.8 An empirical review on the effects of outdated data and outliers in composite indicators

Updating data for composite indicators to improve their performance was researched by Kaufmann et al. (2006) on the Worldwide governance indicator by the World Bank. Kaufmann et al. (2006) updated six indicators measuring world governance in more than two hundred countries. Data for these indicators were obtained worldwide from international and national data sources and private and public opinions on governance for the given countries. Kaufmann et al. (2006) used the unobserved component model to standardise the data from different sources into comparable units. The standardised units were then aggregated into a governance indicator using the average weights of the available data. Kaufmann et al. (2006), calculated a margin of error to reflect the missing data. From the results, updating data for the indicators helps keep a trend with governance changes while informing the impacts of governance changes for the given countries' development (Kaufmann et al., 2006). The study contributed to knowledge on the benefit of timely and annually updating data to make composite indicators more useful in policy making and academics.

Quintano et al. (2010) verified the Markov Chain Monte Carlo (MCMC), propensity scores and mixed models' performance with and without outliers using data with 30% missing values. Quintano et al. (2010) first imputed missing values without removing outliers. Then the detected outliers (five per cent) were removed from the data, after which the models were again used to impute the remaining missing data. Quintano et al. (2010) then compared the performance of the models before and after removing outliers. The missing data imputation models' performance significantly improved after removing the outliers (Quintano et al., 2010). For example, the propensity scores model's mean improved by 35% after removing the outliers (Quintano et al., 2010). However, the MCMC and mixture models were robust with or without outliers but performed best in the absence of outliers (Quintano et al., 2010). Quintano et al. (2010) concluded that the presence of outliers influenced the missing data imputation models' performances. The research contributes to future studies as missing data and outliers are a challenge in most fields.

Thomas et al. (2017) analysed the GFSI 2016 results in the presence of outliers and the impact of the outliers in the robustness of the GFSI. Thomas et al. (2017), studied the shape of the distribution of the GFSI dimensions indicators to identify potential outliers. Skewness and kurtosis for each of the indicators were computed – indicators with absolute values greater than two for skewness and absolute values greater than 3.5 for kurtosis were treated as outliers (Thomas et al., 2017). Six indicators were identified as outliers in the 2016 GFSI database (Thomas et al., 2017). The winsorisation method was applied to remove the outliers, but only for the continuous variable (Thomas et al., 2017). The winsorisation method does not work on the discrete variable (Thomas et al., 2017). The scores and rank of countries before and after the winsorisation of the outliers were then compared. Thomas et al. (2017) concluded that most countries with outliers data point only shifted in the rank by one or two positions. The largest shift was upwards by six positions, indicating that outliers' effect on the final score and rank was not essential (Thomas et al., 2017).

Benin et al. (2020) assessed how improving data quality (accuracy, age of data, consistency, data frequency, ease of update, timeliness, transparency and validation) would improve African countries' policy making for the CAADP implementation. Benin et al. (2020) analysed the effect of data reporting rate (measured by the data values reported as a percentage of total data values required) and quality of the reported data (measured as a percentage of the reported data that had no issues). Five African countries were piloted using the 2018 Biennial Review as the base year to compare with the 2020 Biennial Review after updating and improving the data. Benin et al. (2020) used the difference-in-difference (DID) approach (change in the data reporting rate between 2018 and 2020 Biennial Review) to assess the performance of the piloted countries relative to the non piloted countries.

The results indicated an improvement in the five piloted countries' performance in both data reporting rate (quantity of data) and quality of the reported data in the 2020 Biennial Review compared to like piloted countries with no similar improvements (Benin et al., 2020). For example, Kenya, one of the piloted countries, increased its data quantity score (data reporting rate) by 3.8 per cent – from 88.0 in 2018 to 91.7 in 2020 (Benin et al., 2020). Kenya's data quality also improved by a 2.8 score in 2020 reporting Biennial Review (Benin et al., 2020). Benin et al. (2020) concluded that continuous and timely updating data was critical towards achieving the Malabo Declaration on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods. However, more effort is needed to fill in data gaps (missing data) for critical indicators such as those of ending hunger and halving poverty.

Closset et al. (2014), assessed the effect of missing data in the Human Asset Index (HAI) of the United Nations Committee for Development Policy (UN-CDP) in a retrospective study. Data for the HAI dimensions were normalised using the min-max procedure then rescaled from zero to 100. Closset et al. (2014) assigned the weights through an averaging process, which assumed all indicators to have equal weights. Most indicators for developing countries in the HAI index were not up to date or current. To correct for the missing current data, Closset et al. (2014) used econometric regression and nearest neighbour to impute the missing values. The results revealed a high correlation of countries' scores with no effects of outliers after imputing missing data, which could imply that outliers in the databases might have impacted countries' scores in the HAI index (Closset et al., 2014). However, Closset et al. (2014) highlighted that the missing data imputation methods (econometric regression and nearest neighbour imputation) should be improved in future studies but should strictly follow the UN-CDP methodology for constructing the HAI index. The UN-CDP methodology for constructing the HAI index includes data aggregation, normalisation, missing data imputation, weighting, and variable selection. Closset et al. (2014) further recommended gathering new data for future studies on the HAI dimensions to improve the index (Closset et al., 2014).

2.9 Summary

From the review of literature, the robustness of a composite indicator could be affected by the use of outdated data and the presence of outliers in a database. The review of literature revealed that outdated data and generally missing data from databases a problem of concern in research. Outdated data hinder useful information and must be updated for a composite indicator to be reliable and robust. Outliers, which might result from estimated or missing data, could act as unintended benchmarks leading to biased results in a composite indicator. Outliers could also hinder the reliability of results when statistically imputing or updating missing data and must therefore be removed from any composite indicator to increase its reliability. It was also evident from the literature reviewed that composite indicators' construction process is subjective and must be made transparent for future studies who want to use or analyse the composite indicator.

CHAPTER 3: KENYA'S FOOD SECURITY STATUS

3.1 Introduction

Kenya's food security situation and food security statistics are presented in this chapter. The chapter further examines Kenya's performance in the GFSI since 2012 and the food security policies implemented in the country. Lastly, drivers of food security in Kenya and how they contribute to Kenya's overall performance in composite indicators such as the GFSI are discussed.

3.2 An overview of Kenya's food security

Kenya has one of the largest economies in East Africa, with an annual GDP of 95.503 billion (WorldBank, 2019). Agriculture is a significant contributor to Kenya's GDP and creates employment annually directly (on farms) and indirectly (processing) to millions of Kenyans in urban and rural areas (Hickey et al., 2012). Approximately 84% of the country is arid and semi-arid land unsuitable for rain-fed agriculture, while only 16% of the countries' land has potential for rainfed agricultural productivity (Hickey et al., 2012; GoK, 2019b). Because of the limited suitable land for agriculture in Kenya, food insecurity remains a crucial challenge, coupled with other factors affecting access, affordability and food production (Bryan et al., 2013). Moreover, Kenya is among the food insecure countries in Sub-saharan Africa. The GHI classifies Kenya among the countries with severe hunger levels. For example, in the 2019 GHI result, Kenya scored 25.2, which was higher than the 9.9 low scores according to the GHI (IFPRI, 2019). Like other Sub Saharan countries, Kenya's food insecurity challenge hinders the provision of the right to food in desired preference, quantities and qualities to its citizens (Bryan et al., 2013; Clover, 2003).

In Sub-sahara Africa, some of the causes of food insecurity include climate change characterised by drought and floods, conflicts, poverty, lack of infrastructure, limited public investment in agriculture, politics, rapid population growth and the scarcity of proper research and extension services (Clover, 2003). Furthermore, these challenges have resulted in persistent chronic and transitory food insecurity in Kenya - climate change and poverty are the most important contributors to Kenya’s persistent chronic and transitory food insecurity (Nyariki and Wiggins, 1997).

Building resilience at a household, individual, and national level is critical in ensuring food accessibility, affordability and availability despite food insecurity challenges (Bryan et al., 2013). The management of the environment and the natural resources, poverty reduction, increasing public expenditure in agricultural research and development and strengthening social protection are ways to build resilience to improve Kenya's food security (Bryan et al., 2013; Clover, 2003).

3.3 Food security statistics for Kenya

Statistics show that food insecurity is prevalent in Kenya (IPC, 2020). Nine per cent of the population (1.3 million people) were estimated to have faced a crisis or worse acute food insecurity (IPC Level 3 and above) by February 2020 (IPC, 2020). Further, 296,500 of the population were in an emergency (IPC Level 4) in February 2020 (IPC, 2020). Out of the 23 affected counties, 19 counties were worst affected (IPC Level 3), mainly from the Arid and Semi-Arid Lands (ASAL). Despite Kenya receiving above-average rainfall in 2020, the increased acute food insecurity cases primarily resulted from the floods caused by the prolonged rains (IPC, 2020; FEWS.NET, 2020b). Some of the consequences of the prolonged rains in Kenya included damage and loss of livelihoods, displacements of people, loss of lives and widespread outbreaks of livestock diseases (FEWS.NET, 2020a; IPC, 2020). However, despite the high levels of food-insecure people in Kenya, Figure 3.1 shows that since the year 2000, the prevalence of stunting, wasting and mortality in children under five years has reduced (IFPRI, 2019).

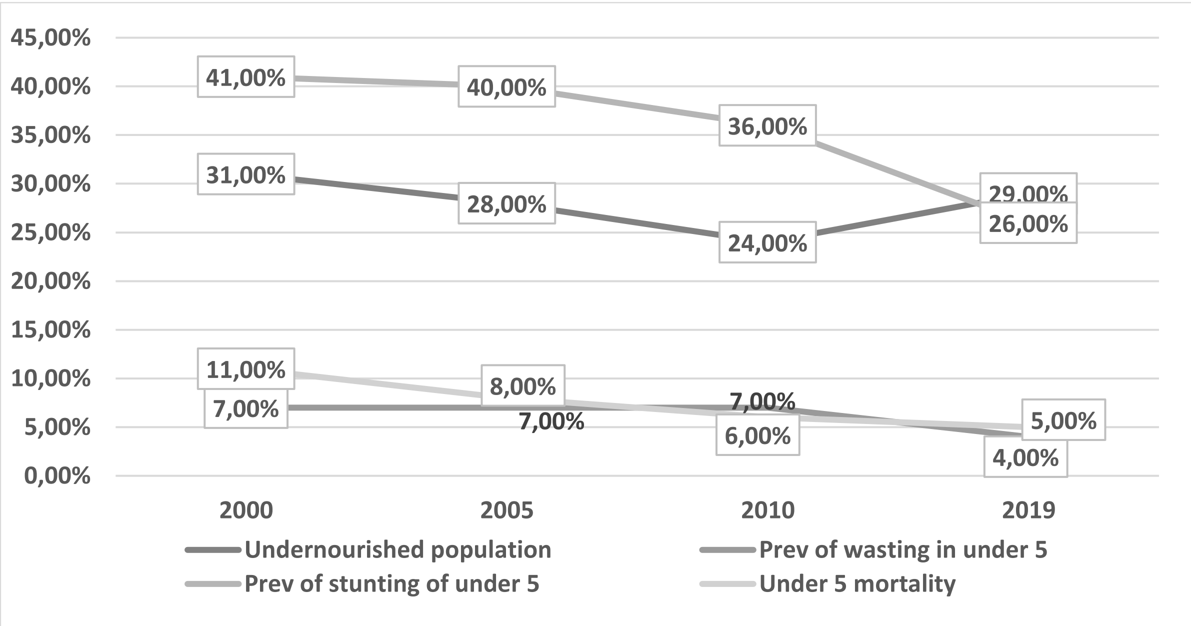

Figure 3.1: Kenya's proportion of the undernourished population, the prevalence of wasting, stunting and mortality in under five years.
Author: IFPRI (2019).

Improved drinking water sources, sanitation and improved maternal health care, could be attributed to the reduced stunting, wasting and the prevalence of undernourishment (Masibo and Makoka, 2012). However, Masibo and Makoka (2012) have noted that this reduction has been gradual, especially among rural households compared to urban households, mainly due to the rural areas' high poverty levels.

3.4 Kenya's Performance in the GFSI since 2012

Kenya's scores in the GFSI dimensions since 2012-2019 is as shown in Figure 3.2.

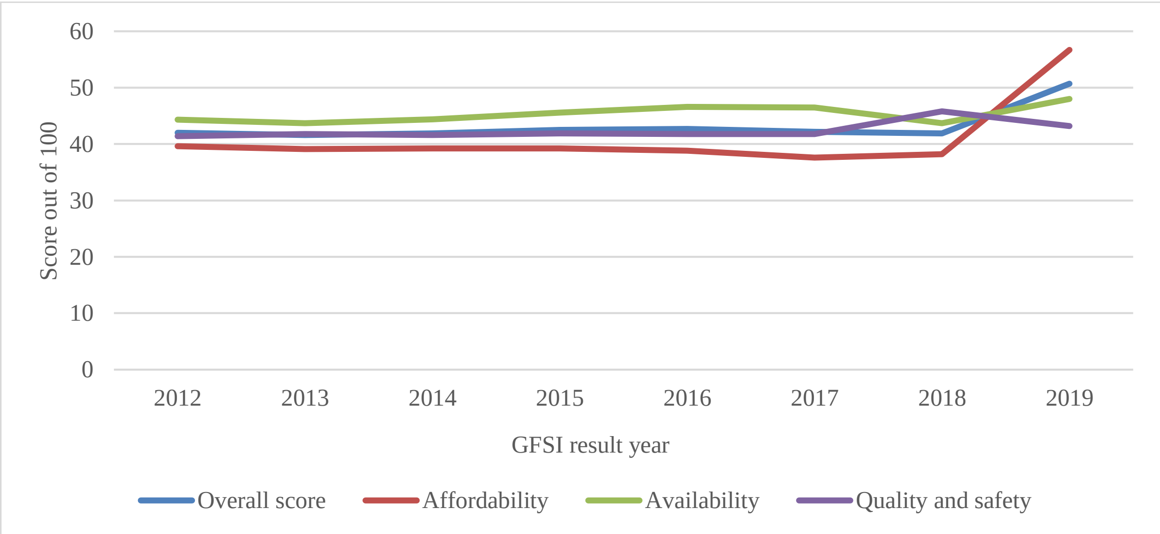

Figure 3.2: Kenya's scores out of 100 in the GFSI since 2012-2019
Source: Author's compilation from (EIU, 2019)

Kenya has performed poorly in all the GFSI dimensions since 2012. However, the affordability dimension had the most significant improvement in score of 56.7 out of 100 in 2019 compared to the previous GFSI affordability dimension scores. The affordability dimension score improvement could be attributed to the introduction of a new indicator measuring the change in the average food cost to replace food consumption as a share of household expenditure by the 2019 GFSI (EIU, 2019). The indicator measuring the change in average food cost had the highest score (95.3 out of 100) for Kenya in the 2019 GFSI affordability dimension compared to the other indicators in the same dimension (EIU, 2019).

Updating Kenya's indicator for the proportion of the population living under the global poverty line could have also contributed to improved affordability dimension scores. The GFSI updated Kenya's proportion of the population living under the global poverty line from 2005 to 2015, thereby improving the overall affordability dimension score from 38.2 in 2018 to 56.7 out of 100 in 2019 (18.5 points) (EIU, 2019).

In terms of the overall GFSI rank, Kenya has been ranked among the bottom 30 countries since 2012. The availability dimension had the most significant improvement in rank in the 2019 GFSI than the affordability and quality and safety dimension (Figure 3.3). The availability dimension rank improved by eight positions from 101 to 93 relative to the 113 countries. The improvement in rank for the availability dimension could be attributed to improved performance in the food loss, urban absorption capacity and the volatility of agricultural production indicators in 2019 compared to 2018 - these indicators scored 80 and above out of 100 (EIU, 2019).

Kenya's availability dimension rank could have also improved in 2019 compared to 2018 due to the relative political stability experienced in 2019 compared to 2018. The political uncertainty posed by the nullification of the presidential election results in 2017 might have influenced Kenya's 2018 GFSI availability rank (EIU, 2018). EIU (2018) have highlighted that political and social dynamics shape food systems' economic context, particularly whether and how farmers invest in agricultural production. Political instability causes economic uncertainties making it risky for farmers to plant crops expecting that their efforts and inputs will not pay off at harvest time, thereby affecting food availability and overall food affordability due to shortages (EIU, 2018). EIU (2018) highlighted Kenya's political instability as a contributing factor to its poor performance in 2018; thus, the considerable improvement in 2019 post the presidential election.

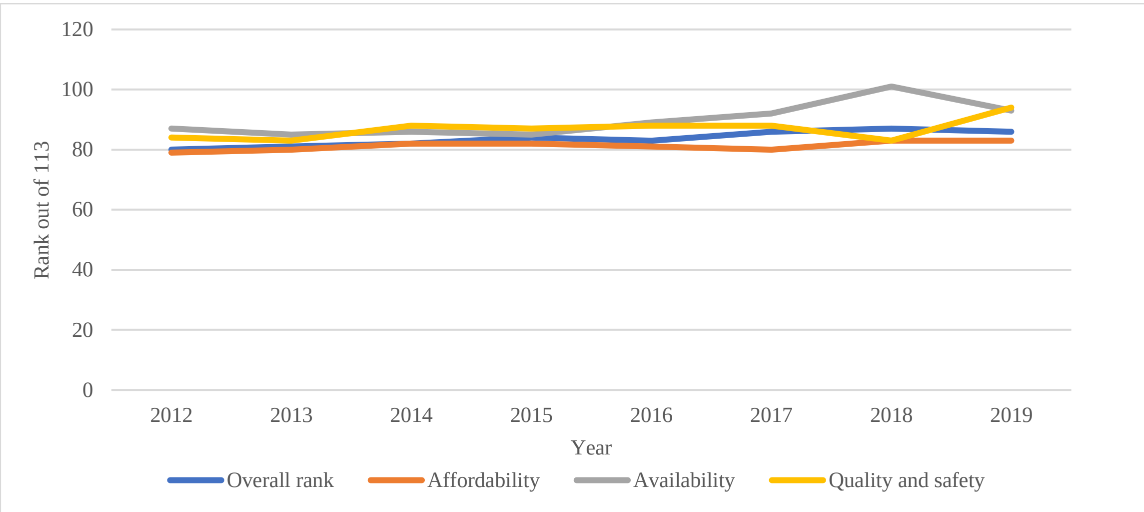

Figure 3.3: Kenya's rank out of 113 countries in the GFSI since 2012-2019.
Source: Author's compilation from (EIU, 2019).

3.5 Policy context of Kenya's food security

The Constitution of Kenya (2010 Article 43 (1) (c)) states that every Kenyan has the right to be free from hunger and to have adequate food of acceptable quality (Wafula and Odula, 2018). The Kenyan government is considered responsible for ensuring food secure environments for all Kenyans in all food security dimensions, that is, accessibility, availability, stability and utilisation (Wafula and Odula, 2018). In an attempt to ensure food security in Kenya and consequently better performance in benchmarking by food security composite indicators, the government has implemented different policies. One such policy is the Big Four Agenda, a midterm policy implemented from 2018 to 2022 (GoK, 2018). Even though the Big Four Agenda aims to improve other critical sectors such as health care provision, housing and job creation, it prioritises food security as the first critical pillar for development in achieving vision 2030 (GoK, 2018). The Big Four agendas' targets for improving food security include; enhancing the national grain reserves, increasing maize production, improving the road network for market accessibility and food distributions, providing fertiliser subsidies to farmers and providing supporting amenities to irrigation such as electricity (GoK, 2018).

Another policy for improving Kenya's food security is the National Food and Nutrition Security Policy Framework (KNFSNP) 2017-2022 (Gok, 2017). The KNFSNP is a midterm policy that aims to ensure Kenyans have the means to access affordable, nutritious and personally preferred foods (Gok, 2017). Besides food accessibility and preference, the KNFSNP promotes food utilisation through consumption patterns, including a balanced diet with essential micronutrients that maximise health and minimise diseases (Gok, 2017). The KNFSNP policy promotes sustainable production and supply of safe and high-quality food to ensure stability (Gok, 2017).

Kenya has also implemented policies distinctively targeting the improvement of nutrition intervention activities provided by the government and nutrition stakeholders (GoK, 2012). The National Nutrition Action Plan (NNAP), implemented between 2012 to 2017, was a midterm plan for ensuring food utilisation and adequate consumption of balanced diets and essential micronutrients (GoK, 2012). The KNFSNP was essentially a continuation of the NNAP. Some of the targets of the NNAP were to improve the nutritional status of women of reproductive age (15-49 years) and children under the age of five years, improve nutrition in schools and other institutions, improve overall access to quality and curative nutrition services, prevent deterioration of nutritional status and save lives of vulnerable groups in emergencies and lastly, to reduce the prevalence of micronutrient deficiencies in the population (GoK, 2012). Compared to 2000, stunting and overall child mortality have declined in the country, which could be attributed to food fortification or supplementation implemented through the NNAP (Linda et al., 2020; Masibo and Makoka, 2012; GoK, 2012). Kenya's better performance in the nutritional standards and the micronutrient availability in the 2019 GFSI stresses the NNAP policy's contributions to Kenya's food security (EIU, 2019).

One long-term plan for improving Kenya's food security was the Agricultural Sector Growth and Transformation Strategy (ASTGS) from 2019-2029 (GOK, 2019c). The ten-year plan is a strategy to transform Kenya's agricultural sector into a commercial, modernised and vibrant sector that supports economic development sustainably and is committed to regional and global growth (GOK, 2019c). Some of the ASTGs strategies include; boosting household food resilience by reducing the number of food-insecure Kenyans in the arid and semi-arid lands, increasing small-scale farmers, pastoralists and fisherfolk average annual incomes by directly benefiting households, increasing agricultural output and value addition by expanding agricultural GDP, increasing the agro-processing sectors' contribution to the economy, improving nutrition and protecting households against environmental and fiscal shocks and reducing the cost of food in the country (GOK, 2019c).

While the successful implementation of these policies can enhance Kenya's achievement of the SDG, CAADP agreements and overall performance in composite indicators such as the GFSI (GOK, 2019c), Poulton and Kanyinga (2014) note that, successful implementation of these policies remains a challenge in Kenya. Poulton and Kanyinga (2014) give an example of one such policy; the strategy for revitalising agriculture (SRA) implemented from 2004 to 2014. Despite being a useful policy for improving agriculture and food security in Kenya, the SRA policy implementation was not as successful as intended. Factors such as corruption and politics, among others, hindered the success of the policy (Poulton and Kanyinga, 2014). Some of the aims of the SRA were to reform the role of the state in the agricultural sector as a way of achieving food security and refocus the government's role in the provision of vital public goods, such as research and extension services, roads and irrigation infrastructure (Poulton and Kanyinga, 2014). Hickey et al. (2012) also stress that despite these numerous policies implemented and institutional structures to improve agriculture and food security in Kenya, there has been limited progress towards achieving food security. Individuals are still vulnerable to cyclical shocks that threaten food accessibility, availability, stability and utilisation, requiring urgent attention (Hickey et al., 2012)**.**

3.6 Drivers of food insecurity in Kenya

Several factors can be considered to contribute to Kenya's food insecurity. These causes of food insecurity can be either demand or supply factors. Demand causes of food insecurity include but not limited to poverty, rapid population growth and urbanisation, whereas supply causes include climate change and high input prices, among others (Emongor, 2011). Effectively addressing these challenges could reduce Kenya's food insecurity while improving benchmarking performance by food security composite indicators.

3.6.1 Climate change

Climate change is a significant contributing factor to food insecurity in Kenya (Ochieng et al., 2016). Millions of people face hunger due to climate variability, causing drought, unpredictable and unreliable rainfall patterns, reduced soil moisture and low agricultural production levels (Ochieng et al., 2016). Devereux (2009) has stressed that drought is one of the significant causes of persistent famine in the Horn of Africa. In Kenya, climate change has resulted in persistent drought, negatively impacting Kenya's ASAL region (worst affected) (FAO, 2017). Sever instances of drought in Kenya result in hunger, malnutrition and mortality among millions of vulnerable individuals. For example, in 2014, Kenya's Government declared an impending drought a national disaster where an estimated 1.6 million people were affected (Lolemtum et al., 2017). Similarly, in 2017, Kenya's government also declared a severe drought a national disaster as it affected over 23 out of the 47 counties with close to 2.7 million people declared severely food insecure and in urgent need of emergency food aid (FAO, 2017; Lolemtum et al., 2017). Other than drought, climate change in Kenya has also contributed to floods caused by prolonged above-average rainfalls, resulting in acute food insecurity and loss of livelihoods and lives (IPC, 2020; FEWS.NET, 2020a).

Climate shocks also result in conflict, especially in resource-constrained environments (Fan et al., 2014). Consequently, these conflicts aggravate vulnerability by increasing poverty, rendering affected places inaccessible for food deliveries and causing widespread hunger and malnutrition (Fan et al., 2014). The scarcity of pasture water and loss of livelihoods among the pastoralist communities exacerbates conflict in the ASAL regions (Demombynes and Kiringai, 2011). Migration of people from conflict and drought affected neighbouring countries of Ethiopia or Somalia into the Daadab refugee camp of Kenya worsen the region's food insecurity situation (Fan et al., 2014). Further, the migrations increase demand for food, pasture and the overall congestions in the camp, increasing the spread of diseases such as cholera due to poor living conditions, lack of proper sanitation and lack of water (Fan et al., 2014; Bryan et al., 2013). Conflict mitigation and resolution by improving the sound management of the available natural resources in an all-inclusive manner are essential among the pastoralist communities to fight hunger and improve nutrition while strengthening livelihoods (Fan et al., 2014).

Adapting agriculture to climate change at the national, household and farm level is also crucial to reducing food insecurity (Kabubo-Mariara and Kabara, 2018). At the national level, investment in drought and heat tolerant crop varieties, investing in irrigation infrastructure, insurance for farmers and a mixture of strategies to reduce livelihood risks will enhance production and increase food security (Bryan et al., 2013; Kabubo-Mariara and Kabara, 2018). Moreover, such efforts of strengthening national food security will improve Kenya's performance in benchmarking by composite indicators such as the GFSI. Adaptation methods at the farm level include changes in crop management systems through changing crop varieties and planting dates, water harvesting and soil and water conservation measures and tillage practices (Bryan et al., 2013).

3.6.2 High food prices

Global food systems are interconnected through international trade and could positively or negatively affect global food security (Natalini et al., 2019). The positive effect of international trade is that countries that cannot grow food can import from countries with surpluses. The adverse effect of shocks is the disruptions of global supply chains, which affect countries relying on food importation (Natalini et al., 2019). Due to its limited resources to produce enough food, Kenya relies heavily on international and regional trade to import cereals and other food products (Emongor, 2011; Musembi and Scott-Villiers, 2015). For example, Kenya's food security was affected by spikes in international food prices during the world crisis of 2007/2008 (Von Braun et al., 2008; Musembi and Scott-Villiers, 2015). Moreover, the post-election violence experienced in the country during the same period (2007/2008) worsened the situation hindering food affordability and availability (Emongor, 2011).

Food prices in Kenya have increased compared to non-food items (Emongor, 2011; GoK, 2019d). Musembi and Scott-Villiers (2015) note that even though food prices in the country could be responding to global prices, a closer examination reveals that the prices rise sharply and stay higher for longer in Kenya compared to the global prices. Furthermore, Kenya's food prices do not always fall even during high production years (Musembi and Scott-Villiers, 2015). Domestic politics and policies are some of the reasons for high food prices despite high production. Demombynes and Kiringai (2011) highlight that Kenya levies imports on food grain even during crises. As a result, citizens use means such as food riots, street demonstrations and public debates to get the governments attention to acting (Musembi and Scott-Villiers, 2015; Natalini et al., 2019).

High food prices raise food security concerns, especially among the poor in society (Von Braun et al., 2008). High food prices hinder affordability even if there is enough food supply in the country (Emongor, 2011; Von Braun et al., 2008). Poor households who spend significant proportions of their income on purchasing food have limited substitution options during such price spikes, which affect their consumption of enough calories (Emongor, 2011). Therefore, households tend to shift to cheaper, less balanced diets, reduce the number of meals or reduce food portions as coping strategies which, in the long run, affect their nutrition and health (Von Braun et al., 2008).

3.6.3 Poverty

The proportion of Kenyans living on less than the international poverty line (US$1.90 per day in 2011 PPP) was 36.1% in 2015/16, a decline from 46.8% in 2005/06 (WorldBank, 2019). While the proportion of the Kenyan population living below the global poverty line might have declined in 2015, 36.1% of the Kenyan population still live below the global poverty line (WorldBank, 2020a). Poverty remains relatively high in Kenya and is a primary cause of persistent chronic food insecurity (WorldBank, 2020a). Kenya's poverty situation has barely changed since independence despite the several measures and efforts used to tackle it (Oluoko-Odingo, 2009).

Poverty is exceptionally high among rural households who depend on rainfed agriculture to produce food for consumption and as a source of income in Kenya (Oluoko-Odingo, 2009). Most rural households do not produce enough food to sustain themselves due to continued crop failures caused by persistent drought and insufficient and unreliable rainfall (Emongor, 2011). As a result, these households cannot produce enough to sell to earn income to purchase the food they do not produce or other essential items (Emongor, 2011). Therefore, households engage in off-farm activities by selling their labour to increase food consumption or rely on food aid and government assistance to survive, especially during the lean seasons (Emongor, 2011; Nyariki and Wiggins, 1997).

3.6.4 Rapid population growth

Kenya has one of the fastest-growing populations. The recent population census for 2019 revealed that Kenya has a population of 47.6 million people, compared to 37.7 million people in the 2009 census, indicating an increase of 9.9 million people within ten years (GoK, 2019a). However, the population is expected to continue to grow further as per 2050 world population growth projections, especially in Africa (Godfray et al., 2010). In Kenya, 75.1% of the total population comprises individuals below 35 years spread in urban and rural areas. The proportion of the population residing in rural areas is 68.9%, while the urban areas account for 31.1% (GoK, 2019a).

Agriculture's ability to support the growing population is an issue of great concern (Rosegrant and Cline, 2003). Even though food production has continued to grow than population growth, people still do not have enough protein and energy in their diets (Godfray et al., 2010). Moreover, more people globally are estimated to suffer from some form of micronutrient malnourishment compared to the year 2000s (Godfray et al., 2010). FAO et al. (2020) highlight that globally, in 2019, 21.3% of children under five years of age were estimated to be stunted, 6.9% wasted and 5.6% overweight. Adult obesity is also rising; FAO et al. (2020) project an increase from 13.1% in 2016 to 40% by 2025 when the global obesity rate increases at a 2.6% rate per year.

Some causes of rapid population growth in Kenya include cultural beliefs. In Kenya, most cultures typically associate large families with wealth, prestige and security (Bremner, 2012). However, more often, these rural households with large families do not have the financial capacity to provide essential commodities such as adequate food, proper education and health care (Bremner, 2012). Consequently, these large families result in widespread cyclical poverty among poor rural households (Oluoko-Odingo, 2009).

Reducing food loss and wastage is one way to feed the growing population (Kimiywe, 2015). However, despite more than nine million people facing food insecurity in the country, Kenya experiences a 30-40% food loss, translating to 50 million bags valued at 272 355,88 US dollars annually (Kimiywe, 2015). The food loss and wastage in Kenya occurs mainly due to inefficient post-harvest handling, a lack of sufficient storage or cooling facilities, inadequate infrastructure and the lack of markets for produce (Kimiywe, 2015).

3.6.5 Urbanisation

Urbanisation is a significant challenge to food security in sub-Saharan Africa and Kenya is no exception (Berger and van Helvoirt, 2018). In Kenya, urbanisation arises due to rural-urban migration posed by unemployment, search for better education, healthcare services and social amenities (Owuor, 2019). However, economic growth and development are necessary to enhance urban dwellers' quality of life (Owuor, 2019). Due to limited economic growth and development in Kenya, urbanisation has resulted in the mushrooming of slums (Emongor, 2011). Poverty aggravates the living conditions in slums, characterised by a lack of essential services such as clean water, health care services and sanitation among vulnerable households (Emongor, 2011).

Compared to other major cities in Kenya, Nairobi is more food insecure. The slum settlements have been reported as the worst affected (Berger and van Helvoirt, 2018). Low-income levels hinder access to food by households who have to purchase food, pay rent, electricity and transport with little income (Owuor, 2019). As a result, households may reduce the number of meals eaten in a day, sanitation expenditure, education and health as coping mechanisms to secure food. Other households may engage in crime as a coping strategy (Berger and van Helvoirt, 2018; Emongor, 2011).

Urbanisation has led to agricultural land encroachment, reducing food production (Godfray et al., 2010). Urbanisation also undermines sound nutrition, mostly due to increased consumption of fast food, causing obesity among the urban and peri-urban dwellers (Steyn et al., 2012). The high cost of living in cities makes it difficult for the household to provide nutritious foods essential for child growth and development (Owuor, 2019). Consequently, stunting and wasting among children below five years is prevalent in the slums (Steyn et al., 2012). However, the Kenyan government has made considerable effort to ensure essential micronutrients are available to Kenyans (Linda et al., 2020). Mandatory fortification of staple foods has been one way of ensuring essential micronutrients are available in the food supplied to all households (Linda et al., 2020)**.**

3.7 Chapter summary

In this section, Kenya’s food security status and food insecurity drivers in the country were discussed. From the literature reviewed, it was evidenced that Kenya has implemented numerous policies to mitigate food insecurity. However, Kenya needs to make considerable effort to implement her policies and improve food security. Overall, shocks such as drought, high food prices and poverty threaten food accessibility, availability, stability and utilisation in the country, affecting Kenya's performance in the food security composite indicators such as the GFSI.

CHAPTER 4: A REVIEW OF THE GLOBAL FOOD SECURITY INDEX METHODOLOGY

4.1 Introduction

In this chapter, the Global Food Security Index (GFSI) is described in detail - showing its dimensions, indicators and sub-indicators as per the methodology set out in the 2019 GFSI report (EIU, 2019). The weighting method to rank countries used by the GFSI is discussed and its impact on countries' rankings. Further, the min-max normalisation technique used by the GFSI is discussed. Lastly, the chapter explains the GFSI data sources and data years and how the data year impacts scores and rank for the 113 countries included in the 2019 GFSI.

4.2 The Global Food Security Index

The GFSI is a composite indicator developed in 2012 by the Economist Intelligence Unit. The GFSI assesses global food security at the national level in 113 countries annually. Both developed and developing countries are included in the index to determine which countries are most and least vulnerable to food insecurity (EIU, 2012). The GFSI also includes countries with large populations in the index to cover much of the world's population, as mentioned in chapter one. The countries included in the GFSI are to reflect regional diversity and economic importance (EIU, 2012). (Izraelov and Silber, 2019; Maricic et al., 2016) have highlighted that the GFSI is remarkably one of the best food security composite indicators.

The GFSI serves as a useful diagnostic tool for food security policymakers. Private and public sectors use the GFSI as an essential strategic decision making tool to analyse food consumption trends and determine which social support to implement for future food security related issues (Turan et al., 2018). Studies (Thomas et al., 2017; Pangaribowo et al., 2013) have compared the GFSI with other existing international food security composite indicators and have concluded that the GFSI indicators correlate well with the existing indicators such as GHI and the PoU. Therefore, it implies that the GFSI dimensions measure food security efficiently as the other existing indicators (Pangaribowo et al., 2013; Thomas et al., 2017). Moreover, the GFSI has the advantage of including both the low and high-income countries in the index, unlike the GHI, which only assesses emerging economies (Pangaribowo et al., 2013).

The GFSI is dynamic as it uses qualitative and quantitative data to measure food security (Maricic et al., 2016). The quantitative data are from credible international data sources, such as the FAO, WB, WFP, WTO. By contrast, the qualitative data are created by the EIU panel of experts based on available data from the development banks, government websites, and surveys adjusted to compute the GFSI values (EIU, 2019). Because the GFSI annually assesses contributing factors to food security in countries, the GFSI is expected to use current data for reporting for the given years. However, Thomas et al. (2017) highlight that one challenge of computing a composite indicator with global coverage such as the GFSI is the availability of updated data, evidenced in the GFSI's use of outdated indicators. Therefore, the GFSI's quantitative data can represent a country's food security situation only to the extent that the outdated data still depict the current situation, for example, when using 2013 data to report the 2019 food security situation of a country (Thomas et al., 2017).

4.3 The GFSI dimensions and indicator definitions

The GFSI measures food security in the dimensions of affordability, availability and quality and safety using 34 indicators shown in Table 4.1. The panel of experts at EIU determines the indicators included in the index (EIU, 2012). Natural resource and resilience, a risk adjustment factor, was added to the GFSI as the fourth component in 2017 (EIU, 2017). The GFSI in 2012 was assessing 25 indicators across 105 countries (EIU, 2012). In 2013, two countries (Ireland and Singapore) were added to the index together with two indicators in the availability dimension (corruption and urban absorption capacity) (EIU, 2013). In 2014, two more countries (Kuwait and the United Arab Emirates) were introduced together with food loss in the availability dimension (EIU, 2014). However, in 2019, the EIU removed two indicators from the GFSI (EIU, 2019). In the affordability dimension, the indicator assessing food consumption as a proportion of total household expenditure was replaced with the change in average food costs, while in the quality and safety dimension, presence of the formal grocery sector was replaced with the ability to store food safely (EIU, 2012). The GFSI highlighted in its 2019 methodology that the indicators are replaced when the data sources are no longer updated on a regular basis (EIU, 2019).

Out of the 34 indicators in the 2019 GFSI results, 16 indicators were qualitative, while 18 were quantitative indicators. The affordability dimension had nine indicators and sub-indicators that explore the capacity of people within a country to pay for food and the cost people face under normal circumstances and during price-related shocks (Thomas et al., 2017). The availability dimension had fourteen indicators and sub-indicators that explore elements that impact food supply and ease of accessing food within a country.

Table 4.1: The GFSI dimensions and sub-indicators

Dimension	Indicators	Source	Data year
Affordability	Change in average food costs	FAO	2014-18
	The proportion of the population under the global poverty line	World Bank, World Development Indicator	2008-17
	Gross domestic product per capita (US$PPP)	The Economist Intelligence Unit (EIU)	2018
	Agricultural import tariffs	World Trade Organisation (WTO)	2012-18
	Presence of food safety-net programmes :	EIU scoring	2019
	Presence of food safety-net programmes	Qualitative scoring by EIU analysts	2019
	Funding for food safety-net programmes	Qualitative scoring by EIU analysts	2019
	Coverage of food safety-net programmes	Qualitative scoring by EIU analysts	2019
	Operation of food safety-net programmes	Qualitative scoring by EIU analysts	2019
	Access to financing for farmers	Qualitative scoring by EIU analysts	2019
Availability	Sufficiency of supply:	EIU scoring	
	Average food supply	FAO	2016-18
	Change in dependency on chronic food aid	OECD	2013-17
	Public expenditure on agricultural research and development	United Nations	2010-17
	Agricultural infrastructure:	EIU scoring	2004-15
	Existence of adequate crop storage facilities	Qualitative scoring by EIU analysts	2019
	Road infrastructure	EIU Risk Briefing	2019
	Port infrastructure	EIU Risk Briefing	2019
	Air transport infrastructure	EIU Risk Briefing	2019
	Rail infrastructure	EIU Risk Briefing	2019
	Irrigation infrastructure	FAO	2016
	The volatility of agricultural production	USDA	2012-2016
	Political stability risk	EIU Risk Briefing	2019
	Corruption	EIU Risk Briefing	2019
	Urban absorption capacity	World Bank, World Development Indicators; EIU	2015-2019
	Food loss	FAO	2013
Quality and Safety	Dietary diversity	FAO	2011-13
	Nutritional standards:	EIU scoring	
	National dietary guidelines	Qualitative scoring by EIU analysts based on WHO, FAO and national health ministry documents	2019
	National nutrition plan or strategy	Qualitative scoring by EIU analysts based on WHO, FAO and national health ministry documents	2019
	Nutrition monitoring and surveillance	Qualitative scoring by EIU analysts based on WHO, FAO and national health ministry documents	2019
	Micronutrient availability:	EIU scoring	
	Dietary availability of vitamin A	Global Nutrient Database	2013
	Dietary availability of iron	Global Nutrient Database	2013
	Dietary availability of zinc	Global Nutrient Database	2013
	Protein quality	EIU calculation based on data from FAO, WHO and US Department of Agriculture (USDA) Nutrient Database	2011-2013
	Food safety:	EIU scoring	
	Agency to ensure the safety and health of food	Qualitative scoring by EIU analysts	2019
	Percentage of population with access to potable water	World Bank	2017
	Ability to store food safely	United Nations	2017

Source: (EIU, 2019).

The availability dimension further assesses how structural aspects such as infrastructure determine a country's capacity to produce and distribute food and the elements that might obstruct robust availability (Chen et al., 2019). The quality and safety dimension contained eleven indicators and sub-indicators that assess the nutritional quality of average diets and food safety environment in a country (Izraelov and Silber, 2019; Thomas et al., 2017). Lastly, the natural resource and resilience component determines the impact of climate-related and natural resource risks on food security in a country (EIU, 2019). The latter dimension is not included in the standard GFSI.

4.4 The GFSI methodology

A precise and transparent methodology when constructing a composite indicator is critical for achieving unbiased country performances (JRC-EC, 2008). The 2019 GFSI methodology clearly outlines the normalisation and weighting procedures used to construct the GFSI. However, the aggregation method used by the GFSI is not included in the methodology, while the EIU panel of experts estimates the missing quantitative data (EIU, 2019). The subsections describe the GFSI data normalisation and weighting.

4.4.1 The GFSI's data normalisation method

The indicators selected by the EIU panel of experts are normalised to rebase the raw indicator data into a standard unit to allow data aggregation. The normalisation of indicators for which a higher value indicates a favourable environment like average food supply is:

$$X = (x - Min(x))/(Max(x) - Min(x))$$

Min(x) is the lowest value and Max(x) is the highest value in the 113 countries for any given indicator. The values are transformed from zero to one range into a zero to 100 score after normalisation. As a result, countries with the highest raw data will score 100, while countries with the lowest raw data will score zero (EIU, 2019).

The normalisation of indicators which a high value indicates unfavourable food security environment like the volatility of agricultural production is:

$$X = (Max(x))/(Max(x)-Min(x))$$

Min(x) is the lowest and Max(x) is the highest in the 113 countries for any given indicator. The normalised values are then transformed into a positive number on a scale of zero to 100 to make it directly comparable with other indicators.

4.4.2 The GFSI's weighting method

The EIU uses two sets of weighting methods. The first is equal weighting, which assumes all indicators are equally essential and distribute weights evenly to all indicators. The second is the peer panel recommendation weighting, which averages the weights suggested by five EIU expert panel members. The panel of expert weighting is the default weighting used by the GFSI to rank countries. Various studies (Chen et al., 2019; Izraelov and Silber, 2019; Maricic et al., 2016) have criticised the default weighting by the EIU panel of experts for being subjective and biased. Chen et al. (2019), suggested the use of hierarchal data envelope analysis to assign weights in the GFSI, while Maricic et al. (2016), proposed the use of a multivariate composite I-Distance (CIDI) approach. Izraelov and Silber (2019), applied principal component analysis and data envelopment analysis on the GFSI to assign weights to the indicators statistically. Chen et al. (2019), Izraelov and Silber (2019) and Maricic et al. (2016), concluded that while the rank was not significantly different from that of the EIU, the statistical techniques produce unbiased and reliable scores and rank than those obtained by EIU's subjective default weighting.

In the GFSI weighting, the availability dimension is weighted higher than affordability and quality and safety dimensions. The availability dimension is weighted 44%, while the affordability and quality and safety dimensions are weighted 40% and 16%, respectively. Thomas et al. (2017), highlight that even though the EIU considers affordability and availability dimensions to be of greater statistical importance, the quality and safety dimension is equally essential in the index. Moreover, weights assigned to some individual indicators in GFSI dimensions do not correspond to their statistical importance for the dimension (Thomas et al., 2017). For example, public expenditure on agricultural research and development weights 8.1%, lower than 9.91% weight for urban absorption capacity even though the public expenditure on agricultural research and development correlates more with the availability dimension than urban absorption capacity (Thomas et al., 2017). Thomas et al. (2017), have stressed that the GFSI developers should justify the assigning of weight and the statistical importance of an indicator within the GFSI.

Thomas et al. (2017), concluded that the GFSI is robust in measuring food security but should be used alongside other indicators measuring food security outcomes; the GFSI only measures contributing factors to food security. One limitation of the GFSI highlighted by Thomas et al.

(2017), is that the GFSI does not include information about inequality among the poor or food-insecure individuals or households. Instead, the GFSI measure the contributing factors to food security at the national level (Thomas et al., 2017; Izraelov and Silber, 2019).

Turan et al. (2018), highlights that under the GFSI's affordability dimension, the Gross Domestic Product (GDP) per capita has more weight. As the GDP per capita increases, the proportion of the population living under the global poverty line also has considerable improvement (Turan et al., 2018). Food consumption as a share of household expenditure contributes significantly to countries overall performance in the dimension. A large proportion of the population devoting a significant proportion of their income to purchasing food indicates underdevelopment within a country, leading to overall poor performance in the index. However, one of the weaknesses of the GFSI, as identified by Turan et al. (2018), is its failure to take into consideration the variations in different areas in a country and suggests the inclusion of Gini ratios in the index.

In the availability dimension, average food supply is the indicator of more importance (weight 73.3%) (EIU, 2019). Sufficient food supply is essential towards achieving food security due to increased dietary intake (EIU, 2012). Change in dependency on chronic food aid is also an indicator of importance to the availability dimension with a weight of 26.7%. However, some indicators, such as the volatility of agricultural production and the urban absorption capacity, have minimal impact on the availability dimension (cosmetic indicators) (Thomas et al., 2017). In the quality and safety dimension, the indicator for the proportion of the population with access to potable water weights 42.9%, higher than the national dietary guideline that weights 34.6% (EIU, 2019). The indicator with the least weight is food safety which weight 16.9%.

Naftanaila et al. (2019), assessed the GFSI by developing an optimised global food security index to determine Romania's position relative to countries in Europe. The reason for calculating an optimised global food security index was to include only sub-indicators that significantly contributed to the dimensions of the GFSI (Naftanaila et al., 2019). In this method, only the first four sub-indicators that had a significant contribution for each dimension were considered. This method uses a mathematical process that only included indicators with significant contributions to the dimensions leading to a country's relevant hierarchy. Naftanaila et al. (2019) concluded that the optimised global food security index was applicable in analysing food security by the GFSI.

4.5 Chapter summary

The GFSI indicators, sub-indicators and methodology were presented in this chapter. Like other previous studies on the GFSI, this study found the GFSI robust in its methodology and well correlated with other food security indicators. However, the weighting method used by the GFSI for the dimensions and indicators has been questioned by previous studies, which the GFSI needs to justify further.

CHAPTER 5: METHODS AND PROCEDURES FOR ACHIEVING THE STUDY'S OBJECTIVE

5.1 Introduction

The methods and procedures applied to achieve the study's objectives are presented in this chapter. Both quantitative data analysis and descriptive statistics carried out in the Excel spreadsheet and Stata version 15.1 software are described. Lastly, the section outlines the methods used for outliers and outdated data detection and the methods used for testing their statistical significance.

5.2 Methods of data analysis

The analysis focused on the dimensions of the GFSI (affordability, availability and quality and safety). The analysis aimed to identify outdated data and outliers in the 2019 GFSI and determine their statistical significance to the GFSI score and rank. Outdated data for this study was any indicator with data from 2018 or older. These indicators were considered outdated as the GFSI releases its data annually and 2018 was typically the year before the 2019 GFSI result. Outliers are extreme data points lying far away from the majority of other data points (Kwak and Kim, 2017; Thomas et al., 2017). Outliers in a data sample typically introduce bias into statistical estimates such as mean values, leading to under-or over-estimated resulting values (Kwak and Kim, 2017). Therefore, it is essential to identify and deal with outliers before data analysis (Ghosh and Vogt, 2012; Kwak and Kim, 2017; JRC-EC, 2008). Numerous methods can be used to identify and handle outliers in a data sample. However, some methods are more robust than others. Data analysis results could also drastically change depending on the approach used to treat the outliers, making it crucial to effectively handle the outliers (Kwak and Kim, 2017).

Some methods of identifying outliers include the use of standard deviation, where any data points that do not fall within three standard deviations of the mean are identified as outliers (Kwak and Kim, 2017). This method is considered not to be robust as both mean and standard deviation are sensitive to outliers' presence in a data point (Kwak and Kim, 2017). The other methods of identifying outliers involve median and quartile range, which are robust as they are less sensitive to outliers (Kwak and Kim, 2017). A box plot can also be used to identify outliers where any data point that lies above and below the 75th and 25th percentiles, respectively, are considered outliers (Kwak and Kim, 2017).

This study used the skewness and kurtosis absolute values to study the shape and distribution of the GFSI indicators and determine outliers (Thomas et al., 2017). Any indicators with absolute values above two and 3.5 for skewness and kurtosis, respectively, were considered outliers. The reason for using skewness and kurtosis is that it is robust and the percentiles are generated in this case, which further supports identifying an indicator as an outlier (Thomas et al., 2017; JRC-EC, 2008). After identifying the outliers, different method are applied to treat the outliers to prevent them from acting unintended benchmarks (Thomas et al., 2017; Ghosh and Vogt, 2012). Some ways of handling outliers include trimming, winsorisation, Median Absolute Deviation (MAD) or M-estimation methods (Thomas et al., 2017; Ghosh and Vogt, 2012; JRC-EC, 2008; Leys et al., 2013; Kwak and Kim, 2017).

The study utilised the winsorisation method to remove the identified outliers from the GFSI. Winsorisation is considered robust for removing outliers as the resulting winsorised values are consistent with original data points (Kwak and Kim, 2017). Winsorisation involves replacing the values being tested for outliers with expected value where the outlier values are replaced with the largest or second smallest value in observations excluding outliers (Thomas et al., 2017; Kwak and Kim, 2017). The winsorisation method was also essential in this study, as most of the GFSI indicators are continuous variables (Thomas et al., 2017).

Paired t-tests and Spearman's rank correlation were used to test the statistical significance of the changes caused by updating Kenya's 2019 GFSI database and the statistical significance of outliers' winsorisation. A paired t-test is essential when determining if the mean of a dependent variable is the same in two related groups, who undergo two different conditions such as the winsorisation of outliers in one group. The difference between the paired values is assumed to be normally distributed, while the null hypothesis is that the expected value is equal to zero. The paired t-test was used in this study to determine if the GFSI's mean before and after the winsorisation of outliers and after updating Kenya's outdated indicators would differ from the 2019 GFSI result. The 2019 GFSI result was used as the reference year.

The Spearman rank correlation test is a nonparametric test used to determine the strength of association between two variables that are measured on an ordinal or continuous scale. The Spearman rank correlation test was used in this study to test for the changes in the GFSI rank before and after the winsorisation of outliers and updating Kenya's 2019 GFSI outdated data.

The Spearman's *rho* values were used to determine the correlation between the 2019 GFSI and the winsorised values and updated Kenya's 2019 GFSI indicators. The Spearman's rho values less than one indicate a strong correlation between the two groups: the 2019 GFSI result and the winsorised and updated Kenya's 2019 GFSI values. Table 5.1 summarises the methods and procedures used for the study.

Table 5.1: Summary of the methods and procedures for achieving the study's objective

Sub-problem	**Data source**	**Analytical method approach**	**Specific approach**	**Variables**
Does the 2019 GFSI result contain outdated data and outliers?	The 2019 GFSI database	Quantitative approach	Descriptive statistics Excel calculations The winsorisation of outliers, Paired t-test and Spearman's rank correlation test	All indicators in the 2019 GFSI database
What is the statistically significant effect of outdated data and outliers on the affordability, availability and quality and safety dimensions score for Kenya's 2019 GFSI result?	The 2019 GFSI database	Quantitative approach	Descriptive statistics Excel calculations Paired t-test and Spearman's rank correlation test	All indicators in the 2019 GFSI database
Does updating Kenya's 2019 GFSI data result in a statistically significant change in the overall GFSI score and rank relative to the 113 countries?	The 2019 GFSI database, Kenya National Beaurue of statistics, world bank, Konema, United Nation, USAID	Quantitative approach	Descriptive statistics Excel calculations Paired t-test Spearman's rank correlation test	Updated Kenya's 2019 GFSI database and 2019 GFSI database

Source: Author's compilation.

5.3 Chapter summary

In this chapter, the methodologies used for achieving the research objectives were discussed. Although numerous methodologies exist for handling outliers in composite indicators, different approaches generate different results, some robust while others are not. Therefore, it is critical to identify the type of data (continuous or discrete) and identify and remove outliers before data analysis – outliers could bias results leading to over or underestimation.

CHAPTER 6: RESULTS AND DISCUSSION

6.1 Introduction

The results and discussion of the research objectives findings as stated in chapter one, section 1.4, are presented in this chapter. The first objective was to determine the proportion of outdated data and outliers in the 2019 GFSI. The second objective was to test the statistically significant effect of the outdated data and outliers on Kenya's GFSI dimension scores and ranking in the 2019 GFSI result. Lastly, the third objective was to determine if updating Kenya's outdated data results in a statistically significant change to Kenya's overall GFSI score and rank relative to the 113 countries.

6.2 The proportion of outdated data and outliers in the 2019 GFSI

The study's first objective was to determine the proportion of outdated data and outliers in the 2019 GFSI result. The results for the analyses of outdated data and outliers are presented in the two subsections that follow.

6.2.1 The proportion of outdated data in the 2019 GFSI data

The GFSI attempts to use the most current data from the previous year. For example, the GFSI should have attempted to use available 2018 data when reporting for 2019. However, it was noted that current data was lacking for some indicators. Sixteen (44%) of the 34 indicators reported by the GFSI in 2019 were based on data older than 2018. Data from 2005 was essentially the oldest data point used in the 2019 GFSI for reporting the proportion of the population living under the global poverty line in Azerbaijan. Other older data points included: 2008 for Angola and Japan and 2009 for Mali, Nigeria and Sudan.

As seen in Figure 6.1, six of the indicators reported in the 2019 GFSI were based on 2013 data. The use of such outdated data could constrain the useful information the GFSI conveys (Santeramo, 2015b). All outdated indicators in the GFSI dimensions across the assessed countries are listed in Annex C.

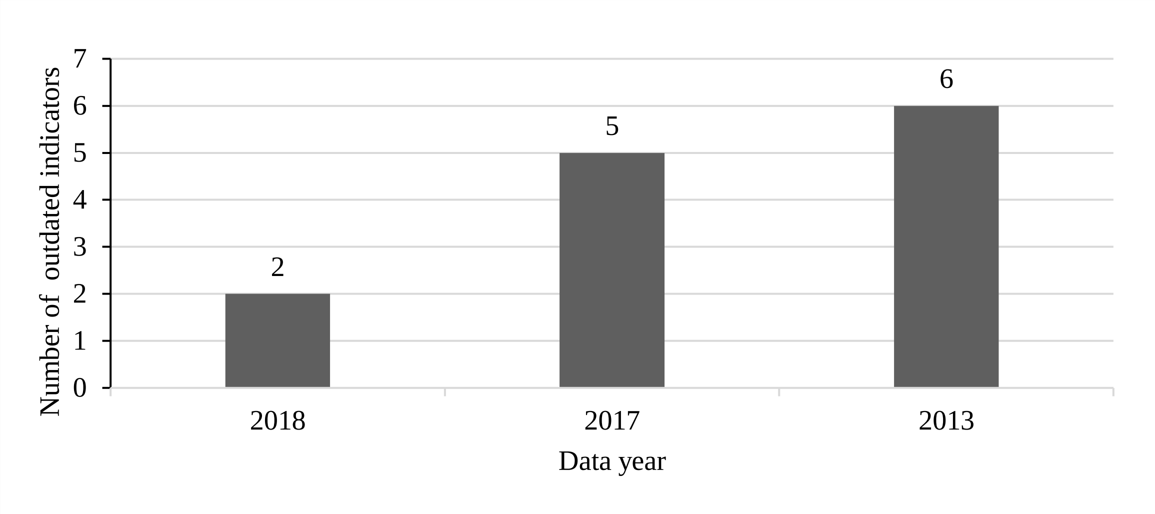

Figure 6.1: Outdated indicators for all countries per data year in the 2019 GFSI database
Source: Author's compilation from GFSI data (EIU, 2019).

The quality and safety dimension had the highest number of outdated data entries. Seven (47%) of the 11 indicators in this dimension used data from 2018 or older. The micronutrient availability, a composite indicator measuring dietary availability of vitamin A, iron and zinc in the foods supplied, used 2013 data (oldest data point in the quality and safety dimension). Micronutrient availability in foods is essential for the mental, physical and social well being of individuals. The lack of micronutrients could lead to increased mortality rates in children and women, reduced work productivity in adults and impaired mental and physical developments in children, among other consequences (Gödecke et al., 2018).

However, despite the critical role that it plays in human health, between 2012 and 2018, the GFSI reported the micronutrient availability indicator based on the average of 2005 to 2007 data (EIU, 2019). The micronutrient availability indicator was updated from 2005-2007 to 2013 data in the 2019 GFSI report. The EIU (2019) highlighted that only 70% of the countries had completed a data collection on undernourishment and nutrient deficiencies over the past five years. Moreover, some countries had also exceeded the five-year threshold without collecting nutrition or undernourishment data (EIU, 2019). Due to the unavailability of updated data, these critical indicators on micronutrient availability were therefore reported based on outdated data

Since 2012, the GFSI also reported dietary diversity and protein quality based on averaged data for 2009 to 2011 (EIU, 2019). Protein quality indicator measured the availability of high-quality proteins in diets, while dietary diversity measured the proportion of non-starchy foods other than cereals, roots and tubers included in dietary energy consumption. High protein quality is critical in providing essential amino acids, while a larger share of non-starchy foods in dietary energy consumption signifies diverse diets inclusive of all food groups (EIU, 2019). However, using outdated data to report the indicators may hinder useful information on countries nutritional quality of average diets.

The ability to store food safely and the proportion of the population with access to potable water were the only quantitative indicators based on 2017 data in the quality and safety dimension. The remaining quantitative indicators (dietary availability of vitamin A, iron and zinc, dietary diversity and protein quality) in this dimension (quality and safety) were all based on 2013 data. The agricultural import tariffs and the gross domestic product per capita (US$ PPP) in the affordability dimension were the only indicators reported based on 2018 data, while the urban absorption capacity (availability dimension) typically used data from 2015-2019. For the qualitative indicators, the panel of experts at EIU qualitatively assigned zero or one values. For other qualitative indicators, the values assigned were zero to four based on the available 2018 data.

6.2.2 The proportion of outliers in the 2019 GFSI database

Indicators with absolute values greater than two for skewness and absolute values greater than 3.5 for kurtosis were treated as outliers. Ten (29%) of the 34 indicators identified as outliers in the 2019 GFSI are shown in Table 6.1. The quality and safety dimension only had one outlier, namely the indicator on the agency to ensure the safety and health of food, which was an outlier for all countries.

Table 6.1: Indicators identified as outliers in 2019 GFSI data

GFSI outlying indicators	Skewness	Kurtosis
Affordability		
The change in average food costs	8.361	79.501
Agricultural import tariffs	2.442	11.062
The presence of food safety-net programmes	3.105	10.642
Availability		
Change in dependency on chronic food aid	7.331	58.548
Public expenditure on agricultural research and development	6.748	51.427
Existence of adequate crop storage facilities	2.717	8.381
Irrigation infrastructure	2.681	12.161
Urban absorption capacity	3.204	21.769
Food loss	2.799	15.941
Quality and safety		
Agency to ensure the safety and health of food	2.283	6.213

Source: Author's compilation from 2019 GFSI data (EIU, 2019).

Safe food promotes health and is free of foodborne diseases caused by microorganisms, such as bacteria, virus, parasites, chemicals and foodborne zoonoses transferred from animals to humans and other associated risks in the food chain (WHO, 2013). Moreover, food safety environment and proper sanitation positively correlate to food security at the household, individual and national level (EIU, 2019). Measures such as food inspection, labelling and traceability (by governments or private institutions) are some ways of ensuring only safe and high-quality foods are supplied to consumers (WHO, 2013).

Six (60%) of the ten identified outliers were in the availability dimension (highest for all dimensions). The availability dimension also had the highest number of outliers (three (50%) of the six identified outliers) in the 2016 GFSI. Indicators on the agency to ensure food safety and health, agricultural import tariffs, food losses, public expenditure on agricultural research and development and urban absorption capacity indicators were outliers in the 2016 and 2019 GFSI data (Thomas et al., 2017). Overall, seven of the ten identified outliers were also the indicators with outdated data, including the change in the average food costs, change in dependency on chronic food aid, food losses, irrigation infrastructure, the proportion of the population living under the global poverty line and public expenditure on agricultural research and development (EIU, 2019).

After identifying the outliers, winsorisation carried out to prevent the outliers from acting as unintended benchmarks. The seven GFSI quantitative indicators were winsorised as shown in Table 6.2: The results of the winsorised outliers in the 2019 GFSI The agency to ensure the safety and health of food, the existence of adequate crop storage facilities and the presence of food safety-net programmes were qualitative indicators and could not be winsorised.

Table 6.2: The results of the winsorised outliers in the 2019 GFSI

Winsorised outliers	Skewness	Kurtosis
Change in average food costs	1.777	5.399
Agricultural import tariffs	1.270	4.862
Change in dependency on chronic food aid	2.358 / 1.665	7.477 / 4.044
Public expenditure on agricultural R&D	1.711	5.786
Irrigation infrastructure	1.571	4.317
Urban absorption capacity	1.273	5.982
Food loss	0.829	2.472

Source: Author's calculation using 2019 GFSI data (EIU, 2019).

6.2.3 The results on Kenya's proportion of outdated data and outliers in the 2019 GFSI database

Kenya had 13 (38%) outdated indicators (older than 2018) out of the 34 indicators in the 2019 GFSI, as shown in Table 6.3. Six (46%) of the indicators reported for Kenya were based on 2013 data – of which five were in the quality and safety dimension, while in the availability dimension, only the indicator measuring food losses was based on 2013 data. Essentially, indicators measuring micronutrient availability (dietary availability of vitamin A, iron and zinc), dietary diversity and protein quality were the oldest data points in Kenya's 2019 GFSI database (2011-2013).

However, Kenya has made considerable effort in terms of improving micronutrient availability. Food fortification was one way of reducing deficiencies of essential micronutrients such as availability of vitamin A, iron and zinc in children and women to reduce morbidity and mortality (Linda et al., 2020). The Kenya National Nutrition Action Plan 2012-2017, a midterm policy highlighted, food fortification, promotion of dietary diversity and supplementation as ways to increase the supply of essential micronutrients to Kenyans (Gok, 2017). Since 2012, the Kenyan government has implemented a mandatory fortification of staple foods. The Kenya Bureau of Standards (KEBS) plays a critical role in ensuring quality and safe foods are available to consumers. KEBS ensures proper labelling, inspection and traceability of the food supplied in markets and food supplements issued in school feeding programmes (Gok, 2017).

Table 6.3: Kenya's outdated data points in the 2019 GFSI

Dimension and indicators	**Data year**
1) Affordability	
The proportion of the population living under the global poverty line	2015
2) Availability	
Change in dependency on chronic food aid	2013-2017
Public expenditure on agricultural R&D	2017
Irrigation infrastructure	2016
The volatility of agricultural production	2012-2016
Food loss	2013
3) Quality and safety	
Dietary diversity	2011-2013
Dietary availability of vitamin A	2013
Dietary availability of iron	2013
Dietary availability of zinc	2013
Protein quality	2011-2013
The proportion of the population with access to potable water	2017
Ability to store food safely	2017

Source: The 2019 GFSI data (EIU, 2019).

The GFSI usually assesses the change in the dependency on chronic food aid and the volatility of agricultural production (availability dimension) based on recently available data over the past five years. The GFSI in 2019 reported the indicators (the change in the dependency on chronic food aid and the volatility of agricultural production) for all countries on average 2013-2017 and 2012-2016 data (outdated) respectively. The dependency on chronic food aid indicator measured how reliant a country had been a recipient of chronic food aid over the past five years.

Despite not being majorly reliant on emergency chronic food aid for the past five years, Kenya suffered a severe drought in 2017, which negatively affected food security (EIU, 2019). More than 2.7 million Kenyan's in the Northern and North-Eastern regions were worst affected, almost entirely depending on emergency food aid during the drought (FAO, 2017; Lolemtum et al., 2017). Due to its extreme economic effects on the economy and overall negative impact on food security, the drought was declared a national disaster (FAO, 2017; FEWS.NET, 2018). However, the GFSI assessing Kenya's change in dependency on chronic food aid using outdated data in 2019 may not take into account the effects caused by the drought (Thomas et al., 2017)

Kenya's indicator of the volatility of agricultural production was also outdated. The volatility of agricultural production measured the fluctuations in agricultural productivity (in standard deviation) over the past five years to predict and plan for a consistent future food supply. The volatilities in agricultural production may arise due to several factors, including but not limited to unpredictable shocks, such as bad weather, diseases, pests or price changes (EIU, 2019). In Kenya, climate change is one key contributing factor to agricultural production's volatility (FAO, 2017; Lolemtum et al., 2017). For example, good planting seasons with average rainfall could be followed by consecutive years of droughts in some areas while other areas could be affected by above-average rainfall, leading to flooding and destruction of crops (FEWS.NET, 2018; FEWS.NET, 2020b). However, the use of outdated data by the GFSI may not consider how factors such as drought or floods contribute to the volatility of agricultural production in Kenya and bias Kenya's score and ranking in the GFSI.

Public expenditure on agricultural research and development measured the ratio of the agricultural share of government expenditure divided by the share of the agricultural value-added to the GDP (EIU, 2019). Public expenditure on agricultural research and development plays a critical role in developing technology and the innovations necessary to increase agricultural productivity while reducing environmental impact (EIU, 2019). Despite playing a critical to Kenya's food security and thereby better performance in the GFSI, Kenya reduced its ratio of public expenditure on agricultural research and development in the 2019 GFSI by a ratio of more than 12 (EIU, 2019).

Kenya's low public expenditure on agricultural research and development was evident in its poor scores towards implementing the Malabo Declaration on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods (Benin et al., 2018). For example, Kenya was highlighted not to be on track in the indicator on public expenditure on agricultural research and development in the 2018 Biennial Review report on progress made towards achieving the Malabo Declaration on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods (Benin et al., 2018). The Biennial Review report recommended that Kenya increase its public expenditure on agricultural research and development (Benin et al., 2018).

Kenya's indicator measuring the proportion of the population living under the global poverty line in the affordability dimension was also outdated (2015 data). The GFSI had reported that 32.7% of the Kenyan population was living below the global poverty line since 2012 (2005 data point) (EIU, 2019). In Kenya, poverty is a challenge caused mainly by economic inequality and corruption (GoK, 2018). Rural areas in Kenya remain the worst affected by poverty (GoK, 2018). The Kenyan Government has implemented short term, midterm and long term policies to fight poverty (GoK, 2018). For example, poverty reduction was one of the government's Big Four Agendas' (GoK, 2018). Other Kenyan Government efforts of fighting poverty include the provision of free maternal health care services, social protection programmes such as cash transfers, urban food subsidies, school feeding programmes and health insurance through the Kenya National Safety Net Programme (NSNP) (GoK, 2018).

The agricultural import tariff indicator measured the country with the most favoured tariffs on all agricultural imports (EIU, 2019). High agricultural import tariffs can increase the cost of food, therefore reducing food affordability. Kenya's agricultural import tariffs have been between 19.7% in 2012 and 20.3%, the highest in 2019 (EIU, 2019). Kenya relies heavily on rainfed agriculture (Musembi and Scott-Villiers, 2015). Only a small proportion of the agricultural land is equipped with irrigation infrastructure (0.6% of the land was equipped with irrigation infrastructure in the 2019 GFSI (EIU, 2019). As a result, Kenya suffers the challenge of maize shortage (staple food), explaining the low agricultural import tariffs. Kenya supplements the low maize production through maize importation from global or regional markets (Musembi and Scott-Villiers, 2015).

The null hypothesis for the first objective was that the 2019 GFSI database did not contain outdated data and outliers. This null hypothesis was rejected because the 2019 GFSI database contained outdated data and outliers. The GFSI reported six indicators based on 2013 data (outdated) in the quality and safety dimension in 2019. Overall, 16 quantitative indicators were reported based on data older than 2018. Only the agricultural import tariffs and the gross domestic product per capita (US$ PPP) indicators reported in the 2019 GFSI were based on 2018 data. Ten indicators had outlier datapoints. The availability dimension had the highest number of outliers in the 2016 and 2019 GFSI (Thomas et al., 2017). Furthermore, indicators reporting on the agency to ensure the safety and health of food, agricultural import tariffs, food losses, the public expenditure on agricultural research and development and urban absorption capacity were outliers in the 2016 and 2019 GFSI data (Thomas et al., 2017).

For Kenya, the findings on the proportion of outdated data and outliers were valid only for outliers - Kenya had no outlier datapoint in the 2019 GFSI. However, despite Kenya not having any outliers in its 2019 GFSI database, outliers in other countries' data point affected Kenya's score and rank as described in section 6. 3. Kenya's 2019 GFSI database had 13 (38%) outdated indicators, of which six (46%) were reported based on 2013 data (the oldest data points) across the availability and quality and safety dimensions. This finding on outdated data for Kenya concurs with (Benin et al., 2020), whose study found Kenya to have outdated data in critical indicators such as ending hunger and halving poverty in the Malabo Declaration on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods. Benin et al. (2020) also found that most available data were in low quantity and quality.

6.3 Paired t-test and Spearman's rank correlation results for the winsorised outliers in the 2019 GFSI

The study's second objective was to determine the statistically significant effect of outdated data and outliers on Kenya's 2019 GFSI dimension scores and rank. First, a global analysis of the impacts of outliers in the GFSI dimensions is discussed, followed by outliers' impact on Kenya's 2019 GFSI dimension scores. The paired t-test on the GFSI mean score before and after the winsorisation of outliers are shown in Table 6.4.

The 2019 GFSI mean score for the affordability and availability dimensions reduced by -6.257 and -3.195 points, respectively, after the winsorisation of outliers. The null hypothesis that there was no statistically significant difference in the GFSI's mean scores before and after the winsorisation of outliers was rejected with the p-values of 0.000, significant at 0.05 significance level (for affordability, availability and overall 2019 GFSI).

Table 6.4: Paired t-test result for the winsorisation of outliers in the GFSI dimensions

Dimensions	The GFSI's mean before the winsorisation	The GFSI's mean after the winsorisation	The GFSI's mean difference	P-value	t-values	Number of observations
Affordability	67.584	61.327	-6.257	0.000***	-13.517	113
Availability	59.416	56.221	-3.195	0.000***	-7.999	113
Quality and safety	60.960	60.958	-0.002	0.762	-0.715	113
Overall	62.929	58.982	-3.947	0.000***	-13.050	113

Ho: mean(diff) = 0 Ha: mean(diff) # 0 degrees of freedom =112
Source: Author's calculation from 2019 GFSI data (EIU, 2019).

The paired t-test result for the quality and safety dimension was not significant (p-value of 0.762 at 0.05 significance level) because no indicator was winsorised for this dimension. Table 6.5 shows the seven countries with outlier indicators in the 2019 GFSI's affordability and availability dimensions. A graphical representation of outliers across different countries is presented in Appendix D.

Note: scores for indicators in all the GFSI dimensions are out of 100.

In the affordability dimension, the change in average food cost was an outlier. The change in the average food costs indicator measured the percentage change in the cost of an average food basket in a country since 2010 as captured through the Food Consumer Price Index (FCPI) (EIU, 2019). The FCPI tracked the change in the cost of an average food basket using 2010 =100 as the base year. A sharp increase in the cost of an average food basket could imply a reduction in food affordability, affecting consumption, especially among low-income households who spend significant proportions of their income on food.

Venezuela had the most significant increase in FCPI of 2695.2% in the 2019 GFSI. The cost of an average food basket in Venezuela increased by 2695.2% in 2019 compared to the same food basket in 2010. Venezuela has experienced political turmoil since 2016, which could be negatively contributing to the increase in food costs. For example, Venezuela's cost for an average food basket had increased only by 649.4% from 2010 to 2015 (EIU, 2019). However, the same food basket cost increased by more than 100% (2695.2%) in 2019 compared to 2010, implying that Venezuela's political situation has worsened, especially after the 2018 presidential elections exacerbating affordability. By contrast, Ireland's cost of an average food basket changed (reduced) by 92.7% in 2019 compared to the cost of the same food basket in 2010 (EIU, 2019). Unlike Venezuela, Ireland is one of the most food-secure countries with high food affordability (EIU, 2019).

Table 6.5: Countries identified to have outliers in the 2019 GFSI database

Indicators outlying in the 2019 GFSI database	**Unit of measuring the indicator**	**Countries with outlying indicators**	**Outlying indicator value**	**2019 GFSI mean**
The change in average food costs	Food CPI	Venezuela	2695.2	186.12
Agricultural import tariffs	Percentage	Egypt	63	15.44
The change in dependency on chronic food aid	Change in emergency food aid per capita over the past five years	Syria	29.8	0.66
Public expenditure on agricultural research and development	The ratio of agriculture share of government expenditure, divided by the value-added agriculture share of GDP	Singapore	11.4	0.56
Irrigation infrastructure	Percentage of land area equipped for irrigation	Egypt	99.5	10.41
Urban absorption capacity	Percentage of real GDP change minus the urban growth rate	Venezuela	-22	0.90
Food losses	The ratio of total waste to total domestic supply quantity (tonnes)	Sierra Leone	34.8	5.60

Source: 2019 GFSI database (EIU, 2019).

Venezuela's affordability score reduced by 1.3 points (15.8 to14.5) after the winsorisation of the change in the average food cost indicator. The result could imply that the presence of outliers in the affordability dimension inflated Venezuela's score by acting as unintended benchmarks (Thomas et al., 2017).

Syria's FCPI also increased by 935.9% from 2010 to 2019. The increase in Syria's FCPI since 2010 could be attributed to the ongoing civil war (EIU, 2019). For example, political stability was one indicator where Syria had the weakest score of less than 20 in the 2019 GFSI result (EIU, 2019). Moreover, Syria lacks essential quality food safety-net programmes, worsening the cost of an average food basket and overall food affordability. The availability of safety net programmes is one way to cushion households against shocks by ensuring continued access and consumption of food by the vulnerable, even with the presence of shocks (EIU, 2019). Syria's affordability score reduced by 18.1 points from 35 to 16.9 after the outliers winsorisation (the change in average food costs).

The urban absorption capacity indicator (availability dimension) was measured in terms of the percentage real GDP change minus the urban growth rate (EIU, 2019). A country's capacity to absorb the stresses placed on it by urban growth influences its ability to ensure food security (EIU, 2019). Venezuela's urban absorption capacity was 22 % lower than any country in the 2019 GFSI. Venezuela's GDP per capita (US$ at PPP) in 2013 was 18,237.2 US dollar, while in 2019, Venezuela's GDP per capita reduced to 8,800.0 US dollars (EIU, 2019). This reduction in Venezuela's GDP contributes to the negative urban absorption capacity because the percentage GDP is directly proportional to the urban growth rate. The higher the percentage GDP, the higher the urban growth rate (EIU, 2019). Venezuela's political turmoil also plays a crucial role in reducing the GDP over the years, especially with its significant inflation (highest in the world), resulting in high food prices, unemployment and overall high living cost (EIU, 2019). Venezuela's availability score was reduced by 1.1 points from 32 to 30.9 after the winsorisation of the urban absorption capacity indicator.

Besides Venezuela, 26 (23%) countries also had negative urban absorption capacities in the 2019 GFSI data. The Sub-Saharan Africa region accounted for 11 (42%) of the countries. The Asia and Pacific, Central and South America, Gulf Cooperation Council and the Middle East and North Africa regions had one, seven, five and two country(s) respectively with negative urban absorption capacities. Saharan African countries typically have a low GDP growth rate compared to industrialised and developed countries; for example, Singapore's GDP in the 2019 GFSI was 101,347.4 US$ at PPP while Burundi's GDP for the same year was 762.0 US$ (the lowest in the GFSI) (EIU, 2019). The low GDP growth rate in Saharan African countries could contribute to the high costs of living, lack of employment or inadequate infrastructure in the urban areas and consequently, low urban absorption capacity (Berger and van Helvoirt, 2018).

By contrast, Equitorial Guinea had a 5.9% higher urban absorption capacity than any country included in the 2019 GFSI. Unlike Venezuela, Equatorial Guinea's GDP has increased from 1,625.6 US dollars in 2012 to 2,630.2 US dollars in 2019 (EIU, 2019). Equatorial Guinea's GDP growth could have contributed to the high urban absorption capacity in the 2019 GFSI. Equatorial Guinea has also made considerable efforts in improving urban lives and the country at large. For example, the country (Equitorial Guinea) launched a Green Climate Fund country programme in October 2019 (GoG, 2019). The Green Climate Fund country programme was a policy documenting strategies to ensure the improved provision of services such as housing, transport and waste management, all of which are essential services to the urban dwellers (GoG, 2019).

The agricultural import tariff indicator measured the average applied most-favoured-nation (MFN) tariff on all agricultural imports as a percentage. High agricultural import tariffs in a country can increase the cost of food imports and result in high food costs for consumers. Egypt had the highest agricultural imports tariff in 2019. Egypt's agricultural import tariff was 63% higher than the mean (15.44%) for all countries in the 2019 GFSI. However, it was noted that Egypt's agricultural imports tariffs value had never been lower than 60% since 2012. Egypt could be imposing high agricultural tariffs to protect the domestic agricultural producers from international competitions (EIU, 2019). For example, Egypt suffered from potato shortages in 2018, which took the government's intervention to increase potato supply. Therefore, Egypt's high agricultural import tariffs could be considered critical in protecting the local potato producers from making losses from competition during such shortages, especially from cheap importation (EIU, 2019).

However, Egypt's high agricultural imports tariffs are mirrored negatively in its poor performance in the affordability dimension compared to the availability and the quality and safety since 2017 (EIU, 2019). For example, Egypt's price of an average food basket had nearly tripled over the last five years, affecting food affordability (EIU, 2019). The increase in the cost of food could typically be explained by factors such as hoarding of the agricultural commodities by local producers to cause shortages and price hikes to gain profits at the expense of the consumers; an example is the case of Egypt's potato shortage of 2018 (EIU, 2019). Egypt's affordability score reduced by 20 points from 57.6 to 37.6 after the agricultural imports tariff indicator's winsorisation.

Egypt was also an outlier in the irrigation infrastructure indicator in the 2019 GFSI. The irrigation infrastructure measured the proportion of cultivated agricultural land area equipped for irrigation in a country. The availability of irrigation infrastructure in a country can support farmers' ability to provide consistent water supply to crops, reducing reliance on rainfed agriculture. Egypt's proportion of cultivated agricultural land area equipped for irrigation was 99.55% higher than the GFSI's mean of 10.41% for all countries. Egypt's high proportion of cultivated agricultural land area equipped for irrigation is because it is a desert country that cannot rely on rain-fed agriculture but irrigation to produce food. Egypt's availability dimension score reduced by four points from 70 to 66 after the winsorisation, signifying that outliers in the availability dimension inflated Egypt's irrigation infrastructures score.

The change in the dependency on chronic food aid indicator measured the change in the dependency on emergency food aid per capita in a country over the past five years (EIU, 2019). A country's dependence on chronic food aid increases when the available food supply is insufficient to meet the population's demand (EIU, 2019). Due to the country's persistent conflict and insecurity, Syria was almost entirely (90%) reliant on emergency food aid in 2019. Syria was one of the countries the GFSI highlighted to have deteriorating food security despite the increase in the average food supply in most regions (EIU, 2019). The absence of quality food safety net programmes also aggravates Syria's dependence on chronic food aid (EIU, 2019). As with Syria, Yemen had also been (97%) heavily dependent on chronic food over the past five years due to persistent conflict and instability. The winsorisation of the change in the dependency on chronic food indicator reduced Syria's availability dimension score by 0.6 points from 38.9 to 38.3.

The EIU (2019) used investments in agricultural research and development as a proxy to measure countries' progress towards achieving SDG 2.a (zero hunger). Public investment in agricultural research and development was a proxy indicator captured by the Agricultural Orientation Index (AOI) to assess countries' investment in technology development, rural infrastructure and agricultural research and extension service. Public expenditure on agricultural research and development measured the ratio of the agricultural share of government expenditure divided by the share of the agricultural value-added to the GDP. Singapore had the highest AOI (ratio of 11.4) in 2019, followed by Switzerland (ratio of 8.1) (EIU, 2019). While Singapore and Switzerland have a high agricultural investment in agricultural research and extension and development indicator, these countries investments agricultural are essentially towards extensive agricultural research and technology development, unlike the developing countries. Singapore's high investment in agricultural research and development could be related to technological development such as plant and animal gene banks to improve production (EIU, 2019). Singapore's availability dimension's score reduced by 0.7 points from 83 to 82.3 after the winsorisation of outliers in the dimension.

By contrast, Zambia was the only African country with a high share of public investment in agriculture at 75% (a ratio of 2.3) in the 2019 GFSI (EIU, 2019). Compared to Zambia's performance in the same indicator (the public investment in agriculture) under the CAADP, Zambia was not on track in the 2018 Biennial Review report on progress made towards achieving the Malabo Declaration on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods. The Biennial Review report recommended Zambia to increase its public expenditure in agriculture to meet the (CAADP) target of ten per cent, enhancing access to agricultural inputs, technologies and agricultural financial services (Benin et al., 2018).

Zambia's government responded to the 2018 Biennial Review's recommendation through the Ministry of Agriculture and the Ministry of Fisheries and Livestock and their stakeholders (Sikombe et al., 2019). Zambia developed action plans to address these gaps (Sikombe et al., 2019). Some of the actions included increasing public expenditure in agriculture by strengthening agriculture's capacity, improving access to agricultural inputs and technologies through enhanced dissemination of research and technical information and skills, among other efforts. Therefore, Zambia could have improved its ratio of government spending on agriculture from the Biennial Review recommendation, which was mirrored in the 2019 GFSI (EIU, 2019). However, Zambia's poor performance in the public expenditure on agricultural research and development indicator (scored 20.4) in the 2019 GFSI contradicts Zambia's high public investment in agriculture compared to other African countries. Zambia's availability dimension score increased by 2.9 points from 51 to 53.9 after the winsorisation of outliers in the dimension.

The GFSI measured food losses (post-harvest and pre-consumer food losses) as a ratio of total domestic supply of crops, livestock and fish commodities in tonnes to total food losses (EIU, 2019). High food losses can reduce overall food availability in a country. Moreover, food losses can reduce farmers' incomes and necessitate overproduction to account for the lost food. As a result, food overproduction places additional strain on land, water, and the environment (EIU, 2019). The GFSI described food losses as a global challenge in its 2019 methodology. However, low-income countries are worst affected than in developed countries (EIU, 2019). For example, in the 2019 GFSI, low-income countries had 10.10 billion tonnes in food losses while high-income countries only had 2.93 tonnes (EIU, 2019). Sierra Leone's food losses were the highest at 34.8 tonnes in the 2019 GFSI. The high food losses in Sierra Leone could be attributed to a lack of storage facilities, inadequate infrastructure and a lack of cold chain facilities – a common problem across most low-income countries (EIU, 2019). Sierra Leone's availability dimension's score reduced by 6.6 from 40.3 to 33.7 after the winsorisation of outliers in the food losses data point.

The changes in the overall 2019 GFSI scores for countries with outlying data points after the winsorisation of outliers are shown inFigure 6.2. Egypt had the highest reduction in the overall 2019 GFSI score of 9.9 points from 64.5 to 54.6, while Singapore and Venezuela's overall 2019 GFSI scores reduced by 1.1 points each (87.4 to 86.3 and 31.2 to 30.1 respectively. Essentially, all the countries with outlying indicators in the 2019 GFSI database reduced in overall 2019 GFSI scores after the winsorisation of outliers, which could imply that the presence of outliers in these countries' data points could have inflated their overall 2019 GFSI scores (Thomas et al., 2017).

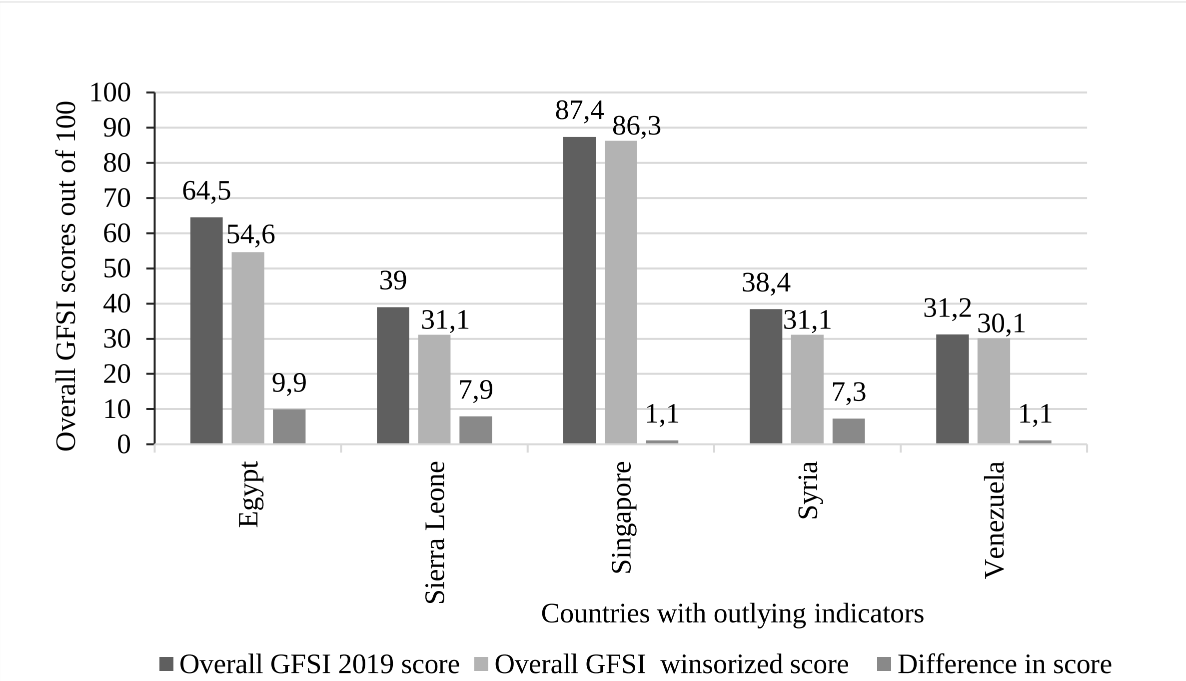

Figure 6.2: Change in overall scores for countries with outlying indicators after the winsorisation of outliers
Source: Author's calculation.

Other countries in the 2019 GFSI without outliers also increased or decreased in scores, while some countries' scores did not change. For example, Singapore, Switzerland and Norway ranked in the top five in the 2019 GFSI reduced in overall 2019 GFSI scores after the winsorisation of outliers. By contrast, Ireland, the United States of America and Finland also ranked among the top five countries in the 2019 GFSI improved in overall 2019 GFSI score after the outliers' winsorisation. Finland, which tied position five with Norway in the overall

2019 GFSI, moved to the top six ranked countries as its overall GFSI score reduced by 1.1 points after the winsorisation of outliers even though it did not have any outlying data point.

While the overall 2019 GFSI scores for the bottom five countries changed after the outliers' winsorisation, their ranks did not shift at all. The same was true for the affordability and availability dimensions - where the bottom and top-five ranked countries did not shift in rank even though their scores reduced after the outliers' winsorisation. The changes in scores for all countries after the winsorisation of outliers in the GFSI dimensions is shown in Appendix A.

6.3.1 The impact of the winsorisation of outliers on Kenya's 2019 GFSI scores

Kenya had an overall GFSI score of 50.7 in 2019, which was 9.5 points improvement compared to 2018's score of 41.9. However, Kenya's overall 2019 GFSI score reduced by six points from 50.7 to 44.7 after the winsorisation of outliers in the affordability and availability dimensions (Figure 6.3). Kenya's overall 2019 GFSI score could have reduced because outliers in other countries' data points inflated Kenya's scores.

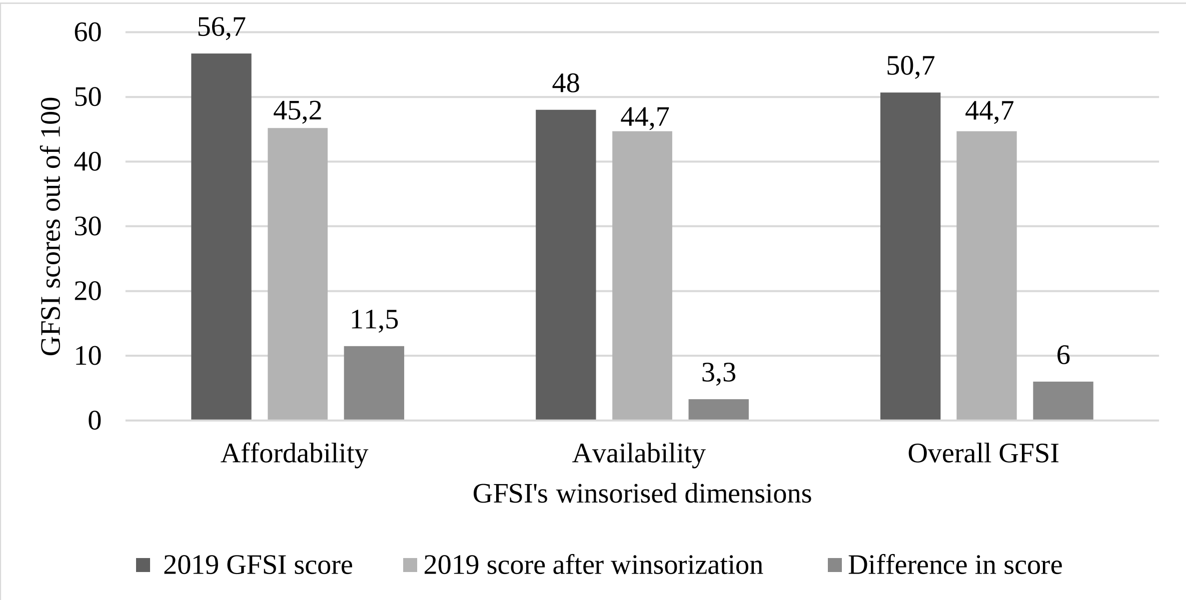

Figure 6.3: Kenya's GFSI scores before and after the winsorisation of outliers.
Source: Author's calculation.

In the affordability dimension, Kenya scored 56.7 in 2019, while in 2018 GFSI Kenya scored 38.2 for the dimension – indicating 18.5 points improvement in 2019 GFSI compared to 2018. Kenya's affordability dimension score reduced by 11.5 points after the winsorisation of the agricultural import tariffs and the change in average food costs data points for Egypt and Venezuela, respectively, in the affordability dimension.

Kenya's availability dimension score also reduced by 3.3 points, from 48.0 to 44.7, after the winsorisation of outliers in other countries data points. Egypt, Syria, Sierra Leone, Singapore and Venezuela's irrigation infrastructure, the change in dependency on chronic food aid, food losses, the public expenditure on agricultural research and development and urban absorption capacity respectively, were outlier data points in the availability dimension. Overall, it could be concluded that outliers in other countries' data points inflated Kenya's overall GFSI, affordability and availability dimension scores by acting as unintended benchmarks, implied by the reduction in scores after the winsorisation of the outliers.

6.3.2 Spearman's rank correlation results for the winsorised outliers in the 2019 GFSI

The Spearman *rho* values in Table 6.6 shows that the GFSI rank in the affordability, availability and the overall 2019 GFSI were not similar after the winsorisation of outliers (Spearman *rho* values close to one). The result meant that the affordability, availability and the overall 2019 GFSI ranks changed after the winsorisation of outliers. The p-values for all the GFSI dimensions were significant at a 0.05 significance level, implying that the winsorisation of the outliers in the 2019 GFSI database changes countries rankings.

Table 6.6: Spearman's rank correlation result on the winsorised 2019 GFSI dimensions

GFSI dimensions	**Observations**	**Spearman's rho**	**p-values**
Affordability	113	0.9829	0.000***
Availability	113	0.9707	0.000***
Quality and safety	113	1.0000	0.000***
Overall GFSI	113	0.9905	0.000***

Source: Author's calculation.

However, the Spearman *rho* value in the quality and safety dimension was equal to one - implying that countries rank in the 2019 GFSI quality and safety dimension before and after the winsorisation of the outliers for the other GFSI dimensions were similar. The reason was that no indicator was winsorised for this dimension (quality and safety dimension).

Note: the GFSI ranks for all countries in the dimension are out of 113 countries

The winsorisation of outliers either increased, decreased or maintained countries rank in the affordability, availability and overall 2019 GFSI. Fourteen countries did not shift in the overall 2019 GFSI rank after the winsorisation of outliers, as shown inbFigure 6.4, while twenty-four countries shifted up or down in overall GFSI rank by one position each. The shifts in all countries rank after the winsorisation of outliers in the 2019 GFSI dimensions are shown in Annex B.

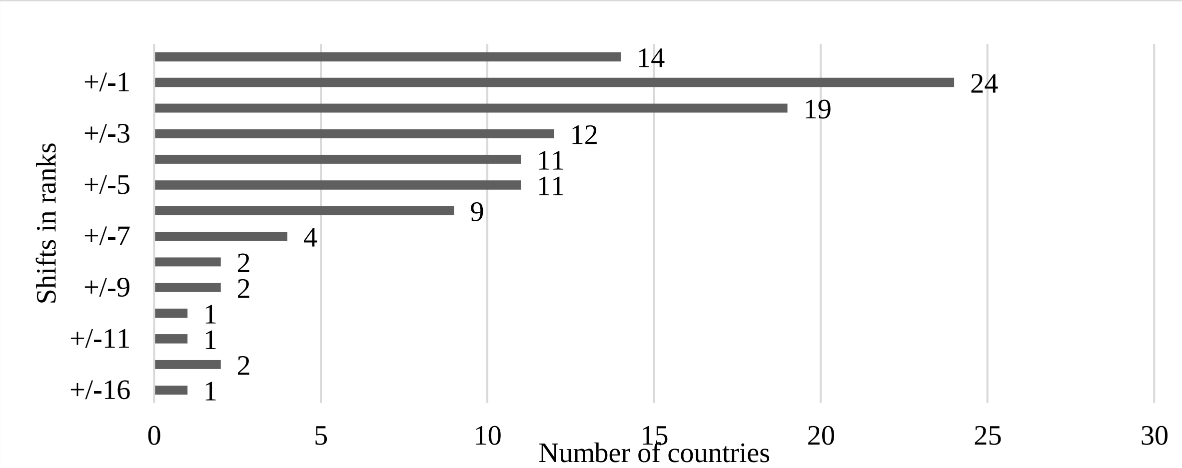

Figure 6.4: Overall shifts in countries' ranking after the winsorisation of outliers in the 2019 GFSI
Source: Author's calculation from the 2019 GFSI data (EIU, 2019).

The shifts in overall ranks for countries with outlying indicators after the outliers' winsorisation is shown in Figure 6.5. Singapore and Venezuela did not shift in overall GFSI rank after the winsorisation of the outliers. However, Egypt had an enormous shift in overall GFSI rank, of 16 positions from 55 to 71. Egypt's enormous shift in rank could be explained by the winsorisation of the agricultural import tariffs and irrigation infrastructure indicators in the affordability and availability dimensions, respectively.

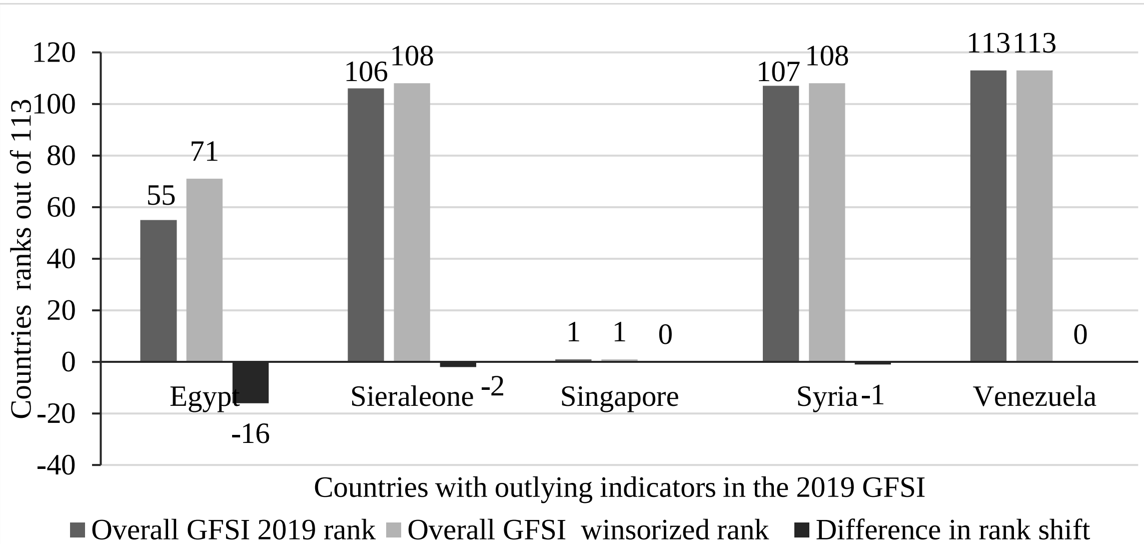

Figure 6.5: Shifts in rank for countries with outlying indicators after the winsorisation of outliers
Source: Author's calculation.

Sierra Leone's overall 2019 GFSI rank shifted by two positions from 106 to 108, while Syria only shifted by one position from 107 to tie rank with Sierra Leone at position 108. Sierra Leone and Syria's food losses and the change in dependency on chronic food aid respectively, were winsorised in the availability dimension.

The shift in countries rankings after the winsorisation of outliers in the affordability dimension is shown in Figure 6.6. Nineteen countries shifted in rank in the affordability dimension by three positions. Fifteen countries did not shift in rank after the outliers' winsorisation in the dimension (affordability).

Among countries with outlying indicators, Singapore retained its rank of position two while Syria and Venezuela were ranked in the second and last positions in the affordability dimension. Egypt, which had an outlier in the agricultural import tariff, had the highest shift in the rank of 16 positions, down from 81 to 97 in the affordability dimension. Sierra Leone only shifted down in rank by two positions from 106 to 108.

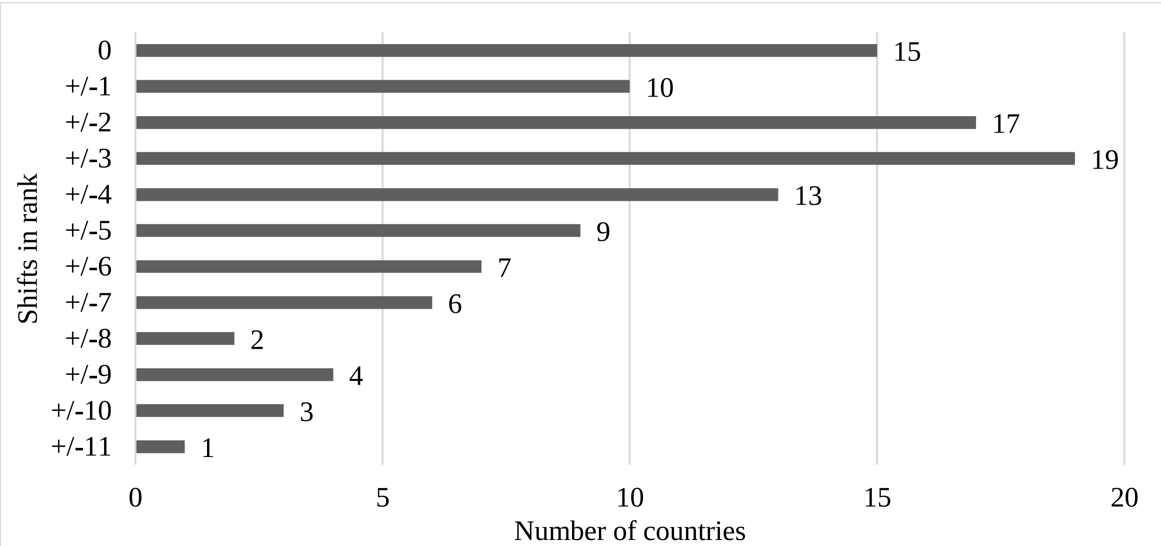

Figure 6.6: Countries' shifts in rank in the affordability dimension after the winsorisation of outliers
Source: Author's calculations.

The shifts in countries rank after the winsorisation of outliers in the 2019 GFSI availability dimension is shown in Figure 6.7. Fifteen countries did not shift in rank after the winsorisation of outliers, while 19 countries shifted up or down in rank by three positions.

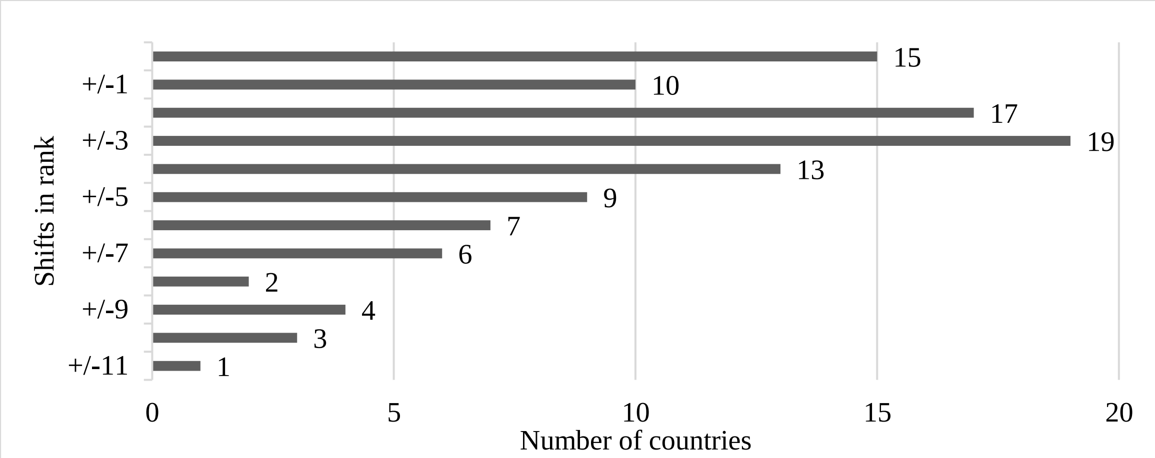

Figure 6.7: Countries' shifts in rank in the availability dimension after the winsorisation of outliers.
Source: Author's calculations.

Syria had the highest shift in rank by ten positions from 109 to 99 in the availability dimension - Syria's change in the dependency on chronic food aid data point was winsorised. Egypt had the second-highest shift in rank by six positions, down from 23 to 29 in the availability dimension. Singapore, which had an outlier in the public expenditure on agricultural research and development indicator, shifted down in rank from the second to the fourth. Venezuela shifted up in rank by three positions from 111 to 108 after the urban absorption capacity indicator was winsorised. Only Sierra Leone, which had an outlier in the food losses data point, maintained position 106 in the availability dimension after the winsorisation of the outliers in the dimension.

6.3.3 Impact of the winsorisation of outliers to Kenya's 2019 GFSI rank

Kenya shifted in the affordability, availability and the overall 2019 GFSI rank after the winsorisation of outliers for other countries in the 2019 GFSI data. Kenya's overall 2019 GFSI rank shifted down by one position, from 86 to 87, while Kenya shifted down in rank by five positions from 83 to 88 in the affordability dimension (Figure 6.8).

However, Kenya's availability dimension's rank improved after the winsorisation of the outliers for other countries in the GFSI dimensions. Kenya shifted up in rank by seven positions in the availability dimension from 93 to 86 - implying that Kenya's rank in the availability dimension was impacted (decreased) by the presence of outliers in the GFSI dimensions - acted as unintended benchmarks (Thomas et al., 2017).

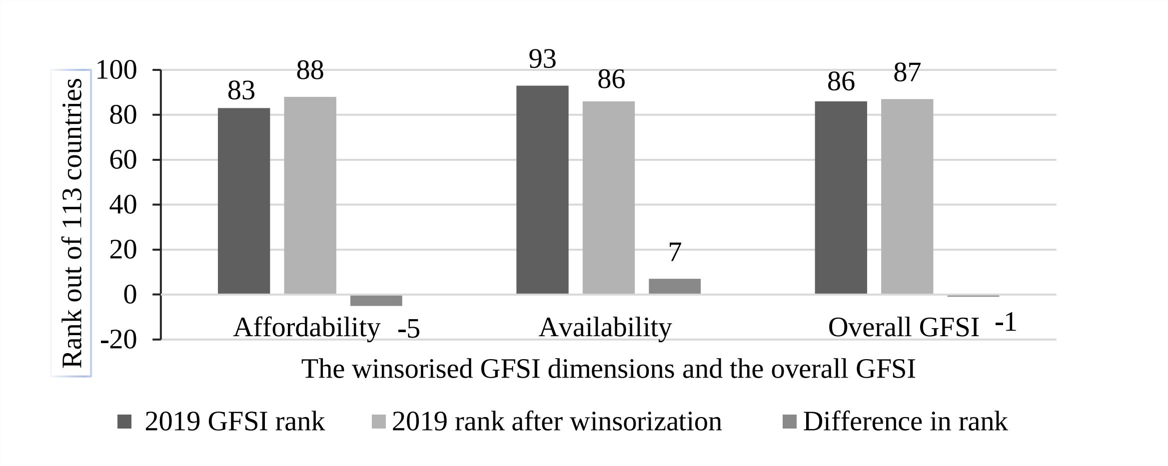

Figure 6.8: Kenya's shifts in 2019 overall GFSI, affordability and availability ranks after the winsorisation of outliers
Source: Author's calculations.

Overall, Egypt and Sierra Leone were outliers in the agricultural import tariff and food losses indicators, respectively, in the 2016 and 2019 GFSI (Thomas et al., 2017). Similarly, the finding on the impact of outliers in the GFSI scores and rank concurred with the 2016 GFSI, where Egypt shifted by more than four positions after the winsorisation of outliers (Thomas et al., 2017). However, contrary to the conclusion by Thomas et al. (2017), that the presence of outliers in the 2016 GFSI was not crucial to the final GFIS scores, the study found that GFSI countries' were impacted by the presence of outliers in the 2019 GFSI even if a country does not have outliers.

6.4 Statistical significance of updating Kenya's outdated data to Kenya's GFSI scores and rank relative to the 113 countries

The study's third objective was to determine if updating Kenya's 2019 GFSI outdated data resulted in a statistically significant change to Kenya's overall GFSI score and rank relative to the 113 countries. Only indicators with data older than 2018 were considered outdated as this was the year before the annual release of the 2019 GFSI results and in line with the definition of outdated data.

Kenya's 2019 GFSI database contained 13 outdated indicators, as discussed in section 6.2.4 (Table 6.3). However, as seen in Table 6.7, only five (38%) of the outdated indicators in Kenya's 2019 GFSI database were updated due to data unavailability. Most websites and data sources searched for updated data; for example, (FAO, 2020; GoK, 2020) had the same data used by the GFSI - this could typically mean that data availability is a challenge, as highlighted by studies on composite indicators (Hudrliková, 2013)

Table 6.7: Comparative data for Kenya's 2019 updated data and the 2019 GFSI data

Updated indicators	2019 GFSI data value	2019 GFSI data year	2019 GFSI data source	Updated data value	Updated data year	Updated data Source
Change in average food costs	214.5	2018	FAO	180.5	2018	Knoema
Gross domestic product per capita (US$ PPP)	3,460.0	2018	EIU	4509.3	2019	World Bank
Dietary diversity	42.0	2011-13	FAO	47.3	2018	KNBS
The proportion of the population with access to potable water	58.9	2017	World Bank	59	2019	Global Waters (USAID)
Ability to store food safely	63.8	2017	United Nations	75	2018	United Nation

Source: Author's compilation.

6.4.1 Paired t-test result for updating Kenya's 2019 GFSI database

The paired t-test to determine if there was a statistically significant difference in the GFSI mean score before and after updating Kenya's 2019 GFSI outdated indicators is shown in Table 6.8Table 6.8. The GFSI affordability and quality and safety dimensions' mean scores increased by 0.003 and 0.021 points, while the overall 2019 GFSI mean score increased by 0.010 points from updating Kenya's five outdated indicators. However, the p-values for the updated GFSI dimensions were not statistically significant at the 0.05 significance level. By contrast, the overall 2019 GFSI was significant at the 0.05 significance level but was not statistical. Therefore, the study accepted the null hypothesis that the GFSI mean before and after updating the outdated indicators for Kenya was not different from zero. The result could imply that, while updating Kenya's outdated indicators increased Kenya's GFSI dimensions and overall scores, the change in score was minimal to impact the overall GFSI mean for all countries.

Table 6.8: Paired t-test result for updating Kenya's 2019 GFSI outdated data

GFSI dimensions	The GFSI mean before updating Kenya's GFSI database	The GFSI mean after updating Kenya's database	The GFSI's mean difference	P-value	t-values	Number of observations
Affordability	67.504	67.507	0.003	0.468	0.729	113
Availability	59.384	59.386	0.002	0.530	0.631	113
Quality and safety	60.960	60.981	0.021	0.344	0.951	113
Overall GFSI	62.888	62.897	0.010	0.048**	2.002	113

Ho:mean(diff) =0 Ha: mean(diff) # 0 degrees of freedom =112

Source: Author's calculation.

Overall, Kenya's quality and safety dimension had the highest increase in the GFSI mean. It had the highest number of updated indicators (the ability to store food safely, dietary diversity, and the proportion of the population with access to potable water). The increase in the GFSI means scores implies the positive impact of updating the data.

6.4.2 Impact of updating Kenya's 2019 GFSI outdated indicators to Kenya's GFSI scores

Kenya's overall 2019 GFSI score increased by 0.5 points from 50.7 to 51.2 after updating five outdated indicators in the affordability and the quality and safety dimension. Kenya's affordability dimension score increased by 0.2 points from 56.7 to 57.2 after updating the change in average food costs and gross domestic product per capita (US$ PPP) indicators in this dimension. The change in the average food cost indicator was updated from 214.5% to 180.5% 2018 data (Knoema, 2020). The gross domestic product per capita (US$ PPP) indicator was updated from 3,460.0 to 4509.3 in US$ PPP using data from the World Bank (WorldBank, 2020b).

In the quality and safety dimension, Kenya's score increased by 2.4 points (43.2 to 45.6) after updating the ability to store food safely, dietary diversity and the proportion of the population with access to potable water indicators. The dietary diversity indicator was updated from 2013 data to 2018 data from the Kenya National Bureau of Statistics (KNBS) (GoK, 2019e).

Kenya's indicators on the ability to store food safely and the proportion of the population with access to potable water were reported in 2019 GFSI based on 2017 data. The ability to store food safely indicator was updated from 2017 to 2018 data, while the proportion of the population with access to potable water was updated from 2017 to 2019 data. Kenya's updated 2019 data on the proportion of the population with access to potable water was obtained from USAID's Global Water website (USAID, 2020).

Overall, Kenya's affordability, availability and the overall 2019 GFSI scores increased after updating the outdated indicators. However, the change in score was minimal to significantly change the overall 2019 GFSI mean score for all countries.

6.4.3 Spearman's rank results for updating Kenya's 2019 GFSI database

The Spearman's *rho* values in Table 6.9 were all equal to one, implying that the 2019 GFSI and the updated 2019 GFSI rank for Kenya relative to the 113 countries were not different. However, Angola, Benin, Cambodia, Kenya and Pakistan shifted in rank after updating Kenya's outdated indicators in the affordability and quality and safety dimensions. These countries' shift in rank implies the positive impact of updating Kenya's data to its score and rank. However, the impact was minimal (not different from zero); 108 countries did not shift in rank.

Table 6.9: Spearman's rank correlation results for updating Kenya's GFSI database

GFSI dimensions	Observations	Spearman's rho	P-values
Affordability	113	1.0000	0.000***
Availability	113	1.0000	0.000***
Quality and safety	113	1.0000	0.000***
Overall GFSI	113	1.0000	0.000***

Source: Author's calculation.

The countries that shifted in rank after updating Kenya's 2019 GFSI database are shown in Figure 6.9. Essentially, Kenya only displaced the immediate countries (Angola, Benin, Cambodia and Pakistan) that had scored higher than it in the affordability, quality and safety dimension and the overall 2019 GFSI score. Benin's overall 2019 GFSI rank shifted down by one position from 85 to 86, while Kenya shifted up in overall 2019 GFSI rank by one position (86 to 85) to replace Benin's initial rank (85).

In the affordability dimension, Kenya displaced Cambodia in rank by one position from 83 to 84 after updating Kenya's change in average food costs and the gross domestic product per capita (US$ PPP). Cambodia and Kenya initially tied position 83 in the 2019 GFSI affordability rank. However, updating Kenya's affordability dimension shifted Kenya up in rank by one position (from 83 to 82) to tie with Honduras position 82.

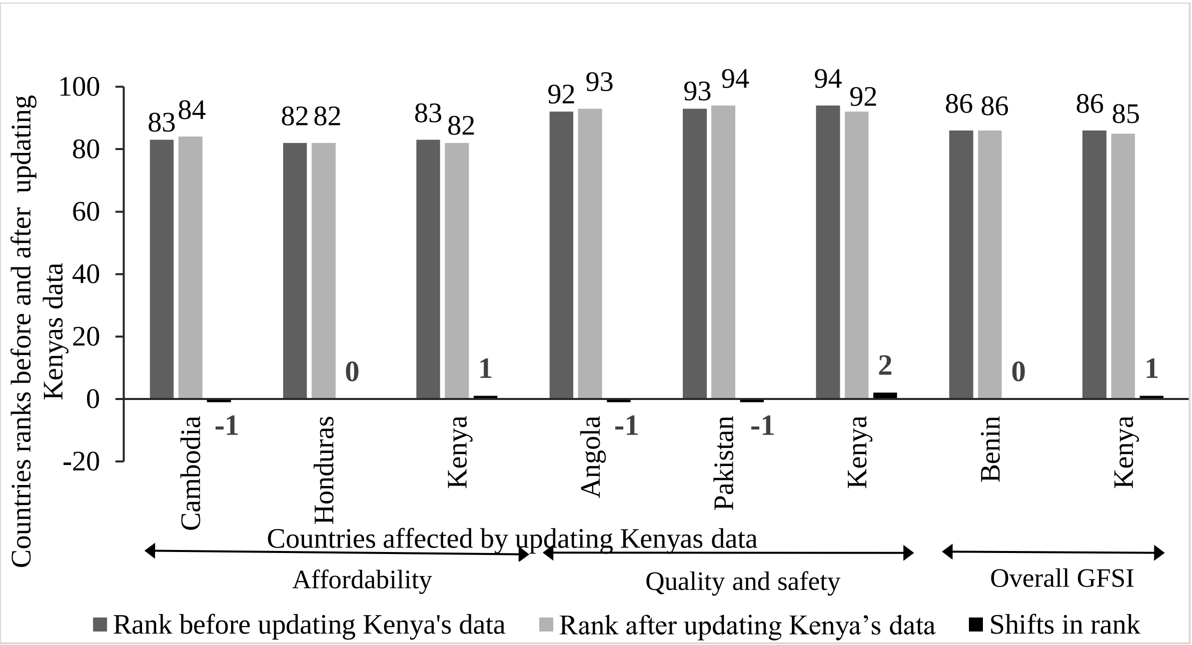

Figure 6.9: Countries shifts in rank after updating Kenya's outdated indicators
Source: Author's calculation.

In the quality and safety dimension, Kenya shifted up in rank by two positions from 94 to 92 from updating the ability to store food safely, dietary diversity and the proportion of the population with access to potable water. Kenya displaced Angola and Pakistan down in rank by one position each - shifting Angola and Pakistan from position 92 to 93 and 93 to 94, respectively.

The improvement in Kenya's score and rank from updating its GFSI outdated indicators was similar to (Benin et al., 2020) findings; after updating CAADP indicators. This study stresses the need for Kenya to update its databases; critical indicators such as the proportion of the population living below the poverty line are reported using outdated data (Benin et al., 2020).

6.5 Chapter summary

The results for the analysis was presented in this chapter. Outliers in the GFSI databases affect countries scores and ranks even if a country does not have outlying data points, making it critical to identify and remove the outliers. Outdated data also affect the GFSI country scores and ranking – Kenya’s score and rank improved after updating its outdated indicators. Overall, it can be concluded that the GFSI should identify and remove outliers and update the outdated indicators o improve the GFSI’s reliability and robustness.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

Over time, developing countries have shown weak performances in benchmarking exercises by composite indicators such as the GFSI. Data unavailability or an updated database due to the financial constraints associated with frequent national data collections are typically among factors limiting these developing countries' performances (Benin et al., 2020). Like other developing countries, Kenya's performance in the GFSI since it was initiated in 2012 has been weak. This study aimed to determine how outdated data and outliers affect Kenya's GFSI score and ranking using the 2019 GFSI result as the base year.

The study's specific objectives were first to determine the proportion of outdated data and outliers in the 2019 GFSI database. The second specific objective was to determine if the outdated data and outliers had a statistically significant effect on Kenya's performance in the 2019 GFSI dimensions scores and rankings. Lastly, the third specific objective was to determine if updating Kenya's 2019 GFSI outdated indicators resulted in a statistically significant change to Kenya's overall 2019 GFSI score and rank relative to the 113 countries. The study tested three hypotheses to achieve the objectives. Winsorisation was used to remove identified outliers, while the Paired t-test and the Spearman rank correlation were used to test the statistical significance of the GFSI scores and ranking, respectively, after the winsorisation of outliers and updating Kenyas's outdated indicators.

Thirteen indicators reported for Kenya in the 2019 GFSI were found to be outdated data. As a result, the study's first hypothesis was rejected due to the outdated indicators in Kenya's 2019 GFSI database. In terms of outliers, Kenya did not have any outliers in its data points. However, the presence of outliers in other countries data points affected Kenya's 2019 GFSI scores and ranking leading to the rejection of the second hypothesis - as Kenya's 2019 GFSI scores and ranking changed after the winsorisation of outliers for other countries data points. Updating Kenya's 2019 GFSI outdated indicators was not significant to Kenya's score and rank. That is, even though Kenya’s score and rank increased from updating the outdated indicators, the change was not significantly different from zero. Therefore, the third hypothesis that updating Kenya's 2019 GFSI outdated indicators did not result in a statistically significant change to Kenya's GFSI score and rank relative to the 113 countries was accepted.

7.2 Conclusions

Overall, the study arrived at three conclusions. First, the outliers in the GFSI data points affects the GFSI's countries' scores and ranking. While the outliers in the GFSI database are generally in specific data points, these outliers affect other countries' score and ranking even if the country itself does not have outliers in its data points. As a result, these outliers could affect the robustness of the GFSI when measuring contributing factors to food security in countries by acting as unintended benchmarks (Thomas et al., 2017). The second conclusion was that despite considerably being one of the best food security composite indicators, the GFSI database contains outdated data that could impact its assessment of countries' scores and ranking. For example, Kenya's 2019 GFSI score and rank increased for the updated indicators in the affordability and quality and safety dimension, thereby increasing Kenya's overall GFSI score. Consequently, the outdated indicators could hinder the GFSI from conveying useful information on countries' food security situations. The outdated data could also hinder countries from tracking progress towards achieving global and regional agreements such as the SDG.

The study's overall conclusion was that despite the GFSI being a robust food security composite indicator, outdated data and outliers affect the GFSI scores and ranking for the assessed countries. In line with the previous studies, the outliers in the GFSI must be identified and removed, while outdated data must be updated.

7.3 Recommendations

First, the study recommended that countries should frequently update and release national data for public access. Because the global goal is to achieve food security and nutrition, open access to data is considered one way for countries to improve global food systems. Open access to national data will not only ease the annual benchmarking process by composite indicators such as the GFSI but will also enable the policy making process due to increased accessibility and availability of national data.

Moreover, open access to such frequently updated national databases will enable researchers to utilise the available data to create new knowledge and products. Consequently, creating new knowledge and products will contribute to evidence-based policy making by formulating essential programmes for achieving food security and nutrition. The availability and open access to national data could also enable the researchers to identify gaps in an economy's different sectors while keeping tracks of the existing implemented programmes on food security or poverty elimination.

Open access to national data will enable composite indicators such as the GFSI to easily access the data for benchmarking exercises, thereby informing countries of their achievements of international or regional commitments such as the SDG. African countries could also benefit from open access to data to identify gaps hindering their achievement of the Malabo Declaration on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods. Benin et al. (2020, have highlighted that the lack of updated national data, especially on critical food security indicators, is one of the hindering factors towards effective policy making in achieving the Malabo Declaration on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods.

Secondly, the GFSI should identify and remove outliers from its data points. As from previous studies on composite indicators, outliers pose a threat to the reliability of composite indicators. When not correctly handled, outliers could hinder the reliability of even the most robust methodologies used for a composite indicator. In line with the previous findings, outliers in the 2019 GFSI were found to impact countries' scores and ranking even if the country itself did not have outliers. As a recommendation, the GFSI should statistically remove the outliers from its database to not act as unintended benchmarks and consequently unreliable results.

7.4 Contribution of the study to the global knowledge

Policymakers often rely on the GFSI results to formulate policies for improving food security at the country, globally and regional levels. However, unreliable results due to outdated data or outliers could affect policy formulation. For example, outliers in one countries’ indicator could inflate another country's score and ranking, thereby hindering the useful information conveyed by the GFSI for the given country. Therefore, this study contributes to the global knowledge of the need to update national data for countries to track the implemented programmes. Further, the study contributes to global knowledge on how outliers could reduce a composite indicator's reliability even in the presence of robust methodologies.

This study also contributes to the global knowledge on the need for frequent national surveys and open access to the national data. Because policymakers use the GFSI results to initiate essential programs such as nutritional feeding or social grant distribution, the GFSI must attempt to use as up-to-date data as possible. Using outdated data on the targeted population may not essentially account for the changes that might have occurred in a country over time.

Therefore, this study stresses countries' need to update national databases and allow open access to the data.

7.5 Recommendations for improvement of the study

The GFSI uses the min-max normalisation method to standardise data from different sources into a comparable unit. While this normalisation method is linked to the GFSI countries ranking, updating the outdated indicators for Kenya from different databases required the data to be re-normalised to make it comparable with the GFSI data. This renormalisation could be considered a limitation of the study because it could affect the GFSI's already normalised data for the other indicators, thereby affecting the indicators' weighting.

7.6 Recommendations for further research

Future research could extend the study to assess the impact of outdated data or outliers on more African countries. For example, the proportion of the population living under the global poverty line in Angola and Sudan was reported in 2019 using 2008 and 2009 data, respectively, which were considered outdated data even before the GFSI was initiated in 2012 study's definition of outdated data. Extending this study to more African countries will stress the need for countries to frequently update data to track their progress towards achieving the SDG goals and regional and national goals implemented to achieve food security and nutrition. Moreover, previous studies have highlighted data unavailability as a critical impeding factor towards achieving the Malabo Declaration on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods. Such a study will also enable countries to understand how outdated data impede efforts towards achieving food security.

This study used the winsorisation method to remove identified outliers in the 2019 GFSI database. However, future studies could advance removing outliers from the GFSI using a different statistical method such as the Median Absolute Deviation (MAD).

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Appendix A: Changes in countries' dimension scores after the winsorisation of outliers

Countries	2019 GFSI affordability scores	The winsorised affordability scores	2019 GFSI availability scores	The winsorized availability scores	2019 overall GFSI score	The winsorised 2019 overall GFSI score
Algeria	67	60.3	56	48.8	60	54.1
Angola	51	29.3	41	30.5	46	32.3
Argentina	79	71.2	60	56.8	71	66.2
Australia	87	86.2	77	76.7	81	81.0
Austria	85	82.2	79	77.1	82	79.8
Azerbaijan	75	68.7	59	59.5	65	62.3
Bahrain	82	79.2	56	54.8	67	64.9
Bangladesh	60	44.2	55	50.1	53	44.6
Belarus	76	56.1	63	64.2	71	63.5
Belgium	84	81.4	76	74.2	81	78.6
Benin	49	45.3	55	42.3	51	44.1
Bolivia	66	59.1	50	49.3	58	54.6
Botswana	70	65.7	61	62.5	64	62.9
Brazil	77	69.6	59	53.6	70	64.9
Bulgaria	79	75.8	54	48.4	66	62.3
Burkina Faso	47	43.8	56	50.6	50	46.4
Burundi	37	29.0	32	18.8	34	25.4
Cambodia	57	51.6	48	42.1	49	44.7
Cameroon	54	49.7	48	34.3	50	42.5
Canada	83	79.8	80	81.7	82	81.7
Chad	40	37.9	35	27.8	37	32.7
Chile	81	75.6	71	69.7	76	72.9
China	75	69.7	67	65.8	71	68.4
Colombia	74	68.8	66	63.9	69	66.7

Congo (Dem. Rep.)	37	32.8	40	34.3	36	31.4
Costa Rica	76	72.0	63	55.8	70	65.5
Cote d'Ivoire	54	50.3	58	53.3	52	48.9
Czech Republic	83	79.0	66	72.2	73	74.2
Denmark	85	82.8	75	73.6	81	79.5
Dominican Republic	68	63.0	61	53.9	64	58.9
Ecuador	69	64.9	56	53.3	62	58.8
Egypt	58	37.6	70	66.0	65	54.6
El Salvador	64	61.0	59	52.6	61	57.0
Ethiopia	50	29.6	53	44.3	49	37.6
Finland	84	81.2	79	84.9	83	84.5
France	84	81.4	75	74.7	80	79.3
Germany	85	81.8	79	77.6	82	79.7
Ghana	66	58.8	62	50.3	63	54.8
Greece	78	75.8	65	62.5	73	71.6
Guatemala	65	56.6	58	49.0	61	53.4
Guinea	47	29.9	52	44.1	47	36.0
Haiti	50	40.1	40	26.1	43	33.3
Honduras	57	53.0	58	56.5	58	55.7
Hungary	81	77.2	66	66.7	73	71.5
India	64	59.4	58	57.5	59	56.5
Indonesia	70	63.8	61	57.8	63	58.5
Ireland	91	89.3	77	81.2	84	85.5
Israel	83	81.0	74	73.9	79	78.3
Italy	83	79.8	68	67.7	76	74.5
Japan	82	79.5	71	70.7	77	75.2
Jordan	71	66.9	55	49.5	61	57.2
Kazakhstan	78	70.3	58	55.6	67	63.5
Kenya	57	45.2	48	44.7	51	44.7

Kuwait	88	85.2	62	61.9	75	73.4
Laos	56	49.8	48	41.5	49	44.2
Madagascar	36	27.5	46	34.9	38	29.9
Malawi	39	19.2	49	41.5	43	31.2
Malaysia	82	78.2	68	67.5	74	72.3
Mali	46	42.3	60	57.8	54	51.9
Mexico	75	68.6	62	60.5	69	66.1
Morocco	62	57.1	64	58.4	63	58.5
Mozambique	43	32.9	48	42.3	41	35.1
Myanmar	59	53.1	57	51.8	57	52.2
Nepal	59	55.2	55	52.1	56	53.6
Netherlands	86	82.9	76	76.2	82	80.9
New Zealand	85	84.4	76	72.4	79	77.4
Nicaragua	64	57.5	48	45.8	54	50.9
Niger	50	48.1	54	45.7	50	45.3
Nigeria	50	35.4	46	31.3	48	36.1
Norway	82	77.5	81	82.6	83	81.8
Oman	78	75.4	58	55.1	68	66.3
Pakistan	63	51.0	56	53.6	57	50.9
Panama	74	70.4	63	64.0	69	67.8
Paraguay	72	67.1	42	34.7	58	52.6
Peru	69	66.5	59	53.5	63	59.8
Philippines	69	64.7	58	57.9	61	59.4
Poland	81	78.1	69	70.2	76	74.9
Portugal	81	78.9	71	69.9	78	76.4
Qatar	99	97.3	64	62.6	81	79.9
Romania	79	77.2	64	66.6	70	70.4
Russia	80	71.8	60	60.1	70	66.5
Rwanda	44	37.2	52	47.1	48	43.4
Saudi Arabia	86	84.7	62	60.8	74	72.4
Senegal	52	47.6	56	53.5	54	51.6

Serbia	74	68.9	53	48.0	63	58.6
Sierra Leone	41	28.5	40	33.7	39	31.1
Singapore	95	93.4	83	82.3	87	86.3
Slovakia	79	75.6	62	62.7	68	67.3
South Africa	71	64.2	65	63.3	67	64.1
South Korea	76	72.4	71	75.3	74	74.0
Spain	82	79.7	66	64.6	76	73.8
Sri Lanka	65	59.3	60	60.6	61	58.8
Sudan	47	25.1	44	36.0	46	33.2
Sweden	85	82.2	78	78.0	83	81.5
Switzerland	84	79.1	84	85.0	83	81.6
Syria	35	16.9	39	38.3	38	31.1
Tajikistan	59	51.1	41	40.0	49	45.5
Tanzania	45	41.1	50	42.0	48	42.3
Thailand	77	73.7	59	59.6	65	64.1
Togo	46	42.8	47	39.3	44	39.4
Tunisia	62	53.1	58	56.6	60	56.1
Turkey	75	59.7	65	57.1	70	60.4
Uganda	46	36.4	46	36.6	46	38.5
Ukraine	64	52.2	50	43.6	57	49.6
United Arab Emirates	90	87.0	64	59.4	77	73.5
United Kingdom	84	81.0	74	75.0	79	78.3
United States	87	85.7	78	81.5	84	84.4
Uruguay	79	70.4	67	59.4	73	66.1
Uzbekistan	66	57.0	55	57.6	59	56.7
Venezuela	16	14.5	32	30.9	31	30.1
Vietnam	75	68.4	60	56.0	65	60.3
Yemen	46	39.4	29	23.3	36	30.8
Zambia	42	30.5	51	53.9	44	41.3

Appendix B: Shifts in countries ranks after the winsorisation of outliers in the 2019 GFSI data

Countries	2019 GFSI affordability ranks	The winsorized affordability ranks	The differences in rank after the winsorisation of outliers	2019 GFSI availability ranks	The winsorised availability ranks	Differences in rank after the winsorisation of outliers in the 2019 GFSI	2019 overall GFSI ranks	The winsorized 2019 overall GFSI ranks	The differences in rank after the winsorisation of outliers
Algeria	64	63	**-1**	74	81	**7**	70	73	**3**
Angola	89	106	**17**	105	109	**4**	100	105	**5**
Argentina	37	42	**5**	51	56	**5**	37	41	**4**
Australia	7	5	**-2**	10	11	**1**	12	9	**-3**
Austria	10	12	**2**	6	10	**4**	10	12	**2**
Azerbaijan	47	50	**3**	56	46	**-10**	53	52	**-1**
Bahrain	26	24	**-2**	70	63	**-7**	50	45	**-5**
Bangladesh	77	89	**12**	79	77	**-2**	83	89	**6**
Belarus	44	73	**29**	42	32	**-10**	36	49	**13**
Belgium	15	15	**0**	12	16	**4**	15	16	**1**
Benin	94	87	**-7**	78	91	**13**	85	91	**6**
Bolivia	66	67	**1**	89	79	**-10**	75	71	**-4**
Botswana	59	56	**-3**	48	38	**-10**	57	51	**-6**
Brazil	43	47	**4**	58	66	**8**	39	45	**6**
Bulgaria	36	33	**-3**	81	82	**1**	51	52	**1**

Burkina Faso	97	90	**-7**	73	75	**2**	87	84	**-3**
Burundi	110	107	**-3**	111	113	**2**	112	113	**1**
Cambodia	83	79	**-4**	92	93	**1**	90	87	**-3**
Cameroon	86	84	**-2**	96	104	**8**	88	93	**5**
Canada	20	20	**0**	4	5	**1**	8	6	**-2**
Chad	107	96	**-11**	110	110	**0**	109	104	**-5**
Chile	32	35	**3**	19	24	**5**	25	29	**4**
China	50	46	**-4**	27	30	**3**	35	35	**0**
Colombia	54	49	**-5**	32	24	**-8**	43	38	**-5**
Congo (Dem. Rep.)	109	102	**-7**	107	105	**-2**	110	106	**-4**
Costa Rica	46	40	**-6**	40	60	**20**	39	44	**5**
Cote d'Ivoire	87	82	**-5**	62	70	**8**	84	83	**-1**
Czech Republic	22	26	**4**	29	20	**-9**	32	24	**-8**
Denmark	10	11	**1**	15	18	**3**	14	14	**0**
Dominican Republic	63	61	**-2**	50	64	**14**	56	58	**2**
Ecuador	60	57	**-3**	71	70	**-1**	63	59	**-4**
Egypt	81	97	**16**	23	29	**6**	55	71	**16**
El Salvador	72	62	**-10**	60	72	**12**	67	65	**-2**
Ethiopia	93	105	**12**	84	88	**4**	91	98	**7**
Finland	16	17	**1**	6	2	**-4**	5	3	**-2**
France	17	15	**-2**	15	15	**0**	16	15	**-1**
Germany	13	14	**1**	5	9	**4**	11	13	**2**
Ghana	65	68	**3**	47	76	**29**	59	70	**11**
Greece	39	33	**-6**	33	38	**5**	31	32	**1**
Guatemala	68	72	**4**	67	80	**13**	68	75	**7**
Guinea	95	104	**9**	85	89	**4**	97	100	**3**

Haiti	91	94	**3**	108	111	**3**	103	102	**-1**
Honduras	82	77	**-5**	64	58	**-6**	73	69	**-4**
Hungary	31	31	**0**	30	27	**-3**	34	33	**-1**
India	70	65	**-5**	61	54	**-7**	72	67	**-5**
Indonesia	58	60	**2**	48	51	**3**	62	62	**0**
Ireland	3	3	**0**	11	7	**-4**	2	2	**0**
Israel	21	18	**-3**	18	17	**-1**	18	17	**-1**
Italy	23	20	**-3**	25	25	**0**	23	23	**0**
Japan	24	23	**-1**	21	21	**0**	21	21	**0**
Jordan	57	54	**-3**	79	78	**-1**	64	64	**0**
Kazakhstan	41	45	**4**	65	61	**-4**	48	49	**1**
Kenya	83	88	**5**	93	86	**-7**	86	87	**1**
Kuwait	5	7	**2**	43	40	**-3**	27	28	**1**
Laos	85	83	**-2**	96	96	**0**	92	90	**-2**
Madagascar	111	109	**-2**	100	102	**2**	108	112	**4**
Malawi	108	111	**3**	91	96	**5**	104	107	**3**
Malaysia	28	28	**0**	26	26	**0**	28	31	**3**
Mali	98	92	**-6**	52	51	**-1**	80	78	**-2**
Mexico	49	51	**2**	43	43	**0**	43	42	**-1**
Morocco	75	70	**-5**	37	49	**12**	59	62	**3**
Mozambique	104	101	**-3**	94	91	**-3**	105	101	**-4**
Myanmar	78	75	**-3**	69	74	**5**	77	77	**0**
Nepal	80	74	**-6**	76	73	**-3**	79	74	**-5**
Netherlands	9	10	**1**	12	12	**0**	9	10	**1**
New Zealand	14	9	**-5**	14	19	**5**	19	19	**0**
Nicaragua	73	69	**-4**	94	85	**-9**	82	80	**-2**
Niger	92	85	**-7**	82	86	**4**	89	86	**-3**
Nigeria	90	100	**10**	99	107	**8**	94	99	**5**
Norway	26	30	**4**	3	3	**0**	5	5	**0**

Oman	39	37	**-2**	67	62	**-5**	46	40	**-6**
Pakistan	74	81	**7**	75	66	**-9**	78	80	**2**
Panama	53	43	**-10**	40	33	**-7**	45	36	**-9**
Paraguay	55	53	**-2**	103	103	**0**	74	76	**2**
Peru	61	55	**-6**	57	68	**11**	58	56	**-2**
Philippines	62	58	**-4**	65	50	**-15**	64	57	**-7**
Poland	30	29	**-1**	24	22	**-2**	24	22	**-2**
Portugal	29	27	**-2**	22	23	**1**	20	20	**0**
Qatar	1	1	**0**	38	37	**-1**	13	11	**-2**
Romania	34	31	**-3**	36	28	**-8**	38	34	**-4**
Russia	33	41	**8**	52	44	**-8**	42	39	**-3**
Rwanda	103	98	**-5**	86	84	**-2**	95	92	**-3**
Saudi Arabia	8	8	**0**	46	41	**-5**	30	30	**0**
Senegal	88	86	**-2**	71	68	**-3**	81	79	**-2**
Serbia	52	48	**-4**	83	83	**0**	59	61	**2**
Sierra Leone	106	108	**2**	106	106	**0**	106	108	**2**
Singapore	2	2	**0**	2	4	**2**	1	1	**0**
Slovakia	38	35	**-3**	45	36	**-9**	47	37	**-10**
South Africa	56	59	**3**	35	35	**0**	48	47	**-1**
South Korea	45	39	**-6**	20	13	**-7**	29	25	**-4**
Spain	25	22	**-3**	31	31	**0**	25	26	**1**
Sri Lanka	69	66	**-3**	54	42	**-12**	66	59	**-7**
Sudan	96	110	**14**	102	101	**-1**	99	103	**4**
Sweden	12	12	**0**	9	8	**-1**	7	8	**1**
Switzerland	17	25	**8**	1	1	**0**	4	7	**3**
Syria	112	112	**0**	109	99	**-10**	107	108	**1**
Tajikistan	79	80	**1**	104	97	**-7**	93	85	**-8**
Tanzania	102	93	**-9**	88	94	**6**	96	94	**-2**
Thailand	42	38	**-4**	59	45	**-14**	52	47	**-5**
Togo	100	91	**-9**	98	98	**0**	102	96	**-6**

Tunisia	75	75	**0**	63	57	**-6**	69	68	**-1**
Turkey	51	64	**13**	34	55	**21**	41	54	**13**
Uganda	99	99	**0**	101	100	**-1**	98	97	**-1**
Ukraine	71	78	**7**	89	90	**1**	76	82	**6**
United Arab Emirates	4	4	**0**	39	47	**8**	21	27	**6**
United Kingdom	19	18	**-1**	17	14	**-3**	17	17	**0**
United States	6	6	**0**	8	6	**-2**	3	4	**1**
Uruguay	34	43	**9**	28	47	**19**	33	42	**9**
Uzbekistan	67	71	**4**	77	53	**-24**	71	66	**-5**
Venezuela	113	113	**0**	111	108	**-3**	113	111	**-2**
Vietnam	48	52	**4**	55	59	**4**	54	55	**1**
Yemen	101	95	**-6**	113	112	**-1**	111	110	**-1**
Zambia	105	103	**-2**	87	64	**-23**	101	95	**-6**

Appendix C: Identified countries and indicators with outdated data in the 2019 GFSI result

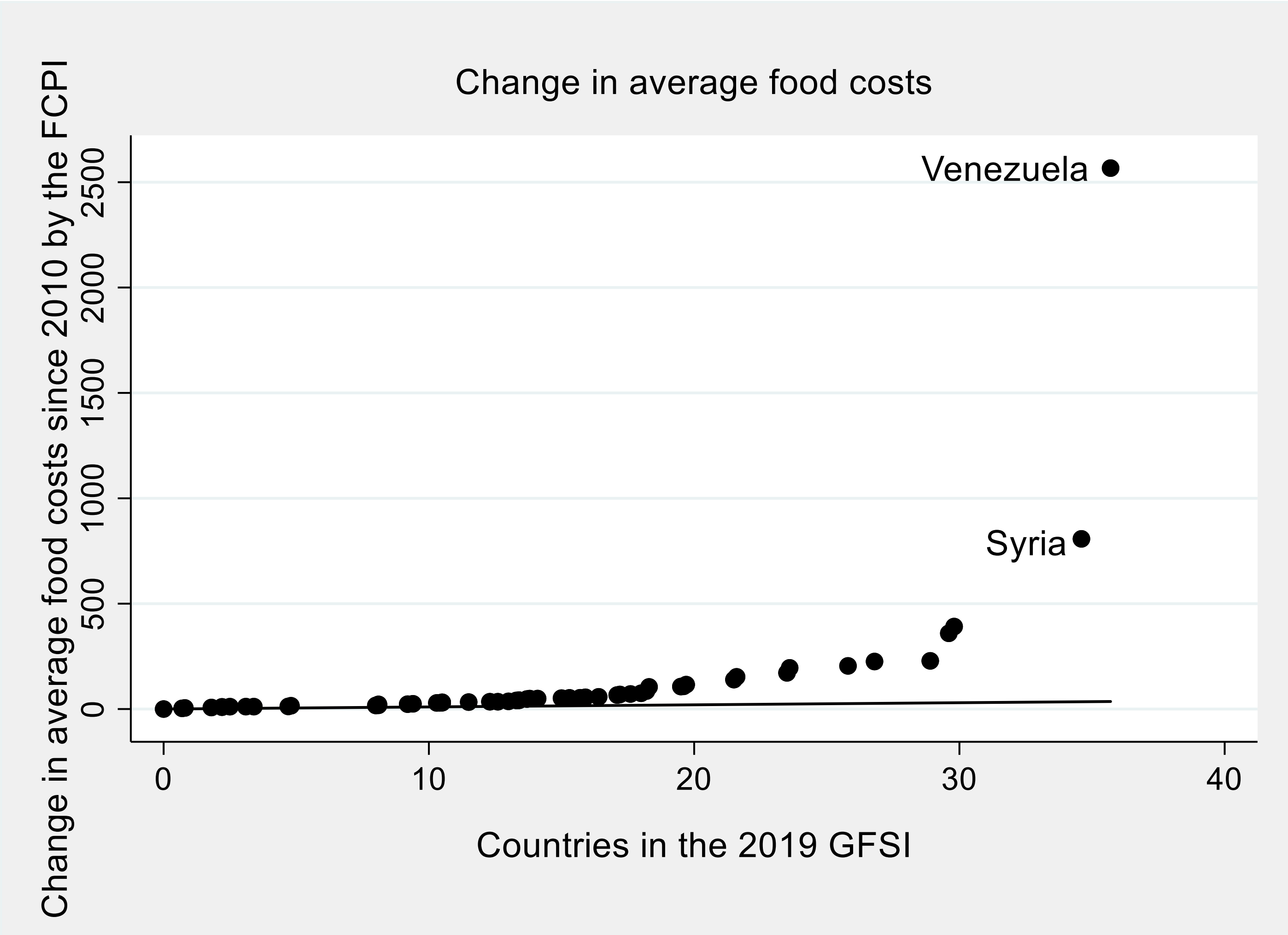
Indicators with outdated data points	Data year	Number of countries with outdated data	Country/countries with outdated data
Affordability dimension			
Agricultural import tariffs	2012	1	Sierra Leone
	2013	1	Syria
	2014	1	Cameroon
	2015	4	Azerbaijan, Congo (Dem. Rep.), Guatemala, Uzbekistan
	2016	4	Chad, Haiti, Nigeria, Tunisia
	2017	9	Cambodia, Israel, Malawi, Malaysia, Morocco, Sudan, Tajikistan, Thailand, Yemen
The change in average food costs	2014	1	Yemen
	2015	2	Sudan, Venezuela
	2017	3	Chad, Congo (Dem. Rep.), Syria
The proportion of the population under the global poverty line	2005	1	Azerbaijan
	2008	2	Angola, Japan
	2009	3	Mali, Nigeria, Sudan
	2010	2	Jordan, Nepal
	2011	6	Algeria, Chad, India, Senegal, Sierra Leone, Tanzania
	2012	6	Congo (Dem. Rep.), Guinea, Haiti, Laos, Madagascar, South Korea
	2013	3	Burundi, Canada, Morocco

Indicators with outdated data points	Data year	Number of countries with outdated data	Country/countries with outdated data
	2014	12	Australia, Bulgaria, Burkina Faso, Cambodia, Cameroon, Guatemala, Mozambique, Nicaragua, Niger, South Africa, Uzbekistan, Yemen
	2015	38	Austria, Belgium, Benin, Botswana, China, Cote d'Ivoire, Czech Republic, Denmark, Egypt, Ethiopia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Kenya, Malaysia, Myanmar, Netherlands, Norway, Pakistan, Philippines, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Spain, Sweden, Switzerland, Tajikistan, Togo, Tunisia, United Kingdom, Zambia
	2016	13	Bangladesh, Dominican Republic, Ghana, Israel, Malawi, Mexico, Rwanda, Sri Lanka, Turkey, Uganda, Ukraine, United States, Vietnam
	2017	17	Argentina, Belarus, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Honduras, Indonesia, Kazakhstan, Panama, Paraguay, Peru, Thailand, Uruguay
Availability dimension			
Change in dependency on chronic food aid	2013-2017	113	All GFSI countries
Dietary diversity	2011-2013	113	All GFSI countries

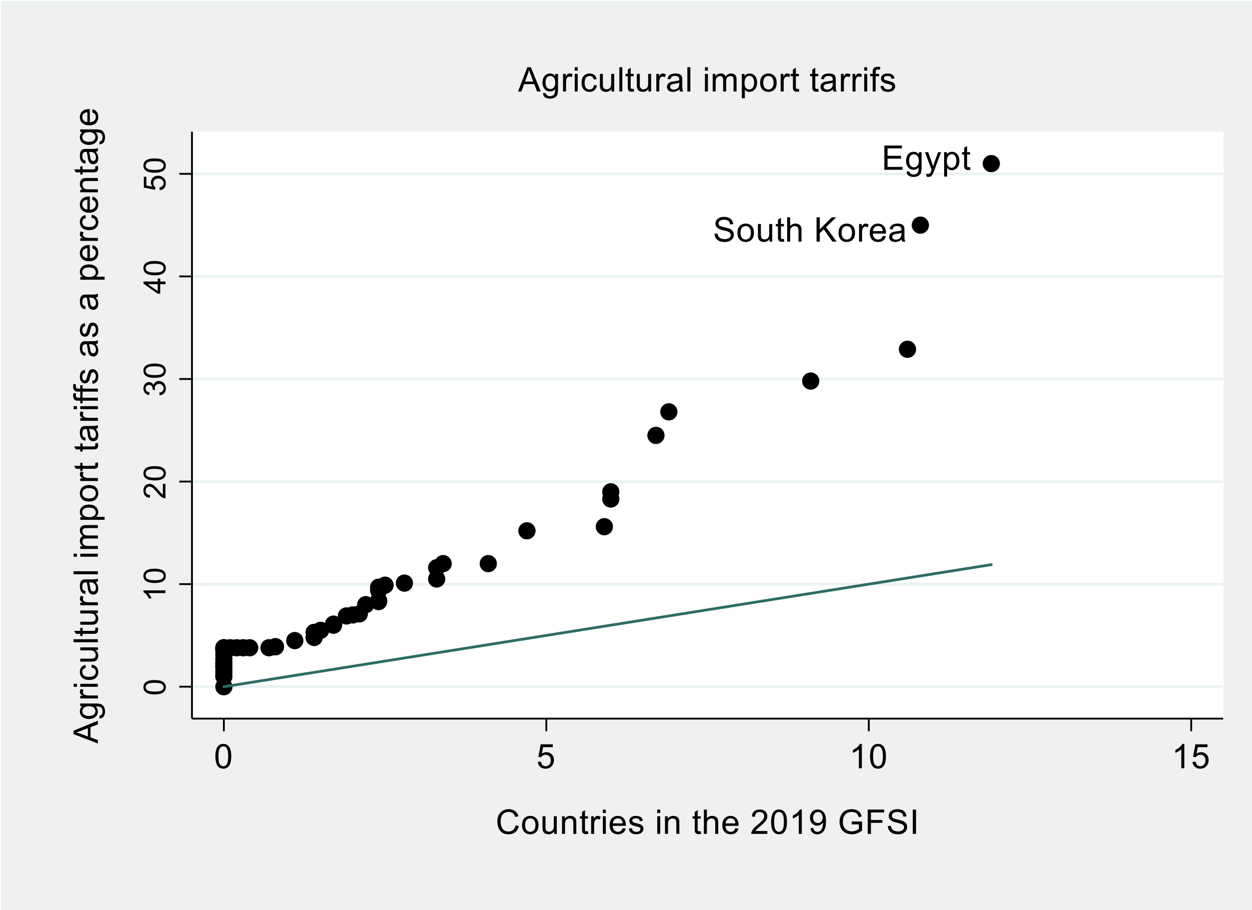
Indicators with outdated data points	**Data year**	**Number of countries with outdated data**	**Country/countries with outdated data**
Food loss	2013	108	All GFSI countries except Bahrain, Burundi, Qatar, Singapore, Syria with estimated values for the indicator and no data year
Irrigation infrastructure	2016	111	All GFSI countries except Ireland and Singapore with estimated values for the indicator and no data year
Public expenditure on agricultural research and development	2010	1	Benin
	2011	1	Mali
	2012	4	Canada, Morocco, Serbia, Tunisia
	2013	3	Burundi, Indonesia, Nigeria
	2014	4	Bolivia, Cote d'Ivoire, Oman,Vietnam
	2015	6	Azerbaijan, Belgium, Ecuador Kuwait, Tanzania, United Arab Emirates
	2016	25	Bangladesh, Bulgaria, Ethiopia, Finland, France, Greece, Hungary, India, Ireland, Israel, Italy, Jordan, Malawi, Mozambique, Pakistan, Portugal, Romania, Slovakia, South Africa, South Korea, Switzerland, Togo, Uganda, United Kingdom, Uzbekistan
	2017	35	Angola, Argentina, Australia, Belarus, Botswana, Brazil, Burkina Faso, Chile, China, Congo (Dem. Rep.), Costa Rica, Czech Republic, Denmark,

Indicators with outdated data points	Data year	Number of countries with outdated data	Country/countries with outdated data
			Dominican Republic, Egypt, El Salvador, Guatemala, Kazakhstan, Kenya, Malaysia, Mexico, Myanmar, Nepal, Netherlands, Norway, Panama, Paraguay, Philippines, Poland, Russia, Rwanda, Singapore, Spain, Sri Lanka, Sweden, Thailand, Turkey, Ukraine, Zambia
The volatility of agricultural production	2012-2016	113	All GFSI countries
Urban absorption capacity	2015-2019	113	All GFSI countries
Quality and Safety dimension			
Ability to store food safely	2017	113	All GFSI countries
Dietary availability of vitamin A	2013	113	All GFSI countries
Dietary availability of iron	2013	113	All GFSI countries
Dietary availability of zinc	2013	113	All GFSI countries
Protein quality	2011-2013	106	All GFSI countries except Bahrain, Burundi, Congo (Dem. Rep.), Oman, Qatar, Singapore, Syria with estimated values for the indicator and no data year
The proportion of the population with access to potable water	2016	1	Argentina
	2017	112	All GFSI countries except Argentina with an estimated value for the indicator and no data year

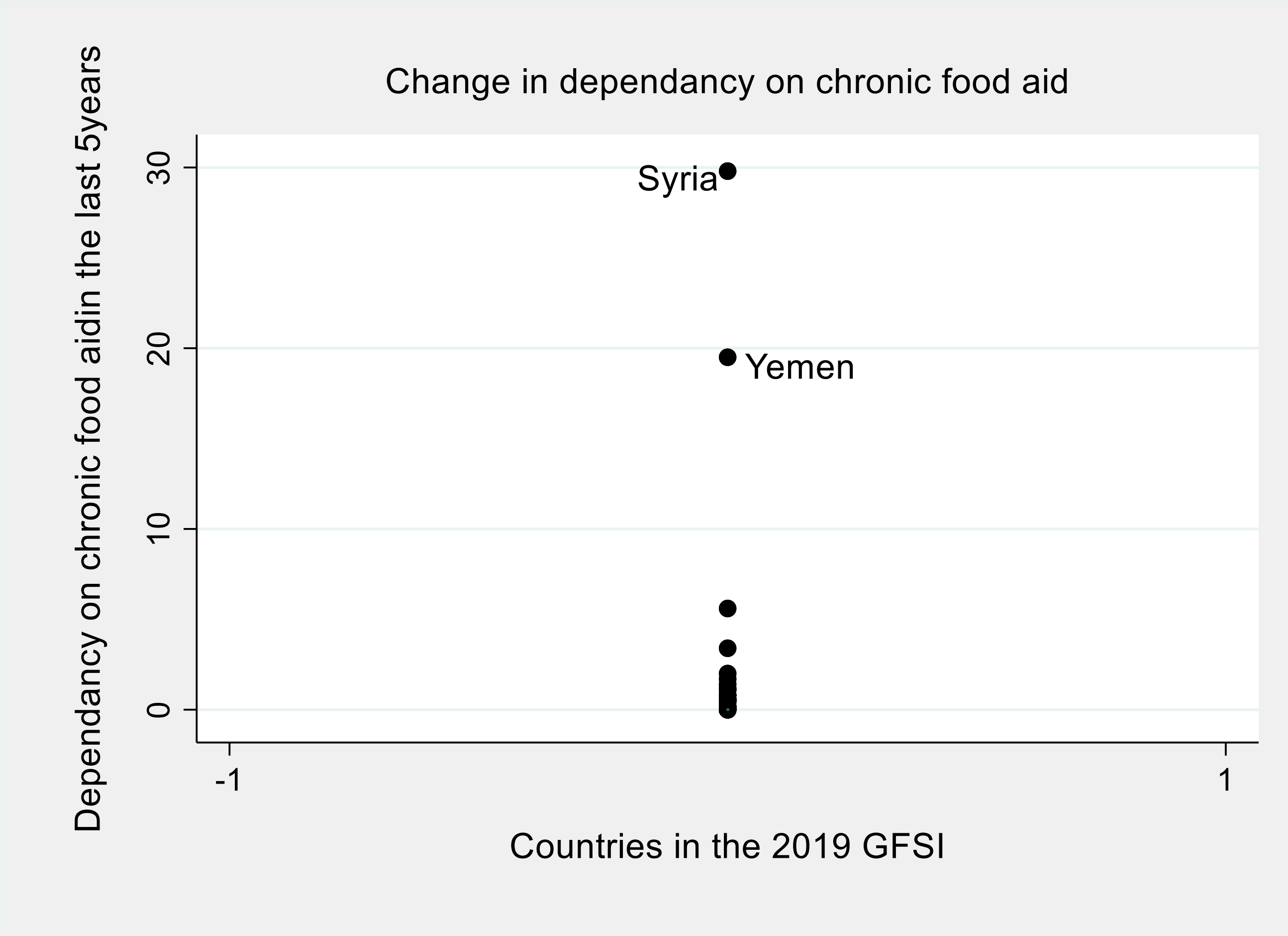
Appendix D: Outlying indicators and countries in the 2019 GFSI result



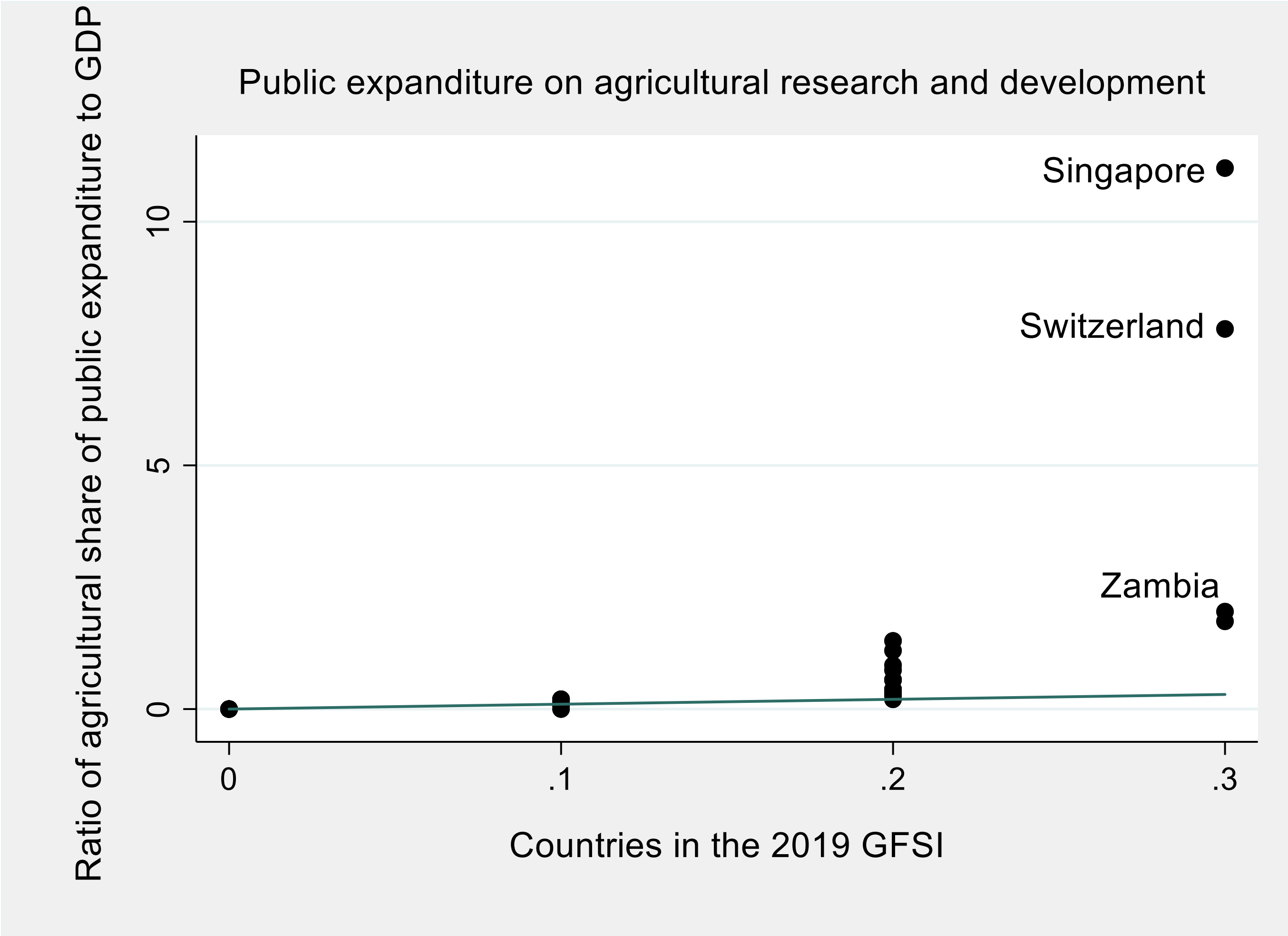
Countries with outlying data points in the change in average food cost indicator



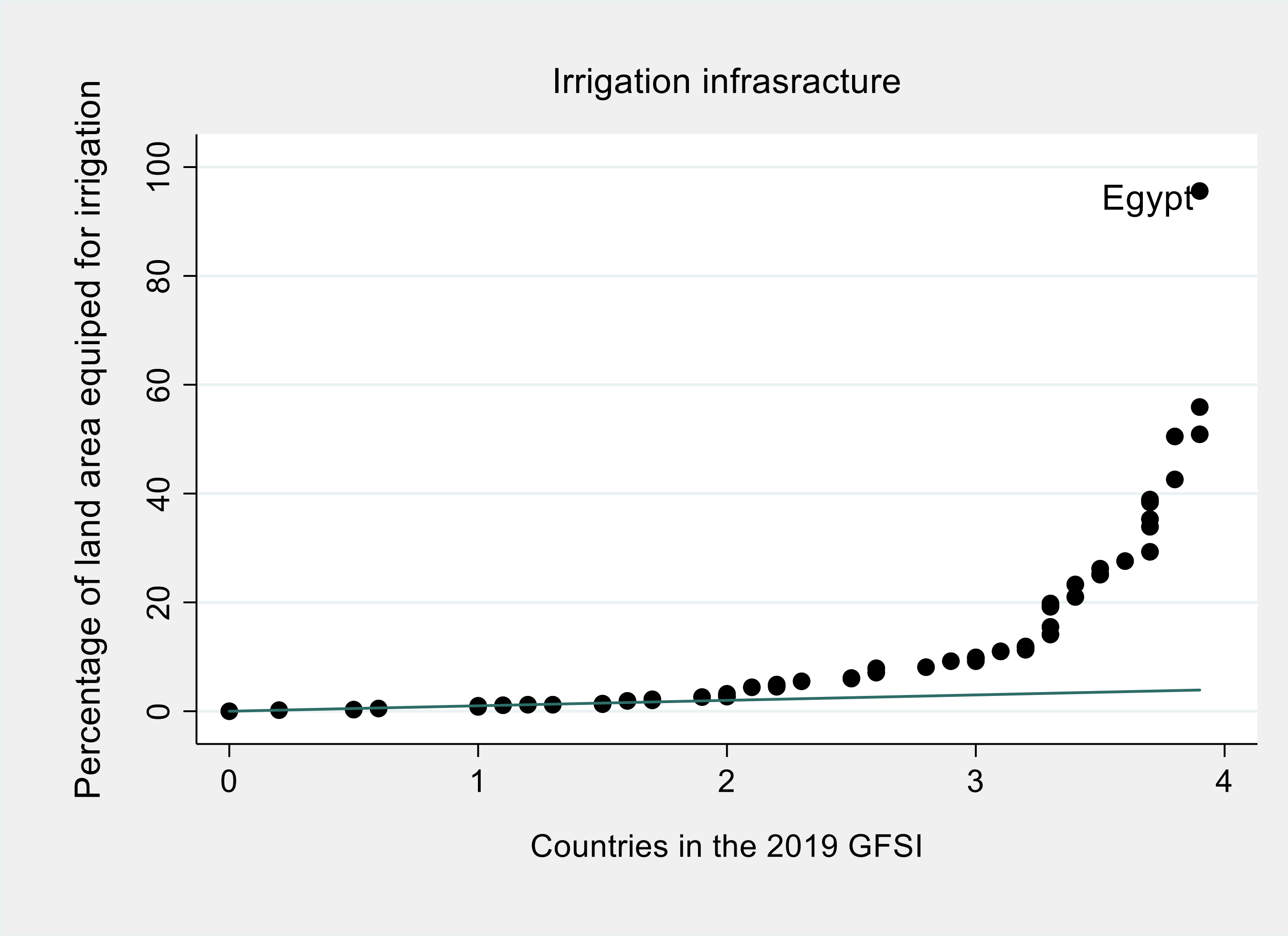
Countries with outlying data points in the agricultural import tariffs indicator



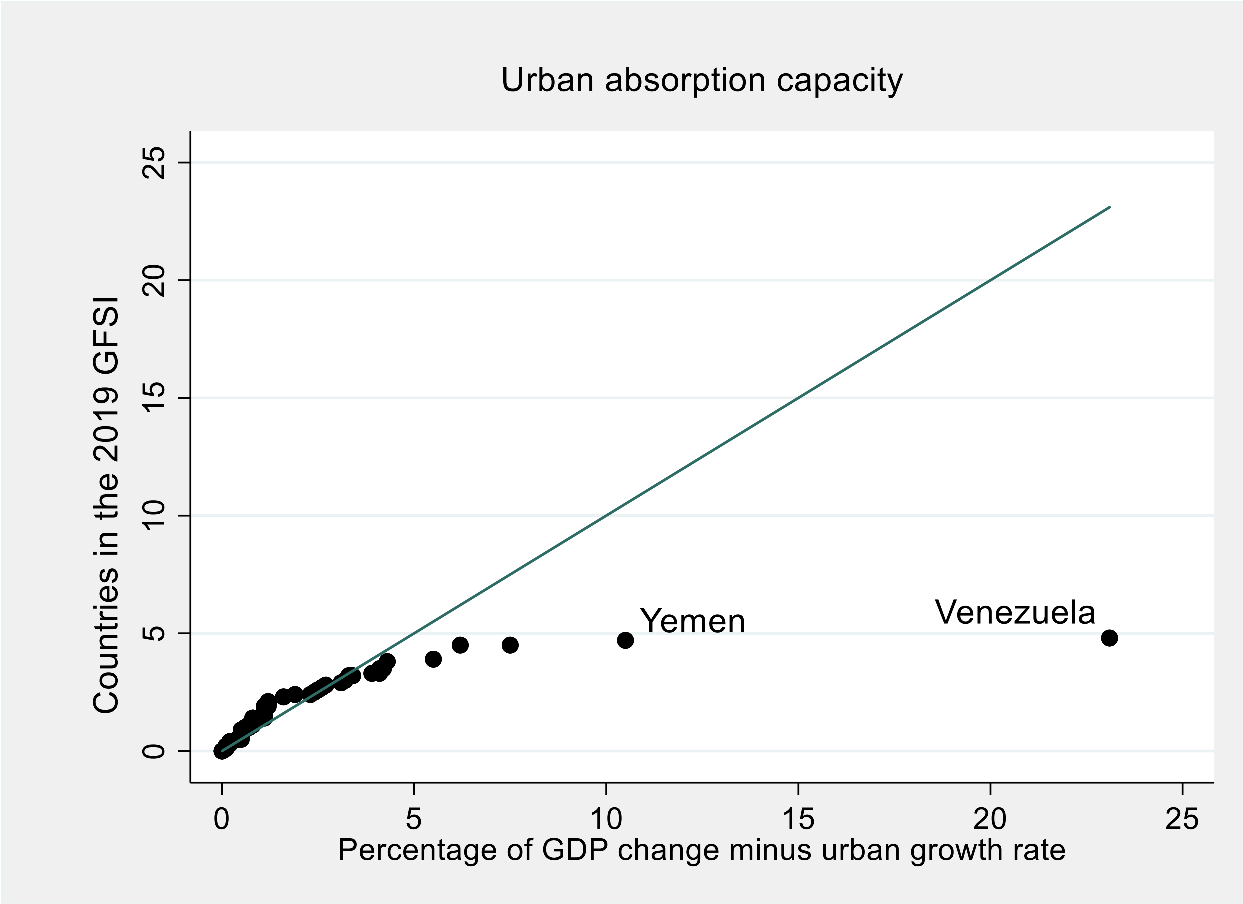
Countries with outlying data points in the change in dependency on chronic food aid indicator



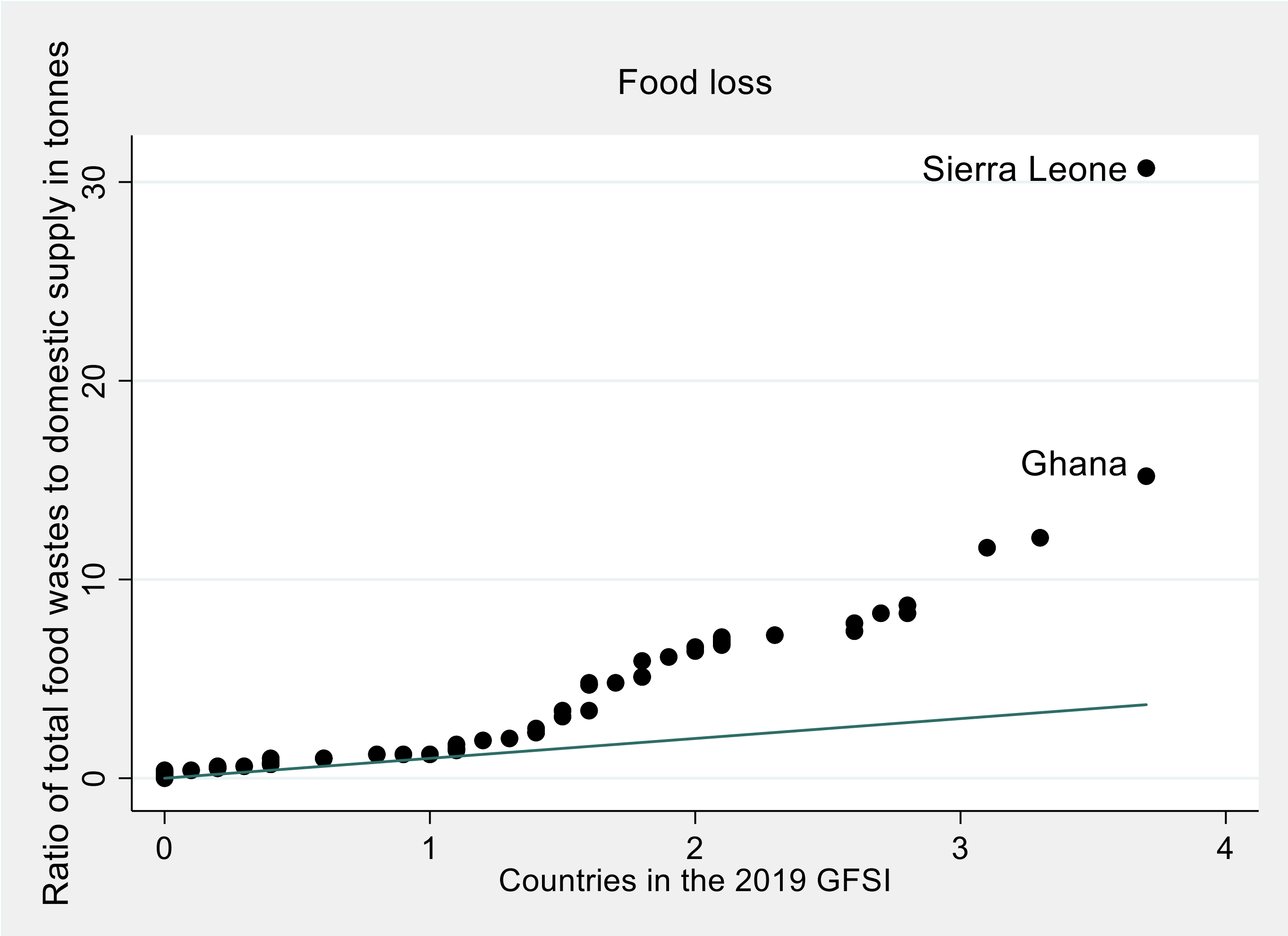
Countries with outlying data points in public expenditure on agricultural research and development indicator



Countries with outlying data points in the irrigation infrastructure indicator



Countries with outlying data points in the urban absorption capacity indicator



Countries with outlying data points in the food loss indicator