The effects of outdated data and outliers on Zambia's 2019 Global Food Security Index score and ranking

By

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DECLARATION

I, Enock Siamayobela, student number 19223537

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- I understand what plagiarism entails and am aware of the University's policy in this regard.
- This dissertation is my original work and where peoples' work has been used, it has been appropriately acknowledged and referenced according to the departmental requirements.
- This dissertation has not been submitted to any other university for the award of a degree.
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DEDICATION

I dedicate this dissertation to my parent, Mr Amos Siamayobela and Mrs Judith Mulumbu, for their unfailing support and encouragement and to my wife and children for their continued support and love and for enduring my absence from home

ABSTRACT

While composite indicators have become a valuable tool in policymaking, benchmarking and public communication processes, outliers and outdated data challenge their reliability. Outliers are large or small values in a database that could act as an unintended benchmark. At the same time, outdated data can arise when databases are not frequently updated and current data are missing in annual benchmarking exercises. Outdated data and outliers can render composite indicators less reliable and lead to misleading results and unreliable benchmarking. Outdated data could also hinder countries from tracking the progress of national, international, regional or global commitments, such as the Malabo commitments and SDGs.

This study assessed the effects of outdated data and outliers on Zambia's 2019 Global Food Security Index (GFSI) score and ranking. The study compared Zambia's score and rank relative to other countries in the Global Food Security Index before and after updating outdated data and winsorisation of outliers found in the 2019 GFSI dataset. Updated data was obtained from alternative sources to calculate updated scores and rankings. Winsorisation removed outliers and replaced them with the net highest or smallest values in the database for the same indicator. Paired t-test and Spearman rank correlation tested the effects of outdated data and outliers.

The study found that the 2019 Global Food Security Index data had ten out of 34 indicators with outlier values from 16 countries. Zambia had an outlier in public expenditure on agricultural research and development indicator. The study also revealed that Zambia had 14 indicators that used outdated data in the 2019 GFSI results. A statistically significant difference was found between the scores after the winsorisation of outliers for the affordability and availability dimensions of and the overall scores. However, despite Zambia's score and rank improving after updating outdated data, the increase in scores and rankings was not statistically significant.

The study concluded that outliers and outdated data in the 2019 Global Food Security Index impacted Zambia's scores and ranking. The study recommended that outliers be identified and removed from composite indicators to avoid unreliable benchmarking settings by policymakers. The study also recommended that Zambia enhance timely quality data collection to update databases and improve the food security score and ranking in different regional and global indexes.

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LIST OF ACRONYMS

ASTI	Agricultural Science and Technology Indicators
CAADP	Comprehensive Africa Agriculture Development Programme
CEIC	Census and Economic Information Center
CES	Constant-Elasticlty-of-Substitution
CFS	Committee on World Food Security
CRI	Commitment to Reducing Inequality
EIU	Economist Intelligence Unit
FAO	Food and Agriculture Organisation
FAOSTAT	The Food and Agriculture Organization Corporate Statistical Database
FISP	Farmer Input Support Programme
FRA	Food Reserve Agency
FSP	Food Security Pack
GFSI	Global Food Security Index
GHI	Global Hunger Index
JRC-EC	Joint Research Centre-European Commission
OECD	Organisation for Economic Co-operation and Development
OHI	Global Ocean Health Index
ReSAKSS	Regional Strategic Analysis and Knowledge Support System
UN MDG	United Nations Millennium Development Goals
UN SDG	United Nations Sustainable Development Goals
VAC	Vulnerability Assessment Committee
WB	World Bank
WFP	World Food Programme
WHO	World Health Organisation
WTO	World Trade Organisation

CHAPTER 1: INTRODUCTION

1.1 Background

Building composite indicators requires the availability of updated and complete datasets (Caccavale and Giuffrida, 2020). Composite indicators can integrate a large amount of information into easily understood formats for the general audience (Freudenberg, 2003b). They are a valuable tool in policymaking, benchmarking and public communication processes due to their ease of interpretation (Santeramo, 2015a; Nardo et al., 2005b).

However, the building of robust composite indicators is challenged by outliers and outdated data that can hinder and affect their reliability in measuring multidimensional concepts (Organisation for Economic Co-operation and Development (OECD), 2008; Nardo et al., 2005a). Composite indicators are made up of individual indicators and weights that collectively reflect each indicator's relative importance combined in a single index (Nardo et al., 2005b; Saisana et al., 2005). These indexes are common in benchmarking economic and business statistics to monitor countries' progress in various policy domains (Nardo et al., 2005b; Saisana et al., 2005). The construction of precise and robust composite indicators can be affected by the quality of both the indicators and the data used (Caccavale and Giuffrida, 2020).

Outliers are extreme observations or values that lie outside the overall pattern of the distribution of variables in a sample (Ghosh and Vogt, 2012). Outliers can lead to unintended benchmarks in composite indicators (Thomas et al., 2017; OECD, 2008). Outdated data arise when composite indicators use data from previous years or estimates due to a lack of current data at the national or global level for specific countries or indicators (Economist Intelligence Unit (EIU), 2019). For example, nutrition data is expensive to collect and so is usually only collected every five years. When outliers are identified in the data, they could either be removed entirely or statistically replaced.

The use of outdated data poses a challenge to reporting reliable information (Caccavale and Giuffrida, 2020). Furthermore, using the same data for several years in a composite indicator may not reflect the environmental, economic and social changes taking place over time (Abberger et al., 2018; Freudenberg, 2003b). The substituting of missing data with the last available data for a country or leaving the specific affected indicators out of the analysis does not permit assessment of performance over time (Cherchye et al., 2011). Outdated data could be updated or replaced with statistically calculated estimates to reflect the dynamics (OECD, 2008).

Several composite indexes that combine the multiple dimensions of food security have been constructed in the last decade (Jones et al., 2013; Santeramo, 2015b). These composite indicators measure different aspects of food security at the individual, household and national level. Some measure food security outcomes, such as the prevalence of stunting among children (Coates, 2013). Others measure food security determinants, such as the average food supply at the national level (Coates, 2013). Some focus on measuring food security dimensions, namely food availability, access, utilisation, stability, sustainability, and agency (HLPE, 2020). Examples of food security composite indexes include, but are not limited to: the Global Hunger Index (GHI), Global Food Security Index (GFSI), the Prevalence of Undernourishment (PoU) and the Food Consumption Score (FCS) (Jones et al., 2013).

The process involved in constructing composite indicators must be transparent to avoid giving misleading results to their users (Santeramo, 2015a; Freudenberg, 2003b). The outcomes of such indexes are sensitive to the nature of their computation, different weighting and aggregation methods and missing and outdated data. These challenges can result in distorted findings and incorrect policy prescriptions (Freudenberg, 2003b). Some methods, such as weighting, can be manipulated to support desired results (Santeramo, 2017; Freudenberg, 2003b). Transparency is needed to avoid misleading results (Santeramo, 2015a; Freudenberg, 2003b).

1.2 Problem statement

The Global Food Security Index (GFSI) is a composite indicator developed in 2012 by the Economist Intelligence Unit (EIU) to monitor progress toward food security at the national level. The GFSI ranks and compares 113 countries using 34 indicators divided into three dimensions, namely the affordability, availability and quality and safety dimensions. In 2017, the GFSI introduced the fourth component of natural resources and resilience (NRR) to assess countries' exposure to climate impacts and how they adapt to natural resource risks. As a composite indicator, the GFSI helps to understand the drivers of food security in the country and the general food security environment (Izraelov and Silber, 2019). The index considers both qualitative and quantitative indicators representing various aspects of food security (Maricic et al., 2016).

The GFSI is considered robust due to its broad data coverage from reliable sources such as Food and Agriculture Organisation (FAO), World Health Organisation (WHO), World Trade Organisation (WTO), World Food Programme (WFP) and World Bank (Chen et al., 2019;

Coates, 2013; Maricic et al., 2016; Thomas et al., 2017; Izraelov and Silber, 2019). The GFSI covers a broad global representation of countries, including developed and developing countries across regions, to reflect the regional differences, economic importance and population size (Izraelov and Silber, 2019).

Studies to test the robustness of the GFSI have shown that the GFSI is statistically coherent and robust to changes in weights and aggregation methods (Chen et al., 2019; Izraelov and Silber, 2019; Jones et al., 2013; Maricic et al., 2016; Thomas et al., 2017). Thomas et al. (2017) researched the robustness of the GFSI in assessing countries' performance. Thomas et al. (2017) concluded that the GSFI is robust and correlated with other food security indicators such as the IFPRI's Global Hunger Index and the FAO's Prevalence of Undernourishment (PoU). Maricic et al. (2016) and Izraelov and Silber (2019) proposed using objective weighting methods such as the I-distance Indicator and data envelopment weighting methods instead of the subjective weights assigned by the EIU's panel of experts to improve the accuracy and rigour of the index. Findings from Maricic et al. (2016) and Izraelov and Silber (2019) have shown that the GFSI is robust to weight changes.

As with all indexes, the GFSI is affected by the presence of outliers and outdated data (EIU, 2019). However, no studies have been conducted to establish how the presence of outliers and the use of outdated data affect individual country scores and rankings. Therefore, this study investigated the effects of outdated data and outliers on the GFSI score and ranking using Zambia as a case study.

1.3 Research questions

The study set out to determine if the 2019 GFSI database contained outdated data and outliers. The overall question was: does correcting the outliers and updating Zambia's outdated data affect the country's score and ranking?

The specific research questions were:

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

ii. What are the statistically significant effects of outdated data and outliers on the affordability, availability and quality and safety dimensions score and ranking for Zambia's 2019 GFSI result?

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

1.4 Study hypotheses

The study's first hypothesis was that the 2019 GFSI did not contain outdated data and outliers. The basis of this assumption was that the EIU obtains its data from reliable international data sources like the World Bank, Food and Agricultural Organization of the United Nations (FAO), the World Trade Organization (WTO) and other sources with broad coverage (Maricic et al., 2016). These data sources are used by other similar food security composite indicators such as the GHI and PoU when comparing the performance of countries. The GFSI, GHI and PoU all rely on existing food security data sources to calculate the proportion of undernourished people worldwide. Therefore, the GFSI was assumed to be relevant and reliable in ranking countries due to its correlation with similar food security indicators and reliable broad data coverage.

The second hypothesis was that there was no statistically significant effect of the outdated data and outliers on Zambia's 2019 GFSI dimension score and ranking. This assumption was premised on the basis that Zambia has consistently performed poorly in many food security indicators. For example, Zambia ranked among the five countries with alarming hunger levels in the GHI and has consistently ranked among the bottom ten countries in the GFSI since 2012 (Bernstein et al., 2019; EIU, 2019). Various factors could contribute to Zambia's poor performance, which relates to the widespread reliance on rain-fed agriculture, limited infrastructure, climate change, and limited dietary diversity (Bernstein et al., 2019). Therefore, the poor scores and ranks in the 2019 GFSI for Zambia could be attributed to these other contributing factors other than outdated data and outliers.

The third hypothesis was that updating Zambia's data and correcting outliers did not result in a statistically significant change in Zambia's overall GFSI score and ranking relative to the 113 countries. However, data coverage for many developing countries is weak. Like other developing countries, Zambia faces data availability challenges (Mukuka and Mofu, 2016) (Benin et al., 2020). These data gaps may hinder a comprehensive assessment in reporting progress and improvement in various interventions and programmes at the country level against the commitments made, especially in critical indicators underlying the commitment to ending hunger and halving poverty in Africa by 2025 as set out in the Malabo and Malabo declarations (Benin et al., 2020).

1.5 Outline of the dissertation

This dissertation consists of seven chapters. The first chapter provides an introduction to the study outlining the background, the problem statement and the objectives. A literature review is presented in chapter two, while the Global Food Security Index (GFSI) methodology is outlined in chapter three. Chapter four presents Zambia's food security status, while the methods and procedures for answering the research questions are presented in chapter five. The results and discussion are presented in chapter six. The dissertation's conclusions and recommendations are presented in the final chapter.

CHAPTER 2: REVIEW OF RELATED LITERATURE

2.1 Introduction

The use of composite indicators to synthesise multiple pieces of information into compact and single phenomenons in food security has emerged in recent decades (Santeramo, 2017). Until the emergency of composite, measuring food security was complicated by the lack of a single metric that combines its multiple indicators to measure its different dimensions (Barrett, 2010). Several indicators have been constructed to satisfy the definition of food security as when "all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" as well as through its six dimensions: availability, access, utilisation, stability, sustainability and agency (High Level Panel of Experts (HLPE), 2020).

However, no single survey instrument exist that collect all food security needed indicator at once (Carletto et al., 2013). For example, to measure the food availability dimension in a country, the GFSI use the sufficiency of food supply, food loss, food imports and infrastructural development indicators. However, infrastructural development, food loss, food imports indicators could also measure the food access dimension in a country. The multiplicity and overlapping nature of indicators used to measure food security make measuring food security complex and may hinder its reliability (Barrett, 2010; Carletto et al., 2013). However, composite indicators can help overcome food security measurement challenges, as composite indicators can aggregate multiple indicators into a single index (Santeramo, 2015a).

While the GFSI is considered a robust measure of food security, some challenges such as outliers and outdated data can affect its ability to capture food security effectively. However, the performance of the GFSI could be improved by continuously updating the databases, replacing outdated indicators and detecting and removing outliers. Moreover, the heterogeneity of existing food security measures and a "lack of consensus on how to rank and compare countries regarding food security has motivated the different international organisations to develop food security composite indexes to synthesise the information" (Santeramo, 2015b, p. 63).

2.2 An overview of food security measurement

The concept of food security has evolved over the years from a narrow focus on national and global food availability to one that incorporates multiple concerns now (Coates, 2013). In the early 1970s, food security was measured primarily by the availability of food at the national and global levels (Hendriks, 2015). Food insecurity was initially conceptualised to be caused by inadequate food supply at the national and global level (Hendriks, 2015). Therefore, increasing food supply through increasing production volumes and yields was seen as the solution to achieving food security (Hendriks, 2015). The availability of sufficient food was monitored using food balance sheets, from which estimates of food available to meet per capita energy needs were derived (Webb et al., 2006). Despite increasing food production, the problem of food insecurity has remained a great concern (Hendriks, 2015).

Following Sen's work in the 1980s, it was realised that production alone could solve the problem of food insecurity. Sen (1982) initiated the debate broadening food security analysis from the narrow focus on national and global food supplies to include access to food. People were not food insecure because the food supply was limited, but because people lacked access to food (Stringer, 2016; Barclay et al., 2019). Sen's work led to a shift from production to food access that significantly impacted food and development policies in the 1980s (Hendriks, 2015). The understanding that high food prices, low incomes, and a lack of resources hindered people's access to food led to policies on poverty reduction, price stabilisation, and social protection to improve food access (Hendriks, 2015).

The evidence that widespread hunger can exist even amidst food availability draws the need to distinguish between households and individual food security (Stringer, 2016). Initially, food security was measured at the household level, not at the individual level (Stringer, 2016). However, food security is a problem from the individual to the global level. Yet, policies deal with it mainly at the national level, and its measurement is at best at the household level (Berry et al., 2015). The focus on the food security at the individual resulted in the utilisation dimension of food security determining food safety and quality that measures how much a person eats and how a person converts food into energy (Berry et al., 2015). Adequate utilisation requires access to health services, access to water, a diet providing sufficient energy and essential nutrients, adequate sanitation and proper feeding practices (Berry et al., 2015).

Despite the shift in food security attention to nutrition associated with the utilisation dimension in the 1990s, dietary quality has remained a challenge (Coates, 2013). Stunting and micronutrient deficiency also continued to rise (Lobell and Burke, 2009). Therefore food security was defined to include nutrition at the world food summit of 1996 (Lobell and Burke, 2009). A food-secure world must not only assure a good balance between availability and diverse nutritional requirements for food; it should also address seasonal or chronic under-nutrition and micronutrient deficiencies (Opara, 2013). Therefore, the world food summit of 1996 defined food security as "when all people at all times have access to sufficient, safe and nutritious food to meet their dietary needs for an active and healthy life" (Food and Agriculture Organisation, 1996). The 2012 redefinition of food security by the Committee on World Food Security added environmental, food preference and sanitation aspects to the food security dimensions (Committee on World Food Security (CFS), 2012). More recently, the importance of preserving the environment, natural resources, and agroecosystems led to sustainability as another dimension of food security (HLPE, 2020; Berry et al., 2015). Furthermore, the HLPE has recommended the inclusion of the sixth dimension of food security, agency. The agency dimension, defined as "the capacity (of individuals or groups) to make their own decisions about food production, processing, distribution and consumption, and their ability to participate in processes which shape food system policies and governance" (HLPE, 2020, p. 7).

The unavailability of data in both coverage and quality could also hinder the measurement of food security. Data availability is a challenge, especially in developing countries (Freudenberg, 2003b; Closset et al., 2014). Though data disclosure and public data reporting rules and policies play an essential role in data availability, in some circumstances, data is simply not collected (Berry et al., 2015). A lack of financial resources and the capacity to carry out frequent national surveys to update databases is one of the major reasons for the unavailability of quality data in these countries (Benin et al., 2020). Due to the unavailability of data, many developing countries are ranked using outdated data or low-quality data due to data that may not reflect the actual food security situation (Benin et al., 2020; Kaufmann et al., 2011). Frequent comprehensive national household surveys could improve data availability (Yerramareddy and Babu, 2018).

Reliable measurement of food security can also be hindered by a lack of open access to national data. Data disclosure rules play an essential role in opening access to data (Barclay et al., 2019). Open access to data is the starting point for making decisions critical in enabling evidence-based policies by decision-makers in governments and private sectors (Yerramareddy and Babu, 2018). However, some African governments do not allow open access to data (Benin et al., 2020). A study by Onyancha (2016) revealed that between 2009 and 2014, Sub-Saharan Africa only contributed a mere 0.03% to the world's total number of data records. A lack of open access, low data disclosure and sharing hinder the communication of helpful information and research findings, reduce scientific transparency and accuracy and research collaboration among researchers, and can negatively impact socio-development (Onyancha, 2016). Therefore, publishing national data is one way of increasing food system analysis toward achieving food security (Yerramareddy and Babu, 2018).

Secondary data sources are relied upon to avoid the high cost of collecting primary data in measuring and quantifying food insecurity (Meade and Rosen, 2002). However, the use of existing secondary data sources could lead to inaccurate measurement, especially if the data is not adequately and sufficiently scrutinised to understand the information that the data conveys (Cafiero, 2013). Composite indicators have been developed to overcome the challenges associated with measuring global food security. There are many composite indicators built over time to measure food security. Food security indicators are diverse. Some food security composite indicators measure food security at the global, national, household or individual levels. Other food security composite indicators measure the drivers of food insecurity, while others measure the outcome of food security. Notable food security indicators include the Global Hunger Index (GHI), the Prevalence of Undernourishment (PoU), the Coping Strategy Index (CSI), Food Consumption Score Index (FCS) and the Human Development Index (HDI).

2.3 The benefits and constraints of composite indicators

While several composite indices have been constructed and widely used, it is essential to understand the cons and pros of composite indicators to be efficiently used. Composite indicators are aggregated indexes comprising of individual indicators and weights that collectively reflect each indicator's relative importance (Nardo et al., 2005b). Composite indicators can summarise the indicators into a single index to score and rank countries in different food security dimensions, thereby minimising the heterogeneity of existing food security indicators (Nardo et al., 2005b). Apart from reducing the size of the set of indicators underlying a certain phenomenon without dropping the information base, composite indicators make it possible to include more information within the existing size. A fundamental assumption underlying the use of composite indicators is that the combination of the constituent parts gives a fair summary of the phenomenon (Barclay et al., 2019). Composite indexes are easy to interpret and can be used for public communication (OECD, 2008). Composite indicators can also facilitate quality improvement efforts by identifying areas that need improvement (Profit et al., 2010). Different composite indicators have been constructed to assess the progress of countries over time (OECD, 2008). Therefore, composite indicators can enable users to compare complex dimensions effectively across countries and over time.

Moreover, indexes can be useful diagnostic tools for prioritising policy issues in a country (Turan et al., 2018).

Despite the importance of composite indicators in aggregating different phenomenon into single indexes and monitoring and benchmarking country performance in terms of food security, environment, social development and health, various factors may hinder their reliability. If poorly constructed or misinterpreted, composite indicators may send misleading results and policy messages that may be misused to support narrow agendas (Nardo et al., 2005b; Profit et al., 2010). Composite indicators may also lead to the implementation of inappropriate policies if some indicators that are difficult to measure or unavailable are excluded from the index. Barclay et al. (2019, p. 338) argue that "what goes into baskets of measures matters" in reference to the construction of composite indicators. Therefore, the choice of indicators to be included in a composite indicator should be clear and transparent to avoid disguising severe failure in some dimensions and difficulties in identifying proper policy actions (OECD, 2008). The choices of indicators to be included in the index may be the target of the political challenge as the selection of indicators is considered subjective (OECD, 2008; Santeramo, 2015b).

Moreover, the use of the same data (last available data or outdated data) in annual reports for several years may also affect the reliability of composite indicators (Abberger et al., 2018). The use of outdated data may not consider economic, environmental, economic or social changes in a country (Abberger et al., 2018). Moreover, the use of outdated data could considerably deteriorate the reliability and performance of the composite, and it reduces the ability of composite indicators to capture recent changes that affect food security situations, such as the impact of climate change (Dialga and Thi Hang Giang, 2017).

2.4 The construction process of composite indicators

There are seven steps involved in building composite indicators (Table 2.1). Although opinions differ on which of the seven steps for constructing composite indicators are most critical and subjective, there is a consensus that they should be constructed in such a way that they satisfy a range of desirable properties (Santeramo, 2015b; Saisana et al., 2005). Composite indicators should rely on a solid conceptual and theoretical framework and their indicators should be readily available and easy to interpret (Santeramo, 2015b). Therefore, transparency in the methodology used is critical as every methodological decision can impact the index's outcome (Santeramo, 2015b).

A study by Hudrliková (2013) revealed that data aggregation, normalisation and weighting methods were the fundamental and subjective components when constructing composite indicators. Santeramo (2015b) showed that normalisation and weighting methods are less crucial decisions, whereas data imputation and aggregation methods must be carefully selected in the construction process as they influence results. Dialga and Thi Hang Giang (2017) stressed that 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. However, Caccavale and Giuffrida (2020) found that the aggregation method has a minimal effect on the output while missing data imputation, normalisation, weighting and variable selection methods cause variability in results. From the studies above, it can be deduced that data imputation, normalisation, weighting and aggregation are the most critical steps in constructing composite indicators.

Furthermore, particular attention must be paid to the method when transforming raw data from different indicators into a single index, as each method may convey different results (Santeramo, 2017). Therefore, to understand the implications of the methodological choices such as missing data imputation, normalisation, weighting and aggregation methods, Nardo et al. (2005b) proposed a multivariate statistic approach to construct composite indicators. The multivariate analysis can be used to study the overall structure of the dataset, assess its suitability and guide subsequent methodological choices (OECD, 2008). Similarly, an uncertainty and sensitivity analysis can be undertaken to assess the robustness of composite indicators (OECD, 2008).

In addition to the steps outlined in Table 2.1, the performance of countries should be profiled at the indicator level to reveal the drivers for the overall good or bad performance or results (OECD, 2008). The constructed composite indicators should be correlated with existing indexes to identify linkages and then present the results of a composite indicator to the targeted audience and end-users clearly and accurately (OECD, 2008).

Table 2.1: Steps for constructing compositor indicators

Steps	**Importance**
Defining the phenomenon under investigation	Essential in identifying the specific indicators relevant to a phenomenon (OECD, 2008). Food security indicators are usually founded on the definition of food security (Santeramo, 2015b)
Selection of variables	To check the quality, strength and weakness of each available and selected indicator and to create a summary table on data characteristics across country and time and source
Imputation of missing data	Needed to provide a complete dataset, estimate missing values, and discuss the presence of outliers in the dataset (OECD, 2008). The reliability of each imputed value should also be measured to explore the impact of imputation on a composite indicator
Data normalisation	Essential to render the selected variables comparable(OECD, 2008). The normalisation method should respect both the theoretical framework and the data properties and robust to the presence of outliers(Nardo et al., 2005b). Example of normalisation methods are min-max normalisation, standardisation and ranking, among others (OECD, 2008)
Weighting	Different weights may be assigned to indicators to reflect their economic importance. The weighting methods must be made explicit and transparent for reference by future studies on the index (Nardo et al., 2005b). Equal weighting, factor analysis, Principal Component Analysis are among the notable examples of weighting methods (Santeramo, 2015b).
Aggregation	To make weights reflect trade-offs between indicators, for example, some indicators compensate for low values in other indicators (Santeramo, 2015b). Examples of aggregation methods are geometric and linear aggregation method
Uncertainty and sensitivity analysis	To identify sources of uncertainty in the building of composite indicators by testing the robustness of the methodologies used for selecting indicators, missing data imputation, aggregation, normalisation and weighting methods (OECD, 2008)

Source: Author's compilation from OECD (2008), Nardo et al. (2005b) and Santeramo (2015b)

2.5 An overview of outdated data in composite indicators

A lack of frequent surveys to update databases may result in outdated data (OECD, 2008). Outdated data could be referred to as missing current data, especially for composite indicators that report the performance of countries in annual benchmarking exercises (Freudenberg, 2003b). Data from previous years could be treated as outdated data because the current phenomenon under investigation lacks current data, which could distort findings on the performance of countries (Freudenberg, 2003b; Abberger et al., 2018). The use of outdated data in composite index construction may result in incorrect policy prescription in benchmarking exercises (Abberger et al., 2018).

Data quality is critical for accurate and relevant measurement of food security (Freudenberg, 2003b). Freudenberg (2003b) argues that lack of relevant data is the most significant problem in constructing composite indicators because the available data may not be comparable across countries or exist only for a few countries. Due to changes in the economic, social or environmental relationships or even historical changes, data collected at a given point in time might not provide a favourable reflection of the same situation in the future (Abberger et al., 2018). The cost of data collection, age of data, the scope of information the data conveys in a measured phenomenon, difficulties in measuring some variable, concept or behaviour and lack of comparable indicators across countries (Kaufmann et al., 2011; Freudenberg, 2003b). Therefore to improve the reliability of composite indicators in keeping up with trends, databases should be continuously updated.

Several methods have been used to handle the problem of missing current data in composite indicators. Some of these methods include using imputed or estimated values to replace outdated data, substituting the last available data for a country with outdated data, or replacing indicators whose databases are no longer updated (Thomas et al., 2017; Santeramo, 2015b). Farhangfar et al. (2007) suggest that missing current data can be ignored or removed from the dataset or filled with new values through imputation to avoid loss of efficiency. For example, the EIU uses estimated values for missing quantitative data, while outdated data replaced with the last available data for the given country (EIU, 2019). However, the use of the last available data may not reflect the actual food security situation in a country and could hinder the robustness of composite indicators from providing up to date global benchmarking exercises (Cherchye et al., 2011; Cherchye et al., 2009). Benin et al. (2020) advocate for updating outdated as the best method to improve the reliability of composite indicators' results.

2.6 An overview of outliers in composite indicators

Outliers have been one of the oldest problems in statistics and research (Hawkins, 1980). Ignoring or excluding outliers can lead to misleading results (Welsh and Ronchetti, 1998). Outliers are extreme observations or values that lie outside the overall pattern of distribution of the variable in a sample (Ghosh and Vogt, 2012; Thomas et al., 2017). Beaumont and Rivest (2009) identify two types of outliers: representative and non-representative outliers. Representative outliers are correctly measured values from sampled observations but are relative extremes compared to the other values and are handled at the survey estimation stage (Beaumont and Rivest, 2009). In contrast, non-representative outliers caused mainly by reporting errors resulting from incorrect values in the sample data and can be unique units in the population (Beaumont and Rivest, 2009). Non-representative outliers are corrected at the data collection and editing stage of a survey (Beaumont and Rivest, 2009).

It is essential to identify and remove outliers when building composite indicators (Nardo et al., 2005b). The outlier detection technique aims to identify suspicious values in variables analysed and confirm that the variables' reported values are correct (Marcos et al., 2018). Identifying outliers allows researchers to choose an adequate and robust technique to remove them (Beaumont and Rivest, 2009).

Outliers can lead to biased results and cause possible misinterpretation of results (Marcos et al., 2018). In composite indicators, outliers are problematic as they become an unintended benchmark (Thomas et al., 2017; Nardo et al., 2005b). Outliers can also distort transformed indicators during normalisation if the normalisation method is sensitive to the presence of outliers (OECD, 2008). Many techniques are used to identify and detect outliers, such as studying the z-scores or the standard deviation, m-estimation and box plot methods (Hawkins, 1980). Outliers may also be detected by examining the shape of the distribution of each indicator and computing the skewness and kurtosis (Thomas et al., 2017). An indicator with an absolute value greater than two and 3.5 for the skewness and kurtosis, respectively, indicates the presence of outliers (Thomas et al., 2017). Nardo et al. (2005b) suggest that outliers should be removed or corrected before normalisation as some normalisation methods are sensitive to the presence of outliers.

The identified and detected outliers can either be removed or replaced statistically through winsorisation (Thomas et al., 2017). Winsorisation implies that the values of indicators with outliers are replaced by their next largest or smallest value until their skewness and kurtosis are below 2 and 3.5, respectively (Thomas et al., 2017). Other methods for removing or correcting outliers include Median Absolute Deviation (MAD), M-estimation and multiple regression (Hawkins, 1980).

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

The construction of composite indicators needs the availability of continuously updated data that is robust to economic, environmental or social changes and reflect the actual phenomenon they measure (Abberger et al., 2018). Abberger et al. (2018) applied a rule-based updating procedure to improve the Swiss Economic Institute Barometer Economic (KOF) composite indicator's performance. The rule-based updating procedure updated indicators at regular intervals as opposed to the *ad hoc* process that updates indicators when the need arises (Abberger et al., 2018). The procedure improved the quality and performance of the selected indicators compared to the *ad hoc* updating process (Abberger et al., 2018). Abberger et al. (2018) concluded that composite indicators need regular indicator selection and updating through data availability and data revisions to prevent them from deteriorating in performance.

A similar study by Benin et al. (2020) assessed how improving data quality (accuracy, age of data, consistency, timeliness, transparency and data frequency) could improve policymaking in African countries during the Comprehensive Africa Agriculture Development Programme (CAADP) implementation. Five Pilot African countries were compared to five non-CAADP countries using the 2018 Biennial Review as a base year to compare with the 2020 Biennial Review outcomes. Benin et al. (2020) used the difference-in-difference approach after updating and improving data. An improvement was seen in the reporting rate and quality of reported data for countries whose data were updated. For example, in Malawi (a country implementing CAADP), the data reporting score improved by 3.0%, from 86.1% in 2018 to 89.1 in 2020 (Benin et al., 2020).

Closset et al. (2014) assessed the effect of missing data in the United Nations Committee Policy (UN-CDP) Human Asset Index (HAI). It was found that most developing countries did not have up to date databases. Closset et al. (2014) updated the outdated data to construct a retrospective series from 1980 to 2011 and used regression and the nearest neighbour to impute missing data values from the incomplete official statistics. The comparison showed marginal discrepancies in scores due to updating primary data for the UN-CDP HAI 2012.

Similarly, Feindouno and Goujon (2016) emphasised that the analysis of trends in the Human Capital Index requires the calculation of retrospective series with a constant definition over time and time series that are updated and comparable over time. However, the construction of retrospective series faces various challenges; the main one is historical data availability, which is especially weak for some components and some developing countries (Feindouno and Goujon, 2016). Another study by Feindouno and Goujon (2019) showed improved scores for Least Developed Countries (LDC) against non-LDC between 1990 and 2014 in Human Assets Index due to improvement in data entries.

Kaufmann et al. (2011) researched the World Bank's Worldwide Governance Indicators by continuously updating indicators for measuring world governance. Kaufmann et al. (2011) concluded that continuous updating of data resulted in constant improvement in performance for governance indicators, and regular updating could help reflect timely monitoring of governance.

Marcos et al. (2018) and Thomas et al. (2017) analysed the effects of outliers on composite indicators. Thomas et al. (2017) assessed the effects of outliers on the robustness of the GFSI in measuring food security by studying the shape of the distribution of the indicators to identify potential outliers. Indicators with absolute skewness and kurtosis values greater than 2 and 3.5, respectively, were treated as outliers and size indicators were identified as outliers in the 2016 GFSI database (Thomas et al., 2017). Winsorisation was applied to remove the outliers (Thomas et al., 2017). Thomas et al. (2017) then compared scores and ranking of countries obtained before and after winsorisation. Outliers had no effects on countries' final score and ranking as most countries only shifted by one or two positions (Thomas et al., 2017). Marcos et al. (2018) used a similar method to identify and remove outliers. Still, they did not test if outliers affected the Commitment to Reducing Inequality (CRI) index scores and ranks for 157 countries.

2.8 Research gap

The literature above clearly shows that outliers and outdated data are problems in constructing or assessing composite indicators. Outliers and outdated data could affect the robustness of a composite indicator in measuring phenomena like food security. Outdated data hinder useful information and must be updated for a composite to be reliable and robust. Outlier could act as unintended benchmarks leading to biased results in composite indicators.

The presence of outliers and the use of outdated data could lead to biased composite indicators scores. Therefore, they should be effectively handled to achieve unbiased scores for countries' ranking in benchmarking exercises and policy formulation (Cherchye et al., 2011). Improving data availability, quality, and reporting rates across countries and at the national level is essential for unbiased and evidence-based policymaking (Yerramareddy and Babu, 2018; Benin et al., 2020).

The GFSI's robustness in measuring food security could be affected by outdated data and outliers in the databases. The problem of outdated data and outliers has not been conclusively dealt with in the earlier studies of the GFSI (Caccavale and Giuffrida, 2020). The GFSI, like other composite indicators, need frequent data of high quality in its annual reporting to inform actual food security situation in countries and globally. Regular data collection through surveys at the national level can help keep track of economics, environment, agriculture, social, climatic and general changes necessary in building up to date composite indicators that reflect performance on development targets (Caccavale and Giuffrida, 2020; Freudenberg, 2003a). The present study sought to update outdated data, identify and correct outliers in the 2019 GFSI database used to generate the 2019 score and ranking of countries with Zambia as a case study.

2.9 Conceptual framework

The conceptual framework for the study is presented in Figure 2.1. It captures the relationship between quality of data, outdated and outliers for achieving robust and unbiased results and how they affect the reliability of GFSI score in policy formulation and benchmarking. The framework suggests that data availability affects the quality of data and indicators used to construct composite indicators. The quality of data is affected by missing current data and the presence of outliers. Where current data is difficult to find, many composite indicators use outdated data or the last available data (Benin et al., 2020).

The framework indicates that outliers and outdated data (and missing data in general) result in biased scores and ranks in a composite indicator. Outdated data and outliers can render composite indicators less reliable and distort countries' relative standing in the composite index (Freudenberg, 2003a; Santeramo, 2017). Outdated data and outliers could also affect the use of the index in tracking a country's performance over time and policy formulation and benchmarking (Caccavale and Giuffrida, 2020).

There are various approaches to handling the problem of outdated data and outliers suggested in the literature. For composite indicators released every year to track changes against a baseline, this framework suggests that updating outdated data with current data is the best way to obtain unbiased scores. The framework also indicates that detecting and resolving outliers before normalizing and aggregating data into a composite score could help get reliable scores and ranks for benchmarking and policy formulation.

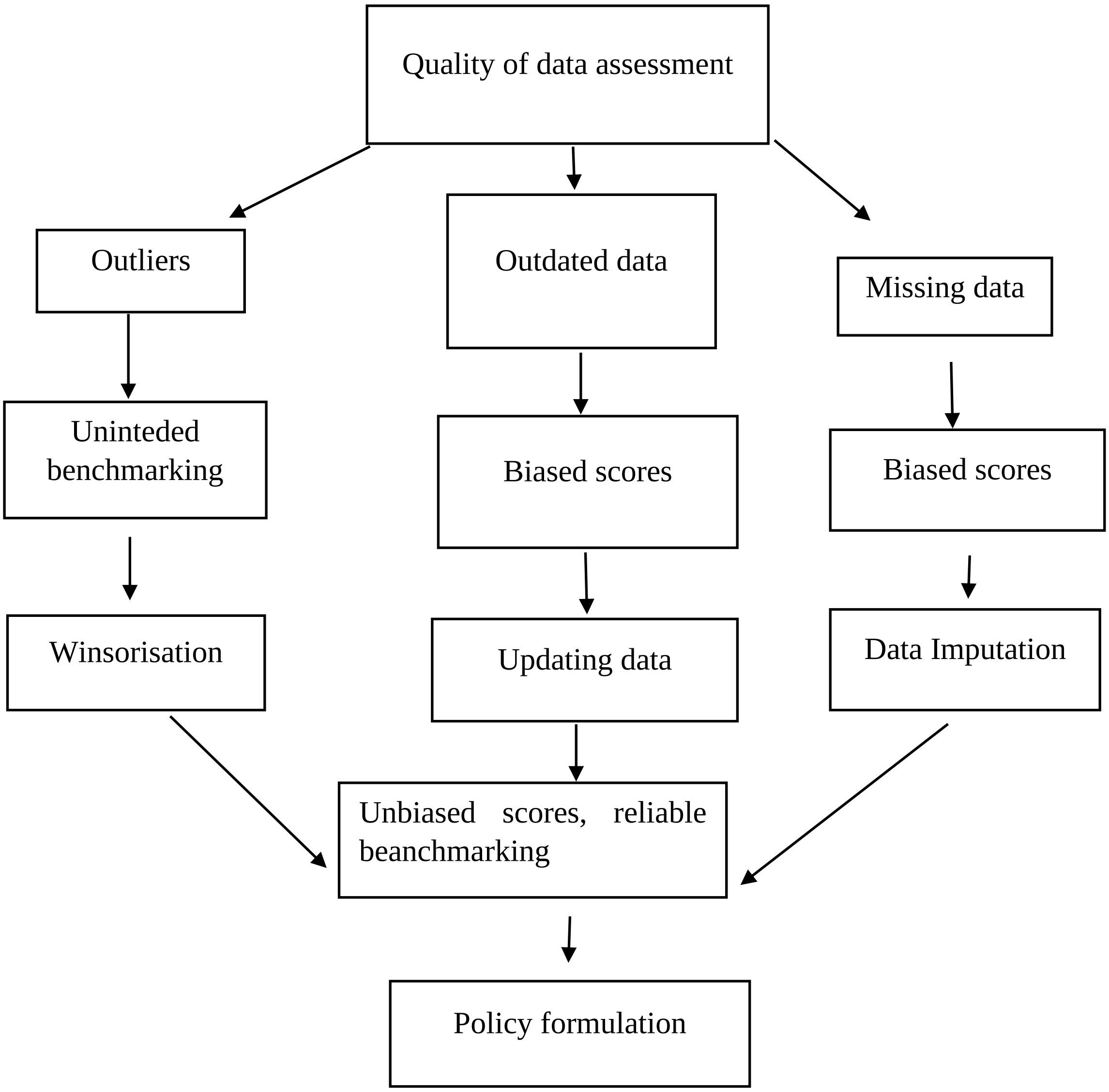

Figure 2.1: Conceptual framework

Source: Compiled by the author.

CHAPTER 3: A REVIEW OF THE GLOBAL FOOD SECURITY INDEX METHODOLOGY

3.1 Introduction

This chapter presents the methodology used by the Economist Intelligence Unit (EIU) to construct the Global Food Security Index (GFSI). The steps involved in constructing the GFSI are presented, starting with the definition of the GFSI dimensions and indicators, then selecting countries and GFSI data sources. Lastly, the chapter discusses the normalisation, weighting and aggregation techniques used by EIU to calculate the GFSI.

3.2 The GFSI dimension and indicator definitions

The GFSI is a multidimensional food security composite indicator developed by the EIU in 2012 to measure and rank the food security situations of 113 countries annually. The GFSI contains 34 indicators determined by the panel of EIU experts to measure the food security situation, as shown in Table 3.1. These indicators are divided into three dimensions: food availability, affordability, quality and safety dimensions. The indicators included in the GFSI are carefully selected by the panel of experts of the EIU to include both quantitative and qualitative aspects of food security (EIU, 2019). Of the 34 indicators in the 2019 GFSI report, 16 were qualitative, while 18 were quantitative indicators (EIU, 2019). The selection of the 113 countries in the index by the EIU was based on population size, regional diversity and economic importance (EIU, 2019). The countries represented in the GFSI are reported by region and divided into higher income, upper middle income, lower middle income, low income, lower middle income, middle- and low-income, lower-middle and low income and middle income (EIU, 2019). The Sub-Saharan region has the highest number of countries at 28, followed by Europe with 26 countries (EIU, 2019).

According to Izraelov and Silber (2019), the GFSI was the most cited food security measure in 2018. Thomas et al. (2017) stressed that the focus of the GFSI is on food security contributing factors rather than on outcomes such as consumption and the nutritional status of a population. Thomas et al. (2017) further contended that the GFSI measures an enabling environment for food security rather than the actual state of food security. Thomas et al. (2017) further highlighted that the GFSI does not include information about inequality among the poor or food-insecure households or individuals. The other weakness of the GFSI was highlighted by

Turan et al. (2018), who noted the GFSI's failure to consider the variations in different areas in a country.

The availability dimension of the GFSI with 11 indicators assesses a country's capacity to produce and distribute food by examining factors that influence food supply, including the risk of food shortages and the ease of access to food at the national level (Izraelov and Silber, 2019). Some of these factors that might influence and obstruct food availability at the national level include agriculture infrastructure, political stability, and food loss. (EIU, 2019).

The affordability dimension assesses people's capacity to pay for food and the cost they face under the normal circumstance to access food and in times of food-related shocks (Thomas et al., 2017). The affordability dimension looks at whether an average individual can purchase food and how the public built structure responds to shocks at the societal or personal level (Chen et al., 2019). The ability and capacity to afford quality food without undue stress are crucial for food security (Chen et al., 2019). Some of the indicators under this dimension are the proportion of the population under global poverty, change in average food cost and gross domestic product per capita (EIU, 2019).

The quality and safety dimension assesses and explores the nutritional quality of average diets and food safety. Access to nutritious food is essential for food safety (Chen et al., 2019). Izraelov and Silber (2019) refer to this dimension as utilisation because it explores energy and nutritional intake by the individuals, diversity of diets and food preparation. The quality and safety dimension contained five indicators and nine sub-indicators (EIU, 2019). The natural resource and resilience dimension explores the impact of climate-related natural resource risks on food security, but it is not included in the standard GFSI (EIU, 2019).

The GFSI includes both developed and developing and low and high-income countries in its annual analysis to reflect regional diversity, population size and economic importance, thereby providing a wide range of countries for comparison (Izraelov and Silber, 2019; Maricic et al., 2016). The comparison of the GFSI with other similar food security indexes showed that the GFSI is strongly correlated with the Global Hunger Index (GHI) but poorly correlated with the Proportion of Undernourishment (PoU) (Thomas et al., 2017). The poor correlation between the GFSI and PoU was due to some indicators in the GFSI that were not related to the PoU, such as political stability risk and agricultural import tariffs (Thomas et al., 2017). Although the GFSI is reportedly robust in measuring food security, it should be used alongside other indicators measuring food security outcomes as the GFSI only measure factors contributing to food security (Thomas et al., 2017).

Table 3.1: Indicators for availability, affordability and quality and safety

Dimensions and Indicators		Source
1	**Affordability**	
1.1	Change in average food costs	National accounts
1.2	Proportion of population under the global poverty line	WB-WDI
1.3	Gross domestic product per capita (US$ PPP)	EIU
1.4	Agricultural import tariffs	WTO
1.5	Presence and quality of food safety net programmes	Qualitative scoring by EIU
1.6	Access to financing for farmers	Qualitative scoring by EIU
2	**Affordability**	
2.1	Sufficiency of supply	EIU scoring
2.1.1	Average food supply	FAO
2.1.2	Change in dependency on chronic food aid	WFP
2.2	Public expenditure on agricultural R&D	EIU estimates
2.3	Agricultural infrastructure	EIU scoring
2.3.1	Existence of adequate crop storage facilities	Qualitative scoring by EIU
2.3.2	Road infrastructure	EIU Risk briefing
2.3.3	Port infrastructure	EIU Risk briefing
2.4	Volatility of agricultural production	FAO
2.5	Political stability risk	EIU Risk briefing
2.6	Corruption	EIU Risk briefing
2.7	Urban absorption capacity	WB, WDI
2.8	Food loss	FAO
3	**Quality and safety**	
3.1	Dietary diversity	FAO
3.2	Nutritional standards	EIU scoring
3.2.1	National dietary guidelines	Qualitative scoring by EIU
3.2.2	National nutrition plan or strategy	Qualitative scoring by EIU
3.2.3.	Nutrition monitoring and surveillance	Qualitative scoring by EIU
3.3	Micronutrient availability	EIU scoring
3.3.1	Dietary availability of vitamin A	FAO
3.3.2	Dietary availability of animal iron	FAO
3.3.3	Dietary availability of vegetal iron	FAO
3.4	Protein safety	EIU
3.5	Food safety	EIU scoring
3.5.1	Agency to ensure the safety and health of food	Qualitative scoring by EIU
3.5.2	Percentage of population with to potable water	WB
3.5.3	Presence of formal grocery sector	Qualitative scoring by EIU

Source: EIU (2019).

3.3 The GFSI data sources

Quantitative data used to calculate the GFSI are obtained from credible international data sources, such as FAO, World Bank, the WFP, the world trade organisation, and many others, are recognised as reliable, as shown in Figure 3.1 (Chen et al., 2019; Thomas et al., 2017). By contrast, the EIU panel of experts created and adjusted qualitative data to compute GFSI values based on available data from government websites, development banks, and surveys (EIU, 2019). The GFSI is expected to use current data to report the food security situation for a given year because it assesses factors contributing to food security annually. However, like any other composite index, the GFSI faces the challenges of the availability of updated data for some indicators and countries. Therefore, the GFSI data can represent a country's food security situation to the extent that data still depicts the current situation (Thomas et al., 2017). Where current data was missing, the EIU either uses estimates or the last available (outdated data) to obtain a complete data set (EIU, 2019).

3.4 The normalisation and aggregation of indicators in the GFSI

The normalisation of the selected indicators is crucial in making indicators comparable as various indicators in the dataset uses different measurement units (OECD, 2008). Several methods are used to normalise raw indicator data into a standard unit such as ranking, standardisation (or z-scores), min-max normalisation, distance to reference measure, the balance of opinion, among others (Freudenberg, 2003a). One advantage of min-max normalisation is that boundaries can be set, and all indicators have an identical range of 0-1 (Talukder et al., 2017). However, this technique is based on extreme values (minimum and maximum) that can strongly influence the score if they are outliers (Talukder et al., 2017).

The indicators selected by the EIU are normalised using a min-max normalisation method. The min-max normalisation method normalises the indicators for which the highest value indicates a favourable food security situation based on Equation 3.1 below.

$$X = (x - Min(x))/(Max(x) - Min(x)) \qquad \text{Equation 3.1}$$

Min(x) and Max(x) are the lowest and highest values in the 113 countries for any given indicator, respectively (EIU, 2019). The raw indicator values are normalised to the 0-1 range and later transformed into a 0-100 score where the countries with the highest raw data score 100 and the countries with the lowest raw data score zero (EIU, 2019).

The normalisation for indicators for which higher values indicate a worse or unfavourable food security situation are normalised based on Equation 3.2 below.

$$\mathrm{X} = (\mathrm{x} - \mathrm{Max}(\mathrm{x}))/(\mathrm{Max}(\mathrm{x}) - \mathrm{Min}(\mathrm{x})). \qquad \text{Equation 3.2}$$

Min(x) and Max(x) are the lowest and highest values in the 113 countries for any given indicator, respectively (EIU, 2019). This min-max normalisation formula transforms an indicator's raw value to a normalised value of 0-1 range. The normalised value is then rescaled from a 0-1 to a 0-100 score. Therefore, countries with the highest value of the indicator score zero, while the countries with the lowest value score 100 (EIU, 2019).

The GFSI model also includes the natural resource and resilience adjustment dimension. Users can decide either to view the results or overall score with or without considering climate and natural related factors (EIU, 2019). This dimension follows the same methodology or data modelling as other dimensions. However, the formula to calculate the adjusted overall score is as follows:

Adjusted overall score = X * (1 - Z) + (X * (Y / 100) * Z) Equation 3.3

Y is the natural resource and resilience score, Z is the adjustment weighting factor, and X is the original overall score. The default setting for the natural resource and resilience adjustment factor weighting is 0.25, equivalent to 25% (EIU, 2019).

In the 2020 GFSI results, the EIU used the upper-lower threshold normalization method to transform raw data into standard units (EIU, 2020). Indicators below or above the mean are transformed where the values around the mean receive zero, whereas those below/above a certain threshold receive -1 and +1, respectively (OECD, 2008). Despite being simple and robust to outliers, the lower-upper threshold method depends on the arbitrariness of the threshold level and could omit absolute level information (OECD, 2008).

3.5 The GFSI weighting method

The last stage of the construction in the GFSI involves the use of weights defined by the EIU panel of experts. The panel of experts have defined two sets of weighting methods. The first option, known as neutral or equal weighting, assumes that indicators have equal importance and distribute weights evenly. The second weighting method, known as peer panel recommendation weighting, averages the weighting suggested by the EIU panel of experts. In the model, the panel of experts weightings is the default weightings. Users can also create their customised weighting to test their assumptions about each indicator's relative importance in the model (EIU, 2019). The EIU assigns weights to the sub-indicators, indicators and dimensions to drive scores for the indicators and the countries (as shown in Table 3.2). The GFSI use the linear aggregation method, also referred to as a simple weighted average of the three-dimension scores, to calculate the overall GFSI score (EIU, 2019).

The affordability dimension is allocated a nominal weight of 2.5 that account for 40% of the weight of the 2019 GFSI score (EIU, 2019). The availability dimension (with eight indicators and eight sub-indicators) has the largest allocation of nominal weights of 2.75, representing 44% of the overall GFSI weights. At the same time, the panel of experts assigned the quality and safety dimension with the nominal weight of one that accounts for only 16% of the GFSI weight.

The default weighting or EIU peer panel recommendation weighting has been criticised in various studies as biased and subjective (Chen et al., 2019; Izraelov and Silber, 2019; Thomas et al., 2017; Maricic et al., 2016). As opposed to the subjective weighting by the EIU, Maricic et al. (2016) proposed the use of the Composite I-Distance (CIDI) approach for obtaining unbiased weights in the GFSI. Chen et al. (2019) suggested using a hierarchical data envelope analysis approach to assign weights in the GFSI, endogenising the weights to avoid subjective weighting for international comparison. Izraelov and Silber (2019) and Thomas et al. (2017) applied principal component analysis on the GFSI to assign weights to the indicators. All these studies (Chen et al., 2019; Izraelov and Silber, 2019; Thomas et al., 2017; Maricic et al., 2016) concluded that the proposed weighting methods give the same results as those proposed by the panel of experts of the EIU. However, Maricic et al. (2016) and Izraelov and Silber (2019) stressed that while the rank was not significantly different from that of the EIU, the proposed statistical objective weighting techniques produce unbiased and reliable scores and rank those obtained by the EIU subjective default weighting.

Furthermore, Thomas et al. (2017) stressed that though the EIU considers affordability and availability of greater statistical importance (assigning higher weights), the quality and safety dimension is equally essential in the index. Thomas et al. (2017) further stressed that the EIU should justify assigning weight and allocating some indicators under the various dimensions. For example, the volatility of agricultural production and urban absorption capacity had no impact on the score attributed to affordability dimensions (Thomas et al., 2017).

Table 3.2: GFSI indicators and weights

1. Affordability	(a) Weight within GFSI	(b) Weight within Affordability	Overall weight (a*b)
1.1 Food consumption as a share of household expenditure	40%	22.22%	8.9%
1.2 Proportion of population under the global poverty line		20.20%	8.1%
1.3 Gross domestic product per capita (PPP)		22.22%	8.9%
1.4 Agricultural import tariffs		10.10%	4.0%
1.5 Presence of food safety-net programmes		14.14%	5.7%
1.6 Access to financing for farmers		11.11%	4.4%
2. Availability	(a) Weight within GFSI	(b) Weight within Availability	Overall weight (a*b)
2.1 Sufficiency of supply	44%	23.42%	10.30%
2.2 Public expenditure on agricultural R&D		8.11%	3.57%
2.3 Agricultural infrastructure		12.61%	5.55%
2.4 Volatility of agricultural production		13.51%	5.94%
2.5 Political stability risk		9.91%	4.36%
2.6 Corruption		9.91%	4.36%
2.7 Urban absorption capacity		9.91%	4.36%
2.8 Food loss		12.61%	5.55%
3. Quality and Safety	(a) Weight within GFSI	(b) Weight within Quality and Safety	Overall weight (a*b)
3.1 Diet diversification	16%	20.34%	3.25%
3.2 Nutritional standards		13.56%	2.17%
3.3 Micronutrient availability		25.42%	4.07%
3.4 Protein quality		23.73%	3.80%
3.5 Food safety		16.95%	2.71%

Source: (EIU, 2019; Maricic et al., 2016).

CHAPTER 4: ZAMBIA’S FOOD SECURITY STATUS

4.1 Introduction

Zambia is among the most food-insecure countries in the world. The GHI classified Zambia among the countries with alarming hunger levels (Bernstein et al., 2019). For example, in 2019 GHI results, Zambia was the fifth hungriest nation, ranking higher than Madagascar, Chad, Yemen and the Central Africa Republic only (Bernstein et al., 2019). Zambia’s food insecurity challenges hinder its citizen from enjoying the provision of the right to food in desired preference, quantities and qualities. Despite making positive strides toward achieving national food security through agricultural production, food insecurity and malnutrition in all its forms, including undernutrition (stunting, wasting and underweight), remains a daunting challenge in Zambia (Mofya-Mukuka and Singogo, 2020). The proportion of undernourished people in the country in 2019 stood at 48%, while 35% of the children were stunted due to poor nutrition (Zambia Statistical Agency (ZSA), 2019).

Agriculture is the mainstay for the country’s population, with 86% of the rural population dependent on agriculture production compared to 14% in the urban areas (Kabisa et al., 2019). The agriculture sector contributes 20% to the country’s GDP, while copper production provides much of the country’s revenue. Zambia has ample water and land resources, with 58% of its 75 million hectares classified as medium to high potential for agriculture production (ITA, 2020). However, only 15% of the land is currently under cultivation, with most farms still dependent on rain-fed agriculture (International Trade Administration (ITA), 2020).

Although Zambia achieved middle-income status in 2011 after years of significant economic progress, economic performance has recently stalled (World Bank, 2019). The economic growth rate declined significantly from 4% in 2018 to 1.4% in 2019, mainly attributed to falling copper prices, declines in agricultural output and low hydroelectric power generation due to insufficient rains (World Bank, 2019).

Zambia’s reliance on rain-fed agriculture means that the country is vulnerable to inter and intra-annual variations in rainfall. Droughts and floods have become more frequent in the recent decade, impacting food production on which Zambia relies (FEWSNET, 2013; VAC, 2019). The country's northern half frequently experiences flooding, while the southern half is more prone to droughts and dry spells. Notably, the drought of 2018/19 reduced crop production by 35%, affecting the food security of about 2.3 million people (IPC, 2019).

4.2 Overview of Zambia's food security status

Food insecurity is prevalent in Zambia. According to the Integrated Phase Classification (IPC) 2020 acute food insecurity analysis, 1.98 million people (29% of the population) were estimated to have faced higher levels of food insecurity (phase 3 or above) by October 2020 (IPC, 2020). The high levels of food insecurity have been attributed to the effects of climate change that have impacted production at the household level (IPC, 2020; IPC, 2019). The northern and northeastern regions of the country experienced high rainfall leading to waterlogging of crops in the 2018/19 season (IPC, 2019). In contrast, the southern, central and western areas received below-normal rainfall resulting in droughts and dry spells that reduced crop production (IPC, 2019).

The effects of climate change have increased acute food insecurity cases through loss of livelihoods, displacements of people and outbreaks of diseases (IPC, 2020). The reduction in production due to droughts and flood has affected the availability of food and access to quality food at household and national level through increased prices of available foods (IPC, 2020).

Furthermore, Zambia has had one of the highest stunting levels, undernourishment and wasting in Africa in the last three decades (see Figure 4.1).

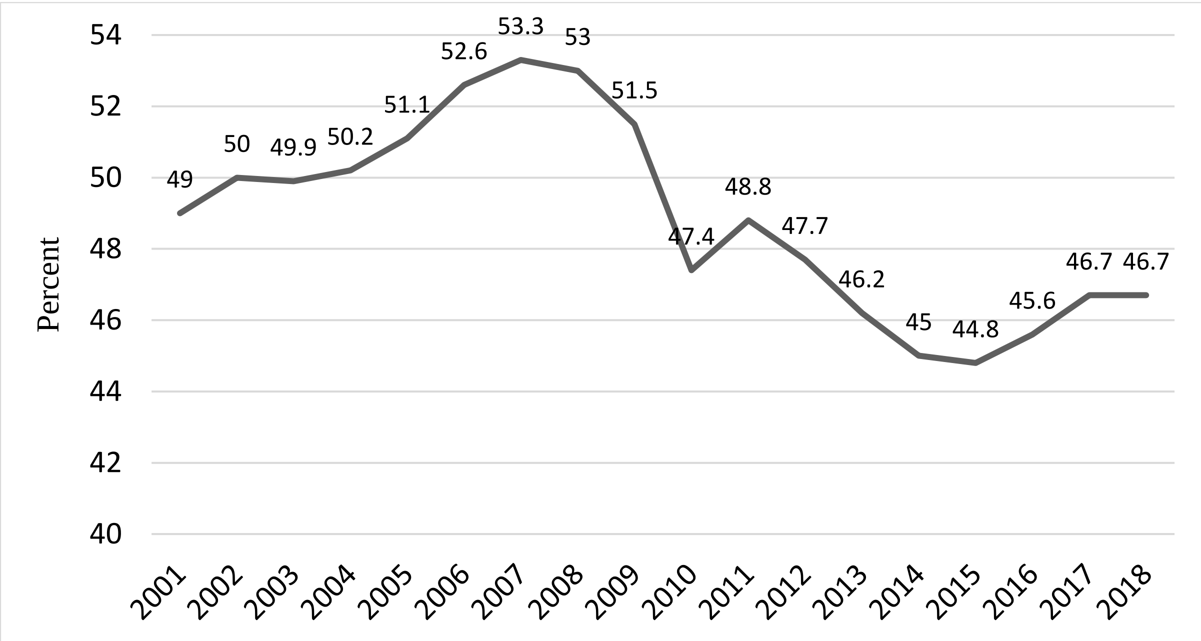

Figure 4.1: Undernourishment in Zambia, 2001-2018

Source: WB (2019) and (ZSA et al., 2019).

In addition to high levels of undernourishment, Zambia is one of the countries in Africa with the highest burden of undernutrition in children under five years of age (Mofya-Mukuka and Singogo, 2020). In 2019 under-five child undernutrition (stunting) was 35%, wasting 4% and underweight 10% (ZSA et al., 2019), as shown in Figure 4.2. Efforts to reduce undernutrition among children have been hampered by high levels of poverty, especially in rural areas where poverty remains a significant challenge (Jonah et al.,2018). Furthermore, Zambia remains unlikely to achieve the 2030 SDG target of zeroing stunting among children as the reduction in stunting have been gradual (Mofya-Mukuka and Singogo, 2020).

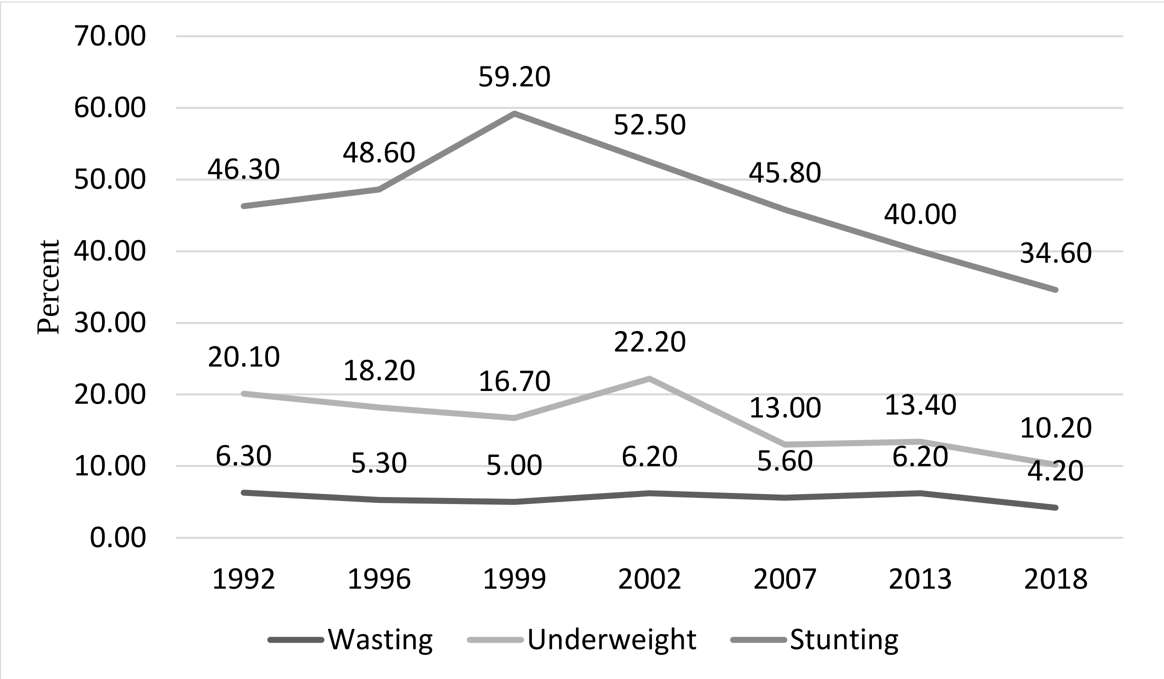

Figure 4.2: Zambia's Stunting, Underweight and Wasting rates, 1992-2018
Source: Zambia Statistical Agency (2019).

4.3 Zambia's performance in the GFSI since 2012

Since the inception of the GFSI in 2012, Zambia has performed poorly in all its dimensions. However, the GFSI trends show that Zambia's food availability has been improving since 2012. The affordability dimension had the most improvement (41.8 out of 100) in 2019 compared to previous affordability scores, as shown in Figure *4.3*. The improvement in the affordability score could be attributed to the GFSI's change in the average food cost indicator to replace food consumption as a share of household expenditure in the 2019 GFSI (EIU, 2019). While Zambia performed poorly in the food consumption indicator (as a share of household expenditure) when the country scored 29.6 out of 100 in 2018, the country scored 98.7 in the change in the average food costs. The 2019 GFSI data for agricultural import tariffs and the Gross domestic product per capita was updated for Zambia, which could have further contributed to the improvement in the affordability score. Figure 4.3 shows Zambia's scores in the GFSI from 2012 to 2019.

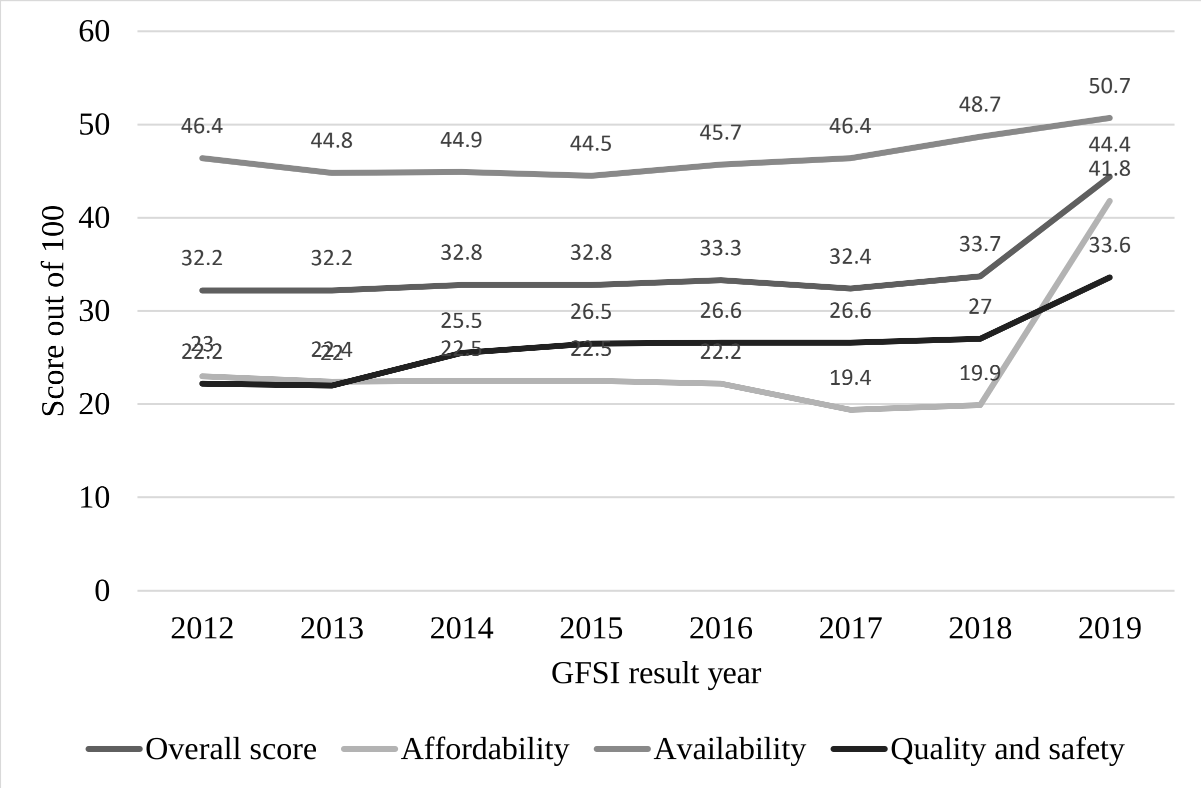

Figure 4.3: Zambia' GFSI scores from 2012 to 2019

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

In the overall GFSI ranking, Zambia has consistently ranked among the bottom 15 countries since 2012, ranking 101 out of 113 in 2019 (EIU, 2019). In the 2019 GFSI, the affordability dimension had the most significant improvement in rank, followed by the quality and safety dimension, as shown in Figure 4.4. The improvement in rank for the affordability dimension could be attributed to introducing the change in the average food cost indicator that replaced the food consumption as a share of household expenditure indicator in the 2019 GFSI results. The improvement in the quality and safety dimension rank could be attributed to improved dietary diversity and micronutrient availability indicators in 2019 compared to 2018 (EIU, 2019; EIU, 2018). The EIU (2019) report also highlighted an improvement in the ability to store food safely due to the expanded access to electricity. The rise in rank for the availability dimension could be attributed to the reduction in the food supply in 2019 due to droughts and flood in different parts of the country (EIU, 2019; IPC, 2019). However, Zambia's ranking in food availability has been relatively stable, between ranking 80 in 2012 and 87 in 2019.

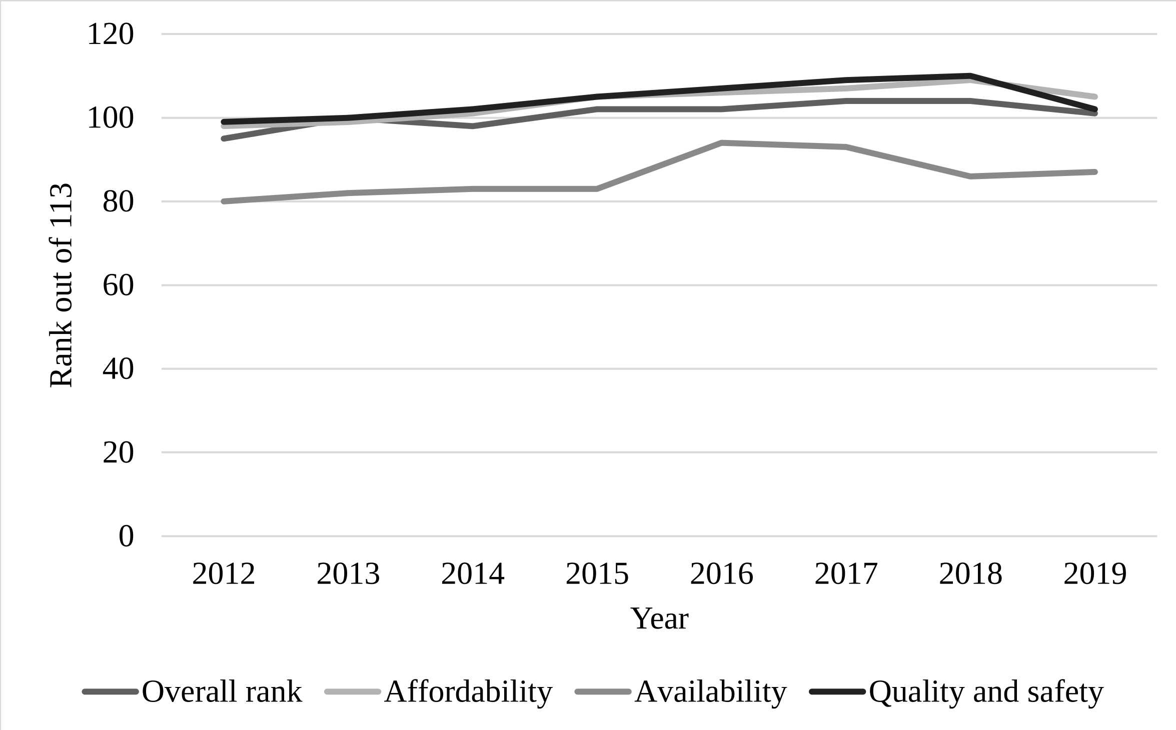

Figure 4.4: Zambia's rank out of 113 countries in the GFSI from 2012 to 2019
Source: Author's compilation with data from EIU (2019).

4.4 The policy context of Zambia's food security

The constitution of the Republic of Zambia does not explicitly guarantee the right to adequate food (FAO, 2021). However, since independence, Zambia has implemented several policies to ensure food and nutrition security and signed various international conventions that support the right to food. Vision 2030, enacted in 2006, spells out the country's vision for a well-nourished and healthy population by 2030 with clear goals and targets for improving the living standard of the citizens (GRZ, 2006). The national Vision 2030 has been implemented through a series of five-year national development plans (GRZ, 2006). The current national development plan being the seventh national development plan (7NDP) covering the period 2017-2021 implemented in line with the SDGs, aspires to see a prosperous middle-income Zambia by 2030 (MNDP, 2017).

In 2006, Zambia developed the National Food and Nutrition Policy (NFNP). The NFNP called for nutrition to be addressed through a multi-sectoral approach and a partnership between the Ministry of Health and the Ministry of Agriculture. Furthermore, the NFNP called for food diversification to promote diet diversity. Through the NFNP, the country developed the national food and nutrition strategic plan in 2011. The NFNP laid out a requirement for the agriculture sector to contribute to improving diets. It also outlined the ‘Most Critical Days Programme’ as a priority in 2013 that identified the promotion of child feeding and diet diversification for women and children (Mwanamwenge and Harris, 2017).

The country has implemented two National Agriculture Policies (NAP). The first NAP was approved in 2004 and set out the vision of the agricultural sector sought to promote the development of an efficient, competitive and sustainable agricultural sector, which assured food security and increased incomes (MACO, 2004). Although there was an improvement in food production and food quality, the policy did not tackle dietary diversity (Mwanamwenge and Harris (2017). The first NAP ran for 12 years, from 2004 to 2015. The second NAP was to run from 2016 to 2020, placing agriculture as the key driver of Zambia’s economic growth. The second NAP incorporated nutrition and production diversity and set out measures and objectives to promote food and nutrition security (MAL, 2016).

Furthermore, Zambia is a signatory to regional and international treaties and conventions seeking to boost agriculture production, end hunger and poverty. In 2014 Zambia signed the Malabo Declaration to allocate 10% of its annual budget to the agricultural sector. Despite spending 9% in 2017, the county’s allocation to the agricultural sector has dropped due to debt servicing (Chapoto et al., 2019).

While successful implementation of these policies can enhance Zambia’s achievement of CAADP agreements, SGDs and improve performance in various composite indicators such as GFSI, successful implementation remains a challenge in Zambia. A lack of coordination among the various ministries, high levels of corruption and inadequate financing have hindered the successful implementation of the Seventh National Development Plan and the NAP (PMRC, 2017; PMRC, 2018).

4.5 Food and nutrition security policy interventions and programmes

A number of policies have supported programmes and interventions that directly and indirectly targeted Zambia’s food security and nutrition, including the Food Reserve Agency, Farmer Input Support Programme, Food Security Pack, Scaling Up Nutrition, the First 1000 Critical days of life, Social cash transfer among others.

The Food Reserve Agency (FRA) was set up in 1972 and amended in 1996 and 2005. The Agency acts as a government output subsidy and buys grain from farmers at guaranteed prices. The FRA also builds strategic government reserves used to regulate and modulate the national grain price. According to Chapoto (2019), the FRA uses both demand and supply-side interventions modalities. On the demand side, the Agency buys grains from smallholder farmers, and on the supply side, it releases maize at subsidised prices to reduce wholesale prices of maizse and its products. The FRA has exclusively focused on maize marketing and is Zambia's dominant maize buyer (Fung et al., 2015). Although selling maise to the FRA can increase farmers income and improve food security, only a small minority of wealthier smallholder farmers with more land sell to the Agency (Mason et al., 2015; Sitko and Kuteya, 2013; Chapoto, 2019).

Furthermore, FRA's high prices affect most rural smallholder farmers as they are net buyers of maize (Chapoto, 2019). FRA activities can incentivise farmers to increase their areas planted (Mason et al., 2015). A three-year panel study of 4,286 households by Fung et al. (2015) concluded that the FRA directly positively affected the welfare of smallholders who sell maize to it (Fung et al., 2015). However, higher levels of FRA activity in a district are associated with higher poverty levels (Fung et al., 2015). Furthermore, FRA interventions also affect consumption through the substitution of other crops with maize (Chapoto, 2019)

The Farmer Input Support Programme (FISP) was introduced in 2002 by the Ministry of Agricultural to secure food security through smallholder maize production by improving access to affordable inputs. While yields improved, the FISP programme has not fulfilled its aim of improving food security, reducing hunger and increasing asset acquisition (Mwanamwenge and Harris, 2017). Mason and Tembo (2015) found that the FISP increased smallholder incomes but had a negligible impact on poverty reduction. Like the FRA, the FISP allocation favours wealthy households and is characterised by late delivery of inputs to farmers (Zinnbauer et al., 2018). Burke et al. (2012) argue that reallocating a more significant proportion of FISP subsidies to smallholder farmers would more effectively reduce poverty.

However, there is little evidence that FISP subsidies have improved national food security or reduced poverty among smallholder farmers (Mason and Tembo, 2015; Zinnbauer et al., 2018). Tossou and Baylis (2018) compared conventional FISP and the electronic vouchers of FISP from a household sample of 1200 smallholder farmers and found that participation in both on average increased maize yields by 41%-55%. However, the maize yield among households that received e-vouchers was 20% lower than those of households that received direct inputs. E-vouchers also improved household food expenditure but had no significant effect on household food consumption score. The FISP programme is plagued with a number of issues that affect its effectiveness as a poverty reduction tool such as delayed distribution of inputs due to financial and logistical challenges resulting in delayed planting by farmers (Sitko et al., 2012). The FISP programme may have a crowd out effect on private agro-dealers and other fertilizer suppliers who may not win tenders in some regions (Sitko et al., 2012). Other concerns include poor targeting of beneficiaries where a vast minority of larger, wealthy farmers are captured at the expense of smallholder farmers, distributing substandard inputs and higher costs to the treasury (Sitko et al., 2012).

The FISP programme is supported by the Food Security Pack programme (FSP). The FSP programme has been implemented as a social safety net by the Ministry of Community Development and Social Welfare. The FSP provides vulnerable but viable smallholder farming households (farmers in rural areas who are too poor to purchase fertilizer) with agricultural inputs to improve small-scale farmer crop productivity and household food security (Mwanamwenge and Harris, 2017). A study by Chilala (2017) of 305 FSP beneficiaries from Kabwe district found that the FSP increased the food security of female-headed household beneficiaries in the Kabwe district of Zambia. Similar results were obtained by Mutondo (2008) in Mansa.

The Ministry of Community Development and Social Welfare introduced the social cash transfer in 2014 after a pilot study found that cash transfers could improve child nutrition (Mwanamwenge and Harris, 2017). The finding from the pilot study showed that cash transfers could improve child nutrition if the households had access to clean water and the mothers were educated (Mwanamwenge and Harris, 2017). One prominent SCT programme was the Zambia Child Grant Programme (CGP), rolled out in 2010 in districts with the highest mortality and poverty rates.

Chakrabarti et al. (2019) found that the CGP in Zambia had no impact on child nutrition but affected some important intermediate outcomes such as household food consumption and improved sanitation. However, the wide range of effects across different development domains makes social cash transfers an essential tool in poverty alleviation and economic development (Chakrabarti et al., 2019). Social cash transfers have a mitigating role against weather socks, especially for households facing consumption and food security stress (Asfaw et al., 2017). A review by Mwanamwenge and Harris (2017) showed that major agricultural and community development programmes in Zambia focus on reducing poverty and food insecurity to tackle hunger and do not explicitly tackle malnutrition.

Zambia has implemented policies and programmes that distinctively target nutrition. Notably, the first 1000 Most Critical Days Programme (MCDP) and the Scaling Up Nutrition (SUN) have been implemented to reduce child malnutrition. However, evaluations of Zambia’s first 1000 most critical days and the SUN programmes on reducing stunting, wasting, and underweight showed mixed results in different districts. Brudevold-Newman et al. (2018) found that stunting rates were unchanged in the Mbala district after implementing the MCDP but significantly changed in Chipata. The MCDP had a significant positive effect on wasting in Mbala but no impact in Chipata (Brudevold-Newman et al., 2018). Brudevold-Newman et al. (2018) also found that MCDP had no effect on underweight in both districts due to high prevailing poverty levels.

4.6 Drivers of food security and nutrition in Zambia

There are many drivers of food insecurity and malnutrition in Zambia. Many researchers have highlighted how Zambia’s reliance on rainfed agriculture affects food security and nutrition. Household food availability and provision correspond to the agricultural pattern, where April to May is the harvesting period, and October to March is the lean period (Mofya-Mukuka and Singogo, 2020). Due to the reliance on rain-fed agriculture, where 78% of the population derive their livelihood, the occurrence of floods, droughts, and erratic rainfall can negatively impact food production, and subsequently, food security and nutrition (Mwanamwenge and Harris, 2017). Figure 4.5 shows Zambia’s cereal production in 2002, with a notable reduction in production from 2017 to 2019 attributed to the effects of climate change (Harris et al., 2019).

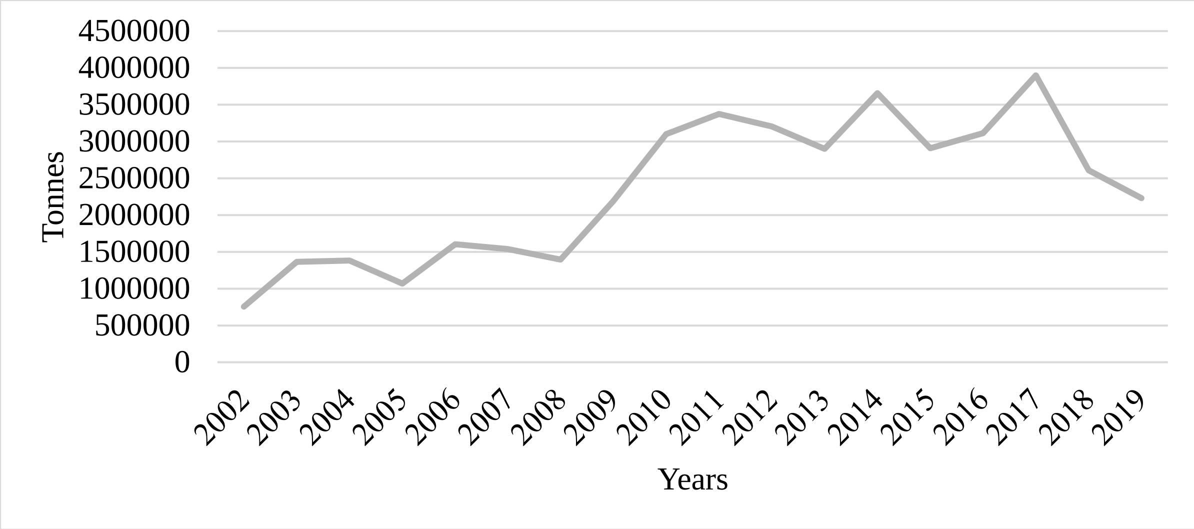

Figure 4.5: Zambia’s cereal production, 2002-2019

Source: FAO (2020).

The effects of climate change have been reflected in the recent decline in agriculture’s contribution, as shown in Figure 4.6. The reduction in agriculture’s contribution to GDP will further reduce Zambia’s GDP per capita, which depends on the share of agriculture to GDP, negatively impacting food access (Kapotwe and Tembo, 2021). Floods, droughts, and dry spells negatively affect the growing seasons and reduce crop yield, especially Zambia’s staple food maise and seriously affect national food security with the rural poor most affected (Phiri et al., 2013).

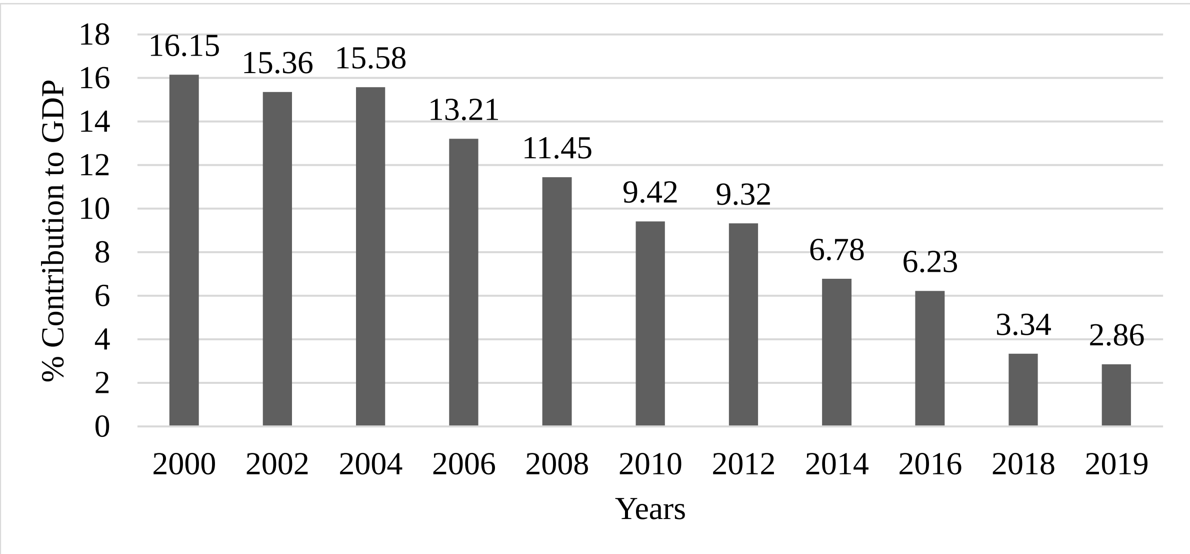

Figure 4.6: GDP share of agriculture 2000-2019

Source: ZSA (2019), World Bank (2019).

The lack of diversity in Zambia's diet has also been a significant driver of undernutrition. Zambia's diet is concentrated around the consumption of maize and its products and typically lacks other equally crucial nutritious foods. For example, many interest groups, such as women and children, do not meet the minimum requirements for a range of micronutrients (Arimond et al., 2010; Caswell et al., 2018). Recent data from the Zambian Demographic and Health Survey (DHS) and other dietary surveys provide data on children but do not offer comprehensive dietary differences between the rural and urban or poor and wealthier households (Harris et al., 2019; Mofya-Mukuka and Singogo, 2020). Diverse and nutrient-rich foods need to be available on the farm and affordable on the market for those who purchase them to improve dietary diversity.

Food prices are also a determinant of food access (Harris et al., 2019), with food generally expensive in rural areas (Miller et al., 2016). Lack of markets primarily in the rural area impedes food access and food security and contributes to high food prices in rural areas. The 2019 Vulnerability and Needs Assessment Committee survey (VAC) found that only 62.3% of households had physical access to operational markets (VAC, 2019). The reports also identified distance to the markets (52.5%), the non-existence of markets (43.9%) and the government's failure to manage high prices (3.3%) as some of the constraints that inhibit physical access to markets in Zambia (VAC, 2019).

Other recent drivers of food insecurity include load-shedding of power supplies, depreciation of the exchange rate and debt repayment (Chitambala, 2019; Kabisa et al., 2019). Due to debt servicing, which was 34% of the national budget in 2019, budget allocation to the Ministry of agriculture was reduced to 3.7% (MoF, 2019). The reduction in budget allocation to the Ministry of Agriculture resulted in a funding reduction to key programmes that directly impact food production and food security, such as the poverty reduction programme, E-Voucher FISP and FRA (Chapoto et al., 2019). As an import-dependent country, currency depreciation affects the interest rate and inflation, increasing domestic food prices (Mofya-Mukuka and Singogo, 2020). As the cost of food rises, many households adopt negative coping strategies to access food. Also, the depreciation of the currency has a negative relationship with GDP (Chitambala, 2019).

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

5.1 Introduction

This chapter presents the methods and procedures applied to achieve the study's objectives. The context of the study, the source of data and the methods used to detect outliers and outdated data are described. The chapter further discusses the statistical methods used for data normalisation, aggregation and weighting and the methods used to test the statistical significance of outliers and outdated data.

5.2 The context of the study and data sources

The study aimed to identify outdated data and outliers in the 2019 GFSI and determine their significance to the GFSI scores and rank. The study analysed data from the 2019 Economist Intelligence Unit (EIU) database to identify and detect outdated data and outliers. The data used by EIU to generate the 2019 GFSI results were obtained from different sources such as the World Bank, WTO, FAO, WFP and national statistical agencies.

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 results. Therefore, the study obtained current updated data for Zambia to replace the outdated data values to get updated scores and ranking. The updated data for different outdated indicators were obtained from open access data sources such as FAOSTAT, ReSAKSS, CEIC data, ASTI dataset, policy reviews, reports, national statistic agencies and publications. Figure 5.1 shows the indicators that needed to be updated for affordability, availability and quality and safety dimensions of the GFSI.

Table 5.1: Indicators with outdated data (2018 or older)

Series	Unit	Year	Action
AFFORDABILITY			
Change in average food costs	Quantitative	2018	Update data
Proportion of population under the global poverty line	Quantitative	2015	Update data
Gross domestic product per capita (US$ PPP)	Quantitative	2018	Update data
Agricultural import tariffs	%	2018	Update data
Presence and quality of food safety net programmes	Qualitative assessment	2019	
Access to financing for farmers	Qualitative assessment	2019	
AVAILABILITY			
Sufficiency of supply			
Average food supply	Quantitative	2016-18	Update data
Change in dependency on chronic food aid	Quantitative	2013-17	Update data
Public expenditure on agricultural R&D	Ratio	2017	Update data
Agricultural infrastructure		2019	
The volatility of agricultural production	standard deviations	2012-16	Update Data
Political stability risk	Qualitative assessment	2019	
Corruption	Qualitative assessment	2019	
Urban absorption capacity	GDP-urban growth rate	2015-19	
Food loss	Quantitative	2013	Update data
QUALITY AND SAFETY			
Dietary diversity	%	2011-13	Update data
Nutritional standards		2019	
Micronutrient availability		2013	Update data
Protein quality	Grams	2011-13	Update data
Food safety			
Agency to ensure the safety and health of food	Qualitative assessment	2019	
Percentage of population with access to potable water	%	2017	Update data
Ability to store food safely	%	2017	Update data

Source: EIU (2019)

5.3 Data analysis method

The data analysis was set out to determine the statistical significance of outliers and outdated on the three dimensions of the GFSI: affordability, availability, and quality and safety dimensions. Outliers are extreme observations or values that lie outside the overall pattern of a distribution of variables in a sample (Ghosh and Vogt, 2012). Outliers typically introduce bias into statistical estimates and can act as unintended benchmarks in composite indicators (Thomas et al., 2017).

Various methods can be used to identify and handle outliers in a data sample, with some methods being robust than others. For example, the standard deviation can be used to identify outliers, where any data values that do not fall within three standard deviations of the mean are identified as outliers (Ghosh and Vogt, 2012). A box plot can be used to identify outliers where any data points that lie above and below the 75^{th} and 25^{th} percentiles, respectively, are considered outliers. The other methods used to identify outliers in a sample is the median and quartile range.

This study identified outliers by studying the shape and distribution of the 2019 GFSI indicators. Any indicators with absolute values above two and 3.5 for skewness and kurtosis were considered outliers. This method is robust in identifying outliers than other methods above. After identifying outliers, different methods can correct them to not act as an unintended benchmark (Ghosh and Vogt, 2012). Trimming, winsorisation, Medium Absolute Deviation (MAD) and M-estimation are methods used to correct or treat outliers (Ghosh and Vogt, 2012). Nardo et al. (2005b) suggest that outliers should be corrected before performing normalisation, as some normalisation methods can be sensitive to outliers. Therefore, before performing the normalisation procedure, all detected outliers were corrected using the winsorisation method.

Winsorisation involves identifying cutoff values in the data (Dehnel, 2014). Values that lie outside the cutoff values are transformed to make them closer to the cutoff value, and they are no longer regarded as outliers (Dehnel, 2014). The general procedure is that values higher than the ninety-fifth percentile are replaced with the ninety-fifth percentile values, and values below the fifth percentile are replaced with the fifth percentile values (Ghosh and Vogt, 2012). This study used the procedure outlined by Thomas et al. (2017), where outlier values of an indicator were replaced with the highest/smallest value of the same indicator in the database. This procedure is repeated until the kurtosis and skewness are below 2 and 3.5, respectively

(Thomas et al., 2017). This winsorisation procedure does not work well with discrete variables (Thomas et al., 2017). However, it was appropriate and essential in this study, as most of the GFSI indicators detected as outliers were continuous variable.

Furthermore, the study used paired t-test and spearman's rank correlation to test the statistical significance of changes caused by updating Zambia's 2019 GFSI database and winsorisation of outliers. A paired t-test is a statistical procedure used to determine if the mean of a dependent variable is different in two related groups who undergo the same treatments or conditions (Zabell, 2008). The paired t-test was also used in this study to determine the statistically significant difference in the GFSI's mean before and after winsorisation of outliers and updating Zambia's outdated indicators with 2019 GFSI results as a reference year.

The Spearman's rank correlation test is a nonparametric test used to determine the direction and strength of correlation between two ranked ordinal or continuous variables (Jackson et al., 2017). The spearman's *rho* can take values from -1 to +1, with +1 indicating a perfect positive correlation, a *rho* of -1 indicating a perfect negative correlation and a *rho* of zero indicating no association between the ranks. The spearman's rank correlation test was used in this study to test for the changes in the GFSI ranks before and after winsorisation of outliers and updating Zambia's 2019 GFSI outdated data.

5.4 Normalisation, aggregation and weighting methods

As indicated in the review of the Global Food Security Index methodology in chapter three, the indicators selected by the EIU are normalised using the min-max normalisation method. This normalisation method transformed the raw data into normalised values of 0-1 ranges and rescaled them to 0-100 to make the data comparable across countries. In the last stage of the derivation of the GFSI, weights defined by the EIU panel of experts are used to aggregate normalised scores of indicators and dimensions to derive the overall scores (Izraelov and Silber, 2019). This study used the min-max normalisation method to normalise the updated and winsorised indicators (indicators corrected from outliers) and the weights as defined by the panel of experts of the EIU. The study used both Stata 15 and Excel to generate scores and run t-tests and spearman rank correlation after updating outdated data and correcting outliers. Table 5.2 summarises the methods and procedures by presenting the sub-problems, data source, indicators and the methods used to answer each research question.

Table 5.2: Summary of methods and procedures

Specific and sub research problem	**Data source**	**Indicators/Variable**	**Approach**
Does the 2019 GFSI result contain outliers?	The 2019 GFSI database	All indicators in the 2019 GFSI database	Descriptive statistics Studying the skewness and kurtosis of indicators Winsorisation of outliers
Does the 2019 GFSI database for Zambia contain outdated data?	The 2019 GFSI database	All indicators in the 2019 GFSI database	Descriptive statistics such as the proportion of indicators with outdated data (data from 2018 or older)
Correcting for the effect of outliers	The 2019 GFSI database	Problematic indicators with skewness and kurtosis values above 2 and 3.5, respectively	Winsorisation of outliers
Updating outdated data	The 2019 GFSI database, World Bank, CEICDATA, and Zambia statistical agency	The 2019 GFSI indicators that outdated for Zambia	Sourcing data from various sources to update outdated data
Does outdated data and outliers have a statistically significant effect on the three components of the 2019 GFSI for Zambia	The 2019 GFSI database	All indicators in the 2019 GFSI database	Spearman's rank correlation and paired t-test for significance test
Does updating Zambia's outdated data result in a statistically significant change in Zambia's overall 2019 GFSI score and rank relative to the 113 countries?	Updated Zambia's 2019 GFSI database and 2019 GFSI database	The comparison of the 2019 GFSI overall score and ranking and Zambia's overall score and ranking after updating data.	Spearman rank correlation (significance difference in ranking of countries) and paired t-test statistics (significance difference in scores before and after updating and correcting outliers)

Source: Author's compilation

CHAPTER 6: RESULTS AND DISCUSSION

6.1 Introduction

This chapter presents and discusses the findings according to the research objectives stated in chapter one. The chapter begins with a descriptive analysis of the first objective to identify indicators with outliers in the overall GFSI dataset and outdated data in the 2019 GFSI dataset for Zambia. The second part of the chapter presents the results of the second objective that sought to test the statistical significance of the outdated data and outliers on Zambia's GFSI dimension scores and ranking in the 2019 GFSI results. Lastly, the chapter presents the third objective results that sought to investigate if updating the data changed Zambia's 2019 overall GFSI score and ranking relative to the 113 countries in the overall GFSI analysis.

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

The two subsections below present the first objective analysis to determine the proportion of outdated data and outliers in the 2019 GFSI result.

6.2.1 The proportion of outliers in the 2019 GFSI database

Table 6.1 presents the result of the skewness and kurtosis of indicators to detect outlier values in the 2019 GFSI dataset. Indicators with an absolute value of skewness and kurtosis higher than two and 3.5, respectively, were seen as outliers and carefully examined before winsorisation. Ten (29%) of 34 indicators were identified as outliers in the 2019 GFSI. Seven of the ten indicators were quantitative indicators, representing 38.8% of all the quantitative indicators in the 2019 GFSI. The other three indicators were qualitative indicators representing 18.8% of qualitative indicators. The three qualitative indicators detected as outliers were the presence of food safety-net programmes, the existence of adequate crop storage facilities and the agency to ensure the safety and health of food indicators.

Six of the ten identified outliers were in the availability dimension (50% of the identified outliers). In the 2016 GFSI database, the availability dimension had four indicators with outliers (Thomas et al., 2017). The indicators on food loss, irrigation infrastructure, urban absorption, public expenditure on agricultural research and development, change in dependency on chronic food aid and the existence of adequate crop storage facilities were outliers in the availability dimension in 2019. The quality and safety dimension had only one outlier, namely the indicator on the agency to ensure the safety and health of food. In contrast, the affordability dimension had three outliers from the change in average food costs, agriculture import tariffs and the presence of food safety-net programmes.

Table 6.1: Indicators identified as outliers in the 2019 GFSI database

GFSI outlying indicators	Skewness	Kurtosis
Affordability		
The change in average food costs	8.361	79.501
Agriculture Import Tariffs	2.442	11.062
The presence of food safety-net programmes	3.105	10.642
Availability dimension		
Change in dependency on Chronic food aid	7.331	58.548
Public expenditure on agricultural R&D	6.648	49.982
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 dimension		
Agency to ensure the safety and health of food	2.283	6.213

Source: Author's compilation using data from the EIU (2019).

After identifying the outliers, they were all winsorised to prevent the outliers from acting as an unintended benchmark. The three qualitative indicators, namely the agency to ensure the safety and health of food, the presence of safety net programmes and the existence of adequate crop storage facilities, could not be winsorised as the winsorisation process used work well with continuous or quantitative variables but not with discrete or qualitative indicators (Thomas et al., 2017). The winsorisation process involved replacing the highest/smallest value of the indicator with an outlier with the next highest/ smallest of the same indicator in the database (Thomas et al., 2017). The results of the winsorised outliers in the 2019 GFSI are shown in Table 6.2.

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

Winsorised outlier indicators	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	1.665	4.044
Public expenditure on agricultural research and development	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 compilation using data from the EIU (2019).

6.2.2 The proportion of outdated data in the 2019 GFSI data for Zambia

Though the GFIS attempts to use the most current data from the previous year in calculating the scores, it was noted that some indicators lacked current data. Fourteen (41%) of the 34 indicators for Zambia reported in the 2019 GFSI used data older than 2018, as shown in Table 6.3. The oldest data for Zambia were for 2013 for food loss, dietary diversity, dietary availability of vitamin A, dietary availability of iron and zinc and protein quality indicators.

Even though micronutrients play a critical role in human health, the GFSI reported Zambia's micronutrient availability indicator based on outdated data from 2013 (EIU, 2019). Furthermore, Zambia's dietary diversity survey data offers little information about changes over time and the difference between rural and urban dietary patterns (Harris et al., 2019). Zambia is also among the 70% of the countries that have not collected nutrition and undernourishment data since 2013 (EIU, 2019). Therefore, outdated data was used for this critical indicator due to the unavailability of updated micronutrient data. Another indicator that used outdated data in the 2019 GFSI results for Zambia has the ability to store food safely and the proportion of the population with access to potable water indicators under the quality and safety dimension. Only the qualitative indicators were up to date in the quality and safety dimension.

The ability to store food safely, a sub-indicator in the quality and safety dimension, assessed access to refrigeration using the proportion of the population with access to electricity in all areas as a proxy indicator (EIU, 2019). The proportion of the population with access to potable water was also outdated (from 2017). The proportion of the population with access to potable water indicator measured the proportion of people with basic water services and those using safely managed water services (EIU, 2019). The ability of a country to provide a clean and consistent water supply is essential for food safety for everything, including washing produce to maintaining appropriate hygiene for food workers (EIU, 2019). Evaluating food safety is also critical to preventing foodborne illnesses.

According to the 2019 GFSI database, the proportion of the population with access to electricity in Zambia in 2017 stood at 40% (EIU, 2019). Low access to storage facilities and electricity could result in food waste and contamination, leading to outbreaks of diseases such as diarrhoea and cholera (Turan et al., 2018). Contaminated water and food have been a significant cause of the recurrent cholera outbreaks in Zambia in the recent decade (Olu et al., 2013; Kapata et al., 2018). However, the government had recently implemented measures to fight the outbreak of cholera and have also improved electricity provision to include many rural areas through the Rural Electrification Authority (REA) (Aggarwal, 2019). Therefore, reporting food safety using data from 2017 could not include the recent improvement in food safety.

Food loss, an indicator that measures post-harvest and pre-consumer food loss as a proportion of the domestic supply, was also reported in the 2019 GFSI using data from 2013. FAO (2019) reported that one-third of the world's food is lost or wasted every year, and 14% of lost food is in Sub-Saharan Africa. Reducing food loss is critical to achieving the zero hunger goal of SDG 2 and ensuring sustainable production and consumption (FAO, 2021). Therefore, using outdated data to report this critical indicator may underestimate the level of loss.

Table 6.3:Status of data for 2019 GFSI indicators for Zambia

Dimension and indicators	Status of data	Data Year
1. Affordability		
1.1 Change in average food costs	Up to date	2018
1.2 Proportion of population under the global poverty line	Outdated data	2015
1.3 Gross domestic product per capita (US$ PPP)	Up to date data	2018
1.4 Agricultural import tariffs	Up to date data	2018
1.5 Presence and quality of food safety net programmes		
1.5.1 Presence of food safety-net programmes	Up to date	2019
1.5.2 Funding for food safety net programmes	Up to date	2019
1.5.3 Coverage of food safety net programmes	Up to date	2019
1.5.4 Operation of food safety-net program	Up to date	2019
1.6 Access to financing for farmers	Up to date	2019
2. Availability		
2.1 Sufficiency of supply		
2.1.1 Average food supply	Up to date data	2018
2.1.2 Change in dependency on chronic food aid	Outdated data	2013-2017
2.2 Public expenditure on agricultural R&D	Outdated data	2017
2.3 Agricultural infrastructure	Up to date	2019
2.3.6 Irrigation infrastructure	Outdated data	2016
2.4 Volatility of agricultural production	Outdated data	2012-2016
2.5 Political stability risk	Up to date data	2019
2.6 Corruption	Up to date data	2019
2.7 Urban absorption capacity	Up to date data	2015-2019
2.8 Food loss	Outdated data	2013
Quality and Safety		
1. Dietary diversity	Outdated data	2011-2013
2. Nutritional standards		
2.1 National dietary guidelines	Up to date data	2019
2.2 National nutrition plan or strategy	Up to date data	2019
2.3 Nutrition monitoring and surveillance	Up to date	2019
3. Micronutrient availability		
3.1 Dietary availability of vitamin A	Outdated data	2013
3.2 Dietary availability of iron	Outdated data	2013
3.3 Dietary availability of zinc	Outdated data	2013
4. Protein quality	Outdated data	2011-2013
5. Food safety		
5.1 Agency to ensure the safety and health of food	Up to date	2019
5.2 Percentage of population with access to potable water	Outdated data	2017
5.3 Ability to store food safely	Outdated data	2017

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

In addition to food loss, the change in dependency on chronic food aid, public expenditure on agricultural research and development and volatility of agricultural production indicators were reported in the 2019 GFSI based on outdated data from 2016 and 2017, respectively (EIU, 2019). The panel of experts at EIU assigns discrete values, either zero or one or zero to four, to qualitative indicators based on the available data from national surveys and international databases (EIU, 2019). These qualitative indicators included national dietary guidelines, agency to ensure the safety and health of food and presence and quality of food safety net programmes.

The public expenditure on agricultural research and development indicator measured the share of agricultural expenditure divided by the share of agricultural value-added to the GDP (EIU, 2019). Public expenditure on research and development is critical in assessing investment in the agricultural sector, including technology development, rural infrastructure, innovation, agricultural research and extension necessary to increase agricultural productivity while reducing environmental impact (EIU, 2019). Despite Zambia allocating at least six per cent of its annual budget toward achieving the Malabo Declaration on Accelerated Agricultural Growth and Transformation for Prosperity and Improved Livelihoods, Zambia performed poorly on public expenditure on research and development (EIU, 2019). The GFSI used data from 2017 to report the 2019 results for public expenditure on agricultural research and development. Although Zambia was not on track in the CAADP 2019 Biennial Review, public expenditure on agriculture as a share of agriculture value added was reported as a strong performance area (Kurtz and Ulimwengu, 2020; AU, 2019). The CAADP 2019 Biennial Review recommended that the government of Zambia should strengthen agricultural data collection and management systems to ensure evidence-based decision making (AU, 2019).

Zambia's indicator measuring the change in dependency on chronic food aid in the availability dimension also used outdated data from 2017. Despite not being heavily reliant on chronic food aid in the last decade, areas worst affected by droughts and floods have relied on food relief from the Disaster Management and Mitigation Unit (DMMU) (IPC, 2019). The droughts and floods of the 2018/19 season reduced crop production by 35%, affecting the country's food security and the economy (IPC, 2019; VAC, 2019). Therefore, assessing Zambia's change in dependency on chronic food aid using outdated data in 2019 may not take into account the effect of the droughts and floods in the 2018/19 season.

Another indicator under the availability dimension that used outdated data for Zambia in the 2019 GFSI result was the volatility of agricultural production. Fluctuation in agricultural productivity can create difficulties in planning and predicting consistent food supply. Therefore, the volatility of agricultural production measured the standard deviation of total factor productivity over the past five years to predict and plan for the future food supply (EIU, 2019). However, the use of outdated data to calculate agricultural productivity volatility cannot consider how floods, droughts and dry spells contribute to volatility in agricultural production and could bias Zambia's GFSI scores and ranking. For example, a good season with rainfall could be followed by consecutive years of below-normal rainfall leading to droughts or above normal rainfall, leading to crop destruction (Chapoto et al., 2019).

The population under the global poverty line under the affordability dimension used data from 2015 in the 2019 GFSI results. In contrast, gross domestic product per capita (US$ PPP) and agricultural import tariffs indicators used data from 2018. According to the 2019 GFSI, the population under the global poverty line in Zambia stood at 44.5% in 2015 (EIU, 2019). The higher poverty levels in Zambia affects people's ability to access nutritious and healthy food. Poverty in Zambia is rooted in historical, geographical and social factors that deny people's access to services and markets (Harris et al., 2019; Rosenberg et al., 2018). Furthermore, corruption, lack of affordable infrastructure and reliance on rain-fed agriculture leave most farmers as net buyers of the staple crop (Harris et al., 2019; Rosenberg et al., 2018). Although the government has implemented policies to reduce and fight poverty in the last decade, poverty levels remained high, primarily in rural areas where poverty was around 78% in 2016 (Harris et al., 2019; FAO et al., 2019).

The gross domestic product per capita (US$PPP), an indicator that measures individual income calculated in the US dollar at the purchasing power parity, assesses the ability of citizens to afford food in the country (EIU, 2019). Zambia has scored poorly in the gross domestic product per capita, averaging 2.5 out of 100 from 2012 to 2019 due to stalled economic performance in recent years (EIU, 2019; WB, 2020b). Furthermore, Zambia's gross domestic product (GDP) growth slowed to 3.1% per annum between 2015 and 2019, mainly attributed to a decline in agricultural output, falling copper prices, insufficient hydropower generation due to erratic rainfall and insufficient policy adjustments to these shocks (WB, 2020b).

The agricultural import tariff, an indicator that measures the country with the most favoured tariffs on agricultural imports, remained constant at 19% for Zambia from 2012. Though

Zambia has recorded bumper grain harvests in the last decade, importing agricultural commodities from neighbouring countries to cover up for shortages in certain foods like onions, fish, and others could explain the low agricultural import tariffs. Furthermore, Zambia suffers from grain shortages in seasons of significant droughts and floods. It relies heavily on rain-fed agriculture, with only a small proportion of land equipped with irrigation infrastructure (EIU, 2019; ZSA et al., 2019).

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

The study rejected the null hypothesis of the first objective that the 2019 GFSI database for Zambia did not contain outdated data and outliers. This null hypothesis was rejected because the 2019 GFSI database for Zambia had both outdated data and outliers, as discussed in sections 6.2.1 and 6.2.2 above. The 2019 GFSI contained ten indicators with outlier data points, of which seven were quantitative indicators and three qualitative indicators, as shown in Table 6.1. The availability dimension had the highest number of indicators with outliers in the 2019 GFSI. The 2016 GFSI had six indicators with outliers values (Thomas et al., 2017). Food loss, urban absorption capacity, public expenditure on agricultural research and development, agricultural import tariffs and agency to ensure the safety and health of food indicators had outlier values in the 2016 and 2019 GFSI data (Thomas et al., 2017).

Zambia also had an outlier for the indicator that measures public expenditure on agricultural research and development. Other countries with outlier values on this indicator were Singapore and Switzerland. Unlike Zambia that is agriculturally based, Singapore and Switzerland have well developed agricultural and research technology to increase agricultural productivity and are industry-based economies. Zambia is one of the African countries that has allocated at least six per cent of its annual budget to the agricultural sector in honour of the Malabo commitment to allocate 10% to the agricultural sector to sustain a six per cent growth per annum in the agricultural GDP (AU, 2019; MoF, 2019).

6.3 The effect of the presence of outliers on the 2019 GFSI scores and ranking of the 113 countries

The study's second objective was to determine the effect of outliers and outdated data on Zambia's scores and ranking in the 2019 GFSI. A paired t-test was run on the overall scores on the three dimensions of the GFSI before and after the winsorisation of outliers, as shown in Table 6.4.

Table 6.4: Paired t-test on the mean scores of the three GFSI dimensions before and after winsorisation of outliers (N=113)

GFSI Dimension	Mean After Winsorisation	Mean before winsorisation	Difference in mean	P-Value
Affordability	62.917	67.584	-4.667	0.000***
Availability	56.171	59.421	-3.250	0.000***
Quality and safety	60.982	59.980	0.002	0.3674
Overall GFSI score	59.900	62.940	-3.040	0.000***

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

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

The winsorisation of the seven indicators with outlier values in the GFSI dataset from the 16 countries, as shown in Table 6.5, resulted in a significant reduction in the mean scores for the affordability and availability dimensions. No indicator was winsorised under quality and safety dimensions due to the use of qualitative data.

The significance and the negative difference in the mean scores for the affordability, availability dimensions and the overall GFSI scores implied a relative reduction in scores after the winsorisation of the outliers. This reduction suggested that outliers inflated the scores and the food security situation of some countries in the GFSI, giving misleading results.

The presence of outlier values in the 2019 GFSI database resulted in higher or lower scores for certain countries than the actual performance. For example, after winsorisation, outliers for irrigation infrastructure and agricultural imports decreased Egypt's GFSI overall score from 65 to 53. Other countries facing economic turmoil and civil unrest, such as Venezuela, Yemen and Syria, had outlier values in the change in the average cost of food, change in the dependency on chronic aid and the urban absorption capacity, as shown in Table 6.5. The decrease in the overall scores after winsorisation for Venezuela, which had the lowest urban absorption capacity value and the biggest change in the average food cost value among the 113 countries in the GFSI, signifies its inability to secure food security for its population.

Table 6.5: Countries identified with outliers values in the 2019 GFSI

Indicators/Variables with outliers	Countries with outlier values
Agriculture Import Tariffs	Egypt and South Korea
Change in average food costs	Venezuela, Angola, Belarus, Sudan and Syria
Change in dependency on Chronic food aid	Syria, Yemen and Haiti
Public expenditure on agricultural R&D	Singapore, Switzerland and Zambia
Irrigation infrastructure	Egypt, Bahrain and Bangladesh
Urban Absorption capacity	Venezuela
Food loss	Sierra Leone and Ghana

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

The change in the indicator for the average cost of food measured the change in the cost of an average food basket in a country as captured through the food Consumer Price Index (CPI). The CPI tracks the change in the cost of the average food basket using 2010 as a base year. The sharp increase in the cost of the average food basket, as witnessed in 2019 in Venezuala, decreased food affordability in the country, especially among low-income households, which in turn affected their consumption. Rising inflation and a slump in production arising from the political turmoil deteriorated Venezuela's food security situation such that the country had the highest increase in CPI in 2019 (2695.5%) (EIU, 2019). Other countries with a significant rise in CPI in 2019 were Angola, Belarus, Sudan and Syria. For example, the consumer price index for Syria increased by 935.9% from 2010 to 2019. Although Angola has maintained political stability since the end of the 27-year civil war in 2002, lower oil prices, currency depreciation, and reduced import of capital goods have resulted in a constant rise in consumer price since 2010 (Klein and Kyei, 2009; Belbute et al., 2016; WB, 2020a). Belarus, Syria and Sudan are recovering from recent political tensions that disrupted domestic economies.

The urban absorption capacity indicator, calculated as the average (annual) real percentage change in GDP minus the urban population growth rate (EIU, 2019). A country's capacity to absorb the stresses placed upon it by urban growth influences its ability to ensure food security. Due to Venezuela's ongoing economic turbulence, the urban population growth rate exceeded real GDP growth in 2019, negatively affecting her ability to ensure food security. In both Yemen and Syria, the decade long ongoing civil wars have reduced people's ability to produce food resulting in increased dependence on chronic food aid. The violent conflict and civil war in Yemen and Syria were catalysts for economic slowdown and food insecurity, leading these countries to alarming hunger levels in 2019 (Bernstein et al., 2019). The conflict in these countries also increased the need and supply of food aid. In both Yemen and Syria, the increase in dependence on chronic food aid was due to the inability of available local supply to meet the population needs. The ongoing conflict and the economic crisis have severely affected children, increased malnutrition, diseases and mortality.

As stated above, some countries with outlier values faced political instability in 2019. Political instability could disrupt access to food, for example, through transport blockages or reduced food aid commitments (EIU, 2019). Due to political instability, Syria had a weak political stability indicator in 2019. Yemen scored zero in political stability and agricultural infrastructure, making it impossible to make food available to the citizens either through aid or own production (EIU, 2019). Figure 6.1 shows the changes in the overall scores after winsorisation for countries with outliers in the 2019 GFSI.

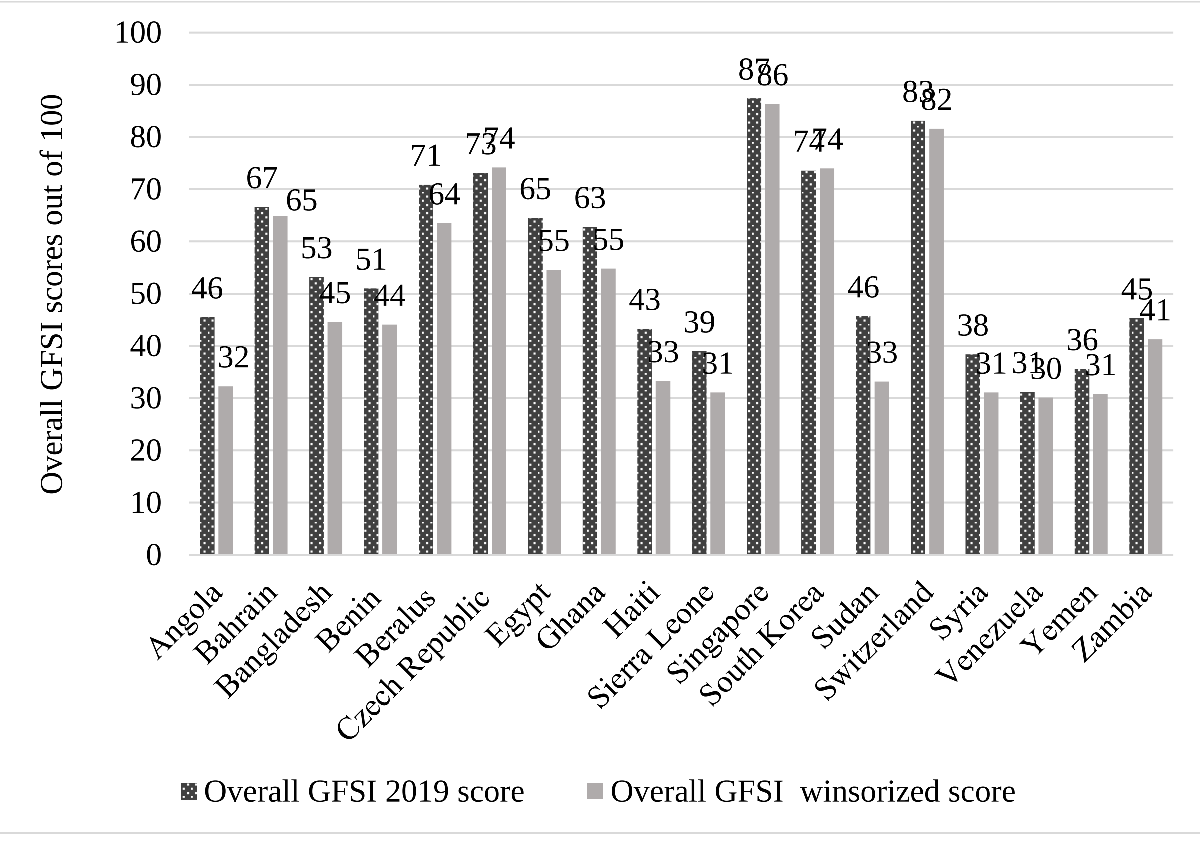

Figure 6.1: Change in the overall score for countries with outlier values

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

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

Zambia scored 44.5 in the 2019 overall GFSI score, an improvement by 10.8 over the 2018 score of 33.7. However, after the winsorisation of outliers for the affordability and availability dimensions, Zambia's overall score reduced from 44.5 to 41. The reduction could have been due to outliers from other countries' data points. In addition, Zambia had an outlier for the public expenditure on agricultural research and development indicators. However, Zambia's public expenditure on agricultural research and development increased from 20.4 in 2019 to 100 after winsorisation.

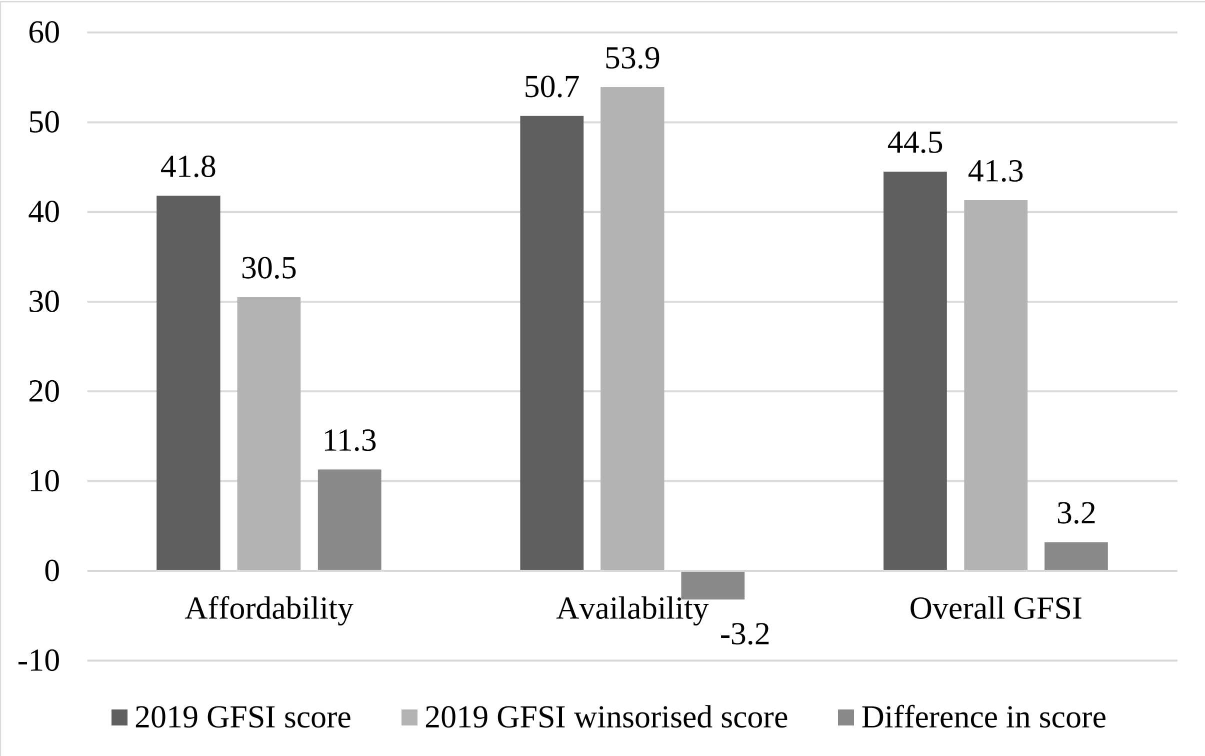

Figure 6.2: Zambia's GFSI scores before and after winsorisation of outliers

Source: Author's compilation.

Zambia's affordability score reduced from 41.8 to 30.5 (11.3 points) after the winsorisation of the data for agricultural import tariffs and the change in the average food cost in the affordability dimension. Though the score of 41.8 in 2019 was an improvement from the score of 19.9 in 2018, it was inflated by the presence of outliers from Egypt and Venezuela. The outlier values for agricultural import and change in the average food costs from Egypt and Venezuela could have resulted in an unintended benchmark as the values of these countries were used as maximum values during normalisation, thereby inflating Zambia's affordability scores.

In contrast, Zambia's availability dimension score increased after winsorisation from 50.7 to 53.9 after the correction of outliers for Belarus, Egypt, Syria, Sierra Leone, Singapore, Venezuela and Zambia. Overall, it could be concluded that outliers affected Zambia's overall GFSI and affordability and availability.

6.3.2 Ranking of countries after the winsorisation of outliers

The winsorisation of outliers resulted in significant shifts in ranks for many countries. The Spearman's rank correlation results in Table 6.6 indicate that the affordability, availability and the overall GFSI ranks were statistically significant, albeit resulting in relatively small changes. The quality and safety dimension had a perfect Spearman rank correlation coefficient because it had no indicator with outliers. The null hypothesis that there was no association between the ranking before and after winsorisation was rejected as all p-values were less than 0.005.

Table 6.6: Spearman's rank correlation test on the GFSI dimensions rankings before and after winsorisation

Dimension	Obs	Spearman's Rho	P-Value	Standard error
Affordability	113	0.9829	0.000***	0.0175
Availability	113	0.9707	0.000***	0.0228
Quality & Safety	113	1.0000	0.000***	0.0004
Overall ranks	113	0.9902	0.000***	0.0133

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

The winsorisation of outliers either maintained, increased, or decreased countries ranking in the overall 2019 GFSI. Table 6.7 showed that 33 (29.2%) countries shifted by five or more rank positions after the winsorisation of the outliers. Fourteen countries maintained their ranks while 24 countries shifted rank up or down by one place. For example, Egypt increased in rank by 16 positions (from 55 to 71), and Turkey increased by 13 positions (from 59 to 70). In contrast, Slovenia and Zambia's ranks decreased by ten and six positions, respectively, signifying an improvement in ranking. The improvement or reduction in ranks after the winsorisation of outliers in countries indicates that outliers in the 2019 GFSI dataset led to lower or higher ranks for some countries like Slovenia and Zambia. The presence of outliers or extreme values in composite indicators could have distorted these countries' actual standing or performance in the 2019 GFSI rankings, affecting benchmarking exercise.

These significant changes in rankings differ from the findings of Thomas et al. (2017), who found that the effect of the outliers on the final scores and ranking of countries with or without winsorisation for the 2016 GFSI ranking was not significant. In contrast, Thomas et al. (2017) found six indicators and ten countries with outliers. This study found eight indicators and 16 countries with outliers, as shown in Table 6.5. The shifts in the ranking of countries in affordability, availability and overall ranks are shown in Appendix B.

Table 6.7: Difference in rankings of countries before and after winsorisation (N=113)

Rank difference	**Number of countries**	**Percentage**
0	14	12.39%
+/-1	24	21.24%
+/-2	19	16.81%
+/-3	12	10.62%
+/-4	11	9.73%
Shift by five or more positions	33	29.20%
Total	113	100

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

Figure 6.1 illustrates the difference in the individual countries' scores with outlier values before and after winsorisation. Only the Czech Republic and South Korea increased their overall scores after the winsorisation of outliers. The Czech Republic and South Korea had an outlier in public expenditure on agricultural research and development and agricultural import tariffs indicators in the 2019 GFSI. The EIU measures the agricultural import tariff as the average most-favoured national tariff on all agricultural imports obtained from the World Trade Organisation (EIU, 2019). Agricultural import tariffs could increase the cost of imported foods, therefore increasing food costs for consumers (EIU, 2019). South Korea, an industry-based economy with an outlier value in agricultural import tariffs, scored zero in this indicator (EIU,2019). On the other hand, the Czech Republic and South Korea had the highest data values import tariff, which meant higher costs in importing agricultural goods, leading to increased costs (EIU, 2019). The linear transformation of data values for the agricultural import tariffs indicator gave the highest scores to countries with lower data values and countries with the highest in the 2019 GFSI dataset, making consumers and importers of agricultural food face higher costs (EIU, 2019).

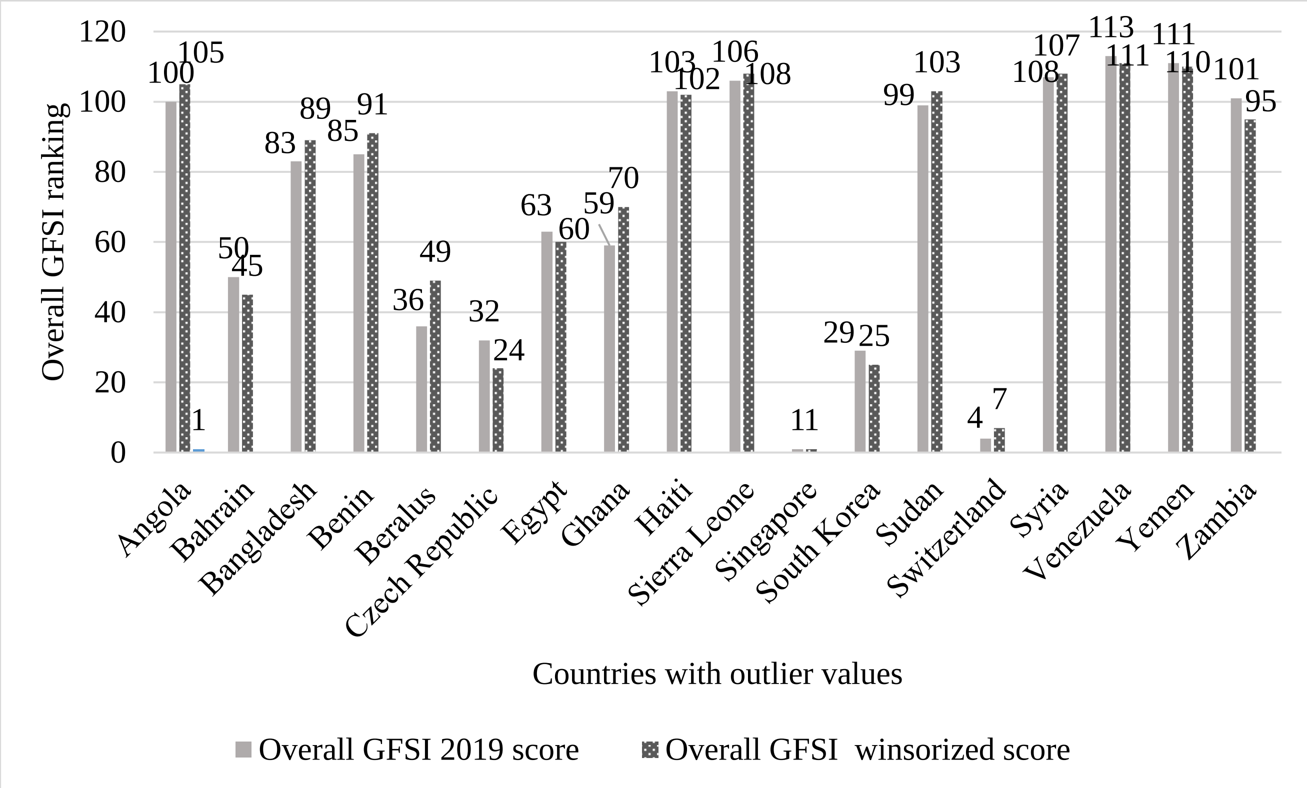

Figure 6.3:Change in the overall ranking of countries with outlier values (N=113)

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

6.3.3 Impact of winsorisation of outliers to Zambia's GFSI rank

After the winsorisation of outliers, Zambia shifted ranks in the affordability, availability and overall 2019 GFSI. Zambia's affordability dimension improved by two points from 105 to 103. In contrast, the availability dimension had the most prominent shift by 23 positions from 87 to 64 after the winsorisation of outliers detected in the 2019 GFSI database. +Thus, Zambia improved in ranks in both the affordability and availability dimensions after the winsorisation of outliers, implying that the inclusion of outliers in the 2019 GFSI results underestimated Zambia's ranking in food affordability and availability. Zambia also improved its overall rank by six places from 101 to 95 after winsorisation.

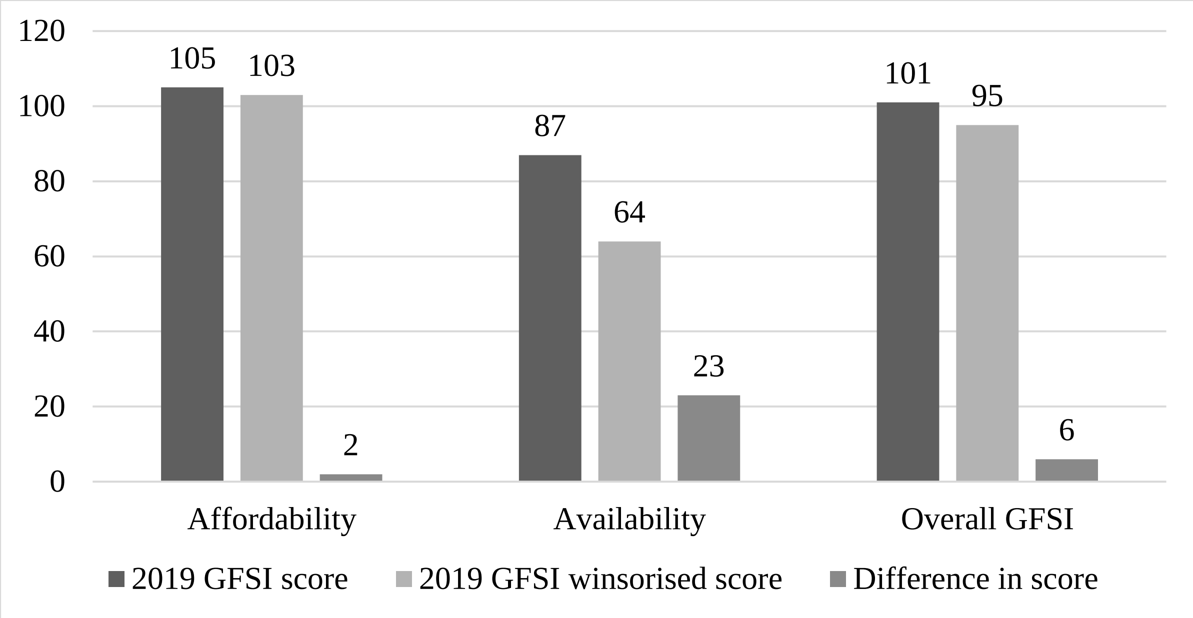

Figure 6.4: Zambia's change in affordability, availability and overall GFSI ranks after winsorisation of outliers

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

6.4 Statistical significance of updating Zambia's data in the 2019 GFSI score and ranking relative to the 113 countries

The third objective of the study was to determine if updating Zambia's 2019 outdated data resulted in a statistically significant change to Zambia's scores and ranks relative to the 113 countries in the 2019 GFSI. In line with the definition of outdated data as set out in chapter five, only indicators that used data older than 2018 were considered outdated.

Due to the unavailability of data, only six of the 14 outdated indicators were updated in this study. Table 6.8 show the source of data for indicators that were updated. The proportion of the population under the global poverty line, change in dependency on chronic food aid, irrigation infrastructure, the volatility of agricultural production, food loss, micronutrient availability, protein quality and ability to store food safely indicators were not updated. Most of the data sources searched for these indicators had the same data values used by the GFSI, indicating data challenges as highlighted by different studies on composite indicators (Freudenberg, 2003b; Hudrliková, 2013).

Table 6.8: Source of data for updated indicators

Updated indicator	Source of new data value	Year
Change in average food costs	World Bank	2019
Gross domestic product per capita (US$ PPP)	CEICDATA (https://www.ceicdata.com/en)	2019
Public expenditure on agricultural R&D	FAO and stasta.com	
Urban absorption capacity	Trading Economics (tradingeconomics.com)	2018
Dietary diversity	tandfonline.com and Maila et al. (2019)	2019
Percentage of population with access to potable water	United Nations (UN) (sdg6data.org/country-or-area/Zambia)	2019

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

6.4.1 Paired t-test results from the effect of updating data on Zambia's 2019 GFSI scores and ranks

After updating the outdated data, Zambia's 2019 GFSI scores increased for the availability, quality and safety dimensions and the overall GFSI score, as shown in Figure 6.5. The quality and safety dimensions had the most prominent increase in scores from 34 to 36, respectively, after updating dietary diversity, percentage of the population with access to potable water, and storing food safely. The affordability dimension scores did not change after updating the data for the change in the average food cost and gross domestic product per capita indicators. The updated data for the change in the average food cost and the gross domestic product indicators was not large enough to change Zambia's affordability dimension scores.

Figure 6.5: Zambia's GSFI scores before and after updating data (N=113).

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

A paired t-test on all three dimensions did not yield statistically significant results, as shown in Table 6.9. The null hypothesis that there was no difference in the mean before and after updating indicators was accepted. The findings mean that the updated scores for the availability, affordability and quality and safety dimensions of the GFSI for Zambia were not significantly different from those calculated by the EIU in the 2019 GFSI. Similarly, the difference in the GFSI score before and after updating Zambia's outdated indicators relative to the 113 countries was not significantly different from zero. However, the increase in score for the availability and quality and safety dimension implied that updating data had a positive impact, even though it was not significant. The result could also mean that, while updating Zambia's outdated indicators increased Zambia's scores, the scores' changes were minimal to change the overall GFSI mean score for all the 113 countries.

Table 6.9: Paired t-test on the scores of the three GFSI dimension before and after updating indicators for Zambia (N=113)

GFSI Dimension	Mean after updating	Mean before updating	Difference in mean	P-value
Affordability	67.503	67.503	0.000	0.3195
Availability	59.425	59.416	0.009	0.3195
Quality and Safety	60.985	60.960	0.025	0.3195
Overall GFSI	62.899	62.895	.004	0.3195

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

6.4.2 Performance of indicators after updating data for Zambia

Figure 6.6 shows Zambia's scores for the updated indicators. After updating data, the dietary diversity and the proportion of the population with access to potable water indicators had the largest increases in scores. The change in the average food cost and GDP per capita (US$PPP) did not increase much. A feeble performance in GDP per capita (US$PPP, which measures individual income in US dollars using purchasing power parity to reflect the affordability of food) meant the reduced ability of citizens to access and afford basic food needs in the country.

Although low, Zambia ranked highest among all African countries regarding public expenditure on agricultural research and development and third among the 113 GFSI countries. After updating public expenditure on agricultural research and development, Zambia's score on this indicator increased from 20.4 to 25.9.

In the 2019 GFSI results for Zambia’s gross domestic product, protein quality, dietary diversity and the presence and quality of the food safety net programmes performed poorly (0-19.9). However, after updating the data from 2013 to 2019, dietary diversity improved somewhat from 17.2 to 26.9. The proportion of the population with access to potable water also improved from 34.7 to 46.2 after updating with data from 2019 data. Updating data for the urban absorption capacity indicator improved the indicator's performance from 73.1 to 78.4.

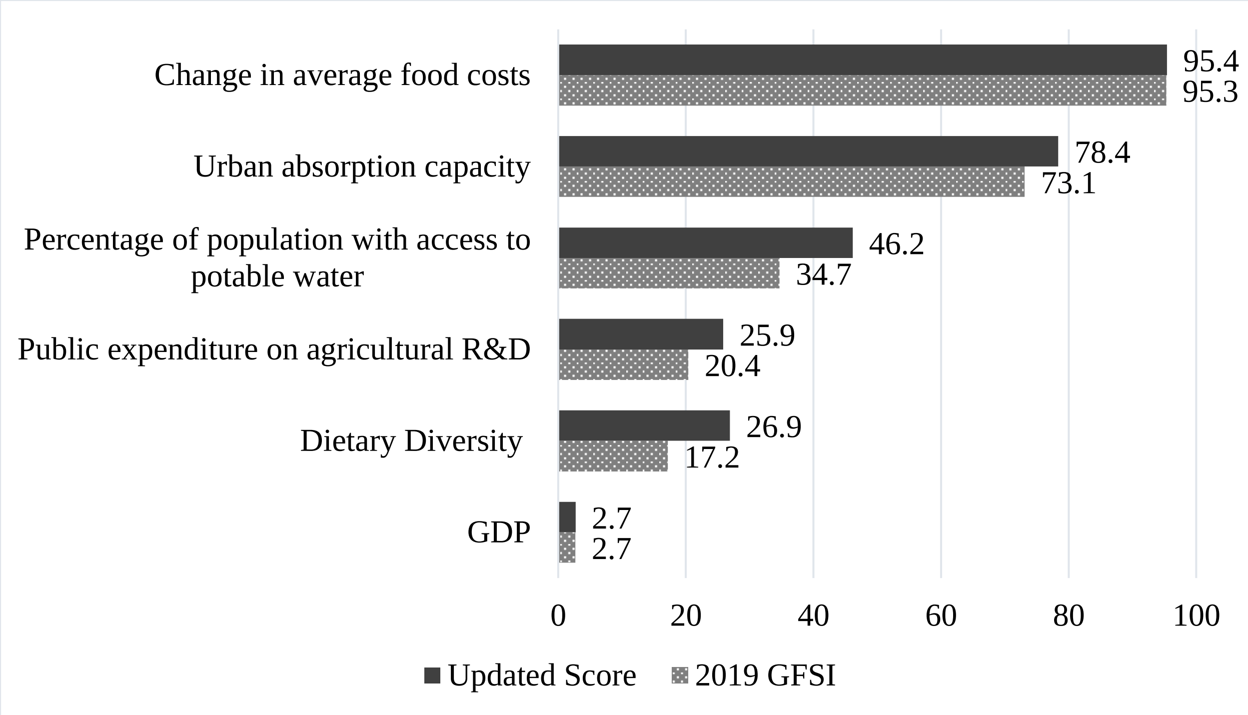

Figure 6.6: Zambia's updated indicator scores (0 to 100 scale).

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

6.4.3 Impact of updating data on Zambia's 2019 GFSI ranking

Figure 6.7 shows Zambia's rankings for the affordability, availability and quality and safety dimensions and the overall ranking after updating data. Relative to the 113 countries in the 2019 GFSI, Zambia only improved ranks for the quality and safety dimension and the overall GFSI. Furthermore, the affordability and availability dimension rankings remained static even after updating the data.

In the overall GFSI ranking, Zambia increased by one position, displacing Angola and Sudan from position 100 and 99, respectively. The improvement in ranking and scores for Zambia stresses the need for Zambia and other countries to update their databases regularly.

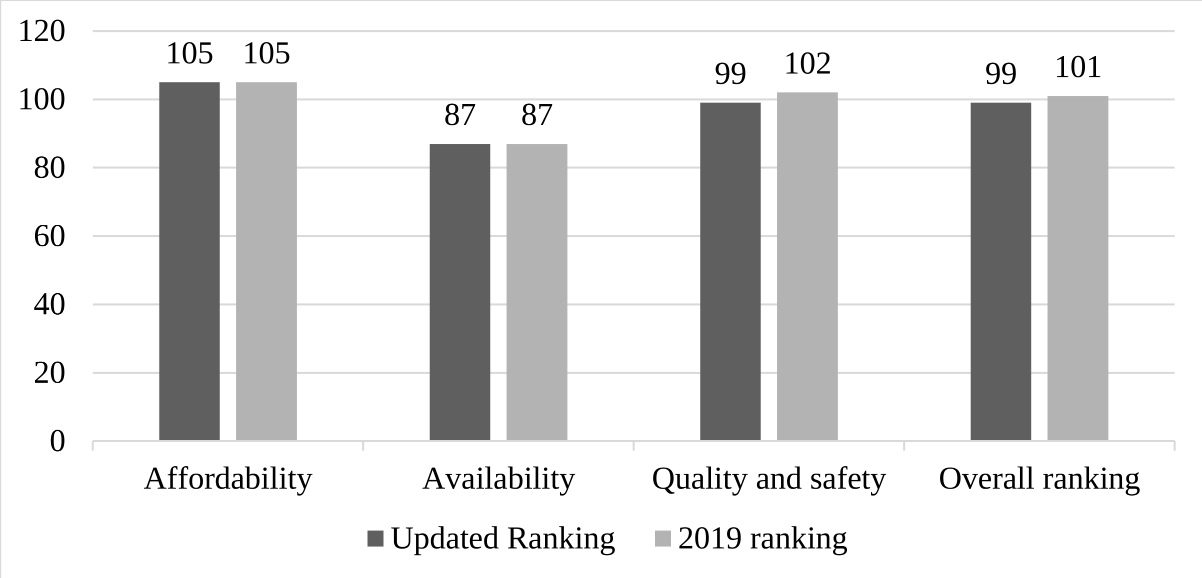

Figure 6.7: Change in Zambia's ranking after updating indicators

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

6.5 Chapter summary

This chapter presented the analysis and discussion of the results obtained in line with the three objectives set in chapter one. The study found that outliers in the GFSI database affect countries scores and rankings. Outliers do not only affect those countries with outlying values but affected other countries. Although not a significant change, Zambia's 2019 GFSI scores and ranking improved after updating outdated data. Therefore, regular updating and availability of updated data are essential to obtain scores and ranks that reflect changes in a country.

CHAPTER 7: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

Composite indicators are increasingly used in policymaking and benchmarking by different countries and stakeholders. However, developing countries have shown weak performance in composite indicator benchmarking exercises over the years due to data unavailability and a lack of frequently updated databases. Updated databases in developing countries are affected by the lack of frequent national surveys due to financial constraints (Freudenberg, 2003b; Benin et al., 2020). The Global Food Security Index (GFSI), a composite indicator, has become a popular measure of different aspects of food security. Zambia's performance on the GFSI has been weak since 2012, when the GFSI was initiated. This study aimed to determine how outdated data and outliers affect Zambia's GFSI scores and ranking using 2019 results 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 significantly affected Zambia's 2019 GFSI score and rankings. The third specific objective was to determine if updating Zambia's outdated data resulted in a statistically significant change in Zambia's overall GFSI score and ranking relative to the 113 countries. The study hypothesised that Zambia's 2019 GFSI database had no outliers and outdated data and that the outdated data and outliers had no statistically significant effect on Zambia's scores and rankings. Further, the study hypothesised that updating Zambia's outdated indicators did not result in a statistically significant change in Zambia's scores and rankings relative to the 113 countries. The identified outliers were winsorised. Paired t-test and Spearman rank correlations were used to test the statistical significance of the GFSI scores and ranking after the winsorisation of outliers and updating Zambia's outdated indicators.

Examining the 2019 EIU database for Zambia showed that 14 of the 34 indicators used outdated data for calculating Zambia's 2019 GFSI scores and ranking. These indicators used data values older than 2018. The 2019 overall GFSI database had ten indicators with outlier values from 16 countries. Zambia had an outlier in the public expenditure on agricultural research and development indicators. Other countries with outliers were Egypt, South Korea, Venezuela, Angola, Belarus, Sudan, Syria, Singapore, Switzerland, Bahrain, Bangladesh, Haiti, Yemen, Sierra Leone and Ghana. Therefore, the study rejected the first hypothesis that Zambia's 2019 had no outliers and outdated data. Comparing the scores before and after winsorisation showed that outliers in the 2019 GFSI database significantly affected Zambia's scores and ranking. The study rejected the null hypothesis that outliers had no statistically significant effect on the 2019 GFSI scores and ranking.

Furthermore, the study found that updating Zambia's 2019 outdated indicators did not significantly change Zambia's scores and ranking. Even though Zambia's scores increased after updating outdated indicators, the changes were not significantly different from zero. The study accepted the third hypothesis that updating Zambia's 2019 GFSI outdated indicators did not result in a statistically significant change in the scores and ranking relative to the 113 countries.

7.2 Conclusions

The study arrived at three conclusions. The first conclusion was that Zambia's 2019 GFSI dataset contained outdated data in 14 of the 34 indicators. These indicators used data from 2017 and older for calculating the 2019 GFSI scores and ranking. The use of outdated data could affect the GFSI's assessment of the countries' scores and ranks. Furthermore, the study concluded that the 2019 overall GFSI contained ten indicators with outlier values. These outlier values were from 16 different countries, with Egypt, Syria and Venezuela, each having two indicators with outlier values. The number of indicators with outlier values increased from the eight detected in a study by Thomas et al. (2017) in 2016.

The second conclusion was that updating Zambia's GFSI outdated data did not significantly change the score and ranking in the three dimensions of the GFSI, food availability, affordability, and quality and safety. However, the scores increased for the updated indicators for availability and quality and safety dimensions, increasing Zambia's overall GFSI.

Thirdly, the study concluded that outliers affected the scores and ranking of countries in the 2019 GFSI results. Comparing scores before and after winsorisation of outlier showed a significant mean score difference for the affordability and availability dimensions except for the quality and safety dimensions. As a result, the outliers could affect the robustness of the GFSI when measuring factors that contribute to food security in countries by acting as unintended benchmarks. Furthermore, outliers in the 2019 GFSI inflated/deflated the scores and ranking of some countries.

Generally, the study concluded that while the GFSI is robust in measuring food security situations in a country, outdated data and outliers affect the scores and ranking of the countries involved. Outliers must be identified and removed, while indicators using outdated data must be updated.

7.3 Recommendations

First, the study recommends that countries should enhance the collection of timely quality data to improve their score and ranking in different regional and global indexes. Governments should further update and release national data for public access because open access to data can improve global food monitoring and evaluation systems. Open access to national data will enable increased availability and access to policymaking and benchmarking by indicators such as the GFSI (Onyancha, 2016). The study also recommended stakeholders advocate for policies that encourage timely data disclosure for public use. Strengthening capacity in identifying data gaps can also help in data collection (Benin et al., 2020). Many studies have identified data gaps in micronutrient availability and their intake, dietary diversity, irrigation infrastructure or the land equipped for agriculture and others (Harris et al., 2019; EIU, 2019). For example, Zambia can maximise its positions of strength in areas such as food availability, food loss and public expenditure on research and development through frequent data collection and updates (EIU, 2019).

Data quality and data availability are crucial in understanding the progress in many commitments at the national, regional, and global levels (Yerramareddy and Babu, 2018). Understanding progress made in achieving vision 2030, CADP commitment, MDG commitment, and other commitments requires stakeholders to improve data collection capacity to reflect countries' progress and actual performance. Open access to data could also help countries identify data gaps hindering progress and achievement of these commitments for accelerated growth and prosperity for all. Therefore, instead of complaining about biased ranking by global indexes, political players and stakeholders are urged to actualise these commitments to improve food security.

Secondly, the study recommends that outliers be resolved before normalising indicators to avoid unreliable benchmarking settings by policymakers. If not correctly handled, extreme values (Outliers) could distort the relative standing of countries in the composite index and hinder composite indicators reliability in measuring food security. Furthermore, outliers in the database can impact the scores and ranking of all countries included in a composite indicator, especially when normalisation procedures (e.g. min-max normalisation) are not robust to the presence of outliers are used (OECD, 2008). Therefore, the winsorisation of outlier values in the datasets could reduce extreme values when constructing composite indicators.

7.4 Contribution of the study to global knowledge

To track the performance of countries in composite indexes across time, accurate and timely data on indicators is critical. The quality of indicators and the quality of data used to construct composite indicators should be checked to minimise outliers and outdated data. Data gaps should always be identified and addressed through a continuous assessment of existing available data (Santeramo, 2015b). The study showed the importance of the evaluation of the underlying data for calculating food security composite indicators. The study contributes to the global knowledge on how outliers could reduce the reliability of composite even when robust weighting, aggregation and normalisation methods are used.

7.5 Recommendations for improvement of the study

Despite the finding that half of the GFSI indicators used outdated data for 2019, the study found that updating data for these indicators did not significantly change Zambia's scores and ranking. Not all the indicators were updated due to data unavailability from alternative sources. Furthermore, the GFSI uses the min-max normalisation method to standardise data from different sources into a comparable unit(EIU, 2019). Updating the outdated indicators for Zambia involved renormalising the same indicators used by the EIU, which could be a limitation as it affects the already normalised GFSI data from other indicators.

7.6 Recommendations for further research

Firstly, future studies should conduct a thorough edit of the entire GFSI data set for the 113 countries to identify similarities in data gaps across different regions represented in the GFSI. For example, this study focused on Zambia alone and could be extended to other countries in Sub-Saharan Africa to ascertain and compare the influence of missing and outdated data among countries. Such a study will enable countries to understand how outdated data impede efforts toward achieving food security and policy benchmarking exercises.

Secondly, this study used min-max normalisation procedures to obtain scores after both winsorisation of outliers from seven indicators and updating outdated data for Zambia. The min-max normalisation depends on the highest and lowest values of an indicator in the dataset (Thomas et al., 2017). Future research could use other normalisation methods outlined in the handbook on constructing composite indicators such as ranking, standardisation balance of opinion and distance to reference country (OECD, 2008). Future studies could also advance other methods of removing outliers in composite indicators, such as the box-cox transformation method.

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Appendix A: GFSI scores before and after winsorisation of outliers

Countries	Affordability score		Availability score		Quality and Safety score		Overall GFSI Score	
	After	Before	After	Before	After	Before	After	Before
Algeria	61	67	49	56	53	53	55	60
Angola	31	51	31	41	45	45	33	46
Argentina	73	79	57	60	79	80	68	71
Australia	89	87	77	77	80	80	83	81
Austria	84	85	77	79	81	81	81	82
Azerbaijan	70	75	59	59	54	54	63	65
Bahrain	81	82	55	56	57	57	67	67
Bangladesh	46	60	50	55	31	31	45	53
Belarus	58	76	64	63	80	80	64	71
Belgium	83	84	74	76	84	84	80	81
Benin	47	49	42	55	46	46	45	51
Bolivia	61	66	49	50	58	58	56	58
Botswana	68	70	63	61	57	57	64	64
Brazil	71	77	54	59	84	84	66	70
Bulgaria	78	79	48	54	67	67	64	66
Burkina Faso	45	47	51	56	42	42	47	50
Burundi	30	37	19	32	34	35	26	34
Cambodia	53	57	42	48	35	35	46	49
Cameroon	51	54	34	48	47	47	44	50
Canada	81	83	82	80	87	87	82	82
Chad	39	40	28	35	33	34	34	37
Chile	78	81	70	71	75	75	74	76
China	71	75	66	67	73	73	69	71
Colombia	70	74	64	66	69	69	68	69
Congo (Dem. Rep.)	35	37	34	40	20	20	32	36
Costa Rica	74	76	56	63	76	76	67	70
Cote d'Ivoire	52	54	53	58	33	33	49	52

Countries	Affordability score		Availability score		Quality and Safety score		Overall GFSI Score	
	After	Before	After	Before	After	Before	After	Before
Czech Republic	81	83	72	66	68	68	75	73
Denmark	85	85	74	75	87	87	81	81
Dominican Republic	65	68	54	61	62	62	60	64
Ecuador	66	69	53	56	58	58	60	62
Egypt	38	58	66	70	66	66	53	65
El Salvador	63	64	53	59	59	59	58	61
Ethiopia	31	50	44	53	39	39	37	49
Finland	83	84	85	79	92	92	85	83
France	83	84	75	75	87	87	80	80
Germany	84	85	78	79	80	80	81	82
Ghana	60	66	50	62	57	57	56	63
Greece	78	78	62	65	86	86	73	73
Guatemala	59	65	49	58	57	58	55	61
Guinea	31	47	44	52	29	29	36	47
Haiti	42	50	26	40	36	36	34	43
Honduras	55	57	56	58	61	61	56	58
Hungary	79	81	67	66	70	71	73	73
India	59	64	57	58	47	47	57	59
Indonesia	66	70	58	61	47	47	60	63
Ireland	91	91	81	77	88	88	87	84
Israel	83	83	74	74	84	84	79	79
Italy	82	83	68	68	80	80	76	76
Japan	81	82	71	71	77	77	76	77
Jordan	68	71	50	55	54	54	58	61
Kazakhstan	72	78	56	58	68	68	65	67
Kenya	46	57	45	48	43	43	45	51
Kuwait	87	88	62	62	76	76	75	75
Laos	52	56	42	48	37	37	45	49

Countries	Affordability score		Availability score		Quality and Safety score		Overall GFSI Score	
	After	Before	After	Before	After	Before	After	Before
Madagascar	29	36	35	46	22	22	30	38
Malawi	21	39	41	49	33	33	31	43
Malaysia	80	82	68	68	71	71	74	74
Mali	44	46	58	60	60	60	52	54
Mexico	70	75	61	62	75	75	67	69
Morocco	58	62	58	64	62	62	59	63
Mozambique	34	43	42	48	21	21	35	41
Myanmar	55	59	52	57	51	51	53	57
Nepal	57	59	52	55	54	54	54	56
Netherlands	85	86	76	76	89	89	82	82
New Zealand	87	85	72	76	73	74	79	79
Nicaragua	59	64	46	48	48	48	52	54
Niger	50	50	46	54	37	37	46	50
Nigeria	37	50	31	46	51	51	37	48
Norway	78	82	83	81	90	91	82	83
Oman	77	78	55	58	74	74	68	68
Pakistan	53	63	54	56	44	44	52	57
Panama	72	74	64	63	72	72	69	69
Paraguay	69	72	35	42	65	65	55	58
Peru	69	69	53	59	60	60	61	63
Philippines	67	69	58	58	50	50	61	61
Poland	80	81	70	69	80	80	76	76
Portugal	81	81	70	71	88	88	77	78
Qatar	100	99	63	64	84	84	82	81
Romania	79	79	67	64	64	64	72	70
Russia	74	80	60	60	71	71	68	70
Rwanda	38	44	47	52	48	49	43	48
Saudi Arabia	87	86	61	62	73	74	74	74
Senegal	49	52	54	56	56	56	52	54

Countries	Affordability score		Availability score		Quality and Safety score		Overall GFSI Score	
	After	Before	After	Before	After	Before	After	Before
Serbia	71	74	48	53	62	62	60	63
Sierra Leone	30	41	34	40	31	31	32	39
Singapore	96	95	82	83	79	79	88	87
Slovakia	77	79	63	62	59	59	69	68
South Africa	66	71	63	65	66	66	65	67
South Korea	72	76	75	71	75	75	74	74
Spain	81	82	65	66	85	85	75	76
Sri Lanka	60	65	61	60	52	52	59	61
Sudan	26	47	36	44	46	46	33	46
Sweden	84	85	78	78	89	89	82	83
Switzerland	79	84	85	84	78	78	81	83
Syria	18	35	38	39	46	46	31	38
Tajikistan	53	59	40	41	47	47	47	49
Tanzania	42	45	42	50	46	46	43	48
Thailand	75	77	60	59	53	53	65	65
Togo	44	46	39	47	31	31	40	44
Tunisia	53	62	57	58	62	62	56	60
Turkey	60	75	57	65	71	71	61	70
Uganda	37	46	37	46	49	49	39	46
Ukraine	54	64	44	50	60	60	51	57
United Arab Emirates	89	90	59	64	79	79	76	77
United Kingdom	83	84	75	74	81	81	79	79
United States	88	87	82	78	89	89	86	84
Uruguay	72	79	59	67	73	73	67	73
Uzbekistan	58	66	58	55	53	53	57	59
Venezuela	16	16	31	32	67	67	30	31
Vietnam	70	75	56	60	52	52	61	65

Countries	Affordability score		Availability score		Quality and Safety score		Overall GFSI Score	
	After	Before	After	Before	After	Before	After	Before
Yemen	41	46	23	29	30	30	32	36
Zambia	**32**	**42**	**54**	**51**	**34**	**34**	**42**	**45**

Source: Author's own computations using EIU data

Appendix B: Ranking of countries before and winsorisation of outliers

Countries	Affordability ranks		Availability ranks		Quality and Safety ranks		Overall GFSI Ranks	
	After	Before	After	Before	After	Before	After	Before
Algeria	63	64	81	74	74	74	73	70
Angola	106	89	109	105	92	92	105	100
Argentina	42	37	56	51	24	23	41	37
Australia	5	7	11	10	20	20	9	12
Austria	12	10	10	6	17	17	12	10
Azerbaijan	50	47	46	56	71	71	51	53
Bahrain	24	26	63	70	67	67	45	50
Bangladesh	89	77	77	79	107	107	89	83
Belarus	73	44	32	42	19	19	49	36
Belgium	15	15	16	12	15	15	16	15
Benin	87	94	92	78	88	88	91	85
Bolivia	67	66	79	89	64	64	71	75
Botswana	56	59	38	48	68	68	50	57
Brazil	47	43	66	58	14	14	45	39
Bulgaria	33	36	82	81	48	48	51	51
Burkina Faso	90	97	75	73	95	95	84	87
Burundi	107	110	113	111	101	101	113	112
Cambodia	79	83	93	92	100	100	87	90
Cameroon	84	86	104	96	85	85	93	88
Canada	20	20	5	4	10	10	6	8
Chad	96	107	110	110	103	103	104	109
Chile	35	32	24	19	33	33	29	25
China	46	50	30	27	38	38	35	35
Colombia	49	54	34	32	44	44	38	43
Congo (Dem. Rep.)	102	109	105	107	113	113	106	110
Costa Rica	40	46	60	40	30	30	44	39
Cote d'Ivoire	82	87	70	62	104	104	83	84
Czech Republic	26	22	20	29	46	46	24	32
Denmark	11	10	18	15	8	8	14	14
Dominican Republic	61	63	64	50	53	53	58	56
Ecuador	57	60	70	71	63	63	60	63
Egypt	97	81	29	23	50	50	71	55
El Salvador	62	72	72	60	62	62	65	67
Ethiopia	105	93	88	84	96	96	98	91
Finland	17	16	2	6	1	1	3	5
France	15	17	15	15	9	9	15	16
Germany	14	13	9	5	21	21	13	11

Countries	Affordability ranks		Availability ranks		Quality and Safety ranks		Overall GFSI Ranks	
	After	Before	After	Before	After	Before	After	Before
Ghana	68	65	76	47	66	66	70	59
Greece	33	39	39	33	11	11	32	31
Guatemala	72	68	80	67	65	65	75	68
Guinea	104	95	89	85	110	110	100	97
Haiti	94	91	110	108	99	99	102	103
Honduras	77	82	58	64	57	57	69	73
Hungary	31	31	27	30	43	43	33	34
India	65	70	54	61	86	85	67	72
Indonesia	60	58	51	48	84	84	62	62
Ireland	3	3	7	11	7	7	2	2
Israel	18	21	17	18	16	16	17	18
Italy	20	23	25	25	22	22	23	23
Japan	23	24	21	21	28	28	21	21
Jordan	54	57	78	79	70	70	64	64
Kazakhstan	45	41	61	65	45	45	58	48
Kenya	88	83	87	93	94	94	87	86
Kuwait	7	5	40	43	29	29	28	27
Laos	83	85	95	96	98	97	90	92
Madagascar	109	111	102	100	111	111	112	108
Malawi	111	108	96	91	105	104	107	104
Malaysia	28	28	26	26	42	42	31	28
Mali	92	98	51	52	59	59	78	80
Mexico	51	49	43	43	31	31	42	43
Morocco	70	75	49	37	55	55	62	59
Mozambique	101	104	91	94	112	112	101	105
Myanmar	75	78	74	69	78	78	77	77
Nepal	74	80	73	76	72	72	74	79
Netherlands	10	9	12	12	5	5	10	9
New Zealand	9	14	19	14	35	35	19	19
Nicaragua	69	73	85	94	83	83	81	82
Niger	85	92	86	82	97	97	86	89
Nigeria	100	90	107	99	79	79	99	94
Norway	30	26	3	3	2	2	5	5
Oman	37	39	62	67	34	34	40	46
Pakistan	81	74	66	75	93	93	80	78
Panama	43	53	33	40	39	39	36	45
Paraguay	53	55	103	103	51	51	76	74
Peru	55	61	68	57	58	58	56	58
Philippines	58	62	50	65	80	80	57	64
Poland	29	30	22	24	23	23	22	24
Portugal	27	29	23	22	6	6	20	20

Countries	**Affordability ranks**		**Availability ranks**		**Quality and Safety ranks**		**Overall GFSI Ranks**	
	After	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**
Qatar	1	1	37	38	13	13	11	13
Romania	31	34	28	36	52	52	34	38
Russia	41	33	44	52	41	41	39	42
Rwanda	98	103	84	86	82	82	92	95
Saudi Arabia	8	8	41	46	35	35	30	30
Senegal	86	88	68	71	69	69	79	81
Serbia	48	52	83	83	56	56	61	59
Sierra Leone	108	106	106	106	107	107	108	106
Singapore	2	2	4	2	25	25	1	1
Slovakia	35	38	36	45	61	61	37	47
South Africa	59	56	35	35	49	49	56	48
South Korea	39	45	13	20	32	32	25	29
Spain	22	25	31	31	12	12	26	25
Sri Lanka	66	69	42	54	76	76	60	66
Sudan	110	96	101	102	90	90	103	99
Sweden	12	12	8	9	3	3	8	7
Switzerland	25	17	1	1	27	27	7	4
Syria	112	112	99	109	88	88	108	107
Tajikistan	80	79	97	104	87	87	85	93
Tanzania	93	102	94	88	91	91	94	96
Thailand	38	42	45	59	75	75	46	52
Togo	91	100	98	98	106	106	96	102
Tunisia	75	75	57	63	54	54	68	69
Turkey	64	51	55	34	40	40	53	41
Uganda	99	99	100	101	81	81	97	98
Ukraine	78	71	90	89	60	60	82	76
United Arab Emirates	4	4	47	39	26	26	27	21
United Kingdom	18	19	14	17	18	18	17	17
United States	6	6	6	8	4	4	4	3
Uruguay	43	34	47	28	37	37	42	33
Uzbekistan	71	67	53	77	73	73	66	71
Venezuela	113	113	108	111	47	47	111	113
Vietnam	52	48	59	55	77	77	54	54
Yemen	95	101	112	113	109	109	110	111
Zambia	**103**	**105**	**64**	**87**	**102**	**102**	**95**	**101**

Source: Author's own computations from EIU data

Appendix C: GFSI Scores Before and after winsorisation and updating

Countries	Affordability score		Availability score		Quality and Safety score		Overall GFSI scores	
	After	Before	After	Before	After	Before	After	Before
Algeria	61	67	49	56	53	53	55	60
Angola	31	51	31	41	45	45	33	46
Argentina	73	79	57	60	79	80	68	71
Australia	89	87	77	77	80	80	83	81
Austria	84	85	77	79	81	81	81	82
Azerbaijan	70	75	59	59	54	54	63	65
Bahrain	81	82	55	56	57	57	67	67
Bangladesh	46	60	50	55	31	31	45	53
Belarus	58	76	64	63	80	80	64	71
Belgium	83	84	74	76	84	84	80	81
Benin	47	49	42	55	46	46	45	51
Bolivia	61	66	49	50	58	58	56	58
Botswana	68	70	63	61	57	57	64	64
Brazil	71	77	54	59	84	84	66	70
Bulgaria	78	79	48	54	67	67	64	66
Burkina Faso	45	47	51	56	42	42	47	50
Burundi	30	37	19	32	34	35	26	34
Cambodia	53	57	42	48	35	35	46	49
Cameroon	51	54	34	48	47	47	44	50
Canada	81	83	82	80	87	87	82	82
Chad	39	40	28	35	33	34	34	37
Chile	78	81	70	71	75	75	74	76
China	71	75	66	67	73	73	69	71
Colombia	70	74	64	66	69	69	68	69
Congo (Dem. Rep.)	35	37	34	40	20	20	32	36

Countries	**Affordability score**		**Availability score**		**Quality and Safety score**		**Overall GFSI scores**	
	After	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**
Costa Rica	74	76	56	63	76	76	67	70
Cote d'Ivoire	52	54	53	58	33	33	49	52
Czech Republic	81	83	72	66	68	68	75	73
Denmark	85	85	74	75	87	87	81	81
Dominican Republic	65	68	54	61	62	62	60	64
Ecuador	66	69	53	56	58	58	60	62
Egypt	38	58	66	70	66	66	53	65
El Salvador	63	64	53	59	59	59	58	61
Ethiopia	31	50	44	53	39	39	37	49
Finland	83	84	85	79	92	92	85	83
France	83	84	75	75	87	87	80	80
Germany	84	85	78	79	80	80	81	82
Ghana	60	66	50	62	57	57	56	63
Greece	78	78	62	65	86	86	73	73
Guatemala	59	65	49	58	57	58	55	61
Guinea	31	47	44	52	29	29	36	47
Haiti	42	50	26	40	36	36	34	43
Honduras	55	57	56	58	61	61	56	58
Hungary	79	81	67	66	70	71	73	73
India	59	64	57	58	47	47	57	59
Indonesia	66	70	58	61	47	47	60	63
Ireland	91	91	81	77	88	88	87	84
Israel	83	83	74	74	84	84	79	79
Italy	82	83	68	68	80	80	76	76
Japan	81	82	71	71	77	77	76	77
Jordan	68	71	50	55	54	54	58	61

Countries	Affordability score		Availability score		Quality and Safety score		Overall GFSI scores	
	After	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**
Kazakhstan	72	78	56	58	68	68	65	67
Kenya	46	57	45	48	43	43	45	51
Kuwait	87	88	62	62	76	76	75	75
Laos	52	56	42	48	37	37	45	49
Madagascar	29	36	35	46	22	22	30	38
Malawi	21	39	41	49	33	33	31	43
Malaysia	80	82	68	68	71	71	74	74
Mali	44	46	58	60	60	60	52	54
Mexico	70	75	61	62	75	75	67	69
Morocco	58	62	58	64	62	62	59	63
Mozambique	34	43	42	48	21	21	35	41
Myanmar	55	59	52	57	51	51	53	57
Nepal	57	59	52	55	54	54	54	56
Netherlands	85	86	76	76	89	89	82	82
New Zealand	87	85	72	76	73	74	79	79
Nicaragua	59	64	46	48	48	48	52	54
Niger	50	50	46	54	37	37	46	50
Nigeria	37	50	31	46	51	51	37	48
Norway	78	82	83	81	90	91	82	83
Oman	77	78	55	58	74	74	68	68
Pakistan	53	63	54	56	44	44	52	57
Panama	72	74	64	63	72	72	69	69
Paraguay	69	72	35	42	65	65	55	58
Peru	69	69	53	59	60	60	61	63
Philippines	67	69	58	58	50	50	61	61
Poland	80	81	70	69	80	80	76	76
Portugal	81	81	70	71	88	88	77	78

Countries	**Affordability score**		**Availability score**		**Quality and Safety score**		**Overall GFSI scores**	
	After	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**
Qatar	100	99	63	64	84	84	82	81
Romania	79	79	67	64	64	64	72	70
Russia	74	80	60	60	71	71	68	70
Rwanda	38	44	47	52	48	49	43	48
Saudi Arabia	87	86	61	62	73	74	74	74
Senegal	49	52	54	56	56	56	52	54
Serbia	71	74	48	53	62	62	60	63
Sierra Leone	30	41	34	40	31	31	32	39
Singapore	96	95	82	83	79	79	88	87
Slovakia	77	79	63	62	59	59	69	68
South Africa	66	71	63	65	66	66	65	67
South Korea	72	76	75	71	75	75	74	74
Spain	81	82	65	66	85	85	75	76
Sri Lanka	60	65	61	60	52	52	59	61
Sudan	26	47	36	44	46	46	33	46
Sweden	84	85	78	78	89	89	82	83
Switzerland	79	84	85	84	78	78	81	83
Syria	18	35	38	39	46	46	31	38
Tajikistan	53	59	40	41	47	47	47	49
Tanzania	42	45	42	50	46	46	43	48
Thailand	75	77	60	59	53	53	65	65
Togo	44	46	39	47	31	31	40	44
Tunisia	53	62	57	58	62	62	56	60
Turkey	60	75	57	65	71	71	61	70
Uganda	37	46	37	46	49	49	39	46
Ukraine	54	64	44	50	60	60	51	57

Countries	**Affordability score**		**Availability score**		**Quality and Safety score**		**Overall GFSI scores**	
	After	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**
United Arab Emirates	89	90	59	64	79	79	76	77
United Kingdom	83	84	75	74	81	81	79	79
United States	88	87	82	78	89	89	86	84
Uruguay	72	79	59	67	73	73	67	73
Uzbekistan	58	66	58	55	53	53	57	59
Venezuela	16	16	31	32	67	67	30	31
Vietnam	70	75	56	60	52	52	61	65
Yemen	41	46	23	29	30	30	32	36
Zambia	**32**	**42**	**54**	**51**	**34**	**34**	**42**	**45**

Source: Author's own computations