An Input-Output-Based Assessment of the Global Food Security Index

Hamad Nabeel, Muna Alansari, Galal M. Abdella, Adeeb A. Kutty, And Issa M. Al Mohannadi
Mechanical and Industrial Engineering Department
College of Engineering, Qatar University
Doha, Qatar

hn2110478@student.qu.edu.qa, 200356160@qu.edu.qa, gmg5005@qu.edu.qa, akutty@qu.edu.qa, ia2005586@qu.edu.qa

Abstract

With the ever-increasing effect of climate change worldwide and many problems like geopolitical issues, population boom, etc., more people are experiencing food insecurity, and many more are at risk. Food security is a very complex topic, but many researchers have tried to arrive at a composite index to measure Food security. One such widely used measure is Global Food Security Index. This research has employed a statistical approach named Data Envelopment Analysis (DEA) to analyze the Global Food Security Index in detail. The indicators used to arrive at the composite score, i.e., GFSI, are only input based, i.e., they consider the existing resources and facilities available which can help a country bolster food security in the country. In contrast to previous approaches, our study takes a different perspective by incorporating output indicators as a means to calculate the composite score for measuring food security in each country. Specifically, we employ an output-based indicator, namely the Prevalence of severe Food Insecurity in the population, expressed as a percentage of the total population. This indicator serves as a measure of the country's effectiveness in achieving food security. By focusing on output indicators, our methodology provides a unique and comprehensive assessment of food security, taking into account the actual outcomes and impacts experienced by the population. We ran a DEA analysis on the GFSI scores for the 35 countries selected for 2017, 2018, and 2019. Different weighting approaches, namely equal weight, expert-based weight, and DEA-assigned weight, were also applied to arrive at the GFSI score. The results were further analyzed and compared to infer meaningful insights.

Keywords:
Food security, Global Food Security Index, Data Envelopment Analysis.

1. Introduction
According to the 1996 World Food Summit organized by the Food and Agriculture Organization (FAO), food security is defined as the state in which all individuals have consistent physical and economic access to safe, sufficient, and nutritious food that aligns with their dietary requirements and personal preferences, enabling them to lead active and healthy lives (Haysom et al. 2018). However, measuring food security poses a complex challenge, involving both technical and political aspects (Kutty et al. 2020; Elhmoud et al. 2021). When conducting food security assessments, it is crucial not only to determine what is being measured but also to approach the measurement process with caution. By employing a proper methodology, it becomes possible to concentrate on vulnerable population groups, identify underlying causes, and estimate the prevalence of food security (Bennbaia et al. 2018). Due to the multidimensional nature of food security and the diverse components it encompasses, developing a comprehensive index that encompasses all aspects of this concept is technically demanding.

According to the Intergovernmental Panel on Climate Change (IPCC 2022), the escalating impacts of climate change pose a significant threat to food access and production, thereby undermining global food security and nutrition, particularly in countries that are already vulnerable. The food system, like other interconnected systems, has faced numerous challenges resulting from global crises such as the Covid-19 pandemic and geopolitical tensions, which have further diminished its resilience. It is crucial to prioritize the development of resilient capacities within the food system to mitigate the effects of climate change and other disruptive factors, ultimately promoting the well-being of humanity.

However, there have been many attempts to create composite indices to measure food security. The Global Hunger Index (GHI) is a 100-point scale that measures hunger and is jointly published annually by Concern Worldwide and Welthungerhilfe International. It is based on four indicators: undernourishment, child stunting, child wasting, and child mortality (Global Hunger Index. 2023). The food Consumption Score (FCS) is determined by considering how frequently a household consumed various food groups seven days before the survey. It is measured by World Food Programme (WFM) (Izraelov et al. 2019). The Household Dietary Diversity Score (HDDS) developed by USAID (United States Agency for International Development) focuses on the number of unique food that the members of a house consume over some time (Heidari-Beni et al. 2022). Anthropometric indicators assess individual nutritional status concerning height, weight, and body size of individuals (Andrew et al. 2013) (Pangaribowo et al. 2013).

The Global Food Security Index (GFSI), developed by the Economist Impact and supported by Corteva Agriscience, is another measure of food security for over 100 countries through three different food security metrics. The GFSI comprises four major categories weighted using five-panel experts' opinions. These are Affordability (six indicators), Availability (eleven indicators), Quality and Safety, and Sustainability and Adaptation (Economist Impact., 2023). Thomas et al. (2013) have pointed out that GFSI focuses on the factors that contribute to food security and doesn't consider the output indicators, like the population's nutritional status.

2. Methodology

This chapter describes the methodology followed in this research from the start until the end to achieve the research objectives. Fig. 1 describes the methodology of the research in pictorial form. As evident in the methodology, the independent and dependent variables are selected; for which the data is collected from credible sources and then

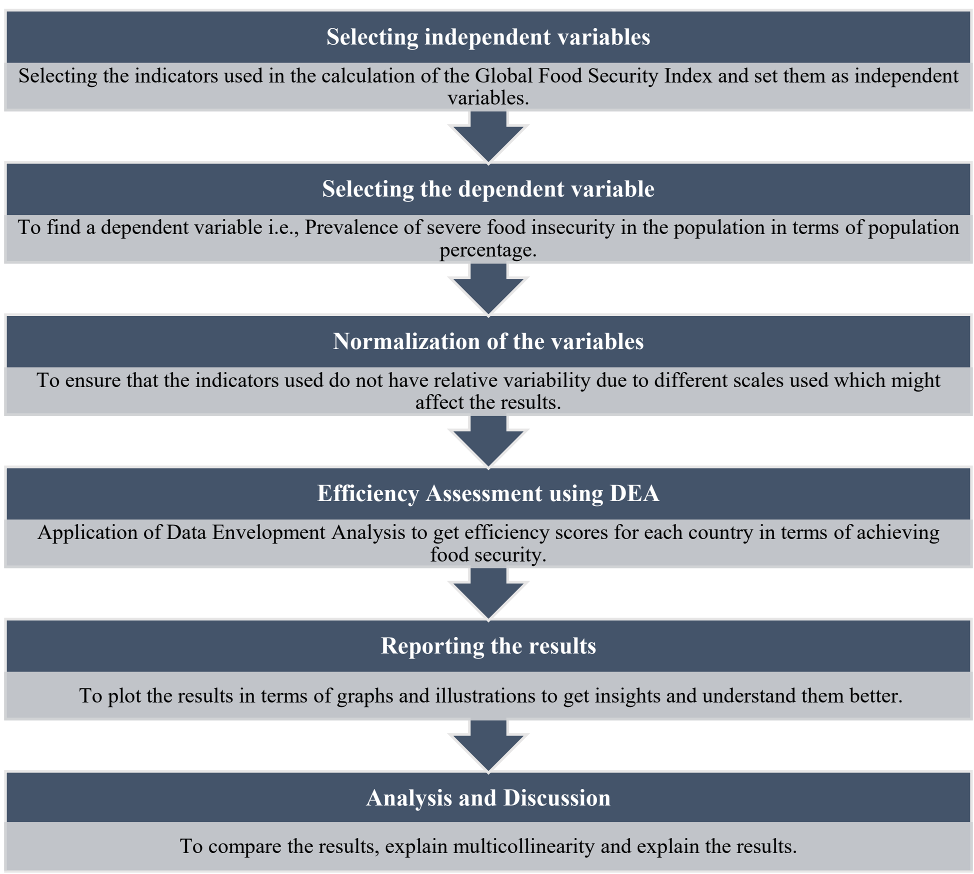

Figure 1. Research methodology

cleaned if needed. It is followed by the normalization of the variables to ensure that relative variability in the existing data due to various scales used doesn't affect the results. The next course of action to be followed is the application of statistical analysis like Data Envelopment Analysis. Finally, the results are analyzed and compared to infer meaningful insights.

2.1 Data Collection

The data for statistical analysis has been sourced from two credible sources. The first data is from the Economist Impact's Global Food Security Index (GFSI), which Corteva Agriscience supports. GFSI has been annually published since 2012 and covers more than 100 countries globally. It evaluates food security based on four pillars: Affordability, Availability, Quality and Safety, and Sustainability & Adaptation.

Each of these dimensions has several indicators which have their own assigned weights. A country's composite index score is measured using a weighted arithmetic average (Economist Impact., 2023). This research focuses on the Global Food Security Index; the data was extracted from 2017 to 2019.

Table 1. below enlists all the indicators used in calculating the Global food Security Index under four dimensions: Affordability, Availability, Quality & Safety, and Sustainability &Adaptation.

1) AFFORDABILITY
1.1) Change in average food costs
1.2) Proportion of population under the global poverty line
1.3) Inequality-adjusted income index
1.4) Agricultural trade
1.5) Food safety net programs
2) AVAILABILITY
2.1) Access to agricultural inputs
2.2) Agricultural research and development
2.3) Farm infrastructure
2.4) Volatility of agricultural production
2.5) Food loss
2.6) Supply chain infrastructure
2.7) Sufficiency of supply
2.8) Political and social barriers to access
2.9) Food security and access policy commitments
3) QUALITY AND SAFETY
3.1) Dietary diversity
3.2) Nutritional standards
3.3) Micronutrient availability
3.4) Protein quality
3.5) Food safety
4) SUSTAINABILITY AND ADAPTATION
4.1) Exposure
4.2) Water
4.3) Land
4.4) Oceans, rivers, and lakes
4.5) Political commitment to adaptation
4.6) Disaster risk management

The second data is the "Prevalence of severe food insecurity in the population (%)" which has been acquired from the Food and Agriculture Organization of the United Nations (FAO). According to FAO, "It is the percentage of people in the population who live in households classified as severely food insecure" (FAO 2023); for a household to be considered as "severely food insecure," when at least one adult of the household is reported to be exposed with conditions like, skipping meals, forced to reduce food quantity, going hungry, going a whole day without eating due to lack of resources or money, etc. at times during the year. We have selected this indicator to cover what GFSI misses as GFSI measures the conditions which can result in food insecurity but not the nutritional state of the population (Thomas et al. 2017). This research selected the 35 common countries residing in both lists, namely the GFSI score and "Prevalence of severe food insecurity in the population" for the analysis.

2.2 Data Processing

The indicators used in Global Food Security Index (GFSI) have different marking scales. Therefore, normalization was applied to the extracted data with the help of maximum minimum rescaling from 0-100 such that 0 represents the worst-case scenario and vice versa (Mukherjee et al. 2015, Abdella et al., 2020, Kucukvar et al. 2020; Kutty et al. 2020 a-c, Kutty et al. 2022a). This helps us by not affecting the results due to a scale change. The Feature Scaling formula given below was used for this purpose.

$$y' = \frac{y - \min(y)}{\max(y) - \min(y)} * 100\% \tag{1}$$

where y stands for the original value, y' represents the normalized value. After data normalization is done and determining GFSI weights, an efficiency assessment is carried out using Data Envelopment Analysis (DEA). For DEA analysis, indicators of all four dimensions of GFSI, namely Affordability, Availability, Quality & Safety, and Sustainability & Adaptation, were considered as inputs. In contrast, the prevalence of severe food insecurity in terms of population percentage has been considered an output. The Decision-Making Units (DMU) for this DEA efficiency assessment are the 35 common countries selected from the GFSI rank list and the "Prevalence of Severe Food Insecurity in the Population" list.

3. Results and Discussion

3.1 DEA Efficiency Analysis with Multiple Scenarios

As illustrated in the methodology, when Data Envelopment Analysis was applied to the GFSI scores of selected 35 countries for the years 2017, 2018, and 2019 obtained through different weighting methods, namely equal weight, expert-based weight, and DEA assigned weight, DEA efficiency scores are generated for each of the countries; see Abdella et al. 2021a, Kutty et al. 2202a, 2023.

According to the analysis of the DEA efficiency assessment, it is evident that the weighting methods employed have minimal influence on the DEA efficiency scores. The results indicate that the deviation between the scores obtained using different weighting methods for the same country is negligible. This insight suggests that the DEA efficiency scores are relatively independent of the weighting methods utilized.

For 2017, the DEA efficiency assessment scores for the 35 selected countries have been illustrated pictorially in Fig. 2. In this figure; we can observe that the DEA efficiency scores achieved through different weighting methods have minute variance. Countries with efficiency scores in the range of 0.8-0.9, like Norway, Finland, the United States, France, etc., have a slight variance in their scores, while countries in the efficiency range of 0.9-1 have very minute variance.

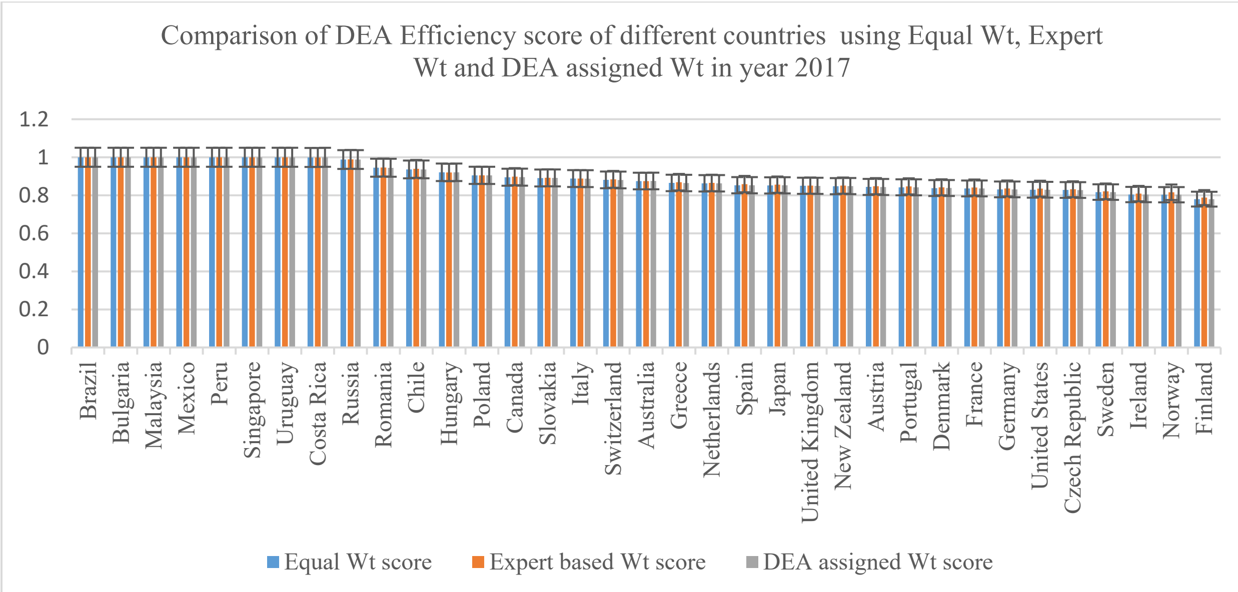

Figure 2. DEA scores of the 35 countries using different weights in 2017.

As evident from the above chart, seven countries, namely Brazil, Bulgaria, Malaysia, Mexico, Peru, Singapore, and Uruguay, have scored an efficiency score of 1 with all three weighting methods: equal weight, expert-based weight, and DEA-assigned weight. It means that compared to other countries, these seven counties are the most efficient in utilizing their existing resources to attain food security in their country. Other countries like Costa Rica and Russia have also scored an efficiency score close to 1, i.e., >0.985. All the other countries in the list achieve a DEA efficiency score of more than 0.8. Finland is at the bottom of the ranking of 35 countries in terms of DEA efficiency assessment, which has achieved a score close to 0.78 with all three weighting methods.

The other significant insight we get from the results is that the countries with an efficiency score of 1 are at the bottom of the Global Food Security (GFSI) rank. As shown in Fig. 3 below in 2017, countries like Brazil, Bulgaria, Malaysia, Mexico, Peru, Singapore, and Uruguay achieved an efficiency score of 1. Still, they have GFSI ranks of 31,32,35,33,27,30, and 29, respectively. This tells us that these countries are performing very well in utilizing whatever resources they have to achieve food security in their respective nations.

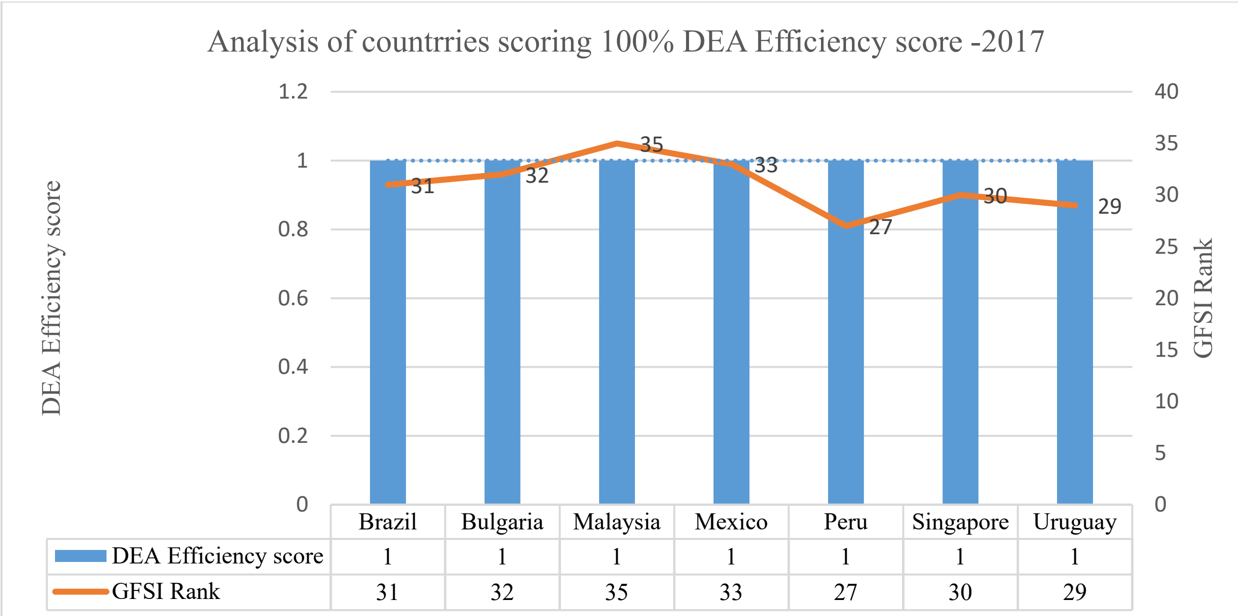

Figure 3. Countries with DEA Efficiency score of 1 and their respective GFSI ranks - 2017.

For 2018, Fig. 4 depicts the DEA efficiency scores of the 35 countries using three different weighting methods: Equal weight, expert-based weight, and DEA-assigned weight. Countries like Kazakhstan, Kuwait, Peru, and Vietnam are the countries that have achieved an efficiency score of 1. The scores signify that these countries are the most efficient of the 35 countries on the list in terms of utilizing existing resources and conditions to achieve food security in their respective countries. Countries like Singapore and Romania have also fared well and achieved an efficiency score of around 0.99, which is close to 1. All the other countries achieved an efficiency score of more than 0.8 except Finland, which has an efficiency score of less than 0.8.

In terms of the variance of the DEA efficiency scores, we can observe that the variance is very low between the scores achieved using three different weights. There is a slight variance in efficiency scores throughout the countries, with countries like Ireland, Norway, Slovakia, etc., having a slightly higher variance than the others; it can be observed in Fig. 4 below.

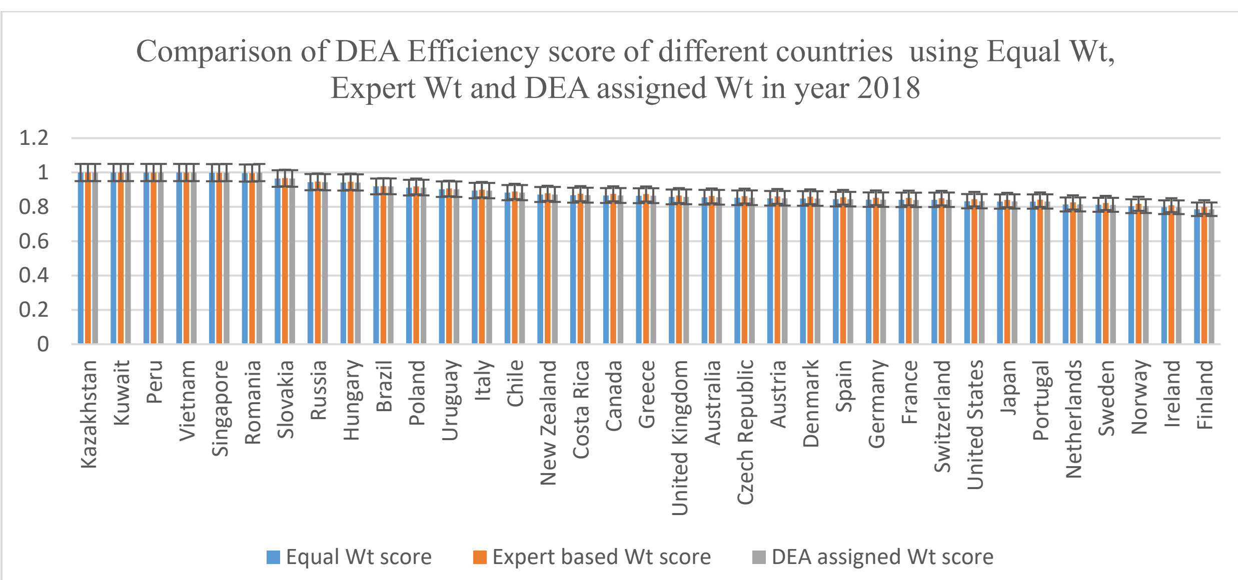

Figure 4. DEA scores of the 35 countries using different weights in 2018.

Moreover, it can be inferred from the data that the countries achieving scores of 1 are mostly those at the bottom of the GFSI rank. The below Fig. 5 shows that for 2018, countries like Kazakhstan, Kuwait, Peru, and Vietnam scored one while their GFSI ranks were 33,34,28, and 35, respectively. This implies that the countries at the bottom of the GFSI rank list use resources and facilities better to achieve food security than those at the top.

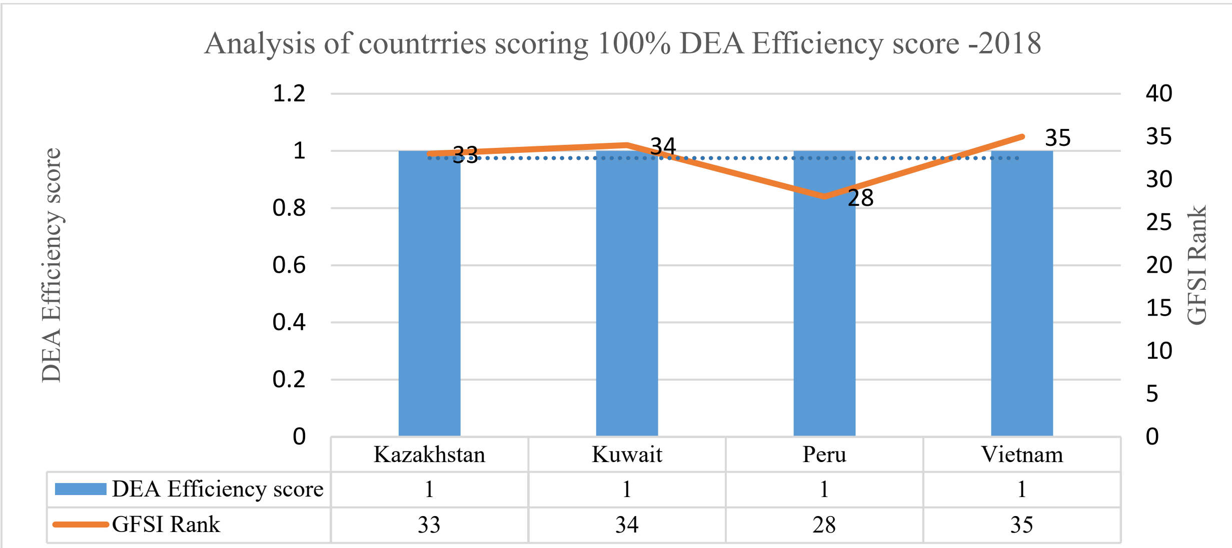

Figure 5. Countries with DEA Efficiency score of 1 and their respective GFSI ranks - 2018.

When we look at the DEA Efficiency scores of the 35 countries using three different weighting methods for 2019, Fig. 6 depicts that the countries like Kuwait, Mexico, Peru, Singapore, and Slovakia have achieved an efficiency score of 1. Another country with an efficiency score close to 1 is Uruguay, which has a score of 0.999. All the other countries have achieved an efficiency score of more than 0.8 except Finland, which has achieved a score close to 0.8 for the Equal Wt case and DEA assigned Wt case, but for an expert-based case, it has achieved a score of 0.813.

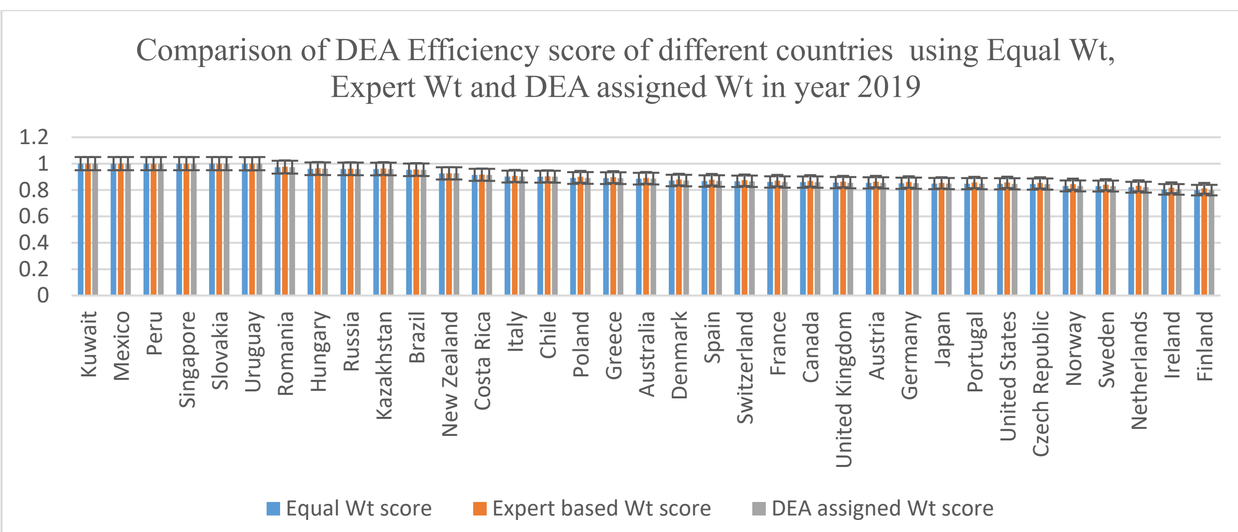

Figure 6. DEA scores of the 35 countries using different weights in 2019.

If we look at the countries that have achieved a score of 1, we notice that all those countries are listed at the bottom of the GFSI rank. Fig. 7 below shows that for 2019, countries like Kuwait, Mexico, Peru, Singapore, and Slovakia got a perfect efficiency score of 1 while ranked 35, 34, 24, 25, and 33 in the GFSI rank list. This signifies that the countries at the bottom of the GFSI rank are doing better with the minimum resources available to achieve food security in their region.

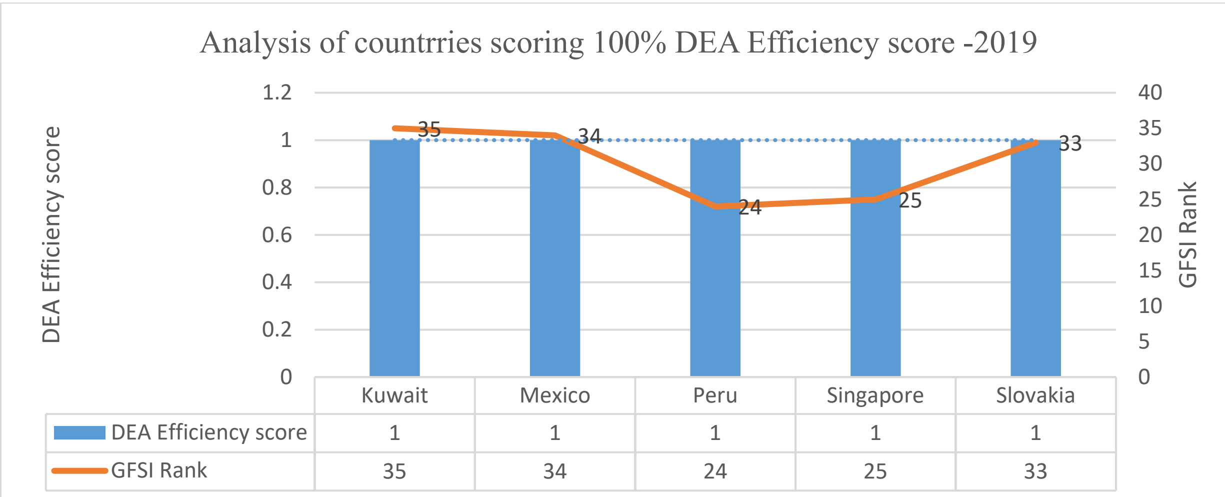

Figure 7. Countries with DEA Efficiency score of 1 and their respective GFSI ranks - 2019.

3.2 DEA Comparison between the GFSI rank and DEA Efficiency score based rank

On realizing that the countries achieving the efficiency score of 1 are the countries placed at the bottom of the GFSI rank for all the years, namely 2017, 2018, and 2019, we plotted the DEA Efficiency score-based rank v/s GFSI rank for all three years. Fig. 8,9,10 depicts the relation between the GFSI rank and DEA Efficiency score-based rank for the expert-based weight case. As is evident from these graphs, the GFSI rank and DEA efficiency score-based rank are opposite. Most of the top countries in the GFSI rank list are at the bottom as per DEA efficiency score-based rank and vice versa.

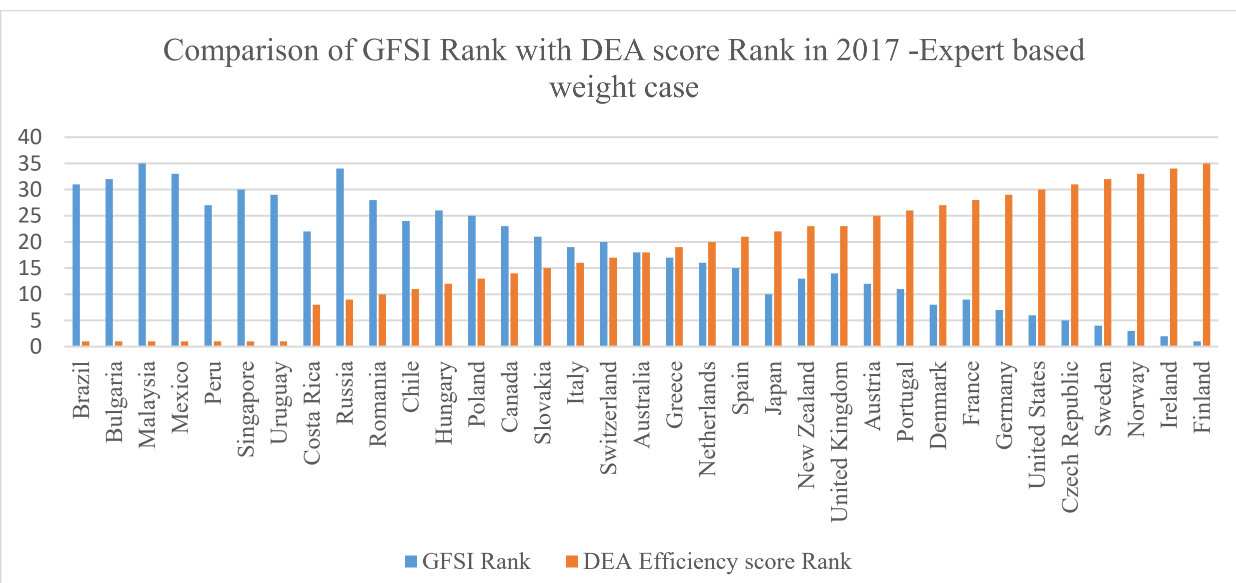

Figure 8. Countries with GFSI rank and their respective DEA score in 2017- Expert based weight case.

Hence, we can infer that the countries at the top of the GFSI rank list have enough or surplus resources and efficient facilities available. In contrast, the countries at the bottom of the GFSI don't have enough resources and facilities but are efficiently using them compared to the GFSI's top-ranking countries. Countries like Finland, Ireland, Sweden, and Norway have consistently placed in the top 5 of the GFSI rank for the years 2017, 2018, and 2019 and have been placed in the bottom 5 of the DEA efficiency score-based rank. This is true for most countries except New Zealand, Greece, etc.

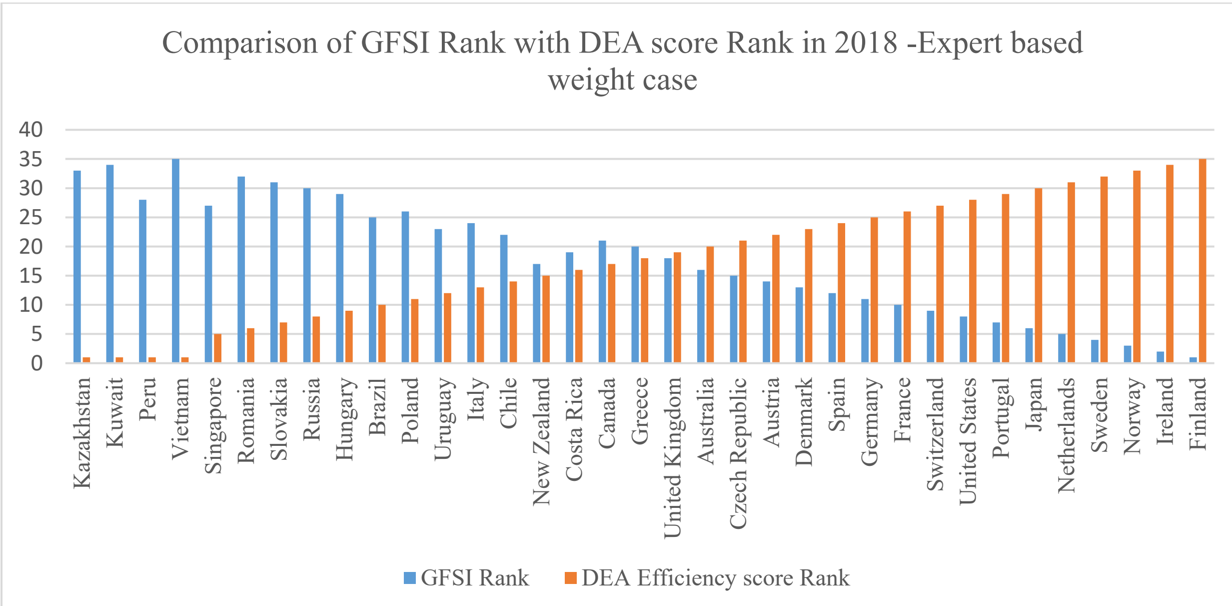

Figure 9. Countries with GFSI rank and their respective DEA score 2018- Expert based weight case.

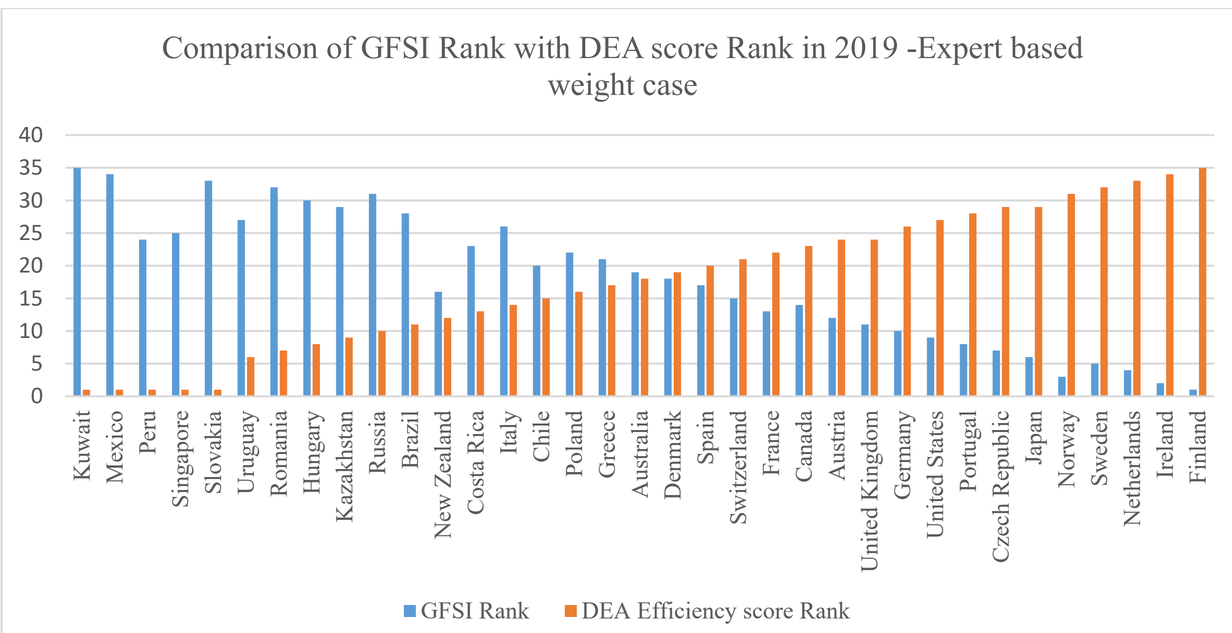

Figure 10. Countries with GFSI rank and their respective DEA score in 2019- Expert based weight case.

4. Conclusion and Recommendation

The research has employed a statistical approach to analyze the Global Food Security Index in detail. The indicators used to arrive at the composite score, i.e., GFSI, are only input based, i.e., they consider the existing resources and facilities available which can help a country bolster food security in the country. Still, they don't consider output indicators to arrive at the composite score used to measure the food security in each country. We used an output-based indicator, i.e., the Prevalence of severe Food Insecurity in the population in terms of population percentage, to gauge the country's effectiveness in Food Security. We applied three different weighting approaches: Equal weight, expert-based weight, and DEA-assigned weight on the data to calculate the GFSI scores.

Based on the statistical analysis performed, it was inferred that the countries at the bottom of the Global food Security Index rank list are the countries achieving the efficiency score of 1. Overall, the bottom-ranked countries of the GFSI rank list perform better than those at the top. The countries at the top of the GFSI rank have excess resources and facilities, which awards them the top position since the GFSI doesn't account for any output indicators regarding food security. When we compared the performance of the countries not just with the input indicators but with the output indicator, i.e., Prevalence of severe Food Insecurity in population, then we found out that the countries at the bottom of the GFSI rank list despite fewer resources and facilities fared better than the countries at the top. If we analyze all the countries which achieved a DEA Efficiency score of 1 through the years 2017, 2018, and 2019 for different weighting cases, it is found that all of these countries are ranked below 20 of the total 35 countries in the list.

Moreover, when we plotted and compared the DEA Efficiency score-based rank v/s GFSI rank, it was clear that the countries at the top in the GFSI rank are placed at the bottom in the DEA Efficiency score-based rank. Similarly, the countries at the bottom of the DEA Efficiency score-based rank are at the top of the GFSI rank list. For example, in 2017, countries like Brazil, Bulgaria, Malaysia, Mexico, Peru, Singapore, and Uruguay achieved an efficiency score of 1, but they have GFSI ranks of 31,32,35,33,27,30, and 29, respectively. The same phenomenon was repeated in 2018 and 2019 by GFSI bottom-placed countries by achieving an efficiency score of 1. Only a few exceptions have arrived where these countries remained in the same region in the rank list, like New Zealand, Greece, etc.

However, it is important to note the nature of that DEA as it doesn't consider the country's cultural, political, and comprehensive view to arriving at results like a human. So, while using the analysis results to frame policies, we must comprehensively view the country's status and capabilities so we don't arrive at wrong and ill-suited policies.

The primary challenge associated with this research was the unavailability of data about the nutritional state of citizens of all the countries for a longer time frame. Nevertheless, it is an opportunity for future research. It works as an extension of this research to study the feasibility of statistical methods which can help countries find their weaknesses and achieve the highest efficiency possible along with a highly food-secured population. For future work, the author recommend to exted some of the advanced regression method in generating weight of the food security dimensions; see for Abdella 2021b. This would provide the decision-makers with small space of indicators the matter that help in clearly identify the oppurtunities of enahnacement for the food security performance.

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Biographies

Hamad Nabeel is earning a master's degree in Engineering Management at Qatar University. In addition, Hamad holds an undergraduate mechanical engineering degree from Anna University**.** Hamad is currently working as Graduate Research Assistant at Qatar University. Hamad's research interest involves lean thinking, sustainability assessment, Green Energy, and Project Management.

Muna Al-Ansari is a driven and accomplished professional currently pursuing a Ph.D. degree in Engineering Management at Qatar University. With a background in computer engineering and an MBA, she serves as Lead of the Unified Communication in Information & Communication Technology department at QatarEnergy. She has received multiple recognitions for her exceptional work, including winning an award for best project and best presentation by Qatar National Research Fund. Her diverse expertise and dedication to making a positive impact position her as a promising figure in her field. Her research interests lie in sustainability, food security assessment, decision support systems, and project management.

Galal Abdella is an associate professor at the Department of Industrial Engineering, College of Engineering, Qatar University. In addition, he is currently the graduate program coordinator for Engineering Management Program at Qatar University. His research area has always been centered on utilizing mathematics and advanced statistical data analysis for high dimensional data processing, circular economy and food security, modeling and simulating rare events, quality data modeling and analysis, and project resource management.

Adeeb A. Kutty is an accomplished professional with a bachelor's degree from University of Calicut, India, in Electrical and Electronics Engineering and a master's degree holder in Technology and Engineering management from Universitat Rovira i Virgili, Tarragona, Kingdom of Spain. His area of research interest includes sustainability and systems engineering, smart cities and regional development, smart mobility and decision support systems, transportation and project management.

Issa M. Al Mohannadi is a seasoned professional with over 25 years of industry experience. Founder and CEO of Msheireb Properties, a subsidiary of Qatar Foundation; Chairman of Qatar Tourism Authority; Vice Chair & Managing Director of Barwa Real Estate; Chairman of Qatar Racing and Equestrian Club Board of Directors; Vice

Chair of Qatar Museums Authority, Board Member, of Qatar Airways; Trustees Board, Doha Film Institute (DFI); Chair and founder Qatar Green Building Council. He has a Bachelor of Science and Natural Gas Engineering from Texas A&M University and several specialized training certificates in executive leadership training and project management from Harvard Business School, INSEAD, Kellogg Business School, and George Washington University, Washington DC. He has received numerous recognitions for contributing to Qatar's rapidly growing business community, including the title 'Property Development CEO of the Year' at the 7th Middle East CEO of the Year Awards organized by the Middle East Institute of Excellence in 2010. Mr. Al Mohannadi is studying for his master's in engineering management at Qatar University, Doha-Qatar.