QATAR UNIVERSITY

COLLEGE OF ENGINEERING

STATISTICAL WEIGHTING BASED MEASUREMENT FOR FOOD QUALITY AND SAFETY DIMENSION OF FOOD SECURITY AND EFFICIENCY ASSESSMENT

BY

SUHILA TARIQ ZAFFER

A Thesis Submitted to

the College of Engineering

in Partial Fulfillment of the Requirements for the Degree of

Masters of Science in Engineering Management

June 2022

COMMITTEE PAGE

The members of the Committee approve the thesis of
Suhila Tariq Zaffer defended on 27/04/2022.

Galal M Mohammed Abdella
Thesis Supervisor

Alper Kiraz
Committee Member

Murat Gunduz
Committee Member

Charitha Dias
Committee Member

Approved:

Khalid Kamal Naji, Dean, College of Engineering

ABSTRACT

ZAFFER, SUHILA T., Masters: June: 2022, Masters of Science in Engineering Management

Title: Statistical Weighting Based Measurement for Food Quality and Safety Dimension of Food Security and Efficiency Assessment

Supervisor of Theis: Galal M Abdella.

The appropriate application of statistical approaches on a data set brings powerful results and insights for solving food security problems for current and future generations. Moreover, it provides resilient integrated measurement methods that seek to be a reference for governments and policymakers. In this spirit, with the focus on the quality and safety of food indicators introduced by the Global Food Security Index (GFSI), this research applies Variable Importance in the Projection approach (VIP) to statistically assign the importance of multiple indicators on achieving a certain level of food security and comparing the results with the weights that are subjectivity assigned by a group of experts. Then the research studies the efficiency for 46 countries on achieving their certain level of food security using GFSI weighted DEA, VIP weighted DEA, and unweighted DEA models.

The results showed that the weights assigned to the indicators using the variable importance in projection approach vary compared to the weights assigned by experts. Although this difference was observed, when using the same method for calculating the overall score, the Weighted Arithmetic Mean (WAM), the ranking slightly changes, and the changes do not exceed ±6 ranks. Moreover, the top countries remain to be Norway, United States, and Netherlands in all five years and despite the changes in the weights used. The results on the efficiency study using weighted DEA and unweighted DEA model showed that countries like Azerbaijan, The Czech Republic, and Slovakia

has always been highly efficient countries despite the model of Data Envelopment Analysis (DEA) used. The efficiency scores have not been noticed to fall below 0.48 in all the models used. Comparing the variance between the models used, the VIP weighted DEA efficiency scores appear to be closer to the results of the unweighted DEA where the linear program assigns the weights based on the output, which was the prevalence of severe food insecurity in the population, in all the models in this research.

DEDICATION

This thesis work is dedicated with a special feeling of gratitude to my supporting parents, family and devoted friends for their constant source of support and encouragement thought out this journey

ACKNOWLEDGMENTS

My sincere thanks go to my advisor Professor Galal Abdella for his patient guidance and invaluable advice throughout this work and for believing. His willingness to give his time and knowledge has been very much appreciated.

I would also like to thank Engineer Adeeb Kutty and Engineer Rania El-Sheikh from Engineering College, Qatar University, for their treasured support, enthusiastic encouragement, and dedicated involvement.

I am grateful to my family for keeping me motivated and confident and my friends for always believing in me.

TABLE OF CONTENTS

DEDICATION v

ACKNOWLEDGMENTS vi

LIST OF TABLES ix

LIST OF FIGURES x

Chapter 1: INTRODUCTION 1

1.1 Background 1

1.2 Research Aim and Motivation 3

1.3 Thesis Outline 3

CHAPTER 2: LITERATURE REVIEW 4

Literature Review Limitation 5

2.1 Recent trend on global food security & safety assessments 5

2.2 Variable selection approaches for food security assessments 6

2.3 Variable importance in projection 10

2.4 Optimization modeling in food security 12

Chapter 3: METHODOLOGY 16

3.1 Data Collection 16

3.1.1 Global Food Security Index. 16

3.1.2 Prevalence of severe food insecurity in the population (%). 17

3.1.3 Countries selection. 18

3.2 Data Set up 18

3.2.1 Normalization. 18

3.2.2 Weighted Arithmetic Mean. 19

3.3 Variable Importance in Projection Approach 19

3.3.1 GFSI Default Weights. 19

3.3.2 VIP Generated Weights. 19

3.4 Efficiency using Data Envelopment Analysis 20

3.4.1 Weighted DEA-based model. 21

3.4.2 Unweighted DEA-based model. 22

Chapter 4: Results, comparison and discussion 23

4.1 Variable Importance in Projection Scores 23

4.2 Statistical weights vs. experts' weights using weighted arithmetic mean 24

4.3 Efficiency Study 25

Chapter 5: Conclusion and remarks 33

References 35

Appendix 45

LIST OF TABLES

Table 1. Summary of the main variable selection techniques for food security assessments. 8

Table 2. Quality and safety indicators for food security by GFSI 17

LIST OF FIGURES

Figure 1. Review Process..4

Figure 2. Diagram showing the outline of methodology's main stages 16

Figure 3. VIP Indicator's scores for years 2015-2016..23

Figure 4. Comparing VIP weights and GFSI weights using weighted arithmetic mean 24

Figure 5. Efficiency scores of VIP weighted DEA...25

Figure 6. Efficiency scores of GFSI weighted DEA...26

Figure 7. Efficiency scores of non-weighted DEA...26

Figure 8. The variance between non-weighted DEA scores and GFSI weighted DEA scores..28

Figure 9. The variance between non-weighted DEA scores and VIP weighted scores 28

Figure 10.a) Botswana efficiency scores 2015-2019 b) Swizerland efficiency scores 2015-2019 29

Figure 11. a) Singapore efficiency scores 2015-2019 b) Italy efficiency scores 2015-2019...30

Figure 12. Denemark efficiency scores 2015- 2019 31

Figure 13. Denmark food security level using VIP weights.......................................31

CHAPTER 1: INTRODUCTION

1.1 Background

One of the most important Sustainable Development Goals is achieving food security and appropriate nutrition (Khanam et al. 2020). Sustainability and food security share multiple characteristics. They are both wide and complicated concepts used by various scientific disciplines, governments, and non-governmental organizations, each of which has its own set of definitions SEE (Alsarayreh et al. 2020; Kucukvar et al. 2021; Kutty et al. 2020; Abdella et al. 2020b). Food security occurs when all people, at all times, have physical and economic access to safe, sufficient, and nutritious food that fits their dietary needs and food preferences for an active and healthy life, according to the 1996 World Food Summit, Food, and Agriculture Organization, and to the most frequently recognized definition (Haysom and Tawodzera 2018). Food security is a vital concern since undernourishment or hungry population hinders economic productivity. The growth of chronic and acute illnesses, endurance, and economic production is affected by malnutrition (Khanam et al., 2020). Measuring food security is both a technical and political concern (Kutty and Abdella 2020; Elhmoud and Kutty 2021). Decisions on what should be measured and how it should be measured from complicated discussions based on resources, time, capacities, and ideological and political viewpoints. Measurement methods that are poorly constructed obscure information can result in negative or wrong food security outcomes (Haysom and Tawodzera 2018; Thomas et al. 2017).

The various conceptual structures of food security, the outcomes and risks of each dimension, and their correlations make food insecurity a wicked problem (Ville et al., 2019). There are multiple ways that researchers are splitting the aspects of food security to study and measure them properly (Abdella et al., 2019). The most comprehensive dimensions derived from the bases of World Food system (WFS) detention are that each person should be able to access food that is adequate in amount, sufficient in nutritional quality, accepted by the culture, safe, consistent, and certain. Those dimensions are at least partially represented by several existing indicators and have been considered lead concerns in many countries (Coates 2013; Al-Obadi et al. 2021). The conceptual framework of the Global Food Security Index (GFSI), which has been created to measure food security levels in multiple countries around the world, consists of three aspects 1) affordability, 2) availability, 3) quality and safety where GFSI will be more elaborated on the upcoming sections (Abdella et al. 2021a). Due to the world's growing population, rapid environmental changes, and the significant agriculture's use of pesticides. Thus, various governments and researchers worldwide have shown a keen interest in food safety and quality studies.

However, what is being measured is not the only concern in food security assessments, but how it is measured. Assessments have to be well-grounded and valid to put up knowledge and help result with accurate evaluations. When the appropriate approaches are selected, this will focus more on high-risk populations, proper causes identification, and prevalence estimation. While applying inappropriate measurement methods, unsuitable data generation scales will result in ill-suited policies and strategic responses. Food security is difficult to assess because of the multidimensionality among its different aspects, and creating a single index that encompasses all aspects of the notion is technically challenging. As a result, there is no such thing as a composite measure of food security. However, there is high diversity in the existing measurements with different actors, where each measurements tool depends on the broad purpose of conducting it (Haysom and Tawodzera 2018).

1.2 Research Aim and Motivation

This thesis aimed to understand food security statistical assessments and provide resilient methods that are statistically based on assessing food security. The research motivations can be summarized into assessing the potential of using a statistical-based method as a weighting approach for future consideration and research by developing a credible statical weights generation and efficiency model. That can be compared to existent subjective methods used to assess food security levels in countries.

1.3 Thesis Outline

The current research paper begins with providing an introduction and a background to the topic, followed by the aim and motivation of the research. A literature review is presented in Chapter 2. The literature review explores the current food quality and safety and food security-related assessments, then discusses the variable assessment techniques used to measure food security levels in countries and the associated benefits and drawbacks of the existing used ones. That being said, the literature also focuses on optimization modeling and the purposes of using them. The literature was used to draw a baseline for this research. Chapter 3 illustrates the methodologies and the sequence of applications employed in the research.

Further, the chapter explains the datasets, data sources, and a diagram for a better understanding of the approaches and methods of the research. Chapter 4 comes out with the findings and begins by caparisoning the methods explained in the methodology and drives to the results and a comprehensive discussion. Chapter 5 aims to conclude the research by providing implications of the findings, the challenges faced during the research, future works, and rooms for further improvements and research. Lastly, the references used are all listed in the Reference section, and the appendix is added for further acquaint and clarification.

CHAPTER 2: LITERATURE REVIEW

This chapter provided a microscopic review covering studies related to food security assessments. The review focuses on four aspects related to food security measurements, namely, 1) Recent trend on global food security & safety assessments, 2) Variable selection approaches for food security assessments, 3) Variable importance in projection approach, 4) Optimization modeling in food security. The stages that this review has gone through are illustrated in

Figure 1.

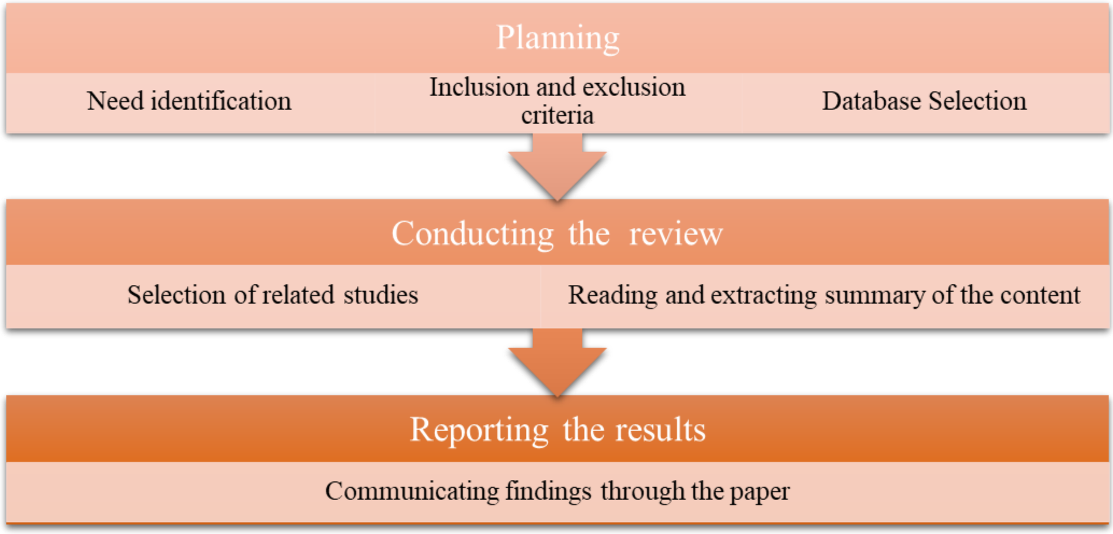


Figure 1. Review Process

At the first stage, the need for this review has been identified, the criteria for selecting papers have been listed, the search was done using a combination of the keywords such as: “Food Security Assessments” AND “Food Safety”, “Food security” AND “Variable selection approach”, “Food security” AND “Optimization Models”. Then further edits on the keywords were made to filter and exclude the unrelated results. In stage 2, the related studies were selected through reading abstracts and based on the quality of the assessment or publication. After that, the selected papers were read, highlighting the papers’ findings. In the last stage, the review results were organized and reported systematically.

Literature Review Limitation

1) The literature attempted to cover only the publications during the last ten years 2011-2021.
2) The search was done in Scopus Online Database.

2.1 Recent trend on global food security & safety assessments

The International Food Policy Research Institute (IFPRI) conducts the Global Hunger Index (GHI) and publish it annually along with achieving the United Nations Sustainable Development Goals (UNSDG) – Goal 2 that pertains to food security and aims to reach zero hunger in 2030, increase food security and enhance nutrition status. Moreover, the Global Nutrition Report presents indicators at the country level that may be used to understand food security (Haug 2018) better. GHI consists of three main indicators, and one of the indicators includes two sub-indicators. An assigned standardized score is given to each indicator. The score assigned is chosen to be somewhat higher than the maximum country-level values reported globally for the one indicator since 1988, so it can measure how the indicator is improving in terms of the highest observed levels. Aggregation is then implemented on the standardized scores to calculate each country's GHI, where each of the three main indicators contributes with equal weight to the GHI score (Grebmer et al., 2017). An index initiated to track the country-level progress toward food security is the Global Food Security Index (GFSI) which is determined through compiling three dimensions of food security as previously mentioned, GFSI in annually produced since 2012 it measures the index of more than 100 countries, the total number of indicators contributes on the GFSI is 28 distributed over the three dimensions. Affordability is reflected by six indicators, availability by 11 indicators, in addition to quality and safety by 11 indicators (Thomas et al., 2017). Other papers have also studied and applied different methods of assessing food security nationally or regionally. For example, in Tanzania, a scheme for Participatory Impact Assessment (FoPIA) was used to measure the sustainability effects of implementing agriculture development interventions known as upgrading strategies to improve food security (Schindler et al. 2016). However, the original FoPIA is usually used on a set of indicators to evaluate the impact of policies on them through obtaining and summarizing participants' opinions on the performance of certain sustainability parameters or policies. Thus, it is considered a semi-quantitative technique (Pass et al., 2019). However, it could be highly subjective since this assessment is based on people's opinions away from any related statistical inputs.

2.2 Variable selection approaches for food security assessments

Assessing food security has been an interesting, controversial topic that gained the attention of many researchers internationally. However, food security is a theoretical construct that can only be measured indirectly (Vaitla et al., 2017). In the last decade, different organizations have been using, merging, and implementing multiple techniques for assessing food security. Therefore, longstanding debates were driven to discuss the best measurement technique used in the food security assessments (Barrett 2010; Carletto et al. 2013). Doreswamy & Nigus (2020) have proposed filter-based feature selection techniques to reveal the best feature selection method according to their correlations with the target variable. Correlation matrix, machine learning, deep learning, and intersection method are food security prediction practices and variable-based selection approaches (Headey and Ecker 2012; Westerveld et al. 2021). The correlation matrix is a table illustrating each food security-related variable (Vaitla et al., 2017). The correlation coefficient mainly ranges between +1, a perfect positive correlation, and -1. Combining machine and deep learning methods is useful for comprehending food security and its complexity (Deléglise et al., 2022). The intersection method is a filter-based selection approach that functions similar to feature importance and univariate method for selecting the best feature technique to achieve a secured food system (Doreswamy and Nigus 2020).

Several interventions have been established to quantify food quality and food security safety in the agricultural system. Recent publications have reviewed the variable/feature selection techniques that have been used in food security assessments. To ensure the accuracy of the variable/feature selection technique, Doreswamy & Nigus (2020) suggested using multiple machine learning algorithms, including K-Nearest Neighbors (KNN), Random Forest (RF), Logistic Regression (LR), and Support Vector Machine (SVM). Kerner et al. (2020) employed K-Nearest Neighbors (KNN) to collect and cluster crop types data to ensure food security in Kenya. Babu & Gajanan (2022) have classified household groups based on certain socioeconomic characteristics to assess food security using K-mean cluster analysis. Egbunu et al. (2021) used Random Forest (RF) to predict climatic changes, helping farmers prepare in advance to avoid the influence of the climate variations; therefore, the yield of crops would certainly be boosted. A binary Logistic Regression (LR) model built by Omotesho et al. (2016) was established to identify factors affecting Nigeria's household food security. Barbosa & Nelson (2016) successfully classified household food security by applying a novel use of Support Vector Machine (SVM) in Brazil.

Variable selection techniques are practical for measuring food quality and ensuring food security safety. However, considering all food security variables might not be a convenient option causing over-fitting and reducing the validity of the results (Wang et al. 2020). A plethora of techniques adopted by multiple studies has been used to assess food security. Statistical variable selection methods, including Selection Operator (LASSO), Least Absolute Shrinkage, Elastic-Net regression and Ridge, have been used extensively for selecting food security-related variables (Abbas et al. 2020; Abdella and Shabaan 2020; Kutty 2020a). A regression model using the L1 regularization technique is known as “Lasso Regression” compared to L2 regularization, which is known as “Ridge Regression” (Ogutu et al., 2012; Abdella et al. 2019). The feature selection procedure can be employed using additional techniques such as Difference of Convex functions Algorithm (DCA) and Variable Importance Projections (VIP). However, these techniques all have the typical objective of decreasing model complexity and vary in what is considered complex (Wang et al. 2020). Each variable/feature selection method is associated with its corresponding advantages and drawbacks. Table 1 summarizes the main selection techniques related to the assessment of food security aligned with the advantages and disadvantages (drawbacks) for each selected method.

Table 1. Summary of the main variable selection techniques for food security assessments.

Variable selection technique	Advantages	Drawbacks	Reference
Difference of Convex functions Algorithm (DCA)	a. The deficiency in solving a class of optimization problems where the objective function is a large sum of non-convex features and a regularization term. b. Do not generate infeasible solutions while searching for an optimum variable.	a. Expensive except when proposing an effective DC decomposition for which the stochastic program has a reasonable price.	(Thi et al. 2017)
Variable Importance Projections (VIP)	a. Allows the user evaluating the importance of individual variables from the predictors. b. Results were easier to interpret than the Selectivity Ratio (SR) method.	a. Less reliable for prediction purposes.	(Zakharov et al. 2019). (Farrés et al. 2015)

Variable selection technique	Advantages	Drawbacks	Reference
L1 regularization (LASSO regression)	a. Provides the summation of the absolute value of weights of food security-related variables. b. Displays sparse solution. c. The output provides multiple solutions, allowing the user to compare the results. d. Allows built-in feature selection. e. Robust/resistance to outliers. f. Facilitates interpretation of the resulting parameters.	a. The cost of possibly discarding variables that still may be relevant. b. Sometimes, the model creates a bias where the forecast relies upon a specific variable.	(Wang et al. 2020)
L2 regularization (Ridge regression)	a. Shrinks the parameters towards zero as much as possible. b. Avoids over-discarding variables as it rarely excludes variables completely.	a. Provides the only summation of square of weights of food security-related variable. b. Displays non-sparse solution. c. The output provides only one solution, restricting the user from comparing the results. d. Does not allow feature selection. e. Unrobust to outliers due to square term. f. Interpretation is more ambiguous as the set of active variables remains stable.	(Wang et al. 2020)

Variable selection technique	Advantages	Drawbacks	Reference
Elastic-Net regression (Adaptive LASSO)	a. The ability to combine the benefits of both regression models (lasso and ridge regression). b. It does not conveniently remove the high collinearity coefficient of the selected approach. c. It enhances the accuracy of the prediction.	Not Applicable.	(Kostov and Davidova 2013)

2.3 Variable importance in projection

For many scientific engineers, variable selection methods and models are a crucial practical issue (Chong and Jun 2005). Variable importance in projection is a statistical method used to identify and select the most important independent variables. Through the comprehensive principal components of the relevant independent variables, VIP may describe the explanatory power of independent variables to the dependent variable. Other variable selection models such as PLS and BPN are widely used, but one cannot neglect their deficiency with small sample size prediction problems. Also, researchers declared that using a few parameters that influence the model for the prediction problems is easier, and effective results in more accurate estimations for those models (Chen et al., 2020)

When there are too many independent variables, the model becomes complex. Many unavoidable correlations between the variables will be observed, which lowers the model’s accuracy, increases the estimate variance, and invalidates the estimation approach, especially when the model includes a small number of samples. Various variable selection methods are commonly practiced because of their simplicity and convenience; however, multicollinearity between the variables provides inaccurate results when applied to small sample size. These methods include stepwise regression analysis, gray correlation analysis, and correlation coefficient analysis. So, the VIP approach became one of the unwell utilized methods for selecting independent variables (Chen et al., 2020), especially when there is a strong correlation between the independent variables on the model (Sun et al., 2018).

VIP method

has been applied in some studies related to blood component testing, epidemiological analysis (Sun et al., 2018), chemical, medical, and food science, and even for planning for the best strategies for an accurate development cost estimation for general aviation air crafts. Where the paper has selected three out five parameters influencing the development cost based on excluding the indicators with significantly lower values of VIP, they also have applied combined regression methods with VIP to test and overcome the inaccuracy that might be resulted by the small sample size and to establish a stable, effective prediction model (Chen et al., 2020).

A group of researchers has applied VIP analysis in near-infrared detection of Dural hematoma. Dural hematoma is a type of brain bleed that occurs after severe brain injury, and the failure to establish an accurate diagnosis could develop irreparable brain damage. Their work has provided a novel technique using VIP analysis to select detectors' locations, where the detectors with significant diagnosis and prediction ability are selected among other locations. By applying Variable Importance in Projection analysis, they reduced the number of detectors from 30 to 4, and this has been remarkably reflected in the accuracy and quality of their prediction model (Sun et al., 2018). VIP expresses the importance of the independent variables to the system and reflects how the dependent variable is represented (Chen et al., 2020).

2.4 Optimization modeling in food security

After variable selection techniques have been discussed, the results of the assessments must be measured and compared. So, this section is meant to review the use of optimization modeling approaches and efficiency analyses in food security assessments to assess the efficiency of individual countries or firms. Efficiency is defined as the ratio of outputs to inputs, and it may also be described as the distance between input and output quantities. The purpose of applying those estimated efficiency tests on certain studies is to assess the performance of a homogenous set of systems, for example, set of countries, set of hospitals, or set of districts that we need to measure who is performing better (Al-Sheeb et al. 2019), after providing a set of explanatory variables (inputs & outputs) (Asmare and Begashaw 2018). Furthermore, optimization and mathematical models are used to enhance the performance of food systems by taking into account multiple dimensions, such as supply chains, production, and operations in the food sector (Namany et al., 2019). The practical implications of the recent research on efficiency measurement have been dominated by efficiency analysis utilizing parametric and nonparametric approaches. Nonparametric frontier approaches are such as the: Free Disposal Hull (FDH) Data Envelopment Analysis (DEA), where the parametric approaches that are mostly used are: distribution-free Approach (DFA), Thick Frontier Approach (TFA), Stochastic Frontier Approach (SFA) (Murillo-Zamorano 2004; Elhmoud et al. 2021). However, the choice of estimation method has been a point of argument (Asmare and Begashaw 2018). Because decision-makers are usually interested in ranking the examined alternatives based on their performance, researchers have started discussing other new methods for assessing efficiency and ranking alternatives (Carrillo and Jorge 2016; Lotfi et al. 2012).

Namany et al. (2019) has introduced a new methodology to contribute to the food security sector's decision-making. The authors utilized Energy-Water-Food (EWF) nexus in a multidimensional approach, considering Qatar's environmental and economic performance of multiple technology options. They implemented and studied three scenarios. The first and second scenarios discussed the current technologies configurations on EWF. In the last scene, they developed a stochastic optimization model to determine the optimal energy and water mix that can impact food security to attain a 40% self-dependency in perishable food production. The findings from the study showed the number of investments needed to reach 40% self-sufficiency and the impacts of investing in technologies on the environment and the country's economy.

Regarding food security and related technological integrations, they mentioned that smart agriculture might be brought to the food sector to improve operational efficiency. Finally, Ibrahim et al. (2019) evaluated OCED countries' efficiency in terms of Water-Energy-Land-Food (WELF-nexus) to maintain the sustainability of current and future generations. The order of countries model generated after applying DEA was used to estimate the WELF efficiency of each country and the annual average efficiency of the countries in 3 years; 2007, 2012, and 2016. To assess the impact of drought on WELF efficiency, Ibrahim et al. (2019) have also performed a sensitivity analysis, where they noticed a decrease of about 13% on average WELF efficiency that was observed earlier. Study results were good for decision-makers and governments to establish policies and strategies to achieve WELF-nexus efficiency.

There are other optimization models, and policy-making assistant tools approach applied by researchers in the food sector. For example, research has been done to evaluate and model the impacts of four water-land allocation alternatives on national food security and farming livelihoods in Egypt, to explore the links between food-land-water under low agriculture resources, particularly water and land. The four scenarios start with the base scenario, optimum land scenario, optimum water scenario, and optimal land and water scenario. The tracking of food security and sustainability aspects is the unique feature of the last scene they applied, which identifies the effect of applying the optimum water and land allocation policies on food security and water sustainability. They applied a nonlinear optimization modeling integrated with the welfare analysis approach on each scenario. They found that the optimum land model, optimum water model, and land-water optimum model compared to the base scenario will significantly increase the production of the total crop, thus enhancing food security status in Egypt. The welfare analysis technique can assist policymakers, and social planners formulate strategies to help them accomplish food security goals (Gohar et al., 2021).

Furthermore, a study was carried out to increase food security in Qatar by achieving efficient waste management. The PolicyCompass system, which was based on a Fuzzy Cognitive Map (FCM), the nonparametric approach, paired with a policy graphic modeling interface, aiming to identify the relationships between organizational behaviors and practices in food supply chains concerning waste. The study's findings contribute to policymakers that could assist them in evaluating the applied policies and building more resilient food chains that could improve food security overall (Irani et al., 2017).

The diversity of using the parametric and nonparametric approaches to get optimized solutions in recent years has been noticed through this literature process. However, many publications were applying it in fields such as agriculture and sustainability that are not directly related to food security, and they can be employed on food security for providing optimized solutions or evaluating the performance of multiple entities SEE

(Kutty et al. 2020a; Kucukvar et al. 2021a; Abdella et al. 2021; Onat et al. 2021; Kutty et al. 2020b). Generally, the parametric method is more appealing when significant measurement mistakes and random events are in the data. Nonparametric analysis, on the other hand, may be a preferable alternative when random disturbances are less of a concern. Thus, Parametric and nonparametric methods are complementary rather than competing methods (Asmare and Begashaw 2018).

CHAPTER 3: METHODOLOGY

This chapter will explain the methods used to achieve the study's objectives, from data collection until adopting the approaches. Figure 2 explains this study's steps to carry out the analysis and achieve its goals.

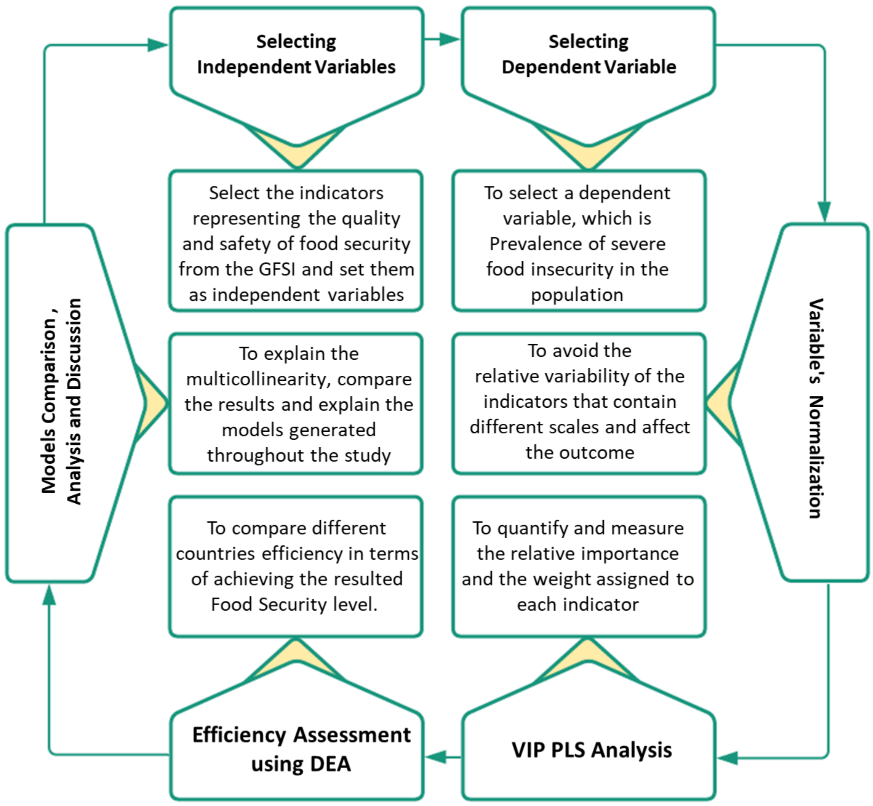


Figure 2. Diagram showing the outline of methodology's main stages

3.1 Data Collection

The data used to perform the analysis are extracted from two reliable resources. Each resource will be explained in addition to the type of data extracted.

3.1.1 Global Food Security Index.

The Economist Intelligence Unit's Global Food Security Index (GFSI) has been published annually since 2012 and covers more than 100 nations. The GFSI's conceptual framework is built around three aspects of food security: affordability, availability, and quality and safety. Each dimension is populated by several indicators, where each indicator has a default weight. The weights are calculated by having the averages of the weights suggested by the members of an expert panel. The score for each country in a certain year is calculated using a weighted arithmetic average (Thomas et al., 2017).

Table 2. Quality and safety indicators for food security by GFSI

1	**Dietary diversity**	
2	**Nutritional standards**	
	2.1	National dietary guidelines
	2.2	National nutrition plan or strategy
	2.3	Nutrition labeling
	2.4	Nutrition monitoring and surveillance
3	**Micronutrient availability**	
	3.1	Dietary availability of vitamin A
	3.2	Dietary availability of iron
	3.3	Dietary availability of zinc
4	**Protein quality**	
5	**Food safety**	
	5.1	Food safety mechanisms
	5.2	Access to drinking water
	5.3	Ability to store food safely

This paper focuses on quality and safety for food security, so the indicators under food quality and safety and their data were extracted for the five years 2015-2019. The indicators are 12 (see Table 2) as a total of indicators and sub-indicators, each with a specific weight. Those indicators have been dealt with as the x variables in the upcoming steps.

3.1.2 Prevalence of severe food insecurity in the population (%).

The prevalence of severe food insecurity in the population (%) is the percentage of people who live in seriously food insecure households. When at least one adult in the household reports having been exposed to several of the most severe experiences, such as being forced to reduce the quantity of their food, skipping meals, going hungry, or having to go for a whole day without eating due to a lack of money or other resources, the household is classified as severely food insecure. The dataset is downloaded from The World Bank Group, a global five institutions' partnership, dedicated to reducing poverty and building a shared prosperity in developing countries through providing sustainable solutions, and it has an open database. The prevalence of severe food insecurity is considered the y variable in this study. That reflects the status of the population in terms of the nation's food security. The importance of using this indicator is highlighted after considering what GFSI misses, which is that GFSI is measuring the conditions that can lead to food security, not the outcomes in terms of food intake or population nutritional status. Instead of measuring real food security levels, the final score of GFSI for each country aims to evaluate the conditions for food security or a suitable and appropriate environment for food security (Thomas et al., 2017).

3.1.3 Countries selection.

We have selected the countries available in both the GFSI dataset and the dataset of the prevalence of severe food insecurity in the population (%). Thus, the analysis is performed on 46 countries from all around the world.

3.2 Data Set up

After all the data needed are extracted, some steps have been taken to set up the data and get it ready for the application of methods and further analysis.

3.2.1 Normalization.

The food security quality and safety indicators have different scales, and in order to avoid the relative variability of the indicators affecting the result, normalization was done on the extracted non-normalized data (Mukherjee et al., 2015). They have been normalized using minimum-maximum rescaling and scaled from 0 to 100, with 100 being the best circumstance. This process makes the data comparison able and meaningful. The used formula is the Feature Scaling formula:

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

where x is the original value, x' is the normalized value.

3.2.2 Weighted Arithmetic Mean.

Each country's GFSI score is calculated using the Weighted Arithmetic Mean (WAM). The WAM was applied using the default GFSI and Variable Importance in Projection (VIP). The WAM score can be calculated using:

$$\bar{X}_w = \frac{\sum_{i=1}^{n} wx}{\sum_{i=1}^{n} w} \tag{2}$$

where $\bar{X}_w$ is the weighted arithmetic mean, n is the number of indicators, x is the contribution of the ith indicator, and w is the weight index.

3.3 Variable Importance in Projection Approach

3.3.1 GFSI Default Weights.

An expert group from government, non-profit organizations, and academics chose which indicators to include in the GFSI and how much weight each indicator should have in the final result. The average weighting suggested by panel a of expert members is then calculated and referred to as the default weight. GFSI can be considered more of a subjective way of assigning the weights to a set of indicators since it is affected by the background and experience of each expert.

3.3.2 VIP Generated Weights.

This approach generates weights to a set of variables based on an analysis of variables values (x values) and an additional variable treated as (y variable). The variable importance for each indicator has been developed using XLSTAT. Appendix B shows an example of the data provided for each year and the result of variable importance in projection (VIP) weights. The x and y variables have been used separately as an input for each year to generate the weights. Unlike the GFSI weights, which are constant for all years, VIP weights fluctuate by year for the same indicator, and this can be attributed to the required usage of the y variable for the VIP approach.

3.4 Efficiency using Data Envelopment Analysis

After the data is ready and normalized and the weights of both Global Food security Index (GFSI) and Variable importance in projection (VIP) are available, efficiency and performance study is performed using Data Envelopment Analysis. Countries are compared using all available resources and services, and the most efficient countries and inefficient countries in terms of achieving food security are identified. Also, Data Envelopment Analysis (DEA) calculates how much resources should be changed to make each inefficient country more efficient. In this study, both weighted and non-weighted DEA has been carried out. Since applying DEA requires specifying inputs and output, the quality & safety indicators have been considered inputs, and the prevalence of severe food insecurity in the population percentage was considered an output where the DMUs are the 46 countries on the study. Several DEA models have been created to assess efficiency and capacity. These mostly fall into input-oriented or output-oriented models (Kucukvar et al., 2022). The Input-Oriented DEA (IO-DEA) multiplier model used in this study is explained in this section.

Let x and y be the inputs and outputs for a respective DMU under the analysis, where i and j refer to inputs and outputs of each category so:

x_i = ith input of particular DMU; y_j = jth output of particular DMU each DMU represents one country and:

Q = Number of inputs > 0; P = Number of outputs > 0; N = Number of DMUs

$$WI = \sum_{i=1}^{Q} u_i x_i \quad ; \quad WO = \sum_{j=1}^{P} v_j y_j$$

The ratio of weighted output (WO) to weighted input (WI) is used to calculate relative efficiency, and its equation is stated below (Kucukvar et al., 2022). u_i represents the weights assigned to input x_i, and v_j represents the weights assigned to output y_j where $u_i \geq 0$ and $v_j \geq 0$. In the unweighted DEA model v_j and u_i, the weights are randomly chosen by linear mathematical programming.

$$Efficiency = \frac{WO}{WI} = \frac{\sum_{j=1}^{P} v_j y_j}{\sum_{i=1}^{Q} u_i x_i} \tag{3}$$

The following is the mathematical formulation for the input-oriented DEA model.

Objective function:

$$Max\ z = \frac{\sum_{j=1}^{P} v_j y_j}{\sum_{i=1}^{Q} u_i x_i} \tag{4}$$

Subject to:

$$v_j \geq 0,\ u_i \geq 0 \text{ for } j = 1 \ldots .\ P \text{ and } i = 1 \ldots .\ Q$$

The objective is to maximize DMU's efficiency score. To ensure that all efficiency scores for all remaining DMUs are less than 1, the first constrain is added, and the second constrain is a non-negativity constrain for the weights assigned to the inputs and outputs. In this study, the model used is the Weighted Slack-based Measure (SBM) Input-oriented (IO) Variable Return to Scale (VRS) model, and it is generated using the statistical "R software" rDEA package from the CRAN library.

3.4.1 Weighted DEA-based model.

Weighted DEA is applied two times. The first one is by assigning GFSI default weights for the inputs in the DEA and assigning an equivalent weight to the output. The second time is by assigning the weights generated by VIP with an equivalent weight for the output.

3.4.2 Unweighted DEA-based model.

For the non-weighted DEA, no weights have been assigned to the inputs nor the outputs, and the linear program generates the weights to compare the efficiency scores of the unweighted-DEA model with DEA models using GFSI and VIP weights. For the non-weighted DEA also, SBM IO-VRS is the model carried out.

CHAPTER 4: RESULTS, COMPARISON AND DISCUSSION

This chapter is dedicated to representing the results after carrying out the steps highlighted in the methodology in Chapter 4 and to discussing the results.

4.1 Variable Importance in Projection Scores

In this section, the weights statistically assigned to each indicator are represented in Figure 3.

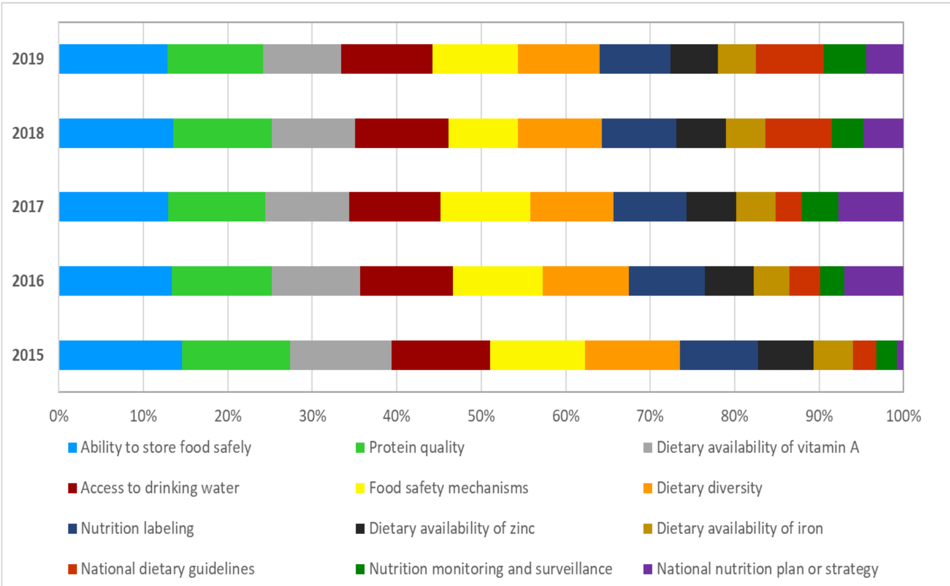


Figure 3. VIP Indicator's scores for years 2015-2016

Each variable has a specific weight that changes each year based on Variable Importance in Projection technique results, as shown in Figure 3. For example, the indicator "Ability to store food safely" has got a weight of 14.6%, 13.4%, 12.95%, 13.52and 12.86% on the years from 2015 – 2019, which is the highest weight among other indicators on each year separately, where "Dietary Diversity" was the sixth important indicator on the period from 2015- 2017 with weights of 11.19%, 10.24%, 9.86% respectively. Then its importance has increased to become the fourth important indicator in 2018 with a weight of 9.96%. It has also been noticed that "Ability to store food safely," "Protein quality," and "Access to drinking water" respectively are the indicators with the highest weights in all years. Comparing Variable Importance in

Projection weights to the default weights of Global Food Security Index, we could see similar prioritization of the indicators. For instance, GFSI has assigned a weight of 23.7% for "Protein quality," which is the highest weight on other indicators.

4.2 Statistical weights vs. experts' weights using weighted arithmetic mean

The comparison performed on 46 countries for five years between VIP weights and GFSI weights when applying the weighted arithmetic mean is shown in Appendix A.

2015			
VIP weights		GFSI weights	
Country	Score	Country	Score
Norway	95.057	Norway	92.149
United States	94.758	United States	91.616
Denmark	93.984	Denmark	89.865
Netherlands	93.119	Netherlands	88.617
Germany	92.742	Germany	88.327
Switzerland	76.003	Poland	67.871
Peru	73.208	Ukraine	65.635
Ecuador	72.584	Tunisia	60.155
Ukraine	69.302	Peru	59.649
El Salvador	67.016	Ecuador	58.546
Cambodia	30.273	Cambodia	26.971
Ethiopia	29.027	Zambia	25.874
Guinea	27.788	Malawi	25.836
Burkina Faso	27.274	Bangladesh	23.635
Malawi	21.708	Ethiopia	23.097

2016			
VIP weights		GFSI weights	
Country	Score	Country	Score
Norway	95.380	Norway	91.799
United States	95.302	United States	91.615
Netherlands	93.811	Netherlands	88.617
Germany	93.487	Germany	88.327
United Kingdom	93.464	United Kingdom	88.101
Singapore	75.107	Singapore	68.321
Peru	74.649	Ukraine	66.395
Ukraine	71.214	Tunisia	60.585
Ecuador	68.924	Peru	59.716
Tunisia	67.588	Ecuador	58.655
Zambia	35.404	Cambodia	27.748
Ethiopia	32.780	Zambia	26.426
Guinea	31.863	Ethiopia	25.757
Burkina Faso	31.640	Bangladesh	24.712
Malawi	21.052	Malawi	22.665

2017			
VIP weights		GFSI weights	
Country	Score	Country	Score
Norway	95.295	Norway	91.799
United States	94.273	United States	91.232
France	93.802	France	88.975
Netherlands	93.724	Netherlands	88.968
Germany	93.224	Germany	88.327
Singapore	74.231	Singapore	68.496
Peru	71.807	Ukraine	65.659
Ukraine	70.155	Tunisia	59.199
Honduras	68.282	Peru	58.005
Ecuador	66.473	Ecuador	56.609
Ethiopia	34.684	Nigeria	31.263
Guinea	33.672	Guinea	28.052
Burkina Faso	33.036	Ethiopia	25.885
Zambia	29.973	Zambia	23.415
Malawi	22.124	Malawi	22.698

2018			
VIP weights		GFSI weights	
Country	Score	Country	Score
Norway	95.071	Norway	91.387
United States	94.874	United States	91.363
Netherlands	94.325	Netherlands	90.278
France	94.308	France	90.087
Denmark	94.077	Denmark	89.346
Hungary	78.299	Slovakia	66.543
Ecuador	75.408	Ukraine	62.339
Ukraine	67.519	Tunisia	61.348
El Salvador	66.276	Ecuador	59.403
Peru	65.040	Algeria	56.337
Guinea	31.553	Nigeria	30.773
Burkina Faso	29.160	Guinea	29.097
Uganda	27.325	Ethiopia	26.246
Zambia	25.370	Malawi	23.948
Malawi	24.717	Zambia	21.871

2019			
VIP weights		GFSI weights	
Country	Score	Country	Score
Norway	95.573	Norway	92.067
United States	95.254	United States	91.724
Canada	94.371	Canada	89.730
United Kingdom	92.982	Netherlands	89.266
Netherlands	92.201	France	89.049
Hungary	76.249	Ukraine	66.205
Slovakia	74.727	Slovakia	65.602
Ecuador	73.272	Tunisia	60.308
Peru	70.125	Ecuador	57.719
Tunisia	62.306	Peru	56.226
Guinea	29.932	Bangladesh	28.631
Burkina Faso	28.307	Guinea	27.605
Uganda	26.839	Ethiopia	26.288
Malawi	22.508	Malawi	21.755
Zambia	20.436	Zambia	17.760

Figure 4. Comparing VIP weights and GFSI weights using weighted arithmetic mean

This section compares 15 countries out of the 46; 5 ranked top, 5 ranked bottoms, and five in the middle (see Figure 4).

Of course, the ranking is slightly changing when using different weights, but we could say that the countries keep appearing on their batch, for example, Norway, United States, and Netherlands keep showing in the top five countries in both scenarios in all years, the same also applies for Ecuador on the middle five countries and Malawi in the five lowest-ranking countries. This has also been noticed in the 46 countries using Global Food Security Index weights or Variable Importance in Projection weights when applying the weighted arithmetic mean slightly changes the country's ranking by not exceeding six ranks if not keeping the same rank.

4.3 Efficiency Study

To compare the three scenarios of applying DEA, the average efficiency scores assigned to the countries from 2015-2019 have been calculated and represented in Figure 5, Figure 6, and Figure 7. The figures show the average efficiency scores of randomly chosen 27 countries.

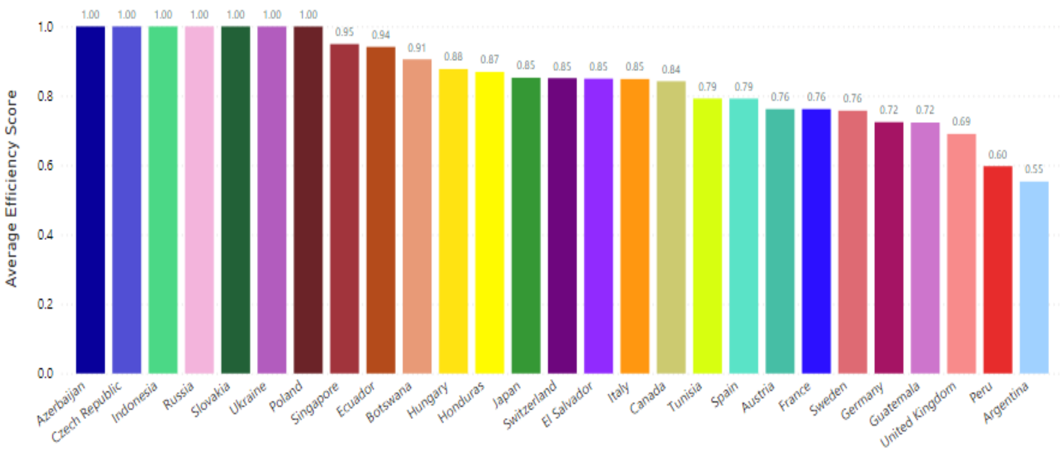


Figure 5. Efficiency scores of VIP weighted DEA

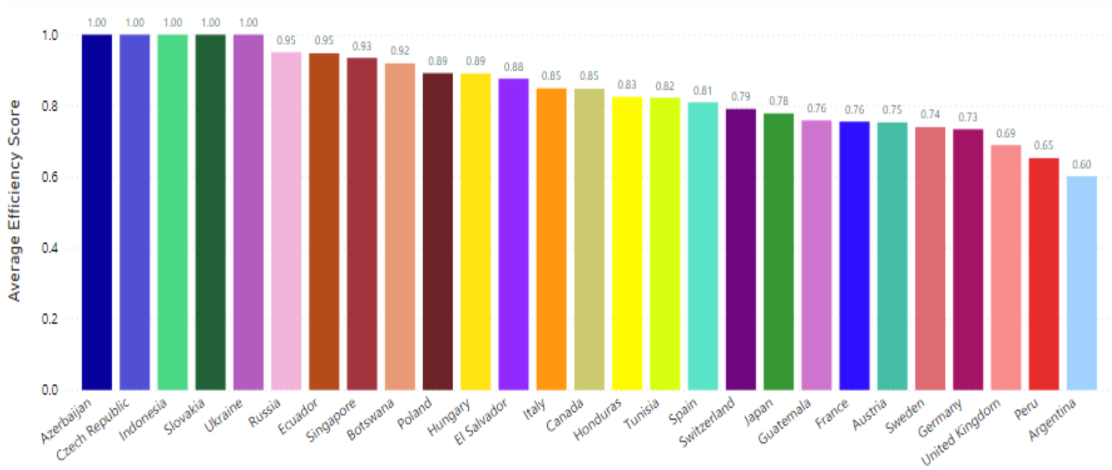


Figure 6. Efficiency scores of GFSI weighted DEA

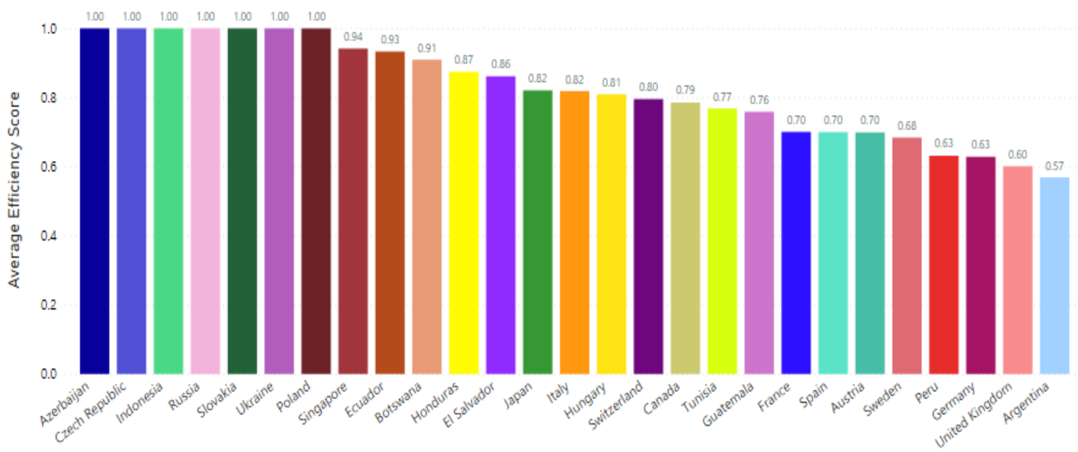


Figure 7. Efficiency scores of non-weighted DEA

After applying the weighted DEA, the first scenario in Figure 5 represents the results using variable importance in projection (VIP) weights. Countries like Azerbaijan, Czech Republic, Japan, Russia, and Slovakia got a score of 1, in other words, they are the countries falling on the efficiency frontier in addition to some other countries, which means they are efficient on achieving their certain level of food secured population (output). Japan, Switzerland, El Salvador, and Italy got an average efficiency score of 0.85, which means that improvements to achieve better efficiency, which will be discussed in the upcoming parts of the discussion and analysis. Figure 6 represents the second scenario that depicts the average efficiency scores when applying weighted DEA with GFSI weights. Figure 6 shows that some countries have also been classified as efficient such as Azerbaijan, Ukraine, Slovakia, and Poland. The difference in the scores between the first and second scenarios is noticed in countries like Spain which has an average of 0.79 efficiency score on the first scenario and then drops to 0.7 in the second scenario. Austria also has an average efficiency of 0.76, then drops to 0.7 on the second scenario using GFSI weighted DEA. Honduras, El Salvador, and Botswana had almost the same efficiency score in both scenarios. The countries ranked on the top as efficient countries do not change in both scenarios. Although average efficiency scores for some countries do vary between the first and the second scenario, we can note that the ranking is not majorly affected. For Canada and Tunisia, we can see that they fell in the same rank in both scenarios. However, their efficiency score is not the same. For example, Canada changes from an efficiency score of 0.84 to a score of 0.79.

Slight differences have been observed when comparing the last scenario of the non-weighted DEA with the first two scenarios in Figure 5 and Figure 6. Moreover, there is no noticeable change in the rank of the efficient countries. Russia appears to have an improved capacity of 5% compared with its rank using the weighted DEA.

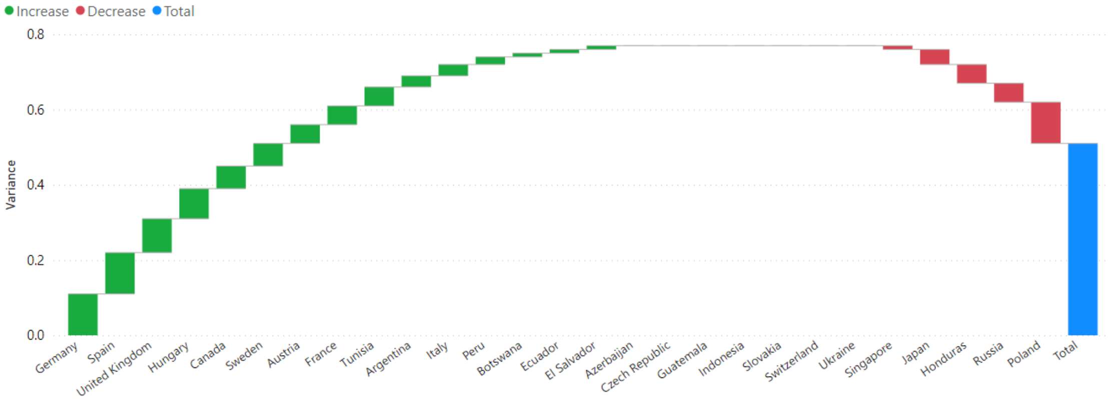


Figure 8. The variance between non-weighted DEA scores and GFSI weighted DEA scores

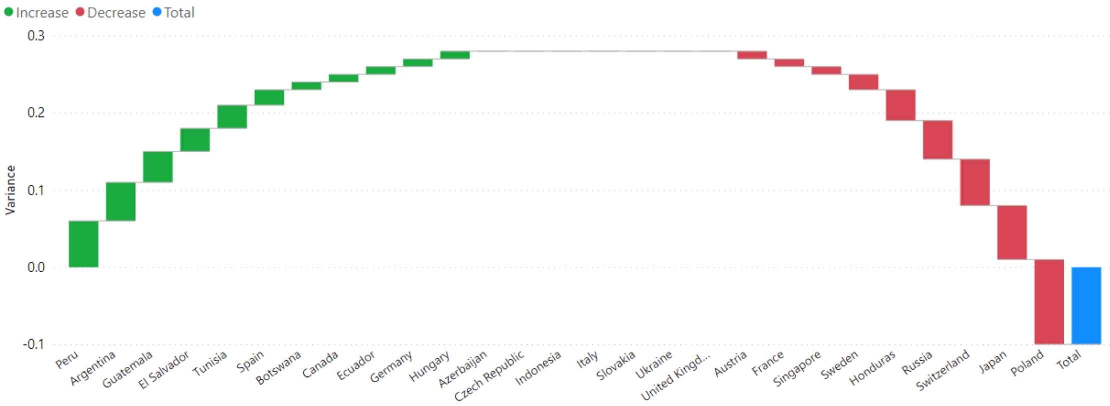
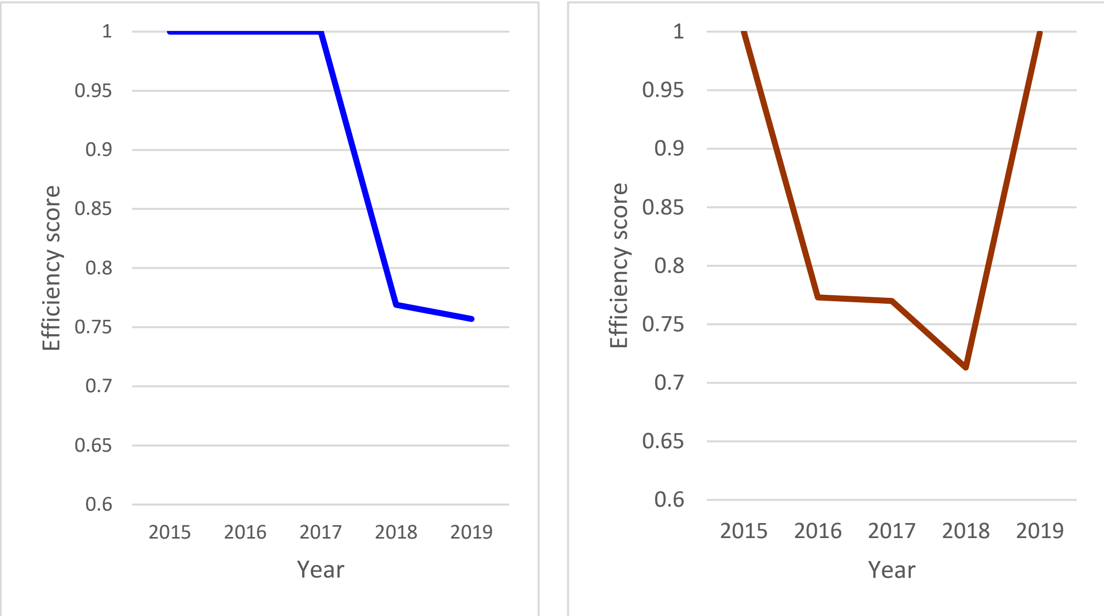


Figure 9. The variance between non-weighted DEA scores and VIP weighted scores

The results of the three scenarios are compared. The results show that the un-weighted DEA score assigned to each country is closer to the VIP weighted DEA score when the total variance between the scores of the GFSI weighted DEA and non-weighted DEA is equal to 0.51, as Figure 8 shows. The absolute variance is calculated to be 1.5, while the variance between the scores of the VIP weighted DEA and non-weighted DEA is equal to -0.1, as shown in Figure 9, where the absolute variance is 0.6. In both comparisons of the scores in Figure 8 and Figure 9, seven countries match with the non-weighted DEA.

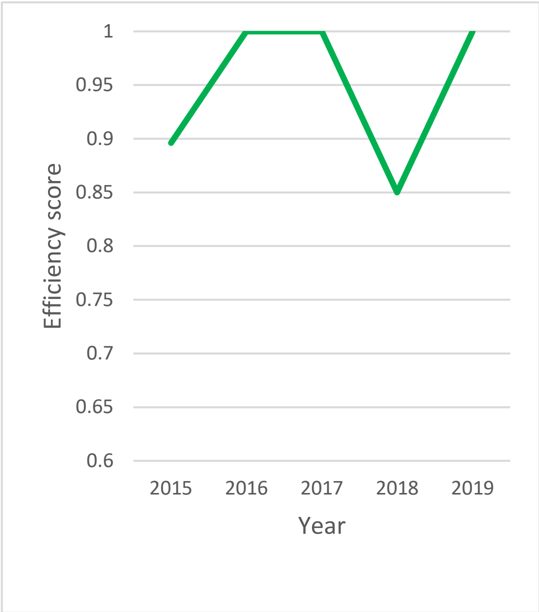
When countries like Azerbaijan, Czech Republic, and Indonesia obtain an efficiency score of 1 on each induvial year from 2015 to 2019, other countries obtain different efficiency score in each year, that sometimes might be a drop on the efficiency score and in some other cases achieving an efficiency of 1 in a certain year after being inefficient. We have zoomed on some of the countries that has observed such a noticeable change in efficiency scores from 2015 to 2019. The efficiency scores illustrated below are the ones that resulted from using VIP weighted DEA.



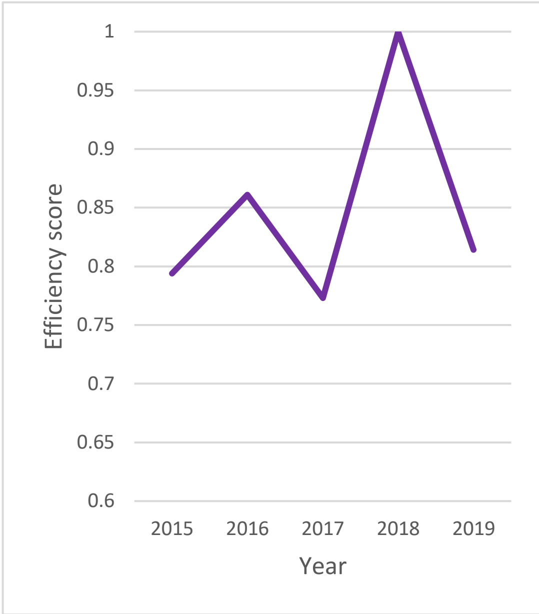
a) b)

Figure 10.a) Botswana efficiency scores 2015-2019 b) Swizerland efficiency scores 2015-2019

Figure 10a shows that Botswana after being efficient for three consecutive years, its efficiency drops to almost 0.8 in 2018 and 2019. Figure 10b shows that Switzerland after being classified efficient in 2015, the efficiency score drops between 0.71-0.77 in 2016-2018 and then achieves an efficiency score of 0.99 in 2019.



a)



b)

Figure 11. a) Singapore efficiency scores 2015-2019 b) Italy efficiency scores 2015-2019

Singapore efficiency scores did not fall below 0.85, which is the score in 2018, and it has been classified as efficient in 2016, 2017, and 2019. In Figure 11b, Italy has got an efficiency score of 1 in 2018 only where it has experienced efficiency scores 0.77 and 0.86 in the other years, which means Botswana, Switzerland, Italy, and Singapore in addition to other countries do have a chance of improving the system of the country to become more efficient on the years where efficiency scores have fallen below 1, based on the DEA model on this study.

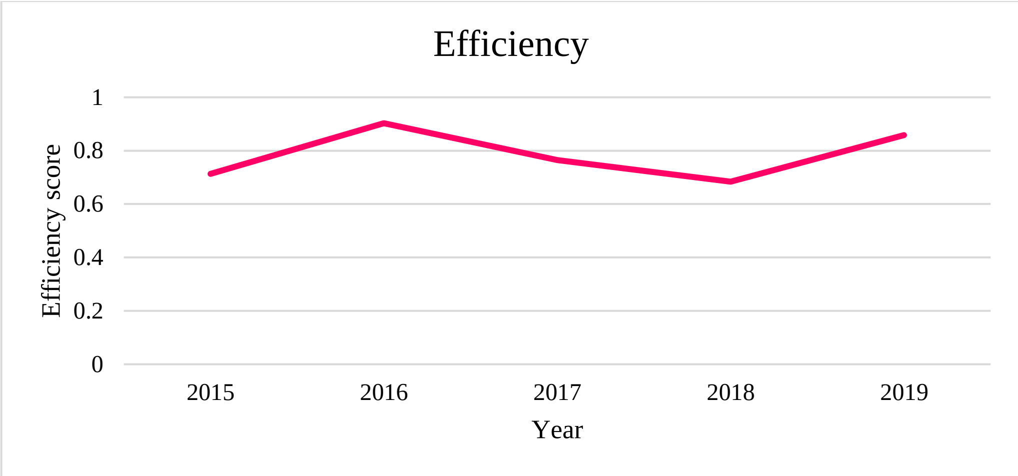


Figure 12. Denemark efficiency scores 2015- 2019

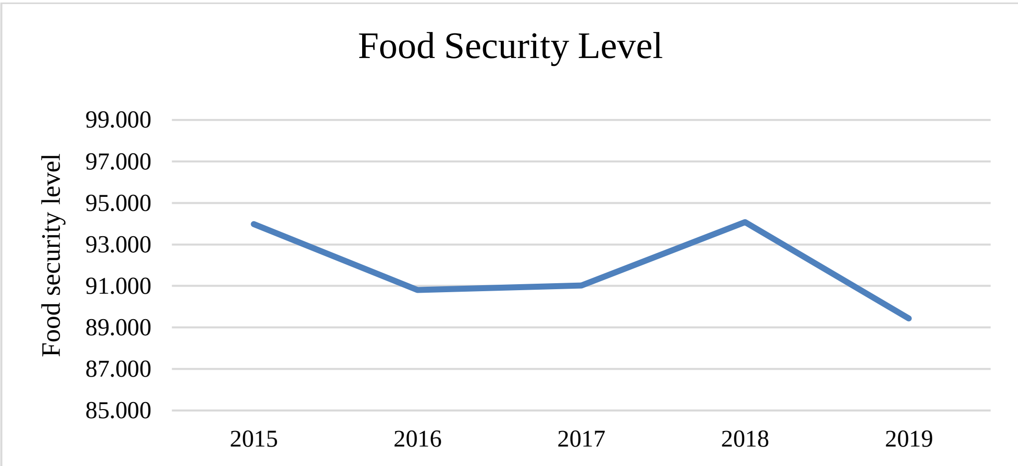


Figure 13. Denmark food security level using VIP weights

Some countries achieved a food security score higher than 90 and have efficiency scores lower than 1 in some of the years. For example, Denmark has food security levels above 89, as Figure 13 demonstrates. However, the efficiency scores appear to be always below 1 in Figure 12. This can be attributed to the nature of the results DEA provides since DEA and the input-oriented model minimize the use of inputs to produce the given output level, which is in this study the actual percentage of the population who are not living in a food-insecure environment. Unlike the output-oriented model that works on maximizing the output with the certainly provided inputs (resources). The model performed in this study set out options of how the country could perform more efficiently using fewer resources yet provide the same food security level in the population. Moreover, DEA calculates relative efficiency scores rather than absolute efficiency scores; in other words, even though the countries on the efficient frontier are given an efficiency score of 1, they might boost their output even further.

CHAPTER 5: CONCLUSION AND REMARKS

This research has proposed using a purely statistical approach to determining attributes' weights by incorporating outputs and outcomes affected by certain attributes in food security assessments. The study has focused on the quality and safety of food security attributes, being the most qualitative indicators to measure, and compared the method used to the existing method grounded on assigning weights to the set of attributes decided by the experts' subjective opinion. The interest to utilize a statistical method to set out the importance of a set of food security attributes was initiated after observing the current need for to use food security index in conjunction with other attributed if food insecurity or attributes that do measure the status of the population not only the resources used to attain food security. The research has further studied the efficiency of 46 countries in terms of resources used to achieve their certain level of food security, to capture the opportunities for improving countries' efficiency. The results show that although the ranking of importance of the indicators between the weights assigned by a panel of experts and the weights assigned using Variable Importance in Projection (VIP), was not enormous and major, there was a noticeable difference in the weights. However, those differences in the weights did not significantly affect the ranking of the countries when using the same scoring method, which was the Weighted Arithmetic Mean (WAM). The results on the efficiency study using weighted and unweighted-Data Envelopment Analysis model (DEA) showed that countries like Azerbaijan, The Czech Republic, and Slovakia has always been highly efficient countries despite the model of DEA used. The efficiency scores have not been noticed to fall below 0.48, and this score has been given to Argentina in one year using weighted DEA.

The limitations found in this method are related to the importance of the availability of historical data. The VIP approach needs a record for the indicators that have to assign weights to, for at least one period of time, so it can be possible for the Variable Importance in Projection method to study the data provided and result with reasonably credible weights. Furthermore, on the DEA, it is important to understand the nature of the results DEA provides since policies and strategies application based on DEA without a comprehensive view of the country's status and the capabilities it has could lead to wrong and unwell suit policies.

The main challenge faced during this research can be summarized as the lack of a proper big recent set of data that reflects the nutritional status and population health status for all countries for a consecutive number of years, which has limited the outcomes we are measuring. Nevertheless, this is considered room for future research and work, in addition to the further extension on this work to project DEA results study the feasibility of application not only to achieve the certain level the countries have achieved but also and to achieve the maximum level of food security.

REFERENCES

Abbas, F., Afzaal, H., Farooque, A. A., & Tang, S. (2020). Crop yield prediction through proximal sensing and machine learning algorithms. Agronomy, 10(7), 1046.

Abdella, G. M., & Shaaban, K. (2021). Modeling the impact of weather conditions on pedestrian injury counts using LASSO-based poisson model. Arabian Journal for Science and Engineering, 46(5), 4719-4730.

Abdella, G. M., Kim, J., Al-Khalifa, K. N., & Hamouda, A. M. (2019). Penalized Conway-Maxwell-Poisson regression for modelling dispersed discrete data: The case study of motor vehicle crash frequency. Safety Science, 120, 157-163.

Abdella, G. M., Kucukvar, M., Ismail, R., Abdelsalam, A. G., Onat, N. C., & Dawoud, O. (2021a). A mixed model-based Johnson's relative weights for eco-efficiency assessment: The case for global food consumption. Environmental Impact Assessment Review, 89, 106588.

Abdella, G. M., Kucukvar, M., Kutty, A. A., Abdelsalam, A. G., Sen, B., Bulak, M. E., & Onat, N. C. (2021). A novel approach for developing composite eco-efficiency indicators: The case for US food consumption. Journal of Cleaner Production, 299, 126931.

Abdella, G. M., Kucukvar, M., Onat, N. C., Al-Yafay, H. M., & Bulak, M. E. (2020b). Sustainability assessment and modeling based on supervised machine learning techniques: The case for food consumption. Journal of Cleaner Production, 251, 119661.

Abdella, G. M., Maleki, M. R., Kim, S., Al-Khalifa, K. N., & Hamouda, A. M. S. (2020a). Phase-I monitoring of high-dimensional covariance matrix using an adaptive thresholding LASSO rule. Computers & Industrial Engineering, 144, 106465.

Al Sheeb, B., Abdella, G. M., Hamouda, A. M., & Abdulwahed, M. S. (2019). Predictive modeling of first-year student performance in engineering education using sequential penalization-based regression. Journal of Statistics and Management Systems, 22(1), 31-50.

Al-Obadi, M., Kutty, A. A., Abdella, G. M., Kucukvar, M., & Bulak, M. E. (2021). Carbon footprints across the food supply chain: A microscopic review on food waste-related sustainability assessment. In Proceedings of the 11th Annual International Conference on Industrial Engineering and Operations Management (pp. 7-11).

Alsarayreh, M. M. M., AlSuwaidi, M. F., Al Sharif, R. A., & Kutty, A. A. (2020, April). The factors affecting CO 2 emission in the European union countries: A statistical approach to sustainability across the food industry. In 2020 IEEE 7th international conference on industrial engineering and applications (ICIEA) (pp. 599-604). IEEE.

Asmare, E., & Begashaw, A. (2018). Review on parametric and nonparametric methods of efficiency analysis. Biostatistics and Bioinformatics, 2(2), 1-7.

Babu, S., Gajanan, S., & Sanyal, P. (2014). Food security, poverty and nutrition policy analysis: statistical methods and applications. Academic Press.

Barbosa, R. M., & Nelson, D. R. (2016). The use of support vector machine to analyze food security in a region of Brazil. Applied Artificial Intelligence, 30(4), 318-330.

Barrett, C. B. (2010). Measuring food insecurity. Science, 327(5967), 825-828.

Carletto, C., Zezza, A., & Banerjee, R. (2013). Towards better measurement of household food security: Harmonizing indicators and the role of household surveys. Global food security, 2(1), 30-40.

Carrillo, M., & Jorge, J. M. (2016). A multiobjective DEA approach to ranking alternatives. Expert systems with applications, 50, 130-139.

Chen, X., Huang, J., & Yi, M. (2020). Cost estimation for general aviation aircrafts using regression models and variable importance in projection analysis. Journal of Cleaner Production, 256, 120648.

Chong, I. G., & Jun, C. H. (2005). Performance of some variable selection methods when multicollinearity is present. Chemometrics and intelligent laboratory systems, 78(1-2), 103-112.

Coates, J. (2013). Build it back better: Deconstructing food security for improved measurement and action. Global Food Security, 2(3), 188-194.

Deléglise, H., Interdonato, R., Bégué, A., d'Hôtel, E. M., Teisseire, M., & Roche, M. (2022). Food security prediction from heterogeneous data combining machine and deep learning methods. Expert Systems with Applications, 190, 116189.

Doreswamy, D., & Nigus, M. (2020, March). Feature Selection Methods for Household Food Insecurity Classification. In 2020 International Conference on Computer Science, Engineering and Applications (ICCSEA) (pp. 1-7). IEEE.

Egbunu, C. O., Ogedengbe, M. T., Yange, T. S., Rufai, M. A., & Muhammed, H. I. (2021). Towards Food Security: the Prediction of Climatic Factors in Nigeria using Random Forest Approach. Journal of Computer Science and Information Technology, 70-81.

Elhmoud, E. R., & Kutty, A. A. (2021, December). Sustainability assessment in aviation industry: a mini-review on the tools, models and methods of assessment. In Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management, Harare, Zimbabwe (pp. 7-10).

Elhmoud, E. R., Kutty, A. A., Abdalla, G. M., Kucukvar, M., Bulak, M. E., & Elkharaz, J. M. (2021, March). Eco-Efficiency Performance of Airlines in Eastern Asia: A Principal Component Analysis Based Sustainability Assessment. In Proceedings of the 11th Annual International Conference on Industrial Engineering and Operations Management, Singapore (pp. 7-11).

European Commission, Joint Research Centre, Thomas, A., d'Hombres, B., Casubolo, C. (2017). The use of the Global Food Security Index to inform the situation in food insecure countries, Publications Office. https://data.europa.eu/doi/10.2760/83356

Farrés, M., Platikanov, S., Tsakovski, S., & Tauler, R. (2015). Comparison of the variable importance in projection (VIP) and of the selectivity ratio (SR) methods for variable selection and interpretation. Journal of Chemometrics, 29(10), 528-536.

Gohar, A. A., Cashman, A., & El-bardisy, H. A. H. (2021). Modeling the impacts of water-land allocation alternatives on food security and agricultural livelihoods in Egypt: Welfare analysis approach. Environmental Development, 39, 100650.

Haug, R. (2018). Food security indicators: how to measure and communicate results.

Haysom, G., & Tawodzera, G. (2018). "Measurement drives diagnosis and response": Gaps in transferring food security assessment to the urban scale. Food Policy, 74, 117-125.

Headey, D. D., & Ecker, O., Improving the measurement of food security, no. 012225, p. 32, 2012.

Ibrahim, M. D., Ferreira, D. C., Daneshvar, S., & Marques, R. C. (2019). Transnational resource generativity: efficiency analysis and target setting of water, energy, land, and food nexus for OECD countries. Science of the Total Environment, 697, 134017.

Irani, Z., Sharif, A. M., Lee, H., Aktas, E., Topaloğlu, Z., van't Wout, T., & Huda, S. (2018). Managing food security through food waste and loss: Small data to big data. Computers & Operations Research, 98, 367-383.

Kerner, H., Nakalembe, C., & Becker-Reshef, I. (2020). Field-level crop type classification with k nearest neighbors: a baseline for a new Kenya smallholder dataset. arXiv preprint arXiv:2004.03023.

Khanam, M., Ara, G., Rahman, A. S., Islam, Z., Farhad, S., Khan, S. S., ... & Ahmed, T. (2020). Factors affecting food security in women enrolled in a program for Vulnerable Group Development. Current Developments in Nutrition, 4(4), nzaa037.

Kostov, P., & Davidova, S. (2013). A quantile regression analysis of the effect of farmers' attitudes and perceptions on market participation. Journal of Agricultural Economics, 64(1), 112-132.

Kucukvar, M., Kutty, A. A., Al-Hamrani, A., Kim, D., Nofal, N., Onat, N. C., ... & Al-Nahhal, W. (2021). How circular design can contribute to social sustainability and legacy of the FIFA World Cup Qatar 2022™? The case of innovative shipping container stadium. Environmental Impact Assessment Review, 91, 106665.

Kucukvar, M., Onat, N. C., Kutty, A. A., Abdella, G. M., Bulak, M. E., Ansari, F., & Kumbaroglu, G. (2022). Environmental efficiency of electric vehicles in Europe under various electricity production mix scenarios. Journal of Cleaner Production, 335, 130291a.

Kucukvar, M., Onat, N. C., Kutty, A. A., Abdella, G. M., Bulak, M. E., Ansari, F., & Kumbaroglu, G. (2022). Environmental efficiency of electric vehicles in Europe under various electricity production mix scenarios. Journal of Cleaner Production, 335, 130291.

Kutty, A. A., Abdella, G. M., & Kucukvar, M. (2020a, September). Ridge Penalization-based weighting approach for Eco-Efficiency assessment: The case in the food industry in the United States. In IOP conference series: Materials science and engineering (Vol. 947, No. 1, p. 012003). IOP Publishing.

Kutty, A. A., Abdella, G. M., Kucukvar, M., Onat, N. C., & Bulu, M. (2020b). A system thinking approach for harmonizing smart and sustainable city initiatives with United Nations sustainable development goals. Sustainable Development, 28(5), 1347-1365.

Kutty, A. A., Yetiskin, Z., Abraham, M. M., Nooh, M. A., Kucukvar, M., & Abdalla, G. M. (2020). An empirical assessment on the transportation sustainability indicators and their impact on economic productivity. In Proceedings of the 5th NA Conference on Industrial Engineering and Operations Management (pp. 10-14).

Le Thi, H. A., Le, H. M., Phan, D. N., & Tran, B. (2017, July). Stochastic DCA for the large-sum of non-convex functions problem and its application to group variable selection in classification. In International Conference on Machine Learning (pp. 3394-3403). PMLR.

Lotfi, F. H., Rostamy-Malkhalifeh, M., Aghayi, N., Beigi, Z. G., & Gholami, K. (2013). An improved method for ranking alternatives in multiple criteria decision analysis. Applied Mathematical Modelling, 37(1-2), 25-33.

Mortada, S., Abou Najm, M., Yassine, A., El Fadel, M., & Alamiddine, I. (2018). Towards sustainable water-food nexus: an optimization approach. Journal of Cleaner Production, 178, 408-418.

Mukherjee, R., Sengupta, D., & Sikdar, S. K. (2015). Selection of Sustainable Processes Using Sustainability Footprint Method: A Case Study of Methanol Production from Carbon Dioxide. In Computer Aided Chemical Engineering (Vol. 36, pp. 311-329). Elsevier.

Murillo-Zamorano, L. R. (2004). Economic efficiency and frontier techniques. Journal of Economic surveys, 18(1), 33-77.

Namany, S., Al-Ansari, T., & Govindan, R. (2019). Optimisation of the energy, water, and food nexus for food security scenarios. Computers & Chemical Engineering, 129, 106513.

Ogutu, J. O., Schulz-Streeck, T., & Piepho, H. P. (2012, December). Genomic selection using regularized linear regression models: ridge regression, lasso, elastic net and their extensions. In BMC proceedings (Vol. 6, No. 2, pp. 1-6). BioMed Central.

Omotesho, O. A., Adewumi, M. O., Muhammad-Lawal, A., & Ayinde, O. E. (2016). Determinants of food security among the rural farming households in Kwara State, Nigeria. African Journal of General Agriculture, 2(1).

Onat, N. C., Abdella, G. M., Kucukvar, M., Kutty, A. A., Al-Nuaimi, M., Kumbaroğlu, G., & Bulu, M. (2021). How eco-efficient are electric vehicles across Europe?

A regionalized life cycle assessment-based eco-efficiency analysis. Sustainable Development, 29(5), 941-956.

Paas, W., Accatino, F., Antonioli, F., Appel, F., Bardají, I., Coopmans, I., ... & Reidsma, P. (2019). Participatory impact assessment of sustainability and resilience of EU farming systems.

Saint Ville, A., Po, J. Y. T., Sen, A., Bui, A., & Melgar-Quiñonez, H. (2019). Food security and the Food Insecurity Experience Scale (FIES): ensuring progress by 2030. Food Security, 11(3), 483-491.

Saint Ville, A., Po, J. Y. T., Sen, A., Bui, A., & Melgar-Quiñonez, H. (2019). Food security and the Food Insecurity Experience Scale (FIES): ensuring progress by 2030. Food Security, 11(3), 483-491.

Schindler, J., Graef, F., König, H. J., Mchau, D., Saidia, P., & Sieber, S. (2016). Sustainability impact assessment to improve food security of smallholders in Tanzania. Environmental Impact Assessment Review, 60, 52-63.

Schindler, J., Graef, F., König, H. J., Mchau, D., Saidia, P., & Sieber, S. (2016). Sustainability impact assessment to improve food security of smallholders in Tanzania. Environmental Impact Assessment Review, 60, 52-63.

Sun, Q., Zhang, Y., Ma, J., Tian, F., Wang, H., & Liu, D. (2018). Detector location selection based on VIP analysis in near-infrared detection of dural hematoma. Saudi journal of biological sciences, 25(3), 452-456.

Thomas, A. C., D’Hombres, B., Casubolo, C., Kayitakire, F., & Saisana, M. (2017). The use of the Global Food Security Index to inform the situation in food insecure countries. JRC Science Hub, European Union.

Thomas, A. C., D'Hombres, B., Casubolo, C., Kayitakire, F., & Saisana, M. (2017). The use of the Global Food Security Index to inform the situation in food insecure countries. JRC Science Hub, European Union.

Vaitla, B., Coates, J., Glaeser, L., Hillbruner, C., Biswal, P., & Maxwell, D. (2017). The measurement of household food security: Correlation and latent variable analysis of alternative indicators in a large multi-country dataset. Food Policy, 68, 193-205.

Vaitla, B., Coates, J., Glaeser, L., Hillbruner, C., Biswal, P., & Maxwell, D. (2017). The measurement of household food security: Correlation and latent variable analysis of alternative indicators in a large multi-country dataset. Food Policy, 68, 193-205.

Von Grebmer, K., Bernstein, J., Hossain, N., Brown, T., Prasai, N., Yohannes, Y., ... & Foley, C. (2017). 2017 Global Hunger Index: the inequalities of hunger. Intl Food Policy Res Inst.

Wang, D., Andree, B. P. J., Chamorro, A. F., & Girouard Spencer, P. (2020). Stochastic modeling of food insecurity.

Westerveld, J. J., van den Homberg, M. J., Nobre, G. G., van den Berg, D. L., Teklesadik, A. D., & Stuit, S. M. (2021). Forecasting transitions in the state of food security with machine learning using transferable features. Science of the Total Environment, 786, 147366.

Zakharov, V. P., Bratchenko, I. A., Artemyev, D. N., Myakinin, O. O., Kozlov, S. V., Moryatov, A. A., & Orlov, A. E. (2019). Multimodal Optical Biopsy and Imaging of Skin Cancer. In Neurophotonics and Biomedical Spectroscopy (pp. 449-476). Elsevier.

Zhou, J., Sun, H. C., Wang, Z., Cong, W. M., Wang, J. H., Zeng, M. S., ... & Fan, J. (2018). Guidelines for diagnosis and treatment of primary liver cancer in China (2017 Edition). Liver cancer, 7(3), 235-260

APPENDIX

Appendix A: Results of the comparison between the rank using GFSI default weights and VIP generated weights

Comparison between the rank using GFSI defult weights and VIP generated weights

2015				2016				2017				2018				2019			
VIP weights		GFSI weights		VIP weights		GFSI weights		VIP weights		GFSI weights		VIP weights		GFSI weights		VIP weights		GFSI weights	
Country	Score	Country	Score	Country	Score	Country	Score	Country	Score	Country	Score	Country	Score	Country	Score	Country	Score	Country	Score
Norway	95.057	Norway	92.149	Norway	95.380	Norway	91.799	Norway	95.295	Norway	91.799	Norway	95.071	Norway	91.387	Norway	95.573	Norway	92.067
United States	94.758	United States	91.616	United States	95.302	United States	91.615	United States	94.273	United States	91.232	United States	94.874	United States	91.363	United States	95.254	United States	91.724
Denmark	93.984	Denmark	89.865	Netherlands	93.811	Netherlands	88.617	France	93.802	France	88.975	Netherlands	94.325	Netherlands	90.278	Canada	94.371	Canada	89.730
Netherlands	93.119	Netherlands	88.617	Germany	93.487	Germany	88.327	Netherlands	93.724	Netherlands	88.968	France	94.308	France	90.087	United Kingdom	92.982	Netherlands	89.266
Germany	92.742	Germany	88.327	United Kingdom	93.464	United Kingdom	88.101	Germany	93.224	Germany	88.327	Denmark	94.077	Denmark	89.346	Netherlands	92.201	France	89.049
United Kingdom	92.742	United Kingdom	88.101	Sweden	90.934	Denmark	85.925	Austria	93.126	United Kingdom	87.720	Austria	93.900	Austria	89.282	France	92.163	Austria	88.264
Spain	91.287	Spain	86.130	Denmark	90.800	France	85.386	United Kingdom	92.532	Austria	87.588	Sweden	93.559	Sweden	89.228	Sweden	91.823	Sweden	88.214
France	90.574	France	85.386	France	90.409	Sweden	84.707	Sweden	91.399	Denmark	85.925	United Kingdom	92.736	United Kingdom	87.091	Austria	91.780	United Kingdom	87.038
Sweden	90.059	Sweden	84.707	Austria	89.710	Austria	83.999	Denmark	91.024	Sweden	85.034	Germany	92.279	Germany	86.488	Switzerland	91.388	Denmark	86.080
Austria	89.227	Austria	83.969	Switzerland	89.185	Spain	82.541	Switzerland	88.969	Spain	82.541	Argentina	91.116	Canada	86.169	Germany	90.217	Germany	85.463
Italy	87.261	Italy	80.567	Spain	88.571	Italy	80.555	Spain	88.736	Italy	80.639	Switzerland	91.039	Argentina	84.574	Argentina	89.617	Switzerland	84.446
Czech Republic	86.115	Hungary	78.584	Italy	87.306	Switzerland	80.025	Italy	88.303	Switzerland	80.025	Poland	88.364	Switzerland	84.446	Denmark	89.437	Italy	83.988
Canada	85.600	Czech Republic	77.565	Czech Republic	86.890	Hungary	78.966	Canada	87.085	Hungary	78.966	Canada	86.344	Spain	82.601	Poland	87.689	Argentina	83.887
Hungary	85.142	Canada	74.504	Canada	86.581	Czech Republic	77.915	Hungary	86.410	Canada	78.042	Czech Republic	86.257	Poland	81.870	Italy	86.401	Spain	81.946
Japan	84.049	Japan	73.963	Hungary	86.262	Canada	77.693	Argentina	86.259	Czech Republic	77.915	Russia	85.465	Italy	81.465	Japan	85.918	Poland	81.812
Russia	80.252	Switzerland	73.245	Japan	85.559	Argentina	74.465	Japan	85.419	Russia	75.852	Japan	85.276	Czech Republic	78.876	Russia	84.636	Russia	77.742
Slovakia	79.656	Singapore	71.735	Argentina	85.111	Japan	73.960	Czech Republic	85.300	Argentina	74.811	Spain	84.073	Russia	77.486	Spain	82.002	Czech Republic	77.215
Argentina	78.600	Russia	71.719	Slovakia	83.446	Slovakia	72.116	Russia	83.649	Japan	73.958	Italy	82.058	Singapore	74.870	Czech Republic	80.769	Japan	74.135
Poland	78.282	Argentina	69.739	Poland	82.683	Russia	71.722	Poland	82.899	Slovakia	72.477	Slovakia	79.650	Japan	73.886	Singapore	77.879	Singapore	73.564
Singapore	76.307	Slovakia	68.483	Russia	80.184	Poland	71.489	Slovakia	82.077	Poland	71.882	Singapore	79.503	Hungary	72.015	Ukraine	76.607	Hungary	70.983
Switzerland	76.003	Poland	67.871	Singapore	75.107	Singapore	68.321	Singapore	74.231	Singapore	68.496	Hungary	78.299	Slovakia	66.543	Hungary	76.249	Ukraine	66.205
Peru	73.208	Ukraine	65.635	Peru	74.649	Ukraine	66.395	Peru	71.807	Ukraine	65.659	Ecuador	75.408	Ukraine	62.339	Slovakia	74.727	Slovakia	65.602
Ecuador	72.584	Tunisia	60.155	Ukraine	71.214	Tunisia	60.585	Ukraine	70.155	Tunisia	59.199	Ukraine	67.519	Tunisia	61.348	Ecuador	73.272	Tunisia	60.308
Ukraine	69.302	Peru	59.649	Ecuador	68.924	Peru	59.716	Honduras	68.282	Peru	58.005	El Salvador	66.276	Ecuador	59.403	Peru	70.125	Ecuador	57.719
El Salvador	67.016	Ecuador	58.546	Tunisia	67.588	Ecuador	58.655	Ecuador	66.473	Ecuador	56.609	Peru	65.040	Algeria	56.337	Tunisia	62.306	Peru	56.226
Tunisia	65.941	El Salvador	54.270	Honduras	66.582	Algeria	54.565	Tunisia	65.807	Algeria	55.650	Tunisia	64.193	El Salvador	54.843	El Salvador	57.432	Algeria	53.047
Guatemala	64.262	Algeria	53.824	Indonesia	65.357	Azerbaijan	52.685	Azerbaijan	65.292	Azerbaijan	53.092	Algeria	61.242	Peru	53.949	Algeria	56.959	El Salvador	49.767
Honduras	62.329	Honduras	53.569	Guatemala	64.612	Honduras	52.260	Algeria	65.264	Honduras	52.697	Ghana	61.056	Azerbaijan	53.580	Ghana	56.034	Azerbaijan	48.179
Azerbaijan	62.224	Azerbaijan	52.634	Azerbaijan	63.973	El Salvador	51.585	Guatemala	63.564	El Salvador	51.725	Azerbaijan	60.663	Ghana	49.995	Honduras	54.416	Honduras	47.260
Indonesia	61.655	Guatemala	50.334	El Salvador	62.911	Guatemala	49.178	El Salvador	63.221	Ghana	49.169	Guatemala	59.679	Guatemala	48.050	Guatemala	53.998	Ghana	46.749
Algeria	59.967	Senegal	47.064	Algeria	62.681	Ghana	48.543	Indonesia	62.794	Guatemala	48.346	Honduras	57.796	Honduras	47.320	Indonesia	53.827	Botswana	46.083
Ghana	50.883	Ghana	44.576	Ghana	58.023	Botswana	44.265	Ghana	60.353	Botswana	48.080	Indonesia	57.586	Botswana	47.242	Azerbaijan	52.456	Senegal	45.213
Botswana	46.030	Indonesia	43.747	Nepal	51.107	Indonesia	43.811	Bangladesh	54.999	Senegal	43.473	Bangladesh	55.335	Senegal	45.624	Bangladesh	51.334	Guatemala	44.720
Senegal	45.242	Botswana	41.941	Botswana	45.917	Senegal	43.737	Nepal	52.001	Kenya	43.311	Kenya	53.075	Kenya	45.345	Nepal	49.377	Sudan	40.131
Nepal	42.416	Uganda	41.606	Kenya	44.436	Uganda	41.801	Botswana	49.705	Indonesia	40.300	Nepal	50.185	Sudan	40.421	Nigeria	47.147	Kenya	40.105
Kenya	42.378	Kenya	40.789	Uganda	44.235	Kenya	40.138	Kenya	49.513	Nepal	39.628	Botswana	46.955	Indonesia	39.655	Botswana	45.729	Nepal	37.743
Uganda	39.132	Sudan	39.986	Senegal	41.489	Nepal	39.655	Cambodia	44.541	Uganda	38.614	Cambodia	46.885	Nepal	38.060	Senegal	45.155	Indonesia	37.076
Sudan	35.693	Nepal	35.397	Nigeria	41.250	Sudan	39.329	Senegal	42.578	Sudan	38.476	Senegal	46.102	Cambodia	34.789	Kenya	45.099	Nigeria	34.682
Nigeria	34.655	Burkina Faso	32.020	Bangladesh	39.600	Nigeria	32.336	Nigeria	40.694	Cambodia	32.856	Sudan	39.945	Bangladesh	32.158	Cambodia	43.774	Cambodia	31.852
Bangladesh	32.863	Nigeria	30.915	Sudan	39.287	Burkina Faso	31.906	Sudan	40.582	Bangladesh	32.089	Nigeria	36.829	Uganda	31.796	Sudan	41.142	Uganda	31.204
Zambia	31.020	Guinea	28.533	Cambodia	35.967	Guinea	28.046	Uganda	37.320	Burkina Faso	31.663	Ethiopia	33.445	Burkina Faso	31.782	Ethiopia	33.214	Burkina Faso	30.861
Cambodia	30.273	Cambodia	26.971	Zambia	35.404	Cambodia	27.748	Ethiopia	34.684	Nigeria	31.263	Guinea	31.553	Nigeria	30.773	Guinea	29.932	Bangladesh	28.631
Ethiopia	29.027	Zambia	25.874	Ethiopia	32.780	Zambia	26.426	Guinea	33.672	Guinea	28.052	Burkina Faso	29.160	Guinea	29.097	Burkina Faso	28.307	Guinea	27.605
Guinea	27.788	Malawi	25.836	Guinea	31.863	Ethiopia	25.757	Burkina Faso	33.036	Ethiopia	25.885	Uganda	27.325	Ethiopia	26.246	Uganda	26.839	Ethiopia	26.288
Burkina Faso	27.274	Bangladesh	23.635	Burkina Faso	31.640	Bangladesh	24.712	Zambia	29.973	Zambia	23.415	Zambia	25.370	Malawi	23.948	Malawi	22.508	Malawi	21.755
Malawi	21.708	Ethiopia	23.097	Malawi	21.052	Malawi	22.665	Malawi	22.124	Malawi	22.698	Malawi	24.717	Zambia	21.871	Zambia	20.436	Zambia	17.760

Appendix B: Input data on XLSTAT for VIP results, a sample of the year 2015

Countries	Y value	Dietary diversity	National dietary guidelines	National nutrition plan or strategy	Nutrition labeling	Nutrition monitoring and surveillance	Dietary availability of vitamin A	Dietary availability of iron	Dietary availability of zinc	Protein quality	Food safety mechanisms	Access to drinking water	Ability to store food safely
Algeria	13	43.10345	0	100	0	100	100	63.265857	15.558699	40.4535	53	88.7367	98.9011
Argentina	5.8	77.58621	0	100	100	100	100	42.672065	71.145686	47.494	60	98.0213	99.34066
Austria	1.1	93.10345	0	100	100	100	100	46.153846	68.175389	85.6802	93	100	100
Azerbaijan	0	31.03448	0	100	0	100	100	64.804318	18.953324	37.1122	93	80.6697	100
Bangladesh	13.3	0	0	100	0	100	0	14.682861	1.5558699	9.18854	73	94.6728	57.69231
Botswana	19.6	55.17241	0	0	0	0	100	44.642375	27.015559	27.685	33	76.1035	53.73626
Burkina Faso	10	25.86207	0	100	0	100	50	54.709852	55.586987	10.6205	33	24.5053	7.032967
Cambodia	16.9	15.51724	0	100	0	100	0	14.62888	11.881188	21.7184	67	52.968	50.43956
Canada	0.6	89.65517	0	0	100	100	100	48.421053	73.408769	58.2339	100	98.9346	100
Czech Republic	0.7	84.48276	100	100	100	0	100	39.487179	35.643564	78.5203	100	99.8478	100
Denmark	1	89.65517	100	100	100	100	100	44.993252	76.944837	94.0334	100	100	100
Ecuador	6	75.86207	0	0	100	100	100	17.300945	5.2333805	47.494	80	85.0837	97.8022
El Salvador	13.8	55.17241	0	100	100	100	50	37.597841	33.380481	31.5036	93	86.4536	94.50549
Ethiopia	14.5	6.896552	0	0	100	100	50	38.05668	57.2843	5.60859	0	0	29.89011
France	1.6	86.2069	0	100	100	100	100	43.724696	69.306931	96.42	100	100	100
Germany	1	89.65517	100	100	100	100	100	37.327935	56.435644	97.6134	100	100	100
Ghana	7.6	29.31034	0	100	0	100	100	54.709852	47.241867	15.3938	67	62.5571	67.8022
Guatemala	16.1	56.89655	0	100	100	100	50	32.65857	18.953324	20.0477	100	86.758	86.7033
Guinea	44.3	31.03448	0	100	0	100	50	22.132254	19.377652	8.47255	27	43.5312	24.61538
Honduras	14.2	58.62069	100	100	100	100	50	32.361673	18.387553	29.5943	47	87.0624	85.93407
Hungary	1.4	86.2069	0	100	100	100	100	38.245614	9.0523338	92.8401	93	100	100
Indonesia	0.7	18.96552	100	100	100	100	50	20.431849	7.4964639	19.3317	100	77.3212	96.15385
Italy	1.2	81.03448	0	100	100	100	100	52.145749	68.882603	79.7136	92	99.3912	100
Japan	0	67.24138	100	100	100	100	100	36.167341	16.973126	71.3604	100	98.1735	100
Kenya	17.3	39.65517	0	100	0	100	100	31.848853	27.58133	19.9284	73	31.5068	33.95604
Malawi	51.8	15.51724	100	100	0	100	0	35.438596	28.571429	6.32458	40	44.14	0
Nepal	10.4	20.68966	0	100	0	100	50	37.408907	34.653465	10.9785	47	78.5388	75.38462
Netherlands	1.5	91.37931	100	100	100	100	100	35.465587	67.609618	94.0334	100	100	100
Nigeria	6.6	24.13793	0	100	0	100	50	40.350877	23.762376	5.48926	53	43.9878	51.20879
Norway	1.1	86.2069	100	100	100	100	100	73.279352	67.18529	100	100	100	100
Peru	13.5	43.10345	0	100	100	100	100	31.524966	23.479491	52.864	100	81.4307	91.31868
Poland	1.8	68.96552	0	100	100	100	100	44.939271	53.465347	49.8807	73	96.4992	100
Russia	0.7	68.96552	0	100	100	0	100	50.337382	47.949081	80.3103	80	94.3683	100
Senegal	14.5	32.75862	0	100	0	100	50	100	100	15.6325	40	59.3607	52.74725
Singapore	1	62.93103	100	100	0	100	100	52.982456	61.386139	56.6826	100	100	100
Slovakia	1.1	74.13793	0	100	100	0	100	40.539811	4.8090523	75.2983	100	98.4779	100
Spain	1.1	89.65517	100	100	100	100	100	38.920378	42.291372	92.8401	100	100	100
Sudan	13.4	70.68966	0	100	0	100	50	0	25.318246	27.685	40	28.9193	37.69231
Sweden	0.8	91.37931	100	100	100	100	100	41.862348	73.550212	76.1337	87	100	100
Switzerland	1.5	100	0	100	0	100	100	33.765182	44.130127	59.4272	100	100	100
Tunisia	9.1	50	0	100	0	100	100	71.22807	21.499293	49.642	80	89.6499	99.67033
Uganda	17.5	62.06897	100	100	0	100	100	26.261808	0	9.42721	87	9.74125	5.384615
Ukraine	2	67.24138	0	100	0	0	100	43.724696	32.248939	77.2076	85	91.7808	100
United Kingdom	1.9	84.48276	100	100	100	100	100	47.82726	62.376238	95.2267	100	100	100
United States	1.1	96.55172	100	100	100	100	100	37.408907	72.984441	100	100	98.7823	100
Zambia	21.8	15.51724	0	100	0	100	50	25.263158	9.1937765	0	100	33.6377	20.98901

Appendix C: A sample of the results generated after applying VIP weights for the year 2015

Variable	VIP(1)	Standard deviation	Lower bound(95 %)	Upper bound(95 %)
Ability to store food safely	1.544	0.164	1.213	1.875
Protein quality	1.347	0.109	1.129	1.566
Dietary availability of vitamin A	1.271	0.280	0.707	1.836
Access to drinking water	1.231	0.112	1.006	1.456
Food safety mechanisms	1.194	0.199	0.792	1.596
Dietary diversity	1.183	0.107	0.967	1.399
Nutrition labeling	0.982	0.131	0.718	1.246
Dietary availability of zinc	0.689	0.185	0.317	1.061
Dietary availability of iron	0.499	0.193	0.110	0.888
National dietary guidelines	0.293	0.444	-0.602	1.188
Nutrition monitoring and surveillance	0.248	0.226	-0.207	0.703
National nutrition plan or strategy	0.091	0.190	-0.292	0.473