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

Valiant O Odhiambo[1], Sheryl L Hendriks[1*] and Eness P Mutsvangwa-Sammie[1]

[1]Department of Agricultural Economics, Extension and Rural Development, University of Pretoria, South Africa.

* Corresponding author: sheryl.hendriks@up.ac.za

Abstract

Composite indicators have gained popularity in various research areas. However, the determination of an appropriate weighting method is challenging. Subjective weighting methods 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. 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 Economist Intelligence Unit's (EIU) panel of experts uses a subjective weighting of indicators in the GFSI model. 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 was analysed using a principal component analysis (PCA) to derive objectively weighted NRR scores and ranks. The objectively and subjectively weighted NRR ranks were strongly correlated (rho = 0.831), implying that the GFSI model was not strongly statistically biased. The study concluded that subjective weighting of the NRR component of the GFSI may still provide relatively fair country scores and ranks. However, an objective weighting of the NRR component could improve the reliability of the NRR component of the GFSI and build greater trust.

Keywords: Economist intelligence unit global food security index; Natural resources and resilience; Adjusted overall global food security index; Principal components analysis; Food security

1 Introduction

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 methods 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).

Paruolo et al. (2013), noted a common assumption in the linear aggregation (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).

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.

The scarcity of natural resources already constrains economic growth and food (Sweileh 2020). The 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). The policymakers seek a working guide to improving their targeting and monitoring efforts for food security. An assessment of climate-related and natural resource risks is important for policymakers to make future decisions (Sweileh 2020). Also, national food security and climate-related performance scores may incentivise the government's progress towards global targets (Santeramo 2015a), such as sustainable food systems. A biased measurement of national food security and climate-related performance may drive misdiagnosis and inappropriate responses (Headey and Ecker 2013). Therefore, an evidence-based understanding of a country's progress in managing natural resource risks may help countries identify the areas that need intervention (Caccavale and Giuffrida 2020).

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 involves 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). 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). Examples of objective weighting methods are principal component analysis, factor analysis, regression analysis and unobserved component analysis (OECD 2008). 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. Examples of subjective weighting methods are the expert/public opinion-based weighting (public opinion, analytic hierarchy process and conjoint analysis) and equal weighting (OECD 2008).

Several studies have assessed the EIU panel of expert's application of weightings. Maricic et al. (2016), scrutinised the 2015 GFSI weighting process by applying the Composite I-Distance Indicator (CIDI) method and concluded that the GFSI was based on reliable data sources like the World Bank but biased weights. 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), concluded that the GFSI and H-DEA weighting schemes gave similar ranks but slightly different weights and scores. For this reason, Chen et al. (2019), suggested that the designers of the GFSI should consider using the H-DEA as it does not rely on experts' opinions. Finally, Izraelov and Silber (2019), applied the Data Envelopment Analysis (DEA), Principal Component Analysis (PCA) and Lower Convex Hull (LCH) methods to assess the 2015 GFSI. Izraelov and Silber (2019), concluded that the GFSI weighting process was not significantly statistically biased as the compared rank of countries were highly correlated. While Maricic et al. (2016) and Chen et al. (2019), recommended the adoption of the CIDI weights and H-DEA weights respectively, Izraelov and Silber (2019), suggested continued use of the GFSI weights.

However, these studies did not conduct tests to evaluate any statistical significant change in the GFSI scores and ranks due to alternative weightings. Also, the NRR component of the GFSI was still new to many researchers. 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. The EIU panel of experts may use the findings of this study as a guide to improving the design of the efforts for global food security. Also, the empirical evidence may help boost governments' confidence in the annual GFSI results.

This paper is organised as follows. Section two describes the methodology used by the GFSI. Section three describes the methods and procedures used in this study. Section four presents the results and discussions. Finally, the fifth section provides conclusions and recommendations.

2 The methodology of the Global Food Security Index

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 food security environment at the national level (EIU 2018). Since 2012, the GFSI has produced annual reports containing the analysis for 113 developing and developed countries (EIU 2019).

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 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 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). The affordability component of the GFSI includes ten indicators. The availability component of the GFSI includes sixteen indicators and 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). 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). 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.

In 2017, the GFSI added a fourth component for the 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 to food security (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 includes 21 indicators within seven components. The NRR indicators measure different information depending on the NRR component within which they are included. 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. For example, 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). 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). The inclusion of the NRR indicators by the EIU expert panel implies that countries should undertake measures to build resilience to climate-related risks and improve food systems. For example, countries should adopt less water-intensive but high yielding crops, agricultural practices and techniques (ICRISAT 2017). 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 Supplementary Table 1.

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 (1):

$$z_i = (x_i - Min(x_i))/(Max(x_i) - Min(x_i)) \quad (1)$$

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 (EIU 2019), are normalised as specified in Equation (2) and the interpretation is the same.

$$z_i = (x_i - Max(x_i))/(Max(x_i) - Min(x_i)) \quad (2)$$

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). The GFSI uses linear aggregation (the weighted arithmetic average) to compute the scores of countries. 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). The GFSI scores for countries are stated on a range of zero to 100, where 100 is the most favourable score. Linear aggregation method is defined as illustrated in Equation (3):

$$y = \sum_{i=1}^{n} w_i z_i \tag{3}$$

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 $0 \leq w_i \leq 1$, for all $i = 1, 2, \ldots, n$ (EIU 2019; OECD 2008).

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).

Since 2017, the overall GFSI scores of 113 countries have been adjusted by the NRR scores as specified in Equation (4):

$$A = x(1-z) + (x\,z(y/100)) \tag{4}$$

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). The overall GFSI score was adjusted downwards based on the NRR score and the selected adjustment factor weighting. The higher the NRR score, the lower the adjustment of the overall GFSI score. A rise in the adjustment factor weighting z from 25% towards 100% would increasingly reduce the overall GFSI score, thereby changing the adjusted overall GFSI scores and ranks (EIU 2019). Considering the 2019 GFSI model, Ireland attained position one and an adjusted overall GFSI score of 77.9 using the 25% adjustment factor. By contrast, Finland attained position one and an adjusted overall GFSI score of 72.1 using the 50% adjustment factor. Therefore, increasing the adjustment factor weighting may raise focus on the long-term sustainability of food systems.

3 Methods and procedures

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. 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.

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 (5):

$$C_j = \sum_{i=1}^{n} r_{ij} z_i \tag{5}$$

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). This study adopted the following four steps recommended by Nardo et al. (2005) and OECD (2008) to derive the weights for the variables objectively.

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 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). The data was considered adequate for a PCA if Bartlett's test of sphericity was significant (*p*-value < 0.05) (Parinet et al. 2004).

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.

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).

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 (6):

$$w_{ij} = \frac{r^2{}_{ij}}{e_j} \tag{6}$$

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 $i = 1, 2, \ldots, n$ (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.

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 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. 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.

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). 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. 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.

4 Results and discussion

The KMO value was 0.682, while Bartlett's test of sphericity was significant (p-value < 0.05)

for the NRR indicators. These results confirmed that the normalised GFSI data set was appropriate for conducting a PCA of the NRR indicators (Parinet et al. 2004).

4.1 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. The NRR weights based on the PCA (objective) and GFSI models showed substantial differences as presented in Supplementary Table 2.

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.

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). When looking at the NRR indicators, 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.

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 Supplementary Table 3, 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.

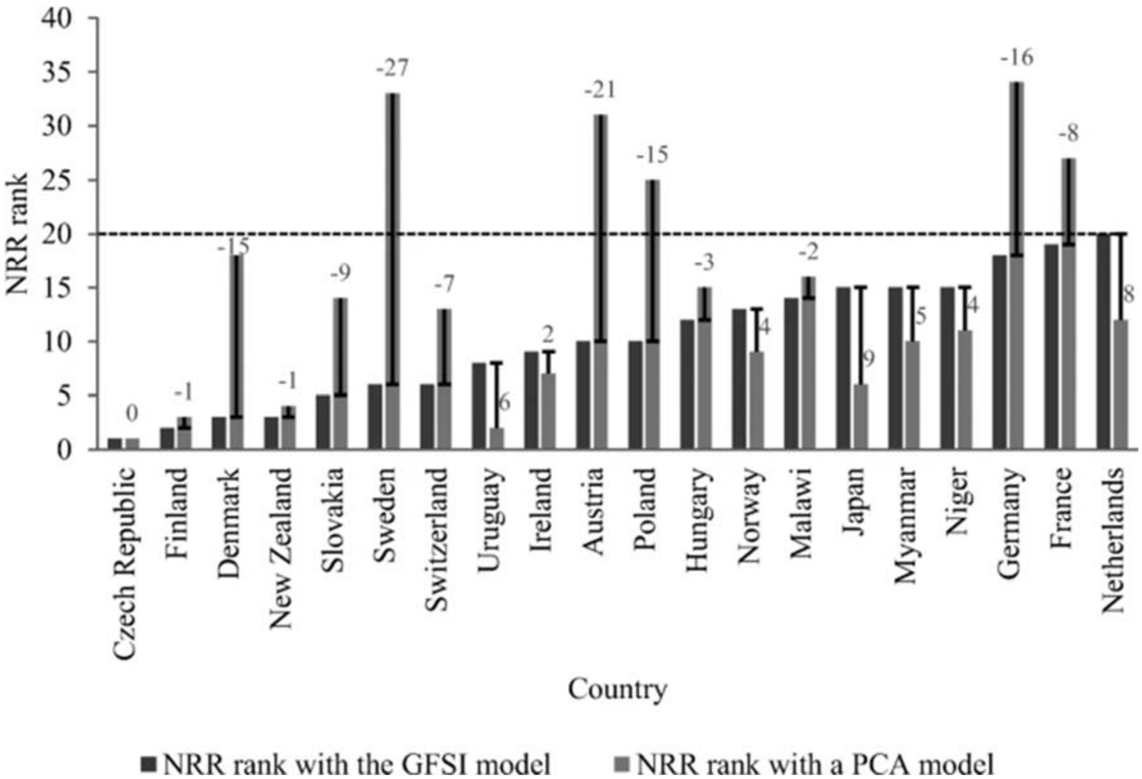

Fig. 1. Comparison of the NRR ranks of the top twenty countries (rank 1–20) based on the subjective GFSI and objective PCA weighting models. *Source: Author's work using GFSI data (EIU,* 2019*)*

A weighted arithmetic average of the NRR components' score values with their PCA weights produced the NRR scores and rank of countries (Supplementary Table 4). 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 (Fig. 1). For example, Sweden moved from position six to 33, whereas France was displaced from position 19 to 27. 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). Malawi and Niger were among the top twenty countries due to high scores for the water, oceans and adaptive capacity components despite the frequent droughts, floods, high rates of deforestation and soil degradation (Enaruvbe and Atafo 2016; McCarthy et al. 2021). Most of the top twenty countries retained their cohort due to their highest levels of economic development and enhanced coordination of climate-related and food security policies (Candel 2016). Notably, countries that had high scores in the NRR components with extensive weights had a higher chance of a more favourable NRR score and rank.

The twenty lowest-ranked countries (position 94-113) also experienced changes in their NRR rank. Most of the lowest-ranked twenty countries kept their cohort positions except for Vietnam, Sri Lanka, Nepal, India and Peru that increased their rank when the PCA weighting model was used (Fig. 2). For example, while Vietnam increased its rank from position 94 to 83, Peru improved from 102 to 69. The bottom twenty countries, mostly African countries except Tajikistan, Haiti, Syria, Yemen and Venezuela, are less developed economically (Candel 2016). 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.

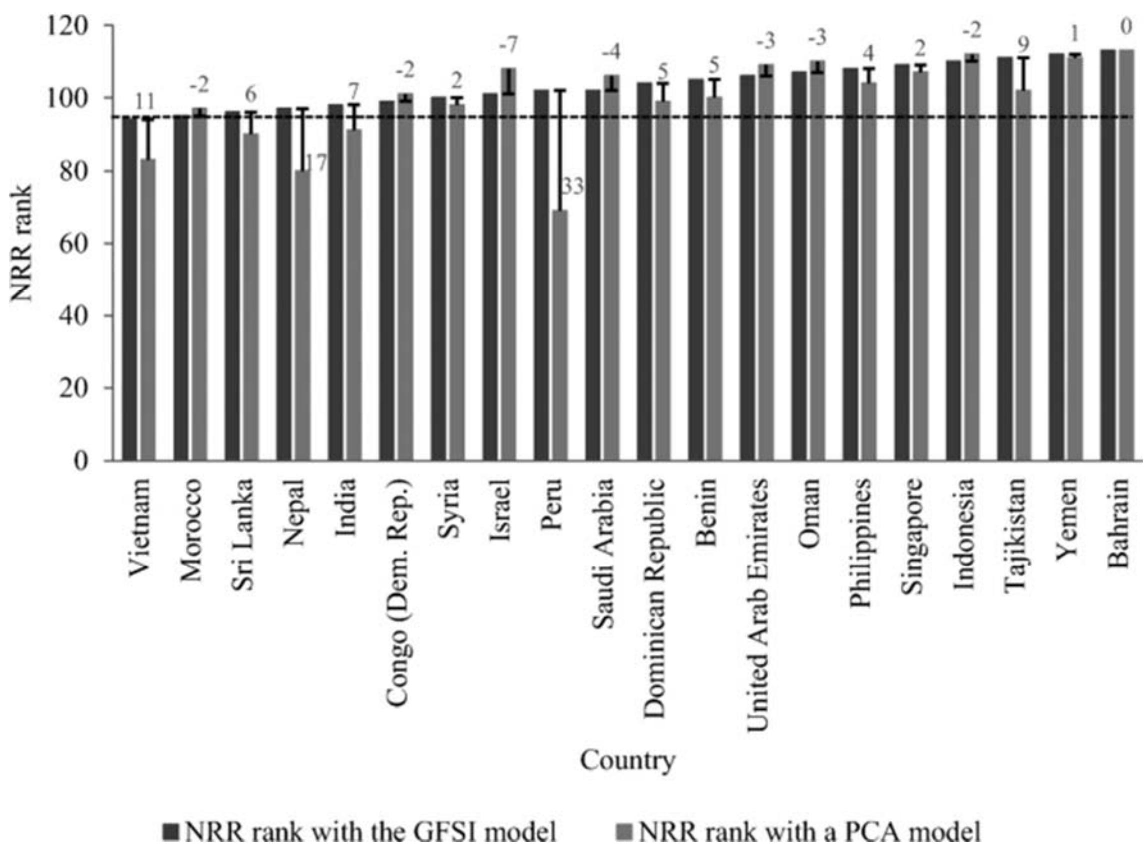

Fig. 2. Comparison of the NRR ranks of the bottom twenty countries (rank 94–113) based on the subjective GFSI and objective PCA weighting models. *Source: Author's work using GFSI data (EIU,* 2019*)*

The Czech Republic remained in the top rank one after the PCA model was used, just as Maricic et al. (2016) observed that the United States retained the top-ranked position, 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.

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.

In Table 1, the results of a paired t-test 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 1. Results of paired t-test for the NRR scores of countries based on the objective PCA and subjective 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 2, 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.

Table 2. Results of Spearman's rank correlation test for the NRR component rank of countries based on the objective PCA and subjective 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 5 % level, $n = 113$ countries

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

4.2 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 Table 3, several differences emerged among the countries' adjusted overall GFSI scores and rank 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 (Fig. 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.

Table 3. Countries' adjusted overall GFSI scores and ranks derived using subjectively weighted (GFSI model) and objectively weighted (PCA model) NRR scores 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
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
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

Rank 1=best, the score ranges 0–100 where 100=best

Source: Author's calculations and EIU (2019)

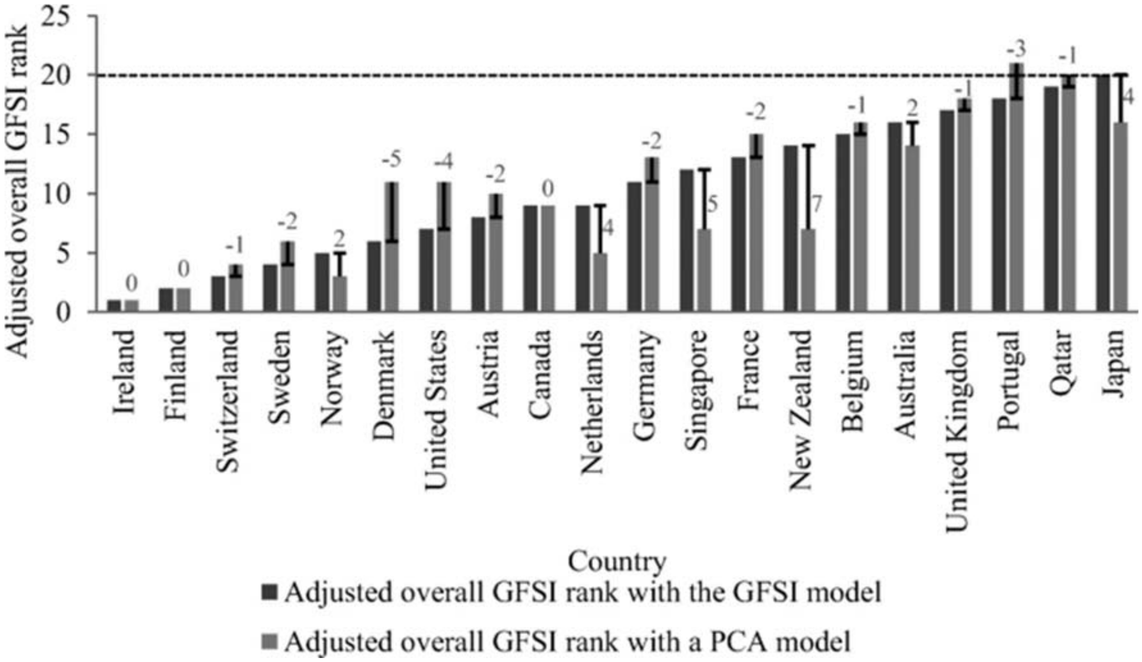

Fig. 3. Comparison of the adjusted overall GFSI ranks of the top twenty countries (rank 1–20) derived using the subjectively weighted (GFSI model) and objectively weighted (PCA model) NRR scores. *Source: Author's work using GFSI data (EIU,* 2019*)*

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 the PCA model was applied (Fig. 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.

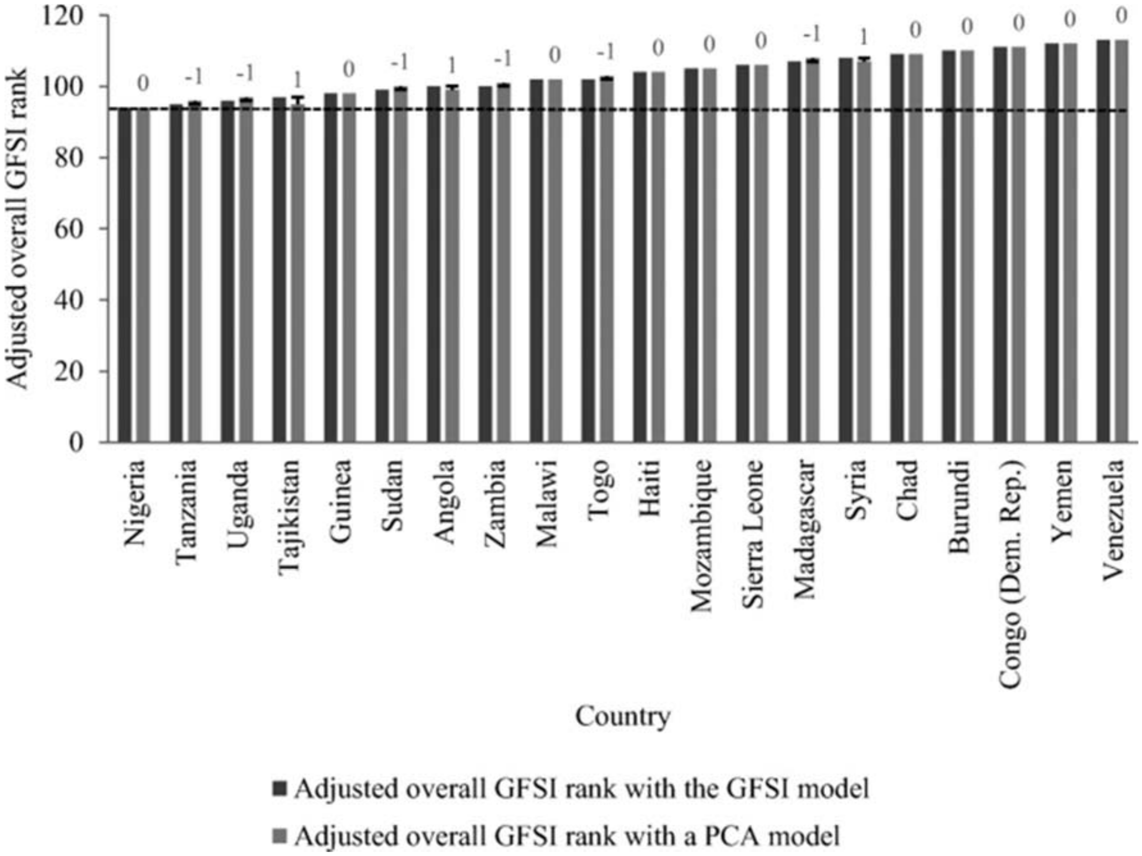

Fig. 4. Comparison of the adjusted overall GFSI ranks of the bottom twenty countries (rank 94–113) derived using the subjectively weighted (GFSI model) and objectively weighted (PCA model) NRR scores. *Source: Author's work using GFSI data (EIU,* 2019*)*

Despite the use of objectively weighted NRR scores, Ireland and Finland retained their first and second rank 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 subjectively 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. Countries required higher performance for the NRR indicators with greater weights to achieve higher NRR scores and ranks, including adjusted overall GFSI scores and ranks.

The results of a paired t-test, as presented in Table 4, showed a lower objectively adjusted overall GFSI scores (mean = 52.496 ± 12.912) compared to the subjectively 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 could offer an alternative approach to understanding global food security development and improvement.

Table 4. Results of paired t-test for the countries' adjusted overall GFSI scores derived using subjectively weighted (GFSI model) and objectively weighted (PCA model) NRR scores 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 showed a statistically significant rank correlation coefficient (rho = 0.995 at five per cent significance level) with a p-value less than 0.05 ($p < 0.05$), signifying that the two separate ranks were closely related. 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.

Table 5. Results of Spearman's rank correlation test for the countries' adjusted overall GFSI ranks derived using subjectively weighted (GFSI model) and objectively weighted (PCA model) NRR scores for 2019

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

* Significant at the 5 % level, $n = 113$ countries

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

The results for the second specific research

5 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 found that 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. 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 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 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.

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 need 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 in the dimensions and overall score and ranks. 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 may also motivate governments to invest in data collection, management and publication for access by the EIU experts. Data distribution can influence the ability of the weights to reflect a perceived level of importance of the indicators (Becker et al. 2017). If the data distribution changes, the objective weights will reflect a new level of importance of indicators and new scores and ranks of countries (Decancq and Lugo 2013).

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.

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. 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.

Conflict of interest The authors declared that they have no conflict of interest.

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