The effect of an objective weighting of the Global Food Security Index's natural resources and resilience component on country scores and ranking

by

Valiant Otieno Odhiambo

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Department of Agricultural Economics, Extension and Rural Development,

Faculty of Natural Resources and Agricultural Sciences

University of Pretoria

Supervisors:

Prof. Sheryl L. Hendriks

Dr. Eness P. Mutsvangwa-Sammie

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Declaration

I, Valiant Otieno Odhiambo, declare that this dissertation, which I hereby submit for a Master of Agricultural Science in Agricultural Economics at the University of Pretoria, is my own work. I have not previously submitted it for a degree at this or any other tertiary institution.

Signature: …………………………

Date: March 2021

Dedication

I dedicate this dissertation to my mum and siblings and to my wife Velma for her unfailing support, encouragement and motivation, including her endurance during my absence. Lastly, I dedicate this work to my God, who has always worked in me to act and fulfil his good purpose.

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Abstract

Composite indicators have gained popularity in various research areas, such as performance monitoring and decision making. However, the determination of an appropriate weighting method is a significant problem in the creation of composite indices. Weighting methods significantly affect the results of composite indicators in a benchmarking context. Subjective weighting processes are criticised for their potential bias that may reduce stakeholders' trust in the results of a composite index. By contrast, objective weighting processes are perceived to provide unbiased results that may overcome trust issues in the subjective judgements of the experts who construct composite indices. The Global Food Security Index (GFSI) is a composite indicator that measures the comparative level of food insecurity for 113 countries. The initial components of the GFSI included the affordability, availability and quality and safety components. In 2017, the GFSI added a fourth component for natural resources and resilience (NRR) as a risk to food security.

The scarcity of natural resources already constrains economic growth and food security. The climate-related conditions will profoundly affect those countries that are least resilient. The national food security and climate-related performance scores are politically sensitive for governments. Both are essential for incentivising progress towards global targets. Moreover, the policymakers are seeking a working guide to improving their targeting and monitoring efforts for food security.

The Economist Intelligence Unit's (EIU) panel of experts uses a subjective weighting of indicators in the GFSI model. The subjective assessment of sensitive indicators may negate trust in the dimensions and overall score and ranks. An objective weighting approach to the NRR component of the GFSI may provide an evidence-based understanding of a country's progress in the management of natural resource risks and build the confidence of countries in the reliability of the index. No studies yet have explored the effect of an objective weighting of the new NRR component of the GFSI on country scores and ranks. This study set out to assess whether an objective weighting of the NRR component of the GFSI significantly changed the country scores and ranks compared to the subjective weighting process.

The GFSI data set of 113 countries was analysed using a principal component analysis (PCA) to derive objectively weighted NRR scores and ranks. The objectively weighted NRR scores were then used to adjust the overall GFSI scores and ranks. The Kaiser-Meyer-Olkin (KMO) test was 0.682, indicating that the PCA was suitable for analysing the GFSI data. A paired t-test showed that on average, the objectively weighted NRR scores were lower than the subjectively weighted scores. However, a Spearman's correlation indicated that the objectively and subjectively weighted NRR ranks were strongly correlated (rho = 0.831). The study concluded that the NRR ranks and the adjusted overall GFSI rank of countries would change slightly if an objective weighting technique was applied to the NRR component of the GFSI. However, the subjectively (GFSI model) and objectively (PCA model) weighted NRR ranks were highly correlated, indicating that the subjectively weighted GFSI model was not strongly statistically biased. The findings implied that the subjective weighting of the NRR component of the GFSI may still provide relatively fair country scores and ranks for comparison purposes. However, the existence of subjectivity in the weighting of the NRR component may affect the trustworthiness of the GFSI results among governments and policymakers. An objective weighting of the NRR component could overcome the subjectivity of EIU's weighting approach, improving the reliability of the NRR component of the GFSI and building greater trust.

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List of acronyms

AHP	Analytic Hierarchy Process
BAP	Budget Allocation Process
BOD	Benefit of the Doubt Approach
CA	Conjoint Analysis
CCAFS	Climate Change, Agriculture and Food Security
CGIAR	Consultative Group for International Agricultural Research
CIDI	Composite I-Distance Indicator
DEA	Data Envelopment Analysis
EIU	Economist Intelligence Unit
FA	Factor Analysis
FAO	Food and Agriculture Organisation of the United Nations
GDP	Gross Domestic Product
GFSI	Global Food Security Index
H-DEA	Hierarchical Data Envelopment Analysis
HDI	Human Development Index
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
IFPRI	International Food Policy Research Institute
IWMI	International Water Management Institute
ND-GAIN	Notre Dame Global Adaptation Initiative
NRR	Natural Resources and Resilience
OECD	Organization for Economic Cooperation and Development
PCA	Principal Component Analysis
PO	Public Opinion
RA	Regression Analysis
SDSN	Sustainable Development Solutions Network
UCM	Unobserved Component Models
UN	United Nations
UNDP	United Nations Development Programme
USAID	United States Agency for International Development
WFP	World Food Programme
WRI	World Resources Institute

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Chapter 1: Introduction

1.1 Background to the research problem

Composite indicators have gained popularity in various research areas, such as performance monitoring and decision making (OECD, 2008). However, the determination of an appropriate weighting method is a significant problem in the creation of composite indices. Weighting methods significantly affect the results of composite indicators in a benchmarking context (Nardo et al., 2005). Subjective weighting processes are criticised for their potential bias that may reduce stakeholders' trust in the results of a composite index (Maricic et al., 2016). By contrast, objective weighting processes are perceived to provide unbiased results that may overcome trust issues in the subjective judgements of the experts who construct composite indices. Therefore, the weighting of indicators should be accorded keen attention by the developers of a composite index (Nardo et al., 2005).

The Global Food Security Index (GFSI) is a composite indicator designed by the Economist Intelligence Unit (EIU) as a benchmarking model that measures the comparative level of food insecurity for countries (EIU, 2019). The initial components of the GFSI included the affordability, availability and quality and safety components that measured a specific food security dimension (EIU, 2017). In 2017, the GFSI added a fourth component for natural resources and resilience (NRR) to the initial three dimensions of affordability, availability and quality and safety components (EIU, 2017). This component was added as an adjustment factor to capture changes to the overall food security score in the event of climate-related and natural resource risks and how countries adapt to these risks (EIU, 2019).

The scarcity of natural resources already constrains economic growth and food security (Rosegrant et al., 2014). Moreover, changing climate-related conditions will profoundly affect those countries that are least resilient (Sova et al., 2019). Resilience is defined as the ability to restrain and mitigate crises and disaster, likewise, to anticipate, absorb and bounce back from these shocks in a timely, efficient and sustainable way (FAO, 2013). An evidence-based understanding of a country's progress in the management of natural resource risks may help countries to identify the areas that need intervention (Nardo et al., 2005).

The EIU panel consists of twenty renowned international experts on food security, agricultural policy, climate change and natural resources (EIU, 2019). In the weighting of the GFSI, the EIU panel of experts apply two sets of weightings. The first, known as an equal weighting, assumes that all indicators have the same level of importance (EIU, 2019). The second weighting option of the GFSI is referred to as the 'peer panel recommendation' as it involved averaging the indicator weights suggested by five members of the EIU panel of experts (EIU, 2019). An analyst of the GFSI model has the option of using any of the two mentioned weights provided by the EIU or even applying new weights (EIU, 2019). However, the default setting weights used in the GFSI model is the indicator weights suggested by the EIU experts (EIU, 2019). Several researchers have criticised the EIU weighting scheme as a subjective approach. Many critics claim that the GFSI results needed validation against the results of an objective weighting model (Izraelov and Silber, 2019). The purpose of this study was to explore how an objective weighting of the NRR component of the GFSI affected country scores and ranks.

1.2 Statement of the research problem

As mentioned above, the EIU panel of experts assigned weights to the indicators of the GFSI by averaging the indicator weights suggested by five members of the EIU panel. However, this EIU weighting process of allocating indicator weights may be subjective for two reasons. Firstly, the suggestion of the indicator weights by the EIU experts depends on the knowledge and judgements of these experts. These experts may be conversant with the relative importance of the GFSI indicators (Gan et al., 2017). The EIU experts may assign high weights to focus advocacy efforts for some indicators while penalising other indicators with low weights (Greco et al., 2019). Therefore, the EIU panel of experts may subjectively assign *a priori* (biased) weights to the GFSI indicators (Kao, 2010).

Secondly, the EIU weighting process does not apply statistical techniques to derive the GFSI weights. Statistical methods used for the objective weighting of indicators are known to produce less biased results in a benchmarking context (Decancq and Lugo, 2013). By contrast, subjective weighting processes are criticised for not using statistical software and for their potential bias in the creation of scores and ranks (Maricic et al., 2016). Such criticism of the EIU weighting process may reduce the confidence of countries in the GFSI results.

Several studies have assessed the EIU panel of expert's application of weightings. Chen et al. (2019), applied the Hierarchical Data Envelopment analysis (H-DEA) approach to derive indicator weights in the 2014 GFSI. Chen et al. (2019), noted that the GFSI weights and H-DEA weights for indicators gave similar country ranks but slightly different scores for countries. Izraelov and Silber (2019), applied the Data Envelopment Analysis (DEA), Principal Component Analysis (PCA) and Lower Convex Hull (LCH) approaches to assess the 2015

GFSI. Izraelov and Silber (2019), concluded that the GFSI weights selected by the EIU experts were not biased as the compared rank of countries were similar. Finally, Maricic et al. (2016), scrutinised the 2015 GFSI weighting process by applying the Composite I-Distance Indicator (CIDI) method and concluded that the weights in the GFSI model were biased. The biased GFSI weights could provide questionable GFSI results to countries, policymakers and researchers and reduce their trust (Maricic et al., 2016). However, these studies did not conduct tests to evaluate the statistical significance change in the GFSI scores and ranks due to alternative weightings. Also, the NRR component of the GFSI was still new to many researchers. Therefore, this study set out to determine how an objective weighting of the NRR component of the GFSI affected country scores and ranks.

The national food security and climate-related performance scores are politically sensitive for governments (Santeramo, 2015a). Both are essential for incentivising progress towards global targets. The objective assessment of indicators for the NRR component of the GFSI may boost the confidence of governments in the GFSI results. The policymakers may use the findings of this study as a guide to improving their targeting and monitoring efforts for food security. Finally, the EIU panel of experts may use the findings of this study to improve the design of the efforts for food security.

1.3 Research questions

This study set out to explore how an objective weighting of the NRR component of the GFSI affected the scores and rank of countries. The specific research questions addressed were:

i. Did the objective weighting significantly change the countries' NRR scores and ranks compared to the subjective weighting of the NRR component of the GFSI?
ii. Did the objective NRR adjustment of the overall GFSI significantly change the countries' adjusted overall GFSI scores and ranks compared to the subjective NRR adjustment?

1.4 Research hypotheses

The hypothesis for the research question one assumed that the objective weighting significantly changed the countries' NRR scores and ranks compared to the subjective weighting of the NRR component of the GFSI. The hypothesis for the research question two assumed that the objective NRR adjustment of the overall GFSI significantly changed the countries' adjusted overall GFSI scores and ranks compared to the subjective NRR adjustment.

The justification for the two mentioned hypotheses was as follows. Firstly, the subjective weighting process for the NRR component of the GFSI does not involve the use of statistical techniques to derive indicator weights. An application of statistical software for the objective weighting of NRR indicators may provide less biased NRR scores and ranks (Chen et al., 2019). However, the objective weights for the NRR component of the GFSI derived using statistical techniques might significantly change with changes in data to give new trade-offs between indicators (Decancq and Lugo, 2013). Statistical methods for weighting indicators are known to change the weights in composite indices depending on data used (Becker et al., 2017; Paruolo et al., 2013). The changing weights may help countries with high scores for the indicators that received extensive weights to have a greater chance for higher NRR scores (Nardo et al., 2005).

Secondly, the judgements of the EIU experts may have influenced the subjective weighting of the NRR component of the GFSI in 2017 by focussing on particular indicators (Alemi-Ardakani et al., 2016). For example, the EIU experts may have assigned a higher weight (21.43%) to the exposure to temperature rise to raise country focus on this indicator compared to the storm severity indicator with a lower weight (7.14%). These panel of experts may have assigned *a priori* weights that distort the NRR scores and rank of countries (Kao, 2010; Maricic et al., 2016). Conversely, an objective weighting of the NRR component would rely on statistical techniques (Izraelov and Silber, 2019) and could provide *a posteriori* (unbiased) weights free of *ad hoc* restrictions (Kao, 2010). As a result, the NRR scores and ranks might significantly change for the countries that performed better or poorly on the indicators with higher objective weights compared to subjective weights (Nardo et al., 2005). Finally, the NRR scores were used to adjust the overall GFSI scores and rank of countries. The objectively weighted NRR scores may significantly change the countries' adjusted overall GFSI scores and ranks formerly obtained using subjectively weighted NRR scores.

1.5 Outline of the dissertation

The dissertation consists of six chapters. Chapter one has presented the introduction and rationale for the study. Chapter two provides a review of the related literature on which the research and conceptual framework were based. The third chapter describes the methodology used by the GFSI. Chapter four describes the methods used in this study. Chapter five presents the results and discussions. Finally, the sixth chapter provides the conclusions, recommendations, and suggestions for the improvement of the study and further research.

Chapter 2: Review of the related literature

2.1 Introduction

Weighting methods can significantly affect the results of composite indicators in a benchmarking context (Nardo et al., 2005). The determination of an appropriate weighting method is a significant problem in the creation of composite indices (OECD, 2008). As with other composite indicators, the GFSI may have the problem of *ad hoc* restrictions in indicator weights (Freudenberg, 2003). A study by Maricic et al. (2016), indicated that the GFSI was based on reliable data sources but biased weights. It is crucial to understand how the objective weighting of the NRR component of the GFSI affects the countries' scores and ranks in this dimension and when combined in the overall index.

This chapter reviews the related literature on composite indicators. The chapter starts by reviewing the theoretical background of composite indicators, followed by the classification of weighting methods. The empirical studies on composite indicators are then reviewed to identify the research gap and to build the conceptual framework (Figure 2.1).

2.2 The theoretical background of composite indicators

The use of composite indicators to score and rank countries based on multiple dimensions has increased over the last two decades (Greco et al., 2019). As shown in Table 2.1, composite indicators have been useful in performance monitoring, benchmarking comparisons and decision making in different research areas (OECD, 2008; Reale et al., 2017). A composite indicator is created when individual indicators are combined into a single index to measure multifaceted concepts which cannot be measured by an individual indicator (OECD, 2008). Measuring food security is one such case where a single, unidimensional indicator does not cover the multiple aspects. Jacobs et al. (2004), asserted that a composite indicator succinctly conveys performance information in a single score used in developing policy priorities.

A composite indicator's usefulness is dependent on its underlying construction (OECD, 2008). For this reason, Böhringer and Jochem (2007), noted that composite indicators are not exempt from criticism despite their extensive use. Some critique pertains to lack of consistency and transparency in the creation of such indices (Grupp and Mogee, 2004). Table 2.1 presents the benefits and drawbacks of composite indicators.

Table 2.1: Benefits and drawbacks of composite indicators

Benefits of composite indicators	Drawbacks of composite indicators
• Composite indicators support decision-makers by summarising complex multidimensional issues. • It is easier to interpret a single comparative value. • Countries can be ranked based on complex issues in a benchmarking context. • Composite indicators assess a country's progress towards managing complex issues over time, thereby attracting public interest. • The results of a composite indicator indicate what areas require intervention.	• If misinterpreted or poorly constructed, composite indicators may convey misleading messages. • The subjective judgements of the developers of a composite indicator may influence the selection of sub-indicators and indicator weights. • It may be challenging to determine the root causes of poor performance from a single comparative value of a composite index. • The developers of a composite index may ignore the dimensions of a phenomenon that are difficult to measure.

Source: Adapted from Saisana and Tarantola (2002).

Several composite indicators have been developed for use in various research areas. Table 2.2 provides a list of some of the indicators, including their developer and their area of use.

Table 2.2: Examples of composite indicators

Research area	Composite indicator	The developer of the composite indicator
Food Security	Global Hunger Index (GHI)	International Food Policy Research Institute (IFPRI)
	Hunger and Nutrition Commitment Index (HANCI)	Institute of Development Studies (IDS)
	Global Food Security Index (GFSI)	Economist Intelligence Unit (EIU)
Environment	Sustainable Development Index (SDI)	United Nations
	Environmental Sustainability Index	World Economic Forum (WEF)
Economy	Internal Market Index (IMI)	European Commission (EC)
	Economic Competitiveness Index (ECI)	Institute for Management Development
Technology and Innovation	Technology Achievement Index (TAI)	United Nations Development Programme
	Networked Readiness Index (NRI)	World Economic Forum (WEF)
Society	Corruption Perceptions Index (CPI)	Transparency International
	Human Development Index (HDI)	United Nations Development Programme

Source: Adapted from Jones et al. (2013), OECD (2008) and Pangaribowo et al. (2013).

2.2.1 The construction of composite indicators

Table 2.3 shows the ten universally accepted steps for constructing composite indicators as developed by the Joint Research Centre (JRC) of the European Commission and the Organisation for Economic Cooperation and Development (OECD) (OECD, 2008). Despite the recommendation made by the JRC and OECD, their procedure may not be free of inherent weaknesses (Mazziotta and Pareto, 2017).

Table 2.3: Steps for constructing a composite indicator

Step	**Composite indicator construction activity**
1	The development of the theoretical framework
2	The selection of indicators and data sources
3	The imputation of missing data
4	Multivariate analysis
5	The normalisation and rescaling of data
6	The weighting and aggregation of indicators
7	The uncertainty and sensitivity analyses of the composite index
8	The deconstruction of the components of the composite indicator
9	The testing of the explanatory power of the composite index
10	The visualisation of the results of the composite indicator

Source: OECD (2008).

Constructing a composite indicator is a complex process that involves various steps where the developer makes subjective choices (Mazziotta and Pareto, 2013). These choices may influence the results (Freudenberg, 2003). Each of the ten steps for constructing composite indicators is discussed in the following paragraphs to provide an understanding of the development process of a composite index.

The first step in the construction of a composite indicator involves developing a theoretical framework that links various components and their indicators (OECD, 2008). The constructors of any composite indicator need to clearly define the phenomenon being measured and its components (Santeramo, 2015b). A sound theoretical framework helps in the selection and combination of individual indicators within the components of a composite index (OECD, 2008). For example, the Human Development Index (HDI) was based on the definition that human development exists when people are knowledgeable and enjoying a long healthy life with a decent standard of living (OECD, 2008). Therefore, the HDI measures human development within three broad components: life expectancy, education and GDP per capita (Hou et al., 2015).

The second step for constructing a composite indicator involves the selection of indicators as guided by the theoretical framework (OECD, 2008). The accuracy and quality of composite indicators largely depend on data availability and quality. The data should be of high quality in terms of accuracy, completeness, reliability, relevance and timeliness (OECD, 2008). A lack of data may limit the construction of a composite index.

The imputation of missing data is the third step in the construction of a composite indicator. Missing data hinders the development of sound composite indicators (OECD, 2008). There are three methods of fixing the problem of missing data: case deletion, single imputation and multiple imputations (OECD, 2008). In the event of missing data, case deletion either omits the affected indicator or country from the analysis (Nardo et al., 2005). However, case deletion leads to loss of information, thereby affecting the subsequent analyses and inferences on data (Santeramo, 2015b). Single imputation treats missing data as part of the analysis and applies mode, medium, mean, regression or expectation-maximization imputations (Nardo et al., 2005). However, single imputation may underestimate the variance of the estimates (Santeramo, 2015b). Multiple imputations treat missing data as part of the analysis and apply the Markov chain Monte Carlo (MCMC) algorithm (OECD, 2008). Generally, single and multiple imputations minimise bias in the construction of composite indicators as cases are not deleted (Nardo et al., 2005).

The fourth step in the construction of a composite indicator consists of a multivariate analysis. The data set is assessed to identify its suitability and implications on the proceeding methodological steps such as weighting and aggregation (OECD, 2008). The grouping and analysis can be conducted for individual indicators. To group information on individual indicators, an analyst applies statistical tools such as principal component analysis (PCA). PCA transforms correlated variables into a set of uncorrelated variables using either a correlation matrix or covariance matrix (OECD, 2008). PCA helps explore whether the components of the phenomenon being measured are statistically balanced in the composite index. Grouping information based on the similarity for various indicators involves the use of cluster analysis (CA) (Nardo et al., 2005). CA is a statistical aggregation technique.

The normalisation of indicators is the fifth step in the construction of a composite indicator. Normalisation is the procedure by which the indicators in various scales are transformed to a standard scale that allows comparison (EIU, 2019). Normalisation helps overcome the dominance of outliers in a data set (Freudenberg, 2003). Constructors of composite indicator may use one of normalisation methods such as minimum-maximum, ranking, standardisation, categorical scales, and others. Standardisation and minimum-maximum normalisation methods are most frequently used (El Gibari et al., 2019; OECD, 2008). Standardisation converts indicators to a common scale with a zero mean and standard deviation of one (OECD, 2008). The minimum-maximum method normalises all indicators to an identical range of zero to one (OECD, 2008).

The sixth step in the construction of a composite indicator consists of weighting and aggregation of indicators. The weighting of variables according to an agreed-on and clearly-stated theoretical framework precedes the aggregation process (Santeramo, 2015b). However, it is challenging to develop theoretical frameworks for obtaining coherent weighting methods (Freudenberg, 2003). Variables may be assigned equal weights mostly for simplicity reasons, or they may be allocated varying weights (OECD, 2008). Equal weighting assumes that all indicators have equal importance (Nardo et al., 2005). The methodology of any chosen weighting method should be made transparent as weights significantly influence the results of composite indices (Nardo et al., 2005). Much of the criticisms of composite indicator weighting schemes relate to the subjective nature of some weighting methods (Saltelli, 2007). A detailed discussion of the weighting of indicators is presented in the next sections of this chapter.

The weighted indicators (or components) are then combined into a single composite index using linear, geometric or multi-criteria approach aggregations (OECD, 2008). Linear aggregation is the addition of weighted and normalised indicators such that high scores in some indicators compensate (offset) the low scores in other indicators (Nardo et al., 2005). Geometric aggregation is the product of weighted indicators such that countries with low scores in some indicators require much higher scores on other indicators to improve their ranks (Munda, 2012). Finally, a multi-criteria aggregation is useful when there is no possibility of compensating poor performance in some indicators by higher performance in other indicators (Munda, 2012).

The seventh step for constructing a composite indicator involves uncertainty and sensitivity analyses to test for the robustness of the composite indicator (OECD, 2008). The preceding steps involve several judgements regarding the selection of indicators, normalisation, weighting and aggregation (OECD, 2008). Uncertainty analysis determines the sources of variability in overall scores, such as the selected weights for indicators (Nardo et al., 2005). Sensitivity analysis explores how the normalisation, weighting and aggregation methods of the composite index contributed to the overall scores (OECD, 2008). Sensitivity analysis involves the application of alternative normalisation, weighting and aggregation methods for indicators. The combined use of uncertainty and sensitivity analyses helps improve the structure of a composite indicator (Saisana et al., 2005).

An analyst should address all sources of uncertainty as several judgements made at the various steps for creating a composite indicator may reduce the robustness of a composite index (OECD, 2008). Uncertainties may be assessed in seven stages (OECD, 2008). First, an analyst may include and exclude individual indicators (Nardo et al., 2005). Second, an analyst should determine the data error based on the variance estimates. The third stage would involve the application of alternative editing methods, such as single and multiple imputations (OECD, 2008). Fourth, alternative data normalisation methods such as standardisation, minimum-maximum, rankings and others may be used (OECD, 2008). Fifth, an analyst may apply various subjective and objective weighting methods of composite indicators (Nardo et al., 2005). The use of alternative aggregation methods such as linear, geometric and multi-criteria approach would form the sixth stage (OECD, 2008). Finally, an analyst may apply different plausible weights to assess the uncertainties encountered while constructing composite indicators (Nardo et al., 2005).

The eighth step in the construction of composite indicators involves decomposing a composite indicator to identify the contribution of individual components to the overall scores (OECD, 2008). This contribution may be determined using structural equation modelling, path analysis and Bayesian networks (OECD, 2008). The developers of the composite index identify the primary drivers of a composite indicator score by profiling performance at the indicator level. The outcome of each indicator may be illustrated using a spider diagram (OECD, 2008).

The ninth step of constructing a composite indicator entails testing the explanatory power of composite indicators by linking them to other variables and measures (OECD, 2008). For example, simple cross-plots may link the Technology Achievement Index (TAI) to the GDP per capita to test the explanatory power of the TAI (OECD, 2008). Theoretically, countries with a high GDP per capita are expected to have high TAI scores due to the capacity to invest in technology (OECD, 2008). Likewise, high technology achievement in these countries may lead to higher GDP per capita.

The final step of constructing a composite indicator involves the visualisation of the results using tables, line or bar charts, four-quadrant model and dashboard (Nardo et al., 2005). Visual models indicate what areas require interventions.

2.2.2 The importance of weights in composite indicators

As mentioned in the previous section, the sixth step of constructing a composite indicator involves the weighting and aggregation of indicators. According to Nardo et al. (2005), weights may be allocated to the indicators to reflect their economic significance such as coverage, collection costs and reliability. An analyst may assign higher weights to readily available and easy to measure base indicators while penalising the indicators that are problematic to locate and measure. The data distribution can also significantly influence the ability of the weights to reflect the perceived level of importance of the indicators (Becker et al., 2017; Paruolo et al., 2013). For example, if the data distribution changes, the weights will reflect a new level of importance of indicators (Decancq and Lugo, 2013). Finally, weights significantly influence the results of composite indicators in a benchmarking context (Nardo et al., 2005). This influence is real, especially on an occasion where a higher weight is allocated to indicators with low or high scores. Therefore, the impact of weighting on the importance level of indicators remains a critical research concern (Lindén, 2018).

Linear aggregation (the weighted arithmetic average), is one of the most widely used aggregation methods for composite indicators (Freudenberg, 2003; Langhans et al., 2014). This approach implies that the score of the composite indicator is calculated by the weighted average of the scores for individual indicators (EIU, 2019; OECD, 2008). Paruolo et al. (2013), noted a common assumption in the weighted arithmetic average process where weights are coefficients allocated to reflect the relative importance of each indicator. Albeit intuitively appealing, this assumption is not defensible theoretically as weights in this aggregation setting represent the marginal rate of substitutability between individual indicators (Lindén, 2018). The substitutability of indicators implies that weights show the possibility of compensating for a loss in one indicator with an improvement in another indicator (Decancq and Lugo, 2013; Munda and Nardo, 2005). The weights are perceived to express trade-off ratios between pairs of indicators, inferring a compensatory scheme as opposed to coefficients of relative importance (Freudenberg, 2003; Nardo et al., 2005). Therefore, high scores in some indicators may offset low scores in other indicators to attain a higher composite index score (Greco et al., 2019).

2.3 The classification of weighting in composite indicators

The weighting of indicators precedes the aggregation process in the creation of a composite index. There are various weighting methods for allocating weights in composite indicators. These methods are broadly categorised as subjective, objective and hybrid weighting methods (Alemi-Ardakani et al., 2016; Zardari et al., 2015).

2.3.1 Subjective weighting methods of composite indicators

Subjective weighting methods rely on the explicit knowledge, opinions and preferences of experts (Alemi-Ardakani et al., 2016; OECD, 2008). The experts' experience may be in terms of the relative importance and urgency of indicators as well as the substitution rates between pairs of indicators (Gan et al., 2017). These experts are also assumed to understand the weaknesses, strengths and subtleties of the data (Freudenberg, 2003; Nardo et al., 2005).

According to Freudenberg (2003), subjective weighting approach proceeds in a dual-stage process assuming the possibility of organising related indicators into specific components. First, a subjective weighting method allocates weights to the indicators within each component. In this stage, each component is defined as a weighted average of the values for the individual indicators. The second stage of the subjective weighting scheme involves the allocation of weights. The value of the overall index is computed from a weighted average of the scores for the components. This dual-stage process helps avoid underestimating and overestimating those components for which fewer or more indicators are available (Freudenberg, 2003).

Apart from the challenge of selecting appropriate experts, subjective weighting techniques suffer two main drawbacks. Firstly, subjective weighting methods do not depend on indicators data as weights may be allocated before the collection of all data (Chen et al., 2019). The indicator weights assigned by the panel of experts may stay the same, albeit the yearly changes in data (Decancq and Lugo, 2013). By contrast, the weights derived using a statistical technique mostly change with changes in data to give a true reflection of trade-offs between indicators (Decancq and Lugo, 2013). Secondly, a subjective weighting process does not apply statistical techniques to justify the objectivity and precision of the weight. These weights may subtly reflect the relative importance of indicators where weights represented the personal interests of the experts (Maricic et al., 2016). Examples of subjective weighting methods are the expert/public opinion-based weighting (public opinion, analytic hierarchy process, budget allocation process and conjoint analysis) and equal weighting (Decancq and Lugo, 2013; OECD, 2008).

2.3.2 Objective weighting methods of composite indicators

Objective weighting methods are not reliant on the preferences and knowledge of experts or decision-makers but assign weights based on statistical models and data (Izraelov and Silber, 2019). According to Kao (2010), objective weights are simply called *a posteriori* weights as they are more convincing than subjective weights.

It is important to note that the data set's distribution can influence the ability of the weights to corroborate with the perceived level of importance of the indicators (Becker et al., 2017; Paruolo et al., 2013). For example, if the data distribution changes, the objective weights may also change to give a new reflection of the perceived level of importance of indicators (Decancq and Lugo, 2013). The main challenge of the objective weighting techniques is that they require extensive experience and expertise of the analyst (Alemi-Ardakani et al., 2016). Also, an analyst may manipulate data due to the presence of outliers or missing data, thereby affecting the overall results (OECD, 2008). Examples of objective weighting methods are principal component analysis, factor analysis, the benefit of the doubt approaches, regression analysis and unobserved component analysis (Decancq and Lugo, 2013; OECD, 2008).

2.3.3 Hybrid weighting methods of composite indicators

Hybrid weighting methods attempt to balance the subjective and objective weighting methods (Decancq and Lugo, 2013). Examples of such weighting methods include the stated preference weighting and hedonic approaches.

Stated preference weighting assigns weights to indicators of a composite index based on the opinions of individuals who act as representatives in the society (Horsky et al., 2004). This approach uses survey-based approaches to derive indicator weights. For example, an item (indicator) supported by at least half of the society forms a socially perceived necessity (Decancq and Lugo, 2013). Consequently, the proportion of the population that supported the indicator as a necessity is used to derive its weight (Decancq and Lugo, 2013).

A composite indicator, for example, the human well-being index (HWI), may use hedonic weighting to retrieve information about individuals' self-reported life satisfaction (Schokkaert, 2007). In this case, a regression technique is used to derive weights by linearly regressing life satisfaction on the indicators within various components of the HWI (Decancq and Lugo, 2013). The estimated coefficient of each indicator in the regression function forms the indicator weight. Table 2.4 presents the benefits and drawbacks of various weighting methods.

Table 2.4: Benefits and drawbacks of different weighting methods of composite indicators

Method	Type	Examples	Benefits	Drawbacks
Equal weighting (EW).	Subjective weighting method (equal weighting).	Genuine Savings Index (WorldBank, 1999). Human Development Index (UNDP, 1990).	Simple, straightforward and replicable.	It suffers the problem of double weighting. Weights do not provide insights into the trade-offs between the indicators.
Budget allocation process (BAP).	Subjective weighting method (expert/public opinion-based).	Overall Health System Attainment (Murray et al., 2000). Employment Outlook (OECD, 1999). Eco-indicator 99 (Goedkoop and Spriensma, 2001).	Reliance on expert opinion prevents technical manipulation of weights. High explicitness and transparency.	Weighting may measure the urgency for intervention as opposed to importance. Assigned weights could be region-specific hence not transferable between regions. Application to indicators exceeding ten may create inconsistencies due to cognitive stress felt by the experts.
Analytic hierarchy process (AHP).	Subjective weighting method (expert/public opinion-based).	Index of Environmental Friendliness (Puolamaa et al., 1996). Composite sustainability performance Index (Rajesh Kumar Singh et al., 2007).	Applicable to both quantitative and qualitative data. Reliance on expert opinion prevents technical manipulation of weights. Simple and flexible. High explicitness and transparency. It captures inconsistencies in the replies of respondents.	High computational costs may be required for a high number of pairwise comparisons. Application on numerous indicators per cluster may create inconsistencies due to cognitive stress felt by the experts. Results depend on the experiment's setting and the chosen set of evaluators.
Public opinion (PO).	Subjective weighting method (expert/public opinion-based).	Concern about environmental problems Index (Parker, 1991).	Participatory and transparent. Expression of preference by stakeholders ensures consensus necessary for policy action.	Measures concern as opposed to importance. Assigned weights could be region-specific hence not transferable between regions.

Method	Type	Examples	Benefits	Drawbacks
Conjoint analysis (CA).	Subjective weighting method (expert/public opinion-based).	Indicator of quality of life in the city of Istanbul (Ülengin et al., 2001).	Applicable to both quantitative and qualitative data. Weights do not provide insights into the trade-offs between the indicators. Results are useful in making sustainability plans. Weighting considers respondents' values and the socio-political phenomenon.	Weighting involves a complex estimation process. Weighting process requires a large sample of the respondents. Expression of numerous preferences may be required of each of the many respondents involved.
Principal component analysis/Factor analysis (PCA/FA).	Objective weighting method (Statistic/data-driven).	Environmental Sustainability Index (Sands and Podmore, 2000). Indicators of product market regulation (Nicoletti et al., 2000). The 2005 European eBusiness Readiness Index (Pennoni et al., 2006).	It solves the problem of double weighting. No manipulation of the weights as realised with the restrictions of expert/opinion-based approaches.	Only applicable to indicators that are correlated. Assigned weights do change with changes in the indicator's data. In the presence of outliers, data may suffer spurious variability. Statistical identification and interpretation may be difficult in the event of a small sample and data shortage. Sensitive to the applied methods for factor extraction and rotation.
Regression analysis (RA).	Objective weighting method (Statistic/data-driven).	National Innovation Capacity Index (Porter and Stern, 2001).	It can be applied to indicators that are not correlated. No manipulation of the weights as realised with the restrictions of expert/opinion-based approaches.	Poor results are obtainable in the presence of multi-collinearity (highly correlated indicators). A large amount of data is required to obtain statistical estimates.

Method	Type	Examples	Benefits	Drawbacks
Data envelopment analysis/Benefit of the doubt approach (DEA/BOD).	Objective weighting method (Statistic/data-driven).		Weights are selected to maximise the index for each unit. The endogenously determined weights based on observed performances ensure the sensibility of indicator to national policy priorities. The assigned weights reflect policy priorities making it easy to establish trade-offs.	Assigned weights are country-specific hence not transferable for cross-country comparisons. Manipulation of weights by endogenous weighting instead of experts' opinions lose the method's transparency. Any change in the benchmark performance also changes the assigned weights.
Unobserved component models (UCM).	Objective weighting method (Statistic/data-driven).	The aggregate governance indicators (Kaufmann et al., 1999).	No manipulation of the weights as realised with the restrictions of expert/opinion-based approaches.	Results obtained from inadequate data are less reliable and robust. Highly correlated indicators may lead to the problems of identification. Sensitive to the presence of outliers.

Source: Author's compilation based on Hermans et al. (2008), Nardo et al. (2005) and OECD (2008).

2.4 Review of the empirical studies on composite indicators

This section aims to identify the research gap as a rationale for further exploration. The following paragraphs point to a review of the empirical studies exploring how weighting methods affect the results of composite indicators.

Nardo et al. (2005), conducted a study on the weighting of indicators in the Technology Achievement Index (TAI) using principal component analysis (PCA) and factor analysis (FA). The developers of the TAI had assigned equal weights to indicators (Nardo et al., 2005). The eight indicators in the TAI included patents, technology exports, royalties, telephones, internet, electricity, mean years of schooling and university education. These researchers observed that PCA and FA weights were different from the equal weights for the TAI indicators. For example, both the PCA and FA assigned a weight of 17% to patents compared to the TAI's weight of 13%. The PCA and FA also assigned a weight of six per cent to technology exports compared to the TAI's weight of 13%.

Nardo et al. (2005), noted that twelve out of twenty-three countries maintained their rank, while eleven countries slightly shifted their rank upon application of FA. For example, Canada dropped from position nine to eleven, whereas Norway improved from position twelve to nine. Nardo et al. (2005), attributed these changes to the allocation of higher weights to indicators on which some countries obtained low or high scores. Also, Nardo et al. (2005), asserted that no consensus on the best weighting method is likely to exist as long as a composite index uses reliable data. However, these researchers used descriptive statistics for the analysis and overlooked the application of statistical tests to compare their results. Nardo et al. (2005), did not compare the scores for the twenty-three countries.

Nguefack-Tsague et al. (2011), provided statistical support for the use of equal weighting of the three indices in the Human Development Index (HDI). Nguefack-Tsague et al. (2011), applied the correlation matrix version of PCA to obtain new weights for the 1975 to 2005 HDI of 177 countries. They then compared the PCA weights with the original weights for the HDI. Nguefack-Tsague et al. (2011), observed that the average normalised PCA weights for the Life Expectancy Index (LEI), Education Index (EI) and Gross Domestic Product Index (GDPI) components were, respectively, 0.337, 0.333 and 0.333, and very close to the 0.333 of the HDI. Kendall's tau rank correlation coefficient ranged from 0.97 to 1.00, indicating that the country ranks obtained with the PCA weights and equal (HDI) weights were highly correlated (Nguefack-Tsague et al., 2011). Nevertheless, these researchers recommended the use of equal weighting to ensure consistency as the weights obtained with the PCA model may not be constant every year. As with Nardo et al. (2005), Nguefack-Tsague et al. (2011), neither computed statistical tests for the difference between the two sets of weights nor compared the PCA scores to the HDI scores.

Maricic et al. (2016), evaluated the GFSI weights and ranks of countries and concluded that the GFSI was based on reliable data sources but biased weights. These researchers proposed the use of Composite I-Distance Indicator (CIDI) model to obtain unbiased weights and a precise rank of countries. Maricic et al. (2016), applied the proposed CIDI, and the 2015 GFSI data set and made two observations. Firstly, the weights assigned to the affordability, availability and quality and safety components of the GFSI changed from 40%, 44% and 16% to 33%, 31% and 36% respectively (EIU, 2019; Maricic et al., 2016). Secondly, the CIDI model changed the country ranks slightly, where 15% of the countries maintained their rank.

However, Maricic et al. (2016), did not compare the CIDI scores with the GFSI scores. To add, these researchers did not conduct statistical tests for the significance of the difference between the CIDI and GFSI weights and ranks. Maricic et al. (2016), overlooked the need for these comparisons as their (Maricic et al., 2016) focus was on the descriptive statistics of the weights obtained using the CIDI and GFSI models.

The ratio of weights assigned to the indicators in a composite index may inform the statistical importance of indicators (Paruolo et al., 2013). Thomas et al. (2017), assessed the statistical importance of indicators in the GFSI using the EIU's 2016 data set. Thomas et al. (2017), applied the PCA to determine the correlation structure of the index and noted that the GFSI had good statistical properties and extensive data coverage. Thomas et al. (2017), then used a squared Pearson's correlation coefficient to compute the statistical importance of the components of the GFSI. The squared Pearson's correlation coefficient measures the variance in a component score that is explained by each indicator within the component (Thomas et al., 2017).

Thomas et al. (2017), observed that the statistical importance of the affordability, availability and quality and safety components of the GFSI were roughly the same, that is, 95%, 91% and 91% respectively. By contrast, the EIU experts had assigned different weights to the GFSI's affordability, availability and quality and safety components as 40%, 44% and 16% respectively (EIU, 2019). The EIU experts had allocated more than twice the weight to the affordability and availability components of the GFSI than to the quality and safety component.

Thomas et al. (2017), concluded that the GFSI weights were not a reflection of the statistical importance of its indicators. However, Thomas et al. (2017), did not compute the scores and ranks of countries.

Chen et al. (2019), attempted to overcome Thomas et al.'s (2017) research shortcomings. Chen et al. (2019), used Hierarchical Data Envelopment analysis (H-DEA) to allocate weights to indicators in the 2014 GFSI. Chen et al. (2019), asserted that weights might show the importance level placed on the components of the GFSI based on the income or region of countries. They concluded that the GFSI and H-DEA weighting schemes gave similar ranks but slightly different weights and scores. For this reason, they suggested that the designers of the GFSI should consider using the H-DEA as it does not rely on experts' opinions.

According to Chen et al. (2019), the proposed H-DEA allowed an analyst to compare the weights allocated for different groups of countries depending on their income levels or region. For example, an analyst may compare Europe's H-DEA weights (importance levels) for the components of the GFSI to North America's H-DEA weights for the same components. Alternatively, an analyst may compare high-income countries' H-DEA weights (importance levels) for the components of the GFSI to low-income countries' H-DEA weights for the same components. As with the H-DEA weights, the average H-DEA scores for the GFSI were based on the income level and origin of countries (Chen et al., 2019).

Chen et al. (2019), observed that high-income countries placed importance on the GFSI's affordability, availability and quality and safety components as 58%, 22% and 20% respectively. By taking low-income countries into account, the H-DEA weights assigned to the mentioned components of the GFSI were 21%, 60% and 19% respectively. Chen et al. (2019), noted that Europe placed importance on the affordability, availability and quality and safety components of the GFSI in the order of 57%, 22% and 21 %. The H-DEA weights assigned to these components of the GFSI based on Sub-Saharan Africa were 21%, 39% and 19% respectively. These H-DEA weights were different from the universal GFSI weights allocated to the affordability, availability and quality and safety components of the GFSI as 40%, 44% and 16% respectively (EIU, 2019).

Chen et al. (2019), also observed that North America and Sub-Saharan Africa obtained the highest and lowest H-DEA mean scores, respectively. Taking countries by income levels, high-income countries had the highest H-DEA mean score, while low-income countries achieved the lowest H-DEA mean score. Chen et al. (2019), attributed the high mean score for high-income countries to the extensive H-DEA weight of 58% for the affordability component of the GFSI. Finally, Chen et al. (2019), observed that the H-DEA model changed 90% of the country ranks, although most of the changes were minor. Also, the top and bottom twenty-five countries (except three countries) retained their top and bottom positions due to the differences in income level.

Furthermore, Chen et al. (2019), observed a Spearman's rank correlation coefficient of 0.983, interpreted as a high correlation (similarity) between the GFSI ranks and H-DEA ranks. The main strength of Chen et al.'s (2019) study was that the H-DEA weights were based on countries' performance to ensure the sensitivity of indicators to trade-offs and national policy priorities (OECD, 2008). However, one of the drawbacks of the H-DEA was that the computed weights were country-specific, making cross country comparisons difficult (OECD, 2008). The H-DEA weight for a particular country may not be the same across all the 113 countries (Chen et al., 2019). As with some of the earlier mentioned studies, the research by Chen et al. (2019), did not conduct statistical tests for the significance of the difference between the H-DEA and GFSI weights and scores. Table 2.5 summarises the reviewed empirical studies.

Unlike Chen et al. (2019), who studied the applicability of a single weighting method on the GFSI, the H-DEA, Izraelov and Silber (2019), applied Data Envelopment Analysis (DEA), Principal Component Analysis (PCA) and Lower Convex Hull (LCH) weighting methods to assess the 2015 GFSI. Izraelov and Silber (2019), concluded that the GFSI weighting process was not significantly statistically biased. While Chen et al. (2019), recommended the adoption of the H-DEA weights, Izraelov and Silber (2019), suggested continued use of the GFSI weights.

Izraelov and Silber (2019), observed that whichever weighting method was used, 11 out of 113 (9.5%) countries maintained their rank and most of the changes in rank were minor. The top ten and bottom ten countries retained their top and bottom positions due to the differences in economic development. Also, the Spearman's rank correlation coefficients ranged from 0.932 to 0.980 for all the methods, confirming that the country ranks were strongly correlated (Izraelov and Silber, 2019). These findings complemented the observation that was made by Chen et al. (2019). The main strength of Izraelov and Silber (2019), was that the GFSI weights were validated against a wide range of alternative weighting models. However, the main drawback was that the computed indicator weights and country scores were not compared with the GFSI weights and scores assigned by the EIU experts.

Table 2.5: Summary of the review of the empirical studies on composite indicators

Author	Population	Model type	Time horizon/Index	Impact on the composite index
Nardo et al. (2005).	23 countries.	Principal Component Analysis (PCA). Factor analysis (FA).	2000 Technology Achievement Index (TAI). Index based on Equal weighting (EW) method.	The PCA weights and FA weights were different from the TAI weights. Twelve countries maintained their rank, while eleven countries slightly shifted their rank upon application of the FA. No statistical tests for the difference between indicators weights, scores and rank of countries were conducted.
Nguefack-Tsague et al. (2011).	177 countries.	Principal Component Analysis (PCA).	1975-2005 Human Development Index (HDI) Index based on Equal weighting (EW) method.	The PCA weights and HDI weights were similar but not identical. A high-rank correlation coefficient ranging from 0.97 to 1.00 was observed. No statistical test for the difference between the HDI and PCA weights was conducted. The HDI scores and the PCA scores of countries were not compared.
Maricic et al. (2016).	20 countries.	Composite I-Distance Indicator (CIDI).	2015 GFSI Index based on EIU panel of experts (default) weighting method.	The CIDI weights were different from the GFSI weights. 15% of countries maintained their GFSI rank with slight changes in the rank of most countries. No statistical tests for the difference between the GFSI and CIDI weights and rank of countries were conducted. The CIDI scores and GFSI scores of countries were not compared.
Thomas et al. (2017).	113 countries.	Squared Pearson's correlation coefficient.	2016 GFSI Index based on EIU panel of experts (default) weighting method.	Weights obtained by the squared Pearson's correlation coefficient were different from GFSI weights. New scores and ranks were neither generated nor compared.
Chen et al. (2019).	110 countries.	Hierarchical Data Envelopment analysis (H-DEA).	2014 GFSI	H-DEA weights were country and region-specific hence different from GFSI weights. A high-rank correlation coefficient of 0.983 was observed.

Author	Population	Model type	Time horizon/Index	Impact on the composite index
			Index based on EIU panel of experts (default) weighting method.	No statistical tests for the difference between the GFSI and H-DEA weights and scores of countries were conducted.
Izraelov and Silber (2019).	105 countries.	Data Envelopment Analysis (DEA). Principal Component Analysis (PCA). Lower Convex Hull (LCH).	2015 GFSI Index based on EIU panel of experts (default) weighting method.	9.5% of countries maintained their GFSI rank with slight changes in the rank of most countries. A high-rank correlation coefficient ranging from 0.932 to 0.980 was observed. Indicators weights and scores of countries were not compared.

Source: Author's compilation.

2.5 Research gap

Some of the reviewed empirical studies explored the effect of an objective weighting of the affordability, availability and quality and safety components of the GFSI on country scores and ranks. In 2017, the EIU panel of experts added the NRR component of the GFSI as an adjustment factor to capture changes to the overall food security in the context of natural resource risks and how countries adapt to these risks (EIU, 2019). Therefore, the NRR component of the GFSI was still new to many researchers.

Most of the reviewed empirical studies did not conduct statistical tests to determine the significance of the difference between the results obtained with the original weighting model and the proposed weighting models. The policymakers who design food security and natural resource policies may require objective GFSI scores and rank of countries to increase their confidence in the GFSI results. This study set out to fill the research gap by exploring how an objective weighting of the NRR component of the GFSI affected country scores and ranks.

2.6 Conceptual framework

As presented in Figure 2.1, the illustrates the hypothesised linkages among variables that were considered important in this study. These linkages helped in understanding how a weighting method influenced the NRR weights, scores and rank of countries.

This study conceptualised that the creators of the NRR component of the GFSI had two choices between subjective and objective weighting of indicators. The first choice depended on the knowledge of experts regarding the importance of each indicator (Alemi-Ardakani et al., 2016). The second choice relied on the availability of data and statistical techniques (Alemi-Ardakani et al., 2016). However, these weighting methods of the NRR component of the GFSI influence the quality of indicators weights such that a subjective weighting scheme may produce biased (*a priori*) weights (Kao, 2010). To the contrary, an objective weighting of indicators may result in unbiased (*a posteriori*) weights (Kao, 2010). To add, *a priori* (subjective) and *a posteriori* (objective) weights, respectively, may lead to biased and unbiased NRR scores as well as imprecise and precise NRR ranks (Maricic et al., 2016). While the subjective weights of indicators may negate trust in the country scores and ranks, objective weights may boost the confidence of stakeholders in the results.

This study further conceptualised that conceptual framework the subjectively weighted NRR scores may produce biased and imprecise adjusted overall GFSI scores and ranks. By contrast, objectively weighted NRR scores would produce unbiased and precise adjusted overall GFSI scores and rank of countries. The next chapter discusses the methodology adopted in the construction of the GFSI.

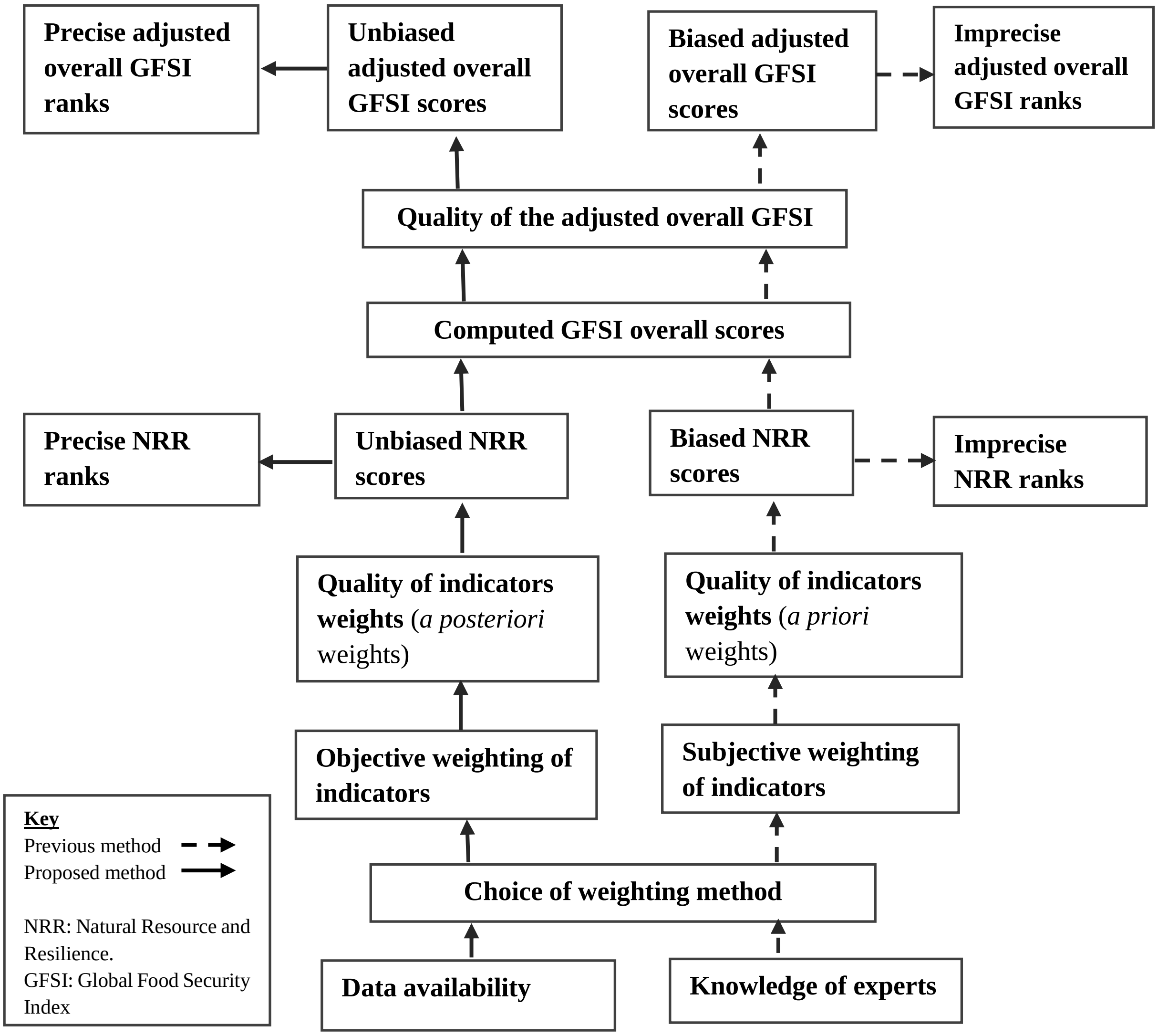

Figure 2.1: Conceptual framework

Source: Author's conceptualisation.

Chapter 3: The methodology of the Global Food Security Index

3.1 Introduction

The use of composite indicators has continued to rise, especially in the measurement of food security at the national level (Santeramo, 2015b). The concept of food security is increasingly used in the design, implementation and evaluation of humanitarian and development programs (Hendriks, 2015). For this reason, the Economist Intelligence Unit (EIU) developed the GFSI to measure the comparative level of food insecurity in countries (EIU, 2019).

The GFSI is a composite indicator that measures food security environment at the national level (EIU, 2018). It is a dynamic qualitative and quantitative benchmarking model sponsored by Corteva Agriscience and has produced annual reports since 2012 (EIU, 2019). These reports have included analysis for 113 developing and developed countries and portray economic significance and regional diversity (EIU, 2019). The initial components of the GFSI included the affordability, availability and quality and safety components. Each of these three components comprised several indicators that measured a specific food security dimension (EIU, 2018). In 2017, the GFSI added a fourth component for natural resources and resilience (NRR) as a risk factor to the overall food security (EIU, 2019). This chapter reviews the methodological framework adopted in the construction of the GFSI.

3.2 The methodological framework of the GFSI

The GFSI was founded on the idea that food security could be analysed within three broad components: affordability, availability and quality and safety (EIU, 2019). The theoretical framework of the GFSI was based on the internationally accepted definition of food security and linked its components and their indicators. The theoretical framework of the GFSI helped in the selection and combination of indicators in the GFSI.

3.3 The selection of indicators and data sources for the GFSI

The selection of indicators for the various GFSI components was guided by the theoretical framework mentioned in section 3.2 above. The indicators of the GFSI required quantitative data, qualitative data and proxies when the required data were unavailable. The EIU draws data for the quantitative indicators from various national and international databases (EIU, 2019). For the quantitative indicators, the EIU uses data from multiple surveys and data sources and makes data estimations based on information from government websites and development banks (EIU, 2019). The indicators for the affordability; availability; quality and safety, and natural resources and resilience components of the GFSI and their data sources are presented in Table 3.1. The following sub-sections discuss the four components of the GFSI.

Table 3.1: Indicators and data sources of the various components of the 2019 GFSI

Component/indicator of the GFSI	Primary source of data	Year
Affordability		
Change in average food costs	Food and Agricultural Organisation (FAO)	2014-2018
Proportion of population under global poverty line	World Bank, World Development Indicators	2008-2017
Gross domestic product per capita	Economist Intelligence Unit (EIU)	2018
Agricultural import tariffs	World Trade Organisation (WTO)	2012-2018
Presence and quality of food safety net programmes	EIU scoring	2019
Presence of food safety-net programmes	EIU qualitative scoring	2019
Funding for food safety net programmes	EIU qualitative scoring	2019
Coverage of food safety net programmes	EIU qualitative scoring	2019
Operation of food safety-net program	EIU qualitative scoring	2019
Access to financing for farmers	EIU qualitative scoring	2019
Availability		
Sufficiency of supply	EIU scoring	-
Average food supply	FAO	2016-2018
Change in dependency on chronic food aid	OECD	2013-2017
Public expenditure on agricultural R&D	United Nations	2010-2017
Agricultural infrastructure	EIU scoring	2004-2015
Existence of adequate crop storage facilities	EIU qualitative scoring	2019
Road infrastructure	EIU Risk Briefing	2019
Port infrastructure	EIU Risk Briefing	2019
Air transport infrastructure	EIU Risk Briefing	2019
Rail infrastructure	EIU Risk Briefing	2019
Irrigation infrastructure	FAO	2016
Volatility of agricultural production	US Department of Agriculture (USDA)	2012-2016
Political stability risk	EIU Risk Briefing	2019
Corruption	EIU Risk Briefing	2019
Urban absorption capacity	World Bank, World Development Indicators, EIU	2015-2019
Food loss	FAO	2013
Quality and safety		
Dietary diversity	FAO	2011-2013
Nutritional standards	EIU scoring	-
National dietary guidelines	EIU qualitative scoring based on WHO, FAO and national health ministry documents	2019
National nutrition plan or strategy	EIU qualitative scoring based on WHO, FAO and national health ministry documents	2019
Nutrition monitoring and surveillance	EIU qualitative scoring based on WHO, FAO and national health ministry documents	2019

Component/indicator of the GFSI	Primary source of data	Year
Micronutrient availability	EIU scoring	-
Dietary availability of vitamin A	Global Nutrient Database	2013
Dietary availability of iron	Global Nutrient Database	2013
Dietary availability of zinc	Global Nutrient Database	2013
Protein quality	EIU calculation based on data from WHO, FAO and USDA Nutrient Database	2011-2013
Food safety	EIU scoring	-
Agency to ensure the safety and health of food	EIU qualitative scoring	2019
Percentage of population with access to potable water	World Bank	2017
Ability to store food safely	United Nations	2017
Natural resources and resilience		
Exposure to climate change risks	EIU scoring	-
Temperature rise	Notre Dame Global Adaptation Initiative (ND-GAIN)	2017
Drought	World Resources Institute (WRI)	2014
Flooding	ND-GAIN	2017
Storm severity	Global Assessment Report on Disaster Risk Reduction	2015
Sea level rise	ND-GAIN	2015
Commitment to managing exposure	Consultative Group on International Agricultural Research (CGIAR)	2016
Water	EIU scoring	-
Agricultural water risk - quantity	WRI	2014
Agricultural water risk – quality	World Resources Institute (WRI)	2014
Land	EIU scoring	-
Land degradation	United Nations	2015
Grassland	FAO	2016
Forest change	World Bank	2001-2016
Oceans	EIU scoring	-
Ocean eutrophication	United Nations	2000-2010
Marine biodiversity	Yale Environmental Performance Index	2018
Marine protected areas	United Nations	2014
Sensitivity to natural resource risks	EIU scoring	-
Food import dependency	FAO	2017
Dependence on natural capital	World Bank	2017
Disaster risk management	United Nations	2017-2018
Adaptive capacity	EIU scoring	-
Early warning measures/ climate-smart agriculture	Consultative Group on International Agricultural Research Program on Climate Change, Agriculture and Food Security (CGIAR-CCAFS)	2017
National agricultural risk management system	World Bank Climate-smart Agriculture Indicators	2017
Demographic stresses	EIU scoring	-
Population growth (2016-2021)	United Nations	2019
Urbanisation (2016-2021)	United Nations	2019

Source: EIU (2019).

3.3.1 The affordability component of the GFSI

The affordability component of the GFSI assesses the capacity of people in a country to pay for food, their vulnerability to food-related shocks and the presence of policies and programmes to support consumers in the face of shocks (EIU, 2019). For example, a drastic rise in the cost of the average basket of food items may indicate a significant decline in food affordability (EIU, 2018). Average income levels of people determine the affordability of food as poverty has the potential to lower people's ability to purchase food or food production inputs (Gustafson, 2013). Likewise, unfavourable agricultural import tariffs raise the cost of food imports and food consumption costs. To the contrary, national government-led food safety net programmes have been considered more sustainable and targeted than private sector-led programmes in assisting the food insecure (EIU, 2019). Food safety net programmes have helped improve the affordability of food among the food insecure. Also, access to financing seems to improve farmers' productivity and ability to provide for their families (Haug and Hella, 2013). The affordability component of the GFSI includes ten indicators.

3.3.2 The availability component of the GFSI

The availability component of the GFSI assesses the factors contributing to the food supply, the ease of access to food, the risk of supply disruption, the national capacity to distribute food and the research efforts to raise agricultural production (EIU, 2019). For example, the progress towards food security must include a sufficient supply of available food (Pérez-Escamilla, 2017). Investment in agricultural research and development and crop storage facilities ensure improved technology and sufficient food supply (EIU, 2019). Likewise, investment in road, rail, air, port and irrigation infrastructure supports food transport and consistent food production (EIU, 2018).

By contrast, higher levels of food losses decrease the amount of food available for human consumption (Ishangulyyev et al., 2019). Political instability disrupts access to food through reduced food aid commitments or transport barriers (EIU, 2018). Inefficiencies in the distribution of food and the use of natural resources due to corruption adversely impact food availability (EIU, 2019). The availability component of the GFSI includes sixteen indicators.

3.3.3 The quality and safety component of the GFSI

The quality and safety component of the GFSI explores the types and nutritional quality of the average diets, including food safety in each country (EIU, 2019). For example, the consumption of a higher proportion of non-starchy foods indicates a greater diversity of dietary food groups (Pérez-Escamilla, 2017). The presence of sanitary regulations such as clean water supply and appropriate food storage helps ensure safe food supply. By contrast, deficiencies in vitamin A, iron and zinc cause blindness, anaemia and a weakened immune system, respectively (Pérez-Escamilla, 2017). The quality and safety component of the GFSI includes fourteen indicators.

3.3.4 The natural resources and resilience component of the GFSI

In 2017, the GFSI added a fourth component on natural resources and resilience (NRR) to the existing affordability, availability, and quality and safety components (EIU, 2017). The NRR component was added as a risk or adjustment factor to capture changes to the overall food security in the context of climate-related and natural resource risks and how countries adapt to these risks (EIU, 2019). For example, in the 2019 GFSI report, Singapore was ranked position one in the overall GFSI but dropped eleven places to the twelfth position in the NRR adjustment of the overall GFSI (EIU, 2019).

The NRR component of the GFSI is a dynamic qualitative and quantitative national-level benchmarking model (EIU, 2019). The NRR component of the GFSI includes 21 indicators within seven components (as presented in Table 3.1). The NRR indicators measure different information depending on the NRR component within which they are included. The various information captured by these indicators is converged through weighting and aggregation schemes to reflect the status of each NRR component for any country. The weighting and aggregation process are discussed in the later steps of the methodological framework adopted in the construction of the GFSI. The seven NRR components include exposure to climate change risks, water, land, oceans, sensitivity to natural resource risks, adaptive capacity and demographic stresses (EIU, 2019).

Natural resource risks are generally climate-related, cross-cutting and interconnected, posing a significant impact on the natural resources that drive food systems (EIU, 2018). These natural resource risks affect food systems in six ways. Firstly, climate change risks associated with exposure to temperature rise, drought, flood, storm severity and sea-level rise decrease soil fertility, crop growth and yield (EIU, 2018; Sova et al., 2019). Secondly, agricultural water quantity and quality risks such as the depletion of underground water reduce food production (EIU, 2018). Thirdly, land risks such as land degradation, grassland and forest change pose a threat to agricultural production (EIU, 2018). Fourthly, ocean risks associated with eutrophication and hypoxia, marine protected areas and marine biodiversity threaten the marine ecosystem (Branch et al., 2013; EIU, 2018; FAO, 2018). Fifthly, the level of food import dependency and disaster risk management determine countries' sensitivity or susceptibility to climate and natural resource risks (West et al., 2009). Finally, while 80% of the world's hungry people live in natural disasters prone places (WFP, 2017), rapid population growth and urbanisation are likely to raise the demand for food and strain the food systems (FAO, 2017).

As mentioned above, natural resource risks associated with climate change remain a pressing concern for food security and the need for resilience is considered as a matter of urgency (Singh and Sharma, 2018). The EIU expert panel conducts the NRR adjustment of the overall GFSI scores of countries by considering their resilience mechanisms to natural resource risks. The inclusion of the NRR indicators by the EIU expert panel implies that countries should undertake six measures to build resilience to climate-related risks and improve food systems. Firstly, countries should define and execute mitigation and adaptation plans for natural resources and agriculture management in line with the Paris Agreement (UN, 2020). Governments can also conduct climate-focused crop research to identify future climate zones and adaptable crops, thus enabling farmers to prepare with more resilient seeds and crops. Secondly, countries should adopt less water-intensive but high yielding crops, agricultural practices and techniques (ICRISAT, 2017). Thirdly, countries may adopt improved crop diversification, grazing land and forest management, and rehabilitation of degraded lands (Altieri et al., 2015).

Fourthly, while improved enforcement of marine protected areas boosts fish and shellfish populations, countries should also expand the coastal mangroves to curb ocean acidification, sea-level rise and severe storms (Roberts et al., 2017). Voluntary and mandatory efforts to limit fertilizers, manure and sewerage discharge into oceans can protect marine systems (Kroon et al., 2014). Fifthly, countries should establish and co-ordinate effective disaster risk management to limit the impact of natural disasters on food systems (Weichselgartner and Pigeon, 2015). Finally, governments should be committed to establishing and monitoring early-warning measures to advise farmers about an impending threat and how to limit their possible impacts (EIU, 2018). Also, investing in climate-smart agriculture (CSA) practices may improve resilience to climate and natural resource risks (Sova et al., 2019).

3.4 The imputation of missing data for the GFSI

The imputation of missing data is one of the methodological steps in the construction of composite indicators (OECD, 2008). Apart from drawing data for the quantitative indicators from the national and international databases (EIU, 2017), the EIU also estimate figures for missing data (EIU, 2019). The EIU expert panel derives qualitative data by making estimations based on information from government websites and development banks (EIU, 2019). Table 3.1 shows the ten indicators for which EIU made estimations in the 2019 GFSI report.

3.5 The normalisation and rescaling of data for the GFSI

The EIU normalises the GFSI data using a minimum-maximum normalisation method (EIU, 2019). The indicators such as road infrastructure and national agricultural risk management system for which a high value implies a favourable situation for food security are normalised as specified in Equation 3.1:

$$z_i = (x_i - \mathrm{Min}(x_i))/(\mathrm{Max}(x_i) - \mathrm{Min}(x_i)) \qquad \text{Equation 3.1}$$

where z_i is the normalised value of the i^{th} indicator, x_i is the actual value of the i^{th} indicator, $Min(x_i)$ and $Max(x_i)$ are, respectively, the lowest and highest values of the i^{th} indicator in the 113 countries, for all $i = 1, 2, \ldots, n$. This procedure normalises the values of all indicators to an identical range of zero to one. The normalised values are then rescaled from a range of zero to one to scores ranging from zero to 100. Consequently, a country with the highest or lowest value of the indicator scores 100 or zero (EIU, 2019).

The indicators such as drought and flooding for which a high value implies an unfavourable situation for food security are normalised as specified in Equation 3.2:

$$z_i = (x_i - \mathrm{Max}(x_i))/(\mathrm{Max}(x_i) - \mathrm{Min}(x_i)) \qquad \text{Equation 3.2}$$

where the interpretation of the function is as illustrated in the preceding paragraph (EIU, 2019).

3.6 The weighting and aggregation of indicators and components of the GFSI

The EIU panel is composed of twenty renowned experts on food security, agricultural policy, climate change and natural resources from international institutions (EIU, 2019). The EIU applies either equal weights or peer panel suggested weights to GFSI indicators. The EIU panel of experts assigned weights to the indicators of the GFSI by averaging the indicator weights suggested by five members of the EIU panel (EIU, 2019). An analyst of the GFSI model has the option of using the GFSI weights suggested by the EIU experts or even applying new weights (EIU, 2019). However, the EIU panel of experts recommends the suggested weights in the GFSI model used to create the annual GFSI report (Table 3.2).

Table 3.2: Nominal weights for the indicators of the NRR component of the GFSI

Component within the NRR component of the GFSI	Weight	Indicator within the component	Weight
1. Exposure	3.00	Temperature rise	3.00
		Drought	2.75
		Flooding	2.50
		Storm severity	1.00
		Sea level rise	2.75
		Commitment to managing exposure	2.00
2. Water	2.00	Agricultural water risk – quantity	4.00
		Agricultural water risk – quality	1.00
3. Land	2.00	Land degradation	3.00
		Grassland	1.00
		Forest change	1.00
4. Oceans	1.75	Ocean eutrophication	3.00
		Marine biodiversity	3.00
		Marine protected areas	1.00
5. Sensitivity	1.50	Food import dependency	1.50
		Dependence on natural capital	1.00
		Disaster risk management	2.50
6. Adaptive capacity	2.50	Early warning measures/ climate-smart agriculture	1.00
		National agricultural risk management system	1.00
7. Demographic stresses	1.00	Population growth (2016-2021)	3.00
		Urbanisation (2016-2021)	1.00

Source: EIU (2019).

The GFSI uses linear aggregation (the weighted arithmetic average) to compute the scores of countries (EIU, 2019). Linear aggregation implies that the score of the overall index (or component of the index) is calculated by a weighted average of the scores for individual components (or indicators) (EIU, 2019). As with the normalised data for indicators, the GFSI scores for countries are stated on a continuous range of zero to 100, where 100 is the most favourable score. Linear aggregation method is defined as illustrated in Equation 3.3:

$$y = \sum_{i=1}^{n} w_i z_i \qquad \text{Equation 3.3}$$

where y is the value of the overall index (or component of the index), z_i is the normalised value of the i^{th} indicator, and w_i is the weight allocated to z_i, with $\sum_{i=1}^{n} w_i = 1$ and $0 \le w_i \le 1$, for all $i = 1, 2, \ldots, n$ (EIU, 2019; OECD, 2008).

3.7 The deconstruction of the components of the GFSI

The EIU disaggregates the components of the GFSI to extend the analysis, shedding light on countries' performance. The EIU analysts document and explain the relative importance of the components of the GFSI (EIU, 2019). The main drivers of the GFSI scores are identified by profiling countries' performance at the indicator or component level.

3.8 The visualisation of results of the GFSI

The EIU uses various tables and scatterplots to visualise the results of GFSI to decision-makers and users (EIU, 2019). The GFSI model is available online along with the weights, data and methodological documentation (EIU, 2019). The GFSI model allows users to apply alternative methods regarding data, weighting, normalisation, and others to replicate sensitivity tests (EIU, 2019; Nardo et al., 2005).

3.9 The adjustment of overall GFSI scores for countries

Since 2017, the overall GFSI scores of 113 countries have been adjusted by the NRR scores as specified in Equation 3.4:

$$A = x(1-z) + (x\,z(y/100)) \qquad \text{Equation 3.4}$$

where A is the adjusted overall GFSI score, x is the original overall GFSI score, y is the NRR score, and z is the adjustment factor weighting, where the default z is 0.25 = 25% (EIU, 2019).

Although the methodological framework of GFSI has extensive indicators and data coverage, its weighting scheme follows a subjective approach. The EIU panel of experts (default) weights may be biased and might not reflect the relative importance of indicators (Maricic et al., 2016; Thomas et al., 2017). For this reason, this study set out to explore how an objective weighting of the NRR component of the GFSI influenced the scores and rank of countries. The next chapter presents the methods and procedures followed in this analysis.

Chapter 4: Methods and procedures

4.1 Introduction

This study set out to explore how an objective weighting of the NRR component of the GFSI affected the scores and rank of countries. The first specific research question addressed whether an objective weighting significantly changed the countries' NRR scores and ranks compared to the subjective weighting of the NRR component of the GFSI. The second specific research question addressed whether the objective NRR adjustment significantly changed the countries' adjusted overall GFSI scores and ranks compared to the subjective NRR adjustment of the overall GFSI. This chapter discusses the research approach, data sources, data analysis techniques and the methodological assumptions and limitations of the study.

4.2 Research approach

This study used the GFSI data set of 113 countries compiled in the 2019 database of the Economist Intelligence Unit (EIU) responsible for the construction of the GFSI. Table 4.1 summarises the specific research questions with associated indicators and analytical methods.

Table 4.1: Summary of the research methodological approach

Specific research question	**Data source**	**Variable/indicator**	**Analytical approach**	**Specific approach**
Did the objective weighting significantly change the countries' NRR scores and ranks compared to the subjective weighting of the NRR component of the GFSI?	EIU's 2019 GFSI data set	21 indicators within the seven NRR components NRR weights and NRR scores NRR ranks	Quantitative approach	Principal component analysis (PCA) Paired t-test Spearman's rank correlation test Descriptive statistics
Did the objective NRR adjustment significantly change the countries' adjusted overall GFSI scores and ranks compared to the subjective NRR adjustment of the overall GFSI?	EIU's 2019 GFSI data set	NRR scores, overall GFSI scores and adjusted overall GFSI scores Adjusted overall GFSI ranks	Quantitative approach	Paired t-test Descriptive statistics Spearman's rank correlation test

Source: Author's work.

4.3 Data analysis techniques

The researcher extracted the 2019 GFSI data of 113 countries from the EIU database (EIU, 2019) and proceeded with the analytical methods and procedures. The independent variables analysed in this study were drawn from the 21 indicators within seven components of the NRR component of the GFSI. Annexure A describes these indicators in details, including their definition, construction and rationale. The dependent variables used were the NRR component weights, NRR scores and ranks, overall GFSI scores, and adjusted overall GFSI scores and ranks from the GFSI model. A principal component analysis (PCA) was used as an objective weighting scheme of the NRR component of the GFSI. The GFSI data was loaded onto the Stata 15 statistical software and a PCA, paired t-test, and Spearman's rank correlation test conducted. The specific methodologies relating to the specific research questions addressed in the study are discussed in the following sections.

4.3.1 Principal component analysis

PCA is a statistical technique that combines and transforms a set of *n* correlated variables (indicators) *z* linearly into uncorrelated principal components *C,* as defined in Equation 4.1:

$$C_j = \sum_{i=1}^{n} r_{ij} z_i \qquad \text{Equation 4.1}$$

where C_j is the value of the j^{th} principal component, z_i is the normalised value of the i^{th} indicator, and r_{ij} is the component loading on the j^{th} principal component attached to z_i with $\sum_{i=1}^{n} r^2{}_{ij} = 1$ and $0 \leq r^2{}_{ij} \leq 1$, for all $i = 1, 2, \ldots, n$ (Izraelov and Silber, 2019). The r_{ij} were then estimated using Stata 15 statistical software to derive the component loadings.

The correlation matrix version of PCA was applied to standardise the original variables to zero means, and unit standard deviations (Nardo et al., 2005). This standardisation created an even influence of all variables on the principal components (Jolliffe and Cadima, 2016). Also, weights derived from the correlation matrix would remain unaffected with linear changes in the measurement unit of the original variables (Nguefack-Tsague et al., 2011). This study adopted the following four steps recommended by Nardo et al. (2005) and OECD (2008) to derive the weights for the variables objectively.

4.3.1.1 Step 1: Suitability test for principal component analysis

The Kaiser-Meyer-Olkin (KMO) test (OECD, 2008) and Bartlett's test of sphericity (Parinet et al., 2004) were conducted to examine the suitability of the normalised GFSI data for a PCA.

The KMO measured the sampling adequacy by determining whether or not the size of the partial correlations between all pairs of indicators was small (OECD, 2008). The partial correlations denoted the strength of the relationship between any pair of indicators when the other indicators were held constant (Watson, 2017). A smaller value of these partial correlation coefficients would indicate that the KMO measure was likely to be close to 1.0 (Watson, 2017). The data was considered suitable for a PCA if the KMO value was at least 0.5 (Parinet et al., 2004).

The Bartlett's test of sphericity tested the null hypothesis that all pairs of indicators in any correlation matrix were not correlated (Parinet et al., 2004). A high correlation between a pair of indicators would indicate that they were likely to share a common principal component (OECD, 2008). The data was considered adequate for a PCA if Bartlett's test of sphericity was significant (p-value < 0.05) (Parinet et al., 2004).

4.3.1.2 Step 2: Eigenvalues computation and selection of principal components

Theoretically, the number of principal components would equal the number of indicators used (OECD, 2008). As recommended by Kaiser (1960), a principal component was selected for further analytical steps only if it had an Eigenvalue greater than 1.0.

4.3.1.3 Step 3: Rotation of principal components

The principal components were rotated using the varimax normalised rotation (Nardo et al., 2005) to ensure high component loadings for a few indicators and low component loadings for the rest (OECD, 2008). This procedure entailed a perpendicular rotation of the matrix of component loadings until each principal component was maximised (Nardo et al., 2005). As a result, a more interpretable and simplified solution was achievable (OECD, 2008). Only the rotated component loadings greater than ±0.3 (significant loadings) were kept for the final construction step (Kutcher et al., 2013).

4.3.1.4 Step 4: Construction and extraction of weights

The final rotated component loadings (> ±0.3) were first normalised by obtaining their squares (OECD, 2008). These squared component loadings represented the proportion of the total variance of a given indicator explained by the associated principal component (Nardo et al., 2005). The weights for indicators of the NRR component of the GFSI were then constructed, as shown in Equation 4.2:

$$w_{ij} = \frac{r^2_{ij}}{e_j} \qquad \text{Equation 4.2}$$

where w_{ij} was the weight for the i^{th} indicator in the j^{th} principal component, r^2_{ij} was the squared component loading attached to the i^{th} indicator, and e_j was the Eigenvalue of the j^{th} principal component with $0 \leq w_{ij} \leq 1$, for all $i = 1, 2, ..., n$ (Gómez-Limón and Riesgo, 2009). Each indicator was then assigned to a specific principal component based on the highest w_{ij} across all principal components (Gómez-Limón and Riesgo, 2009).

The PCA weights for 21 indicators within the seven components of the NRR component of the GFSI were rescaled to unit sum to retain comparability (OECD, 2008). The rescaling involved the division of each indicator's weight by the total weights for all indicators within a particular NRR component. A linear aggregation (EIU, 2019) procedure was conducted to compute the score value of each of the seven NRR components. This procedure involved a weighted arithmetic average of indicators' normalised data with the rescaled PCA weights.

The previously discussed four weighting steps of PCA were again followed to assign a weight to each of the seven NRR components. In this procedural stage, the researcher used the newly computed score values of the NRR components as the data for the PCA model. Just as the NRR indicators' weights were rescaled to unit sum, the same rescaling was done for the weights for the seven NRR components.

4.3.2 NRR scores and ranks based on the objective and subjective weighting models

The first specific research question addressed whether an objective weighting significantly changed the countries' NRR scores and ranks compared to the subjective weighting of the NRR component of the GFSI. The PCA described in the preceding section was used to derive objective weights for the 21 indicators within the seven components the NRR component of the GFSI. These PCA weights were average weighted with the NRR components' score values to obtain the overall NRR scores and rank of countries (EIU, 2019). This weighted arithmetic average (linear aggregation) approach was described under the methodology of the GFSI (see Chapter 3, section 3.6 of this study). The NRR scores were stated on a continuous range of zero to 100, where 100 was the most favourable score (EIU, 2019).

The hypothesis for the research question one assumed that objective weighting significantly changed the countries' NRR scores and ranks compared to the subjective weighting of the NRR component of the GFSI. This hypothesis was tested as follows. Firstly, a paired t-test was used to test for the significance of the difference between PCA (objective) and GFSI (subjective) weights at five per cent significance level. This statistical test technique was most preferred as it offered a simple hypothesis test for the significance of the difference between two mean values for two groups based on the same variables and data (Stoltzfus, 2015). A paired t-test was defined by Equation 4.3:

$$t = \frac{d}{s/\sqrt{n}} \qquad \text{Equation 4.3}$$

where *t* was the t-test statistic of the paired t-test, *d* was the mean difference between the paired observations or variables, *s* was the standard deviation of *d*, *n* was the sample size and $s/\sqrt{n}$ provided the standard error of *d* (Kim, 2015).

Secondly, a paired t-test was used to test for the significance of the difference between the countries' objective and subjective weighted NRR scores. Finally, a Spearman's rank correlation was used to test whether the subjectively and objectively weighted NRR ranks were significantly different. This test was conducted at five per cent significance level. A Spearman's rank correlation test was specified in Equation 4.4:

$$R = 1 - \frac{6\sum d^2}{n(n^2\text{-}n)} \qquad \text{Equation 4.4}$$

where *R* was the Spearman's rank correlation coefficient, *d* was the rank difference between the paired countries, and *n* was the number of paired countries (Gautheir, 2001) (n = 113 countries).

4.3.3 Objective and subjective NRR adjustment of the overall GFSI scores and ranks

The second specific research question addressed whether the objective NRR adjustment of the overall GFSI significantly changed the countries' adjusted overall GFSI scores and ranks. The countries' NRR scores obtained with the PCA model were used to adjust their overall GFSI scores at an adjustment factor weighting of 25% (EIU, 2019). This adjustment procedure was explained under the methodology of the GFSI (see Chapter 3, section 3.9 of this study).

The hypothesis for the research question two assumed that the objective NRR adjustment of the overall GFSI significantly changed the countries' adjusted overall GFSI scores and ranks compared to the subjective NRR adjustment. This hypothesis was tested as follows. Firstly, a paired t-test was used to test for the significance of the difference between countries' adjusted overall GFSI scores obtained using an objective and subjective NRR adjustment at five per cent significance level. Secondly, a Spearman's rank correlation was used to test whether the countries' adjusted overall GFSI ranks obtained using an objective and subjective NRR adjustment were significantly different. This test was conducted at five per cent significance level.

4.4 Limitations of the methodological approach

Several methodological limitations were identified in this study. Firstly, the 2019 GFSI data was sourced from the EIU database made up of data from various sources (EIU, 2019). The problems of outdated data could limit the quality of the GFSI data (OECD, 2008). Secondly, the study was limited to an objective weighting of the NRR component of the GFSI to derive objective adjusted overall GFSI scores and ranks. The EIU weights for the affordability, availability, and quality and safety components of the GFSI were held constant. This limitation implied a partial understanding of the influence of the objectively weighted NRR scores on the countries' adjusted overall GFSI scores and ranks.

4.5 Assumptions of the methodological approach

This study identified the following two methodological assumptions. Firstly, the study assumed that the 2019 GFSI data set in the EIU database was drawn from reliable data sources and data coverage. Secondly, a PCA approach was assumed to be sensitive to the data such that additional data for any GFSI reporting year would significantly change the previous year's weights for the NRR indicators.

Chapter 5: Results and discussion

5.1 Introduction

This chapter presents and discusses the findings of the study. The chapter is organised into three sections to address the specific research questions. The first and second sections discuss the results of the PCA for the NRR indicators and NRR components, respectively. The third section addresses the comparative results of the objective and subjective weighting of the NRR component of the GFSI. Finally, section four compares the results of objectively and subjectively adjusted overall GFSI scores and rank of countries.

5.2 Principal component analysis results for the NRR indicators

This study set out to explore how an objective weighting of the NRR component of the GFSI influenced the country scores and ranks. The following results were obtained from the four steps of the PCA (objective weighting model) performed for the 21 indicators of the NRR component of the GFSI.

5.2.1 Step 1: Results of the suitability test for PCA of the NRR indicators

As presented in Table 5.1, the KMO value was 0.682, while Bartlett's test of sphericity was significant (p-value < 0.05). These results confirmed that the normalised GFSI data set was acceptable for conducting a PCA of the NRR indicators (Parinet et al., 2004).

Table 5.1 Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity (N = 21 NRR indicators)

Test	Value	
Kaiser-Meyer-Olkin		0.682
Bartlett's test of sphericity	Chi-square	979.798
	Degrees of freedom	210
	P-value	0.000

Source: Author's calculations, using Stata 15 statistical software.

5.2.2 Step 2: Results of Eigenvalues computation and selection of principal components

Principal component one (Eigenvalue of 4.011) accounted for the maximum variability in the original data for all the individual NRR indicators (Table 5.2). Any principal component with an Eigenvalue exceeding 1.0 was considered to be significant in a PCA procedure (Kaiser, 1960; OECD, 2008). The first five principal components with Eigenvalues greater than 1.0, cumulatively explaining 0.735 (73.5%) of variability in the original data were selected for further analytical steps.

Table 5.2: Eigenvalues of the principal components of the NRR indicators

Principal component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	4.011	0.548	0.191	0.191
Component 2	3.464	1.613	0.165	0.356
Component 3	1.850	0.326	0.088	0.444
Component 4	1.525	0.252	0.073	0.517
Component 5	1.272	0.133	0.061	0.577
Component 6	1.139	0.033	0.054	0.631
Component 7	1.106	0.044	0.053	0.684
Component 8	1.062	0.194	0.051	0.735
Component 9	0.868	0.037	0.041	0.776
Component 10	0.831	0.225	0.040	0.816
Component 11	0.605	0.059	0.029	0.845
Component 12	0.546	0.023	0.026	0.871
Component 13	0.523	0.059	0.025	0.895
Component 14	0.464	0.051	0.022	0.917
Component 15	0.412	0.055	0.020	0.937
Component 16	0.357	0.054	0.017	0.954
Component 17	0.303	0.060	0.014	0.969
Component 18	0.243	0.040	0.012	0.980
Component 19	0.203	0.053	0.010	0.990
Component 20	0.151	0.086	0.007	0.997
Component 21	0.064		0.003	1.000

Source: Author's calculations, PCA using Stata 15 statistical software.

As shown in Table 5.3, most of the NRR indicators had significant unrotated component loadings (highlighted loadings > ±0.3) (Kutcher et al., 2013). Notably, seven out of 21 (33.33%) NRR indicators demonstrated significant loadings (±0.3) on more than one principal component. For example, the *sea level rise* indicator had high loadings for principal component four, five and seven. The first principal component had large negative associations with *agricultural water risk – quantity* (-0.306) and *agricultural water risk – quality* (-0.354). This principal component also demonstrated significant positive loadings with *population growth* (0.367) and *urbanisation* (0.397). These observations suggested that the first principal component primarily measured the indicators within the NRR components of *water* and *demographic stresses*. While the *grassland* indicator was captured by the sixth, seventh and eighth principal components, its associate *forest change* indicator was primarily measured by principal component eight.

Table 5.3 Unrotated component loadings of indicators of the NRR component of the GFSI

Variable/indicator	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Component 7	Component 8	Unexplained
Temperature rise	0.180	0.269	-0.188	**-0.310**	-0.035	-0.005	0.282	0.087	0.311
Drought	-0.052	0.039	**0.577**	0.096	0.177	0.129	-0.199	0.044	0.250
Flooding	0.059	**-0.332**	-0.049	-0.011	**0.437**	0.043	0.159	-0.118	0.312
Storm severity	-0.169	**0.338**	0.165	-0.143	-0.123	-0.165	0.051	0.173	0.323
Sea level rise	-0.099	0.041	0.071	**-0.340**	**0.387**	-0.129	**0.455**	-0.160	0.305
Commitment to managing exposure	0.046	**0.383**	-0.155	0.298	0.073	-0.175	-0.036	-0.006	0.261
Agricultural water risk – quantity	**-0.306**	0.245	0.188	0.295	0.089	0.132	0.049	-0.103	0.174
Agricultural water risk – quality	**-0.354**	0.209	0.178	0.139	0.191	0.078	0.153	-0.078	0.173
Land degradation	0.104	0.070	-0.221	**0.367**	**0.406**	-0.238	-0.106	-0.058	0.354
Grassland	0.034	-0.011	-0.112	0.220	0.076	**0.368**	**0.573**	**0.459**	0.150
Forest change	0.204	0.010	-0.016	0.051	0.114	-0.053	-0.194	**0.721**	0.215
Ocean eutrophication	-0.242	-0.110	-0.222	0.110	0.172	**0.459**	-0.074	-0.023	0.329
Marine biodiversity	-0.093	0.207	-0.283	-0.257	0.099	**0.435**	**-0.316**	-0.109	0.217
Marine protected areas	-0.194	0.264	**-0.324**	-0.184	0.019	0.167	-0.188	0.075	0.285
Food import dependency	0.035	**0.352**	0.175	**-0.321**	0.040	-0.024	0.078	0.029	0.341
Dependence on natural capital	**0.374**	-0.047	0.032	-0.049	-0.005	0.158	-0.011	-0.224	0.343
Disaster risk management	0.067	0.049	0.172	0.224	**-0.477**	**0.331**	0.189	-0.096	0.379
Early warning measures/ climate-smart agriculture	0.131	**0.355**	-0.143	0.299	0.027	-0.138	0.030	-0.125	0.280
National agricultural risk management system	0.298	0.121	-0.181	0.138	-0.143	0.034	0.200	-0.276	0.351
Population growth (2016-2021)	**0.367**	0.167	0.270	-0.040	0.245	0.200	-0.106	-0.016	0.091
Urbanisation (2016-2021)	**0.397**	0.149	0.151	-0.025	0.168	0.256	-0.086	-0.039	0.127

Note: Only the principal components with an Eigenvalue greater than 1.0 are shown. Component loadings greater than ±0.3 are highlighted.

Source: Author's calculations, PCA using Stata 15 statistical software.

5.2.3 Step 3: Rotated principal components results

Varimax normalised rotation indicated that all the indicators loaded significantly on at least one of the principal components (Table 5.4). Eighteen out of 21 indicators significantly loaded on a single principal component while the rest loaded across two components. For example, the *temperature rise* indicator had a significant loading for the third principal component (0.407) only. The *disaster risk management* indicator demonstrated significant loadings across principal components six (-0.470) and eight (0.364). A*gricultural water risk – quantity* and *agricultural water risk – quality* indicators previously associated with the unrotated principal component one revealed significant associations with the rotated principal component two.

The *population growth* and *urbanisation* indicators maintained high positive loadings for the principal component one despite the rotation procedure. The loadings of these two indicators for the unrotated principal component one were respectively 0.367 and 0.397. Likewise, their loadings for the rotated principal component one were 0.579 and 0.545 in the order mentioned. All the indicators of *oceans* component of the NRR component of the GFSI had high positive loadings for the fifth principal component.

5.2.4 Step 4: Results of the construction and extraction of weights for the NRR indicators

Only the significant rotated component loadings exceeding ±0.3 in step three were retained for the final construction step (Kutcher et al., 2013). The empty spaces in Table 5.5 indicated that the rotated component loadings were insignificant hence assumed in this construction step. When looking across the rows of Table 5.5 for each NRR indicator, it was observed that the *drought*, *ocean eutrophication* and *disaster risk management* indicators were each allocated two different weights. However, only the highest weight in a row was assigned to each of these indicators. For example, although *drought* was weighted with 0.030 (principal component one) and 0.052 (principal component two), the latter (0.052) provided its best measure.

Generally, the assigned weights to the NRR indicators ranged from 0.031-0.658 with *grassland* reaping the highest weight (0.658). This observation showed that the *grassland* indicator had a high importance level compared to the *dependence on natural capital* (weight 0.031) indicator (Nardo et al., 2005).

Table 5.4 Rotated component loadings of the NRR indicators

Variable/indicator	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Component 7	Component 8	Unexplained
Temperature rise	0.034	-0.245	**0.407**	0.061	0.117	0.117	0.226	0.123	0.311
Drought	**0.346**	**0.425**	-0.008	-0.162	-0.157	-0.073	-0.154	-0.235	0.250
Flooding	0.100	-0.010	-0.291	-0.071	-0.054	**0.489**	0.078	0.015	0.312
Storm severity	-0.118	0.139	**0.450**	0.022	-0.032	-0.110	-0.028	-0.125	0.323
Sea level rise	-0.021	0.110	0.292	-0.089	-0.071	**0.625**	0.076	0.150	0.305
Commitment to managing exposure	-0.018	0.084	0.078	**0.528**	0.026	-0.075	0.004	-0.021	0.261
Agricultural water risk – quantity	-0.018	**0.534**	-0.006	0.135	0.035	-0.071	0.038	0.053	0.174
Agricultural water risk – quality	-0.068	**0.508**	0.082	0.058	0.036	0.115	0.061	0.027	0.173
Land degradation	0.033	0.021	-0.255	**0.539**	-0.029	0.233	-0.066	-0.137	0.354
Grassland	-0.005	0.081	-0.030	-0.015	-0.031	0.038	**0.853**	-0.067	0.150
Forest change	0.116	-0.223	0.037	0.084	-0.030	-0.137	0.244	**-0.683**	0.215
Ocean eutrophication	-0.015	0.194	**-0.344**	-0.093	**0.422**	0.046	0.183	0.012	0.329
Marine biodiversity	0.157	-0.004	0.001	-0.056	**0.686**	-0.021	-0.080	0.046	0.217
Marine protected areas	-0.103	-0.022	0.134	0.071	**0.523**	-0.042	-0.005	-0.074	0.285
Food import dependency	0.157	0.057	**0.479**	-0.034	0.059	0.070	-0.038	-0.004	0.341
Dependence on natural capital	**0.353**	-0.174	-0.081	-0.026	-0.022	0.002	-0.028	0.239	0.343
Disaster risk management	0.078	0.135	-0.023	-0.134	-0.118	**-0.470**	0.243	**0.364**	0.379
Early warning measures/ climate-smart agriculture	0.040	0.051	0.056	**0.509**	-0.018	-0.074	0.011	0.130	0.280
National agricultural risk management system	0.105	-0.159	-0.016	0.244	-0.050	-0.060	0.111	**0.422**	0.351
Population growth (2016-2021)	**0.579**	0.048	0.068	0.032	-0.008	0.042	-0.011	-0.063	0.091
Urbanisation (2016-2021)	**0.545**	-0.032	0.022	0.046	0.053	-0.008	0.045	0.018	0.127

Note: Varimax normalised rotation used. Component loadings greater than ±0.3 are highlighted.

Source: Author's calculations, PCA using Stata 15 statistical software.

Table 5.5 Weights for indicators of the NRR component of the GFSI

Variable/indicator	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Component 7	Component 8
Temperature rise			**0.090**					
Drought	0.030	**0.052**						
Flooding						**0.210**		
Storm severity			**0.109**					
Sea level rise						**0.343**		
Commitment to managing exposure				**0.183**				
Agricultural water risk – quantity		**0.082**						
Agricultural water risk – quality		**0.074**						
Land degradation				**0.191**				
Grassland							**0.658**	
Forest change								**0.440**
Ocean eutrophication			0.064		**0.140**			
Marine biodiversity					**0.371**			
Marine protected areas					**0.215**			
Food import dependency			**0.124**					
Dependence on natural capital	**0.031**							
Disaster risk management						**0.194**		0.125
Early warning measures/ climate-smart agriculture				**0.170**				
National agricultural risk management system								**0.168**
Population growth (2016-2021)	**0.083**							
Urbanisation (2016-2021)	**0.074**							

Note: Highest weight assigned to each NRR indicator across all principal components is highlighted.

Source: Author's calculations, PCA using Stata 15 statistical software.

5.3 Principal component analysis results for the NRR components

A weighted arithmetic average of the NRR indicators data with their PCA weights produced the score values of the seven NRR components (EIU, 2019). A repeat of the four steps of PCA using these NRR components' score values as the data provided the following results.

5.3.1 Step 1: Suitability test results for PCA of the NRR components

The value of the KMO was 0.534, and Bartlett's test of sphericity was significant (p-value < 0.05), as presented in Table 5.6. These results were in line with the suitability requirements for conducting a PCA of the NRR components (Parinet et al., 2004).

Table 5.6 Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity (N = seven NRR components)

Test	Value	
Kaiser-Meyer-Olkin		0.534
Bartlett's test of sphericity	Chi-square	94.779
	Degrees of freedom	21
	P-value	0.000

Source: Author's calculations, using Stata 15 statistical software.

5.3.2 Step 2: Results based on computed Eigenvalues of principal components

The results in Table 5.7 revealed the presence of three principal components with Eigenvalues greater than 1.0, explaining 26.2%, 23.0%, and 14.6% of the variance. These three principal components accounting for 63.7% of the total variance, were extracted for further analysis.

Table 5.7: Eigenvalues of the NRR components

Principal component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	1.832	0.223	0.262	0.262
Component 2	1.608	0.587	0.230	0.491
Component 3	1.022	0.214	0.146	0.637
Component 4	0.807	0.032	0.115	0.753
Component 5	0.775	0.218	0.111	0.863
Component 6	0.557	0.158	0.080	0.943
Component 7	0.399		0.057	1.000

Source: Author's calculations, PCA using Stata 15 statistical software.

Table 5.8 shows that all the NRR components had unrotated component loadings exceeding ±0.3. The results revealed that five out of seven (71.43%) NRR components were captured by more than one principal component. The first principal component was significantly associated with all the NRR components at the exception of *exposure*. Further observations indicated that all the NRR components were positively correlated with the second principal component. Also, the third principal component offered a perfect measurement of the *sensitivity* component of the NRR component of the GFSI.

Table 5.8 Unrotated component loadings of sub-components of the NRR component of the GFSI

Variable/sub-component	Component 1	Component 2	Component 3	Unexplained
Exposure	0.015	**0.623**	0.222	0.326
Water	**-0.371**	**0.494**	-0.169	0.327
Land	**0.361**	0.000	**0.557**	0.444
Oceans	**-0.303**	**0.393**	0.133	0.565
Sensitivity	**0.315**	0.152	**-0.770**	0.176
Adaptive capacity	**0.440**	**0.425**	0.021	0.354
Demographic stresses	**0.590**	0.099	0.010	0.347

Note: Only the principal components with an Eigenvalue greater than 1.0 are shown. Component loadings greater than ±0.3 are highlighted.

Source: Author's calculations, PCA using Stata 15 statistical software.

5.3.3 Step 3: Results of the rotated component loadings of the NRR components

The rotated component loadings (Table 5.9) showed that the principal components one and two were positively correlated with all the NRR components that had significant loadings. Varimax normalised rotation minimised the double loading of NRR components across the principal components from 71.43% to 42.86% (three out of seven NRR components). The *sensitivity* component demonstrated the most significant component loading (0.780), suggesting that it could possess the highest importance level. Component loadings more than ±0.3 were used as the cutoff in the construction of weights (Kutcher et al., 2013), although most loadings exceeded ±0.5.

Table 5.9 Rotated component loadings of the NRR components

Variable/sub-component	Component 1	Component 2	Component 3	Unexplained
Exposure	**0.319**	**0.564**	-0.134	0.326
Water	-0.104	**0.585**	0.240	0.327
Land	**0.349**	-0.100	**-0.556**	0.444
Oceans	-0.074	**0.503**	-0.074	0.565
Sensitivity	**0.305**	-0.114	**0.780**	0.176
Adaptive capacity	**0.589**	0.165	0.033	0.354
Demographic stresses	**0.566**	-0.193	-0.003	0.347

Note: Varimax normalised rotation used. Component loadings greater than ±0.3 are highlighted.

Source: Author's calculations, PCA using Stata 15 statistical software.

5.3.4 Step 4: Results of the construction and extraction of weights for the NRR components

The *exposure, oceans* and *sensitivity* components were each weighted with two different values across the rows in Table 5.10. However, only their highest weights (0.198, 0.302, and 0.596 respectively); as primarily captured by principal components two and three were considered. The weights assigned to the NRR components ranged from 0.158-0.596. As predicted by the rotated component loadings in Table 5.9 above, the *sensitivity* component (weighted 0.596) proved to be a major determinant of the NRR component of the GFSI. The indicators of the *sensitivity* component could have had higher importance levels compared to other indicators for the NRR component of the GFSI (Paruolo et al., 2013). The *sensitivity* component measured the susceptibility of countries to natural resource risks based on the level of disaster risk management and dependence on food import and natural capital (EIU, 2019). This component informs countries of the needed improvements to limit the impact of natural disasters on food systems (Weichselgartner and Pigeon, 2015).

Table 5.10 Weights for sub-components of the NRR component of the GFSI

Variable/sub-component	Component 1	Component 2	Component 3
Exposure	0.055	**0.198**	
Water		**0.212**	
Land	0.067		**0.302**
Oceans		**0.158**	
Sensitivity	0.051		**0.596**
Adaptive capacity	**0.189**		
Demographic stresses	**0.175**		

Note: Highest weight assigned to each NRR component across all principal components is highlighted.

Source: Author's calculations, PCA using Stata 15 statistical software.

5.4 Comparative results of the PCA and GFSI models for the NRR scores and ranks

The first specific research question addressed whether an objective weighting of the NRR component of the GFSI significantly changed the countries' NRR scores and ranks compared to the subjective weighting approach. A comparison of the weights for the NRR component of the GFSI based on the PCA (objective) and GFSI models showed substantial differences (Table 5.11). The NRR weights changed with the use of the statistical model (PCA) as observed in similar studies by Maricic et al. (2016) and Thomas et al. (2017). For example, the GFSI model placed *demographic stresses* (weight 7.27%) and *exposure* to climate change risks (weight

21.82%) as the least and most significant NRR components. Conversely, the PCA model weighted the *oceans* (weight 8.61%) and *sensitivity* to natural resource risks (weight 32.56%) as the least and largest contributors to the NRR component of the GFSI. These results suggested that the EIU expert panel simply weighted the *exposure* component based on the perceived economic significance of its indicators (Nardo et al., 2005).

The *sensitivity* component went through the most extensive changes among all the seven NRR components. The weight assigned to the *sensitivity* component increased from 10.91% to 32.56% with PCA weighting. This observation indicated that the countries' level of sensitivity to climate and natural resource risks heavily determined their susceptibility to these risks (West et al., 2009). The *water* and *land* components were each weighted with 14.55% according to the GFSI model but assigned different weights (11.61% and 16.53% respectively) with the PCA model. This comparison of the GFSI and PCA models showed that *water* and *land* components did not have the same importance level within the NRR component of the GFSI.

When looking at the NRR indicators, the s*ea-level rise* indicator within the *exposure* component witnessed the largest weight increase from 19.64% to 34.79% (+15.15%). This observation showed that s*ea-level rise* ought to have been considered by the EIU expert panel as the most critical indicator within the *exposure* component only. Notably, even a small rise in sea-level can cause flooding, salination, and destruction of crops and fish (Sova et al., 2019). The *ocean eutrophication* and *marine biodiversity* indicators were assigned the same overall weight (5.45%) with the GFSI model but different overall weights (1.66% and 4.40%) with the PCA model. Weights were allocated as coefficients that reflect the relative importance of each indicator in the determination of the overall index score (Paruolo et al., 2013). These observed overall weights with the PCA model showed that *marine biodiversity* indicator was more important than the *ocean eutrophication* indicator.

The GFSI model regarded *agricultural water risk – quantity* (overall weight 11.64%) as the most significant indicator of the NRR component of the GFSI. However, the PCA model rewarded the *disaster risk management* indicator with a high overall weight of 18.08%, placing it above all other indicators. Nardo et al. (2005), asserted that weights influence the results of composite indicators in a benchmarking context. Therefore, the high overall weight for *disaster risk management* from the PCA model suggested that this indicator may have the greatest influence in the computation of countries' NRR scores and ranks.

Table 5.11: Comparative weights for the NRR component of the GFSI based on the GFSI and PCA models

Component/indicator	GFSI model			PCA model		
1. Exposure	**Weight within NRR (g)**	**Weight within Exposure (f)**	**Overall weight (g*f)**	**Weight within NRR (g)**	**Weight within Exposure (f)**	**Overall weight (g*f)**
Temperature rise	21.82%	21.43%	4.68%	10.80%	9.10%	0.98%
Drought		19.64%	4.29%		5.28%	0.57%
Flooding		17.86%	3.90%		21.26%	2.30%
Storm severity		7.14%	1.56%		11.08%	1.20%
Sea level rise		19.64%	4.29%		34.79%	3.76%
Commitment to managing exposure		14.29%	3.12%		18.50%	2.00%
2. Water	**Weight within NRR (g)**	**Weight within water (f)**	**Overall weight (g*f)**	**Weight within NRR (g)**	**Weight within water (f)**	**Overall weight (g*f)**
Agricultural water risk – quantity	14.55%	80.00%	11.64%	11.61%	52.51%	6.10%
Agricultural water risk – quality		20.00%	2.91%		47.49%	5.51%
3. Land	**Weight within NRR (g)**	**Weight within land (f)**	**Overall weight (g*f)**	**Weight within NRR (g)**	**Weight within land (f)**	**Overall weight (g*f)**
Land degradation	14.55%	60.00%	8.73%	16.53%	14.81%	2.45%
Grassland		20.00%	2.91%		51.06%	8.44%
Forest change		20.00%	2.91%		34.14%	5.64%
4. Oceans	**Weight within NRR (g)**	**Weight within oceans (f)**	**Overall weight (g*f)**	**Weight within NRR (g)**	**Weight within oceans (f)**	**Overall weight (g*f)**
Ocean eutrophication	12.73%	42.86%	5.45%	8.61%	19.30%	1.66%
Marine biodiversity		42.86%	5.45%		51.05%	4.40%
Marine protected areas		14.29%	1.82%		29.65%	2.55%
5. Sensitivity	**Weight within NRR (g)**	**Weight within sensitivity (f)**	**Overall weight (g*f)**	**Weight within NRR (g)**	**Weight within sensitivity (f)**	**Overall weight (g*f)**
Food import dependency	10.91%	30.00%	3.27%	32.56%	35.54%	11.57%
Dependence on natural capital		20.00%	2.18%		8.92%	2.90%
Disaster risk management		50.00%	5.45%		55.54%	18.08%
6. Adaptive capacity (AC)	**Weight within NRR (g)**	**Weight within AC (f)**	**Overall weight (g*f)**	**Weight within NRR (g)**	**Weight within AC (f)**	**Overall weight (g*f)**
Early warning measures/ climate-smart agriculture	18.18%	50.00%	9.09%	10.34%	50.34%	5.20%
National agricultural risk management system		50.00%	9.09%		49.66%	5.14%
7. Demographic stresses (DS)	**Weight within NRR (g)**	**Weight within DS (f)**	**Overall weight (g*f)**	**Weight within NRR (g)**	**Weight within DS (f)**	**Overall weight (g*f)**
Population growth (2016-2021)	7.27%	75.00%	5.45%	9.56%	52.76%	5.04%
Urbanisation (2016-2021)		25.00%	1.82%		47.25%	4.52%

Note: g = weight of the NRR component, f = weight of indicator within the NRR component.

Source: Author's calculations, PCA using Stata 15 statistical software and EIU (2019).

A paired t-test was run on the weights for the NRR component of the GFSI to determine whether there was a statistically significant difference between the weights assigned with PCA and GFSI models. As presented in Table 5.12, the PCA weights were lower (mean = 0.208 ± 0.153) compared to the GFSI weights (mean = 1.991 ± 0.912). A statistically significant decrease in weights by 1.784 (95% confidence level) and *p*-value less than 0.05 ($p < 0.05$) were observed among the PCA weights. The hypothesis that objective weighting significantly changed the weights compared to the subjective weighting of the NRR component of the GFSI was accepted. This finding was in agreement with the assertion made by Maricic et al. (2016) that the default GFSI weights were not a reflection of the relative importance of its indicators.

Table 5.12 Results of paired t-test for the PCA and GFSI weights for the NRR component of the GFSI

Weight	Observation	Mean	Standard error	Standard deviation	95% confidence interval	
					Lower bound	Upper bound
PCA weight	28	0.208	0.029	0.153	0.148	0.267
GFSI weight	28	1.991	0.172	0.912	1.638	2.345
Difference		-1.784	0.179	0.950	-2.152	-1.415

t-value = -9.938 and *p*-value = 0.000 at 95% confidence level

Source: Author's calculations, using Stata 15 statistical software.

A weighted arithmetic average of the NRR components' score values with their PCA weights produced the NRR scores and rank of countries, as presented in Annexure B. When looking at the top twenty countries based on the GFSI model, 19 out of 20 countries changed their NRR rank with the use of the PCA model. However, these top twenty countries retained their cohort at the exception of five countries, namely Sweden, Austria, Poland, Germany and France (Figure 5.1). A cohort as used in this section referred to a group of twenty countries with the highest or lowest NRR rank (Position 1-20 or position 94-113). The five countries (Sweden, Austria, Poland, Germany and France) were displaced to other ranks outside the cohort. For example, Sweden moved from position six to 33, whereas France was displaced from position 19 to 27.

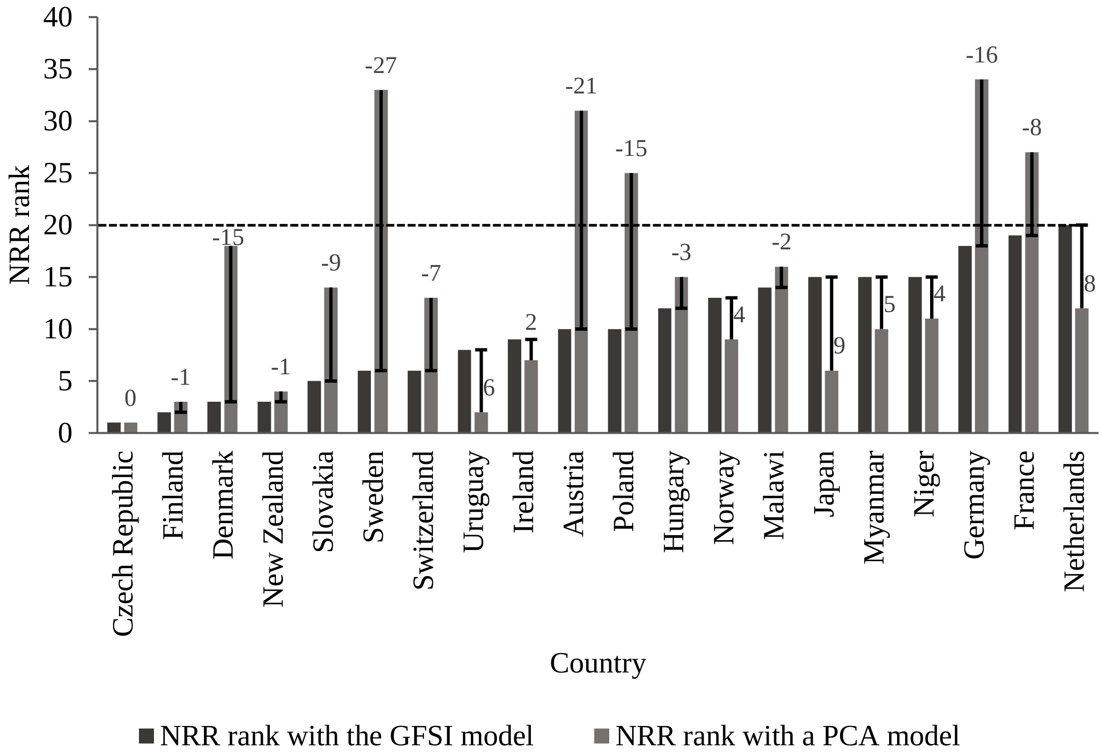

Figure 5.1: Comparison of the NRR ranks of the top twenty countries (rank 1-20) based on the GFSI and PCA models

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

The bottom twenty countries (position 94-113) also experienced changes in their NRR rank. Most of the bottom twenty countries kept their cohort except for Vietnam, Sri Lanka, Nepal, India and Peru that increased their rank when the PCA weighting model was used (Figure 5.2). For example, while Vietnam increased its rank from position 94 to 83, Peru improved from 102 to 69. These observations were similar to the findings of Chen et al. (2019) and Izraelov and Silber (2019), who observed that the top and bottom twenty countries remained in their cohort no matter the weighting model used.

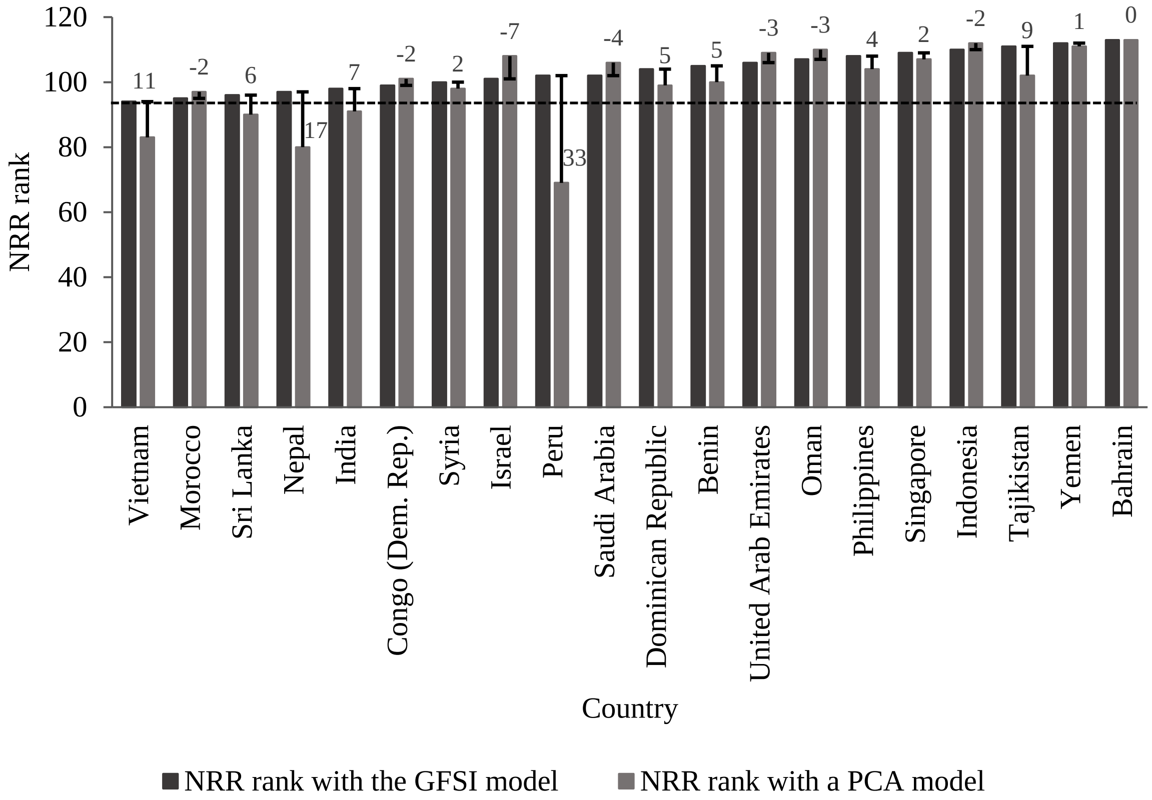

Figure 5.2: Comparison of the NRR ranks of the bottom twenty countries (rank 94-113) based on the GFSI and PCA models

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

The Czech Republic remained in position one after the PCA model was used, just as Maricic et al. (2016) observed that the United States retained position one, no matter the weighting model used. Ukraine was assigned position 53 (score 57.0) with the GFSI weighting model but position five (score 72.1) with the PCA model. The NRR score for Ukraine improved by 15.1 points as a result of its high score on the *sensitivity* (99.3) and *demographic stresses* (94.0) components. The PCA weighting model had assigned high weights (compared to the GFSI weights) to the *sensitivity* (32.56%) and *demographic stresses* (9.56%) components on which Ukraine performed best. The results suggested that Ukraine's food policymakers should base their strategies on sensitivity to natural resource risks and stresses from demographic factors.

Ecuador advanced the most, moving 68 places (from rank 91 to 23) by improving its score from 48.4 to 60.1 with the PCA weighting. This increment was due to the high performance of Ecuador on the *land* (76.0) and *demographic stresses* (56.8) components which had higher PCA weights compared to the GFSI weights. The NRR score for South Africa increased from 50.4 to 60.6, making it the next improved country by 61 places (from position 82 to 21) after Ecuador. As with Ecuador, South Africa had high achievements on the *land* (PCA model =

74.0, GFSI model = 43.8) and *demographic stresses* (PCA model = 57.5, GFSI model = 55.9) components. In contrast, Honduras significantly dropped by 35 places from position 39 to 74. This decline resulted from the poor performance of Honduras on the *sensitivity* (from 50.0 to 13.7) component. The *sensitivity* component was assigned a higher PCA weight (32.56%) relative to the GFSI weight (10.91%), thereby playing a significant role in the determination of countries' NRR scores. A higher weight meant that countries needed to devote more effort to improving the associated indicator and obtain a higher NRR score (Chen et al., 2019).

The PCA weighting model changed the NRR scores for 112 out of 113 (99.12%) countries, where 21 countries changed their score by more than ±10.0. In addition, 109 out of 113 (6.46%) countries shifted their positions with 52 of them changing their rank by more than ten places. Generally, the rank of countries changed slightly with the objective weighting (PCA) model. The observed rank changes corroborated with the findings of Chen et al. (2019) and Maricic et al. (2016), who also noted slight shifts in countries positions with objective weighting models.

A paired t-test was applied to determine whether there was a statistically significant difference between the countries' NRR scores derived with PCA and GFSI weighting models (Table 5.13). Results showed that the countries' NRR scores were lower for the PCA model (mean = 52.177 ± 10.255) relative to the GFSI model (mean = 57.135 ± 9.176). A statistically significant decrease in the NRR scores by 4.958 (95% confidence level) points and *p*-value less than 0.05 ($p < 0.05$) were observed. On average, the weights assigned to the NRR component of the GFSI by the EIU expert panel (GFSI model) were higher compared to the PCA model. These high GFSI weights were reflected on the higher NRR scores for countries. The decrease in the NRR scores that were obtained using the PCA model indicated that the amount of the weight assigned to the NRR indicators significantly determined the countries' NRR scores. Therefore, the postulated hypothesis that objective weighting significantly changed the countries' NRR scores compared to the subjective weighting of the NRR component of the GFSI was accepted.

Table 5.13 Results of paired t-test for the NRR scores of countries based on the PCA and GFSI weighting models for 2019

Score	Observation	Mean	Standard error	Standard deviation	95% confidence interval	
					Lower bound	Upper bound
PCA score	113	52.177	0.967	10.255	50.260	54.094
GFSI score	113	57.135	0.863	9.176	55.425	58.846
Difference		-4.958	0.548	5.823	-6.044	-3.873

t-value = -9.051 and *p*-value = 0.000 at 95% confidence level.

Source: Author's calculations, using Stata 15 statistical software.

A Spearman's rank correlation test was used to determine whether the country ranks obtained using PCA and GFSI weighting models were significantly different. In Table 5.14, results showed a statistically significant rank correlation coefficient (rho = 0.831 at five per cent significance level) associated with a *p*-value less than 0.05 ($p < 0.05$). The high Spearman's rank correlation coefficient suggested that the NRR ranks based on the GFSI and PCA models were strongly correlated (closely related). An objective (PCA) weighting changed the country ranks, but the changes were not significant. The stated null hypothesis that an objective weighting significantly changed the countries' NRR ranks compared to the subjective weighting of the NRR component of the GFSI was rejected. This finding suggested that the application of subjective (GFSI model) or objective (PCA model) weighting approaches would provide similar NRR ranks. These findings were in concurrence with the observations made by Chen et al. (2019), and Izraelov and Silber (2019), who noted that objective and subjective weighting models gave similar ranks. However, for international comparisons, the use of the objective weighting model appeared more useful in attracting the countries' confidence in the GFSI reports.

Table 5.14 Results of Spearman's rank correlation test for the NRR component rank of countries based on the PCA and GFSI weighting models for 2019

	GFSI rank	**PCA rank**
GFSI rank	1.000	
PCA rank	0.831*	1.000
P-value	0.000	

* Significant at the five per cent level, n = 113 countries.

Source: Author's calculations, using Stata 15 statistical software.

Results for the first specific research question showed that the PCA weights assigned to the NRR component of the GFSI were significantly lower than those from the GFSI model. On average, these PCA (objective) weights yielded NRR scores that were lower than those derived using the GFSI (subjective) weights. Conversely, the NRR ranks obtained using the mentioned two separate weights were closely related. Therefore, the hypothesis that objective weighting significantly changed the countries' NRR scores and ranks compared to the subjective weighting of the NRR component of the GFSI was accepted but not in totality. The partial acceptance of the stated hypothesis was due to the similar NRR ranks but different NRR scores for countries derived using GFSI and PCA weighting models. This decision implied that while the PCA model significantly changed the NRR weights and scores but not its ranks, the EIU expert panel ranks appeared reasonable. However, the PCA weighting model, which relied on a statistical scheme, could provide the NRR weights, scores and ranks free of subjectivity.

5.5 Results of the objective versus subjective NRR adjustment of the overall GFSI scores and ranks

The second specific research question addressed whether the objective NRR adjustment significantly changed the countries' adjusted overall GFSI scores and ranks compared to the subjective NRR adjustment of the overall GFSI. The NRR scores derived using the PCA weights were used to adjust the overall GFSI scores and ranks objectively. As shown in Annexure C, several differences emerged among the countries' adjusted overall GFSI scores and ranks obtained with the objective and subjective NRR adjustments. The GFSI model had awarded the adjusted overall GFSI scores ranging between 70.5-77.9 to the top twenty countries. These countries portrayed the highest levels of economic development, including overall food security performance. Seventeen out of twenty countries changed their adjusted overall GFSI rank when the PCA model was applied. The top twenty countries also retained their adjusted overall GFSI rank cohort (position 1-20) except Portugal, which moved to position 21 (Figure 5.3). These countries' adjusted overall GFSI scores decreased from a range of 70.5-77.9 to 68.7-77.7 due to a decline in their objectively weighted NRR scores.

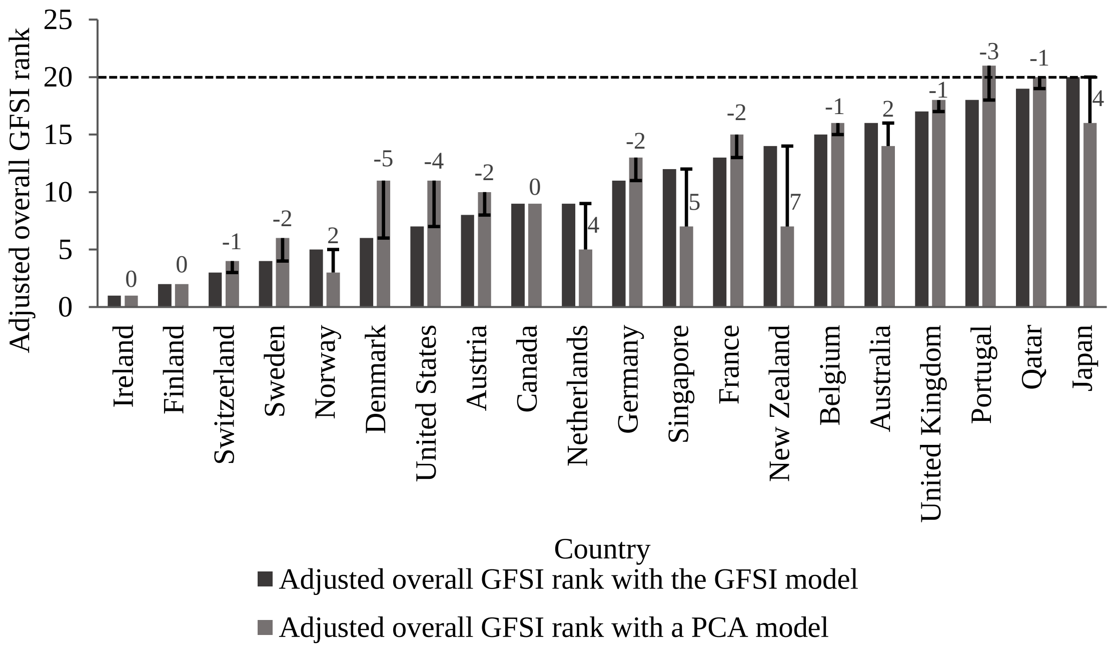

Figure 5.3: Comparison of the adjusted overall GFSI ranks of the top twenty countries (rank 1-20) based on the GFSI and PCA models

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

According to the GFSI model, the bottom twenty countries with the lowest adjusted overall GFSI scores had the lowest overall GFSI scores. These countries, mostly African countries except Tajikistan, Haiti, Syria, Yemen and Venezuela, retained their adjusted overall GFSI rank cohort (rank 94-113) when PCA model was applied (Figure 5.4). Considering that these bottom twenty countries are less developed economically, the choice of the NRR adjustment did not substantially influence their adjusted overall GFSI scores and ranks.

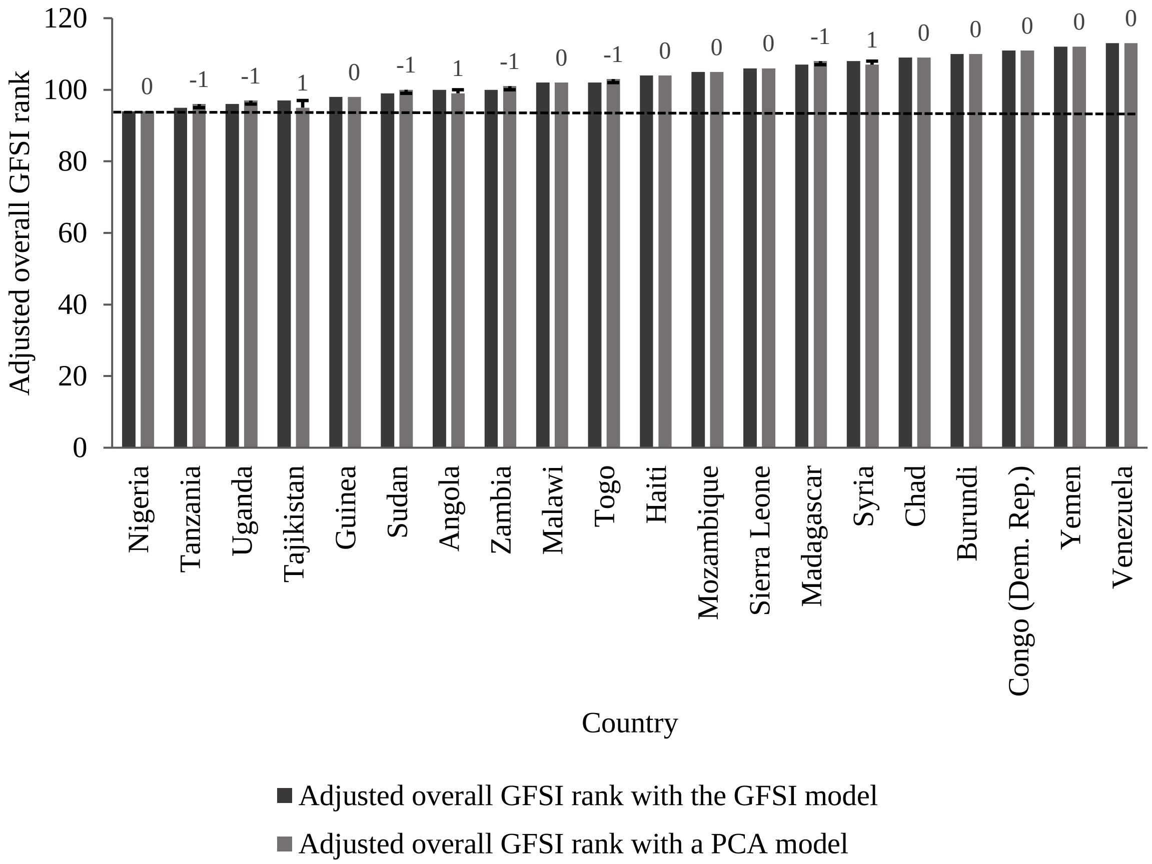

Figure 5.4: Comparison of the adjusted overall GFSI ranks of the bottom twenty countries (rank 94-113) based on the GFSI and PCA models

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

The EIU expert panel had assigned an overall GFSI score of 87.4 and position one to Singapore. However, with the subjective NRR adjustment of the countries' overall GFSI scores, Singapore moved from position one (overall GFSI rank) to position 12 (adjusted overall GFSI rank). Conversely, the objective NRR adjustment of the overall GFSI scores for countries improved the rank of Singapore by five places from position 12 to seven. Despite the use of objectively weighted NRR scores, Ireland and Finland retained their first and second positions respectively for the adjusted overall GFSI. Ireland and Finland maintained their rank due to their high overall GFSI scores (84.0 and 82.9) and NRR scores (70.2 and 74.5).

The subjective adjusted overall GFSI rank of Mexico was position 46, but its rank improved to position 37 with the objective NRR adjustment of the GFSI scores. Mexico's high objectively weighted NRR score (59.7) led to an increase in its adjusted overall GFSI score by 1.5 points and rank by nine places. Ukraine was the most improved country from position 77 to 63, while both Russia and Honduras significantly dropped their rank by six places. The adjusted overall GFSI rank of Ukraine improved by 2.1 points due to its high NRR score (72.1 compared to 57.1). Russia had a relatively high score (69.7) for the overall GFSI, but an 8.8 points drop in its NRR score resulted in a decline in its adjusted overall GFSI score from 63.6 to 62.1.

The use of objectively weighted NRR scores to adjust the overall GFSI scores amplified the role of indicators' weights in understanding the countries' food security context. The observations made hitherto showed that weighting models determined the outcome of the NRR scores, which in turn influenced the results of the adjusted overall GFSI scores. For example, the PCA results for the NRR indicators revealed five primary drivers of the NRR component of the GFSI. These critical NRR indicators included *disaster risk management*, *food import dependency*, *grassland*, *agricultural water risk – quantity*, and *forest change* in that order. Countries required higher performance for these mentioned NRR indicators to achieve higher NRR scores and ranks, including adjusted overall GFSI scores and ranks.

The objective NRR adjustment of the overall GFSI scores changed the adjusted overall GFSI scores of 111 out of 113 (98.23%) countries. However, most of these changes in scores were minor, and only twelve countries had a 2.0 to 3.0 change in their adjusted overall GFSI score. These slight changes in the countries' adjusted overall GFSI scores were not surprising as their overall GFSI scores were not derived objectively with the PCA weighting model. Also, 88 out of 113 (77.88%) countries shifted their adjusted overall GFSI rank, and only eight countries changed positions by more than five places.

A paired t-test was conducted to determine whether there was a statistically significant difference between countries' adjusted overall GFSI scores obtained with the objective and subjective NRR adjustment of the overall GFSI scores. Results in Table 5.15 showed a lower objective adjusted overall GFSI scores (mean = 52.496 ± 12.912) compared to the subjective adjusted overall GFSI scores (mean = 56.258 ± 13.008). Further observations showed a statistically significant decrease in the countries' adjusted overall GFSI scores by 0.761 (95% confidence level) points and *p*-value less than 0.05 ($p < 0.05$). This mean difference was due to the countries' objectively weighted NRR scores which produced a lower adjusted overall GFSI scores compared to the subjective weighted NRR scores. Therefore, the hypothesis that the objective NRR adjustment of the overall GFSI scores significantly changed the countries' adjusted overall GFSI scores compared to the subjective NRR adjustment was accepted. This decision implied that objectively weighted NRR scores, free of subjective criticisms could offer an alternative approach to understanding global food security development and improvement.

Table 5.15 Results of paired t-test for the adjusted overall GFSI scores of countries based on the PCA and GFSI models for 2019

Score	Observation	Mean	Standard error	Standard deviation	95% confidence interval	
					Lower bound	Upper bound
PCA score	113	55.496	1.215	12.912	53.090	57.903
GFSI score	113	56.258	1.224	13.008	53.833	58.682
Difference		-0.761	0.092	0.974	-0.943	-0.580

t-value = -8.309 and *p*-value = 0.000 at 95% confidence level.

Source: Author's calculations, using Stata 15 statistical software.

A Spearman's rank correlation test was applied to determine whether the countries' adjusted overall GFSI ranks obtained by the objective and subjective NRR adjustment of the overall GFSI ranks were significantly different. Results in Table 5.16 showed a statistically significant rank correlation coefficient (rho = 0.995 at five per cent significance level) with a *p*-value less than 0.05 ($p < 0.05$). This Spearman's rank correlation coefficient (0.995) was close to 1.0, signifying that the two separate ranks were closely related. The objective NRR adjustment of the overall GFSI ranks changed the countries' adjusted overall GFSI ranks, but the changes were minor. That was to say, although the countries' objectively weighted NRR scores produced lower adjusted overall GFSI scores than those from the EIU, their ranks were not significantly different. Therefore, the null hypothesis that objective NRR adjustment of the overall GFSI scores significantly changed the countries' adjusted overall GFSI ranks compared to the subjective NRR adjustment was rejected.

The rejection of the stated null hypothesis based on the similarity of the objective and subjective adjusted overall GFSI ranks implied the need to improve the GFSI model. This improvement could be achieved by applying a PCA weighting model to minimise the degree of subjectivity of the GFSI weighting model in a global food security benchmarking process. The objectively weighted NRR scores could provide the end-users (policymakers and countries) of the GFSI reports with an unquestionable adjusted food security status of countries.

Table 5.16 Results of Spearman's rank correlation test for the adjusted overall GFSI rank of countries based on the PCA and GFSI models for 2019

	GFSI rank	**PCA rank**
GFSI rank	1.000	
PCA rank	0.995*	1.000
P-value	0.000	

* Significant at the five per cent level, n = 113 countries.

Source: Author's calculations, using Stata 15 statistical software.

The results for the second specific research question showed that the objective adjusted overall GFSI scores were on average lower than the subjective adjusted overall GFSI scores. However, both the subjectively and objectively weighted NRR scores produced similar adjusted overall GFSI ranks. The hypothesis that the objective NRR adjustment of the overall GFSI scores significantly changed the countries' adjusted overall GFSI scores and rank compared to the subjective NRR adjustment was partially accepted. The partial acceptance of the postulated hypothesis was due to the similar adjusted overall GFSI ranks, but different scores for countries obtained using GFSI and PCA weighted NRR scores. This decision implied that the GFSI ranks were plausible, but the use of a PCA weighting model could provide an unbiased measure of countries' food security situation for international comparisons.

Chapter 6: Conclusions and recommendations

The purpose of this study was to explore how an objective weighting of the NRR component of the GFSI affected the scores and rank of countries. The study accomplished this purpose by addressing two specific research questions. Firstly, the study determined whether an objective weighting significantly changed the countries' NRR scores and ranks compared to the subjective weighting of the NRR component of the GFSI. Secondly, the study addressed whether the objective NRR adjustment significantly changed the countries' adjusted overall GFSI scores and ranks compared to the subjective NRR adjustment of the overall GFSI.

This study tested two hypotheses:

i. The objective weighting significantly changed the countries' NRR scores and ranks compared to the subjective weighting of the NRR component of the GFSI.
ii. The objective NRR adjustment of the overall GFSI significantly changed the countries' adjusted overall GFSI scores and ranks compared to the subjective NRR adjustment.

The stated hypothesis that the objective weighting significantly changed the weights for the NRR component of the GFSI was accepted. On average, the objective weights derived using the PCA model were significantly lower compared to the subjective (GFSI model) weights assigned by the EIU. The different sets of NRR weights led to significant effects on the countries' NRR scores. The PCA (objective) weights produced the NRR scores for countries that were on average lower than the scores derived using the GFSI (subjective) weights. The stated hypothesis that the objective weighting significantly changed the countries' NRR scores compared to the subjective weighting of the NRR component of the GFSI was accepted. The change in the NRR scores was due to the poor performance (low scores) of various countries on the NRR indicators on which the PCA model assigned high weights compared to the GFSI model.

However, the findings indicated a high correlation between the objectively and subjectively weighted NRR ranks. Therefore, the null hypothesis that the objective weighting significantly changed the countries' NRR ranks compared to the subjective weighting of the NRR component of the GFSI was rejected.

On average, the objectively weighted adjusted overall GFSI scores were lower than the subjectively weighted scores due to the lower objective (PCA) weight. Thus, the hypothesis that the objective NRR adjustment of the overall GFSI significantly changed the countries' adjusted overall GFSI scores and rank compared to the subjective NRR adjustment was accepted. Further results indicated that the subjectively weighted adjusted overall GFSI ranks of countries were closely related to the objectively weighted ranks. For this reason, the postulated null hypothesis that the objective NRR adjustment of the overall GFSI significantly changed the countries' adjusted overall GFSI ranks compared to the subjective NRR adjustment was rejected.

Finally, the results of this study corroborated with the findings of Chen et al. (2019), who used the Hierarchical Data Envelopment analysis (H-DEA) model on the 2014 GFSI data an concluded that the GFSI weighting model was less biased than the H-DEA model. The results of the current study also concurred with the findings of Izraelov and Silber (2019), who used Data Envelopment Analysis (DEA), Principal Component Analysis (PCA) and Lower Convex Hull (LCH) on the 2015 GFSI and concluded that the GFSI weights selected by the EIU panel of experts were not biased. However, the results for this study did not concur with the findings of Maricic et al. (2016), who applied the Composite I-Distance Indicator (CIDI) model and the 2015 GFSI data and asserted that the GFSI weighting model provided biased results.

6.1 Conclusions

Although the objective and subjective weighting of the NRR component of the GFSI provided different importance levels to the indicators, the interpretation of the influence of weights on the NRR scores was the same. A high weight assigned to an indicator may indicate a higher level of importance of the indicator in a composite index. An indicator with a high importance level implies that the indicator has a greater influence on the overall score of the composite index. For example, the objective (PCA) weighting model provided the highest importance level (weight) to the NRR's *sensitivity* component. Countries that had a high score in the *sensitivity* component had a higher chance of a more favourable NRR score. By contrast, the objective (PCA) weighting model assigned the highest level of importance (weight) to the NRR's *exposure* component. As with the *sensitivity* component, countries that had a high score in the *exposure* component had a better chance of a more favourable NRR score. Therefore, the interpretation of the influence of objective and subjective weights on the NRR scores was the same. This conclusion implied that the subjective weighting of the NRR component of the GFSI may still be worthwhile pursuing as it provided less biased weights.

The study concluded that the NRR ranks and the adjusted overall GFSI rank of countries would change slightly if an objective weighting technique was applied to the NRR component of the GFSI. The change in rank of countries may urge the governments to take measures that would improve their position. However, the subjectively (GFSI model) and objectively (PCA model) weighted NRR ranks were highly correlated, indicating that the subjectively weighted GFSI model was not strongly statistically biased. The findings implied that the subjective weighting of the NRR component of the GFSI may still provide relatively fair country scores and ranks for comparison purposes.

The policy implications of this study were that the application of a particular weighting process for indicators may alter the food security and climate-related performance scores and ranks of countries. Both national food security and climate-related performance scores are politically sensitive for governments. Both are essential for incentivising progress towards global targets. Also, the policymakers are seeking a working guide to improving their targeting and monitoring efforts for food security. While the GFSI methodology and data are both published and available for scrutiny, the subjective assessment of sensitive indicators may negate trust among governments and policymakers in the dimensions and overall score and ranks. An objective weighting of the NRR component could overcome the subjectivity of EIU's weighting approach, improving the reliability of the NRR component of the GFSI and building greater trust. Governments may then confidently understand their food security implications, including the need for improvements.

Finally, while the results of this study corroborated with the findings of Chen et al. (2019) and Izraelov and Silber (2019), who concluded that the GFSI weights selected by the EIU panel of experts were not biased for earlier data sets, the results did not concur with the findings of Maricic et al. (2016), who asserted that the GFSI weighting model provided biased results for the other dimensions of the GFSI.

6.2 Recommendations

There is a need for the developers of the GFSI to apply an objective weighting model to boost the confidence of governments and policymakers in the GFSI results. The use of actual data to derive the indicator weights, scores and ranks of countries may motivate governments to invest in data collection, management and publication for access by the EIU experts.

6.3 The contribution of the study to global knowledge

This research has provided an evidence-based understanding of the objective weighting scheme's influence on NRR weights, scores, and ranks. No study of this nature has been published since the inclusion of the NRR component of the GFSI in 2017. The EIU panel of experts may use the findings of this study as a guide to improving the design of the efforts for food security. The results of this study revealed that there was a high correlation between the subjectively and objectively weighted NRR ranks, indicating that the GFSI results were not statistically biased. However, the research's empirical evidence may help boost governments' confidence in the annual GFSI results.

6.4 Recommendations for improvement of the study

The objective weighting of indicators could have included the other three components of the GFSI (the affordability, availability and quality and safety components) instead of only the NRR component. Consequently, governments and policymakers will clearly understand the implications for food security improvement and development. That is to say, the objective and subjective weights for the GFSI components may provide a comparative importance level of indicators and help identify what areas need intervention for food security improvement.

The use of only one methodological weighting approach, principal component analysis, may have narrowed the scope of objective weighting. An application of more objective weighting models will broaden the comparison of methods across a subjective to objective spectrum. The wide range of objective weighting processes will also ensure that one weighting scheme's limitation is complemented by the other for improved comparative results.

6.5 Recommendations for further research

Similar research could be conducted across income levels and regional groups to compare and identify where significant improvements in natural resources management are most needed. For example, a researcher may draw comparative analyses along high-income versus low-income countries or sub-Saharan African versus European countries. These analyses will assist in developing a country to regional level top policy priorities concerning natural resources, resilience and food security.

Finally, additional research was recommended to compare the indicators of the NRR component of the GFSI with the indicators of other indices. For example, a study may compare the ranking of countries by the NRR component of the GFSI and the Environmental Sustainability Index (Saisana et al., 2005). This comparison will help determine the sensitivity of the country ranks to the list of indicators selected.

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Annexure A: Indicators of the NRR component of the GFSI in the 2019 GFSI report

Indicator		Primary source(s)	Year	Indicator definitions and construction	Indicator rationale
4.1	Exposure	EIU scoring	-	A composite indicator that measures exposure to and management of the impacts of climate change. Subindicators include: • Temperature rise • Drought • Flooding • Storm severity (AAL) • Sea level rise • Commitment to managing exposure	
4.1.1	Temperature rise	ND-GAIN	2017	A measure of projected temperature rise based on a linear transformation of data values (0 = least vulnerable) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value scores 0.	Temperature rise affects agricultural production, both in terms of types of crops able to be grown in the area and the quantity produced.
4.1.2	Drought	World Resources Institute (WRI) Aqueduct	2014	A measure of historic susceptibility of drought based on a linear transformation of data values (0-5, where 5 = most risk) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value scores 0	Susceptibility to drought can lead to unpredictable crop loss and declines in food supply in certain years.
4.1.3	Flooding	ND-GAIN	2017	A measure of projected susceptibility to flooding based on a linear transformation of data values (0 =least vulnerable) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value scores 0.	Susceptibility to flooding can lead to unpredictable crop loss and declines in food supply in certain years.
4.1.4	Storm severity (AAL)	Global Assessment Report on Disaster Risk Reduction	2015	A measure of historical susceptibility to damage from storms (aside from flooding). Measured as annual average loss (AAL) from earthquakes, wind, storm surge and tsunamis. Linear transformation of data values (US$m) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value scores 0.	Susceptibility to severe storms can lead to unpredictable crop loss and declines in food supply in certain years.
4.1.5	Sea level rise	ND-GAIN	2017	A measure of projected sea level rise. For landlocked countries, an estimate is provided based on the country's major coastal trading partners. Linear transformation of data values (0 = least vulnerable) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value scores 0.	Sea level rise can lead to increased unpredictable crop loss and soil salinity, as well as declines in food supply in certain years.
4.1.6	Commitment to managing exposure	CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)	2016	Assessment of whether countries are committed to addressing agriculture-related climate exposure and natural resource management under the Nationally Determined Contributions (NDC). NDC mitigation measures include croplands, grasslands, forest management, degraded lands, coasts and peatlands. NDC adaptation measures include water management, soil, fisheries and aquaculture, and agroforestry. The high-income countries that do not cover adaptation in their NDCs were given full credit for adaptation measures based on proxy scoring. Qualitative measurement from 0-13: 0 = No commitments 13 = Full commitment	National commitments to addressing exposure-related factors are a sign of political will and investments to mitigate these risks to agriculture.
4.2	Water	EIU scoring	-	A composite indicator that measures the health of fresh-water resources and how depletion might impact agriculture. Subindicators include: • Agricultural water risk – quantity • Agricultural water risk – quality	
4.2.1	Agricultural water risk – quantity	WRI Aqueduct	2014	Assessment of the ratio of total annual water withdrawals to total available annual renewable supply. Data is based on the WRI's agriculture weighting scheme and is an average of baseline water stress, inter-annual variability, seasonal variability, upstream storage and groundwater stress. Linear transformation of data values (0-5, where 5 = highest risk) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value score 0.	Overall water availability may influence agricultural water supply.
4.2.2	Agricultural water risk – quality	WRI Aqueduct	2014	Assessment of the risk that water might be polluted. Data is based on the WRI's agriculture weighting scheme for return flow ratio and upstream protected land. Linear transformation of data values (0-5, where 5 =highest risk) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value score 0.	Water pollution may impact the quality and availability of water for agricultural purposes.
4.3	Land	EIU scoring	-	A composite indicator that measures the health of land, and how land degradation might impact agriculture. Subindicators include: • Land degradation • Grassland • Forest change	
4.3.1	Land degradation	United Nations	2015	Proportion of land that is degraded over total land area.	Land degradation may impact the quality and availability of soil and arable land.
4.3.2	Grassland	FAO	2016	Assessment of greenhouse gas emissions from the drainage of organic soils (e.g. peatlands) under grassland based on a linear transformation of data values (Net emissions / removals of CO_2, gigagrams) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value scores 0.	Grasslands act as carbon sinks that help to maintain organic matter in the soil. Loss of grasslands may impact the quality and availability of soil and arable land.
4.3.3	Forest change	World Bank	2001-16	Assessment of the health of forests based on a linear transformation of data values (change in forest areas as a percentage of total land area) to a fixed range of 0-100. The country with the highest data value scores 100 and the country with the lowest data value scores 0.	Forests help store groundwater and act as carbon sinks, preserving ecosystems. Loss of forests and ecosystems changes may impact agricultural productivity.

Indicator		Primary source(s)	Year	Indicator definitions and construction	Indicator rationale
4.4.3	Marine protected areas	United Nations	2014	Assessment of the percentage of territorial waters that are protected areas. Measures the average proportion of Marine Key Biodiversity Areas (KBAs) covered by protected areas.	Preservation of protected waters helps to maintain marine ecosystems, which preserves fish as a food source while also protecting against overfishing.
4.5	Sensitivity	EIU scoring	-	A composite indicator that measures how susceptible countries are to the depletion of natural resources and agricultural productivity. Subindicators include: • Food import dependency • Dependence on natural capital • Disaster risk management	
4.5.1	Food import dependency	FAO	2017	Assessment of how dependent a country is on cereal imports based on linear transformation of data values (ratio) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value scores 0.	If climate and natural resource risks negatively impact agricultural production, countries that are dependent on imports could become more vulnerable to food shortages as major agricultural producers limit food exports to feed their own populations.
4.5.2	Dependence on natural capital	World Bank	2017	Assessment of how dependent a country is on natural resources for economic output based on linear transformation of data value (sum of forest rents and mineral rents as a percentage of GDP) to a fixed range of 0-100.The country with the lowest data value scores 100 and the country with the highest data value scores 0.	In countries dependent on natural resources, natural resource shortages could impact the economy and affect incomes, making it harder to purchase food.
4.5.3	Disaster risk management	United Nations	2017-18	Assessment of whether countries are co-ordinating their disaster risk management and their adaptation and mitigation measures. For countries not covered by the dataset, the EIU has undertaken qualitative research. Where information is not publicly available, the EIU has not given credit.	Adaptation and mitigation measures help to reduce the impact of natural disasters, which can impact both agricultural productivity and supply through storage, imports and exports.
4.6	Adaptive capacity	EIU scoring	-	A composite indicator that measures the degree to which countries are creating systems and adopting practices to manage the risk that exposure poses to the agricultural sector. Subindicators include: • Early warning measures / climate smart agriculture • National agricultural risk management system	
4.6.1	Early warning measures / climate smart agriculture	CCAFS	2017	Assessment of commitment to developing early-warning measures for the agricultural sector and investing in climate-smart agriculture practices. The high-income countries that do not cover adaptation in their NDCs were given full credit based on proxy scoring. Qualitative measurement from 0-2: 0 = No commitment 2 = High commitment	Commitments to early-warning measures for agriculture can improve country resilience for climate and natural resource risks.
4.6.2	National agricultural risk management system	World Bank Climate Smart Agriculture Indicators	2017	Assessment of a country's commitment to managing risk to the agricultural sector. Underlying metrics include grain stock management, agricultural insurance and agricultural information systems. For countries not covered by the World Bank's Climate Smart Agriculture Indicators, the EIU has undertaken qualitative research. Where information is not publicly available, the EIU has not given credit. Qualitative assessment from 0-6: 0 = No commitment 6 = High commitment	Commitments to risk management practices for agriculture can improve country resilience for climate and natural resource risks.
4.7	Demographic stresses	EIU scoring	-	A composite indicator that measures the degree to which demographic stresses might increase countries' sensitivity to agriculture-related climate exposure and natural resource risk. Subindicators include: • Population growth (2016-21) • Urbanisation (2016-21)	
4.7.1	Population growth (2016-21)	United Nations	2019	Forecast population growth based on linear transformation of data values (population growth percentage, 2016-21) to a fixed range of 0-100. The country with the lowest data value scores100 and the country with the highest data value scores 0.	Rapid population growth increases demand for food, straining food systems.
4.7.2	Urbanisation (2016-21)	United Nations	2019	Forecast urban growth based on linear transformation of data values (urbanisation rate, 2016-21) to a fixed range of 0-100. The country with the lowest data value scores 100 and the country with the highest data value scores 0.	Rapid urbanisation can disrupt food systems, putting strain on production and infrastructure.

Source: EIU (2019).

Annexure B: A comparison of the NRR component scores and ranks of countries based on the PCA and GFSI weighting models for 2019

Country	GFSI model		PCA model		Score difference	Rank difference
	Score	Rank	Score	Rank		
Czech Republic	75.5	1	80.0	1	4.5	0
Finland	74.0	2	74.5	3	0.5	-1
Denmark	73.9	3	61.4	18	-12.5	-15
New Zealand	73.9	3	74.4	4	0.5	-1
Slovakia	73.1	5	64.7	14	-8.4	-9
Sweden	72.1	6	58.3	33	-13.8	-27
Switzerland	72.1	6	67.2	13	-4.9	-7
Uruguay	71.6	8	76.1	2	4.5	6
Ireland	71.0	9	70.2	7	-0.8	2
Austria	69.6	10	58.7	31	-10.9	-21
Poland	69.6	10	60.0	25	-9.6	-15
Hungary	69.5	12	63.9	15	-5.6	-3
Norway	69.0	13	69.7	9	0.7	4
Malawi	68.7	14	63.2	16	-5.5	-2
Japan	68.5	15	70.5	6	2.0	9
Myanmar	68.5	15	69.3	10	0.8	5
Niger	68.5	15	68.6	11	0.1	4
Germany	68.4	18	57.6	34	-10.8	-16
France	68.3	19	59.8	27	-8.5	-8
Netherlands	67.4	20	67.8	12	0.4	8
Cote d'Ivoire	67.1	21	54.2	44	-12.9	-23
Spain	66.3	22	54.6	43	-11.7	-21
Romania	66.2	23	58.8	29	-7.4	-6
Bulgaria	65.3	24	60.1	23	-5.2	1
Canada	65.3	24	57.1	37	-8.2	-13
Russia	65.1	26	56.3	39	-8.8	-13
Uganda	65.0	27	55.2	41	-9.8	-14
Greece	64.8	28	54.9	42	-9.9	-14
Portugal	64.8	28	52.6	51	-12.2	-23
Italy	64.5	30	53.8	46	-10.7	-16
Burundi	64.2	31	60.8	19	-3.4	12
United Kingdom	63.8	32	53.7	48	-10.1	-16
Belgium	62.9	33	51.6	55	-11.3	-22
Kazakhstan	62.9	33	70.1	8	7.2	25
Burkina Faso	62.6	35	50.7	58	-11.9	-23
Rwanda	62.6	35	53.8	46	-8.8	-11
Serbia	62.2	37	58.5	32	-3.7	5
Laos	62.1	38	53.5	49	-8.6	-11
Honduras	61.5	39	47.0	74	-14.5	-35
United States	61.4	40	49.7	62	-11.7	-22
Venezuela	61.2	41	51.3	57	-9.9	-16
Mali	61.0	42	51.5	56	-9.5	-14
Zambia	61.0	42	48.8	64	-12.2	-22

Country	GFSI model		PCA model		Score difference	Rank difference
	Score	Rank	Score	Rank		
Chile	60.1	44	58.8	29	-1.3	15
Turkey	60.0	45	50.0	61	-10.0	-16
Thailand	59.0	46	57.4	35	-1.6	11
Egypt	58.9	47	54.1	45	-4.8	2
Costa Rica	58.5	48	62.2	17	3.7	31
Botswana	58.3	49	52.3	52	-6.0	-3
Paraguay	58.3	49	52.8	50	-5.5	-1
Tanzania	57.7	51	48.6	66	-9.1	-15
Nicaragua	57.5	52	47.3	71	-10.2	-19
Pakistan	57.0	53	47.3	71	-9.7	-18
Ukraine	57.0	53	72.1	5	15.1	48
Uzbekistan	57.0	53	48.8	64	-8.2	-11
El Salvador	56.9	56	46.9	75	-10.0	-19
Colombia	56.4	57	60.6	21	4.2	36
Madagascar	56.3	58	45.3	81	-11.0	-23
Belarus	56.0	59	52.0	53	-4.0	6
Togo	56.0	59	47.3	71	-8.7	-12
South Korea	55.8	61	60.8	19	5.0	42
Bolivia	55.6	62	49.7	62	-5.9	0
Brazil	55.6	62	50.2	60	-5.4	2
Argentina	55.5	64	51.8	54	-3.7	10
Australia	55.5	64	57.1	37	1.6	27
Nigeria	55.2	66	48.3	67	-6.9	-1
Senegal	55.0	67	46.6	76	-8.4	-9
Jordan	54.9	68	46.2	79	-8.7	-11
China	54.5	69	47.4	69	-7.1	0
Cambodia	53.3	70	44.7	84	-8.6	-14
Haiti	53.2	71	43.9	88	-9.3	-17
Ghana	53.0	72	46.5	77	-6.5	-5
Chad	52.9	73	47.6	68	-5.3	5
Malaysia	52.8	74	60.0	25	7.2	49
Angola	52.1	75	50.3	59	-1.8	16
Sudan	52.1	75	44.0	87	-8.1	-12
Cameroon	52.0	77	45.0	82	-7.0	-5
Kuwait	51.5	78	57.3	36	5.8	42
Ethiopia	51.2	79	46.3	78	-4.9	1
Mexico	50.8	80	59.7	28	8.9	52
Kenya	50.6	81	44.6	85	-6.0	-4
South Africa	50.4	82	60.6	21	10.2	61
Bangladesh	50.2	83	44.4	86	-5.8	-3
Sierra Leone	50.2	83	42.9	91	-7.3	-8
Azerbaijan	49.9	85	43.9	88	-6.0	-3
Guatemala	49.7	86	42.3	95	-7.4	-9
Tunisia	49.5	87	42.5	94	-7.0	-7
Mozambique	49.0	88	55.6	40	6.6	48
Panama	49.0	88	42.7	93	-6.3	-5

Country	GFSI model		PCA model		Score difference	Rank difference
	Score	Rank	Score	Rank		
Qatar	48.7	90	38.3	105	-10.4	-15
Ecuador	48.4	91	60.1	23	11.7	68
Algeria	48.3	92	40.3	103	-8.0	-11
Guinea	48.3	92	41.7	96	-6.6	-4
Vietnam	48.2	94	44.9	83	-3.3	11
Morocco	47.9	95	41.6	97	-6.3	-2
Sri Lanka	47.7	96	43.5	90	-4.2	6
Nepal	47.5	97	45.9	80	-1.6	17
India	46.7	98	42.9	91	-3.8	7
Congo (Dem. Rep.)	45.4	99	40.6	101	-4.8	-2
Syria	45.2	100	41.5	98	-3.7	2
Israel	44.8	101	37.5	108	-7.3	-7
Peru	44.4	102	47.4	69	3.0	33
Saudi Arabia	44.4	102	38.2	106	-6.2	-4
Dominican Republic	44.2	104	40.9	99	-3.3	5
Benin	44.1	105	40.8	100	-3.3	5
United Arab Emirates	43.9	106	37.3	109	-6.6	-3
Oman	43.8	107	36.0	110	-7.8	-3
Philippines	42.5	108	39.5	104	-3.0	4
Singapore	42.4	109	37.8	107	-4.6	2
Indonesia	40.7	110	32.9	112	-7.8	-2
Tajikistan	40.5	111	40.5	102	0.0	9
Yemen	40.4	112	34.5	111	-5.9	1
Bahrain	39.0	113	30.2	113	-8.8	0

Note: Rank 1 = best, the score ranges 0-100 where 100 = best

Source: Author's calculations and EIU (2019).

Annexure C: Countries' adjusted overall GFSI scores and ranks according to the PCA and GFSI adjustment models for 2019

Country	GFSI model				PCA model			Difference	
	Overall GFSI score	NRR score	Adjusted overall GFSI score	Adjusted overall GFSI rank	NRR score	Adjusted overall GFSI score	Adjusted overall GFSI rank	Score	Rank
Ireland	84.0	71.0	**77.9**	**1**	70.2	**77.7**	**1**	-0.2	0
Finland	82.9	74.0	**77.5**	**2**	74.5	**77.6**	**2**	0.1	0
Switzerland	83.1	72.1	**77.3**	**3**	67.2	**76.3**	**4**	-1.0	-1
Sweden	82.7	72.1	**76.9**	**4**	58.3	**74.1**	**6**	-2.8	-2
Norway	82.9	69.0	**76.5**	**5**	69.7	**76.6**	**3**	0.1	2
Denmark	81.0	73.9	**75.7**	**6**	61.4	**73.2**	**11**	-2.5	-5
United States	83.7	61.4	**75.6**	**7**	49.7	**73.2**	**11**	-2.4	-4
Austria	81.7	69.6	**75.5**	**8**	58.7	**73.3**	**10**	-2.2	-2
Canada	82.4	65.3	**75.3**	**9**	57.1	**73.6**	**9**	-1.7	0
Netherlands	82.0	67.4	**75.3**	**9**	67.8	**75.4**	**5**	0.1	4
Germany	81.5	68.4	**75.1**	**11**	57.6	**72.9**	**13**	-2.2	-2
Singapore	87.4	42.4	**74.8**	**12**	37.8	**73.8**	**7**	-1.0	5
France	80.4	68.3	**74.0**	**13**	59.8	**72.3**	**15**	-1.7	-2
New Zealand	78.8	73.9	**73.7**	**14**	74.4	**73.8**	**7**	0.1	7
Belgium	80.7	62.9	**73.2**	**15**	51.6	**70.9**	**16**	-2.3	-1
Australia	81.4	55.5	**72.3**	**16**	57.1	**72.7**	**14**	0.4	2
United Kingdom	79.1	63.8	**71.9**	**17**	53.7	**69.9**	**18**	-2.0	-1
Portugal	77.8	64.8	**71.0**	**18**	52.6	**68.6**	**21**	-2.4	-3
Qatar	81.2	48.7	**70.8**	**19**	38.3	**68.7**	**20**	-2.1	-1
Japan	76.5	68.5	**70.5**	**20**	70.5	**70.9**	**16**	0.4	4
Poland	75.6	69.6	**69.9**	**21**	60.0	**68.0**	**23**	-1.9	-2
Italy	75.8	64.5	**69.1**	**22**	53.8	**67.0**	**25**	-2.1	-3
Spain	75.5	66.3	**69.1**	**22**	54.6	**66.9**	**26**	-2.2	-4
Czech Republic	73.1	75.5	**68.6**	**24**	80.0	**69.4**	**19**	0.8	5
Israel	79.0	44.8	**68.1**	**25**	37.5	**66.7**	**28**	-1.4	-3
Chile	75.5	60.1	**68.0**	**26**	58.8	**67.7**	**24**	-0.3	2
Uruguay	72.8	71.6	**67.6**	**27**	76.1	**68.5**	**22**	0.9	5
Hungary	72.7	69.5	**67.2**	**28**	63.9	**66.1**	**31**	-1.1	-3
Greece	73.4	64.8	**66.9**	**29**	54.9	**65.1**	**32**	-1.8	-3
United Arab Emirates	76.5	43.9	**65.8**	**30**	37.3	**64.5**	**33**	-1.3	-3
Kuwait	74.8	51.5	**65.7**	**31**	57.3	**66.8**	**27**	1.1	4
South Korea	73.6	55.8	**65.5**	**32**	60.8	**66.4**	**29**	0.9	3
Malaysia	73.8	52.8	**65.1**	**33**	60.0	**66.4**	**29**	1.3	4
Romania	70.2	66.2	**64.3**	**34**	58.8	**63.0**	**35**	-1.3	-1
Slovakia	68.3	73.1	**63.7**	**35**	64.7	**62.3**	**39**	-1.4	-4
Russia	69.7	65.1	**63.6**	**36**	56.3	**62.1**	**42**	-1.5	-6
Saudi Arabia	73.5	44.4	**63.3**	**37**	38.2	**62.1**	**42**	-1.2	-5
Belarus	70.9	56.0	**63.1**	**38**	52.0	**62.4**	**37**	-0.7	1
Argentina	70.8	55.5	**62.9**	**39**	51.8	**62.3**	**39**	-0.6	0

Country	GFSI model				PCA model			Difference	
	Overall GFSI score	**NRR score**	**Adjusted overall GFSI score**	**Adjusted overall GFSI rank**	**NRR score**	**Adjusted overall GFSI score**	**Adjusted overall GFSI rank**	**Score**	**Rank**
China	71.0	54.5	**62.9**	**39**	47.4	**61.7**	**44**	-1.2	-5
Costa Rica	70.1	58.5	**62.8**	**41**	62.2	**63.5**	**34**	0.7	7
Turkey	69.8	60.0	**62.8**	**41**	50.0	**61.1**	**46**	-1.7	-5
Brazil	70.1	55.6	**62.3**	**43**	50.2	**61.4**	**45**	-0.9	-2
Colombia	69.4	56.4	**61.8**	**44**	60.6	**62.6**	**36**	0.8	8
Kazakhstan	67.3	62.9	**61.1**	**45**	70.1	**62.3**	**39**	1.2	6
Mexico	69.4	50.8	**60.9**	**46**	59.7	**62.4**	**37**	1.5	9
Bulgaria	66.2	65.3	**60.5**	**47**	60.1	**59.6**	**48**	-0.9	-1
Panama	68.8	49.0	**60.0**	**48**	42.7	**58.9**	**49**	-1.1	-1
South Africa	67.3	50.4	**59.0**	**49**	60.6	**60.7**	**47**	1.7	2
Oman	68.4	43.8	**58.8**	**50**	36.0	**57.5**	**51**	-1.3	-1
Thailand	65.1	59.0	**58.4**	**51**	57.4	**58.2**	**50**	-0.2	1
Egypt	64.5	58.9	**57.9**	**52**	54.1	**57.1**	**52**	-0.8	0
Botswana	63.8	58.3	**57.1**	**53**	52.3	**56.2**	**54**	-0.9	-1
Serbia	62.8	62.2	**56.9**	**54**	58.5	**56.3**	**53**	-0.6	1
Azerbaijan	64.8	49.9	**56.7**	**55**	43.9	**55.7**	**55**	-1.0	0
Bahrain	66.6	39.0	**56.4**	**56**	30.2	**55.0**	**58**	-1.4	-2
Vietnam	64.6	48.2	**56.2**	**57**	44.9	**55.7**	**55**	-0.5	2
Ghana	62.8	53.0	**55.4**	**58**	46.5	**54.4**	**61**	-1.0	-3
Dominican Republic	64.2	44.2	**55.2**	**59**	40.9	**54.7**	**60**	-0.5	-1
Morocco	62.8	47.9	**54.6**	**60**	41.6	**53.6**	**62**	-1.0	-2
Peru	63.3	44.4	**54.5**	**61**	47.4	**55.0**	**58**	0.5	3
El Salvador	60.7	56.9	**54.2**	**62**	46.9	**52.6**	**65**	-1.6	-3
Jordan	61.0	54.9	**54.1**	**63**	46.2	**52.8**	**64**	-1.3	-1
Ecuador	61.8	48.4	**53.8**	**64**	60.1	**55.6**	**57**	1.8	7
Indonesia	62.6	40.7	**53.3**	**65**	32.9	**52.1**	**68**	-1.2	-3
Guatemala	60.6	49.7	**53.0**	**66**	42.3	**51.9**	**69**	-1.1	-3
Sri Lanka	60.8	47.7	**52.9**	**67**	43.5	**52.2**	**67**	-0.7	0
Uzbekistan	59.0	57.0	**52.7**	**68**	48.8	**51.4**	**72**	-1.3	-4
Myanmar	57.0	68.5	**52.5**	**69**	69.3	**52.6**	**65**	0.1	4
Tunisia	60.1	49.5	**52.5**	**69**	42.5	**51.5**	**71**	-1.0	-2
Honduras	58.0	61.5	**52.4**	**71**	47.0	**50.3**	**77**	-2.1	-6
Philippines	61.0	42.5	**52.2**	**72**	39.5	**51.8**	**70**	-0.4	2
Algeria	59.8	48.3	**52.1**	**73**	40.3	**50.9**	**74**	-1.2	-1
Paraguay	57.9	58.3	**51.9**	**74**	52.8	**51.1**	**73**	-0.8	1
Bolivia	57.7	55.6	**51.3**	**75**	49.7	**50.4**	**76**	-0.9	-1
India	58.9	46.7	**51.1**	**76**	42.9	**50.5**	**75**	-0.6	1
Ukraine	57.1	57.0	**51.0**	**77**	72.1	**53.1**	**63**	2.1	14
Pakistan	56.8	57.0	**50.7**	**78**	47.3	**49.3**	**78**	-1.4	0
Mali	54.4	61.0	**49.1**	**79**	51.5	**47.8**	**80**	-1.3	-1
Nepal	56.4	47.5	**49.0**	**80**	45.9	**48.8**	**79**	-0.2	1
Nicaragua	54.2	57.5	**48.4**	**81**	47.3	**47.1**	**81**	-1.3	0
Senegal	54.3	55.0	**48.2**	**82**	46.6	**47.1**	**81**	-1.1	1

Country	GFSI model				PCA model			Difference	
	Overall GFSI score	NRR score	Adjusted overall GFSI score	Adjusted overall GFSI rank	NRR score	Adjusted overall GFSI score	Adjusted overall GFSI rank	Score	Rank
Cote d'Ivoire	52.3	67.1	**48.0**	**83**	54.2	**46.3**	**83**	-1.7	0
Bangladesh	53.2	50.2	**46.6**	**84**	44.4	**45.8**	**84**	-0.8	0
Niger	49.6	68.5	**45.7**	**85**	68.6	**45.7**	**85**	0.0	0
Burkina Faso	50.1	62.6	**45.4**	**86**	50.7	**43.9**	**86**	-1.5	0
Kenya	50.7	50.6	**44.4**	**87**	44.6	**43.7**	**87**	-0.7	0
Laos	49.1	62.1	**44.4**	**87**	53.5	**43.4**	**89**	-1.0	-2
Benin	51.0	44.1	**43.9**	**89**	40.8	**43.5**	**88**	-0.4	1
Cameroon	49.9	52.0	**43.9**	**89**	45.0	**43.0**	**90**	-0.9	-1
Rwanda	48.2	62.6	**43.7**	**91**	53.8	**42.6**	**91**	-1.1	0
Cambodia	49.4	53.3	**43.6**	**92**	44.7	**42.6**	**91**	-1.0	1
Ethiopia	49.2	51.2	**43.2**	**93**	46.3	**42.6**	**91**	-0.6	2
Nigeria	48.4	55.2	**43.0**	**94**	48.3	**42.1**	**94**	-0.9	0
Tanzania	47.6	57.7	**42.6**	**95**	48.6	**41.5**	**96**	-1.1	-1
Uganda	46.2	65.0	**42.2**	**96**	55.2	**41.0**	**97**	-1.2	-1
Tajikistan	49.0	40.5	**41.7**	**97**	40.5	**41.7**	**95**	0.0	2
Guinea	46.7	48.3	**40.7**	**98**	41.7	**39.9**	**98**	-0.8	0
Sudan	45.7	52.1	**40.2**	**99**	44.0	**39.3**	**100**	-0.9	-1
Angola	45.5	52.1	**40.1**	**100**	50.3	**39.8**	**99**	-0.3	1
Zambia	44.4	61.0	**40.1**	**100**	48.8	**38.7**	**101**	-1.4	-1
Malawi	42.5	68.7	**39.2**	**102**	63.2	**38.6**	**102**	-0.6	0
Togo	44.0	56.0	**39.2**	**102**	47.3	**38.2**	**103**	-1.0	-1
Haiti	43.3	53.2	**38.2**	**104**	43.9	**37.2**	**104**	-1.0	0
Mozambique	41.4	49.0	**36.1**	**105**	55.6	**36.8**	**105**	0.7	0
Sierra Leone	39.0	50.2	**34.1**	**106**	42.9	**33.4**	**106**	-0.7	0
Madagascar	37.9	56.3	**33.8**	**107**	45.3	**32.7**	**108**	-1.1	-1
Syria	38.4	45.2	**33.1**	**108**	41.5	**32.8**	**107**	-0.3	1
Chad	36.9	52.9	**32.6**	**109**	47.6	**32.1**	**109**	-0.5	0
Burundi	34.3	64.2	**31.2**	**110**	60.8	**30.9**	**110**	-0.3	0
Congo (Dem. Rep.)	35.7	45.4	**30.8**	**111**	40.6	**30.4**	**111**	-0.4	0
Yemen	35.6	40.4	**30.3**	**112**	34.5	**29.8**	**112**	-0.5	0
Venezuela	31.2	61.2	**28.2**	**113**	51.3	**27.4**	**113**	-0.8	0

Note: Rank 1 = best, the score ranges 0-100 where 100 = best

Source: Author's calculations and EIU (2019).